Baker Hughes Hackathon

Predictive Modeling (Team 2)

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José David Romo López
Juan Diego Sanchez Díaz

Goal

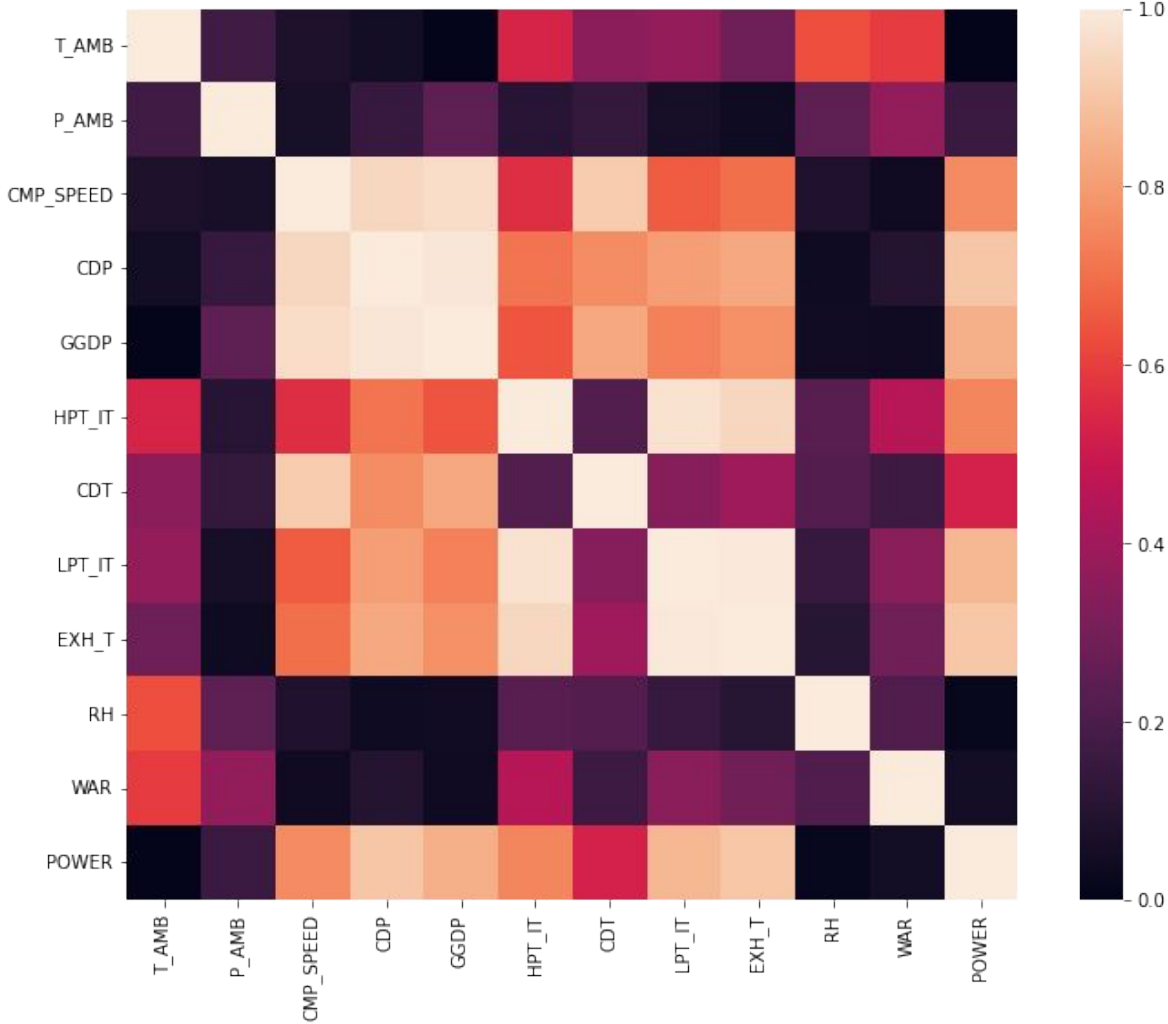
Obtain a predictor using turbine data

Data Transformation

Data Visualization

(all training data)

abs(CorrelationCoeff)
The clearer the better



Data Visualization

(all training data)

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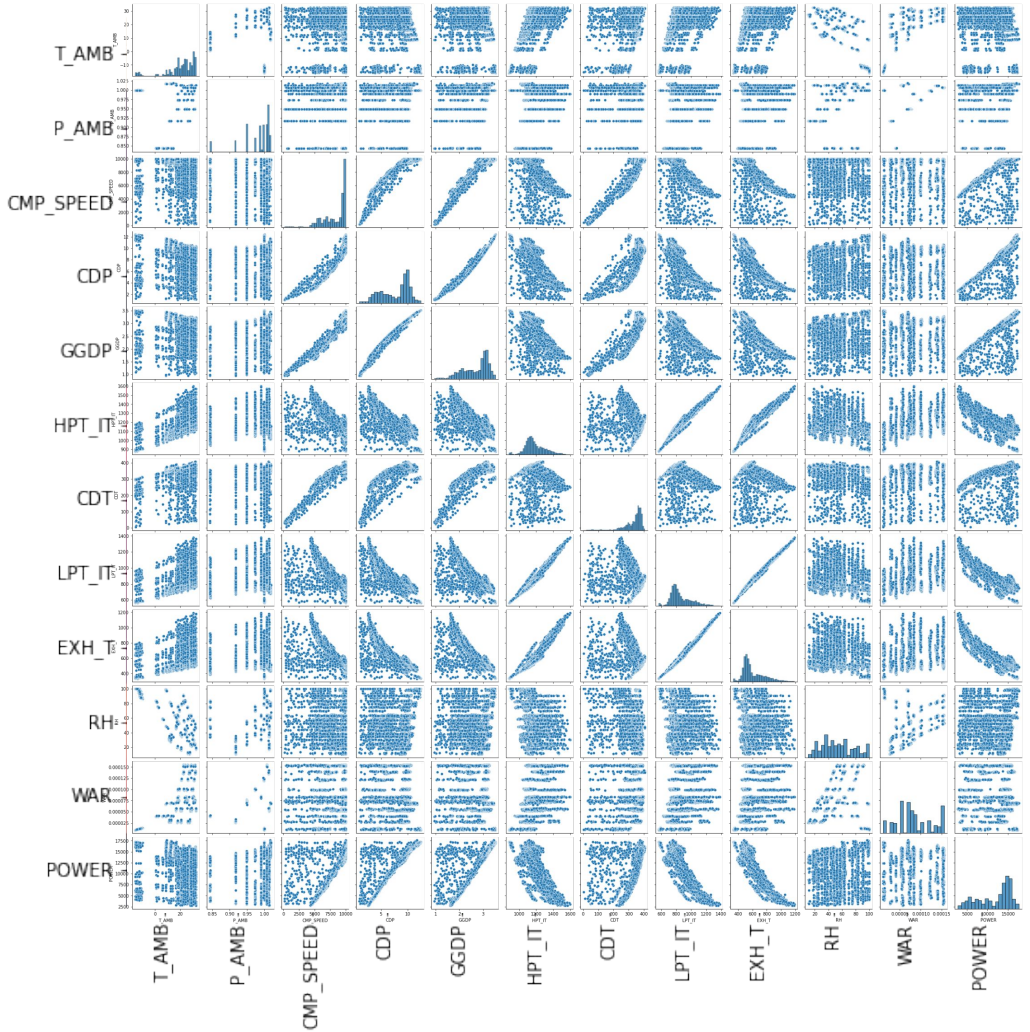

For us the interesting variables are in order:

```
POWER        1.000000
EXH_T        0.903272
CDP          0.898743
LPT_IT       0.863357
GGDP         0.846911
CMP_SPEED    0.758151
HPT_IT       0.746706
CDT          0.525526
P_AMB        0.155483
WAR          0.049835
RH           0.017927
T_AMB        0.004338
Name: POWER, dtype: float64
```

Data Visualization

(all training data)

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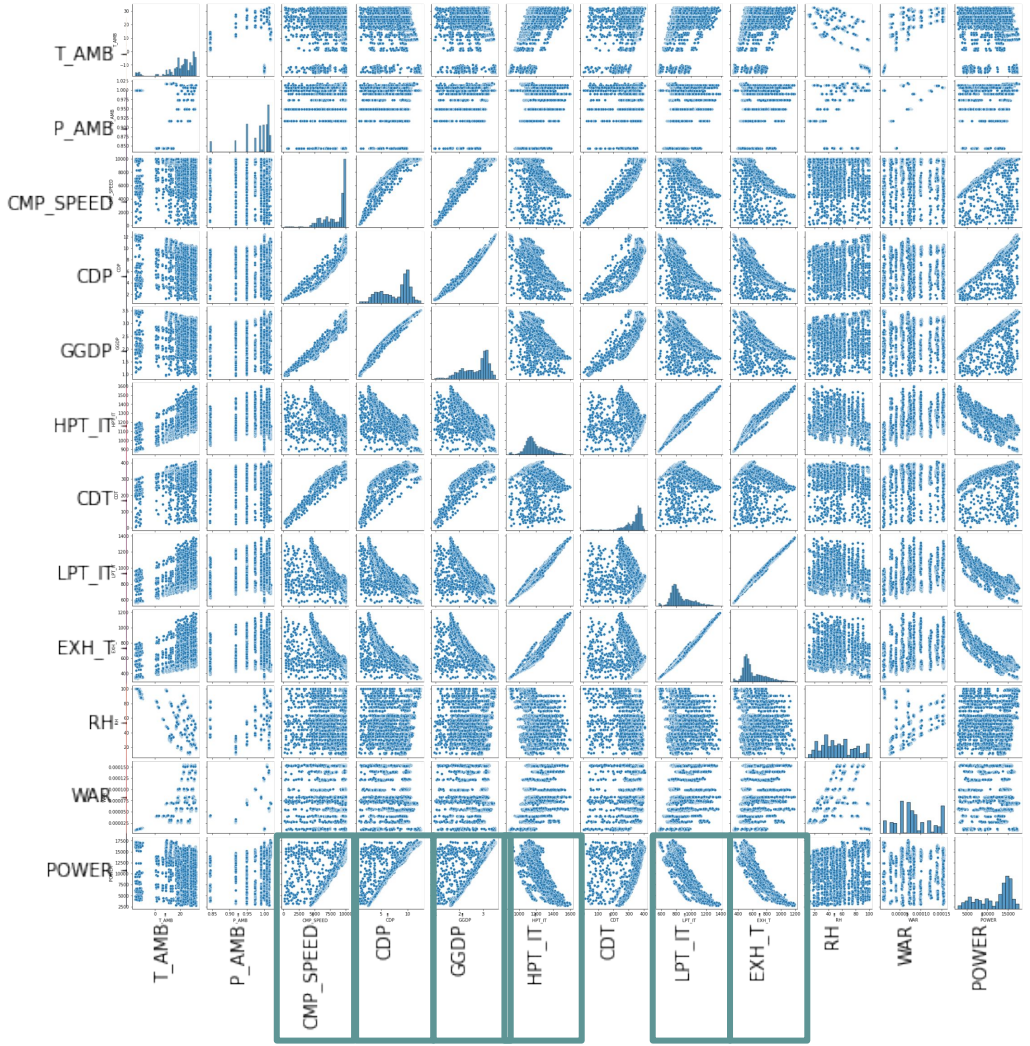
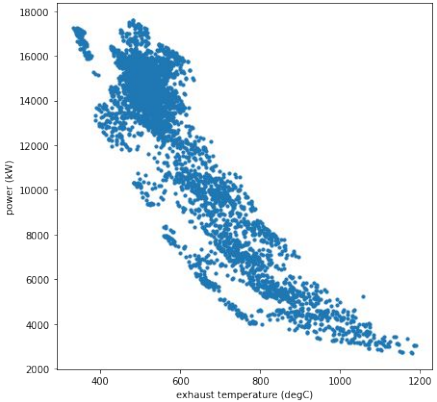
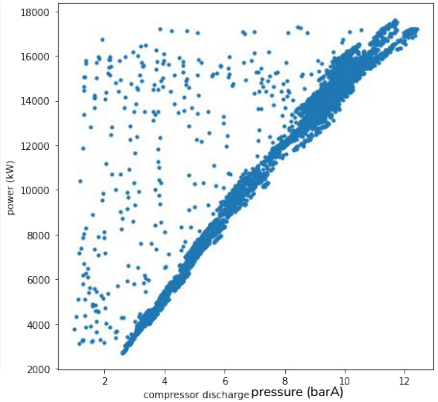
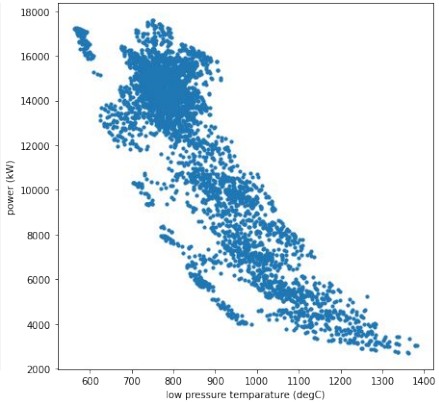


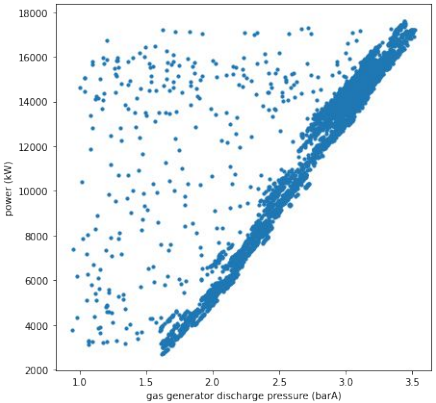
Data Visualization

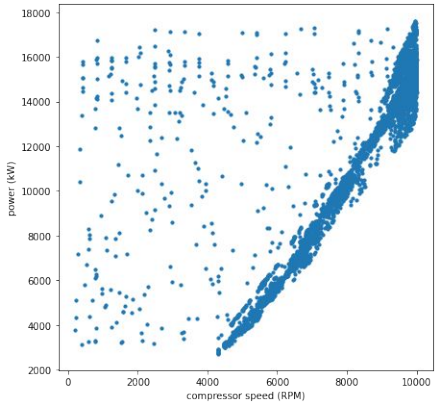
We visualize all the training data

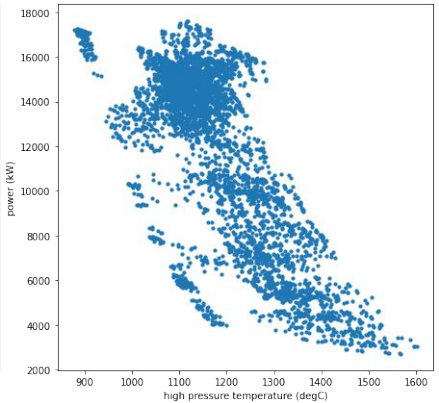










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Name: POWER, dtype: float64
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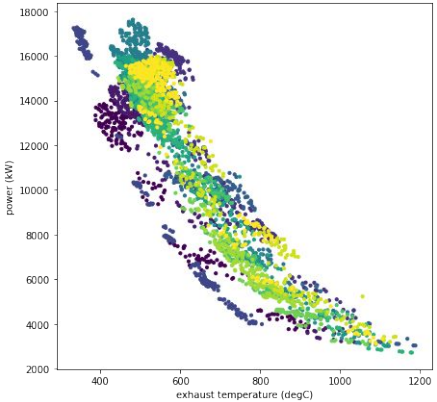
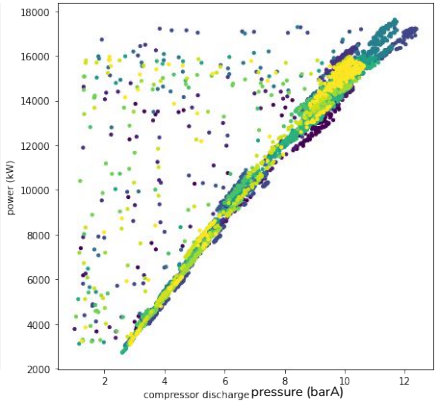
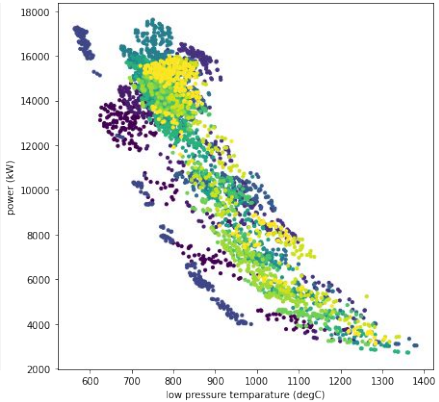
Data Visualization

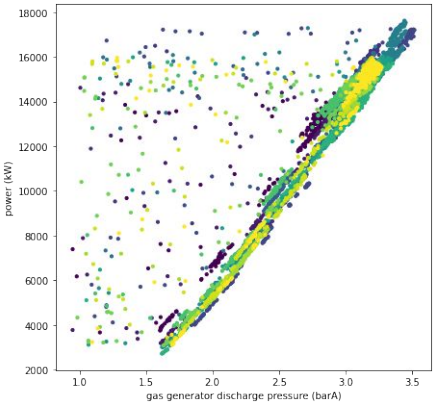
Maybe if we separate distint files. Could be a metadata depandence?

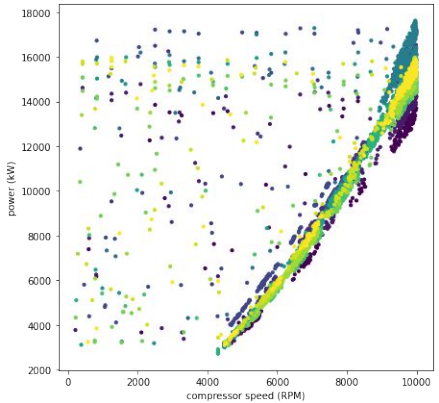
Doesn't look very important.

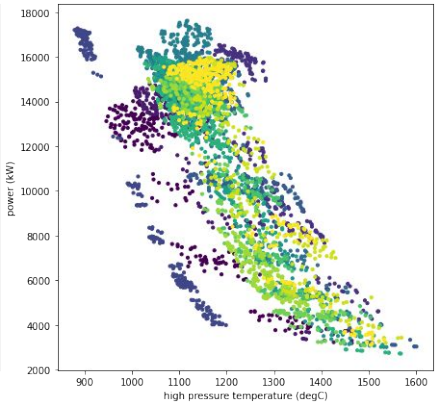










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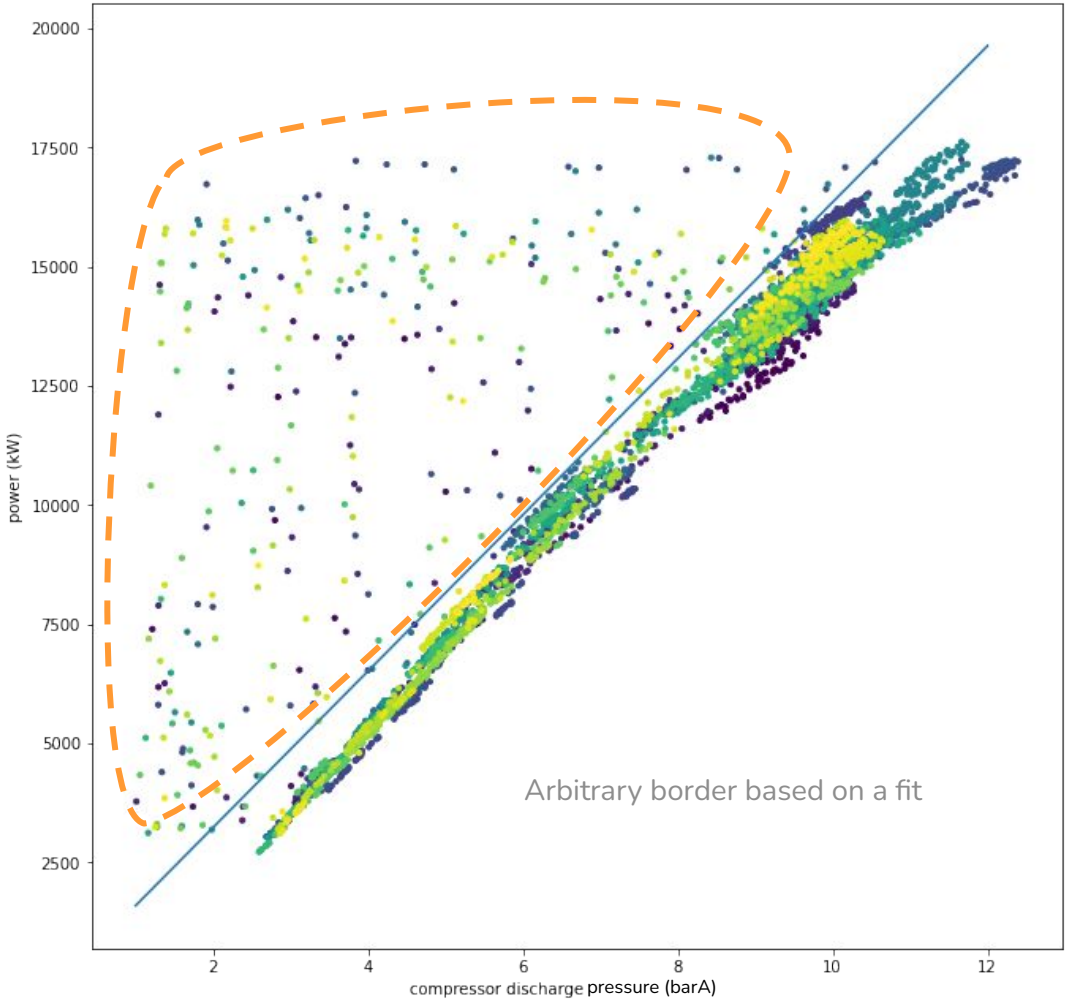
Data Visualization

‘Data’ + **‘Outliers’**

Data: Below the rect
‘Outliers’: Above the rect

The dependence power vs CDP looks like a linear dependence except from the presence of some ’outliers’

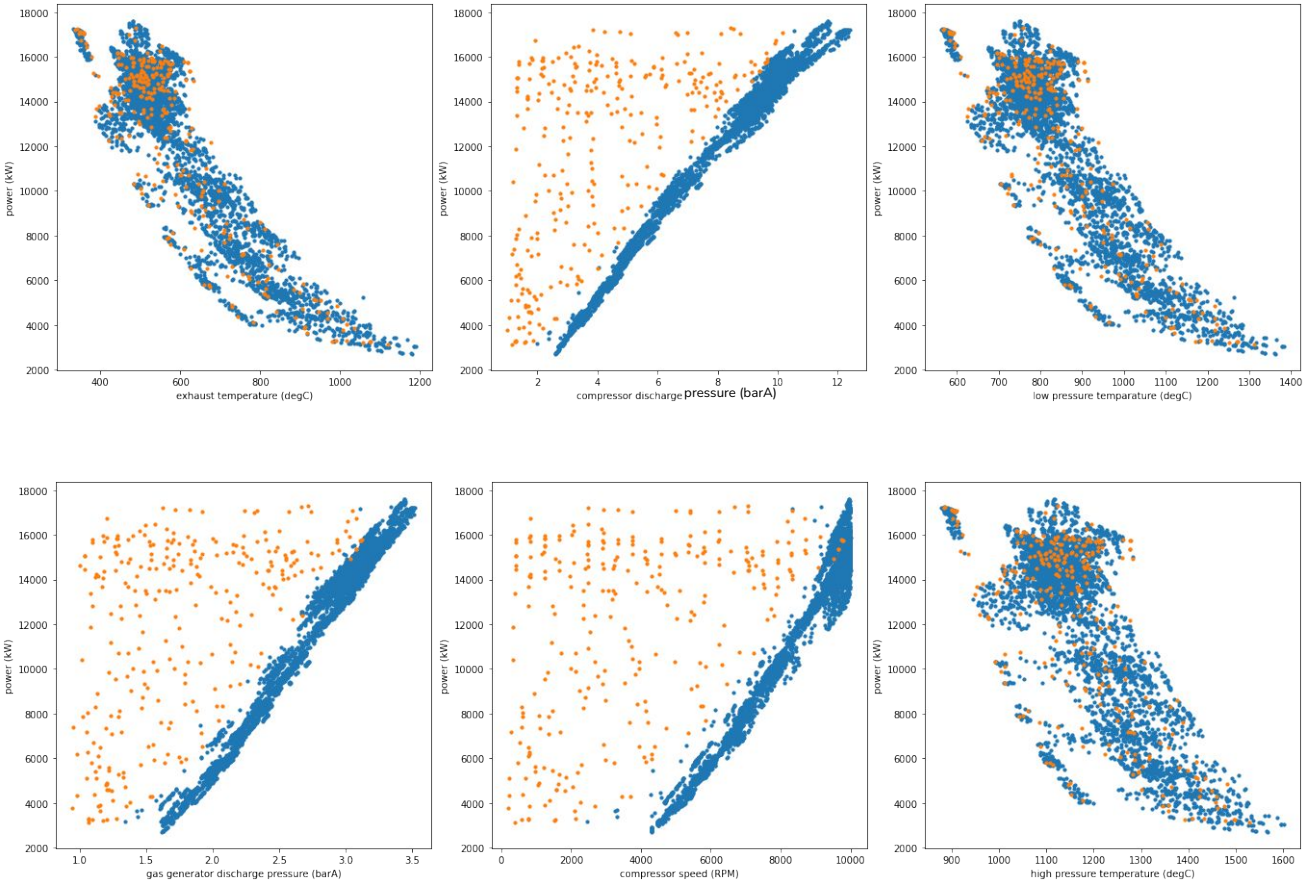


Data Visualization

'Data' + **'Outliers'**

But, are they really outliers?

- ❑ They show a consistent behaviour.
- ❑ They are not <u>rare</u> ~6% of the sample

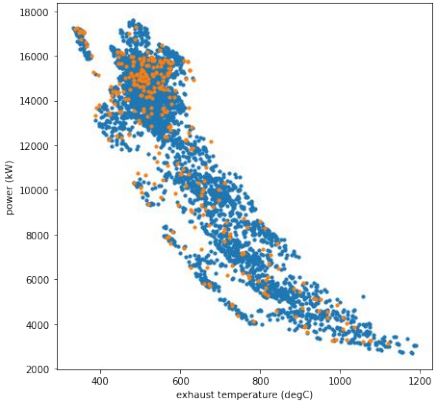


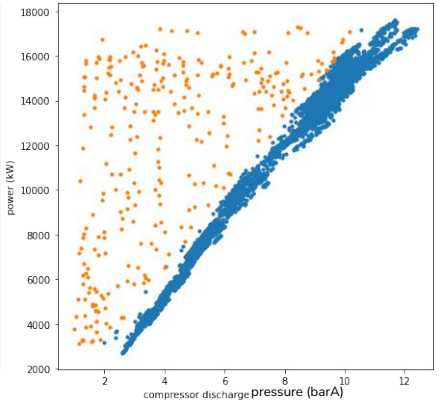
Data Visualization

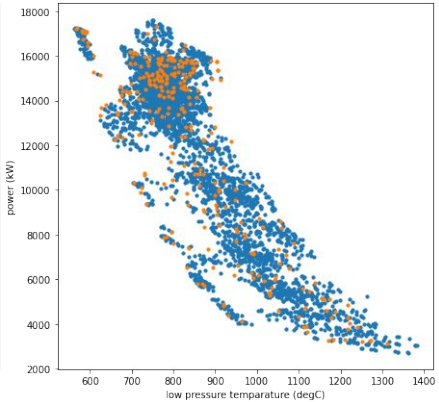
~~'Data'~~ + ~~'Outliers'~~

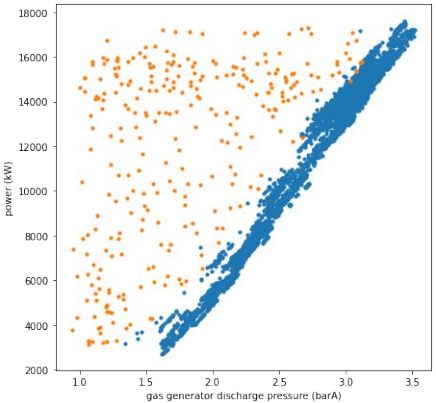
Blue type + **Orange type**

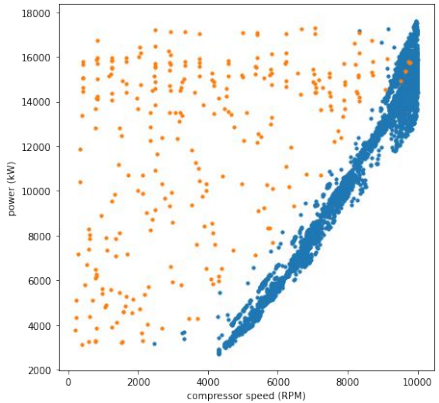
Each with a different estimator method

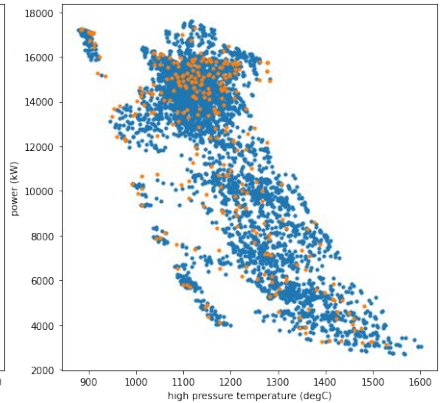








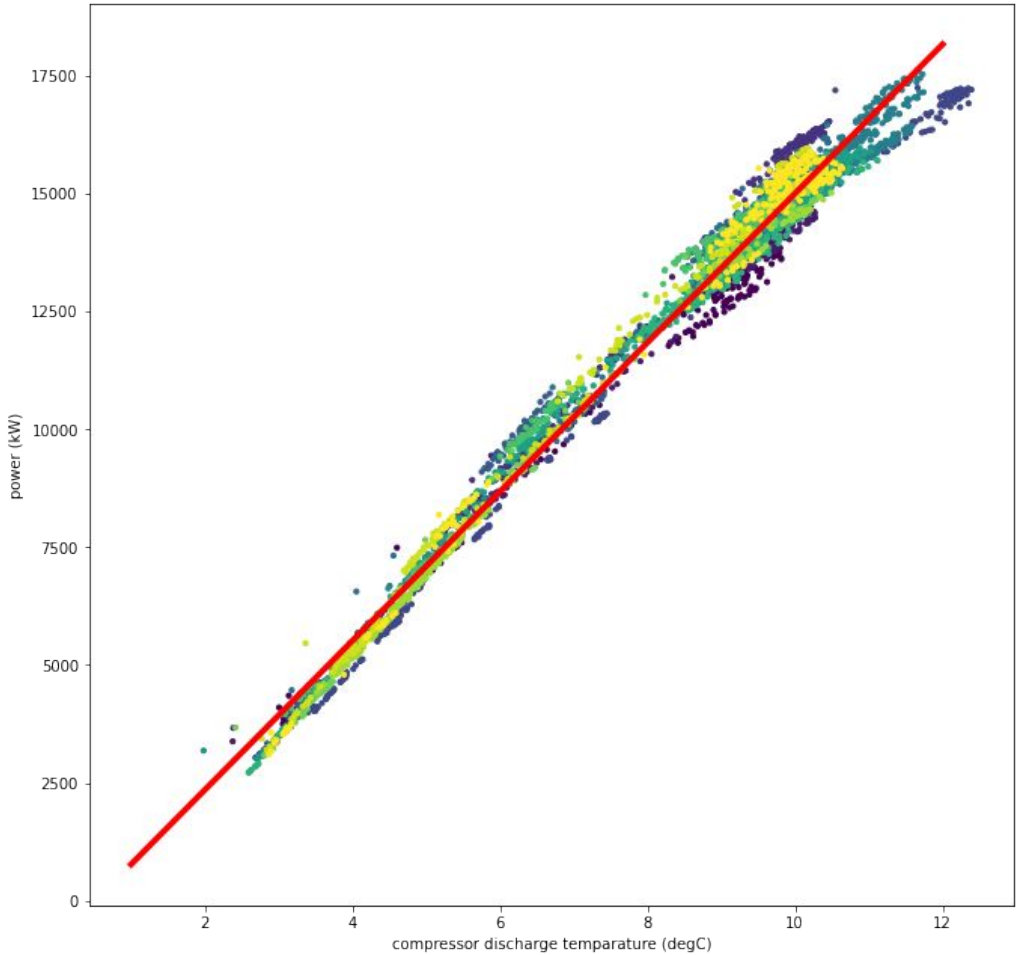




Predictors

Blue (power) predictor

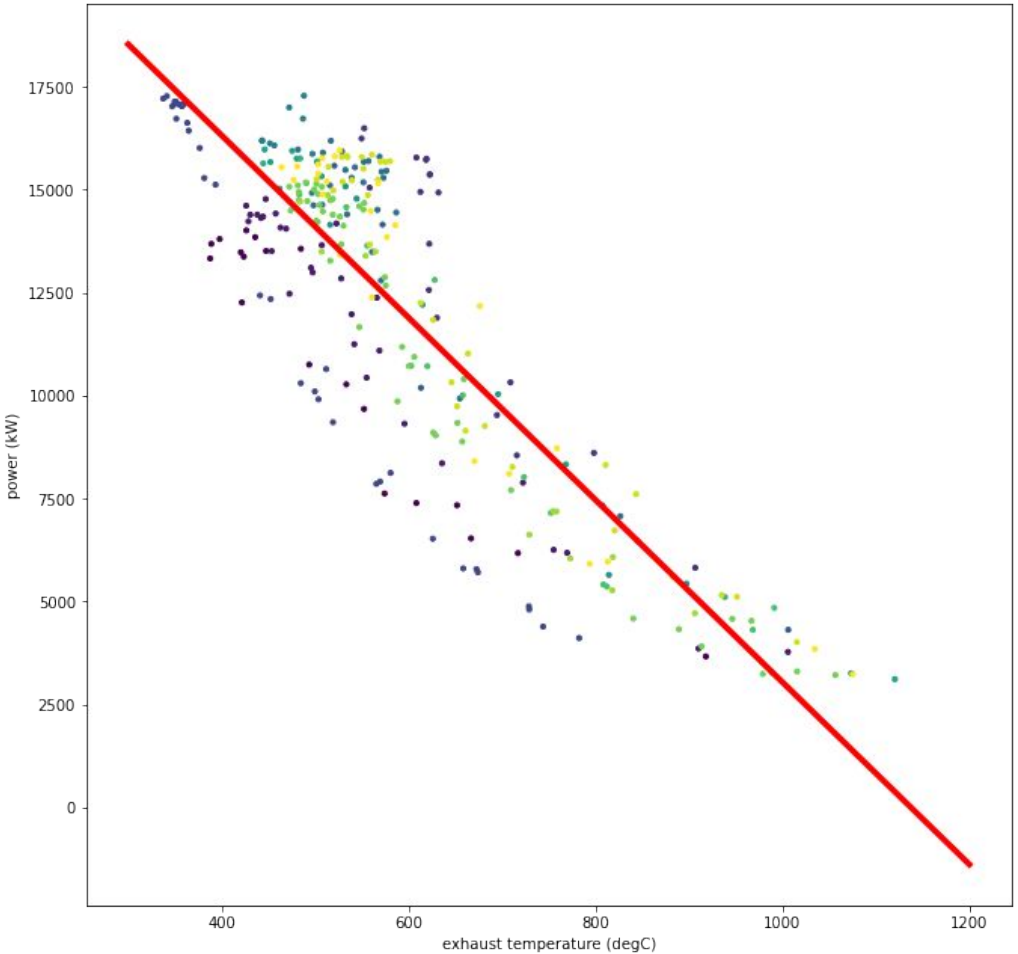
CDP vs POWER
Linear Regression



Predictors

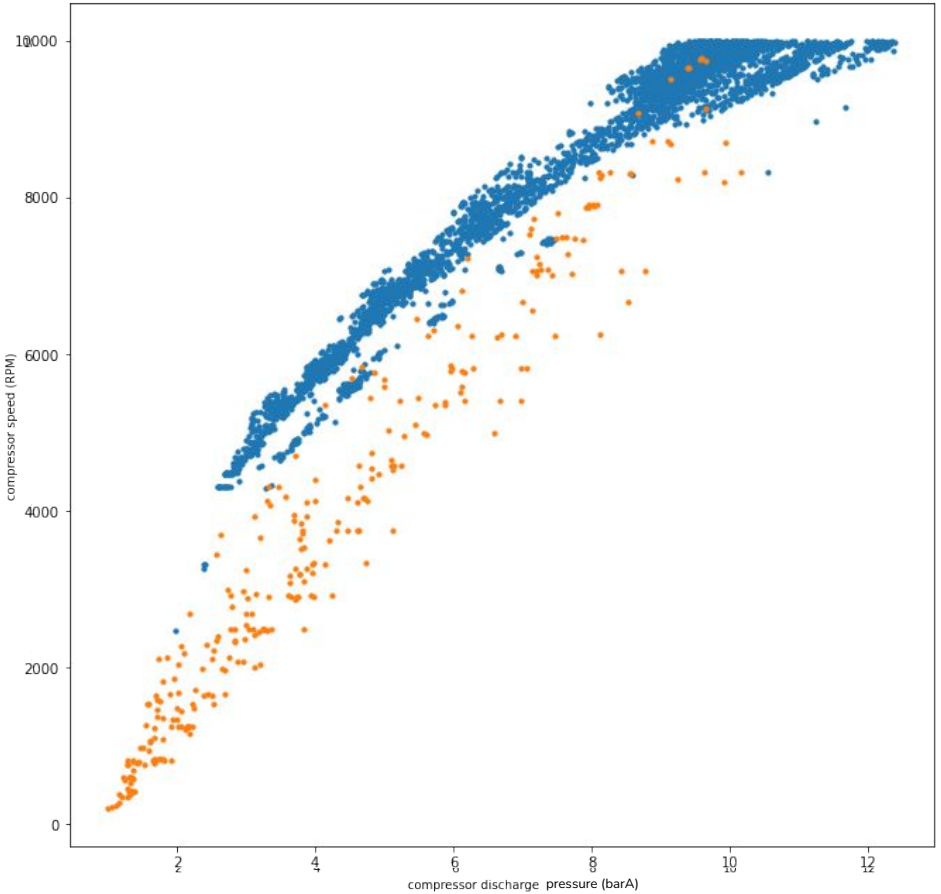
Orange (power)predictor

EXH_T vs POWER
Linear Regression



However, how can we distinguish blue vs orange points?

We could do some clustering training...



First approach

K-means

```
[ ]  x = df_01[['compressor_discharge_pressure[barA]' , 'exhaust_temperature[°C]']].to_numpy()
     y = df_01['label'].to_numpy()

     x_train , x_test , y_train , y_test = train_test_split(x , y , test_size = 0.3)
```

```
modelo_kmeans = KMeans(n_clusters = 2).fit(x_train)
centroides = modelo_kmeans.cluster_centers_
print(centroides)
```

```
[[  8.60940768 447.09607953]
 [  4.05658426 737.20382455]]
```

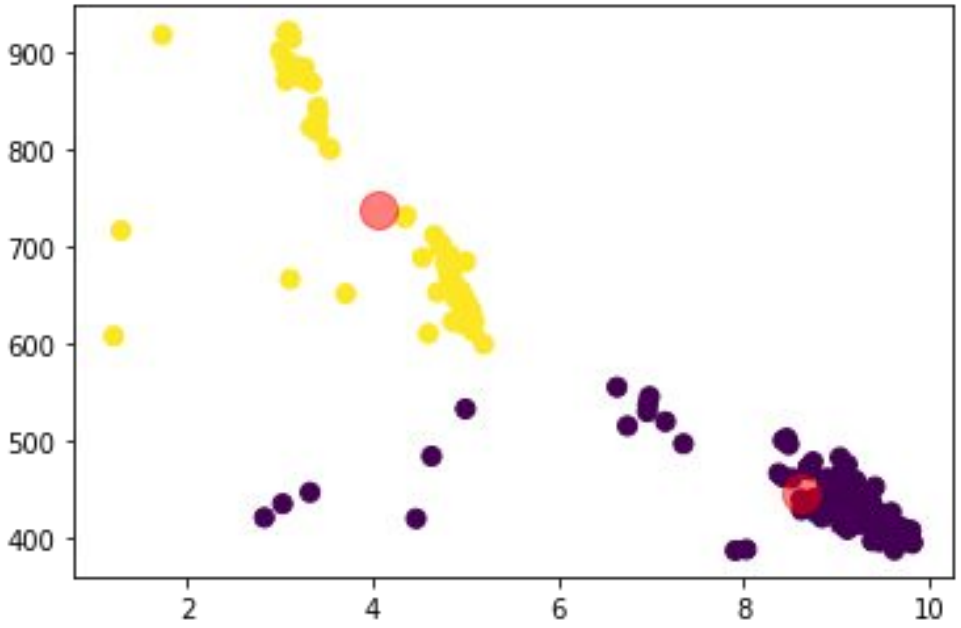
```
[ ]  y_kmeans = modelo_kmeans.predict(x_train)
```

```
[ ]  plt.scatter(x_train[:, 0], x_train[:, 1], c=y_kmeans, s=50, cmap='viridis')

     plt.scatter(centroides[:, 0], centroides[:, 1], c='red', s=200, alpha=0.5);
```

First approach

K-means

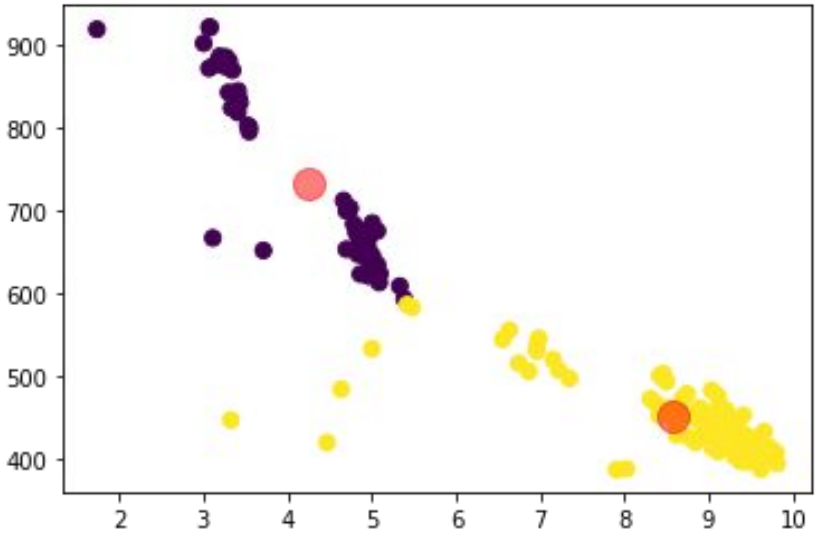


First approach

K-means

```
x = df_01[['compressor_discharge_pressure[barA]' , 'exhaust_temperature[°C]']].to_numpy()
y = df_01['power_output[kW]'].to_numpy()
```

[[4.24034601 731.48913946]
 [8.58409587 452.23910862]]

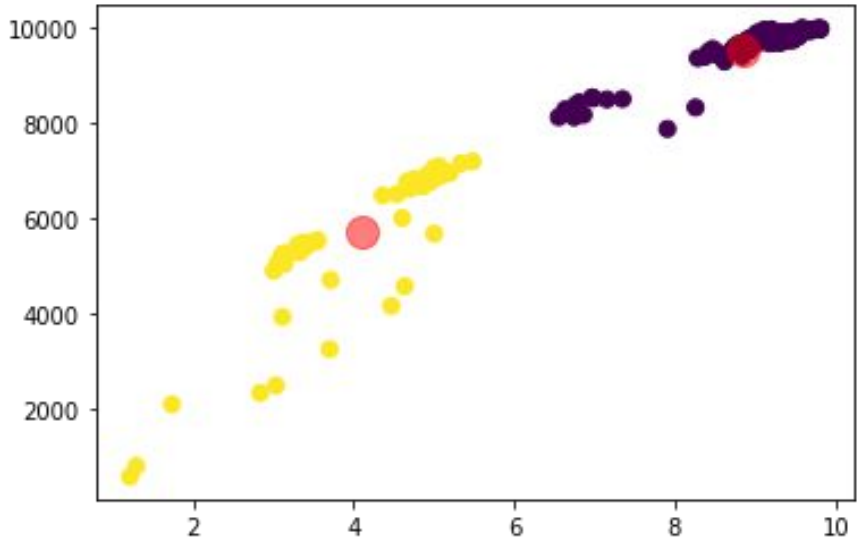


First approach

K-means

```
x = df_01[['compressor_discharge_pressure[barA]' , 'compressor_speed[RPM]']].to_numpy()
y = df_01['power_output[kW]'].to_numpy()
```

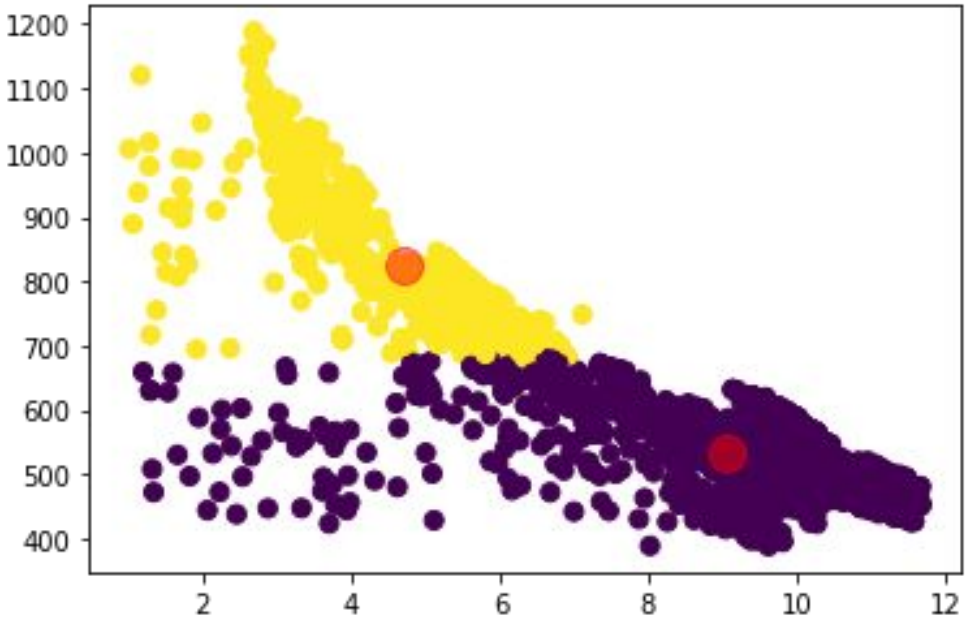
[[8.85408884e+00 9.54425045e+03]
 [4.10239771e+00 5.70094972e+03]]



K-means for complete dataset

```
x = df_01[['compressor_discharge_pressure[barA]' , 'exhaust_temperature[°C]']].to_numpy()
y = df_01['label'].to_numpy()
```

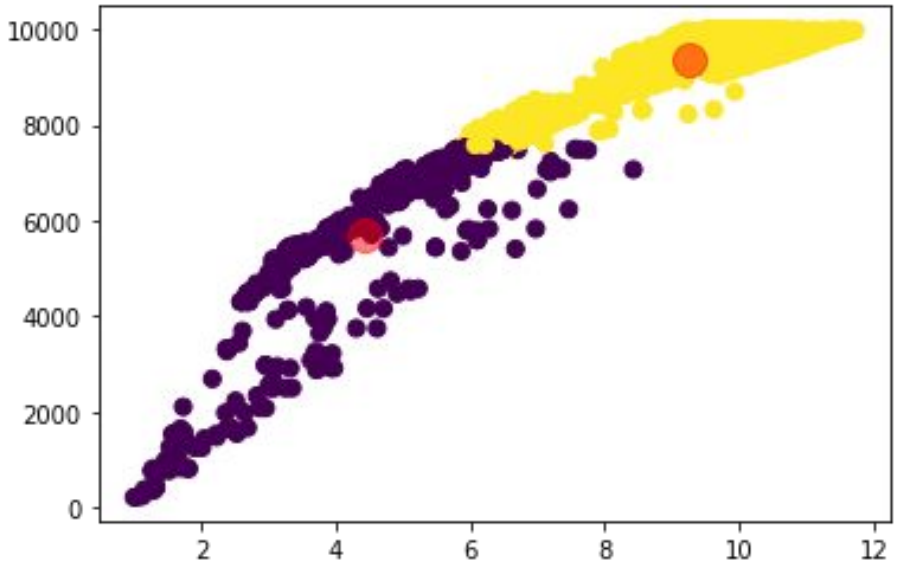
```
[[  9.06245294 531.78161744]
 [  4.69096449 825.6325629 ]]
```



K-means for complete dataset

```
x = df_01[['compressor_discharge_pressure[barA]' , 'compressor_speed[RPM]']].to_numpy()
y = df_01['power_output[kW]'].to_numpy()
```

```
[[4.44718789e+00 5.72056471e+03]
 [9.24431853e+00 9.36459111e+03]]
```



First approach

Linear Regression

x_train shape: (122, 10)
x_test shape: (82, 10)
y_train shape: (122,)
x_test shape: (82,)

Entrenamiento: MSE =1684124.1465175531
Entrenamiento: RMSE = 1297.7380885670086
Pruebas: MSE =2231558.41631598
Pruebas: RMSE = 1493.8401575523333

	valor real	prediccion	diferencia
0	13699.931524	13615.749303	84.182221
1	11832.417851	11771.131817	61.286034
2	3939.408568	4160.865158	-221.456590
3	12985.607738	12963.764149	21.843588
4	13604.550278	13486.608011	117.942267
5	4589.878313	4476.772170	113.106144
6	12845.751340	12458.006525	387.744815
7	12259.119269	11775.590208	483.529061
8	4401.739916	5089.461968	-687.722052
9	10064.378955	9759.047933	305.331022

First approach

Complete dataset

x_train shape: (2099, 10)
x_test shape: (1400, 10)
y_train shape: (2099,)
x_test shape: (1400,)

Entrenamiento: MSE =1175602.1811704403
Entrenamiento: RMSE = 1084.25189931604
Pruebas: MSE =1078603.8319800822
Pruebas: RMSE = 1038.558535654145

```
max_error(Y_test, y_test_predict)
```

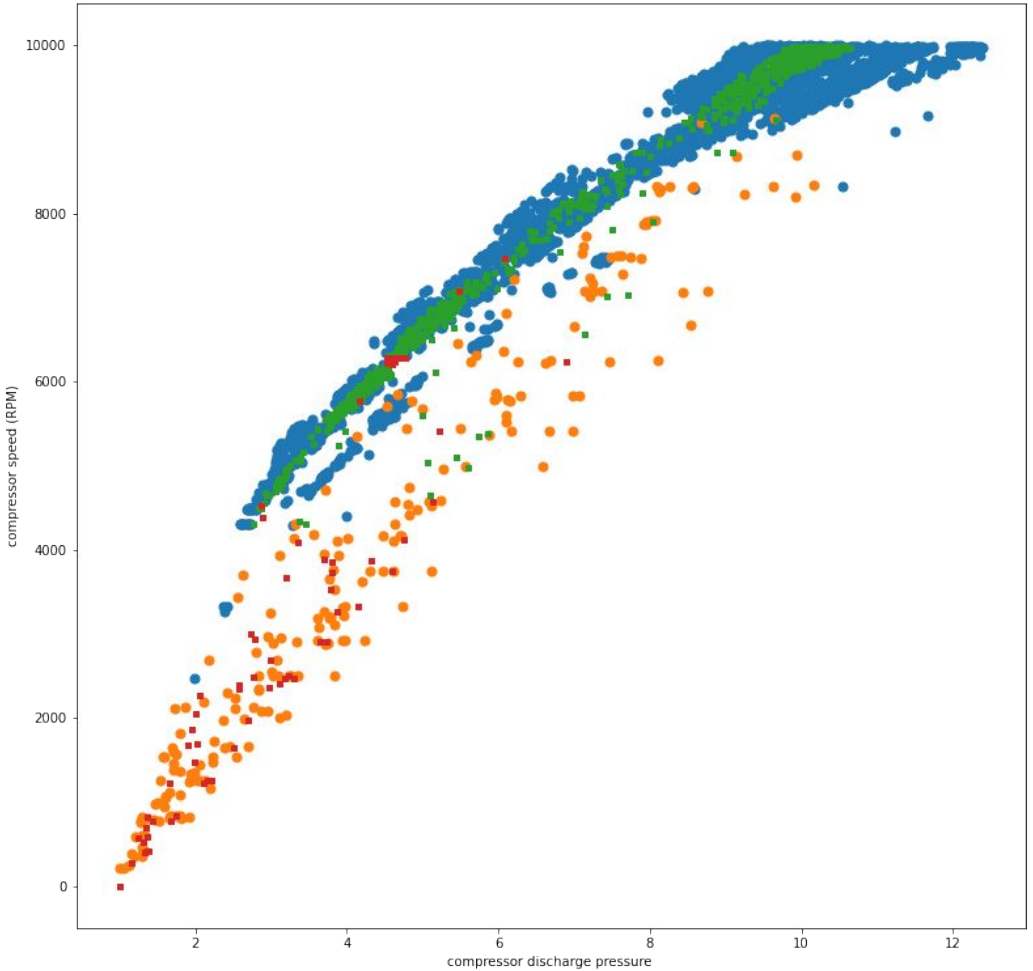
11388.37859014095

	real_value	prediction	difference
0	15045.951577	14981.763186	64.188392
1	13772.934806	13775.173671	-2.238865
2	15499.096459	15609.144670	-110.048211
3	15682.622888	15200.089142	482.533746
4	15961.827590	15928.200787	33.626803
5	14194.978578	14319.029135	-124.050557
6	13286.088486	13062.480177	223.608310
7	9926.411619	9864.001608	62.410011
8	4298.147094	4692.151744	-394.004650
9	13591.638554	13827.083420	-235.444866

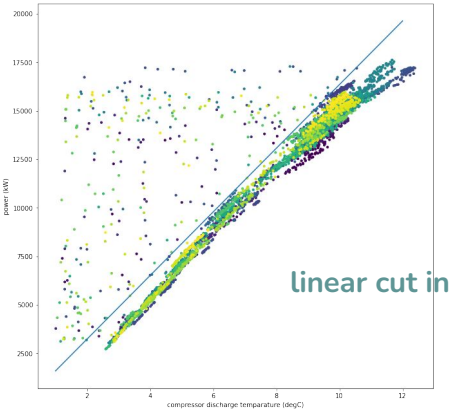
Second approach

k-nearest neighbors

- Train data (blue label from linear cut)
- Train data (orange from linear cut)
- Test data (blue label from kNearNeigh)
- Test data (orange label from kNearNeigh)



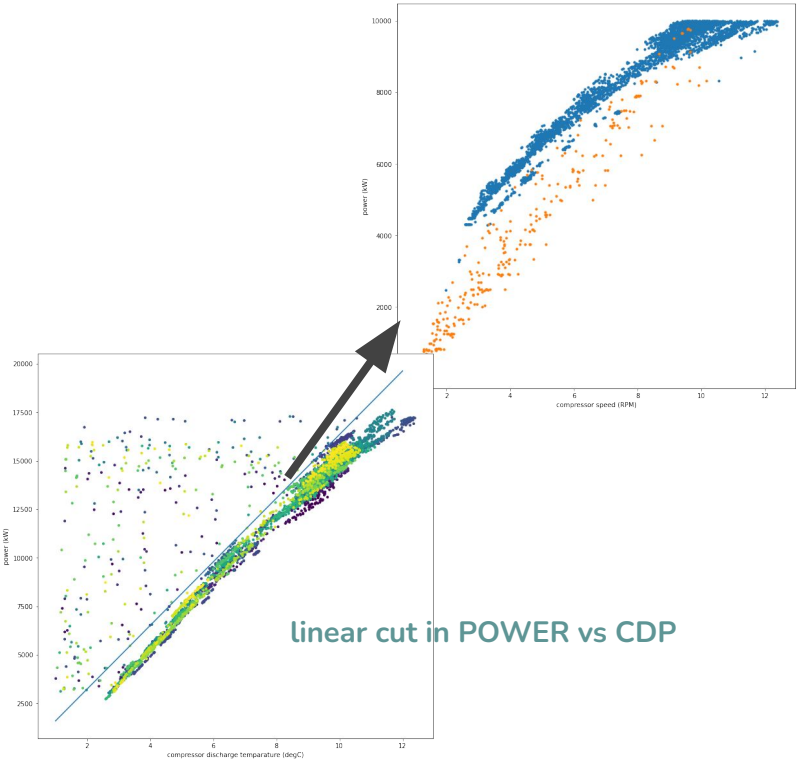
In short words...



linear cut in POWER vs CDP

In short words...

labeling data between **blue** and **orange**



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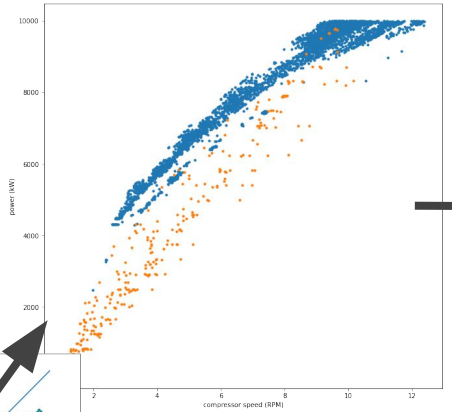
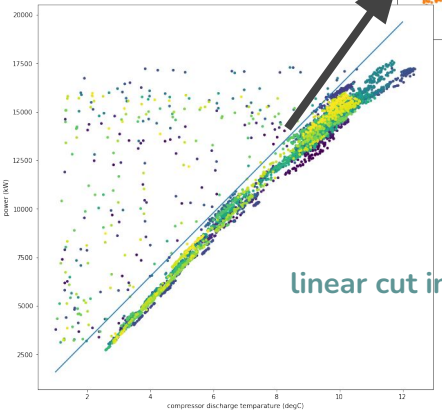
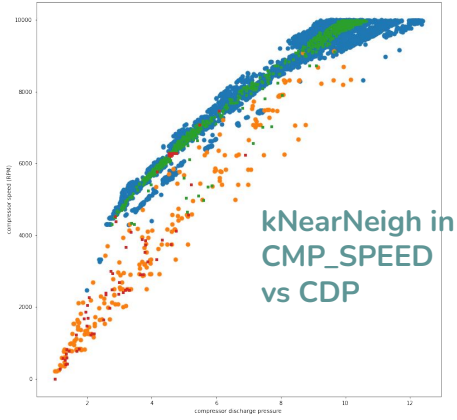




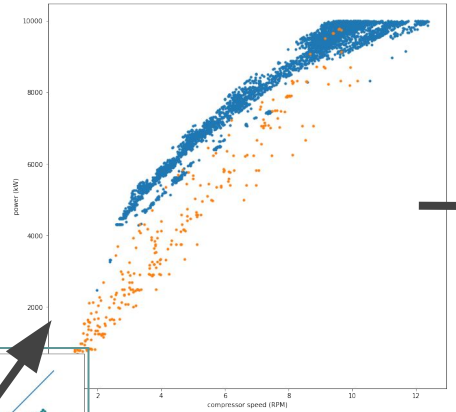
linear cut in POWER vs CDP

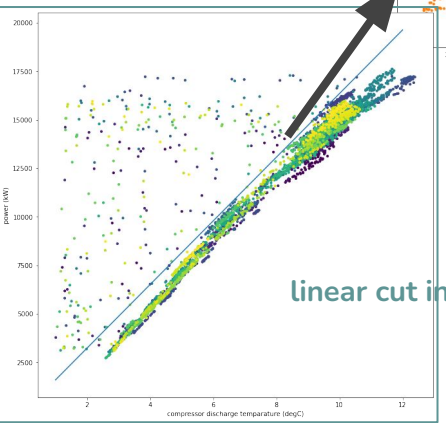


kNearNeigh in CMP_SPEED vs CDP

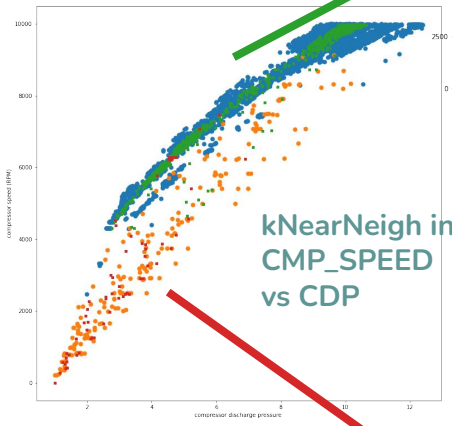
In short words...

labeling data between **blue** and **orange**

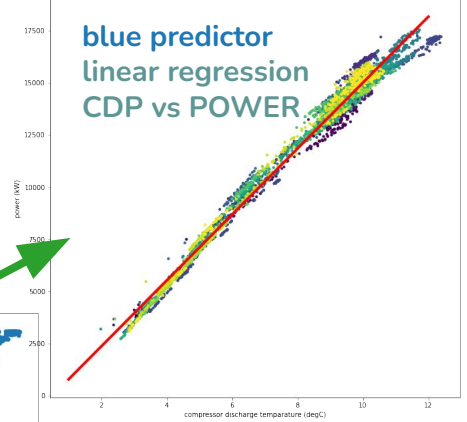




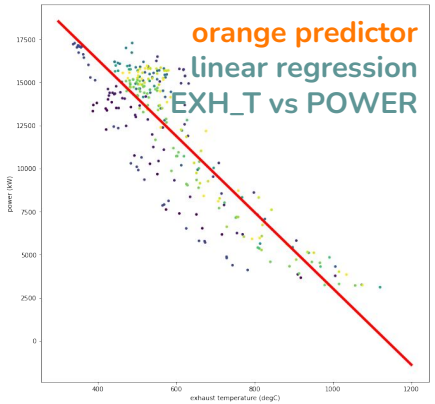
linear cut in POWER vs CDP



kNearNeigh in
CMP_SPEED
vs CDP



blue predictor
linear regression
CDP vs POWER



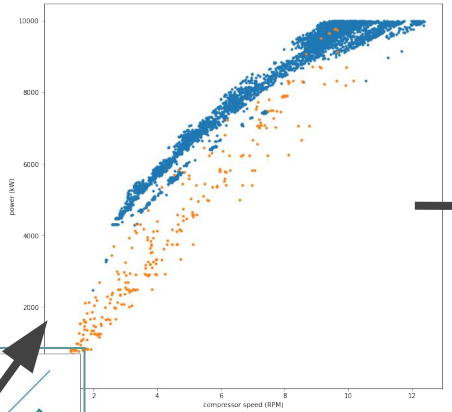
orange predictor
linear regression
EXH_T vs POWER

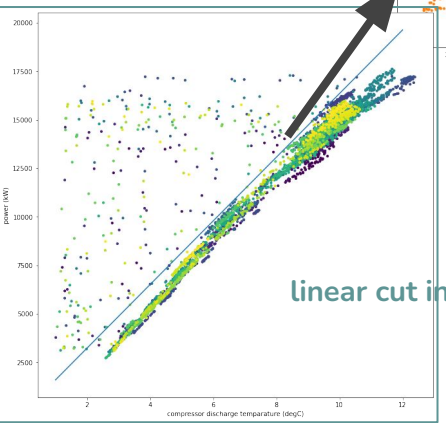
In short words...

Training

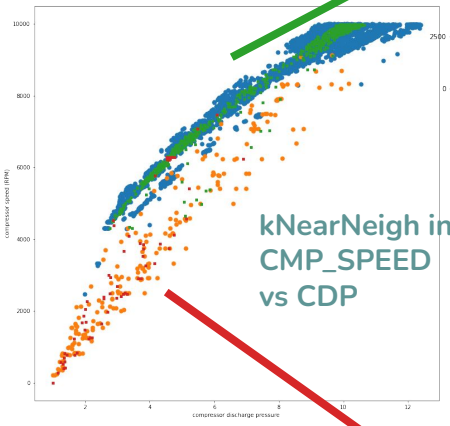
Prediction

labeling data between **blue** and **orange**

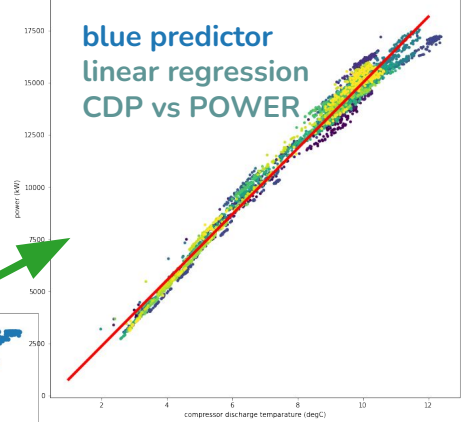




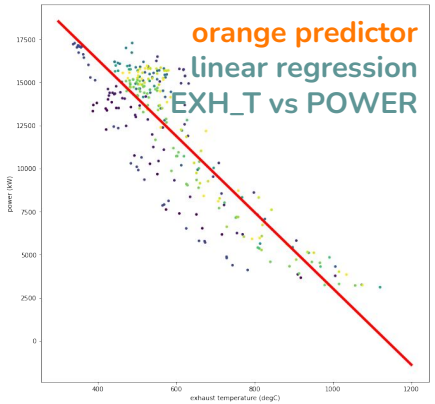
linear cut in POWER vs CDP



kNearNeigh in
CMP_SPEED
vs CDP



blue predictor
linear regression
CDP vs POWER



orange predictor
linear regression
EXH_T vs POWER

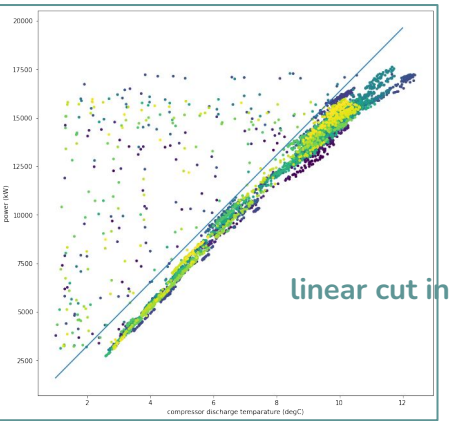
Implementation

For validation purposes, we focus in

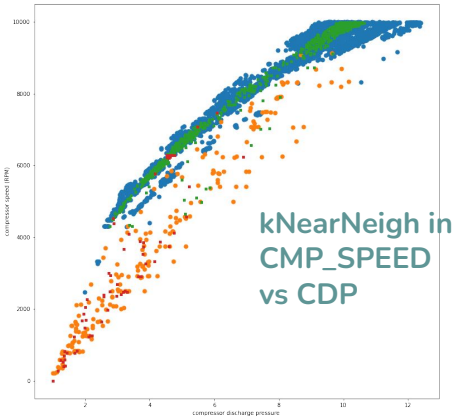
Hyperparameters:

linear cut
- ❑ slope parameter
- ❑ offset parameter

kNearNeigh
- ❑ k value



linear cut in POWER vs CDP



kNearNeigh in CMP_SPEED vs CDP

Implementation

For validation purposes, we focus in

Hyperparameters:

linear cut
- slope parameter
- offset parameter

kNearNeigh
- k value

EXH_T vs POWER linear regression
(Orange predictor)

CDP vs POWER linear regression
(Blue predictor)

```python
class MyModel():
    # default constructor
    def __init__(self, linear_cut_slope = 1640, linear_cut_intercept = 0, knum = 3):
        self.linear_cut_slope = linear_cut_slope
        self.linear_cut_intercept = linear_cut_intercept
        self.knum = knum

    # a method for printing data members
    def train(self, df_tr):
        self.df_tr = df_tr #dataframe for training

        # Linear Regression EXH_T vs POWER
        X_tr = np.array(df_tr['exhaust_temperature']).reshape(-1,1)
        Y_tr = np.array(df_tr['power']).reshape(-1,1)

        self.orange_model = LinearRegression().fit(X_tr, Y_tr)

        # KNeighbors data election with CDP and CMP_SPEED
        self.bluemask = df_tr['power'] < (self.linear_cut_slope)*df_tr['compressor_discharge_pressure'] + (self.linea
        df_X_kmeans = df_tr[['compressor_discharge_pressure', 'compressor_speed']].to_numpy()
        df_Y_kmeans = self.bluemask #np.array([0 for i in df_X_kmeans])

        self.chooseblue = KNeighborsClassifier(self.knum)
        self.chooseblue.fit(df_X_kmeans, df_Y_kmeans)

        # Linear Regression CDP vs POWER
        X_tr = np.array(df_tr['compressor_discharge_pressure']).reshape(-1,1)
        Y_tr = np.array(df_tr['power']).reshape(-1,1)

        self.blue_model = LinearRegression().fit(X_tr[self.bluemask], Y_tr[self.bluemask])

    def predict(self, df_pr): #dataframe for predicting

        # Predict with Linear Regression EXH_T vs POWER
        X_prt = np.array(df_pr['exhaust_temperature']).reshape(-1,1)
        Y_prt = self.orange_model.predict(X_prt)

        # Predict with Linear Regression CDP vs POWER
        X_prt1 = np.array(df_pr['compressor_discharge_pressure']).reshape(-1,1)
        Y_prt1 = self.blue_model.predict(X_prt1)

        # Blue or orange prediction with KNeighbors data
        self.bluelabel = self.chooseblue.predict(df_pr[['compressor_discharge_pressure', 'compressor_speed']].to_nump

        #X_prt = np.array(df_pr['compressor_discharge_pressure']).reshape(-1,1)
        #Y_prt = self.blue_model.predict(X_prt)
        for i in np.arange(len(Y_prt)):
            if (self.bluelabel[i] == True):
                Y_prt[i] = Y_prt1[i]

        for i in np.arange(len(Y_prt)):
            if ((df_pr['exhaust_temperature']==0)[i]==True):
                Y_prt[i] = 0

        return Y_prt
```

Implementation

For validation purposes, we focus in

Hyperparameters:

linear cut
- slope parameter
- offset parameter

kNearNeigh
- k value

EXH_T vs POWER linear regression (Orange predictor)

CDP vs POWER linear regression (Blue predictor)

```python
class MyModel():
    # default constructor
    def __init__(self, linear_cut_slope = 1640, linear_cut_intercept = 0, knum = 3):
        self.linear_cut_slope = linear_cut_slope
        self.linear_cut_intercept = linear_cut_intercept
        self.knum = knum

    # a method for printing data members
    def train(self, df_tr):
        self.df_tr = df_tr #dataframe for training

        # Linear Regression EXH_T vs POWER
        X_tr = np.array(df_tr['exhaust_temperature']).reshape(-1,1)
        Y_tr = np.array(df_tr['power']).reshape(-1,1)

        self.orange_model = LinearRegression().fit(X_tr, Y_tr)

        # KNeighbors data election with CDP and CMP_SPEED
        self.bluemask = df_tr['power'] < (self.linear_cut_slope)*df_tr['compressor_discharge_pressure'] + (self.linea
        df_X_kmeans = df_tr[['compressor_discharge_pressure', 'compressor_speed']].to_numpy()
        df_Y_kmeans = self.bluemask #np.array([0 for i in df_X_kmeans])

        self.chooseblue = KNeighborsClassifier(self.knum)
        self.chooseblue.fit(df_X_kmeans, df_Y_kmeans)

        # Linear Regression CDP vs POWER
        X_tr = np.array(df_tr['compressor_discharge_pressure']).reshape(-1,1)
        Y_tr = np.array(df_tr['power']).reshape(-1,1)

        self.blue_model = LinearRegression().fit(X_tr[self.bluemask], Y_tr[self.bluemask])

    def predict(self, df_pr): #dataframe for predicting

        # Predict with Linear Regression EXH_T vs POWER
        X_prt = np.array(df_pr['exhaust_temperature']).reshape(-1,1)
        Y_prt = self.orange_model.predict(X_prt)

        # Predict with Linear Regression CDP vs POWER
        X_prt1 = np.array(df_pr['compressor_discharge_pressure']).reshape(-1,1)
        Y_prt1 = self.blue_model.predict(X_prt1)

        # Blue or orange prediction with KNeighbors data
        self.bluelabel = self.chooseblue.predict(df_pr[['compressor_discharge_pressure', 'compressor_speed']].to_nump

        #X_prt = np.array(df_pr['compressor_discharge_pressure']).reshape(-1,1)
        #Y_prt = self.blue_model.predict(X_prt)
        for i in np.arange(len(Y_prt)):
            if (self.bluelabel[i] == True):
                Y_prt[i] = Y_prt1[i]

        for i in np.arange(len(Y_prt)):
            if ((df_pr['exhaust_temperature']==0)[i]==True):
                Y_prt[i] = 0

        return Y_prt
```

Implementation

For validation purposes, we focus in

Hyperparameters:

linear cut

- slope parameter
- offset parameter

kNearNeigh

- k value

determination of slope parameter and k value

```
num_folds = 4
k_choices = [1, 2, 3, 5, 8, 10]
intercept_choices = [-250, -125, 0, 125, 250, 375]


df_train_folds = np.array_split(df_train, 4)
accuracies = {}
```

```
for intercept_par in intercept_choices:
    for k in k_choices:
        accuracies[(k,intercept_par)] = []

        for i_folds in np.arange(num_folds):

            classifier = MyModel(linear_cut_intercept = intercept_par, knum = k)

            df_train_foldset = pd.concat(df_train_folds[:i_folds] + df_train_folds[i_folds+1:])
            df_test_foldset = df_train_folds[i_folds]

            classifier.train(df_train_foldset)

            y_val_pred = classifier.predict(df_test_foldset)

            MSE = mean_squared_error(df_test_foldset['power'], y_val_pred)
            RMSE = math.sqrt(MSE)

            #print(RMSE)
            accuracies[(k,intercept_par)].append(RMSE)
```

Implementation

For validation purposes, we focus in

Hyperparameters:

linear cut
- slope parameter
- offset parameter

kNearNeigh
- k value

determination of slope parameter and k value

```
for intercept_par in intercept_choices:
    for k in k_choices:
        print(accuracies[(k,intercept_par)], k,intercept_par)
```

```
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[1176.1748988136167, 1213.7415163514963, 506.85154457416917, 753.791525556725] 2 -250
[1104.2329908659556, 1180.9054821146892, 560.7621590359508, 792.3219989650157] 3 -250
[1114.9724318738902, 1093.1364212209833, 633.0782248148932, 853.0426108837495] 5 -250
[1100.1131734566654, 1101.7766370853446, 621.17422362265, 852.2516153111765] 8 -250
[1092.2061351219018, 1119.9829962622762, 616.6459600142534, 849.1563659031169] 10 -250
[1081.6759188698131, 1185.5624089401147, 438.5999500526191, 800.0040307516825] 1 -125
[1154.3469506957956, 1199.4709511826977, 464.32929221348894, 750.1794890841571] 2 -125
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[1115.1828735946954, 1196.1396277874614, 631.5002747963688, 851.2217841515505] 5 -125
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[1092.2644702488415, 1119.8259609198958, 615.1874323053725, 847.370358769189] 10 -125
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[1092.3509084046932, 1119.192090871778, 614.4254229527345, 846.0628320242532] 10 125
[1082.0567812687184, 1190.6552628236955, 451.41525188481995, 797.345678280727] 1 250
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[1083.1399561255516, 1182.1923411450116, 558.2616498450374, 788.7103312182285] 3 250
[1080.8688021659837, 1195.1355078696163, 630.3270210066001, 849.8754772881183] 5 250
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[1080.9396296817363, 1194.3357614907202, 629.7872965914244, 847.991461198329] 5 375
[1074.9089382959046, 1100.1999504765781, 617.988468225859, 848.5440958314767] 8 375
[1092.4133346102672, 1118.1178637687, 613.7719621186765, 845.4986052978034] 10 375
```

Implementation

For validation purposes, we focus in

Hyperparameters:

linear cut
- ❑ slope parameter
- ❑ offset parameter

kNearNeigh
- ❑ k value

k value = 3
offset parameter = 125

determination of slope parameter and k value

```
for intercept_par in intercept_choices:
    for k in k_choices:
        print(accuracies[(k,intercept_par)], k,intercept_par)
```

```
[1099.1346176699706, 1186.1864374990985, 458.33667232959084, 801.0373755391048] 1 -250
[1176.1748988136167, 1213.7415163514963, 506.85154457416917, 753.791525556725] 2 -250
[1104.2329908659556, 1180.9054821146892, 560.7621590359508, 792.3219989650157] 3 -250
[1114.9724318738902, 1093.1364212209833, 633.0782248148932, 853.0426108837495] 5 -250
[1100.1131734566654, 1101.7766370853446, 621.17422362265, 852.2516153111765] 8 -250
[1092.2061351219018, 1119.9829962622762, 616.6459600142534, 849.1563659031169] 10 -250
[1081.6759188698131, 1185.5624089401147, 438.5999500526191, 800.0040307516825] 1 -125
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[1115.1828735946954, 1196.1396277874614, 631.5002747963688, 851.2217841515505] 5 -125
[1100.338258440857, 1101.7585067040288, 619.7109162712446, 850.4487903815495] 8 -125
[1092.2644702488415, 1119.8259609198958, 615.1874323053725, 847.370358769189] 10 -125
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[1145.7484285694861, 1187.8408412467832, 463.5041476382327, 744.1664981457147] 2 375
[1083.246560962938, 1181.4159354750084, 557.7799779418941, 788.0976953718168] 3 375
[1080.9396296817363, 1194.3357614907202, 629.7872965914244, 847.991461198329] 5 375
[1074.9089382959046, 1100.1999504765781, 617.988468225859, 848.5440958314767] 8 375
[1092.4133346102672, 1118.1178637687, 613.7719621186765, 845.4986052978034] 10 375
```

Application

Post-processing

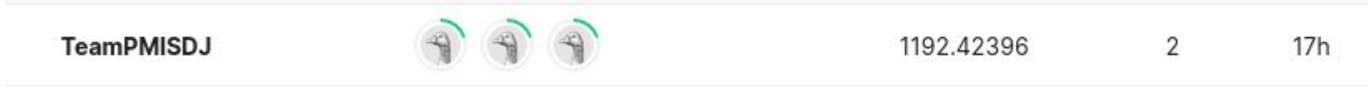
```
# Cambiar el tipo de la variable 'date' a tipo fecha
df_pred_output['date'] = pd.to_datetime(df_pred_output['date'])
```

```
# Modificar la columna de 'date' para que tenga el formato correcto de output
df_pred_output['date'] = df_pred_output['date'].dt.strftime('%-m/%-d/%Y')
```

```
#Guardar predicciones como submission.csv en esta carpeta
df_pred_output.to_csv('submission.csv', index = False)
```

Change date to correct type

Application



What could be improved?

- ❏ More submissions
- ❏ NaN values not considered at the beginning
- ❏ test_data_123.csv has a lot of NaN variables in the **EXH_T** variable, which does not happen in the trainig data, and was fundamental for the method implementation.a
- ❏ More investigation relating the turbines

Conclusions

- A ‘power’ estimation method for the turbines have been developed based on the Machine Learning classical algorithm (k-NearNeigh, LinearReg)
- The method returns values that vary wildly with the dataset (and not so much with the hyperparameters)
- This approach relies on separating into two classes (the **blue** and **orange** ones), in training and using **two different estimators** (both based on LinerReag) at predicting stage.
- The method suffered of the absence of data in the test_data_123.csv file, particularly in the **EXH_T** variable.

Thanks!