

Math Review Notes

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Chapter 1

Introduction

These are notes I've collected on various math topics. I originally created this document to prepare for the GRE Math Subject test. Since then I've expanded it as I've reviewed concepts from past classes and reinforced concepts from new classes. This document is very much a work in progress, with many typos, omissions to be filled in, and probably errors. Nonetheless, I share this document in case it's useful to anyone else as a reference.

I use many sources throughout this document, which I either cite at the beginning of the section (for sources I use broadly) or as I use them (for sources I use for one or two isolated results).

Chapter 2

Linear Algebra

These are my notes from taking EE 588 at USC, Math 541A at USC, and various other sources which I mostly cite within the text. (For more notes on linear algebra, see Section 5.7.1.)

2.1 Properties of Projection Matrices

- i. Formula:

$$P = A(A^T A)^{-1} A^T$$

(Note that if A is an invertible (square) matrix, then $P = A(A^T A)^{-1} A^T = AA^{-1}(A^T)^{-1} A^T = I$.)

The projection matrix projects any vector b into the column space of A . In other words, $p = Pb$ is the component of b in the column space, and the error $e = b - Pb$ is the component in the orthogonal complement. ($I - P$ is also a projection matrix. It projects b onto the orthogonal complement, and the projection is $b - Pb = e$).

(Note that if A is an invertible (square) matrix, then its column space is all of \mathbb{R}^n , so b is already in the column space of A .)

- ii. The projection matrix is **idempotent**: it equals its square— $P^2 = P$.
- iii. The projection matrix is **symmetric**: it equals its transpose— $P^T = P$.
- iv. Conversely, **any symmetric idempotent matrix represents a projection.** P is unique for a given subspace.
- v. If A is an $m \times n$ matrix with rank n , then $\text{rank}(P) = n$. The eigenvalues of P consist of n ones and $m - n$ zeroes. P always contains n independent eigenvectors and is thus diagonalizable.

Suppose A is a square nonsingular matrix and λ is an eigenvalue of A . Then λ^{-1} is an eigenvalue of the matrix A^{-1} .

Proposition 2.1.1. The eigenvalues of an idempotent matrix equal either 0 or 1.

Proof. Let A be an idempotent matrix and let v be a unit-length eigenvector of H with corresponding eigenvalue λ . Then

$$Av = \lambda v \implies A(Av) = A(\lambda v).$$

Then

$$AAv = Av = \lambda v$$

and

$$\lambda Av = \lambda^2 v$$

so we have

$$\lambda v = \lambda^2 v \implies \lambda \in \{0, 1\}.$$

□

The trace of an idempotent matrix with rank r is r .

Theorem 2.1.2 (Math 425b Homework Problem). Let $(V, \langle \cdot, \cdot \rangle)$ be a real or complex vector space. Let W be a finite-dimensional subspace of V with an orthonormal basis $\{w_1, \dots, w_n\}$. For $v \in V$, define the orthogonal projection of v onto W to be

$$\text{proj}_W(v) := \sum_{i=1}^n \langle w_i, v \rangle w_i.$$

Then $\text{proj}_W(v) \in W$ and $v - \text{proj}_W(v) \in W^\perp$, where W^\perp is the orthogonal complement of W . Further, these properties characterize $\text{proj}_W(v)$ uniquely; i.e., if $v = v_1 + v_2 = v - v_1' + v_2'$ with $v_1, v_1' \in W$ and $v_2, v_2' \in W^\perp$ then $v_1 = v_1'$ and $v_2 = v_2'$.

Proof. Since $\{w_1, \dots, w_n\}$ is a basis for W , it holds that $\text{proj}_W(v) \in W$ if and only if for some $(c_1, \dots, c_n) \in \mathbb{R}^n$ it holds that $\text{proj}_W(v) = \sum_{i=1}^n c_i w_i$. But

$$\text{proj}_W(v) = \sum_{i=1}^n \langle w_i, v \rangle w_i$$

so this follows from $c_i := \langle w_i, v \rangle, i \in [n]$. Next we will show that $v - \text{proj}_W(v) \in W^\perp$. This is true if and only if $\langle w, v - \text{proj}_W(v) \rangle = 0$ for all $w \in W$. Let $w \in W$ be expressed as $\sum_{j=1}^n c_j w_j$ for some $(c_1, \dots, c_n) \in \mathbb{R}^n$. Note that since $\{w_1, \dots, w_n\}$ is an orthonormal basis, $\langle w_j, w_i \rangle = \delta_{j,i}$. Then

$$\begin{aligned}
\langle w, v - \text{proj}_W(v) \rangle &= \langle w, v \rangle - \langle w, \text{proj}_W(v) \rangle \\
&= \left\langle \sum_{j=1}^n c_j w_j, v \right\rangle - \left\langle \sum_{j=1}^n c_j w_j, \sum_{i=1}^n \langle w_i, v \rangle w_i \cdot \right\rangle \\
&= \sum_{j=1}^n c_j \langle w_j, v \rangle - \sum_{j=1}^n c_j \left\langle w_j, \sum_{i=1}^n \langle w_i, v \rangle w_i \cdot \right\rangle \\
&= \sum_{j=1}^n c_j \langle w_j, v \rangle - \sum_{j=1}^n \sum_{i=1}^n c_j \langle w_i, v \rangle \langle w_j, w_i \cdot \rangle \\
&= \sum_{j=1}^n c_j \langle w_j, v \rangle - \sum_{j=1}^n \sum_{i=1}^n c_j \langle w_i, v \rangle \delta_{j,i} \\
&= \sum_{j=1}^n c_j \langle w_j, v \rangle - \sum_{j=1}^n c_j \langle w_j, v \rangle \\
&= 0,
\end{aligned}$$

where we used elementary properties of inner products. Lastly, we will show that these properties characterize $\text{proj}_W(v)$ uniquely. Let $v_1, v'_1 \in W$ and $v_2, v'_2 \in W^\perp$. In particular, let $v_1 = \sum_{i=1}^n c_i w_i$ and $v'_1 = \sum_{i=1}^n c'_i w_i$, and note that $\langle w_j, v_2 \rangle = \langle w_j, v'_2 \rangle = 0$ for all $j \in [n]$. Suppose $v_1 + v_2 = v'_1 + v'_2$. Then for all $j \in [n]$,

$$\begin{aligned}
0 &= v_1 + v_2 - (v'_1 + v'_2) = \sum_{i=1}^n (c_i - c'_i) w_i + v_2 - v'_2 \\
\implies \langle w_j, 0 \rangle &= \left\langle w_j, \sum_{i=1}^n (c_i - c'_i) w_i + v_2 - v'_2 \right\rangle = \sum_{i=1}^n \langle w_j, (c_i - c'_i) w_i \rangle + \langle w_j, v_2 \rangle - \langle w_j, v'_2 \rangle \\
\implies 0 &= c_j - c'_j,
\end{aligned} \tag{2.1}$$

so $v_1 = v'_1$. Then from (2.1) we have

$$0 = v_2 - v'_2 \iff v_2 = v'_2.$$

□

Theorem 2.1.3 (Math 425b Homework Problem). Let $(V, \langle \cdot, \cdot \rangle)$ be a real or complex vector space. Let W be a finite-dimensional subspace of V with an orthonormal basis $\{w_1, \dots, w_n\}$. For $v \in V$, define the orthogonal projection of v onto W to be

$$\text{proj}_W(v) := \sum_{i=1}^n \langle w_i, v \rangle w_i.$$

Then $\text{proj}_W(v)$ is the closest element of W to v (in L_2 norm). That is, for any $w \in W$ we have $\|v - \text{proj}_W(v)\|_2 \leq \|v - w\|_2$.

Proof. For any $w \in W$,

$$\begin{aligned} v - w &= v - \text{proj}_W(v) + \text{proj}_W(v) - w \\ \implies \|v - w\|_2^2 &= \|v - \text{proj}_W(v)\|_2^2 + \|\text{proj}_W(v) - w\|_2^2 + 2\|(v - \text{proj}_W(v))(\text{proj}_W(v) - w)\|_2^2 \\ \implies \|v - w\|_2^2 &\geq \|v - \text{proj}_W(v)\|_2^2 \\ \iff \|v - w\|_2 &\geq \|v - \text{proj}_W(v)\|_2. \end{aligned}$$

□

2.2 Eigenvalues, Eigenvectors, Diagonalization, Symmetric Matrices

Notes on Diagonalization

Suppose the $n \times n$ matrix A has n linearly independent eigenvectors. If these eigenvectors are the columns of a matrix S , then $S^{-1}AS$ is a diagonal matrix Λ . The eigenvalues of A are on the diagonal of Λ :

$$S^{-1}AS = \Lambda = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix}$$

We call S the **eigenvector matrix** and Λ the **eigenvalue matrix**.

1. If the matrix A has no repeated eigenvalues, then its n eigenvectors are automatically independent. Therefore **any matrix with n distinct eigenvalues can be diagonalized**.
2. **The diagonalizing matrix S is not unique.** An eigenvector x can be multiplied by a constant and remains an eigenvector. We can multiply the columns of S by any nonzero constants and produce a new diagonalizing S . Repeated eigenvalues leave even more freedom in S (columns with identical eigenvalues can be interchanged).

(Note that for the trivial example $A = I$, any invertible S will do. $S^{-1}IS$ is always diagonal, and Λ is just I . **All vectors are eigenvectors of the identity.**)

3. **Other matrices S will not produce a diagonal Λ .** Since $\Lambda = S^{-1}AS$, S must satisfy $S\Lambda = AS$. Suppose the first column of S is y . Then the first column of $S\Lambda$ is λ_1y . If this is to agree with the first column of AS , which by matrix multiplication is Ay , then y must be an eigenvector: $Ay = \lambda_1y$. (Note that the *order* of the eigenvectors in S and the eigenvalues in Λ must match.)
4. Not all matrices possess n linearly independent eigenvectors, so **not all matrices are diagonalizable**. **Diagonalizability of A depends on having enough (n) independent eigenvectors. Invertibility of A depends on having nonzero eigenvalues.**

There is no connection between diagonalizability (n independent eigenvectors) and invertibility (no zero eigenvalues). The only indication given by the eigenvalues is that diagonalization can fail only if there are repeated eigenvalues. (But even then, it does not always fail—e.g. I .)

The test is to check, for an eigenvalue that is repeated p times, whether there are p independent eigenvectors—in other words, whether $A - \lambda$ has rank $n - p$.

5. **Projection matrices always contain n independent eigenvectors and thus are always diagonalizable.**

Eigenvalues of Symmetric Matrices: If A is symmetric, then it has the following properties:

1. A has exactly n (not necessarily distinct) eigenvalues
2. There exists a set of n eigenvectors, one for each eigenvalue, that are mutually orthogonal (even if the eigenvalues are not distinct).

Eigenvalues of the Inverse of a Matrix: Suppose A is a square nonsingular matrix and λ is an eigenvalue of A . Then λ^{-1} is an eigenvalue of the matrix A^{-1} . Proof: Note that since A is nonsingular, A^{-1} exists and λ is nonnegative for all eigenvalues of A . Let λ be an eigenvalue of A and let $x \neq 0$ be an eigenvector of A for λ . Suppose A is n by n . Then we have

$$A^{-1}x = A^{-1}\lambda^{-1}\lambda x = \lambda^{-1}A^{-1}\lambda x = \lambda^{-1}A^{-1}Ax = \lambda^{-1}x$$

The inverse of a symmetric matrix is symmetric. Proof: Let A be a symmetric matrix.

$$I = I'$$

$$AA^{-1} = (AA^{-1})'$$

$$A^{-1}A = (A^{-1})'A'$$

$$A^{-1}AA^{-1} = (A^{-1})'AA^{-1}$$

$$A^{-1} = (A^{-1})'$$

2.3 Positive Definite Matrices

Proposition 2.3.1. For any real matrix $A \in \mathbb{R}^{m \times n}$ with $m \geq n$, the product $A^T A$ is a positive semidefinite matrix.

Proof. Let z be a non-zero vector. $A^T A$ is positive semidefinite if and only if $z^T A^T A z \geq 0 \forall z \in \{\mathbb{R}^n \setminus \{0\}\}$. Note that $z^T A^T A z = (Az)^T (Az) = \|Az\|_2^2 \geq 0$.

□

Proposition 2.3.2. For any real invertible matrix $A \in \mathbb{R}^{n \times n}$, the product $A^T A$ is a positive definite matrix.

Proof. Let z be a non-zero vector. $A^T A$ is positive definite if and only if $z^T A^T A z > 0 \forall z \in \{\mathbb{R}^n \setminus \{0\}\}$. Note that $z^T A^T A z = (Az)'(Az)$. Because A is invertible and $z \neq 0$, $Az \neq 0$, so $(Az)'(Az) = \|Az\|_2^2 > 0$. □

Proposition 2.3.3 (Math 547 Homework Problem). Let A be an $m \times n$ real matrix with $m \geq n$. Then A has rank n if and only if $A^T A$ is positive definite.

Proof. By Proposition 2.3.1, $A^T A$ is positive semidefinite. Since $A^T A$ is not invertible if one of its eigenvalues equals 0, $A^T A$ is invertible (and therefore full rank) if and only if it is positive definite. But $A^T A \in \mathbb{R}^{n \times n}$ is full rank if and only if the columns of A are linearly independent, for the following reason: multiplying $A^T A$ means taking linear combinations of the rows of A^T (that is, the columns of A) one at a time, with weightings according to the columns of A . These linear combinations will themselves be linearly independent if and only if the rows of A^T (the columns of A) are linearly independent and for the basis of an n -dimensional subspace. And $A^T A$ has linearly independent columns if and only if it is invertible.

So we have shown that $A^T A$ is positive definite if and only if the columns of A are linearly independent. That itself is true if and only if A has rank n . Therefore A has rank n if and only if $A^T A$ is positive definite.

□

Every positive definite matrix is invertible and its inverse is also positive definite.

2.4 Matrix Decompositions

Schur complement, Schur decomposition:

Proposition 2.4.1 (Schur complement formula).

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} (A - BD^{-1}C)^{-1} & -(A - BD^{-1}C)^{-1}BD^{-1} \\ -D^{-1}C(A - BD^{-1}C)^{-1} & D^{-1} + D^{-1}C(A - BD^{-1}C)^{-1}BD^{-1} \end{bmatrix}$$

For information, see Section 9.2.

QR decompositon

Orthogonal Decomposition

Spectral Decomposition (eigenvalue decomposition)

Generalized eigenvalue decomposition

Jordan decomposition

Cholesky decomposition

Theorem 2.4.2 (Proof of existence of Cholesky decomposition (Math 547 exercise)). Let M be a $k \times k$ real symmetric matrix. Then M is positive semidefinite if and only if there exists a real $k \times k$ matrix R such that

$$M = RR^T.$$

In either case, if $r^{(i)}$ denotes the i^{th} row of R , we have

$$m_{ij} = \langle r^{(i)}, r^{(j)} \rangle, \quad \forall 1 \leq i, j \leq k.$$

Proof. By the Spectral Theorem, we can write $M = V\Lambda V^T$ where $V \in \mathbb{R}^{k \times k}$ is orthogonal and Λ is diagonal, with the diagonal entries equal to the eigenvalues of M ; that is,

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix}.$$

Since M is real symmetric, M is positive semidefinite if and only if its eigenvalues are nonnegative; that is, M is positive semidefinite if and only if the diagonal entries of Λ are nonnegative. This is true if and only if we can take the square root

$$\Lambda^{1/2} = \begin{bmatrix} \sqrt{\lambda_1} & 0 & \dots & 0 \\ 0 & \sqrt{\lambda_2} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sqrt{\lambda_n} \end{bmatrix}$$

and write

$$M = V\Lambda^{1/2}\Lambda^{1/2}V^T = V\Lambda^{1/2} \left(V\Lambda^{1/2}\right)^T.$$

Let $R := V\Lambda^{1/2}$ to complete the proof. □

2.4.1 Singular value decomposition and Pseudo-inverse

Suppose $X \in \mathbb{R}^{n \times p}$ with $\text{rank}(X) = r \leq \min\{n, p\}$. Note that $X^T X$ is positive semi-definite by Proposition 2.3.1. Therefore by the Spectral Decomposition Theorem, we can find a factorization

$$X^T X = V D V^T \tag{2.2}$$

where the columns of V are orthonormal eigenvectors of $X^T X$ and D is a diagonal matrix containing the eigenvalues of $X^T X$ on the diagonal. Since these eigenvalues are nonnegative, let $D = \Sigma^2$ for the positive semi-definite diagonal matrix $\Sigma := D^{1/2}$. Note that $\text{rank}(X^T X) = r \leq p$, so D contains r nonzero entries.

If $r < p$ then $X^T X$ will only have $r < p$ eigenvectors, so r columns of V will form an orthonormal basis for the r -dimensional column space of $X^T X$. But then there exist $p - r$ vectors that are orthogonal to each other and the first r vectors of V , such that if these vectors form the last $p - r$ columns of V , then V is still orthogonal and its columns still span \mathbb{R}^p . Further, the factorization (2.2) still holds since in this case these columns will be multiplied by the 0 entries in D anyway. Lastly, since these vectors are orthogonal to a basis for the column space of $X^T X$, these vectors lie in the null space of $X^T X$. That is, for any one of these columns v_j ,

$$X^T X v_j = 0_{p \times 1} \implies v_j^T X^T X v_j = 0 \iff (X v_j)^T X v_j = 0 \iff X v_j = 0_{p \times 1}$$

so v_j also lies in the nullspace of X . Next, consider the matrix $XV \in \mathbb{R}^{n \times p}$. We know that

$$\left(\underbrace{\begin{matrix} X \\ V \end{matrix}}_{n \times p \quad p \times p} \right)^T \underbrace{\begin{matrix} X \\ V \end{matrix}}_{n \times p \quad p \times p} = \underbrace{V^T}_{p \times p} \underbrace{\begin{matrix} X^T \\ X \end{matrix}}_{p \times n} \underbrace{\begin{matrix} X \\ V \end{matrix}}_{n \times p \quad p \times p} = V^T V D V^T V = V^T V \Sigma^2 V^T V = \Sigma^2. \quad (2.3)$$

Let $\tilde{D}^{1/2} \in \mathbb{R}^{r \times r}$ be a diagonal matrix containing the r nonzero entries of Σ so that we can write

$$\Sigma = \begin{bmatrix} \tilde{D}^{1/2} & 0_{r \times (p-r)} \\ 0_{(p-r) \times r} & 0_{(p-r) \times (p-r)} \end{bmatrix}$$

Then if we define

$$\tilde{\Sigma} := \begin{bmatrix} \tilde{D}^{-1/2} & 0_{r \times (p-r)} \\ 0_{(p-r) \times r} & 0_{(p-r) \times (p-r)} \end{bmatrix}$$

we have

$$(XV\tilde{\Sigma})^T XV\tilde{\Sigma} = \tilde{\Sigma} V^T X^T XV\tilde{\Sigma} = \tilde{\Sigma} V^T V \Sigma^2 V^T V \tilde{\Sigma} = \tilde{\Sigma} \Sigma^2 \tilde{\Sigma} = \begin{bmatrix} I_{r \times r} & 0_{r \times (p-r)} \\ 0_{(p-r) \times r} & 0_{(p-r) \times (p-r)} \end{bmatrix} \quad (2.4)$$

since

$$\tilde{\Sigma} \Sigma = \begin{bmatrix} \tilde{D}^{-1/2} & 0_{r \times (p-r)} \\ 0_{(p-r) \times r} & 0_{(p-r) \times (p-r)} \end{bmatrix} \begin{bmatrix} \tilde{D}^{1/2} & 0_{r \times (p-r)} \\ 0_{(p-r) \times r} & 0_{(p-r) \times (p-r)} \end{bmatrix} = \begin{bmatrix} I_{r \times r} & 0_{r \times (p-r)} \\ 0_{(p-r) \times r} & 0_{(p-r) \times (p-r)} \end{bmatrix} = \Sigma \tilde{\Sigma}.$$

That is, $XV\tilde{\Sigma} \in \mathbb{R}^{n \times p}$ contains r orthogonal columns. By (2.3), the $p - r$ remaining columns of XV equal 0. Let $U := XV\tilde{\Sigma}$. Then we have

$$U\Sigma = XV\tilde{\Sigma}\Sigma = XV \begin{bmatrix} I_{r \times r} & 0_{r \times (p-r)} \\ 0_{(p-r) \times r} & 0_{(p-r) \times (p-r)} \end{bmatrix} = XV \quad (2.5)$$

where the last step follows because the last $p - r$ columns of V lie in the nullspace of X , so they already equaled 0 anyway. Finally, multiply both sides of (2.5) by V^T on the right to obtain the **singular value decomposition**

$$X = U\Sigma V^T.$$

Now let's examine the properties of this decomposition. We argued earlier that the last $p - r$ columns of V lie in the nullspace of X . It follows that since the first r columns of V are orthonormal and orthogonal to the nullspace of X , the first r columns of V are orthonormal basis vectors for the row space of X .

Next, we have already shown that $U = XV\tilde{\Sigma}$ contains r orthogonal columns, and of course these columns lie in the column space of X . Therefore the first r columns of U form an orthonormal basis for the column space of X .

Now identity (2.5) yields a useful way of thinking about the singular value decomposition. V is a special orthonormal basis for the rowspace of X (perhaps with some extra orthogonal vectors spanning the nullspace of X if X does not have full column rank) with the property that when they are linearly transformed by X , $XV = U\Sigma$ forms r orthogonal vectors spanning the column space of X (plus $p - r$ 0 vectors if X doesn't have full column rank).

If we like, we can decompose $U\Sigma$ into unit vectors U and a diagonal vector Σ containing the lengths of the orthogonal vectors $U\Sigma$ on its diagonal. Then U is an orthonormal basis for the column space of X .

We call the diagonal entries of Σ the **singular values** of X : $\sigma_i \in \mathbb{R}, i \in \{1, \dots, r\}$.

The first r nonzero columns of $U\Sigma$ are called the **principal components** of X . The columns of $U \in \mathbb{R}^n$ are also called the **normalized principal components** of X . Sometimes we call the columns of $V \in \mathbb{R}^p$ the **principal component directions** of X , the **principal directions**, or the **principal axes**. Note that

$$X = U\Sigma V^T \implies U\Sigma = XV;$$

that is, the principal components $U\Sigma$ can be seen as the projections of X onto the principal axes.

Lastly, although we have already examined the properties of $X^T X$, consider the decomposition

$$XX^T = \hat{U}\hat{D}\hat{U}^T \tag{2.6}$$

for some positive semidefinite diagonal matrix $\hat{D} \in \mathbb{R}^{n \times n}$ and some orthonormal matrix $\hat{U} \in \mathbb{R}^{n \times n}$, which exists by the Spectral Theorem. Now consider expressing this in terms of the singular value decomposition:

$$XX^T = \underbrace{U}_{n \times p} \underbrace{\Sigma}_{p \times p} \underbrace{V^T}_{p \times p} (\underbrace{U}_{n \times p} \underbrace{\Sigma}_{p \times p} \underbrace{V^T}_{p \times p})^T = \underbrace{U}_{n \times p} \underbrace{\Sigma}_{p \times p} \underbrace{V^T}_{p \times p} \underbrace{V}_{p \times p} \underbrace{\Sigma}_{p \times p} \underbrace{U^T}_{p \times n} = \underbrace{U}_{n \times p} \underbrace{\Sigma^2}_{p \times p} \underbrace{U^T}_{p \times n}, \tag{2.7}$$

so we can form

$$\hat{U} = [U \quad u_{r+1} \quad \cdots \quad u_n]$$

(where u_{r+1}, \dots, u_n are orthonormal vectors completing an orthonormal basis for \mathbb{R}^n in the columns of \hat{U}) and

$$\hat{D} = \begin{bmatrix} \Sigma^2 & 0_{p \times (n-p)} \\ 0_{(n-p) \times p} & 0_{(n-p) \times (n-p)} \end{bmatrix}$$

to yield (2.6) from (2.7).

⋮

Math 547 explanation: Suppose $X \in \mathbb{R}^{n \times p}$. Since $X^T X \in \mathbb{R}^{p \times p}$, by the Spectral Theorem, there exists an orthogonal matrix $Q \in \mathbb{R}^{p \times p}$ and a real diagonal matrix $D \in \mathbb{R}^{p \times p}$ such that

$$X^T X = Q^T D Q.$$

The entries of D (the eigenvalues of $X^T X$) are nonnegative because if $v \in \mathbb{R}^p$ is an eigenvector of $X^T X$ with corresponding eigenvalue λ ,

$$\lambda \|v\|_2^2 = v^T (\lambda v) = v^T (X^T X v) = (Xv)^T (Xv) = \|Xv\|_2^2 \geq 0.$$

Similarly, $XX^T \in \mathbb{R}^{n \times n}$ and there exists an orthogonal $R \in \mathbb{R}^{n \times n}$ and a diagonal $G \in \mathbb{R}^{n \times n}$ such that

$$XX^T = R^T G R.$$

Since $D \succeq 0$, we can write

$$X = \underbrace{R^T}_{n \times n} \underbrace{\sqrt{D}}_{p \times p} \underbrace{Q}_{p \times p}$$

⋮

$$X = \underbrace{U}_{N \times p} \underbrace{D}_{p \times p} \underbrace{V^T}_{p \times p}$$

since

$$(R^T \sqrt{D} Q)^T R^T \sqrt{D} Q = Q^T \sqrt{D} R R^T \sqrt{D} Q = Q^T D Q = X^T X$$

and

$$R^T \sqrt{D} Q \left(R^T \sqrt{D} Q \right)^T = R^T \sqrt{D} Q Q^T \sqrt{D} R = R^T D R = \dots = R^T G R = X X^T.$$

Singular value decomposition of a vector

Suppose $X \in \mathbb{R}^{n \times 1}$, so $\text{rank}(X) = 1$. Suppose also $X \neq 0$. Then $X^T \in \mathbb{R}$, so $V \in \mathbb{R}$ and therefore $D \in \mathbb{R}$.

⋮

<https://math.stackexchange.com/questions/1181800/singular-value-decomposition-of-column-row-vectors>

2.4.2 Principal Components

Again, the p columns of $U\Sigma \in \mathbb{R}^n$ are the **principal components** of X . The first principal component direction $v_1 \in \mathbb{R}^p$ satisfies the condition $z_1 := Xv_1$ has the largest sample variance among all normalized linear combinations of the columns of X . That is, v_1 satisfies

$$v_1 = \arg \max_{v \in \mathbb{R}^p, \|v\|_2=1} \text{Var}(Xv) = \arg \max_{v \in \mathbb{R}^p, \|v\|_2=1} v^T (X^T X) v$$

Note that $z_1 = Xv_1 = \sigma_1 u_1$, so z_1 is the first principal component of X and u_1 is the normalized first principal component. The singular values are the

2.4.3 Low rank matrix approximation

Note that using the singular value decomposition we can express X as a sum of rank 1 matrices:

$$X = U\Sigma V^T = \sum_{i=1}^r \sigma_i u_i v_i^T$$

An intuitive “best” way to approximate X as a rank $k < r$ matrix is to take the first k of these terms:

$$X \approx X_k = \sum_{i=1}^k \sigma_i u_i v_i^T = U_k \Sigma_k V_k^T$$

where $U_k \in \mathbb{R}^{n \times k}$ contains only the first k columns of U (corresponding to the k largest singular values), $\Sigma_k \in \mathbb{R}^{k \times k}$ contains the $k \times k$ top-left submatrix of Σ , and $V_k \in \mathbb{R}^{p \times k}$ contains the first k columns of V . It turns out this is the best low-rank approximation of X in the sense that for any other rank- k matrix B of size $n \times p$,

$$\|X - X_k\|_F^2 \leq \|X - B\|_F^2.$$

2.5 Inverting Matrices

Theorem 2.5.1 (Woodbury Matrix Identity (or Sherman-Morrison-Woodbury formula)). For $A \in \mathbb{R}^{n \times n}$, $U \in \mathbb{R}^{n \times k}$, $C \in \mathbb{R}^{k \times k}$, and $V \in \mathbb{R}^{v \times n}$,

$$(A + UCV)^{-1} = A^{-1} - A^{-1}U(C^{-1} + VA^{-1}U)^{-1}VA^{-1}.$$

Theorem 2.5.2 (Binomial Inverse Thereom).

2.6 Other

Frobenius norm

From appendix of Time Series:

Quadratic forms

Special matrices

Difference Equations

2.7 Practice Problems

[The Power Method] This exercise gives an algorithm for finding the eigenvectors and eigenvalues of a symmetric matrix. In modern statistics, this is often a useful thing to do. The Power Method described below is not the best algorithm for this task, but it is perhaps the easiest to describe and analyze.

Let A be an $n \times n$ real symmetric matrix. Let $\lambda_1 \geq \dots \geq \lambda_n$ be the (unknown) eigenvalues of A , and let $v_1, \dots, v_n \in \mathbb{R}^n$ be the corresponding (unknown) eigenvectors of A such that $|v_i| = 1$ and such that $Av_i = \lambda_i v_i$ for all $1 \leq i \leq n$.

Given A , our first goal is to find v_1 and λ_1 . For simplicity, assume that $1/2 < \lambda_1 < 1$, and $0 \leq \lambda_n \leq \dots \leq \lambda_2 < 1/4$. Suppose we have found a vector $v \in \mathbb{R}^n$ such that $|v| = 1$ and $|\langle v, v_1 \rangle| > 1/n$. Let k be a positive integer. Show that

$$A^k v$$

approximates v_1 well as k becomes large. More specifically, show that for all $k \geq 1$,

$$|A^k v - \langle v, v_1 \rangle \lambda_1^k v_1|^2 \leq \frac{n-1}{16^k}.$$

(Hint: use the spectral theorem for symmetric matrices.)

Solution. Since the eigenvectors for A are orthogonal, they form a basis for \mathbb{R}^n , so for any $v \in \mathbb{R}^n$ we have $v = \sum_{i=1}^n c_i v_i$ for some $c = (c_1, \dots, c_n) \in \mathbb{R}^n$. It also follows then that $\langle v, v_1 \rangle = \langle \sum_{i=1}^n c_i v_i, v_1 \rangle = c_1 v'_1 v_1 = c_1$. And finally, since $\|v\| = 1$ and $\|v_i\| = 1$ for all i , clearly we have $-1 \leq c_i \leq 1$. Using these facts, we have

$$\begin{aligned} \|A^k v - \langle v, v_1 \rangle \lambda_1^k v_1\|^2 &= \left\| \sum_{i=1}^n \lambda_i^k c_i v_i - \langle v, v_1 \rangle \lambda_1^k v_1 \right\|^2 = \left\| \sum_{i=1}^n \lambda_i^k c_i v_i - \lambda_1^k c_1 v_1 \right\|^2 = \left\| \sum_{i=2}^n \lambda_i^k c_i v_i \right\|^2 \\ &= \sum_{i=2}^n \lambda_i^{2k} c_i^2 v_i' v_i = \sum_{i=2}^n \lambda_i^{2k} c_i^2 \end{aligned}$$

Since by assumption $0 \leq \lambda_n \leq \dots \leq \lambda_2 \leq 1/4$, $\lambda_i^{2k} \leq 1/16^k$ for all i , so we have

$$\|A^k v - \langle v, v_1 \rangle \lambda_1^k v_1\|^2 \leq \frac{1}{16^k} \sum_{i=2}^n c_i^2$$

Since $-1 \leq c_i \leq 1 \implies 0 \leq c_i^2 \leq 1$, we have $\sum_{i=2}^n c_i^2 \leq n - 1$, so this can be written as

$$\boxed{\|A^k v - \langle v, v_1 \rangle \lambda_1^k v_1\|^2 \leq \frac{n-1}{16^k}}$$

Remark 1. Since $|\langle v, v_1 \rangle| \lambda_1^k > 2^{-k}/n$, this inequality implies that $A^k v$ is approximately an eigenvector of A with eigenvalue λ_1 . That is, by the triangle inequality,

$$|A(A^k v) - \lambda_1(A^k v)| \leq |A^{k+1} v - \langle v, v_1 \rangle \lambda_1^{k+1} v_1| + \lambda_1 |\langle v, v_1 \rangle \lambda_1^k v_1 - A^k v| \leq 2 \frac{\sqrt{n-1}}{4^k}.$$

Moreover, by the reverse triangle inequality,

$$|A^k v| = |A^k v - \langle v, v_1 \rangle \lambda_1^k v_1 + \langle v, v_1 \rangle \lambda_1^k v_1| \geq \frac{1}{n} 2^{-k} - \frac{\sqrt{n-1}}{4^k}.$$

If we take k to be large (say $k > 10 \log n$), and if we define $z : equals A^k v$, then z is approximately an eigenvector of A , that is

$$|A \frac{A^k v ||A^k v| - \lambda_1 \frac{A^k v}{||A^k v||}}{\leq} 4n^{3/2} 2^{-k} \leq 4n^{-4}.$$

And to approximately find the first eigenvalue λ_1 , we simply compute

$$\frac{z^T A z}{z^T z}.$$

That is, we have approximately found the first eigenvector and eigenvalue of A .

To find the second eigenvector and eigenvalue, we can repeat the above procedure, where we start by choosing v such that $\langle v, v_1 \rangle = 0$, $|v| = 1$ and $|\langle v, v_2 \rangle| > 1/(10\sqrt{n})$. To find the third eigenvector and eigenvalue, we can repeat the above procedure, where we start by choosing v such that $\langle v, v_1 \rangle = \langle v, v_2 \rangle = 0$, $|v| = 1$ and $|\langle v, v_3 \rangle| > 1/(10\sqrt{n})$. And so on.

Google's PageRank algorithm uses the power method to rank websites very rapidly. In particular, they let n be the number of websites on the internet (so that n is roughly 10^9). They then define an $n \times n$ matrix

C where $C_{ij} = 1$ if there is a hyperlink between websites i and j , and $C_{ij} = 0$ otherwise. Then, they let B be an $n \times n$ matrix such that B_{ij} is 1 divided by the number of 1's in the i^{th} row of C , if $C_{ij} = 1$, and $B_{ij} = 0$ otherwise. Finally, they define

$$A = (.85)B + (.15)D/n$$

where D is an $n \times n$ matrix all of whose entries are 1.

The power method finds the eigenvector v_1 of A , and the size of the i^{th} entry of v_1 is proportional to the “rank” of website i .

12. Let A be a 2×2 matrix for which there is a constant k such that the sum of the entries in each row and each column is k . Which of the following must be an eigenvector of A ?

I. $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$

II. $\begin{pmatrix} 0 \\ 1 \end{pmatrix}$

III. $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$

- (A) I only (B) II only (C) III only (D) I and II only (E) I, II, and III

Solution 12. (C) This condition makes the matrix of the form

$$\begin{pmatrix} a & b \\ b & a \end{pmatrix}.$$

There is no reason that $a = 0$ or $b = 0$, so there is no reason $(1, 0)$ or $(0, 1)$ should be eigenvectors. But it is easy to verify that $(1, 1)$ must be.

24. Consider the system of linear equations

$$\begin{aligned} w + 3x + 2y + 2z &= 0 \\ w + 4x + y &= 0 \\ 3w + 5x + 10y + 14z &= 0 \\ 2w + 5x + 5y + 6z &= 0 \end{aligned}$$

with solutions of the form (w, x, y, z) , where w, x, y , and z are real. Which of the following statements is FALSE?

- (A) The system is consistent.
 (B) The system has infinitely many solutions.
 (C) The sum of any two solutions is a solution.
 (D) $(-5, 1, 1, 0)$ is a solution.
 (E) Every solution is a scalar multiple of $(-5, 1, 1, 0)$.

Solution 24. (E) Looking at our answers, we can verify directly that $(-5, 1, 1, 0)$ is a solution. Any multiple of $(-5, 1, 1, 0)$ is also a solution, which shows that (A), (B), (C), and (D) are all true – leaving only (E). Another solution, for example, is $(0, 2, -8, 5)$

$$A = \begin{pmatrix} 1 & 2 & 3 & 4 & 5 \\ 0 & 2 & 3 & 4 & 5 \\ 0 & 0 & 3 & 4 & 5 \\ 0 & 0 & 0 & 4 & 5 \\ 0 & 0 & 0 & 0 & 5 \end{pmatrix}$$

34. Which of the following statements about the real matrix shown above is FALSE?
- (A) A is invertible.
 - (B) If $\mathbf{x} \in \mathbb{R}^5$ and $A\mathbf{x} = \mathbf{x}$, then $\mathbf{x} = \mathbf{0}$.
 - (C) The last row of A^2 is $(0 \ 0 \ 0 \ 0 \ 25)$.
 - (D) A can be transformed into the 5×5 identity matrix by a sequence of elementary row operations.
 - (E) $\det(A) = 120$

Solution 34. (B) An upper triangular matrix is easily verified to be invertible so long as its diagonal entries are all nonzero. Specifically, $\det A$ is still the product of its diagonal entries, so (E) and (D) and (A) are all true. (C) can easily be verified to be true by computing that the bottom-right corner is 25 (the product of upper triangular matrices still being upper triangular). This leaves (B). (B) can be checked directly to be false: if we let $x = (1, 0, 0, 0, 0)$, then $Ax = x$.

37. Let V be a finite-dimensional real vector space and let P be a linear transformation of V such that $P^2 = P$. Which of the following must be true?
- I. P is invertible.
 - II. P is diagonalizable.
 - III. P is either the identity transformation or the zero transformation.
- (A) None
 - (B) I only
 - (C) II only
 - (D) III only
 - (E) II and III

Solution 37. (C) $P^2 = P$ means that P is projection onto some subspace. There is no reason to believe that this should be invertible, but it should definitely be diagonalisable (with eigenbasis some basis of that subspace). III also need not be true if the subspace is anything proper or nontrivial.

50. Let A be a real 2×2 matrix. Which of the following statements must be true?

- I. All of the entries of A^2 are nonnegative.
 - II. The determinant of A^2 is nonnegative.
 - III. If A has two distinct eigenvalues, then A^2 has two distinct eigenvalues.
- (A) I only (B) II only (C) III only (D) II and III only (E) I, II, and III

Solution 50. (B) There is no reason that all the entries of A^2 need to be nonnegative. Its determinant must be nonnegative though: $\det(A^2) = (\det A)^2$. For III, suppose A is the diagonal matrix with entries $\pm\lambda$. Then those are its eigenvalues, and they are distinct so long as $\lambda \neq 0$. But A^2 has only one eigenvalue: λ^2 .

51. Which of the following is an orthonormal basis for the column space of the real matrix $\begin{pmatrix} 1 & -1 & 2 & -3 \\ -1 & 1 & -3 & 2 \\ 2 & -2 & 5 & -5 \end{pmatrix}$?

(A) $\left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} \right\}$

(B) $\left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \right\}$

(C) $\left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \frac{2}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} \\ 0 \end{pmatrix} \right\}$

(D) $\left\{ \begin{pmatrix} 1 \\ -1 \\ 2 \end{pmatrix}, \begin{pmatrix} 2 \\ -3 \\ 5 \end{pmatrix} \right\}$

(E) $\left\{ \begin{pmatrix} \frac{1}{\sqrt{6}} \\ -\frac{1}{\sqrt{6}} \\ \frac{2}{\sqrt{6}} \end{pmatrix}, \begin{pmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{pmatrix} \right\}$

Solution 51. (E) The basis (C) is not orthogonal and (D) is not normal, so we can rule those out. We can throw out the first column, since it is the negation of the second. A little bit of math shows that the remaining 3×3 matrix has determinant 0, so the rank of our column space is 2. That leaves only (A) and (E), but (A) cannot be correct. Our column space contains vectors that have nonzero third entry, so cannot lie in the span of that basis.

Chapter 3

Calculus

These notes include some screenshots from Wikipedia as well as from *Calculus* by Gilbert Strang, available at <https://ocw.mit.edu/ans7870/resources/Strang/Edited/Calculus/Calculus.pdf>. I also used parts from some other resources which I mention when they arise.

3.1 Differentiation and common derivatives and integrals to know

Theorem 3.1.1 (Clairaut's Theorem). Let $z = f(x, y)$ be a two variable real-valued function that is defined on a disk \mathcal{D} that contains the point (a, b) . Then if $\frac{\partial^2 z}{\partial x \partial y}$ and $\frac{\partial^2 z}{\partial y \partial x}$ are continuous on \mathcal{D} , $\frac{\partial^2 z}{\partial x \partial y} = \frac{\partial^2 z}{\partial y \partial x}$.

$$\begin{aligned}\frac{d}{dx}(\sin^{-1} x) &= \frac{1}{\sqrt{1-x^2}} & \frac{d}{dx}(\ln(x)) &= \frac{1}{x}, \quad x > 0 \\ \frac{d}{dx}(\cos^{-1} x) &= -\frac{1}{\sqrt{1-x^2}} & \frac{d}{dx}(\ln|x|) &= \frac{1}{x}, \quad x \neq 0 \\ \frac{d}{dx}(\tan^{-1} x) &= \frac{1}{1+x^2} & \frac{d}{dx}(\log_a(x)) &= \frac{1}{x \ln a}, \quad x > 0\end{aligned}$$

$$\begin{aligned}\int \tan u \, du &= \ln|\sec u| + c \\ \int \sec u \, du &= \ln|\sec u + \tan u| + c \\ \int \frac{1}{a^2+u^2} \, du &= \frac{1}{a} \tan^{-1}\left(\frac{u}{a}\right) + c \\ \int \frac{1}{\sqrt{a^2-u^2}} \, du &= \sin^{-1}\left(\frac{u}{a}\right) + c\end{aligned}$$

$$\int \ln u \, du = u \ln(u) - u + c$$

$$\int \sinh x \, dx = \cosh x + C \quad \int \cosh x \, dx = \sinh x + C$$

3.2 Matrix Differentiation

Recommended resource: “Matrix Differentiation (and some other stuff)” by Randal J. Barnes (Department of Civil Engineering, University of Minnesota). Available for download at <https://atmos.washington.edu/~dennis/MatrixCalculus.pdf>. See also Section 5.7.3 of these notes for more on this material.

More information not contained in that pdf (from the appendix of *Convex Optimization* by Stephen Boyd and Lieven Vandenberghe, available for free download at <https://web.stanford.edu/~boyd/cvxbook/>):

Chain rule. Suppose $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is differentiable at $x \in \text{int dom } f$ and $g : \mathbb{R}^m \rightarrow \mathbb{R}^p$ is differentiable at $f(x) \in \text{int dom } g$. Define the composition $h : \mathbb{R}^n \rightarrow \mathbb{R}^p$ by $h(z) = g(f(x))$. Then

$$Dh(x) = Dg(f(x))Df(x)$$

In particular, if $f : \mathbb{R}^n \rightarrow \mathbb{R}$ and $g : \mathbb{R} \rightarrow \mathbb{R}$,

$$\nabla h(x) = g'(f(x))\nabla f(x)$$

Example with an affine function. Suppose $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is differentiable, $A \in \mathbb{R}^{n \times p}$, and $b \in \mathbb{R}^n$. Define $g : \mathbb{R}^p \rightarrow \mathbb{R}^m$ as $g(x) = f(Ax + b)$ with $\text{dom } g = \{x \mid Ax + b \in \text{dom } f\}$. Then

$$\nabla g(x) = A^T \nabla f(Ax + b)$$

Example 2. Consider $f : \mathbb{R}^n \rightarrow \mathbb{R}$ where

$$f(x) = \log \sum_{i=1}^m \exp(a_i^T x + b_i) =$$

where $a_1, \dots, a_m \in \mathbb{R}^n$ and $b_1, \dots, b_m \in \mathbb{R}$. Note that $f(\cdot)$ can be expressed as a composition of $Ax + b$ (where $A \in \mathbb{R}^{m \times n}$ has rows a_1^T, \dots, a_m^T) and the function $g : \mathbb{R}^m \rightarrow \mathbb{R}$ given by $g(y) = \log(\sum_{i=1}^m \exp(y_i))$. We have

$$\nabla g(y) = \left[\sum_{i=1}^m e^{y_i} \right]^{-1} (\exp(y_1) \dots \exp(y_m))^T$$

so applying the chain rule yields

$$\nabla f(x) = \left[\sum_{i=1}^m \exp(a_i^T x + b_i) \right]^{-1} A^T z$$

where $z_i = \exp(a_i^T x + b_i)$, $i = 1, \dots, m$.

Hessians. The Hessian matrix of $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is denoted by $\nabla^2 f(x)$ and is given by

$$\nabla^2 f(x)_{ij} = \frac{\partial^2 f(x)}{\partial x_i \partial x_j}, \quad i = 1, 2, \dots, n, \quad j = 1, 2, \dots, n$$

The quadratic function

$$f(x_0) + \nabla f(x_0)^T(x - x_0) + \frac{1}{2}(x - x_0)^T \nabla^2 f(x_0)(x - x_0)$$

is called the **second-order approximation of f near x_0** .

Chain rule for second derivative. A chain rule for the second derivative is difficult in general. Here are some special cases.

Composition with scalar function. Suppose $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $g : \mathbb{R} \rightarrow \mathbb{R}$, and $h(x) = g(f(x))$. We have

$$\nabla^2 h(x) = g'(f(x)) \nabla^2 f(x) + g''(f(x)) \nabla f(x) \nabla f(x)^T$$

Composition with affine function. Suppose $f : \mathbb{R} \rightarrow \mathbb{R}$, $a \in \mathbb{R}^m$, $b \in \mathbb{R}$. Define $g : \mathbb{R}^m \rightarrow \mathbb{R}$ by $g(x) = f(a^T x + b)$. Then

$$\nabla^2 g(x) = a^T \nabla^2 f(a^T x + b) a$$

More generally, suppose $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $A \in \mathbb{R}^{n \times m}$, and $b \in \mathbb{R}^n$. Define $g : \mathbb{R}^m \rightarrow \mathbb{R}$ by $g(x) = f(Ax + b)$. Then

$$\nabla^2 g(x) = A^T \nabla^2 f(Ax + b) A$$

3.3 Some theorems in higher dimensions

Proposition 3.3.1 (Change of Variables). If U is a “nice” subset of \mathbb{R}^2 and ϕ is an injective differentiable function on U , then

$$\int_{\phi(U)} f(u, v) dudv = \int_U f(\phi(x, y)) |J\phi(x, y)| dx dy$$

where $J\phi(x, y)$ is the Jacobian of ϕ at (x, y) .

Taylor’s Theorem (first order). (borrowed from <https://www.roose-hulman.edu/~bryan/lottamath/mTaylor.pdf>) Consider a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$. Let $a \in \mathbb{R}^n$ be a fixed point. Then Taylor’s Theorem states:

If $f(x)$ is differentiable on an open ball B around a and $x \in B$ then

$$f(x) = f(a) + \nabla f(b)^T(x - a)$$

for some b on the line segment joining a and x .

This can also be expressed as follows. Let $x, y \in \mathbb{R}^n$. If $f(x)$ is continuously differentiable, then

$$f(y) = f(x) + \nabla f(tx + (1-t)y)^T(y - x)$$

for some $t \in [0, 1]$.

Proof. Consider $g(z) = f(zy + (1-z)x)$. If f is differentiable then so is g . Then by the Mean Value Theorem, for some $t \in (0, 1)$ we have $g(1) - g(0) = g'(t)$. By the chain rule,

$$g'(t) = \nabla f(x + t(y - x))^T(y - x)$$

Using $g(1) = f(y)$ and $g(0) = f(x)$, we have

$$\iff \nabla f(tx + (1-t)y)^T(y - x) = g(1) - g(0) = f(y) - f(x)$$

□

Taylor's Theorem (second order). Consider a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$. Let $a \in \mathbb{R}^n$ be a fixed point. Then Taylor's Theorem states:

If $f(x)$ is twice differentiable on an open ball B around a and $x \in B$ then

$$f(x) = f(a) + (x - a)^T \nabla f(a) + \frac{1}{2}(x - a)^T \nabla^2 f(b)(x - a)$$

for some b on the line segment joining a and x .

This can also be expressed as follows. Let $x, y \in \mathbb{R}^n$. If $f(x)$ is twice continuously differentiable, then

$$f(y) = f(x) + \nabla f(x)^T(y - x) + \frac{1}{2}(y - x)^T \nabla^2 f(ty + (1-t)x)(y - x)$$

for some $t \in [0, 1]$.

Proof. Consider $g(z) = f(zy + (1-z)x)$. If f is differentiable then so is g . Then by the second order case of Taylor's Theorem in one dimension, for some $t \in (0, 1)$ we have $g(1) = g(0) + g'(0) + (1/2)g''(t)$. By the chain rule,

$$g''(t) = \frac{\partial}{\partial t} \nabla f(x + t(y - x))^T(y - x) = (y - x)^T \nabla^2 f(x + t(y - x))^T(y - x)$$

Using this result along with $g(1) = f(y)$, $g(0) = f(x)$, and $g'(0) = \nabla f(x)^T(y - x)$, we have

$$f(y) = f(x) + \nabla f(x)^T(y - x) + \frac{1}{2}(y - x)^T \nabla^2 f(x + t(y - x))^T(y - x)$$

□

3.4 Optimizing functions of several variables

Functions of two variables [edit]

Suppose that $f(x, y)$ is a differentiable [real function](#) of two variables whose second [partial derivatives](#) exist. The [Hessian matrix](#) H of f is the 2×2 matrix of partial derivatives of f :

$$H(x, y) = \begin{pmatrix} f_{xx}(x, y) & f_{xy}(x, y) \\ f_{yx}(x, y) & f_{yy}(x, y) \end{pmatrix}.$$

Define $D(x, y)$ to be the [determinant](#)

$$D(x, y) = \det(H(x, y)) = f_{xx}(x, y)f_{yy}(x, y) - (f_{xy}(x, y))^2,$$

of H . Finally, suppose that (a, b) is a critical point of f (that is, $f_x(a, b) = f_y(a, b) = 0$). Then the second partial derivative test asserts the following:^[1]

1. If $D(a, b) > 0$ and $f_{xx}(a, b) > 0$ then (a, b) is a local minimum of f .
2. If $D(a, b) > 0$ and $f_{xx}(a, b) < 0$ then (a, b) is a local maximum of f .
3. If $D(a, b) < 0$ then (a, b) is a [saddle point](#) of f .
4. If $D(a, b) = 0$ then the second derivative test is inconclusive, and the point (a, b) could be any of a minimum, maximum or saddle point.

Functions of many variables [edit]

For a function f of two or more variables, there is a generalization of the rule above. In this context, instead of examining the determinant of the Hessian matrix, one must look at the [eigenvalues](#) of the Hessian matrix at the critical point. The following test can be applied at any critical point (a, b, \dots) for which the Hessian matrix is [invertible](#):

1. If the Hessian is [positive definite](#) (equivalently, has all eigenvalues positive) at (a, b, \dots) , then f attains a local minimum at (a, b, \dots) .
2. If the Hessian is [negative definite](#) (equivalently, has all eigenvalues negative) at (a, b, \dots) , then f attains a local maximum at (a, b, \dots) .
3. If the Hessian has both positive and negative eigenvalues then (a, b, \dots) is a saddle point for f (and in fact this is true even if (a, b, \dots) is degenerate).

3.5 Lagrange Multipliers

: to flesh out! <http://tutorial.math.lamar.edu/Classes/CalcIII/LagrangeMultipliers.aspx>

3.6 Line Integrals

(p. 555 of Strang book)

Suppose a force in two-dimensional space is given by $\mathbf{F} = Mi + Nj$. Then the work done by this force on a particle moving along a curve C is given by

$$W = \int_C \mathbf{F} \cdot d\mathbf{R} = \int_C Mdx + Ndy$$

Along a curve in three-dimensional space the work done by a three-dimensional force $\mathbf{F} = Mi + Nj + Pk$ is given by

$$W = \int_C \mathbf{F} \cdot \mathbf{T} ds = \int_C \mathbf{F} \cdot d\mathbf{R} = \int_C Mdx + Ndy + Pdz$$

where the tangent vector \mathbf{T} is given by

$$\mathbf{T} = \frac{d\mathbf{R}}{ds}$$

Green's Theorem: Suppose the region R is bounded by the simple closed piecewise smooth curve C . Then an integral over R equals a line integral around C :

$$\oint_C \mathbf{F} \cdot d\mathbf{R} = \oint_C Mdx + Ndy = \int \int_R \left(\frac{\partial N}{\partial x} - \frac{\partial M}{\partial y} \right) dx dy$$

Line integrals chapter! <http://tutorial.math.lamar.edu/Classes/CalcIII/LineIntegralsIntro.aspx>

Surface integrals chapter! <http://tutorial.math.lamar.edu/Classes/CalcIII/SurfaceIntegralsIntro.aspx>

3.7 Miscellaneous

13A The tangent plane at (x_0, y_0, z_0) has the same slopes as the surface $z = f(x, y)$. The equation of the tangent plane (a linear equation) is

$$z - z_0 = \left(\frac{\partial f}{\partial x} \right)_0 (x - x_0) + \left(\frac{\partial f}{\partial y} \right)_0 (y - y_0). \quad (1)$$

The normal vector \mathbf{N} to that plane has components $(\partial f / \partial x)_0, (\partial f / \partial y)_0, -1$.

13B The tangent plane to the surface $F(x, y, z) = c$ has the linear equation

$$\left(\frac{\partial F}{\partial x}\right)_0(x - x_0) + \left(\frac{\partial F}{\partial y}\right)_0(y - y_0) + \left(\frac{\partial F}{\partial z}\right)_0(z - z_0) = 0. \quad (7)$$

The normal vector is $\mathbf{N} = \left(\frac{\partial F}{\partial x}\right)_0 \mathbf{i} + \left(\frac{\partial F}{\partial y}\right)_0 \mathbf{j} + \left(\frac{\partial F}{\partial z}\right)_0 \mathbf{k}$.

$$dz = (\partial z / \partial x)_0 dx + (\partial z / \partial y)_0 dy \quad \text{or} \quad df = f_x dx + f_y dy. \quad (10)$$

This is the **total differential**. All letters dz and df and dw can be used, but ∂z and ∂f are not used. Differentials suggest small movements in x and y ; then dz is the resulting movement in z . On the tangent plane, equation (10) holds exactly.

The **directional derivative**, denoted $D_v f(x, y)$, is a derivative of a multivariable function in the direction of a vector v . It is the scalar projection of the gradient onto v .

$$D_v f(x, y) = \text{comp}_v \nabla f(x, y) = \frac{\nabla f(x, y) \cdot v}{|v|}$$

3.8 Practice Problems

13F The directional derivative is $D_u f = (\text{grad } f) \cdot u$. The level direction is perpendicular to $\text{grad } f$, since $D_u f = 0$. **The slope $D_u f$ is largest when u is parallel to $\text{grad } f$** . That maximum slope is the length $|\text{grad } f| = \sqrt{f_x^2 + f_y^2}$:

$$\text{for } u = \frac{\text{grad } f}{|\text{grad } f|} \quad \text{the slope is } (\text{grad } f) \cdot u = \frac{|\text{grad } f|^2}{|\text{grad } f|} = |\text{grad } f|.$$

$$\int_C g(x, y) ds = \text{limit of } \sum_{i=1}^N g(x_i, y_i) \Delta s_i \quad \text{as } (\Delta s)_{\max} \rightarrow 0.$$

The differential ds becomes $(ds/dt)dt$. Everything changes over to t :

$$\int g(x, y) ds = \int_{t=a}^{t=b} g(x(t), y(t)) \sqrt{(dx/dt)^2 + (dy/dt)^2} dt.$$

19. Let f and g be twice-differentiable real-valued functions defined on \mathbb{R} . If $f'(x) > g'(x)$ for all $x > 0$, which of the following inequalities must be true for all $x > 0$?

- (A) $f(x) > g(x)$
- (B) $f''(x) > g''(x)$
- (C) $f(x) - f(0) > g(x) - g(0)$
- (D) $f'(x) - f'(0) > g'(x) - g'(0)$
- (E) $f''(x) - f''(0) > g''(x) - g''(0)$

Solution 19. (C) There is no reason that $f(x) > g(x)$, or that $f''(x) > g''(x)$. But we do know that

$$\int_0^x f'(t) dt > \int_0^x g'(t) dt \implies f(x) - f(0) > g(x) - g(0).$$

This is precisely an answer.

22. What is the volume of the solid in xyz -space bounded by the surfaces $y = x^2$, $y = 2 - x^2$, $z = 0$, and $z = y + 3$?

- (A) $\frac{8}{3}$
- (B) $\frac{16}{3}$
- (C) $\frac{32}{3}$
- (D) $\frac{104}{105}$
- (E) $\frac{208}{105}$

Solution 22. (C) It looks like our x -coordinates are running over $[-1, 1]$, with y depending on x and z depending on y . To find the volume of the solid, we just need to integrate the constant function 1. We must therefore compute

$$\begin{aligned} \int_{-1}^1 \int_{x^2}^{2-x^2} \int_0^{y+3} 1 dz dy dx &= \int_{-1}^1 \int_{x^2}^{2-x^2} y + 3 dy dx \\ &= \int_{-1}^1 ((2 - x^2)^2 / 2 + 3(2 - x^2)) - ((x^2)^2 / 2 + 3(x^2)) dx \\ &= \int_{-1}^1 8 - 8x^2 dx \\ &= 8x - 8x^3 / 3 \Big|_{-1}^1 = (8 - 8/3) - (-8 + 8/3) = 32/3. \end{aligned}$$

24. Let h be the function defined by $h(x) = \int_0^{x^2} e^{x+t} dt$ for all real numbers x . Then $h'(1) =$

- (A) $e - 1$
- (B) e^2
- (C) $e^2 - e$
- (D) $2e^2$
- (E) $3e^2 - e$

Solution 24. (E) We can actually just integrate this, and not worry about differentiation under the integral.

$$\int_0^{x^2} e^{x+t} dt = e^x \int_0^{x^2} e^t dt = e^x (e^{x^2} - 1) = e^{x^2+x} - e^x.$$

Then deriving that,

$$h'(x) = (2x+1)e^{x^2+x} - e^x,$$

whence our result follows immediately.

26. Let $f(x, y) = x^2 - 2xy + y^3$ for all real x and y . Which of the following is true?

- (A) f has all of its relative extrema on the line $x = y$.
- (B) f has all of its relative extrema on the parabola $x = y^2$.
- (C) f has a relative minimum at $(0, 0)$.
- (D) f has an absolute minimum at $\left(\frac{2}{3}, \frac{2}{3}\right)$.
- (E) f has an absolute minimum at $(1, 1)$.

Solution 26. (A) We are concerned about its extrema, we should find some partial derivatives.

$$f_x = 2x - 2y, \quad f_y = -2x + 3y^2.$$

We would like to know when they are both zero. The first equation gives us $x = y$ and the second gives us $2x = 3y^2$, so that

$$2y = 3y^2 \implies (3y-2)y = 0 \implies y = 0, 2/3.$$

Therefore our solutions are $(0, 0)$ and $(2/3, 2/3)$. Indeed, our relative extrema are all on the line $x = y$. To do some more checking (which you should not do on the actual test),

$$f_{xx} = 2, \quad f_{yy} = 6y, \quad f_{xy} = f_{yx} = -2.$$

Then the determinant of the Hessian is $12y - 4$. This shows that $(0, 0)$ is a saddle point. There is no reason that $(2/3, 2/3)$ is an absolute minimum without further verification, and $(1, 1)$ needn't be an extreme point.

27. Consider the two planes $x + 3y - 2z = 7$ and $2x + y - 3z = 0$ in \mathbb{R}^3 . Which of the following sets is the intersection of these planes?

- (A) \emptyset
- (B) $\{(0, 3, 1)\}$
- (C) $\{(x, y, z) : x = t, y = 3t, z = 7 - 2t, t \in \mathbb{R}\}$
- (D) $\{(x, y, z) : x = 7t, y = 3 + t, z = 1 + 5t, t \in \mathbb{R}\}$
- (E) $\{(x, y, z) : x - 2y - z = -7\}$

Solution 27. (D) First, we know that the intersection of two planes in \mathbb{R}^3 should be either a plane or a line. In our case, the two planes are definitely not the same, so we will obtain a line. The slope of the line can be found by taking the cross product of the normal vectors of the two planes in question.

$$(1, 3, -2) \times (2, 1, -3) = \det \begin{bmatrix} i & j & k \\ 1 & 3 & -2 \\ 2 & 1 & -3 \end{bmatrix} = (-7, -1, -5).$$

The only solution corresponding to this slope is (D), as the coefficients of t in (x, y, z) are $(7, 1, 5)$.

32. $\frac{d}{dx} \int_{x^3}^{x^4} e^{t^2} dt =$
- (A) $e^{x^6} (e^{x^8-x^6} - 1)$ (B) $4x^3 e^{x^8}$ (C) $\frac{1}{\sqrt{1-e^{x^2}}}$ (D) $\frac{e^{x^2}}{x^2} - 1$ (E) $x^2 e^{x^6} (4xe^{x^8-x^6} - 3)$

Solution 32. (E) We can sort this out in two steps and apply the fundamental theorem to each.

$$\frac{d}{dx} \left(\int_{x^3}^0 e^{t^2} dx + \int_0^{x^4} e^{t^2} dx \right)$$

For the first,

$$\frac{d}{dx} \int_{x^3}^0 e^{t^2} dx = -\frac{d}{dx} \int_0^{x^3} e^{t^2} dx = -3x^2 e^{x^6}$$

For the second,

$$\frac{d}{dx} \int_0^{x^4} e^{t^2} dx = 4x^3 e^{x^8}.$$

All told, our integral is $x^2 e^{x^6} (4xe^{x^8-x^6} - 3)$.

41. Let ℓ be the line that is the intersection of the planes $x + y + z = 3$ and $x - y + z = 5$ in \mathbb{R}^3 . An equation of the plane that contains $(0, 0, 0)$ and is perpendicular to ℓ is

- (A) $x - z = 0$
 (B) $x + y + z = 0$
 (C) $x - y - z = 0$
 (D) $x + z = 0$
 (E) $x + y - z = 0$

Solution 41. (A) The first plane is determined by the normal vector $(1, 1, 1)$, and the second determined by $(1, -1, 1)$. Therefore the slope of ℓ is determined by a vector perpendicular to those, i.e. the cross product.

$$(1, 1, 1) \times (1, -1, 1) = \det \begin{bmatrix} i & j & k \\ 1 & 1 & 1 \\ 1 & -1 & 1 \end{bmatrix} = (2, 0, -2).$$

41. Let C be the circle $x^2 + y^2 = 1$ oriented counterclockwise in the xy -plane. What is the value of the line integral $\oint_C (2x - y) dx + (x + 3y) dy$?

- (A) 0 (B) 1 (C) $\frac{\pi}{2}$ (D) π (E) 2π

Solution 41. (E) This is a classic Green's theorem problem.

$$\oint_{\partial D} L dx + M dy = \iint_D \left(\frac{\partial M}{\partial x} - \frac{\partial L}{\partial y} \right) dx dy.$$

In our case,

$$\oint_C (2x - y) dx + (x + 3y) dy = \iint_D (1 + 1) dx dy = 2A,$$

where A is the area of the unit circle, i.e. π .

So that is the slope of ℓ . We need this to be the normal vector for the plane in question, so it seems that $(1, 0, -1)$ is our best bet (out of the given options).

$$\begin{aligned} y' + xy &= x \\ y(0) &= -1 \end{aligned}$$

44. If y is a real-valued function defined on the real line and satisfying the initial value problem above, then $\lim_{x \rightarrow -\infty} y(x) =$

- (A) 0 (B) 1 (C) -1 (D) ∞ (E) $-\infty$

Solution 44. (B) Putting it in simpler terms,

$$\frac{dy}{dx} + xy = x \implies \frac{dy}{dx} = x(1 - y) \implies \frac{dy}{1-y} = x dx.$$

Integrating both sides, we obtain

$$-\log(1-y) = x^2/2 + C' \implies 1-y = Ce^{-x^2/2} \implies y = 1 - Ce^{-x^2/2}.$$

Solving the initial value problem gives $C = 2$. Furthermore, as $x \rightarrow -\infty$, the second term above vanishes so we get 1 in the limit.

48. Let g be the function defined by $g(x, y, z) = 3x^2y + z$ for all real x, y , and z . Which of the following is the best approximation of the directional derivative of g at the point $(0, 0, \pi)$ in the direction of the vector $\mathbf{i} + 2\mathbf{j} + 3\mathbf{k}$? (Note: \mathbf{i}, \mathbf{j} , and \mathbf{k} are the standard basis vectors in \mathbb{R}^3 .)
- (A) 0.2 (B) 0.8 (C) 1.4 (D) 2.0 (E) 2.6

Solution 48. (B) It would be good to recall the formula for the directional derivative. We take the gradient of the function then take its scalar product with the normalised vector in the direction we want. To begin,

$$\nabla g = (6xy, 3x^2, 1).$$

At the point $(0, 0, \pi)$, we have $\nabla g = (0, 0, 1)$. That works out pretty well for us. The normalised version of the vector $(1, 2, 3)$ is $(1/\sqrt{14}, 2/\sqrt{14}, 3/\sqrt{14})$. Dotting this with $(0, 0, 1)$ gives $3/\sqrt{14}$, and since $\sqrt{14} = 3.5$ or so our answer should be closer to 0.8 than 0.2.

48. Consider the theorem: If f and f' are both strictly increasing real-valued functions on the interval $(0, \infty)$, then $\lim_{x \rightarrow \infty} f(x) = \infty$. The following argument is suggested as a proof of this theorem.

- (1) By the Mean Value Theorem, there is a c_1 in the interval $(1, 2)$ such that

$$f'(c_1) = \frac{f(2) - f(1)}{2 - 1} = f(2) - f(1) > 0.$$

- (2) For each $x > 2$, there is a c_x in $(2, x)$ such that $\frac{f(x) - f(2)}{x - 2} = f'(c_x)$.

- (3) For each $x > 2$, $\frac{f(x) - f(2)}{x - 2} = f'(c_x) > f'(c_1)$ since f' is strictly increasing.

- (4) For each $x > 2$, $f(x) > f(2) + (x - 2)f'(c_1)$.

- (5) $\lim_{x \rightarrow \infty} f(x) = \infty$

Which of the following statements is true?

- (A) The argument is valid.
 (B) The argument is not valid since the hypotheses of the Mean Value Theorem are not satisfied in (1) and (2).
 (C) The argument is not valid since (3) is not valid.
 (D) The argument is not valid since (4) cannot be deduced from the previous steps.
 (E) The argument is not valid since (4) does not imply (5).

Solution 48. (A) The only issue here seems to be that (4) implies that $f(x)$ gets very large so long as $f'(c_1)$ is positive. But we know that it is, since f is a strictly increasing function. Therefore everything is satisfactory.

Chapter 4

Differential Equations

For more on ODEs, see Section 5.6.5 of these notes.

61. A tank initially contains a salt solution of 3 grams of salt dissolved in 100 liters of water. A salt solution containing 0.02 grams of salt per liter of water is sprayed into the tank at a rate of 4 liters per minute. The sprayed solution is continually mixed with the salt solution in the tank, and the mixture flows out of the tank at a rate of 4 liters per minute. If the mixing is instantaneous, how many grams of salt are in the tank after 100 minutes have elapsed?

(A) 2 (B) $2 - e^{-2}$ (C) $2 + e^{-2}$ (D) $2 - e^{-4}$ (E) $2 + e^{-4}$

Solution 61. (E) We can set this up as a differential equation. Let s denote the amount of salt in the tank, and let t denote time. We have the initial condition of $s(0) = 3$. $s'(t)$ depends on two factors: the salt flowing in and the salt flowing out. The salt flows in constantly at a rate of 0.08 grams per minute, and the salt flows out at a rate of $4 \cdot (s/100) = s/25$ grams per minute. Therefore

$$s'(t) = \frac{ds}{dt} = 0.08 - s(t)/25 \implies \frac{ds}{dt} = 0.04(2 - s) \implies \frac{ds}{2 - s} = 0.04 dt.$$

Doing the usual calculus,

$$-\log(2 - s) = 0.04t + C' \implies 2 - s = Ce^{-0.04t} \implies s(t) = 2 - Ce^{-0.04t}.$$

The initial condition tells us that $C = -1$, so $s(t) = 2 + e^{-0.04t}$. Plugging in $t = 100$ gives our answer.

Chapter 5

Real Analysis

These are my notes from Math 4650: Analysis I at Cal State LA, Math 425B: Fundamental Concepts of Analysis at USC taught by Andrew Manion and the textbook [Pugh, 2015], the textbook [Rudin, 1976], as well as Prof. Steven Heilman's notes from Math 541A at USC.

5.1 Midterm 1

5.1.1 Homework 1

Definition 5.1. Let $S \subseteq \mathbb{R}$. We say that S is **bounded from above** if $\exists b \in \mathbb{R}$ where

$$s \leq b \quad \forall s \in S$$

If this is the case, we call b an **upper bound** of S .

If $b \leq c$ for all upper bounds c of S , we call b the **supremum** of S : $b = \sup(S)$.

Definition 5.2. We say that S is **bounded from below** if $\exists a \in \mathbb{R}$ where

$$s \geq a \quad \forall s \in S$$

If this is the case, we call a a **lower bound** of S .

If $a \geq d$ for all lower bounds d of S , we call a the **infimum** of S : $a = \inf(S)$.

Proposition 5.1.1. Useful Sup/Inf Fact: Let $S \in \mathbb{R}$, $S \neq \emptyset$.

- (1) Suppose S is bounded from above by an element b . Then $b = \sup(S) \iff \forall \epsilon > 0 \exists x \in S$ with

$$b - \epsilon < x \leq b$$

- (2) Suppose S is bounded from below by an element a . Then $a = \inf(S) \iff \forall \epsilon > 0 \exists x \in S$ with

$$a \leq x < a + \epsilon$$

Completeness Axiom: Let S be a nonempty subset of \mathbb{R} . If S is bounded from above, then $\sup(S)$ exists. If S is bounded from below, then $\inf(S)$ exists.

Facts about absolute value:

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Proposition 5.1.2. $|x - y| < \epsilon \iff y - \epsilon < x < y + \epsilon$.

Proof. In notes 08/23. □

-

Proposition 5.1.3. $|ab| = |a||b|$.

Proof.

$$\begin{aligned} |ab| &= \begin{cases} ab & ab \geq 0 \\ -ab & ab < 0 \end{cases} = \begin{cases} ab & a \geq 0, b \geq 0 \\ -ab & a \geq 0, b < 0 \\ -ab & a < 0, b \geq 0 \\ ab & a < 0, b < 0 \end{cases} = \begin{cases} ab & a \geq 0, b \geq 0 \\ a(-b) & a \geq 0, b < 0 \\ (-a)b & a < 0, b \geq 0 \\ (-a)(-b) & a < 0, b < 0 \end{cases} \\ &= \begin{cases} |a||b| & a \geq 0, b \geq 0 \\ |a||b| & a \geq 0, b < 0 \\ |a||b| & a < 0, b \geq 0 \\ |a||b| & a < 0, b < 0 \end{cases} \implies |ab| = |a||b| \end{aligned}$$

□

-

Proposition 5.1.4. Let $\epsilon > 0$. Then $|a| < \epsilon \iff -\epsilon < a < \epsilon$.

Proof. Follows from Proposition 5.1.2 if $x = a$, $y = 0$. □

-

Proposition 5.1.5. $-|a| \leq a \leq |a|$

Proof. Follows from Proposition 5.1.2 if $x = a$, $y = 0$, $\epsilon = |a|$. □

-

Theorem 5.1.6. Triangle Inequality: $|a + b| \leq |a| + |b|$.

Proof. In notes 08/23. □

Corollary 5.1.6.1. Triangle Inequality: $|a - b| \leq |a| + |b|$.

Proof. Follows from Theorem 5.1.6, let $b = -b$. □

Remark 2. See also Theorem 8.2.11.

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Proposition 5.1.7. $| |a| - |b| | \leq |a - b|$.

Proof. By Proposition 5.1.2, $| |a| - |b| | \leq |a - b|$ if and only if

$$|b| - |a - b| \leq |a| \leq |b| + |a - b| \quad (5.1)$$

The left half of (5.1) is true by the Triangle Inequality (Theorem 5.1.6):

$$|b| = |a - (a - b)| \leq |a| + |a - b| \iff |b| \leq |a| + |a - b| \iff |b| - |a - b| \leq |a|$$

The right half of (5.1) is also true by the Triangle Inequality (Theorem 5.1.6):

$$|a| = |b + a - b| \leq |b| + |a - b|$$

Therefore

$$| |a| - |b| | \leq |a - b|.$$

□

Proof. (Alternative proof.) Note that by the Triangle Inequality (Theorem 5.1.6),

$$|a| = |a - b + b| \leq |a - b| + |b| \implies |a| - |b| \leq |a - b|$$

Also,

$$|b| = |b - a + a| \leq |b - a| + |a| \implies -|b - a| \leq |a| - |b| \implies -|a - b| \leq |a| - |b|$$

where the last step follows from Proposition 5.1.9. Therefore

$$-|a - b| \leq |a| - |b| \leq |a - b|$$

and by Proposition 5.1.2,

$$| |a| - |b| | \leq |a - b|.$$

□

•

Proposition 5.1.8. If $a < x < b$ and $a < y < b$ then $|x - y| < b - a$.

Proof.

$$y > a \implies -y < -a \implies b - y < b - a$$

$$b > y \implies b - y = |b - y| \implies |b - y| < b - a$$

By the Triangle Inequality (Theorem 5.1.6),

$$|x - y| = |x - b + b - y| \leq |x - b| + |b - y|$$

Since $b < x$, $|x - b| > 0$. Therefore $|x - y| < |b - y|$.

$$\implies |x - y| < |b - y| < b - a$$

$$\implies |x - y| < b - a$$

□

Proof. (Alternative proof.) Break into two cases.

- **Case 1:** $x \geq y$. Then $|x - y| = x - y$. We know $a < x < b \implies 0 < x - a < b - a$.

$$a < y \implies -a > -y \implies x - a > x - y \implies x - y < x - a < b - a$$

$$\implies |x - y| < b - a$$

- **Case 2:** $x < y$. Then $|x - y| = y - x$. We know $a < y < b \implies 0 < y - a < b - a$.

$$a < x \implies -a > -x \implies y - a > y - x \implies y - x < y - a < b - a$$

$$\implies |x - y| < b - a$$

□

•

Proposition 5.1.9. $|a - b| = |b - a|$

Proof. $|a - b| = |(-1)(b - a)| = |-1||b - a| = |b - a|$, where the second-to-last step follows from Proposition 5.1.2.

□

5.1.2 Homework 2

Definition 5.3. A sequence (a_n) of real numbers is said to **converge** to a **limit** $L \in \mathbb{R}$ if $\forall \epsilon > 0 \exists N > 0$ where

$$n \geq N \implies |a_n - L| < \epsilon$$

We say that (a_n) **diverges** if it does not converge.

Definition 5.4. A sequence (a_n) of real numbers is **bounded** if $\exists M > 0$ where $\forall n \in \mathbb{N}$

$$|a_n| \leq M.$$

Theorem 5.1.10. If (a_n) converges then (a_n) is bounded.

Definition 5.5. Let (a_n) be a sequence of real numbers. We say that (a_n) is a **Cauchy sequence** if $\forall \epsilon > 0 \exists N$ where

$$n, m \geq N \implies |a_n - a_m| < \epsilon$$

Theorem 5.1.11. (a_n) is Cauchy if and only if (a_n) converges.

Corollary 5.1.11.1. If (a_n) is Cauchy then (a_n) is bounded.

Proof. Let $\epsilon = 1$. Since (a_n) is Cauchy, $\exists N > 0 \mid n, m \geq N \implies$

$$|a_n - a_m| < 1$$

So, $n \geq N \implies$

$$|a_n - a_N| < 1 \iff a_N - 1 < a_n < a_N + 1 \implies |a_n| < |a_N + 1| \leq |a_N| + 1$$

Let $M = \max\{|a_1|, |a_2|, \dots, |a_{N-1}|, |a_N| + 1\}$. Then $|a_n| \leq M \forall n \geq 1$. Therefore (a_n) is bounded.

□

Theorem 5.1.12. (Squeeze theorem.) Suppose that $\{a_n\}$, $\{b_n\}$, and $\{c_n\}$ are sequences of real numbers such that $a_n \leq b_n \leq c_n$ for all n . If both $\{a_n\}$ and $\{c_n\}$ converge to L , then $\{b_n\}$ converges to L .

Proof. Let $\epsilon > 0$. (a_n) converges to $L \implies$

$$\forall \epsilon > 0 \exists N_A \mid n \geq N_A \implies |a_n - L| < \epsilon$$

(c_n) converges to $L \implies$

$$\forall \epsilon > 0 \exists N_C \mid n \geq N_C \implies |c_n - L| < \epsilon$$

Let $N = \max\{N_A, N_C\}$. Then by one of our absolute values rules, $n \geq N \implies$

$$|a_n - L| < \epsilon \iff L - \epsilon < a_n < L + \epsilon$$

$$|c_n - L| < \epsilon \iff L - \epsilon < c_n < L + \epsilon$$

Therefore since $a_n \leq b_n \leq c_n$,

$$L - \epsilon < a_n \leq b_n \leq c_n < L + \epsilon \implies L - \epsilon < b_n < L + \epsilon \iff |b_n - L| < \epsilon$$

Therefore (b_n) converges to L .

□

Proposition 5.1.13. Limits of sequences in \mathbb{R} are unique: if $a_n : \mathbb{N} \rightarrow \mathbb{R}$ is a sequence, $\lim a_n = L$, and $\lim a_n = L'$, then $L = L'$.

Proof. Let $L, L' \in \mathbb{R}$, with $\lim_{n \rightarrow \infty} a_n = L$ and $\lim_{n \rightarrow \infty} a_n = L'$. Then for all $\epsilon > 0$ there exists $N \in \mathbb{N}$ such that for all $n \geq N$ we have $|a_n - L| < \epsilon$, and there exists $N' \in \mathbb{N}$ such that for all $n \geq N'$ we have $|a_n - L'| < \epsilon$. Suppose $L \neq L'$, and let $\epsilon := \frac{1}{2}|L - L'| > 0$. But then for all $n \geq \max\{N, N'\}$,

$$2\epsilon = |L - L'| = |L - a_n + a_n - L'| \leq |a_n - L| + |a_n - L'| < \epsilon + \epsilon = 2\epsilon,$$

contradiction. Therefore $L = L'$.

□

Theorem 5.1.14. Suppose that $\{a_n\}$ and $\{b_n\}$ are sequences of real numbers such that $a_n \leq b_n$ for all n . If $\{a_n\}$ and $\{b_n\}$ converge to A and B respectively, then $A \leq B$.

Proof. Suppose $A > B$. Then let $\epsilon = \frac{A-B}{4} > 0$. (a_n) converges to $A \implies$

$$\exists N_A \mid n \geq N_A \implies |a_n - A| < \epsilon \iff A - \epsilon < a_n < A + \epsilon$$

(b_n) converges to $B \implies$

$$\exists N_B \mid n \geq N_B \implies |b_n - B| < \epsilon \iff B - \epsilon < b_n < B + \epsilon$$

Then if $n > \max\{N_A, N_B\}$,

$$A - \epsilon < a_n < A + \epsilon \iff A - \frac{A-B}{4} < a_n < A + \frac{A-B}{4} \iff \frac{3A}{4} + \frac{B}{4} < a_n < \frac{5A}{4} - \frac{B}{4}$$

$$B - \epsilon < b_n < B + \epsilon \iff B - \frac{A-B}{4} < b_n < B + \frac{A-B}{4} \iff \frac{5B}{4} - \frac{A}{4} < b_n < \frac{3B}{4} + \frac{A}{4}$$

This implies

$$b_n < \frac{3B}{4} + \frac{A}{4} = \frac{B}{4} + \frac{A}{4} + \frac{2B}{4} < \frac{B}{4} + \frac{A}{4} + \frac{2A}{4} = \frac{3A}{4} + \frac{B}{4} < a_n$$

Contradiction, since it is given that $a_n \leq b_n \forall n$. Therefore $A \leq B$.

□

5.2 Midterm 2

5.2.1 Homework 3

Definition 5.6. (Limits of functions at infinity.) Let f be a real-valued function defined on some set D where D contains an interval of the form (a, ∞) . Let $L \in \mathbb{R}$. We say

$$\lim_{x \rightarrow \infty} f(x) = L$$

if $\forall \epsilon > 0 \exists N \in \mathbb{R}$ where

$$x \geq N \implies |f(x) - L| < \epsilon.$$

Definition 5.7. Let $D \subseteq \mathbb{R}$. Let $a \in \mathbb{R}$. We say that a is a **limit point** (or “cluster point,” or “accumulation point”) of D if $\forall \delta > 0 \exists x \in D$ where

$$x \neq a \text{ and } |x - a| < \delta$$

(Note that a may or may not be contained in D .)

Definition 5.8. (Limit of a function at a .) Let $D \subseteq \mathbb{R}$ and $f : D \rightarrow \mathbb{R}$. Let a be a limit point of D . Let $x \in D$. We say that f has a *limit as x tends to a* if $\exists L \in \mathbb{R}$ where $\forall \epsilon > 0 \exists \delta > 0$ such that

$$0 < |x - a| < \delta \implies |f(x) - L| < \epsilon$$

and we write

$$\lim_{x \rightarrow a} f(x) = L$$

Proposition 5.2.1. (Properties of Limits.) Let $D \subseteq \mathbb{R}$ and let a be a limit point of D . Suppose $f : D \rightarrow \mathbb{R}$ and $g : D \rightarrow \mathbb{R}$. Let $\alpha \in \mathbb{R}$.

(1) If $\lim_{x \rightarrow a} f(x) = L$ and $\lim_{x \rightarrow a} g(x) = M$ then

(a)

$$\lim_{x \rightarrow a} \alpha = \alpha$$

(b)

$$\lim_{x \rightarrow a} [f(x) + g(x)] = L + M$$

(c)

$$\lim_{x \rightarrow a} [f(x) - g(x)] = L - M$$

(d)

$$\lim_{x \rightarrow a} [f(x) \cdot g(x)] = L \cdot M$$

(e)

$$\lim_{x \rightarrow a} [\alpha \cdot f(x)] = \alpha \cdot L$$

(2) If $h : D \rightarrow \mathbb{R}$ and $h(x) \neq 0 \forall x \in D$ and $\lim_{x \rightarrow a} h(x) = H \neq 0$, then

$$\lim_{x \rightarrow a} \frac{1}{h(x)} = \frac{1}{H}$$

Note that properties (2) and (1)(d) combined imply

$$\lim_{x \rightarrow a} \frac{f(x)}{h(x)} = \frac{L}{H}$$

5.2.2 Homework 4

Definition 5.9. (Continuity.) Let $D \subseteq \mathbb{R}$ and $f : D \rightarrow \mathbb{R}$ and $a \in D$. Then f is **continuous** at a if $\lim_{x \rightarrow a} f(x)$ exists and

$$\lim_{x \rightarrow a} f(x) = f(a)$$

Remark 3. if f is continuous at a , then we can say $\forall \epsilon > 0 \exists \delta > 0$ such that

$$|x - a| < \delta \implies |f(x) - L| < \epsilon$$

that is, we don't need to say $0 < |x - a| < \delta$.

Definition 5.10. If $B \subseteq D$, then f is **continuous on B** if f is continuous at every $b \in B$.

Theorem 5.2.2. (Intermediate Value Theorem.) Let f be continuous on $[a, b]$ and suppose $f(a) < f(b)$. $\forall d$ such that

$$f(a) < d < f(b)$$

$\exists c \in \mathbb{R}$ where

$$a < c < b, f(c) = d.$$

5.3 Real Numbers (Chapter 1 of Pugh [2015]; also from Homework 6 of Math 4650 at Cal State LA)

Definition 5.11. (Uniform Continuity (from Math 4650).) Let $D \subseteq \mathbb{R}$ and let $f : D \rightarrow \mathbb{R}$. We say that f is **uniformly continuous** on D if $\forall \epsilon > 0 \exists \delta > 0$ where

$$x, y \in D \text{ and } 0 < |x - y| < \delta \implies |f(x) - f(y)| < \epsilon$$

Theorem 5.3.1. (Uniform continuity implies continuity; from Math 4650.) Suppose $f : D \rightarrow \mathbb{R}$ where $D \subseteq \mathbb{R}$. If f is uniformly continuous on D , then f is continuous at every $a \in D$.

Theorem 5.3.2 (Theorem 2.42 in Pugh [2015]). Every continuous function defined on a compact set is uniformly continuous.

Definition 5.12. Let S be any set, and let $s, s', s'' \in S$. An **equivalence relation** on S is a relation $s \sim s'$ that holds between some members $s, s' \in S$ and satisfies three properties:

- (a) $s \sim s$
- (b) $s \sim s'$ implies $s' \sim s$.
- (c) $s \sim s'$ and $s' \sim s''$ implies that $s \sim s''$.

An **equivalence class** containing s consists of all elements $s' \in S$ equivalent to s . It is denoted by $[s]$. The element s is **representative** of its equivalence class. Equivalence classes are disjoint subsets.

Definition 5.13 (Well-defined; from *Logical Prerequisites* of Lang [2005]; p. 11 of pdf, p. X of book). Let A be a set with an equivalence relation and let E be an equivalence class of elements in A . We sometimes try to define a map of E into some set B . To define such a map f , we sometimes first give its value on a representative of E and then show that it is independent of the choice of representative $x \in E$. In that case we say f is **well-defined**.

5.4 A Taste of Topology (Chapter 2 of Pugh [2015]; also from Homework 5 of Math 4650 at Cal State LA)

Definition 5.14 (from Math 4650). Let $S \subseteq \mathbb{R}$. We say $x \in \mathbb{R}$ is an **interior point** of S if there exists an open interval (a, b) where

$$x \in (a, b) \text{ and } (a, b) \subseteq S.$$

Definition 5.15 (Open sets; from Math 4650). Let $S \subseteq \mathbb{R}$. We say S is **open** if every $x \in S$ is an interior point of S .

Definition 5.16 (Metric space; from Pugh [2015] Section 2.1, p. 67 of pdf, p. 57 of book.). A **metric space** is a set M , the elements of which are referred to as points of M , together with a **metric** d satisfying positive definiteness, symmetry, and the triangle inequality. The metric $d(x, y)$ is a real number defined for all points $x, y \in M$, and $d(x, y)$ is called the **distance** from the point x to the point y .

Strictly speaking, it is the pair (M, d) which is a metric space, but often M itself is referred to as a metric space.

The main examples of metric spaces are \mathbb{R}^n and their subsets, using the Euclidean metric. A subset $M \subset \mathbb{R}^n$ becomes a metric space when we declare the distance between points of M to be their Euclidean distance apart as points in \mathbb{R}^n . We say that M **inherits** its metric from \mathbb{R}^n and is a **metric subspace** of \mathbb{R}^n .

Definition 5.17 (Open sets; from Pugh [2015] Section 2.3.). Let M be a metric space and let S be a subspace of M . S is a **closed set** if it contains all its limit points.

Definition 5.18 (Closed sets; from Math 4650). Let $S \subseteq \mathbb{R}$. We say S is **closed** if $\mathbb{R} \setminus S$ is open.

Definition 5.19 (Closed sets; from Pugh [2015] Section 2.3.). Let M be a metric space and let S be a subspace of M . S is an **open set** if for every $p \in S$ there exists an $r > 0$ such that

$$d(p, q) < r \implies q \in S.$$

Theorem 5.4.1 (from Math 4650). A set is closed if and only if it contains all of its limit points.

(Facts about open and closed sets; from Math 4650.) Suppose $a, b \in \mathbb{R}$. Then

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Proposition 5.4.2 (from Math 4650). (a, ∞) is open.

Proof. Let $x \in (a, \infty)$. Since $x > a$, $\exists \epsilon > 0 \mid a + \epsilon = x$. Then $a = x - \epsilon < x - \frac{\epsilon}{2} < x < x + \frac{\epsilon}{2} < \infty$. Therefore $x \in (x - \frac{\epsilon}{2}, x + \frac{\epsilon}{2}) \subseteq (a, \infty)$, so (a, ∞) is open. \square

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Proposition 5.4.3. $(-\infty, b)$ is open.

Proof. Let $x \in (-\infty, b)$. Since $x < b$, $\exists \epsilon > 0 \mid b - \epsilon = x$. Then $-\infty < x - \frac{\epsilon}{2} < x < x + \frac{\epsilon}{2} < x + \epsilon = b$. Therefore $x \in (x - \frac{\epsilon}{2}, x + \frac{\epsilon}{2}) \subseteq (-\infty, b)$, so $(-\infty, b)$ is open. \square

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Proposition 5.4.4. (a, b) is open.

Proof. In class notes. \square

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Proposition 5.4.5. If $a < b$, then $[a, b]$ is closed.

Proof. Consider $\mathbb{R} \setminus [a, b] = (-\infty, a) \cup (b, \infty)$. By Proposition 5.4.3, $(-\infty, a)$ is open. By Proposition ra.hw5.5b, (b, ∞) is open. By Proposition 5.4.6, the union of two open sets is open. Therefore $\mathbb{R} \setminus [a, b]$ is open, so $[a, b]$ is closed. \square

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Proposition 5.4.6 (from Math 4650). If A and B are open, then $A \cup B$ is open.

Proof. Since A is open, $\forall x_A \in A \exists (a_A, b_A) \subseteq A \mid x_A \in (a_A, b_A)$. Since B is open, $\forall x_B \in B \exists (a_B, b_B) \subseteq B \mid x_B \in (a_B, b_B)$.

Let $x \in A \cup B$. If $x \in A$, then per above $\exists (a_A, b_A) \subseteq A \subseteq A \cup B \mid x_A \in (a_A, b_A)$. If $x \in B$, then per above $\exists (a_B, b_B) \subseteq B \subseteq A \cup B \mid x_B \in (a_B, b_B)$. Therefore $A \cup B$ is open. \square

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Proposition 5.4.7 (from Math 4650). If A and B are open, then $A \cap B$ is open.

Proof. Since A is open, $\forall x_A \in A \exists (a_A, b_A) \subseteq A \mid x_A \in (a_A, b_A)$. Since B is open, $\forall x_B \in B \exists (a_B, b_B) \subseteq B \mid x_B \in (a_B, b_B)$.

Let $x \in A \cap B$. Then $x \in A$ and $x \in B$, so $\exists (a_A, b_A) \subseteq A \mid x_A \in (a_A, b_A)$, and $\exists (a_B, b_B) \subseteq B \mid x_B \in (a_B, b_B)$. Let $a = \max\{a_A, a_B\}$, and $b = \min\{b_A, b_B\}$. Since $x > a$ and $x < b$, $x \in (a, b)$. Since $(a, b) \subseteq (a_A, b_A) \subseteq A$ and $(a, b) \subseteq (a_B, b_B) \subseteq B$, $(a, b) \subseteq A \cap B$. Therefore $A \cap B$ is open. \square

•

Proposition 5.4.8 (from Math 4650). If A and B are closed, then $A \cup B$ is closed.

Proof. Since A is closed, $\mathbb{R} \setminus A$ is open. Since B is closed, $\mathbb{R} \setminus B$ is open. $\mathbb{R} \setminus (A \cup B) = (\mathbb{R} \setminus A) \cap (\mathbb{R} \setminus B)$. By Proposition 5.4.7 the intersection of two open sets is open. Therefore $\mathbb{R} \setminus (A \cup B)$ is open, so $A \cup B$ is closed.

□

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Proposition 5.4.9 (from Math 4650). If A and B are closed, then $A \cap B$ is closed.

Proof. Since A is closed, $\mathbb{R} \setminus A$ is open. Since B is closed, $\mathbb{R} \setminus B$ is open. $\mathbb{R} \setminus (A \cap B) = (\mathbb{R} \setminus A) \cup (\mathbb{R} \setminus B)$. By Proposition 5.4.6, the union of two open sets is open. Therefore $\mathbb{R} \setminus (A \cap B)$ is open, so $A \cap B$ is closed.

□

•

Proposition 5.4.10 (from Math 4650). \mathbb{R} is open and closed.

Proof. Let $\epsilon > 0$. Let $x \in \mathbb{R}$. Then $x - \epsilon, x + \epsilon \in \mathbb{R}$, and $x \in (x - \epsilon, x + \epsilon)$. Therefore \mathbb{R} is open. \mathbb{R} is closed because by Proposition 5.4.11, $\mathbb{R} \setminus \mathbb{R} = \emptyset$ is open.

□

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Proposition 5.4.11 (from Math 4650). \emptyset is open and closed.

Proof. To show that a set S is open, we must show that $\forall x \in S \exists S' \subseteq S | x \in S'$ where S' is open. Since there are no $x \in \emptyset$, this condition is satisfied for \emptyset . \emptyset is closed because per Proposition 5.4.10, $\mathbb{R} \setminus \emptyset = \mathbb{R}$ is open.

□

Proposition 5.4.12 (from Math 4650). Let x_1, x_2, \dots, x_n be real numbers. Let S be the finite set $S = \{x_1, x_2, \dots, x_n\}$. Then S is closed.

Proof. Consider $\mathbb{R} \setminus S = (-\infty, x_1) \cup (x_1, x_2) \cup \dots \cup (x_{n-1}, x_n) \cup (x_n, \infty)$. $(-\infty, x_1)$ is open by Proposition 5.4.3. (x_n, ∞) is open by Proposition 5.4.2.

Consider (x_i, x_{i+1}) where $i \in \{1, 2, 3, \dots, n-1\}$. Let $x \in (x_i, x_{i+1})$. Then since $x > x_i$ and $x < x_{i+1}$, $\exists \epsilon > 0 | x_i + \epsilon = x$ and $\exists \delta > 0 | x_{i+1} - \delta = x$. Then $x_i = x - \epsilon < x - \frac{\epsilon}{2} < x < x + \frac{\delta}{2} < x + \delta = x_{i+1}$. Therefore $x \in (x - \epsilon, x + \delta) \subseteq (x_i, x_{i+1})$, so (x_i, x_{i+1}) is open.

Finally, since $\mathbb{R} \setminus S$, by Proposition 5.4.2 (and induction) $\mathbb{R} \setminus S$ is open. Therefore S is closed.

□

Proposition 5.4.13 (from Math 4650). Let x_1, x_2, \dots, x_n be real numbers. Let S be the finite set $S = \{x_1, x_2, \dots, x_n\}$. Then S has no limit points.

Proof. Per Definition 5.7, we seek to show that (1) $\forall x_i \in S \exists \delta_i$ such that $\forall x_j \in D(x_j \neq x_i)$

$$|x_j - x_i| \geq \delta_i$$

and (2) $\forall x \in \mathbb{R} \setminus S \exists \delta_x$ such that $\forall x_i \in D$

$$|x_i - x| \geq \delta_x$$

(1) Let $x_i \in S$. Let $\delta_i = \frac{1}{2} \min\{|x_i - x_k| \mid x_k \neq x_i\}$. Then $\forall x_j \neq x_i \in S$,

$$|x_i - x_j| \geq |x_i - x_k| > \delta_i$$

(2) Let $x \in \mathbb{R} \setminus S$. Let $\delta_x = \frac{1}{2} \min\{|x - x_i| \mid x_i \in S\}$. Then

$$|x_i - x| \geq \min\{|x - x_i| \mid x_i \in S\} > \delta_x$$

□

Definition 5.20 (from Math 4650). Let $S \subseteq \mathbb{R}$. An **open cover** of S is a collection $X = \{\mathcal{O}_\alpha \mid \alpha \in I\}$ where each set \mathcal{O}_α is an open subset of \mathbb{R} such that

$$S \subseteq \bigcup_{\alpha \in I} \mathcal{O}_\alpha$$

(Here I is some set that indexes the \mathcal{O}_α).

Definition 5.21 (from Math 4650). If $X' \subseteq X$ such that

$$S \subseteq \bigcup_{\mathcal{O}_\alpha \in X'} \mathcal{O}_\alpha$$

then X' is called a **subcover** of S contained in X . In addition, if X' is finite then we call X' a **finite subcover** of S contained in X .

Definition 5.22 (Compactness; from Math 4650.). Let $S \subseteq \mathbb{R}$. We say that S is **compact** if every open cover of S contains a finite subcover.

Definition 5.23 (Compactness; from Pugh [2015] Section 2.4.). A subset A of a metric space M is (sequentially) **compact** if every sequence (a_n) in A has a subsequence (a_{n_k}) that converges to a limit in A .

Definition 5.24 (from Math 4650). Let $S \subseteq \mathbb{R}$. We say that S is **bounded** if $\exists M > 0$ where $S \subseteq [-M, M]$.

Remark 4. S is bounded if and only if $|s| \leq M \forall s \in S$.

Theorem 5.4.14 (Heine-Borel Theorem; from Math 4650; Theorem 2.33 in Pugh [2015]). Let $S \subseteq \mathbb{R}^m$. S is compact if and only if S is closed and bounded.

Proposition 5.4.15 (from Math 4650). Let x_1, x_2, \dots, x_n be real numbers. Let S be the finite set $S = \{x_1, x_2, \dots, x_n\}$. Then S is compact.

Proof. Let $\{\mathcal{O}_\alpha\}$ be an open cover of S . By definition of open cover, $\forall i \exists O_{\alpha_i}$ such that $x_i \in O_{\alpha_i}$. Thus, $\{O_{\alpha_1}, O_{\alpha_2}, \dots, O_{\alpha_n}\}$ is a finite subcover of S . □

Proposition 5.4.16 (from Math 4650). Let A and B be compact subsets of \mathbb{R} . Then $A \cap B$ is compact.

Proof. Since $A \cap B \subseteq A$, $A \cap B \subseteq [-M_A, M_A]$. Therefore $A \cap B$ is bounded.

Since $A \cap B$ is closed and bounded, by the Heine-Borel Theorem (Theorem 5.4.14), $A \cap B$ is compact.

□

Proposition 5.4.17 (from Math 4650). Let A and B be compact subsets of \mathbb{R} . Then $A \cup B$ is compact.

Proof. Let $M = \max\{M_A, M_B\}$. Note that $[-M_A, M_A] \subseteq [M, M]$ and $[-M_B, M_B] \subseteq [-M, M]$. This implies $A \subseteq [-M, M]$ and $B \subseteq [-M, M]$. Therefore $A \cup B \subseteq [-M, M]$.

Since $A \cup B$ is closed and bounded, by the Heine-Borel Theorem (Theorem 5.4.14), $A \cup B$ is compact. \square

Theorem 5.4.18 (from Math 4650). Let $f : D \rightarrow \mathbb{R}$ be continuous on D . If $X \subseteq D$ and X is compact (closed and bounded), then

$$f(\bar{X}) = \{f(x) \mid x \in X\}$$

is compact (closed and bounded).

Corollary 5.4.18.1. Suppose $f : D \rightarrow \mathbb{R}$ where D is closed and bounded. Then there exists $a, b \in D$ where $f(a)$ is the min of f on D and $f(b)$ is the max of f on D .

Definition 5.25 (Section 2.3 of Pugh [2015]). A **topological space** is an ordered pair (X, \mathcal{T}) , where X is a set and \mathcal{T} is a collection of subsets of X satisfying the following axioms:

1. \emptyset and X belong to \mathcal{T} .
2. Any union of elements of \mathcal{T} is an element of \mathcal{T}
3. The intersection of any finite number of members of \mathcal{T} belongs to \mathcal{T} .

The elements of \mathcal{T} are called **open sets** and the collection \mathcal{T} is called a **topology** on X .

Theorem 5.4.19 (Theorem 2.6 in Pugh [2015]). A metric space and all of its open subsets form a topological space.

Theorem 5.4.20 (Urysohn's subsequence principle; Exercise 1.6.8 in ?). Let x_n be a sequence in a topological space X (e.g., \mathbb{R}), and let x be a point in X . Then the following are equivalent:

- (a) x_n converges to x .
- (b) Every subsequence of x_n converges to x .
- (c) Every subsequence of x_n has a further subsequence that converges to x .

Definition 5.26. An **isomorphism** is a mapping between two structures of the same type that can be reversed by an inverse mapping.

Definition 5.27 (Section 2.2 of Pugh [2015]). Let M and N be topological spaces (see Definition 5.25). Let $f : M \rightarrow N$ be a bijection. If f is continuous and the inverse bijection $f^{-1} : N \rightarrow M$ is also continuous then f is a **homeomorphism**. (That is, a homeomorphism is an isomorphism of topological spaces, or a bicontinuous bijection.)

Definition 5.28. Let (M, d_M) and (N, d_N) be metric spaces. An **isometry** is a bijection $f : M \rightarrow N$ that preserves distance: for all $p, q \in M$ we have $d_N(f(p), f(q)) = d_M(p, q)$. An isometry of M is a homeomorphism $i : M \rightarrow M$ such that $d_M(i(x), i(y)) = d_M(x, y)$ for all $x, y \in M$. (That is, an isometry is an isomorphism of metric spaces.)

5.5 Functions of a Real Variable; Differentiation, Riemann Integration, and Series (Chapter 3 of Pugh [2015])

Theorem 5.5.1 (Theorem 3.21 in Pugh [2015]). A bounded function is Riemann integrable if and only if for every $\epsilon > 0$ there exists a partition P_0 of $[a, b]$ such that $U(f, P_0) - L(f, P_0) < \epsilon$, where $U(f, P_0) := \sup_T \{R(f, P_0, T)\}$ is the upper sum of f with respect to P_0 and $L(f, P_0) := \inf_T \{R(f, P_0, T)\}$ is the lower sum.

5.6 Function Spaces (Chapter 4 of Pugh [2015])

5.6.1 Uniform Convergence and C^0 (Section 4.1 of Pugh [2015])

Definition 5.29 (Pointwise convergence; from Section 4.1 of Pugh [2015]). Let \mathcal{X} be a set, let (\mathcal{Y}, d) be a metric space. Let $f_n : \mathcal{X} \rightarrow \mathcal{Y}$ be functions for $n \geq 1$. Let $f : \mathcal{X} \rightarrow \mathcal{Y}$ be another function. We say f_n converges to f pointwise if for all $x \in \mathcal{X}$, the sequence $\{f_n(x)\}_{n=1}^\infty$ converges to $f(x)$ as a sequence of points in \mathcal{Y} . I.e., if for all $\epsilon > 0$ and for all $x \in \mathcal{X}$, there exists N (maybe depending on ϵ and x) such that for $n \geq N$, we have $d(f_n(x), f(x)) < \epsilon$.

Definition 5.30 (Uniform convergence; from Section 4.1 of Pugh [2015]). Let \mathcal{X} be a set, let (\mathcal{Y}, d) be a metric space. Let $f_n : \mathcal{X} \rightarrow \mathcal{Y}$ be functions for $n \geq 1$. Let $f : \mathcal{X} \rightarrow \mathcal{Y}$ be another function. We say f_n converges uniformly to f if for all $\epsilon > 0$, there exists N (maybe depending on ϵ but not x) such that for $n \geq N$ and for all $x \in \mathcal{X}$, we have $d(f_n(x), f(x)) < \epsilon$.

Remark 5. Note that uniform convergence implies pointwise convergence. This fact implies that uniform limits are unique, since limits in metric space (\mathcal{Y}, d) are unique, so the pointwise limits of sequences of functions are unique.

For an example of pointwise but not uniform convergence, see Example 5.1 below.

Theorem 5.6.1 (Cauchy 1821; Theorem 4.1 from Pugh [2015]). Let (X, d) and (Y, d') be metric spaces. Let $f_n : X \rightarrow Y$ be continuous at $x_0 \in X$ for all $n \geq 1$. Suppose f_n converges uniformly to f for some $f : X \rightarrow Y$. Then f is continuous at x_0 . (This implies that if all f_n are continuous everywhere and f_n converges uniformly to f then f is continuous everywhere.)

Proof. Let $\epsilon > 0$. Choose $N \geq 1$ such that we have

$$d'(f_n(x), f(x)) < \epsilon/3 \quad \text{for } n \geq N \text{ and for all } x \in X. \quad (5.2)$$

The function f_N is continuous at x_0 , so there exists $\delta > 0$ such that if $x \in X$ and $d(x, x_0) < \delta$, then $d'(f_N(x), f_N(x_0)) < \epsilon/3$. Then if $x \in X$, $n \geq N$, and $d(x, x_0) < \delta$, by (5.2)

$$d'(f(x), f(x_0)) \leq d'(f(x), f_n(x)) + d'(f_n(x), f_n(x_0)) + d'(f_n(x_0), f(x_0)) < \frac{\epsilon}{3} + \frac{\epsilon}{3} + \frac{\epsilon}{3} = \epsilon.$$

□

We can also show an alternative proof, but we need a few definitions and results.

Definition 5.31 (Directed sets and nets; from Homework 1 in 425B). Let (X, d) be a metric space. Let A be a set with a binary relation \preceq satisfying

- (a) $a \preceq a$ for all $a \in A$ (reflexivity),
- (b) if $a \preceq b$ and $b \preceq c$ then $a \preceq c$ (transitivity), and
- (c) for any $a, b \in A$ there exists $c \in A$ with $a \preceq c$ and $b \preceq c$ (upper bounds exist).

Such a set A is called a **directed set**. A function $f : A \rightarrow X$ is called a **net** from A to X .

If f is a net from A to \mathbb{R} , we say that f **converges to a limit** L if for every $\epsilon > 0$ there exists an element $a_0 \in A$ such that for all $a \in A$ with $a_0 \preceq a$ we have $|f(a) - L| < \epsilon$. We write $\lim f = L$.

More generally, a net **converges to** $I \in X$ if for every $\epsilon > 0$ there exists $a_0 \in A$ such that for all $a \in A$ with $a_0 \preceq a$ we have $d(f(a), I) < \epsilon$.

Proposition 5.6.2. Limits of nets in \mathbb{R} are unique: if $f : A \rightarrow \mathbb{R}$ is a net, $\lim f = L$, and $\lim f = L'$, then $L = L'$.

Proof. Let $L, L' \in \mathbb{R}$, with $\lim f = L$ and $\lim f = L'$. Then for all $\epsilon > 0$ there exists $N \in A$ such that for all $n \in A$ such that $N \preceq n$ we have $|f(n) - L| < \epsilon$, and there exists $N' \in A$ such that for all $n \in A$ such that $N' \preceq n$ we have $|f(n) - L'| < \epsilon$. Suppose $L \neq L'$, and let $\epsilon := \frac{1}{2}|L - L'| > 0$. Choose some $N^* \in A$ such that $N \preceq N^*$ and $N' \preceq N^*$ (such an N^* exists by Property 3 of the relation \preceq from Definition 5.31). Then

$$2\epsilon = |L - L'| = |L - f(N^*) + f(N^*) - L'| \leq |f(N^*) - L| + |f(N^*) - L'| < \epsilon + \epsilon = 2\epsilon,$$

contradiction. Therefore $L = L'$. □

Proposition 5.6.3. For a closed interval $[a, b]$, the set A of partition pairs / tagged partitions (P, T) of $[a, b]$ is a directed set given the relation $(P, T) \preceq (P', T')$ when P' is a refinement of P .

Proof. We will check one at a time that the conditions of Definition 5.31 hold.

- **Reflexivity:** The definition on p.168 (Section 3.2) of Pugh [2015] says that a partition P' is a refinement of P if $P \subset P'$. If we interpret this to mean P is a subset of P' but not necessarily a proper subset (sometimes written $P \subseteq P'$), then it holds that $P \preceq P$ for all $(P, T) \in A$, satisfying reflexivity.
- **Transitivity:** Suppose we have $(P_1, T_1), (P_2, T_2), (P_3, T_3) \in A$ with $(P_1, T_1) \preceq (P_2, T_2)$ and $(P_2, T_2) \preceq (P_3, T_3)$. By definition, $P_1 \subset P_2$ and $P_2 \subset P_3$, so by transitivity of sets $P_1 \subset P_3$. Therefore $(P_1, T_1) \preceq (P_3, T_3)$ as desired.
- **Upper bounds exist:** Let $(P_1, T_1), (P_2, T_2) \in A$. Let $P^* := P_1 \cup P_2$ (this is a set of finite cardinality upper-bounded by $|P_1| + |P_2|$), and let T^* be any valid set of $|P^*| - 1$ sample points relative to P^* . Then since $P_1 \subset P^*$ and $P_2 \subset P^*$, we have $(P_1, T_1) \preceq (P^*, T^*)$ and $(P_2, T_2) \preceq (P^*, T^*)$.

□

Proposition 5.6.4. For a function $f : [a, b] \rightarrow \mathbb{R}$, the net from A to \mathbb{R} given by $(P, T) \mapsto R(f, P, T)$ converges to a real number $I \in \mathbb{R}$ if and only if f is Riemann integrable with integral I .

Proof. • **Riemann integrability implies convergence of the net:** Suppose f is Riemann integrable with integral $I \in \mathbb{R}$. Let $\epsilon > 0$. By the definition in Section 3.2 of Pugh [2015], we know that there exists $\delta > 0$ such that for any partition pair (P^*, T^*) satisfying $\text{mesh } P^* < \delta$, $|R(f, P^*, T^*) - I| < \epsilon$. Fix one such partition pair (P_0, T_0) . Consider any $(P, T) \in A$ with $(P_0, T_0) \preceq (P, T)$. Since P is a refinement of P_0 , $P_0 \subset P$, so $\text{mesh } P \leq \text{mesh } P_0 < \delta$. By the definition of Riemann integrability, we have that $\text{mesh } P < \delta \implies |R(f, P, T) - I| < \epsilon$. Therefore for all $(P, T) \in A$ with $(P_0, T_0) \preceq (P, T)$ we have $|R(f, P, T) - I| < \epsilon$ and the net converges to I .

• **Convergence of the net implies Riemann integrability:** Let $\epsilon > 0$. Suppose the net $(P, T) \mapsto R(f, P, T)$ converges to $I \in \mathbb{R}$. Then there exists $(P_0, T_0) \in A$ such that for all $(P, T) \in A$ with $(P_0, T_0) \preceq (P, T)$ (that is, $P_0 \subset P$), we have $|R(f, P, T) - I| < \epsilon/2$.

First we will show by contradiction that this implies f is bounded. Let $R := R(f, P_0, T_0)$. Since $(P_0, T_0) \preceq (P_0, T_0)$, we have $|R - I| < \epsilon/2$. Denote the elements of P_0 as $P_0 = \{x_0, \dots, x_n\}$ and T_0 as $\{t_1, \dots, t_n\}$. Suppose f is unbounded on $[a, b]$. Then there is also a subinterval $[x_{i_0-1}, x_{i_0}]$ on which it is unbounded. Choose a new set $T'_0 = \{t'_1, \dots, t'_n\}$ with $t'_i = t_i$ for all $i \neq i_0$ and choose t'_{i_0} such that $|f(t'_{i_0}) - f(t_{i_0})| \Delta x_{i_0} > \epsilon$, where $\Delta x_{i_0} := x_{i_0} - x_{i_0-1}$ (such a t'_{i_0} exists because the supremum of $\{|f(t)| : x_{i_0-1} \leq t \leq x_{i_0}\}$ is ∞). Let $R' := R(f, P_0, T'_0)$. Then $|R - R'| > \epsilon$, and also $|R' - I| < \epsilon/2$ since $(P_0, T_0) \preceq (P_0, T'_0)$. But

$$\epsilon < |R - R'| = |R - I + I - R'| \leq |R - I| + |R' - I| < \epsilon/2 + \epsilon/2 = \epsilon,$$

contradiction.

Next, let $T_U := \arg \sup_T \{R(f, P_0, T)\}$ and let $T_L := \arg \inf_T \{R(f, P_0, T)\}$, and denote $U(f, P_0) := R(f, P_0, T_U)$ and $L(f, P_0) := R(f, P_0, T_L)$. Then $(P_0, T_0) \preceq (P_0, T_L)$ and $(P_0, T_0) \preceq (P_0, T_U)$, so $|L(f, P_0) - I| = I - L(f, P_0) < \epsilon/2$ and $|U(f, P_0) - I| = U(f, P_0) - I < \epsilon/2$. Then

$$U(f, P_0) - L(f, P_0) = U(f, P_0) - I + I - L(f, P_0) < \epsilon.$$

Applying Theorem 5.5.1 completes the proof.

□

Lemma 5.6.5 (Math 425b Homework 2). Let A be a directed set. Consider a sequence $f_n(a)$ of nets from A to a metric space Y . Assume that

- (a) For each fixed n , the net $f_n(a)$ converges uniformly to a limit L_n in Y .
- (b) The nets f_n converge uniformly (as a sequence of functions $A \rightarrow Y$) to some net $f : A \rightarrow Y$.

Then the limits $(L_n)_{n=1}^\infty$ form a Cauchy sequence in Y .

Proof. Let $\epsilon > 0$ be arbitrary. The limits $(L_n)_{n=1}^\infty$ form a Cauchy sequence in Y if there exists $N \in \mathbb{N}$ such that for all $n, k \geq N$ we have $d(L_n, L_m) < \epsilon$. Because the nets f_n converge uniformly, by the Cauchy

convergence criterion (Theorem 1.6 in Pugh [2015], or the completeness of \mathbb{R} , Theorem 1.5) we know that for all $a \in A$ there exists N such that for all $n, m \geq N$ we have $d(f_n(a), f_m(a)) < \epsilon/3$ for all $a \in A$.

Next, consider fixed integers $n, m \geq N$. By assumption, the net $f_n(a)$ converges to $L_n \in Y$, so there exists $a_1 \in A$ such that for all $a \in A$ with $a_1 \preceq a$, we have $d(f_n(a), L_n) < \epsilon/3$. Similarly, because $\lim f_m = L_m$ there exists $a_2 \in A$ such that for all $a \in A$ with $a_2 \preceq a$, we have $d(f_m(a), L_m) < \epsilon/3$. By the upper bound property of directed sets (from Definition 5.31), there exists $a_0 \in A$ with $a_1 \preceq a_0$ and $a_2 \preceq a_0$, and we have $d(L_n, f_n(a_0)) < \epsilon/3$ and $d(f_m(a_0), L_m) < \epsilon/3$. Putting this together, we have

$$d(L_n, L_m) \leq d(L_n, f_n(a_0)) + d(f_n(a_0), f_m(a_0)) + d(f_m(a_0), L_m) < \epsilon/3 + \epsilon/3 + \epsilon/3 = \epsilon.$$

□

Lemma 5.6.6 (Math 425b Homework 2). Let A be a directed set. Consider a sequence $f_n(a)$ of nets from A to a metric space Y . Assume that

- (a) For each fixed n , the net $f_n(a)$ converges uniformly to a limit L_n in Y .
- (b) The nets f_n converge uniformly (as a sequence of functions $A \rightarrow Y$) to some net $f : A \rightarrow Y$.
- (c) The sequence $(L_n)_{n=1}^{\infty}$ converges to some limit $L \in Y$.

Then the limit of f (as a net from A to Y) exists and equals L .

Proof. Let $\epsilon > 0$. Suppose the sequence $(L_n)_{n=1}^{\infty}$ converges to some limit $L \in Y$. Then there exists $N \in \mathbb{N}$ such that there exists $n \geq N$ with $d(L_n, L) < \epsilon/3$.

Next, note that $d(f(a), L_n) \leq d(f(a), f_n(a)) + d(f_n(a), L_n)$. Because $f_n(a)$ converges to L_n , we know there exists $a_0 \in A$ such that for all $a_2 \in A$ satisfying $a_0 \preceq a$ we have $d(f_n(a_2), L_n) < \epsilon/3$. Choose one such a_2 . Further, since f_n converges uniformly to f , there exists $a'_0 \in A$ such that for all $a_1 \in A$ satisfying $a'_0 \preceq a_1$, it holds that $d(f(a_1), f_n(a_1)) < \epsilon/3$.

Choose $a_0 \in A$ satisfying $a_1 \preceq a_0$ and $a_2 \preceq a_0$ (again, this a_0 exists by the upper bound property of directed sets from Definition 5.31). Then for all $a_0 \preceq a$,

$$d(f(a), L) \leq d(f(a), L_n) + d(L_n, L) \leq d(f(a), f_n(a)) + d(f_n(a), L_n) + d(L_n, L) < \epsilon/3 + \epsilon/3 + \epsilon/3 = \epsilon.$$

□

Now we are ready to present a different proof of Theorem 5.6.1.

Alternative proof of Theorem 5.6.1, using directed sets and nets. Let (X, d) and (Y, d') be metric spaces. Let (f_n) be a sequence of functions from X to Y . Fix $x \in X$, and let $\epsilon > 0$. Suppose each $f_n : X \rightarrow Y$ is continuous at x ; that is, we know that for all $n \in \mathbb{N}$, there exists $\delta_n > 0$ such that for all $\tilde{x}_n \in X$ satisfying $d(\tilde{x}_n, x) < \delta_n$ it holds that $d'(f_n(\tilde{x}_n), f_n(x)) < \epsilon$. Further, suppose that the sequence of functions (f_n) converge uniformly to $f : X \rightarrow Y$. That is, there exists $N \in \mathbb{N}$ such that for all $n \geq N$ we have that

$$d'(f_n(x_0), f(x_0)) < \epsilon \quad \forall x_0 \in X. \quad (5.3)$$

We then want to show that f is continuous at x ; that is, there exists $\delta > 0$ such that for every $\tilde{x} \in X$ satisfying $d(\tilde{x}, x) < \delta$ we have $d'(f(x), f(\tilde{x})) < \epsilon$.

Consider the directed set $A = X \setminus \{x\}$ with ordering relation $a \preceq a'$ if $d(a', x) \leq d(a, x)$. Let each function f_n be restricted to a function from A to Y (a net from A to Y).

First, suppose x is a non-isolated point and consider a function $g : X \rightarrow Y$. Let $\epsilon_g > 0$. We will show that g is continuous at $x = X$ if and only if the restriction of g to A viewed as a net from A to Y converges as a net to $g(x)$. That is, we will show that

$$\begin{aligned} \exists \delta_g > 0 \text{ s.t. } d(\tilde{x}_g, x) < \delta_g \implies d'(g(\tilde{x}_g), g(x)) < \epsilon_g \\ \text{if and only if} \\ \exists \hat{x}_g \in A \text{ s.t. } \hat{x}_g \preceq x \implies d'(g(\hat{x}_g), g(x)) < \epsilon_g. \end{aligned}$$

Suppose there exists $\delta_g > 0$ such that $d(\tilde{x}_g, x) < \delta_g \implies d'(g(\tilde{x}_g), g(x)) < \epsilon_g$. Then take any such \tilde{x}_g (such a point exists since x is a non-isolated point) and let $\hat{x}_g = \tilde{x}_g$. Then for all $\hat{x} \in X$ satisfying $\hat{x}_g \preceq \hat{x}$, we have $d(\hat{x}, x) \leq d(\hat{x}_g, x) = d(\tilde{x}_g, x) < \delta$, so it holds that $d'(g(\hat{x}_g), g(x)) < \epsilon_g$. Clearly the converse of this argument holds as well.

Because of this fact, since $f_n(x)$ is continuous at $x \in X$ for all $n \in \mathbb{N}$, we know that the restriction of f_n to A as a net from A to Y converges as a net to $f_n(x)$.

The sequence $(f_n(x))_{n=1}^{\infty}$ converges to $L \in Y$ if there exists $N \in \mathbb{N}$ such that $n \geq N \implies d'(f_n(x), L) < \epsilon$. But this is exactly what we know from (5.3), with $L = f(x)$.

We now have that for each n , the net $f_n(a)$ converges to a limit L_n in Y , the nets f_n converge uniformly as a sequence of functions $A \rightarrow Y$ to $f : A \rightarrow Y$, and the sequence $(L_n)_{n=1}^{\infty}$ converges to $f(x) \in Y$. Therefore we know from Lemma 5.6.6 that the limit of f as a net from A to Y exists and equals L . We also know from Lemma 5.6.5 that the limits $(L_n)_{n=1}^{\infty}$ form a Cauchy sequence in Y . Therefore f is continuous at x .

⋮

Then it follows that for every $\tilde{x} \in X$ satisfying $d(\tilde{x}, x) < \delta$ we have

$$d'(f(x), f(\tilde{x})) \leq \dots < \epsilon.$$

□

What about if you only have pointwise convergence? Then the proof of Theorem 5.6.1 won't work. Consider the sawtooth wave example: the limit is not continuous. There exist easier counterexamples as well.

Example 5.1 (From Section 4.1, p. 212 of Pugh [2015]). Let $X = [0, 1]$, $Y = \mathbb{R}$, $f_n(x) = x^n$. Let $f : [0, 1] \rightarrow \mathbb{R}$ be defined by

$$f(x) = \begin{cases} 0, & 0 \leq x < 1, \\ 1, & x = 1 \end{cases}$$

As before, f_n converges to f pointwise but not uniformly. f_n is continuous on $[0, 1]$ for all n but f is not. See Figure 5.1.

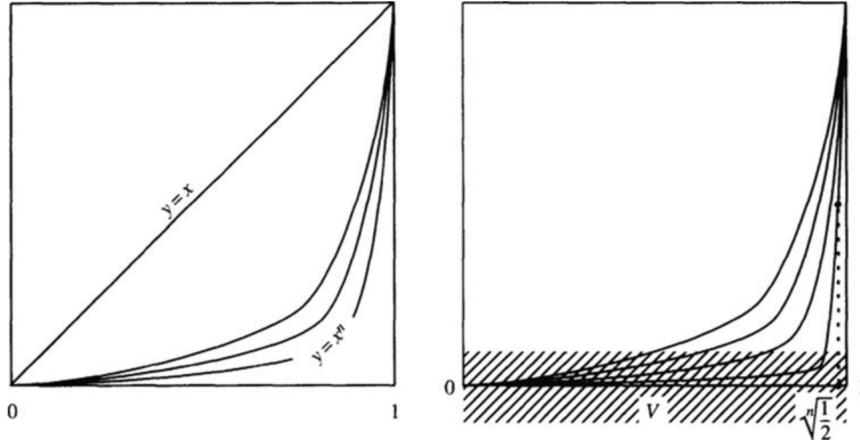


Figure 5.1: Figure 88 from Section 4.1, p. 213 of Pugh [2015]

Proposition 5.6.7. In Example 5.1, if we restrict f_n and f to the open interval from 0 to 1 (so that f is simply the 0 function on this interval) f_n does not converge uniformly to f on this interval.

Proof. Suppose f_n converges uniformly to 0 (the pointwise limit). Take $\epsilon = 1/2$. Can choose $N \geq 1$ such that $|x^n - 0| < 1/2$ for all $n \geq N$, and for all $x \in (0, 1)$. Let $x = (3/4)^{1/N}$. (N th roots exist by IVT.) Then $|x^N - 0| = 3/4$ which is not less than $1/2$.

□

Proposition 5.6.8. Consider the intervals $E_1 := [0, 1/2] = [1 - (1/2)^0, 1 - (1/2)^1]$, $E_2 := [1/2, 1 - 1/2^2] = [1 - (1/2)^1, 1 - (1/2)^2]$, $[1 - 1/2^2, 1 - 1/2^3], \dots$. On each E_j , f_n converges uniformly to f .

Proof. Observe that on interval E_j , we have uniform continuity by the following argument: for $\epsilon > 0$, let $N_j = \left\lceil \frac{\log(\epsilon)}{\log(1 - \frac{1}{2^j})} \right\rceil$. Note that it follows that for $n > N_j$,

$$n > \frac{\log(\epsilon)}{\log(1 - \frac{1}{2^j})} \iff n \log\left(1 - \frac{1}{2^j}\right) < \log(\epsilon) \iff \left(1 - \frac{1}{2^j}\right)^n < \epsilon.$$

Then if $n \geq N_j$, for all $x \in E_j$,

$$f_n(x) = x^n \leq \left(1 - \frac{1}{2^j}\right)^n < \epsilon.$$

□

Exercise 1. Let X be a set, (Y, d) be a metric space. Let $x_0 \in X$ be fixed. Let $f : X \rightarrow Y$ be a function. Then the following are equivalent:

1. There exists $m \in \mathbb{R}$ such that $d(f(x_0), f(x)) \leq m$ for all $x \in X$.
2. There exists $x_1 \in X$ and $m \in \mathbb{R}$ such that $d(f(x_1), f(x_2)) \leq m$ for all $x_2 \in X$.
3. There exists $m \in \mathbb{R}$ such that $d(f(x_1), f(x_2)) \leq m$ for all $x_1, x_2 \in X$.

Definition 5.32. If $f : X \rightarrow (Y, d)$ satisfies the statements in Exercise 1, then f is called **bounded**.

Definition 5.33 ($C_b(X, Y)$; defined Section 4.1 of Pugh [2015], p. 224 of pdf). Let X be a set and (Y, d) be a metric space. Define $C_b(X, Y)$ as the set of bounded functions from X to Y .

We would like to define a metric on $C_b(X, Y)$ related to uniform convergence. Key point: metric $d : X \times X \rightarrow \mathbb{R}$, **not** $\mathbb{R} \cup \infty$. That is, any two points in the metric space must be finite distances away from each other (which is why we need boundedness). We will set this up with this lemma.

Lemma 5.6.9. If $f, g \in C_b(X, Y)$, then

$$\sup_{\underbrace{x \in X}_{\text{will use for distance}}} d(f(x), g(x)) < \infty.$$

Proof. Let $x_0 \in X$. Choose M, N such that $d(f(x), f(x_0)) \leq M$ for all $x \in X$ and $d(g(x), g(x_0)) \leq N$ for all x (these exist since $C_b(X, Y)$ consists of bounded functions). Then for $x \in X$, we have

$$d(f(x), g(x)) \leq d(f(x), f(x_0)) + d(f(x_0), g(x_0)) + d(g(x_0), g(x)) \leq \underbrace{M + d(f(x_0), g(x_0)) + N}_{\text{finite quantity independent of } x}$$

Since this upper bound is finite, the result follows.

□

Definition 5.34 (Sup metric; defined Section 4.1 of Pugh [2015], p. 224 of pdf). For $f, g \in C_b(X, Y)$, let $d_\infty(f, g) := \sup_{x \in X} d(f(x), g(x))$.

Exercise 2. The metric space axioms hold for $d_\infty(f, g)$.

Theorem 5.6.10 (Theorem 4.2 in Pugh [2015]). X set, (Y, d) metric space. If $f_n \in C_b(X, Y)$ for $n \geq 1$ and $f \in C_b(X, Y)$, then f_n converges uniformly to f if and only if $f_n \xrightarrow{d_\infty} f$.

Proof. f_n converges uniformly to f if and only if for every $\epsilon > 0$ there exists $N \geq 1$ such that for all $n \geq N$, $d(f_n(x), f(x)) < \epsilon/2$ for all $x \in X$. This is true if and only if for every $\epsilon > 0$ there exists $N \geq 1$ such that for all $n \geq N$,

$$\sup_{x \in X} d(f_n(x), f(x)) = d_\infty(f_n, f) \leq \epsilon/2 < \epsilon,$$

so $f_n \xrightarrow{d_\infty} f$.

□

Does this adequately characterize uniform convergence of bounded functions? yes.

Proposition 5.6.11 (Uniform convergence preserves boundedness). If $f_n : X \rightarrow Y$ is bounded for all n and f_n converges uniformly to f , then f is bounded.

Proof. Let $x_0 \in X$. By uniform convergence, can choose $N \geq 1$ such that for all $n \geq N$ and all $x \in X$, we have $d(f_n(x), f(x)) < 1$. We know f_N is bounded; this implies there exists M such that $d(f_N(x), f_N(x_0)) \leq M$ for all $x \in X$. Note that

$$d(f(x), f(x_0)) \leq d(f(x), f_N(x)) + d(f_N(x), f_N(x_0)) + d(f_N(x_0), f(x_0)) \leq 1 + M + 1 = M + 2$$

which does not depend on x . This implies f is bounded.

□

Corollary 5.6.11.1 (similar to Theorem 4.2 in Pugh [2015]). If $f_n \in C_b(X, Y)$ for $n \geq 1$, then (f_n) converges uniformly if and only if (f_n) converges in $C_b(X, Y)$. (functional analysis perspective of uniform convergence.)

Now study metric space properties of $C_b(X, Y)$. For now: if Y is complete then $C_b(X, Y)$ is complete: every Cauchy sequence in $C_b(X, Y)$ converges. But this result isn't unique to bounded functions.

Definition 5.35. X set, (Y, d) metric space. A sequence of functions $f_n : X \rightarrow Y$ is **uniformly Cauchy** if for every $\epsilon > 0$ there exists $N \geq 1$ such that for $n, m \geq N$ we have $d(f_n(x), f_m(x)) < \epsilon$ for all $x \in X$.

If all f_n are bounded, then a sequence is uniformly Cauchy if and only if the sequence is Cauchy in $C_b(X, Y)$.

Theorem 5.6.12. X set, (Y, d) metric space. If (Y, d) is complete, then any uniformly Cauchy sequence of functions $f_n : X \rightarrow Y$ is uniformly convergent.

Proof. Let $f_n : X \rightarrow Y$ for $n \geq 1$ be a uniformly Cauchy sequence. First we will show f_n converges pointwise. Then we will show the convergence is uniform.

Given $x \in X$, the sequence $(f_n(x))_{n=1}^\infty$ is a Cauchy sequence in Y since

$$d(f_n(x_0), f_m(x_0)) \leq \sup_{x \in X} \{d(f_n(x), f_m(x))\} = d_\infty(f_n, f_m).$$

Since Y is complete, $(f_n(x))_{n=1}^\infty$ converges to some point of Y . Call this point $f(x)$. (Limits are unique implies f is well-defined.) So by construction, $f_n \rightarrow f$ pointwise. Next we will show that it converges uniformly.

Let $\epsilon > 0$. By the uniform Cauchy condition, there exists $N \in \mathbb{N}$ such that if $n, m \geq N$, then $d_\infty(f_n, f_m) < \epsilon/2$.

We will now show that for all $n \geq N$ and all $x \in X$, we have $d(f_n(x), f(x)) < \epsilon$. Given $x \in X$, the sequence $(f_n(x))_{n=1}^{\infty}$ converges to $f(x)$ in Y . Thus, we can choose $M^*(x)$ such that for $m \geq M^*(x)$, we have $d(f_m(x), f(x)) < \epsilon/2$. Define $M(x) := \max\{M^*(x), N\}$. Now, for $n \geq N$ we have

$$d(f_n(x), f(x)) \leq d(f_n, f_{M(x)}) + d(f_{M(x)}(x), f(x)) < \underbrace{\epsilon/2}_{\text{uniform Cauchy condition}} + \epsilon/2 = \epsilon.$$

□

Corollary 5.6.12.1 (Theorem 4.3 in Pugh [2015]). If (Y, d) is complete then $(C_b(X, Y), d_{\infty})$ is complete.

Proof. Cauchy sequence (f_n) in $C_b(X, Y)$ is uniformly Cauchy by Theorem 5.6.12. So it is uniformly convergent. Since uniform convergence preserves boundedness, limit f must be in $C_b(X, Y)$, so f_n converges to a limit in the metric space C_b .

□

Note: if (f_n) is uniformly convergent then it's uniformly Cauchy.

Definition 5.36. Assume both (X, d) and (Y, d') are metric spaces. $(C^0(X, Y) \subset C_b(X, Y))$ is the set of bounded continuous functions $X \rightarrow Y$. We can restrict d_{∞} to $C_0(X, Y)$ and get a metric subspace.

Corollary 5.6.12.2 (Corollary to Theorem 5.6.1; Corollary 4.4 in Pugh [2015]). $C^0(X, Y)$ is a closed subset of $C_b(X, Y)$.

Proof. If we have a sequence in $C^0(X, Y)$ that converges in d_{∞} to some $f \in C_b(X, Y)$, we want to show that $f \in C^0$. But f_n converges uniformly to f , so f is bounded and continuous by Theorem 5.6.1, so $f \in C^0(X, Y)$.

□

Corollary 5.6.12.3 (Corollary to Theorem 5.6.12). If (Y, d') is complete then $C^0(X, Y)$ is complete.

Proof. A closed subset of a complete metric space is complete as a metric subspace. (Closure comes from Corollary 5.6.12.2.)

□

Theorem 5.6.13 (Dini's Theorem (Math 425B homework 1)). Let X be a compact metric space and let $f_n : X \rightarrow \mathbb{R}$ be a sequence of continuous functions. Assume that the functions f_n converge pointwise to $f : X \rightarrow \mathbb{R}$, that f is continuous, and that for all $x \in X$, the sequence $(f_n(x))_{n=1}^{\infty}$ is a decreasing sequence of real numbers. Then f_n converges uniformly to f .

Proof. Consider an arbitrary $\epsilon > 0$. For each $n \in \mathbb{N}$, consider the set $U_n := \{x : f_n(x) - f(x) < \epsilon\} \subseteq X$. First we will show that U_n is open. If U_n is empty, then it is (trivially) open. Suppose U_n is not empty and consider a point $u \in U_n$. $f_n(u) - f(u) = \epsilon_u \in [0, \epsilon]$; let $\epsilon' := \epsilon - \epsilon_u$, so $\epsilon' \in (0, \epsilon]$. Since f and f_n are continuous, $f_n - f$ is continuous, so there exists a $\delta > 0$ such that $t, u \in X$ and $d(t, u) < \delta \implies |f_n(t) - f(t) - (f_n(u) - f(u))| < \epsilon'$. But

$$\begin{aligned} |f_n(t) - f(t) - (f_n(u) - f(u))| < \epsilon' \iff f_n(u) - f(u) - \epsilon' &< f_n(t) - f(t) < f_n(u) - f(u) + \epsilon' \\ &\implies f_n(t) - f(t) < \epsilon_u + \epsilon' = \epsilon; \end{aligned}$$

that is, all such t are in U_n . The open set $\{t : t \in X, d(t, u) < \delta\}$ is therefore a subset of U_n . U_n either consists of one set like this or the union of more than one such set; either way, U_n is open.

Next we will show that the U_n cover X ; that is, $X \subseteq \bigcup_{n=1}^{\infty} U_n$. Since f_n converges pointwise to f , we know that for any $x \in X$ there exists a finite $N_x \in \mathbb{N}$ such that for $n \geq N_x$ we have $|f_n(x) - f(x)| = f_n(x) - f(x) < \epsilon$. Let $N^* := \max_x \{N_x\}$ (this quantity is well-defined since X is compact). Then for all $n \geq N^*$ we have that for all $x \in X$, $f_n(x) - f(x) < \epsilon$, so $X \subseteq \bigcup_{n=N^*}^{\infty} U_n \subseteq \bigcup_{n=1}^{\infty} U_n$.

Next, consider $n < n'$ for $n, n' \in \mathbb{N}$. We will show that since $U_n = \{x : f_n(x) - f(x) < \epsilon\}$ and $U_{n'} = \{x : f_{n'}(x) - f(x) < \epsilon\}$,

$$U_n \subseteq U_{n'} \quad \forall n, n' \in \mathbb{N}, n < n' \tag{5.4}$$

by the following argument. Consider any $u \in U_n$. u satisfies $f_n(u) - f(u) < \epsilon$. Since $f_{n'}(u) \leq f_n(u)$, u also satisfies $f_{n'}(u) - f(u) < \epsilon$, so $u \in U_{n'}^1$.

X is compact, so there exists a reduction of $\bigcup_{n=1}^{\infty} U_n$ to a finite subcover of X ; that is, there exists a finite set $\mathcal{S} \subset \mathbb{N}$ such that $\bigcup_{s \in \mathcal{S}} U_s = X$. Let $s^* := \max \{\mathcal{S}\}$ (of course $s^* < \infty$ since \mathcal{S} is finite). By (5.4), we have that for any $s \in \mathcal{S}$, $U_s \subseteq U_{s^*}$. Therefore $X = \bigcup_{s \in \mathcal{S}} U_s = U_{s^*}$, so for all $n \geq s^*$ and all $x \in X$, $|f_n(x) - f(x)| = f_n(x) - f(x) < \epsilon$.

□

Proposition 5.6.14 (Uniform continuity is preserved under uniform convergence (Math 425b Homework 2)). Let (X, d) and (Y, d') be metric spaces. Let $f_n : X \rightarrow Y$ be uniformly continuous for all $n \geq 1$. Suppose f_n converges uniformly to f for some $f : X \rightarrow Y$. Then f is uniformly continuous. (This implies that if all f_n are uniformly continuous and f_n converges uniformly to f then f is uniformly continuous.)

Proof. Let $\epsilon > 0$. Choose $N \geq 1$ such that we have

$$d'(f_n(x), f(x)) < \epsilon/3 \quad \text{for } n \geq N \text{ and for all } x \in X. \tag{5.5}$$

The function f_N is uniformly continuous, so there exists $\delta > 0$ such that

$$d'(f_N(x), f_N(x_0)) < \epsilon/3 \quad \forall x, x_0 \in X \text{ with } d(x, x_0) < \delta. \tag{5.6}$$

¹Note that U_n is not necessarily a proper subset of $U_{n'}$. For example, consider $f(x) := 0$ and the sequence of functions defined by $f_n(x) := 1/n$; note that these functions satisfy the assumptions of this theorem. Let $\tilde{n} := \min \{n \in \mathbb{N} : 1/n < \epsilon\}$. Then

$$U_n = \begin{cases} X, & n \geq \tilde{n}, \\ \emptyset, & n < \tilde{n}, \end{cases}$$

so for any $n, n' \in \{1, \dots, \tilde{n}-1\}$ or $n, n' \in \{\tilde{n}, \tilde{n}+1, \dots\}$, we have that $U_n = U_{n'}^1$.

This δ works for uniform continuity of f because for any $x, x_0 \in X$ with $d(x, x_0) < \delta$,

$$d'(f(x), f(x_0)) \leq d'(f(x), f_N(x)) + d'(f_N(x), f_N(x_0)) + d'(f_N(x_0), f(x_0)) < \underbrace{\frac{\epsilon}{3}}_{\text{by (5.5)}} + \underbrace{\frac{\epsilon}{3}}_{\text{by (5.6)}} + \underbrace{\frac{\epsilon}{3}}_{\text{by (5.5)}} = \epsilon.$$

□

Definition 5.37 ($C^k(X, Y)$). In general (say for $\mathbb{R} \rightarrow \mathbb{R}$): $C^k(\mathbb{R}, \mathbb{R})$ is the set of k times continuously differentiable functions. (Generalization of notation that C^0 means continuous.) Here, we assume bounded continuity to have a d_∞ norm. For $k = 0$, metric spaces are ok. For $k > 1$, have derivatives, so harder to generalize to metric spaces. Sometimes $C^\infty(\mathbb{R}, \mathbb{R})$ is called the set of **smooth** functions (infinitely differentiable).

If X is a set and V is a vector space (say \mathbb{R} or \mathbb{C}), then the set of functions from X to V forms a vector space itself.

$$\begin{aligned}(f + g)(x) &:= f(x) + g(x) \\ (cf)(x) &:= c(f(x))\end{aligned}$$

So if $f_n : X \rightarrow V$, makes sense to consider $\sum_{n=1}^N f_n$, the partial sum. But we need V to also be a metric space in order to talk about convergence, so we will use a normed vector space $(V, \|\cdot\|)$.

Definition 5.38 (Normed vector space). $(V, \|\cdot\|)$ is a **normed vector space** if $\|\cdot\| : V \rightarrow \mathbb{R}$ satisfies

1. $\|v\| \geq 0$ for all v , $\|v\| = 0 \iff v = 0$.
2. $\|cv\| = |c|\|v\|$ for all $c \in \mathbb{R}$ or \mathbb{C} , $v \in V$.
3. $\|v + w\| \leq \|v\| + \|w\|$ for all $v, w \in V$.

More generally: $f(V, \langle \cdot, \cdot \rangle)$ is an inner product space, can define a norm on V by $\|v\| = \sqrt{\langle v, v \rangle}$. But not every norm comes from an inner product. (can deduce norm axioms from inner product axioms.)

Exercise 3. If $(V, \|\cdot\|)$ is a normed vector space, then $d(v, w) := \|v - w\|$ is a metric on V .

So, for a vector (inner product) space it is easy to get a norm. So we can talk about $C_b(X, V)$, etc.

Have a vector space of all functions $X \rightarrow V$ with no restrictions.

Exercise 4. $C_b(X, V)$ is a vector subspace of all functions $X \rightarrow V$ since if f, g are bounded then $f + g$ is bounded and if f is bounded, then for $c \in \mathbb{R}$ or $c \in \mathbb{C}$, cf is bounded, and also a zero function $X \rightarrow V$ is bounded.

So $C_b(X, V)$ is itself a vector space. We have the metric d_∞ on the vector space $C_b(X, V)$. Question: is there a norm on $C_b(X, V)$ inducing the metric d_∞ ? Yes, the **sup-norm** or ∞ -norm.

Definition 5.39. Let X be a set and $(V, \|\cdot\|)$ be a normed vector space. If $f \in C_b(X, V)$ then the **sup-norm** or **∞ -norm** is defined as

$$\|f\|_\infty = \|f\|_{\sup} := \sup_{x \in X} \|f(x)\|.$$

Note that $\|f\|_\infty = d_\infty(f, 0)$. Examples: see Figure 5.2.

Exercise 5. $\|f\|_\infty$ is a norm on $C_b(X, Y)$ and $d_\infty(f, g) = \|f - g\|_\infty$. (That is, the metric induced by $\|\cdot\|_\infty$ is d_∞ .)

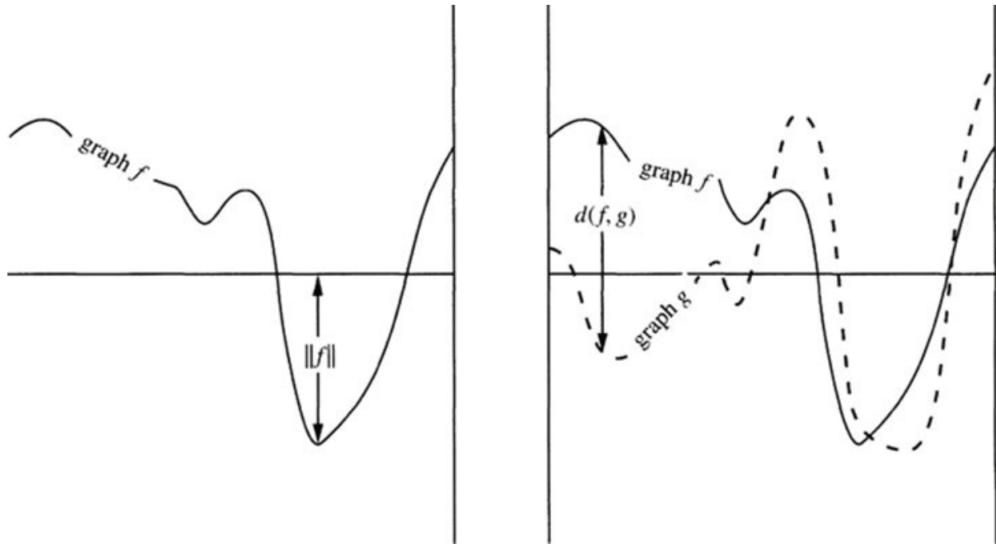


Figure 90 The sup norm of f and the sup distance between f and g

Figure 5.2: Illustration of sup norm, Figure 90 in section 4.1 of Pugh [2015].

We have special terminology for complete normed vector spaces (and inner product spaces).

Definition 5.40 (Banach space). A **Banach space** is a normed vector space $(V, \|\cdot\|)$ that is complete in the induced norm. (key concept in functional analysis.)

Definition 5.41 (Hilbert space). A **Hilbert space** is an inner product space that is complete in the induced metric (a Banach space for an inner product space).

Roughly: in physics, the “space of states” for quantum systems.

Now, if X is a set and $(V, \|\cdot\|)$ is a normed vector space, we can talk about series of functions $\sum_{n=1}^{\infty} f_n$ for $f_n : X \rightarrow V$.

Definition 5.42. Let X be a set and $(V, \|\cdot\|)$ be a normed vector space. Let $f_n : X \rightarrow V$ be functions for $n \in \mathbb{N}$.

1. We say that the series $\sum_{n=1}^{\infty} f_n$ **converges pointwise** to some $f : X \rightarrow V$ if the sequence of partial sums

$$\left(\sum_{n=1}^N f_n \right)_{N=1}^\infty$$

converges pointwise to f .

2. We say that the series $\sum_{n=1}^\infty f_n$ **converges uniformly** to some $f : X \rightarrow V$ if the sequence of partial sums

$$\left(\sum_{n=1}^N f_n \right)_{N=1}^\infty$$

converges uniformly to f .

Different types of convergence for a series $A = \sum_{n=1}^\infty v_n$ ($v_n \in V, (V, \|\cdot\|)$ a Banach space).

Consider also a series of functions $B = \sum_{n=1}^\infty f_n$ for $f_n : X \rightarrow V$ with $(V, \|\cdot\|)$ a Banach space. (Absolute convergence is easiest in a Banach space, since we can use completeness.)

To show $\sum_{n=1}^\infty v_n$ converges in V , it's enough to show the sequence of partial sums is Cauchy since V is complete. Similarly, to show that $\sum_{n=1}^\infty f_n$ converges uniformly to $f : X \rightarrow V$, it's enough to show the sequence of partial sums is uniformly Cauchy (again, because of completeness, which applies since we are in a Banach space).

Exercise 6. (A) Consider the series $\sum_{n=1}^\infty v_n$ with $(V, \|\cdot\|)$ a normed vector space and $v_n \in V$. Then

$$\left(\sum_{n=1}^N v_n \right)_{N=1}^\infty$$

is Cauchy if and only if for every $\epsilon > 0$ there exists N such that for $N \leq m, n$ we have

$$\left\| \sum_{k=m}^n v_k \right\| < \epsilon$$

Note:

$$\left\| \sum_{k=1}^n v_k - \sum_{k=1}^m v_k \right\| = \left\| \sum_{k=m+1}^n v_k \right\|$$

if $n > m$. Now fix bookkeeping.

(If seems trivial, don't worry about it, but can work out details if you want.)

(B) X set, $(V, \|\cdot\|)$ a normed vector space, $f_n : X \rightarrow V$. Then

$$\left(\sum_{n=1}^N f_n \right)_{N=1}^\infty$$

is uniformly Cauchy if and only if for every $\epsilon > 0$ there exists N such that for all $N \leq m < n$ and for all $x \in X$ we have

$$\left\| \sum_{k=m}^n f_k(x) \right\| < \epsilon.$$

In the setting of $\sum_{n=1}^{\infty} f_n$, have uniform vs. pointwise distinction; in both settings, have absolute vs. conditional distinction.

Definition 5.43. Let $(V, \|\cdot\|)$ be a Banach space. A series

$$\sum_{n=1}^{\infty} v_n$$

of elements $v_n \in V$ **converges absolutely** if the series of real numbers

$$\sum_{n=1}^{\infty} \|v_n\|$$

converges in \mathbb{R} .

Proposition 5.6.15. Let $(V, \|\cdot\|)$ be a Banach space. If

$$\sum_{n=1}^{\infty} v_n$$

converges absolutely then it converges in V .

Proof. It suffices to show that

$$\left(\sum_{n=1}^N v_n \right)_{N=1}^{\infty}$$

is Cauchy. We know that

$$\left(\sum_{n=1}^N \|v_n\| \right)_{N=1}^{\infty}$$

converges in \mathbb{R} . Given $\epsilon > 0$, there exists N such that for $N \leq m < n$ we have

$$\left| \sum_{k=m}^n \|v_k\| \right| < \epsilon.$$

Then if $N \leq m < n$ we have

$$\left\| \sum_{k=m}^n v_k \right\| \leq \sum_{k=m}^n \|v_k\| = \left| \sum_{k=m}^n \|v_k\| \right| < \epsilon.$$

So

$$\left(\sum_{n=1}^N v_n \right)_{N=1}^\infty$$

is Cauchy and thus convergent.

□

Definition 5.44. Let X be a set and let $(V, \|\cdot\|)$ be a Banach space. Let $f_n : X \rightarrow V$. Then

$$\sum_{n=1}^\infty f_n$$

converges absolutely if for all $x \in X$,

$$\sum_{n=1}^\infty f_n(x)$$

converges absolutely. (In other words, converging absolutely means converging absolutely pointwise.)

Definition 5.45 (less standard naming). Let X be a set and let $(V, \|\cdot\|)$ be a Banach space. Let $f_n : X \rightarrow V$. Then

$$\sum_{n=1}^\infty f_n$$

converges absolutely uniformly if

$$\sum_{n=1}^\infty \|f_n(x)\|$$

converges uniformly as a series of functions from X to \mathbb{R} . (note: $\|f_n(x)\|$ is a function $X \rightarrow \mathbb{R}$ whereas $\|f_n\|_\infty = \|f_n\|_{\sup}$ is a single real number, and it only exists if f is bounded.)

Proposition 5.6.16 (Absolute uniform convergence implies absolute convergence and uniform convergence). Let X be a set and let $(V, \|\cdot\|)$ be a Banach space. Let $f_n : X \rightarrow V$ be functions. If

$$\sum_{n=1}^\infty f_n$$

converges absolutely uniformly, then it converges absolutely (pointwise) and converges uniformly.

Proof. It is clear that absolute uniform convergence implies absolute pointwise convergence. So we want to show that

$$\left(\sum_{n=1}^N f_n \right)_{N=1}^\infty$$

converges uniformly. It is enough to show that

$$\left(\sum_{n=1}^N f_n \right)_{N=1}^\infty$$

is uniformly Cauchy. We know that

$$\left(\sum_{n=1}^N \|f_n\| \right)_{N=1}^\infty$$

is uniformly convergent, so it is uniformly Cauchy. Thus, given $\epsilon > 0$ there exists $N \in \mathbb{N}$ such that for $N \leq m < n$ and $x \in X$, we have

$$\left| \sum_{k=m}^n \|f_k(x)\| \right| < \epsilon.$$

Now if $N \leq m < n$, then

$$\left\| \sum_{k=m}^n f_k(x) \right\| \leq \sum_{k=m}^n \|f_k(x)\| < \epsilon.$$

Thus

$$\left(\sum_{n=1}^N f_n \right)_{N=1}^\infty$$

is uniformly Cauchy, and therefore uniformly convergent by the completeness of V .

□

Now look at bounded functions $f_n : X \rightarrow V$, where $\|f_n\|_\infty$ makes sense in \mathbb{R} (i.e. is finite). Now we can look at

$$\sum_{n=1}^\infty \|f_n\|_\infty$$

is a real number (series of real numbers).

Theorem 5.6.17 (Weierstrass M-test; Theorem 4.5 in Pugh [2015], Theorem 7.10 in Rudin [1976], p. 148 of text/p. 157 of pdf). Let X be a set and let $(V, \|\cdot\|)$ be a normed vector space. Let $f_n \in C_b(X, Y)$ be functions. If

$$\sum_{n=1}^{\infty} \|f_n\|_{\infty}$$

converges as a series in \mathbb{R} , then

$$\sum_{n=1}^{\infty} f_n$$

converges uniformly as a series of functions from $X \rightarrow \mathbb{R}$. (Further, if V is a Banach space, it converges absolutely uniformly, so absolutely and uniformly.)

Proof. Since \mathbb{R} is complete, it suffices to show that

$$\left(\sum_{n=1}^N \|f_n\| \right)_{N=1}^{\infty}$$

is uniformly Cauchy. We know that

$$\left(\sum_{n=1}^N \|f_n\|_{\infty} \right)_{N=1}^{\infty}$$

is a Cauchy sequence in \mathbb{R} . That means that given $\epsilon > 0$, there exists N such that if $N \leq m < n$ then

$$\left| \sum_{k=m}^n \|f_k\|_{\infty} \right| < \epsilon.$$

If $N \leq m < n$ and $x \in X$, we have

$$\sum_{k=m}^n \|f_k(x)\| \leq \sum_{k=m}^n \sup_{x' \in X} \|f_k(x')\| = \sum_{k=m}^n \|f_k\|_{\infty} < \epsilon.$$

□

Theorem 5.6.18 (Weierstrass M-test, classical version, also appears in Pugh [2015]). Let X be a set and let $(V, \|\cdot\|)$ be a Banach space. Let $f_n : X \rightarrow V$ be bounded and suppose that for all (sufficiently large) n , we have constants $M_n \in \mathbb{R}$ such that

$$\|f_n\|_{\infty} \leq M_n, \quad \text{and} \quad \sum_{n=1}^{\infty} M_n \text{ converges.}$$

Then $\sum_{n=1}^{\infty} f_n$ converges absolutely and uniformly.

Proof. Use previous version plus comparison test for series. □

The Weierstrass M-test can be used to deduce uniform convergence properties for series (particularly power series). Before applying this to power series, we will study uniform convergence and integrals/derivatives. (We are still building towards showing that power series can be differentiated term-by-term inside the disc of convergence; thus they're smooth functions. Thus, power series are C^∞ in their disc of convergence.)

Integrals: let $[a, b] \in \mathbb{R}$. Let $\mathcal{R}[a, b]$ be the set of Riemann integrable functions from $[a, b]$ to \mathbb{R} (or \mathbb{C}). Recall that (properly) Riemann integrable functions are bounded (Theorem 3.16 in Pugh [2015]). So, $\mathcal{R}[a, b] \subseteq C_b([a, b], \mathbb{R})$.

Proposition 5.6.19 (Lebesgue's integrability condition). $f \in C_b([a, b], \mathbb{R})$ is Riemann integrable if and only if $\text{disc}(f)$ (the set of discontinuities of f) is a **null set** (i.e., a set of measure 0).

Theorem 5.6.20 (Theorem 4.6 in Pugh [2015]). $\mathcal{R}[a, b]$ is a closed subset of $C_b([a, b], \mathbb{R})$, i.e.: if $f_n \in \mathcal{R}[a, b]$ and f_n converges uniformly to some $f \in C_b([a, b], \mathbb{R})$ (i.e., $f_n \xrightarrow{d_\infty} f$), then $f \in \mathcal{R}[a, b]$. Another way to say this: the uniform limit of Riemann integrable functions is Riemann integrable. Furthermore,

$$\int_a^b f(x) dx = \lim_{n \rightarrow \infty} \int_a^b f_n(x) dx; \quad (5.7)$$

i.e.,

$$\int_a^b \lim_{n \rightarrow \infty} f_n(x) dx = \lim_{n \rightarrow \infty} \int_a^b f_n(x) dx.$$

Proof of Theorem 5.6.20. Use Lebesgue's integrability condition: since we know that f_n is Riemann integrable, Lebesgue's integrability condition tells us that $\text{disc}(f_n)$ is a null set. The countable union of null sets is a null set, so $\bigcup_{n=1}^{\infty} \text{disc}(f_n)$ is a null set.

Therefore $\text{disc}(f) \subseteq \bigcup_{n=1}^{\infty} \text{disc}(f_n)$ is a sufficient condition to show that $f \in \mathcal{R}[a, b]$. We claim this is true. That is, we want to show that if $x \in \text{disc}(f)$, then $x \in \text{disc}(f)_n$ for some n ; we will prove the contrapositive. Suppose $x \notin \text{disc}(f)_n$ for any n for some $x \in [a, b]$; that is, f_n is continuous at x for all $n \in \mathbb{N}$. Since we assumed f_n converges uniformly to f , we have that f is continuous at x from Theorem 5.6.1. Therefore $x \notin \text{disc}(f)$. Thus, this proves the claim, so $f \in \mathcal{R}[a, b]$.

Next we will show that (5.7) holds. By uniform convergence of $(f_n)_{n=1}^{\infty}$ to f , given $\epsilon > 0$ there exists N such that if $n \geq N$ then $d_\infty(f_n, f) < \epsilon/(b - a)$. Now for $n \geq N$,

$$\begin{aligned} \left| \int_a^b f(t) dt - \int_a^b f_n(x) dx \right| &= \left| \int_a^b [f(x) - f_n(x)] dx \right| \leq \int_a^b |f(x) - f_n(x)| dx \leq \int_a^b d_\infty(f_n, f) dx \\ &< \frac{\epsilon}{b - a} \cdot (b - a) = \epsilon. \end{aligned}$$

□

Alternative Proof of Theorem 5.6.20 (425b Homework 2). Let A be the set of tagged partitions (P, T) of $[a, b]$ with the refinement ordering \preceq from Definition 5.31. Let $\epsilon > 0$. First we will show the nets $R(f_n, P, T)$ converge uniformly to $R(f, P, T)$. The nets converge uniformly if there exists $N \in \mathbb{N}$ such that for all $n \geq N$, for all $(P, T) \in A$ we have $|R(f_n, P, T) - R(f, P, T)| < \epsilon$.

Because the f_n converge uniformly to f , we know that there exists $N \in \mathbb{N}$ such that for all $n \geq N$ we have that

$$|f_n(x) - f(x)| < \frac{\epsilon}{b-a} \quad \forall x \in [a, b]. \quad (5.8)$$

Therefore we have that for all (P, T) in A and for all $n \geq N$,

$$\begin{aligned} |R(f_n, P, T) - R(f, P, T)| &= \left| \sum_{i=1}^n f_n(t_i) \Delta x_i - \sum_{i=1}^n f(t_i) \Delta x_i \right| = \left| \sum_{i=1}^n [f_n(t_i) - f(t_i)] \Delta x_i \right| \\ &\leq \sum_{i=1}^n |f_n(t_i) - f(t_i)| \Delta x_i \leq \sum_{i=1}^n \frac{\epsilon}{b-a} \Delta x_i = \frac{\epsilon}{b-a} \sum_{i=1}^n \Delta x_i = \frac{\epsilon}{b-a} (b-a) = \epsilon. \end{aligned}$$

By Proposition 5.6.4, since each function $f_n : [a, b] \rightarrow \mathbb{R}$ is Riemann integrable, each net $(P_n, T_n) \mapsto R(f_n, P_n, T_n)$ converges to a limit $I_n \in \mathbb{R}$. From Lemma 5.6.5, we know that because this is true and because we have shown that the nets converge uniformly to $R(f, P, T)$, the limits $(I_n)_{n=1}^\infty$ form a Cauchy sequence in \mathbb{R} . Therefore by the completeness of \mathbb{R} , the limits $(I_n)_{n=1}^\infty$ converge to some limit $I \in \mathbb{R}$, which means that by Lemma 5.6.6 the limit of $(P, T) \mapsto R(f, P, T)$ exists and equals I .

By Proposition 5.6.4, Riemann integrability of f is equivalent of convergence of the net $(P, T) \mapsto R(f, P, T)$, a net from A to \mathbb{R} . Therefore, because the net $(P, T) \mapsto R(f, P, T)$ converges to I , f is Riemann integrable with integral I .

□

Corollary 5.6.20.1 (Theorem 4.8 in Pugh [2015]). If $f_n \in \mathcal{R}[a, b]$ and the series $\sum_{n=1}^\infty$ converges uniformly to some f , then $f \in \mathcal{R}[a, b]$ and $\int_a^b f(x) dx = \sum_{n=1}^\infty \int_a^b f_n(x) dx$. I.e.,

$$\int_a^b \sum_{n=1}^\infty f_n(x) dx = \sum_{n=1}^\infty \int_a^b f_n(x) dx.$$

Proof. Apply Theorem 5.6.20 to

$$\left(\sum_{n=1}^N f_n \right)_{N=1}^\infty.$$

□

Corollary 5.6.20.2 (Corollary 4.7 in Pugh [2015]). If $f_n \in \mathcal{R}[a, b]$, f_n converges uniformly to f , then the function $\int_a^x f_n(t) dt$ converges uniformly to $\int_a^x f(t) dt$. (i.e., converges uniformly in $x \in [a, b]$.)

Proof. Similar to proof of Theorem 5.6.20. Given $\epsilon > 0$, choose N such that $d_\infty(f_n, f) < \epsilon/(b - a)$ for all $n \geq N$. If $n \geq N$, then

$$\begin{aligned} \left| \int_a^x f(t) dt - \int_a^x f_n(t) dt \right| &= \left| \int_a^x [f(t) - f_n(t)] dt \right| \leq \int_a^x |f(t) - f_n(t)| dt \leq \int_a^x d_\infty(f_n, f) dt \\ &< \frac{\epsilon}{b - a} \cdot (b - a) = \epsilon \end{aligned}$$

(since $\int_a^x 1 dx \leq \int_a^b 1 dx = b - a$). □

Question: must the uniform limit of differentiable functions be differentiable? No.

Example 5.2. Let $f_n : [-1, 1] \rightarrow \mathbb{R}$ be defined by $f_n(x) := \sqrt{x^2 + 1/n}$. Let $f(x) := \sqrt{x^2} = |x|$. $f(\cdot)$ is not differentiable at 0, but each $f_n(x)$ is. (We will show below that f_n converges uniformly to f .) So, differentiability (at one point) is lost in the limit.

Proposition 5.6.21. f_n converges uniformly to f .

Proof. We will apply Dini's Theorem (Theorem 5.6.13). Note that $[-1, 1]$ is a compact metric space. $f_n(x) = \sqrt{x^2 + 1/n}$ is a sequence of continuous functions, and for all $x \in [-1, 1]$, the sequence $(\sqrt{x^2 + 1/n})_{n=1}^\infty$ is a decreasing sequence of real numbers since $1/n$ is decreasing in n and $\sqrt{\cdot}$ is a monotonic transformation in \mathbb{R}_+ . We also have that $f(x) = |x|$ is continuous.

It only remains to be shown that the functions f_n converge pointwise to f . Let $\epsilon > 0$ and let $\tilde{x} \in [-1, 1]$. We want to find $N \in \mathbb{N}$ such that for all $n \geq N$ it holds that $\left| \sqrt{\tilde{x}^2 + 1/n} - \sqrt{\tilde{x}^2} \right| = \sqrt{\tilde{x}^2 + 1/n} - \sqrt{\tilde{x}^2} < \epsilon$. For all $n \geq 1$ we have

$$\begin{aligned} \sqrt{\tilde{x}^2 + 1/n} - \sqrt{\tilde{x}^2} < \epsilon &\iff \tilde{x}^2 + \frac{1}{n} < (\epsilon + \sqrt{\tilde{x}^2})^2 \iff \frac{1}{n} < \epsilon^2 + 2\epsilon\sqrt{\tilde{x}^2} + \tilde{x}^2 - \tilde{x}^2 \\ &\iff n > \frac{1}{\epsilon^2 + 2\epsilon\sqrt{\tilde{x}^2}}. \end{aligned}$$

Therefore set $N := \left\lceil (\epsilon^2 + 2\epsilon\sqrt{\tilde{x}^2})^{-1} + 1 \right\rceil$ to complete the proof. □

In fact, the uniform limit of smooth functions can be nowhere differentiable (even though it is continuous, since it is the uniform limit of continuous functions.)

Theorem 5.6.22 (Theorem 4.9 from Pugh [2015]). The uniform limit of a sequence of differentiable functions is differentiable provided that the sequence of derivatives also converges uniformly.

Theorem 5.6.23 (Theorem 4.10 from Pugh [2015]). A uniformly convergent series of differentiable functions can be differentiated term-by-term, provided that the derivative series converges uniformly. That is,

$$\frac{d}{dx} \left(\sum_{k=0}^{\infty} f_k(x) \right) = \sum_{k=0}^{\infty} \frac{d}{dx} (f_k(x))$$

Proof. Apply Theorem 5.6.22 to the sequence of partial sums.

□

Theorem 5.6.24 (Math 425b Homework 3). Let $[a, b] \subset \mathbb{R}$ and let $f_n : [a, b] \rightarrow \mathbb{R}$ be continuously differentiable (C^1) functions. Suppose that the derivatives f'_n converge uniformly to a function $g : [a, b] \rightarrow \mathbb{R}$ and that for some $x_0 \in [a, b]$ the function values $f_n(x_0)$ converge to some limit $L \in \mathbb{R}$ (i.e., f_n converges “pointwise somewhere,” a very weak condition). Then the functions f_n converge uniformly to a differentiable function $f : [a, b] \rightarrow \mathbb{R}$ with $f' = g$.

Proof. By the Fundamental Theorem of Calculus (Theorem 3.34 in Pugh [2015]), we have that for all $x \in [a, b]$, for a fixed $x_0 \in [a, b]$

$$\int_{x_0}^x f'_n(t) dt = f_n(x) - f_n(x_0) = f_n(x) - C_n \iff f_n(x) = C_n + \int_{x_0}^x f'_n(t) dt$$

where $C_n := f_n(x_0)$.

Let $\epsilon > 0$. We have that $f_n : [a, b] \rightarrow \mathbb{R}$ are C^1 for all n and that the derivatives f'_n converge uniformly to g ; that is, there exists $N' \in \mathbb{N}$ such that for all $n \geq N'$ we have $|f'_n(x) - g(x)| < \epsilon/(2|x - x_0|)$ for all $x \in [a, b]$. We also have that for some $x_0 \in [a, b]$, there exists $N'' \in \mathbb{N}$ such that for all $n \geq N''$, $|f_n(x_0) - L| = |C_n - L| < \epsilon/2$. Let $N := \max\{N', N''\}$. Then for all $n \geq N$ and for all $x \in [a, b]$ it holds that

$$\begin{aligned} \left| f_n(x) - \left(L + \int_{x_0}^x g(t) dt \right) \right| &= \left| C_n + \int_{x_0}^x f'_n(t) dt - \left(L + \int_{x_0}^x g(t) dt \right) \right| \\ &= \left| C_n - L + \int_{x_0}^x [f'_n(x) - g(x)] dx \right| \leq |C_n - L| + \left| \int_{x_0}^x [f'_n(x) - g(x)] dx \right| \\ &\leq |C_n - L| + \int_{x_0}^x |[f'_n(x) - g(x)]| dx < \frac{\epsilon}{2} + |x_0 - x| \cdot \frac{\epsilon}{2|x_0 - x|} = \epsilon; \end{aligned}$$

that is, $f_n(x)$ converges uniformly to $L + \int_{x_0}^x g(t) dt$. Let $f : [a, b] \rightarrow \mathbb{R}$ be defined by $f(x) := L + \int_{x_0}^x g(t) dt$. It remains to show that f is differentiable and $f' = g$. Again applying the Fundamental Theorem of Calculus, we have

$$\frac{d}{dx} f(x) = \frac{d}{dx} \left(L + \int_{x_0}^x g(t) dt \right) = \frac{d}{dx} (L) + \frac{d}{dx} \left(\int_{x_0}^x g(t) dt \right) = g(x).$$

□

Definition 5.46. Let (X, d) and (Y, d') be metric spaces and let $f_n : X \rightarrow Y$ be a sequence of functions. Let $f : X \rightarrow Y$ be another function. We say that $(f_n)_{n=1}^{\infty}$ **converges compactly** to f if for any compact subset $K \subset X$, the restrictions of f_n to K converge uniformly to the restriction of f to K . We say $(f_n)_{n=1}^{\infty}$ **converges locally uniformly** to f if for any $x \in X$ there exists an open neighborhood U of x such that the restrictions of f_n to U converge uniformly to the restriction of f to U .

Definition 5.47. Let (X, d) be a metric space. We say that (X, d) is **locally compact** if for all $x \in X$ there exists an open set U and a compact set K such that $x \in U \subseteq K \subseteq X$.

Proposition 5.6.25 (Math 425b Homework 3). Let (X, d) be a locally compact metric space. Let $f_n, f : X \rightarrow Y$ be functions. The functions f_n converge compactly to f if and only if they converge locally uniformly to f .

Proof. Let $K \subset X$ be an arbitrary compact subset of X . We have that (X, d) is locally compact; that is, for all $x \in X$ there exist $x \in U \subset K$ with U open.

- **Compact convergence implies local uniform convergence:** Let $\epsilon' > 0$. Let K' be an arbitrary compact subset of X . We will assume that $(f_n)_{n=1}^{\infty}$ converges compactly to f ; that is, the restrictions of f_n to K' converge uniformly to the restriction of f to K' . That is, there exists $N' \in \mathbb{N}$ such that for all $n \geq N'$, $d'(f_n(x), f(x)) < \epsilon'$ for all $x \in K'$. By local compactness, for all $x \in X$ there exists an open set U' with $x \in U' \subset K'$ with U' open. Since $U' \subset K'$, it holds that for all $n \geq N'$, $d'(f_n(x), f(x)) < \epsilon'$ for all $x \in U'$. Therefore the restrictions of f_n to U' converge uniformly to the restriction of f to U' .
- **Local uniform convergence implies compact convergence:** Let $\epsilon'' > 0$. We will assume that $(f_n)_{n=1}^{\infty}$ converges locally uniformly to f ; that is, for any $x'' \in X$ there exists an open neighborhood U'' of x'' such that the restrictions of f_n to U'' converge uniformly to the restriction of f to U'' .

We want to show that for any compact subset K'' of X there exists an $N'' \in \mathbb{N}$ such that for all $n \geq N''$, $d'(f_n(x), f(x)) < \epsilon''$ for all $x \in K''$.

Consider an arbitrary compact subset K'' of X . For every $\tilde{x}'' \in K''$, by assumption there exists an open set \tilde{U}'' with $\tilde{x}'' \in \tilde{U}'' \subset \tilde{K}'' \subset X$ such that the restrictions of f_n to each \tilde{U}'' converge uniformly to the restriction of f to \tilde{U}'' . That is, for each set there exists $\tilde{N}'' \in \mathbb{N}$ such that for all $n \geq N$ and for all $\tilde{x}'' \in \tilde{U}''$ it holds that $d'(f(\tilde{x}''), f_n(\tilde{x}'')) < \epsilon$. Note that the union of all such \tilde{U}'' (which might be an infinite number of sets) is an open cover of K'' . Because K'' is compact, this open cover of K'' reduces to a finite subcover, so there exists a finite number of these sets that cover K'' . Let the union of these sets (the finite subcover) be \mathcal{U} . Among each of these sets, let N'' be the maximum of all the \tilde{N}'' (this number is well-defined since there is a finite number of the \tilde{N}''). Then for all $x \in \mathcal{U}$ and for all $n \geq N''$ it holds that $d'(f_n(x), f(x)) < \epsilon$. Since $K'' \subset \mathcal{U}$, the result follows.

□

Definition 5.48. For $f \in C^0([a, b], \mathbb{R})$, define $\|f\|_1 := \int_a^b |f(x)| dx$. (The norm axioms hold for $\|\cdot\|_1$.)

For $[a, b] \subset \mathbb{R}$, consider the vector space $C^0([a, b], \mathbb{R})$ (we could take functions into \mathbb{C} instead and have a complex vector space). We have a norm $\|\cdot\|_\infty$ on $C^0([a, b], \mathbb{R})$ making it into a Banach space.

Proposition 5.6.26 (Math 425b Homework 3). If $f_n, f \in C^0([a, b], \mathbb{R})$ and f_n converge to f in $\|\cdot\|_\infty$ then f_n converges to f in $\|\cdot\|$. However, the opposite does not hold; converging in $\|\cdot\|_1$ does not imply convergence in $\|\cdot\|_\infty$.

Proof. Let $f_n, f \in C^0([a, b], \mathbb{R})$. Let $\epsilon > 0$. Suppose f_n converges to f in $\|\cdot\|_\infty$; that is, there exists $N \in \mathbb{N}$ such that for all $n \geq N$, $\|f_n - f\|_\infty = \sup_{x \in [a, b]} \{|f_n(x) - f(x)|\} < \epsilon/[2(b-a)]$. But then for all $n \geq N$,

$$\|f_n - f\|_1 = \int_a^b |f_n(x) - f(x)| dx \leq \int_a^b \sup_{x \in [a, b]} \{|f_n(x) - f(x)|\} dx = \frac{\epsilon}{2(b-a)} \cdot (b-a) = \frac{\epsilon}{2} < \epsilon.$$

For a counterexample showing that converging in $\|\cdot\|_1$ does not imply convergence in $\|\cdot\|_\infty$, define $f_n : [0, 1] \rightarrow \mathbb{R}$ by $f_n(x) = x^n$ and define $f : [0, 1] \rightarrow \mathbb{R}$ by $f(x) = 0$. Clearly $f_n, f \in C^0([0, 1], \mathbb{R})$. Let $\epsilon > 0$. Note that

$$\|f_n - f\|_1 < \epsilon \iff \int_0^1 x^n dx < \epsilon \iff \left[\frac{x^{n+1}}{n+1} \right]_0^1 < \epsilon \iff \frac{1}{n+1} < \epsilon \iff n > \frac{1}{\epsilon} - 1,$$

so for all $n \geq \lceil 1/\epsilon \rceil$ it holds that $\|f_n - f\|_1 < \epsilon$. Therefore f_n converges to f in $\|\cdot\|_1$. However,

$$\|f_n - f\|_\infty = \sup_{x \in [0, 1]} \{|x^n|\} \geq |1^n| = 1 \quad \forall n \in \mathbb{N},$$

so f_n does not converge to f in $\|\cdot\|_\infty$.

□

Proposition 5.6.27 (Math 425b Homework 3). $(C^0([0, 1], \mathbb{R}), \|\cdot\|_1)$ is not complete (i.e. not a Banach space).

Proof. Let $f_n : [0, 1] \rightarrow \mathbb{R}$ be defined by

$$f_n(x) = \begin{cases} 0, & 0 \leq x \leq \frac{n-1}{2n}, \\ \frac{1-0}{1/2-(n-1)/2n} \left(x - \frac{n-1}{2n} \right), & \frac{n-1}{2n} < x \leq 1/2, \\ 1, & 1/2 < x \leq 1, \end{cases} = \begin{cases} 0, & 0 \leq x \leq \frac{n-1}{2n}, \\ 2nx - n + 1, & \frac{n-1}{2n} < x \leq 1/2, \\ 1, & 1/2 < x \leq 1, \end{cases}$$

for $n \in \mathbb{N}$. First we will show that these functions are Cauchy in d_1 . Let $\epsilon > 0$. For $n, m \in \mathbb{N}$ with $n < m$, we have

$$\begin{aligned}
& \int_0^1 |f_n(x) - f_m(x)| \, dx \\
&= \int_0^{(n-1)/2n} |0 - 0| \, dx + \int_{(n-1)/2n}^{(m-1)/2m} |2nx - n + 1 - 0| \, dx \\
&\quad + \int_{(m-1)/2m}^{1/2} |2nx - n + 1 - (2mx - m + 1)| \, dx + \int_{1/2}^1 |1 - 1| \, dx \\
&= \int_{(n-1)/2n}^{(m-1)/2m} (2nx - n + 1) \, dx + \int_{(m-1)/2m}^{1/2} |(n-m)(2x-1)| \, dx \\
&= [nx^2 - (n-1)x]_{(n-1)/2n}^{(m-1)/2m} + (n-m)[x - x^2]_{(m-1)/2m}^{1/2} \\
&= \left[n \left(\frac{m-1}{2m} \right)^2 - (n-1) \left(\frac{m-1}{2m} \right) \right] - \left[n \left(\frac{n-1}{2n} \right)^2 - (n-1) \left(\frac{n-1}{2n} \right) \right] \\
&\quad + (n-m) \left[\frac{1}{2} - \frac{1}{4} - \left(\frac{m-1}{2m} - \left[\frac{m-1}{2m} \right]^2 \right) \right] \\
&= \frac{n}{4} \left[\left(\frac{m-1}{m} \right)^2 - \left(\frac{n-1}{n} \right)^2 \right] - \left(\frac{n-1}{2} \right) \left(\frac{m-1}{m} - \frac{n-1}{n} \right) \\
&\quad + (n-m) \left[\frac{1}{4} - \frac{2m(m-1) - (m-1)^2}{4m^2} \right]
\end{aligned}$$

⋮

□

5.6.2 Power Series (Section 4.2 of Pugh [2015])

Note: if $z_0 \in \mathbb{C}$, can consider power series $\sum_{n=0}^{\infty} c_n(z - z_0)^n$ (where $c_n \in \mathbb{C}$): as a function of $z \in \mathbb{Z}$. We can still use

$$R = \frac{1}{\limsup_{n \rightarrow \infty} |c_n|^{1/n}} \tag{5.9}$$

and if $|z - z_0| < R$ then the series converges absolutely, if $|z - z_0| > R$ then the series diverges (and this is the unique R with these properties). We can call $B_R(z_0)$ the open ball of radius R at z_0 and the disk of convergence.

Theorem 5.6.28 (Theorem 4.11 from Pugh [2015]). Let $\sum_{n=0}^{\infty} c_n(x - x_0)^n$ be a real power series. Let R be its radius of convergence, given by (5.9). If we have $r \in [0, R)$, then the series $\sum_{n=0}^{\infty} c_n(x - x_0)^n$ converges uniformly on $[-r + x_0, r + x_0]$.

Proof. Basic idea: use convergence of geometric series to study power series.

Chose β with $r < \beta < R$; such a β exists since $r < R$. Then $1/R < 1/\beta \iff \limsup_{n \rightarrow \infty} |c_n|^{1/n} < 1/\beta$. Recall:

$$\limsup_{n \rightarrow \infty} |c_n|^{1/n} = \lim_{n \rightarrow \infty} \left(\sup_{n' \geq n} |c_{n'}|^{1/n'} \right)$$

(as n increases we have a smaller set that we are taking a supremum over, so the quantity we are taking the limit of is nonincreasing with n .) So $\limsup_{n \rightarrow \infty} |c_n|^{1/n} < 1/\beta$ implies there exists an n_0 such that

$$\sup_{n' \geq n_0} |c_{n'}|^{1/n'} < \frac{1}{\beta};$$

i.e., for $n' \geq n_0$ we have

$$|c_{n'}|^{1/n'} < 1/\beta \iff |c_{n'}| < \beta^{-n'}.$$

Without loss of generality, let $x_0 = 0$. For $x \in [-r, r]$ and $n \geq n_0$ we have

$$|c_n x^n| < \beta^{-n} r^n = \underbrace{\left(\frac{r}{\beta}\right)^n}_{:= M_n}$$

(note that $r/\beta < 1$). By the Weierstrass M-test, if $\sum_{n=n_0}^{\infty} M_n$ is finite then $\sum_{n=n_0}^{\infty} c_n x^n$ converges uniformly on $[-r, r]$ (which is true if and only if $\sum_{n=0}^{\infty} c_n x^n$ converges uniformly on $[-r, r]$). But

$$\sum_{n=0}^{\infty} \left(\frac{r}{\beta}\right)^n = \frac{1}{1 - r/\beta},$$

which is finite, proving the theorem. □

Corollary 5.6.28.1. $\sum_{n=0}^{\infty} c_n (x - x_0)^n$ converges compactly/locally uniformly on its interval of convergence $(-R + x_0, R + x_0)$.

Proof. Exercise. Show every compact subset $K \subset (-R + x_0, R + x_0)$ is contained in some $[-r + x_0, r + x_0]$. □

Theorem 5.6.29. Complex version: $\sum_{n=0}^{\infty} c_n (z - z_0)^n$ converges compactly/locally uniformly on its open disk of convergence $B_R(z_0)$.

Proof. Basically same; $K \subset \overline{B_r}(z_0) \subset B_R(z_0)$ for some $0 \leq r < R$ where $\overline{B_r}$ is the closure of B_r . □

Interlude: complex analysis approach to differentiating power series.

Definition 5.49. Let $D \subseteq \mathcal{C}$ be open. A function $f : D \rightarrow \mathcal{C}$ is **complex differentiable** or **holomorphic** if for each $z \in D$ the limit of

$$\frac{\Delta f}{\Delta z} = \frac{f(z + \Delta z) - f(z)}{\Delta z}$$

exists as $\Delta z \rightarrow 0$ in \mathbb{C} . (The limit, if it exists, is a complex number.)

Theorem 5.6.30. if $\Omega \subset \mathbb{C}$ is open, $f_n : \Omega \rightarrow \mathbb{C}$ are **holomorphic** functions (complex differentiable) and f_n converge compactly/locally to some $f : \Omega \rightarrow \mathbb{C}$, then f is holomorphic and $f'(z) = \lim_{n \rightarrow \infty} f'_n(z)$.

Note that converging compactly/locally uniformly is weaker than uniform convergence. So somehow complex differentiability is easier to get than real differentiability. (Proven using different methods: Cauchy integral theorem, etc.)

Let's use this result. Apply this to power series. Note: $\sum_{n=0}^N c_n(z - z_0)^n$ is a (complex) polynomial. Some basic facts about complex differentiability: it's holomorphic and

$$\frac{d}{dz} \left(\sum_{n=0}^N c_n(z - z_0)^n \right)$$

can be differentiated using the usual rules for real number differentiation. Thus by the above theorem, complex power series can be (complex) differentiated term-by-term on their disk of convergence implies (not hard to prove) version. for real series, we'll give a different proof.

Theorem 5.6.31 (Theorem 4.12 in Pugh [2015]). Let $\sum_{k=0}^{\infty} c_k(x - x_0)^k$ be a real power series. Let R be its radius of convergence. Then $\sum_{k=0}^{\infty} c_k(x - x_0)^k$ is differentiable on $(-R + x_0, R + x_0)$ with derivative $\sum_{k=1}^{\infty} k c_k(x - x_0)^{k-1}$, which has the same radius of convergence.

In particular, the differentiated series

$$\sum_{k=1}^{\infty} k c_k(x - x_0)^{k-1}$$

and the integrated series

$$\sum_{k=0}^{\infty} \frac{c_k}{k+1} (x - x_0)^{k+1}$$

have the same radius of convergence R as the original series $\sum_{k=0}^{\infty} c_k(x - x_0)^k$.

(crucial fact about power series: you can differentiate them like you'd like to.)

To prove this, we will need some lemmas.

Lemma 5.6.32 (Math 425b Homework 4). Suppose a_n, b_n are sequences of real numbers with $a_n \geq 0$ and $b_n \geq 0$ for all n . Show that $\sup a_n b_n \leq \sup a_n \sup b_n$, as long as the right side of the inequality is not an indeterminate form $0 \times \infty$ or $\infty \times 0$.

Proof. Suppose $\sup_n a_n \in (-\infty, \infty)$, $\sup_n b_n \in (-\infty, \infty)$. Let $n' \in \mathbb{N}$. Observe that $a_{n'} b_{n'} \leq \sup_n \{a_n\} b_{n'} \leq \sup_n \{a_n\} \sup_n \{b_n\}$. Since this statement is true for all n , it follows that $\sup_n \{a_n b_n\} \leq \sup_n \{a_n\} \sup_n \{b_n\}$.

Clearly $\sup_n a_n > -\infty$ and $\sup_n b_n > -\infty$ (in fact, $\sup_n a_n \geq 0$ and $\sup_n b_n \geq 0$), so the only other cases we need to consider are if one or both of the suprema equal infinity. But if this is true, then $\sup_n \{a_n\} \sup_n \{b_n\} = \infty$ and the inequality holds trivially.

□

Lemma 5.6.33 (Math 425b Homework 4). Suppose a_n, b_n are sequences of real numbers with $a_n \geq 0$ and $b_n \geq 0$ for all n . Then

$$\limsup a_n b_n \leq \limsup a_n \limsup b_n,$$

as long as the right side of the inequality is not an indeterminate form $0 \times \infty$ or $\infty \times 0$ (and we can assume the limit of a product sequence is equal to the product of limits).

Proof. Recall that $\limsup a_n b_n = \lim_{N \rightarrow \infty} \sup_{n \geq N} \{a_n b_n\}$. For a fixed $N \in \mathbb{N}$, consider the sequences $(\tilde{a}_n^{(N)})_{n=1}^{\infty}$ and $(\tilde{b}_n^{(N)})_{n=1}^{\infty}$ defined by

$$\tilde{a}_n^{(N)} = \begin{cases} 0, & n < N, \\ a_n, & n \geq N, \end{cases} \quad \text{and} \quad \tilde{b}_n^{(N)} = \begin{cases} 0, & n < N, \\ b_n, & n \geq N. \end{cases}$$

Note that $\sup \tilde{a}_n^{(N)} = \sup_{n \geq N} a_n$, etc. Since these are sequences of nonnegative real numbers for all $N \in \mathbb{N}$, we know from Lemma 5.6.32 that $\sup \tilde{a}_n^{(N)} \tilde{b}_n^{(N)} \leq \sup \tilde{a}_n^{(N)} \sup \tilde{b}_n^{(N)}$ for all $n \in \mathbb{N}$ and $N \in \mathbb{N}$ as long as the right side of the inequality is not an indeterminate form $0 \times \infty$ or $\infty \times 0$. Then

$$\begin{aligned} & \sup \tilde{a}_n^{(N)} \tilde{b}_n^{(N)} \leq \sup \tilde{a}_n^{(N)} \sup \tilde{b}_n^{(N)} \\ \iff & \lim_{N \rightarrow \infty} \left(\sup \tilde{a}_n^{(N)} \tilde{b}_n^{(N)} \right) \leq \lim_{N \rightarrow \infty} \left(\sup \tilde{a}_n^{(N)} \sup \tilde{b}_n^{(N)} \right) \\ \iff & \lim_{N \rightarrow \infty} \left(\sup \tilde{a}_n^{(N)} \tilde{b}_n^{(N)} \right) \leq \lim_{N \rightarrow \infty} \left(\sup \tilde{a}_n^{(N)} \right) \lim_{N \rightarrow \infty} \left(\sup \tilde{b}_n^{(N)} \right) \\ \iff & \lim_{N \rightarrow \infty} \left(\sup_{n \geq N} a_n \tilde{b}_n^{(N)} \right) \leq \lim_{N \rightarrow \infty} \left(\sup_{n \geq N} a_n \right) \lim_{N \rightarrow \infty} \left(\sup_{n \geq N} b_n \right) \\ \iff & \limsup a_n b_n \leq \limsup a_n \limsup b_n, \end{aligned}$$

where we used the assumption that the limit of a product sequence is equal to the product of limits.

□

Lemma 5.6.34 (Math 425b Homework 4). Suppose a_n, b_n are sequences of real numbers with $a_n \geq 0$ and $b_n \geq 0$ for all n . Assume that $\lim_{n \rightarrow \infty} a_n = A$ with $0 < A < \infty$, and write $B = \limsup b_n \in [0, \infty]$. Show that

$$\limsup a_n b_n = AB.$$

Proof. If $B = \infty$, it holds trivially that $\limsup a_n b_n \leq AB$. Suppose $B \in [0, \infty)$. Since $\lim_{n \rightarrow \infty} a_n = A \in \mathbb{R}_+$ and $\limsup b_n = B \in \mathbb{R}_+$, it holds that $\limsup a_n = \lim a_n = A$ and likewise for b_n . Then by Lemma 5.6.33

$$\limsup a_n b_n \leq \limsup a_n \limsup b_n = \lim a_n \lim b_n = AB.$$

Now we will show the reverse inequality. First, suppose $B \in [0, \infty)$. Let $\epsilon > 0$. Because $\lim a_n = A$, there exists N_a such that for all $n \geq N_a$ we have $|a_n - A| < \epsilon \implies a_n > A - \epsilon$. Since $a_n, b_n \geq 0$ it follows that for all $N \geq N_a$

$$\sup_{n \geq N} a_n b_n \geq \sup_{n \geq N} (A - \epsilon) b_n = (A - \epsilon) \sup_{n \geq N} b_n = (A - \epsilon) B.$$

Therefore it follows from the ϵ -principle (Theorem 1.8 in Pugh [2015]) that $\sup_{n \geq N} a_n b_n \geq AB$ for all sufficiently large N , which in turn implies $\limsup a_n b_n \geq AB$.

Now suppose $B = \infty$. We have that there exists N'_a such that for all $n \geq N'_a$, $|A - a_n| < A/2 \implies a_n > A - A/2 = A/2$. Let $M \in \mathbb{R}_+$. Similarly, here exists N'_b such that for all $n \geq N'_b$, $b_n \geq 2M/A$. Let $N' := \max\{N'_a, N'_b\}$, then for all $n \geq N'$ it holds that $a_n b_n > (A/2)(2M/A) = M$. Since M is arbitrary, it follows that in this case $\limsup a_n b_n \geq M$ for any $M \in \mathbb{R}_+$; that is, $\limsup a_n b_n = \infty$.

□

Now we can prove the main result.

Proof of Theorem 5.6.31 (from Homework 4, Math 425b). We will rely on the identities

$$\lim_{k \rightarrow \infty} k^{1/k} = 1, \quad \lim_{k \rightarrow \infty} \left(\frac{1}{k+1} \right)^{1/k} = 1 \tag{5.10}$$

and

$$\limsup \sqrt[k]{k|c_k|} = \limsup \sqrt[k]{|c_k|} = \limsup \sqrt[k]{\frac{|c_k|}{k+1}}, \tag{5.11}$$

which we will prove later. Assuming these hold, note that by Theorem 3.44 in Pugh [2015], the radius of convergence of the power series $\sum_{k=0}^{\infty} c_k(x-x_0)^k$ is

$$R = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{|c_k|}}.$$

We will show that $\sum_{k=1}^{\infty} k c_k (x-x_0)^{k-1} = \sum_{k'=0}^{\infty} (k'+1) c_{k'+1} (x-x_0)^{k'}$ and $\sum_{k=1}^{\infty} k c_k (x-x_0)^k$ have the same radii of convergence using the Root Test (Theorem 3.42 in Pugh [2015]). Let the radius of convergence of the first series be R'_1 and the radius of convergence of the second series be R_1 . Then in the first case, by Lemma 5.6.34

$$\begin{aligned} \limsup_{k' \rightarrow \infty} \sqrt[k']{(k'+1)c_{k'+1}} &= \limsup_{k' \rightarrow \infty} (k'+1)^{1/k'} |c_{k'+1}|^{1/k'} = \limsup_{k' \rightarrow \infty} (k'+1)^{1/k'} \cdot \limsup_{k' \rightarrow \infty} |c_{k'+1}|^{1/k'} \\ &= \lim_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ (n'+1)^{1/n'} \right\} \cdot \lim_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ |c_{n'+1}|^{1/n'} \right\} = \lim_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ n'^{1/n'} \right\} \cdot \lim_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ |c_{n'}|^{1/n'} \right\} \end{aligned}$$

$$\implies R'_1 = \frac{1}{\limsup_{k' \rightarrow \infty} \sqrt[k']{(k'+1)c_{k'+1}}} = \frac{1}{\limsup_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ \sqrt[n']{n' |c_{n'}|} \right\}}$$

and the radius convergence of the second is

$$R_1 = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{|kc_k|}} = \frac{1}{\limsup_{k \rightarrow \infty} \sup_{n \geq k} \left\{ \sqrt[n]{n |c_n|} \right\}} = R'_1.$$

Similarly, let the radius of convergence of $\sum_{k=0}^{\infty} \frac{c_k}{k+1} (x-x_0)^{k+1} = \sum_{k'=1}^{\infty} \frac{c_{k'-1}}{k'} (x-x_0)^{k'}$ be given by R'_2 and the radius of convergence of $\sum_{k=0}^{\infty} \frac{c_k}{k+1} (x-x_0)^k$ be given by R_2 . Then in the first case, by Lemma 5.6.34

$$\begin{aligned} \limsup_{k' \rightarrow \infty} \sqrt[k']{\left| \frac{c_{k'-1}}{k'} \right|} &= \limsup_{k' \rightarrow \infty} \left\{ k'^{-1/k'} |c_{k'-1}|^{1/k'} \right\} = \limsup_{k' \rightarrow \infty} \left\{ k'^{-1/k'} \right\} \limsup_{k' \rightarrow \infty} \left\{ |c_{k'-1}|^{1/k'} \right\} \\ &= \lim_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ n'^{-1/n'} \right\} \cdot \lim_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ |c_{n'-1}|^{1/n'} \right\} = \lim_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ (n'+1)^{-1/n'} \right\} \cdot \lim_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ |c_{n'}|^{1/n'} \right\} \end{aligned}$$

$$\implies R'_2 = \frac{1}{\limsup_{k' \rightarrow \infty} \sqrt[k']{\left| \frac{c_{k'-1}}{k'+1} \right|}} = \frac{1}{\limsup_{k' \rightarrow \infty} \sup_{n' \geq k'} \left\{ \sqrt[n']{(n'+1)^{-1} |c_{n'}|} \right\}}$$

and the radius convergence of the second is

$$R_2 = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{\left| \frac{c_k}{k+1} \right|}} = \frac{1}{\limsup_{k \rightarrow \infty} \sup_{n \geq k} \left\{ \sqrt[n]{(n+1)^{-1} |c_n|} \right\}} = R'_2.$$

Next, observe that the radius of convergence of $\sum_{k=1}^{\infty} kc_k (x-x_0)^k$ (and therefore the radius of convergence of the differentiated series $\sum_{k=1}^{\infty} kc_k (x-x_0)^{k-1} = \sum_{k'=0}^{\infty} (k'+1)c_{k'+1} (x-x_0)^{k'}$) is given by

$$R_1 = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{|kc_k|}} = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{k |c_k|}} = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{|c_k|}} = R,$$

where we used (5.11). Similarly, the radius of convergence of the series $\sum_{k=0}^{\infty} \frac{c_k}{k+1} (x-x_0)^{k+1}$ (and therefore the radius of convergence of the integrated series $\sum_{k=0}^{\infty} \frac{c_k}{k+1} (x-x_0)^{k+1}$) is

$$R_2 = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{|(k+1)^{-1} c_k|}} = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{(k+1)^{-1} |c_k|}} = \frac{1}{\limsup_{k \rightarrow \infty} \sqrt[k]{|c_k|}} = R,$$

where we used (5.11).

It only remains to verify (5.10) and (5.11). To show that (5.10) holds, note that

$$\lim_{k \rightarrow \infty} k^{1/k} = \lim_{k \rightarrow \infty} \exp \left\{ \frac{1}{k} \log(k) \right\} = \exp \left\{ \lim_{k \rightarrow \infty} \left(\frac{\log(k)}{k} \right) \right\} = \exp \left\{ \lim_{k \rightarrow \infty} \left(\frac{1}{k} \right) \right\} = 1,$$

where we applied L'Hopital's Rule. Next,

$$\begin{aligned} \lim_{k \rightarrow \infty} \left(\frac{1}{k+1} \right)^{1/k} &= \lim_{k \rightarrow \infty} \exp \left\{ \frac{1}{k} \log \left(\frac{1}{k+1} \right) \right\} = \exp \left\{ \lim_{k \rightarrow \infty} \left[\frac{1}{k} \log \left(\frac{1}{k+1} \right) \right] \right\} \\ &= \exp \left\{ \lim_{k \rightarrow \infty} \left[\frac{k+1}{1} \cdot \frac{-1}{(k+1)^2} \right] \right\} = \exp \left\{ \lim_{k \rightarrow \infty} \left[\frac{-1}{k+1} \right] \right\} = 1, \end{aligned}$$

where we applied L'Hopital's Rule, verifying (5.10). We will conclude by verifying (5.11). Let $\limsup |c_k|^{1/k} := B$. Since $|c_k| \geq 0$ for all $k \in \mathbb{N}$, $B \in [0, \infty]$. We already have from (5.10) that $\lim k^{1/k} = \lim (k+1)^{-1/k} = 1$, so $\limsup k^{1/k} = \limsup (k+1)^{-1/k} = 1$. Since $k^{1/k} \geq 0$ for all $k \in \mathbb{N}$ and likewise with $(k+1)^{-1/k}$, by Lemma 5.6.34 we have

$$\limsup \sqrt[k]{k|c_k|} = \limsup k^{1/k} |c_k|^{1/k} = \limsup k^{1/k} \limsup |c_k|^{1/k} = \limsup |c_k|^{1/k}.$$

Similarly,

$$\limsup \sqrt[k]{\frac{|c_k|}{k+1}} = \limsup \left(\frac{1}{k+1} \right)^{1/k} |c_k|^{1/k} = \limsup \left(\frac{1}{k+1} \right)^{1/k} \limsup |c_k|^{1/k} = \limsup |c_k|^{1/k}.$$

□

Proof of Theorem 5.6.31 (in-class sketch). Idea: first show the radius is unchanged when we pass from the original series to the derivative. Then show that the differentiated series converges uniformly on compact subsets (from M-test). Finally, use theorem on uniform convergence of derivatives.

Rigorously: first part will be on Homework 4. From there:

$$R = \frac{1}{\limsup_{n \rightarrow \infty} |nc_n|^{1/n}}.$$

Assume it holds that the radius is unchanged when we pass from the original series to the derivative. Without loss of generality, let $x_0 = 0$. For any $0 \leq r < R$, we know that $\sum_{n=1}^{\infty} nc_n x^{n-1}$ converges uniformly on $[-r, r]$, so it converges uniformly on $(-r, r)$. (For $x \in (-r, r)$, derivative of a function on $(-R, R)$ restricted to $(-r, r)$ is same as derivative of a function on $(-R, R)$).

Let $f_N := \sum_{n=0}^N c_n x^n$ on $(-r, r)$. Thus $f'_N = \sum_{n=0}^N nc_n x^{n-1}$ on $(-r, r)$. This converges uniformly to $g := \sum_{n=1}^{\infty} nc_n x^{n-1}$ on $(-r, r)$. Also, f_N converges to $f = \sum_{n=0}^{\infty} c_n x^n$ on $(-r, r)$. So f is differentiable on $(-r, r)$ with derivative g .

Since any $X \in (-R, R)$ is in some $(-r, r)$ for some $0 \leq r < R$, it follows that $\sum_{n=0}^{\infty} c_n x^n$ is differentiable on $(-R, R)$ with derivative $\sum_{n=1}^{\infty} nc_n x^{n-1}$.

□

Definition 5.50. A function $f : (a, b) \rightarrow \mathbb{R}$ is **(real) analytic** if for all $x_0 \in (a, b)$, there exists a power series $\sum_{n=0}^{\infty} c_n(x - x_0)^n$ (centered at x_0) with positive radius of convergence such that for all $x \in \mathcal{U}$ with \mathcal{U} open, where \mathcal{U} is a subset of the intersection of the interval of convergence and (a, b) , we have

$$f(x) = \sum_{n=0}^{\infty} c_n(x - x_0)^n.$$

Definition 5.51. $\Omega \subset \mathbb{C}$ is open: $f : \Omega \rightarrow \mathbb{C}$ is **(complex) analytic** if for all $z_0 \in \mathbb{C}$, there exists a series $\sum_{n=0}^{\infty} c_n(z - z_0)^n$ with a positive radius of convergence such that $f(z) = \sum_{n=0}^{\infty} c_n(z - z_0)^n$ in an open neighborhood of z_0 contained in the intersection of Ω and the disk of convergence.

Remark 6. It is somewhat unintuitive that being analytic is necessary for being holomorphic. In real functional analysis, even being C^1 is a stronger condition than being differentiable. Note that being C^∞ is a weaker condition than being analytic; some functions are C^∞ but not analytic. So in complex functional analysis, this “hierarchy” collapses.

Theorem 5.6.35 (Math 520). $f : \Omega \rightarrow \mathbb{C}$ is holomorphic if and only if f is complex analytic.

What haven't we proved rigorously from calc 1 class?

- Transcendental functions (\exp, \sin, \cos , etc.)
- Convergent power series are analytic in their interval/disc of convergence (not a tautology—not obvious that at any point in this interval, a new power series exists that expresses the function locally). (Proven in Section 4.6)
- “Given a smooth $f : (a, b) \rightarrow \mathbb{R}$, is f equal to its Taylor series in an open neighborhood of each $x_0 \in \mathbb{R}$? e.g.

$$f(x) = \begin{cases} 0, & x \leq 0 \\ e^{-1/x}, & x > 0 \end{cases}$$

Taylor series at 0: all derivatives equal 0, so all coefficients equal 0. So converges but not to function.

The above question is equivalent to the question “is f analytic?” Since if $f(x) = \sum_{n=0}^{\infty} c_n(x - x_0)^n$ for x near x_0 , then by term-by-term differentiation it is easy to see $f(x_0) = c_0, f'(x_0) = c_1, f''(x_0) = 2c_2, \dots, f^{(r)}(x_0) = r!c_r$. So, having local derivative growth rate bounded comes if and only if f is analytic. (Proven in Section 4.6)

To finish 4.2; transcendental functions. Can define and prove basic properties using power series or differential equations (this is done in Section 4.5). (See Chapter 8 of Rudin [1976] for more content.)

Definition 5.52 (Natural exponential function).

$$\exp(x) = e^x := \sum_{n=0}^{\infty} \frac{x^n}{n!}.$$

Remark 7. Using techniques from 4.6 or 4.5 (Picard's Theorem), you can define e^x another way and show that the definitions agree. For example,

$$\log(x) := \int_1^x \frac{1}{t} dt$$

is a way to define the natural logarithm. Then can show that $\log : (0, \infty) \rightarrow \mathbb{R}$ is a bijection, then can define the exponential function to be the inverse of this function.

Another way to see the definitions are the same:

$$\exp(x) = \sum_{n=0}^{\infty} \frac{x^n}{n!}$$

can prove term-by-term that exponential is differentiable (even smooth on \mathbb{R}) and that its derivative equals itself and $\exp(0) = 1$.

Or; if defining \exp as the inverse of \log , use the inverse derivative formula with the same initial condition to get the same \exp function.

Also: Picard's Theorem in 4.5 will imply that these two definitions of \exp are the same. Very general way to understand \exp , \sin , \cos , etc. determined by the ODEs they satisfy.

Definition 5.53. For $x \in \mathbb{R}$,

$$\sin(x) := \sum_{n=0}^{\infty} (-1)^n \frac{x^{2n+1}}{(2n+1)!}, \quad \cos(x) := \sum_{n=0}^{\infty} (-1)^n \frac{x^{2n}}{(2n)!}, \quad \tan(x) = \frac{\sin(x)}{\cos(x)}, \text{ etc.}$$

Exercise 7. $R = \infty$ for these power series. By term-by-term differentiation, get $\sin' = \cos$, $\cos' = -\sin$. So we get second-order differential equations $\sin'' = -\sin(0) = 0$, $\sin'(0) = 1$. Similarly, $\cos'' = -\cos$, $\cos(0) = 1$, $\cos'(0) = 0$.

Can also take these definitions for complex numbers and show $e^{i\theta} = \cos(\theta) + i \sin(\theta)$.

How can we deduce new power series from old ones? (Can integrate/differentiate old ones.) For example, power series for $\log(x)$. We know that (from the sum of an infinite geometric series)

$$\frac{1}{1-x} = \sum_{n=0}^{\infty} x^n, \quad x \in (-1, 1)$$

with a radius of 1. We also know

$$\frac{1}{1+x} = \sum_{n=0}^{\infty} (-1)^n x^n, \quad x \in (-1, 1)$$

Then

$$\log(1+x) = \int_0^x \frac{1}{1+t} dt = \int_0^x \sum_{n=0}^{\infty} (-1)^t x^t dt = \sum_{n=0}^{\infty} (-1)^n \frac{x^{n+1}}{n+1}, \quad x \in (-1, 1).$$

Theorem 5.6.36 (Theorem 4.13 in Pugh [2015]). Any analytic function is C^∞ .

Remark 8. It turns out that the complex analogue of this statement is also true.

Proof. This follows immediately from term-by-term differentiation. In particular, an analytic function f is defined by a convergent power series. By Theorem 5.6.31, the derivative of f is given by a convergent power series with the same radius of convergence, so repeated differentiation is valid and f is smooth. \square

Theorem 5.6.37 (From Math 520). $\Omega \subset \mathbb{C}$ open, $f : \Omega \rightarrow \mathbb{C}$ is holomorphic, $z_0 \in \Omega$, then Taylor series of f at z_0

$$\sum_{n=0}^{\infty} \frac{f^{(n)}(z_0)}{n!} (z - z_0)^n$$

converges to f on any open ball $B_R(z_0)$ with $B_R(z_0) \subset \Omega$. (so radius of convergence greater than or equal to R .) See Figure 5.3.

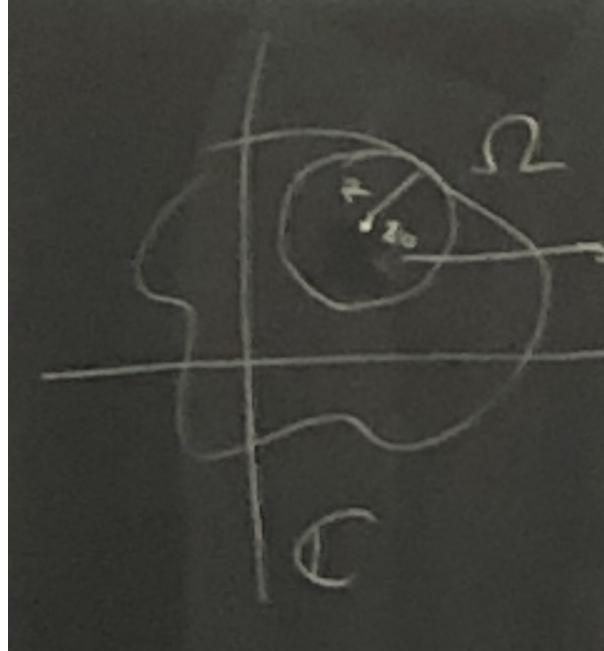


Figure 5.3: If $B_R(z_0)$ fits in Ω then the Taylor series converges to f at least on $B_R(z_0)$. See Theorem 5.6.37.

Pugh (end of section 4.2): compare $1/(1+x^2)$ to e^x . Think about $1/(1+z^2)$ in complex numbers; it blows up at $z = \pm i$. So the largest possible radius of convergence in the complex plane is 1. That's basically why the radius of convergence of the Taylor series of $1/(1+x^2)$ centered at 0 is only 1.

5.6.3 Compactness and Equicontinuity in C^0 (Section 4.3 of Pugh [2015])

Recall: X set, Y complete metric space, then $C_b(X, Y)$ is complete (Corollary 5.6.12.1). If X is a metric space, then $C^0(X, Y)$ is complete (Corollary 5.6.12.3). How about if Y is compact? Is $C^0(X, Y)$ compact?

Example 5.3. $X = [n]$ with discrete metric. $C^0([n], \mathbb{R}) \approx \mathbb{R}^n$ with ℓ^1 metric, $d(x, y) = \max |x_i - y_i|$. Then $C^0([n], [-1, 1]) \approx [-1, 1]^n$ with ℓ^1 metric.

In this case, $[-1, 1]^n$ is compact in the usual metric, so compact here.

But: now let $X := \mathbb{N}$. Consider $(C^0(\mathbb{N}, [-1, 1]), d_\infty)$. Is this compact? No. Counterexample: $f_n(x) = \begin{cases} 1, & x = n \\ 0, & x \neq n \end{cases}$. Exercise: there does not exist a uniformly convergent subsequence for this sequence. So $C^0(\mathbb{N}, [-1, 1])$ is not compact.

One way to think about this: $C^0(\mathbb{N}, [-1, 1])$ is the closed unit ball in $C^0(\mathbb{N}, \mathbb{R})$. This is a Banach space under $\|\cdot\|_\infty$. This is an infinite dimensional vector space. In a finite-dimensional normed vector space, can show that the closed unit ball is compact. But in infinite dimensional vector spaces that usually goes wrong.

Definition 5.54 (Equicontinuity; definition 7.22 in Rudin [1976], p.165 of pdf, p.156 of book). Let $(X, d), (Y, d')$ be metric spaces. Let \mathcal{E} be a set of functions from X to Y . \mathcal{E} is called **equicontinuous** if for every $\epsilon > 0$ there exists $\delta > 0$ depending only on ϵ such that for all $x, x' \in X$ with $d(x, x') < \delta$ and for all $f \in \mathcal{E}$ we have $d'(f(x), f(x')) < \epsilon$.

Note: if \mathcal{E} is equicontinuous and $f \in \mathcal{E}$ then f is uniformly continuous. So being equicontinuous is like being uniformly continuous together.

Can also formulate “pointwise equicontinuity:” δ can depend on a fixed point x_0 (but cannot depend on $f \in \mathcal{E}$).

Sequence of functions $(f_n)_{n=1}^\infty$: can take $\mathcal{E} = \{f_n : n \geq 1\}$ and ask if \mathcal{E} is equicontinuous. Write explicitly what this means:

Definition 5.55. $f_n : X \rightarrow Y$, with X, Y metric spaces. $(f_n)_{n=1}^\infty$ is an equicontinuous sequence if for every $\epsilon > 0$ there exists $\delta > 0$ such that if $x, x' \in X$, $d(x, x') < \delta$ then for every $n \in \mathbb{N}$, $d'(f_n(x), f_n(x')) < \epsilon$.

Last time: finished Section 4.2 of Pugh [2015]. Learned a trick for determining the radius of convergence of an infinite series geometrically if you go to \mathbb{C} .

Next we discussed that in infinite dimensional normed vector spaces, the closed unit ball might not be compact. (In fact, the closed unit ball is compact if and only if it is finite-dimensional. Recall: definition of dimension is the number of elements in a basis for the space.) Next we discussed how to ensure compactness of subsets of $C^0(X, \mathbb{R})$ where X is a compact metric space. One way is if the space is totally bounded and complete, but this is harder than applying Heine-Borel (Theorem 2.33 in Pugh [2015], Theorem 5.4.14 in these notes) to the equivalent question for subsets of \mathbb{R}^m , where you just need to show the set is closed and bounded. Can we get an analogous result to Heine-Borel for subsets of $C^0(X, \mathbb{R})$ (where X is a compact metric space)? Yes: it turns out $\mathcal{E} \subset C^0(X, \mathbb{R})$ is compact if and only if it is closed, bounded, and equicontinuous. (We will show this in Theorem 5.6.50.)

Example 5.4 (Non-example: sequence of functions that is not equicontinuous). Let $X = [0, 1]$ and $Y = \mathbb{R}$. Let $f_n(x) = x^n$. We will show that the set $\{f_n\}_{n=1}^\infty$ is not equicontinuous. Assume there

exists $\delta \in (0, 1)$ such that if $s, t \in [0, 1]$ and $|s - t| < \delta$ and $n \geq 1$, then $|f_n(s) - f_n(t)| < 1/2$ (that is, let $\epsilon = 1/2$). We know $\lim_{n \rightarrow \infty} (1 - \delta/2)^n = 0$, so there exists n^* with $(1 - \delta/2)^{n^*} < 1/2$. Then

$$|f_{n^*}(1 - \delta/2) - f_{n^*}(1)| = \left| \underbrace{(1 - \delta/2)^{n^*}}_{<1/2} - \underbrace{1^{n^*}}_{=1} \right| > \frac{1}{2},$$

contradiction. Therefore $\{f_n\}_{n=1}^\infty$ is not equicontinuous.

Note: these functions are a sequence of functions in the closed unit ball of $(C^0([0, 1], \mathbb{R}), \|\cdot\|_\infty)$ with no convergent subsequence. (This is true because if the limit existed it would be a uniform limit since we are using the $\|\cdot\|_\infty$ norm, and then the uniform limit would equal the pointwise limit since each of the individual functions are continuous. But the pointwise limit is not continuous.)

From this example we get an intuition that equicontinuity is related to the slopes of functions in the subset being bounded in some sense. How do we ensure equicontinuity? We can do it if we can bound the slopes of the functions, in the sense of the following definition.

Definition 5.56. Let (X, d) and (Y, d') be metric spaces. Let $f : X \rightarrow Y$. Then

1. $M \in \mathbb{R}$ is a **Lipschitz constant** for f if

$$\forall x, x' \in X, \text{ we have } d'(f(x), f(x')) \leq M \cdot d(x, x').$$

2. $M \in \mathbb{R}$ is a **uniform Lipschitz constant** for a set of functions $\mathcal{E} \subseteq C^0(X, Y)$ if

$$\forall f \in \mathcal{E} \text{ and } \forall x, x' \in X \text{ we have } d'(f(x), f(x')) \leq M \cdot d(x, x').$$

Think of M as a “global steepness bound” for f . Note that f having a Lipschitz constant M (that is, f is **Lipschitz continuous**) implies that f is uniformly continuous. (Proof: exercise. Hint: given ϵ , take $\delta = \epsilon/M$.)

Proposition 5.6.38. If a uniform Lipschitz constant M exists for a $\mathcal{E} \subset C^0(X, Y)$, then \mathcal{E} is equicontinuous.

Proof. Let $\epsilon > 0$. Take $\delta := \epsilon/M$. If $x, x' \in X$, $d(x, x') < \delta$, and $f \in \mathcal{E}$, then

$$d'(f(x), f(x')) \leq M d(x, x') < M \cdot \frac{\epsilon}{M} = \epsilon.$$

□

This makes sense when X, Y are metric spaces. Lipschitz constants are global bounds on steepness. What about local bounds?

Corollary 5.6.38.1. If \mathcal{E} is a set of differentiable functions from $[a, b]$ to \mathbb{R} (or \mathbb{C}) and there exists $M \in \mathbb{R}$ such that $|f'(\theta)| \leq M$ for all $f \in \mathcal{E}$ and for all $\theta \in [a, b]$, then \mathcal{E} is equicontinuous.

Proof. By the Mean Value Theorem, M is a uniform Lipschitz constant for \mathcal{E} . This implies that \mathcal{E} is equicontinuous. (Details: exercise.)

□

Example 5.5 (Sanity check). Let $X = [0, 1]$. Let $Y = \mathbb{R}$. Let $f_n(x) = x^n$. Based on what we've just done, there shouldn't be a uniform bound on $|f'_n(\theta)|$ for all n, θ , because if there were, this would imply equicontinuity.

Let's check: we have $f'_n(x) = nx^{n-1}$. Note that $\|f'_n\|_\infty = n$. Question: does there exist any M such that $\|f'_n\|_\infty \leq M$ for all n ? Of course not: there is no M such that for all $n \in \mathbb{N}$, $n \leq M$. So everything is consistent.

A couple more remarks: Generalized Heine-Borel: we will show in Theorem 5.6.50 (Theorem 4.18 in Pugh [2015]) that $\mathcal{E} \subset C^0(X, \mathbb{R})$ with X is compact if and only if \mathcal{E} is closed, bounded, and equicontinuous. Is this really a generalization—does it recover the usual Heine-Borel theorem (Theorem 2.33 in Pugh [2015], Theorem 5.4.14 in these notes)? Yes. Consider $X = \{1, \dots, n\}$. Any subset of $C^0(\{1, \dots, n\}, \mathbb{R})$ is equicontinuous. (We can think of the set $C^0(\{1, \dots, n\}, \mathbb{R})$ as being an alternative way of expressing \mathbb{R}^n itself.) Thus, $\mathcal{E} \subset \mathbb{R}^n$ is compact if and only if \mathcal{E} is closed and bounded. That is, Heine-Borel can be thought of as an application of Theorem 5.6.50 in the special case of the set $C^0(\{1, \dots, n\}, \mathbb{R})$.

Proposition 5.6.39 (Math 425b Homework 5). Let $\{f_1, \dots, f_k\}$ be a finite set of uniformly continuous functions from X to Y , where (X, d) and (Y, d') are metric spaces. Then $\{f_1, \dots, f_k\}$ is equicontinuous.

Proof. Let $\epsilon > 0$. Because all the f_i are continuous, for every $i \in \{1, \dots, k\}$ there exists δ_i such that for all $x \in X$, $d(x, x') < \delta_i \implies d'(f_i(x), f_i(x')) < \epsilon$. Let $\delta := \min_{i \in \{1, \dots, k\}} \delta_i$. Then for all $i \in \{1, \dots, k\}$, $(d(x, x') < \delta_i \implies d'(f_i(x), f_i(x')) < \epsilon)$.

□

Proposition 5.6.40 (Math 425b Homework 5). Let $\{f_\alpha\}_{\alpha \in A}$ be an equicontinuous set of functions from X to Y , and let g be a uniformly continuous function from Y to Z , where (X, d_X) , (Y, d_Y) , and (Z, d_Z) are metric spaces. Then the set of functions $\{g \circ f_\alpha\}_{\alpha \in A}$ is equicontinuous.

Proof. Let $\epsilon > 0$. Because g is uniformly continuous, there exists $\delta > 0$ such that for any $y, y' \in Y$, $d_Y(y, y') < \delta \implies d_Z(g(y), g(y')) < \epsilon$. Because $\{f_\alpha\}_{\alpha \in A}$ is equicontinuous, there exists an $\eta > 0$ such that for all $\alpha \in A$, $d_X(x, x') < \eta \implies d_Y(f_\alpha(x), f_\alpha(x')) < \delta$. Therefore for all $\alpha \in A$, $d_X(x, x') < \eta \implies d_Z(g(f_\alpha(x)), g(f_\alpha(x'))) < \epsilon$, so $\{g \circ f_\alpha\}_{\alpha \in A}$ is equicontinuous.

□

Proposition 5.6.41 (Math 425b Homework 5; Exercise 4.8 in Pugh [2015]). The sequence of functions $f_n : \mathbb{R} \rightarrow \mathbb{R}$ defined by

$$f_n(x) = \cos(n + x) + \log \left(1 + \frac{1}{\sqrt{n+2}} \sin^2(n^n x) \right)$$

is equicontinuous.

Proof. First we will show that the sequence $g_n(x) = \frac{1}{\sqrt{n+2}} \sin^2(n^n x)$ is equicontinuous. Let $\epsilon > 0$, and let $N := \lceil 4\epsilon^{-2} - 2 \rceil + 1$ so that $(n+2)^{-1/2} < \epsilon/2$ for all $n \geq N$. By Proposition 5.6.39, the functions $\{f_1, \dots, f_{N-1}\}$ are equicontinuous; that is, there exists $\delta > 0$ such that for all $x \in \mathbb{R}$ $|x - x'| < \delta \implies |g_n(x) - g_n(x')| < \epsilon$ for all $n \in \{1, \dots, N-1\}$. Observe that for all $n \geq N$

$$g_n(x) = \frac{\sin^2(n^n x)}{\sqrt{n+2}} < \frac{\epsilon}{2} \cdot \sin^2(n^n x) \leq \frac{\epsilon}{2}$$

for all $x \in \mathbb{R}$ since $\sin^2(x) \in [0, 1]$ for all $x \in \mathbb{R}$. Therefore for all $n \geq N$ and all $x, x' \in \mathbb{R}$ it holds that

$$|g_n(x) - g_n(x')| < \left| \frac{\epsilon}{2} + \frac{\epsilon}{2} \right| = \epsilon.$$

In particular, this holds if $|x - x'| < \delta$, so $(g_n)_{n=1}^\infty$ is equicontinuous. Next we will show that $(\cos(n+x))_{n=1}^\infty$ is an equicontinuous sequence on $[0, 2\pi]$. By Proposition 5.6.38, a sufficient condition to show this is that there exists $M \in \mathbb{R}$ such that

$$\left| \frac{d}{d\theta} \cos(n+x) \right| \leq M \quad \forall n \in \{1, 2, \dots\}, \forall x \in [0, 2\pi].$$

This follows since

$$\left| \frac{d}{d\theta} \cos(n+x) \right| = |\sin(n+x)| \leq 1 \quad \forall n \in \mathbb{N}, \forall x \in \mathbb{R}.$$

Then by the periodicity of $\cos(\cdot)$, $(\cos(n+x))_{n=1}^\infty$ is an equicontinuous sequence everywhere.

By the fact that the sum of two equicontinuous sequences is equicontinuous, the result follows if we can show that $\left(\log \left[1 + \frac{\sin^2(n^n x)}{\sqrt{n+2}} \right] \right)_{n=1}^\infty$ is equicontinuous. We showed above that g_n is equicontinuous, so since the sum of two equicontinuous sequences is equicontinuous, $\left(1 + \frac{\sin^2(n^n x)}{\sqrt{n+2}} \right)_{n=1}^\infty$ is equicontinuous. By Proposition 5.6.40, we would be done if $\log(\cdot)$ were uniformly continuous, but that is not true. However, it holds that

$$1 \leq 1 + \frac{\sin^2(n^n x)}{\sqrt{n+2}} \leq 2 \quad \forall n \in \mathbb{N},$$

so by Proposition 5.6.40 it is enough to show that $\log(\cdot)$ is uniformly continuous on $[1, 2]$.

We claim this is true. As in the proof of Proposition 5.6.38, if there exists $M \in \mathbb{R}$ such that $\left| \frac{d}{d\theta} \log(\theta) \right| \leq M$ for all $\theta \in [1, 2]$, then by the Mean Value Theorem M is a uniform Lipschitz constant for $\log(\cdot)$ on $[1, 2]$ and then $\log(\cdot)$ is uniformly continuous on $[1, 2]$. Note that for $\theta \in [1, 2]$,

$$\left| \frac{d}{d\theta} \log(\theta) \right| = \frac{1}{\theta} \in \left[\frac{1}{2}, 1 \right]$$

so $\left| \frac{d}{d\theta} \log(\theta) \right| \leq 1$ for all $\theta \in [1, 2]$ and the result follows.

□

Proposition 5.6.42 (Math 425b Homework 5; Pugh [2015] Exercise. 4.22). A sequence of smooth equicontinuous functions $f_n : [a, b] \rightarrow \mathbb{R}$ does not necessarily have uniformly bounded derivatives.

Proof. Consider $f_n : [0, 2\pi] \rightarrow \mathbb{R}$ defined by

$$f_n(x) := \frac{\sin^2(n^n x)}{\sqrt{n+2}} \quad \forall n \in \mathbb{N}.$$

Clearly $f_n \in C^\infty([0, 2\pi], \mathbb{R})$ so f_n is smooth for all $n \in \mathbb{N}$. We showed in the proof of Proposition 5.6.41 that $(f_n)_{n=1}^\infty$ is equicontinuous. However,

$$\frac{d}{dx} f_n(x) = \frac{2 \sin(n^n x) \cdot n^n}{\sqrt{n+2}} - \frac{1}{2(n+2)^{3/2}} \cdot \sin^2(n^n x),$$

which is a sequence that is not uniformly bounded over n since if $x = \frac{\pi}{2n^n}$ (so $\sin(n^n x) = 1$)

$$\begin{aligned} \lim_{n \rightarrow \infty} \frac{d}{dx} f_n(x) &= \lim_{n \rightarrow \infty} \left[\frac{2 \sin(n^n x) \cdot n^n}{\sqrt{n+2}} - \frac{1}{2(n+2)^{3/2}} \cdot \sin^2(n^n x) \right] \\ &= \lim_{n \rightarrow \infty} \left[\frac{2 \cdot n^n}{\sqrt{n+2}} - \frac{1}{2(n+2)^{3/2}} \right] \\ &= \infty. \end{aligned}$$

□

Before proving the Arzela-Ascoli Theorem (Theorem 4.14 in Pugh [2015]) we will recall a concept from Math 425a and prove some lemmas.

Definition 5.57 (Dense metric spaces (see also Definition 5.58 for a special case)). Let (X, d) be a metric space. $A \subset X$ is **dense** if any of the following equivalent statements hold:

1. For all $x \in X$ and all $\epsilon > 0$, there exists $a \in A$ with $d(x, a) < \epsilon$.
2. Each point in X is the limit of a sequence in A .
3. $\overline{A} = X$ (where \overline{A} denotes the closure of A).

Example 5.6. Some examples: $\mathbb{Q} \subset \mathbb{R}$ is countable and dense. $\mathbb{Q} \cap [a, b] \subset [a, b]$ is countable and dense.

Lemma 5.6.43. If X is a compact metric space then X has a countable dense subset A . (That is, X is **separable**.)

Proof. X is totally bounded, so there exists a finite subset A_n of X such that

$$\bigcup_{a \in A_n} B_{1/n}(a) = X.$$

Let $A := \bigcup_{n \geq 1} A_n$, a countable subset of X . Want to show: $\overline{A} = X$. Use condition 1 from Definition 5.57: if $x \in X$ and $\epsilon > 0$, then choose n sufficiently large such that $1/n < \epsilon$. Thus there exists $a \in A_n \subset A$ with $x \in B_{1/n}(a) \subset B_\epsilon(a)$, so $d(x, a) < \epsilon$. Thus $\overline{A} = X$.

□

Lemma 5.6.44 (Math 425b Homework 5). Let X be a compact metric space and let $A = \{a_n\}_{n \geq 1}$ be a countable dense subset of X . Then for any $\delta > 0$ there exists M such that for any $x \in X$ we have $d(x, a_i) < \delta$ for some i with $1 \leq i \leq M$.

Proof. Let $\delta > 0$. Because $A = \{a_1, \dots\}$ is dense in X , $\bigcup_{i=1}^{\infty} B_\delta(a_i)$ covers X . Because X is a compact metric space, by Theorem 2.63 in Pugh [2015], $\bigcup_{i=1}^{\infty} B_\delta(a_i)$ has a finite subcover. That is, there are finitely many points $x_1, \dots, x_M \in A$ such that

$$X \subset \bigcup_{i=1}^M B_\delta(a_i).$$

Therefore for some $i \in \{1, \dots, M\}$ it holds that $d(x, a_i) < \delta$.

□

Theorem 5.6.45 (Arzela-Ascoli Propagation Theorem (Theorem 4.16 in Pugh [2015])). Let X be a compact metric space. Let $A \subseteq X$ be a countable dense subset of X (such a set A is guaranteed to exist by Lemma 5.6.43). Let Y be a complete metric space. Let $(f_n)_{n=1}^{\infty}$ be an equicontinuous sequence of functions $X \rightarrow Y$. If $(f_n(a))_{n=1}^{\infty}$ converges as a sequence in Y for all points $a \in A$, then f_n converge uniformly to some f on X .

Proof. Let $\epsilon > 0$. Then equicontinuity implies that for all $n \in \mathbb{N}$ there exists $\delta = \delta_\epsilon$ such that $d(x, x') < \delta \implies d(f_n(x), f_n(x')) < \epsilon/3$ for all $n \in \mathbb{N}$. Since A is countable, call its elements $\{a_1, \dots, a_n, \dots\}$. Because X is compact, Lemma 5.6.44 guarantees that for some $J \in \mathbb{N}$, for all $x \in X$ there exists $j \in \{n_1, \dots, n_J\} \subset \{1, 2, \dots\}$ such that $d(x, a_j) < \delta$. By the pointwise convergence assumption, for any $j \in \{n_1, \dots, n_J\}$, $(f_n(a_j))_{n=1}^{\infty}$ is convergent in Y . So it is Cauchy, so there exists N_j such that for all $n, m \geq N_j$ and for all $j \in \{n_1, \dots, n_J\}$ it holds that

$$d(f_n(a_j), f_m(a_j)) < \epsilon/3. \quad (5.12)$$

Let $N := \max_{j \in \{n_1, \dots, n_J\}} \{N_j\}$; this quantity is well-defined since it is the maximum over a finite countable set. Then for any $n, m \geq N$, for all $x \in X$ there exists a_j such that $d(x, a_j) < \delta$; for this a_j it holds that

$$\begin{aligned} d(f_n(x), f_m(x)) &\leq d(f_n(x), f_n(a_j)) + d(f_n(a_j), f_m(a_j)) + d(f_m(a_j), f_m(x)) \\ &< \underbrace{\frac{\epsilon}{3}}_{\text{by equicontinuity}} + \underbrace{\frac{\epsilon}{3}}_{\text{by (5.12)}} + \underbrace{\frac{\epsilon}{3}}_{\text{by equicontinuity}} \\ &= \epsilon. \end{aligned}$$

Since Y is complete and (f_n) are uniformly Cauchy, f_n is uniformly convergent.

□

Theorem 5.6.46 (Bolzano-Weierstrass Theorem; Theorem 2.31 in Pugh [2015]). Every bounded sequence in \mathbb{R}^m has a convergent subsequence.

Theorem 5.6.47 (Theorem 7.23 in Rudin [1976], p.156, p.165 of pdf). If (f_n) is a pointwise bounded sequence of complex functions on a countable set E , then (f_n) has a subsequence f_{n_k} such that $(f_{n_k}(x))$ converges for every $x \in E$.

Proof. Let $(x_i), i \in \{1, 2, \dots\}$ be the points of E , arranged in a sequence. Since $(f_n(x_1))$ is bounded, by the Bolzano-Weierstrass Theorem (Theorem 5.6.46) there exists a subsequence (which we will denote by $S_1 = (f_{1,k}) = \{f_{1,1}, f_{1,2}, f_{1,3}, \dots\}$) of (f_n) such that $(f_{1,k}(x_1))$ converges as $k \rightarrow \infty$.

Now consider the sequence $(f_{1,k}(x_2))$. This sequence is also bounded (it is a subsequence of a bounded sequence), so it has its own subsequence $S_2 = (f_{2,k}) = \{f_{2,1}, f_{2,2}, f_{2,3}, \dots\}$ such that $(f_{2,k}(x_2))$ converges as $k \rightarrow \infty$.

We can continue in this way, creating sequences S_n such that (a) S_n is a subsequence of S_{n-1} for $n \in \{2, 3, 4, \dots\}$, (b) $(f_{n,k}(x_n))$ converges as $k \rightarrow \infty$, and (c) the order in which the functions appear is the same in each sequence (we only remove functions, so as n increases functions may move to the left in the sequence but never to the right).

Now go down the diagonal of the array, considering the sequence $S = \{f_{1,1}, f_{2,2}, f_{3,3}, \dots\}$. This sequence (except possibly its first $n - 1$ terms) is a subsequence of S_n for all $n = 1, 2, 3, \dots$. Therefore $(f_{n,n}(x_i))$ converges as $n \rightarrow \infty$ for all $x_i \in E$.

□

Theorem 5.6.48 (Arzela-Ascoli Theorem (Theorem 7.25 in Rudin [1976], p. 158; simliar to Theorem 4.14 in Pugh [2015])). Let X be a compact metric space. Let $(f_n)_{n=1}^\infty$ be a sequence of functions $f_n : X \rightarrow \mathbb{R}$ (or \mathbb{C}). Assume

1. $\{f_n\}$ is equicontinuous, and
2. $\{f_n\}$ is pointwise bounded (for all $x \in X$, there exists M_x such that for all $n \in \mathbb{N}$, $|f_n(x)| \leq M_x$).

Then

1. $\{f_n\}$ are uniformly bounded (there exists M such that for all n and for all x , $|f_n(x)| \leq M$), and
2. $\{f_n\}$ have a uniform convergent subsequence.

Remark 9. This version is a little stronger than the version stated in Pugh [2015]. It's also a traditional version that is not maximally general.

Exercise: $\{f_n\}$ having a uniform convergent subsequence is equivalent to the sequence $(f_n)_{n=1}^\infty$ being **relatively compact** (its closure is compact) in $C^0(X, \mathbb{R})$.

Proof. 1. By equicontinuity there exists δ such that for any $x, x' \in X$ if $d(x, x') < \delta$ then $|f_n(x) - f_n(x')| < 1$ for all n . Because X is a compact metric space, by Theorem 2.63 in Pugh [2015] X has a finite subcover. That is, we can pick a finite $J \in \mathbb{N}$ such that $X \subset \bigcup_{j=1}^J B_\delta(a_j)$. Because f_n is

pointwise bounded by assumption, there exists M_j such that $|f_n(a_j)| < M_j$ for all $n \in \mathbb{N}$. Let $M := \max_{j \in \{n_1, \dots, n_J\}} M_j$. Then for all $x \in X$,

$$|f_n(x)| \leq |f_n(x) - f_n(a_j)| + |f_n(a_j)| < M + 1$$

which is independent of x . Therefore the $\{f_n\}$ are uniformly bounded.

2. Let $A = \{a_1, \dots, a_n, \dots\} \subseteq X$ be a dense, countable subset of X (such a set A is guaranteed to exist by Lemma 5.6.43). By Theorem 5.6.47, (f_n) has a subsequence $(f_{n_i}) = (g_i)$ (for simplicity of notation) such that $(g_i(x))$ converges for every $x \in A$. We will show that (g_i) converges uniformly on X . Let $\epsilon > 0$. By equicontinuity there exists $\delta > 0$ such that if $d(x, x') < \delta$ then

$$|f_n(x) - f_n(x')| < \epsilon/3 \quad \forall n. \quad (5.13)$$

Because $A = \{a_1, \dots\}$ is dense in X , $\bigcup_{j=1}^{\infty} B_{\delta}(a_j)$ covers X . Because X is compact, by Theorem 2.63 in Pugh [2015] $\bigcup_{i=1}^{\infty} B_{\delta}(a_i)$ has a finite subcover. That is, there are finitely many points $a_1, \dots, a_J \in A$ such that

$$X \subset \bigcup_{j=1}^J B_{\delta}(a_j).$$

Since $(g_i(x))$ converges for every $x \in A$, there exists $N \in \mathbb{N}$ such that

$$|g_m(x_j) - g_n(x_j)| < \frac{\epsilon}{3} \quad \forall m, n \geq N, \text{ and any } j \in [J]. \quad (5.14)$$

If $x \in X$, $x \in B_{\delta}(x_j)$ for some j , so for every i there exists some $j \in [J]$ such that $|x - x_j| < \delta$ and therefore $|g_i(x) - g_i(x_j)| < \epsilon/3$. If $i \geq N$ and $k \geq N$, it follows that for some $j \in [J]$

$$|g_i(x) - g_k(x)| \leq \underbrace{|g_i(x) - g_i(x_j)|}_{\text{by (5.13)}} + \underbrace{|g_i(x_j) - g_k(x_j)|}_{\text{by (5.14)}} + \underbrace{|g_k(x_j) - g_k(x)|}_{\text{by (5.13)}} < \epsilon.$$

□

Theorem 5.6.49 (Arzela-Ascoli Theorem for functions into compact metric spaces). Let X and Y be compact metric spaces. Then any equicontinuous sequence of functions $f_n : X \rightarrow Y$ has a uniformly convergent subsequence.

Proof. This follows immediately from Theorem 5.6.48. (Note that the functions must be pointwise bounded since X and Y are compact.)

□

Now we will discuss some applications of Arzela-Ascoli (Theorem 5.6.48).

Theorem 5.6.50 (Generalized Heine-Borel in a Function Space, Theorem 4.18 in Pugh [2015]). Let X be a compact metric space. Let $\mathcal{E} \subset (C^0(X, \mathbb{R}), \|\cdot\|_{\infty})$. Then \mathcal{E} is compact if and only if \mathcal{E} is closed, bounded, and equicontinuous.

Proof. \implies : Let $\epsilon > 0$. Suppose \mathcal{E} is compact. Then by Theorem 2.65 in Pugh [2015] it is closed and totally bounded, so there is a finite covering of \mathcal{E} by neighborhoods in C^0 having radius $\epsilon/3$, say $B_{\epsilon/3}(f_k)$, with $k \in [n]$. So if $f \in \mathcal{E}$ then for some k we have $f \in B_{\epsilon/3}(f_k)$. Also, by equicontinuity each f_k is uniformly continuous, so there exists a $\delta > 0$ such that $|s - t| < \delta \implies \|f_k(s) - f_k(t)\|_\infty < \epsilon/3$. Then $|s - t| < \delta$ implies

$$|f(s) - f(t)| \leq |f(s) - f_k(s)| + |f_k(s) - f_k(t)| + |f_k(t) - f(t)| < \epsilon/3 + \epsilon/3 + \epsilon/3 = \epsilon.$$

Therefore \mathcal{E} is equicontinuous.

\impliedby : Assume that \mathcal{E} is closed, bounded, and equicontinuous. If (f_n) is a sequence in \mathcal{E} , by the fact that \mathcal{E} is bounded then (f_n) are uniformly bounded pointwise. Then by Arzela-Ascoli (Theorem 5.6.48) there exists a subsequence (f_{n_k}) that converges uniformly to a limit. Because \mathcal{E} is closed, the limit lies in \mathcal{E} . Therefore \mathcal{E} is compact (see Definition 5.23).

□

Proposition 5.6.51 (Corollary 4.17 in Pugh [2015]). Suppose $f_n : [a, b] \rightarrow \mathbb{R}$ is a sequence of differentiable C^1 functions whose derivatives are uniformly bounded. If there exists one point $x_0 \in [a, b]$ such that the sequence $(f_n(x_0))$ is bounded as $n \rightarrow \infty$, then (f_n) has a convergent subsequence such that f_n converges uniformly to f on the whole interval $[a, b]$ and $f' = g$ **not sure about this convergence of derivative part**.

Proof. Let M be a bound for the derivatives $|f'_n(x)|$, valid for all $n \in \mathbb{N}$ and all $x \in [a, b]$. Equicontinuity of (f_n) follows from the Mean Value Theorem:

$$|s - t| < \delta \implies |f_n(s) - f_n(t)| = |f'_n(\theta)||s - t| \leq M\delta$$

for some θ between s and t . Thus given $\epsilon > 0$ the choice $\delta = \epsilon/(M + 1)$ shows that (f_n) is equicontinuous: in particular, for all $n \in \mathbb{N}$ it holds that

$$|s - t| < \frac{\epsilon}{M + 1} \implies |f_n(s) - f_n(t)| = |f'_n(\theta)||s - t| \leq M \cdot \frac{\epsilon}{M + 1} < \epsilon.$$

Let C be a bound for $|f_n(x_0)|$, valid for all $n \in \mathbb{N}$ (by assumption). Then

$$|f_n(x)| \leq |f_n(x) - f_n(x_0)| + |f_n(x_0)| \leq M|x - x_0| + C \leq M|b - a| + C$$

shows that the sequence (f_n) is bounded in C^0 . Then by Arzela-Ascoli (Theorem 5.6.48) there exists a subsequence (f_{n_k}) that converges uniformly to a limit on the whole interval. **not sure about convergence of derivative**

□

Proposition 5.6.52 (Math 425b Homework 5; Pugh [2015] Exercise. 4.23 (a) and (b)). Let (M, d) be a compact metric space, and let (i_n) be a sequence of isometries $i_n : M \rightarrow M$. Then there exists a subsequence i_{n_k} that converges to an isometry i as $k \rightarrow \infty$, and the space of self-isometries of M is compact.

Proof. Let $\epsilon > 0$. Then for all $n \in \mathbb{N}$ and for all $m, m' \in M$

$$d(m, m') < \epsilon \implies d(i_n(m), i_n(m')) = d(m, m') < \epsilon,$$

so $(i_n)_{n=1}^{\infty}$ is equicontinuous. Then by Theorem 5.6.49, $(i_n)_{n=1}^{\infty}$ has a subsequence $(i_{n_1}, i_{n_2}, \dots)$ converging uniformly to a limit $i : M \rightarrow M$.

It remains to show that this limit is an isometry. By the definition of continuity in Section 2.2 of Pugh [2015], the limit of a continuous function of convergent sequences is the function of the limits of the sequences. Metrics are continuous by Theorem 2.20 in Pugh [2015]. So a subsequence $(d(i_{n_1}(m), i_{n_1}(m')), d(i_{n_2}(m), i_{n_2}(m')), \dots)$ converges to $d(i(m), i(m'))$. The sequence itself can be written

$$(d(i_{n_1}(m), i_{n_1}(m')), d(i_{n_2}(m), i_{n_2}(m')), \dots) = (d(m, m'), d(m, m'), \dots)$$

since each i_n is an isometry. This constant sequence converges to $d(m, m')$, so $d(i(m), i(m')) = d(m, m')$ and i is an isometry.

Because we have shown that every sequence of isometries (i_n) from M to M has a subsequence that converges to an isometry from M to M , we have shown that the space of self-isometries of M is compact.

□

5.6.4 Uniform Approximation in C^0 (Section 4.4 of Pugh [2015])

Definition 5.58 (Dense sets of functions; special case of Definition 5.57). Let X be a set of functions. X is **dense** in $C^0([a, b], \mathbb{R})$ if for each $f \in C^0$ and each $\epsilon > 0$ there exists a function $p \in X$ such that for all $x \in [a, b]$, $|f(x) - p(x)| < \epsilon$.

Theorem 5.6.53 (Weierstrass Approximation Theorem; Thereom 4.19 in Pugh [2015]). The set of polynomials is dense in $C^0([a, b], \mathbb{R})$.

(Alternatively: Let $f \in C^0([0, 1], \mathbb{R})$ (or $C^0([0, 1], \mathbb{C})$). Then the polynomials $p_n(x) = \sum_{k=0}^n f(k/n)f_k(x)$ converge uniformly to f on $[0, 1]$.)

Remark 10. See p. 229 of Pugh [2015] (p. 239 of pdf), Proof #1.

We will sketch the proof that the result generalizes from $[0, 1]$ to $[a, b]$. We have isomorphisms (mappings between two structures of the same type that can be reversed by inverse mappings; see Definition 5.26) of \mathbb{R} -vector spaces $C^0([0, 1], \mathbb{R})$ to and from $C^0([a, b], \mathbb{R})$. Suppose we have $f \in C^0([0, 1], \mathbb{R})$; we can send it to $x \mapsto f([x - a]/[b - a])$ in $C^0([a, b], \mathbb{R})$. Conversely, we can send a function $g \in C^0([a, b], \mathbb{R})$ to $C^0([0, 1], \mathbb{R})$ via the map $x \mapsto g(a + x[b - a])$. It can be checked that these isomorphisms are linear, compose to the identity in either order, and preserve $\|\cdot\|_{\infty}$. They also send polynomials to polynomials.

First we will show a lemma.

Lemma 5.6.54. $x(1 - x) \leq 1/4$ for all $x \in \mathbb{R}$.

Proof. $f(x) = x(1-x) = -x^2 + x$ is differentiable; $f'(x) = -2x + 1 = 0 \iff x = 1/2$. We see that f' is continuous on \mathbb{R} and $f'(x) > 0$ for $x \in (-\infty, 1/2)$ and $f'(x) < 0$ for $x \in (1/2, \infty)$, so $f(x)$ has a global maximum at $x = 1/2$; that is, $x(1-x) \leq f(1/2) = 1/2(1-1/2) = 1/4$ for all $x \in \mathbb{R}$.

□

Proof of Weierstrass Approximation Theorem (Theorem 5.6.53). For a given $n \geq 1$ and for $k \in \{0, \dots, n\}$, let r_k be the Bernstein basis polynomial

$$r_k(x) = \binom{n}{k} x^k (1-x)^{n-k}.$$

Define

$$p_n(x) := \sum_{k=0}^n f(k/n) r_k(x).$$

We want to show that the polynomial functions p_n converge uniformly to f on $[0, 1]$. Let $\epsilon > 0$. Note that f is uniformly continuous and bounded because it is a continuous function on a compact set. So, there exists $\delta > 0$ such that for any $x, y \in [0, 1]$,

$$|x - y| < \delta \implies |f(x) - f(y)| < \epsilon/2, \quad (5.15)$$

and there exists $M \in (0, \infty)$ such that

$$|f(x)| \leq M \quad (5.16)$$

for all $x \in [0, 1]$. Let $N \geq M/(\epsilon\delta^2)$. We want to show that for any $n \geq N$, $|p_n(x) - f(x)| < \epsilon$ for all $x \in [0, 1]$.

Fix $x \in [0, 1]$. Since $\sum_{k=0}^n r_k(x) = 1$, we have $f(x) = f(x) \sum_{k=0}^n r_k(x) = \sum_{k=0}^n f(x)r_k(x)$. Then

$$|p_n(x) - f(x)| = \left| \sum_{k=0}^n f(k/n) r_k(x) - \sum_{k=0}^n f(x) r_k(x) \right| = \left| \sum_{k=0}^n [f(k/n) - f(x)] r_k(x) \right|. \quad (5.17)$$

Let $K_1 := \{k \in \{0, \dots, n\} : |k/n - x| < \delta\}$, and let $K_2 := \{0, \dots, n\} \setminus K_1$. Observe that for all $k \in K_1$, $|f(k/n) - f(x)| < \epsilon/2$ by (5.15), so

$$\left| \sum_{k \in K_1} [f(k/n) - f(x)] r_k(x) \right| \leq \sum_{k=0}^n |[f(k/n) - f(x)] r_k(x)| < \sum_{k=0}^n \frac{\epsilon}{2} |r_k(x)| = \frac{\epsilon}{2} \sum_{k=0}^n r_k(x) = \frac{\epsilon}{2} \quad (5.18)$$

where we used $r_k(x) \geq 0$ for all k . Next, by (5.16) $|f(k/n) - f(x)| \leq |f(k/n)| + |f(x)| \leq 2M \leq 2\epsilon\delta^2 n$ (using the definition of N and $n \geq N$), so

$$\left| \sum_{k \in K_2} [f(k/n) - f(x)] r_k(x) \right| \leq \sum_{k \in K_2} 2\epsilon \delta^2 n r_k(x).$$

Since $k \in K_2 \iff |k/n - x| \geq \delta \iff |k - nx| \geq \delta n \implies (k - nx)^2 \geq (n\delta)^2$, we have (using $\sum_{k=1}^n (k - nx)^2 r_k(x) = nx(1-x)$)

$$\sum_{k \in K_2} 2\epsilon \delta^2 n r_k(x) = \frac{2\epsilon}{n} \sum_{k \in K_2} (n\delta)^2 r_k(x) \leq \frac{2\epsilon}{n} \sum_{k=1}^n (k - nx)^2 r_k(x) = \frac{2\epsilon}{n} nx(1-x) \leq 2\epsilon \cdot \frac{1}{4} = \frac{\epsilon}{2}$$

where we applied Lemma 5.6.54 in the last step, yielding

$$\left| \sum_{k \in K_2} [f(k/n) - f(x)] r_k(x) \right| \leq \frac{\epsilon}{2}. \quad (5.19)$$

Therefore using (5.18) and (5.19) we can write (5.17) as

$$\begin{aligned} |p_n(x) - f(x)| &= \left| \sum_{k \in K_1} [f(k/n) - f(x)] r_k(x) + \sum_{k \in K_2} [f(k/n) - f(x)] r_k(x) \right| \\ &\leq \left| \sum_{k \in K_1} [f(k/n) - f(x)] r_k(x) \right| + \left| \sum_{k \in K_2} [f(k/n) - f(x)] r_k(x) \right| \\ &< \frac{\epsilon}{2} + \frac{\epsilon}{2} \\ &= \epsilon. \end{aligned}$$

□

Definition 5.59 (Definition 7.28 in Rudin [1976], p. 170 of pdf, p.161). A family A of complex functions defined on a set X is a **function algebra** if A is closed under addition, multiplication, and scalar multiplication (and does not necessarily include a multiplicative identity). That is, if $f, g \in A$ and $c \in \mathbb{C}$, then $f + g \in A$, $fg \in A$, and $cf \in A$. (We also consider algebras of real functions; in this case, the conditions only must hold for all $c \in \mathbb{R}$.)

If A has the property that $f \in A$ whenever $f_n \in A$ for $n \in \mathbb{N}$ and f_n converges uniformly to f on X , then A is said to be **uniformly closed**.

Let B be the set of all functions that are limits of uniformly convergent sequences of members of A . Then B is called the **uniform closure** of A .

In-class definition: a “non-unital subalgebra of $C^0(X, \mathbb{R})$. Also an \mathbb{R} -algebra: a ring (see Definition 15.3) that’s also an \mathbb{R} vector space; structures are compatible. e.g. $C^0(X, \mathbb{R})$ is an \mathbb{R} -algebra. A sub-algebra is closed under addition, scalar multiplication, and ring multiplication, and contains a scalar multiplicative identity. A non-unital sub-algebra is the same but it might not contain a multiplicative identity. (Note that the multiplicative identity for $C^0(X, \mathbb{R})$ is the constant function $f(x) = 1$.)

Example 5.7. The set of all polynomials is an algebra. The Weierstrass Approximation Theorem may be stated by saying that the set of continuous functions on $[a, b]$ is the uniform closure of the set of polynomials on $[a, b]$.

Definition 5.60 (Definition 7.30 in Rudin [1976], p. 171 of pdf, p.162). Let A be a family of functions on a set X . A vanishes nowhere if $\forall x \in X$ there exists $f \in A$ with $f(x) \neq 0$. (That is, there is no $x \in X$ with $f(x) = 0$ for all $f \in A$.)

Definition 5.61 (Definition 7.30 in Rudin [1976], p. 171 of pdf, p.162). Let A be a family of functions on a set X . A separates points on X if $\forall x \neq x' \in X$ there exists $f \in A$ with $f(x) \neq f(x')$.

Example 5.8. The algebra of all polynomials in one variable clearly vanishes nowhere and separates points on \mathbb{R} . An example of an algebra that does not separate points is the set of all even polynomials, say on $[-1, 1]$ since $f(-x) = f(x)$ for every even function f .

Theorem 5.6.55 (Stone-Weierstrass Theorem (Theorem 4.20 in Pugh [2015], Theorem 7.32 in Rudin [1976], p. 171 of pdf, p.162)). Let X be a compact metric space. Let $A \subset C^0(X, \mathbb{R})$ or $C^0(X, \mathbb{C})$. Then if A is a function algebra that vanishes nowhere in X and A separates points on X , then A is dense in $(C^0(X, \mathbb{R}), \|\cdot\|_\infty)$.

Equivalent conclusion: $\overline{A} = C^0(X, \mathbb{R})$ in uniform metric. That is, the uniform closure B of A consists of all real continuous functions on X .

Remark 11. The Weierstrass Approximation Theorem (Theorem 5.6.53) is a special case of the Stone-Weierstrass Theorem.

Theorem 5.6.56 (Complex Stone-Weierstrass Theorem; similar to Theorem 7.33 in Rudin [1976], p. 174 of pdf, p.165). If $A \subset C^0(X, \mathbb{C})$ is a function algebra that is closed under complex conjugation, A vanishes nowhere, and A separates points, then A is dense in $(C^0(X, \mathbb{C}), \|\cdot\|_\infty)$ (that is, $\overline{A} = C^0(X, \mathbb{C})$).

Remark 12. Why is the complex conjugate assumption needed? Let $X := \{|z| \leq 1 | z \in \mathbb{C}\}$. Note that X is compact. Let A be the space of complex polynomials; that is, $A = \text{span}_{\mathbb{C}}(1, z, z^2, \dots)$. It can be shown that A is a function algebra, separates points, and vanishes nowhere. Let $f(z) = \bar{z}$; this is not holomorphic. If $p_n \in A$ and p_n converges uniformly to f on X , then p_n converges uniformly to f on $\{|z| < 1 | z \in \mathbb{C}\}$. Thus p_n (which are holomorphic) converges uniformly to f on any compact $K \subset \{|z| = 1 | z \in \mathbb{C}\}$. This implies (by Theorem 5.6.30) that f is holomorphic, contradiction. So we need A to be closed under complex conjugation.

Now we will prove Theorem 5.6.55. We will need to use the Weierstrass Approximation Theorem (Theorem 5.6.53) for $f(x) = |x|$ on $[-1, 1]$ (could prove what we need directly for this function, but we might as well use the result since we have it). We will show some lemmas first

Lemma 5.6.57 (Lemma 4.22 in Pugh [2015]; Similar to Theorem 7.29 in Rudin [1976], p. 170 of pdf, p.161). If X is compact and $A \subset C^0(X, \mathbb{R})$ is a function algebra, then so is its closure \overline{A} .

Proof. We will show \overline{A} is closed under addition, scalar multiplication, and function multiplication. (We will prove that it is true for addition; the other two cases are similar.) Let $f, g \in \overline{A}$. We have $f_n \in A$ with f_n converging uniformly to f and $g_n \in A$ with g_n converging uniformly to g . A is closed under addition by assumption, so $f_n + g_n \in A$. The limits of nets are linear (exercise), so we have that $f_n + g_n$ converges uniformly to $f + g$. Thus $f + g$ is a uniform limit of elements of A , so $f + g \in \overline{A}$.

The proof of closure under scalar multiplication and function multiplication are similar.

□

Lemma 5.6.58. Let $f \in C^0([a, b], \mathbb{R})$ and let $x_0 \in [a, b]$ with $f(x_0) = 0$. Given $\epsilon > 0$, there exists a polynomial p on $[a, b]$ with $p(x_0) = 0$ and $|f(x) - p(x)| < \epsilon$ for all $x \in [a, b]$.

Proof. Given $\epsilon > 0$, choose a polynomial q such that $|f(x) - q(x)| < \epsilon/2$ for all $x \in [a, b]$. q might not vanish at x_0 , but $p := q - q(x_0)$ is a polynomial that vanishes at x_0 by construction. Since $|q(x) - f(x)| < \epsilon/2$ for all x , plug in x_0 and get $|q(x_0)|M\epsilon/2$. Now, for $x \in [a, b]$, we have

$$|p(x) - f(x)| = |q(x) - q(x_0) - f(x)| \leq |q(x) - f(x)| + |q(x_0)| < \epsilon/2 + \epsilon/2 = \epsilon.$$

□

Lemma 5.6.59 (step 1 of proof of Theorem 7.32 in Rudin [1976], p. 171 of pdf, p.162). If $A \subset C^0(X, \mathbb{R})$ is a function algebra and $f \in \overline{A}$ (the closure of A) then $|f| \in \overline{A}$.

Proof. Consider the absolute value function $|\cdot| : [-\|f\|_\infty, \|f\|_\infty] \rightarrow \mathbb{R}$. (Note that $[-\|f\|_\infty, \|f\|_\infty]$ is a compact subset of \mathbb{R} .) The function $|\cdot| : [-\|f\|_\infty, \|f\|_\infty] \rightarrow \mathbb{R}$ is continuous since $|\cdot| : \mathbb{R} \rightarrow \mathbb{R}$ is continuous. We can factor $|f| : X \rightarrow \mathbb{R}$ as $X \xrightarrow{f} [-\|f\|_\infty, \|f\|_\infty] \xrightarrow{|\cdot|} \mathbb{R}$. The function $|\cdot| : [-\|f\|_\infty, \|f\|_\infty] \rightarrow \mathbb{R}$ vanishes at $x = 0$. So, given $\epsilon > 0$, we can choose a polynomial p such that $p(0) = 0$ and $|p(x) - |x|| < \epsilon$ for $x \in [-\|f\|_\infty, \|f\|_\infty]$. We can write $p(x) = c_1x + \dots + c_kx^k$ (no constant term since $p(0) = 0$). The function $g : X \xrightarrow{f} [-\|f\|_\infty, \|f\|_\infty] \xrightarrow{p} \mathbb{R}$ is given by $g(x) = p(f(x)) = \sum_{i=1}^k c_i f^i(x)$. So $g = \sum_{i=1}^k c_i f^i$. Since $f \in \overline{A}$ and \overline{A} is a function algebra, we have $g \in \overline{A}$. We want to show that $||f(x)| - g(x)|| < \epsilon$ for all $x \in X$. Indeed, for $x \in X$ we have

$$||f(x)| - g(x)|| = ||f(x)| - p(f(x))|| = ||y - p(y)||$$

where $y = f(x) \in [-\|f\|_\infty, \|f\|_\infty]$. But we chose p such that $||y - p(y)|| < \epsilon$ for all $y \in [-\|f\|_\infty, \|f\|_\infty]$. So $||f(x)| - g(x)|| < \epsilon$ as desired.

We've shown that if $f \in \overline{A}$, then there exists $g \in \overline{A}$ with $d_\infty(|f|, g) < \epsilon$. This implies there exists a sequence of functions in \overline{A} converging uniformly to $|f|$, so $|f| = \overline{\overline{A}} = \overline{A}$. So we've proven that if $f \in \overline{A}$ then $|f| \in \overline{A}$.

□

Corollary 5.6.59.1 (step 2 of proof of Theorem 7.32 in Rudin [1976], p. 171 of pdf, p.162). If $A \subset C^0(X, \mathbb{R})$ is a function algebra and $f, g \in \overline{A}$ then $\max\{f, g\} \in \overline{A}$ (the pointwise max). (Similarly, $\min\{f, g\} \in \overline{A}$.) (closed under maxes and mins—it's a **lattice**.)

Proof. Observe that

$$\max\{f, g\} = \frac{f+g}{2} + \frac{|f-g|}{2}.$$

Each of these functions is in \overline{A} (since the absolute value function is by Lemma 5.6.59) since \overline{A} is a function algebra, and their sum is as well. Similarly,

$$\min\{f, g\} = \frac{f+g}{2} - \frac{|f-g|}{2} \in \overline{A}.$$

□

Lemma 5.6.60 (Theorem 7.31 in Rudin [1976], p. 171 of pdf, p.162; Lemma 4.21 in Pugh [2015]). Suppose $A \in C^0(X, \mathbb{R})$ satisfies all the hypotheses of the Stone-Weierstrass Theorem. Let $x_1 \neq x_2 \in X$ and let $c_1, c_2 \in \mathbb{R}$. Then there exists $f \in A$ such that $f(x_1) = c_1$ and $f(x_2) = c_2$. (Can specify values at any two points of X ; stronger condition than separating points. Some map from A to \mathbb{R}^2 is surjective.)

Proof. Consider the linear transformations $\Phi : A \rightarrow \mathbb{R}^2$ defined by $\Phi(f) = (f(x_1), f(x_2))$, where A is a function algebra, so a vector subspace of $C^0(X, \mathbb{R})$. Check that Φ is linear:

$$\Phi(f+g) = ((f+g)(x_1), (f+g)(x_2)) = (f(x_1)+g(x_1), f(x_2)+g(x_2)) = (f(x_1), f(x_2)) + (g(x_1), g(x_2)) = \Phi(f) + \Phi(g).$$

Similarly, $\Phi(cf) = c\phi(f)$ for $c \in \mathbb{R}$. The image of Φ must be a vector subapce of \mathbb{R}^2 , so it must have dimension 0, 1, or 2. We will show that the dimension is 2, which is true if and only if Φ is surjective, which is equivalent to the lemma holding. We want to show that $\text{rank}(\Phi) = 2$ (the dimension of the image), not 0 or 1.

First we will show $\text{rank}(\Phi) \neq 0$. If $\text{rank}(\Phi) = 0$, then Φ is the 0 map; that is, for any $f \in A$, $\Phi(f) = (f(x_1), f(x_2)) = (0, 0)$. But this contradicts that f vanishes nowhere.

Next suppose $\text{rank}(\Phi) = 1$. Then the image of Φ is a line through the origin in \mathbb{R}^2 . There are three possible cases:

- **Case 1:** This line is the $x-axis$. Then for all $f \in A$, $\Phi(f) = (f(x_1), f(x_2)) = (k, 0)$ for some $k \in \mathbb{R}$. But this contradicts that A vanishes nowhere.
- **Case 2:** This line is the $y-axis$. This leads to a similar contradiction.
- **Case 3:** The line is some other line. Then for $f \in A$, we have $f(x_1) = 0 \iff f(x_2) = 0$. A separates points means there exists $f \in A$ with $f(x_1) \neq f(x_2)$ (so neither $f(x_1)$ nor $f(x_2)$ is zero). Idea: consider $f - f(x_1)$. If this function is in A , then it vanishes at x_1 (by construction) but not at x_2 (because $f(x_1) \neq f(x_2)$). But why is $f - f(x_1) \in A$? ($f(x_1)$ is a constant function—it might not be in A .) Consider $f \cdot (f - f(x_1)) = f^2 - f \cdot f(x_1) \in A$ because A is closed under multiplication, subtraction, and scalar multiplication. Let $g := f \cdot (f - f(x_1)) \in A$. We have $g(x_1) = 0$ by construction; however,

$$g(x_2) = \underbrace{f(x_2)}_{\neq 0} \cdot \underbrace{(f(x_2) - f(x_1))}_{\neq 0}.$$

This contradicts what we showed earlier: for $f \in A$ it holds that $f(x_1) = 0 \iff f(x_2) = 0$. Thus we have ruled out all possibilities except $\text{rank}(\Phi) = 2$; that is, for all $(c_1, c_2) \in \mathbb{R}^2$ there exists $f \in A$ with $(f(x_1), f(x_2)) = (c_1, c_2)$.

□

Now we are ready to prove the Stone-Weierstrass Theorem.

Proof of Theorem 5.6.55. Let $F \in C^0(X, \mathbb{R})$. Let $\epsilon > 0$. It is sufficient to find $G \in \overline{A}$ such that $\|F - G\|_\infty < \epsilon$; that is, $|F(x) - G(x)| < \epsilon$ for all $x \in X$. If this is true for all ϵ , then $F \in \overline{\overline{A}} = \overline{A}$ (because it's the uniform limit of elements of \overline{A}).

For any two points $p \neq q \in X$, by Lemma 5.6.60 there exist $H_{p,q} \in A$ such that $H_{p,q}(p) = F(p)$ and $H_{p,q}(q) = F(q)$.

Also pick $H_{p,p}$ for each $p \in X$ such that $H_{p,p}(p) = F(p)$.

Claim: Given a fixed p , consider $H_{p,q}$ for various q . In an open neighborhood of q , we have $H_{p,q}(x) > F(x) - \epsilon$. To see why, consider the continuous function $x \mapsto H_{p,q}(x) - F(x) + \epsilon$. This function takes value $\epsilon > 0$ at $x = q$. Thus, there exists an open neighborhood $U_{p,q}$ of q such that $H_{p,q} - F + \epsilon > 0$ on $U_{p,q}$; i.e., $H_{p,q}(x) > F(x) - \epsilon$ on $U_{p,q}$. For our fixed p , the set $\{U_{p,q} : q \in X\}$ is an open cover of X . (Important for this to work: we picked $H_{p,p}$.) Since X is compact, there exists a finite subcover; that is, for some $k \in \mathbb{N}$ there exist $q_1, \dots, q_k \in X$ with $X = \bigcup_{i=1}^k U_{p,q_i}$. Define $G_p : X \rightarrow \mathbb{R} := \max_{i \in [k]} \{H_{p,q_i}\}$. Note that $G_p \in \overline{A}$ by Corollary 5.6.59.1.

So for any $x \in X$, $x \in U_{p,q_i}$ for some $i \in [k]$, which means $G_p(x) \geq H_{p,q_i}(x) > F(x) - \epsilon$. So $G_p > F - \epsilon$ everywhere. Now run the same argument for $\{G_p\}$. We claim that on an open neighborhood V_p of p , we have $G_p < F + \epsilon$; i.e., $G_p(x) < F(x) + \epsilon$ for all $x \in V_p$. To see why, observe that the function $x \mapsto F(x) + \epsilon - G_p(x)$ is continuous and takes the value $\epsilon > 0$ at $x = p$, so there exists V_p as desired.

The family of sets $\{V_p\}_{p \in X}$ is an open cover of X . X is compact, so there exists a finite subcover $X = \bigcup_{i=1}^\ell V_{p_i}$. Let $G := \min_{i \in [\ell]} \{G_{p_i}\}$. (Again, $G \in \overline{A}$ by Corollary 5.6.59.1.) Any point $x \in X$ is in some V_{p_i} , so $G(x) \leq G_{p_i}(x) < F(x) + \epsilon$. Also, $G(x) = G_{p_i}(x)$ for some i , and $G_{p_i}(x) > F(x) - \epsilon$ by construction of G_{p_i} . Thus for all $x \in X$, we have $F(x) - \epsilon < G(x) < F(x) + \epsilon$.

□

Proof of Theorem 5.6.56. Let $A_R := \{\text{real and imaginary parts of functions } G \in A\} \subset C^0(X, \mathbb{R})$. (Note: if $G \in A$ then $\operatorname{Re}(G) = \frac{G + \overline{G}}{2} \in A$, $\operatorname{Im}(G) = \frac{G - \overline{G}}{2i} \in A$.)

So $A_R \subset A \cap C^0(X, \mathbb{R})$. It's clear that if $G \in A \cap C^0(X, \mathbb{R})$ then $G = \operatorname{Re}(G)$ so $G \in A_R$. Therefore $A \cap C^0(X, \mathbb{R}) \subset A_R$, so we have $A_R = A \cap C^0(X, \mathbb{R})$. We want to show that Theorem 5.6.55 applies to A_R .

First, observe that A_R is a function algebra since $A \subset C^0(X, \mathbb{C})$ and $C^0(X, \mathbb{R}) \subset C^0(X, \mathbb{C})$ are closed under addition, scalar multiplication, and function multiplication.

Next, A_R vanishes nowhere because if there exists $x \in X$ with $(\operatorname{Re} G)(x) = 0$, $(\operatorname{Im} G)(x) = 0$ for all $G \in A$, therefore $G(x) = 0$ for all $G \in A$, so A vanishes nowhere.

Next, A_R separates points: we know that if $x_1 \neq x_2 \in X$, then there exists $G \in A$ with $G(x_1) \neq G(x_2)$. This implies that either $(\operatorname{Re} G)(x_1) \neq (\operatorname{Re} G)(x_2)$ (and note that $(\operatorname{Re} G) \in A_R$) or $(\operatorname{Im} G)(x_1) \neq (\operatorname{Im} G)(x_2)$ (and note that $(\operatorname{Im} G) \in A_R$). Thus, A_R separates points.

Now let $F \in C^0(X, \mathbb{C})$; write $F = u + iv$ for $u, v \in C^0(X, \mathbb{R})$. Given $\epsilon > 0$, there exists $G_1 \in A_R$ with $|U(x) - G_1(x)| < \epsilon/2$ for all $x \in X$. Also, there exists $G_2 \in A_R$ with $|V(x) - G_2(x)| < \epsilon/2$ for all $x \in X$.

Now: $G_1 \in A_R \subset A$, $G_2 \in A_R \subset A$, so $G_1 + iG_2 \in A$, and for all $x \in X$,

$$\left| \underbrace{F(x)}_{U(x)+iV(x)} - (G_1 + iG_2)(x) \right| \leq U(x) - G_1(x) + |V(x) - G_2(x)| < \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon.$$

□

Now we will discuss some applications of Theorem 5.6.55.

Example 5.9 (Example on p. 239 of Pugh [2015] (p. 249 of pdf)). Let D^2 be the closed unit disk in \mathbb{R}^2 . Let $F : D^2 \rightarrow \mathbb{R}^2$ be continuous. We want $G : D^2 \rightarrow \mathbb{R}^2$ approximating F uniformly, such that $G(x) = 0$ for only finitely many x .

Proof. Let $A \subset C^0(D^2, \mathbb{R})$ be the set of two-variable polynomials; known as $\mathbb{R}[x, y]$. We can also write this as $\text{span}_{\mathbb{R}}\{x^i y^j \mid i, j \in \mathbb{Z}_+\}$. Since A is a span, it is closed under addition and scalar multiplication. Also, $(x^i y^j)(x^k y^\ell) = x^{i+k} y^{j+\ell}$. Apply this to linear combinations, then A is closed under function multiplication. So A is a function algebra.

Now check the assumptions of Theorem 5.6.55. A vanishes nowhere since it contains constant functions. We will check if A vanishes nowhere. If $(x_1, y_1) \neq (x_2, y_2) \in D^2$, then $(x - x_1) \in A$ vanishes at (x_1, y_1) but not (x_2, y_2) . Otherwise if $y_1 \neq y_2$ then $(y - y_1) \in A$ vanishes at (x_1, y_1) but not (x_2, y_2) . Therefore we can apply Theorem 5.6.55 on A .

Write $F(x) = (F_1(x), F_2(x))$, with $F_i \in C^0(D^2, \mathbb{R})$. Then there exists $p_1 \in A$ with $\|p_1 - F_1\|_\infty < \epsilon/\sqrt{2}$, and there exists $p_2 \in A$ with $\|p_2 - F_2\|_\infty < \epsilon/\sqrt{2}$. This implies that $(p_1, p_2) : D^2 \rightarrow \mathbb{R}^2$ satisfies $\|(p_1, p_2) - F\|_\infty < \sqrt{\epsilon^2/2 + \epsilon^2/2} = \epsilon$.

We can assume without loss of generality that the coordinate functions $F_1(x), F_2(x)$ are polynomials. So if F_1, F_2 jointly vanish at a finite number of points, we're done. Given the same ϵ as before, $(f_1 + \delta, F_2)$ is ϵ -close to F_1, F_2 in $\|\cdot\|_\infty$ as long as $\delta < \epsilon$. This is true for infinitely many δ . Let $F_\delta = F_1 + \delta$.

$\mathbb{R}[x, y]$ is a UFD (**unique factorization domain**); thus, F_δ has a unique factorization into irreducible polynomials over \mathbb{R} . Similarly, F_2 has a unique factorization into irreducible polynomials over \mathbb{R} . And crucially, if $\delta \neq \delta'$ then F_δ and $F_{\delta'}$ have no common factors of positive degree in $\mathbb{R}[x, y]$ (because if they did then the constant function $\delta - \delta'$ would have polynomial factors of degree greater than 0 which is a contradiction of the basic algebraic properties of this ring (see Definition 15.3)). F_2 has finitely many factors, so they are factors of finitely many F_δ s, so there exists $\delta < \epsilon$ with $F_1 + \delta$ and F_2 having no common factors.

A fact from algebra is that given $P, Q \in \mathbb{R}[x, y]$, can compute the resultant $\text{Res}(P, Q) \in \mathbb{R}[x]$, which is nonzero if P and Q have no common factors. If $\text{Res}(P, Q)(x) \neq 0$ then $P(x, \cdot)$ and $Q(x, \cdot)$ have no common roots y . It is true that $\text{Res}(P, Q)(x) \neq 0$ for all but finitely many x since $\text{Res}(P, Q)(x)$ is a polynomial. For given x with $\text{Res}(P, Q)(x) = 0$, consider $P(X, \cdot)$ and $Q(X, \cdot)$ as polynomials in $\mathbb{R}[y]$. They each have finitely many roots, so there exist finitely many (x, y) with $P(x, y) = Q(x, y) = 0$. This finishes the application.

□

5.6.5 Contractions and ODEs (Section 4.5 of Pugh [2015])

Definition 5.62. Let X be a set, let $f : X \rightarrow X$ be a function. $x \in X$ is called a **fixed point** of f if $f(x) = x$.

Definition 5.63 (Contractions; p. 240 of Pugh [2015]; Definition 9.22 in Rudin [1976], p. 229 of pdf, p. 220). Let M be a metric space. A **contraction** of M is a mapping $f : M \rightarrow M$ such that for some constant $k < 1$ and for all $x, y \in M$ we have

$$d(f(x), f(y)) \leq kd(x, y);$$

i.e., f has a Lipschitz constant less than 1. (See also Definition 14.10. For more on contraction mappings, see Section 14.22.6.)

Note: f is a “weak contraction” if $d(f(x), f(y)) < d(x, y)$ for all $x, y \in X$. (Doesn’t necessarily imply that f is a contraction mapping; we will see an example later.)

example: let $X = [1, \infty)$. Since $X \subset \mathbb{R}$, X is complete. Define $f : X \rightarrow X$ by $f(x) = x + 1/x$. f has no fixed point ($x+1/x > x$ for $x \in X$). f is a weak contraction, i.e., for $x_1 \neq x_2 \in X$, we have $|f(x_1) - f(x_2)| < |x_1 - x_2|$. See why: if $x_1 > x_2 \geq 1$ then

$$|(x_1 + 1/x_1) - (x_2 + 1/x_2)| = |x_1 - x_2 + (1/x_1 - 1/x_2)|$$

Note that $1/x_2 - 1/x_1 \leq x_1 - x_2$ (equivalently, $x_1 - x_2 \leq x_1 x_2 (x_1 - x_2)$; equivalently, $1 \leq x_2 x_1$ since $x_1, x_2 \geq 1$). So f is a weak contraction but has no fixed point.

Theorem 5.6.61 (Banach contraction principle, Banach 1922; Theorem 4.24 in Pugh [2015], p. 240; Theorem 9.23 in Rudin [1976], p. 229 of pdf, p. 220). Let (X, d) be a complete metric space. Let $F : X \rightarrow X$ be a contraction. Then there exists a unique fixed point $x_0 \in X$ of f , and for any $x \in X$, the sequence of iterates $(f^n(x))_{n=1}^{\infty}$ (where $f^n(x) = f \circ f \circ \dots \circ f(x)$) converges to x_0 .

Before proving Theorem 5.6.61, we will discuss one other result and lay out a sketch of a proof (the full proof requires graduate-level algebraic topology).

Theorem 5.6.62 (Brouwer Fixed-Point Theorem; Theorem 4.24 in Pugh [2015], p. 240). Any continuous map $f : D^m \rightarrow D^n$ has at least one fixed point (where D^m is the closed unit ball in \mathbb{R}^m).

Proof. First begin with $n = 1$. Then $f : [-1, 1] \rightarrow [-1, 1]$ is continuous. Let $g(x) := f(x) - x$. Note that $g(-1) \geq 0$, $g(1) \leq 0$. So by the intermediate value theorem, there exists $x \in [-1, 1]$ with $g(x) = 0$; i.e., $f(x) = x$.

For a general n , if $f : D^n \rightarrow D^n$ has no fixed point, then define $g : D^n \mapsto \partial(D^n) = S^{n-1}$ by $g(x) = \frac{f(x)-x}{\|f(x)-x\|}$. Then $g|_{S^n} : S^{n-1} \rightarrow S^{n-1}$ induces a map on $(n-1)$ th homology group. ... (requires graduate level algebraic topology).

□

Now we will prove Theorem 5.6.61.

Proof of Theorem 5.6.61. Let (X, d) be a complete metric space and let $f : X \rightarrow X$ be a contraction with $k < 1$. First we will show that any fixed point must be unique.

If $x_1 \neq x_2 \in X$ and $f(x_1) = x_1$ and $f(x_2) = x_2$, then because f is a contraction mapping, $d(f(x_1), f(x_2)) \leq kd(x_1, x_2) < d(x_1, x_2)$. However, because $f(x_1) = f(x_2)$, it must hold that $d(f(x_1), f(x_2)) = d(x_1, x_2)$, contradiction.

To prove the rest of the theorem, start with some $x \in X$ and show that (1) the sequence $(f^n(x))_{n=1}^{\infty}$ converges to something and (2) the limit is a fixed point of f . Since X is complete, to show (1) it's enough to show that $(f^n(x))_{n=1}^{\infty}$ is Cauchy. Write $x_n := f^n(x)$ for notational convenience. We want to show that $(x_n)_{n=1}^{\infty}$ is Cauchy. We claim that $d(x_n, x_{n+1}) \leq k^n d(x_0, x_1)$ for all n . To see this, observe that $d(x_n, x_{n+1}) = d(f(x_{n-1}), f(x_n)) \leq kd(x_{n-1}, x_n) \leq k \cdot k^{n-2} d(x_1, x_2)$, where the last step follows by induction.

Now: $\sum_{k=1}^{\infty} k^n$ converges because $k < 1$, so this is a geometric series. Therefore the sequence of partial sums converges, so it is Cauchy. Given $\epsilon > 0$, choose N such that if $m, \ell \geq N$ then $\sum_{n=m}^{\ell-1} k^n < \epsilon/d(x_0, x_1)$. Then if $\ell > m \geq N$, we have

$$\begin{aligned} d(x_m, x_\ell) &\leq d(x_m, x_{m+1}) + d(x_{m+1}, x_{m+2}) + \dots + d(x_{\ell-1}, x_\ell) \\ &\leq k^m d(x_0, x_1) + k^{m+1} d(x_0, x_1) + \dots + k^{\ell-1} d(x_0, x_1) \\ &= \left(\sum_{n=m}^{\ell-1} k^n \right) d(x_0, x_1) \\ &< \frac{\epsilon}{d(x_0, x_1)} \cdot d(x_0, x_1) = \epsilon. \end{aligned}$$

So $(x_n)_{n=0}^{\infty}$ is a Cauchy sequence in X , so it converges to some point $x' \in X$. Now we will show that x' is a fixed point of f . We have $(x_n) \rightarrow x'$. f is continuous, so it sends convergent sequences to convergent sequences. That is, $(f(x_n))$ converges to $f(x')$, which can be written as (x_{n+1}) converges to $f(x')$. This is the same sequence, so x_n converges to x' and also $f(x')$. By uniqueness of limits, $f(x') = x'$, so x' is a (the) fixed point of f .

□

Next we will discuss some basic results on ordinary differential equations (ODEs). (For more on differential equations, see Section 4 of these notes.) Picard's Theorem gives us the existence and uniqueness of solutions to initial value problems for systems of first order ODEs given a Lipschitz continuity assumption.

Also consider systems of first order ODEs. In particular, we can phrase a second order ODE as a system of first order ODEs. For example, suppose we have $x'' - 4x' + 3x = 0$. Let $u(t) = x(t), v(t) = x'(t)$. Then we have

$$u'(t) = v(t), \quad v'(t) - 4v(t) + 3u(t) = 0.$$

Thus given a solution $x(t)$ to $x'' - 4x' + 3x = 0$, we get $u(t), v(t)$ satisfying

$$\begin{bmatrix} u \\ v \end{bmatrix}' = \begin{bmatrix} 0 & 1 \\ 4 & -3 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix}. \quad (5.20)$$

Conversely, given (u, v) solving this system, then $x(t) := u(t)$ solves the original system. So, existence/uniqueness of solutions for first order systems implies existence/uniqueness for higher order systems too.

What is a first order system in general? (maybe nonlinear, etc.)

Example 5.10.

$$\begin{bmatrix} u \\ v \end{bmatrix}' = \begin{bmatrix} 0 & 1 \\ 4 & -3 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix}.$$

Call

$$\gamma(t) := \begin{bmatrix} u \\ v \end{bmatrix}' = \begin{bmatrix} 0 & 1 \\ 4 & -3 \end{bmatrix},$$

a path in \mathbb{R}^2 . We can write

$$\gamma'(t) = \begin{bmatrix} 0 & 1 \\ 4 & -3 \end{bmatrix} \gamma(t).$$

For $w \in \mathbb{R}^2$, let

$$F(w) = \begin{bmatrix} 0 & 1 \\ 4 & -3 \end{bmatrix} w.$$

Our first order system is $\gamma' = F(\gamma)$. Geometrically, F is a vector field (see Definition 5.83) on \mathbb{R}^2 . Then $\gamma(t)$ solves the system if and only if the velocity vector $\gamma'(t)$ agrees with the vector $F(\gamma(t))$ for all t .

(This is an example of a linear F ; in general F need not be linear. In the nonlinear case, of course we won't be able to use matrices to express F .)

Definition 5.64. Let $U \subset \mathbb{R}^m$ and let $F : U \rightarrow \mathbb{R}^m$ be a function. A path $\gamma : (a, b) \rightarrow U$ **solves the system corresponding to F** if

1. γ is differentiable, and
2. $\gamma'(t) = F(\gamma(t))$ for all $t \in (a, b)$.

Furthermore, if $t_0 \in (a, b)$ and $\gamma(t_0) = p \in U$, then γ is said to solve the **initial value problem (IVP)**

$$\gamma' = F(\gamma), \quad \gamma(t_0) = p.$$

(This type of system is “autonomous.”)

More generally: suppose $\Omega \subset \mathbb{R} \times \mathbb{R}^m$ is open. Let $F : \Omega \rightarrow \mathbb{R}^m$ be a function (think $F(t, \gamma(t))$ instead of $F(\gamma(t))$). A solution to the first order system of ODEs corresponds to F with initial value p at time t_0 is defined to be a differentiable function $\gamma : (a, b) \rightarrow \mathbb{R}^m$ (with $t_0 \in (a, b)$) such that

1. $(t, \gamma(t)) \in \Omega$ for all $t \in (a, b)$,
2. $\gamma'(t) = F(t, \gamma(t))$ for all $t \in (a, b)$, and
3. $\gamma(t_0) = p$.

For example, a non-autonomous ODE is $x'' - t^2x' + e^tx = e^{3t}$. (Picard's Theorem in this general setting is just messier, not fundamentally harder. However, we will not address it in class since it is messy.)

Theorem 5.6.63 (Picard's Theorem). Let Ω be an open subset of $\mathbb{R} \times \mathbb{R}^m$ and let $F : \Omega \rightarrow \mathbb{R}^m$ be a function ($F(t, y)$ for $t \in \mathbb{R}$ and $y \in \mathbb{R}^m$) such that F is continuous and F is “locally uniformly Lipschitz in y ” (for all $(t_0, y_0) \in \Omega$, there exists an open neighborhood $V \subset \Omega$ of (t_0, y_0) and there exists $L \geq 0$ such that for $(t, y), (t, y')$ in V (same t), we have $\|F(t, y) - F(t, y')\| \leq L\|y - y'\|$) (the “uniformly” means “uniformly in t ”). Then for all $(t_0, y_0) \in \Omega$, there exists an open interval (a, b) of \mathbb{R} containing t_0 and a solution γ to the initial value problem $\gamma'(t) = F(t, \gamma(t)), \gamma(t_0) = y_0$ defined on (a, b) .

Further, if γ and $\tilde{\gamma}$ are two local solutions to the initial value problem, then $\gamma = \tilde{\gamma}$ on some (possibly smaller) open neighborhood of t_0 in \mathbb{R} .

(In particular: say $m = 1$. So we have $F(t, y)$ where $y \in \mathbb{R}$. $\Omega \subset \mathbb{R} \times \mathbb{R}$ is open, $F : \Omega \rightarrow \mathbb{R}$ such that F is continuous and $\frac{\partial F}{\partial y}$ is continuous on Ω . This implies that on a compact subset $[t_0 - \epsilon_1, t_0 + \epsilon_1] \times [y_0 - \epsilon_2, y_0 + \epsilon_2] \subset \Omega$, $\frac{\partial F}{\partial y}$ is bounded (say by L); L works in general then as a local uniform Lipschitz constant near (t_0, y_0) . Then the assumptions of Picard's Theorem hold, so initial value problems of the form $\gamma'(t) = F(t, \gamma(t)), \gamma(t_0) = y_0$ have unique solutions locally.)

Theorem 5.6.64 (Picard-Lindelof Theorem for autonomous systems (Special version we'll prove: Theorem 4.25 in Pugh [2015])). Let $U \subset \mathbb{R}^m$ be open and let $F : U \rightarrow \mathbb{R}^m$ be a function such that F is **locally Lipschitz continuous** (which implies continuity; see Definition 5.88): for all $y_0 \in U$ there exists an open neighborhood V of y_0 in U and there exists $L \geq 0$ such that $\|F(y) - F(y')\| \leq L\|y - y'\|$ for all $y, y' \in V$ (don't need to say “uniformly Lipschitz” because there's no separate t variable that F has to be uniformly Lipschitz over). Let $t_0 \in \mathbb{R}$ and let $y_0 \in U$. Then initial value problems of the form $\gamma'(t) = F(\gamma(t)), \gamma(t_0) = y_0$ have unique solutions locally (existence + uniqueness).

We will need some lemmas and definitions. For starters, we'll need integrals of functions $\gamma : \mathbb{R} \rightarrow \mathbb{R}^m$ (vector-valued functions).

Definition 5.6.5. Let $F : [a, b] \rightarrow \mathbb{R}^m$ ($F = [F_1 \ F_2 \ \dots \ F_m]^T$, so $F_i : [a, b] \rightarrow \mathbb{R}$). F is called **Riemann integrable** if each F_i is Riemann integrable. If so, then

$$\int_a^b F(t) dt := \begin{bmatrix} \int_a^b F_1(t) dt \\ \int_a^b F_2(t) dt \\ \vdots \\ \int_a^b F_m(t) dt \end{bmatrix}.$$

Proposition 5.6.65. Let A be a set of tagged partitions (P, T) of $[a, b]$. For $(P, T) \in A$, let

$$R(F, P, T) := \begin{bmatrix} R(F_1, P, T) \\ R(F_2, P, T) \\ \vdots \\ R(F_m, P, T) \end{bmatrix} = \sum_{i=1}^n F(t_i)(x_i - x_{i-1}) \quad \text{if } (P, T) = (x_0 < \dots < x_n, t_1 < \dots < t_n).$$

Assignment $(P, T) \mapsto R(F, P, T)$ is a net in \mathbb{R}^m , mapping A to \mathbb{R}^m (recall Definition 5.31). Then

1. F is Riemann integrable if and only if this net converges; if so, $\int_a^b F(t)dt$ is the limit of the net in \mathbb{R}^m . (also equivalent to using a mesh-based condition, as Riemann did, or a Darboux-style condition.)
2. Continuous (vector-valued) functions $F : [a, b] \rightarrow \mathbb{R}^m$ are Riemann integrable.
3. If F' exists and is continuous (F is C^1), then $\int_a^b F'(t)dt = F(b) - F(a)$.
- 4.

$$\left\| \int_a^b F(t)dt \right\|_2 \leq M(b-a)$$

where $M := \sup_{t \in [a, b]} \|F(t)\|_2$.

Proof. 1. F is Riemann integrable with integral $\mathbf{I} = (I_1, \dots, I_m)^T$ if and only if each I_i is Riemann integrable with integral I_i . This is true if and only if $\lim_{(P, T)} R(F_i, P, T)$ exists and equals I_i for $i \in [m]$, which is true if and only if $\lim_{(P, T)} R(F, P, T)$ exists and equals \mathbf{I} . (We know from Corollary 2.19 in Pugh [2015] that a sequence in \mathbb{R}^m converges to \mathbf{I} if and only if each component converges to I_i in \mathbb{R} . True for nets too with the same proof.)

2. If F is continuous then each F_i is continuous, which implies each I_i is Riemann integrable, which by definition means that F is Riemann integrable.

- 3.

$$\int_a^b F'(t)dt = \int_a^b \begin{bmatrix} F'_1(t) \\ \vdots \\ F'_m(t) \end{bmatrix} dt = \begin{bmatrix} \int_a^b F_1(t)dt \\ \vdots \\ \int_a^b F_m(t)dt \end{bmatrix} = \begin{bmatrix} F_1(b) - F_1(a) \\ \vdots \\ F_m(b) - F_m(a) \end{bmatrix} = F(b) - F(a).$$

- 4.

$$\left\| \int_a^b F(t)dt \right\|_2 = \left\| \lim_{(P, T)} R(F, P, T) \right\|_2 = \lim_{(P, T)} \|R(F, P, T)\|_2$$

where the limit may come out from the norm because norms are continuous: $\|\cdot\|$ sends convergent sequences to convergent sequences, so preserves limits of sequences; same applies here for nets, with the same proof. We have

$$\|R(F, P, T)\|_2 \leq \sum_{i=1}^n \|R(t_i)\|_2 (x_i - x_{i-1}) \leq M \sum_{i=1}^n (x_i - x_{i-1}) = M(b-a).$$

□

Lemma 5.6.66. Let $\Omega \subset \mathbb{R} \times \mathbb{R}^m$ be open. Let $F : \Omega \rightarrow \mathbb{R}^m$ be continuous. Let $\gamma : (a, b) \rightarrow \mathbb{R}^m$ be a continuous function such that $(t, \gamma(t)) \in \Omega$ for all $t \in (a, b)$. Let $t_0 \in (a, b)$. Then γ is differentiable on (a, b) with $\gamma'(t) = F(t, \gamma(t))$ for all t if and only if $\gamma(t) = \gamma(t_0) + \int_{t_0}^t F(s, \gamma(s))ds$.

Proof. Assuming the first statement holds, by the Fundamental Theorem of Calculus,

$$\gamma(t) - \gamma(t_0) = \int_{t_0}^t \gamma'(s) ds = \int_{t_0}^t F(s, \gamma(s)) ds,$$

proving (2). (We can apply the FTC because γ' is continuous since $\gamma'(s) = F(s, \gamma(s))$, and both γ and F are continuous.)

Assuming (2) holds, γ is differentiable since $\gamma(t_0) + \int_{t_0}^t F(s, \gamma(s)) ds$ is differentiable (recall $F(s, \gamma(s))$ is continuous). Then by the Fundamental Theorem of Calculus, $\gamma'(t) = F(t, \gamma(t))$.

□

Now we are ready to prove Picard's Theorem.

Proof of Theorem 5.6.64. Without loss of generality, F is Lipschitz on U (otherwise, replace U with an open neighborhood V of y_0 in U on which F is Lipschitz). Let L be a Lipschitz constant for F on U ; i.e., $\|F(y_1) - F(y_2)\| \leq L\|y_1 - y_2\|$ for all $y_1, y_2 \in U$. For convenience, assume without loss of generality $t_0 = 0$.

Choose $r > 0$ such that $\overline{B_r(y_0)} \in U^2$. Let $N := \overline{B_r(y_0)}$. N is compact and F is continuous, so F attains a finite maximum on N ; that is, there exists M such that $\|F(x)\|_2 \leq M$ for all $x \in N$. Choose $\tau > 0$ such that $\tau < \min\{\frac{r}{M}, \frac{1}{L}\}$. (It is possible to remove the condition that $\tau < 1/L$, but it makes the proof harder.)

We'll show (1) that there exists a solution γ on $[-\tau, \tau]$ with $\gamma(0) = y_0$ and (2) any two solutions to this IVP on $[-\tau, \tau]$ are equal (which implies local uniqueness). Let $\mathcal{C} = C^0([-\tau, \tau], N)$. Since N is compact, \mathcal{C} is a complete metric space with the uniform metric d_∞ . Therefore if we can find a contraction mapping then a unique fixed point will exist. We'll define $\Phi : \mathcal{C} \rightarrow \mathcal{C}$ to be a contraction such that $\gamma \in \mathcal{C}$ is a fixed point of Φ if and only if γ solves the integral equation $\gamma(t) = y_0 + \int_0^t F(\gamma(s)) ds$.

How to find Φ : Picard iteration. For $\gamma \in \mathcal{C}$, let $\Phi(\gamma) := y_0 + \int_0^t F(\gamma(s)) ds$. (Note: $\Phi(\gamma)(0) = y_0$, so it has the right initial value.)

We claim that $\Phi(\gamma) \in \mathcal{C}$; that is, $\Phi : \mathcal{C} \rightarrow \mathcal{C}$. Observe that $\Phi(\gamma)$ is some function $[-\tau, \tau] \rightarrow \mathbb{R}^m$; we want to show that $\Phi(\gamma)(t) \in N$ for all $t \in [-\tau, \tau]$. Indeed,

$$\|\Phi(\gamma)(t) - y_0\|_2 = (\text{by definition}) \left\| \int_0^t F(\gamma(s)) ds \right\|_2 \leq M(t - 0) = Mt \leq M\tau < r$$

since $\|F(x)\|_2 \leq M$ for all $x \in N$ and $\gamma(s) \in N$ for all s because $\gamma \in \mathcal{C}$ by assumption. This implies $\Phi(\gamma)(t) \in N$ for all $t \in [-\tau, \tau]$; i.e., $\Phi(\gamma) \in \mathcal{C}$. (Also note: $\Phi(\gamma)$ is continuous by the Fundamental Theorem of Calculus.)

It remains to show that Φ is a contraction; then it has a unique fixed point. We claim Φ is a contraction with constant $k := \tau L$ (which is less than 1 by assumption that $\tau < 1/L$). Let $\gamma, \sigma \in \mathcal{C}$. We want to show that $d_{\sup}(\Phi(\gamma), \Phi(\sigma)) \leq k d_{\sup}(\gamma, \sigma)$ (note that norms don't exist since this is only a metric space, not a vector space). We have

²We can fit a closed ball inside U because clearly we can fit an open ball inside U ; if this open ball is of radius $2r$, then we can fit a closed ball of radius r .

$$\begin{aligned}
d_{\sup}(\Phi(\gamma), \Phi(\sigma)) &= \sup_{t \in [-\tau, \tau]} \left\| y_0 + \int_0^t F(\gamma(s)) ds - y_0 - \int_0^t F(\sigma(s)) ds \right\|_2 \\
&= \sup_{t \in [-\tau, \tau]} \left\| \int_0^t [F(\gamma(s)) - F(\sigma(s))] ds \right\|_2 \\
&\leq \underbrace{(t - 0)}_{\leq \tau} \sup_{t \in [-\tau, \tau]} \|F(\gamma(s)) - F(\sigma(s))\|_2 \\
&\leq \tau \sup_{t \in [-\tau, \tau]} L \|\gamma(t) - \sigma(t)\|_2 \\
&= \tau L d_{\sup}(\gamma, \sigma),
\end{aligned}$$

so $d_{\sup}(\Phi(\gamma), \Phi(\sigma)) \leq k d_{\sup}(\gamma, \sigma)$, so Φ is a contraction. Therefore Φ has a unique fixed point γ , and $\Phi(\gamma) = \gamma$ implies $\phi(t)$ is differentiable and the unique solution to the IVP locally.

Any other solution $\sigma(t)$ defined on $[-\tau, \tau]$ is also a fixed point of Φ . Since a contraction mapping has a unique fixed point, $\gamma = \sigma$.

□

Definition 5.66 (p. 246 of Pugh [2015], p. 256 of pdf). The **flow** associated with a first order system is defined as follows. Assume $U = \mathbb{R}^m$ and $F : \mathbb{R}^m \rightarrow \mathbb{R}^m$ is globally Lipschitz. We can show that solutions to $\gamma'(t) = F(\gamma(t))$ exist for all time and are unique (problem from Homework 9). Given t , can consider $y_0 \mapsto \gamma(t)$ if γ is a solution with $\gamma(0) = y_0$. In particular, define $\phi : \mathbb{R} \times \mathbb{R}^m \rightarrow \mathbb{R}^m$ by $\phi(t, y) := \gamma(t)$ where $\gamma : \mathbb{R} \rightarrow \mathbb{R}^m$ is the unique solution to $\gamma' = F(\gamma), \gamma(0) = y$. $\phi(t, y)$ is called the **flow** associated with the vector field F (see Definition 5.83).

Think of $\phi(t, y)$ as the flow of y along the vector field F for t seconds. It turns out we can show ϕ is continuous jointly in t and y ; that is, it has continuous dependence on its initial conditions (see Proposition 5.6.69 below). It also turns out that if F is C^k (all partial derivatives up to the k th order exist and are continuous), then ϕ is C^k , for $1 \leq k \leq \infty$. (Note that this implies F is locally Lipschitz; see Definition 5.88.)

Local version works too: say $F : U \rightarrow \mathbb{R}^m$ is locally Lipschitz, and let $y_0 \in U$. It turns out this implies that there exists an open neighborhood V of y_0 and there exists $t_0 \in \mathbb{R}_{++}$ such that (1) F is Lipschitz on V and (2) for every $y \in V$, the solution to the IVP $\gamma' = F(\gamma), \gamma(0) = y$ is defined at least on $(-t_0, t_0)$. Thus we can define $\phi : (-t_0, t_0) \times V \rightarrow \mathbb{R}^m$ where $\phi(t, y) := \gamma(t)$ for the unique solution γ to the IVP $\gamma' = F(\gamma), \gamma(0) = y$. In this case, ϕ is continuous and if F is C^k for some $1 \leq k \leq \infty$, then ϕ is C^k .

Here's a basic fact about flows: intuitively, after flowing for time t_1 and then flowing from that position for t_2 , you should be in the same place as if you just initially flowed for time $t_1 + t_2$. More precisely, assume we're in the global case ($F : \mathbb{R}^m \rightarrow \mathbb{R}^m$ is Lipschitz), although the local version is true too. Let $\phi : \mathbb{R} \times \mathbb{R}^m$ be the flow associated with F .

Proposition 5.6.67. For all $t_1, t_2 \in \mathbb{R}$ and any $y \in \mathbb{R}^m$, we have $\phi(t_1 + t_2, y) = \phi(t_2, \phi(t_1, y))$.

Proof. Fix t_1, y and let $\gamma(t) := \phi(t + t_1, y)$. (Note that this is a solution: $\gamma' = F(\gamma)$, since $\frac{\partial}{\partial t}(t + t_1) = 1$.) Let $\zeta(t) := \phi(t, \phi(t_1, y))$. Observe that $\zeta' = F(\zeta)$ and $\zeta(0) = \phi(t_1, y)$ by construction. Therefore $\zeta(0) = \phi(t_1, y)$. By global uniqueness (proven on Homework 9), we have $\phi(t_2) = \zeta(t_2)$ for all t_2 . Therefore $\phi(t_1 + t_2, y) = \phi(t_2, \phi(t_1, y))$ for all t_1, t_2, y .

□

Note that applying Proposition 5.6.67 yields $\phi(-t, \phi(t, y)) = \phi(0, y) = y$. So $\phi(t, \cdot)$ is invertible with inverse $\phi(-t, \cdot)$. By continuous dependence on initial conditions, $\phi(t, \cdot)$ and its inverse are continuous. That is, $\phi(t, \cdot)$ is a homeomorphism (see Definition 5.27) from \mathbb{R}^m to \mathbb{R}^m .

We can view the flow construction as giving a map $\Phi : \mathbb{R} \mapsto \text{Homeo}(\mathbb{R}^m)$, $t \mapsto \phi(t, \cdot)$. By Proposition 5.6.67, we have $\Phi(t_1 + t_2) = \Phi(t_2) \circ \Phi(t_1)$ because $\Phi(t_1 + t_2)(y) = \phi(t_1 + t_2, y) = \phi(t_2, \phi(t_1, y)) = \phi(t_2, \Phi(t_1)(y)) = \Phi(t_2)(\Phi(t_1)(y))$. So we have group structures on \mathbb{R} and $\text{Homeo}(\mathbb{R}^m)$. (on \mathbb{R} , the group structure is addition of numbers; on $\text{Homeo}(\mathbb{R}^m)$, the group structure is composition of homeomorphisms.) Then the Proposition says $\Phi : \mathbb{R} \rightarrow \text{Homeo}(\mathbb{R}^m)$ is a group homomorphism.

If F were smooth, then $\Phi : \mathbb{R} \mapsto \text{Diffeo}(\mathbb{R}^m)$, where $\text{Diffeo}(\mathbb{R}^m)$ is a set of smooth functions with smooth inverses. In some situations, we have even more structure in the self-maps of \mathbb{R}^m . For instance, below we have $\Phi : \mathbb{R} \rightarrow \text{Symplectomorphisms}(\mathbb{R}^{2n})$.

Next we will apply flows using an example from physics.

Example 5.11. Let $H : \mathbb{R}^{2n} \rightarrow \mathbb{R}$ be a C^∞ function; call it the **Hamiltonian** function. We will think of \mathbb{R}^m as consisting of coordinates $\underbrace{q_1, \dots, q_n}_{\text{position coordinates}}, \underbrace{p_1, \dots, p_n}_{\text{momentum}}$. We can refer to \mathbb{R}^{2n} as the **phase space**

of a classical physical system, so a point in \mathbb{R}^{2n} is the state of the system. Our observable quantities are \mathbb{R} -valued functions on \mathbb{R}^{2n} . We want to learn how the states and observable quantities evolve over time. (More generally, a phase space is a kind of symplectic manifold—see Definition 5.77.)

Let the **Hamiltonian vector field** X_H be the vector field on \mathbb{R}^{2n} defined by

$$X_H(q_1, \dots, q_n, p_1, \dots, p_n) := \begin{bmatrix} \frac{\partial H}{\partial p_1}(q_1, \dots, q_n, p_1, \dots, p_n) \\ \vdots \\ \frac{\partial H}{\partial p_n}(q_1, \dots, q_n, p_1, \dots, p_n) \\ -\frac{\partial H}{\partial q_1}(q_1, \dots, q_n, p_1, \dots, p_n) \\ \vdots \\ -\frac{\partial H}{\partial q_n}(q_1, \dots, q_n, p_1, \dots, p_n) \end{bmatrix},$$

the symplectic analogue of the gradient ∇H . (X_H corresponds to F in our general setup of ODEs, where F is a vector field on $U \subset \mathbb{R}^m$ with $m = 2n$.) Locally, X_H defines a flow $\phi_H : (-t_0, t_0) \times V \mapsto \mathbb{R}^{2n}$. (We'll assume it's global for now.) So $\phi_H : \mathbb{R} \times \mathbb{R}^{2n} \rightarrow \mathbb{R}^{2n}$.

Theorem 5.6.68 (Result from classical physics). ϕ_H determines how the state of the system evolves over time. $\phi_H : \mathbb{R} \times \mathbb{R}^{2n} \rightarrow \mathbb{R}^{2n}$ is equivalent to (via “currying”) $\Phi_H : \mathbb{R} \rightarrow \text{Homeo}(\mathbb{R}^{2n})$ (actually, maps to **symplectomorphisms** of \mathbb{R}^{2n} , which are even more structured: they are diffeomorphisms that preserve symplectic structure.)

Definition 5.6.67 (Diffeomorphism). A **diffeomorphism** is an isomorphism (mapping between two structures of the same type that can be reversed by an inverse mapping; see Definition 5.26) of spaces equipped with a differential structure, typically differentiable manifolds (see Definition 5.77).

A C^r diffeomorphism is a C^r bijection whose inverse is C^r for $1 \leq r \leq \infty$ (differentiable function with a differentiable inverse).

(Note that a diffeomorphism is a homeomorphism—see Definition 5.27.)

Note that since differentiability implies continuity, every diffeomorphism is a homeomorphism.

Example 5.12. Just because a function is C^r does not mean its inverse is C^r . For example, consider $f(x) = x^3$. It is a smooth homeomorphism from \mathbb{R} to \mathbb{R} but it is not a diffeomorphism because its inverse fails to be differentiable at the origin.

Proposition 5.6.69. The function $y_0 \mapsto \gamma(t)$ depends continuously on y_0 . (continuous dependence on initial conditions).

5.7 Multivariable Calculus (Chapter 5 of Pugh [2015])

5.7.1 Linear Algebra (Section 5.1 of Pugh [2015])

(For more notes on linear algebra, see Section 2.)

Theorem 5.7.1. Linear transformations are unbounded in sup norm (except $T = 0$).

Proof. Suppose T is a linear transformation with $T(v_0) \neq 0$ and $\|T(v)\| \leq M \in \mathbb{R}_+$ for all v . Then

$$\left\| T \left(\frac{(M+1)v_0}{\|T(v_0)\|} \right) \right\| = \frac{(M+1)}{\|T(v_0)\|} \|T(v_0)\| = M+1,$$

contradiction. □

For this reason, it's not so useful to look at $\|\cdot\|_\infty$ for linear transformations. Is there a more useful norm on linear transformations? Yes: the operator norm (basic ingredient of functional analysis).

Definition 5.68 (p. 279 of Pugh [2015], p. 289 of pdf). Let V, W be normed vector spaces (possibly infinite-dimensional). Let $T : V \rightarrow W$ be a linear transformation. Define

$$\|T\|_{\text{op}} := \sup_{v \neq 0 \in V} \frac{\|T(v)\|}{\|v\|} \in \mathbb{R}_+ \cup \{\infty\}.$$

(It turns out the following expressions are equivalent:)

$$\begin{aligned} \|T\|_{\text{op}} &= \sup_{v \in V, \|v\|=1} \|T(v)\| \\ &= \inf \{c \in \mathbb{R} \mid \|T(v)\| \leq c\|v\| \forall v \in V\}. \end{aligned}$$

Also, an immediate consequence of the definition is that $\|T(v)\| \leq \|T\|_{\text{op}}\|v\|$ for all $v \in V$.

A question we would like to know the answer to: which T have finite operator norm?

Theorem 5.7.2 (Theorem 5.2 in Pugh [2015]). Let V, W be normed vector spaces (especially infinite dimensional spaces; we'll talk about finite dimensional spaces soon; easier) and let $T : V \rightarrow W$ be a linear transformation. The following are equivalent:

1. $\|T\|_{\text{op}} < \infty$.
2. T is Lipschitz continuous.
3. T is uniformly continuous.
4. T is continuous.
5. T is continuous at the origin.

(Note that this shows that continuity at one point comes if and only if T is continuous everywhere. So T being linear is a strong restriction.)

Proof. 1 implies 2: Given (1), we claim that $\|T\|_{\text{op}}$ is a Lipschitz constant for T (given norms on V, W). Indeed: if $v_1 \neq v_2 \in V$, then

$$\|T\|_{\text{op}} \geq \frac{\|T(v_2 - v_1)\|}{\|v_2 - v_1\|} = \frac{\|T(v_2) - T(v_1)\|}{\|v_2 - v_1\|},$$

so $\|T(v_2) - T(v_1)\| \leq \|T\|_{\text{op}} \|v_2 - v_1\|$ if $v_1 \neq v_2$ (also true if $v_1 = v_2$). Therefore $\|T\|_{\text{op}}$ is a Lipschitz constant for T (recall Definition 5.56).

2 implies 3 implies 4 implies 5: already shown by definitions of these terms.

5 implies 1: Assume T is continuous at the origin. Then for $\epsilon = 1$ there exists $\delta > 0$ such that if $v \in V$ with $\|v - 0\| < \delta$ then $\|T(v) - 0\| < 1$. We claim that $\|T\|_{\text{op}} \leq 2/\delta$. To see this, note that for any $v \in V$ and $v \neq 0$, we have

$$\left\| \frac{\delta}{2} \frac{v}{\|v\|} \right\| = \frac{\delta}{2},$$

Thus, by continuity for any $v \in V$

$$\left\| T \left(\frac{\delta}{2} \frac{v}{\|v\|} \right) \right\| < 1 \iff \frac{\delta}{2\|v\|} \|T(v)\| < 1 \iff \frac{\|T(v)\|}{\|v\|} < \frac{2}{\delta}.$$

so $\sup_{v \in V} \frac{\|T(v)\|}{\|v\|} = \|T\|_{\text{op}} \leq \frac{2}{\delta}$.

□

Definition 5.69. If $T : V \rightarrow W$ satisfies any of the equivalent properties in Theorem 5.7.2, T is called a **bounded linear transformation/map/operator** (usually for the $V = W$ case) or a **continuous linear transformation/map/operator**.

Definition 5.70. Let $\mathcal{L}(V, W)$ be the set of bounded linear transformations from V to W . (It's a vector space itself, and it has a norm $\|\cdot\|_{\text{op}}$. Exercise: the norm axioms are satisfied. Check that $\|T + S\|_{\text{op}} \leq \|T\|_{\text{op}} + \|S\|_{\text{op}}$, NOT $\frac{\|T(v_1+v_2)\|}{\|v_1+v_2\|}$.

Fact we won't prove: if V, W are Banach spaces than $\mathcal{L}(V, W)$ is a Banach space. $\mathcal{L}(V, W)$: can add, do scalar multiplication (vector space structure), and also can compose linear transformations. A natural question: how does that interact with operator norm?

Proposition 5.7.3. If $S : V \rightarrow W$ and $T : W \rightarrow Z$ are linear transformations with V, W, Z normed vector spaces, then

$$\|T \circ S\|_{\text{op}} \leq \|T\|_{\text{op}} \|S\|_{\text{op}}.$$

Proof.

$$\|T \circ S\|_{\text{op}} = \sup_{v \neq 0 \in V} \left\{ \frac{\|T(S(v))\|}{\|v\|} \right\} = \max \left\{ \sup_{\{v \in V : v \neq 0, S(v) \neq 0\}} \left\{ \frac{\|T(S(v))\|}{\|v\|} \right\}, \sup_{\{v \in V : v \neq 0, S(v) = 0\}} \left\{ \frac{\|T(S(v))\|}{\|v\|} \right\} \right\}$$

Observe that if $S(v) = 0$ then $T(S(v)) = 0$ so $\sup_{\{v \in V : v \neq 0, S(v) = 0\}} \left\{ \frac{\|T(S(v))\|}{\|v\|} \right\} = 0$. Therefore since the operator norm is nonnegative, $\sup_{\{v \in V : v \neq 0, S(v) \neq 0\}} \left\{ \frac{\|T(S(v))\|}{\|v\|} \right\} \geq \sup_{\{v \in V : v \neq 0, S(v) = 0\}} \left\{ \frac{\|T(S(v))\|}{\|v\|} \right\}$ and we have

$$\begin{aligned} \|T \circ S\|_{\text{op}} &= \sup_{\{v \in V : v \neq 0, S(v) \neq 0\}} \left\{ \frac{\|T(S(v))\|}{\|v\|} \right\} \\ &= \sup_{\{v \in V : v \neq 0, S(v) \neq 0\}} \left\{ \frac{\|T(S(v))\|}{\|S(v)\|} \cdot \frac{\|S(v)\|}{\|v\|} \right\} \\ &\leq \sup_{w \neq 0 \in W} \left\{ \frac{\|T(w)\|}{\|w\|} \right\} \cdot \sup_{v \neq 0 \in V} \left\{ \frac{\|S(v)\|}{\|v\|} \right\} \\ &= \|T\|_{\text{op}} \|S\|_{\text{op}}. \end{aligned}$$

□

Restrict to case $V = W = Z$, so S, T are operators on V . $\mathcal{L}(V, V)$ is not just a vector space; it's an algebra (ring (see Definition 15.3 and vector space at the same time) over \mathbb{R} or \mathbb{C}).

Definition 5.71. An algebra A over \mathbb{R} or \mathbb{C} is called a **Banach algebra** if as a vector space it has a complete norm $\|\cdot\|$ such that $\|a_1 a_2\| \leq \|a_1\| \|a_2\|$ for all $a_1, a_2 \in A$.

Corollary 5.7.3.1 (Corollary to Proposition 5.7.3). If $(V, \|\cdot\|)$ is a Banach space, then $(\mathcal{L}(V, V), \|\cdot\|_{\text{op}})$ is a Banach algebra.

Definition 5.72. If V is a vector space, a **linear functional** on V is a linear transformation $\alpha : V \rightarrow \mathbb{R}$ (similar definition for \mathbb{C}).

Definition 5.73 (Dual Space). If V is a vector space, the **dual space** V^* to V is the vector space of linear functionals on V .

Definition 5.74 (Covectors and dual spaces; definition from Chapter 11 of Lee [2012], p. 287 of pdf, p.272 of book). Let V be a finite-dimensional real vector space. We define a **covector** on V to be a real-valued linear functional on V , that is, a linear map $\omega : V \rightarrow \mathbb{R}$. The space of all covectors on V is itself a real vector space under the obvious operations of pointwise addition and scalar multiplication. It is denoted by V^* and called the **dual space of V** .

Example 5.13. If $V = \mathbb{R}^n$ is the set of column vectors of size n , then the set of linear maps V^* from V to \mathbb{R} is a set of row vectors of size n (then elements of V^* can be matrix multiplied by elements of V yielding real numbers).

What about if V is a normed vector space with $\dim(V) = \infty$? If V^* is the set of all linear functionals on V (disregarding norm), then V^* is “too big.” Instead, define the continuous dual of V .

Definition 5.75. $V^* := \mathcal{L}(V, \mathbb{R})$ is a vector space of continuous linear functionals on V . V^* has the operator norm as its norm: for all $\alpha \in V^*$, $\|\alpha\|_{\text{op}} = \sup_{v \in V, v \neq 0} \frac{|\alpha(v)|}{\|v\|}$.

We will focus for now on the finite-dimensional case (much easier).

Definition 5.76. Let V be a vector space, and let $\|\cdot\|_1$ and $\|\cdot\|_2$ be norms on V . Then $\|\cdot\|_1$ and $\|\cdot\|_2$ are **comparable** if there exist $c_1, c_2 > 0$ such that for all $v \in V$ we have $\|v\|_1 \leq c_1 \|v\|_2$ and $\|v\|_2 \leq c_2 \|v\|_1$.

Theorem 5.7.4 (Comparability of norms; from Homework 10). Let V be a finite-dimensional vector space over \mathbb{R} . Any two norms on V are comparable.

Proof. First we will prove two lemmas.

Lemma 5.7.5. Let V be a finite-dimensional vector space over \mathbb{R} . Let $\dim(V) = n$ be a basis for V , let $\beta = \{e_1, \dots, e_n\}$, and define a norm $\|\cdot\|_\beta$ on V by

$$\left\| \sum_{i=1}^n v^i e_i \right\|_\beta := \sqrt{\sum_{i=1}^n (v^i)^2}. \quad (5.21)$$

Any norm $\|\cdot\|_1 : V \rightarrow \mathbb{R}$ is continuous when V is given the metric induced by $\|\cdot\|_\beta$.

Proof. By the Triangle Inequality (satisfied by any norm by definition)

$$\|v\|_1 = \|v - w + w\|_1 \leq \|v - w\|_1 + \|w\|_1 \implies \|v\|_1 - \|w\|_1 \leq \|v - w\|_1$$

Also,

$$\|w\|_1 = \|w - v + v\|_1 \leq \|w - v\|_1 + \|v\|_1 \implies -\|w - v\|_1 \leq \|v\|_1 - \|w\|_1 \iff -\|v - w\|_1 \leq \|v\|_1 - \|w\|_1$$

Therefore $-\|v - w\|_1 \leq \|v\|_1 - \|w\|_1 \leq \|v - w\|_1$, so

$$| \|v\|_1 - \|w\|_1 | \leq \|v - w\|_1. \quad (5.22)$$

Let $\epsilon > 0$. We will find $\delta > 0$ such that $\|v - w\|_\beta < \delta \implies |\|v\|_1 - \|w\|_1| < \epsilon$, showing that $\|\cdot\|_1 : V \rightarrow \mathbb{R}$ is continuous when V is given the metric induced by $\|\cdot\|_\beta$. Write v as $v = \sum_{i=1}^n v^i e_i$ and likewise $w = \sum_{i=1}^n w^i e_i$, so

$$\|v - w\|_1 = \left\| \sum_{i=1}^n (v^i - w^i) e_i \right\|_1 \leq \sum_{i=1}^n \|(v^i - w^i) e_i\|_1 = \sum_{i=1}^n |v^i - w^i| \|e_i\|_1 = \sum_{i=1}^n |v^i - w^i|,$$

so

$$\sum_{i=1}^n |v^i - w^i| < \epsilon \implies \|v - w\|_1 < \epsilon. \quad (5.23)$$

Suppose $|v_i - w_i| < 1$ for all i ; then $(v_i - w_i)^2 < \delta \implies |v_i - w_i| < \delta$. Therefore if $|v_i - w_i| < 1$ for all i and letting $\delta = \sqrt{\epsilon}$,

$$\begin{aligned} \|v - w\|_\beta < \delta &\iff \left\| \sum_{i=1}^n (v^i - w^i) e_i \right\|_\beta < \sqrt{\epsilon} \\ &\iff \sqrt{\sum_{i=1}^n (v^i - w^i)^2} < \sqrt{\epsilon} \\ &\iff \sum_{i=1}^n (v^i - w^i)^2 < \epsilon \\ (\text{by assumption } |v_i - w_i| < 1 \text{ for all } i) &\implies \sum_{i=1}^n |v^i - w^i| < \epsilon \\ (\text{by (5.23)}) &\implies \|v - w\|_1 < \epsilon \\ (\text{by (5.22)}) &\implies |\|v\|_1 - \|w\|_1| < \epsilon. \end{aligned}$$

□

Lemma 5.7.6 (Transitivity of norm comparability). Let V be a finite-dimensional vector space over \mathbb{R} and let $\|\cdot\|_1$, $\|\cdot\|_2$, and $\|\cdot\|_3$ be norms on V . If $\|\cdot\|_1$ is comparable to $\|\cdot\|_2$ and $\|\cdot\|_2$ is comparable to $\|\cdot\|_3$, then $\|\cdot\|_1$ is comparable to $\|\cdot\|_3$.

Proof. If $\|\cdot\|_1$ is comparable to $\|\cdot\|_2$ then there exists constants c_{12} and c_{21} such that for all $v \in V$

$$\|v\|_1 \leq c_{12} \|v\|_2, \quad \|v\|_2 \leq c_{21} \|v\|_1.$$

Similarly, if $\|\cdot\|_2$ and $\|\cdot\|_3$ are comparable then

$$\|v\|_2 \leq c_{23} \|v\|_3, \quad \|v\|_3 \leq c_{32} \|v\|_2$$

for every $v \in V$ for some constants c_{23} and c_{32} . It follows that for every $v \in V$

$$\|v\|_1 \leq c_{12}\|v\|_2 \leq c_{12}c_{23}\|v\|_3$$

and

$$\|v\|_3 \leq c_{32}\|v\|_2 \leq c_{32}c_{21}\|v\|_1.$$

□

Now we can prove the main result. Again, let $\dim(V) = n$ be a basis for V , let $\beta = \{e_1, \dots, e_n\}$, and consider the norm $\|\cdot\|_\beta$ on V defined by (5.21). Consider the restriction of $\|\cdot\|_1$ to the $\|\cdot\|_\beta$ -unit sphere $S := \{v \in V \mid \|v\|_\beta = 1\}$. S is closed and totally bounded by construction, and every finite-dimensional normed vector space is complete, so by the Generalized Heine-Borel Theorem (Theorem 2.65 in Pugh [2015]) S is compact. Since S is bounded, it follows that for some $M \in (0, \infty)$

$$\|\tilde{v}\|_1 \leq M \quad \forall \tilde{v} \in S. \quad (5.24)$$

Further, since S does not contain the zero vector, it holds that there exists $m \in (0, M]$ such that

$$m \leq \|\tilde{v}\|_1 \quad \forall \tilde{v} \in S. \quad (5.25)$$

Now consider a general $v \in V$. We can express any $v \in V$ as $v = c\tilde{v}$ for some $c \in \mathbb{R}$ and some $\tilde{v} \in S$. By norm axioms, it holds that for any $c \in \mathbb{R}$ $\|cv\|_\beta = |c|\|v\|_\beta$, so in particular $\|v\|_\beta = \|c\tilde{v}\|_\beta = |c|\|\tilde{v}\|_\beta = |c|$. Then it follows from (5.24) that for any $v \in V$ there exists some $c \in \mathbb{R}$ such that

$$\|v\|_1 = \|c\tilde{v}\|_1 = |c|\|\tilde{v}\|_1 = \|v\|_\beta\|\tilde{v}\|_1 \leq M\|v\|_\beta$$

and from (5.25) we have

$$\|v\|_1 = \|c\tilde{v}\|_1 = |c|\|\tilde{v}\|_1 = \|v\|_\beta\|\tilde{v}\|_1 \geq m\|v\|_\beta \iff \|v\|_\beta \leq \frac{1}{m}\|\tilde{v}\|_1.$$

Therefore $\|\cdot\|_\beta$ and $\|\cdot\|_1$ are comparable. By the same argument, $\|\cdot\|_\beta$ and $\|\cdot\|_2$ are comparable. Therefore by transitivity of norm comparability (Lemma 5.7.6), $\|\cdot\|_1$ and $\|\cdot\|_2$ are comparable.

□

Corollary 5.7.6.1 (Corollary to Theorem 5.7.4). $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is continuous in the Euclidean norms if and only if f is continuous given any norms on $\mathbb{R}^n, \mathbb{R}^m$.

Corollary 5.7.6.2 (Corollary to Theorem 5.7.4). Let V, W be finite-dimensional vector spaces over \mathbb{R} or \mathbb{C} . Then any linear transformation $T : V \rightarrow W$ is continuous given any choice of norms for V, W .

Proof. Pick isomorphisms $V \cong \mathbb{R}^n$ and $W \cong \mathbb{R}^m$ (mappings between two structures of the same type that can be reversed by inverse mappings; see Definition 5.26); get norms on V, W by transforming Euclidean norms on $\mathbb{R}^n, \mathbb{R}^m$ to V, W . Under these isomorphisms, T acts by a matrix ($T(v) = Av$ for $v \in \mathbb{R}^n$).

Each entry of Av ($a_{i1}v_1 + \dots + a_{in}v_n$) is a continuous function of $v \in \mathbb{R}^n$, so T is continuous in these norms, and therefore in any norms on V, W .

□

So if V, W are finite-dimensional (say $\dim(V) = n$ and $\dim(W) = m$), then $\mathcal{L}(V, W)$ is the set of all linear transformations from V to W . We can choose bases for V and W and make a basis $\text{mat}_{m \times n}(\mathbb{R}) = \mathbb{R}^{m \times n}$ (or \mathbb{C}) which is the set of $m \times n$ matrices with entries in \mathbb{R} (or \mathbb{C}). We can also order the entries in some way and express these matrices as vectors in $\mathbb{R}^{m \cdot n}$.

Thus, we have many norms on $\mathcal{L}(V, W)$.

- We can pick the operator norm on $\mathcal{L}(V, W)$ for any choice of norms on V, W .
- We have many norms on \mathbb{R}^{mn} (e.g. Euclidean norm, ℓ_1 norm, ℓ_∞ norm)

All of these norms are comparable.

Corollary 5.7.6.3 (Corollary to Theorem 5.7.4). If $U \subset \mathbb{R}^k$ is open and $A : U \rightarrow \text{mat}_{m \times n}(\mathbb{R})$ is a function ($A(x)$ is a matrix-valued function of $x \in U$), then

1. each entry of A is a continuous function from U to \mathbb{R} (“ A is continuous given ℓ_∞ norm on $\text{mat}_{m \times n}(\mathbb{R})$ ”) if and only if
2. for $x_0 \in U$, given $\epsilon > 0$, there exists $\delta > 0$ such that if $\|x - x_0\| < \delta$ then $\|A(x) - A(x_0)\|_{\text{op}} < \epsilon$ (“ A is continuous given its operator norm on $\text{mat}_{m \times n}(\mathbb{R})$ ”).

Now we will discuss some intuition for the $\|\cdot\|_{\text{op}}$ on $\text{mat}_{m \times n}(\mathbb{R})$.

Theorem 5.7.7 (Spectral Theorem). Let $A \in \text{mat}_{m \times n}(\mathbb{R})$ where $m = n$ and $A = A^T$. Then A has an orthonormal eigenbasis v_1, \dots, v_n with eigenvalues $\lambda_1, \dots, \lambda_n$.

Proposition 5.7.8. Let $A \in \text{mat}_{m \times n}(\mathbb{R})$ where $m = n$ and $A = A^T$. Then $\|A\|_{\text{op}} = |\lambda_1|$ (the absolute value of the largest eigenvalue).

Proof. For $v \in V$, write $v = c_1v_1 + \dots + c_nv_n$ (uniquely). Then

$$Av = \sum_{i=1}^n c_i Av_i = \sum_{i=1}^n c_i \lambda_i v_i.$$

By orthonormality, we then have

$$\|Av\|_2^2 = \sum_{i=1}^n |c_i|^2 |\lambda_i|^2 \leq |\lambda_1|^2 \sum_{i=1}^n |c_i|^2 = |\lambda_1|^2 \|v\|_2^2.$$

If $v \neq 0$, this means $\frac{\|Av\|_2}{\|v\|_2} \leq |\lambda_1|$, so $\|A\|_{\text{op}} \leq |\lambda_1|$. On the other hand, $\frac{\|Av_1\|_2}{\|v_1\|_2} = |\lambda_1| \frac{\|v_1\|_2}{\|v_1\|_2} = |\lambda_1|$. So $\|A\|_{\text{op}} \geq |\lambda_1|$.

□

Now consider the general case: $A \in \text{mat}_{m \times n}(\mathbb{R})$. Write A in its singular value decomposition $A = U\Sigma V^T$ where U is an $m \times m$ orthogonal matrix, V is an $n \times n$ orthogonal matrix, and Σ is the $m \times n$ matrix containing the singular values on the diagonal (see Section 2.4.1 for details on the singular value decomposition).

Proposition 5.7.9. Let $A \in \text{mat}_{m \times n}(\mathbb{R})$. Then $\|A\|_{\text{op}} = \sigma_1$ (the largest singular value).

Proof. For $v \in \mathbb{R}^n$, write $v = c_1 v_1 + \dots + c_n v_n$ (uniquely), where v_i are the orthonormal basis vectors of \mathbb{R}^n forming the columns of V . Let $\text{rank}(A) = k \leq \min\{m, n\}$. Then

$$Av = U\Sigma V^T v = \sum_{i=1}^k c_i \underbrace{U}_{m \times k} \underbrace{\Sigma}_{k \times k} \underbrace{V^T}_{k \times n} v_i = \sum_{i=1}^k c_i U \Sigma e_i = \sum_{i=1}^k c_i \sigma_i u_i.$$

(where e_i is the standard basis vector for \mathbb{R}^n). By orthonormality, we then have

$$\|Av\|_2^2 = \sum_{i=1}^k |c_i|^2 \sigma_i^2 \leq \sigma_1^2 \sum_{i=1}^n |c_i|^2 = \sigma_1^2 \|v\|_2^2.$$

If $v \neq 0$, this means $\frac{\|Av\|_2}{\|v\|_2} \leq \sigma_1$, so $\|A\|_{\text{op}} \leq \sigma_1$. On the other hand, $\frac{\|Av_1\|_2}{\|v_1\|_2} = \sigma_1 \frac{\|v_1\|_2}{\|v_1\|_2} = \sigma_1$. So $\|A\|_{\text{op}} \geq \sigma_1$.

□

5.7.2 Manifolds (Chapter 5 of Spivak [1971])

Definition 5.77 (Manifold; definition from section 5.1 of Spivak [1971], p. 122 of pdf, p. 109 of book). A subset M of \mathbb{R}^n is called a **k -dimensional manifold** (in \mathbb{R}^n) if for every point $x \in M$ the following condition is satisfied: there is an open set U containing x , an open set $V \subset \mathbb{R}^n$, and a diffeomorphism $h : U \rightarrow V$ (recall Definition 5.67) such that

$$h(U \cap M) = V \cap (\mathbb{R}^k \times \{0\}) = \{y \in V : y^{k+1} = \dots = y^n = 0\}.$$

(In other words, $U \cap M$ is, “up to diffeomorphism,” simply $\mathbb{R}^k \times \{0\}$.)

Definition 5.78 (Topological manifold; definition from Lee [2012], p. 17 of pdf, p. 2 of book). Suppose M is a topological space (see Definition 5.25). We say that M is a **topological manifold of dimension n** or a **topological n -manifold** if it has the following properties:

1. M is a **Hausdorff space**: for every pair of distinct points $p, q \in M$, there are disjoint open subsets $U, V \subseteq M$ such that $p \in U$ and $q \in V$. (This is automatically satisfied for any metric space.)
2. M is **second-countable**: there exists a countable basis for the topology of M .
3. M is **locally Euclidean of dimension n** : each point of M has a neighborhood that is homeomorphic to an open subset of \mathbb{R}^n .

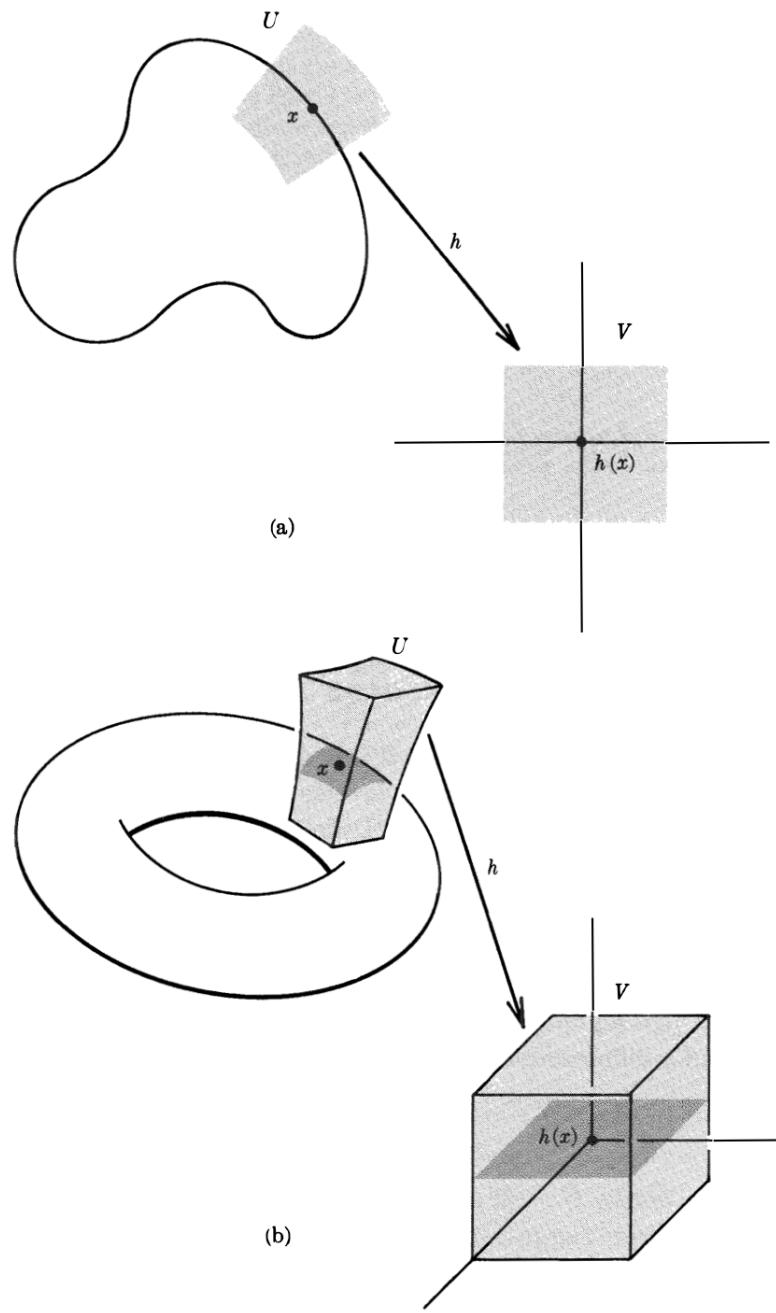


Figure 5.4: Figure 5.1 in Spivak [1971]. (a) A one-dimensional manifold in \mathbb{R}^2 . (b) A two-dimensional manifold in \mathbb{R}^3 .

The third property means, more specifically, that for each $p \in M$ we can find

- an open subset $U \subseteq M$ containing p ,
- an open subset $\hat{U} \subseteq \mathbb{R}^n$, and
- a homeomorphism $\phi : U \rightarrow \hat{U}$.

Example 5.14. See Figure 5.4 for some examples of manifolds. There are two extreme cases of this definition. \mathbb{R}^n itself is a topological n -manifold: it is Hausdorff because it is a metric space, and it is second-countable because the set of open balls with rational centers and rational radii is a countable basis for its topology.

and an open subset of \mathbb{R}^n is an n -dimensional manifold.

Also, a point in \mathbb{R}^n is a 0-dimensional manifold,

One common example of an n -dimensional manifold is the n -sphere S^n , defined as $\{x \in \mathbb{R}^{n+1} : |x| = 1\}$. The fact that S^n is an n -dimensional manifold can be verified by definition, or more easily by the following result.

Theorem 5.7.10 (Theorem 5-1 in Spivak [1971], p. 124 of pdf, p. 111 of book). Let $A \subset \mathbb{R}^n$ be open and let $g : A \rightarrow \mathbb{R}^p$ be a differentiable function such that $g'(x) = (Dg)_x \in \mathbb{R}^{p \times n}$ has rank p whenever $g(x) = 0$. Then $g^{-1}(0)$ is an $(n - p)$ -dimensional manifold in \mathbb{R}^n .

Proof. Immediate from Theorem 5.7.27.

□

Note that $S^n = g^{-1}(0)$, where $g : \mathbb{R}^{n+1} \rightarrow \mathbb{R}$ is defined by $g(x) = |x|^2 - 1$.

Definition 5.79 (Coordinate system or coordinate chart; definition from Spivak [1971], p. 124 of pdf, p. 111 of book). Let $M \subset \mathbb{R}^n$, let $x \in M$, and let U be an open set containing x . Let $W \subset \mathbb{R}^k$. A **coordinate system** around x is a one-to-one differentiable function $f : W \rightarrow \mathbb{R}^n$ such that

1. $f(W) = M \cap U$,
2. $f'(y)$ has rank k for each $y \in W$, and
3. $f^{-1} : f(W) \rightarrow W$ is continuous.

See Figure 5.6.

Definition 5.80 (Coordinate system or coordinate chart; definition from Lee [2012], p. 19 of pdf, p. 4 of book). Let M be a topological n -manifold (see Definition 5.78). A **coordinate chart** (or just a **chart**) on M is a pair (U, ϕ) , where U is an open subset of M and $\phi : U \rightarrow \hat{U}$ is a homeomorphism from U to an open subset $\hat{U} = \phi(U) \subseteq \mathbb{R}^n$ (see Figure 5.5). By the definition of a topological manifold, each point $p \in M$ is contained in the domain of some chart (U, ϕ) .

If $\phi(p) = 0$, we say the chart is **centered at p** . If (U, ϕ) is any chart whose domain contains p , it is easy to obtain a new chart centered at p by subtracting the constant vector $\phi(p)$.

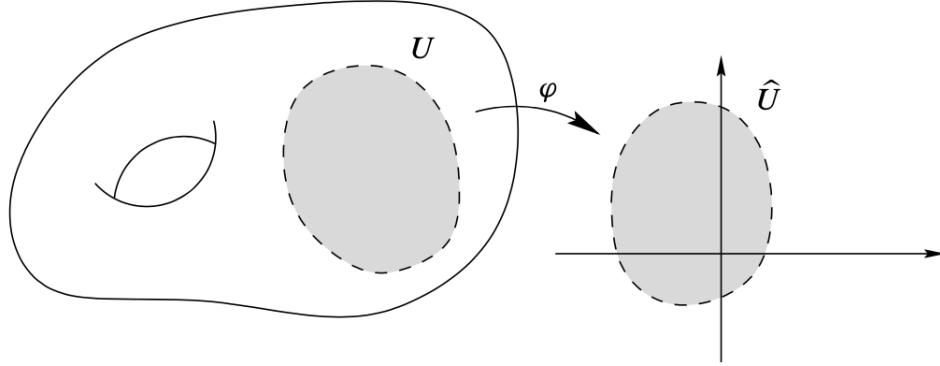
**Fig. 1.2** A coordinate chart

Figure 5.5: Figure 1.2 in Lee [2012]; a coordinate chart.

Given a chart (U, ϕ) , we call the set U a **coordinate domain**, or a **coordinate neighborhood** of each of its points.

The following alternative characterization of manifolds is important.

Theorem 5.7.11 (Theorem 5-2 in Spivak [1971], p. 124 of pdf, p. 111 of book). Let $M \subset \mathbb{R}^n$, let $x \in M$, and let U be an open set containing x . Let $W \subset \mathbb{R}^k$. M is a k -dimensional manifold if and only if for each $x \in M$ there is an open set U containing x and an open set $W \subset \mathbb{R}^k$ with a coordinate chart $f : W \rightarrow \mathbb{R}^n$.

5.7.3 Differentiability of functions from $\mathbb{R}^n \rightarrow \mathbb{R}^m$ (Section 5.2 of Pugh [2015])

(See also Section 3.2 for more on this material.)

Definition 5.81 (Tangent space; from Section 4.2 of Spivak [1971], p. 86 of book, p. 99 of pdf). Let $p \in \mathbb{R}^n$. The set of all pairs (p, v) for $v \in \mathbb{R}^n$ is denoted \mathbb{R}_p^n and called the **tangent space** of \mathbb{R}^n at p . This set is made into a vector space by defining

$$(p, v) + (p, w) = (p, v + w), \quad a \cdot (p, v) = (p, av)$$

for $v, w \in \mathbb{R}^n$ and $a \in \mathbb{R}$. In 425b, we use the notation $(T\mathbb{R}^n)_p$.

Definition 5.82 (Tangent space; from Section 3.1 of Lee [2012], p. 66 of pdf, p. 51 of book). Given a point $a \in \mathbb{R}^n$, define the **geometric tangent space to \mathbb{R}^n at a** , denoted by \mathbb{R}_a^n , to be the set $\{a\} \times \mathbb{R}^n = \{(a, v) : v \in \mathbb{R}^n\}$. A **geometric tangent vector** in \mathbb{R}^n is an element of \mathbb{R}_a^n for some $a \in \mathbb{R}^n$.

As a matter of notation, we abbreviate (a, v) as v_a or sometimes $v|_a$. In 425b, we use the notation $(T\mathbb{R}^n)_a$.

We think of the vector v_a as the vector v with its initial point at a . The set \mathbb{R}_a^n is a real vector space under the natural operations $v_a + w_a = (v + w)_a$ and $c(v_a) = (cv)_a$. The vectors $e_i|_a, i \in [n]$, are a basis for \mathbb{R}_a^n .

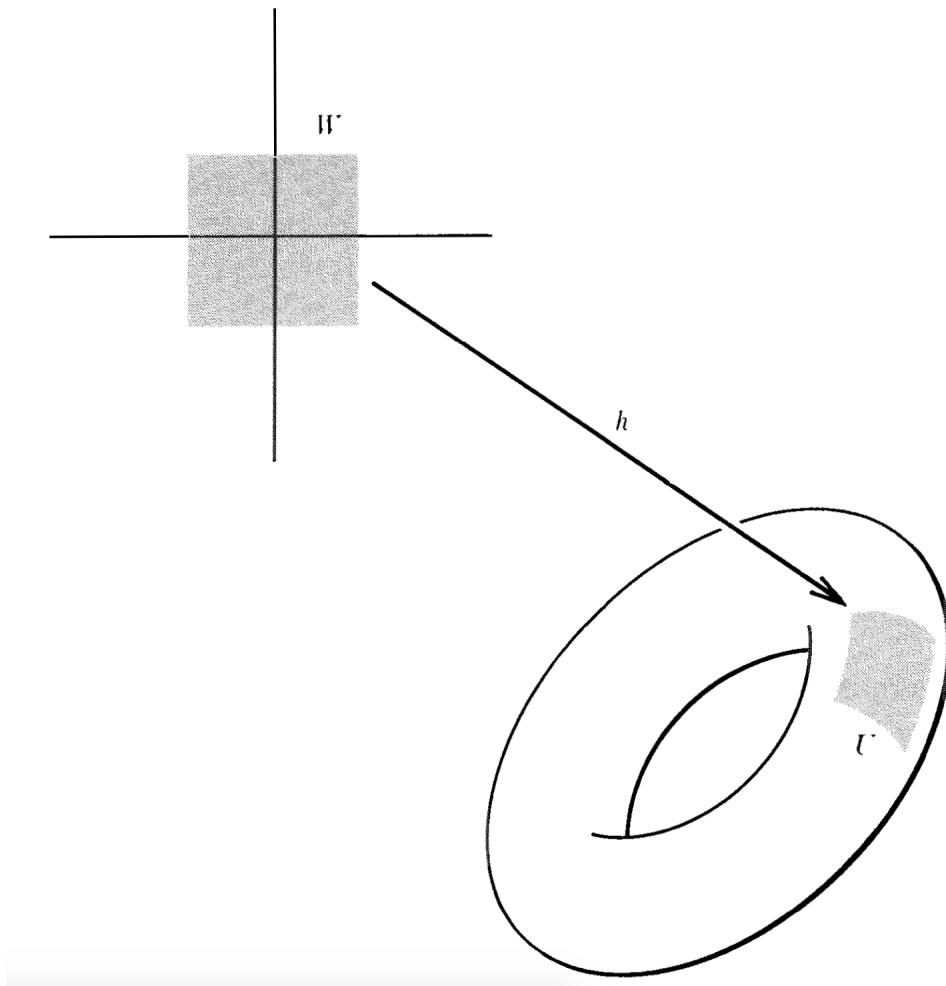


Figure 5.6: Figure 5-2 in Spivak [1971], for Theorem 5.7.11.

Any operations which is possible in a vector space may be performed in each \mathbb{R}_p^n . If a selection of a vector is made in each \mathbb{R}_p^n , we obtain a **vector field**.

Definition 5.83 (Vector field; Section 4.2 of Spivak [1971], p. 100 of pdf, p. 87 of book). A **vector field** is a function F such that $F(p) \in \mathbb{R}_p^n$ for each $p \in \mathbb{R}^n$. For each p there are numbers $F^1(p), \dots, F^n(p)$ such that

$$F(p) = F^1(p) \cdot (e_1)_p + \dots + F^n(p) \cdot (e_n)_p.$$

We thus obtain n **component functions** $F^i : \mathbb{R}^n \rightarrow \mathbb{R}$. The vector field is called continuous, differentiable, etc. if the functions F^i are. Similar definitions can be made for a vector field defined only on an open subset of \mathbb{R}^n . Operations on vectors yield operations on vector fields when applied at each point separately. For example, if F and G are vector fields and f is a function, we define

$$\begin{aligned}(F + G)(p) &= F(p) + G(p), \\ \langle F, G \rangle(p) &= \langle F(p), G(p) \rangle, \\ (f \cdot F)(p) &= f(p)F(p).\end{aligned}$$

If F_1, \dots, F_{n-1} are vector fields on \mathbb{R}^n , then we can similarly define

$$(F_1 \times \dots \times F_{n-1})(p) = F_1(p) \times \dots \times F_{n-1}(p).$$

Matrix for $(DF)_p$ in standard bases for $\mathbb{R}^n, \mathbb{R}^m$ (**Jacobian**):

$$\begin{bmatrix} \frac{\partial F_1}{\partial x_1}(p) & \cdots & \frac{\partial F_1}{\partial x_n}(p) \\ \vdots & \ddots & \vdots \\ \frac{\partial F_m}{\partial x_1}(p) & \cdots & \frac{\partial F_m}{\partial x_n}(p) \end{bmatrix}$$

We can use this as the definition and we'd be fine for C^1 functions (note: haven't yet defined C classes for multivariate functions). Important to know about another approach based on an idea of linear approximations.

Definition 5.84 (Total derivative; Section 5.2 of Pugh [2015], p. 282 (p. 292 of pdf)). Let $f : U \rightarrow \mathbb{R}^m$ be given where U is an open subset of \mathbb{R}^n . The function F is **differentiable** at $p \in U$ with **(total) derivative** (or **Frechet derivative**) $(DF)_p = T$ if $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation and

$$\lim_{\|v\| \rightarrow 0} \frac{F(p+v) - F(p) - T(v)}{\|v\|} = 0;$$

that is, (book definition)

$$R(v) := f(p+v) - f(p) - T(v) \implies \lim_{\|v\| \rightarrow 0} \frac{R(v)}{\|v\|} = 0.$$

Proposition 5.7.12 (Similar to Theorem 5.5 in Pugh [2015]). Let $U \subset \mathbb{R}^n$ be open. Let $F : U \rightarrow \mathbb{R}^m$ be a function and let $p \in U$. Let $F = \begin{bmatrix} F_1 \\ \vdots \\ F_m \end{bmatrix}$, $F_i : U \rightarrow \mathbb{R}$. Then

$$\begin{array}{l} 1. F \text{ is differentiable at } p \text{ with derivative } T(v) = Av \text{ } (A \in \text{Mat}_{m \times n}(\mathbb{R})), \text{ if and only if} \\ 2. \text{ Each } f_i \text{ is differentiable at } p \text{ with derivative } T_i(v) = [a_{i1} \quad \cdots \quad a_{in}] \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}. \end{array}$$

1. F is differentiable at p with derivative $T(v) = Av$ ($A \in \text{Mat}_{m \times n}(\mathbb{R})$), if and only if

$$2. \text{ Each } f_i \text{ is differentiable at } p \text{ with derivative } T_i(v) = [a_{i1} \quad \cdots \quad a_{in}] \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}.$$

Proof. (1) is true if and only if $\lim_{\|v\| \rightarrow 0} \frac{F(p+v)-F(p)-T(v)}{\|v\|} = 0$, which is true if and only if each coordinate of $\frac{F(p+v)-F(p)-T(v)}{\|v\|} \rightarrow 0$ as $v \rightarrow 0$, which is true if and only if (2) is true.

□

Next we will talk about uniqueness. We want to show that $T = (DF)_p$ is unique if it exists. This is easy if we use the chain rule (the book is quicker and more direct but a bit redundant).

Proposition 5.7.13 (Differentiability implies continuity; Theorem 5.6 in Pugh [2015]). Let $U \subset \mathbb{R}^n$ be open. Let $p \in U$, $F : U \rightarrow \mathbb{R}^m$. If F is differentiable at p with derivative T , then F is continuous at p .

Proof. We have $F(p+v) = F(p) + T(v) + R_F(v)$, where $\lim_{v \rightarrow 0} \frac{\|R_F(v)\|}{\|v\|} = 0$. This implies $\lim_{v \rightarrow 0} \|R_F(v)\| = 0$ (note: $\|R_F(v)\| \leq \frac{\|R_F(v)\|}{\|v\|} \cdot \|v\| \leq 1$). Therefore $\lim_{v \rightarrow 0} F(p+v) = F(p) + 0 + 0$; that is, for every $\epsilon > 0$ there exists $\delta > 0$ such that $\|v\|_2 < \delta \implies \|F(p+v) - F(p)\|_2 < \epsilon$, so F is continuous at p .

□

Theorem 5.7.14 (Chain rule; Theorem 5.9(c) in Pugh [2015]). Let $U \subset \mathbb{R}^n$ be open. Let $V \subset \mathbb{R}^m$ be open. Let $F : U \rightarrow V$ and let $G : V \rightarrow \mathbb{R}^k$ be functions such that (1) F is differentiable at p (with derivative A) and (2) G is differentiable at $F(p) = q \in V$ (with derivative B). Then $G \circ F$ is differentiable at p with derivative $B \circ A$.

Note that if the derivative is unique, then $(D(G \circ F))_p = (DG)_{f(p)} \circ (DF)_p$ (composing then linearly approximating is the same as linearly approximating then composing).

Proof. Let $R_F = R_{F,p,A}$, a function of $v \in \mathbb{R}^n$. $R_F(v) = F(p+v) - F(p) - Av$, so

$$F(p+v) = F(p) + Av + R_F(v). \tag{5.26}$$

Let $R_G = R_{G,q,B}$, a function of $w \in \mathbb{R}^m$. $R_G(w) = G(q+w) - G(q) - Bw$, so

$$G(q+w) = G(q) + Bw + R_G(w). \tag{5.27}$$

Let $R_{G \circ F} = R_{G \circ F,p,BA}$. We want to show that $\lim_{v \rightarrow 0} \frac{R_{G \circ F}}{\|v\|} = 0$.

We have

$$\begin{aligned}
R_{G \circ F}(v) &= (G \circ F)(p + v) - (G \circ F)(p) - BA v \\
&= G(F(p + v)) - G(\underbrace{F(p)}_{=q}) - BA v \\
&\quad (\text{by (5.26)}) = G(F(p) + Av + R_F(v)) - G(q) - BA v \\
(\text{by (5.27) and } F(p) = q) &= G(q) + B(Av + R_F(v)) + R_G(Av + R_F(v)) - G(q) - BA v \\
&= BR_F(v) + R_G(Av + R_F(v)).
\end{aligned}$$

Thus,

$$\frac{\|R_{G \circ F}(v)\|}{\|v\|} \leq \frac{\|BR_F(v)\|}{\|v\|} + \frac{\|R_G(Av + R_F(v))\|}{\|v\|}. \quad (5.28)$$

We want to show both terms on the right in (5.28) go to 0 as $v \rightarrow 0$. First,

$$\frac{\|BR_F(v)\|}{\|v\|} \leq \|B\|_{\text{op}} \frac{\|R_F(v)\|}{\|v\|} \rightarrow 0$$

as $v \rightarrow 0$ by differentiability of F (since $\|B\|_{\text{op}} < \infty$). Next, for v with $Av + R_F(v) = 0$, we have

$$R_G(Av + R_F(v)) = R_G(0) = 0$$

since $R_G(w) = G(q + w) - G(q) - Bw \implies R_G(0) = G(q) - G(q) - 0 = 0$. Thus the second term in (5.28) is 0 if $v \neq 0$ and $Av + R_F(v) = 0$. For x with $Av + R_F(v) \neq 0$, we have

$$\frac{\|R_G(Av + R_F(v))\|}{\|v\|} = \frac{\|R_G(Av + R_F(v))\|}{\|Av + R_F(v)\|} \frac{\|Av + R_F(v)\|}{\|v\|}$$

As $v \rightarrow 0$ we have $Av + R_F(v) \rightarrow 0$, since matrix multiplication by A is continuous and $R_F(v) = F(p + v) - F(p) - Av$ is continuous at $v = 0$ (since differentiability of F at p implies continuity of F at p by Proposition 5.7.13). Since $\lim_{v \rightarrow 0} (Av + R_F(v)) = 0$ and $\lim_{w \rightarrow 0} \frac{\|R_G(w)\|}{\|w\|} = 0$, we have

$$\lim_{v \rightarrow 0} \frac{\|R_G(Av + R_F(v))\|}{\|Av + R_F(v)\|} = 0.$$

From here it is enough to show that $\lim_{v \rightarrow 0} \frac{\|Av + R_F(v)\|}{\|v\|}$ is bounded. Observe that

$$\frac{\|Av + R_F(v)\|}{\|v\|} \leq \frac{\|Av\|}{\|v\|} + \frac{\|R_F(v)\|}{\|v\|} \leq \|A\|_{\text{op}} + 0.$$

□

An important geometric interpretation that gives us the uniqueness of derivatives: $(DF)p$ is determined by how it acts on velocity vectors of curves (see notes).

Corollary 5.7.14.1. Let $U \subset \mathbb{R}^n$ be open. Let $p \in U$, $F : U \rightarrow \mathbb{R}^m$. Let $0 \in (a, b)$ and let $\gamma : (a, b) \rightarrow U$ be a differentiable function (curve) with $\gamma(t_0) = p$. Then $(DF)_p(\gamma'(t_0)) = (F \circ \gamma)'(t_0)$.

Proof. By the chain rule (Theorem 5.7.14), $F \circ \gamma$ is differentiable at t_0 with $(D(F \circ \gamma))_{t_0} = (DF)_{\gamma(t_0)}(D\gamma)_{t_0} = (DF)_p(D\gamma)_{t_0}$. Viewed as a $m \times 1$ matrix, we showed last time that $(D(F \circ \gamma))_{t_0} = (F \circ \gamma)'(t_0)$. Viewed as an $n \times 1$ matrix, we showed that $(D\gamma)_{t_0} = \gamma'(t_0)$.

□

Corollary 5.7.14.2. If F is differentiable at $\gamma(t_0) = p$ with derivative $T = (DF)_p$, then

$$T(v) = \lim_{t \rightarrow 0} \frac{F(p + tv) - F(p)}{t}.$$

(since the right side is independent of T , this shows T is unique.)

Proof. Let $\gamma(t) = p + tv$; then the right hand side is $(F \circ \gamma)'(t_0)$ (using $\gamma(t_0) = p$).

□

If $\lim_{t \rightarrow 0} \frac{f(p+tv) - f(p)}{t}$ exists for all v (this is $(DF)_p(v)$) and this quantity is linear in v , is F (Frechet) differentiable at p ? No. For example, $F : \mathbb{R}^2 \rightarrow \mathbb{R}$,

$$F(x, y) = \begin{cases} \frac{x^3y}{x^4+y^2}, & (x, y) \neq (0, 0), \\ (0, 0), & (x, y) = (0, 0). \end{cases}$$

Exercise (Pugh [2015] ex. 18 and 19, ch 5; more discussion on why to prefer Frechet): directional derivative exists and equals 0 for all v but F is not differentiable at $(0, 0)$.

Proposition 5.7.15 (Theorem 5.9(a) and 5.9(b) in Pugh [2015]). Let $U \subset \mathbb{R}^n$ be open. Let $p \in U$, $F, G : U \rightarrow \mathbb{R}^m$.

- (a) If F and G are differentiable at p then $F + G$ is differentiable at p with $D(F + G)p = (DF)p + (DG)p$.
- (b) If $c \in \mathbb{R}$ then cF is differentiable at p with $D(cF)p = c(DF)p$.
- (c) Any constant function $F : U \rightarrow \mathbb{R}^m$ is differentiable with derivative 0 everywhere.
- (d) If $F : U \rightarrow \mathbb{R}^m$ is affine linear ($F(x) = Ax + y_0$ for some $A \in \mathbb{R}^{m \times n}$, $y_0 \in \mathbb{R}^m$) then F is differentiable at all points of U with derivative A .

Proof. (a)

$$\begin{aligned} & \frac{\|(F + G)(p + v) - (F + G)(p) - ((DF)p + (DG)p)(v)\|}{\|v\|} \\ & \leq \frac{\|F(p + v) - F(p) - (DF)p(v)\|}{\|v\|} + \frac{\|G(p + v) - G(p) - (DG)p(v)\|}{\|v\|}. \end{aligned}$$

Each of these terms goes to 0 as $v \rightarrow 0$ by differentiability of F and G .

(b)

$$\frac{\|(cF)(p+v) - (cF)(p) - D[cF]_p(v)\|}{\|v\|} \leq c \frac{\|F(p+v) - F(p) - (DF)_p(v)\|}{\|v\|}$$

which goes to 0 as $v \rightarrow 0$ by differentiability of F .

(c)

(d) If $F(x) = Ax + y_0$ then

$$\frac{F(p+v) - F(p) - Av}{\|v\|} = \frac{A(p+v) - A(p) - A(v)}{\|v\|} = \frac{0}{\|v\|} \rightarrow 0$$

as $v \rightarrow 0$. □

Definition 5.85. Let $U \subset \mathbb{R}^n$ be open. Let $p \in U$ and let $F : U \rightarrow \mathbb{R}^m$. Let $1 \leq i \leq n$. The i^{th} **partial derivative** of F at p , $\frac{\partial F}{\partial x_i}(p)$, is defined to be

$$\frac{\partial F}{\partial x_i}(p) := \lim_{t \rightarrow 0} \frac{F(p+te_i) - F(p)}{t}$$

(if it exists) where e_i is the i^{th} standard basis vector for \mathbb{R}^n (the directional derivative of F in the direction e_i). If F is differentiable, it also equals $(DF)_p(e_i) = (F \circ \gamma)'(0)$ where $\gamma(t) = p + te_i$.

Remark 13. If $F : U \rightarrow \mathbb{R}^m$ and $\frac{\partial F}{\partial x_i}(p)$ exists for all $p \in U$, then $\frac{\partial F}{\partial x_i} : U \rightarrow \mathbb{R}^m$ (just the F). This implies we can (try to) take successive derivatives, e.g., we can do

$$\frac{\partial^2 F}{\partial x_j \partial x_i} := \frac{\partial}{\partial x_j} \left(\frac{\partial F}{\partial x_i} \right),$$

etc., and keep getting functions from U to \mathbb{R}^m as long as the partial derivatives keep existing.

Definition 5.86. Let $F : U \rightarrow \mathbb{R}^m$ is of **class C^k** (we can also say F is a C^k **function**) if all partial derivatives of F of orders $\leq k$ exist and are continuous in U . (We use this notation with $k = \infty$ if this is true for all orders, not “infinite orders.”) We call C^∞ functions **smooth**.

Theorem 5.7.16. If $F : U \rightarrow \mathbb{R}^m$ is of class C^1 , then F is differentiable at all $p \in U$ and $(DF)_p : \mathbb{R}^n \rightarrow \mathbb{R}^m$ has standard basis matrix

$$\begin{bmatrix} \frac{\partial F_1}{\partial x_1}(p) & \dots & \frac{\partial F_1}{\partial x_n}(p) \\ \vdots & \ddots & \vdots \\ \frac{\partial F_m}{\partial x_1}(p) & \dots & \frac{\partial F_m}{\partial x_n}(p) \end{bmatrix} \tag{5.29}$$

Remark 14. Note that the columns are $\frac{\partial F}{\partial x_i}(p)$ for $i \in [n]$. This makes sense: if $\lim_{t \rightarrow 0} \frac{F(p+v) - F(p)}{t}$ is linear in v , then the i^{th} column of its standard basis matrix should be obtained by plugging $v = e_i$ into $\lim_{t \rightarrow 0} \frac{F(p+v) - F(p)}{t}$.

Proof. Let J be the matrix (5.29). Let $T(v) = Jv$ ($T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ linear). Let $R(v) = F(p+v) - F(p) - Jv$. For $i \in [m]$, let $R_i(v)$ be the i^{th} coordinate of $R(v)$. Then

$$R_i(v) = F_i(p+v) - F_i(p) - \left[\frac{\partial F_i}{\partial x_1}(p) \quad \cdots \quad \frac{\partial F_i}{\partial x_n}(p) \right] v.$$

It suffices to show $\frac{R_i(v)}{\|v\|} \rightarrow 0$ as $v \rightarrow 0$ for $i \in [m]$. (Then each point of $\frac{R(v)}{\|v\|} \rightarrow 0$, so $\frac{R(v)}{\|v\|} \rightarrow 0$ as $v \rightarrow 0$.) Given $\epsilon > 0$, choose $\delta > 0$ such that if $\|v\| < \delta$ then (a) $p+v \in U$ and b) $\left| \frac{\partial F_i}{\partial x_j}(p+d) - \frac{\partial F_i}{\partial x_j}(p) \right| < \epsilon/n$ for $j \in [n]$ (i is fixed). (Recall that using the C^1 assumption, $\frac{\partial F_i}{\partial x_j}$ is continuous at p for $j \in [n]$.)

We claim that if $\|v\| < \delta$ then $\frac{|R_i(v)|}{\|v\|} < \epsilon$, proving the theorem. To see this, let v be fixed with $\|v\| < \delta$ ($v = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}$). We have

$$R_i(v) = F_i(p+v) - F_i(p) - V_1 \frac{\partial F_i}{\partial x_1}(p) - \cdots - v_n \frac{\partial F_i}{\partial x_n}(p).$$

We can write

$$\begin{aligned} F_i(p+v) - F_i(p) &= F_i(p+V_1 e_1 + \dots + v_n e_n) - F_i(p) \\ &= F_i(p+v_1 e_1 + \dots + v_n e_n) - F_i(p+V_1 e_1 + \dots + v_{n-1} e_{n-1}) \\ &\quad + F_i(p+v_1 e_1 + \dots + v_{n-1} e_{n-1}) - F_i(p+v_1 e_1 + \dots + v_{n-2} e_{n-2}) \\ &\quad + F_i(p+v_1 e_1 + \dots + v_{n-2} e_{n-2}) - \dots + F_i(p+v_1 e_1) - F_i(p) \end{aligned}$$

It suffices to show

$$\frac{|F_i(p+v_1 e_1 + \dots + v_j e_j) - F_i(p+V_1 e_1 + \dots + v_{j-1} e_{j-1})|}{\|v\|} < \epsilon/n$$

for $2 \leq j \leq n$. We will use the one-variable MVT. First: if $v_j = 0$, then $p_j = p_{j-1}$ and the whole thing is 0. Assume note. Use a path σ_j starting at p_{j-1} and ending at p_j (these paths σ form the “staircase path” from p to $p+v$ shown in Figure 108, p. 285 (p. 295 of pdf) in Pugh [2015]). Indeed: let $\sigma_j(t) := p_{j-1} + tv_j e_j$ for $t \in [0, 1]$. $F_i \circ \sigma_j(t) = F_i(p_{j-1} + tv_j e_j)$; derivative quotient is

$$\begin{aligned} \lim_{t' \rightarrow t} \frac{F_i(p_{j-1} + t' v_j e_j) - F_i(p_{j-1} + tv_j e_j)}{t' - t} &= v_j \lim_{t' \rightarrow t} \frac{F_i(p_{j-1} + t' v_j e_j) - F_i(p_{j-1} + tv_j e_j)}{v_j t' - v_j t} \\ &= \lim_{t' \rightarrow t} \frac{F_i(p_{j-1} + t' v_j e_j) - F_i(p_{j-1} + tv_j e_j)}{t' - t} \\ &= \frac{\partial F_i}{\partial x_j}(p_{j-1} + te_j) \end{aligned}$$

since $t' \rightarrow t \iff v_j t' \rightarrow v_j t$. $\frac{\partial F_i}{\partial x_j}(p_{j-1} + te_j)$ exists for all $t \in [0, 1]$, so we get $F_i \circ \sigma_j$ is a differentiable function from $[0, 1] \rightarrow \mathbb{R}$ with derivative $v_j \frac{\partial F_i}{\partial x_j}(p_{j-1} + te_j)$ at the point $t \in [0, 1]$. Let $p_{ij} := p_{j-1} + te_j$.

By the Mean Value Theorem, there exists $t \in [0, 1]$ with $F_i(\sigma_j(1)) - F_i(\sigma_j(0)) = v_j \frac{\partial F_i}{\partial x_j}(p_{ij})$ ($\sigma_j(1) = p_j$, $\sigma_j(0) = p_{j-1}$). Thus,

$$\begin{aligned} \left| \frac{F_i(p_j) - F_i(p_{j-1}) - \frac{\partial F_i}{\partial x_j}(p)v_j}{\|v\|} \right| &= \frac{1}{\|v\|} \left| v_j \left(\frac{\partial F_i}{\partial x_j}(p_{ij}) - \frac{\partial F_i}{\partial x_j}(p) \right) \right| \\ &\leq \left| \frac{\partial F_i}{\partial x_j}(p_{ij}) - \frac{\partial F_i}{\partial x_j}(p) \right| \\ &< \frac{\epsilon}{n} \end{aligned}$$

where we used $|v_i|/\|v\| \leq 1$, and the last step follows since $\|p_{ij} - p\| < \delta$ (indeed: $p_{ij} - p = v_1 e_1 + \dots + v_{j-1} e_{j-1} + t v_j e_j$ for $t \in [0, 1]$, and $v = v_1 e_1 + \dots + v_n e_n$, so $\|p_{ij} - p\| \leq \|v\| < \delta$, finishing the proof.

□

Example 5.15. Define $F : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ by

$$F(x, y, z) := \begin{bmatrix} e^z \cos(y) \\ e^{-z} \sin(y) \\ x^2 + y^2 + z^3 \end{bmatrix}.$$

Is F differentiable? Yes, F is C^1 (even C^∞) by inspection of each component. In particular,

$$(DF)_{(x,y,z)} = \begin{bmatrix} 0 & -e^z \sin(y) & e^z \cos(y) \\ 0 & e^{-z} \cos(y) & -e^{-z} \sin(y) \\ 2x & 2y & 2z \end{bmatrix}.$$

Theorem 5.7.17 (Mean Value Theorem for functions from \mathbb{R}^n to \mathbb{R}). Let $U \subset \mathbb{R}^n$ be open. Let $F : U \rightarrow \mathbb{R}$ be differentiable. Let $p, q \in U$ such that $p + t(q - p) \in U$ for $t \in [0, 1]$. Then there exists $\theta \in [0, 1]$ with $F(q) - F(p) = (DF)_{p+\theta(q-p)}(q - p)$.

Proof. Apply the one-variable Mean Value Theorem to $F(p + t(q - p))$, a differentiable function from $[0, 1] \rightarrow \mathbb{R}$. The derivative at θ is $(DF)_{p+\theta(q-p)}(q - p)$. Then

$$F(\underbrace{p + 1(q - p)}_q) - F(\underbrace{p + 0(q - p)}_p) = ((DF)_{p+\theta(q-p)}(q - p))(1 - 0).$$

□

On the other hand, the case of vector-valued functions isn't so simple.

Example 5.16. Consider $F : \mathbb{R} \rightarrow \mathbb{R}^2$ defined by $F(t) = (\cos t, \sin t)$. Then observe that

$$\underbrace{F(2\pi) - F(0)}_0 = ?(DF)_t(2\pi - 0) \quad \text{for any } t?$$

But

$$\begin{bmatrix} -\sin t \\ \cos(t) \end{bmatrix} \neq 0$$

for any t .

What do we do in this case?

Theorem 5.7.18 (Mean value inequality; Theorem 5.11 in Pugh [2015], p. 298 of pdf, p. 288 of book). Let $U \subset \mathbb{R}^n$ be open. Let $F : U \rightarrow \mathbb{R}^m$ be differentiable. Let $p, q \in U$ such that the line segment $\{p + t(q - p) \mid t \in [0, 1]\} \subset U$. Then

$$\|F(q) - F(p)\| \leq \left(\sup_{t \in [0, 1]} \|(DF)_{p+t(q-p)}\|_{\text{op}} \right) \|q - p\|$$

(Note that this is upper-bounded by

$$\left(\sup_{x \in U} \|(DF)_x\|_{\text{op}} \right) \|q - p\|,$$

which is the version shown in Pugh [2015].)

Proof. If we can show that for some $M \in \mathbb{R}$ $\langle F(q) - F(p), u \rangle \leq M\|q - p\|$ for all unit vectors $u \in \mathbb{R}^m$, then we're done because we can take $u = (F(q) - F(p))/\|F(q) - F(p)\|$ and get the statement of the theorem. Let $v := q - p$ and let

$$g(t) := \langle F(p + tv), u \rangle = \sum_{i=1}^m u_i F_i(p + tv)$$

(if $u = (u_1, \dots, u_m)^\top$ and $F = (F_1, \dots, F_m)^\top$). Each F_i is differentiable, and $t \mapsto p + tv$ is differentiable, so $F_i(p + tv)$ is a differentiable function of t . Sums and scalar multiples of differentiable functions are differentiable by Proposition 5.7.15, so $g(t)$ is differentiable. In particular,

$$g'(t) = \sum_{i=1}^m u_i (DF_i)_{p+tv}(v) = \langle (DF)_{p+tv}(v), u \rangle.$$

(Note that this equation also results from the Leibniz rule, although we didn't prove the Leibniz rule.) By the one-dimensional Mean Value Theorem for g , there exists $\theta \in [0, 1]$ with

$$g'(\theta)(1 - 0) = g(1) - g(0) = \langle F(q), u \rangle - \langle F(p), u \rangle = \langle F(q) - F(p), u \rangle$$

Observe that

$$g'(\theta)(1 - 0) = \langle (DF)_{p+\theta v}(v), u \rangle \leq (\text{by Cauchy-Schwarz}) \underbrace{\|(DF)_{p+\theta v}(v)\|}_{\leq M} \underbrace{\|u\|}_{= \|q-p\|} \leq \underbrace{\|(DF)_{p+\theta v}\|_{\text{op}}}_{\leq M} \underbrace{\|v\|}_{= \|q-p\|}.$$

So we've shown $\langle F(q) - F(p), u \rangle \leq M\|q - p\|$ for all unit vectors $u \in \mathbb{R}^m$, proving the theorem. \square

Theorem 5.7.19 (C^1 Mean Value Theorem: may do later).

Corollary 5.7.19.1. If $U \subset \mathbb{R}^n$ is open and connected and $F : U \rightarrow \mathbb{R}^m$ is differentiable with $(DF)_x = 0$ for all $x \in U$, then F is constant.

Proof. Exercise, use topological fact: any two points in U can be connected by a differentiable path γ since U is connected. \square

Theorem 5.7.20 (Differentiation under the integral sign). Let $f : [a, b] \times (c, d) \rightarrow \mathbb{R}$ (or \mathbb{R}^m) be a continuous function. Assume $\frac{\partial f}{\partial y}(x, y)$ is also continuous. Let $F(y) = \int_a^b f(x, y) dx$. Then F is differentiable on (c, d) with $F'(y) = \int_a^b \frac{\partial f}{\partial y}(x, y) dx$; i.e., $\frac{\partial}{\partial y} \int_a^b f(x, y) dx = \int_a^b \frac{\partial f}{\partial y}(x, y) dx$.

Remark 15. Better theorems exist under Lebesgue theory.

Proof. In the book, uses C^1 Mean Value Theorem. We'll skip for now. \square

5.7.4 Implicit and Inverse Functions Theorems (Section 5.4 of Pugh [2015])

We will start with the Implicit Function Theorem and use it to deduce the Inverse Function Theorem. Here is the basic idea: say we have $n + m$ variables $x_1, \dots, x_n, y_1, \dots, y_m$, and we impose m nonlinear constraints: we look at points $(x, y) := (x_1, \dots, x_n, y_1, \dots, y_m)$ such that $F(x, y) = z$ where $F : \mathbb{R}^{n+m} \rightarrow \mathbb{R}^m$ is some function and $z \in \mathbb{R}^m$. (F has coordinates F_1, \dots, F_m ; $F(x, y) = z$ amounts to m scalar equations. So we have m constraints $F_i(x, y) = z_i$, $i \in [m]$.)

Example 5.17. Let $n = 1, m = 1, F(x, y) = x^2 + y^2, z = 1$. Then $(x, y) \in \mathbb{R}^2$ must lie on the unit circle.

Let $(x_0, y_0) \in F^{-1}(z)$ (the level set of F at level z). The main question for the Implicit Function Theorem is: locally near (x_0, y_0) , can we write $F^{-1}(z)$ as a graph of y as a function of x (or x as a function of y)?

In this case, if $(x_0, y_0) \neq (\pm 1, 0)$, then we can write the local part of the circle as a graph of y as a function of x , namely $y = \pm\sqrt{1 - x^2}$ (pick which one depending on sign of y_0). However if $(x_0, y_0) \in \{(1, 0), (-1, 0)\}$, we can't express y locally as a function of x , although we can express x as a function of y (although not near $(0, \pm 1)$). So we have four open subsets of the circle where $F^{-1}(z)$ can be written locally as a graph.

Definition 5.87. Let $f : A \rightarrow B$ be a function. The **graph** of f is the set S of all pairs $(a, b) \in A \times B$ such that $b = f(a)$.

Theorem 5.7.21 (Implicit Function Theorem (Dini 1876; Theorem 5.22 in Pugh [2015])). Let $U \subset \mathbb{R}^{m+n}$ be open. Let $F : U \rightarrow \mathbb{R}^m$ be a class of C^r functions for $r \geq 1$. Let $(x_0, y_0) \in U$ ($x_0 \in \mathbb{R}^n, y_0 \in \mathbb{R}^m$), let $z_0 \in \mathbb{R}^m$ with $F(x_0, y_0) = z_0$, and $(DF)_{(x_0, y_0)} \in \mathbb{R}^{m \times (n+m)}$ have the form $[A \ B]$ with $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{m \times m}$ with B invertible³. Then there exists $r, \tau > 0$ such that $B_\tau(x_0) \times B_r(y_0) \subset U$ such that there exists a unique function $g : B_\tau(x_0) \rightarrow B_r(y_0)$ with $F^{-1}(z_0) \cap (B_\tau(x_0) \times B_r(y_0)) = \text{graph}(g) = \{(x, g(x)) : x \in B_\tau(x_0)\}$ (see Definition 5.87). This function g is of class C^r .

(For notational ease, assume without loss of generality that (x_0, y_0) is the origin in \mathbb{R}^{n+m} and $z_0 = 0 \in \mathbb{R}^m$.)

We will prove some lemmas before proving this result.

Definition 5.88. A function g is **locally Lipschitz** at 0 if there exists L such that for $x \in B_\tau(0)$ small enough, we have $\|g(x) - g(0)\| \leq L\|x - 0\|$. (See also Theorem 5.6.64.)

Lemma 5.7.22. Let $U \subset \mathbb{R}^{m+n}$ be open. Let $F : U \rightarrow \mathbb{R}^m$ be a class of C^r functions for $r \geq 1$. Let $(\underbrace{0}_{\in \mathbb{R}^n}, \underbrace{0}_{\in \mathbb{R}^m}) \in U$, let $F^{-1}(\underbrace{0}_{\in \mathbb{R}^m}) = (\underbrace{0}_{\in \mathbb{R}^n}, \underbrace{0}_{\in \mathbb{R}^m})$, and $(DF)_{(0,0)} \in \mathbb{R}^{m \times (n+m)}$ have the form $[A \ B]$ with $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{m \times m}$ with $B = \left[\frac{\partial F_i(0,0)}{\partial y_j} \right]$ invertible (equivalently, the linear transformation represented by B is an isomorphism from \mathbb{R}^m to \mathbb{R}^m). Then there exists $r, \tau > 0$ such that $B_\tau(0) \times B_r(0) \subset U$ such that there exists a unique function $g : \underbrace{B_\tau(0)}_{\subset \mathbb{R}^n} \rightarrow \underbrace{B_r(0)}_{\subset \mathbb{R}^m}$ with $F^{-1}(0) \cap (B_\tau(0) \times B_r(0)) = \text{graph}(g) = \{(x, g(x)) : x \in B_\tau(0)\}$. This function g is locally Lipschitz at 0.

Proof. For any $(x, y) \in U$, let

$$\begin{aligned} R(x, y) &:= F(x, y) - F(0, 0) - [A \ B] \begin{bmatrix} x \\ y \end{bmatrix} \\ &= F(x, y) - F(0, 0) - Ax - By \\ \implies F(x, y) &= Ax + By + R(x, y), \end{aligned}$$

where $A := \left[\frac{\partial F_i(x_0, y_0)}{\partial x_j} \right]$ and the last expression is the Taylor expression for F so R is sublinear. Then for $(x, y) \in U$, we have

$$\begin{aligned} F(x, y) = 0 &\iff Ax + By + R(x, y) = 0 \\ &\iff By = -Ax - R(x, y) \\ &\iff y = -B^{-1}(Ax + R(x, y)). \end{aligned} \tag{5.30}$$

If R does not depend on y , then (5.30) is an explicit formula for $g(x)$. In general, we hope to show that R depends very weakly on y , so that we can switch it to the left side of (5.30), absorbing it in the y -term.

Choose $r > 0$ such that $\underbrace{B_r(0)}_{\subset \mathbb{R}^n} \times \underbrace{B_r(0)}_{\subset \mathbb{R}^m} \subset U$. Let $K_x : \underbrace{B_r(0)}_{\subset \mathbb{R}^m} \rightarrow \mathbb{R}^m$ be defined by $K_x(y) := -B^{-1}(Ax + R(x, y))$ (the right side of (5.30)) for a fixed $x \in B_r(0) \subset \mathbb{R}^n$.

³Note that any full rank matrix of size $m \times (m+n)$ can have this form, possibly after permuting columns.

In particular, we would like to find a fixed point of $K_x(y) := -B^{-1}(Ax + R(x, y))$, so we hope to show K_x contracts and that K_x maps a complete metric space onto itself (namely $\overline{B_r(0)}$) (so that we can apply the Banach Contraction Principle, Theorem 5.6.61). Note that $R(x, y)$ is a C^r function of (x, y) since F is. Also, $(DR)_{(0,0)} = 0$.

Let $\frac{\partial R}{\partial y}(x, y)$ be the “partial Jacobian” of R , using only the partial derivatives from y (so it has M columns—a function from U to $\mathbb{R}^{m \times m}$). Because R is at least C^1 , every entry of $\frac{\partial R}{\partial y}(x, y)$ is continuous. Then by Corollary 5.7.6.3, we have that $\frac{\partial R}{\partial y}(x, y)$ is continuous if we use the operator norm as the metric in $\mathbb{R}^{m \times m}$ (see the second part of Corollary 5.7.6.3 for the formal statement; written in shorthand notation as $\frac{\partial R}{\partial y}(x, y) : U \mapsto (\mathbb{R}^{m \times m}, \|\cdot\|_{\text{op}})$ is continuous). Therefore there exists $r > 0$ such that

$$(x, y) \in U, \|x\| \leq r, \|y\| \leq r \implies \left\| \frac{\partial R}{\partial y}(x, y) \right\| < \frac{1}{2\|B^{-1}\|_{\text{op}}}. \quad (5.31)$$

For notational ease, let $B_{(x,y)} := \begin{bmatrix} \frac{\partial F_i(x,y)}{\partial y_j} \end{bmatrix} = \frac{\partial F}{\partial y}(x, y)$ (i.e., $(DF)_{(x,y)} = [A_{(x,y)} \ B_{(x,y)}]$). Note that $\det(B_{(0,0)}) \neq 0$ since B is invertible at $(0, 0)$, and $\det : \mathbb{R}^{m \times m} \mapsto \mathbb{R}$ is a continuous function, so for sufficiently small r we have that $\det(B_{(x,y)}) \neq 0$ if $\|x\|, \|y\| \leq r$.

Note that for $\|x\|, \|y_1\|, \|y_2\| \leq r$ we have

$$\begin{aligned} \|K_x(y_1) - K_x(y_2)\| &= \| -B^{-1}(Ax + R(x, y_1)) - [-B^{-1}(Ax + R(x, y_2))] \| \\ &= \| -B^{-1}[R(x, y_1) - R(x, y_2)] \| \\ &\leq \|B^{-1}\|_{\text{op}} \|R(x, y_1) - R(x, y_2)\| \\ &\quad (\text{for some } t \in [0, 1] \text{ by the MVT}) \leq \|B^{-1}\|_{\text{op}} \left\| \frac{\partial R}{\partial x}(x, y_1 + t(y_2 - y_1)) \cdot (x - x) \right. \\ &\quad \left. + \frac{\partial R}{\partial y}(x, y_1 + t(y_2 - y_1)) \cdot (y_1 - y_2) \right\| \\ &\leq \|B^{-1}\|_{\text{op}} \left\| \frac{\partial R}{\partial y}(x, y_1 + t(y_2 - y_1)) \right\|_{\text{op}} \|y_1 - y_2\| \\ &\quad (\text{by (5.31)}) < \frac{1}{2} \|y_1 - y_2\|. \end{aligned} \quad (5.32)$$

Therefore $K_x(y)$ brings points closer together. We will also show that it maps $\overline{B_r(0)}$ into itself. We would like to show that for sufficiently small x , the function $x \mapsto K_x(0) = -B^{-1}(Ax + R(x, 0))$ makes y smaller. Since $x \mapsto K_x(0) = -B^{-1}(Ax + R(x, 0))$ is continuous in x , there exists $\tau > 0$ such that if $\|x\| \leq \tau$ then $\|K_x(0)\| \leq r/2$. Then if $\|x\| \leq \tau$ and $\|y\| \leq r$, we have

$$\begin{aligned} \|K_x(y)\| &= \|K_x(y) - K_x(0) + K_x(0)\| \\ &\leq \|K_x(y) - K_x(0)\| + \|K_x(0)\| \\ &\quad (\text{by (5.32)}) \leq \frac{1}{2} \underbrace{\|y - 0\|}_{\leq r} + \underbrace{\|K_x(0)\|}_{\leq r/2} \\ &\leq r. \end{aligned} \quad (5.33)$$

We have established that if $\|x\| \leq \tau$ then K_x maps $\overline{B_r(0)} \subset \mathbb{R}^m$ into $\overline{B_r(0)} \subset \mathbb{R}^m$ and is a contraction. Since $\overline{B_r(0)} \subset \mathbb{R}^m$ is compact and therefore complete, we can now apply the Banach Contraction Principle, Theorem 5.6.61, to conclude that K_x has a unique fixed point in $\overline{B_r(0)}$. Call this point $g(x)$. By construction, $F^{-1}(0) \cap (\overline{B_\tau(0)} \times \overline{B_r(0)})$ is graph(g) (see Definition 5.87).

Next, we will find a local Lipschitz constant for g . Note that $g(0)$, the unique fixed point of $K_0(y)$, is 0, since $(0, 0)$ is the unique point in $(\overline{B_\tau(0)} \times \overline{B_r(0)}) \cap F^{-1}(0)$ with x coordinate 0. Also note that since R is sublinear, for small enough x we have $\|R(x, 0)\| \leq \|A\|_{\text{op}}\|x\|$. Since $g(x) = K_x(g(x))$, for small enough x we have

$$\begin{aligned}
\|g(x)\| &= \|K_x(g(x)) - K_x(g(0)) + K_x(g(0))\| \\
&\leq \|K_x(g(x)) - K_x(g(0))\| + \|K_x(g(0))\| \\
(\text{by (5.32) and def of } K_x(0)) \quad &\leq \frac{1}{2}\|g(x) - g(0)\| + \|B^{-1}(Ax + R(x, 0))\| \\
&\leq \frac{1}{2}\|g(x)\| + \|B^{-1}\|_{\text{op}}\|Ax + R(x, 0)\| \\
(\text{using the fact about small } x) \quad &\leq \frac{1}{2}\|g(x)\| + \|B^{-1}\|_{\text{op}} \cdot 2\|A\|_{\text{op}}\|x\| \\
\iff \quad &\|g(x)\| - \frac{1}{2}\|g(x)\| \leq 2\|B^{-1}\|_{\text{op}}\|A\|_{\text{op}}\|x\| \\
\iff \quad &\|g(x)\| \leq 4\|B^{-1}\|_{\text{op}}\|A\|_{\text{op}}\|x\|,
\end{aligned}$$

so for small enough x , $4\|B^{-1}\|_{\text{op}}\|A\|_{\text{op}}$ is a local Lipschitz constant for g . Let $L := \|B^{-1}\|_{\text{op}}\|A\|_{\text{op}}$ so we can write the constant as $4L$. This implies continuity of g at 0, so there exists $\tau > 0$ (smaller than before) such that $g(B_\tau(0)) \subset B_r(0)$ (open balls). By construction, we have $F^{-1}(0) \cap (B_\tau(0) \times B_r(0)) = \text{graph}(g)$, because for $(x, y) \in B_\tau(0) \times B_r(0)$ we have $F(x, y) = 0 \iff y = g(x)$. Since two functions with the same graph are equal, g is the unique function with this property.

□

Lemma 5.7.23. In Lemma 5.7.22, the unique function g is differentiable at zero, with derivative $-B^{-1}A$ where $(DF)_{(0,0)} = [A \ B] \in \mathbb{R}^{m \times (n+m)}$ ($A \in \mathbb{R}^{m \times n}$, $B \in \mathbb{R}^{m \times m}$).

Proof. Recall: for $x \in B_\tau(0)$, $g(x)$ is the unique fixed point of $y \mapsto -B^{-1}(Ax + R(x, y)) = k_x(y)$ in $\overline{B_r(0)}$ (the closure of $B_r(0)$). We know $g(x) \in B_r(0)$. We then have $g(x) = K_x(g(x)) = -B^{-1}(Ax + R(x, g(x)))$. Thus,

$$\begin{aligned}
\|g(x) - \underbrace{g(0)}_{=0} - (-B^{-1}A)x\| &= \| -B^{-1}[Ax + R(x, g(x))] + B^{-1}Ax \| \\
&= \|B^{-1}[R(x, g(x))]\| \\
&\leq \|B^{-1}\|_{\text{op}}\|R(x, g(x))\|.
\end{aligned}$$

Thus, for $x \neq 0$

$$\frac{\|g(x) - g(0) - (-B^{-1}A)x\|}{\|x\|} \leq \|B^{-1}\|_{\text{op}} \frac{\|R(x, g(x))\|}{\|(x, g(x))\|} \cdot \frac{\|(x, g(x))\|}{\|x\|}.$$

Observe that $\frac{\|R(x, g(x))\|}{\|(x, g(x))\|} \rightarrow 0$ as $x \rightarrow 0$ because $(x, g(x)) \rightarrow 0$ as $x \rightarrow 0$ since g is continuous at 0; also using the fact that F is C^r , and therefore C^1 , and therefore differentiable. Further, $\frac{\|(x, g(x))\|}{\|x\|}$ is bounded, because we have

$$\|(x, g(x))\| \leq C(\|x\| + \|g(x)\|) \leq C(\|x\| + 4L\|x\|)$$

for small enough x , where C is some constant that is independent of x and L is the constant from the previous lemma (the first inequality follows from comparability of norms). Therefore

$$\frac{\|(x, g(x))\|}{\|x\|} \leq C(1 + 4L)$$

for small enough x . So,

$$\frac{\|g(x) - g(0) - (-B^{-1}A)x\|}{\|x\|} \rightarrow \|B^{-1}\|_{\text{op}} \cdot 0 \cdot C(1 + 4L) = 0$$

as $x \rightarrow 0$.

□

Lemma 5.7.24 (appears in book, but weakly justified (“origin is as good as any other point”)). In Lemma 5.7.22, the unique function g is differentiable on $B_\tau(0)$ with derivative $-B_{(x, g(x))}^{-1}A_{(x, g(x))}$, where $(DF)_{(x, y)} = [A_{x,y} \ B_{x,y}] \in \mathbb{R}^{m \times (n+m)}$, where $A_{x,y} \in \mathbb{R}^{m \times n}$ and $B_{x,y} \in \mathbb{R}^{m \times m}$.

Proof. Let $x_0 \in B_\tau(0)$ and let $y_0 = g(x_0)$. Let $\tilde{F}(x, y) := F(x + x_0, y + y_0)$. Note that $\tilde{F}(x, y)$ is C^r since F is C^r , and it is defined in $B_{\tau'}(0) \times B_{r'}(0)$ as long as $\tau' < \tau - \|x_0\|$, $r' < r - \|y_0\|$. We can apply the previous results to $\tilde{F}: B_{\tau'}(0) \times B_{r'}(0) \rightarrow \mathbb{R}^m$: there exists $\tau'' \leq \tau'$ and a function $\tilde{g} = B_{\tau''}(0) \mapsto B_{r'}(0)$ (really $B_{\tau''}(0)$ for some $r'' \leq r'$, but still maps onto the larger set $B_{r'}(0)$) such that $\tilde{F}(x, \tilde{g}(x)) = 0$ for all $x \in B_{\tau''}(0)$, and \tilde{g} is differentiable at 0, with derivative

$$-\left(\frac{d\tilde{F}}{dy}(0, 0)\right)^{-1} \left(\frac{d\tilde{F}}{dx}(0, 0)\right).$$

We claim that $g(x) = \tilde{g}(x - x_0) + y_0$. To see why, note that $g(x)$ is the unique fixed point on $B_r(0)$ with $F(x, g(x)) = 0$. But we also have $F(x, \tilde{g}(x - x_0) + y_0) = \tilde{F}(x - x_0,)$. . . Thus, $g(x) = \tilde{g}(x - x_0) + y_0$.

So, by the Chain Rule (Theorem 5.7.14), g is differentiable at x_0 with

$$(Dg)_{x_0} + (Dy)_0 = -\left(\frac{\partial \tilde{F}}{\partial}\right)$$

□

Lemma 5.7.25. The unique function g from Lemma 5.7.22 is of class C^1 .

Proof. We need to show each entry of $(Dg)_x$ is a continuous function of $x \in B_\tau(0)$. We have $(Dg)_x = -B_{x,g(x)}^{-1} A_{x,g(x)}$. The entries of $A_{x,y}$ and $B_{x,y}$ are partial derivatives of components of F , which is C^r and therefore C^1 , so they're continuous functions of $(x, y) \in U$. g is differentiable on $B_\tau(0)$, so it is continuous on $B_\tau(0)$. Thus, the entries of $A_{x,g(x)}$ and $B_{x,g(x)}$ are continuous functions of $x \in B_\tau(0)$.

We can deal with $B_{x,g(x)}^{-1}$ using Cramer's rule:

$$B_{x,g(x)}^{-1} = \frac{1}{\det(B_{x,g(x)})} \cdot (\text{cofactor}(B_{x,g(x)}))^\top$$

where the cofactor matrix $\text{cofactor}(B_{x,g(x)})$ has each entry in row i and column j corresponding to the cofactor as when computing row/column expansions. Since $\det(B_{x,g(x)})$ is a polynomial function in the entries of $B_{x,g(x)}$, it is continuous in x . $\text{cofactor}(B_{x,g(x)})$ is also built out of determinants, which are polynomial functions of the entries, so it is continuous in x . So the entries of $B_{x,g(x)}^{-1}$ are continuous in x , which means the entries of $-B_{x,g(x)}^{-1} A_{x,g(x)}$ are continuous in x , so g is C^1 .

□

Lemma 5.7.26. The function g from Lemma 5.7.22 is C^r (assuming F is C^r).

Proof. We will induct on $r \geq 1$. We have the base case from the previous lemma. For a general r , suppose that g is class C^{r-1} . Note that it's enough to show that the entries of $(Dg)_x$ are C^{r-1} function of x , because the r th order partial derivatives are the $(r-1)$ th order partials of the first order partials. We have $(Dg)_x = -B_{x,g(x)}^{-1} A_{x,g(x)}$. The entries of $A_{x,y}$ and $B_{x,y}$ are C^{r-1} since F is C^r . Also, g is C^{r-1} by above. Therefore the entries of $A_{x,g(x)}$ and $B_{x,g(x)}$ are C^{r-1} functions of x . By the same Cramer's rule reasoning as above, the result follows.

□

Proof of Implicit Function Theorem (Theorem 5.7.21). Follows from Lemmas 5.7.22 and 5.7.26.

□

for all $(x_0, y_0) \in F^{-1}(z_0)$,

i.e. $F^{-1}(z_0)$ is a “nonsingular level set.” For any point $(x_0, y_0) \in F^{-1}(z_0)$, we have a homeomorphism $(x, g(x)) : B_\tau(x_0) \mapsto F^{-1}(z_0) \cap V$

an open subset of $F^{-1}(z_0)$ containing (x_0, y_0) .

$x \mapsto (x, g(x)) \in F^{-1}(z_0) \cap V$. The map (id, g) is a homeomorphism since the projection $(x, y) \mapsto x$ restricted to $F^{-1}(z_0) \cap V$ is the inverse of (id, g) and is continuous.

The implicit function theorem tells us that F being C^∞ implies g is C^∞ implies (id, g)

Thus, these homemorphisms form a smooth atlas on $F^{-1}(z_0)$, giving $F^{-1}(z_0)$ the structure of a smooth manifold. (Note: the definition of a smooth manifold is only reasonable because the above is true—see Definition 5.77.)

The following is a useful result for manifolds (see Theorem 5.7.10) that is closely related to the Implicit Function Theorem.

Theorem 5.7.27 (Theorem 2-13 in Spivak [1971], p. 56 of pdf, p.443 of book). Let $f : \mathbb{R}^n \rightarrow \mathbb{R}^p$ be C^r for $r \geq 1$ in an open set containing x_0 , where $p \leq n$. If $f(x_0) = 0$ and $(Df)_{x_0} \in \mathbb{R}^{p \times n}$ has rank p , then there is an open set $A \subset \mathbb{R}^n$ containing x_0 and a differentiable function $h : A \rightarrow \mathbb{R}^n$ with differentiable inverse such that

$$f \circ h(x^1, \dots, x^n) = (x^{n-p+1}, \dots, x^n).$$

Now we will discuss the Inverse Function Theorem.

Definition 5.89. If $U \subset \mathbb{R}^n$ is open and $V \subset \mathbb{R}^m$ is open, then $F : U \rightarrow V$ is a C^r **diffeomorphism** (recall Definition 5.67) (for $r \geq 1$) if (1) F is C^r , (2) F is invertible, and (3) F^{-1} is C^r .

Note that this is only possible when $n = m$, because $\text{Id}_a = F^{-1} \cdot F$. Take the total derivative of both sides and apply the chain rule (Theorem 5.7.14):

$$= \text{Id}_{\mathbb{R}^n} = (DF)_{f(p)} \circ (DF)_p \quad \forall p \in U.$$

Similarly, $\text{Id}_{\mathbb{R}^m} = (DF)_p \circ (DF^{-1})_{F(p)}$ for all $p \in U$. This implies $(DF)_p$ is invertible for all p (inverse $(DF^{-1})_{F(p)}$, so $(DF)_p$ is square $n = m$).

So we see that F is “nonlinearly invertible” then $(DF)_p$ is “linearly invertible” for all p . Like in the Implicit Function Theorem, we want to go backwards locally.

Theorem 5.7.28 (Inverse Function Theorem). Let $U_0 \subset \mathbb{R}^n$ be open, let $f : U_0 \rightarrow \mathbb{R}^m$ be a C^r function for $r \geq 1$, $p \in U_0$. If $(DF)_p$ is invertible, then $n = m$ and there exists an open subset $U \subset U_0$, $V \subset \mathbb{R}^m$ containing p and $f(p)$ respectively such that f is a C^r diffeomorphism from U to V (i.e. f is a locally C^r diffeomorphism at p).

Proof. We will apply the Implicit Function Theorem. Define $F : U_0 \times \mathbb{R}^n \rightarrow \mathbb{R}^n$ by $F(x, y) = f(x) - y$ for $x \in U_0, y \in \mathbb{R}^n$. Let $q = f(p) \in \mathbb{R}^m$. We have $F(p, q) = q - q = 0$, so $(p, q) \in F^{-1}(0)$. The Jacobian matrix of F at (p, q) is

$$\begin{aligned} (DF)_{(p,q)} &= \begin{bmatrix} \frac{\partial F}{\partial x}(p, q) & \frac{\partial F}{\partial y}(p, q) \end{bmatrix} \\ &= [(Df)_p \quad -\mathbf{I}_n], \end{aligned}$$

where \mathbf{I}_n is the $n \times n$ identity matrix. Recall that $(Df)_p \in \mathbb{R}^{n \times n}$ is invertible by assumption, and of course $-\mathbf{I}_n$ is invertible. Then by the Implicit Function Theorem, there exist open neighborhoods $U_p \subset U_0$ and $V_q \subset \mathbb{R}^n$ of p and q and a unique function $h : V_q \rightarrow U_p$ such that

$$F^{-1}(0) \cap (U_p, V_q) = \text{graph}(h) = \{(y, h(y)) : y \in V_q\}$$

and h is C^r . By construction, we have $F(h(y), y) = 0$ for all $y \in V_q$. Therefore $0 = f(h(y)) - y \iff f(h(y)) = y$, for all $y \in V_q$, so $f \circ h = \text{id}_{V_q}$.

Now we run the same argument in reverse. Define : $G : U_q \times V_p \rightarrow \mathbb{R}^n$ by $G(x, y) = x - h(y)$. Of course, $h(q) = p$ because $(p, q) = F^{-1}(0) \cap (U_p \times V_q) = \text{graph}(h)$, so we have $G(p, q) = p - h(q) = 0$. Then the Jacobian matrix of G at (p, q) is

$$(DG)_{(p,q)} = [\mathbf{I}_m \quad -(Dh)_q].$$

Note that since $p = h(q)$,

$$f \circ h = \text{id}_{V_q} \implies (Df)_{h(q)} \circ (Dh)_q = \text{Id}_{\mathbb{R}^n} \iff (Df)_p \circ (Dh)_q = \text{Id}_{\mathbb{R}^n},$$

where we applied the Chain Rule. So $(Dh)_q$ is invertible. Therefore by the Implicit Function Theorem, there exists an open neighborhood $U'_p \times V'_q \subset U_p \times V_q$ of (p, q) and a unique function $g : U'_p \rightarrow V'_q$ such that

$$G^{-1}(0) \cap (U'_p \times V'_q) = \text{graph}(g) = \{(x, g(x)) : x \in U'_p\}.$$

Again, we have $G(x, g(x)) = 0$ for all $x \in U'_p$, so $h(g(x)) = x$. Therefore $0 = x - h(g(x)) \iff h \circ g = \text{id}_{U'_p}$.

Note that for points $x \in U'_p$, $g(x) = f(x)$ (i.e., g is the restriction of f to U'_p). To see why, note that for $x \in U'_p$, we have $g(x) \in V'_q \subset V_q$. Since $f \circ h = \text{id}_{V_q}$, we have $g(x) = f(h(g(x))) = f(x)$ (where we used that $h \circ g = \text{id}_{U'_p}$).

Finally, let $U := U'_p \subset \mathbb{R}^n$ and let $V := h^{-1}(U) \subset V'_q \subset \mathbb{R}^n$. Observe that f maps U into V since for any $x \in U'_p$, $f(x) = g(x) = h^{-1}(x)$. Also, h maps V into U because for any $v \in h^{-1}(U)$ we have $h(v) = x$ for some $x \in U$. Therefore f is a C^r diffeomorphism from U to V .

□

5.7.5 Tensors (Homeworks 11 - 14 in Math 425b, Chapter 16 of Lang [2005])

Definition 5.90 (Direct sums; definition from Homework 11, 425b). Let S be any set. Assume that for every $s \in S$ we have a vector space V_s over \mathbb{R} . Define

$$\bigoplus_{s \in S} V_s,$$

the **direct sum** of the vector spaces V_s to be the set of functions $f : S \rightarrow \bigcup_{s' \in S} V_{s'}$ such that $f(s) \in V_s$ for all $s \in S$, and such that $f(s) = 0$ for all but finitely many $s \in S$. (note that the union is a “disjoint union;” the vector spaces $V_{s'}$ are not given as subsets of a larger set *a priori*.)

For $f, g \in \bigoplus_{s \in S} V_s$, define $f + g$ by $(f + g)(s) = f(s) + g(s)$. For $c \in \mathbb{R}$, define cf by $(cf)(s) = c(f(s))$.

Definition 5.91 (Direct sums; definition from Section 1.7 of Lang [2005], p. 36 of textbook (p. 51 of pdf)). Let $\{V_s\}_{s \in S}$ be a family of abelian groups (recall Definition 15.1). Define

$$\bigoplus_{s \in S} V_s$$

to be the subset of the direct product $\prod V_s$ consisting of all families $(x_s)_{s \in S}$ with $x_s \in V_s$ such that $x_s = 0$ for all but a finite number of indices s .

For $v_i \in V_{s_i}$, $i \in [n]$, $\bigoplus_{s \in S} V_s$ is the vector space of all linear combinations $c_1 v_1 + \dots + c_n v_n$ (where $s_1 \neq \dots \neq s_n$). The linear combinations are finite sums since $f(s) = 0$ for all but finitely many $s \in S$.

Definition 5.92. Let S be any set. Assume that for every $s \in S$ we have a vector space V_s over \mathbb{R} . Define the **free vector space** on S to be

$$F(S) := \bigoplus_{s \in S} \mathbb{R};$$

the set of functions $f : S \rightarrow \mathbb{R}$ such that $f(s) \in \mathbb{R}$ for all $s \in S$, and such that $f(s) = 0$ for all but finitely many $s \in S$. That is, it is a direct sum where we take each vector space V_s to be \mathbb{R} . An **inclusion map** is defined to be the function $i : S \rightarrow F(S)$ sending $s \in S$ to the function $i(s) : S \rightarrow \mathbb{R}$ defined by

$$i(s)(s') = \begin{cases} 1, & s' = s, \\ 0, & \text{otherwise.} \end{cases}$$

$F(S)$ is the vector space of all linear combinations of elements of S . The elements of S form a basis for $F(S)$ by definition. Equivalently, $F(S)$ is a way to construct a vector space having a given set S as a basis.

Proposition 5.7.29 (Homework 11 problem 4). (a) $\bigoplus_{s \in S} V_s$ is closed under the above addition and scalar multiplication properties.

- (b) Suppose S has two elements; let $S = \{s, t\}$. Then $V_s \oplus V_t$ is isomorphic to the vector space of ordered pairs (v, w) where $v \in V_s$, $w \in V_t$ (i.e., the Cartesian product $V_s \times V_t$), and addition and scalar multiplication are given by $(v, w) + (v', w') = (v + v', w + w')$ and $c(v, w) = (cv, cw)$.
- (c) Let V be any vector space and let $g : S \rightarrow V$ be any function. Then there exists a unique linear transformation $T : F(S) \rightarrow V$ such that $g = T \circ i$. Equivalently, the following diagram commutes:

$$\begin{array}{ccc} F(S) & \xrightarrow{T} & V \\ i \uparrow & \nearrow g & \\ S & & \end{array}$$

Proof. (a) We will check that sums and scalar multiples preserve the quality of vanishing at all but finitely many s .

For sums, observe that for $f, g \in \bigoplus_{s \in S} V_s$ we have $(f + g)(s) = f(s) + g(s)$. By definition $f(s)$ and $g(s)$ both equal 0 for all but finitely many $s \in S$; therefore the same is true for $f(s) + g(s)$ and $(f + g)(s)$.

For scalar multiplication, since for $f \in \bigoplus_{s \in S} V_s$ we have $(cf)(s) = cf(s)$ and $f(s)$ equals 0 for all but finitely many $s \in S$, the same is true for $cf(s)$ for any scalar c and therefore for $(cf)(s)$.

- (b) For $f \in V_s \oplus V_t$, let $f(s) = v$ and $f(t) = w$ and define the linear map to $V_s \times V_t$ by $f \mapsto (f(s), f(t)) = (v, w)$. Observe that this map is linear because $cf \mapsto ((cf)(s), (cf)(t)) = (c(f(s)), c(f(t))) = c(f(s), f(t)) = c(v, w)$ and for g satisfying $g(s) = v'$ and $g(t) = w'$ we have $f + g \mapsto ((f(s), f(t)) + (g(s), g(t))) = (v, w) + (v', w') = (v + v', w + w')$. Note also that all of these mappings are bijective.
- (c) For $f \in F(S)$, define $T(f)$ to be the element of V given by $\sum_{s \in S} f(s)g(s)$ (recall that $f(s) \in \mathbb{R}$ and $g(s) \in V$). Observe that since $f(s) = 0$ for all but finitely many s , $\sum_{s \in S} f(s)g(s)$ is finite. We see that T is linear since

$$T(cf) = \sum_{s \in S} (cf)(s)g(s) = \sum_{s \in S} cf(s)g(s) = c \sum_{s \in S} f(s)g(s) = cT(f)$$

and for another $f' \in F(S)$

$$T(f + f') = \sum_{s \in S} (f + f')(s)g(s) = \sum_{s \in S} [f(s) + f'(s)]g(s) = \sum_{s \in S} f(s)g(s) + \sum_{s \in S} f'(s)g(s) = T(f) + T(f').$$

Then the diagram commutes because for any $s \in S$

$$(T \circ i)(s) = \sum_{s' \in S} i(s)(s')g(s) = \sum_{s' \in S, s' \neq s} 0 \cdot g(s) + 1 \cdot g(s) = g(s).$$

Now we will show uniqueness. Suppose T and T' are two linear maps such that the diagram commutes, so we have $T(i(s)) = g(s) = T'(i(s))$. Let $f \in F(S)$. Observe that

$$f(s) = \sum_{s' \in S} i(s)(s')f(s) = \sum_{s' \in S, f(s') \neq 0} i(s)(s')f(s),$$

which is a finite sum by the requirement that $f(s) = 0$ for all but finitely many $s \in S$. Now (using the linearity of T and T')

$$\begin{aligned} T(f(s)) &= T \left(\sum_{s' \in S, f(s') \neq 0} i(s)(s')f(s) \right) \\ &= \sum_{s' \in S, f(s') \neq 0} T(i(s)(s')f(s)) \\ &= \sum_{s' \in S, f(s') \neq 0} f(s)T(i(s)(s')) \\ &= \sum_{s' \in S, f(s') \neq 0} f(s)g(s) \\ &= \sum_{s' \in S, f(s') \neq 0} f(s)T'(i(s)(s')) \\ &= \sum_{s' \in S, f(s') \neq 0} T'(i(s)(s')f(s)) \\ &= T' \left(\sum_{s' \in S, f(s') \neq 0} i(s)(s')f(s) \right) \\ &= T'(f(s)). \end{aligned}$$

Therefore $T(f) = T'(f)$, showing uniqueness.

□

Part (c) of Proposition 5.7.29 shows that any function g from a set S to a vector space V can be extended linearly in a unique way to a linear transformation defined on $F(S) := \bigoplus_{s \in S} \mathbb{R}$, the vector space of formal linear combinations of elements of S .

Definition 5.93 (Quotient Vector Space). Let V be a vector space and let W be a subspace of V . Define an equivalence relation on V by stating that $v_1 \sim v_2$ if $v_1 - v_2 \in W$. Let V/W denote the set of equivalence classes under this relation (see Definition 5.12). The space V/W is called a **quotient vector space**.

If $v \in V$, let $[v]$ denote its equivalence class. For two elements α, β of V/W , define $\alpha + \beta$ to be $[v_1 + v_2]$ where $\alpha = [v_1]$ and $\beta = [v_2]$. Also, for $c \in \mathbb{R}$, define $c\alpha$ to be $[cv]$ where $\alpha = [v]$.

Proposition 5.7.30. The quotient vector space V/W satisfies the vector space axioms under the above definitions of addition and scalar multiplication. Also, if V has dimension n and W has dimension m , then V/W has dimension $n - m$.

Proposition 5.7.31 (Math 425b Homework 12 problem). $\alpha + \beta$ and $c\alpha$ as defined in Definition 5.93 are well-defined (i.e., independent of the choice of v_1 and v_2 representing α and β).

Proof. Let $v_1, v'_1, v_2, v'_2 \in V$ and let $c \in \mathbb{R}$. Suppose that $v_1 \sim v'_1$ and $v_2 \sim v'_2$; that is, $v_1 - v'_1 \in W$ and $v_2 - v'_2 \in W$. Since W is a subspace of V (and therefore a vector space), it is closed under addition, so $v_1 - v'_1 + v_2 - v'_2 \in W$. It also satisfies associativity of addition, so $(v_1 + v_2) - (v'_1 + v'_2) \in W$. Therefore $(v_1 + v_2) \sim (v'_1 + v'_2)$.

Next, observe that for any $w \in W$, we have $cw \in W$. Therefore $c(v_1 - v'_1) \in W$, which means $cv_1 - cv'_1 \in W$ (and $cv_1 \sim cv'_1$) by distributivity of scalar multiplication with respect to vector addition. Since these statements would be true for any $\tilde{v}_1, \tilde{v}'_1 \in \alpha$, $\tilde{v}_2, \tilde{v}'_2 \in \beta$, or $c \in \mathbb{R}$, this shows that $\alpha + \beta$ and $c\alpha$ are well-defined.

□

Proposition 5.7.32 (Math 425b Homework 12 problem). Let V be a vector space and let W be a subspace of V . Let Z be another vector space and let $f : V \rightarrow Z$ be a linear map such that $f(w) = 0$ for all $w \in W$. Let $p : V \rightarrow V/W$ denote the linear map sending $v \rightarrow [v]$. Then there exists a unique linear map $g : V/W \rightarrow Z$ such that $f = g \circ p$.

Proof. First we will show existence. Define $g([v]) := f(v)$. To see that this is well-defined, consider another $v' \in V$ such that $v - v' \in W$; that is, $v \sim v'$. Observe that $f(v) - f(v') = f(v - v') = 0$ (by assumption that $f(w) = 0$ for all $w \in W$), and since $[v] = [v']$, $g([v]) - g([v']) = g([v]) - g([v]) = 0$. Now consider an arbitrary $v' \in V$ such that $v - v' \notin W$. Note that $f(v + v') = f(v) + f(v')$, and from Exercise 1, we have $[v] + [v'] = [v + v']$, so $g([v + v']) = g([v]) + g([v'])$. Finally, for any $c \in \mathbb{R}$ we have $f(cv) = cf(v)$, and since from Exercise 1 we have $[cv] = c[v]$, we have $g([cv]) = g(c[v]) = cg([v])$ by linearity of g .

Now we will show uniqueness. Note that any $\alpha \in V/W$ is equal to $[v] = p(v)$ for some $v \in V$. Consider two maps g and \tilde{g} that make the diagram commute; that is, $g([v']) = f(v')$ and $\tilde{g}([v']) = f(v')$ for any $v' \in V$. Then for any $\alpha \in V/W$, we have $g(\alpha) = g([v]) = f(v) = \tilde{g}([v]) = \tilde{g}(\alpha)$.

□

Let V and W be vector spaces over \mathbb{R} . Consider the free vector space $F(V \times W)$ (see Definition 5.92). It is the set of functions $f : V \times W \rightarrow \mathbb{R}^2$. $F(V \times W)$ is the vector space of all linear combinations of elements of $V \times W$. The elements of $V \times W$ form a basis for $F(V \times W)$ by definition.

Given an element $(v, w) \in V \times W$, we view (v, w) as an element of $F(V \times W)$ via the inclusion map $i : V \times W \rightarrow F(V \times W)$. Any element of $F(V \times W)$ is a finite linear combination of such elements (v, w) .

Note that $F(V \times W)$ disregards the vector space structures on V and W , and just treats $V \times W$ as the set of ordered pairs (v, w) where $v \in V$ and $w \in W$. For example, if $v \neq 0 \in V$, then $(v, 0)$ and $(2v, 0)$ are linearly independent in $F(V \times W)$, even though v and $2v$ are not linearly independent in V .

Definition 5.94 (Tensor product). Let S be the subset of $F(V \times W)$ consisting of the following elements:

- $(v, w) + (v', w) - (v + v', w)$ for all $v, v' \in V$ and $w \in W$.
- $(v, w) + (v', w) - (v, w + w')$ for all $v \in V$ and $w, w' \in W$.
- $c(v, w) - (cv, w)$ for all $v \in V$, $w \in W$, and $c \in \mathbb{R}$.
- $c(v, w) - (v, cw)$ for all $v \in V$, $w \in W$, and $c \in \mathbb{R}$.

Define

$$V \otimes W := \frac{F(V \times W)}{\text{span}(S)}.$$

That is, for $f_1 : V \times W \rightarrow \mathbb{R}^2 \in F(V \times W)$ and $f_2 : V \times W \rightarrow \mathbb{R}^2 \in F(V \times W)$, for an equivalence relation defined as $f_1 \sim f_2$ if $f_1 - f_2 \in \text{span}(S)$, $V \otimes W$ is the quotient vector space consisting of the set of equivalence classes under this relation. In particular, if we view (v, w) as an element of $F(V \times W)$ via the inclusion map $i : V \times W \rightarrow F(V \times W)$ (recall Definition 5.92), we can characterize the equivalence relation by $(v_1, w_1) \sim (v_2, w_2)$ if $(v_1, w_1) - (v_2, w_2) \in \text{span}(S)$. Then $V \otimes W$ is the quotient vector space consisting of the set of equivalence classes under this relation.

Given an element (v, w) of $F(V \times W)$, its class $[(v, w)]$ in the quotient space $V \otimes W$ will be denoted by $v \otimes w$. Note that not every element of $V \otimes W$ can be written as $v \otimes w$ for some $v \in V$ and $w \in W$ (since not every function $f : V \times W \rightarrow \mathbb{R}^2$ can be expressed as the inclusion map of a single $(v, w) \in V \times W$). Elements like $v \otimes w$ are called **pure tensors**. In general, an element of $V \otimes W$ is a linear combination of pure tensors.

See also Section 4.1 of Spivak [1971] (p. 88 of pdf, p. 75 of book).

Example 5.18. The tensor product of zero copies of \mathbb{R}^n is defined to be \mathbb{R} . (This is relevant later in the dimensions of spaces of alternating multilinear functionals.)

Definition 5.95 (Bilinear maps; also in Section 5.2 of Pugh [2015], p. 297 of pdf, p. 287 of book). Let V, W, Z be vector spaces over \mathbb{R} . A map $f : V \times W \rightarrow Z$ is said to be **bilinear** if

- $f(v + cv', w) = f(v, w) + cf(v', w)$ for all $v, v' \in V$, $w \in W$, and $c \in \mathbb{R}$.
- $f(v, w + cw') = f(v, w) + cf(v, w')$ for all $v \in V$, $w, w' \in W$, and $c \in \mathbb{R}$.

For a generalization of this concept, see multilinear maps (Definition 5.100).

Proposition 5.7.33 (Math 425b Homework 12 Problem 3). The map $\pi : V \times W \rightarrow V \otimes W$ sending (v, w) to $v \otimes w$ is bilinear.

Proof. We will show that $\pi(v + cv', w) = \pi(v, w) + c\pi(v', w)$. Let $c \in \mathbb{R}$, $v, v' \in V$, $w \in W$. Note that since $cv' \in V$, we have

$$\begin{aligned} (v + cv', w) - (v, w) - c(v', w) &= (v + cv', w) - (v, w) - c(v', w) - (cv', w) + (cv', w) \\ &= -\underbrace{(v, w) + (cv', w)}_{\in S} - \underbrace{(v + cv', w) - c(v', w) - (cv', w)}_{\in S}. \end{aligned}$$

Therefore $(v + cv', w) - (v, w) - c(v', w)$ is in the span of S . That means it is in the equivalence class $[0]$, so $0 = \pi((v + cv', w) - (v, w) - c(v', w)) = \pi(v + cv', w) - \pi(v, w) - c\pi(v', w) \iff \pi(v + cv', w) = \pi(v, w) + c\pi(v', w)$. The other equation is similar.

□

Tensor products have a “universal property:” roughly speaking, a bilinear map from $V \times W$ to Z is the same as a linear map from $V \otimes W$ to Z .

Proposition 5.7.34 (Math 425b Homework 12 Problem 4). Let V, W, Z be vector spaces over \mathbb{R} . Let $f : V \times W \rightarrow Z$ be a bilinear map. Let $\pi : V \times W \rightarrow V \otimes W$ be defined by $\pi(v, w) := v \otimes w$. Then there exists a unique linear map $g : V \otimes W \rightarrow Z$ such that $f = g \circ \pi$.

Using this universal property, we have $V \otimes W \cong W \otimes V$ for any vector spaces V and W . Other standard properties also follow, like $(V \otimes W) \otimes Z \cong V \otimes (W \otimes Z)$. One can also deduce relations like $V \otimes (W_1 \oplus W_2) \cong (V \otimes W_1) \oplus (V \otimes W_2)$; i.e., tensor products distributed over direct sums (up to isomorphism). The vector space \mathbb{R} acts as a “unit” for the tensor product operations: for any V , we have $V \otimes \mathbb{R} \cong V$.

It follows that if V has dimension n , so $V \cong \mathbb{R}^n \cong \underbrace{\mathbb{R} \oplus \dots \oplus \mathbb{R}}_{n \text{ terms}}$, and W has dimension m , then

$$V \otimes W \cong (\underbrace{\mathbb{R} \oplus \dots \oplus \mathbb{R}}_{n \text{ terms}}) \otimes (\underbrace{\mathbb{R} \oplus \dots \oplus \mathbb{R}}_{m \text{ terms}}),$$

which expands out to nm copies of \mathbb{R} . Thus, $V \otimes W$ has dimension nm . Concretely, if $\{e_i\}$ forms a basis for V and $\{f_j\}$ forms a basis for W , then $\{e_i \otimes f_j\}$ forms a basis for $V \otimes W$ (see also Theorem 4-1 in [Spivak \[1971\]](#), p. 89 of pdf, p. 76 of book).

Mathematicians often define a vector to be an element of a vector space. Correspondingly, one can define a tensor as follows.

Definition 5.96 (Tensors). A **tensor of rank k** is an element of the vector space $V_1 \otimes \dots \otimes V_k$ for some $k \geq 1$ (i.e., a tensor is a vector in the space $V_1 \otimes \dots \otimes V_k$).

Along with tensor products, another essential operation on vector spaces is the notion of the dual space (recall Definition 5.73).

Definition 5.97 (Basis vectors for dual space; 425b Homework 13). If $\{e_i\}$ is a basis for V , define the linear functionals $e_i^* : V \rightarrow \mathbb{R} \in V^*$ by

$$e_i^*(e_j) := \delta_{i,j} = \begin{cases} 1, & i = j, \\ 0, & i \neq j, \end{cases}$$

where V^* is the dual space of V (recall Definition 5.73). (Following the up/down notation mentioned below, one often writes e^i instead of e_i^* .) In Proposition 5.7.35, we show that these vectors are a basis for V^* .

Remark 16. In some contexts it is common to present tensors as being higher-dimensional analogues of vectors and matrices. If a vector is a one-dimensional array of numbers and a matrix is a two-dimensional array, a tensor of rank k should be a k -dimensional array. One can connect this view with tensors with Definition 5.96 as follows: given bases $\{e_{i,j}\}_j$ for each V_i , one gets a basis for $V_1 \otimes \cdots \otimes V_k$ by taking tensor products of basis vectors as defined in Definition 5.94 (see Theorem 4-1 in Spivak [1971], p. 89 of pdf, p. 76 of book). An arbitrary element of $V_1 \otimes \cdots \otimes V_k$ can be expanded as a linear combination of basis vectors; one has a unique coefficient c_{j_1, \dots, j_k} on each basis vector $e_{1,j_1} \otimes \cdots \otimes e_{k,j_k}$. One organizes these coefficients into an array of the appropriate dimensionality:

- For $k = 1$, the coefficients c_j form a one-dimensional array (vector),
- For $k = 2$, the coefficients c_{j_1, j_2} form a two-dimensional array (matrix),
- For $k = 3$, the coefficients c_{j_1, j_2, j_3} form a three-dimensional array (rank-3 tensor), etc.

Now that we have dual vector spaces, we often prefer to view a matrix as representing a linear transformation between vector spaces $T : V \rightarrow W$ and then interpret this transformation as an element of $W \otimes V^*$ (still a rank-2 tensor, but involving a dual on one of the factors).

Definition 5.98 (Covariant tensors). Let V_1, \dots, V_k be fixed vector spaces. An element x of $V_1 \otimes \cdots \otimes V_k$ is called a **covariant tensor**. We write its coefficient on a basis vector $e_{1,j_1} \otimes \cdots \otimes e_{k,j_k}$ as x^{j_1, \dots, j_k} (i.e., we use “up indices”).

Definition 5.99 (Contravariant tensors). Let V_1, \dots, V_k be fixed vector spaces. An element x of $V_1^* \otimes \cdots \otimes V_k^*$ is called a **contravariant tensor**. We write its coefficient on the dual basis vector $e^{1,j_1} \otimes \cdots \otimes e^{k,j_k}$ as x_{j_1, \dots, j_k} (i.e., we use “down indices”).

In between these extreme cases, we have various types of **mixed tensors** whose coefficients have both up and down indices.

Remark 17. The up/down notation is part of “Einstein notation,” developed by Albert Einstein for use in relativity. Another part of the convention is to write only the coefficients and note the basis vectors they’re multiplied by when specifying a tensor. For example,

- A vector $x = \sum_i x^i e_i$ in V gets written as x^i ,
- A dual vector $x = \sum_i x_i e^i \in V^*$ gets written as x_i ,
- A rank-2 covariant tensor $\sum_{i,j} x^{i,j} e_i \otimes f_j$ in $V \otimes W$ gets written as $x^{i,j}$ where $\{f_j\}$ is the given basis for W ,

- A rank-2 mixed tensor $\sum_{i,j} x_j^i e_i \otimes f^j$ in $W \otimes V^*$ gets written as x_j^i ,
- A rank-2 contravariant tensor $\sum_{i,j} x_{i,j} e^i \otimes f^j$ in $V^* \otimes W^*$ gets written as $x_{i,j}$.

Often one will consider certain sums of these coefficients; the convention is that one sums over repeated indices (one must be up and the other down) and omits the sum symbol. For example, let a_j^i represent an element of $W \otimes V^*$ (corresponding to a linear transformation T from V to W ; in fact, in the assumed bases, a_j^i is the usual matrix entry of T in row i and column j). Mathematically, we would write a_j^i as $\sum_{i,j} a_j^i e_i \otimes f^j$. Let v^i represent a vector in V ; mathematically, we would write v^i as $\sum_i v^i e_i$. Applying the transformation $a - j^i$ to the vector v^i gives $\sum_{i,j} a_j^i v^j f_i$ (a vector in W), and the convention is to write this vector as simply $a_j^i v^j$ (the sum over j is implicit, as is the sum over i with the “invisible” basis vectors f_i). You know this quantity represents a vector since it has one ‘free’ index i and this index is up.

Proposition 5.7.35 (Math 425b Homework 13 Problem 1; similar to Theorem 4-1 in Spivak [1971], p. 89 of pdf, p. 76 of book, also Proposition 11.1 in Lee [2012]). Let V be a finite-dimensional vector space with basis $\{e_i\}$. Define the linear functionals $e_i^* \in V^*$ by

$$e_i^*(e_j) := \delta_{i,j} = \begin{cases} 1, & i = j, \\ 0, & i \neq j \end{cases}$$

as in Definition 5.97. The linear functionals $\{e_i^*\}$ form a basis for V^* . Further, V^* has the same dimension as V .

Also, if V and W are finite-dimensional with bases $\{e_i\}$ and $\{f_j\}$, then the elements $e_i \otimes f_j$ form a basis for $V \otimes W$; in particular, the dimension of $V \otimes W$ is the product of the dimensions of V and W .

Proof. To show that $\{e_i^*\}$ forms a basis for V^* , we will show that the $\{e_i^*\}$ are linearly independent and that they span V^* . Let $n := |\{e_i^*\}| = \dim(V)$. Since $\{e_i\}$ is a basis for V , for every $v \in V$ there exists a unique $(c_1, \dots, c_n) \in \mathbb{R}^n$ such that $v = \sum_{i=1}^n c_i e_i$. Suppose for some $(c_1^*, \dots, c_n^*) \in \mathbb{R}^n$ we have $\sum_{j=1}^n c_j^* e_j^*(v) = 0$ for all $v \in V$. Then for any $v \in V$

$$0 = \sum_{j=1}^n c_j^* e_j^*(v) = \sum_{j=1}^n c_j^* e_j^* \left(\sum_{i=1}^n c_i e_i \right) = \sum_{j=1}^n c_j^* \sum_{i=1}^n c_i e_j^*(e_i) = \sum_{i=1}^n c_i^* c_i e_i^*(e_i) = \sum_{i=1}^n c_i^* c_i$$

(where the third equality follows from the fact that e_j^* is linear and the fourth equality follows from $e_j^*(e_i) = 0$ for all $j \neq i$), which only holds for all $v \in V$ if $(c_1^*, \dots, c_n^*) = (0, \dots, 0)$. Therefore the $\{e_i^*\}$ are linearly independent. Next we will show that the $\{e_i^*\}$ span V^* . Let $\phi : V \rightarrow \mathbb{R}$ be an arbitrary linear functional. We will show in particular that $\phi(v) = \sum_{j=1}^n c_j^* e_j^*(v)$ for some $(c_1^*, \dots, c_n^*) \in \mathbb{R}^n$ for any $v = \sum_{i=1}^n c_i e_i \in V$. We have

$$\begin{aligned} \phi(v) &= \phi \left(\sum_{j=1}^n c_j e_j \right) = \sum_{j=1}^n c_j \phi(e_j) = \sum_{j=1}^n \phi(e_j) c_j e_j^*(e_j) = \sum_{j=1}^n \phi(e_j) \sum_{i=1}^n c_i e_j^*(e_i) = \sum_{j=1}^n \phi(e_j) e_j^* \left(\sum_{i=1}^n c_i e_i \right) \\ &= \sum_{j=1}^n \phi(e_j) \cdot e_j^*(v) = \sum_{j=1}^n c_j^* \cdot e_j^*(v) \end{aligned}$$

where $(c_1^*, \dots, c_n^*) = (\phi(e_1), \dots, \phi(e_n))$.

Next we will show that if V and W are finite-dimensional with bases $\{e_i\}$ and $\{f_j\}$, then the elements $e_i \otimes f_j$ form a basis for $V \otimes W$; in particular, the dimension of $V \otimes W$ is the product of dimensions of V and W . We can write V as $\mathbb{R} \oplus \dots \oplus \mathbb{R}$, with n copies of \mathbb{R} . Similarly, we can write W as $\mathbb{R} \oplus \dots \oplus \mathbb{R}$, with $\dim(W)$ copies of \mathbb{R} .

We will use the fact that if V_1, V_2, W are vector spaces and $T_1 : V_1 \rightarrow W, T_2, V_2 \rightarrow W$ are linear maps, there exists a unique linear map $T : (V_1 \oplus V_2) \rightarrow W$ such that $T((v_1, 0)) = T_1(v_1)$ and $T((0, v_2)) = T_2(v_2)$.

□

Proposition 5.7.36 (Math 425b Homework 13 Problem 2). Let V and W be vector spaces over \mathbb{R} . Define a map $T : V^* \times W^* \rightarrow (V \otimes W)^*$ that sends $(\phi, \psi) \in V^* \times W^*$ to $(v \otimes w) \mapsto \phi(v)\psi(w) \in (V \otimes W)^*$ (recall Definition 5.73 for the definition of the dual spaces V^* and W^*). This map T is well-defined and bilinear (recall Definition 5.95), and thus induces a linear map $V^* \otimes W^* \rightarrow (V \otimes W)^*$. Further, if V and W are finite-dimensional, this induced map is an isomorphism.

Remark 18. The left side $(V \otimes W)^*$ of the isomorphism in Proposition 5.7.36 can be identified as the space of bilinear maps from $V \times W$ to \mathbb{R} . Proposition 5.7.36 shows that this space of bilinear maps can also be described as $V^* \otimes W^*$, when V and W are finite-dimensional. More generally, if all spaces V_i are finite-dimensional we can identify $V_1^* \otimes \dots \otimes V_n^*$ with the space of multilinear maps from $V_1 \times \dots \times V_n$ into \mathbb{R} .

Even more generally, if all spaces V_i and W_j are finite-dimensional, we can identify $V_1^* \otimes \dots \otimes V_n^* \otimes W_1 \otimes \dots \otimes W_m$ with the space of multilinear maps from $V_1 \times \dots \times V_n$ to $W_1 \otimes \dots \otimes W_m$. A special case is when $n = m = 1$; we can identify $V^* \otimes W$ (or $W \otimes V$) with the space of linear maps from V to W .

5.7.6 Differential Forms (Section 5.8 of Pugh [2015]; Chapter 10 of Rudin [1976])

Definition 5.100 (Multilinear functionals; Section 5.9 of Pugh [2015]). A map $\beta : \underbrace{\mathbb{R}^n \times \dots \times \mathbb{R}^n}_{k \text{ times}} \rightarrow \mathbb{R}$ which is linear in each vector variable separately is a **k -multilinear functional**. That is, for $i \in [k]$ we have

$$\beta(x_1, \dots, x_i + cx'_i, \dots, x_k) = \beta(x_1, \dots, x_i, \dots, x_k) + c\beta(x_1, \dots, x'_i, \dots, x_k).$$

A bilinear map is a 2-multilinear map; see Definition 5.95.

Definition 5.101 (Symmetric groups and permutations). We call the set of all permutations of $[k]$ (of size $k!$) the **symmetric group on k** and denote it by S_k . We refer to its elements as $\sigma \in S_k$. The number of transpositions modulo 2 in any factorization of σ into transpositions is well-defined and denoted by $\text{sgn}(\sigma)$.

See Section 15.3.

Definition 5.102 (Alternating multilinear functionals; Section 5.9 of Pugh [2015], Section 4.1 of Spivak [1971] (p. 91 of pdf, p. 78 of book)). A k -multilinear functional $\beta : \mathbb{R}^n \times \dots \times \mathbb{R}^n \rightarrow \mathbb{R}$ is **alternating** if for each permutation $\sigma \in S_k$ we have

$$\beta(v_1, \dots, v_k) = \text{sgn}(\sigma)\beta(v_{\sigma(1)}, \dots, v_{\sigma(k)}).$$

The set of alternating k -linear forms is a vector space. In particular, we denote by $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ the vector space of multilinear maps $\alpha : \underbrace{\mathbb{R}^n \times \cdots \times \mathbb{R}^n}_{k \text{ times}} \rightarrow \mathbb{R}$ with

$$\alpha(v_1, \dots, v_{i+1}, v_i, \dots, v_k) = -\alpha(v_1, \dots, v_i, v_{i+1}, \dots, v_k)$$

for $1 \leq i \leq k$. (In [Spivak \[1971\]](#), this space is denoted by $\Lambda^k(V)$.)

Example 5.19. The set of 1-multilinear functionals is the set of linear functionals from $\mathbb{R}^n \rightarrow \mathbb{R}$.

Example 5.20. The set of 2-multilinear functionals is the set of bilinear functionals from $\mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ satisfying

$$\beta(v, w) = -\beta(w, v)$$

for all $v, w \in \mathbb{R}^n$.

Example 5.21. The set of 0-multilinear functionals is \mathbb{R} .

Definition 5.103 (Differential k -forms; from Math 425B Homeworks 13 and 14). A differential k -form on $U \subset \mathbb{R}^n$ is a function $\alpha : U \rightarrow \text{Alt}_k(\mathbb{R}^n, \mathbb{R})$.

From Remark 18, $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ can be viewed as a subspace of $\underbrace{(\mathbb{R}^n)^* \otimes \cdots \otimes (\mathbb{R}^n)^*}_{k \text{ times}}$ (recall Definition 5.94 for the definition of the tensor product \otimes , and recall Definition 5.73 for the definition of the dual space $(\mathbb{R}^n)^*$). So a differential k -form is a particular type of rank- k contravariant tensor field on U (namely one that satisfies the “alternating property” at each point). While this perspective is not strictly speaking necessary to define differential k -forms, it is very useful when defining wedge products (see Definition 5.107 and 5.117).

C^r regularity for differential k -forms can be defined by looking at their coordinates in any basis for the finite-dimensional vector space $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ (independently of the choice of basis). That is, we say that α is of class C^r if its coordinates in the standard basis of $(\mathbb{R}^n)^* \otimes \cdots \otimes (\mathbb{R}^n)^*$ (equivalently, any basis for this vector space) are C^r functions from U to \mathbb{R} .

That is, a differential k -form on U is a function α from U to $\underbrace{(\mathbb{R}^n)^* \otimes \cdots \otimes (\mathbb{R}^n)^*}_{k \text{ times}}$ which is alternating in the following sense: viewing $\alpha(p) \in (\mathbb{R}^n)^* \otimes \cdots \otimes (\mathbb{R}^n)^*$ as an element of $(\mathbb{R}^n \otimes \cdots \otimes \mathbb{R}^n)^*$ **by the below Propositions [which?]** (i.e., a multilinear map from $\mathbb{R}^n \times \cdots \times \mathbb{R}^n$ to \mathbb{R}), the map $\alpha(p)$ is alternating in the sense that for all k -tuples (v_1, \dots, v_k) of vectors in \mathbb{R}^n , we have

$$\alpha(p)(v_1 \otimes \cdots \otimes v_i \otimes v_{i+1} \otimes \cdots \otimes v_k) = -\alpha(p)(v_1 \otimes \cdots \otimes v_{i+1} \otimes v_i \otimes \cdots \otimes v_k)$$

for any i with $1 \leq i \leq k-1$.

Example 5.22.)

Let $U \subset \mathbb{R}^n$ be open. Since $\text{Alt}_0(\mathbb{R}^n, \mathbb{R}) = \mathbb{R}$ (see Example 5.21), a **differential 0-form** on U is a function $f : U \rightarrow \mathbb{R}$.

Example 5.23. Let $U \subset \mathbb{R}^n$ be open. A **differential 1-form** on U is a function $\alpha : U \rightarrow (\mathbb{R}^n)^*$. Given any basis $\{\phi_1, \dots, \phi_n\}$ for $(\mathbb{R}^n)^*$, we can write $\alpha(p) = a_1(p)\phi_1 + \dots + a_n(p)\phi_n$, where a_1, \dots, a_n are functions from U to \mathbb{R} . We say that α is of class C^r ($1 \leq r \leq \infty$) if all the functions a_i are of class C^r . Since changes of basis on \mathbb{R}^n are C^∞ (even linear) functions, this notion is independent of the choice of basis $\{\phi_1, \dots, \phi_n\}$.

Since $\text{Alt}_1(\mathbb{R}^n, \mathbb{R})$ is the set of linear functionals from $\mathbb{R}^n \rightarrow \mathbb{R}$ (see Example 5.19), we can also say that a differential 1-form α , evaluated at a point $p \in U$, gives a linear functional $\alpha(p)$ from \mathbb{R}^n to \mathbb{R} .

Also, any 1-form α on $[a, b]$ is $f(t)dt$ for some function f .

Given a basis for \mathbb{R}^n (in particular, the standard basis), one can identify differential 1-forms on U with **vector fields** on U (see Definition 5.83); i.e., functions from U to \mathbb{R}^n (rather than $(\mathbb{R}^n)^*$) (see Remark 19).

Definition 5.104 (Differential 1-forms; from Pugh [2015] Section 5.8, p. 337 of pdf, p. 327 of book). A **differential 1-form** is a function that sends paths to real numbers and which can be expressed as a path integral (for example, $f dx + g dy$ is a 1-form).

Example 5.24 (Example from Pugh [2015] Section 5.8, p. 337 of pdf, p. 327 of book). Consider a path integral as its defined in calculus:

$$\int_C (f dx + g dy) = \int_0^1 f(x(t), y(t)) \frac{dx(t)}{dt} dt + \int_0^1 g(x(t), y(t)) \frac{dy(t)}{dt} dt, \quad (5.34)$$

where f and g are smooth real-valued functions of (x, y) and C is a smooth path parameterized by $(x(t), y(t))$ as t varies on $[0, 1]$. Taking the dual approach of differential forms, we will think of the integral as a number that depends on the path C . What property of C does the differential 1-form $f dx + g dy$ measure?

Consider the case $f(x, y) = 1$ and $g(x, y) = 0$. Then the path integral (5.34) is

$$\int_C dx = \int_0^1 \frac{dx(t)}{dt} dt = x(1) - x(0),$$

the “net x-variation” of the path C . In functional notation, we can write $dx : C \mapsto x(1) - x(0)$, so dx assigns to each path C its net x -variation. Similarly, dy assigns to each path its net y -variation.

For a general $f dx$, the function f “weights” x -variation. If the path C passes through a region in which f is large, its x -variation is magnified accordingly, and the integral $\int_C f dx$ reflects the net f -weighted x -variation of C . Similarly, $g dy$ assigns a path to its net g -weighted variation, and the 1-form $f dx + g dy$ assigns to C the sum of the two variations. See Figure 5.7.

Example 5.25. Note that $\text{Alt}_2(\mathbb{R}^n, \mathbb{R})$ is the set of bilinear functionals from $\beta : \mathbb{R}^2 \rightarrow \mathbb{R}$ satisfying $\beta(v, w) = -\beta(w, v)$ for all $(v, w) \in \mathbb{R}^2$ (see Example 5.20). Therefore a differential 2-form α , evaluated at a point $p \in U$, gives a bilinear map $\alpha(p)$ from $\mathbb{R}^n \times \mathbb{R}^n$ to \mathbb{R} such that $\alpha(p)(v, w) = -\alpha(p)(w, v)$ for all $v, w \in \mathbb{R}^n$.

There are four fundamental operations on differential forms that we need to understand.

1. **Exterior derivative:** if α is a k -form (say C^∞), then we have a $(k+1)$ -form $d\alpha$. This operation will generalize the gradient (Remark 19), curl, and divergence operations (Proposition 5.7.44). See

Figure 121 suggests why $\int_C y \, dx$ is positive and $\int_{C'} y \, dx$ is negative: The weight factor is positive on C and negative on C' . On the other hand, if the weight factor is the constant c then both integrals are $c(q - p)$.

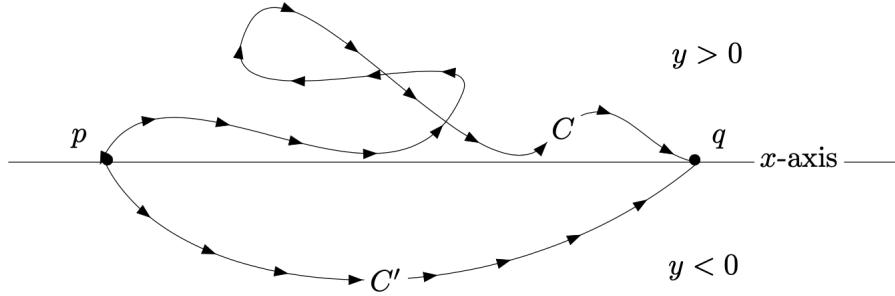


Figure 121 C and C' are paths from p to q where p and q lie on the x -axis. The integrals $\int_C y \, dx$ and $\int_{C'} y \, dx$ express the net y -weighted x -variation along C and C' .

Figure 5.7: Figure 121 from Pugh [2015], illustrating 1-forms.

Definition 5.105 for the exterior derivative of a 0-form (also called a differential) and Definition 5.108 for the exterior derivative of a k -form.

2. **Wedge product:** if α is a k -form and β is an ℓ -form, then we have a $(k + \ell)$ -form $\alpha \wedge \beta$ (this operation will generalize the cross product of vectors in \mathbb{R}^3). See Definition 5.107 and Definition 5.117.
3. **Pullback:** if α is a k -form on U and $F : V \rightarrow U$ is smooth where $V \subset \mathbb{R}^m$ is open (for some m), then we have a k -form $F^*(\alpha)$ on V . (See also Definition 5.106 below for the definition of pullbacks of 1-forms and Definition 5.120 for the general definition.)
4. **Integration:** if α is a k -form on a k -dimensional cube $[0, 1]^k \subset \mathbb{R}^k$ (it's okay that this isn't an open set although α should at least be right-continuous), we have a real number $\int_{[0,1]^k} \alpha$. (We can also integrate on more general rectangular sets than just $[0, 1]^k$.) Combined with pullbacks, this operation will let us generalize line integrals and surface integrals. (See also Example 5.24.)

Example 5.26. Integration of zero-forms on \mathbb{R}^0 is just evaluation at the unique point $0 \in \mathbb{R}^0$.

Also, any 1-form α on $[a, b]$ is $f(t)dt$ for some function f , and if f is smooth or just Riemann integrable, we can just define $\int_{[a,b]} \alpha := \int_a^b f(t)dt$ as usual.

Now we will consider less trivial operations than just 0-forms and 1-forms. We will start by studying the exterior derivative df of a zero-form f (also known as the differential of f), closely related to the gradient of f .

Definition 5.105 (Exterior derivative of a 0-form (differential)). Let $U \subset \mathbb{R}^n$ be open and let $f : U \rightarrow \mathbb{R}$ be a smooth function (0-form). Define a differential 1-form df by the equation

$$df(p) = (Df)_p.$$

(In other words, df is just the Jacobian Df (see Theorem 5.7.16), which at a point p gives a linear map from \mathbb{R}^n to \mathbb{R} .) Basically the transpose of the gradient. See also Definition 5.108 for the exterior derivative of a k -form.

Proposition 5.7.37 (Math 425b Homework 13 Problem 3). Let $\{e_1, \dots, e_n\}$ be the standard basis vectors of \mathbb{R}^n and let $\{e_1^*, \dots, e_n^*\}$ be their dual basis vectors (see Definition 5.97). Let f be as above; prove that

$$df = \frac{\partial f}{\partial x^1} e_1^* + \dots + \frac{\partial f}{\partial x^n} e_n^*.$$

(we use “up indices” x^i rather than “down indices” x_i to match the physics conventions; a physicist may write df as $\frac{\partial f}{\partial x^i}$ or even as $\partial_i f$, which is a 1-form since the i index is down, because up indices in a denominator are down. See Remark 17.)

Proof. It is enough to show that $df(p)(e_i) = \frac{\partial f}{\partial x^i}(p)$ for each i and each $p \in U$. Since for each $p \in U$ we have

$$(DF)_p = \begin{bmatrix} \frac{\partial F_1}{\partial x_1}(p) & \cdots & \frac{\partial F_1}{\partial x_n}(p) \\ \vdots & \ddots & \vdots \\ \frac{\partial F_m}{\partial x_1}(p) & \cdots & \frac{\partial F_m}{\partial x_n}(p) \end{bmatrix},$$

it holds that

$$(DF)_p e_i = \begin{bmatrix} \frac{\partial F_1}{\partial x_1}(p) & \cdots & \frac{\partial F_1}{\partial x_n}(p) \\ \vdots & \ddots & \vdots \\ \frac{\partial F_m}{\partial x_1}(p) & \cdots & \frac{\partial F_m}{\partial x_n}(p) \end{bmatrix} \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} = \sum_{j=1}^n \frac{\partial F_i}{\partial x_j}(p) = \frac{\partial f}{\partial x^i}(p)$$

for each i . Therefore $df(p)(e_i) = \frac{\partial f}{\partial x^i}(p)$ for each i and each $p \in U$. □

Remark 19 (From 425b Homework 13 Problem 4; Theorem 4-7 in Spivak [1971] (p. 102 of pdf, p. 89 of book)). Given a basis for \mathbb{R}^n (in particular, the standard basis), one can identify differential 1-forms on U with **vector fields** on U (see Definition 5.83); i.e., functions from U to \mathbb{R}^n (rather than $(\mathbb{R}^n)^*$). The vector field associated to the 1-form df is the **gradient** of f , denoted ∇f :

$$\nabla f = \frac{\partial f}{\partial x^1} e_1 + \dots + \frac{\partial f}{\partial x^n} e_n.$$

In general, df is a bit more natural of an object than ∇f , since it doesn’t require any choice of basis to define.

One can also identify 1-forms and vector fields by picking an inner product for \mathbb{R}^n , rather than a basis. On a general smooth manifold M (see Definition 5.77), the 1-form df for a function $f : M \rightarrow \mathbb{R}$ is always defined, but the gradient ∇f requires a choice of “Riemannian metric” on M (inner product on each tangent space; see Definition 5.81). In Einstein notation (see Remark 17), one sometimes writes $\partial^i f$ for the

gradient of f , as opposed to the 1-form $\partial_i f$. The Riemannian metric itself can be viewed as a function on M with values in $(\mathbb{R}^n)^* \otimes (\mathbb{R}^n)^*$ (recall Definition 5.94 for the definition of the tensor product \otimes), since an inner product on \mathbb{R}^n is a bilinear map from $\mathbb{R}^n \times \mathbb{R}^n$ to \mathbb{R} . Thus, as mentioned in a remark towards the end of Homework 12 (not in these notes yet), the metric is determined locally by functions g_{ij} on M for $1 \leq i, j \leq \dim(M)$. The gradient of f is determined uniquely by the formula $\partial_i f = g_{ij} \partial^j f$ (note the implicit sum over j); for the usual metric on \mathbb{R}^n , $g_{ij} = \delta_{ij}$.

Proposition 5.7.38 (Homework 13 Problem 4). Recall that for $1 \leq i \leq n$, we have a coordinate projection function $x^i : U \rightarrow \mathbb{R}$ (sending a point in U to its i th coordinate), and thus a 1-form dx^i . For all $p \in U$, we have $dx^i(p) = e_i^*$, where $\{e_i\}$ is the standard basis of \mathbb{R}^n .

It follows that if $f : U \rightarrow \mathbb{R}$ is a smooth function as above, then we can write

$$df = \frac{\partial f}{\partial x^1} dx^1 + \dots + \frac{\partial f}{\partial x^n} dx^n,$$

a natural-looking formula.

Proof. By Proposition 5.7.37 we have that for all $p \in U$,

$$dx^i(p) = \sum_{j=1}^n \frac{\partial x^i}{\partial x^j} e_j^* = \frac{\partial x^i}{\partial x^i} e_i^* = e_i^*$$

where $\{e_i\}$ is the standard basis of \mathbb{R}^n . □

Definition 5.106 (Pullbacks of 1-forms). Let $V \subset \mathbb{R}^m$ be open and let α be a differential 1-form on V (a function from V to $(\mathbb{R}^m)^*$). Let $U \subset \mathbb{R}^n$ be open and let $F : U \rightarrow V$ be a smooth function. The **pullback** $F^*(\alpha)$ is the differential 1-form on U (that is, a function from U to $(\mathbb{R}^n)^*$, so a function from U to the space of functionals with domain \mathbb{R}^n) defined at a point $p \in U$ by

$$(F^*(\alpha))_p(v) := \alpha_{F(p)}((DF)_p(v))$$

for $v \in \mathbb{R}^n$. (Note that $(DF)_p(v) \in \mathbb{R}^m$, so it makes sense to evaluate $\alpha_{F(p)}$ on the vector $(DF)_p(v)$.) See also Definition 5.120 for the general definition of pullbacks.

Example 5.27. The pullback of a zero-form f by a function F is just defined to be $f \circ F$.

The idea is that to pull back a differential 1-form by F , you push forward the corresponding “input vector” v by DF ; the same idea is used to define pullbacks of k -forms (see Definition 5.120).

Proposition 5.7.39 (Math 425b Homework 13 Problem 5). (a) If $f : V \rightarrow \mathbb{R}$ is a smooth function and $F : U \rightarrow V$ is smooth, then

$$F * (df) = d(f \circ F) = d(F^*(f)).$$

(That is, pullbacks commute with exterior derivatives acting on zero-forms.)

(b) If $\alpha = f_1\alpha_1 + \dots + f_N\alpha_N$, then

$$F^*(\alpha) = (f_1 \circ F)F^*(\alpha_1) + \dots + (f_N \circ F)F^*(\alpha_N).$$

(c) If $\alpha = f_1dx^1 + \dots + f_mdx^m$ and $\mathbf{r} : [a, b] \rightarrow V$ is a smooth pair with components r_1, \dots, r_m , then

$$\mathbf{r}^*(\alpha) = f_1(\mathbf{r}(t))r'_1(t)dt + \dots + f_m(\mathbf{r}(t))r'_m(t)dt.$$

Start of Homework 14: Now we will begin working with k -forms with $k > 1$. An important goal will be understanding the standard identifications

- 0-forms on \mathbb{R}^3 correspond to functions on \mathbb{R}^3 (see Example 5.22);
- 1-forms on \mathbb{R}^3 correspond to vector fields (see Definition 5.83) on \mathbb{R}^3 (see Example 5.23);
- 2-forms on \mathbb{R}^3 correspond to vector fields on \mathbb{R}^3 ; and
- 3-forms on \mathbb{R}^3 correspond to functions on \mathbb{R}^3 .

All k -forms on \mathbb{R}^3 are zero if $k > 3$.

Remark 20. Implicitly, these identifications use the standard inner product/Riemannian metric on \mathbb{R}^3 , as with the identification between df and ∇f discussed in Remark 19.

Note that when working only with functions and vector fields, it may not be immediately clear whether a vector field \mathbf{F} came from a 1-form or a 2-form (or a legitimate vector field); similarly, a given function f might represent a 3-form instead of a 0-form.

Given these identifications, we will see that

- The gradient operator ∇ taking functions to vector fields (see Definition 5.83) becomes identified with the exterior derivative d taking 0-forms to 1-forms (see Remark 19).
- The curl operation curl (or $\nabla \times$), taking vector fields to vector fields, becomes identified with the exterior derivative d taking 1-forms to 2-forms (Proposition 5.7.44).
- The divergence operator div (or $\nabla \cdot$), taking vector fields to functions, becomes identified with the exterior derivative d taking 2-forms to 3-forms (Proposition 5.7.44).

The relations $\text{curl} \circ \nabla = 0$ and $\text{div} \circ \text{curl} = 0$ are special cases of the fundamental property $d^2 = 0$ for the exterior derivative.

Recall Definition 5.103. The identifications we want will become more plausible once we know that

- $\dim \text{Alt}_0(\mathbb{R}^3, \mathbb{R}) = 1$, (recall Example 5.18)
- $\dim \text{Alt}_1(\mathbb{R}^3, \mathbb{R}) = 3$ (recall Proposition 5.7.37),
- $\dim \text{Alt}_2(\mathbb{R}^3, \mathbb{R}) = 3$ (Proposition 5.7.40), and

- $\dim \text{Alt}_3(\mathbb{R}^3, \mathbb{R}) = 1$ (Proposition 5.7.42).

In general, $\dim \text{Alt}_k(\mathbb{R}^n, \mathbb{R}) = \binom{n}{k}$ (and equals 0 unless $0 \leq k \leq n$). The case of Alt_0 is tautological since the tensor product of 0 copies of \mathbb{R}^n is defined to be \mathbb{R} (see Example 5.22). The case of Alt_1 just says that $(\mathbb{R}^n)^*$ has dimension n , which follows from **a proposition from Homework 13 [which?]** and Example 5.23.

These dimension counts will follow from the fact that the wedge products $\{dx^{i_1} \wedge \cdots \wedge dx^{i_k} : 1 \leq i_1 \leq \cdots \leq i_k \leq n\}$ form a basis for $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$, but for this to make sense, we first need to define wedge products.

Definition 5.107 (Abstract definition of wedge products). If $\phi, \psi \in (\mathbb{R}^n)^*$, define an alternating bilinear map (an element of $\text{Alt}_2(\mathbb{R}^n, \mathbb{R})$) $\phi \wedge \psi$ from $\mathbb{R}^n \times \mathbb{R}^n$ to \mathbb{R} by

$$(\phi \wedge \psi)(v, w) := \frac{1}{2}(\phi(v)\psi(w) - \phi(w)\psi(v)).$$

If α and β are 1-forms on U (that is, α and β are functions from U to $(\mathbb{R}^n)^*$, see Example 5.23), then $\alpha \wedge \beta$ is a 2-form on U defined by $(\alpha \wedge \beta)(p) := \alpha(p) \wedge \beta(p)$ (wedge products of differential forms are defined “pointwise;” see also Example 5.25).

Note that we have $\psi \wedge \phi = -\phi \wedge \psi$ (so $\phi \wedge \phi = 0$), and that wedge products are bilinear:

$$(c_1\phi_1 + c_2\phi_2) \wedge \psi = c_1\phi_1 \wedge \psi + c_2\phi_2 \wedge \psi,$$

and similarly in the second slot.

More generally, if α is a k -form and β is an ℓ -form, then $\alpha \wedge \beta$ is a $(k + \ell)$ -form.

See also the differently formulated definition in Section 4.1 of [Spivak \[1971\]](#) (p. 92 of pdf, p. 79 of book).

Example 5.28. The wedge product of a zero-form f with any k -form is always defined as ordinary scalar multiplication by the value of f at each point.

Proposition 5.7.40 (425b Homework 14 Problem 1). $\{dx \wedge dy, dx \wedge dz, dy \wedge dz\}$ is a basis for the vector space of alternating bilinear maps from $\mathbb{R}^3 \times \mathbb{R}^3$ to \mathbb{R} .

(Strictly speaking, dx , dy , and dz are differential 1-forms defined on \mathbb{R}^3 , so we should evaluate them at a point $p \in \mathbb{R}^3$, but their values are independent of p and it is standard to just write dx , dy , and dz .)

Proof. From Proposition 5.7.38, we have $dx(p) = e_1^*$, $dy(p) = e_2^*$, and $dz(p) = e_3^*$ for any $p \in \mathbb{R}^3$, so we want to show that $\{e_1^* \wedge e_2^*, e_1^* \wedge e_3^*, e_2^* \wedge e_3^*\}$ is a basis for $\text{Alt}_2(\mathbb{R}^n, \mathbb{R})$. By definition, since each $e_i^* \wedge e_j^* \in \text{Alt}_2(\mathbb{R}^n, \mathbb{R})$, they are all bilinear and alternating. We want to show that this set of three maps is linearly independent and spans the space of alternating bilinear maps.

Recall Definition 5.97. Let $v, w \in \mathbb{R}^n$ with $v = \sum_{i=1}^n c_{vi}e_i$ and $w = \sum_{i=1}^n c_{wi}e_i$, where e_i are the standard basis vectors for \mathbb{R}^n . Then

$$e_j^*(v) = \sum_{i=1}^n c_{vi}e_j^*(e_i) = \sum_{i=1}^n c_{vi}\delta_{ij} = c_{vj} \quad \forall j \in [n]$$

and similarly $e_j^*(w) = c_{wj}$. So for $i \neq j \in [n]$ we have

$$(e_i^* \wedge e_j^*)(v, w) = \frac{1}{2}(e_i^*(v)e_j^*(w) - e_i^*(w)e_j^*(v)) = \frac{1}{2}(c_{vi}c_{wj} - c_{wi}c_{vj}). \quad (5.35)$$

First we will show linear independence. $\{e_1^* \wedge e_2^*, e_1^* \wedge e_3^*, e_2^* \wedge e_3^*\}$ are independent if

$$c_1(e_1^* \wedge e_2^*) + c_2(e_1^* \wedge e_3^*) + c_3(e_2^* \wedge e_3^*) = 0 \iff c_1 = c_2 = c_3 = 0.$$

By (5.35), we have

$$\begin{aligned} & c_1(e_1^* \wedge e_2^*)(v, w) + c_2(e_1^* \wedge e_3^*)(v, w) + c_3(e_2^* \wedge e_3^*)(v, w) = 0 \\ \iff & c_1 \cdot \frac{1}{2}(c_{v1}c_{w2} - c_{w1}c_{v2}) + c_2 \cdot \frac{1}{2}(c_{v1}c_{w3} - c_{w1}c_{v3}) + c_3 \cdot \frac{1}{2}(c_{v2}c_{w3} - c_{w2}c_{v3}) = 0 \\ \iff & c_1 = c_2 = c_3 = 0, \end{aligned}$$

since none of the terms cancel. Next we will show that $\{e_1^* \wedge e_2^*, e_1^* \wedge e_3^*, e_2^* \wedge e_3^*\}$ spans the space of alternating bilinear maps $\text{Alt}_2(\mathbb{R}^n, \mathbb{R})$. Consider an arbitrary map $\Phi \in \text{Alt}_2(\mathbb{R}^n, \mathbb{R})$. For $(e_i, e_j) \in \mathbb{R}^n \times \mathbb{R}^n$ with $i < j$, we have $\Phi(e_1, e_2) =$,

□

In multivariable calculus, one often studies the cross product of vectors in \mathbb{R}^3 . Viewed in terms of the dual space $(\mathbb{R}^3)^*$ instead of \mathbb{R}^3 , the below proposition shows that the cross product becomes a special case of the wedge product, taking in two elements of $(\mathbb{R}^3)^* = \text{Alt}_1(\mathbb{R}^3, \mathbb{R})$ and producing an element of the three-dimensional space $\text{Alt}_2(\mathbb{R}^3, \mathbb{R})$.

Proposition 5.7.41 (425b Homework 14 Problem 2). For an element $a = a_1e_1^* + a_2e_2^* + a_3e_3^*$ of $(\mathbb{R}^3)^* = \text{Alt}_1(\mathbb{R}^3, \mathbb{R})$, define $\Phi(a) \in \mathbb{R}^3$ to be the vector (a_1, a_2, a_3) . Similarly, for an element $\alpha = a_{12}e_1^* \wedge e_2^* + a_{13}e_1^* \wedge e_3^* + a_{23}e_2^* \wedge e_3^*$ of $\text{Alt}_2(\mathbb{R}^3, \mathbb{R})$, define $\Phi(\alpha) \in \mathbb{R}^3$ to be $(a_{23}, -a_{13}, a_{12})$.

Then for $\alpha, \beta \in (\mathbb{R}^3)^*$, we have

$$\Phi(\alpha \wedge \beta) = \Phi(\alpha) \times \Phi(\beta),$$

where \times denotes the usual cross product of vectors in \mathbb{R}^3 .

Remark 21. Seeing that $(a_{23}, -a_{13}, a_{12})$ is the natural vector in \mathbb{R}^3 to define a given element of $\text{Alt}_2(\mathbb{R}^3, \mathbb{R})$ involves looking at the Hodge star operator (covered later in these notes). Note that the minus sign disappears if you use the basis vector $e_3^* \wedge e_1^*$ rather than $e_1^* \wedge e_3^*$ in the basis for $\text{Alt}_2(\mathbb{R}^3, \mathbb{R})$.

Proof. Expressing α as $a_1e_1^* + a_2e_2^* + a_3e_3^*$ and $\beta = b_1e_1^* + b_2e_2^* + b_3e_3^*$, we have

$$\begin{aligned}
\alpha \wedge \beta &= (a_1 e_1^* + a_2 e_2^* + a_3 e_3^*) \wedge (b_1 e_1^* + b_2 e_2^* + b_3 e_3^*) \\
&= a_1 e_1^* \wedge (b_1 e_1^* + b_2 e_2^* + b_3 e_3^*) + a_2 e_2^* \wedge (b_1 e_1^* + b_2 e_2^* + b_3 e_3^*) + a_3 e_3^* \wedge (b_1 e_1^* + b_2 e_2^* + b_3 e_3^*) \\
&= a_1 b_1 e_1^* \wedge e_1^* + a_1 b_2 e_1^* \wedge e_2^* + a_1 b_3 e_1^* \wedge e_3^* + a_2 b_1 e_2^* \wedge e_1^* + a_2 b_2 e_2^* \wedge e_2^* + a_2 b_3 e_2^* \wedge e_3^* \\
&\quad + a_3 b_1 e_3^* \wedge e_1^* + a_3 b_2 e_3^* \wedge e_2^* + a_3 b_3 e_3^* \wedge e_3^* \\
&= a_1 b_2 e_1^* \wedge e_2^* + a_1 b_3 e_1^* \wedge e_3^* - a_2 b_1 e_1^* \wedge e_2^* + a_2 b_3 e_2^* \wedge e_3^* - a_3 b_1 e_1^* \wedge e_3^* - a_3 b_2 e_2^* \wedge e_3^* \\
&= (a_1 b_2 - a_2 b_1) e_1^* \wedge e_2^* + (a_1 b_3 - a_3 b_1) e_1^* \wedge e_3^* + (a_2 b_3 - a_3 b_2) e_2^* \wedge e_3^*.
\end{aligned}$$

Now we have $\alpha \wedge \beta$ in terms of the basis $\{e_1^* \wedge e_2^*, e_1^* \wedge e_3^*, e_2^* \wedge e_3^*\}$ for $\text{Alt}_2(\mathbb{R}^3, \mathbb{R})$. Then

$$\begin{aligned}
\Phi(\alpha \wedge \beta) &= \Phi((a_1 b_2 - a_2 b_1) e_1^* \wedge e_2^* + (a_1 b_3 - a_3 b_1) e_1^* \wedge e_3^* + (a_2 b_3 - a_3 b_2) e_2^* \wedge e_3^*) \\
&= (a_2 b_3 - a_3 b_2, a_3 b_1 - a_1 b_3, a_1 b_2 - a_2 b_1) \\
&= (a_2 b_3 - a_3 b_2) e_1 + (a_3 b_1 - a_1 b_3) e_2 + (a_1 b_2 - a_2 b_1) e_3.
\end{aligned}$$

On the other hand,

$$\Phi(\alpha) = (a_1, a_2, a_3) = a_1 e_1 + a_2 e_2 + a_3 e_3, \quad \Phi(\beta) = (b_1, b_2, b_3) = b_1 e_1 + b_2 e_2 + b_3 e_3.$$

By computing the cross product as in multivariable calculus, we have

$$\Phi(\alpha) \times \Phi(\beta) = \begin{vmatrix} e_1 & e_2 & e_3 \\ a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \end{vmatrix} = (a_2 b_3 - a_3 b_2) e_1 - (a_1 b_3 - a_3 b_1) e_2 + (a_1 b_2 - a_2 b_1) e_3 = \Phi(\alpha \wedge \beta).$$

□

More generally, the abstract definition of wedge products (Definitions 5.107 and 5.117) will imply that if ϕ_1, \dots, ϕ_k are in $(\mathbb{R}^n)^*$, then

$$\phi_1 \wedge \cdots \wedge \phi_k = \frac{1}{k!} \left(\sum_{\sigma \in S_k} (-1)^{\text{sgn}(\sigma)} \phi_{\sigma(1)} \otimes \cdots \otimes \phi_{\sigma(k)} \right), \quad (5.36)$$

where S_k and $\text{sgn}(\sigma)$ are as defined in Definition 5.101 (and recall Definition 5.94 for the definition of the tensor product \otimes). Definition 5.107 (see also Definition 5.117) also implies basic properties like associativity of wedge products, and makes it clear that wedge products of elements of $(\mathbb{R}^n)^* = \text{Alt}_1(\mathbb{R}^n, \mathbb{R})$ form a spanning set for $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$.

Thus, (5.36) suffices for computing all wedge products. In particular, for $\phi_1, \phi_2, \phi_3 \in (\mathbb{R}^3)^*$, we have

$$\phi_1 \wedge \phi_2 \wedge \phi_3 = \frac{1}{6} (\phi_1 \otimes \phi_2 \otimes \phi_3 - \phi_1 \otimes \phi_3 \otimes \phi_2 + \phi_2 \otimes \phi_3 \otimes \phi_1 - \phi_2 \otimes \phi_1 \otimes \phi_3 + \phi_3 \otimes \phi_1 \otimes \phi_2 - \phi_3 \otimes \phi_2 \otimes \phi_1). \quad (5.37)$$

Proposition 5.7.42 (425b Homework 14 Problem 3). $\{dx \wedge dy \wedge dz\}$ is a basis for $\text{Alt}_3(\mathbb{R}^n, \mathbb{R})$.

To recap, we now have the following facts:

- A 0-form on \mathbb{R}^3 is a function f on \mathbb{R}^3 (Example 5.22).
- A 1-form on \mathbb{R}^3 can be written uniquely as $fdx + gdy + hdz$ where f, g, h are functions on \mathbb{R}^3 .
- A 2-form on \mathbb{R}^3 can be written uniquely as $f dx \wedge dy + g ds \wedge dz + h dy \wedge dz$ where f, g, h are functions on \mathbb{R}^3 (Proposition 5.7.40).
- A 3-form of \mathbb{R}^3 can be written uniquely as $f dx \wedge dy \wedge dz$ where f is a function on \mathbb{R}^3 (Proposition 5.7.42).

It turns out that in general, a differential k -form α on \mathbb{R}^n can be written uniquely as

$$\alpha = \sum_{1 \leq i_1 \leq \dots \leq i_k \leq n} f_{i_1, \dots, i_k} dx^{i_1} \wedge \dots \wedge dx^{i_k}.$$

(This is Theorem 4-5 in Spivak [1971], p. 94 of pdf, p. 81 of book.) This expression is especially convenient when defining the exterior derivative.

Definition 5.108 (Exterior derivative of a k -form). Let

$$\alpha = \sum_{1 \leq i_1 \leq \dots \leq i_k \leq n} f_{i_1, \dots, i_k} dx^{i_1} \wedge \dots \wedge dx^{i_k}$$

be a differential k -form on an open subset U of \mathbb{R}^n . Its **exterior derivative** $d\alpha$ is the $(k+1)$ -form on U defined by

$$d\alpha = \sum_{1 \leq i_1 \leq \dots \leq i_k \leq n} (df_{i_1, \dots, i_k} \wedge dx^{i_1} \wedge \dots \wedge dx^{i_k}).$$

Thus, if $\alpha = f$ is a 0-form, then $d\alpha = df$ as defined in Definition 5.105 for the exterior derivative of a 0-form (also called a differential).

A crucial fact about d is that $d \circ d = 0$, i.e., $d(d(\alpha)) = 0$ for any k -form α . One can prove this in general; here we'll just prove it for forms on \mathbb{R}^3 .

Proposition 5.7.43 (425b Homework 14 Problem 4). $d \circ d = 0$ for d acting on

- (a) 0-forms on \mathbb{R}^3 and
- (b) 1-forms on \mathbb{R}^3 .

(The equation is automatic for 2-forms and 3-forms on \mathbb{R}^3 .)

Proof. We will use the following result:

Corollary 5.7.43.1 (Corollary 5.17 of Pugh [2015]). Corresponding mixed second partial derivatives of a second-differentiable function are equal:

$$\frac{\partial^2 f_k(p)}{\partial x_i \partial x_j} = \frac{\partial^2 f_k(p)}{\partial x_j \partial x_i}.$$

(a) From the previous problem set, we have

$$df = \frac{\partial f}{\partial x} dx + \frac{\partial f}{\partial y} dy + \frac{\partial f}{\partial z} dz.$$

Then

$$\begin{aligned} d(df) &= d\left(\frac{\partial f}{\partial x} dx + \frac{\partial f}{\partial y} dy + \frac{\partial f}{\partial z} dz\right) \\ &= d\left(\frac{\partial f}{\partial x}\right) \wedge dx + d\left(\frac{\partial f}{\partial y}\right) \wedge dy + d\left(\frac{\partial f}{\partial z}\right) \wedge dz \\ (\text{by Proposition 5.7.38}) \quad &= \left(\frac{\partial^2 f}{\partial x \partial x} dx + \frac{\partial^2 f}{\partial y \partial x} dy + \frac{\partial^2 f}{\partial z \partial x} dz\right) \wedge dx + \left(\frac{\partial^2 f}{\partial x \partial y} dx + \frac{\partial^2 f}{\partial y \partial y} dy + \frac{\partial^2 f}{\partial z \partial y} dz\right) \wedge dy \\ &\quad + \left(\frac{\partial^2 f}{\partial x \partial z} dx + \frac{\partial^2 f}{\partial y \partial z} dy + \frac{\partial^2 f}{\partial z \partial z} dz\right) \wedge dz \\ &= \frac{\partial^2 f}{\partial y \partial x} dy \wedge dx + \frac{\partial^2 f}{\partial z \partial x} dz \wedge dx + \frac{\partial^2 f}{\partial x \partial y} dx \wedge dy + \frac{\partial^2 f}{\partial z \partial y} dz \wedge dy \\ &\quad + \frac{\partial^2 f}{\partial x \partial z} dx \wedge dz + \frac{\partial^2 f}{\partial y \partial z} dy \wedge dz \\ &= -\frac{\partial^2 f}{\partial x \partial y} dx \wedge dy - \frac{\partial^2 f}{\partial x \partial z} dx \wedge dz + \frac{\partial^2 f}{\partial x \partial y} dx \wedge dy - \frac{\partial^2 f}{\partial y \partial z} dy \wedge dz \\ &\quad + \frac{\partial^2 f}{\partial x \partial z} dx \wedge dz + \frac{\partial^2 f}{\partial y \partial z} dy \wedge dz \\ &= 0. \end{aligned}$$

where we applied Corollary 5.17 of Pugh [2015]

(b) For a 1-form $\alpha = f dx + g dy + h dz$, we have $d(\alpha) = d(fd x + gd y + hd z) = df dx + dg dy + dh dz$, so

$$\begin{aligned} d(df(\alpha)) &= d(df dx + dg dy + dh dz) \\ &= d\left(\left[\frac{\partial f}{\partial x} dx + \frac{\partial f}{\partial y} dy + \frac{\partial f}{\partial z} dz\right] dx + \left[\frac{\partial g}{\partial x} dx + \frac{\partial g}{\partial y} dy + \frac{\partial g}{\partial z} dz\right] dy + \left[\frac{\partial h}{\partial x} dx + \frac{\partial h}{\partial y} dy + \frac{\partial h}{\partial z} dz\right] dz\right) \\ &= d\left(\left[\frac{\partial f}{\partial x} dx + \frac{\partial f}{\partial y} dy + \frac{\partial f}{\partial z} dz\right]\right) dx \wedge dx + d\left(\left[\frac{\partial g}{\partial x} dx + \frac{\partial g}{\partial y} dy + \frac{\partial g}{\partial z} dz\right]\right) dy \wedge dy + d\left(\left[\frac{\partial h}{\partial x} dx + \frac{\partial h}{\partial y} dy + \frac{\partial h}{\partial z} dz\right]\right) dz \wedge dz \\ &= 0. \end{aligned}$$

□

Recapping again, we can interpret k -forms on \mathbb{R}^3 in terms of familiar vector calculus quantities as follows, compatibly with Proposition 5.7.41.

Proposition 5.7.44 (425b Homework 14 Problem 5). (a) Let α be a 1-form on \mathbb{R}^3 . Let $\mathbf{V} = V_1 e_1 + v_2 e_2 + V_3 e_3$ be the corresponding vector field (see Definition 5.83). Then the 2-form $d\alpha$ corresponds to the vector field $\text{curl}(\mathbf{V})$.

(b) Let β be a 2-form on \mathbb{R}^3 . Let $\mathbf{W} = W_1 e_1 + W_2 e_2 + W_3 e_3$ be the corresponding vector field. Then the 3-form $d\beta$ corresponds to the function $\text{div}(\mathbf{W})$.

Proposition 5.7.45 (Math 425b Final Exam problem). Let $\mathbf{F} = (F_1, F_2, F_3)^\top$ be a vector field on \mathbb{R}^3 . Let ω be the 2-form corresponding to the vector field \mathbf{F} in the usual way. Then $d\omega = \left(\frac{\partial F_1}{\partial x} + \frac{\partial F_2}{\partial y} + \frac{\partial F_3}{\partial z} \right) dx \wedge dy \wedge dz$, which corresponds to the divergence of \mathbf{F} .

Proof. This vector field corresponds with the 2-form $\omega = F_1 dy \wedge dz + F_2 dz \wedge dx + F_3 dx \wedge dy = F_1 dy \wedge dz - F_2 dx \wedge dz + F_3 dx \wedge dy$. We have

$$\begin{aligned} d\omega &= d(F_1 dy \wedge dz + F_2 dz \wedge dx + F_3 dx \wedge dy) \\ &= dF_1 \wedge dy \wedge dz + dF_2 \wedge dz \wedge dx + dF_3 \wedge dx \wedge dy \\ &= \left(\frac{\partial F_1}{\partial x} dx + \frac{\partial F_1}{\partial y} dy + \frac{\partial F_1}{\partial z} dz \right) \wedge dy \wedge dz + \left(\frac{\partial F_2}{\partial x} dx + \frac{\partial F_2}{\partial y} dy + \frac{\partial F_2}{\partial z} dz \right) \wedge dz \wedge dx \\ &\quad + \left(\frac{\partial F_3}{\partial x} dx + \frac{\partial F_3}{\partial y} dy + \frac{\partial F_3}{\partial z} dz \right) \wedge dx \wedge dy \\ &= \frac{\partial F_1}{\partial x} dx \wedge dy \wedge dz + \frac{\partial F_1}{\partial y} dy \wedge dz \wedge dx + \frac{\partial F_1}{\partial z} dz \wedge dy \wedge dx + \frac{\partial F_2}{\partial x} dx \wedge dz \wedge dx + \frac{\partial F_2}{\partial y} dy \wedge dz \wedge dx \\ &\quad + \frac{\partial F_2}{\partial z} dz \wedge dx \wedge dz + \frac{\partial F_3}{\partial x} dx \wedge dx \wedge dy + \frac{\partial F_3}{\partial y} dy \wedge dx \wedge dy + \frac{\partial F_3}{\partial z} dz \wedge dx \wedge dy \\ &= \frac{\partial F_1}{\partial x} dx \wedge dy \wedge dz + 0 - \frac{\partial F_1}{\partial z} dz \wedge dz \wedge dy - \frac{\partial F_2}{\partial x} dx \wedge dx \wedge dz + \frac{\partial F_2}{\partial y} dx \wedge dy \wedge dz \\ &\quad + 0 + 0 - \frac{\partial F_3}{\partial y} dy \wedge dy \wedge dx + \frac{\partial F_3}{\partial z} dx \wedge dy \wedge dz \\ &= \left(\frac{\partial F_1}{\partial x} + \frac{\partial F_2}{\partial y} + \frac{\partial F_3}{\partial z} \right) dx \wedge dy \wedge dz. \end{aligned}$$

By Proposition 5.7.44, if ω is a 2-form on \mathbb{R}^3 and \mathbf{F} is the corresponding vector field, then $d\omega$ corresponds to $\text{div}(\mathbf{F})$. This makes sense because

$$\text{div}(\mathbf{F}) = \nabla \cdot \mathbf{F} = \frac{\partial F_1}{\partial x} + \frac{\partial F_2}{\partial y} + \frac{\partial F_3}{\partial z},$$

which corresponds to the 3-form $\left(\frac{\partial F_1}{\partial x} + \frac{\partial F_2}{\partial y} + \frac{\partial F_3}{\partial z} \right) dx \wedge dy \wedge dz$.

□

Homework 15

One abstract way to define the tangent space $(T\mathbb{R}^n)_p$ at a point $p \in \mathbb{R}^n$ (see Definition 5.81) is as a set of equivalence classes of differentiable or smooth curves γ with $\gamma(0) = p$, where the equivalence relation is $\gamma_1 \sim \gamma_2 \iff \gamma'_1(0) = \gamma'_2(0)$. (On a manifold you'd require that this holds in some, or equivalently any, coordinate chart; see Definition 5.80.) It's clear that for \mathbb{R}^n we can think of an equivalence class $[\gamma]$ as being uniquely determined by the velocity vector $\gamma'(0)$, so that the set of equivalences classes can be identified with \mathbb{R}^n , and we can pass the vector-space structure of \mathbb{R}^n to this set of equivalence classes (making it an n -dimensional vector space).

We will consider the cotangent space $(T^*\mathbb{R}^n)_p$. It will consist of the sorts of things that give linear functionals on tangent vectors—a reasonable thing to think of for this is “functions.” If f is a smooth function, then the directional derivative of f with respect to tangent vectors v should give a linear functional on the tangent space (abstractly, this functional is $v \mapsto (Df)_p(v)$).

So we would like to define $(T^*\mathbb{R}^n)_p$ as a vector space of functions. The first issue that arises is that spaces of functions are typically infinite-dimensional. One reason why this is is that functions have values at points far away from p , but these values should be irrelevant for directional derivatives, so to work toward a finite-dimensional cotangent space, we will use the following concept.

Definition 5.109. Let $p \in \mathbb{R}^n$ and consider the set \mathcal{F} of pairs (U, f) where U is an open neighborhood of p and $f : U \rightarrow \mathbb{R}$ is a smooth function. Define an equivalence relation on \mathcal{F} by $(U_1, f_1) \sim (U_2, f_2)$ if there exists $U \subset U_1 \cap U_2$ with $p \in U$ such that f_1 and f_2 are equal on all points of U (i.e., they agree when restricted to U). The set of equivalence classes \mathcal{F}/\sim is denoted by $C^\infty(\mathbb{R}^n)_p$, the “stalk at p of the sheaf of smooth functions on \mathbb{R}^n .” Elements of $C^\infty(\mathbb{R}^n)_p$, i.e. equivalence classes $[U, f]$, are called **germs of smooth functions at p** .

Definition 5.110 (Tangent covectors on manifolds; p. 275 of Lee [2012], p. 290 of pdf). Let M be a smooth manifold with or without boundary. For each $p \in M$, we define the **cotangent space at p** , denoted by T_p^*M or $(T^*M)_p$, to be the dual space to $T_p M$: $T_p^*M = (T_p M)^*$, or $(T^*M)_p = ((TM)_p)^*$. Elements of T_p^*M are called **tangent covectors at p** , or just **covectors at p** .

:

Definition 5.111. A **vector bundle**/ M is a vector space V_p for each $p \in M$, “ranging smoothly.” TM is the **tangent bundle** of M .

Definition 5.112. If $V : \{V_p : p \in M\}$ is a vector bundle/ M , then a **section** of V is a map $M \xrightarrow{\sigma} \bigcup_{p \in M} V_p$ such that for all $p \in M$, $\sigma(p) \in V_p$.

Thus, a vector field on M (see Definition 5.83) is a section of the tangent bundle.

Similarly, we have another vector bundle on M : the value at the point p is the dual vector space $(TM)_p$, the **cotangent space** of M at p . This bundle is called the **cotangent bundle** of M , written T^*M . A differential 1-form on M is a **section of the cotangent bundle**. (A differential k -form on M is a section of the k th exterior power of the cotangent bundle, $\wedge^k T^*M$.)

Note: standard vector calculus textbooks (e.g. [Stewart \[2015\]](#)) turns all 1-forms on \mathbb{R}^n into vector fields (implicitly using standard inner product/Riemannian metric on \mathbb{R}^n ; see Remark 19). This is why ∇f is familiar while df is not.

We will also see: 2-forms, 3-forms on \mathbb{R}^3 are turned into vector fields and functions, respectively.

Now we will consider line integrals and integrals of 1-forms on curves and 1-manifolds (see Definition 5.77). [Stewart \[2015\]](#) discusses 3 types of line integrals. We can understand all three in terms of integrals of 1-forms on curves C . But, we need to consider C as its own manifold that we can integrate things on. If M is a manifold of dimension n , what can I integrate on M ? Answer: a **top-degree differential form** (similar to saying “a function,” but when $M \neq \mathbb{R}^n$, this distinction is important). Case we care about now:

- $M = [a, b] \subset \mathbb{R}$: “1-manifold with boundary.” Let $t \in M$. Any 1-form on M is $\alpha = f(t)dt$ for some smooth function f . Can define $\int_{[a,b]} \alpha := \int_a^b \alpha = \int_a^b f(t)dt$.

Note that differential forms language gives meaning to $f(t)$ and dt individually. $f(t)$ is a 0-form, dt is a 1-form, can multiply together. (However, you can’t divide differential forms— $\frac{dy}{dx}$ can’t be understood in terms of differential forms.)

- C : **curve** in \mathbb{R}^2 (or $\mathbb{R}^3, \mathbb{R}^n$, etc.). e.g. C is a circle centered at the origin with radius 1. If we have a function f on C , we don’t know how to integrate it (*a priori*). But if we have a 1-form α on C , we should be able to integrate it.

How to define this? Pick a parameterization of C , $\mathbf{r} = [a, b] \mapsto C \subset \mathbb{R}^n$ (want \mathbb{R} to be nice enough: $\mathbf{r}'(t) \neq 0$ for all t , \mathbf{r} is surjective, \mathbf{r} is injective except possibly at finitely many points). Then define

$$\int_C \alpha := \int_{[a,b]} \mathbf{r}^*(\alpha). \quad (5.38)$$

Can show it’s independent of \mathbf{r} , as long as the orientation (the direction we travel on the curve) matches the orientation of \mathbf{r} (“orientation compatible”). This allows us to compute $\int_C \alpha$.

If α is a 1-form on \mathbb{R}^n , $\alpha = \alpha_1 dx^1 + \dots + \alpha_n dx^n$. Can view α as giving a 1-form on C (pullback of α via inclusion $C \hookrightarrow \mathbb{R}^n$; recall Definitions 5.106 and 5.120). Then we can compute $\int_C \alpha$ by picking \mathbf{r} and using (5.38); this will be concrete and will recover line integrals of vector fields (see Definition 5.83).

Definition 5.113 (From [Stewart \[2015\]](#)). 1. **Line integral of a scalar field/function on C with respect to arc length:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ (or $C \rightarrow \mathbb{R}$) be a smooth function. The line integral $\int_C f ds = \int_C f(\mathbf{r}) ds$ is defined by

$$\int_C f ds := \int_a^b f(\mathbf{r}(t)) \|\mathbf{r}'(t)\| dt.$$

(This definition is independent of the parameterization \mathbf{r} , as long as orientations are respected.) If $\gamma(a) = \gamma(b)$ (C is closed), we can write $\oint_C f ds$.

2. **Line integral of a scalar field/function on C with respect to dx :** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ (or $C \rightarrow \mathbb{R}$) be a smooth function. The line integral $\int_C f dx = \int_C f(\mathbf{r}) dx$ is defined by

$$\int_C f dx := \int_a^b f(\mathbf{r}(t)) r'_i(t) dt,$$

where $\mathbf{r} = (r_1, \dots, r_n)^\top$. For example, let $P = P(x, y)$ be a function from \mathbb{R}^2 to \mathbb{R} . We can take

$$\int_C P(x, y) dx = \int_C P dx = \int_a^b P(r_1(t), r_2(t)) r'_1(t) dt$$

and $\int_C P(x, y) dy = \int_C P dy$, etc. (See Example 5.24.)

3. **Line integral of a vector field (see Definition 5.83) on C :** Let $\mathbf{F} : \mathbb{R}^n \rightarrow \mathbb{R}^n$ (or $C \rightarrow \mathbb{R}^n$) be a vector field on C . The line integral $\int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r} = \int_C \mathbf{F} \cdot d\mathbf{r}$ is defined by

$$\int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r} := \int_a^b \mathbf{F}(\mathbf{r}(t)) \cdot \mathbf{r}'(t) dt,$$

Proposition 5.7.46. Let P be a function on \mathbb{R}^n , so that $P dx$ is a 1-form on \mathbb{R}^n . Let C, \mathbf{r} be as above. Then the definitions of $\int_C P dx^i$ as in Definitions 5.113 and [in the above differential 1-form sense] agree.

Proof. Note $P dx^i$ is a 1-form on \mathbb{R}^n , pulled back to C . So starting from the 1-form formulation, we have

$$\begin{aligned} \int_C P dx^i &= \int_{[a,b]} \mathbf{r}^*(P dx^i) \quad (\text{using (5.38)}) \\ (\text{by Proposition 5.7.39(b)}) \quad &= \int_{[a,b]} (P \circ \mathbf{r}) \mathbf{r}^*(dx^i) \\ (\text{by Proposition 5.7.39(a)}) \quad &= \int_{[a,b]} (P \circ \mathbf{r}) d(\mathbf{r}^*(x_i)) \\ &= \int_{[a,b]} (P \circ \mathbf{r}) d(r_i) \\ &= \int_{[a,b]} (P \circ \mathbf{r}) r'_i(t) dt \quad (\text{at a point } t \in [a,b], \text{ by HW 13}), \end{aligned}$$

which is the calculus definition of an integral in Definition 5.113 part (2). (See also Example 5.24.)

□

Now we will address Definition 5.113 part (3). Write $\mathbf{F} = (F_1, \dots, F_n)^\top$ (a vector field (see Definition 5.83) on \mathbb{R}^n and let $\alpha := F_1 dx^1 + \dots + F_n dx^n$, a 1-form on \mathbb{R}^n . These have the usual correspondence from the homework.

Proposition 5.7.47. The definition $\int_C \alpha$ in 1-forms matches the Definition 5.113 part (3) for $\int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r}$.

Proof. Starting from the 1-form definition, we have

$$\begin{aligned} \int_C \alpha &= \int_{[a,b]} \mathbf{r}^*(\alpha) \quad (\text{using (5.38)}) \\ &= \int_{[a,b]} \mathbf{r}^*(F_1 dx^1 + \dots + F_n dx^n) \\ (\text{by Proposition 5.7.39(c)}) \quad &= \int_{[a,b]} F_1(\mathbf{r}(t)) r'_1(t) dt + \dots + \int_{[a,b]} F_n(\mathbf{r}(t)) r'_n(t) dt \\ &= \int_{[a,b]} \left(F_1(\mathbf{r}(t)) r'_1(t) + \dots + \int_{[a,b]} F_n(\mathbf{r}(t)) r'_n(t) \right) dt \\ &= \int_C \mathbf{F}(\mathbf{r}(t)) \cdot \mathbf{r}'(t) dt \\ &= \int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r}. \end{aligned}$$

□

For example, if $\mathbf{F}(x, y) = (P(x, y), Q(x, y))^\top$, then $\int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r} = \int_C (P(x, y)dx + Q(x, y)dy)$, which is a 1-form integral of type 2 from Definition 5.113. [Stewart \[2015\]](#) gives a similar computation as the relationship between Type 2/3 integrals.

4/24 notes

Finally, we will address Type 1 integrals from Definition 5.113. The general principle is that on a curve $C \subset \mathbb{R}^n$, parameterized by a smooth function \mathbf{r} (so $\mathbf{r} : [a, b] \rightarrow C \subset \mathbb{R}^n$), there exists a unique 1-form α on C (a function from C to $(\mathbb{R}^n)^*$) with

$$\mathbf{r}^*(\alpha) = \|\mathbf{r}'(t)\|dt.$$

α is typically called ds , the “arc length 1-form on C .“ That is, ds is the unique 1-form on C such that

$$\mathbf{r}^*(ds) = \|\mathbf{r}'(t)\|dt. \quad (5.39)$$

Recall from Definition 5.106 that at a point $t \in [a, b]$ and for $v \in \mathbb{R}$, we have that the pullback $\mathbf{r}^*(ds)$ is the differential 1-form on $[a, b]$ (that is, a function from $[a, b]$ to $(\mathbb{R})^*$, so a function from $[a, b]$ to the space of functionals with domain \mathbb{R}) defined at a point $t \in [a, b]$ by

$$(\mathbf{r}^*(ds))_t(v) := ds_{\mathbf{r}(t)}((D\mathbf{r})_t(v))$$

for $v \in \mathbb{R}$. (Note that $(D\mathbf{r})_t(v) \in \mathbb{R}^n$, so it makes sense to evaluate $ds_{\mathbf{r}(t)}$ on the vector $(D\mathbf{r})_t(v)$.)

Warning: this is not d of something; ds is historical notation. In particular, if \mathbf{r} is injective, define $\mathbf{r} : [a, b] \rightarrow C \subset \mathbb{R}^n$. Let s be the unique function on C such that $s(\mathbf{r}(t)) = \int_a^t \|\mathbf{r}'(u)\| du$. Then ds is d applied to s (the exterior derivative of s). However, if \mathbf{r} is not injective (e.g. $\mathbf{r}(a) = \mathbf{r}(b)$ for a closed curve), then $s(\mathbf{r}(a)) = 0$ while $s(\mathbf{r}(b)) \neq 0$ (this is the arc length of C). This is impossible if $\mathbf{r}(a) = \mathbf{r}(b)$. So in this case, ds is not d of s . (not important aside: ds is a generator for the deRham cohomology group $H'(C)$ (see Remarks on homework).)

Given a type (1) integral $\int_C f ds$, we have a 1-form $f ds$ on C . We expect the classical type (1) integral is the integral of this 1-form.

Proposition 5.7.48. The definition of $\int_C f ds$ as defined from the above function from f on C agrees with the definition from Definition 5.113 part (1).

Proof. Starting from the 1-form definition,

$$\begin{aligned}
\int_C f \, ds &:= \int_{[a,b]} \mathbf{r}^*(f \, ds) \quad (\text{using (5.38)}) \\
(\text{by Proposition 5.7.39(b)}) \quad &= \int_{[a,b]} (f \circ \mathbf{r}) \mathbf{r}^*(ds) \\
&= \int_a^b f(\mathbf{r}(t)) \mathbf{r}^*(ds) \\
(\text{using (5.39)}) \quad &= \int_a^b f(\mathbf{r}(t)) \|\mathbf{r}'(t)\| dt,
\end{aligned}$$

which matches Definition 5.113 part (1). □

Remark 22. Interesting fact about 1-forms on C : any 1-form on C is of the form $\alpha = f \, ds$; i.e., α is some function times arc-length 1-form ds . i.e. integrals of type (1) are just as general as integrals of type (3). In particular, any 1-form α on C (corresponding to a vector field \mathbf{F} on C) (see Definition 5.83) can be written as $\alpha = (\mathbf{F} \cdot \mathbf{T})ds$. Therefore classical line integrals are integrals of 1-forms on curves. (We will see later that the same is true for surface integrals and 2-forms.)

If we have a vector field \mathbf{F} on C and we want to interpret $\int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r}$ as a type (1) integral, we can write

$$\int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r} = \int_a^b \mathbf{F}(\mathbf{r}(t)) \cdot \mathbf{r}'(t) dt = \int_a^b \mathbf{F}(\mathbf{r}(t)) \cdot \underbrace{\frac{\mathbf{r}'(t)}{\|\mathbf{r}'(t)\|}}_{\text{unit tangent vector}} \|\mathbf{r}'(t)\| dt$$

Let $\mathbf{T}(\mathbf{r}(t)) := \frac{\mathbf{r}'(t)}{\|\mathbf{r}'(t)\|}$ where \mathbf{T} is the unique vector field on C defined this way. (This really makes most sense if \mathbf{r} is injective.) Then we can write this as

$$\int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r} = \int_a^b (\mathbf{F}(\mathbf{r}(t)) \cdot \mathbf{T}(\mathbf{r}(t))) \|\mathbf{r}'(t)\| dt = \int_C (\mathbf{F} \cdot \mathbf{T}) ds$$

where $\mathbf{F} \cdot \mathbf{T}$ is a scalar field on C obtained from the original \mathbf{F} (vector field on C ; see Definition 5.83) by the dot product with \mathbf{T} (a fixed vector field on C). (See Proposition 5.7.49.) Thus, $\int_C (\mathbf{F} \cdot \mathbf{T}) ds$ is another standard notation for $\int_C \mathbf{F}(\mathbf{r}) \cdot d\mathbf{r} = \int_C \alpha$. This shows that in terms of forms, any 1-form α on C (corresponding to a vector field \mathbf{F} on C) can be written as $\alpha = (\mathbf{F} \cdot \mathbf{T}) ds$.

Proposition 5.7.49 (Math 425b Final Exam problem). Let C be a curve in \mathbb{R}^n parameterized by $\mathbf{r} : [a, b] \rightarrow C \subset \mathbb{R}^n$. Assume that \mathbf{r} is smooth when viewed as a map from $[a, b]$ to \mathbb{R}^n (i.e. $i \circ \mathbf{r}$ is smooth where $i : C \rightarrow \mathbb{R}^n$ is the inclusion map), that \mathbf{r} is bijective, and that $\mathbf{r}'(t) \neq 0$ for all $t \in [a, b]$.

Let α be a 1-form on \mathbb{R}^n , corresponding to a vector field \mathbf{F} on \mathbb{R}^n under the usual correspondence. Then

$$\int_C \alpha = \int_C (\mathbf{F} \cdot \mathbf{T}) ds.$$

Proof. ds is the unique 1-form on C such that $\mathbf{r}^*(ds) = \|\mathbf{r}'(t)\| dt$. The unit tangent vector function can be defined on C in terms of \mathbf{r} by $\mathbf{T}(\mathbf{r}(t)) := \frac{\mathbf{r}'(t)}{\|\mathbf{r}'(t)\|}$ (note that this definition is okay since by assumption $\mathbf{r}'(t) \neq 0$ for all $t \in [a, b]$). Let

$$\mathbf{F} = \begin{bmatrix} F_1 \\ \vdots \\ F_n \end{bmatrix}.$$

The 1-form α on \mathbb{R}^n corresponding to \mathbf{F} in the usual way can be written as

$$\alpha = F_1 dx_1 + \dots + F_n dx_n.$$

Then we have

$$\begin{aligned}
\int_C \alpha &= \int_{[a,b]} \mathbf{r}^*(\alpha) \quad (\text{using (5.38)}) \\
&= \int_{[a,b]} \mathbf{r}^* \left(\sum_{i=1}^n F_i dx_i \right) \\
(\text{by Proposition 5.7.39(c)}) \quad &= \int_{[a,b]} \sum_{i=1}^n F_i(\mathbf{r}(t)) r'_i(t) dt \\
&= \int_a^b \mathbf{F}(\mathbf{r}) \cdot \mathbf{r}'(t) dt \\
&= \int_a^b \left(\mathbf{F}(\mathbf{r}(t)) \cdot \frac{\mathbf{r}'(t)}{\|\mathbf{r}'(t)\|} \right) \|\mathbf{r}'(t)\| dt \\
&= \int_a^b (\mathbf{F}(\mathbf{r}(t)) \cdot \mathbf{T}(\mathbf{r}(t))) \|\mathbf{r}'(t)\| dt \\
&= \int_a^b (\mathbf{F}(\mathbf{r}(t)) \cdot \mathbf{T}(\mathbf{r}(t))) \mathbf{r}^*(ds) \\
(\text{by Proposition 5.7.39(a); permissible because } \mathbf{r} \text{ is injective}) \quad &= \int_a^b (\mathbf{F}(\mathbf{r}(t)) \cdot \mathbf{T}(\mathbf{r}(t))) d(s \circ \mathbf{r}) \\
&= \int_C (\mathbf{F} \cdot \mathbf{T}) ds.
\end{aligned}$$

□

Note: In Section 5.8 of Pugh [2015], differential 1-forms are defined by how they pair with curves C (or \mathbf{r}) to give an integral $\int_C \alpha$. I.e., if α is a differential 1-form in the sense described in these notes, α gives a functional on the set of parameterized curves $\mathbf{r} : [0, 1] \rightarrow \mathbb{R}^n$ by $\Phi_\alpha(\mathbf{r} : [a, b] \rightarrow \mathbb{R}^n) := \int_C \alpha$, $C = \text{image}(\mathbf{r})$. Pugh [2015] defines α in terms of Φ_α ; this is non-standard, but follows Rudin [1976] for pedagogical reasons (to hide the algebra). We are doing the algebra-based approach. In this viewpoint, a differential form doesn't mean anything at a point. In ours, it does—it's an alternating multilinear map (see Definition 5.100).

Example 5.29 (Line integrals in complex analysis). We often encounter integrals like $\int_C f(z) dz$ where C is a curve in the complex plane. We can interpret this in the following way. First, consider that $\mathbb{C} \cong \mathbb{R}^2$. We can write $z = x + iy$, where z is the identity function on \mathbb{C} , x is the first coordinate in \mathbb{R}^2 , and y is the second coordinate in \mathbb{R}^2 . Now we can take d of these functions on \mathbb{R}^2 , and get the 1-form

$dz = dx + idy$ on \mathbb{R}^2 . (It's ok to do complex-valued differential 1-forms $\text{Alt}_k(\mathbb{R}^n, \mathbb{C})$ (with \mathbb{R} multilinear) or $\text{Alt}_k(\mathbb{C}^n, \mathbb{C})$ (with \mathbb{C} multilinear)). Then

$$\int_C f(z) dz = \int_C f(x, y) dx + i \int_C f(x, y) dy$$

(and usually we write $f = u + iv$ and expand further). Now this integral is in the form of the integrals we've worked with in these notes.

Some terminology: if f is a holomorphic function, then $f(z)dz$ is a holomorphic 1-form while $f(z)d\bar{z} = f(z)(dx - idy)$ is not a holomorphic 1-form.

find definition of smooth manifold

in inclusion map notes:

Summary: if \mathbf{F} is a vector field (see Definition 5.83) on a curve $C \subset \mathbb{R}^n$, the corresponding 1-form on C is

$$\underbrace{(\mathbf{F} \cdot \mathbf{T})}_{\text{function on } C} \underbrace{ds}_{\text{arc-length 1-form of } C} .$$

This explains why $\int_C (\mathbf{F} \cdot \mathbf{T}) ds$ occurs so often in vector calculus (e.g., line integrals).

Definition 5.114 (Closed differential forms; p. 92 of Spivak [1971], p. 105 of pdf). A differential form α is called **closed** if $d\alpha = 0$.

Definition 5.115 (Exact differential forms; p. 92 of Spivak [1971], p. 105 of pdf). A differential form α is called **exact** if $\alpha = df$ for some function (0-form) f .

Remark 23. Theorem 4-10 in Spivak [1971] shows that every exact form is closed.

4/27 notes: FTC for line integrals, wedge products, multiple integrals, surface integrals, etc.

Theorem 5.7.50 (Fundamental Theorem of Calculus for line integrals). Let C be a curve in \mathbb{R}^n (the image of $\mathbf{r} : [a, b] \rightarrow \mathbb{R}^n$ where $\mathbf{r}'(t) \neq 0$ and \mathbf{r} is injective except maybe at the endpoints). Let $f : C \rightarrow \mathbb{R}$ be a smooth function (∇f : vector field on C). Then

$$\int_C (\nabla f \cdot \mathbf{T}) ds = f(\mathbf{r}(b)) - f(\mathbf{r}(a)).$$

(In particular, this means $\oint (\nabla f \cdot \mathbf{T}) ds = 0$, where \oint denotes that the endpoints are equal so the curve is closed.)

Proof.

$$\begin{aligned}
 \int_C (\nabla f \cdot \mathbf{T}) ds &= (\text{by result from 4/24}) \int_C df \\
 &:= \int_{[a,b]} \mathbf{r}^*(df) \\
 &= \int_{[a,b]} d(f \circ \mathbf{r}) \\
 &= \int_a^b \frac{df \circ \mathbf{r}}{dt} dt \\
 (\text{by FTC}) \quad &= f(\mathbf{r}(b)) - f(\mathbf{r}(a)).
 \end{aligned}$$

□

We can write this in forms language as

$$\int_C df = \int_{\partial C} f$$

(where ∂C means “boundary of C ”). In fact, we can generalize this.

Theorem 5.7.51 (Generalized Stokes’ Theorem). If M is a smooth n -manifold (see Definition 5.77) with boundary⁴ and ω is an $(n-1)$ -form on M , then

$$\int_M d\omega = \int_{\underbrace{\partial M}_{\text{boundary of } M}} \underbrace{\omega}_{\text{really } i^*(\omega)}$$

(where $i : \partial M \rightarrow M$ is the inclusion operator).

Remark 24. This theorem implies Green’s Theorem, Stokes’ Theorem, the Divergence Theorem, and more. Our goal for the remainder of class will be to see how this generalizes the classical theorems.

First, one remark about 1-forms.

Remark 25. Consider a first order ODE $y'(x) = F(x, y(x))$ (this is not autonomous). A method for solving this: write $F(x, y) = \frac{-P(x, y)}{Q(x, y)}$ for some functions $P(x, y)$ and $Q(x, y)$. (Note that there is not a unique way of doing this—exist several valid choices of P and Q .) The ODE is

$$\frac{dy}{dx} = \frac{-P(x, y)}{Q(x, y)},$$

i.e., $P(x, y) + Q(x, y) \frac{dy}{dx} = 0$. Now we “multiply by dx ” (not meaningful in our formulation with differential forms):

$$\underbrace{P(x, y)dx + Q(x, y)dy}_{\text{looks like a 1-form}} = 0. \tag{5.40}$$

⁴we will not precisely define this term here; treat this as an intuitive notion for now

Now we will try to find a function $f(x, y)$ with $df = P(x, y)dx + Q(x, y)dy$. (Recall a 1-form α is called **exact** if $\alpha = df$; see Definition 5.115.) If we can find f , then $\frac{\partial f}{\partial x} = P$, $\frac{\partial f}{\partial y} = Q$, so the ODE is $\frac{\partial f}{\partial x} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial x} = 0$, or $\begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix} \begin{bmatrix} 1 \\ \frac{dy}{dx} \end{bmatrix} = 0$. By the Chain Rule (Theorem 5.7.14) we can write this as

$$= \frac{d}{dx}(f(x, y(x))) = (DF)_{(x, y(x))} \left(\begin{bmatrix} 1 \\ y'(x) \end{bmatrix} \right) = 0.$$

Then we can integrate, which yields $f(x, y(x)) = c$ for some $c \in \mathbb{R}$. Then (try to) solve for $y(x)$ as a function of x (by the Implicit Function Theorem, this is usually possible).

How can we express this in the language of differential forms? The equation (5.40) is suspect given the unallowed transformations we did. Should mean P and Q are the zero function, which is not what we want. The missing ingredient is pullbacks (Definitions 5.106 and 5.120).

Proposition 5.7.52. A function $y = y(x)$ solves the ODE $y' = \frac{-P(x, y)}{Q(x, y)}$ if and only if $\gamma^*(Pdx + Qdy) = 0$, where $\gamma(t) := (t, y(t))$.

Proof.

$$\begin{aligned} \gamma^*(P(x, y)dx + Q(x, y)dy) &= P(t, y(t))d(x \circ \gamma) + Q(t, y(t))d(y \circ \gamma) \\ &= P(t, y(t))d(t) + Q(t, y(t))d(y(t)) \\ &= P(t, y(t))dt + Q(t, y(t))y'(t)dt \\ &= (P(t, y(t)) + Q(t, y(t))y'(t))dt \\ &= 0 \quad \iff \text{coefficient of } dt \text{ equals 0 for all } t, \end{aligned}$$

which is true if and only if $y(t)$ solves the ODE.

□

To summarize: we can view any first order ODE $y' = F(x, y)$ as an equation $\gamma^*(\alpha) = 0$ for some non-unique choice of 1-form α on \mathbb{R}^2 . So an equation for an unknown function of y is equivalent to an equation for an unknown path γ of the form $\gamma(t) = (t, y(t))$. Saying “the ODE is exact” is bad, since α is not unique. Should say α is exact (see Definition 5.115). Indeed:

Theorem 5.7.53. If $F : \mathbb{R}^2 \rightarrow \mathbb{R}$ is smooth, there exist smooth functions $P(x, y), Q(x, y) : \mathbb{R}^2 \rightarrow \mathbb{R}$ with $F(x, y) = -\frac{P(x, y)}{Q(x, y)}$ and $Pdx + Qdy$ is an exact 1-form (see Definition 5.115) on \mathbb{R}^2 .

Equivalently: if $P(x, y)dx + Q(x, y)dy$ is a 1-form on \mathbb{R}^2 such that P, Q don't both vanish at (x, y) , then there exists a smooth function $\mu(x, y) : \mathbb{R}^2 \rightarrow \mathbb{R}$ such that $\mu Pdx + \mu Qdy$ is exact. (note: $-\frac{\mu P}{\mu Q} = -\frac{P}{Q}$.)

Definition 5.116. A function μ like this (that we multiply a 1-form by to get an exact 1-form) is called an **integrating factor** for the 1-form $Pdx + Qdy$.

So the theorem is saying any nonvanishing 1-form α on \mathbb{R}^2 has an integrating factor. (It turns out that on \mathbb{R}^n you need $\alpha^n d\alpha = 0$; see the Frobenius theorem in differential geometry.) So you can solve an arbitrary first-order ODE $y' = F(x, y)$ by finding an integrating factor, then applying the above method. Finding an integrating factor is hard in general: if $\alpha = (P(x)y - Q(x))dx + dy$, then can take $e^{\int P(x)dx}$ as an integrating factor (compare with ODE books), but other than tricks in special cases like this, the general problem is hard.

Remark 26. We can often say that given $\alpha = Pdx + Qdy$, we can test if it's exact by taking $d\alpha = \left(\frac{\partial Q}{\partial x} - \frac{\partial P}{\partial y}\right)dx \wedge dy$. If this is 0, α is closed (see Definition 5.114) and (usually) exact. This statement depends on the domain U that α is defined on—all closed 1-forms on U are exact if and only if (by definition of H') $H'(U) = 0$, where $H'(U)$ is the de Rham cohomology group of U : $H'(U) = \frac{\text{closed 1 forms on } U}{\text{exact 1-forms on } U}$.

4/29 notes

Definition 5.117 (In-class general definition of wedge products). If V is a finite-dimensional vector space over \mathbb{R} (or \mathbb{C} or any field), the **tensor algebra** of V , denoted by $T^\cdot(V)$, is defined to be

$$\bigoplus_{k \geq 0} \underbrace{V \oplus \dots \oplus V}_{k \text{ factors}} = \mathbb{R} \oplus V \oplus (V \oplus V) \oplus \dots$$

(The summand $V \oplus \dots \oplus V$ with k factors is called $T^k V$, the **k th tensor power** of V . We have a bilinear map $T^k V \times T^\ell V \rightarrow T^{k+\ell} V$ (from the linear map $\text{id} : T^k V \otimes T^\ell V \rightarrow T^{k+\ell} V$) giving us a multiplication operator on $T^\cdot V$ (so we have a ring (see Definition 15.3 or \mathbb{R} -algebra structure) (and recall Definition 5.94 for the definition of the tensor product \otimes)).

For example,

$$\underbrace{(V_1 \otimes V_2)}_{\in T^2(V)} \underbrace{(V_3 \otimes V_4 \otimes V_5)}_{\in T^3(V)} := \underbrace{V_1 \otimes V_2 \otimes V_3 \otimes V_4 \otimes V_5}_{\in T^5(V)}$$

Definition 5.118. The **exterior algebra** $\wedge^\cdot V$ is defined to be $(T^\cdot V)/(x \otimes x : x \in V)$, where $V = T^{-1}(v)$. Regarding $(x \otimes x : x \in V)$: R ring (see Definition 15.3: $I \subset R$ is **ideal** if it's closed under addition and if $r \in R$; see Definition 15.7, $s \in I$ then $rs \in I$). (Recall Definition 5.94 for the definition of the tensor product \otimes .) Exercise: R/I is also a ring defined like V/W for vector spaces.

If $S \subset R$ is any subset, then (S) is defined to be the ideal generated by S (“ring version of span,” see Definition 15.8). It equals $\text{span}_{\mathbb{R}}\{rs : r \in R, s \in S\}$. (This is an ideal of R .)

Exercise 8. 1. $\wedge^\cdot(V) = \bigoplus_{k \geq 0} \wedge^k V$, where $\wedge^k V$ is the image of $T^k V$ in quotient $\wedge^\cdot V = TV/(x \otimes x)$. ($T^k V$ is the set of equivalence classes of $\sum_i v_{i1} \otimes \dots \otimes v_{ik}$ (k factors))

Multiplication sends $\wedge^k V \times \wedge^\ell V \rightarrow \wedge^{k+\ell} V$.

Abstractly: $T^\cdot V$ is a **graded ring** (the degree- k part is $T^k V$). $(x \otimes x : x \in V)$ [note: not sure if the symbol between x s in this part is \otimes or \oplus] is a **homogeneous ideal** of $T^\cdot V$. We have a “quadratic” ideal.

Quotient of a graded ring by homogeneous ideal is itself a graded ring.

2.

$$\begin{aligned} \{v \in V^{\otimes k} = \text{swap}_i(v) = -v\} &\rightarrow \wedge^k V \\ v + 1 \otimes \dots \otimes v_k &\rightarrow \frac{1}{k!}(v_n \otimes \dots \otimes v_k) \end{aligned}$$

(where $\text{swap}_i(v)$ sends $v_1 \otimes \dots \otimes v_i \otimes v_{i+1} \otimes \dots \otimes v_k$ to $v_1 \otimes \dots \otimes v_{i+1} \otimes v_i \otimes \dots \otimes v_k$. Exercise: this is a well-defined map from $V^{\otimes k}$ to itself.)

[$V^{\otimes k}$ is “ V tensor k ”] This is really a map $V^{\otimes k} \rightarrow \wedge^k V$, $v + 1 \otimes \dots \otimes v_k \rightarrow \frac{1}{k!}(v_1 \otimes \dots \otimes v_k)$, and we can restrict to $\{v \in V^{\otimes k} : \text{swap}_i(v) = -v \forall i\}$, a vector subspace of $V^{\otimes k}$.

The exercise is: The natural map from above is an isomorphism with inverse

$$[v_1 \otimes \dots \otimes v_k] \mapsto \sum_{\sigma \in S_k} \text{sign}(\sigma) v_{\sigma(1)} \otimes \dots \otimes v_{\sigma(k)}.$$

(To check this is well-defined: could define as $\wedge^k V$ by defining on T^*V and checking the ideal $(x \otimes x : x \in V)$ gets sent to 0.)

Note: the second map looks like what appeared on the homework, but without the $1/k!$ factor. The homework conventions are non-standard. Should use above conventions instead.

Notation: write $v_1 \wedge \dots \wedge v_k$ for the equivalence class of $v_1 \otimes \dots \otimes v_k$ in the quotient $\wedge^k V$. If $\alpha \in \wedge^k V$, $\beta \in \wedge^\ell V$, then write $\alpha \wedge \beta$ for their product in $\wedge^{k+\ell} V$.

We can apply this to differential forms. Take $V = (\mathbb{R}^n)^*$. Then $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ can be viewed as a subspace of $V^{\otimes k}$. (From the homework: $\text{Alt}_k(\mathbb{R}^n, \mathbb{R}) \subset (\mathbb{R}^n \otimes \dots \otimes \mathbb{R}^n)^* = (\mathbb{R}^n)^* \otimes \dots \otimes (\mathbb{R}^n)^* = V \otimes \dots \otimes V = V^{\otimes k}$.) Specifically, it's $\{\psi \in (\mathbb{R}^n)^* \otimes \dots \otimes (\mathbb{R}^n)^* : \text{swap}_i(\psi) = -\psi \quad \forall i\}$.

The previous exercise gives us an isomorphism between $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ and $\wedge^k((\mathbb{R}^n)^*)$. Corollary: a differential k -form on $U \subset \mathbb{R}^n$ (U open) is a function from $U \rightarrow \wedge^k((\mathbb{R}^n)^*)$.

Definition 5.119. If α is a k -form on U and β is an ℓ -form on U , define the $(k + \ell)$ -form $\alpha \wedge \beta$ on U by

$$(\alpha \wedge \beta)_p := \underbrace{\alpha_p}_{\wedge^k((\mathbb{R}^n)^*)} \wedge \underbrace{\beta_p}_{\wedge^\ell((\mathbb{R}^n)^*)}$$

The result is in $\wedge^{k+\ell}((\mathbb{R}^n)^*)$ as desired.

Upshot: wedge products are trivial to define in the “quotient description:” sum over permutations appearing when relating to the subspace description.

Corollary 5.7.53.1. If $\alpha \in \text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ and $\beta \in \text{Alt}_\ell(\mathbb{R}^n, \mathbb{R})$, then $\alpha \wedge \beta \in \text{Alt}_{k+\ell}(\mathbb{R}^n, \mathbb{R})$ sends $v_1, \dots, v_{k+\ell}$ to

$$\frac{1}{k! \ell} \sum_{\sigma \in S_{k+\ell}} \text{sign}(\sigma) \alpha(v_{\sigma(1)}, \dots, v_{\sigma(k)}) \beta(v_{\sigma(1)}, \dots, v_{\sigma(k)})$$

Proof. exercise: important to use lecture conventions over homework conventions, especially about factorial placement.

□

Certain things follow immediately from the quotient setup.

- Wedge products are associative (since ring multiplication is associative).
- $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ (or $\wedge^k((\mathbb{R}^n)^*)$) is spanned by wedge products of things in $\text{Alt}_1(\mathbb{R}^n, \mathbb{R}) = \wedge^1((\mathbb{R}^n)^*) = (\mathbb{R}^n)^*$. (Why? $T^k((\mathbb{R}^n)^*)$ is spanned by pure k -tensors of $(\mathbb{R}^n)^*$, and in general, for vector

spaces $W \subset V$, a spanning set for V gives a spanning set for V/W . Thus, $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ is spanned by $\{dx_{i_1} \wedge \dots \wedge dx_{i_k} : 1 \leq i_1 \leq n, \dots, 1 \leq i_k \leq n\}$.

Exercise: can use properties of wedge products to reduce to smaller spanning set: $\{dx_{i_1} \wedge \dots \wedge dx_{i_n} : 1 \leq i_1 < \dots < i_k \leq n\}$. (basic properties like: $dx_i \wedge dx_j = -dx_j \wedge dx_i$, since $(dx_i + dx_j) \wedge (dx_i + dx_j) = 0$. in general: $\alpha \wedge \beta = (-1)^{k\ell} \beta \wedge \alpha$ if $\alpha \in \wedge^k V, \beta \in \wedge^\ell V$. e.g. $dx \wedge dy, dx \wedge dz, dy \wedge dz$ form a basis for $\text{Alt}_2(\mathbb{R}^3, \mathbb{R})$ as in homework, $dx \wedge dy \wedge dz$ is a basis for $\text{Alt}_3(\mathbb{R}^3, \mathbb{R})$.

5/1 Notes covering pullbacks and 1-forms in general (have so far only done for 1-forms). For pullbacks: use $\text{Alt}_k(\mathbb{R}^n, \mathbb{R})$ instead of $\wedge^k((\mathbb{R}^n)^*)$.

Definition 5.120 (Pullbacks). Let $U \subset \mathbb{R}^n$ be open, $V \subset \mathbb{R}^m$ be open, and let $F : U \rightarrow V$ be smooth. Let α be a k -form on V ($\alpha : V \rightarrow \text{Alt}_k(\mathbb{R}^m, \mathbb{R})$). Define a k -form $F^*\alpha$ on U ($F^*\alpha : U \rightarrow \text{Alt}_k(\mathbb{R}^n, \mathbb{R})$) by

$$(F^*(\alpha))_p(\underbrace{v_1}_{\text{vector in } \mathbb{R}^n}, \dots, v_k) := \alpha_{f(p)}(\underbrace{(DF)_p(v_1)}_{\text{"pushforward vectors" in } \mathbb{R}^m}, \dots, (DF)_p(v_k)).$$

One can check that this is multilinear and alternating in the inputs v_1, \dots, v_k . One can also check that is is smooth assuming α is smooth.

Pullbacks and wedge products: we have the formula $F^*(\alpha \wedge \beta) = F^*(\alpha) \wedge F^*(\beta)$ if α is a k -form and β is an ℓ -form (can check using concrete $\frac{1}{k!\ell!} \sum \dots$ definition for $\alpha \wedge \beta$).

Exterior derivatives and wedge products: we have $F^*(d\alpha) = d(F^*\alpha)$ (can check using chain rule, Theorem 5.7.14).

Pullbacks and integrals: below.

Also: wedge products and exterior derivatives: we have the formula $d(\alpha \wedge \beta) = (d\alpha) \wedge \beta + (-1)^k \alpha \wedge (d\beta)$ if α is a k -form. You can check that the sign shows up; intuition: there is a general pattern where d has “degree 1” in some sense, α has degree k . The general sign rule is that when commuting an object of degree k with an object of degree ℓ , the sign is multiplied by $(-1)^{k\ell}$ (“super sign rule”—see within Supersymmetry and Morse theory).

Now we will discuss integrals of n -forms on n -manifolds M . (We need multiple integrals, which is Pugh [2015] section 5.7. Or, just learning Lebesgue theory envelops what we need to know about multiple integrals.) The idea is to use partitions of unity to reduce to the case of n -forms on \mathbb{R}^n (n -forms are completely supported, so 0 outside a compact set), then use your favorite multi-vcr ??? integration theory in \mathbb{R}^n .

As before: if r is a parameterization of a surface S and α is a 2-form on S , then $\int_S \alpha := \int_{\text{domain of } r} r^* \alpha$.

Now we will discuss Riemann integration of compactly supported functions on \mathbb{R}^n . The book discusses functions on $[a_1, b_1] \times \dots \times [a_n, b_n] = Q$ (a hyperprism). Any compactly supported function on \mathbb{R}^n is zero outside some cube Q . If we can define $\int_Q f dx_1 \dots dx_n$, then we can define $\int_{\mathbb{R}^n} f dx_1 \dots dx_n$ by picking any Q such that $f = 0$ outside Q , then setting $\int_{\mathbb{R}^n} f dx_1 \dots dx_n := \int_Q f dx_1 \dots dx_n - n$. (Can check: this is independent of the choice of Q .)

Pugh [2015] discusses Riemann integrability for functions $f : Q \rightarrow \mathbb{R}$. There is a mesh definition, a Darboux-style definition, and a limits of nets definition; all three are equivalent. Lebesgue’s criterion for Riemann integrability (f is continuous except on a null set) still holds.

New: Fubini's Theorem (save real versions for Lebesgue theory (see Theorem 5.11.6 below), where it is properly covered; we will do a very simple version that covers our needs.).

Theorem 5.7.54 (Fubini's Theorem, as stated in 425b). Let $f : Q \rightarrow \mathbb{R}$ be continuous. Then f is Riemann integrable on Q and $\int_Q f dx_1 \dots dx_n$ (the classical Riemann integral) equals

$$\int_{a_1}^{b_1} \left(\int_{a_2}^{b_2} \dots \int_{a_n}^{b_n} f dx_n \dots dx_2 \right) dx_1,$$

the “iterated integral.” Further, the order is irrelevant.

Theorem 5.7.55 (Fubini's Theorem). Let $h : \mathbb{R}^2 \rightarrow \mathbb{R}$ be a continuous function such that $\int \int_{\mathbb{R}^2} |h(x, y)| dx dy < \infty$. Then

$$\int \int_{\mathbb{R}^2} h(x, y) dx dy = \int_{\mathbb{R}} \left(\int_{\mathbb{R}} h(x, y) dx \right) dy = \int_{\mathbb{R}} \left(\int_{\mathbb{R}} h(x, y) dy \right) dx$$

Note: the measure theoretic version of Fubini's Theorem requires less than continuity, only integrability.

Finally, the change of variables formula. This is a multivariable analogue of u -substitution.

Theorem 5.7.56. Let $\phi : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a C^1 diffeomorphism and let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a compactly supported Riemann integrable function. Then

$$\int_{\mathbb{R}^n} f dx_1 \dots dx_n = \int_{\mathbb{R}^n} \underbrace{(f \circ \phi)}_{\substack{\text{also compactly supported} \\ \text{“Jacobian determinant”}}} \underbrace{|\det(J\phi)|}_{\substack{| \det(J\phi) | \\ \text{“Jacobian determinant”}}} dx_1 \dots dx_n.$$

Proof. Not easy, takes several pages in Pugh [2015].

□

As above: use this to define $\int_M \omega$, where ω is an n -form on M . (ω : also a common name for differential forms.)

Proposition 5.7.57 (Integrals and pullbacks). If M, N are smooth n -manifolds and $f : M \rightarrow N$ is a diffeomorphism, and ω is an n -form on N , then

$$\int_N \omega = \int_M f^* \omega.$$

Exercise: is this correctly stated? subtle question of orientations; gloss over for now.

Sketch of proof. In chart, $w = g dy_1 \wedge \dots \wedge dy_n$ (y_i are the coordinates on N). This implies

$$f^* \omega = (g \circ f) d(y_1 \circ f) \wedge \dots \wedge d(y_n \circ f)$$

where f_i are the “coordinates” of f . We can write this as

□

Integrals and wedge products: $\int_M (\alpha \wedge \beta)$ vs. $\int_? \alpha \wedge \int_? \beta$: can’t say much here based on what we’ve covered so far.

Theorem 5.7.58 (Stokes’ Theorem). Let ω be a $n - 1$ -form on M with boundary ∂M . Then $\int_M d\omega = \int_{\partial M} \omega$.

On Monday (final lecture), we will see how this generalizes Green’s Theorem, Stokes’ Theorem, and the Divergence Theorem.

5/4/20

Definition 5.121 (orientation; rough definition). An **orientation** on a smooth n -manifold M is an equivalence class of smooth atlases \mathcal{A} such that $\det J\phi > 0$ for all transition maps ϕ , modulo $A \sim A'$ if their union still satisfies this positive Jacobian determinant property.

The definition of $\int_M \omega$ requires choice of orientation on M ; the other choice gives $-\int_M \omega$.

Definition 5.122. $f : M \rightarrow N$ (smooth) is **orientation-preserving** if $\det(Jf) > 0$ in some (equivalently: any) coordinate charts compatible with the orientation.

Theorem 5.7.59. If $f : M \rightarrow N$ is an orientation-preserving diffeomorphism and ω is an n -form on N , then

$$\int_N \omega = \int_M f^* \omega.$$

Sketch of proof. same as before (?)

□

For $C \in \mathbb{R}^n$, orientation is encoded by the unit tangent vector field \mathbf{T} (\mathbf{r} is an “oriented parameterization” if $\mathbf{r}'(t)/\|\mathbf{r}'(t)\| = \mathbf{T}(\mathbf{r}(t))$ (as opposed to $-\mathbf{T}(\mathbf{r}(t))$)).

For $S \in \mathbb{R}^3$ parameterized by $\mathbf{r}(u, v)$, orientation on S is encoded by the unit normal vector \hat{n} (vector-valued ($\in \mathbb{R}^3$) function on S). (\mathbf{r} is an **oriented parameterization** is

$$\frac{\frac{\partial \mathbf{r}}{\partial u} \times \frac{\partial \mathbf{r}}{\partial v}}{\left\| \frac{\partial \mathbf{r}}{\partial u} \times \frac{\partial \mathbf{r}}{\partial v} \right\|} = \hat{n} \quad \forall u, v \quad (\text{not } -\hat{n})$$

Thus, parameterization of $C \subset \mathbb{R}^n$, or $S \subset \mathbb{R}^3$, gives an orientation.

important thing: this theorem about pullbacks and integrals is about orientations preserving integrals.

Next we will proceed to Stokes’ and Divergence theorems. We will start with Green’s Theorem.

Theorem 5.7.60 (Green's Theorem (somewhat imprecise statement) (stated by Green in 1828, proven by Riemann in 1851)). Let $D \subset \mathbb{R}^2$ be a “region” bounded by a (say smooth) curve C . D is given the “usual orientation,” and C has an induced orientation⁵— C is parameterized counterclockwise. A classical line integral of the form $\oint_C \underbrace{Pdx + Qdy}_{\text{1-form on } D}$ (if the 1-form is defined on the whole bulk) is equal to

$$\int \int_D \left(\underbrace{\frac{\partial Q}{\partial x} - \frac{\partial P}{\partial y}}_{\text{1-form on } D} \right) dx dy$$

(The underlined 1-form can be extended by zero outside D ; get a compactly supported function on \mathbb{R}^n (not continuous; ok if D is “nice.”))

Proof. Let $\omega := Pdx + Qdy$, a 1-form on D . Then

$$d\omega = \left(\frac{\partial Q}{\partial x} - \frac{\partial P}{\partial y} \right) dx dy,$$

so

$$\oint_C \omega = (\text{by Generalized Stokes' Theorem}) \int_D d\omega = \int \int_D \left(\frac{\partial Q}{\partial x} - \frac{\partial P}{\partial y} \right) dx dy = \int \int_D \left(\frac{\partial Q}{\partial x} - \frac{\partial P}{\partial y} \right) dx dy.$$

□

For classical Stokes’ and divergence theorems, we need **surface integrals/fluxes** (applied terminology).

Let $S \subset \mathbb{R}^3$ be a surface parameterized by $\mathbf{r} : K \rightarrow S \subset \mathbb{R}^3$ where K is a compact subset of \mathbb{R}^2 (“nice enough,” not a Cantor set). (Classically you write $\mathbf{r} : K \rightarrow \mathbb{R}^3$, which we would call $i \circ \mathbf{r}$; we’ll sometimes be ambiguous about i , like for curves.)

We want an “area form” (2-form) dA on S , analogous to ds on a curve C .

Definition 5.123. The **vector area function** of (S, \mathbf{r}) is a function $\mathbf{A} : K \rightarrow \mathbb{R}^3$ defined by

$$\mathbf{A}(u, v) := \frac{\partial \mathbf{r}}{\partial u}(u, v) \times \frac{\partial \mathbf{r}}{\partial v}(u, v).$$

Note that $\mathbf{A}(u, v)$ is normal to S and its length is proportional to both $\frac{\partial \mathbf{r}}{\partial u}$ and $\frac{\partial \mathbf{r}}{\partial v}$.

The **unit normal vector function** $\hat{n} : K \rightarrow \mathbb{R}^3$ is defined by

$$\hat{n}(u, v) := \frac{\mathbf{A}(u, v)}{\|\mathbf{A}(u, v)\|}.$$

⁵In general, if M is an oriented smooth manifold with boundary, then you get an induced “boundary orientation” on ∂M , so $\int_M d\omega = \int_{\partial M} \omega$ makes sense.

Note that $\|\mathbf{A}(u, v)\| \neq 0$ since $\frac{\partial \mathbf{r}}{\partial u}$ and $\frac{\partial \mathbf{r}}{\partial v}$ are linearly independent for all (u, v) (this should be assumed as part of “niceness” for \mathbf{r}).

We'll usually view \hat{n} as a function on S , defined by

$$\hat{n}(\mathbf{r}(u, v)) := \frac{\mathbf{A}(u, v)}{\|\mathbf{A}(u, v)\|}.$$

Proposition 5.7.61. There exists a unique 2-form dA on S such that

$$\mathbf{r}^*(dA) = \|\mathbf{A}\| du \wedge dv = \left\| \frac{\partial \mathbf{r}}{\partial u}(u, v) \times \frac{\partial \mathbf{r}}{\partial v}(u, v) \right\| du \wedge dv.$$

Proof. Basically true by definition; can define things by what they look like in a parameterization. If not considering different \mathbf{r} , then don't need to check independence of \mathbf{r} , etc.

□

Definition 5.124 (Classical). If f is a function on $S \subset \mathbb{R}^3$, then

$$\int \int_S f dA := \int \int_K f(\mathbf{r}(u, v)) \left\| \frac{\partial \mathbf{r}}{\partial u}(u, v) \times \frac{\partial \mathbf{r}}{\partial v}(u, v) \right\| du \wedge dv.$$

typical notation for forms

Proposition 5.7.62. The classical definition of $\int \int_S f dA$ is equal to

$$\overbrace{\int_S}^{\begin{matrix} \text{2-form} \\ \text{f} dA \end{matrix}} f dA.$$

Proof.

$$\underbrace{\int_S f dA}_{\text{2-form}} := \int_K \mathbf{r}^*(f dA) = \int_K f(\mathbf{r}) \left\| \frac{\partial \mathbf{r}}{\partial u}(u, v) \times \frac{\partial \mathbf{r}}{\partial v}(u, v) \right\| du \wedge dv = \int \int_K f(\mathbf{r}(u, v)) \left\| \frac{\partial \mathbf{r}}{\partial u}(u, v) \times \frac{\partial \mathbf{r}}{\partial v}(u, v) \right\| du \wedge dv.$$

□

This is the first kind of surface integral defined in [Stewart \[2015\]](#). [Stewart \[2015\]](#) Uses these to define surface integrals of vector fields on S .

Definition 5.125 (Classical). If \mathbf{F} is a vector field on S (here and in analogous situations, defined to be a function from S to \mathbb{R}^3 ; not necessarily a tangent vector field to S), then

$$\int \int_S \mathbf{F} \cdot d\mathbf{A} := \int \int_S (\mathbf{F} \cdot \hat{n}) dA$$

(Both sides of the equation are equally common notation, but the right side indicates more clearly how the integral is defined; $f = \mathbf{F} \cdot \hat{n}$ is a function on S and we know $\int \int_S f dA$. The left side is the surface integral of \mathbf{F} on S , or the flux of \mathbf{F} across S .)

This is analogous to $\int_C (\mathbf{F} \cdot \mathbf{T}) ds$. Why \hat{n} here and not \mathbf{T} ? Why \mathbf{T} for curves? Answer: curves in \mathbb{R}^n are a 1-form α on C , so a 1-form α on \mathbb{R}^n , which can be viewed as a vector field \mathbf{F} on \mathbb{R}^n , which we can restrict to a vector field \mathbf{F} on C . Then $\alpha = (\mathbf{F} \cdot \mathbf{T}) ds$, so this is the most natural thing to integrate on C .

For surfaces: let α be a 2-form on $S \subset \mathbb{R}^3$. We can extend this to a 2-form α on \mathbb{R}^3 , which corresponds in the usual way to a vector field \mathbf{F} on \mathbb{R}^3 . Then we can restrict it to S to get a vector field \mathbf{F} on S .

Proposition 5.7.63. $\alpha = (\mathbf{F} \cdot \hat{n}) dA$.

Proof. Write

$$\mathbf{F} = \begin{bmatrix} F_1 \\ F_2 \\ F_3 \end{bmatrix};$$

corresponds to $\alpha = F_3 dx \wedge dy - F_2 dx \wedge dz + F_1 dy \wedge dz$ as in the homework. We want to show

$$\mathbf{r}^*(\alpha) \tag{5.41}$$

is equal to

$$\mathbf{r}^*((\mathbf{F} \cdot \hat{n}) dA). \tag{5.42}$$

Let

$$\mathbf{r}(u, v) := \begin{bmatrix} r_1(u, v) \\ r_2(u, v) \\ r_3(u, v) \end{bmatrix}.$$

Then (5.41) is

$$\begin{aligned} & \mathbf{r}^*(F_3 dx \wedge dy - F_2 dx \wedge dz + F_1 dy \wedge dz) \\ &= (F_3 \cdot \mathbf{r}) dr_1 \wedge dr_2 - (F_2 \cdot \mathbf{r}) dr_1 \wedge dr_3 + (F_1 \cdot \mathbf{r}) dr_2 \wedge dr_3 \\ &= (F_3 \circ \mathbf{r}) \det(J_{\mathbf{r}_{12}}) - \dots \end{aligned}$$

Note that

Meanwhile, (5.42) equals

$$\mathbf{r}^*((\mathbf{F} \cdot \hat{n}) dA) \tag{5.43}$$

$$=((\mathbf{F} \circ \mathbf{r})(\hat{n} \circ \mathbf{r})) \|\mathbf{A}(u, v)\| du \wedge dv \tag{5.44}$$

$$=((\mathbf{F} \circ \mathbf{r}) \cdot \frac{\mathbf{A}(u, v)}{\|\mathbf{A}(u, v)\|}) \|\mathbf{A}(u, v)\| du \wedge dv \tag{5.45}$$

$$=((\mathbf{F}(\mathbf{r}(u, v)) \cdot \mathbf{A}(u, v)) du \wedge dv \tag{5.46}$$

Note that

$$\frac{\partial \mathbf{r}}{\partial u} \times \frac{\partial \mathbf{r}}{\partial v} = \hat{i} \begin{vmatrix} \frac{\partial r_2}{\partial u} & \frac{\partial r_2}{\partial v} \\ \frac{\partial r_3}{\partial u} & \frac{\partial r_3}{\partial v} \end{vmatrix} - \hat{j} \det(J_{\mathbf{r}_{13}}) + \hat{k} \det(J_{\mathbf{r}_{12}}).$$

Then

$$\mathbf{F}(\mathbf{r}(u, v)) \cdot \mathbf{A}(u, v) = F_1(\mathbf{r}*, v) \det(J_{\mathbf{r}_{2,3}}) - F_2(\mathbf{r}(u, v)) \det(J_{\mathbf{r}_{13}}) + F_1(\mathbf{r}(u, v) \det J_{\mathbf{r}_{12}}.$$

But that's what we got for (5.41). □

Corollary 5.7.63.1. $\int_S \underbrace{\alpha}_{2-form} = \underbrace{\int \int_S (\mathbf{F} \cdot \hat{n}) dA}_{\text{classical}}$, where \mathbf{F} , α correspond as above.

Now we can state

Theorem 5.7.64 (Stokes' Theorem). If $S \subset \mathbb{R}^3$ is an oriented surface with boundary C and \mathbf{F} is a vector field on S , then

$$\oint_C (\mathbf{F} \cdot \mathbf{T}) ds = \int \int_S ((\nabla \times \mathbf{F}) \cdot \hat{n}) dA.$$

(where $\nabla \times \mathbf{F} = \text{curl}(\mathbf{F})$).

Proof. Extend \mathbf{F} to \mathbb{R}^3 ; write $F = [F_1 \ F_2 \ F_3]^\top$ with corresponding 1-form $\alpha := F_1 dx + F_2 dy + F_3 dz$. Then

$$\oint_C (\mathbf{F} \cdot \mathbf{T}) ds = \int_C \alpha = (\text{by Generalized Stokes' Theorem}) \int_S d\alpha = (\text{by above + homework}) \int \int_S ((\nabla \times \mathbf{F}) \cdot \hat{n}) dA.$$

□

Theorem 5.7.65 (Gauss Divergence Theorem). If S is the boundary of $\Omega \in \mathbb{R}^3$ and \mathbf{F} is a vector field on Ω , then

$$\iint_S (\mathbf{F} \cdot \hat{n}) dA = \iiint_\Omega (\nabla \cdot \mathbf{F}) dx dy dz$$

where $\nabla \cdot \mathbf{F} = \text{divergence}(\mathbf{F})$.

Proof. Write $\mathbf{F} = [F_1 \ F_2 \ f_3]^\top$; corresponding 2-form on \mathbb{R}^3 is $\alpha = F_3 dx \wedge dy - F_2 dx \wedge dz + F_1 dy \wedge dz$. Then

$$\begin{aligned}
& \iint_S (\mathbf{F} \cdot \hat{\mathbf{n}}) dA \\
&= \int_S \alpha \\
&= (\text{by Stokes' Theorem}) \int_{\Omega} d\alpha \\
&= \text{by Homework} \int_{\Omega} (\nabla \cdot \mathbf{F}) dx \wedge dy \wedge dz \\
&= \iiint_{\Omega} (\nabla \cdot \mathbf{F}) dx dy dz.
\end{aligned}$$

(the homework property is that a function corresponding to a 3-form $d\alpha$ is the divergence $\nabla \cdot \mathbf{F}$)

□

5.8 Gateaux Derivatives (Section 1.6 of Koroljuk et al. [1994], Section 6.2 of Serfling [1980])

5.9 Preliminaries to Measure Theory (Chapter 0 of ?)

A primary goal of this course is integration in as general a context as possible. In particular, want to avoid assumptions of continuity, because it is not always a natural assumption.

Example 5.30. Define

$$L^2[0, 1] = \left\{ f : [0, 1] \rightarrow \mathbb{R} : \int_0^1 f^2(x) dx < \infty \right\}.$$

Distance in $L^2[0, 1]$:

$$d_2(f, g) = \left[\int_0^1 (f(x) - g(x))^2 dx \right]^{1/2}.$$

$f_n \rightarrow f$ in L^2 means $d_2(f_n, f) \rightarrow 0$. Suppose we restrict to continuous functions:

$$L_C^2[0, 1] = \{ \text{all continuous functions in } L^2[0, 1] \}.$$

We may then have sequences $\{f_n\}$ in $L_C^2[0, 1]$ which converge

5.10 Measures (Chapter 1 of ?)

Definition 5.126 (p. 25 of?). Let (X, \mathcal{M}, μ) be a measure space. If $\mu(X) < \infty$ (which implies that $\mu(E) < \infty$ for all $E \in \mathcal{M}$), μ is called **finite**. If $X = \cup_{j=1}^{\infty} E_j$ where $E_j \in \mathcal{M}$ and $\mu(E_j) < \infty$ for all j , μ is called **σ -finite**. More generally, if $E = \cup_{j=1}^{\infty} E_j$ where $E_j \in \mathcal{M}$ and $\mu(E_j) < \infty$ for all j , the set E is said to be **σ -finite** for μ . If for each $E \in \mathcal{M}$ with $\mu(E) = \infty$ there exists $F \in \mathcal{M}$ with $F \subset E$ and $0 < \mu(F) < \infty$, μ is called **semifinite**.

Theorem 5.10.1 (Theorem 1.8 in?). Let (X, \mathcal{M}, μ) be a measure space.

- (a) (**Montonicity.**) If $E, F \in \mathcal{M}$ and $E \subset F$, then $\mu(E) \leq \mu(F)$.
- (b) (**Subadditivity.**) If $\{E_j\}_{j=1}^{\infty} \subset \mathcal{M}$, then $\mu(\cup_{j=1}^{\infty} E_j) \leq \sum_{j=1}^{\infty} \mu(E_j)$.
- (c) (**Continuity from below.**) If $\{E_j\}_{j=1}^{\infty} \subset \mathcal{M}$ and $E_1 \subset E_2 \subset \dots$, then $\mu(\cup_{j=1}^{\infty} E_j) = \lim_{j \rightarrow \infty} \mu(E_j)$.
- (d) (**Continuity from above.**) If $\{E_j\}_{j=1}^{\infty} \subset \mathcal{M}$, $\mu(E_1) < \infty$, and $E_1 \supset E_2 \supset \dots$, then $\mu(\cap_{j=1}^{\infty} E_j) = \lim_{j \rightarrow \infty} \mu(E_j)$.

5.11 Integration (Chapter 2 of ?)

Definition 5.127. Given a measure space (X, \mathcal{M}, μ) ,

$$L^+ := \text{the space of all measurable functions from } X \text{ to } [0, \infty).$$

Definition 5.128. Given a measure space (X, \mathcal{M}, μ) , denote by L^1 the space of all integrable functions on X ; that is, the set of all functions such that $\int |f| < \infty$.

Theorem 5.11.1 (Monotone Convergence Theorem; Theorem 2.14 in?). If $\{f_n\}$ is a sequence in L^+ such that $f_j \leq f_{j+1}$ for all j and $f = \lim_{n \rightarrow \infty} f_n (= \sup_n f_n)$, then

$$\left(\int \lim_{n \rightarrow \infty} f_n = \right) \int f = \lim_{n \rightarrow \infty} \int f_n.$$

Theorem 5.11.2 (Fatou's Lemma; Theorem 2.18 in?). If $\{f_n\}$ is any sequence in L^+ , then

$$\int (\liminf f_n) \leq \liminf \int f_n.$$

Theorem 5.11.3 (Dominated Convergence Theorem; Theorem 2.24 in?). Let $f_n \in L^1$ and $f_n \rightarrow f$ almost everywhere. Suppose there exists $g \in L^1$ with $|f_n| \leq g$ for all n . Then $f \in L^1$ and $\int f = \lim_n \int f_n$.

Remark 27. See also Theorem 6.4.2 for an application of this theorem to probability.

Remark 28. Let $\{f_n\}$ be measurable functions on (X, \mathcal{M}, μ) , $\overline{\mathcal{M}}$ be the completion of \mathcal{M} , and $f_n \rightarrow f$ almost everywhere. Then we know $\{x : \{f_n(x)\} \text{ converges}\} \in \mathcal{M}$ by the assumption that each f_n is measurable. However, since the convergence is merely almost everywhere, we only know $\{x : f_n(x) \rightarrow f(x)\} \in \overline{\mathcal{M}}$ because we don't know about f on null sets.

Note that $g(x) = \lim_n f_n(x)$ is defined for $x \in E$, and g is measurable from (X, \mathcal{M}) . $g = f$ almost everywhere, but $\{g \neq f\}$ may only be in $\overline{\mathcal{M}}$.

There is a null set $N \in \mathcal{M}$ with $\{x : f_n(x) \not\rightarrow f(x)\} \subset N$. If we change f to 0 on N then still $f_n \rightarrow f$ almost everywhere, but now f is measurable for \mathcal{M} .

Proof. Change f to 0 on a null set so that f is measurable (per Remark 28). Since $|f_n| \leq g$ for all n , we have $|f| \leq g$, so $f \in L^1$. We can handle the real and imaginary parts separately for complex-valued function, so assume f is real-valued. It is sufficient to show

$$\liminf_n \int f_n \geq \int f \geq \limsup_n \int f_n. \quad (5.47)$$

Note that

$$\begin{aligned} |f_n| &\leq g \\ \iff -g &\leq f_n \leq g \\ \iff g + f_n &\geq 0, \quad g - f_n \geq 0, \end{aligned}$$

so $f_n + g \in L^+$ and $g - f_n \in L^+$. Therefore by Fatou's Lemma,

$$\begin{aligned} \liminf_n \int (f_n + g) &\geq \int \liminf_n \{f_n + g\} \\ &= \int (f + g) \\ \iff \liminf_n \int f_n &\geq \int f, \end{aligned}$$

where we subtracted $\int g$. This shows the left inequality in (5.47) holds. Similarly,

$$\begin{aligned} -\limsup_n \int (f_n - g) &= \liminf_n \int (g - f_n) \geq \int \liminf_n \{g - f_n\} \\ &= \int (g - f) \\ \iff \liminf_n \int (-f_n) &\geq \int (-f) \\ \iff \limsup_n \int f_n &\leq \int f, \end{aligned}$$

which proves the right inequality in (5.47).

□

Consider the point mass measure

$$\delta_a(E) = \begin{cases} 1, & a \in E, \\ 0, & \text{otherwise.} \end{cases}$$

What is $\int f d\delta_a$? First consider a simple $\phi = \sum_{j=1}^n c_j \chi_{E_j}$:

$$\int \phi d\delta_a = \sum_{i=1}^n c_i \delta_a(E_i) = \sum_{i=1}^n \sum_{j:a \in E_j} c_j = \phi(a).$$

For $f \geq 0$, taking limits of ϕ_n up to f shows

$$\int f \, d\delta_a = f(a).$$

For a general $f = f^+ - f^-$ we can show the same thing. The counting measure is defined by

$$\mu(E) = \sum_{x \in E} \mathbb{1}(x \in \mathbb{N}) = \sum_{n=1}^{\infty} \delta_n(E) = |\mathbb{N} \cap E|,$$

where $\mathbb{1}(\cdot) = 1$ if \cdot holds and 0 otherwise. For simplicity, we can take $\mathcal{M} = \mathcal{P}(\mathbb{N})$.

Proposition 5.11.4. For $\phi : \mathbb{N} \rightarrow \mathbb{R}$ a simple sequence with only finitely many term values (that is, the set of numbers that appears in the sequence is finite),

$$\int \phi \, d\mu = \int \phi \, d\left(\sum_{n=1}^{\infty} \delta_n\right) = \sum_{n=1}^{\infty} \int \phi \, d\delta_n$$

where μ is the counting measure

Proof. Take $\mathcal{M} = \mathcal{P}(\mathbb{N})$. Since $\phi = \sum_{j=1}^n c_j \chi_{E_j}$ (and recall that $E_j \in \mathcal{P}(\mathbb{N})$),

$$\begin{aligned} \int \phi \, d\mu &= \sum_{j=1}^n c_j \mu(E_j) \\ &= \sum_{j=1}^n c_j \sum_{n'=1}^{\infty} \delta_{n'}(E_j) \\ &= \sum_{j=1}^n c_j |E_j| \\ &\stackrel{(*)}{=} \sum_{n=1}^{\infty} \sum_{j:n \in E_j} c_j \\ &= \sum_{n=1}^{\infty} \sum_{j=1}^n c_j \delta_n(E_j) \\ &= \sum_{n=1}^{\infty} \int \phi \, d\delta_n \end{aligned}$$

where $(*)$ follows because c_j appears $|E_j|$ times in the sum on the right.

□

Proposition 5.11.5. Let $u : \mathbb{N} \rightarrow \mathbb{R}_+$ be a positive sequence. Then

$$\int u \, d\mu = \sum_{n=1}^{\infty} u(n)$$

for the measure space $(\mathbb{N}, \mathcal{P}(\mathbb{N}), \mu)$, where μ is the counting measure.

Proof. Express μ as

$$\mu = \sum_{j=1}^{\infty} \delta_j.$$

Define

$$u_n(k) = \begin{cases} u(k), & k \leq n, \\ 0, & k > n \end{cases} = \sum_{k=1}^n u(k) \chi_{\{k\}}.$$

Note that $u_n(k)$ is a simple function for all $n \in \mathbb{N}$. Therefore

$$\int u_n d\mu = \sum_{k=1}^n u(k) \mu(\{k\}) = \sum_{k=1}^n u(k).$$

Since $0 \leq u_n \leq u$ and $\lim_{n \rightarrow \infty} u_n = u$, by the Monotone Convergence Theorem we have

$$\int_{\mathbb{N}} u d\mu = \int_{\mathbb{N}} \lim_{n \rightarrow \infty} u_n d\mu = \lim_{n \rightarrow \infty} \int_{\mathbb{N}} u_n d\mu = \lim_{n \rightarrow \infty} \sum_{k=1}^n u(k) = \sum_{k=1}^{\infty} u(k).$$

□

Corollary 5.11.5.1. Let u_1, \dots, u_n be a finite positive sequence. Then

$$\int u d\mu = \sum_{i=1}^n u_i$$

for the measure space $(\mathbb{N}, \mathcal{P}(\mathbb{N}), \mu)$, where μ is the counting measure.

Proof. Apply Proposition 5.11.5 to the sequence

$$u(i) = \begin{cases} u_i, & i \leq n, \\ 0, & i > n. \end{cases}$$

□

Corollary 5.11.5.2. Let $u : \mathbb{N} \rightarrow \mathbb{R}$ be a sequence. Suppose

$$\sum_{n=1}^{\infty} |u(n)| < \infty.$$

Then

$$\int u d\mu = \sum_{n=1}^{\infty} u(n)$$

for the measure space $(\mathbb{N}, \mathcal{P}(\mathbb{N}), \mu)$, where μ is the counting measure.

Proof. We have

$$\int u d\mu = \int u^+ d\mu - \int u^- d\mu.$$

By Proposition 5.11.5,

$$\int u^+ d\mu = \sum_{n=1}^{\infty} u^+(n), \quad \int u^- d\mu = \sum_{n=1}^{\infty} u^-(n).$$

By assumption,

$$\begin{aligned}
 & \sum_{n=1}^{\infty} |u(n)| < \infty \\
 \iff & \sum_{n=1}^{\infty} (u^+(n) + u^-(n)) < \infty \\
 \iff & \sum_{n=1}^{\infty} u^+(n) + \sum_{n=1}^{\infty} u^-(n) < \infty \\
 \iff & \sum_{n=1}^{\infty} u^+(n) < \infty, \quad \sum_{n=1}^{\infty} u^-(n) < \infty
 \end{aligned}$$

since these are both nonnegative sequences. Therefore

$$\begin{aligned}
 \int u \, d\mu &= \int u^+ \, d\mu - \int u^- \, d\mu \\
 &= \sum_{n=1}^{\infty} u^+(n) - \sum_{n=1}^{\infty} u^-(n) \\
 &= \sum_{n=1}^{\infty} (u^+(n) - u^-(n)) \\
 &= \sum_{n=1}^{\infty} u(n).
 \end{aligned}$$

□

Definition 5.129 ((p. 65 of ?)). Let (X, \mathcal{M}, μ) and (Y, \mathcal{N}, ν) be measure spaces. If $E \subset X \times Y$, for $x \in X$ and $y \in Y$ we define the **x -section** E_x and the **y -section** E^y of E by

$$E_x := \{y \in Y : (x, y) \in E\}, \quad E^y := \{x \in X : (x, y) \in E\}.$$

Also, if f is a function on $X \times Y$ we define the **x -section** f_x and the **y -section** f^y of f by

$$f_x(y) = f^y(x) = f(x, y).$$

Thus, for example, $(\chi_E)_x = \chi_{E_x}$ and $(\chi_E)^y = \chi_{E^y}$.

Theorem 5.11.6 (The Fubini-Tonelli Theorem; Theorem 2.37 in ?). Suppose (X, \mathcal{M}, μ) and (Y, \mathcal{N}, ν) are σ -finite measure spaces.

- (a) (Tonelli.) If $f \in L^+(X \times Y)$, then the functions $g(x) = \int f_x \, d\nu$ and $h(y) = \int f^y \, d\mu$ are in $L^+(X)$ and $L^+(Y)$ respectively, and

$$\int f \, d(\mu \times \nu) = \int \left[\int f(x, y) \, d\nu(y) \right] d\mu(x) = \int \left[\int f(x, y) \, d\mu(x) \right] d\nu(y). \quad (5.48)$$

- (b) (Fubini.) If $f \in L^1(\mu \times \nu)$, then $f_x \in L^1(\nu)$ for almost every $x \in X$, $f^y \in L^1(\mu)$ for almost every $y \in Y$, the almost everywhere-defined functions $g(x) = \int f_x \, d\nu$ and $h(y) = \int f^y \, d\mu$ are in $L^1(\mu)$ and $L^1(\nu)$, respectively, and (5.48) holds.

Remark 29. Recall Theorem 5.7.54 gave a simpler, non-measure-theoretic version of Fubini's Theorem.

5.12 Signed Measures and Differentiation (Chapter 3 of ?)

Theorem 5.12.1 (The Lebesgue-Radon-Nikodym Theorem; Theorem 3.8 in ?). Let ν be a σ -finite signed measure and μ a σ -finite positive measure on (X, \mathcal{M}) . There exist unique σ -finite signed measures λ, ρ on (X, \mathcal{M}) such that

$$\lambda \perp \mu, \quad \rho \ll \mu, \quad \text{and} \quad \nu = \lambda + \rho.$$

Moreover, there is an extended μ -integrable function $f : X \rightarrow \mathbb{R}$ such that $d\rho = f d\mu$ (that is, $\rho(E) = \int_E f d\mu$), and any two such functions are equal μ -almost everywhere.

Definition 5.130. The decomposition $\nu = \lambda + \rho$ where $\lambda \perp \mu$ and $\rho \ll \mu$ is called the **Lebesgue decomposition** of ν with respect to μ . In the case where $\nu \ll \mu$, Theorem 5.12.1 says that $d\nu = f d\mu$ for some f . This result is usually known as the **Radon-Nikodym Theorem**, and f is called the **Radon-Nikodym derivative** of ν with respect to μ . We denote it by $d\nu/d\mu$:

$$d\nu = \frac{d\nu}{d\mu} d\mu \quad \left(\iff \nu(E) = \int_E \frac{d\nu}{d\mu} d\mu \right).$$

(Strictly speaking, $d\nu/d\mu$ should be construed as the class of functions equal to f μ -almost everywhere.)

Theorem 5.12.2 (Theorem 3.22 in ?). Let ν be a regular signed or complex Borel measure on \mathbb{R}^n , and let $d\nu = d\lambda + f dm$ be its Lebesgue-Radon-Nikodym representation. Then for m -almost every $x \in \mathbb{R}^n$,

$$\lim_{r \rightarrow 0} \frac{\nu(E_r)}{m(E_r)} = f(x)$$

for every family $\{E_r\}_{r>0}$ that shrinks nicely to x .

5.13 Elements of Functional Analysis (Chapter 5 of ?)

5.14 Problems from Practice Math GRE Subject Tests

38. Let A and B be nonempty subsets of \mathbb{R} and let $f : A \rightarrow B$ be a function. If $C \subseteq A$ and $D \subseteq B$, which of the following must be true?

(A) $C \subseteq f^{-1}(f(C))$

(B) $D \subseteq f(f^{-1}(D))$

(C) $f^{-1}(f(C)) \subseteq C$

Solution 38. (A) Neither of the equalities should hold – these are in fact nonsense statements, as one side lies in A and the other in B . To unravel the remaining two sets,

$$f^{-1}(f(C)) = \{x \in A : f(x) \in f(C)\}, \quad f(f^{-1}(D)) = f(\{y \in A : f(y) \in D\})$$

Clearly the second set must always be contained in D , but not the other way around. Similarly the first set certainly contains all $c \in C$ (as $f(c) \in f(C)$) but not the other way around.

47. The function $f : \mathbb{R} \rightarrow \mathbb{R}$ is defined as follows.

$$f(x) = \begin{cases} 3x^2 & \text{if } x \in \mathbb{Q} \\ -5x^2 & \text{if } x \notin \mathbb{Q} \end{cases}$$

Which of the following is true?

- (A) f is discontinuous at all $x \in \mathbb{R}$.
- (B) f is continuous only at $x = 0$ and differentiable only at $x = 0$.
- (C) f is continuous only at $x = 0$ and nondifferentiable at all $x \in \mathbb{R}$.
- (D) f is continuous at all $x \in \mathbb{Q}$ and nondifferentiable at all $x \in \mathbb{R}$.
- (E) f is continuous at all $x \notin \mathbb{Q}$ and nondifferentiable at all $x \in \mathbb{R}$.

Solution 47. (B) A classic kind of problem. We are clearly continuous and differentiable at 0. Anywhere else, near a rational number there is an irrational number and vice versa. Therefore there can be no continuity anywhere but at 0, and hence no differentiability either.

57. For each positive integer n , let x_n be a real number in the open interval $\left(0, \frac{1}{n}\right)$. Which of the following statements must be true?

- I. $\lim_{n \rightarrow \infty} x_n = 0$
 - II. If f is a continuous real-valued function defined on $(0, 1)$, then $\{f(x_n)\}_{n=1}^{\infty}$ is a Cauchy sequence.
 - III. If g is a uniformly continuous real-valued function defined on $(0, 1)$, then $\lim_{n \rightarrow \infty} g(x_n)$ exists.
- (A) I only (B) I and II only (C) I and III only (D) II and III only (E) I, II, and III

Solution 57. (C) I is true, since $\lim_{n \rightarrow \infty} x_n$ must be bounded between 0 and $\lim_{n \rightarrow \infty} 1/n = 0$. Unfortunately, x_n does not converge inside $(0, 1)$. There is no reason therefore that $f(x_n)$ should be a convergent sequence – suppose that $f(x) = 1/x$, so that $f(x_n)$ is certainly not Cauchy. However, if g is uniformly continuous, then g extends to a continuous function on $[0, 1]$. Now x_n is a convergent sequence, so $\lim_{n \rightarrow \infty} g(x_n) = g(\lim_{n \rightarrow \infty} x_n) = g(0)$ exists.

60. A real-valued function f defined on \mathbb{R} has the following property.

For every positive number ϵ , there exists a positive number δ such that

$$|f(x) - f(1)| \geq \epsilon \text{ whenever } |x - 1| \geq \delta.$$

This property is equivalent to which of the following statements about f ?

- (A) f is continuous at $x = 1$.
- (B) f is discontinuous at $x = 1$.
- (C) f is unbounded.
- (D) $\lim_{|x| \rightarrow \infty} |f(x)| = \infty$
- (E) $\int_0^{\infty} |f(x)| dx = \infty$

Solution 60. (D) While it looks like this is the opposite of continuity, that should read ‘there exists $\epsilon > 0$ ’. What the statement says is that we not only get arbitrarily far away from $f(1)$, but we must for all x sufficiently far away from 1. So as $|x|$ gets very large, so does $|f(x)|$.

63. For any nonempty sets A and B of real numbers, let $A \cdot B$ be the set defined by

$$A \cdot B = \{xy : x \in A \text{ and } y \in B\}.$$

If A and B are nonempty bounded sets of real numbers and if $\sup(A) > \sup(B)$, then $\sup(A \cdot B) =$

- (A) $\sup(A) \sup(B)$
- (B) $\sup(A) \inf(B)$
- (C) $\max\{\sup(A) \sup(B), \inf(A) \inf(B)\}$
- (D) $\max\{\sup(A) \sup(B), \sup(A) \inf(B)\}$
- (E) $\max\{\sup(A) \sup(B), \inf(A) \sup(B), \inf(A) \inf(B)\}$

Solution 63. (E) The supremum is either going to be the product of the two largest positive numbers in A and B or the product of the two smallest negative numbers in A and B . That means we should look for $\sup \cdot \sup$ or $\inf \cdot \inf$. However, it might be the case that B contains only negative numbers and A contains only positive numbers. Then the largest value in $A \cdot B$ will be attained by the smallest positive element of A and the largest negative element of B , giving us our third option: $\inf A \cdot \sup B$.

Chapter 6

Probability

These are my notes from taking Math 505A at USC taught by Sergey Lototsky, Math 541A at USC taught by Steven Heilman, ISE 620 at USC taught by Sheldon Ross (as well as the corresponding textbooks *Introduction to Probability Models* [Ross, 2014] and *Stochastic Processes* [Ross, 2008] by Sheldon Ross) and the textbook *Probability and Random Processes* (Grimmett and Stirzaker) 3rd edition [Grimmett and Stirzaker, 2001], Math 541B at USC taught by Stanislav Minsker, Statistics 100B at UCLA taught by Nicolas Christou, as well as a few other sources I cite within the text.

6.1 To Know for Math 505A Midterm 1 (Discrete Random Variables)

6.1.1 Definitions

Definition 6.1. The **probability mass function** of a discrete random variable X is the function $f : \mathbb{R} \rightarrow [0, 1]$ given by $f(x) = \Pr(X = x)$.

Definition 6.2. The **(cumulative) distribution function** of a discrete random variable F is given by

$$F(x) = \sum_{i:x_i \leq x} f(x_i)$$

Definition 6.3. The **joint probability mass function** $f : \mathbb{R}^2 \rightarrow [0, 1]$ of two discrete random variables X and Y is given by

$$f(x, y) = \Pr(X = x \cap Y = y)$$

Definition 6.4. The **joint distribution function** $F : \mathbb{R}^2 \rightarrow [0, 1]$ is given by

$$F(x, y) = \Pr(X \leq x \cap Y \leq y)$$

Definition 6.5. If $\Pr(B) > 0$ then the **conditional probability** that A occurs given that B occurs is defined to be

$$\Pr(A | B) = \frac{\Pr(A \cap B)}{\Pr(B)}$$

Definition 6.6. (Independent sets.) Let A_1, A_2, \dots be subsets of a sample space Ω , and let \mathbb{P} be a probability law on Ω . We say that A_1, A_2, \dots are **independent** if for any finite subset S of $\{1, 2, \dots\}$, we have

$$\mathbb{P}\left(\bigcap_{i \in S} A_i\right) = \prod_{i \in S} \mathbb{P}(A_i)$$

Definition 6.7. (Notation.) Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable. Let $B \subseteq \mathbb{R}$. We define $\{X \in B\} := \{\omega \in \Omega : X(\omega) \in B\}$.

Definition 6.8. (Independence of random variables.) Random variables X_1, X_2, \dots are **independent** if for every $B_1, B_2, \dots \subseteq \mathbb{R}$, the events $\{X_1 \in B_1\}, \{X_2 \in B_2\}, \dots$ are independent; that is,

$$\mathbb{P}\left(\bigcap_{i=1}^n \{X_i \in B_i\}\right) = \prod_{i=1}^n \mathbb{P}(\{X_i \in B_i\})$$

Remark 30. A more informal definition is as follows: Two random variables X and Y are **independent** if and only if $\Pr(X \cap Y) = \Pr(X) \Pr(Y)$.

Theorem 6.1.1. (Law of total probability). If X is a random variable and Y is a discrete random variable taking on values y_1, y_2, \dots, y_n , then $\Pr(X) = \sum_i \Pr(X | Y = y_i) \cdot \Pr(Y = y_i)$. (Can be used to prove independence.)

Lemma 6.1.2. Let $B_1, A_1, A_2, \dots, A_m$ be subsets of a sample space Ω and let \mathbb{P} be a probability law on Ω . Let X_1, X_2, \dots, X_m , and Z be random variables. If Z is independent of X_i for all $i \in 1, \dots, m$, then

$$\mathbb{P}\left(\bigcap_{i=1}^m \{X_i \in A_i\} \cap Z \in B_1\right) = \mathbb{P}\left(\bigcap_{i=1}^m \{X_i \in A_i\}\right) \mathbb{P}(Z \in B_1).$$

That is, $\bigcap_{i=1}^m X_i$ is independent of Z .

Proof. Note that by the definition of conditional probability,

$$\begin{aligned} \mathbb{P}\left(\bigcap_{i=1}^m X_i \in A_i \mid Z \in B_1\right) &= \frac{\mathbb{P}(\bigcap_{i=1}^m \{X_i \in A_i\} \cap Z \in B_1)}{\mathbb{P}(Z \in B_1)} \\ &= \frac{\prod_{j=1}^{m-1} [\mathbb{P}(X_j \in A_j \mid \bigcap_{k=j+1}^m \{X_k \in A_k\} \cap Z \in B_1)] \cdot \mathbb{P}(X_m \in A_m \cap Z \in B_1)}{\mathbb{P}(Z \in B_1)} \\ &= \frac{\prod_{j=1}^{m-1} [\mathbb{P}(X_j \in A_j \mid \bigcap_{k=j+1}^m \{X_k \in A_k\}, Z \in B_1)] \cdot \mathbb{P}(X_m \in A_m \mid Z \in B_1) \mathbb{P}(Z \in B_1)}{\mathbb{P}(Z \in B_1)} \end{aligned}$$

Cancelling and using the independence of X_i and Z for all i , we have

$$= \prod_{j=1}^{m-1} [\mathbb{P}(X_j \in A_j \mid \bigcap_{k=j+1}^m \{X_k \in A_k\}) \cdot \mathbb{P}(X_m \in A_m)] = \mathbb{P}\left(\bigcap_{i=1}^m \{X_i \in A_i\}\right)$$

Then the result follows since

$$\mathbb{P}\left(\bigcap_{i=1}^m \{X_i \in A_i\} \cap Z \in B_1\right) = \mathbb{P}\left(\bigcap_{i=1}^m X_i \in A_i \mid Z \in B_1\right) \mathbb{P}(Z \in B_1) = \mathbb{P}\left(\bigcap_{i=1}^m \{X_i \in A_i\}\right) \mathbb{P}(Z \in B_1).$$

□

Definition 6.9. Two random variables X and Y are **uncorrelated** if $\mathbb{E}(XY) = \mathbb{E}(X)\mathbb{E}(Y)$.

Proposition 6.1.3. (a) Two random variables are uncorrelated if and only if their covariance $\text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}(X))(Y - \mathbb{E}(Y))] = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y)$ equals 0.

(b) If X and Y are independent then they are uncorrelated.

Theorem 6.1.4. If X and Y are independent and $g, h : \mathbb{R} \rightarrow \mathbb{R}$, then $g(X)$ and $h(Y)$ are also independent.

Definition 6.10. We say that a nonnegative random variable X is **lattice** with period d if

$$\sum_{n=0}^{\infty} \Pr(X = nd) = 1$$

and d is the largest number that satisfies this equation.

Remark 31. Most common discrete random variables are lattice, but not all discrete random variables are. For example, the discrete random variable X such that

$$\Pr(X = 1/i) = p_i > 0, \quad i \geq 1$$

such that $\sum_{i=1}^{\infty} p_i = 1$ is not lattice. Another example is

$$X = \begin{cases} 1 & \text{with probability } 1/2 \\ \sqrt{2} & \text{with probability } 1/2 \end{cases}$$

because there is no d such that there are integers m and n so that

$$1 = md$$

$$\sqrt{2} = nd.$$

(If there were, then we would have

$$\frac{n}{m} = \frac{nd}{md} = \sqrt{2}$$

but there are no integers n and m such that this is true, since $\sqrt{2}$ is irrational.)

6.1.2 Conditioning

Definition 6.11. The **conditional distribution function** of Y given $X = x$, written $F_{Y|X}(\cdot | x)$, is defined by

$$F_{Y|X}(y | x) = \Pr(Y \leq y | X = x)$$

Definition 6.12. The **conditional probability mass function** of Y given $X = x$, written $f_{Y|X}(\cdot | x)$, is defined by

$$f_{Y|X}(y | x) = \Pr(Y = y | X = x)$$

Definition 6.13 (Conditional Expectation (Math 541B definition)). Let X, Y be random variables, and assume that $\mathbb{E}|X| < \infty$. Then the conditional expectation of X given Y , denoted $\mathbb{E}(X | Y)$, is a function of Y : $g(Y) = \mathbb{E}(X | Y)$ such that for any bounded f ,

$$\mathbb{E}(Xf(Y)) = \mathbb{E}(g(Y)f(Y))$$

Now assume that $\mathbb{E}X^2 < \infty$, $\mathbb{E}Y^2 < \infty$. Consider the Hilbert space $(\mathbb{H}, \langle \cdot, \cdot \rangle)$ consisting of all random variables with finite second moment and $\langle X, Y \rangle := \mathbb{E}(XY)$. Consider $L(Y) = \{\text{all random variables of the form } X = \phi(Y) \text{ where } \mathbb{E}Z^2 < \infty\}$ ¹. Then $\mathbb{E}(X | Y)$ is the orthogonal projection of X onto the subspace $L(Y)$. Indeed,

$$\mathbb{E}(X \cdot f(Y)) = \langle X, f(Y) \rangle = \mathbb{E}(\mathbb{E}(X | Y)f(Y)) = \langle \mathbb{E}(X | Y), f(Y) \rangle$$

$$\iff \forall f, \langle X - \mathbb{E}(X | Y), f(Y) \rangle = 0.$$

(because $\mathbb{E}[(X - \mathbb{E}(X | Y)) \cdot f(Y)] = \mathbb{E}(\mathbb{E}[Xf(Y) | Y] - \mathbb{E}[\mathbb{E}(X | Y)f(Y) | Y]) = \dots$)

$(f(Y) \in L(Y))$.

Remark 32. Think of expectation as the best summary of a random variable with one value, and conditional expectation as the best summary of one random variable as a function of another random variable.

Remark 33.

¹clear that this subspace is linear: any linear combination of square integrable functions of Y is also square integrable. less clear that this is a closed space; that is, that any limit of functions in this space is also in this space. But it turns out that it is, so since this is a closed linear subspace.

Example 6.1. Assume (X, Y) has joint pdf $p(x, y)$. Then $\mathbb{E}(X \mid Y = y) = \int_{\mathbb{R}} x p_{X|Y}(x \mid y) dx$, where $p_{X|Y}(x \mid y)$ is the conditional density of X given Y ; that is,

$$p_{X|Y}(x \mid y) = p(x, y) \Big/ \int_{x \in \mathbb{R}} p(x, y) dx.$$

Theorem 6.1.5. Iterated expectations:

- (i) $\mathbb{E}[\mathbb{E}(X \mid Y)] = \mathbb{E}(X)$ (**Law of Total Expectation**)
- (ii) $\mathbb{E}[(X \mid Y) \mid Z] = \mathbb{E}(X \mid Y)$
- (iii) $\mathbb{E}(E(XY \mid Y)) = \mathbb{E}(Y\mathbb{E}(X \mid Y))$

Proof. (i) Discrete case:

$$\begin{aligned} \mathbb{E}[\mathbb{E}(X \mid Y)] &= \sum_y \mathbb{E}(X \mid Y = y) \Pr(Y = y) = \sum_y \sum_x x \Pr(X = x \mid Y = y) \Pr(Y = y) \\ &= \sum_y \sum_x x \Pr(X = x \cap Y = y) = \sum_x x \sum_y \Pr(X = x \cap Y = y) = \sum_x x \Pr(X = x) = \mathbb{E}(X) \end{aligned}$$

Continuous case:

$$\begin{aligned} \mathbb{E}[\mathbb{E}(X \mid Y)] &= \int_{-\infty}^{\infty} \mathbb{E}(X \mid Y = y) f_Y(y) dy = \text{(by definition 1.75)} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} x f_{X|Y}(x \mid y) dx \right) f_Y(y) dy \\ &\quad \text{(by Fubini's Theorem, Theorem 5.7.55)} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} x f_{X|Y}(x \mid y) f_Y(y) dy \right) dx = \int_{-\infty}^{\infty} x f_X(x) dx = \mathbb{E}(X) \end{aligned}$$

□

Definition 6.14. Conditional Variance: $\text{Var}(X \mid Y) = \mathbb{E}[(X - \mathbb{E}(X \mid Y))^2 \mid Y]$

Theorem 6.1.6 (Conditional Expectation as a Random Variable). (i) Let X, Y be random variables such that (X, Y) is uniformly distributed on the triangle $\{(x, y) \in \mathbb{R}^2 : x \geq 0, y \geq 0, x + y \leq 1\}$. Then

$$\mathbb{E}(X \mid Y) = \frac{1}{2}(1 - Y).$$

(ii) Total Expectation Theorem:

$$\mathbb{E}(\mathbb{E}(X \mid Y)) = \mathbb{E}(X).$$

- If X is a random variable, and if $f(t) := \mathbb{E}(X - t)^2$, $t \in \mathbb{R}$, then the function $f : \mathbb{R} \rightarrow \mathbb{R}$ is uniquely minimized when $t = \mathbb{E}X$. A similar minimizing property holds for conditional expectation. Let $h : \mathbb{R} \rightarrow \mathbb{R}$. Then the quantity $\mathbb{E}(X - h(Y))^2$ is minimized among all functions $h : \mathbb{R} \rightarrow \mathbb{R}$ when $h(Y) = \mathbb{E}(X \mid Y)$.

(iii)

$$\begin{aligned}\mathbb{E}(Xh(Y)|Y) &= h(Y)\mathbb{E}(X|Y). \\ \mathbb{E}(\mathbb{E}(X|h(Y))|Y) &= \mathbb{E}(X|h(Y)).\end{aligned}$$

(iv)

$$\begin{aligned}\mathbb{E}(X|X) &= X. \\ \mathbb{E}(X+Y|Z) &= \mathbb{E}(X|Z) + \mathbb{E}(Y|Z).\end{aligned}$$

(v) If Z is independent of X and Y , then

$$\mathbb{E}(X|Y, Z) = \mathbb{E}(X|Y).$$

(Here $\mathbb{E}(X|Y, Z)$ is notation for $\mathbb{E}(X|(Y, Z))$ where (Y, Z) is interpreted as a random vector, so that X is conditioned on the random vector (Y, Z) .)

Proof. (i) Note that since $0 \leq x$ and $x+y \leq 1$, conditional on $y = y \geq 0$ x is uniformly distributed on $[0, 1-y]$. That is,

$$\Pr(X \leq x | Y = y) = \begin{cases} 0 & x < 0 \\ x/(1-y) & 0 \leq x < 1-y \\ 1 & x \geq 1-y \end{cases}$$

Since the expected value of a random variable uniformly distributed on $[a, b]$ is $(a+b)/2$, it follows

that $\mathbb{E}(X | Y = y) = (0+1-y)/2 = (1/2)(1-y)$. Therefore $\boxed{\mathbb{E}(X | Y) = \frac{1}{2}(1-Y)}$.

(ii) • Discrete case:

$$\begin{aligned}\mathbb{E}[\mathbb{E}(X | Y)] &= \sum_y \mathbb{E}(X | Y = y) \Pr(Y = y) = \sum_y \sum_x x \Pr(X = x | Y = y) \Pr(Y = y) \\ &= \sum_y \sum_x x \Pr(X = x \cap Y = y) = \sum_x x \sum_y \Pr(X = x \cap Y = y) = \sum_x x \Pr(X = x) = \mathbb{E}(X)\end{aligned}$$

• Continuous case:

$$\begin{aligned}\mathbb{E}[\mathbb{E}(X | Y)] &= \int_{-\infty}^{\infty} \mathbb{E}(X | Y = y) f_Y(y) dy = \text{(by definition 1.75)} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} x f_{X|Y}(x | y) dx \right) f_Y(y) dy \\ &\quad \text{(by Fubini's Theorem)} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} x f_{X|Y}(x | y) f_Y(y) dy \right) dx = \int_{-\infty}^{\infty} x f_X(x) dx = \mathbb{E}(X)\end{aligned}$$

• Next we will show that the quantity $\mathbb{E}(X - h(Y))^2$ is minimized among all functions $h : \mathbb{R} \rightarrow \mathbb{R}$ when $h(Y) = \mathbb{E}(X | Y)$. We seek

$$\arg \min_{\{h: \mathbb{R} \rightarrow \mathbb{R}\}} \mathbb{E}(X - h(Y))^2 = \arg \min_{\{h: \mathbb{R} \rightarrow \mathbb{R}\}} [\mathbb{E}(X^2) - 2\mathbb{E}[h(Y)]\mathbb{E}(X) + \mathbb{E}[h(Y)^2]].$$

This expression is quadratic in $\mathbb{E}[h(Y)]$. Differentiating with respect to $\mathbb{E}[h(Y)]$ and setting equal to 0, we have

$$2\mathbb{E}[h(Y)] - 2\mathbb{E}(X) = 0 \iff \mathbb{E}[h(Y)] = \mathbb{E}(X) \implies \boxed{\arg \min_{\{h: \mathbb{R} \rightarrow \mathbb{R}\}} \mathbb{E}(X - h(Y))^2 = \mathbb{E}(X | Y)}$$

(iii) • Discrete case:

$$\mathbb{E}(Xh(Y)|Y) = \sum_{x \in \mathbb{R}} x \cdot h(Y) \cdot \Pr(X = x | Y) = h(Y) \sum_{x \in \mathbb{R}} x \cdot \Pr(X = x | Y) = h(Y)\mathbb{E}(X | Y).$$

Continuous case:

$$\mathbb{E}(Xh(Y)|Y) = \int_{x \in \mathbb{R}} x \cdot h(Y) \cdot f_{X|Y}(x) = h(Y) \int_{x \in \mathbb{R}} x \cdot f_{X|Y}(x) = h(Y)\mathbb{E}(X | Y).$$

• Discrete case: Note that

$$\mathbb{E}[X | h(Y)] = \sum_{x \in \mathbb{R}} x \Pr(X = x | h(Y)) = \sum_{x \in \mathbb{R}} x\mathbb{E}[\mathbf{1}_{\{X=x\}} | h(Y)]$$

where $\mathbf{1}_{\{X=x\}}$ is an indicator variable for X taking on the value x . Note that $\mathbb{E}[\mathbf{1}_{\{X=x\}} | h(Y)]$ is a function of Y (and a random variable). Then we have

$$\begin{aligned} \mathbb{E}(\mathbb{E}(X | h(Y)) | Y) &= \mathbb{E}\left(\sum_{x \in \mathbb{R}} x\mathbb{E}[\mathbf{1}_{\{X=x\}} | h(Y)] | Y\right) = \sum_{x \in \mathbb{R}} \mathbb{E}[x\mathbb{E}[\mathbf{1}_{\{X=x\}} | h(Y)] | Y] \\ &= (\text{by the previous result}) \sum_{x \in \mathbb{R}} \mathbb{E}[\mathbf{1}_{\{X=x\}} | h(Y)]\mathbb{E}[x | Y] = \sum_{x \in \mathbb{R}} \Pr(X = x | h(Y)) \cdot x = \mathbb{E}(X|h(Y)). \end{aligned}$$

Continuous case: Note that

$$\mathbb{E}[X | h(Y)] = \int_{x \in \mathbb{R}} x f_{X|h(Y)}(x) dx.$$

Note that for a fixed x , $f_{X|h(Y)}(x)$ is a function of Y (and a random variable). Then we have

$$\begin{aligned} \mathbb{E}(\mathbb{E}(X | h(Y)) | Y) &= \mathbb{E}\left(\int_{x \in \mathbb{R}} x f_{X|h(Y)}(x) dx | Y\right) = \int_{x \in \mathbb{R}} \mathbb{E}[x \cdot f_{X|h(Y)}(x) | Y] dx \\ &= (\text{by the previous result}) \int_{x \in \mathbb{R}} f_{X|h(Y)}(x)\mathbb{E}[x | Y] dx = \int_{x \in \mathbb{R}} f_{X|h(Y)}(x) \cdot x = \mathbb{E}(X|h(Y)). \end{aligned}$$

(iv) • Discrete case:

$$\mathbb{E}(X|X) = \sum_{x \in \mathbb{R}} x \Pr(X = x | X)$$

Note that

$$\Pr(X = x | X) = \begin{cases} 1 & x = X \\ 0 & \text{otherwise} \end{cases}$$

so we have

$$\mathbb{E}(X|X) = \sum_{x \in \mathbb{R}} x \Pr(X = x | X) = \dots + 0 + 0 + X + 0 + 0 + \dots = X.$$

Continuous case:

$$\mathbb{E}(X|X) = \int_{x \in \mathbb{R}} x \cdot dF_X$$

Note that

$$\Pr(X \leq x | X) = F_{X|X}(x) = \begin{cases} 0 & x < X \\ 1 & x \geq X \end{cases}$$

so we have

$$\mathbb{E}(X|X) = \int_{x \in \mathbb{R}} x \cdot dF_X = X.$$

- Discrete case:

$$\begin{aligned} \mathbb{E}(X + Y | Z = z) &= \sum_{x \in \mathbb{Z}} \sum_{y \in \mathbb{Z}} (x + y) \Pr(X = x, Y = y | Z) \\ &= \sum_{x \in \mathbb{Z}} \sum_{y \in \mathbb{Z}} x \Pr(X = x, Y = y | Z) + \sum_{x \in \mathbb{Z}} \sum_{y \in \mathbb{Z}} y \Pr(X = x, Y = y | Z) \\ &= \sum_{x \in \mathbb{R}} x \Pr(X = x | Z) + \sum_{y \in \mathbb{R}} y \Pr(Y = y | Z) = \mathbb{E}(X|Z) + \mathbb{E}(Y|Z). \end{aligned}$$

Continuous case:

$$\begin{aligned} \mathbb{E}(X + Y | Z = z) &= \int_{x \in \mathbb{R}} \int_{y \in \mathbb{R}} (x + y) \Pr(X = x, Y = y | Z) dy dx \\ &= \int_{x \in \mathbb{R}} \int_{y \in \mathbb{R}} x \Pr(X = x, Y = y | Z) dy dx + \int_{x \in \mathbb{R}} \int_{y \in \mathbb{R}} y \Pr(X = x, Y = y | Z) dy dx \\ &= \int_{x \in \mathbb{R}} x \Pr(X = x | Z) dx + \int_{y \in \mathbb{R}} y \Pr(Y = y | Z) dy = \mathbb{E}(X|Z) + \mathbb{E}(Y|Z). \end{aligned}$$

- (v) Note by the definition of conditional probability that

$$\mathbb{P}(X = x | Y = y \cap Z = z) = \frac{\mathbb{P}(X = x \cap \{Y = y \cap Z = z\})}{\mathbb{P}(Y = y \cap Z = z)}$$

Using the independence of X and Y from Z and Lemma 6.1.2, we can express this as

$$= \frac{\mathbb{P}(X = x \cap Y = y) \mathbb{P}(Z = z)}{\mathbb{P}(Y = y) \mathbb{P}(Z = z)} = \frac{\mathbb{P}(X = x \cap Y = y)}{\mathbb{P}(Y = y)} = \mathbb{P}(X = x | Y = y)$$

by the definition of conditional probability. So $\mathbb{P}(X = x | Y = y, Z) = \mathbb{P}(X = x, Y = y)$. Therefore we have (in the discrete case)

$$\mathbb{E}(X | Y = y, Z) = \sum_{x \in \mathbb{R}} x \mathbb{P}(X = x | Y = y, Z) = \sum_{x \in \mathbb{R}} x \mathbb{P}(X = x, Y = y) = \mathbb{E}(X | Y = y) = g(y)$$

which implies that $\mathbb{E}(X | Y, Z) = g(Y) = \mathbb{E}(X | Y)$. In the continuous case, note that

$$F_{X|Y,Z}(x) = \mathbb{P}(X \leq x | Y, Z) = \mathbb{P}(X \leq x | Y) = F_{X|Y}(x)$$

by Lemma 6.1.2. Therefore we have

$$\mathbb{E}(X | Y, Z) = \int_{x \in \mathbb{R}} x dF_{X|Y,Z}(x) = \int_{x \in \mathbb{R}} x dF_{X|Y}(x) = \mathbb{E}(X | Y).$$

□

Corollary 6.1.6.1.

$$\mathbb{E}(h(Y) | Y) = h(Y).$$

Proof. Use the first result in part (iii) of Theorem 6.1.6 with $X = 1$ and note that $\mathbb{E}(1 | Y) = 1$.

□

Corollary 6.1.6.2.

$$\mathbb{E}[\mathbb{E}(X | Y)) | Y] = \mathbb{E}(X | Y).$$

Proof. Use the second result in part (iii) of Theorem 6.1.6 with $h(Y) = Y$.

□

Lemma 6.1.7. If $X \geq Z$ then $\mathbb{E}(X|Y) \geq \mathbb{E}(Z|Y)$.

Proof. Suppose that X and Z are nonnegative. Note that

$$\mathbb{E}(X | Y) = \int_0^\infty \Pr(X > t | Y) dt \geq \int_0^\infty \Pr(Z > t | Y) dt = \mathbb{E}(Z | Y)$$

where the third step follows since $X \geq Z$. If X and Z are not nonnegative, then

$$\begin{aligned} \mathbb{E}(X | Y) &= \mathbb{E}(\max\{X, 0\} | Y) - \mathbb{E}(\max\{-X, 0\} | Y) \\ &= \int_0^\infty \Pr(\max\{X, 0\} > t | Y) dt - \int_0^\infty \Pr(\max\{-X, 0\} > t | Y) dt \\ &\geq \int_0^\infty \Pr(\max\{Z, 0\} > t | Y) dt - \int_0^\infty \Pr(\max\{-Z, 0\} > t | Y) dt = \mathbb{E}(Z | Y) \end{aligned}$$

where the inequality follows since $X \geq Z$.

□

6.1.3 Convolution

Theorem 6.1.8. Sums of random variables. If X and Y are independent then

$$\Pr(X + Y = z) = f_{X+Y}(z) = \sum_x f_X(x)f_Y(z - x) = \sum_y f_X(z - y)f_Y(y)$$

Remark 34. Convolution on the integers. Let X, Y be independent integer-valued random variables. Let $t \in \mathbb{Z}$.

$$\begin{aligned} \Pr(X + Y = t) &= \sum_{j,k \in \mathbb{Z}: j+k=t} \Pr(X = j, Y = k) = \sum_{j \in F} \Pr(X = j, Y = t - j) = \sum_{j \in \mathbb{Z}} \Pr(X = j) \Pr(Y = t - j) \\ &= \sum_{j \in \mathbb{Z}} p_X(j)p_Y(t - j) \end{aligned}$$

Definition 6.15. Let $g, h : \mathbb{Z} \rightarrow \mathbb{R}$ be functions. The **convolution** of g and h , denoted by $g * h$, is a function $g * h : \mathbb{Z} \rightarrow \mathbb{R}$ defined by

$$(g * h)(t) = \sum_{j \in \mathbb{Z}} g(j)h(t - j) \quad \forall t \in \mathbb{Z}$$

Definition 6.16. (Convolution on the real line.) Let $g, h : \mathbb{R} \rightarrow \mathbb{R}$ be functions. The **convolution** of g and h , denoted by $g * h$, is a function $g * h : \mathbb{R} \rightarrow \mathbb{R}$ defined by

$$(g * h)(t) = \int_{-\infty}^{\infty} g(x)h(t - x)dx, \quad \forall t \in \mathbb{R}$$

Proposition 6.1.9. Let X, Y be two continuous independent random variables such that $\Pr(X + Y \leq t)$ is differentiable with respect to $t \in \mathbb{R}$. Then

$$f_{X+Y}(t) = (f_X * f_Y)(t), \quad \forall t \in \mathbb{R}$$

Proof.

$$\Pr(X + Y \leq t) = \int_{\{(x,y) \in \mathbb{R}^2: x+y \leq t\}} f_{X,Y}(x,y)dxdy = \int_{x=-\infty}^{x=\infty} \int_{y=-\infty}^{y=t-x} f_X(x)f_Y(y)dydx$$

Then, since $\Pr(X + Y \leq t)$ is differentiable with respect to t , we have by the Fundamental Theorem of Calculus

$$f_{X+Y}(t) = \frac{d}{dt} \Pr(X + Y \leq t) = \int_{x=-\infty}^{x=\infty} f_X(x) \frac{d}{dt} \int_{y=-\infty}^{y=t-x} f_Y(y)dydx = \int_{x=-\infty}^{x=\infty} f_X(x)f_Y(t - x)dx$$

□

Example 6.2. Let X, Y be independent standard Gaussian random variables. Then by Proposition 6.1.9, $X + Y$ has density

$$\begin{aligned} f_{X+Y}(t) &= \int_{-\infty}^{\infty} f_X(x)f_Y(t-x)dx = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-x^2/2}e^{-(t-x)^2/2}dx \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-x^2+tx-t^2/2}dx = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-(x-t/2)^2-t^2/4-t^2/2}dx \\ &= e^{-t^2/4} \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-(x-t/2)^2}dx = \frac{1}{2\pi} e^{-t^2/4} \int_{-\infty}^{\infty} e^{-x^2}dx \end{aligned}$$

Let $x = y/\sqrt{2}, dx = dy/\sqrt{2}$.

$$\begin{aligned} &= \frac{1}{2\pi} e^{-t^2/4} \int_{-\infty}^{\infty} e^{-y^2/2} \cdot \frac{1}{\sqrt{2}} dy = \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{2}} e^{-t^2/4} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-y^2/2} dy \\ &= \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{2}} e^{-t^2/4} \frac{1}{\sqrt{2\pi}} \end{aligned}$$

which is the density for a Gaussian random variable distributed as $\mathcal{N}(0, 1)$.

Definition 6.17. (Convolved cdfs; Ross's in-class definition from ISE 620.) Suppose we have random variables X and Y with cdfs F_X and F_Y and pdfs f_X and f_Y . Then

$$\begin{aligned} (F_Y * F_X)(t) &= \Pr(X + Y \leq t) = \int_{-\infty}^{\infty} \Pr(X + Y \leq t | X = x) f_X(x) dx \\ &= \int_{-\infty}^{\infty} F_Y(t - x) f_X(x) dx \end{aligned}$$

6.1.4 Compound Random Variables

Definition 6.18. Let $\{X_i\}$ be i.i.d. random variables. Let N be a random variable taking on positive integer values. Let

$$S = \sum_{i=1}^N X_i$$

Then S is a **compound random variable**.

Proposition 6.1.10. (Wald's Equation.) Let $\{X_i\}$ be i.i.d. random variables with mean $\mathbb{E}(X)$. Let N be a random variable taking on positive integer values, and let $S = \sum_{i=1}^N X_i$. Then $\mathbb{E}(S) = \mathbb{E}(N)\mathbb{E}(X)$.

Proof.

$$\mathbb{E}(S | N) = \mathbb{E}\left(\sum_{i=1}^N X_i\right) = \sum_{i=1}^N \mathbb{E}(X_i) = N\mathbb{E}(X)$$

$$\mathbb{E}(S) = \mathbb{E}(\mathbb{E}[S | N]) = \mathbb{E}(N\mathbb{E}(X)) = \mathbb{E}(N)\mathbb{E}(X)$$

□

Proposition 6.1.11. Let $\{X_i\}$ be i.i.d. random variables with mean $\mathbb{E}(X)$. Let N be a random variable taking on positive integer values, and let $S = \sum_{i=1}^N X_i$. Then $\text{Cov}(N, S) = \mathbb{E}(X)\text{Var}(N)$.

Proof. Let $\mathbb{E}(X_i) = \mathbb{E}(X)$ for all i . We will use the result from Wald's Equation (Proposition 6.1.10: $E(S) = \mathbb{E}(X)\mathbb{E}(N)$). We have

$$\text{Cov}(N, S) = \mathbb{E}(NS) - \mathbb{E}(N)\mathbb{E}(S) = \mathbb{E}[\mathbb{E}(NS | N)] - \mathbb{E}(N)\mathbb{E}(N)\mathbb{E}(X) = \mathbb{E}[N\mathbb{E}(S | N)] - \mathbb{E}(N)^2\mathbb{E}(X) \quad (6.1)$$

Note that

$$\mathbb{E}(S | N) = \mathbb{E}\left(\sum_{i=1}^N X_i\right) = \sum_{i=1}^N \mathbb{E}(X_i) = N\mathbb{E}(X) \implies \mathbb{E}[N\mathbb{E}(S | N)] = \mathbb{E}(N^2\mathbb{E}(X)) = \mathbb{E}(X)\mathbb{E}(N^2)$$

Plugging this into (6.1) yields

$$\text{Cov}(N, S) = \mathbb{E}(X)\mathbb{E}(N^2) - \mathbb{E}(N)^2\mathbb{E}(X) = \mathbb{E}(X)[\mathbb{E}(N^2) - \mathbb{E}(N)^2] = \mathbb{E}(X)\text{Var}(N)$$

□

Definition 6.19 (Compound Poisson random variable). Let N be a Poisson random variable. Let X_1, X_2, \dots be independent and identically distributed random variables that are also independent of N . Then

$$S := \sum_{i=1}^N X_i$$

is called a **compound Poisson random variable**.

Proposition 6.1.12 (Variance of a compound Poisson random variable, from Ross *Introduction to Probability Models*). For a compound Poisson random variable $S = \sum_{i=1}^N X_i$ having $\mathbb{E}(N) = \lambda, \mathbb{E}(X_i) = \mu, \text{Var}(X_i) = \sigma^2$,

$$\text{Var}(S) = \lambda\sigma^2 + \lambda\mu^2 = \lambda\mathbb{E}(X^2).$$

6.1.5 Odds and Ends

Proposition 6.1.13. Inclusion-Exclusion Principle:

(a)

$$\Pr \left(\bigcup_{i=1}^n A_i \right) = \sum_{k=1}^n (-1)^{k+1} \left(\sum_{1 \leq i_1 < \dots < i_k \leq m} \Pr(A_{i1} \cap \dots \cap A_{ik}) \right)$$

(b)

$$\left| \bigcup_{i=1}^n A_i \right| = \sum_{k=1}^n (-1)^{k+1} \left(\sum_{1 \leq i_1 < \dots < i_k \leq m} |A_{i1} \cap \dots \cap A_{ik}| \right)$$

To prove this, we will first prove the Multi-Binomial Theorem.

Lemma 6.1.14. (Multi-Binomial Theorem)

$$\prod_{i=1}^d (x_i + y_i)^{n_i} = \sum_{k_1=0}^{n_1} \sum_{k_2=0}^{n_2} \dots \sum_{k_d=0}^{n_d} \binom{n_1}{k_1} x_1^{k_1} y_1^{n_1-k_1} \binom{n_2}{k_2} x_2^{k_2} y_2^{n_2-k_2} \dots \binom{n_d}{k_d} x_d^{k_d} y_d^{n_d-k_d}$$

Proof.

□

We are now ready to prove the Inclusion-Exclusion Principle.

Proof. (Proof of (a).) Begin by noting that

$$\mathbf{1}_{\{\bigcup_{i=1}^n A_i\}} = 1 - \prod_{i=1}^n (1 - \mathbf{1}_{\{A_i\}}) \quad (6.2)$$

because the expression on the right will equal 1 if at least one term in the product equals 0 (that is, if $\mathbf{1}_{\{A_i\}} = 1$ for some $i \in 1, \dots, n$) and will equal 0 if every term in the product equals 1 (if $\mathbf{1}_{\{A_i\}} = 0$ for every $i \in 1, \dots, n$), which is exactly what we want. Expanding the right side of (6.2) using the Multi-Binomial Theorem (Lemma 6.1.14), we have

$$\begin{aligned} &= 1 - \prod_{i=1}^n (1 - \mathbf{1}_{\{A_i\}}) = 1 - (1 - \mathbf{1}_{\{A_1\}})(1 - \mathbf{1}_{\{A_2\}}) \cdots (1 - \mathbf{1}_{\{A_n\}}) \\ &= 1 - \left[1 + \sum_{k=1}^n (-1)^k \left(\sum_{1 \leq i_1 < \dots < i_k \leq k} \mathbf{1}_{\{A_{i1}\}} \cdots \mathbf{1}_{\{A_{ik}\}} \right) \right] = -1 \cdot \sum_{k=1}^n (-1)^k \left(\sum_{1 \leq i_1 < \dots < i_k \leq k} \mathbf{1}_{\{A_{i1} \cap \dots \cap A_{ik}\}} \right) \\ &= \sum_{k=1}^n (-1)^{k+1} \left(\sum_{1 \leq i_1 < \dots < i_k \leq k} \mathbf{1}_{\{A_{i1} \cap \dots \cap A_{ik}\}} \right) \end{aligned}$$

$$\implies \mathbf{1}_{\{\cup_{i=1}^n A_i\}} = \sum_{k=1}^n (-1)^{k+1} \left(\sum_{1 \leq i_1 < \dots < i_k \leq k} \mathbf{1}_{\{A_{i_1} \cap \dots \cap A_{i_k}\}} \right) \quad (6.3)$$

Taking expectations of both sides of (6.3) yields

$$\begin{aligned} \Pr(\cup_{i=1}^n A_i) &= \mathbb{E} \left[\sum_{k=1}^n (-1)^{k+1} \left(\sum_{1 \leq i_1 < \dots < i_k \leq k} \mathbf{1}_{\{A_{i_1} \cap \dots \cap A_{i_k}\}} \right) \right] \\ &= \sum_{k=1}^n (-1)^{k+1} \left(\sum_{1 \leq i_1 < \dots < i_k \leq k} \mathbb{E}[\mathbf{1}_{\{A_{i_1} \cap \dots \cap A_{i_k}\}}] \right) \\ &= \sum_{k=1}^n (-1)^{k+1} \left(\sum_{1 \leq i_1 < \dots < i_k \leq k} \Pr(A_{i_1} \cap \dots \cap A_{i_k}) \right) \end{aligned}$$

□

Proposition 6.1.15 (a nice trick for upper bounding binomial sums, from Math 547). For $d < n$,

$$\sum_{i=0}^d \binom{n}{i} \leq \left(\frac{en}{d} \right)^d.$$

Proof.

$$\sum_{i=0}^d \binom{n}{i} (d/n)^d \leq \sum_{i=0}^d \binom{n}{i} (d/n)^i \leq \sum_{i=0}^n \binom{n}{i} (d/n)^i = [1 + (d/n)]^n \leq e^d \iff \sum_{i=0}^d \binom{n}{i} \leq \left(\frac{en}{d} \right)^d.$$

□

Proposition 6.1.16. (Proposition 1.6.1 in Sheldon Ross *A First Course in Probability*.) There are $\binom{n-1}{r-1}$ distinct positive integer-valued vectors $(x_1, x_2, \dots, x_r), x_i > 0 \forall i$ satisfying the equation $x_1 + x_2 + \dots + x_r = n$.

Proof. (Not rigorous, but a justification.) Imagine we have n indistinguishable objects to allocate to r people. We lay out the n objects and take $r - 1$ sticks to place in the $n - 1$ spaces between them. The first person gets all the objects to the left of the leftmost stick, the second person gets the objects between the leftmost and second leftmost stick, and so on, until the last person gets all the objects to the right of the rightmost stick. The constraint that x_i be positive is equivalent to saying that each person must receive at least one object. Therefore we must place each stick in a different place. There are $\binom{n-1}{r-1}$ ways to do this.

□

Proposition 6.1.17. (Proposition 1.6.2 in Sheldon Ross *A First Course in Probability*.) There are $\binom{n+r-1}{r-1}$ distinct nonnegative integer-valued vectors $(x_1, x_2, \dots, x_r), x_i \geq 0 \forall i$ satisfying the equation $x_1 + x_2 + \dots + x_r = n$.

Proof. We would like to solve the problem

$$x_1 + x_2 + \dots + x_r = n, x_i \geq 0 \quad \forall i$$

Note that we can transform this problem in the following way:

$$x_1 + 1 + x_2 + 1 + \dots + x_r + 1 = n + 1 \cdot r, x_i + 1 \geq 1 \quad \forall i$$

Letting $y_i = x_i + 1$, we have the equivalent system

$$y_1 + y_2 + \dots + y_r = n + r, y_i \geq 1 \quad \forall i$$

Since $y_i \geq 1 \iff y_i > 0$, by Proposition 6.1.16, the number of distinct solutions to this equation is $\binom{n+r-1}{r-1}$.

□

Proposition 6.1.18. More generally, if we desire solutions to $x_1 + x_2 + \dots + x_r = n$ such that $x_i \geq k \in \mathbb{N}$, then $\binom{n+r \cdot (1-k)-1}{r-1} = \binom{n+r-1-rk}{r-1}$ solutions are possible.

Proof. We can construct a similar argument to that used in the proof of Proposition 6.1.17 by adding $r \cdot (1-k)$ to each side of $x_1 + x_2 + \dots + x_r = n$:

$$x_1 + 1 - k + x_2 + 1 - k + \dots + x_r + 1 - k = n + r \cdot (1 - k), x_i \geq k \quad \forall i$$

Then substitute $y_i = x_i + 1 - k$ to yield

$$y_1 + y_2 + \dots + y_r = n + r \cdot (1 - k), y_i + k - 1 \geq k \quad \forall i$$

then apply Proposition 6.1.16 noting that $y_i + k - 1 \geq k \iff y_i \geq 1 \iff x_i \geq k$ to yield the result. □

Proposition 6.1.19. Even more generally, suppose we desire solutions to $x_1 + x_2 + \dots + x_r = n$ such that $x_1 \geq k_1 \in \mathbb{N}, x_2 \geq k_2 \in \mathbb{N}, \dots, x_r \geq k_r \in \mathbb{N}$. Then

$$\binom{n + \sum_{i=1}^r (1 - k_i) - 1}{r - 1} = \binom{n + r - 1 - \sum_{i=1}^r k_i}{r - 1}$$

solutions are possible.

Proof. Very similar to the proof of Proposition 6.1.18. Add $\sum_{i=1}^r (1 - k_i)$ to each side of $x_1 + x_2 + \dots + x_r = n$:

$$x_1 + 1 - k_1 + x_2 + 1 - k_2 + \dots + x_r + 1 - k_r = n + \sum_{i=1}^r (1 - k_i), x_i \geq k_i \quad \forall i$$

Then substitute $y_i = x_i + 1 - k_i$ to yield

$$y_1 + y_2 + \dots + y_r = n + \sum_{i=1}^r (1 - k_i), \quad y_i + k_i - 1 \geq k_i \quad \forall i$$

Finally, apply Proposition 6.1.16 noting that $y_i + k_i - 1 \geq k_i \iff y_i \geq 1 \iff x_i \geq k_i$ to yield the result. \square

Proposition 6.1.20. Suppose we desire solutions to $x_1 + x_2 + \dots + x_r = n$ such that $\tau \leq r$ of the $\{x_i\}$ exceed some threshold k . For example, if we have $x_1 \geq k, x_2 \geq k, \dots, x_\tau \geq k$, with $x_{\tau+1}, \dots, x_r$ taking on arbitrary values, then the condition is satisfied. (The particular x_i that exceed k does not matter, as long as τ of them exceed k). Then

$$\binom{r}{\tau} \binom{n+r-1-k\tau}{r-1}$$

solutions are possible.

Proof. By Proposition 6.1.19, the number of ways this condition can be met for a particular set of τ variables x_i is $\binom{n+r-1-k\tau}{r-1}$. Since there are $\binom{r}{\tau}$ ways to choose which τ variables will exceed k , the result follows. \square

6.1.6 Methods for Calculating Quantities

- Expectation
-

Definition 6.20. (Math 541A definition 1.37.) Let Ω be a sample space, let \mathbb{P} be a probability law on Ω . Let X be a random variable on Ω . Assume that X takes on nonnegative values; that is, $X : \Omega \rightarrow [0, \infty)$. We define the **expected value** of X by

$$\mathbb{E}(X) = \int_0^\infty \mathbb{P}(X > t) dt$$

In analytic notation, $\mathbb{E}(X) = \int_{\Omega} X(\omega) d\mathbb{P}(\omega)$. More generally, if $g : [0 \rightarrow \infty) \rightarrow [0 \rightarrow \infty)$ is a differentiable function such that g' is continuous and $g(0) = 0$, we define

$$\mathbb{E}(g(X)) = \int_0^\infty g'(t) \mathbb{P}(X > t) dt$$

For a general random variable X , if $\mathbb{E}(\max\{X, 0\}) < \infty$ and if $\mathbb{E}(\max\{-X, 0\}) < \infty$, we then define $\mathbb{E}(X) = \mathbb{E}(\max\{X, 0\}) - \mathbb{E}(\max\{-X, 0\})$. Otherwise, we say that $\mathbb{E}(X)$ is undefined.

Definition 6.21. In the above, taking $g(t) = t^n$ for any positive integer n , for any $t \geq 0$, we have

$$\mathbb{E}(X^n) = \int_0^\infty nt^{n-1} \mathbb{P}(X > t) dt$$

Remark 35. If we assume that the expected value and the integral on \mathbb{R} can be commuted, then the following derivation of the formula for $\mathbb{E}(g(X))$ can be given. From the Fundamental Theorem of Calculus, we have

$$g(X) = \int_0^X g'(t)dt = \int_0^\infty g'(t)\mathbf{1}_{\{X>t\}}dt$$

where $\mathbf{1}_{\{X>t\}}$ is an indicator variable. Therefore

$$\mathbb{E}(g(X)) = \int_0^\infty g'(t)\mathbf{1}_{\{X>t\}}dt = \int_0^\infty g'(t)\mathbb{E}(\mathbf{1}_{\{X>t\}}) = \int_0^\infty g'(t)\mathbb{P}(X > t)dt.$$

Definition 6.22. (Discrete random variables.) $\mathbb{E}(X) = \sum_x x \Pr(X = x)$

Theorem 6.1.21. (a) $\mathbb{E}(aX + bY) = a\mathbb{E}(X) + b\mathbb{E}(Y)$

(b) If $X \geq 0$ then $\mathbb{E}(X) \geq 0$

Theorem 6.1.22. Expectation of sums is sum of expectations if sum is finite or if sum is infinite and all variables are positive, but not necessarily otherwise.

Example 6.3 (Example 4.18 in *Introduction to Probability Models*). Consider a sequence of discrete random variables X_1, X_2, \dots such that $X_i = 1$ with probability 1/2 and $X_i = -1$ with probability 1/2. Let N be a stopping time:

$$N = \min\{n : X_1 + \dots + X_n = 1\} \implies 1 = X_1 + \dots + X_N.$$

Let $I\{i \leq N\}$ be an indicator variable for $i \leq N$. So

$$1 = \sum_{i=1}^N X_i = \sum_{i=1}^\infty X_i I\{i \leq N\}.$$

Taking expectations we have

$$1 = \mathbb{E} \sum_{i=1}^\infty X_i I\{i \leq N\}.$$

Note that $N \geq i$ if and only if you have not yet stopped after the first $i - 1$ games, so it depends on the results of the previous games but not on X_i . So $I\{i \leq N\}$ and X_i are independent. Therefore

$$\mathbb{E}[X_i I\{i \leq N\}] = \mathbb{E}(X_i) \mathbb{E}(I\{i \leq N\}) = 0$$

since $\mathbb{E}(X_i) = 0$. So

$$\sum_{i=1}^\infty \mathbb{E}[X_i I\{i \leq N\}] = \sum_{i=1}^\infty 0 = 0$$

which means that

$$\mathbb{E} \sum_{i=1}^\infty X_i I\{i \leq N\} \neq \sum_{i=1}^\infty \mathbb{E}[X_i I\{i \leq N\}].$$

See also Example 7.37 in the Stochastic Processes notes.

—

Theorem 6.1.23. Law of the Unconscious Statistician: If X has mass function f , and $g : \mathbb{R} \rightarrow \mathbb{R}$, then

$$\mathbb{E}(g(X)) = \sum_x g(x)f(x)$$

—

Theorem 6.1.24. Expectation is a linear operator: $\mathbb{E}(\sum_i X_i) = \sum_i \mathbb{E}(X_i)$

—

Theorem 6.1.25. (Layer cake formulation.) If N is a discrete random variable taking on non-negative values, then $\mathbb{E}(N) = \sum_{i=1}^{\infty} \Pr(N \geq i)$.

Proof. Let $\mathbf{1}_{\{i \leq N\}}$ be an indicator variable. Then

$$N = \sum_{i=1}^{\infty} \mathbf{1}_{\{i \leq N\}}.$$

Take expectations of both sides to yield the result. □

Remark 36. Also note that we can derive this result from Definition 6.20:

$$\mathbb{E}(X) = \int_0^{\infty} \Pr(X > t) dt = \sum_{k=1}^{\infty} \int_{k-1}^k \Pr(X > t) dt = \sum_{k=1}^{\infty} \Pr(X \geq k) = \sum_{k=0}^{\infty} \Pr(X > k).$$

Using Fubini's Theorem (Theorem 5.7.55) to rearrange the sum, we can arrive at

$$\begin{aligned} \mathbb{E}(X) &= \sum_{k=0}^{\infty} \Pr(X > k) = \sum_{k=0}^{\infty} \sum_{j=k+1}^{\infty} \Pr(X = j) = \sum_{0 \leq k < j < \text{infty}} \Pr(X = j) \\ &= \sum_{j=0}^{\infty} \sum_{k=0}^j \Pr(X = j) = \sum_{j=0}^{\infty} j \Pr(X = j) \end{aligned}$$

which is the usual definition for a discrete random variable.

- For the conditional expectation of one Gaussian random variable on another when the covariance or correlation between them is known, see Proposition 6.3.36. For the conditional expectation of a set of Gaussian random variables on another set when the covariance matrix is known, see Proposition 6.3.37.

- Variance

—

Definition 6.23. $\text{Var}(X) = \mathbb{E}(X - \mathbb{E}(X))^2$

—

Proposition 6.1.26. (Useful reformulation:) $\text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2$

—

Theorem 6.1.27. (Some useful results):

- (a) $\text{Var}(aX) = a^2 \text{Var}(X)$

- (b) $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$
 - (c) $\text{Var}(aX \pm bY) = a^2\text{Var}(X) + b^2\text{Var}(Y) \pm 2ab\text{Cov}(X, Y)$
 - (d) **Variance-Covariance Expansion.** $\text{Var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{Var}(X_i) + 2 \sum_{1 \leq i < j \leq n} \text{Cov}(X_i, X_j)$
-

Definition 6.24. Conditional variance:

$$\text{Var}(X | Y) = \mathbb{E}[(X - \mathbb{E}(X | Y))^2 | Y]$$

Theorem 6.1.28. Law of Total Variance: $\text{Var}(X) = \text{Var}(\mathbb{E}(X | Y)) + \mathbb{E}(\text{Var}(X | Y))$

Proof.

$$\text{Var}(\mathbb{E}(X | Y)) = \mathbb{E}[(\mathbb{E}(X | Y))^2] - [\mathbb{E}(\mathbb{E}(X | Y))]^2 = \mathbb{E}[(\mathbb{E}(X | Y))^2] - \mathbb{E}(X)^2 \quad (6.4)$$

$$\text{Var}(X | Y) = \mathbb{E}(X^2 | Y) - (\mathbb{E}(X | Y))^2 \implies \mathbb{E}[\text{Var}(X | Y)] = \mathbb{E}(X^2) - \mathbb{E}[(\mathbb{E}(X | Y))^2] \quad (6.5)$$

Adding together (6.4) and (6.5) yields

$$\begin{aligned} \text{Var}(\mathbb{E}(X | Y)) + \mathbb{E}(\text{Var}(X | Y)) &= \mathbb{E}[(\mathbb{E}(X | Y))^2] - \mathbb{E}(X)^2 + \mathbb{E}(X^2) - \mathbb{E}[(\mathbb{E}(X | Y))^2] \\ &= \mathbb{E}(X^2) - \mathbb{E}(X)^2 = \text{Var}(X) \end{aligned}$$

□

Corollary 6.1.28.1. (Rao-Blackwell Theorem.) $\text{Var}(X) \geq \text{Var}(\mathbb{E}(X | Y))$

Proof. Follows immediately from Theorem 6.1.28 by noting that since the variance is nonnegative, $\mathbb{E}(\text{Var}(X | Y)) \geq 0$.

□

Proposition 6.1.29. If $c \in \mathbb{R}$, then $\text{Var}(c) = 0$.

- For the conditional variance of one Gaussian random variable on another when the covariance or correlation between them is known, see Proposition 6.3.36. For the conditional variance of a set of Gaussian random variables on another set when the covariance matrix is known, see Proposition 6.3.37.

- Covariance
-

Definition 6.25. $\text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}(X))(Y - \mathbb{E}(Y))]$

Proposition 6.1.30. (Useful reformulation): $\text{Cov}(X, Y) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y)$

Theorem 6.1.31. (Some useful results):

- (a) $\text{Cov}(aX, BY) = ab\text{Cov}(X, Y)$
 - (b) $\text{Cov}(X, X) = \text{Var}(X)$
 - (c) $\text{Cov}(aX + bY) = ac\text{Var}(X) + bd\text{Var}(Y) + (ad + bc)\text{Cov}(X, Y)$
 - (d) $\text{Cov}(X_1 + X_2, Y) = \text{Cov}(X_1, Y) + \text{Cov}(X_2, Y)$
 - (e) $\text{Cov}\left(\sum_{i=1}^n X_i, Y\right) = \sum_{i=1}^n \text{Cov}(X_i, Y)$
 - (f) $\text{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j\right) = \sum_{i=1}^n \sum_{j=1}^m \text{Cov}(X_i, Y_j)$
-

Definition 6.26. Conditional covariance:

$$\text{Cov}(X, Y | Z) = \mathbb{E}(XY | Z) - \mathbb{E}(X | Z)\mathbb{E}(Y | Z) = \mathbb{E}[(X - \mathbb{E}(X | Z))(Y - \mathbb{E}(Y | Z)) | Z]$$

Theorem 6.1.32. Law of Total Covariance:

$$\text{Cov}(X, Y) = \mathbb{E}(\text{Cov}(X, Y | Z)) + \text{Cov}(\mathbb{E}(X | Z), \mathbb{E}(Y | Z))$$

6.1.7 Discrete Random Variable Distributions

Binomial: Binomial(n, p) (sum of n Bernoulli random variables)

- Mass function: $\Pr(X = k) = \binom{n}{k} p^k (1-p)^{n-k}$
- Distribution: $\Pr(X \leq k) = \sum_{i=0}^k \binom{n}{i} p^i (1-p)^{n-i}$
- Expectation: $\mathbb{E}(X) = np$
- Variance: $\text{Var}(X) = np(1-p)$

For an interesting result relating binomial and Poisson random variables, see Proposition 6.1.38.

Multinomial:

Definition 6.27 (Multinomial($n, p_1, p_2, \dots, p_{r-1}$) distribution). Suppose that n independent trials, each of which results in either outcome $1, 2, \dots, r$ with respective probabilities p_1, p_2, \dots, p_r (with $\sum_i p_i = 1$), are performed. Let N_i denote the number of trials resulting in outcome i . Then the joint distribution of N_1, \dots, N_r is called the **multinomial distribution**.

- Mass function:

$$\Pr(\mathbf{N} = \mathbf{N}) = \binom{n}{N_1, N_2, \dots, N_r} \prod_{i=1}^r p_i^{N_i} = \frac{n!}{N_1! N_2! \dots N_r!} \prod_{i=1}^r p_i^{N_i}$$

Proof. For $r = 2$, we have the binomial distribution: $\Pr(N_1 = x_1) = \binom{n}{x_1} p_1^{x_1} (1 - p_1)^{n-x_1}$; $\Pr(N_2 = x_2) = \binom{n}{x_2} p_2^{x_2} (1 - p_2)^{n-x_2}$. But in the general case, it is still true that N_i is a binomial random variable for all i . So in general we have $\Pr(N_i = x_i) = \binom{n}{x_i} p_i^{x_i} (1 - p_i)^{n_i-x_i}$, $i \in \{1, 2, \dots, r\}$.

We would like the distribution of the random vector $\mathbf{N} = (N_1, \dots, N_r)$. First consider the case where $n = 1$; that is, the Multinoulli distribution. Note that in this case, we have $\Pr(\mathbf{N} = \mathbf{N}) = \prod_{i=1}^r p_i^{\mathcal{N}_i}$, where \mathcal{N}_i are the entries of the observed vector \mathbf{N} ($\mathcal{N}_i \in \{0, 1\}$).

Now consider an arbitrary $n \in \mathbb{N}$. Then \mathbf{N} is the sum of n Multinoulli random variables. Just as before, the probability of a particular \mathbf{N} obtained in a particular ordering is $\Pr(\mathbf{N} = \mathbf{N}) = \prod_{i=1}^r p_i^{\mathcal{N}_i}$. However, we must also consider the number of possible orderings in which these successes could have occurred. This number of orderings is exactly equal to the multinomial coefficient,

$$\binom{n}{\mathcal{N}_1, \mathcal{N}_2, \dots, \mathcal{N}_r} = \frac{n!}{\mathcal{N}_1! \mathcal{N}_2! \dots \mathcal{N}_r!}$$

Therefore the joint probability mass function for \mathbf{N} is

$$\Pr(\mathbf{N} = \mathbf{N}) = \binom{n}{\mathcal{N}_1, \mathcal{N}_2, \dots, \mathcal{N}_r} \prod_{i=1}^r p_i^{\mathcal{N}_i} = \frac{n!}{\mathcal{N}_1! \mathcal{N}_2! \dots \mathcal{N}_r!} \prod_{i=1}^r p_i^{\mathcal{N}_i}$$

□

- Distribution: $\Pr(X \leq k) =$
- Expectation: $\mathbb{E}(X) =$
- Variance: $\text{Var}(X) =$

Proposition 6.1.33. $\text{Cov}(N_i, N_j) = -np_i p_j$.

Proof. For a Multinoulli random variable ($\text{Multinomial}(1, p_1, \dots, p_{r-1})$), we have

$$\text{Cov}(N_i, N_j) = \mathbb{E}(N_i N_j) - \mathbb{E}(N_i) \mathbb{E}(N_j) = 0 - p_i p_j = -p_i p_j$$

(where $\mathbb{E}(N_i N_j) = 0$ because at least one of them must equal 0). Since a multinomial random variable is the sum of n independent Multinoulli random variables, in the general case we have

$$\text{Cov}(N_i, N_j) = -np_i p_j.$$

□

Proposition 6.1.34. Let $X = (X_1, \dots, X_k)$ have multinomial distribution $\text{Multinomial}(n; \theta_1, \dots, \theta_k)$. Then the maximum likelihood estimator of $\theta = (\theta_1, \dots, \theta_k)$ is

$$\hat{\theta}^{(mle)} = \begin{bmatrix} \hat{\theta}_1^{(mle)} \\ \vdots \\ \hat{\theta}_k^{(mle)} \end{bmatrix} = \begin{bmatrix} x_1/n \\ \vdots \\ x_k/n \end{bmatrix}.$$

Proof. We have for all $\{X \in \mathbb{Z}_+^k : \sum_{i=1}^k X_i = n\}$

$$\Pr(X = (x_1, \dots, x_k)) = \binom{n}{x_1, \dots, x_k} \prod_{i=1}^k \theta_i^{x_i} = \frac{n!}{x_1! x_2! \dots x_k!} \prod_{i=1}^k \theta_i^{x_i}$$

so the log likelihood is

$$\ell_n(\theta) = \log \left(\frac{n!}{x_1! x_2! \dots x_k!} \right) + \sum_{i=1}^k x_i \log(\theta_i) = \log \left(\frac{n!}{x_1! x_2! \dots x_k!} \right) + x^T \log(\theta).$$

where $\log(\theta) = (\log(\theta_1), \dots, \log(\theta_k))$. Then

$$\frac{d}{d\theta_i} \ell_n(\theta) = \frac{x_i}{\theta_i}, \quad i \in [k]$$

But we have the constraint $g(\theta) = \sum_{i=1}^k \theta_i = 1$, so we can use Lagrange multipliers to write

$$\frac{d}{d\theta_i} g(\theta) = 1 \implies \begin{bmatrix} x_1/\hat{\theta}_1^{(mle)} \\ \vdots \\ x_k/\hat{\theta}_k^{(mle)} \end{bmatrix} = \lambda \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \iff \begin{bmatrix} \hat{\theta}_1^{(mle)} \\ \vdots \\ \hat{\theta}_k^{(mle)} \end{bmatrix} = \begin{bmatrix} \lambda x_1 \\ \vdots \\ \lambda x_k \end{bmatrix}$$

for some $\lambda \in \mathbb{R}_+$. Finally,

$$\sum_{i=1}^k \hat{\theta}_i^{(mle)} = 1 \iff \sum_{i=1}^k \lambda x_i = 1 \iff \lambda = \frac{1}{n} \iff \begin{bmatrix} \hat{\theta}_1^{(mle)} \\ \vdots \\ \hat{\theta}_k^{(mle)} \end{bmatrix} = \begin{bmatrix} x_1/n \\ \vdots \\ x_k/n \end{bmatrix}.$$

□

Poisson: Poisson(λ): an approximation of the binomial distribution for n very large, p very small, $np \rightarrow \lambda \in (0, \infty)$.

- Mass function:

$$\Pr(X = k) = \frac{e^{-\lambda} \lambda^k}{k!}$$

- Distribution: $\Pr(X \leq k) = \sum_{i=0}^k \frac{e^{-\lambda} \lambda^i}{i!}$
- Expectation: $\mathbb{E}(X) = \lambda$ (derive from basic definitions)
- Variance: $\text{Var}(X) = \lambda$
- Moment-generating function: $M_X(t) = e^{\lambda(e^t - 1)}$
- Characteristic function:

$$\mathbb{E} e^{itX} = \sum_{k=0}^{\infty} e^{-\lambda} \frac{\lambda^k e^{itk}}{k!} = \exp \{ \lambda(e^{it} - 1) \}$$

Proposition 6.1.35. Let $X \sim \text{Binomial}(n, p)$. Then

$$\lim_{n \rightarrow \infty, p \rightarrow 0, np \rightarrow \lambda} X \sim \text{Poisson}(np).$$

Proof.

$$\begin{aligned} & \lim_{n \rightarrow \infty, p \rightarrow 0, np \rightarrow \lambda} \binom{n}{k} p^k (1-p)^{n-k} = \lim_{n \rightarrow \infty, p \rightarrow 0, np \rightarrow \lambda} \frac{n!}{(n-k)! k!} p^k (1-p)^{n-k} \\ &= \frac{1}{k!} \cdot \lim_{n \rightarrow \infty, p \rightarrow 0, np \rightarrow \lambda} (1-p)^{n-k} p^k \prod_{i=0}^{k-1} (n-i) = \frac{1}{k!} \cdot \lim_{n \rightarrow \infty, p \rightarrow 0, np \rightarrow \lambda} \left(1 - \frac{np}{n}\right)^{n-k} p^k \prod_{i=0}^{k-1} (n-i) \end{aligned}$$

Using $\lim_{n \rightarrow \infty} (1 - \lambda/n)^n = \exp(\lambda)$, and letting $\lambda = np$, we have

$$= \frac{\exp(-np)(np)^k}{k!} = \boxed{\frac{\exp(-\lambda)\lambda^k}{k!}} \sim \text{Poisson}(np)$$

□

Proposition 6.1.36. Let $X \sim \text{Poisson}(\lambda)$. If λ is sufficiently large (say $\lambda > 20$, then we can use the approximation

$$X \sim \mathcal{N}(\lambda, \lambda)$$

Proof. (Informal justification.) By Proposition 6.1.35, a Poisson distribution can be thought of as a close approximation of a binomial distribution. Since a binomial distribution can be approximated by a normal distribution for n large and np not too large, the same is true of a Poisson distribution. □

Proposition 6.1.37. Suppose $X \sim \text{Poisson}(\mu)$, $Y \sim \text{Poisson}(\nu)$, with $X \perp\!\!\!\perp Y$. Then $\{X + Y\} \sim \text{Poisson}(\mu + \nu)$.

Proof. (exercise; use characteristic functions.)

□

Proposition 6.1.38. Suppose $X \sim \text{Poisson}(\mu)$, $Y \sim \text{Poisson}(\nu)$, with $X \perp\!\!\!\perp Y$. Then $\{X \mid X + Y = t\} \sim \text{Bin}(t, \mu/(\mu + \nu))$

Proof.

$$\mathbb{P}_{\mu, \nu}(X = x \mid X + Y = t) = \frac{\mathbb{P}_{\mu, \nu}(X = x, Y = t - x)}{\mathbb{P}_{\mu, \nu}(X + Y = t)} = \frac{\mu^x}{x!} e^{-\mu} \cdot \frac{\nu^{t-x}}{(t-x)!} e^{-\nu} \cdot \frac{t! e^{\mu+\nu}}{(\mu+\nu)^t}$$

where we used Proposition 6.1.37 to get $\{X + Y\} \sim \text{Poisson}(\mu + \nu)$.

$$= \binom{t}{x} \left(\frac{\mu}{\mu+\nu}\right)^x \left(\frac{\nu}{\mu+\nu}\right)^{t-x}$$

so $\{X \mid T = t\} \sim \text{Bin}(t, \mu/(\mu + \nu))$.

□

Remark 37. A similar result exists when a sum of three or more Poisson random variables is known; the conditional distribution is multinomial.

Proposition 6.1.39. Suppose $\tilde{N} \sim \text{Poisson}(\lambda)$ and $X \mid \tilde{N} \sim \text{Binom}(\tilde{N}, p)$. Then X and $\tilde{N} - X$ are independent and $X \sim \text{Poisson}(\lambda p)$ and $\tilde{N} - X \sim \text{Poisson}(\lambda[1 - p])$.

Proof.

$$\begin{aligned}\mathbb{P}(X = x, \tilde{N} - X = n - x) &= \mathbb{P}(X = x, \tilde{N} = n) \\ &= \frac{e^{-\lambda} \lambda^n}{n!} \binom{n}{x} p^x (1-p)^{n-x} \\ &= e^{-\lambda p} e^{-\lambda(1-p)} \frac{\lambda^{x+(n-x)}}{n!} \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x} \\ &= \frac{e^{-\lambda p} p^x}{x!} \lambda^x \cdot \frac{e^{-\lambda(1-p)} (1-p)^{n-x}}{(n-x)!} \lambda^{n-x} \\ &= \mathbb{P}(\text{Poisson}(\lambda p) = x) \cdot \mathbb{P}(\text{Poisson}(\lambda[1 - p]) = n - x).\end{aligned}$$

□

Geometric: $G_1(p)$: the number of Bernoulli trials before the first success.

- Mass function: $\Pr(X = k) = p(1 - p)^{k-1}$
- Distribution: $\Pr(X \leq k) = \sum_{i=1}^k p(1 - p)^{k-1}$
- Expectation: $\mathbb{E}(X) = 1/p$
- Variance: $\text{Var}(X) = (1 - p)/p^2$

Negative binomial: $\text{NB}(r, p)$: The number of Bernoulli trials required for r successes. (Can be derived as the sum of r identically distributed geometric random variables.)

- Mass function: $\Pr(X = k) = \binom{k-1}{r-1} p^r (1 - p)^{k-r}$
- Distribution: $\Pr(X \leq k) = \sum_{i=r}^k \binom{i-1}{r-1} p^r (1 - p)^{i-r}$
- Expectation: $\mathbb{E}(X) = \frac{r}{p}$
- Variance: $\text{Var}(X) = \frac{r(1-p)}{p^2}$
- Moment-generating function:

$$M_X(t) = \frac{(pe^t)^r}{[1 - (1 - p)e^t]^r}$$

Hypergeometric: Hypergeometric(N, M, K): When drawing a sample of size K from a group of N items, M of which are special, X is the number of special items retrieved.

- Mass function:

$$\Pr(X = k) = \frac{\binom{M}{k} \binom{N-M}{K-k}}{\binom{N}{K}}$$

- Distribution:

$$\Pr(X \leq k) = \sum_{i=0}^k \frac{\binom{M}{i} \binom{N-M}{K-i}}{\binom{N}{K}}$$

- Expectation: $\mathbb{E}(X) = \frac{MK}{N}$

Proof. Let Y_j be an indicator variable for special item j being selected. Note that $X = \sum_{j=1}^M Y_j$ and that

$$\mathbb{E}(Y_j) = \frac{\binom{1}{1} \binom{N-1}{K-1}}{\binom{N}{K}} = \frac{1 \cdot \frac{(N-1)!}{(N-K)!(K-1)!}}{\frac{N!}{(N-K)!K!}} = \frac{K}{N},$$

so we have

$$\mathbb{E}(X) = \mathbb{E}\left(\sum_{j=1}^M Y_j\right) = \sum_{j=1}^M \mathbb{E}(Y_j) = \frac{MK}{N}.$$

Alternative proof:

Let Z_i be an indicator variable for the i th selected item to be special. Then $X = \sum_{i=1}^K Z_i$ and $\mathbb{E}(Z_i) = \frac{M}{N}$, so we have

$$\mathbb{E}(X) = \mathbb{E}\left(\sum_{i=1}^K Z_i\right) = \sum_{i=1}^K \mathbb{E}(Z_i) = \frac{MK}{N}.$$

Variance: $\text{Var}(X) =$ (find by indicator method. Proof from notes, I think this may have errors:)

$$\begin{aligned}
 & \text{Ex } X \sim \mathcal{H}(M, m, n) \\
 & X = \sum_{k=1}^n X_k \quad X_k = \begin{cases} 1, & \text{if element is "special"} \\ 0, & \text{if not.} \end{cases} \\
 & \mathbb{E}(X_k) = \frac{m}{M} \quad \Rightarrow \quad \mathbb{E}(X) = n \cdot \frac{m}{M} \\
 & \mathbb{V}_{\text{var}}(X) = \sum_{k=1}^n \mathbb{V}_{\text{var}}(X_k) + \sum_{k \neq m} \sum_{m=1}^n \mathbb{Cov}(X_k, X_m) \\
 & = n \rho(1-\rho) - 2 \binom{n}{2} \left[\frac{m(m-1)}{M(M-1)} - \left(\frac{m}{M}\right)^2 \right]
 \end{aligned}$$

Proposition 6.1.40. Let $X \sim \text{Hypergeometric}(N, M, K)$. Then

$$\lim_{M,N \rightarrow \infty, M/N \rightarrow p} \Pr(X = k) \sim \text{Binomial}(K, p)$$

Proof.

$$\begin{aligned} \lim_{M,N \rightarrow \infty, M/N \rightarrow p} p_k(M, N, K) &= \lim_{M,N \rightarrow \infty, M/N \rightarrow p} \frac{\binom{M}{k} \binom{N-M}{K-k}}{\binom{N}{K}} \\ &= \lim_{M,N \rightarrow \infty, M/N \rightarrow p} \frac{M!(N-M)!/[k!(M-k)!(K-k)!(N-M-K+k)!]}{N!/[K!(N-K)!]} \\ &= \lim_{M,N \rightarrow \infty, M/N \rightarrow p} \frac{K!}{(K-k)!k!} \cdot \frac{M!(N-M)!(N-K)!}{N!(M-k)!(N-M-K+k)!} \\ &= \lim_{M,N \rightarrow \infty, M/N \rightarrow p} \binom{K}{k} \cdot \frac{M!/(M-k)!}{N!/(N-k)!} \cdot \frac{(N-M)!(N-K)!}{(N-k)!(N-M-(K-k))!} \\ &= \binom{K}{k} \lim_{M,N \rightarrow \infty, M/N \rightarrow p} \frac{M!/(M-k)!}{N!/(N-k)!} \cdot \frac{(N-M)!(N-M-(K-k))!}{(N-K+(K-k))!/(N-K)!} \\ &= \binom{K}{k} \lim_{M,N \rightarrow \infty, M/N \rightarrow p} \prod_{i=0}^{k-1} \frac{M-i}{N-i} \cdot \prod_{j=0}^{K-k-1} \frac{N-M-j}{N-K+1+j} \\ &= \binom{K}{k} \left(\frac{M}{N}\right)^k \left(\frac{N-M}{N}\right)^{K-k} \\ &= \binom{K}{k} \left(\frac{M}{N}\right)^k \left(1 - \frac{M}{N}\right)^{K-k} = \binom{K}{k} p^k (1-p)^{K-k} \end{aligned}$$

□

6.1.8 Indicator Method

Proposition 6.1.41. If $\mathbf{1}_{A_k}$ is an indicator then

(a)

$$\text{Cov}(\mathbf{1}_{A_k}, \mathbf{1}_{A_m}) = \mathbb{E}(\mathbf{1}_{A_k} \mathbf{1}_{A_m}) - \mathbb{E}(\mathbf{1}_{A_k})\mathbb{E}(\mathbf{1}_{A_m}) = \Pr(A_k \cap A_m) - \Pr(A_k)\Pr(A_m)$$

(b)

$$\text{Var}(\mathbf{1}_{A_k}) = \mathbb{E}(\mathbf{1}_{A_k}^2) = \mathbb{E}(\mathbf{1}_{A_k})^2 = \Pr(A_k) - (\Pr(A_k))^2$$

Theorem 6.1.42. X is independent of Y if and only if X is independent of $\mathbf{1}_A$, $A \in Y$.

Example problems: 505A Homework 3 problem 9(a)

Worked examples in p. 56 - 59 of Grimmett and Stirzaker 3rd edition.

6.1.9 Linear transformations of random variables

6.1.10 Poisson Paradigm (Poisson approximation for indicator method)

Theorem 6.1.43. (Theorem 4.12.9, p. 129 of Grimmett and Stirzaker.) Let A_i be an event. If $X = \sum_{i=1}^m \mathbf{1}_{A_i}$ where $\mathbf{1}_{A_i}$ is an indicator variable for A_i , and the A_i are only weakly dependent on each other, then

$$\text{As } m \rightarrow \infty, \quad X \sim \text{Poisson}(\mathbb{E}(X))$$

More specifically, let B_i be n independent Bernoulli random variables with probabilities p_i . If $Y = \sum_{i=1}^n B_i$ then

$$\text{As } n \rightarrow \infty, \quad Y \sim \text{Poisson}\left(\mathbb{E}\left(\sum_i B_i\right)\right) = \text{Poisson}\left(\sum_i \mathbb{E}B_i\right) = \text{Poisson}\left(\sum_i p_i\right)$$

Proof. Full proof available in Grimmett and Stirzaker, section 4.12, page 129. A justification of the first claim is as follows: if the A_i are independent and $\Pr(A_i) = p \forall i$, then $X \sim \text{Binomial}(m, p)$. Then by Proposition 6.1.35, the result follows. It turns out that this result holds up if the probabilities are not necessarily identical (but all small) and the variables are not necessarily independent (but only weakly dependent). \square

Solution. Alternative Solution to Exercise 9 (Matching Problem):

Let X be the number of matches. Let $P_n = \Pr(X = 0)$ given that there are n people. Let Y be an indicator variable for the first person who receives their sandwich receiving the correct one. Note that

$$P_n = \Pr(X = 0) = \Pr(X = 0 \mid Y = 1)(1/n) + \Pr(X = 0 \mid Y = 0)(n - 1)/n.$$

Note that if the first person didn't match ($Y = 0$), we have $n - 2$ people with their hats left, but one of the remaining $n - 1$ people can't get their sandwich because it was taken by the first person. Therefore

$$\Pr(X = 0 \mid Y = 0) = \Pr(\{\text{the extra person selects the first person's hat, and the rest of the people pick the wrong hat}\})$$

$$+ \Pr(\{\text{the extra person does not select the first person's hat, and the rest of the people don't have any matches}\})$$

$$= \frac{1}{n-1} \cdot P_{n-2} + P_{n-1}$$

This yields

$$P_n = \frac{1}{n} P_{n-2} + \frac{n-1}{n} P_{n-1} \iff P_n - P_{n-1} = -\frac{1}{n} (P_{n-1} - P_{n-2})$$

which is a recursive formula. Now we seek to find a closed form solution. We have

$$P_3 - P_2 = -\frac{1}{3}(P_2 - P_1) = -\frac{1}{3!} \iff P_3 = P_2 - \frac{1}{3!} = \frac{1}{2!} - \frac{1}{3!}$$

$$P_4 - P_3 = -\frac{1}{4}(P_3 - P_2) = \frac{1}{4!} \iff P_4 = P_3 + \frac{1}{4!} = \frac{1}{2!} - \frac{1}{3!} + \frac{1}{4!}$$

⋮

$$P_n = \frac{1}{2!} - \frac{1}{3!} + \frac{1}{4!} - \dots + \frac{(-1)^n}{n!} = \sum_{k=0}^n \frac{(-1)^k}{k!} \rightarrow e^{-1} \text{ as } n \rightarrow \infty$$

so we see that for large n we approximately have $P_n \sim \text{Poisson}(1)$.

Now we consider $\Pr(X = k)$. Consider a set of k people who all have matches and no one else matches. The probability that everyone in a set of k people match is $(n - k)!/n!$. The probability that none of the other $n - k$ people match is P_{n-k} per above. Since there are $\binom{n}{k}$ ways to chose groups of k people, we have

$$\Pr(X = k) = \binom{n}{k} \frac{(n - k)!}{n!} \cdot P_{n-k} = \frac{P_{n-k}}{k!} \xrightarrow{n \rightarrow \infty} \frac{e^{-1} 1^k}{k!}$$

so again we see that for large n we approximately have $P_n \sim \text{Poisson}(1)$.

6.1.11 Asymptotic Distributions

Proposition 6.1.44.

$$e^x = \lim_{n \rightarrow \infty} \left(1 + \frac{x}{n}\right)^n$$

Theorem 6.1.45. Stirling's Formula:

$$n! \sim n^n e^{-n} \sqrt{2\pi n}$$

That is,

$$\lim_{n \rightarrow \infty} \frac{n^n e^{-n} \sqrt{2\pi n}}{n!} = 1.$$

6.2 Worked problems

6.2.1 Example Problems That Will Likely Appear on Midterm (and Final)

- (1) (a) **Fall 2011 Problem 1 (same as HW1 problem 5; similar to HW3 problem 2(5).)** Let A and B be events such that $0 < \Pr(A) < 1$. Show that if $\Pr(B | A) = \Pr(B | A^c)$, then A and B are independent.
- (b) Let X and Y be two discrete random variables, each taking only two possible values. Show that if $\mathbb{E}(XY) = \mathbb{E}(X)\mathbb{E}(Y)$ then X and Y are independent.

Solution.

- (a) A and B are independent if and only if

$$\Pr(A \cap B) = \Pr(A) \cdot \Pr(B)$$

We know that

$$\Pr(B) = \Pr(B|A) \cdot \Pr(A) + \Pr(B|A^c) \cdot \Pr(A^c)$$

$$= \Pr(B|A) \cdot \Pr(A) + \Pr(B|A) \cdot (1 - \Pr(A)) = \Pr(B|A) \cdot \Pr(A) + \Pr(B|A) - \Pr(B|A) \cdot \Pr(A)$$

$$= \Pr(B|A)$$

Also, we know that since $\Pr(A) \neq 0$,

$$\Pr(B|A) = \frac{\Pr(A \cap B)}{\Pr(A)}$$

Per above $\Pr(B|A) = \Pr(B)$, so we have

$$\Pr(B) = \frac{\Pr(A \cap B)}{\Pr(A)}$$

$$\Pr(A \cap B) = \Pr(A) \cdot \Pr(B)$$

which is what we were trying to prove. So the answer is true.

- (b) Without loss of generality, let X and Y have mass functions

$$X = \begin{cases} x_1 & \text{with probability } \Pr(A) \\ x_2 & \text{with probability } \Pr(A^c) \end{cases}$$

$$Y = \begin{cases} y_1 & \text{with probability } \Pr(B) \\ y_2 & \text{with probability } \Pr(B^c) \end{cases}$$

Then $X \perp\!\!\!\perp Y \iff \Pr(A \cap B) = \Pr(A) \Pr(B)$. Let $\alpha = X - x_2$, $\beta = Y - y_2$; that is,

$$\alpha = \begin{cases} x_1 - x_2 & \text{with probability } \Pr(A) \\ 0 & \text{with probability } \Pr(A^c) \end{cases}$$

$$\beta = \begin{cases} y_1 - y_2 & \text{with probability } \Pr(B) \\ 0 & \text{with probability } \Pr(B^c) \end{cases}$$

Then we have

- $\mathbb{E}(\alpha) = (x_1 - x_2) \Pr(A)$
- $\mathbb{E}(\beta) = (y_1 - y_2) \Pr(B)$
- $\mathbb{E}(\alpha\beta) = (x_1 - x_2)(y_1 - y_2) \Pr(A \cap B)$

which we can use to obtain

$$\begin{aligned} \mathbb{E}(XY) &= \mathbb{E}[(\alpha + x_2)(\beta + y_2)] = \mathbb{E}(\alpha\beta) + y_2\mathbb{E}(\alpha) + x_2\mathbb{E}(\beta) + x_2y_2 \\ &= (x_1 - x_2)(y_1 - y_2) \Pr(A \cap B) + y_2(x_1 - x_2) \Pr(A) + x_2(y_1 - y_2) \Pr(B) + x_2y_2 \end{aligned} \quad (6.6)$$

$$\begin{aligned} \mathbb{E}(X)\mathbb{E}(Y) &= \mathbb{E}(\alpha + x_2)\mathbb{E}(\beta + y_2) = [x_2 + (x_1 - x_2)\Pr(A)][y_2 + (y_1 - y_2)\Pr(B)] \\ &= x_2y_2 + x_2(y_1 - y_2)\Pr(B) + y_2(x_1 - x_2)\Pr(A) + (x_1 - x_2)(y_1 - y_2)\Pr(A)\Pr(B) \end{aligned} \quad (6.7)$$

Using $\mathbb{E}(XY) = \mathbb{E}(X)\mathbb{E}(Y)$, we set (6.6) and (6.7) equal to each other. Canceling terms appearing in both yields

$$(x_1 - x_2)(y_1 - y_2) \Pr(A \cap B) = (x_1 - x_2)(y_1 - y_2) \Pr(A) \Pr(B) \iff \Pr(A \cap B) = \Pr(A) \Pr(B)$$

which proves the independence of X and Y if $\mathbb{E}(XY) = \mathbb{E}(X)\mathbb{E}(Y)$.

- (2) **Fall 2013 Qual Problem 1.** Consider a sequence of independent tosses of a pair of fair dice. Compute the probability that the sum 4 will occur before the sum 5.

Solution. Let Y_k be the outcome of the k th toss. Let X_{k1} be the number of the first die on the k th toss and X_{k2} be the outcome of the second die. Note that

$$\Pr(Y_k = 4) = \Pr(X_{k1} = 1 \cap X_{k2} = 3) + \Pr(X_{k1} = 2 \cap X_{k2} = 2) + \Pr(X_{k1} = 3 \cap X_{k2} = 1) = 3 \cdot \frac{1}{36} = \frac{1}{12}$$

$$\Pr(Y_k = 5) = \Pr(X_{k1} = 1 \cap X_{k2} = 4) + \Pr(X_{k1} = 2 \cap X_{k2} = 3) + \Pr(X_{k1} = 3 \cap X_{k2} = 2)$$

$$+ \Pr(X_{k1} = 4 \cap X_{k2} = 1) = 4 \cdot \frac{1}{36} = \frac{1}{9}$$

Let A_k be the event that $Y_k = 4$ and $Y_j \neq 4$ or 5, $j = 1, \dots, k-1$. Note that all A_k are mutually exclusive and

$$\Pr(A_k) = \frac{1}{12} \cdot \left(1 - \frac{3+4}{36}\right)^{k-1} = \frac{1}{12} \cdot \left(\frac{29}{36}\right)^{k-1}.$$

Then

$$\Pr(\{\text{roll a 4 before a 5}\}) = \Pr\left(\bigcup_{k=1}^{\infty} A_k\right) = \sum_{k=1}^{\infty} \Pr(A_k) = \frac{1}{12} \sum_{k=1}^{\infty} \left(\frac{29}{36}\right)^{k-1} = \frac{1/12}{1 - 29/36}$$

$$= \frac{3}{36-29} = \boxed{\frac{3}{7}}$$

- (3) **Spring 2013 Problem 1, in notes from 09/21.** Let X and Y be random variables such that $\mathbb{E}(X | Y) = Y, \mathbb{E}(Y | X) = X, \mathbb{E}(X^2) < \infty, \mathbb{E}(Y^2) < \infty$. Show that $\mathbb{E}(X - Y)^2 = 0$ (or equivalently, show $\Pr(X = Y) = 1$).

Solution.

$$\mathbb{E}(X - Y)^2 = \mathbb{E}(X^2 - 2XY + Y^2) = \mathbb{E}(X^2) - 2\mathbb{E}(XY) + \mathbb{E}(Y^2)$$

$$\mathbb{E}(XY) = \mathbb{E}(\mathbb{E}(XY | Y)) = \mathbb{E}(Y\mathbb{E}(X | Y)) = \mathbb{E}(Y \cdot Y) = \mathbb{E}(Y^2)$$

Also,

$$\mathbb{E}(XY) = \mathbb{E}(\mathbb{E}(XY | X)) = \mathbb{E}(X\mathbb{E}(Y | X)) = \mathbb{E}(X \cdot X) = \mathbb{E}(X^2)$$

Therefore

$$\mathbb{E}(X - Y)^2 = 0$$

- (4) **Fall 2016 Problem 4.** Consider a group of $n \geq 4$ people, among whom are Alice, Bob, Charles, and Diana, standing in a row. Assume that all possible orderings of the n people are equally likely.

- (a) Compute the probability that Charles stands somewhere between Alice and Bob. (Note: this does not mean that the three are necessarily adjacent; there can be other people between Alice and Bob.)
- (b) Compute the probability that Diana stands somewhere between Alice and Bob given that Charles stands somewhere between Alice and Bob.
- (c) Let X be the number of people who stand between Alice and Bob. Compute the expected value and the variance of X . (Note: Alice and Bob themselves are not counted in this number.)

Solution.

- (a) For this part, n does not make a difference; all we need to know is the ordering of A , B , and C . This is because conditional on a specific ordering of A , B , and C , all arrangements of everyone else are equally likely; and conversely, the a particular ordering of A , B , and C is independent of which three particular slots are made available to them. Examining the permutations of A , B , and C , two of them have C in the middle, so the answer is $2/6 = \boxed{1/3}$.
- (b) Similarly, the answer is independent of n , so we work with $n = 4$. All possible orderings with Charles between Alice and Bob are as follows:

$$ACDB, ADCB, BCDA, BDCA, ACBD, BCAD, DACB, DBCA$$

The first four of these have Diana between Alice and Bob, so the answer is $4/8 = \boxed{1/2}$.

- (c) Let I_k be an indicator variable for the event that person k is between A and B . By the result from part (a), $\mathbb{E}(I_k) = 1/3$. Then we have

$$\text{Var}(I_k) = \mathbb{E}(I_k^2) - \mathbb{E}(I_k)^2 = 1^2 \cdot \Pr(I_k = 1) - \frac{1}{9} = \frac{1}{3} - \frac{1}{9} = \frac{2}{9}$$

Noting that the four arrangements above with Charles and Diana in between Alice and Bob are the only ones where this will be the case of the $4! = 24$ possible orderings, we have

$$\mathbb{E}(I_k I_j) = \frac{4}{24} = \frac{1}{6}$$

so

$$\text{Cov}(I_j, I_k) = \mathbb{E}(I_k I_j) - \mathbb{E}(I_k)\mathbb{E}(I_j) = \frac{1}{6} - \frac{1}{9} = \frac{1}{18}$$

Therefore

$$\begin{aligned} \mathbb{E}(X) &= \mathbb{E}\left(\sum_{i=1}^{n-2} I_k\right) = \sum_{i=1}^{n-2} \frac{1}{3} = \frac{n-2}{3} \\ \text{Var}(X) &= \text{Var}\left(\sum_{i=1}^{n-2} I_k\right) = \sum_{i=1}^{n-2} \text{Var}(I_k) + 2 \sum_{1 \leq j < k \leq n-2} \text{Cov}(I_j, I_k) = \frac{2(n-2)}{9} + [(n-2)^2 - (n-2)] \cdot \frac{1}{18} \\ &= \frac{4(n-2)}{18} + \frac{(n-2)(n-3)}{18} = \boxed{\frac{(n-2)(n+1)}{18}} \end{aligned}$$

- (5) **Spring 2015 Problem 2.** A deck of 52 cards is shuffled thoroughly. Someone goes through all 52 cards, scoring 1 point each time 2 cards of the same value are consecutive (that is, when two consecutive cards have the same rank but different suits). For example, the sequence 9H, 8H, 7D, 6C, 7S, 7H, 7C scores 2 points, one for the 7H following the 7S, one for the 7C following the 7H. Let X be the total score.

- (a) Compute $\mathbb{E}(X)$.
- (b) Compute $\Pr(X = 39)$. (Note that there are 13 different ranks and you cannot score more than 3 per rank.)
- (c) In the line below, circle the number that you think is the closest to the value $\Pr(X = 0)$ and briefly explain your choice:

$$\frac{1}{1000}, \quad \frac{1}{500}, \quad \frac{1}{100}, \quad \frac{1}{50}, \quad \frac{1}{20}, \quad \frac{1}{10}, \quad \frac{1}{5}, \quad \frac{1}{2}$$

Solution.

- (a) Start by assuming the permutation is cyclic (that is, after the last card you go back to the beginning). Let Y be the number of matches in this situation. Let A_i be the event that the i th card is followed by a match. Then $\Pr(A_i) = 3/51 = 1/17$, so

$$Y = \sum_{k=1}^{52} \mathbf{1}_{\{A_i\}} \implies \mathbb{E}(Y) = \sum_{i=1}^{52} \mathbb{E}(\mathbf{1}_{\{A_i\}}) = \sum_{i=1}^{52} \Pr(A_i) = 52 \cdot 1/17 = 52/17$$

Note that $\mathbb{E}(Y) = \mathbb{E}(X) + \mathbb{E}(\mathbf{1}_{\{A_i\}})$ because if the permutation is cyclic then you have one extra opportunity to match at the end.

$$\implies \mathbb{E}(X) = \frac{52}{17} - \frac{1}{17} = \frac{51}{17} = \boxed{3}$$

- (b) $\Pr(X = 39) = \Pr(\{\text{all possible matches occur}\})$, so in this event all cards of the same rank are clustered together. There are 13 clusters of 4 cards, so there are $13!$ ways to order the clusters and $4!$ ways to order the cards within each cluster. Therefore

$$\boxed{\Pr(X = 39) = \frac{13!(4!)^{13}}{52!}}$$

- (c) Because A_i are only weakly dependent and $\Pr(A_i)$ is small for all A_i , we can use the Poisson approximation (see Section 6.1.10); that is, $X \sim \text{Poisson}(\mathbb{E}(X)) = \text{Poisson}(3)$. Therefore

$$\Pr(X = 0) \approx \frac{e^{-3} \cdot 3^0}{0!} = \frac{1}{e^3} \approx \frac{1}{2.8^3} \approx \boxed{\frac{1}{20}}$$

6.2.2 Problems we did in class that professor mentioned

(Fall 2014 Problem 1) (Variation of Midterm problem 1 above) Let A and B be two events with $0 < \Pr(A) < 1$, $0 < \Pr(B) < 1$. Define the random variables $\xi = \xi(\omega)$ and $\eta = \eta(\omega)$ by

$$\xi(\omega) = \begin{cases} 5 & \text{if } \omega \in A \\ -7 & \text{if } \omega \notin A \end{cases}, \quad \eta(\omega) = \begin{cases} 2 & \text{if } \omega \in B \\ 3 & \text{if } \omega \notin B \end{cases}$$

True or false: the events A and B are independent if and only if the random variables ξ and η are uncorrelated?

Solution. (\implies) Suppose A and B are independent. Then ξ and η are uncorrelated if and only if $\mathbb{E}(\xi\eta) = \mathbb{E}(\xi)\mathbb{E}(\eta)$. We can write $\xi = 5 \cdot \mathbf{1}_A - 7 \cdot \mathbf{1}_{A^c}$ and $\eta = 2 \cdot \mathbf{1}_B + 3 \cdot \mathbf{1}_{B^c}$. So we have

$$\xi\eta = (5 \cdot \mathbf{1}_A - 7 \cdot \mathbf{1}_{A^c})(2 \cdot \mathbf{1}_B + 3 \cdot \mathbf{1}_{B^c}) = 10 \cdot \mathbf{1}_{A \cap B} + 15 \cdot \mathbf{1}_{A \cap B^c} - 14 \cdot \mathbf{1}_{A^c \cap B} - 21 \cdot \mathbf{1}_{A^c \cap B^c}$$

$$\implies \mathbb{E}(\xi\eta) = 10 \Pr(A \cap B) + 15 \Pr(A \cap B^c) - 14 \Pr(A^c \cap B) - 21 \Pr(A^c \cap B^c)$$

Then

$$\mathbb{E}(\xi)\mathbb{E}(\eta) = (5 \Pr(A) - 7 \Pr(A^c))(2 \Pr(B) + 3 \Pr(B^c))$$

$$= 10 \Pr(A \cap B) + 15 \Pr(A \cap B^c) - 14 \Pr(A^c \cap B) - 21 \Pr(A^c \cap B^c) = \mathbb{E}(\xi\eta)$$

where the second-to-last step follows from the independence of A and B . Therefore η and ξ are uncorrelated.

(\Leftarrow) Now suppose η and ξ are uncorrelated. Then ξ and η are independent if and only if $\Pr(\xi \cap \eta) = \Pr(\xi)\Pr(\eta)$. Define

$$\alpha(\omega) = \xi(\omega) + 7 = \begin{cases} 12 & \text{if } \omega \in A \\ 0 & \text{if } \omega \notin A \end{cases}, \quad \beta(\omega) = \eta(\omega) - 3 = \begin{cases} -1 & \text{if } \omega \in B \\ 0 & \text{if } \omega \notin B \end{cases}$$

Then we have

$$(\alpha\beta)(\omega) = \begin{cases} -12 & \text{if } \omega \in A \cap B \\ 0 & \text{otherwise} \end{cases}$$

Then

$$\mathbb{E}(\xi\eta) = \mathbb{E}[(\alpha - 7)(\beta + 3)] = \mathbb{E}(\alpha\beta) + 3\mathbb{E}(\alpha) - 7\mathbb{E}(\beta) - 21$$

$$\mathbb{E}(\xi)\mathbb{E}(\eta) = (\mathbb{E}(\alpha) - 7)(\mathbb{E}(\beta) + 3) = \mathbb{E}(\alpha)\mathbb{E}(\beta) - 7\mathbb{E}(\beta) + 3\mathbb{E}(\alpha) - 21$$

Since by assumption $\mathbb{E}(\xi\eta) = \mathbb{E}(\xi)\mathbb{E}(\eta)$, this yields $\mathbb{E}(\alpha\beta) = \mathbb{E}(\alpha)\mathbb{E}(\beta)$. But

$$\mathbb{E}(\alpha\beta) = -12\Pr(A \cap B), \quad \mathbb{E}(\alpha)\mathbb{E}(\beta) = 12\Pr(A)(-1)\Pr(B) = -12\Pr(A)\Pr(B)$$

Therefore $\Pr(\xi \cap \eta) = \Pr(\xi)\Pr(\eta)$ and ξ and η are independent.

Exercise 9. Example (Letter/envelope matching problem; sometimes referred to as Montmort's matching problem). An assistant brings n sandwiches for n employees at a company. Each employee ordered a unique sandwich, but unfortunately the assistant forgot to ask that the sandwiches be labeled, so they are all indistinguishable, wrapped in the same paper. The assistant plans to distribute one sandwich to each employee and hope for the best. Let X be the number of sandwiches that are delivered to the correct person.

- (a) What is the probability of at least one match; that is, $\Pr(X \geq 1)$?
- (b) What is the probability of r correct matches?
- (c) What $\mathbb{E}(X)$?
- (d) What is $\text{Var}(X)$?

Solution.

- (a) Let A_k be an indicator variable for the event that sandwich k is matched to the correct employee.
Then

$$\Pr(X \geq 1) = \Pr\left(\bigcup_{k=1}^n A_k\right)$$

Consider that if there are k correct matches, there are $\binom{n}{k}$ sets of k sandwiches that could be correctly distributed. Also, the probability of a particular set of k sandwiches being correctly distributed is $(n - k)!/n!$. So we have

$$\Pr(X = k) = \binom{n}{k} \frac{(n - k)!}{n!}$$

Therefore by the Inclusion-Exclusion Principle (Proposition 6.1.13),

$$\begin{aligned} \Pr\left(\bigcup_{k=1}^n A_k\right) &= \sum_{k=1}^n (-1)^{k-1} \Pr(X = k) = \sum_{k=1}^n (-1)^{k-1} \binom{n}{k} \frac{(n - k)!}{n!} = \sum_{k=1}^n (-1)^{k-1} \frac{n!}{(n - k)!k!} \frac{(n - k)!}{n!} \\ &= \sum_{k=1}^n \frac{(-1)^{k-1}}{k!} = \frac{(-1)^0}{0!} - \sum_{k=0}^n \frac{(-1)^k}{k!} = \boxed{1 - \sum_{k=0}^n \frac{(-1)^k}{k!}} \end{aligned}$$

As $n \rightarrow \infty$, we have

$$1 - \sum_{k=0}^n \frac{(-1)^k}{k!} \rightarrow 1 - e^{-1} = \boxed{1 - \frac{1}{e}}$$

- (b) Clearly there is only one way to match all the sandwiches correctly, so $\Pr(X = r \mid r = n) = 1/n!$. Also, note that it is impossible to match all but one sandwich, so $\Pr(X = r \mid r = n - 1) = 0$. Only the cases for $r \leq n - 2$ are nontrivial. Using a similar argument as part (a), we see that for any set of m sandwiches, the probability that at least one was correctly distributed is

$$\Pr\left(\bigcup_{k=1}^m A_k\right) = \sum_{k=1}^m (-1)^{k-1} \frac{(n - k)!}{n!}$$

and that the probability that *any* set of m sandwiches contained at least one correct match is

$$\begin{aligned} \sum_{k=1}^m (-1)^{k-1} \binom{n}{k} \frac{(n - k)!}{n!} &= \sum_{k=1}^m (-1)^{k-1} \frac{n!}{(n - k)!k!} \frac{(n - k)!}{n!} \\ &= \sum_{k=1}^m \frac{(-1)^{k-1}}{k!} = 1 + \sum_{k=2}^m \frac{(-1)^{k-1}}{k!} = 1 - \sum_{k=2}^m \frac{(-1)^k}{k!} \end{aligned}$$

So for $m \geq 2$, the probability of *no* correct matches is $\sum_{k=2}^m \frac{(-1)^k}{k!}$ if $n \geq 2$, and of course 0 if $n = 1$. Therefore the probability of r matches is the probability of any one set of r sandwiches all matching and none of the remaining $n - r$ sandwiches matching times the number of sets of r sandwiches; that is,

$$\begin{aligned} \Pr(X = r \mid r \leq n - 2) &= \binom{n}{r} \cdot \frac{(n - r)!}{n!} \cdot \left(\sum_{k=2}^{n-r} \frac{(-1)^k}{k!} \right) = \frac{r!}{(n - r)!r!} \cdot \frac{(n - r)!}{n!} \sum_{k=2}^{n-r} \frac{(-1)^k}{k!} \\ &= \frac{1}{r!} \sum_{k=2}^{n-r} \frac{(-1)^k}{k!} \end{aligned}$$

Therefore we have

$$\Pr(X = r) = \begin{cases} \frac{1}{r!} \sum_{k=2}^{n-r} \frac{(-1)^k}{k!} & r \leq n-2 \\ 0 & r = n-1 \\ \frac{1}{r!} & r = n \end{cases}$$

(c)

$$\mathbb{E}(X) = \mathbb{E}\left(\sum_{k=1}^n A_k\right) = \sum_{k=1}^n \mathbb{E}(A_k) = \sum_{k=1}^n \Pr(A_k = 1) = n \cdot \frac{1}{n} = \boxed{1}$$

(d)

$$\text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2$$

$$\mathbb{E}(X^2) = \mathbb{E}\left(\sum_{k=1}^n A_k\right)^2 = \mathbb{E}\left(\sum_{k=1}^n A_k^2 + 2 \sum_{1 \leq i < j \leq n} A_i A_j\right) = \sum_{k=1}^n \mathbb{E}(A_k^2) + 2 \sum_{1 \leq i < j \leq n} \mathbb{E}(A_i A_j)$$

Because

$$\mathbb{E}(A_k^2) = 1^2 \cdot \Pr(A_k = 1) = \frac{1}{n}$$

$$\mathbb{E}(A_i A_j) = \Pr(A_i = 1 \cap A_j = 1) = \frac{(n-2)!}{n!} = \frac{1}{n(n-1)} = \frac{1}{2} \cdot \binom{n}{2}^{-1}$$

we have

$$\mathbb{E}(X^2) = \sum_{k=1}^n \frac{1}{n} + 2 \sum_{1 \leq i < j \leq n} \frac{1}{n(n-1)} = 1 + 2 \cdot \binom{n}{2} \cdot \frac{1}{2} \cdot \binom{n}{2}^{-1} = 2$$

$$\implies \text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2 = 2 - 1 = \boxed{1}$$

HW3 Problem 2(5). Verify: $\mathbb{E}(X | Y) = \mathbb{E}(X)$ if X and Y are independent.**Solution.** X and Y are independent if and only if

$$\Pr(X \cap Y) = \Pr(X) \cdot \Pr(Y) \iff \Pr(X = x \cap Y = y) = \Pr(X = x) \Pr(Y = y)$$

$$\iff \Pr(X = x | Y = y) \cdot \Pr(Y = y) = \Pr(X = x) \Pr(Y = y) \iff \Pr(X = x | Y = y) = \Pr(X = x)$$

$$\implies \mathbb{E}(X | Y) = \sum_x x \cdot \Pr(X = x | Y = y) = \sum_x x \cdot \Pr(X = x) = \mathbb{E}(X)$$

HW3 Problem 2 (parts 1 - 4). Verify:

$$(1) \quad \mathbb{E}(\mathbb{E}(X | Y)) = \mathbb{E}(X)$$

- (2) $\mathbb{E}(g(Y)X | Y) = g(Y)\mathbb{E}(X | Y)$
 (3) $\text{Cov}(\mathbb{E}(X | Y), Y) = \text{Cov}(X, Y)$
 (4) Y and $X - \mathbb{E}(X | Y)$ are uncorrelated.

Solution.

(1)

$$\begin{aligned}\mathbb{E}(\mathbb{E}(X | Y)) &= \sum_y \mathbb{E}(X | Y) \Pr(Y = y) = \sum_y \left[\sum_x x \cdot \Pr(X = x | Y = y) \Pr(Y = y) \right] \\ &= \sum_y \left[\sum_x x \cdot \Pr(X = x \cap Y = y) \right] = \sum_y \left[\sum_x x \cdot \Pr(Y = y | X = x) \cdot \Pr(X = x) \right] \\ &= \sum_x \left[x \cdot \Pr(X = x) \cdot \sum_y (\Pr(Y = y | X = x)) \right] = \sum_x \left[x \cdot \Pr(X = x) \cdot 1 \right] \\ &= \mathbb{E}(X)\end{aligned}$$

(2) 2

(3)

$$\begin{aligned}\text{Cov}(\mathbb{E}(X | Y), Y) &= \mathbb{E} \left(\left[\mathbb{E}(X | Y) - \mathbb{E}(\mathbb{E}(X | Y)) \right] \left[Y - \mathbb{E}(Y) \right] \right) \\ &= \mathbb{E} \left(\left[\mathbb{E}(X | Y) - \mathbb{E}(X) \right] \left[Y - \mathbb{E}(Y) \right] \right) = \mathbb{E} \left(\mathbb{E}(X | Y)Y - \mathbb{E}(X)Y - \mathbb{E}(X | Y)\mathbb{E}(Y) + \mathbb{E}(X)\mathbb{E}(Y) \right) \\ &= \mathbb{E}(\mathbb{E}(X | Y)Y) - \mathbb{E}(X)\mathbb{E}(Y) - \mathbb{E}(Y)\mathbb{E}(\mathbb{E}(X | Y)) + \mathbb{E}(X)\mathbb{E}(Y) = \mathbb{E}(\mathbb{E}(X | Y)Y) - \mathbb{E}(Y)\mathbb{E}(X) \\ &= \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y) = \text{Cov}(X, Y)\end{aligned}$$

(4) Y and $X - \mathbb{E}(X | Y)$ are uncorrelated if and only if $\text{Cov}(Y, X - \mathbb{E}(X | Y)) = 0 \iff \mathbb{E}(Y \cdot [X - \mathbb{E}(X | Y)]) - \mathbb{E}(Y)\mathbb{E}(X - \mathbb{E}(X | Y)) = 0$.

$$\begin{aligned}\mathbb{E}(Y \cdot [X - \mathbb{E}(X | Y)]) - \mathbb{E}(Y)\mathbb{E}(X - \mathbb{E}(X | Y)) &= \mathbb{E}(YX - Y\mathbb{E}(X | Y)) - \mathbb{E}(Y)\mathbb{E}(X) + \mathbb{E}(Y)\mathbb{E}(\mathbb{E}(X | Y)) \\ &= \mathbb{E}(YX) - \mathbb{E}(Y\mathbb{E}(X | Y)) - \mathbb{E}(Y)\mathbb{E}(X) + \mathbb{E}(Y)\mathbb{E}(X) = \mathbb{E}(YX) - \mathbb{E}(YX) = 0\end{aligned}$$

Spring 2018 Problem 2 (did not complete)

2. Consider positions 1 to n arranged in a circle, so that 2 comes after 1, 3 comes after 2, ..., n comes after $n - 1$, and 1 comes after n . Similarly, take 1 to n as values, with cyclic order, and consider all $n!$ ways to assign values to positions, bijectively, with all $n!$ possibilities equally likely. For $i = 1$ to n , let X_i be the indicator that position i and the one following are filled in with two consecutive values in increasing order, and define

$$S_n = \sum_{i=1}^n X_i, \quad T_n = \sum_{i=1}^n iX_i$$

For example, with $n = 6$ and the circular arrangement 314562, we get $X_3 = 1$ since 45 are consecutive in increasing order, and similarly $X_4 = X_6 = 1$, so that $S_6 = 3, T_6 = 13$.

- a) Compute the mean and the variance of S_n .
- b) Compute the mean and the variance of T_n .

Fall 2008 Problem 2 (HW1 Problem 10). Consider a lottery with n^2 tickets, of which only n tickets win prizes. Let p_n be the probability that, out of n randomly selected tickets, at least one wins a prize. Compute $\lim_{n \rightarrow \infty} p_n$.

Solution. There are $\binom{n^2}{n}$ possible sets of n tickets. The number of these sets that do not contain at least one winner (that is, they only contain members of the $n^2 - n$ losing tickets) is $\binom{n^2-n}{n}$. Therefore the probability of selecting a set of n tickets that contains at least one winner is

$$\begin{aligned} p_n &= 1 - \binom{n^2-n}{n} / \binom{n^2}{n} = 1 - \frac{(n^2-n)!}{n!(n^2-n-n)!} / \frac{(n^2)!}{(n^2-n)!n!} = 1 - \frac{(n^2-n)!}{n!(n^2-2n)!} \cdot \frac{(n^2-n)!n!}{(n^2)!} \\ &= 1 - \frac{(n^2-n)!}{(n^2-2n)!} \cdot \frac{(n^2-n)!}{(n^2)!} = 1 - \prod_{i=0}^{n-1} (n^2-n-i) / \prod_{i=0}^{n-1} (n^2-i) = 1 - \prod_{i=0}^{n-1} \frac{n^2-n-i}{n^2-i} \\ &= 1 - \prod_{i=0}^{n-1} \left(\frac{n^2-i}{n^2-i} - \frac{n}{n^2-i} \right) = 1 - \prod_{i=0}^{n-1} \left(1 - \frac{n}{n^2-i} \right) \end{aligned}$$

Therefore

$$\begin{aligned} \lim_{n \rightarrow \infty} p_n &= \lim_{n \rightarrow \infty} \left[1 - \prod_{i=0}^{n-1} \left(1 - \frac{n}{n^2-i} \right) \right] = 1 - \lim_{n \rightarrow \infty} \prod_{i=0}^n \left(1 - \frac{n}{n^2-i} \right) = 1 - \lim_{n \rightarrow \infty} \prod_{i=0}^n \left(1 - \frac{n \cdot \frac{1}{n}}{\frac{n^2}{n} - \frac{i}{n}} \right) \\ &= 1 - \lim_{n \rightarrow \infty} \prod_{i=0}^n \left(1 - \frac{1}{n - \frac{i}{n}} \right) = 1 - \lim_{n \rightarrow \infty} \prod_{i=0}^n \left(1 - \frac{1}{n} \right) = 1 - \lim_{n \rightarrow \infty} \left(1 - \frac{1}{n} \right)^n = \boxed{1 - \exp(-1)} \end{aligned}$$

6.2.3 Problems we did on homework

Fall 2017 Problem 2 (Homework 3 Problem 6). An urn contains $2n$ balls, coming in pairs: two balls are labeled “1”, two balls are labeled “2”, ..., two balls are labeled “ n ”. A sample of size n is taken with-

out replacement. Denote by N the number of pairs in the sample. Compute the expected value and the variance of N . **You do not need to simplify the expression for the variance.**

Solution. Let X_k be an indicator variable for both balls labeled k being in the sample. Note that

$$\mathbb{E}(X_k) = \Pr(X_k = 1) = \frac{\binom{2n-2}{n-2}}{\binom{2n}{n}} = \frac{(2n-2)!}{(n-2)!n!} \Big/ \frac{(2n)!}{n!n!} = \frac{(2n-2)!n!}{(2n)!(n-2)!} = \frac{n(n-1)}{2n(2n-1)} = \frac{n-1}{2(2n-1)}$$

Now since $N = \sum_{k=1}^n X_k$, we have

$$\mathbb{E}(N) = \mathbb{E}\left(\sum_{k=1}^n X_k\right) = \sum_{k=1}^n \mathbb{E}(X_k) = \boxed{\frac{n(n-1)}{2(2n-1)}}$$

To obtain the variance, note that

$$\mathbb{E}(N^2) = \mathbb{E}\left(\sum_{k=1}^n X_k\right)^2 = \mathbb{E}\left(\sum_{k=1}^n X_k^2 + 2 \sum_{1 \leq i < j \leq n} X_i X_j\right) = \sum_{k=1}^n \mathbb{E}(X_k^2) + 2 \sum_{1 \leq i < j \leq n} \mathbb{E}(X_i X_j)$$

Because

$$\mathbb{E}(X_k^2) = 1^2 \cdot \Pr(X_k = 1) = \mathbb{E}(X_k) = \frac{n-1}{2(2n-1)}$$

$$\begin{aligned} \mathbb{E}(X_i X_j) &= \Pr(X_i = 1 \cap X_j = 1) = \frac{\binom{2n-4}{n-4}}{\binom{2n}{n}} = \frac{(2n-4)!}{(n-4)!n!} \Big/ \frac{(2n)!}{n!n!} = \frac{(2n-4)!n!}{(2n)!(n-4)!} \\ &= \frac{n(n-1)(n-2)(n-3)}{2n(2n-1)(2n-2)(2n-3)} = \frac{(n-1)(n-2)(n-3)}{2(2n-1)(2n-2)(2n-3)} \end{aligned}$$

we have

$$\begin{aligned} \mathbb{E}(N^2) &= \sum_{k=1}^n \frac{n-1}{2(2n-1)} + 2 \sum_{1 \leq i < j \leq n} \frac{(n-1)(n-2)(n-3)}{2(2n-1)(2n-2)(2n-3)} = \frac{n(n-1)}{2(2n-1)} + 2 \binom{n}{2} \frac{(2n-4)!n!}{(2n)!(n-4)!} \\ &= \frac{n(n-1)}{2(2n-1)} + \frac{n!}{(n-2)!} \cdot \frac{(2n-4)!n!}{(2n)!(n-4)!} = \frac{n(n-1)}{2(2n-1)} + n(n-1) \cdot \frac{(n-1)(n-2)(n-3)}{2(2n-1)(2n-2)(2n-3)} \\ &= \frac{n(n-1)}{2(2n-1)} + \frac{n(n-1)^2(n-2)(n-3)}{2(2n-1)(2n-2)(2n-3)} \\ \implies \text{Var}(N) &= \mathbb{E}(N^2) - \mathbb{E}(N)^2 = \boxed{\frac{n(n-1)}{2(2n-1)} + \frac{n(n-1)^2(n-2)(n-3)}{2(2n-1)(2n-2)(2n-3)} - \frac{n^2(n-1)^2}{4(2n-1)^2}} \end{aligned}$$

Fall 2017 Problem 3 (HW3 Problem 8—almost full solution)

Let U_1, U_2, \dots be iid random variables, uniformly distributed on $[0, 1]$, and let N be a Poisson random variable with mean value equal to 1. Assume that N is independent of U_1, U_2, \dots and define

$$Y = \begin{cases} 0 & \text{if } N = 0 \\ \max_{1 \leq i \leq N} U_i & \text{if } N > 0 \end{cases}$$

Compute the expected value of Y .

Solution. Since Y is a function of N , let $Y = y(N)$. By the Law of the Unconscious Statistician,

$$\mathbb{E}(Y) = \mathbb{E}(\mathbb{E}(Y | N)) = \mathbb{E}(\mathbb{E}(\max_{1 \leq i \leq N} U_i | N = n))$$

Let $Z_n = \max_{1 \leq i \leq n} U_i$. The cdf of Z_n can be calculated as follows:

$$\Pr(Z_n \leq x) = \Pr(\max_{1 \leq i \leq n} U_i \leq x) = \Pr(U_1 \leq x \cap U_2 \leq x \cap \dots \cap U_n \leq x) = x^n$$

for $x \in [0, 1]$. Therefore the pdf of Z_n is its derivative, nx^{n-1} . So we have

$$\mathbb{E}(\max_{1 \leq i \leq N} U_i | N = n) = \mathbb{E}(Z_n) = \int_0^1 x n x^{n-1} dx = n \int_0^1 x^n dx = n \frac{x^{n+1}}{n+1} \Big|_0^1 = \frac{n}{n+1}$$

Plugging this into the expression for $\mathbb{E}(Y)$ yields

$$\begin{aligned} \mathbb{E}(Y) &= \mathbb{E}(\mathbb{E}(Y | N)) = \sum_{n=0}^{\infty} \frac{n}{n+1} \Pr(N = n) = \sum_{n=1}^{\infty} \frac{n}{n+1} \frac{\exp(-1) 1^n}{n!} \\ &= \frac{1}{e} \sum_{n=1}^{\infty} \frac{n+1-1}{(n+1)!} = \frac{1}{e} \left(\sum_{n=1}^{\infty} \frac{n+1}{(n+1)!} - \sum_{n=1}^{\infty} \frac{1}{(n+1)!} \right) = \frac{1}{e} \left(\sum_{n=1}^{\infty} \frac{1}{n!} - \sum_{m=2}^{\infty} \frac{1}{m!} \right) \\ &= \frac{1}{e} [e - 1 - (e - 1 - 1)] = \boxed{\frac{1}{e}} \end{aligned}$$

Fall 2013 Problem 3/Spring 2011 Problem 2 (HW3 Problem 9; coupon collector problem)

Only parts I didn't do: Let D be the event that no box receives more than 1 ball. Fix $a \in (0, 1)$. If both $n, d \rightarrow \infty$ together, what relation must they satisfy in order to have $\Pr(D) \rightarrow a$?

HW3 Problem 9. Consider n (different) balls placed at random in m boxes so that each of m^n configurations is equally likely.

- (a) Compute the expected value and the variance of the number of empty boxes.

- (b) Show that if $\lim_{m,n \rightarrow \infty} m \exp(-n/m) = \lambda \in (0, \infty)$, then, in the same limit, the number of empty boxes has Poisson distribution with parameter λ .
- (c) For $k \geq 1$ such that $k+3 \leq m$, define the event A_k that the boxes $k, k+1, k+2, k+3$ are empty. Assuming that $m > 8$, compute $\Pr(A_1 \cup A_3 \cup A_5)$. How will the answer change if $m = 8$?
- (d) Now imagine that the balls are dropped one-by-one (with each ball equally likely to go into any of the m boxes, independent of all other balls), and denote by N_m the minimal number of balls required to fill all the boxes. Compute $\mathbb{E}(N_m)$, $\text{Var}(N_m)$ and

$$\lim_{m \rightarrow \infty} \Pr\left(\frac{N_m - m \log m}{m} \leq x\right)$$

- (e) Suppose we instead place an unlimited number of balls into the m boxes until we have k consecutive balls land in the same box (it doesn't matter which box). What is the expected number of balls we will drop until this happens?

Solution.

- (a) Let A_i be the event that the i th box is empty. Let $\mathbf{1}_{A_i}$ be the indicator for A_i . Then $X = \sum_{i=1}^m \mathbf{1}_{A_i}$.

$$\mathbb{E}(X) = \mathbb{E}\left(\sum_{i=1}^m \mathbf{1}_{A_i}\right) = \sum_{i=1}^m (\mathbb{E}\mathbf{1}_{A_i}) = \sum_{i=1}^m \Pr(A_i) = \sum_{i=1}^m \left(\frac{m-1}{m}\right)^n = \boxed{\frac{(m-1)^n}{m^{n-1}}}$$

$$\text{Var}(X) = \text{Var}\left(\sum_{i=1}^m \mathbf{1}_{A_i}\right) = \sum_{i=1}^m \text{Var}(\mathbf{1}_{A_i}) + 2 \sum_{1 \leq i < j \leq m} \text{Cov}(\mathbf{1}_{A_i}, \mathbf{1}_{A_j})$$

$$\text{Var}(\mathbf{1}_{A_i}, \mathbf{1}_{A_j}) = \mathbb{E}(\mathbf{1}_{A_i} \mathbf{1}_{A_j}) - \mathbb{E}(\mathbf{1}_{A_i})^2 = \Pr(A_i \cap A_j) - \Pr(A_i)^2 = \left(\frac{m-1}{m}\right)^n - \left(\frac{m-1}{m}\right)^{2n}$$

$$\text{Cov}(\mathbf{1}_{A_i}, \mathbf{1}_{A_j}) = \mathbb{E}(\mathbf{1}_{A_i} \mathbf{1}_{A_j}) - \mathbb{E}(\mathbf{1}_{A_i}) \mathbb{E}(\mathbf{1}_{A_j}) = \Pr(A_i \cap A_j) - \Pr(A_i) \Pr(A_j) = \left(\frac{m-2}{m}\right)^n - \left(\frac{m-1}{m}\right)^{2n}$$

$$\begin{aligned} \implies \text{Var}(X) &= m \cdot \left[\left(\frac{m-1}{m}\right)^n - \left(\frac{m-1}{m}\right)^{2n} \right] + \frac{m!}{(m-2)!} \left[\left(\frac{m-2}{m}\right)^n - \left(\frac{m-1}{m}\right)^{2n} \right] \\ &= \frac{(m-1)^n}{m^{n-1}} - \frac{(m-1)^{2n}}{m^{2n-1}} + (m^2 - m) \left[\left(\frac{m-2}{m}\right)^n - \left(\frac{m-1}{m}\right)^{2n} \right] \end{aligned}$$

$$\boxed{\text{Var}(X) = \frac{(m-1)^n}{m^{n-1}} - \frac{(m-1)^{2n}}{m^{2n-1}} + (m-1) \left[\frac{(m-2)^n}{m^{n-1}} - \frac{(m-1)^{2n}}{m^{2n-1}} \right]}$$

- (b) Note that

$$X = \sum_{i=1}^m \mathbf{1}_{A_i}$$

and that the A_i are only weakly dependent on each other, especially as m and n increase. Therefore as $m, n \rightarrow \infty$, the Poisson paradigm (see Section 6.1.10) suggests $X \sim \text{Poisson}(\mathbb{E}(X))$. We have

$$\mathbb{E}(X) = \frac{(m-1)^n}{m^{n-1}}$$

so

$$\begin{aligned} \lim_{n,m \rightarrow \infty} \mathbb{E}(X) &= \lim_{n,m \rightarrow \infty} m \cdot \left(\frac{m-1}{m} \right)^n = \lim_{n,m \rightarrow \infty} m \cdot \left(1 - \frac{1}{m} \right)^n = \lim_{n,m \rightarrow \infty} m \cdot \left[\left(1 - \frac{1}{m} \right)^m \right]^{n/m} \\ &\approx \lim_{n,m \rightarrow \infty} m \cdot [e^{-1}]^{n/m} = \lim_{n,m \rightarrow \infty} m e^{-n/m} \end{aligned}$$

Using

$$\lim_{m,n \rightarrow \infty} m \exp(-n/m) = \lambda \in (0, \infty)$$

we have $\boxed{X \sim \text{Poisson}(\lambda) \text{ as } m, n \rightarrow \infty}$.

(c)

$$\Pr(A_1 \cup A_3 \cup A_5) = \Pr(A_1) + \Pr(A_3) + \Pr(A_5) - \Pr(A_1 \cap A_3) - \Pr(A_1 \cap A_5) - \Pr(A_3 \cap A_5) + \Pr(A_1 \cap A_3 \cap A_5)$$

We have

$$\begin{aligned} \Pr(A_1) &= \Pr(A_3) = \Pr(A_5) = \left(\frac{m-4}{m} \right)^n \\ \Pr(A_1 \cap A_3) &= \Pr(A_3 \cap A_5) = \left(\frac{m-6}{m} \right)^n \\ \Pr(A_1 \cap A_5) &= \Pr(A_1 \cap A_3 \cap A_5) = \left(\frac{m-8}{m} \right)^n \end{aligned}$$

Therefore

$$\Pr(A_1 \cup A_3 \cup A_5) = 3 \left(\frac{m-4}{m} \right)^n - 2 \left(\frac{m-6}{m} \right)^n = \boxed{\frac{3(m-4)^n - 2(m-6)^n}{m^n}}$$

- (d) N_m is the minimal number of balls required to fill all the boxes. Let T_i be the number of balls that have to be dropped to fill the i th box after $i-1$ boxes have been filled. The probability of filling a new box after $i-1$ boxes have been filled is $\frac{m-(i-1)}{m}$. (Note that T_1 should be identically 1 regardless of $m \geq 1$; this checks out using this expression.) Therefore T_i has a geometric distribution with $E(T_i) = \frac{m}{m-(i-1)}$. Since $N_m = \sum_{i=1}^m T_i$, we have

$$\mathbb{E}(N_m) = \mathbb{E} \left(\sum_{i=1}^m T_i \right) = \sum_{i=1}^m \mathbb{E}(T_i) = \sum_{i=1}^m \frac{m}{m-(i-1)} = \boxed{m \sum_{i=1}^m \frac{1}{i}}$$

Because the T_i are independent, we have

$$\text{Var}(N_m) = \text{Var} \left(\sum_{i=1}^m T_i \right) = \sum_{i=1}^m \text{Var}(T_i) = \sum_{i=1}^m \left(1 - \frac{m-(i-1)}{m} \right) \left/ \left(\frac{m-(i-1)}{m} \right)^2 \right.$$

$$= \sum_{i=1}^m \frac{i-1}{m} \cdot \left(\frac{m}{m-(i-1)} \right)^2 = \boxed{m \sum_{i=1}^m \frac{i-1}{[m-(i-1)]^2}}$$

Finally, to find

$$\lim_{m \rightarrow \infty} \Pr \left(\frac{N_m - m \log m}{m} \leq x \right)$$

begin by noting that we can also express N_m as

$$\Pr(N_m \leq k) = \Pr(X_{m,k} = 0)$$

where $X_{m,k}$ is defined as X is in part (b) with k being the number of balls that have been dropped so far, $k \in \mathbb{N} \geq m$. (For $k < m$, $\Pr(N_m \leq k) = 0$.)

Again, let $A_{i,k}$ be the event that the i th box is empty after dropping k balls. Then because $X_{m,k} = \sum_{i=1}^m \mathbf{1}_{A_{i,k}}$ and the $A_{i,k}$ are only weakly dependent on each other (especially as m becomes large), the Poisson paradigm (see Section 6.1.10) again suggests that as $m \rightarrow \infty$, $X_{m,k} \sim \text{Poisson}(\lambda_k)$ where $\lambda_k = \mathbb{E}(X_{m,k})$ is defined as above. Therefore we have

$$\begin{aligned} \lim_{m \rightarrow \infty} \Pr \left(\frac{N_m - m \log m}{m} \leq x \right) &= \lim_{m \rightarrow \infty} \Pr(N_m \leq xm + m \log m) = \lim_{m \rightarrow \infty} \Pr(X_{m,xm+m \log m} \\ &= 0) \approx \frac{\exp(-\lambda_{xm+m \log m}) \cdot \lambda_{xm+m \log m}^0}{0!} = \exp(-\lambda_{xm+m \log m}) \end{aligned}$$

And we have

$$\begin{aligned} \lambda_{xm+m \log m} &= \lim_{m \rightarrow \infty} m \exp \left(-\frac{xm + m \log m}{m} \right) = \lim_{m \rightarrow \infty} m \exp(-x - \log m) = \lim_{m \rightarrow \infty} m/m \exp(-x) \\ &= \exp(-x) \end{aligned}$$

which yields

$$\boxed{\lim_{m \rightarrow \infty} \Pr \left(\frac{N_m - m \log m}{m} \leq x \right) = \exp(\exp(-x))}$$

- (e) Let $N = N_k$ be the number of balls that are dropped until k consecutive balls land in the same box, and likewise for N_{k-1} . Suppose we have already observed $k-1$ consecutive outcomes (of any kind) in N_{k-1} trials. Then we finish on the next term (by having another consecutive outcome) with probability $1/m$. Otherwise we have a different outcome and then repeat the same process again. So we have

$$\mathbb{E}(N_k | N_{k-1}) = N_{k-1} + 1 \cdot \frac{1}{m} + \mathbb{E}(N_k) \cdot \left(1 - \frac{1}{m} \right)$$

Therefore

$$\mathbb{E}(N) = \mathbb{E}(N_k) = \mathbb{E}[\mathbb{E}(N_k \mid N_{k-1})] = \mathbb{E}(N_{k-1}) + \frac{1}{m} + \left(1 - \frac{1}{m}\right)\mathbb{E}(N_k)$$

$$\iff \frac{1}{m}\mathbb{E}(N_k) = \mathbb{E}(N_{k-1}) + \frac{1}{m} \iff \mathbb{E}(N_k) = m\mathbb{E}(N_{k-1}) + 1$$

We have a recursive formula. Note that $\mathbb{E}(N_1) = 1$ because the number of trials until there is 1 consecutive outcome of any kind is simply 1. We can then calculate as follows:

$$\mathbb{E}(N_2) = m\mathbb{E}(N_{2-1}) + 1 = m + 1$$

$$\mathbb{E}(N_3) = m\mathbb{E}(N_{3-1}) + 1 = m(m + 1) + 1 = 1 + m + m^2$$

$$\mathbb{E}(N_4) = m\mathbb{E}(N_{4-1}) + 1 = m(1 + m + m^2) + 1 = 1 + m + m^2 + m^3$$

$$\vdots$$

$$\mathbb{E}(N_k) = \sum_{i=0}^{k-1} m^i = \frac{1 \cdot (1 - m^k)}{1 - m} = \boxed{\frac{m^k - 1}{m - 1}}$$

Fall 2012 Problem 1 (HW2 Problem 10/HW 1 Problem 9) Only part I didn't do: Find the mean and variance of $S_n = X_1 + \dots + X_n$, the total number of white balls added to the urn up to time n .

HW1 Problem 9. An urn contains b black and w white balls. At each step, a ball is removed from the urn at random and then put back together with one more ball of the same color. Compute the probability p_n to get a black ball on step n , $n \geq 1$.

Solution. Step 1:

$$p_1 = \frac{b}{b+w}$$

Step 2: We need to separately consider the cases where a black ball was selected on step 1 (with probability p_1) or a white ball (with probability $1 - p_1$).

$$\begin{aligned} p_2 &= p_1 \cdot \frac{b+1}{b+w+1} + (1 - p_1) \cdot \frac{b}{b+w+1} = p_1 \left(\frac{b+1}{b+w+1} - \frac{b}{b+w+1} \right) + \frac{b}{b+w+1} \\ &= p_1 \left(\frac{1}{b+w+1} + \frac{1}{p_1} \frac{b}{b+w+1} \right) = p_1 \left(\frac{1}{b+w+1} + \frac{b+w}{b} \frac{b}{b+w+1} \right) \\ &= p_1 \left(\frac{b+w+1}{b+w+1} \right) = p_1 \end{aligned}$$

$$\implies p_2 = p_1 = \frac{b}{b+w}$$

Step 3: Regardless of the previous steps, there are now $b + w + 2$ balls in the urn. Since we know that $p_1 = p_2$, the probability that we have selected k black balls so far (and thus, the probability that there are currently $b + k$ black balls in the urn) is given by

$$\begin{aligned} \Pr(k \text{ balls chosen in first 2 rounds}) &= \binom{2}{k} p_1^k (1 - p_1)^{2-k} = \binom{2}{k} \left(\frac{b}{b+w}\right)^k \left(\frac{w}{b+w}\right)^{2-k} \\ &= \binom{2}{k} \frac{b^k w^{2-k}}{(b+w)^2} \end{aligned}$$

for $k \in \{0, 1, 2\}$. Given that we have selected k black balls so far, the probability of selecting a black ball this time is $\frac{b+k}{b+w+2}$. Therefore the probability of selecting a black ball this round is

$$\begin{aligned} p_3 &= \sum_{k=0}^2 \binom{2}{k} \frac{b^k w^{2-k}}{(b+w)^2} \frac{b+k}{b+w+2} = \frac{1}{(b+w+2)(b+w)^2} \sum_{k=0}^2 \binom{2}{k} (b+k) b^k w^{2-k} \\ &= \frac{1}{(b+w+2)(b+w)^2} \left(\binom{2}{0} bw^2 + \binom{2}{1} (b+1)bw + \binom{2}{2} (b+2)b^2 \right) \\ &= \frac{bw^2 + 2(b+1)bw + (b+2)b^2}{(b+w+2)(b+w)^2} = \frac{b}{b+w} \left(\frac{w^2 + 2bw + 2w + b^2 + 2b}{b^2 + bw + 2b + wb + w^2 + 2w} \right) \\ &= \frac{b}{b+w} \left(\frac{w^2 + 2bw + 2w + b^2 + 2b}{b^2 + 2bw + 2b + w^2 + 2w} \right) = \frac{b}{b+w} = p_1 \end{aligned}$$

There seems to be a clear pattern here. Let's find the general formula by induction.

Step $n+1$: Assume that the probability of choosing a black ball on steps $1, 2, \dots, n$ was $\frac{b}{b+w}$ each time.

(a bunch of boring stuff, then it worked.)

HW2 Problem 10. Random variables (X_1, \dots, X_n) are called *exchangeable* if $\Pr(X_1 = x_1, \dots, X_n = x_n) = \Pr(X_{\tau(1)} = x_1, \dots, X_{\tau(n)} = x_n)$ for all real numbers x_1, \dots, x_n and every permutation τ of the set $\{1, \dots, n\}$. In the setting of Problem 9 from Homework 1, let $X_k = 1$ if a white ball is drawn on step k , and $X_k = 0$ otherwise. Show that the random variables X_1, \dots, X_n are exchangeable for every $n \geq 2$.

Solution. For $n = 2$: There are two cases which we must show are equal to show exchangeability:

$$\Pr(X_1 = 0, X_2 = 1) = \Pr(X_1 = 1, X_2 = 0)$$

First,

$$\Pr(X_1 = 0, X_2 = 1) = \Pr(\text{black first}) \Pr(\text{white second} \mid \text{black first}) = \left(\frac{b}{b+w} \right) \left(\frac{w}{b+w+1} \right)$$

$$\left(\frac{w}{b+w} \right) \left(\frac{b}{b+w+1} \right) = \Pr(X_1 = 1, X_2 = 0)$$

which proves exchangeability for $n = 2$. In the general case, we seek to show that X_1, \dots, X_n are exchangeable. That is, in all $n+1$ unordered sets $\mathbb{X}_k = \{x_{1k}, x_{2k}, \dots, x_{nk} \mid x_{ik} \in \{0, 1\}, \sum_i x_{ik} = k\}$, in all $\binom{n}{k}$ permutations of \mathbb{X}_k ,

$$\Pr(\mathbb{X}_{kj}) = \Pr(\mathbb{X}_{kj'})$$

where j and j' denote different permutations of \mathbb{X}_k . That is,

$$\Pr(X_1 = x_{1k}, X_2 = x_{2k}, \dots, X_n = x_{nk}) = \Pr(X_{j_1} = x_{1k}, X_{j_2} = x_{2k}, \dots, X_{j_n} = x_{nk})$$

where j_1, j_2, \dots, j_n index the permuted variables. Consider \mathbb{X}_{kj^*} where all k white balls are chosen first and all $n-k$ black balls are chosen last. We have

$$\Pr(\mathbb{X}_{kj^*}) = \prod_{i=1}^k \left(\frac{w+i-1}{b+w+i-1} \right) \cdot \prod_{i=k+1}^n \left(\frac{b+i-k-1}{b+w+i-1} \right)$$

$$= \prod_{i=1}^n \left(\frac{1}{b+w+i-1} \right) \cdot \left[\prod_{i=1}^k (w+i-1) \prod_{i=k+1}^n (b+i-k-1) \right] = \prod_{i=1}^n \left(\frac{1}{b+w+i-1} \right) \cdot \left[\prod_{i=1}^k (w+i-1) \prod_{i'=1}^{n-k} (b+i'-1) \right]$$

It is easy to see that the leftmost product will always equal the product of the denominators, regardless of the permutation, since one ball is added to the urn after every draw. Similarly, regardless of permutation, the numerator of the probability of drawing the i th white ball will always equal $w+i-1$, the number of white balls already in the urn. Likewise, the numerator of the probability of drawing the i' th black ball is always $b+i'-1$. Because multiplication is commutative, all permutations of these numbers will have equal products. Therefore $\Pr(\mathbb{X}_{kj^*}) = \Pr(\mathbb{X}_{kj})$ for all k . That is,

$$\Pr(X_1 = x_1, \dots, X_n = x_n) = \Pr(X_{\tau(1)} = x_1, \dots, X_{\tau(n)} = x_n)$$

for all $(x_1, \dots, x_n) \in \mathbb{R}^n$, all $n \in \mathbb{Z}$ such that $n \geq 2$, all permutations τ .

Homework 2 Problem 2. Consider the function

$$f(x) = \begin{cases} C(2x - x^2) & 0 < x < 2 \\ 0 & \text{otherwise} \end{cases}$$

- (a) Could f be a distribution function? If so, determine C .
 (b) Could f be a probability density function? If so, determine C .

Solution.

(a) If f is a distribution function, $\lim_{x \rightarrow -\infty} f(x) = 0$, $\lim_{x \rightarrow \infty} f(x) = 1$, and $f'(x) \geq 0 \forall x \in \mathbb{R}$. f clearly does not meet the second or third conditions and is therefore not a distribution function.

(b) If f is a density function then $\int_{-\infty}^{\infty} f(x)dx = 1$ and $f(x) \geq 0 \forall x \in \mathbb{R}$.

$$\begin{aligned} \int_{-\infty}^{\infty} f(x)dx &= \int_0^2 C(2x - x^2)dx = C \left[x^2 - \frac{x^3}{3} \right]_0^2 = C \left(4 - \frac{8}{3} - 0 \right) = C \cdot \frac{4}{3} \\ &= 1 \iff C = \frac{3}{4} \end{aligned}$$

Next we check that f is always nonnegative. It equals zero except on $(0, 2)$.

$$\frac{3}{4}(2x - x^2) \geq 0 \iff x(2 - x) \geq 0 \iff x \in (0, 2)$$

Therefore f is nonnegative $\forall x \in \mathbb{R}$, so f is a probability density function if $C = \frac{3}{4}$.

HW1 Problem 8. Two people, A and B , are involved in a duel. The rules are simple: shoot at each other once; if at least one is hit, the duel is over, if both miss, repeat (go to the next round), and so on. Denote by p_A and p_B the probabilities that A hits B and B hits A with one shot, and assume that hitting/missing is independent from round to round. Compute the probabilities of the following events:
 (a) the duel ends and A is not hit; (b) the duel ends and both are hit; (c) the duel ends after round number n ; (d) the duel ends after round number n GIVEN that A is not hit; (e) the duel ends after n rounds GIVEN that both are hit; (f) the duel goes on forever.

Solution.

- (a) Let A_k denote the event that the duel is ended by A shooting B in the k th round (with neither person being shot in the first $k - 1$ rounds). Note that $\{A_k | k = 1, 2, \dots\}$ are all mutually exclusive. Therefore the probability of the duel ending without A being hit is $\sum_{k=1}^{\infty} A_k$. Because the probabilities in each round are constant and independent,

$$A_k = (1 - p_A)^{k-1} p_A (1 - p_B)^k$$

So the probability that the duel ends and A is not hit is

$$\sum_{k=1}^{\infty} A_k = \sum_{k=1}^{\infty} (1 - p_A)^{k-1} p_A (1 - p_B)^k = p_A (1 - p_B) \sum_{k=1}^{\infty} (1 - p_A)^{k-1} (1 - p_B)^k$$

This is an infinite geometric series. Since the ratio $(1 - p_A)(1 - p_B)$ has absolute value less than 1, the sum can be calculated.

$$\sum_{k=1}^{\infty} A_k = p_A (1 - p_B) \cdot \frac{1}{1 - (1 - p_A)(1 - p_B)} = \frac{p_A (1 - p_B)}{p_A + p_B - p_A p_B} = \boxed{\frac{p_A (1 - p_B)}{p_A (1 - p_B) + p_B}}$$

- (b) Similar to part (a). Let C_k denote the event that the duel is ended with both players being shot in the k th round (with neither person being shot in the first $k - 1$ rounds). Again, $\{C_k|k = 1, 2, \dots\}$ are all mutually exclusive, so the probability of the duel ending in these circumstances is $\sum_{k=1}^{\infty} C_k$. We have

$$C_k = (1 - p_A)^{k-1} p_A (1 - p_B)^{k-1} p_B$$

$$\begin{aligned} \sum_{k=1}^{\infty} C_k &= \sum_{k=1}^{\infty} (1 - p_A)^{k-1} p_A (1 - p_B)^{k-1} p_B = p_A p_B \sum_{k=1}^{\infty} (1 - p_A)^{k-1} (1 - p_B)^{k-1} \\ &= p_A p_B \cdot \frac{1}{1 - (1 - p_A)(1 - p_B)} = \boxed{\frac{p_A p_B}{p_A + p_B - p_A p_B}} \end{aligned}$$

Note that this value is less than the answer from part (a) if $p_B < \frac{1}{2}$ and greater if $p_B > \frac{1}{2}$

- (c) Let B_k denote the event that the duel is ended by B shooting A in the k th round (with neither person being shot in the first $k - 1$ rounds), with

$$B_k = (1 - p_A)^k p_B (1 - p_B)^{k-1}$$

Let A_k and C_k be defined as above. Note that $\{A_k|k = 1, 2, \dots\}$, $\{B_k|k = 1, 2, \dots\}$, $\{C_k|k = 1, 2, \dots\}$ are all mutually exclusive, and that the event that the duel ends in round n is $\{A_n \cup B_n \cup C_n\}$. So the probability of the duel ending in round n is

$$\Pr(A_n \cup B_n \cup C_n) = \Pr(A_n) + \Pr(B_n) + \Pr(C_n)$$

$$\begin{aligned} &= (1 - p_A)^{n-1} p_A (1 - p_B)^n + (1 - p_A)^n p_B (1 - p_B)^{n-1} + (1 - p_A)^{n-1} p_A (1 - p_B)^{n-1} p_B \\ &= (1 - p_A)^{n-1} (1 - p_B)^{n-1} [p_A (1 - p_B) + (1 - p_A) p_B + p_A p_B] \\ &= \boxed{(1 - p_A)^{n-1} (1 - p_B)^{n-1} (p_A + p_B - p_A p_B)} \end{aligned}$$

- (d) Let A_k , B_k , C_k be defined as above. The event that the duel ends at round n without A being hit is given by $\{A_n\}$.

$$\Pr(A_n) = \boxed{(1 - p_A)^{n-1} p_A (1 - p_B)^n}$$

- (e) Let A_k , B_k , C_k be defined as above. The event that the duel ends at round n with both players being hit is given by $\{C_n\}$.

$$\Pr(C_n) = \boxed{(1 - p_A)^{n-1} p_A (1 - p_B)^{n-1} p_B}$$

- (f) Let A_k , B_k , C_k be defined as above. The probability that the duel never ends is equal to 1 - the probability that the duel ends at some point, which is $\{A_k|k = 1, 2, \dots\} \cup \{B_k|k = 1, 2, \dots\} \cup \{C_k|k = 1, 2, \dots\}$. Since all of these events are mutually exclusive, we have

$$1 - \Pr(\{A_k|k = 1, 2, \dots\} \cup \{B_k|k = 1, 2, \dots\} \cup \{C_k|k = 1, 2, \dots\}) = 1 - \sum_{k=1}^{\infty} (A_k + B_k + C_k)$$

$$\begin{aligned}
&= 1 - \sum_{k=1}^{\infty} ((1-p_A)^{k-1} p_A (1-p_B)^k + (1-p_A)^k p_B (1-p_B)^{k-1} + (1-p_A)^{k-1} p_A (1-p_B)^{k-1} p_B) \\
&= 1 - [p_A(1-p_B) + (1-p_A)p_B + p_A p_B] \sum_{k=1}^{\infty} (1-p_A)^{k-1} (1-p_B)^{k-1} \\
&= 1 - [p_A(1-p_A p_B) + p_B - p_A)p_B + p_A p_B] \cdot \frac{1}{1 - (1-p_A)(1-p_B)} \\
&= 1 - \frac{p_A - p_A p_B + p_B - p_A p_B + p_A p_B}{p_A + p_B - p_A p_B} = 1 - \frac{p_A + p_B - p_A p_B}{p_A + p_B - p_A p_B} = \boxed{0}
\end{aligned}$$

Homework 1 Problem 1.

- (I) Seven different gifts are distributed among 10 children. How many different outcomes are possible if every child can receive (a) at most one gift, (b) at most two gifts, (c) any number of gifts?
- (II) Answer the same questions if the gifts are identical (but the children are still different).

Solution.

(I) (a) $\binom{10}{7} 7! = \boxed{604,800}$

(b) Clearly all outcomes that satisfy part (I)(a) also satisfy these conditions, so we start with $\binom{10}{7} 7! = 604,800$ possible outcomes. In addition, the following outcomes are possible:

(i) **A set of 6 children receive gifts; one child receives two gifts.** There are $\binom{10}{6}$ ways to pick a group of 6 children to receive the gifts. Next, there are $\binom{6}{1} = 6$ ways to choose which child receives two gifts. Finally, there are $7!/2!$ unique ways to distribute the gifts among the children once a particular partition is chosen (since order matters for all of the gifts except for the two that are received by the same child).

(ii) **A set of 5 children receive gifts; two children receive two gifts.** There are $\binom{10}{5}$ ways to pick a group of 5 children to receive the gifts. Next, there are $\binom{5}{2}$ ways to choose which of these children receive one gift and which receive two. Finally, there are $7!/(2!2!)$ unique ways to distribute the gifts among the children once a particular partition is chosen (since order matters for all of the gifts except for the two batches of two gifts that are received by the same child).

(Note that without the restriction that a child can receive at most two gifts, another possibility is that 1 child could receive 3 gifts, but that wouldn't work in this case.)

(iii) **A set of 4 children receive gifts; three children each receive two gifts.** There are $\binom{10}{4}$ ways to pick a group of 4 children to receive the gifts. Next, there are $\binom{4}{3} = 4$ ways to choose which of these children receive one gift and which receive two. Finally, there are $7!/(2!2!2!)$ unique ways to distribute the gifts among the children once a particular partition is chosen (since order matters for all of the gifts except for the three batches of two gifts that are received by the same child).

(Again, there are other possibilities for 4 children to receive 7 gifts, but none that satisfy the condition that no child receives more than 2 gifts.)

Clearly each of these outcomes are mutually exclusive. Therefore the answer is

$$\begin{aligned}
 & \binom{10}{7}7! + \binom{10}{6} \cdot \binom{6}{1} \cdot \frac{7!}{2!} + \binom{10}{5} \cdot \binom{5}{2} \cdot \frac{7!}{2!2!} + \binom{10}{4} \cdot \binom{4}{3} \cdot \frac{7!}{2!2!2!} \\
 &= 7! \cdot \left(\frac{10!}{3!} + \frac{10!}{6!4!} \cdot 6 \cdot \frac{1}{2} + \frac{10!}{5!5!} \cdot \frac{5!}{3!2!} \cdot \frac{1}{4} + \frac{10!}{4!6!} \cdot \frac{4!}{3!} \cdot \frac{1}{8} \right) \\
 &= 7!10! \cdot \left(\frac{1}{3!} + \frac{1}{6!4!} \cdot \frac{6}{2} + \frac{1}{5!} \cdot \frac{1}{3!2!} \cdot \frac{1}{4} + \frac{1}{6!3!} \cdot \frac{1}{8} \right) \\
 &= \boxed{7,484,400}
 \end{aligned}$$

(c) $10^7 = \boxed{10,000,000}$

(II) (a) $\binom{10}{7} = \boxed{120}$

(b) Clearly all outcomes that satisfy part (I)(a) also satisfy these conditions, so we start with $\binom{10}{7} = 120$ possible outcomes. In addition, the following outcomes are possible:

- (i) A set of 6 children receive gifts; one child receives two gifts (6 distinct ways this could happen for each set of 6 children).
- (ii) A set of 5 children receive gifts; two children receive two gifts ($\binom{5}{2}$ distinct ways this could happen for each set of 5 children).
- (iii) A set of 4 children receive gifts; three children each receive two gifts (4 distinct ways this could happen for each set of 4 children).

Clearly each of these outcomes are mutually exclusive. Therefore the answer is

$$\binom{10}{7} + \binom{10}{6} \cdot \binom{6}{7-6} + \binom{10}{5} \cdot \binom{5}{7-5} + \binom{10}{4} \cdot \binom{4}{7-4} = \boxed{4,740}$$

(c) By Proposition 6.1.17, the number of nonnegative integer-valued vectors (x_1, x_2, \dots, x_r) satisfying the equation

$$x_1 + x_2 + \dots + x_r = n$$

is equal to $\binom{n+r-1}{r-1} = \binom{7+10-1}{10-1} = \boxed{11,440}$.

Homework 1 Problem 2.

- (I) 20 different gifts are distributed among seven children. How many different outcomes are possible if every child can receive (a) at least one gift, (b) at least two gifts, (c) any number of gifts?
- (II) Answer the same questions if the gifts are identical (but the children are still different).
- (III) Now try to generalize problems (1) and (2).

Solution.

- (I) (a) There are 7^{20} possible allocations of gifts if we have no restrictions. If one child doesn't get a gift, there are $\binom{7}{1}$ ways to choose which child that is and 6^{20} subsequent allocations of gifts. Likewise, there are $\binom{7}{2} \cdot (7-2)^{20}$ ways to allocate the gifts if two children don't receive gifts, $\binom{7}{3} \cdot (7-3)^{20}$ ways if three children don't receive gifts, $\binom{7}{4} \cdot (7-4)^{20}$ ways if four children don't receive gifts, $\binom{7}{5} \cdot (7-5)^{20}$ ways if five children don't receive gifts, and $\binom{7}{6} \cdot (7-6)^{20}$ ways if six children don't receive gifts.

Let A_i denote the number of allocations in which i children do not receive gifts. In order to make the calculation, we must use the Inclusion-Exclusion principle (Proposition 6.1.13) (because, for example, some of the allocations in which three children don't receive gifts include allocations where four or more children don't receive gifts, and we don't want to double-count). Therefore the number of ways that at least one child can not receive a gift (i.e. the complement of every child receiving at least one gift) is

$$\begin{aligned} \left| \bigcup_{i=1}^6 A_i \right| &= \sum_{i=1}^6 |A_i| - \sum_{1 \leq i < j \leq 6} |A_i \cap A_j| + \sum_{1 \leq i < j < k \leq 6} |A_i \cap A_j \cap A_k| - \dots \\ &\quad + (-1)^{6-1} |A_1 \cap A_2 \cap A_3 \cap \dots \cap A_6| \end{aligned}$$

Fortunately, these allocations are nested in the sense that all the allocations where e.g. 5 children do not receive gifts are a subset of all the allocations where 4 children do not receive gifts; that is

$$A_6 \subset A_5 \subset A_4 \subset A_3 \subset A_2 \subset A_1$$

which implies e.g.

$$A_1 \cap A_2 \cap A_3 \cap \dots \cap A_6 = A_6,$$

$$\sum_{1 \leq i < j \leq 6} |A_i \cap A_j| = 5|A_6| + 4|A_5| + 3|A_4| + 2|A_3| + |A_2|$$

So we have

$$\begin{aligned} \left| \bigcup_{i=1}^6 A_i \right| &= |A_6| + |A_5| + |A_4| + |A_3| + |A_2| + |A_1| - (5|A_6| + 4|A_5| + 3|A_4| + 2|A_3| + |A_2|) \\ &\quad + (4|A_6| + 3|A_5| + 2|A_4| + |A_3|) - (3|A_6| + 2|A_5| + |A_4|) + \dots - |A_6| \\ &= |A_1| - |A_2| + |A_3| - |A_4| + |A_5| - |A_6| \\ &= \binom{7}{1} \cdot 6^{20} - \binom{7}{2} \cdot (7-2)^{20} + \binom{7}{3} \cdot (7-3)^{20} - \binom{7}{4} \cdot (7-4)^{20} \\ &\quad + \binom{7}{5} \cdot (7-5)^{20} - \binom{7}{6} \cdot (7-6)^{20} \end{aligned}$$

The final answer is

$$7^{20} - \left| \bigcup_{i=1}^6 A_i \right| = 7^{20} - \binom{7}{1} \cdot 6^{20} + \binom{7}{2} \cdot (7-2)^{20} - \binom{7}{3} \cdot (7-3)^{20} + \binom{7}{4} \cdot (7-4)^{20} \\ - \binom{7}{5} \cdot (7-5)^{20} + \binom{7}{6} \cdot (7-6)^{20} \approx [5.616 \cdot 10^{16}]$$

- (b) Similar to above, but more complicated. The complement of every child receiving at least two gifts is that at least one child doesn't receive a gift (same as above) or at least one child only receives one gift. So we start from the baseline answer above, and subtract out all the possible allocations in which at least one child receives one gift.

If one child only receives one gift (and the rest receive more than one), there are $\binom{7}{1}$ ways to choose which child that is, $\binom{20}{1}$ ways to choose which gift that child receives, and 6^{20-1} allocations of the remaining gifts. If two children receive only one gift, there are $\binom{7}{2}$ ways to choose which children those are, $\binom{20}{2} \cdot 2!$ ways to choose which gifts those children get and distribute them among those children, and $(7-2)^{20-2}$ ways to allocate the remaining gifts. Likewise, if three children receive only one gift there are $\binom{7}{3} \binom{20}{3} \cdot 3! \cdot (7-3)^{20-3}$ ways to allocate the gifts, $\binom{7}{4} \binom{20}{4} \cdot 4! \cdot (7-4)^{20-4}$ ways if four children receive only one gift, $\binom{7}{5} \binom{20}{5} \cdot 5! \cdot (7-5)^{20-5}$ ways if five children receive only one gift, and $\binom{7}{6} \binom{20}{6} \cdot 6! \cdot (7-6)^{20-6}$ ways if six children don't receive gifts.

Let B_j be the event that j children receive only one gift. Note that $B_1 \cap A_i$ is nonempty $\forall i < 7-1$, $B_2 \cap A_i$ is nonempty $\forall i < 7-2$, and in general, $B_j \cap A_i$ is nonempty $\forall i < 7-j, j \in \{1, 2, \dots, 6\}$. Applying the Inclusion-Exclusion Principle (Proposition 6.1.13) in a similar way as in part (I)(a), the answer is

$$7^{20} - \left| \bigcup_{i=1}^6 A_i \right| - \left| \bigcup_{j=1}^6 B_j \right| + \sum_{i \in \{1, \dots, 6\}, j \in \{1, \dots, 6\}} \left| A_i \cap B_j \right|$$

Per part (I)(a), the first two terms approximately equal $5.616 \cdot 10^{16}$. Clearly

$$\bigcup_{i \in \{1, \dots, 6\}, j \in \{1, \dots, 6\}} \left(A_i \cap B_j \right) \subset \bigcup_{j=1}^6 B_j$$

which implies

$$-\left| \bigcup_{j=1}^6 B_j \right| + \left| \bigcap_{i \in \{1, \dots, 6\}, j \in \{1, \dots, 6\}} B_j \right| < 0$$

so the answer to this part will be less than $5.616 \cdot 10^{16}$, which makes sense.

Calculating $\left| \bigcup_{j=1}^6 B_j \right|$ is not too difficult using Inclusion-Exclusion:

$$\left| \bigcup_{j=1}^6 B_j \right| = \sum_{j=1}^6 |B_j| - \sum_{1 \leq j < k \leq 6} |B_j \cap B_k| + \sum_{1 \leq j < k < \ell \leq 6} |B_j \cap B_k \cap B_\ell| - \dots \\ + (-1)^{6-1} |B_1 \cap B_2 \cap B_3 \cap \dots \cap B_6|$$

where since

$$B_6 \subset B_5 \subset B_4 \subset B_3 \subset B_2 \subset B_1$$

which implies e.g.

$$B_1 \cap B_2 \cap B_3 \cap \dots \cap B_6 = B_6,$$

$$\sum_{1 \leq j < k \leq 6} |B_j \cap B_k| = 5|B_6| + 4|B_5| + 3|B_4| + 2|B_3| + |B_2|$$

we have

$$\begin{aligned} \left| \bigcup_{j=1}^6 B_j \right| &= |B_6| + |B_5| + |B_4| + |B_3| + |B_2| + |B_1| - (5|B_6| + 4|B_5| + 3|B_4| + 2|B_3| + |B_2|) \\ &\quad + (4|B_6| + 3|B_5| + 2|B_4| + |B_3|) - (3|B_6| + 2|B_5| + |B_4|) + \dots - |B_6| \\ &= |B_1| - |B_2| + |B_3| - |B_4| + |B_5| - |B_6| \\ &= \binom{7}{1} \binom{20}{1} \cdot (7-1)^{20-1} - \binom{7}{2} \binom{20}{2} \cdot 2! \cdot (7-2)^{20-2} + \binom{7}{3} \binom{20}{3} \cdot 3! \cdot (7-3)^{20-3} - \binom{7}{4} \binom{20}{4} \cdot 4! \cdot (7-4)^{20-4} \\ &\quad + \binom{7}{5} \binom{20}{5} \cdot 5! \cdot (7-5)^{20-5} - \binom{7}{6} \binom{20}{6} \cdot 6! \cdot (7-6)^{20-6} \\ &\approx 5.846 \cdot 10^{16} \end{aligned}$$

However, calculating

$$\sum_{i \in \{1, \dots, 6\}, j \in \{1, \dots, 6\}} |A_i \cap B_j|$$

is very difficult because, for example, $B_2 \cap A_3$ is nonempty but $B_2 \not\subset A_3$ and $A_3 \not\subset B_2$.

(c) $7^{20} \approx 7.979 \cdot 10^{16}$

(II) (a) By Proposition 6.1.16, there are $\binom{19}{6} = 27,132$ ways to do this.

(b) Similar to Problem 1 part (II)(c), if the vector (x_1, x_2, \dots, x_7) represents the number of gifts given to each child, we would like a solution such that

$$x_1 + x_2 + \dots + x_7 = 20, x_i \geq 2 \forall i$$

By Proposition 6.1.18, the number of possible allocations under these conditions, is $\binom{20+7 \cdot (1-2)-1}{7-1} = \binom{12}{6} = 924$.

(c) By Proposition 6.1.17, the number of nonnegative integer-valued vectors (x_1, x_2, \dots, x_r) satisfying the equation

$$x_1 + x_2 + \dots + x_r = n$$

is equal to $\binom{n+r-1}{r-1}$. In distributing 20 identical gifts to 7 different children, we can imagine the vector $(x_1, x_2, \dots, x_{10})$ represents the number of gifts given to each child (where x_i is a nonnegative integer for all i). So we have $n = 20$ and $r = 7$. Therefore the number of possible allocations is

$$\binom{20+7-1}{7-1} = \boxed{165, 765, 600}$$

(III) Generalization of 1(I): If there are g distinguishable gifts and $c \geq g$ children, the number of distinct allocations if each child can receive

- (a) at most one gift is $\binom{c}{g}g!$.
- (b) at most two gifts is

$$\sum_{i=c-g+1}^g \binom{c}{i} \cdot \binom{i}{g-i} \cdot \frac{g!}{(2!)^{g-i}}$$

- (c) any number of gifts is c^g .

Generalization of 1(II): If there are g identical gifts and $c \geq g$ children, the number of distinct allocations if each child can receive

- (a) at most one gift is $\binom{c}{g}$.
- (b) at most two gifts is

$$\sum_{i=c-g+1}^g \binom{c}{i} \cdot \binom{i}{g-i}$$

- (c) any number of gifts is $\binom{g+c-1}{c-1}$

Generalization of 2(I): If there are g distinguishable gifts and $c \leq g$ children, the number of distinct allocations if each child must receive

- (a) at least one gift is

$$c^g - \sum_{i=1}^{c-1} (-1)^{i+1} \binom{c}{i} \cdot (c-i)^g$$

- (b) at least two gifts is

$$c^g - \sum_{i=1}^{c-1} (-1)^{i+1} \binom{c}{i} \cdot (c-i)^g - \sum_{i=1}^{c-1} (-1)^{i+1} \binom{c}{i} \binom{g}{i} \cdot i! \cdot (c-i)^{g-i}$$

- (c) any number of gifts is c^g

Generalization of 2(II): If there are g identical gifts and $c \leq g$ children, the number of distinct allocations if each child must receive

- (a) at least one gift is

$$\binom{g-1}{c-1}$$

(b) at least two gifts is

$$\binom{g-c-1}{c-1}$$

(c) any number of gifts is

$$\binom{g+c-1}{c-1}$$

Homework 1 Problem 4. You have \$20K to invest, and have a choice of stocks, bonds, mutual funds, or a CD. Investments must be made in multiples of \$1K, and there are minimal amounts to be invested: \$2K in stocks, \$2K in bonds, \$3K in mutual funds, and \$4K in the CD. Count the number of choices in each situation: (a) You want to invest in all four, (b) you want to invest in at least three out of four.

Solution.

(a) If the vector $(x_S, x_B, x_{MF}, x_{CD})$ represents the amount of money (in thousands of dollars) invested in each instrument, we would like a solution such that

$$x_S + x_B + x_{MF} + x_{CD} = 20$$

where

$$x_S \geq 2, x_B \geq 2, x_{MF} \geq 3, x_{CD} \geq 4$$

In a way similar to the proof for Proposition 6.1.18, note that we can transform this problem in the following way:

$$x_S - 1 + x_B - 1 + x_{MF} - 2 + x_{CD} - 3 = 20 - (1 + 1 + 2 + 3)$$

where

$$x_S - 1 \geq 1, x_B - 1 \geq 1, x_{MF} - 2 \geq 1, x_{CD} - 3 \geq 1$$

Letting $y_S = x_S - 1, y_B = x_B - 1, y_{MF} = x_{MF} - 2, y_{CD} = x_{CD} - 3$, we have the equivalent system

$$y_S + y_B + y_{MF} + y_{CD} = 13, y \geq 1 \quad \forall y$$

By Proposition 6.1.16, the number of distinct solutions to this equation, and therefore the number of possible allocations under these conditions, is $\binom{13-1}{4-1} = \boxed{220}$.

(b) Enumerate the $\binom{4}{3} = 4$ possibilities.

(i) **Invest in stocks, bonds, and mutual funds.**

$$x_S + x_B + x_{MF} = 20$$

where

$$x_S \geq 2, x_B \geq 2, x_{MF} \geq 3$$

Note that we can transform this problem in the following way:

$$x_S - 1 + x_B - 1 + x_{MF} - 2 = 20 - (1 + 1 + 2)$$

where

$$x_S - 1 \geq 1, x_B - 1 \geq 1, x_{MF} - 2 \geq 1$$

Letting $y_S = x_S - 1, y_B = x_B - 1, y_{MF} = x_{MF} - 2$, we have the equivalent system

$$y_S + y_B + y_{MF} = 16, y \geq 1 \forall y$$

Therefore the number of possible allocations under these conditions is $\binom{16-1}{3-1} = [105]$.

(ii) **Invest in stocks, bonds, and CDs.**

$$x_S + x_B + x_{CD} = 20$$

where

$$x_S \geq 2, x_B \geq 2, x_{CD} \geq 4$$

Note that we can transform this problem in the following way:

$$x_S - 1 + x_B - 1 + x_{CD} - 3 = 20 - (1 + 1 + 3)$$

where

$$x_S - 1 \geq 1, x_B - 1 \geq 1, x_{CD} - 3 \geq 1$$

Letting $y_S = x_S - 1, y_B = x_B - 1, y_{CD} = x_{CD} - 3$, we have the equivalent system

$$y_S + y_B + y_{CD} = 15, y \geq 1 \forall y$$

Therefore the number of possible allocations under these conditions is $\binom{15-1}{3-1} = [91]$.

(iii) **Invest in stocks, mutual funds, and CDs.**

$$x_S + x_{MF} + x_{CD} = 2$$

where

$$x_S \geq 2, x_{MF} \geq 3, x_{CD} \geq 4$$

Note that we can transform this problem in the following way:

$$x_S - 1 + x_{MF} - 2 + x_{CD} - 3 = 20 - (1 + 2 + 3)$$

where

$$x_S - 1 \geq 1, x_{MF} - 2 \geq 1, x_{CD} - 3 \geq 1$$

Letting $y_S = x_S - 1, y_{MF} = x_{MF} - 2, y_{CD} = x_{CD} - 3$, we have the equivalent system

$$y_S + y_{MF} + y_{CD} = 14, y \geq 1 \forall y$$

Therefore the number of possible allocations under these conditions is $\binom{14-1}{3-1} = [78]$.

(iv) **Invest in bonds, mutual funds, and CDs.**

$$x_B + x_{MF} + x_{CD} = 2$$

where

$$x_B \geq 2, x_{MF} \geq 3, x_{CD} \geq 4$$

Note that we can transform this problem in the following way:

$$x_B - 1 + x_{MF} - 2 + x_{CD} - 3 = 20 - (1 + 2 + 3)$$

where

$$x_B - 1 \geq 1, x_{MF} - 2 \geq 1, x_{CD} - 3 \geq 1$$

Letting $y_B = x_B - 1, y_{MF} = x_{MF} - 2, y_{CD} = x_{CD} - 3$, we have the equivalent system

$$y_B + y_{MF} + y_{CD} = 14, y \geq 1 \forall y$$

therefore the number of possible allocations under these conditions is $\binom{14-1}{3-1} = \boxed{78}$.

(v) **Invest in all four:** per part 4(a), there are $\boxed{220}$ ways to do this.

Note that all of these possibilities are mutually exclusive. Therefore the total number is

$$\binom{16-1}{3-1} + \binom{15-1}{3-1} + \binom{14-1}{3-1} + \binom{14-1}{3-1} + \binom{13-1}{4-1} = 105 + 91 + 78 + 78 + 220 = \boxed{572}$$

6.2.4 DSO Statistics Group Screening Exam Problems

Exercise 10 (2017 DSO Statistics Group In-Class Screening Exam, Question 1). Let X_1, X_2, \dots, X_k be independent standard normal random variables and $\gamma_1(t), \dots, \gamma_k(t)$ infinitely differentiable functions of a real variable defined on a closed, bounded interval, such that $\sum_{i=1}^k \gamma_i^2(t) = 1$ for all t . Let $Z(t) = \sum_{i=1}^k \gamma_i(t)X_i$. Let $\dot{Z}(t), \ddot{Z}(t)$, etc. denote first, second, etc. derivatives of $Z(t)$ with respect to t .

- (a) Show that $\text{Cov}(Z(t), \dot{Z}(t)) = 0$.
- (b) Evaluate $\mathbb{E}(Z(t) | \ddot{Z}(t))$ in terms of $\ddot{Z}(t)$ and expressions of the form

$$\sum_{i=1}^k (\gamma_i(t))^a (\delta^m \gamma_i(t)/\delta t^m)^b,$$

for some a, b, m values.

Solution.

(a)

$$\dot{Z}(t) = \frac{\partial}{\partial t} \sum_{i=1}^k \gamma_i(t)X_i = \sum_{i=1}^k \dot{\gamma}_i(t)X_i$$

$$\implies \mathbb{E}(\dot{Z}(t)) = \sum_{i=1}^k \mathbb{E}(\dot{\gamma}_i(t)X_i) = 0$$

$$\implies \text{Cov}(Z(t), \dot{Z}(t)) = \mathbb{E}[(Z(t) - \mathbb{E}[Z(t)])(\dot{Z}(t) - \mathbb{E}[\dot{Z}(t)])] = \mathbb{E}[Z(t)\dot{Z}(t)]$$

$$= \mathbb{E} \left[\left(\sum_{i=1}^k \gamma_i(t)X_i \right) \left(\sum_{i=1}^k \dot{\gamma}_i(t)X_i \right) \right] = \sum_{i=1}^k \mathbb{E}(\gamma_i(t)\dot{\gamma}_i(t)X_i^2) + 0 = \sum_{i=1}^k \gamma_i(t)\dot{\gamma}_i(t)$$

since $\mathbb{E}(X_i^2) = 1$. But

$$\sum_{i=1}^k \gamma_i \dot{\gamma}_i(t) = 0 \quad (6.8)$$

because

$$\sum_{i=1}^k \gamma_i^2(t) = 1 \iff \frac{\partial}{\partial t} \left(\sum_{i=1}^k \gamma_i^2(t) \right) = 0 \iff 2 \sum_{i=1}^k \gamma_i(t) \dot{\gamma}_i(t) = 0,$$

so the conclusion follows.

(b)

$$Z(t) = \sum_{i=1}^k \gamma_i(t) X_i \implies Z(t) \sim \mathcal{N} \left(0, \sum_{i=1}^k \gamma_i^2(t) \right) = \mathcal{N}(0, 1)$$

$$\ddot{Z}(t) = \sum_{i=1}^k \ddot{\gamma}_i(t) X_i \implies \ddot{Z}(t) \sim \mathcal{N} \left(0, \sum_{i=1}^k \ddot{\gamma}_i^2(t) \right)$$

Also, we have

$$\text{Cov}(Z(t), \ddot{Z}(t)) = \mathbb{E}[(Z(t) - \mathbb{E}[Z(t)])(\ddot{Z}(t) - \mathbb{E}[\ddot{Z}(t)])] = \mathbb{E}[Z(t)\ddot{Z}(t)]$$

$$= \mathbb{E} \left[\left(\sum_{i=1}^k \gamma_i(t) X_i \right) \left(\sum_{i=1}^k \ddot{\gamma}_i(t) X_i \right) \right] = \sum_{i=1}^k \mathbb{E}(\gamma_i(t) \ddot{\gamma}_i(t) X_i^2) + 0 = \sum_{i=1}^k \gamma_i(t) \ddot{\gamma}_i(t) = - \sum_{i=1}^k \dot{\gamma}_i^2(t)$$

because differentiating (6.8) yields

$$\frac{\partial}{\partial t} \sum_{i=1}^k \gamma_i \dot{\gamma}_i(t) = 0 \iff \sum_{i=1}^k (\dot{\gamma}_i^2(t) + \gamma_i(t) \ddot{\gamma}_i(t)) = 0 \iff \sum_{i=1}^k \gamma_i(t) \ddot{\gamma}_i(t) = - \sum_{i=1}^k \dot{\gamma}_i^2(t).$$

Since both distributions are Gaussian, we have

$$\mathbb{E}(Z(t) | \ddot{Z}(t)) = \mathbb{E}[Z(t)] + \frac{\text{Cov}[Z(t), \ddot{Z}(t)]}{\text{Var}[\ddot{Z}(t)]} (\ddot{Z}(t) - \mathbb{E}[\ddot{Z}(t)]) = \left[\sum_{i=1}^k \dot{\gamma}_i^2(t) \right]^{-1} \cdot \left[- \sum_{i=1}^k \dot{\gamma}_i^2(t) \right] \ddot{Z}(t).$$

Exercise 11 (2018 DSO Statistics Group In-Class Screening Exam, Question 1). (a) For each $x > 0$, let $M(x)$ be a real-valued random variable and set $M(0) = 0$. Assume that the random function $M(x)$ is monotone non-decreasing on $[0, \infty)$. Define $T(y) := \inf\{x \geq 0 : M(x) \geq y\}$. Suppose that $e^{-1}T(y)$ converges in distribution to an Exponential(λ) random variable when $y \rightarrow \infty$.

- (i) Find non-random $a(x)$ and $b(x) > 0$ such that $(M(x) - a(x))/b(x)$ converges in distribution for $x \rightarrow \infty$ to a non-degenerate random variable.
 - (ii) Provide the distribution function of the limit random variable. What is the name of this distribution?
- (b) Let $X \sim \text{Bin}(n, p)$. Find $\mathbb{E}(1/(i + X))$, for $i = 1, 2$. Hint: Recall that $\int x^\alpha dx = x^{\alpha+1}/(\alpha+1) + C$ for $\alpha \neq -1$.

Solution.

(a) (i) We have

$$T(y) = \inf\{x \geq 0 : M(x) \geq y\}; \quad \lim_{y \rightarrow \infty} \Pr(e^{-y} T(y) \leq a) = 1 - e^{-\lambda a} \quad \forall a \geq 0.$$

Note that

$$\lim_{y \rightarrow \infty} \Pr(e^{-y} T(y) \leq a) = \lim_{y \rightarrow \infty} \Pr(T(y) \leq ae^y)$$

Because $T(y) = \inf\{x \geq 0 : M(x) \geq y\}$ and $M(\cdot)$ is monotonically increasing, we have the inequality $M(z) \geq y$ for all $z \geq x$. Therefore $T(y) \leq ae^y \iff M(ae^y) \geq y$. Let $z = ae^y \implies y = \log(z/a)$; then we have

$$\lim_{y \rightarrow \infty} \Pr(T(y) \leq ae^y) = \lim_{y \rightarrow \infty} \Pr(M(ae^y) \geq y) = \lim_{z \rightarrow \infty} \Pr(M(z) \geq \log(z) - \log(a))$$

Let $b = -\log a$ to get

$$\begin{aligned} &= \lim_{z \rightarrow \infty} \Pr(M(z) - \log(z) \geq b) = 1 - e^{-\lambda a} \implies \lim_{z \rightarrow \infty} \Pr(M(z) - \log(z) \geq b) = 1 - e^{-\lambda e^{-b}} \\ &\iff \lim_{z \rightarrow \infty} \Pr(M(z) - \log(z) \leq b) = e^{-\lambda e^{-b}} \end{aligned}$$

(ii) The distribution function is $F(x) = e^{-\lambda e^{-x}}$, a Gumbel distribution with parameter λ . This is a proper cdf because $\lim_{x \rightarrow \infty} F(x) = 1$ and $\lim_{x \rightarrow -\infty} F(x) = 0$.

(b) Using hint:

$$\begin{aligned} &\int_0^1 t^x dt = \left[\frac{t^{x+1}}{x+1} \right]_0^1 = \frac{1}{x+1} \\ &\iff \mathbb{E} \left[\int_0^1 t^X dt \right] = \mathbb{E} \left(\frac{1}{X+1} \right) \iff \int_0^1 \mathbb{E}(t^X) dt = \mathbb{E} \left(\frac{1}{X+1} \right) \\ &\iff \int_0^1 \sum_{i=0}^n t^i \Pr(X=i) dt = \mathbb{E} \left(\frac{1}{X+1} \right) \iff \int_0^1 \sum_{i=0}^n t^i \binom{n}{i} p^i (1-p)^{n-i} dt = \mathbb{E} \left(\frac{1}{X+1} \right) \\ &\iff (1-p)^n \int_0^1 \sum_{i=0}^n \binom{n}{i} \left(\frac{tp}{1-p} \right)^i dt = \mathbb{E} \left(\frac{1}{X+1} \right) \\ &\iff (1-p)^n \int_0^1 \left(1 + \frac{tp}{1-p} \right)^n dt = \mathbb{E} \left(\frac{1}{X+1} \right) \\ &\iff \int_0^1 (1-p+tp)^n dt = \mathbb{E} \left(\frac{1}{X+1} \right) \end{aligned}$$

Let $u = 1-p+tp \implies du = p dt$. Then we can write

$$\frac{1}{p} \int_{1-p}^1 u^n du = \mathbb{E} \left(\frac{1}{X+1} \right) \iff \frac{1}{p} \left[\frac{u^{n+1}}{n+1} \right]_{1-p}^1 = \mathbb{E} \left(\frac{1}{X+1} \right) \iff \mathbb{E} \left(\frac{1}{X+1} \right) = \frac{1}{p} \left[\frac{1 - (1-p)^{n+1}}{n+1} \right]$$

Now we consider $\mathbb{E}\left[\frac{1}{X+2}\right]$.

$$\begin{aligned}
 & \int_0^1 t^{x+1} dt = \left[\frac{t^{x+2}}{x+2} \right]_0^1 = \frac{1}{x+2} \\
 \iff & \mathbb{E}\left[\int_0^1 t^{X+1} dt\right] = \mathbb{E}\left(\frac{1}{X+2}\right) \iff \int_0^1 \mathbb{E}(t^{X+1}) dt = \mathbb{E}\left(\frac{1}{X+2}\right) \\
 \iff & \int_0^1 \sum_{i=0}^n t^{i+1} \Pr(X=i) dt = \mathbb{E}\left(\frac{1}{X+2}\right) \iff \int_0^1 \sum_{i=0}^n t^{i+1} \binom{n}{i} p^i (1-p)^{n-i} dt = \mathbb{E}\left(\frac{1}{X+2}\right) \\
 \iff & (1-p)^n \int_0^1 t \sum_{i=0}^n \binom{n}{i} \left(\frac{tp}{1-p}\right)^i dt = \mathbb{E}\left(\frac{1}{X+2}\right) \\
 \iff & (1-p)^n \int_0^1 t \left(1 + \frac{tp}{1-p}\right)^n dt = \mathbb{E}\left(\frac{1}{X+2}\right) \\
 \iff & \int_0^1 t (1-p+tp)^n dt = \mathbb{E}\left(\frac{1}{X+2}\right)
 \end{aligned}$$

Let $u = 1 - p + tp \implies du = p dt$ and $t = (u + p - 1)/p$. Then we can write

$$\begin{aligned}
 \frac{1}{p^2} \int_{1-p}^1 u^n (u + p - 1) du &= \mathbb{E}\left(\frac{1}{X+2}\right) \iff \frac{1}{p^2} \int_{1-p}^1 [u^{n+1} + (p-1)u^n] du = \mathbb{E}\left(\frac{1}{X+2}\right) \\
 \iff \frac{1}{p^2} \left[\frac{u^{n+2}}{n+2} + (p-1) \frac{u^{n+1}}{n+1} \right]_{1-p}^1 &= \mathbb{E}\left(\frac{1}{X+2}\right) \\
 \iff \mathbb{E}\left(\frac{1}{X+2}\right) &= \frac{1}{p^2} \left[\frac{1 - (1-p)^{n+2}}{n+2} - (1-p) \frac{1 - (1-p)^{n+1}}{n+1} \right]
 \end{aligned}$$

6.3 To Know for Math 505A Midterm 2

6.3.1 Definitions

Definition 6.28. A random variable X is **continuous** if its distribution function $F(x) = \Pr(X \leq x)$ can be written as

$$F(x) = \int_{-\infty}^x f(u) du$$

for some integrable $f : \mathbb{R} \rightarrow [0, \infty)$.

Definition 6.29. The function f is called the **(probability) density function** of the continuous random variable X .

Proposition 6.3.1. If X has pdf $f_X(x)$, then for $\mu \in \mathbb{R}$, $\sigma > 0$,

$$h(x) = \frac{1}{\sigma} f_X\left(\frac{x - \mu}{\sigma}\right)$$

is a pdf. In this setting μ is sometimes called a “location parameter” and σ is called a “scale parameter.”

Definition 6.30. The **joint distribution function** of X and Y is the function $F : \mathbb{R}^2 \rightarrow [0, 1]$ given by

$$F(x, y) = \Pr(X \leq x \cap Y \leq y)$$

Definition 6.31. The random variables X and Y are **jointly continuous** with **joint (probability) density function** $f : \mathbb{R}^2 \rightarrow [0, \infty)$ if

$$F(x, y) = \int_{v=-\infty}^y \int_{u=-\infty}^x f(u, v) du dv \text{ for each } x, y \in \mathbb{R}$$

Definition 6.32. Two continuous random variables are **independent** if and only if $\{X \leq x\}$ and $\{Y \leq y\}$ are independent events for all $x, y \in \mathbb{R}$.

Ways to show independence:

- Use Definition 6.32: show that $\Pr(X \leq x \cap Y \leq y) = \Pr(X \leq x) \Pr(Y \leq y)$ for all $x, y \in \mathbb{R}$.
-

Theorem 6.3.2. The random variables X and Y are independent if and only if $F(x, y) = F_X(x)F_Y(y)$ for all $x, y \in \mathbb{R}$.

•

Proposition 6.3.3. For continuous random variables, the previous condition is equivalent to requiring $f(x, y) = f_X(x)f_Y(y)$.

•

Theorem 6.3.4. If two variables are bivariate normal, they are independent if and only if their covariance

$$\text{Cov}(X, Y) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xyf(x, y)dxdy$$

is equal to 0.

Theorem 6.3.5. (Change of variables.) Let X_1, Y_1 be random variables with joint PDF f_{X_1, Y_1} . Let X_2, Y_2 be random variables with joint PDF f_{X_2, Y_2} . Let $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ and let $S : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ so that $ST(x, y) = (x, y)$ and $TS(x, y) = (x, y)$ for every $(x, y) \in \mathbb{R}^2$. Let $J(x, y)$ denote the determinant of the Jacobian of S at (x, y) . Then

$$f_{X_2, Y_2}(x, y) = f_{X_1, Y_1}(S(x, y)) |J(x, y)|.$$

Proof. If the transformation from X_1, Y_1 to X_2, Y_2 is given by $S(X_1, Y_1) = (X_2, Y_2)$, then the change of variables formula from calculus is as follows:

$$\int \int_A f_{X_1, Y_1}(x, y) dx dy = \int \int_B f_{X_1, Y_1}(S(x, y)) |J(x, y)| dx dy$$

where $A \subseteq \text{domain}(f_{X_1, Y_1}(\cdot))$, B is the transformation of the region A under S , and $|J(x, y)|$ is the Jacobian of S at (x, y) . It follows from the definition of joint pdfs that the integrand on the right is the joint pdf of (X_2, Y_2) ; that is,

$$f_{X_2, Y_2}(x, y) = f_{X_1, Y_1}(S(x, y)) |J(x, y)|.$$

□

- Characteristic functions:

Theorem 6.3.6. X and Y are independent if and only if $\phi_{X,Y}(s, t) = \phi_X(s)\phi_Y(t)$.

Theorem 6.3.7. (Theorem 4.2.3, Grimmett and Stirzaker.) Let X and Y be random variables, and let $g, h : \mathbb{R} \rightarrow \mathbb{R}$. If X and Y are independent, then so are $g(X)$ and $h(Y)$.

Definition 6.33. The **correlation coefficient** between random variables X and Y is given by

$$\rho = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$$

Theorem 6.3.8. The correlation coefficient satisfies $|\rho| \leq 1$.

Proof. Apply the Cauchy-Schwarz Inequality (Theorem 8.2.4) to $X - \mathbb{E}(X)$ and $Y - \mathbb{E}(Y)$:

$$\text{Cov}(X, Y)^2 = (\mathbb{E}[(X - \mathbb{E}(X))(Y - \mathbb{E}(Y))]^2)^2 \leq \mathbb{E}[(X - \mathbb{E}(X))^2]\mathbb{E}[(Y - \mathbb{E}(Y))^2] = \text{Var}(X)\text{Var}(Y)$$

$$\iff \frac{\text{Cov}(X, Y)^2}{\text{Var}(X)\text{Var}(Y)} \leq 1 \iff \rho^2 \leq 1 \iff |\rho| \leq 1$$

□

Theorem 6.3.9. (Stein identity or Stein's Lemma.) Let $X \sim \mathcal{N}(\mu, \sigma^2)$. Let $g : \mathbb{R} \rightarrow \mathbb{R}$ be a continuously differentiable function such that g and g' have polynomial volume growth. That is, $\exists a, b > 0$ such that $|g(x)|, |g'(x)| \leq a(1 + |x|)^b$, $\forall x \in \mathbb{R}$. Then

$$\mathbb{E}[(X - \mu)g(X)] = \sigma^2 \mathbb{E}g'(X).$$

Proof. Examining the left side, we have

$$\mathbb{E}[(X - \mu)g(X)] = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} (x - \mu)g(x)e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

We will use integration by parts with $u = g(x) \implies du = g'(x)dx$, $dv = (x - \mu) \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) dx \implies v = -\sigma^2 \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$ to yield the result:

$$\begin{aligned}\mathbb{E}[(X - \mu)g(X)] &= \frac{1}{\sqrt{2\pi\sigma^2}} \left(\left[-g(x) \cdot -\sigma^2 \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \right]_{-\infty}^{\infty} + \sigma^2 \int_{-\infty}^{\infty} g'(x) \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) dx \right) \\ &= 0 + \sigma^2 \mathbb{E}(g'(X)).\end{aligned}$$

□

Example 6.4. Using Theorem 6.3.9, recursively compute $\mathbb{E}X^k$ for any positive integer k . Alternatively, for any $t > 0$, show that $\mathbb{E}e^{tX} = e^{t^2/2}$, i.e. compute the **moment generating function** of X . Then, using $\frac{d^k}{dt^k}|_{t=0} \mathbb{E}e^{tX} = \mathbb{E}X^k$ and using the power series expansion of the exponential, compute $\mathbb{E}X^k$ directly from the identity $\mathbb{E}e^{tX} = e^{t^2/2}$.

Solution. We can use this result to recursively calculate $\mathbb{E}(X^k)$ for any positive integer k . Suppose we have $\mathbb{E}(X^{k-1})$. Letting $g(X) = X^{k-1} \implies g'(X) = (k-1)X^{k-2}$, we have

$$\mathbb{E}(X^k) = \mathbb{E}(X \cdot X^{k-1}) = \mathbb{E}(Xg(X)) = \mathbb{E}(g'(X)) \iff \boxed{\mathbb{E}(X^k) = (k-1)\mathbb{E}(X^{k-2})}.$$

Since $X \sim \mathcal{N}(0, 1)$, we have $\mathbb{E}(X) = 0$, $\mathbb{E}(X^2) = \text{Var}(X) + \mathbb{E}(X)^2 = 1 + 0 = 1$. Therefore we have

$$\mathbb{E}(X^k) = \begin{cases} \prod_{i=1}^{(k-1)/2} (k - (2i-1)) \mathbb{E}(X) & k \text{ is odd} \\ \prod_{i=1}^{k/2} (k - (2i-1)) \mathbb{E}(X^2) & k \text{ is even} \end{cases}$$

$$\mathbb{E}(X^k) = \begin{cases} 0 & k \text{ is odd} \\ \prod_{i=1}^{k/2} (k - (2i-1)) & k \text{ is even} \end{cases}$$

6.3.2 Probability-Generating Functions

Definition 6.34.

$$G_X(s) = \mathbb{E}(s^X)$$

Theorem 6.3.10. Some useful properties:

- (a) $\mathbb{E}(X) = G'_X(1)$, $\mathbb{E}[X(X-1)\cdots(X-k+1)] = G^{(k)}(1)$
- (b) If X and Y are independent then $G_{X+Y}(s) = G_X(s)G_Y(s)$.

6.3.3 Moment-Generating Functions

Definition 6.35.

$$M_X(t) = \mathbb{E}(e^{tX})$$

Theorem 6.3.11 (Some useful properties). (a) $\mathbb{E}(X) = M'_X(0)$, $\mathbb{E}(X^k) = M^{(k)}(0)$

(b) If X_1, X_2, \dots, X_n are independent then $M_{X_1+X_2+\dots+X_n}(t) = \prod_{i=1}^n M_{X_i}(t)$.

Proof. (a)

(b)

$$M_{X_1+X_2+\dots+X_n}(t) = \mathbb{E} \exp \left(t \sum_{i=1}^n X_i \right) = \mathbb{E} \prod_{i=1}^n e^{tX_i} = \prod_{i=1}^n \mathbb{E} e^{tX_i} = \prod_{i=1}^n M_{X_i}(t).$$

□

6.3.4 Characteristic Functions

Definition 6.36. The **characteristic function** $\phi_X : \mathbb{R} \rightarrow \mathbb{C}$ of a random variable X is defined as

$$\phi_X(t) := \mathbb{E}(e^{itX}) = \int_{\mathbb{R}} e^{itx} dF_X(x) = \int_{\mathbb{R}} e^{itx} f_X(x) dx = \mathbb{E} \cos(tX) + i\mathbb{E} \sin(tX).$$

Note that this formula suggests how we take the expectation of a complex-valued random variable: if $Z \in \mathbb{C}$ we define

$$\mathbb{E}Z = \mathbb{E}(\operatorname{Re}(Z)) + i\mathbb{E}(\operatorname{Im}(Z)).$$

Definition 6.37. The **modulus** of the complex number $z = a + bi$ is $|a + bi| = (a^2 + b^2)^{1/2}$.

Theorem 6.3.12 (Theorem 3.3.1 in Durrett [2019]). All characteristic functions have the following properties:

(a) $\phi(0) = 1$,

(b) They are Hermitian: $\phi(-t) = \overline{\phi(t)}$,

(c) $|\phi(t)| = |\mathbb{E}e^{itX}| \leq \mathbb{E}|e^{itX}| = 1$,

(d) $|\phi(t+h) - \phi(t)| \leq \mathbb{E}|e^{ihX} - 1|$, so $\phi(t)$ is uniformly continuous on $(-\infty, \infty)$.

(e) $\mathbb{E}e^{it(aX+b)} = e^{itb}\phi(at)$.

Proof. (a) Obvious.

(b)

$$\phi(-t) = \mathbb{E} \cos(-tX) + i\mathbb{E} \sin(-tX) = \mathbb{E} \cos(tX) - i\mathbb{E} \sin(tX) = \overline{\phi(t)}.$$

(c) The inequality follows from Jensen's inequality. For the last equality, note that

$$\mathbb{E}|e^{itX}| = \mathbb{E}|\cos(tX) + i\sin(tX)| = 1.$$

(d)

$$\begin{aligned}
|\phi(t+h) - \phi(t)| &= \left| \mathbb{E} \left(e^{i(t+h)X} - e^{itX} \right) \right| \\
&\leq \mathbb{E} \left| e^{i(t+h)X} - e^{itX} \right| \\
&= \mathbb{E} \left| e^{itX} (e^{ihX} - 1) \right| \\
&= \dots \\
&= \mathbb{E} |e^{ihX} - 1|.
\end{aligned}$$

Then uniform convergence follows from the bounded convergence theorem (Theorem 1.5.3 in [Durrett \[2019\]](#)).

(e)

$$\mathbb{E} e^{it(aX+b)} = e^{itb} \mathbb{E} e^{itaX} = e^{itb} \phi(at).$$

□

Theorem 6.3.13 (Theorem 3.3.2 in Durrett [2019]). If X_1 and X_2 are independent and have characteristic functions ϕ_1 and ϕ_2 then $X_1 + X_2$ has characteristic function $\phi_1(t)\phi_2(t)$.

Proof.

$$\mathbb{E} e^{it(X_1+X_2)} = \mathbb{E} [e^{itX_1} e^{itX_2}] = \mathbb{E} e^{itX_1} \mathbb{E} e^{itX_2}.$$

□

Definition 6.38 (Characteristic function of a random vector). The **characteristic function** $\phi : \mathbb{R}^n \rightarrow \mathbb{C}$ of a random vector $\mathbf{u} \in \mathbb{R}^n$ is defined as

$$\phi_{\mathbf{u}}(\mathbf{s}) = \mathbb{E} [\exp \{i\mathbf{s}^\top \mathbf{u}\}] = \int_{\mathbb{R}} \dots \int_{\mathbb{R}} \exp \{i\mathbf{s}^\top \mathbf{u}\} dF_{u_1}(u_1) \dots dF_{u_n}(u_n).$$

Sometimes we may write the **joint characteristic function** of two random variables X and Y (for example) as

$$\phi_{X,Y}(s,t) := \mathbb{E} \exp \{i(sX + tY)\};$$

note that if and only if X and Y we are independent we have

$$\phi_{X,Y}(s,t) = \mathbb{E} [\exp \{isX\} \exp \{itY\}] = \mathbb{E} [\exp \{isX\}] \mathbb{E} [\exp \{itY\}] = \phi_X(s)\phi_Y(t).$$

Similarly, the joint characteristic function of two random vectors \mathbf{X} and \mathbf{Y} is

$$\phi_{\mathbf{X},\mathbf{Y}}(\mathbf{s},\mathbf{t}) = \mathbb{E} \exp \{i(\mathbf{s}^\top \mathbf{X} + \mathbf{t}^\top \mathbf{Y})\},$$

and if and only if \mathbf{X} and \mathbf{Y} we are independent we have

$$\phi_{\mathbf{X}, \mathbf{Y}}(\mathbf{s}, \mathbf{t}) = \mathbb{E} [\exp \{i\mathbf{s}^\top \mathbf{X}\} \exp \{i\mathbf{t}^\top \mathbf{Y}\}] = \mathbb{E} [\exp \{i\mathbf{s}^\top \mathbf{X}\}] \mathbb{E} [\exp \{i\mathbf{t}^\top \mathbf{Y}\}] = \phi_{\mathbf{X}}(\mathbf{s}) \phi_{\mathbf{Y}}(\mathbf{t}).$$

(See also Theorem 6.3.15 part (d) below.)

Proposition 6.3.14. Necessary and sufficient conditions for a function to be a characteristic function:

- (a) $\phi_X(0) = 1$
- (b) $|\phi(t)| \leq 1 \forall t$
- (c) ϕ is uniformly continuous on \mathbb{R}
- (d) ϕ is positive semidefinite; that is,

$$\sum_{i,j} \phi(t_j - t_k) z_j \bar{z}_k \geq 0 \text{ for all real } t_1, t_2, \dots, t_n \text{ and complex } z_1, z_2, \dots, z_n$$

Or, equivalently, or every set of real numbers t_1, t_2, \dots, t_n , the matrix $\phi(t_i - t_j), i, j \in \{1, 2, \dots, n\}$ is Hermitian and nonnegative definite.

Remark 38. Relationship between characteristic functions and probability and moment-generating functions:

$$\phi_X(t) = M_X(it) = G_X(e^{it})$$

- Theorem 6.3.15 (Some useful properties).** (a) $X \perp\!\!\!\perp Y \implies \phi_{X+Y}(t) = \phi_X(t)\phi_Y(t)$
- (b) $Y = aX + b \implies \phi_Y(t) = e^{itb}\phi_X(at)$
- (c) $\phi_X^{(k)}(0) = i^k \mathbb{E}(X^k)$
- (d) $\phi_{X,Y}(s,t) = \mathbb{E}(e^{isX} e^{itY})$
- (e) $X \perp\!\!\!\perp Y \iff \phi_{X,Y}(s,t) = \phi_X(s)\phi_Y(t)$

Theorem 6.3.16. Other facts from notes on course website

- (a) If $\phi(t)$ is even, $\phi(0) = 1$, ϕ is convex for $t > 0$, and $\lim_{t \rightarrow \infty} \phi(t) = 0$, then ϕ is a characteristic function of an absolutely continuous random variable.
- (b) If ϕ is a characteristic function and $\phi(t) = 1 + o(t^2), t \rightarrow 0$, then $\phi(t) = 1$ for all t . The random variable with such a characteristic function must have zero mean and zero variance. In particular, if $r > 2$, then $\exp(-|t|^r)$ is not a characteristic function.
- (c) If $\phi(t) = e^{p(t)}$ is a characteristic function and $p = p(t)$ is a polynomial, then the degree of p is at most 2. For example, $e^{t^2 - t^4}$ is not a characteristic function.
- (d) If ξ is absolutely continuous, then $\lim_{|t| \rightarrow \infty} |\phi_\xi(t)| = 0$ (Riemann-Lebesgue).
- (e) If $\int_{-\infty}^{\infty} |\phi_\xi(t)| dt < \infty$, then ξ is absolutely continuous with pdf

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(-itx) \phi(t) dt$$

6.3.5 Continuous Random Variable Distributions

Uniform: $U(a, b)$

- Probability density function:

$$f(x) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

- Cumulative distribution function:

$$F(x) = \Pr(X \leq x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ 1 & x > b \end{cases}$$

- Probability-generating function:
- Moment-generating function:

$$M_X(t) = \frac{1}{(b-a)t} [\exp(bt) - \exp(at)]$$

Proof.

$$M_X(t) = \mathbb{E}(\exp(tX)) = \int_a^b \frac{1}{b-a} \cdot \exp(tx) dx = \frac{1}{b-a} \left[\frac{1}{t} \exp(tx) \right]_a^b = \frac{1}{(b-a)t} [\exp(bt) - \exp(at)]$$

□

- Characteristic function:

$$\frac{2}{(b-a)t} \sin\left(\frac{1}{2}(b-a)t\right) \exp\left(i(a+b)\frac{t}{2}\right)$$

- Expectation: $\mathbb{E}(X) = (b-a)/2$
- Variance: $\text{Var}(X) = (b-a)^2/12$

Proposition 6.3.17. If $X \sim U(0, 1)$, then $Y = -\log(X) \sim \text{Exponential}(1)$.

Proof.

$$\begin{aligned} \Pr(Y \leq y) &= \Pr(-\log(X) \leq y) = \Pr(\log(X) \geq -y) = \Pr(X \geq e^{-y}) = \int_{\exp(-y)}^{\infty} f_X(t) dt = \int_{\exp(-y)}^1 dt \\ &= 1 - e^{-y} \end{aligned}$$

which is the cdf for an exponential distribution with mean 1. □

Proposition 6.3.18. Let X_1, \dots, X_n be i.i.d. random variables with $X_1 \sim \text{Unif}(0, 1)$. Then the pdf of $Q = \prod_{i=1}^n X_i$ is $f_Q(y) = \frac{(-\log y)^{n-1}}{(n-1)!}$.

Proof. By Proposition 6.3.17, $-\log(X_i) \sim \text{Exponential}(1)$ for all $i \in [n]$. By Corollary 6.3.26.1,

$$\begin{aligned} & \sum_{i=1}^n -\log(X_i) \sim \text{Gamma}(n, 1) \\ \iff & -\log\left(\prod_{i=1}^n X_i\right) \sim \text{Gamma}(n, 1) \end{aligned}$$

That is, $-\log(\prod_{i=1}^n X_i)$ has pdf

$$f(x) = \frac{1}{1^n \Gamma(n)} x^{n-1} e^{-x/1} = \frac{1}{(n-1)!} x^{n-1} e^{-x}.$$

So for all $t \geq 0$,

$$\begin{aligned} & \mathbb{P}\left(-\log\left(\prod_{i=1}^n X_i\right) \geq t\right) = \int_t^\infty \frac{1}{(n-1)!} x^{n-1} e^{-x} dx \\ \iff & \mathbb{P}\left(\log\left(\prod_{i=1}^n X_i\right) \leq -t\right) = \int_t^\infty \frac{1}{(n-1)!} x^{n-1} e^{-x} dx \\ \iff & \mathbb{P}\left(\prod_{i=1}^n X_i \leq e^{-t}\right) = \int_t^\infty \frac{1}{(n-1)!} x^{n-1} e^{-x} dx \\ \iff & \mathbb{P}(Q \leq y) = \int_{-\log y}^\infty \frac{1}{(n-1)!} x^{n-1} e^{-x} dx \\ \iff & F_Q(y) = 1 - \int_0^{-\log y} \frac{1}{(n-1)!} x^{n-1} e^{-x} dx \end{aligned}$$

where $e^{-t} = y \iff t = -\log(y)$ (so $y \in (0, 1]$). Finally, the pdf of Q is

$$\begin{aligned} \frac{\partial F_Q(y)}{\partial y} &= \frac{\partial}{\partial y} \left(1 - \int_0^{-\log y} \frac{1}{(n-1)!} x^{n-1} e^{-x} dx \right) \\ &= - \left(\frac{1}{(n-1)!} (-\log y)^{n-1} e^{\log y} \right) \cdot \frac{-1}{y} \\ &= \frac{(-\log y)^{n-1}}{(n-1)!} \end{aligned}$$

□

Proposition 6.3.19. If U_1, U_2, \dots, U_p are independent and have uniform distributions, then $-2 \sum_{j=1}^p \log(U_j)$ has a χ_{2p}^2 distribution.

Proof. Apply Propositions 6.3.17 and 6.3.28. □

Normal (or Gaussian): $\mathcal{N}(\mu, \sigma^2)$

- Probability density function:

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

- Cumulative distribution function: $F(x) = \Pr(X \leq x) =$
- Probability-generating function:
- Moment-generating function: $M_X(t) = \exp(\mu t + \sigma^2 t^2/2)$
- Characteristic function: $\phi(t) = \exp(i\mu t - (1/2)\sigma^2 t^2)$. Standard normal: $\phi(t) = \exp((-1/2)t^2)$.
- Expectation: $\mathbb{E}(X) = \mu$
- Variance: $\text{Var}(X) = \sigma^2$

Theorem 6.3.20. Let $X := \Omega \rightarrow \mathbb{R}^n$ be a random Gaussian variable with the **standard Gaussian distribution**:

$$\Pr(X \in A) := \int_A e^{-(x_1^2 + \dots + x_n^2)/2} dx (2\pi)^{-n/2}, \quad \forall A \subset \mathbb{R}^n \text{ measurable.}$$

Let v_1, \dots, v_m be vectors in \mathbb{R}^n . Let $\langle \cdot, \cdot \rangle : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ be the standard inner product on \mathbb{R}^n , so that $\langle x, y \rangle := \sum_{i=1}^n x_i y_i$ for any $x = (x_1, \dots, x_n), y = (y_1, \dots, y_n) \in \mathbb{R}^n$.

Let $v \in \mathbb{R}^n$. Then $\langle X, v \rangle$ is a mean zero Gaussian with variance $\langle v, v \rangle$.

Remark 39. Similar to Exercise 6.2. You can then use an induction argument to prove the case for the sum of arbitrarily many Gaussian random variables.

Proof. Let $X = (X_1, X_2, \dots, X_n)$ and $v = (v_1, v_2, \dots, v_n)$. Then $\langle X, v \rangle = \sum_{i=1}^n X_i v_i$. Let $Y_i = v_i X_i$, so $\langle X, v \rangle = \sum_{i=1}^n Y_i$. Note that $Y_i \sim \mathcal{N}(0, v_i^2)$. Recall that the moment-generating function of a Gaussian random variable is $\mathbb{E}e^{tX} = e^{\mu t + \sigma^2 t^2/2}$, so we have $M_{Y_i}(t) = \exp(v_i^2 t^2/2)$. Next we seek the distribution of $\sum_{i=1}^n v_i X_i = \sum_{i=1}^n Y_i$. From Proposition 1.67, we have

$$M_{Y_1+Y_2+\dots+Y_n}(t) = \mathbb{E} \exp\left(t \sum_{i=1}^n Y_i\right) = \mathbb{E} \prod_{i=1}^n e^{t Y_i} = \prod_{i=1}^n \mathbb{E} e^{t Y_i} = \prod_{i=1}^n M_{Y_i}(t).$$

Then

$$\prod_{i=1}^n M_{Y_i}(t) = \prod_{i=1}^n \exp(v_i^2 t^2/2) = \exp\left(\frac{t^2}{2} \sum_{i=1}^n v_i^2\right) = \exp\left(\frac{t^2}{2} \cdot \langle v, v \rangle\right)$$

which is the same as the moment-generating function for a mean zero Gaussian random variable with variance $\langle v, v \rangle$. By the provided uniqueness result from Problem 6 (“If Y and Z are two random variables whose MGFs coincide in a neighborhood of 0 ($\exists \delta > 0$ for which $M_Y(u) = M_Z(u) < \infty$ for all $u \in [-\delta, \delta]$), then Y and Z have the same distribution.”), the result follows. \square

Proposition 6.3.21. Let X_1, X_2, \dots, X_n be i.i.d. random sample from $\mathcal{N}(\mu, \sigma)$. Then the sum of these n observations $T = \sum_{i=1}^n X_i$ also follows the normal distribution.

Proof.

$$T = \sum_{i=1}^n X_i = X_1 + X_2 + \dots + X_n$$

Since X_i is $\mathcal{N}(\mu, \sigma)$, we have

$$M_{X_i}(t) = \exp\left(\mu t + \frac{t^2 \sigma^2}{2}\right)$$

Since all observations are independent, we have

$$M_T(t) = \prod_{i=1}^n M_{X_i}(t) = \left(\exp\left(\mu t + \frac{t^2 \sigma^2}{2}\right) \right)^n = \boxed{\exp\left(n\mu t + \frac{t^2 n \sigma^2}{2}\right)}$$

which is the moment generating function for a normal distribution with mean $n\mu$ and standard deviation $\sigma\sqrt{n}$.

□

Lognormal: If the random variable X follows the normal distribution with $\mu = 0, \sigma^2 = 1$ and $Y = e^X$, then Y has a lognormal distribution.

- Probability density function:

$$f_X(x) = \frac{1}{x\sqrt{2\pi}} \exp\left(\frac{-1}{2}(\log(x))^2\right)$$

Proof.

$$F_Y(y) = \Pr(Y \leq y) = \Pr(e^X \leq y) = \Pr(X \leq \log(y)) \implies F_Y(y) = F_X(\log(y))$$

$$\implies f_Y(y) = \frac{d}{dy} F_X(\log(y)) = f_X(\log(y)) \frac{1}{y}$$

$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}x^2} \implies f_Y(y) = \frac{1}{y\sqrt{2\pi}} \exp\left(\frac{-1}{2}(\log(y))^2\right)$$

□

- Cumulative distribution function: $F(x) = \Pr(X \leq x) =$
- Probability-generating function:
- Moment-generating function: $M_X(t) =$
- Characteristic function: $\phi(t) =$

- Expectation: $\mathbb{E}(X) =$
- Variance: $\text{Var}(X) =$

Gamma: $\Gamma(\alpha, \beta)$

- Probability density function:

$$f(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} = \frac{1}{\Gamma(\alpha, \beta)} x^{\alpha-1} e^{-x/\beta}$$

- Cumulative distribution function:

$$F(x) = \Pr(X \leq x) =$$

- Probability-generating function:
- Moment-generating function:

$$\left(\frac{1/\beta}{1/\beta - t} \right)^\alpha = \left(\frac{1}{1 - \beta t} \right)^\alpha$$

Proof.

$$\mathbb{E}(e^{tX}) = \int_{\mathbb{R}} e^{tx} f(x) dx = \int_0^\infty e^{tx} \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty x^{\alpha-1} e^{-x(1/\beta - t)} dx$$

Using integration by parts, one can find the identity

$$\int_0^\infty x^a e^{-bx} dx = \frac{\Gamma(a+1)}{b^{a+1}}.$$

Using this yields

$$\boxed{\mathbb{E}(e^{tX}) = \frac{1}{\beta^\alpha \Gamma(\alpha)} \frac{\Gamma(\alpha)}{(1/\beta - t)^\alpha} = \left(\frac{1/\beta}{1/\beta - t} \right)^\alpha = \left(\frac{1}{1 - \beta t} \right)^\alpha}$$

□

- Characteristic function:
- Expectation: $\mathbb{E}(X) = \alpha\beta$
- Variance: $\text{Var}(X) = \alpha\beta^2$

Proposition 6.3.22. Let $X_i \sim \text{Gamma}(\alpha_i, \beta)$ for $i = 1, 2, \dots, n$. Then

$$\sum_{i=1}^n X_i \sim \text{Gamma} \left(\sum_{i=1}^n \alpha_i, \beta \right).$$

Proof. Using the moment-generating function for a Gamma distribution as well as Theorem 6.3.11(b), we have

$$M_{X_1+\dots+X_n}(t) = \prod_{i=1}^n M_{X_i}(t) = \prod_{i=1}^n \left(\frac{1}{1-\beta t} \right)^{\alpha_i} = \left(\frac{1}{1-\beta t} \right)^{\sum_{i=1}^n \alpha_i}$$

which is the same as the moment-generating function for a $\Gamma(\sum_{i=1}^n \alpha_i, \beta)$ distribution. By the provided uniqueness result (“If Y and Z are two random variables whose MGFs coincide in a neighborhood of 0 ($\exists \delta > 0$ for which $M_Y(u) = M_Z(u) < \infty$ for all $u \in [-\delta, \delta]$), then Y and Z have the same distribution.”), the result follows. \square

Proposition 6.3.23. Let $X \sim \text{Gamma}(\alpha, \beta)$. Then as $\beta \rightarrow \infty$, $X \xrightarrow{d} \mathcal{N}(\alpha\beta, \alpha\beta^2)$.

Proof. See <http://www.math.wm.edu/~leemis/chart/UDR/PDFs/GammaNormal1.pdf>. \square

Proposition 6.3.24 (Stats 100B homework problem). The method of moments estimators for α and β are

$$\hat{\alpha} = \frac{n\bar{x}^2}{\sum_{i=1}^n (X_i^2 - \bar{x}^2)}$$

$$\hat{\beta} = \frac{1}{n\bar{x}} \sum_{i=1}^n (X_i^2 - \bar{x}^2)$$

Proof.

$$\mathbb{E}(X) = \alpha\beta \implies \hat{\alpha}\hat{\beta} = \bar{x}$$

$$\hat{\alpha} = \frac{\bar{x}}{\hat{\beta}}$$

$$\text{Var}(X) = \alpha\beta^2 = \mathbb{E}(X^2) - (\mathbb{E}(X))^2$$

$$\implies \hat{\alpha}\hat{\beta}^2 = \frac{1}{n} \sum_{i=1}^n X_i^2 - \bar{x}^2$$

$$\frac{\bar{x}}{\hat{\beta}}\hat{\beta}^2 = \frac{1}{n} \sum_{i=1}^n X_i^2 - \bar{x}^2$$

$$\bar{x}\hat{\beta} = \frac{1}{n} \sum_{i=1}^n X_i^2 - \bar{x}^2$$

$$\hat{\beta} = \frac{1}{n\bar{x}} \sum_{i=1}^n X_i^2 - \bar{x} = \frac{1}{n\bar{x}} \sum_{i=1}^n X_i^2 - \frac{n\bar{x}^2}{n\bar{x}}$$

$$\hat{\beta} = \frac{1}{n\bar{x}} \sum_{i=1}^n (X_i^2 - \bar{x}^2)$$

$$\implies \hat{\alpha} = \frac{\bar{x}}{\hat{\beta}} = \frac{n\bar{x}^2}{\sum_{i=1}^n (X_i^2 - \bar{x}^2)}$$

□

Proposition 6.3.25. The Gamma distribution has the following scaling property—if X has a $\Gamma(\alpha, \beta)$ distribution, then for any $k > 0$, kX has a $\Gamma(\alpha, k\beta)$ distribution.

Proof. We have

$$M_X(t) = \left(\frac{1}{1 - \beta t} \right)^\alpha,$$

so

$$M_{kX}(t) = M_X(kt) = \left(\frac{1}{1 - \beta kt} \right)^\alpha,$$

which is the moment-generating function for a $\Gamma(\alpha, k\beta)$ distribution. □

Proposition 6.3.26 (Some useful formulae and integrals related to the gamma function).

- Definition:

$$\Gamma(z) = \int_0^\infty x^{z-1} e^{-x} dx$$

- Beta function (see also the information on the Beta distribution):

$$B(z_1, z_2) := \int_0^1 t^{z_1-1} (1-t)^{z_2-1} dt = \frac{\Gamma(z_1)\Gamma(z_2)}{\Gamma(z_1 + z_2)}$$

- Generalization of the factorial function:

$$\Gamma(z+1) = z\Gamma(z)$$

(in particular, for any integer $n \geq 1$, $\Gamma(n) = (n-1)!$.)

- $\Gamma(1/2) = \sqrt{\pi}$.
- Using integration by parts, one can find the identity

$$\int_0^\infty x^a e^{-bx} dx = \frac{\Gamma(a+1)}{b^{a+1}}.$$

- **Euler's Reflection Formula:** For $z \notin \mathbb{Z}$,

$$\Gamma(1-z)\Gamma(z) = \frac{\pi}{\sin(\pi z)}$$

- **Legendre Duplication Formula:**

$$\Gamma(z)\Gamma\left(z + \frac{1}{2}\right) = 2^{1-2z}\sqrt{\pi}\Gamma(2z)$$

- For all $z \in \mathbb{C}$,

$$\lim_{n \rightarrow \infty} \frac{\Gamma(n+z)}{\Gamma(n)n^z} = 1.$$

- From 2018 DSO Statistics Screening Exam:

$$\lim_{x \rightarrow 0} x\Gamma(x) = 1$$

- See Theorem 6.1.45 (Stirling's Formula)

$$\Gamma(n+1) \sim n^n e^{-n} \sqrt{2\pi n}$$

That is,

$$\lim_{n \rightarrow \infty} \frac{n^n e^{-n} \sqrt{2\pi n}}{\Gamma(n+1)} = 1.$$

χ_k^2 (**chi-squared**): special case of a gamma distribution: $\Gamma(k/2, 2)$. Also the sum of k independent standard normally distributed variables.

- Probability density function:

$$f(x) = \frac{1}{2^{k/2}\Gamma(k/2)} x^{k/2-1} e^{-x/2} = \frac{1}{\Gamma(k/2, 2)} x^{k/2-1} e^{-x/2}$$

For χ_1^2 : $f(x) = \frac{1}{\sqrt{2\pi}} e^{-x/2} x^{-1/2}$. For χ_2^2 : $f(x) = \frac{1}{2} e^{-x^2}, x > 0$.

Proof. See notes from Math 541A. □

- Cumulative distribution function: $F(x) = \Pr(X \leq x) =$
- Probability-generating function:
- Moment-generating function: $(1 - 2t)^{-k/2}$ for $t < 1/2$
- Characteristic function:
- Expectation: $\mathbb{E}(X) = k/2 \cdot 2 = k$
- Variance: $\text{Var}(X) = k/2 \cdot 2^2 = 2k$

Exponential: (special case of a gamma distribution: $\Gamma(1, \beta)$. Also a special case of a Weibull distribution with $\beta = 1$.)

- Probability density function: $f(x) = \frac{1}{\beta} \exp(-x/\beta) = \lambda e^{-\lambda x}$
- Cumulative distribution function: $F(x) = \Pr(X \leq x) = 1 - e^{-\lambda x}$
- Probability-generating function:
- Moment-generating function: $\frac{\lambda}{\lambda-t}$

- Characteristic function:
- Expectation: $\mathbb{E}(X) = \beta = \lambda^{-1}$

Proof.

$$\mathbb{E}(X) = \int_0^\infty \bar{F}(t)dt = \int_0^\infty e^{-\lambda t}dt = \frac{1}{\lambda}$$

□

- Variance: $\text{Var}(X) = \beta^2 = \lambda^{-2}$

Proof. See Definition 6.21 above for the definition of $E(X^n)$. Then using that:

$$\mathbb{E}(X^2) = 2 \int_0^\infty te^{-\lambda t}dt = \frac{2}{\lambda} \int_0^\infty \lambda te^{-\lambda t}dt = \frac{2}{\lambda} \mathbb{E}(X) = \frac{2}{\lambda^2}$$

Then use $\text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2$ to yield the result. □

Remark 40. Note also the general case:

$$\mathbb{E}(X^n) = n \int_0^\infty t^{n-1} \bar{F}(t)dt = n \int_0^\infty t^{n-1} e^{-\lambda t}dt = \frac{n}{\lambda} \mathbb{E}(X^{n-1})$$

Corollary 6.3.26.1 (Corollary to Proposition 6.3.22). Let X_1, \dots, X_n be i.i.d. Exponential(β). Then

$$\sum_{i=1}^n X_i \sim \text{Gamma}(n, 1/\lambda) = \text{Gamma}(n, \beta).$$

Proof. Since $X_i \sim \text{Exponential}(\beta) = \text{Gamma}(1, \beta)$, by Proposition 6.3.22 we have

$$\sum_{i=1}^n X_i \sim \text{Gamma}\left(\sum_{i=1}^n 1, \beta\right) = \text{Gamma}(n, \beta).$$

□

Proposition 6.3.27. Exponential random variables are not sub-gaussian.

Proof. It suffices to show there is no σ^2 such that $\mathbb{E}[\exp\{\theta(x - 1/\lambda)\}] \leq \exp\{\sigma^2\theta^2/2\}$ for all $\theta \geq 0$. But

$$\begin{aligned} & \mathbb{E}[\exp\{\theta(x - 1/\lambda)\}] \leq \exp\{\sigma^2\theta^2/2\} \\ \iff & \mathbb{E}[\exp\{\theta x\}] \leq \exp\{\theta/\lambda + \sigma^2\theta^2/2\} \\ \iff & \frac{\lambda}{\lambda - \theta} \leq \exp\{\theta/\lambda + \sigma^2\theta^2/2\} \end{aligned}$$

Take limit as $\theta \rightarrow \lambda$, LHS to ∞ , RHS to $\exp\{1 + \theta^2\lambda^2/2\}$

□

Proposition 6.3.28. If X is an exponential random variable with mean 1, then $2X$ has a χ^2 distribution with two degrees of freedom.

Proof. Since X has a $\Gamma(1, 1)$ distribution, by Proposition 6.3.25 $2X$ has a $\Gamma(1, 2)$ distribution, which is a χ^2 random variable with 2 degrees of freedom. \square

For much more on exponential random variables, see Section 6.3.6.

Cauchy:

- Probability density function:

$$f(x) = \frac{1}{\pi(1+x^2)} \text{ (standard Cauchy) , } f(x) = \frac{1}{\pi\sigma(1+(x-\mu)^2/\sigma^2)} \text{ (general)}$$

- Cumulative distribution function: $F(x) = \Pr(X \leq x) =$
- Probability-generating function:
- Moment-generating function:
- Characteristic function:
- Expectation: does not exist
- Variance: does not exist (Cauchy distribution has no moments.)

Beta: Recall:

$$\begin{aligned} B(\alpha, \beta) &:= \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} \\ \implies \frac{B(\alpha+1, \beta)}{B(\alpha, \beta)} &= \frac{\Gamma(\alpha+1)\Gamma(\beta)}{\Gamma(\alpha+1+\beta)} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} = \frac{\alpha}{\alpha+\beta} \end{aligned}$$

- Probability density function:

$$f(x) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}(x)^{\alpha-1}(1-x)^{\beta-1}$$

- Cumulative distribution function: $F(x) = \Pr(X \leq x) =$
- Probability-generating function:
- Moment-generating function:

$$1 + \sum_{k=1}^{\infty} \left(\prod_{r=0}^{k-1} \frac{\alpha+r}{\alpha+\beta+r} \right) \frac{t^k}{k!}$$

- Characteristic function:
- Expectation: $\mathbb{E}(X) = \frac{\alpha}{\alpha+\beta}$
- Variance:

$$\text{Var}(X) = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

Student's t_n : can be defined as

$$T = \frac{Z}{\sqrt{V/v}} \implies T \sim t_v$$

where $Z \sim \mathcal{N}(0, 1)$, $V \sim \chi_v^2$, and $Z \perp\!\!\!\perp V$.

- Probability density function:

$$f(x) = \frac{\Gamma((n+1)/2)}{\sqrt{n\pi} \cdot \Gamma(n/2)} \left(1 + \frac{x^2}{n}\right)^{-(n+1)/2}$$

- Cumulative distribution function: $F(x) = \Pr(X \leq x) =$
- Probability-generating function:
- Moment-generating function:
- Characteristic function:
- Expectation: $\mathbb{E}(X) = 0$
- Variance: $\text{Var}(X) = n/(n-2)$

Snedecor's F -distribution: can be defined as

$$X = \frac{U/d_1}{V/d_2} \implies X \sim F_{d_1, d_2}$$

where $U \sim \chi_{d_1}^2$, $V \sim \chi_{d_2}^2$, and $U \perp\!\!\!\perp V$.

- Probability density function:

$$\begin{aligned} f(x) &= \frac{t^{(p/2)-1} (p/q)^{p/2} \Gamma((p+q)/2)}{\Gamma(p/2) \Gamma(q/2)} \left(1 + t(p/q)\right)^{-(p+q)/2}, \quad \forall t > 0 \\ &= p^{p/2} q^{q/2} \cdot \frac{\Gamma([p+q]/2)}{\Gamma(p/2) \Gamma(q/2)} \cdot \frac{t^{p/2-1}}{(pt+q)^{(p+q)/2}} \end{aligned}$$

- Cumulative distribution function: $F(x) =$
- Probability-generating function:
- Moment-generating function:
- Characteristic function:
- Expectation: $\mathbb{E}(X) =$
- Variance: $\text{Var}(X) =$

Proposition 6.3.29. Let X be a chi squared random variables with p degrees of freedom. Let Y be a chi squared random variable with q degrees of freedom, with X and Y independent. Then $(X/p)/(Y/q)$ is an F -distributed random variable with p and q degrees of freedom.

Proof. Let $c = p/2$, $d = q/2$. Note that

$$f_X(x) = \frac{1}{\Gamma(c)2^c} x^{c-1} e^{-x/2}, \quad x > 0$$

$$f_Y(y) = \frac{1}{\Gamma(d)2^d} y^{d-1} e^{-y/2}, \quad y > 0$$

We first seek $F_{X/Y}(t)$. Note that $F_{X/Y}(t) = \Pr(X/Y \leq t) = \Pr(X \leq tY)$. Thinking about this graphically, we can calculate this as

$$\Pr(X \leq tY) = \int_0^\infty \int_0^{ty} f_{X,Y}(x,y) dx dy$$

By assumption, X and Y are independent, so

$$f_{X,Y}(x,y) = \frac{1}{\Gamma(c)\Gamma(d)2^{c+d}}x^{c-1}y^{d-1}e^{-x/2}e^{-y/2}$$

Plugging this in we have

$$\begin{aligned}\Pr(X \leq tY) &= \frac{1}{\Gamma(c)\Gamma(d)2^{c+d}} \int_0^\infty \int_0^{ty} x^{c-1}y^{d-1}e^{-x/2}e^{-y/2} dx dy \\ &= \frac{1}{\Gamma(c)\Gamma(d)2^{c+d}} \int_0^\infty \int_0^{ty} x^{c-1}e^{-x/2} dx y^{d-1}e^{-y/2} dy\end{aligned}$$

Rather than solving this integral, we next differentiate with respect to t :

$$\begin{aligned}f_{X/Y}(t) &= \frac{d}{dt} F_{X/Y}(t) = \frac{1}{\Gamma(c)\Gamma(d)2^{c+d}} \int_0^\infty y(ty)^{c-1}e^{-ty/2} y^{d-1}e^{-y/2} dy \\ &= \frac{t^{c-1}}{\Gamma(c)\Gamma(d)2^{c+d}} \int_0^\infty y^{c+d-1}e^{-y(t+1)/2} dy\end{aligned}\tag{6.9}$$

Compare the integrand of (6.9) to the pdf of a Gamma distributed random variable

$$f(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}$$

to see that with some manipulations we can express the integrand of (6.9) as the pdf of a Gamma distributed random variable with parameters $\alpha = c + d$, $\beta = 2/(t+1)$:

$$f_{X/Y}(t) = \frac{t^{c-1}\Gamma(c+d)}{\Gamma(c)\Gamma(d)(t+1)^{c+d}} \int_0^\infty \frac{1}{[2/(t+1)]^{c+d}\Gamma(c+d)} y^{c+d-1}e^{-y(t+1)/2} dy$$

Then the integral becomes 1, so we have

$$f_{X/Y}(t) = \frac{t^{c-1}\Gamma(c+d)}{\Gamma(c)\Gamma(d)(t+1)^{c+d}}$$

Substitute back in $c = p/2$, $d = q/2$:

$$f_{X/Y}(t) = \frac{\Gamma([p+q]/2)}{\Gamma(p/2)\Gamma(q/2)} \cdot \frac{t^{p/2-1}}{(t+1)^{(p+q)/2}}$$

Now take into account the constants:

$$\begin{aligned}f_{(X/p)/(Y/q)}(t) &= \frac{p}{q} f_{X/Y}\left(\frac{p}{q}t\right) = \frac{p}{q} \cdot \frac{\Gamma([p+q]/2)}{\Gamma(p/2)\Gamma(q/2)} \cdot \frac{(pt/q)^{p/2-1}}{(pt/q+1)^{(p+q)/2}} \\ &= \frac{t^{(p/2)-1}(p/q)^{p/2}\Gamma((p+q)/2)}{\Gamma(p/2)\Gamma(q/2)} \left(1+t(p/q)\right)^{-(p+q)/2}\end{aligned}$$

(or this can be expressed as)

$$= \left(\frac{p}{q}\right)^{p/2} \cdot \frac{\Gamma([p+q]/2)}{\Gamma(p/2)\Gamma(q/2)} \cdot \frac{t^{p/2-1}q^{(p+q)/2}}{(pt+q)^{(p+q)/2}} = p^{p/2}q^{q/2} \cdot \frac{\Gamma([p+q]/2)}{\Gamma(p/2)\Gamma(q/2)} \cdot \frac{t^{p/2-1}}{(pt+q)^{(p+q)/2}}$$

□

Weibull:

- Probability density function: $f(x) = \alpha\beta x^{\beta-1} \exp(-\alpha x^\beta)$
- Cumulative distribution function: $F(x) = \Pr(X \leq x) = 1 - \exp(-\alpha x^\beta)$
- Probability-generating function:
- Moment-generating function:
- Characteristic function:
- Expectation: $\mathbb{E}(X) =$
- Variance: $\text{Var}(X) =$

Pareto: (parameters α, x_m)

- Probability density function: $f(x) = \alpha x_m^\alpha / x^{\alpha+1}$ for $x \geq 1, 0$ otherwise.
- Cumulative distribution function: $F(x) = 1 - (x_m/x)^\alpha$ for $x \geq 1, 0$ otherwise.
- Probability-generating function:
- Moment-generating function:
- Characteristic function:
- Expectation: $\mathbb{E}(X) = \alpha x_m / (\alpha - 1)$ for $\alpha > 1, \infty$ otherwise.
- Variance: $\text{Var}(X) = \frac{x_m^2 \alpha}{(\alpha-1)^2 (\alpha-2)}$ for $\alpha > 2, \infty$ otherwise.

6.3.6 More on Exponential Random Variables

Remark 41. Recall Proposition 6.3.17: If $X \sim U(0, 1)$, then $Y = -\log(X) \sim \text{Exponential}(1)$.

Proposition 6.3.30. Let X be a random variable. Then X is exponentially distributed if and only if X has the **memoryless** property; that is,

$$\Pr(X > s + t \mid X > t) = \Pr(X > s) \quad \forall s, t \geq 0$$

or, equivalently,

$$\Pr(X > s + t) = \Pr(X > s) \Pr(X > t) \quad \forall s, t \geq 0$$

Proof. See Ross *Introduction to Probability Models* section 5.2.2. □

Remark 42. Exponential distributions can be derived as follows: Let X be a nonnegative random variable with cdf F and pdf f . Define the **failure** or **hazard rate**

$$\lambda(t) = \frac{f(t)}{1 - F(t)}$$

The intuition for the hazard rate is as follows: think of X as the lifetime and consider the probability that a unit with age t fails within some timespan $(t, t+h)$ with h small; that is, $\Pr(t < X < t+h \mid X > t)$. Letting $1 - F(t) = \bar{F}(t)$, we have

$$\Pr(t < X < t+h \mid X > t) = \frac{\Pr(t < X < t+h)}{\Pr(X > t)} = \frac{\int_t^{t+h} f(s)ds}{\bar{F}(t)} \approx \frac{f(t)}{\bar{F}(t)} \text{ for small } h$$

If this quantity is constant at λ (i.e. the process is “memoryless,” see Proposition 6.3.30), we have an exponential distribution:

$$\lambda = \frac{f(t)}{\bar{F}(t)} = \frac{\lambda e^{-\lambda t}}{e^{-\lambda t}}$$

Indeed, a process is memoryless if and only if it is exponential. To see this, note that

$$\int_0^t \lambda(s)ds = \int_0^t \frac{f(s)}{1-F(s)}ds$$

Letting $u = 1 - F(s) \implies du = -f(s)ds$, we have

$$\begin{aligned} &= \int_{u=1}^{u=\bar{F}(t)} -\frac{du}{u} ds = \int_{\bar{F}(t)}^1 \frac{du}{u} ds = \log(1) - \log(\bar{F}(t)) = -\log \bar{F}(t) \\ &\implies \int_0^t \lambda(s)ds = -\log \bar{F}(t) \implies \boxed{\bar{F}(t) = \exp\left(-\int_0^t \lambda(s)ds\right)} \end{aligned}$$

If the process is memoryless, we must have $\lambda(s) = \lambda$ (constant). Then $\bar{F}(t) = \exp(-\lambda t)$ and we have the exponential distribution. See the Weibull distribution below for a more general case.

Proposition 6.3.31. Let X be an exponential random variable. Then

- (a) $\mathbb{E}(X - s \mid X > s) = \mathbb{E}(X)$
- (b) $\mathbb{E}(X - s) = \Pr(X > s)\mathbb{E}(X)$ and

Proof. (a) By the memoryless property (Proposition 6.3.30), $\Pr(X > t+s \mid X > s) = \Pr(X - s > t \mid X > s) = \Pr(X > t)$. Then we have

$$\mathbb{E}(X - s \mid X > s) = \int_0^\infty \Pr(X - s > t \mid X > s)dt = \int_0^\infty \Pr(X > t)dt = \mathbb{E}(X)$$

- (b) By the memoryless property (Proposition 6.3.30), $\Pr(X > t+s) = \Pr(X - s > t) = \Pr(X > t)\Pr(X > s)$. Then we have

$$\mathbb{E}(X - s) = \int_0^\infty \Pr(X > t)\Pr(X > s)dt = \Pr(X > s) \int_0^\infty \Pr(X > t)dt = \Pr(X > s)\mathbb{E}(X)$$

□

Proposition 6.3.32. Let X be an exponential random variable. Then $X - t \mid X > t$ is identically distributed as X .

Proof. Because X is memoryless, we know by Proposition 6.3.30 that $\Pr(X > s+t \mid X > t) = \Pr(X > s)$, which is to say $\Pr(X \leq s+t \mid X > t) = \Pr(X \leq s) \iff \Pr(X - t \leq s \mid X > t) = \Pr(X \leq s)$; that is, $X - t \mid X > t$ and X have identical distributions.

□

Proposition 6.3.33. Let X be an exponential random variable. Then $\mathbb{E}[X^2 | X > t] = \mathbb{E}[(X + t)^2]$.

Proof. By Proposition 6.3.32, X and $X - t | X > t$ have identical distributions. That means they have identical variances, so

$$\text{Var}(X - t | X > t) = \text{Var}(X) \iff \mathbb{E}[(X - t)^2 | X > t] - [\mathbb{E}(X - t | X > t)]^2 = \mathbb{E}(X^2) - [\mathbb{E}(X)]^2.$$

Using $\mathbb{E}(X - t | X > t) = \mathbb{E}(X)$ we have

$$\mathbb{E}[(X - t)^2 | X > t] - [\mathbb{E}(X)]^2 = \mathbb{E}(X^2) - [\mathbb{E}(X)]^2 \iff \mathbb{E}[(X - t)^2 | X > t] = \mathbb{E}(X^2)$$

$$\mathbb{E}[(X - t)^2 | X > t] - [\mathbb{E}(X)]^2 = \mathbb{E}(X^2) - [\mathbb{E}(X)]^2 \iff \mathbb{E}[X^2 - 2tX + t^2 | X > t] = \mathbb{E}(X^2)$$

$$\iff \mathbb{E}[X^2 | X > t] - 2t\mathbb{E}(X | X > t) + t^2 = \mathbb{E}(X^2) \iff \mathbb{E}[X^2 | X > t] = \mathbb{E}(X^2) + 2t\mathbb{E}(X | X > t) - t^2$$

Using $\mathbb{E}(X | X > t) = t + \mathbb{E}(X)$, we have

$$\mathbb{E}[X^2 | X > t] = \mathbb{E}(X^2) + 2t(t + \mathbb{E}(X)) - t^2 = \mathbb{E}(X^2) + 2t\mathbb{E}(X) + t^2 = \mathbb{E}[(X + t)^2]$$

□

Example 6.5. (ISE 620): Enter a bank with one teller, 5 present upon your arrival, all service times are exponential with parameter 1. T is time you spend in system.

$$\begin{aligned} \mathbb{E}(T) &= R + \sum_{i=1}^t S_i \implies \mathbb{E}(T) = \mathbb{E}(R) + \sum_{i=1}^5 \mathbb{E}(S_i) \\ \mathbb{E}(T) &= \mathbb{E}(R) + \frac{5}{\lambda} = \frac{6}{\lambda} \end{aligned}$$

Example 6.6. (ISE 620): Suppose $X \sim \text{Exponential}(\lambda)$ and $Y \sim \text{Exponential}(\mu)$. Then

$$\Pr(X < Y) = \int_0^\infty \Pr(Y > X | X = x) \cdot \lambda e^{-\lambda x} dx = \int_0^\infty e^{-\mu x} \lambda e^{-\lambda x} dx = \lambda \int_0^\infty e^{-(\lambda+\mu)x} dx = \boxed{\frac{\lambda}{\lambda+\mu}}$$

Remark 43. (ISE 620). The following is an intuitive explanation for why $\min\{X, Y\}$ is distributed exponentially if X and Y are exponential: Suppose we require two machines with failure times X and Y distributed exponentially, and we need both to work. If at time t they are both still working, the remaining expected time is the same as initially because of the memoryless property (Proposition 6.3.30). Thus $\min\{X, Y\}$ is also memoryless, and exponential. Do the math:

$$\Pr(\min\{X, Y\} > t) = \Pr(X > t, Y > t) = e^{-\lambda t} e^{-\mu t} = e^{-(\lambda+\mu)t}$$

The same is not true for maximum:

$$\Pr(\max\{X, Y\} > t) = (1 - e^{-\lambda t})(1 - e^{-\mu t})$$

which is not exponential. Intuitively, if we only need one machine to be working, just because we are working at time t does not mean we are in the same position as we were initially; one machine could have failed. Now the general case: $X_1, \dots, X_n \sim \text{Exponential}(\lambda_i)$.

$$\Pr(\min\{X_i\} > t) = \Pr(X_1 > t \cap \dots \cap X_n > t) = \prod_{i=1}^n \Pr(X_i > t) = \exp\left(t \sum_{i=1}^n \lambda_i\right)$$

so the minimum of an arbitrary number of exponential random variables is distributed exponentially. Now

$$\Pr(X_i < \min_{j \neq i} \{X_j\}) = \Pr(X_i < Z)$$

where $Z \sim \text{Exponential}(\sum_{j \neq i} \lambda_j)$. So by the other example, this probability is $\lambda_i / \sum_{j=1}^n \lambda_j$.

Proposition 6.3.34. (ISE 620). If X and Y are independent exponential random variables, $\min\{X, Y\}$ is independent of whether X or Y is smaller. That is

$$\Pr(\min\{X, Y\} > t \mid X < Y) = \Pr(\min\{X, Y\} > t).$$

Proof.

$$\begin{aligned} \Pr(\min\{X, Y\} > t \mid X < Y) &= \frac{\Pr(Y > X > t)}{\Pr(X < Y)} = \frac{1}{\lambda/(\lambda + \mu)} \cdot \int_0^\infty \Pr(Y > X > t \mid X = s) \lambda e^{-\lambda s} ds \\ &= \frac{\lambda + \mu}{\lambda} \int_t^\infty e^{-\mu s} \lambda e^{-\lambda s} ds = \int_t^\infty (\lambda + \mu) e^{-(\lambda + \mu)s} ds = e^{-(\lambda + \mu)t} = \Pr(\min\{X, Y\} > t) \end{aligned}$$

□

Example 6.7. (ISE 620). You have two servers with exponential service times with parameters μ_1 and μ_2 . You wait until the first person is done serving a customer, then you are served by that server. T is the time you spend in the system. What is $E(T)$?

$$\begin{aligned} \mathbb{E}(T) &= \mathbb{E}(T \mid \mu_1) \Pr(\mu_1) + \mathbb{E}(T \mid \mu_2) \Pr(\mu_2) = \mathbb{E}(T \mid \mu_1) \frac{\mu_1}{\mu_1 + \mu_2} + \mathbb{E}(T \mid \mu_2) \frac{\mu_2}{\mu_1 + \mu_2} \\ &= \left(\frac{1}{\mu_1} + \mathbb{E}(X_1 \mid X_1 < X_2) \right) \frac{\mu_1}{\mu_1 + \mu_2} + \left(\frac{1}{\mu_2} + \mathbb{E}(X_2 \mid X_2 < X_1) \right) \frac{\mu_2}{\mu_1 + \mu_2} \\ &= \left(\frac{1}{\mu_1} + \mathbb{E}(\min\{X_1, X_2\}) \right) \frac{\mu_1}{\mu_1 + \mu_2} + \left(\frac{1}{\mu_2} + \mathbb{E}(\min\{X_1, X_2\}) \right) \frac{\mu_2}{\mu_1 + \mu_2} \\ &= \left(\frac{1}{\mu_1} + \frac{1}{\mu_1 + \mu_2} \right) \frac{\mu_1}{\mu_1 + \mu_2} + \left(\frac{1}{\mu_2} + \frac{1}{\mu_1 + \mu_2} \right) \frac{\mu_2}{\mu_1 + \mu_2} \end{aligned}$$

Proposition 6.3.35. (Equation (5.5) in Sheldon Ross *Introduction to Probability Models*.) For independent exponential variables T_1 and T_2 with means $1/\lambda_1$ and $1/\lambda_2$, $\Pr(T_2 < T_1) = \frac{\lambda_2}{\lambda_1 + \lambda_2}$.

Proof.

$$\begin{aligned}\Pr(T_2 < T_1) &= \int_0^\infty \Pr(T_2 < T_1 \mid T_2 = t) \lambda_2 e^{-\lambda_2 t} dt = \int_0^\infty \Pr(t < T_1) \lambda_2 e^{-\lambda_2 t} dt = \int_0^\infty e^{-\lambda_1 t} \lambda_2 e^{-\lambda_2 t} dt \\ &= \int_0^\infty \lambda_2 e^{-(\lambda_1 + \lambda_2)t} dt = \frac{\lambda_2}{\lambda_1 + \lambda_2}\end{aligned}$$

□

6.3.7 Multivariate Gaussian (Normal) Distributions

Definition 6.39. From <http://pluto.huji.ac.il/~pchiga/teaching/MathStat/SIAnotes2013.pdf> (definition 2b6): A random vector $X = (X_1, X_2)$ is Gaussian with mean $\mu = (\mu_1, \mu_2)$ and the covariance matrix

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$$

if it has a joint pdf of the form

$$f_X(x) = \frac{1}{2\pi\sigma_2\sigma_2\sqrt{1-\rho^2}} \exp \left[-\frac{1}{2} \frac{1}{1-\rho^2} \left(\frac{(x_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1\sigma_2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2} \right) \right]$$

for $x \in \mathbb{R}^2$.

Definition 6.40. (From Heilman Math 541A; Vector-valued Gaussian random variables.) $Z := (Z_1, \dots, Z_d) \in \mathbb{R}^d$ is a **Gaussian random vector** if for all $v \in \mathbb{R}^d$, $\langle v, Z \rangle$ is a Gaussian random variable (in the usual sense). Equivalently, any linear combination of Z_1, \dots, Z_d is a Gaussian random variable. Also, tZ has covariance matrix $a_{ij} = \mathbb{E}[(Z_i - \mathbb{E}(Z_i))(Z_j - \mathbb{E}(Z_j))]$, $1 \leq i < j \leq d$.

Definition 6.41. A random vector $\mathbf{X} = (X_1, X_2, \dots, X_p)$ is Gaussian with mean $\boldsymbol{\mu} = (\mu_1, \mu_2, \dots, \mu_p)$ and covariance matrix $\boldsymbol{\Sigma} = [\sigma_{ij}]$ if it has a joint pdf of the form

$$f_{\boldsymbol{\mu}, \boldsymbol{\Sigma}}(\mathbf{x}) = (2\pi)^{-p/2} |\boldsymbol{\Sigma}|^{-1/2} \cdot \exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right).$$

Definition 6.42 (Multivariate Normal distribution, Math 541B definition). $Y \in \mathbb{R}^d$ is multivariate normal if and only if there exist $B \in \mathbb{R}^{d \times k}$ and $C \in \mathbb{R}^d$ such that $Y = BX + C$ where $X = (X_1, \dots, X_k)$ with $X_j \sim \mathcal{N}(0, 1)$ for all $j \in [k]$ and $X_j \perp\!\!\!\perp X_i$ for all $i, j \in [k], i \neq j$.

Proposition 6.3.36. [Conditional distribution of one Gaussian random variable on another.] From <http://pluto.huji.ac.il/~pchiga/teaching/MathStat/SIAnotes2013.pdf> (Proposition 3c1)]

Let X be a Gaussian random variable in \mathbb{R}^2 such that

$$\begin{bmatrix} X_1 \\ X_2 \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} \right) = \mathcal{N} \left(\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \sigma_{12}^2 \\ \sigma_{12}^2 & \sigma_2^2 \end{bmatrix} \right)$$

Then $f_{X_1|X_2}(x_1; x_2)$ is Gaussian with the (conditional) mean

$$\mathbb{E}(X_1 | X_2 = x_2) = \mu_1 + \frac{\rho\sigma_1}{\sigma_2}(x_2 - \mu_2) = \mu_1 + \frac{\sigma_{12}^2}{\sigma_2^2}(x_2 - \mu_2)$$

and the (conditional) variance

$$\text{Var}(X_1 | X_2 = x_2) = \sigma_1^2(1 - \rho^2) = \sigma_1^2 - \frac{\sigma_{12}^4}{\sigma_2^2}$$

That is, the conditional distribution of X_1 given $X_2 = x_2$ is

$$X_1 | X_2 = x_2 \sim \mathcal{N} \left(\mu_1 + \rho \frac{\sigma_1}{\sigma_2}(x_2 - \mu_2), (1 - \rho^2)\sigma_1^2 \right) = \mathcal{N} \left(\mu_1 + \frac{\sigma_{12}^2}{\sigma_2^2}(x_2 - \mu_2), \sigma_1^2 - \frac{\sigma_{12}^4}{\sigma_2^2} \right)$$

Proposition 6.3.37 (Generalization of Proposition 6.3.36; from https://en.wikipedia.org/wiki/Multivariate_normal_distribution#Conditional_distributions)
Suppose

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix}, \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{12}^T & \boldsymbol{\Sigma}_{22} \end{bmatrix} \right)$$

where $\boldsymbol{\mu}_1 \in \mathbb{R}^q$, $\boldsymbol{\mu}_2 \in \mathbb{R}^{p-q}$, $\boldsymbol{\Sigma}_{11} \in \mathbb{R}^{q \times q}$, $\boldsymbol{\Sigma}_{12} \in \mathbb{R}^{(p-q) \times q}$, and $\boldsymbol{\Sigma}_{22} \in \mathbb{R}^{(p-q) \times (p-q)}$. Then

$$\{\mathbf{X}_1 | \mathbf{X}_2\} \sim \mathcal{N}(\boldsymbol{\mu}_1 + \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}(\mathbf{X}_2 - \boldsymbol{\mu}_2), \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{12}^T) \quad (6.10)$$

Remark 44. Note that the conditional covariance matrix in (6.10) is the Schur complement (see Sections 9.2 and 2.4) of $\boldsymbol{\Sigma}_{22}$ in $\boldsymbol{\Sigma}$.

Remark 45. A similar Berry-Esseen theorem (Theorem 8.6.8) exists for multivariate Gaussian distributions.

Remark 46. Note that this matches the OLS coefficients in the univariate case. In other words, the univariate OLS formula can be derived using only this fact.

Recall Theorem 6.3.4: if two variables are bivariate normal, they are independent if and only if their covariance

$$\text{Cov}(X, Y) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xyf(x, y)dxdy$$

equals 0.

Proposition 6.3.38 (Stats 100B homework problem). Let $(X_i, Y_i), i = 1, 2, \dots, n$, be a random sample from a bivariate normal distribution, where $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$ are independent.. Then the joint moment generating function of (\bar{X}, \bar{Y}) is

$$\exp\left(\mathbf{t}'\boldsymbol{\mu} + \frac{1}{2}\mathbf{t}'\frac{1}{n}\boldsymbol{\Sigma}\mathbf{t}\right) \sim \mathcal{N}\left(\boldsymbol{\mu}, \frac{1}{n}\boldsymbol{\Sigma}\right)$$

and (\bar{X}, \bar{Y}) is bivariate normal with mean $\boldsymbol{\mu}$ and variance-covariance matrix $\frac{1}{n}\boldsymbol{\Sigma}$.

Proof. Let $\mathbf{W}_i = (X_i, Y_i)$. Then the moment-generating function of $\mathbf{W}_i \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ is given by

$$M_{\mathbf{W}_i}(\mathbf{t}) = \exp(\mathbf{t}'\boldsymbol{\mu} + \frac{1}{2}\mathbf{t}'\boldsymbol{\Sigma}\mathbf{t})$$

where $\boldsymbol{\mu}$ is a two-dimensional column vector and $\boldsymbol{\Sigma}$ is a two-by-two matrix. Then

$$(\bar{X}, \bar{Y}) = \frac{1}{n} \sum_{i=1}^n \mathbf{W}_i(\mathbf{t}) = \sum_{i=1}^n \frac{1}{n} \mathbf{W}_i(\mathbf{t})$$

Since $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$ are independent,

$$\begin{aligned} M_{(\bar{X}, \bar{Y})}(\mathbf{t}) &= \prod_{i=1}^n M_{\mathbf{W}_i}\left(\frac{1}{n}\mathbf{t}\right) \\ &= \left[\exp\left(\frac{1}{n}\mathbf{t}'\boldsymbol{\mu} + \frac{1}{2}\frac{1}{n}\mathbf{t}'\boldsymbol{\Sigma}\frac{1}{n}\mathbf{t}\right) \right]^n = \exp\left(n\frac{1}{n}\mathbf{t}'\boldsymbol{\mu} + \frac{1}{2}n\frac{1}{n^2}\mathbf{t}'\boldsymbol{\Sigma}\mathbf{t}\right) \\ &= \exp\left(\mathbf{t}'\boldsymbol{\mu} + \frac{1}{2}\mathbf{t}'\frac{1}{n}\boldsymbol{\Sigma}\mathbf{t}\right) \sim \mathcal{N}\left(\boldsymbol{\mu}, \frac{1}{n}\boldsymbol{\Sigma}\right) \end{aligned}$$

Thus (\bar{X}, \bar{Y}) is bivariate normal with mean $\boldsymbol{\mu}$ and variance-covariance matrix $\frac{1}{n}\boldsymbol{\Sigma}$.

□

Example 6.8 (Example from 541B). Let $X \sim \mathcal{N}(0, 1)$. Define

$$Y := \begin{cases} X & |X| \leq a \\ -X & |X| > a \end{cases}$$

Then (a) for any $a > 0$, $Y \sim \mathcal{N}(0, 1)$, (b) $\exists a > 0$ such that $\mathbb{E}(XY) = 0$. However, X and Y are clearly not independent. In particular the joint distribution of X and Y is not multivariate normal.

6.4 Exponential Families

(For more notes, see Section 14.14 on generalized linear models.)

Definition 6.43. Informally, an **exponential family** is a family of probability distributions that depends on a parameter $w \in \mathbb{R}^k$.

Formally, let n, k be positive integers and let μ be a *measure* on \mathbb{R}^n (that is, a probability law that does not necessarily sum to 1). Let $t_1, \dots, t_k : \mathbb{R}^n \rightarrow \mathbb{R}$. Let $h : \mathbb{R}^n \rightarrow [0, \infty]$, and assume h is not identically zero. For any $w = (w_1, \dots, w_k) \in \mathbb{R}^k$, define

$$a(w) := \log \left[\int_{\mathbb{R}^n} h(x) \exp \left(\sum_{i=1}^k w_i t_i(x) \right) d\mu(x) \right], \quad \forall x \in \mathbb{R}^n$$

The set $\{w \in \mathbb{R}^k\}$ is called the **natural parameter space**. On this set, the function

$$f_w(x) := h(x) \exp \left(\sum_{i=1}^k w_i t_i(x) - a(w) \right), \quad \forall x \in \mathbb{R}^n$$

satisfies $\int_{\mathbb{R}^n} f_w(x) d\mu(x) = 1$ (by the definition of $a(w)$). (Why?)

$$\int_{\mathbb{R}^n} f_w(x) d\mu(x) = \frac{\int_{\mathbb{R}^n} h(x) \exp \left(\sum_{i=1}^k w_i t_i(x) \right) d\mu(x)}{\int_{\mathbb{R}^n} h(x) \exp \left(\sum_{i=1}^k w_i t_i(x) \right) d\mu(x)} = 1.$$

So, the set of functions (which can be interpreted as probability density functions, or as probability mass functions according to μ) $\{f_w : \theta \in \Theta : a(w(\theta)) < \infty\}$ is called a **k -parameter exponential family in canonical form**.

More generally, let $\Theta \subseteq \mathbb{R}^k$ be any set and let $w : \Theta \rightarrow \mathbb{R}^k$. We define a **k -parameter exponential family** to be a set of functions $\{f_\theta : \theta \in \Theta\}$, where

$$f_\theta(x) := h(x) \exp \left(\sum_{i=1}^k w_i(\theta) t_i(x) - a(w(\theta)) \right), \quad \forall x \in \mathbb{R}^n$$

satisfies

Also, an exponential family is called **curved** if the dimension of Θ is less than k .

Example 6.9. A Gaussian random variable has mean μ and standard deviation σ , and is in an exponential family:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), \quad \mu \in \mathbb{R}, \sigma > 0$$

In this case, $k = 2$.

⋮

(Continuation of example 3.2.) If we instead write this in canonical form, we get

$$a(w) = \frac{\mu^2}{2\sigma^2} + \log(\sigma) = \left(\frac{\mu}{\sigma^2}\right)^2 \left[(-2)\frac{(-1)}{\sigma^2}\right]^{-1} - \frac{1}{2} \log\left((-2)\frac{(-1)}{2\sigma^2}\right) = \frac{w_1^2}{4w_2} - \frac{1}{2} \log(-2w_2)$$

That is, in this case you can get rid of the thetas and write this in canonical form. Define

$$f_w(x) = h(x) \exp\left(\sum_{i=1}^2 w_i t_i(x) - a(w)\right), \quad \forall x \in \mathbb{R}$$

where w ranges in $\{(w_1, w_2) \in \mathbb{R}^2 : w_2 > 0\}$.

Remark 47. (notes remark 3.4) **(location family.)** Let X be a random variable with density $f : \mathbb{R} \rightarrow \mathbb{R}$. Let $\mu \in \mathbb{R}$. Then the densities $\{f(x + \mu)\}_{\mu \in \mathbb{R}}$ are called a **location family** of X . This family may or may not be an exponential family.

Remark 48. (notes remark 3.6) **(Scale family.)** Let X be a random variable with density $f : \mathbb{R} \rightarrow \mathbb{R}$. Let $\sigma > 0$. The family of densities $\{\sigma^{-1}f(x/\sigma)\}_{\sigma>0}$ is called a **scale family**. Note

$$\int_{\mathbb{R}} \sigma^{-1} f(x/\sigma) dx = \int_{\mathbb{R}} f(y) dy = 1$$

(substituting $y = x/\sigma$, $dy = dx/\sigma$).

Remark 49. (notes remark 3.7) **(Location and scale family.)** The family of densities $\{\sigma^{-1}f((x + \mu)/\sigma)\}_{\sigma>0, \mu \in \mathbb{R}}$ is called a **location and scale family**. This family may or may not be an exponential family (although Gaussian random variables are one example where it is.)

Exercise 12. Try to write a binomial random variable with parameters n and p as a two-parameter exponential family. (Note: it's impossible to do, but instructive to try.)

$$\Pr(X = x) = \binom{n}{x} p^x (1-p)^{n-x} = \frac{n!}{(n-x)!x!} p^x (1-p)^{n-x} = \frac{n!}{(n-x)!x!} \exp(x \log(p)) (1-p)^{n-x} = \dots$$

It turns out you can do it with one parameter with p , but not with two parameters with n .

Example 6.10 (Example 3.15 in 541A notes). Write a binomial random variable with parameters n and p as an exponential family (when n is fixed), then take derivatives in p .

Recall

$$\Pr(X = x) = \binom{n}{x} p^x (1-p)^{n-x}, \quad 0 \text{ for any other } x.$$

Keep n fixed and look at p .

$$\binom{n}{x} p^x (1-p)^{n-x} = \binom{n}{x} \exp(x \log p + (n-x) \log(1-p)) = \binom{n}{x} \exp[x \log(p/(1-p)) - (-1)n \log(1-p)]$$

Define $h : \mathbb{R} \rightarrow \mathbb{R}$ so that

$$h(x) = \begin{cases} \binom{n}{x} & 0 \leq x \leq n \text{ is an integer} \\ 0 & \text{otherwise} \end{cases}$$

Let $\theta := p, \Theta := (0, 1), t(x) := x, w(\theta) := \log(\theta/(1-\theta)), a(w(\theta)) = -n \log(1-\theta)$.

So, $f_\theta(x) := h(x) \exp[w(\theta)t(x) - a(w(\theta))], \forall x \in \mathbb{R}$.

Now we will take derivatives. As in previous example (last class),

$$e^{-a(w(\theta))} \frac{\partial}{\partial \theta_1} e^{a(w(\theta))} = \mathbb{E}_\theta \left(\sum_{i=1}^k \frac{\partial w_i}{\partial \theta_1} t_i \right)$$

So in this case

$$e^{-a(w(\theta))} \frac{\partial}{\partial \theta_1} e^{a(w(\theta))} = \mathbb{E}_\theta \left(\frac{d}{d\theta} w(\theta) t \right).$$

Plugging in yields

$$(1-\theta)^n \frac{d}{d\theta} (1-\theta)^{-n} = \frac{n}{1-\theta}$$

on the left side and

$$= \left(\frac{1}{\theta} + \frac{1}{1-\theta} \right) \mathbb{E}_\theta(X) = \mathbb{E}_\theta(X) \left(\frac{1}{\theta(1-\theta)} \right)$$

on the right side which yields

$$\mathbb{E}_\theta(X) = \frac{n}{1-\theta} (\theta(1-\theta)) = n\theta \implies \mathbb{E}(X) = pn$$

Remark 50. This is a probability mass function since it is defined only on integers.

Example 6.11 (GSBA 604). Suppose $Y \sim \text{Poisson}(\mu)$. Express it as an exponential family.

Solution.

$$\begin{aligned}\mathbb{P}_\mu(Y = y) &= \frac{e^{-\mu}\mu^y}{y!}, \quad y \in \{0, 1, \dots\} \\ &= \frac{e^{y \log \mu - \mu}}{y!}\end{aligned}$$

So the natural parameter η is $\log \mu$, the normalizing function $\psi(\eta) = \mu$, and the carrier density $c(y) = 1/y!$.

6.4.1 Differential identities (Generalization of Moment-Generating Functions)

Recall that the moment-generating function for a Gaussian random variable is

$$\mathbb{E}(e^{tX}) = e^{t^2/2} \quad \forall t \in \mathbb{R}$$

Consequently,

$$\left. \frac{d^m}{dt^m} \right|_{t=0} \mathbb{E}(e^{tX}) = \mathbb{E}(X^m)$$

for any integer $m > 0$. We can do a similar thing for an exponential family—we can differentiate the parameters of exponential families and find out information about the exponential family. As in Definition 6.43, let

$$a(w) := \log \int_{\mathbb{R}^n} h(x) \exp \left(\sum_{i=1}^k w_i t_i(x) \right) d\mu(x)$$

Define

$$W := \{w \in \mathbb{R}^k : a(w) < \infty\}.$$

Question: Is $a(w)$ differentiable?

Lemma 6.4.1 (Lemma 3.8 in 541A notes). The function $a(w)$ is continuous and has continuous partial derivatives of all orders on the interior of W . Moreover, we can compute these derivatives by differentiating under the integral sign.

Proof. We prove only the case of a first order partial derivative. Consider the case of the partial derivative with respect to w_1 at w in the interior of W . Let $e_1 = (1, 0, \dots, 0) \in \mathbb{R}^k$. Since the exponential function is analytic, it suffices to show that the partial derivative of $e^{a(w)}$ exists in the direction e_1 . We form the difference quotient for $e^{a(w)}$ as follows:

$$\begin{aligned} \frac{\exp[a(w + \epsilon e_1)] - \exp[a(w)]}{\epsilon} &= \frac{1}{\epsilon} \int_{\mathbb{R}^n} h(x) \left[\exp\left(\epsilon t_1(x) + \sum_{i=1}^k w_i t_i(x)\right) - \exp\left(\sum_{i=1}^k w_i t_i(x)\right) \right] d\mu(x) \\ &= \int_{\mathbb{R}^n} h(x) \frac{\exp[\epsilon t_1(x)] - 1}{\epsilon} \exp\left(\sum_{i=1}^k w_i t_i(x)\right) d\mu(x). \end{aligned} \quad (6.11)$$

By the Mean Value Theorem,

$$\frac{|e^a - 1|}{a} = \frac{|e^a - e^0|}{a - 0} \leq e^a \text{ if } a > 0, \text{ or } 1 \text{ if } a < 0$$

so we have

$$|e^a - 1| \leq |a| \max\{1, e^a\} \leq |a|e^{|a|} \leq e^{2|a|} \leq e^{2a} + e^{-2a} \quad \forall a \in \mathbb{R}.$$

In particular, if $a = \epsilon t_1(x)$, we have

$$|e^{\epsilon t_1(x)} - 1| \leq e^{2\epsilon t_1(x)} + e^{-2\epsilon t_1(x)} \quad (6.12)$$

Therefore, examining the integrand of (6.11), we have

$$\begin{aligned} \left| h(x) \frac{\exp[\epsilon t_1(x)] - 1}{\epsilon} \exp\left(\sum_{i=1}^k w_i t_i(x)\right) \right| &\leq h(x) \left| \frac{\exp[\epsilon t_1(x)] - 1}{\epsilon} \right| \exp\left(\sum_{i=1}^k w_i t_i(x)\right) \\ &\leq (\text{by (6.12)}) h(x) (e^{2\epsilon t_1(x)} + e^{-2\epsilon t_1(x)}) \exp\left(\sum_{i=1}^k w_i t_i(x)\right) \\ &\vdots \\ &= h(x)|t_1(x)| \exp\left(\epsilon t_1(x) + \sum_{i=1}^k w_i t_i(x)\right) + h(x)|t_1(x)| \exp\left(-\epsilon t_1(x) + \sum_{i=1}^k w_i t_i(x)\right) \end{aligned} \quad (6.13)$$

If both of the expressions in (6.13) always have finite expected value uniformly for all $\epsilon > 0$, we will be done by the Dominated Convergence Theorem (Theorem 6.4.2; see also Theorem 5.11.3). (Assuming those things are bounded uniformly in expectation then the limit of the integrals is the integral of the limits.)

□

Remark 51. Notes from proof of Lemma 3.8.

$\left|\frac{e^a - 1}{a}\right| \leq e^a + e^{-a}$. Then

$$\left| h(x) \exp \left(\epsilon t_1(x) + \sum_{i=1}^k w_i t_i(x) \right) - \exp \left(\sum_{i=1}^k w_i t_i(x) \right) \right| \leq h(x) \exp \left(\sum_{i=1}^k w_i t_i(x) \right) |t_1(x)| \left(\exp(\epsilon t_1(x)) + \exp(-\epsilon t_1(x)) \right)$$

Theorem 6.4.2 (Dominated convergence theorem (Math 541A)). Let $X_1, X_2, \dots : \Omega \rightarrow \mathbb{R}$ and $Y : \Omega \rightarrow [0, \infty)$ such that $|X_i| \leq Y$ for all $i \geq 1$ and $\mathbb{E}(Y) < \infty$. Assume X_1, X_2, \dots converges almost surely to $X : \Omega \rightarrow \mathbb{R}$. Then

$$\lim_{i \rightarrow \infty} \mathbb{E}(x_i) = \mathbb{E}\left(\lim_{i \rightarrow \infty} X_i\right) = \mathbb{E}(X)$$

Remark 52. See also Theorem 5.11.3.

Corollary 6.4.2.1 (Corollary 3.11 in 541A notes.). Let $\epsilon > 0$. Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable such that $\mathbb{E}(e^{wX}) < \infty$ for all $w \in (-\epsilon, \epsilon)$. Then for any integer $n \geq 1$, $\mathbb{E}(X^n)$ exists and

$$\frac{d^n}{dw^n} \Big|_{w=0} e^{wX} = \mathbb{E}(X^n).$$

Proof. Apply Lemma 6.4.1 when $\mu = \mathbb{P}, h = 1, k = 1, t(x) = x$: we see that

$$a(w) = \log \int_{\mathbb{R}^n} e^{wx} d\mathbb{P}(x)$$

□

Proof (GSBA 604 proof, just for first two moments). Notation: The density is

$$g_\eta(y) = c(y) \exp\{\eta y - \psi(\eta)\}$$

where $c(y)$ is the **carrier density**, η is the **natural parameter**, and $\psi(\cdot)$ is the **normalizing function**, chosen so that it is a proper density: that is, choose $\psi(\eta)$ such that

$$\int_{\mathbb{R}} g_\eta(y) dy = 1,$$

so

$$e^{-\psi(y)} = \left(\int_{\mathbb{R}} c(y) e^{\eta y} dy \right)^{-1}$$

Now

$$\int g_\eta(y) dy = 1$$

differentiate with respect to η :

$$\begin{aligned} \int e^{\eta y - \psi(\eta)} [y - \frac{d\psi(\eta)}{d\eta}] c(y) dy &= 0 \\ \implies \int y g_\eta(y) dy - \frac{d\psi(\eta)}{d\eta} \int e^{\eta y - \psi(\eta)} c(y) dy &= 0 \quad (6.14) \end{aligned}$$

so then $\mathbb{E}(y) - \frac{d\psi(\eta)}{d\eta} = 0 \implies \mathbb{E}(y) = \frac{d\psi(\eta)}{d\eta}$.

Next,

$$\begin{aligned} \int y \frac{dg_\eta(y)}{d\eta} dy - \frac{d\psi^2(\eta)}{d\eta^2} &= 0 \\ \implies \int y \cdot e^{\eta y - \psi(\eta)} (y - \frac{d\psi(\eta)}{d\eta}) c(y) dy - \frac{d\psi^2(\eta)}{d\eta^2} &= 0 \\ \implies \int y^2 g_\eta(y) dy - \frac{d\psi(\eta)}{d\eta} \underbrace{\int y e^{\eta y - \psi(\eta)} c(y) dy}_{\frac{d\psi(\eta)}{d\eta}} - \frac{d\psi^2(\eta)}{d\eta^2} &= 0 \\ \implies \mathbb{E}(Y^2) - \left[\frac{d\psi(\eta)}{d\eta} \right]^2 - \frac{d\psi^2(\eta)}{d\eta^2} &= 0 \\ \implies \mathbb{E}(Y^2) - [\mathbb{E}(Y)]^2 &= \frac{d\psi^2(\eta)}{d\eta^2}. \end{aligned}$$

□

Remark 53. Notes from example 3.13.

$$\begin{aligned} e^{-a(w)} \frac{\partial}{\partial w_2} e^{a(w)} &= \int_{\mathbb{R}} t_1(x) h(x) \exp \left(\sum_{i=1}^k w_i t_i(x) - a(w) \right) dx \\ &= \int_{\mathbb{R}} t_1(x) f_x(x) dx \quad (6.15) \end{aligned}$$

So by chain rule

$$\begin{aligned} e^{-a(w(\theta))} \frac{\partial}{\partial \theta_1} e^{a(w(\theta))} &= e^{-a(w(\theta))} \sum_i \frac{\partial e^{a(w)}}{\partial w_i} \frac{\partial w_i}{\partial \theta_1} \\ &= (\text{by (6.15)}) \sum_{i=1}^k \frac{\partial w_i}{\partial \theta_1} \mathbb{E}_\theta t_i = \mathbb{E}_\theta \left(\sum_{i=1}^k t_i \frac{\partial w_i}{\partial \theta_1} \right) \quad (6.16) \end{aligned}$$

Example 6.12. Recall Example 3.3. Gaussian, mean μ , variance σ^2 . $\theta = (\theta_1, \theta_2) = (\mu, \sigma^2)$, $t_1(x) = x$, $t_2(x) = x^2$, $w_1(\theta) = \theta_1/\theta_2 = \mu/\sigma^2$, $w_2(\theta) = -1/(2\sigma^2) = -1/(2\theta_2)$, $a(w(\theta)) = \theta_1^2/(2\theta_2) + (1/2) \log(\theta_2) = \mu^2/(2\sigma^2) + \log(\sigma^2)$.

Complete both sides of (6.16).

$$e^{-a(w(\theta))} \frac{\partial}{\partial \theta_1} e^{a(w(\theta))} = \frac{\theta_1}{\theta_2} = \frac{\mu}{\sigma^2}$$

$$\frac{\partial}{\partial \theta_1} e^{a(w(\theta))} = \frac{d}{d\theta_1} \sqrt{\theta_2} \exp\left(\frac{\theta_1^2}{2\theta_2}\right) = \frac{\theta_1}{\theta_2} \exp(a(w(\theta)))$$

Right side:

$$\frac{dw_1}{d\theta_2} = \frac{1}{\theta_2}, \quad \frac{dw_2}{d\theta_1} = 0$$

$$\implies \mathbb{E}_\theta \left(\sum_{i=1}^k t_i \frac{dw_i}{d\theta_1} \right) = \mathbb{E}_\theta(t_1 \frac{dw_1}{d\theta_1} + t_2 \frac{dw_2}{d\theta_1})$$

$$= \mathbb{E}_\theta(x/\theta_2) \implies \mathbb{E}_\theta(x) = \theta_1 = \mu$$

Theorem 6.4.3 (Theorem 3.4.2 from Casella and Berger). If X is a random variable in an exponential family, then

$$\mathbb{E} \left(\sum_{i=1}^k \frac{\partial w_i(\theta)}{\partial \theta_j} t_i(X) \right) = \frac{\partial}{\partial \theta_j} a(w(\theta)). \quad (6.17)$$

Example 6.13. Recall Example 3.3 again: Gaussian, mean μ , variance σ^2 . $\theta = (\theta_1, \theta_2) = (\mu, \sigma^2)$, $t_1(x) = x$, $t_2(x) = x^2$ k $w_1(\theta) = \theta_1/\theta_2 = \mu/\sigma^2$, $w_2(\theta) = -1/(2\sigma^2) = -1/(2\theta_2)$, $a(w(\theta)) = \theta_1^2/(2\theta_2) + (1/2)\log(\theta_2) = \mu^2/(2\sigma^2) + \log(\sigma^2)$.

Complete both sides of (6.17).

$$\frac{\partial}{\partial \theta_1} a(w(\theta)) = \frac{\partial}{\partial \theta_1} \left(\theta_1^2/(2\theta_2) + (1/2)\log(\theta_2) \right) = \frac{\theta_1}{\theta_2}.$$

Left side:

$$\begin{aligned} \mathbb{E} \left(\sum_{i=1}^k \frac{\partial w_i(\theta)}{\partial \theta_1} t_i(X) \right) &= \mathbb{E} \left(\frac{\partial}{\partial \theta_1} w_1(\theta) t_1(X) + \frac{\partial}{\partial \theta_1} w_2(\theta) t_2(X) \right) = \mathbb{E} \left(\frac{\partial}{\partial \theta_1} \frac{\theta_1}{\theta_2} \cdot x - \frac{1}{2} \frac{\partial}{\partial \theta_1} \frac{1}{\theta_2} x^2 \right) \\ &= \frac{1}{\theta_2} \mathbb{E}(x) \\ \implies \frac{1}{\theta_2} \mathbb{E}(x) &= \frac{\theta_1}{\theta_2} \implies \mathbb{E}(X) = \theta_1 = \mu. \end{aligned}$$

Repeating by taking the partial derivatives with respect to θ_2 instead:

$$\frac{\partial}{\partial \theta_2} a(w(\theta)) = \frac{\partial}{\partial \theta_2} \left(\theta_1^2/(2\theta_2) + (1/2)\log(\theta_2) \right) = \frac{\theta_1^2}{2} \cdot \frac{-1}{\theta_2^2} + \frac{1}{2\theta_2} = \frac{\theta_2 - \theta_1^2}{2\theta_2^2}$$

Left side:

$$\begin{aligned}
& \mathbb{E} \left(\sum_{i=1}^k \frac{\partial w_i(\theta)}{\partial \theta_2} t_i(X) \right) = \mathbb{E} \left(\frac{\partial}{\partial \theta_2} w_1(\theta) t_1(X) + \frac{\partial}{\partial \theta_2} w_2(\theta) t_2(X) \right) = \mathbb{E} \left(\frac{\partial}{\partial \theta_2} \frac{\theta_1}{\theta_2} \cdot x - \frac{1}{2} \frac{\partial}{\partial \theta_2} \frac{1}{\theta_2} x^2 \right) \\
& = \mathbb{E} \left(-\frac{\theta_1}{\theta_2^2} \cdot x + \frac{1}{2\theta_2^2} x^2 \right) = -\frac{\theta_1}{\theta_2^2} \mathbb{E}(X) + \frac{1}{2\theta_2^2} \mathbb{E}(X^2) = -\frac{\theta_1^2}{\theta_2^2} + \frac{1}{2\theta_2^2} \mathbb{E}(X^2) \\
& \implies -\frac{\theta_1^2}{\theta_2^2} + \frac{1}{2\theta_2^2} \mathbb{E}(X^2) = \frac{\theta_2 - \theta_1^2}{2\theta_2^2} \iff -2\theta_1^2 + \mathbb{E}(X^2) = \theta_2 - \theta_1^2 \iff \mathbb{E}(X)^2 = \theta_2 + \theta_1^2 = \sigma^2 + \mu^2.
\end{aligned}$$

6.5 KL Divergence (DSO 607)

Let $f(\cdot | \theta) : \mathbb{R}^k \rightarrow \mathbb{R}^n$ be a family of parameterized probability densities with $\theta \in \Theta$. Suppose the true model is parameterized by $\theta_0 \in \mathbb{R}^s$, and we are interested in comparing a different model parameterized by $\theta \in \mathbb{R}^k$ to this model. The likelihood ratio $\tau : \mathbb{R}^n \rightarrow \mathbb{R}$ defined by $\tau(x; \theta, \theta_0) := f(x | \theta)/f(x | \theta_0)$ is a good tool for this comparison. Define the **discrimination** between θ and θ_0 at x to be $\Phi(\tau(x; \theta, \theta_0))$ for some function $\Phi : \mathbb{R} \rightarrow \mathbb{R}$, and define the **mean discrimination** $D(\theta; \theta_0) : \mathbb{R}^k \rightarrow \mathbb{R}$ between θ and θ_0 as

$$D(\theta; \theta_0) := \int_{\mathbb{R}^n} \Phi(\tau(x; \theta, \theta_0)) \cdot f(x | \theta_0) dx = \mathbb{E}_{\theta_0} [\Phi(\tau(X; \theta, \theta_0))].$$

To choose Φ so that $D(\theta; \theta_0)$ behaves like a distance, we would like $\Phi(1) = 0$ since this covers the case where $\theta = \theta_0$, because under the assumption that $f(x | \theta) = f(x | \theta_0) \forall x \in \mathbb{R}^n \iff \theta = \theta_0$, we have $\tau(x; \theta, \theta_0) = 1 \forall x \in \mathbb{R}^n \iff \theta = \theta_0$. In particular, we would like this to be the minimum of the function; that is, $\tau''(1; \theta, \theta_0) > 0$. Lastly, we would also like $\tau'(x; \theta, \theta_0) > 0 \forall x \in \mathbb{R}^n$. One such choice is $\Phi(t) := -2 \log(t)$. This yields the **Kullback-Leibler (KL) divergence** $I(\theta; \theta_0) : \mathbb{R}^k \rightarrow \mathbb{R}$

$$\begin{aligned}
I(\theta; \theta_0) &= D(\theta_0, \theta) := -2 \int_{\mathbb{R}^n} \log \left(\frac{f(x | \theta)}{f(x | \theta_0)} \right) \cdot f(x | \theta_0) dx \\
&= 2 \int_{\mathbb{R}^n} [\log(f(x | \theta_0)) - \log(f(x | \theta))] \cdot f(x | \theta_0) dx = 2\mathbb{E}_{\theta_0} [\log(f(X | \theta_0))] - 2\mathbb{E}_{\theta_0} [\log(f(X | \theta))] \\
&= 2\mathbb{E}_{\theta_0} \log \left(\frac{f_{\theta_0}(X)}{f_{\theta}(X)} \right).
\end{aligned}$$

Note that it is non-symmetric. It is also non-negative. It equals the expected likelihood ratio. Used in information theory; mutual information relation.

Definition 6.44 (Mutual information; from GSBA 604). Suppose we have two independent variables X and Y . If they are independent, we have $P_{(X,Y)} = P_X \cdot P_Y$. Then the **mutual information** between X and Y is $D(P_{(X,Y)}, P_X \cdot P_Y)$.

Also, the **entropy** of X with density f is equal to $\int f(x) \log f(x) dx = \mathbb{E}_X \log(f(x))$.

Of course, in practice we will estimate θ_0 as best as we can, by maximizing the **probabilistic negentropy**

$$\mathbb{E}_Z I(\theta; \hat{\theta}_0(Z)) := 2\mathbb{E}_{\theta_0} [\log(f(X | \theta_0)) - 2\mathbb{E}_{\theta_0, Z} [\log(f(X | \hat{\theta}_0(Z)))]]$$

where Z describes the probability distribution of the sample data and $\hat{\theta}_0(Z)$ is our estimate of θ_0 from the data.

Way we wrote this in DSO 607: KL Divergence of density f (estimated) from density g (true model/distribution):

$$I(g; f) = \int [\log g(z)] g(z) dz - \int [\log f(z)] g(z) dz = \mathbb{E}_g \log(g(z)) - \mathbb{E}_g (\log(f(z)))$$

GSBA 604: Notice that for exponential families,

$$\begin{aligned} \frac{1}{2}D(\theta_0, \theta) &= (\theta_0 - \theta)\mathbb{E}_{\theta_0}(X) - [\psi(\theta_0) - \psi(\theta)] = (\theta_0 - \theta) \frac{d}{d\theta_0} \psi(\theta_0) - [\psi(\theta_0) - \psi(\theta)] \\ &\implies \psi(\theta_0) + [\theta - \theta_0] \frac{d}{d\theta_0} \psi(\theta_0) + \frac{1}{2}D(\theta_0, \theta) = \psi(\theta). \end{aligned}$$

where $\mathbb{E}_{\theta_0}(X) = \frac{d}{d\theta_0} \psi(\theta_0) = \mu(\theta_0)$. For a visual image of this formula, see Figure 6.1 (similar figure in p. 16 of exponential family notes).

One application of KL Divergence is AIC for model selection; see Section 14.4.1. See also Section 10.4.6.

6.6 Worked problems

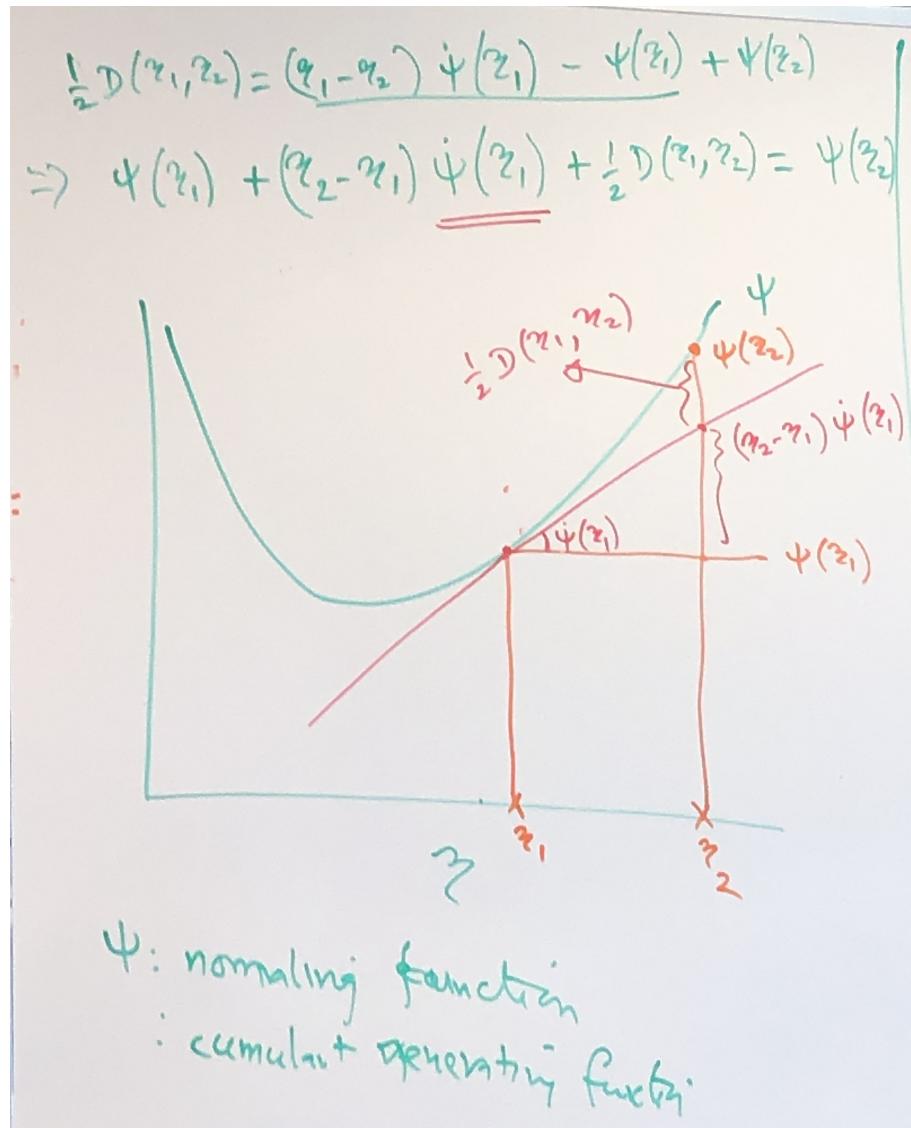
6.6.1 Example Problems That Will Likely Appear on Midterm (and Final)

- (1) Let X be uniform on $[1, 5]$, let Y be uniform on $[0, 1]$, and assume that X and Y are independent.
 - (a) Compute the probability density function of the product XY .
 - (b) **Only part included on midterm.** Compute the cumulative distribution function of the ratio X/Y .
 - (c) Compute the characteristic function of the sum $X + Y$.
 - (d) Compute the moment-generating function of the random variable $X - \ln(Y)$.

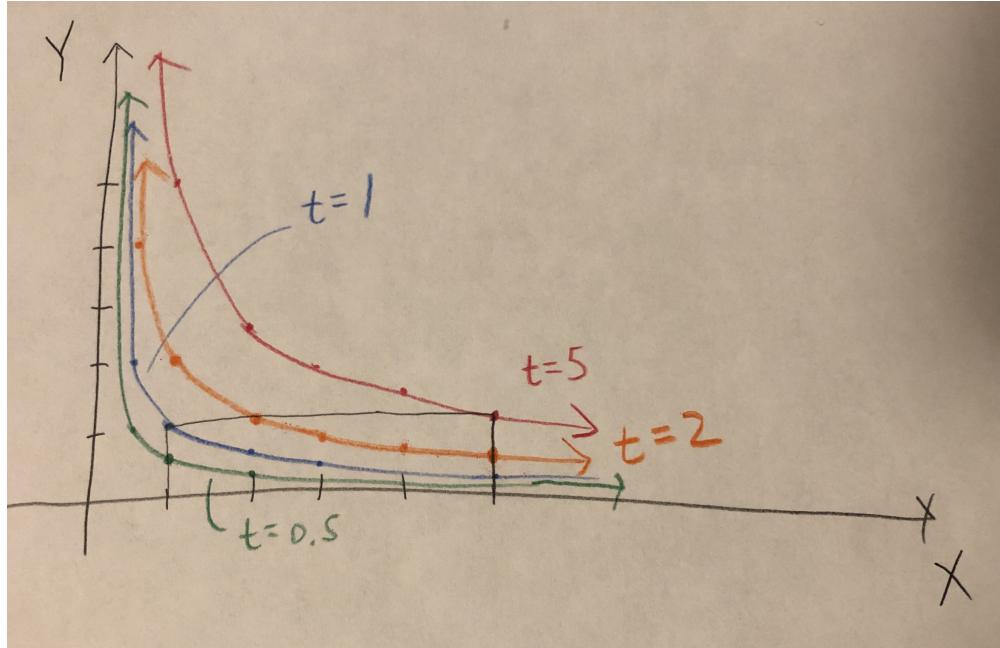
Solution.

- (a) We will find the cdf and then differentiate to yield the pdf. Observe that

$$F_{XY}(t) = \Pr(XY \leq t) = \Pr(Y \leq tX^{-1})$$

Figure 6.1: Photo of KL divergence (with different notation; $\theta_0 = \eta_1$, $\theta = \eta_2$).

Plotting the density function of XY along with plots of $F_{XY}(t)$ as a function of X for various values of t , we have the following:



Now since both X and Y are distributed uniformly, for a given t , $\Pr(Y \leq tX^{-1})$ is the area under the curve and in the rectangle, weighted by $1/4$ since the rectangle has total area 4 but total probability 1. It is clear that the four regimes we need to consider are (1) $t < 0$, (2) $0 \leq t < 1$, (3) $1 \leq t < 5$, and (4) $t \geq 5$.

- (1) $t < 0$: The curve lies below the rectangle, so there is no area below the curve and in the rectangle. Therefore $\boxed{\Pr(Y \leq tX^{-1} \mid t < 0) = 0}$. (This is also clear since tX^{-1} would be a negative number and Y is nonnegative.)
- (2) $0 \leq t < 1$: Integrating the relevant area, we have

$$\Pr(Y \leq tX^{-1} \mid 0 \leq t < 1) = \frac{1}{4} \int_1^5 \frac{t}{x} dx = \frac{t}{4} [\log(x)]_1^5 = \boxed{\frac{t}{4} \log(5)}$$

- (3) $1 \leq t < 5$: In this case, the area is a rectangle of height 1 and width $t - 1$ plus the area under the curve from t to 5.

$$\Pr(Y \leq tX^{-1} \mid 1 \leq t < 5) = \frac{1}{4} \left(1 \cdot (t-1) + \int_t^5 \frac{t}{x} dx \right) = \frac{1}{4} \left(t-1 + t [\log(x)]_t^5 \right) = \boxed{\frac{1}{4} [t(1 + \log(5/t)) - 1]}$$

- (4) $t \geq 5$: In this case, the entire rectangle lies below the curve. Therefore $\boxed{\Pr(Y \leq tX^{-1} \mid t \geq 5) = 1}$.

So we have

$$F_{XY}(t) = \begin{cases} 0 & t < 0 \\ \frac{t}{4} \log(5) & 0 \leq t < 1 \\ \frac{1}{4} [t(1 + \log(5/t)) - 1] & 1 \leq t < 5 \\ 1 & t \geq 5 \end{cases}$$

Finally, differentiating yields

$$f_{XY}(t) = \begin{cases} 0 & t < 0 \\ \frac{1}{4} \log(5) & 0 \leq t < 1 \\ \frac{1}{4} \log\left(\frac{5}{t}\right) & 1 \leq t < 5 \\ 0 & t \geq 5 \end{cases}$$

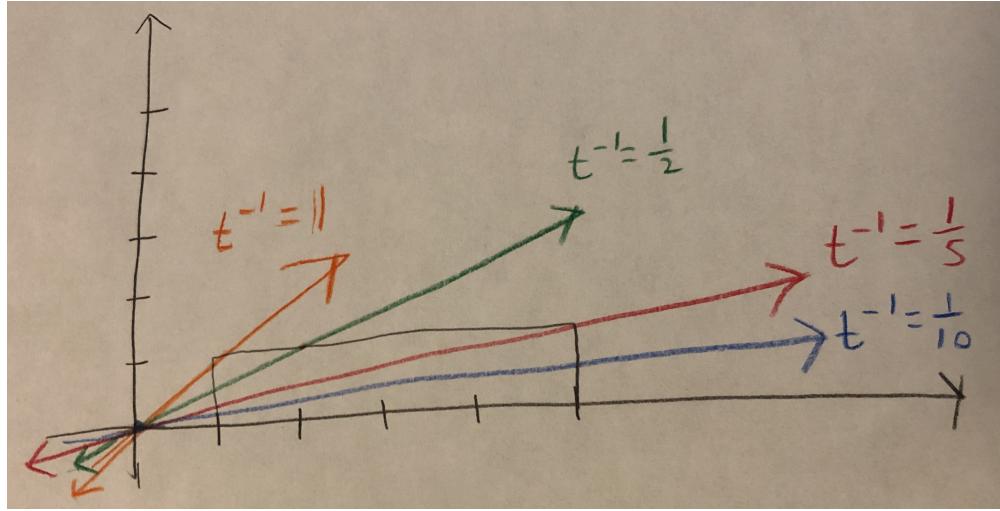
since

$$\begin{aligned} \frac{d}{dt} \left(\frac{1}{4} [t(1 + \log(5/t)) - 1] \right) &= \frac{1}{4} \left[1 + \log(5/t) + t \left(\frac{1}{5/t} \cdot -5 \cdot t^{-2} \right) \right] = \frac{1}{4} \left[1 + \log(5/t) + t(-1 \cdot t^{-2}) \right] \\ &= \frac{1}{4} \log\left(\frac{5}{t}\right) \end{aligned}$$

(b) **Only part included on midterm.** We will proceed in a similar way as part (a). Observe that

$$F_{X/Y}(t) = \Pr\left(\frac{X}{Y} \leq t\right) = \Pr(Y \geq X/t)$$

Plotting the density function of X/Y along with plots of $F_{X/Y}(t)$ as a function of X for various values of t , we have the following:



Now since both X and Y are distributed uniformly, for a given t , $\Pr(Y \geq X/t)$ is the area above the curve and in the rectangle, weighted by $1/4$ since the rectangle has total area 4 but total probability 1. It is clear that the three regimes we need to consider are (1) $t^{-1} \geq 1 \iff t \leq 1$, (2) $1/5 \leq t^{-1} < 1 \iff 1 < t \leq 5$, and (3) $0 < t^{-1} < 1/5 \iff t > 5$.

- (1) $t \leq 1$: The curve lies above the rectangle, so there is no area above the curve and in the rectangle. Therefore $\Pr(Y \geq X/t \mid t \leq 1) = 0$. (This is also clear since X/t would have to be greater than 1 and Y is less than or equal to 1.)
- (2) $1 < t \leq 5$: The relevant area is the triangle above the green line in the rectangle. Note that it intersects the vertical line at $Y = 1/t$ and the horizontal line at $X = t$.

$$\Pr(Y \geq X/t \mid 1 < t \leq 5) = \frac{1}{4} \cdot \frac{1}{2} \left(1 - \frac{1}{t} \right) (t - 1) = \frac{1}{8} \left(t - 1 - 1 + \frac{1}{t} \right) = \frac{1}{8} \left(t - 2 + \frac{1}{t} \right)$$

- (3) $t > 5$: In this case, the area is a trapezoid above the blue line and in the rectangle. Note that the blue line intersects the left vertical line at $Y = 1/t$ and the right vertical line at $Y = 5/t$.

$$\Pr(Y \geq X/t \mid t > 5) = \frac{1}{4} \cdot \frac{1}{2} \cdot \left(1 - \frac{1}{t} + 1 - \frac{5}{t}\right) \cdot 4 = \frac{1}{2} \cdot \left(2 - \frac{6}{t}\right) = 1 - \frac{3}{t}$$

So we have

$$F_{XY}(t) = \begin{cases} 0 & t \leq 1 \\ \frac{1}{8} \left(t - 2 + \frac{1}{t}\right) & 1 < t \leq 5 \\ 1 - \frac{3}{t} & t > 5 \end{cases}$$

- (c) The characteristic function for a uniform distribution on $[a, b]$ is

$$\frac{2}{(b-a)t} \sin\left(\frac{1}{2}(b-a)t\right) \exp\left(i(a+b)\frac{t}{2}\right).$$

Using the fact that $X \perp\!\!\!\perp Y \implies \phi_{X+Y}(t) = \phi_X(t)\phi_Y(t)$, we have

$$\begin{aligned} \phi_{X+Y}(t) &= \phi_X(t)\phi_Y(t) = \frac{2}{(5-1)t} \sin\left(\frac{1}{2}(5-1)t\right) \exp\left(i(5+1)\frac{t}{2}\right) \cdot \frac{2}{t} \sin\left(\frac{1}{2}t\right) \exp\left(i\frac{t}{2}\right) \\ &= \frac{1}{2t} \sin(2t) \exp(3it) \cdot \frac{2}{t} \sin\left(\frac{1}{2}t\right) \exp\left(i\frac{t}{2}\right) = \boxed{\frac{1}{t^2} \exp\left(\frac{7}{2}it\right) \cdot \sin(2t) \sin\left(\frac{1}{2}t\right)} \end{aligned}$$

- (d) The moment-generating function for a uniform distribution on $[a, b]$ is

$$M_X(t) = \mathbb{E}(\exp(tx)) = \int_a^b \frac{1}{b-a} \cdot \exp(tx) dx = \frac{1}{b-a} \left[\frac{1}{t} \exp(tx) \right]_a^b = \frac{1}{(b-a)t} [\exp(bt) - \exp(at)]$$

Therefore the moment-generating function for X is $t^{-1}[\exp(t) - 1]$. Note that

$$\Pr(Y \leq y) = \Pr(-\log(X) \leq y) = \Pr(\log(X) \geq -y) = \Pr(X \geq e^{-y}) = \int_{\exp(-y)}^{\infty} dt = \int_{\exp(-y)}^1 dt$$

Substituting $t = e^{-u}$ (so that we have $u = -\log(t)$, $dt = -e^{-u}du$, we have

$$\Pr(Y \leq y) = - \int_y^0 e^{-u} du = [e^{-u}]_y^0 = 1 - e^{-y}$$

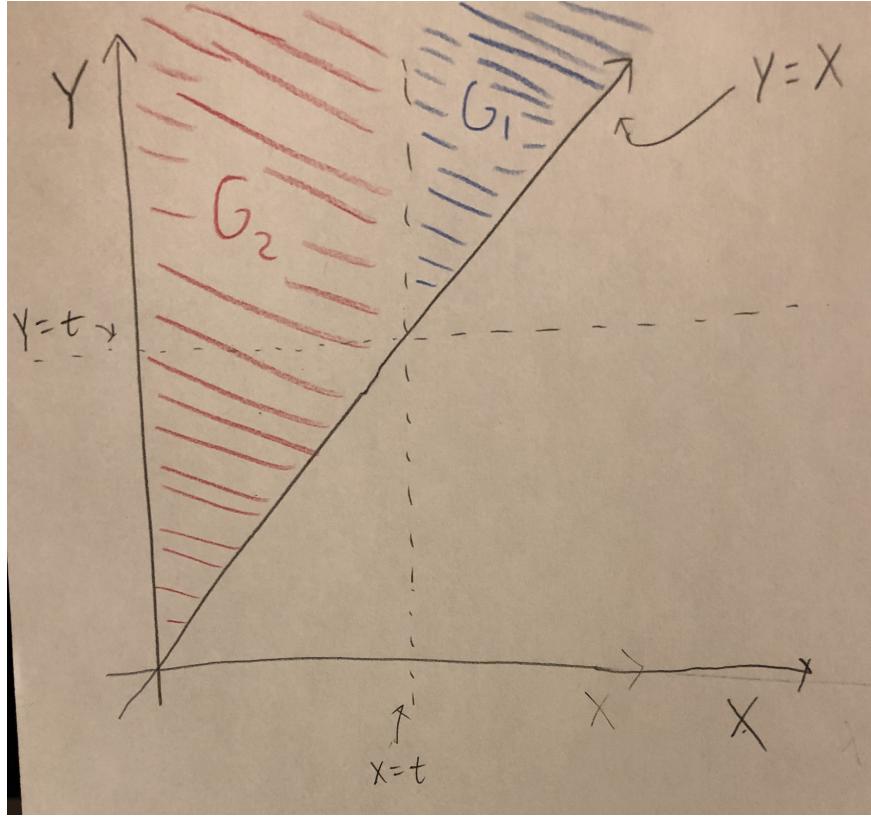
which is the cdf for an exponential distribution with mean 1. Therefore $Y = -\log(X) \sim \text{Exponential}(1)$, so

$$M_Y(t) = \frac{1}{1-t}$$

Using the fact that if X and Y are independent then $M_{X+Y}(t) = M_X(t)M_Y(t)$, we have

$$M_{X+Y}(t) = M_X(t)M_Y(t) = \frac{\exp(t) - 1}{t} \cdot \frac{1}{1-t} = \boxed{\frac{\exp(t) - 1}{t - t^2}}$$

Figure 6.2: Diagram for Fall 2016 Problem 2.



- (2) **Fall 2016 Problem 2.** Let X and Y be i.i.d. exponential with mean 1. Show that for every $t > 0$ the events $\{\omega : \min\{X, Y\} > t\}$ and $\{\omega : X < Y\}$ are independent.

Solution. Note that $\min\{X, Y\} > t \iff X > t \cap Y > t$.

- $\Pr(\min\{X, Y\} > t) = \Pr(X > t \cap Y > t) = \Pr(X > t) \Pr(Y > t)$

$$= \int_t^\infty e^{-x} dx \int_t^\infty e^{-y} dy = -e^{-x}\Big|_t^\infty - e^{-y}\Big|_t^\infty = \boxed{e^{-2t}}$$

- $\Pr(X < Y)$: Note that in Figure 2, the region that satisfies this condition is region G_1 plus G_2 (note that X and Y are nonnegative). Therefore we can find this probability by integrating the joint pdf over that region.

$$\Pr(X < Y) = \iint_{\{G_1+G_2\}} f_{X,Y}(x,y) dxdy$$

Note that the joint pdf is the probability of the marginal pdfs since X and Y are independent.

$$\begin{aligned} &= \int_0^\infty \int_x^\infty e^{-x-y} dy dx = \int_0^\infty e^{-x} \int_x^\infty e^{-y} dy dx \\ &\quad \int_x^\infty e^{-y} dy = -e^{-y}\Big|_x^\infty = e^{-x} \\ \implies \Pr(X < Y) &= \int_0^\infty e^{-2x} dx = -\frac{1}{2}e^{-2x}\Big|_0^\infty = \boxed{\frac{1}{2}} \end{aligned}$$

- $\Pr(X < Y \cap \min\{X, Y\} > t)$: Note that in Figure 2, the region that satisfies this condition is region G_1 . Therefore we can find this probability by integrating the joint pdf over that region.

$$\begin{aligned}\Pr(X < Y \cap \min\{X, Y\} > t) &= \int_{G_1} \int f_{X,Y}(x,y) dx dy = \int_t^\infty \int_t^y e^{-x-y} dx dy = \int_t^\infty e^{-y} \int_t^y e^{-x} dx dy \\ &\quad \int_t^y e^{-x} dx = -e^{-x} \Big|_t^y = -e^{-y} + e^{-t} \\ \implies \Pr(X < Y \cap \min\{X, Y\} > t) &= \int_t^\infty e^{-y} (-e^{-y} + e^{-t}) dy = \int_t^\infty (e^{-t-y} - e^{-2y}) dy \\ &= \frac{1}{2} e^{-2y} - e^{-t} e^{-y} \Big|_t^\infty = -\frac{1}{2} e^{-2t} - e^{-2t} = \boxed{\frac{1}{2} e^{-2t}}\end{aligned}$$

Note that

$$\Pr(X < Y \cap \min\{X, Y\} > t) = \frac{1}{2} \cdot e^{-2t} = \Pr(X < Y) \Pr(\min\{X, Y\} > t)$$

Therefore the events $\{\omega : \min\{X, Y\} > t\}$ and $\{\omega : X < Y\}$ are independent for every $t > 0$.

- (3) In a certain area, earthquakes happen at a frequency of one every four days. What is the probability that more than 100 earthquakes will occur in this area in one year (365 days)?

Solution. We can think of this as a Poisson process (see section 7.2) with $\lambda = 1/4$. Then there are two ways to obtain the answer: we can either examine the number of earthquakes in a 365 day period $N(365)$ and find the probability that $N(365) > 100$, or we can examine the number of days until the 101st earthquake T_{101} and find the probability that $T_{101} < 365$.

- (i) **Number of earthquakes in 365 days:** Let $N(t)$ be the number of earthquakes that occur in t days after the start of this process. By Theorem 7.2.3, $N(t) \sim \text{Poisson}(t \cdot 1/4)$. Then

$$\Pr(N(t) > 100) = \sum_{j=101}^{\infty} \frac{(365 \cdot 1/4)^j \exp(-365 \cdot 1/4)}{j!}$$

To obtain an answer for this, we can use the normal approximation to a Poisson distribution (Proposition 6.1.36):

$$\begin{aligned}N(t) \sim \mathcal{N}(t/4, t/4) \implies \Pr(N(365) > 100) &\approx \Pr\left(\mathcal{N}(0, 1) > \frac{100.5 - 365/4}{\sqrt{365/4}}\right) \\ &= \Pr\left(\mathcal{N}(0, 1) > \frac{100.5 - 91.25}{\sqrt{91.25}}\right) \approx \Pr\left(\mathcal{N}(0, 1) > \frac{9.25}{9.1}\right) \approx \boxed{0.1664}\end{aligned}$$

- (ii) **Number of days before 100th earthquake:** Let T_n be the number of days until the n th earthquake happens. By Corollary 7.2.4.1, $T_n \sim \text{Gamma}(n, 4)$. Then

$$\Pr(T_{101} < 365) = \int_0^{365} \frac{1}{\Gamma(101, 4)} x^{101-1} e^{-x/4} dx$$

To obtain an answer for this, we can use the normal approximation to a Gamma distribution (Proposition 6.3.23):

$$T_n \sim \mathcal{N}(404, 1616) \implies \Pr(T_{101} < 365) \approx \Pr\left(\mathcal{N}(0, 1) < \frac{365 - 404}{\sqrt{1616}}\right) \approx \Pr\left(\mathcal{N}(0, 1) < \frac{-40}{40}\right)$$

$$= \Pr(\mathcal{N}(0, 1) < -1) \approx [0.1660]$$

6.6.2 More Problems From Homework

Homework 5 Problem 4.

Let X_1, X_2, \dots be i.i.d. having moment-generating functions $M_X = M_X(t), t \in (-\infty, \infty)$. Let N be an integer-valued random variable with moment-generating function $M_N = M_N(t), t \in (-\infty, \infty)$. Assume that N is independent of all X_k and define $S = \sum_{k=1}^N X_k$. Confirm that the random variable S has the moment-generating function $M_S = M_S(t)$ defined for all $t \in (-\infty, \infty)$ and

$$M_S(t) = M_N(M_X(t))$$

Then use the result to derive the formulae

$$\mathbb{E}(S) = \mu_N \mu_X, \text{Var}(S) = (\sigma_N^2 - \mu_N) \mu_X^2 + \mu_N \sigma_X^2$$

where $\mu_N = \mathbb{E}(N)$, $\mu_X = \mathbb{E}(X_1)$, $\sigma_N^2 = \text{Var}(N)$, and $\sigma_X^2 = \text{Var}(X_1)$. How will the above computations change if we use the characteristic function ϕ_X instead of the moment-generating function M_X ?

Solution.

$$\begin{aligned} M_S(t) &= \mathbb{E}(e^{tS}) = \mathbb{E}[\mathbb{E}(e^{tS} \mid N)] = \sum_{n=0}^{\infty} \mathbb{E}(e^{tS} \mid N = n) \Pr(N = n) = \sum_{n=0}^{\infty} \mathbb{E}(e^{t(X_1+X_2+\dots+X_n)} \mid N = n) \Pr(N = n) \\ &= \sum_{n=0}^{\infty} \mathbb{E}(e^{tX_1} e^{tX_2} \cdots e^{tX_n}) \Pr(N = n) \end{aligned}$$

By independence of the X_i we have

$$= \sum_{n=0}^{\infty} \mathbb{E}(e^{tX_1}) \mathbb{E}(e^{tX_2}) \cdots \mathbb{E}(e^{tX_n}) \Pr(N = n)$$

which, since the X_i are i.i.d., can be written as

$$= \sum_{n=0}^{\infty} \mathbb{E}(e^{tX_1})^n \Pr(N = n) = \sum_{n=0}^{\infty} (M_X(t))^n \Pr(N = n)$$

But since $G_N(s) = \mathbb{E}(s^N) = \sum_{n=0}^{\infty} s^n \Pr(N = n)$, this can be written as

$$M_S(t) = G_N(M_X(t))$$

as desired. Note that

$$M'_S(t) = G'_N(M_X(t)) M'_X(t)$$

$$M''_S(t) = G''_N(M_X(t))(M'_X(t))^2 + G'_N(M_X(t))M''_X(t)$$

So we have

- $\mathbb{E}(S) = M'_S(0) = G'_N(M_X(0))M'_X(0) = G'_N(1)\mathbb{E}(X_1) = \mathbb{E}(N)\mathbb{E}(X_1) = \mu_N\mu_X$
- $\text{Var}(S) = \mathbb{E}(S^2) - \mathbb{E}(S)^2 = M''_S(0) - (M'_S(0))^2$

$$\begin{aligned} &= G''_N(M_X(0))(M'_X(0))^2 + G'_N(M_X(0))M''_X(0) - \mu_N^2\mu_X^2 = G''_N(1)\mathbb{E}(X_1)^2 + G'_N(1)\text{Var}(X_1) - \mu_N^2\mu_X^2 \\ &= \mathbb{E}[N(N-1)]\mathbb{E}(X_1)^2 + \mathbb{E}(N)\text{Var}(X_1) - \mu_N^2\mu_X^2 = \mathbb{E}[N^2 - N]\mathbb{E}(X_1)^2 + \mathbb{E}(N)\text{Var}(X_1) - \mu_N^2\mu_X^2 \\ &= [\mathbb{E}(N^2) - \mathbb{E}(N)^2 + \mathbb{E}(N)^2 - \mathbb{E}(N)]\mathbb{E}(X_1)^2 + \mathbb{E}(N)\text{Var}(X_1) - \mu_N^2\mu_X^2 = \\ &= [\text{Var}(N) + \mathbb{E}(N)^2 - \mathbb{E}(N)]\mathbb{E}(X_1)^2 + \mathbb{E}(N)\text{Var}(X_1) - \mu_N^2\mu_X^2 = (\sigma_N^2 + \mu_N^2 - \mu_N)\mu_X^2 + \mu_N\sigma_X^2 - \mu_N^2\mu_X^2 \\ &= \boxed{(\sigma_N^2 - \mu_N)\mu_X^2 + \mu_N\sigma_X^2} \end{aligned}$$

To use the characteristic function ϕ_X instead of the moment generating function M_X , we would do the following:

$$\begin{aligned} \phi_S(t) &= \mathbb{E}(e^{itS}) = \mathbb{E}[\mathbb{E}(e^{itS} \mid N)] = \sum_{n=0}^{\infty} \mathbb{E}(e^{itS} \mid N = n) \Pr(N = n) = \sum_{n=0}^{\infty} \mathbb{E}(e^{it(X_1+X_2+\dots+X_n)} \mid N = n) \Pr(N = n) \\ &= \sum_{n=0}^{\infty} \mathbb{E}(e^{itX_1} e^{tX_2} \dots e^{itX_n}) \Pr(N = n) \end{aligned}$$

By independence of the X_i we have

$$= \sum_{n=0}^{\infty} \mathbb{E}(e^{itX_1}) \mathbb{E}(e^{itX_2}) \cdots \mathbb{E}(e^{itX_n}) \Pr(N = n)$$

which, since the X_i are i.i.d., can be written as

$$= \sum_{n=0}^{\infty} \mathbb{E}(e^{itX_1})^n \Pr(N = n) = \sum_{n=0}^{\infty} (\phi_X(t))^n \Pr(N = n)$$

But since $G_N(s) = \mathbb{E}(s^N) = \sum_{n=0}^{\infty} s^n \Pr(N = n)$, this can be written as

$$\phi_S(t) = G_N(\phi_X(t))$$

Homework 5 Problem 7.

- (a) Let X_1, X_2, \dots, X_n be independent with mean zero and finite third moment. Prove that

$$\mathbb{E}(X_1 + \dots + X_n)^3 = \mathbb{E}X_1^3 + \dots + \mathbb{E}X_n^3$$

Solution.

- (a) Let $\mathbb{E}(\exp(itX_i)) = \phi_{X_i}(t_i)$. Let $S_n = \sum_{i=1}^n X_i$. Then by independence the characteristic function for S_n is

$$\mathbb{E}(\exp(itS_n)) = \phi_{S_n}(t) = \prod_{i=1}^n \phi_{X_i}(t)$$

Then

$$\mathbb{E}(X_1 + X_2 + \dots + X_n)^3 = \mathbb{E}(S_n^3) = \phi_{S_n}^{(3)}(0)$$

$$= \sum_{i=1}^n \phi_{X_i}^{(3)}(0) \cdot \left(\prod_{j \in \{1, \dots, n\}, j \neq i} \phi_{X_j}(0) \right) + C \left[\sum_{i=1}^n \cdot \left(\sum_{j \in \{1, \dots, n\}, j \neq i} \phi_{X_i}^{(2)}(0) \phi_{X_j}^{(1)}(0) \right) \cdot \left(\prod_{k \in \{1, \dots, n\}, k \neq i, j} \phi_{X_k}(0) \right) \right]$$

where C is some coefficient resulting from the multinomial expansion of S_n after repeated differentiation product rules. But because $\mathbb{E}(X_i) = 0$, $\phi_{X_i}^{(1)}(0) = 0 \forall i$, so the second term goes to 0. Therefore we have

$$\mathbb{E}(X_1 + X_2 + \dots + X_n)^3 = \sum_{i=1}^n \phi_{X_i}^{(3)}(0) \cdot \left(\prod_{j \in \{1, \dots, n\}, j \neq i} \phi_{X_j}(0) \right) = \sum_{i=1}^n \mathbb{E}(X_i^3) \cdot 1^{n-1} = \sum_{i=1}^n \mathbb{E}(X_i^3)$$

as desired.

Homework 6 Problem 10.

- (a) For $p \in (0, 1)$, let $x(p)$ be the smallest number of people so that there is a better than $100 \cdot p\%$ chance to have at least two born on the same day. Find an approximate expression for $x(p)$, and sketch the graph of the function $x = x(p)$.
- (b) Repeat part (a) when you want at least three people to share a birthday.

Solution.

- (a) Let $f(x)$ be the probability of no matches in birthdays in a group of x people; that is,

$$f(x) = \frac{365 \cdot 364 \cdot 363 \cdots (365 - x + 1)}{365^x} = \frac{1}{365^x} \cdot \frac{365!}{(365 - x)!} = \left(1 - \frac{1}{365}\right) \left(1 - \frac{2}{365}\right) \cdots \left(1 - \frac{x-1}{365}\right)$$

Using the first order Taylor approximation $\exp(-k/x) \approx 1 - k/x$, we have

$$f(x) = \left(1 - \frac{1}{365}\right) \left(1 - \frac{2}{365}\right) \cdots \left(1 - \frac{x-1}{365}\right) \approx \exp(-1/365) \exp(-2/365) \cdots \exp(-(x-1)/365)$$

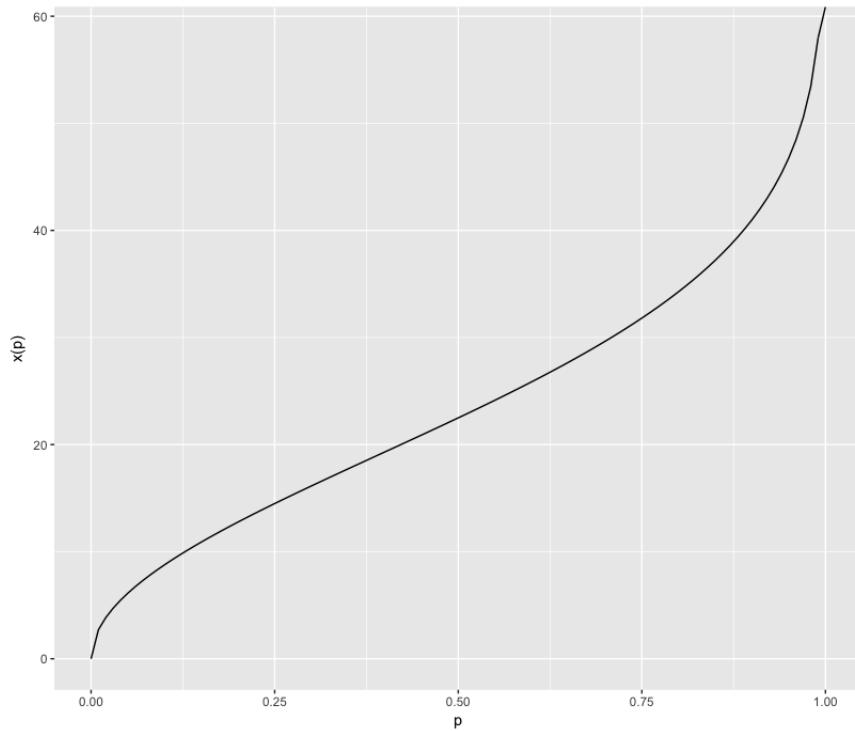
$$= e^{-(x^2-x)/(2 \cdot 365)}$$

We want the probability of a match to be at least p ; that is, $f(x) \leq 1 - p$. Setting this equal to $q = 1 - p$, we have

$$e^{-(x^2-x)/(2 \cdot 365)} = q \iff -\frac{x^2 - x}{730} = \log(q) \iff x^2 - x + 730 \log(q) = 0$$

$$\implies x = 0.5 + \sqrt{1/4 + 730 \log(1/q)} \approx \boxed{\sqrt{2 \cdot 365 \log(1/q)}}$$

where we discard the negative root because we have to have a nonnegative number of people, and we don't worry about the decimals since this is an approximation and we have to round up to the nearest whole person anyway.



- (b) For a group of three people, the Poisson approximation (see Section 6.1.10) is more convenient. The number of groups of 3 people in a room of x people is $\binom{x}{3}$. For a group of three people, the probability that all three have the same birthday is $1 \cdot 1/365 \cdot 1/365 = 365^{-2}$. Therefore we can think of the number of matches of three people as distributed Poisson with expectation $\binom{x}{3} \cdot 365^{-2}$. Then we have the probability of at least one “success” (triplet with three matched birthdays) is

$$1 - \frac{\exp(-\lambda)\lambda^0}{0!} = 1 - \exp\left(-\binom{x}{3} \cdot 365^{-2}\right)$$

We set this equal to p and solve:

$$\begin{aligned} p = 1 - \exp\left(-\binom{x}{3} \cdot 365^{-2}\right) &\iff -\binom{x}{3} \cdot 365^{-2} = \log(1-p) \iff \frac{x!}{(x-3)!3!} = 365^2 \cdot \log\left(\frac{1}{1-p}\right) \\ &\iff x(x-1)(x-2) = 6 \cdot 365^2 \cdot \log\left(\frac{1}{1-p}\right) \iff (x^2-x)(x-2) = x^3 - 3x^2 + 2x = 6 \cdot 365^2 \cdot \log\left(\frac{1}{1-p}\right) \end{aligned}$$

This has a unique real solution, but it is hard to find.

Exercise 13. Let X, Y, Z be independent uniform on $(0, 1)$. Compute the cdfs of XY , X/Y , and XY/Z .

Solution.

Using the information from part (a), and the fact that $f_X(x) = 1$ (for $x \in [0, 1]$) and likewise for $f_Y(y)$:

- XY :

$$\begin{aligned}
F_{XY}(z) &= \int_0^\infty f_X(x) \int_{-\infty}^{z/x} f_Y(y) dy dx - \int_{-\infty}^0 f_X(x) \int_\infty^{z/x} f_Y(y) dy dx \\
&= \int_0^1 [(z/x) \mathbf{1}_{\{0 < z/x \leq 1\}} + \mathbf{1}_{\{z/x > 1\}}] dx = \int_0^1 [(z/x) \mathbf{1}_{\{z \leq x\}} + \mathbf{1}_{\{z > x\}}] dx = \int_0^z dx + \int_z^1 (z/x) dx \\
&= z + z \log(x) \Big|_z^1 = z + z \log(1) - z \log(z) = z(1 - \log(z))
\end{aligned}$$

$$\implies F_{XY}(z) = \begin{cases} 0 & z \leq 0 \\ z(1 - \log(z)) & 0 < z \leq 1 \\ 1 & z > 1 \end{cases}$$

- X/Y :

$$\begin{aligned}
F_{X/Y}(z) &= \int_0^\infty f_Y(y) \int_{-\infty}^{zy} f_X(x) dx dy - \int_{-\infty}^0 f_Y(y) \int_\infty^{zy} f_X(x) dx dy \\
&= \int_0^1 [zy \mathbf{1}_{\{0 < zy \leq 1\}} + \mathbf{1}_{\{zy > 1\}}] dy = \int_0^1 [zy \mathbf{1}_{\{y > 0 \cap y \leq 1/z\}} + \mathbf{1}_{\{y > 1/z\}}] dy = \int_0^{1/z} zy \cdot dy + \int_{1/z}^1 dy \\
&= \frac{zy^2}{2} \Big|_0^{1/z} + (1 - 1/z) = \frac{z}{2z^2} + 1 - \frac{2}{2z} = 1 - \frac{1}{2z} \\
\implies F_{X/Y}(z) &= \begin{cases} 0 & z \leq 0 \\ 1 - \frac{1}{2z} & 0 < z \leq 1 \\ 1 & z > 1 \end{cases} \\
&= \begin{cases} 0 & z \leq 0 \\ z/2 & 0 < z \leq 1 \\ 1 - \frac{1}{2z} & z > 1 \end{cases}
\end{aligned}$$

- XY/Z : Consider this the cdf of the quotient of $W = XY$ and Z .

$$\begin{aligned}
F_U(u) &= \int_0^\infty f_Z(z) \int_{-\infty}^{uz} f_W(w) dw dz - \int_{-\infty}^0 f_Z(z) \int_\infty^{uz} f_W(w) dw dz \\
&= \int_0^1 \int_0^{uz} -\log(w) \mathbf{1}_{\{0 < uz \leq 1\}} dw dz = \int_0^1 -[w \log(w) - w]_0^{uz} \mathbf{1}_{\{0 < z \leq 1/u\}} dz \\
&= \int_0^{1/u} uz [1 - \log(uz)] dz = \frac{u}{4} z^2 (3 - 2 \log(uz)) \Big|_0^{1/u} = \frac{u}{4u^2} (3 - 2 \log(1)) - 0 = \frac{3}{4u} \\
\implies F_{XY/Z}(u) &= \begin{cases} 0 & u \leq 0 \\ \frac{3}{4u} & 0 < u \leq 3/4 \\ 1 & u > 3/4 \end{cases}
\end{aligned}$$

6.7 Random Matrix Theory

Definition 6.45 (Wigner-type random matrix). $H \in \mathbb{R}^{N \times N}$ is a **Wigner-type random matrix** if each entry H_{ij} equals either 1 or -1 with equal probability and H is symmetric ($H = H^+$). Other than the symmetry restriction, the entries are independent.

Remark 54. Because a Wigner-type random matrix is symmetric, the eigenvalues are real.

Example 6.14. 10 i.i.d. random variables X_1, \dots, X_{10} , where $\Pr(X_1 = m) = 1/3$ for $m \in \{2, 3, 4\}$. What is the distribution of $S = \sum_k X_k$?

This is not an interesting problem since a computer can easily calculate the answer, even if the number of random variables is in the thousands.

Example 6.15. n i.i.d. random variables X_1, \dots, X_n , where n is large. Find $f(n)$ and $g(n)$ such that

$$Z_n = \frac{S_n - f(n)}{g(n)}$$

has a nontrivial limiting distribution.

Solution.

We know if $\mathbb{E}X_k^2 < \infty$, choosing $f(n) = n\mathbb{E}X_1$ and $g(n) = \sqrt{n\text{Var}(X_1)}$ allows convergence to a standard Gaussian random variable under the Central Limit Theorem. Also note that if n is large, $S_n \approx n\mathbb{E}X_1$ and $(S_n - n\mathbb{E}X_1) = \mathcal{O}\left(\sqrt{n\text{Var}(X_1)}\right)$.

Let \hat{S}_n be the largest eigenvalue of a Wigner random matrix H_n . It turns out that $\hat{S}_n \approx 2\sqrt{n}$ and $\hat{S} - 2\sqrt{n} = \mathcal{O}(n^{1/6})$. Lastly,

$$\frac{\hat{S} - 2\sqrt{n}}{n^{1/6}}$$

converges in distribution to a Tracy-Widom distribution [Johnstone, 2001].

Exercise 14. Suppose X_1, \dots, X_n are i.i.d. uniform on $[0, 1]$. Let Y_1, \dots, Y_n be the order statistics $X_{(1)}, \dots, X_{(n)}$. Let $Z_n = Y_{n/2+1} - Y_{n/2}$. Find $f(n), g(n)$ such that

$$\frac{Z_n - f(n)}{g(n)} \xrightarrow{d} \text{non-trivial distribution.}$$

Example 6.16. Let $X_n = \sum_{k=1}^n X_k$ where $X_k \sim \text{Ber}(1/2)$. We know that

$$\frac{S_n - n/2}{1/2\sqrt{n}} \xrightarrow{d} \mathcal{N}(0, 1).$$

However, what is $\mathbb{P}(S_n > 0.6n)$? It turns out that $\mathcal{P}(S_n > 0.6n) \sim e^{-cn}$.

For a Gaussian Orthogonal Ensemble, eigenvalues tend to be between -2 and 2. Difference between adjacent eigenvalues $\lambda_i - \lambda_{i+1}$ is of interest. Tends to be of order $1/n$, so after multiplying by n , tends to be of order 1.

$$n(\lambda_i - \lambda_{i+1}) \xrightarrow{d} \text{Gaudin-Mehta distribution.}$$

Approximately given by Wigner's

$$\mathbb{P}(s) = \frac{\pi s}{2} e^{-\frac{\pi}{4}s^2}.$$

Bulk Universality Conjecture: Gap distribution for the bulk eigenvalues for a large generic d -regular graph converges to this distribution.

Universality Conjecture (Wigner-Dyson-Mehta): bulk eigenvalue statistics are universal, depending only on the symmetry class of the matrix ensemble, regardless of the distribution of individual matrix entries. Proven by Erdos, Yau, and Tau and Vu (under 4th moment condition)

6.7.1 Large Deviation Theory

Wigner-type matrix H . Let the eigenvalues be $\lambda_1, \dots, \lambda_n \in \mathbb{R}$. Suppose we normalize H by dividing it by the square root of n ; that is, let $H_1 = H/\sqrt{n}$. Define a measure

$$\mu_n := \frac{1}{n} \sum_{k=1}^n \delta_{\lambda_k}$$

so for $I \subset \mathbb{R}$,

$$\mu_n(I) = \#\{i : \lambda_i \in I\}.$$

Note that μ_n is random because H is random. We will show that

$$\mu_n \xrightarrow{a.s.} \mu.$$

Proposition 6.7.1. For any continuous smooth function g ,

$$\int g(t) d\mu_n(t) \xrightarrow{a.s.} \int g(t) d\mu(t).$$

We can also write this as

$$\langle \mu_n, g \rangle \xrightarrow{a.s.} \langle \mu, g \rangle.$$

In other words, for any interval $[a, b] \subset \mathbb{R}$,

$$\mu_n([a, b]) \xrightarrow{a.s.} \mu([a, b]).$$

where

$$d\mu = \frac{1}{2\pi} \sqrt{(4 - x^2)_+} dx$$

where

$$(4 - x^2)_+ = \begin{cases} 4 - x^2 & 4 - x^2 \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Roughly speaking, for a Wigner random matrix where $\mathbb{E} H_{ij} = 0$ and $\mathbb{E} H_{ij}^2 = 1$ and $\mathbb{E} H_{ij}^p$ exists and is finite for all p , if n is large then the number of eigenvalues of H_n in the interval $[a, b]$ divided by n is close to the number

$$\int_a^b \frac{1}{2\pi} \sqrt{(4 - x^2)_+} dx.$$

Let $\lambda_n^{(n)}$ be the largest eigenvalue of H_n . We have that

$$\frac{\lambda_n^{(n)} - 2}{n^{2/3}} \xrightarrow{d} \text{Tracy-Widom distribution.}$$

Proposition 6.7.2. Suppose $k = \lfloor n/2 \rfloor$. Let $\lambda_k^{(n)}$ be the k -th smallest eigenvalue of H_n . γ_k is defined as

$$\int_{-2}^{\gamma_k} \frac{1}{2\pi} \sqrt{(4 - x^2)_+} dx = \frac{k}{n}$$

Then

$$(1) \quad \lambda_k^{(n)} \approx \gamma_k$$

$$(2) \quad \lambda_k^{(n)} - \gamma_k = \mathcal{O}\left(\frac{1}{2}\sqrt{\log n}\right).$$

(3)

$$\frac{\lambda_k^{(n)} - \gamma_k}{n^{-1}\sqrt{\log n}} \xrightarrow{d} \mathcal{N}(0, 1).$$

These results hold regardless of the exact distribution of H_{ij} . This property is referred to as **universality**. (Like the Central Limit Theorem.)

Proposition 6.7.3. Fix $a, b \in \mathbb{R}$, $E_0 \in \mathbb{R}$.

$$I_{E_0, a, b} = [E_0 + a/n, E_0 + b/n].$$

Then the number of eigenvalues of H in $I_{E_0, a, b}$ is $\mathcal{O}(1)$. (Regardless of the exact distribution of H_{ij} .)

Proposition 6.7.4. Let $\lambda_k^{(n)}$ be an eigenvalue of H_n . Let $u_k^{(n)}$ be the corresponding unit-length eigenvector; that is,

$$Hu_k^{(n)} = \lambda_k^{(n)} u_k^{(n)}, \quad \|u_k^{(n)}\|_2 = 1.$$

Then

1. For all fixed $w \in \mathbb{R}^n$ such that $\|wrVert_2 = 1$,

$$\frac{|\langle w, u_k^{(n)} \rangle|^2}{1/n} \xrightarrow{d} (\mathcal{N}(0, 1))^2.$$

2. Let $g_k^w := |\langle w, u_k^{(n)} \rangle|^2$. Then for $k \neq \ell$,

$$(g_k^w, g_\ell^w) \xrightarrow{d} ([\mathcal{N}(0, 1)]^2, [\mathcal{N}(0, 1)]^2)$$

and the two vectors are independent.

3. Let w, w' be two orthogonal unit vectors ($\langle w, w' \rangle = 0$). Then

$$(g_k^w, g_k^{w'}) \xrightarrow{d} ([\mathcal{N}(0, 1)]^2, [\mathcal{N}(0, 1)]^2)$$

and the two vectors are independent.

Let X have i.i.d. entries but it is not necessarily symmetric. We will investigate the eigenvalues of $X^T X$, which converge to a Marchenko–Pastur distribution.

Let X have eigenvalues $\lambda_k \in \mathbb{C}$. Let $\mu_n = n^{-1} \sum_{k=1}^n \delta_{\lambda_k}$. Then $n\mu_n(A)$ is the number of eigenvalues of X in A for $A \subset \mathbb{C}$.

$$\mu(A) = \frac{\text{Area}(A \cap D)}{\pi}, \quad D := \{z : |z| \leq 1\}.$$

This is called a **circular law** (density $1/\pi$ in D , 0 outside of D). Results exist if $\mathbb{E}X_i = 0$, $\mathbb{E}X_{ij}^2 = 1$.

Proposition 6.7.5. $z \in \mathbb{C}$, $B_n = z^\ell$, $\ell = N^{-1/2+\delta}$, then the number of eigenvalues of X in B_n is roughly $\pi^{-1}\ell^2 n$. where B_n is a box with width ℓ .

Proposition 6.7.6. Suppose u_k is an eigenvector of X with $\|u_k\|_2 = 1$. Let $u_k(m)$ be the m th component of X . Note $\|u_k\|_2^2 = 1$, u_k has n components. With high probability,

$$\max_m |u_k(m)|^2 \leq n^{-1+\epsilon} \quad \forall \epsilon > 0.$$

Delocalization: eigenvectors are spread out fairly uniformly over a range of possible values.

Opposite case: Suppose we have a diagonal random matrix \tilde{X}_{ij} . Then the eigenvectors are the unit vectors e_i , so the eigenvectors are very localized.

Some other Wigner-type random matrices:

- (1) H , $\mathbb{E}H_{ij} = 0$, $\mathbb{E}H_{ij}^2 = \mathcal{O}(1)$, $\sum \mathbb{E}(H_{ij})^2 = N$. This is a generalized Wigner random matrix.
- (2) Remove the condition that $\sum \mathbb{E}(H_{ij})^2 = N$. This is a **universal Wigner matrix**. In this case, the eigenvectors may have some favored direction.
- (3) $\mathbb{E}H_{ij}^2 = 1$ but mean is not 0. Then similar results.
- (4) Suppose X is Wigner and T is a fixed matrix. Then there are results for TX .
- (5) H_{ij} does not have order 1 all the time; that is, some entries are on different scales than others (some much larger). Examples:
 - (a) Sparse matrix, like Erdos-Renyi matrix. E-R graph: line connecting V_i, V_j if and only iff $A_{ij} = 1$. $\mathbb{P}(A_{ij} = 1) = p(n)$, some function of n . All A_{ij} are independent of each other besides the fact that A is symmetric.
 $A = H + A_0$, where A_{ij} is defined as above, $\mathbb{E}H_{ij} = 0$, $\mathbb{E}H_{ij}^2 = p_n(1 - p_n)$. Note that if $p_n \ll 1$,

⋮

we have

$$\text{Var}\left(\frac{1}{\sqrt{p_n}}A_{ij}\right) \approx 1, \quad \mathbb{E}\left(\frac{1}{\sqrt{p_n}}A_{ij}\right) \approx 0,$$

but $\hat{A} = p_n^{-1/2}A$, $\hat{A}_{ij} \gg 1$; that is, this is a sparse matrix with mostly 0 entries, and the entries that are nonzero are large.

- (b) **Band matrix.** $H_{ij} \cdot f(|i - j|)$, where

$$f(m) = \begin{cases} 1 & m \leq W \\ 0 & m > W. \end{cases}$$

The interesting case is when $W \ll n$.

Topics:

- **Topic 1:** For a matrix A , find optimal m and M such that for all x , $m\|x\| < \|Ax\| < M\|x\|$ (i.e., m is the smallest singular value and M is the largest). Then the condition number is $\kappa(A) = M/m$.

Suppose $A \in \mathbb{R}^{n \times m}$, $a_{ij} = g_{ij}$, $g_{ij} \sim \mathcal{N}(0, 1)$. Marchenko–Pastur Law:

$$\|A\| \approx \sqrt{n} + \sqrt{m}$$

$$\sigma_{\min}(A) \approx \sqrt{n} - \sqrt{m}$$

If A is a tall matrix, $n \gg m$, then $\kappa(A)$ is constant. In square case, $\sigma_{\min}(A) < 0 \iff A$ is invertible.

- **Least Singular Value of square matrices:** Intuition: eigenvector should not have a preference—“uniform on the sphere.” True for Gaussian matrices.

Typical $X \sim \text{Uniform}(S^{n-1})$:

$$X = \begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix}$$

$$\mathbb{E}|X_i|^2 = \frac{1}{n} \sum_{i=1}^n \mathbb{E}|X_j|^2 = \frac{1}{n}$$

where we used the fact that X is a unit vector. Therefore $|X_i| \sim n^{-1/2}$.

- $\|X\|_\infty = \max_j |X_j|$:
 $\mathbb{P}(|X_i| > t/\sqrt{n}) \leq \exp(-C_1 t^2)$ for $t > C_1$.

$$\mathbb{P}\left(|X_i| > \frac{R\sqrt{\log n}}{\sqrt{n}}\right) \leq \exp(-CR^2 \log n)$$

$$\mathbb{P}\left(\exists j \text{ such that } |X_j| > \frac{R\sqrt{\log n}}{\sqrt{n}}\right) < n \exp(-CR^2 \log n)$$

$$\|X\|_\infty \leq R\sqrt{\frac{\log n}{n}} \text{ with probability } \geq 1 - n^{1-CR^2}.$$

- **Topic 2:** ℓ_∞ delocalization. Suppose we have A with $\mathbb{E}a_{ij} = 0$, $\mathbb{E}A_{ij}^2 = 1$. Eigenvector v , $\|v\|_2 = 1 \implies \|v\|_\infty < \frac{\log C}{\sqrt{n}}$.
- **Topic 3:** No-gap delocalization of eigenvectors.

$$X = \begin{pmatrix} \sqrt{2/n} \\ \vdots \\ \sqrt{2/n} \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

(first $n/2$ entries are $\sqrt{2/n}$, rest are 0.)

For every $I \subset \{1, \dots, n\}$ with $|I| = \epsilon n$, let I index over the nonzero entries of an eigenvector. Want to show that $\|V_i\|_2 \geq \epsilon^c$.

- **Topic 0:** Subgaussian random matrices

Linear algebra: $A \in \mathbb{R}^{n \times m}$. Singular value decomposition:

$$A = U\Sigma V^T$$

where $UU^T = I_n$, $VV^T = I_m$, and Σ is a diagonal matrix with diagonal entries equal to the singular values.

6.7.2 Band Matrix

$n \times n$ random matrix with bandwidth w . $H_{ij} \neq 0 \implies |i - j| \leq w$. Let $w = n^a$ for $0 < a < 1$. We have for the nonzero entries, $H_{ij} = \pm 1$, $\mathbb{E}H_{ij} = 0$, $\mathbb{E}H_{ij}^2 = 1$.

Let H be a Wigner band matrix. Since H is symmetric, decompose H as $H = UDU^+$, where D is diagonal. Then $H^m = UDU^+U^mU^+$. When H is a band matrix with reasonably small w , then for any eigenvector u of H , usually $|u(k)|^2$ is contained within a narrow range.

Roughly speaking, for each eigenvector u_k of H there exists an integer a_k , where $1 \leq a_k \leq n$, such that $u(k) \approx 0$ if $|k \cdot a| \gg w^2$.

From linear algebra: if λ_ℓ and u_ℓ are corresponding eigenvalues and eigenvectors of H ,

$$[H^m]_{bc} = \sum_\ell \lambda_\ell^m u_\ell(b) u_\ell^+(c).$$

As you raise the matrix to higher and higher powers, the bandwidth will initially increase but eventually won't.

$$u_\ell(b) \neq 0, u_\ell(c) \neq 0 \implies |b - c| = o(w^2).$$

This is so-called **localization** of a band matrix. **Conjecture:** this occurs for $w = n^a$ when $a < 1/2$. When $a > 1/2$ we have delocalization.

For $d = 3$, a band matrix is delocalized as long as $a > 0$.

1. **GOE/GUE:** Wigner-type random matrix (e.g., $\mathbb{E}H_{ij} = 0$, $\mathbb{E}H_{ij}^2 = 1$). If $H_{ij} \sim \mathcal{N}(0, 1)$, then it's called GOE (Gaussian orthogonal *). If H is GOE, then for any orthogonal matrix O ($OO^+ = I$), then OHO^+ has the same distribution as H . Also, the probability density of $\lambda_1, \dots, \lambda_n$ of H is

$$\prod e^{-\sum_k 1/4\lambda_k^2} \prod_{i < j} |\lambda_i - \lambda_j|.$$

this is an **orthogonal polynomial**.

Recall important properties of Wigner matrix: independent entries, orthogonal invariance. For a symmetric matrix, the only solution is a GOE matrix. For Hermitian, must be GUE.

2. **Comparison Method:** unknown X , known \tilde{X} , for Wigner, $\mathbb{E}\lambda_n^{(n)} \approx \mathbb{E}_n^{(n)}$.

Look at Central Limit Theorem again: X_i i.i.d., $\mathbb{E}X_i = 0$, $\mathbb{E}X_i^2 = 1$, then

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i \xrightarrow{d} \mathcal{N}(0, 1).$$

Special case: if $X_i \sim \mathcal{N}(0, 1)$, result holds exactly even in finite samples.

Need to prove:

$$\mu_n \rightarrow \mathcal{N}(0, 1) = \mu$$

Need to prove: for all $f \in C_{b,c}^\infty$ (smooth functions), $\langle f, \mu_n \rangle \rightarrow \langle f, \mu \rangle$. For all f ,

$$\mathbb{E}f\left(\frac{\sum_i X_i}{\sqrt{n}}\right) \rightarrow \mathbb{E}f(Z),$$

where $Z \sim \mathcal{N}(0, 1)$. So need to prove

$$\mathbb{E}f\left(\frac{\sum_i X_i}{\sqrt{n}}\right) - \mathbb{E}f\left(\frac{\sum_i X_i^G}{\sqrt{n}}\right) = o(1) \quad (6.18)$$

where X_i^G is Gaussian. (show the thing we want to study and something we know about (Gaussian R.V.s) are close together)

Let

$$S_n = \sum_{i=1}^n X_i, \quad S_n^G = \sum_{i=1}^n X_i^G, \quad \tilde{S}_n^k = \sum_{i=1}^k X_i + \sum_{i=k+1}^n X_i^G.$$

Note that $\tilde{S}_n^n = S_n$ and $\tilde{S}_n^0 = S_n^G$. We can express the left side of (6.18) as

$$\sum_k \left[\mathbb{E}f\left(\frac{\tilde{S}_n^{k+1}}{\sqrt{n}}\right) - \mathbb{E}f\left(\frac{\tilde{S}_n^k}{\sqrt{n}}\right) \right]$$

6.7.3 Subgaussian Random Variable

$g \sim \mathcal{N}(0, 1)$, $t \rightarrow \frac{1}{\sqrt{2\pi}} \exp(-t^2/2)$. Fact

1.

$$\mathbb{P}(|g| > t) \leq 2 \exp(-Ct^2)$$

2.

$$G = \begin{pmatrix} g_1 \\ \vdots \\ g_n \end{pmatrix}$$

$g_i \sim \mathcal{N}(0, 1)$, with density function $x \rightarrow (2\pi)^{-n/2} \exp(-\sum_i X_i^2/2)$.

So the density only depends on $\|X\|_2$, density is invariant under rotation, which means if U is an orthogonal matrix, then $UG \sim G$.

Definition 6.46 (Subgaussian random variable). A random variable X is called **subgaussian** if

$$\|X\|_\Psi = \inf \left\{ s > 0 : \mathbb{E}F\left(\frac{|X|}{s}\right) \leq 1 \right\} < \infty$$

("find s such that $\mathbb{E}F(|X|/s) = 1$ ")

Remark 55. $\|\cdot\|_\Psi$ is a norm (the **subgaussian norm**); one can check that it satisfies the triangle inequality, homogeneity, and it is nonnegative.

Proposition 6.7.7. The following are equivalent:

1. There exists a κ such that $\|X\|_{\Psi} \leq \kappa$.
2. There exists a κ such that for all $t > 0$, $\mathbb{P}(|X| > t) \leq 2 \exp(-t^2/\kappa^2)$.
3. There exists a κ such that $\sup_{p>1} \left\{ \frac{\mathbb{E}(|X|^p)^{1/p}}{\sqrt{p}} \right\} \leq \kappa$.
4. There exists a κ such that $\mathbb{E} \exp(\lambda X) \leq 2 \exp(\lambda^2 \kappa^2)$.
5. (only when $\mathbb{E}X = 0$) $\mathbb{E} \exp(\lambda X) \leq \exp(C\lambda^2 \kappa^2)$.

Proof. First we show that (1) implies (2). We will use exponential Markov's inequality: if Z is nonnegative,

$$\mathbb{P}(Z < t) \leq \frac{\mathbb{E}Z}{t}$$

$$\begin{aligned} \mathbb{P}(|X| > t) &= \mathbb{P}(\exp(|X|^2/\kappa^2) > \exp(t^2/\kappa^2)) \leq \frac{\mathbb{E} \exp(|X|^2/\kappa^2)}{\exp(t^2/\kappa^2)} = \frac{\mathbb{E}[f(|X|/\kappa) + 1]}{\exp(t^2/\kappa^2)} \\ &\leq \frac{2}{\exp(t^2/\kappa^2)} = 2 \exp(-t^2/\kappa^2). \end{aligned}$$

which implies g is subgaussian. Now we show that 2 implies 3.

$$\mathbb{E}|X|^p = \mathbb{E}\left(\int_0^{|X|^p} 1 dt\right) = \int_0^\infty \mathbf{1}_{[t,\infty)}(|X|^p) dt = \int_0^\infty \mathbb{P}(|X|^p < Mt) dt$$

Let $u^p = t$. We will use integration by parts

$$\begin{aligned} &= \int_0^\infty pu^{p-1} \mathbb{P}(|X| > u) du \leq \int_0^\infty pu^{p-1} 2 \exp(-u^2/\kappa^2) du = \int_0^\infty \underbrace{pu^{p-2}}_w \cdot \underbrace{u2 \exp(-u^2/\kappa^2)}_{v'} du \\ &= [uv]_0^\infty - \int_0^\infty w' v du = pu^{p-2}(-\kappa^2 \exp(-u^2/\kappa^2))_0^\infty + \int_0^\infty p(p-2)u^{p-3}\kappa^2 \exp(-u^2/\kappa^2) du \\ &= p(p-2)(p-4)C^p \kappa^p \leq C^p 9p^{p/2} \kappa^p \end{aligned}$$

p th root $\implies \sqrt{p}C\kappa$.

Next we will show 3 implies 1.

⋮

□

Proposition 6.7.8. Consider $a \in S^{n-1}$. Suppose X_1, \dots, X_n are mean 0 with $\|X_i\|_\Psi \leq \kappa$ for all i . Then $\sum_i a_i X_i$ is subgaussian (for all $n \in \mathbb{Z}_{++}$).

Proof.

$$\begin{aligned} \mathbb{E} \exp \left(\lambda \sum_i a_i X_i \right) &= \mathbb{E} \prod_i \exp(\lambda a_i X_i) = \prod_i \mathbb{E} \exp(\lambda a_i X_i) \leq \prod_i \mathbb{E} \exp(C \lambda^2 a_i^2 \kappa^2) \\ &= \mathbb{E} \exp \left(C \lambda^2 \left(\sum_i a_i^2 \right) \kappa^2 \right) = \mathbb{E} \exp(C_1 \lambda^2 \kappa^2). \end{aligned}$$

Therefore $\sum_i a_i X_i$ is subgaussian (and $\|\sum_i a_i X_i\|_\Psi \leq C_1 \kappa$).

□

Examples of subgaussian random variables: Gaussian, Bernoulli, bounded.

Definition 6.47 (Hilbert-Schmidt Norm).

$$\|A\|_{HS} = \sqrt{\sum_{i,j} a_{ij}^2}.$$

Remark 56. Note

$$\text{Tr}(A^* A) = \|A\|_{HS}^2 = \sum_i s_i^2(A)$$

(the sum of the squared singular values of A).

Proposition 6.7.9 (Hanson-Wright Inequality).

Proof.

□

6.7.4 Topic 1: Invertibility of Matrices

Very tall case: Suppose $A \in \mathbb{R}^{n \times m}$, with $n \gg m$. Entries a_{ij} are independent with $\mathbb{E} a_{ij} = 0$, $\mathbb{E} a_{ij}^2 = 1$, and $\|a_{ij}\|_\Psi \leq \kappa$. A left inverse of A , A^+ exists if the smallest singular value of A is positive; that is, $\delta_m(A) > 0$. Then the columns of A span \mathbb{R}^m , and there exists a matrix A^+ such that $A^+ A = I_m$.

Proposition 6.7.10 (Operator norm of A).

$$\mathbb{P}(\|A\| \geq R(\sqrt{n} + \sqrt{m})) \leq \exp(-C_2 R^2 (\sqrt{n} + \sqrt{m})^2)$$

for $R > C_1$.

Proof.

•

$$\|A\| = \max_{x \in S^{n-1}} \|Ax\|_2 = \max_{x \in S^{n-1}} \max_{y \in S^{n-1}} \langle y, Ax \rangle$$

- For fixed $y \in S^{n-1}$, $x \in S^{n-1}$,

$$\langle y, Ax \rangle = \sum_{i,j} y_i a_{ij} x_j$$

Using the subgaussianity of a_{ij} ,

$$\left\| \sum_{i,j} x_i x_j a_{ij} \right\|_{\Psi} \leq C \sqrt{\sum_{i,j} (y_i x_j)^2 \kappa} = CK$$

Using the second definition of the subgaussian norm,

$$\implies \mathbb{P}(|\langle y, Ax \rangle| > t) \leq 2 \exp(-Ct^2/\kappa^2)$$

We need an upper bound for all $x \in S^{m-1}, y \in S^{n-1}$.

Definition 6.48 (ϵ -net). $\mathcal{M} \subseteq S^{m-1}$ is an ϵ -net of S^{m-1} , if for all $x \in S^{m-1}$, there exists an $x' \in \mathcal{M}$ such that $\|x - x'\|_2 \leq \epsilon$.

Take a $1/4$ -net in S^{m-1} , called \mathcal{M} . Likewise, take a $1/4$ -net in S^{n-1} , called \mathcal{N} .

$$\mathbb{P}(\exists x \in \mathcal{M}, y \in \mathcal{N} \text{ s.t. } |\langle y, Ax \rangle| > t) \leq |\mathcal{M}| |\mathcal{N}| \exp(-Ct^2).$$

Suppose for all $x \in \mathcal{M}, y \in \mathcal{N}$, we have $|\langle y, Ax \rangle| \leq t$. Let $x_0 \in S^{m-1}, y_0 \in S^{n-1}$ such that $\|A\| = \langle y_0, Ax_0 \rangle$. Take $y \in \mathcal{N}, x \in \mathcal{M}$ such that $\|y - y_0\| \leq 1/4, \|x - x_0\| \leq 1/4$. Then

$$\|A\| = \langle y, Ax_0 \rangle + \langle y_0 - y, Ax_0 \rangle \leq \langle y, Ax_0 \rangle + \|y_0 - y\| \|A\|$$

$$\begin{aligned} &= \langle y, Ax \rangle + \langle y, A(x_0 - x) \rangle + \frac{1}{4} \|A\| \leq \langle y, Ax \rangle + \|y\| \|A\| \|x_0 - x\| + \frac{1}{4} \|A\| \\ &\implies \|A\| \leq \langle y, Ax \rangle + \frac{1}{2} \|A\| \end{aligned}$$

$$\iff \|A\| \leq 2 \langle y, Ax \rangle \leq 2t$$

since we already have $|\langle y, Ax \rangle| \leq t$.

Then

$$\mathbb{P}(\forall x \in \mathcal{M}, \forall y \in \mathcal{N}, |\langle y, Ax \rangle| \leq t) \geq 1 - |\mathcal{M}| |\mathcal{N}| \exp(-Ct^2/\kappa^2)$$

therefore with probability at least $1 - |\mathcal{M}| |\mathcal{N}| \exp(-Ct^2/\kappa^2)$, we have $\|A\| \leq 2t$.

□

Next, adjust t according to $|\mathcal{M}||\mathcal{N}|$ to maximize the probability.

Proposition 6.7.11. For $\epsilon < 1$, let \mathcal{N} be an ϵ -net of S^{n-1} . Then \mathcal{N} satisfies $|\mathcal{N}| < (3/\epsilon)^n$.

Proof. Let B_2^n denote the Euclidean unit ball in \mathbb{R}^n . Then $x + \epsilon B_2^n = \{x + \epsilon y : y \in B_2^n\}$. We will show that for all $x, y \in \mathcal{N}$,

$$(x + \epsilon/2B_2^n) \cap (y + \epsilon/2B_2^n) = \emptyset.$$

Construct \mathcal{N} by picking a point $x_1 \in S^{n-1}$, x_2 so that $|x_1 - x_2| > \epsilon$, keep choosing points until there isn't any more empty space. Once we stop, there are no more points in S^{n-1} such that its epsilon distance away from all points in \mathcal{N} which means \mathcal{N} is an epsilon net. Then

$$\bigcup_{x \in \mathcal{N}} (x + \epsilon/2B_2^n) \subset (1 + \epsilon/2)B_2^n,$$

so

$$\begin{aligned} \left| \bigcup_{x \in \mathcal{N}} (x + \epsilon/2B_2^n) \right| &< |(1 + \epsilon/2)B_2^n| \implies |\mathcal{N}| \cdot |\epsilon/2B_2^n| < |1 + \epsilon/2B_2^n| \\ &\implies |\mathcal{N}|(\epsilon/2)^n < (1 + \epsilon/2)^n \implies |\mathcal{N}| < (2/\epsilon + 1)^n < (3/\epsilon)^n. \end{aligned}$$

□

Proposition 6.7.12 (Paley-Zygmund Inequality). If Z is a nonnegative random variable with $\mathbb{E}Z = 1$, $\mathbb{E}Z^2 < K$, then for $\lambda \in (0, 1)$, there exists $p > 0$ such that $\mathbb{P}(Z > \lambda) > p$.

Proof.

$$\begin{aligned} 1 = \mathbb{E}Z &= \mathbb{E}Z\mathbf{1}_{\{Z \in [0, \lambda]\}} + \mathbb{E}Z\mathbf{1}_{\{Z \in (\lambda, \infty)\}} \leq \lambda + \sqrt{\mathbb{E}Z^2 \mathbb{E}(\mathbf{1}_{\{Z \in (\lambda, \infty)\}})} \leq \lambda + \sqrt{K\mathbb{P}(Z > \lambda)} \\ &\iff \frac{(1 - \lambda)^2}{K} \leq \mathbb{P}(Z > \lambda), \end{aligned}$$

which proves the statement for $p = \frac{(1-\lambda)^2}{K}$.

□

6.7.5 Random Graphs

1. **Erdos-Renyi graph:** $\mathcal{G}(N, p)$ line connecting V_i, V_j if and only iff $A_{ij} = 1$. $\mathbb{P}(A_{ij} = 1) = p(n)$, some function of n . All A_{ij} are independent of each other besides the fact that A is symmetric. connected with probability p .
2. **Random d -regular graph model:** $\mathcal{G}_{n,d}$: set of d -regular graphs with n vertices.

These are used for statistical inference, particularly community detection.

$$|G_{nd}| = \Pr(G \text{ simple}) \cdot \frac{(nd - 1)!!}{(d!)^n}$$

Theorem 6.7.13. $\mathbb{P}(G \text{ is simple}) = e^{-(d^2 - 1)/4}$.

Remark 57. It doesn't go to 0 as $n \rightarrow \infty$.

1.

$$|G_{nd}| = (1 + o(1))e^{-(d^2 - 1)/2} \cdot \frac{(nd - 1)!!}{(d!)^n}$$

2. efficient way to sample a d -regular graph. Expected waiting time is $e^{(d^2 - 1)/4}$.
3. If you can probe property A is true for the configuration model with probability $1 - o(1)$, then the same thing is true for the uniform model.

$$o(1) = \mathbb{P}(A \text{ is not true}) \geq \mathbb{P}(\mathcal{G} \text{ is simple}, A \text{ is not true for } \mathcal{G})$$

$$= \mathbb{P}(A \text{ is not true} \mid \mathcal{G} \text{ is simple})\mathbb{P}(\mathcal{G} \text{ simple})$$

$$\approx \mathbb{P}_{\text{uniform}}(A \text{ is not true})e^{-(d^2 - 1)/4}$$

$$\mathbb{P}_{\text{uniform}}(A \text{ is not true}) = o(1) \text{ as } n \rightarrow \infty.$$

6.8 Distance Correlation

Definition 6.49 ($\|\cdot\|_w$ -norm for complex functions; Definition 1 in Székely et al. [2007]). For complex functions γ defined on $\mathbb{R}^p \times \mathbb{R}^q$, the $\|\cdot\|_w$ -norm in the weighted L_2 space of functions on \mathbb{R}^{p+q} is defined by

$$\|\gamma(t, s)\|_w^2 := \int_{\mathbb{R}^{p+q}} |\gamma(t, s)|^2 w(t, s) dt ds,$$

where $w(t, s)$ is an arbitrary positive weight function for which the integral above exists.

The distance covariance is the $\|\cdot\|_w$ distance between the characteristic functions of two random variables with a suitably chosen weight function. That is, the distance covariance between X and Y is

$$\begin{aligned}\mathcal{V}^2(X, Y; w) &:= \|\phi_{X,Y}(t, s) - \phi_X(t)\phi_Y(s)\|_w^2 \\ &= \int_{\mathbb{R}^{p+q}} |\phi_{X,Y}(t, s) - \phi_X(t)\phi_Y(s)|^2 w(t, s) dt ds,\end{aligned}$$

where $\phi_X(t)$ is the characteristic function of X , $\phi_Y(s)$ is the characteristic function of Y , and $\phi_{X,Y}(t, s)$ is the joint characteristic function of X and Y (see Definition 6.38). We will also define a kind of distance variance

$$\mathcal{V}^2(X; w) = \int_{\mathbb{R}^{p+q}} |\phi_{X,Y}(t, s) - \phi_X(t)\phi_Y(s)|^2 w(t, s) dt ds.$$

This distance will be 0 if and only if X and Y are independent. Then we will construct distance correlation from distance covariance in an analogous way to how Pearson correlation is defined from covariance.

We want to choose $w(t, s)$ in a way so that the distance correlation is scale invariant (i.e., doesn't change if the units of the variables change). We will also want the distance correlation to be positive for dependent variables. Finally, we will also want $w(t, s)$ not to be integrable over \mathbb{R}^{p+q} . The reason why is that if $w(t, s)$ is integrable and both X and Y have finite variance, one can show using Taylor expansions of the underlying characteristic functions that

$$\lim_{\epsilon \rightarrow 0} \frac{\mathcal{V}^2(\epsilon X, \epsilon Y; w)}{\sqrt{\mathcal{V}^2(\epsilon X; w)\mathcal{V}^2(\epsilon Y; w)}} = \rho^2(X, Y),$$

where $\rho^2(X, Y)$ is the square of the Pearson correlation between X and Y (the coefficient of determination). Of course, ρ may equal 0 even if X and Y are dependent. So if w is integrable, the distance correlation can be arbitrarily close to zero even if X and Y are dependent. It turns out the below choice of w does what we want and yields relatively simple results.

Definition 6.50 (Distance Covariance; Definition 2 in Székely et al. [2007]). Let $\mathbf{X} \in \mathbb{R}^p$ and $\mathbf{Y} \in \mathbb{R}^q$ be random vectors. The **distance covariance** $\mathcal{V}(X, Y)$ between \mathbf{X} and \mathbf{Y} is defined by

$$\begin{aligned}\mathcal{V}^2(X, Y) &:= \|\phi_{\mathbf{X}, \mathbf{Y}}(\mathbf{t}, \mathbf{s}) - \phi_{\mathbf{X}}(\mathbf{t})\phi_{\mathbf{Y}}(\mathbf{s})\|_w^2 \\ &= \int_{\mathbb{R}^{p+q}} \|\phi_{\mathbf{X}, \mathbf{Y}}(\mathbf{t}, \mathbf{s}) - \phi_{\mathbf{X}}(\mathbf{t})\phi_{\mathbf{Y}}(\mathbf{s})\|^2 w(\mathbf{t}, \mathbf{s}) d\mathbf{t} d\mathbf{s}\end{aligned}$$

(that is, $\mathcal{V}(X, Y)$ is the square root of this quantity) where

$$w(\mathbf{t}, \mathbf{s}) := \frac{1}{c_p c_q |t|_p^{1+p} |s|_q^{1+q}}$$

where

$$c_d := \frac{\pi^{(1+d)/2}}{\Gamma((1+d)/2)}.$$

Distance variance is defined as the square root of

$$\mathcal{V}^2(X) = \int_{\mathbb{R}^{p+q}} |\phi_{X,Y}(t,s) - \phi_X(t)\phi_Y(s)|^2 w(t,s) dt ds$$

using the same choice of w .

Definition 6.51 (Distance correlation; Definition 3 in Székely et al. [2007]). The **distance correlation** (dCor) between random vectors \mathbf{X} and \mathbf{Y} with finite first moments is the nonnegative number $\mathcal{R}(\mathbf{X}, \mathbf{Y})$ defined by

$$\mathcal{R}^2(\mathbf{X}, \mathbf{Y}) = \begin{cases} \frac{\mathcal{V}^2(\mathbf{X}, \mathbf{Y})}{\sqrt{\mathcal{V}^2(\mathbf{X})\mathcal{V}^2(\mathbf{Y})}} & \mathcal{V}^2(\mathbf{X})\mathcal{V}^2(\mathbf{Y}) > 0, \\ 0, & \mathcal{V}^2(\mathbf{X})\mathcal{V}^2(\mathbf{Y}) = 0. \end{cases}$$

In Remark 3, Székely et al. [2007] show that if $\mathbb{E}\|\mathbf{X}\|_p^2 < \infty$ and $\mathbb{E}\|\mathbf{Y}\|_q^2 < \infty$,

$$\mathcal{V}^2(\mathbf{X}, \mathbf{Y}) = S_1 + S_2 - 2S_3,$$

where

$$\begin{aligned} S_1 &:= \mathbb{E} [\|\mathbf{X}_1 - \mathbf{X}_2\|_p \|\mathbf{Y}_1 - \mathbf{Y}_2\|_q], \\ S_2 &:= \mathbb{E} \|\mathbf{X}_1 - \mathbf{X}_2\|_p \mathbb{E} \|\mathbf{Y}_1 - \mathbf{Y}_2\|_q, \quad \text{and} \\ S_3 &:= \mathbb{E} (\|\mathbf{X}_1 - \mathbf{X}_2\|_p \|\mathbf{Y}_1 - \mathbf{Y}_3\|_q), \end{aligned}$$

where \mathbf{X}_1 and \mathbf{X}_2 are two independent draws of \mathbf{X} (and likewise for \mathbf{Y}). Given a random sample $\{(\mathbf{X}_1, \mathbf{Y}_1), \dots, (\mathbf{X}_n, \mathbf{Y}_n)\}$, they suggest the moment estimator

$$\hat{\mathcal{V}}^2(\mathbf{X}, \mathbf{Y}) = \hat{S}_1 + \hat{S}_2 - 2\hat{S}_3$$

where

$$\begin{aligned} \hat{S}_1 &:= \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n \|\mathbf{X}_i - \mathbf{X}_j\|_p \|\mathbf{Y}_i - \mathbf{Y}_j\|_q, \\ \hat{S}_2 &:= \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n \|\mathbf{X}_i - \mathbf{X}_j\|_p \cdot \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n \|\mathbf{Y}_i - \mathbf{Y}_j\|_q, \quad \text{and} \\ \hat{S}_3 &:= \frac{1}{n^3} \sum_{i=1}^n \sum_{j=1}^n \sum_{\ell=1}^n \|\mathbf{X}_i - \mathbf{X}_j\|_p \|\mathbf{Y}_i - \mathbf{Y}_{\ell}\|_q. \end{aligned}$$

Li et al. [2012] propose using distance correlation for screening, noting “it allows for arbitrary regression relationship of \mathbf{y} onto \mathbf{X} , regardless of whether it is linear or nonlinear. The distance correlation also permits univariate and multivariate responses, regardless of whether it is continuous, discrete, or categorical. In addition, it allows for groupwise predictors. Thus, this distance correlation-based screening procedure is completely model-free.”

Chapter 7

Stochastic Processes

These notes are based on my notes from ISE 620 at USC taught by Sheldon Ross (along with the textbooks *Stochastic Processes* [Ross, 2008] and *Introduction to Probability Models* [Ross, 2014] by Sheldon Ross) *Time Series and Panel Data Econometrics* (1st edition) by M. Hashem Pesaran [Pesaran, 2015] and coursework for Economics 613: Economic and Financial Time Series I at USC, as well as notes from *Probability and Random Processes* by Grimmett and Stirzaker [Grimmett and Stirzaker, 2001].

7.1 Preliminaries

Definition 7.1. A **stochastic process** is a collection of random variables $X(t), t \geq 0$ (in the continuous case) or X_1, X_2, \dots in the discrete case such that ...

Definition 7.2. A stochastic process $\{N(t), t \geq 0\}$ is said to be a **counting process** if $N(t)$ represents the total number of events that have occurred up to time t . Hence, a counting process $N(t)$ must satisfy

- (i) $N(t) \geq 0$
- (ii) $N(t)$ is integer-valued.
- (iii) If $s < t$ then $N(s) \leq N(t)$.
- (iv) For $s < t$, $N(s) - N(t)$ equals the number of events that have occurred in the interval $(s, t]$.

Definition 7.3. We say a counting process $\{N(t), t \geq 0\}$ has **independent increments** if the numbers of events that occur in disjoint time intervals are independent; that is, for all $t_0 < t_1 < \dots < t_n$, $N(t_1) - N(t_0), \dots, N(t_n) - N(t_{n-1})$ are independent.

Definition 7.4. A counting process $\{N(t), t \geq 0\}$ has **stationary** increments if the distribution of the number of events that occur in any interval of time depends only on the length of the time interval. That is, if $N(t+s) - N(s)$ has a distribution that does not depend on s (is the same for all s ; only depends on t).

7.2 Poisson Processes

Definition 7.5 (Poisson Process, Grimmett and Stirzaker definition). A **Poisson process with intensity λ** is a process $N = \{N(t) : t \geq 0\}$ taking values in $S = \{0, 1, 2, \dots\}$ such that

(a) $N(0) = 0$; if $s < t$ then $N(s) \leq N(t)$.

(b) $\Pr(N(t+h) = n+m \mid N(t) = n) = \begin{cases} \lambda h + o(h) & \text{if } m = 1, \\ o(h) & \text{if } m > 1; \\ 1 - \lambda h + o(h) & \text{if } m = 0 \end{cases}$

(c) If $s < t$, the number $N(t) - N(s)$ of emissions in the interval $(s, t]$ is independent of the times of emissions during $[0, s]$.

Remark 58. λ can be interpreted as the average or long-run frequency of the Poisson process.

Definition 7.6 (Poisson Process, Ross definition, 2.1.2 in Stochastic Processes). The counting process $\{N(t) : t \geq 0\}$ is said to be a **Poisson process with rate λ** if

(a) $N(0) = 0$

(b) $\{N(t) : t \geq 0\}$ has independent increments

(c) $\Pr(N(t+h) - N(t) = 1) = \lambda h + o(h)$

(d) $\Pr(N(t+h) - N(t) \geq 2) = o(h)$

Remark 59. Note that a Poisson process has stationary increments.

Lemma 7.2.1 (ISE 620 Ross Lemma 1). Let $N(t)$ be a Poisson process. For a fixed time s , let $N_s(t) = N(s+t) - N(s)$ be the difference between two Poisson processes. Then $\{N_s(t), t \geq 0\}$ is a Poisson process.

Proof. We verify the conditions in Definition 7.6.

(a) $N_s(0) = N(s) - N(s) = 0$, QED.

(b) $\{N_s(t) : t \geq 0\}$ has independent increments, yes.

(c) $\Pr(N_s(t+h) - N_s(t) = 1) = \Pr(N(s+t+h) - N_s(s+t) = 1) = \lambda h + o(h)$, QED.

(d) $\Pr(N_s(t+h) - N_s(t) \geq 2) = (\Pr(N(s+t+h) - N_s(s+t) \geq 2) = o(h)$, QED.

□

Lemma 7.2.2 (ISE 620 Ross Lemma 2). Let $N(t)$ be a Poisson process. Then $P_0(t) = \Pr(N(t) = 0) = e^{-\lambda t}$.

Proof.

$$P_0(t+h) = \Pr(N(t+h) = 0) = \Pr(N(t+h) = 0, N(t) = 0)$$

$$= \Pr(N(t) = 0) \Pr(N(t+h) - N(t) = 0) \text{ (by independent increments)}$$

Using conditions (iii) and (iv) of Definition 7.6,

$$P_0(t+h) = P_0(t)(1 - \lambda h - o(h)) = P_0(t)(1 - \lambda h) + o(h)$$

$$\iff \frac{P_0(t+h) - P_0(t)}{h} = \frac{-\lambda h P_0(t)}{h} + \frac{o(h)}{h}$$

Taking the limit as $h \rightarrow 0$, we have

$$P'_0(t) = -\lambda P_0(t) \iff \frac{P'_0(t)}{P_0(t)} = -\lambda \iff \log(P_0(t)) = -\lambda t + C$$

$$\iff P_0(t) = \lambda e^{-\lambda t} \iff P_0(0) = 1$$

□

Theorem 7.2.3. [Grimmett and Stirzaker theorem 6.8.2] Let $N(t)$ be a Poisson process with intensity λ . Then $N(t)$ has the Poisson distribution with parameter λt ; that is,

$$\Pr(N(t) = j) = \frac{(\lambda t)^j \exp(-\lambda t)}{j!}, \quad j = 0, 1, 2, \dots$$

Proof. See Grimmett and Stirzaker section 6.8.2, page 247. Ross proof:

$$\Pr(N(t) = n) = \frac{1}{\Pr(X_{n+1} = t-s \mid X_n = s)} \int_0^t \Pr(N(t) = n \mid S_n = s) \lambda e^{-\lambda s} \frac{(\lambda s)^{n-1}}{(n-1)!} ds = 1$$

$$= \Pr(X_{n+1} > t-s) = e^{-\lambda(t-s)}$$

$$\Pr(N(t) = n) = \int_0^t e^{-\lambda(t-s)} \lambda e^{-\lambda s} \frac{(\lambda s)^{n-1}}{(n-1)!} ds$$

$$= \frac{e^{-\lambda t} \lambda^n}{(n-1)!} \int_0^t s^{n-1} ds = e^{-\lambda t} \frac{(\lambda t)^n}{n!}$$

□

Corollary 7.2.3.1. $N(t+s) - N(s) \sim \text{Poisson}(\lambda t)$

Proof. By Lemma 7.2.1, ?? is a Poisson process. . .

□

Definition 7.7 (Poisson Process, Ross definition, 2.1.1 in Stochastic Processes). The counting process $\{N(t) : t \geq 0\}$ is said to be a **Poisson process with rate λ** if

- (a) $N(0) = 0$
- (b) $\{N(t) : t \geq 0\}$ has independent increments
- (c) The number of events in any interval of length t is Poisson distributed with mean λt . That is, for all $s, t \geq 0$,

$$\Pr(N(t+s) - N(s) = n) = e^{-\lambda t} \frac{(\lambda t)^n}{n!}, \quad n = 0, 1, \dots$$

Remark 60. Note that it follows from condition (iii) in Definition 7.7 that a Poisson process has stationary increments and also that $\mathbb{E}(N(t)) = \lambda t$.

Definition 7.8 (Ross Stochastic Processes definition, Section 2.2). Let X_n denote the time between the $n-1$ st and n th event in a Poisson process. The sequence $\{X_n, n \geq 1\}$ is called the **sequence of interarrival times**.

Definition 7.9 (Grimmett and Stirzaker definition). Let $N(t)$ be a Poisson process with intensity λ . Let T_0, T_1, \dots be given by

$$T_0 = 0, T_n = \inf\{t : N(t) = n\} \tag{7.1}$$

so that T_n is the time of the n th arrival. The **interarrival times** are the random variables X_1, X_2, \dots given by

$$X_n = T_n - T_{n-1}. \tag{7.2}$$

Remark 61. From knowledge of N , we can find the values of X_1, X_2, \dots by (7.1) and (7.2). Conversely, we can construct N from knowledge of the X_i by

$$T_n = \sum_{i=1}^n X_i, \quad N(t) = \max\{n : T_n \leq t\} \tag{7.3}$$

Theorem 7.2.4. (Grimmett and Stirzaker theorem 6.8.10.) Let $N(t)$ be a Poisson process with intensity λ . Let T_0, T_1, \dots be given by (7.1) and let X_n be given by (7.2). Then the random variables $\{X_n\}$ are independent, each having an exponential distribution with parameter λ .

Proof. See Grimmett and Stirzaker section 6.8.2, page 249. □

Corollary 7.2.4.1. Let $N(t)$ be a Poisson process with intensity λ . Let T_0, T_1, \dots be given by (7.1). Then $T_n \sim \text{Gamma}(n, \lambda^{-1})$.

Proof. By (7.3), $T_n = \sum_{i=1}^n X_i$. $X_i \sim \text{Exponential}(\lambda)$ by Theorem 7.2.4, which means $X_i \sim \text{Gamma}(1, \lambda^{-1})$. Then by Proposition 6.3.22, $T_n \sim \text{Gamma}(n, \lambda^{-1})$. □

Lemma 7.2.5 (ISE 620 Ross in-class Lemma 3, Proposition 2.2.1 in Stochastic Processes). Let $N(t)$ be a Poisson process. Let X_1, X_2, \dots be the interarrival times. Then X_1, X_2, \dots are independently and identically distributed as $\text{Exponential}(\lambda)$. Since the sum of exponential distributions is Gamma, we have $S_n = \sum_{i=1}^n X_i \sim \text{Gamma}(n, 1/\lambda)$.

Proof. See proof on page 64 (section 2.2) of *Stochastic Processes*. Follows from Lemmas 7.2.1 and 7.2.2. \square

Remark 62. If the arrival times are IID exponential, then the process is Poisson. (Will come later in notes.)

Remark 63.

$$X_1 < t \iff N(t) = 1$$

$$\Pr(X_2 > t \mid X_a = s) = \Pr(N(S+t) - N(s) = 0 \mid X_1 = s) = \Pr(N(s+t) - N(s) = 0) = \Pr(N_s(t) = 0) = e^{-\lambda t}$$

Theorem 7.2.6. Suppose events occur in a Poisson process with parameter lambda, $\text{PP}(\lambda)$. Let $N(t)$ be the number of events that occur by time t . Suppose each event is independent of all that has previously occurred; that is, each event is type $i = 1, \dots, r$ with probability p_i , and $\sum_{i=1}^r p_i = 1$. Let $N_i(t)$ be the number of type i events that occur by time t . $\{N_i(t)\} \sim \text{PP}(\lambda p_i)$. Moreover, these processes are independent for different i .

Proof. Verify axioms of Poisson process:

1. $N_i(0) = 0$
2. independent increments? Yes, the number of type i events in each interval is totally independent of what happened in previous intervals.
3. $\Pr(N_i(t+h) - N_i(t) = 1) = \Pr(N(t+h) - N(t) = 1, \text{ event is type } i + \dots)$
probability of two or more events (and then one of them is type i) is $o(h)$.

$$= \lambda h p_i + o(h)$$

4. $\Pr(N_i(t+h) - N_i(t) \geq 2) \leq \Pr(N(t_h) - N(t) \geq 2) = o(h)$

Therefore $N_i(t)$ is a Poisson process with rate λp_i . We could have also proven this by looking at the interarrival times and showing that they are i.i.d. exponential. \square

Proof: Alternative, stronger statement.

$$\Pr(N_1(t) = n_1, N_2(t) = n_2, \dots, N_r(t) = n_r)$$

we want to show that these random variables are independent. Let $n = \sum_{i=1}^r n_i$. Then

$$= \Pr(N_1(t) = n_1, \dots, N_r(t) = n_r \mid N(t) = n) \Pr(N(t) = n)$$

But this is a Multinomial distribution. So we have

$$\begin{aligned} &= \frac{n!}{n_1! \cdots n_r!} \prod_{i=1}^r p_i^{n_i} \cdot e^{-\lambda t} \frac{(\lambda t)^{\sum_i n_i}}{n!} \\ &\quad \prod_{i=1}^r e^{-\lambda t p_i} \frac{(\lambda t p_i)^{n_i}}{n_i!} \end{aligned}$$

And these are just Poisson probabilities.

Then using Proposition 7.2.7, we have independence (???) □

Proposition 7.2.7 (offhand claim Ross made). If $\Pr(X = n, Y = m) = g(n)h(m)$ (that is, if probability can be broken into products of functions) then variables are independent.

Proof.

$$\Pr(X = n) = \sum_m g(n)h(m) = g(n)C_h$$

$$\Pr(Y = m) = h(m) \sum_n g(n) = h(m)C_g$$

$$1 = \sum_n \sum_m g(n)h(m) = C_g C_h$$

So this is true as long as $C_g C_h = 1$ which it does. □

Example 7.1. Suppose in particular $\lambda = 10$ so we expect 10 people to arrive every hour, either men or women. What is the expected number of women to arrive given that 7 men arrived? (5—women and men's arrivals are independent.)

Example 7.2 (Coupon collecting problem, see also probability notes.). r types of coupons collected with probability p_1, \dots, p_r . Let N be the number of coupons you collect until you have a complete set. What is $\mathbb{E}(N)$?

Solution. Let $m(\mathcal{S})$ be the mean number of draws required to obtain at least one coupon of type i for each $i \in \mathcal{S}$. Note that $m(\emptyset) = 0$, and

$$m(\mathcal{S}) = 1 + \sum_{i \in \mathcal{S}} p_i m(\mathcal{S} \setminus i) + \sum_{i \notin \mathcal{S}} p_i m(\mathcal{S})$$

$$\implies m(\mathcal{S}) = \frac{1 + \sum_{i \in \mathcal{S}} p_i m(\mathcal{S} \setminus i)}{\sum_{i \notin \mathcal{S}} p_i}$$

But unless r is small this is going to be hard to compute, so this doesn't really work.

Solution. New idea: Let N_i be the number of draws required to obtain types $1, \dots, i$. We want N_r . Note that $\mathbb{E}(N_1) = 1/p_1$. We have $N_{i+1} = N_i + A$ where A is the additional time required.

$$\mathbb{E}(N_{i+1}) = \mathbb{E}(N_i) + \mathbb{E}(A)$$

if there is a type $i+1$ in the original group, then $\mathbb{E}(A) = 0$. If not, note that

$$\begin{aligned}\mathbb{E}(A) &= \begin{cases} 1/(p_i + 1) & \Pr(\{\text{a type } i+1 \text{ coupon has not already been collected}\}) \\ 0 & \Pr(\{\text{a type } i+1 \text{ coupon has already been collected}\}) \end{cases} \\ \implies \mathbb{E}(A) &= \frac{1}{p_i + 1} \cdot \Pr(\{\text{a type } i+1 \text{ coupon has not already been collected}\}) \\ \implies \mathbb{E}(A) &= \frac{1}{p_i + 1} \cdot \Pr(\{\text{type } i+1 \text{ is the last of types } 1, \dots, i+1 \text{ to be collected}\}) \\ &= \frac{1}{p_i + 1} \cdot \frac{\sum_{j=1}^{i+1} p_j}{p_{i+1}}\end{aligned}$$

this didn't work either.

Solution.

Let N_i be the number to get type i . So $N_i \sim \text{Geometric}(p_i)$. Then $N = \max\{N_i\}$. So

$$\Pr(N \leq k) = \Pr(N_1 \leq k, \dots, N_r \leq k)$$

but you can't multiply out probabilities because N_i is not independent.

7.2.1 Poissonization Trick

Suppose we collect coupons at times distributed according to a Poisson process with rate $\lambda = 1$. Let event type i be the event of collecting a type i coupon. Let T_i be the time until collecting a type i coupon. Note that by Theorem 7.2.6 and Lemma 7.2.5, $T_i \sim \text{Exponential}(\lambda \cdot p_i) = \text{Exponential}(p_i)$. Then the time to collect at least one of every type is $T = \max_i\{T_i\}$. And by Theorem 7.2.6, the T_i are all independent. Return to the coupon collecting problem:

Solution. Recall the layer cake formulation for expected value:

$$\mathbb{E}(T) = \int_0^\infty \Pr(T > t) dt$$

We have (using independence of the T_i)

$$\Pr(T > t) = 1 - \Pr(T \leq t) = 1 - \Pr(T_1 \leq t, \dots, T_r \leq t) = 1 - \prod_{i=1}^r \Pr(T_i \leq t) = 1 - \prod_{i=1}^r (1 - e^{-p_i t})$$

$$\implies \boxed{\mathbb{E}(T) = \int_0^\infty \left(1 - \prod_{i=1}^r (1 - e^{-p_i t}) \right) dt}$$

$$= \sum_i \frac{1}{p_i} - \sum_{i < j} \frac{1}{p_i + p_j} + \sum_{i,j,k} \frac{1}{[p_i + p_j + p_k]} - \dots + \frac{(-1)^{r+1}}{p_1 + \dots + p_r}$$

But we want $\mathbb{E}(N)$. Recall that T is the time of the N th event. So

$$T = \sum_{i=1}^N X_i$$

where X_1, X_2, \dots are the interarrival times of a Poisson process with rate $\lambda = 1$. But N is independent of X_1, X_2, \dots (the type of coupons you get has nothing to do with the time between coupons). So T is a compound random variable. Therefore

$$\mathbb{E}(T) = \mathbb{E}(N)\mathbb{E}(X) = \mathbb{E}(N) \cdot \frac{1}{\lambda} = \mathbb{E}(N)$$

Therefore we have $\boxed{\mathbb{E}(N) = \int_0^\infty \left(1 - \prod_{i=1}^r (1 - e^{-p_i t}) \right) dt}$.

Example 7.3. A type is a *singleton* if after you get a complete set, you have only one object of that type. Suppose we collect coupons until we have at least one of every type, and that all coupons are equally likely to be collected on each draw. What is the expected number of singletons when you stop?

Solution. Let X be the number of singletons when you stop. Let I_j be an indicator variable for type j being a singleton. Then

$$\mathbb{E}(X) = \mathbb{E}\left[\sum_{j=1}^r I_j\right] = \sum_{j=1}^r \mathbb{E}(I_j) = \sum_{j=1}^r \Pr(\{j \text{ is a singleton}\})$$

⋮

$$= \frac{1}{r} \sum_{i=1}^r \frac{1}{r-i+1}$$

⋮

Let T_i be the time you get your first type i coupon. The probability we want is that at the time when you have at least one of every type except j , you have either 0 or 1 coupons of type j . That is, if $S_2^{(j)}$ is the time the second card of type j is selected, we must have $S_2^{(j)} > \max_{i \neq j} \{T_i\}$. So we seek $\Pr(S_2^{(j)} > \max_{i \neq j} \{T_i\})$. Note that $S_2^{(j)} \sim \text{Gamma}(2, p_j)$ by Corollary 7.2.4.1, so

$$f_{S_2^{(j)}}(s) = \frac{1}{p_j^2} s^{2-1} e^{-p_j s} = p_j e^{-p_j s} p_j \cdot s.$$

So we have

$$\begin{aligned} \Pr(I_j = 1) &= \Pr(S_2^{(j)} > \max_{i \neq j} \{T_i\}) = \int_0^\infty \Pr(\max_{i \neq j} \{T_i\} < S_2^{(j)} \mid S_2^{(j)} = s) \cdot f_{S_2^{(j)}}(s) ds \\ &= \int_0^\infty \prod_{i \neq j} (1 - e^{-p_i s}) \cdot p_j e^{-p_j s} p_j \cdot s \cdot ds \end{aligned}$$

which yields

$$\boxed{\mathbb{E}(X) = \sum_{j=1}^r p_j^2 \int_0^\infty e^{-p_j s} \cdot s \cdot \prod_{i \neq j} (1 - e^{-p_i s}) \cdot ds}$$

Remark 64. Per Example 7.4, suppose people arrive at a bus stop according to a Poisson process with rate λ . A bus arrives at (fixed) time T . Let W be the sum of the waiting times for everyone at the bus stop. Let S_j be the arrival time of the j th person. (Note that if X_i are the interarrival times then $S_j = \sum_{i=1}^j X_i$.) The number of people who get on the bus is $N(t)$, the Poisson counting process. So

$$W = \sum_{i=1}^{N(T)} (T - S_i) = N(T)T - \sum_{i=1}^{N(T)} S_i$$

Proposition 7.2.8. In a Poisson process, if we know that one event has occurred by time t , then the distribution of times of the event is uniform between 0 and t . That is,

$$S_1 < x \mid N(t) = 1 \sim U(0, t)$$

Proof.

$$\begin{aligned} \Pr(S_1 < x \mid N(t) = 1) &= \frac{\Pr(S_1 < x \cap N(t) = 1)}{\Pr(N(t) = 1)} = \frac{\Pr(N(x) = 1 \cap N(t) - N(x) = 0)}{\exp(-\lambda t) \lambda t} \\ &= \frac{\Pr(N(x) = 1) \Pr(N(t) - N(x) = 0)}{\exp(-\lambda t) \lambda t} = \frac{\lambda x e^{-\lambda x} \cdot e^{-\lambda(t-x)}}{\exp(-\lambda t) \lambda t} = \frac{x}{t} \end{aligned}$$

which is the cdf for a random variable distributed as $U(0, t)$.

□

Remark 65. If $X_i \sim U(0, t)$, then $f(x) = 1/t$, $0 < x < t$, so per Proposition 10.1.2,

$$f_{X_{(1)}, \dots, X_{(n)}}(x_1, \dots, x_n) = \frac{n!}{t^n}, \quad 0 < x < t$$

Theorem 7.2.9. In a Poisson process, if we know that n events have occurred by time t ($N(t) = n$), then the set of event times $\{S_1, \dots, S_n\}$ are distributed as a set of n i.i.d. uniform random variables between 0 and t . That is, the unordered times are distributed uniformly on the interval.

More precisely: Given $N(t) = n$, S_1, \dots, S_n are distributed as order statistics of n i.i.d. $U(0, t)$ random variables.

Proof. We will examine the density function

$$f_{S_1, \dots, S_n, |N(t)=n}(t_1, \dots, t_n), \quad 0 < t_1 < \dots < t_n < t$$

Per the above remark, we want to show that this is $n!/t^n$. Note that by Bayes' Theorem

$$f_{S_1, \dots, S_n, |N(t)=n}(t_1, \dots, t_n) = \frac{f_{S_1, \dots, S_n}(t_1, \dots, t_n) \cdot \Pr(N(t) = n \mid S_1 = t_1, \dots, S_n = t_n)}{\Pr(N(t) = n)}. \quad (7.4)$$

Let X_1, X_2, \dots be the interarrival times. So the condition above is equivalent to $X_1 = t_1, X_2 = t_2 - t_1, \dots, X_n = t_n - t_{n-1}$. Recall that all the $\{X_i\}$ are independent. So we have

$$f_{S_1, \dots, S_n}(t_1, \dots, t_n) = f_{X_1, \dots, X_n}(t_1, t_2 - t_1, \dots, t_n - t_{n-1})$$

Also, we can interpret $\Pr(N(t) = n \mid S_1 = t_1, \dots, S_n = t_n)$ as the probability that there are 0 arrivals between times t_n and t ; that is,

$$\Pr(N(t) = n \mid S_1 = t_1, \dots, S_n = t_n) = e^{-\lambda(t-t_n)}$$

So we can write (7.4) as

$$\begin{aligned} f_{S_1, \dots, S_n, |N(t)=n}(t_1, \dots, t_n) &= \frac{f_{X_1, \dots, X_n}(t_2 - t_1, \dots, t_n - t_{n-1}) \cdot e^{-\lambda(t-t_n)}}{e^{-\lambda t}(\lambda t)^n/n!} \\ &= \frac{\lambda e^{-\lambda t_1} \lambda e^{-\lambda(t_2-t_1)} \dots \lambda e^{-\lambda(t_n-t_{n-1})} \cdot e^{-\lambda(t-t_n)}}{e^{-\lambda t}(\lambda t)^n/n!} \\ &= \frac{e^{-\lambda t} \lambda^n}{e^{-\lambda t}(\lambda t)^n/n!} = \frac{n!}{t^n} \end{aligned}$$

□

Example 7.4. Suppose people arrive at a bus stop according to a Poisson process with rate λ . A bus arrives at (fixed) time T . What is the expected value of W , the sum of the waiting times for everyone at the bus stop?

Solution. Let S_j be the arrival time of the j th person. (Note that if X_i are the interarrival times then $S_j = \sum_{i=1}^j X_i$.) The number of people who get on the bus is $N(t)$, the Poisson counting process. So

$$W = \sum_{j=1}^{N(T)} (T - S_j) = N(T)T - \sum_{j=1}^{N(T)} S_j$$

$$\mathbb{E}(W) = \mathbb{E}(N(T)T) - \mathbb{E}\left(\sum_{j=1}^{N(T)} S_j\right) = \lambda T^2 - \mathbb{E}\left(\sum_{j=1}^{N(T)} S_j\right)$$

Note that by Theorem 7.2.9, if $\{U_i\}$ are i.i.d. uniform random variables on $[0, t]$,

$$\mathbb{E}\left(\sum_{j=1}^{N(T)} S_j \mid N(T) = n\right) = \mathbb{E}\left(\sum_{j=1}^n S_j \mid N(T) = n\right) = \mathbb{E}\left(\sum_{j=1}^n U_i\right);$$

that is, if we know that n arrivals have occurred by time T , then the (unordered) arrival times are distributed uniformly on $[0, T]$. But

$$\mathbb{E}\left(\sum_{j=1}^n U_i\right) = \sum_{j=1}^n \mathbb{E}U_i = \frac{nT}{2}$$

Also note that because the U_i is independent from $N(T)$ (the arrival time of the j th person has nothing to do with how many people arrive by time T), $\sum_{j=1}^{N(T)} S_j$ is a compound random variable, which means

$$\mathbb{E}\left(\sum_{j=1}^{N(T)} S_j\right) = \mathbb{E}\left[\mathbb{E}\left(\sum_{j=1}^{N(T)} S_j \mid N(T) = n\right)\right] = \mathbb{E}\left(\frac{N(T)T}{2}\right) = \boxed{\frac{\lambda T^2}{2}}$$

⋮

Note that the sum of the ordered values is equal to the sum of the unordered values, so we have

$$\mathbb{E}\left(\sum_{i=1}^n X_{(i)}\right) = \mathbb{E}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \mathbb{E}(X_i) = n\mu$$

Example 7.5. Another thing: Let I_j be an indicator variable for the event $X_{(j)} < t$. We are interested in the distribution of $\sum_{j=1}^n I_j$.

Solution. Note that the I_j is not independent because if $I_1 = 0$ (so the smallest one is greater than t) then it must be the case that $I_2 = 0$ too. Also note that the sum of the ordered values less than t is the

same as the sum of the unordered values less than t . So this is distributed as binomial with parameters n and $p = F(t)$.

Example 7.6. Suppose that shocks occur according to a Poisson process with rate λ . Let D_i be the damage caused by shock i , where $\{D_i\}$ are i.i.d. and independent of $\{N(t)\}$. The damages dissipate at an exponential rate α ; that is, damage of value d has value de^{-as} after a time s . Damages are cumulative. What is the total damage by time t ?

Solution. We have

$$D(t) = \sum_{i=1}^{N(t)} D_i e^{-a(t-S_i)}$$

so

$$\begin{aligned} \mathbb{E}(D(t) \mid N(t) = n) &= \mathbb{E}\left(\sum_{i=1}^{N(t)} D_i e^{-a(t-S_i)} \mid N(t) = n\right) = \sum_{i=1}^{N(t)} \mathbb{E}(D_i e^{-a(t-S_i)} \mid N(t) = n) \\ &= \sum_{i=1}^{N(t)} \mathbb{E}(D_i) \mathbb{E}(e^{-a(t-S_i)} \mid N(t) = n) = \mathbb{E}(D_i) e^{-at} \sum_{i=1}^n \mathbb{E}(e^{aS_i} \mid N(t) = n) \end{aligned}$$

Let $\{U_i\}$ be i.i.d. random variables on $[0, t]$. Then by Theorem 7.2.9, we can write this as

$$\begin{aligned} &= \mathbb{E}(D_i) e^{-at} \sum_{i=1}^n \mathbb{E}(e^{aU_i} \mid N(t) = n) = \mathbb{E}(D_i) e^{-at} \cdot n \int_0^t \frac{e^{ax}}{t} dx = \mathbb{E}(D_i) e^{-at} \cdot \frac{n}{at} (e^{at} - 1) \\ &= \mathbb{E}(D_i) \cdot \frac{n}{at} (1 - e^{-at}) \end{aligned}$$

So finally we have

$$\mathbb{E}(D(t)) = \mathbb{E}[\mathbb{E}(D(t) \mid N(t) = n)] = \mathbb{E}\left[\mathbb{E}(D_i) \cdot \frac{N(t)}{at} (1 - e^{-at})\right] = \mathbb{E}(D_i) \cdot \frac{\mathbb{E}(N(t))}{at} (1 - e^{-at}) = \boxed{\mathbb{E}(D_i) \cdot \frac{\lambda}{a} (1 - e^{-at})}$$

7.2.2 Time Sampling Poisson Processes

Proposition 7.2.10 (Time Sampling (Proposition 5.3 in Introduction to Probability Models)). Suppose we have events that happen as a Poisson process with rate λ . Each event is of type $1, \dots, r$ independently of what has come before. An event at time s is type i with probability $P_i(s)$. Let $N_i(t)$ be the number of type i events by time t . Then $N_1(t), \dots, N_r(t)$ are independent Poisson random variables with mean $\mathbb{E}[N_i(t)] = \lambda \int_0^t P_i(s) ds$.

Proof. I'm not sure this proof makes sense? Note that

$$\Pr(N_1(t) = n_1, \dots, N_r(t) = n_r) = \Pr(N_1(t) = n_1, \dots, N_r(t) = n_r \mid N(t) = \sum_{i=1}^r n_i) \cdot \Pr\left(N(t) = \sum_{i=1}^r n_i\right).$$

Given $N(t) = n$, the n event times are i.i.d. $U(0, t)$ by Theorem 7.2.9. Let P_i be the probability that a particular event is of type i given a time t and the fact that $N(t) = n$. Then

$$P_i = \int_0^t P_i(s) \cdot f_U(s) ds = \int_0^t \frac{P_i(s)}{t} ds$$

Since $\Pr\left(N(t) = \sum_{i=1}^r n_i\right) = e^{-\lambda t}$, we have

$$\Pr(N_1(t) = n_1, \dots, N_r(t) = n_r) = \frac{n!}{n_1! \cdots n_r!} P_1^{n_1} \cdots P_r^{n_r} e^{-\lambda t}$$

□

Remark 66. Notation for Queueing: in many cases we suppose times between successive arrivals are independent with a common distribution F . Then it is a renewal process. (If they are exponential, we get a Poisson process.) We have the following notation for a renewal process if k number of servers and G is the distribution of the service time:

$$F/G/k$$

If the distribution is exponential, we use M (for “memoryless” or “Markovian”). (E stands for Erlang, sum of i.i.d. exponentials).

Example 7.7. We have an $M/G/\infty$ queuing system. Arrivals are a Poisson process with rate λ . Fix t and let $X(t)$ be the number of people in the system at time t . Let $Y(t)$ be the number of people who have completed service at time t . Let the events be arrivals of customers, and call it a Type 1 event if the customer is still in the system at time t , and Type 2 if the customer completes service by time t (and Type 3 otherwise).

Suppose a customer arrives at time $s < t$. Then the customer is Type 1 if their service time exceeds $t - s$, which happens with probability $P_1(s) = \bar{G}(t - s)$. Similarly $P_2(s) = G(t - s)$. Let $N_1(t)$ be the number of Type I events that happen by time t and similarly for $N_2(t)$. Then by Proposition 7.2.10 we have

$$X(t) = N_1(t) \sim \text{Poisson}\left(\lambda \int_0^t \bar{G}(t-s) ds\right) = \text{Poisson}\left(\lambda \int_0^t \bar{G}(y) dy\right)$$

and

$$Y(t) = N_2(t) \sim \text{Poisson}\left(\lambda \int_0^t G(t-s) ds\right) = \text{Poisson}\left(\lambda \int_0^t G(y) dy\right)$$

which implies the independence of $X(t)$ and $Y(t)$.

7.2.3 Nonstationary Poisson Processes

Definition 7.10 (Nonstationary Poisson process.). The counting process $\{N(t), t \geq 0\}$ is said to be a **nonstationary Poisson process** (or **nonhomogeneous Poisson process**) with intensity function $\lambda(t), t \geq 0$ if

- (i) $N(0) = 0$.
- (ii) $\{N(t)\}$ has independent increments.
- (iii) $\Pr(N(t+h) - N(t) = 1) = \lambda(t)h + o(h)$.
- (iv) $\Pr(N(t+h) - N(t) \geq 2) = o(h)$.

Remark 67. Note the similarities to Definition 7.6.

Lemma 7.2.11. Let $\{N(t), t \geq 0\}$ be a nonstationary Poisson process. Let $N_s(t) = N(s+t) - N(s)$. Then $\{N_s(t), t \geq 0\}$ is a nonstationary Poisson Process with intensity $\lambda_s(t) = \lambda(s+t)$.

Remark 68. Note the similarity to Lemma 7.2.1.

Proof. Note the parts of Definition 7.10 above:

- (i) $N_s(0) = N(s) - N(s) = 0$.
- (ii) $\{N_s(t)\} = \{N(s+t) - N(s)\}$ has independent increments since $N(t)$ has independent increments.
- (iii) **Not sure about this part?** $\Pr(N_s(t+h) - N_s(t) = 1) = \Pr(N(s+t+h) - N(s) - [N(s+t) - N(s)] = 1) = \Pr(N(s+t+h) - N(s+t) = 1) = \lambda(t)h + o(h)$.
- (iv) $\Pr(N_s(t+h) - N_s(t) \geq 2) = o(h)$ by similar argument to (iii).

□

Definition 7.11. Let $m(t) = \int_0^t \lambda(s)ds$. Note that $m'(t) = \lambda(t)$. We call $m(t)$ the **mean value function**.

Remark 69. Note that the mean value function for $N_s(t)$ is

$$m_s(t) = \int_0^t \lambda_s(y)dy = \int_0^t \lambda(s+y)dy = \int_s^{s+t} \lambda(x)dx = m(t+s) - m(s).$$

Lemma 7.2.12. Let $N(t)$ be a nonstationary Poisson process. Then $\Pr(N(t) = 0) = e^{-m(t)}$ for any $t \geq 0$.

Remark 70. Note the similarity to Lemma 7.2.2.

Proof. Let $P(t) = \Pr(N(t) = 0)$. Then by independent increments

$$\Pr(N(t+h) = 0) = \Pr(N(t) = 0 \cap N(t+h) - N(t) = 0) = \Pr(N(t) = 0) \cdot \Pr(N(t+h) - N(t) = 0) \quad (7.5)$$

Let $P_0(t+h) = \Pr(N(t+h) = 0)$. Then using Definition 7.10 we have

$$\Pr(N(t+h) - N(t) = 0) = 1 - \Pr(N(t+h) - N(t) = 1) - \Pr(N(t+h) - N(t) \geq 2) = 1 - \lambda(t+h) + o(h)$$

so we can write (7.5) as

$$P_0(t+h) = P_0(t)[1 - \lambda(t+h) + o(h)]$$

$$\iff \frac{P_0(t+h) - P_0(t)}{h} = -\lambda(t+h) \frac{P_0(t)}{h} + \frac{o(h)}{h}$$

Taking the limit as $h \rightarrow 0$ yields

$$\begin{aligned} P'_0(t) = -\lambda(t)P_0(t) &\iff \int_0^s \frac{P'_0(t)}{P_0(t)} ds = \int_0^s -\lambda(t) dt \iff \log P_0(t) = \int_0^s -\lambda(t) dt \Big|_0^s \\ &\iff P_0(s) = e^{-m(s)} \end{aligned}$$

□

Remark 71 (Interarrival times). Let T_1 be the time of the first event. Note that $T_1 > t \iff N(t) = 0$. So

$$\bar{F}_{T_1}(t) = \Pr(T_1 > t) = \Pr(N(t) = 0) = e^{-m(t)}$$

which means

$$f_{T_1}(t) = \frac{d}{dt}(-\bar{F}_{T_1}(t)) = m'(t)e^{-m(t)} = \lambda(t)e^{-m(t)}.$$

Note that because $\lambda(t)$ is not constant, the interarrival times are not i.i.d.

Theorem 7.2.13. Let $N(t)$ be the counting process for a nonstationary Poisson process. Then $N(t) \sim \text{Poisson}(m(t))$.

Proof. We must show that

$$\Pr(N(t) = n) = e^{-m(t)} \frac{(m(t))^n}{n!}, \quad n = 0, 1, \dots$$

We have already shown that $\Pr(N(t) = 0) = e^{-m(t)} \frac{(m(t))^0}{0!} = e^{-m(t)}$ this is true when $n = 0$ in Lemma 7.2.12. We will show that this expression holds for $n = 1, 2, \dots$ by induction. Assume for a fixed n

$$\Pr(N(t) = n) = e^{-m(t)} \frac{(m(t))^n}{n!}.$$

We seek

$$\Pr(N(t) = n + 1) = \int_0^t \Pr(N(t) = n + 1 \mid T_1 = s) f_{T_1}(s) ds \quad (7.6)$$

Note that (using the property of independent increments)

$$\begin{aligned} \Pr(N(t) = n + 1 \mid T_1 = s) &= \Pr(N(t) - N(s) = n \mid T_1 = s) = \Pr(N(t) - N(s) = n) \\ &= \Pr(N_s(t - s) = n) \end{aligned}$$

By Lemma 7.2.11 above, $N_s(\cdot)$ is a Poisson process. So using that and the induction hypothesis, we have

$$\Pr(N(t) = n + 1 \mid T_1 = s) = e^{-m_s(t-s)} \frac{(m_s(t-s))^n}{n!} = e^{-[m(t)-m(s)]} \frac{[m(t)-m(s)]^n}{n!}.$$

Substituting this expression back in to (7.6) and using $f_{T_1}(t) = \lambda(t)e^{-m(t)}$, we have

$$\begin{aligned} \Pr(N(t) = n + 1) &= \int_0^t e^{-[m(t)-m(s)]} \frac{[m(t)-m(s)]^n}{n!} \cdot \lambda(s)e^{-m(s)} ds \\ &= \frac{e^{-m(t)}}{n!} \int_0^t [m(t)-m(s)]^n \cdot \lambda(s) ds \end{aligned}$$

Substituting $y = m(t) - m(s) \implies dy = -\lambda(s)ds$, we have

$$= \frac{e^{-m(t)}}{n!} \int_{m(t)}^0 -y^n dy = \frac{e^{-m(t)}}{n!} \int_0^{m(t)} y^n dy = e^{-m(t)} \frac{(m(t))^{n+1}}{(n+1)!}.$$

Therefore the result follows by induction. \square

Corollary 7.2.13.1. $N(t+s) - N(s) \sim \text{Poisson}(m(t+s) - m(s)) = \text{Poisson}(\int_s^{s+t} \lambda(y) dy)$.

Proof. Follows almost immediately from Theorem 7.2.13, since if $N(t) \sim \text{Poisson}(m(t))$,

\square

Proposition 7.2.14. Suppose events occur according to a Poisson process with rate λ . $\{N(t)\}$ is the counting process. An event at time s is type 1 with probability $p(s)$. Let $N_1(t)$ be the number of type 1 events by time t . Then $\{N_1(t)\}$ is a nonhomogeneous Poisson Process with intensity $\lambda(t) = \lambda p(t)$.

Remark 72. Note the similarity to Proposition 7.2.10.

Proof. Note the parts of Definition 7.10 above:

- (i) $N_1(0) = 0$: yes.
- (ii) $\{N_1(t)\}$ has independent increments: yes, follows pretty much immediately.
- (iii) Since the probability of exactly one event in the interval that happens to be type 1 is $\lambda h P_1(t)$, we have $\Pr(N_1(t+h) - N_1(t) = 1) = \lambda h P_1(t) = \lambda(t)h + o(h)$.
- (iv) $\Pr(N_1(t+h) - N_1(t) \geq 2) = o(h)$ by similar argument to (iii).

□

So now we have that $N_1(t) \sim \text{Poisson}(\int_0^t \lambda p_1(s)ds)$. So if every time an event happens it is of type i with a certain probability that varies over time, the counting process is for each is a nonstationary Poisson process, and all the processes are independent. (Another way to understand the time sampling result from before.)

What if the arrival process is nonstationary and the probability of a type i event is also time varying? $\lambda(t), p(t)$. It's a nonstationary PP with intensity $\lambda(t)p(t)$. (Probability in an interval is $\lambda(t)hp(t) + o(h)$.)

One more result about $M/G/\infty$ processes:

Theorem 7.2.15 (Example 5.25 in *Introduction to Probability Models*). The **departure process** from an $M/G/\infty$ queue is a nonstationary Poisson process with intensity function $\lambda(t) = \lambda G(t)$.

Proof. Let $D(t)$ be the number of departures by time t . Examine the axioms of Definition 7.10 above:

- (i) $D(0) = 0$: yes.
- (ii) $\{D(t)\}$ has independent increments: think of each arrival as an event. Types: type 1 if they depart in interval 1, 2 if they depart in 2, 3 if they depart in 3, 4 if they depart elsewhere, where 1, 2, and 3 are sequential nonoverlapping intervals. Note that for a given arrival time, the type of the event is dependent only on the service time. Since the arrival times are independent by assumption and the service times are also independent, the increments are independent.
- (iii) $\Pr(D(t+h) - D(t) = 1)$: Call an event type 1 if they depart in the interval $(t, t+h)$. Then $P_1(s) = G(t+h+s) - G(t+s) = g(t-s) \cdot h + o(h)$. So

$$D(t+h) - D(t) \sim \text{Poisson}(\lambda h \int_0^t g(t-s)ds + o(h)) = \text{Poisson}(\lambda h \int_0^t g(y)dy + o(h)) \text{Poisson}(\lambda h G(t) + o(h))$$

which means $\Pr(D(t+h) - D(t) = 1) = \lambda G(t)h e^{-\lambda G(t)h} =$ (by Taylor expansion of exp) $\lambda G(t)h + o(h)$ which is what we wanted to show.

- (iv) $\Pr(D(t+h) - D(t) \geq 2) = 1 - (\Pr(D(t+h) - D(t) = 0) - (\Pr(D(t+h) - D(t) = 1) = 1 - e^{-\lambda G(t)h} - \lambda G(t)h + o(h) =$ (by Taylor expansion of exp) $1 + \lambda G(t)h - \lambda G(t)h + o(h) = o(h)$.

□

Remark 73. Notice in the limit as $t \rightarrow \infty$ it converges to a Poisson process with rate λ .

Example 7.8. Poisson process, event i is associated with reward V_i . $\{X(t), t \geq 0\}$ is amount of money you get at time t .

$$X(t) = \sum_{i=1}^r V_i N_i(t) \quad (7.7)$$

or

$$\mathbb{E}(X(t)) = \sum V_i \mathbb{E}(V_i(t)) = \sum V_i \lambda \alpha_i t = \lambda t \sum \alpha_i v_i = \lambda t \mathbb{E}(X)$$

nice thing about this representation is $V_i N_i(t)$ are independent, so variance is sum of variances. Using $\text{Var}(N_i(t)) = \lambda \alpha_i t$,

$$\text{Var}(X(t)) = \sum_{i=1}^r V_i^2 \lambda \alpha_i t = \lambda t \sum V_i^2 \alpha_i = \lambda t \mathbb{E}(X^2)$$

so we verified the formulas we derived a different way.

Note that $N_i(t)$ is approximately Gaussian for large t (because Poisson goes to normal for large t). Therefore when t is large $X(t)$ is also approximately Gaussian.

7.2.4 Queueing Systems

Say we have a $M/G/1$ queuing process. That is, arrivals are $PP(\lambda)$, the service time has distribution G , and there is one server. Note that if no one is in line, the waiting time (length of an “idle period”) until the next arrival is exponential (since it’s a Poisson process). Consider the “busy periods,” that is, the time from when a customer arrives until the time the next idle period starts.

Let B be the length of a busy period. Let S be the service time of the initial customer. Note that B is independent from what happened before. Let A be the additional time after the first customer is served until the next idle period so that $B = S + A$. Let $N(S)$ be the number of arrivals during S . Note that A depends on $N(S)$.

Suppose $N(S) = n$. If $n = 0$, then $A = 0$. If $n = 1$, A has the same distribution as B_1 . If $n = 2$, A has the same distribution as the sum of two B s. And so on. This tells us we can say

$$B = S + \sum_{i=1}^{N(S)} B_i$$

If we condition on $S = s$,

$$\{B \mid S = s\} = s + \sum_{i=1}^{N(s)} B_i$$

Note that $\sum_{i=1}^{N(s)} B_i$ is a compound Poisson random variable. So

$$\mathbb{E}(B \mid S = s) = s + \mathbb{E}(N(s))\mathbb{E}(B_i) = s + \mathbb{E}(B)\lambda s$$

$$\text{Var}(B \mid S = s) = \lambda s \mathbb{E}(B^2)$$

or

$$\mathbb{E}(B \mid S) = S + \mathbb{E}(N(S))\mathbb{E}(B_i) = S + \mathbb{E}(B)\lambda S$$

$$\text{Var}(B \mid S) = \lambda S \mathbb{E}(B^2)$$

So

$$\mathbb{E}(B) = \mathbb{E}[\mathbb{E}(B \mid S)] = \mathbb{E}(S) + \lambda \mathbb{E}(S)\mathbb{E}(B) \implies \boxed{\mathbb{E}(B) = \frac{\mathbb{E}(S)}{1 - \lambda \mathbb{E}(S)}}$$

Note the similarity to the sum of an infinite geometric series. Similarly, if $\lambda \mathbb{E}(S) \geq 1 \iff \mathbb{E}(S) \geq 1/\lambda$ then the expected waiting time is infinite because the arrival times under the Poisson process ($1/\lambda$ in expectation) are faster in expectation than the service times. Also,

$$\text{Var}(B) = \lambda \mathbb{E}(S)\mathbb{E}(B^2) + (1 + \lambda \mathbb{E}(B))^2 \text{Var}(S)$$

Note that $\text{Var}(B) = \mathbb{E}(B)^2$, etc., then you work out the answer (see textbook for complete answer.)

End of Poisson processes

7.3 Renewal Processes

Definition 7.12 (Stieltjes Integral).

$$\int_a^b h(x)dF(x) = \lim_{n \rightarrow \infty} \sum_{i=1}^n h(x_i)(F(x_i) - F(x_{i-1}))$$

In particular, we often suppose that $F(x)$ is the distribution function for a random variable X . Then we have (if X is continuous)

$$\int_a^b h(x)dF(x) = \lim_{n \rightarrow \infty} \sum_{i=1}^n h(x_i)(\Pr(x_{i-1} < X \leq x_i)) = \int_a^b h(x)f_X(x)dx = \mathbb{E}(h(X))$$

or if X is discrete

$$\int_a^b h(x)dF(x) = \lim_{n \rightarrow \infty} \sum_{i=1}^n h(x_i)(\Pr(x_{i-1} < X \leq x_i)) = \mathbb{E}(h(X)).$$

Generalization of Poisson processes. A counting process where the interarrival times are i.i.d. Let X_1, X_2, \dots be i.i.d. non-negative random variables with distribution function F . We require $F(0) = \Pr(X \leq 0) = \Pr(X = 0) < 1$. Let

$$\mathbb{E}(X_1) = \mu = \int_0^\infty x dF(x) = \int_0^\infty \bar{F}(t)dt$$

where $0 < \mu \leq \infty$. Let $N(t)$ be the counting process (this is the largest value of n for which the n th event has occurred at time t , so $N(t) = \max\{n : S_n \leq t\}$). Let S_n be the arrival time for the n th event. Define $S_0 = 0, S_n = \sum_{i=1}^n X_i$.

Definition 7.13 (Renewal process; Definition 3.1.1 in *Stochastic Processes*). Let $\{X_n, n = 1, 2, \dots\}$ be a sequence of nonnegative independent random variables with a common distribution F . To avoid trivialities, suppose that $F(0) = \Pr(\{X_n = 0\}) < 1$. We shall interpret X_n as the time between the $(n - 1)$ st and n th event. Let

$$S_0 = 0, \quad S_n = \sum_{i=1}^n X_i, n \geq 1$$

so that S_n is the time of the n th event. As the number of events by time t will equal the largest value of n for which the n th event occurs before or at time t , we have that $N(t)$, the number of events by time t , is given by

$$N(t) = \sup\{n : S_n \leq t\}.$$

The counting process $\{N(t), t \geq 0\}$ is called a **renewal process**. We can write this as $\{N(t), t \geq 0\}$ as a renewal process with intensity distribution F .

Remark 74. Let $\mu = \mathbb{E}(X_n) = \int_0^\infty x dF(x)$ denote the mean time between successive events and note that from the assumptions $X_n \geq 0$ and $F(0) < 1$ it follows that $0 < \mu \leq \infty$.

Every time an event occurs is a “renewal:” from that time on, all the arrivals are i.i.d. (Between events it is unclear what is going on until the next event happens; depends on the nature of F . If we have a Poisson process, then it is memoryless, but otherwise it is not.)

Example 7.9 (St. Petersburg Paradox). Idea: you play a game, you get the amount of money X . In order to play the game you have to pay, so what's a fair amount to pay? Belief: $\mathbb{E}(X)$ (that's a rational price).

Game: fair coin, flip until heads occurs. If it occurs on trial n , you win 2^n dollars. Note that

$$\mathbb{E}(X) = \sum_{i=1}^{\infty} 2^i \cdot \left(\frac{1}{2}\right)^i = \infty.$$

Proposition 7.3.1. With probability 1, $N(t) < \infty$ for all t .

Proof.

$$\frac{S_n}{n} = \frac{X_1 + \dots + X_n}{n} \xrightarrow{a.s.} \mu > 0 \text{ as } n \rightarrow \infty$$

Because the denominator goes to ∞ and the ratio doesn't go to 0, we must have $S_n \xrightarrow{a.s.} \infty$. Therefore $\Pr(N(t) < \infty) = 1$ for all t .

□

Proposition 7.3.2. With probability 1, $N(\infty) = \lim_{t \rightarrow \infty} N(t) = \infty$. (There's never a last renewal—there will always be another.)

Proof. Recall **Boole's Inequality** (which can be proven in a similar manner to Theorem 7.6.17):

$$\Pr\left(\bigcup_{n=1}^{\infty} \{A_n\}\right) \leq \sum_{n=1}^{\infty} \Pr(A_n)$$

(with equality if the events are disjoint). Then

$$\Pr(N(\infty) < \infty) = \Pr(X_n = \infty) \text{ (for some } n) = \Pr\left(\bigcup_{n=1}^{\infty} \{X_n = \infty\}\right) \leq \sum_{n=1}^{\infty} \Pr(X_n = \infty) = 0$$

□

Definition 7.14 (Notation for n -fold self-convolution). Recall the notation for convolution: if $X \sim F \perp\!\!\!\perp Y \sim G$, we have $X + Y \sim F * G$. Then

$$S_n \sim F * F * \dots * F(t).$$

Let

$$F_n(t) := F * F * \dots * F(t)$$

the n -fold convolution of F with itself. (In general, this is very hard to get a closed-form notation for except in some simple cases. More of a theoretical construct than something practical to compute.)

Proposition 7.3.3. $\Pr(N(t) = n) = F_n(t) - F_{n+1}(t)$.

Proof.

$$N(t) \geq n \iff S_n \leq t.$$

$$\implies \Pr(N(t) \geq n) = \Pr(S_n \leq t)$$

Then we have

$$\Pr(N(t) = n) = \Pr(N(t) \geq n) - \Pr(N(t) \geq n+1) = F_n(t) - F_{n+1}(t).$$

(Again, this is more of a theoretical construct than something practical to compute.)

□

Definition 7.15 (Renewal function). Let $m(t) = \mathbb{E}(N(t))$. We call $m(t)$ the **renewal function**.

Remark 75.

$$m(t) = \sum_{n=1}^{\infty} \Pr(N(t) \geq n) = \sum_{n=1}^{\infty} F_n(t).$$

Lemma 7.3.4. $m(t) < \infty$ for all t .

Proof. Skipped in class, not very enlightening.

□

Proposition 7.3.5 (Renewal Equation).

$$m(t) = F(t) + \int_0^t m(t-s)dF(s).$$

Proof.

$$m(t) = \mathbb{E}(N(t)) = \int_0^\infty \mathbb{E}(N(t) \mid X_1 = s)dF(s)$$

Note that

$$\mathbb{E}(N(t) \mid X_1 = s) = \begin{cases} 1 + m(t-s) & s \leq t \\ 0 & s > t \end{cases}$$

so we have

$$m(t) = \int_0^t (1 + m(t-s))dF(s) = F(t) + \int_0^t m(t-s)dF(s)$$

□

Remark 76. Remember we did a problem where $X_i \sim \text{Unif}(0, 1)$ and asked how many you have to sum until the number of greater than 1. We ended up with $1/e$. This is the smallest value of n for which the event occurred after time n (or something?)

$$N = \min\{X_1 + \dots + X_n > 1\} = N(1) + 1$$

(the first event that occurred after time 1. We showed that this was equal to e basically by solving the renewal equation. Only feasible because of uniform distribution between 0 and 1.)

Remark 77. Note that

$$S_{N(t)} := (\text{time of the most recent event before or at time } t),$$

$$S_{N(t+1)} := (\text{time of the first event after time } t).$$

At what rate do renewals occur?

Theorem 7.3.6 (Strong Law for Renewal Processes).

$$\frac{N(t)}{t} \xrightarrow{\text{a.s.}} \frac{1}{\mu}$$

(Intuitively: since X_i are the time between renewals, the average time between renewals is $\mathbb{E}(X_i) = \mu$. So the average rate of renewals is equal to one over the average time between events.)

Proof. Note that

$$S_{N(t)} \leq t < S_{N(t)+1}$$

$$\iff \frac{S_{N(t)}}{N(t)} \leq \frac{t}{N(t)} < \frac{S_{N(t)+1}}{N(t)}$$

As $t \rightarrow \infty$, the quantity on the left converges to the mean by the Strong Law of Large Numbers (see the proof of Proposition 7.3.1 above). For the quantity on the right, we have

$$\frac{S_{N(t)+1}}{N(t)} = \frac{S_{N(t)+1}}{N(t)+1} \cdot \frac{N(t)+1}{N(t)} \xrightarrow{\text{a.s.}} \mu \cdot 1$$

which means

$$\frac{t}{N(t)} \xrightarrow{\text{a.s.}} \mu \iff \frac{N(t)}{t} \xrightarrow{\text{a.s.}} \frac{1}{\mu}.$$

□

Remark 78. In many applications: X_1, X_2, \dots are independent non-negative random variables. $X_1 \sim G$, $X_i \sim F, i \geq 1$. (That is, once the first event occurs we have a renewal process, but before then we don't.)

Definition 7.16 (Delayed renewal process). Define

$$N_d(t) := \max\{n : X_1 + \dots + X_n \leq t\}.$$

We call $\{N_d(t), t \geq 0\}$ a **delayed renewal process**.

Remark 79. Almost all limiting results for renewal processes apply for delayed renewal processes as well. (In the long run, that first waiting period doesn't really make a difference.) For example, consider the Strong Law for Renewal Processes (Theorem 7.3.6) (quick note: let $N(s) = -1, s < 0$):

$$N_d(t) = 1 + N(t - X_1) \iff \frac{N_d(t)}{t} = \frac{1}{t} + \frac{N(t - X_1)}{t - X_1} \frac{t - X_1}{t}$$

By the Strong Law for Renewal processes,

$$\frac{N(t - X_1)}{t - X_1} \xrightarrow{\text{a.s.}} \frac{1}{\mu_F}$$

where $\mu_F = \int_0^\infty \bar{F}(t)dt$. Since $\lim_{t \rightarrow \infty} \frac{t - X_1}{t} = 1$, we have the same result as for the Strong Law for Renewal Processes:

$$\frac{N_d(t)}{t} \xrightarrow{\text{a.s.}} \frac{1}{\mu_F}$$

Example 7.10. Arrivals to a single server queue according to a Poisson process with rate λ . However, they will only enter if the server is free when they arrive. Service time has distribution G . (This is often called a **loss model** or **Erlang loss model**, more generally with k servers.)

- (a) At what rate do customers enter the system?
- (b) What proportion of arrivals enter the system?

Solution.

- (a) Note that the events of customers entering are a renewal process because everything probabilistically starts all over again when a customer arrived. Specifically it's a delayed renewal process because the time of the first arrival is exponential with rate λ , but the rest of them are more complicated because there must be a service and an arrival (the sum of two random variables). So the rate of arrivals is 1 over the expected time between events, or

$$\frac{1}{\mathbb{E}(S + I)}$$

where S is the service time and I is the interarrival time for the next customer. Let $\mathbb{E}(X) = \mu_G = \int_0^\infty \bar{G}(t)dt$. Then

$$\mathbb{E}(S + I) = \mu_G + \frac{1}{\lambda}$$

so the answer is

$$\frac{1}{\mu_G + \frac{1}{\lambda}} = \boxed{\frac{\lambda}{1 + \lambda\mu_G}}.$$

(b) Rate of service arrivals divided by overall rates of arrivals:

$$\frac{\lambda}{1 + \lambda\mu_G} / \lambda = \boxed{\frac{1}{1 + \lambda\mu_G}}.$$

Example 7.11. Suppose we have a bin with an infinite number of coins. Each coin has value p of landing on heads, and suppose the value of p for a randomly chosen coin is distributed as Uniform(0, 1). We draw coins and flip them. Every turn we can either draw a new coin or flip one of the coins we already have. If we want to maximize the proportion of coins that flip heads, what is the optimal strategy?

Solution. Consider a strategy of giving up on a coin if it comes up tails once. Every time you flip tails, the process renews. Let $N(n)$ be the number of tails in the first n flips. Then $N(n)$ is a renewal process. So we know that

$$\frac{N(n)}{n} \xrightarrow{a.s.} \frac{1}{\mathbb{E}(T)}$$

where T is the time between tails. Let P be a random variable for the probability of a coin flipping heads and note that

$$\mathbb{E}(T) = \int_0^1 \mathbb{E}(T \mid P = p) dp = \int_0^1 \frac{1}{1-p} dp = -\log(1-p) \Big|_0^1 = \infty$$

so the long-run proportion of coins that land heads is 1.

Proposition 7.3.7 (Homework problem; *Introduction to Probability Models* Ch. 7 Problem 30). For a renewal process, let $A(t) = t - S_{N(t)}$ be the age at time t . If $\mu < \infty$, then

$$\frac{A(t)}{t} \xrightarrow{w.p.1} 0.$$

Proof. We hope to show that

$$\frac{t - S_{N(t)}}{t} \xrightarrow{w.p.1} 0.$$

Note that

$$\frac{t - S_{N(t)}}{t} = \frac{t - S_{N(t)}}{N(t)} \cdot \frac{N(t)}{t} = \left(\frac{t}{N(t)} - \frac{S_{N(t)}}{N(t)} \right) \frac{N(t)}{t}$$

By the Strong Law for Renewal Processes (Theorem 7.3.6), $\frac{N(t)}{t} \xrightarrow{w.p.1} \mu^{-1}$, where $\mu = \mathbb{E}(X)$ is the expected interarrival time. Since the expected interarrival time is finite, $N(t) \rightarrow \infty$ as $t \rightarrow \infty$. Therefore

$$\frac{S_{N(t)}}{N(t)} = \frac{X_1 + \dots + X_{N(t)}}{N(t)} \xrightarrow{w.p.1} \mu.$$

Lastly, since $N(t) > 0$ with probability 1 as $t \rightarrow \infty$ and $t > 0$, by the Continuous Mapping Theorem (Theorem asym.contmappthm),

$$\frac{t}{N(t)} = \left(\frac{N(t)}{t} \right)^{-1} \xrightarrow{w.p.1} (\mu^{-1})^{-1} = \mu.$$

Therefore by another application of the Continuous Mapping Theorem (Theorem asym.contmappthm),

$$\frac{t - S_{N(t)}}{t} = \left(\frac{t}{N(t)} - \frac{S_{N(t)}}{N(t)} \right) \frac{N(t)}{t} \xrightarrow{w.p.1} (\mu - \mu) \cdot \mu^{-1} = 0.$$

□

7.3.1 Stopping Times

Definition 7.17 (Stopping times). Let X_1, X_2, \dots be independent random variables. We say the non-negative integer valued random variable N is a **stopping time** for X_1, X_2, \dots if the event $\{N = n\}$ is independent of X_{n+1}, X_{n+2}, \dots . (This definition is more general than saying it must depend on previous times because it could be random and not depend on anything (except the current one) or you could have a finite memory, etc.)

Theorem 7.3.8 (Wald's Equation). Suppose X_1, X_2, \dots are i.i.d. with $\mathbb{E}(X) < \infty$. Let N be a stopping time for X_1, X_2, \dots such that $\mathbb{E}(N) < \infty$. Then

$$\mathbb{E}\left(\sum_{i=1}^N X_i\right) = \mathbb{E}(N)\mathbb{E}(X).$$

Remark 80. Note the similarity to compound random variables. But the proof differs because N is not independent of the $\{X_i\}$.

Proof. Let I_i be an indicator variable for $I \leq N$. Then

$$\sum_{i=1}^N X_i = \sum_{i=1}^{\infty} X_i I_i \implies \mathbb{E}\left(\sum_{i=1}^N X_i\right) = \mathbb{E}\left(\sum_{i=1}^{\infty} X_i I_i\right) = \sum_{i=1}^{\infty} \mathbb{E}(X_i I_i)$$

Note that I_i depends on X_1, \dots, X_{i-1} but not on X_i (it only depends on whether you play the i th game, not the outcome of that game. You only decide whether to play the i th game based on the outcomes of the previous games.). Therefore $X_i \perp\!\!\!\perp I_i$. So we have

$$= \sum_{i=1}^{\infty} \mathbb{E}(X_i) \mathbb{E}(I_i) = \mathbb{E}(X) \sum_{i=1}^{\infty} \mathbb{E}(I_i) = \mathbb{E}(X) \sum_{i=1}^{\infty} \Pr(N \geq i) = \mathbb{E}(X) \mathbb{E}(N)$$

or we can write

$$\mathbb{E}(X) \sum_{i=1}^{\infty} \mathbb{E}(I_i) = \mathbb{E}(X) \mathbb{E}\left(\sum_{i=1}^{\infty} I_i\right) = \mathbb{E}(X) \mathbb{E}(N).$$

□

Remark 81. How do we justify

$$\mathbb{E}\left(\sum_{i=1}^{\infty} X_i I_i\right) = \sum_{i=1}^{\infty} \mathbb{E}(X_i I_i)?$$

Do the same thing again but replace all the X_i with $|X_i|$. Then the proof works, and Wald's Equation follows by Lebesgue's Dominated Convergence Theorem (Theorem 5.11.3).

Example 7.12. Let

$$X_i = \begin{cases} 1 & \text{with probability } p \\ 0 & \text{otherwise} \end{cases}$$

One stopping time could be $N_1 = \min\{n : X_1 + \dots + X_n = k\}$. Then by Wald's Equation (Theorem 7.3.8),

$$\mathbb{E}\left(\sum_{i=1}^N X_i\right) = \mathbb{E}(N)\mathbb{E}(X) \iff k = \mathbb{E}(N)(p) \implies \mathbb{E}(N) = \frac{k}{p}.$$

Another could be $N_2 = \min\{n : X_{n-1} = X_n = 1\}$.

Example 7.13. Let

$$X_i = \begin{cases} 1 & \text{with probability } p \\ -1 & \text{with probability } 1-p \end{cases}$$

with $p > 1/2$. Note that $\mathbb{E}(X_i) = 2p - 1 > 0$. One stopping time could be $N = \min\{n : X_1 + \dots + X_n = 10\}$. (Note that by the Strong Law of Large Numbers, with probability 1 this will eventually happen.) Then by Wald's Equation (Theorem 7.3.8),

$$\mathbb{E}\left(\sum_{i=1}^N X_i\right) = \mathbb{E}(N)\mathbb{E}(X) \iff 10 = \mathbb{E}(N)(2p - 1) \implies \mathbb{E}(N) = \frac{10}{2p - 1}.$$

What's the mean amount of time until you're up by one dollar?

$$m = 1 + (1-p)\mathbb{E}(\text{up } 2) = 1 + (1-p)2m$$

Possible stopping rule: stop when you're winning money.

$$1 = \sum_{i=1}^N X_i = \mathbb{E}(N)\mathbb{E}(X) = 0$$

but it turns out Wald's equation doesn't apply because $\mathbb{E}(N) = \infty$ (the mean number of plays to get ahead is infinite).

Example 7.14. Let

$$X_i = \begin{cases} 1 & \text{with probability } 1/2 \\ -1 & \text{with probability } 1/2 \end{cases}$$

with $p > 1/2$. Note that $\mathbb{E}(X_i) = 2p - 1 > 0$. One stopping time could be $N = \min\{n : X_1 + \dots + X_n = 1\}$. It turns out from Markov chain theory that this will eventually happen with probability 1. We can't apply Wald's Equation (Theorem 7.3.8) because $\mathbb{E}(N)$ is not finite. Note that if we try, a contradiction results:

$$1 = \mathbb{E}(N) \cdot 0 = 0$$

Example 7.15. Let $U_i \sim \text{Uniform}(0, 1)$, U_i i.i.d. One stopping time is $N = \min\{n : U_n > 0.8\}$. Then by Wald's Equation (Theorem 7.3.8),

$$\mathbb{E}\left(\sum_{i=1}^N X_i\right) = \mathbb{E}(N)\mathbb{E}(X) = 10 \cdot 0 = 0$$

so the expected winnings when you stop is 0 (regardless of your stopping time, since it's a fair game).

Back to renewal theory: Let X_1, X_2, \dots be a sequence of random variables with interarrival times distributed as F . Note that $N(t) = 5 \iff X_1 + \dots + X_5 \leq t, X_1 + \dots + X_6 > t$ so this is not a stopping time. But we could stop at the first event that occurs after time t , so $N(t) + 1$ is a stopping time. Note that

$$N(t) + 1 = n \iff N(t) = n - 1, X_1 + \dots + X_{n-1} \leq t, X_1 + \dots + X_n > t.$$

(You can't say "I'll stop at the last event before t " because at the time of that event you wouldn't have been able to know it was the last event before t .)

Corollary 7.3.8.1 (Corollary to Wald's Equation).

$$\mathbb{E}\left(\sum_{i=1}^{N(t)+1} X_i\right) = \mu(m(t) + 1)$$

Theorem 7.3.9 (Elementary Renewal Theorem).

$$\frac{m(t)}{t} \xrightarrow{\text{a.s.}} \frac{1}{\mu}.$$

Proof. Note that

$$S_{N(t)+1} > t$$

We have

$$\mathbb{E}(S_{N(t)+1}) > t$$

Using Corollary 7.3.8.1,

$$\mu(m(t) + 1) > t \iff m(t) + 1 > \frac{t}{\mu} \iff \frac{m(t)}{t} > \frac{1}{\mu} - \frac{1}{t}$$

Then as $t \rightarrow \infty$

$$\liminf \frac{m(t)}{t} \geq \frac{1}{\mu}.$$

So if we can show $\liminf \frac{m(t)}{t} \leq \frac{1}{\mu}$, we're done. Assume $\Pr(X_i \leq M) = 1$ for some $M \in \mathbb{R}$. Then

$$\begin{aligned} S_{N(t)+1} < t + M &\implies \mu(m(t) + 1) < t + M \implies m(t) < \frac{t}{\mu} + \frac{M}{\mu} - 1 \\ &\implies \frac{m(t)}{t} < \frac{1}{\mu} + \frac{M}{t\mu} - \frac{1}{t} \\ &\implies \limsup \frac{m(t)}{t} \leq \frac{1}{\mu}. \end{aligned}$$

Now consider the general case. Consider X_1, X_2, \dots . Let

$$X_i^* = \begin{cases} X_i & \text{if } X_i \leq M \\ M & \text{if } X_i > M \end{cases}$$

and let $N^*(t) = \max\{n : X_1^* + \dots + X_n^* \leq t\}$. Then since $N^*(t)$ has smaller interarrival times than $N(t)$,

$$\begin{aligned} N(T) \leq N^*(t) &\implies \frac{\mathbb{E}(N(t))}{t} \leq \frac{\mathbb{E}(N^*(t))}{t} \\ &\implies \lim \frac{m(t)}{t} \leq \lim \frac{\mathbb{E}(N^*(t))}{t} = \frac{1}{\mathbb{E}(X_i^*)} \end{aligned}$$

Note that (since $X_I^* = X_I$ if $X_i \leq M$)

$$\mathbb{E}(X_i^*) = \int_0^M x dF(x) + M\bar{F}(M) \rightarrow \mu + 0 = \mu \text{ as } M \rightarrow \infty$$

so

$$\lim \frac{m(t)}{t} \leq \frac{1}{\mathbb{E}(\min\{X, M\})}$$

which is true for every M . Letting $M \rightarrow \infty$, we have

$$\mathbb{E}(\min\{X, M\}) \rightarrow \mathbb{E}(X) \text{ as } M \rightarrow \infty$$

by Lebesgue's Monotone convergence theorem (Theorem 5.11.1; “if you have a sequence of variables $X_n \leq X_{n+1} \leq \dots$ then $\mathbb{E}(\lim_{n \rightarrow \infty} X_n) = \lim_{n \rightarrow \infty} \mathbb{E}(X_n)$ ”).

□

Remark 82. This technique is called “coupling;” relating something you don’t know to something you do.

Remark 83. Why doesn’t the Elementary Renewal Theorem follow from the Strong Law for Renewal Processes (Theorem 7.3.6)? Consider this counterexample: Let $U \sim \text{Uniform}(0, 1)$ and let X_n be a random variable such that

$$X_n = \begin{cases} n & U < 1/n \\ 0 & U > 1/n \end{cases}$$

Of course with probability 1, $U > 0$; that is, $U = \epsilon > 0$. Note that $X_n = 0$ for all n sufficiently large ($1/n < \epsilon$). So we see that $X_n \xrightarrow{a.s.} 0$. But for all n sufficiently large

$$\mathbb{E}(X_n) = n \cdot \frac{1}{n} = 1.$$

So we have

$$\lim_{n \rightarrow \infty} X_n = 0 = \mathbb{E}(\lim_{n \rightarrow \infty} X_n) \neq \lim_{n \rightarrow \infty} \mathbb{E}(X_n) = 1$$

In summary, just because $\frac{N(t)}{t} \xrightarrow{a.s.} \frac{1}{\mu}$ doesn’t mean $\frac{m(t)}{t} \xrightarrow{a.s.} \frac{1}{\mu}$.

Proposition 7.3.10. Consider a delayed renewal process $N_d(t)$ and let $m_d(t) = \mathbb{E}(N_d(t))$. Recall that the first arrival has distribution G and the rest have distribution F . Then $m_d(t) \xrightarrow{a.s.} 1/\mu$.

Proof.

$$m_d(t) = \int_0^t \mathbb{E}(N_d(t) | X_1 = s) dG(s)$$

Note that

$$\mathbb{E}(N_d(t) \mid X_1 = s) = 1 + m(t - s)$$

so we have

$$\begin{aligned} m_d(t) &= \int_0^t (1 + m(t - s)) dG(s) = G(t) + \int_0^t m(t - s) dG(s) \\ \iff \frac{m_d(t)}{t} &= \frac{G(t)}{t} + \frac{1}{t} \int_0^t m(t - s) dG(s) \xrightarrow{a.s.} \frac{1}{\mu} \end{aligned}$$

by using $m(y)/y \xrightarrow{a.s.} 1/\mu$. (Details can be fleshed out.)

□

Proposition 7.3.11. Suppose X_1, X_2, \dots are integer valued, and there is only one renewal at a time. Suppose $\Pr(X_i = 0) = 0$. Then

Proof. Note that

$$\frac{\mathbb{E}(N_d(t))}{n} \rightarrow \frac{1}{\mu}$$

by the Strong Law for Renewal Processes (Theorem 7.3.6). Note that

$$N_d(n) = \sum_{j=1}^n I_j$$

where I_j is an indicator variable for whether there is a renewal at time j . Then

$$\mathbb{E}(N_d(n)) = \sum_{j=1}^n \mathbb{E}(I_j) = \sum_{j=1}^n \Pr(I_j = 1)$$

Then by the Elementary Renewal Theorem (Theorem 7.3.9),

$$\frac{1}{n} \sum_{j=1}^n \Pr(I_j = 1) \xrightarrow{a.s.} \frac{1}{\mathbb{E}(X_i)}$$

□

Recall we say that $a_n \rightarrow a$ pointwise if $\lim_{n \rightarrow \infty} a_n = a$.

Definition 7.18 (Caesaro Convergence). We say a_n Caesaro converges to a if

$$\frac{a_1 + \dots + a_n}{n} \rightarrow a \text{ as } n \rightarrow \infty.$$

Remark 84. Pointwise convergence implies Caesaro convergence, but not the other way around.

When does $\Pr(\{\text{renewal at } n\}) \rightarrow 1/\mu$? Let $\Pr(\{\text{renewal at } j\}) = P_j$ and suppose $P_n \rightarrow P^*$. This implies Caesaro convergence

$$\frac{P_1 + \dots + P_n}{n} \rightarrow p^*$$

and $p^* = 1/\mu$ where μ is the expected time between renewals.

These examples are very confusing—look for explanations in textbook? Seems to be same as Section 7.9.2 in *Introduction to Probability Models*.

Example 7.16. Let Y_1, Y_2, \dots i.i.d. Suppose $p_j = \Pr(Y_i = j)$. We will keep doing draws until we observe the pattern 1, 2, 1, 3, 4, 1, 2, 1. Let N be the number of trials until this occurs. What is $\mathbb{E}(N)$?

Solution. Suppose we consider the process as continuing to happen forever even after a pattern appears, and treat a pattern arriving as an event. let $N(n)$ be the number of events by n . Is $\{N(n)\}$ a renewal process? That is, once an event occurs does everything start all over? Yes, so it's either an ordinary or delayed renewal process. Note that it's delayed because the last three digits of the pattern match the first three, so once a pattern has just happened, another one could happen in 5 draws. Note that

$$\Pr(\text{pattern appears at time } n) = P_1 P_2 \dots = P_1^4 P_2^2 P_3 P_4$$

so the expected time between renewals is $1/(P_1^4 P_2^2 P_3 P_4)$, except that we need to take into account the fact that we already have the first three digits of the pattern if we just got one. Note that

$$\Pr(\text{pattern appears at time } n \mid \text{just had pattern}) = P_1^2 P_2 P_3 P_4$$

We can look at this a different way. The time until we get a pattern T_p is the time until we get 1,2,1 T_{121} plus the time until we get the rest of the pattern T_{rest} .

$$T_p = T_{121} + T_{rest} \implies \mathbb{E}(T_p) = \mathbb{E}(T_{121}) + 1/(P_1^4 P_2^2 P_3 P_4)$$

Then $\Pr(\text{renewal at } n) = P_1^2 P_2$ so the expected time between renewals is $1/(P_1^2 P_2)$. Then the time between renewals is the additional time between renewals given that you currently have 1, so

$$\mathbb{E}(\text{time between renewals}) = \mathbb{E}(\text{additional time when you have a 1}) = 1/(P_1^2 P_2)$$

Do it again: time to get to 1,2,1 is time to get to 1 plus additional:

$$T_{121} = T_1 + T_{21} \implies \mathbb{E}(T_{121}) = \mathbb{E}(T_1) + 1/(P_1^2 P_2) = 1/P_1 + 1/(P_1^2 P_2)$$

putting this all together, we have

$$\mathbb{E}(T_p) = 1/P_1 + /P_1^2 P_2 + 1/(P_1^4 P_2^2 P_3 P_4).$$

Example 7.17. Flips coins, get heads with probability P . Then T_k is the time to land k heads in a row. What is the expected time until k heads in a row?

Solution. Note that the probability of a renewal at n is p^k . So the expected time between renewals is equal to $1/p^k$ not taking into account that the next time we could use the heads we already have. Note that

$$T_k = T_{k-1} + T_{rest}$$

so

$$\mathbb{E}(T_k) = \mathbb{E}(T_{k-1} + 1/p^k) = 1/p^k + \mathbb{E}(T_{k-2}) + 1/(p^{k-1}) + \dots$$

7.4 ISE 620 Midterm Solutions

Exercise 15.

$$\text{Var}\left(\sum_{i=1}^n X_i\right)$$

Solution.

$$\text{Var}\left(\sum_{i=1}^n X_i\right) = \text{Var}\left(\sum_{i=1}^n (n+1-i)X_i\right) = \sum_{i=1}^n \frac{(n+1-i)^2}{\lambda^2} = \sum_{j=1}^n j^2/\lambda^2$$

or

$$\text{Var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{Var}(S_i) + 2 \sum_{1 \leq i < j \leq n} \text{Cov}(S_i, S_j)$$

Note that

$$\text{Cov}(S_i, S_j) = \text{Cov}\left(S_i, S_i + \sum_{k=i+1}^j X_k\right) = \text{Var}(S_i) + 0 = i/\lambda^2$$

Exercise 16.

$$\text{Var}\left(\sum_{i=1}^{N(t)} S_i \mid N(t)\right)$$

Solution.

$$\text{Var}\left(\sum_{i=1}^{N(t)} S_i \mid N(t) = n\right) = \text{Var}\left(\sum_{i=1}^n U_i\right)$$

where $U_1, \dots, U_n \sim \text{i.i.d. } U(0, t)$ and they are ordered. Since the sum of the ordered values is the same as the sum of the unordered values and they are i.i.d., we have

$$\text{Var}\left(\sum_{i=1}^n U_i\right) = \sum_{i=1}^n \text{Var}(U_i) = \frac{nt^2}{12}.$$

Exercise 17. A wins point with probability p_1 if A is server, A wins with probability p_2 if B serves. (a) serve next if you just won. (b) alternate serve.

Solution.

- (a) A serving is a renewal. Suppose A just won a point. Let X be the number of games until A wins again. Frequency with which A wins converges to $1/\mathbb{E}(X)$ by the Strong Law for Renewal Processes (Theorem 7.3.6). Condition on who wins next game. Let Y be an indicator variable for A winning the next game. Then

$$\mathbb{E}(X) = \mathbb{E}(X \mid Y = 1)p_1 + \mathbb{E}(X \mid Y = 0)(1 - p_1)$$

Note that if $Y = 1$, $X = 1$. For $\mathbb{E}(X \mid Y = 0)$, B keeps serving until A wins, so the number of games until A wins is a geometric random variable with probability p_2 , so the mean is $1/p_2$. So we have

$$\mathbb{E}(X) = 1 \cdot p_1 + (1 + 1/p_2)(1 - p_1) = 1 + \frac{1 - p_1}{p_2} = \frac{p_2 + 1 - p_1}{p_2}$$

and the rate is

$$\frac{p_2}{p_2 + 1 - p_1}$$

- (b) Not a renewal—everything doesn't start all over again when A wins a point, because just because A just won doesn't tell us anything about who wins. A renewal would happen every time A wins on her serve. Let X be the number of games until the next renewal. Then the answer we seek is $1/\mathbb{E}(X)$. Let Y be an indicator variable for A winning on her next serve. Note that

$$\mathbb{E}(X) = \mathbb{E}(X \mid Y = 1)p_1 + \mathbb{E}(X \mid Y = 0)(1 - p_1)$$

Note that $\mathbb{E}(X \mid Y = 1) = 2$, $\mathbb{E}(X \mid Y = 0) = 2 + \mathbb{E}(X)$. So we have

$$\mathbb{E}(X) = 2p_1 + (2 + \mathbb{E}(X))(1 - p_1) \iff p_1\mathbb{E}(X) = 2p_1 + 2 - 2p_1 \iff \mathbb{E}(X) = 2/p_1$$

Do the same thing again for when A wins on B 's serve. Then add them together.

A renewal would happen every time A wins on B 's serve. Let Z be the number of games until the next renewal. Then the answer we seek is $1/\mathbb{E}(Z)$. Let Y be an indicator variable for A winning on B 's next serve. Note that

$$\mathbb{E}(Z) = \mathbb{E}(Z | Y = 1)p_2 + \mathbb{E}(Z | Y = 0)(1 - p_2)$$

Note that $\mathbb{E}(Z | Y = 1) = 2$, $\mathbb{E}(Z | Y = 0) = 2 + \mathbb{E}(Z)$. So we have

$$\mathbb{E}(Z) = 2p_2 + (2 + \mathbb{E}(Z))(1 - p_2) \iff p_1\mathbb{E}(Z) = 2p_2 + 2 - 2p_2 \iff \mathbb{E}(Z) = 2/p_2$$

So the long-run proportion of games won by A is

$$\frac{1}{\mathbb{E}(X)} + \frac{1}{\mathbb{E}(Z)} = \frac{p_1 + p_2}{2}.$$

Exercise 18. $M/G/\infty$, $\Pr(X(t) = j | N(t) = n)$.

Solution.

The arrival times are i.i.d. uniform on $(0, t)$. So each one has the same probability of being in the system at time t , and the number who are in the system is a binomial random variable.

$$\Pr(X(t) = j | N(t) = n) = \binom{n}{j} p^j (1-p)^{n-j}$$

where p is the probability of being in the system at time t :

$$p = \int_0^t \Pr(\text{in system} | \text{arrived at } s) \cdot (1/t) ds = \frac{1}{t} \int_0^t \bar{G}(t-s) ds.$$

Exercise 19. number of claims N poisson with mean lambda, claim amounts ‘are uniformly distributed on $(0, 1)$, we want $\mathbb{E}(\max\{X_1, \dots, X_N\})$.

Solution. Note that

$$\Pr(\max\{X_1, \dots, X_n\} \leq t) = t^n \implies \Pr(\max\{X_1, \dots, X_n\} > t) = 1 - t^n$$

$$\implies \mathbb{E}(\max\{X_1, \dots, X_n\}) = \int_0^1 (1 - t^n) dt = \frac{n}{n+1} = 1 - \frac{1}{n+1}$$

so this is the expected value if we condition on n . Therefore

$$\mathbb{E}(\max\{X_1, \dots, X_N\}) = \mathbb{E}(\max\{X_1, \dots, X_N\} | N = n) \Pr(N = n)$$

$$= \sum_{n=0}^{\infty} \left(1 - \frac{1}{n+1}\right) \cdot e^{-\lambda} \frac{\lambda^n}{n!} = \dots$$

Exercise 20.

$$\mathbb{E}(X(t) \mid N(s) = n)$$

where

$$X(t) = \sum_{i=1}^{N(t)} X_i$$

Solution.

We have

$$\begin{aligned} X(t) \mid N(s) = n &= \sum_{i=1}^{N(s)} X_i + \sum_{i=N(s)+1}^{N(t)} X_i = \sum_{i=1}^n X_i + \sum_{i=N(s)+1}^{N(t)} X_i \\ \implies \mathbb{E}(X(t) \mid N(s)) &= \mathbb{E}\left(\sum_{i=1}^n X_i\right) + \mathbb{E}\left(\sum_{i=N(s)+1}^{N(t)} X_i\right) = n\mathbb{E}(X) + \mathbb{E}(X)\lambda(t-s) \end{aligned}$$

where $\lambda(t-s)$ is the expected number of events between s and t .

7.5 Renewal Reward Processes (Section 4.7 in *Introduction to Probability Models*, 3.6 Stochastic Processes)

Definition 7.19 (Renewal reward process). Suppose we have a renewal process with interarrival times X_1, X_2, \dots . Suppose we receive a reward R_i when renewal i occurs (after time X_i from the previous renewal). The reward is allowed to depend on what happens during the previous period X_i , but every time renewal happens, process starts again. So we assume the vectors $(X_i, R_i), i \geq 1$ are i.i.d. Let $R(t)$ be the total reward by time t ; that is,

$$R(t) = \sum_{i=1}^{N(t)} R_i.$$

Then $\{R(t), t \geq 0\}$ is a **renewal reward process**.

Proposition 7.5.1 (Proposition 7.3 in *Introduction to Probability Models*; sometimes called Renewal Reward Theorem).

(a)

$$\frac{R(t)}{t} \xrightarrow{\text{a.s.}} \frac{\mathbb{E}(R)}{\mathbb{E}(X)}$$

(generalization of strong law)

(b)

$$\frac{\mathbb{E}(R(t))}{t} \xrightarrow{a.s.} \frac{\mathbb{E}(R)}{\mathbb{E}(X)}$$

Proof. (a)

$$\frac{R(t)}{t} = \frac{1}{t} \sum_{i=1}^{N(t)} R_i = \frac{1}{N(t)} \sum_{i=1}^{N(t)} R_i \cdot \frac{N(t)}{t}$$

Since $N(t) \rightarrow \infty$ as $t \rightarrow \infty$, by Strong Law of Large Numbers (Theorem 8.6.4)

$$\frac{1}{N(t)} \sum_{i=1}^{N(t)} R_i \xrightarrow{a.s.} \mathbb{E}(R)$$

By Strong Law for Renewal Processes (Theorem 7.3.6),

$$\frac{N(t)}{t} \xrightarrow{a.s.} 1/\mathbb{E}(X).$$

Then by the Continuous Mapping Theorem (Theorem 8.4.13), the result follows.

(b)

□

Example 7.18 (Same as exam question). A wins point with probability p_1 if A is server, A wins with probability p_2 if B serves. alternate serve.

Solution. Every time A serves is a renewal. 1 reward each time A wins a point. Expected earning per cycle is $p_1 + p_2$. Cycles are length 2. Works out to $(p_1 + p_2)/2$.

Proposition 7.5.2. We've assumed that the renewal is earned at the end of the cycle. But the result holds even if the reward is earned during the interval gradually, not all at once at the end of the renewal interval (assuming all rewards are nonnegative). So

$$\frac{R(t)}{t} \xrightarrow{a.s.} \frac{\mathbb{E}(R)}{\mathbb{E}(X)}.$$

Also,

$$\mathbb{E}\left[\frac{R(t)}{t}\right] \xrightarrow{a.s.} \frac{\mathbb{E}(R)}{\mathbb{E}(X)}.$$

Proof. $R(t)$ is the total reward you get by time t . So $\sum_{i=1}^{N(t)} R_i \leq R(t)$ (the inequality holds if you've earned a bit since the last renewal). We have

$$\sum_{i=1}^{N(t)} R_i \leq R(t) \leq \sum_{i=1}^{N(t)+1} R_i$$

Dividing through by t :

$$\frac{1}{t} \sum_{i=1}^{N(t)} R_i \leq \frac{R(t)}{t} \leq \frac{1}{N(t)+1} \sum_{i=1}^{N(t)+1} R_i \cdot \frac{N(t)+1}{t}$$

But by Proposition 7.5.1

$$\frac{1}{t} \sum_{i=1}^{N(t)} R_i \xrightarrow{a.s.} \mathbb{E}(R)/\mathbb{E}(X),$$

$$\frac{1}{N(t)+1} \sum_{i=1}^{N(t)+1} R_i \xrightarrow{a.s.} \mathbb{E}(R)$$

$$\frac{N(t)+1}{t} \xrightarrow{a.s.} 1/\mathbb{E}(X)$$

So by the Continuous Mapping Theorem,

$$\frac{R(t)}{t} \xrightarrow{a.s.} \frac{\mathbb{E}(R)}{\mathbb{E}(X)}.$$

□

Example 7.19 (Similar to Example 7.15 in *Introduction to Probability Models*). People arrive to train station in a Poisson process with rate λ . K is the cost to dispatch the train. Suppose we incur a cost c per unit of time waiting per customer. What dispatching policy minimizes the long-run average cost per unit time?

Solution.

The structure of the optimal policy is to wait until a certain number of people arrive and then dispatch a train (n policy). So we want to determine this number. (Another policy is a t policy: dispatch a train every t units of time. But it turns out the best n policy is better than the best t policy. We may be interested in the difference in minimal costs because t policies are easier to employ and more convenient for customers.)

- (a) **n -policy:** Note that every time we dispatch a train, there is a renewal. At every renewal time there is a cost incurred. The long run average cost per unit time is the expected cost during a cycle divided by the expected time of a cycle. Note that the expected time between cycles is the expected amount of time for n people to arrive, which is simply n/λ . The cost of a cycle is

$$cX_2 + 2cX_3 + 3cX_4 + \dots + (n-1)cX_n + K$$

so the expected cost is

$$\mathbb{E}(X)(c + 2c + 3c + \dots + (n-1)c) + K = \frac{c(n-1)n}{\lambda} + K$$

Therefore taking the ratio, the average cost per cycle is

$$\left(\frac{1}{\lambda} \frac{c(n-1)n}{2} + K \right) / \left(\frac{n}{\lambda} \right) = \frac{c(n-1)}{2} + \frac{\lambda K}{n}.$$

Now we want to pick n to minimize this quantity. Treat n as continuous and take the derivative.

$$\frac{c}{2} - \frac{\lambda K}{n^2} = 0 \iff n = \sqrt{\frac{2\lambda K}{c}}$$

which makes the minimum average cost

$$\frac{1}{2} \left(c \sqrt{\frac{2\lambda K}{c}} - c \right) + K \sqrt{\frac{c}{2\lambda K}} = \sqrt{2\lambda c K} - \frac{c}{2}.$$

(b) **t -policy:** Dispatch a train every t time units. Note that we have a renewal every time you dispatch a train. The average cost per unit time is the expected cost per cycle $\mathbb{E}(C)$ divided by t . Note that

$$\begin{aligned} C &= c \sum_{i=1}^{N(t)} (t - S_i) = c \left(t N(t) - \sum_{i=1}^{N(t)} S_i \right) + K \\ \implies \mathbb{E}(C) &= c \mathbb{E} \left(t N(t) - \sum_{i=1}^{N(t)} S_i \right) + K = c \left[\lambda t^2 - \mathbb{E} \left(\sum_{i=1}^{N(t)} S_i \right) \right] + K \end{aligned}$$

Note that

$$\mathbb{E} \left(\sum_{i=1}^{N(t)} S_i \mid N(t) = n \right) = \mathbb{E} \left(\sum_{i=1}^n S_i \right) = \mathbb{E} \left(\sum_{i=1}^n U_i \right) = \frac{nt}{2} \implies \mathbb{E} \left(\sum_{i=1}^{N(t)} S_i \mid N(t) \right) = \frac{t N(t)}{2}$$

where $U_i \sim \text{U}(0, t)$.

$$\begin{aligned} \implies \mathbb{E}(C) &= c \lambda t^2 - c \mathbb{E} \left[\mathbb{E} \left(\sum_{i=1}^{N(t)} S_i \mid N(t) \right) \right] + K = c \lambda t^2 - c \mathbb{E} \left[\frac{t N(t)}{2} \right] + K = c \lambda t^2 - c \frac{\lambda t^2}{2} + K \\ \implies \mathbb{E}(C) &= \frac{c \lambda t^2}{2} + K \end{aligned}$$

Therefore the average cost per cycle is

$$\frac{1}{t} \cdot \left(\frac{c \lambda t^2}{2} + K \right) = \frac{\lambda c t}{2} + \frac{K}{t}$$

We seek the best t to minimize this cost. Take the derivative with respect to t .

$$\frac{\lambda c}{2} - \frac{K}{t^2} = 0 \implies t = \sqrt{\frac{2K}{\lambda c}}$$

So the minimum average cost is

$$\sqrt{\frac{2K}{\lambda c}} \frac{\lambda c}{2} + \frac{K}{t} \sqrt{\frac{\lambda c}{2K}} = K \sqrt{\frac{\lambda c}{2K}}.$$

Example 7.20. It costs C to buy a new car. The car lasts for a time L having distribution F before it fails. If the car fails, you incur cost K . Suppose you have a policy of buying a new car when the old car either fails or reaches a certain age t .

Solution. Note that a renewal occurs when you get a new car or when it fails. The cost per cycle is C if $L > t$, $C + K$ if $L \leq t$. The time for a cycle is $\min\{L, t\}$. Therefore the average cost per unit time is the expected cost of a cycle $C + K \Pr(L < t) = C + KF(t)$. The average lifetime is

$$\int_0^t x dF(x) + \int_t^\infty t dF(x) = \int_0^t x dF(x) + t \bar{F}(t).$$

Therefore the average cost per cycle is

$$\left(c + KF(t) \right) / \left(\int_0^t x dF(x) + t \bar{F}(t) \right).$$

Definition 7.20 (Age of a renewal process). We call $A(t) = t - S_{N(t)}$ the **age of the renewal process at time t** .

Definition 7.21 (Excess (or residual) lifetime at time t). We call $Y(t) = S_{N(t)+1} - t$ be the **excess (or residual) lifetime of a renewal process at time t** .

Proposition 7.5.3. Let X be the interarrival time for a renewal reward process. Then

(a) with probability 1,

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t A(s) ds = \frac{\mathbb{E}(X^2)}{2\mathbb{E}(X)}.$$

(b) With probability 1,

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t Y(s) ds = \frac{\mathbb{E}(X^2)}{2\mathbb{E}(X)}.$$

(c) With probability 1,

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t \mathbb{E}[A(s)] ds = \frac{\mathbb{E}(X^2)}{2\mathbb{E}(X)}.$$

(d) With probability 1,

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t \mathbb{E}[Y(s)] ds = \frac{\mathbb{E}(X^2)}{2\mathbb{E}(X)}.$$

Proof. (a) Imagine we earn a reward at a rate equal to the age of the renewal process. Then the amount earned by time t is

$$\int_0^t A(s) ds.$$

When there is a new renewal, the process starts over again, so this is a renewal reward process. The reward earned during each cycle is

$$\int_0^X t dt = \frac{X^2}{2}.$$

Taking expectations and taking the ratio of these in the limit, we have

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t A(s) ds = \frac{\mathbb{E}(X^2)}{2\mathbb{E}(X)}.$$

For more detail, see Example 7.18 in *Introduction to Probability Models*.

- (b) Imagine we earn a reward at a rate equal to the residual lifetime of the renewal process. Then the amount earned by time t is

$$\int_0^t Y(s) ds.$$

When there is a new renewal, the process starts over again, so this is a renewal reward process. The reward earned during each cycle is

$$\int_0^X (X - s) ds = X^2 - \frac{X^2}{2} = \frac{X^2}{2}.$$

Taking expectations and taking the ratio of these in the limit, we have

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t A(s) ds = \frac{\mathbb{E}(X^2)}{2\mathbb{E}(X)}.$$

For more detail, see Example 7.19 in *Introduction to Probability Models*.

- (c) Similar to (a).
 (d) Similar to (c).

□

Remark 85. This makes sense because if the process is infinitely long, if you look at it backwards in time the distribution of renewals is the same as if you look forward in time. But when you switch direction, the residual lifetimes and ages reverse meaning. Therefore since the distribution doesn't change depending on the direction you look at it from, the long-term expected residual lifetime and age ought to be equal.

Proposition 7.5.4 (Homework 7, *Introduction to Probability Models* Ch. 7 Problem 30).

$$\frac{A(t)}{t} \xrightarrow{a.s.} 0.$$

Proof. $A(t)$ is the time since the last renewal; that is, $A(t) = t - S_{N(t)}$. So we hope to show that with probability one,

$$\frac{t - S_{N(t)}}{t} \rightarrow 0 \text{ as } t \rightarrow \infty$$

(or, equivalently)

$$\frac{t - S_{N(t)}}{t} \xrightarrow{w.p.1} 0.$$

Note that

$$\frac{t - S_{N(t)}}{t} = \frac{t - S_{N(t)}}{N(t)} \cdot \frac{N(t)}{t} = \left(\frac{t}{N(t)} - \frac{S_{N(t)}}{N(t)} \right) \frac{N(t)}{t}$$

By the Strong Law for Renewal Processes (Theorem 7.3.6), $\frac{N(t)}{t} \xrightarrow{w.p.1} \mu^{-1}$, where $\mu = \mathbb{E}(X)$ is the expected interarrival time. Since the expected interarrival time is finite, $N(t) \rightarrow \infty$ as $t \rightarrow \infty$. Therefore

$$\frac{S_{N(t)}}{N(t)} = \frac{X_1 + \dots + X_{N(t)}}{N(t)} \xrightarrow{w.p.1} \mu.$$

Lastly, since $N(t) > 0$ with probability 1 as $t \rightarrow \infty$ and $t > 0$, by the Continuous Mapping Theorem

$$\frac{t}{N(t)} = \left(\frac{N(t)}{t} \right)^{-1} \xrightarrow{w.p.1} (\mu^{-1})^{-1} = \mu.$$

Therefore by another application of the Continuous Mapping Theorem,

$$\frac{t - S_{N(t)}}{t} = \left(\frac{t}{N(t)} - \frac{S_{N(t)}}{N(t)} \right) \frac{N(t)}{t} \xrightarrow{w.p.1} (\mu - \mu) \cdot \mu^{-1} = 0.$$

□

Example 7.21 (Similar to Example 7.20 in *Introduction to Probability Models*). People arrive to a bus stop in a Poisson process with rate λ . Buses arrive in an independent renewal process after time T with distribution F where $\mathbb{E}(T) = \mu$.

- (a) What is the long-run average number of people picked up by a bus when it arrives?
- (b) Suppose busses arrive according to a Poisson process with rate λ ; that is, $F(t) = 1 - e^{-\alpha t}$. What is the long-run average number of people waiting at any given time (averaged over all time)?
- (c) What is the average amount of time a person waits for a bus (averaged over all people)? (Let W_i be the waiting time of person i . We seek $\lim_{n \rightarrow \infty} \sum_{i=1}^n W_i/n$.)

Solution.

- (a) Every time a bus arrives, we have a renewal. The number of people picked up by a bus is $N(T)$. Note that $\{N(t)\} \sim PP(\lambda)$. Note that

$$\mathbb{E}(N(T) | T = t) = \mathbb{E}(N(t) | T = t) = (\text{by independence}) \mathbb{E}(N(t)) = \lambda t \implies \mathbb{E}(N(T) | T) = \lambda T$$

$$\implies \mathbb{E}(N(T)) = \mathbb{E}(\mathbb{E}(N(T) | T)) = \lambda \mathbb{E}(T) = \lambda \mu.$$

(b) Let $N_s(s)$ be the number of people waiting at time s . We seek

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t N_w(s) ds.$$

Imagine that at time s we earn at a rate $N_w(s)$. Then we want the average reward per unit time. Then this is a renewal reward process, where renewals happen when a bus arrive. The expected reward earned per cycle is

$$\frac{1}{\mathbb{E}(T)} \cdot \mathbb{E}\left(\int_0^T N(s) ds\right) \quad (7.8)$$

Note that

$$\begin{aligned} \mathbb{E}\left(\int_0^T N(s) ds \mid T = t\right) &= \mathbb{E}\left(\int_0^t N(s) ds\right) = (\text{by Fubini's Theorem}) \int_0^t \mathbb{E}(N(s)) ds = \int_0^t \lambda s ds = \frac{\lambda t^2}{2} \\ &\implies \mathbb{E}\left(\int_0^T N(s) ds \mid T\right) = \frac{\lambda T^2}{2} \end{aligned}$$

Therefore we have that the expected reward earned per cycle is (plugging into (7.8))

$$\frac{\lambda \mathbb{E}(T^2)}{2 \mathbb{E}(T)}.$$

Because arrivals occur in a Poisson process ($F(t) = 1 - e^{-\alpha t}$), we have $\mathbb{E}(T) = \alpha^{-1}$, $\mathbb{E}(T^2) = 2\alpha^{-2}$. Therefore the expected reward earned per cycle is

$$\frac{\lambda 2\alpha^{-2}}{2\alpha^{-1}} = \frac{\lambda}{\alpha}.$$

(c) $\frac{\lambda}{\alpha}$.

Remark 86. Note that the average number of people picked up by a bus now matches the average number of people waiting at any given time. This is counterintuitive because you would think at the time the bus comes, the most people are there, so the average number of people picked up should be larger than the average number of people waiting in general.

This illustrates the **PASTA principle** and the **inspection paradox**. The paradox is resolved by the fact that the average in (b) is averaged over all time, while the average in (c) is averaged over all people.

Theorem 7.5.5. Queue, customers arrive in a renewal process with distribution F , so

$$\lambda^{-1} = \int_0^\infty \bar{F}(t) dt.$$

Each customer eventually leaves. Let L be the average number of customers in the system, averaged over all time. Let $X(s)$ be the number of customers in the system at time s . Note that

$$L = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t X(s) ds.$$

Let W be the average time a customer spends in the system. Let W_i be the amount of time customer i spends in the system. Note that

$$W = \lim_{n \rightarrow \infty} \frac{W_1 + \dots + W_n}{n}.$$

Then $L = \lambda W$.

Proof.

$$L = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t X(s) ds$$

Suppose we are paid at any time at a rate equal to the number of customers in the system. Then we can interpret L as the average reward per unit time. We can consider a renewal as occurring upon the arrival of the first customer when the system was previously empty. Then we have a renewal reward process. Let T be the time between renewals. Assume the first arrival occurs at time $t = 0$ (so this is not a delayed renewal reward process). Note that

$$L = \frac{1}{\mathbb{E}(T)} \mathbb{E} \left(\int_0^T X(s) ds \right) \iff \mathbb{E} \left(\int_0^T X(s) ds \right) = L \mathbb{E}(T) \quad (7.9)$$

Note that

$$W = \lim_{n \rightarrow \infty} \frac{W_1 + \dots + W_n}{n}$$

Let N be the number of customers served in a busy period. Then when customer $N+1$ arrives, the system is empty and there is a renewal, so T is the time of the $N+1$ st arrival. So

$$T = \sum_{i=1}^N X_i$$

where X_i are the interarrival times (X_i is the time between the i th and $i+1$ st arrival). Note that N depends on the interarrival times; if the interarrival times are small, N will be larger. So this is not a compound random variable, but we can use Wald's Equation (Theorem 7.3.8) if N is a stopping time for X_1, \dots, X_n . Note that $N = 1$ if and only if X_1 is greater than the service time of the initial customer. And in general, $N = k$ depends only on the arrival times up to X_k . So N is a stopping time and we can use Wald's Equation. Therefore

$$\mathbb{E}(T) = \frac{\mathbb{E}(N)}{\lambda}. \quad (7.10)$$

Suppose each customer pays us 1 dollar per unit time. Then at time s we are earning at rate $X(s)$, so

$$\int_0^T X(s)ds$$

is the total amount you earn by time T . But we can also calculate this amount by adding up the amount of time each customer spends in the system:

$$\int_0^T X(s)ds = \sum_{i=1}^N W_i.$$

So we have (using (7.9) and (7.10))

$$\begin{aligned} \mathbb{E}\left(\int_0^T X(s)ds\right) &= \mathbb{E} \sum_{i=1}^N W_i \iff L\mathbb{E}(T) = \mathbb{E} \sum_{i=1}^N W_i \iff L = \frac{\mathbb{E}(\sum_{i=1}^N W_i)}{\mathbb{E}(N)/\lambda} \\ &= (\text{by Wald's Equation}) \frac{\lambda\mathbb{E}(N)\mathbb{E}(W_i)}{\mathbb{E}(N)} = \lambda W. \end{aligned}$$

□

Exercise 21. Queue, customers arrive in a renewal process with distribution F , so

$$\lambda^{-1} = \int_0^\infty \bar{F}(t)dt.$$

Each customer eventually leaves. Let L be the average number of customers in the system, averaged over all time. Let $X(s)$ be the number of customers in the system at time s . Note that

$$L = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t X(s)ds.$$

Let W be the average time a customer spends in the system. Let W_i be the amount of time customer i spends in the system. Note that

$$W = \lim_{n \rightarrow \infty} \frac{W_1 + \dots + W_n}{n}.$$

Solution.

7.5.1 Alternating Renewal Processes (Section 7.5.1 in *Introduction to Probability Models*)

Definition 7.22 (Alternating renewal process). Suppose we have a process that is on for time Y_1 , off for time Z_1 , on for time Y_2 , off for time Z_2 , etc if (X_i, Y_i) , $i \geq 1$ are i.i.d. Call $\{X(t), t \geq 0\}$ an **alternating renewal process**, where $X(t)$ is an indicator variable for the process being on at time t .

Proposition 7.5.6 (Proposition 7.4 in *Introduction to Probability Models*; similar to Theorem 7.5.7 (Theorem 3.4.4 in *Stochastic Processes*)).

(a) The long-run proportion of time that the system is on is

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t I\{X(s) = 1\} ds = \frac{\mathbb{E}(Y)}{\mathbb{E}(Y) + \mathbb{E}(Z)}.$$

(b)

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t \Pr(X(s) = 1) ds = \frac{\mathbb{E}(Y)}{\mathbb{E}(Y) + \mathbb{E}(Z)}.$$

Proof. (a) Imagine we earn 1 dollar per unit time when the system is on and nothing when the system is off. Note that we have a renewal when the system turns back on after having been turned off. So this is a renewal reward process.

(b) Something about

$$\frac{R(t)}{t} \rightarrow \frac{\mathbb{E}(R)}{\mathbb{E}(T)}$$

and

$$\frac{\mathbb{E}R(t)}{t} \rightarrow \frac{\mathbb{E}(R)}{\mathbb{E}(T)}$$

□

Proposition 7.5.7 (Theorem 3.4.4 in *Stochastic Processes*; Similar to Proposition 7.5.6 (Proposition 7.4 in *Introduction to Probability Models*)). If the cycle distribution is not lattice (see Definition 6.10), then

$$\Pr(\text{on at } t) \rightarrow \frac{\mathbb{E}(Y)}{\mathbb{E}(Y) + \mathbb{E}(Z)} \text{ as } t \rightarrow \infty$$

where $\mathbb{E}(Y)$ is the expected length of time intervals when the system is on and $\mathbb{E}(Z)$ is the expected length of time intervals when the system is off.

Example 7.22. Suppose you have insurance and you pay at a rate r_1 until you have an accident. Then the rate is r_2 until s units pass without an accident, in which case you go back to paying rate r_1 . Suppose accidents occur according to a Poisson process with rate λ . Then the probability you have to pay at rate r_1 is

$$\frac{\mathbb{E}(\text{on})}{\mathbb{E}(\text{on}) + \mathbb{E}(\text{off})}.$$

where we define the process to be “on” when your pay rate is r_1 and “off” when your pay rate is r_2 . Note that

$$\mathbb{E}(\text{on}) = 1/\lambda$$

$$\mathbb{E}(\text{off}) = \int_0^\infty \mathbb{E}(\text{off} \mid T = x) \lambda e^{-\lambda x} dx$$

We have

$$\mathbb{E}(\text{off} \mid T = x) = \begin{cases} x + \mathbb{E}(\text{off}) & x < s \\ s & x > s \end{cases}$$

Substituting this in yields

$$\mathbb{E}(\text{off}) = \int_0^s (x + \mathbb{E}(\text{off})) \lambda e^{-\lambda x} dx + s \int_s^\infty \lambda e^{-\lambda x} dx = \int_0^s x \lambda e^{-\lambda x} dx + \mathbb{E}(\text{off})(1 - e^{-\lambda s}) + s e^{-\lambda s}.$$

Recall that the age of the renewal process at time t is $A(t) - t - S_{N(t)}$ and the excess time at t is $Y(t) = S_{N(t)+1} - t$. We have already shown (in Proposition 7.5.3) that

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t A(s) ds = \lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t Y(s) ds = \frac{\mathbb{E}(X^2)}{2\mathbb{E}(X)}.$$

Example 7.23 (Example 7.28 in *Introduction to Probability Models*). $M/G/\infty$ queue, (arrivals are a Poisson Process). Consider the system to be “on” if the system is empty and “off” when the system is not empty (busy period). Note that $\mathbb{E}(\text{on}) = \lambda^{-1}$. Let $\mathbb{E}(B)$ be the expected length of the “off” time (busy period). Find $\mathbb{E}(B)$.

Solution. A busy time starts when a first customer arrives. The long-run proportion of time the system is on is

$$\frac{\mathbb{E}(\text{on})}{\mathbb{E}(\text{on}) + \mathbb{E}(\text{off})}.$$

By Proposition 7.5.7, since this is nonlattice, this equals the limiting probability that the system is on at time t . That is,

$$\lim_{t \rightarrow \infty} \Pr(\text{on at } t) = \frac{\mathbb{E}(\text{on})}{\mathbb{E}(\text{on}) + \mathbb{E}(\text{off})}.$$

Let $X(t)$ be the number remaining in the system at time t . By Proposition 7.2.10,

$$X(T) \sim \text{Poisson} \left(\lambda \int_0^T \bar{G}(s) ds \right).$$

So

$$\lim_{t \rightarrow \infty} \Pr(\text{on at } t) = \Pr(X(t) = 0) = \exp \left(-\lambda \int_0^t \bar{G}(s) ds \right)$$

Plugging in we have **might have made a mistake here:** $S \sim G$, then $\lim_{t \rightarrow \infty} \Pr(\text{on at } t) = \mathbb{E}(S)$

$$\exp \left(-\lambda \int_0^t \bar{G}(s) ds \right) = \frac{\lambda^{-1}}{\lambda^{-1} + \mathbb{E}(\text{off})}.$$

think this bottom one below might be the right one

$$\exp \left(-\mathbb{E}(S) \right) = \frac{\lambda^{-1}}{\lambda^{-1} + \mathbb{E}(\text{off})}.$$

Definition 7.23 (Equilibrium distribution of a renewal process). We call

$$F_e(x) = \frac{1}{\mu} \int_0^x \bar{F}(t) dt$$

the **equilibrium distribution** of a renewal process with interarrival distribution F , where μ is the expected length of a cycle in the renewal process.

Proposition 7.5.8 (Age of equilibrium distribution; restatement of Theorem 7.5.7 (Theorem 3.4.4 in *Stochastic Processes*); similar to Examples 7.26 and 7.27 in *Introduction to Probability Models*; Similar to Proposition 7.5.6 (Proposition 7.4 in *Introduction to Probability Models*)). With probability 1, the long-run proportion of time that the age is less than x is

$$\lim_{s \rightarrow \infty} \frac{1}{s} \int_0^s I\{A(t) < x\} dt = F_e(x)$$

and the long-run proportion of the time that the excess is less than x

$$\lim_{s \rightarrow \infty} \frac{1}{s} \int_0^s I\{Y(t) < x\} dt = F_e(x)$$

both equal $F_e(x) = \frac{1}{\mu} \int_0^x \bar{F}(t) dt$. These are also equal to

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t \Pr(A(s) < x) ds = F_e(x)$$

and

$$\lim_{t \rightarrow \infty} \frac{1}{t} \int_0^t \Pr(Y(s) < x) ds = F_e(x)$$

If F is not lattice, then

$$\lim \Pr(A(t) < a) = \lim \Pr(Y(t) < a) = F_e(t).$$

Proof. Say the system is “on” at time t if $A(t) < x$, “off” otherwise. A cycle is a renewal. So the system is “on” for the first x units of a renewal cycle, and then it is “off.” Once a renewal occurs, the age goes back to 0, so this is an alternating renewal process. The “on” time in a cycle is $\min\{x, X\}$ because it’s on for the first x units of time the item is in use of a cycle, unless the cycle is less than x , in which case it’s on for the whole length of the cycle. Therefore we have that the expected “on” time is

$$\frac{\mathbb{E}(\text{on time in cycle})}{\mu} = \frac{\mathbb{E}(\min\{x, X\})}{\mu} = F_e(x)$$

where μ is the average length of a cycle. Note that

$$\mathbb{E}(\min\{x, X\}) = \int_0^\infty \Pr(\min\{x, X\} > t) dt = \int_0^x \bar{F}(t) dt$$

so we have that the expected “on” time is

$$\frac{1}{\mu} \int_0^x \bar{F}(t) dt = F_e(x)$$

Now we will show that the expected excess is the same as the expected age. Say that the system is “on” at t if $Y(t) > x$ and “off” otherwise. A cycle happens every time a renewal occurs. So if a renewal cycle is longer than x , the system will be initially on and then become off for the last x time units of a renewal. So the off time is $\min\{x, X\}$. Again, by a similar argument as above we get the same result. (Intuitively this makes sense because the distribution of interarrival times is the same if you look backward in time as it is if you look forward in time.)

□

Recall Proposition 7.5.3: The average age and average excess both equal $\mathbb{E}(X^2)/(2\mathbb{E}(X))$. Note that

$$A(t) + Y(t) = S_{N(t)+1} - S_{N(t)} = X_{N(t)+1}.$$

Proposition 7.5.9 ([Proposition 3.4.6 in *Stochastic Processes*]). With probability 1, the average value of $X_{N(t)+1}$ is

$$\frac{\mathbb{E}(X^2)}{\mathbb{E}(x)} > \mathbb{E}(X)$$

Proof. Suppose $X_e \sim F_e$ where

$$F_e(x) = \frac{1}{\mu} \int_0^x \bar{F}(y) dy$$

Note that

$$\frac{dF_e(x)}{dx} = \frac{\bar{F}(x)}{\mu}$$

We have

$$\begin{aligned}\mathbb{E}(X_e) &= \int_0^\infty x dF_e(x) = \int_0^\infty x \frac{\bar{F}(x)}{\mu} dx = \int_0^\infty \frac{x}{\mu} \int_x^\infty dF(y) dx = (\text{by Fubini's Theorem}) \int_0^\infty \int_0^y \frac{x}{\mu} dx dF(y) \\ &= \int_0^\infty \frac{y^2}{2\mu} dF(y) = \frac{\mathbb{E}(X^2)}{2\mu}\end{aligned}$$

□

Proposition 7.5.10 (Problem on homework 7; inspection paradox).

$$\Pr(X_{N(t)+1} > x) > \bar{F}(x).$$

7.5.2 Equilibrium renewal processes

Definition 7.24 (Equilibrium renewal process). Suppose we have a delayed renewal process where $X_1 \sim F_e$, $X_i \sim F \forall i > 1$. Then $\{N_e(t), t \geq 0\}$ is called an **equilibrium renewal process**. (the time until the first event has the equilibrium distribution.) We let $m_e(t) = \mathbb{E}(N_e(t))$.

Example 7.24. Suppose you arrive at some time t during a renewal process with finite expected renewal time μ . Then you will have to wait $Y(t)$ time until the next renewal. Let F_t be the distribution function of $Y(t)$. After that first arrival, all of the other arrival times will have distribution F . If the time t at which you start observing is very large, you observe an equilibrium renewal process (because $F_t \rightarrow F_e$ as $t \rightarrow \infty$).

Proposition 7.5.11 (Theorem 3.5.2 from *Stochastic Processes*). Let $\{N_e(t), t \geq 0\}$ be an equilibrium renewal process. Let the excess at time t of $\{N_e(t)\}$ be $Y_e(t)$.

- (1) $Y_e(t) \sim F_e$ for all t .
- (2) $N_e(t+s) - N_e(t)$ has the same distribution for all t (this counting process has stationary increments—see Definition 7.4).
- (3) $m_e(t) = t/\mu$.

Proof (More of an intuitive argument than a complete proof). (1) Consider an ordinary renewal process with interarrival times distributed as F . Suppose we start observing at a very large time t' , so we are observing an equilibrium renewal process. That is, the time until the first event is distributed as F_e . We'd like to know the time until the next event after you've waited a time t . We have

$$Y_e(t) = Y(t+t') \sim F_e$$

since t' is very very large.

- (2) Similar argument—after arriving after a very large amount of time, the distribution is in equilibrium, so it makes no difference when you start watching, just matters how large s is.

(3)

$$N_e(t+s) = N_e(t+s) - N_e(t) + N_e(t)$$

$$\iff \mathbb{E}(N_e(t+s)) = \mathbb{E}[N_e(t+s) - N_e(t)] + \mathbb{E}[N_e(t)] \iff m_e(t+s) = m_e(s) + m_e(t)$$

where $\mathbb{E}(N_e(t+s)) = m_e(t+s)$ by definition, $\mathbb{E}[N_e(t+s) - N_e(t)] = m_e(s)$ by the result from part (2), and $\mathbb{E}[N_e(t)] = m_e(t)$ by definition. It is the case that $f(x+y) = f(x) + f(y) \implies f(x) = cx$ for some constant c if f is measurable. Because of that, we have that

$$m_e(t) = ct$$

where c is some constant. By the Elementary Renewal Theorem (Theorem 7.3.9),

$$\frac{m_e(t)}{t} \rightarrow \frac{1}{\mu}$$

which implies that c is μ^{-1} .

□

Proving that the previous statement is true for any measurable function requires measure theory, but it is easy to prove it is true if f is differentiable.

Lemma 7.5.12. If f is differentiable, $f(x+h) = f(x) + f(h)$.

Proof. Note that

$$\lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h} = f'(x)$$

Note that

$$\lim_{h \rightarrow 0} \frac{f(h)}{h} = f'(0)$$

Then $f'(x) = c$, $f(x) = cx + k$, so $f(x) = cx$.

□

Theorem 7.5.13 (Blackwell's Theorem (Theorem 3.4.1 in *Stochastic Processes*, p.110)). (i)

If F is not lattice, then

$$m(t+a) - m(t) \rightarrow \frac{a}{\mu} \text{ as } t \rightarrow \infty$$

(ii) If F is lattice with period d , then

$$\mathbb{E}(\text{number of renewals at } nd) \rightarrow \frac{d}{\mu} \text{ as } n \rightarrow \infty.$$

Remark 87. If $\Pr(X_i = 0) = 0$ then this means that $\Pr(\text{renewal at } nd) \rightarrow d/\mu$ as $n \rightarrow \infty$.

Proof (intuitive; rigorous proof is quite technical). (i) If you arrive at time t , then $\{N(s), s \geq 0\}$ is a delayed renewal process. That is, X_1 has the distribution of $Y(t) \sim F_t$, and the remaining $X_i \sim F$. So

$$m(t+a) - m(t) = \mathbb{E}[N_t(a)].$$

We already know that as $t \rightarrow \infty$, $F_t \rightarrow F_e$. So as $t \rightarrow \infty$, $m(t+a) - m(t) = \mathbb{E}[N_t(a)] \rightarrow \mathbb{E}[N_e(a)]$. But by Proposition 7.5.11, **the result follows (??)**.

(ii) Suppose we have a renewal process where

$$\sum_{i=0}^{\infty} \Pr(X = i) = 1.$$

Then $m(n)$ is the expected number of renewals by time n . That is,

$$m(n) = \mathbb{E} \sum_{i=0}^n (\text{number of renewals at } i) = \sum_{i=0}^n \mathbb{E}(\text{number of renewals at } i)$$

Then by the Elementary Renewal Theorem (Theorem 7.3.9),

$$\frac{m(n)}{n} = \frac{1}{n} \sum_{i=0}^n \mathbb{E}(\text{number of renewals at } i) \rightarrow \frac{1}{\mu}$$

In general, this does not imply that

$$\mathbb{E}(\text{number of renewals at } nd) \rightarrow \frac{d}{\mu} \text{ as } n \rightarrow \infty.$$

For example, consider the discrete random variable

$$X_i = \begin{cases} 2 & \text{with probability } 1/2 \\ 4 & \text{with probability } 1/2 \end{cases}$$

Then

$$\mathbb{E}(\text{number of renewals at } n) = m(n) = \frac{1}{n} \sum_{i=1}^n \mathbb{E}(\text{number of renewals at } i) \rightarrow \frac{1}{\mu}$$

But of course all of these sums are 0 when i is odd. So we could also write this as

$$m(n) = \sum_{i=1}^{\lfloor n/2 \rfloor} n/2 \frac{1}{n} \mathbb{E}(\text{number of renewals at } 2i) \rightarrow \frac{1}{\mu}$$

$$\iff m(n) = \frac{1}{2} \sum_{i=1}^{\lfloor n/2 \rfloor} n/2 \frac{1}{n/2} \mathbb{E}(\text{number of renewals at } 2i) \rightarrow \frac{1}{\mu}$$

$$\iff m(n) = \sum_{i=1}^{\lfloor n/2 \rfloor} n/2 \frac{1}{n/2} \mathbb{E}(\text{number of renewals at } 2i) \rightarrow \frac{2}{\mu}$$

⋮

You get pointwise convergence in the lattice case with period d when d is the period.

□

Recall Proposition 7.5.3: The average age and average excess both equal $\mathbb{E}(X^2)/(2\mathbb{E}(X_e))$, where $X_e \sim F_e$.

Theorem 7.5.14 (Proposition 3.4.6 in *Stochastic Processes*). If F is not lattice,

$$\lim_{t \rightarrow \infty} \mathbb{E}(A(t)) = \lim_{t \rightarrow \infty} \mathbb{E}(Y(t)) = \frac{\mathbb{E}(X^2)}{2\mathbb{E}(X)}.$$

Proof. Won't prove; requires Key Renewal Theorem, which is beyond scope of this course. Some notes: we know that $F_{Y(t)} \rightarrow F_e$, or $Y(t) \rightarrow Y(\infty)$ where $Y(\infty) \sim F_e$. Then

$$\lim \mathbb{E}(Y(t)) = (? \text{ can't justify now}) \mathbb{E}(\lim(Y(t))) = \mathbb{E}(X_\infty)$$

□

Corollary 7.5.14.1 (Corollary 3.4.7 in *Stochastic Processes*, p. 121). If $\mathbb{E}(X^2) < \infty$ and F is nonlattice, then

$$m(t) - \frac{t}{\mu} \rightarrow \frac{\mathbb{E}(X^2)}{2\mu^2} - 1 \text{ as } t \rightarrow \infty$$

Proof. Recall that by Wald's Equation (Theorem 7.3.8),

$$\mathbb{E}\left(\sum_{i=1}^{N(t)+1} X_i\right) = \mu(m(t) + 1)$$

So

$$\mu(m(t) + 1) = \mathbb{E}(t + Y(t)) = t + \mathbb{E}(Y(t)) \iff m(t) + 1 = \frac{t}{\mu} + \frac{\mathbb{E}(Y(t))}{\mu} \iff m(t) - \frac{t}{\mu} = \frac{\mathbb{E}(Y(t))}{\mu} - 1$$

$$\implies m(t) - \frac{t}{\mu} \rightarrow \frac{\mathbb{E}(X^2)}{2\mu^2} - 1 \text{ as } t \rightarrow \infty$$

$$\implies m(t) \approx \frac{t}{\mu} + \frac{\mathbb{E}(X^2)}{2\mu^2} - 1$$

□

Theorem 7.5.15 (Central Limit Theorem for Renewal Processes; Theorem 7.3 in *Introduction to Probability Models*). Let $N(t)$ be a renewal process. Then

$$N(t) \xrightarrow{d} \mathcal{N}\left(\frac{t}{\mu}, \frac{t\sigma^2}{\mu^3}\right)$$

where $\mu = \mathbb{E}(X_i)$ and $\sigma^2 = \text{Var}(X_i)$.

Remark 88. If the renewal process is a Poisson process with rate λ , then $F(x) = 1 - e^{-\lambda x}$. Then $\mu = \mathbb{E}(X) = \lambda^{-1}$, $\sigma^2 = \text{Var}(X) = \lambda^{-2}$, $t/\mu = \lambda t$, $t\sigma^2/\mu^2 = t\lambda^3/\lambda^2 = \lambda t$, which implies the limiting distribution is $\mathcal{N}(\lambda t, \lambda t)$, as expected.

Proof. Note that $N(t) < n$ if and only if the n th event occurred after t , or $X_1 + \dots + X_n > t$. So

$$\Pr(N(t) < n) = \Pr(X_1 + \dots + X_n > t)$$

Then by the Central Limit Theorem,

$$X_1 + \dots + X_n \sim \mathcal{N}(n\mu, n\sigma^2) \text{ (approximately)}$$

⋮

□

7.5.3 Regenerative Processes

Theorem 7.5.16 (Theorem 3.7.1 in *Stochastic Processes*). Let $\{X(t), t \geq 0\}$ be a stochastic process with state space $\{0, 1, 2, \dots\}$ having the property that there exist time points at which the state restarts itself (with probability 1). Let S_1, S_2, \dots constitute the event times of a renewal process. We call $X(t)$ a **regenerative process**. So $\{S_1, S_2, \dots\}$ constitute the event times of a renewal process. We say a cycle is completed every time a renewal occurs. Let $N(t) = \max\{n : S_n \leq t\}$ denote the number of cycles by time t .

If F , the distribution of a cycle, has a density over some interval, and if $\mathbb{E}(S_1) < \infty$, then

$$P_j = \lim_{t \rightarrow \infty} \Pr(X(t) = j) = \frac{\mathbb{E}(\text{amount of time in state } j \text{ in a cycle})}{\mathbb{E}(\text{time of a cycle})}.$$

7.5.4 Example of Renewal Reward Processes to Patterns

Example 7.25 (Seems to be similar to Section 7.9.2 in *Introduction to Probability Models*). Suppose we have i.i.d. data. Number i appears with probability p_i . We want to see the mean time until we

see the pattern 1213121. An event is when the pattern appears. The next event is the next time the pattern appears, but we can't use data from the last event. Earn \$1 whenever the last 7 values are 1313121 (so you *are* allowed to use previous values for the reward process). That is, if the cycle is

$$\dots 1213121 \mid 312\mathbf{1} \dots 1213121 \mid$$

the events happen at the | marks, but in between there were two rewards (one at the second event, one at the bold 1). So this is a delayed renewal reward process $(X_i, R_i), i \geq 2$. Note that the limiting results will be the same for the delayed renewal process as for the normal one. So the expected average reward per unit time is the expected reward during the cycle divided by the expected time of a cycle;

$$\mathbb{E}(\text{average reward per unit time}) = \frac{\mathbb{E}(\text{reward during the cycle})}{\mathbb{E}(T)}$$

We want $\mathbb{E}(T)$, the expected length of a cycle. We know $\mathbb{E}(\text{average reward per unit time})$ is

$$\mathbb{E}(\text{average reward per unit time}) = p_1^4 p_2^2 p_3$$

Now we want $\mathbb{E}(\text{reward during the cycle})$. Suppose a cycle just ended (the pattern just appeared). Then we could earn a reward after 4 values (if the last 4 terms of the pattern appear again) after 6 values (if the last 6 terms of the pattern appear again). And we will earn a reward when the cycle ends (after the full pattern appears again). So if Y_i is the reward earned during after i new values,

$$\text{reward during the cycle} = Y_4 + Y_6 + 1 \implies \mathbb{E}(\text{reward during the cycle}) = \mathbb{E}(Y_4) + \mathbb{E}(Y_6) + 1 = p_1^2 p_2 p_3 + p_1^3 p_2^2 p_3 + 1$$

$$\implies \mathbb{E}(T) = \frac{p_1^2 p_2 p_3 + p_1^3 p_2^2 p_3 + 1}{p_1^4 p_2^2 p_3} = \frac{1}{p_1^2 p_2} + \frac{1}{p_1} + \frac{1}{p_1^4 p_2^2 p_3}$$

Note that the mean time between renewals is $\frac{1}{p_1^4 p_2^2 p_3}$, the mean time to get 121 is $\frac{1}{p_1^2 p_2}$, and the mean time to get 1 is $\frac{1}{p_1}$.

Example 7.26 (Similar to example 7.38 in *Introduction to Probability Models*). Suppose we are flipping coins, probability of flipping heads is p . The pattern is n heads in a row. Cycle is. a pattern without using data from last cycle. Get a reward of 1 each time the last n values were all heads. Then

$$p^n = \mathbb{E}(\text{average reward per unit time}) = \frac{\mathbb{E}(\text{reward during the cycle})}{\mathbb{E}(T)}$$

Note that

$$\text{reward during the cycle} = Y_1 + \dots + Y_{n-1} + 1 \implies \mathbb{E}(\text{reward during the cycle}) = \sum_{i=1}^{n-1} \mathbb{E}(Y_i) + 1$$

$$\begin{aligned}
&= \sum_{i=1}^{n-1} p^i + 1 \\
\implies p^n = \frac{1}{\mathbb{E}(T)} \left(\sum_{i=1}^{n-1} p^i + 1 \right) &\implies \mathbb{E}(T) = p^{-n} \left(\sum_{i=1}^{n-1} p^i + 1 \right) = \left(\frac{1}{p}\right)^n + \left(\frac{1}{p}\right)^{n-1} + \dots + \frac{1}{p}
\end{aligned}$$

7.6 Markov Chains (Chapter 4 of *Stochastic Processes*; Chapter 4 of *Introduction to Probability Models*)

Suppose we have X_0, X_1, X_2, \dots , where X_n is the state of the system at time n . The set of possible values of states are the nonnegative integers (the number of possible states will be either finite or countable). In a Markov chain, the probability of reaching state j given that you are currently in state i is P_{ij} ; that is,

$$\Pr(X_{n+1} = j \mid X_n = i, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) = P_{ij}$$

That is, the next state depends only on the current state, not any of the previous states (all the information is contained in the current state). In other words, every starts over again when you reach state i ; so there is a renewal every time you reach state i . We say a system has the **Markovian property** if given the present state X_n , the next state X_{n+1} is independent of the past X_{n-1}, X_{n-2}, \dots

Definition 7.25 (Markov chain). Let S be the set of possible values of a system. S must be either finite or countably infinite (in general we will take $S = \mathbb{N}$). Then $\{X_0, X_1, \dots\}$ is said to be a **Markov chain** with transition probabilities $\Pr(X_{n+1} = j \mid X_n = i)P_{i,j}$, $i, j \in S$ if

$$\Pr(X_{n+1} = j \mid X_n = i, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) = \Pr(X_{n+1} = j \mid X_n = i) = P_{ij}.$$

We call the matrix

$$P = [P_{ij}]$$

the **transition probability matrix**. Note that $\sum_j P_{ij} = 1$, so the the rows of the transition probability matrix all add to 1.

Remark 89. Given the initial state $\Pr(X_0 = i_0)$ and the probability transition matrix, all probabilities about X_0, X_1, \dots can (in theory) be determined. That is,

Note that

$$\Pr(X_n = i_n) = \sum_{i_0, i_1, \dots, i_{n-1}} \Pr(X_0 = i_0) P_{i_0, i_1} P_{i_1, i_2} \dots, P_{i_{n-1}, i_n}.$$

Example 7.27 (Examples 4.1 and 4.4 in *Introduction to Probability Models*). Suppose we have a state based on weather today and yesterday. Then probability of rain tomorrow is the following:

$$\begin{cases} dd \rightarrow r & \text{with probability 0.3} \\ rd \rightarrow r & \text{with probability 0.4} \\ dr \rightarrow r & \text{with probability 0.6} \\ rr \rightarrow r & \text{with probability 0.7} \end{cases}$$

The transition matrix looks as follows:

$$P = \begin{bmatrix} & dd & rd & dr & rr \\ dd & 0.7 & 0 & 0.3 & 0 \\ rd & 0.6 & 0 & 0.4 & 0 \\ dr & 0 & 0.4 & 0 & 0.6 \\ rr & 0 & 0.3 & 0 & 0.7 \end{bmatrix}$$

Example 7.28 (Random walk; examples 4.5 and 4.6 in *Introduction to Probability Models*).

$$P_{i,i+1} = p, P_{i,i-1} = 1 - p, \quad S = \mathbb{Z}$$

One example is Gambler's Ruin: $X_0 = i$, stop when fortune is either 0 or N . (See Example 7.41 and several solutions in Grimmett and Stirzaker.)

Example 7.29 (Similar to example 4.10 in *Introduction to Probability Models*, similar to homework problem from Math 505A). Urn with 2 balls, red and blue. Each period, choose ball from urn at random. If red then replace with blue. If blue then replace with red with probability 0.7, with blue with probability 0.3. What is the long-run proportion of time the chosen ball is red?

Solution. Let X_n be an indicator variable for the n th ball chosen to be red. Note that if you just chose a red ball, it is not clear what the probability of choosing a red ball next is, because it depends on what color the other ball in the urn is. So consider the state of the Markov chain to be the number of red balls in the urn, and let X_n be the number of red balls in the urn before the n th withdrawal. Then we have the following transition matrix:

$$P = \begin{bmatrix} P_{00} & P_{01} & P_{02} \\ P_{10} & P_{11} & P_{12} \\ P_{20} & P_{21} & P_{22} \end{bmatrix} = \begin{bmatrix} 0.3 & 0.7 & 0 \\ 0.5 & 0.5 \cdot 0.3 & 0.5 \cdot 0.7 \\ 0 & 1 & 0 \end{bmatrix}$$

Let π_j be the long-run proportion of the time the system is in state j . Note that every time we reach state j everything starts all over again, so that's a renewal (ordinary renewal process) if you are certain to eventually return to state j (we will assume this is true for now). We have

$$\pi_0 \cdot 0 + \pi_1 \cdot \frac{1}{2} + \pi_2 = \pi_2 + \frac{1}{2}\pi_1$$

is the long-run probability of choosing a red ball.

Example 7.30 (Embedded Markov chain; example 4.1(a) in *Stochastic Processes*). $M/G/1$ queueing process. The number of people currently in the system is not Markovian, but it would be if the service time were exponential (since then it wouldn't matter how long the customer had been in service).

But the number of people in the system immediately after the n th service completion is Markovian. (Called an **embedded Markov chain** because it is a Markov chain if you only look at it at certain times.)

Note that

$$\begin{aligned} P_{0j} = a_j &= \Pr(j \text{ arrivals during service time}) = \int_0^\infty \Pr(j \text{ arrivals during service time } t) dG(t) \\ &= \int_0^\infty e^{-\lambda t} \frac{(\lambda t)^j}{j!} dG(t) \end{aligned}$$

More generally, note that for $i > 0, j \geq i - 1$

$$\begin{aligned} P_{ij} = a_{j-i+1} &= \Pr(j-i+1 \text{ arrivals during service time}) = \int_0^\infty \Pr(j-i+1 \text{ arrivals during service time } t) dG(t) \\ &= \int_0^\infty e^{-\lambda t} \frac{(\lambda t)^{(j-i+1)}}{(j-i+1)!} dG(t). \end{aligned}$$

Example 7.31 (Example 4.1(b) in *Stochastic Processes*). if X_n is the number of people in the system as seen by the n th arrival, then this is an (embedded) Markov chain.

⋮

We want $P_{ij}, j > 0$. If n is the number of people served, then

$$i + 1 - n = j \iff n = i + 1 - j$$

Then

$$P_{ij} = \int \Pr(i + 1 - j \text{ services in time } T \mid T = s) dF(s) = \int e^{-\mu s} \frac{(\mu s)^{i+1-j}}{(i+1-j)!} dF(s)$$

P_{i0} is different because if we end with 0 people, all of the previous people had to depart. But they could have departed at any time before the next person arrived. Imagine that when all the customers leave, the server keeps serving “imaginary” customers. Then P_{i0} is the probability of at least $i + 1$ customers (real or imaginary) being served.

Definition 7.26 (n-step transition probabilities).

$$P_{ij}^n = \Pr(X_n = j \mid X_0 = i)$$

7.6.1 Chapman-Kolmogorov Equations—section 4.2 of *Introduction to Probability Models*, section 4.2 of *Stochastic Processes* (p. 178 of pdf)

Proposition 7.6.1 (Chapman-Kolmogorov Equations).

Definition 7.27 (Matrix of n -step transition probabilities).

$$\mathbf{P}^{(n)} = [P_{ij}^n]$$

Example 7.32 (Similar to example 4.10 in *Introduction to Probability Models*). Urn initially has 1 red ball 1 blue. At each stage choose a ball at random. If red, replace with blue. If blue, replace with blue with probability 1/3 or red with probability 2/3. What is the probability that the 5th ball selected is red?

Solution. Note that per the example from last time, knowing the ball you just drew is not sufficient to have a Markov chain (need to know color of other ball in urn to get probabilities of next state). So let X_n be the number of red balls in the urn after you draw the n th ball, and note that $X_0 = 1$. Note that there are three states. The probability transition matrix is

$$P = \begin{bmatrix} P_{00} & P_{01} & P_{02} \\ P_{10} & P_{11} & P_{12} \\ P_{20} & P_{21} & P_{22} \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & 0 \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{3} \\ 0 & 1 & 0 \end{bmatrix}$$

Note that the probability the 5th ball selected is red is equal to

$$\sum_{i=1}^2 \Pr(\text{5th ball is red } | X_4 = i) P_{1i}^4 = 0 \cdot P_{10}^4 + \frac{1}{2} P_{11}^4 + 1 \cdot P_{12}^4$$

Now we calculate P^4 .

$$P^2 = \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & 0 \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{3} \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & 0 \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{3} \\ 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} \frac{4}{9} & \frac{3}{9} & \frac{2}{9} \\ \frac{3}{12} & \frac{25}{36} & \frac{2}{36} \\ \frac{1}{2} & \frac{1}{6} & \frac{1}{3} \end{bmatrix}$$

$$P^4 = P^2 P^2 = \begin{bmatrix} \frac{4}{9} & \frac{3}{9} & \frac{2}{9} \\ \frac{3}{12} & \frac{25}{36} & \frac{2}{36} \\ \frac{1}{2} & \frac{1}{6} & \frac{1}{3} \end{bmatrix} \begin{bmatrix} \frac{4}{9} & \frac{3}{9} & \frac{2}{9} \\ \frac{3}{12} & \frac{25}{36} & \frac{2}{36} \\ \frac{1}{2} & \frac{1}{6} & \frac{1}{3} \end{bmatrix} = \dots$$

Example 7.33 (Example 4.12 from *Introduction to Probability Models*). Part (c) (not in book): N is the number of flips until either a run of 3 heads or 3 tails. $\Pr(N = 8)$?

Solution. Say start at state 0, state i if you are on a run of i heads for $i = 1, 2, 3$, and state i if you are on a state of $i - 3$ tails, $i = 4, 5, 6$. Then we have

$$P = \begin{bmatrix} P_{00} & P_{01} & P_{02} & P_{03} & P_{04} & P_{05} & P_{06} \\ P_{10} & P_{11} & P_{12} & P_{13} & P_{14} & P_{15} & P_{16} \\ P_{20} & P_{21} & P_{22} & P_{23} & P_{24} & P_{25} & P_{26} \\ P_{30} & P_{31} & P_{32} & P_{33} & P_{34} & P_{35} & P_{36} \\ P_{40} & P_{41} & P_{42} & P_{43} & P_{44} & P_{45} & P_{46} \\ P_{50} & P_{51} & P_{52} & P_{53} & P_{54} & P_{55} & P_{56} \\ P_{60} & P_{61} & P_{62} & P_{63} & P_{64} & P_{65} & P_{66} \end{bmatrix} = \begin{bmatrix} 0 & p & 0 & 0 & 1-p & 0 & 0 \\ 0 & 0 & p & 0 & 1-p & 0 & 0 \\ 0 & 0 & 0 & p & 1-p & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & p & 0 & 0 & 0 & 1-p & 0 \\ 0 & p & 0 & 0 & 0 & 0 & 1-p \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

In general, if T_i is the number of transitions to enter state i even state 0 is 0, we can change state i into an absorbing state.

7.6.2 Classification of States (Section 4.3 of *Introduction to Probability Models*)

We say state j is *accessible* from state i if for some $n \geq 0$ $P_{ij}^n > 0$. Note that $P_{ij}^n = \Pr(X_n = j \mid X_0 = i)$. So j is accessible from i if and only if starting in i it is possible that the Markov chain is every in j . So if j is not accessible from i

$$\Pr(\text{ever in } j \mid X_0 = i) = \Pr\left(\bigcup_n \{X_n = j\} \mid X_0 = i\right) \leq \sum_n \Pr(\{X_n = j\} \mid X_0 = i) = 0$$

Two states i and j that are accessible to each other are said to *communicate*, and we write $i \leftrightarrow j$. Two states that communicate are said to be in the same *class*.

A Markov chain is **irreducible** if there is only one class.

Example 7.34.

$$P = \begin{bmatrix} 0.2 & 0.8 & 0 & 0 & 0 \\ 0.3 & 0.7 & 0 & 0 & 0 \\ 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0 & 0 & 0 & 0.1 & 0.9 \\ 0 & 0 & 0 & 0.5 & 0.5 \end{bmatrix}$$

Then the classes are $\{0, 1\}$, $\{2\}$, and $\{3, 4\}$. Note that for the classes $\{0, 1\}$ and $\{3, 4\}$ you will stay there forever—they are essentially Markov chains themselves. But if you start in state 2 you will eventually go to one of the other states and never go back. In contrast consider

$$P = \begin{bmatrix} 0.2 & 0.8 & 0 & 0 & 0 \\ 0.3 & 0.7 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0.1 & 0.9 \\ 0 & 0 & 0 & 0.5 & 0.5 \end{bmatrix}$$

where all three states have this property. We can merge classes $\{2\}$ and $\{3, 4\}$ like this:

$$P = \begin{bmatrix} 0.2 & 0.8 & 0 & 0 & 0 \\ 0.3 & 0.7 & 0 & 0 & 0 \\ 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0 & 0 & 0 & 0.1 & 0.9 \\ 0 & 0 & 0.1 & 0.5 & 0.4 \end{bmatrix}$$

Let N_k be the number of transitions until you first enter state k . (discussion on p. 195 - 196 of *Introduction to Probability Models*.)

Example 7.35 (Example 4.12 in *Introduction to Probability Models*).

$$\Pr(N = 8) = P_{02}^7 p = P_{00}^5 p^3$$

Definition 7.28. For any states i and j in a Markov process, let f_{ij}^n be the probability that starting in i the first transition into j occurs at time n . Formally,

$$f_{ij}^0 = 0, \quad f_{ij}^n = \Pr(X_n = j, X_k \neq j, k = 1, \dots, n-1 \mid X_0 = i).$$

Let

$$f_{ij} = \sum_{n=1}^{\infty} f_{ij}^n.$$

Then f_{ij} denotes the probability of ever making a transition into state j given that the process starts in i .

Proposition 7.6.2 (Homework problem; Problem 4.4 in *Stochastic Processes*).

$$P_{ij}^n = \sum_{k=0}^n f_{ij}^k P_{jj}^{n-k}.$$

Proof. Recall that P_{ij}^n is the probability that a process in state i will be in state j after n additional transitions. Also, f_{ij}^n is the probability that starting in i the first transition into j occurs at time n . Note that

$$P_{ij}^n = \sum_{k=0}^n \Pr(\text{first reach } j \text{ at time } k) \cdot \Pr(\text{end at } j \text{ starting from } j \text{ in } n-j \text{ steps}) = \sum_{k=0}^n f_{ij}^k P_{jj}^{n-k}.$$

□

Proposition 7.6.3 (Homework problem; Problem 4.5 in *Stochastic Processes*). Let

$$P_{ij/k} = \Pr(X_n = j, X_\ell \neq k, \ell = 1, \dots, n-1 \mid X_0 = i).$$

(This is the probability that at time n we are in state j and we never reached state k between time 0 and n , given that we started in state i .) Then for $i \neq j$,

$$P_{ij}^n = \sum_{k=0}^n P_{ii}^k P_{ij/k}^{n-k}.$$

Proof. There are two classes of ways we can reach j starting from i : we either go back to i at some point and then end up at j , or we go straight to j without ever going back to i . If we go back to i for the last time at time $k \in \{1, \dots, n-1\}$, we can end up at j at time n with probability $P_{ij/i}^{n-k}$. We end up back at state i for the last time at time k before time n (regardless of what happened before time k) with probability P_{ii}^k . Therefore,

$$\text{for } i \neq j, P_{ij}^n = \sum_{k=0}^n P_{ii}^k P_{ij/i}^{n-k}.$$

□

Definition 7.29 (Recurrent state). We call state i **recurrent** if starting in i the Markov Chain returns to i with probability 1.

Definition 7.30 (Transient state). We call state i **transient** if starting in i the probability the Markov Chain returns to i is less than 1.

Proposition 7.6.4 (Proposition 4.1 in *Introduction to Probability Models*, Proposition 4.2.3 in *Stochastic Processes*). In a Markov chain, state i is recurrent if

$$\sum_{n=1}^{\infty} P_{ii}^n = \infty$$

and transient if

$$\sum_{n=1}^{\infty} P_{ii}^n < \infty.$$

Proof. State i is recurrent if with probability 1 a process starting at i will eventually return to i . However, by the Markovian property it follows that this process will return again to i with probability 1, and so on. There is no last term, so with probability 1, the number of visits to i will be infinite.

On the other hand, suppose i is transient. Then each time the process returns to i there is a positive probability $1 - f_{ii}$ that it will never again return. That is, the probability the total time in i is n periods given you start in i is

$$f_{ii}^{n_i-1}(1 - f_{ii}).$$

Therefore the number of visits is geometric with finite mean $(1 - f_{ii})^{-1}$. Let I_n be an indicator variable for $X_n = i$. Then the total number of visits to state i is $\sum_{n=0}^{\infty} I_n$ and the expected number of visits if we start at i is

$$\mathbb{E} \sum_{n=0}^{\infty} \{I_n = 1 \mid X_0 = i\} = \sum_{n=0}^{\infty} \mathbb{E}\{I_n = 1 \mid X_0 = i\} = \sum_{n=0}^{\infty} \Pr\{X_n = i \mid X_0 = i\}$$

□

Corollary 7.6.4.1 (Corollary 4.2 in *Introduction to Probability Models*, Corollary 4.2.4 in *Stochastic Processes*). If state i is recurrent and state i communicates with state j , then state j is recurrent.

Proof. Let m and n be such that $P_{ij}^n < 0$, $P_{ji}^m > 0$ (these values exist since i and j communicate). Then for any $s \geq 0$,

$$P_{jj}^{m+n+s} \geq P_{ji}^m P_{ii}^s P_{ij}^n.$$

Therefore

$$\sum_{s=0}^{\infty} P_{jj}^{m+n+s} \geq P_{ji}^m P_{ij}^n \sum_{s=0}^{\infty} P_{ii}^s = \infty \implies \sum_{n=0}^{\infty} P_{jj}^n = \infty$$

where $\sum_{s=0}^{\infty} P_{ii}^s = \infty$ by definition of i being recurrent.

□

Corollary 7.6.4.2 (Corollary 4.2.5 in *Stochastic Processes*). If state i is recurrent and state i communicates with state j , then

$$f_{ij} = \Pr(\text{ever enter } j \mid X_0 = i) = 1$$

Proof. Suppose $X_0 = i$, and let n be such that $P_{ij}^n > 0$. Say that we miss opportunity 1 if $X_n \neq j$. If we miss opportunity 1, then let T_1 denote the next time we enter i . Note that T_1 is finite with probability 1 by Corollary 7.6.4.1. Say we miss opportunity 2 if $X_{T_1+n} \neq j$. If opportunity 2 is missed, let T_2 denote the next time we enter i and say we miss opportunity 3 if $X_{T_2+n} \neq j$, and so on. It is easy to see that the opportunity number of the first success is a geometric random variable with mean $1/P_{ij}^n$, and is thus finite with probability 1. The result follows since i being recurrent implies that the number of potential opportunities is infinite.

□

So we have the recurrence and transience are class properties (if one element in the class has them, they all do).

Example 7.36 (Simple random walk; example 4.18 in *Introduction to Probability Models*).

$$\frac{(2n)!}{n!n!} \frac{(2n)^{2n+1/2} e^{-2n} \sqrt{2\pi}}{n^{2n+1} e^{-2n} 2\pi} = \frac{4^n}{\sqrt{n\pi}}$$

Homework problem: If R is a recurrent class, $i \in R$, $j \notin R$, then $P_{ij} = 0$. Why? Suppose $P_{ij} > 0$. But since i doesn't communicate with j , $P_{ij}^n = 0$ for all n . Contradiction.

7.6.3 Long-Run Proportions and Limiting Probabilities (Limit Theorems) (4.4 in *Introduction to Probability Models*, 4.3 in *Stochastic Processes*)

Let π_j be the long-run proportion of the time you are in state j . That is,

$$\pi_j = \lim_{n \rightarrow \infty} \frac{N_n(j)}{n}$$

where $N_n(j)$ is the time in j during the first n periods. Then this equals $1/m_j$ where m_j is the expected time to re-enter j given that we started in j if state j is recurrent.

Bad approach to find:

$$\begin{aligned} m_j &= \sum_k \mathbb{E}[\text{return to } j \mid X_1 = k] P_{jk} = P_{jj} + \sum_{k \neq j} (1 + m_{kj}) P_{jk} = 1 + \sum_{k \neq j} m_{kj} P_{jk} \\ m_{ij} &= 1 + \sum_{k \neq j} P_{ik} m_{kj} \end{aligned}$$

for $|S|$ states.

Proposition 7.6.5 (Proposition 4.4 in *Introduction to Probability Models*). If the Markov chain is irreducible and recurrent, then for any initial state,

$$\pi_j = \frac{1}{m_j}.$$

Proposition 7.6.6 (Proposition 4.5 in *Introduction to Probability Models*).

Theorem 7.6.7 (Theorem 4.1 in *Introduction to Probability Models*). In an irreducible Markov chain is positive recurrent, then the long-run proportions are the unique solution of the equations

$$\pi_j = \sum_i \pi_i P_{ij}, \quad j \geq 1$$

$$\sum_j \pi_j = 1.$$

Moreover, if there is no solution of the preceding linear equations, then the Markov chain is either transient or null recurrent and all $\pi_{ij} = 0$.

Proof. π_i is the long-run proportion of time you are in state i ; think of it as the long-run proportion of transitions that come from i . These transitions go to j with probability P_{ij} . So $\pi_i P_{ij}$ is the long-run proportion of transitions that go from i to j . If we sum over all i then we get the long-run proportion of transitions that go into j , which is the same as the proportion of time you're in j . So

$$\pi_j = \sum_i \pi_i P_{ij}$$

□

For an irreducible Markov chain, let $N_n(j)$ be the number of transitions into j by time n . Every time we reach state j we have a renewal. By the Strong Law for Renewal Processes (Theorem 7.3.6),

$$\frac{N_n(t)}{n} \xrightarrow{a.s.} \frac{1}{m_{jj}}$$

where m_{jj} is the expected number of transitions returning to j given that $X_0 = j$. By the Elementary Renewal Theorem (Theorem 7.3.9),

$$\lim_{s \rightarrow \infty} \frac{\mathbb{E}(N_n(s))}{n} = \frac{1}{m_{jj}}.$$

Note that

$$N_n(j) = \sum_{k=1}^n I_k$$

where I_k is an indicator variable for $X_k = j$.

$$\implies \frac{1}{n} \sum_{k=1}^n \Pr(X_k = j) \xrightarrow{a.s.} \frac{1}{m_{jj}}.$$

Let $\pi_j = \frac{1}{m_{jj}}$.

Definition 7.31. If state j is recurrent, call it **positive recurrent** if $m_{jj} < \infty$ and **null recurrent** if $m_{jj} = \infty$.

Remark 90. Being positive recurrent is equivalent to $\pi_j > 0$.

Proposition 7.6.8 (Proposition 4.3.2 in *Stochastic Processes* (p.185 of pdf)). Positive (null) recurrence is a class property.

Proof. Suppose state i is positive recurrent; that is $\pi_i > 0$. We will show that if it communicates with another state j , that state must be recurrent. Let n be such that $P_{ij}^n > 0$; such an n exists since i and j communicate.. Then $\pi_i P_{ij}^n$ is the long-run proportion of the time the chain is in state i and will be in state j n time periods later (or the proportion of time that the Markov chain is in state j and was in state i n time periods earlier). Since this is less than or equal to the proportion of time the Markov chain is in state j , we have

$$\pi_i P_{ij}^n \leq \pi_j$$

But since $\pi_i > 0$, we have

$$0 < \pi_i P_{ij}^n \leq \pi_j \implies \pi_j > 0.$$

□

Remark 91. This also shows that null recurrence is a class property (because if one element of the class is not positive recurrent, it must be that they are all not positive recurrent).

Note that if we have a Markov chain with $m < \infty$ states. we have to have

$$\begin{aligned} \sum_{j=1}^m N_n(0) = n &\iff \frac{1}{m} \sum_{j=1}^m N_n(0) = 1 \\ \implies 1 = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{j=1}^m N_n(0) &= \sum_{j=1}^m \lim_{n \rightarrow \infty} \frac{N_n(0)}{n} = \sum_{j=1}^m \pi_j \end{aligned}$$

so all the π_j have to add up to 1.

Definition 7.32. The non-negative numbers $x_j, j \in S$ are said to be **stationary probabilities** of a Markov chain if

$$x_j = \sum_i x_i P_{ij}, \quad i \in S$$

$$\sum_{j \in S} x_j = 1.$$

Definition 7.33 (p. 185 of *Stochastic Processes* pdf). A probability distribution $\{P_j, j \geq 0\}$ is said to be **stationary** for the Markov chain if

$$P_j = \sum_{i=0}^{\infty} P_i P_{ij}, \quad j \geq 0.$$

Lemma 7.6.9. Suppose $\{x_i, i \in S\}$ is a stationary probability vector for a Markov chain. If $\Pr(X_0 = i) = x_i, i \in S$ $\Pr(X_n = j) = x_j, j \in S$ for all n .

Proof. We will prove this by induction on n for X_n . The case $n = 0$ is true by assumption. Assume $\Pr(X_n = i) = x_i, i \in S$. Then

$$\Pr(X_{n+1} = j) = \sum_{i \in S} \Pr(X_{n+1} = j | X_n = i) \Pr(X_n = i) = \sum_{i \in S} P_{ij} x_i = x_j$$

where the last step follows by Definition 7.32. □

By the Elementary Renewal Theorem (Theorem 7.3.9),

$$\sum_{k=1}^n \frac{1}{n} \Pr(X_k = j) \xrightarrow{a.s.} \frac{1}{m_{jj}}.$$

Suppose the initial state is chosen randomly according to the probability vector.

Proposition 7.6.10 (Stationary probability vector is π_j). If x_j is a stationary probability vector then $x_j = \pi_j$, $j \in S$.

Proof. Let x_j be a stationary probability vector. Suppose $\Pr(X_0 = i) = x_i$, $i \in S$. Then $\Pr(X_k = j) = x_j$ for all k by Lemma 7.6.9. By the Elementary Renewal Theorem (Theorem 7.3.9),

$$\frac{1}{n} \Pr(X_k = j) \xrightarrow{a.s.} \pi_j.$$

But also

$$\lim_{n \rightarrow \infty} \frac{1}{n} \Pr(X_k = j) = x_j$$

so $\pi_j = x_j$.

□

Definition 7.34 (Ergodic Markov chain state; p.174 of pdf of *Stochastic Processes*). A positive recurrent, aperiodic state is called **ergodic**.

Definition 7.35 (Ergodic Markov chain; p.188 of pdf of *Stochastic Processes*). We say a Markov chain is **ergodic** if all states are positive recurrent; that is,

$$\pi_j = \lim_{n \rightarrow \infty} P_{ij}^n > 0.$$

In this case, $\{\pi_j, j = 0, 1, 2, \dots\}$ is a stationary distribution and there exists no other stationary distribution.

Definition 7.36. A Markov chain that can only return to a state in a multiple of $d > 1$ steps is said to be **periodic** and does not have limiting probabilities. That is, $P_{ij}^n = 0$ except when n is a multiple of d and d is the largest such integer.

An irreducible chain that is not periodic is said to be **aperiodic**.

Lemma 7.6.11. Periodicity is a class property. That is, if i communicates with j then i and j have the same period.

Proof. Requires non-trivial results from algebra to prove.

□

Also, $P_{jj}^{nd} \rightarrow d/m_{jj}$. For an aperiodic irreducible Markov chain, $P_{ij}^n \rightarrow 1/m_{jj} = \pi_j$. (Related to Blackwell's Theorem.)

Example 7.37 (Example 4.18 in *Introduction to Probability Models*). Stopping time:

$$N = \min\{n : X_1 + \dots + X_n = 1\} \implies 1 = X_1 + \dots + X_N$$

Apply Wald's Equation (Theorem 7.3.8):

$$1 = \mathbb{E}[X_1 + \dots + X_N] = \mathbb{E}(X)\mathbb{E}(N) = 0$$

So Wald's equation leads to a contradiction, meaning its assumptions weren't satisfied, which must be because $\mathbb{E}(N) = \infty$. See also Example 6.3 in the Probability notes.

Example 7.38 (Example 4.24 in *Introduction to Probability Models*). Not an alternating renewal process because in general it depends on which “up” state you enter into. Typically use renewal reward processes to find average length of “up” and “down” periods.

Theorem 7.6.12 (Theorem 4.3.3 in *Stochastic Processes*, p. 186 of pdf). Suppose we have an irreducible aperiodic Markov chain. If it is either transient or null recurrent, then there are no solutions of the equations

$$x_j = \sum_{i \in S} x_i P_{ij}, \quad j \in S,$$

$$\sum_j X_j = 1.$$

If it is positive recurrent, then $\{\pi_j, j \in S\}$ uniquely satisfy the preceding equations. (There is no irreducible finite state Markov chain.)

Proof. Suppose a Markov chain is positive recurrent. Fix a state 0 and consider the Markov chain to start a new cycle each time it transitions into state 0. Think of this as a renewal reward process: suppose you earn 1 each time a transition into state j occurs (renewal each time you reach state 0 again). Then the average reward per unit time is π_j . But this also equals

$$\frac{\mathbb{E}(N_j)}{\mathbb{E}(N)}$$

where N_j is the number of transitions into state j during a cycle and N is the number of transitions in a cycle, so $N = \sum_j N_j$. Let N_{ij} be the number of transitions from state i to j in a cycle, so $N_j = \sum_{i \in S} N_{ij}$. Then we have

$$\mathbb{E}(N_j) = \sum_{i \in S} \mathbb{E}(N_{ij})$$

Let I_k is an indicator variable for transitioning from i to j with $\mathbb{E}(I_k) = P_{ij}$. Then $N_{ij} = \sum_{k=1}^{N_i} I_k$. Note that N_i is a stopping time for I_1, I_2, \dots because it depends on what happened before but not on the future. Therefore by Wald's Equation (Theorem 7.3.8),

$$\mathbb{E}(N_{ij}) = \mathbb{E} \sum_{k=1}^{N_i} I_k = \mathbb{E}(I_k) \mathbb{E}(N_i) = \mathbb{E}(N_i) P_{ij}.$$

Using that we have

$$\begin{aligned} \mathbb{E}(N_j) &= \sum_{i \in S} \mathbb{E}(N_{ij}) = \sum_{i \in S} \mathbb{E}(N_i) P_{ij} \\ \implies \frac{\mathbb{E}(N_j)}{\mathbb{E}(N)} &= \sum_{i \in S} \frac{\mathbb{E}(N_i)}{\mathbb{E}(N)} P_{ij} \iff \pi_j = \sum_i \pi_i P_{ij}. \end{aligned}$$

Also note that

$$\sum_j \pi_j = \sum_j \frac{\mathbb{E}(N_j)}{\mathbb{E}(N)} = \frac{\sum_j \mathbb{E}(N_j)}{\sum_j \mathbb{E}(N_j)} = 1.$$

□

Example 7.39 (Similar to section 4.1.1 in *Introduction to Probability Models*). Suppose we have a 2 state Markov chain for the weather. 0 means dry, 1 means rain. dry to dry with probability 0.7, rain to rain with probability 0.6. So

$$P = \begin{bmatrix} 0.7 & 0.3 \\ 0.4 & 0.6 \end{bmatrix}$$

Then π_j are the unique solutions to

$$\pi_j = \sum_i \pi_i P_{ij}, \quad \sum_j \pi_j = 1.$$

So we have

$$\pi_0 = \pi_0 P_{00} + \pi_1 P_{10}, \quad \pi_1 = \pi_0 P_{01} + \pi_1 P_{11}, \quad \pi_0 + \pi_1 = 1.$$

$$\implies \begin{bmatrix} (1 - P_{00}) & -P_{10} \\ -P_{01} & (1 - P_{11}) \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \pi_0 \\ \pi_1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Solving yields $\pi_0 = 4/7$, $\pi_1 = 3/7$.

Definition 7.37. A Markov chain is said to be **doubly stochastic** if the sums of the columns of the transition probability matrix also add to 1 (the rows must always add to 1). That is,

$$\sum_i P_{ij} = 1, \quad \forall j \in S$$

Proposition 7.6.13. Suppose you have an irreducible Markov chain with $m < \infty$ states that is doubly stochastic. Then

$$\pi_j = \frac{1}{m}, \quad j = 1, \dots, m$$

That is, all the long-run proportions are the same.

Proof. Recall that π_j is the unique solution to $\pi_j = \sum_i \pi_i P_{ij}$ and that $\sum_j \pi_j = 1$. For $\pi_j = 1/m$, clearly the second condition is satisfied, so we need to verify the first state. That is we need to verify that

$$\frac{1}{m} = \frac{1}{m} \sum_i P_{ij} \iff \sum_i P_{ij} = 1$$

which is true if the Markov chain is doubly stochastic.

□

Remark 92. In practice if there is a Markov chain with more than three states and you are asked to find the long-run proportions, it is likely a doubly-stochastic Markov chain.

Example 7.40 (Example 4.25 in *Introduction to Probability Models*). Hotel, number of new guests every day is Poisson with mean λ . Each guest that stays the night will independently check out the next day with probability $p = 1 - \alpha$. (So the number of days each guest stays are independent geometric random variables.)

$$X_n = i \implies X_{n+1} = \text{Bin}(i, \alpha) * \text{Poisson}(\lambda)$$

where $*$ is being used for a sum to stress the independence of the random variables.

$$P_{ij} = \Pr(\text{Bin}(i, \alpha) + \text{Poisson}(\lambda) = j)$$

⋮

Part (c): Suppose the number of people initially there X_0 is distributed $\text{Poisson}(\beta)$. Then the number of that cohort who remains the next day is $\text{Poisson}(\alpha\beta)$. So $X_1 \sim \text{Poisson}(\alpha\beta + \lambda)$. So to find the limiting distribution (where it's the same every day from now on), we need

$$\beta = \lambda + \alpha\beta \iff \beta = \frac{\lambda}{1 - \alpha} \implies \pi_j = \exp\left(-\frac{\lambda}{1 - \alpha}\right) \left(\frac{\lambda}{1 - \alpha}\right)^j / j!$$

Proposition 7.6.14 (Proposition 4.4.2 in *Stochastic Processes*; relevant to Gambler's Ruin). If j is a recurrent state in a Markov chain, then the set of probabilities $\{f_{ij}, i \in T\}$ satisfies

$$f_{ij} = \sum_{k \in T} P_{ik} f_{kj} + \sum_{k \in R} P_{ik}, \quad i \in T$$

where R denotes the set of states communicating with j .

Example 7.41 (Gambler's Ruin; Section 4.5.1 of *Introduction to Probability Models*, Example 4.4(A) in *Stochastic Processes* (p. 197 of pdf)). Also discussed drug testing example immediately afterward in section 4.5.1 of *Introduction to Probability Models*, and what happens as $N \rightarrow \infty$ (p. 199 of pdf of *Stochastic Processes*).

7.6.4 Branching Processes (Section 4.7 of *Introduction to Probability Models*, Section 4.5 of *Stochastic Processes*)

Proposition 7.6.15 (Theorem 4.5.1 in *Stochastic Processes* (p. 203 of pdf)). (i) If $\mu \leq 1$, then $\pi_0 = 1$. (ii) If $\mu > 1$, $\pi_0 < 1$. (iii) π_0 is the smallest positive number satisfying

$$\pi_0 = \sum_{j=0}^{\infty} \pi_0^j P_j.$$

Proof. (i) Using

$$X_n = \sum_{i=1}^{X_{n-1}} Z_i,$$

we have

$$\mathbb{E}(X_n | X_{n-1}) = X_{n-1} \cdot \sum_{j=0}^{\infty} j P_j = X_{n-1} \mu$$

$$\implies \mathbb{E}(X_n) = \mu \mathbb{E}(X_{n-1}) = \mu^2 \mathbb{E}(X_{n-2}) = \dots = \mu^n \mathbb{E}(X_0) = \mu^n.$$

Suppose $\mu < 1$. By Markov's Inequality (Lemma 8.2.1),

$$\Pr(X_n \geq 1) \leq \mathbb{E}(X_n) = \mu^n \implies \lim_{n \rightarrow \infty} \Pr(X_n \geq 1) = 0.$$

When $\mu = 1$, can prove using a convexity argument and constraints $P_0 > 0, P_0 + P_1 < 1$ (see *Stochastic Processes*).

(ii) In *Stochastic Processes*.

(iii) Suppose $x > 0$ satisfies

$$x = \sum_{j=0}^{\infty} x^j P_j.$$

We will show by induction that $x \geq \Pr(X_n = 0 \mid X_0 = 1)$ for all n . To start we need to show that $x \geq \Pr(X_n = 0 \mid X_0 = 1)$. But

$$\Pr(X_0 = 0 \mid X_0 = 1) = P_0 \leq \sum_{j=0}^{\infty} x^j P_j = x$$

so that follows. Now we assume $x \geq \Pr(X_n = 0 \mid X_0 = 1)$. We would like to show that this implies $x \geq \Pr(X_{n+1} = 0 \mid X_0 = 1)$. Note that

$$\Pr(X_{n+1} = 0 \mid X_0 = 1) = \sum_{j=0}^{\infty} \Pr(X_{n+1} = 0 \mid X_1 = j, X_0 = 1) = \sum_{j=0}^{\infty} \Pr(X_{n+1} = 0 \mid X_1 = j) P_j$$

But $\Pr(X_{n+1} = 0 \mid X_1 = j) = (\Pr(X_{n+1} = 0 \mid X_1 = 1))^j$ for the following reason: if there are j people to begin with, imagine they each had their own independent branching process. The probability that you reach 0 eventually is equal to the joint probability that all j processes reach 0 eventually. So we have

$$\sum_{j=0}^{\infty} \Pr(X_{n+1} = 0 \mid X_1 = j) P_j = \sum_{j=0}^{\infty} P_j (\Pr(X_{n+1} = 0 \mid X_1 = 1))^j \leq \sum_{j=0}^{\infty} P_j x^j = x$$

where the second to last step follows by the inductive hypothesis.

□

7.6.5 A Markov Chain Model of Algorithmic Efficiency (Section 4.6.1 of *Stochastic Processes*)

Definition 7.38. A set of events A_2, A_2, \dots is said to be an **increasing sequence** if $A_n \subseteq A_{n+1}$ and a **decreasing sequence** if $A_n \supseteq A_{n+1}$. If $A_n, n \geq 1$ is increasing, define

$$\lim_{n \rightarrow \infty} A_n = \bigcup_{n=1}^{\infty} A_n.$$

If $A_n, n \geq 1$ is decreasing, define

$$\lim_{n \rightarrow \infty} A_n = \bigcap_{n=1}^{\infty} A_n.$$

The **limit infimum** is the set of all points contained in all but a finite number of A_1, A_2, \dots . The **limit supremum** is the set of all points contained in an infinite number of A_1, A_2, \dots . Note that for an increasing sequence the limit infimum is a subset of the limit supremum.

Lemma 7.6.16. For any events A_1, A_2, \dots there are events B_1, B_2, \dots that are mutually exclusive ($B_i \cap B_j = \emptyset, i \neq j$) such that

$$B_i \cap B_j = \emptyset, \quad \bigcup_{i=1}^n B_i = \left(\bigcup_{i=1}^n A_i \text{ for } n = 1, 2, \dots \right), \quad \bigcup_{i=1}^{\infty} B_i = \left(\bigcup_{i=1}^{\infty} A_i \right).$$

Proof. Let $B_1 = A_1$, $B_2 = A_2 \setminus A_1$, $B_3 = A_3 \setminus \{A_1 \cup A_2\}$, \dots , $B_n = A_n \setminus \{A_1 \cup \dots \cup A_{n-1}\} = A_n \setminus \left\{ \bigcup_{i=1}^{n-1} A_i \right\}$. \square

Theorem 7.6.17. Probability is a continuous set function. That is, if A_n is an increasing or decreasing sequence then

$$\lim_{n \rightarrow \infty} \Pr(A_n) = \Pr\left(\bigcup_{n=1}^{\infty} A_n\right) = \Pr\left(\lim_{n \rightarrow \infty} A_n\right).$$

Proof. Let A_1, A_2, \dots be events. Per Lemma 7.6.16, define B_1, B_2, \dots such that $B_i \cap B_j = \emptyset$ and $\bigcup_{i=1}^n B_i = (\bigcup_{i=1}^n A_i)$ for $n = 1, 2, \dots$, $\bigcup_{i=1}^{\infty} B_i = (\bigcup_{i=1}^{\infty} A_i)$. Suppose A_n is increasing, so that $A_n \subseteq A_{n+1}$. Then

$$\Pr\left(\lim_{n \rightarrow \infty} A_n\right) = \Pr\left(\bigcup_{i=1}^{\infty} A_i\right) = \Pr\left(\bigcup_{i=1}^{\infty} B_i\right) = \sum_{i=1}^{\infty} \Pr(B_i)$$

where the last equality follows since the B_i are disjoint. Continuing we have

$$= \lim_{n \rightarrow \infty} \sum_{i=1}^n \Pr(B_i) = \lim_{n \rightarrow \infty} \Pr\left(\bigcup_{i=1}^n B_i\right) = \lim_{n \rightarrow \infty} \Pr\left(\bigcup_{i=1}^n A_i\right) = \lim_{n \rightarrow \infty} \Pr(A_n)$$

where the last step follows since A_n is an increasing sequence.

\square

Remark 93. Can prove Boole's Inequality by a similar logic:

$$\Pr\left(\bigcup_{i=1}^n A_i\right) = \Pr\left(\bigcup_{i=1}^n B_i\right) = \sum_{i=1}^n \Pr(B_i) \leq \sum_{i=1}^n \Pr(A_i)$$

where the last step follows since $B_i \subseteq A_i$.

Remark 94. Consider the Gambler's Ruin problem (Example 7.41). Let A_N be the event of reaching 0 before N given $X_0 = i$. Note that $A_N \subseteq A_{N+1}$. So we have

$$\lim_{N \rightarrow \infty} \Pr(A_N) = \Pr\left(\lim_{N \rightarrow \infty} A_N\right) = \Pr\left(\bigcup_{N=1}^{\infty} A_N\right)$$

where the last quantity is clearly the probability that the gambler eventually goes to 0, matching our interpretation in Example 7.41.

Similarly, in the proof of Proposition 7.6.15 for branching processes, we claimed

$$\Pr(\text{population dies out}) = \lim_{n \rightarrow \infty} \Pr(X_n = 0).$$

Note that $\{X_n = 0\} \subset \{X_{n+1} = 0\}$ so

$$\lim_{n \rightarrow \infty} \{X_n = 0\} = \bigcup_{n=1}^{\infty} \{X_n = 0\}$$

again matching what we assumed.

7.6.6 Time Reversible Markov Chains (Section 4.8 of *Introduction to Probability Models*, Section 4.7 of *Stochastic Processes*)

Proposition 7.6.18 (Unlabeled at beginning of each section). Given a stationary Markov chain $X_n, X_{n+1}, X_{n+2}, \dots$, the reverse process $X_n, X_{n-1}, X_{n-2}, \dots$ is a Markov chain with transition probabilities

$$Q_{ij} = P_{ij}^* = \frac{\pi_j P_{ji}}{\pi_i}.$$

Proof.

$$\begin{aligned} Q_{ij} &= \Pr(X_m = j \mid X_{m+1} = i) = \frac{\Pr(X_m = j \cap X_{m+1} = i)}{\Pr(X_{m+1} = i)} = \frac{\Pr(X_m = j) \Pr(X_{m+1} = i \mid X_m = j)}{\Pr(X_{m+1} = i)} \\ &= \frac{\pi_j P_{ji}}{\pi_i}. \end{aligned} \tag{7.11}$$

□

Definition 7.39 (Time reversible Markov chain). Suppose for a Markov chain, the reverse transition probabilities Q_{ij} equal the corresponding forward transition probabilities P_{ij} for all i, j . Then the Markov chain is said to be **time reversible**. The condition $Q_{ij} = P_{ij}$ can also be written (per (7.11)) as

$$\pi_i P_{ij} = \pi_j P_{ji}, \quad \forall i, j.$$

Theorem 7.6.19 (Theorem 4.7.2 in *Stochastic Processes* (p. 220 of pdf)). A stationary Markov chain is time reversible if and only if starting in state i , any path back to i has the same probability as the reverse path, for all i . That is, if

$$P_{i,i_1} P_{i_1,i_2} \cdots P_{i_k,i} = P_{i,i_k} P_{i_k,i_{k-1}} \cdots P_{i_1,i}$$

for all states i, i_1, \dots, i_k .

Theorem 7.6.20 (Theorem 4.2 in *Introduction to Probability Models*). An ergodic (all states positive recurrent; see Definition 7.35) Markov chain for which $P_{ij} = 0$ whenever $P_{ji} = 0$ is time reversible if and only if starting in state i , any path back to i has the same probability as the reverse path, for all i . That is, if

$$P_{i,i_1} P_{i_1,i_2} \cdots P_{i_k,i} = P_{i,i_k} P_{i_k,i_{k-1}} \cdots P_{i_1,i}$$

for all states i, i_1, \dots, i_k .

Proposition 7.6.21 (Proposition 4.9 in *Introduction to Probability Models*, Theorem 4.7.3 in *Stochastic Processes* (p. 222 of pdf)). Consider an irreducible Markov chain $\{X_n\}$ with transition probabilities P_{ij} . If $\{X_j, j \in S\}$ is stationary, and there exist positive numbers $x_i, i \geq 0$ and a transition probability matrix Q such that

$$x_i P_{ij} = x_j Q_{ji}, \quad i \neq j$$

$$\sum x_i = 1$$

then the Markov chain is reversible, $\pi_j = x_j$ are the stationary probabilities for both the original and the reversed chain, and the Q_{ij} are the transition probabilities of the reversed chain.

Proof. Assume the above. we have

$$\sum_i x_i P_{ij} = \sum_i x_j P_{ji} = x_j$$

so these x_j satisfy the stationarity equations and the solution is unique, so $x_j = \pi_j$. \square

Example 7.42 (Similar to Example 4.35 in *Introduction to Probability Models*, Gambler's Ruin-type problem).

Example 7.43 (Similar to Example 4.36 in *Introduction to Probability Models*, Proposition 4.7.1 in *Stochastic Processes* (p. 217 of pdf; weighted graph problem)).

Example 7.44 (Example 4.37 in *Introduction to Probability Models*, Example 4.7(b) in *Stochastic Processes* (p. 221 of pdf; list, items requested, then move up one position in the list; average position)). Note the similarity to *Introduction to Probability Models* problem 4.26 (from Homework 10).

7.6.7 Semi-Markov Processes (Section 4.8 of *Stochastic Processes* (p. 224 of pdf), Section 7.6 of *Introduction to Probability Models*)

Definition 7.40 (Semi-Markov Process). Suppose the stochastic process $\{X(t), t \geq 0\}$ takes on values $\{0, 1, \dots, M\}$. Then $\{X(t), t \geq 0\}$ is called a **semi-Markov process**.

Why semi-Markov? What happens next doesn't just depend on your current state, it also depends on how long you've been there. But it's semi-Markov because just after a transition you know everything.

7.7 ISE 620

Exercise 22. (“Best Prize” problem.) There are n prizes that are presented one at a time in a random order. Each prize has a defined value, and there is a defined ordering of the value of the prizes. Each

time you see a prize, you only know the value of that prize relative to the prizes already seen—the value of later prizes remains unknown. Each time a prize is presented, we either accept it or reject it. You only get one prize, so once you accept it, you're done. Once you reject a prize, you can't get it back. Your goal is to maximize the probability of accepting the best prize. What do you do (what is the optimal policy)?

Solution. The only strategy that makes sense is to accept a prize if it is a *candidate*—that is, the best you've seen so far. You should never accept a prize that isn't a candidate unless you get to the last prize. Let P_n be the probability of getting the best prize. Then we expect P_n to approach 0 as n approaches infinity. Note that if it were good to accept the k th prize if it were a candidate, then it would definitely be better to accept the $k + 1$ th candidate if it were a candidate. So a good policy (k -policy) is to let k prizes go by, then accept the first candidate to come afterward.

Let X be the position of the best prize. We will condition on the best prize being in position i . Then

$$P_k(\text{best}) = \sum_{i=1}^n P_k(\text{best} \mid X = i) \Pr(X = i) = \frac{1}{n} \sum_{i=1}^n P_k(\text{best} \mid X = i)$$

Note that because in order for you to win, none of the prizes between position k and i can be candidates (or else you would accept them and not get the best prize). So the best of the first $i - 1$ prizes must be among the first k prizes in order for you to get the best prize.

$$P_k(\text{best} \mid X = i) = \begin{cases} 0 & i \leq k \\ \Pr(\{\text{best of } 1, \dots, i-1 \text{ is among the first } k\}) & k > i \end{cases}$$

and

$$\Pr(\{\text{best of } 1, \dots, i-1 \text{ is among the first } k\}) = \frac{k}{i-1}$$

so

$$P_k(\text{best}) = \frac{1}{n} \sum_{i=k+1}^n \frac{k}{i-1} = \frac{k}{n} \sum_{j=k}^{n-1} \frac{1}{j} \approx \frac{k}{n} \int_k^{n-1} \frac{dx}{x} = \frac{k}{n} \log(x) \Big|_k^{n-1} = \frac{k}{n} \log\left(\frac{n-1}{k}\right) \approx \boxed{\frac{k}{n} \log\left(\frac{n}{k}\right)}.$$

Now we want to choose k that maximizes this quantity. Generalize to letting x equal any real number in the expression

$$f(x) = \frac{x}{n} \log\left(\frac{n}{x}\right) \implies f'(x) = \frac{x}{n} \frac{1}{x} \left(-\frac{n}{x^2}\right) + \log\left(\frac{n}{x}\right) \frac{1}{n}$$

Setting equal to 0 we have

$$\frac{1}{n} = \frac{1}{n} \log\left(\frac{n}{x}\right) \implies \frac{n}{x} = e \implies \boxed{x = \frac{n}{e}}$$

so the optimal strategy is to let about $1/e$ of the prizes go by, then choose the first candidate to come by afterward.

Remark 95. The probability of getting the best prize is then

$$f\left(\frac{n}{e}\right) = \frac{1}{e} \log(e) = \frac{1}{e}$$

regardless of $n!$

Exercise 23. (Ballot problem.) Suppose we have candidates A and B with votes counted in random order. A has n votes, B has m with $n > m$. What is the probability that A is always ahead in the count at every stage of the vote?

Solution. Let $\Pr(\{A \text{ is always ahead}\}) = P(n, m) = P_{n,m}$. Then

$$\begin{aligned} P_{n,m} &= \Pr(\{A \text{ is always ahead}\} \mid \{A \text{ receives the first vote}\}) \cdot \frac{n}{n+m} \\ &\quad + \Pr(\{A \text{ is always ahead}\} \mid \{B \text{ receives the first vote}\}) \cdot \frac{m}{n+m} \\ &= \Pr(\{A \text{ is always ahead}\} \mid \{A \text{ receives the first vote}\}) \cdot \frac{n}{n+m} + 0 \\ &= Q_{n-1,m} \cdot \frac{n}{n+m} \end{aligned}$$

where Q represents the probability that A is never behind (since going forward ties would be ok because A starts out ahead). We have

$$Q_{nm} = \Pr(\{A \text{ is never behind}\}) = \frac{n}{n+m} \Pr(\{A \text{ is never behind}\} \mid \{A \text{ gets first vote}\})$$

Note that $\Pr(\{A \text{ is never behind}\} \mid \{A \text{ gets first vote}\}) = Q_{n-1,m-1}$. But now things are more complicated because A could afford to be behind by 1 going forward. So this strategy is not working. Try instead to condition on who gets the last vote.

$$\begin{aligned} P_{n,m} &= \Pr(\{A \text{ is always ahead}\} \mid \{A \text{ receives the last vote}\}) \cdot \frac{n}{n+m} \\ &\quad + \Pr(\{A \text{ is always ahead}\} \mid \{B \text{ receives the last vote}\}) \cdot \frac{m}{n+m} \\ &= P_{n-1,m} \cdot \frac{n}{n+m} + P_{n,m-1} \cdot \frac{m}{n+m} \end{aligned}$$

We can work this out recursively using the boundary conditions

$$P_{n,n} = 2, \quad P_{n,0} = 1, \quad n > 0$$

We will try to guess the answer.

$$P_{2,1} = \Pr(\{A \text{ gets the first two votes}\}) = \frac{1}{3}$$

$$P_{n,1} = \Pr(\{\text{first two votes are for } A\}) = \frac{n}{n+1} \cdot \frac{n-1}{n} = \frac{n-1}{n+1}$$

$$P_{3,2} = \frac{3}{5} \cdot \frac{2}{4} \cdot \Pr(\{A \text{ is not the last of the remaining votes}\}) = \frac{3}{5} \cdot \frac{2}{4} \cdot \frac{2}{3} = \frac{1}{5}$$

$$P_{4,2} = \frac{4}{6} \cdot \frac{3}{5} \cdot \Pr(\{B \text{ does not get next two votes}\}) = \frac{4}{6} \cdot \frac{3}{5} \cdot \left(1 - \frac{2}{4} \cdot \frac{1}{3}\right) = \frac{4}{6} \cdot \frac{3}{5} \cdot \frac{5}{6} = \frac{1}{3}$$

$$\begin{aligned} P_{4,3} &= \frac{4}{7} \cdot \frac{3}{6} \cdot \left(\Pr(\{\text{next is } A\}) \cdot \Pr(\{\text{not 3 } B \text{ votes in a row}\}) + \Pr(\{\text{next is } B\}) \cdot \Pr(\{ \right. \\ &\quad \left. = \frac{4}{7} \cdot \frac{3}{6} \cdot \left(\frac{2}{5} \cdot \frac{3}{4} + \frac{3}{5} \cdot \frac{2}{4} \cdot \frac{2}{3} \right) \right) \end{aligned}$$

⋮

It seems that

$$P_{n,m} = \frac{n-m}{n+m}$$

We can argue this solution is unique or we can argue it is true by induction.

7.8 DSO Statistics Group Screening Exam Problems

Exercise 24 (2016 DSO Statistics Group In-Class Screening Exam, Question 1). Let $\{V_n\}$ be i.i.d. non-negative random variables. Fixing $r > 0$ and $q \in (0, 1]$, consider the sequence $W_0 = 1$ and $W_n = (qr + (1-q)V_n)W_{n-1}, n \geq 1$. A motivating example of W_n is recording the relative growth of a portfolio where a constant fraction q of one's wealth is re-invested each year in a risk-less asset that grows by r per year, with the remainder re-invested in a risky asset whose annual growth factors are random V_n .

- (a) Show that $n^{-1} \log W_n \xrightarrow{a.s.} w(q)$, where $w(q) = \mathbb{E} \log(qr + (1-q)V_1)$.
- (b) Show that $q \rightarrow w(q)$ is concave on $(0, 1]$.

- (c) Using Jensen's Inequality, show that $w(q) \leq w(\bar{q})$ in case $\mathbb{E}V_1 \leq r$. Further, show that if $\mathbb{E}V_1^{-1} \leq r^{-1}$ then the almost sure convergence also applies for $q = 0$ and $w(q) \leq w(0)$.

Solution.

- (a) Note that

$$W_1 = (qr + (1 - q)V_1)W_0 = qr + (1 - q)V_1$$

$$W_2 = (qr + (1 - q)V_2)W_1 = (qr + (1 - q)V_2)(qr + (1 - q)V_1)$$

$$W_3 = (qr + (1 - q)V_3)W_2 = (qr + (1 - q)V_3)(qr + (1 - q)V_2)(qr + (1 - q)V_1) = \prod_{i=1}^3 (qr + (1 - q)V_i)$$

⋮

$$W_n = \prod_{i=1}^n (qr + (1 - q)V_i)$$

$$\implies n^{-1} \log(W_n) = \frac{1}{n} \sum_{i=1}^n (qr + (1 - q)V_i)$$

$\{qr + (1 - q)V_i\}$ is a sequence of i.i.d. nonnegative random variables, so by the Strong Law of Large Numbers, the conclusion follows if $\mathbb{E}[|qr + (1 - q)V_1|] = \mathbb{E}[qr + (1 - q)V_1] = qr + (1 - q)\mathbb{E}(V_1) < \infty$.

- (b) Since $w(q)$ is twice differentiable, a sufficient condition for concavity is $w''(q) \leq 0$ for all $q \in (0, 1]$.

$$w(q) = \mathbb{E} \log[qr + (1 - q)V_1] = \mathbb{E} \log[q(r - V_1) + V_1]$$

$$w'(q) = \frac{\partial}{\partial q} \mathbb{E} \log[q(r - V_1) + V_1] = \mathbb{E} \left(\frac{\partial}{\partial q} \log[q(r - V_1) + V_1] \right) = \mathbb{E} \left(\frac{r - V_1}{q(r - V_1) + V_1} \right) \quad (7.12)$$

$$\begin{aligned} w''(q) &= \mathbb{E} \left(\frac{\partial}{\partial q} \frac{r - V_1}{q(r - V_1) + V_1} \right) = \mathbb{E} \left((r - V_1) \cdot \frac{\partial}{\partial q} [q(r - V_1) + V_1]^{-1} \right) \\ &= \mathbb{E} \left((r - V_1) \cdot (-1) [q(r - V_1) + V_1]^{-2} \cdot (r - V_1) \right) = -\mathbb{E} \left(\left[\frac{(r - V_1)}{q(r - V_1) + V_1} \right]^2 \right) \end{aligned} \quad (7.13)$$

This is -1 times the expectation of a nonnegative random variable, so by Markov's Inequality we have

$$\mathbb{E} \left(\left[\frac{(r - V_1)}{q(r - V_1) + V_1} \right]^2 \right) \geq 0 \iff w''(q) \leq 0 \quad \forall q \in (0, 1],$$

proving concavity.

(c) By Jensen's Inequality and the concavity of $q \rightarrow \log[qr + (1 - q)V_1]$, we have

$$\begin{aligned} w(q) &= \mathbb{E} \log[qr + (1 - q)V_1] \leq \log \mathbb{E}[qr + (1 - q)V_1] = \log(qr + (1 - q)\mathbb{E}[V_1]) \\ &\leq \log(qr + (1 - q)r) = \log(r) = \mathbb{E} \log(r) = w(1). \end{aligned}$$

where the third step used $\mathbb{E}(V_1) \leq r$ and the second-to-last step used the fact that r is non-random.
For $q = 0$, we have

$$n^{-1} \log(W_n) = \frac{1}{n} \sum_{i=1}^n V_i.$$

$\{V_i\}$ is a sequence of i.i.d. nonnegative random variables, so by the Strong Law of Large Numbers, almost sure convergence applies if $\mathbb{E}[|V_1|] = \mathbb{E}[V_1] < \infty$. **But this is the same condition as in the case $q \in (0, 1]$.**

To show $w(q) \leq w(0)$, we will show that $w(q)$ is nonincreasing on $[0, 1]$. Recall from (7.12)

$$w'(q) = \mathbb{E} \left(\frac{r - V_1}{q(r - V_1) + V_1} \right)$$

We will show that (7.12) is upper-bounded by 0 on $[0, 1]$. Plugging in $q = 0$ yields

$$w'(0) = \mathbb{E} \left(\frac{r - V_1}{V_1} \right) = \mathbb{E}(rV_1^{-1} - 1) = r\mathbb{E}(V_1^{-1}) - 1 \leq 1 - 1 = 0,$$

where we used the assumption $\mathbb{E}(V_1^{-1}) \leq r$ on the second-to-last step. Recall that the second derivative (7.13) is continuous and nonpositive on $(0, 1]$. Therefore the first derivative (7.12) never exceeds $q(0) = 0$ on $[0, 1]$, so $w(q) \leq w(0)$.

7.9 Simple Random Walk

Definition 7.41. Let $\{X_i\}$ be i.i.d. We have

$$X_i = \begin{cases} 1 & \text{with probability } p \\ -1 & \text{with probability } 1 - p \end{cases}$$

Let $S_k = \sum_{i=1}^k X_i$. Then $\{S_k\}$ is a **simple random walk**. (It is simple because the outcomes are either 1 or -1.)

7.10 Martingales

Definition. Let $\{y_t\}_{t=0}^{\infty}$ be a sequence of random variables, and let Ω_t denote the information set available at date t , which at least contains $\{y_t, y_{t-1}, y_{t-2}, \dots\}$. If $\mathbb{E}(y_t \mid \Omega_{t-1}) = y_{t-1}$ holds then $\{y_t\}$ is a martingale process with respect to Ω_t .

Definition. Let $\{y_t\}_{t=1}^{\infty}$ be a sequence of random variables, and let Ω_t denote the information set available at date t , which at least contains $\{y_t, y_{t-1}, y_{t-2}, \dots\}$. If $\mathbb{E}(y_t \mid \Omega_{t-1}) = 0$, then $\{y_t\}$ is a martingale difference process with respect to Ω_t .

7.11 Brownian Motion

Appendix B.13, Brownian motion. A standard Brownian motion $b(\cdot)$ is a continuous-time stochastic process associating each date $a \in [0, 1]$ with the scalar $b(a)$ such that

- (i) $b(0) = 0$
- (ii) For any dates $0 \leq a_1 \leq a_2 \leq \dots \leq a_k \leq 1$ the changes $[b(a_2) - b(a_1)], [b(a_3) - b(a_2)], \dots, [b(a_k) - b(a_{k-1})]$ are independent multivariate Gaussian with $b(a) - b(s) \sim \mathcal{N}(0, a - s)$.
- (iii) For any given realization, $b(a)$ is continuous in a with probability 1.

Other continuous time processes can be generated from the standard Brownian motion. For example, a Brownian motion with variance σ^2 can be obtained as

$$w(a) = \sigma b(a)$$

where $b(a)$ is a standard Brownian motion.

The continuous time process

$$\mathbf{w}(a) = \boldsymbol{\Sigma}^{1/2} \mathbf{b}(a)$$

is a Brownian motion with covariance matrix $\boldsymbol{\Sigma}$.

Definition 26 (Wiener process). Let $\Delta w(t)$ be the change in $w(t)$ during the time interval dt . Then $w(t)$ is said to follow a Wiener process if

$$\Delta w(t) = \epsilon_t \sqrt{dt}, \quad \epsilon_t \sim IID(0, 1)$$

and $w(t)$ denotes the value of the $w(\cdot)$ at date t . Clearly,

$$\mathbb{E}[\Delta w(t)] = 0, \text{ and } \text{Var}[\Delta w(t)] = dt$$

Theorem 7.11.1. Donsker's Theorem, Theorem 43, p.335, Section 15.6.3. Let $a \in [0, 1)$, $t \in [0, T]$, and suppose $(J - 1)/T \leq a < J/T$, $J = 1, 2, \dots, T$. Define

$$R_T(a) = \frac{1}{\sqrt{T}} s_{[Ta]}$$

where

$$s_{[Ta]} = \epsilon_1 + \epsilon_2 + \dots + \epsilon_{[Ta]}$$

$[Ta]$ denotes the largest integer part of Ta and $s_{[Ta]} = 0$ if $[Ta] = 0$. Then $R_T(a)$ weakly converges to $w(a)$, i.e.,

$$R_T(a) \rightarrow w(a)$$

where $w(a)$ is a Wiener process. Note that when $a = 1$, $R_T(1) = 1/\sqrt{T} \cdot S_{[T]} = 1/\sqrt{T} \cdot (\epsilon_1 + \epsilon_2 + \dots + \epsilon_T)$. Since ϵ_t 's are IID, by the central limit theorem, $R_T(1) \rightarrow \mathcal{N}(0, 1)$.

Similar (Theorem 2.1 in [Phillips and Durlauf \[1986\]](#)): Let $\{u_t\}$ be a sequence satisfying $\mathbb{E}(u_t) = 0$, $\gamma(0) = \mathbb{E}(T^{-1}S_t^2) \rightarrow \sigma^2 < \infty$ as $T \rightarrow \infty$, $\{u_t\}$ is square summable, $\sup_t \{\mathbb{E}(|u_t|^\beta)\} < \infty$ for some $2 \leq \beta < \infty$ and all t , $\gamma(h) = \mathbb{E}(T^{-1}(y_t - y_{t-h})^2) \rightarrow K_h < \infty$ as $\min\{h, T\} \rightarrow \infty$. Then $X_T(t) \Rightarrow W(t)$ as $T \rightarrow \infty$, where $W(t)$ is a Wiener process.

Theorem 7.11.2. Continuous Mapping Theorem (Theorem 44 of Pesaran in 15.6.3). Let $a \in [0, 1)$, $i \in [0, n]$, and suppose $(J - 1)/n \leq a < J/n$, $J = 1, 2, \dots, n$. Define $R_n(a) = n^{-1/2} S_{[n \cdot a]}$. If $f(\cdot)$ is continuous over $[0, 1)$, then

$$f[R_n(a)] \xrightarrow{d} f[w(a)]$$

Chapter 8

Asymptotics and Convergence

These notes are based on my notes from chapter 8 of *Time Series and Panel Data Econometrics* (1st edition) by M. Hashem Pesaran [Pesaran, 2015] and coursework for Economics 613: Economic and Financial Time Series I at USC, as well as Math 505A and Math 541A at USC and chapter 7 from *Probability and Random Processes* (Grimmett and Stirzaker) 3rd edition [Grimmett and Stirzaker, 2001].

8.1 Preliminaries (5.9 and 7.1, Grimmett and Stirzaker)

Definition 8.1. Definition 7.1.4, Grimmett and Stirzaker. If for all $x \in [0, 1]$ the sequence $\{f_n(x)\}$ of real numbers satisfies $f_n(x) \rightarrow f(x)$ as $n \rightarrow \infty$ then we say $f_n \rightarrow f$ **pointwise**.

Remark 96. In practice pointwise convergence is often not useful for functions because a sequence of functions may be continuous while its limit is not. For instance, consider $\{f_n : f_n = x^n \forall x \in [0, 1]\}$. Then f_n is continuous for all n but

$$\lim_{n \rightarrow \infty} f_n = \begin{cases} 0 & x \leq 1 \\ 1 & x = 1 \end{cases}$$

Instead, the following definition is often more useful.

Definition 8.2. (from class notes.) We say that f_n **uniformly converges to f on $[a, b]$** if for every $\epsilon > 0$ there exists N such that for every $n > N$,

$$\forall x \in [a, b] |f_n(x) - f(x)| < \epsilon$$

Definition 8.3. (Definition 7.1.5, Grimmett and Stirzaker.) Let V be a collection of functions mapping $[0, 1]$ into \mathbb{R} and assume V is endowed with a function $\|\cdot\| : V \rightarrow \mathbb{R}$ satisfying

- (a) $\|f\| \geq 0$ for all $f \in V$
- (b) $\|f\| = 0$ if and only if f is the zero function (or equivalent to it)

- (c) $\|af\| = |a| \cdot \|f\|$ for all $a \in \mathbb{R}$, $f \in V$
- (d) $\|f + g\| \leq \|f\| + \|g\|$ (Triangle Inequality)

The function $\|\cdot\|$ is called a **norm**. If $\{f_n\}$ is a sequence of members of V then we say that $f_n \rightarrow f$ **with respect to the norm** $\|\cdot\|$ if $\|f_n - f\| \rightarrow 0$ as $n \rightarrow \infty$.

Definition 8.4. (Definition 7.16, Grimmett and Stirzaker.) Let $\epsilon > 0$ be prescribed, and define the distance between two functions $g, h : [0, 1] \rightarrow \mathbb{R}$ by

$$d_\epsilon(g, h) = \int_E dx$$

where $E = \{u \in [0, 1] : |g(u) - h(u)| > \epsilon\}$. We say that $f_n \rightarrow f$ **in measure** if

$$d_\epsilon(f_n, f) \rightarrow 0 \text{ as } n \rightarrow \infty \text{ for all } \epsilon > 0$$

Theorem 8.1.1. Inversion Theorem (Theorem 5.9.2, Grimmett and Stirzaker). Let X have distribution function F and characteristic function ϕ . Define $\bar{F} : \mathbb{R} \rightarrow [0, 1]$ by

$$\bar{F}(x) = \frac{1}{2} [F(x) + \lim_{y \rightarrow x^-} F(y)]$$

Then

$$\bar{F}(b) - \bar{F}(a) = \lim_{N \rightarrow \infty} \int_{-N}^N \frac{\exp(-iat) - \exp(-ibt)}{2\pi it} \cdot \phi(t) dt$$

Proof. See Kingman and Taylor [1966]. □

Corollary 8.1.1.1. Corollary 5.9.3. Random variables X and Y have the same characteristic function if and only if they have the same distribution function.

Proof. Available in Grimmett and Stirzaker section 5.9, pp. 189 - 190. □

Definition 8.5. (Definition 5.9.4, Grimmett and Stirzaker.) We say that the sequence F_1, F_2, \dots of distribution functions **converges** to the distribution function F (written $F_n \rightarrow F$) if $F(x) = \lim_{n \rightarrow \infty} F_n(x)$ at each point x where F is continuous.

Theorem 8.1.2. Continuity theorem (Thereom 5.9.5; in notes from Friday 10/26, Lecture 28). Suppose that F_1, F_2, \dots is a sequence of distribution functions with corresponding characteristic functions ϕ_1, ϕ_2, \dots

- (a) If $F_n(x) \rightarrow F(x)$ for some distribution function F with characteristic function ϕ (at x where F is continuous), then $\phi_n(t) \rightarrow \phi(t)$ for all t .
- (b) Conversely, if $\phi(t) = \lim_{n \rightarrow \infty} \phi_n(t)$ exists and $\phi(t)$ is continuous at $t = 0$, then ϕ is the characteristic function of some distribution function F , and $F_n \rightarrow F$.

Proof. See Kingman and Taylor [1966]. □

8.2 Inequalities (8.6 of Pesaran)

Inequalities

- Probabilities

—

Lemma 8.2.1. Markov's Inequality (Grimmett and Stirzaker p. 311, 319) : Let $X : \Omega \rightarrow [-\infty, \infty]$ be a random variable. Then for all $a > 0$,

$$\Pr(|X| \geq a) \leq \frac{\mathbb{E}(|X|)}{a}$$

Proof. Note $t \cdot \mathbf{1}_{\{|X| \geq t\}} \leq |X|$, where $\mathbf{1}$ is the indicator function. Dividing both sides by t and taking expectations, we have

$$\mathbb{E}(\mathbf{1}_{\{|X| \geq t\}}) \leq \frac{\mathbb{E}|X|}{t} \iff \Pr(|X| \geq t) \leq \frac{\mathbb{E}|X|}{t}, \quad \forall t > 0.$$

□

Corollary 8.2.1.1. If n is a positive integer, then

$$\Pr(|X| \geq t) \leq \frac{\mathbb{E}(|X|^n)}{t^n} \quad \forall t > 0$$

Proof. By Markov's Inequality (Theorem 8.2.1),

$$\Pr(|X| \geq t) = \Pr(|X|^n \geq t^n) \leq \frac{\mathbb{E}(|X|^n)}{t^n}$$

□

—

Theorem 8.2.2 (Chebyshev's Inequality (probability p. 319)). Let $X : \Omega \rightarrow [-\infty, \infty]$ be an (integrable) random variable with $\mathbb{E}(X^2) < \infty$. Then for any real number $k > 0$

$$\Pr(|X - \mathbb{E}(X)| \geq k\sqrt{\text{Var}(X)}) \leq \frac{1}{k^2}$$

This can also be written as

$$\Pr(|X - \mathbb{E}(X)| \geq k) \leq \frac{\text{Var}(X)}{k^2}$$

(Can be used to demonstrate consistency of estimators: if we can show that as $T \rightarrow \infty$ $\text{Var}(X) = \sigma^2 \rightarrow 0$, then this implies $\Pr(|X - \mu| \geq k\sigma) \rightarrow 0$ as $T \rightarrow \infty$, showing consistency.)

—

Theorem 8.2.3. Chernoff For $x \geq 0$, $a > 0$, $\forall t > 0$,

$$\Pr(X \geq a) = \Pr(e^{tX} \geq e^{ta}) \leq \frac{\mathbb{E}(e^{tX})}{e^{ta}}$$

- Moments

Theorem 8.2.4 (Cauchy-Schwarz (and Bunyakovsky)). If X and Y are random variables with finite variance then

$$\mathbb{E}(XY)^2 \leq \mathbb{E}(X^2)\mathbb{E}(Y^2)$$

Note that this can is a corollary of Theorem 8.2.7 with $p = q = 2$. We can also prove this theorem on its own in a different one. We first prove a useful result.

Lemma 8.2.5. If $\text{Var}(X) = 0$ then X is almost surely constant; that is, $\Pr(X = a) = 1$ for some $a \in \mathbb{R}$.

Proof. Note that because $\text{Var}(X) = 0 < \infty$, we know that $\mathbb{E}(X)$ and $\mathbb{E}(X^2)$ exist. We have

$$\text{Var}(X) = \mathbb{E}[(X - \mathbb{E}(X))^2] = 0$$

Let $Y = (X - \mathbb{E}(X))^2$. Note that $Y = (X - \mathbb{E}(X))^2 \geq 0$ and that $\mathbb{E}(Y) = \text{Var}(X) = 0$. Therefore $\Pr(Y = 0) = 1$, so $\Pr(Y \neq 0) = 0$. To see why, in the case that X is discrete,

$$\mathbb{E}(Y) = \sum_{k=0}^{\infty} k \cdot \Pr(Y = k) = \text{Var}(X) = 0$$

which is true if and only if $\Pr(Y = k) = 0$ for all $k > 0$. Since we already showed that $\Pr(Y < 0) = 0$, it follows that $\Pr(Y = 0) = 1$. In the continuous case,

$$\mathbb{E}(Y) = \int_0^{\infty} y \cdot f_Y(y) dy = \text{Var}(X) = 0$$

which implies that $f_Y(x) = 0$ for all $x > 0$. Again, since $\Pr(Y < 0) = 0$, we have $\Pr(Y \neq 0) = 0$. But $Y = 0 \iff X = \mathbb{E}(X)$ so we have $\Pr(X = \mathbb{E}(X)) = 1$. \square

Remark 97. Note that Lemma 8.2.5 along with Proposition 6.1.29 imply that X has variance 0 if and only if it is (almost surely) constant.

We are now ready to prove the Cauchy-Schwarz Inequality.

Proof. if $\mathbb{E}(X^2) = 0$ or $\mathbb{E}(Y^2) = 0$, the Cauchy-Schwarz Inequality follows immediately. To see why, suppose without loss of generality that $\mathbb{E}(X^2) = 0$. Then the right side is 0. Also, $0 \leq \text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2 = -\mathbb{E}(X)^2$. Since $\mathbb{E}(X)^2 \geq 0$, we must have $\mathbb{E}(X)^2 = 0$ and therefore $\text{Var}(X) = 0$. Therefore by Lemma 8.2.5, X is almost surely constant, which means that $\text{Cov}(X, Y) = 0$.

In the case that $\mathbb{E}(X^2) > 0$ and $\mathbb{E}(Y^2) > 0$, for $a, b \in \mathbb{R}$, let $Z = aX - bY$. Then

$$0 \leq \mathbb{E}(Z^2) = a^2\mathbb{E}(X^2) - 2ab\mathbb{E}(XY) + b^2\mathbb{E}(Y^2) \tag{8.1}$$

The right side of (8.1) is quadratic in a . Because it is greater than or equal to zero, it has at most one real root, which means its discriminant must be non-positive. That is, if $b \neq 0$,

$$(-2b\mathbb{E}(XY))^2 - 4b^2\mathbb{E}(X^2)\mathbb{E}(Y^2) \leq 0 \iff \mathbb{E}(XY)^2 - \mathbb{E}(X^2)\mathbb{E}(Y^2) \leq 0$$

which yields the result. Note that equality holds if and only if $\Pr(aX = bY) = 1$ because the discriminant is zero if and only if the quadratic has a real root, which occurs if and only if

$$\mathbb{E}[(aX - bY)^2] = 0$$

which is true if and only if $\Pr(aX = bY) = 1$ by Lemma 8.2.5 and Proposition 6.1.29. \square

Definition 8.6. Let $\phi : \mathbb{R} \rightarrow \mathbb{R}$. We say that ϕ is **convex** if for any $x, y \in \mathbb{R}$ and for any $t \in [0, 1]$, we have

$$\phi(tx + (1-t)y) \leq t\phi(x) + (1-t)\phi(y)$$

Theorem 8.2.6 (Jensen's Inequality, from Math 541A. Also Grimmett and Stirzaker p.181, 349). Let $X : \Omega \rightarrow [-\infty, \infty]$ be a random variable. Let $\phi : \mathbb{R} \rightarrow \mathbb{R}$ be convex. If $\mathbb{E}|X| < \infty$ and $\mathbb{E}|\phi(X)| < \infty$, then

$$\phi(\mathbb{E}X) \leq \mathbb{E}\phi(X).$$

(See also Theorem 9.1.5.)

For the definition of convexity, see Definition 9.1.

Proof. Note that from Theorem 9.1.3, for any $y \in \mathbb{R}$ there exists a constant a and a function L such that

$$a(x - y) + \phi(y) \leq \phi(x) \quad \forall x \in \mathbb{R}$$

Letting $y = \mathbb{E}(X)$ we have

$$a(X - \mathbb{E}X) + \phi(\mathbb{E}X) \leq \phi(X)$$

Since expectations preserve inequalities,

$$\mathbb{E}[a(X - \mathbb{E}X) + \phi(\mathbb{E}X)] \leq \mathbb{E}\phi(X)$$

But

$$\mathbb{E}[a(X - \mathbb{E}X) + \phi(\mathbb{E}X)] = a(\mathbb{E}X - \mathbb{E}X) + \mathbb{E}(\phi(\mathbb{E}X)) = \phi(\mathbb{E}X)$$

which yields

$$\phi(\mathbb{E}X) \leq \mathbb{E}\phi(X).$$

\square

For some corollaries, see section 9.1.

Theorem 8.2.7. [Hölder (Grimmett and Stirzaker p. 143, 319; Theorem 1.99 in Math 541A lecture notes) Generalization of Cauchy-Schwarz] Let $X, Y : \Omega \rightarrow \mathbb{R}$ be random variables. For $p, q \geq 1$ satisfying $1/p + 1/q = 1$ we have

$$\mathbb{E}(|XY|) \leq (\mathbb{E}(|X^p|))^{1/p} (\mathbb{E}(|Y^q|))^{1/q} = \|X\|_p \|Y\|_q.$$

The equality case happens only if X is a constant multiple of Y with probability 1. Note that the case $p = q = 2$ recovers the Cauchy-Schwarz Inequality (Theorem 8.2.4).

Proof. Assume without loss of generality that $\|X\|_p = \|Y\|_q = 1$. Also, the case $p = 1, q = \infty$ follows from the triangle inequality, so we assume $1 < p < \infty$. From concavity of the log function, we have

$$\begin{aligned} \log((x^p)^{1/p}(y^q)^{1/q}) &= (1/p)\log(x^p) + (1/q)\log(y^q) \\ &\leq \log\left(\frac{1}{p}x^p + \frac{1}{q}y^q\right) \\ \implies (x^p)^{1/p}(y^q)^{1/q} &\leq \frac{1}{p}x^p + \frac{1}{q}y^q \end{aligned}$$

Fixing an $\omega \in \Omega$, we have

$$|X(\omega)Y(\omega)| = (|X(\omega)|^p)^{1/p}(|Y(\omega)|^q)^{1/q} \leq \frac{1}{p}|X(\omega)|^p + \frac{1}{q}|Y(\omega)|^q$$

Integrating we have...

□

Theorem 8.2.8 (Hölder (vector form)). For any $u, v \in \mathbb{R}^n$,

$$|u^T v| \leq \|u\|_p \|v\|_q$$

for any $p, q \in [0, \infty]$ satisfying $1/p + 1/q = 1$.

—

Theorem 8.2.9. Minkowski (Grimmett and Stirzaker p. p. 143) For $p \geq 1$,

$$[\mathbb{E}(|X + Y|^p)]^{1/p} \leq (\mathbb{E}|X^p|)^{1/p} + (\mathbb{E}|Y^p|)^{1/p}$$

– Useful for showing lower order moments are finite (e.g. finite variance implies finite mean).

Lemma 8.2.10. Lyapunov's Inequality (Grimmett and Stirzaker p. 143). For $0 < r \leq s < \infty$,

$$\mathbb{E}(|X|^r)^{1/r} \leq \mathbb{E}(|X|^s)^{1/s}$$

—

Theorem 8.2.11. Triangle Inequality: Let $X, Y : \Omega \rightarrow \mathbb{R}$ be random variables. Let $1 \leq p \leq \infty$. Then

$$\|X + Y\|_p \leq \|X\|_p + \|Y\|_p, 1 \leq p \leq \infty$$

Proof. The case $p = \infty$ follows from the scalar triangle inequality, so assume $1 \leq p < \infty$. By scaling, we may assume $\|X\|_p = 1 - t, \|Y\|_p = t$, for some $t \in (0, 1)$ (zeroes and infinities being trivial). Define $V := X/(1 - t), W := Y/t$. Then by convexity of $x \rightarrow |x|^p$ on \mathbb{R} ,

$$|(1 - t)V(\omega) + t(W(\omega))|^p \leq (1 - t)|V(\omega)|^p + t|W(\omega)|^p$$

Take expectation of both sides:

$$\mathbb{E}|X + Y|^p \leq (a - t)^{1-p}\mathbb{E}(|X|^p) + t^{1-p}\mathbb{E}(|Y|^p)$$

Since $\|X\|_p = t$, $\|Y\|_p = 1 - t$, we have that the right side is $1 - t + t = 1$. (Note: $\|Y\|_p = t$, $\mathbb{E}|Y|^p = t^p$, $\|X\|_p = 1 - t$ Therefore

$$(\mathbb{E}|X+Y|^p)^{1/p} = \|X+Y\|_p \leq 1$$

□

Remark 98. See also Theorem 5.1.6 and Corollary 5.1.6.1.

Theorem 8.2.12 (Chernoff Bound). Let X be a random variable and let $r > 0$. Define $M_X(t) := \mathbb{E}e^{tX}$ for any $t \in \mathbb{R}$. Then for any $t > 0$,

$$\mathbb{P}(X > r) \leq e^{-tr} M_X(t).$$

Proof. Using Markov's Inequality (Theorem 8.2.1) on e^{tX} , we have

$$\Pr(X \geq r) = \Pr(e^{tX} \geq e^{tr}) \leq \frac{\mathbb{E}e^{tX}}{e^{tr}} = e^{-tr} M_X(t), \quad \forall t > 0.$$

□

Remark 99. Consequently, if X_1, \dots, X_n are independent random variables with the same CDF, and if $r, t > 0$,

$$\mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n X_i > r\right) \leq e^{-trn} (M_{X_1}(t))^n.$$

For example, if X_1, \dots, X_n are independent Bernoulli random variables with parameter $0 < p < 1$, and if $r, t > 0$,

$$\mathbb{P}\left(\frac{X_1 + \dots + X_n}{n} - p > r\right) \leq e^{-trn} (pe^t + (1-p))^n.$$

And if we choose t appropriately, then the quantity $\mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n (X_i - p) > r\right)$ becomes exponentially small as either n or r become large. That is, $\frac{1}{n} \sum_{i=1}^n X_i$ becomes very close to its mean. Importantly, the Chernoff bound is much stronger than either Markov's or Chebyshev's inequality, since they only respectively imply that

$$\mathbb{P}\left(\left|\frac{X_1 + \dots + X_n}{n} - p\right| > r\right) \leq \frac{2p(1-p)}{r}, \quad \mathbb{P}\left(\left|\frac{X_1 + \dots + X_n}{n} - p\right| > r\right) \leq \frac{p(1-p)}{nr^2}.$$

8.3 Modes of Convergence (7.2 of Grimmett and Stirzaker, 8.2 and 8.4 of Pesaran)

Let $\{X_n\} = \{X_1, X_2, \dots\}$ and X be random variables defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

Definition 8.7. Convergence in probability. $\{X_n\}$ is said to **converge in probability** to X if

- Grimmett and Strizaker definition:

$$\lim_{n \rightarrow \infty} \Pr(|X_n - X| > \epsilon) = 0, \text{ for every } \epsilon > 0$$

- Pesaran definition:

$$\lim_{n \rightarrow \infty} \Pr(|X_n - X| < \epsilon) = 1, \text{ for every } \epsilon > 0$$

- More formal (from Math 541A):

$$\forall \epsilon > 0, \lim_{n \rightarrow \infty} \Pr(\{\omega \in \Omega : |X_n(\omega) - X(\omega)| > \epsilon\}) = 0$$

Remark 100. This mode of convergence is also often denoted by $X_n \xrightarrow{p} X$ and when X is a fixed constant it is referred to as the **probability limit of X_n** , written as $\text{Plim}(X_n) = x$, as $n \rightarrow \infty$.

The above concept is readily extended to multivariate cases where $\{\mathbf{X}_n, n = 1, 2, \dots\}$ denote m -dimensional vectors of random variables. Then the condition is

$$\lim_{n \rightarrow \infty} \Pr(\|\mathbf{X}_n - \mathbf{X}\| < \epsilon) = 1, \text{ for every } \epsilon > 0$$

where $\|\cdot\|$ denotes an appropriate norm (say ℓ_2). Convergence in probability is often referred to as "weak convergence" (in contrast to convergence with probability 1, below).

Definition 8.8. Convergence with probability 1 or almost surely. The sequence of random variables $\{X_n\}$ is said to **converge with probability 1** (or **almost surely**) to X if

- (505A class notes definition)

$$\Pr(\{\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = X(\omega)\}) = 1$$

(Note: pointwise convergence can hardly ever be shown here and is not useful.)

- Grimmett and Stirzaker textbook definition:

$$\Pr(\{\omega \in \Omega : X_n(\omega) \rightarrow X(\omega) \text{ as } n \rightarrow \infty\}) = 1$$

- Pesaran textbook definition:

$$\Pr\left(\lim_{n \rightarrow \infty} X_n = X\right) = 1$$

Remark 101. This is often written as $X_n \xrightarrow{w.p.1} X$ or $X_n \xrightarrow{a.s.} X$. An equivalent condition for convergence with probability 1 is given by

$$\lim_{n \rightarrow \infty} \Pr(|X_m - X| < \epsilon, \text{ for all } m \geq n) = 1, \text{ for every } \epsilon > 0$$

which shows that convergence in probability is a special case of convergence with probability 1 (obtained by setting $m = n$). Convergence with probability 1 is stronger than convergence in probability and is often referred to as "strong convergence."

Definition 8.9. **Convergence in r -th mean** or **convergence in ℓ_p** . $X_n \rightarrow X$ in **r th mean** (or in ℓ_p) where $r \geq 1$ (or $0 < p \leq \infty$) if $\mathbb{E}|X_n|^r| < \infty$ for all n and

$$\lim_{n \rightarrow \infty} \mathbb{E}(|X_n - X|^r) = 0$$

or if $\|X\|_p < \infty$ and

$$\lim_{n \rightarrow \infty} \|X_n - X\|_p = 0$$

Remark 102. Recall that $\|X\|_p := (\mathbb{E}(X^p))^{1/p}$ if $0 < p < \infty$ and $\|X\|_\infty := \inf\{c > 0 : \Pr(|X| \leq c) = 1\}$. Note that if $p < 1$, $\|\cdot\|_p$ is no longer a norm because it does not satisfy the Triangle Inequality (Corollary ?? and Theorem 8.2.11), but this property still holds. Convergence in r th mean is often written $X_n \xrightarrow{r} X$.

Definition 8.10. Convergence in Distribution. Let X_1, X_2, \dots have distribution functions $F_1(\cdot), F_2(\cdot), \dots$ respectively. Then X_n is said to **converge in distribution to X** if

$$\lim_{n \rightarrow \infty} \Pr(X_n \leq u) = \Pr(X \leq u)$$

for all u at which $F_X(x) = \Pr(X \leq x)$ is continuous. This can also be written

$$\lim_{n \rightarrow \infty} F_n(u) = F(u)$$

for all u at which F is continuous.

Remark 103. Convergence in distribution is usually denoted by $X_n \xrightarrow{d} X$, $X_n \xrightarrow{L} X$, or $F_n \implies F$. By the Continuity Theorem (Theorem 8.1.2, section 8.1), this is equivalent to

$$\lim_{n \rightarrow \infty} \phi_{X_n}(t) = \phi_X(t), \quad t \in \mathbb{R}.$$

Note that the random variables are allowed to have different domains.

Definition 8.11. (Convergence in distribution for vector-valued random variables.) We say that random variables $Y^{(1)}, \dots, : \Omega \rightarrow \mathbb{R}^d$ **converge in distribution** to $Y : \Omega \rightarrow \mathbb{R}^d$ if for all $v \in \mathbb{R}^d$, $\langle v, Y^{(1)} \rangle, \langle v, Y^{(2)} \rangle, \dots$ converges in distribution to $\langle v, Y \rangle$.

Theorem 8.3.1 ((Theorem 7.2.3, Grimmett and Stirzaker.)). The following implications hold:

- (a) $(X_n \xrightarrow{a.s.} X) \implies (X_n \xrightarrow{p} X)$
- (b) $(X_n \xrightarrow{r} X) \implies (X_n \xrightarrow{p} X)$ for any $r \geq 1$
- (c) $(X_n \xrightarrow{p} X) \implies (X_n \xrightarrow{d} X)$

Also, if $r > s \geq 1$, then $(X_n \xrightarrow{r} X) \implies (X_n \xrightarrow{s} X)$. No other implications hold in general.

Proof. (a) By Markov's Inequality (Lemma 8.2.1),

$$\Pr(|X_n - X| > \epsilon) \leq \frac{\mathbb{E}|X_n - X|}{\epsilon} \quad \text{for all } \epsilon > 0$$

Therefore if $X_n \xrightarrow{1} X$; that is, $\lim_{n \rightarrow \infty} \mathbb{E}(|X_n - X|) = 0$, then $\lim_{n \rightarrow \infty} \Pr(|X_n - X| > \epsilon) = 0$ for every $\epsilon > 0$, so $X_n \xrightarrow{p} X$.

(b) Let $\epsilon > 0$ and let $0 < r < \infty$. From Markov's Inequality,

$$\Pr(|X_n - X| > \epsilon) = \Pr(|X_n - X|^r > \epsilon^r) \leq \frac{\mathbb{E}|X_n - X|^r}{\epsilon^r}$$

The right side converges to zero by assumption. Therefore X_1, X_2, \dots converges to X in probability. The case $r = \infty$ follows from any case $r < \infty$, since for example

$$(\mathbb{E}(X_n) - X)^2 \leq \mathbb{E}(|X_n - X|^2) \leq \|X_n - X\|_\infty$$

which shows that L_∞ convergence implies L_2 convergence. So since L_2 convergence implies convergence in probability, L_∞ convergence does too. We can also see this by simply examining the definition of the L_∞ norm:

$$\|X_n - X\|_\infty := \inf\{c > 0 : \Pr(|X_n - X| \leq c) = 1\}.$$

Clearly if this number goes to 0, then $X_n \xrightarrow{p} X$.

(c)

□

Remark 104. Here are counterexamples showing that the converses are not always true:

(a) To see the converse fails, define an independent sequence $\{X_n\}$ by

$$X_n = \begin{cases} n^3 & \text{with probability } n^{-2} \\ 0 & \text{with probability } 1 - n^{-2} \end{cases}$$

Then $\Pr(|X| > \epsilon) = n^{-2}$ for all large n , and so $X_n \xrightarrow{p} 0$. However, $\mathbb{E}|X_n| = n \rightarrow \infty$.

(b) To see why the converse is false, fix $0 < r < \infty$, let $\Omega := [0, 1]$ with \mathbb{P} uniform on Ω and consider $X_n := n^{1/r} \mathbf{1}_{\{[0, 1/n]\}}$. Then X_1, X_2, \dots converges in probability to 0 since if $1 > \epsilon > 0$, then $\mathbb{P}(|X_n - 0| > \epsilon) \leq \mathbb{P}([0, 1/n]) = 1/n \rightarrow 0$ as $n \rightarrow \infty$. However, X_1, X_2, \dots does not converge in L_r to 0 since $\mathbb{E}|X_n - 0|^r = n/n = 1$ for all $n \geq 1$.

(c)

Theorem 8.3.2. Some exceptions (Theorem 7.2.4).

(a) If $X_n \xrightarrow{d} c$ where c is constant, then $X_n \xrightarrow{p} c$.

(b) If $X_n \xrightarrow{p} X$ and $\Pr(|X_n| \leq k) = 0$ for all n and some k , then $X_n \xrightarrow{r} X$ for all $r \geq 1$.

(c) If $P_n(\epsilon) = \Pr(|X_n - X| > \epsilon)$ satisfies $\sum_n P_n(\epsilon) < \infty$ for all $\epsilon > 0$, then $X_n \xrightarrow{a.s.} X$.

Proof. (Part (c).) Let $A_n(\epsilon) = \{|X_n - X| > \epsilon\}$ (so that $P_n(\epsilon) = \Pr[A_n(\epsilon)]$), and let $B_m(\epsilon) = \bigcup_{n \geq m} A_n(\epsilon)$. Then

$$\Pr(B_m(\epsilon)) \leq \sum_{n=m}^{\infty} \Pr(A_n(\epsilon))$$

so $\lim_{m \rightarrow \infty} \Pr(B_m(\epsilon)) = 0$ whenever $\sum_n \Pr(A_n(\epsilon)) < \infty$. See also Lemma 8.4.1 part (b). \square

Lemma 8.3.3. (Lemma 7.2.6 from Grimmett and Stirzaker)

(a) If $r > s \geq 1$ and $X_n \xrightarrow{r} X$, then $X_n \xrightarrow{s} X$.

(b) If $X_n \xrightarrow{1} X$ then $X_n \xrightarrow{p} X$.

The converse assertions fail in general.

Proof. (a) Using Lyapunov's Inequality (Lemma 8.2.10), if $r > s \geq 1$

$$[\mathbb{E}(|X_n - X|^s)]^{1/s} \leq [\mathbb{E}(|X_n - X|^r)]^{1/r}$$

Therefore if $X_n \xrightarrow{r} X$ (meaning $\lim_{n \rightarrow \infty} \mathbb{E}(|X_n - X|^r) = 0$), (then $\lim_{n \rightarrow \infty} \mathbb{E}(|X_n - X|^s) = 0$, so $X_n \xrightarrow{s} X$. We show the converse fails by counterexample:

$$X_n = \begin{cases} n & \text{with probability } n^{(-1/2)(r+s)} \\ 0 & \text{with probability } 1 - n^{(-1/2)(r+s)} \end{cases}$$

Then $\mathbb{E}|X_n^s| = n^{(1/2)(s-r)} \rightarrow 0$ and $\mathbb{E}|X_n^r| = n^{(1/2)(r-s)} \rightarrow \infty$.

(b) See proof of Theorem 8.3.1(a).

\square

8.4 More on convergence (7.2 of Grimmett and Stirzaker)

Other theorems to include: Kolmogorov's Maximal Inequality, Kolmogorov Three-Series Test, Lindeberg Feller Central Limit Theorem, **this and more at beginning of Mike's 505A qual solutions.**

Definition 8.12. Cauchy Convergence. We say that the sequence $\{X_n : n \geq 1\}$ of random variables on the probability space $(\Omega, \mathcal{F}, \mathbb{P})$ is **almost surely Cauchy convergent** if

$$\Pr(\{\omega \in \Omega : X_m(\omega) - X_n(\omega) \rightarrow 0 \text{ as } m, n \rightarrow \infty\}) = 1$$

That is, the set of points ω of the sample space for which the real sequence $\{X_n(\omega) : n \geq 1\}$ is Cauchy convergent is an event having probability 1.

Lemma 8.4.1. (Lemma 7.2.10, Grimmett and Stirzaker.) Let $A_n(\epsilon) = \{|X_n - X| > \epsilon\}$ and $B_m(\epsilon) = \cup_{n \geq m} A_n(\epsilon)$. Then:

- (a) $X_n \xrightarrow{a.s.} X$ if and only if $\Pr(B_m(\epsilon)) \rightarrow 0$ as $m \rightarrow \infty$ for all $\epsilon > 0$.
- (b) $X_n \xrightarrow{a.s.} X$ if $\sum_n \Pr(A_n(\epsilon)) < \infty$ for all $\epsilon > 0$.
- (c) If $X_n \xrightarrow{a.s.} X$ then $X_n \xrightarrow{p} X$, but the converse fails in general.

Proof. (a)

- (b) As for Theorem 8.3.2 part (c).
- (c) To see the converse fails, define an independent sequence $\{X_n\}$ by

$$X_n = \begin{cases} 1 & \text{with probability } n^{-1} \\ 0 & \text{with probability } 1 - n^{-1} \end{cases}$$

Clearly $X_n \xrightarrow{p} 0$. However, if $0 < \epsilon < 1$,

$$\begin{aligned} \Pr(B_m(\epsilon)) &= 1 - \lim_{r \rightarrow \infty} \Pr(X_n = 0 \text{ for all } n \text{ such that } m \leq n \leq r) \text{ (by Lemma 1.3.5)} \\ &= 1 - \left(1 - \frac{1}{m}\right) \left(1 - \frac{1}{m+1}\right) \cdots \text{ (by independence)} \\ &= 1 - \lim_{M \rightarrow \infty} \left(\frac{m-1}{m} \cdot \frac{m}{m+1} \cdot \frac{m+1}{m+2} \cdots \frac{M}{M+1}\right) \\ &= 1 - \lim_{M \rightarrow \infty} \frac{m-1}{M+1} = 1 \end{aligned}$$

and so $\{X_n\}$ does not converge almost surely.

□

Lemma 8.4.2. (Lemma 7.2.12, Grimmett and Stirzaker.) There exist sequences which

- (a) converge almost surely but not in mean,
- (b) converge in mean but not almost surely.

Proof. (a) As for Lemma 8.3.3 part (b).

□

Theorem 8.4.3. (Theorem 7.2.13, Grimmett and Stirzaker.) If $X_n \xrightarrow{p} X$, there exists a non-random increasing sequence of integers n_1, n_2, \dots such that $X_{n_i} \xrightarrow{a.s.} X$ as $i \rightarrow \infty$.

Theorem 8.4.4. Skorokhod's representation theorem (Theorem 7.2.14, Grimmett and Stirzaker). If $\{X_n\}$ and X with distribution functions $\{F_n\}$ and F are such that $X_n \xrightarrow{d} X$ (or equivalently, $F_n \rightarrow F$) as $n \rightarrow \infty$, then there exists a probability space $(\Omega', \mathcal{F}', \mathbb{P}')$ and random variables $\{Y_n\}$ and Y mapping Ω' into \mathbb{R} such that

- (a) $\{Y_n\}$ and Y have distribution functions $\{F_n\}$ and F
- (b) $Y_n \xrightarrow{a.s.} Y$ as $n \rightarrow \infty$

Therefore, although X_n may fail to converge to X in any mode other than in distribution, there exists a sequence $\{Y_n\}$ such that Y_n is distributed identically to X_n for every n , which converges almost surely to a copy of X .

Theorem 8.4.5. (Theorem 7.2.19, Grimmett and Stirzaker; same as Portmanteau Theorem?)
The following three statements are equivalent:

- (a) $X_n \xrightarrow{d} X$
- (b) $\mathbb{E}[g(X_n)] \rightarrow \mathbb{E}[g(X)]$ for all bounded continuous functions g .
- (c) $\mathbb{E}[g(X_n)] \rightarrow \mathbb{E}[g(X)]$ for all functions g of the form $g(x) = f(x)\mathbf{1}_{[a,b]}(x)$ where f is continuous on $[a, b]$ and a and b are points of continuity of the distribution function of the random variable X .

Theorem 8.4.6. (Grimmett and Stirzaker Theorem 7.3.9.)

- (a) If $X_n \xrightarrow{a.s.} X$ and $Y_n \xrightarrow{a.s.} Y$ then $X_n + Y_n \xrightarrow{a.s.} X + Y$.
- (b) If $X_n \xrightarrow{r} X$ and $Y_n \xrightarrow{r} Y$ then $X_n + Y_n \xrightarrow{r} X + Y$.
- (c) If $X_n \xrightarrow{p} X$ and $Y_n \xrightarrow{p} Y$ then $X_n + Y_n \xrightarrow{p} X + Y$.
- (d) It is not in general true that $X_n + Y_n \xrightarrow{d} X + Y$ whenever $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{d} Y$.

Proposition 8.4.7. Almost sure convergence does not imply convergence in L_2 , and convergence in L_2 does not imply almost sure convergence. That is, find random variables that converge in L_2 but not almost surely. Then, find random variables that converge almost surely but not in L_2 .

Proof. (a) **Almost sure convergence does not imply ℓ_2 convergence:** Let $Z_n := n\mathbf{1}_{[0,1/n]}$. Then Z_1, Z_2, \dots converges almost surely to 0 since $\lim_{n \rightarrow \infty} Z_n = 0$ for all $\omega \in (0, 1]$, but it does not converge in L_2 since $\mathbb{E}(Z_n - 0)^2 = \mathbb{E}Z_n^2 = n^2\mathbb{E}\mathbf{1}_{[0,1/n]} = n \rightarrow \infty$ as $n \rightarrow \infty$.

(b) **ℓ_2 convergence does not imply almost sure convergence:** Define an independent sequence $\{X_n\}$ by

$$X_n = \begin{cases} 1 & \text{with probability } n^{-1} \\ 0 & \text{with probability } 1 - n^{-1} \end{cases}$$

and let $B_m(\epsilon) = \cup_{n \geq m} \{|X_n - X| > \epsilon\}$. $X_n \xrightarrow{2} 0$ because

$$\lim_{n \rightarrow \infty} \|X_n - 0\|_2 = 0$$

However, if $0 < \epsilon < 1$,

$$\Pr(B_m(\epsilon)) = 1 - \lim_{r \rightarrow \infty} \Pr(X_n = 0 \text{ for all } n \text{ such that } m \leq n \leq r)$$

$$\begin{aligned}
&= 1 - \left(1 - \frac{1}{m}\right) \left(1 - \frac{1}{m+1}\right) \cdots \text{(by independence)} \\
&= 1 - \lim_{M \rightarrow \infty} \left(\frac{m-1}{m} \cdot \frac{m}{m+1} \cdot \frac{m+1}{m+2} \cdots \frac{M}{M+1} \right) \\
&= 1 - \lim_{M \rightarrow \infty} \frac{m-1}{M+1} = 1
\end{aligned}$$

and so $\{X_n\}$ does not converge almost surely.

□

Theorem 8.4.8. Borel-Cantelli lemmas (Grimmett and Stirzaker Theorem 7.3.10.) Let $\{A_n\}$ be an infinite sequence of events from some probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Let $A = \bigcap_n \bigcup_{m=n}^{\infty} A_m = \limsup_{n \rightarrow \infty} A_n = \{A_n \text{ i.o.}\}$ be the event that infinitely many of the A_n occur. Then:

- (a) $\Pr(A) = 0$ if $\sum_n \Pr(A_n) < \infty$. (That is, with probability 1 only finitely many of the events occur. If each event is an indicator, the sum of them is finite.)
- (b) $\Pr(A) = 1$ if $\sum_n \Pr(A_n) = \infty$ and A_1, A_2, \dots are independent events.

Proof. (a) We have that $A \subseteq \bigcup_{m=n}^{\infty} A_m$ for all n , so

$$\Pr(A) \leq \sum_{m=n}^{\infty} \Pr(A_m) \rightarrow 0 \text{ as } n \rightarrow \infty$$

whenever $\sum_n \Pr(A_n) < \infty$.

Proof from 541B: Let

$$I_j(\omega) = \begin{cases} 1, & \omega \in A_j \\ 0, & \omega \notin A_j. \end{cases}$$

Then we need to show that $\sum_{j=1}^{\infty} I_j(\omega) < \infty$ with probability 1. Observe that

$$\mathbb{E} \left(\sum_{j=1}^{\infty} I_j \right) = \sum_{j=1}^{\infty} \mathbb{E}(I_j) = \sum_{j=1}^{\infty} \mathbb{P}(A_j)$$

where the last sum is finite by assumption. (Switching of the sum and expectation is allowed by Monotone Convergence Theorem (Theorem 5.11.1) or Fatou's Lemma (Theorem 5.11.2) because of monotonicity: $g_k = \sum_{j=1}^k I_j$ is increasing in k .)

- (b) One can confirm that

$$A^c = \bigcup_n \bigcap_{m=n}^{\infty} A_m^c$$

But

$$\begin{aligned} \Pr\left(\bigcap_{m=n}^{\infty} A_m^c\right) &= \lim_{r \rightarrow \infty} \Pr\left(\bigcap_{m=n}^r A_m^c\right) = \prod_{m=n}^{\infty} [1 - \Pr(A_m)] \text{ (by independence)} \leq \prod_{m=n}^{\infty} \exp(-\Pr(A_m)) \\ &= \exp\left(-\sum_{m=n}^{\infty} \Pr(A_m)\right) = 0 \end{aligned}$$

whenever $\sum_n \Pr(A_n) = \infty$, where the fourth step follows since $1 - x \leq e^{-x}$ if $x \geq 0$. Thus

$$\Pr(A^c) = \lim_{n \rightarrow \infty} \Pr\left(\bigcap_{m=n}^{\infty} A_m^c\right) = 0$$

so $\Pr(A) = 1$.

□

Theorem 8.4.9. Kolmogorov's Two-Series Theorem. Let X_1, X_2, \dots be independent random variables with $\mathbb{E}(X_n) = \mu_n$ and $\text{Var}(X_n) = \sigma_n^2$ such that $\sum_{n=1}^{\infty} \mu_n < \infty$ and $\sum_{n=1}^{\infty} \sigma_n^2 < \infty$. Then $\sum_{n=1}^{\infty} X_n$ converges in \mathbb{R} almost surely.

Proof. Available on wikipedia, https://en.wikipedia.org/wiki/Kolmogorov%27s_two-series_theorem.

□

8.4.1 Slutsky's Convergence Theorems (8.4.1 of Pesaran, 7.3 of Grimmett and Stirzaker)

Theorem 8.4.10. Theorem 6 of Pesaran, Section 8.4.1, p. 173. Let $\{x_t, y_t\}, t = 1, 2, \dots$ be a sequence of pairs of random variables with $y_t \xrightarrow{d} y$ and $|y_t - x_t| \xrightarrow{p} 0$. Then $x_t \xrightarrow{d} y$.

Theorem 8.4.11. Theorem 7 in Pesaran, on p.318 (section 7.3) of Grimmett and Stirzaker. (Section 8.4.1, p. 174) If $x_t \xrightarrow{d} x$ and $y_t \xrightarrow{p} c$ where c is a finite constant, then

- (i) $x_t + y_t \xrightarrow{d} x + c$
- (ii) $y_t x_t \xrightarrow{d} cx$
- (iii) $x_t/y_t \xrightarrow{d} x/c$, if $c \neq 0$.

Theorem 8.4.12. on p.318 (section 7.3) of Grimmett and Stirzaker. Suppose that $X_n \xrightarrow{d} 0$ and $Y_n \xrightarrow{p} Y$, and let $g : \mathbb{R}^2 \rightarrow \mathbb{R}$ be such that $g(x, y)$ is a continuous function of y for all x , and $g(x, y)$ is continuous at $x = 0$ for all y . Then $g(X_n, Y_n) \xrightarrow{p} g(0, Y)$.

Theorem 8.4.13 (Continuous Mapping Theorem (Theorem 9 of Pesaran, Section 8.4.1, p. 176: convergence properties of transformed sequences.)). Suppose $\{x_j\}$, $\{y_j\}$, x , and y are $k \times 1$ vectors of random variables on a probability space, and let $\mathbf{g}(\cdot)$ be a continuous vector-valued function. (Alternatively, suppose g has the set of discontinuity points D_g such that $\Pr(X \in D_g) = 0$.) Then

- (i) $x_j \xrightarrow{a.s.} x \implies \mathbf{g}(x_j) \xrightarrow{a.s.} \mathbf{g}(x)$

- (ii) $\mathbf{x}_j \xrightarrow{p} x \implies \mathbf{g}(\mathbf{x}_j) \xrightarrow{p} \mathbf{g}(x)$
- (iii) $\mathbf{x}_j \xrightarrow{d} x \implies \mathbf{g}(\mathbf{x}_j) \xrightarrow{d} \mathbf{g}(x)$
- (iv) $\mathbf{x}_j - \mathbf{y}_j \xrightarrow{p} \mathbf{0}$ and $\mathbf{y}_j \xrightarrow{d} \mathbf{y} \implies \mathbf{g}(\mathbf{x}_j) - \mathbf{g}(\mathbf{y}_j) \xrightarrow{d} \mathbf{0}(x)$

where $x = (c_1, \dots, c_k) \in \mathbb{R}^k$.

Proof (part (b), continuous case, one-dimensional codomain). Let $\mathbf{x}_j = (M_{j,1}, \dots, M_{j,k})$. We have that

$$\begin{aligned} \forall \epsilon_j > 0, \lim_{n \rightarrow \infty} \Pr(\{\omega \in \Omega : |M_{j,n}(\omega) - c_j| > \epsilon_j\}) &= 0, \quad \forall j \in \{1, \dots, k\}. \\ \iff \forall \epsilon_j > 0, \lim_{n \rightarrow \infty} \Pr(\{\omega \in \Omega : |M_{j,n}(\omega) - c_j| < \epsilon_j\}) &= 1, \quad \forall j \in \{1, \dots, k\}. \end{aligned} \quad (8.2)$$

Because g is continuous, we have that for every $\epsilon^* > 0$ there exists a $\delta^* > 0$ such that

$$0 < \|(M_{1,n}(\omega), \dots, M_{j,n}(\omega))\|_2 < \delta^* \implies |g(M_{1,n}(\omega), \dots, M_{j,n}(\omega)) - g(c_1, \dots, c_j)| < \epsilon^*. \quad (8.3)$$

Note that since in \mathbb{R} the L_2 and L_1 norms are equivalent,

$$\begin{aligned} |M_{j,n}(\omega) - c_j| < \epsilon_j &\iff \|M_{j,n}(\omega) - c_j\|_2 < \epsilon_j \implies \sum_{j=1}^k \|M_{j,n}(\omega) - c_j\|_2 < \sum_{j=1}^k \epsilon_j \\ &\implies \|(M_{1,n}(\omega), \dots, M_{j,n}(\omega))\|_2 < \sum_{j=1}^k \epsilon_j \end{aligned}$$

where the last step follows by the Triangle Inequality. Therefore letting $\delta^* = \sum_{j=1}^k \epsilon_j$, we have

$$\begin{aligned} \Pr(\{\omega \in \Omega : |M_{j,n}(\omega) - c_j| < \epsilon_j\}) &\leq \Pr(0 < \|(M_{1,n}(\omega), \dots, M_{j,n}(\omega))\|_2 < \delta^*) \\ &\leq \Pr(\{\omega \in \Omega : |g(M_{1,n}(\omega), \dots, M_{j,n}(\omega)) - g(c_1, \dots, c_j)| < \epsilon^*\}) \end{aligned}$$

where the last step follows from (8.3). So

$$\Pr(\{\omega \in \Omega : |M_{j,n}(\omega) - c_j| < \epsilon_j\}) \leq \Pr(\{\omega \in \Omega : |g(M_{1,n}(\omega), \dots, M_{j,n}(\omega)) - g(c_1, \dots, c_j)| < \epsilon^*\}). \quad (8.4)$$

Taking limits of (8.4) and substituting in (8.2), we have

$$\forall \epsilon^* > 0, \lim_{n \rightarrow \infty} \Pr(\{\omega \in \Omega : |g(M_{1,n}(\omega), \dots, M_{j,n}(\omega)) - g(c_1, \dots, c_j)| < \epsilon^*\}) \geq 1$$

$$\iff \forall \epsilon^* > 0, \lim_{n \rightarrow \infty} \Pr(\{\omega \in \Omega : |g(M_{1,n}(\omega), \dots, M_{j,n}(\omega)) - g(c_1, \dots, c_j)| > \epsilon^*\}) = 0$$

$$\iff g(M_{1,n}, \dots, M_{j,n}) \xrightarrow{p} g(c_1, \dots, c_j).$$

For remaining parts, see Serfling [1980] or Rao [1973]. □

See also:

Theorem 8.4.14. (Theorem 7.2.18, Grimmett and Stirzaker.) If $X_n \xrightarrow{d} X$ and $g : \mathbb{R} \rightarrow \mathbb{R}$ is continuous, then $g(X_n) \xrightarrow{d} g(X)$.

8.5 Stochastic orders $\mathcal{O}_p(\cdot)$ and $o_p(\cdot)$ (Pesaran 8.5)

Definition 8.13 (Pesaran 8.5 Definition 6.). Let $\{a_t\}$ be a sequence of positive numbers and $\{x_t\}$ be a sequence of random variables. Then

- (i) $x_t = \mathcal{O}_p(a_t)$, or x_t/a_t is bounded in probability, if for every $\epsilon > 0$ there exist real numbers M_ϵ and N_ϵ such that

$$\Pr\left(\frac{|x_t|}{a_t} > M_\epsilon\right) < \epsilon, \quad \text{for } t > N_\epsilon$$

- (ii) $x_t = o_p(a_t)$ if

$$\frac{x_t}{a_t} \xrightarrow{p} 0$$

Definition 8.14 (Ross ISE 620 Definition). We say that $f(x)$ is $o(h)$ if $\lim_{h \rightarrow 0} f(h)/h = 0$.

8.6 Laws of Large Numbers and Central Limit Theorems (Pesaran 8.6; Grimmett and Stirzaker 7.4, 7.5)

Theorem 8.6.1. Weak Law of Large Numbers (Khinchine) (Pesaran 8.6 Theorem 10, Grimmett and Stirzaker Theorem 7.4.7, 541A notes Theorem 2.10). Suppose that $\{X_k\}$ is a sequence of (i) independent (ii) identically distributed random variables with (iii) constant means, i.e., $\mathbb{E}(X_k) = \mu < \infty$. Then

$$\overline{X}_k = \frac{1}{n} \sum_{k=1}^n X_k \xrightarrow{p} \mu$$

Theorem 8.6.2. Weak Law of Large Numbers (Chebyshev) (Pesaran Section 8.6, p. 178, Theorem 11.) Let $\{X_k\}$ be a sequence of random variables. If (i) $\mathbb{E}(X_k) = \mu_k$, (ii) $\text{Var}(X_k) = \sigma_k^2$, and (iii) $\text{Cov}(X_k, X_j) = 0, k \neq j$, and (iv)

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n \sigma_k^2 < \infty$$

then we have $\bar{X}_n - \bar{\mu}_n \xrightarrow{p} 0$, where $\bar{\mu}_n = n^{-1} \sum_{k=1}^n \mu_k$.

Theorem 8.6.3. Strong Law of Large Numbers (Grimmett and Stirzakker Theorem 7.4.3). Let $\{X_k\}$ be a sequence of (i) independent (ii) identically distributed random variables with (iii) $\mathbb{E}(X_k) = \mu$ and (iv) $\mathbb{E}(X_k^2) < \infty$. Then

$$\frac{1}{n} \sum_{k=1}^n X_k \rightarrow \mu \text{ almost surely and in mean square.}$$

Theorem 8.6.4 (Strong Law of Large Numbers (Grimmett and Stirzakker Theorem 7.5.1, 541A notes Theorem 2.11)). Let $\{X_k\}$ be a sequence of (i) independent (ii) identically distributed random variables. Then if and only if (iii) $\mathbb{E}|X_k| < \infty$,

$$\frac{1}{n} \sum_{k=1}^n X_k \xrightarrow{a.s.} \mu$$

Theorem 8.6.5. Strong Law of Large Numbers 1 (Kolmogorov) (Pesaran 8.8 Theorem 12).

Let $\{X_k\}$ be a sequence of (i) independent random variables with (ii) $\mathbb{E}(X_k) = \mu_k < \infty$ and (ii) $\text{Var}(X_k) = \sigma_k^2$ such that (iii)

$$\sum_{k=1}^{\infty} \frac{\sigma_k^2}{k^2} < \infty$$

Then $\bar{X}_n - \bar{\mu}_n \xrightarrow{wp^1} 0$. If the independence assumption (i) is replaced by a lack of correlation (i.e. $\text{Cov}(X_k, X_j) = 0, k \neq j$), the convergence of $\bar{X}_n - \bar{\mu}_n$ with probability one requires the stronger condition

$$\sum_{k=1}^{\infty} \frac{\sigma_k^2 (\log k)^2}{k^2} < \infty$$

Theorem 8.6.6. Strong Law of Large Numbers 2 (Pesaran 8.8 Theorem 13) Suppose that X_1, X_2, \dots are (i) independent random variables, and that (ii) $\mathbb{E}(X_k) = 0$, (iii) $\mathbb{E}(X_k^4) \leq M \forall k$ where M is an arbitrary positive constant. Then

$$\bar{X}_n = \frac{1}{n} \sum_{k=1}^n X_k \xrightarrow{a.s.} 0$$

Theorem 8.6.7. Central Limit Theorem (Grimmett and Stirzaker theorem 5.10.4.) Let X_1, X_2, \dots be a sequence of independent identically distributed random variables with finite mean μ and finite non-zero variance σ^2 , and let $S_n = \sum_{i=1}^n X_i$. Then

$$\frac{S_n - n\mu}{\sqrt{n}\sigma^2} \xrightarrow{d} \mathcal{N}(0, 1)$$

Theorem 8.6.8. (Berry-Esseen Central Limit Theorem.) There exists $c > 0$ such that the following holds. Let X_1, X_2, \dots be i.i.d. real-valued random variables with mean zero, variance 1, and $\mathbb{E}(|X_1|)^3 < \infty$. Let Z be a standard Gaussian random variable. Then for any $n \geq 1$,

$$\sup_{t \in \mathbb{R}} \left| \Pr \left(\frac{X_1 + \dots + X_n}{\sqrt{n}} \leq t \right) - \Pr(Z \leq t) \right| \leq c \cdot \frac{\mathbb{E}(|X_1|^3)}{\sqrt{n}}$$

Remark 105. You can look up what the c is; Heilman doesn't think it's any bigger than around 10.

Theorem 8.6.9. (Central Limit Theorem in \mathbb{R}^d , Heilman notes Theorem 2.33.) Let $X^{(1)}, X^{(2)}, \dots$ be a sequence of independent identically distributed \mathbb{R}^d -valued random variables. (Notation: we write $X^{(1)} = (X_1^{(1)}, \dots, X_d^{(1)})$.) Assume $\mathbb{E}(X^{(n)}) = \mu$ for all $n \geq 1$ and for any $1 \leq i < j \leq d$, all of the covariances

$$a_{ij} = \mathbb{E}[(X_i^{(1)} - \mathbb{E}(X_i^{(1)}))(X_j^{(1)} - \mathbb{E}(X_j^{(1)}))]$$

are finite. Let $S_n = \sum_{i=1}^n X^{(i)}$. Then as $n \rightarrow \infty$,

$$\frac{S_n - n\mu}{\sqrt{n}} \xrightarrow{d} \mathcal{N}(0, [a_{ij}])$$

Theorem 8.6.10. (Grimmett and Stirzaker theorem 5.10.5.) Let X_1, X_2, \dots be independent random variables satisfying $\mathbb{E}(X_j) = 0$, $\text{Var}(X_j) = \sigma_j^2$, $\mathbb{E}|X_j^3| < \infty$ such that

$$\lim_{n \rightarrow \infty} \frac{1}{\sigma(n)^3} \sum_{j=1}^n \mathbb{E}|X_j^3| = 0$$

where $\sigma(n)^2 = \text{Var}(\sum_{j=1}^n X_j) = \sum_{j=1}^n \sigma_j^2$. Then

$$\frac{1}{\sigma(n)} \sum_{j=1}^n X_j \xrightarrow{d} \mathcal{N}(0, 1)$$

Proof. See Loeve [1977], p. 287] and Grimmett and Stirzaker Problem 5.12.40. □

Lemma 8.6.11. Lindeberg's Condition: Let $\{X_k\}$ be a sequence of independent (not necessarily identically distributed) random variables with expectations μ_k and finite variances σ_k^2 . Let $s_n^2 = \sum_{k=1}^n \sigma_k^2$. If such a sequence of independent random variables X_k satisfies the condition

$$\lim_{n \rightarrow \infty} \frac{1}{s_n^2} \sum_{k=1}^n \mathbb{E}[(X_k - \mu_k)^2] \cdot \mathbf{1}_{\{|X_k - \mu_k| > \epsilon s_n\}} = 0$$

for all $\epsilon > 0$ then the central limit theorem holds; that is, the random variables

$$Z_n = \frac{1}{s_n} \sum_{k=1}^n (X_k - \mu_k)$$

converge in distribution to $\mathcal{N}(0, 1)$ as $n \rightarrow \infty$.

8.7 The case of dependent and heterogeneously distributed observations (Pesaran 8.8)

Theorem 8.7.1. Central limit theorem for martingale difference sequences (Pesaran 8.8 Theorem 28). Let $\{x_t\}$ be a martingale difference sequence with respect to the information set Ω_t . Let $\bar{\sigma}_T^2 = \text{Var}(\sqrt{T}\bar{x}_T) = T^{-1} \sum_{t=1}^T \sigma_t^2$. If $\mathbb{E}(|x_t|^r) < K < \infty$ for any $r > 2$ and for all t , and

$$\frac{1}{T} \sum_{t=1}^T x_t^2 - \bar{\sigma}_T^2 \xrightarrow{p} 0$$

then $\sqrt{T}\bar{x}_T/\bar{\sigma}_T \xrightarrow{d} \mathcal{N}(0, 1)$.

8.8 Worked Examples from Math 505A Midterm 2

- (1) (a) **Fall 2010 Problem 1.** Let X_k , $k \geq 1$, be i.i.d. random variables with mean 1 and variance 1. Show that the limit

$$\lim_{n \rightarrow \infty} \frac{\sum_{k=1}^n X_k}{\sum_{k=1}^n X_k^2}$$

exists in an appropriate sense, and identify the limit.

- (b) **Not included on midterm or final.** Let $(X_j)_{j \geq 1}$ be i.i.d. uniform on $(-1, 1)$. Let

$$Y_n = \frac{\sum_{j=1}^n X_j}{\sum_{j=1}^n X_j^2 + \sum_{j=1}^n X_j^3}$$

Prove that $\lim_{n \rightarrow \infty} \sqrt{n}Y_n$ exists in an appropriate sense, and identify the limit.

Solution.

(a)

$$\lim_{n \rightarrow \infty} \frac{\sum_{k=1}^n X_k}{\sum_{k=1}^n X_k^2} = \lim_{n \rightarrow \infty} \frac{n^{-1} \sum_{k=1}^n X_k}{n^{-1} \sum_{k=1}^n X_k^2}$$

Since X_1, X_2, \dots are i.i.d., $E(X_1^2) = \text{Var}(X_1) + (\mathbb{E}(X_1))^2 = 2 < \infty$, we have

$$n^{-1} \sum_{k=1}^n X_k \xrightarrow{a.s.} \mathbb{E}(X_1) = 1 \text{ as } n \rightarrow \infty$$

by Theorem 8.6.3 (Strong Law of Large Numbers). Also, X_1^2, X_2^2, \dots are clearly identically distributed, and are independent by Theorem 4.2.3 ("If X and Y are independent, then so are $g(X)$

and $g(Y)$."). It is clear also that $\mathbb{E}(|X_1^2|) = \mathbb{E}(X_1^2) = \text{Var}(X_1) + \mathbb{E}(X_1)^2 = 1+1 = 2 < \infty$. Therefore by Theorem 8.6.4 (Strong Law of Large Numbers),

$$n^{-1} \sum_{k=1}^n X_k^2 \xrightarrow{a.s.} \mathbb{E}(X_1^2) = 2 \text{ as } n \rightarrow \infty$$

(From here I had two different ways of finishing the problem.)

- Because we have almost sure convergence in the numerator and denominator, by the Continuous Mapping Theorem (Theorem 8.4.13),

$$\lim_{n \rightarrow \infty} \frac{n^{-1} \sum_{k=1}^n X_k}{n^{-1} \sum_{k=1}^n X_k^2} = \frac{\lim_{n \rightarrow \infty} n^{-1} \sum_{k=1}^n X_k}{\lim_{n \rightarrow \infty} n^{-1} \sum_{k=1}^n X_k^2} \xrightarrow{a.s.} \boxed{\frac{1}{2}}$$

- Then, using one of Slutsky's convergence theorems (Theorem 8.4.11: "If $x_t \xrightarrow{d} x$ and $y_t \xrightarrow{p} c$ where c is a finite constant, then $x_t/y_t \xrightarrow{d} x/c$, if $c \neq 0$."), we have

$$\frac{n^{-1} \sum_{k=1}^n X_k}{n^{-1} \sum_{k=1}^n X_k^2} \xrightarrow{d} \frac{\mathbb{E}(X_1)}{\mathbb{E}(X_1^2)} = \frac{\mathbb{E}(X_1)}{\text{Var}(X_1) + \mathbb{E}(X_1)^2} = \frac{1}{1+1} = \frac{1}{2}$$

But then, by Theorem 8.3.2 (Theorem 7.2.4(a) in Grimmett and Stirzaker: "If $X_n \xrightarrow{d} c$ where c is constant, then $X_n \xrightarrow{p} c$."), we have $\frac{n^{-1} \sum_{k=1}^n X_k}{n^{-1} \sum_{k=1}^n X_k^2} \xrightarrow{p} 1/2$.

(b) (Not included on midterm or final.)

$$Y_n = \frac{\sum_{j=1}^n X_j}{\sum_{j=1}^n X_j^2 + \sum_{j=1}^n X_j^3} = \frac{n^{-1} \sum_{j=1}^n X_j}{n^{-1} \sum_{j=1}^n X_j^2 + n^{-1} \sum_{j=1}^n X_j^3}$$

Note that $\mathbb{E}(X_1) = 0$, $\mathbb{E}(X_1^2) = \text{Var}(X_1) + \mathbb{E}(X_1)^2 = (1 - -1)^2/12 + 0^2 = 1/3$, $\mathbb{E}(X_1^3) = (1/2) \int_{-1}^1 x^3 dx = 0$. (We derived the formulae for the first three moments of a uniform distribution on Homework 4 problem 2(2).)

$$\implies \sqrt{n} Y_n = \frac{\sqrt{1/3} (\sum_{j=1}^n X_j - n\mathbb{E}(X_1)) / \sqrt{n \cdot 1/3}}{n^{-1} \sum_{j=1}^n X_j^2 + n^{-1} \sum_{j=1}^n X_j^3}$$

By the Central Limit Theorem (Theorem 8.6.7),

$$\frac{\sum_{j=1}^n X_j - n\mathbb{E}(X_1)}{\sqrt{n \cdot 1/3}} \xrightarrow{d} \mathcal{N}(0, 1)$$

By the Law of Large Numbers (Theorem 8.6.4), since $\mathbb{E}(|X_1^2|) = \mathbb{E}(X_1^2) = 1/3 < \infty$,

$$\frac{1}{n} \sum_{j=1}^n X_j^2 \xrightarrow{a.s.} \mathbb{E}(X_1^2) = 1/3$$

By the Law of Large Numbers (Theorem 8.6.4), since $\mathbb{E}(|X_1^3|) = (1/2) \int_{-1}^1 |x^3| dx = \int_0^1 x^3 dx = 1/4 < \infty$,

$$\frac{1}{n} \sum_{j=1}^n X_j^3 \xrightarrow{a.s.} \mathbb{E}(X_1^3) = 0$$

In the denominator, since we have almost sure convergence, the regular rules of calculus/real analysis apply. That is, using the above results,

$$n^{-1} \sum_{j=1}^n X_j^2 + n^{-1} \sum_{j=1}^n X_j^3 \xrightarrow{a.s.} 1/3$$

Therefore

$$\sqrt{n}Y_n = \frac{\sqrt{1/3}(\sum_{j=1}^n X_j - n\mathbb{E}(X_1))/\sqrt{n \cdot 1/3}}{n^{-1} \sum_{j=1}^n X_j^2 + n^{-1} \sum_{j=1}^n X_j^3} \xrightarrow{d} \frac{\sqrt{1/3}}{1/3} \mathcal{N}(0, 1) = \boxed{\mathcal{N}(0, 3)}$$

- (2) **Fall 2010 Problem 2.** Fix $p \in (0, 1)$ and consider independent Poisson random variables $X_k, k \geq 1$ with

$$\mathbb{E}X_k = \frac{p^k}{k}$$

Verify that the sum $\sum_{k=1}^{\infty} kX_k$ converges with probability one and determine the distribution of the random variable $Y = \sum_{k=1}^{\infty} kX_k$.

Solution. Melike's solution (use for midterm): We have $\mathbb{E}[kX_k] = p^k$ and $\sum_{k=1}^{\infty} p^k = p/(1-p) < \infty$, and $\text{Var}(kX_k) = kp^k$ and

$$\sum_{k=1}^{\infty} kp^k = p \sum_{k=1}^{\infty} kp^{k-1} = p \frac{d}{dp} \sum_{k=1}^{\infty} p^k = p \frac{d}{dp} \frac{p}{1-p} = p \cdot \frac{(1-p) - p(-1)}{(1-p)^2} = \frac{p}{(1-p)^2} < \infty$$

Since the sequence $\{Y_k\}_{k \geq 1}$ is independent, by Kolmogorov's Two Series Theorem (Theorem 8.4.9: “Let X_1, X_2, \dots be independent random variables with $\mathbb{E}(X_n) = \mu_n$ and $\text{Var}(X_n) = \sigma_n^2$ such that $\sum_{n=1}^{\infty} \mu_n < \infty$ and $\sum_{n=1}^{\infty} \sigma_n^2 < \infty$. Then $\sum_{n=1}^{\infty} X_n$ converges in \mathbb{R} almost surely.”), we conclude that $\sum_{k=1}^{\infty} kX_k$ converges almost surely.

To find the distribution of Y , let X be a Poisson random variable and consider its probability generating function:

$$G_X(s) = \mathbb{E}(s^X) = \sum_{k=0}^{\infty} s^k e^{-\lambda} \frac{\lambda^k}{k!} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{(\lambda s)^k}{k!} = e^{-\lambda} e^{\lambda s} = e^{\lambda(s-1)}$$

So $\mathbb{E}(s^{X_k}) = \exp\left(\frac{p^k}{k}(s-1)\right)$ and $\mathbb{E}(s^{kX_k}) = \mathbb{E}[(s^k)^{X_k}] = \exp\left(\frac{p^k}{k}(s^k-1)\right)$. Then define $Y_n = \sum_{k=1}^n kX_k$ and consider

$$\begin{aligned} G_{Y_n}(s) &= \mathbb{E}(s^{Y_n}) = \mathbb{E}\left(\prod_{k=1}^n s^{kX_k}\right) = \prod_{k=1}^n \mathbb{E}(s^{kX_k}) = \prod_{k=1}^n \exp\left(\frac{p^k}{k}(s^k-1)\right) = \exp\left(\sum_{k=1}^n \frac{p^k}{k}(s^k-1)\right) \\ &= \exp\left(\sum_{k=1}^n \frac{(ps)^k}{k} - \sum_{k=1}^n \frac{p^k}{k}\right) \end{aligned}$$

Now, by taking limits as $n \rightarrow \infty$ (since we are allowed to take limit inside of expectation here), we get

$$G_Y(s) = \mathbb{E}(s^Y) = \exp\left(\sum_{k=1}^{\infty} \frac{(ps)^k}{k} - \sum_{k=1}^{\infty} \frac{p^k}{k}\right) = \exp\left(\int \sum_{k=1}^{\infty} (ps)^{k-1} dp - \int \sum_{k=1}^{\infty} p^{k-1} dp\right)$$

$$\begin{aligned}
&= \exp \left(\int \frac{1}{1-ps} dp - \int \frac{1}{1-p} dp \right) = \exp(-\log(1-ps) + \log(1-p)), \quad -1 \leq ps < 1 \text{ and } -1 \leq p < 1 \\
&= \frac{1-p}{1-ps}, \quad -1 \leq ps < 1
\end{aligned}$$

Since we know $\Pr(X = k) = \frac{G_X^{(k)}(0)}{k!}$, we have

$$\begin{aligned}
G_Y(s) &= \frac{1-p}{1-sp}, \quad G'(s) = \frac{p(1-p)}{(1-sp)^2}, \quad G''(s) = \frac{2p^2(1-p)}{(1-sp)^3}, \quad G^{(3)}(s) = \frac{3 \cdot 2p^3(1-p)}{(1-sp)^3}, \dots \\
G^{(k)}(s) &= \frac{k!p^k(1-p)}{(1-sp)^k} \text{ for } k = 0, 1, 2, \dots
\end{aligned}$$

So we have

$$\begin{aligned}
\Pr(Y = k) &= (1-p)p^k, \quad k = 0, 1, 2, \dots \\
&= \Pr(G_1(1-p) = k+1) = \Pr(G_1(1-p) - 1 = k)
\end{aligned}$$

which means $Y \sim G_1(1-p) - 1$.

(3) Spring 2017 Problem 3.

- (a) Consider the sequence $\{X_k, k \geq 1\}$ of random variables such that X_1 is uniform on $(0, 1)$ and, given X_k , the distribution of X_{k+1} is uniform on $(0, CX_k)$, where $\sqrt{3} < C < 2$.
 - (i) For $n \geq 1$, compute the conditional expectation $\mathbb{E}(X_{n+1}^r | X_n)$.
 - (ii) For $n \geq 1$, compute $\mathbb{E}(X_n^r)$.
 - (iii) Show that $\lim_{x \rightarrow \infty} X_n = 0$ in ℓ_1 and with probability one, but not in ℓ_2 .
 - (iv) Investigate the same questions for all other values of $C > 0$.
- (b) Let $a > 0$, let $X_n, n \geq 1$ be i.i.d. random variables that are uniform on $(0, a)$, and let $Y_n = \prod_{k=1}^n X_k$. Determine, with a proof, all values of a for which $\lim_{n \rightarrow \infty} Y_n = 0$ with probability one.

Solution.

- (a) (i) We have that $X_{n+1} | X_n \sim U(0, CX_n)$. Therefore

$$\begin{aligned}
\mathbb{E}(X_{n+1}^r | X_n) &= \frac{1}{CX_n} \int_0^{CX_n} x^r dx = \frac{1}{CX_n} \cdot \frac{x^{r+1}}{r+1} \Big|_0^{CX_n} = \frac{C^r X_n^r}{r+1} \\
\implies \mathbb{E}(X_{n+1}^r) &= \mathbb{E}[\mathbb{E}(X_{n+1}^r | X_n)] = \frac{C^r}{r+1} \cdot \mathbb{E}(X_n^r) \\
\implies \boxed{\mathbb{E}(X_{n+1}^r | X_n) = \frac{C^r}{r+1} X_n^r}
\end{aligned}$$

- (ii) Note that $E(X_1^r) = \int_0^1 x^r dr = 1/(r+1)$. Therefore

$$\mathbb{E}(X_{n+1}^r) = \frac{C^r}{r+1} \cdot \mathbb{E}(X_n^r) = \left(\frac{C^r}{r+1} \right)^n \cdot \mathbb{E}(X_1^r) = \boxed{\left(\frac{C^r}{r+1} \right)^n \cdot \frac{1}{r+1}}$$

- (iii) We would like to show that $X_n \xrightarrow{w.p.1} 0$ and that $X_n \xrightarrow{1} 0$, but that the same result does not follow for the ℓ_2 norm.

- **Convergence with probability one:** We seek to show that $\Pr(\{\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = 0\}) = 1$. By Markov's Inequality (Lemma 8.2.1), we have

$$\Pr(|X_n| \geq a) \leq \frac{\mathbb{E}(X_n)}{a} \quad \forall a > 0$$

$$\iff \Pr(|X_n| \geq a) \leq \left(\frac{C^1}{1+1}\right)^{n-1} \cdot \frac{1}{1+1} \cdot \frac{1}{a} = \left(\frac{C}{2}\right)^{n-1} \cdot \frac{1}{2a} \quad \forall a > 0$$

Since $\sqrt{3} < C < 2$, $\sqrt{3}/2 < C/2 < 1$. Since $X_n \in [0, CX_{n-1}]$, $X_n \geq 0$, so $|X_n| = X_n$. Therefore we have

$$\Pr(\lim_{n \rightarrow \infty} |X_n| \geq a) = \Pr(\lim_{n \rightarrow \infty} X_n \geq a) \leq \lim_{n \rightarrow \infty} \left(\frac{C}{2}\right)^{n-1} \cdot \frac{1}{2a} = 0 \quad \forall a > 0$$

Since $|X_n| \geq 0$, this implies that $\Pr(\lim_{n \rightarrow \infty} X_n = 0) = \Pr(\{\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = 0\}) = 1$, so by the Borel-Cantelli Lemma (Theorem 8.4.8), X_n converges to 0 with probability 1.

- **Convergence in ℓ_1 norm:** We seek to show that $\lim_{n \rightarrow \infty} \mathbb{E}(|X_n|) = 0$. Since $X_n \in [0, CX_{n-1}]$, $X_n \geq 0$, so $|X_n| = X_n$. Therefore

$$\lim_{n \rightarrow \infty} \mathbb{E}(|X_n|) = \lim_{n \rightarrow \infty} \mathbb{E}(X_n) = \lim_{n \rightarrow \infty} \left(\frac{C}{2}\right)^{n-1} \cdot \frac{1}{2}$$

Since $\sqrt{3} < C < 2$, $\sqrt{3}/2 < C/2 < 1$, so $C/2 < 1$. Therefore we have

$$\lim_{n \rightarrow \infty} \mathbb{E}(|X_n|) = \lim_{n \rightarrow \infty} \left(\frac{C}{2}\right)^{n-1} \cdot \frac{1}{2} = 0$$

so X_n converges to 0 in 1st mean.

- **Convergence in ℓ_2 norm:** We seek to show that $\lim_{n \rightarrow \infty} \mathbb{E}(|X_n|^2) \neq 0$. We have

$$\lim_{n \rightarrow \infty} \mathbb{E}(|X_n|^2) = \lim_{n \rightarrow \infty} \mathbb{E}(X_n^2) = \lim_{n \rightarrow \infty} \left(\frac{C^2}{3}\right)^{n-1} \cdot \frac{1}{3}$$

Since $\sqrt{3} < C < 2$, $3/3 < C^2/3 < 4/3$, so $C^2/3 > 1$. Therefore we have

$$\lim_{n \rightarrow \infty} \mathbb{E}(|X_n|^2) = \lim_{n \rightarrow \infty} \left(\frac{C^2}{3}\right)^{n-1} \cdot \frac{1}{3} = \infty \neq 0$$

so X_n does not converge to 0 in 2nd mean.

- (iv) From the above, it is clear that for convergence with probability one or in 1st mean we require $0 < C/2 < 1$ and for convergence in second mean we require $0 < C^2/3 < 1$. For $0 < C < \sqrt{3}$, we see that X_n would converge to zero in 2nd mean since this would imply that $0 < C^2/3 < 1$. It would also still converge to 0 in 1st mean (and with probability 1) since we would have $(0 < C/2 < \sqrt{3}/2 < 1)$.

For $C = \sqrt{3}$, X_n would still converge to 0 with probability one and in 1st mean for the same reasons. However, it would not converge in 2nd mean because we would have

$$\lim_{n \rightarrow \infty} \mathbb{E}(|X_n|^2) = \lim_{n \rightarrow \infty} \left(\frac{\sqrt{3}^2}{3}\right)^{n-1} \cdot \frac{1}{3} = \frac{1}{3} \neq 0$$

For $C \geq 2$, it would diverge in all three cases, since in this case $C/2 \geq 2/2 = 1$ and $C^2/3 \geq 4/3 > 1$.

(b) **Probably won't be on midterm.** Note that

$$\lim_{n \rightarrow \infty} Y_n = \lim_{n \rightarrow \infty} \prod_{k=1}^n X_k = 0 \iff \log(Y_n) = \log\left(\prod_{k=1}^n X_k\right) = \sum_{k=1}^n \log(X_k) \rightarrow -\infty$$

Note that

$$\mathbb{E}[\log(Y_n)] = \mathbb{E}\left(\sum_{k=1}^n \log(X_k)\right) = \sum_{k=1}^n \mathbb{E}[\log(X_k)] = \sum_{k=1}^n \mathbb{E}[\log(X_1)] = \sum_{k=1}^n \int_0^a (\log(x)/a) dx$$

$$= \sum_{k=1}^n \frac{1}{a} [x \log x - x]_0^a = \sum_{k=1}^n \frac{a \log a - a}{a} = \sum_{k=1}^n (\log(a) - 1) = n(\log(a) - 1)$$

As $n \rightarrow \infty$ we have

$$\mathbb{E}[\log(Y_n)] = \begin{cases} -\infty & a < e \\ 0 & a = e \\ \infty & a > e \end{cases}$$

Since $\mathbb{E}[\log(Y_n)] \rightarrow \infty$ for $a < e$, we have $\lim_{n \rightarrow \infty} Y_n = 0$ for $a < e$. Therefore

$$\lim_{n \rightarrow \infty} Y_n = \lim_{n \rightarrow \infty} \prod_{k=1}^n X_k = 0 \iff a < e.$$

8.9 Estimators and Central Limit Theorems (DSO 607)

Lyapunov (?) condition: can prove central limit theorem if we check 3rd moment. Lindeberg's Condition (Lemma 8.6.11)

Chapter 9

Convex Optimization

These are my notes from taking EE 588 at USC taught by Mahdi Soltanolkotabi and the textbook *Convex Optimization* (Boyd and Vandenberghe) 7th printing [Boyd et al., 2004], as well as Math 541A at USC taught by Steven Heilman.

Need to cover:

- Update rules for optimization problems (e.g. gradient descent, be able to write down gradient, etc.)
- Know which algorithms are useful in which settings
- Homework-like problems from first part of class (no proofs though) (Boyd homework is good practice)
- Understand how to derive algorithms
- Understand how to calculate gradients, proximal functions, etc.
- Understand examples, how to run algorithms
- Only conceptual thing: duality question (write down dual)
- Formulate problems as convex optimization problems

Do not need to cover:

- ADMM
- Proofs from 2nd half of class (rates of convergence, etc.)
- Coding

9.1 Convex Functions

Definition 9.1 (Math 541A definition). Let $\phi : \mathbb{R} \rightarrow \mathbb{R}$. We say that ϕ is **convex** if, for any $x, y \in \mathbb{R}$ and for any $t \in [0, 1]$, we have

$$\phi(tx + (1 - t)y) \leq t\phi(x) + (1 - t)\phi(y).$$

Definition 9.2 (Strict convexity, Math 541A notes definition 6.6). Let $\phi : \mathbb{R} \rightarrow \mathbb{R}$. We say that ϕ is **strictly convex** if, for any $x, y \in \mathbb{R}, x \neq y$ and for any $t \in (0, 1)$, we have

$$\phi(tx + (1-t)y) < t\phi(x) + (1-t)\phi(y).$$

Definition 9.3 (Convex function in \mathbb{R}^n , Math 541A Definition). Let $\phi : \mathbb{R}^n \rightarrow \mathbb{R}$. We say that ϕ is **convex** if, for any $x, y \in \mathbb{R}^n$ and for any $t \in [0, 1]$, we have

$$\phi(tx + (1-t)y) \leq t\phi(x) + (1-t)\phi(y). \quad (9.1)$$

Lemma 9.1.1 (Result from Math 541A Homework 2). The slope of a convex function is nondecreasing. More formally, let $\phi : \mathbb{R} \rightarrow \mathbb{R}$ be a convex function. For any $x \in \mathbb{R}$, let

$$M_R := \left\{ \frac{\phi(c) - \phi(x)}{c - x} : c > x \right\}, \quad M_L := \left\{ \frac{\phi(x) - \phi(b)}{x - b} : b < x \right\}$$

be the slopes of the secant lines through ϕ using points to the right and left of x , respectively. Then for any $m \in M_R, p \in M_L$ we have $m \geq p$.

Proof. Fix $x \in \mathbb{R}$. Let $m \in M_R, p \in M_L$. By definition, there exist $b < x < c$ such that

$$m = \frac{\phi(c) - \phi(x)}{c - x}, \quad p = \frac{\phi(x) - \phi(b)}{x - b}.$$

Let $t \in (0, 1)$ such that

$$tb + (1-t)c = x. \quad (9.2)$$

Then we have

$$\begin{aligned} m \geq p &\iff \frac{\phi(c) - \phi(x)}{c - x} \geq \frac{\phi(x) - \phi(b)}{x - b} \iff (x - b)(\phi(c) - \phi(x)) \geq (c - x)(\phi(x) - \phi(b)) \\ &\iff (x - b)\phi(c) + b\phi(x) \geq c\phi(x) - (c - x)\phi(b) \end{aligned}$$

From (9.2), we have $x - b = tb + (1-t)c - b = (t-1)b + (1-t)c = (1-t)(c-b)$ and $t(b-c) = x - c \iff t(c-b) = c - x$. Therefore

$$\begin{aligned} (x - b)\phi(c) + b\phi(x) \geq c\phi(x) - (c - x)\phi(b) &\iff (1-t)(c-b)\phi(c) + b\phi(x) \geq c\phi(x) - t(c-b)\phi(b) \\ &\iff (1-t)(c-b)\phi(c) \geq (c-b)\phi(x) - t(c-b)\phi(b) \iff (1-t)\phi(c) + t\phi(b) \geq \phi(x) \end{aligned}$$

But $t\phi(b) + (1-t)\phi(c) \geq \phi(x)$ since ϕ is convex. Therefore $m \geq p$.

□

Lemma 9.1.2. Let f be a concave function, and let ∂f denote its subgradient. Then ∂f is nonincreasing. That is, for any x, y and for any $g_y \in \partial f(y)$ and $g_x \in \partial f(x)$ it holds that $(g_y - g_x)^T(y - x) \leq 0$.

Proof. By Theorem 9.1.3, it holds that $f(y) \leq f(x) + g_x^T(y - x)$ and that $f(x) \leq f(y) + g_y^T(x - y)$. Adding these yields $f(y) + f(x) \geq f(x) + f(y) + g_x^T(y - x) - g_y^T(y - x) \iff (0 \geq (g_x - g_y)^T(y - x))$.

□

Theorem 9.1.3 (Result from 541A Homework 2; equivalent conditions for convexity). Let $\phi : \mathbb{R} \rightarrow \mathbb{R}$. Then ϕ is convex if and only if: for any $y \in \mathbb{R}$, there exists a constant a and there exists a function $L : \mathbb{R} \rightarrow \mathbb{R}$ defined by $L(x) = a(x - y) + \phi(y)$, $x \in \mathbb{R}$, such that $L(y) = \phi(y)$ and such that $L(x) \leq \phi(x)$ for all $x \in \mathbb{R}$. (In the case that ϕ is differentiable, the latter condition says that ϕ lies above all of its tangent lines.)

Proof. \implies : As in Lemma 9.1.1, let

$$M_R := \left\{ \frac{\phi(c) - \phi(y)}{c - y} : c > y \right\}, \quad M_L := \left\{ \frac{\phi(y) - \phi(b)}{y - b} : b < y \right\}$$

be the slopes of the secant lines through ϕ using points to the right and left of y , respectively. Then by Lemma 9.1.1, for any $m \in M_R$, $p \in M_L$ we have $m \geq p$, so we can choose some $a_0 \in \mathbb{R}$ such that $p \leq a_0 \leq m$ for all $p \in M_L, m \in M_R$. Then let $L : \mathbb{R} \rightarrow \mathbb{R}$ be defined by $L(x) = a_0(x - y) + \phi(y)$, $x \in \mathbb{R}$. Note that $L(y) = \phi(y)$.

We argue that $L(x) \leq \phi(x)$ for all $x \in \mathbb{R}$ by contradiction. Suppose there is some $z \in \mathbb{R}$ with $L(z) > \phi(z)$. Note that $z \neq y$ because we have already shown that $L(y) = \phi(y)$. Then we have

$$L(z) > \phi(z) \iff a_0(z - y) + \phi(y) > \phi(z) \tag{9.3}$$

If $z > y$, then we can solve (9.3) for a_0 as follows:

$$a_0 > \frac{\phi(z) - \phi(y)}{z - y}$$

But $z \in M_R$, so we have $\frac{\phi(z) - \phi(y)}{z - y} > a_0$. Contradiction. If $z < y$, we solve (9.3) for a_0 as follows:

$$a_0 < \frac{\phi(z) - \phi(y)}{z - y} = \frac{\phi(y) - \phi(z)}{y - z}$$

But $z \in M_L$, so we have $\frac{\phi(y) - \phi(z)}{y - z} < a_0$. Contradiction. Therefore for every $z \in \mathbb{R}$ we have $L(z) \leq \phi(z)$ as desired.

\impliedby : Now suppose that for any $y \in \mathbb{R}$ there exists a constant a and a function $L : \mathbb{R} \rightarrow \mathbb{R}$ defined by $L(x) = a(x - y) + \phi(y)$, $x \in \mathbb{R}$, such that $L(y) = \phi(y)$ and such that $L(x) \leq \phi(x)$ for all $x \in \mathbb{R}$.

Fix $b, c \in \mathbb{R}$ and let $t \in (0, 1)$. Set $y := tb + (1 - t)c$. Then by assumption we can write

$$a(b - y) + \phi(y) \leq \phi(b), \quad a(c - y) + \phi(y) \leq \phi(c)$$

Multiply by $t > 0$ and $(1 - t) > 0$ respectively to yield

$$ta(b - y) + t\phi(y) \leq t\phi(b), \quad (1 - t)a(c - y) + (1 - t)\phi(y) \leq (1 - t)\phi(c) \quad (9.4)$$

Note that

$$\begin{aligned} ta(b - y) + (1 - t)a(c - y) &= a(tb - ty + (c - y - ct + yt)) = a(tb + c - y - ct) \\ &= a(tb + c(1 - t) - tb - (1 - t)c) = 0 \end{aligned}$$

So adding the inequalities in (9.4) yields

$$\begin{aligned} t\phi(y) + (1 - t)\phi(y) &\leq t\phi(b) + (1 - t)\phi(c) \iff \phi(y) \leq t\phi(b) + (1 - t)\phi(c) \\ &\iff \phi(tb + (1 - t)c) \leq t\phi(b) + (1 - t)\phi(c). \end{aligned}$$

□

My original proof from submitted homework. If ϕ is differentiable at y , let $a = \phi'(y)$. If not, let a be any subgradient of ϕ at y . Then $L(x)$ is (a) tangent line to ϕ at y , which should be lesser than or equal to ϕ for all $x \in \mathbb{R}$ if ϕ is convex. If and only if this is true at every $y \in \mathbb{R}$ (the tangent line is a global underestimator at y for every $y \in \mathbb{R}$), then ϕ must be convex. We proceed to show this formally:

⇒ : We will show that if ϕ is convex; that is, if for any $x, y \in \mathbb{R}$ and for any $t \in [0, 1]$, we have

$$\phi(tx + (1 - t)y) \leq t\phi(x) + (1 - t)\phi(y) \quad (9.5)$$

then the inequality

$$\phi'(y)(x - y) + \phi(y) \leq \phi(x) \quad \forall x \in \mathbb{R} \quad (9.6)$$

holds. Starting from (9.5) note that

$$\phi(tx + (1 - t)y) \leq t\phi(x) + (1 - t)\phi(y) \implies \phi(tx + (1 - t)y) - \phi(x) \leq (1 - t)(\phi(y) - \phi(x))$$

Suppose $y > x$. Then $tx + (1-t)y - x = (1-t)(y-x) > 0$, so we can divide by it on both sides:

$$\implies \frac{\phi(tx + (1-t)y) - \phi(x)}{tx + (1-t)y - x} \leq \frac{(1-t)(\phi(y) - \phi(x))}{(1-t)(y-x)} \implies \frac{\phi(tx + (1-t)y) - \phi(x)}{tx + (1-t)y - x} \leq \frac{\phi(y) - \phi(x)}{y - x}$$

Taking the limit as $t \rightarrow 1$ yields

$$\phi'(x) \leq \frac{\phi(y) - \phi(x)}{y - x}$$

if ϕ is differentiable, which is (equivalent to) what we hoped to prove. The case where $x > y$ is analogous.

\Leftarrow : We will show that if (9.6) holds then ϕ is convex; that is, (9.5) holds for any $x, y \in \mathbb{R}$ and for any $t \in [0, 1]$. Starting from (9.6) note that

$$\phi'(y)(x-y) + \phi(y) \leq \phi(x) \iff \phi'(y) \leq \frac{\phi(x) - \phi(y)}{x-y} \quad \forall x, y \in \mathbb{R}$$

□

Theorem 9.1.4 (Global minimum of convex functions; Math 541A Homework problem). Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a convex function. Let $x \in \mathbb{R}^n$ be a local minimum of f . Then

- (a) x is a global minimum of f .
- (b) If f is strictly convex, then there is at most one global minimum of f .
- (c) If f is a C^1 function (all derivatives of f exist and are continuous), and $x \in \mathbb{R}^n$ satisfies $\nabla f(x) = 0$, then x is a global minimum of f .

Proof. (a) Since x is a local minimum, we have that there exists $\epsilon > 0$ such that $f(x) \leq f(y) \forall y \in B(x, \epsilon)$ where $B(x, \epsilon) \subseteq \mathbb{R}^n$ is an n -dimensional L_2 ball of radius ϵ centered at x . Suppose there exists some $z \in \mathbb{R}^n$ such that $f(z) < f(x)$. Then by convexity of f , for $t \in [0, 1]$,

$$f(tx + (1-t)z) \leq tf(x) + (1-t)f(z) < tf(x) + (1-t)f(x) = f(x)$$

which when $t = 1$ leads to the contradiction $f(x) < f(x)$. (Also, for $t = 1 - \delta$ with δ sufficiently small, we get $f(x') \leq tf(x) + (1-t)f(z) < f(x)$ where $x' = tx + (1-t)z$ such that $x' \in B(x, \epsilon)$, contradicting the fact that $f(x)$ is a local minimum.) Therefore there is no $z \in \mathbb{R}^n$ such that $f(z) < f(x)$, so x is a global minimum.

- (b) If f is strictly convex, for any $z \in \{\mathbb{R}^n \setminus x\}$ we have

$$f(tx + (1-t)z) < tf(x) + (1-t)f(z), \quad \forall x, z \in \mathbb{R}^n, x \neq z \tag{9.7}$$

We have already shown that there exists no $z \in \{\mathbb{R}^n \setminus x\}$ such that $f(z) < f(x)$. Suppose there is more than one global minimum of f ; that is, there exists $z \in \{\mathbb{R}^n \setminus x\}$ such that $f(z) = f(x)$. That is, for all $y \in \{\mathbb{R}^n \setminus \{x, z\}\}$,

$$f(x) = f(z) \leq f(y). \quad (9.8)$$

But then by strict convexity,

$$f\left(\frac{x+z}{2}\right) < \frac{1}{2}f(x) + \frac{1}{2}f(z) = \frac{1}{2}f(x) + \frac{1}{2}f(x) = f(x)$$

which contradicts (9.8) if $y = (x+z)/2$. Therefore the global minimum of f is unique.

- (c) Recall from Exercise 4 in Homework 2 that f is convex if and only if for any $x \in \mathbb{R}^n$ there exists a constant $a \in \mathbb{R}^n$ and a function $L : \mathbb{R}^n \rightarrow \mathbb{R}$ defined by $L(y) = a^T(y - x) + f(x)$, $y \in \mathbb{R}^n$ such that $L(x) = f(x)$ and $L(y) \leq f(y)$ for all $y \in \mathbb{R}^n$. Further, if f is a C^1 function then this function exists for $a = \nabla f(x)$. That is,

$$f(y) \geq f(x) + \nabla f^T(x)(y - x), \quad \forall y \in \mathbb{R}^n.$$

Since $\nabla f(x) = 0$, if we plug in $y = x$ we get

$$f(y) \geq f(x), \quad \forall y \in \mathbb{R}^n.$$

□

Theorem 9.1.5 (Jensen's Inequality, from Math 541A). Let $X : \Omega \rightarrow [-\infty, \infty]$ be a random variable. Let $\phi : \mathbb{R} \rightarrow \mathbb{R}$ be convex. Assume that $\mathbb{E}|X| < \infty$ and $\mathbb{E}|\phi(X)| < \infty$. Then

$$\phi(\mathbb{E}X) \leq \mathbb{E}\phi(X).$$

Proof. Note that from Theorem 9.1.3, for any $y \in \mathbb{R}$ there exists a constant a and a function L such that

$$a(x - y) + \phi(y) \leq \phi(x) \quad \forall x \in \mathbb{R}$$

Letting $y = \mathbb{E}(X)$ we have

$$a(X - \mathbb{E}X) + \phi(\mathbb{E}X) \leq \phi(X)$$

Since expectations preserve inequalities,

$$\mathbb{E}[a(X - \mathbb{E}X) + \phi(\mathbb{E}X)] \leq \mathbb{E}\phi(X)$$

But

$$\mathbb{E}[a(X - \mathbb{E}X) + \phi(\mathbb{E}X)] = a(\mathbb{E}X - \mathbb{E}X) + \mathbb{E}(\phi(\mathbb{E}X)) = \phi(\mathbb{E}X)$$

which yields

$$\phi(\mathbb{E}X) \leq \mathbb{E}\phi(X).$$

□

Corollary 9.1.5.1 (Jensen's Inequality: EE 588 Formulation). f is convex if and only if

$$f\left(\frac{a+b}{2}\right) \leq \frac{f(a) + f(b)}{2}$$

for all $a, b \in \text{dom}(f)$.

Proof. Follows from Theorem 9.1.5 if X is a discrete random variable that equals a or b each with probability $1/2$ and $\phi(X) = f(X)$. Note that $\phi(X)$ is convex.

□

Corollary 9.1.5.2 (Triangle Inequality). Let $X : \Omega \rightarrow [-\infty, \infty]$ be a random variable with $\mathbb{E}|X| < \infty$. Then

$$|\mathbb{E}X| \leq \mathbb{E}|X|.$$

Proof. Note that $\phi(x) = |x|$ is convex by the definition of convexity: for any $x, y \in \mathbb{R}$ and for any $t \in (0, 1)$, we have

$$\phi(tx + (1-t)y) = |tx + (1-t)y| \leq \dots = t|x| + (1-t)|y| = t\phi(x) + (1-t)\phi(y).$$

Then the result follows immediately from Jensen's Inequality (Theorem 9.1.5) using $\phi(X) = |X|$:

$$|\mathbb{E}X| \leq \mathbb{E}|X|$$

□

Theorem 9.1.6 (Conditional Jensen Inequality). Let $X, Y : \Omega \rightarrow \mathbb{R}$ be random variables that are either both discrete or both continuous. Let $\phi : \mathbb{R} \rightarrow \mathbb{R}$ be convex. Then

$$\phi(\mathbb{E}(X|Y)) \leq \mathbb{E}(\phi(X)|Y).$$

If ϕ is strictly convex, then equality holds only if X is constant on any set where Y is constant. That is, (by an Exercise from the previous homework) equality holds only if X is a function of Y .

Proof. Recall that from Exercise 4 in Homework 2 that since ϕ is convex, for any $y \in \mathbb{R}$ there exists a constant a and a function L such that

$$a(x - y) + \phi(y) \leq \phi(x) \quad \forall x \in \mathbb{R}$$

Letting $x = X$ and $y = \mathbb{E}(X | Y)$ we have

$$a(X - \mathbb{E}(X | Y)) + \phi(\mathbb{E}(X | Y)) \leq \phi(X)$$

Since by Lemma 6.1.7 conditional expectations preserve inequalities,

$$\mathbb{E}[a(X - \mathbb{E}[X | Y]) + \phi(\mathbb{E}[X | Y]) | Y] \leq \mathbb{E}(\phi(X) | Y)$$

But

$$\mathbb{E}[a(X - \mathbb{E}[X | Y]) + \phi(\mathbb{E}[X | Y]) | Y] = a(\mathbb{E}[X | Y] - \mathbb{E}[\mathbb{E}(X | Y) | Y]) + \mathbb{E}[\phi(\mathbb{E}[X | Y]) | Y].$$

By Corollary 6.1.6.1 (letting $h(Y) = \phi(\mathbb{E}[X | Y])$), $\mathbb{E}[\phi(\mathbb{E}[X | Y]) | Y] = \phi(\mathbb{E}[X | Y])$. By Corollary 6.1.6.2, $\mathbb{E}[\mathbb{E}(X | Y) | Y] = \mathbb{E}(X | Y)$. Therefore we have

$$= a(\mathbb{E}[X | Y] - \mathbb{E}[X | Y]) + \phi(\mathbb{E}[X | Y]) = \phi(\mathbb{E}(X | Y))$$

which yields

$$\phi(\mathbb{E}(X | Y)) \leq \mathbb{E}(\phi(X) | Y).$$

□

Theorem 9.1.7 (Multivariate Jensen's Inequality (Exercise 1.6.2 in Durrett [2019])). Suppose $\phi : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex. Let X_1, \dots, X_n be random variables with $\mathbb{E}|\phi(X_1, \dots, X_n)| < \infty$ and $\mathbb{E}|X_i| < \infty$ for all $i \in [n]$. Then

$$\mathbb{E}\phi(X_1, \dots, X_n) \geq \phi(\mathbb{E}X_1, \dots, \mathbb{E}X_n).$$

Proposition 9.1.8 (Convexity of affine functions). Let $c \in \mathbb{R}^n$ and $d \in \mathbb{R}$ be fixed. Let $x \in \mathbb{R}^n$. Then the function $f(x) = c^T x + d$ is convex.

Proof. We will show that f satisfies (9.1) for any $x, y \in \mathbb{R}^n$ and any $t \in [0, 1]$:

$$\begin{aligned} f(tx + (1-t)y) &= c^T(tx + (1-t)y) + d = c^T(tx + (1-t)y) + d = tc^T x + td + (1-t)c^T y + (1-t)d \\ &= t[c^T x + d] + (1-t)[c^T y + d] = tf(x) + (1-t)f(y). \end{aligned}$$

In particular, (9.1) is satisfied with equality.

□

Proposition 9.1.9 (Convexity of quadratic forms). Let $A \in \mathbb{R}^{m \times n}$ and $k > 0$ be fixed. Let $x \in \mathbb{R}^n$. Then the function $f(x) = kx^T A^T Ax$ is convex.

Proof. We will show that f satisfies the definition of convexity. Plugging $\phi(x) = kx^T A^T Ax$ into the left side of (9.1), we have

$$\begin{aligned}
& k(tx + (1-t)y)^T A^T A(tx + (1-t)y) = k(tx^T + (1-t)y^T)A^T A(tx + (1-t)y) \\
&= k[tx^T A^T A tx + tx^T A^T A(1-t)y + (1-t)y^T A^T A tx + (1-t)y^T A^T A(1-t)y] \\
&= k[t^2 x^T A^T A x + t(1-t)x^T A^T A y + t(1-t)y^T A^T A x + (1-t)^2 y^T A^T A y]
\end{aligned}$$

Note that $x^T A^T A y \in \mathbb{R} = [x^T A^T A y]^T = y^T A^T A x$, so we have

$$= k[t^2 x^T A^T A x + 2t(1-t)x^T A^T A y + (1-t)^2 y^T A^T A y] \quad (9.9)$$

Plugging $\phi(x) = kx^T A^T Ax$ into the right side of (9.1) yields

$$ktx^T A^T Ax + k(1-t)y^T A^T Ay \quad (9.10)$$

We can verify the inequality in (9.1) by subtracting (9.10) from (9.9) to see if a negative number results:

$$\begin{aligned}
& kt^2 x^T A^T A x + 2kt(1-t)x^T A^T A y + k(1-t)^2 y^T A^T A y - ktx^T A^T A x - k(1-t)y^T A^T A y \\
&= kt(t-1)x^T A^T A x + 2kt(1-t)x^T A^T A y + k(1-t)[1-t-1]y^T A^T A y \\
&= -kt(1-t)[x^T A^T A x - 2x^T A^T A y + y^T A^T A y] = -kt(1-t)[x^T A^T - y^T A^T][A x - A y] \\
&= -kt(1-t)[A(x-y)]^T A(x-y) \leq 0
\end{aligned}$$

for all $x, y \in \mathbb{R}^n$ and any $t \in [0, 1]$ since $-kt(1-t) \leq 0$ (with equality only when $t = 0$ or $t = 1$) and $[A(x-y)]^T A(x-y) \geq 0$ (with equality only when $x = y$). This verifies the inequality in (9.1), which proves that $kx^T A^T Ax$ is convex. \square

Proposition 9.1.10 (Sum of convex functions is convex). Let $f_1, \dots, f_n : \mathbb{R}^n \rightarrow \mathbb{R}$ be (strictly) convex functions. Then the function $g(x) := \sum_{i=1}^n f_i(x)$ is (strictly) convex.

Proof. Since f_i is convex for all $i \in \{1, \dots, n\}$, f_i satisfies

$$f_i(tx + (1-t)y) \leq tf_i(x) + (1-t)f_i(y), \quad \forall i \in \{1, \dots, n\}.$$

We make use of these inequalities to show that g satisfies (9.1) for any $x, y \in \mathbb{R}^n$ and any $t \in [0, 1]$:

$$\begin{aligned} g(tx + (1-t)y) &= \sum_{i=1}^n f_i(tx + (1-t)y) \leq \sum_{i=1}^n [tf_i(x) + (1-t)f_i(y)] \\ &= t \sum_{i=1}^n f_i(x) + (1-t) \sum_{i=1}^n f_i(y) = tg(x) + (1-t)g(y) \end{aligned}$$

which proves the result. (Note that if the initial inequality is strict then strict convexity follows.)

□

Proposition 9.1.11 (Exercise 6.43 in Math 541A Lecture Notes). Let $f_1, \dots, f_n : \mathbb{R} \rightarrow \mathbb{R}$ be n strictly convex functions. Define $g : \mathbb{R}^n \rightarrow \mathbb{R}$ by

$$g(x_1, \dots, x_n) := \sum_{i=1}^n f_i(x_i), \quad \forall (x_1, \dots, x_n) \in \mathbb{R}^n.$$

Then $g : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex.

Proof. Since f_i is strictly convex for all $i \in \{1, \dots, n\}$, we have that for any $x_i, y_i \in \mathbb{R}$, for all $t \in (0, 1)$

$$f_i(tx_i + (1-t)y_i) < tf_i(x_i) + (1-t)f_i(y_i).$$

Therefore for any $x, y \in \mathbb{R}^n$ (where $x = (x_1, \dots, x_n), y = (y_1, \dots, y_n)$), for all $t \in (0, 1)$

$$\begin{aligned} g(tx + (1-t)y) &= \sum_{i=1}^n f_i(tx_i + (1-t)y_i) < \sum_{i=1}^n [tf_i(x_i) + (1-t)f_i(y_i)] = t \sum_{i=1}^n f_i(x_i) + (1-t) \sum_{i=1}^n f_i(y_i) \\ &= tg(x) + (1-t)g(y). \end{aligned}$$

□

Proposition 9.1.12 (Exercise 6.44 from Math 541A lecture notes). Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$. Suppose that for any fixed $i \in \{1, \dots, n\}$ and for any $x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n$, the function

$$x_i \mapsto f(x_1, \dots, x_n)$$

is strictly convex. Then f has at most one global minimum.

Proof. An equivalent statement to our assumption is that for any i , f is strictly convex in x_i keeping $(x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$ fixed. That is, if we let $h_i : \mathbb{R} \rightarrow \mathbb{R}$ be defined for all $i \in \{1, \dots, n\}$ by

$$h_i(x_i | (x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)) := f((x_1, \dots, x_n)) \quad \forall i \in \{1, \dots, n\},$$

then h_i is strictly convex for all $i \in \{1, \dots, n\}$. That is, for any $x_i, y_i \in \mathbb{R}$, for all $t \in (0, 1)$

$$\begin{aligned} h_i(tx_i + (1-t)y_i \mid (tx_1 + (1-t)y_1, \dots, tx_{i-1} + (1-t)y_{i-1}, tx_{i+1} + (1-t)y_{i+1}, \dots, tx_n + (1-t)y_n)) \\ < th_i(x_i \mid (x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)) + (1-t)h_i(y_i \mid (y_1, \dots, y_{i-1}, y_{i+1}, \dots, y_n)). \end{aligned} \quad (9.11)$$

By Theorem 9.1.4(b), there is at most one global minimum of f if it is strictly convex, so all we need to show is that f is strictly convex. That is, we must show that for all $(x_1, \dots, x_n), (y_1, \dots, y_n) \in \mathbb{R}^n$, for all $t \in (0, 1)$,

$$f(t(x_1, \dots, x_n) + (1-t)(y_1, \dots, y_n)) < tf((x_1, \dots, x_n)) + (1-t)f((y_1, \dots, y_n)). \quad (9.12)$$

We will argue by contradiction. Suppose that for some $(x_1^*, \dots, x_n^*) \in \mathbb{R}^n$ and $(y_1^*, \dots, y_n^*) \in \mathbb{R}^n$, (9.12) does not hold. That is,

$$f(t^*(x_1^*, \dots, x_n^*) + (1-t^*)(y_1^*, \dots, y_n^*)) \geq t^*f((x_1^*, \dots, x_n^*)) + (1-t^*)f((y_1^*, \dots, y_n^*)).$$

for some $t^* \in (0, 1)$. This is equivalent to

$$\begin{aligned} h_1(t^*x_1^* + (1-t^*)y_1^* \mid (t^*x_2^* + (1-t^*)y_2^*, \dots, t^*x_n^* + (1-t^*)y_n^*)) \\ \geq t^*h_1(x_1^* \mid (x_2^*, \dots, x_n^*)) + (1-t^*)h_1(y_1^* \mid (y_2^*, \dots, y_n^*)). \end{aligned}$$

But this contradicts (9.11). Therefore (9.12) holds for all $(x_1, \dots, x_n), (y_1, \dots, y_n) \in \mathbb{R}^n$, for all $t \in (0, 1)$, so f is strictly convex, which means (by Theorem 9.1.4(b)) that f has at most one global minimum.

□

Proposition 9.1.13. Let A be a real $m \times n$ matrix. Let $x \in \mathbb{R}^n$ and let $b \in \mathbb{R}^m$. Then the function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ defined by $f(x) = \frac{1}{2}\|Ax - b\|^2$ is convex.

Proof. We have

$$\begin{aligned} f(x) &= \frac{1}{2}\|Ax - b\|^2 = \frac{1}{2}(Ax - b)^T(Ax - b) = \frac{1}{2}(x^T A^T - b^T)(Ax - b) \\ &= \frac{1}{2}(x^T A^T Ax - b^T Ax - x^T A^T b + b^T b) = \frac{1}{2}x^T A^T Ax - b^T Ax + \frac{1}{2}b^T b \end{aligned}$$

where the last step follows because $b^T Ax \in \mathbb{R} = (b^T Ax)^T = x^T A^T b$ since a real number equals its transpose. The affine function $-b^T Ax + \frac{1}{2}b^T b$ is convex by Proposition 9.1.8, and the quadratic form $\frac{1}{2}x^T A^T Ax$ is convex by Proposition 9.1.9. Since the sum of convex functions is convex by Proposition 9.1.10, the result follows.

□

Remark 106. Moreover,

$$\nabla f(x) = A^T(Ax - b), \quad D^2f(x) = A^T A.$$

(Here D^2f denotes the matrix of second derivatives of f .)

So, if $\nabla f(x) = 0$, i.e. if $A^T Ax = A^T b$, then x is the global minimum of f . And if A has full rank, then $A^T A$ is invertible, so that $x = (A^T A)^{-1} A^T b$ is the global minimum of f .

Proposition 9.1.14 (Convexity of norms). Every norm on \mathbb{R}^n is convex.

Proof. Suppose we have a generic norm $\|\cdot\|_*$ in \mathbb{R}^n . Because $\|\cdot\|_*$ is a norm, it satisfies the triangle inequality; that is, for all $x, y \in \mathbb{R}^n$, $\|x + y\|_* \leq \|x\|_* + \|y\|_*$. Further, for any $t \in [0, 1]$, we have

$$\|tx + (1-t)y\|_* \leq \|tx\|_* + \|(1-t)y\|_* = t\|x\|_* + (1-t)\|y\|_*$$

where the last step also follows from a property of all norms.

□

Proposition 9.1.15 (Mentioned in in-class 541A review; might have been on HW?). If ϕ is strictly convex and $\mathbb{E}(\phi(X)) = \phi(\mathbb{E}(X))$ then X is almost surely constant.

Proposition 9.1.16 (2018 DSO Statistics Group In-Class Screening Exam, Question 5). The function $f(\theta) = (\|\theta\|_1)^2$ is convex.

Proof. Note that

$$\|tx + (1-t)y\|_1 \leq \|tx\|_1 + \|(1-t)y\|_1 = t\|x\|_1 + (1-t)\|y\|_1 \quad (9.13)$$

where the first step follows by the Triangle Inequality (which all norms satisfy, including the ℓ_1 norm) and the second step follows by the homogeneity property of norms. Therefore $\|\theta\|_1$ is convex. Next, by (9.13) and the monotonicity of $g(\theta) = \theta^2$ when $\theta \geq 0$,

$$\begin{aligned} f(tx + (1-t)y) &= (\|tx + (1-t)y\|_1)^2 \leq (t\|x\|_1 + (1-t)\|y\|_1)^2 \\ &= t^2\|x\|_1^2 + (1-t)^2\|y\|_1^2 + 2t(1-t)\|x\|_1\|y\|_1 \end{aligned}$$

and

$$tf(x) + (1-t)f(y) = t\|x\|_1^2 + (1-t)\|y\|_1^2$$

Taking the difference of these yields

$$tf(x) + (1-t)f(y) - f(tx + (1-t)y) \geq t\|x\|_1^2 + (1-t)\|y\|_1^2 - (t^2\|x\|_1^2 + (1-t)^2\|y\|_1^2 + 2t(1-t)\|x\|_1\|y\|_1)$$

$$\begin{aligned}
&= (t - t^2) \|x\|_1^2 + [(1 - t) - (1 - t)^2] \|y\|_1^2 - 2t(1 - t) \|x\|_1 \|y\|_1 \\
&= (t - t^2) (\|x\|_1^2 + \|y\|_1^2 - 2\|x\|_1 \|y\|_1) = t(1 - t)(\|x\|_1 - \|y\|_1)^2 \geq 0
\end{aligned}$$

$$\iff tf(x) + (1 - t)f(y) \geq f(tx + (1 - t)y)$$

which proves convexity.

□

9.2 Schur Complement Trick

9.2.1 Definition

For a matrix $X \in \mathbf{S}^n$ partitioned as

$$X = \begin{bmatrix} A & B \\ B^T & C \end{bmatrix}$$

the Schur complement is (if $\det(A) \neq 0$)

$$S = C - B^T A^{-1} B$$

The Schur complement has two useful properties in convex analysis.

Theorem 9.2.1. (a) $X \succ 0$ if and only if $A \succ 0$ and $S \succ 0$.

(b) If $A \succ 0$, then $X \succeq 0$ if and only if $S \succeq 0$.

9.2.2 The Trick

Suppose we are trying to express a problem as a semidefinite program (SDP); that is, in the form

$$\begin{aligned}
&\text{minimize} && c^T x \\
&\text{subject to} && x_1 F_1 + \dots + x_n F_n + G \preceq 0 \\
& && Ax = b
\end{aligned}$$

where $G, F_1, \dots, F_n \in \mathbf{S}^k$ and $A \in \mathbb{R}^{p \times n}$. If we have a constraint of the form $c^T F(x)^{-1} c \leq t$ where $F(x)$ is symmetric and positive definite and $t \in \mathbb{R}$, by Theorem 9.2.1(b) we can write

$$c^T F(x)^{-1} c \leq t \iff \begin{bmatrix} F(x) & c \\ c^T & t \end{bmatrix} \succeq 0$$

in order to get our constraint in the form required for an SDP.

9.2.3 Example 1: Last Year's Final, Question 2(b)

Suppose we have the constraints

$$\begin{aligned} Ax + b &\geq 0 \\ \frac{(c^T x)^2}{d^T x} &\leq t \end{aligned}$$

which we would like to express in an SDP. By Theorem 9.2.1(b) we can write

$$\frac{(c^T x)^2}{d^T x} \leq t \iff d^T x - (c^T x)^T t^{-1} c^T x \geq 0 \iff \begin{bmatrix} t & c^T x \\ c^T x & d^T x \end{bmatrix} \succeq 0$$

Since

$$Ax + b \geq 0 \iff \text{diag}(Ax + b) \succeq 0$$

we can finally write our constraints as

$$\begin{bmatrix} \text{diag}(Ax + b) & 0 & 0 \\ 0 & t & c^T x \\ 0 & c^T x & d^T x \end{bmatrix} \succeq 0$$

9.2.4 Example 2: Last Year's Final, Question 4(b)

Suppose we have the constraints

$$\begin{aligned} Ax + b &\geq 0 \\ \frac{(c^T x)^2}{d^T x} &\leq t \end{aligned}$$

which we would like to express in an SDP. By Theorem 9.2.1(b) we can write

$$\frac{(c^T x)^2}{d^T x} \leq t \iff d^T x - (c^T x)^T t^{-1} c^T x \geq 0 \iff \begin{bmatrix} t & c^T x \\ c^T x & d^T x \end{bmatrix} \succeq 0$$

Since

$$Ax + b \geq 0 \iff \text{diag}(Ax + b) \succeq 0$$

we can finally write our constraints as

$$\begin{bmatrix} \text{diag}(Ax + b) & 0 & 0 \\ 0 & t & c^T x \\ 0 & c^T x & d^T x \end{bmatrix} \succeq 0$$

9.3 Duality

Theorem 9.3.1. Slater's condition/constraint qualification: Strong duality holds for a convex problem

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, i = 1, \dots, m \\ & && Ax = b \end{aligned}$$

if it is strictly feasible, i.e., there exists at least one x in the domain of f_0 such that $f_i(x) < 0$, $i = 1, 2, \dots, m$, $Ax = b$.

9.4 MLE estimates

For linear estimates with iid noise

$$y_i = a_i^T x + v_i, i = 1, \dots, m$$

where a is observed and $x \in \mathbb{R}^n$ are the parameters to be estimated, the likelihood function is

$$p_x(y) = \prod_{i=1}^m \Pr(v_i = y_i - a_i^T x \mid x)$$

Therefore the log likelihood function is:

$$\ell_x(y) = \sum_{i=1}^m \log[\Pr(v_i = y_i - a_i^T x \mid x)]$$

9.5 Practice Final (2017 Final)

- (1) (a) Strictly convex. Multiply by x/x (allowed in this case since $x > 0$) to get $\frac{x^2}{x+1}$ which is a quadratic over linear, which is convex in \mathbb{R}^{++} according to CVX rules.

- (b) Not convex, it is convex for $x \geq -1$, but there is a boundary problem at $x = -1$. Note that Jensen's inequality (Theorem 9.1.5.1)

$$\frac{f(a) + f(b)}{2} \geq f\left(\frac{a+b}{2}\right)$$

is violated because

$$\frac{f(-1.3) + f(-0.9)}{2} = \frac{2.3 + 0}{2} = 1.15 \leq 2.2 = f(-1.1) = f\left(\frac{-1.3 + -0.9}{2}\right)$$

(c)

(d)

$$f(x) = \sup \log \left(\frac{p(t)}{q(t)} \right) = \sup \{ \log p(t) - \log q(t) \} = \sup \{ \log \left(\sum_{i=1}^n \exp(x_i \sin(it)) \right) - \sum_{i=1}^n x_i \sin(it) \}$$

- (e) The proximal mapping is

$$\begin{aligned} \text{prox}_{\mathcal{R}}(z) &= \arg \min_y \frac{1}{2} \|z - y\|_2^2 + \mathcal{R}(y) = \arg \min_y \frac{1}{2} \sum_{i=1}^n (z_i - y_i)^2 + \sum_{i=1}^n w_i |y_i| \\ &= \arg \min_y \frac{1}{2} \sum_{i=1}^n [(z_i - y_i)^2 + w_i |y_i|] \end{aligned}$$

Taking the gradient of the inside quantity with respect to y , we have

$$\nabla(y) = \begin{pmatrix} \frac{1}{2} \cdot 2(z_1 - y_1) + \mathbf{sign}(y_1)w_1 \\ \frac{1}{2} \cdot 2(z_2 - y_2) + \mathbf{sign}(y_2)w_2 \\ \vdots \\ \frac{1}{2} \cdot 2(z_n - y_n) + \mathbf{sign}(y_n)w_n \end{pmatrix} = \begin{pmatrix} z_1 - y_1 + \mathbf{sign}(y_1)w_1 \\ z_2 - y_2 + \mathbf{sign}(y_2)w_2 \\ \vdots \\ z_n - y_n + \mathbf{sign}(y_n)w_n \end{pmatrix}$$

Setting equal to 0, we have

$$y = \begin{pmatrix} z_1 \pm w_1 \\ z_2 \pm w_2 \\ \vdots \\ z_n \pm w_n \end{pmatrix}$$

- (2) (a) The constraint is convex (affine). The denominator is affine. Since $c^T x = x^T c$, the numerator

$$(c^T x)^2 = (c^T x)(c^T x) = x^T c c^T x = x^T (cc^T)x$$

is convex since cc^T is positive semidefinite.

- (b) We start by using the epigraph trick to transform the problem:

$$\begin{aligned} &\text{minimize} && t \\ &\text{subject to} && \frac{(c^T x)^2}{d^T x} \leq t \\ & && Ax + b \geq 0 \end{aligned}$$

We are trying to express this problem as a semidefinite program (SDP); that is, in the form

$$\begin{aligned} & \text{minimize} && c^T x \\ & \text{subject to} && x_1 F_1 + \dots + x_n F_n + G \preceq 0 \\ & && Ax = b \end{aligned}$$

where $G, F_1, \dots, F_n \in \mathbf{S}^k$ and $A \in \mathbb{R}^{p \times n}$. The first constraint

$$\frac{(c^T x)^2}{d^T x} \leq t$$

can be expressed in the form

$$(c^T x)^2 \leq t d^T x \iff (c^T x c^T - t d^T) x \leq 0$$

We have a constraint

$$Ax + b \geq 0$$

which can be expressed in the form

$$Ax \geq -b$$

$$c^T F(x)^{-1} c \leq t$$

where $F(x)$ is symmetric and positive definite and $t \in \mathbb{R}$, by Theorem 9.2.1(b) we can write

$$c^T F(x)^{-1} c \leq t \iff \begin{bmatrix} F(x) & c \\ c^T & t \end{bmatrix} \succeq 0$$

in order to get our constraint in the form required for an SDP.

- (3) (a) Yes, g is convex over \mathcal{X} since it is quadratic over linear.
- (b) The only points satisfying the constraint have $x_1 = 0$. Therefore the primal optimal value (the only feasible value) is $e^0 = \boxed{1}$.
- (c) Lagrangian:

$$L(x, \lambda) = e^{-x_1} + \lambda(x_1^2/x_2)$$

The Lagrangian obtains its minimum value of 0 when $x_2 = x_1^3$ and $x_1 \rightarrow \infty$. Thus, its dual function ($g(\lambda) = \min_x L(x, \lambda)$) is

$$g(\lambda) = 0$$

The dual problem is then

maximize	0
subject to	$\lambda \geq 0$

- (d) The optimal value of the dual problem is 0. Strong duality does not hold since the optimum of the dual problem is less than the optimum of the primal problem. We can also tell this because Slater's Condition (Theorem 9.3.1) is violated; that is, there is no (x_1, x_2) that is strictly feasible since x_1 must equal 0, which is on the boundary of the feasible region.

(e) Now for the primal problem, instead of $x_1 = 0$, we have

$$\frac{x_1^2}{x_2} \leq u \iff x_1^2 \leq ux_2 \implies -\sqrt{ux_2} \leq x_1 \leq \sqrt{ux_2}$$

Since e^{-x_1} is minimized as $x_1 \rightarrow \infty$, our optimal solution is $x_2 \rightarrow \infty, x_1 = \sqrt{ux_2} \rightarrow \infty$ yielding a primal optimal value of $\boxed{0}$. For the dual problem, we have

$$L(x, \lambda) = e^{-x_1} + \lambda \left(\frac{x_1^2}{x_2} - u \right)$$

Dual function ($g(\lambda) = \min_x L(x, \lambda)$):

$$\frac{x_1^2}{x_2} - u = 0 \implies x_2 = \frac{x_1^2}{u}$$

and let $x_1 \rightarrow -\infty$ to yield

$$g(\lambda) = 0$$

The dual problem is then

maximize 0

with optimal value 0, so there is no longer a duality gap. We can also tell this because Slater's Condition (Theorem 9.3.1) is satisfied; that is, there exists an (x_1, x_2) which is strictly feasible (say $(x_1, x_2) = (\sqrt{u}, 10)$).

(4) (a) Yes, the set is convex. If $(u_i, v_i) = \mathbf{u}_i$, each

$$\sqrt{(x - u_i)^2 + (y - v_i)^2} = \|\mathbf{x} - \mathbf{u}_i\|_2$$

is convex in \mathbf{x} . Therefore the function

$$\sum_{i=1}^k \|\mathbf{x} - \mathbf{u}_i\|_2$$

is convex. For any fixed d , this set is a sublevel set of this function, which is convex since the function is convex.

(b) This is a feasibility problem:

$$\begin{aligned} &\text{find} && \mathbf{x} \\ &\text{subject to} && \sum_{i=1}^k \|\mathbf{x} - \mathbf{u}_i\| \leq d \\ & && \sum_{i=1}^j \|\mathbf{x} - \mathbf{v}_i\| \leq e \end{aligned}$$

or

$$\begin{aligned}
& \text{minimize} && 0 \\
& \text{subject to} && \sum_{i=1}^k \|\mathbf{x} - \mathbf{u}_i\| \leq d \\
& && \sum_{i=1}^j \|\mathbf{x} - \mathbf{v}_i\| \leq e
\end{aligned}$$

for two sets of points in \mathbb{R}^2 $\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{v}_1, \dots, \mathbf{v}_j$. We would like to express these constraints as matrix inequalities in order to have an SDP. To do this, first rewrite the problem as

$$\begin{aligned}
& \text{minimize} && 0 \\
& \text{subject to} && \|\mathbf{x} - \mathbf{u}_i\| \leq t_i, i = 1, \dots, k \\
& && \|\mathbf{x} - \mathbf{v}_i\| \leq s_i, s = 1, \dots, j \\
& && \mathbf{1}^T t \leq d \\
& && \mathbf{1}^T s \leq e
\end{aligned}$$

Then note that we can use the Schur trick:

$$(\mathbf{x} - \mathbf{u}_i)^T I (\mathbf{x} - \mathbf{u}_i) \leq t_i \iff \begin{bmatrix} I & \mathbf{x} - \mathbf{u}_i \\ (\mathbf{x} - \mathbf{u}_i)^T & t_i \end{bmatrix} \succeq 0$$

and write the optimization problem as an SDP:

$$\begin{aligned}
& \text{minimize} && 0 \\
& \text{subject to} && \begin{bmatrix} I & \mathbf{x} - \mathbf{u}_i \\ (\mathbf{x} - \mathbf{u}_i)^T & t_i \end{bmatrix} \succeq 0, i = 1, \dots, k \\
& && \begin{bmatrix} I & \mathbf{x} - \mathbf{v}_i \\ (\mathbf{x} - \mathbf{v}_i)^T & s_i \end{bmatrix} \succeq 0, s = 1, \dots, j \\
& && \mathbf{1}^T t \leq d \\
& && \mathbf{1}^T s \leq e
\end{aligned}$$

(5) (a) To minimize the MSE:

$$\mathcal{L}(z) = \sum_r (y_r - |a_r^T x|^2)^2$$

For MLE estimate:

$$p_x(y) = \prod_{r=1}^m \Pr(w_r = y_r - (a_r^T x)^2 \mid x) = \frac{1}{(y_r - (a_r^T x)^2)!} \cdot \exp(-(a_r^T x)^2) \cdot (a_r^T x)^{2[y_r - (a_r^T x)^2]}$$

Therefore the log likelihood function is:

$$\begin{aligned}
\ell_x(y) &= \sum_{i=1}^m \log[\Pr(y_i - a_i^T x \mid x)] = \sum_{i=1}^m \log \left[\frac{1}{(y_r - (a_r^T x)^2)!} \cdot \exp(-(a_r^T x)^2) \cdot (a_r^T x)^{2[y_r - (a_r^T x)^2]} \right] \\
&= \sum_{i=1}^m \log \left[\frac{1}{(y_r - (a_r^T x)^2)!} \right] - (a_r^T x)^2 + 2[y_r - (a_r^T x)^2] \cdot \log[(a_r^T x)]
\end{aligned}$$

(b) b

(c) c

(d) d

(e) e

Chapter 10

Mathematical Statistics

These are my notes from taking Math 541A at USC taught by Steven Heilman as well as *Statistical Inference* (2nd edition) by Casella and Berger [[Casella and Berger, 2001](#)], *Testing Statistical Hypotheses* by Lehmann and Romano [[Lehmann and Romano, 2005](#)], Statistics 100B at UCLA taught by Nicolas Christou, ISE 620 at USC taught by Sheldon Ross, Math 505A at USC taught by Sergey Lototsky, and a few other sources I cite within the text.

10.1 Order Statistics

Definition 10.1 (Order statistics (from Math 541A, more precise)). Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable. Let X_1, \dots, X_n be a random sample of size n from X . Define $X_{(1)} := \min_{1 \leq i \leq n} X_i$, and for any $2 \leq i \leq n$, inductively define

$$X_i := \min \left\{ \{X_1, \dots, X_n\} \setminus \{X_{(1)}, \dots, X_{(i-1)}\} \right\},$$

so that

$$X_{(1)} \leq X_{(2)} \leq \dots \leq X_{(n)} = \max_{1 \leq i \leq n} X_i.$$

The random variables $X_{(1)}, \dots, X_{(n)}$ are called the **order statistics** of X_1, \dots, X_n .

Definition 10.2 (Order statistics (from ISE 620, more informal)). Let $X_1, \dots, X_n \sim \text{iid } F$ with $F' = f$. Define $X_{(1)}$ as the smallest among X_1, \dots, X_n , $X_{(2)}$ as the 2nd smallest, and so on, up to $X_{(n)}$, the largest of the group. We call $X_{(1)}, \dots, X_{(n)}$ the **order statistics** of X_1, \dots, X_n .

Proposition 10.1.1 (Order statistics distribution function; from Math 541A). Suppose X is a discrete random variable and we can order the values that X takes as $x_1 < x_2 < \dots$. For any $i \geq 1$, define $p_i := \Pr(X \leq x_i)$. Then for any $1 \leq i, j \leq n$,

$$\Pr(X_{(j)} \leq x_i) = \sum_{k=j}^n \binom{n}{k} p_i^k (1-p_i)^{n-k}.$$

Proof. Note that $\{X_{(j)} \leq x_i\}$ is equivalent to the event that j or more of the X_i are less than or equal to x_i regardless of order; that is, x_i is the k th smallest observed value. Let A_k be the event that exactly k of the X_i are less than or equal to x_i regardless of order. Then

$$\{X_{(j)} \leq x_i\} = \bigcup_{k=j}^n A_k.$$

Then since (by definition of p_i)

$$\Pr(A_k) = \binom{n}{k} p_i^k (1-p_i)^{n-k}$$

and using the fact that the $\{A_k\}$ are disjoint, we have

$$\Pr(\{X_{(j)} \leq x_i\}) = \Pr\left(\bigcup_{k=j}^n A_k\right) = \sum_{k=1}^n \Pr(A_k) = \sum_{k=1}^n \binom{n}{k} p_i^k (1-p_i)^{n-k}.$$

□

Corollary 10.1.1.1. If X is a continuous random variable with density f_X and cumulative distribution function F_X , then for any $1 \leq j \leq n$, $F_{X_{(j)}}$ has density

$$f_{X_{(j)}}(x) := \frac{n!}{(j-1)!(n-j)!} f_X(x) (F_X(x))^{j-1} (1-F_X(x))^{n-j}, \quad \forall x \in \mathbb{R}.$$

Proof. In order for $X_{(j)}$ to be in the interval $[x, x + \epsilon]$ for small ϵ , it must be that $j - 1$ of the observed U_i to be less than x and $n - j$ of them to be greater than x . That is,

$$\begin{aligned} \mathbb{P}(X_{(j)} \in [x, x + \epsilon]) &= \mathbb{P}(X_i \in [x, x + \epsilon] \text{ for some } i) \mathbb{P}(j-1 \text{ of the other } X_i \text{ are less than } x, \text{ rest are greater}) \\ &= n \mathbb{P}(X_1 \in [x, x + \epsilon]) \mathbb{P}(j-1 \text{ of the other } X_i \text{ are less than } x, \text{ rest are greater}) \\ &\approx n f_X(x) \epsilon \left[\binom{n-1}{j-1} F_X(x)^{j-1} (1-F_X(x))^{n-j} \right] \\ \implies f_{X_{(j)}}(x) &= n f_X(x) \left[\binom{n-1}{j-1} F_X(x)^{j-1} (1-F_X(x))^{n-j} \right]. \end{aligned}$$

□

Proposition 10.1.2 (Order statistics joint density function; result from ISE 620). The joint density of the order statistics is

$$f_{X_{(1)}, \dots, X_{(n)}}(x_1, \dots, x_n) = n! \prod_{i=1}^n f(x_i).$$

Proof. Start with $n = 2$. We seek $f_{X_{(1)}, X_{(2)}}(x_1, x_2)$. Note that $X_{(1)} = x_1, X_{(2)} = x_2$ if $X_1 = x_1, X_2 = x_2$ or if $X_1 = x_2, X_2 = x_1$. These are mutually exclusive events, so their density is equal to the sums of the two densities. That is,

$$f_{X_{(1)}, X_{(2)}}(x_1, x_2) = f_{X_1, X_2}(x_1, x_2) + f_{X_1, X_2}(x_2, x_1) = 2f(x_1)f(x_2)$$

where the last step follows from the i.i.d. distributions. Generalizing, we have

$$f_{X_{(1)}, \dots, X_{(n)}}(x_1, \dots, x_n) = n! \prod_{i=1}^n f(x_i).$$

□

Proposition 10.1.3 (Distribution of order statistics of uniform random variable; from 541A). Let X be a random variable uniformly distributed in $[0, 1]$. Then for any $1 \leq j \leq n$, $X_{(j)}$ is a beta distributed random variable with parameters j and $n + 1 - j$.

Proof. Note that for a uniform distribution on $[0, 1]$, $f_X(x) = 1, x \in [0, 1]$ and $F_X(x) = x, x \in [0, 1]$. Therefore by Corollary 10.1.1.1 we have

$$\begin{aligned} f_{X_{(j)}}(x) &= \frac{n!}{(j-1)!(n-j)!} x^{j-1} (1-x)^{n-j}, \quad x \in [0, 1] \\ &= \frac{\Gamma(n+1)}{\Gamma(j)\Gamma(n+1-j)} x^{j-1} (1-x)^{n+1-j-1} \end{aligned}$$

which is the pdf for a beta distribution with parameters j and $n + 1 - j$.

□

Corollary 10.1.3.1. Let X be a random variable uniformly distributed in $[0, 1]$. Then $\mathbb{E}X_{(j)} = \frac{j}{n+1}$

Proof. Follows from Proposition 10.1.3 since the mean of such a beta distribution is $\frac{j}{n+1}$.

□

Proposition 10.1.4 (Result from 541A). Let $a, b \in \mathbb{R}$ with $a < b$. Let U be the number of indices $1 \leq j \leq n$ such that $X_j \leq a$. Let V be the number of indices $1 \leq j \leq n$ such that $a < X_j \leq b$. Then the vector $(U, V, n - U - V)$ is a multinomial random variable, so that for any nonnegative integers u, v with $u + v \leq n$, we have

$$\begin{aligned} \mathbb{P}(U = u, V = v, n - U - V = n - u - v) \\ = \frac{n!}{u!v!(n-u-v)!} F_X(a)^u (F_X(b) - F_X(a))^v (1 - F_X(v))^{n-u-v}. \end{aligned}$$

Consequently, for any $1 \leq i, j \leq n$,

$$\mathbb{P}(X_{(i)} \leq a, X_{(j)} \leq b) = \mathbb{P}(U \geq i, U + V \geq j) = \sum_{k=i}^{j-1} \sum_{m=j-k}^{n-k} \mathbb{P}(U = k, V = m) + \mathbb{P}(U \geq j).$$

So, it is possible to write an explicit formula for the joint distribution of $X_{(i)}$ and $X_{(j)}$.

Proof. We can define a multinomial distribution as follows (from Sheldon Ross *Stochastic Processes*, see Definition 6.27): “Suppose that n independent trials, each of which results in either outcome $1, 2, \dots, r$ with respective probabilities p_1, p_2, \dots, p_r (with $\sum_i p_i = 1$), are performed. Let N_i denote the number of

trials resulting in outcome i . Then the joint distribution of N_1, \dots, N_r is called the **multinomial distribution**." In this case $r = 3$. If we define outcome 1 to be $X_j \leq a$, outcome 2 to be $a < X_j \leq b$, and outcome 3 to be $X_j > b$, then the counts $(U, V, n - U - V)$ meet this definition exactly, with $p_1 = \Pr(X_j \leq a) = F_X(a)$, $p_2 = \Pr(a < X_j \leq b) = F_X(b) - F_X(a)$, $p_3 = \Pr(X_j > b) = 1 - F_X(b)$. Since the pmf of a multinomial distribution with $r = 3$ is

$$\Pr((N_1, N_2, N_3) = (n_1, n_2, n_3)) = \binom{n}{n_1, n_2, n_3} p_1^{n_1} p_2^{n_2} p_3^{n_3} = \frac{n!}{n_1! n_2! n_3!} p_1^{n_1} p_2^{n_2} p_3^{n_3}$$

we have in this case

$$\Pr(U = u, V = v, n - U - V = n - u - v) = \frac{n!}{u! v! (n - u - v)!} F_X(a)^u (F_X(b) - F_X(a))^v (1 - F_X(v))^{n-u-v}$$

as desired. \square

Definition 10.3 (Median; Math 505A defintion). The real number m is called a **median** of a random variable X if

$$\Pr(X \leq m) \geq 1/2, \quad \Pr(X \geq m) \geq 1/2.$$

Proposition 10.1.5 (Math 505A homework problem). (a) Every random variable has at least one median.

(b) The set of all medians is a closed interval of the real line.

Proof. (a) Suppose the cdf of X , $F_X : \mathbb{R} \rightarrow [0, 1]$, is continuous. Because $F_X(x) = \Pr(X \leq x)$ is a cdf, it is also monotonically increasing. By the Intermediate Value Theorem, there exists at least one $m \in \mathbb{R}$ such that $F_X(m) = 1/2$. Because $\Pr(X \leq m) = 1/2 \geq 1/2$ and $\Pr(X \geq m) = 1 - \Pr(X < m) = 1 - 1/2 \geq 1/2$, m is a median.

Suppose F_X is not continuous. If it contains $1/2$ in its range, then m such that $F_X(m) = 1/2$ is a median. If there is no $m \in \mathbb{R}$ such that $F_X(m) = 1/2$, then $m = \inf(\{x \mid F_X(x) \geq 1/2\})$ is a median. To see why, note first that $\Pr(X \leq m) = F_X(m) \geq 1/2$. Second,

$$\Pr(X \geq m) = 1 - \Pr(X < m) = 1 - \lim_{x \rightarrow m^-} F_X(x) \geq 1 - 1/2 = 1/2$$

because F_X is right continuous. Therefore m is a median of X .

(b) We show that all medians of X must be in one interval by contradiction. Suppose a and b are medians of X but c is not, where $a < c < b$. By the definition of median, $F_X(a) \geq 1/2$ and $F_X(b) \geq 1/2$. Because c is not a median, $F_X(c) < 1/2$. This implies that F_X is decreasing on the interval from a to c , which contradicts the fact that the distribution function F_X monotonically increases.

Finally we prove that all medians of X are in a closed interval. Let \mathcal{A} be the set of all medians of X ; that is, $\mathcal{A} = \{x \mid \Pr(X \leq x) \geq 1/2, \Pr(X \geq x) \geq 1/2\} = \{x \mid F_X(x) \geq 1/2, \lim_{y \rightarrow x^-} F_X(y) \leq 1/2\}$. We will show that \mathcal{A} contains its infimum and its supremum. The argument above shows that $a = \inf(\{x \mid F_X(x) \geq 1/2\})$ satisfies $\lim_{y \rightarrow a^-} F_X(y) \leq 1/2$; that is, $a \in \mathcal{A}$. Since there is no lower value k which satisfies $F_X(k) \geq 1/2$, $a = \inf(\mathcal{A})$, so \mathcal{A} contains its infimum.

Let $b = \sup\{x \mid \lim_{y \rightarrow x^-} F_X(y) \leq 1/2\}$. Because b is the supremum of a set containing a , $b \geq a$. Therefore because F_X is nondecreasing, $F_X(b) \geq F_X(a) \geq 1/2$, which shows that $b \in \mathcal{A}$. Since b is the supremum of the set of all values satisfying $\lim_{y \rightarrow x^-} F_X(y) \leq 1/2$, b is the supremum of \mathcal{A} . Therefore \mathcal{A} contains its infimum and supremum, and the set of all medians of X is closed.

□

Remark 107. One example of a random variable which has a median of length L : X is a discrete random variable with the following mass function:

$$\Pr(X = 0) = 0.5$$

$$\Pr(X = L) = 0.5$$

Then $m \in [0, L]$ are medians.

10.2 Random Samples

Definition 10.4 (Random Sample). Let $n > 0$ be an integer. A **random sample** of size n is a sequence X_1, \dots, X_n of independent identically distributed random variables.

Definition 10.5 (Statistic). Let n, k be positive integers. Let X_1, \dots, X_n be a random sample of size n . Let $f : \mathbb{R}^n \rightarrow \mathbb{R}^k$ be a (measureable) function. A **statistic** is a random variable of the form $Y := f(X_1, \dots, X_n)$. The distribution of Y is called a **sampling distribution**.

Definition 10.6 (Sample mean). The **sample mean** of a random sample X_1, \dots, X_n of size n , denoted \bar{X} , is the following statistic:

$$\bar{X} := \frac{1}{n} \sum_{i=1}^n X_i.$$

Proposition 10.2.1. Suppose we have a random sample of size n from an i.i.d. distribution X_1, X_2, \dots, X_n with $\mathbb{E}(X_1) = \mu$ in \mathbb{R} , $\text{Var}(X_1) = \sigma^2 < \infty$. Then

- (a) $\mathbb{E}(\bar{X}) = \mathbb{E}(X_1)$.
- (b) $\text{Var}(\bar{X}) = \sigma^2/n$.

Proof. (a)

$$\mathbb{E}(\bar{X}) = \mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n} \sum_{i=1}^n \mathbb{E}X_i = \frac{1}{n} \cdot n\mu = \mu$$

(b) Using the independence of the X_i ,

$$\text{Var}(\bar{X}) = \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i\right) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{1}{n^2} \cdot n\sigma^2 = \boxed{\frac{\sigma^2}{n}}$$

□

Proposition 10.2.2 (Stats 100B homework problem). Suppose that X_1, \dots, X_m and Y_1, \dots, Y_n are two samples, with $X \sim \mathcal{N}(\mu_1, \sigma_1)$ and $Y \sim \mathcal{N}(\mu_2, \sigma_2)$. The difference between the sample means, $\bar{X} - \bar{Y}$, is then a linear combination of $m + n$ normal random variables. Then

- a. $\mathbb{E}(\bar{X} - \bar{Y}) = \mu_1 - \mu_2$.
- b. $\text{Var}(\bar{X} - \bar{Y}) = \frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}$.
- c. The distribution of $\bar{X} - \bar{Y}$ is normal with mean and variance equal to the previous results.

Proof. a.

$$\begin{aligned} \bar{X} &= \frac{1}{m} \sum_{i=1}^m X_i, \quad \bar{Y} = \frac{1}{n} \sum_{j=1}^n Y_j \\ \mathbb{E}(\bar{X} - \bar{Y}) &= \mathbb{E}\left(\frac{1}{m} \sum_{i=1}^m X_i - \frac{1}{n} \sum_{j=1}^n Y_j\right) = \frac{1}{m} \mathbb{E}\left(\sum_{i=1}^m X_i\right) - \frac{1}{n} \mathbb{E}\left(\sum_{j=1}^n Y_j\right) \\ &= \frac{1}{m} \sum_{i=1}^m \mathbb{E}(X_i) - \frac{1}{n} \sum_{j=1}^n \mathbb{E}(Y_j) = \frac{1}{m} \sum_{i=1}^m \mu_1 - \frac{1}{n} \sum_{j=1}^n \mu_2 = \frac{1}{m} m \cdot \mu_1 - \frac{1}{n} n \cdot \mu_2 \\ &\implies \mathbb{E}(\bar{X} - \bar{Y}) = \mu_1 - \mu_2 \end{aligned}$$

b. Since X and Y are independent,

$$\begin{aligned} \text{Var}(\bar{X} - \bar{Y}) &= \text{Var}(\bar{X}) + \text{Var}(\bar{Y}) \\ &= \mathbb{E}[(\bar{X} - \mathbb{E}[\bar{X}])^2] + \mathbb{E}[(\bar{Y} - \mathbb{E}[\bar{Y}])^2] \\ &= \mathbb{E}\left(\frac{1}{m} \sum_{i=1}^m X_i - \mu_1\right)^2 + \mathbb{E}\left(\frac{1}{n} \sum_{j=1}^n Y_j - \mu_2\right)^2 \\ &= \mathbb{E}\left(\frac{1}{m} \sum_{i=1}^m (X_i - m\frac{1}{m}\mu_1)\right)^2 + \mathbb{E}\left(\frac{1}{n} \sum_{j=1}^n (Y_j - n\frac{1}{n}\mu_2)\right)^2 \\ &= \frac{1}{m^2} \mathbb{E}\left(\sum_{i=1}^m (X_i - \mu_1)\right)^2 + \frac{1}{n^2} \mathbb{E}\left(\sum_{j=1}^n (Y_j - \mu_2)\right)^2 \end{aligned}$$

Since X_i and X_j are independent for $i \neq j$ (and likewise for Y), $\text{Cov}(X_i, X_j) = 0$ for $i \neq j$, so

$$\mathbb{E}[(X_i - \mu_1)(X_j - \mu_1)] = 0$$

for $i \neq j$ (and likewise for Y). Therefore the above equation can be written as

$$\begin{aligned} & \frac{1}{m^2} \mathbb{E} \left(\sum_{i=1}^m (X_i - \mu_1)^2 \right) + \frac{1}{n^2} \mathbb{E} \left(\sum_{j=1}^n (Y_j - \mu_2)^2 \right) \\ & \frac{1}{m^2} \sum_{i=1}^m \mathbb{E} (X_i - \mu_1)^2 + \frac{1}{n^2} \sum_{j=1}^n \mathbb{E} (Y_j - \mu_2)^2 \\ & = \frac{1}{m^2} \left(\sum_{i=1}^m \sigma_1^2 \right) + \frac{1}{n^2} \left(\sum_{j=1}^n \sigma_2^2 \right) = \frac{1}{m^2} m \cdot \sigma_1^2 + \frac{1}{n^2} n \cdot \sigma_2^2 \\ & \implies \text{Var}(\bar{X} - \bar{Y}) = \frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n} \end{aligned}$$

c.

$$M_{X_i}(t) = \exp \left(\mu_1 t + \frac{t^2 \sigma_1^2}{2} \right), \quad M_{Y_i}(t) = \exp \left(\mu_2 t + \frac{t^2 \sigma_2^2}{2} \right)$$

Since individual observations from X and Y are independent,

$$M_{\bar{X}}(t) = \prod_{i=1}^m M_{X_i} \left(\frac{1}{m} t \right), \quad M_{\bar{Y}}(t) = \prod_{j=1}^n M_{Y_j} \left(\frac{1}{n} t \right)$$

and

$$\begin{aligned} M_{\bar{X} - \bar{Y}}(t) &= M_{\bar{X}}(t) M_{-\bar{Y}}(t) = M_{\bar{X}}(t) M_{\bar{Y}}(-t) = \prod_{i=1}^m M_{X_i} \left(\frac{1}{m} t \right) \prod_{j=1}^n M_{Y_j} \left(\frac{-1}{n} t \right) \\ &= \left[M_{X_i} \left(\frac{t}{m} \right) \right]^m \left[M_{Y_j} \left(\frac{-t}{n} \right) \right]^n = \left[\exp \left(\frac{\mu_1 t}{m} + \frac{t^2 \sigma_1^2}{2m^2} \right) \right]^m \left[\exp \left(\frac{-\mu_2 t}{n} + \frac{(-t)^2 \sigma_2^2}{2n^2} \right) \right]^n \\ &= \exp \left(\frac{m \mu_1 t}{m} + \frac{m t^2 \sigma_1^2}{2m^2} \right) \exp \left(\frac{-n \mu_2 t}{n} + \frac{n t^2 \sigma_2^2}{2n^2} \right) \\ &\implies \boxed{M_{\bar{X} - \bar{Y}}(t) = \exp \left[(\mu_1 - \mu_2)t + \frac{1}{2} t^2 \left(\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n} \right) \right]} \end{aligned}$$

This is the moment generating function of a normal distribution with mean $\mu_1 - \mu_2$ and variance $\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}$, consistent with the results from parts (a) and (b).

□

Definition 10.7 (Sample variance). Let $n > 1$. The **sample variance** of a random sample X_1, \dots, X_n of size n , denoted S^2 , is the following statistic:

$$S^2 := \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2.$$

The **sample standard deviation** of a random sample of size n is $\sqrt{S^2}$.

Proposition 10.2.3 (Unbiasedness of sample variance). Suppose we have a random sample of size n from an i.i.d. distribution X_1, X_2, \dots, X_n with $\mathbb{E}(X_1) = \mu$ in \mathbb{R} , $\text{Var}(X_1) = \sigma^2 < \infty$. Then $\mathbb{E}(S^2) = \sigma^2$. Further, S^2 is a consistent estimator of σ^2 .

Proof. We have

$$\begin{aligned}\mathbb{E}(S^2) &= \mathbb{E}\left(\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2\right) = \frac{1}{n-1} \mathbb{E}\left(\sum_{i=1}^n X_i^2 - 2X_i\bar{X} + \bar{X}^2\right) \\ &= \frac{1}{n-1} \left(\sum_{i=1}^n \mathbb{E}(X_i^2) - 2\mathbb{E}\left(\bar{X} \sum_{i=1}^n X_i\right) + n\mathbb{E}\bar{X}^2 \right) = \frac{1}{n-1} \left(n\mathbb{E}(X_i^2) - 2n\mathbb{E}\bar{X}^2 + n\mathbb{E}\bar{X}^2 \right) \\ &= \frac{n}{n-1} (\mathbb{E}(X_i^2) - \mathbb{E}\bar{X}^2) = \frac{n}{n-1} (\text{Var}(X_i) + \mathbb{E}(X_i)^2 - [\text{Var}(\bar{X}) + \mathbb{E}(\bar{X})^2])\end{aligned}$$

Using the results from Proposition 10.2.1, we have

$$\mathbb{E}(S^2) = \frac{n}{n-1} (\sigma^2 + \mu^2 - [\sigma^2/n + \mu^2]) = \frac{n}{n-1} \cdot \frac{(n-1)\sigma^2}{n} = \boxed{\sigma^2}$$

□

Alternative proof from Stats 100B homework.

$$\mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2\right) = \frac{1}{n} \mathbb{E}\left(\sum_{i=1}^n (x_i - \mu)^2\right)$$

Assuming independence of samples, this can be written as

$$\frac{1}{n} \sum_{i=1}^n \mathbb{E}((x_i - \mu)^2) = \frac{1}{n} n\sigma^2 = \boxed{\sigma^2}$$

Since S^2 is unbiased, it is a consistent estimator if we can show $\text{Var}(S^2) \rightarrow 0$ as $n \rightarrow \infty$. We have

$$\text{Var}\left(\frac{(n-1)S^2}{\sigma^2}\right) = 2(n-1)$$

$$\frac{(n-1)^2}{\sigma^4} \text{Var}(S^2) = 2(n-1)$$

$$\text{Var}(S^2) = \frac{2\sigma^4}{n-1}$$

$$\implies \lim_{n \rightarrow \infty} \text{Var}(S^2) = \lim_{n \rightarrow \infty} \frac{2\sigma^4}{n-1} = \boxed{0}$$

Therefore S^2 is a consistent estimator of σ^2 .

□

Proposition 10.2.4 (Example 11.2.6 in Lehmann and Romano [2005]).

$$S^2 \xrightarrow{P} \sigma^2.$$

Proof. By the Weak Law of Large Numbers, $\bar{X}_n \xrightarrow{P} \mu$ and $n^{-1} \sum_{i=1}^n X_i^2 \xrightarrow{P} \mathbb{E}(X_1)^2 = \mu^2 + \sigma^2$. Therefore by one of Slutsky's convergence theorems (Theorem 8.4.11) and the Continuous Mapping Theorem,

$$\frac{1}{n} \sum_{i=1}^n X_i^2 - (\bar{X}_n)^2 \xrightarrow{P} \sigma^2 \iff \frac{n-1}{n} S^2 \xrightarrow{P} \sigma^2 \iff S^2 \xrightarrow{P} \sigma^2.$$

□

Lemma 10.2.5. Let $X := (X_1, \dots, X_n)$ be i.i.d. mean zero, variance 1 Gaussian random variables. Let $v_1, \dots, v_n \in \mathbb{R}^n$. Then $\langle X, v_1 \rangle, \dots, \langle X, v_n \rangle$ are independent if and only if v_1, \dots, v_m are pairwise orthogonal; that is, $\langle v_i, v_j \rangle = 0 \forall 1 \leq i < j \leq m$.

Proof. By Theorem 6.3.20, we have that for any $v \in \mathbb{R}^n$, $\langle X, v \rangle$ is a mean zero Gaussian with variance $\langle v, v \rangle$. For notational convenience, let $\langle X, v_k \rangle = A_k$. Because all the A_k are Gaussian random variables by Theorem 6.3.20, the A_k are uncorrelated if and only if they are independent. That is, we would like to show that their covariances

$$\mathbb{E}[(A_k - \mathbb{E}A_k)(A_\ell - \mathbb{E}A_\ell)]$$

equal zero for all $\{(k, \ell) : k, \ell \in \{1, 2, \dots, m\}, k \neq \ell\}$ if and only if the vectors v_1, \dots, v_m are pairwise orthogonal; that is, $\langle v_k, v_\ell \rangle = 0$ for all $\{(k, \ell) : k, \ell \in \{1, 2, \dots, m\}, k \neq \ell\}$. Note that since $A_k = \sum_{i=1}^n X_i v_{ki}$, $\mathbb{E}(A_k) = \sum_{i=1}^n v_{ki} \mathbb{E}(X_i)$. So for any $\{(k, \ell) : k, \ell \in \{1, 2, \dots, m\}, k \neq \ell\}$ we have

$$\begin{aligned} \mathbb{E}[(A_k - \mathbb{E}A_k)(A_\ell - \mathbb{E}A_\ell)] &= \mathbb{E}\left[\left(\sum_{i=1}^n X_i v_{ki} - \sum_{i=1}^n v_{ki} \mathbb{E}(X_i)\right)\left(\sum_{i=1}^n X_i v_{\ell i} - \sum_{i=1}^n v_{\ell i} \mathbb{E}(X_i)\right)\right] \\ &= \mathbb{E}\left[\left(\sum_{i=1}^n X_i v_{ki}\right)\left(\sum_{i=1}^n X_i v_{\ell i}\right) - \left(\sum_{i=1}^n X_i v_{ki}\right)\left(\sum_{i=1}^n v_{\ell i} \mathbb{E}(X_i)\right) \right. \\ &\quad \left. - \left(\sum_{i=1}^n v_{ki} \mathbb{E}(X_i)\right)\left(\sum_{i=1}^n X_i v_{\ell i}\right) + \left(\sum_{i=1}^n v_{ki} \mathbb{E}(X_i)\right)\left(\sum_{i=1}^n v_{\ell i} \mathbb{E}(X_i)\right)\right] \\ &= \mathbb{E}\left(\sum_{i=1}^n X_i^2 v_{ki} v_{\ell i} + \sum_{\{a,b \in \{1, \dots, n\}, a \neq b\}} X_a X_b v_{ka} v_{\ell b}\right) - 2\mathbb{E}\left(\sum_{i=1}^n X_i \mathbb{E}(X_i) v_{ki} v_{\ell i} + \sum_{\{a,b \in \{1, \dots, n\}, a \neq b\}} X_a \mathbb{E}(X_b) v_{ka} v_{\ell b}\right) \\ &\quad + \mathbb{E}\left(\sum_{i=1}^n \mathbb{E}(X_i)^2 v_{ki} v_{\ell i} + \sum_{\{a,b \in \{1, \dots, n\}, a \neq b\}} \mathbb{E}(X_a) \mathbb{E}(X_b) v_{ka} v_{\ell b}\right) \end{aligned}$$

Recall that $\mathbb{E}(X_i) = 0$ for all i . Also, due to independence of the X_i , all of the terms that involve $\mathbb{E}(X_a X_b)$, $a \neq b$ disappear. This leaves only

$$= \mathbb{E} \left(\sum_{i=1}^n X_i^2 v_{ki} v_{\ell i} \right) = \sum_{i=1}^n \mathbb{E}(X_i^2) v_{ki} v_{\ell i} = \mathbb{E}(X_1^2) \sum_{i=1}^n v_{ki} v_{\ell i} \quad (10.1)$$

where the last step follows from the i.i.d. distributions of X_i . Recall

$$\langle v_k, v_\ell \rangle = 0 \iff \sum_{i=1}^n v_{ki} v_{\ell i} = 0.$$

Since $\mathbb{E}(X_1^2) \neq 0$, (10.1) equals 0 for all $\{(k, \ell) : k, \ell \in \{1, 2, \dots, m\}, k \neq \ell\}$ if and only if $\langle v_k, v_\ell \rangle = 0$ for all $\{(k, \ell) : k, \ell \in \{1, 2, \dots, m\}, k \neq \ell\}$. Therefore the random variables $\langle X, v_1 \rangle, \dots, \langle X, v_m \rangle$ are independent if and only if the vectors v_1, \dots, v_m are pairwise orthogonal.

□

Proposition 10.2.6 (Proposition 4.7 in 541A notes). Let $n \geq 2$ be an integer. Let X_1, \dots, X_n be a random sample from the Gaussian distribution with mean $\mu \in \mathbb{R}$ and variance $\sigma^2 > 0$. Let \bar{X} be the sample mean and let S be the sample standard deviation. Then

- (i) \bar{X} and S are independent random variables.
- (ii) \bar{X} is a Gaussian random variable with mean μ and variance σ^2/n .
- (iii) $(n-1)S^2/\sigma^2$ is a χ^2 -distributed random variable with $n-1$ degrees of freedom.

Proof. (i) Replace X_1, \dots, X_n with $X_1 - \mu, \dots, X_n - \mu$ so that $\mu = 0$. Also divide by σ so that $\sigma = 1$. Note that \bar{X} is independent of all random variables $X_2 - \bar{X}, \dots, X_n - \bar{X}$ by Lemma 10.2.5 because for example

$$X_2 - \bar{X} = \langle X_2, e_2 - \frac{1}{n}(1, 1, \dots, 1) \rangle$$

where the second vector in the inner product is orthogonal to $(1, 1, \dots, 1)$ (in fact, $(1, \dots, 1)$ is orthogonal to anything in the span of these vectors). Likewise for all the remaining vectors you could use to construct X_i . (Note that the other random variables [e.g. $X_2 - \bar{X}$ and $X_3 - \bar{X}$] are not independent.)

So the proof will be complete if we can write S as a function of $X_2 - \bar{X}, \dots, X_n - \bar{X}$. Observe

$$\begin{aligned} (n-1)S^2 &= \sum_{i=1}^n (X_i - \bar{X})^2 = (X_1 - \bar{X})^2 + \sum_{i=2}^n (X_i - \bar{X})^2 = \left(n\bar{X} - \left[\sum_{i=2}^n X_i \right] - \bar{X} \right)^2 + \sum_{i=2}^n (X_i - \bar{X})^2 \\ &= \left(\sum_{i=2}^n (X_i - \bar{X}) \right)^2 + \sum_{i=2}^n (X_i - \bar{X})^2 \end{aligned}$$

(ii) Follows from Proposition 1.45, Example 1.108, and Exercise 1.58 in 541A notes (condense later?)

If $n = 2$, we have

$$\begin{aligned} S^2 &= \frac{1}{2-1} \sum_{i=1}^2 (X_i - \bar{X}_2)^2 = \left(X_1 - \frac{X_1 + X_2}{2} \right)^2 + \left(X_2 - \frac{X_1 + X_2}{2} \right)^2 \\ &= \left(\frac{X_1 - X_2}{2} \right)^2 + \left(\frac{X_2 - X_1}{2} \right)^2 = 2 \cdot \frac{1}{4} \cdot (X_1 - X_2)^2 = \left[\frac{1}{\sqrt{2}} (X_1 - X_2) \right]^2 \end{aligned}$$

Since $\{X_1 - X_2\} \sim \mathcal{N}(0, 2\sigma^2)$, we have

$$\frac{1}{\sqrt{2}\sigma} (X_1 - X_2) \sim \mathcal{N}(0, 1),$$

so

$$\begin{aligned} S^2 &= \frac{1}{\sigma^2} \left[\frac{1}{\sqrt{2}} (X_1 - X_2) \right]^2 \sim \chi_1^2. \\ \frac{(n-1)S^2}{\sigma^2} &= \frac{1}{\sigma^2} \sum_{i=1}^n (X_i - \bar{X}_n)^2 = \frac{1}{\sigma^2} \sum_{i=1}^n (X_i - \bar{X}_n)^2 \end{aligned}$$

Next we will induct on n . Some tedious algebra shows that

$$\frac{nS_{n+1}^2}{\sigma^2} = \frac{n-1}{\sigma^2} S_n^2 + \frac{1}{\sigma^2} \frac{n}{n+1} (X_{n+1} - \bar{X}_n)^2, \quad \forall n \geq 2,$$

where S_n^2 is the sample variance for n independent Gaussian random variables. It can also be shown through simple algebra that

$$\{(X_{n+1} - \bar{X}_n)\} \sim \mathcal{N}(0, \sigma^2(n+1)/n),$$

so

$$\frac{1}{\sigma^2} \frac{n}{n+1} (X_{n+1} - \bar{X}_n)^2 \sim \chi_1^2.$$

It can be shown by first principles (i.e., without Basu's Theorem) that $\bar{X}_n \perp\!\!\!\perp S_n^2$, and clearly $X_{n+1} \perp\!\!\!\perp S^2$. Therefore we have shown that if $(n-1)S_n^2/\sigma^2 \sim \chi_{n-1}^2$, it follows that $nS_{n+1}^2/\sigma^2 \sim \chi_n^2$, concluding the proof that

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2.$$

To show that S^2 is ancillary for μ , simply observe that

$$S^2 \sim \frac{\sigma^2}{n-1} \chi_{n-1}^2;$$

that is, the distribution of S^2 depends only on n and σ^2 , not μ . Therefore by definition S^2 is ancillary for μ .

- (iii) Like above, replace X_1, \dots, X_n with $X_1 - \mu, \dots, X_n - \mu$ so that $\mu = 0$. Also divide by σ so that $\sigma = 1$. We will prove by induction. Let $\bar{X}_n := \frac{1}{n} \sum_{i=1}^n X_i$ and let $S_n^2 := \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2$. In the case $n = 2$ we have

$$\begin{aligned} S_2^2 &= \left(X_1 - \frac{1}{2}(X_1 + X_2) \right)^2 + \left(X_2 - \frac{1}{2}(X_1 + X_2) \right)^2 = \frac{1}{4}(X_2 - X_1)^2 + \frac{1}{4}(X_2 - X_1)^2 = \frac{1}{2}(X_2 - X_1)^2 \\ &= \left(\frac{1}{\sqrt{2}}(X_2 - X_1) \right)^2 \end{aligned}$$

Note that $1/\sqrt{2}(X_2 - X_1)$ is a mean zero Gaussian random variable with variance 1 (see example 1.108 in 541A notes for details). So S_2^2 is χ_1^2 by Definition 1.33 in 541A notes.

We now induct on n . From Lemma 4.8 in 541A notes (will prove later),

$$nS_{n+1}^2 = (n-1)S_n^2 + \frac{n}{n+1}(X_{n+1} - \bar{X}_n)^2, \quad \forall n \geq 2$$

From the first item, S_n is independent of \bar{X}_n . Also, X_{n+1} is independent of S_n by Proposition 1.61 in Math 541A notes, since S_n is a function of X_1, \dots, X_n , which are independent of X_{n+1} . So S_n is independent of $(X_{n+1} - \bar{X}_n)^2$. By the inductive hypothesis, $(n-1)S_n^2$ is a χ_{n-1}^2 random variable. From Example 1.108 in Math 541A notes, $X_{n+1} - \bar{X}_n$ is a Gaussian random variable with mean zero and variance $1 + 1/n = (n+1)/n$ so that $\sqrt{n/(n+1)}(X_{n+1} - \bar{X}_n)$ is a mean zero Gaussian with variance 1, implying $n/(n+1)(X_{n+1} - \bar{X}_n)^2$ is χ^2 . Definition 1.33 in 541A notes then implies that nS_{n+1} is a χ_n^2 random variable, completing the inductive step.

□

Lemma 10.2.7 (Lemma 4.8 in 541A notes.).

Let X_1, X_2, \dots be random variables. For any $n \geq 2$, let $\bar{X}_n := (1/n) \sum_{i=1}^n X_i$ and let $S_n^2 := 1/(n-1) \sum_{i=1}^n (X_i - \bar{X}_n)^2$. Then

$$nS_{n+1}^2 - (n-1)S_n^2 = \frac{n}{n+1}(X_{n+1} - \bar{X}_n)^2.$$

Proof.

$$nS_{n+1}^2 - (n-1)S_n^2 = \sum_{i=1}^{n+1} (X_i - \bar{X}_{n+1})^2 - \sum_{i=1}^n (X_i - \bar{X}_n)^2$$

Note:

$$(a-b)^2 - (a-c)^2 = a^2 - 2ab + b^2 - a^2 - c^2 + 2ac = b^2 - c^2 + 2a(c-b)$$

$$= (b-c)[(b+c) - 2a] = (b-c)(b+c-2a)$$

for all real a, b, c . Using $a = X_n, b = \bar{X}_{n+1}, c = \bar{X}_n$ we have

$$\begin{aligned}
&= (X_{n+1} - \bar{X}_{n+1})^2 + \sum_{i=1}^n (\bar{X}_{n+1} - \bar{X}_n)(\bar{X}_{n+1} + \bar{X}_n - 2X_i) \\
&= (X_{n+1} - \bar{X}_{n+1})^2 + (\bar{X}_{n+1} - \bar{X}_n) \sum_{i=1}^n (\bar{X}_{n+1} + \bar{X}_n - 2X_i) \\
&= (X_{n+1} - \bar{X}_{n+1})^2 + (\bar{X}_{n+1} - \bar{X}_n) \cdot n(\bar{X}_{n+1} + \bar{X}_n - 2\bar{X}_n) \\
&= (X_{n+1}(1 - 1/(n+1)) - \frac{n}{n+1}\bar{X}_n)^2 + n(\bar{X}_{n+1} - \bar{X}_n)^2 \\
&= \frac{n^2}{(n+1)^2}(X_{n+1} - \bar{X}_n)^2 + n(\frac{X_{n+1}}{n+1} + (\frac{1}{n+1} - \frac{1}{n})\sum_{i=1}^n X_i)^2
\end{aligned}$$

Algebra: $1/(n+1) - 1/n = \frac{n-(n+1)}{n(n+1)} = -\frac{1}{n(n+1)}$. So we have

$$\begin{aligned}
&= \frac{n^2}{(n+1)^2}(X_{n+1} - \bar{X}_n)^2 + \frac{n}{(n+1)^2}(X_{n+1} - \frac{1}{n}\sum_{i=1}^n X_i)^2 \\
&= \frac{n^2}{(n+1)^2}(X_{n+1} - \bar{X}_n)^2 + \frac{n}{(n+1)^2}(X_{n+1} - \bar{X}_n)^2 \\
&= \frac{n^2+n}{(n+1)^2}(X_{n+1} - \bar{X}_n)^2 = \frac{n}{n+1}(X_{n+1} - \bar{X}_n)^2
\end{aligned}$$

□

Proposition 10.2.8 (Proposition 4.9 in 541A notes). Let X be a standard Gaussian random variable. Let Y be a χ_p^2 random variable. Assume that X and Y are independent. Then $X/\sqrt{Y/p}$ has the following density, known as **Student's t-distribution** with p = degrees of freedom: ($p = n + 1$?)

$$f_{X/(Y/\sqrt{p})}(t) := \frac{\Gamma((p+1)/2)}{\sqrt{p}\sqrt{\pi}\Gamma(p/2)} \left(1 + \frac{t^2}{p}\right)^{-(p+1)/2}, \quad \forall t \in \mathbb{R}$$

(should have $p + 1$ in a bunch of the expressions above? that's what was written on board, not in notes.)

Proof. Let $Z := \sqrt{Y/p}$. We find the density of Z as follows. Let $t > 0$. Then

$$f_Z(y) = \frac{d}{dy} \Big|_{y=0} \Pr(Z \leq y) = \frac{d}{dy} \Big|_{y=0} \Pr(Y \leq y^2 p)$$

$$\begin{aligned}
&= \frac{d}{dy} \Big|_{y=0} \int_0^{y^2 p} \frac{x^{(p/2)-1} e^{-x/2}}{2^{p/2} \Gamma(p/2)} dx = 2yp \cdot p^{(p/2)-1} y^{p-2} e^{-y^2 p/2} \cdot \frac{1}{2^{p/2} \Gamma(p/2)} \\
&= p^{p/2} y^{p-1} e^{-y^2 p/2} \cdot \frac{1}{2^{p/2-1} \Gamma(p/2)}
\end{aligned}$$

⋮ skipped this stuff in class proof

$$\Pr(X/Z \leq t) = \Pr(X \leq tZ)$$

$$= \text{(by definition of joint density)} \int \int_{\{(x,y) \in \mathbb{R}^2 : x \leq ty\}} f_X(x) f_Z(y) dx dy$$

We use the change of variables formula:

$$\int \int_{\phi(U)} f(x, y) dx dy = \int \int_U f(\phi(a, b)) |\text{Jac } \phi(a, b)| da db$$

$$\phi : \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

$$\phi(a, b) = (ab, a)$$

$$\phi^{-1}(x, y) = (y, x/y)$$

We chose x/y as the second variable so that an upper limit of the variable will end up being t after the transformation. We need the Jacobian of ϕ :

$$|\text{Jac } \phi(a, b)| = \left| \det \begin{pmatrix} b & a \\ 1 & 0 \end{pmatrix} \right| = |a|$$

By the change in variables formula,

$$\begin{aligned}
&\int \int_{\phi(U)} f(x, y) dx dy = \int \int_U f(\phi(a, b)) |\text{Jac } \phi(a, b)| da db \\
&= \int \int_{\{(a,b) \in \mathbb{R}^2 : a \geq 0, b \leq t\}} f_X(ab) f_Z(a) |a| da db \\
&\implies \Pr(X/Z \leq t) = \int_{-\infty}^t \int_0^\infty |a| f_X(ab) f_Z(a) da db
\end{aligned}$$

By the Fundamental Theorem of Calculus,

$$f_{X/Z}(t) = \frac{d}{dt} \Pr(X/Z \leq t) = \int_0^\infty |a| f_X(at) f_Z(a) da = \int_0^\infty a f_X(at) f_Z(a) da$$

By the definitions of X and Z ,

$$\begin{aligned} &= \frac{1}{2^{-p/2-1}\Gamma(p/2)} \int_0^\infty a \cdot \frac{1}{\sqrt{2\pi}} e^{-(a^2 t^2)/2} \cdot p^{p/2} a^{p-1} e^{-a^2 p/2} da \\ &= \frac{p^{p/2}}{2^{-p/2-1}\Gamma(p/2)\sqrt{2\pi}} \int_0^\infty e^{-[a^2(t^2+p)]/2} \cdot a^p da \end{aligned}$$

Change of variables: let $x = a^2$, $dx = 2ada$, $da = \frac{1}{2a}dx = 1/(2\sqrt{x})dx$. Then this integral is

$$= c \int_0^\infty e^{-[x(t^2+p)]/2} \cdot x^{p/2-1/2} da, \quad \text{where } c = \frac{p^{p/2}}{2^{p/2}\sqrt{2\pi}\Gamma(p/2)}$$

So the integrand is a Gamma density function with parameters α, β : $\alpha - 1 = p/2 - 1/2 \iff \alpha = p/2 + 1/2$, $\beta = 2/(t^2 + p)$. So if we multiply and divide $\beta^\alpha \Gamma(\alpha)$

So

$$\begin{aligned} f_{X/Z}(t) &= \frac{p^{p/2}}{2^{p/2}\sqrt{2\pi}\Gamma(p/2)} \cdot \beta^\alpha \Gamma(\alpha) \cdot 1 = \frac{p^{p/2}\Gamma((p_1)/2)}{2^{p/2}\sqrt{2\pi}\Gamma(p/2)} \cdot \left(\frac{2}{t^2 + p}\right)^{(p-1)/2} \\ &= \frac{p^{p/2}\Gamma((p+1)/2)}{\sqrt{\pi}\Gamma(p/2)} \cdot (t^2 + p)^{-(p+1)/2} = \frac{\Gamma((p+1)/2)}{\sqrt{\pi p}\Gamma(p/2)} \cdot (1 + t^2/p)^{-(p+1)/2} \end{aligned}$$

□

Remark 108 (Remark 4.10 in 541A notes). If X_1, \dots, X_n is a random sample from a Gaussian distribution with mean $\mu \in \mathbb{R}$, standard deviation $\sigma < 0$, then

$$\frac{\bar{X} - \mu}{S/\sqrt{n}}$$

also has Student's t distribution. ($\bar{X} := n^{-1} \sum_{i=1}^n X_i$, $S = \sqrt{(n-1)^{n-1} \sum_{i=1}^n (X_i - \bar{X})^2}$.)

Proposition 10.2.9 (Stats 100B homework 3 problem). Let X_1, X_2 be a random sample from a normal distribution with a mean μ and standard deviation σ . Then $(n-1)s^2/\sigma^2$ has a χ_1^2 distribution.

Proof.

$$\begin{aligned}
s^2 &= \frac{1}{2-1} \sum_{i=1}^2 (X_i - \bar{X})^2 = (X_1 - \bar{X})^2 + (X_2 - \bar{X})^2 = (X_1 - \frac{X_1 + X_2}{2})^2 + (X_2 - \frac{X_1 + X_2}{2})^2 \\
&= X_1^2 - 2X_1(\frac{X_1 + X_2}{2}) + (\frac{X_1 + X_2}{2})^2 + X_2^2 - 2X_2(\frac{X_1 + X_2}{2}) + (\frac{X_1 + X_2}{2})^2 \\
&= X_1^2 + X_2^2 - X_1(X_1 + X_2) - X_2(X_1 + X_2) + 2(\frac{X_1 + X_2}{2})^2 \\
&= X_1^2 + X_2^2 - (X_1 + X_2)(X_1 + X_2) + \frac{(X_1 + X_2)^2}{2} \\
&= \frac{1}{2}(2X_1^2 + 2X_2^2) - \frac{1}{2}(X_1^2 + 2X_1X_2 + X_2^2) \\
&= \frac{1}{2}(X_1^2 - 2X_1X_2 + X_2^2)
\end{aligned}$$

$$s^2 = \frac{1}{2}(X_1 - X_2)^2$$

$$\implies \frac{(n-1)s^2}{\sigma^2} = (2-1)\frac{1}{2\sigma^2}(X_1 - X_2)^2 = \left(\frac{X_1 - X_2}{\sigma\sqrt{2}}\right)^2$$

Since X_1 and X_2 are normal,

$$X_1 - X_2 \sim \mathcal{N}(\mu - \mu, \sqrt{\sigma^2 + \sigma^2}) = \mathcal{N}(0, \sigma\sqrt{2}) \implies \frac{X_1 - X_2}{\sigma\sqrt{2}} \sim \mathcal{N}(0, 1)$$

$$\implies \left(\frac{X_1 - X_2}{\sigma\sqrt{2}}\right)^2 = \frac{(n-1)s^2}{\sigma^2} \sim \chi_1^2$$

□

Proposition 10.2.10 (Stats 100B homework problem). Suppose two independent random samples of n_1 and n_2 observations are selected from two normal populations. Further, assume that the populations possess a common variance σ^2 which is unknown. Let the sample variances be S_1^2 and S_2^2 and assume they are unbiased. Then the pooled estimator for σ^2

$$S^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$$

is unbiased and has variance $\frac{2\sigma^4}{n_1+n_2-2}$.

Proof. First we show S^2 is unbiased.

$$\begin{aligned}\mathbb{E}(S^2) &= \mathbb{E}\left(\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}\right) = \frac{n_1 - 1}{n_1 + n_2 - 2}\mathbb{E}(S_1^2) + \frac{n_2 - 1}{n_1 + n_2 - 2}\mathbb{E}(S_2^2) \\ &= \frac{n_1 - 1}{n_1 + n_2 - 2}\sigma^2 + \frac{n_2 - 1}{n_1 + n_2 - 2}\sigma^2 = \frac{(n_1 + n_2 - 2)\sigma^2}{n_1 + n_2 - 2} = \boxed{\sigma^2}\end{aligned}$$

Now we derive its variance.

$$\text{Var}(S^2) = \text{Var}\left(\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}\right)$$

Since S_1 and S_2 are independent, this can be written as

$$\frac{1}{(n_1 + n_2 - 2)^2} \left(\text{Var}[(n_1 - 1)S_1^2] + \text{Var}[(n_2 - 1)S_2^2] \right)$$

Since the populations are normal, we know

$$\begin{aligned}\frac{(n_i - 1)S_i^2}{\sigma^2} &\sim \chi_{n_i - 1}^2 \implies \text{Var}\left(\frac{(n_i - 1)S_i^2}{\sigma^2}\right) = 2(n_i - 1) \\ \text{Var}(S^2) &= \frac{\sigma^4}{(n_1 + n_2 - 2)^2} \left(\text{Var}\left[\frac{(n_1 - 1)S_1^2}{\sigma^2}\right] + \text{Var}\left[\frac{(n_2 - 1)S_2^2}{\sigma^2}\right] \right) \\ &= \frac{\sigma^4}{(n_1 + n_2 - 2)^2} (2(n_1 - 1) + 2(n_2 - 1)) = \sigma^4 \frac{2(n_1 + n_2 - 2)}{(n_1 + n_2 - 2)^2} \\ &= \frac{2\sigma^4}{n_1 + n_2 - 2}\end{aligned}$$

□

Proposition 10.2.11 (Stats 100B Homework problem). Suppose that X_1, \dots, X_m and Y_1, \dots, Y_n are two samples, with $X \sim \mathcal{N}(\mu_1, \sigma_1)$ and $Y \sim \mathcal{N}(\mu_2, \sigma_2)$. The difference between the sample means, $\bar{X} - \bar{Y}$, is then a linear combination of $m + n$ normal random variables.

- a. $\mathbb{E}(\bar{X} - \bar{Y})$.
- b. $\text{Var}(\bar{X} - \bar{Y})$
- c. The distribution of $\bar{X} - \bar{Y}$ is normal.

Proof. a.

$$\begin{aligned}\bar{X} &= \frac{1}{m} \sum_{i=1}^m X_i, \quad \bar{Y} = \frac{1}{n} \sum_{j=1}^n Y_j \\ \mathbb{E}(\bar{X} - \bar{Y}) &= \mathbb{E}\left(\frac{1}{m} \sum_{i=1}^m X_i - \frac{1}{n} \sum_{j=1}^n Y_j\right) = \frac{1}{m} \mathbb{E}\left(\sum_{i=1}^m X_i\right) - \frac{1}{n} \mathbb{E}\left(\sum_{j=1}^n Y_j\right) \\ &= \frac{1}{m} \sum_{i=1}^m \mathbb{E}(X_i) - \frac{1}{n} \sum_{j=1}^n \mathbb{E}(Y_j) = \frac{1}{m} \sum_{i=1}^m \mu_1 - \frac{1}{n} \sum_{j=1}^n \mu_2 = \frac{1}{m} m \cdot \mu_1 - \frac{1}{n} n \cdot \mu_2 \\ \boxed{\mathbb{E}(\bar{X} - \bar{Y}) = \mu_1 - \mu_2}\end{aligned}$$

b. Since X and Y are independent,

$$\begin{aligned}\text{Var}(\bar{X} - \bar{Y}) &= \text{Var}(\bar{X}) + \text{Var}(\bar{Y}) \\ &= \mathbb{E}[(\bar{X} - \mathbb{E}[\bar{X}])^2] + \mathbb{E}[(\bar{Y} - \mathbb{E}[\bar{Y}])^2] \\ &= \mathbb{E}\left(\frac{1}{m} \sum_{i=1}^m X_i - \mu_1\right)^2 + \mathbb{E}\left(\frac{1}{n} \sum_{j=1}^n Y_j - \mu_2\right)^2 \\ &= \mathbb{E}\left(\frac{1}{m} \sum_{i=1}^m (X_i - m \frac{1}{m} \mu_1)\right)^2 + \mathbb{E}\left(\frac{1}{n} \sum_{j=1}^n (Y_j - n \frac{1}{n} \mu_2)\right)^2 \\ &= \frac{1}{m^2} \mathbb{E}\left(\sum_{i=1}^m (X_i - \mu_1)\right)^2 + \frac{1}{n^2} \mathbb{E}\left(\sum_{j=1}^n (Y_j - \mu_2)\right)^2\end{aligned}$$

Since X_i and X_j are independent for $i \neq j$ (and likewise for Y), $\text{Cov}(X_i, X_j) = 0$ for $i \neq j$, so

$$\mathbb{E}[(X_i - \mu_1)(X_j - \mu_1)] = 0$$

for $i \neq j$ (and likewise for Y). Therefore the above equation can be written as

$$\begin{aligned}&\frac{1}{m^2} \mathbb{E}\left(\sum_{i=1}^m (X_i - \mu_1)^2\right) + \frac{1}{n^2} \mathbb{E}\left(\sum_{j=1}^n (Y_j - \mu_2)^2\right) \\ &\frac{1}{m^2} \sum_{i=1}^m \mathbb{E}(X_i - \mu_1)^2 + \frac{1}{n^2} \sum_{j=1}^n \mathbb{E}(Y_j - \mu_2)^2 \\ &= \frac{1}{m^2} \left(\sum_{i=1}^m \sigma_1^2\right) + \frac{1}{n^2} \left(\sum_{j=1}^n \sigma_2^2\right) = \frac{1}{m^2} m \cdot \sigma_1^2 + \frac{1}{n^2} n \cdot \sigma_2^2\end{aligned}$$

$$\boxed{\text{Var}(\bar{X} - \bar{Y}) = \frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}}$$

c.

$$M_{X_i}(t) = \exp\left(\mu_1 t + \frac{t^2 \sigma_1^2}{2}\right), \quad M_{Y_i}(t) = \exp\left(\mu_2 t + \frac{t^2 \sigma_2^2}{2}\right)$$

Since individual observations from X and Y are independent,

$$M_{\bar{X}}(t) = \prod_{i=1}^m M_{X_i}\left(\frac{1}{m}t\right), \quad M_{\bar{Y}}(t) = \prod_{j=1}^n M_{Y_j}\left(\frac{1}{n}t\right)$$

and

$$\begin{aligned} M_{\bar{X}-\bar{Y}}(t) &= M_{\bar{X}}(t)M_{-\bar{Y}}(t) = M_{\bar{X}}(t)M_{\bar{Y}}(-t) = \prod_{i=1}^m M_{X_i}\left(\frac{1}{m}t\right) \prod_{j=1}^n M_{Y_j}\left(\frac{-1}{n}t\right) \\ &= \left[M_{X_i}\left(\frac{t}{m}\right)\right]^m \left[M_{Y_j}\left(\frac{-t}{n}\right)\right]^n = \left[\exp\left(\frac{\mu_1 t}{m} + \frac{t^2 \sigma_1^2}{2m^2}\right)\right]^m \left[\exp\left(\frac{-\mu_2 t}{n} + \frac{(-t)^2 \sigma_2^2}{2n^2}\right)\right]^n \\ &= \exp\left(\frac{m\mu_1 t}{m} + \frac{mt^2 \sigma_1^2}{2m^2}\right) \exp\left(\frac{-n\mu_2 t}{n} + \frac{nt^2 \sigma_2^2}{2n^2}\right) \\ \implies M_{\bar{X}-\bar{Y}}(t) &= \exp\left[(\mu_1 - \mu_2)t + \frac{1}{2}t^2\left(\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}\right)\right] \end{aligned}$$

This is the moment generating function of a normal distribution with mean $\mu_1 - \mu_2$ and variance $\frac{\sigma_1^2}{m} + \frac{\sigma_2^2}{n}$, consistent with the results from parts (a) and (b).

□

10.2.1 The Delta Method

Theorem 10.2.12 (Delta Method, Theorem 4.14 in 541A notes, 5.5.24 in Casella and Berger [2001],). Let $\theta \in \mathbb{R}$. Let Y_1, Y_2, \dots be random variables such that $\sqrt{n}(Y_n - \theta)$ converges in distribution to a mean zero Gaussian random variable with variance $\sigma^2 > 0$. Let $f : \mathbb{R} \rightarrow \mathbb{R}$. Assume that f' exists and is continuous, and $f'(\theta) \neq 0$. Then

$$\sqrt{n}(f(Y_n) - f(\theta)) \xrightarrow{d} \mathcal{N}(0, \sigma^2(f'(\theta))^2).$$

Proof from new class notes. Since $f'(\theta)$ exists, we have that for all $y \in \mathbb{R}$,

$$f(y) = f(\theta) + f'(\theta)(y - \theta) + R(y - \theta),$$

where $R(y) = o(|y|)$ as $|y| \rightarrow 0$. In particular,

$$\sqrt{n}[f(Y_n) - f(\theta)] = \underbrace{f'(\theta)}_{(\text{constant})} \underbrace{\sqrt{n}(Y_n - \theta)}_{\implies \mathcal{N}(0, \sigma^2)} + \underbrace{\sqrt{n}R(Y_n - \theta)}_{?}. \quad (10.2)$$

where we note that $\sqrt{n}(Y_n - \theta) \xrightarrow{d} \mathcal{N}(0, \sigma^2)$ by assumption. Since it is multiplied by $f'(\theta) \in \mathbb{R}$, the product of these two terms converges to $\mathcal{N}(0, \sigma^2[f'(\theta)]^2)$ by Slutsky's Theorem (Theorem 8.4.11(b)). We seek

to show what happens to the third term of (10.2) as $n \rightarrow \infty$ (the result follows if the term converges in probability to 0). Note that for any $n \geq 1$ and for any $s, t > 0$,

$$\begin{aligned} \Pr(\sqrt{n}|R(Y_n - \theta)| > t) &= \Pr\left(\sqrt{n}|R(Y_n - \theta)| > t \cap |Y_n - \theta| > \frac{st}{\sqrt{n}}\right) \\ &\quad + \Pr\left(\sqrt{n}|R(Y_n - \theta)| > t \cap |Y_n - \theta| \leq \frac{st}{\sqrt{n}}\right) \\ &\leq \Pr(|Y_n - \theta| > st/\sqrt{n}) + \Pr(\sqrt{n}|R(Y_n - \theta)| > t \cap |Y_n - \theta| \leq st/\sqrt{n}). \end{aligned} \quad (10.3)$$

Since we already have by assumption $\sqrt{n}(Y_n - \theta) \xrightarrow{d} \mathcal{N}(0, \sigma^2)$, it follows that as $n \rightarrow \infty$, the first term goes to

$$2 \int_{st}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy.$$

$|Y_n - \theta| \xrightarrow{p} 0$. (For completeness, a detailed argument is included in the below lemma.) It then follows that the second term converges in probability to 0 if $\lim_{n \rightarrow \infty} \Pr(|Y_n - \theta| > t/\sqrt{n}) = 0$ because $\lim_{z \rightarrow 0} h(z)/z = 0$. Therefore for any $t > 0$,

$$\lim_{n \rightarrow \infty} \Pr(\sqrt{n}|h(Y_n - \theta)| > t) = 0 \iff \sqrt{n}|h(Y_n - \theta)| \xrightarrow{p} 0$$

which yields the result by (10.2).

□

Theorem 10.2.13 (Delta Method (GSBA 604 presentation, p. 15 of MLE notes)). Let X, Y be two random variables with $Y = H(X)$ where H is smooth. Suppose $\mathbb{E}(X) = \mu$ and $\text{Var}(X) = \sigma^2$. Then $\mathbb{E}(Y) = H(\mu)$ and $\text{Var}(Y) = [H'(\mu)]^2\sigma^2$. When $x = \hat{\mu}_{MLE}$ and $Y = \hat{\Xi}$,

$$\text{Var}_\eta(\hat{\xi}) = \frac{\left[\frac{d}{d\eta}h(\eta)\right]^2}{n\text{Var}_\eta(\hat{\xi})}.$$

Remark 109. Note that this follows from the Delta Method (Theorem 10.2.12) and functional equivariance of the MLE (Proposition 10.4.15).

Lemma 10.2.14. Under the same assumptions and notation as in Theorem 10.2.12,

$$\lim_{n \rightarrow \infty} \Pr(|Y_n - \theta| > t/\sqrt{n}) = 0$$

Proof. We will examine the behavior of the right side of (10.3) as $n \rightarrow \infty$ by looking at the first term and showing that $Y_n - \theta$ converges in probability to 0. If $t > 0$, then $\Pr(|Y_n - \theta| > t) = \Pr(\sqrt{n}|Y_n - \theta| > t\sqrt{n})$, and if $c > 0$ is a constant, then for sufficiently large n , the last quantity is at most $\Pr(\sqrt{n}|Y_n - \theta| > c)$. So we have

$$\Pr(|Y_n - \theta| > t) = \Pr(\sqrt{n}|Y_n - \theta| > t\sqrt{n}) \leq \Pr(\sqrt{n}|Y_n - \theta| > c)$$

But as $n \rightarrow \infty$, c can be any constant (arbitrarily large). So

$$\lim_{n \rightarrow \infty} \Pr(\sqrt{n}|Y_n - \theta| > t) \leq \int_c^{\infty} e^{-y^2/2} \frac{1}{\sqrt{2\pi}} dy.$$

Therefore

$$\lim_{n \rightarrow \infty} \Pr(|Y_n - \theta| > t/\sqrt{n}) = 0.$$

□

Theorem 10.2.15 (Convergence Theorem with Bounded Moment, Theorem 4.16 in 541A notes.).

Let X_1, X_2, \dots be random variables that converge in distribution to a random variable X . Assume $\exists \epsilon > 0, c < \infty$ such that $\mathbb{E}(|X_n|^{1+\epsilon}) \leq c, \forall n \geq 1$. Then

$$\mathbb{E}(X) = \lim_{n \rightarrow \infty} \mathbb{E}(X_n).$$

Proof. In Heilman's Graduate Probability Notes, Theorem 1.59 and Exercise 3.8(iii).

□

If $f'(\theta) = 0$ in the Delta Method, we can instead use a second order Taylor expansion as follows.

Theorem 10.2.16 (Second Order Delta Method, Theorem 4.17 in Math 541A Notes.). Let $\theta \in \mathbb{R}$. Let Y_1, Y_2, \dots be random variables such that $\sqrt{n}(Y_n - \theta)$ converges in distribution to a mean zero Gaussian random variable with variance $\sigma^2 > 0$. Let $f : \mathbb{R} \rightarrow \mathbb{R}$. Assume that f'' exists and is continuous, $f'(\theta) = 0$ and $f''(\theta) \neq 0$. Then

$$n(f(Y_n) - f(\theta))$$

converges in distribution to a χ_1^2 random variable multiplied by $\sigma^2 \frac{1}{2}|f''(\theta)|$ as $n \rightarrow \infty$.

Proof. Using a second order Taylor expansion of f , there exists a random Z_n between θ and Y_n such that

$$f(Y_n) = f(\theta) + f'(\theta)(Y_n - \theta) + \frac{1}{2}f''(Z_n)(Y_n - \theta)^2 = f(\theta) + \frac{1}{2}f''(Z_n)(Y_n - \theta)^2 \quad (10.4)$$

where the second equality follows because $f'(\theta) = 0$. As in the proof of Theorem 10.2.12, $Z_n \xrightarrow{p} \theta$. Since f'' is continuous, $f''(Z_n)$ converges in probability to $f''(\theta)$ by Proposition 2.36 in the Math 541A notes (Theorem 8.4.13, continuous functions conserve convergence in probability). Therefore using (10.4),

$$n(f(Y_n) - f(\theta)) = \frac{1}{2}f''(Z_n) \cdot n(Y_n - \theta)^2$$

Note that $\sqrt{n}(Y_n - \theta)$ converges in distribution to a mean zero Gaussian random variable by assumption, so $n(Y_n - \theta)^2$ converges in distribution to a χ_1^2 random variable by Proposition 2.36 in the Math 541A notes (Theorem 8.4.13). So since $f''(Z_n)$ converges in probability to a constant, by Proposition 2.36 in the Math 541A notes (Slutsky's Theorem, Theorem 8.4.11), the right side converges in probability to $\frac{1}{2}f''(\theta)\sigma^2$ multiplied by a χ_1^2 random variable.

□

10.2.2 Simulation of Random Variables

Proposition 10.2.17. If $X : \Omega \rightarrow \mathbb{R}$ is an arbitrary random variable with cumulative distribution function $F : \mathbb{R} \rightarrow [0, 1]$, then the function F^{-1} (if it exists) is a random variable on $[0, 1]$ with the uniform probability law on $(0, 1)$ that is equal in distribution to X .

Proof. Starting with the cdf of $F^{-1}(u)$,

$$\Pr(s \in [0, 1] : F^{-1}(s) \leq t) = \Pr(s \in [0, 1] : F(t) > s) = F(t) = \Pr(\omega \in \Omega : X(\omega) \leq t)$$

where the third equality uses the definition of a uniform probability law on $(0, 1)$. □

Remark 110. If F^{-1} does not exist, it can still work if you construct a generalized inverse of F as follows:

Proposition 10.2.18 (Exercise 4.20 in Math 541A notes). Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable on a sample space Ω equipped with a probability law \mathbb{P} . For any $t \in \mathbb{R}$ let $F(t) := \mathbb{P}(X \leq t)$. For any $s \in (0, 1)$ define

$$Y(s) := \sup\{t \in \mathbb{R} : F(t) < s\}.$$

So Y is a random variable on $(0, 1)$ with the uniform probability law on $(0, 1)$. Then X and Y are equal in distribution. That is, $\mathbb{P}(Y \leq t) = F(t)$ for all $t \in \mathbb{R}$.

Proof. Note that since F is a cumulative distribution function, F is nondecreasing and F is right-continuous. So we have

$$\sup\{t \in \mathbb{R} : F(t) < s\} = \begin{cases} F^{-1}(s) & \text{if } F \text{ is strictly increasing (i.e. invertible) near } s \\ \inf\{x : F(x) = F(s)\} & \text{if } F \text{ is constant near } s \end{cases}$$

That is, the only time this quantity is different from $F^{-1}(s)$ is when $F^{-1}(\cdot)$ is undefined because F is constant on some interval around s . But if that is the case, $F(\sup\{t \in \mathbb{R} : F(t) < s\}) = F(\inf\{x : F(x) = F(s)\}) = s$ anyway. With that in mind we proceed:

$$\begin{aligned} \mathbb{P}(Y \leq t) &= \mathbb{P}(s \in (0, 1) : Y(s) \leq t) = \mathbb{P}(s \in (0, 1) : \sup\{t' \in \mathbb{R} : F(t') < s\} \leq t) \\ &= \mathbb{P}(s \in (0, 1) : F(\sup\{t' \in \mathbb{R} : F(t') < s\}) \leq F(t)) = \mathbb{P}(s \in (0, 1) : s \leq F(t)) \\ &= \mathbb{P}(s \in (0, 1) : F(t) > s) = F(t) = \Pr(\omega \in \Omega : X(\omega) \leq t). \end{aligned}$$
□

Example 10.1 (Example 4.22 in Math 541A notes). Let X be an exponential random variable with parameter 1.

$$\Pr(X \leq t) = \int_0^t e^{-x} dx = [-e^{-x}]_0^t = 1 - e^{-t} = F(t)$$

We seek $F^{-1}(t)$:

$$1 - e^{-y} = t \iff e^{-y} = 1 - t \iff -y = \log(1 - t) \iff y = -\log(1 - t) \implies F^{-1}(t) = -\log(1 - t)$$

So to simulate an exponential random variable with parameter 1, sample $-\log(1 - U)$ where $U \sim \text{U}(0, 1)$.

Remark 111. What if the cdf is hard to compute? For example, in a Gaussian distribution:

$$F(t) = \int_{-\infty}^t (2\pi)^{-1/2} \exp(-x^2/2) dx.$$

F^{-1} cannot be described using elementary formulas, so $F^{-1}(u)$ is not the best way to simulate a Gaussian random variable. When using the Central Limit Theorem approach (see 541A notes for details), Edgeworth expansion says: if we replace U_1, \dots, U_n with i.i.d. X_1, \dots, X_n and the first m moments of X_1 agree with the first m moments of Gaussian random variables, then the error in the CLT approximation to a Gaussian is $n^{-(m-1)/2}$. (See https://en.wikipedia.org/wiki/Edgeworth_series.) But this is still inefficient, because one Gaussian sample requires n uniform samples.

Proposition 10.2.19 (Box-Muller Algorithm). Let U_1, U_2 be independent random variable distributed in $(0, 1)$. Define

$$R := \sqrt{-2 \log(U_1)}$$

this density is something like $e^{-x^2/2}$

$$\Psi := 2\pi U_2$$

$$X := R \cos(\Psi), \quad Y := R \sin(\Psi)$$

Then X, Y are independent standard Gaussian random variables.

Proof. Homework problem.

□

10.3 Data Reduction

Suppose we have some data and an exponential family. We would like to find the parameter θ among the exponential family that fits the data well. Suppose we have a large data set, maybe so large that you can't store all the data in RAM at once. What is the "least memory" or "most efficient" method for finding θ ? The answer: try to find a statistic that captures all the relevant information about θ . For example, to find the mean of a Gaussian sample, use the sample mean. You don't have to store all the raw data, you can just store the sample mean. The following is a generalization of this concept:

10.3.1 Sufficient Statistics

Definition 10.8 (Sufficient Statistic; definition 5.1 in Math 541A notes). Suppose X_1, \dots, X_n is a sample of size n from a distribution f where $f \in \{f_\theta : \theta \in \Theta\}$ is a family of distributions (such as an exponential family). Let $g : \mathbb{R}^n \rightarrow \mathbb{R}^k$ so that $Y := g(X_1, \dots, X_n)$ is a statistic. We say that Y is a **sufficient statistic** for θ if for every $y \in \mathbb{R}^k$ and for every $\theta \in \Theta$, the conditional distribution of (X_1, \dots, X_n) given $Y = y$ (with respect to probabilities given by f_θ) does not depend on θ . That is, Y provides sufficient information to determine θ from X_1, \dots, X_n .

Remark 112. Based on a comment Heilman made on class, this definition assumes independence of the random variables? Basically everything in this class does?

Definition 10.9 (Sufficiency (Math 541B in-class definition)). $T(X_1, \dots, X_n)$ is **sufficient** for θ (more precisely, for the statistical model $\{P_\theta, \theta \in \Theta\}$) if

$$\mathbb{P}_\theta((X_1, \dots, X_n) \in A \mid T(X_1, \dots, X_n) = t) = \mu_t(A).$$

In particular, this probability does not depend on θ .

Goldstein lecture: Suppose we have a model $\{f_\theta : \theta \in \Theta\}$ which we interpret as a set of densities or mass functions. We have $\Theta \subseteq \mathbb{R}^p$, and we know the model up to p parameters. Example; we have $X_1, X_2, \dots, X_n \sim$ i.i.d. f_θ where $\theta \in (\mu, \sigma^2)$, $\mu \in \mathbb{R}$, where $f_\theta \sim \mathcal{N}(\mu, \sigma^2)$, then

$$\Theta = \{(\mu, \sigma^2) : \mu \in \mathbb{R}, \sigma^2 > 0\}.$$

Example 10.2 (Example 5.2 in 541A notes). Let X_1, \dots, X_n be a random sample of size n from a Bernoulli distribution with parameter $0 < \theta < 1$. Then $Y := X_1 + \dots + X_n$ is sufficient for θ .

Proposition 10.3.1 (Example 5.2 in 541A notes). Let X_1, \dots, X_n be a random sample of size n from a Bernoulli distribution with parameter $0 < \theta < 1$. Let $Y := X_1 + \dots + X_n$. Then

$$\mathbb{P}_\theta(X = x \mid Y = y) = \begin{cases} 0 & y \neq \sum_i x_i \\ \binom{n}{y} & \sum_i x_i = y \end{cases}$$

Remark 113. If a statistic is sufficient for θ , then we can use that sufficient statistic to re-create the data (or re-create an equivalent data set with the same statistical properties as far we are concerned with estimating the parameter of interest).

Proof. Let $x_1, \dots, x_n \in [0, 1]$. Let $0 \leq y \leq n$ be an integer. Then Y is binomial with parameters n and θ . We may assume $y = x_1 + \dots + x_n$, otherwise there is nothing to show. Using the definition of conditional probability,

$$\begin{aligned} \Pr((X_1, \dots, X_n) = (x_1, \dots, x_n) \mid Y = y) &= \frac{1}{\Pr(Y = y)} \cdot \Pr((X_1, \dots, X_n) = (x_1, \dots, x_n) \cap Y = y) \\ &= \frac{1}{\Pr(Y = y)} \cdot \Pr((X_1, \dots, X_n) = (x_1, \dots, x_n)) \end{aligned}$$

Using independence and the definition of a binomial distribution, we have

$$\begin{aligned} &= \frac{1}{\binom{n}{y}\theta^y(1-\theta)^{n-y}} \cdot \prod_{i=1}^n \Pr(X_i = x_i) = \frac{1}{\binom{n}{y}\theta^y(1-\theta)^{n-y}} \cdot \prod_{i=1}^n \theta^{x_i}(1-\theta)^{1-x_i} \\ &= \frac{1}{\binom{n}{y}\theta^y(1-\theta)^{n-y}} \cdot \theta^y(1-\theta)^{n-y} = \frac{1}{\binom{n}{y}}. \end{aligned}$$

Since this expression does not depend on θ , Y is sufficient for θ .

□

Example 10.3 (Example 5.3 in 541A notes). Let X_1, \dots, X_n be a sample of size n from a Gaussian distribution with known variance $\sigma^2 > 0$ and unknown mean $\mu \in \mathbb{R}$. Then $Y := (X_1, \dots, X_n)/n$ is a sufficient statistic for μ .

Proof. Note that Y is a Gaussian random variable with mean μ and variance σ^2/n . Let $x_1, \dots, x_n \in \mathbb{R}$ and let $y = (x_1 + \dots + x_n)/n$. Then

$$f_{X_1, \dots, X_n|Y}(x_1, \dots, x_n \mid y) = \frac{1}{f_Y(y)} \cdot f_{X_1, \dots, X_n, Y}(x_1, \dots, x_n, y) = \frac{1}{f_Y(y)} \cdot f_{X_1, \dots, X_n}(x_1, \dots, x_n, y)$$

Since

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(\frac{-x^2 - \mu^2 + 2\mu x}{2\sigma^2}\right)$$

we have

$$\begin{aligned} &= \frac{1}{f_Y(y)} \cdot \prod_{i=1}^n f_{X_i}(x_i) = \frac{1}{f_Y(y)} \cdot \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n \cdot \exp\left(-\frac{1}{2\sigma^2}(x_1^2 + \dots + x_n^2) - \frac{n\mu^2}{2\sigma^2} + \frac{\mu}{\sigma^2} \sum_{i=1}^n x_i\right) \\ &= \frac{\left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n \cdot \exp\left(-\frac{1}{2\sigma^2}(x_1^2 + \dots + x_n^2) - \frac{n\mu^2}{2\sigma^2} + \frac{\mu}{\sigma^2} \sum_{i=1}^n x_i\right)}{n^{1/2}(\sigma^2 2\pi)^{-1/2} \exp\left(-\frac{n}{2\sigma^2}y^2 - \frac{n}{2\sigma^2}\mu^2 + \frac{n\mu}{\sigma^2}y\right)} \end{aligned}$$

$$= \frac{\left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n \cdot \exp\left(-\frac{1}{2\sigma^2}(x_1^2 + \dots + x_n^2)\right)}{n^{1/2}(\sigma^2 2\pi)^{-1/2} \exp\left(-\frac{n}{2\sigma^2}y^2\right)}$$

Because μ does not appear in this expression, Y is sufficient for μ .

□

Theorem 10.3.2 (Theorem 6.2.2 in Casella and Berger [2001], not in 541A lecture notes). If $p(x | \theta)$ is the joint pdf or pmf of a random sample $\mathbf{X} = X_1, \dots, X_n$ and $q(t | \theta)$ is the pdf or pmf of the statistic $T(\mathbf{X})$, then $T(\mathbf{X})$ is a sufficient statistic for θ if, for every $\mathbf{x} = x_1, \dots, x_n$ in the sample space, the ratio $p(\mathbf{x} | \theta)/q(T(\mathbf{x} | \theta))$ is constant as a function of θ .

Theorem 10.3.3 (Neyman-Fisher Factorization Theorem, Theorem 5.4 in 541A notes). Suppose $X = (X_1, \dots, X_n)$ is a random sample of size n from a distribution f where $f \in \{f_\theta : \theta \in \Theta\}$ is a family of probability density functions or probability mass functions. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}^k$, so $Y := t(X_1, \dots, X_n)$ is a statistic. Then Y is sufficient for θ if and only if there exists a nonnegative $\{g_\theta : \theta \in \Theta\}$, $h : \mathbb{R}^n \rightarrow \mathbb{R}$, $g_\theta : \mathbb{R}^k \rightarrow \mathbb{R}$ such that

$$f_\theta(x) = g_\theta(t(x))h(x), \quad \forall x \in \mathbb{R}^n, \quad \forall \theta \in \Theta. \quad (10.5)$$

Proof. We will prove only the discrete case to avoid measure theory. For a general case, see Keener Section 6.4.

Suppose Y is sufficient. Let $x \in \mathbb{R}^n$. Note that by definition and using $Y = t(X)$,

$$f_\theta(x) = \mathbb{P}_\theta(X = x) = \mathbb{P}_\theta(X = x \cap t(X) = t(x)) = \mathbb{P}_\theta(Y = t(x))\mathbb{P}_\theta(X = x | Y = t(x))$$

By sufficiency, $\mathbb{P}_\theta(X = x | Y = t(x))$ does not depend on θ . Therefore we can satisfy (10.5) with $g_\theta(t(x)) = \mathbb{P}_\theta(Y = t(x))$, $h(x) = \mathbb{P}_\theta(X = x | Y = t(x))$, so the factorization holds.

Now suppose there exists a nonnegative $\{g_\theta : \theta \in \Theta\}$, $h : \mathbb{R}^n \rightarrow \mathbb{R}$, $g_\theta : \mathbb{R}^k \rightarrow \mathbb{R}$ such that

$$f_\theta(x) = g_\theta(t(x))h(x), \quad \forall x \in \mathbb{R}^n, \quad \forall \theta \in \Theta.$$

Define $r_\theta(z) := \mathbb{P}_\theta(t(X) = z) \quad \forall z \in \mathbb{R}^k$ (the probability mass function for $t(X)$). Also define $t^{-1}t(x) := \{y \in \mathbb{R}^n; t(y) = t(x)\} \quad \forall x \in \mathbb{R}^n$. To show sufficiency, we need to show that $\mathbb{P}_\theta(X = x | Y = t(x))$ does not depend on θ . Note that

$$\mathbb{P}_\theta(X = x | Y = t(x)) = \frac{f_\theta(x)}{f_Y(t(x))} = \frac{f_\theta(x)}{r_\theta(t(x))}$$

Using our assumption and the Total Probability Theorem, we have

$$= \frac{g_\theta(t(x)h(x))}{\mathbb{P}_\theta(t(X) = t(x))} = \frac{g_\theta(t(x))h(x)}{\sum_{z \in t^{-1}t(x)} \mathbb{P}_\theta(X = z)} = \frac{g_\theta(t(x))h(x)}{\sum_{z \in t^{-1}t(x)} f_\theta(z)} = \frac{g_\theta(t(x))h(x)}{\sum_{z \in t^{-1}t(x)} g_\theta(t(z))h(z)}$$

By definition of $t^{-1}t(z)$, we can write this as

$$= \frac{g_\theta(t(x))h(x)}{\sum_{z \in t^{-1}t(x)} g_\theta(t(x))h(z)} = \frac{g_\theta(t(x))h(x)}{g_\theta(t(x)) \sum_{z \in t^{-1}t(x)} h(z)} = \frac{h(x)}{\sum_{z \in t^{-1}t(x)} h(z)}$$

where the second-to-last step follows since $t(x)$ is constant for all $z \in t^{-1}t(x)$. Since this expression does not contain θ , Y is sufficient for θ .

□

Remark 114. Intuition: data only cares about θ through $t(x)$.

To use the Factorization Theorem (Theorem 10.3.3) to find a sufficient statistic, we factor the joint pdf of the sample into two parts, with one part not depending on θ . The other part, the one that depends on θ , usually depends on the sample only through the function $t(x)$, and this function is a sufficient statistic for θ .

Exercise 25. Suppose $X_1, X_2, \dots, X_n \sim \text{i.i.d. } \mathcal{N}(0, 1)$. So density is

$$\frac{1}{\sqrt{2\pi}} e^{-1/2(x-\theta)^2}$$

Show that

$$e^{-1/2(x^2 - 2x\theta + \theta^2)} =$$

$$f_\theta(x) = \left(\frac{1}{2\pi}\right)^{n/2} e^{2/12 \sum_i X_i^2} e^{\theta \sum_i X_i - n\theta^2/2}$$

so if $t(x) = \sum_{i=1}^n X_i$, $h(x) = \left(\frac{1}{2\pi}\right)^{n/2} e^{2/12 \sum_i X_i^2}$, $g_\theta(t(x)) = e^{\theta \sum_i X_i - n\theta^2/2}$, then by the Factorization Theorem (Theorem 10.3.3) this (\bar{x}) is a sufficient statistic.

Remark 115. In this case, if we deleted the original data we could recreate the original data by sampling from a $\mathcal{N}(0, 1)$ distribution, then add the difference between the mean we get and the original sample mean to get an equivalent data set to the original one.

Remark 116. Suppose we define $t(x) := x$, $\forall x \in \mathbb{R}^n$. Then $Y = t(X_1, \dots, X_n) = (X_1, \dots, X_n)$ is (trivially) sufficient for θ . In general there will be infinitely many sufficient statistics for θ . For instance, in Example 10.3.1, $(X_1 + \dots + X_n)^2$ is also sufficient. So is $(X_1 + \dots + X_n)^3$, etc. More generally, any invertible function of any sufficient statistic is itself sufficient.

We can see that (X_1, \dots, X_n) is sufficient for θ if $(t(x_1, \dots, x_n)) = (x_1, \dots, x_n)$, $g_\theta = f_\theta$, $h = 1$. But this is not really helpful. We see we are interested in sufficient statistics that are smaller—reduce the data (in some sense) as much as possible.

10.3.2 Minimal Sufficient Statistics

Proposition 10.3.4. Suppose $X = (X_1, \dots, X_n)$ is a random sample of size n from a distribution f where $f \in \{f_\theta : \theta \in \Theta\}$ is a family of probability density functions or probability mass functions. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}^k$. Let $Y := t(X_1, \dots, X_n)$. Assume Y is sufficient of θ . Let $a : \mathbb{R}^n \rightarrow \mathbb{R}^m$, let $Z := u(X_1, \dots, X_n)$. suppose there exists $r : \mathbb{R}^m \rightarrow \mathbb{R}^k$ such that $r(u(x)) = t(x)$ for all $x \in \mathbb{R}^n$. That is, suppose $Y = r(Z)$. Then Z is sufficient for θ .

Proof.

$$f_\theta(x) = g_\theta(t(x))h(x) = g_\theta(r(u(x)))h(x)$$

there exists $g_\theta : \mathbb{R}^k \rightarrow [0, \infty)$. Y is sufficient.

Define

$$\tilde{g}_\theta(y) := g_\theta(r(y)) \quad \forall y \in \mathbb{R}^m$$

So

$$f_\theta(x) = \tilde{g}_\theta(u(x))h(x) \quad \forall x \in \mathbb{R}^n.$$

□

Definition 10.10 (Minimal sufficient statistic). Suppose $X = (X_1, \dots, X_n)$ is a random sample of size n from a distribution f where $f \in \{f_\theta : \theta \in \Theta\}$ is a family of probability density functions or probability mass functions. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}^k$. Let $Y := t(X_1, \dots, X_n)$. Assume Y is sufficient of θ . Then Y is a **minimal sufficient statistic** for θ if for every statistic $Z : \Omega \rightarrow \mathbb{R}^m$ that is sufficient for θ there exists a function $\mathbb{R}^m \rightarrow \mathbb{R}^k$ such that $Y = r(Z)$.

Remark 117. Minimal sufficient statistics are not in general unique (because if you take any one-to-one function you get another one), but they are unique up to invertible transformations. (This is true because if Y and Z are both minimal sufficient, $Y = r(Z)$ and $Z = s(Y)$, so $Y = r(s(Y))$, $Z = s(r(Z))$). They exist under mild assumptions (for a family of densities or probability mass functions).

Proposition 10.3.5 (Proposition Larry Goldstein gave in class; Proposition 5.12 in notes).

Suppose X_1, \dots, X_n is a random sample of size n from a distribution f where $f \in \{f_\theta : \theta \in \Theta\}$, is a family of probability density functions or probability mass functions ($\Theta \in \mathbb{R}^n$). (In the case of probability mass functions, we also assume that the set $\cup_{\theta \in \Theta} \{x \in \mathbb{R}^n : f_\theta(x) > 0\}$ is countable.) Then there exists a statistic Y that is minimal sufficient for θ .

Proof where θ is countable. By relabeling, let $\Theta = \{1, 2, \dots\}$. We say for x, y sequences, we define the equivalence relation $x \sim y$ if $\exists \alpha \in \mathbb{R}$ such that $x = \alpha y$. Finite

$$t : \mathbb{R}^n \rightarrow \mathbb{R}^m / \sim, \quad \Theta = \{1, \dots, m\}$$

$$t(x) = (f_1(x), f_2(x), \dots, f_m(x))$$

these likelihood are multiples of each other where α is a constant. The likelihood ratio is a constant not depending on θ . If they have the same $t(x)$ then we have that.

□

Theorem 10.3.6 (Theorem 5.8 in 541A notes). Let $\{f_\theta : \theta \in \Theta\}$ be a family of probability density functions or probability mass functions. Let X_1, \dots, X_n be a random sample from a member of the family. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}^m$ and define $Y := t(X_1, \dots, X_n)$. Assume that Y is sufficient for θ . Y is minimal sufficient if and only if the following condition holds for every $x, y \in \mathbb{R}^n$:

There exists $c(x, y) \in \mathbb{R}$ that does not depend on θ such that $f_\theta(x) = c(x, y)f_\theta(y) \quad \forall \theta \in \Theta$

if and only if

$$t(x) = t(y).$$

Proof. We are only considering probability mass functions to make things easier. We first prove sufficiency. We will show that the condition holding implies that Y is minimal sufficient.

Recall the likelihood ratio:

$$\frac{f_\theta(x)}{f_\theta(y)}$$

Note that the condition is equivalent to the likelihood ratio not depending on θ if and only if $t(x) = t(y)$. Consider the range $R = \{t(x) : x \in \mathbb{R}^n\}$ and then for $t \in R$ let $S_t = \{y : S(y) = t\}$. If t is in R , then there must be some z so that $t(z)$ is that t . This ensures that S_t is nonempty (there is at least one z so that $t(z) = t$). Let $t(x) \in R$, then $S_{t(x)}$ is nonempty (in particular it contains x). Pick any y you like in $t(x)$: $y \in S$. S depends on $t(x)$ so we can index it by $t(x)$: $y_{t(x)} \in S_{t(x)}$. let $y_t \in S_t$. Note that

$$t(y_{t(x)}) = t(x)$$

But now by the assumption, we have

There exists $c(x, y_{t(x)}) \in \mathbb{R}$ that does not depend on θ such that $f_\theta(x) = c(x, y_{t(x)})f_\theta(y_{t(x)}) \quad \forall \theta \in \Theta$

Then note that if $h(x) = c(x, y_{t(x)})$, $g_\theta(t) = f_\theta(y_t) \iff g_\theta(t(x)) = f_\theta(y_{t(x)})$, we meet the conditions for the Factorization Theorem (Theorem 10.3.3). So using the Factorization Theorem, Y is sufficient.

⋮

Part we did in class on Friday 02/15: evidently (according to Goldstein) this shows that the statistic is minimal but not necessarily sufficient. Let $Z = u(X_1, \dots, X_n)$ be any other sufficient statistic. We need to eventually show that Y is a function of Z . By the Factorization Theorem (Theorem 10.3.3), there exists $h : \mathbb{R}^m \rightarrow \mathbb{R}$, $g_\theta : \mathbb{R}^n \rightarrow \mathbb{R}$ such that for all $\theta \in \Theta$,

$$f_\theta(x) = g'_\theta(u(x))h'(x), \quad \forall x \in \mathbb{R}^n.$$

Let $y \in \mathbb{R}^n$. If $h'(y) = 0$, then $f_\theta(y) = 0$ for all $\theta \in \Theta$. So, $\mathbb{P}_\theta(y \in \mathbb{R}^n : h'(y) = 0) = 0$ for all $\theta \in \Theta$. So we can ignore this possibility since it's a probability 0 event and assume $h'(y) > 0, \forall y \in \mathbb{R}^n$.

Now let $x, y \in \mathbb{R}^n$ such that $u(x) = u(y)$. **By an exercise we're going to do later**, if $t(x) = t(y)$ then t is a function of u , so we will be done if we can show that $t(x) = t(y)$. Note that since $u(x) = u(y)$, for any $\theta \in \Theta$

$$f_\theta(x) = g'_\theta(u(x))h'(x) = \frac{g'_\theta(u(y))h'(x)}{f_\theta(y)} \frac{h'(x)}{h'(y)} = f_\theta(y) \frac{h'(x)}{h'(y)}, \quad \text{for all } \theta \in \Theta$$

So define $c(x, y) = h'(x)/h'(y)$, we have

$$f_\theta(x) = f_\theta(y)c(x, y), \quad \forall \theta \in \Theta$$

Therefore $t(x) = t(y)$, so we're done showing that if the condition holds then Y is minimal sufficient.

Then next thing to show is that if Y is minimal sufficient then the condition holds.

⋮

For any $z \in \{t(x) : x \in \mathbb{R}^n\}$, let x_z be any element of $t^{-1}(z)$

□

Proposition 10.3.7 (Exercise 5.10 in Math 541A notes). Let $\{f_\theta : \theta \in \Theta\}$ be a k -parameter exponential family $\{f_\theta : \theta \in \Theta, a(w(\theta)) < \infty\}$ of probability density functions or probability mass functions, where

$$f_\theta(x) := h(x) \exp \left(\sum_{i=1}^k w_i(\theta) t_i(x) - a(w(\theta)) \right), \quad \forall x \in \mathbb{R}.$$

For any $\theta \in \Theta$, let $w(\theta) = (w_1(\theta), \dots, w_k(\theta))$. Assume that the following subset of \mathbb{R}^k is k -dimensional:

$$\{(w_1(\theta), \dots, w_k(\theta)) \in \mathbb{R}^k : \theta \in \Theta\}.$$

That is, if $x \in \mathbb{R}^k$ satisfies $\langle x, y \rangle = 0$ for all y in this set, then $x = 0$.

Let $X = (X_1, \dots, X_n)$ be a random sample of size n from f_θ . Define $t : \mathbb{R}^n \rightarrow \mathbb{R}^n$ by

$$t(X) := \sum_{j=1}^n (t_1(X_j), \dots, t_n(X_j)).$$

Then $t(X)$ is minimal sufficient for θ .

Proof. First note that $t(X)$ is sufficient by the Factorization Theorem (Theorem 10.3.3) because we have for any $x = (x_1, \dots, x_n) \in \mathbb{R}^n$

$$\begin{aligned} f_\theta(x) &= \prod_{j=1}^n \left[h(x_j) \exp \left(\sum_{i=1}^k w_i(\theta) t_i(x_j) - a(w(\theta)) \right) \right] = \exp \left(\sum_{j=1}^n \sum_{i=1}^k w_i(\theta) t_i(x_j) - n \cdot a(w(\theta)) \right) \prod_{j=1}^n h(x_j) \\ &= g_\theta(t(x)) h(x), \quad \forall x \in \mathbb{R}^n \end{aligned}$$

where

$$h(x) = \prod_{j=1}^n h(x_j), \quad g_\theta(t(x)) = \exp \left(\sum_{j=1}^n \sum_{i=1}^k w_i(\theta) t_i(x_j) \right).$$

Now we will show minimal sufficiency using Theorem 5.8 from the lecture notes (Theorem 10.3.6). We seek to show that for every $x, y \in \mathbb{R}^n$, the likelihood ratio $\frac{f_\theta(x)}{f_\theta(y)}$ is constant (the constant may depend on x and y) if and only if $t(x) = t(y)$. Let $x, y \in \mathbb{R}^n$. Suppose there is some constant $c(x, y) > 0$ that may depend on x and y but not θ such that

$$\begin{aligned} &\exp \left(\sum_{j=1}^n \sum_{i=1}^k w_i(\theta) t_i(x_j) - n \cdot a(w(\theta)) \right) \prod_{j=1}^n h(x_j) \\ &= c(x, y) \exp \left(\sum_{j=1}^n \sum_{i=1}^k w_i(\theta) t_i(y_j) - n \cdot a(w(\theta)) \right) \prod_{j=1}^n h(y_j) \\ \iff &\exp \left(\sum_{j=1}^n \sum_{i=1}^k w_i(\theta) t_i(x_j) \right) = c_1(x, y) \exp \left(\sum_{j=1}^n \sum_{i=1}^k w_i(\theta) t_i(y_j) \right) \end{aligned}$$

(where cancellation of the h functions is permissible since they depend only on x and y , so we can let $c_1(x, y) = c(x, y) \cdot \prod_{j=1}^n h(y_j) / \prod_{j=1}^n h(x_j) > 0$)

$$\iff \sum_{j=1}^n \sum_{i=1}^k w_i(\theta) t_i(x_j) = c_2(x, y) + \sum_{j=1}^n \sum_{i=1}^k w_i(\theta) t_i(y_j)$$

where $c_2(x, y) = \log(c_1(x, y))$. Then if θ_0, θ_1 are any two points in Θ ,

$$\sum_{j=1}^n \sum_{i=1}^k w_i(\theta_0) t_i(x_j) - \sum_{j=1}^n \sum_{i=1}^k w_i(\theta_1) t_i(x_j) = \sum_{j=1}^n \sum_{i=1}^k w_i(\theta_0) t_i(y_j) - \sum_{j=1}^n \sum_{i=1}^k w_i(\theta_1) t_i(y_j)$$

(where the $c_2(x, y)$ terms cancel since (x, y) is held fixed.)

$$\begin{aligned} &\iff \sum_{j=1}^n \sum_{i=1}^k [w_i(\theta_0) - w_i(\theta_1)] t_i(x_j) = \sum_{j=1}^n \sum_{i=1}^k [w_i(\theta_0) - w_i(\theta_1)] t_i(y_j) \\ &\iff \sum_{j=1}^n \sum_{i=1}^k [w_i(\theta_0) - w_i(\theta_1)] [t_i(x_j) - t_i(y_j)] = 0. \end{aligned}$$

This equation holds for all $\theta \in \Theta$ if and only if $t_i(x_j) - t_i(y_j) = 0, i = 1, \dots, k, j = 1, \dots, n$; that is, it holds if and only if $t(x) = t(y)$. Therefore we have shown that $t(\cdot)$ is minimal sufficient by Theorem 10.3.6.

□

Remark 118. Note that the assumption of the exercise is always satisfied for an exponential family in canonical form. From this proposition we can conclude that if we sample from a Gaussian with unknown mean μ and variance $\sigma^2 > 0$, then \bar{X} is minimal sufficient for θ and (\bar{X}, S) is minimal sufficient for (μ, σ^2) .

Proposition 10.3.8 (Exercise 5.13 in Math 541A notes). Let $\mathbb{P}_1, \mathbb{P}_2$ be two probability laws on the sample space $\Omega = \mathbb{R}$. Suppose these laws have densities $f_1, f_2 : \mathbb{R} \rightarrow [0, \infty)$ so that

$$\mathbb{P}_i(A) = \int_A f_i(x) dx, \quad \forall i = 1, 2, \quad \forall A \subseteq \mathbb{R}.$$

Then

(a)

$$\sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \frac{1}{2} \int_{\mathbb{R}} |f_1(x) - f_2(x)| dx.$$

(b) If $\mathbb{P}_1, \mathbb{P}_2$ are probability laws on $\Omega = \mathbb{Z}$

$$\sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \frac{1}{2} \sum_{z \in \mathbb{Z}} |\mathbb{P}_1(z) - \mathbb{P}_2(z)|.$$

Proof. (a) Note that $\sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)|$ returns the difference in areas under f_1 and f_2 in the region $A \subset \mathbb{R}$ where that difference is positive. Suppose without loss of generality that

$$\sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \sup_{A \subseteq \mathbb{R}} \{\mathbb{P}_1(A) - \mathbb{P}_2(A)\}. \quad (10.6)$$

(There is no loss of generality because in the case that $\sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \sup_{A \subseteq \mathbb{R}} \{\mathbb{P}_2(A) - \mathbb{P}_1(A)\}$, we can simply switch the names of \mathbb{P}_1 and \mathbb{P}_2 to get the desired result.) Then the region A which maximizes the quantity on the right side of (10.6) is the suggested region, $A := \{x \in \mathbb{R} : f_1(x) > f_2(x)\}$. That is,

$$\sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \int_A (f_1(x) - f_2(x))dx.$$

Note that

$$\begin{aligned} \int_{\mathbb{R}} |f_1(x) - f_2(x)|dx &= \int_A |f_1(x) - f_2(x)|dx + \int_{\mathbb{R} \setminus A} |f_1(x) - f_2(x)|dx \\ \iff \int_{\mathbb{R}} |f_1(x) - f_2(x)|dx &= \int_A (f_1(x) - f_2(x))dx + \int_{\mathbb{R} \setminus A} (f_2(x) - f_1(x))dx. \end{aligned} \quad (10.7)$$

Since we already have $\int_A (f_1(x) - f_2(x))dx = \sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)|$, if it is also true that $\int_{\mathbb{R} \setminus A} (f_2(x) - f_1(x))dx = \sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)|$ we are done by (10.7), so this is what we will show next. Let $\int_A f_2(x)dx = a_2$ and let $\int_A f_1(x)dx = a_1$, so that

$$\sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \int_A (f_1(x) - f_2(x))dx = a_1 - a_2.$$

Note that

$$1 = \int_{\mathbb{R}} f_2(x)dx = \int_A f_2(x)dx + \int_{\mathbb{R} \setminus A} f_2(x)dx = a_2 + \int_{\mathbb{R} \setminus A} f_2(x)dx \iff \int_{\mathbb{R} \setminus A} f_2(x)dx = 1 - a_2,$$

and similarly $\int_{\mathbb{R} \setminus A} f_1(x)dx = 1 - a_1$. Therefore

$$\int_{\mathbb{R} \setminus A} (f_2(x) - f_1(x))dx = \int_{\mathbb{R} \setminus A} f_2(x)dx - \int_{\mathbb{R} \setminus A} f_1(x)dx = 1 - a_2 - (1 - a_1) = a_1 - a_2 = \sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)|.$$

So by (10.7), we have

$$\int_{\mathbb{R}} |f_1(x) - f_2(x)|dx = 2 \sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| \iff \sup_{A \subseteq \mathbb{R}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \frac{1}{2} \int_{\mathbb{R}} |f_1(x) - f_2(x)|dx.$$

- (b) Analogous to the proof of (a). Note that $\sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)|$ returns the difference in probabilities for those numbers in the set $A \subset \mathbb{Z}$ where that difference is positive. Suppose without loss of generality that

$$\sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \sup_{A \subseteq \mathbb{Z}} \{\mathbb{P}_1(A) - \mathbb{P}_2(A)\}. \quad (10.8)$$

(There is no loss of generality because in the case that $\sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \sup_{A \subseteq \mathbb{Z}} \{\mathbb{P}_2(A) - \mathbb{P}_1(A)\}$, we can simply switch the names of \mathbb{P}_1 and \mathbb{P}_2 to get the desired result.) Then the set A which maximizes the quantity on the right side of (10.8) can be defined as (similarly to part (a)) $A := \{z \in \mathbb{Z} : \mathbb{P}_1(z) > \mathbb{P}_2(z)\}$. That is,

$$\sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \sum_{z \in A} \mathbb{P}_1(z) - \mathbb{P}_2(z).$$

Note that

$$\begin{aligned} \sum_{z \in \mathbb{Z}} |\mathbb{P}_1(z) - \mathbb{P}_2(z)| &= \sum_{z \in A} |\mathbb{P}_1(z) - \mathbb{P}_2(z)| + \sum_{z \in \{\mathbb{Z} \setminus A\}} |\mathbb{P}_1(z) - \mathbb{P}_2(z)| \\ \iff \sum_{z \in \mathbb{Z}} |\mathbb{P}_1(z) - \mathbb{P}_2(z)| &= \sum_{z \in A} \mathbb{P}_1(z) - \mathbb{P}_2(z) + \sum_{z \in \{\mathbb{Z} \setminus A\}} (\mathbb{P}_2(z) - \mathbb{P}_1(z)). \end{aligned} \quad (10.9)$$

Since we already have $\sum_{z \in A} \mathbb{P}_1(z) - \mathbb{P}_2(z) = \sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)|$, if it is also true that $\sum_{z \in \{\mathbb{Z} \setminus A\}} (\mathbb{P}_2(z) - \mathbb{P}_1(z)) = \sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)|$ we are done by (10.9), so this is what we will show next. Let $\sum_{z \in A} \mathbb{P}_2(z) = a_2$ and let $\sum_{z \in A} \mathbb{P}_1(z) = a_1$, so that

$$\sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \sum_{z \in A} \mathbb{P}_1(z) - \mathbb{P}_2(z) = a_1 - a_2.$$

Note that

$$1 = \sum_{z \in \mathbb{Z}} \mathbb{P}_2(z) = \sum_{z \in A} \mathbb{P}_2(z) + \sum_{z \in \{\mathbb{Z} \setminus A\}} \mathbb{P}_2(z) = a_2 + \sum_{z \in \{\mathbb{Z} \setminus A\}} \mathbb{P}_2(z) \iff \sum_{z \in \{\mathbb{Z} \setminus A\}} \mathbb{P}_2(z) = 1 - a_2,$$

and similarly $\sum_{z \in \{\mathbb{Z} \setminus A\}} \mathbb{P}_1(z) = 1 - a_1$. Therefore

$$\sum_{z \in \{\mathbb{Z} \setminus A\}} (\mathbb{P}_2(z) - \mathbb{P}_1(z)) = \sum_{z \in \{\mathbb{Z} \setminus A\}} \mathbb{P}_2(z) - \sum_{z \in \{\mathbb{Z} \setminus A\}} \mathbb{P}_1(z) = 1 - a_2 - (1 - a_1) = a_1 - a_2 = \sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)|.$$

So by (10.9), we have

$$\sum_{z \in \mathbb{Z}} |\mathbb{P}_1(z) - \mathbb{P}_2(z)| = 2 \sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| \iff \sup_{A \subseteq \mathbb{Z}} |\mathbb{P}_1(A) - \mathbb{P}_2(A)| = \frac{1}{2} \sum_{z \in \mathbb{Z}} |\mathbb{P}_1(z) - \mathbb{P}_2(z)|.$$

□

10.3.3 Ancillary Statistics

Definition 10.11 (Ancillary Statistic). Suppose X_1, \dots, X_n is a random sample of size n from a distribution f where $f \in \{f_\theta : \theta \in \Theta\}$ is a family of distributions. A statistic $Y = t(X_1, \dots, X_n)$, $t : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is **ancillary** for θ if the distribution of Y does not depend on θ .

Example 10.4. [Example from 541B lecture]

$X_1, \dots, X_n \sim \mathcal{N}(\mu, 1)$. Then $V(x) := X_1 - \bar{X}$ is ancillary. Proof: let $X_d = \mu + X'_d$, $X'_d \sim \mathcal{N}(0, 1)$. Then

$$\bar{X} = \frac{1}{n} \sum_{j=1}^n X_j = \mu + \bar{X}'.$$

so

$$V(X_1, \dots, X_n) = \mu + X'_1 - \mu - \bar{X}' = X'_1 - \bar{X}'$$

Since X' does not depend on μ , $V(X_1, \dots, X_n)$ is ancillary for μ .

Example 10.5 (Example 5.15 from 541A notes). Let X_1, \dots, X_n be random sample of size n from the location family for the Cauchy distribution:

$$f_\theta(x) := \prod_{i=1}^n \frac{1}{\pi} \frac{1}{1 + (x_i - \theta)^2}, \quad \forall x = (x_1, \dots, x_n) \in \mathbb{R}^n, \quad \forall \theta \in \mathbb{R}.$$

Then the order statistics $X_{(1)} \leq \dots \leq X_{(n)}$ are minimal sufficient for θ .

Proof. Sufficiency follows by the Factorization Theorem (Theorem 10.3.3, Theorem 5.4 in Math 541A notes) (**usually the easiest way to prove sufficiency**) since if $t(x) := (x_{(1)}, \dots, x_{(n)})$, then $f_\theta(t(x)) = f_\theta(x)$ (because $t(x)$ is just a permutation so the product won't change).

To get minimal sufficiency, apply Theorem 10.3.6 (Theorem 5.8 in 541A notes). Recall we have minimal sufficiency if the following condition holds for every $x, y \in \mathbb{R}^n$:

There exists $c(x, y) \in \mathbb{R}$ that does not depend on θ such that $f_\theta(x) = c(x, y)f_\theta(y) \quad \forall \theta \in \Theta$
if and only if

$$t(x) = t(y).$$

Let's try to show it.

$$\frac{f_\theta(x)}{f_\theta(y)} = \prod_{i=1}^n \frac{1}{\pi} \frac{1}{1 + (x_i - \theta)^2} \Bigg/ \prod_{i=1}^n \frac{1}{\pi} \frac{1}{1 + (y_i - \theta)^2} = \prod_{i=1}^n [1 + (y_i - \theta)^2] \Bigg/ \prod_{i=1}^n [1 + (x_i - \theta)^2] \quad (10.10)$$

Keep x, y fixed, $\theta \in \mathbb{R}$ variable. Then the likelihood ratio (10.10) does not depend on θ if and only if the roots in θ on top are equal to the roots on bottom. Roots on top: $\theta = y_i \pm \sqrt{-1}, 1 \leq i \leq n$. Roots on bottom: $\theta = x_i \pm \sqrt{-1}, 1 \leq i \leq n$. So we can see this is true if and only if the vector (x_1, \dots, x_n) is a permutation of (y_1, \dots, y_n) , which is exactly the case if $t(x) = t(y)$.

□

However, this statistic has ancillary information. Specifically, $X_{(n)} - X_{(1)}$ is ancillary (its distribution does not depend on θ).

Proof. Let Z_1, \dots, Z_n be independent centered Cauchy random variables; that is, they all have density $\frac{1}{\pi} \frac{1}{1+a^2}, a \in \mathbb{R}$. Then $X_i = Z_i + \theta, \forall 1 \leq i \leq n, \forall \theta \in \mathbb{R}$. Also, $X_{(i)} = Z_{(i)} + \theta$. So $X_{(n)} - X_{(1)} = Z_{(n)} - Z_{(1)}$

does not depend on $\theta \in \mathbb{R}$. So, $X_{(n)} - X_{(1)}$ is ancillary for θ . That is, there exists a constant c that does not depend on θ such that $\mathbb{E}_\theta[X_{(n)} - X_{(1)} - c] = 0$ for all $\theta \in \mathbb{R}$.

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $f(x_1, \dots, x_n) = x_n - x_1 - c \forall (x_1, \dots, x_n) \in \mathbb{R}^n$. Then $\mathbb{E}_\theta f(Y) = 0, \forall \theta \in \Theta, Y = (X_{(1)}, \dots, X_{(n)})$. Note that $f \neq 0$ (in fact $f(Y) \neq 0$ with probability 1).

□

10.3.4 Complete Statistics

Definition 10.12 (Complete statistic; definition 5.16 in 541A notes). Suppose X_1, \dots, X_n is a random sample of size n from a distribution f where $f \in \{f_\theta : \theta \in \Theta\}$ is a family of distributions. A statistic $Y = t(X_1, \dots, X_n), t : \mathbb{R}^n \rightarrow \mathbb{R}^k$ is **complete** for θ if the following holds:

For any $f : \mathbb{R}^k \rightarrow \mathbb{R}$ such that $\mathbb{E}_\theta f(Y) = 0 \forall \theta \in \Theta$, it holds that $f(Y) = 0$.

Intuition: Y has no “excess information.”

Definition 10.13 (541B definition). T is **complete** for $\{f_\theta, \theta \in \Theta\}$ if

$$\mathbb{E}_\theta \phi(T) = 0 \forall \theta \implies \phi(T) = 0 \text{ almost surely.}$$

Remark 119. If a statistic has ancillary information, then it is not complete. Therefore if a statistic is complete, it is not ancillary. Minimal sufficient statistics pretty much always exist, but a complete sufficient statistic might not exist (see [example from homework 4](#)).

Remark 120. A complete statistic may not be sufficient (example: a constant).

Example 10.6 (Exercise 5.19 in Math 541A notes). The following is an example of a statistic Y that is complete and nonconstant, but not sufficient. Suppose X_1, \dots, X_n is a random sample of known size n from a Bernoulli distribution with unknown probability parameter $\theta \in (0, 1)$. Let

$$Y = t(X_1, \dots, X_n) = \sum_{i=1}^{n-1} X_i.$$

Then Y is complete for μ because for any $f : \mathbb{R}^m \rightarrow \mathbb{R}$, suppose

$$0 = \mathbb{E}_\theta f(Y) = \sum_{j=0}^{n-1} f(j) \Pr(Y = j \mid \theta) = \sum_{j=0}^{n-1} f(j) \binom{n-1}{j} \theta^j (1-\theta)^{n-1-j}, \quad \forall \theta \in (0, 1).$$

Divide by $(1-\theta)^{n-1}$ and let $\alpha = \theta/(1-\theta)$ for notational ease. (Note that since $\theta \in (0, 1)$, $\alpha > 0$.)

$$0 = \sum_{j=0}^{n-1} f(j) \binom{n-1}{j} \theta^j \frac{(1-\theta)^{n-1-j}}{(1-\theta)^{n-1}} = \sum_{j=0}^{n-1} f(j) \binom{n-1}{j} \left(\frac{\theta}{1-\theta}\right)^j = \sum_{j=0}^{n-1} f(j) \binom{n-1}{j} \alpha^j, \quad \forall \alpha > 0.$$

The sum on the right side is a polynomial in $\alpha > 0$. That means the sum on the right can only equal 0 if every coefficient on the polynomial equals zero. $\binom{n}{j}$ is of course nonzero for all $j \in 0, \dots, n - 1$. Therefore for all $\alpha > 0$ we have that $\mathbb{E}_\theta f(Y) = 0$ only if $f(Y) = 0$, so Y is complete.

However, Y is not sufficient for μ . Using the definition of conditional probability,

$$\begin{aligned} \Pr((X_1, \dots, X_n) = (x_1, \dots, x_n) \mid Y = y) &= \frac{1}{\Pr(Y = y)} \cdot \Pr((X_1, \dots, X_n) = (x_1, \dots, x_n) \cap Y = y) \\ &= \frac{1}{\Pr(Y = y)} \cdot \Pr((X_1, \dots, X_n) = (x_1, \dots, x_n)) \end{aligned}$$

Using independence and the definition of a binomial distribution, we have

$$\begin{aligned} &= \frac{1}{\binom{n-1}{y}\theta^y(1-\theta)^{n-1-y}} \cdot \prod_{i=1}^n \Pr(X_i = x_i) = \frac{1}{\binom{n-1}{y}\theta^y(1-\theta)^{n-1-y}} \cdot \prod_{i=1}^n \theta^{x_i}(1-\theta)^{1-x_i} \\ &= \frac{1}{\binom{n-1}{y}\theta^y(1-\theta)^{n-1-y}} \cdot \theta^y(1-\theta)^{n-y} = \frac{1-\theta}{\binom{n-1}{y}}. \end{aligned}$$

Because $\Pr((X_1, \dots, X_n) = (x_1, \dots, x_n) \mid Y = y) = (1-\theta)/\binom{n-1}{y}$ depends on θ , Y is not sufficient for θ .

Exercise 26 (Exercise 5.20 in Math 541A notes). This exercise shows that a complete sufficient statistic might not exist.

Let X_1, \dots, X_n be a random sample of size n from the uniform distribution on the three points $\{\theta, \theta + 1, \theta + 2\}$, where $\theta \in \mathbb{Z}$.

- (a) Show that the vector $Y := (X_{(1)}, X_{(n)})$ is minimal sufficient for θ .
- (b) Show that Y is not complete by considering $X_{(n)} - X_{(1)}$.
- (c) Using minimal sufficiency, conclude that any sufficient statistic for θ is not complete.

Proof. (a) First we need to show that Y is sufficient for θ . Informally, it makes sense that this would be the case because there are three possibilities:

- (1) If θ and $\theta + 2$ appear in the data set, we can identify θ with certainty as the smallest of them. Simply observing $x_{(1)}$ and $x_{(n)}$ would show us the smallest and largest observations, which would be 2 units apart. Then we would know that the these observations are θ and $\theta + 2$, and we could identify θ with certainty. (Note that it doesn't matter in this case whether we observe $\theta + 1$.)
- (2) If only the values $\{\theta, \theta + 1\}$ or $\{\theta + 1, \theta + 2\}$ appear in the data set, we have to guess which one of these pairs we observed. If we guess that we have observed $\theta + 1$ and $\theta + 2$ and subtract one from the smallest observation to estimate θ , or we can guess that we have observed θ and $\theta + 1$ and use the smallest value as our estimate for θ . (Or we can hedge and take the mean of these values.) In any case, simply observing $x_{(1)}$ and $x_{(n)}$ would show us the smallest and largest observations, which would be 1 apart, leaving us in the same position as if we had all the data.

- (3) If only one value appears, we have to guess if it is θ , $\theta + 1$, or $\theta + 2$ in a way similar to if we only observe two values. But if we observe that the smallest and largest values are equal, we are observing the same information and we are in the same position for estimating θ as if we had all of the data.

We can formally show that Y is sufficient using the Factorization Theorem (Theorem 10.3.3). Note that because on each trial we observe θ , $\theta + 1$, or $\theta + 2$ with equal probability, the mass function for the unordered observations $f_{u,\theta} : \mathbb{Z}^n \rightarrow \mathbb{R}$ is the same as that of a multinomial distribution with three outcomes with equal probabilities. That is, if $n_0 = \sum_{i=1}^n \mathbf{1}_{\{x_i=\theta\}}$ (where $\mathbf{1}_{\{x_i=\theta\}}$ is an indicator variable for the i th observation having value θ), $n_1 = \sum_{i=1}^n \mathbf{1}_{\{x_i=\theta+1\}}$, and $n_2 = \sum_{i=1}^n \mathbf{1}_{\{x_i=\theta+2\}}$, we have

$$f_{u,\theta}(x) = \binom{n}{n_0, n_1, n_2} \left(\frac{1}{3}\right)^n = \frac{n!}{n_0! n_1! n_2!} \left(\frac{1}{3}\right)^n.$$

But taking into account the order in which we observe the samples, the probability of observing any one sample of size n ($x = (x_1, \dots, x_n)$) is simply

$$f_\theta(x) = \begin{cases} \left(\frac{1}{3}\right)^n & x_1 \in \{\theta, \theta + 1, \theta + 2\}, \dots, x_n \in \{\theta, \theta + 1, \theta + 2\} \\ 0 & \text{otherwise.} \end{cases}$$

We have $t : \mathbb{Z}^n \rightarrow \mathbb{Z}^2$ is given by

$$t(X_1, \dots, X_n) = (X_{(1)}, X_{(n)}).$$

Choose

$$h(x) = (1/3)^n, \quad g_\theta(t(x)) = \begin{cases} 1 & t(x) \in \{\theta, \theta + 1, \theta + 2\} \times \{\theta, \theta + 1, \theta + 2\} \\ 0 & \text{otherwise.} \end{cases} \quad (10.11)$$

Then we have $f_\theta(x) = g_\theta(t(x))h(x)$, as desired. Now we will use Theorem 10.3.6 (Theorem 5.8 from the lecture notes) to show that Y is not only sufficient, but is also minimal sufficient. Let $x, z \in \mathbb{Z}^n$, and let $y_x = (x_{(1)}, x_{(n)})$, $y_z = (z_{(1)}, z_{(n)})$. We seek to show that for every $x, z \in \mathbb{Z}^n$, the likelihood ratio $\frac{f_\theta(x)}{f_\theta(z)}$ is constant (the constant may depend on x and z) if and only if $y_x = y_z$. (We only need to consider $x, z \in \mathbb{Z}^n$ rather than all of \mathbb{R}^n because since $\theta \in \mathbb{Z}$, $X_i \in \mathbb{Z} \forall i \in \{1, \dots, n\}, \forall \theta \in \Theta$.) Using the expressions in (10.11), we can write the equation in (10.12) as

$$f_\theta(x) = c(x, y)f_\theta(z) \iff g_\theta(t(x)) \left(\frac{1}{3}\right)^n = c(x, z)g_\theta(t(z)) \left(\frac{1}{3}\right)^n \iff g_\theta(t(x)) = c(x, z)g_\theta(t(z)) \quad (10.12)$$

I will argue that the equality in (10.12) only holds for some $c(x, z) \in \mathbb{R}$ if $t(x) = t(z)$. Suppose we have observed data x and z from a distribution with a specific θ_0 . There are three cases to consider:

- (1) $t(x) = \{\theta_0, \theta_0 + 2\}$ (**full information**): Then the only θ for which $g_\theta(t(x)) \neq 0$ is $\theta = \theta_0$. (This corresponds to situation (1) above.)
- (2) $t(x) = \{\theta_0, \theta_0 + 1\}$ **or** $\{\theta_0, \theta_0 + 1\}$: Then $g_\theta(t(x)) \neq 0$ for two values of θ . In the first case, those two values will be $\theta_0 - 1$ and θ_0 . In the second case, those two values will be θ_0 and $\theta_0 + 1$. (This corresponds to situation (2) above.)

- (3) $t(x) = \{\theta_0, \theta_0\}, \{\theta_0 + 1, \theta_0 + 1\}$, or $\{\theta_0 + 2, \theta_0 + 2\}$: Then $g_\theta(t(x)) \neq 0$ for three values of θ . In the first case, those three values will be $\theta_0 - 2, \theta_0 - 1$, and θ_0 . In the second case, those three values will be $\theta_0 - 1, \theta_0$, and $\theta_0 + 1$. In the last case, those three values will be $\theta_0, \theta_0 + 1$, and $\theta_0 + 2$. (This corresponds to situation (3) above.)

I have enumerated all possible values of $t(x)$ or $t(z)$ for a given true $\theta = \theta_0$, and note that there is no overlap among any of the possibilities for what values of θ will yield identical values of $g_\theta(t(x))$ and $g_\theta(t(z))$ for all θ . That is, that is true (and (10.12) holds for all $\theta \in \Theta = \mathbb{Z}$) if and only if $t(x) = t(z)$, which is what we were trying to show. So Y is minimal sufficient.

- (b) Recall the definition of a complete statistic:

Definition 10.14 (Complete statistic; definition 5.16 in 541A notes). Suppose X_1, \dots, X_n is a random sample of size n from a distribution f where $f \in \{f_\theta : \theta \in \Theta\}$ is a family of distributions. A statistic $Y = t(X_1, \dots, X_n), t : \mathbb{R}^n \rightarrow \mathbb{R}^k$ is **complete** for θ if the following holds:

$$\text{For any } f : \mathbb{R}^k \rightarrow \mathbb{R} \text{ such that } \mathbb{E}_\theta f(Y) = 0 \ \forall \theta \in \Theta, \text{ it holds that } f(Y) = 0.$$

We will show that Y is not complete by showing that Y contains ancillary information. Specifically, we will show that $\mathbb{E}_\theta[f(Y)] \neq 0$ where $f(Y) = X_{(n)} - X_{(1)} - c$ for some $c \in \mathbb{Z}$.

Let Z_1, \dots, Z_n be a random sample of size n from the uniform distribution on the three points $\{0, 1, 2\}$. Then $X_i = Z_i + \theta, \forall 1 \leq i \leq n, \forall \theta \in \mathbb{Z}$. Also, $X_{(i)} = Z_{(i)} + \theta$. So $X_{(n)} - X_{(1)} = Z_{(n)} - Z_{(1)}$ does not depend on $\theta \in \mathbb{Z}$. So, $X_{(n)} - X_{(1)}$ is ancillary for θ . That is, there exists a constant $c \in \mathbb{Z}$ that does not depend on θ such that $\mathbb{E}_\theta[X_{(n)} - X_{(1)} - c] = 0$ for all $\theta \in \mathbb{Z}$.

Define this c and let $f : \mathbb{Z}^2 \rightarrow \mathbb{Z}$ be $f(x_1, x_n) := x_n - x_1 - c \ \forall (x_1, x_n) \in \mathbb{R}^n$. Then $\mathbb{E}_\theta f(Y) = 0, \forall \theta \in \Theta, Y = (X_{(1)}, X_{(n)})$.

- (c) Let S be any sufficient statistic for θ . Since Y is minimal sufficient, there exists a function ϕ such that $Y = \phi(\theta)$. Therefore S is not complete because $\mathbb{E}_\theta(f(\phi(S))) = \mathbb{E}_\theta(f(Y)) = 0$ for all $\theta \in \mathbb{Z}$. So any sufficient statistic for θ is not complete.

□

Example 10.7 (Discrete RV example, Example 5.21 in Math 541A notes; return to Example 10.3.1). Suppose we take a sample of size n from a Bernoulli distribution with parameter $0 < \theta < 1$. We already showed $Y := X_1 + \dots + X_n$ is sufficient for θ . Now we show Y is complete.

Proof. Let $f : \mathbb{R} \rightarrow \mathbb{R}$ with $\mathbb{E}_\theta f(Y) = 0 \ \forall \theta \in \Theta$. Since Y is binomial,

$$0 = \mathbb{E}_\theta f(Y) = \sum_{j=0}^n f(j) \binom{n}{j} \theta^j (1-\theta)^{n-j}, \quad \forall \theta \in (0, 1)$$

Let $\alpha = \theta/(1-\theta)$ and divide by $(1-\theta)^n$:

$$0 = \sum_{j=0}^n f(j) \binom{n}{j} \alpha^j, \quad \forall \alpha > 0.$$

The sum on the right side is a polynomial in $\alpha > 0$. That means the sum on the right can only equal 0 if every coefficient on the polynomial equals zero. $\binom{n}{j}$ is of course nonzero for all $j \in 0, \dots, n - 1$. Therefore for all $\alpha > 0$ we have that $\mathbb{E}_\theta f(Y) = 0$ only if we have $f(j) = 0$ for all $0 \leq j \leq n$, so $f(Y) = 0$ so Y is complete.

□

Example 10.8 (Continuous RV example; return to Example 10.3). For a random sample from a Gaussian distribution with known variance $\sigma^2 > 0$ and unknown $\mu \in \mathbb{R}$, we showed that $Y = (X_1 + \dots + X_n)/n$ is sufficient for μ . Now we will show it is complete.

Proof. Found this proof confusing For simplicity, let $\sigma = 1, n = 1$. Let $f : \mathbb{R} \rightarrow \mathbb{R}$ with $\mathbb{E}_\mu |f(Y)| < \infty$ for all $\mu \in \mathbb{R}$. Then

$$0 = \mathbb{E}_\mu(f(Y)) = \int_{-\infty}^{\infty} f(y) \exp\left(-\frac{(y-\mu)^2}{2}\right) \frac{1}{\sqrt{2\pi}} dy, \quad \forall \mu \in \mathbb{R}$$

Multiplying both sides by $e^{\mu^2/2} \sqrt{2\pi}$ yields

$$0 = \int_{-\infty}^{\infty} f(y) e^{-y^2/2} e^{y\mu} dy, \quad \forall \mu \in \mathbb{R} \tag{10.13}$$

If $f(y) \geq 0$, we are done since (10.13) is the moment generating function of a random variable with density

$$\frac{f(y)e^{-y^2/2}}{\int_{\mathbb{R}} f(x)e^{-x^2/2} dx}$$

Then by Theorem 9.2 from the appendix of the Math 541A notes (uniqueness of moment-generating functions), this describes a unique random variable. But this is a contradiction because we can't divide by 0. (???)

In the case that f is positive and negative at different points, we write $f = f_+ - f_-$ where $f_+(x) := \max\{f(x), 0\}$ and $f_-(x) := \max\{-f(x), 0\}$. use (10.13) for any μ and divide by case $\mu = 0$,

$$\int_{-\infty}^{\infty} f_-(y) e^{-y^2/2} e^{y\mu} dy, \quad \int_{-\infty}^{\infty} f_-(y) e^{-y^2/2} dy$$

which yields

$$\int_{-\infty}^{\infty} f_+(y) e^{-y^2/2} e^{y\mu} dy / \int_{-\infty}^{\infty} f_-(y) e^{-y^2/2} dy$$

so we are done again by Theorem 9.2. So $f_y = f_-$, $f = f_+ - f_- = 0$.

So basically we started by assuming that the expression equals zero and concluded that f must equal 0; therefore the statistic is complete.

□

Remark 121. Later we will show that complete and sufficient statistics are minimal sufficient.

Exercise 27 (Conditional expectation exercise relevant to proof of Bahadur's Theorem). Let $X, Y : \Omega \rightarrow \mathbb{R}$ both be discrete or both continuous. For all y in the range of Y , define $g(y) := \mathbb{E}(X | Y = y)$. Define the conditional expectation of X given Y , denoted $\mathbb{E}(X | Y)$, as the random variable $g(Y)$.

Solution: Theorem 6.1.6

Theorem 10.3.9 (Bahadur's Theorem; Theorem 5.25 in Math 541A notes). If Y is a complete sufficient statistic for a family $\{f_\theta : \theta \in \Theta\}$ of probability densities or probability mass functions, then Y is a minimal sufficient statistic for θ .

Remark 122. By Remark 5.11 in Math 541A notes, a complete sufficient statistic is unique up to an invertible map. Also by Example 5.15 in Math 541A notes, the converse of Bahadur's Theorem is false.

Proof. By Proposition 10.3.5 (Proposition 5.12 in Math 541A notes), there exists a minimal sufficient statistic Z for θ . To show that Y is minimal sufficient, it suffices to find a function r such that $Y = r(Z)$. Define $r(Z) = \mathbb{E}_\theta(Y | Z)$. Since Z is minimal sufficient and Y is sufficient by assumption, there exists a function u such that $Z = u(Y)$. By conditioning on Y we have by Exercise 27 (Exercise 5.24 in the Math 541A notes)

$$\mathbb{E}_\theta(r(u(Y))) = \mathbb{E}_\theta(r(Z)) = \mathbb{E}_\theta[\mathbb{E}_\theta(r(Z) | Y)] = \mathbb{E}_\theta[\mathbb{E}_\theta(\mathbb{E}_\theta(Y | Z) | Y)] = \mathbb{E}_\theta[\mathbb{E}_\theta(\mathbb{E}_\theta(Y | u(Y)) | Y)]$$

$$= \mathbb{E}_\theta[\mathbb{E}_\theta(Y | u(Y))] = \mathbb{E}_\theta(Y).$$

That is, $\mathbb{E}_\theta(r(u(Y)) - Y) = 0$ for all $\theta \in \Theta$. Since Y is complete, we conclude that $r(u(Y)) = Y$, and since $r(u(Y)) = r(Z)$, we have $r(Z) = Y$, as desired.

□

Basu's theorem tells us that a complete sufficient statistic implies independence from any ancillary statistic. So complete sufficient statistics have no ancillary information, unlike minimal sufficient statistics.

Theorem 10.3.10 (Basu's Theorem, Theorem 5.27 in Math 541A notes). Let $Y : \Omega \rightarrow \mathbb{R}^k$ and $Z : \Omega \rightarrow \mathbb{R}^m$ be statistics. If Y is a complete sufficient statistic for $\{f_\theta : \theta \in \Theta\}$ and Z is ancillary for θ , then for all $\theta \in \Theta$, Y and Z are independent with respect to f_θ .

Proof. Let $A \subseteq \mathbb{R}^k$ and $B \subseteq \mathbb{R}^m$. We need to show that

$$\mathbb{P}_\theta(Y \in A, Z \in B) = \mathbb{P}_\theta(Y \in A)\mathbb{P}_\theta(Z \in B), \quad \forall \theta \in \Theta.$$

Note that

$$\mathbb{P}_\theta(Y \in A, Z \in B) = \mathbb{E}_\theta \mathbf{1}_{\{Y \in A\}} \mathbf{1}_{\{Z \in B\}} = \mathbb{E}_\theta \mathbb{E}_\theta(\mathbf{1}_{\{Y \in A\}} \mathbf{1}_{\{Z \in B\}} \mid Y) = \mathbb{E}_\theta[\mathbf{1}_{\{Y \in A\}} \mathbb{E}_\theta(\mathbf{1}_{\{Z \in B\}} \mid Y)].$$

Let $g(Y) := \mathbb{E}_\theta(\mathbf{1}_{\{Z \in B\}} \mid Y)$. Then

$$\mathbb{E}_\theta(g(Y)) = \mathbb{E}_\theta(\mathbb{E}_\theta(\mathbf{1}_{\{Z \in B\}} \mid Y)) = \mathbb{E}_\theta(\mathbf{1}_{\{Z \in B\}}) = \mathbb{P}_\theta(Z \in B). \quad (10.14)$$

Let $c := \mathbb{P}_\theta(Z \in B) = \mathbb{E}_\theta(g(Y)) = \mathbb{E}_\theta[\mathbb{E}_\theta(\mathbf{1}_{\{Z \in B\}} \mid Y)]$. Then c does not depend on θ since Z is ancillary by assumption. Then $\mathbb{E}_\theta(g(Y) - c) = 0, \forall \theta \in \Theta$ for all $\theta \in \Theta$. Note that $g(Y) := \mathbb{E}_\theta(\mathbf{1}_{\{Z \in B\}} \mid Y)$ does not depend on θ since Y is sufficient. Since Y is complete, $g(Y) - c = 0 \iff g(Y) = c$, so Y is constant. Therefore by (10.14)

$$c = \mathbb{E}_\theta(c) = \mathbb{E}_\theta(g(Y)) = \mathbb{P}_\theta(Z \in B),$$

so we have

$$\mathbb{P}_\theta(Y \in A, Z \in B) = \mathbb{P}_\theta(Y \in A)g(Y) = \mathbb{P}_\theta(Y \in A)c = \mathbb{P}_\theta(Y \in A)\mathbb{P}_\theta(Z \in B), \quad \forall \theta \in \Theta.$$

as desired. \square

Example 10.9 (Example from 541B). $X_1, \dots, X_n \sim \mathcal{N}(\mu, 1)$, i.i.d. Then \bar{X}_n is complete sufficient for μ . Therefore by Basu's Theorem (Theorem 10.3.10) and Example 10.4, \bar{X}_n and $X_1 - \bar{X}_n$ are independent.

Example 10.10. By Basu's Theorem (Theorem 10.3.10), the sample mean and sample variance of a random sample of a Gaussian random variable are independent.

Theorem 10.3.11 (Complete statistics in the exponential family; Theorem 6.2.25 in Casella and Berger [2001]). Let X_1, \dots, X_n be i.i.d. observations from an exponential family with pdf or pmf of the form

$$f(x \mid \boldsymbol{\theta}) = h(x)c(\boldsymbol{\theta}) \exp\left(\sum_{j=1}^k w(\theta_j)t_j(x)\right)$$

where $\boldsymbol{\theta} = (\theta_1, \dots, \theta_k)$, $\boldsymbol{\theta} \in \Theta$. Then the statistic

$$T(X) = \left(\sum_{i=1}^n t_1(X_i), \dots, \sum_{i=1}^n t_k(X_i) \right)$$

is complete as long as the parameter space Θ contains an open set in \mathbb{R}^k .

10.4 Point Estimation

Definition 10.15 (Point estimator). Let X_1, \dots, X_n be a random sample of size n from a family of distribution $\{f_\theta : \theta \in \Theta\}$. If Y is a statistic that is used to estimate the parameter θ that fits the data at hand, we then refer to Y as a **point estimator** or **estimator**.

10.4.1 Heuristic Principles for Finding Good Estimators

Definition 10.16 (Likelihood, Definition 6.1 in Math 541A notes). Let X_1, \dots, X_n be a random sample of size n from a family of distributions $\{f_\theta : \theta \in \Theta\}$. If we have data $x \in \mathbb{R}^n$, then the function $L : \Theta \rightarrow [0, \infty)$ defined by $L(\theta) := f_\theta(x)$ is called the **likelihood function**.

- **Likelihood principle:** All data relevant to estimating the parameter θ is contained in the likelihood function.
- **Sufficiency principle:** If $Y = t(X_1, \dots, X_n)$ is a sufficient statistic and if we have two results $x, y \in \mathbb{R}^n$ from an experiment with the same statistics $t(x) = t(y)$, then our estimate of the parameter θ should be the same for either experimental result.
- **Equivariance principle:** If the family of distributions $\{f_\theta : \theta \in \Theta\}$ is invariant under some symmetry, then the estimator of θ should respect the same symmetry. (For example, a location family is invariant under translation, so an estimator for the location parameter should commute with translations.)

10.4.2 Evaluating Estimators

We can enumerate several desirable properties for estimators.

Definition 10.17 (Unbiasedness, Definition 6.2 in Math 541A notes). Let X_1, \dots, X_n be a random sample of size n from a family of distributions $\{f_\theta : \theta \in \Theta\}$. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}^k$ and let $Y := t(X_1, \dots, X_n)$ be an estimator for $g(\theta)$. Let $g : \Theta \rightarrow \mathbb{R}^k$. We say that Y is **unbiased** for $g(\theta)$ if $\mathbb{E}_\theta Y = g(\theta)$ for all $\theta \in \Theta$.

One common way to check the quality of an estimator is the mean squared error, or squared L_2 norm, of the estimator minus θ , $\mathbb{E}_\theta(Y - g(\theta))^2$. If the estimator is unbiased, this quantity is equal to the variance of Y .

Definition 10.18 (UMVU, sometimes called MVUE (minimum variance unbiased estimator); Definition 6.3 in Math 541A Notes). Let X_1, \dots, X_n be a random sample of size n from a family of distributions $\{f_\theta : \theta \in \Theta\}$. Let $g : \Theta \rightarrow \mathbb{R}$. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}$ and let $Y := t(X_1, \dots, X_n)$ be an unbiased estimator for $g(\theta)$. We say that Y is **uniformly minimum variance unbiased (UMVU)** if, for any other unbiased estimator Z for $g(\theta)$, we have $\text{Var}_\theta(Y) \leq \text{Var}_\theta(Z)$ for all $\theta \in \Theta$.

Remark 123. The “uniform” property has to do with the fact that this inequality must hold for every $\theta \in \Theta$ (as opposed to for a particular θ , or averaged over all $\theta \in \Theta$, or something like that).

Example 10.11 (Math 541B example). Suppose $X \sim \text{Bin}(3, \theta)$, $\theta \in [0, 1]$. Does there exist an unbiased estimator of θ^5 ? No. Assume that $T(X)$ is unbiased for θ^5 , so that

$$\mathbb{E}_\theta T(x) = \sum_{j=0}^3 T(j) \binom{3}{j} \theta^j (1-\theta)^{3-j} = \theta^5 \quad \forall \theta \in [0, 1].$$

But this cannot be, because the quantity on the left side of the last equality is a third degree polynomial in θ and the quantity on the right side is a 5th degree polynomial. So the only powers of θ that are possible to estimate unbiasedly in this case are powers less than or equal to 3.

Example 10.12 (Math 541B example). $X_1, \dots, X_n \sim \mathcal{N}(\mu, 1), \mu \in \mathbb{R}$. Let $g(\mu) = \mathbb{P}_\mu(X_1 \leq x)$. Find a UMVUE of $g(\mu)$.

Solution.

Consider $S(X_1, \dots, X_n) = I\{X_1 \leq x\}$ (an indicator function). Then $\mathbb{E}_\mu S(X_1, \dots, X_n) = g(\mu)$. Define

$$\hat{S}(X_1, \dots, X_n) := \mathbb{E}[I\{X_1 \leq x\} | \bar{X}_n].$$

Then by Lehmann-Scheffe (Theorem 10.4.3), \hat{S} is UMVU. Note that

$$\hat{S}(X_1, \dots, X_n) = \mathbb{E}[I\{X_1 - \bar{X}_n \leq x - \bar{X}_n\} | \bar{X}_n]$$

By Example 10.4, $X_1 - \bar{X}_n$ is independent of \bar{X}_n , so we can write

$$= \mathbb{E}[I\{X_1 - \bar{X}_n \leq x - \bar{X}_n\}] = \mathbb{P}[X_1 - \bar{X}_n \leq x - \bar{X}_n] = \phi\left(\sqrt{\frac{n}{n+1}}(x - \bar{X}_n)\right)$$

where $\phi(\cdot)$ is the cdf of a standard Gaussian random variable.

More generally, given a family of distributions $\{f_{\tilde{\theta}} : \tilde{\theta} \in \Theta\}$, we could be given a **loss function** $L(\theta, y) : \Theta \times \mathbb{R}^k \rightarrow \mathbb{R}$ and be asked to minimize the **risk function** $r(\theta, Y) := \mathbb{E}_{\tilde{\theta}}(\ell(\theta, Y))$ over all possible estimators Y . In the case of mean squared error loss, we have $L(\theta, y) := (y - g(\theta))^2$ for all $y, \theta \in \mathbb{R}$.

The Rao-Blackwell Theorem says that if $L(\theta, y)$ is convex in y then we can create an optimal estimator for $g(\theta)$ from a sufficient statistic and any estimator for $g(\theta)$ (we can lower the risk of an estimator Y by conditioning on a sufficient statistic Z).

Theorem 10.4.1 (Rao-Blackwell; Theorem 6.4 in Math 541A notes). Let Z be a sufficient statistic for $\{f_\theta : \theta \in \Theta\}$ and let Y be an estimator for $g(\theta)$. Define $W := \mathbb{E}_\theta(Y | Z)$. Let $\theta \in \Theta$. Then

$$\text{Var}_\theta(W) \leq \text{Var}_\theta(Y).$$

Further, let $r(\theta, y) < \infty$ and such that $\ell(\theta, y)$ is convex in y . Then

$$r(\theta, W) \leq r(\theta, Y).$$

Proof. To get the first statement, note that

$$\begin{aligned}\text{Var}_\theta(W) &= \mathbb{E}_\theta [W - g(\theta)]^2 \\ &= \mathbb{E}_\theta [\mathbb{E}_\theta(Y | Z) - g(\theta)]^2 \\ &= \mathbb{E}_\theta [\mathbb{E}_\theta(Y - g(\theta) | Z)]^2 \\ &\leq \mathbb{E}_\theta [\mathbb{E}_\theta([Y - g(\theta)]^2 | Z)] \\ &= \mathbb{E}_\theta [(Y - g(\theta))^2] \\ &= \text{Var}_\theta(Y),\end{aligned}$$

where the inequality follows that $\text{Var}(W) = \mathbb{E}W^2 - (\mathbb{E}W)^2 \geq 0$ for any random variable W (in this case, $W = Y - g(\theta) | Z$, and there is equality only if $\text{Var}(W) = 0$; that is, $Y - g(\theta)$ can take just one value for each value of T , so Y is a deterministic function of T .

To get the second statement, note that since Z is sufficient, W does not depend on θ . By the Conditional Jensen's Inequality (Theorem 9.1.6) and using the convexity of $\ell(\theta, y)$ in y ,

$$\ell(\theta, w) = \ell(\theta, \mathbb{E}_{\tilde{\theta}}(Y | Z)) \leq \mathbb{E}_{\tilde{\theta}}[\ell(\theta, Y) | Z].$$

Take expectations of both sides to get

$$\mathbb{E}_{\tilde{\theta}}\ell(\theta, w) = r(\theta, W) \leq \mathbb{E}_{\tilde{\theta}}\mathbb{E}_{\tilde{\theta}}[\ell(\theta, Y) | Z] = \mathbb{E}_{\tilde{\theta}}\ell(\theta, Y) = r(\theta, Y).$$

□

Definition 10.19 (Definition 6.4 in 541A notes; MISSED SOME NOTES TODAY). We say Y is **uniformly minimum risk unbiased** (UMRU) if for any other unbiased estimator Z for $g(\theta)$,

$$r(\theta, Y) \leq r(\theta, z), \quad \forall \theta \in \Theta$$

Remark 124. Unfortunately, UMRU or UMVU may not exist. More fundamentally, an unbiased estimator for $g(\theta)$ may not exist. For example, let X be a binomial random variable with known n , unknown $0 < \theta < 1$, and $g(\theta) = \theta/(1 - \theta)$. Then no unbiased estimator exists for $g(\theta)$. Why?

$$\mathbb{E}_\theta t(X) = \sum_{j=0}^n t(j) \binom{n}{j} \theta^j (1 - \theta)^{n-j}, \quad \forall \theta \in \Theta, \text{ by definition of } X.$$

where the summation is a polynomial of degree at most n in θ . Then it is impossible to have $\mathbb{E}_\theta t(x) = g(\theta)$ when $g(\theta) = \theta/(1 - \theta)$.

Recall the definition of strict convexity (Definition 9.2).

Theorem 10.4.2 (Rao-Blackwell restated; Theorem 6.7 in Math 541A notes). Let Z be a sufficient statistic for $\{f_\theta : \theta \in \Theta\}$ and let Y be an estimator for $g(\theta)$. Define $W := \mathbb{E}_\theta(Y | Z)$. Let $\theta \in \Theta$ with $r(\theta, y) < \infty$ and such that $\ell(\theta, y)$ is convex in y . Then

$$r(\theta, W) \leq r(\theta, Y).$$

Further, if $\ell(\theta, y)$ is strictly convex in $y \in \mathbb{R}$, then $r(\theta, W) < r(\theta, Y)$ unless $W = Y$ (that is, there is a unique minimizer of the risk).

So Z makes the estimator better. Question: can we construct $\mathbb{E}_\theta(Y | Z)$ to be UMRS?

Remark 125 (Remark 6.9 in Math 541A notes). $\mathbb{E}_\theta W = \mathbb{E}_\theta \mathbb{E}_\theta(Y | Z) = \mathbb{E}_\theta Y$. So if Y is unbiased for $g(\theta)$, then so is W .

Remark 126. What happens if Z is constant in Rao-Blackwell? Then in general Z will not be sufficient, so W might depend on θ which is not allowed. Put another way, if Z has insufficient information, then W gets messed up (??).

Example 10.13. Let X_1, \dots, X_n be a random sample with unknown mean $\mu \in \mathbb{R}$. We want to construct an estimator for μ using Rao-Blackwell. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}$ so that $t(x_1, \dots, x_n) = x_1$ for all $x = (x_1, \dots, x_n) \in \mathbb{R}^n$. Let $Y = t(X_1, \dots, X_n) = X_1$. Note that Y is unbiased. First use of Rao-Blackwell: use $Z = (X_1, \dots, X_n)$. Then by Exercise 5.24,

$$W := \mathbb{E}_\mu(X_1 | (X_1, \dots, X_n)) = \mathbb{E}(X_1 | X_1) = X_1.$$

We can think of this as failing to improve the estimator because we used “too much” information. Second try: use $Z = \sum_{i=1}^n X_i$. Note that in the Gaussian case Z is sufficient for μ and unbiased for $n\mu$. Since X_1, \dots, X_n are i.i.d. for all $1 \leq k \leq \ell \leq n$ the joint distribution of $(X_k, \sum_{i=1}^n X_i)$ is the same as the joint distribution of $(X_\ell, \sum_{i=1}^n X_i)$. So

$$\mathbb{E}(X_k | \sum_{i=1}^n X_i) = \mathbb{E}(X_\ell | \sum_{i=1}^n X_i).$$

So we have

$$W := \mathbb{E}_\mu\left(X_1 | \sum_{i=1}^n X_i\right) = \frac{1}{n} \sum_{j=1}^n \mathbb{E}_\mu\left(X_j | \sum_{i=1}^n X_i\right) = \frac{1}{n} \mathbb{E}_\mu\left(\sum_{j=1}^n X_j | \sum_{i=1}^n X_i\right) = \frac{1}{n} \sum_{i=1}^n X_i.$$

So we started with a trivial estimator X_1 and ended up with the sample mean using Rao-Blackwell.

Theorem 10.4.3 (Lehmann-Scheffe, Theorem 6.13 in Math 541A notes). Let Z be a complete sufficient statistic for a family of distributions $\{f_\theta : \theta \in \Theta\}$. Let Y be an unbiased estimator for $g(\theta)$. Define $W := \mathbb{E}_\theta(Y | Z)$. (Since Z is sufficient, W does not depend on θ .) Then W is UMRS for $g(\theta)$. Further, if $\ell(\theta, y)$ is strictly convex in y for all $\theta \in \Theta$, then W is unique. In particular, W is the unique UMVU for $g(\theta)$.

Proof. W is unbiased by Remark 6.10 in math 541A notes (“ $\mathbb{E}_\theta W = \mathbb{E}_\theta \mathbb{E}_\theta(Y | Z) = \mathbb{E}_\theta Y$. So if Y is unbiased for $g(\theta)$, then so is W .”) We first show W does not depend on Y . Let Y' be an unbiased estimator for $g(\theta)$. We show that $\mathbb{E}_\theta(Y | Z) = \mathbb{E}_\theta(Y' | Z)$ for all $\theta \in \Theta$. Note that

$$\mathbb{E}_\theta(\mathbb{E}_\theta(Y | Z) - \mathbb{E}_\theta(Y' | Z)) = \mathbb{E}_\theta(Y - Y') = g(\theta) - g(\theta) = 0, \forall \theta \in \Theta$$

Note that $\mathbb{E}_\theta(Y | Z)$ and $\mathbb{E}_\theta(Y' | Z)$ are functions of Z . Therefore since Z is complete, $\mathbb{E}_\theta(Y | Z) = \mathbb{E}_\theta(Y' | Z)$ for all $\theta \in \Theta$.

Next, by Rao Blackwell,

$$r(\theta, Y') = r(\theta, \mathbb{E}_\theta(Y' | Z)) = r(\theta, \mathbb{E}_\theta(Y | Z)) = r(\theta, W), \forall \theta \in \Theta.$$

□

Remark 127 (**Remark 6.14 in Math 541A notes, Theorem 7.3.23 in Casella and Berger [2001, p. 347]**). Let $Z : \Omega \rightarrow \mathbb{R}^k$ be a complete sufficient statistic for $\{f_\theta : \theta \in \Theta\}$ and let $h : \mathbb{R}^k \rightarrow \mathbb{R}^m$. Let $g(\theta) := \mathbb{E}_\theta h(Z)$ for all $\theta \in \Theta$. Then $h(Z)$ is unbiased for $g(\theta)$, since $\mathbb{E}_\theta h(Z) = g(\theta) = \mathbb{E}_\theta(g(\theta))$. Applying Theorem 10.4.3, we have

$$W := \mathbb{E}_\theta(h(Z) | Z) = \mathbb{E}_\theta(\mathbb{E}_\theta[h(Z) | h(Z)] | Z) = \mathbb{E}_\theta[h(Z) | h(Z)] = h(Z).$$

Therefore by Theorem 10.4.3, $h(Z)$ is UMVU for $g(\theta)$. That is, any function of a complete sufficient statistic is UMVU for its expected value. So one way to find a UMVU is to come up with a function of a complete sufficient statistic that is unbiased for a given function $g(\theta)$.

Summary of methods for finding UMVU (given a complete sufficient statistic Z , want to estimate $g(\theta)$)

- (1) **(Condition method/Rao-Blackwell):** Follow Theorem 10.4.3: find an unbiased Y and let $W := \mathbb{E}_\theta(Y | Z)$. (problem: can be hard to find an unbiased Y .)
- (2) Solve for $h : \mathbb{R}^k \rightarrow \mathbb{R}$ satisfying

$$\mathbb{E}_\theta h(Z) = g(\theta) \tag{10.15}$$

by the above remark, (10.15) will also give you the UMVU. Then $h(Z)$ is UMVU for $g(\theta)$. By “solve”, consider that we have g and Z and somehow solve for the h satisfying (10.15). For example if Z is binomial the left side of (10.15) will be the sum of a bunch of numbers. Find the h values that satisfy (10.15), if possible.

- (3) **(Luck method):** Somehow guess the h such that (10.15) is satisfied.

Example 10.14. Suppose we are sampling from a Gaussian distribution with unknown mean and variance. By the Factorization Theorem and Exercise 5.23 (**on homework 4**), we know (\bar{X}, S^2) is complete sufficient of (μ, σ^2) (sufficiency follows by the Factorization Theorem (Theorem 10.3.3), completeness follows by the exercise). For example, using method (2) above, \bar{X} is UMVU for μ (with finite σ) by method (3) above, since \bar{X} is a function of (\bar{X}, S^2) , $h(x, y) := x$, $g(\mu, \sigma^2) := \mu$ (then (10.15) is satisfied). Similarly, S^2 is UMVU for σ^2 by (3) using $h(x, y) := y$, $g(\mu, \sigma^2) := \sigma^2$ (then (10.15) is satisfied).

Suppose we want a UMVU for μ^2 . Try guessing $(\bar{X})^2$ as an estimator. Note that

$$\mathbb{E}[(\bar{X})^2] = \mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2 = \frac{1}{n^2} \left(\sum_{i=1}^n \mathbb{E}X_i^2 + 2 \sum_{1 \leq i < j \leq n} \mathbb{E}X_i \mathbb{E}X_j \right) = \dots = \mu^2 + \sigma^2/n$$

So,

$$\mathbb{E}\left(\bar{X}^2 - S^2/n\right) = \mu^2$$

which means that $\bar{X}^2 - S^2/n$ is UMVU since it is a function of (\bar{X}, S^2) .

Example 10.15. Try Method (2). Let X be a binomial random variable with known parameter n and unknown $0 < \theta < 1$. Suppose we want to estimate $g(\theta) := \theta(1 - \theta)$. Solve (10.15): find the h satisfying

$$\theta(1 - \theta) = \mathbb{E}_\theta h(X)$$

$$\iff \theta(1 - \theta) = \sum_{j=0}^n h(j) \binom{n}{j} \theta^j (1 - \theta)^{n-j}, \quad \forall \theta \in (0, 1)$$

For convenience, let $a := \theta/(1 - \theta)$, so that $a(1 - \theta) = \theta \iff \theta = a/(1 + a)$, $1 - \theta = 1/(1 + a)$. Then we have

$$(1 - \theta)^{-n} = \sum_{j=0}^n h(j) \binom{n}{j} a^j = \theta(1 - \theta)^{1-n} = \frac{a}{1+a} \left(\frac{1}{1+a}\right)^{1-n} = a(1+a)^{n-2} \quad (10.16)$$

So we want to solve for $h(j)$ so that for all $a > 0$,

$$\sum_{j=0}^n h(j) \binom{n}{j} a^j = a(1+a)^{n-2} = (\text{RHS of (10.16), by binomial theorem}) a \sum_{j=0}^{n-2} \binom{n-2}{j} a^j = \sum_{j=1}^{n-1} \binom{n-2}{j-1} a^j$$

We need the coefficients to match up one by one. So $h(0) = h(n) = 0$, and then it works if $h(j) \binom{n}{j} = \binom{n-2}{j-1}$ for all $j \in 1, \dots, n-1$. So

$$h(j) = \frac{\binom{n-2}{j-1}}{\binom{n}{j}} = \frac{(n-2)!}{n!} \frac{(n-j)!j!}{| } (n-j-1)!(j-1)! = \frac{(n-j)j}{n(n-1)}$$

So in fact,

$$h(j) = \frac{(n-j)j}{n(n-1)}, \quad \forall 0 \leq j \leq n$$

Therefore the UMVU for $\theta(1 - \theta)$ is

$$\frac{X(n - X)}{n(n - 1)}.$$

Example 10.16. Try Method (1). Suppose we have n independent samples X_1, \dots, X_n from a Bernoulli distribution with unknown $\theta \in (0, 1)$. From Example 6.10 (Example 3.15 in Math 541A notes) and Exercise 5.23 in Math 541A notes, a complete sufficient statistic is $Z := \sum_{i=1}^n X_i$ is complete and sufficient for θ . Also, $(1/n) \sum_{i=1}^n X_i$ is unbiased for θ . So, $(1/n) \sum_{i=1}^n X_i - i$ is UMVU for θ . Suppose we want to estimate θ^2 . We need an unbiased estimator Y for θ^2 . Let $Y = X_1 X_2$. Then $\mathbb{E}(Y) = \mathbb{E}(X_1)\mathbb{E}(X_2) = \theta^2$. By Theorem 10.4.3, $W := \mathbb{E}_\theta(Y | Z)$ is UMVU for σ^2 . Note, $Y = 1$ when $X_1 = X_2 = 1$ and 0 otherwise. So

$$\begin{aligned} \mathbb{E}_\theta(Y | Z = z) &= \mathbb{E}_\theta(\mathbf{1}_{\{X_1=X_2=1\}} | Z = z) = \mathbb{P}_\theta(X_1 = X_2 = 1 | Z = z) = \mathbb{P}_\theta(X_1 = X_2 = 1 | \sum_{i=1}^n X_i = z) \\ &= \frac{1}{\mathbb{P}_\theta\left(\sum_{i=1}^n X_i = z\right)} \cdot \mathbb{P}_\theta\left(X_1 = X_2 = 1 \cap \sum_{i=1}^n X_i = z\right) \\ &= \frac{1}{\mathbb{P}_\theta\left(\sum_{i=1}^n X_i = z\right)} \cdot \mathbb{P}_\theta\left(X_1 = X_2 = 1 \cap \sum_{i=3}^n X_i = z - 2\right) \\ &= \frac{\theta^2 \binom{n-2}{z-2} \theta^{z-2} (1-\theta)^{n-z}}{\binom{n}{z} \theta^z (1-\theta)^{n-z}} = \frac{\binom{n-z}{z-2}}{\binom{n}{z}} = \frac{(n-z)!(n-z)!z!}{n!(n-z)!(z-2)!} = \frac{z(z-1)}{n(n-1)} \end{aligned}$$

So we have shown that for all $0 \leq Z \leq n$,

$$\mathbb{E}_\theta(Y | Z = z) = \frac{z(z-1)}{n(n-1)}.$$

So, by Theorem 10.4.3,

$$W := \mathbb{E}_\theta(Y | Z) = \frac{Z(Z-1)}{n(n-1)}$$

is UMVU for θ^2 .

Question: If W_1 is UMVU for $g_1(\theta)$ and W_2 is UMVU for $g_2(\theta)$, is $W_1 + W_2$ UMVU for $g_1(\theta) + g_2(\theta)$? If there is a complete sufficient statistic, then by Lehmann-Scheffe (Theorem 10.4.3), $W_1 = \mathbb{E}_\theta(Y_1 | Z)$, $W_2 = \mathbb{E}_\theta(Y_2 | Z)$ where Y_1 is unbiased for g_1 , Y_2 is unbiased for g_2 . Then

$$W_1 + W_2 = \mathbb{E}_\theta(Y_1 + Y_2 | Z).$$

Note: $\mathbb{E}_\theta(Y_1+Y_2) = \mathbb{E}_\theta Y_1 + \mathbb{E}_\theta Y_2 = g_1(\theta) + g_2(\theta) = g_Z(2\theta)$. So W_1+W_2 is UMVU by Lehmann-Scheffe (Theorem 10.4.3) for $g_1(\theta) + g_2(\theta)$. But is it true if we don't have a complete sufficient statistic (and this argument doesn't apply)? **yes, by the theorem below; this condition will clearly hold across sums.**

Theorem 10.4.4 (Alternate Characterization of UMVU; Theorem 6.18 in Math 541A notes). Let $f \in \{f_\theta : \theta \in \Theta\}$ be a family of distributions and let $g : \Theta \rightarrow \mathbb{R}$. Let W be an unbiased estimator for $g(\theta)$ (note that the existence of an unbiased estimator is a nontrivial assumption). Let $L_2(\Omega)$ be the set of statistics with finite second moment. Then $W \in L_2(\Omega)$ is UMVU for $g(\theta)$ if and only if for any $\theta \in \Theta$,

$$\mathbb{E}_\theta(WU) = 0, \quad \forall U \in L_2(\Omega) \text{ that are unbiased estimators of } 0$$

Thinking of this as an inner product, we have to be orthogonal to all such U .

Proof. Assume W is UMVU for $g(\theta)$. Let U be an unbiased estimator of 0. Let $s \in \mathbb{R}$, consider $W + sU$. Note that $W + sU$ is also unbiased for $g(\theta)$. Since W is UMVU,

$$\begin{aligned} \text{Var}_\theta(W) &\leq \text{Var}_\theta(W + sU) = \text{Var}_\theta(W) + s^2 \text{Var}_\theta(U) + 2s \text{Cov}_\theta(W, U) \\ &= \text{Var}_\theta(W) + s^2 \text{Var}(U) + 2s \mathbb{E}_\theta[(W - \mathbb{E}_\theta(W))U], \quad \forall \theta \in \Theta. \end{aligned}$$

Note that we have equality when $s = 0$. Also, the derivative of the right side with respect to s must be 0 when $s = 0$ or else the inequality does not hold (the minimum value occurs at $s = 0$ if and only if the derivative of the right side in s is 0 at $s = 0$). Note that the derivative of the right side is

$$0 = 2\mathbb{E}_\theta[(W - \mathbb{E}_\theta W)U] = 2\mathbb{E}_\theta(WU).$$

The converse is also true because this reasoning can be reversed, since if Y is any unbiased estimator for $g(\theta)$, then $U := W - Y$ is an unbiased estimator for 0, and $Y = W + sU$ with $s = 1$. We have

$$\text{Var}_\theta(Y) = \text{Var}_\theta(W - U) = \text{Var}_\theta W + \text{Var}_\theta U + 2\text{Cov}_\theta(W, U) = \text{Var}_\theta W + \text{Var}_\theta U + 2\mathbb{E}_\theta(WU)$$

So $\text{Var}_\theta Y \geq \text{Var}_\theta W$ for all $\theta \in \Theta$.

□

Remark 128. If we have a complete sufficient statistic, better to use the earlier methods in general (unless it is really complicated to work with). If we don't have a complete sufficient statistic, use this theorem.

10.4.3 Efficiency of an Estimator

Another desirable property of an estimator is high efficiency—“good” with a small number of samples. One way to quantify this notion is to define a notion of “information” and try to maximize the information content of the estimator.

Definition 10.20 (Fisher Information, Definition 6.19 in Math 541A notes). Let $f \in \{f_\theta : \theta \in \Theta\}$ be a family of multivariate probability densities or probability mass functions. Assume $\Theta \subseteq \mathbb{R}$ (this is a one-parameter situation). Let X be a random variable with distribution f_θ . Define the **Fisher information** of the family to be

$$I(\theta) = I_X(\theta) := \mathbb{E}_\theta \left(\frac{d}{d\theta} \log f_\theta(X) \right)^2, \quad \forall \theta \in \Theta$$

if this quantity exists and is finite.

(See also Section 14.14 for connections to generalized linear models.)

Remark 129. Note that if X is continuous,

$$\mathbb{E}_\theta \left(\frac{d}{d\theta} \log f_\theta(X) \right) = \int_{\mathbb{R}^n} \frac{1}{f_\theta(x)} \frac{d}{d\theta} f_\theta(x) \cdot f_\theta(x) dx = \int_{\mathbb{R}^n} \frac{d}{d\theta} f_\theta(x) dx = \frac{d}{d\theta} \int_{\mathbb{R}^n} f_\theta(x) dx = \frac{d}{d\theta} 1 = 0.$$

So we could have equivalently defined the Fisher information as

$$I_X(\theta) = \text{Var}_\theta \left(\frac{d}{d\theta} \log f_\theta(X) \right)$$

Example 10.17 (Example 6.20 in Math 541A notes). Let $\theta > 0$, let

$$f_\theta(x) := \frac{1}{\sigma\sqrt{2\pi}} \exp \left(-\frac{(x-\theta)^2}{2\sigma^2} \right), \quad \forall \theta \in \mathbb{R} = \Theta, \forall x \in \mathbb{R}.$$

Then

$$I(\theta) = \text{Var}_\theta \left(\frac{d}{d\theta} - \frac{(x-\theta)^2}{2\sigma^2} \right) = \frac{1}{\sigma^4} \text{Var}_\theta(x-\theta) = \frac{\sigma^2}{\sigma^4} = \frac{1}{\sigma^2}.$$

Observe that a small σ means large $I(\theta)$ in this case.

Proposition 10.4.5 (Proposition 6.21 in Math 541A notes). Let X be a random variable with distribution from $\{f_\theta : \theta \in \Theta\}$ (densities or mass functions). Let Y be a random variable with distribution from $\{g_\theta : \theta \in \Theta\}$ (densities or mass functions). Assume $\Theta \subseteq \mathbb{R}$ (one parameter in θ). If X and Y are independent, then

$$I_{(X,Y)}(\theta) = I_X(\theta)I_Y(\theta).$$

Proof. This proof will just be for the case of densities (continuous random variables; the case for probability mass functions is similar). Since X and Y are independent, (X, Y) has a distribution with density $f_\theta(x)g_\theta(y)$, for all $x, y \in \mathbb{R}$. Also, $\frac{d}{d\theta} \log f_\theta(X)$ and $\frac{d}{d\theta} \log g_\theta(Y)$ are independent for all $\theta \in \Theta$. So,

$$I_{(X,Y)}(\theta) = \text{Var}_\theta \left(\frac{d}{d\theta} \log[f_\theta(X)g_\theta(Y)] \right) = \text{Var}_\theta \left(\frac{d}{d\theta} \log[f_\theta(X)] + \frac{d}{d\theta} \log[g_\theta(Y)] \right)$$

By independence we can write

$$= \text{Var}_\theta \left(\frac{d}{d\theta} \log[f_\theta(X)] \right) + \text{Var}_\theta \left(\frac{d}{d\theta} \log[g_\theta(Y)] \right) = I_X(\theta) + I_Y(\theta).$$

□

Remark 130. This is consistent with a notion of “information” since if variables are independent, the information is the sum of the information of each variable. This proof also shows the main reason why the logarithm is in the definition of the Fisher information—it brings a product to a sum.

Proposition 10.4.6 (Exercise 6.22 in Math 541A notes). Let X be a random variable with distribution from $\{f_\theta : \theta \in \Theta\}$ (densities or mass functions). Let Y be a random variable with distribution from $\{g_\theta : \theta \in \Theta\}$ (densities or mass functions). Then

$$I_{(X,Y)}(\theta) = I_X(\theta) + I_{Y|X=x}(\theta), \quad \forall \theta \in \Theta, x \in \mathbb{R}.$$

Proof. Recall that $Y | X$ has density $f_{X,Y}(x,y)/f_X(x)$ for any fixed x . And if X, Y are discrete random variables, recall that $Y | X$ has mass function $\mathbb{P}(X=x, Y=y)/\mathbb{P}(Y=y)$.

$$\begin{aligned} I_{(X,Y)}(\theta) &= \text{Var}_\theta \left(\frac{d}{d\theta} \log[f_{\theta(X,Y)}(x,y)] \right) = \text{Var}_\theta \left(\frac{d}{d\theta} \log[f_\theta(x)f_{\theta(Y|X=x)}(y)] \right) \\ &= \text{Var}_\theta \left(\frac{d}{d\theta} \log[f_\theta(X)] + \frac{d}{d\theta} \log[f_{\theta(Y|X=x)}(y)] \right) \end{aligned}$$

Note that $Y | X = x$ is independent of X (because we have conditioned out the dependence). Therefore we have

$$= \text{Var}_\theta \left(\frac{d}{d\theta} \log[f_\theta(X)] \right) + \text{Var}_\theta \left(\frac{d}{d\theta} \log[f_{\theta(Y|X=x)}(y)] \right) = I_X(\theta) + I_{Y|X=x}(\theta).$$

□

Theorem 10.4.7 (Cramer-Rao/Information Inequality, Theorem 6.23 in Math 541A Notes).

Let $X : \Omega \rightarrow \mathbb{R}^n$ be a random variable with distribution from a family of multivariable probability densities or probability mass functions $\{f_\theta : \theta \in \Theta\}$ with $\Theta \subseteq \mathbb{R}$ and Θ an open interval. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}$ and let $Y := t(X)$ be a statistic. For any $\theta \in \Theta$ let $g(\theta) := \mathbb{E}_\theta Y$. Assume $g'(\theta)$ and $\frac{\partial p_\theta(x)}{\partial \theta}$ exist for all x . Assume the set $A = \{x : p_\theta(x) = 0\}$ does not depend on θ , and assume the Fisher information $I_X(\theta)$ is finite and nonzero. Lastly, assume

$$\frac{d}{d\theta} \int T(x)p_\theta(x) dx = \int T(x) \frac{d}{d\theta} p_\theta(x) dx.$$

Then

$$\text{Var}_\theta(Y) \geq \frac{|g'(\theta)|^2}{I_X(\theta)}, \quad \forall \theta \in \Theta.$$

In particular, if Y is unbiased for θ , then $g(\theta) = \theta$, so,

$$\text{Var}_\theta(Y) \geq \frac{1}{I_X(\theta)}, \quad \forall \theta \in \Theta.$$

Equality occurs for some $\theta \in \Theta$ only when $\frac{d}{d\theta} \log f_\theta(x)$ and $Y - \mathbb{E}_\theta Y$ are multiples of each other.

Remark 131. For a one-parameter family of distributions, the equality case of Theorem 10.4.7 gives a new way to find a UMVU that avoids any discussion of complete sufficient statistics. This is another way to find a UMVU ($\frac{d}{d\theta} \log f_\theta(X)$) that sidesteps the need for a complete sufficient statistic. That is, to find a UMVU, we look for affine functions of $\frac{d}{d\theta} \log f_\theta(X)$.

Proof.

$$|g'(\theta)| = \left| \frac{d}{d\theta} \int_{\mathbb{R}} f_\theta(x) t(x) dx \right| = \left| \int_{\mathbb{R}} \left(\frac{d}{d\theta} \log f_\theta(x) \right) t(x) f_\theta(x) dx \right| = \left| \mathbb{E}_\theta \frac{d}{d\theta} \log f_\theta(X) t(X) \right|$$

Note that $\mathbb{E}_\theta \frac{d}{d\theta} \log f_\theta(X) = 0$, so this can be written as

$$= \left| \text{Cov}_\theta \left(\frac{d}{d\theta} \log f_\theta(X), t(X) \right) \right|$$

Then by Remark 1.63 in math 541A notes, by the Cauchy-Schwarz inequality,

$$\mathbb{E}[(X - \mathbb{E}X)(Y - \mathbb{E}Y)] \leq \sqrt{\text{Var}_\theta(X)\text{Var}_\theta(Y)},$$

so we have

$$\begin{aligned} \left| \text{Cov}_\theta \left(\frac{d}{d\theta} \log f_\theta(X), t(X) \right) \right| &\leq \sqrt{\text{Var}_\theta \left(\frac{d}{d\theta} \log f_\theta(X) \right) \text{Var}_\theta(Y)} = \sqrt{I_X(\theta)} \sqrt{\text{Var}_\theta(Y)} \\ \iff |g'(\theta)|^2 &\leq I_X(\theta) \text{Var}_\theta(Y) \iff \text{Var}_\theta(Y) \geq \frac{|g'(\theta)|^2}{I_X(\theta)}, \quad \forall \theta \in \Theta. \end{aligned}$$

Recall that equality occurs in the Cauchy-Schwarz inequality if and only if $\frac{d}{d\theta} \log f_\theta(x)$ is a constant multiple of $Y - \mathbb{E}_\theta Y$ with probability 1. (See also Corollary 7.3.15 in Casella and Berger [2001, p. 341].)

□

Example 10.18 (Example 6.24). Suppose $f_\theta(x) := \theta x^{\theta-1} \mathbf{1}_{0 < x < 1}$ for all $x \in \mathbb{R}, \theta > 0$. (This is a beta distribution with $\beta = 1$.) We have

$$\frac{d}{d\theta} \log f_\theta(x) = \frac{1}{\theta} + \log x, \quad \forall 0 < x < 1.$$

A vector $X = (X_1, \dots, X_n)$ of n independent samples from f_θ is distributed according to the product $\prod_{i=1}^n f_\theta(x_i)$, so that

$$\frac{d}{d\theta} \log \prod_{i=1}^n f_\theta(x_i) = \frac{d}{d\theta} \sum_{i=1}^n \log f_\theta(x_i) = \sum_{i=1}^n \left(\frac{1}{\theta} + \log x_i \right) = n \left(\frac{1}{\theta} + \frac{1}{n} \log \prod_{i=1}^n x_i \right), \quad \forall 0 < x_i < 1, 1 \leq i \leq n.$$

Then by Theorem 10.4.7 (Theorem 6.23 in Math 541A notes), any function of $\frac{d}{d\theta} \log \prod_{i=1}^n f_\theta(X_i)$ (plus a constant) is UMVU of its expectation. So, e.g.

$$Y := -\frac{1}{n} \log \prod_{i=1}^n X_i$$

is UMVU of its expectation, and $\mathbb{E}_\theta Y = \theta^{-1}$ since $\mathbb{E}_\theta \frac{d}{d\theta} \log \prod_{i=1}^n f_\theta(X_i) = \mathbb{E} n \left(\frac{1}{\theta} + \frac{1}{n} \log \prod_{i=1}^n x_i \right) = 0$.

Definition 10.21 (Efficiency, Definition 6.25 in Math 541A notes). Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable with distribution from a family of multivariable probability densities or probability mass functions $\{f_\theta : \theta \in \Theta\}$ with $\Theta \in \mathbb{R}$. Let $t : \mathbb{R}^n \rightarrow \mathbb{R}$ and let $Y := t(X)$ be a statistic. Define the **efficiency** of Y to be

$$\frac{1}{I_X(\theta) \text{Var}_\theta(Y)}, \quad \forall \theta \in \Theta$$

if this quantity exists and is finite. If Z is another statistic, we define the **relative efficiency** of Y to Z to be

$$\frac{I_X(\theta) \text{Var}_\theta(Z)}{I_X(\theta) \text{Var}_\theta(Y)} = \frac{\text{Var}_\theta(Z)}{\text{Var}_\theta(Y)}, \quad \forall \theta \in \Theta.$$

Definition 10.22 (Efficient estimator; Math 541B definition). We say that $\hat{\theta}_n$ is an **efficient** estimator of θ if and only if its variance achieves the Cramer-Rao lower bound (**and it is unbiased?**).

Definition 10.23 (Efficient estimator; Math 541B definition). We say that $\hat{\theta}_n$ is an **efficient** estimator of θ if and only if

$$\sqrt{n}(\hat{\theta}_n - \theta) \xrightarrow{d} \mathcal{N}\left(0, \frac{1}{I(\theta)}\right).$$

Superefficiency (Math 541B). Let $X_1, \dots, X_n \sim \mathcal{N}(\mu, 1)$. Then \bar{X}_n is efficient, and it is also asymptotically efficient. Now consider **Hodge's Estimator**:

$$T'(X_1, \dots, X_n) := \begin{cases} \bar{X}_n & |\bar{X}_n| \geq n^{-1/4} \\ 0 & |\bar{X}_n| < n^{-1/4}. \end{cases}$$

Claim: $\sqrt{n}(T' - \theta) \xrightarrow{d} \mathcal{N}(0, 1)$ for $\theta \neq 0$. Moreover, for $r_n(T' - \theta) \xrightarrow{p} 0$ for any sequence r_n when $\mu = 0$.

10.4.4 Bayes Estimation

In Bayes estimation, the parameter $\theta \in \Theta$ is regarded as a random variable Ψ . The distribution of Ψ reflects our prior knowledge about the probable values of Ψ . Then, given that $\Psi = \theta$, the conditional distribution of $X | \Psi = \theta$ is assumed to be $\{f_\theta : \theta \in \Theta\}$, where $f_\theta : \mathbb{R}^n \rightarrow [0, \infty)$. Suppose $t : \mathbb{R}^n \rightarrow \mathbb{R}^k$ and we have a statistic $Y := t(X)$ and a loss function $\ell : \mathbb{R}^k \times \mathbb{R}^k \rightarrow \mathbb{R}$. Let $g : \Theta \rightarrow \mathbb{R}^k$.

Definition 10.24 (Bayes estimator, Definition 6.26 in Math 541A notes). A **Bayes estimator** Y for $g(\theta)$ with respect to Ψ is defined such that

$$\mathbb{E}\ell(g(\Psi), Y) \leq \mathbb{E}\ell(g(\Psi), Z)$$

for all estimators Z . Here the expectation is with respect to both Ψ and Y . Note that we have not made any assumptions about bias for Y or Z . To find a Bayes estimator, it is sufficient to minimize the conditional risk.

Remark 132. $t(X)$ can depend on Ψ .

Proposition 10.4.8 (Proposition 6.27 in Math 541A notes). Suppose there exists $t : \mathbb{R}^k \rightarrow \mathbb{R}$ such that for almost every $x \in \mathbb{R}^n$, $Y := t(X)$ minimizes

$$\mathbb{E}(\ell(g(\Psi), Z) | X = x)$$

over all estimators Z . Then $t(X)$ is a Bayes estimator for $g(\theta)$ with respect to Ψ .

Proof. By assumption,

$$\mathbb{E}(\ell(g(\Psi), t(X)) | X = x) \leq \mathbb{E}(\ell(g(\Psi), Y) | X = x)$$

for any estimator Y and for almost every x . Taking expected values of both sides, we get

$$\mathbb{E}\ell(g(\Psi), t(X)) \leq \mathbb{E}\ell(g(\Psi), Y).$$

□

Example 10.19 (Example 6.29 in Math 541A notes). Suppose $n = 1$, $g(\theta) = \theta$, and $\ell(\Psi, Y) = (\Psi - Y)^2$. The minimum value of

$$\mathbb{E}[(\Psi - Y(X))^2 | X = x] = \mathbb{E}(\Psi^2 - 2\Psi t(X) + (t(X))^2 | X = x)$$

$$= \mathbb{E}(\Psi^2 | X = x) - 2t(X)\mathbb{E}(\Psi | X = x) + (t(X))^2$$

(where we remove expressions with x from the expectation because we take x to be fixed) occurs when $t(x) = \mathbb{E}(\Psi | X = x)$. So in this specific case the Bayes estimator is $Y = t(X) = \mathbb{E}(\Psi | X)$.

Given that $\Psi = \theta < 0$, suppose X is uniform on the interval $[0, \theta]$. (Suppose X is a single sample $n = 1$ from this distribution.) Also assume that Ψ has the gamma distribution with parameters $\alpha = 2$ and $\beta = 1$, so that Ψ has density $\theta e^{-\theta} \mathbf{1}_{\{\theta>0\}}$. The joint distribution of X and Ψ is then

$$f_{\Psi, X}(\theta, x) := \frac{1}{\theta} \mathbf{1}_{\{0 < x < \theta\}} \theta e^{-\theta} \mathbf{1}_{\{\theta>0\}} = \mathbf{1}_{\{0 < x < \theta\}} e^{-\theta}.$$

The marginal distribution of X is then

$$f_X(x) = \mathbf{1}_{\{x>0\}} \int_{-\infty}^{\infty} f_{\Psi, X}(\theta, x) d\theta = \mathbf{1}_{\{x>0\}} \int_x^{\infty} e^{-\theta} d\theta = \mathbf{1}_{\{x>0\}} e^{-x}.$$

So the conditional distribution of Ψ given X is

$$f_{\Psi|X=x}(\theta | x) = \frac{f_{\Psi, X}(\theta, x)}{f_X(x)} = \frac{e^{-\theta} \mathbf{1}_{\{0 < x < \theta\}}}{e^{-x} \mathbf{1}_{\{x>0\}}} = e^{x-\theta} \mathbf{1}_{\{0 < x < \theta\}}.$$

So,

$$\mathbb{E}(\Psi | X = x) = \int_{-\infty}^{\infty} \theta f_{\Psi|X=x}(\theta | x) d\theta = e^x \int_x^{\infty} \theta e^{-\theta} d\theta = e^x ((x+1)e^{-x}) = x + 1.$$

So the Bayes estimator is $Y = t(X) = \mathbb{E}(\Psi | X) = X + 1$. This estimator minimizes $\mathbb{E}(Y - Z)^2$ over all estimators Z . ($\ell(a, b) = (a - b)^2$, $g(\theta) = \theta$, $\mathbb{E}\ell(g(\Psi), Z)$).

In contrast, the UMVU for one sample is $2X$ by Theorem 10.4.3, since $2X$ is complete sufficient and unbiased for θ and $\mathbb{E}_\theta(2X | 2X) = 2X$. (X uniform on $[0, \theta]$, θ unknown, $\mathbb{E}_\theta X = \theta/2, \forall \theta < 0$.)

(Not obvious) For n samples, $(1 + n^{-1})X_{(n)}$ is the UMVU for θ . Note that $2X$ is recovered when $n = 1$. Remarks: this estimator seems to be sufficient because you could factorize it as in the Factorization Theorem (Theorem 10.3.3).

Exercise 28 (2018 DSO Statistics Group In-Class Screening Exam, Question 3). Suppose that given the vector μ , the random vector X has a normal distribution in \mathbb{R}^n with mean μ and identity covariance matrix. We want to make inference about $\|\mu\|^2$.

- (a) Find an unbiased estimate of $\|\mu\|^2$. Call this estimator $\hat{\delta}_{\text{unbiased}}$.
- (b) Suppose that a Bayesian has a proper prior distribution for μ that is Gaussian with mean vector 0 and covariance kI , where k is any fixed positive real number and I is the identity matrix. He wants to minimize mean squared error (MSE). The estimator minimizing the MSE is the posterior mean of $\|\mu\|^2$, i.e., $\mathbb{E}(\|\mu\|^2 | X)$. Find this estimator. Call this estimator $\hat{\delta}_{\text{proper}}$.

- (c) Suppose now the Bayesian uses the uniform prior (which is also called a “flat” or “noninformative” prior) for μ . Report $\mathbb{E}(\|\mu\|^2 | X)$ in this case. Call it $\hat{\delta}_{\text{flat}}$. Report $\hat{\delta}_{\text{flat}} - \hat{\delta}_{\text{unbiased}}$.
- (d) Now, if the true distribution of μ is indeed Gaussian with mean vector 0 and covariance kI , then show that with respect to the unconditional (i.e. marginal) distribution of X , the Bayes estimator $\hat{\delta}_{\text{proper}}$ is closer in Euclidean distance to $\hat{\delta}_{\text{unbiased}}$ than it is to $\hat{\delta}_{\text{flat}}$ when n is large. That is, show

$$\mathbb{E} \left(\hat{\delta}_{\text{proper}} - \hat{\delta}_{\text{unbiased}} \right)^2 < \mathbb{E} \left(\hat{\delta}_{\text{flat}} - \hat{\delta}_{\text{unbiased}} \right)^2$$

for large n , where the expectation is over the unconditional distribution of X , which is

$$\int_{\mathbb{R}^n} f(x | \mu) \pi(\mu) d\mu$$

with $f(x | \mu) = \mathcal{N}_n(\mu, I)$ and $\pi(\mu) = \mathcal{N}_n(0, kI)$. (Hint: let $\hat{D} = \hat{\delta}_{\text{proper}} - \hat{\delta}_{\text{unbiased}}$. Compute the mean and variance of \hat{D} under the unconditional distribution of X .)

Solution.

- (a) We have

$$X | \mu \sim \mathcal{N}(\mu, \mathbf{I}_n)$$

Let $X = (X_1, \dots, X_n)^T$ and let $\mu = (\mu_1, \dots, \mu_n)^T$. Notice that

$$\begin{aligned} \mathbb{E}(\mathbf{X}^T \mathbf{X}) &= \mathbb{E}[\mathbb{E}(\mathbf{X}^T \mathbf{X} | \mu)] = \mathbb{E} [\mathbb{E} (X_1^2 + X_2^2 + \dots + X_n^2 | \mu)] = \mathbb{E} \left[\sum_{i=1}^n \mathbb{E}(X_i^2 | \mu) \right] \\ &= \mathbb{E} \left[\sum_{i=1}^n \text{Var}(X_i | \mu) + \mathbb{E}(X_i | \mu)^2 \right] = \mathbb{E} \left[\sum_{i=1}^n 1 + \mu_i^2 \right] = n + \mathbb{E}\|\mu\|_2^2 \\ &\implies \mathbb{E}(\mathbf{X}^T \mathbf{X} - n) = \mathbb{E}\|\mu\|_2^2 \end{aligned}$$

Therefore $\boxed{\hat{\delta}_{\text{unbiased}} = \mathbf{X}^T \mathbf{X} - n}$ is unbiased for $\mathbb{E}\|\mu\|_2^2$ (and given μ it is unbiased for $\|\mu\|_2^2$).

- (b) We will begin by finding the posterior distribution of μ . The prior distribution of μ is

$$f(\boldsymbol{\mu}) = (2\pi)^{-n/2} |k\mathbf{I}_n|^{-1/2} \cdot \exp \left(-\frac{1}{2} \boldsymbol{\mu}^T (k\mathbf{I}_n)^{-1} \boldsymbol{\mu} \right) = \frac{1}{\sqrt{(2\pi k)^n}} \exp \left(-\frac{1}{2k} \boldsymbol{\mu}^T \boldsymbol{\mu} \right).$$

The likelihood is

$$\begin{aligned} f_{\mathbf{X} | \boldsymbol{\mu}}(\mathbf{x} | \boldsymbol{\mu}) &= (2\pi)^{-n/2} |\mathbf{I}_n|^{-1/2} \cdot \exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T (\mathbf{I}_n)^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right) \\ &= (2\pi)^{-n/2} \exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T (\mathbf{x} - \boldsymbol{\mu}) \right). \end{aligned}$$

So the unconditional distribution of \mathbf{X} is

$$\begin{aligned}
f_{\mathbf{X}}(\mathbf{x}) &= \int_{\mathbb{R}^n} f_{\mathbf{X}|\boldsymbol{\mu}}(\mathbf{x} \mid \boldsymbol{\mu}) f(\boldsymbol{\mu}) d\boldsymbol{\mu} \\
&= \int_{\mathbb{R}^n} (2\pi)^{-n/2} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T(\mathbf{x} - \boldsymbol{\mu})\right) \cdot \frac{1}{\sqrt{(2\pi k)^n}} \exp\left(-\frac{1}{2k}\boldsymbol{\mu}^T\boldsymbol{\mu}\right) d\boldsymbol{\mu} \\
&= \frac{1}{(2\pi\sqrt{k})^n} \int_{\mathbb{R}^n} \exp\left(-\frac{1}{2}\left[\boldsymbol{\mu}^T\boldsymbol{\mu} + \frac{1}{k}\boldsymbol{\mu}^T\boldsymbol{\mu} - 2\mathbf{x}^T\boldsymbol{\mu} + \mathbf{x}^T\mathbf{x}\right]\right) d\boldsymbol{\mu} \\
&= \frac{1}{(2\pi\sqrt{k})^n} \int_{\mathbb{R}^n} \exp\left(-\frac{k+1}{2k}\left[\boldsymbol{\mu}^T\boldsymbol{\mu} - \frac{2k}{k+1}\mathbf{x}^T\boldsymbol{\mu}\right] - \frac{1}{2}\mathbf{x}^T\mathbf{x}\right) d\boldsymbol{\mu} \\
&= \frac{1}{(2\pi\sqrt{k})^n} \int_{\mathbb{R}^n} \exp\left(-\frac{k+1}{2k}\left[\boldsymbol{\mu}^T\boldsymbol{\mu} - \frac{2k}{k+1}\mathbf{x}^T\boldsymbol{\mu} + \left(\frac{k}{k+1}\right)^2\mathbf{x}^T\mathbf{x}\right] - \left(-\frac{k+1}{2k}\right)\left(\frac{k}{k+1}\right)^2\mathbf{x}^T\mathbf{x} - \frac{1}{2}\mathbf{x}^T\mathbf{x}\right) d\boldsymbol{\mu} \\
&= \frac{1}{(2\pi\sqrt{k})^n} \int_{\mathbb{R}^n} \exp\left(-\frac{k+1}{2k}\left[\left(\boldsymbol{\mu} - \frac{k}{k+1}\mathbf{x}\right)^T\left(\boldsymbol{\mu} - \frac{k}{k+1}\mathbf{x}\right)\right] - \frac{1}{2}\left[-\left(\frac{k}{k+1}\right)\mathbf{x}^T\mathbf{x} + \frac{k+1}{k+1}\mathbf{x}^T\mathbf{x}\right]\right) d\boldsymbol{\mu} \\
&= \frac{1}{(2\pi\sqrt{k})^n} \int_{\mathbb{R}^n} \exp\left(-\frac{k+1}{2k}\left[\left(\boldsymbol{\mu} - \frac{k}{k+1}\mathbf{x}\right)^T\left(\boldsymbol{\mu} - \frac{k}{k+1}\mathbf{x}\right)\right]\right) \exp\left(-\frac{1}{2}\frac{1}{k+1}\mathbf{x}^T\mathbf{x}\right) d\boldsymbol{\mu} \\
&= \frac{1}{\sqrt{(2\pi k)^n}} \exp\left(-\frac{1}{2}\frac{1}{k+1}\mathbf{x}^T\mathbf{x}\right) \left(\frac{k}{k+1}\right)^{n/2} \\
&\cdot \int_{\mathbb{R}^n} \frac{1}{\sqrt{(2\pi)^n}} \cdot \left(\frac{k}{k+1}\right)^{-n/2} \exp\left(-\frac{1}{2}\left(\boldsymbol{\mu} - \frac{k}{k+1}\mathbf{x}\right)^T\left(\frac{k}{k+1}\mathbf{I}_n\right)^{-1}\left(\boldsymbol{\mu} - \frac{k}{k+1}\mathbf{x}\right)\right) d\boldsymbol{\mu}
\end{aligned}$$

The second row is the integral over \mathbb{R}^n of an n -dimensional multivariate Gaussian distribution with mean $k/(k+1)\mathbf{x}$ and covariance $k/(k+1)\mathbf{I}_n$, so it equals 1. Then we are left with

$$\begin{aligned}
f_{\mathbf{X}}(\mathbf{x}) &= \frac{1}{\sqrt{(2\pi)^n}} \frac{1}{k^{n/2}} \exp\left(-\frac{1}{2}\frac{1}{k+1}\mathbf{x}^T\mathbf{x}\right) \left(\frac{k}{k+1}\right)^{n/2} \\
&= \frac{1}{\sqrt{(2\pi)^n}} [(k+1)^n]^{-1/2} \exp\left(-\frac{1}{2}\mathbf{x}^T((k+1)\mathbf{I}_n)^{-1}\mathbf{x}\right) \tag{10.17}
\end{aligned}$$

which is the density of an n -dimensional multivariate Gaussian random variable with mean $\mathbf{0}$ and covariance $(k+1)\mathbf{I}_n$. Therefore the posterior distribution of $\boldsymbol{\mu}$ is

$$\begin{aligned}
f_{\boldsymbol{\mu}|\mathbf{X}}(\boldsymbol{\mu} \mid \mathbf{x}) &= \frac{f_{\mathbf{X}|\boldsymbol{\mu}}(\mathbf{x} \mid \boldsymbol{\mu}) f(\boldsymbol{\mu})}{f_{\mathbf{X}}(\mathbf{x})} \\
&= \left[\frac{1}{(2\pi\sqrt{k})^n} \exp\left(-\frac{1}{2}\left[\boldsymbol{\mu}^T\boldsymbol{\mu} + \frac{1}{k}\boldsymbol{\mu}^T\boldsymbol{\mu} - 2\mathbf{x}^T\boldsymbol{\mu} + \mathbf{x}^T\mathbf{x}\right]\right) \right] \Bigg/ \left[\frac{1}{\sqrt{(2\pi)^n}} [(k+1)^n]^{-1/2} \exp\left(-\frac{1}{2}\frac{1}{k+1}\mathbf{x}^T\mathbf{x}\right) \right]
\end{aligned}$$

$$\begin{aligned}
&= \frac{1}{\sqrt{(2\pi)^n}} \left(\frac{k+1}{k} \right)^{n/2} \exp \left(-\frac{k+1}{2k} \left[\left(\boldsymbol{\mu} - \frac{k}{k+1} \mathbf{x} \right)^T \left(\boldsymbol{\mu} - \frac{k}{k+1} \mathbf{x} \right) \right] - \frac{1}{2} \frac{1}{k+1} \mathbf{x}^T \mathbf{x} + \frac{1}{2} \frac{1}{k+1} \mathbf{x}^T \mathbf{x} \right) \\
&= \frac{1}{\sqrt{(2\pi)^n}} \left(\frac{k+1}{k} \right)^{n/2} \exp \left(-\frac{k+1}{2k} \left(\boldsymbol{\mu} - \frac{k}{k+1} \mathbf{x} \right)^T \left(\boldsymbol{\mu} - \frac{k}{k+1} \mathbf{x} \right) \right) \\
&= \frac{1}{\sqrt{(2\pi)^n}} \cdot \left(\frac{k}{k+1} \right)^{-n/2} \exp \left(-\frac{1}{2} \left(\boldsymbol{\mu} - \frac{k}{k+1} \mathbf{x} \right)^T \left(\frac{k}{k+1} \mathbf{I}_n \right)^{-1} \left(\boldsymbol{\mu} - \frac{k}{k+1} \mathbf{x} \right) \right)
\end{aligned}$$

which is an n -dimensional multivariate Gaussian distribution with mean $k/(k+1)\mathbf{x}$ and covariance $k/(k+1)\mathbf{I}_n$. That is, conditional on \mathbf{X} , $\boldsymbol{\mu} = (\mu_1, \dots, \mu_n)$, where

$$\begin{aligned}
&\mu_i \mid \mathbf{X} \stackrel{i.i.d.}{\sim} \mathcal{N} \left(\frac{k}{k+1} X_i, \frac{k}{k+1} \right). \\
&\iff \left(\mu_i - \frac{k}{k+1} X_i \right) \frac{k+1}{k} \mid \mathbf{X} \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1) \iff \frac{k+1}{k} \mu_i - X_i \mid \mathbf{X} \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1) \\
&\implies \mathbb{E} \left(\left[\frac{k+1}{k} \mu_i - X_i \right]^2 \mid \mathbf{X} \right) = 1 \iff \mathbb{E} \left(\left[\frac{k+1}{k} \right]^2 \mu_i^2 + X_i^2 - 2 \frac{k+1}{k} \mu_i X_i \mid \mathbf{X} \right) = 1 \quad (10.18)
\end{aligned}$$

So,

$$\begin{aligned}
\hat{\delta}_{\text{proper}} &= \mathbb{E} (\|\boldsymbol{\mu}\|_2^2 \mid \mathbf{X}) = \mathbb{E} \left(\sum_{i=1}^n \mu_i^2 \mid \mathbf{X} \right) = \left[\frac{k}{k+1} \right]^2 \mathbb{E} \left(\sum_{i=1}^n \left[\frac{k+1}{k} \right]^2 \mu_i^2 \mid \mathbf{X} \right) \\
&= \left[\frac{k}{k+1} \right]^2 \mathbb{E} \left(\sum_{i=1}^n \left[\frac{k+1}{k} \right]^2 \mu_i^2 + X_i^2 - 2 \frac{k+1}{k} \mu_i X_i \mid \mathbf{X} \right) - \left[\frac{k}{k+1} \right]^2 \mathbb{E} \left(\sum_{i=1}^n X_i^2 - 2 \frac{k+1}{k} \mu_i X_i \mid \mathbf{X} \right) \\
&= \left[\frac{k}{k+1} \right]^2 - \left[\frac{k}{k+1} \right]^2 \sum_{i=1}^n X_i^2 + 2 \frac{k+1}{k} \left[\frac{k}{k+1} \right]^2 \sum_{i=1}^n X_i \mathbb{E} (\mu_i \mid \mathbf{X}) \\
&= \left[\frac{k}{k+1} \right]^2 - \left[\frac{k}{k+1} \right]^2 \sum_{i=1}^n X_i^2 + 2 \frac{k}{k+1} \sum_{i=1}^n X_i \cdot \frac{k}{k+1} X_i \\
&= \left[\frac{k}{k+1} \right]^2 + 2 \left[\frac{k}{k+1} \right]^2 \sum_{i=1}^n X_i^2 - \left[\frac{k}{k+1} \right]^2 \sum_{i=1}^n X_i^2 = \left[\frac{k}{k+1} \right]^2 (1 + \mathbf{X}^T \mathbf{X}).
\end{aligned}$$

- (c) We will again begin by finding the posterior distribution of μ . The (improper) prior distribution of μ is constant; that is, for some $c \in \mathbb{R}$,

$$f(\boldsymbol{\mu}) = c, \quad \forall \boldsymbol{\mu} \in \mathbb{R}^n.$$

The likelihood is

$$\begin{aligned} f_{\mathbf{X}|\boldsymbol{\mu}}(\mathbf{x} \mid \boldsymbol{\mu}) &= (2\pi)^{-n/2} |\mathbf{I}_n|^{-1/2} \cdot \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T (\mathbf{I}_n)^{-1} (\mathbf{x} - \boldsymbol{\mu})\right) \\ &= (2\pi)^{-n/2} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T (\mathbf{x} - \boldsymbol{\mu})\right). \end{aligned}$$

So the unconditional distribution of \mathbf{X} is

$$\begin{aligned} f_{\mathbf{X}}(\mathbf{x}) &= \int_{\mathbb{R}^n} f_{\mathbf{X}|\boldsymbol{\mu}}(\mathbf{x} \mid \boldsymbol{\mu}) f(\boldsymbol{\mu}) d\boldsymbol{\mu} = c \int_{\mathbb{R}^n} (2\pi)^{-n/2} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T (\mathbf{x} - \boldsymbol{\mu})\right) d\boldsymbol{\mu} \\ &= c \int_{\mathbb{R}^n} (2\pi)^{-n/2} \exp\left(-\frac{1}{2}(\boldsymbol{\mu} - \mathbf{x})^T (\boldsymbol{\mu} - \mathbf{x})\right) d\boldsymbol{\mu} \end{aligned}$$

The expression inside the integral is the density of a Gaussian random variable with mean \mathbf{x} and covariance \mathbf{I}_n , so the integral evaluates to 1. Therefore the unconditional distribution of \mathbf{X} is also flat. Therefore the posterior distribution of $\boldsymbol{\mu}$ is the same as the likelihood:

$$f_{\boldsymbol{\mu}|\mathbf{X}}(\boldsymbol{\mu} \mid \mathbf{x}) = \frac{f_{\mathbf{X}|\boldsymbol{\mu}}(\mathbf{x} \mid \boldsymbol{\mu}) f(\boldsymbol{\mu})}{f_{\mathbf{X}}(\mathbf{x})} = (2\pi)^{-n/2} \exp\left(-\frac{1}{2}(\boldsymbol{\mu} - \mathbf{x})^T (\boldsymbol{\mu} - \mathbf{x})\right);$$

that is, conditional on \mathbf{X} , $\boldsymbol{\mu}$ is normally distributed with mean \mathbf{X} and covariance \mathbf{I}_n . So conditional on \mathbf{X} , $\boldsymbol{\mu} = (\mu_1, \dots, \mu_n)$, where

$$\mu_i \mid \mathbf{X} \stackrel{i.i.d.}{\sim} \mathcal{N}(X_i, 1).$$

$$\iff \mu_i - X_i \mid \mathbf{X} \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1) \implies \mathbb{E}([\mu_i - X_i]^2 \mid \mathbf{X}) = 1 \iff \mathbb{E}(\mu_i^2 + X_i^2 - 2\mu_i X_i \mid \mathbf{X}) = 1 \quad (10.19)$$

So,

$$\begin{aligned} \hat{\delta}_{\text{flat}} &= \mathbb{E}(\|\boldsymbol{\mu}\|_2^2 \mid \mathbf{X}) = \mathbb{E}\left(\sum_{i=1}^n \mu_i^2 \mid \mathbf{X}\right) = \mathbb{E}\left(\sum_{i=1}^n \mu_i^2 + X_i^2 - 2\mu_i X_i \mid \mathbf{X}\right) - \mathbb{E}\left(\sum_{i=1}^n X_i^2 - 2\mu_i X_i \mid \mathbf{X}\right) \\ &= 1 - \sum_{i=1}^n X_i^2 + 2 \sum_{i=1}^n X_i \mathbb{E}(\mu_i \mid \mathbf{X}) = 1 - \sum_{i=1}^n X_i^2 + 2 \sum_{i=1}^n X_i^2 = 1 + \mathbf{X}^T \mathbf{X}. \end{aligned}$$

So,

$$\hat{\delta}_{\text{flat}} - \hat{\delta}_{\text{unbiased}} = 1 + \mathbf{X}^T \mathbf{X} - (\mathbf{X}^T \mathbf{X} - n) = 1 + n. \quad (10.20)$$

(d) If the true distribution of $\boldsymbol{\mu}$ is the prior from part (b), then the marginal distribution of \mathbf{X} is (10.17):

$$= \frac{1}{\sqrt{(2\pi)^n}} [(k+1)^n]^{-1/2} \exp\left(-\frac{1}{2} \mathbf{x}^T ((k+1)\mathbf{I}_n)^{-1} \mathbf{x}\right);$$

that is, $\mathbf{X} \sim \mathcal{N}(\mathbf{0}, (k+1)\mathbf{I}_n)$. (Note that this means $(k+1)^{-1} X_i$ is standard Gaussian and i.i.d. for all $i \in \{1, \dots, n\}$.) Per the suggestion, let

$$\begin{aligned}\hat{D} &= \hat{\delta}_{\text{proper}} - \hat{\delta}_{\text{unbiased}} = \left[\frac{k}{k+1} \right]^2 (1 + \mathbf{X}^T \mathbf{X}) - (\mathbf{X}^T \mathbf{X} - n) = \frac{k^2 - (k^2 + 2k + 1)}{(k+1)^2} \mathbf{X}^T \mathbf{X} + \left[\frac{k}{k+1} \right]^2 + n \\ &= -\frac{2k+1}{(k+1)^2} \mathbf{X}^T \mathbf{X} + \left[\frac{k}{k+1} \right]^2 + n\end{aligned}\quad (10.21)$$

Since from (10.20) we have

$$\mathbb{E} \left(\hat{\delta}_{\text{proper}} - \hat{\delta}_{\text{unbiased}} \right)^2 = n^2 + 2n + 1,$$

we seek

$$\mathbb{E} \left(\hat{\delta}_{\text{flat}} - \hat{\delta}_{\text{unbiased}} \right)^2 = \mathbb{E}(\hat{D}^2) = \text{Var}(\hat{D}) + [\mathbb{E}(\hat{D})]^2.$$

Note that since $(k+1)^{-1} X_i \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1)$ for all $i \in \{1, \dots, n\}$,

$$\sum_{i=1}^n ((k+1)^{-1} X_i)^2 \sim \chi_n^2,$$

so

$$\mathbb{E} \left[\sum_{i=1}^n \left(\frac{1}{k+1} X_i \right)^2 \right] = n \iff \frac{1}{(k+1)^2} \mathbb{E} \left[\sum_{i=1}^n X_i^2 \right] = n \iff \mathbb{E} \left[\sum_{i=1}^n X_i^2 \right] = n(k+1)^2,$$

and

$$\text{Var} \left[\sum_{i=1}^n \left(\frac{1}{k+1} X_i \right)^2 \right] = 2n \iff \frac{1}{(k+1)^4} \text{Var} \left[\sum_{i=1}^n X_i^2 \right] = 2n \iff \text{Var} \left[\sum_{i=1}^n X_i^2 \right] = 2n(k+1)^4.$$

Under the unconditional distribution of \mathbf{X} ,

$$\begin{aligned}\mathbb{E}(\hat{D}) &= \mathbb{E} \left(-\frac{2k+1}{(k+1)^2} \mathbf{X}^T \mathbf{X} + \left[\frac{k}{k+1} \right]^2 + n \right) = -\frac{2k+1}{(k+1)^2} \mathbb{E}(\mathbf{X}^T \mathbf{X}) + \left[\frac{k}{k+1} \right]^2 + n \\ &= -\frac{2k+1}{(k+1)^2} \mathbb{E} \left(\sum_{i=1}^n X_i^2 \right) + \left[\frac{k}{k+1} \right]^2 + n = -\frac{2k+1}{(k+1)^2} n(k+1)^2 + \left[\frac{k}{k+1} \right]^2 + n \\ &= -n \frac{(2k+1)(k^2 + 2k + 1) + k^2}{(k+1)^2} + n = n \left[\frac{k^2 + 2k + 1}{(k+1)^2} - \frac{2k^3 + 4k^2 + 2k + k^2 + 2k + 1 + k^2}{(k+1)^2} \right] \\ &= n \left[\frac{-2k^3 - 5k^2 - 2k}{(k+1)^2} \right] = -n \left[\frac{2k^3 + 5k^2 + 2k}{(k+1)^2} \right]\end{aligned}$$

Next,

$$\text{Var}(\hat{D}) = \text{Var} \left(-\frac{2k+1}{(k+1)^2} \mathbf{X}^T \mathbf{X} + \left[\frac{k}{k+1} \right]^2 + n \right) = \frac{(2k+1)^2}{(k+1)^4} \text{Var} \left(\sum_{i=1}^n X_i^2 \right)$$

$$= \frac{(2k+1)^2}{(k+1)^4} 2n(k+1)^4 = 2n(2k+1)^2$$

So

$$\mathbb{E} \left(\hat{\delta}_{\text{flat}} - \hat{\delta}_{\text{unbiased}} \right)^2 = 2n(2k+1)^2 + \left(-n \left[\frac{2k^3 + 5k^2 + 2k}{(k+1)^2} \right] \right)^2 = n^2 \left[\frac{2k^3 + 5k^2 + 2k}{(k+1)^2} \right]^2 + n \cdot 2(2k+1)^2$$

$$\approx 4k^2 n^2 + 8k^2 n,$$

so in general when $k \geq 1$ and n is large,, $\mathbb{E} \left(\hat{\delta}_{\text{flat}} - \hat{\delta}_{\text{unbiased}} \right)^2 > \mathbb{E} \left(\hat{\delta}_{\text{proper}} - \hat{\delta}_{\text{unbiased}} \right)^2$; that is, the flat prior Bayes estimator is further from the unbiased estimator than the proper prior Bayes estimator.

10.4.5 Method of Moments

Definition 10.25 (Consistency, Definition 6.30 in Math 541A notes). Let $\{f_\theta : \theta \in \Theta\}$ be a family of distributions. Let Y_1, Y_2, \dots be a sequence of estimators of $g(\theta)$. We say that Y_1, Y_2, \dots is **consistent** for $g(\theta)$ if for any $\theta \in \Theta$, Y_1, Y_2, \dots converges in probability to the constant value $g(\theta)$ with respect to the probability distribution f_θ . That is, $Y_n \xrightarrow{P} g(\theta)$. (Typically we will take Y_n to be a function of a random sample of size n for all $n \geq 1$.)

Example 10.20 (Example 6.31 in Math 541A notes). Let X_1, \dots, X_n be a random sample of size n with distribution f_θ . The Weak Law of Large Numbers (Theorem 8.6.1) says that the sample mean is consistent when $\mathbb{E}_\theta |X_1| < \infty$ for all $\theta \in \Theta$. More generally, if $j \geq 1$ is a positive integer such that $\mathbb{E}_\theta |X_1|^j < \infty$ for all $\theta \in \Theta$, then the j th sample moment

$$M_j = M_{j,n}(\theta) := \frac{1}{n} \sum_{i=1}^n X_i^j$$

is a consistent estimator for $\mu_j(\theta) := \mathbb{E} X_1^j$.

Definition 10.26 (Method of Moments, Definition 6.32 in Math 541A notes). Let $g : \Theta \rightarrow \mathbb{R}^k$. Suppose we want to estimate $g(\theta)$ for any $\theta \in \Theta$. Suppose there exists $h : \mathbb{R}^j \rightarrow \mathbb{R}^k$ such that $g(\theta) = h(\mu_1, \dots, \mu_j)$. Then the estimator

$$h(M_1, \dots, M_j)$$

is a **method of moments** estimator for $g(\theta)$, where M_j is the j th sample moment

$$M_j = M_{j,n}(\theta) := \frac{1}{n} \sum_{i=1}^n X_i^j$$

Example 10.21 (Example 6.33 in Math 541A notes). Recall that the standard deviation is

$$\sqrt{\text{Var}(X)} = \sqrt{\mathbb{E}(X^2) - [\mathbb{E}(X)]^2}.$$

To estimate the standard deviation, we can use $\Theta = \mathbb{R} \times (0, \infty) = \{(\mu_1, \mu_2) : \mu_1 \in \mathbb{R}, \mu_2 > 0\}$, $j = 2$, and $h(\mu_1, \mu_2) = \sqrt{\mu_2 - \mu_1^2}$, so that the method of moments estimator of the standard deviation is $\sqrt{M_2 - M_1^2}$.

Remark 133. The method of moments estimator is not necessarily unbiased.

10.4.6 Maximum likelihood estimator

Definition 10.27 (Maximum Likelihood Estimator (Math 541B Definition)). $P = \{P_\theta, \theta \in \Theta\}$, X_1, \dots, X_n i.i.d. $P_{\theta_0}, \theta_0 \in \Theta$. The likelihood function

$$L_n(\theta | X_1, \dots, X_n) := \prod_{j=1}^n p_\theta(x_j)$$

$$\ell_n(\theta | X_1, \dots, X_n) = \log(L_n(\theta | X_1, \dots, X_n)) = \sum_{i=1}^n \log p_\theta(X_j)$$

Then the MLE $\hat{\theta}_n$ is defined as

$$\hat{\theta}_n \in \arg \max_{\theta \in \Theta} \{L_n(\theta)\} = \arg \max_{\theta \in \Theta} \{\ell_n(\theta)\}.$$

Remark 134. Under some reasonable assumptions, the maximum likelihood estimator is consistent. However, the MLE does not always exist and might not be unique. See Keener for details.

Remark 135 (Math 541 B remarks). Equivalently, $\hat{\theta}_n$ maximizes

$$\begin{aligned} & \prod_{j=1}^n \frac{p_\theta(X_j)}{p_{\theta_0}(X_j)} \\ \iff & \hat{\theta}_n = \arg \max_{\theta \in \Theta} \left\{ \frac{1}{n} \sum_{i=1}^n \log \left[\frac{p_\theta(X_j)}{p_{\theta_0}(X_j)} \right] \right\} \end{aligned}$$

As $n \rightarrow \infty$, for every $\theta \in \Theta$, by the Law of Large Numbers

$$\begin{aligned} & \frac{1}{n} \sum_{i=1}^n \log \left[\frac{p_\theta(X_j)}{p_{\theta_0}(X_j)} \right] \xrightarrow{\text{a.s.}} \mathbb{E}_{\theta_0} \log \left(\frac{p_\theta(X)}{p_{\theta_0}(X)} \right) \\ \iff & \hat{\theta}_n \approx \arg \min_{\theta \in \Theta} \mathbb{E}_{\theta_0} \log \left(\frac{p_{\theta_0}(X)}{p_\theta(X)} \right) =: KL(p_{\theta_0} || p_\theta) \end{aligned}$$

where $KL(p_{\theta_0} || p_\theta)$ is the **Kullback-Leibler Divergence**. Facts:

1.

$$KL(p_{\theta_0} || p_{\theta}) = 0 \iff p_{\theta_0} = p_{\theta} \iff \theta = \theta_0 \text{ (identifiability)}$$

Proof.

$$KL(p_{\theta_0} || p_{\theta}) = \mathbb{E}_{\theta_0} - \log \left(\frac{p_{\theta}(X)}{p_{\theta_0}(x)} \right) \geq \text{(by Jensen's Inequality)} - \log \left(\mathbb{E}_{\theta_0} \left[\log \left(\frac{p_{\theta}(X)}{p_{\theta_0}(x)} \right) \right] \right) = 0$$

for Jensen's Inequality, equality holds if and only if

$$\mathbb{P} \left(\frac{p_{\theta}(X)}{p_{\theta_0}(x)} = 1 \right) = 1$$

□

2. $KL(p||q)$ is not a distance: $KL(p||q) \neq KL(q||p)$, and the KL divergence does not satisfy the Triangle Inequality.
3. **total variational distance** (Definition 13.1.2 in Lehmann and Romano [2005]): (in principle, existence of density is not required, but typically we assume a density exists)

$$TV(P, Q) := \sup_A |P(A) - Q(A)| = \frac{1}{2} \int |p - q| d\mu$$

Pinsker's Inequality:

$$TV(P, Q) \leq \sqrt{\frac{KL(P||Q)}{2}}.$$

Hellinger's Distance (Definition 13.1.3 in Lehmann and Romano [2005]): (need to assume existence of density)

$$H^2(P, Q) := \int (\sqrt{p} - \sqrt{q})^2 d\mu$$

(ℓ_2 distance between square roots of densities. See also Definition 10.38.)

Le Cann's Inequality:

$$TV(P, Q) \geq \frac{1}{2} H^2(P, Q)$$

Using Pinsker's Inequality and Le Cann's Inequality, you can relate KL divergence to Hellinger's Distance.

For more information on KL Divergence, see Sections 6.5 and 14.4.1).

Proposition 10.4.9 (Math 541A Proposition 6.40). For all $i \in 1, \dots, n$, if $\Theta \rightarrow f_{\theta}(x_i)$ is strictly log-concave, then $\ell(\theta)$ has at most one maximum value.

Remark 136. One example of a function whose log likelihood has no maximum value is $\exp(-e^{-\theta})$ (as in an extreme value distribution).

Remark 137. Intuition of Lemma 6.50 in Math 541A: if distribution follows θ then it is more likely to match distribution function of f_{θ} than f_{ω} .

Note on Theorem 6.53: exponential family is an example of a family that satisfies condition (a).

Note from proof:

$$\sqrt{n}\ell_n(\theta) = \frac{1}{\sqrt{n}} \left(\sum_{i=1}^n \log f_\theta(x_i) - \mathbb{E}(\log f_\theta(x_i)) \right) \xrightarrow{d} \mathcal{N}\left(0, \frac{1}{I_{X_1}(\theta)}\right)$$

by the Central Limit Theorem (and Assumption 3 for the variance) since $\mathbb{E}(\log f_\theta(x_i)) = 0$. Also,

$$\ell''_n(\theta') = \frac{1}{n} \sum_{i=1}^n \frac{d^2}{d[\theta']^2} \log f_{\theta'}(x_i)$$

which explains the applicability of the Weak Law of Large Numbers.

Proposition 10.4.10 (Stats 100B homework problem). Suppose X_1, X_2, \dots, X_n is a random sample from a Bernoulli(p) distribution. Let $X = \sum_{i=1}^n X_i$. Then

- (a) The maximum likelihood estimator of p is $\hat{p} = X/n$.
- (b) The maximum likelihood estimator attains the Cramer-Rao lower bound.
- (c) The maximum likelihood estimator is a consistent estimator for p .
- (d) $\frac{\hat{p}(1-\hat{p})}{n-1}$ is an unbiased estimator for $\text{Var}(\hat{p}) = p(1-p)/n$.

Proof. a. Bernoulli random variable:

$$P(X_i = x) = p^x (1-p)^{1-x}$$

Assuming independent samples,

$$\begin{aligned} L &= \prod_{i=1}^n p^{X_i} (1-p)^{1-X_i} = p^{\sum_{i=1}^n X_i} (1-p)^{\sum_{i=1}^n 1-X_i} \\ \log(L) &= \sum_{i=1}^n X_i \log(p) + \left(\sum_{i=1}^n 1-X_i \right) \log(1-p) \\ \frac{d \log(L)}{dp} &= \frac{1}{p} \sum_{i=1}^n X_i - \frac{1}{1-p} \sum_{i=1}^n (1-X_i) = 0 \\ \frac{1}{\hat{p}} \sum_{i=1}^n X_i &= \frac{1}{1-\hat{p}} \sum_{i=1}^n (1-X_i) \\ (1-\hat{p}) \sum_{i=1}^n X_i &= \hat{p} \sum_{i=1}^n (1-X_i) \\ \sum_{i=1}^n X_i &= \hat{p} \sum_{i=1}^n (X_i + 1 - X_i) \end{aligned}$$

$$\sum_{i=1}^n X_i = n\hat{p}$$

$$\boxed{\hat{p} = \frac{1}{n} \sum_{i=1}^n X_i}$$

b.

$$\text{Var}(\hat{p}) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i\right)$$

Since X_i are independent, we can write this as

$$\frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i)$$

And since X_i is Bernoulli, $\text{Var}(X_i) = p(1-p)$.

$$= \frac{1}{n^2} \sum_{i=1}^n p(1-p) = \frac{1}{n^2} np(1-p) = \boxed{\frac{p(1-p)}{n}}$$

Cramer-Rao lower bound:

$$\text{Var}(\hat{\theta}) \geq 1/\left(-n\mathbb{E}\left[\frac{\partial^2 \log(f(X; \theta))}{\partial \theta^2}\right]\right)$$

$$\frac{\partial}{\partial p} \log(p^x(1-p)^{1-x}) = \frac{\partial}{\partial p}(x \log(p) + (1-x) \log(1-p)) = \frac{x}{p} - \frac{1-x}{1-p}$$

$$\frac{\partial^2 \log(f(X; \theta))}{\partial \theta^2} = \frac{\partial}{\partial p}\left(\frac{x}{p} - \frac{1-x}{1-p}\right) = -\frac{x}{p^2} - \frac{1-x}{(1-p)^2}$$

$$\mathbb{E}\left[\frac{\partial^2 \log(f(X; \theta^2))}{\partial \theta^2}\right] = \mathbb{E}\left(-\frac{x}{p^2} - \frac{1-x}{(1-p)^2}\right) = -\frac{1}{p^2}\mathbb{E}(x) - \frac{1}{(1-p)^2}\mathbb{E}(1-x) = -\frac{1}{p^2}p - \frac{1}{(1-p)^2}(1-p)$$

$$= -\frac{1}{p} - \frac{1}{1-p} = -\frac{1-p}{p(1-p)} - \frac{p}{p(1-p)} = \frac{-1}{p(1-p)}$$

$$\implies \text{Var}(\hat{p}) \geq 1/\left(-n\left(\frac{-1}{p(1-p)}\right)\right) = \frac{p(1-p)}{n} = \text{Var}(\hat{p})$$

c. (1) Unbiased:

$$E\left(\frac{X}{n}\right) = \frac{np}{p} = p$$

(2) $\text{Var}(\hat{\theta}) \rightarrow 0$ as $n \rightarrow \infty$:

$$\lim_{n \rightarrow \infty} \text{Var}\left(\frac{X}{n}\right) = \lim_{n \rightarrow \infty} \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \lim_{n \rightarrow \infty} \frac{1}{n^2} \cdot np(1-p) = \lim_{n \rightarrow \infty} \frac{p(1-p)}{n} = \boxed{0}$$

Therefore $\frac{X}{n}$ is a consistent estimator of p .

d.

$$\begin{aligned}
\mathbb{E}(\hat{\sigma}^2) &= \mathbb{E}\left[\frac{1}{n}\left(\frac{X}{n}(1 - \frac{X}{n})\right)\right] = \mathbb{E}\left[\frac{X(n-X)}{n^3}\right] = \frac{1}{n^3}\mathbb{E}[nX - (X)^2] = \frac{1}{n^2}\mathbb{E}(X) - \frac{1}{n^3}\mathbb{E}(X^2) \\
&= \frac{1}{n^2} \cdot np - \frac{1}{n^3}(\text{Var}(X) + (E(X))^2) = \frac{p}{n} - \frac{np(1-p)}{n^3} - \frac{p^2n^2}{n^3} = \frac{pn - p + p^2 - p^2n}{n^2} \\
&= \frac{p(n-1+p-pn)}{n^2} = \frac{p(n-1)(1-p)}{n^2}
\end{aligned}$$

This is a biased estimator since $\text{Var}(X) = \frac{p(1-p)}{n}$ (since X is binomial).

$$c \cdot \frac{p(n-1)(1-p)}{n^2} = \frac{p(1-p)}{n} \implies \boxed{c = \frac{n}{n-1}}$$

□

Proposition 10.4.11 (Stats 100B homework problem). Suppose that X follows a geometric distribution and we take an i.i.d. sample of size n . Then the maximum likelihood estimator of p is

$$\hat{p} = \frac{n}{\sum_{i=1}^n X_i} = \frac{1}{\bar{X}}.$$

Proof. Since sample is i.i.d.:

$$L = \prod_{i=1}^n p(1-p)^{X_i-1} = p^n(1-p)^{-n+\sum_{i=1}^n X_i}$$

$$\log(L) = n \log(p) + \left(-n + \sum_{i=1}^n X_i\right) \log(1-p)$$

$$\frac{d \log(L)}{dp} = \frac{n}{p} - \frac{1}{1-p} \left(-n + \sum_{i=1}^n X_i\right) = 0$$

$$\frac{n}{\hat{p}} = \frac{1}{1-\hat{p}} \left(-n + \sum_{i=1}^n X_i\right)$$

$$(1-\hat{p})\hat{p} = -n\hat{p} + \hat{p} \sum_{i=1}^n X_i$$

$$n = \hat{p} \sum_{i=1}^n X_i$$

$$\hat{p} = \frac{n}{\sum_{i=1}^n X_i} = \frac{1}{\bar{X}}$$

□

Proposition 10.4.12 (Stats 100B homework problem). Suppose X_1, X_2, \dots, X_n is a random sample from a $\text{Poisson}(\lambda)$ distribution. Then

- (a) The maximum likelihood estimator of λ is

$$\hat{\lambda} = \frac{1}{n} \sum_{i=1}^n X_i.$$

- (b) The variance of the maximum likelihood estimator is

$$\text{Var}(\hat{\lambda}) = \frac{\lambda}{n}$$

- (c) The maximum likelihood estimator is a minimum variance unbiased estimator.
(d) The maximum likelihood estimator is consistent.

Proof. (a)

$$f(X_i; \lambda) = \frac{\lambda^{X_i} e^{-\lambda}}{X_i!}$$

Assuming the samples are independent,

$$\begin{aligned} L &= \prod_{i=1}^n \frac{\lambda^{X_i} e^{-\lambda}}{X_i!} = \left(e^{-n\lambda} \lambda^{\sum_{i=1}^n X_i} \right) / \prod_{i=1}^n X_i! \\ \log(L) &= -n\lambda + \left(\sum_{i=1}^n X_i \right) \log(\lambda) - \sum_{i=1}^n \log(X_i!) \\ \frac{d \log(L)}{d\lambda} &= -n + \frac{1}{\lambda} \sum_{i=1}^n X_i = 0 \\ \implies \hat{\lambda} &= \frac{1}{n} \sum_{i=1}^n X_i = \bar{x} \end{aligned}$$

- (b)

$$\text{Var}(\hat{\lambda}) = \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i\right)$$

Since X_i are i.i.d. this can be written as

$$= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{1}{n^2} \sum_{i=1}^n \lambda = \frac{\lambda}{n}$$

- (c) Cramer-Rao lower bound:

$$\text{Var}(\hat{\lambda}) \geq 1 / \left(-n \mathbb{E} \left[\frac{\partial^2 \log(f(X; \lambda))}{\partial \lambda^2} \right] \right)$$

$$\log(f(X; \lambda)) = \log \left(\frac{\lambda^{X_i} e^{-\lambda}}{X_i!} \right) = X_i \log(\lambda) - \lambda - \log(X_i!)$$

$$\frac{\partial}{\partial \lambda} \log(f(X; \lambda)) = \frac{1}{\lambda} X_i - 1$$

$$\frac{\partial^2 \log(f(X; \lambda))}{\partial \lambda^2} = -\frac{1}{\lambda^2} X_i$$

$$\mathbb{E}\left[\frac{\partial^2 \log(f(X; \lambda^2))}{\partial \lambda}\right] = -\frac{1}{\lambda^2} \mathbb{E}(X_i) = -\frac{1}{\lambda^2} \lambda = -\frac{1}{\lambda}$$

$$\implies \text{Var}(\hat{\lambda}) \geq 1/\left(-n\mathbb{E}\left[\frac{\partial^2 \log(f(X; \lambda))}{\partial \lambda^2}\right]\right) = \frac{1}{n/\lambda} = \boxed{\frac{\lambda}{n} = \text{Var}(\hat{\lambda})}$$

Since $\text{Var}(\hat{\lambda})$ equals the Cramer-Rao lower bound, $\hat{\lambda}$ is a MVUE.

- (d) We already know the MLE is unbiased. To show consistency, we show $\text{Var}(\hat{\theta}) \rightarrow 0$ as $n \rightarrow \infty$.

$$\lim_{n \rightarrow \infty} \text{Var}(\hat{\lambda}) = \lim_{n \rightarrow \infty} \frac{\lambda}{n} = \boxed{0}$$

Therefore $\hat{\lambda}$ is a consistent estimator of λ . □

Proposition 10.4.13 (Stats 100B homework problem, similar to Math 541A example 6.47).
Suppose X_1, X_2, \dots, X_n is a random sample from a Exponential(λ) distribution. Then the maximum likelihood estimator of λ is

$$\hat{\lambda} = n / \sum_{i=1}^n X_i = \frac{1}{\bar{X}}.$$

Proof.

$$f(X_i; \lambda) = \lambda e^{-\lambda X_i}$$

Assuming the samples are independent,

$$\begin{aligned} L &= \prod_{i=1}^n \lambda e^{-\lambda X_i} = \lambda^n \exp(-\lambda \sum_{i=1}^n X_i) \\ \iff \log(L) &= n \log(\lambda) + -\lambda \sum_{i=1}^n X_i \\ \iff \frac{d \log(L)}{d \lambda} &= \frac{n}{\lambda} - \sum_{i=1}^n X_i = 0 \\ \implies \hat{\lambda} &= n / \sum_{i=1}^n X_i = \frac{1}{\bar{X}} \end{aligned}$$

□

Proposition 10.4.14 (Stats 100B homework problem; similar to Math 541A Example 6.45).

Let X_1, X_2, \dots, X_n be an i.i.d. random sample from a normal population with mean zero and unknown variance σ^2 . Then

- (a) The maximum likelihood estimator of σ^2 is

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n X_i^2.$$

- (b) The maximum likelihood estimator of σ^2 is biased, but asymptotically unbiased.

- (c) The maximum likelihood estimator of σ^2 has variance

$$\text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i^2\right) = \frac{2\sigma^4}{n}$$

and is consistent.

- (d) The variance of the maximum likelihood estimator of σ^2 reaches the Cramer-Rao lower bound.

- (e) The maximum likelihood estimator of μ is

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n X_i$$

and it is unbiased and UMVU/MVUE.

Proof. a. Since sample is i.i.d. $\mathcal{N}(0, \sigma^2)$:

$$\begin{aligned} L &= \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left[\frac{X_i - \mu}{\sigma}\right]^2\right) = (2\pi\sigma^2)^{-n/2} \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \mu)^2\right) \\ \log(L) &= -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \mu)^2 = -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\sigma^2) - (\sigma^2)^{-1} \frac{1}{2} \sum_{i=1}^n (X_i - \mu)^2 \\ \frac{\partial \log(L)}{\partial \sigma^2} &= -\frac{n}{2} \frac{1}{\sigma^2} + (\sigma^2)^{-2} \frac{1}{2} \sum_{i=1}^n (X_i - \mu)^2 = 0 \\ \frac{\sum_{i=1}^n (X_i - \mu)^2}{(\hat{\sigma}^2)^2} &= \frac{n}{\hat{\sigma}^2} \\ \hat{\sigma}^2 &= \frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2 \end{aligned}$$

- b. something wrong with this part

$$\mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n X_i^2\right) = \frac{1}{n} \mathbb{E}\left(\sum_{i=1}^n X_i^2\right)$$

Since the sample is i.i.d., this can be written as

$$\frac{1}{n} \sum_{i=1}^n \mathbb{E}(X_i^2)$$

Since $X_i \sim \mathcal{N}(0, \sigma^2)$, $X_i^2 / \sigma^2 \sim \chi_1^2$. So we have

$$\mathbb{E}\left(\frac{X_i^2}{\sigma^2}\right) = 1$$

$$\frac{1}{\sigma^2} \mathbb{E}(X_i^2) = 1$$

$$\mathbb{E}(X_i^2) = \sigma^2$$

Therefore

$$\mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n X_i^2\right) = \frac{1}{n} \sum_{i=1}^n \sigma^2 = \frac{1}{n} n \sigma^2 = \boxed{\sigma^2}$$

However it is asymptotically biased: that is,

$$\lim_{n \rightarrow \infty} \frac{\mathbb{E}(\hat{\sigma}^2)}{\sigma^2} = 1$$

c.

$$\text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i^2\right) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i^2\right)$$

Since X_i is i.i.d. this can be written as

$$\frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i^2)$$

Again, , $X_i^2 / \sigma^2 \sim \chi_1^2$, so we have

$$\text{Var}\left(\frac{X_i^2}{\sigma^2}\right) = 2$$

$$\frac{1}{\sigma^4} \text{Var}(X_i^2) = 2$$

$$\text{Var}(X_i^2) = 2\sigma^4$$

Therefore

$$\text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i^2\right) = \frac{1}{n^2} \sum_{i=1}^n 2\sigma^4 = \frac{2n\sigma^4}{n^2} = \boxed{\frac{2\sigma^4}{n}}$$

Test for consistency (already known that estimate is unbiased):

$$\lim_{n \rightarrow \infty} \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i^2\right) = \lim_{n \rightarrow \infty} \frac{2\sigma^4}{n} = \boxed{0}$$

So this is a consistent estimator of σ^2 .

d. Cramer-Rao lower bound:

$$\text{Var}(\hat{\theta}) \geq 1 / \left(-n \mathbb{E} \left[\frac{\partial^2 \log(f(X; \theta))}{\partial \theta^2} \right] \right)$$

$$\log(f(X; \theta)) = \log \left[\frac{1}{\sigma \sqrt{2\pi}} \exp \left(-\frac{1}{2} \left[\frac{X_i}{\sigma} \right]^2 \right) \right] = -\frac{1}{2} \log(2\pi) - \frac{1}{2} \log(\sigma^2) - \frac{1}{2} X_i^2 (\sigma^2)^{-1}$$

$$\frac{\partial}{\partial \sigma^2} \left(-\frac{1}{2} \log(2\pi) - \frac{1}{2} \log(\sigma^2) - \frac{1}{2} X_i^2 (\sigma^2)^{-1} \right) = -\frac{1}{2\sigma^2} + \frac{1}{2} (X_i)^2 (\sigma^2)^{-2}$$

$$\frac{\partial^2 \log(f(X; \theta))}{\partial (\sigma^2)^2} = \frac{1}{2} (\sigma^2)^{-2} - X_i^2 (\sigma^2)^{-3}$$

$$\mathbb{E} \left[\frac{\partial^2 \log(f(X; \theta^2))}{\partial \theta^2} \right] = \mathbb{E} \left[\frac{1}{2} (\sigma^2)^{-2} - X_i^2 (\sigma^2)^{-3} \right] = \frac{1}{2\theta^4} - \frac{1}{\theta^6} \mathbb{E}(X_i^2) = \frac{1}{2\theta^4} - \frac{\theta^2}{\theta^6} = -\frac{1}{2\theta^4}$$

$$\implies \text{Var}(\hat{\sigma}^2) \geq 1 / \left(-n \mathbb{E} \left[\frac{\partial^2 \log(f(X; \theta))}{\partial \theta^2} \right] \right) = \frac{1}{n/(2\theta^4)} = \boxed{\frac{2\theta^4}{n}}$$

Therefore the variance of this estimator is equal to the Cramer-Rao lower bound.

Alternative solution (Math 541A):

$$I_X(\sigma) = I_{(X_1, \dots, X_n)}(\sigma) = (\text{by Proposition 10.4.5 (Proposition 6.21 in Math 541A notes)}) n I_{X_1}(\sigma)$$

$$\begin{aligned} &= n \text{Var}_\sigma \left(\frac{d}{d\sigma} \log \left(\frac{1}{\sigma \sqrt{2\pi}} \exp \left(-\frac{(X_1 - \mu)^2}{2\sigma^2} \right) \right) \right) \text{ (by definition of Fisher information)} \\ &= n \text{Var}_\sigma \left[-\frac{1}{\sigma} - \frac{d}{d\sigma} \left(\frac{(-X_1 - \mu)^2}{2\sigma^2} \right) \right] = n\sigma^{-6} \text{Var}_\sigma((X_1 - \mu)^2) \\ &= n\sigma^{-6} (\mathbb{E}(X_1 - \mu)^4 - [\mathbb{E}(X_1 - \mu)^2]^2) = n\sigma^{-6} \sigma^4 (3 - 1) = \frac{2n}{\sigma^2}. \end{aligned}$$

By Cramer-Rao,

$$\text{Var}_\sigma(z) \geq \frac{|g'(\sigma)|^2}{I_X(\sigma)}$$

Note that $g(\sigma) = \mathbb{E}Y = \frac{n-1}{n}\sigma^2$ and that $\mathbb{E} \sum_{j=1}^n (X_j - \bar{X})^2 = \sigma^2(n-1)$. If Z is unbiased for σ^2 ,

$$g'(\sigma) = \frac{2\sigma(n-1)}{n} |g'(\sigma)|^2 = \frac{4\sigma^2(n-1)^2}{n^2}$$

So,

$$\text{Var}_\sigma(z) \geq \frac{4\sigma^2(n-1)^2}{n^2 2n\sigma^2} = \frac{2(n-1)^2 \sigma^4}{n^3}.$$

Note that

$$\frac{n-1}{\sigma^2} \sum_{j=1}^n (X_j - \bar{X})^2 \sim \chi_{n-1}^2$$

⋮

Note that

$$\begin{aligned} \frac{(n-1)S_n^2}{\sigma^2} \sim \chi_n^2 &\implies \text{Var}\left(\frac{1}{\sigma^2} \sum_{i=1}^n (X_i - \bar{X})^2\right) = (n-1) \cdot 2 \\ \implies \text{Var}(\hat{\sigma}^2) &= \text{Var}_\sigma\left(\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2\right) = \frac{1}{n^2} \sigma^4 \text{Var}_\sigma\left(\sigma^{-2} \sum_{i=1}^n (X_i - \bar{X})^2\right) = \frac{2\sigma^4(n-1)}{n^2} \end{aligned}$$

e.

$$\begin{aligned} \log(L) &= -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\sigma^2) - (\sigma^2)^{-1} \frac{1}{2} \sum_{i=1}^n X_i^2 \\ \frac{\partial \log(L)}{\partial \mu} &= \sum_{i=1}^n \frac{x_i - \mu}{\sigma^2} = 0 \iff n\mu = \sum_{i=1}^n x_i \iff \mu = \frac{1}{n} \sum_{i=1}^n x_i \\ \implies \hat{\mu} &= \frac{1}{n} \sum_{i=1}^n X_i \end{aligned}$$

Also note that

$$\mathbb{E}(\hat{\mu}) = \mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n} \cdot n\mu = \mu.$$

□

Example 10.22 (Example 6.46, Math 541A notes). Alternative solution at <https://math.stackexchange.com/questions/49543/maximum-estimator-method-more-known-as-mle-of-a-uniform-distribution>

Proposition 10.4.15 (Functional Equivariance of the MLE; Proposition 6.49 from Lecture Notes, Theorem 7.2.10 in Casella and Berger [2001]). Let $g : \Theta \rightarrow \Theta'$ be a bijection. Suppose Y is the MLE of θ . Then $g(Y)$ is the MLE of $g(\theta)$.

Proof (case when g is invertible). Note that if $\ell(\theta)$ is the likelihood function for θ , then the likelihood function for $g(\theta)$ can be expressed as

$$\ell(g(\theta)) = \prod_{i=1}^n f_\theta(x_i | g^{-1}(g(\theta))) = \ell(g^{-1}(g(\theta))) = \ell(g^{-1}(\theta'))$$

where $\theta' = g(\theta)$. By definition of the MLE, $Y = t(X_1, \dots, X_n)$ achieves the maximum value of $\theta \mapsto \ell(\theta)$. Therefore we can equivalently say $g(Y) = g(t(X_1, \dots, X_n))$ achieves the maximum value of $\theta' \mapsto \ell(g^{-1}(\theta'))$.

(For a proof when g is not invertible, see Theorem 7.2.10 in Casella and Berger [2001][p.320].)

□

Proposition 10.4.16 (Math 541A Homework Problem). Let X_1, \dots, X_n be a random sample of size n , so that X_1 has the Laplace density $\frac{1}{2}e^{-|x-\theta|}$ for all $x \in \mathbb{R}$, where $\theta \in \mathbb{R}$ is unknown. Then the MLE of θ is the median.

Proof.

$$f(x_i; \theta) = \frac{1}{2}e^{-|x_i - \theta|}$$

$$\implies L = \prod_{i=1}^n \frac{1}{2}e^{-|x_i - \theta|} = 2^{-n} \exp\left(-\sum_{i=1}^n |x_i - \theta|\right)$$

$$\implies \log(L) = -n \log(2) - \sum_{i=1}^n |x_i - \theta| \implies \frac{d \log(L)}{d\theta} = -\sum_{i=1}^n \frac{d}{d\theta} |x_i - \theta| = -\sum_{i=1}^n \text{sgn}(x_i - \theta)$$

since $\frac{d|x|}{dx} = \text{sgn}(x)$. Next set this equal to 0 and solve:

$$-\sum_{i=1}^n \text{sgn}(x_i - \hat{\theta}_{MLE}) = 0$$

Notice that if n is even then the median set as $\hat{\theta}_{MLE}$ satisfies the above equation. If n is odd, the median is still the best we can do. So the MLE is the median.

□

10.4.7 Bayes estimator

10.4.8 EM Algorithm

Remark 138 (Correction to Remark 6.57). If Y is constant, the algorithm just outputs θ_0 in one step by the Likelihood Inequality (Lemma 6.50 in lecture notes):

$$\mathbb{E}_\theta \log \left(\frac{f_\theta(X)}{f_\omega(X)} \right) \geq 0 \iff \mathbb{E}_\theta \log f_\theta(X) - \mathbb{E}_\theta \log f_\omega(X) \geq 0$$

has equality only when $\omega = \theta$ (if $\mathbb{P}_\theta \neq \mathbb{P}_\omega \forall \theta \neq \omega$). So

$$\mathbb{E}_\theta \log f_\theta(X) \geq \mathbb{E}_\theta \log f_\omega(X).$$

Remark 139 (note on proof of Lemma 6.58).

$$Y = t(X), \quad f_{X,Y}(x, y) = f_X(x) \mathbf{1}_{y=t(x)}.$$

10.4.9 Comparison of estimators

10.5 Resampling and Bias Reduction

10.5.1 Jackknife Resampling

$$Z_n := Y_n + (n-1) \left(Y_n - \frac{1}{n} \sum_{i=1}^n t_{n-1}(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n) \right)$$

10.5.2 Bootstrapping

Suppose X_1, \dots, X_n i.i.d. from \mathbb{P}_θ . $\hat{\theta} = \hat{\theta}(X_1, \dots, X_n)$ is an estimator for θ . Question: what is the distribution of $\hat{\theta} - \theta$, or

$$\frac{\hat{\theta} - \theta}{\hat{\sigma}} \tag{10.22}$$

(where $\hat{\sigma}$ is an estimator of standard deviation)? Another scenario: T_n is a test statistic. What is the distribution of T_n under the null hypothesis?

Definition 10.28 (Parametric bootstrap). Let $\hat{X}_1, \dots, \hat{X}_n$ be an i.i.d. sample from $\mathbb{P}_{\hat{\theta}}$. Consider

$$\hat{T}(\hat{X}_1, \dots, \hat{X}_n, \hat{\theta}) = \frac{\hat{\theta}(\hat{X}_1, \dots, \hat{X}_n) - \hat{\theta}(X_1, \dots, X_n)}{\hat{\sigma}(\hat{X}_1, \dots, \hat{X}_n)}. \tag{10.23}$$

(Unlike in (10.22), note that all of the quantities in (10.23) are known—data dependent, can compute.)

Example 10.23. $\mathcal{N}(\theta, \sigma^2)$. $\hat{\theta}(X_1, \dots, X_n) = n^{-1} \sum_{i=1}^n X_i$, $\hat{\sigma}^2(X_1, \dots, X_n) = (n-1)^{-1} \sum_{i=1}^n (X_i - \bar{X}_i)^2$.

Question: when are the distributions of T and \hat{T} “close”? Intuition: if $T(\theta, X_1, \dots, X_n)$ is continuous with respect to all variables, then bootstrap should work.

Definition 10.29 (Non-parametric bootstrap). Estimate distribution of \mathbb{P} via empirical distribution:

$$\hat{\mathbb{P}}_n := \hat{\mathbb{P}}_n(\mathcal{A}) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}\{X_i \in \mathcal{A}\}$$

In other words, $\hat{\mathbb{P}}_n$ is a uniform distribution on $\{X_1, \dots, X_n\}$. Sampling from $\hat{\mathbb{P}}_n$ is easy—corresponds to a multinomial distribution.

Treats the distribution itself as a parameter. Used when nothing is known about the distribution of the data, or when sampling from \mathbb{P}_θ is difficult. Note that $\mathbb{E}_{\mathbb{P}} \hat{\mathbb{P}}_n(\mathcal{A}) = \mathbb{P}(\mathcal{A})$.

Example 10.24. X_1, \dots, X_n i.i.d. \mathbb{P} , Y_1, \dots, Y_m i.i.d. \mathbb{Q} . Let μ_P, μ_Q be the means of \mathbb{P} and \mathbb{Q} respectively. $H_0 : \mu_P = \mu_Q$, $H_a : \mu_P \neq \mu_Q$. Consider the test statistic

$$T = \frac{\bar{X} - \bar{Y}}{S_{n+m}}$$

where

$$S_{n+m} := \frac{n-1}{m+n-2} S_X^2 + \frac{m-1}{m+n-2} S_Y^2$$

is the **pooled variance**. What is the distribution of T under H_0 ? Let

$$\bar{Z} := \frac{1}{n+m} \left(\sum_{i=1}^n X_i + \sum_{i=1}^m Y_i \right),$$

and let

$$\tilde{X}_i = X_i - \bar{X}_n + \bar{Z}, \quad i \in [n], \quad \tilde{Y}_i = Y_i - \bar{Y}_m + \bar{Z}, \quad i \in [m].$$

Then $\tilde{X}_1, \dots, \tilde{X}_n$ and $\tilde{Y}_1, \dots, \tilde{Y}_m$ can be used to model the distribution under H_0 . For $i \in [B]$, repeat the following:

1. Sample $\hat{X}_1^{(i)}, \dots, \hat{X}_n^{(i)}$ from $\hat{\mathbb{P}}_n(\tilde{X}_1, \dots, \tilde{X}_n)$.
2. Sample $\hat{Y}_1^{(i)}, \dots, \hat{Y}_n^{(i)}$ from $\hat{\mathbb{P}}_m(\tilde{Y}_1, \dots, \tilde{Y}_n)$.
3. Compute $\hat{T}^{(i)} = T(\hat{X}_1^{(i)}, \dots, \hat{X}_n^{(i)}, \hat{Y}_1^{(i)}, \dots, \hat{Y}_n^{(i)})$.

For each C , compute

$$\hat{\mathbb{P}}(\hat{T} \geq C) = \frac{1}{B} \sum_{i=1}^B \mathbb{1}\{\hat{T}^{(i)} \geq C\}.$$

To obtain a test of size α , select C such that

$$\hat{\mathbb{P}}(\hat{T} \geq C) = \alpha.$$

Example 10.25 ((Non-parametric) Bootstrap failure). Let X_1, \dots, X_n be i.i.d. $\text{Uniform}[0, \theta]$. Let $T_n = n(\theta - \hat{\theta}_n)$, where $\hat{\theta}_n = \max\{X_1, \dots, X_n\} = X_{(n)}$, the maximum likelihood estimator of θ . Let

$$\hat{T}_n = n(\hat{\theta}_n(X_1, \dots, X_n) - \hat{\theta}_n(\hat{X}_1, \dots, \hat{X}_n)) = n(\max(X_1, \dots, X_n) - \max(\hat{X}_1, \dots, \hat{X}_n)) = n(X_{(n)} - \hat{X}_{(n)}).$$

Are the distributions of T_n and \hat{T}_n close? Turns out no. Note that $\mathbb{P}(\hat{X}_1 = X_1) = n^{-1}$ for $i \in [n]$, and note that $\hat{X}_{(n)} \leq X_{(n)}$, so $\hat{T}_n \geq 0$. Fix $t \geq 0$.

$$\begin{aligned}
\mathbb{P}(\hat{T}_n \leq t \mid X_1, \dots, X_n) &\geq \mathbb{P}(\hat{T}_n = 0 \mid X_1, \dots, X_n) \\
&= \mathbb{P}(\text{at least one among } \hat{X}_1, \dots, \hat{X}_n \text{ is equal to } X_{(n)} \mid X_1, \dots, X_n) \\
&= 1 - \mathbb{P}(\text{none of } \hat{X}_1, \dots, \hat{X}_n \text{ are equal to } X_{(n)} \mid X_1, \dots, X_n) = 1 - \left(\frac{n-1}{n}\right)^n \xrightarrow{n \rightarrow \infty} 1 - \frac{1}{e}. \quad (10.24)
\end{aligned}$$

At the same time,

$$\begin{aligned}
\mathbb{P}_\theta(T_n \leq t) &= \mathbb{P}(n(\theta - X_{(n)}) \leq t) = \mathbb{P}\left(X_{(n)} \geq \theta - \frac{t}{n}\right) = 1 - \mathbb{P}\left(X_{(n)} \leq \theta - \frac{t}{n}\right) \\
&= 1 - \mathbb{P}\left(\bigcap_{i=1}^n \left\{X_i \leq \theta - \frac{t}{n}\right\}\right) = 1 - \left[\mathbb{P}\left(X_1 \leq \theta - \frac{t}{n}\right)\right]^n = 1 - \left[1 + \frac{-t/\theta}{n}\right]^n \quad (10.25) \\
\implies \lim_{n \rightarrow \infty} \mathbb{P}_\theta(T_n \leq t) &= \lim_{n \rightarrow \infty} \mathbb{P}(n(\theta - X_{(n)}) \leq t) = 1 - \lim_{n \rightarrow \infty} \left[1 + \frac{-t/\theta}{n}\right]^n = 1 - \exp\left(-\frac{t}{\theta}\right).
\end{aligned}$$

Since the lower bound in (10.24) does not depend on t , bootstrap fails. Exercise: does parametric bootstrap work here?

Theorem 10.5.1. Assume that $\mathbb{E}X_1 = \mu$, $\text{Var}(X_1) = \sigma^2$, $\mathbb{E}|X_1 - \mu|^3 < \infty$. Let $\hat{\mu}_n = \bar{X}_n = n^{-1} \sum_{i=1}^n X_i$, $F_n(t) = \mathbb{P}(\sqrt{n}(\hat{\mu}_n - \mu) \leq t)$. Let $\hat{X}_1, \dots, \hat{X}_n$ be i.i.d. from \hat{P}_n , and let

$$\hat{\mu}^* = \frac{1}{n} \sum_{i=1}^n \hat{X}_i, \quad \hat{F}_n(t) = \mathbb{P}(\sqrt{n}(\hat{\mu}^* - \hat{\mu}_n) \leq t \mid X_1, \dots, X_n)$$

Then

$$\sup_{t \in \mathbb{R}} |\hat{F}_n(t) - F_n(t)| = o_{\mathbb{P}}(1) \text{ as } n \rightarrow \infty.$$

Proof. Let $\phi_\sigma(t)$ be the CDF of $\mathcal{N}(0, \sigma^2)$. We have

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \hat{\mu}_n)^2 = \text{Var}(\hat{X}_n), \quad \hat{\mu}_n = \frac{1}{n} \sum_{i=1}^n X_i = \mathbb{E}_{\hat{P}_n} \hat{X}_1.$$

Note that

$$\begin{aligned}
\sup_{t \in \mathbb{R}} |F_n(t) - \hat{F}_n(t)| &= \sup_{t \in \mathbb{R}} \left| F_n(t) - \phi_\sigma(t) + \phi_\sigma(t) - \phi_{\hat{\sigma}}(t) + \phi_{\hat{\sigma}}(t) - \hat{F}_n(t) \right| \\
&\leq \sup_{t \in \mathbb{R}} \underbrace{|F_n(t) - \phi_\sigma(t)|}_{\text{error in normal approximation; close by Berry-Esseen}} + \sup_{t \in \mathbb{R}} \underbrace{|\phi_\sigma(t) - \phi_{\hat{\sigma}}(t)|}_{\text{close since } \hat{\sigma}^2 \text{ is consistent}} + \sup_{t \in \mathbb{R}} \underbrace{|\phi_{\hat{\sigma}}(t) - \hat{F}_n(t)|}_{\text{close by Berry-Esseen}}
\end{aligned}$$

It remains to estimate all three terms. By Berry-Esseen,

$$\sup_{t \in \mathbb{R}} |F_n(t) - \phi_\sigma(t)| \leq \frac{3\mathbb{E}|X_1 - \mu|^3}{\sigma^3 \sqrt{n}}.$$

By applying Berry-Esseen conditionally on X_1, \dots, X_n ,

$$\sup_{t \in \mathbb{R}} |\hat{F}_n(t) - \phi_{\hat{\sigma}}(t)| \leq 3 \frac{\hat{\gamma}}{\hat{\sigma}^3 \sqrt{n}}$$

where

$$\hat{\gamma} := \frac{1}{n} \sum_{i=1}^n |X_i - \bar{X}_n|^3 = \mathbb{E}_{\hat{\mathbb{P}}_n} \left| X - \mathbb{E}_{\hat{\mathbb{P}}_n} X \right|^3.$$

By the Strong Law of Large Numbers, $\bar{X}_n \xrightarrow{a.s.} \mu$, $\hat{\gamma} \xrightarrow{a.s.} \mathbb{E}|X_1 - \mu|^3$, $\hat{\sigma}^2 \xrightarrow{a.s.} \sigma^2$. Hence

$$\frac{3\hat{\gamma}}{(\hat{\sigma}^2)^{3/2} \sqrt{n}} = o_{\mathbb{P}}(1).$$

Finally, let $\sigma_1, \sigma_2 > 0$ be fixed. Then

$$\sup_{t \in \mathbb{R}} |\phi_{\sigma_1}(t) - \phi_{\sigma_2}(t)| = \sup_t \left| \int_{-\infty}^t \left(\frac{1}{\sqrt{2\pi}\sigma_1} \exp \left\{ -\frac{y^2}{2\sigma_1^2} \right\} - \frac{1}{\sqrt{2\pi}\sigma_2} \exp \left\{ -\frac{y^2}{2\sigma_2^2} \right\} \right) dy \right|$$

Note that

$$\begin{aligned} \frac{1}{\sigma_1} \exp \left\{ -\frac{y^2}{2\sigma_1^2} \right\} + \frac{1}{\sigma_1} \exp \left\{ -\frac{y^2}{2\sigma_2^2} \right\} - \frac{1}{\sigma_1} \exp \left\{ -\frac{y^2}{2\sigma_2^2} \right\} - \frac{1}{\sigma_2} \exp \left\{ -\frac{y^2}{2\sigma_2^2} \right\} \\ = \underbrace{\frac{1}{\sigma_1} \left(\exp \left\{ -\frac{y^2}{2\sigma_1^2} \right\} - \exp \left\{ -\frac{y^2}{2\sigma_2^2} \right\} \right)}_{A_1} + \underbrace{\exp \left\{ -\frac{y^2}{2\sigma_2^2} \right\} \left(\frac{1}{\sigma_1} - \frac{1}{\sigma_2} \right)}_{A_2} \end{aligned}$$

Then

$$A_1 = \frac{1}{\sigma_1} \exp \left\{ -\frac{y^2}{2\sigma_1^2} \right\} \left(1 - \exp \left\{ -\frac{y^2}{2} \underbrace{\left[\frac{1}{\sigma_2^2} - \frac{1}{\sigma_1^2} \right]}_{>0} \right\} \right)$$

For $x > 0$, $1 - e^{-x} \leq x$. Hence

$$A_1 \leq \frac{1}{\sigma_1} \exp \left\{ -\frac{y^2}{2\sigma_1^2} \right\} \cdot \frac{y^2}{2} \left[\frac{1}{\sigma_2^2} - \frac{1}{\sigma_1^2} \right] = \frac{1}{\sigma_1} \frac{y^2}{2} \exp \left\{ -\frac{y^2}{2\sigma_1^2} \right\} \frac{\sigma_1^2 - \sigma_2^2}{\sigma_1^2 \sigma_2^2}.$$

On the other hand,

$$A_2 = \exp\left\{-\frac{y^2}{2\sigma_2^2}\right\} \left(\frac{1}{\sigma_1} - \frac{1}{\sigma_2}\right) = \exp\left\{-\frac{y^2}{2\sigma_2^2}\right\} \left(\frac{\sigma_2 - \sigma_1}{\sigma_1}\right)$$

so

$$\sup_{t \in \mathbb{R}} |\phi_\sigma(t) - \phi_{\sigma_2}(t)| \leq \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{y^2}{2\sigma_1} \exp\left\{-\frac{y^2}{2\sigma_1^2}\right\} dy \cdot \left| \frac{\sigma_1^2 - \sigma_2^2}{\sigma_1^2 \sigma_2^2} \right| + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{1}{\sigma_2} \exp\left\{-\frac{y^2}{2\sigma_2^2}\right\} dy \frac{|\sigma_2 - \sigma_1|}{\sigma_1}$$

Hence $\sup_{t \in \mathbb{R}} |\phi_\sigma(t) - \phi_{\sigma_2}(t)| \rightarrow 0$ as $\sigma_1 \rightarrow \sigma_2$. Apply this with $\sigma_1^2 = \sigma_2$, $\sigma_2^2 = \hat{\sigma}^2$ to yield the result. \square

Bootstrap and Bias Corrections. Suppose that X is a random variable with $\mathbb{E}X = \mu$, $\text{Var}(X) = \sigma^2$, $\mathbb{E}|X|^3 < \infty$. Assume that we are interested in estimating $g(\mu)$ where g is a smooth function. The **plug-in estimator** of $g(\mu)$ is $g(\hat{\mu}_n)$ where $\hat{\mu}_n$ is an estimator of μ . In particular, if nothing is known about X , $\hat{\mu}_n$ will be the sample mean \bar{X}_n . In general, $g(\bar{X}_n)$ is a biased estimator of $g(\mu)$. The bias is

$$\text{bias}(g(\bar{X}_n)) := \mathbb{E}g(\bar{X}_n) - g(\mu).$$

The goal is to estimate $\widehat{\text{bias}}(g(\bar{X}_n))$ using the bootstrap and replace $g(\bar{X}_n)$ with the bias-corrected estimator $g(\bar{X}_n) - \widehat{\text{bias}}(g(\bar{X}_n))$. Estimating the bias: For $i \in [B]$,

1. Generate the bootstrap sample $\hat{X}_1^{(i)}, \dots, \hat{X}_n^{(i)}$.
2. $\hat{\Theta}^{(i)} = g\left(\widehat{\bar{X}}_n^{(i)}\right)$.
3. Let

$$\widehat{\text{bias}}(g(\bar{X}_n)) := \frac{1}{B} \sum_{i=1}^B g\left(\widehat{\bar{X}}_n^{(i)}\right) - g(\bar{X}_n).$$

Question: what is the bias of $g(\bar{X}_n) - \widehat{\text{bias}}(g(\bar{X}_n))$? Observe that

$$\begin{aligned} g(\bar{X}_n) - g(\mu) &= g(\mu + \bar{X}_n - \mu) - g(\mu) \\ &= g'(\mu)(\bar{X}_n - \mu) + \frac{1}{2}g''(\mu)(\bar{X}_n - \mu)^2 + \underbrace{o((\bar{X}_n - \mu)^2)}_{o_{\mathbb{P}}((n^{-1/2})^2)} + \frac{g'''(\tau)}{6}(\bar{X}_n - \mu)^3 \\ &\implies \mathbb{E}g(\bar{X}_n) - g(\mu) = \frac{1}{2}g''(\mu)\frac{\sigma^2}{n} + o(n^{-1}). \end{aligned}$$

Similarly,

$$g(\widehat{\bar{X}}_n) - g(\bar{X}_n) = g'(\bar{X}_n)(\widehat{\bar{X}}_n^{(i)} - \bar{X}_n) + \frac{1}{2}g''(\bar{X}_n)(\widehat{\bar{X}}_n^{(i)} - \bar{X}_n)^2 + o_{\mathbb{P}}(1/n).$$

Hence

$$\mathbb{E}_{\mathbb{P}} g\left(\widehat{\bar{X}}_n^{(i)}\right) - g(\bar{X}_n) = \frac{1}{2}g''(\bar{X}_n)\frac{S_n^2}{n} + o(n^{-1})$$

where

$$S_n^2 = \frac{1}{n} \sum_{j=1}^n (X_j - \bar{X}_n)^2.$$

Look at how close estimate is to actual bias:

$$\begin{aligned} \text{bias}(g(\bar{X}_n)) - \widehat{\text{bias}}(g(\bar{X}_n)) &= \frac{1}{2}g''(\mu)\frac{\sigma^2}{n} - \frac{1}{2}g''(\bar{X}_n)\frac{S_n^2}{n} + o_{\mathbb{P}}(n^{-1}) \\ &= \frac{1}{2}g''(\mu)\frac{\sigma^2}{n} - \frac{1}{2}g''(\bar{X}_n)\frac{S_n^2}{n} + \frac{1}{2}g''(\mu)\frac{S^2}{n} - \frac{1}{2}g''(\mu)\frac{S^2}{n} + o_{\mathbb{P}}(n^{-1}) \\ &= \frac{1}{2}g''(\mu)\left(\frac{\sigma^2 - S_n^2}{n}\right) + \frac{S^2}{n}\frac{1}{2}[g''(\mu) - g''(\bar{X}_n)] + o_{\mathbb{P}}(n^{-1}) = o_{\mathbb{P}}(n^{-1}) + o_{\mathbb{P}}(n^{-1}) = o_{\mathbb{P}}(n^{-1}) = o_{\mathbb{P}}(n^{-1}). \end{aligned}$$

Example 10.26 (Trimmed mean). X_1, \dots, X_n i.i.d. Let $X_{(1)}, \dots, X_{(n)}$ be the order statistics. Pick $\alpha \in (0, 1/2)$. Define

$$\hat{\mu}_\alpha := \frac{1}{|i \in \{\lfloor n\alpha \rfloor, \dots, n - \lfloor n\alpha \rfloor\}|} \sum_{i \in \{\lfloor n\alpha \rfloor, \dots, n - \lfloor n\alpha \rfloor\}} X_{(i)}.$$

Exercise: what is the bias of this estimator? (Hint: prove that $\mathbb{E}X = \int_0^1 F^{-1}(t) dt$ where $F(t)$ is the cdf of X .)

Exercise 29. look carefully at this problem—could be on final.

X_1, X_2, X_3 i.i.d. with cdf F . Let $X_{(i)}$ be the order statistics, $i \in [3]$. Let $\hat{X}_1, \hat{X}_2, \hat{X}_3$ be the bootstrap sample, and $\hat{X}_{(1)}, \hat{X}_{(2)}, \hat{X}_{(3)}$ be the bootstrap order statistics.

- (a) Find the distribution of $\hat{X}_{(2)}$.
- (b) Find the bootstrap estimate of the bias of the sample median.
- (c) Find the bootstrap estimate of the variance of the sample median.

Solution.

(a)

$$\mathbb{P}(\hat{X}_{(2)} \leq X_{(i)}) = \mathbb{P}(\hat{X}_{(1)} \leq X_{(i)}, \hat{X}_{(2)} \leq X_{(i)}) = \sum_{j=2}^3 \binom{3}{j} \left(\frac{i}{3}\right)^j \left(1 - \frac{1}{3}\right)^{3-j}.$$

because the probability that one of the bootstrap sampled variables is less than or equal to the i th smallest sample is equal to $i/3$, so the probability that the two smallest bootstrap sampled variables are less than or equal to the i th smallest sample is equal to the probability that a binomial random variable with $n = 3, p = i/3$ equals 2 or 3. For $i = 1$, this equals $7/27$; for $i = 2$, this equals $20/27$; for $i = 3$, this equals 1. So then

$$\mathbb{P}(\hat{X}_{(2)} = X_{(1)}) = 7/27; \quad \mathbb{P}(\hat{X}_{(2)} = X_{(2)}) = 13/27; \quad \mathbb{P}(\hat{X}_{(2)} = X_{(3)}) = 7/27.$$

(b)

$$\widehat{\text{bias}} = \mathbb{E}_{\hat{\mathbb{P}}_3}(\hat{X}_2) - X_{(2)} = \frac{7}{27}X_{(1)} + \frac{13}{27}X_{(2)} + \frac{7}{27}X_{(3)} - X_{(2)} = \frac{7}{27}X_{(1)} - \frac{14}{27}X_{(2)} - \frac{7}{22}X_{(3)}.$$

(c) Note that

$$\mathbb{E}_{\hat{\mathbb{P}}_3}(\hat{X}_2 | X_1, X_2, X_3) = \frac{7}{27}X_{(1)} + \frac{13}{27}X_{(2)} + \frac{7}{27}X_{(3)}, \quad \mathbb{E}_{\hat{\mathbb{P}}_3}(\hat{X}_2^2 | X_1, X_2, X_3) = \frac{7}{27}X_{(1)}^2 + \frac{13}{27}X_{(2)}^2 + \frac{7}{27}X_{(3)}^2,$$

so the bootstrap estimator of the variance is

$$\begin{aligned} \widehat{\text{Var}}(\hat{X}_{(2)} | X_1, X_2, X_3) &= \mathbb{E}_{\hat{\mathbb{P}}_3}[\hat{X}_2^2 | X_1, X_2, X_3] - \mathbb{E}_{\hat{\mathbb{P}}_3}[\hat{X}_2 | X_1, X_2, X_3]^2 \\ &= \frac{7}{27}X_{(1)}^2 + \frac{13}{27}X_{(2)}^2 + \frac{7}{27}X_{(3)}^2 - \left(\frac{1}{27^2}\right)(7X_{(1)} + 13X_{(2)} + 7X_{(3)})^2 \\ &= \frac{7}{27}X_{(1)}^2 + \frac{13}{27}X_{(2)}^2 + \frac{7}{27}X_{(3)}^2 - \frac{1}{27^2}(49X_{(1)}^2 + 2 \cdot 91X_{(1)}X_{(2)} + 2 \cdot 49X_{(1)}X_{(3)} + 169X_{(2)}^2 + 2 \cdot 91X_{(2)}X_{(3)} + 49X_{(3)}^2) \\ &= \left(\frac{7}{27} - \frac{49}{27^2}\right)X_{(1)}^2 + \left(\frac{13}{27} - \frac{169}{27^2}\right)X_{(2)}^2 + \left(\frac{7}{27} - \frac{49}{27^2}\right)X_{(3)}^2 - \frac{1}{27^2}(2 \cdot 91X_{(1)}X_{(2)} + 2 \cdot 49X_{(1)}X_{(3)} + 2 \cdot 91X_{(2)}X_{(3)}) \\ &= \boxed{\frac{140}{729}X_{(1)}^2 + \frac{182}{729}X_{(2)}^2 + \frac{140}{729}X_{(3)}^2 - \frac{182}{729}X_{(1)}X_{(2)} - \frac{98}{729}X_{(1)}X_{(3)} - \frac{182}{729}X_{(2)}X_{(3)}}. \end{aligned}$$

10.6 Some Concentration of Measure

Lemma 10.6.1 (DSO 699 Spring 2021). Let $X_i \sim \mathcal{N}(0, \sigma^2)$, $i \in [n]$. (not necessarily independent!) Let $Z = \max_{i \in [n]} |X_i|$. Then

$$\mathbb{E}[Z] \leq \sigma \sqrt{2 \log(2n)}.$$

Proof.

$$\begin{aligned}
\mathbb{E}[Z] &= \mathbb{E} \left[\max_{i \in [n]} |X_i| \right] \\
&= \frac{1}{\theta} \log \left[\exp \left\{ \mathbb{E} \left[\theta \max_{i \in [n]} |X_i| \right] \right\} \right] \\
&\stackrel{(*)}{\leq} \frac{1}{\theta} \log \left[\mathbb{E} \left[\exp \left\{ \theta \max_{i \in [n]} X_i \right\} \right] \right] \\
&= \frac{1}{\theta} \log \left[\mathbb{E} \left[\max_{i \in [n]} \exp \{ \theta X_i \} \right] \right] \\
&\leq \frac{1}{\theta} \log \left[\mathbb{E} \left[\sum_{i \in [n]} \exp \{ \theta X_i \} \right] \right] \\
&= \frac{1}{\theta} \log \left[2ne^{\theta^2 \sigma^2 / 2} \right] \\
&= \frac{1}{\theta} \log [2n] + \theta \sigma^2 / 2
\end{aligned}$$

where $(*)$ follows from Jensen's inequality. Optimize over $\theta \geq 0$ to get $\theta^* = \sqrt{2 \log(2n)}/\sigma$. Then the result follows. \square

Remark 140. Using the union bound, you can use this result to bound $\mathbb{P}(Z > \mathbb{E}Z + t)$.

10.6.1 Concentration for Independent Sums

Can generate similar results for other random variables—just need different bound on moment-generating function (generally is fine as long as values of random variable are bounded between two real numbers, but more work to prove). However, doesn't work when values aren't bounded (e.g. for Gaussian random variables).

- What about other unbounded random variables?
- What about dependent random variables?

General question: **how far is a random variable from its mean?** Will first address functions of independent Gaussian random variables.

Definition 10.30 (Lipschitz functions). A real-valued function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is called **Lipschitz continuous** or **L -Lipschitz** if there exists a positive real constant L such that for all $x_1, x_2 \in \mathbb{R}^n$,

$$|f(x_1) - f(x_2)| \leq L \|x_1 - x_2\|_2.$$

Theorem 10.6.2 (Theorem 8.5 in 541A notes). Note from proof: use the fact that since f is 1-Lipschitz, $\|\frac{df(X)}{dx_i}\|_2^2 \leq 1$.

Theorem 10.6.3 (Theorem 8.6 in 541A notes). Notes from proof: change bounds on integral to $8a/\pi$. Then since $u \geq 8a/\pi \iff -a \geq -\pi u/8$, we have

$$\|\Pi(X)\| > u \implies \|\Pi(X)\| - a > u - a \geq u - \pi/8u > u/2.$$

Therefore

$$\Pr(\|\Pi(X)\| > u) = \Pr(\|\Pi(X)\| > u) \geq \Pr(|\|\Pi(x)\| - a| > u/2).$$

⋮

Loose bound: $a^2 e^{-a^2} \leq 10$ for all $a > 0$. ($k > 1$).

⋮

$$\mathbb{E}\|\Pi(X)\|^4 \leq 2^{12}a^4 + 10^6k^2$$

then by Jensen's Inequality,

$$a^4 = (\mathbb{E}\|\Pi(X)\|)^4 \leq (\mathbb{E}\|\Pi(X)\|^2)^2$$

So $2^{12}a^4 \leq 2^{12}(\mathbb{E}\|\Pi(X)\|^2)^2$. Then we chose 10^{10} to make things easy and say

$$2^{12}a^4 + 10^6k^2 \leq 10^{10}(\mathbb{E}\|\Pi(X)\|^2)^2.$$

Summary:

$$Z := \|\Pi(X)\|^2, \quad \mathbb{E}(Z^2) = k, \quad \mathbb{E}(Z^4) \leq 10^{10}(\mathbb{E}(Z^2))^2.$$

⋮

Union bound (Boole's Inequality)

10.7 Math 541B

Definition 10.31 (Statistical model). A **statistical model** is a family of probability distributions $\mathcal{P} = \{P_\theta, \theta \in \Theta\}$. Assume that X_1, \dots, X_n are i.i.d. from $P_{\theta_0}, \theta_0 \in \Theta$.

Definition 10.32 (Identifiability).

$$\theta_1 \neq \theta_1 \implies P_{\theta_1} \neq P_{\theta_2}.$$

Definition 10.33 (Estimator). An **estimator** $\hat{\theta}(X_1, \dots, X_n)$ is any measurable function of the data (X_1, \dots, X_n) .

Definition 10.34 (Bias). The **bias** of an estimator is defined via

$$B(\hat{\theta}) := \mathbb{E}_{\theta_0} \hat{\theta}(X_1, \dots, X_n) - \theta_0.$$

Example 10.27. Alice wants to send a message to Bob. A message is a sequence of symbols from $\{a, b, \dots, z\} = \mathcal{A}$. **prefix-free codebook:** \mathcal{A} : sequence of 0, 1.

Theorem 10.7.1 (Shannon's Theorem). Assume that X has values in \mathcal{A} and has distribution D . To minimize $\mathbb{E}_\rho(\text{number of bits})$, the codebook has to use about $\log_2(1/P(\beta))$ digits to encode $\rho \in \mathcal{A}$. Then

$$\mathbb{E}_\rho[\text{number of bits}] = \sum_{\beta \in \mathcal{A}} D(\beta) \log_2(1/p(\rho))$$

this is the entropy of D .

Assume that the codebook is created assuming that the true distribution of symbols is P but actually the true distribution is Q . In this case, the expected number of bits is

$$\mathbb{E}_Q[\text{number of bits}] = \sum_{\beta \in \mathcal{A}} Q(\beta) \log_2(1/p(\beta)).$$

we can also write this as the entropy of Q etc.

$$= \underbrace{\sum_{\beta \in \mathcal{A}} Q(\beta) \log_2(1/Q(\beta))}_{\text{entropy of } Q, \text{ Ent}(Q)} + \underbrace{\sum_{\beta} Q(\beta) \log(Q(\beta)/p(\beta))}_{KL(Q||P)}$$

so the roots of MLE are in information theory.

10.8 Hypothesis Testing

Why is the likelihood ratio useful for hypothesis testing? It is a sufficient statistic. Suppose we have $H_0 : X \sim P$, $H_1 : X \sim Q$, and $\theta = 1 \implies \mathbb{P}_\theta = Q$, $\theta = 0 \implies \mathbb{P}_\theta = P$. Then the likelihood function is

$$L(\theta | X) = q(x)^{I\{\theta=1\}} p(x)^{1-I\{\theta=1\}} = \left(\frac{q(x)}{p(x)} \right)^{I\{\theta=1\}} \cdot p(x),$$

so the likelihood ratio is a sufficient statistic by the Factorization Theorem.

Bayes testing:

Prior probability π on H_0 (that distribution is on P), $1 - \pi$ on H_a (distribution on Q). The if $\alpha_\phi := \mathbb{E}_P(\phi(X))$ is the probability of a type I error and $1\beta_\phi := 1 - \mathbb{E}_Q(\phi(X))$ is the probability of a type II error, we want to minimize the Bayes risk:

$$R_\pi(\phi) := \pi\alpha_\phi + (1 - \pi)(1 - \beta_\phi).$$

The Bayes test is

$$\phi_{\pi}^*(X) = \begin{cases} 1 & L(X) < (1-\pi)/\pi \\ \gamma & L(X) = (1-\pi)/\pi \\ 0 & L(X) > (1-\pi)/\pi \end{cases}$$

where $L(X) = P(X)/Q(X)$ is the likelihood ratio.

Mimax: minimize worst case:

$$\min \{ \max \{ \alpha_{\phi}, 1 - \beta_{\phi} \} \} .$$

Neymann-Pearson: acceptable Type I error rate α . So we have the constraint $\mathbb{E}_P(\phi(X)) \leq \alpha$. Maximize power subject to this constraint.

All give roughly similar tests.

Theorem 10.8.1. Assume that for some $\pi_* \in [0, 1]$ that the Bayes test $\phi_{\pi_*}^*$ satisfies

$$\alpha_{\phi_{\pi_*}}^* = 1 - \beta_{\phi_{\pi_*}}^*. \quad (10.26)$$

Then $\phi_{\pi_*}^*$ is minimax. Moreover, a π_* with this desired property always exists.

Proof. Assume that $\phi_{\pi_*}^*$ is a Bayes test satisfying (10.26), but is not minimax. Then there must exist $\tilde{\phi}$ such that

$$\min \left\{ \max \left\{ \alpha_{\tilde{\phi}}, 1 - \beta_{\tilde{\phi}} \right\} \right\} < \min \left\{ \max \left\{ \alpha_{\phi_{\pi_*}}^*, 1 - \beta_{\phi_{\pi_*}}^* \right\} \right\}$$

and note that

$$\max \left\{ \alpha_{\tilde{\phi}}, 1 - \beta_{\tilde{\phi}} \right\} < \max \left\{ \alpha_{\phi_{\pi_*}}^*, 1 - \beta_{\phi_{\pi_*}}^* \right\} = \phi_{\pi_*}^* \text{ (by (10.26))}$$

We have

$$R_{\pi_*}(\tilde{\phi}) = \pi_* \alpha_{\tilde{\phi}} + (1 - \pi_*)(1 - \beta_{\tilde{\phi}}) < \pi_* \alpha_{\phi_{\pi_*}}^* + (1 - \pi_*)(1 - \beta_{\phi_{\pi_*}}^*) = R_{\pi_*}(\phi_{\pi_*}^*)$$

But this contradicts the fact that the Bayes test minimizes this ...

To prove existence, consider for $\pi \in [0, 1]$ the non-randomized test

$$\phi_{\pi} = \begin{cases} 1 & L(X) \leq (1-\pi)/\pi \\ 0 & L(x) > (1-\pi)/\pi \end{cases}$$

Since the range of π varies the Type I and Type II error rate, if we could show this function is continuous in π then we would be done by the Intermediate Value Theorem (the point where both error rates are equal would exist). We can accommodate the possibility of a jump discontinuity right at what would have been the best value by using a randomized test that takes an appropriate convex combination

□

Theorem 10.8.2 (same theorem, re-stated on 09/13). $X : \Omega \rightarrow S$. $H_0 : X \sim P$. $X_a : X \sim Q$. Assume μ is a probability measure on Ω . And P has density p with respect to μ , Q has density q with respect to μ . Let $\phi : S \rightarrow [0, 1]$ be a measurable function (randomized statistical test; the value it takes is interpreted as a probability). Let $\alpha_\phi := \mathbb{E}_P \phi(X)$ be the probability of a Type I error, and let $\beta_\phi := \mathbb{E}_Q \phi(X)$.

Assume $\pi_* \in [0, 1]$. Then the Bayes optimal test $\phi_{\pi_*}^*$ is such that $\alpha_{\phi_{\pi_*}^*} = 1 - \beta_{\phi_{\pi_*}^*}$. Then $\phi_{\pi_*}^*$ is minimax optimal. Moreover, π_* with required properties holds.

Proof of second claim. We now show that π_* and $\phi_{\pi_*}^*$ exist. Let $\pi \in [0, 1]$. Consider the non-randomized

$$\phi_\pi(x) = \begin{cases} 1 & \text{if } \frac{p(x)}{q(x)} \leq \frac{1-\pi}{\pi} \\ 0 & \text{if } \frac{p(x)}{q(x)} > \frac{1-\pi}{\pi} \end{cases}$$

Let

$$L(x) := \frac{p(x)}{q(x)}.$$

Consider

$$\begin{aligned} G(\pi) &:= \underbrace{Q(L(x) > (1-\pi)/\pi)}_{\mathbb{P} \text{ type II errors of } \pi_\pi} - \underbrace{P(L(x) \leq (1-\pi)/\pi)}_{\mathbb{P} \text{ type I error of } \phi_\pi} \\ &= Q(L(x) > (1-\pi)/\pi) + P(L(x) > (1-\pi)/\pi) - 1 \end{aligned}$$

Observe:

- (a) $\lim_{\pi \rightarrow 0^+} G(\pi) = -1$, since the probability of being over infinity is 0.
- (b) $G(1) = Q(L(x) > 0) + P(L(x) > 0) - 1 = Q(L(x) > 0) \geq 0$.
- (c) G is nondecreasing, continuous from the left (because a CDF is right continuous, but the arguments are decreasing as π increases, so instead it is left continuous.) So, G will either intersect the π axis or it will jump over it. That is, there exists $\pi_* \in (0, 1]$ such that either (i) $G(\pi_*) = 0$ or (ii) G jumps over the π axis; $G(\pi_*) < 0$ and $\lim_{\pi \rightarrow \pi_*^+} G(\pi) > 0$.

Case (i). In this case we are done. $\phi_{\pi_*}^*$ is minimax optimal by the first part of the theorem.

Case (ii). Let $\gamma := G(\pi_*^+)/G(\pi_*^+) - G(\pi_*) \in (0, 1)$. Let

$$\phi'_{\pi_*} = \begin{cases} 1 & L(x) < (1 - \pi_*)/\pi_* \\ \gamma & L(x) = (1 - \pi_*)/\pi_* \\ 0 & L(x) > (1 - \pi_*)/\pi_* \end{cases}$$

ϕ'_{π_*} is (randomized) Bayes optimal for the prior π_* . Note: The difference of type II and type I errors of ϕ'_{π_*} is

$$\underbrace{Q(L(x) > (1 - \pi_*)/\pi_*) + (1 - \gamma)Q(L(x) = (1 - \pi_*)/\pi_*)}_{\text{Type II error}} - \underbrace{P(L(x) < (1 - \pi_*)/\pi_*) - \gamma P(L(x) = (1 - \pi_*)/\pi_*)}_{\text{Type I error}}$$

Using $P(L(x) < (1 - \pi_*)/\pi_*) = 1 - P(L(x) > (1 - \pi_*)/\pi_*) - P(L(x) = (1 - \pi_*)/\pi_*)$, we can write this as

$$= Q(L(x) > (1 - \pi_*)/\pi_*) + P(L(x) > (1 - \pi_*)/\pi_*) - 1 + (1 - \gamma)[Q(L(x) = (1 - \pi_*)/\pi_*) + P(L(x) = (1 - \pi_*)/\pi_*)] \quad (10.27)$$

For the γ we defined, (10.27) is 0. Why?

$$1 - \gamma = -G(\pi_*)/(G(\pi_*^+) - G(\pi_*))$$

Recall that a jump in a cdf occurs when the corresponding random variable takes on a fixed value with nonzero probability. Compute

$$G(\pi_*^+) - G(\pi_*) = Q(L(x) = (1 - \pi)/\pi) - P(L(x) = (1 - \pi)/\pi).$$

so we see everything cancels;

$$-(1 - \gamma)[Q(L(x) = (1 - \pi_*)/\pi_*) + P(L(x) = (1 - \pi_*)/\pi_*)] = Q(L(x) > (1 - \pi_*)/\pi_*) + P(L(x) > (1 - \pi_*)/\pi_*) - 1$$

and (10.27) equals 0. That is, the difference is zero, so ϕ'_{π_*} is minimax optimal by the first part of the theorem.

□

10.8.1 Neyman-Pearson Tests

Definition 10.35 (Power function; definition 8.3.1 in Casella and Berger [2001]). The **power function** of a hypothesis test with rejection region R is the function of θ defined by

$$\beta(\theta) := \mathbb{P}_\theta(x \in R).$$

Motivation: some errors are worse than others. Goal: control Type I error, keeping it small for any sample size.

Define the **test function** $\phi(x)$ to be an indicator of x being in the rejection region for a test:

$$\phi(x) = \begin{cases} 1 & x \in R \\ 0 & x \notin R \end{cases}.$$

Let Φ be a set of such tests.

Definition 10.36 (UMP; Definition 8.3.11 in Casella and Berger [2001],). ϕ^* is **uniformly most powerful** (UMP) of size $\alpha \in [0, 1]$ if it achieves the maximum value of B_ϕ subject to $\alpha_\phi \leq \alpha$ over all randomized tests $\phi \in \Phi$. That is, it is uniformly most powerful if and only if it solves

$$\begin{aligned} \phi^* = \arg \max_{\phi \in \Phi} \quad & \beta_\phi(\theta_a) \\ \text{subject to} \quad & \beta_\phi(\theta_0) \leq \alpha \quad \forall \theta_0 \in \Theta_0 \end{aligned} \quad \forall \theta_a \in \Theta_a.$$

or (given in class, definitely less formal notation)

$$\beta_\phi = \mathbb{E}_Q \phi(x) \rightarrow \max_{\phi \in \Phi} \text{ s.t. } \alpha_\phi = \mathbb{E}_p \phi(x) \leq \alpha.$$

Lemma 10.8.3 (Neyman-Pearson; Theorem 8.3.12, p. 388 in Casella and Berger [2001], Theorem 3.2.1 in Lehmann and Romano [2005]). Consider testing $H_0 : \theta = \theta_0$ versus $H_1 : \theta = \theta_1$, where the pdf or pmf corresponding to θ_i is $f(x | \theta_i)$, $i \in \{0, 1\}$. Suppose we have a test ϕ^* such that

$$\phi^* = \begin{cases} 1, & f(x | \theta_1) > cf(x | \theta_0) \quad (q(x) > cp(x)) \\ 0, & f(x | \theta_1) < cf(x | \theta_0) \quad (q(x) < cp(x)) \end{cases} \quad (10.28)$$

(recall that $\phi^*(x) = 1$ when $x \in R$ and 0 otherwise) for some $c \geq 0$ and

$$\alpha_{\phi^*} = \mathbb{P}_{\theta_0}(x \in R) = \beta^*(\theta_0) = \alpha \quad (10.29)$$

(where β^* is the power test for ϕ^*). Then

1. Any test ϕ^* that satisfies (10.28) and (10.29) is a UMP level α test.
2. There exist $c \geq 0$ and ϕ^* that satisfy (10.28) and (10.29).
3. If $\tilde{\phi}$ is UMP of size α , then it satisfies (10.28) almost surely. Moreover, $\alpha_{\tilde{\phi}} = \alpha$ unless $p_{\tilde{\phi}} = 1$. (In other words, the only complication/exception is if you have a test that has power 1 and Type I error rate less than α ; then obviously you choose the test with power 1 and minimal Type I error rate, which will be less than α .)

(Claim from Casella and Berger [2001]) If there exists a test satisfying (10.28) and (10.29), then every UMP level α test is a size α test (satisfies (10.29)) and every UMP level α test satisfies (10.28) except perhaps on a set A satisfying $\mathbb{P}_{\theta_0}(X \in A) = \mathbb{P}_{\theta_1}(x \in A) = 0$.

Proof (in-class, 541B). 1. Suppose that ϕ is the test function for another level α test; that is, if β is the power function for ϕ ,

$$\sup_{\theta \in \{\theta_0\}} \beta(\theta) = \beta(\theta_0) \leq \alpha. \quad (10.30)$$

Note that

$$\int_S (\phi^* - \phi) [f(x | \theta_1) - cf(x | \theta_0)] d\mu \geq 0 \quad (10.31)$$

for the following reason: by (10.28), when $x \in R$, $\phi^* = 1$, so $\phi^* - \phi \in [0, 1]$. Also, in this region, $f(x | \theta_1) > cf(x | \theta_0)$, so the second term is positive. On the other hand, when $x \in R^C$, $\phi^* = 0$, so $\phi^* - \phi \in [-1, 0]$, and $f(x | \theta_1) < cf(x | \theta_0)$ so the second term is negative.

On the other hand, we can rewrite (10.31) as follows:

$$\begin{aligned} 0 &\leq \int_S \phi^* f(x | \theta_1) d\mu - \int_S \phi f(x | \theta_1) d\mu - c \int_S \phi^* f(x | \theta_0) d\mu + c \int_S \phi f(x | \theta_0) d\mu \\ &\iff 0 \leq \beta^*(\theta_1) - \beta(\theta_1) - c [\beta^*(\theta_0) - \beta(\theta_0)] \end{aligned} \quad (10.32)$$

(where β^* is the power function for ϕ^* and β is the power function for ϕ). Note that $c [\beta^*(\theta_0) - \beta(\theta_0)] \geq 0$ since $c \geq 0$ by assumption, $\beta^*(\theta_0) = \alpha$ by (10.29), and $\beta(\theta_0) \leq \alpha$ by (10.30). Therefore by (10.32),

$$0 \leq \beta^*(\theta_1) - \beta(\theta_1) - c [\beta^*(\theta_0) - \beta(\theta_0)] \leq \beta^*(\theta_1) - \beta(\theta_1);$$

that is, β^* is UMP over all level α tests.

2. We will use the randomization possible when $q(x) = cp(x)$ to make the Type I error rate equal α exactly. Consider the test

$$\phi^*(x) = \begin{cases} 1, & q(x) > cp(x) \\ \gamma, & q(x) = cp(x) \\ 0, & q(x) < cp(x) \end{cases} \quad (10.33)$$

for some $\gamma \in [0, 1]$ and some $c \geq 0$. The size of ϕ^* is

$$\begin{aligned} \alpha_{\phi^*} &= \mathbb{P}_P(x : q(x) > cp(x)) + \gamma \mathbb{P}_P(x : q(x) = cp(x)) \\ &= \int_S \phi^*(x)p(x) d\mu \end{aligned}$$

so it remains to show that for any $\alpha \in [0, 1]$, there exists c, γ such that $\alpha_{\phi^*} = \alpha$. Let $H(c) := \mathbb{P}_P(x : q(x) \leq cp(x))$. Then

- (a) $H(c)$ is non-decreasing.

(b) $H(c)$ is right-continuous (like a cdf, because of the \leq).

Then $\alpha_{\phi^*} = (1 - H(c)) + \gamma[H(c) - \lim_{y \rightarrow c^+} H(y)]$, and we want this to equal α . (Notice that this equation is very similar to the ones we encountered when studying minimax tests.) We will consider two cases.

- (a) If there exists a c such that $1 - H(c) = \alpha$, simply take $\gamma = 0$.
- (b) If there does not exist a c such that $1 - H(c) = \alpha$; that is, $1 - H(c) < \alpha$, $\lim_{y \rightarrow c^+} 1 - H(y) > \alpha$, we can set γ appropriately. (Exercise: find the γ .)

More notes:

$$H(c) = \mathbb{P}(x : q(x) \leq cp(x)) = \mathbb{P}(x : q(x)/p(x) \leq c).$$

We can divide by $p(x)$ because the probability that $p(x) = 0$ is 0. Now H is kind of like a distribution function. Consider:

$c < 0 \implies H(c) = 0$. Also, as $c \rightarrow \infty$, $H \rightarrow 1$. So we can always solve for $c \geq 0$, $\gamma \in [0, 1]$ such that

$$1 - H(c) + \gamma[H(c) - H(c^-)] = \alpha.$$

We will show that for any $0 \leq \alpha \leq 1$ there exist $c(\alpha)$ and $\gamma(\alpha)$ such that $\mathbb{E}_P \Phi^*(X) = \alpha$ (meaning the test Φ^* has size α). We have

$$\phi^*(x) = \begin{cases} 1, & q(x) > c(\alpha)p(x) \\ \gamma(\alpha), & q(x) = c(\alpha)p(x) \\ 0, & q(x) < c(\alpha)p(x) \end{cases}$$

We seek $c(\alpha)$ and $\gamma(\alpha)$ satisfying

$$\alpha = \mathbb{E}_P \phi^*(X) = \mathbb{P}_P(\{x : q(x) > cp(x)\}) + \gamma(\alpha) \mathbb{P}_P(\{x : q(x) = cp(x)\}) \quad (10.34)$$

First, simply let

$c(\alpha) := \inf_{c \in \mathbb{R}} \{c : \mathbb{P}_P(\{x : q(x) > cp(x)\}) \leq \alpha\} = \inf_{c \in \mathbb{R}} \left\{ c : \mathbb{P}_P \left(\left\{ x : \frac{q(x)}{p(x)} > c \right\} \right) \leq \alpha \right\}$

(10.35)

(where we can divide by $p(x)$ since we are evaluating this probability over P so we only need to consider x such that $p(x) > 0$). Suppose that

$$\mathbb{P}_P(q(x)/p(x) = c) = 0. \quad (10.36)$$

Then we do not need to find $\gamma(\alpha)$ because ϕ^* is already fully defined by this $c(\alpha)$: that is, it holds that the minimum of the set in (10.35) exists and is the infimum, so

$$\mathbb{P}_P \left(\left\{ x : \frac{q(x)}{p(x)} > c(\alpha) \right\} \right) = \alpha$$

and we are done with an arbitrary $\gamma(\alpha)$, say $\gamma(\alpha) = 0$. The case where (10.36) does not hold is more complicated. Let

$$a(k) := \mathbb{P}_P(\{x : q(x) > kp(x)\}) = \mathbb{P}_P\left(\left\{x : \frac{q(x)}{p(x)} > k\right\}\right)$$

(again, the last step is permissible since we are calculating this probability under P). Then since $a(k)$ is the probability that the random variable $q(X)/p(X)$ exceeds k under P , $1 - a(k)$ can be considered as the cdf of the random variable $q(x)/p(x)$ as a function of k , with $\lim_{k \rightarrow -\infty}(1 - a(k)) = 0$ and $\lim_{k \rightarrow \infty}(1 - a(k)) = 1$. This means that $1 - a(k)$ is nondecreasing right-continuous, so $a(k)$ is nonincreasing and right-continuous. As a consequence,

$$\mathbb{P}_P(q(x)/p(x) = c(\alpha)) = [1 - a(c(\alpha))] - \lim_{y \rightarrow c(\alpha)^-} [1 - a(y)] = \lim_{y \rightarrow c(\alpha)^-} a(y) - a(c(\alpha)) =: a(c(\alpha)^-) - a(c(\alpha)),$$

(where the last step simply introduces a simpler notation) and we have

$$\mathbb{P}_P(q(x)/p(x) = c(\alpha)) \neq 0 \iff a(c(\alpha)^-) - a(c(\alpha)) \neq 0. \quad (10.37)$$

If (10.37) holds, $\mathbb{P}_P\left(\left\{x : \frac{q(x)}{p(x)} > c(\alpha)\right\}\right) < \alpha$; in particular,

$$\mathbb{P}_P\left(\frac{q(x)}{p(x)} > c(\alpha)\right) = a(c(\alpha)) < \alpha.$$

Therefore in general (without any assumptions about whether $\mathbb{P}_P(\{x : q(x) = c(\alpha)p(x)\}) = 0$) the size of ϕ as defined in (10.34) is

$$\begin{aligned} \mathbb{E}_P(\phi^*(X)) &= \mathbb{P}_P(\{x : q(x)/p(x) > c(\alpha)\}) + \gamma(\alpha)\mathbb{P}_P(\{x : q(x)/p(x) = c(\alpha)\}) \\ &= a(c(\alpha)) + \gamma(\alpha)[a(c(\alpha)^-) - a(c(\alpha))] \end{aligned}$$

Because of this, it is clear that defining

$$\begin{aligned} \gamma(\alpha) &:= \begin{cases} \frac{\alpha - a(c(\alpha))}{a(c(\alpha)^-) - a(c(\alpha))}, & \mathbb{P}_P(q(x)/p(x) = c(\alpha)) \neq 0 \\ 0, & \mathbb{P}_P(q(x)/p(x) = c(\alpha)) = 0 \end{cases} = \begin{cases} \frac{\alpha - a(c(\alpha))}{a(c(\alpha)^-) - a(c(\alpha))}, & a(c(\alpha)^-) - a(c(\alpha)) \neq 0 \\ 0, & a(c(\alpha)^-) - a(c(\alpha)) = 0 \end{cases} \\ &= \begin{cases} \frac{\alpha - \mathbb{P}_P(\{x : q(x) > c(\alpha)p(x)\})}{\mathbb{P}_P(\{x : q(x) > c(\alpha)p(x)\}) - \mathbb{P}_P(\{x : q(x) = c(\alpha)p(x)\})}, & \mathbb{P}_P(\{x : q(x) > c(\alpha)^-p(x)\}) - \mathbb{P}_P(\{x : q(x) > c(\alpha)p(x)\}) \neq 0 \\ 0, & \mathbb{P}_P(\{x : q(x) > c(\alpha)^-p(x)\}) - \mathbb{P}_P(\{x : q(x) > c(\alpha)p(x)\}) = 0 \end{cases} \end{aligned}$$

leads to (10.34) being satisfied.

3. Consider again (10.31), except now let ϕ be any UMP level α test. Since by part (1) ϕ^* is also UMP level α , we have $\beta^*(\theta_1) = \beta(\theta_1)$, so from (10.32) we have

$$0 \leq \beta^*(\theta_1) - \beta(\theta_1) - c[\beta^*(\theta_0) - \beta(\theta_0)] = c[\beta(\theta_0) - \beta^*(\theta_0)] \implies \beta(\theta_0) - \beta^*(\theta_0) \geq 0$$

Recall that $\beta^*(\theta_0) = \alpha$ by (10.29), so $\beta(\theta_0) \geq \alpha$. But $\beta(\theta_0) \leq \alpha$ since it is UMP level α . Therefore we must have $\beta(\theta_0) = \alpha$, so ϕ satisfies (10.29) (unless there is a set A such that $\int_S f(x | \theta_1) dx = \int_S f(x | \theta_0) dx = 0$).

(Notes from class) Consider

$$A = \int_S (\phi^* - \tilde{\phi}) \underbrace{(q - cp)}_{\text{positive on } c_+} d\mu \quad (10.38)$$

where ϕ^* is the UMP test (10.33) from part (2). Then (10.38) is greater than or equal to 0 ($A \geq 0$) by part 1 of the lemma. On the other hand,

$$A = \underbrace{\beta_{\phi^*} - \beta_{\tilde{\phi}}}_{=0 \text{ if they are both UMP}} - \underbrace{c}_{\geq 0} \begin{pmatrix} \alpha_{\phi^*} - \alpha_{\tilde{\phi}} \\ =\alpha \\ \leq\alpha \end{pmatrix}.$$

They must both be UMP tests, so the above notes follow. So either $c = 0$ or $\alpha_{\phi^*} = \alpha_{\tilde{\phi}}$. If $c = 0$,

$$\beta_{\phi^*} = \int \phi^*(x) q(x) d\mu = 1$$

$$\tilde{\phi} = \begin{cases} 1, & q(x) > 0 \\ 0, & q(x) \leq 0 \end{cases}$$

(but of course $q(x)$ is never negative). Then $\beta_{\tilde{\phi}} = \int \tilde{\phi}(x) q(x) d\mu = 1$.

Note that we don't need to know the γ , because

The other possibility is $\alpha_{\phi^*} = \alpha_{\tilde{\phi}} = \alpha$. Consider the set $c_+ = \{x : q(x) > cp(x)\} \implies \tilde{\phi}(x) = 1$ on c_+ . And $c_- = \{x : q(x) < cp(x)\} \implies \tilde{\phi}(x) = 0$ on c_- . Finally, since $\alpha_{\tilde{\phi}} = \alpha_{\phi^*} = \alpha$, $\tilde{\phi}(x) = \gamma$ when $q(x) = cp(x)$, then γ is the same for ϕ^* , so the tests must be equal.

□

Geometric illustration (Figure 10.1): consider the mapping $T : \Phi \rightarrow [0, 1] \times [0, 1]$ where Φ is the set of all possible tests where $T(\phi) = (\alpha_\phi, \beta_\phi)$. Observation: $(\alpha, \beta) \in \text{im}(T) \implies (1 - \alpha, 1 - \beta) \in \text{im}(T)$ because if $T(\phi) = (\alpha, \beta)$, then $T(1 - \phi) = (1 - \alpha, 1 - \beta)$. So we have symmetry around the point $(1/2, 1/2)$. This picture shows why there is an exception if $\beta = 1$; then you want the test with minimum α given maximum power. But in practical terms this case is not really important; this is more of a technical detail.

- Exercise 30.**
1. Let ϕ^* be the MP test of size α . Then $\beta_{\phi^*} \geq \alpha$. Moreover, β_{ϕ^*} is strictly greater than α unless $P = Q$ (Use N-P lemma, part 1).
 2. Let X_1, \dots, X_n be i.i.d. uniform. $H_0 : X_1, \dots, X_n \sim U(0, 1)$. $H_a : X_1, \dots, X_n \sim U(1/3, 2/3)$. Derive a UMP test of size α for all values of α .

Solution.

1.

2.

$$q(x_1, \dots, x_n) = e^n \prod_{i=1}^n I\{x_i \in [1/3, 2/3]\} = e^n I\{x_1, \dots, x_n \in [1/3, 2/3]\}$$

Similarly,

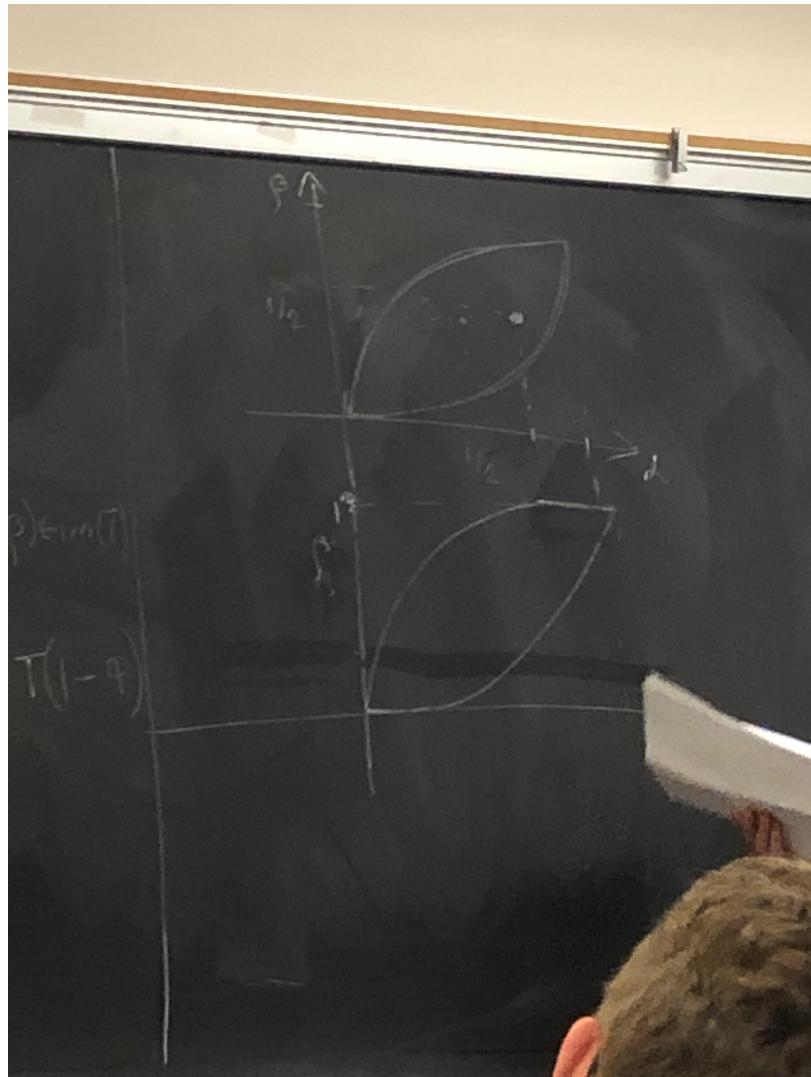


Figure 10.1: Sets of possible Neyman-Pearson tests; similar to Figure 3.1 in [Lehmann and Romano \[2005\]](#).

$$p(x_1, \dots, x_n) = I\{x_1, \dots, x_n \in [0, 1]\}.$$

Note that the ratio q/p only takes on three values. By the Neyman-Pearson Lemma (Lemma 10.8.3), the most powerful test ϕ^* is either

$$\phi_1^*(x_1, \dots, x_n) = \begin{cases} 1, & q(x_1, \dots, x_n)/p(x_1, \dots, x_n) = 3^n \\ \gamma, & q(x_1, \dots, x_n)/p(x_1, \dots, x_n) = 0 \end{cases}$$

or

$$\phi_2^*(x_1, \dots, x_n) = \begin{cases} \gamma, & q(x_1, \dots, x_n)/p(x_1, \dots, x_n) = 3^n \\ 0, & q(x_1, \dots, x_n)/p(x_1, \dots, x_n) = 0 \end{cases}$$

Now

$$\begin{aligned} \alpha_{\phi_1^*} &= \mathbb{E}_P \phi_1^*(X_1, \dots, X_n) = 1 \cdot \mathbb{P}(X_1, \dots, X_n \in [1/3, 2/3]) + \gamma \mathbb{P}(\text{at least one } X_j \text{ is outside } [1/3, 2/3]) \\ &= 3^{-n} + \gamma(1 - 3^{-n}) = \alpha \end{aligned}$$

which has a solution for $\gamma(\alpha)$ for $\alpha \geq 3^{-n}$. On the other hand,

$$\begin{aligned} \alpha_{\phi_2^*} &= \mathbb{E}_P \phi_2^*(X_1, \dots, X_n) = \gamma \mathbb{P}(X_1, \dots, X_n \in [1/3, 2/3]) + 0 \cdot \mathbb{P}(\text{at least one } X_j \text{ is outside } [1/3, 2/3]) \\ &= \gamma 3^{-n} = \alpha \end{aligned}$$

which has a unique solution $\gamma(\alpha)$ for $\alpha \leq 3^{-n}$. So for a test with a very small α , you need to consider a strictly randomized test like $\alpha_{\phi_2^*}$.

Theorem 10.8.4 (Went over last time). We have a sequence X_1, \dots, X_n distributed i.i.d. Last time we showed that the following hypothesis testing problem:

$$H_0 : X_1, \dots, X_n \sim P, \quad H_A : X_1, \dots, X_n \sim Q$$

with

$$\frac{dP}{d\mu} = p, \quad \frac{dQ}{d\mu} = q$$

using the test

$$\phi^*(x_1, \dots, x_n) = \begin{cases} 1, & \prod_{i=1}^n q(x_i) > c \prod_{i=1}^n p(x_i) \\ \gamma, & \prod_{i=1}^n q(x_i) = c \prod_{i=1}^n p(x_i) \\ 0, & \prod_{i=1}^n q(x_i) < c \prod_{i=1}^n p(x_i) \end{cases} \quad (10.39)$$

is UMP of size $\alpha = \mathbb{E}_P(\phi^*)(X_1, \dots, X_n)$ (given the correct choice of γ).

Remark 141. Intuition: if the likelihood function for Q exceeds the likelihood function of P by a reasonable amount (determined by c), choose Q to be more likely than P .

Also, ϕ^* of this kind is referred to as a *Neyman-Pearson test*.

Proposition 10.8.5 (Math 541B Midterm Problem 2). The uniformly least powerful test of size $\alpha > 0$ is

Proof. Consider again the mapping $T : \Phi \rightarrow [0, 1] \times [0, 1]$ where Φ is the set of all possible tests where $T(\phi) = (\alpha_\phi, \beta_\phi)$ (See Figure 10.1). Observation: $(\alpha, \beta) \in \text{im}(T) \implies (1 - \alpha, 1 - \beta) \in \text{im}(T)$ because if $T(\phi) = (\alpha, \beta)$, then $T(1 - \phi) = (1 - \alpha, 1 - \beta)$. So we have symmetry around the point $(1/2, 1/2)$. Because of this, we can see that if we find the UMP test of size $1 - \alpha$ and reverse the rejection and acceptance regions, we obtain the uniformly least powerful test of size α . By the Neyman-Pearson Lemma, the uniformly most powerful test of size α is

$$\phi^*(x) = \begin{cases} 1, & q(x) > cp(x) \\ 0, & q(x) \leq cp(x) \end{cases}$$

for c chosen so that the size of the test is $1 - \alpha$. Then the uniformly least powerful test of size α is

$$\tilde{\phi}^*(x) = \begin{cases} 1, & q(x) \leq cp(x) \\ 0, & q(x) > cp(x). \end{cases}$$

□

10.8.2 Consistency of Neyman-Pearson Tests

We want the test to be consistent—as we collect more data and $n \rightarrow \infty$, errors of both types go to 0. We hope to show the consistency of Neyman-Pearson tests.

Definition 10.37 (Consistency of a hypothesis test). Consider the framework of the Neyman-Pearson lemma (Lemma 10.8.3, described above). A sequence of tests $\{\phi_n\}_{n \geq 1}$, where $\phi_n = \phi_n(x_1, \dots, x_n)$ is *consistent* if and only if

$$\alpha_{\phi_n} = \mathbb{E}_P \phi_n(X_1, \dots, X_n) \rightarrow 0, \quad \text{and } \beta_{\phi_n} = \mathbb{E}_Q \phi_n(X_1, \dots, X_n) \rightarrow 1 \quad \text{as } n \rightarrow \infty.$$

It turns out that c grows with n , and the growth condition of the size of this c_n is related to a measure of distance between P and Q (Hellinger distance).

Recall the following definition:

Definition 10.38 (Hellinger Distance and Affinity (Definition 13.1.3 in Lehmann and Romano [2005])). The *Hellinger distance* between probability laws P and Q is defined as

$$H^2(P, Q) := \int_S (\sqrt{p} - \sqrt{q})^2 d\mu = 2 \int_S (1 - \sqrt{pq}) d\mu = 2 - 2 \int_S \sqrt{pq} d\mu.$$

(See also Section 10.4.6.) Further,

$$A(P, Q) := \int \sqrt{pq} d\mu$$

is known as the *Hellinger affinity*.

Remark 142. This is a true distance—it satisfies the Triangle Inequality, $H(P, Q) = 0$ if and only if $P = Q$ almost everywhere.

Lemma 10.8.6. Let $X \sim P$ and $Y \sim Q$. Let X_1, \dots, X_n be i.i.d. copies of X and likewise for Y_1, \dots, Y_n , so $(X_1, \dots, X_n) \sim P^n$ and $(Y_1, \dots, Y_n) \sim Q^n$. Then

$$A(P^n, Q^n) = [A(P, Q)]^n.$$

Proof.

$$A(P^n, Q^n) = \int \sqrt{p(x_1, \dots, x_n)} \sqrt{q(x_1, \dots, x_n)} d\mu^n = \prod_{j=1}^n \int \sqrt{p(x_j)q(x_j)} d\mu_j = [A(P, Q)]^n.$$

□

Theorem 10.8.7 (Consistency of Neyman-Pearson tests). Assume that $\rho := A(P, Q) < 1$. Then take any sequence $\{c_n\} \subset \mathbb{R}_+$ such that

$$\rho^{2n} \ll c_n \ll \rho^{-2n}. \quad (10.40)$$

Then any sequence $\{\phi_n\}_{n \geq 1}$ of Neyman-Pearson tests corresponding to $\{c_n\}_{n \geq 1}$ is consistent.

Proof. First, we will show that $\alpha_{\phi_n} \rightarrow 0$ under these conditions. Recall the definition of ϕ from (10.39).

$$\begin{aligned} \alpha_{\phi_n} &= \int \phi(x_1, \dots, x_n) p(x_1, \dots, x_n) d\mu^n \\ &\leq \int I\left\{\frac{\prod_{i=1}^n q(x_i)}{\prod_{i=1}^n p(x_i)} \geq c_n\right\} p(x_1) \cdots p(x_n) d\mu^n = \int I\left\{\frac{\prod_{i=1}^n q(x_i)}{c_n \prod_{i=1}^n p(x_i)} \geq 1\right\} p(x_1) \cdots p(x_n) d\mu^n \\ &\leq \int \sqrt{\frac{q(x_1) \cdots q(x_n)}{c_n p(x_1) \cdots p(x_n)}} p(x_1) \cdots p(x_n) d\mu^n \\ &= \frac{1}{\sqrt{c_n}} \int \sqrt{q(x_1) \cdots q(x_n)} \sqrt{p(x_1) \cdots p(x_n)} d\mu^n = \rho^n c_n^{-1/2} \rightarrow 0 \text{ as } n \rightarrow \infty. \end{aligned}$$

(The second inequality follows because when the indicator equals 0 the square root term is greater than or equal to 0 but when the indicator equals 1 the square root term is greater than or equal to 1. The last step follows by assumption of the lemma.)

Now consider the Type II error $1 - \beta_{\phi_n}$.

$$\begin{aligned}
1 - \beta_{\phi_n} &= \int [1 - \phi(x_1, \dots, x_n)] q(x_1) \cdots q(x_n) \, d\mu^n \\
&\leq \int I\{q(x_1) \cdots q(x_n) \leq cp(x_1) \cdots p(x_n)\} q(x_1) \cdots q(x_n) \, d\mu^n \\
&\leq \int \sqrt{\frac{p(x_1) \cdots p(x_n)}{q(x_1) \cdots q(x_n)}} \cdot c_n \cdot q(x_1) \cdots q(x_n) \, d\mu^n \\
&= \sqrt{c_n} A(P^n, Q^n) = c - n^{1/2} \rho^n \rightarrow 0 \text{ as } n \rightarrow \infty
\end{aligned}$$

□

Remark 143. Intuition: $A(P, Q) < 1 \iff H(P, Q) > 0 \iff P \neq Q$. Also, $a_n \ll b_n \iff a_n = o(b_n)$, and $a_n \gg b_n \iff b_n \ll a_n$. Almost all reasonable sequences satisfy (10.40)—this range is very large.

Basically, this theorem says the Type I and Type II errors converge to 0 geometrically fast (as ρ^n) if P and Q are not too close together.

Proposition 10.8.8 (Stats 100B Homework problem). Let Y_1, Y_2, \dots, Y_n be the outcomes of n independent Bernoulli trials. Then by the Neyman-Pearson lemma (Lemma 10.8.3), the best critical region for testing

$$H_0 : p = p_0 \quad H_a : p > p_0$$

is

$$\frac{y}{n} = \frac{1}{n} \sum Y_i > \frac{\log(K) + n \log\left(\frac{1-p_a}{1-p_0}\right)}{n \log\left(\frac{p_0(1-p_a)}{p_a(1-p_0)}\right)}.$$

Proof.

$$\Pr(\sum Y_i = y) = \binom{n}{y} p_0^y (1-p_0)^{n-y}$$

Using the Neyman-Pearson lemma (let p_a be some particular value of $p > p_0$):

$$\frac{L(p_0)}{L(p_a)} = \frac{\binom{n}{y} p_0^y (1-p_0)^{n-y}}{\binom{n}{y} p_a^y (1-p_a)^{n-y}} < K$$

$$\left(\frac{p_0}{p_a}\right)^y \left(\frac{1-p_0}{1-p_a}\right)^n \left(\frac{1-p_0}{1-p_a}\right)^{-y} < K$$

$$\left(\frac{p_0(1-p_a)}{p_a(1-p_0)}\right)^y < K \left(\frac{1-p_a}{1-p_0}\right)^n$$

$$y \log \left(\frac{p_0(1-p_a)}{p_a(1-p_0)} \right) < \log(K) + n \log \left(\frac{1-p_a}{1-p_0} \right)$$

Aside:

$$\frac{p_0(1-p_a)}{p_a(1-p_0)} = \frac{p_0 - p_0 p_a}{p_a - p_0 p_a} < 1$$

since by assumption $p_a > p_0$. Therefore $\log \left(\frac{p_0(1-p_a)}{p_a(1-p_0)} \right) < 0$. So we have

$$\frac{y}{n} = \frac{1}{n} \sum Y_i > \frac{\log(K) + n \log \left(\frac{1-p_a}{1-p_0} \right)}{n \log \left(\frac{p_0(1-p_a)}{p_a(1-p_0)} \right)}$$

as the form for our critical region.

□

10.8.3 Composite Hypothesis Testing

We will start with one-dimensional family (one parameter), then expand to multiple parameters using tricks based on conditioning and using the principles of sufficiency and completeness.

Definition 10.39 (Composite Hypothesis Test). Assume we have a statistical model $\{P_\theta, \theta \in \Theta\}$. Let $\Theta_0, \Theta_1 \subset \Theta$ be such that $\Theta_0 \cap \Theta_1 = \emptyset$ and $\Theta_0 \cup \Theta_1 = \Theta$. Assume $X \sim P_\theta$ for some $\theta \in \Theta$ (where X may be multivariate). We would like to test the hypotheses

$$H_0 : \theta \in \Theta_0, \quad H_a : \theta \in \Theta_1.$$

Such a test is a *composite hypothesis test*.

The Neyman-Pearson Lemma (Lemma 10.8.3) does not directly apply to composite hypothesis tests, but it turns out we can use the Neyman-Pearson lemma to prove some results about some composite hypothesis tests under some circumstances.

Definition 10.40 (Power function; definition 8.3.1 in Casella and Berger [2001]). The *power function* of a test ϕ is defined as

$$\beta_\phi(\theta) := \mathbb{E}_\theta \phi(X).$$

Remark 144. For $\theta \in \Theta_0$, $\beta_\phi(\theta)$ is the probability of a Type 1 error; for $\theta \in \Theta_1$, $\beta_\phi(\theta)$ is the power of ϕ .

Definition 10.41 (Test size; definition 8.3.6 in Casella and Berger [2001]). The test ϕ is of *size* α if and only if

$$\sup_{\theta \in \Theta_0} \beta_\phi(\theta) \leq \alpha.$$

Definition 10.42 (Uniformly most powerful test; definition 8.3.11 in Casella and Berger [2001]). ϕ^* is the *uniformly most powerful test* of size α if ϕ^* is of size α and $\beta_{\phi^*}(\theta) \geq \beta_\phi(\theta)$ for any other test ϕ of size α for all $\theta \in \Theta_1$.

We will be interested in families with *monotone likelihood ratios*. (Note: for the rest of the class today, $\Theta = [a, b] \subseteq \mathbb{R}$ with $a, b \in [-\infty, \infty]$).

Definition 10.43 (Monotone likelihood ratio; definition 8.3.16 in Casella and Berger [2001]). Let $T(X)$ be a statistic. Consider $\Theta \subseteq \mathbb{R}$ as a segment on the real line. We say that the family of pdfs $\{p_\theta, \theta \in \Theta\}$ has a *monotone likelihood ratio (MLR)* with respect to $T(x)$ if and only if for any $\theta' > \theta''$,

$$\frac{p_{\theta'}(x)}{p_{\theta''}(x)} = \psi_{\theta', \theta''}(T(x))$$

where $\psi_{\theta', \theta''}(\cdot)$ is non-decreasing. (That it is non-decreasing is without loss of generality; in the case that ψ is non-increasing, simply replace $T(x)$ with $-T(x)$ to achieve a non-decreasing ψ).

Example 10.28. Let $X \sim \text{Poisson}(\lambda)$, so

$$p_\lambda(x) = \frac{e^{-\lambda} \lambda^x}{x!}, \quad x \in \mathbb{Z}_+.$$

Then $\{\text{Poisson}(\lambda), \lambda \in \mathbb{R}_+\}$ has a monotone likelihood ratio with respect to $T(x) = x$ by the following argument. Take $\lambda' > \lambda''$. Then

$$\frac{e^{-\lambda'} (\lambda')^x x!}{x! e^{-\lambda''} (\lambda'')^x} = e^{-(\lambda' - \lambda'')} \left(\frac{\lambda'}{\lambda''} \right)^x$$

and

$$\psi_{\lambda', \lambda''}(x) = e^{-(\lambda' - \lambda'')} \left(\frac{\lambda'}{\lambda''} \right)^x$$

is non-decreasing.

Theorem 10.8.9 (Karlin-Rubin; similar to Theorem 8.3.17 in Casella and Berger [2001], Theorem 3.4.1 in Lehmann and Romano [2005]). Assume $\{p_\theta, \theta \in [a, b]\}$ has a monotone likelihood ratio with respect to some sufficient statistic for $\theta \in \mathbb{R}$, $T(x)$. Suppose we want to test

$$H_0 : \theta \leq \theta_0, \quad H_a : \theta > \theta_0.$$

Then there exists $c \geq 0$ and $\gamma \in [0, 1]$ such that

$$\phi^*(x) = \begin{cases} 1, & T(x) > c \\ \gamma, & T(x) = c \\ 0, & T(x) < c \end{cases}$$

is the uniformly most powerful test of size α . (In other words, the UMP test will always be of this form.)

Proof. We will show that this is the uniformly most powerful test over the larger family of tests that satisfy $\mathbb{E}_{\theta_0}\phi(x) = \alpha$ ($\beta_\phi(\theta_0) \leq \alpha$), which contains tests of size α . So if we can find the UMP test for this larger family (and it is a test of size α), then that is also the UMP test for test of size α (satisfying $\sup_{\theta \in \Theta_0} \beta_\phi(\theta) \leq \alpha$).

First note that we can always find c and γ such that

$$\mathbb{E}_{\theta_0}(\phi^*(x)) = \alpha.$$

Define $F(c) := \mathbb{P}_{\theta_0}(\{x : T(x) \leq c\})$. Note that

$$\mathbb{E}_{\theta_0}\psi^*(x) = F(c) + \gamma[F(c) - F(c^+)]$$

where $F(c) - F(c^+)$ is the size of the jump. (The proof of this claim is an exercise.)

Next, take $\theta' > \theta_0$ and consider the simple hypothesis test

$$H'_0 : \theta = \theta_0, \quad H'_a : \theta = \theta'.$$

By the Neyman-Pearson Lemma (Lemma 10.8.3), the most powerful test for this is

$$\phi'(x) = \begin{cases} 1, & p_{\theta'}(x) > c' p_{\theta_0}(x) \\ \gamma', & p_{\theta'}(x) = c' p_{\theta_0}(x) \\ 0, & p_{\theta'}(x) < c' p_{\theta_0}(x) \end{cases} \iff \phi'(x) = \begin{cases} 1, & p_{\theta'}(x)/p_{\theta_0}(x) > c' \\ \gamma', & p_{\theta'}(x)/p_{\theta_0}(x) = c' \\ 0, & p_{\theta'}(x)/p_{\theta_0}(x) < c' \end{cases}$$

But since $p_{\theta'}(x)/p_{\theta_0}(x) = \psi(T(x))$, by the assumption of the monotone likelihood ratio property,

$$\frac{p_{\theta'}(x)}{p_{\theta_0}(x)} > c' \iff T(x) > \psi^{-1}(c').$$

Set $\psi^{-1}(c') = c$ and $\psi^{-1}(\gamma') = \gamma$ (using the values of γ and c from earlier in the proof). Then we have

$$\phi'(x) = \begin{cases} 1, & T(x) > c \\ \gamma', & T(x) = c \\ 0, & T(x) < c \end{cases}$$

as desired. (Moreover, c and γ are uniquely determined by $\mathbb{E}_{\theta_0}(\phi^*) = \alpha$. Note that θ' does not appear anywhere in this test. Since θ' was arbitrary, the proof is almost complete.)

The final argument is to show that this test has size α . Namely, we must show

$$\sup_{\theta \leq \theta_0} \beta_{\phi^*}(\theta) = \sup_{\theta \leq \theta_0} \mathbb{E}_\theta \phi^*(x) \leq \alpha.$$

It is sufficient to show that $\beta_{\phi^*}(\theta)$ is monotone. Take $\theta_1 < \theta_2$. Then by the Neyman-Pearson Lemma (Lemma 10.8.3), we know that ϕ^* is the UMP test for testing

$$H''_0 : \theta = \theta_1 \quad H''_a : \theta = \theta_2$$

of size $\beta_{\phi^*}(\theta)$. Since it is the most powerful test, its power $\mathbb{E}_{\theta_2} \phi^*(x)$ is at least as powerful than the test which is identically equal to $\beta_{\phi^*}(\theta)$; that is, $\mathbb{E}_{\theta_2}(\phi^*(x)) \geq \mathbb{E}_{\theta_1}(\phi^*(x))$.

□

Example 10.29. $X_1, \dots, X_n \sim \mathcal{N}(\mu, 1)$. Test $H_0 : \mu \leq 0$ against $H_1 : \mu > 0$. Find the UMP test.

Solution.

Take $\mu_1 > \mu_2$. Then

$$\begin{aligned} \frac{p_{\mu_1}(x_1, \dots, x_n)}{p_{\mu_2}(x_1, \dots, x_n)} &= \exp \left\{ -\frac{1}{2} \left[\sum_{i=1}^n (x_i - \mu_1)^2 - \sum_{i=1}^n (x_i - \mu_2)^2 \right] \right\} \\ &= \exp \left\{ -\frac{1}{2} \left[n(\mu_1^2 - \mu_2^2) + (\mu_1 - \mu_2) \sum_{i=1}^n x_i \right] \right\} \end{aligned}$$

This is an increasing function with respect to $T(x_1, \dots, x_n) = \sum_{i=1}^n x_i$. Therefore by Theorem 10.8.9, we have that the UMP test is

$$\phi(x_1, \dots, x_n) = \begin{cases} 1, & \sum_{i=1}^n x_i \geq c_\alpha \\ 0, & \sum_{i=1}^n x_i < c_\alpha \end{cases} = \begin{cases} 1, & n^{-1/2} \sum_{i=1}^n x_i \geq c'_\alpha \\ 0, & n^{-1/2} \sum_{i=1}^n x_i < c'_\alpha \end{cases} \quad (10.41)$$

Note that

$$\mathbb{E}_{\mu=0} \phi(X_1, \dots, X_n) = \alpha \iff \mathbb{P} \left(\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i \geq c'_\alpha \right) = \alpha$$

and $n^{-1/2} \sum_{i=1}^n X_i \sim \mathcal{N}(0, 1)$. Therefore $c'_\alpha = z_{1-\alpha}$ (the $1 - \alpha$ quantile of a standard Gaussian distribution). Substituting this into (10.41) defines the UMP test.

Remark 145. The Karlin-Rubin Theorem (Theorem 10.8.9) still applies if the inequalities in the hypothesis test are reversed.

Example 10.30. $X_1, \dots, X_n \sim \mathcal{N}(\mu, 1)$. Test $H_0 : \mu \in [0, 1]$ against $H_1 : \mu < 0 \cup \mu > 1$. Does there exist a UMP test?

Solution.

No. Consider $H'_0 : \mu \in [0, 1]$, $H'_a : \mu > 1$ and $H''_0 : \mu \in [0, 1]$, $H''_a : \mu < 1$. If the UMP test for our test exists, it must be identical to the UMP tests for both of these tests (since it would have to be UMP over every θ). By Theorem 10.8.9, the UMP test in the first case is

$$\phi'(x_1, \dots, x_n) = \begin{cases} 1, & \sum_{i=1}^n x_i \geq c \\ 0, & \sum_{i=1}^n x_i < c. \end{cases}$$

The UMP test in the second case is

$$\phi'(x_1, \dots, x_n) = \begin{cases} 1, & \sum_{i=1}^n x_i \leq c \\ 0, & \sum_{i=1}^n x_i > c. \end{cases}$$

Since these tests are not identical, there is no UMP test for our test.

Theorem 10.8.10 (Generalized Neyman-Pearson Lemma, Theorem 3.6.1 in Lehmann and Romano [2005]). Assume that $f_0, f_1, \dots, f_N : \mathbb{R}^d \rightarrow \mathbb{R}$ such that

$$\int |f_j| d\mu < \infty, \quad j \in \{0, \dots, N\}.$$

1. We seek to maximize the $\int \phi f_0 d\mu$ over all tests ϕ subject to $\int \phi f_j d\mu = \alpha_j, j \in \{1, \dots, N\}$.
2. We seek to maximize the $\int \phi f_0 d\mu$ over all tests ϕ subject to $\int \phi f_j d\mu \leq \alpha_j, j \in \{1, \dots, N\}$.

Suppose there exists k_1, \dots, k_N such that

$$\phi^* = \begin{cases} 1, & f_0(x) > k_1 f_1(x) + \dots + k_N f_N(x) \\ 0, & f_0(x) \leq k_1 f_1(x) + \dots + k_N f_N(x) \end{cases}$$

satisfies $\int \phi^* f_j d\mu = \alpha_j, j \in \{1, \dots, N\}$. Then ϕ^* solves the first problem. Moreover, if $k_1, \dots, k_N \geq 0$, then ϕ^* also solves the second problem.

Example 10.31 (Like Theorem 3.7.1 in Lehmann and Romano [2005]). $\{P_\theta, \theta \in \Theta\}$. $H_0 : \theta \in [\theta_1, \theta_2]$. $H_a : \theta \notin [\theta_1, \theta_2]$. We have

$$p_\theta(x) = \frac{1}{c(\theta)} e^{\theta T(x)}$$

(one-parameter exponential family). Find the UMP unbiased test.

Solution.

For the test to be unbiased, the Type I error rate has to be less than or equal to α (for all $\theta \in [\theta_1, \theta_2]$) and the power has to be greater than or equal to α (for all θ in the rejection region). We will use the Generalized Neyman-Pearson Lemma (Theorem 10.8.10) to show the solution is of the form

$$\phi^*(x) = \begin{cases} 1, & T(x) < c_1 \text{ or } T(x) > c_2 \\ \gamma_1, & T(x) = c_1 \\ \gamma_2, & T(x) = c_2 \\ 0, & T(x) \in (c_1, c_2) \end{cases}$$

such that $\mathbb{E}_{\theta_1} \phi^*(X) = \mathbb{E}_{\theta_2} \phi^*(X) = \alpha$. By the Generalized Neyman-Pearson Lemma, we look for the solution in the form

$$\tilde{\phi}(x) = \begin{cases} 1, & p_{\theta'}(x) > k_1 p_{\theta_1}(x) + k_2 p_{\theta_2}(x) \\ 0, & p_{\theta'}(x) < k_1 p_{\theta_1}(x) + k_2 p_{\theta_2}(x). \end{cases} = \begin{cases} 1, & \frac{1}{c(\theta')} e^{\theta' T(x)} > k_1 \frac{1}{c(\theta_1)} e^{\theta_1 T(x)} + k_2 \frac{1}{c(\theta_2)} e^{\theta_1 T(x)} \\ 0, & \frac{1}{c(\theta')} e^{\theta' T(x)} < k_1 \frac{1}{c(\theta_1)} e^{\theta_1 T(x)} + k_2 \frac{1}{c(\theta_2)} e^{\theta_1 T(x)}. \end{cases} = \begin{cases} 1, & 1 > \tilde{k}_1 e^{(\theta_1 - \theta') T(x)} + \tilde{k}_2 e^{(\theta_2 - \theta') T(x)} \\ 0, & 1 < \tilde{k}_1 e^{(\theta_1 - \theta') T(x)} + \tilde{k}_2 e^{(\theta_2 - \theta') T(x)}. \end{cases} \quad (10.42)$$

Let's analyze the inequality $g(t) < 1$ where

$$g(t) = \tilde{k}_1 e^{a_1 t} + \tilde{k}_2 e^{a_2 t}$$

with $a_1 = \theta_1 - \theta' > 0, a_2 = \theta_2 - \theta' > 0, a_1 < a_2$. Consider the second case.

- (a) $\tilde{k}_1 > 0, \tilde{k}_2 > 0 \implies g(t)$ is increasing. $g(t) < 1 \iff t < c$ for some $c \in \mathbb{R}$. From the Karlin-Rubin Theorem, in this case $\beta_{\tilde{\phi}}(\theta)$ is monotone. But this is impossible, as we require $\beta_{\tilde{\phi}}(\theta_1) = \beta_{\tilde{\phi}}(\theta_2)$.
- (b) $\tilde{k}_1 < 0, \tilde{k}_2 < 0 \implies g(t) < 1$. Examining (10.42) shows that in this case $\tilde{\phi}(x) = 1$ for all x (so $\tilde{\phi}$ always rejects), so we can't have controlled Type I error.
- (c) $\tilde{k}_1 < 0, \tilde{k}_2 > 0$. In this case, $g'(t) = \tilde{k}_1 a_1 e^{a_1 t} + \tilde{k}_2 a_2 e^{a_2 t}$. Then $g'(t) = 0$ has a unique solution (see Figure 10.2), and $g(t) < 1 \iff t \in (c_1, c_2)$ (rejection only happens in this bounded interval). But this can't be a UMP unbiased test because the power function of this test is less than a constant test. We should have high power as our test statistic goes off to infinity or negative infinity, but examining (10.42), we see that $\tilde{\phi}(x) = 0$ as $T(x) \rightarrow \infty$ or $-\infty$.
- (d) $\tilde{k}_1 > 0, \tilde{k}_2 < 0$. Then $g'(t)$ has a unique zero (see Figure 10.3), and $g(t) < 1 \iff t \in (c_1, c_2)$ which gives us the form of the test that we were looking for (we always accept the null hypothesis when this function is more than 1 and reject it when it is less than 1).

It remains to show that $\beta_{\phi^*}(\theta) \leq \alpha$ for all $\theta \in [\theta_1, \theta_2]$ (the power function appears as in Figure 10.4). We can show this in one of two ways.

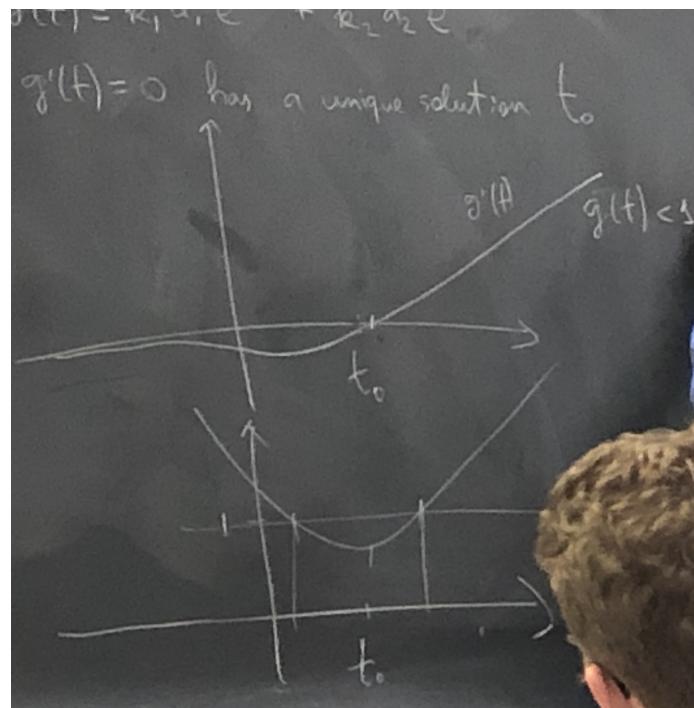


Figure 10.2: Figure for Example 10.31, case (c). This can't be the UMP unbiased test because our power is approaches 0 the further away we get from this narrow interval (we accept the null hypothesis when this function is more than 1).

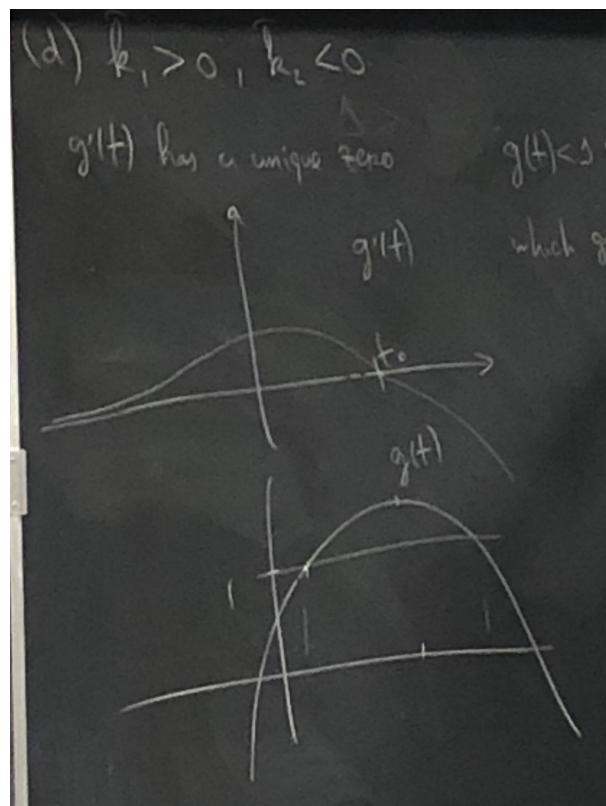


Figure 10.3: Second figure for Example 10.31, case (d). This is the form of the UMP unbiased test.

- (a) $\beta'_{\phi^*}(\theta) = 0$ has a unique solution (then by a similar argument to that used in parts (c) and (d) of the previous part, the power function will have the form we want).
- (b) Lemma: the test ϕ^* minimizes the power at any $\theta' \in (\theta_1, \theta_2)$ among all SOB tests. (proof: exercise, similar mechanics to this).

Remark 146. SOB means "similar on the boundary." Recall that the definition of unbiasedness for a hypothesis test is that for a null hypothesis region Ω_H and an alternative hypothesis region Ω_K , we have

$$\mathbb{E}_{\theta_0} \phi(X) \leq \alpha \quad \forall \theta_0 \in \Theta_H, \quad \mathbb{E}_{\theta_a} \phi(X) \geq \alpha \quad \forall \theta_a \in \Theta_K.$$

If the power function $\beta_\phi(\theta) := \mathbb{E}_\theta \phi(X)$ is a continuous function of θ , unbiasedness implies

$$\beta_\phi(\theta) = \alpha \quad \forall \theta \in \Theta_B, \tag{10.43}$$

where Θ_B is the common boundary of Θ_H and Θ_K ; that is, the set of points θ that are points or limit points of both Ω_H and Ω_K . See Section 4.1 of [Lehmann and Romano \[2005\]](#) and Lemma 10.8.14.

Definition 10.44 ("Similar on the boundary" tests). Tests satisfying (10.43) are said to be **similar on the boundary**.

We can prove this in a way similar to Theorem 3.6.1 in [Lehmann and Romano \[2005\]](#), although the proof is a little different.

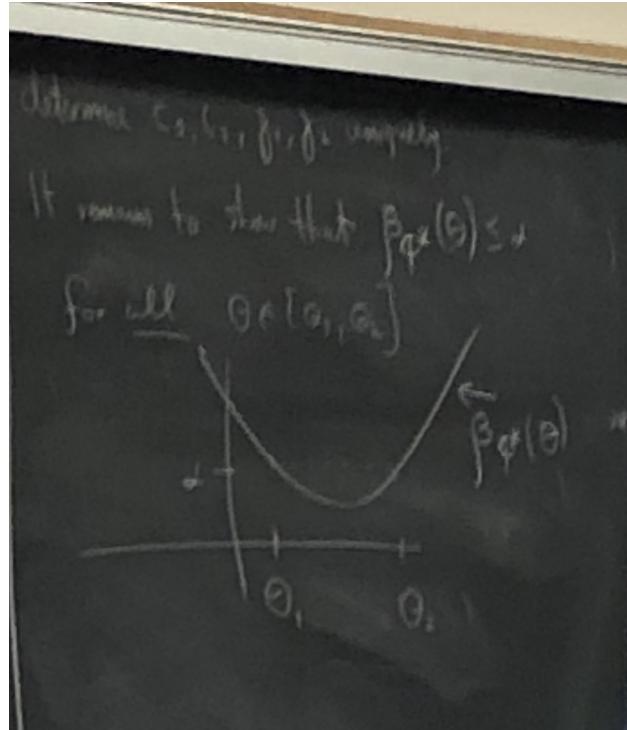


Figure 10.4: Third figure for Example 10.31, the desired form of a power function for our selected test.

Theorem 10.8.11 (Theorem 3.7.1 in Lehmann and Romano [2005]). The most powerful unbiased test for a one-parameter exponential family is

$$\phi^*(x) = \begin{cases} 1, & T(x) < c_1 \text{ or } T(x) > c_2 \\ \gamma_1, & T(x) = c_1 \\ \gamma_2, & T(x) = c_2 \\ 0, & T(x) \in (c_1, c_2) \end{cases}$$

such that

- (a) $\mathbb{E}_{\theta_0}(\phi^*(X)) = \alpha$.
- (b) $\frac{d}{d\theta}\beta_{\phi^*}(\theta)|_{\theta=\theta_0} = 0$ ($\mathbb{E}_{\theta_0}T(X)\phi^*(X) = \alpha\mathbb{E}_{\theta_0}T(X)$).

Proof of constraint (b). For any unbiased test ϕ of size α ,

$$p_\theta(x) = \frac{1}{c(\theta)}e^{\theta T(x)} = \tilde{c}(\theta)e^{\theta T(x)}$$

(letting $\tilde{c}(\theta) = \frac{1}{c(\theta)}$). Then

$$\beta_\phi(\theta) = \int \phi(x)p_\theta(x)d\mu = \int \phi(x)\tilde{c}(\theta)e^{\theta T(x)} d\mu$$

so the derivative is

$$\begin{aligned} \beta'_\phi(\theta) &= \int \phi(x)[\tilde{c}'(\theta) + T(x)\tilde{c}(\theta)]\tilde{c}(\theta)e^{\theta T(x)} d\mu \\ &= \frac{\tilde{c}'(\theta)}{\tilde{c}(\theta)} \int \phi(x)\tilde{c}(\theta)e^{\theta T(x)} d\mu + \int \phi(x)T(x)\tilde{c}(\theta)e^{\theta T(x)} d\mu = \frac{\tilde{c}'(\theta)}{\tilde{c}(\theta)}\mathbb{E}_\theta\phi(X) + \mathbb{E}_\theta\phi(X)T(X) \\ &= \frac{\tilde{c}'(\theta)}{\tilde{c}(\theta)}\alpha + \alpha\mathbb{E}_{\theta_0}T(x) = 0 \implies \frac{\tilde{c}'(\theta)}{\tilde{c}(\theta)} = -E_{\theta_0}T(X) \end{aligned}$$

Hence,

$$\frac{\tilde{c}'(\theta)}{\tilde{c}(\theta)} \underbrace{\mathbb{E}_{\theta_0}\phi(X)}_{\alpha} + \mathbb{E}_{\theta_0}\phi(X)T(X) = 0$$

implies that $-\alpha\mathbb{E}_{\theta_0}T(X) + \mathbb{E}_{\theta_0}\phi(X)T(X) = 0$ so it follows that $\mathbb{E}_{\theta_0}T(X)\phi(X) = \alpha\mathbb{E}_{\theta_0}T(X)$.

⋮

For any unbiased test ϕ , $\beta'_\phi(\theta) = 0$. (We know the test is unbiased: $\phi_\alpha = \alpha$.) Plug $\phi(x) = \alpha$ in to this equation to get

$$\frac{\tilde{c}'(\theta)}{\tilde{c}(\theta)} = -\mathbb{E}_{\theta_0} T(X).$$

□

10.8.4 Locally Most Powerful Tests

Definition 10.45 (Locally most powerful test). Assume that $\{\mathbb{P}_\theta, \theta \in \mathbb{R}\}$ is a statistical model, where p_θ is the probability density function corresponding to \mathbb{P}_θ . Moreover, we will assume the model is “smooth;” that is, for any test Φ , the power function $\beta_\Phi(\theta)$ is differentiable and

$$\frac{d}{d\theta} \beta_\Phi(\theta) = \int \frac{d}{d\theta} p_\theta(x) \cdot \Phi(x) dx. \quad (10.44)$$

Suppose we want to test $H_0 : \theta \leq \theta_0$ against $H_a : \theta > \theta_0$. A **locally most powerful** test of size α is defined as a solution to the optimization problem

$$\begin{aligned} \arg \max_{\Phi: \mathbb{R} \rightarrow [0,1]} \quad & \frac{d}{d\theta} \beta_\Phi(\theta_0) \\ \text{subject to} \quad & \beta_\Phi(\theta_0) = \alpha. \end{aligned} \quad (10.45)$$

The intuition of the locally most powerful test is that it maximizes the power in a small neighborhood of θ_0 by maximizing the slope of the power function at θ_0 .

Proposition 10.8.12 (Math 541B Homework 2 Problem 5). The solution to (10.45) always exists and is of the form

$$\Phi^*(x) = \begin{cases} 1, & \frac{d}{d\theta} p_\theta(x) \Big|_{\theta=\theta_0} > kp_{\theta_0}(x), \\ \gamma, & \frac{d}{d\theta} p_\theta(x) \Big|_{\theta=\theta_0} = kp_{\theta_0}(x), \\ 0, & \frac{d}{d\theta} p_\theta(x) \Big|_{\theta=\theta_0} < kp_{\theta_0}(x), \end{cases}$$

where $\gamma \in [0, 1]$ and k are determined by the size α of the test.

Proof. First we will show that the suggested test always exists and is a size α test under appropriate specifications for k and γ . Then we will show that under the Generalized Neyman-Pearson Lemma (Theorem 10.8.10), this implies that the suggested test is the solution to (10.45). Consider the test

$$\phi^*(x) = \begin{cases} 1, & \frac{d}{d\theta} p_\theta(x) \Big|_{\theta=\theta_0} > kp_{\theta_0}(x) \\ \gamma, & \frac{d}{d\theta} p_\theta(x) \Big|_{\theta=\theta_0} = kp_{\theta_0}(x) \\ 0, & \frac{d}{d\theta} p_\theta(x) \Big|_{\theta=\theta_0} < kp_{\theta_0}(x) \end{cases} \quad (10.46)$$

with $\gamma \in [0, 1]$ and $k \in \mathbb{R}$. Observe that

$$\begin{aligned}\mathbb{E}_{\theta_0} \phi^*(X) &= \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} > kp_{\theta_0}(X) \right) + \gamma \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} = kp_{\theta_0}(X) \right) \\ &= \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > k \right) + \gamma \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) = k \right), \quad (10.47)\end{aligned}$$

where division by $p_{\theta_0}(X)$ is permissible because we are evaluating this expectation over \mathbb{P}_{θ_0} so we only need to include x such that $p_{\theta_0}(x) > 0$ ¹. Define

$$k := \inf_{c \in \mathbb{R}} \left\{ c : \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} > cp_{\theta_0}(X) \right) \leq \alpha \right\} = \inf_{c \in \mathbb{R}} \left\{ c : \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > c \right) \leq \alpha \right\}. \quad (10.48)$$

Suppose that

$$\mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) = k \right) = 0. \quad (10.49)$$

Then we do not need to find γ because ϕ^* is already fully defined by this $c(\alpha)$: that is, it holds that the minimum of the set in (10.48) exists and is the infimum, so

$$\mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > k \right) = \alpha$$

and we are done with an arbitrary γ , say $\gamma = 0$. The case where (10.49) does not hold is more complicated. Let

$$a(m) := \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} > mp_{\theta_0}(X) \right) = \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > m \right).$$

Define the random variable

$$Y := \frac{d}{d\theta} p_\theta(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X)$$

Then since $a(m)$ is the probability that Y exceeds m under \mathbb{P}_{θ_0} , $1 - a(m)$ can be considered as the cdf of Y as a function of m , with $\lim_{m \rightarrow -\infty} (1 - a(m)) = 0$ and $\lim_{m \rightarrow \infty} (1 - a(m)) = 1$. This means that $1 - a(m)$ is nondecreasing right-continuous, so $a(m)$ is nonincreasing and right-continuous. As a consequence,

¹Another way of thinking about this is that the test will not reject for any x such that $p_{\theta_0}(x) = 0$ since with probability 1 these values of x will not be evaluated by the test in the first place.

$$\mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_{\theta}(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) = k \right) = [1 - a(k)] - \lim_{y \rightarrow k^-} [1 - a(y)] = \lim_{y \rightarrow k^-} a(y) - a(k) =: a(k^-) - a(k),$$

(where the last step simply introduces a simpler notation) and we have

$$\mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_{\theta}(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) = k \right) \neq 0 \iff a(k^-) - a(k) \neq 0. \quad (10.50)$$

If (10.50) holds,

$$\mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_{\theta}(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > k \right) = a(k) < \alpha.$$

Therefore in general (without any assumptions about whether $\mathbb{P}_{\theta_0}(Y = k) = 0$) the size of ϕ as defined by setting (10.47) equal to α is

$$\mathbb{E}_{\theta_0}(\phi^*(X)) = \mathbb{P}_{\theta_0}(Y > k) + \gamma \mathbb{P}_{\theta_0}(Y = k) = a(k) + \gamma [a(k^-) - a(k)].$$

Because of this, it is clear that defining

$$\begin{aligned} \gamma := \begin{cases} \frac{\alpha - a(k)}{a(k^-) - a(k)}, & \mathbb{P}_{\theta_0}(Y = k) \neq 0 \\ 0, & \mathbb{P}_{\theta_0}(Y = k) = 0 \end{cases} &= \begin{cases} \frac{\alpha - a(k)}{a(k^-) - a(k)}, & a(k^-) - a(k) \neq 0 \\ 0, & a(k^-) - a(k) = 0 \end{cases} \\ &= \frac{\alpha - \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_{\theta}(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > k \right)}{\mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_{\theta}(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > k^- \right) - \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_{\theta}(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > k \right)} \end{aligned} \quad (10.51)$$

when $\mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_{\theta}(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > k^- \right) - \mathbb{P}_{\theta_0} \left(\frac{d}{d\theta} p_{\theta}(X) \Big|_{\theta=\theta_0} / p_{\theta_0}(X) > k \right) \neq 0$ and 0 otherwise leads to (10.47) equaling α .

So we have that the test defined in (10.46) with k as defined in (10.48) and γ as defined in (10.51) always exists and is a size α test. Finally, note that

$$\phi^*(x)p_{\theta_0}(x) = \begin{cases} p_{\theta_0}(x), & \frac{d}{d\theta} p_{\theta}(x) \Big|_{\theta=\theta_0} > kp_{\theta_0}(x) \\ \gamma p_{\theta_0}(x), & \frac{d}{d\theta} p_{\theta}(x) \Big|_{\theta=\theta_0} = kp_{\theta_0}(x) \\ 0, & \frac{d}{d\theta} p_{\theta}(x) \Big|_{\theta=\theta_0} < kp_{\theta_0}(x) \end{cases}$$

Therefore under this test, the problem we are hoping to solve (10.45) can be expressed as

$$\begin{array}{ll} \underset{\phi: \mathbb{R} \rightarrow [0,1]}{\text{maximize}} & \frac{d}{d\theta} \beta_\phi(\theta) \\ \text{subject to} & \mathbb{E}_{\theta_0} \phi(X) = \alpha \end{array} = \underset{\phi: \mathbb{R} \rightarrow [0,1]}{\text{maximize}} \int \frac{d}{d\theta} p_{\theta}(x) \cdot \phi(x) dx \quad (10.52)$$

subject to $\int_{-\infty}^{\infty} \phi(x)p_{\theta_0}(x) d\mu = \alpha,$

where we used (10.44). Therefore, by the generalized Neyman-Pearson Lemma (Theorem 10.8.10), (10.46) is the solution to (10.52) (and, equivalently, (10.45)).

□

10.8.5 Similarity and Completeness (Section 4.3 of Lehmann and Romano [2005])

Example 10.32. Let X_1, \dots, X_n be i.i.d. $\mathcal{N}(0, \sigma^2)$, $\sigma^2 > 0$. Find the UMP unbiased test for $H_0 : \sigma^2 = \sigma_0^2$, $H_a : \sigma^2 \neq \sigma_0^2$. Assuming that n is large, find the approximate values $c_1(\alpha)$, $c_2(\alpha)$.

Before solving this we will prove a lemma that we have been using implicitly.

Lemma 10.8.13. Suppose that $T(X)$ is sufficient for $\{p_\theta, \theta \in \Theta\}$, and let ϕ be a test. Denote

$$\psi(X) := \mathbb{E}_\theta[\phi(X) \mid T(X)].$$

Then

- (a) $\psi(X)$ is a test.
- (b) $\mathbb{E}_\theta \psi(X) = \mathbb{E}_\theta \phi(X)$.

Proof. (a) Since $T(X)$ is sufficient, the expectation over θ does not matter because we are conditioning on $T(X)$ anyway. That is, the distribution of $\phi(X)$ conditional on $T(X)$ does not depend on θ . Therefore the expectation over θ does not either. (A test takes values between 0 and 1 and doesn't depend on θ , only depends on the data.)

(b)

$$\mathbb{E}_\theta \psi(X) = \mathbb{E}_\theta (\mathbb{E}_\theta[\phi(X) \mid T(X)]) = \mathbb{E}_\theta \phi(X).$$

□

Lemma 10.8.14 (Lemma 4.1.1 in Lehmann and Romano [2005]). If the distributions P_θ are such that the power function of every test is continuous, and if ϕ_0 is UMP among all tests satisfying (10.43) (restated here:)

$$\beta_\phi(\theta) = \alpha \quad \forall \theta \in \omega \tag{10.53}$$

(where ω is the common boundary of the rejection and acceptance regions; that is, the set of points θ that are points or limit points of both regions; often called the boundary family) and is a level α test of H , then ϕ_0 is UMP unbiased. (**short version:** if the power function of every test is continuous, then the UMP test among the class of similar on the boundary (SOB) tests of size α is UMP unbiased of size α .)

Proof. For distributions such that the power function of every test is continuous, the class of SOB tests of size α contains the class of unbiased tests (since being SOB of size α is necessary to be unbiased if the power function of every test is continuous). Therefore the UMP test among the class of SOB tests ϕ^* is at least as powerful as any unbiased test. Further, ϕ^* is unbiased because it is uniformly at least as powerful as $\phi(x) := \alpha$ (since this is an SOB test).

□

Remark 147. By Theorem 2.7.1 in [Lehmann and Romano \[2005\]](#), the power function for a (one-parameter) exponential family is continuous and differentiable.

Definition 10.46 (boundedly complete). $T(X)$ is **boundedly complete** if and only if for any function G such that $|G| \leq 1$ (bounded),

$$\{\mathbb{E}_\theta G(T) = 0 \quad \forall \theta \in \Theta\} \implies G(T) = 0 \text{ a.e.}$$

So if a statistic is complete, it is boundedly complete (if it is complete, the equation holds for all functions G , not just bounded ones). Example:

$$X \in \{-1, 0, 1, 2, \dots\}, \quad \mathbb{P}_\theta(X = k) = \begin{cases} \theta, & k = -1 \\ (1 - \theta)^2 \theta^k, & k \in \{0, 1, \dots\} \end{cases}$$

Then $T(X) = X$ is boundedly complete but not complete.

We want to be able to work with distributions that are more than one dimensional. We can do this by reducing the family to a one-parameter family. We do this in the following way, with tests with Neyman structure. Assume we have $X \sim P_\theta, \theta \in \Theta$. The problem is $H_0 : \theta \in \Theta_0, H_a : \theta \in \Theta_a$, where $\Theta_B := \overline{\Theta_0} \cap \overline{\Theta_a}$ (the intersection of the closures of these sets).

Example: $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$, $H_0 : \mu \leq 0, H_a : \mu > 0$. Then if we plot \mathbb{R}^2 with μ as the horizontal axis and σ^2 as the vertical axis, the acceptance region is Quadrant II (including the top part of the vertical axis) and the rejection region is Quadrant I (not including the top part of the vertical axis). The boundary is the vertical axis ($\Theta_B = \{\mathcal{N}(0, \sigma^2), \sigma^2 > 0\}$).

Approach: take a complete sufficient statistic for the boundary family. We will condition on it and then find tests of size α .

Definition 10.47 (Neyman Structure). Let $T(X)$ be sufficient for the boundary family $\{p_\theta, \theta \in \Theta_B\}$. Test ϕ has **Neyman structure with respect to T** if and only if for some $\alpha \in [0, 1]$

$$\mathbb{E}_\theta[\phi(X) | T(X)] = \alpha, \quad \forall \theta \in \Theta_B.$$

Note that ϕ has Neyman structure implies it is SOB of size α (SOB means "similar on the boundary:" the power function is essentially constant on the boundary. See Definition 10.44 and section 4.1 of [Lehmann and Romano \[2005\]](#).)

Theorem 10.8.15. Suppose T is a sufficient statistic for the boundary family of a SOB test ϕ of size α . Then ϕ has Neyman structure if and only if T is boundedly complete.

Proof. First we will prove this direction: suppose that T is sufficient and boundedly complete. Because ϕ is similar on the boundary (SOB), we have

$$\mathbb{E}_\theta \phi(X) = \alpha \quad \forall \theta \in \Theta_B.$$

But then (letting $G(T) := \mathbb{E}_\theta[\phi(X) | T]$ and using what we know about T)

$$\begin{aligned} \alpha = \mathbb{E}_\theta \phi(X) &= \mathbb{E}_\theta \mathbb{E}_\theta[\phi(X) | T(X)] = \mathbb{E}_\theta G(T) \implies \mathbb{E}_\theta(G(T) - \alpha) = 0, \quad \forall \theta \in \Theta_B \\ &\implies G(T) - \alpha = 0 \text{ a.s.} \quad \implies G(T) = \alpha \text{ a.s.} \quad \forall \theta \in \Theta_B \end{aligned}$$

where the last line followed from the bounded completeness of G . (Recall from Definition 10.47 that ϕ has Neyman structure precisely if $\mathbb{E}_\theta[\phi(X) | T] = \alpha$ for all $\theta \in \Theta_B$. Note that we only need bounded completeness since we must have $0 \leq |G| \leq 1 \forall T$.)

Next, assume an SOB test ϕ of size α has Neyman structure; that is, for a sufficient statistic T for the boundary family,

$$\mathbb{E}_\theta[\phi(X) | T] = \alpha \quad \forall \theta \in \Theta_B.$$

We will prove by contradiction that then T must be boundedly complete. Suppose T is not boundedly complete. Then there must exist some function ψ such that $|\psi| \leq 1$ and $\mathbb{E}_\theta \psi(T) = 0 \forall \theta \in \Theta_B$ but $\psi(T)$ is not identically 0. Define $\phi := \alpha + c\psi(T)$, where we choose $c \neq 0$ such that $0 \leq |\phi| \leq 1$ so that ϕ is a test. Note that $\mathbb{E}_\theta \phi = \alpha$ for all $\theta \in \Theta_B$, so ϕ is SOB of size α . But

$$\mathbb{E}(\phi(x) | T(x)) = \alpha + c\psi(T(x)) \neq \alpha.$$

Therefore by contradiction, we have that T is boundedly complete. □

Remark 148. We already know from Lemma 10.8.14 that if the power function is continuous for all tests (e.g. one parameter exponential family), then the UMP SOB test of size α ϕ^* is the UMP unbiased test of size α . That is, the UMP unbiased test of size α is the solution to the equation

$$\begin{aligned} \arg \max_{\phi: \mathbb{R} \rightarrow [0,1]} \mathbb{E}_\theta(\phi | T) \quad &\forall \theta \in \Theta_A \\ \text{subject to} \quad \beta_\phi(\theta) = \alpha \quad &\forall \theta \in \Theta_B \end{aligned} \tag{10.54}$$

where T is a sufficient statistic for the boundary family, Θ_A is the rejection region, and Θ_B is the boundary family.

Under Theorem 10.8.15, if T is boundedly complete, then any test $\tilde{\phi}$ is an SOB test of size α if and only if it has Neyman structure. So if the power function is continuous for all tests (e.g. one parameter exponential family) and T is a boundedly complete sufficient statistic for the boundary family, then the UMP test in the class of tests with Neyman structure is the UMP unbiased test. That is, the UMP unbiased test is the solution to (10.54).

Theorem 10.8.16. Assume that $X \sim P_\theta$ where

$$p_\theta(x) = \frac{1}{c(\theta)} h(x) \cdot \exp \left\{ \sum_{j=1}^k \theta_j T_j(x) \right\}$$

(canonical exponential family). Then $T(X) = (T_1(X), \dots, T_k(X))$ is a sufficient statistic for the family $\{p_\theta, \theta \in \Theta\}$ provided that Θ has non-empty interior. (See also Proposition 10.3.7.)

See also Theorem 10.3.11 for complete statistics in the exponential family.

Conditioning method: assume that $\beta_\phi(\theta)$ is continuous for any test ϕ .

- (1) The UMP unbiased test ϕ^* must be SOB (because as discussed in the proof of Lemma 10.8.14, SOB is necessary for unbiasedness if $\beta_\phi(\theta)$ is continuous for all tests).
- (2) UMP SOB test of size α is UMP unbiased test of size α (by Lemma 10.8.14).
- (3) Neyman structure implies that it suffices to find the test that maximizes the conditional power $\mathbb{E}_\theta(\phi | T)$ for all $\theta \in \Theta_a$ (see Remark 148).

Example 10.33. $X \sim \text{Poisson}(\mu)$, $Y \sim \text{Poisson}(\nu)$. $H_0 : \mu \leq \nu$, $H_a : \mu > \nu$. Find the UMP unbiased test.

Solution.

$$p_{\mu,\nu}(x,y) = \frac{e^{-(\mu+\nu)} \mu^x \nu^y}{x!y!} = e^{-(\mu+\nu)} e^{x \log \mu + y \log \nu} \cdot \frac{1}{x!y!} = \frac{1}{x!y!} e^{-(\mu+\nu)} e^{x \log(\mu/\nu) + (x+y) \log \nu}$$

Let $\xi := \log(\mu/\nu)$, $\eta = \log \nu$. Then $H_0 : \xi \leq 0$, $H_a : \xi > 0$. We can use an SOB thing where $\Theta_B = \{(\xi, \eta) : \eta = 0\}$ is the boundary family. Then $T(X, Y) = X + Y$ is complete sufficient for the boundary family $\{p_{\xi,\eta} : \xi = 0\}$ by Theorem 10.8.16 (Proposition 10.3.7). Let's condition everything on $T = X + Y$. We need to find $\mathbb{P}(X = x | T = t)$. Note that

$$\mathbb{P}_{\mu,\nu}(X = x | T = t) = \frac{\mathbb{P}_{\mu,\nu}(X = x, Y = t - x)}{\mathbb{P}_{\mu,\nu}(T = t)} = \frac{\mu^x}{x!} e^{-\mu} \cdot \frac{\nu^{t-x}}{(t-x)!} e^{-\nu} \cdot \frac{t! e^{\mu+\nu}}{(\mu+\nu)^t}$$

where we used $T \sim \text{Poisson}(\mu + \nu)$ (exercise; use characteristic functions)

$$= \binom{t}{x} \left(\frac{\mu}{\mu+\nu} \right)^x \left(\frac{\nu}{\mu+\nu} \right)^{t-x}$$

so $\{X | T = t\} \sim \text{Bin}(t, \mu/(\mu + \nu))$.

Note that $\mu \leq \nu \iff p \leq 1/2$, so for our new problem, we have $X \sim \text{Binom}(t, p)$, and we will test $H'_0 : p \leq 1/2, H'_a : p > 1/2$. For this problem we can find the UMP test (not just the UMP unbiased test) because the binomial family has a monotone likelihood ratio with respect to $T(X) = X$ when $p \in (0, 1)$ and t fixed (very straightforward to check).

Then

$$\phi(x) = \begin{cases} 1, & x > c(t) \\ \gamma, & x = c(t) \\ 0, & x < c(t) \end{cases}$$

is UMP. To find $c(t, \alpha)$, use

$$\mathbb{E}_{p=1/2} \phi(X) = \alpha \iff \sum_{x>c(t)} \binom{t}{x} (1/2)^t + \gamma \binom{t}{c(t)} (1/2)^{c(t)} = \alpha. \quad (10.55)$$

(hard to compute in practice; need a computer). So the test for the original problem is

$$\phi(X, Y) = \begin{cases} 1, & X > c(t) \\ \gamma, & x = c(t) \\ 0, & x < c(t) \end{cases}$$

where $t = X + Y$ and $c(t)$ solves (10.55).

Example 10.34. Let $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$, i.i.d. We want to test $H_0 : \sigma^2 \geq \sigma_0^2, H_a : \sigma^2 < \sigma_0^2$. Find the UMP unbiased test.

Solution.

We have

$$p_{\mu, \sigma^2}(x_1, \dots, x_n) = \frac{1}{\sigma^n (2\pi)^{n/2}} \exp \left(\frac{\mu}{\sigma^2} \sum_{j=1}^n x_j - \frac{1}{2\sigma^2} \sum_{j=1}^n x_j^2 \right) \cdot e^{-n\mu/(2\sigma^2)}.$$

Therefore $T = (\sum_{j=1}^n X_j, \sum_{j=1}^n X_j^2)$ is a complete sufficient statistic for (μ, σ^2) . Let

$$\bar{X}_n := n^{-1} \sum_{j=1}^n X_j, \quad S^2 := \frac{1}{n-1} \sum_{j=1}^n (X_j - \bar{X}_n)^2.$$

Then (\bar{X}, S^2) is in one to one correspondence with T . (Why? Use

$$\frac{1}{n} \sum_{j=1}^n (y_j - \bar{y}_j)^2 = \frac{1}{n} \sum_{j=1}^n y_j^2 - (\bar{y}_n)^2$$

for any numbers y_1, \dots, y_n). So (\bar{X}_n, S^2) is also complete sufficient for (μ, σ^2) , so we only need to consider tests that are functions of this complete sufficient statistic. The boundary family in this case Θ_B consists of all normal distributions with variance equal to σ_0^2 ; that is, all normal distributions $\mathcal{N}(\mu, \sigma_0^2)$, $\mu \in \mathbb{R}$. For this family, \bar{X} is a complete sufficient statistic, so we can condition everything on \bar{X} . Hence, we need to find the conditional distribution of S^2 given \bar{X} . Since \bar{X} and S^2 are independent by Basu's Theorem (Theorem 10.3.10; see Proposition 10.2.6 and example 10.9), the problem becomes

$$H_0 : \sigma^2 \geq \sigma_0^2; \quad H_a : \sigma^2 < \sigma_0^2$$

based on our observation S^2 . We know that

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2.$$

by Proposition 10.2.6. Let $\tilde{\sigma}^2 := \sigma^2/(n-1)$. Then the pdf of S^2 is

$$p_{\tilde{\sigma}^2}(x) = \left(\frac{1}{\tilde{\sigma}^2} \right)^{(n-1)/2} x^{(n-1)/2-1} e^{-x/(2\tilde{\sigma}^2)}$$

This means that

$$\frac{p_{\tilde{\sigma}^2}(x)}{p_{\tilde{\sigma}^2}(x)} = \psi_{\tilde{\sigma}^2, \tilde{\sigma}^2}(x)$$

is monotone, so $\tilde{\sigma}^2$ has a monotone likelihood ratio. Then by Karlin-Rubin (Theorem 10.8.9), the UMP unbiased test is

$$\phi^* = \begin{cases} 1, & S^2 \leq c \\ 0, & S^2 > c. \end{cases}$$

To find the test of size α , take $c := \frac{\sigma_0^2}{n-1} (w_\alpha^{(n-1)})$ where $w_\alpha^{(n-1)}$ is the $(1-\alpha)$ quantile of χ_{n-1}^2 .

Remark 149. This may be UMP in general, although we can't prove it with current tools (??). So it is at least UMP unbiased.

Example 10.35. Let $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$, i.i.d. We want to test $H_0 : \mu \geq \mu_0, H_a : \mu < \mu_0$ or $H_0 : \mu = \mu_0, H_a : \mu \neq \mu_0$. Find the UMP unbiased tests for each of these cases.

Solution.

Consider tests ϕ that depend on $T = (\bar{X}, \sum_{j=1}^n X_j^2)$. The boundary family is $\Theta_B = \{\mathcal{N}(\mu_0, \sigma^2), \sigma^2 > 0\}$. A complete sufficient statistic for Θ_B is then

$$S_{\mu_0}^2 := \sum_{j=1}^n (X_j - \mu_0)^2.$$

If we consider

$$T' = \left(\frac{\bar{X} - \mu_0}{\sqrt{S_{\mu_0}^2}}, S_{\mu_0}^2 \right),$$

note that it is one-to-one correspondence with T , so T' is complete sufficient as well. Observe that

(1)

$$\frac{\bar{X} - \mu_0}{\sqrt{S_{\mu_0}^2}} \perp\!\!\!\perp S_{\mu_0}^2$$

(Why? See proof of Proposition 11.3.1.)

(2) For

$$W = \frac{\bar{X} - \mu_0}{\sqrt{S_{\mu_0}^2}}, \quad T'' = \frac{(\bar{X} - \mu_0)}{\sqrt{S^2}} \sqrt{n},$$

we have

$$T'' = \frac{\sqrt{(n-1)n}}{\sqrt{1-nW^2}} W$$

(exercise).

Then

$$g(w) = \left| \frac{\sqrt{(n-1)n}}{\sqrt{1-nw^2}} w \right|$$

is a monotone function of w . Moreover, by the characterization of a Student's t distribution

$$T = \frac{Z}{\sqrt{V/v}} \implies T \sim t_v$$

where $Z \sim \mathcal{N}(0, 1)$, $V \sim \chi_v^2$, and $Z \perp\!\!\!\perp V$, T'' has, under the null hypothesis that $\mu = \mu_0$, a Student's t distribution with $n - 1$ degrees of freedom. Therefore we can conclude that the UMP unbiased test has the form

$$\phi^* = \begin{cases} 1, & |T''| > c \\ 0, & |T''| < c \end{cases}$$

where we choose c to make the test have size α .

10.8.6 Permutation Tests (section 5.8 in Lehmann and Romano [2005], p. 188 of pdf)

Suppose we have $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$ i.i.d. and $Y_1, \dots, Y_m \sim \mathcal{N}(\eta, \sigma^2)$ i.i.d. We would like to test $H_0 : \mu = \eta$ against $H_a : \eta - \mu = \Delta > 0$.

Alternatively: $H_0 : X_1, \dots, X_n, Y_1, \dots, Y_m$ i.i.d. with density f , H_a : the joint density of $X_1, \dots, X_n, Y_1, \dots, Y_m$ has density $f(x_1) \cdots f(x_n)f(y_1 - \Delta) \cdots f(y_m - \Delta), \Delta > 0$.

We are looking for a SOB test of size α . Hence, a test ϕ must satisfy $\mathbb{E}_f \phi = \alpha$ for any f . Define $\mathbb{Z}_1 = X_1, \dots, \mathbb{Z}_n = X_n, \mathbb{Z}_{n+1} = Y_1, \dots, \mathbb{Z}_{n+m} = Y_m$.

Theorem 10.8.17. Consider the following statistical model: $\{p_f : f \text{ is density on } \mathbb{R} \text{ with respect to Lebesgue measure.}\}$ Suppose $X_1, \dots, X_n \sim p_f$ i.i.d. Then $(X_{(1)}, \dots, X_{(n)})$ is a complete sufficient statistic. (That is, for the problem we are considering, the order statistics $(\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)})$ are complete sufficient under H_0 .)

Proof. Sufficiency:

$$\mathbb{P}_f((X_1, \dots, X_n) \in A | X_{(1)}, \dots, X_{(n)}) = \frac{1}{n!} \sum_{\sigma \in S_n} I\{X_{\sigma(1)}, \dots, X_{\sigma(n)} \in A\}$$

which does not depend on any parameters in f , so this proves sufficiency. Completeness: consider the following parametric family

$$\mathbb{P}_{\Theta_1, \dots, \Theta_n}(x_1, \dots, x_n) = c(\Theta_1, \dots, \Theta_n) \exp \left\{ \theta_1 \sum_{i=1}^n x_i + \theta_2 \sum_{i=1}^n x_i^2 + \dots + \theta_n \sum_{i=1}^n x_i^n - \sum_{i=1}^n x_i^{2n} \right\}.$$

From Theorem 10.3.11, we know that

$$Y = \left(\sum_{i=1}^n x_i, \sum_{i=1}^n x_i^2, \dots, \sum_{i=1}^n x_i^n \right)$$

is complete. We will establish this intermediate fact: let

$$W := \left(\underbrace{\sum_{j=1}^n x_j}_{w_1}, \underbrace{\sum_{i < j} x_i x_j}_{w_2}, \sum_{i < j < k} x_i x_j x_k, \dots, \underbrace{x_1 x_2 \cdots x_n}_{w_n} \right).$$

This are symmetric polynomials. We will show that the order statistics T are in one-to-one correspondence with W . Consider the polynomial $p(x) = \prod_{j=1}^n (x - x_j)$. (Of course this polynomial is invariant to permutation of the x_j .) Then the coefficients of the polynomial are given by

$$p(x) = \prod_{j=1}^n (x - x_j) = x^n - w_1 x^{n-1} + w_2 x^{n-2} - \dots + (-1)^n w_n,$$

so $(x_{(1)}, \dots, x_{(n)})$ is in one-to-one correspondence with W . Finally, the fact that W is in one-to-one correspondence with V follows from Newton's Identities: you can establish by induction that

$$v_k - w_1 v_k + w_2 v_{k-2} - \dots + (-1)^k w_{k-1} v_k + (-1)^k w_k = 0$$

for $k = 1, 2, \dots, n$. For example, consider $k = 2$:

$$W = (x_1 + x_2, x_1 x_2), \quad V = (x_1 + x_2, x_1^2 + x_2^2)$$

can always write $x_1 x_2 = [(x_1 + x_2)^2 - (x_1^2 + x_2^2)] / 2$, so knowing W is equivalent to knowing V . Newton's Identities induct on this and show that this is true for any power k .

⋮

(See also Example 4.3.4 in [Lehmann and Romano \[2005\]](#).)

□

Now we will apply the conditioning method by conditioning on $T = (\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)})$. The new problem is then

$$H'_0 : (\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)}) \sim f_{\mathbb{Z}|T}^{(0)} \text{ are uniform on order statistics}, \quad H'_a : (\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)}) \sim f_{\mathbb{Z}|T}^{(a)}$$

Under H_0 , $\mathbb{P}_{H_0}((\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)}) = (z_1, \dots, z_{n+m})) = 1/(n+m)!$ for any specific permutation (z_1, \dots, z_{n+m}) . Let's fix a specific alternative and find the most powerful test against this alternative. Any alternative is of the form $(\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)})$ has joint density h , where h is fixed.

so test is

$$H_0 : X_1, \dots, X_n, Y_1, \dots, Y_m \text{ are i.i.d.}; \quad H_a : X_1, \dots, X_n, Y_1, \dots, Y_m \text{ have joint density } h$$

It turns out that conditional on the order statistics (so that the only randomness left is the way in which they are permuted), the density is given by (10.58).

Theorem 10.8.18 ([Theorem 5.8.1 in Lehmann and Romano \[2005\]](#)).

Lemma 10.8.19 ([See section 5.9 of Lehmann and Romano \[2005\], p. 189 of pdf](#)). Let $(\mathbb{Z}_1, \dots, \mathbb{Z}_{n+m})$ have joint density h . Then for any f ,

$$\mathbb{E}[f(\mathbb{Z}_1, \dots, \mathbb{Z}_{n+m}) | T] = \frac{\sum_{\sigma \in S_{n+m}} f(\mathbb{Z}_{\sigma(1)}, \dots, \mathbb{Z}_{\sigma(n_m)}) h(\mathbb{Z}_{\sigma(1)}, \dots, \mathbb{Z}_{\sigma(n_m)})}{\sum_{\sigma \in S_{n+m}} h(\mathbb{Z}_{\sigma(1)}, \dots, \mathbb{Z})} \quad (10.56)$$

where $T = (\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)})$ and S_{n+m} is a collection of all permutations of $\{1, \dots, n_m\}$.

Proof. Want to show that for any symmetric set \mathcal{A}_0 (meaning that $(z_1, \dots, z_{n_m}) \in \mathcal{A}_0 \iff (z_{\sigma(1)}, \dots, z_{\sigma(n_m)}) \in \mathcal{A}_0$),

$$\int_{\mathcal{A}_0} f(z_1, \dots, z_{n_m}) h(z_1, \dots, z_{n+m}) dz = \mathbb{E}f(\mathbb{Z}_1, \dots, \mathbb{Z}_{n+m}) I\{(\mathbb{Z}_1, \dots, \mathbb{Z}_{n+m}) \in \mathcal{A}_0\} \quad (10.57)$$

Trying to prove:

$$g(T) = \mathbb{E}[f(X) | T] \iff \forall h, \mathbb{E}[f(X)h(T)] = \mathbb{E}[g(T)h(T)].$$

it is always sufficient to prove this for indicator functions because you can approximate any function h as a sum of indicator functions (fact from measure theory). Any set that is measurable with respect to the permutation statistics must be measure theoretic; any set that belongs to the sigma algebra generated by the order statistics must have the property that any permutation is in \mathcal{A}_0 .

We want to show that (10.57) equals

$$\mathbb{E}f_0(\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)}) I\{(\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)}) \in \mathcal{A}_0\}$$

where f_0 is given by the right side of (10.56). By permutation invariance, we have

$$\int f_0(z_1, \dots, z_{m+n}) h(z_{\sigma(1)}, \dots, z_{\sigma(m+n)}) dz = \text{constant}$$

So we have $(n+m)!$ values that are all equal. So we can write

$$\begin{aligned} & \int_{\mathcal{A}_0} f_0(z_1, \dots, z_{n+m}) h(z_1, \dots, z_{n+m}) dz \\ &= \int_{\mathcal{A}_0} f_0(z_1, \dots, z_{n+m}) \frac{1}{(n+m)!} \sum_{\sigma \in S_{n+m}} h(z_{\sigma(1)}, \dots, z_{\sigma(n+m)}) dz \\ &= \frac{1}{(n+m)!} \int_{\mathcal{A}_0} \sum_{\sigma \in S_{n+m}} f_0(z_{\sigma(1)}, \dots, z_{\sigma(n+m)}) h(z_{\sigma(1)}, \dots, z_{\sigma(n+m)}) dz \\ &= \int_{\mathcal{A}_0} f_0(z_{\sigma(1)}, \dots, z_{\sigma(n+m)}) h(z_{\sigma(1)}, \dots, z_{\sigma(n+m)}) dz \end{aligned}$$

since \mathcal{A}_0 is (by assumption) permutation symmetric. So this holds for any permutation. In particular, it holds for the identity permutation, so we can write

$$= \int_{\mathcal{A}_0} f_0(z_1, \dots, z_{n+m}) h(z_{\sigma(1)}, \dots, z_{\sigma(n+m)}) dz$$

We are interested in $f_{\mathbb{Z}|T}^{(a)}$. Take $f = I\{\mathbb{Z}_1 = z_1, \dots, \mathbb{Z}_{n+m} = z_{n+m}\}$ for a specific permutation (z_1, \dots, z_{n+m}) of $(\mathbb{Z}_{(1)}, \dots, \mathbb{Z}_{(n+m)})$. Then

$$f_{\mathbb{Z}|T}^{(a)} = \frac{h(z_1, \dots, z_{n+m})}{\sum_{\sigma \in S_{n+m}} h(z_{\sigma(1)}, \dots, z_{\sigma(n+m)})} \quad (10.58)$$

□

Remark 150. Note that in case where alternative hypothesis is one particular ordering, (10.56) reduces to $1/(n+m)!$ since f is an indicator variable for the particular permutation and the denominator is a sum of the number of all of the permutations.

(next time: apply Neyman-Pearson lemma to (10.58) to show how we finally get the UMP test.) The Neyman-Pearson test:

$$\phi = \begin{cases} 1, & h_{\mathbb{Z}|T}^{(a)}(x_1, \dots, x_n, y_1, \dots, y_m) / h_{\mathbb{Z}|T}^{(0)}(x_1, \dots, x_n, y_1, \dots, y_m) > c(T) \\ \gamma, & h_{\mathbb{Z}|T}^{(a)}(x_1, \dots, x_n, y_1, \dots, y_m) / h_{\mathbb{Z}|T}^{(0)}(x_1, \dots, x_n, y_1, \dots, y_m) = c(T) \\ 0, & h_{\mathbb{Z}|T}^{(a)}(x_1, \dots, x_n, y_1, \dots, y_m) / h_{\mathbb{Z}|T}^{(0)}(x_1, \dots, x_n, y_1, \dots, y_m) < c(T) \end{cases} \quad (10.59)$$

(using data in the specific order, seeing if the likelihood of the data in this specific order is large). Note that the denominator of (10.58) is a function of T (the order statistics) so it can be absorbed into $c(T)$. Therefore this test (10.59) is equivalent to the simpler test

$$\phi = \begin{cases} 1, & h_{\mathbb{Z}|T}^{(a)}(z_1, \dots, z_{n+m}) > c'(T) \\ \gamma, & h_{\mathbb{Z}|T}^{(a)}(z_1, \dots, z_{n+m}) = c'(T) \\ 0, & h_{\mathbb{Z}|T}^{(a)}(z_1, \dots, z_{n+m}) < c'(T) \end{cases} \quad (10.60)$$

We can control the Type I error rate by setting

$$\begin{aligned} \mathbb{E}_{H_0}(\phi) = \alpha \iff \alpha &= \frac{1}{(n+m)!} \sum_{\sigma \in S_{n+m}} I\{h(\mathbb{Z}_{\sigma(1)}, \dots, \mathbb{Z}_{\sigma(n+m)}) > C\} \\ &\quad + \frac{1}{(n+m)!} \gamma \sum_{\sigma \in S_{n+m}} I\{h(\mathbb{Z}_{\sigma(1)}, \dots, \mathbb{Z}_{\sigma(n+m)}) = C\} \end{aligned} \quad (10.61)$$

Example 10.36. Testing hypothesis that treatment is different; assume treatment is random so groups are homogeneous. $H_0 : X_1, \dots, X_n, Y_1, \dots, Y_m$ are i.i.d.; $H_a : X_1, \dots, X_n \sim \mathcal{N}(\mu_1, \sigma^2)$ i.i.d., $Y_1, \dots, Y_m \sim \mathcal{N}(\mu_2, \sigma^2)$ i.i.d. Find the permutation test for the problem.

Solution.

test rejects when this quantity is large

$$\begin{aligned} f(x_1, \dots, x_n, y_1, \dots, y_m) &= \frac{1}{(2\pi\sigma^2)^{(n+m)/2}} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu_1)^2 \right\} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{i=1}^m (y_i - \mu_2)^2 \right\} \\ &= \frac{1}{(2\pi\sigma^2)^{(n+m)/2}} \exp \left\{ -\frac{1}{2\sigma^2} \left[\sum_{i=1}^n (x_i - \mu_1)^2 + \sum_{i=1}^m (y_i - \mu_2)^2 \right] \right\} \end{aligned}$$

note that this is monotone. So test rejects when the sum of squares

$$\begin{aligned}
 \sum_{i=1}^n (x_i - \mu_1)^2 + \sum_{i=1}^m (y_i - \mu_2)^2 &= \sum_{i=1}^n x_i^2 - 2\mu_1 \sum_{i=1}^n x_i + n\mu_1^2 + \sum_{j=1}^m y_j^2 - 2\mu_2 \sum_{j=1}^m y_j + m\mu_2^2 \\
 &= \sum_{i=1}^n x_i^2 + \sum_{j=1}^m y_j^2 + n(\mu_1^2 + \mu_2^2) - 2 \underbrace{\left[\mu_1 \sum_{i=1}^n x_i + \mu_2 \sum_{j=1}^m y_j \right]}_{\text{only part that depends on specific ordering}} \quad (10.62)
 \end{aligned}$$

is small. We can take everything that depends on the sufficient statistic (the order statistics) and shift it to the constant in the hypothesis test. (for example, the sum of squares of all of the numbers depends on the order statistic only, and so does the sum of the constant terms. so everything that does not depend on the specific order of the data can be subsumed into the constant term. So we only need the cross terms in the binomial expansion, and then we determine c' by the solution to (10.61).) Note that the sum of squares is small if and only if

$$\mu_1 \sum_{i=1}^n x_i + \mu_2 \sum_{j=1}^m y_j$$

is large, if and only if

$$\underbrace{(\mu_1 - \mu_2)}_{>0} \sum_{i=1}^n x_i + \underbrace{\mu_2 \left(\sum_{i=1}^n x_i + \sum_{j=1}^m y_j \right)}_{\text{subsumed into } c \text{ since depends only on order statistics}}$$

is large, if and only if $\sum_{i=1}^n x_i$ is large. So we can write the test (10.60) as simply

$$\phi = \begin{cases} 1, & \sum_{i=1}^n x_i > c(T) \\ \gamma, & \sum_{i=1}^n x_i = c(t) \\ 0, & \sum_{i=1}^n x_i < c(T) \end{cases}$$

For example, assume $n = m = 2$. Suppose $x_1 = 4, x_2 = 1, y_1 = 7, y_2 = 3$. Consider all possible permutations, but we don't care about switching x s or y (test statistic is invariant to permutations of x s only), so that's $\binom{4}{2} = 6$ possible orderings. The orderings are given in Table 10.1. Then the test will reject if $X_1 + X_2 \geq 11$. Corresponds to situation when large values in beginning are unusually high; if so, unlikely data are i.i.d. because if that were true then the large and small values would be distributed more uniformly. Then the size of this test would be $\alpha = 1/6$. (If you want smaller α then you need to use a randomized test. But obviously in real life that makes no sense.)

10.8.7 Invariance in Testing (Chapter 6 of Lehmann and Romano [2005])

Example 10.37. $X_1, \dots, X_n \sim \mathcal{N}(\theta_j, 1), j \in [n]$, independent. Consider testing $H_0 : \theta_1 = \theta_2 = \dots = \theta_n = 0$ against $H_1 : \exists j : \theta_j \neq 0$. That is,

Table 10.1: Table for Example 10.36 in case of $n = m = 2$.

1	3	4	7	$\sum_{i=1}^2 X_i$
X	X	Y	Y	4
X	Y	X	Y	5
X	Y	Y	X	8
Y	X	X	Y	7
Y	X	Y	X	10
Y	Y	X	X	11

$$\begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}, I_n \right).$$

Let $\mathbb{O} \in \mathbb{R}^{n \times n}$ be an orthogonal matrix; that is, $\mathbb{O}^T = \mathbb{O}^{-1}$. Then

$$\mathbb{O} \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix} \sim \mathcal{N} \left(\mathbb{O} \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}, I_n \right).$$

Then the problem becomes $H_0 : \theta'_1 = \theta'_2 = \dots = \theta'_n = 0$ against $H_1 : \exists j : \theta'_j \neq 0$ where

$$\theta'_j = \left\langle \mathbb{O} \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}, e_j \right\rangle.$$

Then a “reasonable” test must satisfy $\phi(X) = \phi(\mathbb{O}X)$ for any orthogonal \mathbb{O} . For this to be true, we must have $\phi(X) = \phi(\|X\|_2^2)$ (because we basically need spherical invariance). For such tests, the problem becomes

$$H_0 : \lambda := \sum_{i=1}^n \theta_i^2 = 0, \quad H_a : \lambda > 0.$$

Here $\|X\|_2^2 = \sum_{i=1}^n X_i^2$ has a non-central χ^2 distribution with non-centrality parameter λ . It turns out that this family as a monotone likelihood ratio, so the solution is easy to obtain. The UMP is

$$\phi(x) = \begin{cases} 1, & \sum_{i=1}^n x_i^2 \geq c \\ 0, & \sum_{i=1}^n x_i^2 < c. \end{cases}$$

We will use groups for this (see also Section 15.2).

Definition 10.48. (G, \cdot) is a **group** if

1. $a, b \in G \implies a \cdot b \in G$.
2. There exists $e \in G$ such that $a \cdot e = e \cdot a = a$.
3. For all a , there exists $a^{-1} \in G$ such that $a \cdot a^{-1} = a^{-1} \cdot a = e$.
4. For all $a, b, c \in G$, $(a \cdot b) \cdot c = a \cdot (b \cdot c)$.

Theorem 10.8.20. Assume that $\{\mathbb{P}_\theta | \theta \in \Theta\}$ is an identifiable statistical model ($\theta_1 \neq \theta_2 \implies p_{\theta_1} \neq \mathbb{P}_{\theta_2}$). Suppose

$$X \sim \mathbb{P}_\theta, \quad X \in S (S = \mathbb{R}^d, S = \mathbb{Z}^d).$$

Let G be a group of bijections of S (where the group operation is the composition). Then

$$\mathbb{P}_\theta(gX \in A) = \mathbb{P}_\theta(X \in g^{-1}A) = \mathbb{P}_\theta \cdot g^{-1}(A).$$

Notice that in general gX doesn't have to be in A for a general g . So we require the following assumption.

Assumption: for any $g \in G$ there exists $\bar{g} : \Theta \rightarrow \Theta$ such that $\mathbb{P}_\theta \cdot g^{-1} = \mathbb{P}_{\bar{g}(\theta)}$.

Setup for today: $\{p_\theta, \theta \in \Theta\}$. $X \sim p_\theta, X \in S$. $H_0 : \theta \in \Theta_0, H_a : \theta \in \Theta_a$. Let (G, \cdot) be a group of bijections on $S = \mathbb{R}^n, \mathbb{Z}^n$. Note that $\mathbb{P}_\theta(gX \in A) = \mathbb{P}_\theta(X \in g^{-1}A)$.

Assumption: The distribution $\mathbb{P}_\theta \cdot g^{-1}$ coincides with $\mathbb{P}_{\bar{g}(\theta)}$. True if and only if $\mathbb{P}_\theta(gX \in A) = \mathbb{P}_{\bar{g}(\theta)}(X \in A)$.

Example 10.38. f : fixed pdf. $\{f(\cdot - \theta), \theta \in \mathbb{R}\}$: location family. $g \in G \iff \exists \tau \in \mathbb{R} : g_\tau(x) = x + \tau$. Then $\bar{g}_\tau(\theta) = \theta + \tau$. Indeed,

$$\mathbb{P}_\theta(X + \tau < t) = \mathbb{P}_\theta(X < t - \tau) = \int_{-\infty}^{t-\tau} f(x - \theta) dx$$

Let $y = x + \tau$, then write this as

$$= \int_{-\infty}^t f(y - (\theta + \tau)) dy = \mathbb{P}_{\theta+\tau}(X < t).$$

Theorem 10.8.21. 1. For all $g \in G$, let \bar{g} be a bijection on Θ .

2. (\bar{G}, \circ) is a group (with respect to composition). Here, $\bar{G} = \{\bar{g}, g \in G\}$.
3. $g \in G \implies \bar{g} \in \bar{G}$ is a group homomorphism.

Proof. We will show some initial results. (See also Lemma 6.1.1 in Lehmann and Romano [2005].)

- (a) Injectively, if $\bar{g}(\theta_1) = \bar{g}(\theta_2) \implies \theta_1 = \theta_2$. Assume that $\bar{g}(\theta_1) = \bar{g}(\theta_2)$. Then

$$\mathbb{P}_{\bar{g}(\theta_1)}(X \in A) = \mathbb{P}_{\theta_1}(g(X) \in A) = \mathbb{P}_{\theta_1}(X \in g^{-1}(A))$$

$$\mathbb{P}_{\bar{g}(\theta_2)}(X \in A) = \mathbb{P}_{\theta_2}(g(X) \in A) = \mathbb{P}_{\theta_2}(X \in g^{-1}(A)) = \mathbb{P}_{\theta_1}(X \in g^{-1}(A))$$

Since g is a bijection, this means that $\mathbb{P}_{\theta_1}(X \in B) = \mathbb{P}_{\theta_2}(X \in B)$ for all B . Therefore $\theta_1 = \theta_2$ by identifiability of the model.

(b)

$$\mathbb{P}_\theta(X \in A) = \mathbb{P}_\theta(g(g^{-1}(X)) \in A) = \mathbb{P}_{\bar{g}(\theta)}(g^{-1}(X) \in A) = \mathbb{P}_{\overline{g^{-1}}(\bar{g}(\theta))}(X \in A)$$

Therefore $\overline{g^{-1}}(\bar{g}(\theta)) = \theta \iff (\bar{g})^{-1} = \overline{g^{-1}}$ by identifiability.

(c) **Surjectivity.** Need to show: for all θ , there exists θ' such that $\bar{g}(\theta') = \theta$.

By part (b), $\bar{g}(\overline{g^{-1}}(\theta)) = \theta$ for all θ . So take $\theta' = \overline{g^{-1}}(\theta)$, then we have the result.

Now we can use these to prove what we want. (Should follow easily? especially from part (b).)

1.

2.

3. **look if scribe filled in details?** $g_1 g_2 \rightarrow \bar{g}_1 \circ \bar{g}_2$.

□

Definition 10.49 (invariance of tests with respect to groups). The testing problem $H_0 : \theta \in \Theta_0$ against $H_a : \theta \in \Theta_a$ is invariant with respect to \overline{G} if and only if for all $\bar{g} \in \overline{G}$,

$$\bar{g}(\Theta_0) = \Theta_0, \quad \bar{g}(\Theta_a) = \Theta_a.$$

benefit of this approach: can get tests that are invariant across e.g. rotation (if G is a group of rotations), reduce problem significantly (only need to worry about e.g. length, or other property that is invariant with respect to group).

Definition 10.50 (Orbits). We say that x_1 is equivalent to x_2 ($x_1 \sim x_2$) if and only if there exists $g \in G$ such that $g(x_1) = x_2$. The equivalence classes are called **orbits** (that is, an orbit contains all elements that are equivalent to one another; the orbit of $x \in S$ is $\{g(x) : g \in G\}$).

Example 10.39. If G is a set of rotations, then the orbit is the sphere with radius equal to $\|x\|$.

10.8.8 Maximal Invariants (Section 6.2 of Lehmann and Romano [2005])

Definition 10.51 (Invariants). A map $T : S \rightarrow \mathbb{R}^d$ is **invariant with respect to G** if and only if

$$x_1 \sim x_2 \implies T(x_1) = T(x_2).$$

T is called a **maximal invariant** if and only if T is invariant and

$$T(x_1) = T(x_2) \implies x_1 \sim x_2;$$

so

$$x_1 \sim x_2 \iff T(x_1) = T(x_2).$$

That is, it is constant on the orbits and for each orbit takes on a different value. All maximal invariants are equivalent in the sense that their sets of constancy coincide.

Definition 10.52. Let ϕ be a test. ϕ is **invariant** with respect to G if and only if $\phi(x) = \phi(g(x))$ for all $g \in G, x \in S$.

Definition 10.53 (Invariance of problems). We say that the problem of testing $H_0 : \theta \in \Theta_0$ against $H_a : \theta \in \Theta_a$ remains invariant under a transformation g if \bar{g} preserves both Θ_0 and Θ_a , so that both

$$\bar{g}\Theta_0 = \Theta_0$$

and

$$\bar{g}\Theta = \Theta$$

hold.

Theorem 10.8.22 (Theorem 6.2.1 in Lehmann and Romano [2005]). Let T be a maximal invariant with respect to G . Then test ϕ is G -invariant if and only if $\phi(x) = h(T(x))$ for all $x \in S$ and some function h ; that is, ϕ must depend on x only through $T(x)$.

Proof. Assume that $\phi(x) = h(T(x))$. Take $g \in G$. Then

$$\phi(g(x)) = h(T(g(x))) = h(T(x)) = \phi(x)$$

(where the third step used the maximal invariance of T with respect to G). Conversely, assume that ϕ is G -invariant. Suppose that x_1, x_2 are such that $T(x_1) = T(x_2)$. Then there exists $g \in G$ such that $x_2 = g(x_1)$. Then $\phi(x_2) = \phi(g(x_1)) = \phi(x_1)$, so ϕ is constant on each orbit, so $\phi = h(T)$ for some function h . □

Example 10.40 (Location family (like Example 6.2.1(i) in Lehmann and Romano [2005])). $X_1, \dots, X_n \sim f(\cdot - \theta)$ i.i.d., $\theta \in \mathbb{R}$. Then the invariance transformation is $g(x_1, \dots, x_n) = (x_1 + c, \dots, x_n + c)$ for some $c \in \mathbb{R}$.

$$\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \sim \begin{bmatrix} x'_1 \\ \vdots \\ x'_n \end{bmatrix} \iff \begin{bmatrix} x'_1 \\ \vdots \\ x'_n \end{bmatrix} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} c \\ \vdots \\ c \end{bmatrix}.$$

One maximal invariant is $T = (x_1 - x_2, x_2 - x_3, \dots, x_{n-1} - x_n)$. Another is $T' = (x_1 - x_n, x_2 - x_n, \dots, x_n - x_n)$.

Example 10.41 (Scale family (like Example 6.2.1(ii) in Lehmann and Romano [2005])). $X_1, \dots, X_n \sim \frac{1}{\theta} f(\frac{\cdot}{\theta})$ i.i.d., $\theta \in \mathbb{R}$. Then an invariance transformation is $g \in G \iff \exists c > 0$ such that $g(x_1, \dots, x_n) = (cx_1, \dots, cx_n)$. (Note that $\bar{g}(\theta) = c\theta$.) Then a maximal invariant is $T = (x_1/x_n, \dots, x_n/x_n)$ (if $x_n \neq 0$).

Example 10.42 (Orthogonal transformation (like Example 6.2.1(iii) in Lehmann and Romano [2005])). $X \sim \mathcal{N}(0, \Sigma)$, $X \in \mathbb{R}^d$. G is a group of orthogonal transformations: $\langle gu, gv \rangle = \langle u, v \rangle$ for all $g \in G$, $u, v \in \mathbb{R}^d$. G corresponds to the group of orthogonal matrices. Observe that $\bar{g}(\Sigma) = g\Sigma g^{-1} = g\Sigma g^T$. Indeed, the covariance matrix of gX is

$$\mathbb{E}(gX)(gX)^T = \mathbb{E}gXX^Tg^T = g\mathbb{E}(XX^T)g^T = g\Sigma g^T.$$

A maximal invariant $T(x)$ in this case is $\|X\|_2$.

Example 10.43 (Rank tests (like Example 6.2.2(ii) in Lehmann and Romano [2005])). Suppose X_1, \dots, X_n are i.i.d. with cdf F that is strictly increasing. Let $g \in G$ if and only if there exists f continuous, strictly monotone such that $g(x_1, \dots, x_n) = (f(x_1), \dots, f(x_n))$. (Then the order of the values is always preserved after applying any transformation.) The maximal invariants are then the ranks defined by $R_j(x_1, \dots, x_n) = |\{k : x_k \leq x_j\}|$. In particular, $x_j = x_{R_j}$.

Example 10.44. $X \sim \mathbb{P}_\theta$, $\theta \in \Theta$. $H_0 : \theta \in \Theta_0$, $H_a : \theta \in \Theta_a$. G : a group of bijections. \bar{G} : a corresponding group of bijections on Θ . The problem is G -invariant if and only if for all $g \in G$, $g(\Theta_0) \subseteq \Theta_0$, $g(\Theta_a) \subseteq \Theta_a$. Find the UMP G -invariant test.

Solution.

Know: if $T(x)$ is the maximal invariant, then any G -invariant test depends on T only. Moreover, the power function of a G -invariant test is \bar{G} -invariant: indeed, for all $g \in G$,

$$\beta_\phi(\theta) = \mathbb{E}_\theta \phi(X) = \mathbb{E}_\theta \phi(g(X)) = \mathbb{E}_{\bar{g}(\theta)} \phi(X) = \beta_\phi(\bar{g}(\theta)).$$

Let $\tau(\theta)$ be the maximal invariant with respect to \bar{G} , then the distribution of any G -invariant test depends only on $\tau(\theta)$. In many cases, the problem reduces to testing $H'_0 : \tau(\theta) \leq \tau_0$ against $H'_a : \tau(\theta) > \tau_0$.

Example 10.45. X_1, \dots, X_n i.i.d. $\mathcal{N}(\mu, \sigma^2)$. $H_0 : \sigma^2 \leq \sigma_0^2$, $H_a : \sigma^2 > \sigma_0^2$. Take G to be a group of parallel shifts $(x_1, \dots, x_n) \sim (x_1 + c, \dots, x_n + c)$. (Then the problem is G -invariant, since the variance isn't affected by a shift in the values.) The sufficient statistic is (\bar{X}, S^2) , and a maximal invariant is S^2 . Recall that

$$S^2 = \frac{\sigma^2}{n-1} Z,$$

where $Z \sim \chi_{n-1}^2$. We have

$$\bar{G} : (\mu, \sigma^2) \xrightarrow{\bar{g}} (\mu + c, \sigma^2).$$

Note that

$$\left(\frac{1}{n} \sum_{i=1}^n x_i, \frac{1}{n-1} \sum_{i=1}^n \left[X_j - \frac{1}{n} \sum_{i=1}^n X_i \right]^2 \right) \xrightarrow{g} \left(\frac{1}{n} \sum_{i=1}^n x_i + c, \frac{1}{n-1} \sum_{i=1}^n \left[X_j - \frac{1}{n} \sum_{i=1}^n X_i \right]^2 \right)$$

The maximal invariant is S^2 :

$$S^2 =^d \frac{\sigma^2}{n-1} W,$$

where $W \sim \chi_{n-1}^2$. The pdf of S^2 is

$$f_{S^2}(x) = \frac{1}{2^{(n-1)/2} \Gamma((n-1)/2)} \exp \left\{ -\frac{x}{2\sigma^2} + \left(\frac{n-3}{2} \right) (\log x - \log \sigma^2) \right\}$$

Note that this has an MLR with respect to $T(X) = X$. Therefore by Karlin-Rubin, the UMP invariant test is

$$\phi^* = \begin{cases} 1, & S^2 \geq c \\ 0, & \text{otherwise.} \end{cases}$$

Example 10.46 (Two-sample t - test). $X_1, \dots, X_n \sim \mathcal{N}(\mu_1, \sigma^2)$ i.i.d., $Y_1, \dots, Y_m \sim \mathcal{N}(\mu_2, \sigma^2)$ i.i.d. $H_0 : \mu_1 \geq \mu_2, H_a : \mu_1 < \mu_2$. Note that the ordering of the data is invariant to multiplication by a non-negative number or adding a constant. Therefore a grouping is

$$G : (x_1, \dots, x_n) \xrightarrow{g} (ax_1 + c, \dots, ax_n + c), \quad a > 0, c \in \mathbb{R}.$$

Then the group \overline{G} that acts on the parameters is

$$\overline{G}(\mu_1, \mu_2, \sigma^2) \xrightarrow{\bar{g}} (a\mu_1 + c, a\mu_2 + c, a^2\sigma^2).$$

Sufficient statistic: (\bar{X}, \bar{Y}, S^2) , where S^2 is the pooled variance:

$$S^2 = \frac{1}{m+n-2} \left(\sum_{i=1}^n [X_i - \bar{X}_n]^2 + \sum_{i=1}^m [Y_i - \bar{Y}_m]^2 \right)$$

Note that

$$(\bar{X}, \bar{Y}, S^2) \xrightarrow{g} (a\bar{X} + c, a\bar{Y} + c, a^2 S^2)$$

and a maximal invariant with respect to G

$$T = \frac{\bar{X} - \bar{Y}}{\sqrt{S^2}}.$$

and for the parameters (maximal invariant with respect to \bar{G})

$$\delta = \frac{\tilde{\mu}_1 - \tilde{\mu}_2}{\tilde{\sigma}}$$

So we know the distribution of T can only depend on δ . Note that

$$\text{Var}(\bar{X} - \bar{Y}) = \frac{\sigma^2}{n} + \frac{\sigma^2}{m} = \sigma^2 \frac{n+m}{nm}$$

and we can consider

$$T' = \frac{\bar{X} - \bar{Y}}{\sqrt{S^2}} \sqrt{\frac{nm}{n+m}}$$

which has a t distribution. We can also now consider the different test $H'_0 : \delta \geq 0$, $H_a : \delta < 0$.

Note: if $\delta \neq 0$, then T' has a non-central Student's t -distribution with non-centrality parameter δ . The pdf is (with $\nu = n + m - 2$)

$$f(x) = \nu^{\nu/2} \frac{\exp\left\{-\frac{\nu\delta^2}{2(x^2+\nu)}\right\}}{\sqrt{\pi}\Gamma(\nu/2)2^{(\nu-1)/2}(x^2+\nu)^{(\nu+1)/2}(x^2+\nu)^{(\nu+1)/2}} \int_0^\infty y^\nu \exp\left\{-\frac{1}{2}\left[6 - \frac{\delta x}{\sqrt{x^2+\nu}}\right]\right\} dy$$

But it turns out (not trivial to prove) that T' has a monotone likelihood ratio in δ . The UMP invariant test is therefore

$$\phi^* = \begin{cases} 1, & T' \leq c \\ 0, & T' > c \end{cases}$$

where $c = t_{\alpha, n+m-2} < 0$ (standard Student's t , because due to Karlin-Rubin we can just go with the distribution when $\delta = 0$. Only need to look at pdf to establish that it has an MLR.).

10.8.9 Rank Tests (Section 6.8 and 6.9 of Lehmann and Romano [2005])

Example 10.47. X_1, \dots, X_n i.i.d. with cdf F , pdf f . Y_1, \dots, Y_m i.i.d. with cdf G , pdf g . $H_0 : X_1, \dots, X_n, Y_1, \dots, Y_m$ i.i.d. $\mathcal{N}(\mu, \sigma^2)$, $H_1 : X_1, \dots, X_n \sim \mathcal{N}(\mu_1, \sigma^2)$ i.i.d., $Y_1, \dots, Y_m \sim \mathcal{N}(\mu_2, \sigma^2)$ i.i.d., $\mu_2 > \mu_1$. A natural “generalization” is the following: if we think the data come from a roughly normal distribution but not exactly, we might want to use a permutation test instead. That is,

$$H_0 : F = G, \quad H_a : F(z) \leq G(z) \quad \text{for all } z, \quad \text{and } G \neq F$$

that is, the Y 's are stochastically larger than the X 's. (The last condition implies that there exists an x for which the inequality is strict: $F(x) < G(x)$.) The observations remain invariant under monotonic transformations:

$$G : (x_1, \dots, x_n, y_1, \dots, y_m) \xrightarrow{g} (h(x_1), \dots, h(x_n), h(y_1), \dots, h(y_m))$$

where h is continuous and strictly increasing. Then

$$\overline{G} : (F, G) \xrightarrow{\bar{g}} (F \circ h^{-1}, G \circ h^{-1})$$

where $(F \circ h^{-1})(x) = F(h^{-1}(x)) = \mathbb{P}(h^{-1}(X) \leq x)$, or $h(x)$ has cdf $F \circ h^{-1} = \mathbb{P}(h(x) \leq t) = \mathbb{P}(X \leq h^{-1}(t)) = F(h^{-1}(t))$. Define

$$Z_1 = X_1, \dots, Z_n = X_n, Z_{n+1} = Y_1, \dots, Z_{n+m} = Y_m$$

and let $n + m = N$. Let $Z_{(1)}, \dots, Z_{(n+m)}$ be the order statistics, and define $R_j = \text{rank}(Z_j) = |\{k : Z_k \leq Z_j\}|$. (Note the relationship $Z_{(R_j)} = Z_j$.) Finally, also note that there are $N!$ orderings possible. Ranks are the maximal invariants. Goal: find the distribution of the ranks, namely find $\mathbb{P}(R = r)$. We will use the following result:

Theorem 10.8.23 (Hoeffding's Formula). Assume that ξ_1, \dots, ξ_N are independent random variables and ξ_j has pdf f_j (that is, they might have different distributions). Choose a pdf f_0 such that $f_0 = 0 \implies f_1 = \dots = f_n = 0$. Then

$$\mathbb{P}(R = r) = \frac{1}{n!} \mathbb{E}_{f_0} \left[\frac{\prod_{i=1}^n f_i(V_{(r_i)})}{\prod_{i=1}^m f_0(V_{(r_i)})} \right]$$

where V_1, \dots, V_n are i.i.d. with distribution f_0 .

In our case, take $f_0 := f$, then

$$\mathbb{P}(R = r) = \frac{1}{n!} \mathbb{E}_f \left[\frac{\prod_{i=1}^m g_i(V_{(q_i)})}{\prod_{i=1}^m f(V_{(q_i)})} \right]$$

where g_1, \dots, g_m are the ranks of Y_1, \dots, Y_m among Z_1, \dots, Z_N (the terms corresponding to x will cancel out). **Claim:** Let $Q = (Q_1 < Q_2 < \dots < Q_m)$ be the ordered ranks of Y_1, \dots, Y_m among Z_1, \dots, Z_n . Then Q is sufficient for the distribution of R .

Proof.

$$\mathbb{P}(R = r \mid Q = q) = \frac{\mathbb{P}(R = r, Q = q)}{\mathbb{P}(Q = q)} = \frac{\mathbb{P}(R = r)}{\mathbb{P}(Q = q)}$$

and

$$\begin{aligned} \mathbb{P}(Q = q) &= \sum_{r:Q(r)=q} \mathbb{P}(R = r) = \frac{1}{N!} \sum_{r:Q(r)=q} \mathbb{E}_f \left[\frac{\prod_{i=1}^m g_i(V_{(q_i)})}{\prod_{i=1}^m f(V_{(q_i)})} \right] \\ &= \frac{1}{N!} |\{r : Q(r) = q\}| \mathbb{E}_f \left[\frac{\prod_{i=1}^m g_i(V_{(q_i)})}{\prod_{i=1}^m f(V_{(q_i)})} \right] = \frac{1}{N!} n! m! \mathbb{E}_f \left[\frac{\prod_{i=1}^m g_i(V_{(q_i)})}{\prod_{i=1}^m f(V_{(q_i)})} \right] \end{aligned}$$

Therefore we have

$$\mathbb{P}(R = r \mid Q = q) = \frac{\mathbb{P}(R = r, Q = q)}{\mathbb{P}(Q = q)} = \frac{\mathbb{P}(R = r)}{\mathbb{P}(Q = q)} = \frac{1}{n!m!}$$

which doesn't depend on any parameters, so Q is sufficient for R .

□

Therefore we can consider tests that depend on Q only. Let $U \sim \text{Unif}[0, 1]$. Then $F^{-1}(U)$ has distribution F , since

$$\mathbb{P}(F^{-1}(U) \leq t) = \mathbb{P}(U \leq F(t)) = F(t).$$

Hence

$$\mathbb{P}(R = r) = \frac{1}{n!} \mathbb{E}_f \left[\frac{\prod_{i=1}^m g_i(V_{(q_i)})}{\prod_{i=1}^m f(V_{(q_i)})} \right] = \frac{1}{n!} \mathbb{E}_f \left[\frac{\prod_{i=1}^m g(F^{-1}(U_{(q_i)}))}{\prod_{i=1}^m f(F^{-1}(U_{(q_i)}))} \right]$$

But this is the derivative of a certain expression. Let $\tau(x) = (G \circ F^{-1})(x)$. Then

$$\tau'(x) = G'(F^{-1}(x))(F^{-1})'(x) = \frac{g(F^{-1}(x))}{f(F^{-1}(x))}$$

so

$$\mathbb{P}(R = r) = \frac{1}{n!} \mathbb{E}_f \prod_{i=1}^m \tau'(U_{(q_i)})$$

so τ is the maximal invariant of \bar{G} because the distribution of Q depends only on τ , so it must be the maximal invariant.

Theorem 10.8.24 (Theorem 6.3.2 in Lehmann and Romano [2005]). If $T(x)$ is invariant under G and if $v(\theta)$ is a maximal invariant under the induced group \bar{G} , then the distribution of $T(X)$ depends only on $v(\theta)$.

10.8.10 Likelihood Ratio Tests (Section 12.4.4 of Lehmann and Romano [2005])

Last time:

$$\phi^*(x) = \begin{cases} 1, & \left(\frac{\partial}{\partial \theta} p_\theta(x) \Big|_{\theta=\theta_0} \right) / p_{\theta_0}(x) > c \\ \gamma, & \left(\frac{\partial}{\partial \theta} p_\theta(x) \Big|_{\theta=\theta_0} \right) / p_{\theta_0}(x) = c \\ 0, & \left(\frac{\partial}{\partial \theta} p_\theta(x) \Big|_{\theta=\theta_0} \right) / p_{\theta_0}(x) < c \end{cases}$$

We got

$$\frac{\partial}{\partial \theta} \mathbb{P}(Q = q) = \frac{1}{\binom{N}{m}} \sum_{j=1}^m \alpha(q_j)$$

where

$$\alpha(q_j) = \mathbb{E}_\theta \left[\frac{f'(V_{(q_j)})}{f(V_{(q_j)})} \right]$$

Suppose X_1, \dots, X_n i.i.d. distributed according to $P_\theta \in \{P_\theta, \theta \in \Theta\}$. Suppose P_θ has either density function or mass function p_θ . We will test $H_0 : \theta \in \Theta_0$ against $H_a : \theta \in \Theta_a$. The likelihood ratio is

$$L_n(\theta, x_1, \dots, x_n) = \prod_{j=1}^n p_\theta(x_j)$$

and we will use the log likelihood

$$\ell_n(\theta) = \log L_n(\theta) = \sum_{j=1}^n \log p_\theta(x_j).$$

Then the maximum likelihood estimator (if it is unique) is

$$\hat{\theta}_n := \arg \max_{\theta \in \Theta} \ell_n(\theta).$$

Definition 10.54. Assumption: $\Theta \subseteq \mathbb{R}^d$. Define

$$T_n := \frac{\sup_{\theta \in \Theta_a} L_n(\theta)}{\sup_{\theta \in \Theta_0} L_n(\theta)}$$

Note that this quantity is well-defined even if the MLE is not unique. The likelihood ratio test (LRT) is

$$\phi = \begin{cases} 1, & T_n > c \\ \gamma, & T_n = c \\ 0, & T_n < c \end{cases}$$

for some $c, \gamma > 0$. For simplicity, assume that both

$$\hat{\theta}_n^0 := \arg \max_{\theta \in \Theta_0} L_n(\theta), \quad \hat{\theta}_n^a := \arg \max_{\theta \in \Theta_a} L_n(\theta)$$

exist. Then

$$T_n := \frac{L_n(\hat{\theta}_n^a)}{L_n(\hat{\theta}_n^0)}.$$

Remark 151. In this simplest case,

$$\Theta_0 = \{\theta_0\}, \quad \Theta_a = \{\theta_a\}.$$

Then

$$T_n = \frac{\prod_{j=1}^n p_{\theta_a}(x_j)}{\prod_{j=1}^n p_{\theta_0}(x_j)},$$

and the likelihood ratio test coincides with the Neyman-Pearson test.

Define

$$\tilde{T}_n := \frac{\sup_{\theta \in \Theta} L_n(\theta)}{\sup_{\theta \in \Theta_0} L_n(\theta)} = \frac{L_n(\hat{\theta}_n)}{L_n(\theta_0)} = \max\{T_n, 1\}$$

and define

$$\Lambda_n := \log \tilde{T}_n \geq 0.$$

Then the LRT can be equivalently stated as

$$\phi = \begin{cases} 1, & \Lambda_n > c \\ \gamma, & \Lambda_n = c \\ 0, & \Lambda_n < c \end{cases}$$

Example 10.48 (Example 12.4.6 in Lehmann and Romano [2005], p. 524 of pdf). Let $X \sim \text{Multinomial}(n, p_1, \dots, p_k)$. Assume that $\Theta_0 = \{p_0\}$, where $p_0 = (p_0^{(1)}, \dots, p_0^{(k)})$ and $\Theta_a \in \Delta_k = \{p \neq p_0\}$. (For example, the experiment could be throwing a dice with k faces n times.) Then we have

$$p_\theta(x_1, \dots, x_k) = \frac{n!}{x_1! \cdots x_k!} p_1^{x_1} \cdots p_k^{x_k}.$$

Then

$$\Lambda_n = \log \left(\frac{\sup_{\theta \in \Theta} L_n(\theta)}{\sup_{\theta \in \Theta_0} L_n(\theta)} \right) = \log \left(\frac{L_n(\hat{p}_n)}{L_n(p_0)} \right).$$

The MLE is (exercise)

$$\hat{p}_n = \left(\frac{X_1}{n}, \dots, \frac{X_k}{n} \right) = n \sum_{i=1}^k \frac{X_i}{n} \log \left(\frac{\hat{p}_i}{p_{0,i}} \right) = n \sum_{i=1}^k \hat{p}_i \log \left(\frac{\hat{p}_i}{p_{0,i}} \right)$$

Therefore

$$\Lambda_n = \log \prod_{i=1}^k \left(\frac{X_i}{np_{0,i}} \right)^{x_i}$$

(which is exactly n times the KL divergence between the maximum likelihood estimator and the null hypothesis value.) Now note that

$$\hat{p}_n = n \sum_{i=1}^k (\hat{p}_i - p_{0,i} + p_{0,i}) \log \left(1 + \frac{\hat{p}_i - p_{0,i}}{p_{0,i}} \right)$$

Under H_0 , \hat{p}_i is consistent, so $\hat{p}_i - p_{0,i} = o_{\mathbb{P}}(1)$, meaning that for every $\epsilon > 0$ $\mathbb{P}(|\hat{p}_i - p_{0,i}| > \epsilon) \rightarrow 0$ as $n \rightarrow \infty$. Since $\log(1+x) = x - x^2/2 + o(x^2)$, we have

$$\begin{aligned} \Lambda_n &= n \sum_{i=1}^k (\hat{p}_i \pm p_{0,i}) \left[\frac{\hat{p}_i - p_{0,i}}{p_{0,i}} - \frac{(\hat{p}_i - p_{0,i})^2}{2p_{0,i}^2} + o_{\mathbb{P}}((\hat{p}_i - p_{0,i})^2) \right] \\ &= n \sum_{i=1}^k \left[\frac{(\hat{p}_i - p_{0,i})^2}{2p_{0,i}} + (\hat{p}_i - p_{0,i}) - \underbrace{\frac{1}{2} \frac{(\hat{p}_i - p_{0,i})^3}{2p_{0,i}^2}}_{o_{\mathbb{P}}((\hat{p}_i - p_{0,i})^2)} - \frac{1}{2} \frac{(\hat{p}_i - p_{0,i})^2}{2p_{0,i}} + o_{\mathbb{P}}((\hat{p}_i - p_{0,i})^2) \right] \\ &= \frac{n}{2} \sum_{i=1}^k \left[\frac{(\hat{p}_i - p_{0,i})^2}{p_{0,i}} + \underbrace{(\hat{p}_i - p_{0,i})}_{\mathcal{O}_{\mathbb{P}}(1/\sqrt{n})} + \underbrace{o_{\mathbb{P}}((\hat{p}_i - p_{0,i})^2)}_{o_{\mathbb{P}}(1/n)} \right] = \frac{n}{2} \sum_{i=1}^k \frac{(\hat{p}_i - p_{0,i})^2}{p_{0,i}} + o_{\mathbb{P}}(1) \end{aligned}$$

Hence

$$2\Lambda_n = n \sum_{i=1}^k \underbrace{\frac{(\hat{p}_i - p_{0,i})^2}{p_{0,i}}}_{\text{Pearson's } \chi^2 \text{ statistic}} + o_{\mathbb{P}}(1)$$

Under H_0 , $2\Lambda_n$ is asymptotically distributed as χ_{k-1}^2 .

(Work related to derivation of asymptotics:) Further, as $n \rightarrow \infty$,

$$\sqrt{n} \left(\begin{bmatrix} X_1/n \\ \vdots \\ X_k/n \end{bmatrix} - \begin{bmatrix} p_1 \\ \vdots \\ p_k \end{bmatrix} \right) \xrightarrow{d} \mathcal{N}(0, \Sigma)$$

where $\Sigma_{ii} = p_i(1 - p_i)$, $\Sigma_{ij} = -p_i p_j$, $i \neq j$ (exercise). Σ can be written as

$$\Sigma = \Gamma^{1/2}(I_k - \sqrt{p}\sqrt{p}^T)\Gamma^{1/2}$$

where

$$\sqrt{p} = \begin{bmatrix} \sqrt{p_1} \\ \vdots \\ \sqrt{p_k} \end{bmatrix}, \quad \Gamma = \begin{bmatrix} p_1 & 0 & \cdots & 0 \\ 0 & p_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & p_k \end{bmatrix}$$

(Notice that $\|\sqrt{p}\| = 1$. The representation using $I_k - \sqrt{p}\sqrt{p}^T$ is very helpful when figuring out the asymptotics.)

Example 10.49 (Related to Example 12.4.5 in Lehmann and Romano [2005], p. 523 of pdf). Suppose X_1, \dots, X_n are i.i.d. $\mathcal{N}(\theta, I_d)$, $\theta \in \mathbb{R}^d$. $H_0 : \theta \in L$, where L is a linear subspace of dimension k , and $H_a : \theta \notin L$. We have

$$L_n(\theta) = \frac{1}{(2\pi)^{d/2}} \exp \left\{ -\frac{\sum_{j=1}^n \|x_j - \theta\|_2^2}{2} \right\}$$

so

$$\Lambda_n = \log \left(\frac{\sup_{\theta \in \mathbb{R}^d} L(\theta)}{\sup_{\theta \in L} L_n(\theta)} \right) = \log \left(\frac{L_n(\bar{X}_n)}{\sup_{\theta \in L} L_n(\theta)} \right) = \frac{1}{2} \inf_{\theta \in L} \left[\sum_{j=1}^n \|x_j - \theta\|_2^2 - \sum_{j=1}^n \|x_j - \bar{X}_n\|_2^2 \right]$$

Claim: $2\Lambda_n$ has χ_{d-k}^2 distribution. Indeed, let Π_L be the orthogonal projection onto L . For all $z \in \mathbb{R}^d$,

$$\|z\|_2^2 = l\|\Pi_l z\|_2^2 = \|\Pi_{L^\perp} z\|_2^2$$

where L^\perp is the orthogonal complement of L . Then

$$2\Lambda_n = \inf_{\theta \in L} \left[\sum_{j=1}^n \|\Pi_L(x_j - \theta)\|_2^2 + \sum_{j=1}^n \|\Pi_{L^\perp}(x_j - \theta)\|_2^2 - \sum_{j=1}^n \|\Pi_L(x_j - \bar{X}_n)\|_2^2 - \sum_{j=1}^n \|\Pi_{L^\perp}(x_j - \bar{X}_n)\|_2^2 \right]$$

Note that $\Pi_{L^\perp}\theta = 0$ for any $\theta \in L$. Then

$$\sum_{j=1}^n \|\Pi_L(x_j - \theta)\|_2^2$$

is minimized by $n^{-1} \sum_{i=1}^n \Pi_L x_j = \Pi_l \bar{X}_n$. Hence

$$\begin{aligned}
2\Lambda_n &= \underbrace{\sum_{j=1}^n \|\Pi_L(x_j - \theta)\|_2^2 - \sum_{j=1}^n \|\Pi_L(x_j - \bar{X}_n)\|_2^2 + \sum_{j=1}^n \|\Pi_{L^\perp}x_j\|_2^2}_{0} - \sum_{j=1}^n \|\Pi_{L^\perp}(x_j - \bar{X}_n)\|_2^2 \\
&= 2n \sum_{j=1}^n \langle \Pi_{L^\perp}x_j, \Pi_{L^\perp}\bar{X}_n \rangle - n\|\Pi_{L^\perp}\bar{X}_n\|_2^2 = 2n\|\Pi_{L^\perp}\bar{X}_n\|_2^2 - n\|\Pi_{L^\perp}\bar{X}_n\|_2^2 = n\|\Pi_{L^\perp}\bar{X}_n\|_2^2.
\end{aligned}$$

Finally, observe that for $Z = \sqrt{n}(\bar{X}_n - \theta) \sim \mathcal{N}(0, I_d)$ under H_0 ,

$$n\|\Pi_{L^\perp}\bar{X}_n\|_2^2 = \|\Pi_{L^\perp}Z\|_2^2$$

(since $\theta \in L$). $\Pi_{L^\perp}Z$ is normal, and its covariance has eigenvalues all equal to 1 (since this is a projection matrix). Therefore $\|\Pi_{L^\perp}Z\|_2^2 \sim \chi_{d-k}^2$ as claimed.

Heuristic derivation of the asymptotics of the likelihood ratio test: Suppose X_1, \dots, X_n are i.i.d. from \mathbb{P}_θ , $\theta \in \Theta \subseteq \mathbb{R}^d$. \mathbb{P}_θ has density/pmf p_θ . The family $\{p_\theta, \theta \in \Theta\}$ is *regular* (informally: support of p_θ does not depend on θ and $\log p_\theta(x)$ is smooth with respect to θ ; can do Taylor expansions, etc. The weakest form of regularity conditions is known as QMD (quadratic mean differentiability)).

Theorem 10.8.25 (Wilk's Theorem (see Section 12.4.2 of Lehmann and Romano [2005], p. 518 of pdf)). Assume that we are interested in testing $H_0 : \theta \in \Theta_0 = L$, $H_a : \theta \in \Theta \setminus \Theta_0$, where $\Theta_0 = L$ is an affine subspace of dimension k . **note: in 11/11 notes we defined $L := \Theta_0 - \theta_0$ so that Θ_0 is an affine subspace and L is a linear subspace (θ_0 is the offset).** Not sure if this is different from notes on 11/08 or if I misunderstood on that lecture. Then

$$2\Lambda_n = 2 \log \left(\frac{\sup_{\Theta} L_n(\theta)}{\sup_{\theta \in \Theta_0} L_n(\theta)} \right) \xrightarrow{d} \chi_{d-k}^2$$

under H_0 .

Proof. Define

$$\begin{aligned}
L_n(\theta) &= \prod_{j=1}^n p_\theta(x_j), & \hat{\theta}_n &= \arg \max_{\theta \in \Theta} L_n(\theta), & \hat{\theta}_L &:= \arg \max_{\theta \in \Theta_0} L_n(\theta), & f_\theta(x) &= \log p_\theta(x), \\
f'_\theta(x) &= \frac{d}{d\theta} \log p_\theta(x) = \nabla \log p_\theta(x), & \hat{u}_n &= \sqrt{n}(\hat{\theta}_n - \theta_0), & \hat{u}_{n,L} &= \sqrt{n}(\hat{\theta}_L - \theta_0).
\end{aligned}$$

Let

$$Z_n(u) := \sum_{j=1}^n [f_{\theta_0+u/\sqrt{n}}(x_j) - f_{\theta_0}(x_j)].$$

Note that

$$\begin{aligned}\Lambda_n = \log \frac{\prod_{j=1}^n p_{\hat{\theta}_n}(x_j)}{\prod_{j=1}^n p_{\hat{\theta}_L}(x_j)} &= \sum_{j=1}^n \left[f_{\hat{\theta}_n}(x_j) - f_{\hat{\theta}_L}(x_j) \right] = \sum_{j=1}^n \left[f_{\hat{\theta}_n}(x_j) - f_{\theta_0}(x_j) \right] - \sum_{j=1}^n \left[f_{\hat{\theta}_L}(x_j) - f_{\theta_0}(x_j) \right] \\ &= Z_n(\hat{u}_n) - Z_n(\hat{u}_{n,L}) \quad (10.63)\end{aligned}$$

(since $\hat{\theta}_n = \theta_0 + \hat{u}_n/\sqrt{n}$).

Then we can write the Taylor expansion as

$$\begin{aligned}f_{\theta_0+u/\sqrt{n}}(x) &= f_{\theta_0}(x) + \left\langle f'_{\theta_0}(x), \frac{u}{\sqrt{n}} \right\rangle + \frac{1}{2} \underbrace{\left\langle \underbrace{f''_{\theta_0}(x)}_{\text{Hessian}} \frac{u}{\sqrt{n}}, \frac{u}{\sqrt{n}} \right\rangle}_{\rightarrow 0 \text{ as } u/\sqrt{n} \rightarrow 0 \text{ (or } n \rightarrow \infty)} + \underbrace{R_{\theta_0}\left(\frac{u}{\sqrt{n}}, x\right) \frac{\|u\|_2^2}{n}}_{o_{\mathbb{P}}(1)} \\ Z + n(u) &= \left\langle \frac{1}{\sqrt{n}} \sum_{j=1}^n f'_{\theta_0}(x_j), u \right\rangle + \frac{1}{2} \left\langle \frac{1}{n} \sum_{j=1}^n f''_{\theta_0}(x_j) u, u \right\rangle + \underbrace{\left[\sum_{j=1}^n R_{\theta_0}\left(\frac{u}{\sqrt{n}}, X_j\right) \right] \frac{\|u\|_2^2}{n}}_{o_{\mathbb{P}}(1)}\end{aligned}$$

(randomness comes from fact that x_j are random variables with distribution p_{θ_0}). Note that

$$\frac{1}{n} \sum_{j=1}^n f''_{\theta}(X_j) \rightarrow \mathbb{E} f''_{\theta}(X)$$

with probability 1 by the Strong Law of Large Numbers (applied element-wise in the matrix). Moreover,

$$\frac{1}{\sqrt{n}} \sum_{j=1}^n f'_{\theta_0}(X_j) \xrightarrow{d} \mathcal{N}(0, I(\Theta_0)) \quad (10.64)$$

where $I(\theta_0)$ is the Fisher information matrix. Indeed,

$$\mathbb{E} f'_{\theta}(X_j) = 0$$

$$f'_{\theta_0}(X_j) = \nabla \log p_{\theta}(x_j) = \begin{pmatrix} \frac{\frac{\partial}{\partial \theta_1} p_{\theta}(X_j)}{p_{\theta}(X_j)} \\ \vdots \\ \frac{\frac{\partial}{\partial \theta_d} p_{\theta}(X_j)}{p_{\theta}(X_j)} \end{pmatrix}$$

Then (using regularity assumptions)

$$\mathbb{E} \left[\frac{\frac{\partial}{\partial \theta_1} p_{\theta}(x_1)}{p_{\theta}(x_1)} \right] = \int_{\mathbb{R}^d} \frac{\frac{\partial}{\partial \theta_1} p_{\theta}(y)}{p_{\theta}(y)} p_{\theta}(y) dy = \frac{\partial}{\partial \theta_1} \int_{\mathbb{R}^d} p_{\theta}(y) dy = \frac{\partial}{\partial \theta_1} 1 = 0.$$

By the Central Limit Theorem,

$$\frac{1}{\sqrt{n}} \sum_{j=1}^n f'_\theta(X_j)$$

is approximately normal with covariance equal to the Fisher information

$$\mathbb{E}_{\theta_0} f'_\theta(X) (f'_\theta(X))^T = \mathbb{E}_{\theta_0} (\nabla \log p_{\theta_0}(x)) (\nabla \log p_{\theta_0}(x))^T.$$

Hence

$$Z_n(u) = \langle A_n, u \rangle + \frac{1}{2} \langle B_n u, u \rangle + o_{\mathbb{P}}(1)$$

where

$$A_n = \frac{1}{\sqrt{n}} \sum_{j=1}^n f'_{\theta_0}(X_j), \quad B_n = \frac{1}{n} \sum_{j=1}^n f''_{\theta_0}(X_j).$$

Also,

$$Z_n(u) = \langle A_n, u \rangle - \frac{1}{2} \langle I(\theta_0)u, u \rangle + o_{\mathbb{P}}(1)$$

above from 11/11 lecture; below are my notes from 11/08 lecture which may be wrong?

$$Z_n(u) = \langle A_n, u \rangle + \frac{1}{2} \langle I(\theta_0)u, u \rangle + o_{\mathbb{P}}(1)$$

where $I(\theta_0) := \mathbb{E} f'_{\theta_0}(x)(f'_{\theta_0}(x))^T$ (the Fisher information matrix) since $\mathbb{E} f''_\theta(X_1) = -I(\theta_0)$ (exercise; can see by integration by parts. Do in one-dimensional case and then can see how it works in general.).

One-dimensional case:

$$\int \left(\frac{\partial}{\partial \theta} \log p_\theta(x) \right)^2 p_\theta(x) dx = \int \frac{[p'_\theta(x)]^2}{p_\theta(x)} dx$$

We want to show that this equals

$$\begin{aligned} - \int \frac{\partial^2}{\partial \theta^2} \log[p_\theta(x)] p_\theta(x) dx &= - \int \frac{\partial}{\partial \theta} \left[\frac{p'_\theta(x)}{p_\theta(x)} \right] p_\theta(x) dx = - \int \frac{p''_\theta(x)p_\theta(x) - (p'_\theta(x))^2}{p_\theta(x)} dx \\ &\iff \int \frac{p''_\theta(x)p_\theta(x)}{p_\theta(x)} dx = 0 \end{aligned}$$

By regularity,

$$\frac{\partial}{\partial \theta} \underbrace{\int p_\theta(x) dx}_{=1} = \int \frac{\partial}{\partial \theta} p_\theta(x) dx = 0.$$

Idea: since $\hat{u}_n = \sqrt{n}(\hat{\theta}_n - \theta_0)$ maximizes $Z_n(u)$, it must be close to \tilde{u}_n that maximizes $\langle A_n, u \rangle - (1/2)\langle I(\theta_0)u, u \rangle$ (since they only differ by $o_{\mathbb{P}}(1)$). (to show formally: need to show that $o_{\mathbb{P}}(1)$ term is in fact $o_{\mathbb{P}}(1)$ over all u . takes a lot of work.) Note that \tilde{u}_n must solve $A_n = I(\theta_0)\tilde{u}_n$ because $\langle A_n, u \rangle - (1/2)\langle I(\theta_0)u, u \rangle$ is concave so it is maximized where its gradient equals 0 (exercise). Since $I(\theta_0)$ is invertible, this is given by $\tilde{u}_n = I^{-1}(\theta_0)A_n$. By (10.64), $A_n \xrightarrow{d} \mathcal{N}(0, I(\theta_0))$. Let $Y_n := I^{-1/2}(\theta_0)A_n$; then $Y_n \xrightarrow{d} \mathcal{N}(0, I_d)$. Similarly, \hat{u}_L must be close to \tilde{u}_L that maximizes

$$\langle A_n, u \rangle - \frac{1}{2}\langle I(\theta_0)u, u \rangle$$

over all $u \in L$. Note that

$$\begin{aligned} \langle A_n, u \rangle - \frac{1}{2}\langle I(\theta_0)u, u \rangle &= \langle I^{1/2}(\theta_0)Y_n, u \rangle - \frac{1}{2}\langle I^{1/2}(\theta_0)u, I^{1/2}(\theta_0)u \rangle = \langle I^{1/2}(\theta_0)Y_n, u \rangle - \frac{1}{2}\|I^{1/2}(\theta_0)u\|_2^2 \\ &= \langle I^{1/2}(\theta_0)u, Y_n \rangle - \frac{1}{2}\|I^{1/2}(\theta_0)u\|_2^2 - \frac{1}{2}\|Y_n\|_2^2 + \frac{1}{2}\|Y_n\|_2^2 = -\frac{1}{2}\|I^{1/2}(\theta_0)u - Y_n\|_2^2 + \frac{1}{2}\|Y_n\|_2^2. \end{aligned}$$

Hence \tilde{u}_n minimizes $\|I^{1/2}(\theta_0)u - Y_n\|_2^2$ over $u \in L$. Let $L(\theta_0)$ be the image of L under $I^{1/2}(\theta_0)$. $L(\theta_0)$ is a linear subspace of dimension k . The minimizer of $\|v - Y_n\|_2^2$ over $v \in L(\theta_0)$ is

$$\tilde{v} := \text{proj}_{L(\theta_0)} Y_n = \Pi_{L(\theta_0)} Y_n.$$

Hence $\tilde{u}_{n,L} = I^{-1/2}(\theta_0)\Pi_{L(\theta_0)}Y_n$ and $\tilde{u}_n = I^{-1}(\theta_0)A_n = I^{-1/2}(\theta_0)Y_n$. Then using (10.63),

$$\begin{aligned} \Lambda_n &= Z_n(\hat{u}_n) - Z_n(\hat{u}_{n,L}) = Z_n(\tilde{u}_n) - Z_n(\tilde{u}_{n,L}) + o_{\mathbb{P}}(1) \\ &= \langle A_n, \tilde{u}_n \rangle - \frac{1}{2}\langle I(\theta_0)\tilde{u}_n, \tilde{u}_n \rangle - \langle A_n, \tilde{u}_{n,L} \rangle + \frac{1}{2}\langle I(\theta_0)\tilde{u}_{n,L}, \tilde{u}_{n,L} \rangle + o_{\mathbb{P}}(1) \end{aligned}$$

And

$$\begin{aligned}\langle A_n, \tilde{u}_n \rangle &= \langle I^{1/2}(\theta_0)Y_n, I^{-1/2}(\theta_0)Y_n \rangle = \|Y_n\|_2^2, \\ \frac{1}{2}\langle I(\theta_0)\tilde{u}_l, \tilde{u}_L \rangle &= \frac{1}{2}\langle I(\theta_0)I^{-1/2}(\theta_0)Y_n, I^{-1/2}(\theta_0)Y_n \rangle = \frac{1}{2}\|Y_n\|_2^2, \\ \langle A_n, \tilde{u}_L \rangle &= \langle I^{1/2}(\theta_0)Y_n, I^{-1/2}(\theta_0)\Pi_{L(\theta_0)}Y_n \rangle = \langle Y_n, \Pi_{L(\theta_0)}Y_n \rangle = \|\Pi_{L(\theta_0)}Y_n\|_2^2, \\ \frac{1}{2}\langle I(\theta_0)\hat{u}_L, \hat{u}_L \rangle &= \frac{1}{2}\|\Pi_{L(\theta_0)}Y_n\|_2^2.\end{aligned}$$

So

$$\Lambda_n = \frac{1}{2}\|Y_n\|_2^2 - \frac{1}{2}\|\Pi_{L(\theta_0)}Y_n\|_2^2$$

and by (10.64) we then have

$$2\Lambda_n = \|\Pi_{L(\theta_0)^\perp}Y_n\|_2^2 \xrightarrow{d} \chi_{d-\dim(L(\theta_0))}^2 = \chi_{d-k}^2$$

where we used the general fact that

$$\langle x, \Pi_L x \rangle = \langle \Pi_L x + \Pi_{L^\perp} x, \Pi_L x \rangle = \|\Pi_L x\|_2^2.$$

□

Remark 152. Theorem 10.8.25 is often applied in significance tests for the coefficients in logistic regression.

Remark 153. If Θ_0 is a halfspace and θ_0 is on the boundary, then the χ^2 asymptotics don't hold anymore (because no matter how far we "zoom in", we can't get it to locally "look like" an affine subspace). That is, we can get this to work for $H_0 : \theta = \theta_0$ but not for $H_0 : \theta \leq \theta_0$.

10.8.11 Bahadur's Relative Efficiency (Section 10.4 of Serfling [1980])

Setup: X_1, \dots, X_n i.i.d. from \mathbb{P}_θ , $\theta \in \Theta$. $\{\phi_n\}_{n \geq 1}$ is a sequence of tests for testing $H_0 : \theta \in \Theta_0, H_a : \theta \in \Theta_a$. Let $\theta' \in \Theta_a$. Want to define

$$n(\underbrace{\alpha}_{\text{size}}, \underbrace{\gamma}_{\text{power}}, \theta') := \min \left\{ n \geq 1 : \sup_{\theta \in \Theta_0} \beta_\theta(\phi_n) \leq \alpha, \beta_{\theta'}(\phi_n) \geq \gamma \right\},$$

the smallest sample size required to achieve size α and power γ in the case of alternative θ' . If $\{\phi_n^{(1)}\}_{n \geq 1}$, $\{\phi_n^{(2)}\}_{n \geq 1}$ are two sequences of tests, consider the ratio

$$\lim_{\alpha \rightarrow 0} \frac{n^{(2)}(\alpha, \gamma, \theta')}{n^{(1)}(\alpha, \gamma, \theta')},$$

(if the limit exists), which is called **Bahadur's relative efficiency**. (Clearly we prefer if n is smaller, so we will choose sequence (1) if this ratio is greater than 1 and (2) otherwise). We will be interested in tests of the form

$$\phi = \begin{cases} 1, & T_n \geq C_n \\ 0, & T_n < C_n, \end{cases}$$

where $T_n = T_n(X_1, \dots, X_n)$ is a test statistic. (Note that likelihood ratio tests are of this form.) We will make the following assumptions:

1. Under \mathbb{P}_θ , $T_n \xrightarrow{p} \mu(\theta)$.
2. $-\frac{2}{n} \log(\mathbb{P}_\theta(T_n \geq t)) \xrightarrow{n \rightarrow \infty} \nu(t, \theta)$ and $\mu(\theta)$, $\nu(t, \theta)$ are continuous functions.

Second assumption tells us about the asymptotic behavior of the power function for any θ . Strict assumption; doesn't hold in many cases, does hold in many problems involving normal distribution.

Example 10.50. Recall Example 10.48 with $X \sim \text{Multinomial}(n, \theta_1, \dots, \theta_k)$. We got the likelihood ratio statistic (**this expression below has errors, I couldn't read it**)

$$\begin{aligned} 2\Lambda_n &= n \sum_{j=1}^k \hat{\theta}_j \log(\hat{\theta}_j/\theta_j), \quad \hat{\theta}_j = x_j/n \\ &\iff \frac{2\Lambda_n}{n} = \sum_{j=1}^k \hat{\theta}_j \log(\hat{\theta}_j/\theta_{0,j}). \end{aligned}$$

Under \mathbb{P}_θ , $\hat{\theta}_j \xrightarrow{p} \theta_j$ by the Law of Large Numbers.

$$\frac{2\Lambda_n}{n} \xrightarrow{p} \sum_{j=1}^n \theta_j \log(\theta_j/\theta_{n,j}) = KL(\mathbb{P}_\theta || \mathbb{P}_{\theta_0}) = \mu(\theta)$$

second assumption is harder to check

Example 10.51. $X_1, \dots, X_n \sim \mathcal{N}(\theta, I_d)$. Test $H_0 : \theta \in \Theta_0$ where Θ_0 is an affine subspace, $H_a : \theta \notin \Theta_0$. In Theorem 10.8.25, we obtained

$$2\Lambda_n = \|\Pi_{L^\perp} \bar{X}_n\|_2^2 \cdot n,$$

where L is the linear subspace corresponding to Θ_0 . Then

$$\frac{2\Lambda_n}{n} = \|\Pi_{L^\perp} \bar{X}_n\|_2^2.$$

Under \mathbb{P}_θ , $\bar{X}_n \xrightarrow{p} \theta$, so

$$\|\Pi_{L^\perp} \bar{X}_n\|_2^2 \xrightarrow{p} \|\Pi_{L^\perp} \theta\|_2^2.$$

Example 10.52. $X_1, \dots, X_n \sim \mathcal{N}(\theta, \sigma^2 I_n)$, $\sigma^2 > 0$ is known. Want to test $H_0 : \theta = \mu_0, H_a : \theta \neq \mu_0$. Then can see that likelihood ratio test is (for some $c > 0$)

$$\phi(x) = \begin{cases} 1, & \left| \frac{\sqrt{n}(\bar{x}_n - \mu_0)}{\sigma} \right| \geq c, \\ 0, & \left| \frac{\sqrt{n}(\bar{x}_n - \mu_0)}{\sigma} \right| < c \end{cases}$$

Note that using the test statistic

$$T'_n = \frac{\bar{X}_n - \mu_0}{\sigma}$$

is equivalent to $\frac{\sqrt{n}(\bar{x}_n - \mu_0)}{\sigma}$ (after adjusting c appropriately). Under $\mathcal{N}(\theta, \sigma^2)$, $\bar{X}_n \xrightarrow{p} \theta$, hence $T'_n \xrightarrow{p} (\theta - \mu_0)/\sigma := \mu(\theta)$. Then

$$\begin{aligned} \mathbb{P}_\theta(T'_n \geq t) &= \mathbb{P}_\theta\left(\frac{\bar{X}_n - \mu_0}{\sigma} \geq t\right) = \mathbb{P}_\theta\left(\frac{\bar{X}_n - \theta}{\sigma} \geq t + \frac{\mu_0 - \theta}{\sigma}\right) = \mathbb{P}_\theta\left(\underbrace{\sqrt{n}\frac{(\bar{X}_n - \theta)}{\sigma}}_{\mathcal{N}(0,1)} \geq \sqrt{n}\left[t + \frac{\mu_0 - \theta}{\sigma}\right]\right) \\ &= \exp\left\{-\frac{1}{2}\left[\sqrt{n}\left(t + \frac{\mu_0 - \theta}{\sigma}\right)\right]^2 + o(1)\right\} \approx \exp\left\{-\frac{1}{2}\left[\sqrt{n}\left(t + \frac{\mu_0 - \theta}{\sigma}\right)\right]^2\right\} \end{aligned}$$

where the last step used the result of the following exercise (well-known bound): Let $\phi(t) = \mathbb{P}(\xi \geq t)$ where $\xi \sim \mathcal{N}(0, 1)$. (So $\phi(t) = \int_t^\infty (2\pi)^{-1/2} e^{-x^2/2} dx$.) Then

1. $\phi(t) \leq e^{-t^2/2}$ for any t .
2. $\phi(t) \geq \frac{1}{\sqrt{2\pi}} \frac{t}{1+t^2} e^{-t^2/2}$.

In particular, as $t \rightarrow \infty$,

$$\frac{t^2}{2} \leq -\log \phi(t) \leq \frac{t^2}{2} - \underbrace{\log\left(\frac{1}{\sqrt{2\pi}} \frac{t}{1+t^2}\right)}_{o(t) \text{ as } t \rightarrow \infty}$$

Returning to the problem,

$$-\frac{2}{n} \log [\mathbb{P}_\theta(T'_n \geq t)] = \left(t + \frac{\mu_0 - \theta}{\sigma}\right)^2 / \nu(\theta, t) + \underbrace{o(1)}_{\rightarrow 0 \text{ as } n \rightarrow \infty}.$$

(can see how in practice checking second assumption is hard.) Assume that $\Theta_0 = \{\theta_0\}$. Let $\hat{\alpha}$ be the p -value, i.e.

$$\hat{\alpha}_n = \sup_{\theta_0 \in \Theta_0} \left\{ \underbrace{\mathbb{P}_{\theta_0}(T_n \geq t)}_{G(t)} \Big|_{t=T_n} \right\} = \sup_{\theta_0 \in \Theta_0} \{G(T_n)\}$$

(probability of observing an outcome more extreme than the current one). Note: When $\Theta_0 = \{\theta_0\}$, $\hat{\alpha}_n = \mathbb{P}_{\theta_0}(T_n \geq t)|_{t=T_n}$. Also note that the test of size α rejects if and only if $\hat{\alpha}_n \leq \alpha$. By our assumption,

$$\hat{\alpha}_n = \exp \left\{ -\frac{n}{2} [\nu(T_n, \theta_0) + o(1)] \right\} = \exp \left\{ -\frac{n}{2} \left[\underbrace{\nu(\mu(\theta), \theta_0)}_{\text{"Bahadur's Slope"}} + o_{\mathbb{P}}(1) \right] \right\}$$

because $T_n \xrightarrow{P} \mu(\theta)$.

Claim: for any $\gamma < 1$,

$$\lim_{\alpha \rightarrow 0} n(\alpha, \gamma, \theta') = \frac{\log(1/\alpha)}{\nu(\mu(\theta))} + o(1).$$

$$n(\alpha, \gamma, \theta') = \frac{\log(1/\alpha)}{\nu(\mu(\theta'), \theta')} + o(1).$$

Hence Bahadur's relative efficiency is approximately equal to

$$\frac{\nu_1(\mu_1(\theta'), \theta')}{\nu_2(\mu_2(\theta'), \theta')}$$

"the larger the function ν is, the smaller the sample size is, so the tests with higher Bahadur relative efficiencies." Likelihood ratio tests achieve the asymptotic highest possible Bahadur relative efficiency. Related at its core to the fact that methods based on maximum likelihood reduce some notion of KL divergence between distributions. So achieve information-theoretic lower limits on best possible solutions (since KL-divergence comes from information theory). Note that if BRE is less than 1, $\{\phi_n^{(2)}\}$ is more efficient, which is true if $\nu_2(\mu_2(\theta'), \theta') > \nu_1(\mu_1(\theta'), \theta')$.

Proof of claim. ϕ_n rejects when $\hat{\alpha}_n \leq \alpha$. Hence

$$\beta_{\phi_n}(\theta) = \mathbb{P}_{\theta}(\hat{\alpha}_n \leq \alpha) = \mathbb{P}_{\theta} \left(\exp \left\{ -\frac{n}{2} (\nu(\mu(\theta_0), \theta_0) + o_{\mathbb{P}}(1)) \right\} \leq \alpha \right) = \mathbb{P}_{\theta} \left(n \geq \frac{2 \log(1/\alpha)}{\nu(\mu(\theta_0), \theta_0) + o_{\mathbb{P}}(1)} \right)$$

We want to choose n such that this probability is greater than or equal to γ . Take $\epsilon > 0$ and assume that

$$n = (1 + \epsilon) \frac{2 \log(1/\alpha)}{\nu(\mu(\theta_0), \theta_0)}$$

Then

$$\begin{aligned}\mathbb{P}_\theta \left(n \geq \frac{2 \log(1/\alpha)}{\nu(\mu(\theta_0), \theta_0) + o_{\mathbb{P}}(1)} \right) &= \mathbb{P}_\theta \left(n \geq \frac{2 \log(1/\alpha)}{\nu(\mu(\theta_0), \theta_0)[1 + o_{\mathbb{P}}(1)]} \right) \\ &= \mathbb{P}_\theta \left(1 + \epsilon \geq \frac{1}{1 + o_{\mathbb{P}}(1)} \right) \rightarrow 1 \text{ as } \alpha \rightarrow 0.\end{aligned}$$

So $n(\alpha, \gamma, \theta) < (1 + \epsilon) \frac{2 \log(1/\alpha)}{\nu(\mu(\theta_0), \theta_0)}$. Formally,

$$\lim_{\alpha \rightarrow 0} \frac{n(\alpha, \gamma, \theta)}{\frac{2 \log(1/\alpha)}{\nu(\mu(\theta_0), \theta_0)}} \leq 1 + \epsilon \quad \forall \epsilon > 0.$$

Now take

$$n = (1 - \epsilon) \frac{2 \log(1/\alpha)}{\nu(\mu(\theta_0), \theta_0)}$$

Then

$$\mathbb{P}_\theta \left(1 - \epsilon \geq \frac{1}{1 + o_{\mathbb{P}}(1)} \right) \rightarrow 0 \text{ as } \alpha \rightarrow 0,$$

so

$$\lim_{\alpha \rightarrow 0} \frac{n(\alpha, \gamma, \theta)}{\frac{2 \log(1/\alpha)}{\nu(\mu(\theta_0), \theta_0)}} = 1 \quad \forall \gamma < 1.$$

□

Exercise 31. Assume that $\Theta_0 = \{\theta_0\}$. Under H_0 , $\mathbb{P}_{\theta_0}(\hat{\alpha}_n \leq t) \leq t$, $t \in [0, 1]$. When \mathbb{P}_{θ_0} has density with respect to Lebesgue measure (i.e. $d\mathbb{P}_{\theta_0}(x) = p_{\theta_0}(x) dx$), then under \mathbb{P}_{θ_0} $\hat{\alpha}_n \sim \text{Uniform}[0, 1]$. (Hint: if X has density function $F(x)$, then $F'(x) \sim \text{Uniform}[0, 1]$ when F is continuous.)

Theorem 10.8.26. Let $\{T_n\}_{n \geq 1}$ be any sequence of test statistics, and $\{\phi_n\}_{n \geq 1}$ corresponding tests, $\hat{\alpha}_n$ associated p-values. Then for all $\theta' \in \Theta_a$,

$$\limsup_{n \rightarrow \infty} \left[-\frac{2}{n} \log(\hat{\alpha}_n) \leq 2 \text{KL}(p_{\theta'} || p_{\theta_0}) \right]$$

with probability 1, where $\text{KL}(p_{\theta'} || p_{\theta_0})$ is the KL divergence. (Result also holds for composite null and alternative hypotheses.)

Proof. Let

$$\Lambda_n := \sum_{j=1}^n \log \left(\frac{p_\theta(x_j)}{p_{\theta_0}(x_i)} \right).$$

Take $B > A > 0$. Let

$$\mathcal{E}_n = \left\{ \hat{\alpha}_n \leq e^{-nB}, \frac{\Lambda_n}{n} \leq A \right\}.$$

Then

$$\begin{aligned} \mathbb{P}_\theta(\mathcal{E}_n) &= \int p_\theta(x_1) \cdots p_\theta(x_n) \mathbb{1}\{\hat{\alpha}_n \leq e^{-nB}, \Lambda_n \leq nA\} d\mu_1(x_1) \cdots d\mu_n(x_n) \\ &= \int \underbrace{\frac{p_\theta(x_1) \cdots p_\theta(x_n)}{p_{\theta_0}(x_1) \cdots p_{\theta_0}(x_n)}}_{e^{\Lambda_n}} \mathbb{1}\{\hat{\alpha}_n \leq e^{-nB}, \Lambda_n \leq nA\} p_{\theta_0}(x_1) \cdots p_{\theta_0}(x_n) d\mu_1(x_1) \cdots d\mu_n(x_n) \\ &\leq e^{nA} \int \mathbb{1}\{\hat{\alpha}_n \leq e^{-nB}\} p_{\theta_0}(x_1) \cdots p_{\theta_0}(x_n) d\mu_1(x_1) \cdots d\mu_n(x_n) = e^{nA} \underbrace{\mathbb{P}_{\theta_0}(\hat{\alpha}_n \leq e^{-nB})}_{\leq e^{-nB} \text{ (exercise)}} \\ &\leq e^{nA} e^{-nB} = e^{-n(B-A)} \end{aligned}$$

But

$$\sum_{n \geq 1} \mathbb{P}(\mathcal{E}_n) \leq \sum_{n \geq 1} e^{-n(B-A)} < \infty$$

By Borel-Cantelli lemma, on event Ω_1 of \mathbb{P}_θ probability 1 for n large enough, $\bar{\mathcal{E}}_n$ occur, where

$$\bar{\mathcal{E}}_n = \{\hat{\alpha}_n > e^{-nB}\} \cup \{\Lambda_n > nA\}.$$

Then by the Strong Law of Large Numbers,

$$\frac{1}{n} \sum_{i=1}^n \log \left(\frac{p_\theta(x_j)}{p_{\theta_0}(x_j)} \right) \xrightarrow{n \rightarrow \infty} \mathbb{E}_\theta \log \left(\frac{p_\theta(x_j)}{p_{\theta_0}(x_j)} \right) = KL(p_\theta || p_{\theta_0})$$

with probability 1. If $A > KL(p_\theta || p_{\theta_0})$, then there exists an event Ω_2 such that $\mathbb{P}_\theta(\Omega_2) = 1$ such that on Ω_2 ,

$$\frac{1}{n} \sum_{i=1}^n \log \left(\frac{p_\theta(x_j)}{p_{\theta_0}(x_j)} \right) < A$$

for n large enough (if and only if $\Lambda_n < nA$). On $\Omega_1 \cap \Omega_2$, for all n large enough

$$\hat{\alpha}_n > e^{-nB} \iff -\frac{2}{n} \log(\hat{\alpha}_n) < 2B$$

for n large enough, and $\mathbb{P}_\theta(\Omega_1 \cap \Omega_2) = 1$. But B can be taken arbitrarily close to $KL(p_\theta || p_{\theta_0})$. Therefore the only possibility is

$$\limsup_{n \rightarrow \infty} \left[-\frac{2}{n} \log(\hat{\alpha}_n) \right] \leq 2KL(p_\theta || p_{\theta_0}).$$

□

This upper bound is sharp, as we will show next. In particular, we will show that the upper bound from the previous theorem is achieved by likelihood ratio tests. Assumption: Θ_a is finite. Recall that

$$\tilde{\Lambda}_n := \log \frac{\max_{\theta \in \Theta} \prod_{j=1}^n p_\theta(x_j)}{\prod_{j=1}^n p_{\theta_0}(x_j)} = \log \frac{\max_{\theta \in \Theta} L_n(\theta)}{L_n(\theta_0)}.$$

Theorem 10.8.27. Let

$$\hat{\alpha}_n := \mathbb{P}_{\theta_0} \left(\underbrace{\frac{\tilde{\Lambda}_n}{n}}_{T_n} \geq t \right) \Big|_{t=\tilde{\Lambda}/n}.$$

Then for all $\theta \in \Theta_a$,

$$-\frac{2}{n} \log(\hat{\alpha}_n) \xrightarrow{a.s.} 2KL(p_\theta || p_{\theta_0}).$$

Remark 154. The likelihood ratio test achieves the information theoretic upper bound from the previous theorem. So likelihood ratio tests are asymptotically optimal. (Not necessarily UMP, UMP unbiased, UMP invariant, etc.; weaker claim.)

Proof.

$$\begin{aligned} \mathbb{P}_{\theta_0}(\tilde{\Lambda}_n \geq nt) &= \mathbb{P}_{\theta_0} \left(\log \frac{\max_{\theta \in \Theta} L_n(\theta)}{L_n(\theta_0)} \geq nt \right) = \mathbb{P}_{\theta_0} \left(\max_{\theta \in \Theta} \sum_{j=1}^n \left\{ \log \frac{p_\theta(x_j)}{p_{\theta_0}(x_j)} \right\} \geq nt \right) \\ &\leq (\text{by union bound and assumption of finite } \Theta_a) \sum_{\theta \in \Theta} \mathbb{P}_{\theta_0} \left(\sum_{j=1}^n \log \frac{p_\theta(x_j)}{p_{\theta_0}(x_j)} \geq nt \right) \\ &= \sum_{\theta \in \Theta} \mathbb{P}_{\theta_0} \left(\exp \left\{ \sum_{j=1}^n \log \frac{p_\theta(x_j)}{p_{\theta_0}(x_j)} \right\} \geq e^{nt} \right) \\ &\leq (\text{by Markov's inequality}) \sum_{\theta \in \Theta} \underbrace{\mathbb{E}_{\theta_0} \left(\prod_{j=1}^n \frac{p_\theta(x_j)}{p_{\theta_0}(x_j)} \right)}_{=1} e^{-nt} = \sum_{\theta \in \Theta} \underbrace{\int p_\theta(x_j) p_{\theta_0}(x_j) d\mu}_{=1} e^{-nt} = |\Theta| e^{-nt}. \end{aligned}$$

where $|\Theta|$ is the cardinality of Θ . This implies

$$-\frac{2}{n} \log \mathbb{P}_{\theta_0}(\tilde{\Lambda}_n \geq nt) \geq 2t - 2\frac{\log |\Theta|}{n},$$

so by the definition of $\hat{\alpha}_n$ (plugging in $t = \tilde{\Lambda}/n$),

$$-\frac{2}{n} \log \hat{\alpha}_n \geq 2\frac{\tilde{\Lambda}_n}{n} - 2\frac{\log |\Theta|}{n}.$$

Note that

$$\tilde{\Lambda}_n = \log \frac{\max_{\theta \in \Theta} L_n(\theta)}{L_n(\theta_0)} \geq \log \frac{L_n(\theta')}{L_n(\theta_0)} \quad \forall \theta' \in \Theta.$$

Take θ corresponding to the distribution of X_1, \dots, X_n . Then

$$2\frac{\tilde{\Lambda}_n}{n} \geq 2\frac{1}{n} \sum_{i=1}^n \log \frac{p_\theta(x_j)}{p_{\theta_0}(x_j)} \xrightarrow{n \rightarrow \infty} KL(p_\theta || p_{\theta_0})$$

by the Law of Large Numbers. Hence as $n \rightarrow \infty$

$$\lim_{n \rightarrow \infty} \left(-\frac{2}{n} \log(\hat{\alpha}_n) \geq 2KL(p_\theta || p_{\theta_0}) \right) \implies \lim_{n \rightarrow \infty} -\frac{2}{n} \log(\hat{\alpha}_n) = 2KL(p_\theta || p_{\theta_0})$$

for any $\theta \in \Theta_a$.

□

Proof of Validity of Holm-Bonferroni. Let $P_{(1)} \leq \dots \leq P_{(n)}$ be the sorted p -values. Suppose n_0 of the null hypotheses are true. Let i_0 be the index of the smallest p -value corresponding to a true null hypothesis. By the structure of the method, we have at least one false rejection if and only if P_{i_0} is rejected. This is true if and only if

$$P_{i_0} \leq \frac{\alpha}{n+1-i_0}.$$

Note that at most $n_0 - 1$ of the p -values larger than P_{i_0} are true, so we have the inequality $i_0 + n_0 - 1 \leq n$, which leads to $\frac{1}{n+1-i_0} \leq \frac{1}{n_0}$. So

$$\mathbb{P}\left(P_{i_0} \leq \frac{\alpha}{n+1-i_0}\right) \leq \mathbb{P}\left(P_{i_0} \leq \frac{\alpha}{n_0}\right) \leq \sum_{\{i : H_i \text{ is true}\}} \mathbb{P}\left(p_i \leq \frac{\alpha}{n_0}\right) = n_0 \frac{\alpha}{n_0} = \alpha.$$

□

Elaboration of work on slide 19 of week 3. We will prove that $\mathbb{P}(p_{(j)} > \frac{j\alpha}{n}) = 1 - \alpha$ by induction on n . Clearly this is true for $n = 1$. Now assume that $\mathbb{P}(p_{(j)} > \frac{j\alpha}{n-1}) = 1 - \alpha$. We will use this to show that $\mathbb{P}(p_{(j)} > \frac{j\alpha}{n})$, and then the result is proven.

Denoting $f_{p(n)} = nt^{n-1}$ as the density of $p_{(n)}$, we have

$$\begin{aligned}
 \mathbb{P}(T_n \leq \alpha, p_{(n)} > \alpha) &= \int_{\alpha}^1 \mathbb{P}(T_n \leq \alpha \mid p_{(n)} = t) f_{p(n)}(t) dt \\
 &= \int_{\alpha}^1 \mathbb{P}\left(\min_{1 \leq i \leq n-1} \left\{p_{(i)} \frac{n}{i}\right\} \leq \alpha \mid p_{(n)} = t\right) nt^{n-1} dt \\
 &= \int_{\alpha}^1 \mathbb{P}\left(\min_{1 \leq i \leq n-1} \left\{\frac{p_{(i)}}{t} \frac{n-1}{i}\right\} \leq \frac{\alpha}{t} \frac{n-1}{n} \mid p_{(n)} = t\right) nt^{n-1} dt \\
 &\quad \vdots \\
 &\stackrel{(*)}{=} \int_{\alpha}^1 \frac{\alpha}{t} \frac{n-1}{n} nt^{n-1} dt \\
 &= \alpha \int_{\alpha}^1 (n-1)t^{n-2} dt \\
 &= \alpha [t^{n-1}]_{\alpha}^1 \\
 &= \alpha [1 - \alpha^{n-1}] \\
 &= \alpha - \alpha^n,
 \end{aligned}$$

where we used the inductive hypothesis in (*).

□

Proof of Validity of closure principle. We hope to show that under all configurations of true and false hypothesis, $\mathbb{P}(V \geq 1) \leq \alpha$. Let $N = \{j \in [n] : H_j \text{ is null}\}$ be the set of null hypotheses. Note that $N \subseteq I$ and $\{i\} \subseteq N$. Let $H_n = \bigcap_{i \in N} H_i$, and let $T_i = \min_{I \supseteq \{i\}} \phi_I$. If $T_i = 1$, then $\phi_{H_N} = 1$. Then

$$\mathbb{P}(T_i = 1 \mid H_i \text{ true}) \leq \mathbb{P}(\phi_{H_N} = 1 \mid H_N \text{ is true}) \leq \alpha.$$

□

Proof of Validity of Benjamini-Yekuteli. Let $h_n := 1 + 1/2 + \dots + 1/n \approx \log n$.

$$\begin{aligned}
\text{FDP} &= \frac{V}{\max\{R, 1\}} \\
&= \sum_{i \in H_0} \frac{V_i}{\max\{R, 1\}} \\
&= \sum_{i \in H_0} \sum_{k=1}^n \frac{\mathbb{1}\{p_i \leq \alpha k/n\} \mathbb{1}\{R = k\}}{k} \\
&= \sum_{i \in H_0} \sum_{k=1}^n \sum_{\ell=1}^k \frac{\mathbb{1}\{p_i \in [\alpha_{\ell-1}, \alpha_\ell]\}}{k} \mathbb{1}\{R = k\} \\
&= \sum_{i \in H_0} \sum_{\ell=1}^n \sum_{k=\ell}^n \frac{\mathbb{1}\{p_i \in [\alpha_{\ell-1}, \alpha_\ell]\}}{k} \mathbb{1}\{R = k\} \\
&\leq \sum_{i \in H_0} \sum_{\ell=1}^n \sum_{k=\ell}^n \frac{\mathbb{1}\{p_i \in [\alpha_{\ell-1}, \alpha_\ell]\}}{\ell} \mathbb{1}\{R = k\} \\
&= \sum_{i \in H_0} \sum_{\ell=1}^n \frac{\mathbb{1}\{p_i \in [\alpha_{\ell-1}, \alpha_\ell]\}}{\ell} \sum_{k=\ell}^n \mathbb{1}\{R = k\} \\
&= \sum_{i \in H_0} \sum_{\ell=1}^n \frac{\mathbb{1}\{p_i \in [\alpha_{\ell-1}, \alpha_\ell]\}}{\ell} \mathbb{1}\{R \geq \ell\} \\
&\leq \sum_{i \in H_0} \sum_{\ell=1}^n \frac{\mathbb{1}\{p_i \in [\alpha_{\ell-1}, \alpha_\ell]\}}{\ell}
\end{aligned}$$

where $\alpha_k := \alpha k/n$. Now we take the expectation to get the FDR:

$$\begin{aligned}
\mathbb{E}[\text{FDP}] &\leq \mathbb{E} \left[\sum_{i \in H_0} \sum_{\ell=1}^n \frac{\mathbb{E}[\mathbb{1}\{p_i \in [\alpha_{\ell-1}, \alpha_\ell]\}]}{\ell} \right] \\
&= \sum_{i \in H_0} \sum_{\ell=1}^n \frac{\mathbb{E}[\mathbb{1}\{p_i \in [\alpha_{\ell-1}, \alpha_\ell]\}]}{\ell} \\
&= \sum_{i \in H_0} \sum_{\ell=1}^n \frac{\alpha/n}{\ell} \\
&= \sum_{i \in H_0} \frac{\alpha}{n} \sum_{\ell=1}^n \frac{1}{\ell} \\
&= h_n \sum_{i \in H_0} \frac{\alpha}{n} \\
&= h_n \frac{n_0}{n} \alpha \\
&\leq \alpha h_n.
\end{aligned}$$

□

10.9 Confidence Intervals

10.9.1 Connection Between Testing and Confidence Sets

Definition 10.55. Assume we have a statistical model $X \sim p_\theta, \theta \in \Theta$. A random set $C(X)$ is a $1 - \alpha$ confidence set or confidence region ($\alpha \in (0, 1)$) if and only if $\mathbb{P}_\theta(\theta \in C(X)) \geq 1 - \alpha \forall \theta \in \Theta$.

Remark 155. An acceptance region of a non-randomized test ϕ is the set of all values of the test statistic for which the null hypothesis is not rejected.

Theorem 10.9.1. Let $A(\theta_0)$ be the acceptance region of a non-randomized test for testing $H_0 : \theta = \theta_0; H_a : \theta \in K(\theta_0)$ at level α (e.g., $K(\theta_0) = \{\theta \neq \theta_0\}$). Define $C(x) := \{\theta : x \in A(\theta)\}$. Then $C(X)$ is a $1 - \alpha$ confidence set.

Proof. By definition, $x \in A(\theta) \iff \theta \in C(x)$. Therefore for all $\theta \in \Theta$ $\mathbb{P}_\theta(X \in A(\theta)) = \mathbb{P}_\theta(\theta \in C(X))$. The result follows since by assumption the test is of size α , so $\mathbb{P}_\theta(X \in A(\theta)) \geq 1 - \alpha$.

□

Example 10.53. Suppose $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$ i.i.d. Consider $H_0 : \mu = \mu_0, H_a : \mu \neq \mu_0$. Then (homework problem) the test

$$\phi = \begin{cases} 1, & \left| \frac{\sqrt{n}(\bar{x}_n - \mu_0)}{\sqrt{S^2}} \right| \geq t_{n-1, 1-\alpha/2} \\ 0, & \left| \frac{\sqrt{n}(\bar{x}_n - \mu_0)}{\sqrt{S^2}} \right| < t_{n-1, 1-\alpha/2} \end{cases}$$

is the UMP test.

- (a) Find the acceptance region.

Solution.

(a)

$$A(\mu_0) = \left\{ x : \left| \frac{\sqrt{n}(\bar{x}_n - \mu_0)}{\sqrt{S^2}} \right| < t_{n-1, 1-\alpha/2} \right\}$$

Note that

$$\begin{aligned} \left| \frac{\sqrt{n}(\bar{x}_n - \mu_0)}{\sqrt{S^2}} \right| < t_{n-1, 1-\alpha/2} &\iff -t_{n-1, 1-\alpha/2} < \frac{\sqrt{n}(\bar{x}_n - \mu_0)}{\sqrt{S^2}} < t_{n-1, 1-\alpha/2} \\ &\iff \bar{x}_n - \frac{\sqrt{s^2}t_{n-1, 1-\alpha/2}}{\sqrt{n}} < \mu_0 < \bar{x}_n + \frac{\sqrt{s^2}t_{n-1, 1-\alpha/2}}{\sqrt{n}} \end{aligned}$$

So

$$C(X) = \left[\bar{X}_n - \frac{\sqrt{S^2}t_{n-1, 1-\alpha/2}}{\sqrt{n}}, \bar{X}_n + \frac{\sqrt{S^2}t_{n-1, 1-\alpha/2}}{\sqrt{n}} \right]$$

is a $1 - \alpha$ confidence set.

Definition 10.56. A $(1 - \alpha)$ confidence set $C(X)$ is **unbiased** if and only if $\mathbb{P}_\theta(\theta' \in C(X)) \leq 1 - \alpha$ for all $\theta \neq \theta'$.

An unbiased confidence set can be obtained by inverting an unbiased confidence test.

Theorem 10.9.2. For each θ_0 , let $A^*(\theta_0)$ be the acceptance region of a UMP unbiased test of size α for testing the null hypothesis $H_0 : \theta = \theta_0$ against the alternative $H_a : \theta = \theta_0$. Let $C^*(X)$ be the corresponding confidence set. Then for any other unbiased $(1 - \alpha)$ confidence set $C(X)$,

$$\mathbb{P}_\theta(\theta_0 \in C^*(X)) \leq \mathbb{P}_\theta(\theta_0 \in C(X)) \quad \forall \theta \in \Theta.$$

Proof.

$$\mathbb{P}_\theta(\theta_0 \in C^*(X)) = \mathbb{P}_\theta(X \in A^*(\theta_0))$$

Note that for all $\theta \neq \theta_0$, $\mathbb{P}_\theta(X \in A^*(\theta_0))$ is the probability that the test will accept the null hypothesis given that the alternative hypothesis is true (probability of a Type II error, or $1 - \text{the power}$). The UMP test minimizes this, so we have for any other rejection region $A(\theta_0) := \{x : \theta_0 \in C(x)\}$,

$$\mathbb{P}_\theta(X \in A^*(\theta_0)) \leq \mathbb{P}_\theta(X \in A(\theta_0)) = \mathbb{P}_\theta(\theta_0 \in C(X))$$

□

Theorem 10.9.3 (Pratt). Suppose $X \sim p_\theta, \theta \in \Theta$. Assume that $C(X) = [L(X), U(X)]$ where $L(x), U(x)$ are increasing functions. Then for all θ_0 ,

$$\mathbb{E}[U(X) - L(X)] = \mathbb{E}|C(X)| = \int_{\theta \neq \theta_0} \underbrace{\mathbb{P}_{\theta_0}(\theta \in C(X))}_{\text{probability of a Type II error}} d\theta$$

That is, if we know that $C(X)$ is an interval of this form, then in expectation the minimizer of the integral on the right (the interval corresponding to the UMP test) results in the shortest possible confidence region.

Proof.

$$\begin{aligned} \mathbb{E}_{\theta_0}[U(X) - L(X)] &= \int_{\mathbb{R}} [U(X) - L(X)] p_{\theta_0}(x) dx = \int_{\mathbb{R}} \int_{L(x)}^{U(x)} dt p_{\theta_0}(x) dx = \int_{\mathbb{R}} \int_{U^{-1}(t)}^{L^{-1}(t)} p_{\theta_0}(x) dx dt \\ &= \int_{\mathbb{R}} \mathbb{P}_{\theta_0}(U^{-1}(t) \leq x \leq L^{-1}(t)) dt = \int_{\mathbb{R}} \mathbb{P}_{\theta_0}(t \in C(x)) dt = \int_{t \neq \theta_0} \mathbb{P}_{\theta_0}(t \in C(x)) dt \end{aligned}$$

See Figure 10.5 for an explanation of the change of integrands in the third step (either way finds the probability-weighted area of the whole region between the two curves in all of \mathbb{R}^2).

□

Example 10.54 (“The Rule of Threes”). Suppose $X_1, \dots, X_n \sim \text{Ber}(p)$, i.i.d. Assume that $\sum_{i=1}^n x_i = 0$. Find the 95% upper confidence bound for p . (it is approximately equal to $3/n$).

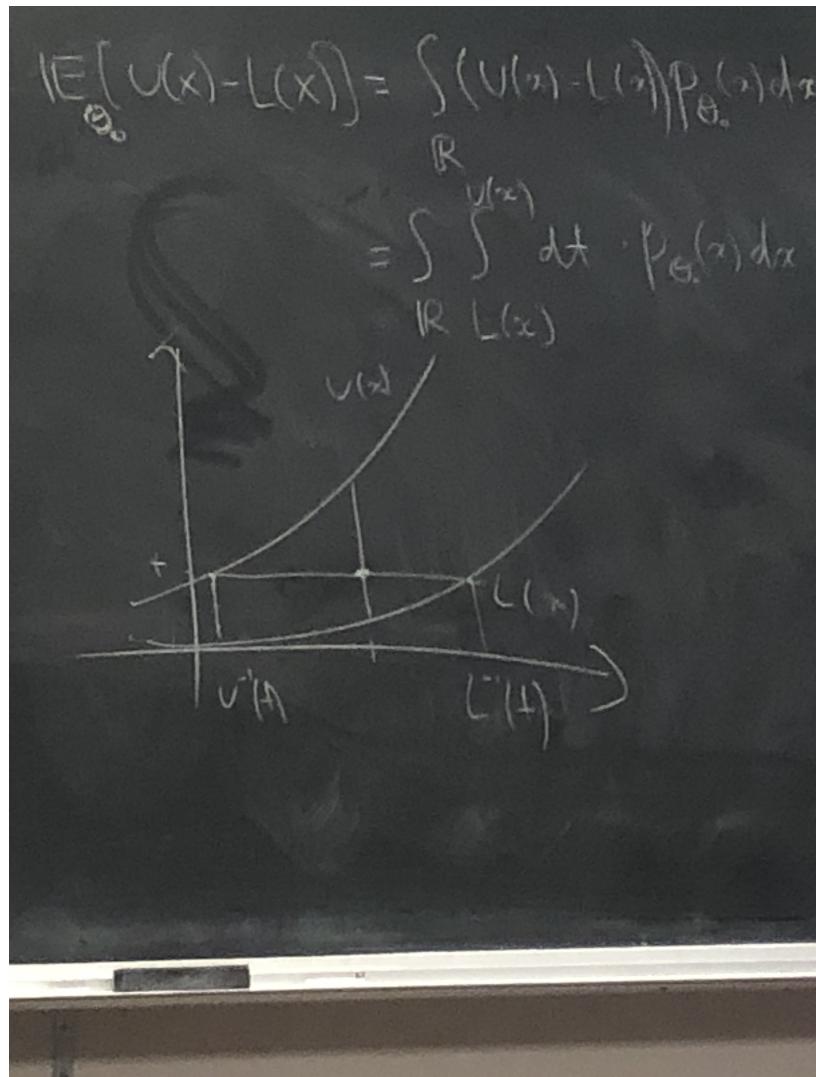


Figure 10.5: Visual depiction of change of integrands in proof of Theorem 10.9.3.

Solution.

Consider testing $H_0 : p \geq p_0$ against $H_a : p < p_0$. We know that $X = \sum_{j=1}^n X_j$ is a complete sufficient statistic and $X \sim \text{Binomial}(n, p)$, so $\mathbb{P}_p(X = x) = \binom{n}{x} p^x (1-p)^{n-x}$, a monotone likelihood ratio with respect to $T(X) = X$. Therefore the UMP (nonrandomized) test is

$$\phi^* = \begin{cases} 1, & X \leq c \\ 0, & X > c \end{cases}$$

(since this test is nonrandomized, it will only be UMP for specific values of α) where $c = c(p_0, \alpha) \in \mathbb{Z}_+$ solves

$$\alpha = \mathbb{P}(\text{Type I error}) = \mathbb{P}_{p_0}(X \leq c) = \sum_{j=0}^{c(p_0, \alpha)} \binom{n}{j} p_0^j (1-p_0)^{n-j}$$

To find the 95% upper confidence bound for p , we want to know for which values of p_0 is 0 in the acceptance region ($0 \in \text{AR}(p_0)$). Note that for this hypothesis test with null hypothesis $p \geq p_0$, the acceptance regions are nested, meaning that $p_1 < p_2 \implies \{\text{the rejection region for } p_1\} \subseteq \{\text{the rejection region for } p_2\} \iff \text{AR}(p_2) \subseteq \text{AR}(p_1)$. Hence we need to find the largest p such that $0 \in \text{AR}(p)$. This p must satisfy

$$\alpha < \mathbb{P}_p(X = 0) = \sum_{j=0}^0 \binom{n}{j} p^j (1-p)^{n-j} \iff (1-p)^n > \alpha \iff p < 1 - \alpha^{1/n}.$$

Then α is small implies $\alpha^{1/n} = e^{\log(\alpha)/n} \approx 1 + \log(\alpha)/n$. Using this, we get $p < -\log(\alpha)/n$. When $\alpha = 0.05$, $-\log(\alpha) = \log(1/0.05) \approx 3$.

Exercise 32. What if we observe 1 success in n trials? Find an equation for a $(1 - \alpha)$ upper confidence bound for p .

10.10 U-Statistics

10.10.1 Basic Definitions and Properties [Serfling, 1980, Sections 5.1 and 5.2], [DasGupta, 2008, Section 15.1]

While the limiting distribution of linear statistics is known from the canonical Central Limit Theorem (under suitable moment conditions), limiting distributions of nonlinear statistics are more difficult. However, a class of nonlinear statistics called **U-Statistics** have a common CLT.

Definition 10.57 (U-Statistics; definition drawing from Section 5.1.1 of Serfling [1980, p. 190 of pdf, p. 172 of book] and DasGupta [2008, Chapter 15, p. 240 of pdf, p. 225 of book]). Let X_1, X_2, \dots be independent observations on a distribution F . (They may be vector-valued, but usually we will consider the real-valued case.) Consider a parametric function $\theta = \theta(F)$ for which there is an unbiased estimator. That is, $\theta(F)$ may be represented as

$$\theta(F) = \mathbb{E}_F [h(X_1, \dots, X_m)] = \int \dots \int h(x_1, \dots, x_m) dF(x_1) \dots dF(x_m)$$

for some function $h = h(x_1, \dots, x_m)$, called a **kernel**. Without loss of generality, we may assume h is symmetric². Of course, $h(X_1, \dots, X_m)$ is an unbiased estimator for $\theta(F)$, but a better unbiased estimate should exist if $n > m$ because $h(X_1, \dots, X_m)$ does not use all of the sample data.

In particular, for any kernel h , the corresponding **U -Statistic of order m with kernel h** for estimation of θ on the basis of a sample X_1, \dots, X_n of size $n \geq m$ is obtained by averaging the kernel h symmetrically over the observations:

$$U_n = U(X_1, \dots, X_n) := \frac{1}{\binom{n}{m}} \sum_c h(X_{i_1}, \dots, X_{i_m}),$$

where \sum_c denotes summation over the $\binom{n}{m}$ combinations of m distinct elements $\{i_1, \dots, i_m\}$ from $[n]$. Clearly, U_n is an unbiased estimate of θ .

Example 10.55 (Example 15.2 in DasGupta [2008]). Let $m = 2$ and $h(x_1, x_2) = (x_1 - x_2)^2/2$. One can show that

$$\frac{1}{\binom{n}{2}} \sum_{i < j} \frac{(X_i - X_j)^2}{2} = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2.$$

That is, the sample variance is a U -statistic.

A U -statistic may be represented as the result of conditioning the kernel on the order statistic; that is, for $n \geq m$,

$$U_n = \mathbb{E} [h(X_1, \dots, X_m) | \mathbf{X}_{(n)}]$$

where $\mathbf{X}_{(n)}$ denotes the order statistic. This implies that any statistic $S = S(X_1, \dots, X_n)$ for unbiased estimation of $\theta = \theta(F)$ may be improved by the corresponding U -statistic.

Theorem 10.10.1 (Optimality property of U -statistics; Serfling [1980, Section 5.14, p. 194 of pdf, p. 176 of book]). Let $S = S(X_1, \dots, X_n)$ be an unbiased estimator of $\theta(F)$ based on a sample X_1, \dots, X_n from the distribution F . Then the corresponding U -statistic is also unbiased and

$$\text{Var}_F(U) \leq \text{Var}_F(S),$$

with equality if and only if $\mathbb{P}_F(U = S) = 1$.

Proof. The kernel associated with S is

²To see why this is without loss of generality, suppose h is not symmetric. Then replace h with the symmetric kernel $(1/m!) \sum_p h(x_{i_1}, \dots, x_{i_m})$ where \sum_p denotes summation over the $m!$ permutations (i_1, \dots, i_m) of $(1, \dots, m)$.

$$\frac{1}{n!} \sum_p S(x_{i_1}, \dots, x_{i_n}),$$

which in this case $m = n$ is the U -statistic associated with itself. That is, the U -statistic associated with S may be expressed as $U = \mathbb{E}(S | \mathbf{X}_{(n)})$. Therefore

$$\mathbb{E}_F(U^2) = \mathbb{E}_F\left(\left[\mathbb{E}_F(S | \mathbf{X}_{(n)})\right]^2\right) \leq \mathbb{E}_F\left(\mathbb{E}_F(S^2 | \mathbf{X}_{(n)})\right) = \mathbb{E}_F(S^2),$$

where the inequality follows from the fact that

$$\text{Var}_F(S | \mathbf{X}_{(n)}) = \mathbb{E}_F(S^2 | \mathbf{X}_{(n)}) - [\mathbb{E}_F(S | \mathbf{X}_{(n)})]^2 \geq 0.$$

with equality if and only if $\mathbb{E}_F(S | \mathbf{X}_{(n)})$ equals S with probability 1. Since $\mathbb{E}_F(U) = \mathbb{E}_F(S)$, the proof is complete. \square

Remark 156. Since $\mathbf{X}_{(n)}$ is sufficient for any family of distributions containing F , the U -statistic is the result of conditioning on a sufficient statistic. Therefore this result is simply a special case of the Rao-Blackwell theorem (Theorem 10.4.1). This further implies that if $\mathbf{X}_{(n)}$ is complete sufficient then the U -statistic is the MVUE of θ by Lehmann-Scheffe (Theorem 10.4.3).

Next we will find the variance of a U -statistic. In order to do this, we will establish some notation that will be useful.

Definition 10.58 (Notation from Section 5.1.5 of Serfling [1980]). For a symmetric kernel $h(x_1, \dots, x_m)$ satisfying $\mathbb{E}_F|h(X_1, \dots, X_m)| < \infty$, we define the associated functions

$$h_c(x_1, \dots, x_c) := \mathbb{E}_F[h(x_1, \dots, x_c, X_{c+1}, \dots, X_m)] = \mathbb{E}_F[h(X_1, \dots, X_m) | (X_1, \dots, X_c) = (x_1, \dots, x_c)]$$

for each $c \in [m-1]$, and define $h_m := h$. Note that for $1 \leq c \leq m-1$,

$$h_c(x_1, \dots, x_c) = \mathbb{E}_F[h_{c+1}(x_1, \dots, x_c, X_{c+1})].$$

Recall $\theta(F) = \mathbb{E}_F[h(X_1, \dots, X_m)]$. Define

$$\tilde{h} := h - \theta(F)$$

and

$$\tilde{h}_c := h_c - \theta(F), \quad c \in [m].$$

Remark 157. Note that since by Definition 10.57

$$U_n = \frac{1}{\binom{n}{m}} \sum_c h(X_{i_1}, \dots, X_{i_m}),$$

it holds that

$$\begin{aligned} U_n - \theta &= \binom{n}{m}^{-1} \sum_c h(X_{i_1}, \dots, X_{i_m}) - \binom{n}{m}^{-1} \binom{n}{m} \theta \\ &= \binom{n}{m}^{-1} \sum_c [h(X_{i_1}, \dots, X_{i_m}) - \theta] \\ &= \binom{n}{m}^{-1} \sum_c \tilde{h}(X_{i_1}, \dots, X_{i_m}). \end{aligned} \quad (10.65)$$

Definition 10.59 (From Section 5.2.1 of Serfling [1980]). Consider a symmetric kernel satisfying $E_F[h^2(X_1, \dots, X_m)] < \infty$. Note that

$$\mathbb{E}_F \tilde{h}_c(X_1, \dots, X_c) = \mathbb{E}_F (\mathbb{E}_F [h(x_1, \dots, x_c, X_{c+1}, \dots, X_m)] - \theta) = 0, \quad \forall c \in [m].$$

Define $\zeta_0 := 0$ and for $c \in [m]$

$$\zeta_c := \text{Var}_F [h_c(X_1, \dots, X_c)] = \mathbb{E}_F [\tilde{h}_c^2(X_1, \dots, X_c)].$$

Example 10.56 (Example A in Section 5.2.1 of Serfling [1980]; extension of Example 10.55).

Again, let $m = 2$ and $h(x_1, x_2) = (x_1 - x_2)^2/2$. We have already shown in Example 10.55 that this U -statistic corresponds to the sample variance; that is, $\mathbb{E}_F[h(X_1, X_2)] = \sigma^2(F) =: \theta(F)$. We have

$$\begin{aligned} \tilde{h}(x_1, x_2) &= h(x_1, x_2) - \sigma^2, \\ h_1(x) &= \mathbb{E}_F [h(X_1, X_2) \mid X_1 = x] = \mathbb{E}_F \left[\frac{1}{2} (x - X_2)^2 \right] = \frac{1}{2} \mathbb{E}_F [x^2 - 2xX_2 + X_2^2] \\ &= \frac{1}{2} (x^2 - 2x\mu + \sigma^2 + \mu^2), \\ \tilde{h}_1(x) &= \frac{1}{2} (x^2 - 2x\mu + \sigma^2 + \mu^2) - \sigma^2 = \frac{1}{2} (x^2 - 2x\mu - \sigma^2 + \mu^2) = \frac{1}{2} ([x - \mu]^2 - \sigma^2), \\ \zeta_1 &= \mathbb{E}_F [\tilde{h}_1^2(X_1)] = \mathbb{E}_F \left[\frac{1}{2} ([X_1 - \mu]^2 - \sigma^2) \right]^2 = \frac{1}{4} \text{Var}_F [(X_1 - \mu)^2] = \frac{1}{4} (\mu_4 - \sigma^4), \\ \mathbb{E}(h^2) &= \frac{1}{4} \mathbb{E} [(X_1 - X_2)^2]^2 = \frac{1}{4} \mathbb{E} [(X_1 - \mu) - (X_2 - \mu)]^4 \\ &= \frac{1}{4} \sum_{j=0}^4 \binom{4}{j} (-1)^{4-j} \mathbb{E} [(X_1 - \mu)^j] \mathbb{E} [(X_2 - \mu)^{4-j}] = \frac{1}{4} (2\mu_4 + 6\sigma^4), \\ \zeta_2 &= \mathbb{E}_F [\tilde{h}_2^2(X_1, X_2)] = \mathbb{E}_F [(h(X_1, X_2) - \sigma^2)^2] = \mathbb{E}_F [h^2(X_1, X_2) - 2\sigma^2 h(X_1, X_2) + \sigma^4] \\ &= \mathbb{E}_F [h^2(X_1, X_2)] - \sigma^4 = \frac{1}{4} (2\mu_4 + 6\sigma^4) - \sigma^4 = \frac{1}{2} (\mu_4 + \sigma^4). \end{aligned}$$

Proposition 10.10.2 (Problem 5.P.3(i) in Serfling [1980]).

$$0 = \zeta_0 \leq \zeta_1 \leq \dots \leq \zeta_m = \text{Var}_F(h) < \infty.$$

Proposition 10.10.3 (Problem 5.P.4 in Serfling [1980]). Consider two sets $\{a_1, \dots, a_m\} \subset [n]$ and $\{b_1, \dots, b_m\} \subset [n]$ of distinct integers. Let $c = |\{a_1, \dots, a_m\} \cap \{b_1, \dots, b_m\}|$ be the number of integers common to both. Then by symmetry of \tilde{h} and independence of $\{X_1, \dots, X_n\}$,

$$\mathbb{E}_F [\tilde{h}(X_{a_1}, \dots, X_{a_m}) \tilde{h}(X_{b_1}, \dots, X_{b_m})] = \zeta_c.$$

Remark 158. Note also that the number of distinct choices for two such sets having exactly c elements in common is $\binom{n}{m} \binom{m}{c} \binom{n-m}{m-c}$. Also, since $\mathbb{E}_F \tilde{h} = 0$, we have that

$$\zeta_c = \text{Cov} (\tilde{h}(X_{a_1}, \dots, X_{a_m}), \tilde{h}(X_{b_1}, \dots, X_{b_m})) = \text{Cov} (h(X_{a_1}, \dots, X_{a_m}), h(X_{b_1}, \dots, X_{b_m}))$$

$$h_c(x_1, \dots, x_c) = \mathbb{E}_F [h_{c+1}(x_1, \dots, x_c, X_{c+1})].$$

Now we can find the variance of a U -statistic. We have

$$\begin{aligned} \text{Var}_F(U_n) &= \mathbb{E}_F [(U_n - \theta)^2] \\ (\text{using (10.65)}) \quad &= \mathbb{E}_F \left[\left(\binom{n}{m}^{-1} \sum_c \tilde{h}(X_{i_1}, \dots, X_{i_m}) \right)^2 \right] \\ &= \binom{n}{m}^{-2} \sum_c \sum_c \mathbb{E}_F [\tilde{h}(X_{a_1}, \dots, X_{a_m}) \tilde{h}(X_{b_1}, \dots, X_{b_m})] \\ (\text{by Proposition 10.10.3}) \quad &= \binom{n}{m}^{-2} \sum_{c=0}^n \binom{n}{m} \binom{m}{c} \binom{n-m}{m-c} \zeta_c \\ (\text{using } \zeta_0 = 0) \quad &= \binom{n}{m}^{-1} \sum_{c=1}^n \binom{m}{c} \binom{n-m}{m-c} \zeta_c. \end{aligned} \tag{10.66}$$

Lemma 10.10.4 (Lemma A in Section 5.2.1 of Serfling [1980]). The variance of U_n is given by (10.66) and satisfies

(i)

$$\frac{m^2}{n} \zeta_1 \leq \text{Var}_F(U_n) \leq \frac{m}{n} \zeta_m,$$

(ii)

$$(n+1)\text{Var}_F(U_{n+1}) \leq n\text{Var}_F(U_n), \quad \text{and}$$

(iii)

$$\text{Var}_F(U_n) = \frac{m^2 \zeta_1}{n} + \mathcal{O}(n^{-2}), \quad n \rightarrow \infty.$$

10.10.2 Asymptotics [Serfling, 1980, Section 5.3], [DasGupta, 2008, Section 15.2]

Asymptotic theory for U -statistics is not straightforward since the summands are in general dependent. Hajek had the idea of projecting U onto the class of linear statistics of the form $n^{-1} \sum_{i=1}^n h(X_i)$. It turns out that the projection is the dominant part and determines the limiting distribution of U .

Definition 10.60 (Hajek projection; Definition from Serfling [1980, Section 5.3.1, p. 206 of pdf, p. 188 of book] and Wager and Athey [2018, Section 3.3]). Assume $\mathbb{E}_F|h| < \infty$. Then the **Hajek projection** of the U -statistic U_n is defined as

$$\hat{U}_n := \theta + \sum_{i=1}^n (\mathbb{E}_F[U_n | X_i] - \theta) = \sum_{i=1}^n \mathbb{E}_F[U_n | X_i] - (n-1)\theta$$

Note that it is a sum of i.i.d. random variables. In terms of the function \tilde{h}_1 , we have

$$\hat{U}_n = \theta + \frac{m}{n} \sum_{i=1}^n \tilde{h}_1(X_i).$$

DasGupta [2008] uses a slightly different convention to define U statistics (their definition projects $U - \theta$ rather than U , so their definition equals the above definition minus θ).

Definition 10.61 (Hajek projection; Definition 15.2 in DasGupta [2008]). The **Hajek projection** of $U - \theta$ onto the class of statistics $\sum_{i=1}^n h(X_i)$ is

$$\hat{U} = \hat{U}_n = \sum_{i=1}^n \mathbb{E}_F(U - \theta | X_i).$$

Theorem 10.10.5 (Theorem 15.1 in DasGupta [2008]). Suppose the kernel h is twice integrable; i.e., $\mathbb{E}h^2 < \infty$. Then

$$\sqrt{n}(U - \hat{U}) \xrightarrow{P} 0$$

and

$$\sqrt{n}(U - \theta) \xrightarrow{D} \mathcal{N}(0, m^2 \zeta_1).$$

Definition 10.62 (Definition 6 in Wager and Athey [2018]). U is $\nu(s)$ -incremental if

$$\frac{\text{Var}[\hat{U}]}{\text{Var}[U]} \gtrsim \nu(s),$$

where

$$f(s) \gtrsim g(s) \iff \liminf_{s \rightarrow \infty} \left(\frac{f(s)}{g(s)} \right) \geq 1.$$

(That is, U is $\nu(s)$ -incremental if

$$\liminf_{s \rightarrow \infty} \left(\frac{\text{Var} [\hat{U}] / \text{Var} [U]}{\nu(s)} \right) \geq 1.$$

10.11 Von Mises Differentiable Statistical Functions and Influence Functions (Section 6.6.1 of Serfling [1980], Chapter 9 of Demidenko [2013]; Section 1.6 of Koroljuk et al. [1994]; Section 10.5 of Efron and Hastie [2016], Shao and Tu [2012], Hampel [1974], Section 30.4 of DasGupta [2008])

Statistical functions are statistics that are representable as functionals $T(F_n)$ of the sample distribution F_n . (Examples include the sample mean and variance.) Typically $T(F_n) - T(F)$ is asymptotically normal.

Definition 10.63 (Linear statistical function). For any function $h(x)$, the statistic

$$T_n = \int h(x) dF_n(x)$$

is a **linear statistical function** (linear in the increments $dF_n(x)$). In particular, the sample moments are linear statistical functions. (If the random variable is discrete-valued, we can write this as

$$\frac{1}{n} \sum_{i=1}^n h(X_i).$$

Example 10.57. Linear statistic functions are statistical functions. Other examples of statistical functions are sample central moments and maximum likelihood estimates.

Proposition 10.11.1 (Informal). The type of asymptotic distribution of a differentiable statistical function $T_n = T(F_n)$ depends upon which is the nonvanishing term in the Taylor series of the functional $T(\cdot)$ at the distribution F of the observations. If it is the linear term, the limit distribution is normal (under the usual restrictions corresponding to the central limit theorem). In other cases, “higher” types of limit distribution result.

10.12 M-Estimators (Chapter 7 of Serfling [1980], Chapter 17 of DasGupta [2008])

Many estimation methods are based on minimization of some function of the observations $\{X_i\}$ and the unknown parameter θ , e.g. the least squares estimator

$$\hat{\theta} = \arg \min_{\theta} \{d(\theta; X_1, \dots, X_n)\} = \arg \min_{\theta} \left\{ \sum_{i=1}^n (X_i - \theta)^2 \right\}.$$

Similarly, the least absolute values estimator of θ is given by

$$\hat{\theta} = \arg \min_{\theta} \left\{ \sum_{i=1}^n |X_i - \theta| \right\}.$$

Maximum likelihood estimation may be regarded as an approach of this type as well. Typically the problem of minimizing a function of data and a parameter reduces to a problem involving solving a system of equations for an estimator $\hat{\theta}$. Statistics given as solutions of equations are called **M-statistics**.

Chapter 11

Linear Regression

These notes are based on my notes from *Time Series and Panel Data Econometrics* (1st edition) by M. Hashem Pesaran [Pesaran, 2015] and coursework for Economics 613: Economic and Financial Time Series I at USC taught by M. Hashem Pesaran, DSO 607 at USC taught by Jinchi Lv, Statistics 100B at UCLA taught by Nicolas Christou, GSBA 604: Regression and Generalized Linear Models for Business Applications at USC taught by Gourab Mukherjee, and the Coursera MOOC “Econometrics: Methods and Applications” from Erasmus University Rotterdam. I also borrowed from some other sources which I mention when I use them.

11.1 Chapter 1: Linear Regression

11.1.1 Preliminaries

Suppose the true model is $y_i = \alpha + \beta x_i + \epsilon_i$. Classical assumptions:

- (i) $\mathbb{E}(\epsilon_i) = 0$
- (ii) $\text{Var}(\epsilon_i | x_i) = \sigma^2$ (constant)
- (iii) $\text{Cov}(\epsilon_i, \epsilon_j) = 0$ if $i \neq j$
- (iv) ϵ_i is uncorrelated to x_i , or $\mathbb{E}(\epsilon_i | x_j) = 0$ for all i, j .

11.1.2 Estimation

$$\hat{\beta} = \frac{n \sum_{i=1}^n x_i y_i - \sum_{i=1}^n x_i \sum_{i=1}^n y_i}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2} = \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - n \bar{x}^2}$$

$$\hat{\alpha} = \bar{y} - \hat{\beta} \bar{x}$$

or

$$\hat{\beta} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{S_{XY}}{S_{XX}}$$

or

$$\hat{\beta} = r \frac{S_{YY}}{S_{XX}}$$

where r is the correlation coefficient.

Let

$$w_i = \frac{x_i - \bar{x}}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

so that

$$\hat{\beta} = \sum_{i=1}^n w_i (y_i - \bar{y}) = \sum_{i=1}^n w_i y_i - \bar{y} \frac{\sum_{i=1}^n x_i - \bar{x}}{\sum_{i=1}^n (x_i - \bar{x})^2} = \sum_{i=1}^n w_i y_i$$

since $\sum_{i=1}^n x_i - \bar{x} = 0$. Then a simple expression for $\text{Var}(\hat{\beta})$ is

$$\text{Var}(\hat{\beta}) = \sum_{i=1}^n w_i^2 \text{Var}(y_i | x_i) = \sum_{i=1}^n w_i^2 \text{Var}(\epsilon | x_i) = \sigma^2 \sum_{i=1}^n w_i^2 = \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\sigma^2}{S_{XX}}$$

We can estimate these quantities as follows:

$$\hat{\sigma}^2 = \frac{1}{n-2} \cdot \sum_{i=1}^n (y_i - \hat{\alpha} - \hat{\beta} x_i)^2$$

Note that

$$\begin{aligned} \hat{\sigma}^2 &= \frac{1}{n-2} \sum_{t=1}^T (y_t - \hat{\alpha} - \hat{\beta} x_t)^2 = \frac{1}{n-2} \sum_{t=1}^T [(y_t - (\bar{y} - \hat{\beta} \bar{x})) - \hat{\beta} x_t]^2 = \frac{1}{n-2} \sum_{t=1}^T (y_t - \bar{y} - \hat{\beta}(x_t - \bar{x}))^2 \\ &= \frac{1}{n-2} \sum_{t=1}^T (y_t - \bar{y})^2 - 2\hat{\beta}(x_t - \bar{x})(y_t - \bar{y}) + \hat{\beta}^2(x_t - \bar{x})^2 \end{aligned}$$

In the case where there is no intercept, we have

$$\hat{\sigma}^2 = \frac{1}{T-1} \sum_{t=1}^T (y_t - \hat{\beta} x_t)^2 = \frac{1}{T-1} \sum_{t=1}^T \left(y_t^2 - 2r \frac{S_{YY}}{S_{XX}} x_t y_t + r^2 \frac{S_{YY}^2}{S_{XX}^2} x_t^2 \right)$$

Also,

$$\widehat{\text{Var}}(\hat{\beta}) = \frac{\hat{\sigma}^2}{S_{XX}} = \frac{1}{n-2} \cdot \frac{\sum_{i=1}^n (y_i - \hat{\alpha} - \hat{\beta}x_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

Correlation coefficient:

$$r^2 = \frac{(\sum_{t=1}^T x_t y_t)^2}{\sum_{t=1}^T x_t^2 \sum_{t=1}^T y_t^2}$$

$$r = \frac{1}{T-1} \frac{S_{XY}}{\sqrt{S_{XX} S_{YY}}}$$

Remark 159. The formulas for the coefficients in univariate OLS can also be derived by considering (x, y) as a bivariate normal distribution and calculating the conditional expectation of y given x . (See Proposition (6.3.36).)

Proposition 11.1.1 (Stats 100B homework problem). Consider the regression model $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$ with x_i fixed and $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$, ϵ_i i.i.d. Let $e_i = y_i - \hat{y}_i$ be the residuals.

(a)

$$\sum_{i=1}^n e_i = 0$$

(b) $\text{Cov}(\bar{Y}, \hat{\beta}_1) = 0$ where \bar{Y} is the sample mean of the y values.

(c)

$$\text{Cov}(e_i, e_j) = \sigma^2 \left(-\frac{1}{n} - \frac{(x_i - \bar{x})(x_j - \bar{x})}{\sum_{k=1}^n (x_k - \bar{x})^2} \right)$$

(d) We can construct a confidence interval for σ^2 as

$$\Pr \left(\frac{\sum_{i=1}^n e_i^2}{\chi^2_{1-\frac{\alpha}{2}; n-2}} \leq \sigma^2 \leq \frac{\sum_{i=1}^n e_i^2}{\chi^2_{\frac{\alpha}{2}; n-2}} \right) = 1 - \alpha$$

Proof. (a)

$$\begin{aligned} \sum_{i=1}^n e_i &= \sum_{i=1}^n (y_i - \hat{y}_i) = \sum_{i=1}^n (y_i - [\bar{y} + \hat{\beta}_1(x_i - \bar{x})]) \\ &= \sum_{i=1}^n \left(y_i - \bar{y} - \frac{\sum(x_i - \bar{x})y_i}{\sum(x_i - \bar{x})^2}(x_i - \bar{x}) \right) = \sum_{i=1}^n y_i - n\bar{y} - \frac{\sum(x_i - \bar{x})y_i}{\sum(x_i - \bar{x})^2} \sum_{i=1}^n (x_i - \bar{x}) \\ &= \sum_{i=1}^n y_i - n\frac{1}{n} \sum_{i=1}^n y_i - \left(\frac{\sum(x_i - \bar{x})y_i}{\sum(x_i - \bar{x})^2} \right) \left[\sum_{i=1}^n \left(x_i - \frac{1}{n} \sum_{i=1}^n x_i \right) \right] \\ &= \sum_{i=1}^n (y_i - \bar{y}) - \left(\frac{\sum(x_i - \bar{x})y_i}{\sum(x_i - \bar{x})^2} \right) \left[\sum_{i=1}^n x_i - \frac{1}{n} \cdot n \sum_{i=1}^n x_i \right] = 0 - 0 = \boxed{0} \end{aligned}$$

Or:

$$\sum_{i=1}^n e_i = \sum_{i=1}^n (y_i - \hat{y}_i) = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = \sum_{i=1}^n (y_i - (\bar{y} - \hat{\beta}_1 \bar{x}) - \hat{\beta}_1 x_i)$$

$$= \sum_{i=1}^n (y_i - \bar{y}) - \hat{\beta}_1 \sum_{i=1}^n (x_i - \bar{x}) = 0$$

(b)

$$\text{Cov}(\bar{Y}, \hat{\beta}_1) = \text{Cov}\left(\frac{1}{n} \sum_{i=1}^n Y_i, \frac{\sum_{i=1}^n (x_i - \bar{x}) Y_i}{\sum_{i=1}^n (x_i - \bar{x})^2}\right) = \frac{1}{n \sum_{i=1}^n (x_i - \bar{x})^2} \text{Cov}\left(\sum_{i=1}^n Y_i, \sum_{i=1}^n (x_i - \bar{x}) Y_i\right)$$

x_i is fixed, $\text{Cov}(Y_i, Y_j) = 0$ for $i \neq j$ by assumption of the model, $\text{Var}(Y_i) = \sigma^2$ by assumption of the model.

$$= \frac{1}{n \sum_{i=1}^n (x_i - \bar{x})^2} \sum_{i=1}^n [(x_i - \bar{x}) \text{Var}(Y_i)] = \frac{\sigma^2}{n \sum_{i=1}^n (x_i - \bar{x})^2} \sum_{i=1}^n (x_i - \bar{x}) = \boxed{0}$$

(c)

$$\text{Cov}(e_i, e_j) = \text{Cov}(y_i - \bar{y} - \hat{\beta}_1(x_i - \bar{x}), y_j - \bar{y} - \hat{\beta}_1(x_j - \bar{x}))$$

$$\begin{aligned} &= \text{Cov}(y_i, y_j) - \text{Cov}(y_i, \bar{y}) - \text{Cov}(y_i, \hat{\beta}_1(x_j - \bar{x})) - \text{Cov}(\bar{y}, y_j) + \text{Cov}(\bar{y}, \bar{y}) + \text{Cov}(\bar{y}, \hat{\beta}_1(x_j - \bar{x})) - \text{Cov}(\hat{\beta}_1(x_i - \bar{x}), y_j) \\ &\quad + \text{Cov}(\hat{\beta}_1(x_i - \bar{x}), \bar{y}) + \text{Cov}(\hat{\beta}_1(x_i - \bar{x}), \hat{\beta}_1(x_j - \bar{x})) \end{aligned}$$

By assumption of the model, $\text{Cov}(y_i, y_j) = 0$.

$$= 0 - \text{Cov}(y_i, \bar{y}) - (x_j - \bar{x}) \text{Cov}(y_i, \hat{\beta}_1) - \text{Cov}(\bar{y}, y_j) + \text{Var}(\bar{y}) + (x_j - \bar{x}) \text{Cov}(\bar{y}, \hat{\beta}_1) - (x_i - \bar{x}) \text{Cov}(\hat{\beta}_1, y_j)$$

$$+ (x_i - \bar{x}) \text{Cov}(\hat{\beta}_1, \bar{y}) + (x_i - \bar{x})(x_j - \bar{x}) \text{Cov}(\hat{\beta}_1, \hat{\beta}_1)$$

In part 7(b) we showed $\text{Cov}(\bar{y}, \hat{\beta}_1) = 0$. $\text{Var}(\bar{y}) = \sigma^2/n$. $\text{Cov}(\hat{\beta}_1, \hat{\beta}_1) = \text{Var}(\hat{\beta}_1) = \sigma^2 / \sum (x_k - \bar{x})^2$. So this simplifies to

$$\begin{aligned} &= -\text{Cov}(y_i, \bar{y}) - (x_j - \bar{x}) \text{Cov}(y_i, \hat{\beta}_1) - \text{Cov}(y_j, \bar{y}) + \frac{\sigma^2}{n} + 0 - (x_i - \bar{x}) \text{Cov}(y_j, \hat{\beta}_1) + 0 + (x_i - \bar{x})(x_j - \bar{x}) \frac{\sigma^2}{\sum_{k=1}^n (x_k - \bar{x})^2} \\ &= -\text{Cov}(y_i, \bar{y}) - (x_j - \bar{x}) \text{Cov}(y_i, \hat{\beta}_1) - \text{Cov}(y_j, \bar{y}) + \frac{\sigma^2}{n} - (x_i - \bar{x}) \text{Cov}(y_j, \hat{\beta}_1) + (x_i - \bar{x})(x_j - \bar{x}) \frac{\sigma^2}{\sum_{k=1}^n (x_k - \bar{x})^2} \end{aligned} \tag{11.1}$$

Find $\text{Cov}(y_i, \bar{y})$, $\text{Cov}(y_j, \bar{y})$, $\text{Cov}(y_i, \hat{\beta}_1)$, and $\text{Cov}(y_j, \hat{\beta}_1)$:

Using that x_i is fixed, $\text{Cov}(Y_i, Y_j) = 0$ for $i \neq j$ by assumption of the model, $\text{Var}(Y_i) = \sigma^2$ by assumption of the model:

$$\text{Cov}(y_i, \bar{y}) = \text{Cov}\left(y_i, \frac{1}{n} \sum_{k=1}^n y_k\right) = \frac{1}{n} \text{Cov}(y_i, y_i) = \frac{\sigma^2}{n}$$

Similarly,

$$\text{Cov}(y_j, \bar{y}) = \frac{\sigma^2}{n}$$

$$\begin{aligned} \text{Cov}(y_i, \hat{\beta}_1) &= \text{Cov}\left(y_i, \frac{\sum_{k=1}^n (x_k - \bar{x}) y_k}{\sum_{k=1}^n (x_k - \bar{x})^2}\right) = \frac{1}{\sum_{k=1}^n (x_k - \bar{x})^2} \text{Cov}\left(y_i, \sum_{k=1}^n (x_k - \bar{x}) y_k\right) \\ &= \frac{1}{\sum_{k=1}^n (x_k - \bar{x})^2} \text{Cov}(y_i, (x_i - \bar{x}) y_i) = \frac{x_i - \bar{x}}{\sum_{k=1}^n (x_k - \bar{x})^2} \text{Var}(y_i) = \frac{x_i - \bar{x}}{\sum_{k=1}^n (x_k - \bar{x})^2} \sigma^2 \end{aligned}$$

Similarly,

$$\text{Cov}(y_j, \hat{\beta}_1) = \frac{x_j - \bar{x}}{\sum_{k=1}^n (x_k - \bar{x})^2} \sigma^2$$

Plugging these in to equation (11.1) yields

$$\begin{aligned} \text{Cov}(e_i, e_j) &= -\frac{\sigma^2}{n} - (x_j - \bar{x}) \frac{(x_i - \bar{x}) \sigma^2}{\sum_{k=1}^n (x_k - \bar{x})^2} - \frac{\sigma^2}{n} + \frac{\sigma^2}{n} - (x_i - \bar{x}) \frac{(x_j - \bar{x}) \sigma^2}{\sum_{k=1}^n (x_k - \bar{x})^2} \\ &\quad + (x_i - \bar{x})(x_j - \bar{x}) \frac{\sigma^2}{\sum_{k=1}^n (x_k - \bar{x})^2} \\ &= \frac{-\sigma^2}{n} - \sigma^2 \frac{(x_i - \bar{x})(x_j - \bar{x})}{\sum_{k=1}^n (x_k - \bar{x})^2} \\ \text{Cov}(e_i, e_j) &= \sigma^2 \left(-\frac{1}{n} - \frac{(x_i - \bar{x})(x_j - \bar{x})}{\sum_{k=1}^n (x_k - \bar{x})^2} \right) \end{aligned}$$

(d) From class notes 08/29:

$$\begin{aligned} \frac{(n-2)S_e^2}{\sigma^2} &\sim \chi_{n-2}^2 \\ \implies \Pr\left(\chi_{\frac{\alpha}{2}; n-2}^2 \leq \frac{(n-2)S_e^2}{\sigma^2} \leq \chi_{1-\frac{\alpha}{2}; n-2}^2\right) &= 1 - \alpha \\ \implies \boxed{\Pr\left(\frac{(n-2)S_e^2}{\chi_{1-\frac{\alpha}{2}; n-2}^2} \leq \sigma^2 \leq \frac{(n-2)S_e^2}{\chi_{\frac{\alpha}{2}; n-2}^2}\right)} &= 1 - \alpha \end{aligned}$$

Since

$$S_e^2 = \frac{1}{n-2} \sum_{i=1}^n e_i^2$$

this interval can be expressed as

$$\Pr \left(\frac{\sum_{i=1}^n e_i^2}{\chi^2_{1-\frac{\alpha}{2};n-2}} \leq \sigma^2 \leq \frac{\sum_{i=1}^n e_i^2}{\chi^2_{\frac{\alpha}{2};n-2}} \right) = 1 - \alpha$$

□

Proposition 11.1.2 (Stats 100B homework problem). Suppose $Y_i = \beta_1 x_i + \epsilon_i$ (no intercept). Suppose x_i is fixed and $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$.

(a) The maximum likelihood estimator of β_1 is

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}$$

which is unbiased. Its variance is $\frac{\sigma^2}{\sum_{i=1}^n x_i^2}$ and it is normally distributed.

(b) The maximum likelihood estimator of σ^2 is

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (y_i - \beta_1 x_i)^2.$$

Proof. (a) First we find the likelihood function to find the MLE. Assuming the n observations are independent,

$$\begin{aligned} L &= \prod_{i=1}^n \frac{1}{\sigma \sqrt{2\pi}} \exp \left(-\frac{1}{2\sigma^2} (y_i - \beta_1 x_i)^2 \right) \\ &= (2\sigma^2 \pi)^{-n/2} \exp \left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_1 x_i)^2 \right) \end{aligned}$$

Next,

$$\begin{aligned} \log(L) &= -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_1 x_i)^2 \\ \frac{d \log(L)}{d\beta_1} &= \frac{d}{d\beta_1} \left(-\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_1 x_i)^2 \right) \\ &= \frac{1}{\sigma^2} \sum_{i=1}^n x_i (y_i - \beta_1 x_i) = 0 \\ \sum_{i=1}^n x_i y_i - \hat{\beta}_1 \sum_{i=1}^n x_i^2 &= 0 \\ \implies \hat{\beta}_1 &= \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2} \end{aligned}$$

Next we show that this estimator is unbiased.

$$\mathbb{E}(\hat{\beta}_1) = \mathbb{E}\left(\frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}\right) = \frac{1}{\sum_{i=1}^n x_i^2} \mathbb{E}\left(\sum_{i=1}^n x_i (\beta_1 x_i + \epsilon_i)\right) = \frac{1}{\sum_{i=1}^n x_i^2} \left[\mathbb{E}\left(\sum_{i=1}^n x_i^2 \beta_1\right) + E\left(\sum_{i=1}^n x_i \epsilon_i\right) \right]$$

Since x_i and β_1 are non-random and ϵ_i are independent, this can be written as

$$\frac{1}{\sum_{i=1}^n x_i^2} \left[\sum_{i=1}^n x_i^2 \beta_1 + \sum_{i=1}^n x_i \mathbb{E}(\epsilon_i) \right] = \frac{1}{\sum_{i=1}^n x_i^2} \beta_1 \sum_{i=1}^n x_i^2 = \beta_1$$

Next we find the variance.

$$\begin{aligned} \text{Var}(\hat{\beta}_1) &= \text{Var}\left(\frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}\right) = \frac{1}{(\sum_{i=1}^n x_i^2)^2} \text{Var}\left(\sum_{i=1}^n x_i (\beta_1 x_i + \epsilon_i)\right) \\ &= \frac{1}{(\sum_{i=1}^n x_i^2)^2} \left[\text{Var}\left(\sum_{i=1}^n x_i^2 \beta_1\right) + \text{Var}\left(\sum_{i=1}^n x_i \epsilon_i\right) \right] \end{aligned}$$

Since x_i and β_1 are non-random and ϵ_i are independent, this can be written as

$$\frac{1}{(\sum_{i=1}^n x_i^2)^2} \left[0 + \sum_{i=1}^n x_i^2 \text{Var}(\epsilon_i) \right] = \frac{1}{(\sum_{i=1}^n x_i^2)^2} \sigma^2 \sum_{i=1}^n x_i^2 = \frac{\sigma^2}{\sum_{i=1}^n x_i^2}$$

β_1 is a linear combination of y_i which is normally distributed, therefore β_1 is normally distributed.

$$\implies \beta_1 \sim \mathcal{N}\left(\beta_1, \frac{\sigma}{\sqrt{\sum_{i=1}^n x_i^2}}\right)$$

(b)

$$\frac{d \log(L)}{d\sigma^2} = \frac{d}{d\sigma^2} \left(-\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_1 x_i)^2 \right)$$

$$= -\frac{n}{2} \frac{1}{2\pi\sigma^2} 2\pi - \frac{1}{2} \left(-\frac{1}{(\sigma^2)^2} \right) \sum_{i=1}^n (y_i - \beta_1 x_i)^2 = -\frac{n}{2\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum_{i=1}^n (y_i - \beta_1 x_i)^2 = 0$$

$$\frac{1}{2(\hat{\sigma}^2)^2} \sum_{i=1}^n (y_i - \beta_1 x_i)^2 = \frac{n}{2\hat{\sigma}^2}$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (y_i - \beta_1 x_i)^2$$

□

Remark 160. More details on this problem available in Math 541A Homework 7.

11.2 Chapter 2: Multiple Regression

General OLS:

$$\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'y = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(\mathbf{X}\beta + u) = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}\beta + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'u = \beta + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'u$$

$$\begin{aligned} \text{Var}(\hat{\beta}) &= \text{Var}(\beta + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'u) = \text{Var}(\beta) + \text{Var}((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'u) = 0 + \mathbb{E}[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'uu'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}] \\ &= \mathbb{E}[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbb{E}(uu' | X)\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}] = \sigma^2\mathbb{E}[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'I_T\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}] = \sigma^2\mathbb{E}[(\mathbf{X}'\mathbf{X})^{-1}] \\ &= \sigma^2(\mathbf{X}'\mathbf{X})^{-1} \end{aligned}$$

Or:

$$\text{Var}[(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^Ty] = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\text{Var}[y]\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T[\sigma^2 I_n]\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}$$

$$= \sigma^2(\mathbf{X}^T\mathbf{X})^{-1}$$

$$\hat{\sigma}^2 = \frac{\hat{\mathbf{u}}'\hat{\mathbf{u}}}{T-k}$$

Proposition 11.2.1 (GSBA 604 Problem). A necessary and sufficient condition for $a'\beta$ to be estimable in a linear model is that a is in the column space of \mathbf{X} .

Proof. Let $a \in \mathbb{R}^{(p+1) \times k}$. A linear combination $a^T\beta \in \mathbb{R}^k$ is estimable if and only if there exists a $\gamma \in \mathbb{R}^{n \times k}$ so that the linear combination $\gamma^T y$ satisfies $\mathbb{E}(\gamma^T y) = a^T\beta$ for all β . That is,

$$\mathbb{E}(\gamma^T y) = a^T\beta \iff \gamma^T \mathbf{X}\beta = a^T\beta \iff \mathbf{X}^T\gamma = a;$$

that is, the columns of a lie in the column space of \mathbf{X}^T .

□

Proposition 11.2.2 (GSBA 604 Problem). Suppose $a'\beta$ is estimable in a linear model. Then its best linear unbiased estimator (BLUE) is unique.

Proof. Let $a \in \mathbb{R}^{(p+1) \times k}$. The BLUE of $a'\beta \in \mathbb{R}^k$ is a random variable solving the equation

$$\underset{b \in \mathbb{R}^k, \mathbb{E}(b)=a'\beta}{\text{minimize}} \quad \text{Var}(b) = \underset{b \in \mathbb{R}^k, \mathbb{E}(b)=a'\beta}{\text{minimize}} \quad \mathbb{E}(b - \mathbb{E}(b))^2 = \underset{b \in \mathbb{R}^k, \mathbb{E}(b)=a'\beta}{\text{minimize}} \quad \mathbb{E}(b - a'\beta)^2$$

This objective is strictly convex in b . From Exercise 1 we know that the set of vectors $b \in \mathbb{R}^k$ satisfying $\mathbb{E}(b) = \alpha^T \beta$ are linear combinations of vectors in the column space of X^T ; that is, this set of vectors is the column space of X^T , which is a subspace and therefore convex. Therefore the minimizer of this problem exists and is unique.

□

Remark 161. By Theorem 11.2.5, the best linear unbiased estimator is $A\hat{\beta}_{OLS}$. We have

$$A\hat{\beta}_{OLS} = A(A^T A)^{-1} A^T y$$

which is unique if it exists (if $A^T A$ is invertible).

Theorem 11.2.3 (Gauss-Markov Theorem, as stated in Pesaran [2015]). Suppose we have data generated by

$$y = X\beta + \epsilon$$

and we make the following assumptions.

1. $\mathbb{E}(\epsilon) = 0$.
2. Homoskedasticity: $\text{Var}(\epsilon_i | X) = \sigma^2 > 0 \quad \forall i$
3. Uncorrelated errors: $\text{Cov}(\epsilon_i, \epsilon_j | X) = 0, \quad \forall i \neq j$.
4. Orthogonality: $\mathbb{E}(\epsilon_i | X) = 0, \quad \forall i$.

Then if $X\beta$ is estimable, then the best linear unbiased estimator (BLUE) of β is $\hat{\beta}_{OLS}$, the least squares estimate. That is, if $\tilde{\beta}$ is an alternative linear unbiased estimator, where $\tilde{\beta} = \hat{\beta}_{OLS} + C^T y$ with $C \in \mathbb{R}^{n \times p}$ and $\mathbb{E}(\tilde{\beta}) = \beta$ for all β , then $\text{Var}(\tilde{\beta} | X) \geq \text{Var}(\hat{\beta}_{OLS} | X)$.

Proof (adapted from Pesaran [2015]). Note that $\text{Var}(\hat{\beta}_{OLS} | X) \leq \text{Var}(\tilde{\beta} | X) \iff \text{Var}(\tilde{\beta} | X) - \text{Var}(\hat{\beta}_{OLS} | X)$ is a positive semidefinite matrix. We have

$$\tilde{\beta} = [(X^T X)^{-1} X^T + C^T]y = [(X^T X)^{-1} X^T + C^T](X\beta + \epsilon) = \beta + (X^T X)^{-1} X^T \epsilon + C^T X \beta + C^T \epsilon$$

Since $\mathbb{E}(\tilde{\beta}) = \beta$ for all β , we have $C^T X \beta = 0$ for all β , so $C^T X = 0$. (Note that since $n \geq p$, $C^T \in \mathbb{R}^{p \times n}$ has at least an $n - p$ -dimensional nullspace.)

$$\implies \tilde{\beta} = \beta + (X^T X)^{-1} X^T \epsilon + C^T \epsilon \iff \tilde{\beta} - \beta = [(X^T X)^{-1} X^T + C^T]\epsilon \tag{11.2}$$

Then

$$\text{Var}(\tilde{\beta}) = \mathbb{E}[(\tilde{\beta} - \beta)(\tilde{\beta} - \beta)^T] = \mathbb{E}[\tilde{\beta}\tilde{\beta}^T - \tilde{\beta}\beta^T - \beta\tilde{\beta}^T + \beta\beta^T] \tag{11.3}$$

Using (11.2) we have

$$\begin{aligned}
& \mathbb{E} [\tilde{\beta} \tilde{\beta}^T] = \mathbb{E} [(\beta + (X^T X)^{-1} X^T \epsilon + C^T \epsilon)(\beta + (X^T X)^{-1} X^T \epsilon + C^T \epsilon)^T] \\
&= \mathbb{E} [\beta \beta^T + \beta \epsilon^T X (X^T X)^{-1} + \beta \epsilon^T X + (X^T X)^{-1} X^T \epsilon \beta^T + (X^T X)^{-1} X^T \epsilon \epsilon^T X (X^T X)^{-1} \\
&\quad + (X^T X)^{-1} X^T \epsilon \epsilon^T C + C^T \epsilon \beta^T + C^T \epsilon \epsilon^T X (X^T X)^{-1} + C^T \epsilon \epsilon^T C] \\
&= \beta \beta^T + (X^T X)^{-1} X^T \mathbb{E} [\epsilon \epsilon^T] X (X^T X)^{-1} + (X^T X)^{-1} X^T \mathbb{E} [\epsilon \epsilon^T] C + C^T \mathbb{E} [\epsilon \epsilon^T] X (X^T X)^{-1} + C^T \mathbb{E} [\epsilon \epsilon^T] C \\
&= \beta \beta^T + \sigma^2 (X^T X)^{-1} + \sigma^2 (X^T X)^{-1} X^T C + \sigma^2 C^T X (X^T X)^{-1} + \sigma^2 C^T C \\
&= \beta \beta^T + \sigma^2 (X^T X)^{-1} + \sigma^2 C^T C
\end{aligned} \tag{11.4}$$

Also,

$$\begin{aligned}
& \tilde{\beta} \tilde{\beta}^T = (\beta + (X^T X)^{-1} X^T \epsilon + C^T \epsilon) \beta^T = \beta \beta^T + (X^T X)^{-1} X^T \epsilon \beta^T + C^T \epsilon \beta^T \\
& \implies \mathbb{E}(\tilde{\beta} \tilde{\beta}^T) = \beta \beta^T, \quad \mathbb{E}(\tilde{\beta} \tilde{\beta}^T) = \mathbb{E}([\tilde{\beta} \tilde{\beta}^T]^T) = \beta \beta^T.
\end{aligned} \tag{11.5}$$

Substituting (11.4) and (11.5) into (11.3), we have

$$\begin{aligned}
\text{Var}(\tilde{\beta}) &= \beta \beta^T + \sigma^2 (X^T X)^{-1} + \sigma^2 C^T C - 2\beta \beta^T + \beta \beta^T \\
&= \sigma^2 [(X^T X)^{-1} + C^T C]
\end{aligned}$$

Therefore (using $\text{Var}(\hat{\beta}_{OLS}) = \sigma^2 (X^T X)^{-1}$)

$$\text{Var}(\tilde{\beta}) - \text{Var}(\hat{\beta}_{OLS}) = \sigma^2 [(X^T X)^{-1} + C^T C - (X^T X)^{-1}] = \sigma^2 C^T C$$

which is a positive semidefinite matrix since the inner product of a matrix with itself is positive semidefinite (see Proposition 2.3.1).

□

Theorem 11.2.4 (Gauss-Markov Theorem, as stated in Faraway [2002]). Suppose

$$y = X\beta + \epsilon$$

with $X \in \mathbb{R}^{n \times p}$ a fixed full rank matrix and $n \geq p$, $\beta \in \mathbb{R}^p$, and $\epsilon \in \mathbb{R}^n$ with $\mathbb{E}(\epsilon) = 0$ and $\text{Var}(\epsilon) = \sigma^2 I_n$. Suppose X is fixed ($\mathbb{E}(Y) = X\beta$). Let $\psi : \mathbb{R}^p \rightarrow \mathbb{R}$ be an estimable function: $\psi := c^T \beta$ for some $c \in \mathbb{R}^p$. Then in the class of all unbiased linear estimates of ψ , $\hat{\psi} = c^T \hat{\beta}$ has the minimum variance and is unique.

Proof (adapted from Faraway [2002]). Suppose for some $a \in \mathbb{R}^n$, $a^T y$ is another unbiased estimator of $c^T \beta$ so that

$$\mathbb{E}(a^T y) = a^T X \beta = c^T \beta, \quad \forall \beta \in \mathbb{R}^p.$$

This implies

$$a^T X = c^T \iff X^T a = c, \quad (11.6)$$

Since X has full column rank, $X^T X$ is full rank and its column space is all of \mathbb{R}^p , so there exists a unique $\lambda \in \mathbb{R}^p$ such that

$$c = X^T X \lambda = X^T a \quad (11.7)$$

(Note that $a = X\lambda + k$ where $k \in \mathbb{R}^n$ is any vector in the $n - p$ -dimensional nullspace of X^T .) Then

$$\begin{aligned} \text{Var}(a^T y) &= \text{Var}(a^T y - c^T \hat{\beta} + c^T \hat{\beta}) = \text{Var}(a^T y - \lambda^T X^T \hat{y} + c^T \hat{\beta}) \\ &= \text{Var}(a^T y - \lambda^T X^T \hat{y}) + \text{Var}(c^T \hat{\beta}) + 2\text{Cov}(a^T y - \lambda^T X^T \hat{y}, c^T \hat{\beta}) \geq \text{Var}(c^T \hat{\beta}) + 2\text{Cov}(a^T y - \lambda^T X^T \hat{y}, c^T \hat{\beta}), \end{aligned} \quad (11.8)$$

so we are done if the covariance in (11.8) is nonnegative.

$$\begin{aligned} \text{Cov}(a^T y - \lambda^T X^T \hat{y}, c^T \hat{\beta}) &= \mathbb{E} \left[(a^T y - \lambda^T X^T \hat{y} - \mathbb{E}[a^T y - \lambda^T X^T \hat{y}]) (c^T \hat{\beta} - \mathbb{E}[c^T \hat{\beta}]) \right] \\ &= \mathbb{E} \left[(a^T (X\beta + \epsilon) - \lambda^T X^T X \hat{\beta} - a^T X \beta + \lambda^T X^T X \beta) (c^T \hat{\beta} - c^T \beta) \right] \\ &= \mathbb{E} \left[(a^T \epsilon - \lambda^T X^T X (\hat{\beta} - \beta)) c^T (\hat{\beta} - \beta) \right] = \mathbb{E} [(a^T \epsilon - \lambda^T X^T X (X^T X)^{-1} X^T \epsilon) c^T (X^T X)^{-1} X^T \epsilon] \\ &= \mathbb{E} [a^T \epsilon c^T (X^T X)^{-1} X^T \epsilon] - \mathbb{E} [\lambda^T X^T \epsilon c^T (X^T X)^{-1} X^T \epsilon] \end{aligned}$$

$$= (a^T - \lambda^T X^T) \mathbb{E} [\epsilon c^T (X^T X)^{-1} X^T \epsilon] = (a^T - \lambda^T X^T) \mathbb{E} [\epsilon (\lambda^T X^T \epsilon)]$$

Note that

$$\begin{aligned} \lambda^T X^T \epsilon &= \sum_{j=1}^n (\lambda^T X^T)_j \epsilon_j \in \mathbb{R}^n \\ \implies (a^T - \lambda^T X^T) \mathbb{E} [\epsilon (\lambda^T X^T \epsilon)] &= (a^T - \lambda^T X^T) \mathbb{E} \begin{bmatrix} \epsilon_1 [\lambda^T X^T \epsilon] \\ \vdots \\ \epsilon_n [\lambda^T X^T \epsilon] \end{bmatrix} \\ &= (a^T - \lambda^T X^T) \mathbb{E} \begin{bmatrix} \epsilon_1 \sum_{j=1}^n (\lambda^T X^T)_j \epsilon_j \\ \vdots \\ \epsilon_n \sum_{j=1}^n (\lambda^T X^T)_j \epsilon_j \end{bmatrix} \end{aligned}$$

Using independence of ϵ_i and ϵ_j for $i \neq j$, we can write this as

$$\begin{aligned} &= (a^T - \lambda^T X^T) \mathbb{E} \begin{bmatrix} \epsilon_1 (\lambda^T X^T)_1 \epsilon_1 \\ \vdots \\ \epsilon_n (\lambda^T X^T)_n \epsilon_n \end{bmatrix} = (a^T - \lambda^T X^T) \sigma^2 \begin{bmatrix} (\lambda^T X^T)_1 \\ \vdots \\ (\lambda^T X^T)_n \end{bmatrix} = \sigma^2 (a^T - \lambda^T X^T) X \lambda \\ &= \sigma^2 (a^T X - \lambda^T X^T X) \lambda = 0 \end{aligned}$$

since by (11.7) $c^T = a^T X = \lambda^T X^T X$.

□

Theorem 11.2.5 (Gauss-Markov Theorem, as stated in Faraway [2002], more general case).
Suppose

$$y = X\beta + \epsilon$$

with $X \in \mathbb{R}^{n \times p}$ a fixed full rank matrix and $n \geq p$, $\beta \in \mathbb{R}^p$, and $\epsilon \in \mathbb{R}^n$ with $\mathbb{E}(\epsilon) = 0$ and $\text{Var}(\epsilon) = \sigma^2 I_n$. Suppose X is fixed ($\mathbb{E}(Y) = X\beta$). Let $\psi : \mathbb{R}^p \rightarrow \mathbb{R}^k$ be an estimable function: $\psi := c^T \beta$ for some full rank $c \in \mathbb{R}^{p \times k}$. Then in the class of all unbiased linear estimates of ψ , $\hat{\psi} = c^T \hat{\beta}$ has the minimum variance and is unique. That is, for some $a \in \mathbb{R}^{n \times k}$ such that $a^T y$ is another unbiased estimator of $c^T \beta$,

$$\text{Var}(a^T y) \succeq \text{Var}(c^T \hat{\beta}).$$

Proof (adapted from Faraway [2002]). First, note that

$$\mathbb{E}(a^T y) = a^T X\beta = c^T \beta, \quad \forall \beta \in \mathbb{R}^p.$$

This implies

$$a^T X = c^T \iff X^T a = c, \quad (11.9)$$

Since X has full column rank, $X^T X$ is full rank and its column space is all of \mathbb{R}^p , so there exists a unique $\lambda \in \mathbb{R}^{p \times k}$ such that

$$c = X^T X \lambda = X^T a \quad (11.10)$$

(Note that $a = X\lambda + b$ for some $b \in \mathbb{R}^{n \times k}$ whose columns lie in the $(n - p)$ -dimensional nullspace of X^T .) Then

$$\begin{aligned} \text{Var}(a^T y) &= \text{Var}(a^T y - c^T \hat{\beta} + c^T \hat{\beta}) = \text{Var}(a^T y - \lambda^T X^T \hat{y} + c^T \hat{\beta}) \\ &= \text{Var}(a^T y - \lambda^T X^T \hat{y}) + \text{Var}(c^T \hat{\beta}) + 2\text{Cov}(a^T y - \lambda^T X^T \hat{y}, c^T \hat{\beta}) \succeq \text{Var}(c^T \hat{\beta}) + 2\text{Cov}(a^T y - \lambda^T X^T \hat{y}, c^T \hat{\beta}), \end{aligned} \quad (11.11)$$

so we are done if the covariance matrix in (11.11) is positive semidefinite.

$$\begin{aligned} \text{Cov}(a^T y - \lambda^T X^T \hat{y}, c^T \hat{\beta}) &= \mathbb{E} \left[(a^T y - \lambda^T X^T \hat{y} - \mathbb{E}[a^T y - \lambda^T X^T \hat{y}]) (c^T \hat{\beta} - \mathbb{E}[c^T \hat{\beta}])^T \right] \\ &= \mathbb{E} \left[(a^T (X\beta + \epsilon) - \lambda^T X^T X \hat{\beta} - a^T X\beta + \lambda^T X^T X \beta) (c^T [\hat{\beta} - \beta])^T \right] \\ &= \mathbb{E} \left[(a^T \epsilon - \lambda^T X^T X (\hat{\beta} - \beta)) (\hat{\beta} - \beta)^T c \right] = \mathbb{E} [(a^T \epsilon - \lambda^T X^T X (X^T X)^{-1} X^T \epsilon) \epsilon^T X (X^T X)^{-1} c] \\ &= \mathbb{E} [a^T \epsilon \epsilon^T X (X^T X)^{-1} c] - \mathbb{E} [\lambda^T X^T \epsilon \epsilon^T X (X^T X)^{-1} c] \\ &= \sigma^2 a^T I_n X (X^T X)^{-1} c - \sigma^2 \lambda^T X^T I_n X (X^T X)^{-1} c = \sigma^2 (a^T X - \lambda^T X^T X) \lambda = 0 \end{aligned}$$

since by (11.10) $c^T = a^T X = \lambda^T X^T X$.

□

11.3 Chapter 3: Hypothesis testing in regression

In this section, I borrow from C. Flinn's notes "Asymptotic Results for the Linear Regression Model," available online at <http://www.econ.nyu.edu/user/flinnc/notes1.pdf>.

Proposition 11.3.1.

$$\hat{\beta} - \beta \sim \mathcal{N}_{p+1}(0, \sigma^2(X^T X)^{-1})$$

Proof.

$$\hat{\beta} = (X^T X)^{-1} X^T (X\beta + \epsilon) = \beta + (X^T X)^{-1} X^T \epsilon \sim \mathcal{N}_{p+1}(\beta, \sigma^2(X^T X)^{-1} X^T I_n X (X^T X)^{-1})$$

$$\iff \hat{\beta} - \beta \sim \mathcal{N}_{p+1}(0, \sigma^2(X^T X)^{-1}) \implies \hat{\beta}_j - \beta_j \sim \mathcal{N}\left(0, \sigma^2[(X^T X)^{-1}]_{jj}\right)$$

$$\iff \frac{\hat{\beta}_j - \beta_j}{\sqrt{\sigma^2[(X^T X)^{-1}]_{jj}}} \sim \mathcal{N}(0, 1). \quad (11.12)$$

□

Proposition 11.3.2.

$$\frac{(n-p-1)\hat{\sigma}^2}{\sigma^2} \sim \chi^2_{n-p-1}.$$

Proof.

$$\hat{\sigma}^2 = \frac{1}{n-p-1} \hat{\epsilon}^T \hat{\epsilon} = \frac{1}{n-p-1} [(I_n - P_X)(X\beta + \epsilon)]^T [(I_n - P_X)(X\beta + \epsilon)]$$

But $P_X X = X(X^T X)^{-1} X^T X = X \implies (I - P_X)X\beta = X\beta - X\beta = 0$, so we can write this as

$$= \frac{1}{n-p-1} [(I_n - P_X)\epsilon]^T [(I_n - P_X)\epsilon] = \frac{1}{n-p-1} \epsilon^T (I_n - P_X)^T (I_n - P_X)\epsilon = \frac{1}{n-p-1} \epsilon^T (I - P_X)\epsilon \quad (11.13)$$

where we used the fact that $I_n - P_X$ is symmetric and idempotent. We have

$$\text{Tr}(I_n - P_X) = \text{Tr}(I) - \text{Tr}(P_X) = n - \text{Tr}(X(X^T X)^{-1} X^T) = n - \text{Tr}((X^T X)^{-1} X^T X) = n - \text{Tr}(I_{p+1}) = n - p - 1.$$

Take the spectral decomposition of $I_n - P_X$:

$$I_n - P_X = Q D Q^T$$

where $Q \in \mathbb{R}^{n \times n}$ is orthogonal and $D \in \mathbb{R}^{n \times n}$ is a diagonal matrix containing the eigenvalues of $I_n - P_X$. Since $I_n - P_X$ is idempotent, all of its eigenvalues equal either 0 or 1, so it must have $n - p - 1$ eigenvalues equal to 1 and $p + 1$ eigenvalues equal to 0. That is,

$$D = \begin{bmatrix} I_{n-p-1} & 0 \\ 0 & 0 \end{bmatrix}$$

Therefore we can write (11.13) as

$$\hat{\sigma}^2 = \frac{1}{n-p-1} \epsilon^T Q D Q^T \epsilon = \frac{1}{n-p-1} \epsilon^T Q D Q^T \epsilon = \frac{1}{n-p-1} (Q^T \epsilon)^T D Q^T \epsilon = \frac{1}{n-p-1} B^T B \quad (11.14)$$

where $B \in \mathbb{R}^n$ is defined by

$$B_i = \begin{cases} (Q^T \epsilon)_i & i \in \{1, \dots, n-p-1\} \\ 0 & i \in \{n-p, \dots, n\}. \end{cases}$$

Note that since $\epsilon \sim \mathcal{N}_n(0, \sigma^2 I_n)$,

$$Q^T \epsilon \sim \mathcal{N}_n(0, Q^T (\sigma^2 I_n) Q) = \mathcal{N}_n(0, \sigma^2 I_n)$$

(since $Q^T Q = I_n$), so

$$\frac{B_i}{\sigma} \sim \begin{cases} \mathcal{N}_{n-p-1}(0, I_{n-p-1}) & i \in \{1, \dots, n-p-1\} \\ 0 & i \in \{n-p, \dots, n\}. \end{cases} \quad (11.15)$$

Using (11.14) and (11.15) we have

$$(n-p-1) \frac{\hat{\sigma}^2}{\sigma^2} = \frac{B^T B}{\sigma^2} \sim \chi_{n-p-1}^2. \quad (11.16)$$

□

Proposition 11.3.3 (GSBA 604 Problem).

$$\frac{(\hat{\beta} - \beta)^T X^T X (\hat{\beta} - \beta)}{(p+1)\hat{\sigma}^2} \sim F(p_1, n-p-1).$$

Proof. Recall that an F distribution can be defined as

$$X = \frac{U/d_1}{V/d_2} \implies X \sim F_{d_1, d_2}$$

where $U \sim \chi_{d_1}^2$, $V \sim \chi_{d_2}^2$, and $U \perp V$. By Proposition 11.3.1,

$$\hat{\beta} - \beta \sim \mathcal{N}_{p+1}(0, \sigma^2 (X^T X)^{-1})$$

$$\implies \frac{\sqrt{X^T X}}{\sigma} (\hat{\beta} - \beta) \sim \mathcal{N}_{p+1}(0, I_{p+1})$$

$$\begin{aligned} \Rightarrow & \left[\sqrt{X^T X} / \sigma(\hat{\beta} - \beta) \right]^T \left[\sqrt{X^T X} / \sigma(\hat{\beta} - \beta) \right] = \frac{1}{\sigma^2} (\hat{\beta} - \beta)^T \left(\sqrt{X^T X} \right)^T \sqrt{X^T X} (\hat{\beta} - \beta) \\ & = \frac{1}{\sigma^2} (\hat{\beta} - \beta)^T X^T X (\hat{\beta} - \beta) \sim \chi_{p+1}^2. \end{aligned}$$

By Proposition 11.3.2,

$$(n - p - 1) \frac{\hat{\sigma}^2}{\sigma^2} \sim \chi_{n-p-1}^2.$$

Therefore

$$\frac{(\hat{\beta} - \beta)^T X^T X (\hat{\beta} - \beta)}{(p+1)\hat{\sigma}^2} = \frac{(\hat{\beta} - \beta)^T X^T X (\hat{\beta} - \beta) / [\sigma^2(p+1)]}{(n-p-1)\hat{\sigma}^2 / [\sigma^2(n-p-1)]} \sim F_{p+1, n-p-1}.$$

□

Proposition 11.3.4. The elements of $\hat{\beta}$ are uncorrelated with (and independent of) the elements of $\hat{\epsilon}$.

Proof.

$$\begin{aligned} \text{Cov}(\hat{\beta}, \hat{\epsilon}) &= \mathbb{E} [(\hat{\beta} - \mathbb{E}(\hat{\beta}))(\hat{\epsilon} - \mathbb{E}(\hat{\epsilon}))^T] \\ &= \mathbb{E} [((X^T X)^{-1} X^T (X\beta + \epsilon) - \beta)((I - P_x)(X\beta + \epsilon) - \mathbb{E}((I - P_x)(X\beta + \epsilon)))^T] \\ &= \mathbb{E} [(\beta + (X^T X)^{-1} X^T \epsilon) - \beta](X\beta + \epsilon - X\beta - P_x \epsilon - \mathbb{E}[X\beta + \epsilon - X\beta - P_x \epsilon])^T \\ &= \mathbb{E} [(X^T X)^{-1} X^T \epsilon (\epsilon - X(X^T X)^{-1} X^T \epsilon)^T] \\ &= \mathbb{E} [(X^T X)^{-1} X^T \epsilon \epsilon^T - (X^T X)^{-1} X^T \epsilon \epsilon^T X (X^T X)^{-1} X^T] \\ &= \sigma^2 (X^T X)^{-1} X^T - \sigma^2 (X^T X)^{-1} X^T X (X^T X)^{-1} X^T \\ &= \sigma^2 (X^T X)^{-1} X^T - \sigma^2 (X^T X)^{-1} X^T = 0. \end{aligned}$$

Since $\hat{\beta}$ and $\hat{\epsilon}$ are Gaussian and uncorrelated, they are independent.

□

Proposition 11.3.5.

$$\frac{\hat{\beta}_j - \beta_j}{\text{se}(\hat{\beta}_j)} \sim t_{n-p-1}.$$

Proof. By Proposition 11.3.1,

$$\frac{\hat{\beta}_j - \beta_j}{\sqrt{\sigma^2 [(X^T X)^{-1}]_{jj}}} \sim \mathcal{N}(0, 1). \quad (11.17)$$

Recall that we define the *standard error* of $\hat{\beta}_j$ to be an estimate of the standard deviation of $\hat{\beta}_j$ that shows up in the denominator of (11.17) that uses the plug-in estimator $\hat{\sigma}^2$ for σ^2 :

$$\text{se}(\hat{\beta}_j) := \sqrt{\hat{\sigma}^2 [(X^T X)^{-1}]_{jj}}. \quad (11.18)$$

By Proposition 11.3.4, $\hat{\beta} \perp\!\!\!\perp \hat{\epsilon}$, and since functions of independent random vectors are also independent and $\hat{\sigma}^2$ is a function of $\hat{\epsilon}$ and not $\hat{\beta}$,

$$\frac{\hat{\beta}_j - \beta_j}{\sqrt{\hat{\sigma}^2 [(X^T X)^{-1}]_{jj}}} \perp\!\!\!\perp (n-p-1) \frac{\hat{\sigma}^2}{\sigma^2}. \quad (11.19)$$

Recall that a Student's *t* distribution can be defined as

$$T = \frac{Z}{\sqrt{V/v}} \implies T \sim t_v$$

where $Z \sim \mathcal{N}(0, 1)$, $V \sim \chi^2_v$, and $Z \perp\!\!\!\perp V$. Using this characterization along with Proposition 11.3.2 (use (11.16)), (11.17), (11.18), and (11.19), we have

$$\begin{aligned} \frac{\hat{\beta}_j - \beta_j}{\text{se}(\hat{\beta}_j)} &= \frac{\hat{\beta}_j - \beta_j}{\sqrt{\hat{\sigma}^2 [(X^T X)^{-1}]_{jj}}} = \frac{\hat{\beta}_j - \beta_j}{\sqrt{\sigma^2 [(X^T X)^{-1}]_{jj}}} \Bigg/ \sqrt{\frac{\hat{\sigma}^2}{\sigma^2}} \\ &= \frac{\hat{\beta}_j - \beta_j}{\sqrt{\sigma^2 [(X^T X)^{-1}]_{jj}}} \Bigg/ \sqrt{(n-p-1) \frac{\hat{\sigma}^2}{\sigma^2}} \Bigg/ (n-p-1) \sim t_{n-p-1}. \end{aligned}$$

□

Lemma 11.3.6.

$$\frac{1}{n} \cdot X' \epsilon \xrightarrow{p} 0$$

Proof. Note that $\mathbb{E} \frac{1}{n} \cdot X' \epsilon = 0$ for any n . Then we have

$$\text{Var}\left(\frac{1}{n} \cdot X' \epsilon\right) = \mathbb{E}\left(\frac{1}{n} \cdot X' \epsilon\right)^2 = n^{-2} \mathbb{E}(X' \epsilon \epsilon' X) = n^{-2} \mathbb{E}(\epsilon \epsilon') X' X = \frac{\sigma^2}{n} \frac{X' X}{n}$$

implying that $\lim_{n \rightarrow \infty} \text{Var}\left(\frac{1}{n} \cdot X' \epsilon\right) = 0$. Therefore the result follows from Chebyshev's Inequality (Theorem 8.2.2). □

Lemma 11.3.7. If ϵ is i.i.d. with $E(\epsilon_i) = 0$ and $\mathbb{E}(\epsilon_i^2) = \sigma^2$ for all i , the elements of the matrix X are uniformly bounded so that $|X_{ij}| < U$ for all i and j and for U finite, and $\lim_{n \rightarrow \infty} X'X/n = Q$ is finite and nonsingular, then

$$\frac{1}{\sqrt{n}} X' \epsilon \xrightarrow{d} \mathcal{N}(0, \sigma^2 Q)$$

Proof. If we have one regressor, then $n^{-1/2} \sum_{i=1}^n X_i \epsilon_i$ is a scalar. Let G_i be the cdf of $X_i \epsilon_i$. Let

$$S_n^2 = \sum_{i=1}^n \text{Var}(X_i \epsilon_i) = \sigma^2 \sum_{i=1}^n X_i^2$$

In this scalar case, $Q = \lim_{n \rightarrow \infty} n^{-1} \sum_i X_i^2$. By the Lindeberg-Feller Theorem, a necessary and sufficient condition for $Z_n \rightarrow \mathcal{N}(0\sigma^2 Q)$ is

$$\lim_{n \rightarrow \infty} \frac{1}{S_n^2} \sum_{i=1}^n \int_{|\omega| > \nu S_n} \omega^2 dG_i(\omega) = 0$$

for all $\nu > 0$. Now $G_i(\omega) = F(\omega/|X_i|)$. Then rewrite the above equation as

$$\lim_{n \rightarrow \infty} \frac{n}{S_n^2} \sum_{i=1}^n \frac{X_i^2}{n} \int_{|\omega/X_i| > \nu S_n/|X_i|} \left(\frac{\omega}{X_i} \right)^2 dF(\omega/|X_i|) = 0$$

Since $\lim_{n \rightarrow \infty} S_n^2 = \lim_{n \rightarrow \infty} n\sigma^2 \sum_{i=1}^n X_i^2/n = n\sigma^2 Q$, we have $\lim_{n \rightarrow \infty} n/S_n^2 = (\sigma^2 Q)^{-1}$, which is a finite and nonzero scalar. Then we need to show

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i^2 \delta_{i,n} = 0$$

where

$$\delta_{i,n} = \int_{|\omega/X_i| > \nu S_n/|X_i|} \left(\frac{\omega}{X_i} \right)^2 dF(\omega/|X_i|)$$

But $\lim_{n \rightarrow \infty} \delta_{i,n} = 0$ for all i and any fixed ν since $|X_i|$ is bounded while $\lim_{n \rightarrow \infty} X_n = \infty$, so the measure of the set $\{|\omega/X_i| > \nu S_n/|X_i|\}$ goes to 0 asymptotically. Since $\lim_{n \rightarrow \infty} n^{-1} \sum_i X_i^2$ is finite and $\lim_{n \rightarrow \infty} \delta_{i,n} = 0$ for all i , $\lim_{n \rightarrow \infty} n^{-1} \sum_i X_i^2 \delta_{i,n} = 0$, so $\frac{1}{n} \cdot X' \epsilon \xrightarrow{p} 0$.

□

Theorem 11.3.8. Under the conditions of Lemma 11.3.7 (ϵ is i.i.d. with $E(\epsilon_i) = 0$ and $\mathbb{E}(\epsilon_i^2) = \sigma^2$ for all i , the elements of the matrix X are uniformly bounded so that $|X_{ij}| < U$ for all i and j and for U finite, and $\lim_{n \rightarrow \infty} X'X/n = Q$ is finite and nonsingular),

$$\sqrt{n}(\hat{\beta} - \beta) \xrightarrow{d} \mathcal{N}(0, \sigma^2 Q^{-1})$$

Proof.

$$\sqrt{n}(\hat{\beta} - \beta) = \left(\frac{X'X}{n} \right)^{-1} \frac{1}{\sqrt{n}} X' \epsilon$$

Since $\lim_{n \rightarrow \infty} (X'X/n)^{-1} = Q^{-1}$ and by Lemma 11.3.7

$$\frac{1}{\sqrt{n}} X' \epsilon \xrightarrow{d} \mathcal{N}(0, \sigma^2 Q)$$

then

$$\sqrt{n}(\hat{\beta} - \beta) \xrightarrow{d} \mathcal{N}(0, \sigma^2 Q^{-1} Q Q^{-1}) = \mathcal{N}(0, \sigma^2 Q^{-1})$$

□

t-test statistic:

$$t = \frac{\hat{\beta} - 0}{s.e.(\hat{\beta})}$$

F-test statistic:

$$F = \left(\frac{T - k - 1}{r} \right) \left(\frac{SSR_R - SSR_U}{SSR_U} \right)$$

Since

$$R^2 = \frac{\sum_t (y_t - \bar{y})^2 - \sum_t (y_t - \hat{y}_t)^2}{\sum_t (y_t - \bar{y})^2} = \frac{\sum_t (y_t - \bar{y})^2 - SSR_U}{\sum_t (y_t - \bar{y})^2}$$

we have

$$SSR_U = \sum_t (y_t - \bar{y})^2 - R^2 \sum_t (y_t - \bar{y})^2 = (1 - R^2) \sum_t (y_t - \bar{y})^2$$

yielding

$$F = \left(\frac{T - k - 1}{r} \right) \left(\frac{\sum_t (y_t - \bar{y})^2 - (1 - R^2) \sum_t (y_t - \bar{y})^2}{(1 - R^2) \sum_t (y_t - \bar{y})^2} \right) = \left(\frac{T - k - 1}{r} \right) \left(\frac{R^2}{1 - R^2} \right)$$

Confidence interval for sums of coefficients. (Two coefficient case.) Suppose we want to test $H_0 : \beta_1 + \beta_2 = k$. Let $\delta = \beta_1 + \beta_2 - k$, $\hat{\delta} = \hat{\beta}_1 + \hat{\beta}_2 - k$. Note that under the null hypothesis $\delta = 0$. We can construct a *t*-statistic

$$t_{\hat{\delta}} = \frac{\hat{\delta} - 0}{\sqrt{\text{Var}(\hat{\delta})}} = \frac{\hat{\beta}_1 + \hat{\beta}_2 - k}{\sqrt{\text{Var}(\hat{\delta})}}$$

where

$$\hat{\text{Var}}(\hat{\delta}) = \hat{\text{Var}}(\hat{\beta}_1) + \hat{\text{Var}}(\hat{\beta}_2) + 2\hat{\text{Cov}}(\hat{\beta}_1, \hat{\beta}_2)$$

This means that a 95% confidence interval for δ can be constructed in the following way:

$$\hat{\delta} \pm t^* \sqrt{\hat{\text{Var}}(\hat{\delta})}$$

where t^* is the 95% critical value for the t -distribution.

11.3.1 ANOVA

$$g_1 = lm(R \sim x_1 + x_2 + x_3 + x_4), \quad g_2 = lm(R \sim x_2 + x_3),$$

$$y = \beta_0 + \sum_{i=1}^4 \beta_i x_i$$

$$H_0 : \beta_1 = \beta_4 = 0, \quad H_A : \text{at least one of } \beta_1, \beta_4 \text{ is not zero.}$$

11.4 Chapter 4: Heteroskedasticity

Under heteroskedasticity, the OLS estimator $\hat{\beta} = (X'X)^{-1}X'y$ is unbiased, but the true covariance matrix of $\hat{\beta}$ no longer matches the OLS formula. For instance, suppose we have

$$y_t = \sum_{i=1}^K \beta_i x_{ti} + u_t$$

where $\text{Var}(u_t) = \sigma^2 z_t^2$.

$$\hat{\beta} = (X'X)^{-1}X'y = (X'X)^{-1}X'X\beta + (X'X)^{-1}X'u = \beta + (X'X)^{-1}X'u$$

$$\implies \mathbb{E}(\hat{\beta}) = \mathbb{E}[\beta] + (X'X)^{-1}X'\mathbb{E}[u] = \beta$$

since $\mathbb{E}(u)$ is still 0. However,

$$\text{Var}(\hat{\beta}) = \mathbb{E}[(\hat{\beta} - \mathbb{E}(\hat{\beta}))(\hat{\beta} - \mathbb{E}(\hat{\beta}))'] = \mathbb{E}[(\beta + (X'X)^{-1}X'u - \beta)(\beta + (X'X)^{-1}X'u - \beta)']$$

$$= \mathbb{E}[(X'X)^{-1}X'u((X'X)^{-1}X'u)'] = \mathbb{E}[(X'X)^{-1}X'u u' X ((X'X)^{-1})']$$

$$\begin{aligned}
&= (X'X)^{-1} X' \mathbb{E}[uu' | X] X (X'X)^{-1} \\
&= (X'X)^{-1} X' \begin{bmatrix} \sigma^2 z_1^2 & 0 & 0 & \dots & 0 \\ 0 & \sigma^2 z_2^2 & 0 & \dots & 0 \\ 0 & 0 & \sigma^2 z_3^2 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & \sigma^2 z_T^2 \end{bmatrix} X (X'X)^{-1} \\
&= \sigma^2 (X'X)^{-1} X' \begin{bmatrix} z_1^2 & 0 & 0 & \dots & 0 \\ 0 & z_2^2 & 0 & \dots & 0 \\ 0 & 0 & z_3^2 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & z_T^2 \end{bmatrix} X (X'X)^{-1}
\end{aligned}$$

which is different from the OLS estimator of the covariance matrix $\sigma^2(X'X)^{-1}$. Therefore the estimate of the variances of $\hat{\beta}$ will be biased if the OLS formulas are used, and the usual t and F tests for $\hat{\beta}$ will be invalid.

11.5 Chapter 5: Autocorrelated disturbances

11.5.1 Generalized Least Squares

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$$

where

$$\mathbb{E}(\mathbf{u} | \mathbf{X}) = 0 \quad \forall t$$

$$\mathbb{E}(\mathbf{u}\mathbf{u}' | \mathbf{X}) = \boldsymbol{\Sigma}$$

where $\boldsymbol{\Sigma}$ is a positive definite matrix.

Suppose

$$y = X\beta + \epsilon$$

where $\epsilon \sim \mathcal{N}(0, \boldsymbol{\Sigma})$. Then

$$\boldsymbol{\Sigma}^{-1/2}y = \boldsymbol{\Sigma}^{-1/2}X\beta + \tilde{\epsilon}$$

where $\tilde{\epsilon} = \boldsymbol{\Sigma}^{-1/2}\epsilon \sim \mathcal{N}(0, 1)$. Now we can do ordinary least squares since the errors of this transformed model are i.i.d.

$$\hat{\beta}_{GLS} = \left(\left[\Sigma^{-1/2} X \right]^T \Sigma^{-1/2} X \right)^{-1} \left[\Sigma^{-1/2} X \right]^T \Sigma^{-1/2} y = (X' \Sigma^{-1} X)^{-1} X' \Sigma^{-1} y$$

$$\text{Var}(\hat{\beta}_{GLS}) = (X' \Sigma^{-1} X)^{-1}$$

Example application: spatial data.

11.5.2 Weighted Least Squares

A closely related idea to generalized least squares is weighted least squares. In this model, weights $a_i \in \mathbb{R}_{++}$ are assigned to each observation; higher weights correspond to observations that are more important for model fit, lower weights correspond to observations that are less important for model fit. If all weights equal 1, we recover ordinary least squares. Let $\mathbf{A} := \text{diag}(a_1, \dots, a_n) \in \mathbb{R}^{n \times n}$. Then weighted least squares minimizes the weighted average loss

$$\mathcal{L} := \frac{1}{n} \sum_{i=1}^n a_i (y_i - \beta^\top \mathbf{x}_i)^2 \quad (11.20)$$

where $\mathbf{x}_i \in \mathbb{R}^p$ and $\beta \in \mathbb{R}^p$.

Proposition 11.5.1. If \mathbf{X} is invertible, the weighted least squares estimator (the unique minimizer of (11.20)) is

$$\hat{\beta} = (\mathbf{X}^\top \mathbf{A} \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{A} \mathbf{y}.$$

Remark 162. Note the relationship between generalized least squares and weighted least squares—generalized least squares is weighted least squares if the disturbances are independent and the weight for observation i is the inverse of the variance of the disturbance for observation i .

Proof. Since all the entries of \mathbf{A} are on the diagonal and positive, $\mathbf{A}^{1/2}$ exists such that $\mathbf{A}^{1/2} \mathbf{A}^{1/2} = \mathbf{A}$. Also, since $\mathbf{A}^{1/2}$ only has diagonal entries, it is symmetric, so $(\mathbf{A}^{1/2})^\top = \mathbf{A}^{1/2}$. We have

$$\begin{aligned} \mathcal{L} &= \frac{1}{n} (\mathbf{y} - \mathbf{X}\beta)^\top \mathbf{A} (\mathbf{y} - \mathbf{X}\beta) \\ &= \frac{1}{n} (\mathbf{y} - \mathbf{X}\beta)^\top \mathbf{A}^{1/2} \mathbf{A}^{1/2} (\mathbf{y} - \mathbf{X}\beta) \\ &= \frac{1}{n} (\mathbf{y}^\top \mathbf{A}^{1/2} - \beta^\top \mathbf{X}^\top \mathbf{A}^{1/2}) (\mathbf{A}^{1/2} \mathbf{y} - \mathbf{A}^{1/2} \mathbf{X}\beta) \\ &= \frac{1}{n} (\mathbf{A}^{1/2} \mathbf{y} - \mathbf{A}^{1/2} \mathbf{X}\beta)^\top (\mathbf{A}^{1/2} \mathbf{y} - \mathbf{A}^{1/2} \mathbf{X}\beta) \end{aligned}$$

Let $\mathbf{y}^* := \mathbf{A}^{1/2} \mathbf{y}$ and let $\mathbf{X}^* := \mathbf{A}^{1/2} \mathbf{X}$. Note that since $\mathbf{A}^{1/2}$ is full rank (invertible), \mathbf{X}^* has the same rank as \mathbf{X} . Then we can write this as

$$\begin{aligned}
\mathcal{L} &= \frac{1}{n} (\mathbf{y}^* - \mathbf{X}^* \boldsymbol{\beta})^\top (\mathbf{y}^* - \mathbf{X}^* \boldsymbol{\beta}) \\
&= \frac{1}{n} ([\mathbf{y}^*]^\top - \boldsymbol{\beta}^\top [\mathbf{X}^*]^\top) (\mathbf{y}^* - \mathbf{X}^* \boldsymbol{\beta}) \\
&= \frac{1}{n} ([\mathbf{y}^*]^\top \mathbf{y}^* - [\mathbf{y}^*]^\top \mathbf{X}^* \boldsymbol{\beta} - \boldsymbol{\beta}^\top [\mathbf{X}^*]^\top \mathbf{y}^* + \boldsymbol{\beta}^\top [\mathbf{X}^*]^\top \mathbf{X}^* \boldsymbol{\beta}) \\
&= \frac{1}{n} ([\mathbf{y}^*]^\top \mathbf{y}^* - 2\boldsymbol{\beta}^\top [\mathbf{X}^*]^\top \mathbf{y}^* + \boldsymbol{\beta}^\top [\mathbf{X}^*]^\top \mathbf{X}^* \boldsymbol{\beta})
\end{aligned}$$

Now we take the gradient.

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \boldsymbol{\beta}} &= \frac{1}{n} \mathbf{0} - \frac{2}{n} [\mathbf{X}^*]^\top \mathbf{y}^* + \frac{2}{n} [\mathbf{X}^*]^\top \mathbf{X}^* \boldsymbol{\beta} \\
&= -\frac{2}{n} [\mathbf{X}^*]^\top \mathbf{y}^* + \frac{2}{n} [\mathbf{X}^*]^\top \mathbf{X}^* \boldsymbol{\beta} \\
&= -\frac{2}{N} [\mathbf{X}^*]^\top \mathbf{y}^* + \frac{2}{N} [\mathbf{X}^*]^\top \mathbf{X}^* \boldsymbol{\beta} \\
&= -\frac{2}{N} [\mathbf{A}^{1/2} \mathbf{X}]^\top \mathbf{A}^{1/2} \mathbf{y} + \frac{2}{N} [\mathbf{A}^{1/2} \mathbf{X}]^\top \mathbf{A}^{1/2} \mathbf{X} \boldsymbol{\beta} \\
&= -\frac{2}{N} \mathbf{X}^\top \mathbf{A}^{1/2} \mathbf{A}^{1/2} \mathbf{y} + \frac{2}{N} \mathbf{X}^\top \mathbf{A}^{1/2} \mathbf{A}^{1/2} \mathbf{X} \boldsymbol{\beta} \\
&= -\frac{2}{N} \mathbf{X}^\top \mathbf{A} \mathbf{y} + \frac{2}{N} \mathbf{X}^\top \mathbf{A} \mathbf{X} \boldsymbol{\beta}
\end{aligned}$$

Set the gradient equal to 0 and solve for $\boldsymbol{\beta}$:

$$\begin{aligned}
\mathbf{0} &= -\frac{2}{N} [\mathbf{X}^*]^\top \mathbf{y}^* + \frac{2}{N} [\mathbf{X}^*]^\top \mathbf{X}^* \boldsymbol{\beta} \\
[\mathbf{X}^*]^\top \mathbf{y}^* &= [\mathbf{X}^*]^\top \mathbf{X}^* \boldsymbol{\beta} \\
([\mathbf{X}^*]^\top \mathbf{X}^*)^{-1} [\mathbf{X}^*]^\top \mathbf{y}^* &= ([\mathbf{X}^*]^\top \mathbf{X}^*)^{-1} [\mathbf{X}^*]^\top \mathbf{X}^* \boldsymbol{\beta} \\
([\mathbf{X}^*]^\top \mathbf{X}^*)^{-1} [\mathbf{X}^*]^\top \mathbf{y}^* &= \boldsymbol{\beta}
\end{aligned}$$

Lastly, we substitute back in $\mathbf{y}^* = \mathbf{A}^{1/2} \mathbf{y}$ and $\mathbf{X}^* = \mathbf{A}^{1/2} \mathbf{X}$ to get our final answer.

$$\begin{aligned}
\hat{\boldsymbol{\beta}} &= \left([\mathbf{A}^{1/2} \mathbf{X}]^\top \mathbf{A}^{1/2} \mathbf{X} \right)^{-1} [\mathbf{A}^{1/2} \mathbf{X}]^\top \mathbf{A}^{1/2} \mathbf{y} \\
&= (\mathbf{X}^\top \mathbf{A}^{1/2} \mathbf{A}^{1/2} \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{A}^{1/2} \mathbf{A}^{1/2} \mathbf{y} \\
&= (\mathbf{X}^\top \mathbf{A} \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{A} \mathbf{y} \\
&= (\mathbf{X}^\top \mathbf{A} \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{A} \mathbf{y}.
\end{aligned}$$

□

11.6 Quantile Regression

Estimate the conditional *median* rather than the conditional mean (as in least squares). Least absolute deviation:

$$\arg \min_{\beta \in \mathbb{R}^p} \sum_{i=1}^n |y_i - x_i' \beta|$$

Problems: no closed form solution; have to solve by linear programming. Good: robust; less changed by fluctuations of outliers. Asymmetric loss:

$$\min_{\beta \in \mathbb{R}^p} \sum_{i=1}^n (1 - \tau) \underbrace{(y_i - x_i' \beta)_+}_{\text{under-estimation}} + \tau \underbrace{(x_i' \beta - y_i)_+}_{\text{over-estimation}}$$

In fixed dimensions:

$$\hat{\beta}(\tau) \xrightarrow{d} \mathcal{N} \left(\beta, (X^T X)^{-1} \frac{\tau(1 - \tau)}{f_\epsilon^2(0)} \right)$$

Suppose $\epsilon \sim \mathcal{N}(0, \sigma^2)$; then $f_\epsilon(0) = 1/\sqrt{2\pi\sigma^2}$, so we have

$$\hat{\beta}(\tau) \xrightarrow{d} \mathcal{N} \left(\beta, 2\pi\sigma^2(X^T X)^{-1}\tau(1 - \tau) \right)$$

This is then maximized for $\tau = 1/2$, and the max value is $1/4 \cdot 2\pi = \pi/2$. For more information on other loss functions, see also Section 14.7.

11.6.1 Detecting outliers in multiple dimensions

Hard because of curse of dimensionality. One thing: project onto lower-dimensional space and then compute distance there. multi-dimensional scaling or dimension reduction methods.

1. random projections
2. nonlinear methods: Iso-map, local linear embedding

Half-space depth (Tukey): make polygons of observations (outer one is the convex hull). Then create convex hulls of inside, keep going. See Figure 11.1.

11.7 Transformed Linear Models

11.7.1 Transformations of response

Consider the transformation

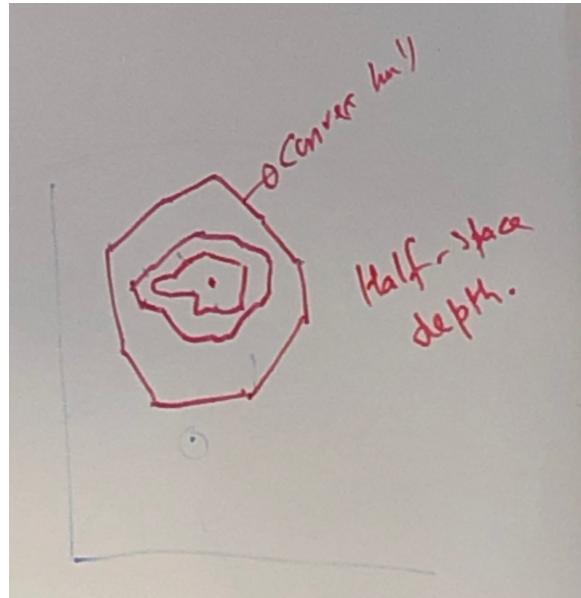


Figure 11.1: Illustration of half-space depth method for detecting outliers.

$$t(y) = \begin{cases} \frac{y^\lambda - 1}{\lambda}, & \lambda \neq 0 \\ \log(y) = \lim_{\lambda \rightarrow 0} \frac{y^\lambda - 1}{\lambda}, & \lambda = 0 \end{cases}$$

One example: **log linear model**.

$$\log y_i = \beta_0 + \beta_1 x_i + \epsilon.$$

Multiplicative model in the true response:

$$y_i = \exp(\beta_0) \cdot \exp(x_1 \beta_1) \cdot \exp(\epsilon_i)$$

If you increase y_i by one unit, then y_i is multiplied by $\exp(\beta_1)$. So in this case rather than talking about linear effects, you talk about percentage changes in the response: $(e^{\beta_1} - 1) \cdot 100\%$.

Square root transformations work well in Poisson models—variance stabilizes.

Consider

$$t_\lambda = x' \beta + \epsilon.$$

Then we have

$$SSE = (t_\lambda - x'_i \hat{\beta}_{OLS})^T (t_\lambda - x'_i \hat{\beta}_{OLS})$$

Try

$$\frac{n}{2} \log \left(\frac{SSE}{n} \right) + \left(\sum_{i=1}^n \log(y_i) \right).$$

for $\lambda = -2, -2, -1/2, 0, 1/2, 1, 2$. We have $2L(\hat{\lambda}) - 2L(\lambda_{true}) \sim \chi_1^2$. If 1 is inside the 95% confidence interval, don't transform; if 1 isn't, do. In a lot of cases, changing the response can be a pain for interpretability.

11.7.2 Transforming predictor values

Add polynomial terms:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_d x_i^d + \epsilon.$$

Want to maintain hierarchy in selecting variables (backward elimination). Advantages: nonlinear curvature. Global: all data have influence on every predicted point.

Chapter 12

Causal Inference and Econometrics

12.1 Generalized Method of Moments (Chapter 13 of Hansen [2020])

12.1.1 Overidentified Moment Equations (Section 13.4 of Hansen [2020])

Consider the instrumental variables model (see Section 12.2.2). The estimator $\hat{\beta}$ is the solution of the moment condition

$$\bar{g}_n(\beta) = \frac{1}{n} \sum_{i=1}^n g_i(\beta) = \frac{1}{n} \sum_{i=1}^n Z_i(Y_i - X_i^\top \beta) = \frac{1}{n} (\mathbf{Z}^\top \mathbf{Y} - \mathbf{Z}^\top \mathbf{X} \beta).$$

If this model is overidentified (that is, the number of instruments ℓ —and therefore moment conditions to satisfy—exceeds the number of variables p in \mathbf{X} —and therefore the number of parameters to estimate in β), in general this estimator does not exist, so the method of moments estimator is not defined.

The idea of the generalized method of moments estimator is to make $\bar{g}_n(\beta)$ as close to zero as possible. Define the vector $\mu := \mathbf{Z}^\top \mathbf{Y} \in \mathbb{R}^\ell$, the matrix $G := \mathbf{Z}^\top \mathbf{X} \in \mathbb{R}^{\ell \times p}$, and the “error” $\eta := \mu - G\beta$. Then we can write the finite-sample analogue of the above equation as

$$\begin{aligned} \mathbf{Z}^\top \mathbf{Y} &= \mathbf{Z}^\top \mathbf{X} \beta + \eta \\ \iff \mu &= G\beta + \eta. \end{aligned}$$

Therefore the least squares estimator (if we take all moment conditions to be equally important) is $\hat{\beta} = (G^\top G)^{-1} G^\top \mu$. In general, we may want to weigh some moment conditions as more important than others (possibly because errors are non-homogeneous, in which case this increases efficiency). Then by analogy to weighted least squares (see Section 11.5.2), for some positive definite weight matrix \mathbf{W} we have the **generalized method of moments estimator**

$$\hat{\beta} := (\mathbf{G}^\top \mathbf{W} \mathbf{G})^{-1} \mathbf{G}^\top \mathbf{W} \boldsymbol{\mu} = (\mathbf{X}^\top \mathbf{Z} \mathbf{W} \mathbf{Z}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{Z} \mathbf{W} \mathbf{Z}^\top \mathbf{Y}. \quad (12.1)$$

This minimizes the weighted sum of squares $\boldsymbol{\eta}^\top \mathbf{W} \boldsymbol{\eta}$.

Definition 12.1 (Generalized Method of Moments estimator; Definition 13.1 in Hansen [2020]). For a positive definite square weight matrix \mathbf{W} , define the GMM criterion function

$$J(\boldsymbol{\beta}) := n \bar{g}_n(\boldsymbol{\beta})^\top \mathbf{W} \bar{g}_n(\boldsymbol{\beta}). \quad (12.2)$$

Then the **generalized method of moments estimator** is

$$\hat{\boldsymbol{\beta}}_{\text{gmm}} := \arg \min_{\boldsymbol{\beta}} \{J_n(\boldsymbol{\beta})\}.$$

Note that GMM includes the method of moments estimator as a special case. This implies that all results for GMM apply to any method of moments estimators. In this case \mathbf{W} does not matter. In the overidentified case, the choice of \mathbf{W} is important.

12.2 Instrumental Variables (Section 4.8 of Cameron and Trivedi [2005])

12.2.1 Inconsistency of OLS and Examples of Endogeneity (Section 4.8.1 of Cameron and Trivedi [2005], Section 12.3 in Hansen [2020])

- **Measurement error in the regressor.** Suppose $\mathbb{E}[Y | Z] = Z^\top \boldsymbol{\beta}$, but Z is not observed; instead, $X = Z + u$ is observed, where u is measurement error with $\mathbb{E}(u) = 0$ and u is independent of e and Z . We have

$$Y = Z^\top \boldsymbol{\beta} + e = (X - u)^\top \boldsymbol{\beta} + e = X^\top \boldsymbol{\beta} + \nu$$

where $\nu = e - u^\top \boldsymbol{\beta}$. Therefore

$$Y = X^\top \boldsymbol{\beta} + \nu,$$

but

$$\mathbb{E}[X\nu] = \mathbb{E}[(Z + u)(e - u^\top \boldsymbol{\beta})] = -\mathbb{E}[uu^\top] \boldsymbol{\beta} \neq 0.$$

Therefore least squares estimation is inconsistent, and X is endogenous. The projection coefficient (the quantity least squares is consistent for) is (in the case $p = 1$)

$$\boldsymbol{\beta}^* = \boldsymbol{\beta} + \frac{\mathbb{E}[X\nu]}{\mathbb{E}[X^2]} = \boldsymbol{\beta} \left(1 - \frac{\mathbb{E}[u^2]}{\mathbb{E}[X^2]}\right).$$

Since $\mathbb{E}[u^2]/\mathbb{E}[X^2] < 1$, the projection coefficient shrinks the structural parameter $\boldsymbol{\beta}$ towards zero. This is called **measurement error bias** or **attenuation bias**.

- **Simultaneous equations bias.** Suppose that quantity Q and price P are determined jointly by demand

$$Q = -\beta_1 P e_1$$

and supply

$$Q = \beta_2 P + e_2,$$

with (for simplicity) $e = (e_1, e_2)$ satisfying $\mathbb{E}[e] = 0$ and $\mathbb{E}[ee'] = I_2$. In matrix notation, we have

$$\begin{aligned} \begin{pmatrix} 1 & \beta_1 \\ 1 & -\beta_2 \end{pmatrix} \begin{pmatrix} Q \\ P \end{pmatrix} &= \begin{pmatrix} e_1 \\ e_2 \end{pmatrix} \\ \iff \quad \begin{pmatrix} Q \\ P \end{pmatrix} &= \begin{pmatrix} 1 & \beta_1 \\ 1 & -\beta_2 \end{pmatrix}^{-1} \begin{pmatrix} e_1 \\ e_2 \end{pmatrix} \\ &= \frac{1}{\beta_1 + \beta_2} \begin{pmatrix} \beta_2 & \beta_1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} e_1 \\ e_2 \end{pmatrix} \\ &= \begin{pmatrix} (\beta_2 e_1 + \beta_1 e_2) / (\beta_1 + \beta_2) \\ (e_1 - e_2) / (\beta_1 + \beta_2) \end{pmatrix}. \end{aligned}$$

The projection of Q on P yields $Q = \beta^* P + e^*$ with $\mathbb{E}[Pe^*] = 0$ and the coefficient defined by projection as

$$\beta^* = \mathbb{E}[P^2]^{-1} \mathbb{E}[PQ] = \frac{\beta_2 - \beta_1}{2}.$$

The projection coefficient β^* equals neither the demand slope β_1 nor the supply slope β_2 , but equals an average of the two. (The fact that it is a simple average is an artifact of the covariance structure.) Hence the OLS estimate satisfies $\hat{\beta} \xrightarrow{P} \beta^*$, and the limit does not equal β_1 or β_2 . The fact that the limit is neither the supply nor demand slope is called **simultaneous equations bias**. This occurs generally when Y and X are jointly determined, as in market equilibrium. Generally, when both the dependent variable and a regressor are simultaneously determined, the variables should be treated as endogenous.

- **Choice variables as regressors.** Suppose we are interested in outcome y , log-earnings, and we have predictor x , years of schooling. We are interested in the causal effect on y of an **exogenous** change in x —a change in amount of schooling that is not the choice of the individual; for example, an increase in the minimum age at which students leave school. The OLS regression model specifies

$$y = \beta x + u$$

where u is an error term. Regression of y on x yields OLS estimate $\hat{\beta}$ of β . If we assume that x is uncorrelated with u , OLS yields a consistent estimator for the true causal effect. However, u (which contains the effects of all variables besides schooling on earnings) could be correlated with x . For example, unobserved *ability* may be correlated with both earnings and increased levels of schooling. In that case, OLS will be consistent for

$$\frac{dy}{dx} = \beta + \frac{du}{dx} > \beta.$$

That is, the positive correlation between x and u means that the linear projection coefficient β^* is upwardly biased relative to the structural coefficient β . The OLS estimator is therefore biased and inconsistent for β , over-estimating the causal effect of education on wages.

This type of endogeneity occurs generally when Y and X are both choices made by an economic agent, even if they are made at different points in time. Generally, when both the dependent variable and a regressor are choice variables made by the same agent, the variables should be treated as endogenous.

A more formal treatment of the linear regression model with K regressors leads to the same conclusion. Under standard assumptions, a necessary condition for consistency of OLS is that $\frac{1}{n}\mathbf{X}^\top \mathbf{u} \xrightarrow{P} \mathbf{0}$; we can see this because

$$\begin{aligned}\hat{\boldsymbol{\beta}} &= (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y} \\ &= \left(\frac{1}{n}\mathbf{X}^\top \mathbf{X}\right)^{-1} \frac{1}{n}\mathbf{X}^\top (\mathbf{X}\boldsymbol{\beta} + \mathbf{u}) \\ &= \left(\frac{1}{n}\mathbf{X}^\top \mathbf{X}\right)^{-1} \frac{1}{n}\mathbf{X}^\top \mathbf{X}\boldsymbol{\beta} + \left(\frac{1}{n}\mathbf{X}^\top \mathbf{X}\right)^{-1} \frac{1}{n}\mathbf{X}^\top \mathbf{u} \\ &= \boldsymbol{\beta} + \left(\frac{1}{n}\mathbf{X}^\top \mathbf{X}\right)^{-1} \frac{1}{n}\mathbf{X}^\top \mathbf{u};\end{aligned}$$

we see this converges to $\boldsymbol{\beta}$ in probability if $\frac{1}{n}\mathbf{X}^\top \mathbf{u} \xrightarrow{P} \mathbf{0}$ (see also Section 4.7.1 of [Cameron and Trivedi \[2005\]](#)).

12.2.2 Instrumental Variable

The inconsistency of OLS is due to the endogeneity of x , meaning that changes in x are associated not only with changes in y but also changes in the error u . What is needed is a method to generate only exogenous variation in x . An obvious way is through a randomized experiment, but for many economic applications such experiments are too expensive, infeasible, or unethical. One alternative approach is using an instrument.

An **instrument** z is a variable that is correlated with x but not with u or directly with y (that is, z is associated with y only through its effect on x).

Definition 12.2 (Instrumental variable; Definition 12.1 in Hansen [2020]). The random vector $Z \in \mathbb{R}^\ell$ is an **instrumental variable** if the following are true:

$$\begin{aligned}\mathbb{E}[Z^\top e] &= 0, \\ \mathbb{E}[ZZ^\top] &= 0, \quad \text{and} \\ \text{rank}(\mathbb{E}[ZX^\top]) &= p.\end{aligned}$$

The first component of this definition is that the instruments are uncorrelated with the regression error. Second, we must exclude linearly dependent instruments. The third condition is often called the **relevance condition** and is essential for the identification of the model. A necessary condition for the relevance condition is $\ell \geq p$.

12.2.3 Instrumental Variables Estimator

For regression with scalar regressor x and scalar instrument z , the **instrumental variables (IV) estimator** is defined as

$$\hat{\beta}_{IV} := (z^\top x)^{-1} z^\top y.$$

This estimator is consistent for the slope coefficient β in the linear model if z is correlated with x and uncorrelated with u .

We will derive this estimator. Note that under our assumptions,

$$\mathbb{E}[y - x\beta | z] = \mathbf{0}.$$

Using this, we have

$$\mathbf{0} = \mathbb{E}[z^\top \mathbf{0}] = \mathbb{E}[z^\top \mathbb{E}[y - x\beta | z]] = \mathbb{E}[\mathbb{E}[z^\top (y - x\beta) | z]] = \mathbb{E}[z^\top (y - x\beta)].$$

If the number of instruments equals the number of regressors ($\dim(z) = p$), the method of moments estimator is then the solution to the corresponding sample moment condition

$$\begin{aligned} & \frac{1}{n} \sum_{i=1}^n z_i(y_i - x_i^\top \hat{\beta}) = \mathbf{0} \\ \iff & z^\top (y - x\hat{\beta}) = \mathbf{0} \\ \iff & z^\top y = z^\top x\hat{\beta} \\ \iff & \hat{\beta} = (z^\top x)^{-1} z^\top y, \end{aligned}$$

as shown in (12.4).

12.2.4 Two-Stage Least Squares (Section 8.3.4 of Greene [2003])

Suppose there may be more instruments than endogenous variables. Then $Z^\top X$ is not invertible (it is rank p but has ℓ rows), and a new analysis is required. Since Z is uncorrelated with e , we can express an approximation \hat{X} of X in the column space of Z by projection:

$$\hat{X} = Z(Z^\top Z)^{-1} Z^\top X.$$

Then we can regress y against \hat{X} to get a consistent estimator for the endogenous (structural) coefficient:

$$\begin{aligned}
\beta_{IV} &= \left(\hat{X}^\top \hat{X} \right)^{-1} \hat{X}^\top y \\
&= \left([Z(Z^\top Z)^{-1} Z^\top X]^\top Z(Z^\top Z)^{-1} Z^\top X \right)^{-1} [Z(Z^\top Z)^{-1} Z^\top X]^\top y \\
&= (X^\top Z(Z^\top Z)^{-1} Z^\top Z(Z^\top Z)^{-1} Z^\top X)^{-1} X^\top Z(Z^\top Z)^{-1} Z^\top y \\
&= (X^\top Z(Z^\top Z)^{-1} Z^\top X)^{-1} X^\top Z(Z^\top Z)^{-1} Z^\top y.
\end{aligned} \tag{12.3}$$

Similarly, when p endogenous regressors are in X and p (an equal number) of instruments are available, we have

$$\hat{\beta}_{IV} := (\mathbf{Z}^\top \mathbf{Z})^{-1} \mathbf{Z}^\top \mathbf{y}. \tag{12.4}$$

12.2.5 LATE/CATE Theorem

Theorem 12.2.1 (LATE Theorem (Special case of Theorem 2 in ?)).

$$\frac{\mathbb{E}[Y_i | Z_i = 1] - \mathbb{E}[Y_i | Z_i = 0]}{\mathbb{E}[A_i | Z_i = 1] - \mathbb{E}[A_i | Z_i = 0]} = \mathbb{E}[Y_i(1) - Y_i(0) | A_i(1) > A_i(0)].$$

Proof.

$$\begin{aligned}
\mathbb{E}[Y_i | Z_i = 1] &= \mathbb{E} \left[\underbrace{Y_i(0) + A_i(Y_i(1) - Y_i(0))}_{Y_i} | Z_i = 1 \right] \\
&= \mathbb{E}[Y_i(0) | Z_i = 1] + \mathbb{E}[A_i(Y_i(1) - Y_i(0)) | Z_i = 1] \\
&\stackrel{(*)}{=} \mathbb{E}[Y_i(0)] + \mathbb{E}[A_i(Y_i(1) - Y_i(0))]
\end{aligned}$$

where $(*)$ follows from the randomization assumption. Similarly,

$$\begin{aligned}
\mathbb{E}[Y_i | Z_i = 0] &= \mathbb{E} \left[\underbrace{Y_i(0) + A_i(Y_i(1) - Y_i(0))}_{Y_i} | Z_i = 0 \right] \\
&= \mathbb{E}[Y_i(0) | Z_i = 0] + \mathbb{E}[A_i(Y_i(1) - Y_i(0)) | Z_i = 0] \\
&\stackrel{(*)}{=} \mathbb{E}[Y_i(0)] + \mathbb{E}[A_i(Y_i(1) - Y_i(0))],
\end{aligned}$$

so

$$\begin{aligned}
\mathbb{E}[Y_i | Z_i = 1] - \mathbb{E}[Y_i | Z_i = 0] &= \mathbb{E}[(A_i(1) - A_i(0))(Y_i(1) - Y_i(0))] \\
&= \mathbb{E}\left[(A_i(1) - A_i(0))(Y_i(1) - Y_i(0)) \mid \underbrace{A_i(1) > A_i(0)}_{(\text{compliers})}\right] \mathbb{P}(A_i(1) > A_i(0)) \\
&\quad + \mathbb{E}\left[(A_i(1) - A_i(0))(Y_i(1) - Y_i(0)) \mid \underbrace{A_i(1) < A_i(0)}_{(\text{defiers})}\right] \mathbb{P}(A_i(1) < A_i(0)) \\
&\stackrel{(**)}{=} \mathbb{E}[(A_i(1) - A_i(0))(Y_i(1) - Y_i(0)) \mid A_i(1) > A_i(0)] \mathbb{P}(A_i(1) > A_i(0))
\end{aligned}$$

where $(**)$ follows from the monotonicity assumption ($\mathbb{P}(A_i(1) < A_i(0)) = 0$). Can get denominator (easier)

$$\mathbb{E}[A_i | Z_i = 1] - \mathbb{E}[A_i | Z_i = 0] = \mathbb{E}[A_i(1) - A_i(0)] = \mathbb{P}(A_i(1) > A_i(0))$$

□

Lemma 12.2.2.

$$\frac{\mathbb{E}[Y_i | Z_i = 1] - \mathbb{E}[Y_i | Z_i = 0]}{\mathbb{E}[A_i | Z_i = 1] - \mathbb{E}[A_i | Z_i = 0]} = \mathbb{E}[Y_i(1) - Y_i(0) | A_i = 1].$$

Proof. We have $Y_i = Y_i(0) + A_i(Y_i(1) - Y_i(0))$. Also, $\mathbb{P}(A_i = 1 | Z_i = 0) = 0$ by the assumption of no defiers. That is, $\mathbb{E}[A_i(Y_i(1) - Y_i(0)) | Z_i = 0] = 0$. Then

$$\begin{aligned}
\mathbb{E}[Y_i | Z_i = 1] - \mathbb{E}[Y_i | Z_i = 0] &= \mathbb{E}[Y_i(0) + A_i(Y_i(1) - Y_i(0)) | Z_i = 1] - \mathbb{E}[Y_i(0) + A_i(Y_i(1) - Y_i(0)) | Z_i = 0] \\
&= \mathbb{E}[A_i(Y_i(1) - Y_i(0)) | Z_i = 1] - \mathbb{E}[A_i(Y_i(1) - Y_i(0)) | Z_i = 0] \\
&= \mathbb{E}[A_i(Y_i(1) - Y_i(0)) | Z_i = 1] \\
&= \mathbb{E}[A_i(Y_i(1) - Y_i(0)) | Z_i = 1, A_i = 1] \cdot \mathbb{P}(A_i = 1 | Z_i = 1) \\
&= \mathbb{E}[A_i(Y_i(1) - Y_i(0)) | A_i = 1] \cdot \mathbb{P}(A_i = 1 | Z_i = 1)
\end{aligned}$$

so this is the numerator.

□

12.2.6 GMM Estimator (Section 13.6 of Hansen [2020])

As discussed in Section 12.1.1, the moment equations for instrumental variables are

$$\mathbf{Z}^\top \mathbf{Y} - \mathbf{Z}^\top \mathbf{X} \boldsymbol{\beta} = 0,$$

so the GMM criterion (12.2) can be written as

$$J(\beta) = n (\mathbf{Z}^\top \mathbf{Y} - \mathbf{Z}^\top \mathbf{X}\beta)^\top \mathbf{W} (\mathbf{Z}^\top \mathbf{Y} - \mathbf{Z}^\top \mathbf{X}\beta).$$

The GMM estimator minimizes $J(\beta)$. The first order conditions are

$$\begin{aligned} 0 &= \frac{\partial}{\partial \beta} J(\hat{\beta}) \\ &= 2 \frac{\partial}{\partial \beta} \bar{g}_n(\hat{\beta})^\top \mathbf{W} \bar{g}_n(\hat{\beta}) \\ &= -2 \left(\frac{1}{n} \mathbf{X}^\top \mathbf{Z} \right) \mathbf{W} \left(\frac{1}{n} \mathbf{Z}^\top (\mathbf{Y} - \mathbf{X}\hat{\beta}) \right). \end{aligned}$$

The solution is the GMM estimator for the overidentified IV model,

$$\hat{\beta}_{\text{gmm}} = (\mathbf{X}^\top \mathbf{Z} \mathbf{W} \mathbf{Z}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{Z} \mathbf{W} \mathbf{Z}^\top \mathbf{Y},$$

the same estimator as in (12.1). The dependence on the estimator \mathbf{W} is only up to scale; that is, if \mathbf{W} is replaced by $c\mathbf{W}$ for some $c > 0$, $\hat{\beta}_{\text{gmm}}$ does not change. When \mathbf{W} is fixed by the user, we call $\hat{\beta}_{\text{gmm}}$ a **one-step GMM** estimator. Note that by comparison to (12.3), we see that if $\mathbf{W} = (\mathbf{Z}^\top \mathbf{Z})^{-1}$ then we have the two stage least squares estimator. Also note that if $\ell = p$ then $\mathbf{X}^\top \mathbf{Z}$ is invertible (as is \mathbf{W} since it is positive definite by assumption) and we have

$$\begin{aligned} \hat{\beta}_{\text{gmm}} &= (\mathbf{Z}^\top \mathbf{X})^{-1} \mathbf{W}^{-1} (\mathbf{X}^\top \mathbf{Z})^{-1} \mathbf{X}^\top \mathbf{Z} \mathbf{W} \mathbf{Z}^\top \mathbf{Y} \\ &= (\mathbf{Z}^\top \mathbf{X})^{-1} \mathbf{W}^{-1} \mathbf{W} \mathbf{Z}^\top \mathbf{Y} \\ &= (\mathbf{Z}^\top \mathbf{X})^{-1} \mathbf{Z}^\top \mathbf{Y}, \end{aligned}$$

which matches the estimator in (12.4).

12.3 DSO 699 [?]

12.3.1 Causal Estimands (Section 1.20 of ?, p. 18)

Different treatment effects:

1.

$$\text{Ave}(Y_i(\text{Asp}) - Y_i(\text{No})) = \frac{1}{N} \sum_{i=1}^N (Y_i(\text{Asp}) - Y_i(\text{No}))$$

$$\text{Ave}(Y_i(\text{Asp}) - Y_i(\text{No})) = \mathbb{E}(Y_i(\text{Asp}) - Y_i(\text{No}))$$

2.

$$\text{Median}(Y_i(\text{Asp}) - Y_i(\text{No}))$$

3.

$$\text{Median}(Y_i(\text{Asp})) - \text{Median}(Y_i(\text{No}))$$

4. (Subpopulations, or heterogeneous treatment effects [HTE])

$$\tau_{fs}(f) = \text{Ave}_{X_i=\text{female}}(Y_i(\text{Asp}) - Y_i(\text{No})) = \frac{1}{N(f)} \sum_{i:X_i=\text{female}} (Y_i(\text{Asp}) - Y_i(\text{No}))$$

Third one is easier to study than second.

12.3.2 Assignment Mechanisms (Chapter 4 of ?)

- Completely randomized design
- Bernoulli assignment
- Bernoulli assignment within blocks
- Probability of treatment depending on covariates
- Randomized within matched pairs

12.4 Regression Methods (Chapter 7 of ?)

Selection bias problem: we have

$$\begin{aligned} Y_i^{\text{obs}} &= \begin{cases} Y_i(1), & W_i = 1, \\ Y_i(0), & W_i = 0 \end{cases} \\ &= Y_i(1)W_i + Y_i(0)(1 - W_i) \\ &= Y_i(0) + (Y_i(1) - Y_i(0))W_i. \end{aligned}$$

Note that

$$\begin{aligned} \mathbb{E}[Y_i^{\text{obs}} \mid W_i = 1] - \mathbb{E}[Y_i^{\text{obs}} \mid W_i = 0] &= \mathbb{E}[Y_i(1) \mid W_i = 1] - \mathbb{E}[Y_i(0) \mid W_i = 0] \\ &= \mathbb{E}[Y_i(1) \mid W_i = 1] - \mathbb{E}[Y_i(0) \mid W_i = 1] + \mathbb{E}[Y_i(0) \mid W_i = 1] - \mathbb{E}[Y_i(0) \mid W_i = 0] \\ &= \underbrace{\mathbb{E}[Y_i(1) - Y_i(0) \mid W_i = 1]}_{\text{average treatment effect on treated}} + \underbrace{\mathbb{E}[Y_i(0) \mid W_i = 1] - \mathbb{E}[Y_i(0) \mid W_i = 0]}_{\text{selection bias}} \end{aligned}$$

Random assignment solves the selection bias issue:

$$\mathbb{P}(W_i = 1 \mid Y_i(0), Y_i(1)) = \mathbb{P}(W_i = 1)$$

$$W_i \perp\!\!\!\perp (Y_i(0), Y_i(1))$$

12.4.1 Linear Regression with No Covariates (Section 7.4 of ?)

Regression approach: Let $\alpha = \mathbb{E}[Y_i(0)]$. Define

$$\epsilon_i = \begin{cases} Y_i^{\text{obs}} - \alpha, & W_i = 0 \\ Y_i^{\text{obs}} - \alpha - \tau, & W_i = 1. \end{cases}$$

(Note that Y_i^{obs} is random due to (1) random sampling of which observational units are included in the sample and (2) (possibly) randomized treatment assignment. We have

$$Y_i^{\text{obs}} = \alpha + \tau W_i + \epsilon_i.$$

In order for least squares to be consistent, we need to verify whether $\mathbb{E}[\epsilon_i \mid W_i = 1] = \mathbb{E}[\epsilon_i \mid W_i = 0]$. Under the assumption that $W_i \perp\!\!\!\perp (Y_i(0), Y_i(1))$,

$$\begin{aligned} \mathbb{E}[\epsilon_i \mid W_i = 1] &= \mathbb{E}[Y_i^{\text{obs}} - \alpha - \tau \mid W_i = 1] \\ &= \mathbb{E}[Y_i(1) - \alpha - \tau \mid W_i = 1] \\ &= \mathbb{E}[Y_i(1)] - \alpha - \tau \\ &= \mathbb{E}[Y_i(1)] - \mathbb{E}[Y_i(0)] - (\mathbb{E}[Y_i(1)] - \mathbb{E}[y_i(0)]) \\ &= 0. \end{aligned}$$

Similarly, under this assumption $\mathbb{E}[\epsilon_i \mid W_i = 0] = 0$. We can estimate τ using OLS:

$$\hat{\tau}^{\text{obs}} = \frac{1}{\sum_{i=1}^N (W_i - \bar{W})^2} \sum_{i=1}^N (Y_i^{\text{obs}} - \bar{Y}^{\text{obs}})(W_i - \bar{W}) = \frac{1}{\sum_{i=1}^N (W_i - \bar{W})^2} \sum_{i=1}^N (Y_i^{\text{obs}} - \bar{Y}^{\text{obs}})W_i$$

We have

$$\sum_{i=1}^N (W_i - \bar{W})^2 = \sum_{i=1}^N W_i^2 - N \bar{W}^2 = N_t - N \left(\frac{N_t}{N}\right)^2 = \frac{NN_t - N_t^2}{N} = \frac{N_t N_c}{N}.$$

In the numerator,

$$\begin{aligned}
\sum_{i=1}^N (Y_i^{\text{obs}} - \bar{Y}^{\text{obs}})(W_i - \bar{W}) &= \sum_{i=1}^N (Y_i^{\text{obs}} - \bar{Y}^{\text{obs}})W_i \\
&= \sum_{i=1}^N Y_i^{\text{obs}}W_i - \sum_{i=1}^N \bar{Y}^{\text{obs}}W_i \\
&= \sum_{\substack{W_i=1 \\ W_i=0}} Y_i(1) - \bar{Y}^{\text{obs}}N_t \\
&= N_t \bar{Y}^{\text{obs}}(1) - \bar{Y}^{\text{obs}}N_t \\
&= N_t (\bar{Y}^{\text{obs}}(1) - \bar{Y}^{\text{obs}}) \\
&= N_t \left(\bar{Y}^{\text{obs}}(1) - \frac{1}{N} \sum_{W_i=1} Y_i(1) - \frac{1}{N} \sum_{W_i=0} Y_i(0) \right) \\
&= N_t \left(\bar{Y}^{\text{obs}}(1) - \frac{N_t}{N} \bar{Y}_t^{\text{obs}}(1) - \frac{N_c}{N} \bar{Y}_c^{\text{obs}}(0) \right) \\
&= \frac{N_t N_c}{N} (\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}) \\
&\vdots \\
&= \sum_{W_i=1} (Y_i(1) - \bar{Y}^{\text{obs}})W_i + \sum_{W_i=0} (Y_i(0) - \bar{Y}^{\text{obs}})W_i \\
&= \sum_{W_i=1} (Y_i(1) - \bar{Y}^{\text{obs}})
\end{aligned}$$

Therefore

$$\hat{\tau}^{\text{obs}} = \frac{N_t N_c}{N} (\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}) / \frac{N_t N_c}{N} = \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}},$$

which is the same as Neyman's estimator. Now consider the variance estimator.

$$\text{Var}(\hat{\tau}^{\text{obs}}) = \frac{\hat{\sigma}_{Y|W}^2}{\sum_{i=1}^N (W_i - \bar{W})^2}.$$

$$\begin{aligned}
\hat{\sigma}_{Y|X}^2 &= \frac{1}{N-2} \sum_{i=1}^N (Y_i^{\text{obs}} - \hat{Y}_I^{\text{obs}})^2 \\
&= \frac{1}{N-2} \left[\left(\sum_{W_i=1} Y_I^{\text{obs}} - \bar{Y}_t^{\text{obs}} \right)^2 + \left(\sum_{W_i=0} Y_I^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right)^2 \right]
\end{aligned}$$

$$\hat{V} = \frac{1}{N-2} \left[\left(\sum_{W_i=1} Y_I^{\text{obs}} - \bar{Y}_t^{\text{obs}} \right)^2 + \left(\sum_{W_i=0} Y_I^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right)^2 \right] / \frac{N_t N_c}{N}$$

$$N\hat{V} \rightarrow \frac{S_t^2}{\rho} + \frac{S_c^2}{1-\rho}$$

Variance estimator (p. 121):

$$\hat{V}^{\text{homosk}} = \left(\frac{1}{N_c} + \frac{1}{N_t} \right) \hat{\sigma}_{Y|w}^2$$

Calculations for heteroskedastic robust variance estimator (p. 121):

$$\left(\sum_{i=1}^N (W_i - \bar{W})^2 \right) = \frac{N_t N_c}{N}.$$

$$\begin{aligned} \hat{\epsilon}_i &= Y_i^{\text{obs}} - \hat{Y}_i^{\text{obs}} = Y_i^{\text{obs}} - \hat{\alpha} - \hat{\tau} W_i \\ &= \begin{cases} Y_i^{\text{obs}} - \hat{\alpha}, & W_i = 0, \\ Y_i^{\text{obs}} - \hat{\alpha} - \hat{\tau}, & W_i = 1 \end{cases} \\ &= \begin{cases} Y_i(0) - (\bar{Y} - \hat{\tau} \bar{W}), & W_i = 0, \\ Y_i(1) - (\bar{Y} - \hat{\tau} \bar{W}) - \hat{\tau}, & W_i = 1 \end{cases} \end{aligned}$$

where $\hat{\alpha} = \bar{Y} - \hat{\tau} \bar{W}$. Consider $W_i = 0$.

$$\begin{aligned} Y_i(0) - (\bar{Y} - \hat{\tau} \bar{W}) &= Y_i(0) - \bar{Y} - \left(\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right) \frac{N_t}{N} \\ &= Y_i(0) - \frac{1}{N} \sum_{i=1}^N Y_i^{\text{obs}} - \frac{1}{N} \sum_{W_i=1} Y_i^{\text{obs}} + \frac{N_t}{N_c N} \sum_{W_i=0} Y_i^{\text{obs}} \\ &= Y_i(0) - \frac{N_t}{N_c N} \left(\frac{N_c}{N_t} \sum_{i=1}^N Y_i^{\text{obs}} - \sum_{W_i=0} Y_i^{\text{obs}} \right) - \frac{1}{N} \sum_{W_i=1} Y_i^{\text{obs}} \\ &= Y_i(0) - \frac{N_t}{N_c N} \left(\frac{N_c}{N_t} \sum_{i=1}^N Y_i^{\text{obs}} - \sum_{W_i=0} Y_i^{\text{obs}} \right) - \frac{1}{N} \sum_{W_i=1} Y_i^{\text{obs}} \\ &= Y_i(0) - \frac{N_t}{N_c N} \left(\frac{N_c}{N_t} \sum_{W_i=1} Y_i^{\text{obs}} + \frac{N_c}{N_t} \sum_{W_i=0} Y_i^{\text{obs}} - \sum_{W_i=0} Y_i^{\text{obs}} \right) - \frac{1}{N} \sum_{W_i=1} Y_i^{\text{obs}} \\ &\vdots \\ &= Y_i(0) - \bar{Y}_c^{\text{obs}} \end{aligned}$$

Similarly, for $W_i = 1$

$$Y_i(1) - (\bar{Y} - \hat{\tau}^{\text{obs}} \bar{W}) - \hat{\tau}^{\text{ols}} = Y_i(1) - \bar{Y}_t^{\text{obs}}.$$

We have

$$\hat{\epsilon}_i = \begin{cases} Y_i(0) - \bar{Y}_c^{\text{obs}}, & W_i = 0 \\ Y_i(1) - \bar{Y}_t^{\text{obs}}, & W_i = 1 \end{cases}$$

$$\begin{aligned} \sum_{i=1}^N \hat{\epsilon}_i^2 (W_i - \bar{W})^2 &= \sum_{W_i=1} \hat{\epsilon}_i^2 (1 - \frac{N_t}{N})^2 + \sum_{W_i=0} \hat{\epsilon}_i^2 (0 - \frac{N_t}{N})^2 \\ &\quad \vdots \\ &= \frac{N_c^2}{N^2} \sum_{W_i=1} (Y_i(1) - \bar{Y}_t^{\text{obs}})^2 + \frac{N_t^2}{N^2} \sum_{W_i=0} (Y_i(0) - \bar{Y}_c^{\text{obs}})^2 \end{aligned}$$

Then

$$\begin{aligned} \hat{V}^{\text{hetero}} &= \frac{1}{N_t^2} \sum_{W_i=1} (Y_i(1) - \bar{Y}_t^{\text{obs}})^2 + \frac{1}{N_c^2} \sum_{W_i=0} (Y_i(0) - \bar{Y}_c^{\text{obs}})^2 \\ &\approx \frac{1}{N_t} S_t^2 + \frac{1}{N_c} S_c^2 \end{aligned}$$

where

$$S_t^2 = \frac{1}{N_t - 1} \sum_{W_i=1} (Y_i(1) - \bar{Y}_t^{\text{obs}})^2$$

We can also use weighted least squares if we think the errors are heteroskedastic. The estimator is

$$\hat{\tau}_{wls} = \sum_{i=1}^N \frac{1}{\sigma_i^2} (y_i - \alpha - \beta^\top w_i)^2$$

with $\sigma_i^2 = \text{Var}(\epsilon_i)$. Then

$$N\hat{V}^{\text{hetero}} \approx \frac{1}{N_t/N} S_t^2 + \frac{1}{N_c/N} S_c^2 \xrightarrow{p} \frac{1}{\rho} \sigma_t^2 + \frac{1}{1-\rho} \sigma_c^2$$

where σ_t^2 is the population variance of $Y_i(1)$ and σ_c^2 is the population variance of $Y_i(0)$.

12.4.2 Linear Regression with Additional Covariates (Section 7.5 of ?)

Notes on Theorem 7.1(i):

$$\begin{aligned}
\tau^* &= \frac{\text{Cov}(Y_i^{\text{obs}}, W_i)}{\text{Var}(Y_i^{\text{obs}})} \\
&= \frac{\mathbb{E}[Y_i^{\text{obs}}W_i] - \mathbb{E}[Y_i^{\text{obs}}]\mathbb{E}[W_i]}{p(1-p)} \\
&= \frac{\mathbb{E}[Y_i(1)W_i] - \mathbb{E}[W_iY_i(1) + (1-W_i)Y_i(0)]p}{p(1-p)} \\
&= \frac{p\mu_t - p[p\mu_t + (1-p)\mu_c]}{p(1-p)} \\
&= \mu_t - \mu_c \\
&= \tau.
\end{aligned}$$

where p is the probability of treatment.

12.4.3 Testing for the Presence of Treatment Effects (Section 7.9 of ?)

12.5 Model-Based Inference for Completely Randomized Experiments (Chapter 8 of ?)

12.5.1 A Simple Example: Naive and More Sophisticated Approaches to Estimation (Section 8.3 of ?)

Theorem 12.5.1. For the mean imputation method,

$$\hat{\tau}_{\text{impute}} = \hat{\tau}^{\text{dif}} = \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}$$

For the sampling imputation method,

$$\mathbb{E} [\hat{\tau}_{\text{impute}} | \mathbf{Y}^{\text{obs}}, \mathbf{W}] = \hat{\tau}^{\text{dif}} = \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}}.$$

Proof. (a) For mean imputation, we impute the missing observation for observation i by taking the mean among all observations j with $W_j = 1 - W_i$. That is,

$$\hat{Y}_i^{\text{mis}} = (1 - W_i) \bar{Y}_t^{\text{obs}} + W_i \bar{Y}_c^{\text{obs}}.$$

Then (using $W_i(1 - W_i) = 0$, $W_i^2 = W_i$, and $(1 - W_i)^2 = (1 - W_i)$ for all i)

$$\begin{aligned}
\hat{\tau}^{\text{impute}} &= \frac{1}{N} \sum_{i=1}^N (2W_i - 1)(Y_i^{\text{obs}} - \hat{Y}_i^{\text{mis}}) \\
&= \frac{1}{N} \sum_{i=1}^N \left(W_i Y_i^{\text{obs}} + (1 - W_i) \hat{Y}_i^{\text{mis}} - \left[(1 - W_i) Y_i^{\text{obs}} + W_i \hat{Y}_i^{\text{mis}} \right] \right) \\
&= \frac{1}{N} \sum_{i=1}^N \left(W_i Y_i^{\text{obs}} + (1 - W_i) \left[(1 - W_i) \bar{Y}_t^{\text{obs}} + W_i \bar{Y}_c^{\text{obs}} \right] \right. \\
&\quad \left. - \left[(1 - W_i) Y_i^{\text{obs}} + W_i \left[(1 - W_i) \bar{Y}_t^{\text{obs}} + W_i \bar{Y}_c^{\text{obs}} \right] \right] \right) \\
&= \frac{1}{N} \sum_{i=1}^N \left(W_i Y_i^{\text{obs}} + (1 - W_i)^2 \bar{Y}_t^{\text{obs}} - \left[(1 - W_i) Y_i^{\text{obs}} + W_i^2 \bar{Y}_c^{\text{obs}} \right] \right) \\
&= \frac{1}{N} \sum_{i=1}^N W_i \left[Y_i^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right] + \frac{1}{N} \sum_{i=1}^N (1 - W_i) \left[\bar{Y}_t^{\text{obs}} - Y_i^{\text{obs}} \right] \\
&= \frac{1}{N} \cdot N_t \left(\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right) + \frac{1}{N} \cdot N_c \left(\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right) \\
&= \frac{N_t + N_c}{N} \left(\bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} \right) \\
&= \bar{Y}_t^{\text{obs}} - \bar{Y}_c^{\text{obs}} \\
&= \hat{\tau}^{\text{dif}}.
\end{aligned}$$

(b) For the second imputation method, observe that \hat{Y}_i^{mis} is a random variable, with

$$\mathbb{E} \left[\hat{Y}_i^{\text{mis}} \mid \{Y_i^{\text{obs}}, W_i\}_{i=1}^N \right] = (1 - W_i) \bar{Y}_t^{\text{obs}} + W_i \bar{Y}_c^{\text{obs}}.$$

$$\begin{aligned}
\mathbb{E} \left[\hat{\tau}^{\text{impute}} \mid \{Y_i^{\text{obs}}, W_i\}_{i=1}^N \right] &= \mathbb{E} \left[\frac{1}{N} \sum_{i=1}^N (2W_i - 1)(Y_i^{\text{obs}} - \hat{Y}_i^{\text{mis}}) \mid \{Y_i^{\text{obs}}, W_i\}_{i=1}^N \right] \\
&= \frac{1}{N} \sum_{i=1}^N (2W_i - 1) \left(Y_i^{\text{obs}} - \mathbb{E} \left[\hat{Y}_i^{\text{mis}} \mid \{Y_i^{\text{obs}}, W_i\}_{i=1}^N \right] \right) \\
&= \frac{1}{N} \sum_{i=1}^N (2W_i - 1) \left(Y_i^{\text{obs}} - \left[(1 - W_i) \bar{Y}_t^{\text{obs}} + W_i \bar{Y}_c^{\text{obs}} \right] \right) \\
&= \frac{1}{N} \sum_{i=1}^N \left(W_i Y_i^{\text{obs}} + (1 - W_i) \hat{Y}_i^{\text{mis}} - \left[(1 - W_i) Y_i^{\text{obs}} + W_i \hat{Y}_i^{\text{mis}} \right] \right).
\end{aligned}$$

Then the rest follows from the proof of part (a). □

12.5.2 Bayesian Model-Based Imputation in the Absence of Covariates (Section 8.4 of ?)

Chapter 13

Time Series

These notes are based on my notes from *Time Series and Panel Data Econometrics* (1st edition) by M. Hashem Pesaran [Pesaran, 2015] as well as coursework for Economics 613: Economic and Financial Time Series I at USC.

13.1 Chapter 6: ARDL Models

In an ARDL model, if the error are serially correlated, then the coefficient estimates are biased (even as $T \rightarrow \infty$).

13.2 Chapters 12 and 13: Intro to Stochastic Processes and Spectral Analysis

Stationarity conditions: $\{X_t\}$ is **strictly stationary** if the joint distribution functions of $\{X_{t_1}, X_{t_2}, \dots, X_{t_k}\}$ and $\{X_{t_1+h}, X_{t_2+h}, \dots, X_{t_k+h}\}$ are identical for all values of t_1, t_2, \dots, t_k and h and all positive integers k .

Definition 13.1. X_t is **weakly (or covariance) stationary** if it has a constant mean and variance and its covariance function $\gamma(t_1, t_2)$ depends only on the absolute difference $|t_1 - t_2|$, namely $\gamma(t_1, t_2) = \gamma(|t_1 - t_2|)$.

Definition 13.2. X_t is said to be **trend stationary** if $y_t = X_t - d_t$ is covariance stationary, where d_t is the perfectly predictable component of X_t .

The process $\{\epsilon_t\}$ is said to be a **white noise process** if it has mean zero, a constant variance, and ϵ_t and ϵ_s are uncorrelated for all $s \neq t$.

Autocovariance generating function: The autocovariance generating function for the general linear stationary process $y_t = \sum_{i=0}^{\infty} a_i \epsilon_{t-i}$ is given by:

$$G(z) = \sigma^2 a(z)a(z^{-1})$$

where $a(z) = \sum_{i=0}^{\infty} a_i z^i$.

Wold's Decomposition (Theorem 42, p. 275, Section 12.5) Any trend-stationary process $\{y_t\}$ can be represented in the form of $y_t = d_t + \sum_{i=0}^{\infty} \alpha_i \epsilon_{t-i}$ where $\alpha_0 = 1$ and $\sum_{i=0}^{\infty} \alpha_i^2 < K < \infty$. The term d_t is a deterministic component, while $\{\epsilon_t\}$ is a serially uncorrelated process: $\epsilon_t = y_t - \mathbb{E}(y_t | y_{t-1}, y_{t-2}, \dots)$.

Stationarity conditions for an ARMA(p, q) process: Consider the ARMA(p, q) process

$$y_t = \sum_{i=1}^p \phi_i y_{t-i} + \sum_{i=0}^q \theta_i \epsilon_{t-i}, \quad \theta_0 = 1$$

The MA part is stationary for any finite q . The AR part is stationary if the roots of the characteristic equation

$$\lambda^t = \sum_{i=1}^p \phi_i \lambda^{t-i}$$

lie strictly inside the unit circle. Alternatively, in terms of $z = \lambda^{-1}$, the process is stationary if the roots of

$$1 - \sum_{i=1}^p \phi_i z^i = 0$$

lie outside the unit circle. The ARMA process is **invertible** (so that y_t can be solved uniquely in terms of its past values) if all the roots of

$$1 - \sum_{i=1}^p \theta_i z^i = 0$$

fall outside the unit circle.

Spectral Density Function: Definition (Equation 13.3):

$$f(\omega) = \frac{1}{2\pi} \sum_{h=-\infty}^{\infty} \gamma(h) e^{ih\omega}, \omega \in (-\pi, \pi)$$

Equation (13.5):

$$f(\omega) = \frac{1}{2\pi} \left[\gamma(0) + 2 \sum_{h=1}^{\infty} \gamma(h) \cos(h\omega) \right], \quad \omega \in [0, \pi]$$

Can also be found using the autocovariance generating function. We have (Equation 13.6, section 13.3.1)

$$f(\omega) = \frac{1}{2\pi} G(e^{i\omega}) = \frac{\sigma^2}{2\pi} a(e^{i\omega}) a(e^{-i\omega})$$

Properties of spectral density function:

- (1) $f(\omega)$ always exists and is bounded if $\gamma(h)$ is absolutely summable.
- (2) $f(\omega)$ is symmetric.
- (3) The spectrum of a stationary process is finite at zero frequency; that is, $f(0) < \infty$.

Linear (time-domain) processes don't have to be stationary, but to write something as a frequency-domain process, it must be stationary.

13.2.1 Worked Examples

Midterm Problem 2 part (1) (chapter 12 exercise 6)

Midterm Problem 2 part (2) (exercise 7 in chapter 12; similar to exercise 1 in chapter 14).
Suppose $\{y_t\}$ has the following general linear process

$$y_t = \mu + \alpha(L)\epsilon_t, \quad \epsilon_t \sim i.i.d. (0, \sigma^2)$$

where $\alpha(L) = \alpha_0 + \alpha_1 L + \alpha_2 L^2 + \dots$; $\alpha_0 = 1$. Let

$$\bar{y}_T = \frac{1}{T} \sum_{t=1}^T y_t$$

$$\gamma(h) = \mathbb{E}[(y_t - \mu)(y_{t-h} - \mu)]$$

$$\hat{\gamma}(h) = \frac{1}{T} \sum_{t=h+1}^T (y_t - \bar{y}_T)(y_{t-h} - \bar{y}_T)$$

Derive the conditions under which

- (a) \bar{y}_T is a consistent estimator of μ as $T \rightarrow \infty$
- (b) For fixed h , $\hat{\gamma}(h)$ is a consistent estimator of $\gamma(h)$ as $T \rightarrow \infty$.

Solution.

- (a) This is an MA(∞) process. By Chebyshev's Inequality (Theorem 8.2.2), \bar{y}_T is a consistent estimator of μ as $T \rightarrow \infty$ if $\lim_{T \rightarrow \infty} \mathbb{E}(\bar{y}_T) = \mathbb{E}(y_T) = \mu$ and $\lim_{T \rightarrow \infty} \text{Var}(\bar{y}_T) = 0$. In this case in particular (MA(∞) process), we can write

$$\bar{y}_T = \frac{1}{T} \sum_{t=1}^T (\mu + \alpha(L)\epsilon_t) = \frac{1}{T} \cdot T\mu + \frac{1}{T} \sum_{t=1}^T \alpha(L)\epsilon_t = \mu + \frac{1}{T} \sum_{t=1}^T \alpha(L)\epsilon_t$$

Then we have

$$\begin{aligned}\mathbb{E}(\bar{y}_T) &= \mu + \frac{1}{T} \mathbb{E} \left(\sum_{t=1}^T \alpha(L) \epsilon_t \right) = \mu + \frac{1}{T} \sum_{t=1}^T \mathbb{E}(\alpha(L) \epsilon_t) = \mu \\ \text{Var}(\bar{y}_T) &= 0 + \frac{1}{T^2} \text{Var} \left(\sum_{t=1}^T \alpha(L) \epsilon_t \right) = \frac{1}{T^2} \sum_{t=1}^T \text{Var}[\alpha(L) \epsilon_t] = \frac{1}{T^2} \sum_{t=1}^T \mathbb{E}[\alpha(L) \epsilon_t]^2 = \frac{1}{T} \alpha(1)^2 \mathbb{E}[\epsilon_t]^2 \\ &= \frac{\sigma^2}{T} \alpha(1)^2\end{aligned}$$

Therefore a sufficient condition for consistency is

$$\lim_{T \rightarrow \infty} \frac{\sigma^2}{T} \alpha(1)^2 = 0 \iff \alpha(1)^2 < \infty \iff \boxed{\sum_{i=0}^{\infty} \alpha_i = 0}$$

(b) See section 13.4.2.

13.3 Some time series and their properties

13.3.1 White noise process:

$$x_t = \epsilon_t, \epsilon_t \sim IID(0, \sigma^2)$$

- Autocovariances:

$$\gamma(0) = \sigma^2$$

$$\gamma(h) = 0, \quad \forall h \neq 0$$

- Spectral density function:

$$f_x(\omega) = \frac{1}{2\pi} \cdot \sigma^2 = \frac{\sigma^2}{2\pi} \text{ (flat spectrum)}$$

13.3.2 MA(1) process:

$$x_t = \epsilon_t + \theta \epsilon_{t-1} \text{ with } \epsilon_t \sim iid(0, \sigma^2), |\rho| < 1.$$

- Autocovariances: By Equation (12.2), the autocovariance function is

$$\text{Cov}(u_t, u_{t-h}) = \gamma(h) = \sigma^2 \sum_{i=0}^{1-|h|} a_i a_{i+|h|} \text{ if } 0 \leq |h| \leq 1$$

$$\implies \mathbb{E}(x_t^2) = \gamma(0) = (1 + \theta^2)\sigma^2$$

$$\mathbb{E}(x_t x_{t-1}) = \gamma(1) = \theta\sigma^2$$

$$\gamma(h) = 0 \quad \forall |h| > 1$$

So the covariance matrix is

$$\begin{pmatrix} \sigma^2(1 + \theta^2) & \sigma^2\theta & 0 & 0 & \cdots & 0 \\ \sigma^2\theta & \sigma^2(1 + \theta^2) & \sigma^2\theta & 0 & \cdots & 0 \\ 0 & \sigma^2\theta & \sigma^2(1 + \theta^2) & \sigma^2\theta & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma^2\theta & \sigma^2(1 + \theta^2) & \sigma^2\theta \\ 0 & 0 & \cdots & 0 & \sigma^2\theta & \sigma^2(1 + \theta^2) \end{pmatrix}$$

$$= \sigma^2(1 + \theta^2)I_T + \sigma^2\theta A$$

where A is defined as in section 14.3.2 (p. 304).

- Spectral density function:

$$f(\omega) = \frac{\sigma^2}{2\pi} [1 + 2\theta \cos(\omega) + \rho^2], \quad \omega \in [0, \pi]$$

13.3.3 MA(∞) process:

This process is covariance stationary.

- Autocovariances:

13.3.4 AR(1) process:

$$x_t = \phi x_{t-1} + \epsilon_t, |\phi| < 1, \epsilon_t \sim IID(0, \sigma^2).$$

- Yule-Walker Equations:

$$\mathbb{E}[x_t x_{t-h}] = \mathbb{E}[\phi x_{t-1} x_{t-h}] + \mathbb{E}[\epsilon x_{t-h}]$$

$$\gamma_h = \phi \gamma_{h-1} + \mathbb{E}[\epsilon x_{t-h}]$$

$$\implies \gamma_0 = \phi \gamma_1 + \sigma^2, \quad \gamma_h = \phi \gamma_{h-1} \quad \forall h \geq 1$$

- Autocovariances:

$$\gamma(0) = \frac{\sigma^2}{1 - \phi^2}$$

$$\gamma_h = \frac{\sigma^2 \phi^h}{1 - \phi^2} = \phi^h \gamma(0) \quad \forall h \geq 1$$

$$\implies \text{Cov}(x) =$$

$$\begin{pmatrix} \sigma^2/(1-\phi^2) & \sigma^2\phi/(1-\phi^2) & \sigma^2\phi^2/(1-\phi^2) & \sigma^2\phi^3/(1-\phi^2) & \dots & \sigma^2\phi^{T-1}/(1-\phi) \\ \sigma^2\phi/(1-\phi) & \sigma^2/(1-\phi^2) & \sigma^2\phi/(1-\phi^2) & \sigma^2\phi^2/(1-\phi^2) & \dots & \sigma^2\phi^{T-2}/(1-\phi^2) \\ \sigma^2\phi^2/(1-\phi^2) & \sigma^2\phi/(1-\phi^2) & \sigma^2/(1-\phi^2) & \sigma^2\phi/(1-\phi^2) & \dots & \sigma^2\phi^{T-3}/(1-\phi^2) \\ \vdots & \vdots & \vdots & \vdots & \dots & \vdots \\ \sigma^2\phi^{T-2}/(1-\phi^2) & \sigma^2\phi^{T-3}/(1-\phi^2) & \dots & \sigma^2\phi/(1-\phi^2) & \sigma^2/(1-\phi^2) & \sigma^2\phi/(1-\phi^2) \\ \sigma^2\phi^{T-1}/(1-\phi^2) & \sigma^2\phi^{T-2}/(1-\phi^2) & \dots & \sigma^2\phi^2/(1-\phi^2) & \sigma^2\phi/(1-\phi^2) & \sigma^2/(1-\phi^2) \end{pmatrix}$$

- If stationary, can be written as an infinite MA process with absolutely summable coefficients

$$x_t = \sum_{i=0}^{\infty} \phi^i \epsilon_{t-i} = \left(\frac{1}{1 - \phi L} \right) \epsilon_t$$

- Autocovariance generating function:

$$G(z) = \left(\frac{\sigma^2}{1 - \phi^2} \right) \left(1 + \sum_{h=1}^{\infty} \phi^h (z^h + z^{-h}) \right)$$

- Spectral density function:

$$f(\omega) = \frac{1}{2\pi} \sum_{h=-\infty}^{\infty} \frac{\sigma^2 \phi^{|h|}}{(1 - \phi^2)} (e^{i\omega})^h = \frac{1}{2\pi} \frac{\sigma^2}{(1 - \phi e^{i\omega})(1 - \phi e^{-i\omega})} = \frac{1}{2\pi} \frac{\sigma^2}{1 - 2\phi \cos(\omega) + \phi^2}$$

13.3.5 AR(2) process:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \epsilon, |\phi_1| < 1, |\phi_2| < 1, \epsilon_t \sim IID(0, \sigma^2).$$

Can be written as

$$x_t = \frac{1}{1 - \phi L} \epsilon_t = \epsilon_t + \phi \epsilon_{t-1} + \phi^2 \epsilon_{t-2} + \dots$$

- Yule-Walker equations:

$$\mathbb{E}[x_t x_{t-h}] = \mathbb{E}[\phi_1 x_{t-1} x_{t-h}] + \mathbb{E}[\phi_2 x_{t-2} x_{t-h}] + \mathbb{E}[\epsilon x_{t-h}]$$

$$\gamma_h = \phi_1 \gamma_{h-1} + \phi_2 \gamma_{h-2} + \mathbb{E}[\epsilon x_{t-h}]$$

$$\implies \boxed{\gamma_0 = \phi_1 \gamma_1 + \phi_2 \gamma_2 + \sigma^2, \quad \gamma_1 = \phi_1 \gamma_0 + \phi_2 \gamma_1, \quad \gamma_2 = \phi_1 \gamma_1 + \phi_2 \gamma_0}$$

- Autocovariances:

13.3.6 AR(p) process:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_p x_{t-p} + \epsilon, \quad |\phi_i| < 1, \quad \epsilon_t \sim IID(0, \sigma^2).$$

- Stationary if the eigenvalues of Φ lie inside the unit circle, which is equivalent to all the roots of

$$\phi(z) = 1 - \phi_1 z - \phi_2 z^2 - \dots - \phi_p z^p = 0$$

being strictly larger than unity. Under this condition the AR process has the infinite-order MA representation'

$$x_t = \sum_{i=0}^{\infty} \alpha_i \epsilon_{t-i}$$

where $\alpha_i = \phi_1 \alpha_{i-1} + \dots + \phi_p \alpha_{i-p}$.

- Autocovariance generating function:

$$G(z) = \frac{\sigma^2}{\phi(z)\phi(z^{-1})}$$

13.3.7 ARMA(1, 1) process:

$$x_t = \phi x_{t-1} + \epsilon_t + \theta \epsilon_{t-1}, \quad \text{with } |\phi| < 1 \quad (\text{implying stationarity}), \quad \mathbb{E}(\epsilon_t^2) = \sigma^2, \quad \mathbb{E}(\epsilon_t \epsilon_s) = 0 \text{ for } t \neq s.$$

- Yule-Walker Equations:

$$\gamma(0) = \phi \gamma(1) + \sigma^2(1 + \theta^2)$$

$$\gamma(1) = \phi \gamma(0) + \sigma^2 \phi^2$$

$$\gamma(h) = \phi \gamma(h-1) \quad \forall h \geq 2$$

- Autocovariances:

$$\gamma(0) = \sigma^2 \left(1 - \frac{(\phi + \theta)^2}{1 - \phi^2} \right)$$

$$\gamma(1) = \sigma^2 \left(\phi + \theta + \frac{(\phi + \theta)^2 \phi}{1 - \phi^2} \right)$$

$$\gamma(2) = \phi^{h-1} \gamma(1) \quad \forall h \geq 2$$

- Autocorrelation function:

$$\rho(h) = \begin{cases} 1 & h = 0 \\ \frac{(\phi+\theta)(1+\phi\theta)}{1+2\phi\theta+\theta^2} & h = 1 \\ \phi^{h-1} \rho(1) & h \geq 2 \end{cases}$$

- Autocovariance generating function: the autocovariance function of an ARMA(p, q) process $\phi(L)y_t = \theta(L)\epsilon_t$ is given by

$$f(\omega) = \sigma^2 \frac{\theta(z)\theta(z^{-1})}{\phi(z)\phi(z^{-1})}$$

Plugging in for the ARMA(1,1) case yields (**double-check**)

$$f(\omega) = \sigma^2 \frac{(1 + \theta)^2}{(1 - \rho)^2}$$

- Spectral Density Function: the spectral density function of an ARMA(p, q) process $\phi(L)y_t = \theta(L)\epsilon_t$ is given by

$$f(\omega) = \frac{\sigma^2}{2\pi} \frac{\theta(e^{i\omega})\theta(e^{-i\omega})}{\phi(e^{i\omega})\phi(e^{-i\omega})}, \quad \omega \in [0, 2\pi]$$

Plugging in for the ARMA(1,1) case yields

$$f_x(\omega) = \frac{\sigma^2}{2\pi} \frac{(e^{i\omega} - \theta e^{i\omega})(e^{-i\omega} - \theta e^{-i\omega})}{(e^{i\omega} - \phi e^{i\omega})(e^{-i\omega} - \phi e^{-i\omega})} = \frac{\sigma^2}{2\pi} \frac{1 - 2\theta + \theta^2}{1 - 2\phi + \phi^2}$$

- If $\phi = \theta$, the ARMA(1,1) process becomes a white noise process. We can see this two ways. The ARMA(1, 1) process can be represented in the following way:

$$(1 - \phi L)y_t = (1 - \theta L)\epsilon_t$$

Therefore $\phi(L) = \theta(L)$ yields $y_t = \epsilon_t$.

We can also see that when $\phi = \theta$, an ARMA(1,1) process is equivalent to a white noise process as follows. Plugging in $\phi = \theta$ to the spectral density function, we have

$$f_x(\omega) = \frac{\sigma^2}{2\pi} \frac{1 - 2\theta + \theta^2}{1 - 2\theta + \theta^2} = \frac{\sigma^2}{2\pi}$$

showing that if $\theta = \phi$, the spectral density function is constant and independent of θ and ϕ . We can see that it in fact is a white noise process. Since a white noise process has the following covariances:

$$\gamma(0) = \sigma^2$$

$$\gamma(h) = 0, \quad \forall h \neq 0$$

for a white noise process we have

$$f_x(\omega) = \frac{1}{2\pi} \cdot \sigma^2 = \frac{\sigma^2}{2\pi}$$

13.4 Chapter 14: Estimation of Stationary Time Series Processes

13.4.1 Sufficient conditions for ergodicity of mean. (Book section 14.2.1)

By Chebyshev's Inequality (see section 8.2), \bar{y}_T is a consistent estimator of μ as $T \rightarrow \infty$ if $\lim_{T \rightarrow \infty} \mathbb{E}(\bar{y}_T) = \mathbb{E}(y_T) = \mu$ and $\lim_{T \rightarrow \infty} \text{Var}(\bar{y}_T) = 0$. We have

$$\begin{aligned} \mathbb{E}(\bar{y}_T) &= \frac{1}{T} \mathbb{E}\left(\sum_{t=1}^T y_t\right) = \frac{1}{T} \sum_{t=1}^T \mathbb{E}(y_t) = \mu \\ \text{Var}(\bar{y}_T) &= \frac{1}{T^2} \text{Var}\left(\sum_{t=1}^T y_t\right) = \frac{1}{T^2} \left(\sum_{t=1}^T \text{Var}(y_t) + 2 \sum_{0 \leq i < j \leq T} \text{Cov}(y_i, y_j) \right) \\ &= \frac{1}{T^2} \left(\sum_{t=1}^T \gamma(0) + 2 \sum_{0 \leq i < j \leq T} \gamma(j-i) \right) = \frac{1}{T^2} \left(T\gamma(0) + 2 \sum_{h=1}^{T-1} (T-h)\gamma(h) \right) \\ &= \frac{1}{T} \left[\gamma(0) + 2 \sum_{h=1}^{T-1} \left(1 - \frac{h}{T} \right) \gamma(h) \right] = \frac{1}{T^2} \mathbf{1}' \text{Var}(\mathbf{y}) \mathbf{1} \end{aligned}$$

where $\mathbf{1}$ is a vector of ones and

$$\text{Var}(\mathbf{y}) = \begin{pmatrix} \gamma(0) & \gamma(1) & \cdots & \gamma(T-2) & \gamma(T-1) \\ \gamma(1) & \gamma(0) & \cdots & \gamma(T-3) & \gamma(T-2) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \gamma(T-2) & \gamma(T-3) & \cdots & \gamma(0) & \gamma(1) \\ \gamma(T-1) & \gamma(T-2) & \cdots & \gamma(1) & \gamma(0) \end{pmatrix}$$

Notice that

$$\left| \gamma(0) + 2 \sum_{h=1}^{T-1} \left(1 - \frac{h}{T} \right) \gamma(h) \right| < \left| 2 \sum_{h=0}^{T-1} \gamma(h) \right| \leq 2 \sum_{h=0}^{T-1} |\gamma(h)|$$

Therefore

$$\sum_{h=0}^{\infty} |\gamma(h)| < \infty$$

is a sufficient condition for

$$\lim_{T \rightarrow \infty} \text{Var}(\bar{y}_T) = \lim_{T \rightarrow \infty} \frac{1}{T} \left[\gamma(0) + 2 \sum_{h=1}^{T-1} \left(1 - \frac{h}{T} \right) \gamma(h) \right] = 0$$

13.4.2 Estimation of autocovariances (Book section 14.2.2).

A moment estimator of $\gamma(h) = \mathbb{E}[(y_t - \mu)(y_{t-h} - \mu)]$ is

$$\hat{\gamma}(h) = \frac{1}{T} \sum_{t=h+1}^T (y_t - \bar{y}_T)(y_{t-h} - \bar{y}_T)$$

By Chebyshev's Inequality (Theorem 8.2.2), $\hat{\gamma}(h)$ is a consistent estimator of $\gamma(h)$ as $T \rightarrow \infty$ if $\lim_{T \rightarrow \infty} \mathbb{E}(\hat{\gamma}(h)) = \gamma(h)$ and $\lim_{T \rightarrow \infty} \text{Var}(\hat{\gamma}(h)) = 0$.

$$\begin{aligned} \hat{\gamma}(h) &= \frac{1}{T} \sum_{t=h+1}^T (y_t - \bar{y}_T)(y_{t-h} - \bar{y}_T) = \frac{1}{T} \sum_{t=h+1}^T (y_t - \mu + \mu - \bar{y}_T)(y_{t-h} - \mu + \mu - \bar{y}_T) \\ &= \frac{1}{T} \sum_{t=h+1}^T (y_t - \mu)(y_{t-h} - \mu) + (y_t - \mu)(\mu - \bar{y}_T) + (\mu - \bar{y}_T)(y_{t-h} - \mu) + (\mu - \bar{y}_T)^2 \\ &= \frac{1}{T} \sum_{t=h+1}^T (y_t - \mu)(y_{t-h} - \mu) + (\mu - \bar{y}_T) \frac{1}{T} \sum_{t=h+1}^T (y_t - \mu) + (\mu - \bar{y}_T) \frac{1}{T} \sum_{t=h+1}^T (y_{t-h} - \mu) + \frac{1}{T} (T-h)(\mu - \bar{y}_T)^2 \\ &\quad \vdots \end{aligned}$$

Because where does this line come from? on page 300 of book/331 of pdf.

$$\bar{y}_T = \mu + \mathcal{O}_p(T^{-1/2})$$

and for any fixed h

$$T^{-1/2} \sum_{t=h+1}^T (y_t - \mu) = \mathcal{O}_p(1)$$

it follows that

$$(\mu - \bar{y}_T) \frac{1}{T} \sum_{t=h+1}^T (y_t - \mu) = \frac{\mu}{T} \sum_{t=h+1}^T (y_t - \mu) - \frac{\bar{y}_T}{\sqrt{T}} \cdot \frac{1}{\sqrt{T}} \sum_{t=h+1}^T (y_t - \mu) = \mathcal{O}_p(T^{-1})$$

$$(\mu - \bar{y}_T) \frac{1}{T} \sum_{t=h+1}^T (y_{t-h} - \mu) = \mathcal{O}_p(T^{-1})$$

$$\frac{1}{T}(T-h)(\mu - \bar{y}_T)^2 = (\mu - \bar{y}_T)^2 - \frac{h}{T}(\mu - \bar{y}_T)^2 = \mathcal{O}_p(T^{-1})$$

$$\implies \hat{\gamma}(h) = \frac{1}{T} \sum_{t=h+1}^T (y_t - \mu)(y_{t-h} - \mu) + \mathcal{O}_p(T^{-1})$$

For $\hat{\gamma}(h)$ to be consistent, we need

$$\frac{1}{T} \sum_{t=h_1}^T (y_t - \mu)(y_{t-h} - \mu) \xrightarrow{p} \gamma(h)$$

First we show that $(y_t - \mu)(y_{t-h} - \mu)$ is a martingale difference process:

$$\mathbb{E}[(y_t - \mu)(y_{t-h} - \mu) | F_{t-h}] = (y_{t-h} - \mu)\mathbb{E}[y_t - \mu | F_{t-h}] = 0$$

We need to show that

$$\mathbb{E}[(y_t - \mu)^2(y_{t-h} - \mu)^2] = \mathbb{E}\left[\left(\sum_{i=0}^{\infty} \alpha_i \epsilon_{t-i}\right)^2 \left(\sum_{j=0}^{\infty} \alpha_j \epsilon_{t-h-j}\right)^2\right] < \infty$$

By the Cauchy-Schwarz Inequality (Theorem 8.2.4), we have

$$\begin{aligned} \mathbb{E}\left[\left(\sum_{i=0}^{\infty} \alpha_i \epsilon_{t-i}\right)^2 \left(\sum_{j=0}^{\infty} \alpha_j \epsilon_{t-h-j}\right)^2\right]^2 &\leq \mathbb{E}\left[\left(\sum_{i=0}^{\infty} \alpha_i \epsilon_{t-i}\right)^2\right]^2 \mathbb{E}\left[\left(\sum_{j=0}^{\infty} \alpha_j \epsilon_{t-h-j}\right)^2\right]^2 \\ &< \infty \iff \mathbb{E}\left[\sum_{i=0}^{\infty} \alpha_i \epsilon_{t-i}\right]^4 < \infty, \quad \mathbb{E}\left[\sum_{j=0}^{\infty} \alpha_j \epsilon_{t-h-j}\right]^4 < \infty \end{aligned}$$

These conditions hold if $\mathbb{E}(\epsilon_t^4) < \infty$ and $\sum_{i=0}^{\infty} |\alpha_i| < \infty$. Then $\mathbb{E}[(y_t - \mu)^2(y_{t-h} - \mu)^2] < \infty$ holds and

$$\hat{\gamma} \xrightarrow{p} \gamma(h)$$

13.4.3 Worked examples

Midterm Problem 3 parts (3) and (4) (similar to 14.7 and 14.8 material). Consider the following ARMA(1, 1) model

$$y_t = \phi y_{t-1} + u_t + \theta u_{t-1}, \text{ for } t = -\infty, \dots, -1, 0, 1, \dots$$

where $|\theta| < 1$, $|\phi| < 1$, and u_t is i.i.d. with mean zero and variance σ_u^2 , $\mathbb{E}(u_t^4) < \infty$.

- (1) Suppose that we have the data $\{y_t : t = 0, 1, \dots, T\}$. Consider the following estimator of ϕ :

$$\hat{\phi}_T = \frac{\sum_{t=2}^T y_t y_{t-2}}{\sum_{t=2}^T y_{t-1} y_{t-2}}$$

Show that $\hat{\phi}$ is a consistent estimator of ϕ and derive the asymptotic distribution of $\sqrt{T}(\hat{\phi}_T - \phi)$. Comment on the case where $\theta = \phi$.

- (2) Suppose that $\sigma_u^2 = 1$ is known. Show that θ can be consistently estimated by

$$\hat{\theta}_T = \frac{1}{T} \sum_{t=1}^T y_t y_{t-1} - \frac{\hat{\phi}_T}{T} \sum_{t=1}^T y_{t-1}^2$$

Solution.

- (1) From the results in Question 2 part 2(b) (in section 13.2.1), since $\mathbb{E}(y_t) = \mathbb{E}(y_{t-1}) = \mathbb{E}(y_{t-2}) = 0$, we know that

$$\hat{\phi}_T = \frac{\sum_{t=2}^T y_t y_{t-2}}{\sum_{t=2}^T y_{t-1} y_{t-2}} = \frac{T^{-1} \sum_{t=2}^T y_t y_{t-2}}{T^{-1} \sum_{t=2}^T y_{t-1} y_{t-2}} \xrightarrow{p} \frac{\gamma(2)}{\gamma(1)}$$

By the result from Question 3 part (2), we have $\gamma(h) = \phi \gamma(h-1)$ for $h \geq 2$. Therefore $\gamma(2)/\gamma(1) = \phi$, so $\hat{\phi}_T$ is a consistent estimator for ϕ . To obtain the asymptotic distribution, note that

$$\begin{aligned} \sqrt{T}(\hat{\phi}_T - \phi) &= \sqrt{T} \left(\frac{T^{-1} \sum_{t=2}^T y_t y_{t-2}}{T^{-1} \sum_{t=2}^T y_{t-1} y_{t-2}} - \phi \right) \\ &= \frac{T^{-1/2} \sum_{t=2}^T (\phi y_{t-1} + u_t + \theta u_{t-1}) y_{t-2}}{T^{-1} \sum_{t=2}^T y_{t-1} y_{t-2}} - \frac{\phi T^{-1/2} \sum_{t=2}^T y_{t-1} y_{t-2}}{T^{-1} \sum_{t=2}^T y_{t-1} y_{t-2}} \\ &= \frac{T^{-1/2} \sum_{t=2}^T (u_t + \theta u_{t-1}) y_{t-2}}{T^{-1} \sum_{t=2}^T y_{t-1} y_{t-2}} \end{aligned}$$

In Question 2 part 2(b) (in section 13.2.1), we showed that

$$\frac{1}{T} \sum_{t=h_1}^T (y_t - \mu)(y_{t-h} - \mu) \xrightarrow{p} \gamma(h)$$

Therefore in the denominator, since $\mathbb{E}(y_{t-1}) = \mathbb{E}(y_{t-h}) = 0$, we have

$$T^{-1} \sum_{t=2}^T y_{t-1} y_{t-2} \xrightarrow{p} \gamma(1)$$

In the numerator,

$$\begin{aligned}
T^{-1/2} \sum_{t=2}^T (u_t + \theta u_{t-1}) y_{t-2} &= \frac{1}{\sqrt{T}} \sum_{t=2}^T [u_t y_{t-2} + \theta u_{t-1} y_{t-2}] \\
&= \frac{1}{\sqrt{T}} \sum_{t=2}^T u_t y_{t-2} + \frac{1}{\sqrt{T}} \sum_{t=2}^T \theta u_{t-1} y_{t-2} = \frac{1}{\sqrt{T}} \left(\sum_{t=2}^{T-1} u_t y_{t-2} + u_T y_{T-2} \right) + \frac{1}{\sqrt{T}} \sum_{t'=1}^{T-1} \theta u_{t'} y_{t'-1} \\
&= \frac{1}{\sqrt{T}} \left(\sum_{t=2}^{T-1} u_t y_{t-2} + u_T y_{T-2} \right) + \frac{1}{\sqrt{T}} \left(\theta u_1 y_0 + \sum_{t=2}^{T-1} \theta u_t y_{t-1} \right) = \frac{1}{\sqrt{T}} \left(\sum_{t=2}^{T-1} u_t (y_{t-2} + \theta y_{t-1}) + \theta u_1 y_0 + u_T y_{T-2} \right)
\end{aligned}$$

Since $\mathbb{E}(u_t(y_{t-2} + \theta y_{t-1}) | F_{t-1}) = 0$. Further, $T^{-1/2}(\theta u_1 y_0 + u_T y_{T-2}) = o_p(1)$. Then by the Central Limit Theorem in martingale difference processes (Theorem (8.7.1)):

Theorem 28 (Central limit theorem for martingale difference sequences). Let $\{x_t\}$ be a martingale difference sequence with respect to the information set Ω_t . Let $\bar{\sigma}_T^2 = \text{Var}(\sqrt{T}\bar{x}_T) = T^{-1} \sum_{t=1}^T \sigma_t^2$. If $\mathbb{E}(|x_t|^r) < K < \infty$, $r > 2$ and for all t , and

$$\frac{1}{T} \sum_{t=1}^T x_t^2 - \bar{\sigma}_T^2 \xrightarrow{p} 0$$

then

$$\sqrt{T} \cdot \frac{\bar{x}_T}{\bar{\sigma}_T} \xrightarrow{d} \mathcal{N}(0, 1)$$

we have

$$\sqrt{T} \cdot \frac{\bar{x}_T}{T^{-1/2} \sqrt{\sum_{t=1}^T \sigma_t^2}} \xrightarrow{d} \mathcal{N}(0, 1)$$

⋮

$$\frac{1}{\sigma^2} \frac{\gamma(1)^2}{(1+\theta)^2 \gamma(0) + 2\theta \gamma(1)} \sqrt{T} (\hat{\phi}_T - \phi) \xrightarrow{d} \mathcal{N}(0, 1)$$

$$\iff \sqrt{T} (\hat{\phi}_T - \phi) \xrightarrow{d} \mathcal{N} \left(0, \sigma^2 \frac{(1+\theta)^2 \gamma(0) + 2\theta \gamma(1)}{\gamma(1)^2} \right)$$

(2) From the results of Question 2 part 2(b) (in section 13.2.1), where we showed that

$$\frac{1}{T} \sum_{t=h_1}^T (y_t - \mu)(y_{t-h} - \mu) \xrightarrow{p} \gamma(h)$$

(and since $\mathbb{E}(y_{t-1}) = \mathbb{E}(y_{t-h}) = 0$,

$$T^{-1} \sum_{t=2}^T y_t y_{t-1} \xrightarrow{p} \gamma(1), \quad T^{-1} \sum_{t=2}^T y_{t-1}^2 \xrightarrow{p} \gamma(0)$$

and by the Weak Law of Large Numbers (Theorem 8.6.1) we have

$$\hat{\theta}_T = \frac{1}{T} \sum_{t=1}^T y_t y_{t-1} - \frac{\hat{\phi}_T}{T} \sum_{t=1}^T y_{t-1}^2 \xrightarrow{P} \gamma(1) - \phi\gamma(0) = \phi\gamma(0) + \theta\sigma^2 - \phi\gamma(0) = \theta$$

Chapter 14 Question 3. The time series $\{y_t\}$ and $\{x_t\}$ are independently generated according to the following schemes:

$$y_t = \lambda y_{t-1} + \epsilon_{1t}, \quad |\lambda| < 1$$

$$x_t = \rho x_{t-1} + \epsilon_{2t}, \quad |\rho| < 1$$

for $t = 1, 2, \dots, T$, where ϵ_{1t} and ϵ_{2t} are non-autocorrelated and distributed independently of each other with zero means and variances equal to σ_1^2 and σ_2^2 respectively. An investigator estimates the simple regression

$$y_t = \beta x_t + u_t \quad t = 1, 2, \dots, T$$

by the OLS method. Show that

(a) $\hat{\beta} \xrightarrow{P} 0$ as $T \rightarrow \infty$

(b)

$$t_{\hat{\beta}}^2 = \frac{\hat{\beta}^2}{\widehat{\text{Var}}(\hat{\beta})} = \frac{(T-1)r^2}{1-r^2}$$

(c)

$$Tr^2 \xrightarrow{P} \frac{1+\lambda\rho}{1-\lambda\rho} \text{ as } T \rightarrow \infty$$

where $\hat{\beta}$ is the OLS estimator of β , $\widehat{\text{Var}}(\hat{\beta})$ is the estimated variance of $\hat{\beta}$, and r is the sample correlation coefficient between x and y , i.e.

$$r^2 = \left(\sum_{t=1}^T x_t y_t \right)^2 \Bigg/ \left(\sum_{t=1}^T x_t^2 \sum_{t=1}^T y_t^2 \right)$$

What are the implications of these results for problems of spurious correlation in economic time series analysis?

Solution.

(a)

$$\hat{\beta} = \frac{\sum_{t=1}^T x_t y_t}{\sum_{t=1}^T x_t^2} = \frac{T^{-1} \sum_{t=1}^T x_t y_t}{T^{-1} \sum_{t=1}^T x_t^2}$$

By the Weak Law of Large Numbers (Theorem 8.6.1), we have

$$T^{-1} \sum_{t=1}^T x_t y_t = T^{-1} \sum_{t=1}^T x_t y_t \xrightarrow{p} \mathbb{E}(x_t y_t) = \text{Cov}(x_t, y_t) = 0$$

because of the i.i.d. distributions of ϵ_1 and ϵ_{2t} . By the Law of Large Numbers (Theorem 8.6.4),

$$T^{-1} \sum_{t=1}^T x_t^2 \xrightarrow{a.s.} \mathbb{E}(x_t^2) = \gamma_x(0) > 0$$

Therefore

$$\hat{\beta} \xrightarrow{p} \frac{0}{\gamma_x(0)} = 0$$

(b)

$$\widehat{\text{Var}}(\hat{\beta}) = \frac{\hat{\sigma}^2}{S_{XX}}$$

where

$$\begin{aligned} \hat{\sigma}^2 &= \frac{1}{T-1} \sum_{t=1}^T (y_t - \hat{\beta} x_t)^2 = \frac{1}{T-1} \sum_{t=1}^T (y_t^2 - 2y_t \hat{\beta} x_t + \hat{\beta}^2 x_t^2) \\ &= \frac{1}{T-1} \sum_{t=1}^T y_t^2 - \frac{1}{T-1} \sum_{t=1}^T \left(2y_t x_t \frac{\sum_{t=1}^T x_t y_t}{\sum_{t=1}^T x_t^2} \right) + \frac{1}{T-1} \sum_{t=1}^T \left(\left[\frac{\sum_{t=1}^T x_t y_t}{\sum_{t=1}^T x_t^2} \right]^2 x_t^2 \right) \\ &= \frac{1}{T-1} \sum_{t=1}^T y_t^2 - 2 \cdot \frac{1}{T-1} \frac{(\sum_{t=1}^T x_t y_t)^2}{\sum_{t=1}^T x_t^2} + \frac{1}{T-1} \frac{(\sum_{t=1}^T x_t y_t)^2}{\sum_{t=1}^T x_t^2} \\ &= \frac{1}{T-1} \left(\sum_{t=1}^T y_t^2 - \frac{(\sum_{t=1}^T x_t y_t)^2}{\sum_{t=1}^T x_t^2} \right) \\ \implies \hat{t}^2 &= \frac{(\sum_{t=1}^T x_t y_t)^2}{(\sum_{t=1}^T x_t^2)^2} \cdot \sum_{t=1}^T x_t^2 \cdot (T-1) \Bigg/ \left(\sum_{t=1}^T y_t^2 - \frac{(\sum_{t=1}^T x_t y_t)^2}{\sum_{t=1}^T x_t^2} \right) \\ &= \frac{(\sum_{t=1}^T x_t y_t)^2}{\sum_{t=1}^T x_t^2} \cdot (T-1) \Bigg/ \left(\sum_{t=1}^T y_t^2 - \frac{(\sum_{t=1}^T x_t y_t)^2}{\sum_{t=1}^T x_t^2} \right) \\ &= \left(\sum_{t=1}^T x_t y_t \right)^2 \cdot (T-1) \Bigg/ \left(\sum_{t=1}^T y_t^2 \sum_{t=1}^T x_t^2 - \left(\sum_{t=1}^T x_t y_t \right)^2 \right) \end{aligned}$$

Note that

$$r^2 = \left(\sum_{t=1}^T x_t y_t \right)^2 \Bigg/ \left(\sum_{t=1}^T x_t^2 \sum_{t=1}^T y_t^2 \right), \quad 1 - r^2 = \left[\sum_{t=1}^T x_t^2 \sum_{t=1}^T y_t^2 - \left(\sum_{t=1}^T x_t y_t \right)^2 \right] \Bigg/ \left(\sum_{t=1}^T x_t^2 \sum_{t=1}^T y_t^2 \right)$$

$$\Rightarrow \frac{r^2}{1-r^2} = \left(\sum_{t=1}^T x_t y_t \right)^2 \Bigg/ \left[\sum_{t=1}^T x_t^2 \sum_{t=1}^T y_t^2 - \left(\sum_{t=1}^T x_t y_t \right)^2 \right]$$

Therefore

$$\hat{t}^2 = \left(\sum_{t=1}^T x_t y_t \right)^2 \cdot (T-1) \Bigg/ \left(\sum_{t=1}^T y_t^2 \sum_{t=1}^T x_t^2 - \left(\sum_{t=1}^T x_t y_t \right)^2 \right) = \boxed{\frac{(T-1)r^2}{1-r^2}}$$

(c)

$$\begin{aligned} Tr^2 &= T \cdot \frac{\left(T^{-1} \sum_{t=1}^T x_t y_t \right)^2}{T^{-1} \sum_{t=1}^T x_t^2 \cdot T^{-1} \sum_{t=1}^T y_t^2} = \frac{T^{-1} (2 \sum_{1 \leq i < j \leq T} x_i x_j y_i y_j + \sum_{t=1}^T x_t^2 y_t^2)}{T^{-1} \sum_{t=1}^T x_t^2 \cdot T^{-1} \sum_{t=1}^T y_t^2} \\ &= \frac{2T^{-1} \sum_{1 \leq i < j \leq T} x_i x_j y_i y_j + T^{-1} \sum_{t=1}^T x_t^2 y_t^2}{T^{-1} \sum_{t=1}^T x_t^2 \cdot T^{-1} \sum_{t=1}^T y_t^2} \end{aligned}$$

Note that

$$2T^{-1} \sum_{1 \leq i < j \leq T} (x_i x_j)(y_i y_j) = \sum_{h=1}^{T-1} 2T^{-1}(T-h)(x_t x_{t-h})(y_t y_{t-h})$$

By the Weak Law of Large Numbers (Theorem 8.6.1) and the independence of x_t and y_t ,

$$\sum_{h=1}^{T-1} 2T^{-1}(T-h)(x_t x_{t-h})(y_t y_{t-h}) \approx 2T^{-1} \sum_{h=1}^{T-1} (x_t x_{t-h})(y_t y_{t-h}) \xrightarrow{p} 2 \sum_{h=1}^{\infty} \gamma_x(h) \gamma_y(h)$$

Recall that for an AR(1) process with coefficient ϕ , $\gamma(h) = \phi^h \gamma(0)$. (See section 13.3.4).

$$= 2 \sum_{h=1}^{\infty} \rho^h \gamma_x(0) \lambda^h \gamma_y(0) = 2 \gamma_x(0) \gamma_y(0) \sum_{h=1}^{\infty} (\rho \lambda)^h$$

By the Weak Law of Large Numbers (Theorem 8.6.1) and the independence of x_t and y_t ,

$$T^{-1} \sum_{t=1}^T x_t^2 y_t^2 \xrightarrow{a.s.} \mathbb{E}(x_t^2 y_t^2) = \mathbb{E}(x_t^2) \mathbb{E}(y_t^2) = \text{Var}(x_t) \text{Var}(y_t) = \sigma_1^2 \sigma_2^2 = \gamma_x(0) \gamma_y(0)$$

Therefore in the numerator, we have

$$\begin{aligned} 2T^{-1} \sum_{1 \leq i < j \leq T} x_i x_j y_i y_j + T^{-1} \sum_{t=1}^T x_t^2 y_t^2 &\xrightarrow{p} 2 \gamma_x(0) \gamma_y(0) \sum_{h=1}^{\infty} (\rho \lambda)^h + \gamma_x(0) \gamma_y(0) \\ &= \gamma_x(0) \gamma_y(0) \left(2 \frac{\rho \lambda}{1 - \rho \lambda} + 1 \right) = \gamma_x(0) \gamma_y(0) \left(\frac{1 + \rho \lambda}{1 - \rho \lambda} \right) \end{aligned}$$

Next we examine the denominator. By the Law of Large Numbers (Theorem 8.6.4),

$$T^{-1} \sum_{t=1}^T x_t^2 \xrightarrow{a.s.} \mathbb{E}(x_t^2) = \text{Var}(x_t) = \gamma_x(0) = \sigma_2^2$$

By the Law of Large Numbers (Theorem 8.6.4),

$$T^{-1} \sum_{t=1}^T y_t^2 \xrightarrow{a.s.} \mathbb{E}(y_t^2) = \gamma_y(0) = \sigma_1^2$$

Therefore in the denominator, we have

$$T^{-1} \sum_{t=1}^T x_t^2 \cdot T^{-1} \sum_{t=1}^T y_t^2 \xrightarrow{a.s.} \gamma_x(0)\gamma_y(0) = \sigma_1^2\sigma_2^2$$

This yields

$$Tr^2 \xrightarrow{p} \frac{1 + \rho\lambda}{1 - \rho\lambda}$$

Lidan's explanation: Because as $T \rightarrow \infty$

$$t_{\hat{\beta}} \rightarrow \sqrt{Tr^2} = \sqrt{\frac{1 + \lambda\rho}{1 - \lambda\rho}}$$

so if $\lambda\rho \approx 1$, at very high probability we will reject the null $\hat{\beta} = 0$ when in fact $\hat{\beta} \xrightarrow{p} 0$.

My original explanation: Because $\hat{\beta}$ converges in probability to 0 and $t_{\hat{\beta}}^2$ is proportional to r^2 (which we would expect to be close to 0), this suggests that a regression of uncorrelated variables should result in an insignificant $\hat{\beta}$, but if r^2 is high due to a spurious correlation, the $\hat{\beta}$ could be found to be statistically significant even if there is no meaningful relationship between x and y .

13.5 Chapter 15: Unit Root Processes

Need to review concepts in this chapter.

13.5.1 Worked Problems

Problem 3. Suppose that a time series of interest can be decomposed into a deterministic trend, a random walk component, and stationary errors:

$$y_t = \alpha + \delta t + \gamma_t + v_t \tag{13.1}$$

$$\gamma_t = \gamma_{t-1} + u_t$$

with

$$v_t \sim iid \mathcal{N}(0, \sigma_v^2), \quad u_t \sim iid \mathcal{N}(0, \sigma_u^2), \quad u_t \perp\!\!\!\perp v_t$$

Let $\lambda = \sigma_u^2 / \sigma_v^2$.

- (a) Show that under $\lambda = 0$, y_t reduces to a trend stationary process.
- (b) Alternatively, suppose that y_t follows an ARIMA(0,1,1) process of the form

$$y_t = \delta + y_{t-1} + w_t \tag{13.2}$$

$$w_t = \epsilon_t + \theta \epsilon_{t-1}$$

where ϵ_t are iid $\mathcal{N}(0, \sigma_\epsilon^2)$. In this case show that under $\theta = -1$, y_t is a trend stationary process.

- (c) Derive a relation between λ and the MA(1) parameter θ , and hence or otherwise show that a test of $\theta = -1$ in (13.2) is equivalent to a test of $\lambda = 0$ in (13.1).
- (d) Show that (13.2) as a characterization of (13.1) implies $\theta < 0$.

Solution.

$$(a) \lambda = 0 \implies \sigma_u^2 = 0 \implies u_t = 0 \text{ (constant)}$$

$$\implies \gamma_t = \gamma_{t-1} + 0 \iff \gamma_t = \gamma_0$$

$$\implies y_t = \alpha + \delta t + \gamma_0 + v_t = (\alpha + \gamma_0) + \delta t + v_t$$

which is trend stationary because $d_t = (\alpha + \gamma_0) + \delta t$ is perfectly predictable, and $y_t - d_t = v_t$ is covariance stationary.

Also note that $\text{Var}(y_t - \delta t) = \sigma_v^2$, $\text{Cov}([y_t - \delta t][y_{t-h} - \delta(t-h)]) = 0$, which implies trend stationarity of y_t . (Recall Definition 13.2: “ X_t is said to be **trend stationary** if $y_t = X_t - d_t$ is covariance stationary, where d_t is the perfectly predictable component of X_t .”)

$$(b) \theta = -1 \implies w_t = \epsilon_t - \epsilon_{t-1} = (1 - L)\epsilon_t$$

$$\implies (1 - L)y_t = \delta + (1 - L)\epsilon_t \iff y_t = (1 - L)^{-1}\delta + \epsilon_t$$

which is trend stationary because $d_t = (1 - L)^{-1}\delta$ is perfectly predictable, and $y_t - d_t = \epsilon_t$ is covariance stationary.

$$(c) \text{ **Lidan's solution:** From (13.1), let}$$

$$\begin{aligned} z_t &= y_t - y_{t-1} = \alpha + \delta t + \gamma_{t-1} + u_t + v_t - (\alpha + \delta(t-1) + \gamma_{t-1} + v_{t-1}) \\ &= \delta + u_t + v_t - v_{t-1} \end{aligned}$$

From (13.2), let

$$a_t = y_t - y_{t-1} = \delta + y_{t-1} + w_t - y_{t-1} = \delta + \epsilon_t + \theta \epsilon_{t-1}$$

Calculate the autocovariances for each and set them equal (using the serial independence of u_t , v_t , and ϵ_t as well as the independence of u_t , v_t , and ϵ_t for all t):

- $\gamma(0) : \text{Var}(z_t) = \text{Var}(a_t) \iff \text{Var}(u_t + v_t - v_{t-1}) = \text{Var}(\epsilon_t + \theta \epsilon_{t-1})$

$$\iff \sigma_u^2 + 2\sigma_v^2 = \sigma_\epsilon^2(1 + \theta^2) \quad (13.3)$$

- $\gamma(1) : \text{Cov}(z_t, z_{t-1}) = \text{Cov}(a_t, a_{t-1}) \iff \text{Cov}(-v_{t-1}, v_{t-1}) = \text{Cov}(\theta \epsilon_{t-1}, \epsilon_{t-1})$

$$\iff -\sigma_v^2 = \theta \sigma_\epsilon^2 \quad (13.4)$$

- $\gamma(h) (h \geq 2) : 0 = 0$

Plugging (13.4) into (13.3) and using $\lambda = \sigma_u^2/\sigma_v^2$ we have

$$\begin{aligned} \sigma_u^2 + 2\sigma_v^2 &= -\frac{\sigma_v^2}{\theta}(1 + \theta^2) \iff \sigma_u^2 = \sigma_v^2(-1/\theta - \theta - 2) \iff \lambda = -1/\theta - \theta - 2 \\ &\iff \theta^2 + (2 + \lambda)\theta + 1 = 0 \iff \theta = \frac{-(2 + \lambda) \pm \sqrt{(2 + \lambda)^2 - 4}}{2} \\ &\iff \boxed{\theta = \frac{-(2 + \lambda) \pm \sqrt{\lambda^2 + 4\lambda}}{2}} \end{aligned}$$

Clearly if $\lambda = 0$ then $\theta = -1$. The reverse is also true:

$$\theta = -1 \implies \lambda = -1/(-1) - (-1) - 2 = 1 + 1 - 2 = 0$$

Therefore a test of $\theta = -1$ in (13.2) is equivalent to a test of $\lambda = 0$ in (13.1).

original solution:

$$y_t = \alpha + \delta t + \gamma_{t-1} + u_t + v_t$$

$$y_{t-1} = \alpha + \delta(t-1) + \gamma_{t-1} + v_{t-1}$$

$$\implies y_t = y_{t-1} + \delta + u_t - v_{t-1} + v_t$$

Comparing this to the second expression, $y_t = \delta + y_{t-1} + \epsilon_t + \theta \epsilon_{t-1}$, they match if $u_t - v_{t-1} + v_t = \epsilon_t + \theta \epsilon_{t-1}$. Since the distributions of ϵ_t and v_t are both i.i.d. normal, this is the case if $\lambda = 0$ (so that $\sigma_u^2 = 0$ and $u_t = 0 \forall t$), $\theta = -1$, and $\sigma_\epsilon^2 = \sigma_v^2$.

(d) **Lidan's Solution:** By (13.4) (which follows from (13.2)),

$$-\sigma_v^2 = \theta\sigma_\epsilon^2 \implies \theta < 0$$

My solution: Again consider (2)

$$y_t = \delta + y_{t-1} + \epsilon_t + \theta\epsilon_{t-1}$$

which is clearly a unit root process with a drift, compared to a re-written version of (1)

$$y_t = \delta + y_{t-1} + u_t + v_t - v_{t-1}$$

which has a strong resemblance to a unit root process with a drift. These match up if $\epsilon_t = u_t + v_t$ and $\theta < 0$.

Problem 4

Homework 4 Problem 3. Let $\{u_t\}$ be an i.i.d. sequence with mean zero and variance σ^2 , and let

$$y_t = u_1 + u_2 + \dots + u_t$$

with $y_0 = 0$.

(a) Show that

$$T^{-3/2} \sum_{t=1}^T y_{t-1} = T^{-1/2} \sum_{t=1}^{T-1} u_t - T^{-3/2} \sum_{t=1}^{T-1} tu_t$$

(b) Show that

$$\begin{bmatrix} T^{-1/2} \sum_{t=1}^T u_t \\ T^{-3/2} \sum_{t=1}^T y_{t-1} \end{bmatrix} \xrightarrow{d} \mathcal{N}\left(0, \begin{bmatrix} 1 & 1/2 \\ 1/2 & 1/3 \end{bmatrix}\right)$$

(c) Use the functional central limit theorem (Donsker's Theorem, Theorem 7.11.1) to show that

$$T^{-3/2} \sum_{t=1}^T y_{t-1} \xrightarrow{d} \sigma \int_0^1 W(r) dr$$

where $W(\cdot)$ is a standard Brownian motion process.

(d) Use parts (a) - (c) to show that

$$T^{-3/2} \sum_{t=1}^T tu_t \xrightarrow{d} \sigma \cdot W(a) - \sigma \int_0^1 W(r) dr$$

Solution.

$$y_t = u_1 + u_2 + \dots + u_t = \sum_{i=1}^t u_i = \sum_{i=0}^t u_i$$

where the last equality follows because $y_0 = 0 \iff u_0 = 0$.

$$u_t \sim iid (0, \sigma^2), \quad y_0 = 0$$

(a)

$$\begin{aligned} T^{-3/2} \sum_{t=1}^T y_{t-1} &= T^{-3/2} \sum_{t=1}^T \left(\sum_{i=0}^{t-1} u_i \right) = T^{-3/2} \sum_{t=1}^T (T - (t-1)) u_{t-1} = T^{-3/2} \sum_{t'=0}^{T-1} (T - t') u_{t'} \\ &= T^{-3/2} \cdot T \sum_{t'=0}^{T-1} u_{t'} - T^{-3/2} \sum_{t'=0}^{T-1} t' u_{t'} = T^{-1/2} \sum_{t'=1}^{T-1} u_{t'} - T^{-3/2} \sum_{t'=1}^{T-1} t' u_{t'} \\ \implies &\boxed{T^{-3/2} \sum_{t=1}^T y_{t-1} = T^{-1/2} \sum_{t'=1}^{T-1} u_{t'} - T^{-3/2} \sum_{t'=1}^{T-1} t' u_{t'}} \end{aligned} \tag{13.5}$$

(b) By the Central Limit Theorem (Theorem 8.6.7), since $u_t \sim (0, \sigma^2)$, we have

$$\frac{1}{\sqrt{T}\sigma^2} \sum_{t=1}^T u_t \xrightarrow{d} \mathcal{N}(0, 1)$$

which implies

$$\boxed{\frac{1}{\sqrt{T}} \sum_{t=1}^T u_t \xrightarrow{d} \mathcal{N}(0, \sigma^2)} \tag{13.6}$$

The distribution of $T^{-3/2} \sum_{t=1}^T y_{t-1}$ is trickier. Note that from (13.5),

$$T^{-3/2} \sum_{t=1}^T y_{t-1} = T^{-1/2} \left(\sum_{t=0}^{T-1} u_t - \sum_{t=0}^{T-1} \frac{tu_t}{T} \right)$$

Note that $x_t = (tu_t)/T$ is a martingale difference process because

$$\mathbb{E} \left(\frac{tu_t}{T} \mid u_{t-1}, u_{t-2}, \dots \right) = 0$$

and $\text{Var}(x_t) = \frac{1}{T^2} \text{Var}(tu_t) = \frac{t^2}{T^2} \sigma^2 < \infty$. By the Central Limit Theorem in martingale difference processes (Theorem (8.7.1)):

Theorem 28 (Central limit theorem for martingale difference sequences). Let $\{x_t\}$ be a martingale difference sequence with respect to the information set Ω_t . Let $\bar{\sigma}_T^2 = \text{Var}(\sqrt{T}\bar{x}_T) = T^{-1} \sum_{t=1}^T \sigma_t^2$. If $\mathbb{E}(|x_t|^r) < K < \infty$ for any $r > 2$ and for all t , and

$$\frac{1}{T} \sum_{t=1}^T x_t^2 - \bar{\sigma}_T^2 \xrightarrow{p} 0$$

then

$$\sqrt{T} \cdot \frac{\bar{x}_T}{\bar{\sigma}_T} \xrightarrow{d} \mathcal{N}(0, 1)$$

since

$$T^{-1} \sum_{t=1}^T \sigma_t^2 = T^{-1} \sum_{t=1}^T \frac{t^2}{T^2} \sigma^2 = \frac{\sigma^2}{T^3} \cdot \frac{T(T+1)(2T+1)}{6} = \frac{\sigma^2}{6} \cdot \frac{2T^2 + 3T + 1}{T^2},$$

$$\mathbb{E}(|x_t|^r) = \mathbb{E}\left(\left|\frac{tu_t}{T}\right|^r\right) = \frac{t^r}{T^r} \mathbb{E}(|u_t|^r)$$

which is finite for $r = 4$ if u_t has finite fourth moment, and since by the Weak Law of Large Numbers (Theorem 8.6.1)

$$\begin{aligned} T^{-1} \sum_{t=1}^T x_t^2 - T^{-1} \sum_{t=1}^T \frac{t^2}{T^2} \sigma^2 &= T^{-1} \sum_{t=1}^T \frac{t^2}{T^2} (u_t^2 - \sigma^2) \\ \left| T^{-1} \sum_{t=1}^T \frac{t^2}{T^2} (u_t^2 - \sigma^2) \right| &\leq \left| T^{-1} \sum_{t=1}^T (u_t^2 - \sigma^2) \right| \leq T^{-1} \sum_{t=1}^T |u_t^2 - \sigma^2| \xrightarrow{p} 0 \\ \implies T^{-1} \sum_{t=1}^T x_t^2 - T^{-1} \sum_{t=1}^T \frac{t^2}{T^2} \sigma^2 &\xrightarrow{p} 0 \end{aligned}$$

we have (if u_t has finite fourth moment)

$$\begin{aligned} &\sqrt{T} \cdot \frac{1}{T} \left(\sum_{t=1}^T \frac{tu_t}{T} \right) \Big/ \sqrt{\frac{\sigma^2}{6} \cdot \frac{2T^2 + 3T + 1}{T^2}} \xrightarrow{d} \mathcal{N}(0, 1) \\ \iff T^{-3/2} \left(\sum_{t=1}^T tu_t \right) \cdot \sqrt{\frac{6}{\sigma^2} \cdot \frac{1}{2T^2 + 3T + 1}} &\xrightarrow{d} \mathcal{N}(0, 1) \implies \sqrt{T} \left(\sum_{t=1}^T tu_t \right) \cdot \sqrt{\frac{6}{\sigma^2} \cdot \frac{1}{2T^2}} \xrightarrow{d} \mathcal{N}(0, 1) \\ \iff T^{-3/2} \left(\sum_{t=1}^T \frac{tu_t}{T} \right) \cdot \sqrt{\frac{3}{\sigma^2}} &\xrightarrow{d} \mathcal{N}(0, 1) \implies T^{-1/2} \frac{\sqrt{3}}{\sigma} \sum_{t=0}^{T-1} \frac{tu_t}{T} \xrightarrow{d} \mathcal{N}(0, 1) \\ \iff T^{-1/2} \sum_{t=0}^{T-1} \frac{tu_t}{T} &\xrightarrow{d} \mathcal{N}\left(0, \frac{\sigma^2}{3}\right) \end{aligned} \tag{13.7}$$

To get the covariance between these distributions, we have (using the serial independence of u_t)

$$\begin{aligned} \text{Cov}\left(T^{-1/2} \sum_{t=0}^{T-1} u_t, T^{-3/2} \sum_{t=0}^{T-1} t u_t\right) &= \mathbb{E}\left[T^{-1/2} \sum_{t=0}^{T-1} u_t \cdot T^{-3/2} \sum_{t=0}^{T-1} t u_t\right] = T^{-2} \cdot \mathbb{E}\left[\sum_{t=0}^{T-1} u_t \cdot \sum_{t=0}^{T-1} t u_t\right] \\ &= T^{-2} \cdot \mathbb{E}\left[\sum_{t=0}^{T-1} t u_t^2\right] = T^{-2} \sum_{t=0}^{T-1} t \mathbb{E}(u_t^2) = \frac{\sigma^2}{T^2} \cdot \frac{T(T-1)}{2} \rightarrow \boxed{\frac{\sigma^2}{2}} \end{aligned} \quad (13.8)$$

Putting (13.6), (13.7), and (13.8) together, we have $T^{-3/2} \sum_{t=1}^T y_{t-1} \xrightarrow{d} \mathcal{N}(0, \sigma^2 + \sigma^2/3 - 2 \cdot \sigma^2/2) = \boxed{\mathcal{N}(0, \sigma^2/3)}.$

Lastly, to get the covariance between these distributions, we have (again using the serial independence of u_t)

$$\begin{aligned} \text{Cov}\left(T^{-1/2} \sum_{t=1}^{T-1} u_t, T^{-3/2} \sum_{t=1}^T y_{t-1}\right) &= T^{-2} \text{Cov}\left(\sum_{t=1}^{T-1} u_t, \sum_{t=1}^T (T-(t-1)) u_{t-1}\right) \\ &= T^{-2} \text{Cov}\left(\sum_{t=1}^{T-1} u_t, \sum_{t'=0}^{T-1} (T-t') u_{t'}\right) = T^{-2} \mathbb{E}\left(\sum_{t=1}^{T-1} (T-t) u_t^2\right) = \frac{(T-1)T - T(T-1)/2}{T^2} \sigma^2 \\ &= \frac{(T-1)T}{2T^2} \sigma^2 \rightarrow \boxed{\sigma^2/2} \end{aligned} \quad (13.9)$$

which yields the result.

(c) Let $r \in [0, 1]$, $t \in [0, T]$. Define

$$R_T(r) = \frac{1}{\sigma \sqrt{T}} y_{[rT]}$$

where $[rT]$ denotes the largest integer part of rT and $y_{[rT]} = 0$ if $[rT] = 0$. That is,

$$R_T(r) = \begin{cases} 0 & 0 \leq r < 1/T \\ \frac{y_1}{\sigma \sqrt{T}} & 1/T \leq r < 2/T \\ \frac{y_2}{\sigma \sqrt{T}} & 2/T \leq r < 3/T \\ \vdots & \vdots \\ \frac{y_{T-1}}{\sigma \sqrt{T}} & (T-1)/T \leq r < 1 \end{cases}$$

We have

$$\begin{aligned} T^{-3/2} \sum_{t=1}^T y_{t-1} &= T^{-3/2} \sum_{t'=0}^{T-1} y_{t'} = T^{-3/2} \sum_{t'=0}^{T-1} (y_{t'-1} + u_{t'}) = \sigma \sum_{t'=0}^{T-1} \int_{t'/T}^{(t'+1)/T} R_T(r) dr + o_p(1) \\ &= \sigma \int_0^1 R_T(r) dr + o_p(1) \implies \sigma \int_0^1 W(r) dr \text{ as } T \rightarrow \infty \end{aligned}$$

where the last step follows from Donsker's Theorem (Theorem 7.11.1, the functional central limit theorem) and the continuous mapping theorem (Theorem 7.11.2) and $W(r)$ is a standard Weiner process.

Donsker's Theorem, Theorem 43, p.335, Section 15.6.3. Let $a \in [0, 1)$, $t \in [0, T]$, and suppose $(J - 1)/T \leq a < J/T$, $J = 1, 2, \dots, T$. Define

$$R_T(a) = \frac{1}{\sqrt{T}} s_{[Ta]}$$

where

$$s_{[Ta]} = \epsilon_1 + \epsilon_2 + \dots + \epsilon_{[Ta]}$$

$[Ta]$ denotes the largest integer part of Ta and $s_{[Ta]} = 0$ if $[Ta] = 0$. Then $R_T(a)$ weakly converges to $w(a)$, i.e.,

$$R_T(a) \rightarrow w(a)$$

where $w(a)$ is a Wiener process. Note that when $a = 1$, $R_T(1) = 1/\sqrt{T} \cdot S_{[T]} = 1/\sqrt{T} \cdot (\epsilon_1 + \epsilon_2 + \dots + \epsilon_T)$. Since ϵ_t 's are IID, by the central limit theorem, $R_T(1) \rightarrow \mathcal{N}(0, 1)$.

Continuous Mapping Theorem (Theorem 44 of Pesaran in 15.6.3). Let $a \in [0, 1)$, $i \in [0, n]$, and suppose $(J - 1)/n \leq a < J/n$, $J = 1, 2, \dots, n$. Define $R_n(a) = n^{-1/2} S_{[n \cdot a]}$. If $f(\cdot)$ is continuous over $[0, 1]$, then

$$f[R_n(a)] \xrightarrow{d} f[w(a)]$$

- (d) We have $T^{-1/2} \sum_{t=1}^T u_t = \sigma \cdot R_T(1) \implies \sigma \cdot W(1)$ by Donsker's Theorem. Using that and the result from (c), we have

$$T^{-3/2} \sum_{t=1}^{T-1} t u_t = T^{-1/2} \sum_{t=1}^{T-1} u_t - T^{-3/2} \sum_{t=1}^T y_{t-1} \xrightarrow{d} \sigma \cdot W(1) - \sigma \int_0^1 W(r) dr$$

13.6 Chapter 17: Introduction to Forecasting

Feel pretty good on concepts

13.6.1 17.7: Iterated and direct multi-step AR methods

Suppose y_t follows the AR(1) model:

$$y_t = a + \phi y_{t-1} + \epsilon_t, \quad |\phi| < 1, \epsilon_t \sim iid(0, \sigma_\epsilon^2) \quad (13.10)$$

$$\iff y_t = \frac{a}{1 - \phi} + \sum_{i=0}^{\infty} \phi^i \epsilon_{t-i}$$

$$\iff y_t = a \left(\frac{1 - \phi^h}{1 - \phi} \right) + \phi^h y_{t-h} + \sum_{j=0}^{h-1} \phi^j \epsilon_{t-j} \quad (13.11)$$

We have two methods for forecasting y_{t+h} $h > 1$ steps ahead.

- (1) **Iterated method:** In this method, we first calculate the OLS estimates of \hat{a}_T and $\hat{\phi}_T$ in Equation (13.12) using all available data Ω_T . Then we use the form of Equation (13.11):

$$\hat{y}_{T+h|T}^* = \hat{a}_T \left(\frac{1 - \hat{\phi}_T^h}{1 - \hat{\phi}_T} \right) + \hat{\phi}_T^h y_T$$

- (2) **Direct method:** We directly calculate OLS estimates of the parameters in Equation (13.11) using all available data Ω_T :

$$\tilde{y}_{T+h|T}^* = \tilde{a}_{h,T} + \tilde{\phi}_{h,T} y_T$$

Proposition 13.6.1. (Pesaran Chapter 17 Proposition 45.) Suppose data is generated by Equation (13.12). If $u_t = \sum_{i=0}^{\infty} \phi^i \epsilon_{t-i}$ and $v_t = \sum_{j=0}^{h-1} \phi^j \epsilon_{t-j}$ are symmetrically distributed around zero and have finite second moments, and if $\mathbb{E}(\hat{\phi}_T)$ and $\mathbb{E}(\tilde{\phi}_{h,T})$ exist, then for any finite T and h we have

$$\mathbb{E}(\hat{y}_{T+h|T}^* - y_{T+h}) = \mathbb{E}(\tilde{y}_{T+h|T}^* - y_{T+h}) = 0$$

13.6.2 Worked Problems

Problem 4 (Homework 5 Question 3)—fine on all but part (c), which even Lidan is hazy on.

Consider the AR(1) model

$$y_t = \phi y_{t-1} + u_t, \quad u_t \sim iid(0, \sigma^2) \quad (13.12)$$

- (a) Derive iterated and direct forecasts of y_{T+2} condition on y_T , and show that they can be estimated as

$$\text{Iterated: } \hat{y}_{T+2|T}^{(it)} = \hat{\phi}^2 y_T$$

$$\text{Direct: } \hat{y}_{T+2|T}^{(d)} = \hat{\phi}_2 y_T$$

where $\hat{\phi}$ and $\hat{\phi}_2$ are OLS coefficients in the regressions of y_t on y_{t-1} and y_{t-2} , respectively, using the M observations $y_{T-M+1}, y_{T-M+2}, \dots, y_T$.

- (b) Show that conditional on y_t ,

$$\mathbb{E}(y_{T+2} - \hat{y}_{T+2|T}^{(it)})^2 = \mathbb{E}(\phi^2 - \hat{\phi}^2)^2 y_T^2 + (1 + \phi^2)\sigma^2$$

$$\mathbb{E}(y_{T+2} - \hat{y}_{T+2|T}^{(d)})^2 = \mathbb{E}(\phi^2 - \hat{\phi}_2)^2 y_T^2 + (1 + \phi^2)\sigma^2$$

(c) Hence, or otherwise, show that

$$\lim_{M \rightarrow \infty} \mathbb{E}(d_{T+2}) = 0$$

where d_{T+2} is the loss differential of the two forecasting methods, defined by

$$d_{T+2} = (y_{T+2} - \hat{y}_{T+2|T}^{(it)})^2 + (y_{T+2} - \hat{y}_{T+2|T}^{(d)})^2$$

Solution.

(a) Note that we can write

$$\begin{aligned} y_t &= \phi[y_{t-2} + u_{t-1}] + u_t = \phi^2 y_{t-2} + u_t + \phi u_{t-1} \\ &\implies y_{T+2} = \phi^2 y_T + u_{T+2} + \phi u_{T+1} \\ &\implies \mathbb{E}(y_{T+2} | y_{T-M+1}, y_{T-M+2}, \dots, y_T) = \phi^2 y_T + \mathbb{E}(u_{T+2} | y_{T-M+1}, \dots, y_T) + \phi \mathbb{E}(u_{T+1} | y_{T-M+1}, \dots, y_T) \\ &= \phi^2 y_T \\ &\iff \mathbb{E}(y_{T+2} | y_{T-M+1}, y_{T-M+2}, \dots, y_T) = \phi^2 y_T \end{aligned} \tag{13.13}$$

If we calculate the OLS estimate $\hat{\phi}$ in Equation (13.12), we can substitute that into Equation (13.13) to obtain the iterated estimate of y_{T+2} :

$$\hat{y}_{T+2|T}^{(it)} = \hat{\phi}^2 y_T$$

Since we have no intercept term, the OLS estimate would be simply

$$\hat{\phi} = (x'x)^{-1}x'y = \frac{\sum_{t=T-M+2}^T y_t y_{t-1}}{\sum_{t=T-M+1}^{T-1} y_t^2}$$

Alternatively, we could directly calculate the OLS estimate $\hat{\phi}_2$ of ϕ^2 in Equation (13.13)

$$\hat{y}_{T+2|T}^{(d)} = \hat{\phi}_2 y_T$$

The OLS estimate would be simply

$$\hat{\phi}_2 = (x'x)^{-1}x'y = \frac{\sum_{t=T-M+3}^T y_t y_{t-2}}{\sum_{t=T-M+1}^{T-2} y_t^2}$$

(b) We have

$$\begin{aligned}
& \mathbb{E}(y_{T+2} - \hat{y}_{T+2|T}^{(it)})^2 = \mathbb{E}(y_{T+2}^2) + \mathbb{E}((\hat{y}_{T+2|T}^{(it)})^2) - 2\mathbb{E}(y_{T+2} \cdot \hat{y}_{T+2|T}^{(it)}) \\
&= \mathbb{E}((\phi^2 y_T + u_{T+2} + \phi u_{T+1})^2) + \mathbb{E}((\hat{\phi}^2 y_T)^2) - 2\mathbb{E}((\phi^2 y_T + u_{T+2} + \phi u_{T+1}) \cdot \hat{\phi}^2 y_T) \\
&= \mathbb{E}(\phi^4 y_T^2 + (u_{T+2} + \phi u_{T+1})^2 + 2\phi^2 y_T(u_{T+2} + \phi u_{T+1})) + y_T^2 \mathbb{E}(\hat{\phi}^2) - 2\phi^2 y_T \mathbb{E}(\hat{\phi}^2 y_T) \\
&= \mathbb{E}(\phi^4) y_T^2 + \mathbb{E}(u_{T+2}^2 + \phi^2 u_{T+1}^2) + y_T^2 \mathbb{E}(\hat{\phi}^2) - 2\phi^2 y_T^2 \mathbb{E}(\hat{\phi}^2) = \mathbb{E}(\phi^4) y_T^2 + (1 + \phi^2) \sigma^2 + y_T^2 \mathbb{E}(\hat{\phi}^2) - 2\phi^2 y_T^2 \mathbb{E}(\hat{\phi}^2) \\
&= y_T^2 [\mathbb{E}(\phi^4 + \hat{\phi}^2 - 2\phi^2 \hat{\phi}^2)] + (1 + \phi^2) \sigma^2 = [\mathbb{E}(\phi^2 - \hat{\phi}^2)^2 y_T^2 + (1 + \phi^2) \sigma^2] \\
& \mathbb{E}(y_{T+2} - \hat{y}_{T+2|T}^{(d)})^2 = \mathbb{E}(y_{T+2}^2) + \mathbb{E}((\hat{y}_{T+2|T}^{(d)})^2) - 2\mathbb{E}(y_{T+2} \cdot \hat{y}_{T+2|T}^{(d)}) \\
&= \mathbb{E}((\phi^2 y_T + u_{T+2} + \phi u_{T+1})^2) + \mathbb{E}((\hat{\phi}_2 y_T)^2) - 2\mathbb{E}((\phi^2 y_T + u_{T+2} + \phi u_{T+1}) \cdot \hat{\phi}_2 y_T) \\
&= \mathbb{E}(\phi^4 y_T^2 + (u_{T+2} + \phi u_{T+1})^2 + 2\phi^2 y_T(u_{T+2} + \phi u_{T+1})) + y_T^2 \mathbb{E}(\hat{\phi}_2) - 2\phi^2 y_T \mathbb{E}(\hat{\phi}_2 y_T) \\
&= \mathbb{E}(\phi^4) y_T^2 + \mathbb{E}(u_{T+2}^2 + \phi^2 u_{T+1}^2) + y_T^2 \mathbb{E}(\hat{\phi}_2) - 2\phi^2 y_T^2 \mathbb{E}(\hat{\phi}_2) = \mathbb{E}(\phi^4) y_T^2 + (1 + \phi^2) \sigma^2 + y_T^2 \mathbb{E}(\hat{\phi}_2) - 2\phi^2 y_T^2 \mathbb{E}(\hat{\phi}_2) \\
&= y_T^2 [\mathbb{E}(\phi^4 + \hat{\phi}_2 - 2\phi^2 \hat{\phi}_2)] + (1 + \phi^2) \sigma^2 = [\mathbb{E}(\phi^2 - \hat{\phi}_2)^2 y_T^2 + (1 + \phi^2) \sigma^2]
\end{aligned}$$

(c) Begin by expanding $\hat{\phi}^2$ in a first order Taylor series about ϕ :

$$\hat{\phi} = \phi + \mathcal{O}_p(M^{-1/2}) \implies \hat{\phi}^2 = \phi^2 + 2\phi(\hat{\phi} - \phi) + \mathcal{O}_p(M^{-1})$$

Then

$$\begin{aligned}
\mathbb{E}[(\hat{\phi}^2 - \phi^2)^2 | y_T] &= \mathbb{E}[(2\phi(\hat{\phi} - \phi) + \mathcal{O}_p(M^{-1}))^2 | y_T] = 4\phi^2 \mathbb{E}[(\hat{\phi} - \phi + \mathcal{O}_p(M^{-1}))^2 | y_T] \\
&= 4\phi^2 \mathbb{E}[(\hat{\phi} - \phi + \mathcal{O}_p(M^{-1}))^2 | y_T]
\end{aligned}$$

13.7 Chapter 18: Measurement and Modeling of Volatility

Maybe review a little, but feel pretty okay on concepts

GARCH(1, 1) model (Pesaran Equation 18.5):

$$h_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \phi_1 h_{t-1}^2, \quad \alpha_0 > 0 \quad (13.14)$$

- This process is unconditionally stationary if $|\alpha_1 + \phi_1| < 1$.
- The unconditional variance exists and is fixed if $|\alpha_1 + \phi_1| < 1$.
- The case where $\alpha_1 + \phi_1 = 1$ is known as the Integrated GARCH(1,1), or IGARCH(1,1) for short. The RiskMetrics exponentially weighted formulation of h_t^2 for large H is a special case of the IGARCH(1,1) model where α_0 is set to 0. RiskMetrics formulation avoids the variance non-existence problem by focusing on H fixed.

13.7.1 Higher order GARCH models (Pesaran Section 18.4.2)

The various members of the GARCH and GARCH-M class of models can be written compactly as

$$y_t = \beta' \mathbf{x}_{t-1} + \gamma h_t^2 + \epsilon_t \quad (13.15)$$

where

$$h_t^2 = \text{Var}(\epsilon_t | \Omega_{t-1}) = \mathbb{E}(\epsilon_t^2 | \Omega_{t-1}) = \alpha_0 + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^p \phi_i h_{t-i}^2 \quad (13.16)$$

and Ω_{t-1} is the information set at time $t - 1$ containing at least $(\mathbf{x}_{t-1}, \mathbf{x}_{t-2}, \dots, y_{t-1}, y_{t-2}, \dots)$. The unconditional variance of ϵ_t is determined by

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \sigma_{t-i}^2 + \sum_{i=1}^p \phi_i \sigma_{t-i}^2$$

and yields a stationary outcome if all the roots of

$$1 - \sum_{i=1}^q \alpha_i \lambda^i + \sum_{i=1}^p \phi_i \lambda^i = 0$$

like outside the unit circle. In that case

$$\text{Var}(\epsilon_t) = \sigma^2 = \frac{\alpha_0}{1 - \sum_{i=1}^q \alpha_i - \sum_{i=1}^p \phi_i} > 0 \quad (13.17)$$

Clearly the necessary condition for (13.16) to be covariance stationary is given by

$$\sum_{i=1}^q \alpha_i + \sum_{i=1}^p \phi_i < 1$$

13.7.2 Testing for GARCH effects (Pesaran Section 18.5.1)

If we consider y_t as periodic data defined by $y_t = r_t - \bar{r}$ with r_t representing, say, asset return and \bar{r} representing the unconditional mean, then we have the GARCH(1,1) representation of volatility:

$$\text{Var}(y_t | \Omega_{t-1}) = h_t^2 = \bar{\sigma}^2(1 - \alpha - \beta) + \alpha y_{t-1}^2 + \beta h_{t-1}^2$$

Then the test for GARCH effects would test

$$H_0 : \alpha = 0$$

against

$$H_1 : \alpha \neq 0$$

GARCH(1,1) can be approximated by ARCH(q):

$$\begin{aligned} \text{Var}(y_t | \Omega_{t-1}) &= \frac{\bar{\sigma}^2(1 - \alpha - \beta)}{1 - \beta} + \alpha y_{t-1}^2 + \alpha\beta y_{t-2}^2 + \dots + \alpha\beta^{q-1} y_{t-q}^2 \\ &= \tilde{\alpha}_0 + \tilde{\alpha}_1 y_{t-1}^2 + \tilde{\alpha}_2 z_{t-2}^2 + \dots + \tilde{\alpha}_q z_{t-q}^2 \end{aligned}$$

which means that we can approximate this hypothesis test by instead using the Lagrange multiplier test proposed by Engle:

$$H_0 : \tilde{\alpha}_1 = \tilde{\alpha}_2 = \dots = \tilde{\alpha}_q$$

against

$$H_1 : \tilde{\alpha}_1 \neq 0, \tilde{\alpha}_2 \neq 0, \dots, \tilde{\alpha}_q \neq 0$$

13.7.3 Worked Problems

Problem 1. Consider the generalized autoregressive heteroskedastic model

$$y_t = h_t z_t$$

where

$$z_t \mid \Omega_{t-1} \sim IID\mathcal{N}(0, 1) \quad (13.18)$$

$$h_t^2 = \text{Var}(y_t \mid \Omega_{t-1}) = \mathbb{E}(y_t^2 \mid \Omega_{t-1}) = \bar{\sigma}^2(1 - \alpha - \beta) + \alpha y_{t-1}^2 + \beta h_{t-1}^2 \quad (13.19)$$

and Ω_t is the information set that contains at least y_t and its lagged values.

- (a) Derive the conditions under which $\{y_t\}$ is a stationary process.
- (b) Are the observations $\{y_t\}$ serially independent and/or serially uncorrelated?
- (c) Develop a test of the GARCH effect and discuss the estimation of the above model by the maximum likelihood method.
- (d) Discuss the relevance of GARCH models for the analysis of financial time series data.

Solution.

- (a) Note that (using the fact that y_t and h_t are conditionally independent given Ω_{t-1})

$$\mathbb{E}(y_t) = \mathbb{E}(h_t z_t) = \mathbb{E}[\mathbb{E}(h_t z_t \mid \Omega_{t-1})] = \mathbb{E}[\mathbb{E}(h_t \mid \Omega_{t-1})\mathbb{E}(z_t \mid \Omega_{t-1})] = \mathbb{E}[\mathbb{E}(h_t \mid \Omega_{t-1}) \cdot 0] = 0$$

We have

$$\text{Var}(y_t) = \mathbb{E}[(y_t - \mathbb{E}(y_t))^2] = \mathbb{E}[y_t^2] = \mathbb{E}[\mathbb{E}(y_t^2 \mid \Omega_{t-1})] = \mathbb{E}(h_t^2) = \mathbb{E}(\bar{\sigma}^2(1 - \alpha - \beta) + \alpha y_{t-1}^2 + \beta h_{t-1}^2)$$

$$= \mathbb{E}(\bar{\sigma}^2(1 - \alpha - \beta)) + \alpha \mathbb{E}(y_{t-1}^2) + \beta \mathbb{E}(h_{t-1}^2) = \bar{\sigma}^2(1 - \alpha - \beta) + (\alpha + \beta)\text{Var}(y_{t-1})$$

Therefore in order for this to be a stationary process, we require $|\alpha + \beta| < 1$.

more stuff I did on original homework

By Definition 13.1 $\{y_t\}$ is a stationary process if it has constant mean and its covariance function depends only on the absolute difference $|t_1 - t_2|$; that is,

$$\text{Cov}(y_{t_1}, y_{t_2}) = \gamma(t_1, t_2) = \gamma(|t_1 - t_2|) \text{ for all } t_1, t_2$$

⋮

In order for this to be true, we must first show that h_t is finite for all t . It is sufficient to find the conditions that make h_t stationary. Using Equation (13.16)

$$h_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^p \phi_i h_{t-i}^2$$

From equation (13.19) we have

$$h_t^2 = \bar{\sigma}^2(1 - \alpha - \beta) + \alpha y_{t-1}^2 + \beta h_{t-1}^2$$

Therefore we note that $p = q = 1$ and we have a GARCH(1,1) model. From Equation (13.14):

$$h_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \phi_1 h_{t-1}^2, \quad \alpha_0 > 0$$

is unconditionally stationary if $|\alpha_1 + \phi_1| < 1$. In this case, we require $|\alpha + \beta| < 1$ for stationarity of h_t .

⋮

Assume without loss of generality that $t_2 \geq t_1$. (Note that this implies $z_{t_2} \perp\!\!\!\perp z_{t_1}, h_{t_2}, h_{t_1} \mid \Omega_{t_2-1}$.)

$$\begin{aligned} \text{Cov}(y_{t_1}, y_{t_2}) &= \mathbb{E}[(y_{t_1} - \mathbb{E}(y_{t_1}))(y_{t_2} - \mathbb{E}(y_{t_2}))] = \mathbb{E}[y_{t_1} y_{t_2}] = \mathbb{E}[h_{t_1} h_{t_2} z_{t_1} z_{t_2}] \\ &= \mathbb{E}[\mathbb{E}(h_{t_1} h_{t_2} z_{t_1} z_{t_2} \mid \Omega_{t_2-1})] = \mathbb{E}[\mathbb{E}(h_{t_1} h_{t_2} z_{t_1} \mid \Omega_{t_2-1}) \mathbb{E}(z_{t_2} \mid \Omega_{t_2-1})] \\ &= \mathbb{E}[\mathbb{E}(h_{t_1} h_{t_2} z_{t_1} \mid \Omega_{t_2-1}) \cdot 0] = \boxed{0} \end{aligned}$$

Therefore given that h_t is finite (that is, given $|\alpha + \beta| < 1$), we have that $\mathbb{E}(y_t) = 0$, $\text{Cov}(y_{t_1}, y_{t_2}) = 0 \quad \forall t_1, t_2$ which implies that under these conditions y_t is stationary.

- (b) y_t is serially uncorrelated because $\text{Cov}(y_{t_1}, y_{t_2}) = 0 \quad \forall t_1, t_2$. However, it is clear that y_t is not serially independent since past values of y_t affect $h_t^2 = \text{Var}(y_t)$. Observe that

$$\Pr(y_t \leq y \mid y_{t-1}) = \Pr(h_t z_t \leq y \mid y_{t-1}) = \Pr\left(z_t \sqrt{\bar{\sigma}^2(1 - \alpha - \beta) + \alpha y_{t-1}^2 + \beta h_{t-1}^2} \leq y \mid y_{t-1}\right)$$

In other words, even though the mean of y_t remains constant, because y_{t-1} affects the variance of y_t , it affects the heaviness of the tails of y_t , changing the probability distribution of y_t . Therefore the conditional cumulative distribution function of y_t given y_{t-1} is not equal to the unconditional cdf, so y_t and y_{t-1} are not independent.

Lidan's Explanation: From (a) we know that $\{y_t\}$ is serially uncorrelated, but they are not necessarily independent because from Equation (13.19) we know that h_t is not independent from h_{t-1} .

- (c) See section 13.7.2.
- (d) **Lidan:** Usually financial time series data are fat-tailed. So the series may not look stationary, and therefore the local variance would be clustered in some very low and very high values. To capture this serial correlation and heterogeneity in volatility, we need to use a GARCH model.

Book: In financial econometrics, ARCH and GARCH are fundamental tools for analyzing the time-variation of conditional variance. In many applications in finance, the assumption that the conditional variance of the disturbances is constant over time is not valid. GARCH models allow for time variation in volatility, relating (unobserved) volatility to squares of past innovations in price changes. However, this approach only partly overcomes the deficiency of the historical measure and continues to respond very slowly when volatility undergoes rapid changes.

13.8 Chapter 21: Vector Autoregressive Models

Feel ok on concepts.

13.8.1 Worked Problems

Problem 1. Consider the bivariate autoregressive model:

$$Y_t = \Phi Y_{t-1} + U_t, \quad U_t \sim IID\mathcal{N}(0, \Sigma) \quad (13.20)$$

where

$$Y_t = (y_{1t}, y_{2t})', \quad Y_{t-1} = (y_{1,t-1}, y_{2,t-1})', \quad U_t = (u_{1t}, u_{2t})'$$

and

$$\Phi = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix} \succ 0$$

- (a) Derive the conditional mean and variance of y_{1t} with respect to y_{2t} and lagged values of y_{1t} and y_{2t} .
- (b) Show that the univariate representation of y_{1t} is an ARMA(2,1) process.

Solution

- (a) Note that

$$y_{1t} = \phi_{11}y_{1,t-1} + \phi_{12}y_{2,t-1} + u_{1t} \quad (13.21)$$

$$y_{2t} = \phi_{21}y_{1,t-1} + \phi_{22}y_{2,t-1} + u_{2t} \quad (13.22)$$

First,

$$\mathbb{E}(y_{1t} | y_{2t}, y_{2,t-1}, y_{2,t-2}, \dots, y_{1,t-1}, y_{1,t-2}, \dots) = \mathbb{E}(y_{1t} | y_{2t}, \Omega_{t-1})$$

$$= \phi_{11}y_{1,t-1} + \phi_{12}y_{2,t-1} + \mathbb{E}(u_{1t} | y_{2t}) = \phi_{11}y_{1,t-1} + \phi_{12}y_{2,t-1} + \mathbb{E}(u_{1t} | \phi_{21}y_{1,t-1} + \phi_{22}y_{2,t-1} + u_{2t})$$

$$= \phi_{11}y_{1,t-1} + \phi_{12}y_{2,t-1} + \mathbb{E}(u_{1t} | u_{2t})$$

Recall Proposition 6.3.36: for a bivariate normal distribution with mean 0, the conditional distribution of u_{1t} given u_{2t} is

$$u_{1t} | u_{2t} \sim \mathcal{N}\left(\rho \frac{\sqrt{\sigma_{11}}}{\sqrt{\sigma_{22}}} u_{2t}, (1 - \rho^2)\sigma_{11}\right)$$

where $\rho = \sigma_{12}/\sqrt{\sigma_{11}}\sqrt{\sigma_{22}}$.

$$\begin{aligned} &\iff u_{1t} | u_{2t} \sim \mathcal{N}\left(\frac{\sigma_{12}}{\sqrt{\sigma_{11}}\sqrt{\sigma_{22}}} \cdot \frac{\sqrt{\sigma_{11}}}{\sqrt{\sigma_{22}}} u_{2t}, \left[1 - \left(\frac{\sigma_{12}}{\sqrt{\sigma_{11}}\sqrt{\sigma_{22}}}\right)^2\right]\sigma_{11}\right) \\ &\iff u_{1t} | u_{2t} \sim \mathcal{N}\left(\frac{\sigma_{12}}{\sigma_{22}}u_{2t}, \sigma_{11} - \frac{\sigma_{12}^2}{\sigma_{22}}\right) \\ &\implies \mathbb{E}(u_{1t} | u_{2t}) = \frac{\sigma_{12}}{\sigma_{22}}u_{2t}, \quad \text{Var}(u_{1t} | u_{2t}) = \sigma_{11} - \frac{\sigma_{12}^2}{\sigma_{22}} \\ &\implies \mathbb{E}(y_{1t} | y_{2t}, \Omega_{t-1}) = \phi_{11}y_{1,t-1} + \phi_{12}y_{2,t-1} + \frac{\sigma_{12}}{\sigma_{22}}u_{2t} \\ &= \phi_{11}y_{1,t-1} + \phi_{12}y_{2,t-1} + \frac{\sigma_{12}}{\sigma_{22}}(y_{2t} - \phi_{21}y_{1,t-1} - \phi_{22}y_{2,t-1}) \\ &= \boxed{\left(\phi_{11} - \frac{\sigma_{12}}{\sigma_{22}}\phi_{21}\right)y_{1,t-1} + \left(\phi_{12} - \frac{\sigma_{12}}{\sigma_{22}}\phi_{22}\right)y_{2,t-1} + \frac{\sigma_{12}}{\sigma_{22}}y_{2t}} \end{aligned}$$

Second,

$$\begin{aligned} \text{Var}(y_{1t} | y_{2t}, \Omega_{t-1}) &= \phi_{11}^2 \text{Var}(y_{1,t-1} | y_{2t}, \Omega_{t-1}) + \phi_{12}^2 \text{Var}(y_{2,t-1} | y_{2t}, \Omega_{t-1}) + \text{Var}(u_{1t} | y_{2t}, \Omega_{t-1}) \\ &= \text{Var}(u_{1t} | u_{2t}) = \boxed{\sigma_{11} - \frac{\sigma_{12}^2}{\sigma_{22}}} \end{aligned}$$

(b) Again, using equations (13.21) and (13.22),

$$\begin{aligned} y_{1t} &= \phi_{11}y_{1,t-1} + \phi_{12}y_{2,t-1} + u_{1t}, \quad y_{2t} = \phi_{21}y_{1,t-1} + \phi_{22}y_{2,t-1} + u_{2t} \\ &\implies (1 - \phi_{11}L)y_{1t} = \phi_{12}Ly_{2t} + u_{1t} \end{aligned} \tag{13.23}$$

$$(1 - \phi_{22}L)y_{2t} = \phi_{21}Ly_{1t} + u_{2t} \tag{13.24}$$

We can multiply $(1 - \phi_{22}L)$ on both sides of (13.23) to yield

$$(1 - \phi_{22}L)(1 - \phi_{11}L)y_{1t} = \phi_{12}L(1 - \phi_{22}L)y_{2t} + (1 - \phi_{22}L)u_{1t}$$

Using (13.24), we have

$$\begin{aligned} (1 - (\phi_{22} + \phi_{11})L + \phi_{11}\phi_{22}L^2)y_{1t} &= \phi_{12}L[\phi_{21}Ly_{1t} + u_{2t}] + (1 - \phi_{22}L)u_{1t} \\ \iff (1 - (\phi_{22} + \phi_{11})L + (\phi_{11}\phi_{22} - \phi_{12}\phi_{21})L^2)y_{1t} &= \phi_{12}Lu_{2t} + (1 - \phi_{22}L)u_{1t} \end{aligned} \quad (13.25)$$

If we can show that the left side of (13.25) is an AR(2) process and the right side is an MA(1) process, we are done. **Lidan:** “It is obvious that the left hand side of (13.25) is an AR(2) process.” The left side is a stationary AR(2) process if the absolute values of all the roots of

$$1 - (\phi_{22} + \phi_{11})z + (\phi_{11}\phi_{22} - \phi_{12}\phi_{21})z^2 = 0$$

are greater than 1. The roots are

$$\begin{aligned} z &= \frac{\phi_{22} + \phi_{11} \pm \sqrt{(\phi_{22} + \phi_{11})^2 - 4(\phi_{11}\phi_{22} - \phi_{12}\phi_{21})}}{2(\phi_{11}\phi_{22} - \phi_{12}\phi_{21})} = \frac{\phi_{22} + \phi_{11} \pm \sqrt{\phi_{22}^2 + \phi_{11}^2 - 2\phi_{22}\phi_{11} + 4\phi_{12}\phi_{21}}}{2(\phi_{11}\phi_{22} - \phi_{12}\phi_{21})} \\ &= \frac{\phi_{22} + \phi_{11} \pm \sqrt{(\phi_{22} - \phi_{11})^2 + 4\phi_{12}\phi_{21}}}{2(\phi_{11}\phi_{22} - \phi_{12}\phi_{21})} \\ &\vdots \end{aligned}$$

To check if the right side of (13.25) is MA(1), we will write $x_t = \phi_{12}Lu_{2t} + (1 - \phi_{22}L)u_{1t}$ as an MA(1) process; that is,

$$x_t = \phi_{12}u_{2,t-1} + u_{1t} - \phi_{22}u_{1,t-1} = \xi_t + \theta\xi_{t-1}$$

with $\xi_t \sim iid(0, \sigma_\xi^2)$, $|\theta| < 1$. If x_t is an MA(1) process, it must satisfy

$$\gamma(0) = \mathbb{E}(x_t^2) = (1 + \theta^2)\sigma_\xi^2, \quad \gamma(1) = \mathbb{E}(x_t x_{t-1}) = \theta\sigma_\xi^2$$

We have (using the serial independence of the u_{1t}, u_{2t})

$$\begin{aligned} \mathbb{E}(x_t^2) &= \mathbb{E}([\phi_{12}u_{2,t-1} + u_{1t} - \phi_{22}u_{1,t-1}]^2) = \mathbb{E}(\phi_{12}^2u_{2,t-1}^2 - 2\phi_{12}\phi_{22}u_{2,t-1}u_{1,t-1} + \phi_{22}^2u_{1,t-1}^2 + u_{1t}^2) \\ &= \phi_{12}^2\mathbb{E}(u_{2,t-1}^2) - 2\phi_{12}\phi_{22}\mathbb{E}(u_{2,t-1}u_{1,t-1}) + \phi_{22}^2\mathbb{E}(u_{1,t-1}^2) + \mathbb{E}(u_{1t}^2) \\ &= \phi_{12}^2\sigma_{22}^2 - 2\phi_{12}\phi_{22}\sigma_{12} + \phi_{22}^2\sigma_{11}^2 + \sigma_{11}^2 = (1 + \phi_{22}^2)\sigma_{11}^2 - 2\phi_{12}\phi_{22}\sigma_{12} + \phi_{12}^2\sigma_{22}^2 \\ \mathbb{E}(x_t x_{t-1}) &= \mathbb{E}([\phi_{12}u_{2,t-1} + u_{1t} - \phi_{22}u_{1,t-1}][\phi_{12}u_{2,t-2} + u_{1,t-1} - \phi_{22}u_{1,t-2}]) \end{aligned}$$

$$= \mathbb{E}(\phi_{12}u_{2,t-1}u_{1,t-1} - \phi_{22}u_{1,t-1}^2) = \phi_{12}\sigma_{12} - \phi_{22}\sigma_{11}$$

Therefore we require

$$(1 + \theta^2)\sigma_\xi^2 = (1 + \phi_{22}^2)\sigma_{11} - 2\phi_{12}\phi_{22}\sigma_{12} + \phi_{12}^2\sigma_{22} \quad (13.26)$$

$$\theta\sigma_\xi^2 = \phi_{12}\sigma_{12} - \phi_{22}\sigma_{11} \quad (13.27)$$

Dividing (13.26) by (13.27) we have

$$\frac{1 + \theta^2}{\theta} = \frac{(1 + \phi_{22}^2)\sigma_{11} - 2\phi_{12}\phi_{22}\sigma_{12} + \phi_{12}^2\sigma_{22}}{\phi_{12}\sigma_{12} - \phi_{22}\sigma_{11}} \quad (13.28)$$

For simplicity, let the right side of (13.28) be $A \in \mathbb{R}$. Then we have

$$\theta^2 - A\theta + 1 = 0 \iff \boxed{\theta_1 = \frac{1}{2}(A + \sqrt{A^2 - 4}), \theta_2 = \frac{1}{2}(A - \sqrt{A^2 - 4})}$$

Then the corresponding σ_ξ^2 are

$$\boxed{\sigma_{\xi,1}^2 = \sigma_{\xi,2}^2 = \frac{\phi_{12}\sigma_{12} - \phi_{22}\sigma_{11}}{\theta_1}}$$

As a double check,

$$\mathbb{E}(x_t x_{t-2}) = \mathbb{E}([\phi_{12}u_{2,t-1} + u_{1t} - \phi_{22}u_{1,t-1}][\phi_{12}u_{2,t-3} + u_{1,t-2} - \phi_{22}u_{1,t-3}]) = 0$$

as expected for an MA(1) process. Therefore the right side of (13.25) is an MA(1) process (provided that $0 < |\theta_1| < 1$ and/or $0 < |\theta_2| < 1$). Since the left side is an AR(2) process, this proves that the univariate representation (13.25) of y_{1t} is an ARMA(2,1) process.

Problem 2. Consider the VAR(2) model in the m -dimensional vector Y_t :

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + U_t, \quad U_t \sim (0, \Sigma) \quad (13.29)$$

where μ is an m -vector of fixed constants.

- (a) Derive the conditions under which the VAR(2) model defined in (13.29) is stationary.
- (b) Derive the error correction form of (13.29) and discuss what is meant by the process Y_t being cointegrated.
- (c) Suppose now that one or more elements of Y_t is I(1). Derive suitable restrictions on the intercepts μ such that despite the I(1) nature of the variables in (13.29), Y_t has a fixed mean. Discuss the importance of such restrictions for the analysis of cointegration.

Solution.

(a) Let

$$Y_t^* = Y_t - (I - \Phi_1 - \Phi_2)^{-1}\mu. \quad (13.30)$$

Then

$$\begin{aligned} Y_t^* &= \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + U_t - (I - \Phi_1 - \Phi_2)^{-1}\mu \\ &= \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + U_t - [(I - \Phi_1 - \Phi_2) + \Phi_1 + \Phi_2](I - \Phi_1 - \Phi_2)^{-1}\mu \\ &= \mu - (I - \Phi_1 - \Phi_2)(I - \Phi_1 - \Phi_2)^{-1}\mu + \Phi_1(Y_{t-1} - (I - \Phi_1 - \Phi_2)^{-1}\mu) + \Phi_2(Y_{t-2} - (I - \Phi_1 - \Phi_2)^{-1}\mu) + U_t \\ &= \Phi_1 Y_{t-1}^* + \Phi_2 Y_{t-2}^* + U_t \end{aligned} \quad (13.31)$$

Equation (13.31) can be rewritten in the companion form as follows:

$$\begin{bmatrix} Y_t^* \\ Y_{t-1}^* \end{bmatrix} = \begin{bmatrix} \Phi_1 & \Phi_2 \\ I & 0 \end{bmatrix} \begin{bmatrix} Y_{t-1}^* \\ Y_{t-2}^* \end{bmatrix} + \begin{bmatrix} U_t \\ 0 \end{bmatrix} \quad (13.32)$$

which is a VAR(1) model. If Y_{-M+1}, Y_{-M+2} are given, equation (13.32) can be solved iteratively from $t = -M + 2$ to obtain

$$\begin{bmatrix} Y_t^* \\ Y_{t-1}^* \end{bmatrix} = \begin{bmatrix} \Phi_1 & \Phi_2 \\ I & 0 \end{bmatrix}^{t+M-2} \begin{bmatrix} Y_{-M+2}^* \\ Y_{-M+1}^* \end{bmatrix} + \sum_{j=0}^{t+M-3} \begin{bmatrix} \Phi_1 & \Phi_2 \\ I & 0 \end{bmatrix}^j \begin{bmatrix} U_{t-j} \\ 0 \end{bmatrix} \quad (13.33)$$

Then the condition for (13.33) to be covariance stationary is for all the eigenvalues of

$$\Phi = \begin{bmatrix} \Phi_1 & \Phi_2 \\ I & 0 \end{bmatrix}$$

to lie inside the unit circle; that is, the solutions of

$$|\Phi - \lambda I_4| = 0$$

must satisfy $|\lambda| < 1$. Equivalently, the stability condition can be written in terms of the roots of the determinantal equation

$$|I_2 - \Phi_1 z - \Phi_2 z^2| = 0$$

in which case the process Y_t^* will be stationary if all the roots lie outside the unit circle ($|z| > 1$). Then if Y_t^* is stationary, so is Y_t , so either of these conditions (plus the invertibility of $(I - \Phi_1 - \Phi_2)$) ensure stationarity of Y_t .

(b) From (13.31) we have

$$Y_t^* = \Phi_1 Y_{t-1}^* + \Phi_2 Y_{t-2}^* + U_t$$

Note that (letting $\Delta Y_t^* = Y_t^* - Y_{t-1}^*$)

$$\begin{aligned} Y_t^* - Y_{t-1}^* + Y_{t-1}^* &= \Phi_1 Y_{t-1}^* + \Phi_2(Y_{t-2}^* - Y_{t-1}^* + Y_{t-1}^*) + U_t \\ \iff \Delta Y_t^* + Y_{t-1}^* &= \Phi_1 Y_{t-1}^* + \Phi_2(Y_{t-1}^* - \Delta Y_{t-1}^*) + U_t \\ \iff \Delta Y_t^* &= -(I - \Phi_1 - \Phi_2)Y_{t-1}^* - \Phi_2 \Delta Y_{t-1}^* + U_t \iff \boxed{\Delta Y_t^* = -\Pi Y_{t-1}^* + \Gamma \Delta Y_{t-1}^* + U_t} \end{aligned}$$

where $\Pi = (I - \Phi_1 - \Phi_2)$ and $\Gamma = -\sum_{i=2}^2 \Phi_i = -\Phi_2$. Because

$$\Delta Y_t^* = Y_t^* - Y_{t-1}^* = Y_t - (I - \Phi_1 - \Phi_2)^{-1}\mu - [Y_{t-1} - (I - \Phi_1 - \Phi_2)^{-1}\mu] = Y_t - Y_{t-1} = \Delta Y_t,$$

this can also be written as

$$\begin{aligned} \Delta Y_t &= -\Pi[Y_{t-1} - (I - \Phi_1 - \Phi_2)^{-1}\mu] + \Gamma \Delta Y_{t-1} + U_t \\ &= -\Pi[Y_{t-1} - \Pi^{-1}\mu] + \Gamma \Delta Y_{t-1} + U_t = \Pi \cdot \Pi^{-1}\mu - \Pi Y_{t-1} + \Gamma \Delta Y_{t-1} + U_t \\ \implies \boxed{\Delta Y_t = \mu - \Pi Y_{t-1} + \Gamma \Delta Y_{t-1} + U_t} \end{aligned} \tag{13.34}$$

For the definition of cointegration, see Definition 13.3 and Section 13.9.1. In this particular case, if $Y_{t-1}^* \sim I(1)$ and the linear combinations ΠY_{t-1}^* of Y_{t-1}^* are covariance stationary (that is, $\Pi Y_{t-1}^* \sim I(0)$), we say Y_t^* is cointegrated (and therefore so is Y_t).

(c) Since (13.34) is $I(0)$, for Y_t to have fixed mean, take expectations on both sides of (13.34):

$$\mu - (I_m - \Phi_1 - \Phi_2)\mathbb{E}(Y_{t-1}) = 0$$

If this restriction is violated, then (13.34) becomes a stationary process with a drift, which implies (13.29) has a time trend.

13.9 Chapter 22: Cointegration Analysis

Feel pretty good except for long run effects, examples we went over in class, the restrictions, and the 5 cases. Don't need to understand SURE.

13.9.1 22.4 Cointegrating VAR: multiple cointegrating relations and 22.5: Identification of long-run effects

Definition 13.3. We say that the m variables in Y_t are *cointegrated* if they are individually integrated (or have a random walk component) but there exist linear combinations of them which are stationary. That is, $y_{it} \sim I(1)$ for $i = 1, 2, \dots, m$, but there exists an $m \times r$ matrix β such that $\beta' Y_t = \xi_t \sim I(0)$.

- In this case r denotes the number of cointegrating vectors, also known as the dimension of the cointegration space.
- The cointegrating relations summarized in the $r \times 1$ vector $\beta' Y_t$ are also known as long-run relations.
- $r = \text{rank}(\Pi)$ is the dimension of the cointegration space.
- Cointegration is present if Π is rank-deficient; that is, $r < m$.

When $\text{rank}(\Pi) = r < m$, we can write Π as

$$\Pi = \alpha \beta' \quad (13.35)$$

where α and β are $m \times r$ matrices of full column rank. Then

$$\Pi y_{t-1} = \alpha \beta' y_{t-1} \sim I(0)$$

and the VECM can be written as

$$\Delta y_t = -\alpha \beta' y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + u_t \quad (13.36)$$

Since α is full rank, we have

$$\beta' y_{t-1} \sim I(0)$$

where $\beta' y_t$ is the r -vector of cointegrating relations, also known as the long-run relations.

However, β as defined above is not uniquely determined. Consider a linear transformation of β by a non-singular $r \times r$ matrix Q : $\tilde{\beta} = \beta Q$. Then since $\text{rank}(\Pi) = r < m$, Π can be expressed as $\Pi = \alpha \beta'$ where α is a rank r $m \times r$ matrix. But consider that

$$\Pi = \alpha \beta = (\alpha Q'^{-1})(Q' \beta') = \tilde{\alpha} \tilde{\beta}'$$

with $\tilde{\alpha} = \alpha Q'^{-1}$. Therefore β is not uniquely determined without r^2 exact- or just-identifying restrictions, r restrictions on each of the r cointegrating relations.

13.9.2 Worked Problems

Problem 2: See Chapter 21 Problem 2.

13.10 Chapter 23: VARX Modeling

Lidan says will not be on final.

13.10.1 Worked Problems

13.11 Chapter 24: Impulse Response Analysis

Feel ok on concepts, should review and do an example problem.

13.11.1 Worked Problems

Chapter 24 Problem 1. Consider the VAR(2) model

$$x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \epsilon_t, \quad \epsilon_t \sim IID(0, \Sigma)$$

in the $m \times 1$ vector of random variables x_t and Σ is the covariance matrix of the errors with typical element σ_{ij} .

- (a) Derive the conditions under which this process is stationary, and show that it has the following moving average representation:

$$x_t = \sum_{j=0}^{\infty} A_j \epsilon_{t-j} \tag{13.37}$$

- (b) Derive the coefficient matrices A_j in terms of Φ_1 and Φ_2 .
(c) Using the above result, write down the orthogonalized (OIR) and generalized impulse (GIR) response functions of one standard error shock (i.e. $\sqrt{\sigma_{ii}}$ to the error of the i th equation, $\epsilon_{it} = s'_i \epsilon_t$, where s_i is an $m \times 1$ selection vector).
(d) What are the main differences between OIR and GIR functions?

Chapter 24 Problem 1 Solution.

- (a) For stationarity conditions, see Ch. 21 Problem 2 in Section 13.8.1. To get the MA representation

$$x_t = \sum_{j=0}^{\infty} A_j \epsilon_{t-j} \tag{13.38}$$

of (13.37) note that

$$(I - \Phi_1 L - \Phi_2 L^2)x_t = \epsilon_t$$

$$\implies x_t = (I - \Phi_1 L - \Phi_2 L^2)^{-1}\epsilon_t = \sum_{j=0}^{\infty} A_j \epsilon_{t-j}$$

for some $\{A_j\}$.

- (b) Now we seek to evaluate $(I - \Phi_1 L - \Phi_2 L^2)^{-1}$. To do this, let $(I - \Phi_1 L - \Phi_2 L^2)^{-1} = A_0 + A_1 L + A_2 L^2 + A_3 L^3 + \dots$ and note that

$$\begin{aligned} & (I - \Phi_1 L - \Phi_2 L^2)(I - \Phi_1 L - \Phi_2 L)^{-1} = I \\ \iff & (I - \Phi_1 L - \Phi_2 L^2)(A_0 + A_1 L + A_2 L^2 + A_3 L^3 + \dots + A_j L^j + \dots) = I \\ \iff & A_0 + (A_1 - \Phi_1)L + (A_2 - \Phi_1 A_1 - \Phi_2)L^2 + (A_3 - \Phi_1 A_2 - \Phi_2 A_1)L^3 + \dots \\ & + (A_j - \Phi_1 A_{j-1} + \Phi_2 A_{j-2})L^j + \dots = I \end{aligned}$$

In order for this equation to hold, all the lag terms must equal zero and the constant matrix A_0 must equal I .

$$\implies [A_0 = I]$$

$$A_1 - \Phi_1 = 0 \iff [A_1 = \Phi_1]$$

$$A_2 - \Phi_1 A_1 - \Phi_2 = 0 \iff A_2 - \Phi_1^2 - \Phi_2 = 0 \iff [A_2 = \Phi_1^2 + \Phi_2]$$

$$A_3 - \Phi_1 A_2 - \Phi_2 A_1 = 0 \iff A_3 - \Phi_1^3 - \Phi_1 \Phi_2 - \Phi_2 \Phi_1 = 0 \iff [A_3 = \Phi_1^3 + \Phi_1 \Phi_2 + \Phi_2 \Phi_1]$$

and, in general,

$$[A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2}]$$

- (c) • **OIR:** We employ the Cholesky decomposition of Σ :

$$\Sigma = PP' \tag{13.39}$$

where P is a lower-triangular matrix. Then the MA representation (13.38) can be written as

$$x_t = \sum_{j=0}^{\infty} (A_j P)(P^{-1} u_{t-j}) = \sum_{j=0}^{\infty} B_j \eta_{t-j} \tag{13.40}$$

where $B_j = A_j P$, $\eta_t = P^{-1} u_t$, so we have

$$\mathbb{E}(\eta_t \eta'_t) = P^{-1} \mathbb{E}(u_t u'_t) (P^{-1})' = P^{-1} \Sigma (P^{-1})' = P^{-1} P P' (P^{-1})' = I_m$$

so the new errors $\eta_{1t}, \eta_{2t}, \dots, \eta_{mt}$ are contemporaneously uncorrelated. Then the orthogonalized impact of a unit shock at time t to the i th equation on y at time $t + n$ is given by

$$B_n e_i, n = 0, 1, \dots \quad (13.41)$$

where e_i is an $m \times 1$ selection vector. Written more compactly, the orthogonalized impulse response function of a unit (one standard error) shock to the i th variable on the j th variable is given by

$$OI_{ij,n} = e'_j A_n P e_i, \quad i, j = 1, 2, \dots, m \quad (13.42)$$

These orthogonalized impulse responses are not unique and depend on the particular ordering of the variables in the VAR. The orthogonalized responses are invariant to the ordering of the variables only if Σ is diagonal.

- **GIR:** If the VAR model is perturbed by a shock of size $\delta_i = \sqrt{\sigma_{ii}}$ to its i th equation at time t , by the definition of the generalized IR function we have

$$GI_y(n, \delta_i, \Omega_{t-1}^0) = \mathbb{E}(y_t | u_{it} = \delta_i, \Omega_{t-1}^0) - \mathbb{E}(y_t | \Omega_{t-1}^0) \quad (13.43)$$

Once again using the MA(∞) representation (13.38) we obtain

$$GI_y(n, \delta_i, \Omega_{t-1}^0) = A_n \mathbb{E}(u_t | u_{it} = \delta_i) \quad (13.44)$$

which is history invariant (i.e. does not depend on Ω_{t-1}^0). The computation of the conditional expectations $\mathbb{E}(u_t | u_{it} = \delta_i)$ depends on the nature of the multivariate distribution assumed for the disturbances u_t . In the case where $u_t \sim IID\mathcal{N}(0, \Sigma)$, we have

$$\mathbb{E}(u_t | u_{it} = \delta_i) = \begin{bmatrix} \sigma_{1i}/\sigma_{ii} \\ \sigma_{2i}/\sigma_{ii} \\ \vdots \\ \sigma_{mi}/\sigma_{ii} \end{bmatrix} \delta_i \quad (13.45)$$

where as before $\Sigma = [\sigma_{ij}]$. Hence for a unit shock $\delta_i = \sqrt{\sigma_{ii}}$ we have

$$GI_y(n, \delta_i = \sqrt{\sigma_{ii}}, \Omega_{t-1}^0) = \frac{A_n \Sigma e_i}{\sqrt{\sigma_{ii}}}, \quad i, j = 1, 2, \dots, m \quad (13.46)$$

The GIRF of a unit shock to the i th equation in the VAR(p) model

$$y_t = \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \dots + \Phi_p y_{t-p} + u_t, \quad u_t \sim IID(0, \Sigma) \quad (13.47)$$

on the j th variable at horizon n is given by the j th element of (13.46), expressed more compactly by

$$GI_y(n, \delta_i = \sqrt{\sigma_{ii}}, \Omega_{t-1}^0) = \frac{e'_j A_n \Sigma e_i}{\sqrt{\sigma_{ii}}}, \quad i, j = 1, 2, \dots, m \quad (13.48)$$

- (d) The GIRF circumvents the problem of the dependence of the orthogonalized impulse responses to the ordering of the variables in the VAR. Unlike the OIR responses in (13.42), the GIR responses in (13.48) are invariant to the ordering of the variables in the VAR. The two responses coincide only for the first variable in the VAR or when Σ is diagonal.

Chapter 24 Problem 4.

Chapter 24 Problem 4 Solution.

13.12 Chapter 33: Theory and Practice of GVAR Modeling

Lidan says will not be on final.

Chapter 14

Statistical Learning

These notes are based on my notes from Math 547: Mathematics of Statistical Learning at USC taught by Steven Heilman, GSBA 604: Regression and Generalized Linear Models for Business Applications at USC taught by Gourab Mukherjee, and DSO 677: Dynamic Programming and Markov Decision Processes taught by Paat Rusmevichientong, which used the textbooks [Bertsekas, 2012a] and [Bertsekas, 2012b]. I also borrowed from some other sources which I mention when I use them.

14.1 Segmented regression, local regression, splines

Broken stick regression/segmented regression: useful if data has two different groups.

$$y = B_\ell(x) + B_r(x) = \beta_0 + \beta_1(c - x)_+ + \beta_2(x - c)_+$$

where c is the breaking point and is fixed (if you use data to choose c , becomes a nonlinear problem). Advantages: more localized

Splines: like combination of broken stick regression and polynomial regression. fit a polynomial in each segment.

for splines: knot selection is important (bias/variance tradeoff)

14.1.1 Local Regression

Local regression: weight chosen by kernel:

$$w_i = \frac{K((x_i - x_0)/\sqrt{v})}{\sum_{i=1}^{M(s)} K((x_i - x_0)/\sqrt{v})}$$

$$\text{dnorm}(x_i, \text{mean} = x_0; \text{sd} = \sqrt{v})$$

$$K((x_i - x_0)/\sqrt{v}) = \phi((x_i - x_0)/\sqrt{v}) \cdot v^{-1/2} = \frac{1}{\sqrt{2\pi v}} \exp - \left(\frac{(x_i - x_0)^2}{2v} \right)$$

so if the distance between two points increases than the weight decreases. This is called kernel density with a Gaussian kernel.

$$x = x_0; \hat{\beta}(x_0); \hat{\sigma}(x_0)$$

Two tuning parameters: v (bandwidth) and s . Disadvantages: hard to interpret, starts to do poorly in high dimensions.

14.1.2 Curse of Dimensionality (brief discussion)

Suppose $x_i : i \in [n] \sim F$ i.i.d. with fixed dimension, and F has bounded support $[a, b]^d$. Let $x \in \text{supp}(F)$. Then

$$\min_x d_2(x, x_i) \sim \frac{1}{n^{1/d}}$$

so goes to 0 as $n \rightarrow \infty$ for fixed d . But bad in d ; for example, if $d = 5$, need $n = 10^5$ for $d = 0.1$. As this minimum distance increases, regularity becomes more difficult.

14.2 Dimension Reduction methods

14.2.1 Principal components regression

(See Section 2.4.2 for more details on principal components.) Given data (y, X) , don't look at y for now. Look for maximum variability direction of X :

$$P_1 = \arg \max_{\|a\|_2=1} \text{Var}(a^T x) = a^T (X^T X) a.$$

then (letting \mathcal{P}_1 be the projection matrix for projecting onto P_1)

$$P_2 = \arg \max_{\|a\|_2=1, \mathcal{P}_1 a=0} \text{Var}(a^T x) = a^T (X^T X) a.$$

and so on. We will regress y against the first M principal components of X for some $M \leq p$, where the principal components are the columns of U :

$$\hat{y}_{(M)}^{\text{PCR}} = \bar{y} + \sum_{m=1}^M \hat{\theta}_m z_m,$$

where $\hat{\theta}_m = (z_m^T y) / (z_m^T z_m)$ since all the z_m are orthogonal. Also, since the z_m are linear combinations of the original x_j , the solution can be expressed in terms of coefficients in the original feature space:

$$\hat{\beta}^{\text{PCR}}(M) = \sum_{m=1}^M \hat{\theta}_m v_m,$$

Works well when high variability directions in the explanatory variables are also interesting attributes to study.

Sometimes if data are in a manifold that isn't linearly parsed, good to use an ISOMAP or LLE (local linear embedding).

(read: starting on p.63 of ESL)

14.2.2 Partial least squares

Does look at y , unlike PCR. $X_{n \times p} \rightarrow W_{n \times 3}$. Start by standardizing all x_j to have mean 0 and unit variance. Then compute $\hat{\phi}_{1j} = \langle x_j, y \rangle$ for each j . Then the derived input $z_1 = \sum_j \hat{\phi}_{1j} x_j$ is the first partial least squares direction. Then y is regressed on z_1 giving coefficient $\hat{\theta}_1$, and then x_1, \dots, x_j are orthogonalized with respect to z_1 . Continue until $M \leq p$ directions have been obtained. (see p. 80 of ESL)

⋮

notes from GSBA 604: First reduced dimension:

$$w_{n \times 1}^{(1)} = X_{n \times 1}^{(1)} + X_{n \times 1}^{(2)} + \dots + X_{n \times 1}^{(p)}$$

proportional correlation $(y, x^{(1)})$ to

14.2.3 Dimension reduction by random matrix

Let $R \in \mathbb{R}^{p \times d}$, $d < p$, with $R_{ij} \sim \mathcal{N}(0, 1)$. Let $\tilde{X} = XR$. By the Johnson-Lindenstrauss lemma, for any $\epsilon > 0$ there exists an R such that

$$(1 - \epsilon) \|\tilde{X}_i - \tilde{X}_j\|_2^2 \leq \|X_i - X_j\|_2^2 \leq (1 + \epsilon) \|\tilde{X}_i - \tilde{X}_j\|_2^2.$$

(isometric transformation—distances are maintained)

14.3 Goodness of fit, residuals, residual diagnostics, leverage

Goodness of fit: F test. Assume $\text{Var}(\epsilon) = \sigma^2 I$ and recall $\hat{\epsilon} = (I - H)\epsilon$. So $\text{Var}(\hat{\epsilon}) = \sigma^2(I - H)$ and $\text{Var}(\hat{\epsilon}_i) = \sigma^2(1 - H_{ii})$. So $h_i := H_{ii}$ is called the **leverage** for the i th case. Some properties: if X is ill-

conditioned (condition number—ratio of largest to smallest eigenvalue of Gram matrix $X^T X$ —is high), then H_{ii} will vary a lot.

Properties: $\sum_i h_i = p + 1$ (because H_{ii} is idempotent, its trace is equal to $p + 1$ —all its eigenvalues are 0 or 1, and it is nonsingular, so all of its eigenvalues are 1). And, all $h_i \geq 1/n$.

Larger h_i result in smaller $\text{Var}(\hat{\epsilon}_i)$, which forces the fit to be close to y_i . Average leverage: $(p + 1)/n$. Rule of thumb: leverages of more than $2(p + 1)/n$ should be looked at closely (they have a large influence on the slope, so if they are incorrect then it's a big problem for the fit).

Standardized or Studentized results:

$$r_i = \frac{\hat{\epsilon}_i}{\text{se}(\hat{\epsilon}_i)} = \frac{\hat{\epsilon}_i}{\hat{\sigma}\sqrt{1 - h_i}}$$

Let $\hat{\beta}_i$ and $\hat{\sigma}_i^2$ be the estimates from the regression with the i th case excluded. Let x_i^T denote the i th row of X , write $X_{(i)}$ for X without the i th row.

⋮

Outlier test: can test for outliers using the fact that each $t_i \sim t(n - p - 2)$ if no outliers are present. Need to do a multiplicity correction for multiple testing (say Bonferroni correction). have to do residual diagnostics.

14.3.1 Residual diagnostics

Consider leverage points (outliers, influential points: points that change the slope a lot).

1. **Partial residual plot:** k th variable. $\hat{\epsilon}^{(k)} = y - \sum_{j \neq k} \beta_j x_j$: residuals without the k th explanatory variable. Plot this against x_k and regress. If the resulting slope $\hat{\beta}_k$ is large, this is an influential point.
2. **Added variable plot:** Regress x_k by other explanatory variables $\hat{\delta}^{(k)}$. Plot $\hat{\epsilon}^{(k)}$ against $\hat{\delta}^{(k)}$.

14.4 DSO 607

Generalized linear models:

$$f_n(z, \beta) = \prod_{i=1}^n \exp [\theta_i z_i - b(\theta_i)h(z_i)], \quad z = (z_1, \dots, z_n)^T$$

Natural parameter θ_i : $\theta_i = x_i^T \beta$, $x_i = \{x_{ij} : j \in \mathcal{M}\}$

$h(z_i)$: normalization constant

linear regression: $b(\theta) = \frac{1}{2}\theta^2$

other: $b(\theta) = \log(1 + e^\theta)$

If $Y = (Y_1, \dots, Y_n)^T \sim F_n(\cdot, \beta)$, then $\mathbb{E}(Y) = (b'(\theta_1), \dots, b'(\theta_n))^T = \mu(\theta)$ and

$\text{Cov}(Y) = \text{diag}\{b''(\theta_1), \dots, b''(\theta_n)\} = \Sigma(\theta)$ where $\theta = X\beta$ and $X = (x_1, \dots, x_n)^T$ is the $n \times d$ design matrix.

Quasi-log-likelihood (“quasi” because error may be misspecified):

$$\ell_n(y, \beta) = y^T X\beta - \mathbf{1}^T b(X\beta) + \mathbf{1}^T h(y)$$

Like MLE, maximizing $\ell_n(y, \beta)$ with respect to β gives the quasi-MLE $\hat{\beta}_n$. Solution exists and is unique due to strict convexity of b , solves the score equation

$$\frac{\partial \ell_n(y, \beta)}{\partial \beta} = x^T [y - \mu(X\beta)] = \mathbf{0}$$

(Intuition of score equation: the columns of X are all orthogonal to the errors (uncorrelated if X is random)).

14.4.1 Akaike Information Criterion (AIC)

AIC: proposed by [Akaike \[1973\]](#) to choose a model by minimizing the Kullback-Leibler (KL) divergence of the fitted model from the true model (or equivalently, maximize the expected log-likelihood). Recall the KL Divergence

$$I(\theta; \theta_0) := 2\mathbb{E}_{\theta_0} [\log(f(X | \theta_0))] - 2\mathbb{E}_{\theta_0} [\log(f(X | \theta))].$$

We will try to maximizing the KL Divergence by estimating θ_0 as best as we can by maximizing the **probabilistic negentropy**

$$\mathbb{E}_Z I(\theta; \hat{\theta}_0(Z)) := 2\mathbb{E}_{\theta_0} [\log(f(X | \theta_0))] - 2\mathbb{E}_{\theta_0, Z} [\log(f(X | \hat{\theta}_0(Z)))] .$$

Because the true model θ_0 is unknown we cannot carry out this maximization directly. Note that as the number of independent observations increases, the **mean log-likelihood ratio**

$$\hat{I}(\theta; \theta_0) := \frac{2}{n} \sum_{i=1}^n \log \frac{f(x_i | \theta_0)}{f(x_i | \theta)} \xrightarrow{P} I(\theta; \theta_0).$$

Because of this, Akaike reasons that maximizing the mean log-likelihood ratio over θ_0 (i.e. computing the maximum likelihood estimate) tend to maximize the entropy. So the maximum likelihood estimate $\hat{\theta}_0(Z)$ is substituted for the unknown θ_0 .

Way we wrote KL Divergence in DSO 607: density f from density g :

$$I(g_n; f_n(\cdot, \beta)) = \int [\log g(z)]g(z)dz - \int [\log f(z)]g(z)dz$$

Akaike [1973] found that up to an additive constant, the KL divergence of the fitted model from the true model can be asymptotically expanded as

$$-\ell_n(\hat{\theta}) + \lambda \dim(\hat{\theta}) = -\ell_n(\hat{\theta}) + \lambda \sum_{j=1}^p \mathbf{1}_{\{\hat{\theta}_j \neq 0\}}$$

where $\ell_n(\theta)$ is the log-likelihood function and $\lambda = 1$. This leads to the Akaike information criterion (AIC) for comparing models:

$$AIC(\hat{\theta}_k(Z)) := n\hat{I}(\hat{\theta}_k(Z; \hat{\theta}_0(Z))) + 2\|\hat{\theta}_k(Z)\|_0 = 2 \sum_{i=1}^n \log \frac{f(x_i | \hat{\theta}_0(Z))}{f(x_i | \hat{\theta}_k(Z))} + 2\|\hat{\theta}_k(Z)\|_0$$

Way we wrote this is DSO 607:

$$AIC(\hat{\theta}) := -2\ell_n(\hat{\theta}) + 2\|\hat{\theta}\|_0$$

Intuition: $\log g(x)$ is the log likelihood. Penalty term can be interpreted as penalty, or as a bias correction since you are doing training and feature selection simultaneously on the same data.

$$I(g_n; f_n(\cdot, \beta)) = \sum_{i=1}^n \left[\int \right]$$

To minimize the KL divergence

$$\frac{\partial I(g_n; f_n(\cdot, \beta))}{\partial \beta} = -X^T[\mathbb{E}(Y) - \mu(X\beta)] = 0$$

the inverse of the Fisher information matrix is the covariance of the MLE (?).

⋮

(For more information on KL Divergence, see Sections 6.5 and 10.4.6). For AIC, we minimize the KL divergence. For BIC, we maximize the Bayes factor (posterior probability for the model).

14.4.2 Bayesian Information Criterion (BIC)

A typical Bayesian model selection procedure is to first give nonzero prior probability α_M om each model M and then prescribe a prior distribution μ_M for the parameter vector in the corresponding model. The

Bayesian principle of model selection is to choose the most probable model *a posteriori*; that is, to choose a model that maximizes the log-marginal likelihood (or the Bayes factor)

$$\log \int \alpha_M \exp[\ell_n(\theta)] d\mu_m(\theta).$$

Schwarz [1978] took a Bayesian approach with prior distributions that have nonzero prior probabilities on some lower dimensional subspaces of \mathbb{R}^p and showed that the negative log-marginal likelihood can be asymptotically expanded as

$$-\ell_n(\hat{\theta}) + \lambda \|\hat{\theta}\|_0$$

where $\lambda = (\log n)/2$. This asymptotic expansion leads to the Bayesian information criterion (BIC) for comparing models:

$$BIC(\hat{\theta}) := -2 \log \left(f(x | \hat{\theta}; \hat{\theta}_{MLE}) \right) + (\log n) \|\hat{\theta}\|_0.$$

where f is the density function parameterized by $\hat{\theta}_{MLE}$, the maximum likelihood estimate for the density given the data x .

Way we wrote this in DSO 607:

$$BIC(\hat{\theta}) := -2\ell_n(\hat{\theta}) + (\log n) \|\hat{\theta}\|_0.$$

⋮

$$B_n^{1/2} A_n (\hat{\beta}_n - \beta_{n,0}) = W_n \xrightarrow{D} \mathcal{N}(0, I_d)$$

$$\hat{\beta}_n - \beta_{n,0} = A_n^{-1} B_n^{1/2} W_n \implies \text{Cov}(\hat{\beta}_n) = \text{Cov}(\hat{\beta} - n - \beta_{n,0})$$

$$= \text{Cov}(A_n^{-1} B_n^{1/2} W_n) = A_n^{-1} B_n^{1/2} \text{Cov}(W_n) B_n^{1/2} A_n^{-1} = A_n^{-1} B_n^{1/2} I_d B_n^{1/2} A_n^{-1} = \boxed{A_n^{-1} B_n A_n^{-1}}$$

Note that if the model is correct, $A_n = B_n$ so this reduces to conventional asymptotic MLE theory ($\text{Cov}(\hat{\beta}_n) = A_n^{-1}$).

⋮

A_n from working model, B_n from true model (unknown).

GBIC in misspecified models: $H_n = A_n^{-1}B_n$ (covariance contrast matrix). Note that when model is specified, $H_n = I_d$ so the log of its determinant is 0 so it vanishes. If not, then it is a misspecification penalty.

⋮

Note: $\log(y, \hat{\beta}_n) > \log(y, \beta_{n,0})$ because $\hat{\beta}_n$ is by definition the MLE on the observed data. But $\mathbb{E}(\log(\tilde{y}, \beta_{n,0})) > \mathbb{E}(\log(\tilde{y}, \hat{\beta}_n))$ because $\beta_{n,0}$ is the true parameter. We have a systematic upward bias when we use the empirical estimate. (p.18 of week 2-2 slides)

Proposition 14.4.1 (Result from “Econometrics: Methods and Applications” homework).

Consider the usual linear model, where $y = X\beta + \epsilon$. Suppose we compare two regressions, which differ in how many variables are included in the matrix X . In the full (unrestricted) model p_1 regressors are included. In the restricted model only a subset of $p_0 < p_1$ regressors are included. Then for large n , selection based on AIC corresponds to an F -test with a critical value of approximately 2.

Proof. Let e_R be the vector of residuals for the restricted model with p_0 parameters and e_U the vector of residuals for the full unrestricted model with p_1 parameters. Then we have the sample standard deviations

$$s_0^2 = \frac{1}{n-p_0} e_R' e_R, s_1^2 = \frac{1}{n-p_1} e_U' e_U \quad (14.1)$$

Recall the AIC:

$$\log(s^2) + \frac{2k}{n}$$

where k is the number of regressors included in the model.

For the small model, we have

$$AIC_0 = \log(s_0^2) + \frac{2p_0}{n}.$$

For the big model, we have

$$AIC_1 = \log(s_1^2) + \frac{2p_1}{n}.$$

Therefore the smallest model is preferred according to the AIC if

$$\begin{aligned} & AIC_0 < AIC_1 \\ \iff & \log(s_0^2) + \frac{2p_0}{n} < \log(s_1^2) + \frac{2p_1}{n} \iff \log(s_0^2) - \log(s_1^2) < \frac{2p_1}{n} - \frac{2p_0}{n} \iff \log\left(\frac{s_0^2}{s_1^2}\right) < \frac{2}{n}(p_1 - p_0) \\ \iff & \frac{s_0^2}{s_1^2} < e^{\frac{2}{n}(p_1 - p_0)} \end{aligned} \quad (14.2)$$

If n is very large, $\frac{2}{n}(p_1 - p_0)$ is small. Therefore, using the first order Taylor approximation $e^x \approx 1 + x$ we can approximate that

$$e^{\frac{2}{n}(p_1 - p_0)} \approx 1 + \frac{2}{n}(p_1 - p_0)$$

(if n is very large.) Substituting this expression into the right side of (14.2) yields

$$\begin{aligned} \frac{s_0^2}{s_1^2} < 1 + \frac{2}{n}(p_1 - p_0) &\iff \frac{s_0^2}{s_1^2} - 1 < \frac{2}{n}(p_1 - p_0) \iff \frac{s_0^2}{s_1^2} - \frac{s_1^2}{s_1^2} < \frac{2}{n}(p_1 - p_0) \\ &\iff \frac{s_0^2 - s_1^2}{s_1^2} < \frac{2}{n}(p_1 - p_0) \end{aligned}$$

for n very large. Plugging in the expressions from (14.1), we have

$$\frac{\frac{1}{n-p_0}e_R'e_R - \frac{1}{n-p_1}e_U'e_U}{\frac{1}{n-p_1}e_U'e_U} < \frac{2}{n}(p_1 - p_0).$$

For large values of n , $n - p_0 \approx n - p_1 \approx n$. This yields

$$\begin{aligned} \frac{\frac{1}{n}e_R'e_R - \frac{1}{n}e_U'e_U}{\frac{1}{n}e_U'e_U} &< \frac{2}{n}(p_1 - p_0) \\ = \frac{e_R'e_R - e_U'e_U}{e_U'e_U} &< \frac{2}{n}(p_1 - p_0) \end{aligned} \tag{14.3}$$

Now recall the F statistic:

$$F = \frac{(e_R'e_R - e_U'e_U)/g}{e_U'e_U/(n-k)} \tag{14.4}$$

where k is the number of explanatory factors in the unrestricted model, and g is the number of explanatory factors removed from the unrestricted model to create the restricted model. Under this test, we believe there is significant evidence to suggest that $\beta \neq 0$ (so the unrestricted model is preferred) if $F > F_{critical}$. Therefore a larger model is preferred if $F > F_{critical}$, and we stay with (prefer) a smaller model if $F < F_{critical}$.

Let $F_{critical} = 2$. Then a smaller model is preferred if $F < 2$:

$$\frac{(e_R'e_R - e_U'e_U)/g}{e_U'e_U/(n-k)} < 2$$

In this case, with p_1 factors in the unrestricted model and p_0 in the restricted model, we get

$$\begin{aligned} \frac{(e_R'e_R - e_U'e_U)/(p_1 - p_0)}{e_U'e_U/(n - p_1)} &< 2 \\ \frac{(e_R'e_R - e_U'e_U)}{e_U'e_U} &< \frac{2(p_1 - p_0)}{n - p_1} \end{aligned}$$

If n is very large, $n - p_1 \approx n$. Substituting this in yields

$$\frac{(e_R'e_R - e_U'e_U)}{e_U'e_U} < \frac{2(p_1 - p_0)}{n} \quad (14.5)$$

which equals (14.3). Our condition for preferring a restricted model when doing an F-test with $F_{critical} = 2$ (and when n is very large) is approximately the same as our condition for preferring a restricted model when using the AIC (when n is very large).

□

14.5 Ridge Regression

If p is large, it tends to be better to shrink the least squares estimator. (Even though this introduces bias, it will likely reduce variance, and the tradeoff will often help for some amount of shrinkage.) This is related to the Stein estimator.

Suppose $\beta \in \mathbb{R}^p$ is an unknown vector, and for all $1 \leq i \leq n$, there are known vectors $x^{(1)}, \dots, x^{(n)} \in \mathbb{R}^p$. Our observed data are $\mathbf{y} = (y_1, \dots, y_n) \in \mathbb{R}^n$. Let \mathbf{X} be the $n \times p$ matrix so that the i^{th} row of \mathbf{X} is the row vector $x^{(i)}$. Assume that $p \leq n$ and the matrix \mathbf{X} has full rank. Let $\lambda > 0$ and consider the quantity

$$\sum_{i=1}^n \left(y_i - x^{(i)\top} \beta \right)^2 + \lambda \|\beta\|_2^2 = \|\mathbf{y} - \mathbf{X}\beta\|_2^2 + \lambda \|\beta\|_2^2 \quad (14.6)$$

The term $\|\beta\|_2^2$ penalizes β from having large entries. By Lagrange Multipliers, a critical point $\hat{\beta}$ of the constrained minimization problem

$$\text{minimize } \sum_{i=1}^n (y_i - \langle x^{(i)}, \beta \rangle)^2 \quad \text{subject to } \|\beta\|_2^2 \leq 1$$

is equivalent to the existence of a $\lambda \in \mathbb{R}$ such that β is a critical point of (14.6). We call the $\hat{\beta}$ that minimizes (14.6) the **ridge regression** estimator for β .

Proposition 14.5.1 (Math 541A Homework Problem). The value of $\hat{\beta} \in \mathbb{R}^p$ that minimizes (14.6) is $\hat{\beta}_{\text{ridge}} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{y}$.

Proof.

$$\begin{aligned} \sum_{i=1}^n \left(y_i - x^{(i)\top} \beta \right)^2 + \lambda \|\beta\|^2 &= (\mathbf{y} - \mathbf{X}\beta)^T (\mathbf{y} - \mathbf{X}\beta) + \lambda \beta^T \beta \\ &= \mathbf{y}^T \mathbf{y} - \mathbf{y}^T \mathbf{X} \beta - \beta^T \mathbf{X}^T \mathbf{y} + \beta^T \mathbf{X}^T \mathbf{X} \beta + \lambda \beta^T \beta = \mathbf{y}^T \mathbf{y} - 2\mathbf{y}^T \mathbf{X} \beta + \beta^T \mathbf{X}^T \mathbf{X} \beta + \lambda \beta^T \beta \end{aligned}$$

where $\mathbf{y}^T \mathbf{X} \beta = \beta^T \mathbf{X}^T \mathbf{y}$ because a scalar equals its transpose. Differentiating with respect to β yields

$$\begin{aligned} -2\mathbf{y}^T \mathbf{X} + 2\beta^T \mathbf{X}^T \mathbf{X} + 2\lambda \beta^T &= 0 \iff \beta^T (2\mathbf{X}^T \mathbf{X} + 2\lambda \mathbf{I}_p) = 2\mathbf{y}^T \mathbf{X} \\ &\iff (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p) \beta = \mathbf{X}^T \mathbf{y} \iff \hat{\beta}_{\text{ridge}} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{y} \end{aligned}$$

where $\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p$ is invertible by the following argument. $\mathbf{X}^T \mathbf{X}$ must be positive semidefinite. In fact, it is positive definite because $\mathbf{X} \in \mathbb{R}^{n \times p}$ has full rank; that is, $\text{rank}(\mathbf{X}) = p$, so $\mathbf{X}^T \mathbf{X} \in \mathbb{R}^{p \times p}$ has rank p (full rank) and is invertible. So $\mathbf{X}^T \mathbf{X}$ is positive definite (all positive eigenvalues). Then since $\text{Tr}(\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p) > \text{Tr}(\mathbf{X}^T \mathbf{X})$, the eigenvalues of $\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p$ are also all positive, which means the determinant of $\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p$ is nonzero, which means it is invertible.

□

Proposition 14.5.2 (DSO 607 Homework Problem). Suppose $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$ where $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I}_n)$.

- (a) The asymptotic behavior of the ridge estimator is as follows: as $\lambda \rightarrow \infty$, $\hat{\boldsymbol{\beta}}_{\text{ridge}} \rightarrow \mathbf{0}$, and as $\lambda \rightarrow 0$, $\hat{\boldsymbol{\beta}}_{\text{ridge}} \rightarrow X^\dagger(\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon})$.
- (b) For any fixed $\lambda > 0$, the probability that each component of the ridge estimator $\hat{\boldsymbol{\beta}}_{\text{ridge}}$ equals 0 is 0.

Proof. (a) Since X is fixed, as $\lambda \rightarrow \infty$ we have

$$\hat{\boldsymbol{\beta}}_{\text{ridge}} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{y} \rightarrow (\lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{y} = \frac{1}{\lambda} \mathbf{I}_p \mathbf{X}^T (\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}) = \frac{1}{\lambda} (\mathbf{X}^T \mathbf{X}\boldsymbol{\beta} + \mathbf{X}^T \boldsymbol{\epsilon}) \rightarrow \mathbf{0}$$

where $\mathbf{0}$ is a p -dimensional vector of zeroes. As $\lambda \rightarrow 0^+$ we have

$$\hat{\boldsymbol{\beta}}_{\text{ridge}} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{y} \rightarrow X^\dagger \mathbf{y} = X^\dagger(\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon})$$

where we substitute the pseudoinverse instead of the inverse because since $\mathbf{X}^T \mathbf{X}$ is rank deficient, $(\mathbf{X}^T \mathbf{X})^{-1}$ does not exist (and because the Moore-Penrose pseudoinverse minimizes the ℓ_2 norm, exactly what the ridge solution will do).

- (b) We have

$$\hat{\boldsymbol{\beta}}_{\text{ridge}} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{y} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T (\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}) = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{X}\boldsymbol{\beta} + (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \boldsymbol{\epsilon}$$

Let e_i be a selection vector, with the i th entry equal to 1 and all other entries equal to 0. Let the i th entry of $\hat{\boldsymbol{\beta}}_{\text{ridge}}$ be $\hat{\beta}_{\text{ridge}}^{(i)} = e_i^T \hat{\boldsymbol{\beta}}_{\text{ridge}}$. We have

$$\Pr(\hat{\beta}_{\text{ridge}}^{(i)} = 0) = \Pr(e_i^T [(\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{X}\boldsymbol{\beta} + (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \boldsymbol{\epsilon}] = 0)$$

$$= \Pr(e_i^T (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \boldsymbol{\epsilon} = -e_i^T (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{X}\boldsymbol{\beta})$$

Since every entry of $\boldsymbol{\epsilon}$ is distributed continuously, the probability of it equaling a particular value is 0. Therefore the probability that each component of the ridge estimator equals 0 is 0. (For an intuitive argument as to why this is, see Figure 14.1.)

□

GSBA 604: using SVD $\mathbf{X} = \mathbf{U}\mathbf{D}\mathbf{V}^T$, we have

$$\begin{aligned}
\hat{y}_{ridge}(\lambda) &= X\hat{\beta}_{ridge}(\lambda) = X(X^T X + \lambda I)^{-1} X^T y = UDV^T(VD^2V^T + \lambda I)^{-1} VDU^T y \\
&= UDV^T(V(D^2 + \lambda I)V^T)^{-1} VDU^T y = UDV^T[(D^2 + \lambda I)V^T]^{-1} V^T VDU^T y = UDV^T V(D^2 + \lambda I)^{-1} D U^T y \\
&= UD(D^2 + \lambda I)^{-1} D U^T y = \sum_{j=1}^n \frac{d_j^2}{d_j^2 + \lambda} u_j u_j^T y \quad (14.7)
\end{aligned}$$

also,

$$\hat{\beta}_{LS} = \sum_{j=1}^n v_j(u_j^T y)$$

so by comparison, what ridge regression is doing is changing the weights of the columns (by weights that are between 0 and 1 for any $\lambda > 0$). Higher d_j 's means higher weights. So the directions that have higher variability are shrunk less.

So in the limit of (14.7) as $\lambda \rightarrow 0^+$, we have

$$\hat{\beta}_{ridge} = (X^T X + \lambda I_p)^{-1} X^T y \rightarrow X^\dagger y = X^\dagger(X\beta + \epsilon) \quad (14.8)$$

where we substitute the pseudoinverse instead of the inverse because since $X^T X$ is rank deficient, $(X^T X)^{-1}$ does not exist (and because the Moore-Penrose pseudoinverse minimizes the ℓ_2 norm, exactly what the ridge solution will do).

$$\hat{y}_{ridge}(\lambda) = X\hat{\beta}_{ridge}(\lambda) \rightarrow \sum_{j=1}^n u_j u_j^T y = UU^T y,$$

which is the least squares solution in the case that $p \leq n$ and this exists, or (14.8) in the general case.

14.6 Lasso

From KKT theory, the correlation between all selected features and residual will be λ (see the remark in Section 14.6.4 for an explanation why).

Consider the linear regression model $y = X\beta + \epsilon$. If we assume the errors ϵ have a multivariate Gaussian distribution, that is,

$$f_\epsilon(t) = \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^n \exp \left(-\frac{t^T t}{2\sigma^2} \right), \quad t = (t_1, \dots, t_n)^T$$

then the log likelihood is

$$\log(f(t)) = n \log[(2\pi\sigma^2)^{-1/2}] - t^T t / (2\sigma^2)$$

Suppose we want the MLE estimator. When we maximize the log likelihood, we can disregard the first term which does not include t (it is constant). So we seek

$$\arg \max_{\beta \in \mathbb{R}^p} \{-t^T t / (2\sigma^2)\} = \arg \max_{\beta \in \mathbb{R}^p} \{-\|y - X\beta\|_2^2 / (2\sigma^2)\}$$

which is the same as

$$\arg \min_{\beta \in \mathbb{R}^p} \{\|y - X\beta\|_2^2 / (2\sigma^2)\}$$

We commonly scale this with an n in the denominator to match the empirical risk; note that this does not affect the arguments which minimize the quantity. When the design matrix X multiplied by $n^{-1/2}$ is orthonormal ($X^T X = nI_p$), the penalized least squares reduces to the minimization of

$$\min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{2n} \|y - X\hat{\beta}\|_2^2 + \frac{1}{2} \|\hat{\beta} - \beta\|_2^2 + \sum_{j=1}^p p_\lambda(|\beta_j|) \right\}$$

where $\hat{\beta} = (X^T X)^{-1} X^T y = nX^T y$ is the OLS estimator. Disregarding the first term which does not contain β , we have a **separable** loss function (we can solve for one parameter at a time):

$$\min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{2} \|\hat{\beta} - \beta\|_2^2 + \sum_{j=1}^p p_\lambda(|\beta_j|) \right\}.$$

So we can consider the univariate penalized least squares function

$$\hat{\theta}(z) = \arg \min_{\theta \in \mathbb{R}} \left\{ \frac{1}{2} (z - \theta)^2 + p_\lambda(|\theta|) \right\}.$$

Antoniadis and Fan [2001] showed that the PLS estimator $\hat{\theta}$ possesses the following properties:

- *sparsity* if $\min_{t \geq 0} \{t + p'_\lambda(t)\} > 0$;
- *approximate unbiasedness* if $p'_\lambda(t) = 0$ for large t ;
- *continuity* if and only if $\arg \min_{t \geq 0} \{t + p'_\lambda(t)\} = 0$. Intuition: if you perturb data a little, the solution should remain similar.

In general, the singularity of the penalty function at the origin (i.e., $p'_\lambda(0+) < 0$) is needed for generating sparsity in variable selection and the concavity is needed to reduce the bias.

To recap: constrained version:

$$\begin{aligned}\hat{\beta}_{\text{lasso}} &= \arg \min_{\beta \in \mathbb{R}^p} \frac{1}{2n} \|y - X\beta\|_2^2 \\ \text{subject to } &\quad \|\beta\|_1 \leq t\end{aligned}$$

Unconstrained version:

$$\hat{\beta}_{\text{lasso}} = \arg \min \left\{ \frac{1}{2n} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \right\}$$

Use $1/n$ to rescale RSS due to $\|1\| - 2 = \sqrt{n}$.

Proposition 14.6.1 (Math 541A Homework Problem). Suppose $\beta \in \mathbb{R}^p$ is an unknown vector, and for all $1 \leq i \leq n$, there are known vectors $x^{(1)}, \dots, x^{(n)} \in \mathbb{R}^p$. Our observed data are $y = (y_1, \dots, y_n)^T \in \mathbb{R}^n$. Let X be the $n \times p$ matrix so that the i^{th} row of X is the row vector $x^{(i)}$. Assume that $p \leq n$ and the matrix X has full rank. Let $\lambda > 0$ and consider the quantity

$$\sum_{i=1}^n \left(y_i - x^{(i)T} \beta \right)^2 + \lambda \sum_{i=1}^p |\beta_i| \tag{14.9}$$

Then there exists a $\hat{\beta} \in \mathbb{R}^p$ that minimizes this quantity (this $\hat{\beta}$ is known as the LASSO, or least absolute shrinkage and selection operator).

Proof. We can write (14.9) as

$$\begin{aligned}\sum_{i=1}^n \left(y_i - x^{(i)T} \beta \right)^2 + \lambda \sum_{i=1}^p |\beta_i| &= \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \\ &= \|y - X\beta\|_2^2 + \lambda \|\beta\|_1\end{aligned}\tag{14.10}$$

By Proposition 9.1.13, $\|y - X\beta\|_2^2$ is convex, and by Proposition 9.1.14, $\lambda \|\beta\|_1$ is convex. Therefore by Proposition 9.1.10, (14.10) is convex. Differentiating and setting equal to 0 yields

$$-2y^T X + 2\beta^T X^T X + \lambda [\text{sgn}(\beta_i)] = 0 \tag{14.11}$$

where $[\text{sgn}(\beta_i)]$ is vector resulting from the sgn function being applied elementwise to β . Since (14.11) is linear in β , it has one solution. Since (14.10) is convex, any solution to (14.11) minimizes (14.9). □

Remark 163. The L_1 penalization term in (14.9) is better at penalizing large entries of β (a similar observation applies in the compressed sensing literature). Unfortunately, there is no closed form solution to (14.9) in general. The constrained minimization problem

$$\text{minimize } \sum_{i=1}^n (y_i - \langle x^{(i)}, \beta \rangle)^2 \quad \text{subject to } \sum_{i=1}^n |\beta_i| \leq 1$$

is morally equivalent to (14.9), but technically Lagrange Multipliers does not apply since the constraint is not differentiable everywhere.

14.6.1 Soft Thresholding

Classical ideas of nonparametric models: kernels (locally constant/linear), splines (smooth basis functions). But wavelets are non-smooth. Why is this beneficial? Some real life functions are non-smooth. (example: image data with noise. There will be non-smooth edges to objects.) Also, the wavelet basis functions are orthonormal (which is closely related to the assumption we made above about the orthonormal design matrix). So when working with wavelets, we have a separable optimization problem. Soft thresholding is something like the lasso idea for wavelets (but before the lasso was developed).

Suppose we wish to recover an unknown function f on $[0, 1]$ from noisy data

$$d_i = f(t_i) + \sigma z_i, \quad i = 0, \dots, n - 1$$

where $t_i = i/n$ and $z_i \sim \mathcal{N}(0, 1)$. The term de-noising is to optimize the mean squared error $n^{-1} E \|\hat{f} - f\|_2^2$. [Donoho and Johnstone \[1994\]](#) proposed a soft-thresholding estimator

$$\hat{\beta}_j = \text{sgn}(\hat{\beta}_j^0)(|\hat{\beta}_j^0| - \gamma)_+$$

where γ is some small number. (So estimator gets shrunk by γ , and if γ is bigger than the original estimator, we set it equal to 0.) They applied this estimator to the coefficients of a wavelet transform of a function measured with noise, then back-transformed to obtain a smooth estimate of the function.

Example 14.1. Suppose we have an image in data in the form of $X \in \mathbb{R}^n$. We have a wavelet basis $W \in \mathbb{R}^{n \times n}$ where W is orthonormal. We transform the image into the frequency domain by

$$Wx \rightarrow \tilde{x}$$

where \tilde{x} is the frequency domain representation. Then we apply soft-thresholding to \tilde{x} to yield \tilde{x}^* , which we hope is de-noised. Finally, we bring the image back into the original domain according to

$$\hat{x} = W^{-1}\tilde{x}^* = W^T\tilde{x}^*.$$

The asymptotic risk of this estimator is

$$[2(\log p) + 1](\sigma^2 + R_{DP})$$

Note that the $2 \log p$ term is related to the result (described informally) below:

Proposition 14.6.2. if we have n i.i.d. $\mathcal{N}(0, 1)$ random variables, the maximum of them is near $\sqrt{2 \log n}$ if n is large. (The order is this large with high probability)

Remark 164. In the language of wavelets, sometimes ℓ_0 penalization is called “hard-thresholding.”

14.6.2 Lasso theory

Drawbacks of previous techniques that lasso helps with: subset selection is interpretable but computationally intensive and not stable because it is a discrete process (small changes in the data can result in very different models being selected). Ridge regression is a continuous process and more stable, but it does not set any coefficients equal to 0 and hence does not give an easily interpretable model.

In the orthonormal design case $X^T X = nI_p$, the lasso solution can be shown to be the same as soft thresholding:

$$\hat{\beta}_j = \text{sgn}(\hat{\beta}_j^0)(|\hat{\beta}_j^0| - \gamma)_+$$

where $\gamma \geq 0$ is determined by the condition $\sum_{j=1}^p |\beta_j| = t$.

Geometry: the criterion $\sum_{i=1}^n (y_i - \sum_{j=1}^p \beta_j x_{ij})^2$ equals the quadratic function (plus a constant)

$$(\beta - \hat{\beta}^0)^T X^T X (\beta - \hat{\beta}^0).$$

Proof.

$$\begin{aligned} \sum_{i=1}^n \left(y_i - \sum_{j=1}^p \beta_j x_{ij} \right)^2 &= \sum_{i=1}^n \left(y_i - X_i \hat{\beta} \right)^2 = (\mathbf{y} - \mathbf{X} \hat{\beta})^T (\mathbf{y} - \mathbf{X} \hat{\beta}) = [\mathbf{X}(\beta^0 - \hat{\beta})]^T [\mathbf{X}(\beta^0 - \hat{\beta})] \\ &= (\beta^0 - \hat{\beta})^T \mathbf{X}^T \mathbf{X} (\beta^0 - \hat{\beta}) \end{aligned}$$

□

The contours (level sets) are therefore elliptical and centered at the OLS estimates. If the constraint region does not have corners, as in ridge regression, zero solutions result with probability zero (see Proposition 14.5.2 and Figure 14.1).

Proposition 14.6.3 (2018 DSO Statistics Group In-Class Screening Exam, Question 5). Consider the optimization problem

$$\underset{\beta \in \mathbb{R}^p}{\text{minimize}} \quad \frac{1}{2} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \tag{14.12}$$

where $y \in \mathbb{R}^n$, $X \in \mathbb{R}^{n \times p}$, and $\lambda > 0$.

(a) The following problem is a dual of (14.12):

$$\underset{u \in \mathbb{R}^n}{\text{maximize}} \quad \frac{1}{2} \|y\|_2^2 - \frac{1}{2} \|y - u\|_2^2 \quad \text{subject to} \quad \|X^T u\|_\infty \leq \lambda.$$

Also, $\hat{u} = y - X\hat{\beta}$, where $\hat{\beta}$ is a solution of (14.12) and \hat{u} is a solution of the dual.

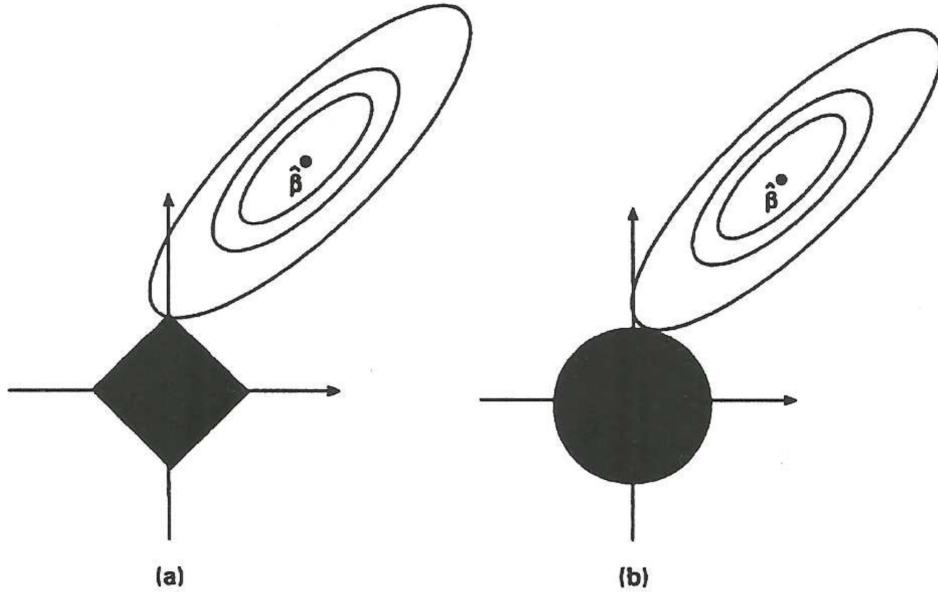


Figure 14.1: Level sets of least squares loss function with feasible sets for (a) lasso and (b) ridge regression in the case of $\beta \in \mathbb{R}^2$.

(b) $\hat{\beta}$ is not necessarily unique, but \hat{u} , $\|y - X\hat{\beta}\|_2^2$, and $\|\hat{\beta}\|_1$ are.

(c) Suppose $y = X\beta^* + \epsilon$, and suppose the tuning parameter λ is chosen to satisfy $\lambda \geq \|X^T\epsilon\|_\infty$. Then

(i)

$$\frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\hat{\beta}\|_1 \leq \frac{1}{2}\|\epsilon\|_2^2 + \lambda\|\beta^*\|_1.$$

(ii)

$$\frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\hat{\beta}\|_1 \geq \frac{1}{2}\|y\|_2^2 - \frac{1}{2}\|X\beta^*\|_2^2.$$

(iii)

$$\frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\hat{\beta}\|_1 \geq \frac{1}{2}\|\epsilon\|_2^2 - \lambda\|\beta^*\|_1.$$

Remark 165. We can express the original optimization problem (14.12) as

$$\begin{aligned} & \underset{\beta \in \mathbb{R}^p, z \in \mathbb{R}^n}{\text{minimize}} \quad \frac{1}{2}\|y - z\|_2^2 + \lambda\|\beta\|_1 \\ & \text{subject to} \quad z = X\beta. \end{aligned} \tag{14.13}$$

We will also refer to another expression of the lasso optimization problem,

$$\begin{aligned} & \underset{\beta \in \mathbb{R}^p}{\text{minimize}} \quad \frac{1}{2}\|y - X\beta\|_2^2 \\ & \text{subject to} \quad \|\beta\|_1 \leq t \end{aligned} \tag{14.14}$$

for some $t > 0$.

Before proving the main results, we will show a few simpler results. Whenever $\lambda > 0$, the lasso objective function (14.12) is the Lagrangian of (14.14). We will prove a useful lemma about the relationship between these functions.

Lemma 14.6.4. For a given $\lambda > 0$, let $\hat{\beta}$ minimize (14.12). Then there is exactly one $t = \|\hat{\beta}\|_1$ such that any $\hat{\beta}$ minimizing (14.12) also minimizes (14.14).

Proof. This must be true by contradiction. First of all, since the objective function of (14.14) is continuous and the feasible region $\|\beta\|_1 \leq t$ is compact, a minimum of (14.14) is guaranteed to exist. Now suppose $\hat{\beta}$ minimizes (14.12) for a fixed λ , with $\|\hat{\beta}\|_1 = t$, but there is a different solution $\hat{\beta}^*$ that is feasible for (14.14) and achieves a lower value. That is,

$$\frac{1}{2}\|y - X\hat{\beta}^*\|_2^2 < \frac{1}{2}\|y - X\hat{\beta}\|_2^2.$$

and $\|\hat{\beta}^*\|_1 \leq \|\hat{\beta}\|_1 = t$. Since $\lambda > 0$, $\|\hat{\beta}\|_1 < \|\hat{\beta}_{global}\|_1$, where $\hat{\beta}_{global}$ is a global minimum for $\frac{1}{2}\|y - X\hat{\beta}\|_2^2$. Since (14.14) is convex and all global minima lie outside the feasible region, $\hat{\beta}^*$ lies on the boundary; that is, $\|\hat{\beta}^*\|_1 = \|\hat{\beta}\|_1 = t$. But then

$$\frac{1}{2}\|y - X\hat{\beta}^*\|_2^2 < \frac{1}{2}\|y - X\hat{\beta}\|_2^2 \iff \frac{1}{2}\|y - X\hat{\beta}^*\|_2^2 + \lambda\|\hat{\beta}^*\|_1 < \frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\hat{\beta}\|_1$$

which contradicts the fact that $\hat{\beta}$ minimizes (14.12).

□

Another useful result follows in a simple way from Lemma 14.6.4.

Proposition 14.6.5. Let \mathcal{B} be the set of all $\hat{\beta}$ that minimize (14.12) for some fixed $\lambda > 0$. Then for any two $\hat{\beta}_1, \hat{\beta}_2 \in \mathcal{B}$, $\|\hat{\beta}_1\|_1 = \|\hat{\beta}_2\|_1$. That is, $\|\hat{\beta}\|_1$ is unique.

Proof. Suppose $\hat{\beta}_1$ and $\hat{\beta}_2$ both minimize (14.12), and (without loss of generality) $\|\hat{\beta}_1\|_1 < \|\hat{\beta}_2\|_1$. By Lemma 14.6.4, these values both minimize (14.14) with $t = \|\hat{\beta}_2\|_1$ (we cannot choose $t = \|\hat{\beta}_1\|_1$ because $\hat{\beta}_1$ is not feasible for that problem). Because the global minimum of (14.14) lies outside the feasible region and (14.14) is convex, all solutions to (14.14) lie on the boundary of the feasible region. But $\|\hat{\beta}_1\|_1 < \|\hat{\beta}_2\|_1$, so $\hat{\beta}_1$ is not on the boundary of the feasible region, contradiction. Therefore $\|\hat{\beta}_1\|_1 = \|\hat{\beta}_2\|_1$ for all solutions $\hat{\beta}_1, \hat{\beta}_2$ to (14.12); that is, $\|\hat{\beta}\|_1$ is unique. (See Osborne et al. [2000] for more details.)

□

Now we are ready to prove Proposition 14.6.3.

Proof of Proposition 14.6.3. (a) The Lagrangian of (14.13) is

$$\mathcal{L}(\beta, z, u) = \frac{1}{2}\|y - z\|_2^2 + \lambda\|\beta\|_1 + u^T(z - X\beta),$$

so the Lagrange dual function is

$$\begin{aligned} \inf_{\beta, z} \{\mathcal{L}(x, u)\} &= \inf_{\beta, z} \left\{ \frac{1}{2} \|y - z\|_2^2 + \lambda \|\beta\|_1 + u^T(z - X\beta) \right\} \\ &= \inf_{\beta, z} \left\{ \frac{1}{2}(y - z)^T(y - z) + u^Tz + \lambda \|\beta\|_1 - u^TX\beta \right\} \end{aligned}$$

This minimization is separable:

$$= \inf_z \left\{ \frac{1}{2} (y^T y - 2y^T z + z^T z) + u^T z \right\} + \inf_\beta \{ \lambda \|\beta\|_1 - u^T X \beta \} \quad (14.15)$$

We will handle each part of (14.15) separately. First, the left side:

$$\inf_z \left\{ \frac{1}{2} (y^T y - 2y^T z + z^T z) + u^T z \right\} = \inf_z \left\{ \frac{1}{2} z^T z + (u - y)^T z + \frac{1}{2} y^T y \right\}$$

Since this is a convex quadratic form, differentiate with respect to z and set equal to zero:

$$z + (u - y) = 0 \implies z = y - u \quad (14.16)$$

$$\implies \inf_z \left\{ \frac{1}{2} z^T z + (u - y)^T z + \frac{1}{2} y^T y \right\} = \frac{1}{2} (y - u)^T (y - u) + (u - y)^T (y - u) + \frac{1}{2} y^T y$$

$$= \frac{1}{2} (y^T y - 2u^T y + u^T u) + 2u^T y - y^T y - u^T u + \frac{1}{2} y^T y = -\frac{1}{2} u^T u + u^T y = \frac{1}{2} y^T y - \frac{1}{2} y^T y + u^T y - \frac{1}{2} u^T u$$

$$= \frac{1}{2} y^T y - \frac{1}{2} (y^T y - 2u^T y + u^T u) = \frac{1}{2} y^T y - \frac{1}{2} (y - u)^T (y - u) = \frac{1}{2} \|y\|_2^2 - \frac{1}{2} \|y - u\|_2^2$$

Next we will minimize the right side of (14.15):

$$\begin{aligned} \inf_\beta \{ \lambda \|\beta\|_1 - u^T X \beta \} &= \inf_\beta \left\{ \lambda \sum_{i=1}^p |\beta_i| - \sum_{i=1}^p [u^T X]_i \beta_i \right\} = \inf_\beta \left\{ \sum_{i=1}^p (\lambda |\beta_i| - [u^T X]_i \beta_i) \right\} \\ &= \inf_\beta \left\{ \sum_{i=1}^p (\text{sgn}(\beta_i) \lambda - [u^T X]_i) \beta_i \right\} = \sum_{i=1}^p \inf_{\beta_i} \{ (\text{sgn}(\beta_i) \lambda - [u^T X]_i) \beta_i \}. \end{aligned}$$

Notice that when β_i is negative, if $(\text{sgn}(\beta_i) \lambda - [u^T X]_i) = -(\lambda + [u^T X]_i)$ is positive there is no lower bound on the quantity we are minimizing; otherwise, when β_i is negative the infimum is 0. When β_i is positive, if $(\text{sgn}(\beta_i) \lambda - [u^T X]_i) = (\lambda - [u^T X]_i)$ is negative there is no lower bound on the quantity we are minimizing; otherwise, when β_i is negative the infimum is 0. That is, the only dual feasible points satisfy for all i

$$-(\lambda + [u^T X]_i) \leq 0, \quad \lambda - [u^T X]_i \geq 0 \iff [u^T X]_i \geq -\lambda, \quad [u^T X]_i \leq \lambda$$

which is equivalent to the condition

$$\|u^T X\|_\infty \leq \lambda.$$

Therefore the Lagrange dual function is

$$\inf_{\beta, z} \{\mathcal{L}(x, u)\} = \frac{1}{2} \|y\|_2^2 - \frac{1}{2} \|y - u\|_2^2 \quad (14.17)$$

subject to the constraint $\|u^T X\|_\infty \leq \lambda$. This quantity represents a lower bound on the minimum value of the original optimization problem for all $u \in \mathbb{R}^p$. The dual problem is to find the best lower bound by maximizing over u ; that is, the dual problem is

$$\begin{aligned} & \underset{u \in \mathbb{R}^p}{\text{maximize}} \quad \frac{1}{2} \|y\|_2^2 - \frac{1}{2} \|y - u\|_2^2 \\ & \text{subject to} \quad \|u^T X\|_\infty \leq \lambda. \end{aligned} \quad (14.18)$$

Lastly, suppose $\hat{\beta}$ and \hat{u} satisfy

$$\begin{aligned} \hat{\beta} &= \arg \min_{\beta \in \mathbb{R}^p} \quad \frac{1}{2} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \quad , \\ \hat{u} &= \arg \max_{u \in \mathbb{R}^p} \quad \frac{1}{2} \|y\|_2^2 - \frac{1}{2} \|y - u\|_2^2 = \arg \min_{u \in \mathbb{R}^p} \quad -\frac{1}{2} \|y\|_2^2 + \frac{1}{2} \|y - u\|_2^2 \\ &\text{subject to} \quad \|u^T X\|_\infty \leq \lambda \quad \text{subject to} \quad \|u^T X\|_\infty \leq \lambda \end{aligned}$$

Then since (14.16) is a requirement for dual feasibility of u and strong duality applies, we have $\hat{u} = y - X\hat{\beta}$.

Remark 166. Note that we could also find the arguments maximizing (14.18) by

$$\begin{aligned} & \arg \min_{u \in \mathbb{R}^p} \quad -\frac{1}{2} \|y\|_2^2 + \frac{1}{2} \|y - u\|_2^2 = \arg \min_{u \in \mathbb{R}^p} \quad \frac{1}{2} \|y - u\|_2^2 \\ & \text{subject to} \quad \|u^T X\|_\infty \leq \lambda. \quad \text{subject to} \quad \|u^T X\|_\infty \leq \lambda. \end{aligned}$$

where the first step follows from the fact that arguments that maximize a function are the same as the arguments that minimize the negative of a function, and the second step follows from the fact that the $-\frac{1}{2} \|y\|_2^2$ term does not include u . Therefore we see that the residual vector u from a lasso fit can be thought of as the projection of y onto the convex polyhedron $C \subset \mathbb{R}^n$ defined by $C := \{u : \|X^T u\|_\infty \leq \lambda\}$.

Another way of saying this is that the lasso estimate $\hat{y} = X\hat{\beta}_{\text{lasso}}$ itself is the residual from projecting y onto C ; that is,

$$X\hat{\beta}_{\text{lasso}} = (I - P_C)y,$$

where P_C is the operator projecting y onto C .

- (b) (i) **Not necessarily unique.** Per Tibshirani [2013], if $\text{rank}(X) < p$, the lasso solution is not necessarily unique. Intuitively, this is because the columns of X are linearly dependent, so there may exist more than one linear combination of the columns that minimizes (14.12). **Jacob's suggestion: counterexample.** X is two columns that are equal; then convex combinations of two solutions are equal as long as same sign (can't be opposite sign because then ℓ_1 could be smaller by setting one equal to 0).
- (ii) **Necessarily unique.** The dual problem (14.18) is strictly concave, so the value \hat{u} that maximizes it is unique.

- (iii) **Necessarily unique** (except in the trivial case $\lambda = 0$). Per part 5(b)(iv), $\|\hat{\beta}\|_1$ is unique. (14.12) is convex, so the minimum $\frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\hat{\beta}\|_1$ is unique. Therefore $\|y - X\hat{\beta}\|_2^2$ must be unique.
Jacob's solution: Since \hat{u} is unique and by (14.16) $\hat{u} = y - X\hat{\beta}$, we must have that $\|\hat{u}\| = \|y - X\hat{\beta}\|$ is unique.
- (iv) **Necessarily unique** (except in the trivial case $\lambda = 0$). This is immediate from Proposition 14.6.5.
- (c) (i) Since β^* is clearly feasible for (14.12) and $\hat{\beta}$ achieves the minimum, we have

$$\frac{1}{2}\|y - X\beta^*\|_2^2 + \lambda\|\beta^*\|_1 \geq \frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\hat{\beta}\|_1 \iff \frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\hat{\beta}\|_1 \leq \frac{1}{2}\|\epsilon\|_2^2 + \lambda\|\beta^*\|_1$$

- (ii) We know that the expression in the dual problem (14.18) is a lower bound for the solution of the primal problem (14.12) for any u feasible for (14.18) (that is, any u satisfying $\|u^T X\|_\infty \leq \lambda$). Therefore we have

$$\frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\beta\|_1 \geq \frac{1}{2}\|y\|_2^2 - \frac{1}{2}\|y - u\|_2^2.$$

Since by assumption $\lambda \geq \|X^T \epsilon\|_\infty$, ϵ is feasible for (14.18). Therefore we have

$$\frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\beta\|_1 \geq \frac{1}{2}\|y\|_2^2 - \frac{1}{2}\|y - \epsilon\|_2^2 = \frac{1}{2}\|y\|_2^2 - \frac{1}{2}\|X\beta^*\|_2^2 \quad (14.19)$$

as desired.

- (iii) We can rewrite the right side of (14.19) as

$$\frac{1}{2}\|y\|_2^2 - \frac{1}{2}\|X\beta^*\|_2^2 = \frac{1}{2}\|X\beta^*\|_2^2 + \frac{1}{2}\|\epsilon\|_2^2 + \epsilon^T X\beta^* - \frac{1}{2}\|X\beta^*\|_2^2 = \frac{1}{2}\|\epsilon\|_2^2 + \epsilon^T X\beta^*. \quad (14.20)$$

By assumption, we have

$$\lambda \geq \|X^T \epsilon\|_\infty \iff \lambda \mathbf{1} - X^T \epsilon \succeq 0 \implies \lambda \mathbf{1} \beta^* - X^T \epsilon \beta^* \succeq 0$$

$$\iff -\lambda \|\beta^*\|_1 \leq \epsilon^T X \beta^* \leq \lambda \|\beta^*\|_1.$$

By Hölder's Inequality, we have for any two vectors $u, v \in \mathbb{R}^n$, $|u^T v| \leq \|u\|_\infty \|v\|_1$. Therefore

$$|\epsilon^T X \beta^*| = |(X^T \epsilon)^T \beta^*| \leq \|X^T \epsilon\|_\infty \|\beta^*\|_1 \leq \lambda \|\beta^*\|_1$$

where the last step used the assumption $\|X^T \epsilon\|_\infty \leq \lambda$. So we have

$$\frac{1}{2}\|\epsilon\|_2^2 + \lambda \|\beta^*\|_1 \leq \frac{1}{2}\|\epsilon\|_2^2 + \epsilon^T X \beta^*.$$

Substituting in to (14.19), using the identity in (14.20), and using the result from part 5(c)(iii) yields

$$\frac{1}{2}\|\epsilon\|_2^2 + \lambda \|\beta^*\|_1 \leq \frac{1}{2}\|\epsilon\|_2^2 + \epsilon^T X \beta^* = \frac{1}{2}\|y\|_2^2 - \frac{1}{2}\|X\beta^*\|_2^2 \leq \frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda \|\beta\|_1$$

as desired.

(iv) We see from parts (i) and (iii) that

$$\begin{aligned} \frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\beta\|_1 - \lambda\|\beta^*\|_1 &\leq \frac{1}{2}\|\epsilon\|_2^2 \leq \frac{1}{2}\|y - X\hat{\beta}\|_2^2 + \lambda\|\beta\|_1 + \lambda\|\beta^*\|_1 \\ \iff \frac{1}{n}\|y - X\hat{\beta}\|_2^2 + \frac{2}{n}\lambda\|\beta\|_1 - \frac{2}{n}\lambda\|\beta^*\|_1 &\leq \frac{1}{n}\|\epsilon\|_2^2 \leq \frac{1}{n}\|y - X\hat{\beta}\|_2^2 + \frac{2}{n}\lambda\|\beta\|_1 + \frac{2}{n}\lambda\|\beta^*\|_1 \end{aligned}$$

that is, we can lower bound and upper bound $\frac{1}{n}\|\epsilon\|_2^2$ by taking the quantity $\frac{1}{n}\|y - X\hat{\beta}\|_2^2 + \frac{2}{n}\lambda\|\beta\|_1$ and adding or subtracting $\frac{2}{n}\lambda\|\beta^*\|_1$. Therefore it seems that the quantity in the middle of this interval, $\frac{1}{n}\|y - X\hat{\beta}\|_2^2 + \frac{2}{n}\lambda\|\beta\|_1$, is a reasonable estimator for $\sigma^2 = \mathbb{E}[n^{-1}\|\epsilon\|_2^2]$.

□

14.6.3 Non-Negative Garotte

This idea inspired the lasso. Proposed by Breiman [1995]. It minimizes

$$\sum_{i=1}^n \left(y_i - \alpha - \sum_{j=1}^p c_j \hat{\beta}_j^o x_{ij} \right)^2 \text{ subject to } c_j \geq 0, \sum_{j=1}^p c_j \leq t$$

It starts with OLS estimates and shrinks them by non-negative factors whose sum is constrained. It depends on both the sign and magnitude of OLS estimates. In contrast, lasso avoids the explicit use of OLS estimates.

14.6.4 LARS—Preliminaries and Intuition

Intuition: the algorithm takes steps from a model where all coefficients are 0 to the biggest model (the unpenalized OLS model). Covariates are considered from the highest correlation with y to the least. (The variable most highly correlated with y is the one at the “least angle” from y .) Recall the original definition of the lasso estimator:

$$\hat{\beta}_{lasso} = \arg \min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{2n} \|y - X\beta\|_2^2 \right\} \text{ subject to } \|\beta\|_1 \leq t \quad (14.21)$$

The more common version now:

$$\hat{\beta}_{lasso} = \arg \min_{\beta \in \mathbb{R}^p} \left\{ \frac{1}{2n} \|y - X\beta\|_2^2 + \lambda\|\beta\|_1 \right\} \quad (14.22)$$

One form can be changed to the other by applying Lagrangians¹. Have to be careful because this is a convex program (quadratic with “linear” constraint—use a slack variable).

¹However, the correspondence between t and λ is **not** one-to-one. Because with $t = \infty$, $\lambda = 0$. But a slightly smaller t would result in the same solution.

Taking the gradient of the loss function in (14.22) yields

$$\begin{aligned} \nabla \left(\frac{1}{2n} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \right) &= \nabla \left(\frac{1}{2n} \|y - X\beta\|_2^2 \right) + \lambda \nabla (\|\beta\|_1) \\ &= -\frac{1}{n} X^T (y - X\beta) + \lambda \nabla (\|\beta\|_1) \end{aligned} \quad (14.23)$$

We set this equal to zero. If the first term equals 0, the residual has to equal 0. For the second part to equal zero, we have to account for the fact that the gradient doesn't exist at 0. In the one-dimensional case $g(t) = |t|$, we have

$$g'(t) = \begin{cases} -1 & t < 0 \\ 1 & t > 0 \end{cases}$$

but it doesn't exist at 0. Instead of using the gradient, we will use ∂ , the subdifferential, which is the set of all subgradients. We have a solution if 0 is in the subdifferential. We can rewrite (14.23) using the subdifferential instead of the gradient:

$$\partial \left(\frac{1}{2n} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \right) = \nabla \left(\frac{1}{2n} \|y - X\beta\|_2^2 \right) + \lambda \partial (\|\beta\|_1) = -\frac{1}{n} X^T (y - X\beta) + \lambda \partial (\|\beta\|_1)$$

Then rather than setting the gradient equal to 0, our condition is

$$0 \in -\frac{1}{n} X^T (y - X\beta) + \lambda \partial (\|\beta\|_1)$$

Note that

$$\partial g(t) = \begin{cases} -1 & t < 0 \\ [-1, 1] & t = 0 \\ 1 & t > 0 \end{cases} = \begin{cases} \text{sgn}(t) & t \neq 0 \\ [-1, 1] & t = 0 \end{cases}$$

so we have

$$0 \in -\frac{1}{n} X^T (y - X\beta) + \lambda \cdot \left[\begin{cases} \text{sgn}(\beta_j) & t \neq 0 \\ [-1, 1] & \beta_j = 0 \end{cases} \right] \quad (14.24)$$

where

$$\left[\begin{cases} \text{sgn}(\beta_j) & t \neq 0 \\ [-1, 1] & \beta_j = 0 \end{cases} \right] \in \mathbb{R}^p$$

is a vector with each entry as specified.

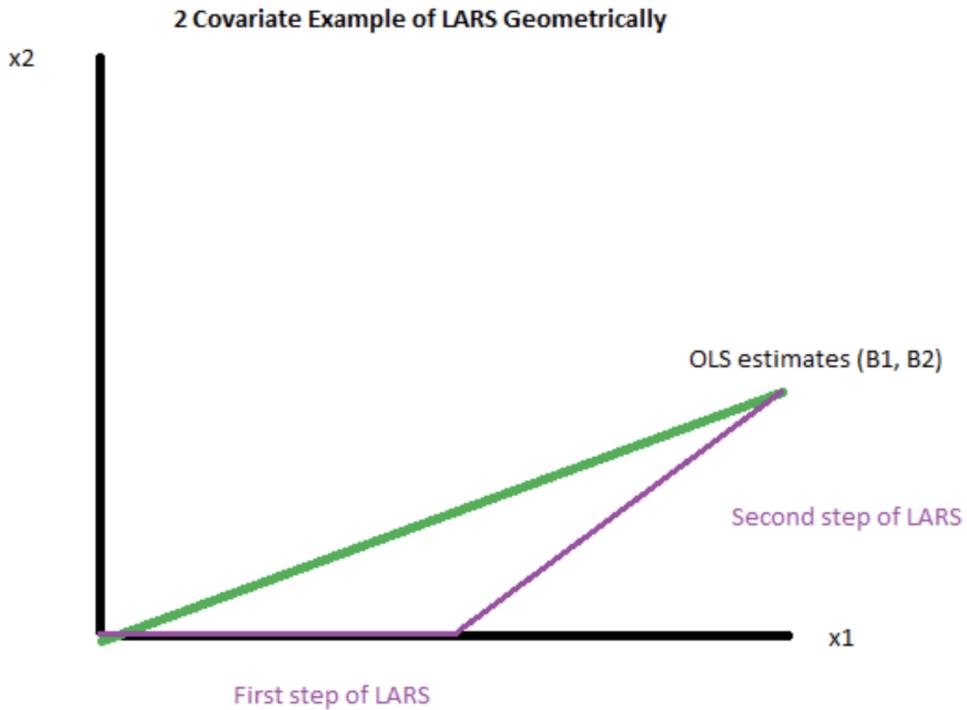


Figure 14.2: LARS figure in 2d case.

Remark 167. (1) Examining the j th component of the separable equation (14.24), if $\beta_j \neq 0$, we have

$$0 = -\frac{1}{n}X_j^T(y - X\beta) + \lambda \cdot \text{sgn}(\beta_j) \iff \frac{1}{n}X_j^T(y - X\beta) = \lambda \cdot \text{sgn}(\beta_j)$$

Note that the left side contains the correlation between X_j and $e = y - X\beta$, the residual vector. **So if lasso chooses k variables, all k of them will have the same correlation with the residual (λ).**

(2) If $\beta_j = 0$, we have

$$0 \in -\frac{1}{n}X^T(y - X\beta) + \lambda \cdot [-1, 1] \iff \left| \frac{1}{n}X^T(y - X\beta) \right| \leq \lambda$$

So for unselected features, the (absolute) correlation should be bounded by λ .

These two conditions relate to the KKT conditions (first order conditions).

So if we start with λ very large and gradually decrease it, we will let in as the first feature the one that is most highly correlated with y —that is, the feature with the *least angle* between it and y .

14.6.5 LARS

In Figure 14.2, note that we choose feature X_1 first because it has the highest correlation with y . As the coefficient on X_1 increases, the correlation between X_1 and the residual with y decreases, while the corre-

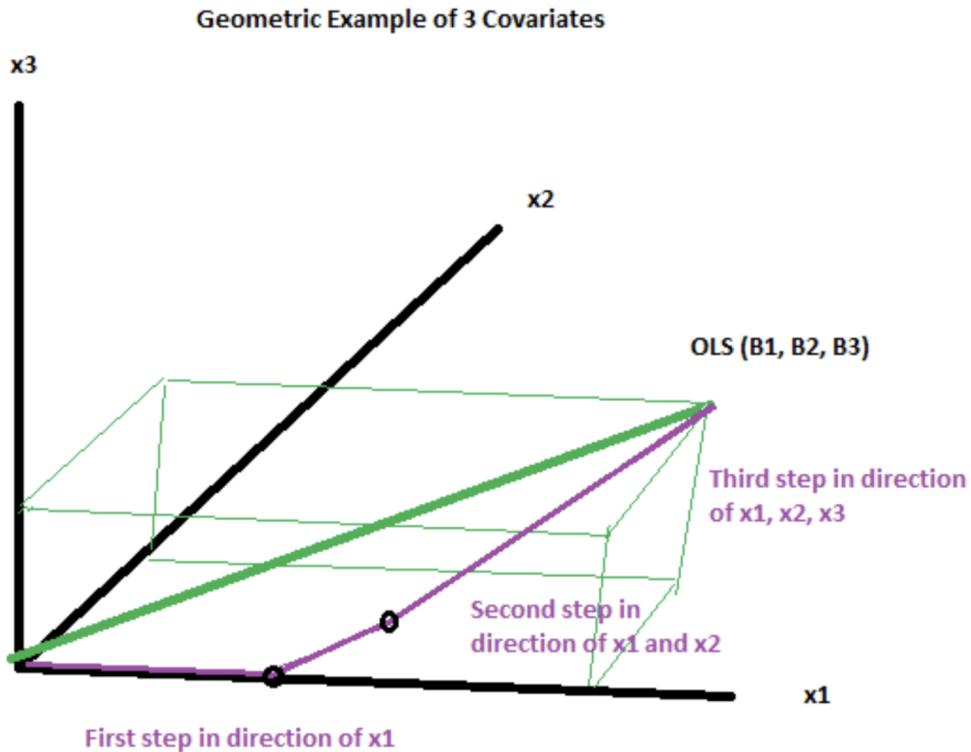


Figure 14.3: LARS figure in 3d case.

lation between X_2 and the residual remains constant (**increases?**). When the correlation between X_1 and the residual becomes equal to the correlation between X_2 and the residual, X_2 enters the lasso path.

Remark 168. Just like in lasso, in LARS the correlation between all included features and the residual are equal (see the remark in Section 14.6.4). However, LARS is a stepwise procedure—once we add a feature, it stays in the model. In the lasso, features can be dropped later in the path after they are selected—whenever β_j becomes 0, it is dropped from the current active set. A feature's sign cannot change in lasso—it is not possible. If we modify the LARS algorithm to have this property (“lasso modification”), then the result is the lasso estimator.

The LARS algorithm for lasso has order $\mathcal{O}(np \cdot \min\{n, p\})$. In particular, if $p > n$ it has order $\mathcal{O}(n^2p)$.

14.7 Loss Functions

Asymmetric loss: may have asymmetry between overestimation and underestimation. For example: in a supply chain, estimate inventory level y_1, \dots, y_n . Let $y_i = x'_i \beta + \epsilon_i$. Underestimating is really bad because then you don't have enough product for customers and they might not come back; overestimating not so bad. Then our loss function:

$$\min_{\beta \in \mathbb{R}^p} \sum_{i=1}^n (1 - \tau) \underbrace{(y_i - x'_i \beta)_+}_{\text{under-estimation}} + \tau \underbrace{(x'_i \beta - y_i)_+}_{\text{over-estimation}}$$

you could choose $\tau = 0.1$ for a 9 to 1 ratio of loss (i.e., underestimation is 9 times as costly as overestimation).

Theorem 14.7.1 (Loss: quadratic). Let $X : \Omega \rightarrow \mathbb{R}$ be a random variable with $\mathbb{E}X^2 < \infty$. Then $\mathbb{E}(X - t)^2$ is minimized for $t \in \mathbb{R}$ uniquely when $t = \mathbb{E}X$.

Proof. We seek

$$\arg \min_t \mathbb{E}(X - t)^2 = \arg \min_t [\mathbb{E}(X^2) - 2t\mathbb{E}(X) + t^2] = \arg \min_t [t^2 - 2t\mathbb{E}(X)]$$

where the last step follows because $\mathbb{E}(X^2)$ is independent of t . This expression is quadratic in t . Differentiating with respect to t and setting equal to 0, we have

$$2t - 2\mathbb{E}(X) = 0 \implies \boxed{\arg \min_t \mathbb{E}(X - t)^2 = \mathbb{E}(X)}$$

□

Huber loss: combines benefits of squared loss (unbiasedness) with MAD loss (robust).

$$L_\delta^H(y, \hat{y}) = (y - \hat{y})^2 \cdot I\{|y - \hat{y}| \leq \delta\} + |y - \hat{y}| \cdot I\{|y - \hat{y}| > \delta\}.$$

Only downside: not that easy to estimate (loss function is not differentiable). Instance of **M-estimation** (more generalized than regression):

$$\hat{\beta}_M = \arg \min_{\beta, \sigma} \sum_{i=1}^n \rho_M \left(\frac{y_i - x'_i \beta}{\sigma} \right)$$

where ρ_M is a loss function. Suppose $y_i = \sum_{j=1}^p x_{ij} \beta_j + \epsilon_i$. Then differentiating the loss function with respect to β yields

$$\frac{\partial}{\partial \beta_k} \left[\sum_{i=1}^n \rho_M \left(\frac{y_i - x'_i \beta}{\sigma} \right) \right] = 0 \quad \text{for } k \in \{1, \dots, p\}.$$

$$= \sum_{i=1}^n \rho'(y_i - x'_i \beta) \cdot \frac{(-x_{ij})}{\sigma}$$

Let $u_i := (y_i - x'_i \beta)/\hat{\sigma}$.

$$\implies \sum_{i=1}^n \underbrace{\frac{\rho'(u_i)}{u_i}}_{\text{weight}} \cdot x_{ij} (y_i - x'_i \beta) = 0$$

Compare to least squares: normal equations $X^T(y - X^T \beta_{OLS}) = 0$, or

$$\sum_{i=1}^n x_{ij}(y_i - x_i' \beta) = 0$$

Now we have this extra weighting term. Algorithm for computing:

1. Use $\hat{\beta}_{OLS}$ as the initial solution; then compute

$$u_i^{(0)} = \frac{y_i' - x_i' \hat{\beta}_{OLS}}{\hat{\sigma}_{OLS}}$$

2. With $w_i^{(0)} = \rho'(u_i)/u_i$, compute

$$\hat{\beta}_{LS}^{(1)} = (X^T W X)^{-1} X^T W y.$$

3. Update weights with $\hat{\beta}_{LS}^{(1)}$.

4. Repeat until convergence. (Convergence is a little tricky but should work.)

For absolute deviation loss, see Section 11.6 on quantile regression.

14.7.1 Feature Selection properties

Model selection consistency: $\Pr(\text{supp}(\hat{\beta}) = \text{supp}(\beta_0)) \rightarrow 1$.

Oracle property: model selection consistency, asymptotic efficiency as efficient as if true model were known (“efficiency” having to do with the variance given n).

Definition 14.1 (Oracle property). Let β^0 denote the true parameter vector for data generated from a linear model. Let S_0 be the true support; that is, $S_0 = \{j : \beta_j^0 \neq 0, j = 1, \dots, p\}$. Denote $\hat{\beta}(\delta)$ the coefficient estimator for fitting procedure δ . We call δ an **oracle procedure** if $\hat{\beta}(\delta)$ asymptotically has the following properties:

- Identifies the right subset model (consistency): $\{j : \hat{\beta}_j \neq 0\} = S_0$.
- Has the optimal estimation rate: $\sqrt{n}(\hat{\beta}(\delta)_{S_0} - \beta_{S_0}^0) \xrightarrow{d} \mathcal{N}(0, \Sigma_0)$ where Σ_0 is the covariance matrix knowing the true subset model.

The lasso problem is convex but not necessarily strictly convex if $p > n$. That is, there is some flat region, so the minimizer may not be unique. Consider the KKT conditions from convex optimization:

$$g(\beta) = \arg \min \left\{ \frac{1}{2n} \|y - X\beta\|_2^2 + \lambda \|\beta\|_1 \right\} = \arg \min \{f_1(\beta) + f_2(\beta)\}$$

Then $\hat{\beta}$ is a lasso solution if and only if 0 is in the subdifferential of $g(\hat{\beta})$. Note that

$$\partial g(\hat{\beta}) = \nabla f_1 + \partial f_2 = \frac{1}{n} X^T (X\beta - y) + \lambda \begin{bmatrix} \vdots \\ \partial|\beta_j| \\ \vdots \end{bmatrix} = \frac{1}{n} X^T (X\beta - y) + \lambda \begin{bmatrix} \vdots \\ \begin{cases} \text{sgn}(\beta_j) & \beta_j \neq 0 \\ [-1, 1] & \beta_j = 0 \end{cases} \\ \vdots \end{bmatrix}$$

Now assume $\text{supp}(\hat{\beta}) = \text{supp}(\beta_0)$ (that is, assume lasso recovers the correct support). Suppose the first s features are nonzero and consider one of them (so we know that we should have $\hat{\beta}_j \neq 0$):

$$0 \in \partial g(\hat{\beta}) \implies 0 \in \partial_j g(\hat{\beta}) = \left[\frac{1}{n} X^T (X\beta - y) \right]_j + \lambda \text{sgn}(\hat{\beta}_j)$$

Therefore

$$\frac{1}{n} X_A^T (X\hat{\beta} - y) + \lambda \text{sgn}(\hat{\beta}_j) = 0 \quad (14.25)$$

where X_A is a submatrix of X containing the columns corresponding to the features in the true support, is our first condition. Next, consider what happens for $j > s$ (features not in the true support). We have

$$\begin{aligned} 0 \in \partial g(\hat{\beta}) \implies 0 \in \partial_j g(\hat{\beta}) &= \left[\frac{1}{n} X^T (X\beta - y) \right]_j + \lambda [-1, 1] \\ &\implies \left\| \frac{1}{n} X_{A^C}^T (X\hat{\beta} - y) \right\|_\infty \leq \lambda \end{aligned} \quad (14.26)$$

where X_{A^C} is a submatrix of X containing the columns corresponding to the features not in the true support, is our boundary condition. Recall the true model

$$y = X\beta_0 + \epsilon$$

and consider the case $X = [X_1 \ X_2]$ where X_1 are the features in the true model and X_2 are noise features; that is, $\beta_0 = \begin{bmatrix} \beta_1 \\ 0 \end{bmatrix}$. Then we are assuming

$$\hat{\beta}_{\text{lasso}} = \begin{bmatrix} \hat{\beta}_1 \\ 0 \end{bmatrix}.$$

We have from (14.25)

$$\begin{aligned} 0 &= \frac{1}{n} X_1^T (X\hat{\beta} - y) + \lambda \text{sgn}(\hat{\beta}_1) = \frac{1}{n} X_1^T (X_1 \hat{\beta}_1 - X_1 \beta_1 - \epsilon) + \lambda \text{sgn}(\hat{\beta}_1) \\ &\iff \frac{1}{n} X_1^T X_1 (\hat{\beta}_1 - \beta_1) = \frac{1}{n} X_1^T \epsilon - \lambda \text{sgn}(\hat{\beta}_1) \end{aligned}$$

Let's assume that $\text{sgn}(\hat{\beta}) = \text{sgn}(\beta_0)$ (sign consistency).

$$\iff \frac{1}{n} X_1^T X_1 (\hat{\beta}_1 - \beta_1) = \frac{1}{n} X_1^T \epsilon - \lambda \text{sgn}(\beta_1)$$

which is linear in $\hat{\beta}$. Solving, we have

$$\iff \hat{\beta}_1 - \beta_1 = (X_1^T X_1)^{-1} (X_1^T \epsilon - n \lambda \text{sgn}(\beta_1)) \iff \hat{\beta}_1 = \beta_1 + (n^{-1} X_1^T X_1)^{-1} (n^{-1} X_1^T \epsilon - \lambda \text{sgn}(\beta_1)) \quad (14.27)$$

Looking at the second (boundary) condition (14.26), we have

$$\left\| \frac{1}{n} X_2^T (X \hat{\beta} - y) \right\|_\infty \leq \lambda. \quad (14.28)$$

Consider that

$$X \hat{\beta} - y = X_1 \hat{\beta}_1 - X_1 \beta_1 - \epsilon = X_1 (\hat{\beta}_1 - \beta_1) - \epsilon$$

Substituting in the result from (14.27) yields

$$X \hat{\beta} - y = X_1 [(n^{-1} X_1^T X_1)^{-1} (n^{-1} X_1^T \epsilon - \lambda \text{sgn}(\beta_1))] - \epsilon$$

which when we plug into (14.28) yields

$$\begin{aligned} & \left\| \frac{1}{n} X_2^T [X_1 (n^{-1} X_1^T X_1)^{-1} (n^{-1} X_1^T \epsilon - \lambda \text{sgn}(\beta_1)) - \epsilon] \right\|_\infty \leq \lambda. \\ \iff & \left\| \frac{1}{n} X_2^T X_1 (n^{-1} X_1^T X_1)^{-1} (n^{-1} X_1^T \epsilon - \lambda \text{sgn}(\beta_1)) - \frac{1}{n} X_2^T \epsilon \right\|_\infty \leq \lambda. \end{aligned}$$

Using the Triangle Inequality, we have

$$\begin{aligned} & \left\| \frac{1}{n} X_2^T X_1 (n^{-1} X_1^T X_1)^{-1} (n^{-1} X_1^T \epsilon - \lambda \text{sgn}(\beta_1)) - \frac{1}{n} X_2^T \epsilon \right\|_\infty \\ & \leq \left\| \frac{1}{n} X_2^T X_1 (n^{-1} X_1^T X_1)^{-1} (n^{-1} X_1^T \epsilon - \lambda \text{sgn}(\beta_1)) \right\|_\infty + \left\| \frac{1}{n} X_2^T \epsilon \right\|_\infty \\ & \leq \left\| \frac{1}{n} X_2^T X_1 (n^{-1} X_1^T X_1)^{-1} \right\|_\infty \cdot \|n^{-1} X_1^T \epsilon - \lambda \text{sgn}(\beta_1)\|_\infty + \left\| \frac{1}{n} X_2^T \epsilon \right\|_\infty \end{aligned} \quad (14.29)$$

Assume that the j th column of X has L_2 norm $n^{1/2}$ (as it would if all entries equaled 1). We have

$$\|n^{-1}X_1^T\epsilon\|_\infty \leq \lambda/2, \quad \|n^{-1}X_2^T\epsilon\|_\infty \leq \lambda/2$$

$$\|n^{-1}X^T\epsilon\|_\infty \leq \lambda/2 \text{ with large probability}$$

Recall that $\lambda = \sigma\sqrt{\frac{c \log p}{n}}$ for some $c > 2$. Then we have (continuing from (14.29)), and using $\|n^{-1}X_2^T\epsilon\| \leq \lambda/2$,

$$\leq \|n^{-1}X_1^T\epsilon\|_\infty + \|\lambda \operatorname{sgn}(\beta_1)\|_\infty$$

$$\|n^{-1}X_2^T X_1 (n^{-1}X_1^T X_1)^{-1}\|_\infty \cdot \underbrace{\|\cdot\|_\infty}_{3/2\lambda} + \underbrace{\|\cdot\|_\infty}_{\lambda/2} \leq \lambda$$

$$\left\| \underbrace{n^{-1}X_2^T X_1}_{\text{corr. between noise and true sample covariance matrix}} \left(\underbrace{n^{-1}X_1^T X_1}_{\text{sample covariance matrix}} \right)^{-1} \right\|_\infty \leq 1/3 \quad (14.30)$$

It turns out we're fine as long as it's less than or equal to 1. This is known as the **irrepresentable condition**. Note that the sample covariance matrix is the same as the sample correlation since the columns are standardized. So this is the correlation between the true variables. Note that this matrix has dimension $(p - s) \times s$ where s is the dimension of the true support. Note that

$$n^{-1}X_2^T X_1 (n^{-1}X_1^T X_1)^{-1} = [X_2^T X_1 (X_1^T X_1)^{-1}]^T = (X_1^T X_1)^T X_1^T X_2$$

which is ordinary least squares for regressing X_2 on X_1 . In the end, the irrepresentable condition says the correlation between the noise and true variables can't be too high.

14.8 Dantzig Selector

Dantzig selector:

$$\begin{aligned} \hat{\beta}_{\text{Dantzig}} &= \arg \min_{\beta \in \mathbb{R}^p} \|\beta\|_1 \\ \text{subject to } & \|n^{-1}X^T(y - X\beta)\|_\infty \leq \lambda \end{aligned}$$

Can be recast as a linear program:

$$\begin{aligned} \hat{\beta}_{\text{Dantzig}} &= \arg \min_{u \in \mathbb{R}^p} \sum_{i=1}^p u_i \\ \text{subject to } & -u \leq \beta \leq u \\ & -\lambda_p \sigma \mathbf{1} \leq n^{-1}X^T(y - X\beta) \leq \lambda_p \sigma \mathbf{1} \end{aligned} \quad (14.31)$$

where $|u|$ denotes the absolute value of u componentwise. (This is a benefit because linear programming is easy to use and very popular in industry and other applications.) Note that $n^{-1}X^t(y - X\beta)$ corresponds to the correlations between the residuals and the design matrix. Recall that in OLS this correlation is 0—the design matrix is orthogonal to the residuals. In the Dantzig selector we relax this, bounding the L_∞ norm by λ . Recall that the gradient of the log-likelihood is the **score function**, in this case $n^{-1}X^T(y - X\beta)$. For example, the score equation in linear regression is $n^{-1}X^Ty = n^{-1}X^TX\beta$. Note:

$$\nabla \left(\frac{1}{2n} \|y - X\beta\|_2^2 \right) = \frac{1}{n} X^T(X\beta - y)$$

Note for Theorem 1: in original paper, assumed columns had L_2 norm 1, resulting in $\lambda_p = \sqrt{2 \log p}$. We are instead assuming each column has L_2 norm \sqrt{n} , which results in $\lambda = \sigma \cdot \sqrt{\frac{c \log p}{n}}$. Intuition of $\log p$ term:

By a theorem in [James et al. \[2009\]](#), the lasso and Dantzig selector estimates equal each other under certain conditions:

Theorem 14.8.1. Let I_L be the support of the lasso estimate $\hat{\beta}_{\text{lasso}}$. Let \mathbf{X}_L be the $n \times |I_L|$ matrix constructed by taking \mathbf{X}_{I_L} and multiplying its columns by the signs of the corresponding coefficients in $\hat{\beta}_{\text{lasso}}$. Suppose that $\lambda_{\text{lasso}} = \lambda_{\text{Dantzig}}$. Then $\hat{\beta}_{\text{lasso}} = \hat{\beta}_{\text{Dantzig}}$ if \mathbf{X}_L has full rank and

$$\mathbf{u} = (\mathbf{X}_L^T \mathbf{X}_L)^{-1} \mathbf{1} \succeq 0 \text{ and } \|\mathbf{X}^T \mathbf{X}_L \mathbf{u}\|_\infty \leq 1$$

where $\mathbf{1}$ is an $|I_L|$ -vector of ones and the vector inequality is understood componentwise.

Corollary 14.8.1.1. If \mathbf{X} is orthonormal ($\mathbf{X}^T \mathbf{X} = \mathbf{I}_p$), then the entire lasso and Dantzig selector coefficient paths are identical.

Proof. For each index set \mathbf{I} , $\mathbf{X}^T \mathbf{X} = \mathbf{I}_{|\mathbf{I}|}$, so clearly both of the conditions of Theorem 14.8.1 are satisfied. □

The entire paths can be identical under another condition presented in the same paper.

Theorem 14.8.2. Suppose that all pairwise correlations between the columns of \mathbf{X} are equal to the same value ρ where $0 \leq \rho < 1$. Then the entire Lasso and Dantzig selector coefficient paths are identical. In addition, when $p = 2$, the same holds for every $\rho \in (-1, 1)$.

14.9 Coordinate Descent

Start with β_1 varying and all other β s fixed. Optimize β_1 . Then cycle through each β_j , run until convergence.

14.10 Total Variational Distance

14.11 Non-parametric regression

One example: LOESS

Another: GAM

14.11.1 Generalized additive models

Suppose $y_i = f(x_i) + \epsilon_i$. Suppose $0 \leq x_1 \leq \dots \leq x_n \leq 1$. Then express

$$f(x) = \sum_{i=1}^{\infty} \theta_i \phi_i(x)$$

where $\int_{\mathbb{R}} f^2(x) dx < \infty$ and the ϕ_i form an orthonormal basis. Assume sparsity:

$$f(x) \approx \sum_{i=1}^p \theta_i \phi_i(x).$$

So

$$y_i = \sum_{i=1}^p \theta_i \phi_i(x) + \epsilon_i, \quad i \in \{1, \dots, n\}$$

and if f is smooth then the coefficient basis is sparse, so θ is sparse, so

$$\|\theta\|_p = \left[\sum_{i=1}^n |\theta_i|^p \right]^{1/p}$$

is small.

Can choose a wavelet basis.

14.12 Mixture regression

Suppose

$$y_i \sim \sum_{k=1}^K \pi_k \cdot \mathcal{N}(X'_i \beta_k, \sigma_k^2 I).$$

Mixture modeling is very useful. Typically estimated by expectation maximization (see Section 10.4.8). One example: spatial analysis. See Figure 14.4. In the black region, slopes and standard deviations will be much higher; outside, will be much lower.

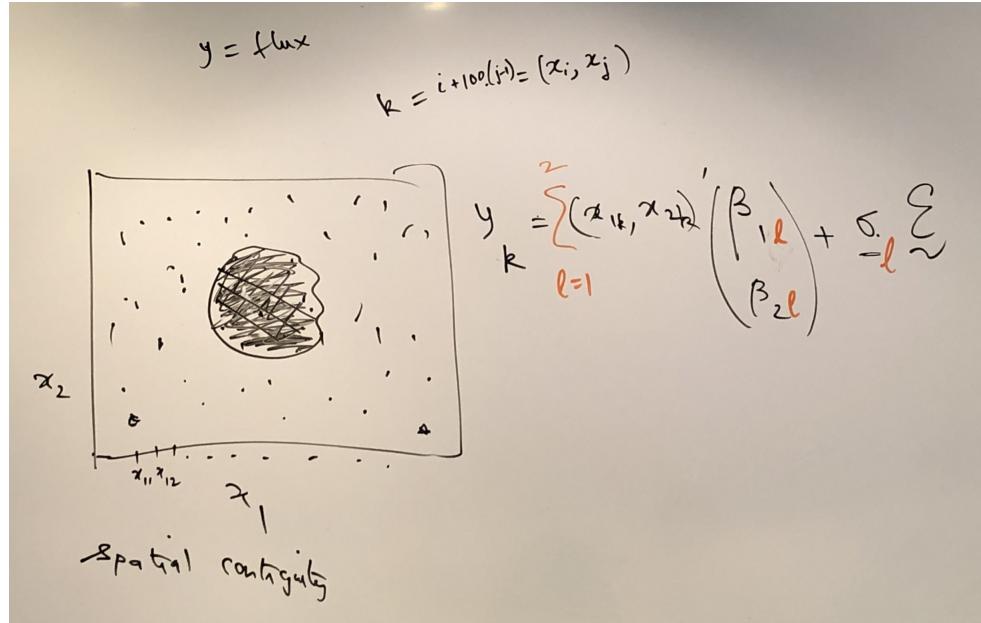


Figure 14.4: Mixture model example.

14.13 Missing observations

14.14 Generalized linear models

Exponential family: binomial, Poisson, Beta, negative binomial, etc. See Section 6.4 for more information on exponential families. The density is

$$g_\eta(y) = c(y) \exp \{ \eta y - \psi(\eta) \}$$

where $c(y)$ is the **carrier density**, η is the **natural parameter**, y is a **sufficient statistic**, and $\psi(\cdot)$ is the **normalizing function** (or **cumulant generating function**), chosen so that it is a proper density: that is, choose $\psi(\eta)$ such that

$$\int_{\mathbb{R}} g_\eta(y) dy = 1,$$

so

$$e^{-\psi(y)} = \left(\int_{\mathbb{R}} c(y) e^{\eta y} dy \right)^{-1}$$

The density is simplest to express in the natural parameter.

Skewness: third centered moment.

$$\frac{\mathbb{E}(Y - \mathbb{E}(Y))^3}{\text{Var}(Y)^{3/2}}$$

kurtosis: 4th centered moment

$$\frac{\mathbb{E}(Y - \mathbb{E}(Y))^4}{\text{Var}(Y)}$$

get excess kurtosis by subtracting 3 (which is Gaussian kurtosis).

In general: cumulant, either centered or raw.

$$K_\gamma = \mathbb{E}(Y - \mathbb{E}(Y))^\gamma, \quad K_\gamma = \mathbb{E}(Y^\gamma)$$

Cumulant generating function:

$$\psi(\eta) - \psi(\eta_0) = \sum_{\gamma=1}^{\infty} K_\gamma \frac{(\eta - \eta_0)^\gamma}{\gamma!}$$

if you know all the cumulants, you know the distribution exactly.

1. **Gaussian variables:** Suppose y_1, y_2, \dots, y_n are i.i.d. $\mathcal{N}(\mu, 1)$.
2. **Gaussian response:** Suppose (y_i, x_i) are i.i.d. pairs in \mathbb{R}^{p+1} with $y_i \sim \mathcal{N}(x'_i \beta, 1)$.
3. **Exponential family variables:** Suppose Y_1, \dots, Y_n are i.i.d. in an exponential family. Then the density of each is $g_\eta(y) = e^{\eta y_0 \psi(\eta)} c(y)$ and the joint density is

$$\prod_{i=1}^n g_\eta(y_i) = \exp \left(\eta \sum_{i=1}^n y_i - n\psi(\eta) \right) \cdot \prod_{i=1}^n c(y_i). \quad (14.32)$$

Then the density of \bar{y} is simply

$$\exp \{n\eta\bar{y} - n\psi(\eta)\}$$

now the natural parameter is $n\eta$ and the normalizing function is $n\psi(\eta)$. So

$$\bar{Y} \sim \left[n \frac{d\psi(\eta)}{d\eta}, n \frac{d\psi^2(\eta)}{d\eta^2} \right].$$

The log likelihood is the log of (14.32):

$$\log L(\eta) = \ell(\eta) = \sum_{i=1}^n \eta y_i - n\psi(\eta) + \sum_{i=1}^n \log c(y_i).$$

The maximum likelihood estimate solves

$$\hat{\eta}_{MLE} := \arg \max_{\eta} \ell(\eta)$$

we have

$$\frac{d}{d\eta} \ell(\eta) = \sum_{i=1}^n y_i - n \frac{d}{d\eta} \psi(\eta), \quad \frac{d^2}{d\eta^2} \ell(\eta) = -n \frac{d^2}{d\eta^2} \psi(\eta) = -n \text{Var}(\eta) < 0$$

so since this function is concave down it has a unique maximum at

$$\sum_{i=1}^n y_i - n \frac{d}{d\eta} \psi(\hat{\eta}_{MLE}) \implies \psi(\hat{\eta}_{MLE}) = \frac{1}{n} \sum_{i=1}^n y_i = \bar{y} \implies \hat{\mu}_{MLE} = \bar{y}$$

That is, the MLE of the mean parameter in an exponential family is the sample mean. Due to the equivariance property of the maximum likelihood estimator, the MLE for any function of the mean parameter is simply the function of the MLE for the mean parameter (see Proposition 10.4.15).

We call the derivative $\frac{d}{d\eta} \ell(\eta)$ the **score function**. If $\xi = h(\eta)$, then by the chain rule

$$\frac{d}{d\xi} \ell(\eta) = \frac{d}{d\eta} \ell(\eta) \Big/ \frac{d\xi}{d\eta}$$

For the mean parameter in particular, we have

$$\frac{d}{d\mu} \ell(\eta) = \frac{d}{d\eta} \ell(\eta) \Big/ \frac{d\mu}{d\eta} = n(\bar{y} - \mu)/\text{Var}_\eta(Y) \quad (14.33)$$

(since $\frac{d}{d\eta} \ell(\eta) = n\bar{y} - n \frac{d}{d\eta} \psi(\eta)$ and $\text{Var}_\eta(Y) = \frac{d\mu}{d\eta}$). Also, since the expectation of the score function $\mathbb{E}(\frac{d}{d\eta} \ell(\eta)) = 0$, we have

$$\text{Var}\left(\frac{d}{d\eta} \ell(\eta)\right) = \mathbb{E}\left[\left(\frac{d}{d\eta} \ell(\eta)\right)^2\right] - \left[\mathbb{E}\left(\frac{d}{d\eta} \ell(\eta)\right)\right]^2 = \mathbb{E}\left[\left(\frac{d}{d\eta} \ell(\eta)\right)^2\right]$$

We call this the **Fisher information**:

$$i_\eta^{(n)}(\xi) := \mathbb{E}\left[\left(\frac{d}{d\eta} \ell(\eta)\right)^2\right]. \quad (14.34)$$

(See also Definition 10.20 and Section 10.4.3 for more on this.) In the case of the mean, we can write this as

$$i_\eta^{(n)}(\eta) = \mathbb{E}\left[\left(n\bar{y} - n \frac{d}{d\eta} \psi(\eta)\right)^2\right] = \text{Var}\left(n\bar{y} - n \frac{d}{d\eta} \psi(\eta)\right) = \text{Var}(n\bar{y}) = n^2 \text{Var}(\bar{y}) = n^2 \text{Var}_\eta(y)/n = n \text{Var}_\eta(y)$$

Then substituting (14.33) into (14.34) we have

$$i_\eta^{(n)}(\mu) = \mathbb{E}\left[\frac{\left(n\bar{y} - n \frac{d}{d\eta} \psi(\eta)\right)^2}{\text{Var}_\eta(y)^2}\right] = \frac{\text{Var}\left[n\bar{y} - n \frac{d}{d\eta} \psi(\eta)\right]}{\text{Var}_\eta(y)^2} = \frac{n \text{Var}_\eta(y)}{\text{Var}_\eta(y)^2} = \frac{n}{\text{Var}_\eta(y)}. \quad (14.35)$$

Note that as n increases, the Fisher information increases linearly. The Fisher information is inversely proportional to the underlying variance. Again, by Proposition 10.4.15, the plug-in estimator for the Fisher Information using the maximum likelihood estimator for the variance is the MLE for the Fisher information:

$$i_{\eta}^{(n)}(\mu) \Big|_{\eta=\hat{\eta}_{MLE}} = \frac{n}{\widehat{\text{Var}}_{\eta}(y)} = \mathbb{E} \left[\left(\frac{d}{d\mu} \ell(\eta) \right)^2 \right] = -\mathbb{E} \left[\frac{d^2}{d\mu^2} \ell(\eta) \right] \Big|_{\eta=\hat{\eta}_{MLE}}$$

In the case of the mean parameter, we can write this as

$$= -\frac{d^2}{d\mu^2} \ell(\eta) \Big|_{\eta=\hat{\eta}_{MLE}}$$

Cramer-Rao lower bound (see Theorem 10.4.7):

$$\text{Var}_{\eta}(\hat{\xi}) \geq \frac{\left(\frac{d}{d\eta} [\mathbb{E}_{\eta}(\hat{\eta})] \right)^2}{i_{\eta}^{(n)}(\xi)}$$

Any estimator that reaches (or approaches asymptotically) this lower bound is **(asymptotically) efficient**. Consider an unbiased estimator $\hat{\xi}$ ($\mathbb{E}(\hat{\xi}) = \xi$): then the bound reduces to

$$\text{Var}_{\eta}(\hat{\xi}) \geq \frac{1}{i_{\eta}^{(n)}(\xi)}$$

Further, suppose we have an unbiased estimator of the mean parameter $\hat{\mu}$. Then using (14.35) we have

$$\text{Var}_{\eta}(\hat{\mu}) \geq \frac{1}{i_{\eta}^{(n)}(\mu)} = \frac{\text{Var}_{\eta}(y)}{n}$$

Since we saw earlier that the MLE has exactly this variance ($\text{Var}(\bar{y}) = \text{Var}_{\eta}(y)/n$), it is the efficient unbiased estimator for μ . (However, it turns out that the plug-in MLE estimator for a function of this mean parameter is not in general the efficient unbiased estimator.)

4. Exponential family model (GLM):

We have Y_1, \dots, Y_n i.i.d. $g_{\eta} \cdot D_n * \eta_1, \eta_2$

14.14.1 Regression models

Suppose $g_{\eta} = e^{\eta y - \psi(\eta)} \cdot c(y)$, and we observe $y_i = g_{\eta_i}$, $i \in [n]$, with $y_i \perp\!\!\!\perp y_j$ for all $i \neq j$. Then

$$g(y_1, \dots, y_n) = \exp \left\{ \sum_{i=1}^n \eta_i y_i - \psi(\eta_i) \right\} \prod_{i=1}^n c(y_i).$$

If $\psi_i = x'_i \beta \in \mathbb{R}^p$ for some β , this is a **hierarchical model**. In particular, it is an **exponential family regression model**. We must have that the natural parameter is a linear function of the covariates. If not ($\eta_i = h(x'_i \beta)$ for some nonlinear h), we get a **curved exponential family** and things are more difficult.

14.14.2 Applications—Categorical Data

1. Poisson

$$\eta_i = \log(\mu_i) = x'_i \beta.$$

Remark 169. Recall that for an exponential family, e.g. Poisson, if $Y \sim \text{Poisson}(\lambda)$, the natural parameter is $\eta = \log \lambda$ and the mean is λ . Then we know that $\check{\psi}(\lambda) = \eta$ check, it's something like that so link function is ψ^{-1} .

Poisson GLM: no response (logit has response) (going off p.37 of slides “m3-poisson-glm.pdf”)

choose model with high p -value (on slide 43) because significance test measures if model fit is significantly worse than saturated model. so if not true, then you want that model.

2. **Binomial** (logistic, probit). Natural parameter for binomial: $\log(\pi/(1 - \pi))$. Link function:

$$\log\left(\frac{\pi}{1 - \pi}\right) = x'_i \beta.$$

$$\begin{aligned} \text{logit}(\pi) &= \log\left(\frac{\pi}{1 - \pi}\right) = \log\left(\frac{\mathbb{P}(Y = 1 \mid X = x_i, Z = z_j)}{\mathbb{P}(Y = 0 \mid X = x_i, Z = z_j)}\right) \\ &= \log\left(\frac{\mathbb{P}(Y = 1, X = x_i, Z = z_j)/\mathbb{P}(X = x_i, Z = z_j)}{\mathbb{P}(Y = 0, X = x_i, Z = z_j)/\mathbb{P}(X = x_i, Z = z_j)}\right) = \log\left(\frac{\mu_{i1k}}{\mu_{i0k}}\right) \\ &= (\lambda + \lambda_i^x + \lambda_1^y + \lambda_k^z + \lambda_{i1}^{xy} + \lambda_{1k}^{yz} + \lambda_{ik}^{xz}) - (\lambda + \lambda_i^x + \lambda_0^y + \lambda_k^z + \lambda_{i0}^{xy} + \lambda_{0k}^{yz} + \lambda_{ik}^{xz}) \\ &\quad = (\lambda_1^y - \lambda_0^y) + (\lambda_{i1}^{xy} - \lambda_{i0}^{xy}) + (\lambda_{1k}^{yz} - \lambda_{0k}^{yz}) \end{aligned}$$

recall the identifiability constraints: first level is 0. So we can write this as

$$= \lambda_1^y + \lambda_{i1}^{xy} + \lambda_{1k}^{yz}$$

If instead $\pi_i = x'_i \beta$, this is not a natural exponential family.

Probit model:

$$\text{probit}[\pi(x)] = \Phi^{-1}(\pi(x)) = x'_i \beta \iff \pi(x) = \Phi(x'_i \beta).$$

3. Multinomial

14.14.3 Applications—Continuous Data

1. **Gaussian**: Link function: $\mu = \mathbb{E}(Y)$.

2. **Binomial**

3. **Multinomial**

14.15 Mixed Effects Models

y_{ij} : i cluster index, $i = 1, \dots, n$, j observation number within each cluster, $j = 1, \dots, d$.

$$y_{ij} = x_i' \beta + z_{ij} v_i + \sigma \epsilon_{ij}$$

so β has to do with fixed effects. example: i is time index, j is student. so for every user you have universal characteristics for the day x_i and user-specific measurements z_{ij} . The z_{ij} effects are called **random effects**. Hierarchical modeling: suppose $z_i \in \mathbb{R}^q$ (q random effects), then we often assume $u_i \sim \mathcal{N}_q(0, \Sigma)$.

Can use with R `lme4` package.

14.16 Miscellaneous Topics

14.16.1 Multinomial Response

c categories in y .

$$\log \left(\frac{\pi_{ij}}{\pi_{ic}} \right) = \text{logit} [\mathbb{P}(y_{ij} = 1 \mid y_{ij} = 1 \text{ or } y_{ic} = 1)] = \sum_{k=1}^p x_{ik} \beta_{kj} = x_i' \beta_j.$$

for $j = 1, \dots, c-1$. row i : (y_{i1}, \dots, y_{ic}) , $\sum_{k=1}^c y_{ik} = 1$ probabilities $(\pi_{i1}, \dots, \pi_{ic})$.

For ordinal random variables:

$$\text{logit}(\mathbb{P}(Y_i \leq j)) = \log \left[\frac{\mathbb{P}(Y_i \leq j)}{\mathbb{P}(Y_i > j)} \right]$$

for example, modeling size S, M, L, XL, XXL to (1, 2, 3, 4, 5). Have a cumulative logit: $\mathbb{P}(Y_i \leq j)$ is nondecreasing as j increases. We have

$$\text{logit}(\mathbb{P}(y_i \leq j)) = \alpha_j + x_i \beta, \quad i \in \{1, \dots, n\}, j \in \{1, \dots, c-1\}$$

under the monotonicity constraint $\alpha_1 \leq \alpha_2 \leq \dots \leq \alpha_{c-1}$.

14.16.2 Zero-inflated response

Suppose $y_i = 0$ with probability $1 - \pi_i$ or has distribution f with probability π_i . That is, $y_i \sim (1 - \pi_i)\delta_0 + \pi_i f(\cdot; \mu_i)$. Assume $\text{logit}(\pi_i) = x_i' \beta$, and if $y_i > 0$, then $\log(\mu_i) = w_i' \gamma$ (μ_i is mean parameter). For example, f may be Poisson if y is discrete or Gaussian if y is continuous: $f = \phi(\cdot; \mu, \sigma)$, $f(y) = \phi((y - \mu)/\sigma)$ To estimate: use maximum likelihood.

$$L(\beta; \gamma, \sigma) = \prod_{i=1}^n (1 - \pi_i)^{I\{y_i=0\}} \left[\pi_i \cdot \frac{1}{\sigma} \phi\left(\frac{y_i - \mu_i}{\sigma}\right) \right]^{I\{Y_i \neq 0\}} = \prod_{i=1}^n \left(\frac{1 - \pi_i}{\pi_i} \right)^{I\{y_i=0\}} \left[\frac{1}{\sigma} \phi\left(\frac{y_i - \mu_i}{\sigma}\right) \right]^{I\{Y_i \neq 0\}}$$

note that we can factorize this as a part that depends on β and a part that depends on γ and σ . Then log likelihood is

$$\underbrace{\sum_{i=1}^n \log\left(\frac{1 - \pi_i}{\pi_i}\right) I\{Y_i = 0\}}_{\ell(\beta)} + \underbrace{\sum_{i=1}^n \left(-\log(\sigma) - \frac{(y_i - \mu_i)^2}{2\sigma^2}\right) I\{Y_i \neq 0\}}_{\ell(\gamma, \sigma)}$$

and

$$\ell(\beta) = - \sum_{i:y_i=0} x_i \beta + \sum_{i=1}^n \log\left(\frac{\exp(x'_i \beta)}{1 + \exp(x'_i \beta)}\right), \quad \ell(\gamma, \sigma) = - \sum_{i:y_i \neq 0} \left(\log(\sigma) + \frac{(y_i - \mu_i)^2}{2\sigma^2}\right) I\{Y_i \neq 0\}$$

and $\log(\mu_i) = w'_i \gamma$.

14.16.3 Overdispersion

Exponential Regression Model

$y_i \sim g_{\eta_i}$, independent. $\eta_i = x'_i \beta$, $\mu_i = \dot{\psi}(\eta_i)$. Likelihood ($L(\eta_i) = \exp(\eta_i y_i - \psi(\eta_i)) \cdot c_0(y_i)$, so (ignoring last part that doesn't depend on η_i) we can write the log likelihood as $\ell(\eta_i) = \eta_i y_i - \psi(\eta_i)$.

Estimating equation: maximizing log-likelihood, the first order equations (differentiate with respect to β):

$$\begin{aligned} \frac{\partial \ell(\beta)}{\partial \beta_j} &= 0, \quad \forall j \in \{1, \dots, p\}, \quad \frac{\partial \ell}{\partial \eta_i} = y_i - \dot{\psi}(\eta_i - i) = y_i - \mu_i \\ \sum_{i=1}^n \frac{\partial \ell_i(\beta)}{\partial \beta_j} &= \sum_{i=1}^n \frac{\partial \ell_i}{\partial \eta_i} \cdot \frac{\partial \eta_i}{\partial \beta_j} = \sum_{i=1}^n (y_i - \mu_i) \cdot x_{ij} = 0, \quad j \in \{1, \dots, p\}. \end{aligned}$$

example use: use a quasi-likelihood approach for modeling count data where variance isn't necessarily fixed. Have over-dispersion parameter; in that case, can use different variance for count data.

Example data: Efron data set from 70s on toxoplasmosis. Reasons for overdispersion:

- subgroups in data

Remedies: GLMs in quasi likelihood ("dispersion parameter") or mixed effects/hierarchical/multi-level modeling.

Example 14.2 (Correlated Binomial Trials). $y_{ij} \sim \text{Bin}(1, \pi_i)$, $i \in [n], j \in [n_i]$. The correlation between y_{ij} and y_{ik} is ρ for $j \neq k$; $|\rho| \leq 1$. We have

$$y_i = \frac{1}{n_i} \sum_{j=1}^{n_i} y_{ij}$$

14.17 Generalized linear mixed models

Nature of γ model: something like GARCH, etc. Point is, only a few parameters.

Why is MLE biased? Remember that MLE for σ^2 is biased, so basically that's why.

For REML (restricted maximum likelihood): start by projecting y onto the nullspace of X so that we don't have to worry about β :

$$y = X\beta + ZU + \epsilon,$$

$$T := (I - P_X) = (I - P_X)ZU + (I - P_X)\epsilon = (I - X(X^T X)^{-1}X^T)ZU + (I - X(X^T X)^{-1}X^T)\epsilon$$

Write down the distribution of T and the likelihood of T . Turns out log likelihood is

$$\ell_n(\gamma) = -\frac{1}{2} \left[(y - X\hat{\beta}_{GLS})^T V^{-1}(\gamma) (y - X\hat{\beta}_{GLS}) + \log(|V(\gamma)|) + \log(|X^T V(\gamma) X|) \right]$$

where again

$$\hat{\beta}_{GLS} := (X^T V(\gamma) X)^{-1} X^T (V(\gamma))^{-1} y.$$

(comes up automatically as a result of projection; not here because of an iterative procedure).

Testing:

1. **Fixed effects (β)**: Partition $X = [X_0 | X_1]$, $\beta = (\beta_0, \beta_1)$. $H_0 : \beta_1 = 0$. Likelihood ratio test:

$$2 \left[\underbrace{\ell(\hat{\beta}, \hat{\sigma}^2; \hat{V})}_{\text{complete model}} - \underbrace{\ell(\hat{\beta}_0, \hat{\sigma}_0^2; \hat{V}_0)}_{\text{null model}} \right] \xrightarrow{d} \chi_{\dim(\beta_1)}^2.$$

Issues: test can be anti-conservative (probability of type 1 error higher than stated α); asymptotics “kick in” very late. Parametric bootstrap can work better.

2. **Random effects (U)**: $H_0 : \sigma_j = 0$ (mean of random effects is 0 by assumption, so if variance is also 0, effect is “not there”). Also do likelihood ratio test, in the end turns out to also be asymptotically χ^2 .

Composite effect: both fixed and random effects. (some economic models only allow random effects if there is also a fixed effect—enforce hierarchy).

14.17.1 Longitudinal data analysis and Generalized Estimating Equations

t for time, i for user/customer. y_{it} has correlation across time. $\mathbb{E}y_{it} = \mu_{it}$, $\text{Var}(y_{it}) = \phi a(\mu_{it})$, $g(\mu_{it}) = X'_{it}\beta + z'_{it}\gamma$ where a can be any arbitrary function (known variance function). If $\phi = 1$, no overdispersion. Estimate ϕ via quasi-likelihood. This case has no correlation across y_{it} . One way to introduce correlation (and parameterize a):

$$\text{Var}(y_{it}) = \phi A_i^{1/2} R(\alpha) A_i^{1/2}$$

where $A_i = \text{diag}(a(\mu_{it}))$. For example, for a moving average $MA(1)$ process, we have

$$R(\alpha) = \begin{bmatrix} 1 & \alpha & 0 & \cdots & 0 \\ \alpha & 1 & \alpha & \cdots & 0 \\ 0 & \alpha & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}$$

14.18 Causal Inference

14.18.1 Factorial Design (see R lab 7)

2 or more discrete factors. Fully cross-classified.

$$y_{ijk} = \mu + X\beta + \underbrace{\alpha_i}_{\text{school}} + \underbrace{\beta_j}_{\text{class}} + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

Nested design:

$$y_{ijk} = \mu + X\beta + \alpha_i + \beta_{ij} + \epsilon_{ijk}.$$

Imbalanced design:

$$y_{ijk} = \underbrace{\mu}_{\text{general effect}} + \underbrace{\alpha_i}_{\text{treatment effect}} + \underbrace{\beta_j}_{\text{block effect}} + \epsilon_{ijk}$$

Complete vs. incomplete design: all treatments do not occur in the same block. Treatment contrast: difference between treatment effect i and j : $\alpha_i - \alpha_j$. BIBD: balanced incomplete block designs. All treatment contrasts are estimable. I treatments, J blocks. Each treatment occurs exactly r times in the design. $n = rI = kJ$. Typically $r \ll J$.

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Exercise 3.16: this inequality talks about the number of misclassifications, not the probability of misclassification under any distribution.

14.19.1 Perceptron Algorithm

Remark 170. Note that the run times only depends on the ℓ_2 norm of the solution loadings w and the ℓ_2 norm of the longest vector in the data set. That sounds good since it doesn't depend on the size of the data, but in the worse case θ can grow exponentially in the dimension of the data.

Also, note that the actual run time is at least linear in the size of the data, since on each iteration the algorithm checks some multiple of m points.

14.19.2 Mercer's Theorem

How is this an infinite-dimensional version of the Exercise? Let M be a $k \times k$ real symmetric matrix. By the Spectral Theorem, there exists an orthogonal Q and a diagonal D such that $M = Q^T D Q$. For all $1 \leq p \leq k$, let λ_p denote the p th diagonal entry of D . Let $\psi_i^p \in \mathbb{R}^k$ denote the i th row of Q . Then

$$m_{ij} = \sum_{p=1}^k \lambda_p \psi_i^{(p)} \psi_j^{(p)}, \quad \forall 1 \leq i, j \leq k.$$

Also, $m(x, y)$ is called a **kernel**.

How to get ψ from $m(x, y)$? Define

$$\ell_2 := \{\}$$

Note: if we could write the algorithm in terms of $m(x, y)$, we don't need to specify this embedding ϕ at all.

14.20 Norms

Proposition 14.20.1. Let $C \subseteq \mathbb{R}^n$ be a symmetric (if $c \in C$ then $-c \in C$) convex set containing 0. Define for all $x \in \mathbb{R}^n$,

$$\|x\|_C := \inf \left\{ t > 0 : \frac{x}{t} \in C \right\}$$

Then $\|x\|_C$ is a norm.

Theorem 14.20.2 (notes from proof of lemma 6.24).

$$d_{2,\mathbb{P}}(f, g)^2 - d_{2,\mathbb{P}_m}(f, g)^2 = (\mathbb{E}_{\mathbb{P}}|f-g|^2)^{1/2} - (\mathbb{E}_{\mathbb{P}_m}|f-g|^2)^{1/2} = \mathbb{E}h(X) - \frac{1}{m} \sum_{i=1}^m h(X_i) = \frac{1}{m} \sum_{i=1}^m (\mathbb{E}h(X) - h(X_i))$$

note from proof of theorem 6.23: needed to bound number of points in order to apply Sauer-Shelah lemma (only applies for finite number of points)

Definition 14.2 (Nuclear norm). Let $A \in \mathbb{R}^{m_1 \times m_2}$. The **nuclear norm** of A , denoted $\|A\|_*$ is given by

$$\|A\|_* := \sum_{j=1}^{\text{rank}(A)} \sigma_j(A),$$

where $\sigma_1(A) \geq \sigma_2(A) \geq \dots \geq \sigma_{\text{rank}(A)}(A)$ are the singular values of A .

Definition 14.3 (Spectral norm or operator norm). Let $A \in \mathbb{R}^{m_1 \times m_2}$. The **Spectral norm** or **operator norm** of A is given by

$$\|A\| := \max_j \sigma_j(A).$$

Exercise 33. Prove that the operator norm is the dual of the nuclear norm. (For any norm $\|\cdot\|'$, its dual norm is defined as

$$\|v\|'_* := \sup_{u: \|u\|' \leq 1} \langle u, v \rangle.$$

That is, prove

$$\|A\| = \sup_{\|B\|_* \leq 1} \text{Tr}(A^T B).$$

14.21 Collaborative Filtering and Trace Regression (Math 541B)

Notation (Netflix problem): m_1 movies, m_2 users, matrix $A_0 \in \mathbb{R}^{m_1 \times m_2}$ (rows correspond to movies, columns correspond to users), $\{A_0\}_{ij} \in [5]$.

14.21.1 Trace Regression

Let $A_1, A_2 \in \mathbb{R}^{m_1 \times m_2}$. Define $\langle A_1, A_2 \rangle := \text{Tr}(A_1^T A_2) = \sum_{i=1}^{m_1} \sum_{j=1}^{m_2} (A_1)_{ij} (A_2)_{ij}$ (equivalent to vectorizing each matrix, then taking inner product). Assume that (X, Y) is a random sample with $X \in \mathbb{R}^{m_1 \times m_2}$, $Y \in \mathbb{R}$ such that $Y = \langle A_0, X \rangle + \xi$ where $A_0 \in \mathbb{R}^{m_1 \times m_2}$, $X \in \mathbb{R}^{m_1 \times m_2}$ is a random measurement matrix, and $\xi \in \mathbb{R}$ is random noise with $\mathbb{E}\xi = 0$, independent of X by assumption.

Example 14.3. Suppose A_0 and X are diagonal; that is, $A_0 = \text{diag}(a_0)$, $X = \text{diag}(x)$, then $\langle A_0, X \rangle = \langle a_0, x \rangle = \sum_{j=1}^{m_1} (a_0)_j x_j$. (This is a standard linear model.)

Example 14.4 (Low-rank matrix completion). Suppose $A_0 \in \mathbb{R}^{m_1 \times m_2}$ has low rank and X has uniform distribution on the set

$$\mathcal{E} := \{e_i(m_1)e_j(m_2)^T, i \in [m_1], j \in [m_2]\}$$

where $e_i(m)$ has the same dimension as m and contains 1 in the i th entry and 0 in every other entry. That is, $e_i(m_1)e_j(m_2)^T$ is a matrix containing a 1 only in entry (i, j) and 0 elsewhere, and

$$\langle A_0, e_i(m_1)e_j(m_2)^T \rangle = (A_0)_{ij}.$$

(Note that it is important that

$$\mathbb{P}(X = e_i e_j^T) > 0 \quad \forall i, j.$$

To see why, assume that we only observe movie ratings from one user. Even if that user rates every single movie and A_0 has rank 1, we still will not be able to make any reasonable predictions about the other users' ratings.) So our model is

$$Y_j = \langle A_0, X_j \rangle + \xi_j, \quad X_j \sim \text{Uniform}(\mathcal{E}), \quad \xi_j \perp\!\!\!\perp X_j, \quad j \in [n].$$

By Exercise 33,

$$\langle A_1, A_2 \rangle \leq \|A_1\| \cdot \|A_2\|_*.$$

(This fact is sometimes known as *trace duality*.) The least squares estimator of A_0 is

$$\hat{A} := \arg \min_{S \in \mathbb{R}^{m_1 \times m_2}} \sum_{j=1}^n (Y_j - \langle S, x_j \rangle)^2.$$

But since $n \ll m_1 m_2$, the solution is not unique; this has too many degrees of freedom. (One solution is

$$\hat{A} = \frac{1}{n} \sum_{j=1}^n Y_j X_j,$$

but this is not low-rank.) (Exercise: calculate $\mathbb{E}\|\hat{A} - A_0\|_F^2$.) One idea is to impose a constraint that $\text{rank}(S) \leq k$. Then the problem becomes

$$\begin{aligned} \hat{A} = \arg \min_{S \in \mathbb{R}^{m_1 \times m_2}} \quad & \sum_{j=1}^n (Y_j - \langle S, x_j \rangle)^2 \\ \text{subject to} \quad & \text{rank}(S) \leq k, \quad k \geq \text{rank}(A_0) \end{aligned}$$

We know that $A_0 \in \mathcal{A} = \{A : \text{rank}(A) \leq k, \|A\|_* \leq \|A_0\|_*\}$. But this problem is non-convex. The idea is to replace \mathcal{A} by its convex hull. Consider the set $\tilde{\mathcal{A}} \subset \mathcal{A}$ defined by

$$\tilde{\mathcal{A}} = \{\pm \|A_0\|_* = uv^T, u \in \mathbb{R}^{m_1}, v \in \mathbb{R}^{m_2}, \|u\|_2 = 1, \|v\|_2 = 1\}.$$

We claim that the convex hull of $\tilde{\mathcal{A}}$ is equal to

$$\|A_0\|_* \cdot B(0, 1, \|\cdot\|_*)$$

where

$$B(0, 1, \|\cdot\|_*) = \{S \in \mathbb{R}^{m_1 \times m_2} : \|S\|_* \leq 1\}.$$

and is also the convex hull of $/\mathcal{A}$. Since the set $\|A_0\|_* \cdot B(0, 1, \|\cdot\|_*)$ contains A and is convex, the convex hull of \mathcal{A} is equal to $\|A_0\|_* \cdot B(0, 1, \|\cdot\|_*)$. (We took $\tilde{\mathcal{A}} \subset \mathcal{A}$ and showed that $\mathcal{A} \subset \text{co}(\tilde{\mathcal{A}})$. Since $\tilde{\mathcal{A}} \subset \mathcal{A}$, $\text{co}(\tilde{\mathcal{A}}) \subseteq \text{co}(\mathcal{A})$, so we must have $\text{co}(\tilde{\mathcal{A}}) = \text{co}(\mathcal{A})$.) So we can change our optimization problem to the convex problem

$$\begin{aligned} \hat{A} &= \arg \min_{S \in \mathbb{R}^{m_1 \times m_2}} \sum_{j=1}^n (Y_j - \langle S, x_j \rangle)^2 \\ &\text{subject to } \|S\|_* \leq \|A_0\|_*. \end{aligned}$$

Lastly, since the nuclear norm of A_0 is unknown, we will replace $\|A_0\|_*$ with a sufficiently large constant:

$$\begin{aligned} \hat{A} &= \arg \min_{S \in \mathbb{R}^{m_1 \times m_2}} \sum_{j=1}^n (Y_j - \langle S, x_j \rangle)^2 \\ &\text{subject to } \|S\|_* \leq t \end{aligned}$$

for some $t > 0$. In practice, we can look at the Lagrangian form:

$$\hat{A}_\lambda := \arg \min_{S \in \mathbb{R}^{m_1 \times m_2}} \left\{ \sum_{j=1}^n (Y_j - \langle S, x_j \rangle)^2 + \lambda \|S\|_* \right\}$$

for some $\lambda \in \mathbb{R}_+$. (Nuclear norm penalization is a convex relaxation.) Consider:

$$\frac{1}{n} \sum_{j=1}^n (Y_j - \langle S, x_j \rangle)^2 + \lambda \|S\|_* = \frac{1}{n} \sum_{j=1}^n Y_j^2 + \frac{1}{n} \sum_{j=1}^n \langle S, x_j \rangle^2 - 2 \left\langle \frac{1}{n} \sum_{i=1}^n X_i Y_i, A \right\rangle + \lambda \|S\|_*$$

Consider the term

$$+ \frac{1}{n} \sum_{j=1}^n \langle S, x_j \rangle^2.$$

By the Law of Large Numbers, this converges to its expectation, so we can replace it with its expectation

$$\mathbb{E}\langle S, x_j \rangle^2 = \sum_{i=1}^{m_1} \sum_{j=1}^{m_2} \frac{1}{m_1 m_2} \underbrace{\langle A_i e_i(m_1) e_j(m_2) \rangle^2}_{A_{ij}} = \frac{1}{m_1 m_2} \sum_{i,j} A_{ij}^2 = \frac{1}{m_1 m_2} \|A\|_F^2.$$

The problem becomes

$$\begin{aligned} \hat{A} &= \arg \min_A \left\{ \frac{1}{m_1 m_2} \|A\|_F^2 - 2 \left\langle \frac{1}{n} \sum_{i=1}^n X_j Y_j, A \right\rangle + \lambda \|S\|_* \right\} \\ &= \arg \min_A \left\{ \|A\|_F^2 - 2 \left\langle \frac{m_1 m_2}{n} \sum_{i=1}^n X_j Y_j, A \right\rangle + \lambda' \|S\|_* \right\} \\ &= \arg \min_A \left\{ \|\tilde{X} - A\|_F^2 + \lambda' \|S\|_* \right\} \end{aligned}$$

where

$$\tilde{X} := \frac{m_1 m_2}{n} \sum_{j=1}^n Y_j X_j.$$

Observe that \tilde{X} is an unbiased estimator of A :

$$\begin{aligned} \mathbb{E}\tilde{X} &= \frac{m_1 m_2}{n} n \mathbb{E} Y X = m_2 m_2 \mathbb{E}(\langle A_0, X \rangle X + \xi X) = m_2 m_2 \mathbb{E}(\langle A_0, X \rangle X) \\ &= m_2 m_2 \sum_{i=1}^{m_1} \sum_{j=1}^{m_2} (A_0)_{ij} e_i(m_1) e_j(m_2) = A_0 \end{aligned}$$

since $\xi \perp\!\!\!\perp X$ and $\mathbb{E}\xi = 0$. (So if the penalty is 0, we have an unbiased estimator for A_0 , but we want the penalty because the unbiased estimator is bad.)

Theorem 14.21.1. \hat{A}_λ is given explicitly by the following:

$$\hat{A}_\lambda = \sum_{j=1}^{\min(m_1, m_2)} \left(\sigma_j(\tilde{X}) - \frac{\lambda m_1 m_2}{2} \right)_+ u_i(\tilde{X}) v_j(\tilde{X})$$

where $x_+ := \max\{0, x\}$ is the soft-thresholding function. (summary: take SVD of \tilde{X} , then apply soft-thresholding to the singular values. soft singular value thresholding.)

Proof. Consider

$$\hat{a}_\lambda = \arg \min_{a \in \mathbb{R}} [(a - x)^2 + \lambda |a|].$$

Then

$$0 \in \partial F(\hat{a}_\lambda) \iff \exists v \in \partial|\hat{a}_\lambda| : 2(\hat{a}_\lambda - x) + \lambda v = 0$$

$$\partial F(a) = \{2(a - x) + \lambda v, v \in \partial|a|\} \implies \hat{a}_\lambda = x - \frac{\lambda}{2}v$$

Two possibilities:

(a)

$$|x| > \frac{\lambda}{2} :$$

take $v = \text{sign}(x)$. Then $\hat{a}_\lambda = (|x| - \lambda/2) \text{sign}(x)$.

(b) $|x| \leq \lambda/2$: If $\hat{a}_\lambda > 0, v = 1$. $\hat{a}_\lambda = x - \lambda/2 < 0$. If $\hat{a}_\lambda < 0, v = -1$. Then $\hat{a}_\lambda = x + \lambda/2 > 0$: contradiction.
So $\hat{a}_\lambda = 0$.

$$\hat{a}_\lambda = (|x| - \lambda/2)_+ \text{sign}(x).$$

□

Fact: let $\|\cdot\|'$ be any norm. Then

$$\partial\|x\|' = \begin{cases} y : \|y\|_*' = 1, \langle y, x \rangle = \|x\|', & x \neq 0, \\ y : \|y\|_*' \leq 1, & x = 0, \end{cases}$$

where $\|\cdot\|_*'$ is the dual norm of $\|\cdot\|'$. Apply this fact to the nuclear norm to get that

$$\partial\|A\|_* = \left\{ \sum_{j=1}^{\text{rank}(A)} u_j(A)v_j(A)^T + \sum_{j=\text{rank}(A)}^{\min(m_1, m_2)} w_1 u_j(A)v_j(A)^T, \quad w_j \in [-1, 1] \right\}.$$

(since singular values are always non-negative, so subdifferential is 1 when singular value is positive and any element of $[-1, 1]$ when singular value is 0.) Let

$$F(A) := \|A - \tilde{X}\|_F^2 + \lambda m_1 m_2 \|A\|_*.$$

A_λ minimizes $F(A)$ if and only if $0 \in \partial F(\hat{A}_\tau)$. Note that

$$\partial F(\hat{A}_\lambda) = \left\{ 2(\hat{A}_\lambda - \tilde{X}) + \lambda m_1 m_2 v, \quad v \in \partial\|\hat{A}_\lambda\|_* \right\}.$$

(a)

$$\sigma_j(\tilde{x}) > \frac{\lambda}{2} m_1 m_2 \implies \sigma_j(\hat{A}_\lambda) = \sigma_j(\tilde{x}) - \frac{\lambda}{2} m_1 m_2.$$

(b)

$$\sigma_j \leq \frac{\lambda}{2} m_2 m_2 \implies \sigma_j(\hat{A}_\lambda) = 0.$$

Question: which choice of w_j 's are required here?

Theorem 14.21.2. Assume that $(X_j, Y_j), j \in [n]$ are i.i.d., $X_j \sim \text{Uniform}(e)$, $|Y_j| \leq \eta$ (maximal rating) with probability 1. Let

$$M = \frac{1}{n} \sum_{j=1}^n \left(Y_j X_j - \underbrace{\frac{A_0}{m_1 m_2}}_{\mathbb{E}(Y_j X_j)} \right).$$

Assume that $\lambda \geq 2\|M\|_1$ (twice the largest singular value of the matrix), and $n \gg \min\{m_1, m_2\} \log(m_1 + m_2)$ (tells us the number of ratings we have observed exceeds at least the minimal dimension of the matrix by some logarithmic factor; have observed a rating for each movie and each user at least once). Then the following holds:

$$\|\hat{A}_\lambda - A_0\|_F^2 \leq \left(\frac{1 + \sqrt{2}}{2} \right)^2 m_1 m_2 \lambda^2 \text{rank}(A_0).$$

(as long as λ is big enough, then estimator performs sufficiently well.)

Proposition 14.21.3. Let

$$\lambda \geq 4\eta \sqrt{\frac{t + \log(m_1 + m_2)}{\min(m_1, m_2)n}}.$$

Then $\lambda \geq 2\|M\|$ with probability greater than or equal to $1 - e^{-t}$.

With these two results, we get that for

$$\lambda = 4\eta \sqrt{\frac{t + \log(m_1 + m_2)}{\min(m_1, m_2)n}},$$

we get

$$\begin{aligned} \|\hat{A}_\lambda - A_0\|^2 &\leq \underbrace{\left(\frac{1 + \sqrt{2}}{2} \right)^2}_{\mathbb{C}} 16 \eta^2 m_1 m_2 \cdot \frac{t + \log(m_1 + m_2)}{\min(m_1, m_2)n} \text{rank}(A_0) \\ &= \frac{\max\{m_1, m_2\} \text{rank}(A_0)}{n} \mathbb{C} \eta^2 (t + \log(m)) \end{aligned}$$

achieves best bound without knowing rank of matrix in advance.

14.22 Dynamic Programming

14.22.1 Introduction to Dynamic Programming and Principle of Optimality (Sections 1.1 - 1.3 of [Bertsekas, 2012a])

Discrete-time dynamic system:

1. System dynamics:

- x_k : state at time k .
- u_k : control/decision in period k . Policy: mapping between state and action you will take (a policy is a state-dependent decision, not a decision).
- w_k : random noise. May depend on x_k, u_k, k itself. But **conditioned on** x_k, U_k , we assume w_k is independent of w_{k-1}, \dots, w_1 .

Model: $x_{k+1} = f_k(x_k, u_k, w_k)$.

2. Additive Cost Structure:

For period $k = 0, 1, \dots, K-1$, cost $g_k(x_k, u_k, w_k)$ in period k . Then terminal cost $g_N(x_N)$. Goal: choose a policy to minimize total expected cost

$$\mathbb{E}_{w_0, \dots, w_{N-1}} \left[\sum_{k=0}^{N-1} g_k(x_k, u_k, w_k) + g_N(x_N) \right].$$

Example 14.5 (Inventory control (Example 1.1.1 in [Bertsekas, 2012a], p.5)). 1. Suppose we have a horizon of N periods. In each period k , x_k = number of units of the product available to sell. (We allow $x_k \leq 0$.) $u_k \geq 0$ is the amount ordered from the supplier in period k . (Assume instantaneous delivery, so zero lead time.) Finally, w_k would be the demand for the product in period k . We will assume $w_k \perp w_j$ for all $k \neq j$. Note that $x_{k+1} = x_k - w_k + u_k =: f_k(x_k, w_k, u_k)$.

2. Costs:

- ordering cost (say $C \cdot u_k$).
- inventory cost: i per unit per period.
- Backorder cost: b per unit per period.

So

$$\begin{aligned} g_k(x_k, u_k, w_k) &= cu_k + i \cdot \underbrace{x_k^+}_{\max\{x_k, 0\}} + b \cdot \underbrace{x_k^-}_{\max\{-x_k, 0\}} = cu_k + i \cdot (x_k + u_k - w_k)^+ + b(w_k - x_k - u_k)^+ \\ &= cu_k + i(x_{k+1})^+ + b(-x_{k+1})^+. \end{aligned}$$

Different notation:

$$\mathcal{G}(x_k, u_k, w_k) = \underbrace{p}_{\text{backorder cost/period}} \cdot \max\{0, -x\} + \underbrace{i}_{\text{inventory cost/period}} \cdot \max\{x, 0\},$$

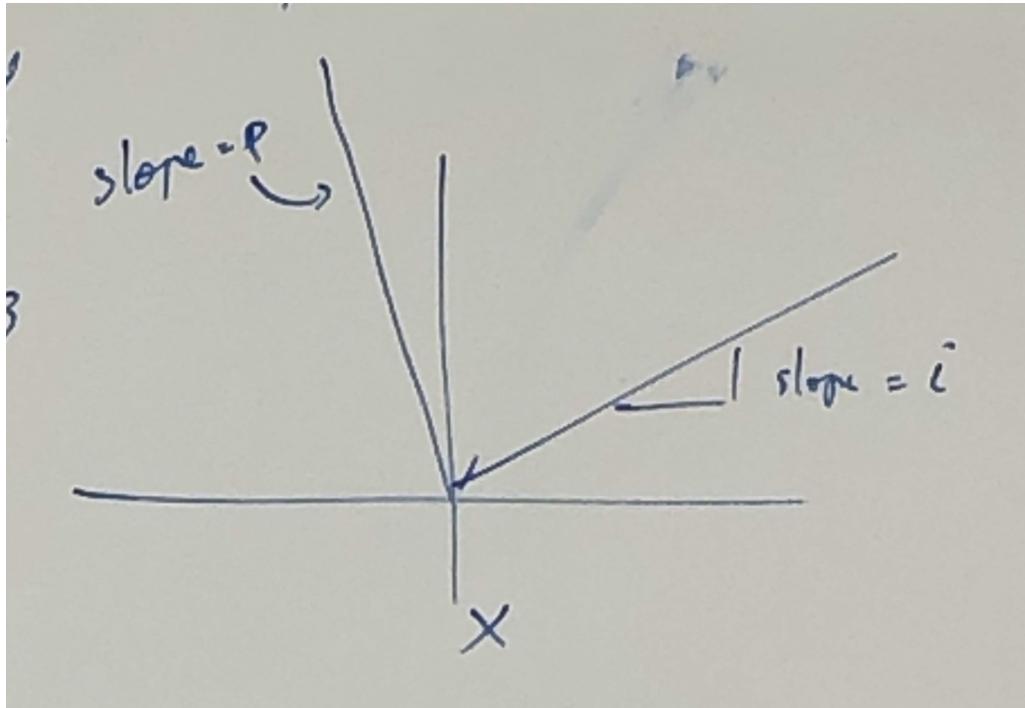


Figure 14.5: Depiction of cost structure for Example 14.5. Note that this function $x \mapsto \mathcal{G}(x)$ is convex in x ; this is relevant in the proof of Theorem 14.22.2.

ordering cost c/unit , assume $p > c$ (see Figure 14.5).

Objective: Minimize

$$\mathbb{E}_{w_0, \dots, w_{N-1}} \left[\sum_{k=0}^{N-1} g_k(x_k, u_k, w_k) + g_n(x_n) \right].$$

or

$$\mathbb{E}_{w_0, \dots, w_{N-1}} \left[\sum_{k=0}^{N-1} c \cdot u_k + \mathcal{G}(x_k + u_k - w_k) \right] = \mathbb{E}_{w_0, \dots, w_{N-1}} \left[\sum_{k=0}^{N-1} c \cdot u_k + p(w_k - x_k - u_k)^+ + i(x_k + u_k - w_k)^+ \right].$$

DP Equation: $J_k(x_k)$: minimum (over all possible policies) expected cost-to-go given that the state at the beginning of the period is x_k :

$$J_k(x_k) = \min_{\Pi^k = (\pi_k, \dots, \pi_{N-1})} \left\{ \mathbb{E}_{w_0, \dots, w_{N-1}} \left[\sum_{\ell=k}^{N-1} c \cdot \pi_\ell(x_\ell) + \mathcal{G}(x_\ell + \pi_\ell(x_\ell) - w_\ell) \right] \right\}.$$

So, for $k \in N-1, N-2, \dots, 0$,

$$J_k(x_k) = \min_{u_k \geq 0} \left\{ c \cdot u_k + \mathbb{E}_{w_k} [\mathcal{G}(x_k + u_k - w_k)] + \mathbb{E}_{w_k} [J_{k+1}(x_k + u_k - w_k)] \right\}.$$

Open loop policy: Determine u_0, u_1, \dots, u_{N-1} in advance.

Definition 14.4. Closed loop policy: u_k is a function of the state x_k .

In particular, let $\mu_k : \mathbb{R} \rightarrow \mathbb{R}_+$ be our policy. Then $\mu_k(x_k)$ is the order quantity in period k given that x_k units remain.

Definition 14.5 (Policy). A **policy** is a sequence of functions

$$\pi = \{\mu_0(\cdot), \dots, \mu_{N-1}(\cdot)\}$$

mapping the state at state k to an action. The cost associated with the policy π given an initial state x_0 is denoted by

$$J_\pi(x_0) = \mathbb{E} \left[\sum_{k=0}^{N-1} (c \cdot \mu_k(x_k) + i \cdot (x_k + \mu_k(x_k) - w_k)^+ + b(w_k - x_k - \mu_k(x_k))^+) + g_n(x_n) \right].$$

Our goal is to find an optimal policy

$$\pi^* \in \arg \min_{\pi \in \Pi} \{J_\pi(x_0)\}.$$

Ideally we would like this policy to be uniformly optimal over all possible x_0 . (Next week: we'll show that an order-up-to policy is optimal for this problem; that is, for each period k there exists a constant $S_k \geq 0$ such that $\mu_k^*(x_k) = [S_k - x_k]^+$. That is, if the amount of inventory you have is less than S_k , order up to that number; otherwise, don't order.)

Basic ingredients:

- (a) Discrete-time system: $x_{k+1} = f_k(x_k, u_k, w_k)$, $k = 0, 1, \dots, N - 1$.
- (b) Independent random noise w_k : w_k can depend on x_k, u_k .
- (c) Constraints on control: $u_k \in \mathcal{U}_k(x_k)$.
- (d) Additive cost.
- (e) Closed loop policy.

Note: when the number of states in the system is discrete/finite, instead of writing $x_{k+1} = f_k(x_k, u_k, w_k)$, you can instead of writing this formula specify transition probabilities, e.g.

$$\mathbb{P}(x_{k+1} = j \mid x_k = i, u_k = u) = P_{ij}(u, k)$$

(i.e. this suffices; all you need is the transition probabilities.)

Note that $J^* : \mathcal{X} \rightarrow \mathbb{R}$ is called an **optimal value function**. We would like an algorithm to find J^* (and π^*). Dynamic programming algorithm: the Bellman equations (or DP equations) relies on the principle of optimality.

Definition 14.6 (Principle of optimality (Section 1.3, p. 20 of [Bertsekas, 2012a])). Suppose $\pi^* = \{\mu_0^*(\cdot), \dots, \mu_{N-1}^*(\cdot)\}$ is an optimal policy. Suppose π^* is used, and a given state x_i occurs in point i with a positive probability. Consider a sub-problem where we are at x_i in period i and wish to minimize the cost-to-go from time i to the end of the horizon (time N),

$$\mathbb{E} \left[\sum_{k=i}^{N-1} (c \cdot \mu_k(x_k) + i \cdot (x_k + \mu_k(x_k) - w_k)^+ + b(w_k - x_k - \mu_k(x_k))^+) + g_N(x_N) \right].$$

Then the truncated policy $\{\mu_i^*(\cdot), \dots, \mu_{N-1}^*(\cdot)\}$ is also optimal for this sub-problem.

Example 14.6 (Analogy). Consider the shortest path from LA to New York. If that path passes through Chicago, then the shortest path from Chicago to New York must be identical to that part of the shortest path from LA to New York.

Implications of the principle of optimality: start with a sub-problem of length 0: use the one at the beginning of period N . Then the cost-to-go is $J_N(x_N) = g_N(x_N)$.

Consider a tail sub-problem of length 1. Suppose we are in state x_{N-1} . Then the optimal policy going forward is

$$\arg \min_{u_{N-1} \geq 0} \{c \cdot u_{N-1} + \mathbb{E} [i \cdot (x_{N-1} + u_{N-1} - w_{N-1})^+ + b(w_{N-1} - x_{N-1} - u_{N-1})^+ + J_N(x_N)]\}$$

We can continue backwards:

$$J_{N-2}(x_{N-2}) = \min_{u_{N-1} \geq 0} \{c \cdot u_{N-2} + \mathbb{E} [i \cdot (x_{N-2} + u_{N-2} - w_{N-2})^+ + b(w_{N-2} - x_{N-2} - u_{N-2})^+ + J_{N-1}(x_{N-1})]\}$$

$$J_k(x_k) = \min_{u_{k+1} \geq 0} \{c \cdot u_k + \mathbb{E} [i \cdot (x_k + u_k - w_k)^+ + b(w_k - x_k - u_k)^+ + J_{k+1}(x_{k+1})]\}$$

and work our way back to $J_0(x_0)$.

Sketch of proof: consider the following backward sequence of functions: $J_N(x_N) = g_N(x_N)$. For $k = N-1, N-2, \dots, 2, 1, 0$,

$$J_k(x_k) = \min_{u_k \in \mathcal{U}_k(x_k)} \{\mathbb{E} [g_k(x_k, u_k, w_k) + J_{k+1}(f_k(x_k, u_k, w_k))]\} \quad (14.36)$$

Theorem 14.22.1 (Optimality of Dynamic Programming Algorithm (Proposition 1.3.1 in [Bertsekas, 2012a], p. 25)). For every initial state x_0 , the optimal cost $J^*(x_0)$ is equal to $J_0(x_0)$. Moreover, if $\mu_k^* = \mu_k^*(x_k)$ minimizes the right hand side of (14.36), then $\pi^* = \{\mu_0^*(\cdot), \dots, \mu_{N-1}^*(\cdot)\}$ is an optimal policy.

Note: μ_k^* is a function that maps the state at time k to an action. u_k is that action.

Proof. For any admissible policy $\pi = \{\mu_0(\cdot), \dots, \mu_{N-1}(\cdot)\}$, let $\pi^k = \{\mu_k(\cdot), \dots, \mu_{N-1}(\cdot)\}$ for the tail subproblem of length $N - k$ (starting from period k). For $k = 0, 1, \dots, N - 1$, let $J_k^*(x_k)$ be the minimum cost-to-go for the $N - k$ stage problem given that we are in state x_k at time k . That is,

$$J_k^*(x_k) = \min_{\pi^k = \{\mu_k(\cdot), \dots, \mu_{N-1}(\cdot)\}} \left\{ \mathbb{E} \left[\sum_{i=k}^{N-1} g_i(x_i, \mu(x_i), w_i) + g_N(x_N) \right] \right\}$$

where $g_i(x_i, \mu(x_i), w_i) = (c \cdot \mu_i(x_i) + i \cdot (x_i + \mu_i(x_i) - w_i)^+ + b(w_i - x_i - \mu_i(x_i))^+)$. (Note: $J_0^*(x_0) = J^*(x_0)$). We'll prove by induction that $J_k^*(x_k) = J_k(x_k)$ for all $k = N, N-1, \dots, 2, 1, 0$.

Base case: is it true that $J_N^*(x_N) = J_N(x_N)$? Yes; just have to minimize $g_N(x_N)$.

Inductive step: Suppose $J_{k+1}^*(x_{k+1}) = J_{k+1}(x_{k+1})$ for all x_{k+1} . We'll now show that $J_k^*(x_k) = J_k(x_k)$ for all x_k . Note that

$$\begin{aligned} J_k^*(x_k) &= \min_{(\mu_k(\cdot), \pi^{k+1})} \left\{ \mathbb{E} \left[g_k(x_k, \mu(x_k), w_k) + \sum_{i=k+1}^{N-1} g_i(x_i, \mu(x_i), w_i) + g_N(x_N) \right] \right\} \\ &= \min_{\mu_k(\cdot)} \left\{ \mathbb{E}[g_k(x_k, \mu(x_k), w_k)] + \min_{\pi^{k+1}} \left\{ \mathbb{E} \left[\sum_{i=k+1}^{N-1} g_i(x_i, \mu(x_i), w_i) + g_N(x_N) \right] \right\} \right\} \\ &= (\text{by definition}) \min_{\mu_k(\cdot)} \{ \mathbb{E}[g_k(x_k, \mu(x_k), w_k)] + J_{k+1}^*(x_{k+1}) \} \\ &= (\text{by inductive hypothesis}) \min_{\mu_k(\cdot)} \{ \mathbb{E}[g_k(x_k, \mu(x_k), w_k)] + J_{k+1}(x_{k+1}) \} \\ &= \min_{u_k \in \mathcal{U}_k(x_k)} \{ \mathbb{E}[g_k(x_k, \mu(x_k), w_k)] + J_{k+1}(f_k(x_k, \mu_k(x_k), w_k)) \}, \end{aligned}$$

verifying that (14.36) is the minimal cost.

□

14.22.2 State Augmentation and Other Reformulations (Section 1.4 of [Bertsekas, 2012a])

- **Time lag:** Suppose that x_{k+1} depends on x_k, u_k , and x_{k-1}, w_{k-1} . Then $x_{k+1} = f(x_k, u_k, w_k, x_{k-1}, w_{k-1})$. Trick: augment the state variable: $\tilde{x}_k = (x_k, x_{k-1}, w_{k-1})$. Then $\tilde{x}_{k+1} = \tilde{f}(\tilde{x}_k, u_k, w_k)$; in particular,

$$\begin{pmatrix} x_{k+1} \\ x_k \\ w_{k-1} \end{pmatrix} = \begin{pmatrix} f(x_k, u_k, w_k, x_{k-1}, w_{k-1}) \\ x_k \\ w_{k-1} \end{pmatrix}$$

- **Forecast:** Suppose at time k we observe a forecast y_k that influences our assessment of the probability distribution of w_k . In particular, suppose w_k can have one of m possible distributions $Q_1(\cdot), \dots, Q_m(\cdot)$. Then the forecast is $y_k \in \{1, \dots, m\}$. Assume y_k is exogenous. Suppose we have a random variable

ξ_k such that if $\xi_k = i$, then w_{k+1} occurs according to probability distribution Q_i , and $\mathbb{P}(\xi_k = i) = p_i$. The state at time k is then $\tilde{x}_k = (x_k, y_k)$, and

$$\tilde{x}_{k+1} = \begin{pmatrix} x_k \\ y_{k+1} \end{pmatrix} = \begin{pmatrix} f_k(x_k, u_k, w_k) \\ \xi_k \end{pmatrix} = \tilde{f}_k((x_k, y_k); u_k, w_k).$$

Then

$$J_k(x_k, y_k) = \min_{u_k \in \mathcal{U}_k} \mathbb{E}_{w_i \sim Q(\cdot)} \left[g_k(x_k, y_k, w_k) + \underbrace{\sum_{j=1}^m \mathbb{P}(\xi_{k+1} = j) \cdot J_{k+1}(x_{k+1}, j)}_{\text{expected cost-to-go}} \right].$$

- **Correlated disturbances:** $w_k = \lambda w_{k-1} + \xi_k$, where ξ_0, \dots, ξ_{N-1} are i.i.d. Then (letting $y_k = w_{k-1}$)

$$\begin{pmatrix} x_{k+1} \\ y_{k+1} \end{pmatrix} = \begin{pmatrix} f_k((x_k, w_k); u_k, \lambda w_{k-1} + \xi - k) \\ \lambda y_k + \xi_k \end{pmatrix}$$

- **Removal of uncontrollable states:** Suppose the state is described by (x_k, y_k) , where $x_{k+1} = f_k((x_k, y_k), u_k, w_k)$ and the evolution of y_k is generated by $\mathbb{P}_k(y_k | x_k)$ and is independent of the control (except from the state x_k). Standard dynamic program:

$$J_k(x - k, y - k) = \min_{u \in \mathcal{U}_k} \mathbb{E}[g_k(x_k, y_k, u_k, w_k) + \mathbb{E}(f_k(x_k, y_k, u_k, w_k))]$$

We would like to reduce the dimension of the state space since y_k is dependent on x_k (and a probability distribution). One way to do this is as follows:

$$\hat{J}_k(x_k) = \mathbb{E}_{y_k} [J_k(x_{k+1}, y_{k+1}) | x_k] = \sum_a \mathbb{P}(y_{k+1} = a | x_k) \cdot J_k(x_k, a).$$

Question: how is $\hat{J}_k(\cdot)$ related to $\hat{J}_{k+1}(\cdot)$?

$$\begin{aligned} \hat{J}_h(x_h) &= \mathbb{E}_{y_h} [J_h(x_h, y_h) | x_h] \\ &= \mathbb{E}_{y_h} \left[\min_{u_k} \left\{ \mathbb{E}_{w_h, x_{k=1}, y_{k+1}} (g_k(x_k, y - k, u_k, w_k) + J_{k+1}(x_{k+1}, y_{k+1}) | x_k, y_k, u_k) \right\} | x_h \right] \\ &= \mathbb{E}_{y_h} \left[\min_{u_k} \left\{ \mathbb{E}_{w_h, x_{k=1}} (g_k(x_k, y - k, u_k, w_k) + \mathbb{E}[J_{k+1}(x_{k+1}, y_{k+1}) | x_k, y_k, w_k] | x_k, y_k, u_k) \right\} | x_h \right] \\ &= \mathbb{E}_{y_h} \left[\min_{u_k} \left\{ \mathbb{E}_{w_h, x_{k=1}} \left(g_k(x_k, y - k, u_k, w_k) + \hat{J}_{k+1}(f_k(x_k, y_k, u_k, w_k) | x_k, y_k, u_k) \right) \right\} | x_h \right] \end{aligned}$$

14.22.3 Inventory Control (Section 3.2 of Bertsekas [2012a])

See Example 14.5 for setup.

Theorem 14.22.2 (Order-up-to Polices Are Optimal). For each period k , there exists a threshold $S_k \geq 0$ such that

$$\mu_k^*(x_k) = [S_k - x_k]^+ = \begin{cases} S_k - x_k, & x_k \leq S_k, \\ 0, & \text{otherwise.} \end{cases}$$

Proof. The DP algorithm is as follows:

$$\begin{aligned} J_N(x_N) &= 0, \\ J_k(x_k) &= \min_{u_k \geq 0} \left\{ c \cdot u_k + \mathbb{E}_{w_k} [\mathcal{G}(x_k + u_k - w_k) + J_{k+1}(x_k + u_k - w_k)] \right\} \end{aligned}$$

where again

$$\mathcal{G}(x_k + u_k - w_k) := \underbrace{p}_{\text{backorder cost/period}} \cdot \max\{0, w_k - x_k - u_k\} + \underbrace{i}_{\text{inventory cost/period}} \cdot \max\{x_k + u_k - w_k, 0\},$$

Note that \mathcal{G} depends on k whenever the probability distribution of w_k depends on k , but we will assume all demands are identically distributed for simplicity (even though the analysis carries through easily if the distribution of demand is time-varying).

Now we will prove a lemma.

Lemma 14.22.3. $J_k(\cdot)$ is convex.

Proof. We will prove the result by induction. The base case is trivially true because $J_N(\cdot) = 0$ (note that we could replace $J_N(\cdot)$ with any convex function and the rest of the proof would follow). Assume $J_{k+1}(\cdot)$ is convex. Recall from Example 14.5

$$\begin{aligned} J_k(x_k) &= \min_{u_k \geq 0} \left\{ c \cdot u_k + \mathbb{E}_{w_k} \left[\mathcal{G}(\underbrace{x_k + u_k - w_k}_{y_k}) + J_{k+1}(x_k + u_k - w_k) \right] \right\} \\ &= \min_{y_k \geq x_k} \left\{ c \cdot (y_k - x_k) + \mathbb{E}_{w_k} [\mathcal{G}(y_k - w_k) + J_{k+1}(y_k - w_k)] \right\} \\ &= -cx_k + \min_{y \geq x_k} \left\{ cy + \mathbb{E}_{w_k} [\mathcal{G}(y - w_k) + J_{k+1}(y - w_k)] \right\} \\ &= -cx_k + \min_{y \geq x_k} \{G_k(y)\} \end{aligned} \tag{14.37}$$

where we let $G_k(y) := cy + \mathbb{E}_{w_k} [\mathcal{G}(y - w_k) + J_{k+1}(y - w_k)]$. We claim that $G_k(y)$ is convex in y by the following argument. First, note that $\mathcal{G}(x) := p \cdot \max\{0, -x\} + i \max\{x, 0\}$ is convex in x . Therefore $\mathbb{E}_{w_k} [\mathcal{G}(y - w_k)]$ is convex in y since it is convex for each w_k and taking expectations preserves convexity.

Next, for each realized value of $w_k = \bar{w}_k$, $y \mapsto \mathcal{G}(y - \bar{w}_k) + J_{k+1}(y - \bar{w}_k)$ is convex because J_{k+1} is a convex function of an affine function and likewise with $\mathcal{G}(y - \bar{w}_k)$ (see Figure 14.5). Therefore the result follows when you take expectations.

We will briefly take a detour to consider the end behavior of $G_k(\cdot)$. As $y \rightarrow \infty$, we know that $cy \rightarrow \infty$. We know that $\mathcal{G}(\cdot)$ is always nonnegative and likewise with $J_{k+1}(y - w_k)$, so we must have that as $y \rightarrow \infty$, $G_k(\cdot) \rightarrow \infty$. As $y \rightarrow -\infty$, because of the assumption that $p > c$ (and that J_{k+1} is convex), we have that $G_k(y) \rightarrow \infty$. Therefore since $G_k(\cdot)$ is continuous, a minimizer of $G_k(\cdot)$ exists.

Let S_k be a minimizer of $G_k(\cdot)$. Note that if $x_k \geq S_k$, then $\min_{y \geq x_k} G_k(y) = G_k(x_k)$ due to the convexity of $G_k(\cdot)$. Clearly if $x_k \leq S_k$, then $\min_{y \geq x_k} G_k(y) = G_k(S_k)$. (Note that if S_k is not the only minimizer, this still holds.) In summary, we have

$$J_k(x_k) = \begin{cases} -cx_k + G_k(S_k) & x_k \leq S_k, \\ -cx_k + G_k(x_k) & x_k > S_k. \end{cases} \quad (14.38)$$

Each of these functions is continuous and convex in y . Therefore $J_k(x_k) = -cx_k + \min_{y \geq x_k} G_k(y)$ is convex in x_k . (See Figure 14.6.)

□

We have shown that a minimizer for G_k is given by S_k if $x_k < S_k$ and x_k otherwise. Then since $u_k = y_k - x_k$ in (14.37), a minimizer for (14.37) is attained at $u_k = S_k - x_k$ if $x_k < S_k$, and at $u_k = 0$ otherwise.

□

Next we will consider fixed orders cost. Before we find the optimal policy in this case, we will define some terms and derive some results we will need.

Definition 14.7 (K -convexity; Definition 3.2.1 in Section 3.2 of Bertsekas [2012a], p. 130). A real-valued function g is **K -convex** for $K \geq 0$ if

$$K + g(z + y) \geq g(y) + z \left(\frac{g(y) - g(y - b)}{b} \right) \quad (14.39)$$

for all $z \geq 0$, $b > 0$, and all $y \in \mathbb{R}$. Equivalent: for all $x < y < z'$,

$$K + g(z') \geq g(y) + (z' - y) \left(\frac{g(y) - g(x)}{y - x} \right). \quad (14.40)$$

(This construction follows from (14.39) by setting $x := y - b < y$ and $z' := z + y \geq y$.)

See Figure 14.7 for an example of a function that is K -convex but not convex.

Intuitively, from (14.40) we can think of this as meaning that the linear approximation of g at $z' = z + y$ by a secant line between y and $x = y - b$ is no more than K greater than $g(z + y)$. To make further sense of this definition, observe from (14.39) that if $K = 0$

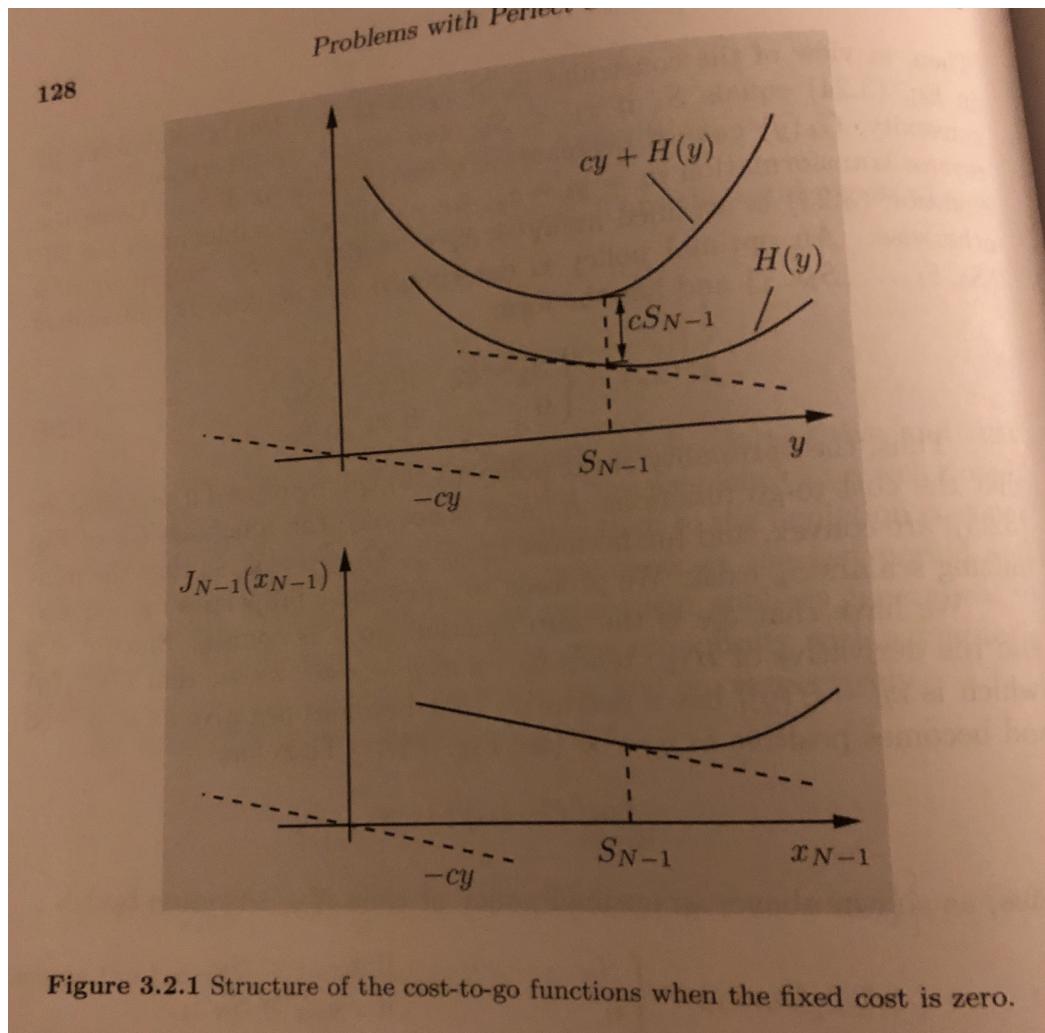


Figure 3.2.1 Structure of the cost-to-go functions when the fixed cost is zero.

Figure 14.6: Cost-to-go function for inventory control problem. (The notation from [Bertsekas \[2012a\]](#) differs slightly from ours, but the lower figure shows that the cost-to-go is linear to the left of the minimizer and convex and nondecreasing to the right of the minimizer, as shown in Equation (14.38)).

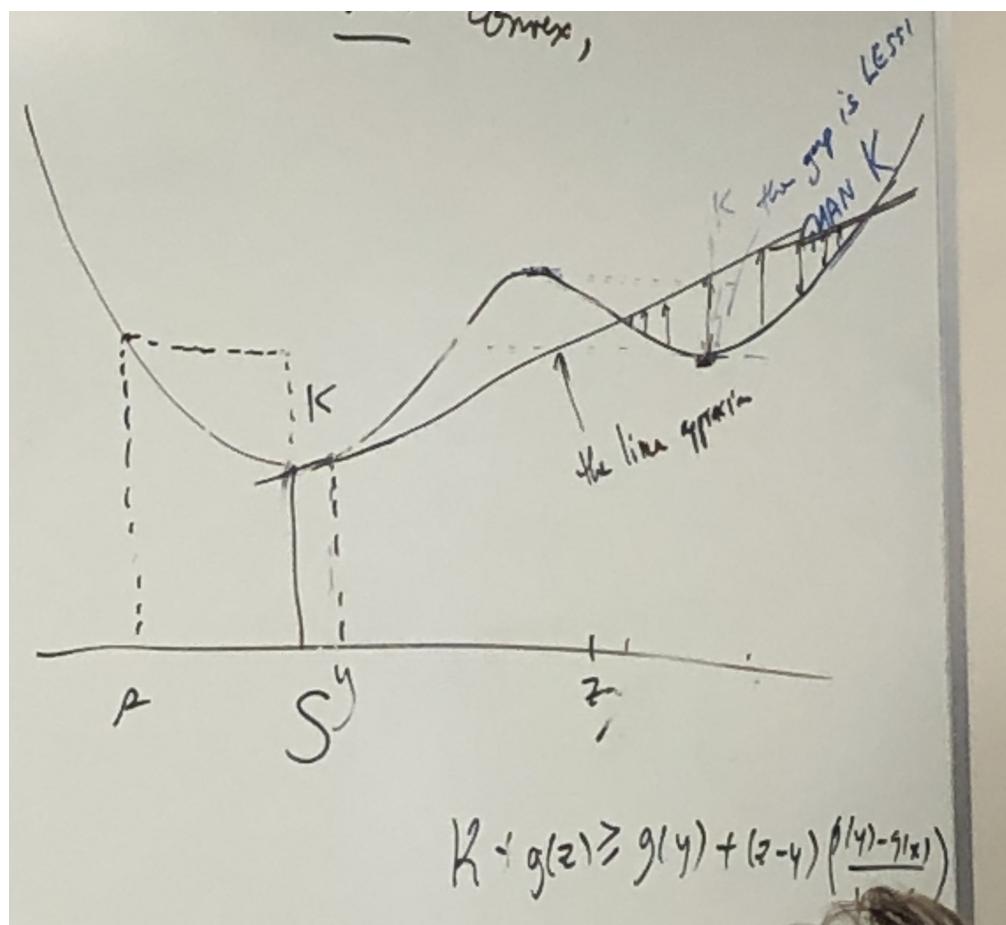


Figure 14.7: Function is K -convex (see Definition 14.7), but not convex.

$$\begin{aligned} g(z+y) &\geq g(y) + z \left(\frac{g(y) - g(y-b)}{b} \right) \\ \iff \quad \frac{g(z+y) - g(y)}{z} &\geq \frac{g(y) - g(y-b)}{b}; \end{aligned}$$

that is, the slopes of the secant lines are nondecreasing, which we know from Lemma 9.1.1 is true of convex functions. For the general case we have

$$\frac{K + g(z+y) - g(y)}{z} \geq \frac{g(y) - g(y-b)}{b}.$$

Next we will show some results about K -convex functions that will be useful.

Proposition 14.22.4 (Lemma 3.2.1 in Bertsekas [2012a]). Properties of K -convex functions:

- (a) A convex function g is 0-convex and K -convex for all $K \geq 0$.
- (b) If g_1 is K -convex and g_2 is L -convex, then $\alpha g_1 + \beta g_2$ is $(\alpha K + \beta L)$ -convex for all $\alpha > 0, \beta > 0$.
- (c) If g is K -convex and w is a random variable, then $y \mapsto \mathbb{E}_w[g(y-w)]$ is also K -convex if $\mathbb{E}_w|g(y-w)| < \infty$ for all y . (Proof: exercise)
- (d) If g is a continuous K -convex function with $g(y) \rightarrow \infty$ as $|y| \rightarrow \infty$, then there exist scalars (s, S) with $s \leq S$ such that
 - (1) $g(S) \leq g(y)$ for all y ,
 - (2) $g(S) + K = g(s) \leq g(y)$ for all $y < s$. (See Figure 14.8.)
 - (3) $g(y)$ is decreasing on $(-\infty, s)$.
 - (4) $g(y) \leq g(z) + K$ for all y, z with $s \leq y \leq z$.

Proof of part (d). (1) Since g is continuous and $\lim_{|y| \rightarrow \infty} g(y) = \infty$, there exists a minimizing point S of g with minimum $g(S)$.

(2) Define $s := \min\{z : g(z) = g(S) + K\}$. Note that $s \leq S$. For all $y < s \leq S$, by K -convexity of g and the definition of s , from (14.40) we have

$$\begin{aligned} K + g(S) &\geq g(s) + (S-s) \left(\frac{g(s) - g(y)}{s-y} \right) \\ \iff 0 &\geq \underbrace{\frac{S-s}{s-y}}_{\geq 0} \cdot [g(s) - g(y)] \\ \iff g(y) &\geq g(s). \end{aligned}$$

(3) For any y_1, y_2 satisfying $y_1 < y_2 < s \leq S$, by K -convexity from (14.40) we have

$$K + g(S) \geq g(y_2) + \frac{S-y_2}{y_2-y_1} (g(y_2) - g(y_1)).$$

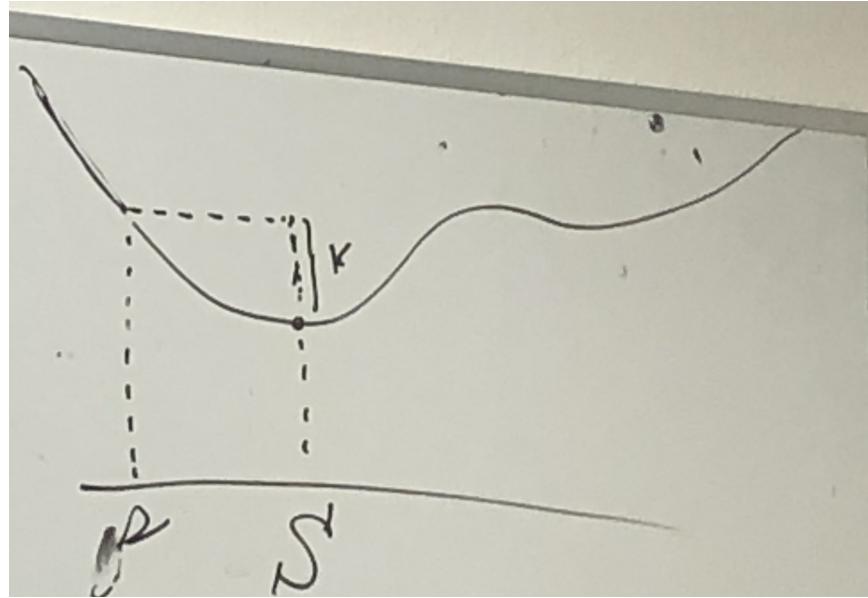


Figure 14.8: default

By (2) above, $g(y_2) > g(s) = g(S) + K$. Therefore

$$0 > g(S) + K - g(y_2) \geq \underbrace{\frac{S - y_2}{y_2 - y_1}}_{>0} (g(y_2) - g(y_1)), \implies g(y_1) > g(y_2).$$

- (4) Note that $g(y) \leq g(z) + K$ holds when $y = z$ (trivially), $y = S$ (because S is a global minimizer of g), or $y = s$ (because $g(S) + K = g(s) \leq g(z) + K$ for all z). Since $s \leq y \leq z$, we only need to consider two cases.

- **Case 1:** Assume $S < y < z$. By K -convexity from (14.40),

$$K + g(z) \geq g(y) + \underbrace{(z - y)}_{>0 \text{ (assumption)}} \cdot \begin{pmatrix} >0 \text{ (} S \text{ global min)} \\ \overbrace{\frac{g(y) - g(S)}{y - S}} \\ >0 \text{ (assumption)} \end{pmatrix} \geq g(y).$$

- **Case 2:** Assume $s < y < S$. By K -convexity from (14.40),

$$\begin{aligned} g(s) &= K + g(S) \geq g(y) + (S - y) \left(\frac{g(y) - g(s)}{y - s} \right) \\ \iff & \left(1 - \underbrace{\frac{y - S}{y - s}}_{>y-S}^{>0} \right) g(s) \geq \left(1 - \frac{y - S}{y - s} \right) g(y) \\ \iff & g(s) \geq g(y). \end{aligned}$$

Then $g(y) \leq g(s) = g(S) + K \leq g(z) + K$.

□

We are now ready to analyze inventory control with fixed costs. Suppose that

$$C(u) = \begin{cases} K + cu, & u > 0, \\ 0, & \text{otherwise} \end{cases}$$

so k is the fixed cost.

Theorem 14.22.5. When there is a fixed cost of order, an (s, S) policy is optimal; that is, for any period k there exists a pair of thresholds (s_k, S_k) with $s_k \leq S_k$ such that

$$\mu_k^*(x_k) = \begin{cases} S_k - x_k, & x_k \leq s_k, \\ 0, & \text{otherwise.} \end{cases} \quad (14.41)$$

Proof. Again let $y := x_k + u_k$. Define $G_k : \mathbb{R} \rightarrow \mathbb{R}$ as follows;

$$G_k(y) := cy + \mathbb{E}_{w_k} [\mathcal{G}(y - w_k) + J_{k+1}(y - w_k)]. \quad (14.42)$$

Then

$$\begin{aligned} J_N(x_N) &= 0, \\ J_k(x_k) &= \min_{u_k > 0} \{C(u_k) + \mathbb{E}[\mathcal{G}(x_k + u_k)] + \mathbb{E}[J_{k+1}(x_k + u_k - w_k)]\} \\ &= \min \left\{ G_k(x_k) - cx_k, \min_{u_k > 0} \{K + G_k(x_k + u_k) - cx_k\} \right\} \\ &= -cx_k + \min \left\{ G_k(x_k), \min_{y > x_k} [k + G_k(y)] \right\}, \quad k \in \{0, \dots, N = 1\}. \end{aligned}$$

where the third line follows because the cost is the minimum of the cost if no order is made (the cost on the left) or the cost if an order is made (the cost on the right), and the fourth line follows by the change of variable $y := x_k + u_k$.

If $G_k(y)$ is convex in y , the result follows quickly, as in the no fixed costs case covered in Theorem 14.22.2 (see Figure 14.9). In particular, the policy (14.41) is optimal, where S_k is a minimizer of $G_k(\cdot)$ and s_k is the smallest value of y for which $G_k(y) = K + G_k(S_k)$.

However, when $K > 0$ it is not necessarily true that G_k is convex. This means it could have multiple minima. Consider Figure 14.10. If it were true that G_k had a form like this, the optimal policy would be to order $(S - x)$ in interval I, zero in intervals II and IV, and $(\tilde{S} - x)$ in interval III.

But it turns out $G_k(\cdot)$ is K -convex, so the form of G_k in Figure 14.10 is impossible. If y_0 is the local maximum in the interval III, we must have for sufficiently small $b > 0$

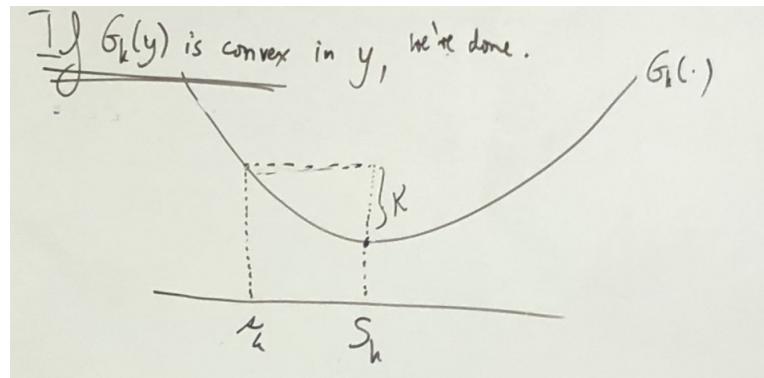


Figure 14.9: If $G_k(\cdot)$ is convex, the policy (14.41) is optimal, where S_k is a minimizer of $G_k(\cdot)$ and s_k is the smallest value of y for which $G_k(y) = K + G_k(S_k)$. However, G_k is not necessarily convex.

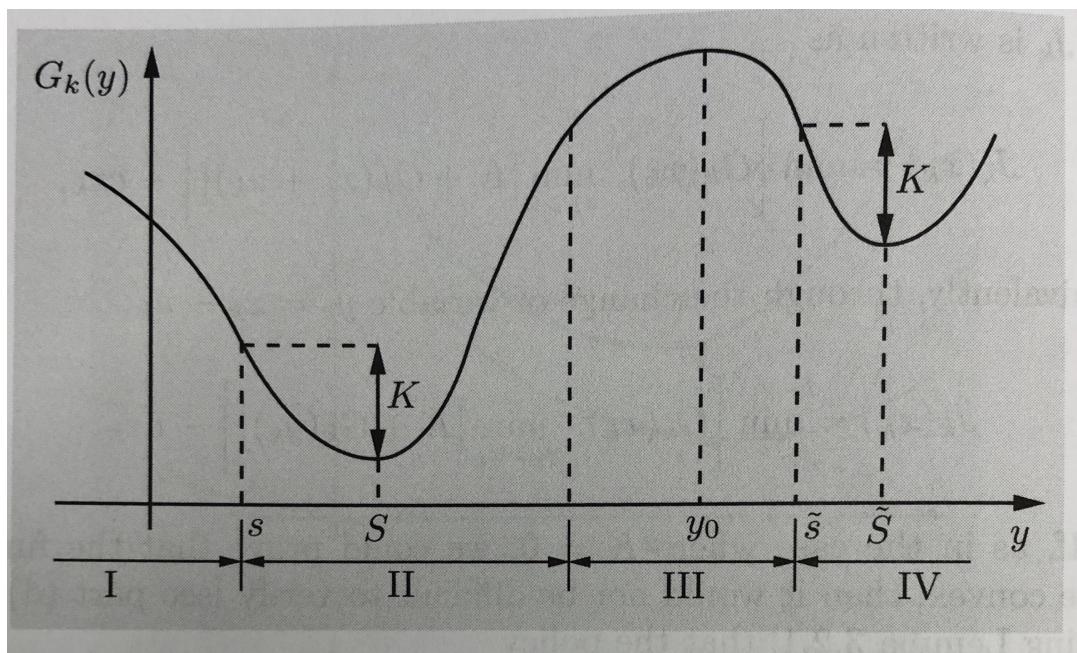


Figure 14.10: Figure 3.2.2 in [Bertsekas \[2012a\]](#).

$$\frac{G_k(y_0) - G_k(y_0 - b)}{b} \geq 0,$$

and from the definition of K -convexity (14.39) it follows that

$$K + G_k(\tilde{S}) \geq G_k(y_0),$$

contradicting the construction shown in Figure 14.10. Then the result will follow from (d)(4) of Proposition 14.22.4, because it is optimal to order up to the minimum if you have less inventory than s_k , but just to the right of s_k the cost of ordering exceeds the savings from ordering, and part (d)(4) of Proposition 14.22.4 guarantees that the cost of ordering will never again go below the savings from ordering. So the result is immediate from Lemma 14.22.6.

□

Lemma 14.22.6. G_k are continuous and K -convex for all k , and $G_k(y) \rightarrow \infty$ as $|y| \rightarrow \infty$. Further, $J_k(\cdot)$ are continuous and K -convex for all k .

Proof of Lemma 14.22.6. We will prove the result by induction. The base case is trivial since $J_N(\cdot) = 0$. Suppose $J_{\ell+1}(\cdot)$ is K -convex. Then

$$G_\ell(y) = \underbrace{cy}_{0-\text{convex}} + \underbrace{\mathbb{E} G(y - w_\ell)}_{0-\text{convex}} + \underbrace{\mathbb{E} [J_{\ell+1}(y - w_\ell)]}_{K-\text{convex by (c) of Proposition 14.22.4}}$$

Therefore $G_\ell(y)$ is K -convex. Therefore by (d) of Proposition 14.22.4, there exist (s_ℓ, S_ℓ) such that

$$G_\ell(S_\ell) = \min_y G_\ell(y), \quad G_\ell(s_\ell) = G_\ell(S_\ell) + K.$$

Then

$$\begin{aligned} J_\ell(x_\ell) &= -c \cdot x_\ell + \min\{G_\ell(x_\ell), \min_{y>x_\ell} [K + G_\ell(y)]\} \\ &= -cx_\ell + \begin{cases} \overbrace{K + G_\ell(S_\ell)}^{=G_\ell(s_\ell)}, & x_\ell \leq s_\ell, \\ G_\ell(x_\ell), & x_\ell > s_\ell \end{cases} \\ &= -cx_\ell + \begin{cases} G_\ell(s_\ell), & x_\ell \leq s_\ell, \\ G_\ell(x_\ell), & x_\ell > s_\ell. \end{cases} \end{aligned} \tag{14.43}$$

(See Figure 14.11 for an illustration of J_ℓ .) J_ℓ is continuous. Is $J_\ell(\cdot)$ convex? No. Consider the point s_ℓ . Left derivative of J_ℓ at s_ℓ is $-c + 0$, right derivative is $-c + \lim_{x \rightarrow s_\ell^+} G'_\ell(x) < -c + 0$ (because G_ℓ is still decreasing at s_ℓ —again see Figure 14.10). If the function were convex, the derivative would be nondecreasing, so this violates convexity.

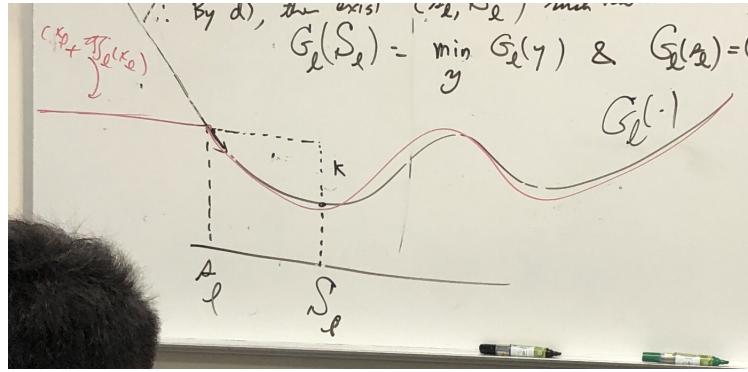


Figure 14.11: The red line is the right part of (14.43) ($J_\ell(x_\ell) + cx_\ell$).

However, we can show that J_ℓ is K -convex. We know from Equation (14.39) in Definition 14.7 that we must verify

$$K + J_\ell(y + z) \geq J_\ell(y) + z \left(\frac{J_\ell(y) - J_\ell(y - b)}{b} \right) \quad (14.44)$$

for all $y \in \mathbb{R}$, for all $z \geq 0, b \geq 0$. There are three cases to consider.

1. $y \geq s_\ell$: Then $y + z \geq s_\ell$. If $y - b \geq s_\ell$, then examining (14.43), the function $J_\ell(\cdot)$ at these points is $-cx_\ell + G_\ell(x_\ell)$ (the sum of a linear function and a K -convex function), so (14.44) holds and K -convexity follows. Suppose $y - b < s_\ell$. We need to verify (14.44); that is,

$$\begin{aligned} K + J_\ell(y + z) &\geq J_\ell(y) + z \left(\frac{J_\ell(y) - J_\ell(y - b)}{b} \right) \\ \iff (\text{by (14.43)}) \quad K + \underbrace{G_\ell(y + z) - c(y + z)}_{=J_\ell(y+z), \text{ since } y+z \geq s_\ell} &\geq \underbrace{G_\ell(y) - cy}_{=J_\ell(y), \text{ since } y \geq s_\ell} + z \left(\frac{\overbrace{G_\ell(y) - cy}^{=J_\ell(y), \text{ since } y \geq s_\ell} - \overbrace{G_\ell(s_\ell) + c(y - b)}^{=J_\ell(y-b), \text{ since } y-b < s_\ell}}{b} \right) \\ \iff \quad K + G_\ell(y + z) - cz &\geq G_\ell(y) + z \left(\frac{G_\ell(y) - G_\ell(s_\ell)}{b} - c \right) \\ \iff \quad K + G_\ell(y + z) &\geq G_\ell(y) + z \left(\frac{G_\ell(y) - G_\ell(s_\ell)}{b} \right), \end{aligned} \quad (14.45)$$

so proving (14.45) is equivalent to proving K -convexity. We will look at two sub-cases:

- **Sub-case 1:** $G_\ell(y) \geq G_\ell(s_\ell)$. By K -convexity of G_ℓ , using (14.40),

$$K + G_\ell(y + z) \geq G_\ell(y) + z \left(\frac{G_\ell(y) - G_\ell(s_\ell)}{y - s_\ell} \right) \geq G_\ell(y) + z \left(\frac{G_\ell(y) - G_\ell(s_\ell)}{b} \right)$$

where the last step follows because $y - b < s_\ell \iff 1/(y - s_\ell) > 1/b$.

- **Sub-case 2:** $G_\ell(y) < G_\ell(s_\ell)$. Then

$$\begin{aligned}
K + G_\ell(y + z) &\geq K + G_\ell(S_\ell) \\
&= G_\ell(s_\ell) \\
&> G_\ell(y) \quad (\text{by assumption of sub-case}) \\
&\geq G_\ell(y) + z \left(\overbrace{\frac{G_\ell(y) - G_\ell(s_\ell)}{b}}^{<0} \right),
\end{aligned}$$

verifying (14.45) and proving K -convexity in this case.

2. $y \leq y + z \leq s_\ell$: In this region, from (14.43) we see that J_ℓ is linear because $y - b \leq y \leq y + z \leq s_\ell$, so all of the J_ℓ in (14.44) are in the region where J_ℓ is constant, so K -convexity should hold trivially. Let's check: (14.44) becomes

$$\begin{aligned}
K - c(y + z) + G_\ell(s_\ell) &\geq -cy + G_\ell(s_\ell) + z \left(\frac{-cy + G_\ell(s_\ell) + c(y - b) - G_\ell(s_\ell)}{b} \right) \\
&\iff K - cz \geq z \left(\frac{-cb}{b} \right),
\end{aligned}$$

so the inequality holds as desired, proving K -convexity in this case.

3. $y \leq s_\ell \leq y + z$: To establish K -convexity, from (14.44) we need to have

$$\begin{aligned}
K + J_\ell(y + z) &\geq J_\ell(y) + \frac{z}{b} (J_\ell(y) - J_\ell(y - b)) \\
&\iff K + \underbrace{G_\ell(y + z) - c(y + z)}_{=J_\ell(y+z) \text{ since } y+z \geq s_\ell} \geq \underbrace{G_\ell(s_\ell) - cy}_{=J_\ell(y) \text{ since } y \leq s_\ell} + \frac{z}{b} \left(\underbrace{G_\ell(s_\ell) - cy}_{=J_\ell(y) \text{ since } y \leq s_\ell} - \underbrace{G_\ell(s_\ell) + c(y - b)}_{=J_\ell(y-b) \text{ since } y-b \leq s_\ell} \right) \\
&\iff K + G_\ell(y + z) - c(y + z) \geq G_\ell(s_\ell) - cy - cz \\
&\iff K + G_\ell(y + z) \geq G_\ell(s_\ell)
\end{aligned} \tag{14.46}$$

But (14.46) is always true because $G_\ell(s_\ell) = G_\ell(S_\ell) + K \leq G_\ell(y + z) + K$ (since $G_\ell(S_\ell)$ is a global minimum), proving K -convexity in this case.

Therefore we have established K -convexity (and continuity) of both $G_\ell(\cdot)$ and $J_\ell(\cdot)$. It also holds that $G_\ell(y) \rightarrow \infty$ as $|y| \rightarrow \infty$. Now recall (14.42): this shows that $G_{\ell-1}(\cdot)$ is K -convex, since it is the sum of something linear, something K -convex (by Proposition 14.22.4 (c)), and something K -convex (as we just showed). But since $w_{\ell-1}$ is bounded, $G_{\ell-1}$ is continuous and $G_{\ell-1}(y) \rightarrow \infty$ as $|y| \rightarrow \infty$, so by the previous argument $J_{\ell-1}$ is K -convex. We can repeat this continually to show the result. □

Remark 171. Also proved this in a 2000 paper “A single-unit approach to multi...” but the proof technique does not generalize to other problems as well (the way this proof does).

14.22.4 Capacity Allocation and Revenue Management

3 levels of revenue management:

1. Strategic: how to segment different markets and differentiate prices; which markets you go after, which subsets of customers, etc. (often done quarterly/annually.)
2. Tactical: (e.g. plane tickets: what's a good pricing strategy to maximize revenue? maybe save tickets for last minute when you can charge a lot?) calculate and update booking limits (done daily/weekly). Use forecasting, optimization, etc.
3. Booking Control/Execution: determine which booking to accept (done in real time)

Today: focus on tactical. 3 components:

1. **Resources:** units of capacities managed by suppliers. Example: seats on a flight leg, hotel room nights, rental car days. (We're interested in setting when resources are constrained.)
2. **Products:** what customers purchase. Each product corresponds to a combination of resources, for example, a ticket from LAX to JFK, may involve a layover (so 2 legs/resources), etc.
3. **Fare classes:** there are fares associated with end product (not just price, also things like layover time, bringing a carry-on, etc.). Each fare class is a combination of a price and restrictions on what/who can purchase a product.

A supplier controls

1. Sets of resources with a fixed and perishable capacity (e.g. plane seats perishable since can't sell tickets for seats on flights in the past).
2. A portfolio of products to offer to customers.
3. A set of fares associated with the end product. (has to do with setting prices, but main goal: the decision to open/close certain fare classes at each moment to maximize revenue.) Revenue: fare that you pay minus commission, etc.

Three problems in tactical revenue management:

1. **Single resource capacity allocation:** how many customers from different fare classes should we allow to book? ("single resource" e.g. direct flight or single night stay in hotel.)
2. **Network revenue management:** how should bookings be managed across a network of resources? (no known exact solution yet. we'll discuss after midterms)
3. **Overbooking:** how to manage bookings when faced with uncertain future no-shows? (standard ad-hoc methods.)

Today we'll focus on single resource capacity allocation.

Example 14.7 (Two-class capacity allocation (Littlewood's formula)). Suppose we have C seats on a plane flight leg on a given date. We have two fare classes: a discounted fair P_d and full fare P_f , with $P_f > P_d$. Suppose the discount fare demand is D_d (number of customers that will arrive with a discount fare) and the full fare demand is D_f . Suppose D_d and D_f are independent, and suppose D_d customers arrive before D_f . Observation: we want to reserve seats for full-fare passengers.

To start, look at marginal analysis. Suppose we have x seats remaining ($C - x$ sold). Focus on the x th seat. Should we open it to a discount passenger or should we sell it? Breakeven point is when $P_d = \mathbb{P}(D_f \geq x)P_f$.

If y^* denotes an **optimal protection level** (how many seats we want to reserve for high-demand customers), then $P_d \leq P_f \mathbb{P}(D_f \geq y^*)$ and $P_d > P_f \mathbb{P}(D_f \geq y^* + 1)$. (Will show this formally). (y^* is the largest number such that $P_d \leq P_f \mathbb{P}(D_f \geq y^*)$). So

$$\begin{aligned} & P_f \mathbb{P}(D_f \geq y^* + 1) < P_d \leq P_f \mathbb{P}(D_f \geq y^*) \\ \iff & \mathbb{P}(D_f \geq y^* + 1) < \frac{P_d}{P_f} \leq \mathbb{P}(D_f \geq y^*) \\ \iff & 1 - \mathbb{P}(D_f \geq y^*) \leq 1 - \frac{P_d}{P_f} < 1 - \mathbb{P}(D_f \geq y^* + 1) \\ \iff & \mathbb{P}(D_f < y^*) \leq 1 - \frac{P_d}{P_f} < \mathbb{P}(D_f < y^* + 1) \\ \implies & y^* = F_f^{-1}(1 - P_d/P_f), \end{aligned}$$

where F_f is the cdf of demand for full-fare passengers. ($1 - P_d/P_f$ quantile). This is known as **Littlewood's formula**. (Recall: $F^{-1}(\alpha) := \inf\{x : F(x) \geq \alpha\}$.) More formally, the expected revenue given a booking limit b (maximum number of seats sold to discount passengers) is

$$\begin{aligned} R(b) &= P_d \mathbb{E}_{D_d} [\min\{b, D_d\}] + P_f \mathbb{E}_{D_f} [\min\{D_f, C - \min\{b, D_d\}\}] \\ &= P_d \mathbb{E}_{D_d} [\min\{b, D_d\}] + P_f \mathbb{E}_{D_f} [\min\{D_f, \max\{C - b, C - D_d\}\}] \end{aligned}$$

Assume D_d and D_f are continuous (so we can take derivatives) and assume we can interchange derivatives and expectations. Then (using almost-everywhere differentiability of the min function)

$$\begin{aligned} R'(b) &= P_d \mathbb{E}[\mathbb{1}\{b < D_d\}] - P_f \mathbb{E}[\mathbb{1}\{b < D_d\} \cdot \mathbb{1}\{D_f > C - b\}] \\ &= P_d \mathbb{P}(b < D_d) - P_f \mathbb{P}(b < D_d) \cdot \mathbb{P}(D_f > C - b) \\ &= \mathbb{P}(b < D_d) [P_d - P_f \mathbb{P}(D_f > C - b)] \\ \implies \text{sgn}(R'(b)) &= \text{sgn} \left(\underbrace{P_d - P_f \mathbb{P}(D_f > C - b)}_{\text{decreasing in } b} \right). \end{aligned}$$

Set equal to 0 to yield $P_d = P_f \mathbb{P}(D_f > C - b^*) \iff C - b^* = F_f^{-1}(1 - P_d/P_f)$. See Figure 14.12.

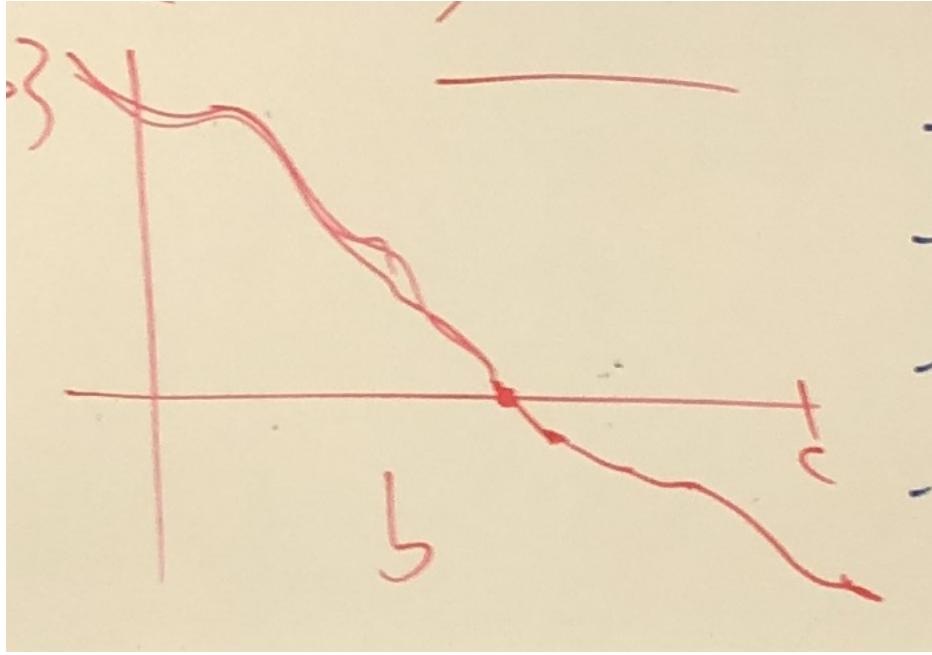


Figure 14.12: Figure for example 14.7.

Example 14.8 (n -class capacity allocation). n fare classes: $P_1 > P_2 > \dots > P_n$. Demand for class i : D_i , all independent. Sequential arrival of demand. Look at as DP. Let x be the number of seats remaining. Let $V_j(x)$ be the max expected seat that can be offered for class $j, j-1, j-2, \dots, 2, 1$, given that we have x seats remaining at the beginning of state j . Goal: compute $V_n(C)$. Initialization: $V_1(x) = P_1 \mathbb{E} \min\{x, D_1\}$,

$$V_j(x) = \max_{y_{j-1} \leq x} \left\{ \underbrace{P_j \mathbb{E} [\min\{D_j, x - y_{j-1}\}] + \mathbb{E} [V_{j+1} (\max\{y_{j-1}, x - D_j\})]}_{W_j(x, y_{j-1})} \right\}$$

where y_{j-1} is the amount of seats reserved for class $j-1, j-2, \dots, 2, 1$.

Theorem 14.22.7. For the capacity allocation problem with C seats (Example 14.8), the optimal booking control policy is given a nested protection level $y_1^* \leq \dots \leq y_n^* = C$. (e.g., y_2^* is the number of seats reserved for class 1 and 2, y_3 is left for 3, 2, and 1, etc. Fixed number independent of remaining capacity.)

For ease of exposition, assume demand is continuous (so we can take derivatives. can just use finite differences if you want to be discrete, just a pain.). First we will need a lemma.

Lemma 14.22.8. Suppose demand and inventory are continuous. Then for each $j \geq 1$,

1. $V_j(\cdot)$ is an increasing and concave function.
2. There exist optimal protection levels y_j^* for $j \in [n]$ that maximize expected revenue, given by the solutions to $V'_{j-1}(y_{j-1}^*) = P_j$.
3. $V'_j(x) \geq V'_{j-1}(x)$ for all x .

Proof. We'll prove that $V_j(\cdot)$ is an increasing and concave function by induction on j . For $j = 1$, $V_1(x) = P_1 \mathbb{E}[\min\{x, D_1\}]$, so it's trivially true. Next, assume that the result holds for $V_{j-1}(\cdot)$. We'll prove that it's true for $V_j(\cdot)$. For all $x \geq y$,

$$W_j(x, y) = P_j \mathbb{E}[\min\{D_j, x - y\}] + \mathbb{E}[V_{j+1}(\max\{y, x - D_j\})], \quad V_j(x) = \min_{y \leq x} W_j(x, y).$$

Then

$$\begin{aligned} \frac{\partial}{\partial y} W_j(x, y) &= -P_j \mathbb{E}[\mathbb{1}\{D_j > x - y\}] + \mathbb{E}[V'_{j-1}(y) \cdot \mathbb{1}\{x - D_j < y\}] \\ &= \mathbb{P}(D_j > x - y)(-P_j + V'_{j-1}(y)). \end{aligned}$$

By the inductive hypothesis, $V_{j-1}(\cdot)$ is concave, so $-P_j + V'_{j-1}(y)$ is decreasing in y . Notice that $V'_{j-1}(0) \geq P_{j-1} > P_j$ since $V'_{j-1}(0)$ is the marginal revenue. Therefore there exists y_{j-1}^* such that for $y < y_{j-1}^*$ $\frac{\partial}{\partial y} W_j(x, y)$ is positive and for $y > y_{j-1}^*$ $\frac{\partial}{\partial y} W_j(x, y)$ is negative. Then

$$V_j(x) = \max_{y \leq x} W_j(x, y) = W_j(x, \min\{x, y_{j-1}^*\})$$

Then the optimal protection level y_{j-1}^* for class $j-1, j-2, \dots, 2, 1$ is the value such that

1. For continuous demand: $V'_{j-1}(y_{j-1}^*) = P_j$. (notice that this is the same as in the two-class case.)
2. For discrete demand (**need for Poisson case in homework 2 question 6**): $y_{j-1}^* = \max\{y : P_j < \Delta V_{j-1}(y)\}$ where $\Delta V_{j-1}(y) = V_{j-1}(y) - V_{j-1}(y-1)$.

Consider the continuous case.

$$V_j(x) = W_j(x, \min\{x, y_{j-1}^*\}) \tag{14.47}$$

$$= P_j \mathbb{E}[\min\{D_j, (x - y_{j-1}^*)^+\}] + \mathbb{E}[V_{j-1}(\max\{x - D_j, \min\{x, y_{j-1}^*\}\})] \tag{14.48}$$

$$= \begin{cases} V_{j-1}(x), & x \leq y_{j-1}^* \\ P_j \mathbb{E}[\min\{D_j, x - y_{j-1}^*\}] + \mathbb{E}[V_{j-1}(\max\{x - D_j, y_{j-1}^*\})], & x \geq y_{j-1}^* \end{cases} \tag{14.49}$$

$$\implies V'_j(x) = \begin{cases} V'_{j-1}(x), & x \leq y_{j-1}^* \\ P_j \mathbb{E}[\mathbb{1}\{D_j > x - y_{j-1}^*\}] + \mathbb{E}[V'_{j-1}(x - D_j) \mathbb{1}\{x - D_j > y_{j-1}^*\}], & x \geq y_{j-1}^* \end{cases} \tag{14.50}$$

Goal: show $V'_j(x)$ is decreasing in x . We already know $V'_{j-1}(x)$ is decreasing in x by inductive hypothesis. So we focus on the other part (when $x \geq y_{j-1}^*$).

$$\begin{aligned} &P_j \mathbb{E}[\mathbb{1}\{D_j > x - y_{j-1}^*\}] + \mathbb{E}[V'_{j-1}(x - D_j) \mathbb{1}\{x - D_j > y_{j-1}^*\}] \\ &= P_j \mathbb{E}[1 - \mathbb{1}\{D_j < x - y_{j-1}^*\}] + \mathbb{E}[V'_{j-1}(x - D_j) \mathbb{1}\{x - D_j > y_{j-1}^*\}] \\ &= P_j + \mathbb{E}[\mathbb{1}\{D_j < x - y_{j-1}^*\}(-P_j + V'_{j-1}(x - D_j))] \end{aligned} \tag{14.51}$$

Note for each D_j , the expression inside the expectation operator is nonincreasing in x (see Figure 14.13). So it holds over expectations that $V'_j(x)$ is nonincreasing in x . Now we want to show that $V'_j(x) \geq V'_{j-1}(x)$ for all x . Again, it holds trivially that if $x \leq y_{j-1}^*$ then $V'_j(x) = V'_{j-1}(x) \geq V'_{j-1}(x)$, so we focus on the case $x \geq y_{j-1}^*$. Note that $\mathbb{1}\{x - D_j \geq y_{j-1}^*\} \geq \mathbb{1}\{x \geq y_{j-1}^*\}$ and that since $V'_{j-1}(\cdot)$ is nonincreasing $V'_{j-1}(x - D_j) \geq V'_{j-1}(x)$. Then from (14.51)

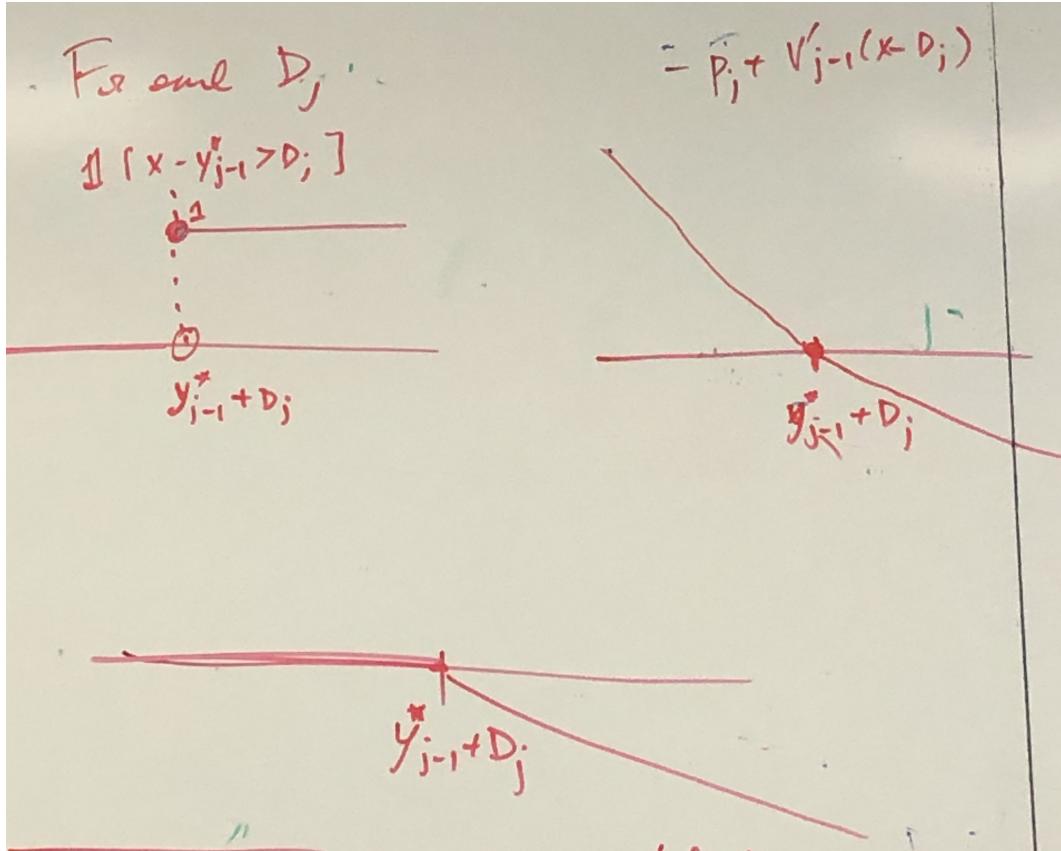


Figure 14.13: The argument of the expectation operator in (14.51) is nonincreasing in x regardless of the value of the random variable D_j , so the expectation itself is nonincreasing in x .

$$\begin{aligned} V'_j(x) &= P_j + \mathbb{E} [\mathbb{1}\{x - D_j \geq y_{j-1}^*\}(-P_j + V'_{j-1}(x - D_j))] \\ &\geq P_j + \mathbb{E} [\mathbb{1}\{x \geq y_{j-1}^*\}(-P_j + V'_{j-1}(x))] \\ &= V'_{j-1}(x). \end{aligned}$$

□

Now we can prove the main result.

Proof of Theorem 14.22.7. It only remains to show that the optimal protection levels are nested. We want to show that $y_j^* \geq y_{j-1}^*$. From Lemma 14.22.8 we know that the optimal protection levels are given by $V'_j(y_j^*) = P_{j+1}$. What does $V'_j(\cdot)$ look like? It's given in (14.50). Since $P_j > P_{j+1}$ and per Lemma 14.22.8 $V'_j(x) \geq V'_{j-1}(x)$ for all x , it holds that $y_{j-1}^* < y_j^*$. See a depiction in Figure 14.14.

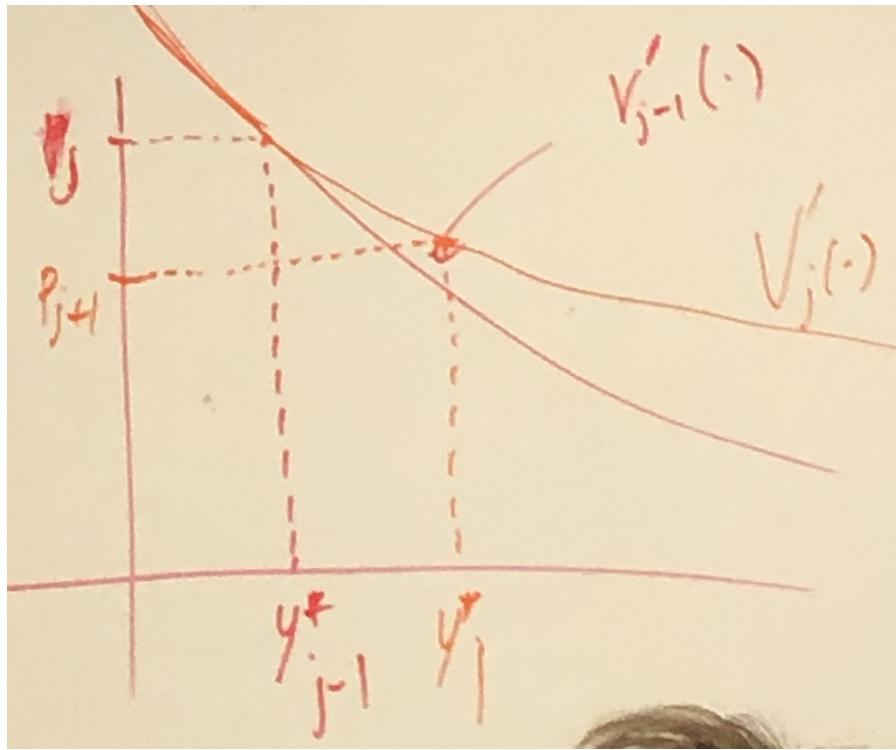


Figure 14.14: Illustration of nested protection levels from Theorem 14.22.7.

□

14.22.5 Optimal Stopping (Section 3.4 of Bertsekas [2012a])

Example 14.9 (Optimal stopping). You own an asset. You are given money $w_h \geq 0$ in period h . If you accept an offer, you can invest the money at a risk-free rate $r > 0$. If you reject the offer, you wait for the next one. Assume w_0, w_1, \dots, w_{N-1} are independent random variables. Goal: maximize the total reward (money) at the end of period N . Now

$$J_k(x) = \max \left\{ \underbrace{(1+r)^{N-k}x}_{\text{if you stop}}, \underbrace{\mathbb{E}[J_{k+1}(w_k)]}_{\text{if you don't stop}} \right\}, \quad J_N(x) = x.$$

Optimal policy: stop (accept the current offer) if and only if

$$x \geq \frac{\mathbb{E}_{w_k}[J_{k+1}(w_k)]}{(1+r)^{N-k}} := \underbrace{\alpha_k}_{\text{threshold in period } k}.$$

Claim: If w_0, w_1, \dots, w_{N-1} are i.i.d., then $\alpha_0 \geq \alpha_1 \geq \dots \geq \alpha_{N-1}$.

Let $V_k(x) := J_k(x)/(1+r)^{N-k}$. We have $V_N(x) = x$,

$$V_k(x) = \max \left\{ x, \underbrace{\frac{\mathbb{E}[V_{k+1}(w)]}{1+r}}_{\text{state independent: no dependence on } x} \right\}.$$

We'll show that $V_0(\cdot) \geq V_1(\cdot) \geq \dots \geq V_{N-1}(\cdot)$. Base case: $V_{N-1}(x) \geq V_N(x)$, obvious. Next:

Suppose $V_{k+1}(\cdot) \geq V_{k+2}(\cdot)$. Then

$$\begin{aligned} V_k(x) &= \max \left\{ x, \frac{\mathbb{E}[V_{k+1}(w)]}{1+r} \right\} \\ &\geq \max \left\{ x, \frac{\mathbb{E}[V_{k+2}(w)]}{1+r} \right\} \\ &= V_{k+1}(x). \end{aligned}$$

Example 14.10 (Exotic options, optimal stopping). Suppose that the price of your asset (option) depends on the prices of $n = 10$ other assets. So the state is (x_1, \dots, x_{10}) . Then

$$J_k(x_1, \dots, x_{10}) = \max \left\{ \underbrace{G(x_1, \dots, x_{10})}_{\text{stop now}}, \underbrace{\mathbb{E}[J_{k+1}(\tilde{x}_1, \dots, \tilde{x}_{10})]}_{\text{don't stop now}} \right\}$$

where $J_k(x_1, \dots, x_{10})$ is the current prices of the 10 assets that influence/determine the value of your “option” or asset and $G(x_1, \dots, x_{10})$ is the reward for selling, and

$$J_N(x_1, \dots, x_N) = g(x_1, \dots, x_{10}).$$

Suppose that x_i takes values $\{1, \dots, 100\}$.

14.22.6 Infinite Horizon (Sections 1.2, 1.5 and 2.1 of [Bertsekas \[2012b\]](#); starts on p. 210 of pdf for Volume 3)

Restatement of setup: infinite horizon problems with discounted cost:

$$x_{k+1} = f(x_k, u_k, w_k)$$

$$J^*(x_0) = \min_{\pi \in \Pi} \mathbb{E} \left[\sum_{k=0}^{\infty} \alpha^k g(x_k, \mu_k(x_k), w_k) \mid x_0 \right]$$

Stationary discrete-time systems

$$x_{k+1} = f(x_k, u_k, w_k), \quad k \in \{0, 1, \dots\}$$

where for all k , $x_k \in \mathcal{X}$ is the state at time k , $u_k \in \mathcal{U}$ is the control, and we require $u_k \in \mathcal{U}(x_k)$ (that is, there is a set of allowable controls given state x_k , and $w_k \in \mathcal{W}$ are disturbances.

Important: the random disturbances $w_k : k \in \{0, 1, 2, \dots\}$ are characterized by a transition probability $\mathbb{P}(\cdot | x_k, u_k)$ that is independent of k . (only dependent on state and control; not time. Nothing indexed by time; assume process is stationary.) Also, $w_k \perp w_{k-1}, w_{k-2}, \dots, w_0$.

Given an initial state x_0 , we want to find a policy $\Pi = \{\mu_0, \mu_1, \mu_2, \dots\}$ where $\mu_k : \mathcal{X} \rightarrow \mathcal{U}$ with $\mu_k(x_k) \in \mathcal{U}(x_k)$ that minimizes the cost for

$$J_\pi(x_0) := \limsup_{N \rightarrow \infty} \mathbb{E}_{w_0, w_1, \dots} \left[\sum_{k=0}^N \alpha^k g(x_k, \mu_k(x_k), w_k) \right]$$

where $\alpha \in (0, 1)$ is the discount factor (typically close to 1).

Let Π be the space of admissible policies. Our goal is to determine an optimal cost function $J^* : \mathcal{X} \rightarrow \mathbb{R}$

$$J_k^* = \min_{\pi \in \Pi} J_\pi(x).$$

Key reason to study infinite horizon problems: in most cases, an optimal policy is stationary: $\Pi^* = \{\mu, \mu, \mu, \dots\}$. If the policy is stationary, we write $J_\mu(\cdot)$ (a policy is a sequence of functions mapping states to actions, but often in this case the policy is stationary, so the sequence is just the same function repeated). A stationary policy is optimal if $J_\mu(x) = J^*(x)$ for all $x \in \mathcal{X}$.

Definition 14.8 (MDP [Markov decision process] Assumption). We assume that the state space \mathcal{X} , the control set \mathcal{U} , and the disturbance space \mathcal{W} are all finite.

The MDP assumption corresponds to the classical finite-state Markov decision process. Let $\mathcal{X} = \{1, \dots, n\}$. The transition matrix is given by

$$P_{ij}(u) = \mathbb{P}(X_{k+1} = j | X_k = i, U_k = u).$$

We can write this using the system dynamics notation as follows:

$$x_{k+1} = f(x_k, u_k, w_k) = w_k$$

For each decision u ,

$$W_{ij}(u) = \{w \in \mathcal{W} | f(i, u, w) = j\}, \quad P_{ij}(u) = \mathbb{P}(W_{ij}(u) | i, u).$$

Example 14.11. $X = \{1, 2\}$, $U = \{A, B\}$.

$$\mathbb{P}_{ij}(u = A) = \begin{pmatrix} 1/2 & 1/2 \\ 3/4 & 1/4 \end{pmatrix}, \quad \mathbb{P}_{ij}(u = B) = \begin{pmatrix} 1/6 & 5/6 \\ 5/6 & 1/6 \end{pmatrix}$$

Define a random disturbance W as follows (we need to specify $\mathbb{P}(W = j \mid i, u)$):

$$\mathbb{P}(W = j \mid i, u) = \begin{cases} 1/2 \text{ for } j = 1, & 1/2 \text{ for } j = 2 \quad \text{if } i = 1, u = A \\ 3/4 \text{ for } j = 1, & 1/4 \text{ for } j = 2 \quad \text{if } i = 2, u = A \\ 1/6 \text{ for } j = 1, & 5/6 \text{ for } j = 2 \quad \text{if } i = 1, u = B \\ 5/6 \text{ for } j = 1, & 1/6 \text{ for } j = 2 \quad \text{if } i = 2, u = B \end{cases}$$

Given the MDP assumption, 2 key questions.

1. Does the optimal cost J^* satisfy some kind of Bellman equation?
2. How do we compute the optimal policy?

Motivation for the Bellman Equations

$J^*(x)$ is the optimal cost function (stationary). Will satisfy (guess, will prove)

$$J^*(x) = \min_{u \in \mathcal{U}(x)} \{\mathbb{E}[g(x, u, w)] + \alpha \mathbb{E}[J^*(f(x, u, w))]\}$$

Consider an arbitrary policy $\pi = \{\mu_0, \mu_1, \mu_2, \dots\}$. Suppose we consider the cumulative cost of the first n states and add some terminal cost $\alpha^n J(x_n)$. The expected total cost is

$$\mathbb{E}_{w_0, \dots, w_{n-1}} \left[\alpha^n J(x_n) + \sum_{k=0}^{n-1} \alpha^k g(x_k, \mu_k(x_k), w_k) \right]$$

Suppose we want to find the minimum cost of N states $H_N(x), \alpha^N J(x)$. For $h \in \{1, 2, \dots, N\}$,

$$H_{n-h}(x) = \min_{u \in \mathcal{U}(x)} \mathbb{E}_w [\alpha^{N-h} g(x, u, w) + H_{n-h+1}(f(x, u, w))].$$

$$\iff H_{n-h-1}(x) = \min_{u \in \mathcal{U}(x)} \mathbb{E}_w [\alpha^{N-h-1} g(x, u, w) + H_{n-h}(f(x, u, w))].$$

let $V_k(x) := \frac{H_{n-k}(x)}{\alpha^{N-k}}$. Then we have the following DP algorithm:

$$V_0(x) = J(x); \quad V_{k+1}(x) = \min_{u \in \mathcal{U}(x)} \mathbb{E}_w [g(x, u, w) + \alpha V_k(f(x, u, w))]$$

Intuition: $V_k(x)$ is the minimum net present value of the cost of an h -stage problem given that we start in state X .

Definition 14.9. A dynamic programming operator $T : \mathbb{R}^{|\mathcal{X}|} \rightarrow \mathbb{R}^{|\mathcal{X}|}$ is defined as follows: given $J : \mathcal{X} \rightarrow \mathbb{R}$, with $J \in \mathbb{R}^{|\mathcal{X}|}$, for all $x \in \mathcal{X}$, $TJ \in \mathbb{R}^{|\mathcal{X}|}$ where

$$(TJ)(x) := \min_{u \in \mathcal{U}(x)} \left\{ \mathbb{E}_w [g(x, u, w) + \alpha J(f(x, u, w))] \right\}$$

Important observation: TJ is the optimal cost for a one stage problem that has a state cost g and a terminal cost αJ .

Similarly, for any stationary policy $\mu : \mathcal{X} \rightarrow \mathcal{U}$ and $J : \mathcal{X} \rightarrow \mathbb{R}$ define $T_\mu : \mathbb{R}^{|\mathcal{X}|} \rightarrow \mathbb{R}^{|\mathcal{X}|}$ such that for all $x \in \mathcal{X}$

$$(T_\mu J)(x) := \mathbb{E}[g(x, \mu(x), w) + \alpha J(f(x, \mu(x), w))]$$

Notation: $T^k = T \circ T \circ \dots \circ T$. T_k is the optimal cost for the k -stage α -discounted problem with an initial state x , cost-per-state g , and terminal cost $\alpha^k J$.

Note; if $\Pi = \{\mu_0, \dots, \mu_{k-1}\}$, then the cost of the policy Π for the k -stage problem with initial state x , cost-per-state g , and terminal cost $\alpha^k J$ is $(T_{\mu_0} T_{\mu_1} \cdots T_{\mu_{k-1}} J)(x)$.

One last remark: since typically $g(x, u, w) \geq 0$, we have the inequality

$$(TJ)(x) \leq \alpha J(f(x, u, w)). \quad (14.52)$$

Definition 14.10 (Contraction Mapping (Section 1.5 of Bertsekas [2012b])). Let $(Y, \|\cdot\|)$ be a real normed vector space. A function $T : Y \rightarrow Y$ is said to be a **contraction mapping** if, for some $\alpha \in (0, 1)$, we have

$$\|Ty - Tz\| \leq \alpha \|y - z\|, \quad \forall y \in Y.$$

The scalar α is said to be the **modulus of contraction** of T .

(See also Definition 5.63. For more on contraction mappings, see Section 5.6.5.)

If Y is a Banach space (that is, complete under the norm $\|\cdot\|$), a contraction mapping $F : Y \rightarrow Y$ has a unique fixed point; that is, the equation $y = Fy$ has a unique solution y^* called the **fixed point** of F . Further, the sequence $\{y_k\}$ generated by the iteration $y_{k+1} = Fy_k$ converges to y^* starting from an arbitrary initial point y_0 .

We will want to show that the dynamic programming operator is a contraction mapping. It will be enough to show that the dynamic programming operator is **monotonic** and has **constant shift**.

Theorem 14.22.9 (Blackwell's Sufficient Conditions). Let $\mathbb{R}^{|X|}$ be a space of bounded functions $J : X \rightarrow \mathbb{R}$ with the sup metric. Let $T : \mathbb{R}^{|X|} \rightarrow \mathbb{R}^{|X|}$ be an operator satisfying two conditions:

1. **(Monotonicity)** If $J, J' \in \mathbb{R}^{|X|}$ and $J(x) \leq J'(x)$ for all $x \in X$, then $(TJ)(x) \leq (TJ')(x)$ for all $x \in X$.
2. **(Discounting)** There exists $\alpha \in (0, 1)$ such that

$$(T(J+c))(x) \leq (TJ)(x) + \alpha c \quad \forall J \in \mathbb{R}^{|X|}, c \geq 0, x \in X.$$

Then T is a contraction mapping with modulus α .

Proof. Let $J, J' \in \mathbb{R}^{|X|}$. Then

$$J(x) = J'(x) + J(x) - J'(x) \leq J'(x) + \sup_{y \in X} |J(y) - J'(y)| = J'(x) + \|J - J'\|_\infty, \quad \forall x \in X,$$

which we can write in shorthand as

$$J \leq J' + \|J - J'\|_\infty.$$

Properties (1) and (2) imply that for some $\alpha \in (0, 1)$

$$\begin{aligned} TJ \leq T(J' + \|J - J'\|_\infty) &\leq TJ' + \alpha\|J - J'\|_\infty & \iff TJ - TJ' \leq \alpha\|J - J'\|_\infty, \\ TJ' \leq T(J + \|J - J'\|_\infty) &\leq TJ + \alpha\|J - J'\|_\infty & \iff TJ' - TJ \leq \alpha\|J - J'\|_\infty. \end{aligned}$$

Combining these, we have

$$\begin{aligned} |(TJ)(x) - (TJ')(x)| &\leq \alpha\|J - J'\|_\infty \quad \forall x \in X \\ \implies \sup_{x \in X} |(TJ)(x) - (TJ')(x)| &\leq \alpha\|J - J'\|_\infty \\ \implies \|TJ - TJ'\|_\infty &\leq \alpha\|J - J'\|_\infty. \end{aligned}$$

□

Now we will show that these properties hold.

Theorem 14.22.10 (Properties of T and T_μ). 1. **Monotonicity:** (Lemma 1.1.1 in Bertsekas [2012b], p.9) for any $J : \mathcal{X} \rightarrow \mathbb{R}$ and $J' : \mathcal{X} \rightarrow \mathbb{R}$ such that $J(x) \leq J'(x)$ for all $x \in \mathcal{X}$, then

$$(T^k J)(x) \leq (T^k J')(x), \quad (T_\mu^k J)(x) \leq (T_\mu^k J')(x).$$

for any $k \geq 0$.

2. **Constant shift (Lemma 1.1.2 in Bertsekas [2012b], p. 9):** For each $k \geq 0$, $J : \mathcal{X} \rightarrow \mathbb{R}$ and scalar r ,

$$[T^k(J + r\mathbf{e})](x) = (T^k J)(x) + \alpha^k r, \quad [T_\mu^k(J + r\mathbf{e})](x) = (T_\mu^k J)(x) + \alpha^k r,$$

where \mathbf{e} is a vector of all 1s.

Proof of monotonicity (Lemma 1.1.1 in Bertsekas [2012b]). □

Proof of constant shift (Lemma 1.1.2 in Bertsekas [2012b]). □

Now we can show that the dynamic programming operator is a contraction mapping.

Theorem 14.22.11 (Proposition 1.2.6 in Bertsekas [2012b]). The dynamic programming operator T is a contraction mapping in the normed vector space $(\mathbb{R}^{|X|}, \|\cdot\|_\infty)$ (where $\|J\|_\infty = \sup_{x \in \mathcal{X}} |J(x)|$).

Proof. Theorem 14.22.10 shows that the sufficient conditions of Theorem 14.22.9 are satisfied for the dynamic programming operator T . □

(For more on contraction mappings, see Section 5.6.5.)

3 questions to prove (similar to Proposition 7.2.1, p. 214 of pdf of 3rd edition):

1. **Convergence of DP algorithm (second part of Proposition 1.5.1 in Bertsekas [2012b], p. 48; second part of Proposition 1.5.4, p. 53):** under the MDP assumption, for every $J : \mathcal{X} \rightarrow \mathbb{R}$ and for any policy $\mu : \mathcal{X} \rightarrow \mathcal{U}$, $J^* = \lim_{k \rightarrow \infty} T^k J$, $J_\mu = \lim_{h \rightarrow \infty} T_\mu^h J$.

note that

$$(TJ^*)(x) = \min_{u \in \mathcal{U}(x)} \{\mathbb{E}[g(x, u, w) + \alpha J^*(f(x, u, w))]\} = J^*(x).$$

Statement in book: If $T : \mathbb{R}^{|X|} \rightarrow \mathbb{R}^{|X|}$ is a contraction mapping with modulus $\alpha \in (0, 1)$, then $\{T^k J\}$ converges to J^* for any $J \in \mathbb{R}^{|X|}$, and we have

$$\|T^k J - J^*\| \leq \alpha^k \|J - J^*\|, \quad k \in \mathbb{N}.$$

notes from review on 2/11/10: J^* is the unique fixed point of T and J_μ is the unique fixed point of T_μ and $J^* = \lim_{k \rightarrow \infty} T^k J$ (used contraction mapping to prove).

2. **Bellman's equations (first part of Proposition 1.5.1 in Bertsekas [2012b], p. 48; first part of Proposition 1.5.4, p. 53).** The optimal cost J^* is the unique solution to the equation

$$J^*(x) = \min_{u \in \mathcal{U}(x)} \{\mathbb{E}[g(x, u, w) + \alpha J^*(f(x, u, w))]\} \tag{14.53}$$

That is, $J^* = TJ^*$. (Statement in book: "If $T : \mathbb{R}^{|X|} \rightarrow \mathbb{R}^{|X|}$ is a contraction mapping with modulus $\alpha \in (0, 1)$, then there exists a unique $J^* \in \mathbb{R}^{|X|}$ such that $J^* = TJ^*$.)

Similarly, for any stationary policy $\mu : \mathcal{X} \rightarrow \mathcal{U}$, the cost associated with μ is the unique solution to the following equation:

$$J_\mu(x) = \mathbb{E}[g(x, \mu(x), w) + \alpha J_\mu(f(x, \mu(x), w))]$$

That is, the only solution to the system of $n = |\mathcal{X}|$ equations $TJ = J$ is optimal.

3. **Optimal control.** A stationary policy μ^* is optimal if and only if $\mu^*(x)$ attains the minimum on the right hand side of the Bellman equation (14.53).

$$T_{\mu^*} J^* = TJ^* \iff J_{\mu^*} = J^*.$$

Proof of convergence of DP algorithm. Want to show: consider an arbitrary J . Consider the sequence $\{T^k J; k = 0, 1, \dots\}$; want to show is Cauchy. For any $m > 0$, want to show

$$\|J_{m+k} - J_k\|_\infty < \epsilon.$$

We have

$$\begin{aligned} \|J_{m+k} - J_k\|_\infty &= \left\| \sum_{i=1}^m (J_{k+i} - J_{k+i-1}) \right\|_\infty \\ &\leq \sum_{i=1}^m \|J_{k+i} - J_{k+i-1}\|_\infty \\ &\leq \sum_{i=1}^m \alpha^{k+i-1} \|J_1 - J_0\|_\infty \quad (\text{by Theorem 14.22.11}) \\ &= \|J_1 - J_0\|_\infty \alpha^k \sum_{i=1}^m \alpha^{i-1} \\ &\leq \frac{\|J_1 - J_0\|_\infty \alpha^k}{1 - \alpha} \end{aligned}$$

since by Theorem 14.22.11

$$\begin{aligned} \|J_{\ell+1} - J_\ell\|_\infty &= \|TJ_\ell - TJ_{\ell-1}\|_\infty \\ &\leq \alpha \|J_\ell - J_{\ell-1}\|_\infty \\ &\leq \alpha^2 \|J_{\ell-1} - J_{\ell-2}\|_\infty \\ &\vdots \\ &\leq \alpha^\ell \|J_1 - J_0\|_\infty \end{aligned}$$

Therefore $\{T^k J : k \geq 0\}$ is Cauchy, and complete. So $\lim_{h \rightarrow \infty} T^h J$ is well-defined.

□

By definition of $T^k J$ and the MDP assumption, the limit is the optimal cost $J^* = \lim_{k \rightarrow \infty} T^k J$.

Proof of statement about Bellman's Equation. Want to prove: J^* is the unique solution to the Bellman equation (14.53). First we will show it is a solution. For any $J : \mathcal{X} \rightarrow \mathbb{R}$,

$$\lim_{h \rightarrow \infty} T^h J = J^*.$$

So it must be that $TJ^* = J^*$ or else convergence is violated. Therefore J^* is a solution to the Bellman equation.

Suppose there exists $J' \neq J^*$ such that $TJ' = J'$. Then $T^3J' = T^2J' = TJ' = J'$, $T^kJ' = J'$ for all k . then ???

□

Proof of statement about Optimal control. Suppose that $TJ^* = T_\mu J^*$. Want to show that $J^* = J_\mu$.

$$J^* = TJ^* \text{ (by convergence of DP algorithm)} = T_\mu J^* \text{ (by hypothesis)}$$

So J^* is a fixed point of T_μ . By (2) T_μ has a unique fixed point given by J_μ . Therefore $J^* = J_\mu$.

Now suppose $J^* = J_\mu$. Want to show: $TJ^* = T_\mu J^*$.

$$J^* = J_\mu \iff TJ^* = T_\mu J_\mu = J_\mu \text{ (by 2)} = J^* \text{ (by hypothesis)} = TJ^* \text{ (by 1)}$$

□

Optimality control using matrix notation: Let $X = \{1, \dots, n\}$. $p_{ij}(u) = \mathbb{P}(X_{k+1} = j \mid X_k = i, u_k = u)$.

$$\begin{aligned} (TJ)(i) &= \min_{u \in \mathcal{U}(i)} \mathbb{E}[g(i, u, w) + \alpha J(f(i, u, w))] \\ &= \min_{u \in \mathcal{U}(i)} \sum_{j=i}^n P_{ij}(u) [g(i, u, j) + \alpha J(j)] \\ &= \min_{u \in \mathcal{U}(i)} \sum_{j=i}^n P_{ij}(u) g(i, u, j) + \alpha \sum_{j=i}^n P_{ij}(u) J(j) \\ \implies TJ(i) &= \min_{u \in \mathcal{U}(i)} \bar{g}(i, u) + \alpha \left[\underbrace{\begin{matrix} P(u) \\ n \times n \text{ matrix} \end{matrix}}_{n \times 1 \text{ vector}} \underbrace{\begin{matrix} J \\ n \times 1 \text{ vector} \end{matrix}}_i \right] \\ \iff \underbrace{TJ}_{n \times 1 \text{ vector}} &= \underbrace{\left[\min_{u \in \mathcal{U}(i)} \bar{g}(i, u) \right]}_{n \times 1 \text{ vector}} + \alpha \left[\underbrace{\begin{matrix} P(u) \\ n \times n \text{ matrix} \end{matrix}}_{n \times 1 \text{ vector}} \underbrace{\begin{matrix} J \\ n \times 1 \text{ vector} \end{matrix}} \right] \end{aligned}$$

Question; given a stationary policy μ , how do I compute $J\mu$?

$$(T_\mu J)(i) = \bar{g}(i, \mu(i)) + \alpha J(j) \sum_{j=i}^n P_{ij}(\mu(i)) J(j)$$

Denote J as an n -vector, likewise with TJ . Denote

$$P_\mu = \begin{pmatrix} P_{11}(\mu(1)) & P_{12}(\mu(1)) & \cdots & P_{1n}(\mu(1)) \\ P_{21}(\mu(2)) & P_{22}(\mu(2)) & \cdots & P_{2n}(\mu(2)) \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1}(\mu(n)) & P_{n2}(\mu(n)) & \cdots & P_{nn}(\mu(n)) \end{pmatrix}$$

where for example $P_{12}(\mu(1))$ is the probability that if I have policy μ and I'm in state 1 I will transition to state 2. And

$$\bar{g}_\mu = \begin{pmatrix} \bar{g}(1, \mu(1)) \\ \vdots \\ \bar{g}(n, \mu(n)) \end{pmatrix}$$

Then $T_\mu J = \bar{g}_\mu + \alpha P_\mu J$. J_μ is the unique fixed point of T_μ .

$$\begin{aligned} T_\mu J_\mu &= J_\mu \\ J_\mu &= \bar{g}_\mu + \alpha P_\mu J_\mu \\ J_\mu &= (I - \alpha P_\mu)^{-1} g_\mu \end{aligned}$$

although this is a bad way to compute because if α is large (e.g. 0.9999), matrix could be very ill-conditioned since largest eigenvalue of a transition matrix is 1.

14.22.7 Value Iterations and Policy Iterations (Sections 2.2 and 2.3 of Bertsekas [2012b]; starts on p. 210 of pdf for Volume 3)

Question: how do I compute J^* and the optimal policy?

1. VI: value iteration (also called successive approximation)

Pick k_0 and start with some J_0 , apply the DP operator T k_0 times, output $T^{k_0} J_0 = \hat{J}$, use \hat{J} as an approximation for J^* , find a policy (“greedy policy”) μ such that $T\hat{J} = T_\mu \hat{J}$. Recall

$$(T\hat{J})(x) = \min_{u \in \mathcal{U}(x)} \left\{ \mathbb{E} \left[g(x, u, w) + \alpha \hat{J}(f(x, u, w)) \right] \right\}$$

Questions:

- (a) how should we pick k ? (need error bound.)
- (b) What is the difference between J_μ and J^* ? Want to show: if \hat{J} is close to J^* , then J_μ is also close to J^* . (cost of your policy in practice will be close to optimal.) Important distinction: $\hat{J} \neq J_{\mu_k}$ (\hat{J} may not be achievable by any policy, let alone a stationary policy).

First question: trivial error bound: recall

$$\|T^k J - J^*\|_\infty = \|T^k J - T^k J^*\|_\infty \leq \alpha^k \|J - J^*\|_\infty$$

(see also Equation (7.9) in Bertsekas 3rd edition Vol. 1, p. 215 of pdf)

Theorem 14.22.12 (Similar to Proposition 2.2.1 in Bertsekas [2012b]; in equation 7.17 (p. 216 of pdf) and 7.23 (p. 219 of pdf) in Bertsekas 3rd edition Vol. 1). Monotonic error bound: for any vector J and state i with $k \geq 0$,

$$(T^k J)(i) + \underline{c}_k \leq (T^{k+1} J)(i) + \underline{c}_{k+1} \leq J^*(i) \leq (T^{k+1} J)(i) + \bar{c}_{k+1} \leq (T^k J)(i) + \bar{c}_k$$

where

$$\underline{c}_k = \frac{\alpha}{1-\alpha} \min_{i \in [n]} \{(T^k J)(i) - (T^{k-1} J)(i)\}, \quad \bar{c}_k = \frac{\alpha}{1-\alpha} \max_{i \in [n]} \{(T^k J)(i) - (T^{k-1} J)(i)\}$$

So when gap between \underline{c}_k and \bar{c}_k is small, you know you are close to converging (because as k increases we know that value converges, so eventually the difference over which you are maximizing and minimizing goes to 0.)

Proof. We will only prove the lower bound (the proof of the upper bound is analogous). Let $\underline{\gamma}_1 := \min_{i \in [n]} \{(TJ)(i) - J(i)\}$. Then if e is the selection vector for the index of this minimum,

$$\begin{aligned} & \underline{\gamma}_1 e \preceq TJ - J \\ \iff & J + \underline{\gamma}_1 e \preceq TJ \end{aligned}$$

where \preceq denotes an element-wise vector inequality. Next recall from (14.52) that $TJ \preceq \alpha J$, so $T\underline{\gamma}_1 e \preceq \alpha \underline{\gamma}_1 e$. Therefore we have from the above that $TJ + \alpha \underline{\gamma}_1 e \preceq TJ + T\underline{\gamma}_1 e \preceq TJ$. It also follows trivially from the above that $J + \underline{\gamma}_1 e + \alpha \underline{\gamma}_1 e \preceq TJ + \alpha \underline{\gamma}_1 e$, so we have

$$\begin{aligned} & \iff J + (1+\alpha) \underline{\gamma}_1 e \preceq TJ + \alpha \underline{\gamma}_1 e \preceq T^2 J \\ \iff & J + (1+\alpha+\alpha^2) \underline{\gamma}_1 e \preceq TJ + \alpha(1+\alpha) \underline{\gamma}_1 e \preceq T^2 J + \alpha^2 \underline{\gamma}_1 e \preceq T^3 J \end{aligned}$$

Applying this repeatedly yields

$$\begin{aligned} J + \left(\sum_{i=0}^k \alpha^i \right) \underline{\gamma}_1 e & \preceq TJ + \left(\sum_{i=1}^k \alpha^i \right) \underline{\gamma}_1 e \\ & \preceq T^2 J + \left(\sum_{i=2}^k \alpha^i \right) \underline{\gamma}_1 e \\ & \vdots \\ & \preceq T^{k+1} J \end{aligned}$$

Take the limit as $k \rightarrow \infty$:

$$J + \underline{\gamma}_1 \frac{e}{1-\alpha} \preceq TJ + \frac{\alpha}{1-\alpha} \underline{\gamma}_1 e \preceq T^2 J + \frac{\alpha^2}{1-\alpha} \underline{\gamma}_1 e \preceq \dots \preceq T^k J + \frac{\alpha^k}{1-\alpha} e \preceq \dots \preceq J^*.$$

Recall:

$$\begin{aligned} \underline{c}_1 &= \frac{\alpha}{1-\alpha} \min_{i \in [n]} \{(TJ)(i) - J(i)\} = \frac{\alpha}{1-\alpha} \underline{\gamma}_1 \\ \implies J + \frac{\underline{c}_1}{\alpha} e &\preceq TJ + \underline{c}_1 e \preceq T^2 J + \alpha \underline{c}_1 e \preceq \dots \preceq T^k J + \alpha^{k-1} \underline{c}_1 e \preceq \dots \preceq J^*, \end{aligned} \tag{14.54}$$

Continuing further, since J is arbitrary, take $J = T^k J$. Then re-do analysis with $J = T^k J$. Then using

$$\underline{\gamma}_{k+1} = \min(T^{k+1}J)(i) - (T^k J)(i) = \underline{c}_{k+1} \left(\frac{1-\alpha}{\alpha} \right)$$

and the same argument will yield

$$T^k J + \frac{\underline{c}_{k+1}}{\alpha} e \preceq T^{k+1} J + \underline{c}_{k+1} e \preceq J^*. \quad (14.55)$$

Next, we will show that

$$\alpha \min_{i \in [n]} \{(TJ)(i) - J(i)\} \leq \min_{i \in [n]} (T^2 J)(i) - (TJ)(i)$$

Note that, by definition of \underline{c}_1 and \underline{c}_2 , proving the above inequality is equivalent to showing that $\alpha \underline{c}_1 \leq \underline{c}_2$. We have from (14.54) that

$$\begin{aligned} TJ + \underline{c}_1 e \preceq T^2 J + \alpha \underline{c}_1 e &\iff (1-\alpha) \underline{c}_1 e \preceq T^2 J - TJ \\ &\iff (1-\alpha) \underline{c}_1 \leq \min_{i=1,\dots,n} (T^2 J)(i) - (TJ)(i) \\ &\iff (1-\alpha) \underline{c}_1 \leq \frac{1-\alpha}{\alpha} \underline{c}_2 \\ &\iff \alpha \underline{c}_1 \leq \underline{c}_2 \end{aligned}$$

Then since from (14.54) $TJ + \underline{c}_1 e \preceq T^2 J + \alpha \underline{c}_1 e$ and $\alpha \underline{c}_1 \leq \underline{c}_2$, it follows that $TJ + \underline{c}_1 e \leq T^2 J + \underline{c}_2 e \leq J^*$. By a similar argument generalizing from (14.55), more generally for any vector J and state i with $k \geq 0$

$$(T^k J)(i) + \underline{c}_k \leq (T^{k+1} J)(i) + \underline{c}_{k+1} \leq J^*(i).$$

□

Theorem 14.22.13. Given \tilde{J} we consider a “greedy policy” μ with respect to \tilde{J} , i.e. $T_\mu \tilde{J} = T \tilde{J}$. Then,

$$\|J_\mu - J^*\| \leq \frac{2\alpha}{1-\alpha} \|\tilde{J} - J^*\|.$$

Remark 172. Due to the MDP assumptions, there are only finitely many policies. So if we make the gap $\|\tilde{J} - J^*\|$ sufficiently small, we can eventually find the optimal policy.

Proof. We know that $T_\mu^k J^* \xrightarrow{k \rightarrow \infty} J_\mu$. So for all k

$$\begin{aligned} \|T_\mu^k J^* - J^*\| &= \left\| \sum_{\ell=1}^k T_\mu^\ell J^* - T_\mu^{\ell-1} J^* \right\| \leq \sum_{\ell=1}^k \|T_\mu^\ell J^* - T_\mu^{\ell-1} J^*\| \leq \sum_{\ell=1}^k \alpha^{k-1} \|T_\mu^\ell J^* - J^*\| \\ &\leq \frac{\|T_\mu J^* - J^*\|}{1-\alpha} \end{aligned}$$

Take limit as $k \rightarrow \infty$ (of the left side),

$$\|J_\mu - J^*\| \leq \frac{\|T_\mu J^* - J^*\|}{1 - \alpha}$$

Now use the fact that μ is a greedy policy.

$$\begin{aligned} \|T_\mu J^* - J^*\| &\leq \|T_\mu J^* - T_\mu \tilde{J}\| + \|T_\mu \tilde{J} - J^*\| \\ &= \|T_\mu J^* - T_\mu \tilde{J}\| + \|T_\mu \tilde{J} - TJ^*\| \\ &\leq 2\alpha \|J^* - \tilde{J}\| \end{aligned}$$

□

2. Policy iteration (PI): idea: start with an initial policy μ , compute J_μ , find an improving policy by acting greedily with respect to J_μ . Description: start with μ^0 . For $k \in \{0, 1, \dots\}$, given a policy μ^k , do two things:

- (a) Policy evaluation: compute J_{μ^k} . (Note: J_{μ^k} is the unique fixed point.)

$$J_{\mu^k} = (I - \alpha P_{\mu^k})^{-1} \bar{g}_{\mu^k}.$$

- (b) Policy improvement: a new policy μ^{k+1} is obtained by acting greedily with respect to J_{μ^k} ; that is, find μ^{k+1} solving

$$T_{\mu^{k+1}} J_{\mu^k} = TJ_{\mu^k}.$$

Note: if $TJ_{\mu^k} = T_{\mu^k}$, we're done (because we've found the optimal policy).

Theorem 14.22.14 (Similar to Proposition 7.2.2 in 3rd Edition Vol. 1 of Bertsekas, p. 217 of pdf). If $T_{\bar{\mu}} J_\mu = TJ_\mu$, then $J_{\bar{\mu}}(i) \leq J_\mu(i)$ for all states i and the inequality is strict for some i if μ is not optimal.

Proof. Since $T_\mu J_\mu = J_\mu$, we have for all states i

$$\begin{aligned} J_\mu(i) &= \bar{g}(i, \mu(i)) + \sum_{j=1}^n P_{ij}(\mu(i)) J_\mu(j) \\ &\geq \min_{u \in \mathcal{A}(i)} \bar{g}(i, u) + \sum_{j=1}^n P_{ij}(u) J_\mu(j) \\ &= (TJ_\mu)(i) \\ &= (T_{\bar{\mu}} J_\mu)(i) \end{aligned}$$

So $J_\mu \geq T_{\bar{\mu}} J_\mu$. Apply $T_{\bar{\mu}}$ again,

$$J_\mu \geq T_{\bar{\mu}} J_\mu \geq T_{\bar{\mu}}^2 J_\mu \geq T_{\bar{\mu}}^3 J_\mu \geq \dots \geq J_{\bar{\mu}}$$

So $J_\mu \geq J_{\bar{\mu}}$. Now we want to show that if μ is not optimal that the inequality is strict for some i ; that is, if $J_\mu = J_{\bar{\mu}}$ then μ is optimal. Note that if $J_\mu = J_{\bar{\mu}}$

$$J_\mu = T_{\bar{\mu}} J_{\bar{\mu}} = T_{\bar{\mu}} J_\mu = \text{ (by assumption of Theorem) } TJ_\mu,$$

so J_μ is a fixed point of T . Since the only fixed point of T is the optimal one, μ is optimal.

□

Example 14.12. $X = \{1, 2\}$, $\mathcal{U} = \{u^1, u^2\}$. We have

$$P(u^1) = \begin{pmatrix} P_{11}(u^1) & P_{12}(u^1) \\ P_{21}(u^1) & P_{22}(u^1) \end{pmatrix} = \begin{pmatrix} 3/4 & 1/4 \\ 3/4 & 1/4 \end{pmatrix}, \quad P(u^2) = \begin{pmatrix} P_{11}(u^2) & P_{12}(u^2) \\ P_{21}(u^2) & P_{22}(u^2) \end{pmatrix} = \begin{pmatrix} 1/4 & 3/4 \\ 1/4 & 3/4 \end{pmatrix},$$

Let $g(1, u^1) = 2, g(1, u^2) = 0.5, g(2, u^1) = 1, g(2, u^2) = 3$, and let $\alpha = 0.9$. Initialization: $\mu^0(1) = u^1, \mu^0(2) = u^2$. Policy evaluation: compute J_{μ^0} as the solution to the equation $T_{\mu^0} J_{\mu^0} = J_{\mu^0}$.

$$J_{\mu^0}(1) = 2 + 0.9 \left[\frac{3}{4} J_{\mu^0}(1) + \frac{1}{4} J_{\mu^0}(2) \right], \quad J_{\mu^0}(2) = 3 + 0.9 \left[\frac{1}{4} J_{\mu^0}(1) + \frac{3}{4} J_{\mu^0}(2) \right]$$

System of two equations, two variables. Solving gives $J_{\mu^0}(1) = 24.12, J_{\mu^0}(2) = 25.96$.

Next, policy improvement. Find a policy $\mu^1 = (\mu^1(1), \mu^1(2))$ such that $T_{\mu^1} J_{\mu^0} = T J_{\mu^0}$. So

$$\begin{aligned} (T J_{\mu^0})(1) &= \min \left\{ 2 + 0.9 \left[\frac{3}{4} \cdot 24.12 + \frac{1}{4} \cdot 25.96 \right], 0.5 + 0.9 \left[\frac{1}{4} \cdot 24.12 + \frac{3}{4} \cdot 25.96 \right] \right\} \\ &= \min\{24.122, 23.45\} = 24.122 \end{aligned}$$

So $\mu^1(1) = u^2$. By a similar calculation,

$$(T J_{\mu^0})(2) = \min\{23.12, 25.95\} = 23.12$$

So $\mu^1(2) = 1$. Next, compute

$$J_{\mu^1} = (I - \alpha P_{\mu^1})^{-1} \cdot g_{\mu^1} = \begin{pmatrix} 1 - \alpha \frac{1}{4} & -\alpha \frac{3}{4} \\ -\alpha \frac{3}{4} & 1 - \alpha \frac{1}{4} \end{pmatrix}^{-1} \cdot \begin{pmatrix} 0.5 \\ 1 \end{pmatrix} = \begin{pmatrix} 7.31 \\ 7.67 \end{pmatrix}$$

If you do another iteration, you will find $T_{\mu^2} J_{\mu^1} = T J_{\mu^1}$, so $\mu^2 = \mu^1$ and you're done.

Now, want to compare value iteration vs. policy iteration. Assume that we have 1 state. Each policy maps the state to an action, but there is only one state, so the policy is just an action. In particular, it defines a line $g_{\mu} + \alpha P_{\mu} J$. Then

$$T J = \min_u \{g_{\mu} + \alpha P_{\mu} J\}$$

The function is increasing, concave, and piecewise linear in J . Each piece corresponds to a policy.

Value iteration: attempts to approximate J^* . Never reaches J^* , but since you have finitely many policies, you eventually reach the optimal policy. See Figure 14.15.

Policy iteration is different. You fall into a policy, representing one piece of the function (one line segment—each one corresponds to a policy). Then compute J_{μ^1} , a fixed point of T_{μ^1} . T_{μ^1} is the extension of the line segment corresponding to policy μ^1 . So J_{μ^1} is the point where that line intersects the 45 degree line $T_{\mu^1} J = J$. Then you plug that point in and solve again, finding the next policy. Generally this approach is way faster (although in the worst case it can be very slow). See Figure 14.16.

3. **Optimistic policy iteration (blend of PI and VI; section 2.3.3 of Bertsekas [2012b])** Start with an initial J_0 . Let $\{m_k : k = 0, 1, \dots\}$ be any sequence of positive integers (say $\{1, 1, 1, \dots\}$). Do the following:

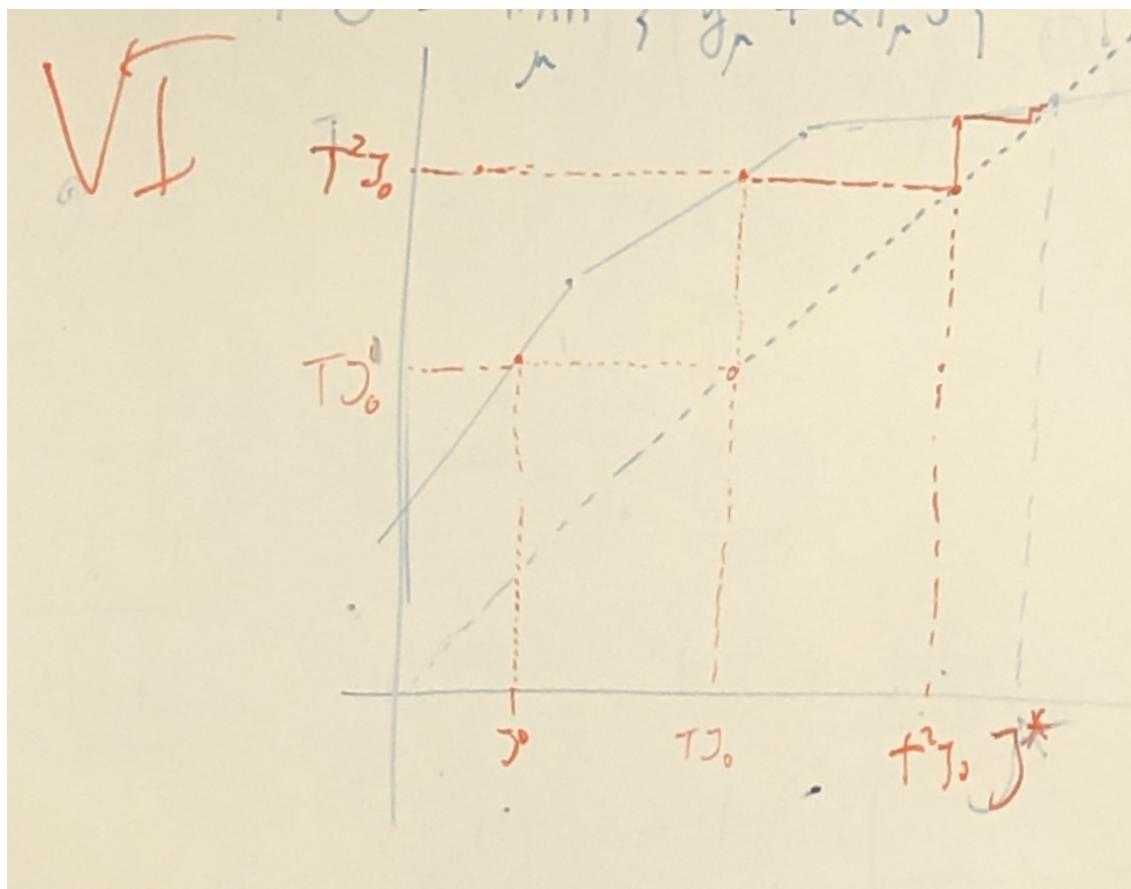


Figure 14.15: Iteration of VI method. Start with J_0 , get TJ_0 , plug in to T , etc. Note that the optimal solution is the intersection of the TJ function and the 45 degree line, since the optimal policy satisfies $TJ^* = J^*$.

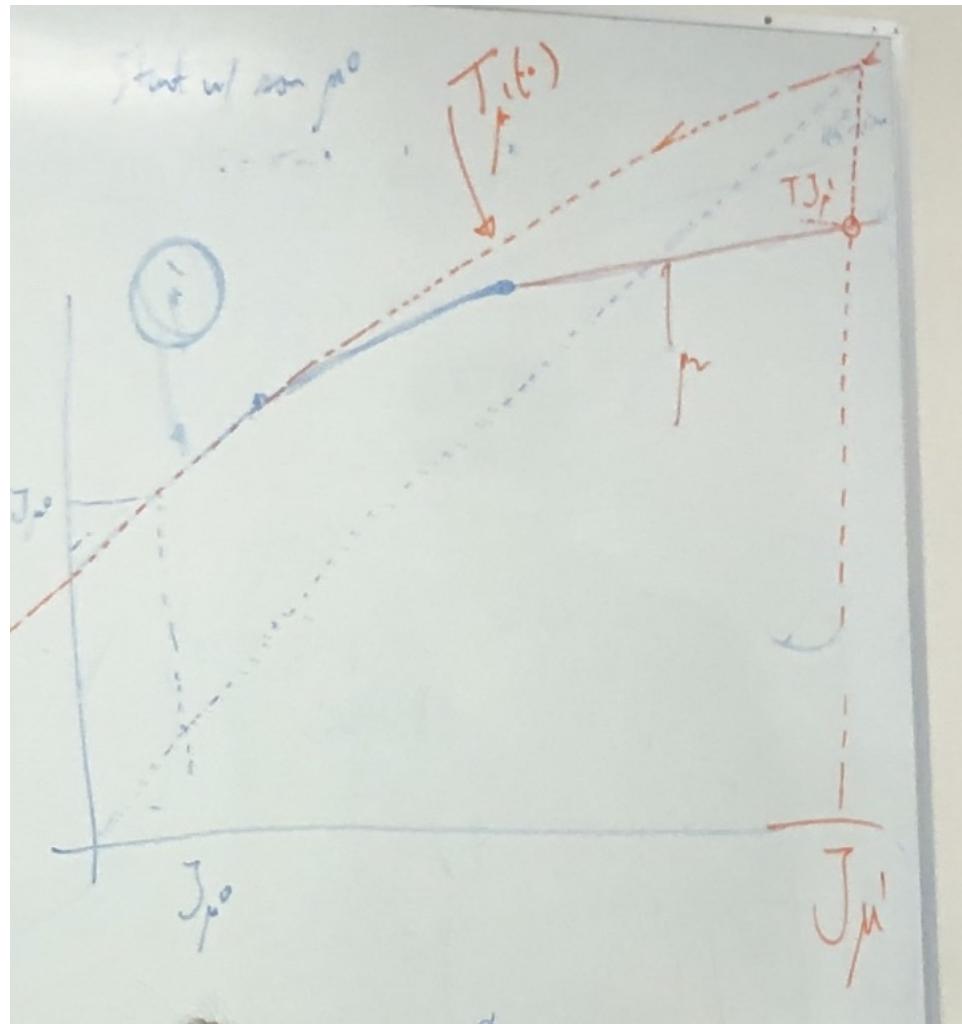


Figure 14.16: Iteration of PI method.

- (a) Take a greedy decision with respect to J_k to get the policy μ^k : $T_{\mu^k} J_k = T J_k$. Then get $J_{k+1} = T_{\mu^k}^{m_k} J_k$. If $m_k = 1$ for all k , we get value iteration: $J_{k+1} = T_{\mu^k} J_k = T J_k$ for all k . If $m_k = \infty$ for all k (or is sufficiently large), we get $J_{k+1} = J_{\mu^k}$, so $T_{\mu^{k+1}} J_{k+1} = T J_{k+1}$. This is policy iteration. So this method subsumes PI and VI, and it doesn't require inverting a matrix like PI. Also we have lots of flexibility; converges to the optimal policy for any sequence (will prove next time).

Theorem 14.22.15 (Proposition 2.3.2 of Bertsekas [2012b]). J_k converges to J^* and μ^k is optimal for all k sufficiently large.

Proof. “the same sequence of policies will be obtained” (p. 105): true because the costs differ only by constants, so the policy resulting in the optimum for both cost functions will be the same.

Prove by induction on k that $\bar{J}_k \leq T\bar{J}_{k-1}$ and $T\bar{J}_k \leq \bar{J}_k$.

Base case: ($k = 1$) we want to show that

$$\bar{J}_1 \leq T\bar{J}_0, \quad T\bar{J}_0 \leq \bar{J}_0.$$

By definition, $T_{\mu^0} \bar{J}_0 = T\bar{J}_0 \leq \bar{J}_0$ where the first step follows by definition of μ^0 and the second follows by our construction of \bar{J}_0 . So then $T_{\mu^0}^m \bar{J}_0 \leq T_{\mu^0}^{m-1} \bar{J}_0$ for all m .

By definition (and using $\bar{J}_1 = T_{\mu^0}^{m_0} \bar{J}_0$)

$$T_{\mu_1} \bar{J}_1 = T\bar{J}_1 \leq T_{\mu^0} \bar{J}_1 = T_{\mu^0}^{m_0+1} \bar{J}_0 \leq T_{\mu^0}^{m_0} \bar{J}_0 = \bar{J}_1$$

where the second-to-last step follows from $T_{\mu^0}^m \bar{J}_0 \leq T_{\mu^0}^{m-1} \bar{J}_0$ for all m . But then $\bar{J}_1 \leq T_{\mu^0} \bar{J}_0$, because to get \bar{J}_1 we applied T_{μ^0} $m_0 \geq 1$ times. Therefore $\bar{J}_1 \leq T\bar{J}_0$.

Inductive step: Assume that $\bar{J}_k \leq T\bar{J}_{k-1}$ and $T\bar{J}_k \leq \bar{J}_k$. We want to show that $\bar{J}_{k+1} \leq T\bar{J}_k$ and $T\bar{J}_{k+1} \leq \bar{J}_{k+1}$.

By definition, $T_{\mu^k} \bar{J}_k = T\bar{J}_k \leq \bar{J}_k$ where the last step follows by the inductive step. Therefore $T_{\mu^k}^m \bar{J}_k \leq T_{\mu^k}^{m-1} \bar{J}_k$ for all m (same argument as above).

Finally,

$$\begin{aligned} T_{\mu^{k+1}} \bar{J}_{k+1} &= T\bar{J}_{k+1} \leq T_{\mu^k} \bar{J}_{k+1} = (\text{by definition of } \bar{J}_{k+1}) T_{\mu^k}^{m_k+1} \bar{J}_k \leq (\text{by above result}) T_{\mu^k}^{m_k} \bar{J}_k \\ &= \bar{J}_{k+1} \leq T_{\mu^k} \bar{J}_k = T\bar{J}_k. \end{aligned}$$

This gives us that $\bar{J}_{k+1} \leq T\bar{J}_k$ and $T\bar{J}_{k+1} \leq \bar{J}_{k+1}$. Now, note that

$$\begin{aligned} \bar{J}_1 &\leq T\bar{J}_0 \\ \iff \bar{J}_2 &\leq T\bar{J}_1 \leq T^2 \bar{J}_0 \\ \iff \bar{J}_3 &\leq T\bar{J}_2 \leq T^2 \bar{J}_1 \leq T^3 \bar{J}_0 \end{aligned}$$

which leads to $\bar{J}_k \leq T^k \bar{J}_0$. Then to show $J^* \leq \bar{J}_k$ for all k , note that

$$T\bar{J}_0 \leq \bar{J}_0 \implies J^* \leq \bar{J}_0$$

because $J^* = \lim_{k \rightarrow \infty} T^k \bar{J}_0$. Also for all ℓ

$$T^\ell \bar{J}_k \leq T^{\ell-1} \bar{J}_k \leq \dots \leq T \bar{J}_k \leq \bar{J}_k.$$

□

Definition 14.11 (One-step look-ahead policy; section 2.3.4, p. 106 of Bertsekas [2012b]). If \tilde{J} is an approximation to J^* , then a one-step look-ahead policy based on \tilde{J} is a policy $\bar{\mu}$ such that $T_{\bar{\mu}} \tilde{J} = T \tilde{J}$.

Note: can be an arbitrary vector \tilde{J} . Also if $\tilde{J} = J_\mu$ for some policy μ , then $J_{\bar{\mu}} \leq J_\mu$. Two-step lookahead:

$$T_{\bar{\mu}}(T \tilde{J}) = T(T \tilde{J}).$$

Theorem 14.22.16 (Proposition 2.3.3, p. 107 of Bertsekas [2012b]). Let $\bar{\mu}$ be the one-step look-ahead policy based on \tilde{J} , i.e., $T_{\bar{\mu}} \tilde{J} = T \tilde{J}$. Let $\hat{J} := T_{\bar{\mu}} \tilde{J} = T \tilde{J}$. Then

- (a) If $\hat{J} \leq \tilde{J}$, then $J_{\bar{\mu}} \leq \hat{J}$.
- (b) $\|J_{\bar{\mu}} - \hat{J}\| \leq \frac{\alpha}{1-\alpha} \|\hat{J} - \tilde{J}\|$, $\|J_{\bar{\mu}} - J^*\| \leq 2\alpha/(1-\alpha) \|\tilde{J} - J^*\|$, and $\|J_{\bar{\mu}} - J^*\| \leq 2/(1-\alpha) \|\tilde{J} - \hat{J}\|$.

Example 14.13 (Example 2.3.1, p. 109 of Bertsekas [2012b]). Note that

$$T \tilde{J}(1) = \min\{0 + \alpha \tilde{J}(2), 2\alpha\epsilon + \alpha \tilde{J}(1)\} = \min\{\alpha\epsilon, \alpha\epsilon\} = \alpha\epsilon$$

and $T \tilde{J}(2) = 0 + \alpha \tilde{J}(2) = \alpha\epsilon$.

So, with the one-step lookahead

$$J_{\bar{\mu}}(1) = \frac{2\alpha\epsilon}{1-\alpha} = \frac{2\alpha}{1-\alpha} \|\tilde{J} - J^*\|$$

So

$$\|J_{\bar{\mu}} - J^*\| = \frac{2\alpha}{1-\alpha} \|\tilde{J} - J^*\|$$

so the bound is tight.

Proposition 14.22.17 (Proposition 2.3.4, p. 111 of Bertsekas [2012b]).

4. Linear programming (LP)

Basic form: $\max c^T x$ s.t. $Ax \leq b, x \geq 0$. Equivalent dual: $\min \pi^T b$ s.t. $\pi^T A \geq c^T, \pi \geq 0$. Dual problem may have a smaller constraint set (number of variables in dual equals number of constraints in the primal). In primal problem: number of constraints equals number of state-action pairs, number of variables equals number of states. So both number of constraints and variables is large. So dual doesn't generally help a lot. But it turns out that for a variety of important problems there are ways to exploit the LP structure.

exam: inventory, revenue management, VI (variants, applications in weird contexts), PI question for sure. so at least those 4 questions. maybe a 5th on one of these topics. optimistic PI maybe. LP no.

14.22.8 Scheduling and Multiarmed Bandit Problems (Section 1.3 of Bertsekas [2012b])

We will examine the multiarmed bandit (MAB) in an infinite horizon discounted reward setting. (One of the few high-dimensional DPs that can be solved feasibly.) See setup on p. 22 of Bertsekas [2012b]. Other notation: $x_k^\ell \in S^\ell$ (state space).

$$J(x^1, \dots, x^n) = \max_{u \in [n]} \{R^u(x^u) + \alpha \mathbb{E}[J(x^1, \dots, x^{u-1}, f^u(x^u, w^u), x^{u+1}, \dots, x^n)]\}$$

(similar to equation (1.12) on p. 23, but without M retirement reward.)

Note this is high-dimensional: if each arm has 10 states, then the number of possible states is 10^m .

Key features:

1. States of idle projects remain fixed.
2. Rewards received only depend on the state of selected arms.
3. Only one product can be chosen.

Gittins in 1970s showed that an optimal policy for this problem is an index rule (equation (1.11) on p. 23). The index associated with each project can be computed by solving a 1 dimensional dynamic program. (i.e., solve n 1-dimensional problems rather than a single n -dimensional problem—much more feasible when n is large.)

First step to proving optimality of this approach: generalize the problem to allow the option of quitting at any time k . Key: the retirement reward M will be crucial in defining our index function.

Theorem 14.22.18 (Proposition 1.3.4 in Bertsekas [2012b], p. 29). For each project ℓ , there exists a function $m^\ell : S^\ell \rightarrow \mathbb{R}$ such that at each time k an optimal policy is given by the rule

- Retire if $M > \max_{h \in [n]} \{m^h(x_k^h)\}$,
- Work on project ℓ if $m^\ell(x_k^\ell) = \max_{h \in [n]} \{m^h(x_k^h)\} \geq M$,

where the index function $m^\ell(x^\ell)$ is as defined in (14.56).

We will get some preliminary results to be able to prove this.

Lemma 14.22.19 (Proposition 1.3.1 in Bertsekas [2012b], p. 29). Let

$$B := \max_\ell \max_{x^\ell} |R^\ell(x^\ell)|.$$

For fixed $x \in S_1 \times \dots \times S_n$, the optimal reward function (as a function of M) $M \mapsto J(x, M)$ has the following properties:

- (a) $M \mapsto J(x, M)$ is convex and monotonically nondecreasing.
- (b) $J(x, M)$ is constant for $M \leq -B/(1 - \alpha)$.
- (c) $J(x, M) = M$ for all $M \geq B/(1 - \alpha)$.

(See Figure 14.17.)

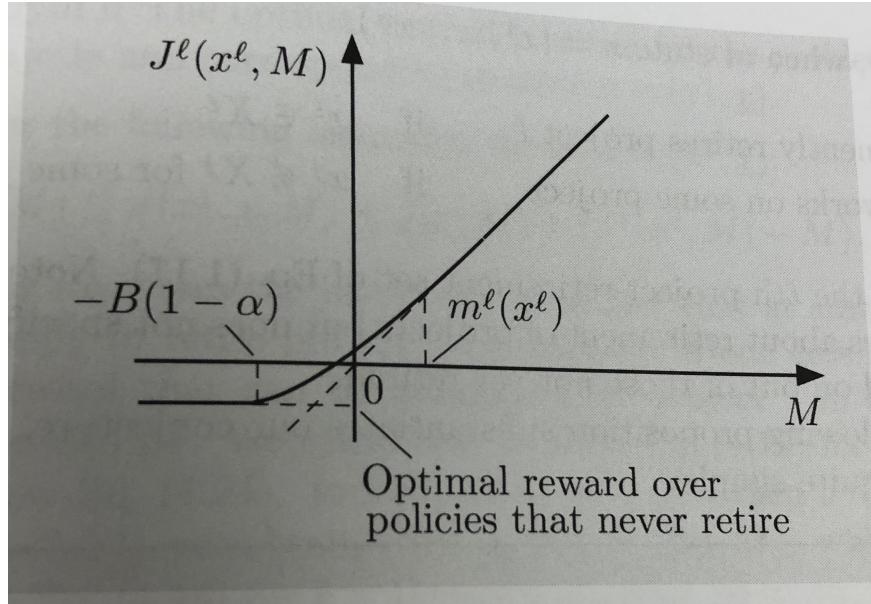


Figure 14.17: Figure 1.3.1 in [Bertsekas \[2012b\]](#), p. 25. Form of the ℓ th project reward function $J^\ell(x^\ell, M)$ for fixed x^ℓ and definition of the index $m^\ell(x^\ell)$.

Proof. (a) inductive step: recall that maximum of convex functions is convex. for each u , get convex functions inside expectation. expectation preserves convexity, adding a constant preserves convexity, max preserves convexity.

- (b) Note that the absolute worst reward you can ever get if you never retire is $-B/(1 - \alpha)$ (sum of infinite series if you get $-B$ every time). So if M is worse than that, never makes sense to quit.
- (c) Reverse of last argument.

□

Consider a situation with only one project (as on bottom of p. 24). There is a minimal value $m^\ell(x^\ell)$ of M for which $J^\ell(x^\ell, M) = M$ (the smallest M that would cause you to want to retire rather than work on your one project). That is,

$$m^\ell(x^\ell) = \inf\{Q : Q = J^\ell(x^\ell, Q)\}. \quad (14.56)$$

Definition 14.12 (Index function; p. 24 of [Bertsekas \[2012b\]](#)). The function $m^\ell(x^\ell)$ as defined in (14.56) is called the **index function** of project ℓ .

The index function is the retirement reward for which we are indifferent between retiring and operating the project when at state x^ℓ . Note that $m^\ell(x^\ell) \leq B/(1 - \alpha)$, because per Lemma 14.22.19, we would always want to retire if $M > B/(1 - \alpha)$.

Total number of curves upper bounded by number of states times number of projects (as opposed to number of states raised to the number of projects—so big reduction). Also, each curve corresponds to a one-dimensional DP.

How do you find $m^\ell(x^\ell)$ in practice? Easy to evaluate at a particular M ; solve the DP (value iteration, policy iteration, etc.). Use a bisection algorithm to find it (similar to finding a zero of a function). Have a bounded interval to start with: $[-B/(1 - \alpha), B/(1 - \alpha)]$. For each DP, number of state-action pairs is number of states times 2 (only 2 actions: retire or continue).

Definition 14.13 (Project-by-Project Retirement Policy (PPR); pp. 25-26 of Bertsekas [2012b]). In a single project problem, the project is operated continuously up to the time that its state falls into the **retirement set**

$$X^\ell = \{x^\ell : m^\ell(x^\ell) < M\}. \quad (14.57)$$

A **project-by-project retirement policy** permanently retires projects in the same way as if they were the only project available:

- Permanently retire project ℓ if $x^\ell \in X^\ell$,
- work on some project if $x^j \notin X^j$ for some j (where X^j is the retirement set (14.57)).

Note that a PPR policy decides about retirement of projects but does not specify the project to be worked on out of those not yet retired.

Proposition 14.22.20 (Proposition 1.3.2 in Bertsekas [2012b]). There exists an optimal PPR policy.

Proof. How to get (1.20):

$$\begin{aligned} m^\ell(x^\ell) \geq M &\implies M \leq R^\ell(x^\ell) + \alpha \mathbb{E}[J^\ell(f^\ell(x^\ell, w^\ell), M)] \\ &\leq R^\ell(x^\ell) + \alpha \mathbb{E}[J(x^1, \dots, x^{\ell-1}, f(x^\ell, w^\ell), x^{\ell+1}, \dots, x^n, M)] \\ &= L^\ell(x, M, J). \end{aligned}$$

□

Proposition 14.22.21 (Proposition 1.3.3 in Bertsekas [2012b]). For fixed x , let K_M denote the (random) retirement time under an optimal policy when the retirement reward is M . Then for all M for which $\partial J(x, M)/\partial M$ exists, we have

$$\frac{\partial J(x, M)}{\partial M} = \mathbb{E} [\alpha^{K_M} \mid x_0 = x].$$

Proof. pp. 28- 29, [Bertsekas, 2012b].

□

Let T_ℓ be the retirement time of project ℓ if it were the only project available and let T be the retirement time for the multiproject problem. We have $T = T_1 + T_2 + \dots + T_n$ because the state of idle projects doesn't change. Further, all the T_ℓ are independent. Therefore

$$\mathbb{E}[\alpha^T] = \mathbb{E}[\alpha^{\sum_{\ell=1}^n T_\ell}] = \prod_{\ell=1}^n \mathbb{E}[\alpha^{T_\ell}].$$

Then Proposition 14.22.21 yields

$$\frac{\partial J(x, M)}{\partial M} = \prod_{\ell=1}^n \frac{\partial J^\ell(x^\ell, M)}{\partial M}. \quad (14.58)$$

We are now ready to prove Theorem 14.22.18.

Proof of Theorem 14.22.18. notes for end of proof: The function $M \mapsto J(x, M)$ and $M \mapsto L^\ell(x, M, J)$ coincide at $M = m(x)$. The derivatives of the two functions are the same for all $M \leq m(x)$. Therefore for all $M \leq m(x)$, $J(x, M) = L^\ell(x, M, J)$, so it's optimal to choose project ℓ .

□

14.22.9 Approximate DP: Q-Learning (Section 6.3.3 of Bertsekas [2012a], Sections 2.2.3, 2.5.3, and 6.1 - 6.6.1 of [Bertsekas, 2012b])

We'll focus on large-scale DP under a discounted cost criterion. Interested in setting when the number of states is extremely large (say 10^{100}).

How do we adapt VI for large-scale setting? $VI : TJ \rightarrow J$.

$$(TJ)(x) = \min_{u \in U(x)} \sum_{y \in S} P_{x,y}(u)[g(x, u, y) + \alpha J(y)].$$

How do we compute the sum when the state space is so large? A potential approach is to use Monte Carlo simulation. We have that $Y \sim P_{x,.}(u)$, and the sum is $\mathbb{E}[g(x, u, Y) + \alpha J(Y)]$. Suppose we want to compute $\mathbb{E}[F(Z)]$ for some function F . The true value is $\sum_{z \in S} \mathbb{P}(z)F(z)$, but if $|S|$ is intractably large, consider an IID sample z_1, \dots, z_K drawn from Z . The Strong Law of Large Numbers tells us $\frac{1}{K} \sum_{k=1}^K F(z_k) \xrightarrow{a.s.} \mathbb{E}[F(Z)]$. If $K \ll |S|$, this sample is much easier to compute.

How large should the number of samples be? Recall Chebyshev's Inequality (8.2.2):

$$\mathbb{P}\left(\left|\frac{1}{K} \sum_{k=1}^K F(z_k) - \mathbb{E}[F(Z)]\right| > \epsilon\right) \leq \delta$$

if $K \geq \frac{1}{\delta} \frac{\text{Var}(F(Z))}{\epsilon^2}$.

We will combine Monte Carlo simulation with VI. To avoid the sum, for each $u \in U(x)$, we can sample y_1, \dots, y_K according to $P_{x,\cdot}(u)$ and approximate

$$\sum_{y \in S} P_{x,y}(u) [g(x, u, y) + \alpha J(y)] \approx \frac{1}{K} \sum_{k=1}^K [g(x, u, y_k) + \alpha J(y_k)].$$

Do we do this for each $u \in U(x)$? (Do we generate a new sample for each $u \in U(x)$?) What about for each x —do I have to update all states simultaneously? Can I update one state at a time?

Definition 14.14. Let

$$Q_k(x_k, u_k) := \mathbb{E}[g_k(x_k, u_k, y_k) + J_{k+1}(f_k(x_k, u_k, y_k))] = \sum_{y \in S} P_{x,y}(u) [g_k(x_k, u_k, y_k) + \alpha J^*(y)].$$

Let the optimal Q^* be defined by

$$Q^*(x, u) := \sum_{y \in S} P_{x,y}(u) [g(x, u, y) + \alpha J^*(y)], \quad J^*(x) = \min_{u \in U(x)} Q^*(x, u).$$

(Note that this is simply a re-writing of Bellman's Equation. See Section 6.3.3 of [Bertsekas \[2012a\]](#), p.339 - 340.)

Suppose we're given $Q_k(\cdot, \cdot)$ based on sample y_1, y_2, \dots, y_{k-1} . Then

$$Q_{k+1}(x, u) = \frac{1}{k} \sum_{\ell=1}^k [g(x, u, y_\ell) + \alpha \min_{v \in U(y_\ell)} Q_\ell(y_\ell, v)].$$

Note: for each iteration, we only have one new sample.

$$Q_{k+1}(x, u) = \frac{1}{k} \left[g(x, u, y_k) + \alpha \min_{v \in U(y_k)} Q_k(y_k, v) \right] + \underbrace{\frac{k-1}{k} \cdot \frac{1}{k-1} \sum_{\ell=1}^{k-1} [g(x, u, y_\ell) + \min_{v \in U(y_\ell)} Q_\ell(y_\ell, v)]}_{Q_k(x, u)}.$$

Therefore

$$\begin{aligned} Q_{k+1}(x, u) &= \frac{1}{k} \left[g(x, u, y_k) + \alpha \min_{v \in U(y_k)} Q_k(y_k, v) \right] + \underbrace{\frac{k-1}{k}}_{=1-1/k} Q_k(x, u) \\ &= Q_k(x, u) + \frac{1}{k} \left[g(x, u, y_k) + \alpha \min_{v \in U(y_k)} Q_k(y_k, v) - Q_k(x, u) \right]. \end{aligned}$$

Q-learning (algorithm from section 6.6.1 of [Bertsekas \[2012b\]](#), p. 496):

$$Q_{k+1}(x, u) = Q_k(x, u) + \gamma_k \left[g(x, u, y_k) + \alpha \min_{v \in U(y_\ell)} Q_k(y_\ell, v) - Q_k(x, u) \right].$$

where γ_k is the step size.

Theorem 14.22.22 (Section 6.6.1 of [Bertsekas \[2012b\]](#), p. 496). If each $Q(x, u)$ is updated infinitely often and $\sum_{k=1}^{\infty} \gamma_k = \infty$, $\sum_{k=1}^{\infty} \gamma_k^2 < \infty$, then $Q_k \rightarrow Q^*$.

(See Section 6.3 of [Bertsekas \[2012b\]](#) for this material.) How do we deal with a huge number of states? Our goal is to compute $\{J^*(x) : x \in S\}$, but $|S|$ is huge. Approximate $J^*(x) \approx \sum_{k=1}^K \phi_k(x) \cdot r_k = (\Phi r)(x)$, where $\Phi \in \mathbb{R}^{|S| \times K}$ and $r \in \mathbb{R}^K$. Important: we do not store Φ explicitly. We compute $\phi_k(x)$ as needed.

Our goal is to find r such that Φr is close to J^* . We do this by projecting J^* onto the span of Φ ; that is, we would like to compute

$$\min_{r \in \mathbb{R}^K} \sum_{x \in S} \pi(x) ((\Phi r)(x) - J^*(x))^2. \quad (14.59)$$

More compact notation:

$$\|\Phi r - J^*\|_{\pi}^2 := (\Phi r - J^*)^T D(\Phi r - J^*)$$

where

$$D = \begin{pmatrix} \pi(1) & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \pi(S) \end{pmatrix}.$$

and $\|\cdot\|_{\pi}$ is a weighted norm under the stationary probability distribution π of the transition matrix P . For any vector J

$$\|J\|_{\pi} = \sqrt{\sum_{x \in S} \pi(x) |J(x)|^2}.$$

Then we can write (14.59) as

$$\min_{r \in \mathbb{R}^K} \|\Phi r - J^*\|_{\pi}^2$$

Instead of summing over all states, we sample the states according to $\pi(\cdot)$, so x_1, x_2, \dots, x_n . Then we find

$$\min_{r \in \mathbb{R}^K} \frac{1}{n} \sum_{i=1}^n ((\Phi r)(x_i) - J^*(x_i))^2.$$

However, this problem is still not tractable because we do not know J^* . Idea: leverage the “closed form” expression for the optimal r^* (if we have J^*)

$$\begin{aligned} 0 &= \nabla_r \|J^* - \Phi r\|_\pi^2 \\ &= \nabla_r [(\Phi r - J^*)^T D (\Phi r - J^*)] \\ &= 2\Phi^T D (\Phi r - J^*) \\ \implies r^* &= (\Phi^T D \Phi)^{-1} \Phi^T D J^*, \\ \Phi r^* &= \Phi (\Phi^T D \Phi)^{-1} \Phi^T D J^*. \end{aligned}$$

Observe that $\Phi(\Phi^T D \Phi)^{-1} \Phi^T D$ is a projection matrix Π .

where Π is the projection onto the basis functions ϕ ; projection with respect to $\|\cdot\|_\pi$, and π is the stationary distribution of the transition matrix P (**key: only one transition matrix, as in optimal stopping; see below**).

Intuition: start with an initial J . Do approximate value iteration:

$$\Pi T J \in \mathbb{R}^{|S|}$$

project TJ into the K -dimensional vector space spanned by ϕ_1, \dots, ϕ_K . Don’t keep track of the full TJ ; instead, just the K coefficients.

Approximate VI: $(\Pi T)^k J$. Caveat: this update can lead to (??).

Example 14.14 (Example 6.4.2 in [Bertsekas \[2012b\]](#), p. 472).

Proposed method: start at $r^{(0)} \in \mathbb{R}^K$. Iteration:

$$\begin{aligned} r^{(k+1)} &= \arg \min_{r \in \mathbb{R}^K} \|\Phi r - T \Phi r^{(k)}\|_\pi^2 \\ \iff \Phi r^{(*k+1)} &= \Pi T(\Pi r^{(k)}), \end{aligned}$$

where $\Pi = \Phi(\Phi^T D \Phi)^{-1} \Phi^T D$, with D as defined before.

Lemma 14.22.23 (Lemma 6.3.1 in [Bertsekas \[2012b\]](#), p. 427). If $\Pi' P = \Pi'$, then $\|PJ\|_\Pi \leq \|J\|_\Pi$.

Proof.

$$\|PJ\|_\Pi^2 = \sum_{x \in S} \pi(x) [(PJ)(x)]^2 = \sum_{x \in S} \pi(x) \left(\sum_{y \in S} P_{x,y} J(y) \right)^2 \leq \text{(by Jensen's inequality)} \sum_{x \in S} \pi(x) \sum_{y \in S} P_{x,y} (J(y))^2 = \sum_{y \in S} [J(y)]^2$$

□

Lemma 14.22.24 (Proposition 6.3.1(a) in Bertsekas [2012b], p. 429). Consider a policy μ . Let P be the transition matrix associated with μ . If $\Pi'P = \Pi'$ then $\|T_\mu J - T_\mu \bar{J}\|_\Pi \leq \alpha \|J - \bar{J}\|_\Pi$.

Proof.

$$\|T_\mu J - T_\mu \bar{J}\|_\Pi^2 = \sum_{x \in S} \pi(x) [(T_\mu J)(x) - (T_\mu \bar{J})(x)]^2 = \sum_{x \in S} \pi(x) \left[\alpha \sum_y P_{x,y} (J(y) - \bar{J}(y)) \right]^2 = \alpha^2 \sum_{x \in S} \pi(x) [(P(J - \bar{J}))(x)]^2 = \alpha^2 \|J - \bar{J}\|_\Pi^2$$

because

$$(T_\mu J)(x) = g(x, \mu(x)) + \alpha \sum_y P_{x,y}(\mu(x))J(y).$$

□

Π is expansive under the sup norm. However...

Lemma 14.22.25 (Proposition 6.3.1(a) in Bertsekas [2012b], p. 429). The projection matrix Π is nonexpansive with respect to $\|\cdot\|_\Pi$; i.e., $\|\Pi J\|_\Pi \leq \|J\|_\Pi$.

Proof. We begin by observing that $J - \Pi J$ is orthogonal to ΠJ .

$$\Pi(J - \Pi J) = \Pi J - \Pi \Pi J = 0.$$

So $J - \Pi J$ is in the nullspace of Φr . Then

$$\|J\|_\pi = \|J - \Pi J\|_\pi + \|\Pi J\|_\pi \geq \|\Pi J\|_\pi.$$

□

We know have that ΠT_μ is a contraction mapping with respect to $\|\cdot\|_\pi$, where π is the stationary distribution with respect to P_μ . This result ends up showing that $Q_{k+1} \rightarrow \hat{Q}$ because $\Pi \circ F$ is a contraction mapping under $\|\cdot\|_\pi$ and \hat{Q} is the unique fixed point of $\Pi \circ F$; that is, $\Pi F \hat{Q} = \hat{Q}$. How do we compute $(\Pi T_\mu)J$ with $J = \Phi r^{(k)}$?

1. Sample x_1, \dots, x_n from π .
2. Solve

$$r^{(k+1)} := \arg \min_{r \in \mathbb{R}^K} \frac{1}{n} \sum_{i=1}^n \left[(\Phi r)(x_i) - (\Phi r^{(k)})(x_i) \right]^2$$

How do you get π ? Simulate using a Markov chain for as long as needed; eventually converges to stationary distribution.

Note: divergence can occur if the wrong norm is used. We have convergence if

1.

$$(TJ)(x) = \sum_{y \in S} P_{x,y} (g(x, y) + \alpha J(y))$$

(only one action)

2. $\pi^T P = \pi^T$.

Heuristic for Approximate VI for general MDP. Initialization: given $\Phi = [\phi_1 \ \dots \ \phi_k]$ and $r^{(0)}$.

1. Given $r^{(k)}$, sample x_1, \dots, x_n from a distribution π . Then

$$r^{(k+1)} := \arg \min_{r \in \mathbb{R}^K} \frac{1}{n} \sum_{i=1}^n \left[(\Phi r)(x_i) - (T\Phi r^{(k)})(x_i) \right]^2.$$

$$(T\Phi r)(x) = \min_{u \in U(x)} \sum_{y \in S} P_{x,y}(u) [g(x, u, y) + \alpha(\Phi r)(y)]^2$$

2.

(can't prove anything about this, just a "hack," but seems to work.)

14.22.10 Optimal Stopping (Section 6.6.4 of Bertsekas [2012b], p. 504)

Key insight: in an optimal stopping problem, there is one transition matrix.

Want a high-dimensional MC. ($X_t \in S : t = 1, 2, \dots$)

DP operator:

$$(TJ)(x) = \max\{g(x), h(x) + \alpha \sum_{y \in S} P_{xy} J(y)\} = h(x) + \max\{g(x) - h(x), \alpha \sum_{y \in S} P_{x,y} J(y)\}.$$

$$TJ = \max\{g, \alpha PJ\}.$$

Still suffer from curse of dimensionality even though we only have one DP.

$$Q^*(x) := \alpha \sum_{y \in S} \phi_{x,y} J^*(y) = \underbrace{\alpha \sum_{y \in S} P_{x,y} \max\{g(y), Q^*(y)\}}_{(FQ^*)(x)}, \quad J^*(x) = \max\{ \underbrace{g(x)}_{\text{reward for stopping}}, \underbrace{Q^*(x)}_{\text{reward for continuing}} \}.$$

Q^* is the optimal value you get if you continue—the **optimal continuation function**.

$$Q^* = \alpha PJ^* = \alpha P \max\{g, Q\} \iff Q^* = FQ^*$$

where $FQ = \alpha P \max\{g, Q\}$. So Q^* is the fixed point of a contraction mapping.

We'll approximate Q^* in general as a sequence of coefficients $r^{(1)}, r^{(2)}, \dots$. Given $r^{(k)}$,

1. Sample $x_{k+1} \sim \pi$, where π is the stationary distribution of P . $y_{k+1} \sim P_{x_{k+1}}$.

2.

$$r^{(k+1)} := \arg \min_{r \in \mathbb{R}^K} \left\{ \frac{1}{k+1} \sum_{\ell=1}^{k+1} \left[(\Phi r)(x_i) - \alpha \max\{g(y_\ell), (\Phi r^{(k)})(y_\ell)\} \right]^2 \right\}$$

(so we are using $(\Phi r^{(k)})(y_\ell)$ as an approximation for $Q^*(y)$).

As $k \rightarrow \infty$, $\|\Phi r - F\Phi r^{(k)}\|_\pi^2$. Again,

$$(FQ)(x) = \alpha \sum_{y \in S} P_{x,y} \max\{g(y), Q(y)\}.$$

With one sample we can get an unbiased estimate of $(FQ^*)(x)$. Does the iterate $Q := \Pi FQ$ converge? Yes.

Lemma 14.22.26 (Proposition 6.6.1 in Bertsekas [2012b], p. 506). F is a contraction mapping with respect to $\|\cdot\|_\pi$.

Proof. p. 506 of Bertsekas [2012b]. □

Question: given k , $(\Pi F)^k Q \rightarrow \tilde{Q}$, how close is \tilde{Q} to Q^* ? Note $\tilde{Q} \neq \Pi Q^*$. Rather, \tilde{Q} is the fixed point of ΠF ; $\tilde{Q} = \Pi F \tilde{Q}$.

Theorem 14.22.27.

$$\|\tilde{Q} - Q^*\|_\pi \leq \frac{1}{\sqrt{1-\alpha^2}} \|\Pi Q^* - Q^*\|_\pi.$$

Proof. Observe that $\tilde{Q} \in \text{span } \Phi$. Also, $\Pi \tilde{Q} \in \text{span } \Phi$. Therefore $\tilde{Q} - \Phi Q^* \perp \Pi Q^* - Q^*$ since $\Pi Q^* - Q^*$ is in the nullspace of Φ . Now

$$\begin{aligned} \|\tilde{Q} - Q^*\|_\pi^2 &= \|\tilde{Q} - \Pi Q^* \Pi Q^* - Q^*\|_\pi^2 \\ &= \|\tilde{Q} - \Pi Q^*\|_\pi^2 + \|\Pi Q^* - Q^*\|_\pi^2 \\ &= \Pi F \tilde{Q} - \Pi F Q^* \|_\pi^2 + \|\Pi Q^* - Q^*\|_\pi^2 \\ &\leq \alpha \|\tilde{Q} - Q^*\|_\pi^2 + \|\Pi Q^* - Q^*\|_\pi^2 \end{aligned}$$

because $\Pi Q^* = \Pi F Q^*$ and ΠF is a contraction mapping. Observe that

$$\|\tilde{Q} - Q^*\|_\pi \leq \frac{\|\Pi Q^* - Q^*\|_\pi^2}{\sqrt{1-\alpha^2}}.$$

□

proved error bound: $\|\hat{Q} - Q^*\|_\pi \leq \frac{1}{\sqrt{1-\alpha^2}} \cdot \|\Pi Q^* - Q^*\|_\pi$. This error bound highlights the importance of choosing a good approximation architecture. Φ has a span of K basis vectors; if it is close to Q^* , so is the projection of Q^* onto the span of Φ .

Question: how well does a policy generated from \hat{Q} perform? An approach: let $\hat{J} := \max\{g, \hat{Q}\}$ and \hat{J} will be our approximation of J^* (the optimal value function). Let μ be a greedy policy with respect to \hat{J} ; that is, $T_\mu \hat{J} = T \hat{J}$. From our lecture in Week 6,

$$\begin{aligned}\|J^* - J_\mu\|_\infty &\leq \frac{2\alpha}{1-\alpha} \\ &\leq \frac{2\alpha}{1-\alpha} \|Q^* - \hat{Q}\|_\infty,\end{aligned}$$

but this distance can diverge to ∞ under $\|\cdot\|_\infty$. So we need a slightly different approach.

A new approach: \hat{Q} is our approximation of Q^* , which is the optimal value of continuing on. Let $\hat{\tau}$ be a random variable for the stopping time derived from \hat{Q} ; that is,

$$\hat{\tau} = \min\{t : \hat{Q}(x_t) \leq g(x_t)\}.$$

x_t is well-defined because we have one transition matrix (one Markov chain). This defines a policy (as long as approximate value of continuing is greater than stopping, keep going; once reversed, stop.) That is, the stopping region derived from \hat{Q} is given by

$$\{x : \hat{Q}(x) \leq g(x)\}.$$

Recall again that x may in general be extremely high-dimensional. Note: the optimal stopping region is

$$\{x : Q^*(x) \leq g(x)\}.$$

The payoff associated with the policy derived from \hat{Q} is given by

$$J_{\hat{\tau}}(x) = \mathbb{E} [\alpha^{\hat{\tau}} g(x_{\hat{\tau}}) \mid X_0 = x]$$

Let

$$\tau^* = \min\{t : Q^*(x_t) \leq g(x_t)\}.$$

denote the (actual) optimal stopping time. The optimal expected reward is

$$J^*(x) = \mathbb{E} [\alpha^{\tau^*} g(x_{\tau^*}) \mid X_0 = x].$$

Our goal is to compare J^* with $J_{\hat{\tau}}$.

Theorem 14.22.28.

$$\|J^* - J_{\hat{\tau}}\|_{\pi} \leq \frac{1}{1-\alpha} \|\hat{Q} - Q^*\|_{\pi}.$$

Remark 173. Observe that combining this result with the result from last time yields

$$\begin{aligned} \|J^* - J_{\hat{\tau}}\|_{\pi} &\leq \frac{1}{1-\alpha} \|\hat{Q} - Q^*\|_{\pi} \\ &\leq \frac{1}{(1-\alpha)\sqrt{1-\alpha^2}} \|\Pi Q^* - Q^*\|_{\pi}. \end{aligned}$$

Proof. Let $Q_{\hat{\tau}}(x)$ be the expected reward of the following policy: continue the process in the next step and follow the policy based on $\hat{\tau}$ thereafter.

We claim that $\|J^* - J_{\hat{\tau}}\|_{\pi} \leq \|Q^* - \hat{Q}\|_{\pi} + \|Q^* - Q_{\hat{\tau}}\|_{\pi}$. (Note that $Q_{\hat{\tau}} \neq \hat{Q}$. \hat{Q} is derived from approximate value iteration; it is the unique fixed point of $\Pi F(\cdot)$. $Q_{\hat{\tau}}$ is the value of a policy.)

To prove this claim, note that

$$\begin{aligned} J^*(x) - J_{\hat{\tau}}(x) &= \begin{cases} \max\{g(x), Q^*(x)\} - g(x), & g(x) \geq \hat{Q}(x), \\ \max\{g(x), Q^*(x)\} - Q_{\hat{\tau}}(x), & g(x) < \hat{Q}(x). \end{cases} \\ &= \begin{cases} g(x) - g(x) = 0, & g(x) \geq \hat{Q}(x), g(x) \geq Q^*(x) \\ Q^*(x) - g(x), & g(x) \geq \hat{Q}(x), g(x) < Q^*(x) \\ Q^*(x) - Q_{\hat{\tau}}(x), & g(x) < \hat{Q}(x), g(x) < Q^*(x), \\ g(x) - Q_{\hat{\tau}}(x), & g(x) < \hat{Q}(x), g(x) \geq Q^*(x). \end{cases} \end{aligned}$$

Consider the cases one at at time.

1. $J^*(x) - J_{\hat{\tau}}(x) = g(x) - g(x) = 0$.
2. Since J^* is optimal, $0 \leq J^*(x) - J_{\hat{\tau}}(x) = Q^*(x) - g(x) \leq Q^*(x) - \hat{Q}(x)$ since by assumption of this case $\hat{Q}(x) \leq g(x)$.
3. We already have what we need: $0 \leq J^*(x) - J_{\hat{\tau}}(x) = Q^*(x) - Q_{\hat{\tau}}(x)$.
4. We have $Q^*(x) \leq g(x) < \hat{Q}(x)$ by assumption. Then

$$\begin{aligned} 0 &\leq J^*(x) - J_{\hat{\tau}}(x) \\ &= g(x) - Q_{\hat{\tau}}(x) \\ &\leq \hat{Q}(x) - Q_{\hat{\tau}}(x) \\ &= \underbrace{\hat{Q}(x) - Q^*(x)}_{\geq 0 \text{ by assumption}} + \underbrace{Q^*(x) - Q_{\hat{\tau}}(x)}_{\geq 0 \text{ because } Q^* \text{ is optimal}} \end{aligned}$$

In all four cases, $\|J^* - J_{\hat{\tau}}\|_{\pi} \leq \|Q^* - \hat{Q}\|_{\pi} + \|Q^* - Q_{\hat{\tau}}\|_{\pi}$, proving the claim.

Now we want to use the claim to prove the theorem. We have

$$\begin{aligned}\|J^* - J_{\hat{\tau}}\|_\pi &\leq \|Q^* - \hat{Q}\|_\pi + \|Q^* - Q_{\hat{\tau}}\|_\pi \\ &= \|Q^* - \hat{Q}\|_\pi + \|\alpha P J^* - \alpha P J_{\hat{\tau}}\|_\pi \\ &\leq \|Q^* - \hat{Q}\|_\pi + \alpha \|J^* - J_{\hat{\tau}}\|_\pi\end{aligned}$$

where the second inequality followed because P is a nonexpansive mapping. Therefore

$$\begin{aligned}\|J^* - J_{\hat{\tau}}\|_\pi &\leq \frac{1}{1-\alpha} \|Q^* - \hat{Q}\|_\pi \\ &\leq \frac{1}{1-\alpha} \cdot \frac{1}{\sqrt{1-\alpha^2}} \|\Pi Q^* - Q^*\|_\pi.\end{aligned}$$

□

α may be very close to 1, in which case this proportion term can get quite large. We can do better than this. We can prove that

$$\|J^* - J_{\hat{\tau}}\|_\pi \leq \frac{2.17}{1-\alpha} \|\Pi Q^* - Q^*\|_\pi.$$

Lemma 14.22.29.

$$\|F\hat{Q} - \hat{Q}\|_\pi \leq (1+\alpha) \|Q^* - \Pi Q^*\|_\pi.$$

Proof. We claim that

$$\underbrace{(F\hat{Q} - \hat{Q})}_{\in \text{nullspace}(\Phi)} + \underbrace{(\Pi Q^* - Q^*)}_{\in \text{nullspace}(\Phi)} \perp \underbrace{\hat{Q} - \Pi Q^*}_{\in \text{span}(\Phi)},$$

where orthogonality is defined in terms of the π -weighted inner product. Recall that \hat{Q} is the unique fixed point of ΠF . So $\hat{Q} = \Pi F \hat{Q}$, therefore $\hat{Q} \in \text{span}(\Phi)$. So ΠQ^* is in the span of Φ , so $Q^* - \Pi Q^*$ is in the nullspace of Φ . Because

$$\Pi(F\hat{Q} - \hat{Q}) = \Pi F \hat{Q} - \Pi \hat{Q} = \hat{Q} - \hat{Q} = 0.$$

Therefore

$$\|F\hat{Q} - Q^*\|_\pi^2 = \|F\hat{Q} - \hat{Q} + \Pi Q^* - Q^* + \hat{Q} - \Pi Q^*\|_\pi^2 = \|F\hat{Q} - \hat{Q} + \Pi Q^* - Q^*\|_\pi^2 + \|\hat{Q} - \Pi Q^*\|_\pi^2$$

where we used orthogonality of $F\hat{Q} - \hat{Q} + \Pi Q^* - Q^*$ and $\hat{Q} - \Pi Q^*$. Therefore

$$\begin{aligned} \|F\hat{Q} - \hat{Q} + \Pi Q^* - Q^*\|_\pi^2 &= \|F\hat{Q} - \underbrace{Q^*}_{=FQ^*}\|_\pi^2 - \|\hat{Q} - \Pi Q^*\|_\pi^2 \leq \alpha^2 \|\hat{Q} - Q^*\|_\pi^2 - \alpha^2 \|\hat{Q} - \Pi Q^*\|_\pi^2 \\ &\leq \alpha^2 \|\Pi Q^* - Q^*\|_\pi^2, \end{aligned}$$

where we used the formula $\|x\| - \|y\| \leq \|x - y\| \iff \|x\| \leq \|x - y\| + \|y\|$. Therefore

$$\|F\hat{Q} - Q^*\|_\pi \leq (1 + \alpha) \|\Pi Q^* - Q^*\|_\pi.$$

□

Lemma 14.22.30.

$$\|F\hat{Q} - Q_{\hat{\tau}}\|_\pi \leq \alpha \|\hat{Q} - Q_{\hat{\tau}}\|_\pi.$$

Proof. Let $\hat{V} := \max\{g, \hat{Q}\}$, and

$$V_{\hat{\tau}}(x) := \begin{cases} g(x), & g(x) \geq \hat{Q}(x), \\ Q_{\hat{\tau}}(x), & g(x) < \hat{Q}(x). \end{cases}$$

By definition,

$$F\hat{Q} = \alpha P \max\{g, \hat{Q}\} = \alpha P\hat{V},$$

$$Q_{\hat{\tau}} = \alpha P V_{\hat{\tau}},$$

so

$$\begin{aligned} \|F\hat{Q} - Q_{\hat{\tau}}\|_\pi &= \|\alpha P\hat{V} - \alpha P V_{\hat{\tau}}\|_\pi \\ &\leq \alpha \|\hat{V} - V_{\hat{\tau}}\|_\pi \\ &\leq \alpha \|\hat{Q} - Q_{\hat{\tau}}\|_\pi. \end{aligned}$$

□

Proof of new and improved error bound:

$$\begin{aligned} \|\hat{Q} - Q_{\hat{\tau}}\|_\pi &\leq \|\hat{Q} - F\hat{Q}\|_\pi + \|F\hat{Q} - Q_{\hat{\tau}}\|_\pi \\ &\leq \|\hat{Q} - F\hat{Q}\|_\pi + \alpha \|\hat{Q} - Q_{\hat{\tau}}\|_\pi \end{aligned}$$

where the second part followed by Lemma 2. **notes continue online**

SARSA: Q_0 in the span of our basis functions Φ .

14.23 Notes on Mathieu and Minsker [2019]

14.23.1 Notation

Let (S, \mathcal{S}) be a measurable space, and $X \in S$ is a random variable with distribution P . Let $\ell : \mathbb{R} \rightarrow \mathbb{R}_+$ be a loss function. We hope to find the function f in a class \mathcal{F} of measurable functions from S to \mathbb{R} minimizing the expected loss $\mathbb{E}\ell(f(X)) = \mathcal{L}(f) = P\ell(f)$. We assume the minimum is attained for a unique $f_* \in \mathcal{F}$.

The true distribution P is usually unknown, so we find a proxy for f_* using the empirical risk minimizer.

Definition 14.15 (Empirical Risk Minimizer and Excess Risk). Let P_N be the empirical distribution of X based on the sample X_1, \dots, X_N . Define the empirical risk for a function f to be

$$\mathcal{L}_N(f) := P_N\ell(f) = \frac{1}{N} \sum_{j=1}^N \ell(f(X_j)).$$

Then the empirical risk minimizer is

$$\tilde{f}_N := \arg \min_{f \in \mathcal{F}} \mathcal{L}_N(f). \quad (14.60)$$

Performance of $f \in \mathcal{F}$ is measured via the **excess risk** $\mathcal{E}(f) := P\ell(f) - P\ell(f_*) = \mathbb{E}[\ell(f(X)) - \ell(f_*(X))]$. The excess risk of \tilde{f}_N is a random variable

$$\mathcal{E}(f) := P\ell(\tilde{f}_N) - P\ell(f_*) = \mathbb{E} \left[\ell \left(\tilde{f}_N(X) \right) \mid X_1, \dots, X_N \right] - \mathbb{E} \ell(f_*(X)).$$

Example 14.15 (Regression).

- $X = (Z, Y) \in \mathbb{R}^d \times \mathbb{R}$.
- $f(Z, Y) = Y - g(Z)$ for some g in a class \mathcal{G} (such as the class of linear functions from $\mathbb{R}^d \rightarrow \mathbb{R}$).
- $\ell(x) = x^2$.
- $f_*(z, y) = y - g_*(z)$, where $g_*(z) = \mathbb{E}(Y \mid Z = z)$.
- $\mathcal{L}_N(f) = \frac{1}{N} \sum_{j=1}^N \ell(f(X_j)) = \frac{1}{N} \sum_{j=1}^N [Y_j - g(Z_j)]^2$.
- $\tilde{f}_N = \arg \min_{f \in \mathcal{F}} \left\{ \frac{1}{N} \sum_{j=1}^N (f(X_j))^2 \right\} = Y - \tilde{g}_N(Z) \quad \text{where} \quad \tilde{g}_N := \arg \min_{g \in \mathcal{G}} \left\{ \frac{1}{N} \sum_{j=1}^N (Y_j - g(Z_j))^2 \right\}$.
-

$$\begin{aligned} \mathcal{E}(f) &= P\ell(\tilde{f}_N) - P\ell(f_*) \\ &= \mathbb{E} \left[\ell \left(\tilde{f}_N(X) \right) \mid X_1, \dots, X_N \right] - \mathbb{E} \ell(f_*(X)) \\ &= \mathbb{E} \left[(Y - \tilde{g}_N(Z))^2 \mid X_1, \dots, X_N \right] - \mathbb{E} [Y - \mathbb{E}(Y \mid Z)]^2 \end{aligned}$$

Definition 14.16. For two sequences $\{a_j\}_{j \geq 1} \subset \mathbb{R}$ and $\{b_j\}_{j \geq 1} \subset \mathbb{R}$ for $j \in \mathbb{N}$, the expression $a_j \lesssim b_j$ means there exists a constant $c > 0$ such that $a_j \leq cb_j$ for all $j \in \mathbb{N}$. $a_j \asymp b_j$ means that $a_j \lesssim b_j$ and $b_j \lesssim a_j$.

For a function $h : \mathbb{R}^d \rightarrow \mathbb{R}$, the authors define

$$\arg \min_{y \in \mathbb{R}^d} h(y) := \{y \in \mathbb{R}^d : h(y) \leq h(x) \quad \forall x \in \mathbb{R}^d\}.$$

Also, $\|h\|_\infty := \text{ess sup } \{|h(y)| : y \in \mathbb{R}^d\}$. $L(h)$ will stand for a Lipschitz constant of h . For $f \in \mathcal{F}$, let $\sigma^2(\ell, f) := \text{Var}(\ell(f(X)))$, and for any subset $\mathcal{F}' \subseteq \mathcal{F}$, denote $\sigma^2(\ell, \mathcal{F}') := \sup_{f \in \mathcal{F}'} \sigma^2(\ell, f)$.

14.23.2 Section 1

The focus of this paper is on the situation when marginal distributions of the process $\{\ell(f(X)), f \in \mathcal{F}\}$ indexed by \mathcal{F} are allowed to be heavy-tailed in the sense that only their first 2 to 4 moments are finite. The authors also consider a framework of *adversarial contamination*, when the initial data set of cardinality N is merged with a set of $\mathcal{O} < N$ outliers generated by an adversary who has an opportunity to inspect the data. The combined data set of cardinality $N^\circ = N + \mathcal{O}$ is presented to the algorithm. (The authors assume an upper bound for proportion of contamination \mathcal{O}/N is known.)

The robust estimator the authors will propose incorporates ideas from a “median-of-means” estimator as well as Catoni’s estimator [Catoni, 2012], which relies on truncation of the data.

Definition 14.17 (Median of means estimator; from Devroye et al. [2016], Section 4.1). Let b be a positive integer and let $x_1^b \in \mathbb{R}^b$. Let $q_{1/2}$ denote the median of the numbers x_1, \dots, x_b ; that is,

$$q_{1/2}(x_1^b) = x_i \quad \text{where } |\{k \in [b] : x_k \leq x_i\}| \geq \frac{b}{2} \text{ and } |\{k \in [b] : x_k \geq x_i\}| \geq \frac{b}{2}.$$

(If more than one i fit the above description, take the smallest one.) Let $\delta \in [e^{1-n/2}, 1]$. Choose $b = \lceil \log(1/\delta) \rceil$ (note that $b \leq n/2$). Now divide $[n]$ into b blocks (disjoint subsets) B_i , $1 \leq i \leq b$, each of size $|B_i| \geq k = \lfloor n/b \rfloor \geq 2$. Given $x_1^n \in \mathbb{R}^n$, define

$$y_{n,\delta,i}(x_1^n) := \frac{1}{|B_i|} \sum_{j \in B_i} x_i,$$

$$y_{n,\delta}(x_1^n) := (y_{n,\delta,i}(x_1^n))_{i=1}^b \in \mathbb{R}^b,$$

and define the median-of-means estimator by

$$\hat{E}_{n,\delta}(x_1^n) := q_{1/2}(y_{n,\delta}(x_1^n)).$$

Definition 14.18 (Robust mean estimators). Let $k \leq N$ be an integer. Assume G_1, \dots, G_k are disjoint subsets of the index set $[N]$ of cardinality $|G_j| = n \geq \lfloor N/k \rfloor$ each. Given $f \in F$, let

$$\bar{\mathcal{L}}_j(f) := \frac{1}{n} \sum_{i \in G_j} \ell(f(X_i))$$

be the empirical mean evaluated over the subsample indexed by G_j . Given a convex, even function $\rho : \mathbb{R} \rightarrow \mathbb{R}_+$ and $\Delta > 0$, set

$$\begin{aligned} \hat{\mathcal{L}}^{(k)}(f) &:= \arg \min_{y \in \mathbb{R}} \left\{ \sum_{j=1}^k \rho \left(\sqrt{n} \cdot \frac{\bar{\mathcal{L}}_j(f) - y}{\Delta} \right) \right\} \\ &= \arg \min_{y \in \mathbb{R}} \left\{ \sum_{j=1}^k \rho \left(\sqrt{n} \cdot \frac{n^{-1} \sum_{i \in G_j} \ell(f(X_i)) - y}{\Delta} \right) \right\} \end{aligned}$$

Remark 174. Note that if $\rho(x) = x^2$, $\hat{\mathcal{L}}^{(k)}(f)$ is equal to the sample mean:

$$\begin{aligned} \hat{\mathcal{L}}^{(k)}(f) &= \arg \min_{y \in \mathbb{R}} \left\{ \sum_{j=1}^k \left(\sqrt{n} \cdot \frac{n^{-1} \sum_{i \in G_j} \ell(f(X_i)) - y}{\Delta} \right)^2 \right\} \\ &= \arg \min_{y \in \mathbb{R}} \left\{ \frac{n}{\Delta^2} \sum_{j=1}^k \left(\frac{1}{n} \sum_{i \in G_j} \ell(f(X_i)) - y \right)^2 \right\} \\ &= \arg \min_{y \in \mathbb{R}} \left\{ \sum_{j=1}^k \left(\frac{1}{n} \sum_{i \in G_j} \ell(f(X_i)) - y \right)^2 \right\} \\ &= \arg \min_{y \in \mathbb{R}} \left\{ \frac{1}{N} \sum_{i=1}^N (\ell(f(X_i)) - y)^2 \right\} \\ &= \frac{1}{N} \sum_{i=1}^N \ell(f(X_i)). \end{aligned}$$

If $\rho(x) = |x|$, it turns out that $\hat{\mathcal{L}}^{(k)}(f)$ is the median-of-means estimator:

$$\begin{aligned} \hat{\mathcal{L}}^{(k)}(f) &= \arg \min_{y \in \mathbb{R}} \left\{ \sum_{j=1}^k \left| \sqrt{n} \cdot \frac{n^{-1} \sum_{i \in G_j} \ell(f(X_i)) - y}{\Delta} \right| \right\} \\ &= \hat{E}_{N,\delta}(\ell(f(X))). \end{aligned}$$

This paper focuses on the situation when ρ is similar to Huber's loss (ρ' is bounded and Lipschitz continuous). It is instructive to consider two cases. First, when $k = N$ (so that $n = 1$) and

$$\Delta \asymp \sqrt{\text{Var}(\ell(f(X)))} \sqrt{N},$$

$\hat{\mathcal{L}}^{(k)}(f)$ is akin to Catoni's estimator. When n is large and

$$\Delta \asymp \sqrt{\text{Var}(\ell(f(X)))},$$

we recover the “median-of-mean”-type estimator. (The standard median-of-means estimator corresponds to $\rho(x) = x$ and can be seen as a limit of $\hat{\mathcal{L}}^{(k)}(f)$ when $\Delta \rightarrow 0$; this case is not covered by results of the paper, as the authors require that ρ' is smooth and Δ is bounded from below.)

We can also construct an estimator that does not depend on the specific choice of subgroups G_1, \dots, G_k .

Definition 14.19 (Permutation-invariant robust mean estimator). Define

$$\mathcal{A}_N^{(n)} := \{J : J \subseteq [N], |J| = n\}.$$

Let h be a measurable, permutation-invariant function of n variables. Recall that a U -statistic of order n with kernel h based on an i.i.d. sample X_1, \dots, X_N is defined as

$$U_{N,n} := \frac{1}{\binom{N}{n}} \sum_{J \in \mathcal{A}_N^{(n)}} h(\{X_j\}_{j \in J})$$

(see Section 10.10). Given $J \in \mathcal{A}_N^{(n)}$, let

$$\bar{\mathcal{L}}(f; J) := \frac{1}{n} \sum_{i \in J} f(X_i).$$

(Note that $\bar{\mathcal{L}}(f; J)$ is a permutation-invariant function of its arguments.) Consider U -statistics of the form

$$U_{N,n}(z; f) = \sum_{J \in \mathcal{A}_N^{(n)}} \rho \left(\sqrt{n} \cdot \frac{\bar{\mathcal{L}}(f; J) - z}{\Delta} \right) = \sum_{J \in \mathcal{A}_N^{(n)}} \rho \left(\sqrt{n} \cdot \frac{n^{-1} \sum_{i \in J} f(X_i) - z}{\Delta} \right).$$

Then the permutation-invariant version of $\hat{\mathcal{L}}^{(k)}(f)$ is naturally defined as

$$\hat{\mathcal{L}}_U^{(k)}(f) := \arg \min_{z \in \mathbb{R}} U_{N,n}(z; f).$$

Assuming that $\hat{\mathcal{L}}^{(k)}(f)$ provides good approximation of the expected loss $\mathcal{L}(f)$ of each individual $f \in \mathcal{F}$, it is natural to consider

$$\hat{f}_N := \arg \min_{f \in \mathcal{F}} \hat{\mathcal{L}}^{(k)}(f)$$

as well as its permutation-invariant analogue

$$\hat{f}_N^U := \arg \min_{f \in \mathcal{F}} \hat{\mathcal{L}}_U^{(k)}(f)$$

as alternatives to standard risk minimization (14.60). The goal of this paper is to get general bounds for the excess risk of the estimators \hat{f}_N and \hat{f}_N^U under minimal assumptions on the stochastic process $\{\ell(f(X)), f \in \mathcal{F}\}$.

14.24 Random Forests and Notes on Chi et al. [2020]

Definition 14.20. A real- or complex-valued function f on a d -dimensional Euclidean space is **Hölder continuous** if there exist nonnegative real constants C and α such that

$$|f(x) - f(y)| \leq C\|x - y\|^\alpha$$

for all x and y in the domain of f . (This condition can be formulated for functions between any two metric spaces.) The number α is called the **exponent** of the Hölder condition. A function on an interval satisfying the condition with $\alpha > 1$ is constant. Note that if $\alpha = 1$ then the function is Lipschitz continuous, and for $\alpha \in (0, 1)$ Hölder continuity is weaker than Lipschitz continuity. For any $\alpha > 0$ the condition implies the function is uniformly continuous.

14.24.1 Section 2 (Terminology and Review of Random Forest)

Definition 14.21. Let \mathcal{T} be the set of rectangles $\mathbf{t} = \times_{j=1}^p t_j \subset \mathbf{t}_0 := [0, 1]^p$, where each t_j is a closed or half-closed interval in $[0, 1]$. A **cell** or **subcell** is an element of \mathcal{T} . A **cut** or **split** is a feature and location pair that can be used for separating the parent cell. That is, for a nonempty cell \mathbf{t} , a cut is a pair (s, c) with $s \in \{1, \dots, p\}$ and $c \in t_s$, and the **daughter cells** obtained by separating \mathbf{t} accordingly are

$$\times_{j=1}^{s-1} t_j \times (t_s \cap [0, c)) \times_{j=s+1}^p t_j$$

and

$$\times_{j=1}^{s-1} t_j \times (t_s \cap [c, 1]) \times_{j=s+1}^p t_j.$$

Observe that the daughter cells of an empty cell are two empty cells. In practice, there will be a restriction of available directions (features) on a cut. At an initial level (i.e., level 0), we have a root cell $\mathbf{t}_0 = [0, 1]^p$. Then two subcells are obtained at level 1 after a cut for the root cell. Then we cut those two subcells to create 4 subcells, and so on. Thus at each level ℓ , when growing a tree there are 2^ℓ subcells to be cut.

Definition 14.22 (A set of level k daughter cell paths). Let $\mathcal{D} \subset \mathcal{T}^k$ be a set composed of 2^k k -tuples (that is, $\#\mathcal{D} = 2^k$). \mathcal{D} is a **set of level k daughter cell paths** (also called a **tree**) if and only if

1. For each $(\mathbf{t}_1, \dots, \mathbf{t}_k) \in \mathcal{D}$, $\mathbf{t}_\ell \in \mathcal{T}$ is a subset of $[0, 1]^p$ and in particular is one of the daughter cells of $\mathbf{t}_{\ell-1}$ for each $\ell \in [k]$, and
2. The set of unique elements in $\{\mathbf{t}_\ell : (\mathbf{t}_1, \dots, \mathbf{t}_k) \in \mathcal{D}\}$ is a partition of \mathbf{t}_0 for each $\ell \in [k]$.

(That is, for any $\ell \in [k]$, the set of unique elements in the ℓ^{th} slot of an element of \mathcal{D} form a partition of $[0, 1]^p$. So for example, the set of unique first entries of elements of this set are two non-overlapping hyperrectangles whose union is $[0, 1]^p$, and the unique last entries of elements of this set form a partition of $[0, 1]^p$ into 2^k non-overlapping hyperrectangles.)

Denote by $\tilde{\mathcal{D}}$ the set of all such sets \mathcal{D} .

Note that a set of level k daughter cell paths $\mathcal{D} \in \tilde{\mathcal{D}}$ has exactly 2^k tuples. Also, as long as there are no empty daughter cells at each level, these 2^k tuples are mutually exclusive.

The random forest algorithm usually puts a restriction on the available feature subset when deciding on the feature for each cut. Denote by $\Theta_k \in \mathcal{P}(\{1, \dots, p\}) = \mathcal{P}([p])$ (where $\mathcal{P}([p])$ denotes the power set of $[p]$) the constraint for each of the 2^{k-1} cuts at level k . Given a set of observations, a sequence of constraints $\{\Theta_i\}_{i=1}^\infty$, and some positive integer k , the random forest algorithm produces a set of level k daughter cell paths (a tree). Most random forest implementations use the CART-split criterion for growing the tree. Then another tree is created using the same set of observations and the same positive integer k but a different sequence of constraints.

Definition 14.23 (Tree growing rule). A **tree growing rule** denoted as $T : \mathbb{N} \times (\mathcal{P}([p]))^k \rightarrow \tilde{\mathcal{D}}$ is a mapping that takes some positive integer k and k feature subset constraints as inputs and outputs a set of level k daughter cell paths (a tree).

Denote by $\#S$ the number of elements in a set S . Let $\{(\mathbf{x}_i, y_i)\}_{i=1}^n$ be a given sample with $\mathbf{x}_i := (x_{i1}, \dots, x_{ip})^\top \in [0, 1]^p$ the p -dimensional random covariate vector and $y_i \in \mathbb{R}$ the response. We define the summation over an empty set as zero.

Definition 14.24 (Sample CART-split criterion). Given a cell $\mathbf{t} \in \mathcal{T}$ and a feature subset $\Theta \in \mathcal{P}([p])$, the sample CART-split criterion is defined as

$$(\hat{j}, \hat{c}) := \arg \min_{j \in \Theta, c \in \{x_{ij} : \mathbf{x}_i \in \mathbf{t}\}} \left\{ \sum_{i \in \{i : \mathbf{x}_i \in \mathbf{t}, x_{ij} < c\}} (\bar{y}_\ell(\mathbf{t}, c) - y_i)^2 + \sum_{i \in \{i : \mathbf{x}_i \in \mathbf{t}, x_{ij} \geq c\}} (\bar{y}_r(\mathbf{t}, c) - y_i)^2 \right\}$$

where

$$\bar{y}_\ell(\mathbf{t}, c) := \sum_{i \in \{i : \mathbf{x}_i \in \mathbf{t}, x_{ij} < c\}} \frac{y_i}{\#\{i : \mathbf{x}_i \in \mathbf{t}, x_{ij} < c\}}, \quad \bar{y}_r(\mathbf{t}, c) := \sum_{i \in \{i : \mathbf{x}_i \in \mathbf{t}, x_{ij} \geq c\}} \frac{y_i}{\#\{i : \mathbf{x}_i \in \mathbf{t}, x_{ij} \geq c\}}$$

The above optimization breaks ties evenly. For a subcell $\mathbf{t} \subset [0, 1]^p$ with $\#\{i : \mathbf{x}_i \in \mathbf{t}\} = 0$, a random cut is optimal.

Definition 14.25 (Sample tree growing rule; Definition 3 in [Chi et al. \[2020\]](#)). For each positive integer k , a subset of sample indices $\mathcal{A} \in \mathcal{P}([n])$, and feature subsets $\Theta_1, \dots, \Theta_k$, the sample tree growing rule

$$\hat{T}_{(n, \mathcal{A})} : (\mathcal{P}([p]))^k \rightarrow \tilde{\mathcal{D}}$$

is such that if $(\mathbf{t}_1, \dots, \mathbf{t}_k) \in \hat{T}_{(n, \mathcal{A})}(\Theta_1, \dots, \Theta_k)$, then for each $\ell \in [k]$, \mathbf{t}_ℓ is one of the daughter cells of $\mathbf{t}_{\ell-1}$ constructed by the sample CART-split criterion with the sample given in \mathcal{A} .

Next we define a level k sample forest model; informally, it is the average of many tree models. Denote by $\mathcal{X}_n := (\mathbf{x}_1^\top, y_1, \dots, \mathbf{x}_n^\top, y_n)^\top \in \{[0, 1]^p \times \mathbb{R}\}^n$.

Definition 14.26 (Level k sample forest model). Let $\tilde{\mathcal{A}} \in \mathcal{P}([n]) \times \dots \times \mathcal{P}([n])$ be a set of sample indices such that the elements in $\tilde{\mathcal{A}}$ do not repeat and are of the same predetermined size; that is, for each $\mathcal{A} \in \tilde{\mathcal{A}}$, it holds that $|\mathcal{A}| = \lceil bn \rceil$ for some $b \in (0, 1]$. Denote by $\hat{m}_{k,T,\mathcal{A}} : (\mathcal{P}([p]))^k \times [0, 1]^p \times \{[0, 1]^p \times \mathbb{R}\}^n \rightarrow \mathbb{R}$ the tree model such that for each $(\mathbf{t}_1, \dots, \mathbf{t}_k) \in T(\Theta_1, \dots, \Theta_k)$ and each $\mathbf{c} \in \mathbf{t}_k$,

$$\hat{m}_{k,T,\mathcal{A}}(\Theta_1, \dots, \Theta_k, \mathbf{c}, \mathcal{X}_n) = \sum_{i \in (\{i : \mathbf{x}_i \in \mathbf{t}_k\} \cap \mathcal{A})} \frac{y_i}{\#(\{i : \mathbf{x}_i \in \mathbf{t}_k\} \cap \mathcal{A})}.$$

Thus the forest model considering random sampling given $\mathbf{c} \in [0, 1]^p$, sample \mathcal{X}_n , and feature constraints is defined as

$$\frac{1}{\#\tilde{\mathcal{A}}} \sum_{\mathcal{A} \in \tilde{\mathcal{A}}} \hat{m}_{k,T,\mathcal{A}}(\Theta_1, \dots, \Theta_k, \mathbf{c}, \mathcal{X}_n).$$

Since standard random forest packages draw random feature subsets as constraints, denote by $\{\Theta_i\}_{i=1}^\infty$ a sequence of random constraints (that is, in the notation we have previously used, $\{\Theta_i\}_{i=1}^\infty$ is a realization of $\{\Theta_i\}_{i=1}^\infty$).

Definition 14.27. The forest prediction (using both random feature subsets and random sampling) given T, \mathbf{X} (a random variable taking on values in $[0, 1]^p$), and \mathcal{X}_n is defined as

$$\mathbb{E} \left(\frac{1}{\#\tilde{\mathcal{A}}} \sum_{\mathcal{A} \in \tilde{\mathcal{A}}} \hat{m}_{k,T,\mathcal{A}}(\Theta_1, \dots, \Theta_k, \mathbf{X}, \mathcal{X}_n) \mid \mathbf{X}, \mathcal{X}_n \right).$$

For the special forest model with $\#\tilde{\mathcal{A}} = 1$ and $\mathcal{A} \in \tilde{\mathcal{A}}$ the full sample indices, we use the following notation:

$$\hat{m}_{k,T}(\Theta_1, \dots, \Theta_k, \mathbf{c}, \mathcal{X}_n) := \frac{1}{\#\tilde{\mathcal{A}}} \sum_{\mathcal{A} \in \tilde{\mathcal{A}}} \hat{m}_{k,T,\mathcal{A}}(\Theta_1, \dots, \Theta_k, \mathbf{c}, \mathcal{X}_n). \quad (14.61)$$

We call this model a **tree model**. It is worth mentioning that both sample forest and tree models are averaged over all possible feature subset constraints. Then the (level k) random forest prediction of a standard random forest algorithm at the test point \mathbf{X} given \mathcal{X}_n is defined as

$$\mathbb{E} \left(\frac{1}{\#\tilde{\mathcal{A}}} \sum_{\mathcal{A} \in \tilde{\mathcal{A}}} \hat{m}_{k,\hat{T}_{(n,\mathcal{A})},\mathcal{A}}(\Theta_1, \dots, \Theta_k, \mathbf{X}, \mathcal{X}_n) \mid \mathbf{X}, \mathcal{X}_n \right), \quad (14.62)$$

where $\tilde{\mathcal{A}}$ is an arbitrary given set.

Remark 175. There are two layers of randomness in the random forest model: the random feature subsets and random sampling. For the random forest prediction in (14.62), both kinds of randomness are taken into account; in particular, all possible feature subsets are included. For practical implementation, it is not required to consider all possible feature subsets. The standard random forest R package grows $B \leq \#A$ trees each of which involves random resampling and feature subsets of size $\lceil \gamma_0 p \rceil$.

14.24.2 Section 3: Approximation Accuracy

Definition 14.28. Denote $\mathbb{P}(\cdot | \mathbf{X} \in \mathbf{t})$ as $\mathbb{P}_{\mathbf{t}}(\cdot)$, and similarly denote $\mathbb{E}(\cdot | \mathbf{X} \in \mathbf{t})$ as $\mathbb{E}_{\mathbf{t}}(\cdot)$. Given a nonempty cell $\mathbf{t} \in \mathcal{T}$ and a feature subset $\Theta \subset \{1, \dots, p\}$, the **best cut** according to the **population CART-split criterion** is defined as

$$(j^*, c^*) := \arg \inf_{j \in \Theta, c \in \mathbf{t}_j} \{\mathbb{P}_{\mathbf{t}}(X_j < c) \text{Var}(m | \{X_j < c\} \cap \{\mathbf{X} \in \mathbf{t}\}) + \mathbb{P}_{\mathbf{t}}(X_j \geq c) \text{Var}(m | \{X_j \geq c\} \cap \{\mathbf{X} \in \mathbf{t}\})\}.$$

Ties are broken randomly. If \mathbf{t} is empty, both of its daughter cells are empty. We define the **best constrained (unconstrained) daughter cells** as the daughter cells resulting from the optimal cut when Θ is a nontrivial (trivial) constraint.

Definition 14.29. The **impurity decrease** of a cut (j, c) given \mathbf{t} is defined to be

$$\text{Var}(m | \mathbf{X} \in \mathbf{t}) - [\mathbb{P}_{\mathbf{t}}(X_j < c) \text{Var}(m | \{X_j < c\} \cap \{\mathbf{X} \in \mathbf{t}\}) + \mathbb{P}_{\mathbf{t}}(X_j \geq c) \text{Var}(m | \{X_j \geq c\} \cap \{\mathbf{X} \in \mathbf{t}\})]. \quad (14.63)$$

Note that the population CART-split criterion from Definition 14.28 maximizes the impurity decrease (and can be equivalently defined this way).

Definition 14.30 (Population tree growing rule; Definition 4 in [Chi et al. \[2020\]](#)). Let the regression function and joint distribution of covariates be given. For each positive integer k and feature subsets $\Theta_1, \dots, \Theta_k$, the **population tree growing rule** T^* is such that if $(\mathbf{t}_1, \dots, \mathbf{t}_k) \in T^*(\Theta_1, \dots, \Theta_k)$, then for each $\ell \in [k]$, \mathbf{t}_ℓ is one of the daughter cells of $\mathbf{t}_{\ell-1}$ constructed by the population CART-split criterion.

Given a tree growing rule T , a level k population tree model is defined as a function $m_{k,T}^*$ of the feature subset constraints $\Theta_1, \dots, \Theta_k$ and a p -dimensional vector such that for each $\mathbf{c} \in \mathbf{t}_k$ and $(\mathbf{t}_1, \dots, \mathbf{t}_k) \in T(\Theta_1, \dots, \Theta_k)$,

$$m_{k,T}^*(\Theta_1, \dots, \Theta_k, \mathbf{c}) = \mathbb{E}(m | \mathbf{X} \in \mathbf{t}_k). \quad (14.64)$$

The prediction at a test point \mathbf{X} is then given by

$$\mathbb{E}(m_{k,T}^*(\Theta_1, \dots, \Theta_k, \mathbf{X}) | \mathbf{X}).$$

Also, the following variance decomposition formula is useful:

Lemma 14.24.1 (Variance decomposition formula; Lemma 1 in [Chi et al. \[2020\]](#)). Let $\mathbf{t} \in [0, 1]^p$ be a given cell, and let \mathbf{t}' and \mathbf{t}'' be two daughter cells of \mathbf{t} . The conditional variance of $m := m(\mathbf{X})$ on \mathbf{t} admits the following decomposition:

$$\begin{aligned} \text{Var}(m | \mathbf{X} \in \mathbf{t}) &= \mathbb{P}_{\mathbf{t}}(\mathbf{X} \in \mathbf{t}') \text{Var}(m | \mathbf{X} \in \mathbf{t}') + \mathbb{P}_{\mathbf{t}}(\mathbf{X} \in \mathbf{t}'') \text{Var}(m | \mathbf{X} \in \mathbf{t}'') \\ &\quad + \mathbb{P}_{\mathbf{t}}(\mathbf{X} \in \mathbf{t}') (\mathbb{E}_{\mathbf{t}'}(m) - \mathbb{E}_{\mathbf{t}}(m))^2 + \mathbb{P}_{\mathbf{t}}(\mathbf{X} \in \mathbf{t}'') (\mathbb{E}_{\mathbf{t}''}(m) - \mathbb{E}_{\mathbf{t}}(m))^2. \end{aligned} \quad (14.65)$$

For notational convenience, define

$$(I)_{\mathbf{t}, \mathbf{t}'} := \mathbb{P}_{\mathbf{t}}(\mathbf{X} \in \mathbf{t}') \text{Var}(m \mid \mathbf{X} \in \mathbf{t}') + \mathbb{P}_{\mathbf{t}}(\mathbf{X} \in \mathbf{t}'') \text{Var}(m \mid \mathbf{X} \in \mathbf{t}'')$$

and

$$(II)_{\mathbf{t}, \mathbf{t}'} := \mathbb{P}_{\mathbf{t}}(\mathbf{X} \in \mathbf{t}') (\mathbb{E}_{\mathbf{t}'}(m) - \mathbb{E}_{\mathbf{t}}(m))^2 + \mathbb{P}_{\mathbf{t}}(\mathbf{X} \in \mathbf{t}'') (\mathbb{E}_{\mathbf{t}''}(m) - \mathbb{E}_{\mathbf{t}}(m))^2$$

so we can write (14.65) as

$$\text{Var}(m \mid \mathbf{X} \in \mathbf{t}) = (I)_{\mathbf{t}, \mathbf{t}'} + (II)_{\mathbf{t}, \mathbf{t}'}.$$

Note that since $\mathbf{t} = \mathbf{t}' \cup \mathbf{t}''$, $(I)_{\mathbf{t}, \mathbf{t}'} = (I)_{\mathbf{t}, \mathbf{t}''}$ and $(II)_{\mathbf{t}, \mathbf{t}'} = (II)_{\mathbf{t}, \mathbf{t}''}$. Note also that the population CART-split criterion from Definition 14.28 minimizes $(I)_{\mathbf{t}, \mathbf{t}'}$ for the case of axis-aligned cuts. Note also that in the case of axis-aligned cuts, the impurity decrease formula (14.63) can be written as

$$\begin{aligned} & \text{Var}(m \mid \mathbf{X} \in \mathbf{t}) - [\mathbb{P}_{\mathbf{t}}(X_j < c) \text{Var}(m \mid \{X_j < c\} \cap \{\mathbf{X} \in \mathbf{t}\}) + \mathbb{P}_{\mathbf{t}}(X_j \geq c) \text{Var}(m \mid \{X_j \geq c\} \cap \{\mathbf{X} \in \mathbf{t}\})] \\ &= \text{Var}(m \mid \mathbf{X} \in \mathbf{t}) - (I)_{\mathbf{t}, \mathbf{t}'} \\ &= (II)_{\mathbf{t}, \mathbf{t}'}. \end{aligned}$$

Therefore the population CART-split criterion from Definition 14.28 maximizes $(II)_{\mathbf{t}, \mathbf{t}'}$. Also, zero impurity on \mathbf{t} means that the regression function on \mathbf{t} is just an intercept.

Technical Conditions

The below conditions are needed for this paper's theoretical results.

- 1. Condition 1: Sufficient Impurity Decrease (SID).** There exist some $\alpha_1 \geq 1$ and $q_1 \geq 1$ such that for each cell \mathbf{t} , $\text{Var}(m \mid \mathbf{X} \in \mathbf{t}) < \alpha_1 ((II)_{\mathbf{t}, \mathbf{t}^*})^{1/q_1}$, where \mathbf{t}^* is one of the best unconstrained daughter cells of \mathbf{t} (recall Definition 14.28).

- For the specific case of $q_1 = 1$, Condition 1 requires that there is a minimum impurity decrease rate (i.e., the inverse of $\alpha_1 - 1$) for each cell when the cell is cut by the corresponding optimal cut. (Note that since $\text{Var}(m \mid \mathbf{X} \in \mathbf{t}) = (I)_{\mathbf{t}, \mathbf{t}'} + (II)_{\mathbf{t}, \mathbf{t}'}$, if $q_1 = 1$,

$$\begin{aligned} \text{Var}(m \mid \mathbf{X} \in \mathbf{t}) < \alpha_1 (II)_{\mathbf{t}, \mathbf{t}^*} &\iff \text{Var}(m \mid \mathbf{X} \in \mathbf{t}) - (I)_{\mathbf{t}, \mathbf{t}'} = (II)_{\mathbf{t}, \mathbf{t}'} < \alpha_1 (II)_{\mathbf{t}, \mathbf{t}^*} - (I)_{\mathbf{t}, \mathbf{t}'} \\ &\iff (I)_{\mathbf{t}, \mathbf{t}'} < (\alpha_1 - 1) (II)_{\mathbf{t}, \mathbf{t}^*} \\ &\iff (II)_{\mathbf{t}, \mathbf{t}^*} > \frac{(I)_{\mathbf{t}, \mathbf{t}'}}{\alpha_1 - 1}. \end{aligned}$$

That is, since $(II)_{\mathbf{t}, \mathbf{t}^*}$ is the impurity decrease, the impurity decrease has to exceed a certain threshold. If $q_1 > 1$ and $\alpha_1 > (II)_{\mathbf{t}, \mathbf{t}^*}^{\frac{q_1-1}{q_1}}$:

$$\begin{aligned}
\text{Var}(m \mid \mathbf{X} \in \mathbf{t}) < \alpha_1 (II)_{\mathbf{t}, \mathbf{t}^*}^{1/q_1} &\iff \text{Var}(m \mid \mathbf{X} \in \mathbf{t}) - (I)_{\mathbf{t}, \mathbf{t}'} = (II)_{\mathbf{t}, \mathbf{t}'} < \alpha_1 (II)_{\mathbf{t}, \mathbf{t}^*}^{1/q_1} - (I)_{\mathbf{t}, \mathbf{t}'} \\
&\iff (I)_{\mathbf{t}, \mathbf{t}'} < \left(\alpha_1 - (II)_{\mathbf{t}, \mathbf{t}^*}^{\frac{q_1-1}{q_1}} \right) (II)_{\mathbf{t}, \mathbf{t}^*}^{1/q_1} \\
&\iff (II)_{\mathbf{t}, \mathbf{t}^*}^{1/q_1} > \frac{1}{\alpha_1 - (II)_{\mathbf{t}, \mathbf{t}^*}^{\frac{q_1-1}{q_1}}} (I)_{\mathbf{t}, \mathbf{t}'}
\end{aligned}$$

2. **Condition 2.** Assume that $|m| \leq M_0$ for some $M_0 > 0$.

3. **Condition 3.** Consider a tree growing rule T such that T depends only on the feature subset constraint and there exists some positive integer k , $\epsilon > 0$, and $\alpha_2 \geq 1$ such that for each $\ell \in [k]$, feature subset constraint $\Theta_1, \dots, \Theta_k$, and $(\mathbf{t}_1, \dots, \mathbf{t}_k) \in T(\Theta_1, \dots, \Theta_k)$,

- (a) $(II)_{\mathbf{t}_{\ell-1}, \mathbf{t}_\ell} \leq \epsilon$ only if $(II)_{\mathbf{t}_{\ell-1}, \mathbf{t}_\ell^*} \leq \alpha_2 \epsilon$, and
- (b) If $(II)_{\mathbf{t}_{\ell-1}, \mathbf{t}_\ell} > \epsilon$, then $(II)_{\mathbf{t}_{\ell-1}, \mathbf{t}_\ell^*} \leq \alpha_2 (II)_{\mathbf{t}_{\ell-1}, \mathbf{t}_\ell}$,

where \mathbf{t}_ℓ^* is one of the best daughter cells of $\mathbf{t}_{\ell-1}$ given the feature subset constraint.

Main Results

Theorem 14.24.2 (Approximation accuracy; Theorem 1 in [Chi et al. \[2020\]](#)). Assume that Conditions 1 - 2 hold and the tree growing rule T satisfies item 1 of Condition 3 with some positive integer k , $\epsilon > 0$, and $\alpha_2 \geq 1$. Then

$$\mathbb{E} [m(\mathbf{X}) - m_{k,T}^*(\Theta_1, \dots, \Theta_k, \mathbf{X})]^2 \leq \alpha_1 (\alpha_2 \epsilon)^{1/q_1} + \left(1 - \gamma_0 \left(\frac{\epsilon}{\epsilon + M_0^2} \right) \right)^k M_0^2,$$

where $m_{k,T}^*$ is the level k population tree model from (14.64) in Definition 14.30 and γ_0 is as described in Remark 175. Moreover, when item 2 of Condition 3 is satisfied and $q_1 = 1$, it holds that

$$\mathbb{E} [m(\mathbf{X}) - m_{k,T}^*(\Theta_1, \dots, \Theta_k, \mathbf{X})]^2 \leq \alpha_1 \alpha_2 \epsilon + \left(1 - \frac{\gamma_0}{\alpha_1 \alpha_2} \right)^k M_0^2.$$

Theorem 14.24.2 provides a general approximation theory on the rate of convergence for random forest without assuming that the covariates are independent. This is the “noiseless case.”

14.24.3 Consistency Rates (Section 4 of [Chi et al. \[2020\]](#)))

[Chi et al.](#) introduce two additional regularity conditions.

- **Condition 4.** Assume that the distribution of covariates \mathbf{X} has a density function f that is bounded away from 0 and ∞ .
- **Condition 5.** Assume that $y_i = m(\mathbf{x}_i) + \epsilon_i$ with \mathbf{x}_i i.i.d. realizations from \mathbf{X} and ϵ_i i.i.d. with mean zero and a symmetric distribution, and $p = \mathcal{O}(n^K)$ for some positive constant K .

These are some basic assumptions in nonparametric regression models. In particular, this allows for polynomially growing dimension p . Some key lemmas follow.

Lemma 14.24.3 (Estimation error; Lemma 2 in [Chi et al. \[2020\]](#)). Assume that Conditions 2 and 5 hold, $0 < \eta < 1/2$, $0 < c < (\log 2)^{-1}(1/2 - \eta)$, and $\mathbb{E}|\epsilon_1|^q < \infty$ for sufficiently large q . Then it holds that for all large n and each $1 \leq k \leq c \log n$,

$$\mathbb{E} \left[m_{k,\hat{T}_n}^*(\Theta_1, \dots, \Theta_k, \mathbf{X}) - \hat{m}_{k,\hat{T}_n}(\Theta_1, \dots, \Theta_k, \mathbf{X}) \right]^2 \leq n^{-\eta},$$

where the sample tree growing rule \hat{T}_n is defined in Definition 14.25 (except with no set of sample indices specified because we are using the special forest model with $\#\tilde{\mathcal{A}} = 1$), the population tree model m^* is defined in (14.64) in Definition 14.30, and the tree model \hat{m}_{k,\hat{T}_n} is defined in (14.61).

Given one sample tree growing rule \hat{T}_n , this lemma establishes the consistency rate at which the sample tree model approaches the population tree model with the same rule.

Lemma 14.24.4 (Approximation error; Lemma 3 in [Chi et al. \[2020\]](#)). Consider a sequence of regression functions $\{m_n\}$ such that m_n satisfies Condition 1 with α_{1n} and q_1 . (For notational simplicity, the subscript of m_n is dropped whenever there is no confusion.) That is, assume that Conditions 1, 2, 4, and 5 hold with $\alpha_{1n} \geq 1$ and $q_1 \geq 1$, $0 < \eta < 1/8$, $0 < c < \eta/\log 2$, $0 < \rho < 1$, and $\mathbb{E}|\epsilon_1|^q < \infty$ for a sufficiently large q . Then it holds that for all large n and $k = \lfloor c \log n \rfloor$,

$$\mathbb{E} \left[m(\mathbf{X}) - m_{k,\hat{T}_n}^*(\Theta_1, \dots, \Theta_k, \mathbf{X}) \right]^2 \leq \alpha_{1n} 2^{1/q_1} (\log n)^{-\frac{1-p}{q_1}}.$$

Moreover, for the regular case with $q_1 = 1$ in Condition 1, it holds that for all large n and $k = \lfloor c \log n \rfloor$,

$$\mathbb{E} \left[m(\mathbf{X}) - m_{k,\hat{T}_n}^*(\Theta_1, \dots, \Theta_k, \mathbf{X}) \right]^2 \leq 2\alpha_{1n} n^{-\eta} + \left(\frac{M_0^2}{1 - \gamma_0} \right) n^{c \log(1 - \gamma_0/(2\alpha_{1n}))}. \quad (14.66)$$

Note the similarity of this result to Theorem 14.24.2 (Theorem 1 in [Chi et al. \[2020\]](#)). The authors prove this result by showing that the tree growing rule using the sample CART-split criterion (with some minor manipulation) satisfies Condition 3; then they use Theorem 14.24.2 to complete the analysis. (To verify that Condition 3 is satisfied, they use high-dimensional estimation theory for sample trees from Theorem 5.)

In the regular case with $q_1 = 1$, if the learning rate is decreasing (i.e. α_{1n} is increasing), the second term of the approximation bound (14.66) dominates. Using the asymptotic expansion

$$\log \left(1 - \frac{\gamma_0}{2\alpha_{1n}} \right) \approx -\frac{\gamma_0}{2\alpha_{1n}},$$

the rate can be simplified as

$$\mathcal{O} \left(n^{-\frac{c\gamma_0}{2\alpha_{1n}}} \right),$$

which means that the approximation error is guaranteed to be controlled when the inverse of impurity decrease rate grows no faster than the order of $\log n$.

Theorem 14.24.5 (Consistency rates; Theorem 2 in [Chi et al. \[2020\]](#)). Assume that Conditions 1, 2, 4, and 5 hold with $\alpha_{1n} \geq 1$ and $q_1 \geq 1, 0 < \eta < 1/8, 0 < c < \eta/\log(2), 0 < \rho < 1$, and $\mathbb{E}|\epsilon_1|^q < \infty$ for a sufficiently large q . Assume also that for each $\mathcal{A} \in \tilde{\mathcal{A}}$ it holds that $\#\mathcal{A} = \lceil bn \rceil$ for some $b \in (0, 1]$. Then it holds that for all large n and $k = \lfloor c \log \lceil bn \rceil \rfloor$,

$$\mathbb{E} \left[m(\mathbf{X}) - \mathbb{E} \left(\frac{1}{\#\tilde{\mathcal{A}}} \sum_{\mathcal{A} \in \tilde{\mathcal{A}}} \hat{m}_{k, \hat{T}_{(n, \mathcal{A})}, \mathcal{A}} (\Theta_1, \dots, \Theta_k, \mathbf{X}, \mathcal{X}_n) \mid \mathbf{X}, \mathcal{X}_n \right) \right]^2 \leq \alpha_{1n} 2^{2+q_1^{-1}} (\log \lceil bn \rceil)^{-\frac{1-\rho}{q_1}}.$$

Moreover, for the regular case with $q_1 = 1$ in Condition 1, it holds that for all large n and $k = \lfloor c \log \lceil bn \rceil \rfloor$,

$$\begin{aligned} \mathbb{E} \left[m(\mathbf{X}) - \mathbb{E} \left(\frac{1}{\#\tilde{\mathcal{A}}} \sum_{\mathcal{A} \in \tilde{\mathcal{A}}} \hat{m}_{k, \hat{T}_{(n, \mathcal{A})}, \mathcal{A}} (\Theta_1, \dots, \Theta_k, \mathbf{X}, \mathcal{X}_n) \mid \mathbf{X}, \mathcal{X}_n \right) \right]^2 \\ \leq 8\alpha_{1n} (\log \lceil bn \rceil)^{-\eta} + \left(\frac{4M_0^2}{1 - \gamma_0} \right) (\lceil bn \rceil)^{c \log(1 - \gamma_0/[2\alpha_{1n}])}. \end{aligned}$$

This is the first result on the consistency rate for the original version of the random forest algorithm. With the consistency rate, a direct application of Jensen's inequality allows extending the technical analysis without subsampling (bagging) to that with subsampling.

Definition 14.31 (Relevant feature; Definition 5 in [Chi et al. \[2020\]](#)). A feature j is said to be **relevant** for $m(\cdot)$ if and only if $0 < \mathbb{E}[\text{Var}(m \mid X_s, s \in [p] \setminus j)] < \infty$. A feature j is said to be **irrelevant** for $m(\cdot)$ if and only if $\mathbb{E}[\text{Var}(m \mid X_s, s \in [p] \setminus j)] = 0$.

The authors denote by S^* the set of all relevant features. Let $\{m_n(\cdot)\}$ be a given sequence of regression functions. The authors introduce an additional natural regularity condition to characterize the magnitude of relevance for relevant features defined in Definition 5.

Condition 6. There exists some constant $\iota \geq 0$ such that for each $n \geq 1$ and $j \in S_n^*$, $\mathbb{E}[\text{Var}(m_n \mid X_s, s \in [p] \setminus \{j\})] \geq n^{-\iota}$, where $\#S_n^* = s_n$ for a sequence $\{s_n\}$.

Theorem 14.24.6 (Role of relevance; Theorem 3 in [Chi et al. \[2020\]](#)). Assume that Conditions 2, 5, and 6 hold and for some $j \in S^*$ it holds that for each $\mathcal{A} \in \tilde{\mathcal{A}}$, $\hat{T}_{(n, \mathcal{A})}$ is such that feature j is not involved in the sample CART-split. Then we have

$$\mathbb{E} \left[m_n(\mathbf{X}) - \mathbb{E} \left(\frac{1}{\#\tilde{\mathcal{A}}} \sum_{\mathcal{A} \in \tilde{\mathcal{A}}} \hat{m}_{k, \hat{T}_{(n, \mathcal{A})}, \mathcal{A}} (\Theta_1, \dots, \Theta_k, \mathbf{X}, \mathcal{X}_n) \mid \mathbf{X}, \mathcal{X}_n \right) \right]^2 \geq n^{-\iota}.$$

This characterizes the precise contribution of each relevant feature toward the consistency of random forest. On the other hand, the consistency result in Theorem 14.24.5 can hold. Therefore if parameter ι is appropriately chosen, a feature screening or selection method may be developed on the basis of Condition 6 introduced above.

14.24.4 A General Estimation Foundation (Section 5 of Chi et al. [2020])

Theorem 14.24.7 (Conditional mean estimation; Theorem 4 in Chi et al. [2020]). Assume that Conditions 2 and 5 hold, $\mathbb{E}|\epsilon_1|^q < \infty$ for a sufficiently large $q > 0$, and $0 < \eta < 1/2$. Then there exists some constant $c > 0$ such that for all large n and each $1 \leq k \leq c \log n$,

$$\mathbb{E} \left(\sup_T \mathbb{E} \left[m_{k,T^\#}^* (\Theta_1, \dots, \Theta_k, \mathbf{X}) - \hat{m}_{k,T^\#}^* (\Theta_1, \dots, \Theta_k, \mathbf{X}, \mathcal{X}_n)^2 \mid \Theta, \mathcal{X}_n \right] \right) \leq n^{-\eta},$$

where the supremum is over all possible deterministic tree growing rules.

Theorem 5 below characterizes the quality of the sample tree growing rule by showing that with mild adjustment it satisfies Condition 3. Then its quality is justified by Theorem 14.24.2.

Theorem 14.24.8 (Sample tree estimation; Theorem 4 in Chi et al. [2020]). Assume that Conditions 2 and 5 hold and $\mathbb{E}(|\epsilon_1|^q) < \infty$ for a sufficiently large q . Let $0 < \eta < 1/8$, $c > 0$, and δ with $2\eta < \delta < 1/4$ be given. Then there exists an \mathcal{X}_n -measurable event \mathbf{U}_n such that for all large n , each $1 \leq k \leq c \log n$, each $\epsilon \geq n^{-\eta}$, and $\alpha_2 = 2$, we have that conditional on event \mathbf{U}_n ,

$\hat{T}_{n,k,n-\delta}$ satisfies Condition 3 with k, ϵ, α_2 .

Moreover, for all large n it holds that $\mathbb{P}(\mathbf{U}_n^c) \leq n^{-1}$.

Chapter 15

Abstract Algebra

These are my notes from reading *Elementary Abstract Algebra* by W. Edwin Clark, available for free download on his website: http://shell.cas.usf.edu/~wclark/#ELEMENTARY_ABSTRACT_ALGEBRA

15.1 Chapter 1: Binary Operations

Definition 1.1 A **binary operation** $*$ on a set S is a function from $S \times S$ to S . If $(a, b) \in S \times S$ then we write $a * b$ to indicate the image of the element (a, b) under the function $*$.

The following lemma explains in more detail exactly what this definition means.

Lemma 1.1 A binary operation $*$ on a set S is a rule for combining two elements of S to produce a third element of S . This rule must satisfy the following conditions:

- (a) $a \in S$ and $b \in S \implies a * b \in S.$ [S is closed under $*$.]
- (b) For all a, b, c, d in S
 $a = c$ and $b = d \implies a * b = c * d.$ [Substitution is permissible.]
- (c) For all a, b, c, d in S
 $a = b \implies a * c = b * c.$
- (d) For all a, b, c, d in S
 $c = d \implies a * c = a * d.$

Definition: A **function** f from the set A to the set B is a rule which assigns to each element $a \in A$ an element $f(a) \in B$ in such a way that the following condition holds for all $x, y \in A$:

$$x = y \implies f(x) = f(y)$$

To indicate that f is a function from A to B we write $f : A \rightarrow B$. The set A is called the **domain** of f and the set B is called the **codomain** of f .

A function $f : A \rightarrow B$ is said to be **one-to-one** or **injective** if the following condition holds for all $x, y \in A$:

$$f(x) = f(y) \implies x = y$$

A function $f : A \rightarrow B$ is said to be **onto** or **surjective** if the following condition holds:

$$\forall b \in B \exists a \in A \mid f(a) = b$$

A function $f : A \rightarrow B$ is said to be **bijective** if it is both one-to-one and onto. Then f is sometimes said to be a **bijection** or a **one-to-one correspondence** between A and B .

15. Let S , T , and U be nonempty sets, and let $f : S \rightarrow T$ and $g : T \rightarrow U$ be functions such that the function $g \circ f : S \rightarrow U$ is one-to-one (injective). Which of the following must be true?
- (A) f is one-to-one.
 - (B) f is onto.
 - (C) g is one-to-one.
 - (D) g is onto.
 - (E) $g \circ f$ is onto.

Solution 15. (A) For a composition of functions, if the first function isn't one-to-one, there's no way the composite is. It's worth mentioning here that the opposite is true for onto: the second function had better be onto.

Let S be a set. The **power set** $\mathcal{P}(S)$ of S is the set of all subsets of S (including S itself).

Definition 1.2 Assume that $*$ is a binary operation on the set S .

1. We say that $*$ is **associative** if

$$x * (y * z) = (x * y) * z \quad \text{for all } x, y, z \in S.$$

2. We say that an element e in S is an **identity** with respect to $*$ if

$$x * e = x \text{ and } e * x = x \quad \text{for all } x \text{ in } S.$$

3. Let $e \in S$ be an identity with respect to $*$. Given $x \in S$ we say that an element $y \in S$ is an **inverse** of x if both

$$x * y = e \text{ and } y * x = e.$$

4. We say that $*$ is **commutative** if

$$x * y = y * x \quad \text{for all } x, y \in S.$$

5. We say that an element a of S is **idempotent** with respect to $*$ if

$$a * a = a.$$

6. We say that an element z of S is a **zero** with respect to $*$ if

$$z * x = z \text{ and } x * z = z \quad \text{for all } x \in S.$$

For each integer $n \geq 2$ define the set

$$\mathbb{Z}_n = \{0, 1, 2, \dots, n - 1\}$$

For all $a, b \in \mathbb{Z}_n$ let

$$a + b = \text{remainder when the ordinary sum of } a \text{ and } b \text{ is divided by } n$$

and

$$a \cdot b = \text{remainder when the ordinary product of } a \text{ and } b \text{ is divided by } n.$$

These binary operations are referred to as **addition modulo n** and **multiplication modulo n** . The integer n in \mathbb{Z}_n is called the **modulus**. The plural of modulus is **moduli**.

Let K denote any one of the following: $\mathbb{Z}, \mathbb{Q}, \mathbb{R}, \mathbb{Z}_n$.

$$M_n(K)$$

is the set of all $n \times n$ matrices containing elements of K .

$$GL(n, K)$$

is the set of all matrices in $M_n(K)$ with non-zero determinant. $(GL(n, k), \cdot)$ is called the **general linear group of degree n over K** . It is non-abelian.

$$SL(n, K) = \{A \in GL(n, K) \mid \det(A) = 1\}$$

$SL(n, K)$ is called the **Special Linear Group of degree n over K** .

15.2 Chapter 2: Groups

Definition 15.1. **Definition** A **group** is an ordered pair $(G, *)$ where G is a set and $*$ is a binary operation on G satisfying the following properties:

1. **The binary operation is associative on G :** $\forall x, y, z \in G$,

$$x * (y * z) = (x * y) * z$$

2. **The binary operation contains a (unique) identity in G :** $\exists e \in G \mid \forall x \in G$

$$e * x = x, x * e = x$$

3. **Every element in G has a (unique) inverse on $*$ in G :** $\forall x \in G \exists y \in G \mid$

$$x * y = e, y * x = e$$

A group $(G, *)$ is said to be **abelian** if $\forall x, y \in G$, $x * y = y * x$. A group is said to be **non-abelian** if it is not abelian.

Theorem 2.2 Let $(G, *)$ be a group with identity e . Then the following hold for all elements a, b, c, d in G :

1. If $a * c = a * b$, then $c = b$. [Left cancellation law for groups.]
2. If $c * a = b * a$, then $c = b$. [Right cancellation law for groups.]
3. Given a and b in G there is a unique element x in G such that $a * x = b$.
4. Given a and b in G there is a unique element x in G such that $x * a = b$.
5. If $a * b = e$ then $a = b^{-1}$ and $b = a^{-1}$. [Characterization of the inverse of an element.]
6. If $a * b = a$ for just one a , then $b = e$.
7. If $b * a = a$ for just one a , then $b = e$.
8. If $a * a = a$, then $a = e$. [The only idempotent in a group is the identity.]
9. $(a^{-1})^{-1} = a$.
10. $(a * b)^{-1} = b^{-1} * a^{-1}$.

15.3 Chapter 3: The Symmetric Groups

If n is a positive integer,

$$[n] = \{1, 2, \dots, n\}$$

A **permutation** of $[n]$ is a one-to-one, onto function from $[n]$ to $[n]$, and

$$S_n$$

is the set of all permutations of $[n]$.

The identity of S_n is the so-called **identity function**

$$\iota : [n] \rightarrow [n]$$

which is defined by the rule

$$\iota(x) = x, \quad \forall x \in [n]$$

The inverse of an element $\sigma \in S_n$: Suppose $\sigma \in S_n$. Since σ is by definition one-to-one and onto, the rule

$$\sigma^{-1}(y) = x \iff \sigma(x) = y$$

defines a function $\sigma^{-1} : [n] \rightarrow [n]$. This function σ^{-1} is also one-to-one and onto and satisfies

$$\sigma\sigma^{-1} = \iota \text{ and } \sigma^{-1}\sigma = \iota$$

so it is the inverse of σ in the group sense also.

Since the binary operation of composition on S_n is associative $[(\gamma\beta)\alpha = \gamma(\beta\alpha)]$, S_n under the binary operation of composition is a group (it is associative, it has an inverse, and it has an identity).

Definition 3.2 Let i_1, i_2, \dots, i_k be a list of k distinct elements from $[n]$. Define a permutation σ in S_n as follows:

$$\begin{aligned}\sigma(i_1) &= i_2 \\ \sigma(i_2) &= i_3 \\ \sigma(i_3) &= i_4 \\ &\vdots && \vdots \\ \sigma(i_{k-1}) &= i_k \\ \sigma(i_k) &= i_1\end{aligned}$$

and if $x \notin \{i_1, i_2, \dots, i_k\}$ then

$$\sigma(x) = x$$

Such a permutation is called a **cycle** or a **k -cycle** and is denoted by

$$(i_1 \ i_2 \ \cdots \ i_k).$$

If $k = 1$ then the cycle $\sigma = (i_1)$ is just the identity function, i.e., $\sigma = \iota$.

Two cycles $(i_1 \ i_2 \ \dots \ i_k)$ and $(j_1 \ j_2 \ \dots \ j_l)$ are said to be **disjoint** if the sets $\{i_1, i_2, \dots, i_k\}$ and $\{j_1, j_2, \dots, j_l\}$ are disjoint.

So for example, the cycles $(1 \ 2 \ 3)$ and $(4 \ 5 \ 8)$ are disjoint, but the cycles $(1 \ 2 \ 3)$ and $(4 \ 2 \ 8)$ are not disjoint.

If σ and τ are disjoint cycles, then $\sigma\tau = \tau\sigma$.

Theorem 3.4 Every element $\sigma \in S_n$, $n \geq 2$, can be written as a product

$$\sigma = \sigma_1 \sigma_2 \cdots \sigma_m \tag{3.1}$$

where $\sigma_1, \sigma_2, \dots, \sigma_m$ are pairwise disjoint cycles, that is, for $i \neq j$, σ_i and σ_j are disjoint. If all 1-cycles of σ are included, the factors are unique except for the order. ■

The factorization (3.1) is called the **disjoint cycle decomposition** of σ .

An element of S_n is called a **transposition** if and only if it is a 2-cycle.

Every element of S_n can be written as a product of transpositions. The factors of such a product are not unique. However, if $\sigma \in S_n$ can be written as a product of k transpositions and if the same σ can also be written as a product of l transpositions, then k and l have the same parity.

A permutation is **even** if it is a product of an even number of transpositions and **odd** if it is a product of an odd number of transpositions. We define the function $\text{sign} : S_n \rightarrow \{1, -1\}$ by

$$\text{sign}(\sigma) = \begin{cases} 1 & \text{if } \sigma \text{ is even} \\ -1 & \text{if } \sigma \text{ is odd} \end{cases}$$

If $n = 1$ then there are no transpositions. In this case, to be complete we define the identity permutation ι to be even.

If σ is a k -cycle, then $\text{sign}(\sigma) = 1$ if k is odd and $\text{sign}(\sigma) = -1$ if k is even.

Remark. Let $A = [a_{ij}]$ be an $n \times n$ matrix. The determinant of A may be defined by the sum

$$\det(A) = \sum_{\sigma \in S_n} \text{sign}(\sigma) a_{1\sigma(1)} a_{2\sigma(2)} \cdots a_{n\sigma(n)}.$$

For example, if $n = 2$ we have only two permutations ι and $(1 \ 2)$. Since $\text{sign}(\iota) = 1$ and $\text{sign}((1 \ 2)) = -1$ we obtain

$$\det(A) = a_{11}a_{22} - a_{12}a_{21}.$$

Definition: If $(G, *)$ is a group, the number of elements in G is called the **order** of G . We use $|G|$ to denote the order of G . Note that $|G|$ may be finite or infinite.

Let

$$A_n$$

be the set of all even permutations in the group S_n . A_n is called the **alternating group of degree n** .

15.4 Chapter 4: Subgroups

Definition: Let G be a group. A **subgroup** of G is a subset H of G which satisfies the following three conditions:

1. $e \in H$
2. $a, b \in H \implies ab \in H$
3. $a \in H \implies a^{-1} \in H$

If H is a subgroup of G , we write $H \leq G$. The subgroups $\{e\}$ and G are said to be **trivial** subgroups of G .

Every finite subgroup may be thought of as a subgroup of one of the groups S_n .

Let A_n be the set of all even permutations in the group S_n . A_n is then a subgroup of S_n . A_n is called the **alternating group of degree n** .

Let a be an element of the group G . If $\exists n \in \mathbb{N} \mid a^n = e$ we say that a has **finite order** and we define

$$\text{o}(a) = \min\{n \in \mathbb{N} \mid a^n = e\}$$

If $a^n \neq e \forall n \in \mathbb{N}$ we say that a has **infinite order** and we define

$$\text{o}(a) = \infty$$

In either case we call $\text{o}(a)$ the **order** of a . Note carefully the difference between the order of a group and the order of an element of a group. Note also that $a = e \iff \text{o}(a) = 1$. So every element of a group other than e has order $n \geq 2$ or ∞ .

Let a be an element of group G . Define

$$\langle a \rangle = \{a^i : i \in \mathbb{Z}\}$$

We call $\langle a \rangle$ the **subgroup of G generated by a** . Note that $e = a^0$ and a^{-1} are in $\langle a \rangle$.

Theorem. For each $a \in G$, $\langle a \rangle$ is a subgroup of G . $\langle a \rangle$ contains a and is the smallest subgroup of G containing a .

Proof of second statement. If H is any subgroup of G containing a , $\langle a \rangle \subseteq H$ since H is closed under taking products and inverses. That is, every subgroup of G containing a also contains $\langle a \rangle$. This implies that $\langle a \rangle$ is the smallest subgroup of G containing a .

Theorem. Let G be a group and let $a \in G$. If $\text{o}(a) = 1$, then $\langle a \rangle = \{e\}$. If $\text{o}(a) = n$ where $n \geq 2$, then

$$\langle a \rangle = \{e, a, a^2, \dots, a^{n-1}\}$$

and the elements $e, a, a^2, \dots, a^{n-1}$ are distinct; that is,

$$\text{o}(a) = |\langle a \rangle|$$

Proof Assume that $\text{o}(a) = n$. The case $n = 1$ is left to the reader. Suppose $n \geq 2$. We must prove two things.

1. If $i \in \mathbb{Z}$ then $a^i \in \{e, a, a^2, \dots, a^{n-1}\}$.
2. The elements $e, a, a^2, \dots, a^{n-1}$ are distinct.

To establish 1 we note that if i is any integer we can write it in the form $i = nq + r$ where $r \in \{0, 1, \dots, n - 1\}$. Here q is the quotient and r is the remainder when i is divided by n . Now using Theorem 2.4 we have

$$a^i = a^{nq+r} = a^{nq}a^r = (a^n)^qa^r = e^qa^r = ea^r = a^r.$$

This proves 1. To prove 2, assume that $a^i = a^j$ where $0 \leq i < j \leq n - 1$. It follows that

$$a^{j-i} = a^{j+(-i)} = a^j a^{-i} = a^i a^{-i} = a^0 = e.$$

But $j - i$ is a positive integer less than n , so $a^{j-i} = e$ contradicts the fact that $\text{o}(a) = n$. So the assumption that $a^i = a^j$ where $0 \leq i < j \leq n - 1$ is false. This implies that 2 holds. It follows that $\langle a \rangle$ contains exactly n elements, that is, $\text{o}(a) = |\langle a \rangle|$.

Theorem. If G is a finite group, then every element of G has finite order.

49. What is the largest order of an element in the group of permutations of 5 objects?

- (A) 5 (B) 6 (C) 12 (D) 15 (E) 120

Solution 49. (B) The greatest order is given by the product of a 2-cycle and a 3-cycle acting on disjoint elements. That gives order 6.

15.5 Chapter 5: The Group of Units of \mathbb{Z}_n

Let $n \geq 2$. An element $a \in \mathbb{Z}_n$ is said to be a **unit** if $\exists b \in \mathbb{Z}_n \mid ab = 1$ (where the product is multiplication modulo n).

The set of all units in \mathbb{Z}_n is denoted by

$$U_n$$

and is a group under multiplication modulo n called the **group of units of \mathbb{Z}_n** .

Theorem. For $n \geq 2$, $U_n = \{a \in \mathbb{Z}_n : \gcd(a, n) = 1\}$

Theorem. p is a prime $\implies \exists a \in U_p \mid U_p = \langle a \rangle$

Theorem. If $n \geq 2$ then U_n contains an element a satisfying $U_n = \langle a \rangle$ if and only if a has one of the following forms: 2, 4, p^k , or $2p^k$ where p is an odd prime and $k \in \mathbb{N}$.

15.6 Chapter 6: Direct Products of Groups

If G_1, G_2, \dots, G_n is a list of n groups we make the Cartesian product $G_1 \times G_2 \times \dots \times G_n$ into a group by defining the binary operation

$$(a_1, a_2, \dots, a_n) \cdot (b_1, b_2, \dots, b_n) = (a_1 \cdot b_1, a_2 \cdot b_2, \dots, a_n \cdot b_n)$$

Here for each $i \in \{1, 2, \dots, n\}$ the product $a_i \cdot b_i$ is the product of a_i and b_i in the group G_i . We call this group the **direct product** of the groups G_1, G_2, \dots, G_n .

The direct product contains an identity and an inverse, and is associative (since it is composed of groups which must themselves be associative), so it is a group per below:

Theorem. If G_1, G_2, \dots, G_n is a list of n groups, the direct product $G = G_1 \times G_2 \times \dots \times G_n$ as defined above is a group. Moreover, if for each i , e_i is the identity of G_i , then e_1, e_2, \dots, e_n is the identity of G , and if

$$\mathbf{a} = (a_1, a_2, \dots, a_n) \in G$$

then the inverse of \mathbf{a} is given by

$$\mathbf{a}^{-1} = (a_1^{-1}, a_2^{-1}, \dots, a_n^{-1})$$

where a_i^{-1} is the inverse of a_i in the group G_i .

15.7 Chapter 7: Isomorphism of Groups

Let $G = \{g_1, g_2, \dots, g_n\}$. Let $\text{o}(g_i) = k_i$ for $i = 1, 2, \dots, n$. We say that the sequence (k_1, k_2, \dots, k_m) is the **order sequence** of the group G . To make the sequence unique we assume the elements are ordered so that $k_1 \leq k_2 \leq \dots \leq k_n$.

Let $(G, *)$ and (H, \bullet) be groups. A function $f : G \rightarrow H$ is said to be a **homomorphism** from G to H if

$$f(a * b) = f(a) \bullet f(b)$$

for all $a, b \in G$. If in addition f is one-to-one and onto, f is said to be an **isomorphism** from G to H .

We say that G and H are **isomorphic** if and only if there is an isomorphism from G to H . We write $G \cong H$ to indicate that G is isomorphic to H .

Isomorphism is an equivalence relation: If G, H , and K are groups then

1. $G \cong G$
2. If $G \cong H$ then $H \cong G$, and
3. If $G \cong H$ and $H \cong K$, then $G \cong K$.

Theorem. Let $(G, *)$ and (H, \bullet) be groups and let $f : G \rightarrow H$ be a homomorphism. Let e_G denote the identity of G , and let e_H denote the identity of H . Then

1. $f(e_G) = e_H$

Proof: Let $x_G \in G$ and let $f(x_G) = x_H \in H$. Then

$$x_H = f(x_G) = f(e_G * x_G) = f(e_G) \bullet f(x_G) = f(e_G) \bullet x_H = e_H \bullet x_H.$$

2. $f(a^{-1}) = f(a)^{-1}$

Proof: $f(a)^{-1} \bullet f(a) = e_H = f(e_G) = f(a^{-1} * a) = f(a^{-1}) \bullet f(a)$

3. $f(a^n) = f(a)^n \forall n \in \mathbb{Z}$

Proof by induction.

Theorem. Let $(G, *)$ and (H, \bullet) be groups and let $f : G \rightarrow H$ be an isomorphism. Then $\text{o}(a) = \text{o}(f(a)) \forall a \in G$. It follows that G and H have the same number of elements of each possible order.

Theorem. If G and H are isomorphic groups, and G is abelian, then so is H .

Proof: Let $a_G, b_G \in G$ and let $f(a_G) = a_H \in H, f(b_G) = b_H \in H$.

$$a_H \bullet b_H = f(a_G) \bullet f(b_G) = f(a_G * b_G) = f(b_G * a_G) = f(b_G) \bullet f(a_G) = b_H \bullet a_H.$$

Definition 15.2 (Cyclic groups and generators). A group G is **cyclic** if there is an element $a \in G$ | $\langle a \rangle = G$. If $\langle a \rangle = G$ then we say that a is a **generator** for G .

Theorem. If G and H are isomorphic groups and G is cyclic then H is cyclic.

Theorem. Let a be an element of group G .

$$1. \text{ o}(a) = \infty \implies \langle a \rangle \cong \mathbb{Z}.$$

$$2. \text{ o}(a) = n \in \mathbb{N} \implies \langle a \rangle \cong \mathbb{Z}_n$$

Cayley's Theorem. If G is a finite group of order n , then there is a subgroup H of S_n such that $G \cong H$.

66. Let \mathbb{Z}_{17} be the ring of integers modulo 17, and let \mathbb{Z}_{17}^\times be the group of units of \mathbb{Z}_{17} under multiplication.

Which of the following are generators of \mathbb{Z}_{17}^\times ?

I. 5

II. 8

III. 16

- (A) None (B) I only (C) II only (D) III only (E) I, II, and III

Solution 66. (B) We need to pick elements of order 16 in $\mathbb{Z}/17^\times$. It is easy to rule out 16 $\equiv -1$, since -1 has order 2. We see that $5^2 = 25 \equiv 8$, so there's no way that 8 can be a generator. We just need to verify that the order of 5 is more than 8, so we can check 5^8 :

$$5^4 = 8^2 = 64 \equiv -4, \quad 5^8 = (-4)^2 = 16 \neq 1.$$

That makes 5 a generator.

15.8 Chapter 8: Cosets and Lagrange's Theorem

Let G be a group and let H be subgroup of G . For each element a of G we define

$$aH = \{ah \mid h \in H\}$$

We call aH the **coset of H in G generated by a** .

Let $a, b \in G$. Then

1. $a \in aH$ (since H must contain an identity; specifically, the identity of G)
2. $|aH| = |H|$ (since ah is unique)
3. $aH \cap bH \neq \emptyset \implies aH = bH$

Lagrange's Theorem. If G is a finite group and $H \leq G$ then $|H|$ divides $|G|$.

Any group of prime order is cyclic; therefore, there is only one such group up to isomorphism.

Exercise 3. Use Lagrange's theorem to prove that any group of prime order is cyclic.

Proof. Let G be a group whose order is a prime p . Since $p > 1$, there is an element $a \in G$ such that $a \neq e$. The group $\langle a \rangle$ generated by a is a subgroup of G . By Lagrange's theorem, the order of $\langle a \rangle$ divides $|G|$. But the only divisors of $|G| = p$ are 1 and p . Since $a \neq e$ we have $|\langle a \rangle| > 1$, so $|\langle a \rangle| = p$. Hence $\langle a \rangle = G$ and G is cyclic. \square

We say that there are k **isomorphism classes of groups of order n** if there are k groups G_1, G_2, \dots, G_k such that

1. if $i \neq j$ then G_i and G_j are not isomorphic, and
2. Every group of order n is isomorphic to G_i for some $i \in \{1, 2, \dots, k\}$.

This is sometimes expressed by saying that "there are k groups of order n up to isomorphism" or that "there are k non-isomorphic groups of order n ."

12. For which integers n such that $3 \leq n \leq 11$ is there only one group of order n (up to isomorphism) ?
- (A) For no such integer n
 - (B) For 3, 5, 7, and 11 only
 - (C) For 3, 5, 7, 9, and 11 only
 - (D) For 4, 6, 8, and 10 only
 - (E) For all such integers n

Solution 12. (B) Any group of prime order is necessarily cyclic, and hence there is only one up to isomorphism. This limits our choices to (B), (C), and (E). But there are two groups of order 9 (at least): $\mathbb{Z}/3 \times \mathbb{Z}/3$ and $\mathbb{Z}/9$. This makes (B) our only option.

In more advanced courses in algebra, it is shown that the number of isomorphism classes of groups of order n for $n \leq 17$ is given by the following table:

<i>Order :</i>	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
<i>Number :</i>	1	1	1	2	1	2	1	5	2	2	1	5	1	2	1	14	1

This table means, for example, that one may find 14 groups of order 16 such that every group of order 16 is isomorphic to one and only one of these 14 groups.

There is only one isomorphism class of groups of order n if n is prime. But there are some non-primes that have this property; for example, 15.

The Fundamental Theorem of Finite Abelian Groups. If G is a finite abelian group of order at least 2, then

$$G \cong \mathbb{Z}_{p_1^{n_1}} \times \mathbb{Z}_{p_2^{n_2}} \times \cdots \times \mathbb{Z}_{p_s^{n_s}}$$

where for each i , p_i is a prime and n_i is a positive integer. Moreover, the prime powers $p_i^{n_i}$ are unique except for the order of the factors.

If the group G in the above theorem has order n then

$$n = p_1^{n_1} p_2^{n_2} \cdots p_s^{n_s}$$

So the p_i may be obtained from the prime factorization of the order of the group G . These primes are not necessarily distinct, so we cannot say what the n_i are. However, we can find all possible choices for the n_i . For example, if G is an abelian group of order $72 = 3^2 \cdot 2^3$ then G is isomorphic to one and only one of the following groups. Note that each corresponds to a way of factoring 72 as a product of prime powers.

$\mathbb{Z}_9 \times \mathbb{Z}_2 \times \mathbb{Z}_2 \times \mathbb{Z}_2$	$72 = 9 \cdot 2 \cdot 2 \cdot 2$
$\mathbb{Z}_9 \times \mathbb{Z}_4 \times \mathbb{Z}_2$	$72 = 9 \cdot 4 \cdot 2$
$\mathbb{Z}_9 \times \mathbb{Z}_8$	$72 = 9 \cdot 8$
$\mathbb{Z}_3 \times \mathbb{Z}_3 \times \mathbb{Z}_2 \times \mathbb{Z}_2 \times \mathbb{Z}_2$	$72 = 3 \cdot 3 \cdot 2 \cdot 2 \cdot 2$
$\mathbb{Z}_3 \times \mathbb{Z}_3 \times \mathbb{Z}_4 \times \mathbb{Z}_2$	$72 = 3 \cdot 3 \cdot 4 \cdot 2$
$\mathbb{Z}_3 \times \mathbb{Z}_3 \times \mathbb{Z}_8$	$72 = 3 \cdot 3 \cdot 8$

Thus there are exactly 6 non-isomorphic abelian groups of order 72.

Corollary. For $n \geq 2$, the number of isomorphism classes of abelian groups of order n is equal to the number of ways to factor n as a product of prime powers (where the order of the factors does not count).

15.9 Chapter 9: Introduction to Ring Theory

Definition 9.1 A **ring** is an ordered triple $(R, +, \cdot)$ where R is a set and $+$ and \cdot are binary operations on R satisfying the following properties:

A1 $a + (b + c) = (a + b) + c$ for all a, b, c in R .

A2 $a + b = b + a$ for all a, b in R .

A3 There is an element $0 \in R$ satisfying $a + 0 = a$ for all a in R .

A4 For every $a \in R$ there is an element $b \in R$ such that $a + b = 0$.

M1 $a \cdot (b \cdot c) = (a \cdot b) \cdot c$ for all a, b, c in R .

D1 $a \cdot (b + c) = a \cdot b + a \cdot c$ for all a, b, c in R .

D2 $(b + c) \cdot a = b \cdot a + c \cdot a$ for all a, b, c in R .

Terminology If $(R, +, \cdot)$ is a ring, the binary operation $+$ is called *addition* and the binary operation \cdot is called *multiplication*. In the future we will usually write ab instead of $a \cdot b$. The element 0 mentioned in A3 is called the **zero** of the ring. Note that we have not assumed that 0 behaves like a *zero*, that is, we have not assumed that $0 \cdot a = a \cdot 0 = 0$ for all $a \in R$. What A3 says is that 0 is an identity with respect to addition. Note that *negative* (as the opposite of *positive*) has no meaning for most rings. We do not assume that multiplication is commutative and we have not assumed that there is an identity for multiplication, much less that elements have inverses with respect to multiplication.

Definition 15.3 (Ring; definition from Section 2.1 of Lang [2005], p. 98 of pdf, p. 83 of book). A **ring** A is a set, together with two laws of composition called multiplication and addition respectively, and written as a product and as a sum respectively, satisfy the following conditions:

1. With respect to addition, A is a commutative group.
2. The multiplication is associative, and has a unit element.
3. For all $x, y, z \in A$, we have $(x + y)z = xz + yz$ and $z(x + y) = zx + zy$. (This is called **distributivity**.)

As usual, we denote the unit element for addition by 0 , and the unit element for multiplication by 1 . We do not assume that $1 \neq 0$.

Definition 15.4. Let A be a ring, and let U be the set of elements of A which have both right and left inverse. Then U is a multiplicative group. Indeed, if a has a right inverse b , so that $ab = 1$, and a left inverse c , so that $ca = 1$, then $c = cab = b$, so $c = b$, and we see that c (or b) is a two-sided inverse, and that c itself has a two-sided inverse, namely a . Therefore U satisfies all the axioms of a multiplicative group, and is called the group of **units** of A . It is sometimes denoted by A^* , and is also called the group

of **invertible** elements of A . A ring A such that $1 \neq 0$ and such that every non-zero element is invertible is called a **division ring**.

Definition 15.5. A ring A is said to be **commutative** if $xy = yx$ for all $x, y \in A$. A commutative division ring is called a **field**. We observe that by definition, a field contains at least two elements, namely 0 and 1.

Definition 15.6. A subset B of a ring A is called a **subring** if it is an additive subgroup, if it contains the multiplicative unit, and if $x, y \in B$ implies $xy \in B$. If that is the case, then B itself is a ring, the laws of operation in B being the same as the laws of operation in A .

For example, the **center** of a ring A is the subset A consisting of all elements of $a \in A$ such that $ax = xa$ for all $x \in A$. (One sees immediately that the center of A is a subring.)

Definition 15.7 (Ideal; definition from Section 2.1 of Lang [2005], p. 101 of pdf, p. 86 of book). A **left ideal** a in a ring A is a subset of A which is a subgroup of the additive group of A , such that $Aa \subset a$ (and hence $Aa = a$ since A contains 1). To define a right ideal, we require $aA = a$, and a **two-sided ideal** is a subset which is both a left and a right ideal. A two-sided ideal is called simply an **ideal**. Note that (0) and A itself are ideals.

Definition 15.8 (Generator; definition from Section 2.1 of Lang [2005], p. 101 of pdf, p. 86 of book). If A is a ring and $a \in A$, then Aa is a left ideal, called **principal**. We say that a is a generator of a (over A). Similarly, AaA is a principal two-sided ideal of we define AaA to be the set of all sums $\sum x_iay_i$ with $x_i, y_i \in A$. More generally, let a_1, \dots, a_n be elements of A . We denote by (a_1, \dots, a_n) the set of elements of A which can be written in the form

$$x_1a_1 + \dots + x_na_n, \quad x_i \in A.$$

Then this set of elements is immediately verified to be a left ideal, and a_1, \dots, a_n are called **generators** of the left ideal.

See also Definition 15.2.

If $\{a_i\}_{i \in I}$ is a family of ideals, then their intersection $\bigcap_{i \in I} a_i$ is also an ideal. Similarly for left ideals. It is easy to verify that if $a = (a_1, \dots, a_n)$ then a is the intersection of all left ideals containing the elements a_1, \dots, a_n .

Definition 15.9. A ring A is said to be **commutative** if $xy = yx$ for all $x, y \in A$. In that case, every left or right ideal is two-sided. A commutative ring such that every ideal is principal and such that $1 \neq 0$ is called a **principal** ring.

23. Let $(\mathbb{Z}_{10}, +, \cdot)$ be the ring of integers modulo 10, and let S be the subset of \mathbb{Z}_{10} represented by $\{0, 2, 4, 6, 8\}$. Which of the following statements is FALSE?
- (A) $(S, +, \cdot)$ is closed under addition modulo 10.
 - (B) $(S, +, \cdot)$ is closed under multiplication modulo 10.
 - (C) $(S, +, \cdot)$ has an identity under addition modulo 10.
 - (D) $(S, +, \cdot)$ has no identity under multiplication modulo 10.
 - (E) $(S, +, \cdot)$ is commutative under addition modulo 10.

Solution 23. (D) Examining the choices, we see $S \subset \mathbb{Z}/10$ is a subgroup of an abelian group. Therefore it still have an additive identity and the operation is commutative. It is also closed under addition and multiplication. While S does not contain the multiplicative identity of $\mathbb{Z}/10$, it does have a multiplicative identity. $6 \in S$ is such an identity, as

$$6x = (5 + 1)x = 5x + x.$$

Since $x \in S$ are all even, $5x = 0$, so $6x = x$.

50. Let R be a ring and let U and V be (two-sided) ideals of R . Which of the following must also be ideals of R ?

I. $U + V = \{u + v : u \in U \text{ and } v \in V\}$

II. $U \cdot V = \{uv : u \in U \text{ and } v \in V\}$

III. $U \cap V$

- (A) II only (B) III only (C) I and II only (D) I and III only (E) I, II, and III

Solution 50. (D) The sum of the ideals is still an ideal: it is clearly closed under addition (using commutativity of addition), and still under left and right multiplication due to the distributive property. The intersection of ideals is still an ideal, which is not too hard to work out. The product of ideals, however, need not be closed under addition. Consider, for example, $R = \mathbb{Z}[X]$, $U = (2, X)$, and $V = (3, X)$ (the ideals generated by two elements). Then we know that $-2X \in U \cdot V$ and $3X \in U \cdot V$, and hence we should expect $3X - 2X = X \in U \cdot V$. However, there is no way to get X as the product of an element of U and an element of V .

18. Let V be the real vector space of all real 2×3 matrices, and let W be the real vector space of all real 4×1 column vectors. If T is a linear transformation from V onto W , what is the dimension of the subspace $\{\mathbf{v} \in V : T(\mathbf{v}) = \mathbf{0}\}$?

- (A) 2 (B) 3 (C) 4 (D) 5 (E) 6

Solution 18. (A) We see that $\dim V = 6$ and $\dim W = 4$. Since $\dim \text{im } T = \dim W = 4$, we must have $\dim \ker T = 6 - 4 = 2$.

Chapter 16

Miscellaneous

16.1 Set Theory

Proposition 16.1.1 (Math 541A Homework Problem). Let A, B, Ω be sets. Let $u : \Omega \rightarrow A$ and let $t : \Omega \rightarrow B$. Assume that, for every $x, y \in \Omega$, if $u(x) = u(y)$, then $t(x) = t(y)$. Show that there exists a function $s : A \rightarrow B$ such that

$$t = s(u).$$

Proof. Let $B' \subseteq B$ be the image of Ω under t (so that t is surjective onto B'). Fix $x \in \Omega$ and let $y \in \Omega$ range over $\{\Omega \setminus x\}$. Let $Y \subseteq \Omega$ be the set of values such that $t(y) = t(x)$ for all $y \in Y$. Then let s map $u(y) \in A$ to $t(y) = t(x) \in B$ for every $y \in Y$.

(Note that if x is not the only value in Ω that t maps to $t(x)$, then Y contains elements other than x ; otherwise, $Y = \{x\}$. In either case this mapping is fine. Note that $u(y_1)$ does not necessarily equal $u(y_2)$ for every $y_1 \neq y_2 \in Y$, but again this does not pose any difficulties for the mapping.)

Since this argument is true for every $x \in \Omega$, we can argue by contradiction that s is surjective onto B' . Let $A' \subseteq A$ be the image of Ω under u (so that u is surjective onto A'). Suppose there is some $b \in B'$ such that there is no unused $a \in A'$ to correspond to it. That is, there are some $y, z \in \Omega$ such that $t(z) \neq t(y)$ but $u(z) = u(y)$. In that case the mapping s would map $u(z)$ and $u(y)$ both to the same value in B' , so one of the values $t(z)$ or $t(y)$ would necessarily be missed. But by assumption there is no $z \in \Omega$ such that $t(z) \neq t(y)$ but $u(z) = u(y)$. (Note the contrapositive of the assumption: “for every $x, y \in \Omega$, if $t(x) \neq t(y)$, then $u(x) \neq u(y)$.”)

□

Remark 176. By showing this mapping exists, we have shown that the cardinality of B' is less than or equal to the cardinality of A' .

16.2 Other

6. Which of the following circles has the greatest number of points of intersection with the parabola $x^2 = y + 4$?

- (A) $x^2 + y^2 = 1$
- (B) $x^2 + y^2 = 2$
- (C) $x^2 + y^2 = 9$
- (D) $x^2 + y^2 = 16$
- (E) $x^2 + y^2 = 25$

Solution 6. (C) We can try to do this algebraically, but non-algebraically is simpler. Graphing $y = x^2 - 4$ shows that the graph crosses the x -axis at ± 2 . Therefore a circle of radius 1 or $\sqrt{2}$ will not intersect the parabola at all. A circle of radius 3 will intersect four times – twice above and twice below the x -axis. A circle of radius 4 will only intersect at one point below the x -axis (and twice above), and a circle of radius 5 will only intersect at the two points above.

19. If z is a complex variable and \bar{z} denotes the complex conjugate of z , what is $\lim_{z \rightarrow 0} \frac{(\bar{z})^2}{z^2}$?

- (A) 0
- (B) 1
- (C) i
- (D) ∞
- (E) The limit does not exist.

Solution 19. (E) Let us represent $z = a + bi$. Then our limit becomes

$$\lim_{(a,b) \rightarrow 0} \frac{(a - bi)^2}{(a + bi)^2} = \lim_{(a,b) \rightarrow 0} \frac{a^2 - b^2 - 2abi}{a^2 - b^2 + 2abi}.$$

If we let $a = 0$ (for instance), it is easy to see that the limit is equal to 1. However, if we let $a = b$, then our limit becomes

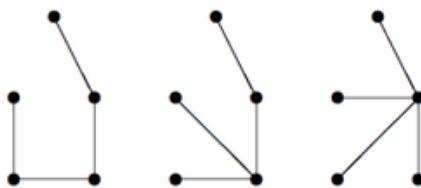
$$\lim_{a \rightarrow 0} \frac{-2a^2i}{2a^2i} = -1.$$

Therefore the limit does not exist.

29. A tree is a connected graph with no cycles. How many nonisomorphic trees with 5 vertices exist?

- (A) 1
- (B) 2
- (C) 3
- (D) 4
- (E) 5

Solution 29. (C) It's probably easiest to draw this out for yourself. The maximum degree of any vertex is 2, 3, or 4. If there is a vertex of degree 4, then our tree looks like a star. If the maximum degree of any vertex is 2, then we have a straight line. In the middle case, we obtain a 3-pointed star to which we attach one more vertex – the choice of branch yields isomorphic graphs. See Figure 1.



38. The maximum number of acute angles in a convex 10-gon in the Euclidean plane is

- (A) 1 (B) 2 (C) 3 (D) 4 (E) 5

Solution 38. (C) The total angle measure of a 10-gon is $180 \cdot 8 = 1440^\circ$. If the polygon is to be convex, all angles must be less than 180° . If we have 5 acute angles, then the remaining 5 angles would have to make up for $> 1440 - 5 \cdot 90 = 990$ degrees. This is impossible to do and remain convex. If we have 4 acute angles, the remaining 6 angles need to make up for $> 1440 - 4 \cdot 90 = 1080$ degrees. This is our edge case, so the answer must be 3 acute angles.

45. How many positive numbers x satisfy the equation $\cos(97x) = x$?

- (A) 1 (B) 15 (C) 31 (D) 49 (E) 96

Solution 45. (C) Certainly our solutions are concentrated in $[0, 1]$. We know that every $2\pi/97$ units in x , we get another period of $\cos(97x)$, and each period must meet $y = x$ twice. Therefore there are

$$\frac{1}{2\pi/97} = \frac{97}{2\pi} \approx \frac{97}{6.3} \approx 15$$

periods in $[0, 1]$ and about 30 meetings. There's only one answer in that range, so we'll stick with it.

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