

OCR Further Maths A Level

Statistics

Formula Sheet

Provided in formula book

Not provided in formula book

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Probability

Permutations and Combinations

Number of permutations of n distinct objects	$n! = n \times (n - 1) \times (n - 2) \dots \times 2 \times 1$
Number of combinations when choosing r objects from n objects	$\binom{n}{r} = {}^n C_r = \frac{n!}{r!(n-r)!}$
Number of permutations of a subset of size r from a set of n distinct objects	${}^n P_r = {}^n C_r \times r! = \frac{n!}{(n-r)!}$
Number of permutations from n objects with r_A of type A , r_B of type B etc.	$\frac{n!}{r_A! r_B! \dots}$

Probability Problems

$n(A)$	The number of ways of making a choice about A
Product principle	$n(A \text{ and } B) = n(A) \times n(B)$
Addition principle (given that A and B are mutually exclusive)	$n(A \text{ or } B) = n(A) + n(B)$
Counting principles in probability (given that all outcomes are equally likely)	$P(A) = \frac{\text{number of outcomes in which } A \text{ occurs}}{\text{total number of possible outcomes}}$



Discrete Random Variables

Average and Spread of Discrete Random Variables

For the random variable taking the values x_i with $P(X = x_i) = p_i$	
Expectation	$\mu = E(X) = \sum x_i p_i$
Variance	$\begin{aligned} \sigma^2 = \text{Var}(X) &= \sum (x_i - \mu)^2 p_i \\ &= \sum x_i^2 p_i - \mu^2 \\ &= E(X^2) - (E(X))^2 \end{aligned}$

Linear Coding with the Mean and Variance

$$\begin{aligned} \text{For } Y &= aX + b: \\ E(Y) &= aE(X) + b \\ \text{Var}(Y) &= a^2 \text{Var}(X) \end{aligned}$$

Binomial Distribution

For $X \sim B(n, p)$
$P(X = x) = \binom{n}{x} p^x (1-p)^{n-x}$
$E(X) = np$
$\text{Var}(X) = np(1-p)$

Discrete Uniform Distribution

For $X \sim U(n)$
$P(X = x) = \frac{1}{n} \text{ for } x = 1, 2, \dots, n$
$E(X) = \frac{n+1}{2}$
$\text{Var}(X) = \frac{n^2 - 1}{12}$



Geometric Distribution

For $X \sim \text{Geo}(p)$

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

for $x = 1, 2, 3 \dots$

$$P(X > x) = (1 - p)^x$$

$$E(X) = \frac{1}{p}$$

$$\text{Var}(X) = \frac{1 - p}{p^2}$$

Poisson Distribution

For $X \sim \text{Po}(\lambda)$

$$P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!} \text{ for } x = 0, 1, 2 \dots$$

$$E(X) = \lambda$$

$$\text{Var}(X) = \lambda$$

$$X \sim \text{Po}(\lambda)$$
$$Y \sim \text{Po}(\mu)$$

$$\text{When } Z = X + Y,$$
$$Z \sim \text{Po}(\lambda + \mu)$$



Continuous Random Variables

Probability Density Function

For a probability function $f(x)$

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

$$f(x) \geq 0$$

$$P(a < X < b) = \int_a^b f(x) dx$$

Mean and Variance of a Continuous Probability Distribution

$$\mu = E(X) = \int_{-\infty}^{\infty} x f(x) dx$$

$$\begin{aligned} \sigma^2 = \text{Var}(X) &= \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx \\ &= \int_{-\infty}^{\infty} x^2 f(x) dx - \mu^2 \end{aligned}$$

Mean and Variance of a Function of a Continuous Variable

$$E(aX + c) = aE(X) + c$$

$$\text{Var}(aX + c) = a^2 \text{Var}(X)$$

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

Cumulative Distribution Function

$$P(X \leq x) = F(x) = \int_{-\infty}^x f(t) dt$$

$$\text{Probability density function} = f(x) = \frac{d}{dx} F(x)$$



Median, Mode, and Percentiles of a Continuous Probability Distribution

Median (m)	$\int_{-\infty}^m f(x) dx = \frac{1}{2}$
Mode	Value of x when $f(x)$ is at the maximum
Lower Quartile (Q_1)	$\int_{-\infty}^{Q_1} f(x) dx = \frac{1}{4}$
Upper Quartile (Q_3)	$\int_{-\infty}^{Q_3} f(x) dx = \frac{3}{4}$

Continuous Uniform Distribution

If X follows a uniform distribution between $[a, b]$

$$f(x) = \frac{1}{b-a} \text{ for } a < x < b$$

$$E(X) = \frac{a+b}{2}$$

$$Var(X) = \frac{(b-a)^2}{12}$$



Exponential Distribution

For $X \sim \text{Exp}(\lambda)$

$$f(x) = \lambda e^{-\lambda x} \text{ for } x \geq 0$$

$$E(X) = \frac{1}{\lambda}$$

$$\text{Var}(X) = \frac{1}{\lambda^2}$$

$$F(x) = \begin{cases} 0, & x < 0 \\ 1 - e^{-\lambda x}, & x \geq 0 \end{cases}$$

Normal Distribution

For $X \sim N(\mu, \sigma^2)$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

$$E(X) = \mu$$

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

Linear Combinations of Random Variables

Linear Combination of Any Independent Variables

Where X and Y are independent random variables

$$E(aX + bY + c) = aE(X) + bE(Y) + c$$

$$\text{Var}(aX + bY + c) = a^2\text{Var}(X) + b^2\text{Var}(Y)$$



Hypothesis Tests and Confidence Intervals

Expectation and Variance of the Sample Mean

$$E(\bar{X}) = \mu$$

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

Sampling Distribution

For $X \sim N(\mu, \sigma^2)$

$$\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

$$\frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \sim N(0, 1)$$

Unbiased Estimate of the Population Mean and Variance

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

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

Central Limit Theorem

The mean of any distribution with $E(X) = \mu$, $\text{Var}(X) = \sigma^2$ and $n > 25$ can be approximated to have a normal distribution

$$\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$



Confidence Intervals

For a population with known variance and normally distributed sample mean	
$c\%$ confidence interval for population mean (μ)	$\left(\bar{x} - z \frac{\sigma}{\sqrt{n}}, \bar{x} + z \frac{\sigma}{\sqrt{n}} \right)$ Where $z = \Phi^{-1} \left(0.5 + \frac{\frac{1}{2}c}{100} \right)$
Width of confidence interval	$2z \frac{\sigma}{\sqrt{n}}$



Chi-squared Tests

Contingency Tables

Expected value in cell i	$E_i = \frac{\text{row total} \times \text{column total}}{\text{overall total}}$
Chi-squared value	$\chi_{\text{calc}}^2 = \frac{\sum(O_i - E_i)^2}{E_i}$
Degrees of freedom in an $n \times m$ contingency table	$v = (n - 1)(m - 1)$

Hypothesis Testing

If variables are independent and

$E_i > 5$ for all i

$$\chi_{\text{calc}}^2 = \frac{\sum(O_i - E_i)^2}{E_i} \approx \chi_v^2$$

Yates' Correction

When $v = 1$

$$\chi_{\text{Yates}}^2 = \frac{\sum |(O_i - E_i) - 0.5|^2}{E_i}$$

Goodness of Fit Test

$v = \text{number of bins} - \text{number of constraints}$

Expected frequency in bin $A =$
 probability of being in bin $A \times \text{total observed frequency}$



Non-parametric Tests

Single Sample Sign Test

For a sample of size n

1. Count the number of observed values above the median stated in H_0 .
2. Find the probability of this value or higher using $B(n, 0.5)$.

Single Sample Wilcoxon Signed Rank Test

1. Assigned ranks according to the differences from median in the order of increasing size.
2. Add a negative sign to the ranks for values below median.
3. Test statistic T is the smaller of W_+ (sum of positive ranks) and W_- (sum of negative ranks).

Wilcoxon Rank Sum Test

For two samples of sizes m and n where $m \leq n$

R_m = sum of ranks of items in sample of size m
 where a lower rank is given to smaller values

Test statistic = W = smaller of R_m and $m(m + n + 1) - R_m$

Approximate Distribution for Large Samples

Wilcoxon Signed Rank test	$T \sim N\left(\frac{1}{4}n(n+1), \frac{1}{24}n(n+1)(2n+1)\right)$
Wilcoxon Rank Sum test (sample of sizes m and n , where $m \leq n$)	$W \sim N\left(\frac{1}{2}m(m+n+1), \frac{1}{12}mn(m+n+1)\right)$



Correlation

Pearson's Product Moment Correlation Coefficient

For a set of bivariate data
with variables X and Y

$$r = \frac{\sum x_i y_i - \frac{\sum x_i \sum y_i}{n}}{\sqrt{\left(\sum x_i^2 - \frac{(\sum x_i)^2}{n}\right) \left(\sum y_i^2 - \frac{(\sum y_i)^2}{n}\right)}}$$

$$= \frac{S_{xy}}{\sqrt{S_{xx} S_{yy}}}$$

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

$$S_{yy} = \sum (y_i - \bar{y})^2 = \sum y_i^2 - \frac{(\sum y_i)^2}{n}$$

$$S_{xy} = \sum (x_i - \bar{x})(y_i - \bar{y}) = \sum x_i y_i - \frac{\sum x_i \sum y_i}{n}$$

Spearman's Rank Correlation Coefficient

$$r_s = 1 - \frac{6 \sum d^2}{n(n^2 - 1)}$$

where d = difference in ranks and n = number of data pairs

Linear Regression

Least Squares Regression Line

$$y = ax + b$$

$$a = \bar{y} - b\bar{x}$$

$$b = \frac{S_{xy}}{S_{xx}} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

