```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from scipy.stats import pearsonr
from sklearn.model_selection import train_test_split as tts
from sklearn.linear_model import LinearRegression as lr
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import cross_val_score as cvs
```

```
column_names = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX', 'P
dataset = pd.read_csv('housing.csv', delimiter=r'\s+', names=column_names)    #importing d
```

```
dataset.head()    #Top 5 rows of dataset
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90

```
dataset.shape   #Shape of dataset (rows, columns)
```

```
(506, 14)
```

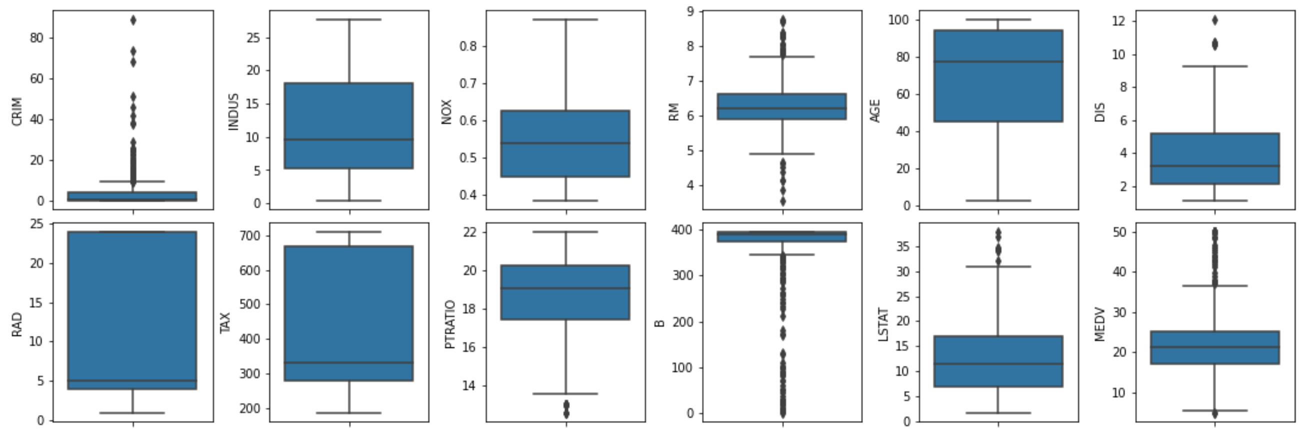
```
dataset.describe()    #describing the dataset to see distribution of data
```

```
dataset = dataset.drop(['ZN', 'CHAS'], axis=1)    #removing variables 'ZN' and 'CHAS' form
```

```
dataset.isnull().sum()      #checking null values
```

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

```
#Plotting boxplots to see if there are any outliers in our data (considering data betwen 2
fig, ax = plt.subplots(ncols=6, nrows=2, figsize=(15, 5))
ax = ax.flatten()
index = 0
for i in dataset.columns:
  sns.boxplot(y=i, data=dataset, ax=ax[index])
  index +=1
plt.tight_layout(pad=0.4)
plt.show()
```




```
#checking percentage/ amount of outliers
for i in dataset.columns:
  dataset.sort_values(by=i, ascending=True, na_position='last')
  q1, q3 = np.nanpercentile(dataset[i], [25,75])
```

```
  iqr = q3-q1
  lower_bound = q1-(1.5*iqr)
  upper_bound = q3+(1.5*iqr)
  outlier_data = dataset[i][(dataset[i] < lower_bound) | (dataset[i] > upper_bound)] #crea
  perc = (outlier_data.count()/dataset[i].count())*100
  print('Outliers in %s is %.2f%% with count %.f' %(i, perc, outlier_data.count()))
  #----------------------code below is for comming sections----------------------
  if i == 'B':
    outlierDataB_index = outlier_data.index
    outlierDataB_LB = dataset[i][(dataset[i] < lower_bound)]
    outlierDataB_UB = dataset[i][(dataset[i] > upper_bound)]
  elif i == 'CRIM':
    outlierDataCRIM_index = outlier_data.index
    outlierDataCRIM_LB = dataset[i][(dataset[i] < lower_bound)]
    outlierDataCRIM_UB = dataset[i][(dataset[i] > upper_bound)]
  elif i == 'MEDV':
    lowerBoundMEDV = lower_bound
    upperBoundMEDV = upper_bound
```

```
Outliers in CRIM is 13.04% with count 66
Outliers in INDUS is 0.00% with count 0
Outliers in NOX is 0.00% with count 0
Outliers in RM is 5.93% with count 30
Outliers in AGE is 0.00% with count 0
Outliers in DIS is 0.99% with count 5
Outliers in RAD is 0.00% with count 0
Outliers in TAX is 0.00% with count 0
Outliers in PTRATIO is 2.96% with count 15
Outliers in B is 15.22% with count 77
Outliers in LSTAT is 1.38% with count 7
Outliers in MEDV is 7.91% with count 40
```

```
dataset2 = dataset.copy() # I copied the data in another variable just for an ease of codi
```

```
#removing extreme outliers form B and CRIM (removing those observations)
removed=[]
outlierDataB_LB.sort_values(ascending=True, inplace=True)
outlierDataB_UB.sort_values(ascending=False, inplace=True)
counter=1
for i in outlierDataB_LB.index:
  if counter<=19:
    dataset2.drop(index=i, inplace=True)
    counter+=1
    removed.append(i)
for i in outlierDataB_UB.index:
  if counter<=38:
    dataset2.drop(index=i, inplace=True)
    counter+=1
    removed.append(i)
for i in outlierDataB_LB.index:
  if counter<=38 and i not in removed:
    dataset2.drop(index=i, inplace=True)
    counter+=1
    removed.append(i)
```

```
outlierDataCRIM_LB.sort_values(ascending=True, inplace=True)
outlierDataCRIM_UB.sort_values(ascending=False, inplace=True)
counter=1
for i in outlierDataCRIM_LB.index:
  if counter<=16 and i not in removed:
    dataset2.drop(index=i, inplace=True)
    counter+=1
    removed.append(i)
for i in outlierDataCRIM_UB.index:
  if counter<=33 and i not in removed:
    dataset2.drop(index=i, inplace=True)
    counter+=1
    removed.append(i)
for i in outlierDataCRIM_LB.index:
  if counter<=33 and i not in removed:
    dataset2.drop(index=i, inplace=True)
    counter+=1
    removed.append(i)
dataset2.shape
```

```
(435, 12)
```

```
dataset3 = dataset2.copy() # I copied the data in another variable just for an ease of cod
```

```
#replacing remaning outliers by mean
for i in dataset.columns:
  dataset.sort_values(by=i, ascending=True, na_position='last')
  q1, q3 = np.nanpercentile(dataset[i], [25,75])
  iqr = q3-q1
  lower_bound = q1-(1.5*iqr)
  upper_bound = q3+(1.5*iqr)
  mean = dataset3[i].mean()
  if i != 'MEDV':
    dataset3.loc[dataset3[i] < lower_bound, [i]] = mean
    dataset3.loc[dataset3[i] > upper_bound, [i]] = mean
  else:
    dataset3.loc[dataset3[i] < lower_bound, [i]] = mean
    dataset3.loc[dataset3[i] > upper_bound, [i]] = 50
```

```
dataset3.describe()
```

	CRIM	INDUS	NOX	RM	A
count	435.000000	435.000000	435.000000	435.000000	435.0000
mean	1.054293	10.008575	0.534257	6.266477	64.7416
std	1.936962	6.741091	0.108957	0.511640	28.3197

Selecting the features which can predict MEDV the best

```
X = dataset3.iloc[:, :-1]     #independent variable(X)
Y = dataset3.iloc[:, 11]      #dependent variable(Y)
```

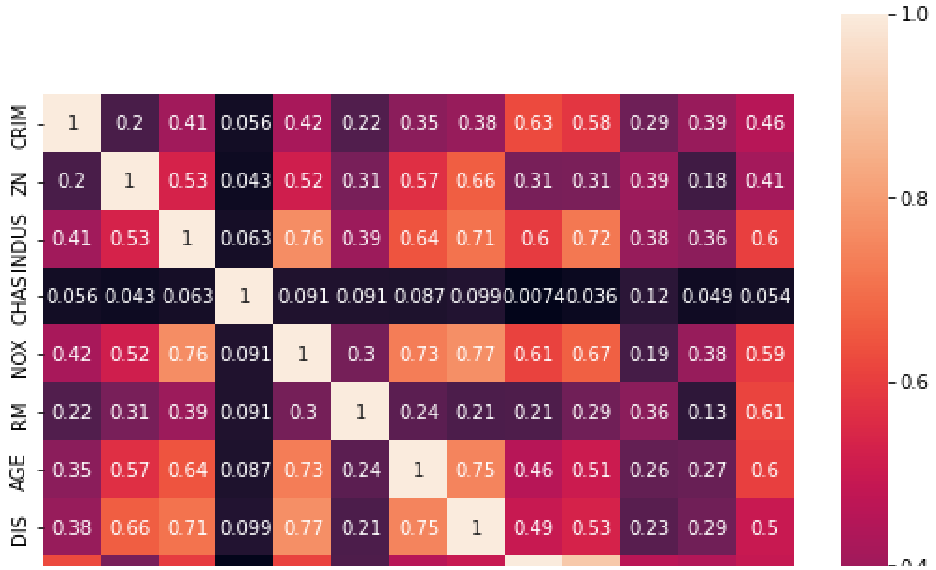
```
#Feature selection using P-Value/ Backward elimination
def BackwardElimination(sl, w):
    for i in range(0, len(w.columns)):
        regressor_OLS = sm.OLS(endog=Y, exog=w).fit()
        max_pvalue = max(regressor_OLS.pvalues)
        pvalues = regressor_OLS.pvalues
        if max_pvalue > SL:
            index_max_pvalue = pvalues[pvalues==max_pvalue].index
            w = w.drop(index_max_pvalue, axis = 1) #delete the valriable for that p value
    return w,pvalues,index_max_pvalue

SL = 0.05
ones = np.ones((435,1))  #adding a columns of ones to X as it is required by statsmodels l
W = X
W.insert(0, 'Constant', ones, True)
W_optimal = W.iloc[:, [0,1,2,3,4,5,6,7,8,9,10,11]]
W_optimal,pvalues,index_max_pvalue = BackwardElimination(SL, W_optimal)
X = W_optimal.drop('Constant', axis=1)
```

```
X.columns   #remaning variables after backward elimination
```

```
Index(['NOX', 'RM', 'DIS', 'RAD', 'TAX', 'PTRATIO', 'LSTAT'], dtype='object')
```

```
#Ploting heatmap using pearson correlation among independent variables
plt.figure(figsize=(9,9))
ax = sns.heatmap(X.corr(method='pearson').abs(), annot=True, square=True)
plt.show()
```



```
X.drop('TAX', axis=1, inplace=True)
X.drop('NOX', axis=1, inplace=True)   #dropping TAX and NOX
X.columns   #remaning columns after removing multicollinearity
```

```
Index(['RM', 'DIS', 'RAD', 'PTRATIO', 'LSTAT'], dtype='object')
```

```
#now checking correlation of each variable with MEDV by pearson method and dropping the on
for i in X.columns:
  corr, _ = pearsonr(X[i], Y)
  print(i,corr)
```

```
RM 0.5619541568173053
DIS 0.10793693577397613
RAD -0.16919893157675941
PTRATIO -0.3805580367664191
LSTAT -0.6793276769216394
```

```
X.drop(['DIS', 'RAD'], axis=1, inplace=True)
```

```
X.columns   #remaning variables/ features that can predict the MEDV most
```

```
Index(['RM', 'PTRATIO', 'LSTAT'], dtype='object')
```

MACHINE LEARNING

```
X_train, X_test, Y_train, Y_test = tts(X, Y, test_size=0.2, random_state=0)    #spliting d
```

Linear regression model:

```
linear = lr()
linear.fit(X_train, Y_train)
Y_pred = linear.predict(X_test)
Y_compare_linear = pd.DataFrame({'Actual': Y_test, 'Predicted': Y_pred})
Y_compare_linear.head() #displaying the comparision btween actual and predicted values of
```

	Actual	Predicted
158	24.3	30.992768
269	20.7	21.073716
54	18.9	17.575853
360	25.0	25.980258

Decission tree model

```
rf = RandomForestRegressor(n_estimators=100)
rf.fit(X_train,Y_train)
Y_pred = rf.predict(X_test)
Y_compare_randomforrest = pd.DataFrame({'Actual': Y_test, 'Predicted': Y_pred})
Y_compare_randomforrest.head() #displaying the comparision btween actual and predicted val
```

	Actual	Predicted
158	24.3	22.669
269	20.7	22.055
54	18.9	17.758
360	25.0	23.722

K-Nearest Neighbour regression model:

```
knn = KNeighborsRegressor(n_neighbors=13)
knn.fit(X_train,Y_train)
Y_pred = knn.predict(X_test)
Y_compare_knn = pd.DataFrame({'Actual': Y_test, 'Predicted': Y_pred})
Y_compare_knn.head() #displaying the comparision btween actual and predicted values of MED
```

	Actual	Predicted
158	24.3	30.530769
269	20.7	20.346154
54	18.9	18.646154
360	25.0	22.384615

Support vector regression model

```
svr = SVR(kernel= 'poly', gamma='scale')
svr.fit(X_train,Y_train)
Y_pred = svr.predict(X_test)
Y_compare_svr = pd.DataFrame({'Actual': Y_test, 'Predicted': Y_pred})
Y_compare_svr.head() #displaying the comparision btween actual and predicted values of MED
```

	Actual	Predicted
158	24.3	26.297366
269	20.7	19.596855
54	18.9	15.838815
360	25.0	24.115036
499	17.5	17.335738

Polynomial regression model

```
polyRegressor = PolynomialFeatures(degree=3)
X_train_poly = polyRegressor.fit_transform(X_train)
X_test_poly = polyRegressor.fit_transform(X_test)
poly = lr()
poly.fit(X_train_poly, Y_train)
Y_pred = poly.predict(X_test_poly)
Y_compare_poly = pd.DataFrame({'Actual': Y_test, 'Predicted': Y_pred})
Y_compare_poly.head() #displaying the comparision btween actual and predicted values of ME
```

	Actual	Predicted
158	24.3	32.860285
269	20.7	19.674236
54	18.9	15.952153
360	25.0	23.712803
499	17.5	18.331182

```
print('According to R squared scorring method we got below scores for out machine learning
modelNames = ['Linear', 'Polynomial', 'Support Vector', 'Random Forrest', 'K-Nearest Neigh
modelRegressors = [linear, poly, svr, rf, knn]
models = pd.DataFrame({'modelNames' : modelNames, 'modelRegressors' : modelRegressors})
counter=0
score=[]
for i in models['modelRegressors']:
  if i is poly:
    none
  else:
    accuracy = cvs(i, X_train, Y_train, scoring='r2', cv=5)
    print('Accuracy of %s Regression model is %.2f' %(models.iloc[counter,0],accuracy.mean
    score.append(accuracy.mean())
```

```
    score.append(accuracy.mean())
  counter+=1
```

```
According to R squared scorring method we got below scores for out machine learning r
Accuracy of Linear Regression model is 0.51
Accuracy of Polynomial Regression model is 0.64
Accuracy of Support Vector Regression model is 0.50
Accuracy of Random Forrest Regression model is 0.72
Accuracy of K-Nearest Neighbour Regression model is 0.64
```