

# Regression Analysis

## Multiple Linear Regression

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Estimating the Regression Line  
and Predicting a New Response



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## About This Lesson



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# Estimating the Regression Line

At some selected value of  $x$ , say  $x^*$ , estimate the “mean response” of  $y$  (the regression line) via

$$\hat{Y}|x^* = \hat{\beta}_0 + \hat{\beta}_1 x^*_1 + \hat{\beta}_2 x^*_2 + \cdots + \hat{\beta}_p x^*_p = x^{*T} \hat{\beta}$$

- Because the estimators of  $\beta$  are normally distributed, so is  $\hat{Y}$ .
- If we know the expected value and variance, we can use the normal distribution of  $\hat{Y}$  to draw inferences on the regression line.

# Estimating the Regression Line

$\hat{y}$  has a normal distribution with

$$E(\hat{Y}|x^*) = x^{*T} \beta = \beta_0 + \beta_1 x^*_1 + \beta_2 x^*_2 + \cdots + \beta_p x^*_p$$

$$\text{Var}(\hat{Y}|x^*) = \sigma^2 x^{*T} (X^T X)^{-1} x^*$$

If we replace the unknown variance with its estimator,  $\hat{\sigma}^2 = \text{MSE}$ , the sampling distribution becomes a  $t$ -distribution with  $n-p-1$  degrees of freedom.

# Confidence Interval for Regression Line

The  $(1 - \alpha)$  **Confidence Interval** for the *mean response* (or regression line) for one instance of predicting variables  $\mathbf{x}^*$  is:

$$\hat{y}|\mathbf{x}^* \pm t_{\alpha/2, n-p-1} \sqrt{\hat{\sigma}^2 \mathbf{x}^{*T} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}^*}$$

The  $(1 - \alpha)$  **Confidence Surface** for all possible instances of the predicting variables is:

$$\hat{y}|\mathbf{x}^* \pm \sqrt{(p+1)F_{\alpha, p+1, n-p-1}} \sqrt{\hat{\sigma}^2 \mathbf{x}^{*T} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}^*}$$

# Predicting a New Response

- One of the primary motivations for regression is to use the regression equation to predict future responses.
- The predicted regression line is the same as the estimated regression line.
- But a prediction is not the same as the regression line estimation. The prediction contains *two* sources of uncertainty:
  - From the parameter estimates (of  $\beta$ s)
  - From the new observation(s)

## Predicting a New Response (*cont'd*)

1. Variation of the estimated regression line:  $\sigma^2 \mathbf{x}^{*T} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}^*$
2. Variation of a new measurement:  $\sigma^2$

The new observation is independent of the regression data, so the total variation in predicting  $\hat{y}^* | \mathbf{x}^*$  is

$$\text{Var}(\hat{Y} | \mathbf{x}^*) = \sigma^2 \mathbf{x}^{*T} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}^* + \sigma^2 (\hat{\sigma}^2 (1 + \mathbf{x}^{*T} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}^*))$$

## Predicting a New Response (*cont'd*)

The  $(1 - \alpha)$  **Prediction Interval** for one new (future)  $\hat{y}^*$  (at  $\mathbf{x}^*$ ) is

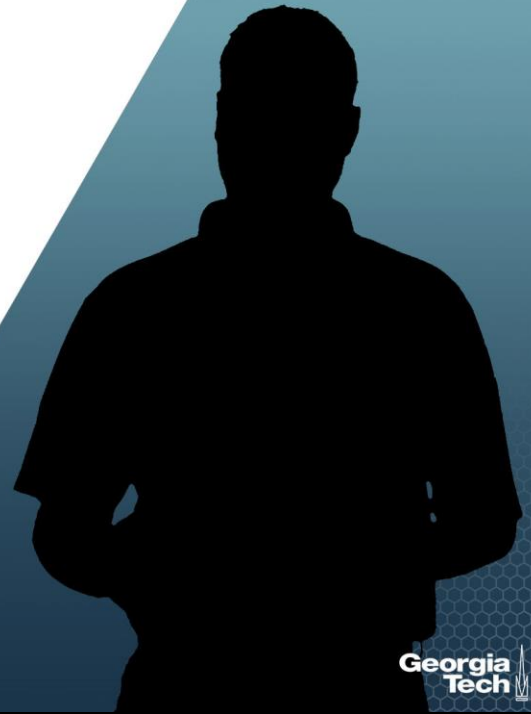
$$\mathbf{x}^{*T} \hat{\boldsymbol{\beta}} \pm t_{\alpha/2, n-p-1} \sqrt{\hat{\sigma}^2 (1 + \mathbf{x}^{*T} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}^*)}$$

$\hat{y} = \mathbf{x}^{*T} \hat{\boldsymbol{\beta}}$  is the same as the line estimate, but the *Prediction Interval* is wider than the *Confidence Interval* for the mean response.

The  $(1 - \alpha)$  **Prediction Interval** for m new (future)  $\hat{y}^*$ s (at  $\mathbf{x}^*$ ) is

$$\hat{y} | \mathbf{x}^* \pm \sqrt{m F_{\alpha, m, n-p-1}} \sqrt{\hat{\sigma}^2 (1 + \mathbf{x}^{*T} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}^*)}$$

# Summary



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