### PREDICTION OF TURBINE ENERGY YIELD

LINEAR REGRESSION WITH FEATURE SELECTION

Machine Learning Foundation
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### TURBINE ENERGY YIELD PREDICTION





### PROBLEM STATEMENT

The goal is to predict Turbine Energy Yield (TEY) using ambient variables as features

#### DATA LOADING AND DESCRIPTION

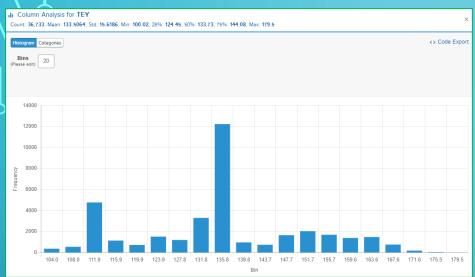
#### Data Source:

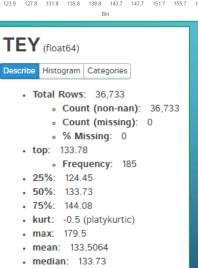
htto://archive.ics.uci.edu/ml/datasets/Gas+Turbine+CO+and+NOx+Emission+Data+Set

Variable (Abbr.)	Unit	Min	Max	Mean
Ambient temperature (AT)	С	6.23	37.10	17.71
Ambient pressure (AP)	mbar	985.85	1036.56	1013.07
Ambient humidity (AH)	(%)	24.08	100.20	77.87
Air filter difference pressure (AFDP)	mbar	2.09	7.61	3.93
Gas turbine exhaust pressure (GTEP)	mbar	17.70	40.72	25.56
Turbine inlet temperature (TIT)	С	1000.85	1100.89	1081.43
Turbine after temperature (TAT)	С	511.04	550.61	546.16
Compressor discharge pressure (CDP)	mbar	9.85	15.16	12.06
Turbine energy yield (TEY)	MWH	100.02	179.50	133.51
Carbon monoxide (CO)	mg/m3	0.00	44.10	2.37
Nitrogen oxides (NOx)	mg/m3	25.90	119.91	65.29

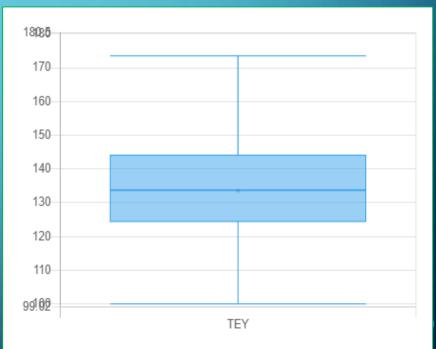
The dataset comprises of 36733 instances of 11 sensor measures. Above is a table showing names of all the columns and their description.

#### **EXPLORATORY DATA ANALYSIS: TARGET**

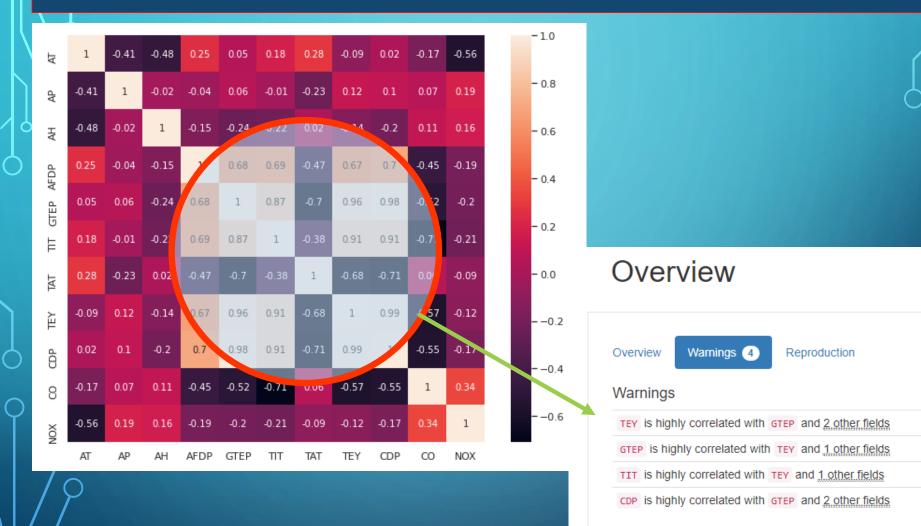




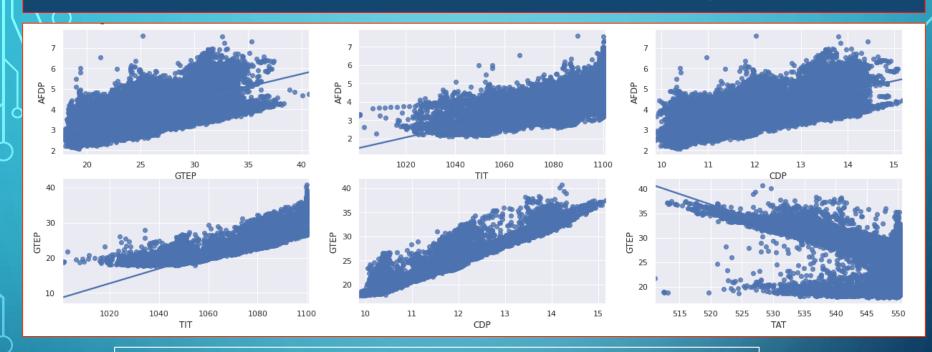
- Target is normally distributed;
- No outliers



#### **EXPLORATORY DATA ANALYSIS: FEATURES**

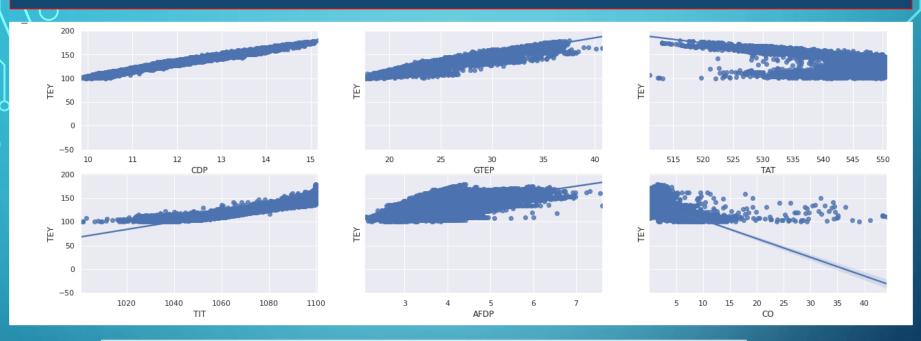


# EXPLORATORY DATA ANALYSIS: HIGH CORRELATION AMONG FEATURES



AFDP, GTEP, CDP, TAT, TIT are highly correlated among each others

## EXPLORATORY DATA ANALYSIS: TARGET VS FEATURES



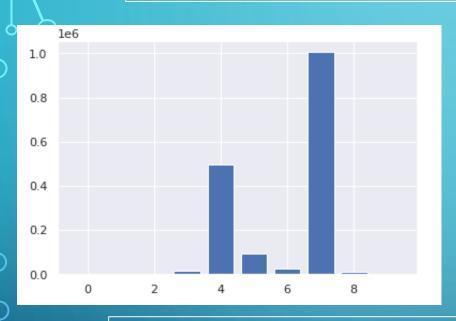
AFDP, GTEP, CDP, TIT, TAT are highly correlated with TEY

### FEATURE SELECTION



### FEATURE SELECTION: USING CORRELATION STATISTICS

#### import SelectKBest and f\_regression

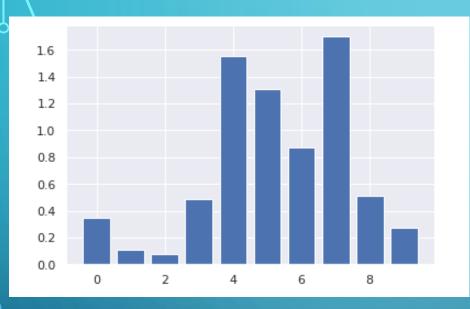


Feature 0: 860.624004
Feature 1: 718.013902
Feature 2: 293.925853
Feature 3: 15789.036161
Feature 4: 496027.685586
Feature 5: 95289.882724
Feature 6: 23891.083505
Feature 7: 1005912.467434
Feature 8: 11633.388290
Feature 9: 67.526325

So 3 to 4 features are having hi impact on the model

### FEATURE SELECTION: USING MUTUAL INFORMATION THEORY

#### import SelectKBest and mutual\_info\_regression

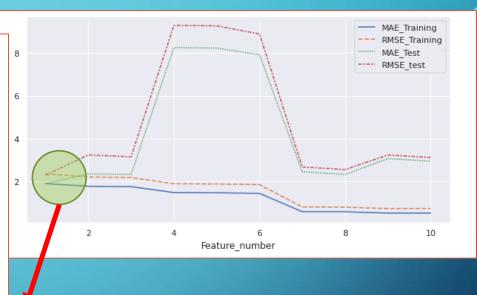


Feature 0: 0.350200
Feature 1: 0.109574
Feature 2: 0.073342
Feature 3: 0.484026
Feature 4: 1.552312
Feature 5: 1.304582
Feature 6: 0.874015
Feature 7: 1.699997
Feature 8: 0.510088
Feature 9: 0.272602

So 3 to 5 features are having hi impact on the model

## FEATURE SELECTION: USING GRIDSEARCH WITH MUTUAL INFORMATION THEORY

	Feature_number	MAE_Training	RMSE_Training	MAE_Test	RMSE_test
0	1	1.905447	2.354340	1.903045	2.302691
1	2	1.782063	2.218478	2.356738	3.244547
2	3	1.765120	2.187249	2.338517	3.154224
3	4	1.490215	1.900632	8.242611	9.281714
4	5	1.480846	1.888095	8.220992	9.255912
5	6	1.451452	1.859275	7.916408	8.881514
6	7	0.597309	0.817165	2.461045	2.682705
7	8	0.595421	0.807878	2.333199	2.559623
8	9	0.531623	0.746790	3.070164	3.237879
9	10	0.531585	0.744256	2.951597	3.124839



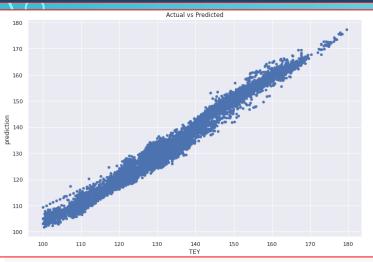
# MAE/RMSE are in same level for both the Train & Test datasets together with a single feature

TEY = -38.03 + 14.227 \* CDP

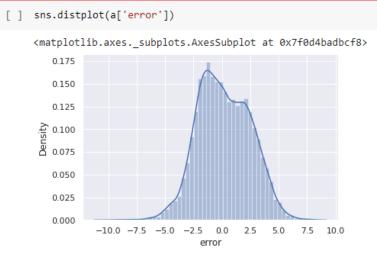
How do we interpret the coefficient (+14.227)

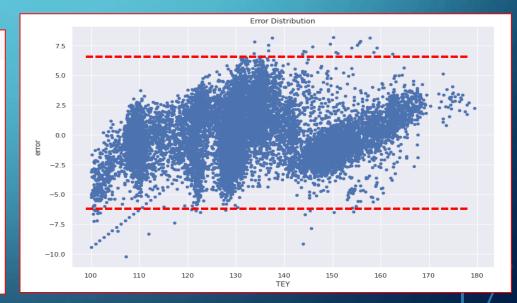
A "unit" increase in CDP is associated with a "14.227 unit" increase in TEY.

### MODEL EVALUATION



# Homoscedasticity has been observed.





### CONCLUSION

- Feature selection is an important criterion when they are strongly correlated among each other.
- Search technique using RMSE and MAE for different number of features in train & test dataset is also an important factor while selecting a model.
- Homoscedasticity observed for the errors.
- This case study can also be referred for feature engineering having more number of features.

# THANKS FOR READING

Lets collaborate and happy to receive any feedback/suggestion/comment at.....

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