mean absolute error.

Boston House Price Prediction is a example of regression analysis and is often used to teach machine learning concepts. The dataset is also used in research to compare the performance of different regression models.

Source Code with Explanation-

```
#Importing the pandas for data processing and numpy for numerical computing
import numpy as np
import pandas as pd
# Importing the Boston Housing dataset from the sklearn
from sklearn.datasets import load_boston
boston = load_boston()
#Converting the data into pandas dataframe
data = pd.DataFrame(boston.data)
#First look at the data
data.head()
```

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

```
#Adding the feature names to the dataframe
data.columns = boston.feature_names
#Adding the target variable to the dataset
data['PRICE'] = boston.target
#Looking at the data with names and target variable
data.head(n=10)
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2
5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3.0	222.0	18.7	394.12	5.21	28.7
6	0.08829	12.5	7.87	0.0	0.524	6.012	66.6	5.5605	5.0	311.0	15.2	395.60	12.43	22.9
7	0.14455	12.5	7.87	0.0	0.524	6.172	96.1	5.9505	5.0	311.0	15.2	396.90	19.15	27.1
8	0.21124	12.5	7.87	0.0	0.524	5.631	100.0	6.0821	5.0	311.0	15.2	386.63	29.93	16.5
9	0.17004	12.5	7.87	0.0	0.524	6.004	85.9	6.5921	5.0	311.0	15.2	386.71	17.10	18.9

```
#Shape of the data
print(data.shape)
#Checking the null values in the dataset
data.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
PRICE      0
dtype: int64
#Checking the statistics of the data
data.describe()
# This is sometimes very useful, for example if you look at the CRIM the max is 88.97 and 75% of the value is below 3.677083 and
# mean is 3.613524 so it means the max values is actually an outlier or there are
```

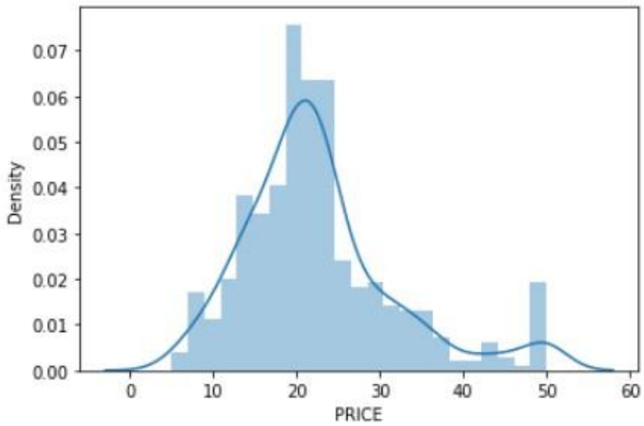
outliers present in the column

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO
count	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
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #    Column    Non-Null Count    Dtype
---   ------    --------------    -----
 0    CRIM      506 non-null      float64
 1    ZN        506 non-null      float64
 2    INDUS     506 non-null      float64
 3    CHAS      506 non-null      float64
 4    NOX       506 non-null      float64
 5    RM        506 non-null      float64
 6    AGE       506 non-null      float64
 7    DIS       506 non-null      float64
 8    RAD       506 non-null      float64
 9    TAX       506 non-null      float64
 10   PTRATIO   506 non-null      float64
 11   B         506 non-null      float64
 12   LSTAT     506 non-null      float64
 13   PRICE     506 non-null      float64
dtypes: float64(14)
memory usage: 55.5 KB
```

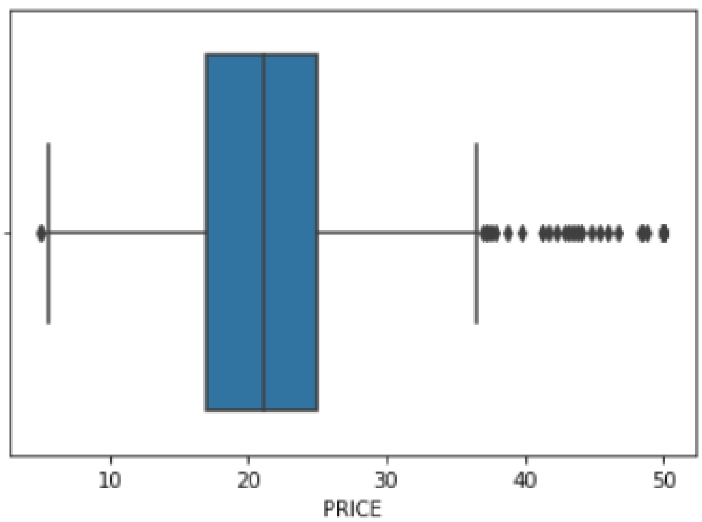
```
#checking the distribution of the target variable
import seaborn as sns
sns.distplot(data.PRICE)
#The distribution seems normal, has not be the data normal we would have perform log transformation or took to square root of the data to make the data normal.
# Normal distribution is need for the machine learning for better predictiblity of the model
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44d082c670>
```



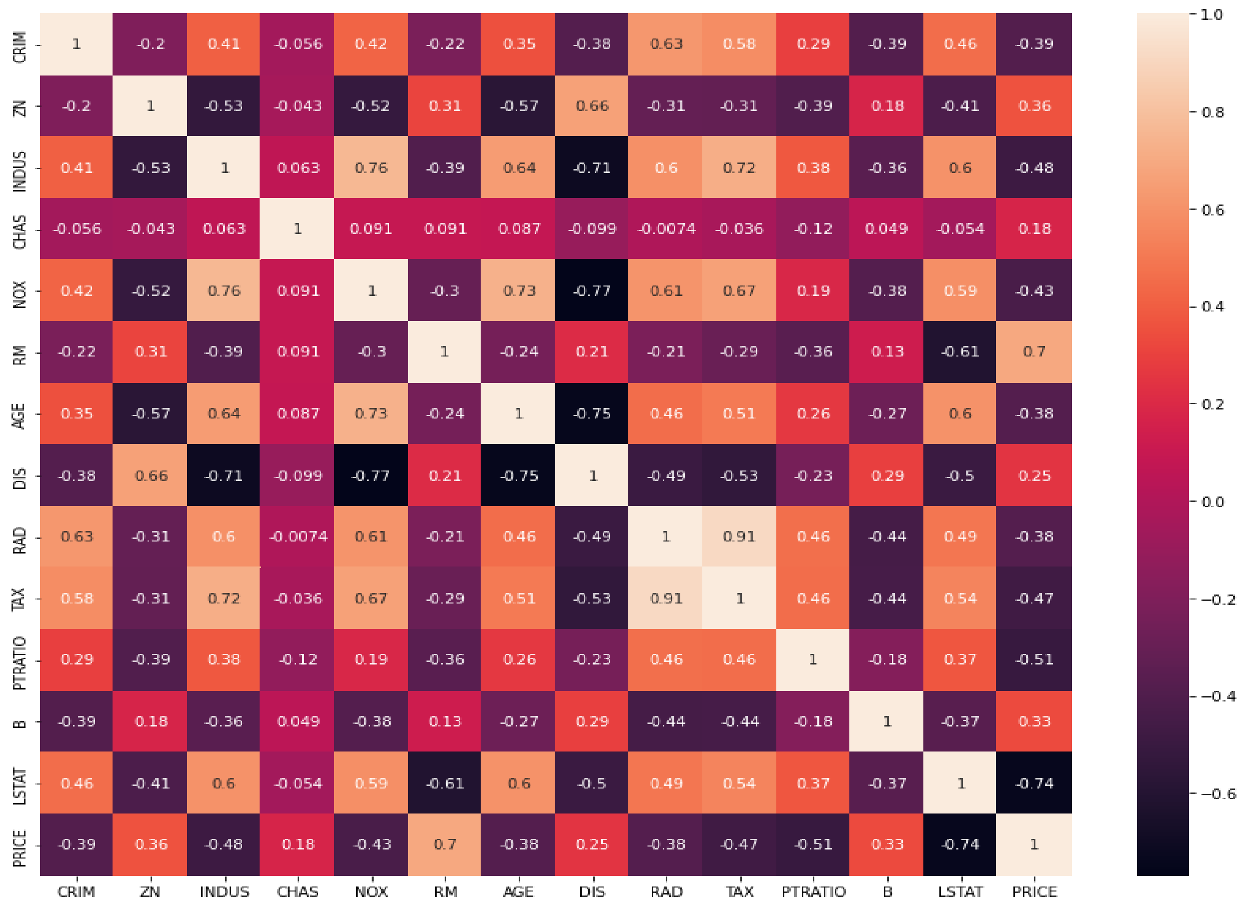

```
#Distribution using box plot
sns.boxplot(data.PRICE)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f44d077ed60>
```

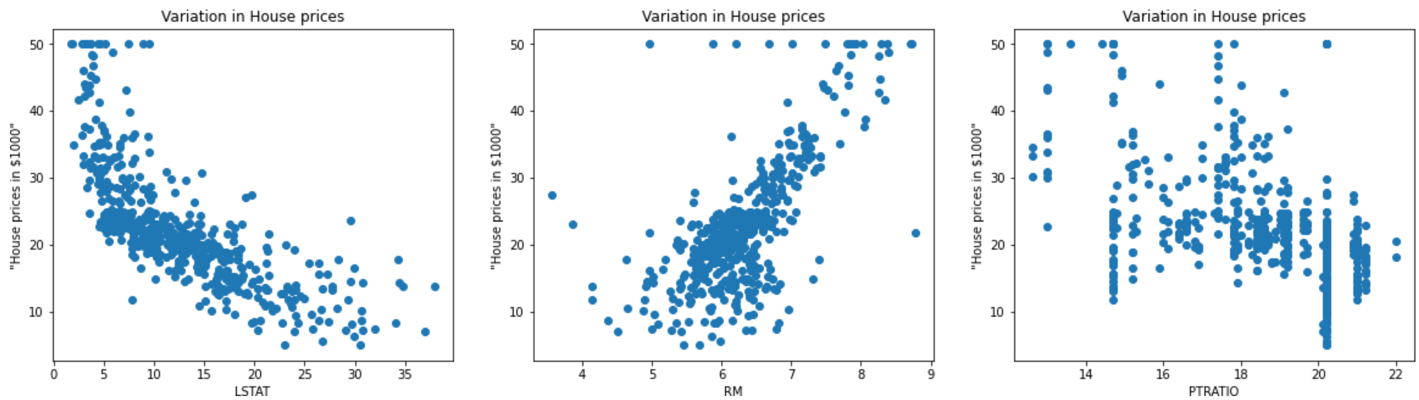



```
#Checking the correlation of the independent feature with the dependent feature
# Correlation is a statistical technique that can show whether and how strongly pairs of variables are related.An intelligent correlation analysis can lead to a greater understanding of your data
#checking Correlation of the data
correlation = data.corr()
correlation.loc['PRICE']
CRIM       -0.388305
```

```
ZN          0.360445
INDUS      -0.483725
CHAS        0.175260
NOX        -0.427321
RM          0.695360
AGE        -0.376955
DIS         0.249929
RAD        -0.381626
TAX        -0.468536
PTRATIO    -0.507787
B           0.333461
LSTAT      -0.737663
PRICE       1.000000
Name: PRICE, dtype: float64
# plotting the heatmap
import matplotlib.pyplot as plt
fig,axes = plt.subplots(figsize=(15,12))
sns.heatmap(correlation,square = True,annot = True)
# By looking at the correlation plot LSAT is negatively correlated with -0.75 and RM is positively correlated to the price and PTRATIO is correlated negatively with -0.51
```



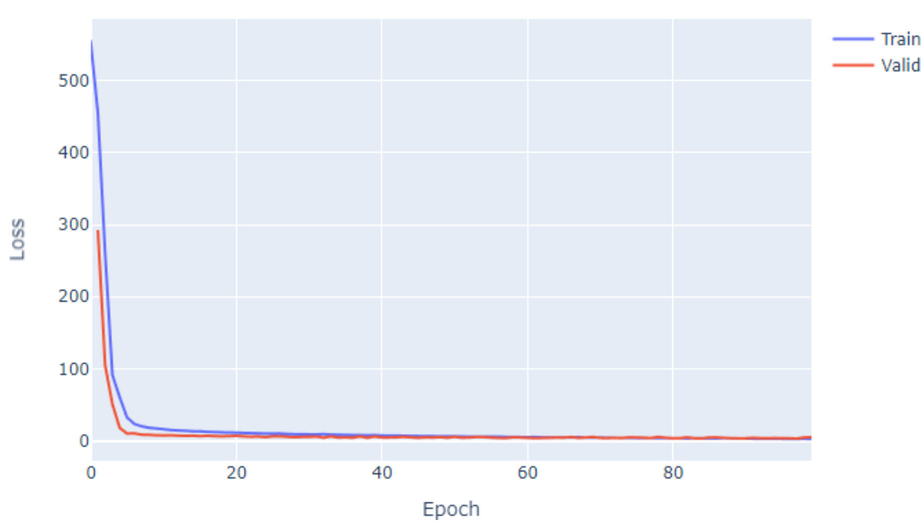
```
# Checking the scatter plot with the most correlated features
plt.figure(figsize = (20,5))
features = ['LSTAT','RM','PTRATIO']
for i, col in enumerate(features):
    plt.subplot(1, len(features) , i+1)
    x = data[col]
    y = data.PRICE
    plt.scatter(x, y, marker='o')
    plt.title("Variation in House prices")
    plt.xlabel(col)
    plt.ylabel('"House prices in $1000"')
```




```
# Splitting the dependent feature and independent feature
#X = data[['LSTAT','RM','PTRATIO']]
X = data.iloc[:,:-1]
y= data.PRICE

# In order to provide a standardized input to our neural network, we need the
perform the normalization of our dataset.
# This can be seen as an step to reduce the differences in scale that may arise
from the existent features.
# We perform this normalization by subtracting the mean from our data and
dividing it by the standard deviation.
# One more time, this normalization should only be performed by using the mean
and standard deviation from the training set,
# in order to avoid any information leak from the test set.

mean = X_train.mean(axis=0)
std = X_train.std(axis=0)

X_train = (X_train - mean) / std
X_test = (X_test - mean) / std
#Linear Regression
from sklearn.linear_model import LinearRegression
```

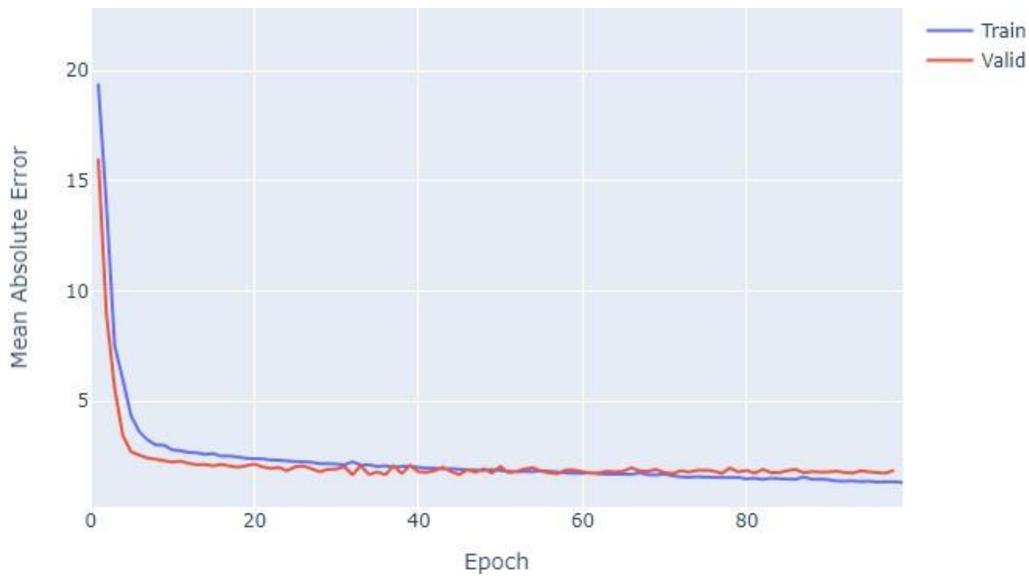
```
regressor = LinearRegression()
#Fitting the model
regressor.fit(X_train,y_train)
# Model Evaluation

#Prediction on the test dataset
y_pred = regressor.predict(X_test)
# Predicting RMSE the Test set results
from sklearn.metrics import mean_squared_error
rmse = (np.sqrt(mean_squared_error(y_test, y_pred)))
print(rmse)

from sklearn.metrics import r2_score
r2 = r2_score(y_test, y_pred)
print(r2)
# Neural Networks
#Scaling the dataset
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
# Due to the small amount of presented data in this dataset, we must be careful
to not create an overly complex model,
# which could lead to overfitting our data. For this, we are going to adopt an
architecture based on two Dense layers,
# the first with 128 and the second with 64 neurons, both using a ReLU activation
function.
# A dense layer with a linear activation will be used as output layer.
# In order to allow us to know if our model is properly learning, we will use a
mean squared error loss function and to report the performance of it we will
adopt the mean average error metric.
# By using the summary method from Keras, we can see that we have a total of
10,113 parameters, which is acceptable for us.

#Creating the neural network model
import keras
from keras.layers import Dense, Activation,Dropout
from keras.models import Sequential

model = Sequential()
model.add(Dense(128,activation  = 'relu',input_dim =13))
model.add(Dense(64,activation  = 'relu'))
```

```
model.add(Dense(32,activation  =  'relu'))
model.add(Dense(16,activation  =  'relu'))
model.add(Dense(1))
#model.compile(optimizer='adam', loss='mse', metrics=['mae'])
model.compile(optimizer = 'adam',loss ='mean_squared_error',metrics=['mae'])
!pip install ann_visualizer
!pip install graphviz
from ann_visualizer.visualize import ann_viz;
#Build your model here
ann_viz(model, title="DEMO ANN");
history = model.fit(X_train, y_train, epochs=100, validation_split=0.05)
# By plotting both loss and mean average error, we can see that our model was
capable of learning patterns in our data without overfitting taking place (as
shown by the validation set curves)
from plotly.subplots import make_subplots
import plotly.graph_objects as go

fig = go.Figure()
fig.add_trace(go.Scattergl(y=history.history['loss'],
                    name='Train'))

fig.add_trace(go.Scattergl(y=history.history['val_loss'],
                    name='Valid'))


fig.update_layout(height=500, width=700,
                  xaxis_title='Epoch',
                  yaxis_title='Loss')
fig.show()
```




```
fig = go.Figure()
```

```
fig.add_trace(go.Scattergl(y=history.history['mae'],
                          name='Train'))

fig.add_trace(go.Scattergl(y=history.history['val_mae'],
                          name='Valid'))


fig.update_layout(height=500, width=700,
                  xaxis_title='Epoch',
                  yaxis_title='Mean Absolute Error')
fig.show()
```




```
#Evaluation of the model
y_pred = model.predict(X_test)
mse_nn, mae_nn = model.evaluate(X_test, y_test)

print('Mean squared error on test data: ', mse_nn)
print('Mean absolute error on test data: ', mae_nn)
```

4/4 [==============================] - 0s 4ms/step - loss: 10.5717 - mae: 2.2670

Mean squared error on test data: 10.571733474731445 Mean absolute error on test data: 2.2669904232025146

```
#Comparison with traditional approaches
#First let's try with a simple algorithm, the Linear Regression:
from sklearn.metrics import mean_absolute_error

lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

```
y_pred_lr = lr_model.predict(X_test)
mse_lr = mean_squared_error(y_test, y_pred_lr)
mae_lr = mean_absolute_error(y_test, y_pred_lr)

print('Mean squared error on test data: ', mse_lr)
print('Mean absolute error on test data: ', mae_lr)
from sklearn.metrics import r2_score
r2 = r2_score(y_test, y_pred)
print(r2)
0.8812832788381159
```

```
# Predicting RMSE the Test set results
from sklearn.metrics import mean_squared_error
rmse = (np.sqrt(mean_squared_error(y_test, y_pred)))
print(rmse)
3.320768607496587
# Make predictions on new data
import sklearn
new_data = sklearn.preprocessing.StandardScaler().fit_transform(([[0.1, 10.0,
5.0, 0, 0.4, 6.0, 50, 6.0, 1, 400, 20, 300, 10]]))
prediction = model.predict(new_data)
print("Predicted house price:", prediction)
1/1 [==============================] - 0s 70ms/step
Predicted house price: [[11.104753]]
```

#new_data = sklearn.preprocessing.StandardScaler().fit_transform(([[0.1, 10.0, 5.0, 0, 0.4, 6.0, 50, 6.0, 1, 400, 20, 300, 10]])) is a line of code that standardizes the input features of a new data point.

In this specific case, we have a new data point represented as a list of 13 numeric values ([0.1, 10.0, 5.0, 0, 0.4, 6.0, 50, 6.0, 1, 400, 20, 300, 10]) that represents the values for the 13 features of the Boston House Price dataset.

The StandardScaler() function from the sklearn.preprocessing module is used to standardize the data. Standardization scales each feature to have zero mean and unit variance, which is a common preprocessing step in machine learning to ensure that all features contribute equally to the model.

The fit_transform() method is used to fit the scaler to the data and apply the standardization transformation. The result is a new data