DS290 Modeling and Simulation. AugDec 2025. Answer Key to Midterm 2

$$. \operatorname{Since} \frac{\partial \sum_{i} e_{i}^{2}}{\partial \beta_{j}} = 0, \operatorname{each} \beta_{j} = \frac{\sum_{i} (x_{ji} - \bar{x}_{j})(y_{i} - \bar{y})}{\sum_{i} (x_{ji} - \bar{x}_{j})^{2}} = \frac{\sum_{i} (x_{ji} - \bar{x}_{j})y_{i}}{\sum_{i} (x_{ji} - \bar{x}_{j})^{2}} = : \frac{S_{x_{j}y}}{S_{x_{j}x_{j}}}, \quad \text{where} \quad \bar{x}_{j} := \frac{\sum_{i=1}^{n} x_{ji}}{n}$$

$$\operatorname{Then,} \operatorname{Var}(\beta_{j}) = \frac{\sum_{i} (x_{ji} - \bar{x}_{j})^{2} \operatorname{Var}(\varepsilon_{i})}{\left(\sum_{i} (x_{ji} - \bar{x}_{j})^{2}\right)^{2}} = \frac{\sigma^{2}}{\sum_{i} (x_{ji} - \bar{x}_{j})^{2}}; E(\beta_{j}) = 0, \operatorname{since}$$

$$\operatorname{Var}(y_{i}) = \operatorname{Var}(\hat{y}_{i}) + \operatorname{Var}(\varepsilon_{i}) = \operatorname{Var}(\varepsilon_{i}) = \sigma^{2} \operatorname{and} \hat{y}_{i} \text{ is a computed quantity.}$$

for each independent random variable y_i .

For unbiased estimator we need to evaluate the following,

$$\begin{split} E\left(\sum_{i=1}^{n}e_{i}^{2}\right) &= \sum_{i=1}^{n}E\left(y_{i} - \frac{\sum_{i=1}^{n}y_{i}}{n} - \sum_{j=1}^{K}\beta_{j}(x_{ji} - \bar{x_{j}})\right)^{2} \\ &= \sum_{i=1}^{n}\left(\frac{1}{n}\right)^{2}\left(E\left(y_{1}^{2}\right) + + E\left(y_{i-1}^{2}\right) + E\left(y_{i+1}^{2}\right) + + E\left(y_{n}^{2}\right)\right) + \left(1 - \frac{1}{n}\right)^{2}E\left(y_{i}^{2}\right) - \left(2\left(\frac{n-1}{n}\right)^{2} + \frac{(n-1)(n-2)}{n^{2}}\right)E\left(y_{i}\right)^{2} \\ &+ \sum_{j=1}^{K}E\left(\beta_{j}^{2}\sum_{i=1}^{n}\left(x_{ji} - \bar{x_{j}}\right)^{2} - 2\beta_{j}\sum_{i=1}^{n}\left(x_{ji} - \bar{x_{j}}\right)\left(y_{i} - \bar{y}\right)\right) \\ &= n\frac{(n-1)}{n}\left(\sigma^{2} + E\left(y_{i}\right)^{2} - E\left(y_{i}\right)^{2}\right) + E\left(\sum_{j=1}^{K}\beta_{j}^{2}S_{x_{j}x_{j}} - 2\beta_{j}^{2}S_{x_{j}x_{j}}\right) \\ &= (n-1)\sigma^{2} - K\sigma^{2} = (n-1-K)\sigma^{2} \\ &\qquad \qquad Therefore, \frac{E\left(\sum_{i=1}^{n}e_{i}^{2}\right)}{(n-1-K)} = Var\left(\varepsilon_{i}\right) = \sigma^{2} \end{split}$$

2.

For this problem the true optimal solution can be computed analytically: $x^* = 2.611$ years, giving an expected cost of \$11,586. This solution is obtained by minimizing the expected cost, which can be written as

$$2000x + \int_0^\infty 20000 I(y \le 1) \frac{e^{-y/x}}{x} dx$$

where I is the indicator function.

3.

Let X represent a process S -T such that S has a distribution that complements the exponential arrival times such that X is normally distributed with zero mean and standard deviation σ . Then:

$$\begin{split} W_{n+1} - w &= \varphi(W_n - w) + X_n \\ W_{n+1} - w &= \varphi^{n+1}(W_0 - w) + \sum_{j=0}^n \varphi^{j_1 - j_2} \chi_j \\ E(W_{n+1}) &= w + \varphi^{n+1}(E(W_0) - w) \to w \quad as \quad n \to \infty \\ Var(W_{n+1}) &= \varphi^{2(n+1)} + \sigma^2 \sum_{j=0}^n \varphi^{(2j)} \to \sigma^2 I(1 - \varphi^2) \quad as \quad n \to \infty \end{split}$$

The first two lines in the above can be obtained by induction.

4.

. In the calculation below, substitute epsilon = 3 and t = 2.821 for 9 degrees of freedom and at 1% confidence level obtained as 0.04/(5-1). Also use S12, S23, S24, S25 in the calculations below.

$\bar{Y}_{.i}$	1	2	3	4	5
	8.9464	6.5448	7.1387	9.5497	11.1213
S_{ij}^2	1	2	3	4	5
1		0.0251	0.0375	0.0330	0.0620
2			0.0028	0.0104	0.0226
3				0.0051	0.0104
4					0.0046

 $t_{0.02(5-1),(10-1)} = \frac{2.085}{}$ 2.821

$$\begin{split} \bar{Y}_{.1} &= 8.9464 > \bar{Y}_{.2} + t\sqrt{S_{12}^2/10} = 6.82216.6861 \\ \bar{Y}_{.3} &= 7.1387 > \bar{Y}_{.2} + t\sqrt{S_{13}^2/10} = 6.71755 \\ \bar{Y}_{.4} &= 9.5497 > \bar{Y}_{.2} + t\sqrt{S_{14}^2/10} = 6.70685 \\ \bar{Y}_{.5} &= 11.1213 > \bar{Y}_{.2} + t\sqrt{S_{15}^2/10} = 6.76693 \\ \bar{Y}_{.5} &= 11.1213 > \bar{Y}_{.2} + t\sqrt{S_{15}^2/10} = 6.6724 \end{split}$$
 Similar Caclulations

Thus, there was adequate data to select the best, policy 2, with 95% confidence.

 $\widehat{S}^2 = \max_{i \neq j} S_{ij}^2 = 0.0620$. The seconde-stage sample size,

$$R = \max\left(R_0, \lceil \frac{t^2\widehat{S^2}}{\epsilon^2} \rceil\right) = \max\left(10, \lceil \frac{(2.625^2)(0.0620)}{3^2} \rceil\right) = 10$$

Thus, 10 replication is sufficient to make statistical comparisons.

Since $\min_{i=1}^{5} \{ \vec{Y}_i \} = \vec{Y}_2$, there was adequate data to conclude that policy 2 has the least expected cost per day with 92% confidence.

5. (a) From the least squares,
$$\frac{\partial}{\partial \beta_1} \sum_{i=1}^n e_i^2 = 0$$
, that is, $\sum_{i=1}^n e_i \frac{\partial}{\partial \beta_1} e_i = 0$, that is, $\sum_{i=1}^n e_i (x_i - \bar{x}) = 0$.
$$\sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n (y_i - \hat{y}_i + \hat{y}_i - \bar{y})^2 = \sum_{i=1}^n e_i^2 + r_i^2 + 2\beta_1 e_i (x_i - \bar{x})$$
$$= \sum_{i=1}^n (e_i^2 + r_i^2) + 2\beta_1 \sum_{i=1}^n e_i (x_i - \bar{x}) = \sum_{i=1}^n e_i^2 + \sum_{i=1}^n r_i^2$$

5(b)
$$(n-(1+2\sum_{k=1}^{n-1}\frac{n-k}{n}\rho_k))\sigma^2$$

6. (a) Test for significance
$$(H_0: \mu_d = 0)$$

Letting $d_i = y_i - z_i, \ \bar{d} = 1.80, S_d = 3.60$
 $t_0 = 1.80/(3.60/\sqrt{4}) = 1.60$

For $\alpha=0.05, t_{3,0.025}=3.18$ Since $|t_0|<3.18$, do not reject the null hypothesis.

(b) Sample size needed for
$$\beta \leq 0.20$$

 $\delta = 2/3.60 = 0.556$
For $\alpha = 0.05, \ \beta \leq 0.20$ and $\delta = 0.556$
 $n = 30$ observations.