

## 2.4: Simultaneous Inference and Important Considerations

Dr. Bean - Stat 5100

Simultaneous inference is when we want to conduct multiple tests of significance at the same time.

### 1 Why Simultaneous Inference?

In handout 2.3, we conducted inference for parameters one at a time. We need to change our approach when looking at multiple parameters simultaneously.

**How and why do we need to change our approach when conducting simultaneous inference?**

(check out [this comic](#) for help).

If we conduct several tests at the same level of significance, the probability of getting one false positive result (a type I) error becomes much higher than  $\alpha$ .

As a result, we need to adjust the level of significance to account for a “multiplicity” of testing.

### 2 Bonferroni Adjustment

Multiplicity:

- Let  $A_j$  = event that an individual  $(1 - \alpha)100\%$  CI does not contain the true value of  $\beta_j$ .
- $P(A_0) = P(A_1) = \alpha \rightarrow$  Type I Error
  - $P(\text{NOT } A_j)$  = probability that an interval contains the true value of  $\beta_j$ .
- **Bonferroni Inequality:**  $P(\text{NOT } A_0 \text{ AND NOT } A_1) \geq 1 - P(A_0) - P(A_1)$

This means that if we conduct  $g$  tests at a confidence level of  $(1 - \frac{\alpha}{g})$ , then we are guaranteed that overall level of confidence for all intervals *considered jointly* will be at least  $(1 - \alpha)$ , we call this the **Bonferroni adjustment**.

- **Bonferroni Advantage:** Can be applied in *any* situation that requires a multiplicity adjustment, including simultaneous intervals for  $\hat{Y}$  at multiple  $X_h$  levels.
- **Bonferroni Disadvantage:** Can be overly conservative, producing inefficient (unnecessarily wide) intervals.

#### Comparison of Simultaneous Intervals for $\hat{Y}$

- Confidence intervals (mean response)
  - Bonferroni

$$\hat{Y} \pm t_{n-p}(1 - \frac{\alpha}{2g}) * s\{\hat{Y}_h\}$$

- Working-Hotelling (WH)

$$\hat{Y} \pm W * s\{\hat{Y}_h\} \quad \left( W = \sqrt{pF_{p,n-p}(1-\alpha)} \right)$$

Notice that the W-statistic does not consider  $g$

- \* WH provides a “confidence band” for the entire regression line (all possible  $X_h$  levels).
- \* This means the WH interval at any individual  $X_h$  will be wider than the t-based confidence interval, but the WH intervals will eventually be narrower than Bonferroni confidence intervals if enough  $X_h$  are considered.
- Prediction intervals (new response)

- Bonferroni

$$\hat{Y} \pm t_{n-p}(1 - \frac{\alpha}{2g}) * s\{\hat{Y}_{h(new)}\}$$

- Scheffe (chef-eh)

$$\hat{Y} \pm S * s\{\hat{Y}_{h(new)}\} \quad \left( S = \sqrt{gF_{g,n-p}(1-\alpha)} \right)$$

**Rule of Thumb:** Always pick the most efficient interval that guarantees your intended type I error ( $\alpha$ ).

Table 1: Summary of Methods for Simultaneous Intervals

Simultaneous Interval on:	Methods
$\beta$ 's	Bonferroni
Population means of $Y$ at multiple $X_h$	Bonferroni or Working-Hotelling
Predictions for $Y$ at multiple $X_h$	Bonferroni or Scheffe

### 3 Inverse Prediction

**Problem:** What is the value of  $X_h$  necessary to achieve a specific value of  $\hat{Y}$ .

**Solution:** solve for  $X$ .

$$\begin{aligned} \hat{Y} &= b_0 + b_1 X_h \\ b_1 X_h &= \hat{Y} - b_0 \\ X_h &= \frac{\hat{Y} - b_0}{b_1} \end{aligned}$$

**Problem:** Use  $Y$  to predict values of  $X$ .

**Solution:** DO NOT solve for  $X$ .

**Why?**

- The least squares slope estimate of regression model that predicts  $Y$  using  $X$ :  $\rho \frac{SD\{Y\}}{SD\{X\}}$ .
- The least squares slope estimate of regression model that predicts  $X$  using  $Y$ :  $\rho \frac{SD\{X\}}{SD\{Y\}}$ .
- Notice that the slopes are NOT inverses of each other.

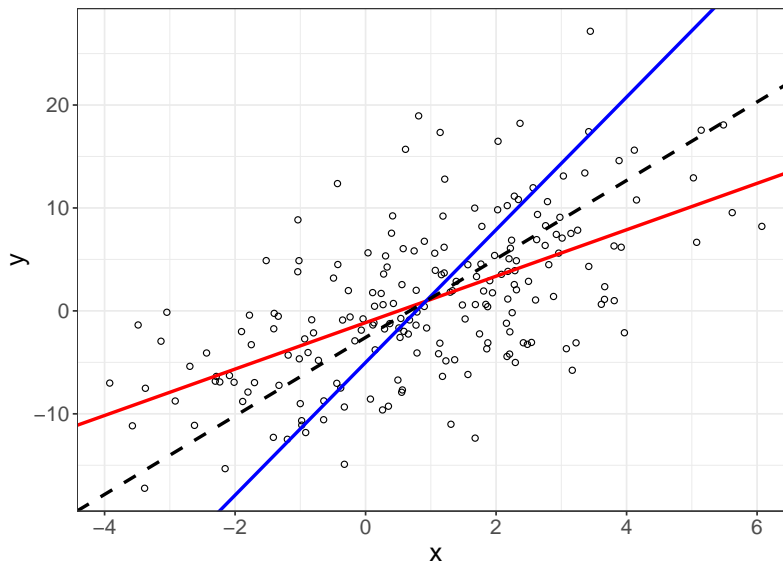


Figure 1: Scatterplot of points along with the regression line that uses  $X$  to predict  $Y$  (red), the regression line that uses  $Y$  to predict  $X$  (blue), the SD line (black).

## 4 Cautions for Linear Regression

- Remedial measures may not fix violations of assumptions
  - May need to abandon OLS regression altogether
- Interpretation: Sometimes the  $X$  vs  $Y$  relationship may look counterintuitive
  - May be the result of omitted predictors
- $R^2$  can be abused
  - Higher  $R^2 \rightarrow$  not always better model
  - Lower  $R^2 \rightarrow$  does not mean there is no linear relationship