# Linear Regression on Boston Housing Dataset

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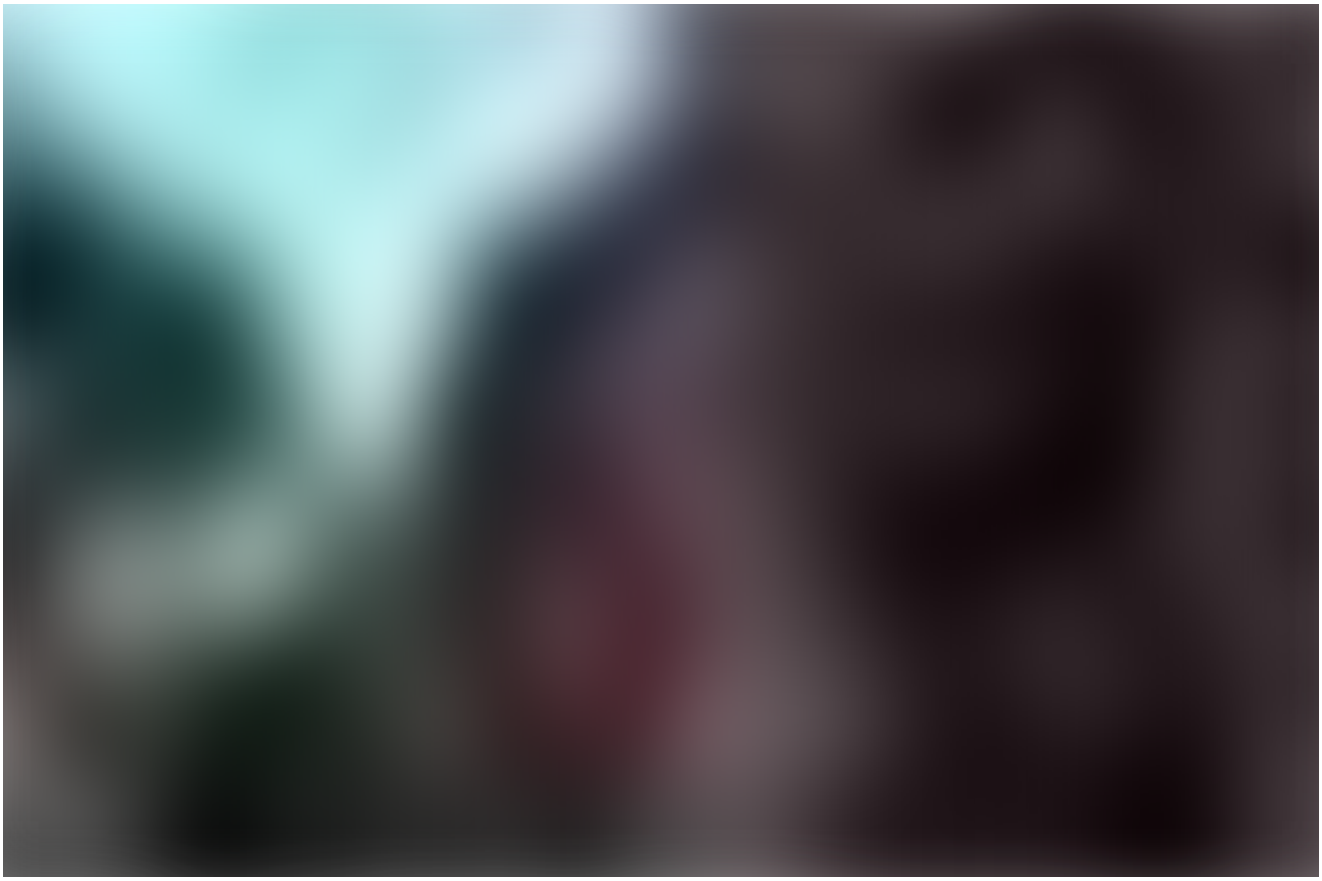
Oct 5, 2018 · 5 min read



Credits: http://www.wbur.org/radioboston/2013/09/18/bostons-housing-challenge

In my previous blog, I covered the basics of linear regression and gradient descent. To get hands-on linear regression we will take an original dataset and apply the concepts that we have learned.

We will take the Housing dataset which contains information about different houses in Boston. This data was originally a part of UCI Machine Learning Repository and has been removed now. We can also access this data from the scikit-learn library. There are

506 samples and 13 feature variables in this dataset. The objective is to predict the value of prices of the house using the given features.

So let's get started.

First, we will import the required libraries.

```
import numpy as np
import matplotlib.pyplot as plt

import pandas as pd
import seaborn as sns

%matplotlib inline
```

Import Libraries.py hosted with ♥ by GitHub view raw

Next, we will load the housing data from the `scikit-learn` library and understand it.

```
from sklearn.datasets import load_boston
boston_dataset = load_boston()
```

Load Boston Data.py hosted with ♥ by GitHub view raw

We print the value of the `boston_dataset` to understand what it contains. `print(boston_dataset.keys())` gives

```
dict_keys(['data', 'target', 'feature_names', 'DESCR'])
```

- *data*: contains the information for various houses
- *target*: prices of the house
- *feature_names*: names of the features
- *DESCR*: describes the dataset

To know more about the features use `boston_dataset.DESCR` The description of all the features is given below:

```
**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 oxide 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 centers
**RAD:** Index of accessibility to radial highways
**TAX:** Full-value property tax rate per $10,000
**PTRATIO:** Pupil-teacher ratio by town
**B:** $1000(Bk - 0.63)^2$, where Bk is the proportion of [people of African American descent] by town
**LSTAT:** Percentage of lower status of the population
**MEDV:** Median value of owner-occupied homes in $1000s

The prices of the house indicated by the variable `MEDV` is our ***target variable*** and the remaining are the ***feature variables*** based on which we will predict the value of a house.

We will now load the data into a pandas dataframe using `pd.DataFrame` . We then print the first 5 rows of the data using `head()`

```
boston = pd.DataFrame(boston_dataset.data, columns=boston_dataset.feature_names)
boston.head()
```

Load data into data frame hosted with ♥ by GitHub view raw

We can see that the target value `MEDV` is missing from the data. We create a new column of target values and add it to the dataframe.

```
boston['MEDV'] = boston_dataset.target
```

Add target to dataframe hosted with ♥ by GitHub view raw

## Data preprocessing

After loading the data, it's a good practice to see if there are any missing values in the data. We count the number of missing values for each feature using `isnull()`

```
boston.isnull().sum()
```

check for null values.py hosted with ♥ by GitHub view raw

However, there are no missing values in this dataset as shown below.

```
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
```

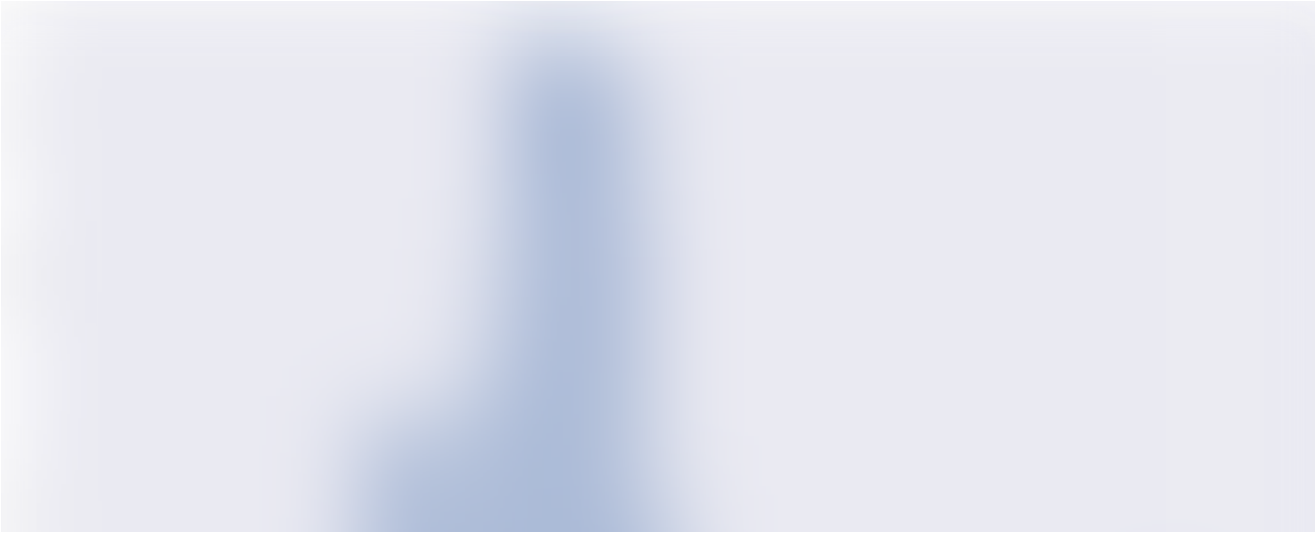
## Exploratory Data Analysis

Exploratory Data Analysis is a very important step before training the model. In this section, we will use some visualizations to understand the relationship of the target variable with other features.

Let's first plot the distribution of the target variable `MEDV`. We will use the `distplot` function from the `seaborn` library.

```
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.distplot(boston['MEDV'], bins=30)
plt.show()
```

visualize the data.py hosted with ♥ by GitHub view raw



We see that the values of `MEDV` are distributed normally with few outliers.

Next, we create a correlation matrix that measures the linear relationships between the variables. The correlation matrix can be formed by using the `corr` function from the pandas dataframe library. We will use the `heatmap` function from the seaborn library to plot the correlation matrix.

```
correlation_matrix = boston.corr().round(2)
# annot = True to print the values inside the square
sns.heatmap(data=correlation_matrix, annot=True)
```

correlation matrix.py hosted with ♥ by GitHub view raw

The correlation coefficient ranges from -1 to 1. If the value is close to 1, it means that there is a strong positive correlation between the two variables. When it is close to -1, the variables have a strong negative correlation.

## Observations:

- To fit a linear regression model, we select those features which have a high correlation with our target variable `MEDV`. By looking at the correlation matrix we can see that `RM` has a strong positive correlation with `MEDV` (0.7) where as `LSTAT` has a high negative correlation with `MEDV` (-0.74).
- An important point in selecting features for a linear regression model is to check for multi-co-linearity. The features `RAD`, `TAX` have a correlation of 0.91. These feature pairs are strongly correlated to each other. We should not select both these features together for training the model. Check this for an explanation. Same goes for the features `DIS` and `AGE` which have a correlation of -0.75.

Based on the above observations we will `RM` and `LSTAT` as our features. Using a scatter plot let's see how these features vary with `MEDV`.

```
plt.figure(figsize=(20, 5))

features = ['LSTAT', 'RM']
target = boston['MEDV']

for i, col in enumerate(features):
    plt.subplot(1, len(features) , i+1)
    x = boston[col]
    y = target
    plt.scatter(x, y, marker='o')
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('MEDV')
```

scatter plot.py hosted with ♥ by GitHub view raw

## Observations:

- The prices increase as the value of RM increases linearly. There are few outliers and the data seems to be capped at 50.
- The prices tend to decrease with an increase in LSTAT. Though it doesn't look to be following exactly a linear line.

## Preparing the data for training the model

We concatenate the `LSTAT` and `RM` columns using `np.c_` provided by the numpy library.

```
X = pd.DataFrame(np.c_[boston['LSTAT'], boston['RM']], columns = ['LSTAT','RM'])
Y = boston['MEDV']
```

prepare data for the model.py hosted with ♥ by GitHub view raw

## Splitting the data into training and testing sets

Next, we split the data into training and testing sets. We train the model with 80% of the samples and test with the remaining 20%. *We do this to assess the model's performance on unseen data*. To split the data we use `train_test_split` function provided by scikit-learn library. We finally print the sizes of our training and test set to verify if the splitting has occurred properly.

```
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state=5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

train_test_split.py hosted with ♥ by GitHub view raw

```
(404, 2)
(102, 2)
(404,)
(102,)
```

## Training and testing the model

We use scikit-learn's `LinearRegression` to train our model on both the training and test sets.

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

lin_model = LinearRegression()
lin_model.fit(X_train, Y_train)
```

linear regression model for boston housing.py hosted with ♥ by GitHub view raw

## Model evaluation

We will evaluate our model using RMSE and R2-score.

```
# model evaluation for training set
y_train_predict = lin_model.predict(X_train)
rmse = (np.sqrt(mean_squared_error(Y_train, y_train_predict)))
r2 = r2_score(Y_train, y_train_predict)

print("The model performance for training set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
print("\n")

# model evaluation for testing set
y_test_predict = lin_model.predict(X_test)
rmse = (np.sqrt(mean_squared_error(Y_test, y_test_predict)))
r2 = r2_score(Y_test, y_test_predict)

print("The model performance for testing set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
```

model evaluation.py hosted with ♥ by GitHub view raw

```
The model performance for training set
--------------------------------------
RMSE is 5.6371293350711955
R2 score is 0.6300745149331701

The model performance for testing set
--------------------------------------
RMSE is 5.137400784702911
R2 score is 0.6628996975186952
```

This is good to start with. In the upcoming blogs, we will look at ways to increase the model's performance.

The complete Jupyter Notebook can be found here.

## Conclusion

In this story, we applied the concepts of linear regression on the Boston housing dataset. I would recommend to try out other datasets as well.

Here are a few places you can look for data

- https://www.kaggle.com/datasets
- https://toolbox.google.com/datasetsearch
- https://archive.ics.uci.edu/ml/datasets.html

Thanks for Reading!!

In the next part of this series, we will cover Polynomial Regression. Do watch this space for more.

Machine Learning Boston Housing Data Linear Regression