



# Statistics Learning Lectures

**Author:** Ziyang Gong

**Date:** July 16, 2021

**Version:** 0.1.0



*Facts are stubborn things, but statistics are pliable. — Mark Twain*

# Contents

<b>I</b>	<b>Calculus</b>	<b>1</b>
1	Limit Theory	2
2	Differential Calculus	3
3	Integral Calculus	4
<b>II</b>	<b>Matrix Theory</b>	<b>5</b>
4	Matrix Norms	6
4.1	Matrix Norms Induced by Vector Norms . . . . .	6
5	Matrix Decompositions	7
5.1	Spectral Decomposition . . . . .	7
5.2	Singular Value Decomposition . . . . .	7
<b>III</b>	<b>Real Analysis</b>	<b>10</b>
6	Measure Theory	11
6.1	Semi-algebras, Algebras and Sigma-algebras . . . . .	11
6.2	Measure . . . . .	12
7	Lebesgue Integration	14
7.1	Properties of the Integral . . . . .	14
7.2	Product Measures . . . . .	15
<b>IV</b>	<b>Functional Analysis</b>	<b>16</b>
<b>V</b>	<b>Probability Theory</b>	<b>17</b>
8	Random Variables	18
8.1	Probability Space . . . . .	18
8.2	Random Variables . . . . .	18
8.3	Distributions . . . . .	19
8.4	Expected Value . . . . .	20

8.5	Independence . . . . .	20
8.6	Moments . . . . .	22
8.7	Characteristic Functions . . . . .	22
<b>9</b>	<b>Convergence of Random Variables</b>	<b>25</b>
9.1	Convergence in Mean . . . . .	25
9.2	Convergence in Probability . . . . .	25
9.3	Convergence in Uninform . . . . .	25
9.4	Convergence in Distribution . . . . .	26
9.5	Almost Sure Convergence . . . . .	28
9.6	Asymptotic Notation for Random Variables . . . . .	29
<b>10</b>	<b>Law of Large Numbers</b>	<b>31</b>
10.1	Weak Law of Large Numbers . . . . .	31
10.2	Strong Law of Large Numbers . . . . .	32
10.3	Uniform Law of Large Numbers . . . . .	33
<b>11</b>	<b>Central Limit Theorems</b>	<b>35</b>
11.1	Classic Central Limit Theorem . . . . .	35
11.2	Central Limit Theorem for independent non-identical Random Variables . . . . .	37
11.3	Central Limit Theorem for dependent Random Variables . . . . .	37
<b>12</b>	<b>The Delta Methods</b>	<b>38</b>
<b>13</b>	<b>Exercises for Probability Theory and Examples</b>	<b>39</b>
13.1	Measure Theory . . . . .	39
13.2	Laws of Large Numbers . . . . .	39
13.3	Central Limit Theorems . . . . .	39
<b>VI</b>	<b>Stochastic Process</b>	<b>41</b>
<b>14</b>	<b>Martingales</b>	<b>42</b>
14.1	Conditional Expectation . . . . .	42
14.2	Martingales . . . . .	42
14.3	Doob's Inequality . . . . .	43
14.4	Uniform Integrability . . . . .	43
14.5	Optional Stopping Theorems . . . . .	43
<b>15</b>	<b>Markov Chains</b>	<b>44</b>
15.1	Markov Chain . . . . .	44
15.2	Markov Properties . . . . .	45
15.3	Recurrence and Transience . . . . .	45

15.4 Stationary Measures . . . . .	47
15.5 Asymptotic Behavior . . . . .	47
15.6 Ergodic Theorems . . . . .	47
<b>16 Brownian Motion</b>	<b>48</b>
16.1 Markov Properties . . . . .	49
16.2 Martingales . . . . .	49
16.3 Sample Paths . . . . .	50
16.4 Itô Stochastic Calculus . . . . .	51
<b>17 Exercises for Probability Theory and Examples</b>	<b>54</b>
17.1 Martingales . . . . .	54
17.2 Markov Chains . . . . .	54
17.3 Ergodic Theorems . . . . .	54
17.4 Brownian Motion . . . . .	54
17.5 Applications to Random Walk . . . . .	54
17.6 Multidimensional Brownian Motion . . . . .	54
<b>VII Statistics Inference</b>	<b>55</b>
<b>18 Introduction</b>	<b>56</b>
18.1 Populations and Samples . . . . .	56
18.2 Statistics . . . . .	56
18.3 Estimators . . . . .	56
<b>19 Maximum Likelihood Estimator</b>	<b>59</b>
19.1 Consistency of MLE . . . . .	59
19.2 Asymptotic Normality of MLE . . . . .	61
19.3 Efficiency of MLE . . . . .	61
<b>20 Minimum-Variance Unbiased Estimator</b>	<b>62</b>
<b>21 Bayes Estimator</b>	<b>65</b>
21.1 Single-Prior Bayes . . . . .	66
21.2 Hierarchical Bayes . . . . .	67
21.3 Empirical Bayes . . . . .	68
21.4 Bayes Prediction . . . . .	68
<b>22 Hypothesis Testing</b>	<b>69</b>

<b>VIII</b>	<b>Convex Optimization</b>	<b>70</b>
<b>23</b>	<b>Convex Sets</b>	<b>71</b>
23.1	Affine and Convex Sets . . . . .	71
23.2	Some Important Examples . . . . .	72
23.3	Generalized Inequalities . . . . .	72
<b>24</b>	<b>Convex Optimization Problems</b>	<b>74</b>
24.1	Generalized Inequality Constraints . . . . .	74
24.2	Vector Optimization . . . . .	74
<b>25</b>	<b>Unconstrained Minimization</b>	<b>75</b>
25.1	Definition of Unconstrained Minimization . . . . .	75
25.2	General Descent Method . . . . .	76
25.3	Gradient Descent Method . . . . .	76
25.4	Steepest Descent Method . . . . .	76
25.5	Newton's Method . . . . .	76
<b>26</b>	<b>Exercises for Convex Optimization</b>	<b>77</b>
26.1	Convex Sets . . . . .	77
<b>IX</b>	<b>Generalized Linear Model</b>	<b>78</b>
<b>27</b>	<b>Generalized Linear Model</b>	<b>79</b>
27.1	Exponential Family . . . . .	79
27.2	Model Assumption . . . . .	79
27.3	Model Estimation . . . . .	80
<b>28</b>	<b>Binary Data</b>	<b>82</b>
28.1	Model Assumption . . . . .	82
28.2	Model Estimation . . . . .	82
<b>29</b>	<b>Polytomous Data</b>	<b>83</b>
29.1	Model Assumption . . . . .	83
29.2	Model Estimation . . . . .	84
<b>30</b>	<b>Count Data</b>	<b>85</b>
30.1	Model Assumption . . . . .	85
30.2	Model Estimation . . . . .	85

<b>31 Survival Data</b>	<b>86</b>
31.1 Survival Data . . . . .	86
31.2 Estimation of Survival Function . . . . .	87
31.3 Proportional Hazards Model . . . . .	88
<b>32 Modified Likelihood</b>	<b>89</b>
32.1 Marginal Likelihood . . . . .	89
32.2 Conditional Likelihood . . . . .	89
32.3 Profile Likelihood . . . . .	90
32.4 Quasi Likelihood . . . . .	90
 <b>X Machine Learning</b>	 <b>91</b>
<b>33 Kernel Methods</b>	<b>92</b>
<b>34 Support Vector Machine</b>	<b>95</b>
<b>35 Linear Discriminant Analysis</b>	<b>96</b>
<b>36 K-Nearest Neighbor</b>	<b>97</b>
<b>37 Decision Tree</b>	<b>98</b>
 <b>XI Random Matrix Theory</b>	 <b>99</b>
<b>38 Wishart and Laguerre Ensembles</b>	<b>100</b>
38.1 Wishart Distribution . . . . .	100
38.2 Joint Distribution of Eigenvalues . . . . .	101
38.3 Average Denisty of Eigenvalues . . . . .	104
38.4 Behavior of the Extremal Eigenvalues . . . . .	105

# **Part I**

## **Calculus**

# Chapter 1 Limit Theory

## Definition 1.1 (Mapping)

Let  $X : \Omega_1 \rightarrow \Omega_2$  be a mapping.

1. For every subset  $B \in \Omega_2$ , the inverse image of  $B$  is

$$X^{-1}(B) = \{\omega : \omega \in \Omega_1, X(\omega) \in B\} := \{X \in B\}.$$

2. For every class





## **Chapter 2 Differential Calculus**

## Chapter 3 Integral Calculus

## **Part II**

# **Matrix Theory**

## Chapter 4 Matrix Norms

### 4.1 Matrix Norms Induced by Vector Norms


# Chapter 5 Matrix Decompositions

## 5.1 Spectral Decomposition

### Definition 5.1 (Eigenvectors and Eigenvalues)

A (non-zero) vector  $\mathbf{v}$  of dimension  $n$  is an **eigenvector** of a square  $n \times n$  matrix  $\mathbf{A}$ , if


$$\mathbf{A}\mathbf{v} = \lambda\mathbf{v} \quad (5.1)$$

where  $\lambda$  is a scalar, termed the **eigenvalue** corresponding to  $\mathbf{v}$ . 

### Definition 5.2 (Spectral Decomposition)

For any  $n \times n$  matrix with  $n$  linearly independent eigenvectors  $\mathbf{q}_i, i = 1, \dots, n$ . Then  $\mathbf{A}$  can be factorized as

$$\mathbf{A} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^{-1}$$

where  $\mathbf{Q}$  is the square  $n \times n$  matrix whose  $i$ -th column is the eigenvector  $\mathbf{q}_i$  of  $\mathbf{A}$ , and  $\mathbf{\Lambda}$  is the diagonal matrix whose diagonal elements are the corresponding eigenvalues,  $\Lambda = \lambda_i$ . This factorization is called eigendecomposition or sometimes spectral decomposition. 

**Example 5.1 Real Symmetric Matrices** As a special case, for every  $n \times n$  real symmetric matrix, the eigenvalues are real and the eigenvectors can be chosen real and orthonormal. Thus a real symmetric matrix  $\mathbf{A}$  can be decomposed as

$$\mathbf{A} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}' \quad (5.2)$$

where  $\mathbf{Q}$  is an orthogonal matrix whose columns are eigenvectors of  $\mathbf{A}$ , and  $\mathbf{\Lambda}$  is a diagonal matrix whose entries are the eigenvalues of  $\mathbf{A}$ .

## 5.2 Singular Value Decomposition

**Proposition 5.1 (Singular Value Decomposition)**

For any matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$ , we have

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}' \quad (5.3)$$

where

- $\mathbf{U} \in \mathbb{R}^{m \times m}$  is an orthogonal matrix whose columns are the eigenvectors of  $\mathbf{A}\mathbf{A}'$
- $\mathbf{V} \in \mathbb{R}^{n \times n}$  is an orthogonal matrix whose columns are the eigenvectors of  $\mathbf{A}'\mathbf{A}$
- $\mathbf{\Sigma} \in \mathbb{R}^{m \times n}$  is an all zero matrix except for the first  $r$  diagonal elements

$$\sigma_i = \Sigma_{ii}, \quad i = 1, 2, \dots, r$$

which is called singular values, that are the square roots of the eigenvalues of  $\mathbf{A}'\mathbf{A}$  and of  $\mathbf{A}\mathbf{A}'$  (these two matrices have the same eigenvalues)



**Remark** We assume above that the singular values are sorted in descending order and the eigenvectors are sorted according to descending order of their eigenvalues.

**Proof** Without loss of generality, we assume  $m \geq n$ . Since for the case  $n > m$ , can then be established by transposing the SVD of  $\mathbf{A}'$ ,

$$\mathbf{A} = (\mathbf{A}')' = (\mathbf{U}'\mathbf{\Sigma}\mathbf{V})' = \mathbf{V}'(\mathbf{U}'\mathbf{\Sigma})' = \mathbf{V}'\mathbf{\Sigma}\mathbf{U}$$

For  $m \geq n$ , suppose  $\text{rank}(\mathbf{A}) = r$ , and then  $\text{rank}(\mathbf{A}'\mathbf{A}) = r$  and the spectral decomposition of  $\mathbf{A}'\mathbf{A}$  be

$$\mathbf{A}'\mathbf{A}\mathbf{V} = \mathbf{V} \text{diag}(\sigma_1^2, \dots, \sigma_r^2, 0, \dots, 0)$$

where  $\sigma_i^2$  are the eigenvalues of  $\mathbf{A}'\mathbf{A}$  and the columns of  $\mathbf{V}$ , denoted  $\mathbf{v}^{(i)}$ , are the corresponding orthonormal eigenvectors.

Let

$$\mathbf{u}^{(i)} = \frac{\mathbf{A}\mathbf{v}^{(i)}}{\sigma_i}$$

then

$$\begin{aligned} \mathbf{A}'\mathbf{u}^{(i)} &= \frac{\mathbf{A}'\mathbf{A}\mathbf{v}^{(i)}}{\sigma_i} = \sigma_i \mathbf{v}^{(i)} \Rightarrow \\ \mathbf{A}\mathbf{A}'\mathbf{u}^{(i)} &= \sigma_i \mathbf{A}\mathbf{v}^{(i)} = \sigma_i^2 \mathbf{u}^{(i)} \end{aligned}$$

implying that  $\mathbf{u}^{(i)}$  are eigenvectors of  $\mathbf{A}\mathbf{A}'$  corresponding to eigenvalues  $\sigma_i^2$ .

Since the eigenvectors  $\mathbf{v}^{(i)}$  are orthonormal, then so are the eigenvectors  $\mathbf{u}^{(i)}$

$$\left(\mathbf{u}^{(i)}\right)' \mathbf{u}^{(j)} = \frac{\left(\mathbf{v}^{(i)}\right)' \mathbf{A}'\mathbf{A}\mathbf{v}^{(j)}}{\sigma_i^2} = \left(\mathbf{v}^{(i)}\right)' \mathbf{v}^{(j)} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$$

We have thus far a matrix  $\mathbf{V}$  whose columns are eigenvectors of  $\mathbf{A}'\mathbf{A}$  with eigenvalues  $\sigma_i^2$ , and a matrix  $\mathbf{U}$  whose columns are  $r$  eigenvectors of  $\mathbf{A}\mathbf{A}'$  corresponding to eigenvalues  $\sigma_i^2$ .

We augment the eigenvectors  $\mathbf{u}^{(i)}, i = 1, \dots, r$  with orthonormal vectors  $\mathbf{u}^{(i)}, i = r + 1, \dots, m$  that span  $\text{null}(\mathbf{A}\mathbf{A}')$ , and together  $\mathbf{u}^{(i)}, i = 1, \dots, m$  are a full orthonormal set of eigenvectors of  $\mathbf{A}\mathbf{A}'$  with eigenvalues  $\sigma_i^2$  (with  $\sigma_i = 0$  for  $i > r$ ).

Since

$$[U'AV]_{ij} = (\mathbf{u}^{(i)})' \mathbf{A} \mathbf{v}^{(j)} = \begin{cases} \sigma_j (\mathbf{u}^{(i)})' \mathbf{u}^{(j)} & i \leq r \\ 0 & i > r \end{cases}$$

we get

$$U'AV = \Sigma$$

where

$$\Sigma = \begin{pmatrix} \text{diag}(\sigma_1, \dots, \sigma_r) \\ \mathbf{0} \end{pmatrix}, \quad \sigma_i = 0 \text{ for } r < i \leq n$$

Consequently, we get the desired decompositions

$$\mathbf{A} = \mathbf{U}\Sigma\mathbf{V}'$$

### 5.2.1 Relationship to Matrix Norm

#### Theorem 5.1

For any matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$ ,

$$\|\mathbf{A}\|_2 = \sigma_{\max}(\mathbf{A}) \quad (5.4)$$

**Proof** For any matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$ , the SVD implies that,

$$\|\mathbf{A}\|_2 = \sup_{\mathbf{x} \neq \mathbf{0}} \frac{\|\mathbf{A}\mathbf{x}\|_2}{\|\mathbf{x}\|_2} = \sup_{\mathbf{x} \neq \mathbf{0}} \frac{\|\mathbf{U}\Sigma\mathbf{V}'\mathbf{x}\|_2}{\|\mathbf{x}\|_2}$$

Since  $\mathbf{U}$  is unitary, that is,

$$\|\mathbf{U}\mathbf{x}\|_2^2 = \mathbf{x}'\mathbf{U}'\mathbf{U}\mathbf{x} = \|\mathbf{x}\|_2^2, \quad \forall \mathbf{x} \in \mathbb{R}^m$$

thus,

$$= \sup_{\mathbf{x} \neq \mathbf{0}} \frac{\|\Sigma\mathbf{V}'\mathbf{x}\|_2}{\|\mathbf{x}\|_2}$$

Let  $\mathbf{y} = \mathbf{V}'\mathbf{x}$ , and since  $\mathbf{V}$  is unitary, we have

$$\|\mathbf{y}\|_2 = \|\mathbf{V}'\mathbf{x}\|_2 = \|\mathbf{x}\|_2 = 1$$

thus,

$$= \sup_{\mathbf{y} \neq \mathbf{0}} \frac{\|\Sigma\mathbf{y}\|_2}{\|\mathbf{y}\|_2} = \sup_{\mathbf{y} \neq \mathbf{0}} \frac{(\sum_{i=1}^r \sigma_i^2 |y_i|^2)^{\frac{1}{2}}}{(\sum_{i=1}^r |y_i|^2)^{\frac{1}{2}}} \leq \sigma_{\max}(\mathbf{A})$$

which takes "=", if  $\mathbf{y} = (1, 0, \dots, 0)'$ .

#### Theorem 5.2

For any matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$ , suppose  $\text{rank}(\mathbf{A}) = n$ , then

$$\min_{\|\mathbf{x}\|_2=1} \|\mathbf{A}\mathbf{x}\|_2 = \sigma_n(\mathbf{A}) \quad (5.5)$$

**Proof** The proof process is analogous to the above theorem.

**Remark** If  $\text{rank}(\mathbf{A}) < n$ , then there is an  $\mathbf{x}$  such that the minimum is zero.

# **Part III**

## **Real Analysis**



# Chapter 6 Measure Theory

## 6.1 Semi-algebras, Algebras and Sigma-algebras

### Definition 6.1 (Semi-algebra)

A nonempty class  $\mathcal{S}$  of subsets of  $\Omega$  is an **semi-algebra** on  $\Omega$  that satisfy

1. if  $A, B \in \mathcal{S}$ , then  $A \cap B \in \mathcal{S}$ .
2. if  $A \in \mathcal{S}$ , then  $A^C$  is a finite disjoint union of sets in  $\mathcal{S}$ , i.e.,

$$A^C = \sum_{i=1}^n A_i, \text{ where } A_i \in \mathcal{S}, A_i \cap A_j = \emptyset, i \neq j.$$



### Definition 6.2 (Algebra)

A nonempty class  $\mathcal{A}$  of subsets of  $\Omega$  is an **algebra** on  $\Omega$  that satisfy

1. if  $A \in \mathcal{A}$ , then  $A^C \in \mathcal{A}$ .
2. if  $A_1, A_2 \in \mathcal{A}$ , then  $A_1 \cup A_2 \in \mathcal{A}$ .



### Definition 6.3 ( $\sigma$ -algebra)

A nonempty class  $\mathcal{F}$  of subsets of  $\Omega$  is a  **$\sigma$ -algebra** on  $\Omega$  that satisfy

1. if  $A \in \mathcal{F}$ , then  $A^C \in \mathcal{F}$ .
2. if  $A_i \in \mathcal{F}$  is a countable sequence of sets, then  $\cup_i A_i \in \mathcal{F}$ .



### Example 6.1 Special $\sigma$ -algebra

1. **Trivial  $\sigma$ -algebra**  $:= \{\emptyset, \Omega\}$ . This is smallest  $\sigma$ -algebra.
2. **Power Set**  $:=$  all subsets of  $\sigma$ , denoted by  $\mathcal{P}(\Omega)$ . This is the largest  $\sigma$ -algebra.
3. **The smallest  $\sigma$ -algebra containing  $A \in \Omega$**   $:= \{\emptyset, A, A^C, \Omega\}$ .

It is easy to define (Lebesgue) measure on the semi-algebra  $\mathcal{S}$ , and then easily to extend it to the algebra  $\overline{\mathcal{S}}$ , finally, we can extend it further to some  $\sigma$ -algebra (mostly consider the smallest one containing  $\mathcal{S}$ ).

### Lemma 6.1

If  $\mathcal{S}$  is a semi-algebra, then

$$\overline{\mathcal{S}} = \{\text{finite disjoint unions of sets in } \mathcal{S}\}$$

is an algebra, denoted by  $\mathcal{A}(\mathcal{S})$ , called **the algebra generated by  $\mathcal{S}$** .



**Proof** Let  $A, B \in \overline{\mathcal{S}}$ , then  $A = \sum_{i=1}^n A_i, B = \sum_{j=1}^m B_j$  with  $A_i, B_j \in \mathcal{S}$ .

**Intersection:** For  $A_i \cap B_j \in \mathcal{S}$  by the definition of semi-algebra  $\mathcal{S}$ , thus

$$A \cap B = \sum_{i=1}^n \sum_{j=1}^m A_i \cap B_j \in \overline{\mathcal{S}}.$$

So  $\overline{\mathcal{S}}$  is closed under (finite) intersection.

**Complement:** For DeMorgan's Law,  $A_i^C \in \mathcal{S}$  by the definition of semi-algebra  $\mathcal{S}$  and  $\overline{\mathcal{S}}$  closed under (finite) intersection that we just shown, thus

$$A^C = \left( \sum_{i=1}^n A_i \right)^C = \cap_{i=1}^n A_i^C \in \overline{\mathcal{S}}.$$

So  $\overline{\mathcal{S}}$  is closed under complement.

**Union:** For DeMorgan's Law and  $\overline{\mathcal{S}}$  closed under (finite) intersection and complement that we just shown, thus

$$A \cup B = (A^C \cap B^C)^C \in \overline{\mathcal{S}}.$$

So  $\overline{\mathcal{S}}$  is closed under (finite) union.

Hence,  $\overline{\mathcal{S}}$  is an algebra.

### Theorem 6.1

For any class  $\mathcal{A}$ , there exists a unique minimal  $\sigma$ -algebra containing  $\mathcal{A}$ , denoted by  $\sigma(\mathcal{A})$ , called *the  $\sigma$ -algebra generated by  $\mathcal{A}$* . In other words,

1.  $\mathcal{A} \subset \sigma(\mathcal{A})$ .
2. For any  $\sigma$ -algebra  $\mathcal{B}$  with  $\mathcal{A} \subset \mathcal{B}$ ,  $\sigma(\mathcal{A}) \subset \mathcal{B}$ .

and  $\sigma(\mathcal{A})$  is unique.



**Proof Existence:**

**Uniqueness:**

**Example 6.2 Borel  $\sigma$ -algebras generated from semi-algebras**

1.

## 6.2 Measure

### Definition 6.4 (Measure)

**Measure** is a nonnegative countably additive set function, that is, a function  $\mu : \mathcal{A} \rightarrow \mathbf{R}$  with

1.  $\mu(A) \geq \mu(\emptyset) = 0$  for all  $A \in \mathcal{A}$ .
2. if  $A_i \in \mathcal{A}$  is a countable sequence of disjoint sets, then

$$\mu(\cup_i A_i) = \sum_i \mu(A_i).$$



### Definition 6.5 (Measure Space)

If  $\mu$  is a measure on a  $\sigma$ -algebra  $\mathcal{A}$  of subsets of  $\Omega$ , the triplet  $(\Omega, \mathcal{A}, \mu)$  is a **measure space**.



**Note** A measure space  $(\Omega, \mathcal{A}, \mu)$  is a **probability space**, if  $\mu(\Omega) = 1$ .

**Property** Let  $\mu$  be a measure on a  $\sigma$ -algebra  $\mathcal{A}$

1. **monotonicity** if  $A \subset B$ , then  $\mu(A) \leq \mu(B)$ .
2. **subadditivity** if  $A \subset \cup_{m=1}^{\infty} A_m$ , then  $\mu(A) \leq \sum_{m=1}^{\infty} \mu(A_m)$ .
3. **continuity from below** if  $A_i \uparrow A$  (i.e.  $A_1 \subset A_2 \subset \dots$  and  $\cup_i A_i = A$ ), then  $\mu(A_i) \uparrow \mu(A)$ .

4. *continuity from above* if  $A_i \downarrow A$  (i.e.  $A_1 \supset A_2 \supset \dots$  and  $\cap_i A_i = A$ ), then  $\mu(A_i) \downarrow \mu(A)$ .

**Proof**

# Chapter 7 Lebesgue Integration

## 7.1 Properties of the Integral

### Theorem 7.1 (Jensen's Inequality)

Let  $(\Omega, \mathcal{A}, \mu)$  be a probability space. If  $f$  is a real-valued function that is  $\mu$ -integrable, and if  $\varphi$  is a convex function on the real line, then:

$$\varphi \left( \int_{\Omega} f d\mu \right) \leq \int_{\Omega} \varphi(f) d\mu. \quad (7.1)$$



**Proof** Let  $x_0 = \int_{\Omega} f d\mu$ . Since the existence of subderivatives for convex functions,  $\exists a, b \in \mathbb{R}$ , such that,

$$\forall x \in \mathbb{R}, \varphi(x) \geq ax + b \text{ and } ax_0 + b = \varphi(x_0).$$

Then, we got

$$\int_{\Omega} \varphi(f) d\mu \geq \int_{\Omega} af + b d\mu = a \int_{\Omega} f d\mu + b = ax_0 + b = \varphi \left( \int_{\Omega} f d\mu \right).$$

### Theorem 7.2 (Hölder's Inequality)

Let  $(\Omega, \mathcal{F}, \mu)$  be a measure space and let  $p, q \in [1, \infty]$  with  $1/p + 1/q = 1$ . Then, for all measurable functions  $f$  and  $g$  on  $\Omega$ ,

$$\int_{\Omega} |f \cdot g| d\mu \leq \|f\|_p \|g\|_q. \quad (7.2)$$



**Proof**

### Theorem 7.3 (Minkowski's Inequality)

Let  $(\Omega, \mathcal{F}, \mu)$  be a measure space and let  $p \in [1, \infty]$ . Then, for all measurable functions  $f$  and  $g$  on  $\Omega$ ,

$$\|f + g\|_p \leq \|f\|_p + \|g\|_p. \quad (7.3)$$



**Proof** Since  $\varphi(x) = x^p$  is a convex function for  $p \in [1, \infty)$ . By its definition,

$$|f + g|^p = \left| 2 \cdot \frac{f}{2} + 2 \cdot \frac{g}{2} \right|^p \leq \frac{1}{2} |2f|^p + \frac{1}{2} |2g|^p = 2^{p-1} (|f|^p + |g|^p).$$

Therefore,

$$|f + g|^p < 2^{p-1} (|f|^p + |g|^p) < \infty.$$

By Hölder's Inequality (7.2),

$$\begin{aligned}
\|f + g\|_p^p &= \int |f + g|^p d\mu \\
&= \int |f + g| \cdot |f + g|^{p-1} d\mu \\
&\leq \int (|f| + |g|) |f + g|^{p-1} d\mu \\
&= \int |f| |f + g|^{p-1} d\mu + \int |g| |f + g|^{p-1} d\mu \\
&\leq \left( \left( \int |f|^p d\mu \right)^{\frac{1}{p}} + \left( \int |g|^p d\mu \right)^{\frac{1}{p}} \right) \left( \int |f + g|^{(p-1)(\frac{p}{p-1})} d\mu \right)^{1-\frac{1}{p}} \\
&= (\|f\|_p + \|g\|_p) \frac{\|f + g\|_p^p}{\|f + g\|_p}
\end{aligned}$$

which means, as  $p \in [1, \infty)$ ,

$$\|f + g\|_p \leq \|f\|_p + \|g\|_p.$$

When  $p = \infty$ ,

*a*

**Theorem 7.4 (Bounded Convergence Theorem)**



**Theorem 7.5 (Fatou's Lemma)**



**Theorem 7.6 (Monotone Convergence Theorem)**



## 7.2 Product Measures

**Theorem 7.7 (Fubini's Theorem)**



## **Part IV**

# **Functional Analysis**

## **Part V**

# **Probability Theory**

# Chapter 8 Random Variables

## Introduction

- Probability Space
- Random Variables
- Distributions
- Expected Value
- Independence
- Characteristic Functions

## 8.1 Probability Space

### Definition 8.1 (Probability Space)

A probability space is a triple  $(\Omega, \mathcal{F}, P)$  consisting of:

1. the sample space  $\Omega$ : an arbitrary non-empty set.
2. the  $\sigma$ -algebra  $\mathcal{F} \subseteq 2^\Omega$ : a set of subsets of  $\Omega$ , called events.
3. the probability measure  $P : \mathcal{F} \rightarrow [0, 1]$ : a function on  $\mathcal{F}$  which is a measure function.



## 8.2 Random Variables

### Definition 8.2 (Random Variable)

A random variable is a measurable function  $X : \Omega \rightarrow S$  from a set of possible outcomes  $(\Omega, \mathcal{F})$  to a measurable space  $(S, \mathcal{S})$ , that is,

$$X^{-1}(B) \equiv \{\omega : X(\omega) \in B\} \in \mathcal{F} \quad \forall B \in \mathcal{S}. \quad (8.1)$$

Typically,  $(S, \mathcal{S}) = (R^d, \mathcal{R}^d)$  ( $d > 1$ ).



How to prove that functions are measurable?

### Theorem 8.1

If  $\{\omega : X(\omega) \in A\} \in \mathcal{F}$  for all  $A \in \mathcal{A}$  and  $\mathcal{A}$  generates  $\mathcal{S}$ , then  $X$  is measurable.



1.



## 8.3 Distributions

### 8.3.1 Definition of Distributions

#### Definition 8.3 (Distribution)

A distribution of random variable  $X$  is a probability function  $P : \mathcal{R} \rightarrow \mathbb{R}$  by setting

$$\mu(A) = P(X \in A) = P(X^{-1}(A)), \quad \text{for } A \in \mathcal{R}. \quad (8.2)$$



#### Definition 8.4 (Distribution Function)

The distribution of a random variable  $X$  is usually described by giving its **distribution function**,

$$F(x) = P(X \leq x). \quad (8.3)$$



#### Definition 8.5 (Density Function)

If the distribution function  $F(x) = P(X \leq x)$  has the form

$$F(x) = \int_{-\infty}^x f(y) dy,$$

that  $X$  has density function  $f$ .



### 8.3.2 Properties of Distributions

#### Theorem 8.2 (Properties of Distribution Function)

Any distribution function  $F$  has the following properties,

1.  $F$  is nondecreasing.
2.  $\lim_{x \rightarrow \infty} F(x) = 1, \lim_{x \rightarrow -\infty} F(x) = 0$ .
3.  $F$  is right continuous, i.e.,  $\lim_{y \downarrow x} F(y) = F(x)$ .
4. If  $F(x-) = \lim_{y \uparrow x} F(y)$ , then  $F(x-) = P(X < x)$ .
5.  $P(X = x) = F(x) - F(x-)$ .



#### Proof

#### Theorem 8.3

If  $F$  satisfies (1), (2), and (3) in Theorem 8.2, then it is the distribution function of some random variable.



#### Proof

#### Theorem 8.4

A distribution function has at most countably many discontinuities



#### Proof

### 8.3.3 Families of Distributions

## 8.4 Expected Value

### Definition 8.6 (Expectation)



### Theorem 8.5 (Bounded Convergence theorem)



### Theorem 8.6 (Fatou's Lemma)

If  $X_n \geq 0$ , then

$$\liminf_{n \rightarrow \infty} EX_n \geq E \left( \liminf_{n \rightarrow \infty} X_n \right). \quad (8.4)$$



### Theorem 8.7 (Monotone Convergence theorem)

If  $0 \leq X_n \uparrow X$ , then

$$EX_n \uparrow EX. \quad (8.5)$$



### Theorem 8.8 (Dominated Convergence theorem)

If  $X_n \rightarrow X$  a.s.,  $|X_n| \leq Y$  for all  $n$ , and  $EY < \infty$ , then

$$EX_n \rightarrow EX. \quad (8.6)$$



## 8.5 Independence

### 8.5.1 Definition of Independence

### Definition 8.7 (Independence)

1. Two events  $A$  and  $B$  are independent if  $P(A \cap B) = P(A)P(B)$ .
2. Two random variables  $X$  and  $Y$  are independent if for all  $C, D \in \mathcal{R}$

$$P(X \in C, Y \in D) = P(X \in C)P(Y \in D). \quad (8.7)$$

3. Two  $\sigma$ -fields  $\mathcal{F}$  and  $\mathcal{G}$  are independent if for all  $A \in \mathcal{F}$  and  $B \in \mathcal{G}$  the events  $A$  and  $B$  are independent.



The second definition is a special case of the third.

### Theorem 8.9

1. If  $X$  and  $Y$  are independent then  $\sigma(X)$  and  $\sigma(Y)$  are independent.
2. Conversely, if  $\mathcal{F}$  and  $\mathcal{G}$  are independent,  $X \in \mathcal{F}$  and  $Y \in \mathcal{G}$ , then  $X$  and  $Y$  are independent.



The first definition is, in turn, a special case of the second.

**Theorem 8.10**

1. If  $A$  and  $B$  are independent, then so are  $A^c$  and  $B$ ,  $A$  and  $B^c$ , and  $A^c$  and  $B^c$ .
2. Conversely, events  $A$  and  $B$  are independent if and only if their indicator random variables  $1_A$  and  $1_B$  are independent.



The definition of independence can be extended to the infinite collection.

**Definition 8.8**

An infinite collection of objects ( $\sigma$ -fields, random variables, or sets) is said to be independent if every finite subcollection is,

1.  $\sigma$ -fields  $\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_n$  are independent if whenever  $A_i \in \mathcal{F}_i$  for  $i = 1, \dots, n$ , we have

$$P\left(\bigcap_{i=1}^n A_i\right) = \prod_{i=1}^n P(A_i). \quad (8.8)$$

2. Random variables  $X_1, \dots, X_n$  are independent if whenever  $B_i \in \mathcal{R}$  for  $i = 1, \dots, n$  we have

$$P\left(\bigcap_{i=1}^n \{X_i \in B_i\}\right) = \prod_{i=1}^n P(X_i \in B_i). \quad (8.9)$$

3. Sets  $A_1, \dots, A_n$  are independent if whenever  $I \subset \{1, \dots, n\}$  we have

$$P\left(\bigcap_{i \in I} A_i\right) = \prod_{i \in I} P(A_i). \quad (8.10)$$



## 8.5.2 Sufficient Conditions for Independence

## 8.5.3 Independence, Distribution, and Expectation

**Theorem 8.11**

Suppose  $X_1, \dots, X_n$  are independent random variables and  $X_i$  has distribution  $\mu_i$ , then  $(X_1, \dots, X_n)$  has distribution  $\mu_1 \times \dots \times \mu_n$ .

**Theorem 8.12**

If  $X_1, \dots, X_n$  are independent and have

1.  $X_i \geq 0$  for all  $i$ , or
2.  $E|X_i| < \infty$  for all  $i$ .

then

$$E\left(\prod_{i=1}^n X_i\right) = \prod_{i=1}^n EX_i \quad (8.11)$$



### 8.5.4 Sums of Independent Random Variables

#### Theorem 8.13 (Convolution for Random Variables)

1. If  $X$  and  $Y$  are independent,  $F(x) = P(X \leq x)$ , and  $G(y) = P(Y \leq y)$ , then

$$P(X + Y \leq z) = \int F(z - y) dG(y). \quad (8.12)$$

2. If  $X$  and  $Y$  are independent,  $X$  with density  $f$  and  $Y$  with distribution function  $G$ , then  $X + Y$  has density

$$h(x) = \int f(x - y) dG(y). \quad (8.13)$$

Suppose  $Y$  has density  $g$ , the last formula can be written as

$$h(x) = \int f(x - y) g(y) dy. \quad (8.14)$$

3. If  $X$  and  $Y$  are independent, integral-valued random variables, then

$$P(X + Y = n) = \sum_m P(X = m) P(Y = n - m). \quad (8.15)$$



## 8.6 Moments

#### Lemma 8.1

If  $Y > 0$  and  $p > 0$ , then

$$E(Y^p) = \int_0^\infty p y^{p-1} P(Y > y) dy. \quad (8.16)$$



## 8.7 Characteristic Functions

### 8.7.1 Definition of Characteristic Functions

#### Definition 8.9 (Characteristic Function)

If  $X$  is a random variable, we define its characteristic function (ch.f) by

$$\varphi(t) = E(e^{itX}) = E(\cos tX) + iE(\sin tX). \quad (8.17)$$




**Note** Euler Equation.

### 8.7.2 Properties of Characteristic Functions

#### Theorem 8.14 (Properties of Characteristic Function)

Any characteristic function has the following properties:

1.  $\varphi(0) = 1$ ,
2.  $\varphi(-t) = \overline{\varphi(t)}$ ,
3.  $|\varphi(t)| = |E e^{itX}| \leq E |e^{itX}| = 1$ ,
4.  $\varphi(t)$  is uniformly continuous on  $(-\infty, \infty)$ ,
5.  $E e^{it(aX+b)} = e^{itb} \varphi(at)$ ,
6. If  $X_1$  and  $X_2$  are independent and have ch.f.'s  $\varphi_1$  and  $\varphi_2$ , then  $X_1 + X_2$  has ch.f.  $\varphi_1(t)\varphi_2(t)$ . 


**Proof**

### 8.7.3 The Inversion Formula

The characteristic function uniquely determines the distribution. This and more is provided by:

#### Theorem 8.15 (The Inversion Formula)

Let  $\varphi(t) = \int e^{itx} \mu(dx)$  where  $\mu$  is a probability measure. If  $a < b$ , then

$$\lim_{T \rightarrow \infty} (2\pi)^{-1} \int_{-T}^T \frac{e^{-ita} - e^{-itb}}{it} \varphi(t) dt = \mu(a, b) + \frac{1}{2} \mu(\{a, b\}) \quad (8.18)$$


**Proof**

#### Theorem 8.16

If  $\int |\varphi(t)| dt < \infty$ , then  $\mu$  has bounded continuous density


$$f(y) = \frac{1}{2\pi} \int e^{-ity} \varphi(t) dt. \quad (8.19)$$


**Proof**

### 8.7.4 Convergence in Distribution

#### Theorem 8.17 (Lèvy's Continuity Theorem)

Let  $\mu_n, 1 \leq n \leq \infty$  be probability measures with ch.f.  $\varphi_n$ .

1. If  $\mu_n \xrightarrow{d} \mu_\infty$ , then  $\varphi_n(t) \rightarrow \varphi_\infty(t)$  for all  $t$ .
2. If  $\varphi_n(t)$  converges pointwise to a limit  $\varphi(t)$  that is continuous at 0, then the associated sequence of distributions  $\mu_n$  is tight and converges weakly to the measure  $\mu$  with characteristic function  $\varphi$ . 

**Proof**

## 8.7.5 Moments and Derivatives

**Theorem 8.18**

If  $\int |x|^n \mu(dx) < \infty$ , then its characteristic function  $\varphi$  has a continuous derivative of order  $n$  given by

$$\varphi^{(n)}(t) = \int (ix)^n e^{itx} \mu(dx). \quad (8.20)$$

**Theorem 8.19**

If  $E|X|^2 < \infty$  then

$$\varphi(t) = 1 + itEX - t^2 E(X^2)/2 + o(t^2). \quad (8.21)$$

**Theorem 8.20**

If  $\limsup_{h \downarrow 0} \{\varphi(h) - 2\varphi(0) + \varphi(-h)\}/h^2 > -\infty$ , then

$$E|X|^2 < \infty. \quad (8.22)$$



# Chapter 9 Convergence of Random Variables

## Introduction

- Convergence in Mean
- Convergence in Probability
- Convergence in Uninform
- Convergence in Distribution
- Almost Sure Convergence

## 9.1 Convergence in Mean

### Definition 9.1 (Convergence in Mean)

A sequence  $\{X_n\}$  of real-valued random variables **converges in the  $r$ -th mean** ( $r \geq 1$ ) towards the random variable  $X$ , if

1. The  $r$ -th absolute moments  $E(|X_n|^r)$  and  $E(|X|^r)$  of  $\{X_n\}$  and  $X$  exist,
2.  $\lim_{n \rightarrow \infty} E(|X_n - X|^r) = 0$ .

Convergence in the  $r$ -th mean is denoted by

$$X_n \xrightarrow{L^r} X. \quad (9.1) \quad \clubsuit$$

## 9.2 Convergence in Probability

### Definition 9.2 (Convergence in Probability)

A sequence  $\{X_n\}$  of real-valued random variables **converges in probability** towards the random variable  $X$ , if

$$\forall \varepsilon > 0, \quad \lim_{n \rightarrow \infty} P(|X_n - X| > \varepsilon) = 0. \quad (9.2)$$

Convergence in probability is denoted by

$$X_n \xrightarrow{p} X. \quad (9.3) \quad \clubsuit$$

## 9.3 Convergence in Uninform

### Definition 9.3 (Convergence in Uninform)



## 9.4 Convergence in Distribution

### Definition 9.4 (Convergence in Distribution)

A sequence  $\{X_n\}$  of real-valued random variables is said to **converge in distribution**, or **converge weakly**, or **converge in law** to a random variable  $X$ , if

$$\lim_{n \rightarrow \infty} F_n(x) = F(x), \quad (9.4)$$

for every number at  $x \in \mathbb{R}$  which  $F$  is continuous. Here  $F_n$  and  $F$  are the cumulative distribution functions of random variables  $X_n$  and  $X$ , respectively.

Convergence in distribution is denoted as

$$X_n \xrightarrow{d} X, \text{ or } X_n \Rightarrow X. \quad (9.5) \quad \clubsuit$$



### Note

- Convergence in Distribution is the weakest form of convergence typically discussed, since it is implied by all other types of convergence mentioned in this chapter.
- Convergence in Distribution does not imply that the sequence of corresponding probability density functions will also converge. However, according to Scheffé's theorem, convergence of the probability density functions implies convergence in distribution.

### Lemma 9.1

If  $F_n \xrightarrow{d} F_\infty$ , then there are random variables  $Y_n, 1 \leq n \leq \infty$ , with distribution  $F_n$  so that

$$Y_n \xrightarrow{a.s.} Y_\infty. \quad (9.6) \quad \heartsuit$$

### Theorem 9.1 (Portmanteau Lemma)

$\{X_n\}$  converges in distribution to  $X$ , if and only if any of the following statements are true,

- $P(X_n \leq x) \rightarrow P(X \leq x)$ , for all continuity points of the distribution of  $X$ .
- $Ef(X_n) \rightarrow Ef(X)$ , for all bounded, continuous (Lipschitz) functions  $f$ .
- $\liminf_{n \rightarrow \infty} P(X_n \in G) \geq P(X_\infty \in G)$ , for all open sets  $G$ .
- $\limsup_{n \rightarrow \infty} P(X_n \in K) \leq P(X_\infty \in K)$ , for all closed sets  $K$ .
- $\lim_{n \rightarrow \infty} P(X_n \in A) = P(X_\infty \in A)$ , for all Borel sets  $A$  with  $P(X_\infty \in \partial A) = 0$ .



### Proof

### Theorem 9.2 (Continuous Mapping Theorem)

Let  $g$  be a measurable function and  $D_g = \{x : g \text{ is discontinuous at } x\}$  with  $P(X \in D_g) = 0$ , then,

$$\begin{aligned} X_n \xrightarrow{d} X &\Rightarrow g(X_n) \xrightarrow{d} g(X), \\ X_n \xrightarrow{p} X &\Rightarrow g(X_n) \xrightarrow{p} g(X), \\ X_n \xrightarrow{a.s.} X &\Rightarrow g(X_n) \xrightarrow{a.s.} g(X). \end{aligned} \quad (9.7)$$



If in addition  $g$  is bounded, then

$$Eg(X_n) \rightarrow Eg(X). \quad (9.8) \quad \heartsuit$$

### Proof

#### Theorem 9.3

If  $X_n \xrightarrow{p} X$ , then

$$X_n \xrightarrow{d} X, \quad (9.9)$$

and that, conversely, if  $X_n \xrightarrow{d} c$ , where  $c$  is a constant, then

$$X_n \xrightarrow{p} c. \quad (9.10) \quad \heartsuit$$

### Proof

1.  $\forall \varepsilon > 0$ , at fixed point  $x$ , since if  $X_n \leq x$  and  $|X_n - X| \leq \varepsilon$ , then  $X \leq x + \varepsilon$ , then

$$\{X \leq x + \varepsilon\} \subset \{X_n \leq x\} \cup \{|X_n - X| > \varepsilon\},$$

similarly, if  $X \leq x - \varepsilon$  and  $|X_n - X| \leq \varepsilon$ , then  $X_n \leq x$ , then

$$\{X_n \leq x\} \subset \{X \leq x - \varepsilon\} \cup \{|X_n - X| > \varepsilon\},$$

then, by the union bound,

$$P(X \leq x + \varepsilon) \leq P(X_n \leq x) + P(|X_n - X| > \varepsilon),$$

$$P(X_n \leq x) \leq P(X \leq x - \varepsilon) + P(|X_n - X| > \varepsilon).$$

So, we got

$$\begin{aligned} P(X \leq x + \varepsilon) - P(|X_n - X| > \varepsilon) &\leq P(X_n \leq x) \\ &\leq P(X \leq x - \varepsilon) + P(|X_n - X| > \varepsilon) \end{aligned}$$

As  $n \rightarrow \infty$ ,  $P(|X_n - X| > \varepsilon) \rightarrow 0$ , then

$$\begin{aligned} P(X \leq x - \varepsilon) &\leq \lim_{n \rightarrow \infty} P(X_n \leq x) \leq P(X \leq x + \varepsilon) \\ &\Rightarrow F(x - \varepsilon) \leq \lim_{n \rightarrow \infty} F_n(x) \leq F(x + \varepsilon) \end{aligned}$$

By the property of distribution (Theorem 8.2), as  $\varepsilon \rightarrow 0$ , then

$$\lim_{n \rightarrow \infty} F_n(x) = F(x),$$

which means,

$$X_n \xrightarrow{d} X.$$

2. Since  $X_n \xrightarrow{d} c$ , where  $c$  is a constant, then  $\forall \varepsilon > 0$ ,

$$\lim_{n \rightarrow \infty} P(X_n \leq c + \varepsilon) = 1 \Rightarrow \lim_{n \rightarrow \infty} P(X_n > c + \varepsilon) = 0$$

$$\lim_{n \rightarrow \infty} P(X_n \leq c - \varepsilon) = 0.$$

Therefore,

$$P(|X_n - c| < \varepsilon) = 0,$$

which means

$$X_n \xrightarrow{p} c.$$

#### Theorem 9.4 (Slutsky's Theorem)

Let  $X_n, Y_n$  be sequences of random variables. If  $X_n \xrightarrow{d} X$  and  $Y_n \xrightarrow{p} c$ , then

1.  $X_n + Y_n \xrightarrow{d} X + c$ .
2.  $X_n Y_n \xrightarrow{d} cX$ .
3.  $X_n / Y_n \xrightarrow{d} X/c$ , provided that  $c$  is invertible.



#### Proof

**Note** However that convergence in distribution of  $X_n \xrightarrow{d} X$  and  $Y_n \xrightarrow{d} Y$  does in general not imply convergence in distribution of  $X_n + Y_n \xrightarrow{d} X + Y$  or of  $X_n Y_n \xrightarrow{d} XY$ .

#### Theorem 9.5 (Cramér-Wold Theorem)



#### Theorem 9.6 (Helly's Selection Theorem)

For every sequence  $F_n$  of distribution functions, there is a subsequence  $F_{n(k)}$  and a right continuous nondecreasing function  $F$  so that  $\lim_{k \rightarrow \infty} F_{n(k)}(y) = F(y)$  at all continuity points  $y$  of  $F$ .



#### Theorem 9.7

Every subsequential limit is the distribution function of a probability measure if and only if the sequence  $F_n$  is tight, i.e., for all  $\epsilon > 0$  there is an  $M_\epsilon$  so that

$$\limsup_{n \rightarrow \infty} 1 - F_n(M_\epsilon) + F_n(-M_\epsilon) \leq \epsilon. \quad (9.11)$$



## 9.5 Almost Sure Convergence

#### Definition 9.5 (Almost Sure Convergence)

A sequence  $\{X_n\}$  of real-valued random variables converges **almost sure** or **almost everywhere** or **with probability 1** or **strongly** towards the random variable  $X$ , if

$$P\left(\lim_{n \rightarrow \infty} X_n = X\right) = 1. \quad (9.12)$$

Almost sure convergence is denoted by

$$X_n \xrightarrow{a.s.} X. \quad (9.13)$$



**Note**

**Theorem 9.8**

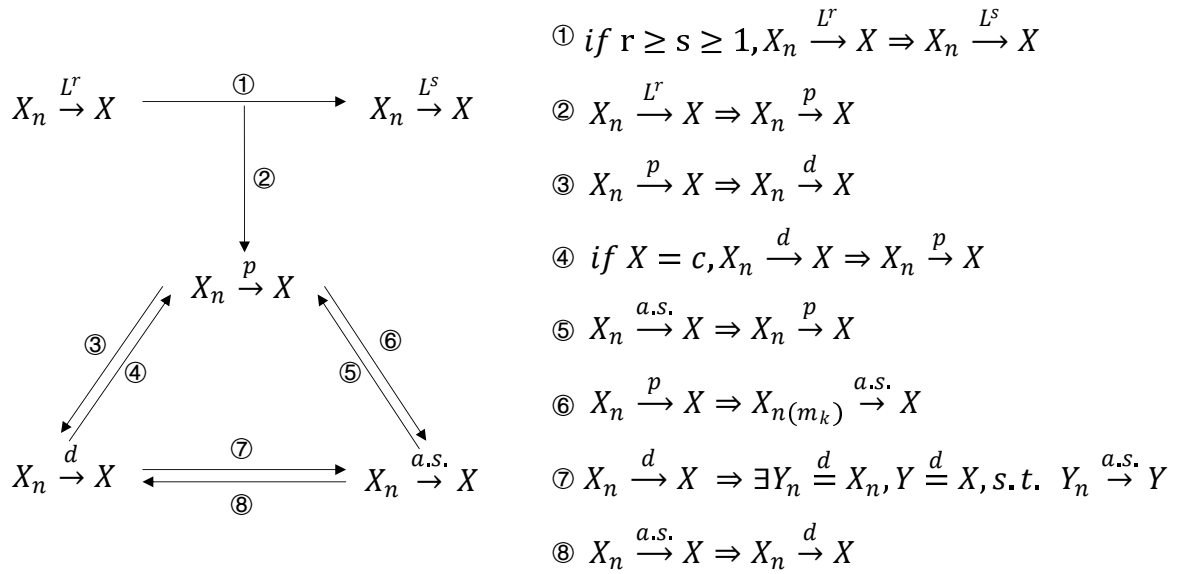
If  $X_n \xrightarrow{a.s.} X$ , then

$$X_n \xrightarrow{p} X. \quad (9.14) \quad \heartsuit$$

**Proof**
**Theorem 9.9**

$X_n \xrightarrow{p} X$  if and only if for all subsequence  $X_{n(m)}$  exists a further subsequence  $X_{n(m_k)}$ , such that

$$X_{n(m_k)} \xrightarrow{a.s.} X. \quad (9.15) \quad \heartsuit$$



**Figure 9.1:** Relations of Convergence of Random Variables

## 9.6 Asymptotic Notation for Random Variables

**Definition 9.6**

A sequence  $\{A_n\}$  of real-valued random variables is of smaller order in probability than a sequence  $\{B_n\}$ , if

$$\frac{A_n}{B_n} \xrightarrow{p} 0. \quad (9.16)$$

Smaller order in probability is denoted by

$$A_n = o_p(B_n). \quad (9.17)$$

Particularly,

$$A_n = o_p(1) \iff A_n \xrightarrow{p} 0. \quad (9.18) \quad \clubsuit$$

**Definition 9.7**

A sequence  $\{A_n\}$  of real-valued random variables is of smaller order than or equal to a sequence  $\{B_n\}$  in probability, if

$$\forall \varepsilon > 0 \exists M_\varepsilon, \quad \lim_{n \rightarrow \infty} P(|A_n| \leq M_\varepsilon |B_n|) \geq 1 - \varepsilon. \quad (9.19)$$

Smaller order than or equal to in probability is denoted by

$$A_n = O_p(B_n). \quad (9.20) \quad \clubsuit$$

**Definition 9.8**

A sequence  $\{A_n\}$  of real-valued random variables is of the same order as a sequence  $\{B_n\}$  in probability, if

$$\forall \varepsilon > 0 \exists m_\varepsilon < M_\varepsilon, \quad \lim_{n \rightarrow \infty} P\left(m_\varepsilon < \frac{|A_n|}{|B_n|} < M_\varepsilon\right) \geq 1 - \varepsilon. \quad (9.21)$$

Same order in probability is denoted by

$$A_n \asymp_p B_n. \quad (9.22) \quad \clubsuit$$

# Chapter 10 Law of Large Numbers

## Introduction

- Weak Law of Large Numbers
- Strong Law of Large Numbers

- Uniform Law of Large Numbers

## 10.1 Weak Law of Large Numbers

### Lemma 10.1

If  $p > 0$  and  $E|Z_n|^p \rightarrow 0$ , then

$$Z_n \xrightarrow{p} 0. \quad (10.1)$$

### Proof

### Theorem 10.1 (Weak Law of Large Numbers with Finite Variances)

Let  $X_1, X_2, \dots$  be i.i.d. random variables with  $EX_i = \mu$  and  $\text{Var}(X_i) \leq C < \infty$ . Suppose  $S_n = X_1 + X_2 + \dots + X_n$ , then

$$S_n/n \xrightarrow{L^2} \mu, \quad S_n/n \xrightarrow{p} \mu. \quad (10.2)$$

### Proof

### Theorem 10.2 (Weak Law of Large Numbers without i.i.d.)

Let  $X_1, X_2, \dots$  be random variables, Suppose  $S_n = X_1 + X_2 + \dots + X_n$ ,  $\mu_n = ES_n$ ,  $\sigma_n^2 = \text{Var}(S_n)$ , if  $\sigma_n^2/b_n^2 \rightarrow 0$ , then

$$\frac{S_n - \mu_n}{b_n} \xrightarrow{p} 0. \quad (10.3)$$

### Proof

### Theorem 10.3 (Weak Law of Large Numbers for Triangular Arrays)

For each  $n$ , let  $X_{n,m}, 1 \leq m \leq n$ , be independent random variables. Suppose  $b_n > 0$  with  $b_n \rightarrow \infty$ ,  $\bar{X}_{n,m} = X_{n,m}I_{(X_{n,m} \leq b_n)}$ , if

- $\sum_{m=1}^n P(|X_{n,m}| > b_n) \rightarrow 0$ , and
- $b_n^{-2} \sum_{m=1}^n E\bar{X}_{n,m}^2 \rightarrow 0$ .

Suppose  $S_n = X_{n,1} + \dots + X_{n,n}$  and  $a_n = \sum_{m=1}^n E\bar{X}_{n,m}$ , then

$$\frac{S_n - a_n}{b_n} \xrightarrow{p} 0. \quad (10.4)$$

### Proof

**Theorem 10.4 (Weak Law of Large Numbers by Feller)**

Let  $X_1, X_2, \dots$  be i.i.d. random variables with

$$\lim_{x \rightarrow 0} xP(|X_i| > x) = 0. \quad (10.5)$$

Suppose  $S_n = X_1 + X_2 + \dots + X_n$ ,  $\mu_n = E(X_1 I_{(|X_1| < n)})$ , then

$$S_n/n - \mu_n \xrightarrow{p} 0. \quad (10.6) \heartsuit$$

**Proof****Theorem 10.5 (Weak Law of Large Numbers)**

Let  $X_1, X_2, \dots$  be i.i.d. random variables with  $E|X_i| < \infty$ . Suppose  $S_n = X_1 + X_2 + \dots + X_n$ ,  $\mu = EX_i$ , then

$$S_n/n \xrightarrow{p} \mu. \quad (10.7) \heartsuit$$

**Proof**

 **Note**  $E|X_i| = \infty$

## 10.2 Strong Law of Large Numbers

### 10.2.1 Borel-Cantelli Lemmas

**Lemma 10.2 (Borel-Cantelli Lemma)**

If  $\sum_{n=1}^{\infty} P(A_n) < \infty$ , then

$$P(A_n \text{ i.o.}) = 0. \quad (10.8) \heartsuit$$

**Lemma 10.3 (The Second Borel-Cantelli Lemma)**

If  $\{A_n\}$  are independent with  $\sum_{n=1}^{\infty} P(A_n) = \infty$ , then,

$$P(A_n \text{ i.o.}) = 1. \quad (10.9) \heartsuit$$

**Corollary 10.1**

Suppose  $\{A_n\}$  are independent with  $P(A_n) < 1, \forall n$ . If  $P(\cup_{n=1}^{\infty} A_n) = 1$  then

$$\sum_{n=1}^{\infty} P(A_n) = \infty, \quad (10.10)$$

and hence  $P(A_n \text{ i.o.}) = 1$  \heartsuit

**Proof**

### 10.2.2 Strong Law of Large Numbers

#### Theorem 10.6 (Strong Law of Large Numbers)

Let  $X_1, X_2, \dots$  be i.i.d. random variables with  $E|X_i| < \infty$ . Suppose  $S_n = X_1 + X_2 + \dots + X_n$ ,  $\mu = EX_i$ , then

$$S_n/n \xrightarrow{a.s.} \mu. \quad (10.11) \quad \heartsuit$$

## 10.3 Uniform Law of Large Numbers

#### Theorem 10.7 (Uniform Law of Large Numbers)

Suppose

1.  $\Theta$  is compact.
2.  $g(X_i, \theta)$  is continuous at each  $\theta \in \Theta$  almost sure.
3.  $g(X_i, \theta)$  is dominated by a function  $G(X_i)$ , i.e.  $|g(X_i, \theta)| \leq G(X_i)$ .
4.  $EG(X_i) < \infty$ .

Then

$$\sup_{\theta \in \Theta} \left| n^{-1} \sum_{i=1}^n g(X_i, \theta) - Eg(X_i, \theta) \right| \xrightarrow{p} 0. \quad (10.12) \quad \heartsuit$$

**Proof** Suppose

$$\Delta_\delta(X_i, \theta_0) = \sup_{\theta \in B(\theta_0, \delta)} g(X_i, \theta) - \inf_{\theta \in B(\theta_0, \delta)} g(X_i, \theta).$$

Since (i)  $\Delta_\delta(X_i, \theta_0) \xrightarrow{a.s.} 0$  by condition (2), (ii)  $\Delta_\delta(X_i, \theta_0) \leq 2 \sup_{\theta \in \Theta} |g(X_i, \theta)| \leq 2G(X_i)$  by condition (3) and (4). Then

$$E \Delta_\delta(X_i, \theta_0) \rightarrow 0, \text{ as } \delta \rightarrow 0.$$

So, for all  $\theta \in \Theta$  and  $\varepsilon > 0$ , there exists  $\delta_\varepsilon(\theta)$  such that

$$E[\Delta_{\delta_\varepsilon(\theta)}(X_i, \theta)] < \varepsilon.$$

Since  $\Theta$  is compact, we can find a finite subcover, such that  $\Theta$  is covered by

$$\cup_{k=1}^K B(\theta_k, \delta_\varepsilon(\theta_k)).$$

$$\begin{aligned} & \sup_{\theta \in \Theta} \left[ n^{-1} \sum_{i=1}^n g(X_i, \theta) - Eg(X_i, \theta) \right] \\ &= \max_k \sup_{\theta \in B(\theta_k, \delta_\varepsilon(\theta_k))} \left[ n^{-1} \sum_{i=1}^n g(X_i, \theta) - Eg(X_i, \theta) \right] \\ &\leq \max_k \left[ n^{-1} \sum_{i=1}^n \sup_{\theta \in B(\theta_k, \delta_\varepsilon(\theta_k))} g(X_i, \theta) - E \inf_{\theta \in B(\theta_k, \delta_\varepsilon(\theta_k))} g(X_i, \theta) \right] \end{aligned}$$

Since

$$E \left| \sup_{\theta \in B(\theta_k, \delta_c(\theta_k))} g(X_i, \theta) \right| \leq E G(X_i) < \infty,$$

by the Weak Law of Large Numbers (Theorem 10.5),

$$\begin{aligned} &= o_p(1) + \max_k \left[ E \sup_{\theta \in B(\theta_k, \delta_\varepsilon(\theta_k))} g(X_i, \theta) - E \inf_{\theta \in B(\theta_k, \delta_\varepsilon(\theta_k))} g(X_i, \theta) \right] \\ &= o_p(1) + \max_k E \Delta_{\delta_\varepsilon(\theta_k)}(X_i, \theta_k) \\ &\leq o_p(1) + \varepsilon \end{aligned}$$

By analogous argument,

$$\inf_{\theta \in \Theta} \left[ n^{-1} \sum_{i=1}^n g(X_i, \theta) - E g(X_i, \theta) \right] \geq o_p(1) - \varepsilon.$$

The desired result follows from the above equation by the fact that  $\varepsilon$  is chosen arbitrarily.



# Chapter 11 Central Limit Theorems

## Introduction

- ❑ Classic Central Limit Theorem
- ❑ Central Limit Theorem for independent non-identical Random Variables
- ❑ Central Limit Theorem for dependent Random Variables

## 11.1 Classic Central Limit Theorem

### 11.1.1 The De Moivre-Laplace Theorem

#### Lemma 11.1 (Stirling's Formula)

$$n! \sim \sqrt{2\pi n} n^{n+\frac{1}{2}} e^{-n} \text{ as } n \rightarrow \infty. \quad (11.1) \quad \heartsuit$$

**Proof**

#### Lemma 11.2

If  $c_j \rightarrow 0$ ,  $a_j \rightarrow \infty$  and  $a_j c_j \rightarrow \lambda$ , then

$$(1 + c_j)^{a_j} \rightarrow e^\lambda. \quad (11.2) \quad \heartsuit$$

**Proof**

#### Theorem 11.1 (The De Moivre-Laplace Theorem)

Let  $X_1, X_2, \dots$  be i.i.d. with  $P(X_1 = 1) = P(X_1 = -1) = 1/2$  and let  $S_n = X_1 + \dots + X_n$ . If  $a < b$ , then as  $m \rightarrow \infty$

$$P(a \leq S_m / \sqrt{m} \leq b) \rightarrow \int_a^b (2\pi)^{-1/2} e^{-x^2/2} dx. \quad (11.3) \quad \heartsuit$$

**Proof** If  $n$  and  $k$  are integers

$$P(S_{2n} = 2k) = \binom{2n}{n+k} 2^{-2n}$$

By lemma 11.1, we have

$$\begin{aligned} \binom{2n}{n+k} &= \frac{(2n)!}{(n+k)!(n-k)!} \\ &\sim \frac{(2n)^{2n}}{(n+k)^{n+k}(n-k)^{n-k}} \cdot \frac{(2\pi(2n))^{1/2}}{(2\pi(n+k))^{1/2}(2\pi(n-k))^{1/2}} \end{aligned}$$

Hence,

$$\begin{aligned}
 P(S_{2n} = 2k) &= \binom{2n}{n+k} 2^{-2n} \\
 &\sim \left(1 + \frac{k}{n}\right)^{-n-k} \cdot \left(1 - \frac{k}{n}\right)^{-n+k} \\
 &\quad \cdot (\pi n)^{-1/2} \cdot \left(1 + \frac{k}{n}\right)^{-1/2} \cdot \left(1 - \frac{k}{n}\right)^{-1/2} \\
 &= \left(1 - \frac{k^2}{n^2}\right)^{-n} \cdot \left(1 + \frac{k}{n}\right)^{-k} \cdot \left(1 - \frac{k}{n}\right)^k \\
 &\quad \cdot (\pi n)^{-1/2} \cdot \left(1 + \frac{k}{n}\right)^{-1/2} \cdot \left(1 - \frac{k}{n}\right)^{-1/2}
 \end{aligned}$$

Let  $2k = x\sqrt{2n}$ , i.e.,  $k = x\sqrt{n/2}$ . By lemma 11.2, we have

$$\begin{aligned}
 \left(1 - \frac{k^2}{n^2}\right)^{-n} &= (1 - x^2/2n)^{-n} \rightarrow e^{x^2/2} \\
 \left(1 + \frac{k}{n}\right)^{-k} &= (1 + x/\sqrt{2n})^{-x\sqrt{n/2}} \rightarrow e^{-x^2/2} \\
 \left(1 - \frac{k}{n}\right)^k &= (1 - x/\sqrt{2n})^{x\sqrt{n/2}} \rightarrow e^{-x^2/2}
 \end{aligned}$$

For this choice of  $k$ ,  $k/n \rightarrow 0$ , so

$$\left(1 + \frac{k}{n}\right)^{-1/2} \cdot \left(1 - \frac{k}{n}\right)^{-1/2} \rightarrow 1.$$

Putting things together, we have

$$P(S_{2n} = 2k) \sim (\pi n)^{-1/2} e^{-x^2/2}, \text{ as } \frac{2k}{\sqrt{2n}} \rightarrow x.$$

Therefore,

$$P(a\sqrt{2n} \leq S_{2n} \leq b\sqrt{2n}) = \sum_{m \in [a\sqrt{2n}, b\sqrt{2n}] \cap 2\mathbb{Z}} P(S_{2n} = m)$$

Let  $m = x\sqrt{2n}$ , we have that this is

$$\approx \sum_{x \in [a, b] \cap (2\mathbb{Z}/\sqrt{2n})} (2\pi)^{-1/2} e^{-x^2/2} \cdot (2/n)^{1/2}$$

where  $2\mathbb{Z}/\sqrt{2n} = \{2z/\sqrt{2n} : z \in \mathbb{Z}\}$ . As  $n \rightarrow \infty$ , the sum just shown is

$$\approx \int_a^b (2\pi)^{-1/2} e^{-x^2/2} dx.$$

To remove the restriction to even integers, observe  $S_{2n+1} = S_{2n} \pm 1$ .

Let  $m = 2n$ , as  $m \rightarrow \infty$ ,

$$P(a \leq S_m/\sqrt{m} \leq b) \rightarrow \int_a^b (2\pi)^{-1/2} e^{-x^2/2} dx.$$

### 11.1.2 Classic Central Limit Theorem

#### Theorem 11.2 (Classic Central Limit Theorem (i.i.d.))

Let  $X_1, X_2, \dots$  be i.i.d. with  $EX_i = \mu$ ,  $\text{Var}(X_i) = \sigma^2 < \infty$ . Let  $S_n = X_1 + X_2 + \dots + X_n$ , then

$$\frac{S_n - n\mu}{\sigma n^{\frac{1}{2}}} \xrightarrow{d} \chi, \quad (11.4)$$

where  $\chi$  has the standard normal distribution.



#### Proof

#### Theorem 11.3 (The Linderberg-Feller Central Limit Theorem)

For each  $n$ , let  $X_{n,m}$ ,  $1 \leq m \leq n$ , be independent random variables with  $EX_{n,m} = 0$ . If

1.  $\sum_{m=1}^n EX_{n,m}^2 \rightarrow \sigma^2 > 0$ .
2.  $\forall \epsilon > 0, \lim_{n \rightarrow \infty} \sum_{m=1}^n E(|X_{n,m}|^2; |X_{n,m}| > \epsilon) = 0$

Then  $S_n = X_{n,1} + \dots + X_{n,n} \xrightarrow{d} \sigma\chi$  as  $n \rightarrow \infty$ .



#### Theorem 11.4 (Berry-Esseen Theorem)

Let  $X_1, X_2, \dots, X_n$  be i.i.d. with distribution  $F$ , which has a mean  $\mu$  and a finite third moment  $\sigma^3$ , then there exists a constant  $C$  (independent of  $F$ ),

$$|G_n(x) - \Phi(x)| \leq \frac{C}{\sqrt{n}} \frac{E|X_1 - \mu|^3}{\sigma^3}, \quad \forall x. \quad (11.5)$$



#### Corollary 11.1

Under the assumptions of Theorem 51,

$$G_n(x) \rightarrow \Phi(x) \text{ as } n \rightarrow \infty$$

for any sequence  $F_n$  with mean  $\xi_n$  and variance  $\sigma_n^2$  for which

$$\frac{E_n |X_1 - \xi_n|^3}{\sigma_n^3} = o(\sqrt{n})$$

and thus in particular if (72) is bounded. Here  $E_n$  denotes the expectation under  $F_n$ .



## 11.2 Central Limit Theorem for independent non-identical Random Variables

#### Theorem 11.5 (The Liapounov Central Limit Theorem)



## 11.3 Central Limit Theorem for dependent Random Variables

## Chapter 12 The Delta Methods

### Theorem 12.1 (Delta Method)

Let  $\{X_n\}$  be a sequence of random variables with

$$\sqrt{n} [X_n - \theta] \xrightarrow{d} \sigma \chi,$$

where  $\theta$  and  $\sigma$  are finite, then for any function  $g$  with the property that  $g'(\theta)$  exists and is non-zero valued,

$$\sqrt{n} [g(X_n) - g(\theta)] \xrightarrow{d} \sigma g'(\theta) \chi.$$



**Proof** Under the assumption that  $g'(\theta)$  is continuous.

Since,  $g'(\theta)$  exists, with the first-order Taylor Approximation:

$$g(X_n) = g(\theta) + g'(\tilde{\theta})(X_n - \theta),$$

where  $\tilde{\theta}$  lies between  $X_n$  and  $\theta$ .

Since  $X_n \xrightarrow{p} \theta$ , and  $|\tilde{\theta} - \theta| < |X_n - \theta|$ , then

$$\tilde{\theta} \xrightarrow{p} \theta,$$

Since  $g'(\theta)$  is continuous, by Continuous Mapping Theorem (9.2),

$$g'(\tilde{\theta}) \xrightarrow{p} g'(\theta).$$

and,

$$\sqrt{n} (g(X_n) - g(\theta)) = \sqrt{n} g'(\tilde{\theta})(X_n - \theta),$$

$$\sqrt{n} [X_n - \theta] \xrightarrow{d} \sigma \chi,$$

by Slutsky's Theorem (9.4),

$$\sqrt{n} [g(X_n) - g(\theta)] \xrightarrow{d} \sigma g'(\theta) \chi.$$

# Chapter 13 Exercises for Probability Theory and Examples

## 13.1 Measure Theory

### Exercise 13.1

1. Show that if  $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots$  are  $\sigma$ -algebras, then  $\cup_i \mathcal{F}_i$  is an algebra.
2. Give an example to show that  $\cup_i \mathcal{F}_i$  need not be a  $\sigma$ -algebra.

### Solution

1. **Complement:** Suppose  $A \in \cup_i \mathcal{F}_i$ , since  $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots$ , assume  $A \in \mathcal{F}_i$ . And each  $\mathcal{F}_i$  is  $\sigma$ -algebra,

$$A^c \in \mathcal{F}_i \subset \cup_i \mathcal{F}_i.$$

**Finite Union:** Suppose  $A_1, A_2 \in \cup_i \mathcal{F}_i$ , since  $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots$ , assume  $A_1 \in \mathcal{F}_i, A_2 \in \mathcal{F}_j$ , such that,

$$A_1, A_2 \in \mathcal{F}_{\max(i,j)}.$$

Since each  $\mathcal{F}_i$  is  $\sigma$ -algebra,

$$A_1 \cup A_2 \in \mathcal{F}_i \subset \cup_i \mathcal{F}_i.$$

2. Let  $\mathcal{F}_i$  be a Borel Set of  $[1, 2 - \frac{1}{i}]$ . Suppose  $A_i = [1, 2 - \frac{1}{i}] \in \mathcal{F}_i$ ,  
 $\cup_i A_i = [1, 2) \notin \cup_i \mathcal{F}_i$ .

## 13.2 Laws of Large Numbers

## 13.3 Central Limit Theorems

Exercise 13.2 Let  $g \geq 0$  be continuous. If  $X_n \xrightarrow{d} X_\infty$ , then

$$\liminf_{n \rightarrow \infty} E g(X_n) \geq E g(X_\infty).$$

**Solution** Let  $Y_n \stackrel{d}{=} X_n, 1 \leq n \leq \infty$  with  $Y_n \xrightarrow{a.s.} Y_\infty$  (Lemma 9.1). Since  $g \geq 0$  be continuous,  $g(Y_n) \xrightarrow{a.s.} g(Y_\infty)$  and  $g(Y_n) \geq 0$  (Theorem 9.2), and the Fatou's Lemma (8.6) implies,

$$\begin{aligned} \liminf_{n \rightarrow \infty} E g(X_n) &= \liminf_{n \rightarrow \infty} E g(Y_n) \geq E \left( \liminf_{n \rightarrow \infty} g(Y_n) \right) \\ &= E g(Y_\infty) = E g(X_\infty). \end{aligned}$$

Exercise 13.3 Suppose  $g, h$  are continuous with  $g(x) > 0$ , and  $|h(x)|/g(x) \rightarrow 0$  as  $|x| \rightarrow \infty$ . If  $F_n \xrightarrow{d} F$  and  $\int g(x) dF_n(x) \leq C < \infty$ , then

$$\int h(x) dF_n(x) \rightarrow \int h(x) dF(x).$$

**Solution**

$$\begin{aligned}
\left| \int h(x) dF_n(x) - \int h(x) dF(x) \right| &= \left| \int_{x \in [-M, M]} h(x) dF_n(x) + \int_{x \notin [-M, M]} h(x) dF_n(x) \right. \\
&\quad \left. - \int_{x \in [-M, M]} h(x) dF(x) - \int_{x \notin [-M, M]} h(x) dF(x) \right| \\
&\leq \left| \int_{x \in [-M, M]} h(x) dF_n(x) - \int_{x \in [-M, M]} h(x) dF(x) \right| \\
&\quad + \left| \int_{x \notin [-M, M]} h(x) dF_n(x) - \int_{x \notin [-M, M]} h(x) dF(x) \right|.
\end{aligned}$$

Let  $X_n, 1 \leq n < \infty$ , with distribution  $F_n$ , so that  $X_n \xrightarrow{a.s.} X$  (Lemma 9.1).

$$\left| \int_{x \in [-M, M]} h(x) dF_n(x) - \int_{x \in [-M, M]} h(x) dF(x) \right| = |E(h(X_n) - h(X)) I_{x \in [-M, M]}|.$$

By Continuity Mapping Theorem (9.2),  $\lim_{n \rightarrow \infty} |E(h(X_n) - h(X)) I_{x \in [-M, M]}| = 0$ .

Since

$$h(x) I_{x \notin [-M, M]} \leq g(x) \sup_{x \notin [-M, M]} \frac{h(x)}{g(x)},$$

and by Exercise 13.2


$$\begin{aligned}
Eg(X) &\leq \liminf_{n \rightarrow \infty} Eg(X_n) = \liminf_{n \rightarrow \infty} \int g(x) dF_n(x) \leq C < \infty, \\
\left| \int_{x \notin [-M, M]} h(x) dF_n(x) - \int_{x \notin [-M, M]} h(x) dF(x) \right| &= |E(h(X_n) - h(X)) I_{x \notin [-M, M]}| \\
&\leq 2E \max(h(X_n), h(X)) I_{x \notin [-M, M]} \leq 2C \sup_{x \notin [-M, M]} \frac{h(x)}{g(x)}.
\end{aligned}$$

Hence, let  $M \rightarrow \infty$ ,


$$\lim_{n \rightarrow \infty} \left| \int h(x) dF_n(x) - \int h(x) dF(x) \right| \leq 2C \sup_{x \notin [-M, M]} \frac{h(x)}{g(x)} \rightarrow 0,$$

which means,


$$\int h(x) dF_n(x) \rightarrow \int h(x) dF(x).$$

 **Exercise 13.4** Let  $X_1, X_2, \dots$  be i.i.d. with  $EX_i = 0$  and  $EX_i^2 = \sigma^2 \in (0, \infty)$ . Then

$$\sum_{m=1}^n X_m / \left( \sum_{m=1}^n X_m^2 \right)^{1/2} \xrightarrow{d} \chi.$$

 **Exercise 13.5** Show that if  $|X_i| \leq M$  and  $\sum_n \text{Var}(X_n) = \infty$ , then

$$(S_n - ES_n) / \sqrt{\text{Var}(S_n)} \xrightarrow{d} \chi.$$

 **Exercise 13.6** Suppose  $EX_i = 0$ ,  $EX_i^2 = 1$  and  $E|X_i|^{2+\delta} \leq C$  for some  $0 < \delta, C < \infty$ . Show that

$$S_n / \sqrt{n} \xrightarrow{d} \chi.$$

## **Part VI**

### **Stochastic Process**

# Chapter 14 Martingales

## 14.1 Conditional Expectation

### Definition 14.1 (Conditional Expectation)



#### Example 14.1

1. If  $X \in \mathcal{F}$ , then

$$E(X | \mathcal{F}) = X.$$

2. If  $X$  is independent of  $\mathcal{F}$ , then

$$E(X | \mathcal{F}) = E(X).$$

3. If  $\Omega_1, \Omega_2, \dots$  is a finite or infinite partition of  $\Omega$  into disjoint sets, each of which has positive probability, and let  $\mathcal{F} = \sigma(\Omega_1, \Omega_2, \dots)$ , then

$$E(X | \mathcal{F}) = \frac{E(X; \Omega_i)}{P(\Omega_i)} \quad \text{on } \Omega_i.$$

#### Property

## 14.2 Martingales

Let  $\mathcal{F}_n$  be a filtration, i.e., an increasing sequence of  $\sigma$ -fields.

### Definition 14.2 (Martingale)

A sequence  $\{X_n\}$  of real-valued random variables is said to be a martingale with respect to  $\mathcal{F}_n$ , if

1.  $X_n$  is integrable, i.e.,  $E|X_n| < \infty$
2.  $X_n$  is adapted to  $\mathcal{F}_n$ , i.e.,  $\forall n, X_n \in \mathcal{F}_n$
3.  $X_n$  satisfies the martingale condition, i.e.,

$$E(X_{n+1} | \mathcal{F}_n) = X_n, \quad \forall n \quad (14.1)$$



**Note** If in the last definition  $=$  is replaced by  $\leq$  or  $\geq$ , then  $X$  is said to be a supermartingale or submartingale, respectively.

#### Example 14.2 Linear Martingale

#### Example 14.3 Quadratic Martingale

#### Example 14.4 Exponential Martingale

**Example 14.5 Random Walk** Suppose  $X_n = X_0 + \xi_1 + \dots + \xi_n$ , where  $X_0$  is constant,  $\xi_m$  are independent and have  $E\xi_m = 0, \sigma_m^2 = E\xi_m^2 < \infty$ . Let  $\mathcal{F}_n = \sigma(\xi_1, \dots, \xi_n)$  for  $n \geq 1$  and take  $\mathcal{F}_0 = \{\emptyset, \Omega\}$ . Show  $X_n$  is a martingale, and  $X_n^2$  is a submartingale.



**Proof** It is obvious that,

$$E |X_n| < \infty, \quad X_n \in \mathcal{F}_n$$

Since  $\xi_{n+1}$  is independent of  $\mathcal{F}_n$ , so using the linearity of conditional expectation, (4.1.1), and Example 4.1.4,

$$E (X_{n+1} | \mathcal{F}_n) = E (X_n | \mathcal{F}_n) + E (\xi_{n+1} | \mathcal{F}_n) = X_n + E \xi_{n+1} = X_n$$

So  $X_n$  is a martingale, and Theorem 4.2.6 implies  $X_n^2$  is a submartingale.



**Note** If we let  $\lambda = x^2$  and apply Theorem 4.4.2 to  $X_n^2$ , we get Kolmogorov's maximal inequality, Theorem 2.5.5:

$$P \left( \max_{1 \leq m \leq n} |X_m| \geq x \right) \leq x^{-2} \text{var} (X_n) \quad (14.2)$$

#### Theorem 14.1 (Orthogonality of Martingale Increments)



#### Theorem 14.2 (Conditional Variance Formula)



#### Definition 14.3 (Predictable Sequence)



#### Definition 14.4 (Stopping Time)



#### Theorem 14.3 (Martingale Convergence Theorem)



## 14.3 Doob's Inequality

#### Theorem 14.4 (Doob's Decomposition)



#### Theorem 14.5 (Doob's Inequality)



#### Theorem 14.6 ( $L^p$ Maximum Inequality)



## 14.4 Uniform Integrability

## 14.5 Optional Stopping Theorems

# Chapter 15 Markov Chains

## 15.1 Markov Chain

### Definition 15.1 (Markov Chain, Simple)

A sequence  $\{X_n\}$  of real-valued random variables is said to be a Markov chain, if for any states  $i_0, \dots, i_{n-1}, i$ , and  $j$

$$P(X_{n+1} = j \mid X_n = i, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) = P(X_{n+1} = j \mid X_n = i) \quad (15.1)$$

and the transition probability is

$$p(i, j) = P(X_{n+1} = j \mid X_n = i) \quad (15.2) \quad \clubsuit$$

**Example 15.1 Random Walk** Suppose  $X_n = X_0 + \xi_1 + \dots + \xi_n$ , where  $X_0$  is constant,  $\xi_m \in \mathbb{Z}^d$  are independent with distribution  $\mu$ . Show  $X_n$  is a Markov chain with transition probability,

$$p(i, j) = \mu(\{j - i\})$$

**Proof** Since  $\xi_m$  are independent with distribution  $\mu$ ,

$$\begin{aligned} &P(X_{n+1} = j \mid X_n = i, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) \\ &= P(X_n + \xi_{n+1} = j \mid X_n = i) = P(\xi_{n+1} = j - i) = \mu(\{j - i\}) \end{aligned}$$

### Definition 15.2 (Branching Processes)

Let  $\xi_i^n, i, n \geq 1$ , be i.i.d. nonnegative integer-valued random variables. Define a sequence  $Z_n, n \geq 0$  by  $Z_0 = 1$  and

$$Z_{n+1} = \begin{cases} \xi_1^{n+1} + \dots + \xi_{Z_n}^{n+1} & Z_n > 0 \\ 0 & Z_n = 0 \end{cases} \quad (15.3)$$

$Z_n$  is called a Branching process. ♣



**Note** The idea behind the definitions is that  $Z_n$  is the number of individuals in the  $n$ -th generation, and each member of the  $n$ -th generation gives birth independently to an identically distributed number of children.

**Example 15.2 Branching Processes** Show branching process is a Markov chain with transition probability,

$$p(i, j) = P\left(\sum_{k=1}^i \xi_k = j\right)$$

**Proof** Since  $\xi_k^n$  are independent with identical distribution,

$$\begin{aligned} &P(Z_{n+1} = j \mid Z_n = i, Z_{n-1} = i_{n-1}, \dots, Z_0 = i_0) \\ &= P\left(\sum_{k=1}^{Z_n} \xi_k^{n+1} = j \mid Z_n = i\right) = P\left(\sum_{k=1}^i \xi_k = j\right) \end{aligned}$$

Suppose  $(S, \mathcal{S})$  be a measurable space, which will be the state space for our Markov chain.

#### Definition 15.3 (Transition Probability)

A function  $p : S \times S \rightarrow \mathbf{R}$  is said to be a transition probability, if

1. For each  $x \in S$ ,  $A \rightarrow p(x, A)$  is a probability measure on  $(S, \mathcal{S})$
2. For each  $A \in \mathcal{S}$ ,  $x \rightarrow p(x, A)$  is a measurable function



#### Definition 15.4 (Markov Chain)

A sequence  $\{X_n\}$  of real-valued random variables with transition probability  $p$  is said to be a Markov chain with respect to  $\mathcal{F}_n$ , if

$$P(X_{n+1} \in B \mid \mathcal{F}_n) = p(X_n, B) \quad (15.4)$$



**Remark** Given a transition probability  $p$  and an initial distribution  $\mu$  on  $(S, \mathcal{S})$ , the consistent set of finite dimensional distributions is

$$P(X_j \in B_j, 0 \leq j \leq n) = \int_{B_0} \mu(dx_0) \int_{B_1} p(x_0, dx_1) \cdots \int_{B_n} p(x_{n-1}, dx_n) F \quad (15.5)$$

## 15.2 Markov Properties

#### Definition 15.5 (Shift Operator)



#### Theorem 15.1 (Markov Property)



#### Corollary 15.1 (Chapman-Kolmogorov Equation)



#### Theorem 15.2 (Strong Markov Property)



## 15.3 Recurrence and Transience

Let  $T_y^0 = 0$ , and for  $k \geq 1$ , and

$$T_y^k = \inf \{n > T_y^{k-1} : X_n = y\} \quad (15.6)$$

then  $T_y^k$  is the time of the  $k$ -th return to  $y$ , where  $T_y^1 > 0$ , so any visit at time 0 does not count.

Let

$$\rho_{xy} = P_x(T_y < \infty) \quad (15.7)$$

and we have

$$P_x(T_y^k < \infty) = \rho_{xy} \rho_{yy}^{k-1} \quad (15.8)$$

**Proof**

Let

$$N(y) = \sum_{n=1}^{\infty} 1_{(X_n=y)} \quad (15.9)$$

be the number of visits to  $y$  at positive times.

#### Definition 15.6 (Recurrent)

A state  $y$  is said to be recurrent if  $\rho_{yy} = 1$ .



**Property** The recurrent state  $y$  has the following properties

1.  $y$  is recurrent if and only if

$$E_y N(y) = \infty.$$

2. If  $x$  is recurrent and  $\rho_{xy} > 0$ , then  $y$  is recurrent and  $\rho_{yx} = 1$ .

#### Definition 15.7

A state  $y$  is said to be transient if  $\rho_{yy} < 1$ .



**Property** The transient state  $y$  has the following properties

1. If  $y$  is transient, then

$$E_x N(y) < \infty, \quad \forall x.$$

**Proof**

$$\begin{aligned} E_x N(y) &= \sum_{k=1}^{\infty} P_x(N(y) \geq k) = \sum_{k=1}^{\infty} P_x(T_y^k < \infty) \\ &= \sum_{k=1}^{\infty} \rho_{xy} \rho_{yy}^{k-1} = \frac{\rho_{xy}}{1 - \rho_{yy}} < \infty \end{aligned}$$

#### Definition 15.8 (Closed State Set)

A set  $C$  of states is said to be closed, if

$$x \in C, \rho_{xy} > 0 \Rightarrow y \in C. \quad (15.10)$$



#### Definition 15.9 (Irreducible State Set)

A set  $D$  of states is said to be irreducible, if

$$x, y \in D \Rightarrow \rho_{xy} > 0. \quad (15.11)$$



#### Theorem 15.3

Let  $C$  be a finite closed set, then

1.  $C$  contains a recurrent state.
2. If  $C$  is irreducible, then all states in  $C$  are recurrent.



#### Theorem 15.4

Suppose  $C_x = \{y : \rho_{xy} > 0\}$ , then  $C_x$  is an irreducible closed set.



**Proof** If  $y, z \in C_x$ , then  $\rho_{yz} \geq \rho_{yx}\rho_{xz} > 0$ . If  $\rho_{yw} > 0$ , then  $\rho_{xw} \geq \rho_{xy}\rho_{yw} > 0$ , so  $w \in C_x$ .

**Example 15.3 A Seven-state Chain** Consider the transition probability,

	1	2	3	4	5	6	7
1	.3	0	0	0	.7	0	0
2	.1	.2	.3	.4	0	0	0
3	0	0	.5	.5	0	0	0
4	0	0	0	.5	0	.5	0
5	.6	0	0	0	.4	0	0
6	0	0	0	.1	0	.1	.8
7	0	0	0	1	0	0	0

try to identify the states that are recurrent and those that are transient.

**Proof**  $\{2, 3\}$  are transition states, and  $\{1, 4, 5, 6, 7\}$  are recurrent states.

**Remark** Suppose  $S$  is finite, for  $x \in S$ ,

1.  $x$  is transient, if

$$\exists y, \rho_{xy} > 0, \text{ s.t. } \rho_{yx} = 0$$

2.  $x$  is recurrent, if

$$\forall y, \rho_{xy} > 0, \text{ s.t. } \rho_{yx} > 0$$

## 15.4 Stationary Measures

## 15.5 Asymptotic Behavior

## 15.6 Ergodic Theorems

### Definition 15.10 (Stationary Sequence)



### Theorem 15.5 (Ergodic Theorem)



### Example 15.4

# Chapter 16 Brownian Motion

## Definition 16.1 (Brownian Motion (1))

A real-valued stochastic process  $B(t), t \geq 0$  is said to be Brownian motion, if

1. for any  $0 = t_0 \leq t_1 \leq \dots \leq t_n$  the increments

$$B(t_1) - B(t_0), \dots, B(t_n) - B(t_{n-1})$$

are independent

2. for any  $s, t \geq 0$  and Borel sets  $A \in \mathbb{R}$ ,

$$P(B(s+t) - B(s) \in A) = \int_A (2\pi t)^{-1/2} \exp(-x^2/2t) dx \quad (16.1)$$

3. the sample paths  $t \rightarrow B(t)$  are a.s. continuous



**Property** For a one-dimensional Brownian motion, if  $B(0) = 0$ , then we have the following properties

1.  $EB_t = 0, \text{Var}(B_t) = t, \quad t \geq 0.$
2.  $\text{Cov}(B_s, B_t) = s, \text{Corr}(B_s, B_t) = \sqrt{\frac{s}{t}}, \quad \forall 0 \leq s \leq t.$

**Proof**

1. Since  $B_t = B_t - B_0 \sim N(0, t)$ , then we have

$$EB_t = 0, \text{Var}(B_t) = t$$

2. Suppose  $0 \leq s \leq t$ ,

$$\text{Cov}(B_s, B_t) = E[(B_s - EB_s)(B_t - EB_t)] = EB_s B_t$$

Let  $B_t = (B_t - B_s) + B_s$ , we have

$$\begin{aligned} EB_s B_t &= E[B_s \cdot ((B_t - B_s) + B_s)] \\ &= E[B_s \cdot (B_t - B_s)] + EB_s^2 \end{aligned}$$

Since  $B_s = B_s - B_0$  and  $B_t - B_s$  are independent,

$$E[B_s \cdot (B_t - B_s)] = EB_s \cdot E[B_t - B_s] = 0$$

Thus

$$\text{Cov}(B_s, B_t) = EB_s^2 = s$$

And

$$\text{Corr}(B_s, B_t) = \frac{\text{Cov}(B_s, B_t)}{\sigma_{B_s} \sigma_{B_t}} = \frac{s}{\sqrt{st}} = \sqrt{\frac{s}{t}}$$

A second equivalent definition of Brownian motion are as followed,

## Definition 16.2 (Brownian Motion (2))

A real-valued stochastic process  $B(t), t \geq 0$ , **starting from 0**, is said to be Brownian motion, if

1.  $B(t)$  is a Gaussian process<sup>a</sup>
2.  $\forall s, t \geq 0, EB_s = 0$  and  $EB_s B_t = s \wedge t$
3. the sample paths  $t \rightarrow B(t)$  are a.s. continuous

<sup>a</sup>Gaussian process, i.e., all its finite dimensional distributions are multivariate normal.



## 16.1 Markov Properties

## 16.2 Martingales

**Example 16.1 Quadratic Martingale** Suppose  $B_t$  is a Brownian motion, then

$$B_t^2 - t$$

is a martingale.

**Proof** Let  $B_t^2 = (B_s + B_t - B_s)^2$ , we have

$$\begin{aligned} E_x(B_t^2 | \mathcal{F}_s) &= E_x(B_s^2 + 2B_s(B_t - B_s) + (B_t - B_s)^2 | \mathcal{F}_s) \\ &= B_s^2 + 2B_s E_x(B_t - B_s | \mathcal{F}_s) + E_x((B_t - B_s)^2 | \mathcal{F}_s) \\ &= B_s^2 + 0 + (t - s) \end{aligned}$$

since  $B_t - B_s$  is independent of  $\mathcal{F}_s$  and has mean 0 and variance  $t - s$ .

**Example 16.2 Exponential Martingale** Suppose  $B_t$  is a Brownian motion, then

$$\exp(\theta B_t - (\theta^2 t/2))$$

is a martingale.

**Proof** Let  $B_t = B_t - B_s + B_s$ , then

$$\begin{aligned} E_x(\exp(\theta B_t) | \mathcal{F}_s) &= \exp(\theta B_s) E(\exp(\theta(B_t - B_s)) | \mathcal{F}_s) \\ &= \exp(\theta B_s) \exp(\theta^2(t - s)/2) \end{aligned}$$

since  $B_t - B_s$  is independent of  $\mathcal{F}_s$  and has mean 0 and variance  $t - s$ . Thus

$$\begin{aligned} E_x(\exp(\theta B_t - (\theta^2 t/2)) | \mathcal{F}_s) &= E_x(\exp(\theta B_t) | \mathcal{F}_s) \cdot \exp(-(\theta^2 t/2)) \\ &= \exp(\theta B_s - (\theta^2 s/2)) \end{aligned}$$

### Theorem 16.1 (Lévy's Martingale Characterization)

Let  $B(t), t \geq 0$ , be a real-valued stochastic process and let  $\mathcal{F}_t = \sigma(B_s, s \leq t)$  be the filtration generated by it. Then  $B(t)$  is a Brownian motion if and only if

1.  $B(0) = 0$  a.s.
2. the sample paths  $t \rightarrow B(t)$  are continuous a.s.
3.  $B(t)$  is a martingale with respect to  $\mathcal{F}_t$
4.  $|B(t)|^2 - t$  is a martingale with respect to  $\mathcal{F}_t$



## 16.3 Sample Paths

Let  $0 = t_0^n < t_1^n < \dots < t_n^n = T$ , where  $t_i^n = \frac{iT}{n}$  be a partition of the interval  $[0, T]$  into  $n$  equal parts, and

$$\Delta_i^n B = B(t_{i+1}^n) - B(t_i^n) \quad (16.2)$$

be the corresponding increments of the Brownian motion  $B(t)$ .

### Theorem 16.2

$$\lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (\Delta_i^n B)^2 = T \quad \text{in } L^2 \quad (16.3)$$



**Proof** Since the increments  $\Delta_i^n B$  are independent and

$$E(\Delta_i^n B) = 0, \quad E((\Delta_i^n B)^2) = \frac{T}{n}, \quad E((\Delta_i^n B)^4) = \frac{3T^2}{n^2}$$

it follows that

$$\begin{aligned} E \left( \left[ \sum_{i=0}^{n-1} (\Delta_i^n B)^2 - T \right]^2 \right) &= E \left( \left[ \sum_{i=0}^{n-1} \left( (\Delta_i^n B)^2 - \frac{T}{n} \right) \right]^2 \right) \\ &= \sum_{i=0}^{n-1} E \left[ \left( (\Delta_i^n B)^2 - \frac{T}{n} \right)^2 \right] \\ &= \sum_{i=0}^{n-1} \left[ E((\Delta_i^n B)^4) - \frac{2T}{n} E((\Delta_i^n B)^2) + \frac{T^2}{n^2} \right] \\ &= \sum_{i=0}^{n-1} \left[ \frac{3T^2}{n^2} - \frac{2T^2}{n^2} + \frac{T^2}{n^2} \right] \\ &= \frac{2T^2}{n} \rightarrow 0, \quad n \rightarrow \infty \end{aligned}$$

### Definition 16.3 (Variation)

The variation of a function  $f : [0, T] \rightarrow \mathbb{R}$  is defined to be

$$\limsup_{\Delta t \rightarrow 0} \sum_{i=0}^{n-1} |f(t_{i+1}) - f(t_i)| \quad (16.4)$$

where  $t = (t_0, t_1, \dots, t_n)$  is a partition of  $[0, T]$ , i.e.  $0 = t_0 < t_1 < \dots < t_n = T$ , and where

$$\Delta t = \max_{i=0, \dots, n-1} |t_{i+1} - t_i| \quad (16.5)$$



### Theorem 16.3

The variation of the paths of  $B(t)$  is infinite a.s..





**Proof** Consider the sequence of partitions  $t^n = (t_0^n, t_1^n, \dots, t_n^n)$  of  $[0, T]$  into  $n$  equal parts. Then

$$\sum_{i=0}^{n-1} |\Delta_i^n B|^2 \leq \left( \max_{i=0, \dots, n-1} |\Delta_i^n B| \right) \sum_{i=0}^{n-1} |\Delta_i^n B|$$

Since the paths of  $B(t)$  are a.s. continuous on  $[0, T]$ ,

$$\lim_{n \rightarrow \infty} \left( \max_{i=0, \dots, n-1} |\Delta_i^n B| \right) = 0 \quad \text{a.s.}$$

By Theorem 16.2, we have

$$\lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (\Delta_i^n B)^2 = T \quad \text{in } L^2$$

Since every sequence of random variables convergent in  $L^2$  has a subsequence convergent a.s. There is a subsequence  $t^{n_k} = (t_0^{n_k}, t_1^{n_k}, \dots, t_{n_k}^{n_k})$  of partitions such that

$$\lim_{k \rightarrow \infty} \sum_{i=0}^{n_k-1} |\Delta_i^{n_k} B|^2 = T \quad \text{a.s.}$$

Since

$$\sum_{i=0}^{n_k-1} |\Delta_i^{n_k} B| \geq \frac{\sum_{i=0}^{n_k-1} |\Delta_i^{n_k} B|^2}{\max_{i=0, \dots, n_k-1} |\Delta_i^{n_k} B|}$$

hence,

$$\lim_{k \rightarrow \infty} \sum_{i=0}^{n_k-1} |\Delta_i^{n_k} B| = \infty \quad \text{a.s.}$$

while

$$\lim_{k \rightarrow \infty} \Delta t^{n_k} = \lim_{k \rightarrow \infty} \frac{T}{n_k} = 0$$

## 16.4 Itô Stochastic Calculus

### Definition 16.4 (Random Step Process)



### Definition 16.5 (Itô Stochastic Integral)

For any  $T > 0$  we shall denote by  $M_T^2$  the space of all stochastic processes  $f(t), t \geq 0$  such that

$$1_{[0, T)} f \in M^2$$

The Itô stochastic integral (from 0 to  $T$ ) of  $f \in M_T^2$  is defined by

$$I_T(f) = I(1_{[0, T)} f) \quad (16.6)$$

which can be denoted by

$$\int_0^T f(t) dB(t) \quad (16.7)$$



**Property** The Itô Stochastic Integral has the following properties:

1. *Linearity:* For  $\forall f, g \in M_t^2, \forall \alpha, \beta \in \mathbb{R}$ ,

$$\int_0^t (\alpha f(r) + \beta g(r)) dB(r) = \alpha \int_0^t f(r) dB(r) + \beta \int_0^t g(r) dB(r) \quad (16.8)$$

2. *Isometry:* For  $\forall f \in M_t^2$ ,

$$E \left( \left| \int_0^t f(r) dB(r) \right|^2 \right) = E \left( \int_0^t |f(r)|^2 dr \right) \quad (16.9)$$

3. *Martingale Property:* For  $\forall f \in M_t^2$  and  $\forall 0 \leq s < t$ ,

$$E \left( \int_0^t f(r) dB(r) \mid \mathcal{F}_s \right) = \int_0^s f(r) dB(r) \quad (16.10)$$

### Proof

#### Definition 16.6 (Itô Process)

A stochastic process  $\xi(t), t \geq 0$  is said to be an Itô process if it has a.s. continuous paths and can be represented as

$$\xi(T) = \xi(0) + \int_0^T a(t) dt + \int_0^T b(t) dB(t) \quad \text{a.s.} \quad (16.11)$$

where  $b(t)$  is a process belonging to  $M_T^2$  for all  $T > 0$  and  $a(t)$  is a process adapted to the filtration  $\mathcal{F}_t$  such that

$$\int_0^T |a(t)| dt < \infty \quad \text{a.s.} \quad (16.12)$$

for all  $T \geq 0$ . The Itô process is denoted by

$$d\xi(t) = a(t) dt + b(t) dB(t) \quad (16.13) \quad \clubsuit$$

**Remark** The class of all adapted processes  $a(t)$  satisfying 16.12 for some  $T > 0$  will be denoted by  $\mathcal{L}_T^1$ .

#### Theorem 16.4 (Itô Formula)

Suppose that  $F(t, x)$  is a real-valued function with continuous partial derivatives  $F_t'(t, x)$ ,  $F_x'(t, x)$  and  $F_{xx}''(t, x)$  for all  $t \geq 0$  and  $x \in \mathbb{R}$ .

1. If  $\xi(t)$  be an Itô process

$$\xi(t) = \xi(0) + \int_0^t a(s) ds + \int_0^t b(s) dB(s)$$

and the process  $b(t)F_x'(t, \xi(t))$  belongs to  $M_T^2$  for all  $T \geq 0$ . Then  $F(t, \xi(t))$  is an Itô process such that

$$\begin{aligned} dF(t, \xi(t)) = & \left( F_t'(t, \xi(t)) + F_x'(t, \xi(t))a(t) + \frac{1}{2}F_{xx}''(t, \xi(t))b(t)^2 \right) dt \\ & + F_x'(t, \xi(t))b(t) dB(t) \end{aligned} \quad (16.14)$$

2. If  $\xi(t)$  be an Brownian Motion, such that  $\xi(t) = B(t)$ , and the process  $F_x'(t, B(t))$  belongs to  $M_T^2$  for all  $T \geq 0$ . Then  $F(t, B(t))$  is an Itô process such that

$$dF(t, B(t)) = \left( F_t'(t, B(t)) + \frac{1}{2}F_{xx}''(t, B(t)) \right) dt + F_x'(t, B(t)) dB(t) \quad (16.15) \quad \heartsuit$$

**Example 16.3 Exponential Martingale** Show that the exponential martingale

$$X(t) = e^{B(t)} e^{-\frac{t}{2}}$$

is an Itô process, and satisfies the equation

$$dX(t) = X(t) dB(t)$$

**Proof** Let  $F(t, x) = e^x e^{-\frac{t}{2}}$ , then we have

$$F'_t(t, x) = -\frac{1}{2}F(t, x), \quad F'_x(t, x) = F(t, x), \quad F''_{xx}(t, x) = F(t, x)$$

thus, by Itô Formula, we have

$$\begin{aligned} dX(t) &= dF(t, B(t)) = \left( F'_t(t, B(t)) + \frac{1}{2}F''_{xx}(t, B(t)) \right) dt + F'_x(t, B(t)) dB(t) \\ &= \left( -\frac{1}{2}F(t, B(t)) + \frac{1}{2}F(t, B(t)) \right) dt + F(t, B(t)) dB(t) \\ &= X(t) dB(t) \end{aligned}$$

**Example 16.4**

**Example 16.5**

# **Chapter 17 Exercises for Probability Theory and Examples**

## **17.1 Martingales**

## **17.2 Markov Chains**

## **17.3 Ergodic Theorems**

## **17.4 Brownian Motion**

## **17.5 Applications to Random Walk**

## **17.6 Multidimensional Brownian Motion**

## **Part VII**

# **Statistics Inference**

# Chapter 18 Introduction

## 18.1 Populations and Samples

## 18.2 Statistics

### 18.2.1 Sufficient Statistics

#### Definition 18.1 (Sufficient Statistics)

A statistic  $T$  is said to be sufficient for  $X$ , or for the family  $\mathcal{P} = \{P_\theta, \theta \in \Omega\}$  of possible distributions of  $X$ , or for  $\theta$ , if the conditional distribution of  $X$  given  $T = t$  is independent of  $\theta$  for all  $t$ .



#### Theorem 18.1 (Fisher–Neyman Factorization Theorem)

If the probability density function is  $p_\theta(x)$ , then  $T$  is sufficient for  $\theta$  if and only if nonnegative functions  $g$  and  $h$  can be found such that

$$p_\theta(x) = h(x)g_\theta[T(x)].$$



**Proof**

### 18.2.2 Complete Statistics

#### Definition 18.2 (Complete Statistics)

A statistic  $T$  is said to be complete, if  $Eg(T) = 0$  for all  $\theta$  and some function  $g$  implies that  $P(g(T) = 0 \mid \theta) = 1$  for all  $\theta$ .



## 18.3 Estimators

#### Definition 18.3 (Estimator)

An estimator is a real-valued function defined over the sample space, that is

$$\delta : \mathbf{X} \rightarrow \mathbb{R}. \quad (18.1)$$

It is used to estimate an estimand,  $\theta$ , a real-valued function of the parameter.



## Unbiasedness

### Definition 18.4 (Unbiasedness)

An estimator  $\hat{\theta}$  of  $\theta$  is unbiased if

$$E\hat{\theta} = \theta, \quad \forall \theta \in \Theta. \quad (18.2) \quad \clubsuit$$



### Note

- Unbiased estimators of  $\theta$  may not exist.
- 

### Example 18.1 Nonexistence of Unbiased Estimator

## Consistency

### Definition 18.5 (Consistency)

An estimator  $\hat{\theta}_n$  of  $\theta$  is consistent if

$$\lim_{n \rightarrow \infty} P\left(\left|\hat{\theta}_n - \theta\right| > \varepsilon\right) = 0, \quad \forall \varepsilon > 0, \quad (18.3)$$

that is,

$$\hat{\theta}_n \xrightarrow{p} \theta. \quad (18.4) \quad \clubsuit$$

### Example 18.2 Consistency of Sample Moments



### Note

1. Unbiased But Consistent
2. Biased But Not Consistent

## Asymptotic Normality

### Definition 18.6 (Asymptotic Normality)

An estimator  $\hat{\theta}_n$  of  $\theta$  is asymptotic normality if

$$\sqrt{n}(\hat{\theta} - \theta) \xrightarrow{d} N(0, \sigma_\theta^2). \quad (18.5) \quad \clubsuit$$

## Efficiency

### Definition 18.7 (Efficiency)



## Robustness

### Definition 18.8 (Robustness)





# Chapter 19 Maximum Likelihood Estimator

Suppose that  $\mathbf{X}_n = (X_1, \dots, X_n)$ , where the  $X_i$  are i.i.d. with common density  $p(x; \theta_0) \in \mathcal{P} = \{p(x; \theta) : \theta \in \Theta\}$ .

We assume that

$\theta_0$  is identified in the sense that if  $\theta \neq \theta_0$  and  $\theta \in \Theta$ , then  $p(x; \theta) \neq p(x; \theta_0)$  with respect to the dominating measure  $\mu$ .

For fixed  $\theta \in \Theta$ , the joint density of  $\mathbf{X}_n$  is equal to the product of the individual densities, i.e.,

$$p(\mathbf{X}_n; \theta) = \prod_{i=1}^n p(x_i; \theta). \quad (19.1)$$

The maximum likelihood estimate for observed  $\mathbf{X}_n$  is the value  $\theta \in \Theta$  which maximizes  $L(\theta; \mathbf{X}_n) := p(\mathbf{X}_n; \theta)$ , i.e.,

$$\hat{\theta}(\mathbf{X}_n) = \max_{\theta \in \Theta} L(\theta; \mathbf{X}_n). \quad (19.2)$$

Equivalently, the MLE can be taken to be the maximum of the standardized log-likelihood,

$$\frac{l(\theta; \mathbf{X}_n)}{n} = \frac{\log L(\theta; \mathbf{X}_n)}{n} = \frac{1}{n} \sum_{i=1}^n \log p(X_i; \theta) = \frac{1}{n} \sum_{i=1}^n l(\theta; X_i). \quad (19.3)$$

Define

$$\begin{aligned} Q(\theta; \mathbf{X}_n) &:= \frac{1}{n} \sum_{i=1}^n l(\theta; X_i), \\ \hat{\theta}(\mathbf{X}_n) &:= \max_{\theta \in \Theta} Q(\theta; \mathbf{X}_n). \end{aligned} \quad (19.4)$$

## 19.1 Consistency of MLE

By the Weak Law of Large Numbers (Theorem 10.5), we can get,

$$\frac{1}{n} \sum_{i=1}^n l(\theta; X_i) \xrightarrow{p} E[l(\theta; X)]. \quad (19.5)$$

Suppose  $Q_0(\theta) = E[l(\theta; X)]$ , then we will show that  $Q_0(\theta)$  is maximized at  $\theta_0$  (i.e., the truth).

### Lemma 19.1

If  $\theta_0$  is identified and  $E_{\theta_0} [|\log p(X; \theta)|] < \infty, \forall \theta \in \Theta$ , then  $Q_0(\theta)$  is uniquely maximized at  $\theta = \theta_0$ .



**Proof**

**Theorem 19.1 (Consistency of MLE)**

Suppose that  $Q(\theta; \mathbf{X}_n)$  is continuous in  $\theta$  and there exists a function  $Q_0(\theta)$  such that

1.  $Q_0(\theta)$  is uniquely maximized at  $\theta_0$ .
2.  $\Theta$  is compact.
3.  $Q_0(\theta)$  is continuous in  $\theta$ .
4.  $Q(\theta; \mathbf{X}_n)$  converges uniformly in probability to  $Q_0(\theta)$ .

then

$$\hat{\theta}(\mathbf{X}_n) \xrightarrow{p} \theta_0. \quad (19.6) \quad \heartsuit$$

**Proof**  $\forall \varepsilon > 0$ , let

$$\Theta(\varepsilon) = \{\theta : \|\theta - \theta_0\| < \varepsilon\}.$$

Since  $\Theta(\varepsilon)$  is an open set, then  $\Theta \cap \Theta(\varepsilon)^C$  is a compact set (Assumption 2).

Since  $Q_0(\theta)$  is a continuous function (Assumption 3), then

$$\theta^* := \sup_{\theta \in \Theta \cap \Theta(\varepsilon)^C} \{Q_0(\theta)\}$$

is achieved for a  $\theta$  in the compact set.

Since  $\theta_0$  is the unique maximized, let

$$Q_0(\theta_0) - Q_0(\theta^*) = \delta > 0.$$

1. For  $\theta \in \Theta \cap \Theta(\varepsilon)^C$ . Let  $A_n = \{\sup_{\theta \in \Theta \cap \Theta(\varepsilon)^C} |Q(\theta; \mathbf{X}_n) - Q_0(\theta)| < \frac{\delta}{2}\}$ , then

$$\begin{aligned} A_n &\Rightarrow Q(\theta; \mathbf{X}_n) < Q_0(\theta) + \frac{\delta}{2} \\ &\leq Q_0(\theta^*) + \frac{\delta}{2} \\ &= Q_0(\theta_0) - \frac{\delta}{2} \end{aligned}$$

2. For  $\theta \in \Theta(\varepsilon)$ . Let  $B_n = \{\sup_{\theta \in \Theta(\varepsilon)} |Q(\theta; \mathbf{X}_n) - Q_0(\theta)| < \frac{\delta}{2}\}$ , then

$$B_n \Rightarrow Q(\theta; \mathbf{X}_n) > Q_0(\theta) - \frac{\delta}{2}, \forall \theta \in \Theta(\varepsilon)$$

By Assumption 1,

$$Q(\theta_0; \mathbf{X}_n) > Q_0(\theta_0) - \frac{\delta}{2}$$

If both  $A_n$  and  $B_n$  hold, then

$$\hat{\theta} \in \Theta(\varepsilon).$$

By Assumption 4, we can concluded that  $P(A_n \cap B_n) \rightarrow 1$ , so

$$P(\hat{\theta} \in \Theta(\varepsilon)) \rightarrow 1,$$

which means,

$$\hat{\theta}(\mathbf{X}_n) \xrightarrow{p} \theta_0.$$

## **19.2 Asymptotic Normality of MLE**


## **19.3 Efficiency of MLE**


## Chapter 20 Minimum-Variance Unbiased Estimator

### Definition 20.1 (UMVU Estimators)

An unbiased estimator  $\delta(\mathbf{X})$  of  $g(\theta)$  is the uniform minimum variance unbiased (UMVU) estimator of  $g(\theta)$  if

$$\text{Var}_\theta \delta(\mathbf{X}) \leq \text{Var}_\theta \delta'(\mathbf{X}), \quad \forall \theta \in \Theta, \quad (20.1)$$

where  $\delta'(\mathbf{X})$  is any other unbiased estimator of  $g(\theta)$ . 

 **Note** If there exists an unbiased estimator of  $g$ , the estimand  $g$  will be called  $U$ -estimable.

1. If  $T(\mathbf{X})$  is a complete sufficient statistic, estimator  $\delta(\mathbf{X})$  that only depends on  $T(\mathbf{X})$ , then for any  $U$ -estimable function  $g(\theta)$  with

$$E_\theta \delta(T(\mathbf{X})) = g(\theta), \quad \forall \theta \in \Theta, \quad (20.2)$$

hence,  $\delta(T(\mathbf{X}))$  is the unique UMVU estimator of  $g(\theta)$ .

2. If  $T(\mathbf{X})$  is a complete sufficient statistic and  $\delta(\mathbf{X})$  is any unbiased estimator of  $g(\theta)$ , then the UMVU estimator of  $g(\theta)$  can be obtained by

$$E[\delta(\mathbf{X}) | T(\mathbf{X})]. \quad (20.3)$$

**Example 20.1 Estimating Polynomials of a Normal Variance** Let  $X_1, \dots, X_n$  be distributed with joint density

$$\frac{1}{(\sqrt{2\pi}\sigma)^n} \exp \left[ -\frac{1}{2\sigma^2} \sum (x_i - \xi)^2 \right]. \quad (20.4)$$

Discussing the UMVU estimators of  $\xi^r$ ,  $\sigma^r$ ,  $\xi/\sigma$ .

**Solution**

1.  $\sigma$  is known:

Since  $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$  is the complete sufficient statistic of  $X_i$ , and

$$E(\bar{X}) = \xi,$$

then the UMVU estimator of  $\xi$  is  $\bar{X}$ .

Therefore, the UMVU estimator of  $\xi^r$  is  $\bar{X}^r$  and the UMVU estimator of  $\xi/\sigma$  is  $\bar{X}/\sigma$ .

2.  $\xi$  is known:

Since  $s^r = \sum (x_i - \xi)^r$  is the complete sufficient statistic of  $X_i$ .

Assume

$$E \left[ \frac{s^r}{\sigma^r} \right] = \frac{1}{K_{n,r}},$$

where  $K_{n,r}$  is a constant depends on  $n, r$ .

Since  $s^2/\sigma^2 \sim \text{Ga}(n/2, 1/2) = \chi^2(n)$ , then

$$E \left[ \frac{s^r}{\sigma^r} \right] = E \left[ \left( \frac{s^2}{\sigma^2} \right)^{\frac{r}{2}} \right] = \int_0^\infty x^{\frac{r}{2}} \frac{1}{2^{\frac{n}{2}} \Gamma(\frac{n}{2})} x^{\frac{n}{2}-1} e^{-\frac{x}{2}} dx = \frac{\Gamma(\frac{n+r}{2})}{\Gamma(\frac{n}{2})} \cdot 2^{\frac{r}{2}}.$$

therefore,

$$K_{n,r} = \frac{\Gamma(\frac{n}{2})}{2^{\frac{r}{2}} \cdot \Gamma(\frac{n+r}{2})}.$$

Hence,

$$E[s^r K_{n,r}] = \sigma^r \text{ and } E[\xi s^{-1} K_{n,-1}] = \xi/\sigma,$$

which means the UMVU estimator of  $\sigma^r$  is  $s^r K_{n,r}$  and the UMVU estimator of  $\xi/\sigma$  is  $\xi s^{-1} K_{n,-1}$ .

### 3. Both $\xi$ and $\sigma$ is unknown:

Since  $(\bar{X}, s_x^r)$  are the complete sufficient statistic of  $X_i$ , where  $s_x^2 = \sum (x_i - \bar{X})^2$ .

Since  $s_x^2/\sigma^2 \sim \chi^2(n-1)$ , then

$$E\left[\frac{s_x^r}{\sigma^r}\right] = \frac{1}{K_{n-1,r}}.$$

Hence,

$$E[s_x^r K_{n-1,r}] = \sigma^r,$$

which means the UMVU estimator of  $\sigma^r$  is  $s_x^r K_{n-1,r}$ , and

$$E(\bar{X}^r) = \xi^r,$$

which means the UMVU estimator of  $\xi^r$  is  $\bar{X}^r$ .

Since  $\bar{X}$  and  $s_x^r$  are independent, then

$$E[\bar{X} s_x^{-1} K_{n-1,-1}] = \xi/\sigma$$

which means the UMVU estimator of  $\xi/\sigma$  is  $\bar{X} s_x^{-1} K_{n-1,-1}$ .

**Example 20.2** Let  $X_1, \dots, X_n$  be i.i.d sample from  $U(\theta_1 - \theta_2, \theta_1 + \theta_2)$ , where  $\theta_1 \in \mathbb{R}, \theta_2 \in \mathbb{R}^+$ . Discussing the UMVU estimators of  $\theta_1, \theta_2$ .

**Solution** Let  $X_{(i)}$  be the  $i$ -th order statistic of  $X_i$ , then  $(X_{(1)}, X_{(n)})$  is the complete and sufficient statistic for  $(\theta_1, \theta_2)$ . Thus it suffices to find a function  $(X_{(1)}, X_{(n)})$ , which is unbiased of  $(\theta_1, \theta_2)$ .

Let

$$Y_i = \frac{X_i - (\theta_1 - \theta_2)}{2\theta_2} \sim U(0, 1),$$

and

$$Y_{(i)} = \frac{X_{(i)} - (\theta_1 - \theta_2)}{2\theta_2},$$

be the  $i$ -th order statistic of  $Y_i$ , then we got

$$\begin{aligned} E[X_{(1)}] &= 2\theta_2 E[Y_{(1)}] + (\theta_1 - \theta_2) \\ &= 2\theta_2 \int_0^1 ny(1-y)^{n-1} dy + (\theta_1 - \theta_2) \\ &= \theta_1 - \frac{3n+1}{n+1}\theta_2 \\ E[X_{(n)}] &= 2\theta_2 E[Y_{(n)}] + (\theta_1 - \theta_2) \\ &= 2\theta_2 \int_0^1 ny^n dy + (\theta_1 - \theta_2) \\ &= \theta_1 + \frac{n-1}{n+1}\theta_2 \end{aligned}$$

---

Thus,

$$\begin{aligned}\theta_1 &= E \left[ \frac{n-1}{4n} X_{(1)} + \frac{3n+1}{4n} X_{(n)} \right], \\ \theta_2 &= E \left[ -\frac{n+1}{4n} X_{(1)} + \frac{n+1}{4n} X_{(n)} \right],\end{aligned}$$

which means the UMVU estimator is

$$\hat{\theta}_1 = \frac{n-1}{4n} X_{(1)} + \frac{3n+1}{4n} X_{(n)}, \quad \hat{\theta}_2 = -\frac{n+1}{4n} X_{(1)} + \frac{n+1}{4n} X_{(n)}.$$

# Chapter 21 Bayes Estimator

We shall look for some estimators that make the risk function  $R(\theta, \delta)$  small in some overall sense. There are two way to solve it: minimize the average risk, minimize the maximum risk.

This chapter will discuss the first method, also known as, Bayes Estimator.

## Definition 21.1 (Bayes Estimator)

The Bayes Estimator  $\delta$  with respect to  $\Lambda$  is minimizing the Bayes Risk of  $\delta$

$$r(\Lambda, \delta) = \int R(\theta, \delta) d\Lambda(\theta) \quad (21.1)$$

where  $\Lambda$  is the probability distribution.



In Bayesian arguments, it is important to keep track of which variables are being conditioned on. Hence, the notations are as followed:

- The density of  $X$  will be denoted by  $X \sim f(x | \theta)$ .
- The prior distribution will be denoted by  $\Pi \sim \pi(\theta | \lambda)$  or  $\Lambda \sim \gamma(\lambda)$ , where  $\lambda$  is another parameter (sometimes called a hyperparameter).
- The posterior distribution, which calculate the conditional distributions as that of  $\theta$  given  $x$  and  $\lambda$ , or  $\lambda$  given  $x$ , which is denoted by  $\Pi \sim \pi(\theta | x, \lambda)$  or  $\Lambda \sim \gamma(\lambda | x)$ , that is

$$\pi(\theta | x, \lambda) = \frac{f(x | \theta) \pi(\theta | \lambda)}{m(x | \lambda)}, \quad (21.2)$$

where marginal distributions  $m(x | \lambda) = \int f(x | \theta) \pi(\theta | \lambda) d\theta$ .

## Theorem 21.1

Let  $\Theta$  have distribution  $\Lambda$ , and given  $\Theta = \theta$ , let  $X$  have distribution  $P_\theta$ . Suppose, the following assumptions hold for the problem of estimating  $g(\Theta)$  with non-negative loss function  $L(\theta, d)$ ,

- There exists an estimator  $\delta_0$  with finite risk.
- For almost all  $x$ , there exists a value  $\delta_\Lambda(x)$  minimizing

$$E\{L[\Theta, \delta(x)] | X = x\}. \quad (21.3)$$

Then,  $\delta_\Lambda(x)$  is a Bayes Estimator.



**Note** Improper prior

## Corollary 21.1

Suppose the assumptions of Theorem 21.1 hold.

1. If  $L(\theta, d) = [d - g(\theta)]^2$ , then

$$\delta_\Lambda(x) = E[g(\Theta) | x]. \quad (21.4)$$


2. If  $L(\theta, d) = w(\theta) [d - g(\theta)]^2$ , then

$$\delta_\Lambda(x) = \frac{E[w(\theta) g(\Theta) | x]}{E[w(\theta) | x]}. \quad (21.5)$$

3. If  $L(\theta, d) = |d - g(\theta)|$ , then  $\delta_\Lambda(x)$  is any median of the conditional distribution of  $\Theta$  given  $x$ .


4. If

$$L(\theta, d) = \begin{cases} 0 & \text{when } |d - \theta| \leq c \\ 1 & \text{when } |d - \theta| > c \end{cases},$$

then  $\delta_\Lambda(x)$  is the midpoint of the interval  $I$  of length  $2c$  which maximizes  $P(\Theta \in I | x)$ . 

### Proof

#### Theorem 21.2

Necessary condition for Bayes Estimator 

Methodologies have been developed to deal with the difficulty which sometimes incorporate frequentist measures to assess the choice of  $\Lambda$ .

- Empirical Bayes.
- Hierarchical Bayes.
- Robust Bayes.
- Objective Bayes.

## 21.1 Single-Prior Bayes

The Single-Prior Bayes model in a general form as

$$\begin{aligned} X | \theta &\sim f(x | \theta), \\ \Theta | \gamma &\sim \pi(\theta | \lambda), \end{aligned} \tag{21.6}$$

where we assume that the functional form of the prior and the value of  $\lambda$  is known (we will write it as  $\gamma = \gamma_0$ ).

Given a loss function  $L(\theta, d)$ , we would then determine the estimator that minimizes

$$\int L(\theta, d(x)) \pi(\theta | x) d\theta, \tag{21.7}$$

where  $\pi(\theta | x)$  is posterior distribution given by

$$\pi(\theta | x) = \frac{f(x | \theta) \pi(\theta | \gamma_0)}{\int f(x | \theta) \pi(\theta | \gamma_0) d\theta}.$$

In general, this Bayes estimator under squared error loss is given by

$$E(\Theta | x) = \frac{\int \theta f(x | \theta) \pi(\theta | \gamma_0) d\theta}{\int f(x | \theta) \pi(\theta | \gamma_0) d\theta}. \tag{21.8}$$

**Example 21.1** Consider

$$\begin{aligned} X_i &\stackrel{\text{i.i.d}}{\sim} N(\mu, \Gamma^{-1}), \quad i = 1, 2, \dots, n \\ \mu &\sim N(0, 1), \\ \Gamma &\sim \text{Gamma}(2, 1), \end{aligned}$$

calculate the Single-Prior Bayes estimator under squared error loss.



**Solution**

$$p(\mathbf{X} | \mu, \Gamma) = \Gamma^n (2\pi)^{-\frac{n}{2}} \exp \left[ -2\Gamma^2 \sum_{i=1}^n (x_i - \mu)^2 \right],$$

$$p(\mu) = \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{\mu^2}{2} \right),$$

$$p(\Gamma) = \frac{1}{\Gamma(2)} \Gamma \exp(-\Gamma).$$

Therefore,

$$h(\mathbf{X}, \mu, \Gamma) = C \Gamma^n \exp \left[ -2\Gamma^2 \sum_{i=1}^n (x_i - \mu)^2 \right] \exp \left( -\frac{\mu^2}{2} \right) \Gamma \exp(-\Gamma),$$

where  $C = \frac{(2\pi)^{-\frac{n+1}{2}}}{\Gamma(2)}$ .

For  $\mu$ , we have

$$\pi(\mu | \mathbf{X}, \Gamma) = \frac{h(\mathbf{X}, \mu, \Gamma)}{p(\mu | \mathbf{X})}$$

For exponential families

**Theorem 21.3**

## 21.2 Hierarchical Bayes

In a Hierarchical Bayes model, rather than specifying the prior distribution as a single function, we specify it in a **hierarchy**. Thus, the Hierarchical Bayes model in a general form as

$$\begin{aligned} X | \theta &\sim f(x | \theta), \\ \Theta | \gamma &\sim \pi(\theta | \gamma), \\ \Gamma &\sim \psi(\gamma), \end{aligned} \tag{21.9}$$

where we assume that  $\psi(\cdot)$  is known and not dependent on any other unknown hyperparameters.



**Note** We can continue this hierarchical modeling and add more stages to the model, but this is not often done in practice.

Given a loss function  $L(\theta, d)$ , we would then determine the estimator that minimizes

$$\int L(\theta, d(x)) \pi(\theta | x) d\theta, \tag{21.10}$$

where  $\pi(\theta | x)$  is posterior distribution given by

$$\pi(\theta | x) = \frac{\int f(x | \theta) \pi(\theta | \gamma) \psi(\gamma) d\gamma}{\int \int f(x | \theta) \pi(\theta | \gamma) \psi(\gamma) d\theta d\gamma}.$$



**Note** The posterior distribution can also be written as

$$\pi(\theta | x) = \int \pi(\theta | x, \gamma) \pi(\gamma | x) d\gamma,$$

where  $\pi(\gamma | x)$  is the posterior distribution of  $\Gamma$ , unconditional on  $\theta$ . The equation 21.10 can be

written as

$$\int L(\theta, d(x)) \pi(\theta | x) d\theta = \int \left[ \int L(\theta, d(x)) \pi(\theta | x, \gamma) d\theta \right] \pi(\gamma | x) d\gamma.$$

which shows that *the Hierarchical Bayes estimator can be thought of as a mixture of Single-Prior estimators.*

**Example 21.2 Poisson Hierarchy** Consider

$$\begin{aligned} X_i | \lambda &\stackrel{\text{i.i.d.}}{\sim} \text{Poisson}(\lambda), \quad i = 1, 2, \dots, n \\ \lambda | b &\sim \text{Gamma}(a, b), \quad a \text{ known}, \\ \frac{1}{b} &\sim \text{Gamma}(k, \tau), \end{aligned} \tag{21.11}$$

calculate the Hierarchical Bayes estimator under squared error loss.

**Theorem 21.4**

For the Hierarchical Bayes model (21.9),

$$K[\pi(\lambda | x), \psi(\lambda)] < K[\pi(\theta | x), \pi(\theta)], \tag{21.12}$$

where  $K$  is the Kullback-Leibler information for discrimination between two densities.



**Proof**



**Note**

## 21.3 Empirical Bayes

## 21.4 Bayes Prediction

## **Chapter 22 Hypothesis Testing**

## **Part VIII**

# **Convex Optimization**

# Chapter 23 Convex Sets

## 23.1 Affine and Convex Sets

### 23.1.1 Affine Sets

#### Definition 23.1 (Affine Set)

A nonempty set  $C$  is said to be **affine set**, if

$$\forall x_1, x_2 \in C, \theta \in \mathbf{R}, \theta x_1 + (1 - \theta)x_2 \in C.$$



### 23.1.2 Convex Sets

#### Definition 23.2 (Convex Set)

A nonempty set  $C$  is said to be **convex set**, if

$$\forall x_1, x_2 \in C, \theta \in [0, 1], \theta x_1 + (1 - \theta)x_2 \in C.$$




#### Definition 23.3 (Convex Hull)

The **convex hull** of said to be set  $C$ , denoted by  $\text{conv } C$  is a set of all convex combinations of points in  $C$ ,

$$\text{conv } C = \{\theta_1 x_1 + \dots + \theta_k x_k | x_i \in C; \theta_i \geq 0, i = 1, \dots, k; \theta_1 + \dots + \theta_k = 1\}.$$



 **Note** The convex hull  $\text{conv } C$  is always convex, which is the minimal convex set that contains  $C$ .

### 23.1.3 Cones

#### Definition 23.4 (Cone)

A nonempty set  $C$  is said to be **cone**, if

$$\forall x \in C, \theta \geq 0, \theta x \in C.$$



#### Definition 23.5 (Convex Cone)

A nonempty set  $C$  is said to be **convex cone**, if

$$\forall x_1, x_2 \in C, \theta_1, \theta_2 \geq 0, \theta_1 x_1 + \theta_2 x_2 \in C.$$



## 23.2 Some Important Examples

### Definition 23.6 (Hyperplane)

A hyperplane is defined to be

$$\{x | a^T x = b\},$$

where  $a \in \mathbf{R}^n, a \neq 0, b \in \mathbf{R}$ .



### Definition 23.7 (Halfspace)

A hyperplane is defined to be

$$\{x | a^T x \leq b\},$$

where  $a \in \mathbf{R}^n, a \neq 0, b \in \mathbf{R}$ .



### Definition 23.8 ((Euclidean) Ball)

A (Euclidean) ball in  $\mathbf{R}^n$  with center  $x_c$  and radius  $r$  is defined to be

$$B(x_c, r) = \{x | \|x - x_c\|_2 \leq r\} = \{x_c + ru | \|u\|_2 \leq 1\},$$

where  $r > 0$ .



### Definition 23.9 (Ellipsoid)

A Ellipsoid in  $\mathbf{R}^n$  with center  $x_c$  is defined to be

$$\mathcal{E} = \{x | (x - x_c)^T P^{-1} (x - x_c) \leq 1\} = \{x_c + Au | \|u\|_2 \leq 1\},$$

where  $P \in \mathbf{S}_{++}^n$  (symmetric positive definite).



## 23.3 Generalized Inequalities

### 23.3.1 Definition of Generalized Inequalities

#### Definition 23.10 (Proper Cone)

A cone  $K \subseteq \mathbf{R}^n$  is said to be proper cone, if

- $K$  is convex.
- $K$  is closed.
- $K$  is solid (nonempty interior).
- $K$  is pointed (contains no line).



#### Definition 23.11 (Generalized Inequalities)

The partial ordering on  $\mathbf{R}^n$  defined by proper cone  $K$ , if

$$y - x \in K, \tag{23.1}$$

which can be denoted by


$$x \preceq_K y \text{ or } y \succeq_K x. \quad (23.2)$$

The strict partial ordering on  $\mathbf{R}^n$  defined by proper cone  $K$ , if

$$y - x \in \text{int } K, \quad (23.3)$$

which can be denoted by

$$x \prec_K y \text{ or } y \succ_K x. \quad (23.4) \quad \clubsuit$$

 **Note** When  $K = \mathbf{R}_+$ , the partial ordering  $\preceq_K$  is the usual ordering  $\leq$  on  $\mathbf{R}$ , and the strict partial ordering  $\prec_K$  is the usual strict ordering  $<$  on  $\mathbf{R}$ .

### 23.3.2 Properties of Generalized Inequalities

#### Theorem 23.1 (Properties of Generalized Inequalities)

A generalized inequality  $\preceq_K$  has the following properties:

- Preserved under addition:
- Transitive:
- Preserved under nonnegative scaling:
- Reflexive:
- Antisymmetric:
- Preserved under limits:

A strict generalized inequality  $\prec_K$  has the following properties:



# Chapter 24 Convex Optimization Problems

## 24.1 Generalized Inequality Constraints

### Definition 24.1 (With Generalized Inequality Constraints)

A convex optimization problem with generalized inequality constraints is defined to be

$$\begin{aligned} \min_x \quad & f_0(x) \\ \text{s.t.} \quad & f_i(x) \preceq_{K_i} 0, \quad i = 1, \dots, m \\ & Ax = b \end{aligned} \tag{24.1}$$

where  $f_0 : \mathbf{R}^n \rightarrow \mathbf{R}$ ,  $K_i \in \mathbf{R}^{k_i}$  are proper convexes, and  $f_i : \mathbf{R}^n \rightarrow \mathbf{R}^{k_i}$  are  $K_i$ -convex.



### 24.1.1 Conic Form Problems

### Definition 24.2 (Conic Form Problem)

A conic form problem is defined to be

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Fx + g \preceq_K 0 \\ & Ax = b \end{aligned} \tag{24.2}$$



### 24.1.2 Semidefinite Programming

## 24.2 Vector Optimization



# Chapter 25 Unconstrained Minimization

## 25.1 Definition of Unconstrained Minimization

### Definition 25.1 (Unconstrained Minimization Problem)

The unconstrained minimization problem is defined to be

$$\min_{\mathbf{x}} f(\mathbf{x}) \quad (25.1)$$

where  $f : \mathbf{R}^n \rightarrow \mathbf{R}$  is convex and twice continuously differentiable.



Assume the problem is solvable, i.e., there exists an optimal point  $\mathbf{x}^*$ , such that,

$$f(\mathbf{x}^*) = \inf_{\mathbf{x}} f(\mathbf{x})$$

and denote it by  $p^*$ . Since  $f$  is differentiable and convex, the point  $\mathbf{x}^*$  be the optimal. if and only if

$$\nabla f(\mathbf{x}^*) = 0 \quad (25.2)$$

Solving (25.1) is equal to finding the solution of (25.2), thus (25.1) can be solved by analytic solution of (25.2) in a few cases, but usually can be solved by an iterative algorithm, i.e.,

$$\exists \mathbf{x}^{(0)}, \mathbf{x}^{(1)}, \dots \in \text{dom } f, \quad \text{s.t. } f(\mathbf{x}^{(k)}) \rightarrow p^*, \quad \text{as } k \rightarrow \infty$$

**Example 25.1 Quadratic Minimization** The general convex quadratic minimization problem has the form

$$\min_{\mathbf{x}} \frac{1}{2} \mathbf{x}' \mathbf{P} \mathbf{x} + \mathbf{q}' \mathbf{x} + r \quad (25.3)$$

where  $\mathbf{P} \in \mathbb{S}_+^n$ ,  $\mathbf{q} \in \mathbb{R}^n$ , and  $r \in \mathbb{R}$ .

**Solution** The optimality conditions is

$$\mathbf{P} \mathbf{x}^* + \mathbf{q} = 0$$

which is a set of linear equations.

1. If  $\mathbf{P} \succ 0$ , exists a unique solution  $\mathbf{x}^* = -\mathbf{P}^{-1} \mathbf{q}$ .
2. If  $\mathbf{P}$  is not positive definite, any solution of  $\mathbf{P} \mathbf{x}^* = -\mathbf{q}$  is optimal for (25.3).

Since  $\mathbf{P}$  is not positive definite, i.e.,  $\mathbf{P} \not\succ 0$ ,

$$\exists \mathbf{v}, \quad \text{s.t. } \mathbf{v}' \mathbf{P} \mathbf{v} < 0$$

Let  $\mathbf{x} = t \mathbf{v}$ , we have

$$f(\mathbf{x}) = t^2 (\mathbf{v}' \mathbf{P} \mathbf{v} / 2) + t (\mathbf{q}' \mathbf{v}) + r$$

which converges to  $-\infty$  as  $t \rightarrow \infty$ .

3. If  $\mathbf{P} \mathbf{x}^* = -\mathbf{q}$  does not have a solution, then (25.3) is unbounded.

This means  $\mathbf{q} \notin \mathcal{R}(\mathbf{P})$ . Express  $\mathbf{q}$  as  $\mathbf{q} = \tilde{\mathbf{q}} + \mathbf{v}$ , where  $\tilde{\mathbf{q}}$  is the Euclidean projection of  $\mathbf{q}$  onto  $\mathcal{R}(\mathbf{P})$ , and take  $\mathbf{v} = \mathbf{q} - \tilde{\mathbf{q}}$ . This vector is nonzero and orthogonal to  $\mathcal{R}(\mathbf{P})$ , i.e.,  $\mathbf{v}' \mathbf{P} \mathbf{v} = 0$ .

It follows that for  $\mathbf{x} = t \mathbf{v}$ , we have

$$f(\mathbf{x}) = t \mathbf{q}' \mathbf{v} + r = t (\tilde{\mathbf{q}} + \mathbf{v})' \mathbf{v} + r = t (\mathbf{v}' \mathbf{v}) + r$$

*which is unbounded below.*

**Example 25.2 Least Square Estimation**

**Example 25.3 Unconstrained Geometric Programming**

**Example 25.4 Analytic Center of Linear Inequalities**

## **25.2 General Descent Method**


## **25.3 Gradient Descent Method**

## **25.4 Steepest Descent Method**

## **25.5 Newton's Method**

# Chapter 26 Exercises for Convex Optimization

## 26.1 Convex Sets

 **Exercise 26.1** Solution set of a quadratic inequality Let  $C \subseteq \mathbf{R}^n$  be the solution set of a quadratic inequality,

$$C = \{x \in \mathbf{R}^n | x^T A x + b^T x + c \leq 0\}$$

with  $A \in \mathbf{S}^n$ ,  $b \in \mathbf{R}^n$ , and  $c \in \mathbf{R}$ .

1. Show that  $C$  is convex if  $A \succeq 0$ .

**Solution**

1. We have to show that  $\theta x + (1 - \theta)y \in C$  for all  $\theta \in [0, 1]$  and  $x, y \in C$ .

$$\begin{aligned} & (\theta x + (1 - \theta)y)^T A (\theta x + (1 - \theta)y) + b^T (\theta x + (1 - \theta)y) + c \\ &= \theta^2 x^T A x + \theta(1 - \theta)(y^T A x + x^T A y) + (1 - \theta)^2 y^T A y + \theta b^T x + (1 - \theta)b^T y + c \\ &= \theta^2(x^T A x + b^T x + c) + (1 - \theta)^2(y^T A y + b^T y + c) - \theta^2(b^T x + c) \\ & \quad - (1 - \theta)^2(b^T y + c) + \theta(1 - \theta)(y^T A x + x^T A y) + \theta b^T x + (1 - \theta)b^T y + c \\ &\leq -\theta^2(b^T x + c) - (1 - \theta)^2(b^T y + c) + \theta(1 - \theta)(y^T A x + x^T A y) \\ & \quad + \theta b^T x + (1 - \theta)b^T y + c \\ &= \theta(1 - \theta)[(b^T x + c) + (b^T y + c) + x^T A x + y^T A y] \\ &\leq \theta(1 - \theta)(-x^T A x - y^T A y + x^T A x + y^T A y) \leq 0 \end{aligned}$$

Therefore,  $\theta x + (1 - \theta)y \in C$ , which shows that  $C$  is convex if  $A \succeq 0$ .

## **Part IX**

# **Generalized Linear Model**

# Chapter 27 Generalized Linear Model

## 27.1 Exponential Family

### Definition 27.1 (Exponential Family)

An exponential family of probability distributions as those distributions whose density is defined to be

$$f(y | \theta, \phi) = \exp \left[ \frac{y\theta - b(\theta)}{a(\phi)} + c(y, \phi) \right] \quad (27.1)$$



**Property** The exponential family have the following properties,

$$E(Y) = b'(\theta) \quad \text{Var}(Y) = b''(\theta)a(\phi).$$

**Proof**

**Table 27.1:** Common Distributions of Exponential Family

Distribution	Parameter(s)	$\theta$	$\phi$	$b(\theta)$	$a(\phi)$	$c(y, \phi)$	$E(Y)$	$\text{Var}(Y)$
Normal	$N(\mu, \sigma^2)$	$\mu$	$\sigma^2$	$\frac{\theta^2}{2}$	$\phi$	$-\frac{1}{2} \left[ \frac{y^2}{\phi} + \log(2\pi\phi) \right]$	$\theta$	$\phi$
Bernoulli	$\text{Bern}(p)$	$\log \left( \frac{p}{1-p} \right)$	1	$\log(1 + e^\theta)$	1	0	$\frac{e^\theta}{1+e^\theta}$	$\frac{e^\theta}{(1+e^\theta)^2}$
Poisson	$P(\mu)$	$\log(\mu)$	1	$e^\theta$	1	$-\log(y!)$	$e^\theta$	$e^\theta$

## 27.2 Model Assumption

Suppose the response  $Y$  has a distribution in the exponential family

$$f(y | \theta, \phi) = \exp \left[ \frac{y\theta - b(\theta)}{a(\phi)} + c(y, \phi) \right]$$

with link function  $g$ , such that,

$$E(Y | \mathbf{X}) = \mu = g^{-1}(\eta), \quad \eta = \mathbf{X}'\boldsymbol{\beta} \quad (27.2)$$

where the link function provides the relationship between the linear predictor and the mean of the distribution function. If  $\eta = \theta$ , the link function is called **canonical link function**.



**Note** A generalized linear model (GLM) is a flexible generalization of ordinary linear regression that allows for the response variable to have an error distribution other than the normal distribution.

**Table 27.2:** Commonly Used Link Functions

Distribution	Support of Distribution	Link Function $g(\mu)$	Mean Function $g^{-1}(\eta)$
Normal	real: $(-\infty, +\infty)$	$\mu$	$\eta$
Bernoulli	integer: $\{0, 1\}$	$\log \left( \frac{\mu}{1-\mu} \right)$	$\frac{1}{1+\exp(-\eta)}$
Poisson	integer: $0, 1, 2, \dots$	$\log(\mu)$	$\exp(\eta)$

## 27.3 Model Estimation

### 27.3.1 Maximum Likelihood

Suppose the log-likelihood function be

$$\ell(\boldsymbol{\beta} \mid \mathbf{X}, y) = \log[f(y \mid \theta, \phi)] = \log[f(y \mid g^{-1}(\eta), \phi)] \quad (27.3)$$

where  $g$  is the canonical link function and  $\eta = \mathbf{X}'\boldsymbol{\beta}$ .

Let

$$U(\boldsymbol{\beta}) = \frac{\partial \ell(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}}, \quad A(\boldsymbol{\beta}) = -\frac{\partial^2 \ell(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}' \partial \boldsymbol{\beta}}$$

be the score function and observed information matrix.

If  $\hat{\boldsymbol{\beta}}$  is the maximum likelihood estimate, then

$$U(\hat{\boldsymbol{\beta}}) = \mathbf{0}$$

By mean value theorem,

$$\begin{aligned} U(\hat{\boldsymbol{\beta}}) - U(\boldsymbol{\beta}_0) &= \frac{\partial U(\boldsymbol{\beta}^*)}{\partial \boldsymbol{\beta}} (\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0) \\ \Rightarrow -U(\boldsymbol{\beta}_0) &= -A(\boldsymbol{\beta}^*) (\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0) \end{aligned}$$

where  $\boldsymbol{\beta}^* \in [\boldsymbol{\beta}_0, \hat{\boldsymbol{\beta}}]$ . Thus,

$$\hat{\boldsymbol{\beta}} = \boldsymbol{\beta}_0 + A^{-1}(\boldsymbol{\beta}^*) U(\boldsymbol{\beta}_0)$$

Suppose  $\hat{\boldsymbol{\beta}}_t, \hat{\boldsymbol{\beta}}_{t+1}$  be the maximum likelihood estimate at the  $t$ -th and  $(t+1)$ -th iterations, respectively. Two algorithms can be used to obtain the maximum likelihood estimate  $\hat{\boldsymbol{\beta}}$ .

1. Newton-Raphson Method:

$$\hat{\boldsymbol{\beta}}_{t+1} = \hat{\boldsymbol{\beta}}_t + A^{-1}(\hat{\boldsymbol{\beta}}_t) U(\hat{\boldsymbol{\beta}}_t) \Leftrightarrow A(\hat{\boldsymbol{\beta}}_t) \hat{\boldsymbol{\beta}}_{t+1} = A(\hat{\boldsymbol{\beta}}_t) \hat{\boldsymbol{\beta}}_t + U(\hat{\boldsymbol{\beta}}_t) \quad (27.4)$$

where

$$U(\boldsymbol{\beta}) = \frac{\partial \ell(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} \quad (27.5)$$

is the score function and

$$A(\boldsymbol{\beta}) = -\frac{\partial^2 \ell(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}' \partial \boldsymbol{\beta}} \quad (27.6)$$

is the observed information matrix.

2. Fisher's Scoring Method:

$$\hat{\boldsymbol{\beta}}_{t+1} = \hat{\boldsymbol{\beta}}_t + I^{-1}(\hat{\boldsymbol{\beta}}_t) U(\hat{\boldsymbol{\beta}}_t) \Leftrightarrow I(\hat{\boldsymbol{\beta}}_t) \hat{\boldsymbol{\beta}}_{t+1} = I(\hat{\boldsymbol{\beta}}_t) \hat{\boldsymbol{\beta}}_t + U(\hat{\boldsymbol{\beta}}_t) \quad (27.7)$$

where  $U(\boldsymbol{\beta})$  is the score function and

$$I(\boldsymbol{\beta}) = E[A(\boldsymbol{\beta})] = -E\left[\frac{\partial^2 \ell(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}' \partial \boldsymbol{\beta}}\right] \quad (27.8)$$

is the Fisher information matrix.

### 27.3.2 Bayesian Methods

# Chapter 28 Binary Data

## 28.1 Model Assumption

Suppose

$$Y \sim b(m, \pi), \quad i = 1, 2, \dots, n \quad (28.1)$$

with link function

$$\eta = g(\pi) = \log\left(\frac{\pi}{1 - \pi}\right) = \mathbf{x}'\boldsymbol{\beta} \quad (28.2)$$

**Remark**

## 28.2 Model Estimation

The likelihood function is

$$f(\boldsymbol{\pi} \mid \mathbf{X}, \mathbf{y}) = \prod_{i=1}^n \binom{m_i}{y_i} \pi_i^{y_i} (1 - \pi_i)^{m_i - y_i} \quad (28.3)$$

and the log-likelihood function is

$$\begin{aligned} \ell(\boldsymbol{\beta}) &= \log[f(\boldsymbol{\pi} \mid \mathbf{X}, \mathbf{y})] = \sum_{i=1}^n \ell_i(\boldsymbol{\beta}) \\ &= \sum_{i=1}^n \left\{ \log \left[ \binom{m_i}{y_i} \right] + y_i \log(\pi_i) + (m_i - y_i) \log(1 - \pi_i) \right\} \\ &= \sum_{i=1}^n \left[ y_i \log\left(\frac{\pi_i}{1 - \pi_i}\right) + m_i \log(1 - \pi_i) \right] + \sum_{i=1}^n \log \left[ \binom{m_i}{y_i} \right] \end{aligned} \quad (28.4)$$

where

$$\pi_i = \frac{\exp(\mathbf{x}'_i \boldsymbol{\beta})}{1 + \exp(\mathbf{x}'_i \boldsymbol{\beta})} \quad (28.5)$$

Thus,

$$\begin{aligned} U_r(\boldsymbol{\beta}) &= \sum_{i=1}^n (y_i - m_i \pi_i) x_{ir} \\ I_{sr}(\boldsymbol{\beta}) &= \sum_{i=1}^n m_i \pi_i (1 - \pi_i) x_{is} x_{ir} \end{aligned}$$



# Chapter 29 Polytomous Data

## Definition 29.1 (Polytomous Data)

A response is polytomous, if the response of an individual or item in a study is **restricted to one of a fixed set of possible values**.



**Remark** There are two types of scales, pure scales and compound scales <sup>1</sup>. For pure scales, there are several types:

1. **Nominal Scale:** a scale used for labeling variables into distinct classifications and does not involve a quantitative value or order.
2. **Ordinal Scale:** a variable measurement scale used to simply depict the order of variables and not the difference between each of the variables.
3. **Interval Scale:** a numerical scale where the order of the variables is known as well as the difference between these variables.

## 29.1 Model Assumption

Let the category probabilities given  $\mathbf{x}_i$  be

$$\pi_j(\mathbf{x}_i) = P(Y = y_j | \mathbf{X} = \mathbf{x}_i) \quad (29.1)$$

and the cumulative probabilities given  $\mathbf{x}_i$  be

$$r_j(\mathbf{x}_i) = P\left(Y \leq \sum_{r \leq j} y_r | \mathbf{X} = \mathbf{x}_i\right) \quad (29.2)$$

where  $i = 1, 2, \dots, n$ ,  $j = 1, 2, \dots, k$ .

Here, multinomial distribution is in many ways the most natural distribution to consider in the context of a polytomous response variable. The density function of the multinomial distribution is,

$$P(Y_1 = y_1, \dots, Y_k = y_k) = \begin{cases} \frac{m!}{y_1! \dots y_k!} \pi_1^{y_1} \cdot \dots \cdot \pi_k^{y_k}, & \sum_{i=1}^k y_i = m \\ 0 & \text{otherwise} \end{cases}$$

for non-negative integers  $y_1, \dots, y_k$ .

As for the link function, we have

### Nominal Scale

$$\pi_j(\mathbf{x}_i) = \frac{\exp[\eta_j(\mathbf{x}_i)]}{\sum_{j=1}^k \exp[\eta_j(\mathbf{x}_i)]} \quad (29.3)$$

where  $\eta_j(\mathbf{x}_i) = \eta_j(\mathbf{x}_0) + (\mathbf{x}_i - \mathbf{x}_0)' \boldsymbol{\beta}_j + \alpha_i$ .

### Ordinal Scale

<sup>1</sup>A bivariate responses with one response ordinal and the other continuous is an example of compound scales.

1. Logistic Scale:

$$\log \left[ \frac{r_j(\mathbf{x}_i)}{1 - r_j(\mathbf{x}_i)} \right] = \theta_j - \mathbf{x}_i' \boldsymbol{\beta} \quad (29.4)$$

2. Complementary Log-Log Scale:

$$\log \{ -\log [1 - r_j(\mathbf{x}_i)] \} = \theta_j - \mathbf{x}_i' \boldsymbol{\beta} \quad (29.5)$$

**Interval Scale** Suppose the  $j$ -th category exits a cardinal number or score,  $s_j$ , where the difference between scores is a measure of distance between or separation of categories.

1.

$$\log \left[ \frac{r_j(\mathbf{x}_i)}{1 - r_j(\mathbf{x}_i)} \right] = \varsigma_0 + \varsigma_1 \left( \frac{s_j + s_{j+1}}{2} \right) - \mathbf{x}_i' \boldsymbol{\beta} - \mathbf{x}_i' \boldsymbol{\xi} (c_j - \bar{c}) \quad (29.6)$$

where  $c_j = \frac{s_j + s_{j+1}}{2}$  or  $c_j = \text{logit} \left( \frac{s_j + s_{j+1}}{2} \right)$ .

2.

$$\pi_j(\mathbf{x}_i) = \frac{\exp [\eta_j(\mathbf{x}_i)]}{\sum_{j=1}^k \exp [\eta_j(\mathbf{x}_i)]} \quad (29.7)$$

where  $\eta_j(\mathbf{x}_i) = \eta_j + (\mathbf{x}_i' \boldsymbol{\beta}) s_j + \alpha_i$ .

3.

$$\sum_{j=1}^k \pi_j(\mathbf{x}_i) s_j = \mathbf{x}_i' \boldsymbol{\beta} \quad (29.8)$$

## 29.2 Model Estimation

## Chapter 30 Count Data

### 30.1 Model Assumption

Departures from the idealized Poisson model are to be expected. Therefore, we avoid the assumption of Poisson variation and assume only that

$$\text{Var} (Y) = \sigma^2 E (Y) \quad (30.1)$$

with link function

$$\log (\mu) = \eta = \mathbf{x}'\boldsymbol{\beta} \quad (30.2)$$

where  $\mu = E (Y \mid \mathbf{X})$ .

### 30.2 Model Estimation

For the response in the Poisson distribution, i.e.

$$P(Y = y \mid \mu) = \frac{e^{-\mu} \mu^y}{y!}$$

and the log-likelihood function is

$$\ell (\boldsymbol{\beta}) \propto \sum_{i=1}^n (y_i \log (\mu_i) - \mu_i) \quad (30.3)$$

where  $\mu_i = E (Y \mid \mathbf{X} = \mathbf{x}_i)$ .

# Chapter 31 Survival Data

## 31.1 Survival Data

### Definition 31.1 (Survival Function)

The survival function<sup>a</sup> is defined to be

$$S(t) = P(T > t) = \int_t^{\infty} f(u) \, du = 1 - F(t). \quad (31.1)$$

where  $t$  is some specified time,  $T$  is a random variable denoting the time of death.

<sup>a</sup>The survival function is the probability that the time of death is later than some specified time  $t$ .



### Definition 31.2 (Lifetime Distribution Function)

The lifetime distribution function is defined to be

$$F(t) = P(T \leq t) \quad (31.2)$$

If  $F$  is differentiable then the derivative, which is the density function of the lifetime distribution<sup>a</sup>, is defined to be

$$f(t) = F'(t) = \frac{d}{dt} F(t) \quad (31.3)$$

<sup>a</sup>The function  $f$  is sometimes called the event density; it is the rate of death or failure events per unit time.



### Definition 31.3 (Hazard Function)

The Hazard function<sup>a</sup> is defined to be

$$\lambda(t) = \lim_{\varepsilon \rightarrow 0^+} \left[ \frac{P(t \leq T < t + \varepsilon \mid T \geq t)}{\varepsilon} \right] = \frac{f(t)}{S(t)} \quad (31.4)$$

<sup>a</sup>The Hazard function is the event rate at time  $t$  conditional on survival until time  $t$  or later (that is,  $T \geq t$ ).



**Property** The relationship among  $\lambda(t)$ ,  $f(t)$ ,  $S(t)$ ,

1.

$$\lambda(t) = -\frac{d \log[S(t)]}{dt} \quad (31.5)$$

2.

$$S(t) = \exp \left[ -\int_0^t \lambda(x) \, dx \right] \quad (31.6)$$

3.

$$f(t) = \lambda(t) \exp \left[ -\int_0^t \lambda(x) \, dx \right] \quad (31.7)$$

**Proof**

**Example 31.1 Constant Hazards** Suppose

$$\lambda(t) = \lambda \quad (31.8)$$

then

$$S(t) = \exp \left[ - \int_0^t \lambda(x) dx \right] = \exp \left[ - \int_0^t \lambda dx \right] = \exp(-\lambda t)$$

$$f(t) = \lambda(t) \exp \left[ - \int_0^t \lambda(x) dx \right] = \lambda \exp \left[ - \int_0^t \lambda dx \right] = \lambda \exp(-\lambda t)$$

which is the exponential distribution.

**Example 31.2 Bathtub Hazards**

$$\lambda(t) = \alpha t + \frac{\beta}{1 + \gamma t} \quad (31.9)$$

## 31.2 Estimation of Survival Function

**Parametric Approach** Suppose  $t_1, t_2, \dots, t_n$  are failure times corresponding to censor indicators  $\delta_1, \delta_2, \dots, \delta_n$ . The likelihood function is

$$\begin{aligned} f(\theta | \mathbf{t}, \boldsymbol{\delta}) &= \prod_{i=1}^n [f(t_i)]^{\delta_i} [S(t_i)]^{1-\delta_i} \\ &= \prod_{i=1}^n \left( \frac{f(t_i)}{S(t_i)} \right)^{\delta_i} S(t_i) \\ &= \prod_{i=1}^n [\lambda(t_i)]^{\delta_i} S(t_i) \end{aligned} \quad (31.10)$$

where  $\lambda(t), S(t)$  depends on some parameter  $\theta$ .

**Example 31.3** Suppose  $T$  have exponential density, that,

$$f(t) = \lambda e^{-\lambda t}, \quad S(t) = e^{-\lambda t}$$

Thus,

$$\begin{aligned} \ell(\lambda) &= \log[\ell(\theta)] = \sum_{i=1}^n [\delta_i \log(\lambda) - \lambda t_i] \\ &= \left( \sum_{i=1}^n \delta_i \right) \log(\lambda) - \lambda \left( \sum_{i=1}^n t_i \right) \end{aligned}$$

Hence,

$$\frac{\partial \ell(\lambda)}{\partial \lambda} = \frac{\sum_{i=1}^n \delta_i}{\lambda} - \sum_{i=1}^n t_i = 0 \Rightarrow \hat{\lambda} = \frac{\sum_{i=1}^n \delta_i}{\sum_{i=1}^n t_i}$$

**Nonparametric Approach** Then, for  $t_{(k)} \leq t < t_{(k+1)}$ ,

$$\begin{aligned} \hat{S}(t) &= \prod_{j=1}^k \left( \frac{n_j - d_j}{n_j} \right) \\ &= \left( 1 - \frac{d_1}{n_1} \right) \left( 1 - \frac{d_2}{n_2} \right) \cdots \left( 1 - \frac{d_k}{n_k} \right) \\ &\approx [1 - \hat{\lambda}(t_1)] [1 - \hat{\lambda}(t_2)] \cdots [1 - \hat{\lambda}(t_k)] \end{aligned} \quad (31.11)$$

where  $\hat{S}(t)$  is referred to as Kaplan-Meier estimate.

## 31.3 Proportional Hazards Model

Suppose  $t_{(1)} < t_{(2)} < \dots < t_{(m)}$  be death times. The number of individuals who alive just before time  $t_{(j)}$ , including those who are about to die at this time, will be denoted  $n_j$ , for  $j = 1, 2, \dots, m$ , and  $d_j$  will denote the number who die at this time. Thus, we have

### 31.3.1 Model Assumption

Let  $t_1, t_2, \dots, t_n$  be the failure times associated with censor indicator  $\delta_1, \delta_2, \dots, \delta_n$  and the covariate vectors  $\mathbf{x}_i$ .

Further, let  $t_{(1)} \leq t_{(2)} \leq \dots \leq t_{(m)}$  be the ordered uncensored failure times corresponding to  $\delta_{(j)} = 1, j = 1, 2, \dots, m$ , and  $x_{(1)}, x_{(2)}, \dots, x_{(m)}$  are the associated covariate vectors. Note  $(j)$  represents the label for the individual who dies at  $t_{(j)}$ .

The proportional hazards model specifying the hazard at time  $t$  for an individual whose covariate vector is  $\mathbf{x}$  is given by

$$\lambda(t) = \lambda_0(t)e^{\mathbf{x}'\boldsymbol{\beta}} \quad (31.12)$$

where  $\lambda_0(t)$  is referred to as the baseline hazard function.

### 31.3.2 Model Estimation

The exact likelihood function is

$$\ell[\boldsymbol{\beta}, \lambda_0(t)] = \prod_{i=1}^n [\lambda_i(t_i)]^{\delta_i} S(t_i) \quad (31.13)$$

depends on both the nonparametric function  $\lambda_0(t)$  and the parameter  $\boldsymbol{\beta}$ . Thus, it might be difficult to estimate  $\lambda_0(t)$  and  $\boldsymbol{\beta}$  simultaneously.

The partial likelihood function is

$$\ell_p(\boldsymbol{\beta}) = \prod_{j=1}^m \frac{e^{\mathbf{x}'_{(j)}\boldsymbol{\beta}}}{\sum_{l \in R(t_{(j)})} e^{\mathbf{x}'_l\boldsymbol{\beta}}} = \prod_{i=1}^n \left[ \frac{e^{\mathbf{x}'_i\boldsymbol{\beta}}}{\sum_{l \in R(t_i)} e^{\mathbf{x}'_l\boldsymbol{\beta}}} \right]^{\delta_i} \quad (31.14)$$

where  $R(t)$  is the set of individuals who are alive and uncensored at a time just prior to  $t_i$ , which is called the risk set.

## Chapter 32 Modified Likelihood

Seek a modified likelihood function that depends on as few of the nuisance parameters as possible while sacrificing as little information as possible.

### 32.1 Marginal Likelihood


### 32.2 Conditional Likelihood

Let  $\theta = (\varphi, \lambda)$ , where  $\varphi$  is the parameter vector of interest and  $\lambda$  is a vector of nuisance parameters. The conditional likelihood can be obtained as follows:

1. Find the complete sufficient statistic  $S_\lambda$ , respectively for  $\lambda$ .
2. Construct the conditional log-likelihood

$$\ell_c = \log(f_{Y|S_\lambda}) \quad (32.1)$$

where  $f_{Y|S_\lambda}$  is the conditional distribution of the response  $Y$  given  $S_\lambda$ .

 **Note** Two cases might occur, that, for fixed  $\varphi_0$ ,  $S_\lambda(\varphi_0)$  depends on  $\varphi_0$ ; or  $S_\lambda(\varphi_0) = S_\lambda$  is independent of  $\varphi_0$ .

1. Independent:
2. Dependent:

#### Example 32.1

**Conditional Likelihood for Exponential Family** Suppose that the log-likelihood for  $\theta = (\varphi, \lambda)$  can be written in the exponential family form

$$\ell(\theta, \mathbf{y}) = \theta' \mathbf{s} - b(\theta) \quad (32.2)$$

Also, suppose  $\ell(\theta, \mathbf{y})$  has a decomposition of the form

$$\ell(\theta, \mathbf{y}) = \varphi' \mathbf{s}_1 + \lambda' \mathbf{s}_2 - b(\varphi, \lambda) \quad (32.3)$$

**Remark** The above decomposition can be achieved only if  $\varphi$  is a linear function of  $\theta$ . The choice of nuisance parameter  $\lambda$  is arbitrary and the inferences regarding  $\varphi$  should be unaffected by the parameterization chosen for  $\lambda$ .

The conditional likelihood of the data  $\mathbf{Y}$  given  $\mathbf{s}_2$  is

$$\ell(\varphi | \mathbf{s}_2) = \varphi' \mathbf{s}_1 - b^*(\varphi, \lambda) \quad (32.4)$$

which is independent of the nuisance parameter and may be used for inferences regarding  $\varphi$ .

**Example 32.2**  $Y_1 \sim P(\mu_1)$ ,  $Y_2 \sim P(\mu_2)$  are independent. Suppose  $\varphi = \log\left(\frac{\mu_2}{\mu_1}\right) = \log(\mu_2) - \log(\mu_1)$  is the parameter of interest and the nuisance parameter is

1.  $\lambda_1 = \log(\mu_1)$ .
- 2.

Then, give the conditional log-likelihood for different nuisance parameter.

**Solution**

1. The log-likelihood function in the form of  $(\varphi, \lambda)$  is

$$\begin{aligned}
 \ell(\phi, \lambda_1) &\propto \log \left[ e^{-(\mu_1 + \mu_2)} \mu_1^{y_1} \mu_2^{y_2} \right] \\
 &= -(\mu_1 + \mu_2) + y_1 \log(\mu_1) + y_2 \log(\mu_2) \\
 &= -\mu_1 \left( 1 + \frac{\mu_2}{\mu_1} \right) + y_1 \log(\mu_1) + y_2 \log(\mu_1) \\
 &\quad - y_2 [\log(\mu_1) - \log(\mu_2)] \\
 &= -e^{\lambda_1} (1 + e^\varphi) + (y_1 + y_2) \lambda_1 - y_2 \varphi \\
 &= s_1 \varphi + s_2 \lambda_1 - b(\varphi, \lambda_1)
 \end{aligned}$$

where  $s_1 = -y_2$ ,  $s_2 = y_1 + y_2$ ,  $b(\varphi, \lambda_1) = e^{\lambda_1} (1 + e^\varphi)$ .

Then, the conditional distribution of  $Y_1, Y_2$  given  $S_2 = Y_1 + Y_2$  is  $b\left(S_2, \frac{\mu_1}{\mu_1 + \mu_2}\right)$ , thus,

$$\begin{aligned}
 \ell(\varphi \mid S_2 = s_2) &\propto y_1 \log\left(\frac{\mu_1}{\mu_1 + \mu_2}\right) + y_2 \log\left(\frac{\mu_2}{\mu_1 + \mu_2}\right) \\
 &= y_1 \log\left(\frac{\mu_1}{\mu_1 + \mu_2}\right) + y_2 \log\left(\frac{\mu_1}{\mu_1 + \mu_2}\right) \\
 &\quad - y_2 \left[ \log\left(\frac{\mu_1}{\mu_1 + \mu_2}\right) - \log\left(\frac{\mu_2}{\mu_1 + \mu_2}\right) \right] \\
 &= (y_1 + y_2) \log\left(\frac{1}{1 + e^\varphi}\right) - y_2 \varphi \\
 &= s_1 \varphi - b^*(\varphi, s_2)
 \end{aligned}$$

where  $b^*(\varphi, s_2) = -s_2 \log\left(\frac{1}{1 + e^\varphi}\right)$ .

## 32.3 Profile Likelihood

## 32.4 Quasi Likelihood



# **Part X**

## **Machine Learning**

## Chapter 33 Kernel Methods

### Definition 33.1 (Positive Definite Kernel)

Let  $\mathcal{X}$  be a set, a function  $K : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$  is called a positive definite kernel on  $\mathcal{X}$  iff it is

1. symmetric, that is,

$$K(\mathbf{x}, \mathbf{x}') = K(\mathbf{x}', \mathbf{x}), \quad \forall \mathbf{x}, \mathbf{x}' \in \mathcal{X} \quad (33.1)$$

2. positive definite, that is,

$$\sum_{i=1}^n \sum_{j=1}^n c_i c_j K(\mathbf{x}_i, \mathbf{x}_j) \geq 0, \quad (33.2)$$

holds for any  $x_1, \dots, x_n \in \mathcal{X}$ , given  $n \in \mathbb{N}$ ,  $c_1, \dots, c_n \in \mathbb{R}$ .



### Theorem 33.1 (Morse-Aronszajn's Theorem)

For any set  $\mathcal{X}$ , suppose  $K : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$  is positive definite, then there is a unique RKHS  $\mathcal{H} \subset \mathbb{R}^{\mathcal{X}}$  with reproducing kernel  $K$ .



### Proof

1. How to build a valid pre-RKHS  $\mathcal{H}_0$ ?

Consider the vector space  $\mathcal{H}_0 \subset \mathbb{R}^{\mathcal{X}}$  spanned by the functions  $\{K(\cdot, \mathbf{x})\}_{\mathbf{x} \in \mathcal{X}}$ . For any  $f, g \in \mathcal{H}_0$ , suppose

$$f = \sum_{i=1}^m a_i K(\cdot, \mathbf{x}_i), \quad g = \sum_{j=1}^n b_j K(\cdot, \mathbf{y}_j)$$

and let the inner product of  $\mathcal{H}_0$  be

$$\langle f, g \rangle = \sum_{i=1}^m \sum_{j=1}^n a_i b_j K(\mathbf{x}_i, \mathbf{y}_j) \quad (33.3)$$

Let  $\mathbf{x} \in \mathcal{X}$ ,

$$\langle f, K(\cdot, \mathbf{x}) \rangle_{\mathcal{H}_0} = \sum_{i=1}^m a_i K(\mathbf{x}, \mathbf{x}_i) = f(\mathbf{x})$$

And, we also have

$$\langle f, g \rangle_{\mathcal{H}_0} = \sum_{i=1}^m a_i g(\mathbf{x}_i) = \sum_{j=1}^n b_j f(\mathbf{y}_j)$$

Suppose

$$f = \sum_{i=1}^m a_i K(\cdot, \mathbf{x}_i), \quad g = \sum_{j=1}^n b_j K(\cdot, \mathbf{y}_j), \quad h = \sum_{k=1}^p c_k K(\cdot, \mathbf{z}_k)$$

(a). Linearity: For any  $\alpha, \beta \in \mathbb{R}$ ,  $\langle \alpha f + \beta g, h \rangle_{\mathcal{H}_0} = \alpha \langle f, h \rangle_{\mathcal{H}_0} + \beta \langle g, h \rangle_{\mathcal{H}_0}$ .

$$\begin{aligned} \langle \alpha f + \beta g, h \rangle_{\mathcal{H}_0} &= \left[ \alpha \sum_{i=1}^m a_i K(\cdot, \mathbf{x}_i) + \beta \sum_{j=1}^n b_j K(\cdot, \mathbf{y}_j) \right] \cdot \sum_{k=1}^p c_k K(\cdot, \mathbf{z}_k) \\ &= \alpha \sum_{i=1}^m \sum_{k=1}^p a_i c_k K(\mathbf{x}_i, \mathbf{z}_k) + \beta \sum_{j=1}^n \sum_{k=1}^p b_j c_k K(\mathbf{y}_j, \mathbf{z}_k) \\ &= \alpha \langle f, h \rangle_{\mathcal{H}_0} + \beta \langle g, h \rangle_{\mathcal{H}_0} \end{aligned}$$

(b). Conjugate Symmetry:  $\langle f, g \rangle_{\mathcal{H}_0} = \langle g, f \rangle_{\mathcal{H}_0}$ .

$$\begin{aligned} \langle f, g \rangle_{\mathcal{H}_0} &= \sum_{i=1}^m \sum_{j=1}^n a_i b_j K(\mathbf{x}_i, \mathbf{y}_j) = \sum_{j=1}^n \sum_{i=1}^m b_j a_i K(\mathbf{y}_j, \mathbf{x}_i) \\ &= \langle g, f \rangle_{\mathcal{H}_0} \end{aligned}$$

(c). Positive Definiteness:  $\langle f, f \rangle_{\mathcal{H}_0} \geq 0$  and  $\langle f, f \rangle_{\mathcal{H}_0} = 0$  if and only if  $f = 0$ .

By positive definiteness of  $K$ , we have:

$$\langle f, f \rangle_{\mathcal{H}_0} = \|f\|_{\mathcal{H}_0}^2 = \sum_{i=1}^m \sum_{j=1}^m a_i a_j K(\mathbf{x}_i, \mathbf{x}_j) \geq 0$$

As for,  $\langle f, f \rangle_{\mathcal{H}_0} = 0$  if and only if  $f = 0$ , we have,

" $\Rightarrow$ " If  $f = 0$ , that is  $f = \sum_{i=1}^m a_i K(\cdot, \mathbf{x}_i) = 0$ , we have

$$\langle f, f \rangle_{\mathcal{H}_0} = \sum_{i=1}^m a_i f = 0$$

" $\Leftarrow$ " For  $\forall \mathbf{x} \in \mathcal{X}$ , by Cauchy-Schwarz Inequality, we have,

$$|f(\mathbf{x})| = |\langle f, K(\cdot, \mathbf{x}) \rangle_{\mathcal{H}_0}| \leq \|f\|_{\mathcal{H}_0} \cdot K(\mathbf{x}, \mathbf{x})^{\frac{1}{2}}$$

therefore, if  $\|f\|_{\mathcal{H}_0} = 0$ , then  $f = 0$

Hence, definition in equation 33.3 is a valid inner product, which is a valid pre-RKHS  $\mathcal{H}_0$ .

### Example 33.1 Common Kernels

$$1. K(\mathbf{x}, \mathbf{y}) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{y}\|^2}{2\sigma^2}\right), \quad \mathbf{x}, \mathbf{y} \in \mathbb{R}^d$$

**Proof**

1. It is obvious that  $K(\mathbf{x}, \mathbf{y})$  is symmetric, we only need to show  $K(\mathbf{x}, \mathbf{y})$  is positive definite.

$$\begin{aligned} K(\mathbf{x}, \mathbf{y}) &= \exp\left(-\frac{\|\mathbf{x}-\mathbf{y}\|^2}{2\sigma^2}\right) \\ &= \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{x}\|^2\right) \cdot \exp\left(\frac{1}{\sigma^2}\langle \mathbf{x}, \mathbf{y} \rangle\right) \cdot \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{y}\|^2\right) \end{aligned}$$

By the Taylor expansion of the exponential function, that

$$\exp\left(\frac{x}{\sigma^2}\right) = \sum_{n=0}^{+\infty} \left\{ \frac{x^n}{\sigma^{2n} \cdot n!} \right\}$$

Hence,

$$\exp\left(\frac{1}{\sigma^2}\langle \mathbf{x}, \mathbf{y} \rangle\right) = \sum_{n=0}^{+\infty} \left\{ \frac{\langle \mathbf{x}, \mathbf{y} \rangle^n}{\sigma^{2n} \cdot n!} \right\}$$

By the Multinomial Theorem, we have

$$\begin{aligned}\langle \mathbf{x}, \mathbf{y} \rangle^n &= \left( \sum_{i=1}^d x_i y_i \right)^n = \sum_{k_1+k_2+\dots+k_d=n} \left[ \binom{n}{k_1, k_2, \dots, k_d} \prod_{i=1}^d (x_i y_i)^{k_i} \right] \\ &= \sum_{k_1+k_2+\dots+k_d=n} \left[ \binom{n}{k_1, k_2, \dots, k_d}^{\frac{1}{2}} \prod_{i=1}^d x_i^{k_i} \cdot \binom{n}{k_1, k_2, \dots, k_d}^{\frac{1}{2}} \prod_{i=1}^d y_i^{k_i} \right]\end{aligned}$$

Therefore,

$$\begin{aligned}K(\mathbf{x}, \mathbf{y}) &= \exp\left(-\frac{\|\mathbf{x} - \mathbf{y}\|^2}{2\sigma^2}\right) = \exp\left(-\frac{\|\mathbf{x}\|^2}{2\sigma^2}\right) \cdot \exp\left(-\frac{\|\mathbf{y}\|^2}{2\sigma^2}\right) \cdot \sum_{n=0}^{+\infty} \left\{ \frac{\langle \mathbf{x}, \mathbf{y} \rangle^n}{\sigma^{2n} \cdot n!} \right\} \\ &= \sum_{n=0}^{+\infty} \frac{\exp\left(-\frac{\|\mathbf{x}\|^2}{2\sigma^2}\right)}{\sigma^n \cdot \sqrt{n!}} \cdot \frac{\exp\left(-\frac{\|\mathbf{y}\|^2}{2\sigma^2}\right)}{\sigma^n \cdot \sqrt{n!}} \cdot \langle \mathbf{x}, \mathbf{y} \rangle^n\end{aligned}$$

Let

$$c_{\sigma,n}(\mathbf{x}) = \frac{\exp\left(-\frac{\|\mathbf{x}\|^2}{2\sigma^2}\right)}{\sigma^n \cdot \sqrt{n!}}, \quad f_{n,\mathbf{k}}(\mathbf{x}) = \binom{n}{k_1, k_2, \dots, k_d}^{\frac{1}{2}} \prod_{i=1}^d x_i^{k_i}$$

then,

$$\begin{aligned}K(\mathbf{x}, \mathbf{y}) &= \sum_{n=0}^{+\infty} \sum_{k_1+k_2+\dots+k_d=n} c_{\sigma,n}(\mathbf{x}) f_{n,\mathbf{k}}(\mathbf{x}) \cdot c_{\sigma,n}(\mathbf{y}) f_{n,\mathbf{k}}(\mathbf{y}) \\ &= \langle \Phi(\mathbf{x}), \Phi(\mathbf{y}) \rangle\end{aligned}$$

where  $\Phi(\mathbf{x})_{\sigma,n,\mathbf{k}} = c_{\sigma,n}(\mathbf{x}) f_{n,\mathbf{k}}(\mathbf{x})$ .

$$\begin{aligned}\sum_{i=1}^n \sum_{j=1}^n c_i c_j K(\mathbf{x}_i, \mathbf{x}_j) &= \sum_{i=1}^n \sum_{j=1}^n c_i c_j \langle \Phi(\mathbf{x}_i), \Phi(\mathbf{x}_j) \rangle \\ &= \left\langle \sum_{i=1}^n c_i \Phi(\mathbf{x}_i), \sum_{i=1}^n c_i \Phi(\mathbf{x}_i) \right\rangle \geq 0\end{aligned}$$

for any  $x_1, \dots, x_n \in \mathcal{X}$ , given  $n \in \mathbb{N}$ ,  $c_1, \dots, c_n \in \mathbb{R}$ , i.e.,  $K(\mathbf{x}, \mathbf{y})$  is positive definite.

# Chapter 34 Support Vector Machine

## Theorem 34.1

The minimizer of

$$\arg \min_g E \{ [1 - Yg(X)]_+ \mid X = x \}$$

is the sign of  $f(x) = \log \frac{p(x)}{1-p(x)}$ , i.e.,

$$\text{sgn} \left[ p(x) - \frac{1}{2} \right]$$

where  $\text{sgn}(\cdot)$  is the sign function.



**Proof** For the hinge loss function, that,

$$\begin{aligned} & E \{ [1 - Yg(X)]_+ \mid X = x \} \\ &= [1 - g(x)]_+ P(Y = 1 \mid X = x) + [1 + g(x)]_+ P(Y = -1 \mid X = x) \\ &= [1 - g(x)]_+ p(x) + [1 + g(x)]_+ [1 - p(x)] \\ &= \begin{cases} [1 - g(x)] p(x), & g(x) < -1 \\ 1 + [1 - 2p(x)] g(x), & -1 \leq g(x) \leq 1 \\ [1 + g(x)] [1 - p(x)], & g(x) > 1 \end{cases} \end{aligned}$$

When  $g(x) < -1$ ,

$$\arg \min_g E \{ [1 - Yg(X)]_+ \mid X = x \} = \arg \min_g [1 - g(x)] p(x) = -1$$

When  $g(x) > 1$ ,

$$\arg \min_g E \{ [1 - Yg(X)]_+ \mid X = x \} = \arg \min_g [1 + g(x)] [1 - p(x)] = 1$$

When  $-1 \leq g(x) \leq 1$ ,

$$\begin{aligned} & \arg \min_g E \{ [1 - Yg(X)]_+ \mid X = x \} \\ &= \arg \min_g \{ 1 + [1 - 2p(x)] g(x) \} \\ &= \begin{cases} -1, & p(x) < \frac{1}{2} \\ 0, & p(x) = \frac{1}{2} \\ 1, & p(x) > \frac{1}{2} \end{cases} \end{aligned}$$

Thus, for the  $g(x) \in [-1, 1]$  the minimizer of  $\arg \min_g E \{ [1 - Yg(X)]_+ \mid X = x \}$  is the sign of  $p(x) - \frac{1}{2}$ , that is the sign of  $f(x) = \log \frac{p(x)}{1-p(x)}$

## **Chapter 35 Linear Discriminant Analysis**

## Chapter 36 K-Nearest Neighbor

## Chapter 37 Decision Tree



# **Part XI**

## **Random Matrix Theory**

## Chapter 38 Wishart and Laguerre Ensembles

Suppose  $\{\mathbf{X}\}$  be a sequence of random vectors defined in  $\mathbb{R}^n$ , such that

$$E(\mathbf{X}) = 0, \quad E(\mathbf{X} \otimes \mathbf{X}) = \mathbf{I}_n$$

and let  $(X_i)_{1 \leq i \leq n}$  be the components of the random vector  $\mathbf{X}$ .

Suppose  $\{m_n\}$  be a sequence defined in  $\mathbb{N}$  such that

$$0 < \underline{\rho} := \liminf_{n \rightarrow \infty} \frac{n}{m_n} \leq \limsup_{n \rightarrow \infty} \frac{n}{m_n} =: \bar{\rho} < \infty$$

Let  $\mathbf{X}^{(1)}, \dots, \mathbf{X}^{(m_n)}$  be i.i.d. copies of  $\mathbf{X}$ , and  $\mathbb{X}$  be the  $m_n \times n$  random matrix with i.i.d. rows  $\mathbf{X}^{(1)}, \dots, \mathbf{X}^{(m_n)}$ , and their empirical covariance matrix is

$$\hat{\Sigma} := \frac{1}{m_n} \sum_{k=1}^{m_n} \mathbf{X}^{(k)} \otimes \mathbf{X}^{(k)} = \frac{1}{m_n} \mathbb{X}' \mathbb{X}$$

which is a  $n \times n$  symmetric positive semidefinite random matrix, and

$$E(\hat{\Sigma}) = E(\mathbf{X} \otimes \mathbf{X}) = \mathbf{I}_n$$

For convenience, we define the random matrix

$$\mathbf{A} := m_n \hat{\Sigma} = \mathbb{X}' \mathbb{X} = \sum_{k=1}^{m_n} \mathbf{X}^{(k)} \otimes \mathbf{X}^{(k)}$$

which is also called Wishart matrix.

### Theorem 38.1

The eigenvalues of  $\mathbf{A}$  are squares of the singular values of  $\mathbb{X}$ , in particular

$$\lambda_{\max}(\mathbf{A}) = s_{\max}(\mathbb{X})^2 = \max_{\|\mathbf{x}\|=1} \|\mathbb{X}\mathbf{x}\|^2 = \|\mathbb{X}\|_2^2 \quad (38.1)$$

if  $m_n \geq n$ , then

$$\lambda_{\min}(\mathbf{A}) = s_{\min}(\mathbb{X})^2 = \min_{\|\mathbf{x}\|=1} \|\mathbb{X}\mathbf{x}\|^2 = \|\mathbb{X}^{-1}\|_2^{-2} \quad (38.2)$$



### 38.1 Wishart Distribution

Specially, if the random variables  $(X_i)_{1 \leq i \leq n}$  are i.i.d. standard Gaussians, then the distribution of the random matrix  $\hat{\Sigma}$  can be derived from the Wishart distribution.

#### Definition 38.1 (Wishart Distribution)

Suppose  $\mathbb{X}$  be a  $p \times n$  matrix, each column of which is independently drawn from a  $p$ -variate normal distribution with zero mean:

$$\mathbf{X}_i = (x_i^1, \dots, x_i^p)' \sim N_p(0, \Sigma)$$

Then the Wishart distribution is the probability distribution of the  $p \times p$  random matrix,

$$\mathbf{M} = \mathbb{X}' \mathbb{X} = \sum_{i=1}^n \mathbf{X}_i \mathbf{X}_i' \quad (38.3)$$

and which can be denoted by

$$\mathbf{M} \sim W_p(\mathbf{\Sigma}, n)$$



If  $n \geq p$ , the probability density function of  $\mathbf{M}$  is

$$f(\mathbf{M}) = \frac{1}{2^{np/2} [\det(\mathbf{\Sigma})]^{n/2} \Gamma_p\left(\frac{n}{2}\right)} \det(\mathbf{M})^{(n-p-1)/2} \exp\left[-\frac{1}{2} \text{tr}(\mathbf{\Sigma}^{-1}\mathbf{M})\right] \quad (38.4)$$

with respect to Lebesgue measure on the cone of symmetric positive definite matrices. Here,  $\Gamma_p$  is the multivariate gamma function defined as

$$\Gamma_p\left(\frac{n}{2}\right) = \pi^{p(p-1)/4} \prod_{j=1}^p \Gamma\left(\frac{n}{2} - \frac{j-1}{2}\right)$$

**Remark** If  $p = \Sigma = 1$ , then this distribution is a chi-squared distribution with  $n$  degrees of freedom.

The probability density function of  $\hat{\mathbf{\Sigma}}$  can be derived from (38.4), since

$$\mathbf{A} \sim W_n(\mathbf{I}_n, m_n), \quad \det(\hat{\mathbf{\Sigma}}) = m_n^{-n} \det(\mathbf{A}), \quad \text{tr}(\hat{\mathbf{\Sigma}}) = m_n^{-1} \text{tr}(\mathbf{A})$$

thus,

$$\frac{m_n^{-n(m_n-n-1)/2+1}}{2^{m_n n/2} \Gamma_n\left(\frac{m_n}{2}\right)} \det(\hat{\mathbf{\Sigma}})^{(m_n-n-1)/2} \exp\left[-\frac{m_n}{2} \text{tr}(\hat{\mathbf{\Sigma}})\right] \quad (38.5)$$

## 38.2 Joint Distribution of Eigenvalues

### Theorem 38.2

The joint probability density function of eigenvalues of  $\hat{\mathbf{\Sigma}}$  is

$$p(\boldsymbol{\lambda}) = \tilde{Q}_{m_n}^{-1} \exp\left(-\frac{m_n}{2} \sum_{k=1}^n \lambda_k\right) \prod_{k=1}^n \lambda_k^{(m_n-n-1)/2} \prod_{i < j} |\lambda_i - \lambda_j| \quad (38.6)$$

where

$$0 \leq \lambda_1 \leq \dots \leq \lambda_n < \infty$$

and  $\tilde{Q}_{m_n}$  is the normalization constant.



**Proof** First, we will give the characteristic function of  $\hat{\mathbf{\Sigma}}$ , i.e.,

$$\varphi_{\hat{\mathbf{\Sigma}}}(\mathbf{P}) = E \left[ \exp \left( i \sum_{1 \leq i \leq j \leq n} P_{ij} \hat{\mathbf{\Sigma}}_{ji} \right) \right] = E \left[ \exp \left( i \text{tr}(\mathbf{P} \hat{\mathbf{\Sigma}}) \right) \right]$$

where  $\{P_{ij}\}_{1 \leq i \leq j \leq n} \in \mathbb{R}^{(n+1)n/2}$  and  $\mathbf{P}$  is a real symmetric matrix, that

$$\mathbf{P} = \left\{ \hat{P}_{ij}, \hat{P}_{ij} = \hat{P}_{ji} \right\}_{i,j=1}^n, \quad \hat{P}_{ij} = \begin{cases} P_{ii}, & i = j \\ P_{ij}/2, & i < j \end{cases}$$

Thus, we have

$$\begin{aligned} &= \int_{\mathbb{R}^{m_n \times n}} \exp \left( i \operatorname{tr} (\mathbf{P} \widehat{\mathbf{\Sigma}}) \right) \cdot (2\pi)^{-m_n n/2} \exp \left( -\frac{1}{2} \sum_{k=1}^{m_n} \sum_{i=1}^n \left( X_i^{(k)} \right)^2 \right) \prod_{k=1}^{m_n} \prod_{i=1}^n dX_i^{(k)} \\ &= \int_{\mathbb{R}^{m_n \times n}} (2\pi)^{-m_n n/2} \exp \left( -\frac{1}{2} \sum_{k=1}^{m_n} \sum_{i=1}^n \sum_{j=1}^n \mathbf{Q}_{ij} X_i^{(k)} X_j^{(k)} \right) \prod_{k=1}^{m_n} \prod_{i=1}^n dX_i^{(k)} \end{aligned}$$

where

$$\mathbf{Q} = \mathbf{I} - \frac{2i}{m_n} \mathbf{P}$$

Since  $(X_i^{(k)})_{1 \leq i \leq n}$  are i.i.d. standard Gaussians,

$$\begin{aligned} &= \left[ \int_{\mathbb{R}^n} (2\pi)^{-n/2} \exp \left( -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \mathbf{Q}_{ij} X_i X_j \right) \prod_{i=1}^n dX_i \right]^{m_n} \\ &= \left[ \int_{\mathbb{R}^n} (2\pi)^{-n/2} \exp \left( -\frac{1}{2} \mathbf{X}' \mathbf{Q} \mathbf{X} \right) d\mathbf{X} \right]^{m_n} \\ &= \left[ \det(\mathbf{Q})^{-\frac{1}{2}} \int_{\mathbb{R}^n} (2\pi)^{-n/2} \exp \left( -\frac{1}{2} (\mathbf{Q}^{\frac{1}{2}} \mathbf{X})' (\mathbf{Q}^{\frac{1}{2}} \mathbf{X}) \right) d\mathbf{Q}^{\frac{1}{2}} \mathbf{X} \right]^{m_n} \\ &= [\det(\mathbf{Q})]^{-m_n/2} \end{aligned}$$

thus,

$$[\det(\mathbf{Q})]^{-m_n/2} = \left[ \det \left( \mathbf{I} - \frac{2i}{m_n} \mathbf{P} \right) \right]^{-m_n/2} = \prod_{k=1}^n \left( 1 - \frac{2i}{m_n} p_k \right)^{-m_n/2} \quad (38.7)$$

where  $\{p_k\}_{k=1}^n$  are the eigenvalues of  $\mathbf{P}$ .

Then, we will show that the characteristic function of (38.6) coincides with the above function. By the Wishart distribution, the probability density of the real symmetric and positive definite random matrix  $\widehat{\mathbf{\Sigma}}$  is

$$\widetilde{Q}_{m_n}^{-1} \exp \left[ -\frac{m_n}{2} \operatorname{tr} (\widehat{\mathbf{\Sigma}}) \right] [\det(\widehat{\mathbf{\Sigma}})]^{(m_n-n-1)/2} d\widehat{\mathbf{\Sigma}} \quad (38.8)$$

where  $\widetilde{Q}_{m_n}$  is the normalization constant. Then, the characteristic function of (38.8), i.e.,

$$\widetilde{Q}_{m_n}^{-1} \int_{\mathcal{S}_n^+} \exp \left[ i \operatorname{tr} (\mathbf{P} \widehat{\mathbf{\Sigma}}) - \frac{m_n}{2} \operatorname{tr} (\widehat{\mathbf{\Sigma}}) \right] [\det(\widehat{\mathbf{\Sigma}})]^{(m_n-n-1)/2} d\widehat{\mathbf{\Sigma}}$$

where the integration is over the set  $\mathcal{S}_n^+$  of  $n \times n$  real symmetric and positive definite matrices.

Since

$$\sum_{k=1}^n \lambda_k = \operatorname{tr} (\widehat{\mathbf{\Sigma}}), \quad \prod_{k=1}^n \lambda_k^{(m_n-n-1)/2} = [\det(\widehat{\mathbf{\Sigma}})]^{(m_n-n-1)/2}$$

and

$$d\widehat{\mathbf{\Sigma}} = \prod_{i < j} |\lambda_i - \lambda_j| d\boldsymbol{\lambda} H_1(dO)$$

where  $H_1$  is the normalized Haar measure of  $O(n)$ , and the integration over  $\boldsymbol{\lambda}$  and  $O \in O(n)$  are independent.

Since the orthogonal invariance of the density of (38.8), we obtain (38.6), and the characteristic

function is

$$Q_n^{-1} \int_{(\mathbb{R}_+)^n} \exp \left[ \sum_{k=1}^n \left( i p_k - \frac{m_n}{2} \right) \lambda_k \right] \prod_{k=1}^n \lambda_k^{(m_n-n-1)/2} \prod_{i<j} |\lambda_i - \lambda_j| d\lambda \quad (38.9)$$

where  $Q_{m_n} = m_n! \tilde{Q}_{m_n}$ .

If we viewed (38.7) and (38.9) as the function of  $\{p_k\}_{k=1}^n \in \mathbb{R}^n$ , then they can be **analytic continuation** to the domain

$$\{p_k + i p'_k, p'_k \geq 0\}_{k=1}^n$$

If we replace  $\{p_k\}_{k=1}^n$  by  $\{i p'_k, p'_k \geq 0\}_{k=1}^n$  on (38.7), since this is a set of uniqueness of both (38.7) and (38.9) analytic functions, we have

$$Q_{m_n}^{-1} \int_{(\mathbb{R}_+)^n} \exp \left[ -\frac{m_n}{2} \sum_{k=1}^n q_k \lambda_k \right] \prod_{k=1}^n \lambda_k^{(m_n-n-1)/2} \prod_{i<j} |\lambda_i - \lambda_j| d\lambda$$

where  $q_k = 1 + \frac{2p'_k}{m_n} \geq 1, k = 1, \dots, n$ , and since

$$\forall i, j \quad \frac{q_i}{q_j} = \frac{1 + \frac{2p'_i}{m_n}}{1 + \frac{2p'_j}{m_n}} \rightarrow 1, \quad \text{as } m_n \rightarrow \infty$$

we have

$$\prod_{i<j} |q_i \lambda_i - q_j \lambda_j| = \prod_{i<j} q_i \left| \lambda_i - \frac{q_j}{q_i} \lambda_j \right| \rightarrow \prod_{k=1}^n q_k^{(n-1)/2} \prod_{i<j} |\lambda_i - \lambda_j|, \quad \text{as } m_n \rightarrow \infty$$

thus,

$$\prod_{k=1}^n q_k^{-m_n/2} \cdot Q_{m_n}^{-1} \int_{(\mathbb{R}_+)^n} \exp \left[ -\frac{m_n}{2} \sum_{k=1}^n q_k \lambda_k \right] \prod_{k=1}^n (q_k \lambda_k)^{(m_n-n-1)/2} \prod_{i<j} |q_i \lambda_i - q_j \lambda_j| d\mathbf{q} d\lambda$$

Since

$$\forall k \quad q_k \lambda_k \rightarrow \lambda_k, \quad \text{as } m_n \rightarrow \infty$$

we can "lifting" from  $\{\lambda_k\}_{k=1}^n$  to  $\mathcal{S}_n^+$  bring the integral to

$$\prod_{k=1}^n \left( 1 + \frac{2p'_k}{m_n} \right)^{-m_n/2} \tilde{Q}_n^{-1} \int_{\mathcal{S}_n^+} \exp \left[ -\frac{m_n}{2} \text{tr}(\hat{\Sigma}) \right] [\det(\hat{\Sigma})]^{(m_n-n-1)/2} d\hat{\Sigma}$$

The integral here is equal to  $\tilde{Q}_n$ , the normalization constant of the probability measure (38.8).

If we replace  $\{i p'_k\}_{k=1}^n$  back by  $\{p_k\}_{k=1}^n$ , then the above expression is

$$\prod_{k=1}^n \left( 1 - \frac{2i}{m_n} p_k \right)^{-m_n/2}$$

which coincides with (38.7).

Thus the probability law of the Wishart matrices of  $\Sigma_n$  given by (38.8) implies that the corresponding joint probability density of eigenvalues is given by (38.6) for  $\Sigma_n$ .

The theorem above can be generalized to a larger form, that,

**Definition 38.2 (Laguerre Orthogonal Ensemble)**

For the  $n \times n$  Laguerre orthogonal ensembles of statistics, the joint probability density function of eigenvalues is for arbitrary parameter  $\beta > 0$  and  $\alpha > -\frac{2}{\beta}$ , is

$$p(\boldsymbol{\lambda}) = K_{\alpha, \beta} \exp \left( -\frac{\beta}{2} \sum_{k=1}^n \lambda_k \right) \prod_{k=1}^n \lambda_k^{\frac{\alpha\beta}{2}} \prod_{i < j} |\lambda_i - \lambda_j|^\beta \quad (38.10)$$

where

$$0 \leq \lambda_1 \leq \dots \leq \lambda_n < \infty$$

and  $K_{n, m}$  are normalization constant.



**Remark** Ensemble is often used in physics and the physics-influenced literature. In probability theory, the term **probability space** is more prevalent.

And Equation (38.10) can be written in the standard Boltzmann-Gibbs form, that,

$$p(\boldsymbol{\lambda}) \propto \exp[-\beta E(\boldsymbol{\lambda})]$$

where

$$E(\boldsymbol{\lambda}) = \frac{1}{2} \sum_{k=1}^n (\lambda_k - \alpha \log \lambda_k) - \frac{1}{2} \sum_{i \neq j} |\lambda_i - \lambda_j| \quad (38.11)$$

For the (38.6), which can be written as (38.10) form, that,

$$p(\boldsymbol{\lambda}) \propto \exp[-\beta m_n E(\boldsymbol{\lambda})]$$

where  $\beta = 1$  and

$$E(\boldsymbol{\lambda}) = \frac{m_n}{2} \sum_{k=1}^n \left[ \lambda_k - \left( \frac{m_n - n - 1}{m_n} \right) \log \lambda_k \right] - \frac{1}{2m_n} \sum_{i \neq j} |\lambda_i - \lambda_j|$$

### 38.3 Average Denisty of Eigenvalues

Before the proof, we will introduce some concepts.

**Theorem 38.3 (Marchenko-Pastur Theorem)**

If

$$\frac{n}{m_n} \rightarrow \rho \in (0, \infty), \quad \text{as } n \rightarrow \infty$$

and the empirical spectral measure of  $\hat{\boldsymbol{\Sigma}}$  tends weakly with probability 1 to the nonrandom measure, i.e.,

$$\frac{1}{m_n} \sum_{k=1}^n \delta_{\lambda_k(\hat{\boldsymbol{\Sigma}})} \xrightarrow{d} \mu_\rho, \quad \text{a.s.} \quad (38.12)$$

where  $\mu_\rho$  is the Marchenko-Pastur distribution on  $[a^-, a^+]$  with  $a^\pm = (1 \pm \sqrt{\rho})^2$  given by

$$\mu_\rho(dx) = \frac{\rho - 1}{\rho} \mathbf{I}_{\rho > 1} \delta_0 + \frac{\sqrt{(a^+ - x)(x - a^-)}}{\rho 2\pi x} \mathbf{I}_{[a^-, a^+]}(x) dx \quad (38.13)$$



**Proof** The normalization constant of eigenvalues of  $\widehat{\Sigma}$  is

$$\begin{aligned}\widetilde{Q}_{m_n} &= \int_{(\mathbb{R}_+)^n} \exp \left( -\frac{m_n}{2} \sum_{k=1}^n \lambda_k \right) \prod_{k=1}^n \lambda_k^{(m_n-n-1)/2} \prod_{i < j} |\lambda_i - \lambda_j| \, d\lambda \\ &= \int_{(\mathbb{R}_+)^n} \exp [-m_n E(\lambda)] \, d\lambda\end{aligned}$$

where

$$E(\lambda) = \frac{m_n}{2} \sum_{k=1}^n \left[ \lambda_k - \left( \frac{m_n - n - 1}{m_n} \right) \log \lambda_k \right] - \frac{1}{2m_n} \sum_{i \neq j} |\lambda_i - \lambda_j|$$

## 38.4 Behavior of the Extremal Eigenvalues

# Bibliography

- [1] Stephen Boyd and Lieven Vandenberghe. *Convex Optimization*. Cambridge, UK ; New York: Cambridge University Press, Mar. 8, 2004. 727 pp. ISBN: 978-0-521-83378-3.
- [2] Zdzislaw Brzezniak and Tomasz Zastawniak. *Basic Stochastic Processes*. Oct. 16, 1998.
- [3] Luc Devroye, Laszlo Györfi, and Gabor Lugosi. *A Probabilistic Theory of Pattern Recognition*. Corrected edition. New York: Springer, Apr. 4, 1996. 653 pp. ISBN: 978-0-387-94618-4.
- [4] Rick Durrett. *Probability: Theory and Examples*. 5th Edition. Cambridge ; New York, NY: Cambridge University Press, May 30, 2019. 430 pp. ISBN: 978-1-108-47368-2.
- [5] E. L. Lehmann. *Elements of Large-Sample Theory*. Springer texts in statistics. New York: Springer, 1999. 631 pp. ISBN: 978-0-387-98595-4.
- [6] E. L. Lehmann and George Casella. *Theory of Point Estimation*. 2nd Edition. Springer texts in statistics. New York: Springer, 1998. 589 pp. ISBN: 978-0-387-98502-2.
- [7] P. McCullagh and John A. Nelder. *Generalized Linear Models*. 2nd Edition. Boca Raton: Chapman and Hall/CRC, Aug. 1, 1989. 532 pp. ISBN: 978-0-412-31760-6.