Linear Regression Models P8111

Lecture 12

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Today's Lecture

- Gauss-Markov theorem
- Maximum likelihood inference
- Regression diagnostics

What's so great about LSEs?

- Nice projection-space interpretation
- They're the "best" linear unbiased estimators
- They're maximum likelihood estimators under Normally-distributed errors

Gauss-Markov theorem

Assume the model

$$y = X\beta + \epsilon$$

where $E(\epsilon) = 0$ and $Var(\epsilon) = \sigma^2 I$. Also assume X is a full rank design matrix.

■ Among all unbiased linear estimators Cy of the regression coefficients β , the LSE has minimum variance and is unique.

We call the LSEs "BLUE".

Gauss-Markov theorem – proof

Gauss-Markov theorem – proof

Gauss-Markov theorem – caveats

The Gauss-Markov theorem is great, but notice the details:

- Assumed $Var(\epsilon) = \sigma^2 I$
- Only talking about unbiased linear estimators

Maximum likelihood estimation

Continue assuming the model

$$y = X\beta + \epsilon$$

where $E(\epsilon) = 0$ and $Var(\epsilon) = \sigma^2 I$.

- Additionally, assume $\epsilon \sim N(0, \sigma^2 I)$
- Put differently, we're imposing the model

$$y \sim N(X\beta, \sigma^2 I)$$

• y is multivariate Normal with uncorrelated entries; the y_i are each independently Normally distributed

Maximum likelihood estimation

Using independently Normal y_i 's:

Maximum likelihood estimation

Using matrix notation:

Regression diagnostics

- Regression diagnostics are tools used to determine whether a given model is consistent with the data
- Usually focus on residuals
- Recall that fitted values are given by $\hat{y} = Hy$ where H is the hat matrix
- Residuals are defined as $y \hat{y} = (I H)y$

$$\hat{\epsilon}$$
 and ϵ

$$\mathbf{E}(\hat{\boldsymbol{\epsilon}}) =$$

$$Var(\hat{\epsilon}) =$$

 Residuals are mean zero, but don't have constant variance nor are they uncorrelated.

$$\hat{\epsilon}$$
 and ϵ

$$\hat{\epsilon} = (I - H)\epsilon$$

- lacksquare If ϵ is Normally distributed, so are the residuals
- Also note residuals sum to zero

Residuals and fitted values

$$Cov(\hat{\epsilon}^T, \hat{y}) = Cov((I - H)y, Hy)$$

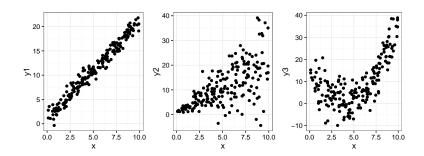
= $(I - H)\sigma^2 IH^T$
= $\sigma^2 (H - H)$

So residuals and fitted values are uncorrelated

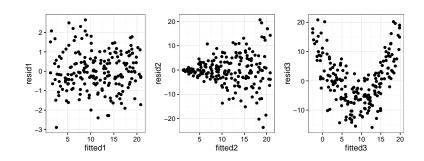
Residuals when model is correct

- Often we plot the residuals against one of the predictors or against the fitted values
- What we look for:
 - $E(\hat{\epsilon}|x) = 0$
 - $V(\hat{\epsilon}|x) = \sigma^2(1 h_{ii})$
- If the model is incorrect, you may be able to spot:
 - ► Patterns in the residuals
 - ► Clear non-constant variance

Some data plots



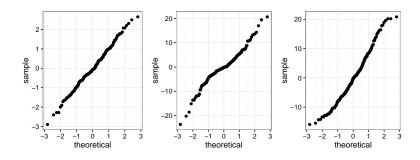
Some residual plots



Checking Normality assumption

- We often assume Normality for the errors
- Useful to check Normality of residuals
- Try a QQ plot:
 - ► Compute the sample quantiles of the residuals
 - ► Compute the quantiles of a standard Normal of size *n*
 - ► Plot these against each other
- Can also use the Shapiro-Wilk test based on correlation between observed and theoretical quantiles

Checking Normality assumption



Checking model structure

- You can plot residuals against each of the predictors, or plot outcomes against predictors
- Keep in mind the MLR uses adjusted relationships; scatterplots don't show that adjustment
- Adjusted variable plots (partial regression plots, added variable plots) can be useful

Adjusted variable plots

- Regress y on everything but x_j ; take residuals $r_{y|-x_j}$
- Regress x_j on everything but x_j ; take residuals $r_{x_j|-x_j}$
- Regress $r_{y|-x_j}$ on $r_{x_j|-x_j}$; slope of this line will match β_j in the full MLR
- Plot of $r_{y|-x_j}$ against $r_{x_j|-x_j}$ shows the "adjusted" relationship

What should you do ...

if your assumptions are violated?

- Depends on the assumption
- For problems with the errors, use LSE anyway; maybe use bootstrap for inference
- For non-linearity, try an augmented model

Today's big ideas

■ Gauss-Markov, MLE, regression diagnostics

■ Suggested reading: Faraway Ch 2.8, Ch 7