boston-aiml

March 17, 2024

[1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme(style = "darkgrid")

import warnings
warnings.filterwarnings("ignore", category = Warning)

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

#Make sure the data is loaded correctly.

[2]:
```
data_url = "http://lib.stat.cmu.edu/datasets/boston"
col_names = boston.feature_names
df = pd.DataFrame(boston.data, columns = col_names)
df['MEDV'] = boston.target

# Make sure the data is loaded correctly.
df.head()
```

[2]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900  1.0  296.0
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671  2.0  242.0
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0

   PTRATIO       B  LSTAT  MEDV
0     15.3  396.90   4.98  24.0
1     17.8  396.90   9.14  21.6
2     17.8  392.83   4.03  34.7
3     18.7  394.63   2.94  33.4
4     18.7  396.90   5.33  36.2
```

#1.The model possible for this house price prediction are "Linear regression model", "Random forest".

#The output for this problem is expected to be a scalar (a constant).

1 2.Model Input / Output

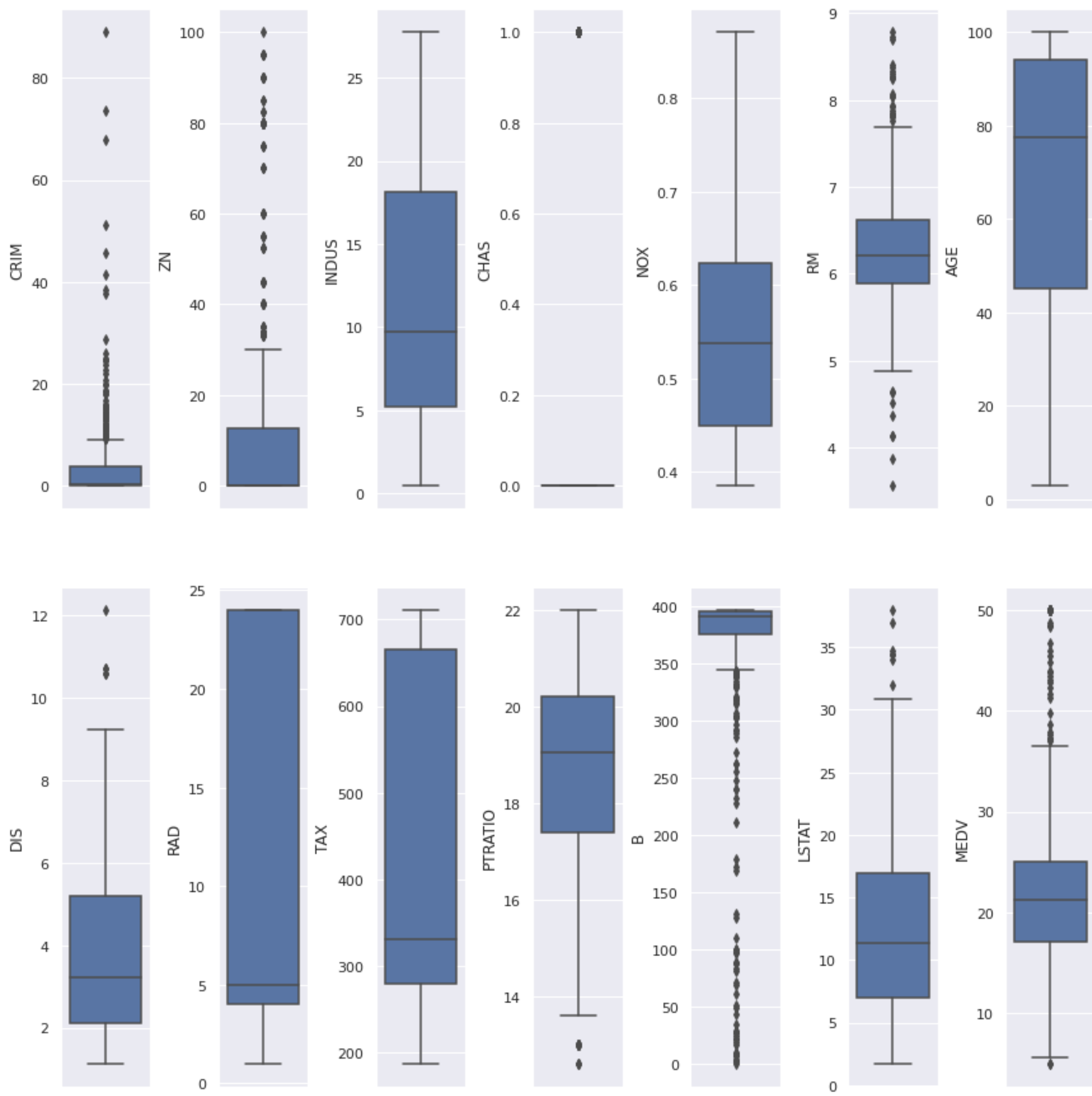
[3]:
```python
x = df.iloc[:,:-1]
y = df["MEDV"]

# According to the defenition in this dataset, it is suitable to define "MEDV"␣
↪as output and others variables as input features.
```

2 3.EDA

[4]:
```python
print(df.describe())
fig, ax = plt.subplots(ncols = 7, nrows = 2,figsize = (12, 12))
index = 0
ax = ax.flatten()
for k, v in df.items():
  sns.boxplot(y = k, data = df, ax = ax[index])
  index += 1

plt.tight_layout(pad = 0.4, w_pad = 0.5, h_pad = 5.0)

# According to the result of brief EDA, CHAS is a dummy, while the others are␣
↪numerical feartures.
# The variaties of the features are quite high; therefore, regularization is␣
↪required.
```

```
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  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
std      8.601545   23.322453    6.860353    0.253994    0.115878    0.702617
min      0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.082045    0.000000    5.190000    0.000000    0.449000    5.885500
50%      0.256510    0.000000    9.690000    0.000000    0.538000    6.208500
75%      3.677083   12.500000   18.100000    0.000000    0.624000    6.623500
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    68.574901    3.795043    9.549407  408.237154   18.455534  356.674032
std     28.148861    2.105710    8.707259  168.537116    2.164946   91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.025000    2.100175    4.000000  279.000000   17.400000  375.377500
50%     77.500000    3.207450    5.000000  330.000000   19.050000  391.440000
75%     94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000
```

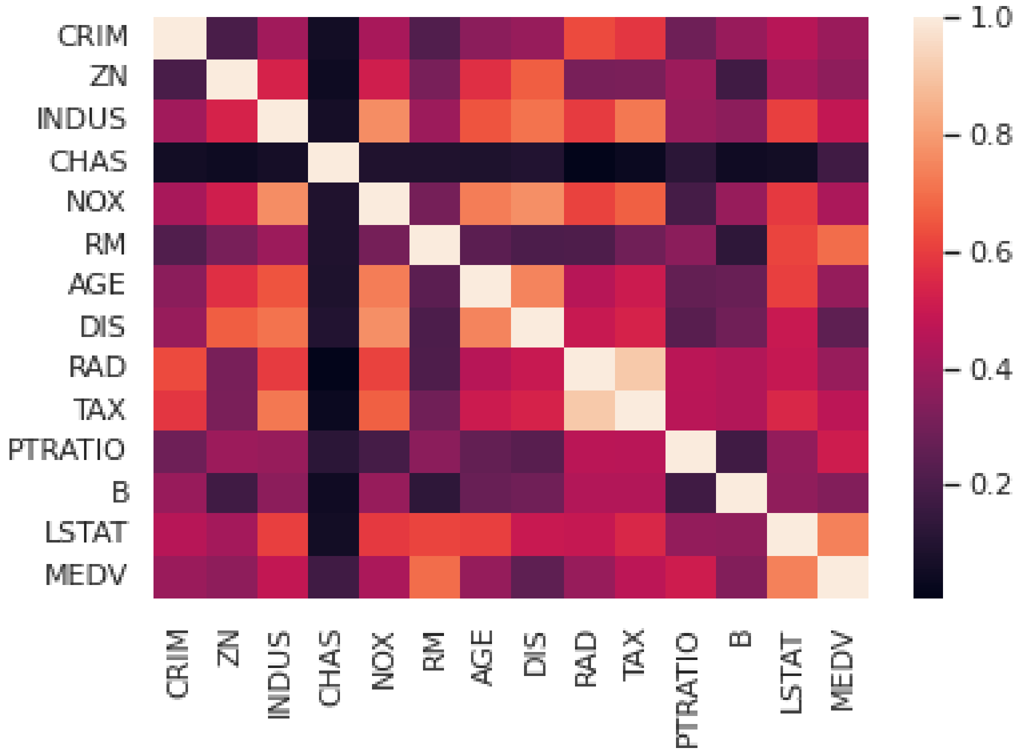
	LSTAT	MEDV
count	506.000000	506.000000
mean	12.653063	22.532806
std	7.141062	9.197104
min	1.730000	5.000000
25%	6.950000	17.025000
50%	11.360000	21.200000
75%	16.955000	25.000000
max	37.970000	50.000000



[5]:
```python
# Absolute correlation coefficients among all variables.
corr = df.corr().abs()
sns.heatmap(corr)
```

```
# It seems that (besides dummy) some of the features are correlated to␣
↪themselves.
```

[5]: <AxesSubplot:>



[6]:
```
# There's no missing value in the dataset.
df.isnull().sum()
```

[6]:
```
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
```

[7]:
```
# DataPreprocessing

# Ignore correlation coefficients which are too low to the output(set at 0.35).
cor_limit = 0.35
corr_list = x[x.columns[:]].apply(lambda x : x.corr(y))
cols = []
for i in corr_list.index:
  if (corr_list[i] >= cor_limit or corr_list[i] <= -cor_limit):
    cols.append(i)

# New data(x, input) with high correlation (HC) coefficients with Y.
HC_x = df[cols]
HC_x.head()
```

[7]:

	CRIM	ZN	INDUS	NOX	RM	AGE	RAD	TAX	PTRATIO	LSTAT
0	0.00632	18.0	2.31	0.538	6.575	65.2	1.0	296.0	15.3	4.98
1	0.02731	0.0	7.07	0.469	6.421	78.9	2.0	242.0	17.8	9.14
2	0.02729	0.0	7.07	0.469	7.185	61.1	2.0	242.0	17.8	4.03
3	0.03237	0.0	2.18	0.458	6.998	45.8	3.0	222.0	18.7	2.94
4	0.06905	0.0	2.18	0.458	7.147	54.2	3.0	222.0	18.7	5.33

[8]:
```
# Regularization. For the large variaties in the input features.
# MaxAbsScaler - For the highest explain power among all scalers from view of
 ↪PCA and high predition accuracy.

from sklearn.preprocessing import MaxAbsScaler
Z = HC_x

scaler = MaxAbsScaler()
scaler.fit(Z)
Z = scaler.transform(Z)

HC_x.iloc[:,:] = Z

"""
#decomposition(PCA if needed)
from sklearn.decomposition import PCA

pca = PCA(n_components = 2)
L = pca.fit_transform(Z)


#explain percentage
pca_explained = PCA()
pca_explained.fit(Z)
```

```
p_pca = np.round(pca_explained.explained_variance_ratio_, 2)
print("The 2 components explain percentage : " +␣
 ↪str(round(p_pca[0]+p_pca[1],4)))
"""
```

[8]:
```
'\n#decomposition(PCA if needed)\nfrom sklearn.decomposition import PCA\n\npca =
PCA(n_components = 2)\nL = pca.fit_transform(Z)\n\n\n#explain
percentage\npca_explained = PCA()\npca_explained.fit(Z)\np_pca =
np.round(pca_explained.explained_variance_ratio_, 2)\nprint("The 2 components
explain percentage : " + str(round(p_pca[0]+p_pca[1],4)))\n'
```

[9]:
```
# Make sure the input is regularized.
HC_x.describe()
```

[9]:

	CRIM	ZN	INDUS	NOX	RM	AGE \
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	0.040612	0.113636	0.401470	0.636849	0.715790	0.685749
std	0.096672	0.233225	0.247309	0.133040	0.080025	0.281489
min	0.000071	0.000000	0.016583	0.442021	0.405581	0.029000
25%	0.000922	0.000000	0.187094	0.515499	0.670330	0.450250
50%	0.002883	0.000000	0.349315	0.617681	0.707118	0.775000
75%	0.041327	0.125000	0.652487	0.716418	0.754385	0.940750
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

	RAD	TAX	PTRATIO	LSTAT
count	506.000000	506.000000	506.000000	506.000000
mean	0.397892	0.574173	0.838888	0.333238
std	0.362802	0.237042	0.098407	0.188071
min	0.041667	0.263010	0.572727	0.045562
25%	0.166667	0.392405	0.790909	0.183039
50%	0.208333	0.464135	0.865909	0.299184
75%	1.000000	0.936709	0.918182	0.446537
max	1.000000	1.000000	1.000000	1.000000

3 4.Training set and Testing set seperation. (by 15%)

[10]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(HC_x, y, test_size = 0.15)
```

4 5.Fitting of each ML model.

[11]:
```
from sklearn import metrics
from sklearn.linear_model import LinearRegression

# Create a Linear Regression Model.
lm = LinearRegression()
```

```
lm.fit(x_train, y_train)
LinearRegression(fit_intercept=True, n_jobs=None)
```

[11]: LinearRegression()

[12]:
```
# Model fitting on training data.
y_pred_lm = lm.predict(x_train)
print('R^2:',round(metrics.r2_score(y_train, y_pred_lm), 4))
print('Adjusted R^2:',round(1 - (1-metrics.r2_score(y_train,␣
 ↪y_pred_lm))*(len(y_train) - 1)/(len(y_train) - x_train.shape[1] - 1),4))
print('MSE:',round(metrics.mean_squared_error(y_train, y_pred_lm),4))
```

```
R^2: 0.6993
Adjusted R^2: 0.6921
MSE: 26.1001
```

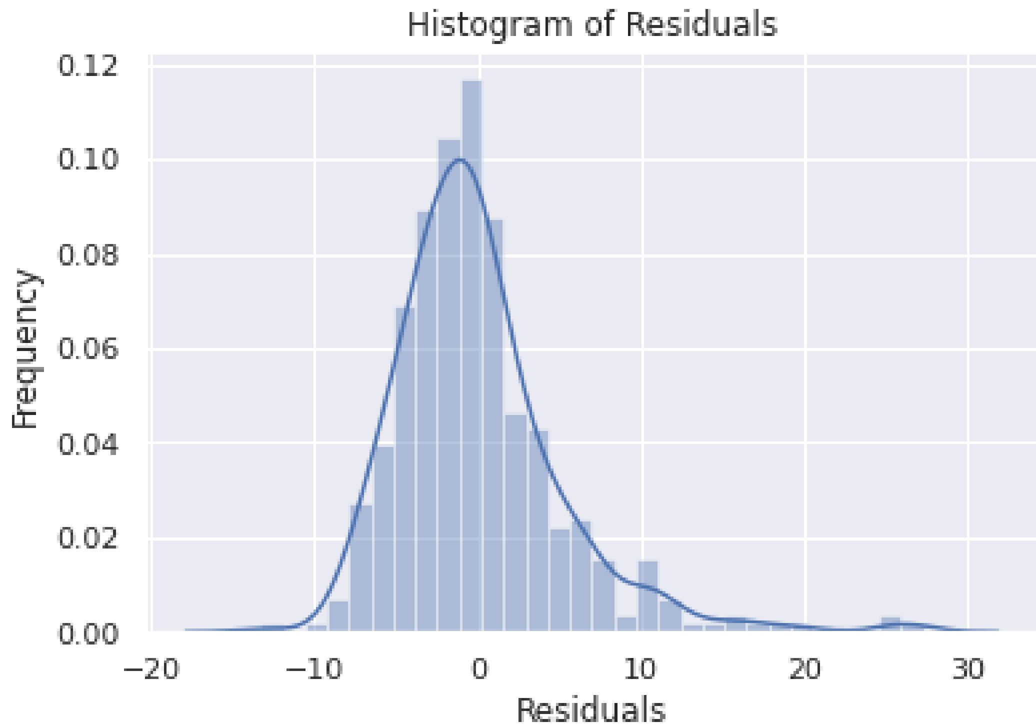
[13]:
```
# Predicting with the testing data.
y_test_pred_lm = lm.predict(x_test)

# Model Evaluation
score_linreg = metrics.r2_score(y_test, y_test_pred_lm)
print('R^2:', round(score_linreg,4))
print('Adjusted R^2:',round(1 - (1-metrics.r2_score(y_test,␣
 ↪y_test_pred_lm))*(len(y_test)-1)/(len(y_test)-x_test.shape[1]-1),4))
print('MSE:',round(metrics.mean_squared_error(y_test, y_test_pred_lm),4))
```

```
R^2: 0.6793
Adjusted R^2: 0.63
MSE: 22.7771
```

[14]:
```
# Visualizing the differences between real prices and predicted prices.
plt.scatter(y_train, y_pred_lm)
plt.xlabel("Real Prices")
plt.ylabel("Predicted Prices")
plt.title("Real Prices vs Predicted prices")
plt.show()
```

[15]:
```
# Checking of Normality of residuals.
from scipy import stats
statsn, pval = stats.normaltest(y_train - y_pred_lm)
print("p_val of normality test is : " + str(pval) + ", so it's normally␣
 ↪distributed." + "\n")

sns.distplot(y_train - y_pred_lm)
plt.title("Histogram of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.show()
```

```
p_val of normality test is : 8.049803151117528e-36, so it's normally
distributed.
```



[16]:
```
# Import Random Forest Regressor.
from sklearn.ensemble import RandomForestRegressor

# Create a Random Forest Regressor.
rfm = RandomForestRegressor()
rfm.fit(x_train, y_train)
```

[16]: RandomForestRegressor()

[17]:
```
# Model fitting on training data.
y_pred_rf = rfm.predict(x_train)
print('R^2:',round(metrics.r2_score(y_train, y_pred_rf),4))
print('Adjusted R^2:',round(1 - (1-metrics.r2_score(y_train,
 ↪y_pred_rf))*(len(y_train)-1)/(len(y_train)-x_train.shape[1]-1),4))
print('MSE:',round(metrics.mean_squared_error(y_train, y_pred_rf),4))
```

```
R^2: 0.976
Adjusted R^2: 0.9754
MSE: 2.083
```

[18]:
```
# Predicting with the testing data.
y_test_pred_rf = rfm.predict(x_test)
```

```
# Model Evaluation
score_rf = round(metrics.r2_score(y_test, y_test_pred_rf),4)
print('R^2:', score_rf)
print('Adjusted R^2:',round(1 - (1-metrics.r2_score(y_test,␣
 ↪y_test_pred_rf))*(len(y_test)-1)/(len(y_test)-x_test.shape[1]-1),4))
print('MSE:',round(metrics.mean_squared_error(y_test, y_test_pred_rf),4))
```

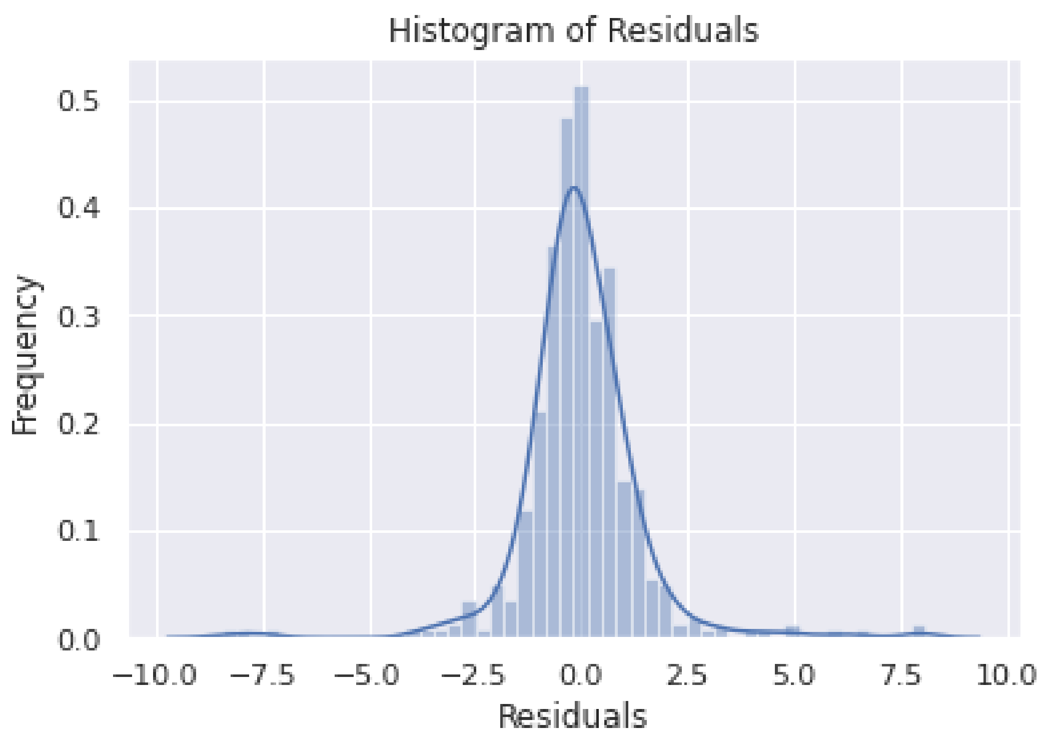
```
R^2: 0.8663
Adjusted R^2: 0.8458
MSE: 9.4939
```

[19]:
```
# Visualizing the differences between actual prices and predicted values
plt.scatter(y_train, y_pred_rf)
plt.xlabel("Real Prices")
plt.ylabel("Predicted Prices")
plt.title("Real Prices vs Predicted prices")
plt.show()
```

[20]:
```
# Checking of Normality of residuals.
statsn, pval = stats.normaltest(y_train - y_pred_rf)
print("p_val of normality test is : " + str(pval) + ", so it's normally␣
 ↪distributed." + "\n")
```

```
sns.distplot(y_train - y_pred_rf)
plt.title("Histogram of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.show()
```

```
p_val of normality test is : 1.3311902577279215e-21, so it's normally
distributed.
```



[21]:
```
# Comparison of Linear Regression model and Random Forest Regressor.
# It seems that both of the model do not occur serios overfitting or inder␣
↪fitting problems.
# Random Forest Regressor seems to be outperforming the Linear Regression model.
```

5 5.Compare the accuracy with the regression models.

[22]:
```
print("The defenition of Acc. Here is referring to R-squared score.")
print("Acc. of Linear Regression Model : " + str(round(score_linreg, 4)))
print("Acc. of Random Forest Model : " + str(round(score_rf, 4)))
```

```
The defenition of Acc. Here is referring to R-squared score.
Acc. of Linear Regression Model : 0.6793
```

```
Acc. of Random Forest Model : 0.8663
```

6 6.Neural Nnetwork

[23]:
```python
import keras

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from sklearn.metrics import r2_score


# Since the prediction accuracy for the output of a scalar would be 0 for most␣
↪of the scenarios.
# Therefore, I decided to define the accuracy of NN model as R^2 as the␣
↪classical linear regession model.
"""
from tensorflow.keras import backend as K

def ssr(y_true, y_pred):
  ss_res = K.sum(K.square(y_true - y_pred))
  ss_tot = K.sum(K.square(y_true - K.mean(y_true)))
  return(1 - (ss_res / (ss_tot + K.epsilon())))
"""
```

[23]:
```
'\nfrom tensorflow.keras import backend as K\n\ndef ssr(y_true, y_pred):\n
ss_res = K.sum(K.square(y_true - y_pred))\n  ss_tot = K.sum(K.square(y_true -
K.mean(y_true)))\n  return(1 - (ss_res / (ss_tot + K.epsilon())))\n'
```

[24]:
```python
# NN Model stacking.
model_nn = Sequential()
model_nn.add(Dense(10, input_dim = len(HC_x.columns)))
model_nn.add(Dense(10))
model_nn.add(Dense(10))
model_nn.add(Dense(1))
model_nn.compile(loss = "mse", optimizer = "rmsprop", metrics = [r2_score],␣
↪run_eagerly = True)

model_nn.summary()
```

```
2022-12-05 13:17:17.832387: I
tensorflow/core/common_runtime/process_util.cc:146] Creating new thread pool
with default inter op setting: 2. Tune using inter_op_parallelism_threads for
best performance.

Model: "sequential"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
dense (Dense)                (None, 10)               110

-----------------------------------------------------------------
dense_1 (Dense)              (None, 10)               110

-----------------------------------------------------------------
dense_2 (Dense)              (None, 10)               110

-----------------------------------------------------------------
dense_3 (Dense)              (None, 1)                11
=================================================================
Total params: 341
Trainable params: 341
Non-trainable params: 0

-----------------------------------------------------------------
```

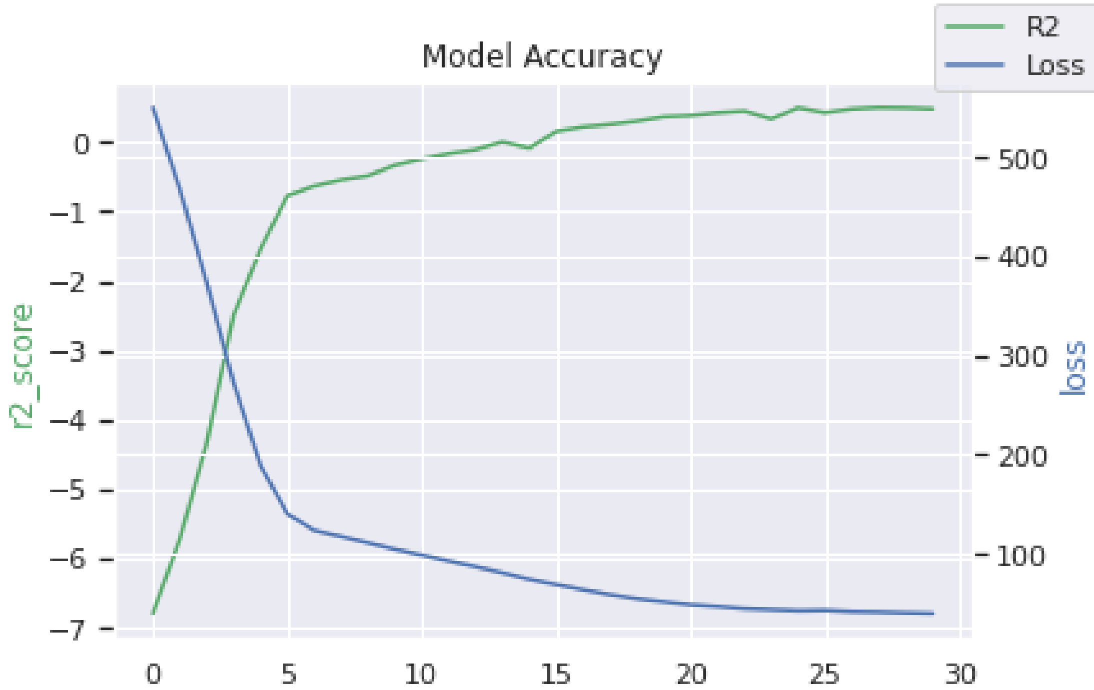
[25]:

```
# NN Model training.
# This dataset is a small one, which may somehow occur overfitting problem.

nn_result = model_nn.fit(x_train, y_train, batch_size = 20, epochs = 30,␣
 ↪validation_split = 0.10)

fig, ax1 = plt.subplots()
ax2 = ax1.twinx()

ax1.plot(nn_result.history["r2_score"], color = "g", label = "R2")
ax2.plot(nn_result.history["loss"], color = "b", label = "Loss")

ax1.set_ylabel("r2_score", color = "g")
ax2.set_ylabel("loss", color = "b")

plt.title("Model Accuracy")
plt.xlabel("epoch")
fig.legend()
plt.show()

print("Brief view on the result of training.")
```

```
2022-12-05 13:17:18.279095: I
tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:185] None of the MLIR
Optimization Passes are enabled (registered 2)

Epoch 1/30
20/20 [==============================] - 5s 60ms/step - loss: 550.2806 -
r2_score: -6.7891 - val_loss: 509.3455 - val_r2_score: -4.6462
Epoch 2/30
20/20 [==============================] - 1s 57ms/step - loss: 468.0719 -
r2_score: -5.7202 - val_loss: 425.5466 - val_r2_score: -3.4199
Epoch 3/30
20/20 [==============================] - 1s 57ms/step - loss: 373.9273 -
```

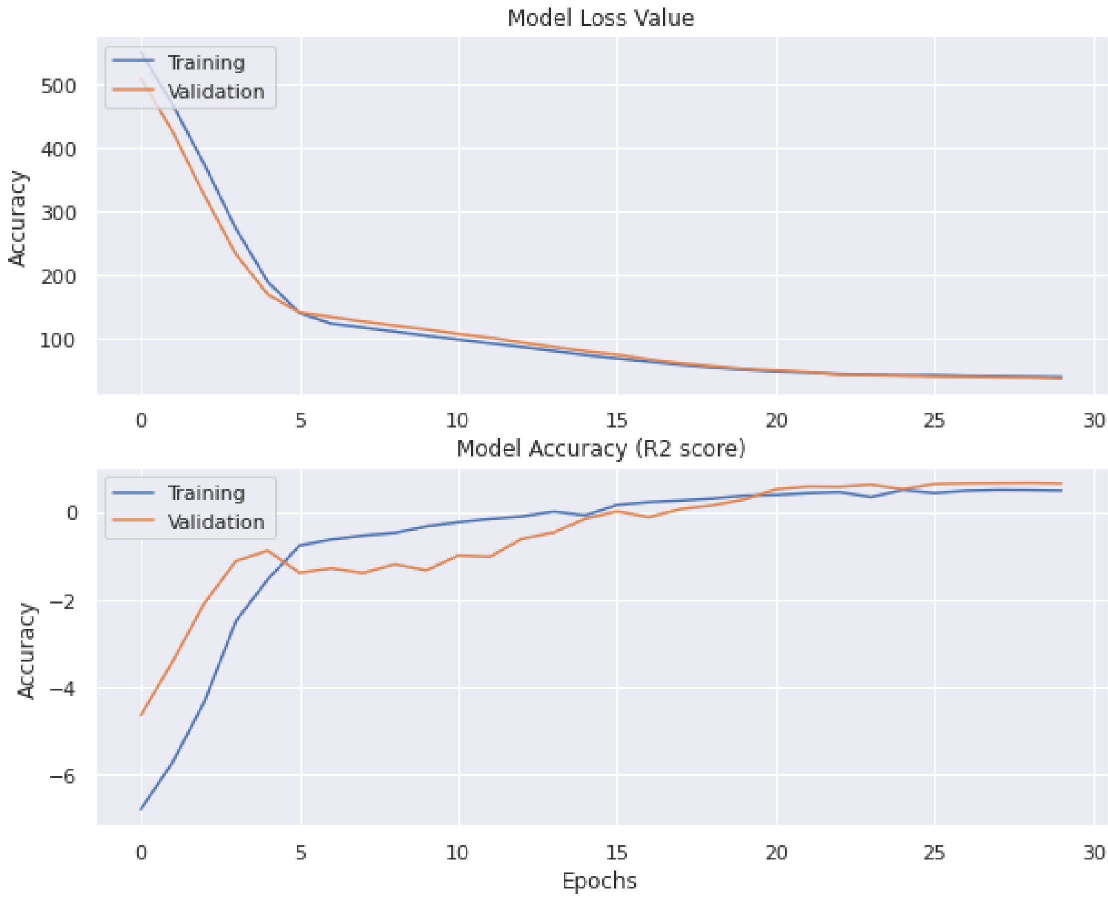
```
r2_score: -4.3381 - val_loss: 325.2667 - val_r2_score: -2.0890
Epoch 4/30
20/20 [==============================] - 1s 57ms/step - loss: 272.6080 -
r2_score: -2.4913 - val_loss: 232.3489 - val_r2_score: -1.1219
Epoch 5/30
20/20 [==============================] - 1s 57ms/step - loss: 189.3460 -
r2_score: -1.5415 - val_loss: 169.6804 - val_r2_score: -0.8865
Epoch 6/30
20/20 [==============================] - 1s 56ms/step - loss: 140.4627 -
r2_score: -0.7720 - val_loss: 141.1949 - val_r2_score: -1.3927
Epoch 7/30
20/20 [==============================] - 1s 56ms/step - loss: 123.6893 -
r2_score: -0.6321 - val_loss: 134.1029 - val_r2_score: -1.2913
Epoch 8/30
20/20 [==============================] - 1s 57ms/step - loss: 117.5221 -
r2_score: -0.5445 - val_loss: 127.1136 - val_r2_score: -1.3974
Epoch 9/30
20/20 [==============================] - 1s 59ms/step - loss: 111.0973 -
r2_score: -0.4840 - val_loss: 120.5698 - val_r2_score: -1.1983
Epoch 10/30
20/20 [==============================] - 1s 57ms/step - loss: 104.5461 -
r2_score: -0.3325 - val_loss: 114.5736 - val_r2_score: -1.3373
Epoch 11/30
20/20 [==============================] - 1s 56ms/step - loss: 98.7414 -
r2_score: -0.2400 - val_loss: 107.4133 - val_r2_score: -0.9971
Epoch 12/30
20/20 [==============================] - 1s 57ms/step - loss: 92.7498 -
r2_score: -0.1641 - val_loss: 101.6103 - val_r2_score: -1.0256
Epoch 13/30
20/20 [==============================] - 1s 57ms/step - loss: 87.0843 -
r2_score: -0.1068 - val_loss: 94.0513 - val_r2_score: -0.6189
Epoch 14/30
20/20 [==============================] - 1s 57ms/step - loss: 80.8990 -
r2_score: 0.0031 - val_loss: 87.0259 - val_r2_score: -0.4735
Epoch 15/30
20/20 [==============================] - 1s 57ms/step - loss: 74.3350 -
r2_score: -0.0844 - val_loss: 80.4614 - val_r2_score: -0.1584
Epoch 16/30
20/20 [==============================] - 1s 56ms/step - loss: 69.0157 -
r2_score: 0.1561 - val_loss: 75.0943 - val_r2_score: 0.0083
Epoch 17/30
20/20 [==============================] - 1s 56ms/step - loss: 63.7904 -
r2_score: 0.2196 - val_loss: 67.5616 - val_r2_score: -0.1237
Epoch 18/30
20/20 [==============================] - 1s 57ms/step - loss: 58.8932 -
r2_score: 0.2561 - val_loss: 61.2925 - val_r2_score: 0.0610
Epoch 19/30
20/20 [==============================] - 1s 59ms/step - loss: 54.7316 -
```

```
r2_score: 0.3030 - val_loss: 56.9293 - val_r2_score: 0.1464
Epoch 20/30
20/20 [==============================] - 1s 57ms/step - loss: 51.6036 -
r2_score: 0.3669 - val_loss: 52.6521 - val_r2_score: 0.2800
Epoch 21/30
20/20 [==============================] - 1s 57ms/step - loss: 48.6013 -
r2_score: 0.3839 - val_loss: 50.2821 - val_r2_score: 0.5113
Epoch 22/30
20/20 [==============================] - 1s 57ms/step - loss: 46.7983 -
r2_score: 0.4243 - val_loss: 47.6687 - val_r2_score: 0.5754
Epoch 23/30
20/20 [==============================] - 1s 57ms/step - loss: 44.6932 -
r2_score: 0.4489 - val_loss: 43.6461 - val_r2_score: 0.5680
Epoch 24/30
20/20 [==============================] - 1s 57ms/step - loss: 43.6698 -
r2_score: 0.3358 - val_loss: 42.9058 - val_r2_score: 0.6188
Epoch 25/30
20/20 [==============================] - 1s 56ms/step - loss: 42.6587 -
r2_score: 0.4956 - val_loss: 42.0499 - val_r2_score: 0.5124
Epoch 26/30
20/20 [==============================] - 1s 57ms/step - loss: 43.0076 -
r2_score: 0.4265 - val_loss: 40.7416 - val_r2_score: 0.6342
Epoch 27/30
20/20 [==============================] - 1s 61ms/step - loss: 41.7197 -
r2_score: 0.4792 - val_loss: 40.5412 - val_r2_score: 0.6510
Epoch 28/30
20/20 [==============================] - 1s 60ms/step - loss: 41.2645 -
r2_score: 0.4988 - val_loss: 39.6165 - val_r2_score: 0.6539
Epoch 29/30
20/20 [==============================] - 1s 57ms/step - loss: 40.5412 -
r2_score: 0.4940 - val_loss: 39.2298 - val_r2_score: 0.6590
Epoch 30/30
20/20 [==============================] - 1s 57ms/step - loss: 39.9451 -
r2_score: 0.4814 - val_loss: 37.5831 - val_r2_score: 0.6471
```



Brief view on the result of training.

[26]:
```
# Examine the process of NN_model on loss and R2 score.
plt.figure(figsize = (10, 8))
plt.subplot(211)

plt.plot(nn_result.history["loss"])
plt.plot(nn_result.history["val_loss"])
plt.title("Model Loss Value")
plt.ylabel("Accuracy")
plt.legend(["Training", "Validation"], loc = "upper left")


plt.subplot(212)

plt.plot(nn_result.history["r2_score"])
plt.plot(nn_result.history["val_r2_score"])
plt.title("Model Accuracy (R2 score)")
plt.ylabel("Accuracy")
plt.xlabel("Epochs")
plt.legend(["Training", "Validation"], loc = "upper left")
plt.show()
```



[27]:

```
# Accuracy of well-trainde NN Model.
scores = model_nn.evaluate(x_test, y_test)
print("Accuracy of CNN is : " + str(round(scores[1],4)))
#The accuracyt is quite unstable...
```

```
3/3 [==============================] - 0s 38ms/step - loss: 38.5716 - r2_score:
0.3765
Accuracy of CNN is : 0.3765
```

[28]:

```
# Compare the accuracy of all the regression models.
print("The defenition of Acc. here is referring to R-squared score.")
print("Acc. of Linear Regression Model : " + str(round(score_linreg, 4)))
print("Acc. of Random Forest Model : " + str(round(score_rf, 4)))
print("Acc. of Neural Network Model : " + str(round(scores[1],4)))
```

```
The defenition of Acc. here is referring to R-squared score.
Acc. of Linear Regression Model : 0.6793
Acc. of Random Forest Model : 0.8663
Acc. of Neural Network Model : 0.3765
```