#### **ISLR**

Chapter 3 Ex. 15

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- 15. This problem involves the Boston data set, which we saw in the lab for this chapter. We will now try to predict per capita crime rate using the other variables in this data set. In other words, per capita crime rate is the response, and the other variables are the predictors.
- (a) For each predictor, fit a simple linear regression model to predict the response. Describe your results.

De	pendent variable:	
<del></del> -	crim	
zn	-0.074***	
	(0.016)	
Constant	4.454***	
	(0.417)	
Observations	506	
R2	0.040	
Adjusted R2	0.038	
•	or 8.435 (df = 504)	
F Statistic 21	.103*** (df = 1; 504)	
Note: *p<	<0.1; **p<0.05; ***p<0.0	01

This model is showing a significant association between crime rate and proportion of residential land zoned for lots over 25,000 sq.ft.

2. Dependent variable:
-----crim
------indus 0.510\*\*\*
(0.051)

Constant -2.064\*\*\* (0.667)

Observations 506 R2 0.165

Adjusted R2 0.164
Residual Std. Error 7.866 (df = 504)
F Statistic 99.817\*\*\* (df = 1; 504)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model is showing a significant association between crime rate and proportion of non-retail business acres per town.

#### Dependent variable:

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crim
----chas -1.893

(1.506)

Constant 3.744\*\*\*

(0.396)

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Observations 506 R2 0.003

Adjusted R2 0.001

Residual Std. Error 8.597 (df = 504)

F Statistic 1.579 (df = 1; 504)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model shows that there is no significant relationship between crime rate and Charles River dummy variable.

Dependent variable:

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crim -----

nox 31.249\*\*\*

(2.999)

Constant -13.720\*\*\*

(1.699)

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Observations 506 R2 0.177

Adjusted R2 0.176
Residual Std. Error 7.810 (df = 504)
F Statistic 108.555\*\*\* (df = 1; 504)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model shows that there is a significant relationship between crime rate and nitrogen oxides concentration.

## Dependent variable:

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crim -----

rm -2.684\*\*\* (0.532)

Constant 20.482\*\*\*

(3.364)

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Observations 506 R2 0.048

Adjusted R2 0.046
Residual Std. Error 8.401 (df = 504)
F Statistic 25.450\*\*\* (df = 1; 504)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model displays a significant relationship between crime rate and the number of rooms per dwelling.

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Dependent variable:

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crim

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age	0.108*** (0.013)
Constant	-3.778*** (0.944)
F Statistic 71.6	506 0.124 0.123 r 8.057 (df = 504) 619*** (df = 1; 504)
Note: *p *p   This model display owner-occupied ur	0.1; **p<0.05; ***p<0.01 vs a significant relationship between crime rate and the proportion of nits built prior to 1940.
	endent variable:
	crim
dis	-1.551*** (0.168)
Constant	9.499*** (0.730)
F Statistic 84.8	506 0.144 0.142 r 7.965 (df = 504) 388*** (df = 1; 504)
Note: *p <td>0.1; **p&lt;0.05; ***p&lt;0.01  s a significant relationship between crime rate and the weighted mean  Boston employment centres.</td>	0.1; **p<0.05; ***p<0.01  s a significant relationship between crime rate and the weighted mean  Boston employment centres.
======= Dep	endent variable:

crim

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rad 0.618\*\*\*

(0.034)

Constant -2.287\*\*\*

(0.443)

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Observations 506 R2 0.391

Adjusted R2 0.390
Residual Std. Error 6.718 (df = 504)
F Statistic 323.935\*\*\* (df = 1; 504)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model displays a significant relationship between crime rate and the index of accessibility to radial highways.

#### Dependent variable:

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crim
-----tax 0.030\*\*\*

(0.002)

Constant -8.528\*\*\*

(0.816)

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Observations 506 R2 0.340

Adjusted R2 0.338
Residual Std. Error 6.997 (df = 504)
F Statistic 259.190\*\*\* (df = 1; 504)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model displays a significant relationship between crime rate and the full-value property-tax rate per \\$10,000.

#### Dependent variable:

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crim	
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ptratio 1.152\*\*\* (0.169)

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Constant -17.647\*\*\*

(3.147)

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Observations 506 R2 0.084

Adjusted R2 0.082 Residual Std. Error 8.240 (df = 504) F Statistic 46.259\*\*\* (df = 1; 504)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model displays a significant relationship between crime rate and the pupil-teacher ratio by town.

Dependent variable:

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crim

black -0.036\*\*\* (0.004)

Constant 16.554\*\*\* (1.426)

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Observations 506 R2 0.148

Adjusted R2 0.147 Residual Std. Error 7.946 (df = 504) F Statistic 87.740\*\*\* (df = 1; 504)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model displays a significant relationship between crime rate and the proportion of blacks by town.

#### Dependent variable:

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	crim
Istat	0.549***

(0.048)

Constant -3.331\*\*\*

(0.694)

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Observations 506 R2 0.208

Adjusted R2 0.206 Residual Std. Error 7.664 (df = 504) F Statistic 132.035\*\*\* (df = 1; 504)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

This model displays a significant relationship between crime rate and the lower status of the population.

#### Dependent variable:

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	crim
medy	O 363***

medv -0.363\*\*\* (0.038)

Constant 11.797\*\*\* (0.934)

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Observations 506 R2 0.151

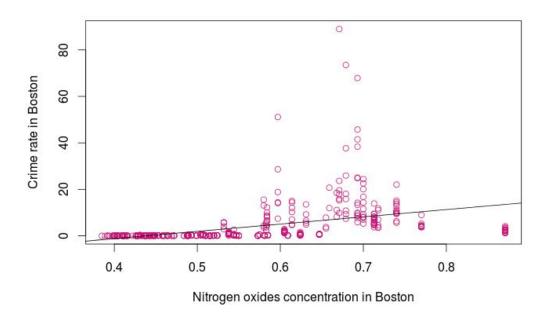
Adjusted R2 0.149
Residual Std. Error 7.934 (df = 504)
F Statistic 89.486\*\*\* (df = 1; 504)

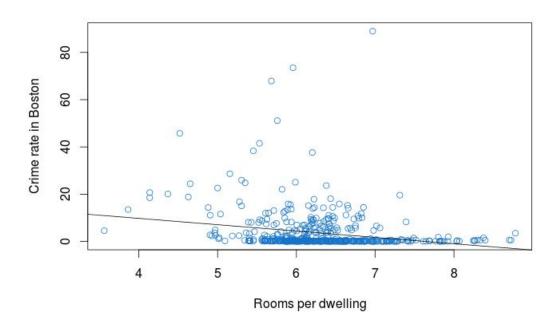
Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

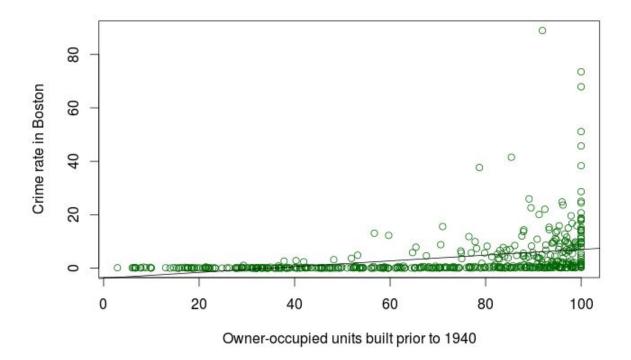
This model displays a significant relationship between crime rate and the median value of owner-occupied homes.

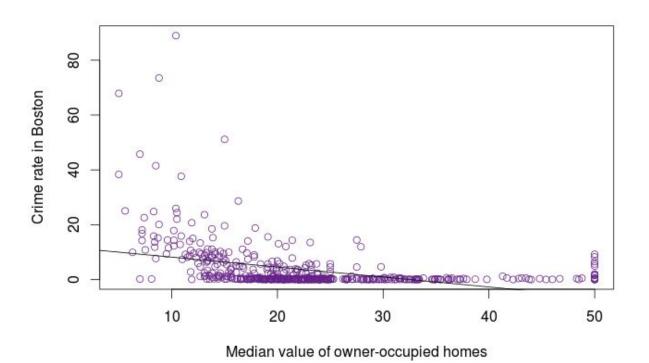
## In which of the models is there a statistically significant association between the predictor and the response? Create some plots to back up your assertions.

All the predictors except for chas showed a significant association when considered with the response individually. However the R<sup>2</sup> value is very low in a lot of cases, which may mean that the relationships are not that significant. Below are some plots demonstrating the relationships:









## (b) Fit a multiple regression model to predict the response using all of the predictors. Describe your results.

> library(stargazer)

> Im.all <- Im(crim ~ ., data = Boston)

## using stargazer for pretty summaries

> stargazer(lm.all, type = "text")

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#### Dependent variable:

	Dependent variable.	
	crim	
zn	0.045**	
	(0.019)	
indus	-0.064	
	(0.083)	
chas	-0.749	
	(1.180)	
nox	-10.314*	
	(5.276)	
rm	0.430	
	(0.613)	
age	0.001	
ŭ	(0.018)	
dis	-0.987***	
	(0.282)	

0.588\*\*\*

(880.0)

-0.004 (0.005)

-0.271 (0.186)

-0.008\*\*

(0.004)

rad

tax

ptratio

black

Istat	0.126*
	(0.076)

medv -0.199\*\*\*

(0.061)

Constant 17.033\*\*

(7.235)

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Observations 506 R2 0.454

Adjusted R2 0.440
Residual Std. Error 6.439 (df = 492)
F Statistic 31.470\*\*\* (df = 13; 492)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## For which predictors can we reject the null hypothesis $H_0$ : $\beta_i = 0$ ?

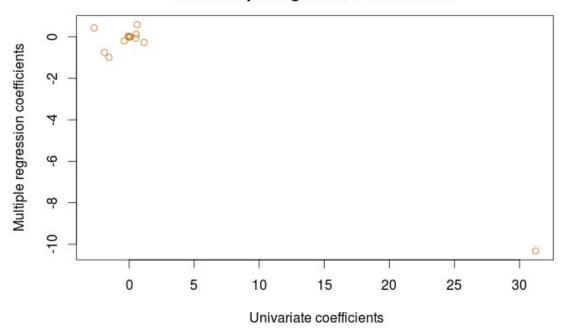
If we decide to keep the variables with the p-value < .01, then we can reject the null hypothesis for dis, rad, medv.

If we decide to keep the variables with the p-value < .05, then we can reject the null hypothesis for the same three variables - dis, rad, medv, - and also for zn and black.

(c) How do your results from (a) compare to your results from (b)? Create a plot displaying the univariate regression coefficients from (a) on the x-axis, and the multiple regression coefficients from (b) on the y-axis. That is, each predictor is displayed as a single point in the plot. Its coefficient in a simple linear regression model is shown on the x-axis, and its coefficient estimate in the multiple linear regression model is shown on the y-axis.

(See next page)

# Comparison of univariate regression coefficients and multiple regression coefficients



(d) Is there evidence of non-linear association between any of the predictors and the response? To answer this question, for each predictor X, fit a model of the form  $Y=\beta_0+\beta_1~X+\beta_2~X^2+\beta_3~X^3+\epsilon.$ 

	Dependent variable:	
	crim	
zn	-0.332*** (0.110)	
I(zn^2)	0.006* (0.004)	
I(zn^3)	-0.00004 (0.00003)	
Constant	4.846***	

Observations 506 R2 0.058

Adjusted R2 0.053 Residual Std. Error 8.372 (df = 502) F Statistic 10.349\*\*\* (df = 3; 502)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

2.

Dependent variable:

crim

indus -1.965\*\*\*

(0.482)

I(indus^2) 0.252\*\*\*

(0.039)

I(indus^3) -0.007\*\*\*

(0.001)

Constant 3.663\*\*

(1.574)

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Observations 506 R2 0.260

Adjusted R2 0.255
Residual Std. Error 7.423 (df = 502)
F Statistic 58.688\*\*\* (df = 3; 502)

3.	
	Dependent variable:

crim

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chas -1.893

(1.506)

I(chas2)

I(chas3)

Constant 3.744\*\*\*

(0.396)

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Observations 506 R2 0.003

Adjusted R2 0.001

Residual Std. Error 8.597 (df = 504)

F Statistic 1.579 (df = 1; 504)

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 4.

### Dependent variable:

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crim

nox -1,279.371\*\*\* (170.397)

I(nox2) 2,248.544\*\*\* (279.899)

I(nox3) -1,245.703\*\*\* (149.282)

Constant 233.087\*\*\*

Observations 506 R2 0.297

Adjusted R2 0.293 Residual Std. Error 7.234 (df = 502) F Statistic 70.687\*\*\* (df = 3; 502)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

5.

#### Dependent variable:

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	crim
rm	-39.150 (31.311)
I(rm2)	4.551

(···· <del>-</del> )	1.001
	(5.010)

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Observations 506 R2 0.068

Adjusted R2 0.062 Residual Std. Error 8.330 (df = 502) F Statistic 12.168\*\*\* (df = 3; 502)

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## Dependent variable:

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	crim
age	0.274 (0.186)
I(age2)	-0.007** (0.004)
I(age3)	0.0001*** (0.00002)
Constant	-2.549 (2.769)

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Observations 506 R2 0.174

Adjusted R2 0.169
Residual Std. Error 7.840 (df = 502)
F Statistic 35.306\*\*\* (df = 3; 502)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

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#### Dependent variable:

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crim

dis -15.554\*\*\* (1.736)

I(dis2) 2.452\*\*\* (0.346)

I(dis3) -0.119\*\*\* (0.020)

Constant 30.048\*\*\* (2.446)

Observations 506 R2 0.278

Adjusted R2 0.274
Residual Std. Error 7.331 (df = 502)
F Statistic 64.374\*\*\* (df = 3; 502)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### Dependent variable:

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	crim
rad	0.513 (1.044)
I(rad2)	-0.075 (0.149)
I(rad3)	0.003 (0.005)
Constant	-0.606 (2.050)

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Observations 506 R2 0.400

Adjusted R2 0.396 Residual Std. Error 6.682 (df = 502) F Statistic 111.573\*\*\* (df = 3; 502)

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#### Dependent variable:

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	crim
tax	-0.153 (0.096)
I(tax2)	0.0004 (0.0002)
I(tax3)	-0.00000 (0.00000)
Constant	19.184 (11.796)

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Observations 506 R2 0.369

Adjusted R2 0.365
Residual Std. Error 6.854 (df = 502)
F Statistic 97.805\*\*\* (df = 3; 502)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

10.

Dependent variable:

crim

ptratio -82.361\*\*\* (27.644)

I(ptratio2) 4.635\*\*\* (1.608)

I(ptratio3) -0.085\*\*\* (0.031)

Constant 477.184\*\*\*

(156.795)

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Observations 506 R2 0.114

Adjusted R2 0.108
Residual Std. Error 8.122 (df = 502)
F Statistic 21.484\*\*\* (df = 3; 502)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### Dependent variable:

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crim

black -0.084 (0.056)

I(black2) 0.0002

(0.0003)

I(black3) -0.00000

(0.00000)

Constant 18.264\*\*\*

(2.305)

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Observations 506

R2 0.150

Adjusted R2 0.145
Residual Std. Error 7.955 (df = 502)
F Statistic 29.492\*\*\* (df = 3; 502)

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### Dependent variable:

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	crim
Istat	-0.449 (0.465)
I(Istat2)	0.056* (0.030)
I(Istat3)	-0.001 (0.001)
Constant	1.201 (2.029)

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Observations 506

R2 0.218

Adjusted R2 0.213 Residual Std. Error 7.629 (df = 502) F Statistic 46.629\*\*\* (df = 3; 502)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Dependent variable:

crim

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medv -5.095\*\*\* (0.434)

I(medv2) 0.155\*\*\* (0.017)

I(medv3) -0.001\*\*\* (0.0002)

Constant 53.166\*\*\*

Observations 506

R2 0.420

Adjusted R2 0.417 Residual Std. Error 6.569 (df = 502) F Statistic 121.272\*\*\* (df = 3; 502)

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Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

indus, nox, age, dis, ptratio and medv seem to have a non-linear association with the response (crim).