Boston_Real_Estate

September 19, 2022

Link a repositorio en GitHub

1 Importar bibliotecas

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

1.1 Importar módulos de Scikit-learn

[ ]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV

from sklearn.neural_network import MLPRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor,␣
↪GradientBoostingRegressor, HistGradientBoostingRegressor
from sklearn.svm import SVR, NuSVR
from sklearn.gaussian_process import GaussianProcessRegressor
```

2 Importar Dataset

- **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 $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 $1000's

[ ]:
```python
url = "https://raw.githubusercontent.com/crisb-7/BostonRealEstate/main/
↪bostonRealEstate.csv"
```

[ ]:
```python
df = pd.read_csv(url)
```

[ ]:
```python
df.head()
```

[ ]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX  PTRATIO  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296     15.3
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242     17.8
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242     17.8
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222     18.7
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222     18.7

        B  LSTAT  MEDV
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90   5.33  36.2
```

3 Exploración del dataset

[ ]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 511 entries, 0 to 510
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     511 non-null    float64
 1   ZN       511 non-null    float64
 2   INDUS    511 non-null    float64
 3   CHAS     511 non-null    int64
 4   NOX      511 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      511 non-null    float64
 7   DIS      511 non-null    float64
 8   RAD      511 non-null    int64
 9   TAX      511 non-null    int64
 10  PTRATIO  511 non-null    float64
 11  B        511 non-null    float64
 12  LSTAT    511 non-null    float64
 13  MEDV     511 non-null    float64
dtypes: float64(11), int64(3)
```

```
memory usage: 56.0 KB
```

Al ver que se tienen solo 5 registros con valores nulos para RM, se quitan estas filas para tener un conjunto de datos homogéneo.

[ ]:
```
df = df.dropna(axis = 0)
df.shape
```

[ ]:
```
(506, 14)
```

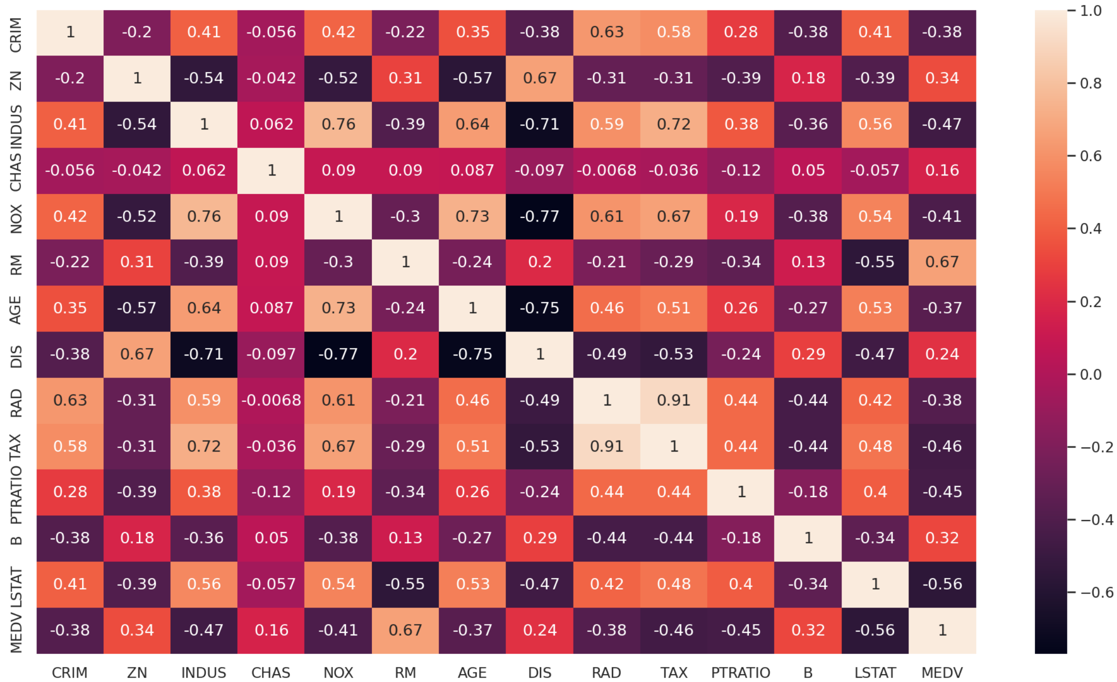
[ ]:
```
df.describe()
```

[ ]:
```
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean     3.617404   11.289526   11.174842    0.069170    0.555209    6.287589
std      8.600123   23.325350    6.824592    0.253994    0.115611    0.703802
min      0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.082268    0.000000    5.190000    0.000000    0.449000    5.885500
50%      0.266005    0.000000    9.690000    0.000000    0.538000    6.209000
75%      3.677083   12.500000   18.100000    0.000000    0.624000    6.629750
max     88.976200  100.000000   27.740000    1.000000    0.871000    8.780000

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean    68.555731    3.775231    9.531621  408.330040   18.498419  356.228379
std     28.161573    2.096147    8.716661  168.382685    2.202078   91.253462
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.025000    2.098500    4.000000  280.250000   17.400000  374.687500
50%     77.500000    3.122200    5.000000  330.000000   19.100000  391.260000
75%     93.975000    5.117675   24.000000  666.000000   20.200000  396.210000
max    100.000000   12.126500   24.000000  711.000000   23.000000  396.900000

            LSTAT        MEDV
count  506.000000  506.000000
mean    12.872569   22.711858
std      7.823528    9.520520
min      1.730000    5.000000
25%      6.950000   17.025000
50%     11.465000   21.200000
75%     17.107500   25.075000
max     76.000000   67.000000
```

[ ]:
```
sns.set(rc={'figure.figsize':(16, 9)})
plt.rcParams["figure.dpi"] = 150
sns.heatmap(df.corr(), annot = True)
plt.show()
```



[ ]:
```
# sns.pairplot(df)
# plt.show()
```

4 Preprocesamiento de los datos

[ ]:
```
scaler = StandardScaler()
```

[ ]:
```
x = scaler.fit_transform(df.drop(columns = "MEDV"))
y = df.MEDV
```

5 División train-test

[ ]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size = 0.90,␣
 ↪random_state = 0)
```

6 Model Cross-validation

[ ]:
```
randomState = 0

Regressors = []
```

```
# Regressors.append(MLPRegressor(random_state = randomState, activation =␣
↪"relu", solver = "adam",
#                         hidden_layer_sizes = (100,), alpha = 0.0001,␣
↪learning_rate = "constant",
#                         learning_rate_init = 0.0005, max_iter = 5000))

Regressors.append(MLPRegressor(random_state = randomState, activation = "relu",␣
↪solver = "adam",
                        hidden_layer_sizes = (100,), alpha = 0.0101, learning_rate␣
↪= "adaptive",
                        learning_rate_init = 0.1, max_iter = 1000))

Regressors.append(KNeighborsRegressor(n_neighbors = 2, weights = "uniform", p =␣
↪1))

Regressors.append(DecisionTreeRegressor(random_state=randomState))

Regressors.append(RandomForestRegressor(n_estimators = 250, max_depth = 7,␣
↪random_state=randomState))

Regressors.append(SVR(C = 40.7, epsilon=0.56))

Regressors.append(NuSVR(C = 31.2, nu=0.5))

Regressors.append(AdaBoostRegressor(random_state = randomState))

Regressors.append(GradientBoostingRegressor(random_state = randomState))

Regressors.append(GaussianProcessRegressor(random_state = randomState))

Regressors.append(HistGradientBoostingRegressor(random_state = randomState))

cv_results = []
cv_train_score = []
for regressor in Regressors:
    cv_train=regressor.fit(x_train, y = y_train)
    cv_train_score.append(regressor.score(x_train, y_train))
    cv_results.append(regressor.score(x_test, y_test))

cv_res = pd.DataFrame({"Algorithm":["NN", "KN","Decision Tree","Random␣
↪Forest","SVR","NuSVR","AdaBoost","GradientBoost", "GaussianProcess",␣
↪"HistGradientBoosting"],
                         "TrainScore":cv_train_score, "TestScore":cv_results})
cv_res.sort_values(by = "TestScore", ascending = False)
```

[ ]:

	Algorithm	TrainScore	TestScore
7	GradientBoost	0.971574	0.909959
3	Random Forest	0.952958	0.854074
0	NN	0.897917	0.823250
9	HistGradientBoosting	0.958757	0.808177
1	KN	0.929634	0.794065
2	Decision Tree	1.000000	0.778517
4	SVR	0.913308	0.746149
5	NuSVR	0.904299	0.719656
6	AdaBoost	0.862871	0.644497
8	GaussianProcess	1.000000	-0.304075