

Introducing our Dataset

```
library(MASS)
library(ISLR)
library(caret)
names(Boston)
```

```
[1] "crim"    "zn"      "indus"   "chas"
"nox"     "rm"      "age"
[8] "dis"     "rad"     "tax"     "ptratio"
"black"   "lstat"   "medv"
```

Background to Our Tool: Linear Regression

-

$$y = xb + c$$

-

-

?

Exploring the data

?Boston

Exploring the data

```
str(Boston)
```

```
'data.frame':  506 obs. of  14 variables:
 $ crim   : num  0.00632 0.02731 0.02729
0.03237 0.06905 ...
 $ zn     : num  18 0 0 0 0 0 12.5 12.5 12.5
12.5 ...
 $ indus  : num  2.31 7.07 7.07 2.18 2.18
2.18 7.87 7.87 7.87 7.87 ...
 $ chas   : int  0 0 0 0 0 0 0 0 0 ...
 $ nox    : num  0.538 0.469 0.469 0.458
0.458 0.458 0.524 0.524 0.524 0.524 ...
 $ rm     : num  6.58 6.42 7.18 7 7.15 ...
 $ age    : num  65.2 78.9 61.1 45.8 54.2
58.7 66.6 96.1 100 85.9 ...
 $ dis    : num  4.09 4.97 4.97 6.06 6.06 ...
 $ rad    : int  1 2 2 3 3 3 5 5 5 ...
 $ tax    : num  296 242 242 222 222 222 311
311 311 311 ...
 $ ptratio: num  15.3 17.8 17.8 18.7 18.7
18.7 15.2 15.2 15.2 15.2 ...
 $ black  : num  397 397 393 395 397 ...
 $ lstat  : num  4.98 9.14 4.03 2.94 5.33 ...
 $ medv   : num  24 21.6 34.7 33.4 36.2 28.7
22.9 27.1 16.5 18.9 ...
```

Exploring the data

```
head(Boston)
```

	crim	zn	indus	chas	nox	rm	age
dis	rad	tax	ptratio	black			
1	0.00632	18	2.31	0	0.538	6.575	65.2
4.0900	1	296	15.3	396.90			
2	0.02731	0	7.07	0	0.469	6.421	78.9
4.9671	2	242	17.8	396.90			
3	0.02729	0	7.07	0	0.469	7.185	61.1
4.9671	2	242	17.8	392.83			
4	0.03237	0	2.18	0	0.458	6.998	45.8
6.0622	3	222	18.7	394.63			
5	0.06905	0	2.18	0	0.458	7.147	54.2
6.0622	3	222	18.7	396.90			
6	0.02985	0	2.18	0	0.458	6.430	58.7
6.0622	3	222	18.7	394.12			
lstat	medv						
1	4.98	24.0					
2	9.14	21.6					
3	4.03	34.7					
4	2.94	33.4					
5	5.33	36.2					
6	5.21	28.7					

Perform the train/test split

- createDataPartition can preserve the relative frequencies in our dependent variable

```
set.seed(7)
train_Index <-
createDataPartition(Boston$medv, p = 0.8,
list=FALSE)
train_Boston <- Boston[train_Index,]
test_Boston <- Boston[-train_Index,]
```

Model 1 Single Variable Linear Regression

```
modell1 <- train(medv ~ lstat, method = 'lm',
data = train_Boston)
# view coefficients
coef(modell1$finalModel)
```

(Intercept)	lstat
34.8025753	-0.9506744

modell1

Linear Regression

407 samples
1 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 407, 407, 407, 407,
407, 407, ...
Resampling results:

RMSE	Rsquared
6.491572	0.5451794

Tuning parameter 'intercept' was held
constant at a value of TRUE

Model 2 Two Variable Linear Regression

```
model2 <- train(medv ~ lstat + age, method =  
'lm', data = train_Boston)  
coef(model2$finalModel)
```

(Intercept)	lstat	age
33.1842068	-1.0460706	0.0412899

model2

Linear Regression

407 samples
2 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 407, 407, 407, 407,
407, 407, ...
Resampling results:

RMSE	Rsquared
6.266065	0.5511262

Tuning parameter 'intercept' was held
constant at a value of TRUE

```
varImp(model2)
```

lm variable importance

	Overall
lstat	100
age	0

Model 3 Multiple Variable Linear Regression

```
model3 <- train(medv ~ ., method = "lm", data = train_Boston)
coef(model3$finalModel)
```

(Intercept)	crim	zn
indus	chas	
37.443258137	-0.114804777	0.041559970
-0.026526572	2.644829514	
nox	rm	age
dis	rad	
-19.104962411	3.919062842	0.012302002
-1.468870235	0.278393830	
tax	ptratio	black
lstat		
-0.010477531	-0.978105565	0.006832878
-0.532421893		

model3

Linear Regression

407 samples
13 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 407, 407, 407, 407, 407, 407, ...
Resampling results:

RMSE	Rsquared
------	----------

5.267044 0.6945903

Tuning parameter 'intercept' was held constant at a value of TRUE

```
varImp(model3)
```

```
lm variable importance
```

	Overall
lstat	100.000
rm	90.086
ptratio	69.081
dis	66.392
nox	46.709
rad	34.644
crim	28.419
chas	27.366
zn	25.067
tax	21.715
black	20.238
age	4.898
indus	0.000

Exercise: Try a few variable combinations yourself

```
## your code goes here ##
```

What might be affecting our model?

-
-

Correlation

- assess correlation by creating a correlation matrix

```
cor(Boston)
```

```
      crim      zn      indus
chas      nox
crim      1.00000000 -0.20046922  0.40658341
-0.055891582  0.42097171
zn      -0.20046922  1.00000000 -0.53382819
-0.042696719 -0.51660371
indus      0.40658341 -0.53382819  1.00000000
0.062938027  0.76365145
chas      -0.05589158 -0.04269672  0.06293803
1.000000000  0.09120281
nox      0.42097171 -0.51660371  0.76365145
0.091202807  1.00000000
rm      -0.21924670  0.31199059 -0.39167585
0.091251225 -0.30218819
age      0.35273425 -0.56953734  0.64477851
0.086517774  0.73147010
dis      -0.37967009  0.66440822 -0.70802699
-0.099175780 -0.76923011
rad      0.62550515 -0.31194783  0.59512927
-0.007368241  0.61144056
tax      0.58276431 -0.31456332  0.72076018
-0.035586518  0.66802320
ptratio  0.28994558 -0.39167855  0.38324756
-0.121515174  0.18893268
black    -0.38506394  0.17552032 -0.35697654
0.048788485 -0.38005064
lstat    0.45562148 -0.41299457  0.60379972
-0.053929298  0.59087892
medv     -0.38830461  0.36044534 -0.48372516
```



```

0.175260177 -0.42732077
          rm          age          dis
rad          tax
crim    -0.21924670  0.35273425 -0.37967009
0.625505145  0.58276431
zn        0.31199059 -0.56953734  0.66440822
-0.311947826 -0.31456332
indus    -0.39167585  0.64477851 -0.70802699
0.595129275  0.72076018
chas      0.09125123  0.08651777 -0.09917578
-0.007368241 -0.03558652
nox      -0.30218819  0.73147010 -0.76923011
0.611440563  0.66802320
rm        1.00000000 -0.24026493  0.20524621
-0.209846668 -0.29204783
age      -0.24026493  1.00000000 -0.74788054
0.456022452  0.50645559
dis       0.20524621 -0.74788054  1.00000000
-0.494587930 -0.53443158
rad      -0.20984667  0.45602245 -0.49458793
1.000000000  0.91022819
tax       -0.29204783  0.50645559 -0.53443158
0.910228189  1.00000000
ptratio -0.35550149  0.26151501 -0.23247054
0.464741179  0.46085304
black     0.12806864 -0.27353398  0.29151167
-0.444412816 -0.44180801
lstat    -0.61380827  0.60233853 -0.49699583
0.488676335  0.54399341
medv     0.69535995 -0.37695457  0.24992873
-0.381626231 -0.46853593
          ptratio          black          lstat
medv
crim     0.2899456 -0.38506394  0.4556215
-0.3883046
zn       -0.3916785  0.17552032 -0.4129946
0.3604453
indus    0.3832476 -0.35697654  0.6037997
-0.4837252

```

```

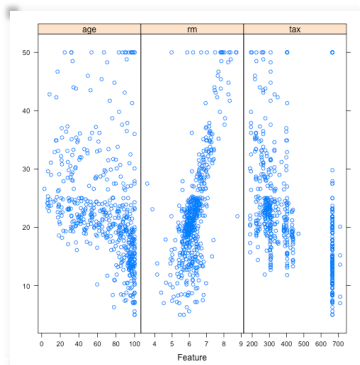
chas     -0.1215152  0.04878848 -0.0539293
0.1752602
nox       0.1889327 -0.38005064  0.5908789
-0.4273208
rm        -0.3555015  0.12806864 -0.6138083
0.6953599
age       0.2615150 -0.27353398  0.6023385
-0.3769546
dis      -0.2324705  0.29151167 -0.4969958
0.2499287
rad       0.4647412 -0.44441282  0.4886763
-0.3816262
tax       0.4608530 -0.44180801  0.5439934
-0.4685359
ptratio  1.0000000 -0.17738330  0.3740443
-0.5077867
black    -0.1773833  1.00000000 -0.3660869
0.3334608
lstat    0.3740443 -0.36608690  1.0000000
-0.7376627
medv     -0.5077867  0.33346082 -0.7376627
1.0000000

```

Looking for outliers

- Scatterplots are useful

```
# small example  
var <- c("rm", "age", "tax")  
featurePlot(x = Boston[, var],  
            y = Boston$medv,  
            plot = "scatter",  
            layout = c(3,1))
```



Improving our model