

Summary of Topics for Midterm Exam #1

STA 371G, Spring 2014

Listed below are the major topics covered in class that are likely to be in Midterm Exam #1:

- Mean (expectation), variance and standard deviation of a random variable.

$$\mathbb{E}[X] = \sum_{i=1}^n x_i P(X = x_i), \quad \text{Var}[X] = \sum_{i=1}^n (x_i - \mathbb{E}[X])^2 P(X = x_i), \quad \text{sd}[X] = \sqrt{\text{Var}[X]}$$

- Add a constant to a random variable, multiply a random variable by a constant.

If $Y = a + bX$, then

$$\mathbb{E}[Y] = a + b\mathbb{E}[X], \quad \text{Var}[Y] = b^2 \text{Var}[X], \quad \text{sd}[Y] = |b| \times \text{sd}[X].$$

- Conditional, joint and marginal probabilities.

$$P(Y = y|X = x) = \frac{P(Y = y, X = x)}{P(X = x)}$$

$$P(Y = y, X = x) = P(Y = y|X = x)P(X = x)$$

$$P(Y = y) = \sum_x P(Y = y, X = x)$$

- Independent random variables, sum of independent random variables.

- Two random variables X and Y are independent if $P(Y = y|X = x) = P(Y = y)$ for all possible x and y .
- If X and Y are independent, then $P(Y = y, X = x) = P(Y = y)P(X = x)$.
- If $Y = a_0 + a_1X_1 + a_2X_2 + \cdots + a_nX_n$, then

$$\mathbb{E}[Y] = a_0 + a_1\mathbb{E}[X_1] + a_2\mathbb{E}[X_2] + \cdots + a_n\mathbb{E}[X_n].$$

If X_i and X_j are independent for $i \neq j$, then we further have

$$\text{Var}[Y] = a_1^2 \text{Var}[X_1] + a_2^2 \text{Var}[X_2] + \cdots + a_n^2 \text{Var}[X_n].$$

- Normal distribution $X \sim \mathcal{N}(\mu, \sigma^2)$, where μ is the mean, σ^2 is the variance, and σ is the standard deviation.
 - Probability density function: area under the curve represents probability.
 - Standard normal distribution $Z \sim \mathcal{N}(0, 1)$.
 - Standardizing a normal random variable $Z = \frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1)$.
 - $P(X < x) = P\left(\frac{X - \mu}{\sigma} < \frac{x - \mu}{\sigma}\right) = P\left(Z < \frac{x - \mu}{\sigma}\right)$.

- $P(-2 < Z < 2) \approx 0.95$; $P(\mu - 2\sigma < X < \mu + 2\sigma) \approx 0.95$.
- Estimate μ and σ^2 when $X \sim \mathcal{N}(\mu, \sigma^2)$.
 - Use the sample mean $\bar{X} = \frac{\sum_{i=1}^n X_i}{n}$ to estimate μ .
 - Use the sample variance $s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$ to estimate σ^2 .
- Sampling distribution of a sample mean \bar{X} :
 - $\bar{X} \sim \mathcal{N}(\mu, \sigma_{\bar{X}}^2 = \frac{\sigma^2}{n})$.
 - The sampling distribution of \bar{X} is useful in determining the quality of \bar{X} as an estimator for the population mean μ .
 - As the population variance σ^2 is usually unknown, we use the sample variance $s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$ to estimate σ^2 and hence s^2/n to estimate $\sigma_{\bar{X}}^2$.
 - 95% confidence interval of μ (approximately): $\bar{X} \pm 2\sqrt{\frac{s^2}{n}}$.
- Binomial distribution and its normal approximation
 - $X \sim \text{Binomial}(n, p)$ can be approximated with $X \sim \mathcal{N}(np, np(1-p))$ if n is large enough and p is not too close to 0 or 1.
 - Estimate the population proportion p when $X \sim \text{Binomial}(n, p)$, where n is the sample size.
 - * Use the sample proportion $\hat{p} = \frac{X}{n}$ to estimate p .
 - * Approximately, we have $\hat{p} \sim \mathcal{N}(p, \frac{\hat{p}(1-\hat{p})}{n})$.
 - * 95% confidence interval of p : $\hat{p} \pm 2\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$.
- Simple Linear Regression
 - Least squares estimation: given n observations $(x_1, y_1), \dots, (x_n, y_n)$, we estimate the intercept b_0 and slope b_1 by finding a straight line $\hat{y}_i = b_0 + b_1 x_i$ that minimizes

$$\sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n [y_i - (b_0 + b_1 x_i)]^2.$$
 - Sample means of X and Y

$$\bar{x} = \frac{\sum_{i=1}^n x_i}{n}, \quad \bar{y} = \frac{\sum_{i=1}^n y_i}{n}.$$
 - Sample covariance

$$\text{Cov}(X, Y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n-1}$$

- Sample correlation

$$r_{xy} = \text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{s_x^2 s_y^2}} = \frac{\text{Cov}(X, Y)}{s_x s_y}.$$

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

$$s_y^2 = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n-1}, \quad s_y = \sqrt{s_y^2}$$

- Least squares estimation:

$$b_0 = \bar{y} - b_1 \bar{x}, \quad b_1 = r_{xy} \frac{s_y}{s_x}$$

- Interpreting covariance, correlation and regression coefficients.
- SST, SSR, SSE

$$\text{SST} = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$\text{SSR} = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 = \sum_{i=1}^n [(b_0 + b_1 x_i) - \bar{y}]^2$$

$$\text{SSE} = \sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n [y_i - (b_0 + b_1 x_i)]^2$$

$$\text{SST} = \text{SSR} + \text{SSE}$$

Note that $\bar{y} = b_0 + b_1 \bar{x}$, $\hat{y}_i = b_0 + b_1 x_i$, $\bar{\hat{y}} = \bar{y}$, and $e_i = y_i - \hat{y}_i = (y_i - \bar{y}) - (\hat{y}_i - \bar{y})$.

- Coefficient of determination:

$$R^2 = \frac{\text{SSR}}{\text{SST}} = 1 - \frac{\text{SSE}}{\text{SST}} = r_{xy}^2$$

- Regression assumptions and statistical model.

$$Y = \beta_0 + \beta_1 X + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

$$y_i \sim \mathcal{N}(\beta_0 + \beta_1 x_i, \sigma^2)$$

Assuming β_0 , β_1 and σ^2 are known, given x_i , the 95% prediction interval of y_i is

$$(\beta_0 + \beta_1 x_i) \pm 2\sigma.$$