# 2.4: Simultaneous Inference and Important Considerations

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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  $\beta_j$ .
- $P(A_0) = P(A_1) = \alpha \rightarrow \text{Type I Error}$ 
  - $P(NOTA_j)$  = probability that an interval contains the true value of  $\beta_j$ .
- Bonferroni Inequality:  $P(\text{NOT}A_0 \text{ AND NOT } A_1) \ge 1 P(A_0) P(A_1)$

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)

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

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)

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

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 of 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.

$$\hat{Y} = b_0 + b_1 X_h$$

$$b_1 X_h = \hat{Y} - b_0$$

$$X_h = \frac{\hat{Y} - b_0}{b_1}$$

**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:  $\rho_{\overline{SD\{X\}}}^{SD\{Y\}}$ .
- 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.

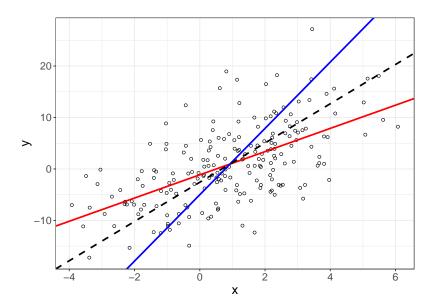


Figure 1: Scatterplot of points along with the regression line that uses X to predict Y (red), the regression line that uses Y to predict X (blue), the SD line (black).

## 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  $R^2 \to \text{not always better model}$
  - Lower  $\mathbb{R}^2 \to \text{does not mean there is no linear relationship}$