

Exercise 3

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Task 2:

Show that $E[\mathbf{z}^T \mathbf{A} \mathbf{z}] = \mu^T \mathbf{A} \mu + \text{Tr}(\mathbf{A} \Sigma)$

$\mathbf{z}^T \mathbf{A} \mathbf{z}$ is a quadratic expression since $\mathbf{A} \in \mathbb{R}^{n \times n}$

- for the quadratic form it holds true that it can be represented in terms of the outer product $\mathbf{z}^T \mathbf{z}$ and the matrix \mathbf{A} . It holds true that

$$\mathbf{z}^T \mathbf{A} \mathbf{z} = \text{Tr}(\mathbf{z}^T \mathbf{A} \mathbf{z})$$

- Therefore:

$$E[\mathbf{z}^T \mathbf{A} \mathbf{z}] = E[\text{Tr}(\mathbf{z}^T \mathbf{A} \mathbf{z})]$$

using cyclic property of the trace we obtain

$$E[\text{Tr}(\mathbf{A} \mathbf{z} \mathbf{z}^T)]$$

Since the trace is a scalar it is its own expectation

$$E[\text{Tr}(\mathbf{A} \mathbf{z} \mathbf{z}^T)] = \text{Tr}(E[\mathbf{A} \mathbf{z} \mathbf{z}^T])$$

linearity of expectation:

$$\text{Tr}(\mathbf{A} E[\mathbf{z} \mathbf{z}^T])$$

$$E[\mathbf{z} \mathbf{z}^T] = \text{Cov}(\mathbf{z}) + E[\mathbf{z}] E[\mathbf{z}]^T$$

Putting it all together set $E[\mathbf{z}] = \mu$ and $\text{Cov}(\mathbf{z}) = \Sigma$ we obtain

$$\text{Tr}(\mathbf{A} \cdot E[\mathbf{z} \mathbf{z}^T]) = \text{Tr}(\mathbf{A} \cdot (\text{Cov}(\mathbf{z}) + E[\mathbf{z}] E[\mathbf{z}]^T))$$

$$\Leftrightarrow \text{Tr}(\mathbf{A} \cdot \text{Cov}(\mathbf{z}) + E[\mathbf{z}] E[\mathbf{z}]^T \mathbf{A})$$

$$\Leftrightarrow \text{Tr}(\mathbf{A} \cdot \text{Cov}(\mathbf{z})) + \text{Tr}(E[\mathbf{z}] E[\mathbf{z}]^T \mathbf{A})$$

$$\Leftrightarrow \text{Tr}(\mathbf{A} \cdot \text{Cov}(\mathbf{z})) + \text{Tr}(E[\mathbf{z}]^T \mathbf{A} E[\mathbf{z}])$$

$$\Rightarrow \text{Tr}(\mathbf{A} \Sigma) + \mu^T \mathbf{A} \mu$$

2. Show that $\text{Cov}(\mathbf{A} \mathbf{z}) = \mathbf{A} \Sigma \mathbf{A}^T$

Coming from univariate case we know that $\text{var}(aX) = a^2 \text{var}(X)$
 $\mathbf{A} \mathbf{A}^T = \mathbf{A}^2$

$$\text{Cov}(\mathbf{A} \mathbf{z}) = E[(\mathbf{A} \mathbf{z} - E(\mathbf{A} \mathbf{z}))(\mathbf{A} \mathbf{z} - E(\mathbf{A} \mathbf{z}))^T]$$

$$\Leftrightarrow E[(\mathbf{A} \mathbf{z} - \mathbf{A} E(\mathbf{z}))(\mathbf{A} \mathbf{z} - \mathbf{A} E(\mathbf{z}))^T]$$

$$\Leftrightarrow E[(\mathbf{A}(\mathbf{z} - E(\mathbf{z}))) (\mathbf{A}(\mathbf{z} - E(\mathbf{z})))^T]$$

$$\Leftrightarrow \mathbf{A} E[(\mathbf{z} - E(\mathbf{z}))(\mathbf{z} - E(\mathbf{z}))^T] \mathbf{A}^T$$

$$\Leftrightarrow \mathbf{A} \text{Cov}(\mathbf{z}) \mathbf{A}^T$$

$$\Leftrightarrow \mathbf{A} \Sigma \mathbf{A}^T$$

3. Show that $\text{Cov}(\hat{\beta}) = (\sigma^2 \mathbf{X}^T \mathbf{X})^{-1}$

we start with $\hat{\beta}$:

$$\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \quad \text{we replace } \mathbf{y} \text{ with } \mathbf{X} \beta + \epsilon$$

$$\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T (\mathbf{X} \beta + \epsilon)$$

$$= (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{X} \beta + (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \epsilon \quad | \text{ we know that } (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{X} = \mathbf{I}$$

$$\Rightarrow \hat{\beta} = \beta + (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \epsilon$$

$$\text{Cov}(\hat{\beta}) = \text{Cov}(\beta + (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \epsilon) \quad | \text{ linearity}$$

$$= \text{Cov}(\beta) + \text{Cov}((\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \epsilon) \quad | \text{Cov}(\beta) = 0$$

$$= \text{Cov}((\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \epsilon) \quad | \text{Cov}(c \mathbf{z}) \text{ where } c \text{ is constant} = c^2 \text{Cov}(\mathbf{z})$$

$$= (\mathbf{X}^T \mathbf{X})^{-1} \text{Cov}(\mathbf{X}^T \epsilon) (\mathbf{X}^T \mathbf{X})^{-1} \quad | \text{Cov}(\mathbf{X}^T \epsilon) = \mathbf{X}^T \text{Cov}(\epsilon) \mathbf{X} = \mathbf{X}^T \sigma^2 \mathbf{I} \mathbf{X} = \sigma^2 \mathbf{X}^T \mathbf{X}$$

$$= (\mathbf{X}^T \mathbf{X})^{-1} (\mathbf{X}^T \mathbf{X} \sigma^2) (\mathbf{X}^T \mathbf{X})^{-1} \quad | (\mathbf{X}^T \mathbf{X})^{-1} (\mathbf{X}^T \mathbf{X} \sigma^2) = \mathbf{I} \sigma^2$$

$$= \sigma^2 (\mathbf{X}^T \mathbf{X})^{-1}$$

Task 3:

we can model this as a binomial distribution:

$$P(AA) = (1-p)^2$$

$$P(Aa) = 2p(1-p)$$

$$P(aa) = p^2$$

$n = x + y + z$ where x, y, z is the number of observations of AA, Aa and aa

$$\text{likelihood } L(AA, Aa, aa; p) = P(AA)^x \cdot P(Aa)^y \cdot P(aa)^z$$

take log

$$\log \text{likelihood } l(L(p)) =$$

$$l(p) = x \log(1-p) + y \log(2p(1-p)) + z \log(p)$$

max-log-likelihood:

$$\frac{dl}{dp} = \frac{-x}{1-p} + \frac{y}{p} + \frac{z}{p} = 0$$