Mercedes-Benz Greener Manufacturing

importing libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')
print(train_data.shape)
print(test_data.shape)
```

```
(4209, 378)
(4209, 377)
```

```
for i in train_data.columns:
    data_type = train_data[i].dtype
    if data_type == 'object':
        print(i)
```

```
X0
X1
X2
X3
X4
X5
X6
X8
```

If for any column(s), the variance is equal to zero, then you need to remove those variable(s).

```
variance = pow(train_data.drop(columns={'ID','y'}).std(),2).to_dict()

null_cnt = 0
for key, value in variance.items():
    if(value==0):
        print('Name = ',key)
        null_cnt = null_cnt+1
print('No of columns which has zero variance = ',null_cnt)
```

```
Name =  X11
Name =  X93
Name =  X107
Name =  X233
Name =  X235
```

```
Name =  X268
Name =  X289
Name =  X290
Name =  X293
Name =  X297
Name =  X330
Name =  X347
No of columns which has zero variance =  12
```

```
train_data =
train_data.drop(columns={'X11','X93','X107','X233','X235','X268','X289
','X290','X293','X297','X330','X347'})
train_data.shape
```

```
(4209, 366)
```

Check for null and unique values for test and train sets

```
train_data.isnull().sum().any()
```

```
False
```

Apply label encoder

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
train_data_feature = train_data.drop(columns={'y','ID'})
train_data_target = train_data.y
print(train_data_feature.shape)
print(train_data_target.shape)
```

```
(4209, 364)
(4209,)
```

```
train_data_feature.describe(include='object')
```

```
          X0    X1    X2    X3    X4    X5    X6    X8
count   4209  4209  4209  4209  4209  4209  4209  4209
unique    47    27    44     7     4    29    12    25
top        z    aa    as     c     d     v     g     j
freq     360   833  1659  1942  4205   231  1042   277
```

```
train_data_feature['X0'] = le.fit_transform(train_data_feature.X0)
train_data_feature['X1'] = le.fit_transform(train_data_feature.X1)
train_data_feature['X2'] = le.fit_transform(train_data_feature.X2)
train_data_feature['X3'] = le.fit_transform(train_data_feature.X3)
train_data_feature['X4'] = le.fit_transform(train_data_feature.X4)
train_data_feature['X5'] = le.fit_transform(train_data_feature.X5)
train_data_feature['X6'] = le.fit_transform(train_data_feature.X6)
train_data_feature['X8'] = le.fit_transform(train_data_feature.X8)
```

PCA (Perform dimensionality reduction)

```
print(train_data_feature.shape)
print(train_data_target.shape)
```

```
(4209, 364)
(4209,)
```

```
from sklearn.decomposition import PCA
pca = PCA(n_components=.95)
```

```
pca.fit(train_data_feature, train_data_target)
```

```
PCA(n_components=0.95)
```

```
train_data_feature_trans = pca.fit_transform(train_data_feature)
print(train_data_feature_trans.shape)
```

```
(4209, 6)
```

Predict your test_df values using XGBoost

Building model using the train data set

```
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
from math import sqrt
```

```
train_x,test_x,train_y,test_y =
train_test_split(train_data_feature_trans,train_data_target,test_size=
.3,random_state=7)
print(train_x.shape)
print(train_y.shape)
print(test_x.shape)
print(test_y.shape)
```

```
(2946, 6)
(2946,)
(1263, 6)
(1263,)
```

XGBoost's hyperparameters tuning

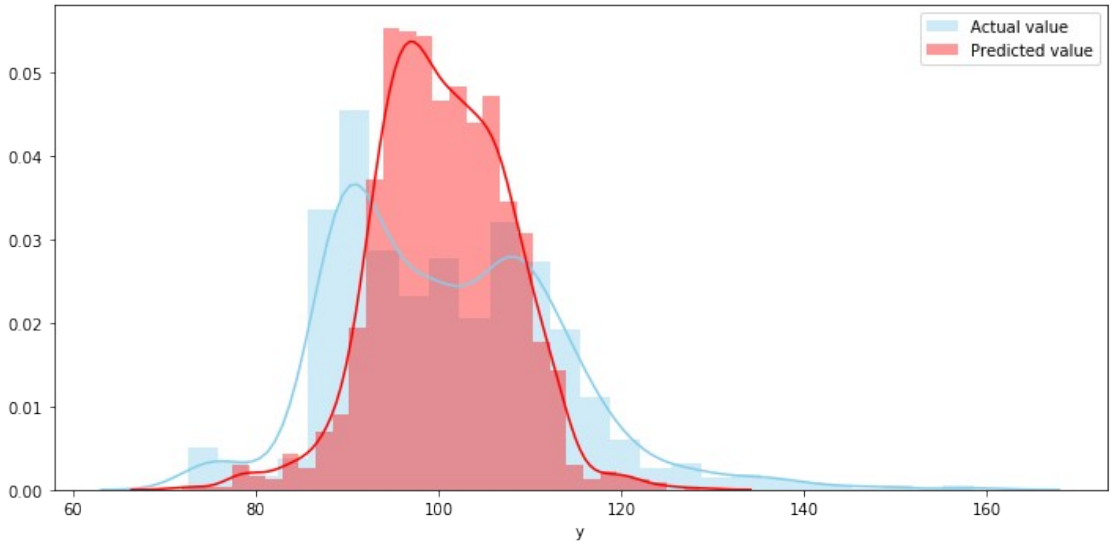
```
xgb_reg = xgb.XGBRegressor(objective ='reg:linear', colsample_bytree =
0.3, learning_rate = 0.4, max_depth = 10, alpha = 6,
                           n_estimators = 20)
model = xgb_reg.fit(train_x,train_y)
print('RMSE =
',sqrt(mean_squared_error(model.predict(test_x),test_y)))
```

```
[14:02:01] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.1/src/objective/regression_obj.cu:188: reg:linear is
```

```
now deprecated in favor of reg:squarederror.
RMSE =  12.288794806074309
```

- After tuning the hyperparameters to meet minimum RMSE, RMSE turned out as 12.29

```
pred_test_y = model.predict(test_x)

plt.figure(figsize=(10,5))

sns.distplot(test_y[test_y<160], color="skyblue", label="Actual
value")
sns.distplot(pred_test_y[pred_test_y<160] , color="red",
label="Predicted value")
plt.legend()

plt.tight_layout()
```



k-fold Cross Validation using XGBoost

```
dmatrix_train =
xgb.DMatrix(data=train_data_feature_trans,label=train_data_target)

params = {'objective':'reg:linear', 'colsample_bytree': 0.3,
'learning_rate': 0.3, 'max_depth': 5, 'alpha': 10}

model_cv = xgb.cv(dtrain=dmatrix_train, params=params, nfold=3,
num_boost_round=50, early_stopping_rounds=10,
                      metrics="rmse", as_pandas=True, seed=7)
model_cv.tail(4)
```

```
[14:02:02] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.1/src/objective/regression_obj.cu:188: reg:linear is
now deprecated in favor of reg:squarederror.
```

```
[14:02:02] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.1/src/objective/regression_obj.cu:188: reg:linear is
now deprecated in favor of reg:squarederror.
[14:02:02] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.1/src/objective/regression_obj.cu:188: reg:linear is
now deprecated in favor of reg:squarederror.
```

	train-rmse-mean	train-rmse-std	test-rmse-mean	test-rmse-std
31	8.935207	0.183408	11.060048	0.736219
32	8.880285	0.174860	11.044371	0.740167
33	8.849045	0.185328	11.049080	0.738352
34	8.792400	0.202135	11.043289	0.728256

Prediction on test data set using XGBoost

Preparing test data set

```
test_data =
test_data.drop(columns={'X11','X93','X107','X233','X235','X268','X289'
,'X290','X293','X297','X330','X347'})
test_data.shape
```

```
(4209, 365)
```

```
test_data.isnull().sum().any()
```

```
False
```

```
test_data_feature = test_data.drop(columns={'ID'})
print(test_data_feature.shape)
```

```
(4209, 364)
```

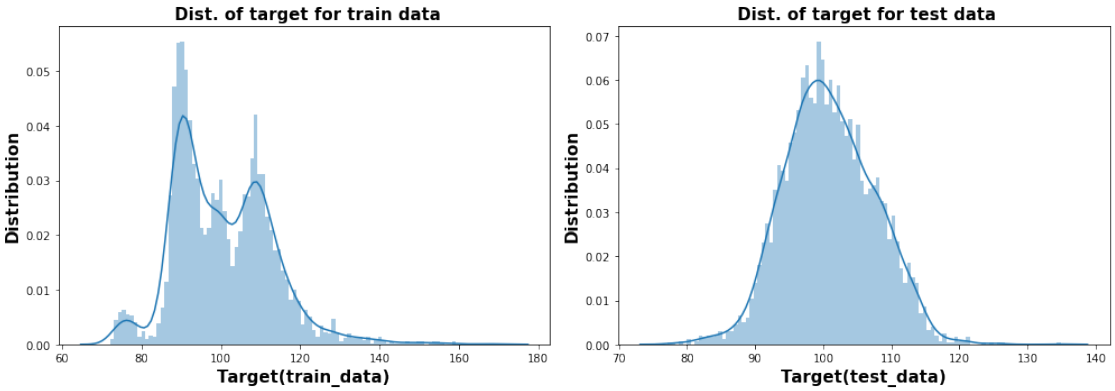
```
test_data_feature.describe(include='object')
```

	X0	X1	X2	X3	X4	X5	X6	X8
count	4209	4209	4209	4209	4209	4209	4209	4209
unique	49	27	45	7	4	32	12	25
top	ak	aa	as	c	d	v	g	e
freq	432	826	1658	1900	4203	246	1073	274

```
test_data_feature['X0'] = le.fit_transform(test_data_feature.X0)
test_data_feature['X1'] = le.fit_transform(test_data_feature.X1)
test_data_feature['X2'] = le.fit_transform(test_data_feature.X2)
test_data_feature['X3'] = le.fit_transform(test_data_feature.X3)
test_data_feature['X4'] = le.fit_transform(test_data_feature.X4)
test_data_feature['X5'] = le.fit_transform(test_data_feature.X5)
test_data_feature['X6'] = le.fit_transform(test_data_feature.X6)
test_data_feature['X8'] = le.fit_transform(test_data_feature.X8)
```

```
pca.fit(test_data_feature)
```

```
PCA(n_components=0.95)

test_data_feature_trans = pca.fit_transform(test_data_feature)
print(test_data_feature_trans.shape)

(4209, 6)

test_pred = model.predict(test_data_feature_trans)
test_pred

array([ 86.12015 ,  92.929794,  98.74635 , ...,  92.836525,
118.76457 ,
        98.46741 ], dtype=float32)

fig, ax = plt.subplots(1,2, figsize=(14,5))

train_plot = sns.distplot(train_data_target[train_data_target<200],
bins=100, kde=True, ax=ax[0])
train_plot.set_xlabel('Target(train_data)', weight='bold', size=15)
train_plot.set_ylabel('Distribution', weight='bold', size=15)
train_plot.set_title(' Dist. of target for train data', weight='bold',
size=15)

test_plot = sns.distplot(test_pred[test_pred<200], bins=100, kde=True,
ax=ax[1])
test_plot.set_xlabel('Target(test_data)', weight='bold', size=15)
test_plot.set_ylabel('Distribution', weight='bold', size=15)
test_plot.set_title(' Dist. of target for test data', weight='bold',
size=15)

plt.tight_layout()
```



This is a pictorial view for comparison between the target for training data-set and predicted target for testing data-set.