**Project - Mercedes-Benz Greener Manufacturing
DESCRIPTION
Reduce the time a Mercedes-Benz spends on the test bench.

Problem Statement Scenario:
Since the first automobile, the Benz Patent Motor Car in 1886, Mercedes-Benz has stood for important automotive innovations. These include the passenger safety cell with a crumple zone, the airbag, and intelligent assistance systems. Mercedes-Benz applies for nearly 2000 patents per year, making the brand the European leader among premium carmakers. Mercedes-Benz is the leader in the premium car industry. With a huge selection of features and options, customers can choose the customized Mercedes-Benz of their dreams.

To ensure the safety and reliability of every unique car configuration before they hit the road, the company's engineers have developed a robust testing system. As one of the world's biggest manufacturers of premium cars, safety and efficiency are paramount on Mercedes-Benz's production lines. However, optimizing the speed of their testing system for many possible feature combinations is complex and time-consuming without a powerful algorithmic approach.

You are required to reduce the time that cars spend on the test bench. Others will work with a dataset representing different permutations of features in a Mercedes-Benz car to predict the time it takes to pass testing. Optimal algorithms will contribute to faster testing, resulting in lower carbon dioxide emissions without reducing Mercedes-Benz's standards.

Following actions should be performed:
-If for any column(s), the variance is equal to zero, then you need to remove those variable(s).
-Check for null and unique values for test and train sets.
-Apply label encoder.
-Perform dimensionality reduction.
-Predict your test_df values using XGBoost

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
train_data=pd.read_csv('D:\DATASET\ML\Mercedes\\train.csv')
test_data=pd.read_csv('D:\DATASET\ML\Mercedes\\test.csv')
train_data.shape
```

Out[2]: (4209, 378)

In [3]:
```
test_data.shape
```

Out[3]: (4209, 377)

In [4]:
```
train_data.head()
```

Out[4]:

| | ID | y | X0 | X1 | X2 | X3 | X4 | X5 | X6 | X8 | ... | X375 | X376 | X377 | X378 | X379 | X380 | X382 | X383 | X384 | X385 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 130.81 | k | v | at | a | d | u | j | o | ... | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | 6 | 88.53 | k | t | av | e | d | y | l | o | ... | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | 7 | 76.26 | az | w | n | c | d | x | j | x | ... | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| **3** | 9 | 80.62 | az | t | n | f | d | x | l | e | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **4** | 13 | 78.02 | az | v | n | f | d | h | d | n | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

5 rows × 378 columns

In [5]:
```
test_data.head()
```

Out[5]:

| | ID | X0 | X1 | X2 | X3 | X4 | X5 | X6 | X8 | X10 | ... | X375 | X376 | X377 | X378 | X379 | X380 | X382 | X383 | X384 | X385 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | az | v | n | f | d | t | a | w | 0 | ... | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | 2 | t | b | ai | a | d | b | g | y | 0 | ... | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | 3 | az | v | as | f | d | a | j | j | 0 | ... | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **3** | 4 | az | l | n | f | d | z | l | n | 0 | ... | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **4** | 5 | w | s | as | c | d | y | i | m | 0 | ... | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

5 rows × 377 columns

In [6]:
```
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).

In [7]:
```
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
```

In [8]:
```
train_data = train_data.drop(columns={'X11','X93','X107','X233','X235','X268','X289','X290','X293','X297','X330','X347'}
train_data.shape
```

Out[8]: (4209, 366)

# # Check for null and unique values for test and train sets

In [9]:
```
train_data.isnull().sum().any()
```

Out[9]: False

# # Apply label encoder

In [10]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

In [12]:
```
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,)
```

In [14]:
```
train_data_feature.describe(include='object')
```

Out[14]:

| | 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 | w | g | j |
| **freq** | 360 | 833 | 1659 | 1942 | 4205 | 231 | 1042 | 277 |

In [15]:
```
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)
```

# # Perform dimensionality reduction.

In [16]:
```
print(train_data_feature.shape)
print(train_data_target.shape)
```

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

In [21]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components=.95)
```

In [22]:
```
pca.fit(train_data_feature, train_data_target)
```

Out[22]:
```
PCA(n_components=0.95)
```

In [23]:
```
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
```

In [25]:
```
import sys
!{sys.executable} -m pip install xgboost
```

```
Collecting xgboost
  Downloading xgboost-1.6.2-py3-none-win_amd64.whl (125.4 MB)
Requirement already satisfied: scipy in c:\users\112987\anaconda3\lib\site-packages (from xgboost) (1.7.3)
Requirement already satisfied: numpy in c:\users\112987\anaconda3\lib\site-packages (from xgboost) (1.21.5)
Installing collected packages: xgboost
Successfully installed xgboost-1.6.2
```

In [27]:
```
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
```

In [30]:
```
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 manually

In [31]:
```
xgb_reg = xgb.XGBRegressor(objective ='reg:linear', colsample_bytree = 0.3, learning_rate = 0.4, max_depth = 10, alpha =
                           n_estimators = 20)
model = xgb_reg.fit(train_x,train_y)
print('RMSE = ',sqrt(mean_squared_error(model.predict(test_x),test_y)))
```

```
[16:09:34] WARNING: C:/Users/administrator/workspace/xgboost-win64_release_1.6.0/src/objective/regression_obj.cu:203: r
eg:linear is now deprecated in favor of reg:squarederror.
RMSE =  12.288794806074309
```

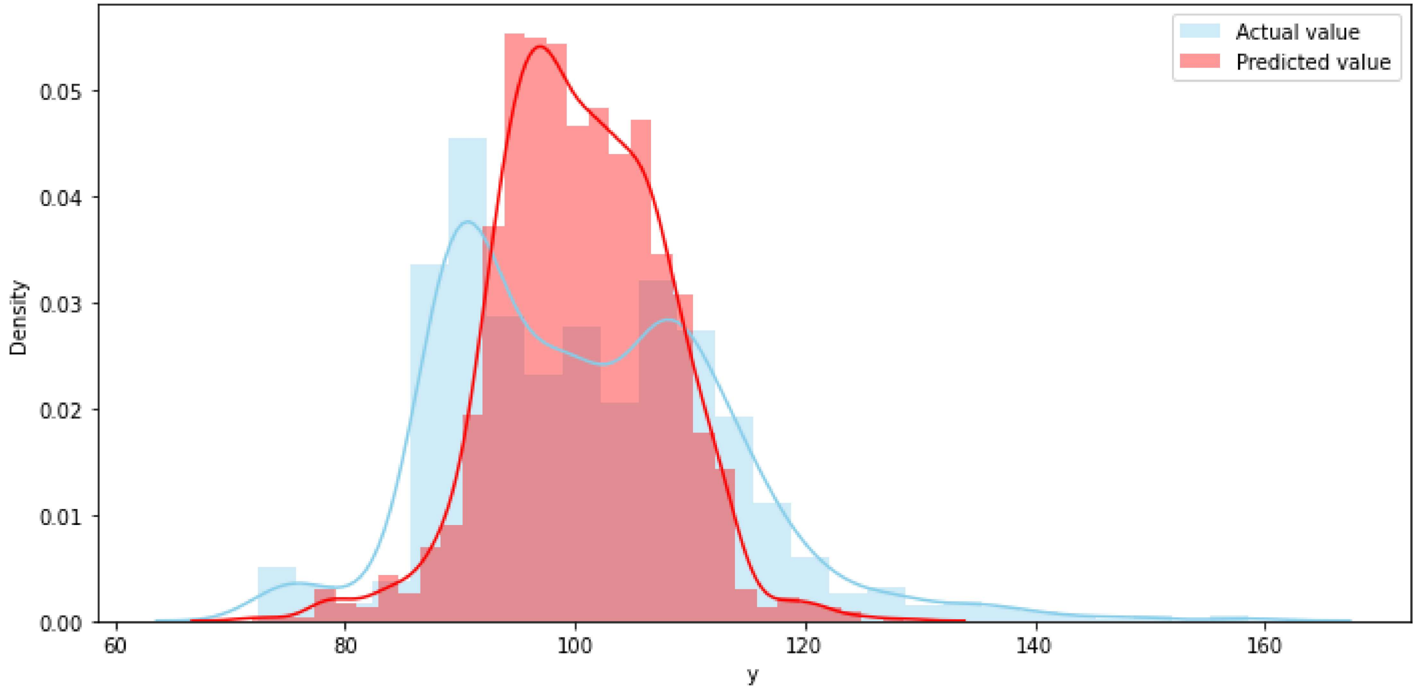
**After tuning the hyperparameters to meet minimum RMSE, RMSE turned out as 12.29

In [32]:
```
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

In [33]:
```
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)
```

```
[16:12:48] WARNING: C:/Users/administrator/workspace/xgboost-win64_release_1.6.0/src/objective/regression_obj.cu:203: r
eg:linear is now deprecated in favor of reg:squarederror.
[16:12:48] WARNING: C:/Users/administrator/workspace/xgboost-win64_release_1.6.0/src/objective/regression_obj.cu:203: r
eg:linear is now deprecated in favor of reg:squarederror.
[16:12:48] WARNING: C:/Users/administrator/workspace/xgboost-win64_release_1.6.0/src/objective/regression_obj.cu:203: r
eg:linear is now deprecated in favor of reg:squarederror.
```

Out[33]:

| | train-rmse-mean | train-rmse-std | test-rmse-mean | test-rmse-std |
|---|---|---|---|---|
| **31** | 8.935207 | 0.183408 | 11.060047 | 0.736219 |
| **32** | 8.880285 | 0.174860 | 11.044372 | 0.740167 |
| **33** | 8.849045 | 0.185327 | 11.049080 | 0.738351 |
| **34** | 8.792400 | 0.202135 | 11.043289 | 0.728256 |

**However, using k-fold cross validation, RMSE comes as 11.04. So the RMSE reduced by ~ 10%

# # Prediction on test data set using XGBoost

**Preparing test data set.

In [34]:
```
test_data = test_data.drop(columns={'X11','X93','X107','X233','X235','X268','X289','X290','X293','X297','X330','X347'})
test_data.shape
```

Out[34]: (4209, 365)

In [35]:
```
test_data.isnull().sum().any()
```

Out[35]:
```
False
```

In [36]:
```
test_data_feature = test_data.drop(columns={'ID'})
print(test_data_feature.shape)
```

```
(4209, 364)
```

In [37]:
```
test_data_feature.describe(include='object')
```

Out[37]:

| | 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 |

In [38]:
```
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)
```

In [39]:
```
pca.fit(test_data_feature)
```

Out[39]:
```
PCA(n_components=0.95)
```

In [40]:
```
test_data_feature_trans = pca.fit_transform(test_data_feature)
print(test_data_feature_trans.shape)
```

```
(4209, 6)
```

In [41]:
```
test_pred = model.predict(test_data_feature_trans)
test_pred
```

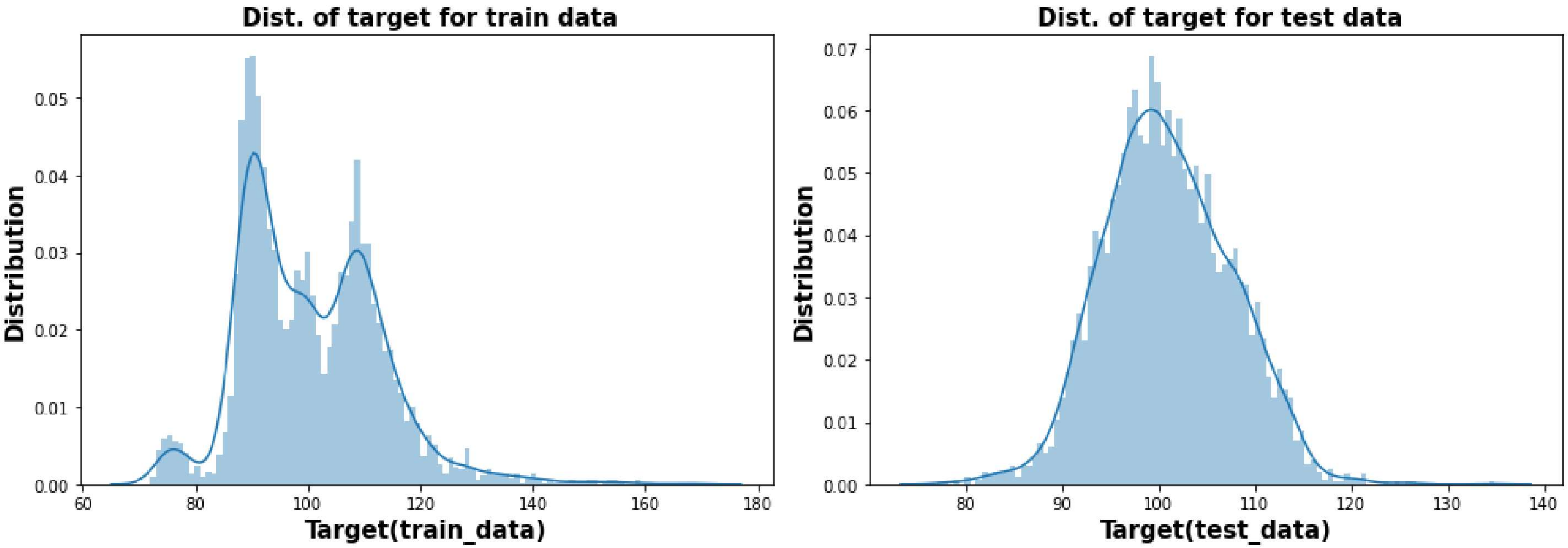
Out[41]:
```
array([ 86.12015 ,  92.929794,  98.74635 , ...,  92.836525, 118.76457 ,
        98.46741 ], dtype=float32)
```

In [42]:
```
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.

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