



### **Estimating the Regression Line**

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

$$\hat{Y}|x^* = \hat{\beta}_0 + \hat{\beta}_1 x_1^* + \hat{\beta}_2 x_2^* + \dots + \hat{\beta}_p x_p^* = x^* \hat{\beta}$$

- 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.

Georgia Tech

2

#### Estimating the Regression Line

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

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

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

If we replace the unknown variance with its estimator,  $\hat{\sigma}^2 = MSE$ , 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 <u>one</u> instance of predicting variables  $\dot{x}$  is:

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

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

$$\hat{y}|\mathbf{\ddot{x}} \pm \sqrt{(p+1)} \mathbf{F}_{\alpha, p+1, n-p-1} \sqrt{\widehat{\sigma}^2 \mathbf{\ddot{x}}^{\mathrm{T}} (\mathbf{X}^{\mathrm{T}} \mathbf{X})^{-1} \mathbf{\ddot{x}}}$$

Georgia Tech

\_

### 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:  $\sigma^2 x^{*T} (X^T X)^{-1} x^*$
- 2. Variation of a new measurement:  $\sigma^2$

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

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

Georgia Tech

7

## Predicting a New Response (cont'd)

The  $(1 - \alpha)$  **Prediction Interval** for <u>one new</u> (future)  $\mathring{y}$  (at  $\mathring{x}$ ) is

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

 $\hat{y} = x^{*T} \hat{\beta}$  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  $\underline{m}$  new (future)  $\dot{y}$ s (at  $x^*$ ) is

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

Georgia Tech

