



5. Linear Regression with

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## 5. Linear Regression with Deterministic Design

### Linear Regression with Deterministic Design

Given  $Y, X$  (say as  $(Y, X)$ ,  $i=1, \dots, n$ )

$LSE \quad \hat{\beta} = \argmin_{\beta \in \mathbb{R}^p} \|Y - X\beta\|^2$

$I = X(X^T X)^{-1} X^T$

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

$X\hat{\beta} = X(X^T X)^{-1} X^T Y = IY = Y$

Orthogonal projection of  $Y$  is  $IY$ ,  $P$

Claim:  $X\hat{\beta} = IY$

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

$X\hat{\beta} = X(X^T X)^{-1} X^T Y = IY$

a transpose for the covariance matrix.

8:56 / 8:56

1.50x

CC

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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  $\mathbf{Y} = \mathbb{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ , where  $\boldsymbol{\varepsilon} = (\varepsilon_1, \dots, \varepsilon_n)$  is a random vector that represents noise. Take note that the only random object on the right hand side is  $\varepsilon$ , 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.  $\text{rank}(\mathbb{X}) = p$ .

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

☐ 0

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

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

☒  $\boldsymbol{\beta}$

☐  $\boldsymbol{\varepsilon}$



**Solution:**

- The model is  $\mathbf{Y} = \mathbb{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ , and  $\boldsymbol{\varepsilon}$  is a random variable. So  $\mathbf{Y}$  should in fact be considered as a random variable.
- Using the formula for  $\hat{\boldsymbol{\beta}}$  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 1 of 2 attempts

**i** 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.  $\varepsilon_1, \dots, \varepsilon_n$  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  $\mathbf{Y} = \mathbb{X}\beta + \varepsilon$ , so  $\mathbf{Y}$  is a random variable that is a translation of  $\varepsilon$  by  $\mathbb{X}\beta$ .
- **"In the deterministic design setting, the LSE  $\hat{\beta}$  is a uniformly distributed random variable"** is true. Note that

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

The random variable  $(\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \varepsilon$  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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