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

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:

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Wed, Jan 29, 2025

Announcements

Last time:

• 3.2 Multiple Linear Regression

Announcements:

2/29

- HW #2 Due Sunday!
- Office hours

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Covered in this lecture

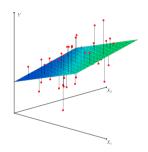
- RSE, R²
- Confidence intervals and prediction intervals
- Qualitative predictors

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Section 1

Continued: Questions to ask of your model

Linear Regression with Multiple Variables



 \bullet 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 .
- $\hat{\mathbf{y}}_i = \hat{\beta}_0 + \hat{\beta}_1 \mathbf{x}_i + \dots + \hat{\beta}_p \mathbf{x}_p$

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

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Review: Questions to ask of your model

- Is at least one of the predictors X_1, \dots, X_p useful in predicting the response?
- ② Do all the predictors help to explain Y, or is only a subset of the predictors useful?

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:

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

R^2 on Advertising data

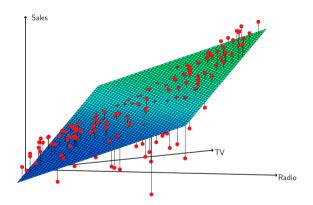
- Just TV: $R^2 = 0.61$
- Just TV and radio: $R^2 = 0.89719$
- All three variables: $R^2 = 0.8972$

RSE on Advertising Data

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

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If all else fails, look at the data



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Q4

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

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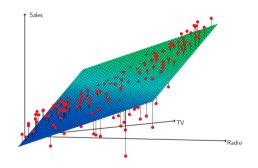
Q4: Making predictions

Given estimates $\hat{\beta}_0, \dots, \hat{\beta}_p$ for β_0, \dots, β_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

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



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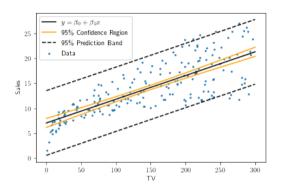
Confidence vs Prediction Model

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.



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Specific to the Advertising Data

Confidence interval: quantify the uncertainty surrounding the <u>average</u> 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% CI for <u>average</u> sales: [10,985, 11,528].

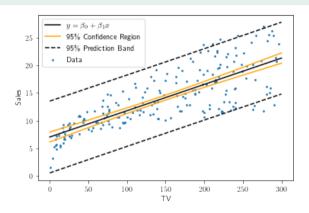
Prediction Interval: quantify the uncertainty in sales for a particular city.

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



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Go take a look at the code under Q4

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Review: Questions to ask of your model

- Is at least one of the predictors X_1, \dots, X_p useful in predicting the response?
- Oo all the predictors help to explain Y, or is only a subset of the predictors useful?
- 4 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

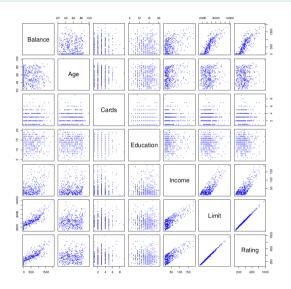
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Reminder: Qualitative vs Quantitative predictors

Quantitative:

Qualitative/Categorical:

New data set! Credit card balance



own: house ownership

student: student status

• status: marital status

• region: East, West, or South

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What if

- ... 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.

One-hot encoding

Create a new variable

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

Model:

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

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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:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

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

Alternative version: ± 1

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

Model:

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

Qualitiative Predictor with More than Two Levels

Region:

South West East

Create spare dummy variables:

$$x_{i1} = \begin{cases} 1 & \text{if } i \text{th person from South} \\ 0 & \text{if } i \text{th person not from South} \end{cases}$$

$$x_{i2} = \begin{cases} 1 & \text{if } i \text{th person from West} \\ 0 & \text{if } i \text{th person not from West} \end{cases}$$

$$\begin{aligned} y_i &= \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i \\ &= \begin{cases} \beta_0 + \beta_1 x_{i1} + \varepsilon_i & \text{if ith person from South} \\ \beta_0 + \beta_2 x_{i2} + \varepsilon_i & \text{if ith person from West} \\ \beta_0 + \varepsilon_i & \text{if ith person from East} \end{cases} \end{aligned}$$

More on multiple levels

	Coefficient	Std. error	t-statistic	<i>p</i> -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

CMSE381_S2025_Schedule : Sheet1

Lec #		Date	Topic	Reading	HW			
1	M	1/13	Intro / Python Review	1				
2	W	1/15	What is statistical learning	2.1				
3	F	1/17	Assessing Model Accuracy	2.2.1, 2.2.2				
	M	1/20	MLK - No Class					
4	W	1/22	Linear Regression	3.1				
5	F	1/24	More Linear Regression	3.1	HW #1 Due			
6	M	1/27	Multi-linear Regression	3.2	Sun 1/26			
7	W	1/29	Probably More Linear Regression	3.3				
8	F	1/31	Last of the Linear Regression		HW #2 Due Sun 2/1			
9	М	2/3	Intro to classification, Bayes classifier, KNN classifier	2.2.3				
10	W	2/5	Logistic Regression	4.1, 4.2, 4.3.1-3				
11	F	2/7	Multiple Logistic Regression / Multinomial Logistic Regression	4.3.4-5	HW #3 Due Sun 2/9			
	M	2/10	Project Day & Review					
	W	2/12	Midterm #1					
12	F	2/14	Leave one out CV	5.1.1, 5.1.2				
13	M	2/17	k-fold CV	5.1.3				
14	W	2/19	More k-fold CV	5.1.4-5				
15	F	2/21	k-fold CV for classification	5.1.5	HW #4 Due Sun 2/23			
16	М	2/24	Subset selection	6.1				

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