### STA260 Summer 2024 Tutorial 11 (11.1, 11.2, 11.3, 11.4)

Disclaimer: STA260 covers extensive material. Tutorials serve as additional aids, but they cannot cover every question type.

### **Relevant Review from Lecture**

Simple Linear Regression model:  $y = \beta_0 + \beta_1 x + \epsilon$ ,  $\epsilon \sim N(0, \sigma^2)$ 

Sum of Squares (To be Minimized):  $SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$ 

**Some Relevant Formulas:** 

1. 
$$\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}}$$
 2.  $\hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \overline{x}$  3.  $V(\hat{\beta}_1) = \frac{\sigma^2}{S_{xx}}$  4.  $V(\hat{\beta}_0) = \sigma^2 \left(\frac{1}{n} + \frac{\overline{x}^2}{S_{xx}}\right)$ 

5. 
$$S_{xy} = \sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y}) = \sum_{i=1}^{n} x_i y_i - n(\overline{x})(\overline{y})$$

6. 
$$S_{xx} = \sum_{i=1}^{n} (x_i - \overline{x})^2 = \sum_{i=1}^{n} x_i^2 - n\overline{x}^2$$

### **Question 1** (11.1 from the textbook)

If  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are the least-squares estimates for the intercept and the slope in a simple linear regression model, show that the least-squares equation  $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$  always goes through the point  $(\bar{x}, \bar{y})$ .

**Hint:** substitute  $\bar{x}$  for x in the least-squares equation and use the fact that  $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$ 

# Question 2 (11.10 from the textbook)

Suppose we have the postulated the model:

$$Y_i = \beta_1 x_i + \epsilon_i, \quad i = 1, 2, ..., n,$$

where the  $\epsilon_i$ 's are independent and identically distributed random variables with  $\mathbb{E}(\epsilon_i) = 0$ . Then  $\hat{y}_i = \hat{\beta}_1 x_i$  is the predicted value of y when  $x = x_i$  and  $SSE = \sum_{i=1}^n [y_i - \hat{\beta}_1 x_i]^2$ . Find the least-squares estimator of  $\beta_1$ . (Notice that the equation  $y = \beta x$  describes a straight line passing through the origin. The model just described often is called the no-intercept model.)

## **Question 3** (11.15 from the textbook)

1. Derive the following identity:

$$SSE = S_{yy} - \hat{\beta}_1 S_{xy}$$

This provides an easier computational method of finding the SSE.

2. Use the computational formula for SSE derived in part (a) to prove that  $SSE \leq SSE$ 

 $S_{yy}$ . [Hint:  $\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}}$ ]

## **Question 4** (11.21 from the textbook)

Suppose that  $Y_1,Y_2,...,Y_n$  are independent normal random variables with  $\mathbb{E}(Y_i)=\beta_0+\beta_1x_i$  and  $\mathbb{V}(Y_i)=\sigma^2$ , for i=1,2,...,n. Find  $Cov(\hat{\beta}_0,\hat{\beta}_1)$ .

Then, prove that if  $\sum_{i=1}^n x_i = 0$  then  $\hat{\beta}_0, \hat{\beta}_1$  are independent.

#### **Continuous Distributions**

| Distribution | Probability Function   | Mean                            | Variance   | Moment-<br>Generating<br>Function                              |
|--------------|--|---------------------------------|--|--|
| Uniform      | $f(y) = \frac{1}{\theta_2 - \theta_1}; \theta_1 \le y \le \theta_2$  | $\frac{\theta_1+\theta_2}{2}$   | $\frac{(\theta_2 - \theta_1)^2}{12}$                   | $\frac{e^{t\theta_2} - e^{t\theta_1}}{t(\theta_2 - \theta_1)}$ |
| Normal       | $f(y) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\left(\frac{1}{2\sigma^2}\right)(y-\mu)^2\right]$ $-\infty < y < +\infty$         | μ                               | $\sigma^2$   | $\exp\left(\mu t + \frac{t^2\sigma^2}{2}\right)$               |
| Exponential  | $f(y) = \frac{1}{\beta} e^{-y/\beta};  \beta > 0$ $0 < y < \infty$   | β                               | $oldsymbol{eta}^2$                                     | $(1-\beta t)^{-1}$   |
| Gamma        | $f(y) = \left[\frac{1}{\Gamma(\alpha)\beta^{\alpha}}\right] y^{\alpha - 1} e^{-y/\beta};$ $0 < y < \infty$                       | αβ                              | $lphaeta^2$  | $(1-\beta t)^{-\alpha}$  |
| Chi-square   | $f(y) = \frac{(y)^{(v/2)-1}e^{-y/2}}{2^{v/2}\Gamma(v/2)};$ $y^2 > 0$   | v                               | 2ν   | $(1-2t)^{-\nu/2}$  |
| Beta         | $f(y) = \left[\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)}\right] y^{\alpha - 1} (1 - y)^{\beta - 1};$ $0 < y < 1$ | $\frac{\alpha}{\alpha + \beta}$ | $\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$ | does not exist in closed form                                  |

#### **Discrete Distributions**

| Distribution      | Probability Function  | Mean           | Variance  | Moment-<br>Generating<br>Function        |
|-------------------|---|----------------|---|--|
| Binomial          | $p(y) = \binom{n}{y} p^{y} (1-p)^{n-y};$<br>$y = 0, 1, \dots, n$  | np             | np(1-p)   | $[pe^t + (1-p)]^n$                       |
| Geometric         | $p(y) = p(1-p)^{y-1};$<br>y = 1, 2,   | $\frac{1}{p}$  | $\frac{1-p}{p^2}$   | $\frac{pe^t}{1 - (1 - p)e^t}$            |
| Hypergeometric    | $p(y) = \frac{\binom{r}{y} \binom{N-r}{n-y}}{\binom{N}{n}};$<br>$y = 0, 1, \dots, n \text{ if } n \le r,$<br>$y = 0, 1, \dots, r \text{ if } n > r$ | $\frac{nr}{N}$ | $n\left(\frac{r}{N}\right)\left(\frac{N-r}{N}\right)\left(\frac{N-n}{N-1}\right)$ |  |
| Poisson           | $p(y) = \frac{\lambda^{y} e^{-\lambda}}{y!};$<br>$y = 0, 1, 2, \dots$   | λ              | λ   | $\exp[\lambda(e^t-1)]$                   |
| Negative binomial | $p(y) = {y-1 \choose r-1} p^r (1-p)^{y-r};$<br>y = r, r+1,  | $\frac{r}{p}$  | $\frac{r(1-p)}{p^2}$  | $\left[\frac{pe^t}{1-(1-p)e^t}\right]^r$ |