

## 5. Linear Regression with Deterministic Design

### Linear Regression with Deterministic Design



a transpose for the covariance matrix.

So I know that  $y$  has this form under this assumption.

So I certainly know what the distribution of this guy

is, because it's just taking a Gaussian and hitting it with a matrix.

And we know this, right?

We know that if I take an  $n$   $\mu$  capital sigma

and I hit it with a matrix  $a$ , get an  $n$   $a$  times  $\mu$  and a sigma

**a transpose for the covariance matrix.**

8:56 / 8:56 1.0x

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## Deterministic Design

1/1 point (graded)

In the setting of **deterministic design** for linear regression, we assume that the design matrix  $\mathbb{X}$  is deterministic instead of random. The **model** still prescribes  $\mathbf{Y} = \mathbb{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$ , where  $\boldsymbol{\epsilon} = (\epsilon_1, \dots, \epsilon_n)$  is a random vector that represents noise. Take note that the only random object on the right hand side is  $\boldsymbol{\epsilon}$ , and that  $\mathbf{Y}$  is **still random**.

For the rest of this section, we will always assume  $(\mathbb{X}^T \mathbb{X})^{-1}$  exists; i.e. **rank**  $(\mathbb{X}) = p$ .

Recall that the Least-Squares Estimator  $\hat{\boldsymbol{\beta}}$  has the formula

$$\hat{\boldsymbol{\beta}} = (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbf{Y}.$$

If we assume that the vector  $\boldsymbol{\epsilon}$  is a random variable with mean  $\mathbb{E}[\boldsymbol{\epsilon}] = \mathbf{0}$ , then in the deterministic design setting: "The LSE  $\hat{\boldsymbol{\beta}}$  is a random variable, with mean..." (choose all that apply)

☐ 0

☒  $(\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbb{E}[\mathbf{Y}]$  ✓

☐  $\mathbb{X}^T \mathbb{X} \boldsymbol{\beta}$

☒  $\beta$  ✓

☐  $\epsilon$



Solution:

- The model is  $\mathbf{Y} = \mathbb{X}\beta + \epsilon$ , and  $\epsilon$  is a random variable. So  $\mathbf{Y}$  should in fact be considered as a random variable.
- Using the formula for  $\hat{\beta}$  and applying linearity of expectation, we obtain:

$$\begin{aligned}\mathbb{E}[\hat{\beta}] &= \mathbb{E}\left[(\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbf{Y}\right] \\ &= \mathbb{E}\left[(\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbb{X} \beta + (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \epsilon\right] \\ &= \beta + (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbb{E}[\epsilon] \\ &= \beta\end{aligned}$$

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You have used 2 of 2 attempts

Answers are displayed within the problem

Uniform Noise

3/3 points (graded)  
Assume that  $n = p$ , so that the number of samples matches the number of covariates, and that  $\mathbb{X}$  has rank  $n$ . Recall that the Least-Squares Estimator  $\hat{\beta}$  has the formula

$$\hat{\beta} = (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbf{Y}.$$

If we assume that the vector  $\epsilon = (\epsilon_1, \dots, \epsilon_n)$  is uniformly distributed in the  $n$ -dimensional box  $[-1, +1]^n$ , then:

"The model is **homoscedastic** ; i.e.  $\epsilon_1, \dots, \epsilon_n$  are i.i.d."

☒ True ✓

☐ False

"In the deterministic design setting,  $\mathbf{Y}$  is also deterministic."

☐ True

☒ False ✓

"In the deterministic design setting, the LSE  $\hat{\beta}$  is a uniformly distributed random variable."

☒ True ✓

☐ False

(You may use the following fact: in the 1-dimensional case, consider  $a \sim \text{Uniform}([0, 1])$  and let  $\lambda > 0$ . Intuitively enough, the distribution of  $b = \lambda a$  is uniform over the interval  $[0, \lambda]$ . More generally, if  $a$  is uniformly distributed over a rectangular region  $R \subset \mathbb{R}^n$  and  $M$  is an  $n \times n$  matrix of full rank, then  $b$  is uniformly distributed over the region  $M(R) \subset \mathbb{R}^n$ , the image of  $R$  under the transformation  $M$ .)

Solution:

- “The model is homoscedastic ; i.e.  $\epsilon_1, \dots, \epsilon_n$  are i.i.d.” is true. The uniform distribution over  $[-1, +1]^n$  is the product distribution of  $n$  uniform distributions over  $[-1, +1]$ . Therefore, each component is i.i.d.
- “In the deterministic design setting,  $\mathbf{Y}$  is also deterministic” is false. The model is  $\mathbf{Y} = \mathbb{X}\beta + \epsilon$ , so  $\mathbf{Y}$  is a random variable that is a translation of  $\epsilon$  by  $\mathbb{X}\beta$ .
- “In the deterministic design setting, the LSE  $\hat{\beta}$  is a uniformly distributed random variable” is true. Note that

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

把误差从n维变换成p维

The random variable  $(\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \epsilon$  is uniformly distributed over the region  $(\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T ([-1, +1]^n)$ . Uniformity is preserved under translation by  $\beta$ , as well.

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You have used 1 of 1 attempt

**i** Answers are displayed within the problem

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