

# Statistical Computing

Compiled Revision Notes

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# Week 1: Fundamental Concepts & Discrete Distributions

## Definitions

- **Population:** The complete collection of all individuals or items under consideration in a statistical study.
- **Sample:** A subset of the population from which information is actually collected.

## Parameters vs Statistics

- **Population Parameters** (constants, usually unknown):
    - $\mu \rightarrow$  population mean
    - $\sigma \rightarrow$  population standard deviation
  - **Sample Statistics** (random variables):
    - $\bar{x} \rightarrow$  sample mean
    - $s \rightarrow$  sample standard deviation
- 

## Measures of Centrality and Variation

### Measures of Centrality (Centre)

1. **Mean ( $\bar{x}$ ):** Arithmetic average

$$\bar{x} = \frac{\sum x_i}{n}$$

2. **Median:** Middle value when data is ordered.
3. **Mode:** Most frequently occurring value.

### Measures of Variation (Spread)

- **Range:** Max – Min. Very sensitive to outliers.
- **Sample Variance ( $s^2$ ):**

$$s^2 = \frac{\sum (x_i - \bar{x})^2}{n - 1}$$

- **Sample Standard Deviation ( $s$ ):**

$$s = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n - 1}}$$

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## Probability Theory Basics

### Core Rules

- **Sample Space ( $\Omega$ ):** Set of all possible outcomes.  $P(\Omega) = 1$
- **Empty Set ( $\emptyset$ ):** Impossible event.  $P(\emptyset) = 0$
- **Probability Bounds:**  $0 \leq P(A) \leq 1$
- **Complement Rule:**  $P(A^c) = 1 - P(A)$ . Notation:  $A^c$ ,  $\bar{A}$ , or  $A'$ .

### Combining Events

- **Intersection (AND):**  $A \cap B$
- **Union (OR):**  $A \cup B$

### Addition Rules

- **General Addition Rule:**  $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
  - **Disjoint (Mutually Exclusive) Events:**
    - Cannot occur together
    - $A \cap B = \emptyset$
    - $P(A \cup B) = P(A) + P(B)$
- 

## Conditional Probability and Independence

### Conditional Probability

Probability that  $B$  occurs given that  $A$  has occurred:

$$P(B | A) = \frac{P(A \cap B)}{P(A)}$$

### Multiplication Law

$$P(A \cap B) = P(B | A) \times P(A)$$

### Independence

Two events are independent if one does not affect the other:

- $P(B | A) = P(B)$ , or
  - $P(A \cap B) = P(A) \times P(B)$
-

## Advanced Probability Theorems

### Bayes' Theorem

Used to reverse conditional probabilities:

$$P(A | B) = \frac{P(B | A) \times P(A)}{P(B)}$$

### Law of Total Probability

If  $A_1, A_2, \dots, A_n$  partition the sample space:

$$P(B) = \sum_{i=1}^n P(B | A_i) \times P(A_i)$$

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## Discrete Random Variables

### Definition

A **Random Variable** ( $X$ ) is a numerical model for a measurement.

- **Discrete RV:** Takes a finite or countably infinite number of values.
- **Bernoulli RV:** Simplest discrete RV.

Takes value:

- 1 for success
- 0 for failure

### Probability Mass Function (pmf)

$$f(x) = P(X = x)$$

### Expected Value (Mean)

The long-run average or centre of gravity:

$$E(X) = \mu = \sum x \cdot P(X = x)$$

*Example (Fair die):*

$$E(X) = 3.5$$

---

## Cumulative Distribution Function (CDF)

$$F(x) = P(X \leq x)$$

- For discrete RVs, the CDF has a **step shape**.
  - **At least rule:**  $P(X \geq k) = 1 - P(X < k)$
- 

## Discrete Probability Distributions

### Binomial Distribution

Used for the number of successes in  $n$  trials.

#### Assumptions (Always state in exams)

1. Fixed number of trials ( $n$ )
2. Constant probability of success ( $p$ )
3. Trials are independent

#### Model

$$P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x}$$

#### Parameters

- **Mean:**  $\mu = np$
- **Standard Deviation:**

$$\sigma = \sqrt{np(1 - p)}$$

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### Poisson Distribution

Used for counting arrivals in a fixed interval of time or space.

#### Assumptions

1. Probability proportional to interval size
2. Probability of two or more arrivals in a very small interval is negligible
3. Non-overlapping intervals are independent

#### Model

$$P(X = x) = \frac{e^{-\alpha t} (\alpha t)^x}{x!}$$

- $\alpha$  = average rate per unit
- $t$  = length of interval

### Key Property (Very Exam Important)

$$\text{Rate} = \lambda = E(X) = \text{Var}(X) = \alpha t$$

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## Week 2: Continuous, Sampling & Hypothesis Testing

### Continuous Random Variables

#### Definition

A continuous random variable can take values anywhere in a continuum, such as height, temperature, or sales.

- **Density Function ( $f(x)$ ):**  
A curve where the area under the curve between two points represents probability.
- **Total Area:**  
The total area under  $f(x)$  is always 1:

$$\int_{-\infty}^{\infty} f(x) dx = 1$$

#### Uniform Distribution

The simplest continuous distribution where probability is constant between  $a$  and  $b$ .

- **PDF:**

$$f(x) = \frac{1}{b-a}, \quad a \leq x \leq b$$

---

### The Normal Distribution

#### Properties

- Defined by **Mean** ( $\mu$ ) and **Variance** ( $\sigma^2$ ).
- Notation:  $X \sim N(\mu, \sigma^2)$

#### Empirical Rule (68, 95, 99.7)

- 68% of data lies within  $\mu \pm 1\sigma$
  - 95% of data lies within  $\mu \pm 2\sigma$
  - 99.7% of data lies within  $\mu \pm 3\sigma$
-

## Sampling Distributions

### Central Limit Theorem (CLT)

Regardless of the population distribution, if sample size  $n$  is large, the distribution of the sample mean  $\bar{X}$  is approximately normal.

- **Mean of  $\bar{X}$ :**  $E(\bar{X}) = \mu$
- **Variance of  $\bar{X}$ :**

$$\text{Var}(\bar{X}) = \frac{\sigma^2}{n}$$

- **Standard Error:**  $\frac{\sigma}{\sqrt{n}}$
- **Z Statistic:**

$$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$$

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## Hypothesis Testing Basics

### Core Concepts

- **Null Hypothesis ( $H_0$ ):**  
Assumed true. Always contains equality ( $=, \leq, \geq$ ).
- **Alternative Hypothesis ( $H_1$ ):**  
The claim we seek evidence for. Always contains inequality ( $\neq, <, >$ ).

### Errors

- **Type I Error ( $\alpha$ ):**  
Rejecting  $H_0$  when it is actually true.
- **Type II Error ( $\beta$ ):**  
Failing to reject  $H_0$  when it is actually false.

### The p-value

The probability of observing a result at least as extreme as the one obtained, assuming  $H_0$  is true.

- **Decision Rule:**  
Reject  $H_0$  if

$$\text{p-value} < \alpha$$

---



## Confidence Intervals

### Definition

An interval constructed around  $\bar{x}$  where we are reasonably confident the true population mean  $\mu$  lies.

- **Interpretation:**

In repeated sampling, 95% of such intervals would contain  $\mu$ .

### Formula (Known $\sigma$ or Large $n$ )

$$\bar{x} \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$$

### Example: Cola Cans

- $\bar{x} = 299.64$
- $n = 100$
- $\sigma = 1.2$

Resulting interval:

$$[299.40, 299.88]$$

Since 300 is not in the interval, reject  $H_0$ .

---

## Hypothesis Tests for Proportions

Used for categorical data.

### Two Approaches

Test	Method	Best For
<code>prop.test</code>	Normal ( $\chi^2$ ) approximation	Large samples ( $n \geq 30$ )
<code>binom.test</code>	Exact binomial probabilities	Small samples or when exact results are needed

### Example: Thanos Snap

- $H_0 : p = 0.5$
- $H_1 : p \neq 0.5$
- Observed: 64 vanished out of 100

### R Code (Approximate):

```
prop.test(64, 100, p = 0.5)
```

- p-value = 0.0069  
Reject  $H_0$ .

**R Code (Exact — preferred for small samples):**

```
binom.test(64, 100, p = 0.5)
```

- p-value = 0.0105  
Reject  $H_0$ .

**binom.test Arguments**

```
binom.test(x, n, p = 0.5, alternative = "two.sided")
```

- x — number of successes observed
- n — number of trials
- p — hypothesised probability of success under  $H_0$
- alternative — "two.sided", "less", or "greater"

**When to Use Each**

- Use **binom.test** when  $n$  is small (roughly  $n < 30$ ), or when you need exact p-values.
  - Use **prop.test** for large samples; it also supports comparing two proportions (`prop.test(c(x1, x2), c(n1, n2))`).
- 

## One Sample t-Test

Used when population variance  $\sigma^2$  is unknown.

- Uses Student's t distribution
- Degrees of freedom:  $df = n - 1$

**Assumptions**

1. Data is numeric and continuous.
2. Data is normally distributed.

**Normality Test: Shapiro-Wilk**

- If p-value  $> 0.05$ , assume normality.

**Example: Corrib River Radiation**

- $H_0 : \mu \geq 5$
- $H_1 : \mu < 5$

**R Code:**

```
t.test(corrib, mu = 5, alternative = "less")
```

- p-value = 0.002  
Reject  $H_0$ . Water is safe.
-

## Comparing Two Means: Independent Samples

Used to compare two separate groups.

### Steps

1. **Check Normality:**

Shapiro-Wilk test on both groups.

2. **Check Variances:**

- Levene's Test (robust)
- Bartlett's Test (requires normality)

If p-value > 0.05, assume equal variances.

3. **Run t-Test:**

- Welch Two Sample t-test (default in R)

### R Code:

```
t.test(x, y, alternative = "less")
```

---

## Comparing Two Means: Paired Samples

Used when observations are dependent or matched.

### Logic

Performs a one sample t-test on the differences between paired observations.

### Example: Diet Study

- $H_1 : \mu_{\text{diff}} > 0$

### R Code:

```
t.test(before, after, paired = TRUE, alternative = "greater")
```

- p-value = 0.02  
Reject  $H_0$ . Diet worked.

### Warning

Using an independent t-test on paired data is incorrect and can increase the chance of a Type II error.

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## Week 3: Enumerative Data Analysis and MLE

### Enumerative Data Analysis (Chi-Squared)

#### Qualitative vs Quantitative

Previously we analysed **quantitative data** (height, weight, marks).

Now we analyse **qualitative (categorical) data**:

- Data consists of **counts / frequencies**
- Examples: Eye colour, Yes/No, Defective/Not defective

We compare **Observed vs Expected frequencies**.

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#### The Chi-Squared Distribution ( $\chi^2$ )

- Not symmetric
  - Right skewed
  - Range:  $0 \rightarrow \infty$
  - Depends on **degrees of freedom (df)**
  - As df increases, it becomes more Normal shaped
  - Right tail area = significance level  $\alpha$
- 

### Chi-Squared Goodness-of-Fit Test

#### Purpose

Tests whether observed categorical data matches a claimed distribution.

#### Test Statistic

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

Where:

- $O$  = Observed frequency
- $E$  = Expected frequency
- $df = k - 1$

Large  $\chi^2$  means observed differs strongly from expected.

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### M&Ms Example

#### Claim ( $H_0$ ):

30% Brown, 20% Yellow, 20% Red, 10% Orange, 10% Green, 10% Blue

### Hypotheses:

- $H_0$ : Distribution matches claim
- $H_1$ : Distribution differs

Reject  $H_0$  if  $\chi_{calc}^2 > \chi_{critical}^2$ .

---

### R Code

```
chocolate <- c(67, 36, 43, 24, 23, 7)
probs <- c(0.3, 0.2, 0.2, 0.1, 0.1, 0.1)
chisq.test(chocolate, p = probs)
```

---

## Chi-Squared Test of Independence

### Purpose

Tests whether two categorical variables are related.

### Hypotheses

- $H_0$ : Variables are independent
  - $H_1$ : Variables are dependent
- 

### Expected Counts Formula

For contingency table:

$$E_{ij} = \frac{(\text{Row Total})(\text{Column Total})}{\text{Grand Total}}$$

Degrees of freedom:

$$df = (r - 1)(c - 1)$$

---

### Assumptions

1. Categorical variables
2. Independent observations
3. Rule of 5:

- At least 80% of expected counts  $\geq 5$
- No expected count  $< 1$

If violated, combine categories or use Fisher's test.

---

### Fisher's Exact Test

Used for small samples.

```
# Independent
wilcox.test(group_A, group_B, alternative = "two.sided")

# Paired
wilcox.test(group_A, group_B, alternative = "two.sided", paired = TRUE)
```

---

### Mann-Whitney U Test / Wilcoxon Test

Used for median

```
wilcox.test
```

### Effect Size: Statistical vs Practical Significance

#### The Problem with Large Samples

- **Statistical significance** tells you if a difference exists.
  - **Practical importance** tells you if the difference matters.
  - With very large  $n$ , even tiny differences can produce small p values.
  - Example: A 2 second improvement may be statistically significant but practically useless.
- 

**The Solution: Effect Size** Effect size measures the **magnitude** of a difference.

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**Chi-Squared Tests: Phi Coefficient** For  $2 \times 2$  tables:

$$\phi = \sqrt{\frac{\chi^2}{n}}$$

**Guidelines:**

- 0.1 small
  - 0.3 medium
  - 0.5 large
- 

**t Tests: Cohen's d** Used when comparing two means.

$$d = \frac{\bar{x}_1 - \bar{x}_2}{s}$$

For independent samples, use the pooled standard deviation.

**Guidelines:**

- 0.2 small
- 0.5 medium
- 0.8+ large

## Maximum Likelihood Estimation

### The Core Idea

How do we find the “best” parameters such as  $\mu$  or  $\lambda$ ?

MLE finds the parameter that makes your data most likely.

- **Fisher's Principle:** Choose parameter  $\theta$  that makes the observed data most probable.
  - Goal: Find  $\theta$  that maximizes  $P(\text{data} \mid \theta)$  i.e. the Likelihood Function  $L(\theta)$ .
- 

### MLE Step by Step

**Likelihood Function** Write the probability of the entire dataset.

If observations are independent:

$$L(\theta) = \prod f(x_i \mid \theta)$$


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**Log-Likelihood** Take the natural log:

$$\ell(\theta) = \sum \ln(f(x_i \mid \theta))$$

Why?

- Differentiating a product is messy
  - Differentiating a sum is easier
  - Logs turn products into sums
- 

**Differentiate** Find derivative with respect to  $\theta$ :

$$\frac{d\ell}{d\theta}$$


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**Solve** Set derivative equal to 0 and solve for  $\theta$ .

This gives the MLE estimate.

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## MLE Examples

### Poisson Distribution (Horse Kicks)

- Data: Counts of deaths by horse kicks (von Bortkiewicz data)
- Model:

$$X \sim \text{Poisson}(\lambda)$$

### MLE Result

$$\hat{\lambda}_{MLE} = \frac{1}{n} \sum x_i = \bar{x}$$

Takeaway: For Poisson, the MLE for  $\lambda$  is the **sample mean**.

---

### Normal Distribution

We estimate two parameters:  $\mu$  and  $\sigma^2$ .

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### Estimating the Mean

$$\hat{\mu} = \bar{x}$$

Takeaway: MLE mean equals the sample mean.

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## Estimating the Variance

$$\hat{\sigma}_{MLE}^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$$

## Bias Issue

- MLE divides by  $n \rightarrow$  biased (underestimates variance)
- Sample variance:

$$s^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$$

Uses Bessel's correction and is unbiased.

Conclusion: For large  $n$ , difference is negligible.

---

## R Implementation

For complex models, solve numerically.

Note: R minimizes functions, so use the **negative log-likelihood**.

```
library(stats4)

# 1. Define Negative Log-Likelihood
nloglik <- function(lambda) {
  return(-sum(dpois(data, lambda, log = TRUE)))
}

# 2. Run Optimizer
fit <- mle(nloglik, start = list(lambda = 1))
summary(fit)
```

---

## Week 4

### Complex MLE & The Need for Optimization

#### When Math Fails (The Gamma Distribution)

- The Gamma distribution models right-skewed data, for example insurance claims.
- It uses two parameters:  $\alpha$  (shape) and  $\beta$  (scale).
- **The Problem:** When you take the derivative of the Gamma log-likelihood and set it equal to 0, there is no simple closed-form solution. You cannot solve it by hand.
- **The Solution:** Numerical optimization. We use a computer to find where the derivative is approximately zero, which corresponds to the peak of the likelihood.

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## Numerical Optimization Methods

When we cannot find the maximum likelihood mathematically, we use algorithms to walk uphill to the peak.

### Gradient Ascent / Descent

- **How it works:** Finds the direction of the steepest slope, the gradient, and takes a step in that direction.
- **Pros:** Simple to implement; only needs first derivatives.
- **Cons:** Slow, linear convergence; choosing the right step size is tricky.

### Newton's Method

- **How it works:** Uses curvature, the Hessian matrix of second derivatives, to fit a quadratic curve and jump straight to its maximum.
- **Pros:** Very fast, quadratic convergence; fewer, smarter steps.
- **Cons:** Fails if the Hessian matrix is not invertible or near saddle points; computationally expensive because it requires second derivatives.

### BFGS (Quasi-Newton)

- **How it works:** Achieves Newton-like speed without computing second derivatives. It approximates the Hessian matrix using previous gradient information.
- **Pros:** Fast, robust, and requires no second derivatives. This is the default in R's `optim()` and `mle()`.

### Nelder-Mead (Simplex)

- **How it works:** Uses no derivatives. It constructs a simplex, a geometric shape of points, that reflects and shrinks over the surface to find the peak.
- **Pros:** Extremely robust; works on non-smooth functions and poor starting values.
- **Cons:** Slow; struggles in high-dimensional problems with many parameters.

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## MLE Optimization in R

### The Negative Log-Likelihood Trick

- R's optimization functions such as `optim()` and `nlm()` are designed to minimize, not maximize.
- To compute the Maximum Likelihood Estimate, we minimize the Negative Log-Likelihood.
- If  $\ell(\theta)$  is the log-likelihood, we minimize  $-\ell(\theta)$ .

## Using log=TRUE

- When computing likelihoods in R, always use `log=TRUE` inside density functions, for example `dgamma(x, shape, scale, log=TRUE)`.
- This computes the log-probability directly, which is more numerically stable than computing a very small probability and then taking its logarithm.

## Optimization Pitfalls

- **Local Maxima:** The algorithm may converge to a smaller local peak instead of the global maximum.
  - **Solution:** Try multiple starting values. If all runs converge to the same point, you likely found the global maximum. If not, the likelihood may be multimodal.
  - **Check Convergence:** In R, `optim()$convergence == 0` indicates successful convergence. Any non-zero value indicates failure.
- 

## Why We Love MLE (Theoretical Properties)

Even when computed numerically, MLE has excellent theoretical properties.

1. **Consistency:** As sample size  $n \rightarrow \infty$ ,  $\hat{\theta} \rightarrow \theta$ .
  2. **Equivariance:** If  $\hat{\theta}$  is the MLE of  $\theta$ , then  $g(\hat{\theta})$  is the MLE of  $g(\theta)$ .
  3. **Asymptotic Normality:** For large samples,  $\hat{\theta} \approx \mathcal{N}\left(\theta, \frac{1}{I(\theta)}\right)$ , where  $I(\theta)$  is the Fisher Information.
  4. **Asymptotic Efficiency:** For large samples, the MLE achieves the minimum possible variance among regular estimators.
- 

## The Likelihood Ratio Test (LRT)

### Concept

Used to compare two nested models to determine whether additional parameters significantly improve model fit.

- $H_0$  (Restricted Model): Parameters are fixed, for example a fair coin with  $p = 0.5$ .
- $H_1$  (Unrestricted Model): Parameters are estimated using MLE, for example  $p = \hat{p}$ .

### The Test Statistic

$$\Lambda = -2 \left[ \ell(\hat{\theta}_0) - \ell(\hat{\theta}) \right]$$

- $\ell(\hat{\theta})$ : Log-likelihood of the unrestricted model.
- $\ell(\hat{\theta}_0)$ : Log-likelihood of the restricted model.

## The Distribution

- Under  $H_0$ ,  $\Lambda \sim \chi^2_{df}$
- Degrees of freedom  $df$  equal the number of restrictions imposed under  $H_0$ .

## Profile Likelihood & Confidence Intervals

- Since the LRT statistic follows a  $\chi^2$  distribution asymptotically, we can invert the test to construct confidence intervals without assuming normality.
- In R, `confint(fit)` computes profile likelihood confidence intervals.

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## Complete Exam Quick Reference Table

Concept / Test	Formula or R Function	Use Case	Key Exam Notes
<b>Sample Mean</b>	$\bar{x} = \frac{\sum x_i}{n}$	Estimate $\mu$	Centre of data
<b>Sample Variance</b>	$s^2 = \frac{\sum (x_i - \bar{x})^2}{n-1}$	Spread	Uses $n - 1$
<b>Sample Std Dev</b>	$s = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}}$	Spread in units	Root of variance
<b>Addition Rule</b>	$P(A \cup B) = P(A) + P(B) - P(A \cap B)$	Combine events	Avoid double counting
<b>Complement Rule</b>	$P(A^c) = 1 - P(A)$	At least one questions	Often simplifies
<b>Conditional Prob</b>	$P(B   A) = \frac{P(A \cap B)}{P(A)}$	Given info	Order matters
<b>Independence</b>	$P(A \cap B) = P(A)P(B)$	Check independence	Only if unrelated
<b>Bayes Theorem</b>	$P(A   B) = \frac{P(B A)P(A)}{P(B)}$	Reverse conditional	Common trap
<b>Binomial Mean</b>	$\mu = np$	Expected successes	Fixed $n, p$
<b>Binomial SD</b>	$\sigma = \sqrt{np(1-p)}$	Spread	Memorise
<b>Poisson Mean</b>	$\mu = \lambda$	Arrivals	Mean = variance
<b>Uniform PDF</b>	$f(x) = \frac{1}{b-a}$	Constant density	Area = probability
<b>Z Statistic</b>	$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$	Mean tests	Known $\sigma$
<b>Confidence Interval</b>	$\bar{x} \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$	Estimate mean	Check if $\mu_0$ inside
<b>Shapiro Wilk Test</b>	<code>shapiro.test(x)</code>	Normality	$H_0$ : Normal
<b>Levene Test</b>	<code>leveneTest()</code>	Compare variances	Robust
<b>Bartlett Test</b>	<code>bartlett.test()</code>	Compare variances	Needs normality
<b>One Sample t Test</b>	<code>t.test(x, mu=...)</code>	Mean vs constant	Unknown $\sigma$
<b>Independent t Test</b>	<code>t.test(x, y)</code>	Two groups	Welch default

Concept / Test	Formula or R Function	Use Case	Key Exam Notes
<b>Paired t Test</b>	<code>t.test(x, y, paired=TRUE)</code>	Before vs after	Uses differences
<b>Proportion Test</b>	<code>prop.test(x, n)</code>	Test proportion	Large samples ( $n \geq 30$ ), normal approx
<b>Exact Binomial Test</b>	<code>binom.test(x, n, p=...)</code>	Test proportion exactly	Small samples; exact binomial p-value
<b>Chi Square Statistic</b>	$\chi^2 = \sum \frac{(O-E)^2}{E}$	Categorical tests	Large = big difference
<b>Goodness of Fit</b>	<code>chisq.test(x, p=probs)</code>	Match distribution	$df = k - 1$
<b>Independence Test</b>	<code>chisq.test(matrix)</code>	Relationship test	$df = (r - 1)(c - 1)$
<b>Fisher Exact Test</b>	<code>fisher.test(matrix)</code>	Small samples	Use if counts < 5
<b>Effect Size (Phi)</b>	$\phi = \sqrt{\frac{\chi^2}{n}}$	Strength of association	0.1 small, 0.3 med, 0.5 large
<b>Cohen's d</b>	$d = \frac{\bar{x}_1 - \bar{x}_2}{s}$	Effect size for mean differences	0.2 small, 0.5 medium, 0.8 large.
<b>Likelihood</b>	$L(\theta) = \prod f(x_i   \theta)$	Parameter estimation	Maximise
<b>Log Likelihood</b>	$\ell(\theta) = \log L(\theta)$	Simplify math	Turns product into sum
<b>MLE Normal Mean</b>	$\hat{\mu} = \bar{x}$	Estimate mean	Same as sample mean
<b>MLE Normal Variance</b>	$\hat{\sigma}^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$	Estimate variance	Biased
<b>BFGS</b>	<code>optim(method="BFGS")</code>	General-purpose MLE optimization	Fast, robust, no second derivatives required
<b>Nelder-Mead</b>	<code>optim(method="Nelder-Mead")</code>	Non-smooth likelihoods	Very robust but slower, weak in high dimensions
<b>Negative Log-Likelihood</b>	$-\sum \log f(x_i   \theta)$	Convert maximization to minimization	R minimizes by default
<b>Convergence Check</b>	<code>fit\$convergence == 0</code>	Verify optimizer success	0 indicates successful convergence
<b>Equivariance (MLE)</b>	If $\hat{\theta}$ is MLE, then $g(\hat{\theta})$ is MLE of $g(\theta)$	Transformations of parameters	Core theoretical property
<b>LRT Statistic</b>	$\Lambda = -2[\ell(\hat{\theta}_0) - \ell(\hat{\theta})]$	Compare nested models	Based on log-likelihood difference

Concept / Test	Formula or R Function	Use Case	Key Exam Notes
<b>LRT Distribution</b>	$\Lambda \sim \chi^2_{df}$	Compute p-values	df equals number of restrictions
<b>Profile Confidence Intervals</b>	<code>confint(fit)</code>	Construct CIs via LRT	Does not rely on normal approximation