```
import pandas as pd
import numpy as npd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
import warnings
warnings.filterwarnings(action='ignore')
from sklearn.model_selection import GridSearchCV, cross_val_score, train_test_split


#Load data
df = pd.read_csv('gas_turbines.csv')
df.head()
```

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	114.70	10.605	3.1547	82.722
1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	114.72	10.598	3.2363	82.776
2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	114.71	10.601	3.2012	82.468
3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	114.72	10.606	3.1923	82.670
4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	114.72	10.612	3.2484	82.311

```
df.shape
```

```
(15039, 11)
```

```
df.columns
```

```
Index(['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'TEY', 'CDP', 'CO',
       'NOX'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15039 entries, 0 to 15038
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   AT      15039 non-null  float64
 1   AP      15039 non-null  float64
 2   AH      15039 non-null  float64
 3   AFDP    15039 non-null  float64
 4   GTEP    15039 non-null  float64
 5   TIT     15039 non-null  float64
 6   TAT     15039 non-null  float64
 7   TEY     15039 non-null  float64
 8   CDP     15039 non-null  float64
 9   CO      15039 non-null  float64
 10  NOX     15039 non-null  float64
```

```
dtypes: float64(11)
memory usage: 1.3 MB
```

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
AT	15039.0	17.764381	7.574323	0.522300	11.408000	18.1860	23.8625	34.9290
AP	15039.0	1013.199240	6.410760	985.850000	1008.900000	1012.8000	1016.9000	1034.2000
AH	15039.0	79.124174	13.793439	30.344000	69.750000	82.2660	90.0435	100.2000
AFDP	15039.0	4.200294	0.760197	2.087400	3.723900	4.1862	4.5509	7.6106
GTEP	15039.0	25.419061	4.173916	17.878000	23.294000	25.0820	27.1840	37.4020
TIT	15039.0	1083.798770	16.527806	1000.800000	1079.600000	1088.7000	1096.0000	1100.8000
TAT	15039.0	545.396183	7.866803	512.450000	542.170000	549.8900	550.0600	550.6100
TEY	15039.0	134.188464	15.829717	100.170000	127.985000	133.7800	140.8950	174.6100
CDP	15039.0	12.102353	1.103196	9.904400	11.622000	12.0250	12.5780	15.0810
CO	15039.0	1.972499	2.222206	0.000388	0.858055	1.3902	2.1604	44.1030
NOX	15039.0	68.190934	10.470586	27.765000	61.303500	66.6010	73.9355	119.8900

EDA & Feature Engineering

```
#check for misssing values
df.isna().sum()
```

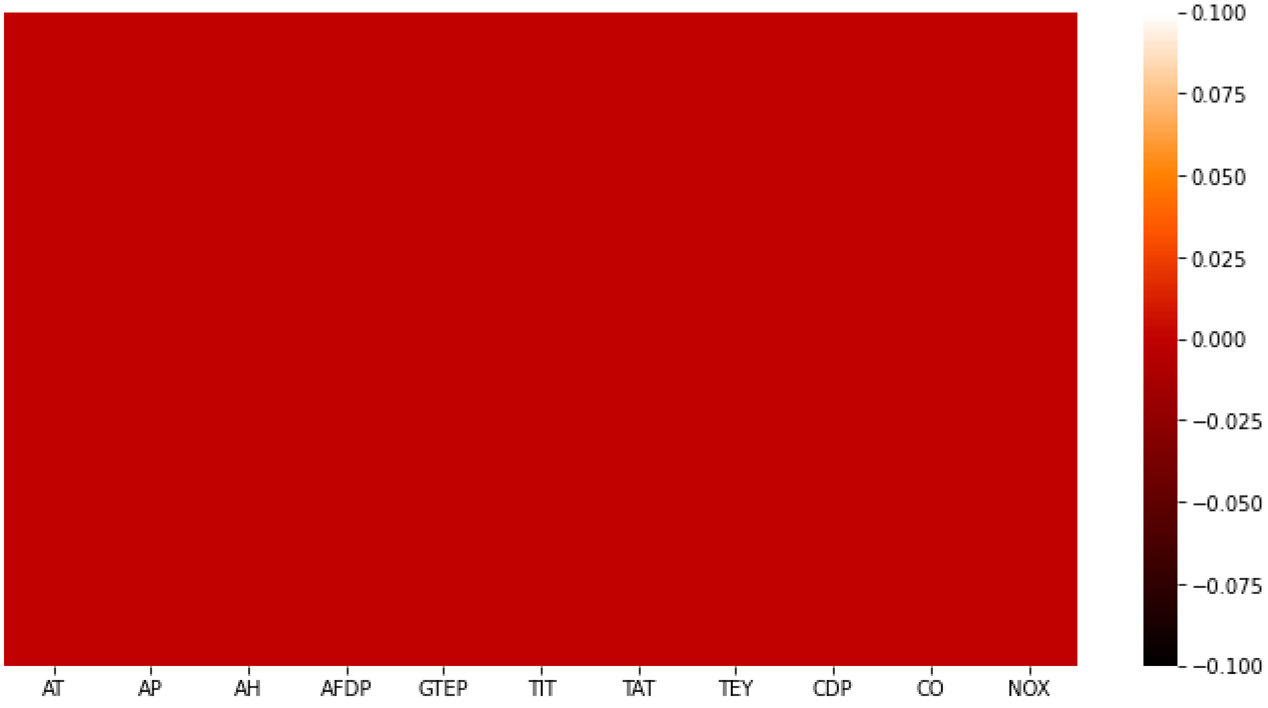
```
AT      0
AP      0
AH      0
AFDP    0
GTEP    0
TIT     0
TAT     0
TEY     0
CDP     0
CO      0
NOX     0
dtype: int64
```

```
df.isna().any()
```

```
AT      False
AP      False
AH      False
AFDP    False
GTEP    False
TIT     False
TAT     False
TEY     False
CDP     False
CO      False
NOX     False
dtype: bool
```

```
plt.rcParams['figure.figsize']=(12,6)
sns.heatmap(df.isna(), cmap =('gist_heat'), yticklabels=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb8482b6fd0>
```




```
#check for duplicate values
df[df.duplicated()].shape
```

```
(0, 11)
```

```
df[df.duplicated()]
```

AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX

```
df.dtypes
```

```
AT      float64
AP      float64
AH      float64
AFDP    float64
GTEP    float64
TIT     float64
TAT     float64
TEY     float64
CDP     float64
CO      float64
NOX     float64
dtype: object
```

```
df.nunique()
```

```
AT      12086
AP        540
AH      12637
AFDP    11314
GTEP     8234
TIT       706
TAT      2340
```

```
TEY       4207
CDP       3611
CO       13096
NOX      11996
dtype: int64
```

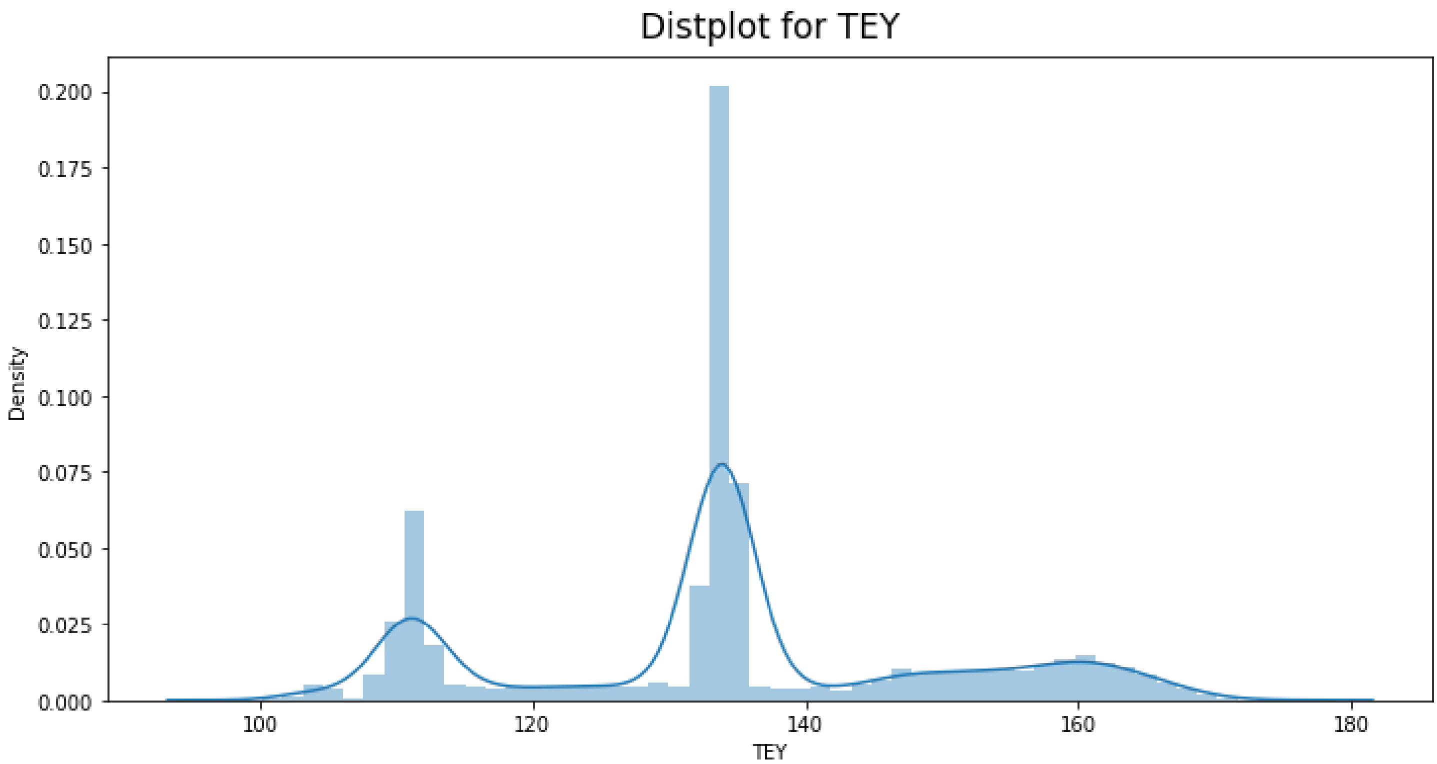
Observation:

- No missing values
- No duplicate values
- All dtypes are correct.

Data Visualisation

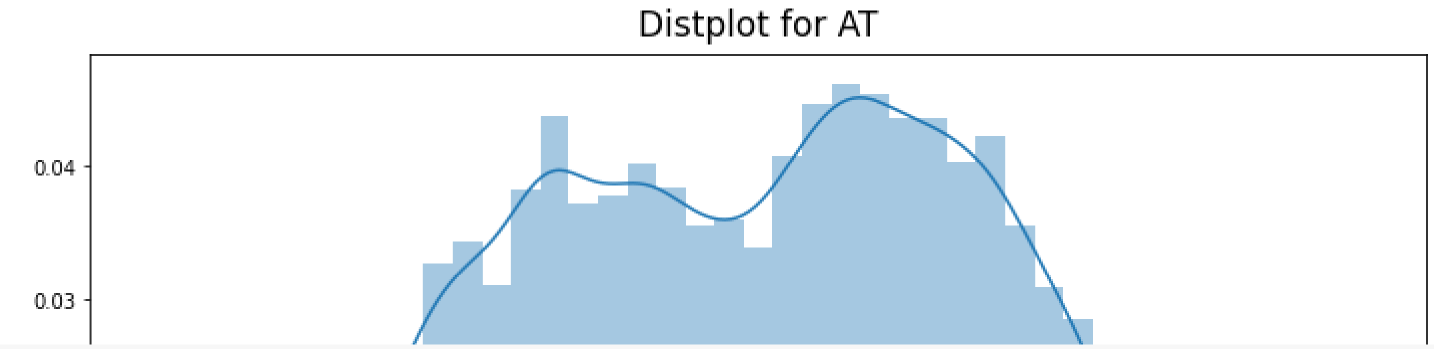
```
#Target variable
plt.title('Distplot for TEY', fontsize=17, y = 1.01)
sns.distplot(df['TEY'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb84598f410>
```



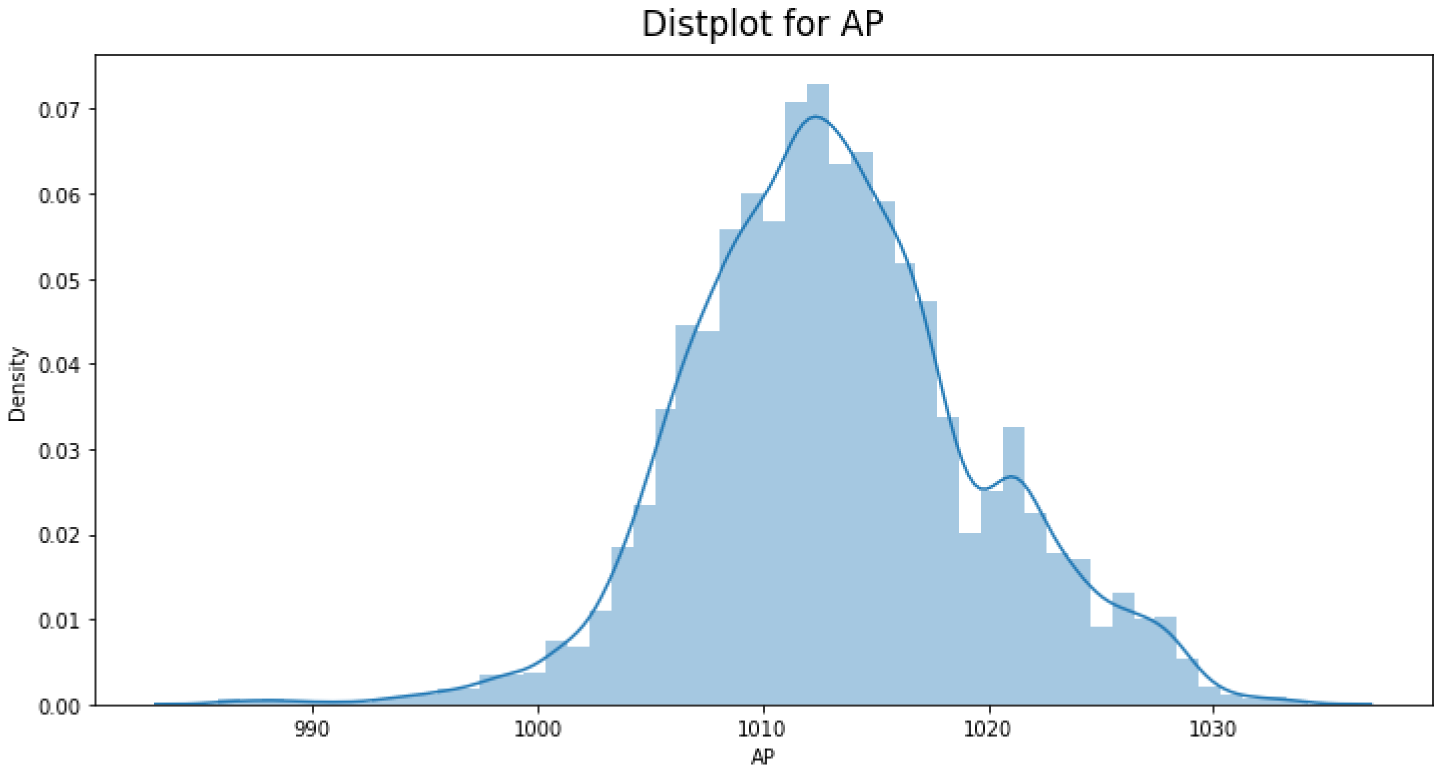

```
plt.title('Distplot for AT', fontsize=17, y = 1.01)
sns.distplot(df['AT'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb8453b5a10>




```
plt.title('Distplot for AP', fontsize=17, y = 1.01)
sns.distplot(df['AP'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb8453159d0>

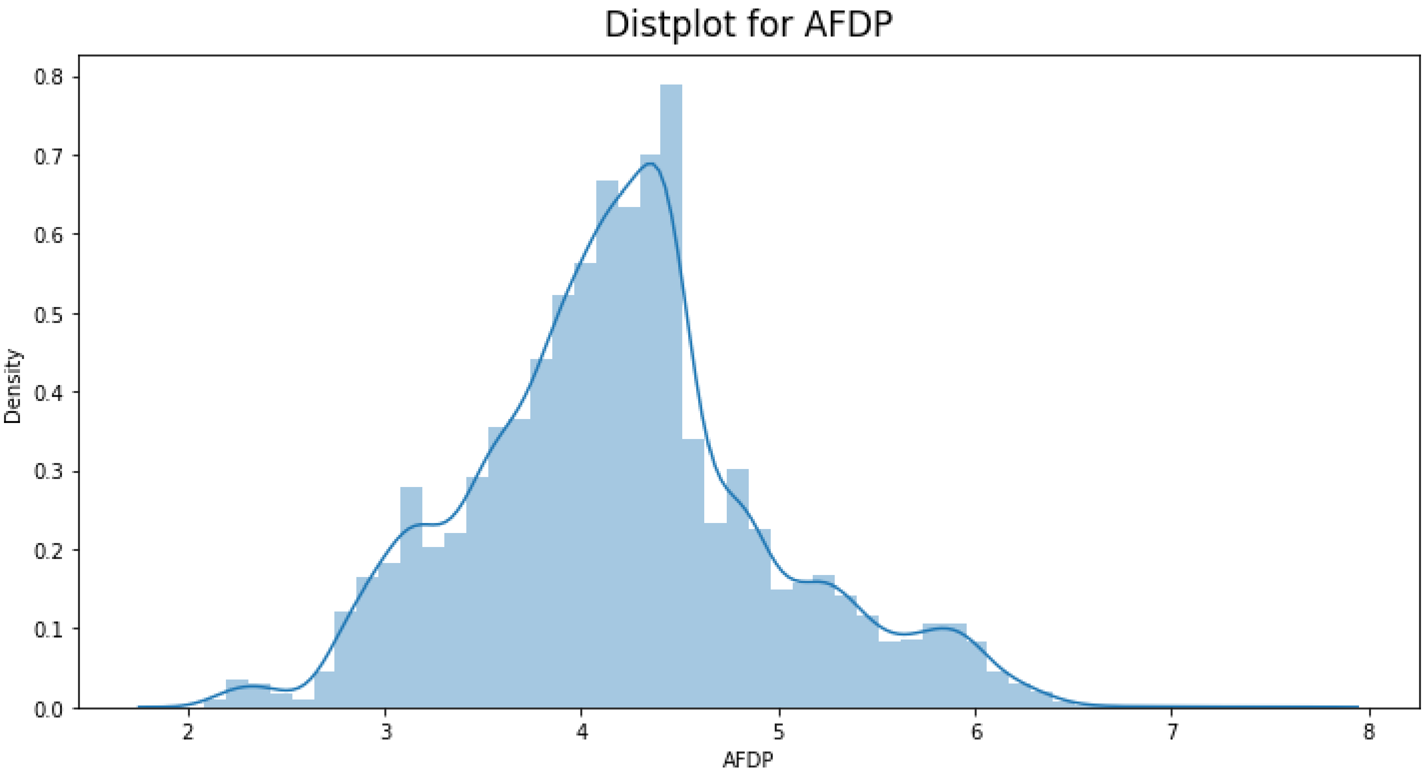



```
plt.title('Distplot for AH', fontsize=17, y = 1.01)
sns.distplot(df['AH'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb84530b5d0>

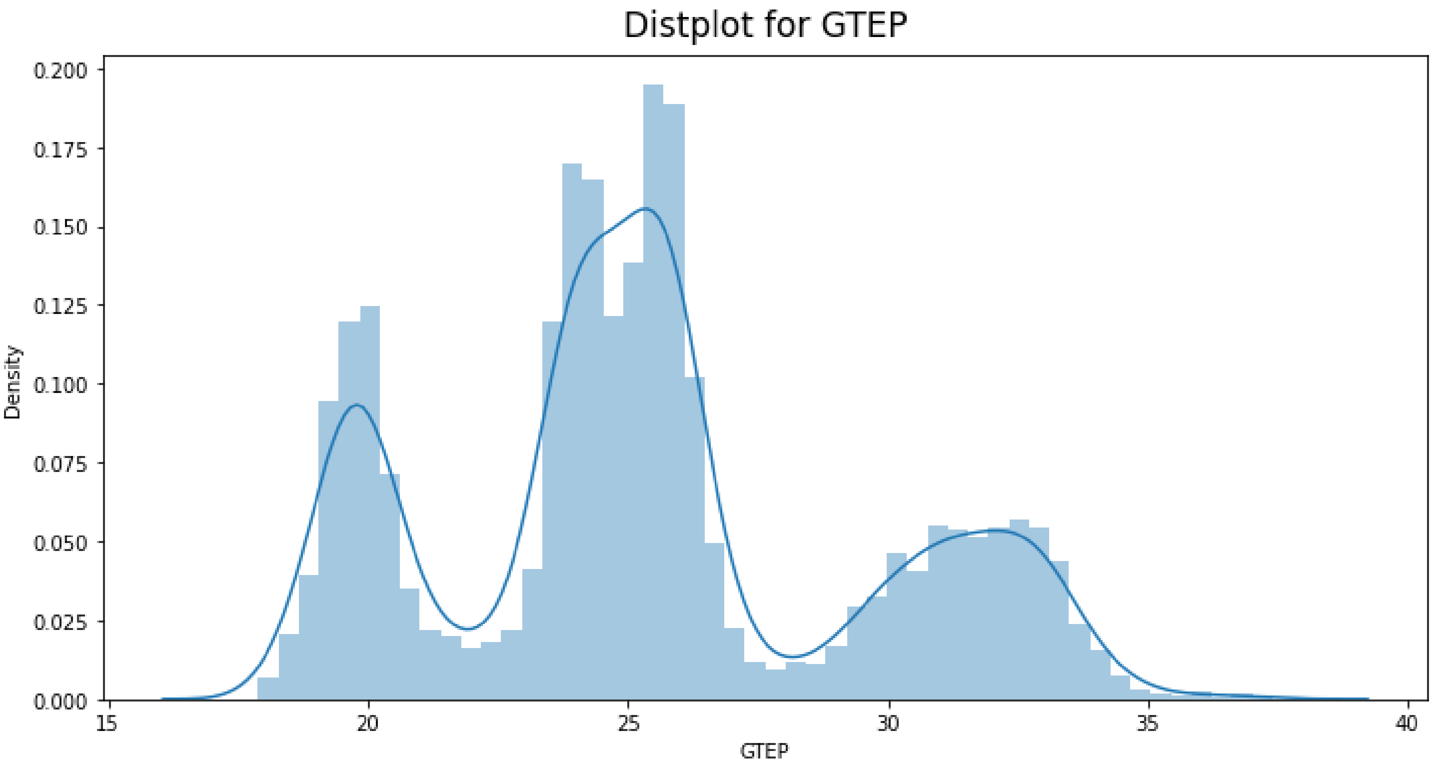

```
plt.title('Distplot for AFDP', fontsize=17, y = 1.01)
sns.distplot(df['AFDP'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb84520ce10>



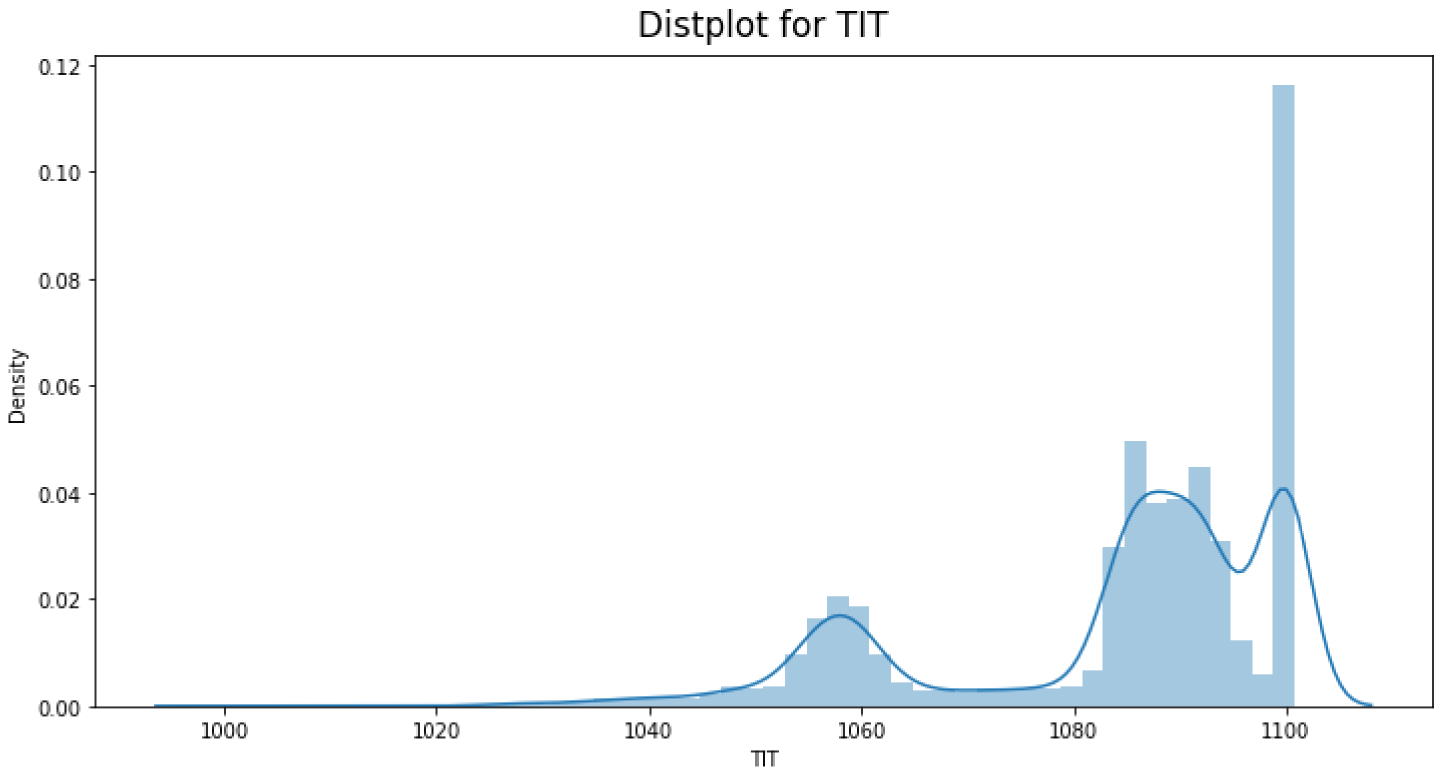

```
plt.title('Distplot for GTEP', fontsize=17, y = 1.01)
sns.distplot(df['GTEP'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f629f872f10>



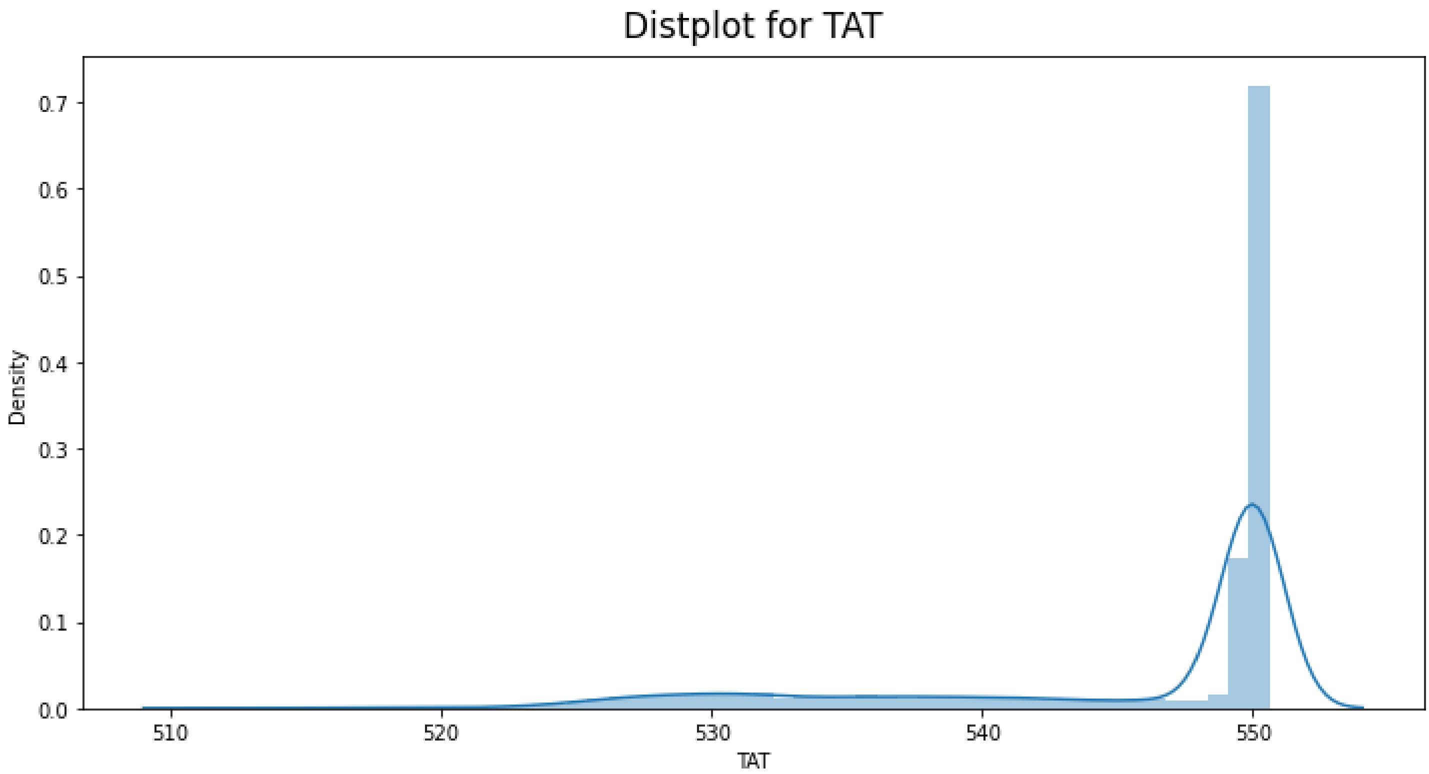

```
plt.title('Distplot for TIT', fontsize=17, y = 1.01)
sns.distplot(df['TIT'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f629f7d9350>
```



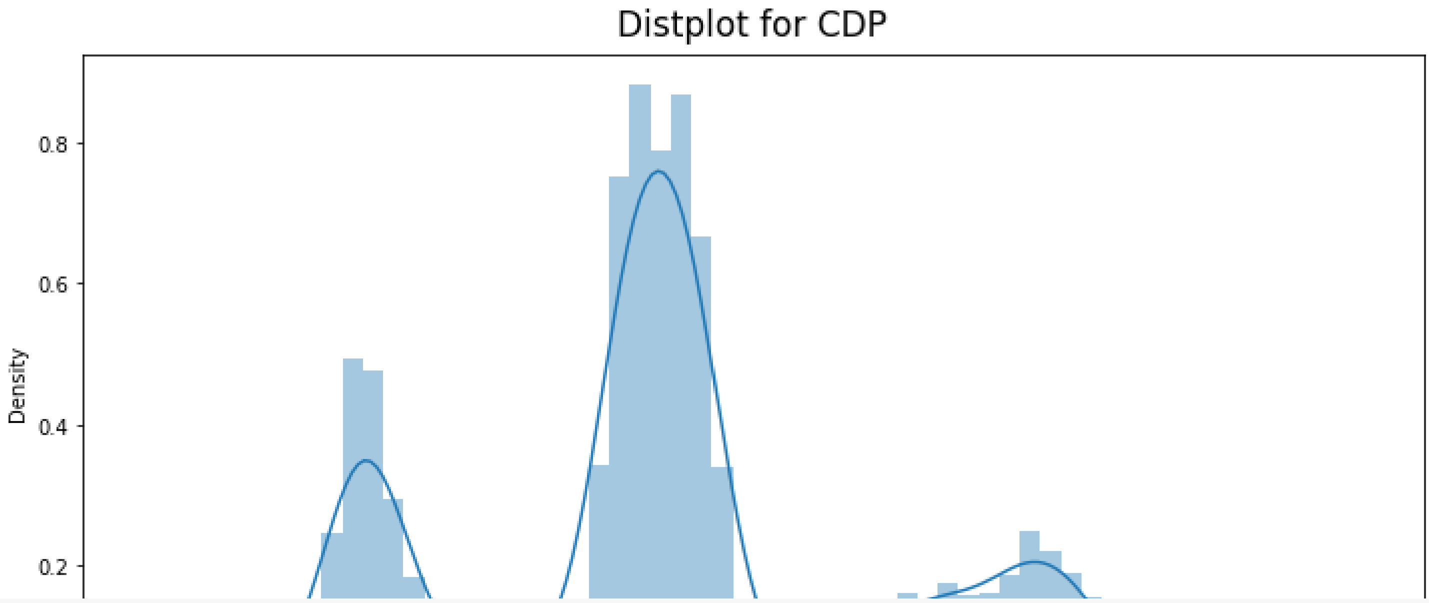

```
plt.title('Distplot for TAT', fontsize=17, y = 1.01)
sns.distplot(df['TAT'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f629fab7bd0>
```



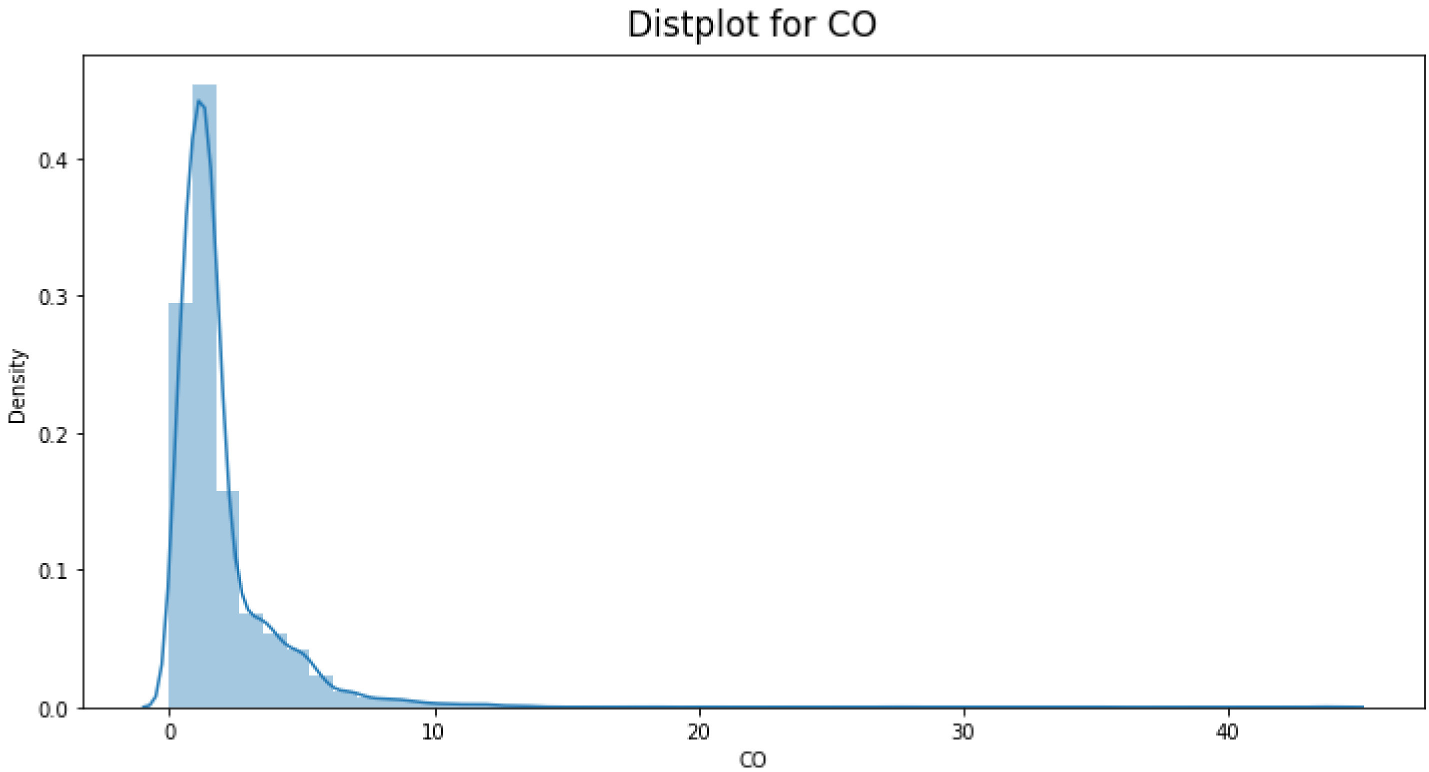

```
plt.title('Distplot for CDP', fontsize=17, y = 1.01)
sns.distplot(df['CDP'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f629f530f90>
```



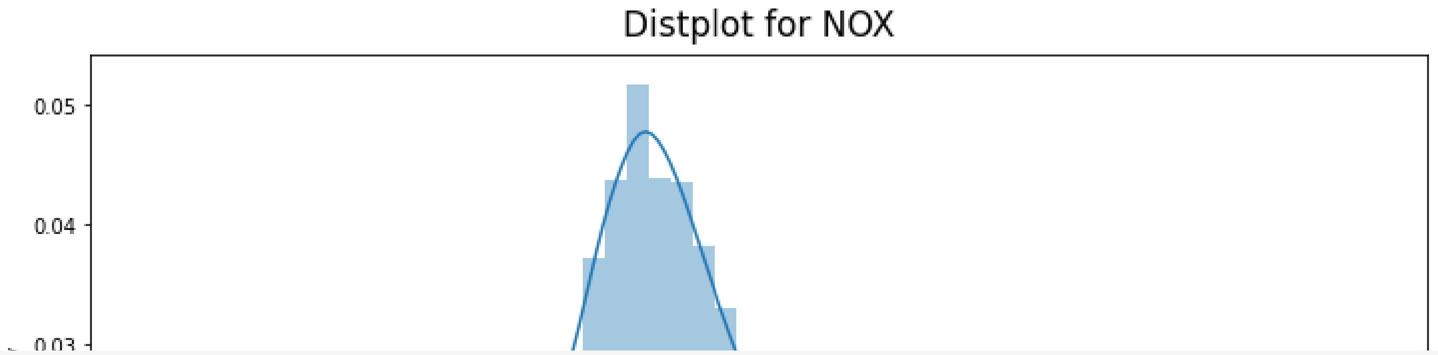

```
plt.title('Distplot for CO', fontsize=17, y = 1.01)
sns.distplot(df['CO'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f629f4022d0>
```

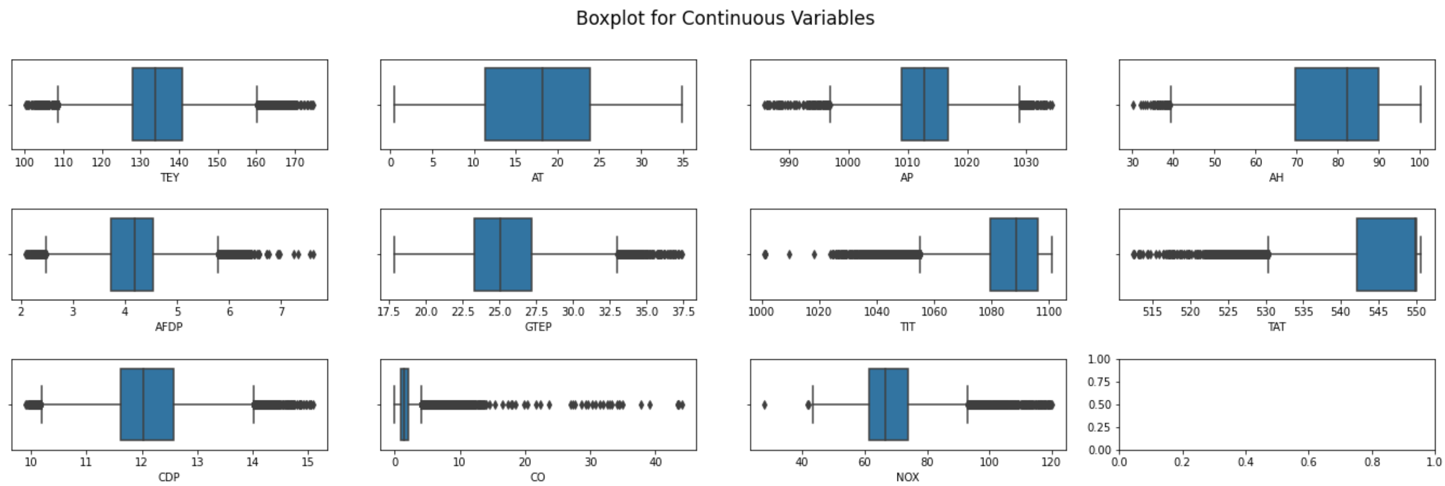



```
plt.title('Distplot for NOX', fontsize=17, y = 1.01)
sns.distplot(df['NOX'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb844b17710>
```



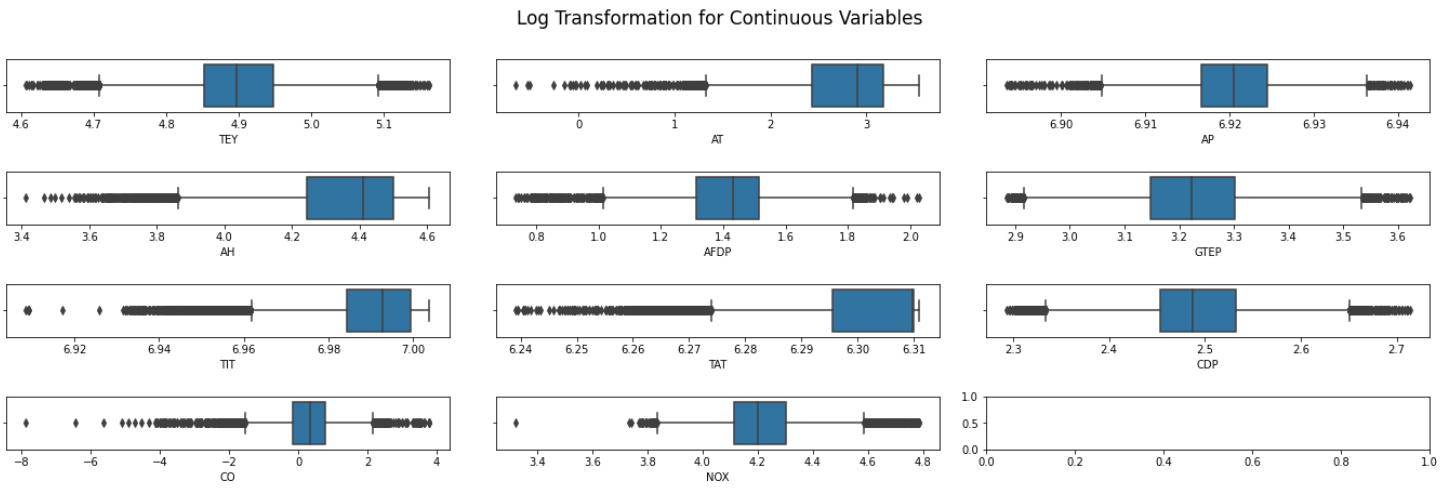

```
#check for outliers
fig, ax=plt.subplots(3,4, figsize=(19,6), sharex= False, sharey = False)
sns.boxplot(df.TEY, ax=ax[0,0])
sns.boxplot(df.AT, ax=ax[0,1])
sns.boxplot(df.AP, ax=ax[0,2])
sns.boxplot(df.AH, ax=ax[0,3])
sns.boxplot(df.AFDP, ax=ax[1,0])
sns.boxplot(df.GTEP, ax=ax[1,1])
sns.boxplot(df.TIT, ax=ax[1,2])
sns.boxplot(df.TAT, ax=ax[1,3])
sns.boxplot(df.CDP, ax=ax[2,0])
sns.boxplot(df.CO, ax=ax[2,1])
sns.boxplot(df.NOX, ax=ax[2,2])
plt.suptitle("Boxplot for Continuous Variables", fontsize= 17, y = 1.06)
plt.tight_layout(pad=2.0)
```



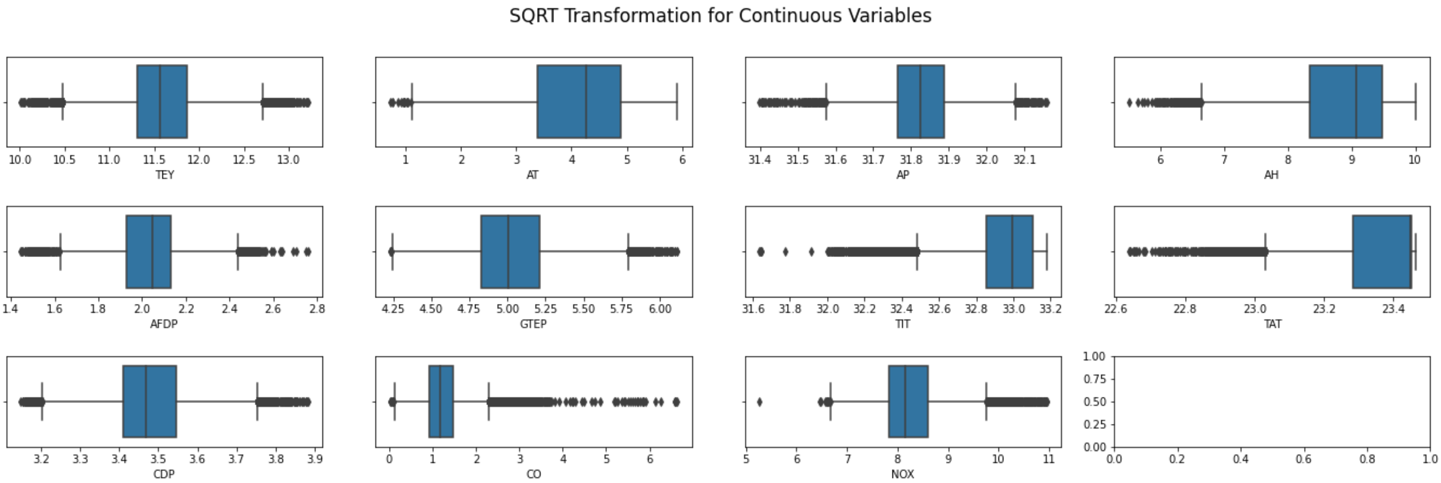
- We have a noisy data.

```
import numpy as np
fig, ax=plt.subplots(4,3, figsize=(19,6), sharex= False, sharey = False)
sns.boxplot(np.log(df.TEY), ax=ax[0,0])
sns.boxplot(np.log(df.AT), ax=ax[0,1])
sns.boxplot(np.log(df.AP), ax=ax[0,2])
```

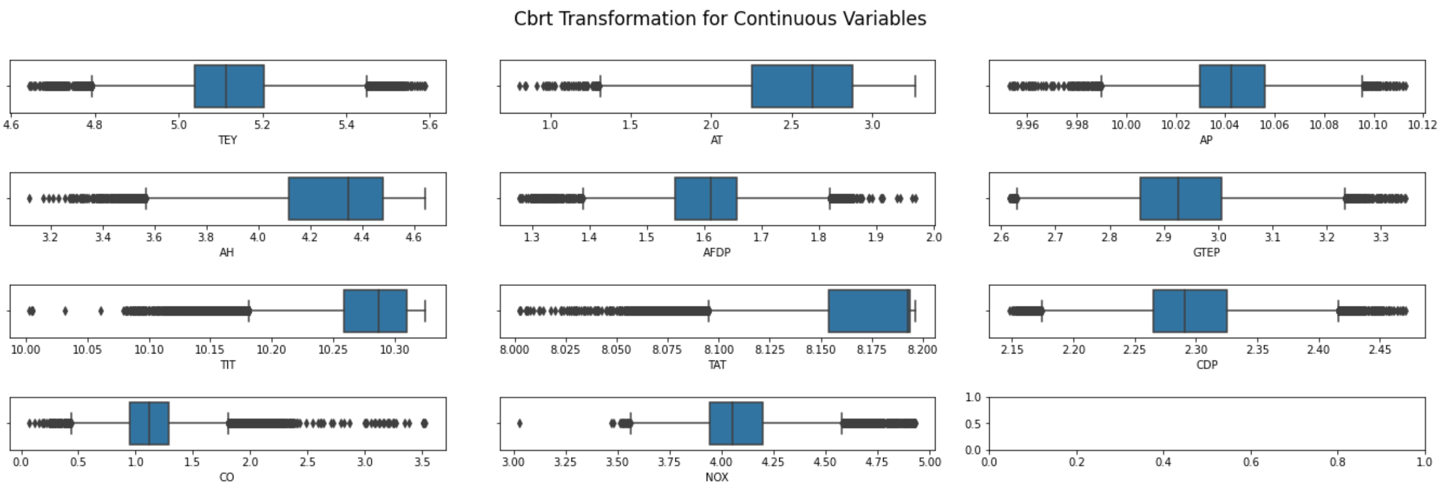
```
sns.boxplot(np.log(df.AH), ax=ax[1,0])
sns.boxplot(np.log(df.AFDP), ax=ax[1,1])
sns.boxplot(np.log(df.GTEP), ax=ax[1,2])
sns.boxplot(np.log(df.TIT), ax=ax[2,0])
sns.boxplot(np.log(df.TAT), ax=ax[2,1])
sns.boxplot(np.log(df.CDP), ax=ax[2,2])
sns.boxplot(np.log(df.CO), ax=ax[3,0])
sns.boxplot(np.log(df.NOX), ax=ax[3,1])
plt.suptitle("Log Transformation for Continuous Variables", fontsize= 17, y = 1.06)
plt.tight_layout(pad=2.0)
```




```
fig, ax=plt.subplots(3,4, figsize=(19,6), sharex= False, sharey = False)
sns.boxplot(np.sqrt(df.TEY), ax=ax[0,0])
sns.boxplot(np.sqrt(df.AT), ax=ax[0,1])
sns.boxplot(np.sqrt(df.AP), ax=ax[0,2])
sns.boxplot(np.sqrt(df.AH), ax=ax[0,3])
sns.boxplot(np.sqrt(df.AFDP), ax=ax[1,0])
sns.boxplot(np.sqrt(df.GTEP), ax=ax[1,1])
sns.boxplot(np.sqrt(df.TIT), ax=ax[1,2])
sns.boxplot(np.sqrt(df.TAT), ax=ax[1,3])
sns.boxplot(np.sqrt(df.CDP), ax=ax[2,0])
sns.boxplot(np.sqrt(df.CO), ax=ax[2,1])
sns.boxplot(np.sqrt(df.NOX), ax=ax[2,2])
plt.suptitle("SQRT Transformation for Continuous Variables", fontsize= 17, y = 1.06)
plt.tight_layout(pad=2.0)
```




```
fig, ax=plt.subplots(4,3, figsize=(19,6), sharex= False, sharey = False)
sns.boxplot(np.cbrt(df.TEY), ax=ax[0,0])
sns.boxplot(np.cbrt(df.AT), ax=ax[0,1])
sns.boxplot(np.cbrt(df.AP), ax=ax[0,2])
sns.boxplot(np.cbrt(df.AH), ax=ax[1,0])
sns.boxplot(np.cbrt(df.AFDP), ax=ax[1,1])
sns.boxplot(np.cbrt(df.GTEP), ax=ax[1,2])
sns.boxplot(np.cbrt(df.TIT), ax=ax[2,0])
sns.boxplot(np.cbrt(df.TAT), ax=ax[2,1])
sns.boxplot(np.cbrt(df.CDP), ax=ax[2,2])
sns.boxplot(np.cbrt(df.CO), ax=ax[3,0])
sns.boxplot(np.cbrt(df.NOX), ax=ax[3,1])
plt.suptitle("Cbrt Transformation for Continuous Variables", fontsize= 17, y = 1.06)
plt.tight_layout(pad=2.0)
```

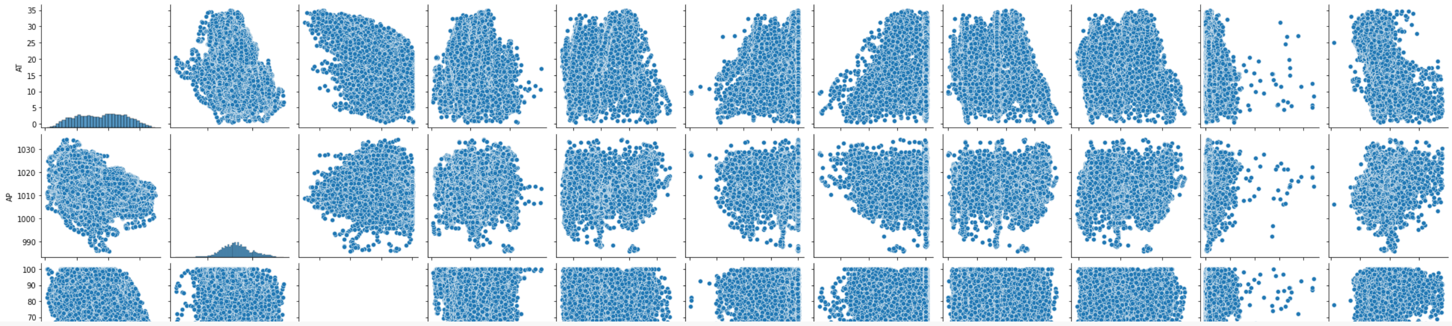


- None of the transformations are helpful to treat the outliers.

Dependency of Target variable on diff Features

```
sns.pairplot(df)
```

<seaborn.axisgrid.PairGrid at 0x7f629ea8d610>



```
corr = pd.DataFrame(data = df.corr().iloc[:,7], index=df.columns)
corr = corr.sort_values(by='TEY', ascending=False)
corr
```

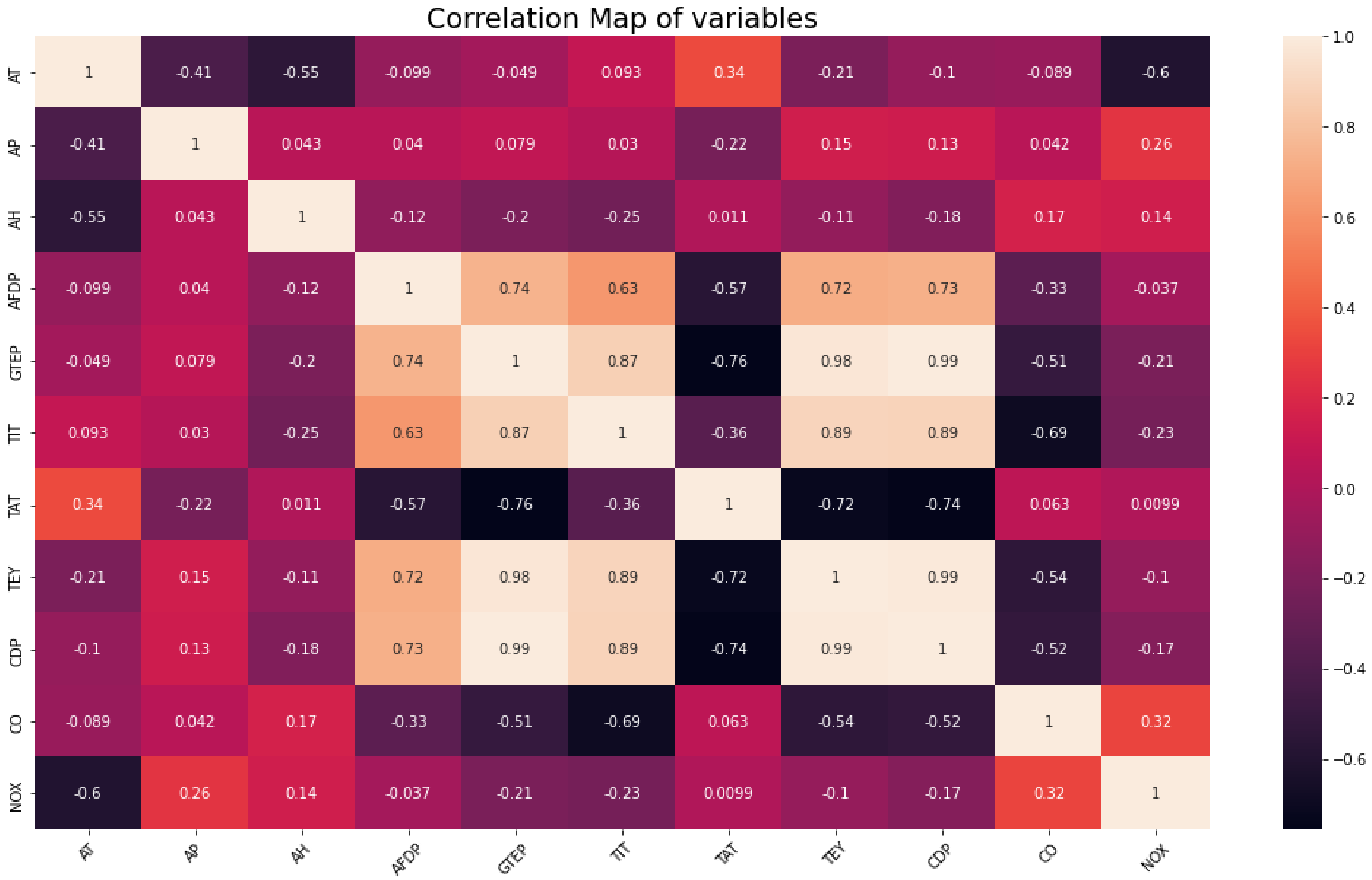
	TEY
TEY	1.000000
CDP	0.988473
GTEP	0.977042
TIT	0.891587
AFDP	0.717995
AP	0.146939
NOX	-0.102631
AH	-0.110272
AT	-0.207495
CO	-0.541751
TAT	-0.720356

```
plt.title("Correlation plot between Target variables and independent variables", y=1.01, fontsize=18
sns.barplot(x = corr.index, y = corr.TEY)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb84092fa90>
```

```
fig= plt.figure(figsize=(18, 10))
sns.heatmap(df.corr(), annot=True);
plt.xticks(rotation=45)
plt.title("Correlation Map of variables", fontsize=19)
```

```
Text(0.5, 1.0, 'Correlation Map of variables')
```



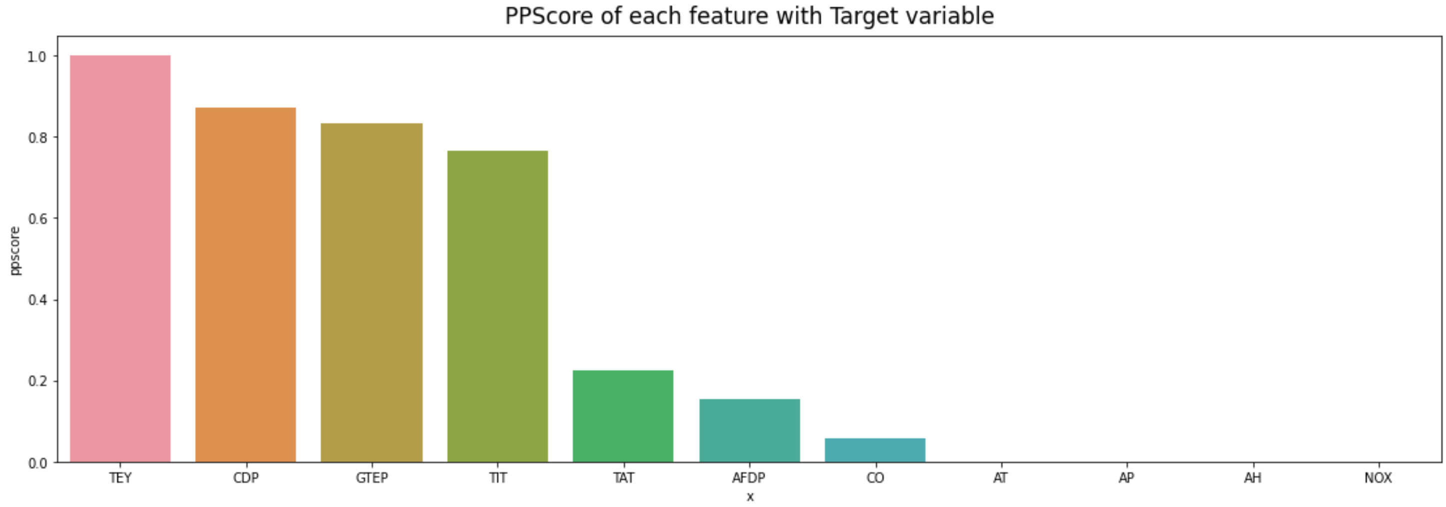

```
!pip install ppscore
```

```
import ppscore as PPS
score = PPS.matrix(df)
score_s = score[score['y']=='TEY']
score_s.sort_values(by="ppscore", ascending=False)
```

	x	y	ppscore	case	is_valid_score	metric	baseline_score	model_score	
84	TEY	TEY	1.000000	predict_itself	True	None	0.000000	1.000000	
95	CDP	TEY	0.872285	regression	True	mean absolute error	11.172076	1.426840	D
51	GTEP	TEY	0.832336	regression	True	mean absolute error	11.172076	1.873154	D
						mean			

```
plt.rcParams['figure.figsize']=(19,6)
sns.barplot(x='x', y='ppscore', data=score_s.sort_values(by='ppscore', ascending=False))
plt.title("PPScore of each feature with Target variable", fontsize=17, y=1.01)
```

```
Text(0.5, 1.01, 'PPScore of each feature with Target variable')
```



Observation:

- From correlation matrix as well as ppscore we can clearly see that TEY is highly dependent on 'CDP', 'GTEP', 'TIT'.
- We can drop 'AT', 'AP', 'AH', 'NOX' as they have very less impact on dependent variables.

Check for outliers

```
#check for outliers
from sklearn.ensemble import IsolationForest
data1=df.copy()

#training the model
clf = IsolationForest(random_state=10, contamination=.001)
clf.fit(data1)
data1['anamoly'] = clf.predict(data1.iloc[:,0:11])
outliers = data1[data1['anamoly']==-1]
```

```
outliers
```

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
261	5.66020	1018.30	86.968	3.8404	21.079	1028.5	523.86	112.02	10.963	43.4280	99.237
553	3.55320	1027.30	90.871	4.2162	21.464	1041.2	531.68	117.76	10.984	8.8254	106.840
763	1.81300	1007.20	74.980	3.6967	19.958	1026.4	528.18	111.72	10.553	12.0900	114.940
764	1.49880	1006.30	76.734	3.7063	20.041	1027.6	528.79	112.28	10.585	11.6520	112.830
765	0.97877	1005.70	78.978	3.7379	20.084	1027.9	528.52	112.71	10.628	11.6910	108.880
993	4.36570	1021.60	85.528	3.9574	20.263	1025.6	525.72	111.35	10.652	12.7860	112.270
6896	17.13200	1010.80	80.503	2.2148	18.484	1034.1	539.98	102.07	10.182	11.5150	110.760
7019	7.02760	997.23	97.761	2.0992	19.227	1037.2	538.53	109.63	10.338	11.0440	105.060
7470	7.04730	1019.60	96.885	2.4558	19.501	1032.0	532.32	109.21	10.567	11.3740	112.230
9920	15.17900	1017.60	71.630	2.7816	18.435	1027.8	533.45	103.64	10.143	12.1440	113.800
13820	14.18300	1023.10	78.110	3.1557	18.869	1025.0	530.16	103.80	10.340	13.3130	116.340
13921	11.58500	1018.20	92.751	3.2518	18.784	1009.5	519.71	100.83	10.253	39.0500	111.780
14100	9.40970	1027.90	82.224	3.3003	18.987	1001.4	512.60	100.32	10.495	23.6290	107.890
14278	9.90780	1026.10	65.923	3.3126	19.366	1024.5	527.21	108.08	10.506	20.2710	105.660
14317	3.93850	1021.30	90.536	3.4765	20.031	1026.6	526.30	111.70	10.683	14.0350	114.700
14320	3.49070	1020.80	91.519	3.5309	20.098	1025.8	525.35	111.91	10.761	11.9210	113.900

- These are the outliers in our data.

Data Preprocessing

```
df.shape
```

```
(15039, 11)
```

```
#drop the outliers
df = df.drop(outliers.index)
df.shape
```

```
(15023, 11)
```

```
#reset index after dropping outliers
df = df.reset_index()
df = df.drop('index', axis = 1)
df
```

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	114.70	10.605	3.1547	82.722
1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	114.72	10.598	3.2363	82.776
2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	114.71	10.601	3.2012	82.468
3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	114.72	10.606	3.1923	82.670
4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	114.72	10.612	3.2484	82.311
...	...	...	...	...	...	...	...	...	...	...	...
15018	9.0301	1005.6	98.460	3.5421	19.164	1049.7	546.21	111.61	10.400	4.5186	79.559
15019	7.8879	1005.9	99.093	3.5059	19.414	1046.3	543.22	111.78	10.433	4.8470	79.917
15020	7.2647	1006.3	99.496	3.4770	19.530	1037.7	537.32	110.19	10.483	7.9632	90.912
15021	7.0060	1006.8	99.008	3.4486	19.377	1043.2	541.24	110.74	10.533	6.2494	93.227

```
df = df.drop(['AT', 'AP', 'AH', 'NOX'], axis=1)
```

15023 rows × 11 columns

```
df.shape
```

```
(15023, 7)
```

Converting independent features into normalised and standardized data

```
#Standardize & Normalize the data
norm = MinMaxScaler()
std = StandardScaler()

df_norm = pd.DataFrame(norm.fit_transform(df), columns=df.columns)            #data between -3 to +3
df_std = pd.DataFrame(std.fit_transform(df), columns=df.columns)            #data between -1 to +1
```

Take a smaller sample to build a model

```
#we will take a small model as this is large data and will take huge amount of time to build model
#to reandomly shuffle and select a % of data
temp = df_std.sample(frac=1)          #shuffle all the data
temp_s = df_std.sample(frac=0.1)      #shuffle and select only 10% of the data randomly to train
```

```
temp_s
```

	AFDP	GTEP	TIT	TAT	TEY	CDP	CO
4236	0.094824	0.207306	0.556420	0.546069	0.033790	0.003612	-0.318267
9990	0.456128	1.473222	0.976474	-1.497751	1.414133	1.430319	-0.279678
2322	0.309764	-1.256373	-1.519499	0.604683	-1.429387	-1.402233	0.724091
13062	-0.080628	0.160802	0.586859	0.633989	-0.028177	0.145104	-0.279958
7003	-2.461941	-1.479304	-1.890851	0.584296	-1.594421	-1.610843	1.086162

Splitting data into target variable and independent variables

```
x = temp_s.drop('TEY', axis=1)
y = temp_s['TEY']
x
```

	AFDP	GTEP	TIT	TAT	CDP	CO
4236	0.094824	0.207306	0.556420	0.546069	0.003612	-0.318267
9990	0.456128	1.473222	0.976474	-1.497751	1.430319	-0.279678
2322	0.309764	-1.256373	-1.519499	0.604683	-1.402233	0.724091
13062	-0.080628	0.160802	0.586859	0.633989	0.145104	-0.279958
7003	-2.461941	-1.479304	-1.890851	0.584296	-1.610843	1.086162
...	...	...	...	...	...	...
7975	-0.625808	-0.471078	0.045050	0.553715	-0.155112	-0.649257
3478	0.072185	0.151213	0.544245	0.567731	0.110638	-0.325817
13094	-1.281156	-1.313424	-1.501236	0.591941	-1.350535	0.497593
3347	-0.143412	-0.122298	0.239858	0.589392	-0.107948	-0.066043
11646	-0.389546	0.134433	0.623385	0.584296	0.142383	-0.544402

1502 rows × 6 columns

Creating train and test data for model validation

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25)
```

```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

```
((1126, 6), (376, 6), (1126,), (376,))
```

Build a Model

```
# Importing the necessary packages
import tensorflow as tf
import keras
from sklearn.model_selection import GridSearchCV, KFold
```

```
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasRegressor
from tensorflow.keras.optimizers import Adam
from keras.layers import Dropout
tf.config.experimental.list_physical_devices('GPU')             #to use GPU for faster processing
```

```
[]
```

```
# create model with 2 hidden layers
def create_model_two_hidden_layers():
    model = Sequential()
    model.add(Dense(5, input_dim=6, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(6, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(10, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(1))

    adam=Adam(lr=0.001)
    model.compile(loss='mse', optimizer=adam, metrics=['mse', 'mae', 'mape'])
    return model
```

```
model1 = create_model_two_hidden_layers()
print("Here is the summary of the model:")
model1.summary()
```

```
Here is the summary of the model:
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 5)                 35

 dense_1 (Dense)             (None, 6)                 36

 dense_2 (Dense)             (None, 10)                70

 dense_3 (Dense)             (None, 1)                 11

=================================================================
Total params: 152
Trainable params: 152
Non-trainable params: 0
_________________________________________________________________
```

```
#create a model with 3 hidden layers
def create_model_three_hidden_layers():
    model = Sequential()
    model.add(Dense(32, input_dim=6, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(32, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(64, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(128, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(1))

    adam=Adam(lr=0.01)
    model.compile(loss='mse', optimizer=adam, metrics=['mse', 'mae', 'mape'])
    return model
```

```
model2 = create_model_three_hidden_layers()
print("Here is the summary of the model2:")
model2.summary()
```

```
Here is the summary of the model2:
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 32)                224

 dense_5 (Dense)             (None, 32)                1056

 dense_6 (Dense)             (None, 64)                2112

 dense_7 (Dense)             (None, 128)               8320

 dense_8 (Dense)             (None, 1)                 129

=================================================================
Total params: 11,841
Trainable params: 11,841
Non-trainable params: 0
_________________________________________________________________
```

```
%%time
epochs=500
batch_size=50

print("Here is the summary of this model:")
model2.summary()

with tf.device('/GPU:0'):
  model2.fit(x_train,y_train, verbose = 0,batch_size = batch_size,epochs = epochs, shuffle=True)
```

```
Here is the summary of this model:
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 32)                224

 dense_5 (Dense)             (None, 32)                1056

 dense_6 (Dense)             (None, 64)                2112

 dense_7 (Dense)             (None, 128)               8320

 dense_8 (Dense)             (None, 1)                 129

=================================================================
Total params: 11,841
Trainable params: 11,841
Non-trainable params: 0
_________________________________________________________________
CPU times: user 28.6 s, sys: 1.7 s, total: 30.3 s
Wall time: 42.7 s
```

```
print("Predicted values:")
```

```
model2.predict(x_test[:10])
```

```
Predicted values:
array([[ 1.4603838 ],
       [ 0.0096969 ],
       [ 0.06686881],
       [-0.0239974 ],
       [-1.4818871 ],
       [ 1.8722074 ],
       [ 0.0253309 ],
       [-0.01755407],
       [-1.0034431 ],
       [-0.01772463]], dtype=float32)
```

```
print('Actual values')
y_test[:10]
```

```
Actual values
1695     1.558933
4364    -0.004782
10877    0.170370
9440    -0.030074
1592    -1.486295
7170     1.912397
4728     0.036319
2112    -0.030707
3898    -0.946298
10948    0.047068
Name: TEY, dtype: float64
```

```
loss, mae, mse, mape = model2.evaluate(x_train, y_train)
print('\n', "Results for model 2:", '\n', "Training Loss:", loss, '\n', "Training Mean Absolute Erro
```

```
36/36 [==============================] - 0s 3ms/step - loss: 0.0052 - mse: 0.0052 - mae: 0.052

 Results for model 2:
 Training Loss: 0.005180281586945057
 Training Mean Absolute Error: 0.005180281586945057
 Training Mean Squared Error: 0.05262265354394913
```

```
loss, mae, mse, mape = model2.evaluate(x_test, y_test)
print('\n', "Results for model 2:", '\n', "Test Loss:", loss, '\n', "Test Mean Absolute Error:" , ma
```

```
12/12 [==============================] - 0s 2ms/step - loss: 0.0059 - mse: 0.0059 - mae: 0.058

 Results for model 2:
 Test Loss: 0.005892517510801554
 Test Mean Absolute Error: 0.005892517510801554
 Test Mean Squared Error: 0.05892687663435936
```

Observations:

- We got pretty good results for this model.
- Train and test errors are also quiet similar, which means our model is not overfitted or underfitted.
- Still we will try to get best results by doing hyperparameter tuning.

Hyperparameter Tuning to get best options for:

- batchsize
- epochs
- neurons
- learning rate
- dropout
- kernel initializer
- activation function

```
# Create the model
#get best value for batch size and epochs by hyperparameter tuning
model = KerasRegressor(build_fn = create_model_three_hidden_layers,verbose = 0)
# Define the grid search parameters
batch_size = [30,50,70]
epochs = [300,500,800]
# Make a dictionary of the grid search parameters
param_grid = dict(batch_size = batch_size,epochs = epochs)
# Build and fit the GridSearchCV
grid = GridSearchCV(estimator = model,param_grid = param_grid,cv = KFold(),verbose = 10)
grid_result = grid.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
[CV 1/5; 1/9] START batch_size=30, epochs=300...................................
[CV 1/5; 1/9] END ...batch_size=30, epochs=300;, score=-0.007 total time=  14.8s
[CV 2/5; 1/9] START batch_size=30, epochs=300...................................
[CV 2/5; 1/9] END ...batch_size=30, epochs=300;, score=-0.007 total time=  16.4s
[CV 3/5; 1/9] START batch_size=30, epochs=300...................................
[CV 3/5; 1/9] END ...batch_size=30, epochs=300;, score=-0.017 total time=  21.4s
[CV 4/5; 1/9] START batch_size=30, epochs=300...................................
[CV 4/5; 1/9] END ...batch_size=30, epochs=300;, score=-0.042 total time=  17.2s
[CV 5/5; 1/9] START batch_size=30, epochs=300...................................
[CV 5/5; 1/9] END ...batch_size=30, epochs=300;, score=-0.011 total time=  24.1s
[CV 1/5; 2/9] START batch_size=30, epochs=500...................................
[CV 1/5; 2/9] END ...batch_size=30, epochs=500;, score=-0.008 total time=  42.4s
[CV 2/5; 2/9] START batch_size=30, epochs=500...................................
[CV 2/5; 2/9] END ...batch_size=30, epochs=500;, score=-0.006 total time=  42.0s
[CV 3/5; 2/9] START batch_size=30, epochs=500...................................
[CV 3/5; 2/9] END ...batch_size=30, epochs=500;, score=-0.008 total time=  30.7s
[CV 4/5; 2/9] START batch_size=30, epochs=500...................................
[CV 4/5; 2/9] END ...batch_size=30, epochs=500;, score=-0.023 total time=  42.0s
[CV 5/5; 2/9] START batch_size=30, epochs=500...................................
[CV 5/5; 2/9] END ...batch_size=30, epochs=500;, score=-0.007 total time=  42.1s
[CV 1/5; 3/9] START batch_size=30, epochs=800...................................
[CV 1/5; 3/9] END ...batch_size=30, epochs=800;, score=-0.007 total time= 1.4min
[CV 2/5; 3/9] START batch_size=30, epochs=800...................................
[CV 2/5; 3/9] END ...batch_size=30, epochs=800;, score=-0.006 total time= 1.4min
[CV 3/5; 3/9] START batch_size=30, epochs=800...................................
[CV 3/5; 3/9] END ...batch_size=30, epochs=800;, score=-0.011 total time=  40.0s
[CV 4/5; 3/9] START batch_size=30, epochs=800...................................
[CV 4/5; 3/9] END ...batch_size=30, epochs=800;, score=-0.024 total time=  41.9s
[CV 5/5; 3/9] START batch_size=30, epochs=800...................................
[CV 5/5; 3/9] END ...batch_size=30, epochs=800;, score=-0.012 total time=  39.8s
[CV 1/5; 4/9] START batch_size=50, epochs=300...................................
[CV 1/5; 4/9] END ...batch_size=50, epochs=300;, score=-0.010 total time=  11.1s
[CV 2/5; 4/9] START batch_size=50, epochs=300...................................
[CV 2/5; 4/9] END ...batch_size=50, epochs=300;, score=-0.012 total time=  11.1s
[CV 3/5; 4/9] START batch_size=50, epochs=300...................................
[CV 3/5; 4/9] END ...batch_size=50, epochs=300;, score=-0.021 total time=  11.2s
[CV 4/5; 4/9] START batch_size=50, epochs=300...................................
```

```
[CV 4/5; 4/9] END ...batch_size=50, epochs=300;, score=-0.022 total time=  11.1s
[CV 5/5; 4/9] START batch_size=50, epochs=300...................................
[CV 5/5; 4/9] END ...batch_size=50, epochs=300;, score=-0.010 total time=  10.3s
[CV 1/5; 5/9] START batch_size=50, epochs=500...................................
[CV 1/5; 5/9] END ...batch_size=50, epochs=500;, score=-0.009 total time=  15.5s
[CV 2/5; 5/9] START batch_size=50, epochs=500...................................
[CV 2/5; 5/9] END ...batch_size=50, epochs=500;, score=-0.008 total time=  18.0s
[CV 3/5; 5/9] START batch_size=50, epochs=500...................................
[CV 3/5; 5/9] END ...batch_size=50, epochs=500;, score=-0.007 total time=  16.4s
[CV 4/5; 5/9] START batch_size=50, epochs=500...................................
[CV 4/5; 5/9] END ...batch_size=50, epochs=500;, score=-0.014 total time=  16.6s
[CV 5/5; 5/9] START batch_size=50, epochs=500...................................
[CV 5/5; 5/9] END ...batch_size=50, epochs=500;, score=-0.009 total time=  16.6s
[CV 1/5; 6/9] START batch_size=50, epochs=800...................................
[CV 1/5; 6/9] END ...batch_size=50, epochs=800;, score=-0.010 total time=  41.8s
[CV 2/5; 6/9] START batch_size=50, epochs=800...................................
[CV 2/5; 6/9] END ...batch_size=50, epochs=800;, score=-0.007 total time=  26.0s
[CV 3/5; 6/9] START batch_size=50, epochs=800...................................
[CV 3/5; 6/9] END ...batch_size=50, epochs=800;, score=-0.012 total time=  26.8s
[CV 4/5; 6/9] START batch_size=50, epochs=800...................................
```

```
# Summarize the results
print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
  print('{},{} with: {}'.format(mean, stdev, param))
```

```
Best : -0.0075393722392618654, using {'batch_size': 70, 'epochs': 300}
-0.016978778317570685,0.013234811332822475 with: {'batch_size': 30, 'epochs': 300}
-0.010405903775244951,0.006226308937440076 with: {'batch_size': 30, 'epochs': 500}
-0.012068143114447594,0.006350046434131595 with: {'batch_size': 30, 'epochs': 800}
-0.014911985024809837,0.005297752932001893 with: {'batch_size': 50, 'epochs': 300}
-0.009465495962649584,0.002510776754568933 with: {'batch_size': 50, 'epochs': 500}
-0.011701966542750597,0.0051470257211605605 with: {'batch_size': 50, 'epochs': 800}
-0.0075393722392618654,0.0009991713483655203 with: {'batch_size': 70, 'epochs': 300}
-0.010204726736992598,0.005419346956061117 with: {'batch_size': 70, 'epochs': 500}
-0.016363509744405747,0.014805524624212349 with: {'batch_size': 70, 'epochs': 800}
```

```
#get best value for learning rate and dropuout by hyperparameter tuning

# Defining the model
%%time
def create_model_three_hidden_layers(learning_rate,dropout_rate):
    model = Sequential()
    model.add(Dense(32,input_dim = 6,kernel_initializer = 'uniform',activation = 'relu'))
    model.add(Dropout(dropout_rate))
    model.add(Dense(32,kernel_initializer = 'uniform',activation = 'relu'))
    model.add(Dropout(dropout_rate))
    model.add(Dense(64,kernel_initializer = 'uniform',activation = 'relu'))
    model.add(Dropout(dropout_rate))
    model.add(Dense(128,kernel_initializer = 'uniform',activation = 'relu'))
    model.add(Dropout(dropout_rate))
    model.add(Dense(1))

    adam = Adam(lr = learning_rate)
    model.compile(loss = 'mse', optimizer = adam,metrics = ['mse', 'mae', 'mape'])
    return model

# Create the model
```

```
model = KerasRegressor(build_fn = create_model_three_hidden_layers,verbose = 0,batch_size = 70,epoch

# Define the grid search parameters

learning_rate = [0.001,0.01,0.1]
dropout_rate = [0.0,0.1,0.2]

# Make a dictionary of the grid search parameters

param_grids = dict(learning_rate = learning_rate,dropout_rate = dropout_rate)

# Build and fit the GridSearchCV

grid = GridSearchCV(estimator = model,param_grid = param_grids,cv = KFold(),verbose = 0)
grid_result = grid.fit(x_train,y_train)
```

```
CPU times: user 8min 41s, sys: 27.8 s, total: 9min 9s
Wall time: 7min 20s
```

```
# Summarize the results
print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
  print('{},{} with: {}'.format(mean, stdev, param))
```

```
Best : -0.0074284222908318044, using {'dropout_rate': 0.0, 'learning_rate': 0.001}
-0.0074284222908318044,0.0012566427059348705 with: {'dropout_rate': 0.0, 'learning_rate': 0.00
-0.008746050018817186,0.002546793388744793 with: {'dropout_rate': 0.0, 'learning_rate': 0.01}
-0.5391489624977112,0.38128600689168873 with: {'dropout_rate': 0.0, 'learning_rate': 0.1}
-0.008981297537684441,0.0017753620043791116 with: {'dropout_rate': 0.1, 'learning_rate': 0.001
-0.018664213083684444,0.007073876261163493 with: {'dropout_rate': 0.1, 'learning_rate': 0.01}
-0.857705608010292,0.36597175007040206 with: {'dropout_rate': 0.1, 'learning_rate': 0.1}
-0.013176053576171399,0.0034455643774916945 with: {'dropout_rate': 0.2, 'learning_rate': 0.001
-0.02149874735623598,0.009798939491706949 with: {'dropout_rate': 0.2, 'learning_rate': 0.01}
-0.9216348528862,0.14326295207399667 with: {'dropout_rate': 0.2, 'learning_rate': 0.1}
```

```
# Defining the model
#get best value for kernel initializer and activation func by hyperparameter tuning
%%time
def create_model_three_hidden_layers(activation_function,init):
    model = Sequential()
    model.add(Dense(32,input_dim = 6,kernel_initializer = init,activation = activation_function))

    model.add(Dense(32,kernel_initializer = init,activation = activation_function))

    model.add(Dense(64,kernel_initializer = init,activation = activation_function))

    model.add(Dense(128,kernel_initializer = init,activation = activation_function))

    model.add(Dense(1))

    adam = Adam(lr = 0.001)
    model.compile(loss = 'mse',optimizer = adam,metrics = ['mse', 'mae', 'mape'])
    return model
```

```
# Create the model

model = KerasRegressor(build_fn = create_model_three_hidden_layers,verbose = 0,batch_size = 70,epoch

# Define the grid search parameters
activation_function = ['softmax','relu','tanh','linear']
init = ['uniform','normal','zero']

# Make a dictionary of the grid search parameters
param_grids = dict(activation_function = activation_function,init = init)

# Build and fit the GridSearchCV

grid = GridSearchCV(estimator = model,param_grid = param_grids,cv = KFold(),verbose = 0)
grid_result = grid.fit(x_train,y_train)
```

```
CPU times: user 11min 32s, sys: 37.1 s, total: 12min 9s
Wall time: 12min 7s
```

```
# Summarize the results
print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
  print('{},{} with: {}'.format(mean, stdev, param))
```

```
Best : -0.0071579206734895704, using {'activation_function': 'relu', 'init': 'uniform'}
-1.0118964791297913,0.06708980991351385 with: {'activation_function': 'softmax', 'init': 'unif
-0.022299112752079964,0.0037154822374961373 with: {'activation_function': 'softmax', 'init': 'n
-1.0119526624679565,0.06694821486159644 with: {'activation_function': 'softmax', 'init': 'zero
-0.0071579206734895704,0.002275348804491385 with: {'activation_function': 'relu', 'init': 'uni
-0.007379146758466959,0.001621315310551405 with: {'activation_function': 'relu', 'init': 'norma
-1.0119281530380249,0.06688031419360685 with: {'activation_function': 'relu', 'init': 'zero'}
-0.012599235028028488,0.001859812763351644 with: {'activation_function': 'tanh', 'init': 'unif
-0.012365044839680196,0.0014994406624064581 with: {'activation_function': 'tanh', 'init': 'norm
-1.0120076894760133,0.06688229711387285 with: {'activation_function': 'tanh', 'init': 'zero'}
-0.013341516815125942,0.001337632287455897 with: {'activation_function': 'linear', 'init': 'un
-0.013167891651391983,0.0015764897496849293 with: {'activation_function': 'linear', 'init': 'no
-1.0117817282676698,0.06695963424456282 with: {'activation_function': 'linear', 'init': 'zero'
```

```
# Defining the model
#get best value for neuron by hyperparameter tuning
%%time
def create_model_three_hidden_layers(neuron1,neuron2,neuron3,neuron4):
    model = Sequential()
    model.add(Dense(neuron1,input_dim = 6,kernel_initializer = 'uniform',activation = 'relu'))
    model.add(Dense(neuron2,input_dim = neuron1,kernel_initializer = 'uniform',activation = 'relu'))
    model.add(Dense(neuron3,input_dim = neuron2,kernel_initializer = 'uniform',activation = 'relu'))
    model.add(Dense(neuron4,input_dim = neuron3,kernel_initializer = 'uniform',activation = 'relu'))
    model.add(Dense(1))

    adam = Adam(lr = 0.001)
    model.compile(loss = 'mse',optimizer = adam,metrics = ['mse', 'mae', 'mape'])
    return model
```

```
# Create the model

model = KerasRegressor(build_fn = create_model_three_hidden_layers,verbose = 0,batch_size = 70,epoch

# Define the grid search parameters

neuron1 = [8,16,32]
neuron2 = [32,64,128]
neuron3 = [32,64,128]
neuron4 = [32,64,128]

# Make a dictionary of the grid search parameters

param_grids = dict(neuron1 = neuron1,neuron2 = neuron2, neuron3 = neuron3, neuron4 = neuron4)

# Build and fit the GridSearchCV

grid = GridSearchCV(estimator = model,param_grid = param_grids,cv = KFold(),verbose = 0)
grid_result = grid.fit(x_train,y_train)
```

```
CPU times: user 1h 27min 32s, sys: 5min 1s, total: 1h 32min 33s
Wall time: 1h 20min 47s
```

```
# Summarize the results
print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
  print('{},{} with: {}'.format(mean, stdev, param))
```

```
Best : -0.006522623915225267, using {'neuron1': 32, 'neuron2': 64, 'neuron3': 64, 'neuron4':
-0.009027735143899918,0.0016703966760312206 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 3
-0.008026432525366545,0.0018345186393841056 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 3
-0.008605633024126291,0.002530353920742668 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 32
-0.009371494874358177,0.0027848141855597005 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 6
-0.00853779846802354,0.0019763297892534592 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 64
-0.008496165927499532,0.0036394701096190774 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 6
-0.00807237820699811,0.001793167837743366 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 128
-0.008483995590358973,0.0014214088260315577 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 1
-0.008200791478157044,0.001421806452893541 with: {'neuron1': 8, 'neuron2': 32, 'neuron3': 12
-0.008190382830798626,0.0013414200168486196 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 3
-0.008483350276947021,0.001517318135433632 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 32
-0.007766674179583788,0.0018709875935996763 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 3
-0.008091395534574986,0.001650821745549662 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 64
-0.008284379448741674,0.0016522382904015968 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 6
-0.007847060449421406,0.00293804896162401 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 64,
-0.007948526553809643,0.002356794490362091 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 12
-0.008474754262715578,0.0025113667487656013 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 1
-0.008409539703279734,0.0026522598375391445 with: {'neuron1': 8, 'neuron2': 64, 'neuron3': 1
-0.008105298411101103,0.0019443908654795186 with: {'neuron1': 8, 'neuron2': 128, 'neuron3':
-0.008194748591631652,0.0022964026502124654 with: {'neuron1': 8, 'neuron2': 128, 'neuron3':
-0.007716016098856926,0.0017939956650294866 with: {'neuron1': 8, 'neuron2': 128, 'neuron3':
-0.008319726679474115,0.002256242104171199 with: {'neuron1': 8, 'neuron2': 128, 'neuron3': 6
-0.008362801093608142,0.00196912285603821 with: {'neuron1': 8, 'neuron2': 128, 'neuron3': 64
-0.00816601337864995,0.0017184391604793705 with: {'neuron1': 8, 'neuron2': 128, 'neuron3': 6
-0.010635808762162923,0.0055904923849624845 with: {'neuron1': 8, 'neuron2': 128, 'neuron3':
-0.008702912461012602,0.002671559925750557 with: {'neuron1': 8, 'neuron2': 128, 'neuron3': 1
-0.007748759537935257,0.0027344589403306323 with: {'neuron1': 8, 'neuron2': 128, 'neuron3':
-0.007806500513106584,0.0020118383613051574 with: {'neuron1': 16, 'neuron2': 32, 'neuron3':
```

```
-0.00800962494686246,0.002216210247408603 with: {'neuron1': 16, 'neuron2': 32, 'neuron3': 32
-0.007659391220659018,0.001490486637272073 with: {'neuron1': 16, 'neuron2': 32, 'neuron3': 3
-0.00847789105027914,0.0022912764323639537 with: {'neuron1': 16, 'neuron2': 32, 'neuron3': 6
-0.007840564846992493,0.0018928099731000587 with: {'neuron1': 16, 'neuron2': 32, 'neuron3':
-0.006894319225102663,0.0015670932888597832 with: {'neuron1': 16, 'neuron2': 32, 'neuron3':
-0.007430214993655681,0.0010697569256640457 with: {'neuron1': 16, 'neuron2': 32, 'neuron3':
-0.007942717429250479,0.0020201989066264497 with: {'neuron1': 16, 'neuron2': 32, 'neuron3':
-0.008054919354617596,0.002541213346361959 with: {'neuron1': 16, 'neuron2': 32, 'neuron3': 1
-0.009540296997874976,0.0036574841281632347 with: {'neuron1': 16, 'neuron2': 64, 'neuron3':
-0.008310491219162941,0.0014452259578308603 with: {'neuron1': 16, 'neuron2': 64, 'neuron3':
-0.007387017272412777,0.002133315088778482 with: {'neuron1': 16, 'neuron2': 64, 'neuron3': 3
-0.0077668757177889345,0.0011512419741164788 with: {'neuron1': 16, 'neuron2': 64, 'neuron3':
-0.008787257131189108,0.003772887981173566 with: {'neuron1': 16, 'neuron2': 64, 'neuron3': 6
-0.008913870994001627,0.0036970793191789834 with: {'neuron1': 16, 'neuron2': 64, 'neuron3':
-0.007325255498290062,0.0014821056958790166 with: {'neuron1': 16, 'neuron2': 64, 'neuron3':
-0.007589743565768003,0.0021661437225019647 with: {'neuron1': 16, 'neuron2': 64, 'neuron3':
-0.007086964696645737,0.0006073766088427502 with: {'neuron1': 16, 'neuron2': 64, 'neuron3':
-0.007996563985943794,0.0018784873736835898 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.007337401527911425,0.0009973490249149725 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.007280860096216202,0.0012246764926879211 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.00732230581343174,0.0016787810886593855 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.007625718507915736,0.0018939254611521875 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.007689707819372416,0.002033442394228267 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.007958983350545169,0.0010946047696677212 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.00818451913073659,0.0023112477974197364 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.00717758284881711,0.0019650800732804795 with: {'neuron1': 16, 'neuron2': 128, 'neuron3':
-0.007754359487444162,0.0016185352979115855 with: {'neuron1': 32, 'neuron2': 32, 'neuron3':
```

```
#create a model with 3 hidden layers with best hyperparameters
def create_model_three_hidden_layers():
    model = Sequential()
    model.add(Dense(8, input_dim=6, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(128, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(64, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(128, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(1))

    adam=Adam(lr=0.001)
    model.compile(loss='mse', optimizer=adam, metrics=['mse', 'mae', 'mape'])
    return model
```

```
%%time
epochs=300
batch_size=70

final_model=create_model_three_hidden_layers()

print("Here is the summary of our final model:")
final_model.summary()

with tf.device('/GPU:0'):
  final_model.fit(x_train,y_train, verbose = 0,batch_size = batch_size,epochs = epochs, shuffle=True
```

```
Here is the summary of our final model:
Model: "sequential_656"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_2911 (Dense)          (None, 8)                 56
```

```
 dense_2912 (Dense)          (None, 128)              1152

 dense_2913 (Dense)          (None, 64)               8256

 dense_2914 (Dense)          (None, 128)              8320

 dense_2915 (Dense)          (None, 1)                129

=================================================================
Total params: 17,913
Trainable params: 17,913
Non-trainable params: 0
_________________________________________________________________
CPU times: user 14.8 s, sys: 784 ms, total: 15.6 s
Wall time: 12.5 s
```

```
loss, mae, mse, mape = final_model.evaluate(x_train, y_train)
print('\n', "Results for final model :", '\n', "Training Loss:", loss, '\n', "Training Mean Absolute
```

```
36/36 [==============================] - 0s 2ms/step - loss: 0.0076 - mse: 0.0076 - mae: 0.065

 Results for final model :
 Training Loss: 0.007562562823295593
 Training Mean Absolute Error: 0.007562562823295593
 Training Mean Squared Error: 0.06554283946752548
```

```
loss_t, mae_t, mse_t, mape_t = final_model.evaluate(x_test, y_test)
print('\n', "Results for final model :", '\n', "Test Loss:", loss_t, '\n', "Test Mean Absolute Error
```

```
12/12 [==============================] - 0s 3ms/step - loss: 0.0091 - mse: 0.0091 - mae: 0.071

 Results for final model :
 Test Loss: 0.009072024375200272
 Test Mean Absolute Error: 0.009072024375200272
 Test Mean Squared Error: 0.07183393836021423
```

Predicting values from Model using same dataset

```
# generating predictions for test data
y_predict_test = model.predict(x_test)

# creating table with test price & predicted price for test
predictions_df = pd.DataFrame(x_test)
predictions_df['Actual'] = y_test
predictions_df['Predicted'] = y_predict_test
print(predictions_df.shape)
predictions_df.head(10)
```

(376, 8)

	AFDP	GTEP	TIT	TAT	CDP	CO	Actual	Predicted
1695	2.391899	1.460277	0.976474	-1.483735	1.375899	-0.718032	1.558933	1.422794
4364	0.364782	0.303909	0.739052	0.577925	0.229455	0.288897	-0.004782	-0.003155
10877	-0.413238	0.213538	0.732965	0.604683	0.143290	-0.780524	0.170370	0.002438
9440	0.471133	-0.099285	0.325086	0.565183	-0.032667	-0.432448	-0.030074	-0.028161
1592	0.314239	-1.434239	-1.787360	0.584296	-1.576377	0.617133	-1.486295	-1.546750
7170	-0.552495	1.856760	0.976474	-2.173078	1.758652	-0.713977	1.912397	1.868405
2112	0.969060	-0.040556	0.318998	0.562634	-0.050807	-0.195557	-0.030707	-0.032214

Visualizing the Relationship between the Actual and Predicted Values Model Validation

```
plt.figure(figsize=(12,8))
plt.xlabel("Actual Values")
plt.ylabel("Predicted values")
plt.title("The Scatterplot of Relationship between Actual Values and Predictions")
plt.scatter(predictions_df['Actual'], predictions_df['Predicted'])
```

<matplotlib.collections.PathCollection at 0x7f36be92f690>