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Project: Machine Learning with Python (Jupyter Notebooks)

Optimization of Testing Process and Prediction of Time to Pass Testing: Mercedes-Benz

Business Scenario:

Mercedes-Benz is a European leader in innovation among premium carmakers. The company would like to apply their innovation efforts toward reducing their carbon footprint by optimizing their manufacturing testing process while maintaining all current safety and efficiency standards. The best method of optimization requires a combination of technical expertise and a powerful algorithmic approach.

Objectives:

Optimize the manufacturing testing process by minimizing the amount of time that cars spend on the test bench while maintaining safety and efficiency standards.

Summary of Data used for Analysis:

Two data sets are available for analysis. The first, the training data set, contains the Test ID (ID), the time it took to complete testing (y), and 376 columns of data pertaining to the car configuration and tests performed. The second, the testing data set, contains the Test ID (ID) and 376 columns of data, also pertaining to the car configuration and tests performed. Each data set contains 4209 unique Test IDs.

Solutions Executive Summary:

Using analysis and dimensionality reduction we reduce the number of columns of data from 376 to 239, while maintaining 95% of the original data. Although we cannot be certain due to the ambiguity of the data provided, we can assume that this means that at least a number of tests can be obsoleted as a result of the data reduction. In order to verify the data and clear all assumptions, it is critical to verify with the quality and testing teams that any and all tests to be removed do not jeopardize the safety and efficiency of the vehicles tested. The predicted total time required for future tests is within 0.6% of the actual calculated time of performed tests.

Solutions Detailed Summary:

In the effort to remove unnecessary tests, we begin by removing all columns in which the variance was zero. This resulted in the removal of a total of 17 columns:

	index	0
0	X11	0.0
1	X93	0.0
2	X107	0.0
3	X233	0.0
4	X235	0.0
5	X268	0.0
6	X289	0.0
7	X290	0.0
8	X293	0.0
9	X297	0.0
10	X330	0.0
11	X347	0.0
12	X257	0.0
13	X258	0.0
14	X295	0.0
15	X296	0.0
16	X369	0.0

We then check for null values within the Test and Train datasets. Because no null values were found in either dataset, no columns are removed.

```
In [33]: train_null = df_train.isnull().sum() / df_train.shape[0]
         test_null = df_test.isnull().sum() / df_test.shape[0]

In [34]: drop_train_null = train_null[train_null>0]
         drop_test_null = test_null[test_null>0]

In [35]: drop_train_null

Out[35]: Series([], dtype: float64)

In [36]: drop_test_null

Out[36]: Series([], dtype: float64)

In [37]: train_null = df_train.isnull().sum()

In [38]: train_null[train_null>0]

Out[38]: Series([], dtype: int64)
```

Next we apply a label encoder, which transforms 54 unique values stored in 8 columns into binary data stored in over 200 columns. We check for unique values between the Test and Train datasets, and proceed to drop 26 columns. We also remove the column “y” form the Train dataset. The Test and Train datasets now carry the same shape and the same columns:

```
In [55]: df_train_d.shape

Out[55]: (4209, 536)

In [56]: df_test_d.shape

Out[56]: (4209, 536)

In [57]: df_train_y.shape

Out[57]: (4209,)
```

We next prepare for dimensionality reduction by standardizing the Test and Train datasets. After standardization we use principal component analysis to describe 95% of the Train data with 239 principal components instead of the inflated 536.

```
In [63]: X_Train_std=pca.transform(X_Train_std)
         X_Test_std=pca.transform(X_Test_std)

In [64]: X_Train_std.shape

Out[64]: (4209, 239)

In [65]: X_Test_std.shape

Out[65]: (4209, 239)
```

Lastly we predict the amount of time that will be required to bench test the Test data. We do this by feeding the standardized Training data and the associated pre-optimized test bench times into the powerful XGBRegressor algorithm. We observe that the predicted test times for the Test data do not vary much from those for the Train data, when we ignore outliers.

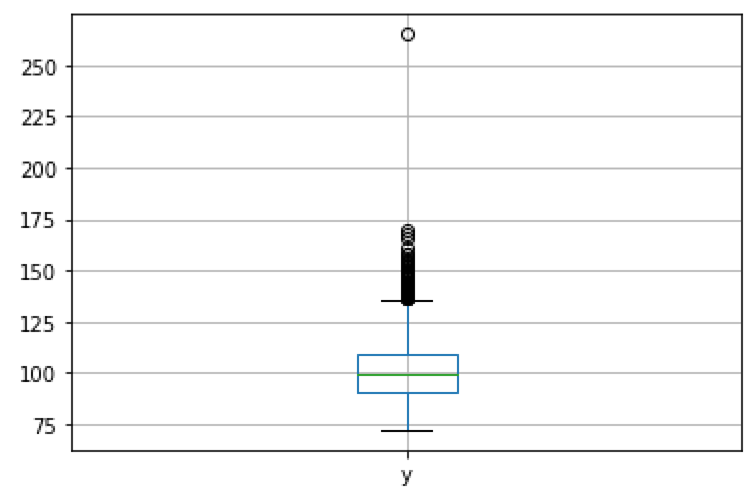
Train Data:

```
df_train_outputs.describe()
```

	ID	y
count	4209.000000	4209.000000
mean	4205.960798	100.669318
std	2437.608688	12.679381
min	0.000000	72.110000
25%	2095.000000	90.820000
50%	4220.000000	99.150000
75%	6314.000000	109.010000
max	8417.000000	265.320000

```
df_train_outputs.boxplot(column = 'y')
```

<AxesSubplot:>



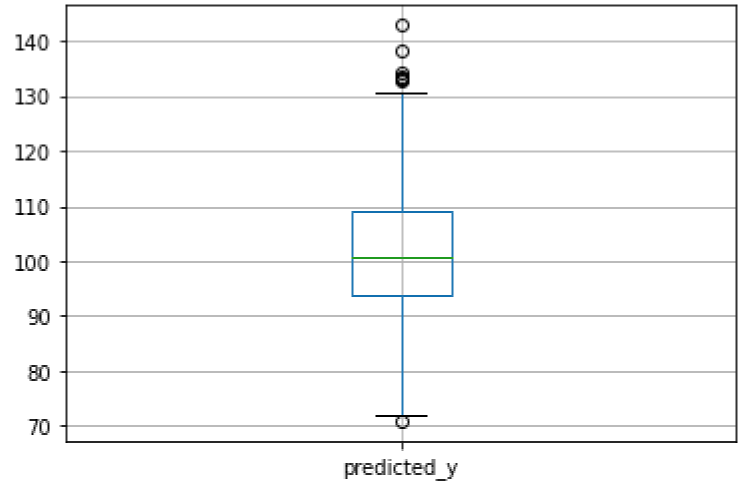
Test Data:

```
df_test_outputs.describe()
```

	ID	predicted_y
count	4209.000000	4209.000000
mean	4211.039202	101.254234
std	2423.078926	9.765374
min	1.000000	70.844231
25%	2115.000000	93.832886
50%	4202.000000	100.800911
75%	6310.000000	109.066719
max	8416.000000	142.908371

```
df_test_outputs.boxplot(column = 'predicted_y')
```

<AxesSubplot:>



We see that the aggregate time for all Test bench testing is nearly 0.6% higher than the aggregate time for all Train bench testing.

```
test_time_mins = sum(df_test_outputs['predicted_y'])
test_time_mins
```

426179.3492126465

```
train_time_mins = sum(df_train_outputs['y'])
train_time_mins
```

423717.1599999995

```
(train_time_mins - test_time_mins)/train_time_mins
```

-0.00581092635626789

Calculations Execution:

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import cross_val_score
import xgboost as xgb
from xgboost import XGBRegressor
```

In [2]:
```
df_train = pd.read_csv("train.csv")
df_test = pd.read_csv("test.csv")
```

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

Out[3]:
```
(4209, 378)
```

In [4]:
```
df_test.shape
```

Out[4]:
```
(4209, 377)
```

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

Out[5]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	X380	X382
0	0	130.81	k	v	at	a	d	u	j	o	...	0	0	1	0	0	0	0
1	6	88.53	k	t	av	e	d	y	l	o	...	1	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
3	9	80.62	az	t	n	f	d	x	l	e	...	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

5 rows × 378 columns

In [6]:
```
df_test.head()
```

Out[6]:

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

5 rows × 377 columns

```
In [7]: # df_train and df_test don't have the same number of columns.
        # Next steps verify which columns are not shared, and then remove those columns
```

```
In [8]: a = df_train.columns
        b = df_test.columns
```

```
In [9]: np.setdiff1d(a,b)
```

```
Out[9]: array(['y'], dtype=object)
```

```
In [10]: np.setdiff1d(b,a)
```

```
Out[10]: array([], dtype=object)
```

```
In [11]: df_train_y = df_train['y']
         df_train_ID = df_train['ID']
         df_test_ID = df_test['ID']
```

```
In [12]: df_train=df_train.drop(['ID','y'], axis=1)
```

```
In [13]: df_test=df_test.drop(['ID'], axis=1)
```

```
In [14]: df_train.shape
```

```
Out[14]: (4209, 376)
```

```
In [15]: df_test.shape
```

```
Out[15]: (4209, 376)
```

```
In [16]: df_train.dtypes.tolist()
```

```
Out[16]: [dtype('O'),
          dtype('O'),
          dtype('O'),
          dtype('O'),
          dtype('O'),
          dtype('O'),
          dtype('O'),
          dtype('O'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
          dtype('int64'),
```

In [17]:
```
df_test.dtypes.tolist()
```

Out[17]:
```
[dtype('O'),
 dtype('O'),
 dtype('O'),
 dtype('O'),
 dtype('O'),
 dtype('O'),
 dtype('O'),
 dtype('O'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
 dtype('int64'),
```

In [18]:
```
# Remove all columns where the variance in either df_train or df_test is equal
```

In [19]:
```
train_var=df_train.var()
test_var=df_test.var()
```

In [20]:
```
drop_train = train_var[train_var==0]
drop_test = test_var[test_var==0]
```

In [21]:
```
drop_train = drop_train.reset_index()
drop_test = drop_test.reset_index()
```

In [22]:
```
drop_all = pd.concat([drop_train, drop_test], ignore_index=True)
```

In [23]:
```
drop_all
```

Out[23]:

	index	0
0	X11	0.0
1	X93	0.0
2	X107	0.0
3	X233	0.0
4	X235	0.0
5	X268	0.0
6	X289	0.0
7	X290	0.0
8	X293	0.0
9	X297	0.0
10	X330	0.0
11	X347	0.0
12	X257	0.0
13	X258	0.0
14	X295	0.0
15	X296	0.0
16	X369	0.0

In [24]:
```
drop_all.shape
```
Out[24]: (17, 2)

In [25]:
```
drop_train.shape
```
Out[25]: (12, 2)

In [26]:
```
drop_test.shape
```
Out[26]: (5, 2)

In [27]:
```
drop_columns = drop_all['index'].tolist()
```

In [28]:
```
df_train=df_train.drop(drop_columns, axis=1)
```

In [29]:
```
df_train.shape
```
Out[29]: (4209, 359)

In [30]:
```
df_test=df_test.drop(drop_columns, axis=1)
```

In [31]:
```
df_test.shape
```
Out[31]: (4209, 359)

In [32]:
```
# Check for null values for test and train sets. Remove columns where >30% of v
# * No null values in either dataframe. So no columns qualify for removal due t
```

In [33]:
```
train_null = df_train.isnull().sum() / df_train.shape[0]
test_null = df_test.isnull().sum() / df_test.shape[0]
```

In [34]:
```
drop_train_null = train_null[train_null>0]
drop_test_null = test_null[test_null>0]
```

In [35]:
```
drop_train_null
```

Out[35]:
```
Series([], dtype: float64)
```

In [36]:
```
drop_test_null
```

Out[36]:
```
Series([], dtype: float64)
```

In [37]:
```
train_null = df_train.isnull().sum()
```

In [38]:
```
train_null[train_null>0]
```

Out[38]:
```
Series([], dtype: int64)
```

In [39]:
```
# Check for Unique Values
```

In [40]:
```
# Apply Label Encoder
# Earlier we calculated the variance of columns in both Test and Train datafram
```

In [41]:
```
X0=df_train['X0'].unique()
X0=X0.tolist()
X1=df_train['X1'].unique()
X1=X1.tolist()
X2=df_train['X2'].unique()
X2=X2.tolist()
X3=df_train['X3'].unique()
X3=X3.tolist()
X4=df_train['X4'].unique()
X4=X4.tolist()
X5=df_train['X5'].unique()
X5=X5.tolist()
X6=df_train['X6'].unique()
X6=X6.tolist()
X8=df_train['X8'].unique()
X8=X8.tolist()
```

In [42]:
```
z=X0+X1+X2+X3+X4+X5+X6+X8
z=np.array(z)
```

In [43]:
```
z=np.unique(z)
z.shape
```

Out[43]:
```
(54,)
```

In [44]:
```
z
```

Out[44]:
```
array(['a', 'aa', 'ab', 'ac', 'ad', 'ae', 'af', 'ag', 'ah', 'ai', 'aj',
       'ak', 'al', 'am', 'an', 'ao', 'ap', 'aq', 'ar', 'as', 'at', 'au',
       'av', 'aw', 'ax', 'ay', 'az', 'b', 'ba', 'bc', 'c', 'd', 'e', 'f',
       'g', 'h', 'i', 'j', 'k', 'l', 'm', 'n', 'o', 'p', 'q', 'r', 's',
       't', 'u', 'v', 'w', 'x', 'y', 'z'], dtype='<U2')
```

In [45]:
```
# We have 54 unique numeric variables across 8 columns.
```

In [46]:
```
df_train_d = pd.get_dummies(df_train, columns=["X0","X1","X2","X3","X4","X5","X
```

In [47]:
```
df_test_d = pd.get_dummies(df_test, columns=["X0","X1","X2","X3","X4","X5","X6"
```

In [48]:
```
df_train_d.shape
```

Out[48]:
```
(4209, 546)
```

In [49]:
```
df_test_d.shape
```

Out[49]:
```
(4209, 552)
```

In [50]:
```
c = df_train_d.columns
d = df_test_d.columns
```

In [51]:
```
e = np.setdiff1d(c,d)
e
```

Out[51]:
```
array(['X0_aa', 'X0_ab', 'X0_ac', 'X0_q', 'X2_aa', 'X2_ar', 'X2_c',
       'X2_l', 'X2_o', 'X5_u'], dtype=object)
```

In [52]:
```
f = np.setdiff1d(d,c)
f
```

Out[52]:
```
array(['X0_ae', 'X0_ag', 'X0_an', 'X0_av', 'X0_bb', 'X0_p', 'X2_ab',
       'X2_ad', 'X2_aj', 'X2_ax', 'X2_u', 'X2_w', 'X5_a', 'X5_b', 'X5_t',
       'X5_z'], dtype=object)
```

In [53]:
```
df_train_d=df_train_d.drop(e, axis=1)
```

In [54]:
```
df_test_d=df_test_d.drop(f, axis=1)
```

In [55]:
```
df_train_d.shape
```

Out[55]:
```
(4209, 536)
```

In [56]:
```
df_test_d.shape
```

Out[56]:
```
(4209, 536)
```

In [57]:
```
df_train_y.shape
```

Out[57]:
```
(4209,)
```

In [58]:
```
# Perform Dimensionality Reduction
```

In [59]:
```
#standardized data
sc = StandardScaler()
sc.fit(df_train_d)
X_Train_std = sc.transform(df_train_d)
X_Test_std = sc.transform(df_test_d)
```

In [60]:
```
pca=PCA(.95)
```

In [61]:
```
pca.fit(X_Train_std)
```

Out[61]:
```
PCA(n_components=0.95)
```

In [62]:
```
pca.n_components_
```

Out[62]:
```
239
```

In [63]:
```
X_Train_std=pca.transform(X_Train_std)
X_Test_std=pca.transform(X_Test_std)
```

In [64]:
```
X_Train_std.shape
```

Out[64]:
```
(4209, 239)
```

In [65]:
```
X_Test_std.shape
```

Out[65]:
```
(4209, 239)
```

In [66]:
```
# ^ 239 Principle Components describe 536 variables!
```

In [67]:
```
xgbr = XGBRegressor()
print(xgbr)
```

```
XGBRegressor(base_score=None, booster=None, colsample_bylevel=None,
             colsample_bynode=None, colsample_bytree=None, gamma=None,
             gpu_id=None, importance_type='gain', interaction_constraints=No
ne,
             learning_rate=None, max_delta_step=None, max_depth=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             random_state=None, reg_alpha=None, reg_lambda=None,
             scale_pos_weight=None, subsample=None, tree_method=None,
             validate_parameters=None, verbosity=None)
```

In [68]:
```
xgbr.fit(X_Train_std, df_train_y)
score = xgbr.score(X_Train_std, df_train_y)
print("Training score: ", score)
```

```
Training score:  0.9691315697840681
```

In [69]:
```
cv_score = cross_val_score(xgbr, X_Train_std, df_train_y, cv=10)
print("CV Mean Score: ", cv_score.mean())
```

```
CV Mean Score:  0.44610269506947847
```

In [70]:
```
predicted_y = xgbr.predict(X_Test_std)
```

In [71]:
```
predicted_y.shape
```

Out[71]:
```
(4209,)
```

```
In [72]: predicted_y
```

```
Out[72]: array([ 74.613976,  90.76615 ,  82.23589 , ...,  94.62366 , 109.953835,
                 90.62505 ], dtype=float32)
```

```
In [73]: df_train_y
```

```
Out[73]: 0       130.81
         1        88.53
         2        76.26
         3        80.62
         4        78.02
                  ...
         4204    107.39
         4205    108.77
         4206    109.22
         4207     87.48
         4208    110.85
         Name: y, Length: 4209, dtype: float64
```

```
In [74]: df_predicted_y = pd.DataFrame(predicted_y, columns=['predicted_y'])
```

```
In [75]: df_predicted_y
```

Out[75]:

	predicted_y
0	74.613976
1	90.766151
2	82.235893
3	76.570267
4	100.413933
...	...
4204	109.702080
4205	93.311920
4206	94.623657
4207	109.953835
4208	90.625053

4209 rows × 1 columns

```
In [76]: df_train_outputs = df_train_ID + df_train_y
```

```
In [77]: df_train_ID = pd.DataFrame(df_train_ID, columns=['ID'])
         df_test_ID = pd.DataFrame(df_test_ID, columns=['ID'])
```

In [78]:
```
df_train_outputs = df_train_ID.join(df_train_y)
df_train_outputs
```

Out[78]:

	ID	y
0	0	130.81
1	6	88.53
2	7	76.26
3	9	80.62
4	13	78.02
...	...	...
4204	8405	107.39
4205	8406	108.77
4206	8412	109.22
4207	8415	87.48
4208	8417	110.85

4209 rows × 2 columns

In [79]:
```
df_test_outputs = df_test_ID.join(df_predicted_y)
df_test_outputs
```

Out[79]:

	ID	predicted_y
0	1	74.613976
1	2	90.766151
2	3	82.235893
3	4	76.570267
4	5	100.413933
...	...	...
4204	8410	109.702080
4205	8411	93.311920
4206	8413	94.623657
4207	8414	109.953835
4208	8416	90.625053

4209 rows × 2 columns

In [80]:
```
df_train_outputs.max()
```

Out[80]:
```
ID     8417.00
y       265.32
dtype: float64
```

In [81]:
```
df_test_outputs.max()
```

Out[81]:
```
ID              8416.000000
predicted_y      142.908371
dtype: float64
```

In [82]:
```
df_train_outputs.describe()
```

Out[82]:

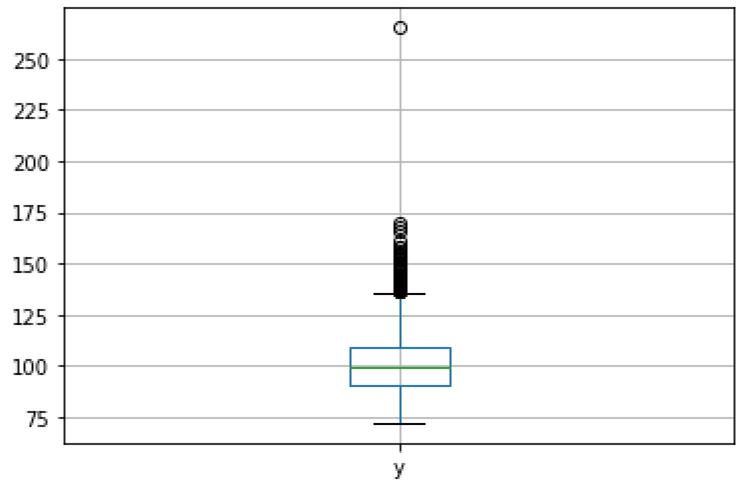
	ID	y
count	4209.000000	4209.000000
mean	4205.960798	100.669318
std	2437.608688	12.679381
min	0.000000	72.110000
25%	2095.000000	90.820000
50%	4220.000000	99.150000
75%	6314.000000	109.010000
max	8417.000000	265.320000

In [83]:
```
df_test_outputs.describe()
```

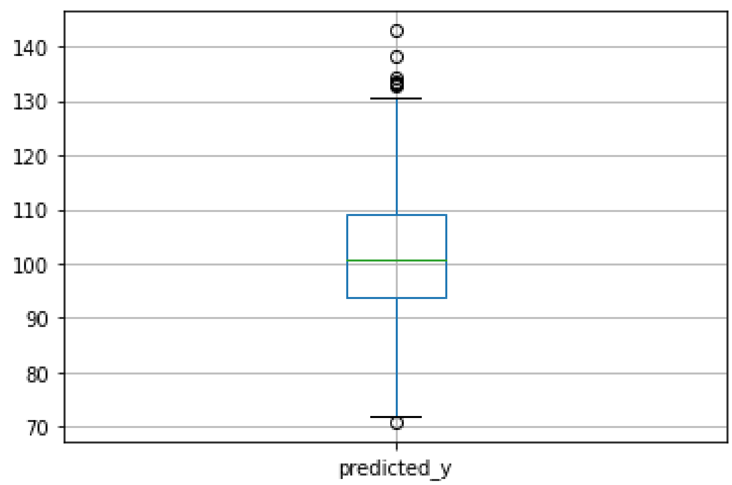
Out[83]:

	ID	predicted_y
count	4209.000000	4209.000000
mean	4211.039202	101.254234
std	2423.078926	9.765374
min	1.000000	70.844231
25%	2115.000000	93.832886
50%	4202.000000	100.800911
75%	6310.000000	109.066719
max	8416.000000	142.908371

In [84]:
```
df_train_outputs.boxplot(column = 'y')
```
Out[84]: <AxesSubplot:>



In [85]:
```
df_test_outputs.boxplot(column = 'predicted_y')
```
Out[85]: <AxesSubplot:>



In [86]:
```
test_time_mins = sum(df_test_outputs['predicted_y'])
test_time_mins
```
Out[86]: 426179.3492126465

In [87]:
```
train_time_mins = sum(df_train_outputs['y'])
train_time_mins
```
Out[87]: 423717.1599999995

In [88]:
```
(train_time_mins - test_time_mins)/train_time_mins
```
Out[88]: -0.00581092635626789

Conclusions:

The Mercedes-Benz test bench process has been optimized using the above procedure. However, the work is not yet complete. It is imperative that we verify with the quality and testing departments that the removal of tests deemed unnecessary will not jeopardize critical safety and efficiency standards of the vehicles tested. It would also be helpful to re-calculate the test time of the Train dataset to reflect the removed tests, in order to more accurately predict the test time of the Test dataset as well as accurately present the time saved as a result of this optimization exercise.