## Ch 3.3: Even More Linear Regression Lecture 7 - CMSE 381

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#### Last time:

• 3.2 Multiple Linear Regression

#### **Announcements:**

- HW #2 Due Sunday!
- Office hours

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- RSE, R<sup>2</sup>
- Confidence intervals and prediction intervals
- Qualitative predictors

# Section 1

## Continued: Questions to ask of your model

### Linear Regression with Multiple Variables



• Predict Y on a multiple variables X

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p x_p + \varepsilon$$

- Find good guesses for  $\hat{\beta}_0$ ,  $\hat{\beta}_1, \cdots$ .
- $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i + \dots + \hat{\beta}_p x_p$

- $e_i = y_i \hat{y}_i$  is the *i*th residual • RSS =  $\sum_i e_i^2$
- RSS is minimized at *least* squares coefficient estimates

### Review: Questions to ask of your model

- Is at least one of the predictors X<sub>1</sub>,..., X<sub>p</sub> useful in predicting the response?
- O all the predictors help to explain Y, or is only a subset of the predictors useful?

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### Q3

How well does the model fit the data?

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## Assessing the accuracy of the module

Almost the same as before

Residual standard error (RSE):

$$RSE = \sqrt{\frac{1}{n-p-1}RSS}$$

R squared:

$$R^{2} = \frac{TSS - RSS}{TSS} = 1 - \frac{RSS}{TSS}$$
$$TSS = \sum_{i} (y_{i} - \overline{y})^{2}$$

- Just TV:  $R^2 = 0.61$
- Just TV and radio:  $R^2 = 0.89719$
- All three variables:  $R^2 = 0.8972$

- Just TV: *RSE* = 3.26
- Just TV and radio: RSE = 1.681
- All three variables: RSE = 1.686

### If all else fails, look at the data



### Q4

Given a set of predictor values, what response value should we predict, and how accurate is our prediction?

Given estimates 
$$\hat{\beta}_0, \cdots, \hat{\beta}_p$$
 for  $\beta_0, \cdots, \beta_p$   
Least squares plane:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \dots + \hat{\beta}_p X_p$$

estimate for the true population regression plane

$$f(X) = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p$$



## Confidence vs Prediction Model

#### **Confidence Interval**

The range likely to contain the population parameter (mean, standard deviation) of interest.

#### **Prediction Interval**

The range that likely contains the value of the dependent variable for a single new observation given specific values of the independent variables.



## Specific to the Advertising Data

**Confidence interval**: quantify the uncertainty surrounding the average sales over a large number of cities.

#### Advertising example:

If \$100K is spent on TV, and \$20K on radio, in each of *n* cities

95% Cl for sales: [10,985, 11,528].

**Prediction Interval:** quantify the uncertainty in sales for a particular city.

#### Advertising example:

Given that \$100,000 is spent on TV advertising and \$20,000 is spent on radio advertising in **Gotham City** 

95% prediction interval for Gotham: [7,930, 14,580].

## Comparing the two



Go take a look at the code under Q4

### Review: Questions to ask of your model

- Is at least one of the predictors X<sub>1</sub>,..., X<sub>p</sub> useful in predicting the response?
- Oo all the predictors help to explain Y, or is only a subset of the predictors useful?
- I How well does the model fit the data?
- Given a set of predictor values, what response value should we predict, and how accurate is our prediction?

# Section 2

## **Qualitative Predictors**

### Reminder: Qualitative vs Quantitative predictors

Quantitative:

Qualitative/Categorical:

### New data set! Credit card balance



- own: house ownership
- student: student status
- status: marital status
- region: East, West, or South

- ... your variables aren't quantitative?
- Home ownership
- Student status
- Major
- Gender
- Ethnicity
- Country of origin

#### Example

Investigate differences in credit card balance between people who own a house and those who don't, ignoring the other variables. Create a new variable

$$x_i = egin{cases} 1 & ext{if } i ext{th person is a student} \ 0 & ext{if } i ext{th person is not a student} \end{cases}$$

Model:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$
$$= \begin{cases} \beta_0 + \beta_1 + \varepsilon_i & \text{if } i\text{th person is student} \\ \beta_0 + \varepsilon_i & \text{if } i\text{th person isn't} \end{cases}$$

## Interpretation

	coef	std err	t	P> t	[0.025	0.975]
Intercept	480.3694	23.434	20.499	0.000	434.300	526.439
Student[T.Yes]	396.4556	74.104	5.350	0.000	250.771	542.140

### Model:

$$y = 480.36 + 396.46 \cdot x_{student}$$

## Who cares about 0/1?

### Old version: 0/1

$$x_i = \begin{cases} 1 & \text{if } i \text{th person is a student} \\ 0 & \text{if } i \text{th person is not a student} \end{cases}$$

Model:

$$\begin{split} y_i &= \beta_0 + \beta_1 x_i + \varepsilon_i \\ &= \begin{cases} \beta_0 + \beta_1 + \varepsilon_i & \text{if } i \text{th person is student} \\ \beta_0 + \varepsilon_i & \text{if } i \text{th person isn't} \end{cases} \end{split}$$

Alternative version:  $\pm 1$ 

 $x_i = \begin{cases} 1 & \text{if } i \text{th person is a student} \\ -1 & \text{if } i \text{th person is not a student} \end{cases}$ 

Model:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$
  
= 
$$\begin{cases} \beta_0 + \beta_1 + \varepsilon_i & \text{if ith person is student} \\ \beta_0 - \beta_1 + \varepsilon_i & \text{if ith person isn't} \end{cases}$$

## Qualitiative Predictor with More than Two Levels



# More on multiple levels

	Coefficient	Std. error	t-statistic	p-value
Intercept	531.00	46.32	11.464	< 0.0001
region[South]	-18.69	65.02	-0.287	0.7740
region[West]	-12.50	56.68	-0.221	0.8260

Do code section on "Playing with multi-level variables"

# Next time

Lec #	Date			Reading	нพ
1	Mon	8/26	Intro / First day stuff / Python Review Pt 1	1	
2	Wed	8/28	What is statistical learning?	2.1	
	Fri	8/30	Class Cancelled (Dr Munch out of town)		
	Mon	9/2	No class - Labor day		
3	Wed	9/4	Assessing Model Accuracy	2.2.1, 2.2.2	
4	4 Fri 9/6 Linear Reg 5 Mon 9/9 More Linear F		Linear Regression	3.1	HW #1 Due
5			More Linear Regression 3.1/3.		Sun 9/8
6	Wed	9/11	Even more linear regression	3.2.2	
7	Fri 9/13		Probably more linear regression	3.3	Hw #2 Due
8	Mon	9/16	Linear regression coding module		Dun 9/15
9	Wed	9/18	Intro to classification, Bayes classifier, KNN classifier	2.2.3	
10	Fri	9/20	Logistic Regression	4.1, 4.2, 4.3.1-3	
11	11 Mon 9/2		Multiple Logistic Regression / Multinomial Logistic Regression /Project day	4.3.4-5	Hw #3 Due Sun 9/22
	Wed	9/25	Review		