Gas-Turbine Emissions Predictions (Regression)

This Dataset consists of 9 continuous predictors, and **2 different response variables**, carbon monoxide (CO) emmission and nitric oxide (NOx) emission, both continuous quantities.

We will explore the data and try different regression models, to find the best one for each dependant (response) variable.

In [9]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
sns.set()


df = pd.read_csv("gt_full.csv")
df = df.drop(columns=["Unnamed: 0"]) #data has a row number column (other than its dataframe id)

df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36733 entries, 0 to 36732
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   AT      36733 non-null  float64
 1   AP      36733 non-null  float64
 2   AH      36733 non-null  float64
 3   AFDP    36733 non-null  float64
 4   GTEP    36733 non-null  float64
 5   TIT     36733 non-null  float64
 6   TAT     36733 non-null  float64
 7   TEY     36733 non-null  float64
 8   CDP     36733 non-null  float64
 9   CO      36733 non-null  float64
 10  NOX     36733 non-null  float64
dtypes: float64(11)
memory usage: 3.1 MB
```

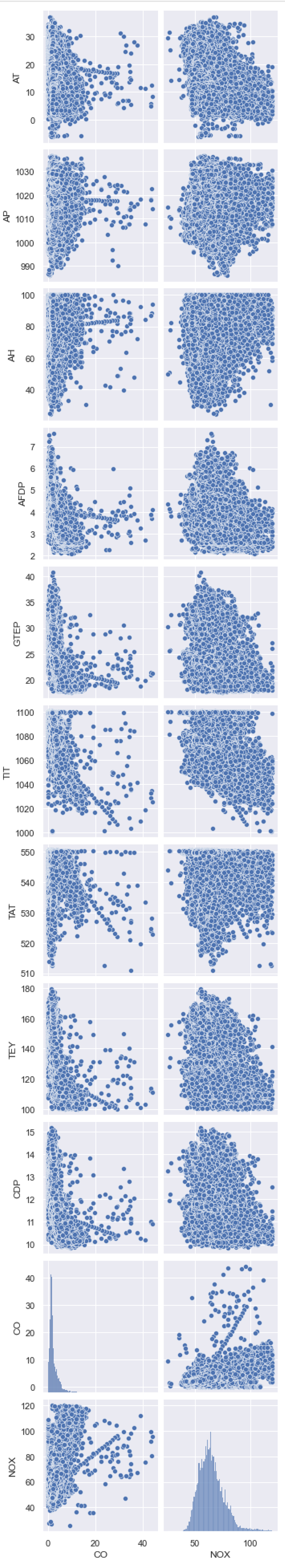
Out[9]:

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
count	36733.000000	36733.000000	36733.000000	36733.000000	36733.000000	36733.000000	36733.000000	36733.000000	36733.000000	36733.000000	36733.000000
mean	17.712726	1013.070165	77.867015	3.925518	25.563801	1081.428084	546.158517	133.506404	12.060525	2.372468	65.293067
std	7.447451	6.463346	14.461355	0.773936	4.195957	17.536373	6.842360	15.618634	1.088795	2.262672	11.678357
min	-6.234800	985.850000	24.085000	2.087400	17.698000	1000.800000	511.040000	100.020000	9.851800	0.000388	25.905000
25%	11.781000	1008.800000	68.188000	3.355600	23.129000	1071.800000	544.720000	124.450000	11.435000	1.182400	57.162000
50%	17.801000	1012.600000	80.470000	3.937700	25.104000	1085.900000	549.880000	133.730000	11.965000	1.713500	63.849000
75%	23.665000	1017.000000	89.376000	4.376900	29.061000	1097.000000	550.040000	144.080000	12.855000	2.842900	71.548000
max	37.103000	1036.600000	100.200000	7.610600	40.716000	1100.900000	550.610000	179.500000	15.159000	44.103000	119.910000

In [5]:

```
sns.pairplot(df, x_vars=["CO", "NOX"])
plt.show()

print("Correlation Matrix: ")
df.corr()[["CO", "NOX"]]
```




```
Correlation Matrix:
```

Out[5]:

	CO	NOX
AT	-0.174326	-0.558174
AP	0.067050	0.191938
AH	0.106586	0.164617
AFDP	-0.448425	-0.188247
GTEP	-0.518909	-0.201630
TIT	-0.706275	-0.213865
TAT	0.058353	-0.092791
TEY	-0.569813	-0.116127
CDP	-0.551027	-0.171256
CO	1.000000	0.340606
NOX	0.340606	1.000000

In [14]:

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.neural_network import MLPRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

y1 = df["CO"]
y2 = df["NOX"]
X = df.drop(columns = ['CO', "NOX"])

def model(model, x, y, model_name):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

    model.fit(X_train, y_train)
    pred_tr = model.predict(X_train)
    pred_te = model.predict(X_test)

    r2_tr = r2_score(y_train, pred_tr)
    r2_te = r2_score(y_test, pred_te)

    mse_tr = mean_squared_error(y_train, pred_tr)
    mse_te = mean_squared_error(y_test, pred_te)

    print("=============================================", "\n")
    print(model_name, "to predict", y.name, "\n")

    print("r2 score for training set: ", r2_tr)
    print("r2 score for testing set: ", r2_te, "\n")

    print("mean squared error for training set: ", mse_tr)
    print("mean squared error for testing set: ", mse_te, "\n")
    #return pred_te

lin = LinearRegression()
rf = RandomForestRegressor()
gb = GradientBoostingRegressor()
net = MLPRegressor(random_state=21)
poly = Pipeline([("poly", PolynomialFeatures(degree=2)), ("regressor", LinearRegression())])

models = [lin, rf, gb, net, poly]
names = ["Linear Regression", "Random Forest", "Gradient Boosting", "MLP Regression (Neural network)",
        "Polynomial Regression (2nd degree)"]
Y = [y1, y2]
for i in range(len(models)):
    for y in Y:
        model(models[i], X, y, names[i])
```

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Linear Regression to predict CO

r2 score for training set:  0.5620158064899403
r2 score for testing set:  0.5673372055271235

mean squared error for training set:  2.2253502820526574
mean squared error for testing set:  2.2651932631617977

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Linear Regression to predict NOX

r2 score for training set:  0.5223543837249878
r2 score for testing set:  0.503491751015686

mean squared error for training set:  65.58333055115381
mean squared error for testing set:  66.32602604760464

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Random Forest to predict CO

r2 score for training set:  0.9644851911559336
r2 score for testing set:  0.7738681835983622

mean squared error for training set:  0.18044689979519618
mean squared error for testing set:  1.1839064362434846

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Random Forest to predict NOX

r2 score for training set:  0.9820357711446861
r2 score for testing set:  0.8718411077128894

mean squared error for training set:  2.4665859352015604
mean squared error for testing set:  17.120098297371086

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Gradient Boosting to predict CO

r2 score for training set:  0.7618356339664657
r2 score for testing set:  0.7282273994329154

mean squared error for training set:  1.210087366121912
mean squared error for testing set:  1.4228574117784816

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Gradient Boosting to predict NOX

r2 score for training set:  0.752619709866879
r2 score for testing set:  0.7357502889984333

mean squared error for training set:  33.9666539099975
mean squared error for testing set:  35.299782532949656

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MLP Regression (Neural network) to predict CO

r2 score for training set:  0.5363842021762031
r2 score for testing set:  0.5352607125112294

mean squared error for training set:  2.3555816893368275
mean squared error for testing set:  2.4331287935879398

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MLP Regression (Neural network) to predict NOX

r2 score for training set:  0.6494141213984839
r2 score for testing set:  0.6394645147706006

mean squared error for training set:  48.137340277925965
mean squared error for testing set:  48.162112177045394

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Polynomial Regression (2nd degree) to predict CO

r2 score for training set:  0.6858657612596089
r2 score for testing set:  0.720095610817878

mean squared error for training set:  1.5960820667544713
mean squared error for testing set:  1.465431150550451

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Polynomial Regression (2nd degree) to predict NOX

r2 score for training set:  0.7642446397428125
r2 score for testing set:  0.7589827217962707

mean squared error for training set:  32.37048806504945
mean squared error for testing set:  32.196279326203815
```

We see that the Random Forest model is the best for both predictors, and performs well.

The gradient boosting (another decision tree model) and polynomial regression models both perform fairly well too.

The MLP does not perform well, which is not unexpected; neural networks can sometimes detect hidden or unseen patterns, but more often perform mediocrely.

Linear Regression doesn't do well either, which is expected, given the low linearity displayed in the pair plot shown above. But I like to always try Linear models, at least for reference (of expected performance).

In [ ]: