Final Course Project: Exploring Boston Housing

17th of January 2020
by Tom K. Wallter

1. Importing and Describing the Data

For my project, I am using the well-known Boston Housing dataset (available on http://www.cs.toronto.edu/~delve/data/boston/bostonDetail.html or on https://www.kaggle.com/vikrishnan/boston-house-price-prediction-regression). This dataset was originally collected by the US Census Service, and first analyzed by D. Harrison and D.L. Rubinfeld in their paper called *"Hedonic prices and the demand for clean air"* in the Journal for Environmental Economics & Management from 1978. The dataset consists of 14 variables and 506 rows of observations that correspond to so-called 'towns', i.e. various subsections of Boston. Table 1 shows the description of the variables that come with the dataset.

The variables can be grouped into three groups: housing-related, social-related, and industry-related. The biggest group are housing-related variables such as average number of rooms per dwelling (RM), the proportion of owner-occupied units built prior to 1940 (AGE), or the median value of owner-occupied homes (MEDV). Under the group of social-related variables fall LSTAT, i.e. % of lower status of the population, or CRIM, i.e. per capita crime rate by town. The industry-related variables include INDUS, which is the proportion of non-retail business acres per town, or NOX, the nitric oxides concentration.

The dataset's associated task is to perform regression analysis using either MEDV or NOX as target, while the other 13 variables would be used as features respectively. In the following sections, I will prepare the dataset with the goal of using MEDV as a target and other variables as features, for predicting the housing prices.

Table 1:

Variable	Description
CRIM	per capita crime rate by town
ZN	proportion of residential land zoned for lots over 25,000 sq.ft.
INDUS	proportion of non-retail business acres per town
CHAS	Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
NOX	nitric oxides concentration (parts per 10 million)
RM	average number of rooms per dwelling
AGE	proportion of owner-occupied units built prior to 1940
DIS	weighted distances to five Boston employment centres

RAD	index of accessibility to radial highways
TAX	full-value property-tax rate per USD 10,000
PTRATIO	pupil-teacher ratio by town
B	1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
LSTAT	% lower status of the population
MEDV	Median value of owner-occupied homes in USD 1000's

2. Plan for Exploratory Data Analysis

Before any dataset can be used for machine learning or data mining, prior steps must be taken to inspect the dataset's quality and explore it for preliminary insights. After importing any dataset, it should be checked for quality and completeness. Data cleaning entails checking:

- if the variables are correctly labelled
- if the data is in the correct data type and format
- for duplicates
- for missing values
- for outliers
- the distributions of features

Feature extraction and engineering consists:

- identifying the features best to predict the target
- scaling numerical features (if necessary)
- fransforming features (if necessary)
- encoding categorical features (if necessary)

3. Data Cleaning, Feature Engineering, and their Results
3.1 Data Cleaning and Quality Check

The data cleaning and quality checking should utilize the dataset's description as guidelines. After importing the dataset, I checked whether all variables are in numerical format, if they have missing or duplicate values. Image 1 shows fortunately all variables have been correctly imported as float type, and possess neither duplicate nor missing values.

Image 1:

```
df_boston.isnull().sum()
```

```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

```
df_boston[df_boston.duplicated()== True]
```

CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV

Table 2 shows the descriptive statistics for the dataset, which can be used to check if all variables confirm their description. Features that are described as expressing a proportion, such ZN, INDUS, AGE, and LSTAT, should only range between 0.0 and 100.0. Table 2 shows that is correct. Moreover, the Boston Housing description tells us that the MEDV target was capped at USD 50,000 by the creators of the dataset. Indeed, Table 2 confirms the values are capped at 50. The CHAS, Charles River dummy variable, can only take on the value 1 if the tract touches with Charles River and 0 if not, as confirmed by Table 2 (quartiles, mean, standard deviation are useless for this feature). RM, DIS, RAD, TAX, and PTRATIO show no salient problems so far.

Table 2:

```
# obtain descriptive stats
descr_data = df_boston.describe()
descr_data.loc["range"] = descr_data.loc['max'] - descr_data.loc['min']
descr_data
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.653063	22.532806
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.141062	9.197104
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.730000	5.000000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.950000	17.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.360000	21.200000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.955000	25.000000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	37.970000	50.000000
range	88.969880	100.000000	27.280000	1.000000	0.486000	5.219000	97.100000	10.996900	23.000000	524.000000	9.400000	396.580000	36.240000	45.000000

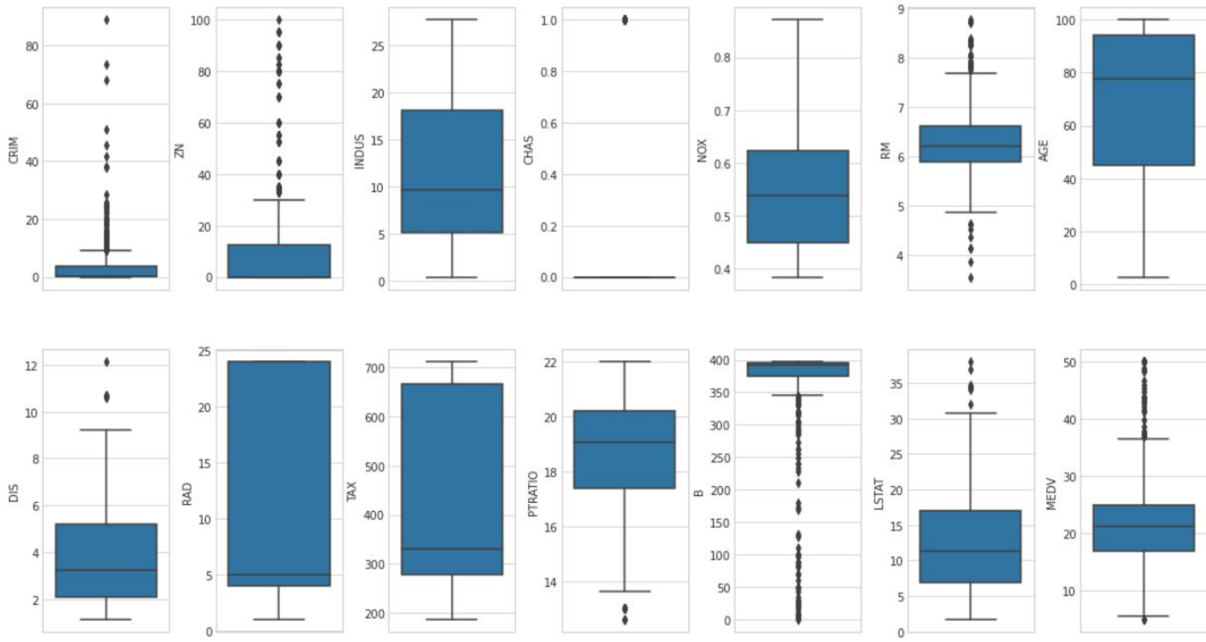
The descriptive statistics also hint at the fact that some variables may be very skewed. Obtaining the percentage of outliers and plotting box plot diagrams (Image 2) for all variables revealed that CRIM, ZN, and B are the top 3 most skewed variables, but also MEDV has a long tail towards high priced houses. Given the small size of the dataset, with only 506 rows, I have decided against dropping the outliers and address in the feature engineering section again (through scaling).

Table 3:

```
# find outliers by computation of IQR
for k, v in df_boston.items():
    q1 = v.quantile(0.25)
    q3 = v.quantile(0.75)
    irq = q3 - q1
    v_col = v[(v <= q1 - 1.5 * irq) | (v >= q3 + 1.5 * irq)]
    perc = np.shape(v_col)[0] * 100.0 / np.shape(df_boston)[0]
    print("Column %s outliers = %.2f%%" % (k, perc))
```

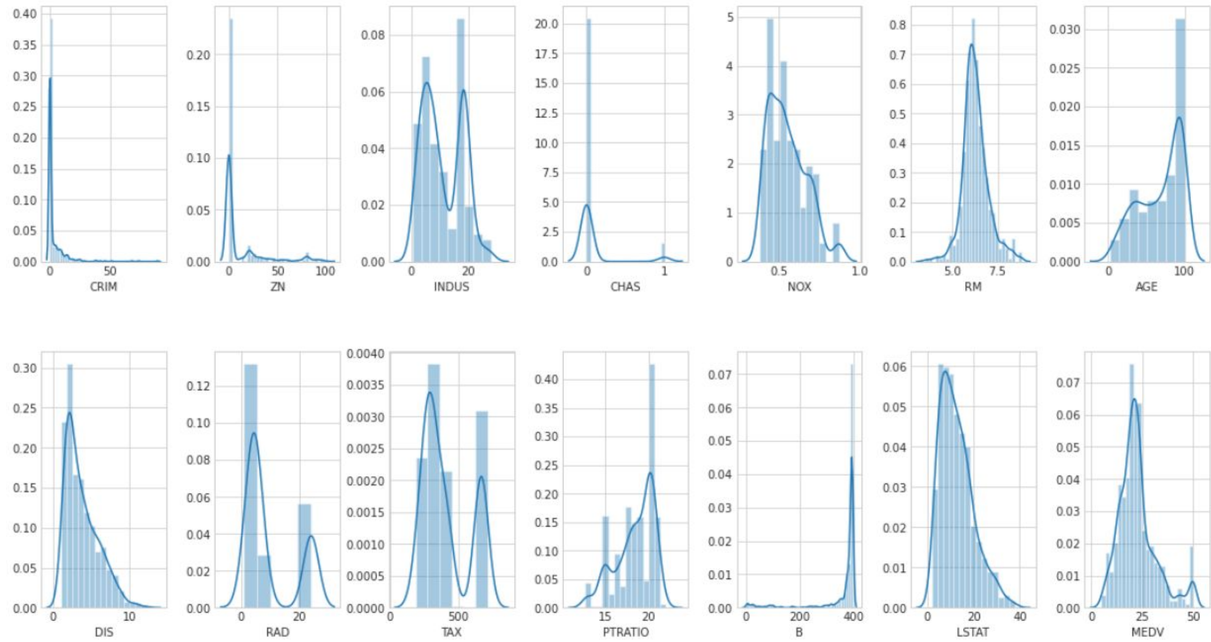
```
Column CRIM outliers = 13.04%
Column ZN outliers = 13.44%
Column INDUS outliers = 0.00%
Column CHAS outliers = 100.00%
Column NOX outliers = 0.00%
Column RM outliers = 5.93%
Column AGE outliers = 0.00%
Column DIS outliers = 0.99%
Column RAD outliers = 0.00%
Column TAX outliers = 0.00%
Column PTRATIO outliers = 2.96%
Column B outliers = 15.22%
Column LSTAT outliers = 1.38%
Column MEDV outliers = 7.91%
```

Image 2:



To have a closer look at the distribution of each variable histogram-and-distribution plot can be created for each. The histograms in Image 3 reveal that variables INDUS, CHAS, RAD, and TAX have a bimodal distribution, and that CRIM, ZN, & B have highly skewed distributions. Except for the CHAS dummy variable, it may be helpful to normalize very skewed features via log transformation.

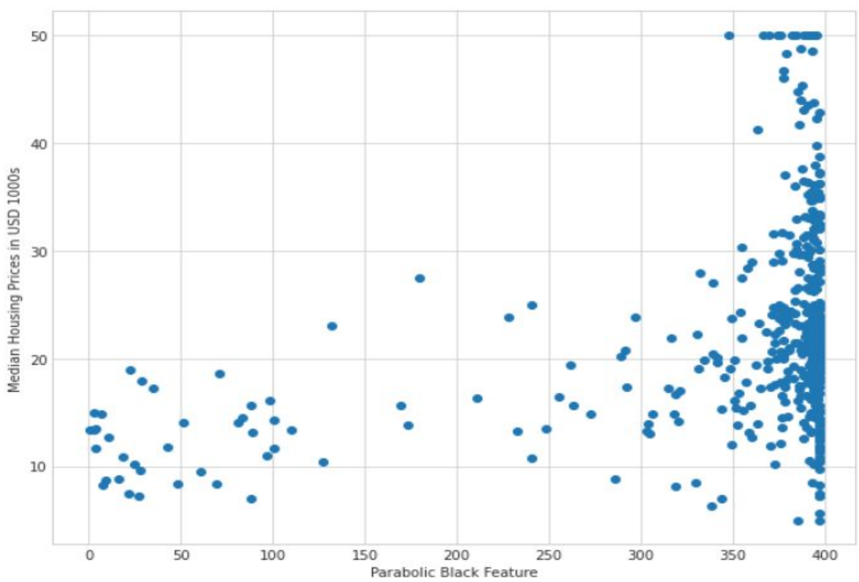
Image 3:



3.2 Feature Engineering

It should be acknowledged that the feature B has already undergone some feature engineering. The description tells us B=1000(Bk-0.63)^2 , where Bk is the proportion of blacks by town. This transformation was motivated by economic considerations by the authors of the original paper. They expected both a high and low proportion of African-American dwellers in a town to correlate with high housing prices as a form of market discrimination against blacks. However, the scatter plot in Image 4 reveals a problem of increasing heteroscedasticity, which means as the proportion of African-American dwellers increases so does the variation in housing prices. Since the original feature, i.e. proportion of black dwellers cannot easily be recovered, this feature will be dropped.

Image 4:



In order to address the problems of skewness and outliers, I have applied logarithmic transformation to CRIM and ZN, the most skewed features. After this, I have applied a min-max scaler to all features excluding the CHAS dummy variable (as it expresses a category not a continuous range of numbers). Now all features have a range from 0 to 1, and should be able to send a clear signal to a ML regression algorithm. Table 4 shows the code and summary statistics of this transformation.

Table 4:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df_feature[['CRIM']] = np.log1p(df_feature[['CRIM']].to_numpy())
df_feature[['ZN']] = np.log1p(df_feature[['ZN']].to_numpy())
df_feature[['CRIM','ZN','INDUS', 'NOX', 'RM','AGE',
          'DIS','RAD', 'TAX','PTRATIO','LSTAT']] = scaler.fit_transform(df_feature[['CRIM','ZN','INDUS','NOX','RM','AGE',
                                                                                    'DIS','RAD','TAX','PTRATIO','LSTAT']].to_numpy())
df_feature.describe()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	LSTAT
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	0.179629	0.206684	0.391378	0.069170	0.349167	0.521869	0.676364	0.242381	0.371713	0.422208	0.622929	0.301409
std	0.227615	0.351200	0.251479	0.253994	0.238431	0.134627	0.289896	0.191482	0.378576	0.321636	0.230313	0.197049
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.016147	0.000000	0.173387	0.000000	0.131687	0.445392	0.433831	0.088259	0.130435	0.175573	0.510638	0.144040
50%	0.049415	0.000000	0.338343	0.000000	0.314815	0.507281	0.768280	0.188949	0.173913	0.272901	0.686170	0.265728
75%	0.341930	0.563948	0.646628	0.000000	0.491770	0.586798	0.938980	0.369088	1.000000	0.914122	0.808511	0.420116
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

4. Hypothesis Testing and Feature Selection

In this section, I will hypothesize and test the direction of the relationship between a few selected features and the target. For linear regression, features are often selected as predictors that have strong and significant correlation with the target. For the sake of brevity, I will pick one feature from each of the three groups that I defined earlier: housing-related, social-related, and industry-related. From the housing-related, I choose RM (average number of rooms) and assume that it correlates positively with MEDV (at $p<0.05$) because as the number of rooms goes so should the median prices for the house. From social-related features, I pick LSTAT (% of lower status) and propose that it has a negative correlation with MEDV (at $p<0.05$) because the lower the income situation in town, the less likely people can afford to buy houses or maintain pricy houses. For the last group, I choose INDUS and assume that it also has a negative correlation with MEDV because the bigger the proportion of industry in a town, the less attractive it is for home-owners.

H_0 : The effects between RM, LSTAT, INDUS and MEDV respectively are due to random chance.
H_1 : The feature RM is positively correlated with MEDV.
H_2 : The feature LSTAT is negatively correlated with MEDV.
H_3 : The feature INDUS is negatively correlated with MEDV.

Table 5 has the Pearson correlation coefficient of each feature with the target, the p-value of the correlation, and whether the relationship is significant at the 95% confidence level. I can reject the null hypothesis that the relations between the above selected features and the target are due to chance. The correlation for RM and MEDV is 0.70, which is positive and strong, confirming my H_1 hypothesis. LSTAT and MEDV have a coefficient of -0.74, which is a strong negative relationship and also significant in line H_2. The correlation coefficient between INDUS and MEDV is r=-0.48. The relationship is not as strong as between RM and MEDV but still significant to confirm H_3.

Table 5:

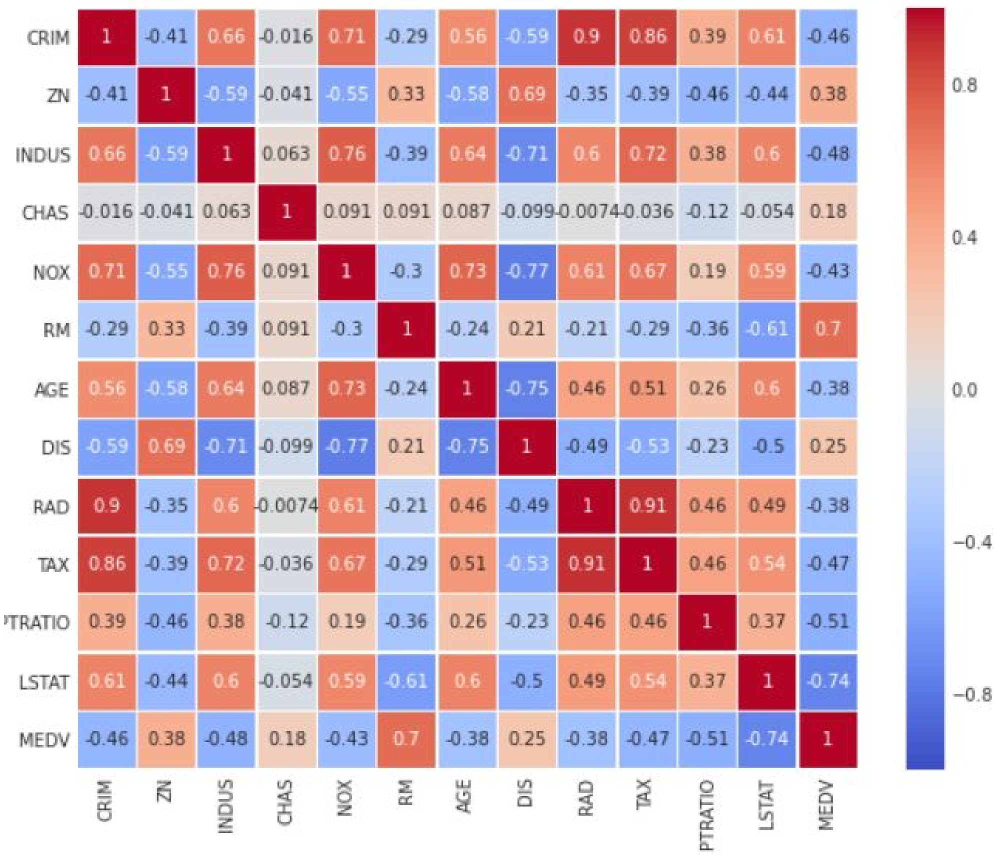
```
from scipy.stats import pearsonr
df_feature['MEDV']= df_boston['MEDV'].values
corr= []
p_value= []
for col in df_feature.columns:
    r= pearsonr(np.array(df_feature[col]), np.array(df_feature.MEDV))
    corr.append(r[0])
    p_value.append(r[1])
p_value = np.array(p_value)
sign = p_value<= 0.05
corr_table = pd.DataFrame(np.round(corr,2),columns=['Correlation with MEDV'],index=df_feature.columns)
corr_table['p-values']=np.round(p_value,5)
corr_table['Significant']=sign
corr_table
```

	Correlation with MEDV	p-values	Significant
CRIM	-0.46	0.00000	True
ZN	0.38	0.00000	True
INDUS	-0.48	0.00000	True
CHAS	0.18	0.00007	True
NOX	-0.43	0.00000	True
RM	0.70	0.00000	True
AGE	-0.38	0.00000	True
DIS	0.25	0.00000	True
RAD	-0.38	0.00000	True
TAX	-0.47	0.00000	True
PTRATIO	-0.51	0.00000	True
LSTAT	-0.74	0.00000	True
MEDV	1.00	0.00000	True

5. Suggestions for Further Analysis

As mentioned in the beginning, one of the tasks associated with the Boston Housing dataset is housing price prediction. A common way of predicting a continuous target from multiple features is Multiple Linear Regression analysis (MLR). For feature selection in MLR, it is not only important to check the correlation of each feature against the target but also of the features against one another to identify multicollinearity. Image 5 shows a correlation matrix of all features to help identify potential multicollinearity. It reveals that, for instance, CRIM is strongly, positively correlated with TAX and RAD; and that TAX and RAD have strong positive correlation. Features pairs with a strong negative correlation are DIS and INDUS; and DIS and NOX. As multicollinearity may bias the coefficients and their significance to the model in MLR, another approach would be to perform a Lasso Regression. Furthermore, a large number of features may make the model unnecessarily complex without helping accuracy. A Lasso Regression can reduce the complexity of the model by reducing the number of coefficients and may also increase the model's accuracy. In the end, the model may require only a few features to accurately predict housing prices in Boston.

Image 5:



6. Quality of the Dataset and Desirable Features

There are some merits and demerits about the quality of the Boston Housing dataset. The merits include that the dataset comes without missing values or duplicate entries, which sped up the data cleaning process. The dataset is clearly summarized from a larger set of data about Boston, in order to obtain median and mean values for various variables. It would be helpful in addition to the median price of houses, there would also be the mean price of houses. The same holds true for the RM variable, where in addition to average number of rooms also the median number of rooms could be useful. If the dataset is used to predict housing prices from social features, the original features about the proportion of African-American dwellers should have been kept alongside the transformed feature. If the dataset would be used for air quality predictions, it may be useful to have more variables on emission gasses, not just NOX, and also about transport. Finally, the position of towns in form longitude and latitude may be useful features for both air quality and housing price predictions.