1 Probability and statistics

1.1 Working with probability distributions

- Given probability distribution $\mathbb{P}$, sample space Ω, and event $A \subseteq \Omega$:
  - $\mathbb{P} \geq 0 \quad \forall A$ (probabilities are nonzero)
  - $\mathbb{P}[\Omega] = 1$ (probabilities sum to 1)
  - $\mathbb{P}[\varnothing] = 0$ (probability of empty set is 0)
  - $\mathbb{P}\left[\bigsqcup_{i=1}^{\infty} A_i\right] = \sum_{i=1}^{\infty} \mathbb{P}\left[A_i\right] = 1$
- Probabilities are independent when the joint probability is equal to the product of the marginal probabilities.

$$A \perp\!\!\!\perp B \iff \mathbb{P}\left[A \cap B\right] = \mathbb{P}\left[A\right] \mathbb{P}\left[B\right]$$

- The conditional probability of A given B is the joint probability of A and B divided by the probability of just B.

$$\mathbb{P}\left[A \mid B\right] = \frac{\mathbb{P}\left[A \cap B\right]}{\mathbb{P}\left[B\right]}$$

- The Probability Mass Function (PMF) is used to describe the behavior of *discrete* probability distributions.

$$f_X(x) = \mathbb{P}\left[X = x\right]$$

- The Probability Density Function (PDF) is the equivalent for *continuous* distributions. We use the PDF to determine the probability that random variable X is between A and B.

$$\mathbb{P}\left[a \leq X \leq b\right] = \int_a^b f(x)\, dx$$

- The Cumulative Distribution Function (CDF) is the integral of the PDF and we use it to determine the probability that random variable X is less than or equal to x. It maps $\mathbb{R} \to [0,1]$ and is monotonically non-decreasing. The left and right limits are 0 and 1 ($\lim_{x\to-\infty} = 0$ and $\lim_{x\to\infty} = 1$).

$$F_X(x) = \mathbb{P}\left[X \leq x\right]$$

1.1.1 Notes on the normal distribution

- The normal distribution is a function of mean μ and variance σ^2
- The simplest case is the **standard normal distribution**, $Z \sim \mathcal{N}(0,1)$, which reduces to:

$$\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}$$

  - Interestingly, others have defined even simpler standard normals. Gauss proposed $\sigma^2 = \frac{1}{2}$, which reduces to:

$$\phi(x) = \frac{e^{-x^2}}{\sqrt{pi}}$$

  - Stigler proposed a formulation with $\sigma^2 = \frac{1}{2\pi}$, leading to:

$$\phi(x) = e^{-\pi x^2}$$

- We can convert any normally distributed variable X to a *standard normal* by subtracting the mean and dividing by the standard deviation.

$$Z = \frac{X - \mu}{\sigma}$$

- **68-95-99.7 rule:** the percentage of values that lie within 1, 2, and 3 standard deviations of the mean of a normal distribution are 68.27%, 95.45%, and 99.73% respectively. A $\mu \pm 3\sigma$ deviation should occur at a frequency of about 1 in 370.
- The Gauss Error Function gives the probability of a RV $Z \sim \mathcal{N}(0, 1/2)$ falling in the range $[-x, x]$:

$$\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2}$$

1.2 Common distributions

	Type	$F_X(x)$	$f_X(x)$	$\mathbb{E}[X]$	$\mathbb{V}[X]$	$M_X(s)$
Uniform	*Discrete*	$\begin{cases} 0 & x < a \\ \frac{\lfloor x \rfloor - a + 1}{b-a} & a \le x \le b \\ 1 & x > b \end{cases}$	$\dfrac{I(a \le x \le b)}{b - a + 1}$	$\dfrac{a+b}{2}$	$\dfrac{(b-a+1)^2 - 1}{12}$	$\dfrac{e^{as} - e^{-(b+1)s}}{s(b-a)}$
Bernoulli	*Discrete*	$(1-p)^{1-x}$	$p^x\,(1-p)^{1-x}$	p	$p(1-p)$	$1 - p + pe^s$
Binomial	*Discrete*	$I_{1-p}(n-x, x+1)$	$\binom{n}{x} p^x\,(1-p)^{n-x}$	np	$np(1-p)$	$(1-p+pe^s)^n$
Multinomial	*Discrete*		$\dfrac{n!}{x_1! \dots x_k!} p_1^{x_1} \cdots p_k^{x_k} \quad \sum_{i=1}^k x_i = n$	$\begin{pmatrix} np_1 \\ \vdots \\ np_k \end{pmatrix}$	$\begin{pmatrix} np_1(1-p_1) & -np_1p_2 \\ -np_2p_1 & \ddots \end{pmatrix}$	$\left(\sum_{i=0}^k p_i e^{s_i}\right)^n$
Poisson	*Discrete*	$e^{-\lambda} \sum_{i=0}^x \dfrac{\lambda^i}{i!}$	$\dfrac{\lambda^x e^{-\lambda}}{x!}$	λ	λ	$e^{\lambda(e^s - 1)}$
Uniform	*Continuous*	$\begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & x > b \end{cases}$	$\dfrac{I(a < x < b)}{b-a}$	$\dfrac{a+b}{2}$	$\dfrac{(b-a)^2}{12}$	$\dfrac{e^{sb} - e^{sa}}{s(b-a)}$
Normal	*Continuous*	$\Phi(x) = \int_{-\infty}^x \phi(t)\,dt$	$\phi(x) = \dfrac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\dfrac{(x-\mu)^2}{2\sigma^2}\right\}$	μ	σ^2	$\exp\left\{\mu s + \dfrac{\sigma^2 s^2}{2}\right\}$
Log-Normal	*Continuous*	$\dfrac{1}{2} + \dfrac{1}{2} \operatorname{erf}\left[\dfrac{\ln x - \mu}{\sqrt{2\sigma^2}}\right]$	$\dfrac{1}{x\sqrt{2\pi\sigma^2}} \exp\left\{-\dfrac{(\ln x - \mu)^2}{2\sigma^2}\right\}$	$e^{\mu + \sigma^2/2}$	$(e^{\sigma^2} - 1)e^{2\mu + \sigma^2}$	
Multivariate Normal	*Continuous*		$(2\pi)^{-k/2} \lvert\Sigma\rvert^{-1/2} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}$	μ	Σ	$\exp\left\{\mu^T s + \dfrac{1}{2} s^T \Sigma s\right\}$
Student's t	*Continuous*	$I_x\left(\dfrac{\nu}{2}, \dfrac{\nu}{2}\right)$	$\dfrac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\,\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \dfrac{x^2}{\nu}\right)^{-(\nu+1)/2}$	$0 \quad \nu > 1$	$\begin{cases} \dfrac{\nu}{\nu - 2} & \nu > 2 \\ \infty & 1 < \nu \le 2 \end{cases}$	
Chi-square	*Continuous*	$\dfrac{1}{\Gamma(k/2)} \gamma\left(\dfrac{k}{2}, \dfrac{x}{2}\right)$	$\dfrac{1}{2^{k/2}\Gamma(k/2)} x^{k/2-1} e^{-x/2}$	k	$2k$	$(1-2s)^{-k/2} \; s < 1/2$
Exponential	*Continuous*	$1 - e^{-x/\beta}$	$\dfrac{1}{\beta} e^{-x/\beta}$	β	β^2	$\dfrac{1}{1 - \frac{s}{\beta}} \; (s < \beta)$

1.3 Hypothesis testing

- Framework for filtering implausible scientific claims
- Basic steps:
  1. State relevant null hypothesis (H_0) and alternative hypothesis (H_1)
     - Two-sided: $H_0 : \theta = \theta_0$ vs $H_1 : \theta \neq \theta_0$
     - One-sided: $H_0 : \theta \leq \theta_0$ vs $H_1 : \theta > \theta_0$
  2. Determine relevant test statistic (T) distribution, typically Student's t or normal distribution
  3. Select significance level (α, often 5% or 1%)
  4. Calculate rejection region (critical region), which contains all values of x for which $T(x)$ is greater than the critical value c: $R = \{x : T(x) > c\}$
  5. Determine whether to accept or reject H_0
- Alternatively, just calculate the p-value (probability given H_0 of getting a result at least as extreme as that which was observed). Reject the null hypothesis if $p \leq \alpha$.
- Common ranges for p-values are:
  - < 0.01: very strong evidence against H_0
  - $[0.01, 0.05]$: strong evidence against H_0
  - $[0.05, 0.10]$: weak evidence against H_0
  - > 0.1: yikes man
- Type I errors (false positives) occur when we incorrectly **reject** the null hypothesis. This is equivalent to α.
- Type II errors (false negatives) occur when we incorrectly **fail to reject** the null hypothesis.

	Retain H_0	Reject H_0
H_0 true	$\surd$	Type I Error (α)
H_1 true	Type II Error (β)	$\surd$ (power)

- *note: should probably have something on multiple comparisons here*

1.4 Bayesian inference

2 Linear algebra

2.1 Objects and notation

- Let scalar $s \in \mathbb{R}$
- Let vector $\boldsymbol{x} \in \mathbb{R}^n$. We should assume that all vectors are 'column vectors' (ie a matrix in $\mathbb{R}^{n \times 1}$)
- Let 2-d matrix $\boldsymbol{A} \in \mathbb{R}^{m \times n}$. We'll identify specific elements like this:

$$\begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \end{bmatrix}$$

  - We'll denote a whole column i of a matrix as $\boldsymbol{A}_{:,i}$ and a row j as $\boldsymbol{A}_{j,:}$
- Tensors extend beyond 2d, eg: $\mathbf{A}_{i,j,k}$

2.2 Basic matrix operations review

- The **transpose** operation mirrors the matrix across the diagonal and is denoted $\boldsymbol{A}^{\mathrm{T}}$.

$$\boldsymbol{A} = \begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \\ A_{3,1} & A_{3,2} \end{bmatrix} \Rightarrow \boldsymbol{A}^{\mathrm{T}} = \begin{bmatrix} A_{1,1} & A_{2,1} & A_{3,1} \\ A_{1,2} & A_{2,2}, & A_{3,2} \end{bmatrix}$$

- Addition of matrices is element-wise, and therefore requires them to be the same shape.

$$C_{i,j} = A_{i,j} + B_{i,j} \qquad \{A, B, C\} \in \mathbb{R}^{m \times n}$$

- The **matrix product** of $\boldsymbol{A} \in \mathbb{R}^{m \times n}$ and $\boldsymbol{B} \in \mathbb{R}^{n \times p}$ is $\boldsymbol{C} \in \mathbb{R}^{m \times p}$. Note that the number of columns in the first matrix must be equal to the number of rows in the second matrix (m). Each element in $\boldsymbol{C}_{i,j}$ can be thought of as the dot product between row i of $\boldsymbol{A}$ and column j of $\boldsymbol{B}$.

$$C_{i,j} = \sum_k A_{i,k} B_{k,j}$$

- Some matrix operation properties:
  - Distributive: $\boldsymbol{A}(\boldsymbol{B} + \boldsymbol{C}) = \boldsymbol{AB} + \boldsymbol{AC}$
  - Associative: $\boldsymbol{A}(\boldsymbol{BC}) = (\boldsymbol{AB})\boldsymbol{C}$
  - **NOT** commutative: $\boldsymbol{AB} \neq \boldsymbol{BA}$
  - Transpose product: $(\boldsymbol{AB})^{\mathrm{T}} = \boldsymbol{B}^{\mathrm{T}} \boldsymbol{A}^{\mathrm{T}}$

2.2.1 The identity matrix

- We'll define the **identity matrix** $\boldsymbol{I}_n$ as the matrix that does not change a vector $\boldsymbol{x}$ of dimension n when they are multiplied together so that $\forall \boldsymbol{x} \in \mathbb{R}^n, \quad \boldsymbol{I}_n \boldsymbol{x} = \boldsymbol{x}$. The identity matrix is just a square matrix with 1 on the diagonal and 0 elsewhere, so for $\boldsymbol{x} \in \mathbb{R}^3$:

$$\boldsymbol{I}_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

2.2.2 Matrix inversion

- The **matrix inverse** of $\boldsymbol{A}$ is denoted $\boldsymbol{A}^{-1}$ and we define it such that:

$$\boldsymbol{A}^{-1}\boldsymbol{A} = \boldsymbol{I}_n$$

- $\boldsymbol{A}$ is **invertible** if it is square ($\in \mathbb{R}^{n\times n}$) and non-singular.
  - A square matrix is **singular** $\iff$ it has a determinant of 0
  - Singular matrices have linearly dependent columns
    * The **determinant** of a matrix (usually denoted $\det(\boldsymbol{A})$ or $|\boldsymbol{A}|$) is a scalar factor that can be computed from the elements of a square matrix. For a 2×2 matrix:

$$\boldsymbol{A} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \Rightarrow |\boldsymbol{A}| = ad - bc$$

2.3 Systems of linear equations

- We can define a **system of linear equations**, $\boldsymbol{A}\boldsymbol{x} = \boldsymbol{b}$. $\boldsymbol{A}$ is a known matrix of coefficients, $\boldsymbol{b}$ is a known vector, and we're trying to solve for vector $\boldsymbol{x}$. The matrix $\boldsymbol{A} \in \mathbb{R}^{m\times n}$ describes a system of m equations with n unknowns.

- This is really the same as writing:

$$x_1 \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{m1} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{m2} \end{bmatrix} + \ldots + x_n \begin{bmatrix} a_{1n} \\ a_{2n} \\ \vdots \\ a_{mn} \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$

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- For other important properties of invertible matrices see **Wikipedia: Invertible matrix theorem**

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3 Differential equations

3.1 1st order differential equations

3.2 2nd order differential equations

3.3