

MVE055-EXAM-NOTES

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Probability

$$\binom{n}{r} = \frac{n!}{r!(n-r)!}$$

$$P[A_1 \cup A_2] = P[A_1] + P[A_2] - P[A_1 \cap A_2]$$

$$P[A_2 | A_1] = \frac{P[A_1 \cap A_2]}{P[A_1]}$$

$$P[A_j | B] = \frac{P[B | A_j] P[A_j]}{\sum_{i=1}^n P[B | A_i] P[A_i]}$$

Series

$$\sum_{k=1}^{\infty} ar^{k-1} = \frac{a}{1-r} \quad |r| < 1$$

$$\sum_{k=1}^n ar^{k-1} = \frac{a(1-r^n)}{1-r}$$

$$\text{Arithmetic Series: } S_n = \frac{n(a_1 + a_n)}{2}$$

Expectancy & Variance

$$E[H(X)] = \sum_{x \in X} H(x) f(x)$$

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

$$E[c] = c, \quad E[cX] = cE[X]$$

$$E[X+Y] = E[X] + E[Y]$$

$$E[XY] = E[X]E[Y] \text{ iff independent}$$

$$\sigma^2 = \text{Var}[X] = E[(X-\mu)^2] = E[X^2] - E[X]^2$$

$$\text{Var}[c] = 0, \quad \text{Var}[cX] = c^2 \text{Var}[X]$$

$$\text{Var}[aX+bY] = a^2 \text{Var}[X] + b^2 \text{Var}[Y] +$$

$$2ab \text{Cov}(X, Y)$$

$$\text{Cov}(X, Y) = E[(X-\mu_x)(Y-\mu_y)]$$

$$\text{Cov}(X, Y) = E[XY] - E[X]E[Y]$$

Moment generating functions

$$m_X(t) = E[e^{tX}]$$

$$\left. \frac{d^k m_X(t)}{dt^k} \right|_{t=0} = E[X^k]$$

$$Y = X_1 + \dots + X_n \iff m_Y(t) = m_{X_1}(t) \dots m_{X_n}(t)$$

$$Y = \alpha + \beta X \rightarrow m_Y(t) = e^{\alpha t} m_X(\beta t)$$

Discrete distributions

$$X \sim \text{Geo}(p) \rightarrow F_X(t) = 1 - (1-p)^{\text{floor}(t)}$$

$$P[X > x] = 1 - P[X \leq x] = 1 - F_X(x) = \sum_{x \in X} f(x)$$

$$f_X(t) = F_X(t) - F_X(t-1)$$

Continuous distributions

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

$$P[a \leq X \leq b] = \int_a^b f_X(x) dx$$

$$P[X = x] = 0$$

$$P[X \geq x] = 1 - P[X \leq x] = 1 - F_X(x)$$

$$F_X(t) = \int_{-\infty}^t f_X(x) dx$$

$$f_X(x) = \frac{dF_X(x)}{dx}$$

Continuity correction

Discrete	Continuous
$P[X=x]$	$P[x-0.5 < X < x+0.5]$
$P[X \leq x]$	$P[X < x+0.5]$
$P[X < x]$	$P[X < x-0.5]$
$P[X \geq x]$	$P[X < x-0.5]$
$P[X > x]$	$P[X < x+0.5]$

Chebyshev's inequality

$$P[|X-\mu| \geq \epsilon] \leq \frac{\sigma^2}{\epsilon^2}$$

$$P[|X-\mu| < \epsilon] > 1 - \frac{\sigma^2}{\epsilon^2}$$

$$\epsilon = k\sigma \rightarrow P[|X-\mu| < k\sigma] \leq 1 - \frac{1}{k^2}$$

Joint Distributions

$$f_{XY} = \sum_{x \in X} \sum_{y \in Y} f_{XY}(x, y) = 1$$

$$f_X(x) = \sum_{y \in Y} f_{XY}(x, y)$$

$$f_Y(y) = \sum_{x \in X} f_{XY}(x, y)$$

$$f_{XY} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) dx dy = 1$$

$$f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x, y) dy$$

$$f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx$$

$$f_{XY}(x, y) = f_X(x) f_Y(y) \text{ iff independent}$$

$$E[H(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} H(x, y) f(x, y) dx dy$$

$$E[XY] = E[H(X, Y)], \quad H(X, Y) = X*Y$$

$$E[X] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{XY}(x, y) dx dy$$

$$E[Y] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f_{XY}(x, y) dx dy$$

$$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}[X] \text{Var}[Y]}}$$

Sample statistics

$$\bar{X} = \sum_{i=1}^n \frac{X_i}{n}$$

$$\text{Median: } P[X \leq m] = P[X \geq m] = \frac{1}{2}$$

$$S^2 = \sum_{i=1}^n \frac{(X_i - \bar{X})^2}{n-1}$$

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

$$\sigma \sim (\text{estimated range})/4, \text{ normal}$$

$$\sigma \sim (\text{estimated range})/6, \text{ unknown}$$

$$\text{Unbiased: } E[\hat{\theta}] = \theta$$

$$\text{Var}[\bar{X}] = \frac{\sigma^2}{n}$$

Confidence interval

$$(n-1)S^2/\sigma^2 = \sum_{i=1}^n (X_i - \bar{X})^2/\sigma^2$$

$$\sim \text{chi-squared}(n-1)$$

$$\frac{Z}{\sqrt{\chi^2/\gamma}} \sim T_\gamma, \quad \frac{\bar{X} - \mu}{\sqrt{S^2/n}} \sim T_{(n-1)}$$

$$\sigma^2 \in \left[\frac{(n-1)S^2}{\chi^2_{\alpha/2}}, \frac{(n-1)S^2}{\chi^2_{1-\alpha/2}} \right]$$

$$\text{General: find } P[-D_{(\alpha/2)} \leq C \leq D_{(\alpha/2)}]$$

$$\sigma^2 \text{ known, } \bar{x} \pm Z_{(\alpha/2)} \sigma \sqrt{n}, Z \sim N(0, 1)$$

$$\sigma^2 \text{ unknown, } \bar{x} \pm t_{\alpha/2} S / \sqrt{n}$$

$$n = \frac{(Z_{\alpha/2})^2 \sigma^2}{d^2}, n = \frac{(Z_{\alpha/2})^2 \hat{\sigma}^2}{d^2}$$

Central limit theorem

For a sample of size n from distribution

with mean μ Variance σ^2 , when n is large \bar{X} is approximately normal with mean μ Variance σ^2/n .

Hypothesis testing

$$\alpha = P[\text{"type 1 error"}] = P[\text{"reject } H_0 \text{"} | H_0]$$

$$\beta = P[\text{"type 2 error"}] = P[\text{"fail reject } H_0 \text{"} | H_0^c]$$

$$\text{"Power of test"} = 1 - \beta$$

Non parametric methods

Sign-test: Calculate median M on the sample of n. Then calculate $X_i - M$ for $x_i \in X$. Let Q_+ denote the number of positive differences. $Q_+ \sim \text{Bin}(n, \frac{1}{2})$. Zeros are assigned two the sign that supports H_0

Wilcoxon rank-test: As before calculate M and $X_i - M$ order the list of differences from least to greatest. Number them 1 to N where 1 is the smallest difference. For equal difference assign the mean rank to each of them. Let W_+ denote the sum of positive ranks and W_- the negative ranks. $W = \min(W_+, W_-)$ Lookup w in table or use normal approximation. This test can also be used for paired data, then use $X_i - Y_i$ instead of $X_i - M_x$

$$E[W] = \frac{n(n+1)}{4}, \text{Var}[W] = \frac{n(n+1)(2n+1)}{24}$$

$$\alpha = W \leq c \text{ or } W \geq C, C = \frac{n(n+1)}{2} - c$$

$$W = \sum_{j=1}^n R_j I_j, \max W \rightarrow I_j = 1.$$

Wilcoxon rank-sum test: Given two samples X_1, X_2, \dots, X_n and y_1, y_2, \dots, y_m , $m \leq n$ pool them and order them from smallest to largest. Assign ranks from 1 to $N+M$, draws are each assigned the average rank. Let W_m = the sum of all ranks belonging to y, the smaller sample. Let c denote the lower critical boundry left tailed tests and C the upper boundry. c is given i given in the table.

$$C = m(m+n+1) - c$$

$$E[W_m] = \frac{m(m+n+1)}{2}$$

$$\text{Var}[W_m] = \frac{mn(m+n+1)}{12}$$

Propotions

$$\hat{p} = \frac{X}{n}, \quad \hat{p} \pm Z_{\alpha/2} \sqrt{\hat{p}(1-\hat{p})/n}$$

$$n = \frac{Z_{\alpha/2}^2 \hat{p}(1-\hat{p})}{d^2}, \hat{p} \text{ estimate known}$$

$$n = \frac{Z_{\alpha/2}^2}{4d^2}, \text{ estimate unknown}$$

$$T = \frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}}$$

$$p_1 - p_2 = \frac{X_1}{n_1} - \frac{X_2}{n_2}$$

$$p_1 - p_2 \pm Z_{\alpha/2} \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}$$

$$\text{When: } p_1 = p_2, \hat{p}_p = \frac{n_1 p_1 + n_2 p_2}{n_1 + n_2}$$

$$T = \frac{\hat{p}_1 - \hat{p}_2}{\hat{p}_p(1-\hat{p}_p)(1/n_1 + 1/n_2)}$$

$$n = Z_{\alpha/2}^2 \frac{\hat{p}_1(1-\hat{p}_2) + \hat{p}_2(1-\hat{p}_1)}{d^2}$$

$$n = \frac{Z_{\alpha/2}^2}{2d^2}$$

Comparing means

$$\mu_1 - \mu_2 = \bar{X}_1 - \bar{X}_2 \sim N(\mu_1 - \mu_2, \sigma_1^2 + \sigma_2^2)$$

$$\frac{\chi_{\gamma_1}^2/\gamma_1}{\chi_{\gamma_2}^2/\gamma_2} \sim F_{\gamma_1, \gamma_2}, \quad \frac{S_1^2}{S_2^2} \sim F_{n_1-1, n_2-1}$$

$$S_p^2 = \frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2}$$

Comparing means:

Variance known:

$$T = \frac{\bar{X}_1 - \bar{X}_2 - (\mu_1 - \mu_2)}{\sqrt{(\sigma_1^2/n_1 + \sigma_2^2/n_2)}} \sim N(\mu_1 - \mu_2, \sigma_1^2 + \sigma_2^2)$$

Variance unknown:

$$\sigma_1^2 = \sigma_2^2, T = \frac{\bar{X}_1 - \bar{X}_2 - (\mu_1 - \mu_2)}{\sqrt{S_p^2(1/n_1 + 1/n_2)}} \sim T_{n_1 + n_2 - 2}$$

$$\sigma_1^2 \neq \sigma_2^2, T = \frac{\bar{X}_1 - \bar{X}_2 - (\mu_1 - \mu_2)}{\sqrt{(S_1^2/n_1 + S_2^2/n_2)}} \sim T_{\gamma}$$

$$\gamma = \frac{(S_1^2/n_1 + S_2^2/n_2)^2}{\frac{(S_1^2/n_1)^2}{n_1-1} + \frac{(S_2^2/n_2)^2}{n_2-1}}$$

Linear regression

$$\mu_{Y|x} = \beta_0 + \beta_1 x, \quad Y|x_i = \beta_0 + \beta_1 x_i + E_i$$

$$E_i \sim N(0, \sigma^2), \quad Y|x \sim N(\mu_{Y|x}, \sigma^2)$$

$$SSE = \sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - b_0 - b_1 x_i)^2$$

$$\text{Minimize SEE: } \frac{dSEE}{db_0} = -2 \sum_{i=1}^n (y_i - b_0 - b_1 x_i)$$

$$\frac{dSEE}{db_1} = -2 \sum_{i=1}^n (y_i - b_0 - b_1 x_i) x_i$$

$$b_1 = \frac{n \sum_{i=1}^n x_i y_i - (\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$b_0 = \bar{y} - b_1 \bar{x}, \quad Y_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$$

$$S_{xx} = \sum (x_i - \bar{x})^2, \quad S_{yy} = \sum (Y_i - \bar{Y})^2$$

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

$$S_{xy} = (x_i - \bar{x})(Y_i - \bar{Y}) = \sum (x_i - \bar{x}) Y_i$$

$$S_{xy} = \frac{(n \sum x_i Y_i - \sum x_i \sum Y_i)}{n}$$

$$b_1 = \frac{S_{xy}}{S_{xx}} = \frac{\sum (x_i - \bar{x}) Y_i}{S_{xx}} = c_1 Y_1 + \dots + c_n Y_n$$

$$c_j = \frac{(x_j - \bar{x}) Y_j}{S_{xx}}, \quad b_1 \sim N\left(\beta_1, \frac{\sigma^2}{S_{xx}}\right)$$

$$b_0 \sim N\left(\beta_0, \frac{\sum x_i^2}{n S_{xx}} \sigma^2\right)$$

$$S^2 = \hat{\sigma}^2 = \frac{SEE}{n-2} = S_{yy} - S_{xx} b_1^2$$

$$T_{n-2} = \frac{b_1 - \beta_1^0}{S/\sqrt{S_{xx}}}, \quad b_1 \pm t_{\alpha/2} S/\sqrt{S_{xx}}$$

$$T_{n-2} = \frac{b_0 - \beta_0^0}{\left(\frac{S\sqrt{\sum x_i^2}}{\sqrt{n S_{xx}}}\right)}, \quad b_0 \pm t_{\alpha/2} S \sqrt{\frac{\sum x_i^2}{n S_{xx}}}$$

$$\hat{\mu}_{Y|x} \sim N\left(\mu, \sigma^2 \left[\frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}\right]\right)$$

$$\hat{\mu}_{Y|x} \pm t_{\alpha/2} S \sqrt{\frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}}$$

$$(\hat{Y}|x - Y|x) = (\hat{\mu}_{Y|x} - Y|x)$$

$$(\hat{Y}|x - Y|x) \sim N\left(0, \sigma^2 \left[1 + \frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}\right]\right)$$

$$T_{n-2} = \frac{\hat{Y}|x - Y|x}{S \sqrt{1 + \frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}}}$$

$$\hat{Y}|x \pm t_{\alpha/2} S \sqrt{1 + \frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}}$$

Partial integration

$$\int u(x) v'(x) dx = u(x) v(x) - \int u'(x) v(x) dx$$

Name	density	def	mgf	μ	σ^2
Gemetric	$(1-p)^{x-1} p$	$x \geq 1$	$\frac{pe^t}{1-qe^t}$	p^{-1}	qp^{-2}
Uniform	$\frac{1}{n}$	$x = x_1 \dots x_n$	$\frac{\sum_{i=1}^n e^{tx}}{n}$	$\frac{\sum_{i=1}^n x_i}{n}$	$\frac{\sum_{i=1}^n x_i^2}{n} - \left(\frac{\sum_{i=1}^n x_i}{n}\right)^2$
Binomial	$\binom{n}{x} p^x (1-p)^{n-x}$	$x = 0, 1, \dots, n$	$(q + pe^t)^n$	np	$np(1-p)$
Poisson	$\frac{e^{-k} k^x}{x!}$	$x = 0, 1, 2, \dots$	$e^{k(e^x - 1)}$	k	k
Exponential	$\frac{1}{\beta} e^{-x/\beta}$	$x > 0, \beta > 0$	$(1 - \beta t)^{-1}$	β	β^2
Uniform	$\frac{1}{b-a}$	$a < x < b$	$\frac{e^{tb} - e^{ta}}{t(b-a)}, t \neq 0, 1, t=0$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$
Normal	$\frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right]$	$-\infty < x < \infty$	$e^{\mu t + \sigma^2 t^2/2}$	μ	σ^2
Chi-squared	$\frac{1}{\Gamma(\gamma/2) 2^{\gamma/2}} x^{\gamma/2-1} e^{-x/2}$	$x > 0$	$(1-2t)^{-\gamma/2}$	γ	2γ