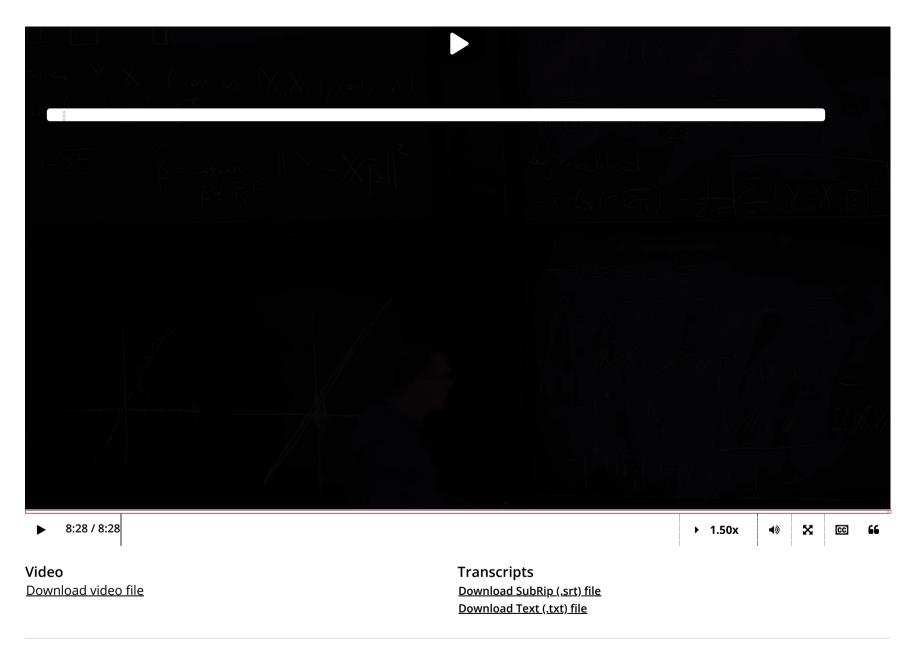


7. Distribution of the Least Square

<u>Course</u> > <u>Unit 6 Linear Regression</u> > <u>Lecture 20: Linear Regression 2</u> > Estimator

## 7. Distribution of the Least Square Estimator Distribution of the Least Square Estimator



## Gaussian Noise

3/3 points (graded)

Recall that the Least-Squares Estimator  $\hat{m{eta}}$  has the formula

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

If we assume that the vector  $\epsilon$  is an n-dimensional Gaussian with mean 0 and covariance  $\sigma^2 I_n$  for some known  $\sigma^2 > 0$ , then:

"The model is **homoscedastic**; i.e.  $\varepsilon_1, \dots, \varepsilon_n$  are i.i.d."

True
False
<b>✓</b>
"In the deterministic design setting, the LSE $\hat{m{eta}}$ is a Gaussian random variable."
True
○ False
<b>✓</b>
"If $\mathbb X$ is a random variable, then the LSE $\hat{m{eta}}$ is still a Gaussian random variable."
True
False

## Solution:

- "The model is homoscedastic; i.e.  $\varepsilon_1, \dots, \varepsilon_n$  are i.i.d." is true. The covariance matrix is a diagonal matrix. Recall the useful fact that the ith coordinate of a multi-dimensional gaussian is also a gaussian. In the case where the covariance matrix is diagonal, the coordinates also happen to be independent. Therefore, the first statement is **true**.
- "In the deterministic design setting, the LSE  $\hat{\beta}$  is a Gaussian random variable" is true. We have

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

By using the result of the first exercise, we arrive at the conclusion that  $\hat{eta}$  is also Gaussian:  $\hat{eta} \sim \mathcal{N}\left(eta, \sigma^2(\mathbb{X}^T\mathbb{X})^{-1}\right)$ .

• "If  $\mathbb X$  is a random variable, then the LSE  $\hat{\beta}$  is still a Gaussian random variable" is false. The assumption that  $\mathbb X$  is deterministic/constant is *crucial.* If  $\mathbb X$  were a generic random variable, then  $\hat{\beta}$  might no longer be Gaussian.

Perhaps the simplest example is the case where  $\mathbb X$  is determined by an unbiased coin flip. Specifically, consider what happens if  $\mathbb X$  takes value  $\mathbb{X}_1$  if the coin comes up heads, otherwise it takes value  $\mathbb{X}_2$ . Then by the law of total probability,  $\hat{eta}$  has density  $rac{f_1}{2}+rac{f_2}{2}$  where  $f_1,f_2$ are densities of Gaussians  $\mathcal{N}(\beta, \sigma^2(\mathbb{X}_1^T\mathbb{X}_1)^{-1})$ ,  $\mathcal{N}(\beta, \sigma^2(\mathbb{X}_2^T\mathbb{X}_2)^{-1})$  respectively. If  $\mathbb{X}_1 \neq \mathbb{X}_2$ , this is not a Gaussian distribution, but a "mixture" of two Gaussians. (Note: this is not to be confused with the density of the sum of two Gaussian random variables, which IS a Gaussian random variable. Summing the densities is different from summing the random variables!) In general, it can be very difficult to write down the distribution of  $\hat{\beta}$  in terms of the distribution of  $\mathbb{X}$ .

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You have used 1 of 1 attempt

**1** Answers are displayed within the problem

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