Ch 3.1-2: (Multi)-Linear Regression Lecture 4 - CMSE 381

Michigan State University

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Dept of Computational Mathematics, Science & Engineering

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Announcements

Last time:

• Started 3.1 - Single linear regression

Announcements:

- Office Hours: Monday-Thursday
- Homework #1 grades and feedback posted
- Homework #2 Due Wed, Jan 24

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Covered in this lecture

- hypothesis test, and p-value for coefficient estimates
- Residual standard error (RSE)
- R squared
- Setup for multiple linear regression

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Section 1

Last time

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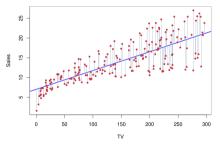
Setup

 Predict Y on a single predictor variable X

$$Y \approx \beta_0 + \beta_1 X$$

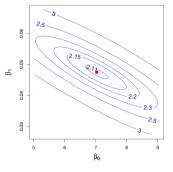
• "≈" "is approximately modeled as"

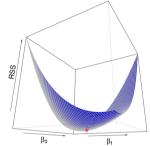
- Given $(x_1, y_1), \dots, (x_n, y_n)$
- Let $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$ be prediction for Y on ith value of X.
- $e_i = y_i \hat{y}_i$ is the *i*th residual



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Least squares criterion: RSS





Residual sum of squares RSS is

RSS =
$$e_1^2 + \dots + e_n^2$$

= $\sum_i (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$

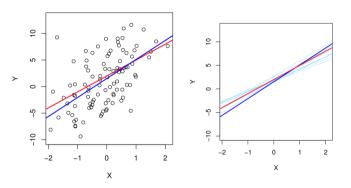
Least squares criterion

Find β_0 and β_1 that minimize the RSS.

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^n (x_i - \overline{x})^2}$$
$$\hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \overline{x}$$

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Linear regression is unbiased



- 100 data points drawn from $Y = 2 + 3X + \varepsilon$
- ε drawn from normal distribution with mean 0
- Red line is true relationship, blue is least squares estimate
- Repeat this 10 times and plot all the found lines (in variations of blue)
- The resulting models are slightly different but are all around the red true relationship

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Section 2

Continue on evaluating models

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Variance of linear regression estimates

Variance of linear regression estimates:

$$SE(\hat{\beta}_0) = \sigma^2 \left[\frac{1}{n} + \frac{\overline{x}^2}{\sum_{i=1}^n (x_i - \overline{x})^2} \right]$$
$$SE(\hat{\beta}_1)^2 = \frac{\sigma^2}{\sum_{i=1}^n (x_i - \overline{x})^2}$$

where $\sigma^2 = \operatorname{Var}(\varepsilon)$

ullet Residual standard error is an estimate of σ

$$RSE = \sqrt{RSS/(n-2)}$$

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Confidence Interval

The 95% confidence interval for β_1 approximately takes the form

$$\hat{\beta}_1 \pm 2 \cdot \text{SE}(\hat{\beta}_1)$$

Same form works for β_0

Interpretation:

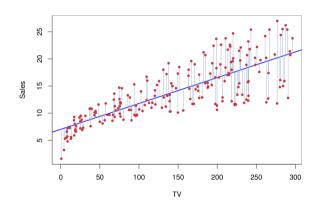
There is approximately a 95% chance that the interval

$$\left[\hat{\beta}_1 - 2 \cdot \operatorname{SE}(\hat{\beta}_1), \hat{\beta}_1 + 2 \cdot \operatorname{SE}(\hat{\beta}_1)\right]$$

will contain β_1 where we repeatedly approximate $\hat{\beta}_1$ using repeated samples.

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CI in Advertising data



For the advertising data set, the 95% CIs are:

• β_1 :: [0.042, 0.053]

• β_0 :: [6.130, 7.935]

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Hypothesis testing

- *H*₀: There is no relationship between *X* and *Y* (null hypothesis)
- H_1 : There is some relationship between X and Y (alternative hypothesis)

$$H_0: \beta_1 = 0$$

 $H_A: \beta_1 \neq 0$

since if $\beta_1=0$ then the model reduces to $Y=\beta_0+\varepsilon$, and thus X is not associated with Y

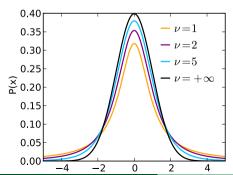
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Test statistic and p-value

Test statistic:

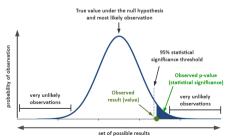
$$t = \frac{\hat{\beta}_1 - 0}{\operatorname{SE}(\hat{\beta}_1)}$$

t-distribution with n-2 degrees of freedom



A small p-value indicates that it is unlikely to observe such a substantial association between the predictor and the response due to chance, in the absence of any real association between the predictor and the response.

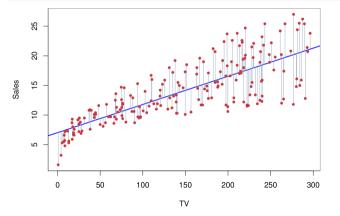
Draw me:



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Advertising example

	Coefficient	Std. error	t-statistic	<i>p</i> -value
Intercept	7.0325	0.4578	15.36	< 0.0001
TV	0.0475	0.0027	17.67	< 0.0001



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Assessing the accuracy of the module: RSE

Quantify the extent to which the model fits the data

Residual standard error (RSE):

$$RSE = \sqrt{\frac{1}{n-2}RSS}$$
$$= \sqrt{\frac{1}{n-2}\sum_{i}(y_i - \hat{y}_i)^2}$$

- $\begin{tabular}{ll} \bullet & \textbf{estimate of the standard deviation of} \\ \varepsilon & \end{tabular}$
- Avg amount that the response will deviate from the true regression line
- avg amount response will deviate from the true regression line

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Assessing the accuracy of the module: R^2

R squared:

$$R^2 = \frac{TSS - RSS}{TSS} = 1 - \frac{RSS}{TSS}$$

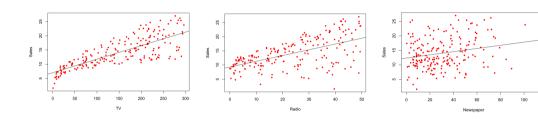
where total sum of squares is

$$TSS = \sum_{i} (y_i - \overline{y})^2$$

- TSS is total variance in teh response *Y*, variability before regression
- RSS amount of variability after the regression
- R² is proportion of variability in Y that can be explained using X
- Close to 1, large proportion of varaiability is explained by regression
- Close to 0, regression does not explain much of the variability in the response

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Advertising example



$$R^2 = 0.61$$

$$R^2 = 0.33$$

$$R^2 = 0.05$$

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Coding group work

Run the section titled "Assessing Coefficient Estimate Accuracy"

Point out that the homework uses the code slightly differently.
statsmodels.formula.api vs
statsmodels.api. You can use whatever you want on the homework.

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Section 3

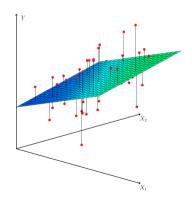
Multiple Linear Regression

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Setup

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

• β_j is avg affect on Y of one unit increase in X_j



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Estimation and Prediction

Given estimates $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_p$, prediction is

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \dots + \hat{\beta}_p x_p$$

Minimize the sum of squares

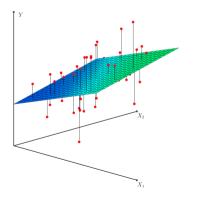
$$RSS = \sum_{i} (y_i - \hat{y}_i)^2$$
$$= \sum_{i} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_1 - \dots - \hat{\beta}_p x_p)$$

Coefficients are closed form but UGLY We won't write them down, your favorite code can do this for us

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Advertising data set example

Sales =
$$\beta_0 + \beta_1 \cdot TV + \beta_2 \cdot radio + \beta_3 \cdot newspaper$$



	Coefficient
Intercept	2.939
TV	0.046
radio	0.189
newspaper	-0.001

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Interpretation of coefficients

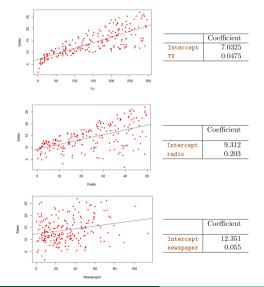
Sales =
$$\beta_0 + \beta_1 \cdot TV + \beta_2 \cdot radio + \beta_3 \cdot newspaper$$

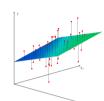
	Coefficient
Intercept	2.939
TV	0.046
radio	0.189
newspaper	-0.001

- Fixing TV and newspaper spending;
 Spending \$1K more on radio results in 189 units additional sales
- What's going on with newspaper? This says no relationship between newspaper and sales

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Single regression vs multi-regression





	Coefficient
Intercept	2.939
TV	0.046
radio	0.189
newspaper	-0.001

Correlation matrix

	TV	radio	newspaper	sales
TV	1.0000	0.0548	0.0567	0.7822
radio		1.0000	0.3541	0.5762
newspaper			1.0000	0.2283
sales				1.0000

- Correlation between radio and newspaper high (0.35)
- Markets with lots of radio also have lots of newspaper ads
- In single reg, newspaper gets credit for radio

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Coding group work

Run the section titled "Multiple Linear Regression"

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