MATH50013 - Probability and Statistics for JMC

Notes by Robert Weingart

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1 Introduction

1.1 Introduction to Uncertainty

1.2 Introduction to Statistics

1.2.1 Population vs. Sample

1.3 Probability AND Statistics

1.4 Statistical Modelling

2 Set Theory Review

2.1 Sets, subsets and complements

2.1.1 Sets

2.1.2 Membership, subsets, equality, complements, and singletons

2.2 Set operations

2.2.1 Venn diagrams, Unions and Intersections

2.2.2 Cartesian Products

2.3 Cardinality

3 Visual and Numerical Summaries

3.1 Visualization

3.1.1 The histogram

Definition. A **histogram** partitions the range of a sample into **bins** and shows what number of data points in each bin. Rather than frequency, the amount shown can also be relative frequency or density.

3.1.2 Empirical CDF

Definition. The **indicator function** is defined as $I(\text{false}) := 0$ and $I(\text{true}) = 1$.

Definition. The **empirical cumulative distribution function** of a sample is

$$F_n(x) := \frac{1}{n} \sum_{i=1}^{n} I(x_i \leq x)$$

3.2 Summary Statistics

3.2.1 Measures of Location

Definition. The **arithmetic mean** is $\bar{x} := \frac{1}{n} \sum_{i=1}^{n} x_i$.

Definition. The **geometric mean** is $x_G := \left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}}$.

Definition. The **harmonic mean** is $x_H := n \left(\sum_{i=1}^n \frac{1}{x_i} \right)^{-1}$

Definition. The i**th order statistic**, written $x_{(i)}$, is the ith smallest value of the sample. For non-integer values of the form $i + \alpha$ with $\alpha \in (0,1)$, we define

$$x_{(i+\alpha)} := (1-\alpha)x_{(i)} + \alpha x_{(i+1)}$$

Definition. The **median** is $x_{\left(\frac{n+1}{2}\right)}$.

Definition. The **mode** is the most frequently occurring value. If there are multiple then the sample is **multimodal**.

3.2.2 Measures of Dispersion

Definition. The **mean square** or **sample variance** is

$$s_x^2 := \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

Definition. The **root mean square** or **sample standard deviation** is

$$s_x := \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}$$

Definition. The **range** is $x_{(n)} - x_{(1)}$.

Definition. The **first quartile** is $x_{\left(\frac{1}{4}(n+1)\right)}$. The **third quartile** is $x_{\left(\frac{3}{4}(n+1)\right)}$. The **interquartile range** is the difference between the third and first quartiles.

3.2.3 Covariance and Correlation

Definition. For a sample where each data point is an (x_i, y_i) pair, the **covariance** is

$$s_{xy} := \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) = \frac{\sum_{i=1}^n x_i y_i}{n} - \bar{x}\bar{y}$$

.

Definition. For a sample as above, the **correlation** is

$$r_{xy} := \frac{s_{xy}}{s_x s_y}$$

3.2.4 Skewness

Definition. The **skewness** is $\frac{1}{n} \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{s} \right)^3$.

3.3 One more visualization: the box-and-whisker plot

Definition. A **box-and-whisker plot** shows the median, first and third quartiles, points within $\frac{3}{2} \times IQR$ of the quartiles, and any outliers.

4 Probability

4.1 The formal structure

4.1.1 σ-algebras

Definition 4.1.1. A **σ-algebra associated with** S is a set $\mathcal{F}$ of subsets of S where $S \in \mathcal{F}$, $\mathcal{F}$ is closed under complements with respect to S, and $\mathcal{F}$ is closed under countable unions.

Proposition. *$\emptyset \in \mathcal{F}$. $\mathcal{F}$ is also closed under countable intersections.*

4.1.2 Probability measure

Definition 4.1.2. A **probability measure** is a function $P : \mathcal{F} \to \mathbb{R}$ where $P(E) \geq 0$ for any E, $P(S) = 1$, and for countably many disjoint sets E_i,

$$P\left(\bigcup_{i=1}^{\infty} E_i\right) = \sum_{i=1}^{\infty} P(E_i)$$

. A triple $(S, \mathcal{F}, P)$ as previously defined is a **probability space**.

4.2 Interpretations of the probability space

4.3 Interpretation of the σ-algebra

4.3.1 The sample space (S)

Definition. The **sample space** S is the set of all possible outcomes of an experiment.

4.3.2 The event space ($\mathcal{F}$)

Definition. An **event** is a subset $E \subset S$. $\mathcal{F}$ is the set of all possible events being considered (which may not include all possible combinations of outcomes).

Definition. E_1 and E_2 are **mutually exclusive** iff $E_1 \cap E_2 = \emptyset$ i.e. they cannot both happen at once.

4.4 Interpretations of the probability measure (P)

4.4.1 Classical interpretation

Definition. In the **classical interpretiation**, S consists of finitely many equally likely **elementary events** and $P(E) = \frac{|E|}{|S|}$. For an infinite S, this can still be applied by replacing cardinality above with a different measure.

4.4.2 Frequentist interpretation

Definition. In the **frequentist interpretation**, when an experiment is repeated infinitely many times, the proportion of trials in which E occurs approaches $P(E)$.

4.4.3 Subjective interpretation

Definition. In the **subjective interpretation**, $P(E)$ is the degree of belief a person has that E occurs.

4.5 A few derivations from the axioms

Proposition. *For $E, F \in \mathcal{F}$,*

- $P(\emptyset) = 0$
- $P(E) \leq 1$
- $P(\overline{E}) = 1 - P(E)$
- $P(E \cup F) = P(E) + P(F) - P(E \cap F)$
- $P(E \cap \overline{F}) = P(E) - P(E \cap F)$
- $E \subseteq F \implies P(E) \leq P(F)$

4.6 Conditional Probability

Definition 4.6.1. For $P(F) > 0$ the **conditional probability of E given F** is

$$P(E \mid F) := \frac{P(E \cap F)}{P(F)}$$

Proposition. *For $P(F) > 0$,*

- *For any $E \in \mathcal{F}$, $P(E \mid F) \geq 0$*
- $P(F \mid F) = 1$
- *For $E_1, \ldots, E_n \in \mathcal{F}$ pairwise disjoint, $P\left(\bigcup_{i=1}^n E_i \mid F\right) = \sum_{i=1}^n P(E_i \mid F)$*

4.7 Independent Events

Definition 4.7.1. $E, F \in \mathcal{F}$ are **independent** iff $P(E \cap F) = P(E)P(F)$. $E_1, \ldots E_n$ are **independent** iff for any subset $E_{i_1}, \ldots, E_{i_l}$ we have $P\left(\bigcap_{j=1}^l E_{i_j}\right) = \prod_{j=1}^l P(E_{i_j})$.

Proposition. *E and F are independent $\implies$ E and $\overline{F}$ are independent.*

Proposition. *E and F are independent $\iff$ $P(E \mid F) = P(E)$.*

4.7.1 More Examples

4.7.2 Conditional Independence

Definition. For $E_1, E_2, F \in \mathcal{F}$, E_1 and E_2 are **conditionally independent given F** iff $P(E_1 \cap E_2 \cap F) = P(E_1 \mid F)P(E_2 \mid F)$.

4.7.3 Joint Events

Definition. When combining multiple independent experiments, a **probability table** can be used to show the probabilities of all elementary events (i.e. combinations of an elementary event in each experiment).

4.8 Bayes's Theorem

Theorem 4.9. *(Bayes's) For $E, F \in \mathcal{F}$ with $P(E) > 0$ and $P(F) > 0$,*

$$P(E \mid F) = \frac{P(F \mid E)P(E)}{P(F)}$$

Theorem 4.10. *(The Law of Total Probability) For a partition $E_1, \dots$ of S, and any $F \in \mathcal{F}$, $P(F) = \sum_i P(F \mid E_i)P(E_i)$.*

Theorem 4.11. *(Bayes's applied to a partition) For a partition $E_1, \dots$ of S with $P(E_i) > 0$ for all i and $F \in \mathcal{F}$ with $P(F) > 0$,*

$$P(E_i \mid F) = \frac{P(F \mid E_i)P(E_i)}{\sum_j P(F \mid E_j)P(E_j)}$$

4.12 More Examples

5 Discrete Random Variables

5.1 Random Variables

Definition 5.1.1. A **random variable** is a measurable mapping $X : S \to \mathbb{R}$ where $\forall x \in \mathbb{R},\ \{s \in S : X(s) \leq x\} \in \mathcal{F}$.

Definition 5.1.2. The **range** of X is $\mathbb{X}$, the image of S under X.

Definition. The **probability distribution** of X is

$$P_X(X \in B) := P(\{s \in S : X(S) \in B\})$$

where $B \subseteq \mathbb{R}$.

Notation. For brevity we write $\{X \in B\} := \{s \in S : X(s) \in B\}$ (TODO: doesn't this make P and P_X interchangeable?) and $\{a < X \leq b\} := \{X \in (a, b]\}$ etc.

5.1.1 Cumulative Distribution Function

Definition 5.1.3. The **cumulative distribution function** of X is $F_X : \mathbb{R} \to [0, 1]$ where $F_X(x) = P_X(X \leq x)$.

Definition. A function f is **right-continuous** iff for any decreasing sequence $x_i \to x$ we have $f(x_i) \to f(x)$.

Proposition. *A CDF is right-continuous.*

Proposition. *F_X is a CDF iff all the following hold:*

- F_X *is right-continuous*
- $F_X(\mathbb{R}) \subseteq [0, 1]$
- F_X *is monotonically increasing*
- $\lim_{x \to -\infty} F_X(x) = 0$
- $\lim_{x \to \infty} F_X(x) = 1$

5.2 Discrete Random Variables

Definition 5.2.1. A random variable is **discrete** iff its range is finite or countably infinite.

Definition 5.2.2. For a DRV X, the **probability mass function** $p_X : \mathbb{R} \to [0, 1]$ is $p_X(x) = P_X(X = x)$ for $x \in \mathbb{X}$ and $p_X(x) = 0$ for $x \notin \mathbb{X}$.

Definition. The **support** of X is $\{x \in \mathbb{R} : p_X(x) > 0\}$. Usually this is $\mathbb{X}$.

5.2.1 Properties of Mass Function p_X

Proposition. *An arbitrary function p_X can be a PMF for X iff $\forall x \in \mathbb{X},\ p_X(x) \geq 0$ and $\sum_{x \in \mathbb{X}} p_X(x) = 1$.*

5.2.2 Discrete Cumulative Distribution Function

Definition. The **cumulative distribution function** of a DRV X is $F_X(x) = P(X \leq x)$ (TODO: is this not what it always is?).

5.2.3 Connection between F_X and p_X

Proposition. *For $\mathbb{X} = \{x_1, \ldots\}$ with the $x_i \leq x_{i+1}$ for all i,*

$$F_X(x) = \sum_{x_i \leq x} p_X(x_i)$$

Equivalently,

$$\forall i \geq 1,\ p_X(x_i) = F_X(x_i) - F_X(x_{i-1})$$

5.2.4 Properties of Discrete CDF F_X

Proposition. *We have*

- $\lim_{x \to -\infty} F_X(x) = 0$
- $\lim_{x \to \infty} F_X(x) = 1$
- $\lim_{h \to 0^+} F_X(x + h) = F_X(x)$
- $a < b \implies F_X(a) \leq F_X(b)$
- *For $a < b$, $P(a < X \leq b) = F_X(b) - F_X(a)$*

5.3 Functions of a discrete random variable

Proposition. *For a DRV X and $g : \mathbb{X} \to \mathbb{R}$, $Y = g(X)$ is also a DRV. We have*

$$p_Y(y) = \sum_{x \in \mathbb{X}: g(x) = y} p_X(x)$$

5.4 Mean and Variance

Notation. All the functions defined in this section are of type $\mathbf{RV} \to \mathbb{R}$.

5.4.1 Expectation

Definition 5.4.1. The **expected value** or **mean** of a DRV X is

$$E_X(X) := \sum_{x \in \mathbb{X}} x p_X(x)$$

It is often abbreviated to $E(X)$. For the case $E_Y(X)$ with $Y \neq X$, see below.

Theorem 5.5. *For a* ***function of interest*** $g : \mathbb{R} \to \mathbb{R}$*, we have*

$$E_X(g(X)) = \sum_{x \in \mathbb{X}} g(x) p_X(x)$$

This is the only situation where we can have $E_X(Y)$ with $X \neq Y$.

Proposition. *E is linear.*

Definition 5.5.1. For a DRV X, the **variance** of X is

$$\operatorname{Var}_X(X) := E_X\left((X - E_X(X))^2\right) = E(X^2) - E(X)^2$$

Proposition. *For $a, b \in \mathbb{R}$, $\operatorname{Var}(aX + b) = a^2 \operatorname{Var}(X)$*

Definition 5.5.2. For a DRV X, the **standard deviation** of X is

$$\operatorname{sd}(X) := \sqrt{\operatorname{Var}_X(X)}$$

Definition 5.5.3. For a DRV X, the **skewness** of X is

$$\gamma_1 := \frac{E_X((X - E_X(X))^3)}{\operatorname{sd}_X(X)^3}$$

5.5.1 Sums of Random Variables

Proposition. *For $X_1, \ldots X_n$ (possibly with different distributions, not necessarily independent) with sum S_n, we have*

$$E(S_n) = \sum_{i=1}^{n} E(X_i)$$

and

$$E\left(\frac{S_n}{n}\right) = \frac{1}{n} \sum_{i=1}^{n} E(X_i)$$

Proposition. *For $X_1, \ldots X_n$ independent with sum S_n, we have*

$$\mathrm{Var}(S_n) = \sum_{i=1}^{n} \mathrm{Var}(X_i)$$

and

$$\mathrm{Var}\left(\frac{S_n}{n}\right) = \frac{1}{n^2} \sum_{i=1}^{n} \mathrm{Var}(X_i)$$

Proposition. *For $X_1, \ldots X_n$ independent and identically distributed with sum S_n, $E(X_i) = \mu$ and $\mathrm{Var}(X_i) = \sigma^2$, we have*

$$E\left(\frac{S_n}{n}\right) = \mu$$

and $\mathrm{Var}\left(\frac{S_n}{n}\right) = \frac{\sigma^2}{n}$

5.6 Some Important Discrete Random Variables

X	$\mathbb{X}$	$p_X(x)$	$E(X)$	$\mathrm{Var}(X)$	γ_1
$X \sim \text{Bernoulli}(p)$	$\{0, 1\}$	$p^x(1-p)^{1-x}$	p	$p(1-p)$	$\frac{1-2p}{\sqrt{p(1-p)}}*$
$X \sim \text{Binomial}(n, p)$	$\{0, \ldots n\}$	$\binom{n}{x} p^x(1-p)^{n-x}$	np	$np(1-p)$	$\frac{1-2p}{\sqrt{np(1-p)}}$
$X \sim \text{Geometric}(p)$	$\{1, 2, \ldots\}$	$p(1-p)^{x-1}$	$\frac{1}{p}$	$\frac{1-p}{p^2}$	$\frac{2-p}{\sqrt{1-p}}$
$X \sim \text{Poisson}(\lambda)$	$\{0, 1, \ldots\}$	$\frac{e^{-\lambda}\lambda^x}{x!}$	λ	λ	$\frac{1}{\sqrt{\lambda}}$
$X \sim \text{U}(\{1, \ldots, n\})$	$\{1, \ldots, n\}$	$\frac{1}{n}$	$\frac{n+1}{2}$	$\frac{n^2-1}{12}$	0

$*$: The skewness of the Bernoulli distribution is not given in the official notes.

5.6.1 Bernoulli Distribution

$X \sim \text{Bernoulli}(p)$ chooses between 1 and 0 where $P(X = 1) = p$.

5.6.2 Binomial Distribution

$X \sim \text{Binomial}(n, p)$ is the total number of successes after n Bernoulli trials with probability p.

5.6.3 Geometric Distribution

$X \sim \text{Geometric}(p)$ is the number of Bernoulli trials with probability p it will take to have the first success.

5.6.4 Poisson Distribution

$X \sim \text{Poisson}(\lambda)$ is the number of occurrences of an event that occurs at a rate of λ.

5.6.5 Discrete Uniform Distribution

$X \sim \text{U}(\{1, \ldots, n\})$ is a random value out of $\{1, \ldots n\}$.

6 Continuous Random Variables

Definition 6.0.1. A random variable X is absolutely **continuous** iff there exists a measurable non-negative function $f_X : \mathbb{R} \to \mathbb{R}$ (the **probability density function**) where

$$\forall B \subseteq \mathbb{R},\ P(X \in B) = \int_{x \in B} f_X(x)dx$$

6.0.1 Continuous Cumulative Distribution Function

Definition 6.0.2. The **cumulative distribution function** of a CRV X is $F_X(x) = P(X \leq x)$ (as for any RV).

Proposition. *For a CRV X, $F_X(x) = \int_{-\infty}^{x} f_X(x')dx'$*

6.0.2 Properties of Continuous F_X and f_X

Proposition. *For a CRV X,*

- $\lim_{x\to-\infty} F_X(x) = 0$
- $\lim_{x\to\infty} F_X(x) = 1$
- *If F_X is differentiable at x then $f_X(x) = F'_X(x)$*
- $\forall a \in \mathbb{R},\ P(X = a) = 0$
- *For $a < b$, $P(a < X \leq b) = F_X(b) - F_X(a)$*
- *$f_X(X)$ is not a probability, so we do not require $f_X(x) \leq 1$*
- *X is uniquely defined by f_X*

Proposition. *An arbitrary function f_X is a PDF for a CRV iff $\forall x \in \mathbb{R},\ f_X(x) \geq 0$ and $\int_{-\infty}^{\infty} f_X(x)dx = 1$ (f_X is **normalised**).*

6.0.3 Transformations

Proposition. *For $Y = g(X)$ with g strictly monotonically increasing, we have*

$$F_Y(y) = F_X(g^{-1}(y))$$

and

$$f_Y(y) = f_X\left(g^{-1}(y)\right) g^{-1\prime}(y)$$

Proposition. *For $Y = g(X)$ with g strictly monotonically decreasing, we have*

$$F_Y(y) = 1 - F_X(g^{-1}(y))$$

and

$$f_Y(y) = -f_X\left(g^{-1}(y)\right) g^{-1\prime}(y)$$

6.1 Mean, Variance and Quantiles

6.1.1 Expectation

Definition 6.1.1. The **mean** or **expectation** of a CRV X is

$$E(X) := \int_{-\infty}^{\infty} x f_X(x) dx$$

Definition. For any measurable **function of interest** $g : \mathbb{R} \to \mathbb{R}$ we have

$$E(g(X)) := \int_{-\infty}^{\infty} g(x) f_X(x) dx$$

Proposition. *E is linear.*

6.1.2 Variance

Definition 6.1.2. The **variance** of a CRV X is

$$\mathrm{Var}_X(X) = E((X - E(X))^2) = E(X^2) - E(X)^2$$

Proposition. *For $a, b \in \mathbb{R}$,* $\mathrm{Var}(aX + b) = a^2 \mathrm{Var}(X)$

6.1.3 Quantiles

Definition 6.1.3. For $\alpha \in [0, 1]$, we α**-quantile** of a CRV X is

$$Q_X(\alpha) := F_X^{-1}(\alpha)$$

so that $P(X \leq Q_X(\alpha)) = \alpha$.

6.2 Some Important Continuous Random Variables

X	$\mathbb{X}$	$f_X(x)$	$F_X(x)$	$E(X)$	$\mathrm{Var}(X)$
$X \sim \mathrm{U}(a, b)$	(a, b)	$\begin{cases} \frac{1}{b-a} & a < x < b \\ 0 & \text{otherwise} \end{cases}$	$\begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & x \geq b \end{cases}$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$
$X \sim \mathrm{Exp}(\lambda)$	$[0, \infty)$	$\lambda e^{-\lambda x}$	$1 - e^{-\lambda x}$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$
$X \sim \mathbb{N}(\mu, \sigma^2)$	$\mathbb{R}$	$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	$\frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{x} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt$	μ	σ^2

6.2.1 Continuous Uniform Distribution

$X \sim \mathrm{U}(a, b)$ or $X \sim \mathrm{Uniform}(a, b)$ is uniformly distributed on the interval (a, b) and 0 elsewhere.

Definition. Tht **standard uniform** is $\mathrm{Uniform}(0, 1)$.

Proposition. $X \sim \mathrm{Uniform}(0, 1) \implies (a + (b - a)X) \sim \mathrm{Uniform}(a, b)$.

6.2.2 Exponential Distribution

$X \sim \text{Exp}(\lambda)$ is the time until an event occurring at rate λ occurs.

Proposition. *$X \sim \text{Exp}(\lambda)$ exhibits the **Lack of Memory Property**:*

$$\forall x, t > 0,\ P(X > t + x \mid X > t) = P(X > x)$$

Proposition. *If the number of events occurring in an interval of size x is $N_x \sim \text{Poisson}(\lambda x)$ then the separation between two events is $X \sim \text{Exp}(\lambda)$.*

6.2.3 Normal (Gaussian) Distribution

$X \sim N(\mu, \sigma^2)$ has no obvious interpretation.

Definition. $X \sim N(0, 1)$ is the **standard normal distribution** or **unit normal distribution**. It has the PDF

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

and the CDF

$$\mathbf{\Phi}(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp\left(-\frac{t^2}{2}\right) dt$$

Proposition. $X \sim N(0, 1) \implies (\sigma X + \mu) \sim N(\mu, \sigma^2)$

Theorem 6.3. *(Central Limit Theorem) For $X_1, \ldots, X_n$ independent and identically distributed with mean μ and variance σ^2,*

$$\lim_{n\to\infty} \frac{\sum_{i=1}^{n} X_i - n\mu}{\sqrt{n}\sigma} \sim N(0, 1)$$

6.4 Further examples

7 Joint Random Variables

Definition 7.0.1. For RVs X and Y with the same sample space, the **joint probability distribution** is $P_{XY}(B_X, B_Y) := P(X^{-1}(B_X) \cap Y^{-1}(B_Y))$ where $B_X, B_Y \subseteq \mathbb{R}$.

7.0.1 Joint Cumulative Distribution Function

Definition 7.0.2. The **joint cumulative distribution function** is $F_{xy}(x, y) := P_{XY}(X \leq x, Y \leq y)$.

Proposition. *$F_X(x) = F_{XY}(x, \infty)$ and $F_Y(y) = F_{XY}(\infty, y)$.*

7.0.2 Properties of Joint CDF F_{XY}

Proposition. *And arbitrary function F_{XY} is a valid joint CDF iff the following hold:*

- $\forall x, y \in \mathbb{R},\ F_{XY}(x, y) \in [0, 1]$
- $\forall x_1, x_2, y \in \mathbb{R},\ x_1 < x_2 \implies F_{XY}(x_1, y) \leq F_{XY}(x_2, y)$
- $\forall x, y_1, y_2 \in \mathbb{R},\ y_1 < y_2 \implies F_{XY}(x, y_1) \leq F_{XY}(x, y_2)$
- $\forall x, y \in \mathbb{R},\ F_{XY}(x, -\infty) = F_{XY}(-\infty, y) = 0$
- $F_{XY}(\infty, \infty) = 1$

7.0.3 Joint Probability Mass Functions

Definition 7.0.3. For DRVs X, Y, the **joint probability mass function** is $p_{XY}(x,y) := P_{XY}(X = x, Y = y)$.

Proposition. $p_X(x) = \sum_{y \in \mathbb{Y}} p_{XY}(x,y)$ *and* $p_Y(y) = \sum_{x \in \mathbb{X}} p_{XY}(x,y)$

Proposition. *An arbitrary function p_{XY} is a valid joint PMF iff $\forall x, y \in \mathbb{R}, p_{XY}(x,y) \in [0,1]$ and $\sum_{y \in \mathbb{Y}} \sum_{x \in \mathbb{X}} p_{XY}(x,y) = 1$.*

7.0.4 Joint Probability Density Functions

Definition. CRVs X and Y are **jointly continuous** iff $\exists f_{XY} : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ where

$$\forall B_{XY} \subseteq \mathbb{R} \times \mathbb{R},\ P_{XY}(B_{XY}) = \int_{(x,y) \in B_{XY}} f_{XY}(x,y) dx dy$$

Then f_{XY} is the **joint probability density function** of X and Y.

Proposition. *For jointly continuous CRVs, we have*

$$F_{XY}(x,y) = \int_{t=-\infty}^{y} \int_{s=-\infty}^{x} f_{XY}(s,t) ds dt$$

Definition 7.0.4. (Not actually a definition) The joint PDF is

$$f_{XY} = \frac{\partial^2}{\partial x \partial y} F_{XY}(x,y)$$

Proposition. $f_X(x) = \int_{y=-\infty}^{\infty} f_{XY}(x,y) dy$ *and* $f_Y(y) = \int_{x=-\infty}^{\infty} f_{XY}(x,y) dx$

Proposition. *An arbitrary function f_{XY} is a valid joint PDF iff $\forall x, y \in \mathbb{R},\ f_{XY}(x,y) \geq 0$ and $\int_{y=-\infty}^{\infty} \int_{x=-\infty}^{\infty} f_{XY}(x,y) dx dy = 1$.*

7.1 Independence, Conditional Probability, Expectation

7.1.1 Independence and conditional probability

Definition. RVs X and Y are **independent** iff $\forall B_X, B_Y \subseteq \mathbb{R},\ P_{XY}(B_X, B_Y) = P_X(B_X) P_Y(B_Y)$.

Definition 7.1.1. CRVs X and Y are **independent** iff $\forall x, y \in \mathbb{R},\ f_{XY}(x,y) = f_X(x) f_Y(y)$.

Definition 7.1.2. For RVs X and Y, the **conditional probability distribution** is

$$P_{Y|X}(B_Y \mid B_X) := \frac{P_{XY}(B_X, B_Y)}{P_X(B_X)}$$

Proposition. *X and Y are independent $\iff \forall B_X, B_Y \subseteq \mathbb{R},\ P_{Y|X}(B_Y \mid B_X) = P_Y(B_Y)$.*

Definition 7.1.3. For CRVs X and Y, the **conditional probability density function** is

$$f_{Y|X}(y \mid x) := \frac{f_{XY}(x,y)}{f_X(x)}$$

Proposition. *X and Y are independent $\iff \forall x, y \in \mathbb{R},\ f_{Y|X}(y \mid x) = f_Y(y)$.*

7.1.2 Expectation

Definition 7.1.4. For DRVs X and Y:

$$E_{XY}(g(X,Y)) := \sum_{y\in\mathbb{Y}}\sum_{x\in\mathbb{X}} g(x,y)p_{XY}(x,y)$$

Definition 7.1.5. For CRVs X and Y:

$$E_{XY}(g(X,Y)) := \int_{y=-\infty}^{\infty}\int_{x=-\infty}^{\infty} g(x,y)f_{XY}(x,y)dxdy$$

Proposition. *Both versions of E are linear.*

Proposition. *$E_{XY}(g_1(X)+g_2(Y)) = E_X(g_1(X)) + E_Y(g_2(y))$. If X and Y are independent then $E_{XY}(g_1(x)g_2(y)) = E_X(g_1(x))E_Y(g_2(y))$.*

7.1.3 Conditional Expectiation

Definition 7.1.6. The **conditional expectation** of Y given $X = x$ is

$$E_{Y|X}(Y \mid X = x) := \sum_{y\in\mathbb{Y}} yp(y \mid x)$$

or

$$E_{Y|X}(Y \mid X = x) := \int_{y=-\infty}^{\infty} yf(y \mid x)dy$$

Definition. The **covariance** of X and Y is

$$\sigma_{XY} = \operatorname{Cov}(X,Y) := E_{XY}((X - E_X(X))(Y - E_Y(Y)))$$

Definition 7.1.7. The **correlation** of X and Y is

$$\rho_{XY} = \operatorname{Cor}(X,Y) := \frac{\sigma_{XY}}{\sigma_X\sigma_Y}$$

Proposition. *X and Y are independent $\implies \sigma_{XY} = \rho_{XY} = 0$.*

7.2 Examples

7.3 Multivariate Transformations

7.3.1 Convolutions (sums of random variables)

Theorem 7.4. *(Convolution Theorem) For independent RVs X and Y and $Z = X + Y$,*

$$p_Z(z) = \sum_{x\in\mathbb{X}} p_X(x)p_Y(z-x)$$

or

$$p_Z(z) = \int_{\mathbb{R}} f_X(x)f_Y(z-x)dx$$

Theorem 7.5. *If $X \sim N(\mu_X, \sigma_X^2)$ and $Y \sim N(\mu_Y, \sigma_Y^2)$ are independent then $X + Y \sim N(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2)$.*

7.5.1 General Bivariate Transformations

Proposition. *For DRVs X and Y with $U = g_1(X,Y)$ and $V = g_2(X,Y)$,*

$$p_{UV}(u,v) = \sum_{(x,y)\in A} p_{XY}(x,y)$$

where

$$A := \{(x,y) : (g_1(x,y), g_2(x,y)) = (u,v)\}$$

Proposition. *For CRVs X and Y with $U = g_1(X,Y)$ and $V = g_2(X,Y)$, and given $u := g_1(x,y)$ and $v := g_2(x,y)$,*

$$f_{UV}(u,v) = f_{XY}(x,y)\left|\frac{\partial x}{\partial u}\frac{\partial y}{\partial v} - \frac{\partial x}{\partial v}\frac{\partial y}{\partial u}\right|$$

where

$$A := \{(x,y) : (g_1(x,y), g_2(x,y)) = (u,v)\}$$

Definition. The **Gamma function** is $\Gamma(\alpha) = \int_0^\infty t^{\alpha-1}e^{-t}dt$, defined for $\alpha \in (0,\infty)$.

Proposition. *We have:*

- $\forall \alpha > 1,\ \Gamma(\alpha) = (\alpha-1)\Gamma(\alpha)$
- $\Gamma(1) = 1$
- $\forall n \in \mathbb{N},\ \Gamma(n) = (n-1)!$
- $\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}$

Definition. The **Gamma distribution** $X \sim \text{Gamma}(\alpha,\beta)$ with $\alpha,\beta > 0$ has the following properties:

- $f_X(x) := \frac{\beta^\alpha}{\Gamma(\alpha)}x^{\alpha-1}e^{-\beta x}$
- $\mathbb{X} = (0,\infty)$
- $E(X) = \frac{\alpha}{\beta}$
- $\text{Var}(X) = \frac{\alpha}{\beta^2}$

Definition. The **Beta function** is $B(\alpha,\beta) := \int_0^1 x^{\alpha-1}(1-x)^{\beta-1}dx = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$.

Definition. The **Beta distribution** $X \sim \text{Beta}(\alpha,\beta)$ has PDF $f_X(x) := \frac{1}{B(\alpha,\beta)}x^{\alpha-1}(1-x)^{\beta-1}$ and $\mathbb{X} = (0,1)$

Theorem 7.6. *If $X \sim \text{Gamma}(\lambda,\beta)$ and $Y \sim \text{Gamma}(\xi,\beta)$ are independent then $X + Y \sim \text{Gamma}(\lambda+\xi,\beta)$*

8 Estimation

Notation. In this section we consider random variables which are known to have a distribution depending on an unknown parameter (so that $X \sim DIST(\theta)$ where $DIST$ is some distribution). Θ is the set of all possible values of θ. For properties of X which depend only on the distribution (essentially all of them), we use the notation $\mid \theta$ to indicate this dependence. For instance, we write $P_{X|\theta}(x \mid \theta)$ to mean whatever $P(X)$ would be if the missing parameter of the distribution were θ. Note that this is entirely unrelated to all previous uses of the symbol | in this document.

8.1 Estimators

Notation. Throughout this section, we consider a set of n independent and identically distributed random variables $\underline{X} = (X_1, \ldots, X_n)$.

Definition 8.1.1. A **statistic** is a random variable T which depends on $\underline{X}$. The corresponding lowercase letter $t : \mathbb{R}^n \to \mathbb{R}$ is used to represent a realised value of T.

Definition. An **estimator** is a statistic used to compute unknown parameters θ of the distribution of $\underline{X}$. Its realised values are called **estimates**.

8.1.1 Point estimates

Definition. A **point estimate** is an estimator which estimates a single unknown parameter θ. The official notes call this an estimate even though, according to the previous definition, it is an estimator rather than an estimate. The distribution of the point estimate, $P_{T|\theta}$, will depend on the same unknown parameter θ.

8.1.2 Bias, Efficiency, Consistency

Definition. The **bias** of an estimator T for a parameter θ is

$$\operatorname{bias}(T, \theta) := E(T - \theta \mid \theta) = E(T \mid \theta) - \theta$$

Definition. T is **unbiased** $\iff \forall \theta \in \Theta,\ \operatorname{bias}(T, \theta) = 0$.

Proposition. *For any distribution, the mean of a sample is an unbiased estimator for the mean of the distribution.*

Definition. The **bias-corrected sample variance** of $\underline{X}$ is

$$S_{n-1}^2 := \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \overline{X})^2$$

This is an unbiased estimator for the variance of any distribution.

Definition. Given two unbiased estimators for the same parameter, $\widehat{\Theta}$ and $\widehat{\Psi}$, $\widehat{\Theta}$ is **more efficient** than $\widehat{\Psi}$ iff

$$\left(\forall \theta \in \Theta,\ \operatorname{Var}\left(\widehat{\Theta} \mid \theta\right) \leq \operatorname{Var}\left(\widehat{\Psi} \mid \theta\right)\right) \wedge \left(\exists \theta \in \Theta : \operatorname{Var}\left(\widehat{\Theta} \mid \theta\right) < \operatorname{Var}\left(\widehat{\Psi} \mid \theta\right)\right)$$

$\widehat{\Theta}$ is **efficient** iff it is more efficient than all other estimators.

Definition. $\widehat{\Theta}$ is **consistent** iff it converges in probability to θ, that is to say

$$\forall \theta \in \Theta,\ \forall \varepsilon > 0,\ \lim_{n\to\infty} P_{\widehat{\Theta}|\theta}\left(\left|\left(\widehat{\Theta} \mid \theta\right) - \theta\right| > \varepsilon\right) = 0$$

Proposition. *$\widehat{\Theta}$ is unbiased $\implies$ $\widehat{\Theta}$ is consistent.*

8.1.3 Maximum Likelihood Estimation

Definition. The **likelihood function** is

$$L(\theta \mid \underline{x}) := \prod_{i=1}^{n} p_{X|\theta}(x_i)$$

or

$$L(\theta \mid \underline{x}) := \prod_{i=1}^{n} f_{X|\theta}(x_i)$$

where $\underline{x} = (x_1, \ldots, x_n)$ is a sample of $\underline{X}$. Note that this is yet another different usage of $|$.

Definition. The **maximum likelihood estimate** is $\widehat{\theta}_{MLE} := \operatorname{argmax}_{\theta\in\Theta} L(\theta \mid \underline{x})$.

Definition. The **log-likelihood function** is $\ell(\theta \mid \underline{x}) := \log L(\theta \mid \underline{x})$

Definition. The **maximum likelihood estimator** is defined like the maximum likelihood estimate and uses the same notation, but uses the RVs $\underline{X}$ instead of a specific sample $\underline{x}$.

8.2 Confidence Intervals

8.2.1 Normal Distribution with Known Variance

Definition. The $(1-\alpha)$ **confidence interval** for the mean μ given a known variance σ^2 is

$$\left[\overline{x} - z_{1-\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}}, \overline{x} + z_{1-\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}}\right]$$

where z_α is the α-quantile of $N(0,1)$. Then a sample of size n with this distribution should have $\overline{x}$ within this range $1-\alpha$ of the time.

8.2.2 Normal Distribution with Unknown Variance

Proposition. *If μ and σ^2 are both unknown then*

$$\frac{\overline{X} - \mu}{S_{n-1}/\mu} \sim \text{Student}(n-1)$$

where

$$S_{n-1} = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n-1}}$$

Then the $(1-\alpha)$ confidence level for μ is

$$\left[\overline{x} - t_{n-1,1-\frac{\alpha}{2}}\frac{s_{n-1}}{\sqrt{n}}, \overline{x} + t_{n-1,1-\frac{\alpha}{2}}\frac{s_{n-1}}{\sqrt{n}}\right]$$

where $t_{\nu,\alpha}$ is the α-quantile of Student(ν).

8.2.3 Another way to view the confidence interval: Neyman construction

Definition. The **Neyman construction** is a graph with values of the estimator along the horizontal axis and values of the parameter along the vertical axis. For each value of the parameter, indicate a belt of values in which the estimator is expected to lie for that value. Draw a vertical line at the observed estimate. Then the range of parameter values whos belts intersect this lane is the confidence interval.

9 Hypothesis Testing

Definition. To test an unknown parameter $\theta \in \Theta$, partition Θ into Θ_0 and Θ_1. The **null hypothesis** is $H_0 : \theta \in \Theta_0$ (usually chosen to represent the absence of a finding - no correlation, the change has no effect on the data etc). The **alternative hypothesis** is $H_1 : \theta \in \Theta_1$. From now on, we use the $|$ notation from the last chapter with H_0 and H_1 instead of individual values of θ.

Definition. To perform a hypothesis test, choose a **rejection region** $R \subseteq \mathbb{R}$ such that $P(T \in R \mid H_0) = \alpha$ is low. This α is the **significance level** of the test. Given an observed value $t(\underline{x})$, reject the null hypothesis iff $t \in R$. The p**-value** of a test is the significance level that lies on the boundary between rejecting and not rejecting the null hypothesis.

9.0.1 Error Rates and Power of a Test

Definition. Type I error occurs when H_0 is rejected, but is actually true. The probability of this is α by definition. **Type II error** occurs when H_0 is not rejected, but actually H_1 is true. Its probability is $\beta := P(T \notin R \mid \theta \in \Theta_1)$.

Definition 9.0.1. The **power** of a hypothesis test is $1 - \beta = P(T \in R \mid \theta \in \Theta_1)$.

Definition. A **simple hypothesis** or **point hypothesis** has the form $\theta = \theta_0$. A **composite hypothesis** has the form $\theta < \theta_0$ or $\theta > \theta_0$. A **two-sided test** tests a simple hypothesis against its negation. A **one-sided test** tests a composite hypothesis against its negation (usually the case $\theta = \theta_0$ is included in H_0).

Dist(s)	H_0	Test Stat	R
$N(\mu, \sigma^2)$	$\mu = \mu_0$	$\frac{\overline{X}-\mu_0}{\sigma/\sqrt{n}}$	$\{z \mid \|z\| > z_{1-\frac{\alpha}{2}}\}$
$N(\mu, \sigma^2)^\star$	$\mu = \mu_0$	$\frac{\overline{X}-\mu}{S_{n-1}/\mu}$	$\{t \mid \|t\| > t_{n-1,1-\frac{\alpha}{2}}\}$
$N(\mu_X, \sigma_X^2)$, $N(\mu_Y, \sigma_Y^2)$	$\mu_X = \mu_Y$	$\frac{\overline{X}-\overline{Y}}{\sqrt{\frac{\sigma_X^2}{n_1}+\frac{\sigma_Y^2}{n_2}}}$	$\{z \mid \|z\| > z_{1-\frac{\alpha}{2}}\}$
$N(\mu_X, \sigma^2)$, $N(\mu_Y, \sigma^2)^\star$	$\mu_X = \mu_Y$	$\frac{\overline{X}-\overline{Y}}{S_{n_1+n_2-2}\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}}$	$\{t \mid \|t\| > t_{n_1+n_2-2,1-\frac{\alpha}{2}}\}$
$\theta \in \mathbb{R}^m, \|\mathbb{X}\| = k$	$\theta = \theta_0$	$\sum_{i=1}^{k} \frac{(O_i-E_i)^2}{E_i}^\dagger$	$\{x^2 \mid x^2 > \chi^2_{k-m-1,1-\alpha}\}$
$\|\mathbb{X}\| = k$, $\|\mathbb{Y}\| = \ell$	X and Y independent	$\sum_{j=1}^{\ell}\sum_{i=1}^{k} \frac{(O_{ij}-E_{ij})^2}{E_{ij}}^\ddagger$	$\{x^2 \mid x^2 > \chi^2_{(k-1)(\ell-1),1-\alpha}\}$

$\star$: σ^2 is not known.
$\dagger$: $O_i = (\text{freq}(\underline{X}, x_i), E_i = np_X(x_i)$
$\ddagger$: $O_{ij} = \text{freq}\left(\underline{(X,Y)}, (x_i, y_j)\right), E_{ij} = \text{freq}(\underline{X}, x_i)\,\text{freq}(\underline{Y}, y_j)$

9.1 Testing for a population mean

9.1.1 Normal Distribution with Known Variance

Proposition. *For n variables i.i.d with distribution $N(\mu, \sigma^2)$ with μ unknown and σ^2 known and a hypothesis $H_0 : \mu = \mu_0$, use the test statistic*

$$Z = \frac{\overline{X} - \mu_0}{\sigma/\sqrt{n}} \sim \mathbf{\Phi}$$

and the rejection region $R = (-\infty, -z_{1-\frac{\alpha}{2}}) \cup (z_{1-\frac{\alpha}{2}}, \infty) = \{z \mid |z| > z_{1-\frac{\alpha}{2}}\}$ has significance level α. The p-value is $2(1 - \mathbf{\Phi}(|z|))$.

9.1.2 Normal Distribution with Unknown Variance

Proposition. *If σ^2 is also unknown then we use*

$$T = \frac{\overline{X} - \mu}{S_{n-1}/\mu} \sim \text{Student}(n-1)$$

and the rejection region $R = (-\infty, -t_{n-1,1-\frac{\alpha}{2}}) \cup (t_{n-1,1-\frac{\alpha}{2}}, \infty) = \{t \mid |t| > t_{n-1,1-\frac{\alpha}{2}}\}$.

Proposition. *$\chi^2(k)$ has mean k and variance $2k$.*

9.2 Testing for differences in population means

9.2.1 Two Sample Problems

Notation. In this section we have a sample $\underline{X} = (X_1, \ldots, X_{n_1})$ i. i. d with distribution P_X and another sample $\underline{Y} = (Y_1, \ldots, Y_{n_2})$ i. i. d with distribution P_Y with μ_X and μ_Y unknown and the samples independent from each other. In the special case where $\underline{X}$ and $\underline{Y}$ are **paired**, $n_1 = n_2$ and each pair (X_i, Y_i) is possibly dependent.

9.2.2 Normal Distributions with Known Variances

Proposition. *If $P_X = N(\mu_X, \sigma_X^2)$ with μ_X unknown and $P_Y = N(\mu_Y, \sigma_Y^2)$ with μ_Y unknown, we can test $H_0 : \mu_X = \mu_Y$ using the test statistic*

$$Z = \frac{\overline{X} - \overline{Y}}{\sqrt{\frac{\sigma_X^2}{n_1} + \frac{\sigma_Y^2}{n_2}}} \sim \mathbf{\Phi}$$

and the rejection region $R = \{z \mid |z| > z_{1-\frac{\alpha}{2}}\}$.

9.2.3 Normal Distributions with Unknown Variances

Definition. If $\sigma_X^2 = \sigma_Y^2 = \sigma^2$ unknown, the **bias-corrected pooled sample variance** is

$$\frac{\sum_{i=1}^{n_1}(X_i - \overline{X})^2 + \sum_{i=1}^{n_2}(Y_i - \overline{Y})^2}{n_1 + n_2 - 2}$$

This is an unbiased estimator for σ^2.

Proposition. *In the situation above, test $H_0 : \mu_X = \mu_Y$ using*

$$T = \frac{\overline{X} - \overline{Y}}{S_{n_1+n_2-2}\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim \text{Student}(n_1 + n_2 - 2)$$

and $R = \{t \mid |t| > t_{n_1+n_2-2,1-\frac{\alpha}{2}}\}$

9.3 Goodness of Fit

9.3.1 Count Data and Chi-Square Tests

Notation. In this section, we have $\underline{X}$ with range $\{x_1, \ldots x_k\}$ and pmf $p_X(j) = P(X = x_j \mid \theta)$ where $\theta \in \mathbb{R}^m$ (there are m unknown parameters which we express as an m-vector). We write $p_j \equiv p_X(j)$ for brevity. Consider the observed frequencies $\underline{O} = (O_1, \ldots, O_k)$ with $O_j = |\{i \in \{1, \ldots, n\} \mid X_i = x_j\}|$ We will not be referring to $\underline{X}$ directly after this, so just ignore the fact that x_i can we can't express extracting values from a sample $\underline{x}$ right now because the notation is the same as the values in the range. For a hypothesis $H_0 : \theta = \theta_0$, we can compute the expected probabilites $\{p_1, \ldots, p_k\}$ and thus the expected frequencies $\underline{E} = (E_1, \ldots E_k)$ with $E_j = np_j$.

Proposition. *In this situation, test $H_0 : \theta = \theta^n$ using the* ***chi-squared statistic***

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \sim \chi^2_{k-m-1}$$

and $R = \{x^2 \mid x^2 > \chi^2_{k-m-1,1-\alpha}\}$

9.3.2 Proportions

9.3.3 Model Checking

9.3.4 Independence

Proposition. *For two DRVs X and Y with ranges $\{x_1, \ldots x_k\}$ and $\{y_1, \ldots, y_\ell\}$, test $H_0 : X$ and Y are independent by creating a* ***contingency table****:*

$$\begin{array}{cccccc} & y_1 & y_2 & \cdots & y_\ell & \\ x_1 & n_{11} & n_{12} & \cdots & n_{1\ell} & n_{1\bullet} \\ x_2 & n_{21} & n_{22} & \cdots & n_{2\ell} & n_{2\bullet} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \cdots \\ x_k & n_{k1} & n_{k2} & \cdots & n_{k\ell} & n_{k\bullet} \\ & n_{\bullet 1} & n_{\bullet 2} & \cdots & n_{\bullet \ell} & n \end{array}$$

where the n_{ij} are the observed frequencies and the numbers at the end of each row and column are the sums of those frequencies. Let the expected frequency at each i, j be $\frac{n_{i\bullet} n_{\bullet j}}{n}$ and perform a chi-squared test on these observations and expectations. Use the rejection region $\{x^2 \mid x^2 > \chi^2_{(k-1)(\ell-1),1-\alpha}\}$.

9.3.5 The χ^2 distribution and degrees of freedom

Proposition. *The parameter of the χ^2 distribution represents the size of the sample minus the number of ways in which the expectations depend on the sample.*

10 Convergence Concepts

10.1 Convergence in Distribution and the Central Limit Theorem

10.1.1 Statement of the Central Limit Theorem

Theorem 10.2. *(Central Limit Theorem) Given a countable sequence of i.i.d. RVs $X_1, X_2, \ldots$ with expected value μ and variance $\sigma^2 < \infty$ (we assume an MGF exists - see definition 10.2.3), let $\overline{X}_n := \frac{1}{n} \sum_{i=1}^n X_i$ and let $G_n(x)$ be the CDF of $\frac{\overline{X}_n - \mu}{\sigma/\sqrt{n}}$. Then*

$$\lim_{n\to\infty} G_n(x) := \mathbf{\Phi}(x)$$

Alternatively, in the notation defined below,

$$\frac{\overline{X}_n - \mu}{\sigma/\sqrt{n}} \xrightarrow{\mathcal{D}} N(0, 1)$$

10.2.1 Convergence in Distribution

Definition 10.2.1. The sequence $X_1, X_2, \ldots$ **converges in distribution** to X iff $\lim_{n\to\infty} F_{X_n} = F_X(x)$ whenever F_X is continuous. We then write $X_n \xrightarrow{\mathcal{D}} X$.

Definition 10.2.2. When $X_n \xrightarrow{\mathcal{D}} X$ and $P(X = c) = 1$ for some c, the limiting distribution of X_n is **degenerate at** c. We write $X_n \xrightarrow{\mathcal{D}} c$.

10.2.2 Moment Generating Functions

Definition 10.2.3. The **moment generating function** of X is $M_X(t) := E(e^{tX})$ when it exists in some neighbourhood of zero.

Theorem 10.3. *If X has an MGF then $E(X^n) = M_X^{(n)}(0)$.*

Proposition. *Properties of the MGF:*

1. $M_{aX+b}(t) = e^{bt} M_X(at)$
2. *For $X_1, \ldots, X_n$ independent and $Z = \sum_{i=1}^n X_i$, $M_Z(t) = \prod_{i=1}^n M_{X_i}(t)$*
3. *For $X_1, \ldots, X_n$ i.i.d., $M_{\overline{X}}(t) = (M_X(t/n))^n$*
4. *$M_X(t)$ exists near zero $\implies \forall r \in \mathbb{N},\ M_X^{(r)}(t)$ exists near zero and $E(|X|^r) < \infty$.*
5. *(Characterisation) If $M_X(t)$ and $M_Y(t)$ exist near zero with $M_X(t) = M_Y(t)$ then $F_X = F_Y$*
6. *(Convergence of MGFs) For a countable sequence $X_1, X_2, \ldots$ with $\lim_{i\to\infty} M_{X_i}(t) = M_X(t)$ in a neighbourhood of zero for some MGF M_X, there is a unique CDF F_X such that $X_n \xrightarrow{\mathcal{D}} X$.*

10.3.1 Proof of the Central Limit Theorem

Theorem 10.4. *The CLT holds when the variables in the sequence have an MGF.*

10.5 Convergence in Probability and Inequalities

10.5.1 Convergence in Probability

Definition 10.5.1. A sequence $X_1, X_2, \ldots$ **converges in probability** to X iff

$$\forall \epsilon > 0,\ \lim_{n\to\infty} P(|X_n - X| < \epsilon) = 1$$

We then write $X_n \xrightarrow{\mathcal{P}} X$.

Theorem 10.6. $X_n \xrightarrow{\mathcal{P}} X \implies X_n \xrightarrow{\mathcal{D}} X$.

10.6.1 The Law of Large Numbers and Chebyshev's Inequality

Theorem 10.7. *(Weak Law of Large Numbers) For a sequence $X_1, X_2, \ldots$ i. i. d. with mean μ and variance $\sigma^2 < \infty$, $\overline{X}_n \xrightarrow{\mathcal{P}} \mu$ (where $\overline{X}_n := \frac{1}{n}\sum_{i=1}^n X_i$).*

Theorem 10.8. *(Chebyshev's Inequality) Given an RV X and $g : \mathbb{R} \to \mathbb{R}^+$,*

$$\forall r > 0,\ P(g(X) \geq r) \leq \frac{E(g(X))}{r}$$

10.8.1 Jensen's Inequality

Theorem 10.9. *(Jensen's Inequality)*

- $g'' \geq 0$ *everywhere (g is convex)* $\implies E(g(X)) \geq g(E(X))$.
- $g'' \leq 0$ *everywhere (g is concave)* $\implies E(g(X)) \leq g(E(X))$.
- g *is linear* $\implies E(g(X)) = g(E(X))$

(The properties need to hold only on the support of X)