

PS-TAT 126
Fall 2020

Hints for Homework I

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Hw1

P1

1. By Def,
$$\begin{aligned}\text{Var}(Z) &= E[(Z - E(Z))^2] \\ &= E[Z^2 - 2ZE(Z) + (E(Z))^2] \\ &= E[Z^2] - [E(Z)]^2\end{aligned}$$

LHS =
$$E[(aZ + bZ')^2] - [E(aZ + bZ')]^2$$

By Def,
$$\begin{aligned}\text{Cov}(Z, Z') &= E(ZZ') - E(Z)E(Z') \\ &= a^2 \text{Var}(Z) + b^2 \text{Var}(Z') + 2ab \text{Cov}(Z, Z') \\ &= \text{RHS}\end{aligned}$$

2. By Def, A collection of events A_1, \dots, A_n are mutually independent if for any subcollection A_{i_1}, \dots, A_{i_k} , we have

$$P\left(\bigcap_{j=1}^k A_{i_j}\right) = \prod_{j=1}^k P(A_{i_j})$$

A_1, \dots, A_n are pairwise independent if any two events are independent, i.e. for any $i \neq j$

$$P(A_i \cap A_j) = P(A_i)P(A_j)$$

N.B. mutually independence is a stronger definition

(a) pairwise independence does NOT imply mutual independence
Give one counter example.
(NOTE: Use Your own example!)

Counter example:

Let sample space $S = \{ \text{3! permutations of } a, b, c \}$
i.e. $S = \begin{Bmatrix} aaa & bbb & ccc \\ abc & bca & cba \\ acb & bac & cab \end{Bmatrix}$

Define $A_i = \{ \text{ith place in the triple is occupied by } a \}$.

Then, $P(A_i) = \frac{1}{3}$, for $i = 1, 2, 3$.

and $P(A_1 \cap A_2) = P(A_1 \cap A_3) = P(A_2 \cap A_3) = \frac{1}{9}$

thus, A_1, A_2, A_3 are pairwise independent.

However,

$$P(A_1 \cap A_2 \cap A_3) = \frac{1}{9} \neq P(A_1)P(A_2)P(A_3)$$

So, A_1, A_2, A_3 are NOT mutually independent.

(b) Mutual independence implies pairwise independence.

By Def of mutual independence, for any sub collection $\{A_{i_1}, A_{i_2}\}$, we have

$$P(A_{i_1}, A_{i_2}) = P(A_{i_1})P(A_{i_2})$$

3. Yes. Because by "linear", we mean we have linearity in parameters, i.e., " β_j 's, not necessarily in covariates.

(NOTE: You should explain more details, and it's better to give an example.)

4. Residuals $e_i = Y_i - \hat{Y}_i$, where $\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i$ is the fitted value (in a SLR)

$$\begin{aligned} \sum_{i=1}^n e_i &= \sum_{i=1}^n (Y_i - \hat{Y}_i) \\ &= \sum_{i=1}^n (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i) \\ &= \sum_{i=1}^n Y_i - n\hat{\beta}_0 - \hat{\beta}_1 \sum_{i=1}^n X_i \quad \text{b/c } \bar{Y} = \hat{\beta}_0 + \hat{\beta}_1 \bar{X} \\ &= 0 \quad \text{b/c } \bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i, \bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \end{aligned}$$

5. • Our goal of regression: $Y = f(x) + \varepsilon$,
where $f(x)$ is the deterministic component, and
is an approximate functional relationship between X and Y .
• Mean function $E(Y|X)$ is important in regression,
because (1) we want to minimize $E[(f(x) - Y)^2] \geq 0$
and (2) we have $E[(f(x) - Y)^2]$

$$= E[(f(x) - E(Y|X))^2] + E[(Y - E(Y|X))^2]$$

By taking $f(x) = E(Y|X)$, we can minimize
LHS of the equation.

This implies the mean function $E(Y|X)$ is the best
representation of the functional relationship
between X and Y (recall $Y \approx f(x)$).

(For details, see P6 to P7 in Lecture 2 slides)
(NOTE: Explain in your own way!)

6. N.B. Use calculus, rather than derive formulae for $\hat{\beta}_0, \hat{\beta}_1$
Goal: $(\hat{\beta}_0, \hat{\beta}_1) = \arg\min_{(\beta_0, \beta_1) \in \mathbb{R}^2} \sum_{n=1}^N (y_n - (\beta_0 + \beta_1 x_n))^2$

$$\text{Let } f(\beta_0, \beta_1) = \sum_{n=1}^N (y_n - (\beta_0 + \beta_1 x_n))^2$$

$$\begin{cases} \frac{\partial f(\beta_0, \beta_1)}{\partial \beta_0} = -2 \sum_{n=1}^N (y_n - (\beta_0 + \beta_1 x_n)) = 0 & (1) \\ \frac{\partial f(\beta_0, \beta_1)}{\partial \beta_1} = -2 \sum_{n=1}^N (y_n - (\beta_0 + \beta_1 x_n)) \cdot x_n = 0 & (2) \end{cases}$$

In this case $N=3$, three data points: $(0,1), (1,0), (1,1)$

$$\begin{cases} -2 [(1 - \beta_0) - (\beta_0 + \beta_1) + 1 - (\beta_0 + \beta_1)] = 0 \\ -2 [0 - (\beta_0 + \beta_1) + 1 - (\beta_0 + \beta_1)] = 0 \end{cases}$$

$$\therefore (\hat{\beta}_0, \hat{\beta}_1) =$$

7. you can use R example on page 12 of Lecture 2 slides.