Multicollinearity of Features - Lab

Introduction

In this lab you'll identify multicollinearity in the Boston Housing Data set.

Objectives

You will be able to:

- Plot heatmaps for the predictors of the Boston dataset
- Understand and calculate correlation matrices

Correlation matrix for the Boston Housing data

Let's reimport the Boston Housing data and let's use the data with the categorical variables for `tax_dummy` and `rad_dummy`

In [5]:
```
import pandas as pd
from sklearn.datasets import load_boston
boston = load_boston()

boston_features = pd.DataFrame(boston.data, columns = boston.feature_names)

# first, create bins for based on the values observed. 5 values will result in 4 bins
bins = [0, 3, 4 , 5, 24]
bins_rad = pd.cut(boston_features['RAD'], bins)
bins_rad = bins_rad.cat.as_unordered()

# first, create bins for based on the values observed. 5 values will result in 4 bins
bins = [0, 250, 300, 360, 460, 712]
bins_tax = pd.cut(boston_features['TAX'], bins)
bins_tax = bins_tax.cat.as_unordered()

tax_dummy = pd.get_dummies(bins_tax, prefix="TAX")
rad_dummy = pd.get_dummies(bins_rad, prefix="RAD")
boston_features = boston_features.drop(["RAD","TAX"], axis=1)
boston_features = pd.concat([boston_features, rad_dummy, tax_dummy], axis=1)
```

In [18]:
```
boston_features.head()
```

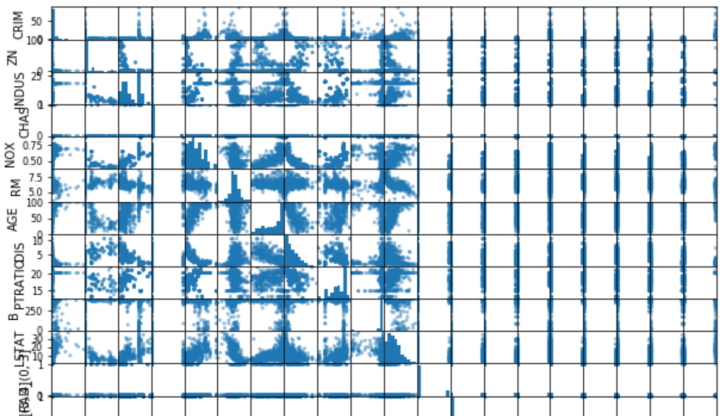
Out[18]:

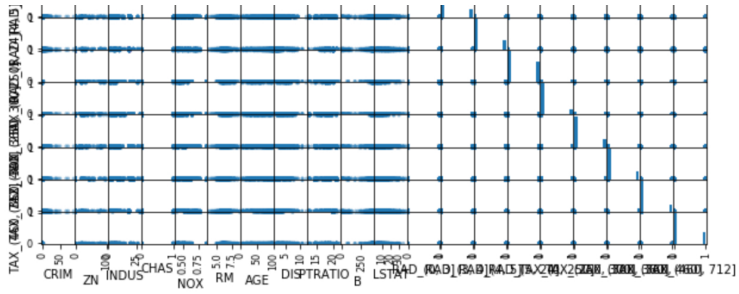
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	PTRATIO	B	LSTAT	RAD_(0, 3]	RAD_(3, 4]	RAD_(4, 5]	RAD_(5, 24]	TAX_(0, 250]	TAX_(250, 300]	TAX_(300 360
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	15.3	396.90	4.98	1	0	0	0	0	1	
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	17.8	396.90	9.14	1	0	0	0	1	0	
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	17.8	392.83	4.03	1	0	0	0	1	0	
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	18.7	394.63	2.94	1	0	0	0	1	0	
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	18.7	396.90	5.33	1	0	0	0	1	0	

Scatter matrix

Create the scatter matrix for the Boston Housing data.

In [19]:
```
pd.plotting.scatter_matrix(boston_features,figsize  = [10, 10]);
```

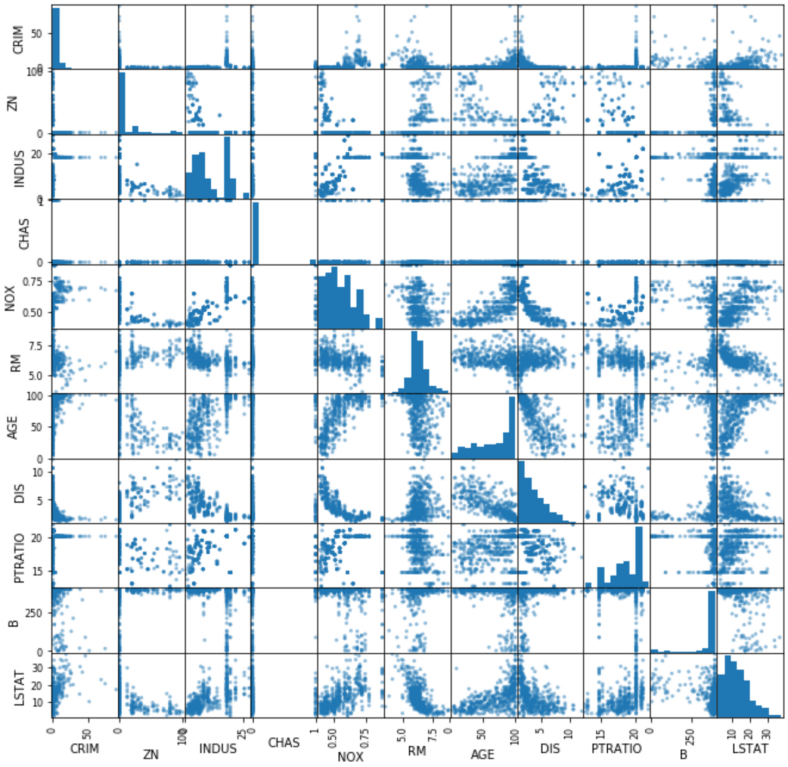




This took a while to load. Not surprisingly, the categorical variables didn't really provide any meaningful result. remove the categorical columns associated with "RAD" and "TAX" from the data again and look at the scatter matrix again.

In [15]:
```
boston_cont = boston_features.iloc[:,0:11]
```

In [17]:
```
pd.plotting.scatter_matrix(boston_cont,figsize  = [11, 11]);
```



Correlation matrix

Next, let's look at the correlation matrix

In [24]:
```
boston_cont.corr()
```

Out[24]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	PTRATIO	B	LSTAT
CRIM	1.000000	-0.199458	0.404471	-0.055295	0.417521	-0.219940	0.350784	-0.377904	0.288250	-0.377365	0.452220
ZN	-0.199458	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408	-0.391679	0.175520	-0.412995
INDUS	0.404471	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.383248	-0.356977	0.603800
CHAS	-0.055295	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.099176	-0.121515	0.048788	-0.053929
NOX	0.417521	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.769230	0.188933	-0.380051	0.590879
RM	-0.219940	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.205246	-0.355501	0.128069	-0.613808
AGE	0.350784	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.747881	0.261515	-0.273534	0.602339
DIS	-0.377904	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.000000	-0.232471	0.291512	-0.496996
PTRATIO	0.288250	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	1.000000	-0.177383	0.374044
B	-0.377365	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.291512	-0.177383	1.000000	-0.366087
LSTAT	0.452220	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.496996	0.374044	-0.366087	1.000000

Return "True" for positive or negative correlations that are bigger than 0.75.

In [28]:
```
abs(boston_cont.corr())>0.75
```

Out[28]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	PTRATIO	B	LSTAT
CRIM	True	False	False	False	False	False	False	False	False	False	False

ZN	False	True	False	False	False	False	False	False	False	False	False
INDUS	False	False	True	False	True	False	False	False	False	False	False
CHAS	False	False	False	True	False	False	False	False	False	False	False
NOX	False	False	True	False	True	False	False	True	False	False	False
RM	False	False	False	False	False	True	False	False	False	False	False
AGE	False	False	False	False	False	False	True	False	False	False	False
DIS	False	False	False	False	True	False	False	True	False	False	False
PTRATIO	False	False	False	False	False	False	False	False	True	False	False
B	False	False	False	False	False	False	False	False	False	True	False
LSTAT	False	False	False	False	False	False	False	False	False	False	True

Remove the most problematic feature from the data.

In [31]:
```
boston_features = boston_features.drop("NOX",axis=1)
```

Summary

Good job! You've now edited the Boston Housing Data so highly correlated variables are removed.