3blq7wmt1

November 13, 2023

Mercedes- Benz Greener Manufacturing

0.0.1 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.

[1]:
```
#Import necessary Libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import xgboost as xgb
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_selection import VarianceThreshold
```

```
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import make_scorer
from sklearn.metrics import r2_score, mean_squared_error
import warnings
```

[2]:
```
#Suppressing warnings for better readability
warnings.filterwarnings("ignore")
```

[3]:
```
#Importing train_data
train_df = pd.read_csv("train.csv")
train_df.head()
```

[3]:
```
   ID       y  X0 X1  X2 X3 X4 X5 X6 X8  …  X375  X376  X377  X378  X379  \
0   0  130.81   k  v  at  a  d  u  j  o  …     0     0     1     0     0
1   6   88.53   k  t  av  e  d  y  l  o  …     1     0     0     0     0
2   7   76.26  az  w   n  c  d  x  j  x  …     0     0     0     0     0
3   9   80.62  az  t   n  f  d  x  l  e  …     0     0     0     0     0
4  13   78.02  az  v   n  f  d  h  d  n  …     0     0     0     0     0

   X380  X382  X383  X384  X385
0     0     0     0     0     0
1     0     0     0     0     0
2     0     1     0     0     0
3     0     0     0     0     0
4     0     0     0     0     0

[5 rows x 378 columns]
```

[4]:
```
#Importing test_data
test_df = pd.read_csv("test.csv")
test_df.head()
```

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

   X382  X383  X384  X385
0     0     0     0     0
1     0     0     0     0
2     0     0     0     0
```

```
3      0      0      0      0
4      0      0      0      0

[5 rows x 377 columns]
```

[5]:
```python
test_df.shape
```

[5]:
```
(4209, 377)
```

[6]:
```python
#Checking the data type of train_df
train_df.dtypes
```

[6]:
```
ID         int64
y        float64
X0        object
X1        object
X2        object
          …
X380       int64
X382       int64
X383       int64
X384       int64
X385       int64
Length: 378, dtype: object
```

[7]:
```python
#Information about train_data
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4209 entries, 0 to 4208
Columns: 378 entries, ID to X385
dtypes: float64(1), int64(369), object(8)
memory usage: 12.1+ MB
```

[8]:
```python
#Printing categorical features in the dataset
print("Categorical Features:")
for i in train_df.columns:
    if train_df[i].dtypes == 'object':
        print(i)
```

```
Categorical Features:
X0
X1
X2
X3
X4
X5
```

```
X6
X8
```

[9]:
```
# Removing the columns 'ID' and 'y' from the data as they are not so important
↪for learning
X_train = train_df.drop(['ID','y'], axis =1)
X_train.head()
```

[9]:
```
  X0 X1  X2 X3 X4 X5 X6 X8  X10  X11  …  X375  X376  X377  X378  X379  \
0  k  v  at  a  d  u  j  o    0    0  …     0     0     1     0     0
1  k  t  av  e  d  y  l  o    0    0  …     1     0     0     0     0
2 az  w   n  c  d  x  j  x    0    0  …     0     0     0     0     0
3 az  t   n  f  d  x  l  e    0    0  …     0     0     0     0     0
4 az  v   n  f  d  h  d  n    0    0  …     0     0     0     0     0

  X380  X382  X383  X384  X385
0    0     0     0     0     0
1    0     0     0     0     0
2    0     1     0     0     0
3    0     0     0     0     0
4    0     0     0     0     0

[5 rows x 376 columns]
```

[10]:
```
X_train.shape
```

[10]:
```
(4209, 376)
```

[11]:
```
#Storing the target feature in y_target
y_train = train_df['y']
```

[12]:
```
y_train.head()
```

[12]:
```
0    130.81
1     88.53
2     76.26
3     80.62
4     78.02
Name: y, dtype: float64
```

[13]:
```
y_train_copy = y_train.copy()
```

[14]:
```
y_train.head()
```

[14]:
```
0    130.81
1     88.53
2     76.26
```

```
3     80.62
4     78.02
Name: y, dtype: float64
```

[15]:
```
id_test = test_df['ID'].values
```

[16]:
```
X_test = test_df.drop('ID', axis = 1)
```

[17]:
```
X_test.head()
```

[17]:
```
   X0 X1  X2 X3 X4 X5 X6 X8  X10  X11  …  X375  X376  X377  X378  X379  \
0  az  v   n  f  d  t  a  w    0    0  …     0     0     0     1     0
1   t  b  ai  a  d  b  g  y    0    0  …     0     0     1     0     0
2  az  v  as  f  d  a  j  j    0    0  …     0     0     0     1     0
3  az  l   n  f  d  z  l  n    0    0  …     0     0     0     1     0
4   w  s  as  c  d  y  i  m    0    0  …     1     0     0     0     0

   X380  X382  X383  X384  X385
0     0     0     0     0     0
1     0     0     0     0     0
2     0     0     0     0     0
3     0     0     0     0     0
4     0     0     0     0     0

[5 rows x 376 columns]
```

[18]:
```
X_test.shape
```

[18]:
```
(4209, 376)
```

0.0.2 Removing Features with Zero Variance

[19]:
```
#Separating numerical features for applying VarianceThreshold
X_train_numerical_features = X_train.iloc[:, 8:]
```

[20]:
```
#Initializing VarianceThreshold with desired threshold (In this case it is Zero)
var_thres = VarianceThreshold(threshold = 0)
```

[21]:
```
#Fitting the VarianceThreshold to the numerical features
var_thres.fit(X_train_numerical_features)
```

[21]:
```
VarianceThreshold(threshold=0)
```

[22]:
```
#Finding the non-constant features
non_constant_features = X_train_numerical_features.columns[var_thres.
 ↪get_support()]
```

[23]:
```python
#Displaying the non-constant features
print('Non-constant features: ', non_constant_features)
```

```
Non-constant features:  Index(['X10', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17',
'X18', 'X19', 'X20',
       …
       'X375', 'X376', 'X377', 'X378', 'X379', 'X380', 'X382', 'X383', 'X384',
       'X385'],
      dtype='object', length=356)
```

[24]:
```python
constant_columns = [column for column in X_train_numerical_features.columns if␣
↪column not in X_train_numerical_features.columns[var_thres.get_support()]]
```

[25]:
```python
for column in constant_columns:
    print(column)
```

```
X11
X93
X107
X233
X235
X268
X289
X290
X293
X297
X330
X347
```

[26]:
```python
X_train_numerical_features.drop(constant_columns, axis = 1, inplace = True)
```

[27]:
```python
#Displaying after removing the columns having zero variance
X_train_numerical_features.head()
```

[27]:

	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	…	X375	X376	X377	\
0	0	0	1	0	0	0	0	1	0	0	…	0	0	1	
1	0	0	0	0	0	0	0	1	0	0	…	1	0	0	
2	0	0	0	0	0	0	1	0	0	0	…	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	…	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	…	0	0	0	

	X378	X379	X380	X382	X383	X384	X385
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0	1	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0

```
[5 rows x 356 columns]
```

0.0.3 Applying Label Encoder

[28]:
```
#Applying Label Encoder to categorical features
LE = LabelEncoder()
```

[29]:
```
X_train_categorical_features = X_train.iloc[:, 0:8]
```

[30]:
```
X_train_categorical_features = X_train_categorical_features.apply(LE.
 ↪fit_transform)
```

[31]:
```
X_train_categorical_features.head()
```

[31]:
```
   X0  X1  X2  X3  X4  X5  X6  X8
0  32  23  17   0   3  24   9  14
1  32  21  19   4   3  28  11  14
2  20  24  34   2   3  27   9  23
3  20  21  34   5   3  27  11   4
4  20  23  34   5   3  12   3  13
```

[32]:
```
#Concatenating categorical and numerical features
Final_X_train = pd.
 ↪concat([X_train_categorical_features,X_train_numerical_features], axis = 1)
```

[33]:
```
Final_X_train.head()
```

[33]:
```
   X0  X1  X2  X3  X4  X5  X6  X8  X10  X12  …  X375  X376  X377  X378  \
0  32  23  17   0   3  24   9  14    0    0  …     0     0     1     0
1  32  21  19   4   3  28  11  14    0    0  …     1     0     0     0
2  20  24  34   2   3  27   9  23    0    0  …     0     0     0     0
3  20  21  34   5   3  27  11   4    0    0  …     0     0     0     0
4  20  23  34   5   3  12   3  13    0    0  …     0     0     0     0

   X379  X380  X382  X383  X384  X385
0     0     0     0     0     0     0
1     0     0     0     0     0     0
2     0     0     1     0     0     0
3     0     0     0     0     0     0
4     0     0     0     0     0     0

[5 rows x 364 columns]
```

[34]:
```
Final_X_train.shape
```

[34]:
```
(4209, 364)
```

[35]:
```
y_train.shape
```

[35]: (4209,)

0.0.4 Applying the same preprocessing steps to the test data

[36]:
```
X_test_categorical_features = X_test.iloc[:,0:8]
```

[37]:
```
X_test_categorical_features.head()
```

[37]:

	X0	X1	X2	X3	X4	X5	X6	X8
0	az	v	n	f	d	t	a	w
1	t	b	ai	a	d	b	g	y
2	az	v	as	f	d	a	j	j
3	az	l	n	f	d	z	l	n
4	w	s	as	c	d	y	i	m

[38]:
```
X_test_categorical_features = X_test_categorical_features.apply(LE.
    ↪fit_transform)
```

[39]:
```
X_test_categorical_features.head()
```

[39]:

	X0	X1	X2	X3	X4	X5	X6	X8
0	21	23	34	5	3	26	0	22
1	42	3	8	0	3	9	6	24
2	21	23	17	5	3	0	9	9
3	21	13	34	5	3	31	11	13
4	45	20	17	2	3	30	8	12

[40]:
```
X_test.drop(X_test.iloc[:,0:8], axis = 1, inplace = True)
```

[41]:
```
var_thres.transform(X_test)
```

[41]:
```
array([[0, 0, 0, …, 0, 0, 0],
       [0, 0, 0, …, 0, 0, 0],
       [0, 0, 0, …, 0, 0, 0],
       …,
       [0, 0, 0, …, 0, 0, 0],
       [0, 0, 1, …, 0, 0, 0],
       [0, 0, 0, …, 0, 0, 0]], dtype=int64)
```

[42]:
```
constant_columns = [column for column in X_test.columns if column not in X_test.
    ↪columns[var_thres.get_support()]]
print(len(constant_columns))
```

```
12
```

[43]:
```
for column in constant_columns:
    print(column)
```

```
X11
X93
X107
X233
X235
X268
X289
X290
X293
X297
X330
X347
```

[44]:
```
X_test.drop(constant_columns, axis =1, inplace = True)
```

[45]:
```
X_test.head()
```

[45]:
```
   X10  X12  X13  X14  X15  X16  X17  X18  X19  X20  …  X375  X376  X377  \
0    0    0    0    0    0    0    0    0    0    0  …     0     0     0
1    0    0    0    0    0    0    0    0    1    0  …     0     0     1
2    0    0    0    1    0    0    0    0    0    0  …     0     0     0
3    0    0    0    0    0    0    0    0    0    0  …     0     0     0
4    0    0    0    1    0    0    0    0    0    0  …     1     0     0

   X378  X379  X380  X382  X383  X384  X385
0     1     0     0     0     0     0     0
1     0     0     0     0     0     0     0
2     1     0     0     0     0     0     0
3     1     0     0     0     0     0     0
4     0     0     0     0     0     0     0

[5 rows x 356 columns]
```

[46]:
```
#Concatenating the categorical features and X_test
Final_X_test=pd.concat([X_test_categorical_features,X_test],axis=1)
Final_X_test.head()
```

[46]:
```
   X0  X1  X2  X3  X4  X5  X6  X8  X10  X12  …  X375  X376  X377  X378  \
0  21  23  34   5   3  26   0  22    0    0  …     0     0     0     1
1  42   3   8   0   3   9   6  24    0    0  …     0     0     1     0
2  21  23  17   5   3   0   9   9    0    0  …     0     0     0     1
3  21  13  34   5   3  31  11  13    0    0  …     0     0     0     1
4  45  20  17   2   3  30   8  12    0    0  …     1     0     0     0
```

```
   X379  X380  X382  X383  X384  X385
0     0     0     0     0     0     0
1     0     0     0     0     0     0
2     0     0     0     0     0     0
3     0     0     0     0     0     0
4     0     0     0     0     0     0

[5 rows x 364 columns]
```

[47]:
```python
Final_X_test.head()
```

[47]:
```
   X0  X1  X2  X3  X4  X5  X6  X8  X10  X12  …  X375  X376  X377  X378  \
0  21  23  34   5   3  26   0  22    0    0  …     0     0     0     1
1  42   3   8   0   3   9   6  24    0    0  …     0     0     1     0
2  21  23  17   5   3   0   9   9    0    0  …     0     0     0     1
3  21  13  34   5   3  31  11  13    0    0  …     0     0     0     1
4  45  20  17   2   3  30   8  12    0    0  …     1     0     0     0

   X379  X380  X382  X383  X384  X385
0     0     0     0     0     0     0
1     0     0     0     0     0     0
2     0     0     0     0     0     0
3     0     0     0     0     0     0
4     0     0     0     0     0     0

[5 rows x 364 columns]
```

[48]:
```python
Final_X_test.shape
```

[48]:
```
(4209, 364)
```

0.0.5 Checking for Null Values and Unique Values in the train and test data

[49]:
```python
# Checking for missing values in the data
def check_missing_values(df):
    if df.isnull().sum().any() == True:
        print("There are missing values in the data")
    else:
        print("There are no missing values in the data")
```

[50]:
```python
check_missing_values(Final_X_train)
```

```
There are no missing values in the data
```

[51]:
```python
check_missing_values(Final_X_test)
```

```
There are no missing values in the data
```

[52]:
```python
# Function to check unique values in each column
def check_unique_values(df):
    for column in df.columns:
        print(f"Unique values in {column}:", df[column].nunique())
```

[53]:
```python
check_unique_values(Final_X_train)
```

```
Unique values in X0: 47
Unique values in X1: 27
Unique values in X2: 44
Unique values in X3: 7
Unique values in X4: 4
Unique values in X5: 29
Unique values in X6: 12
Unique values in X8: 25
Unique values in X10: 2
Unique values in X12: 2
Unique values in X13: 2
Unique values in X14: 2
Unique values in X15: 2
Unique values in X16: 2
Unique values in X17: 2
Unique values in X18: 2
Unique values in X19: 2
Unique values in X20: 2
Unique values in X21: 2
Unique values in X22: 2
Unique values in X23: 2
Unique values in X24: 2
Unique values in X26: 2
Unique values in X27: 2
Unique values in X28: 2
Unique values in X29: 2
Unique values in X30: 2
Unique values in X31: 2
Unique values in X32: 2
Unique values in X33: 2
Unique values in X34: 2
Unique values in X35: 2
Unique values in X36: 2
Unique values in X37: 2
Unique values in X38: 2
Unique values in X39: 2
Unique values in X40: 2
Unique values in X41: 2
Unique values in X42: 2
Unique values in X43: 2
```

```
Unique values in X44: 2
Unique values in X45: 2
Unique values in X46: 2
Unique values in X47: 2
Unique values in X48: 2
Unique values in X49: 2
Unique values in X50: 2
Unique values in X51: 2
Unique values in X52: 2
Unique values in X53: 2
Unique values in X54: 2
Unique values in X55: 2
Unique values in X56: 2
Unique values in X57: 2
Unique values in X58: 2
Unique values in X59: 2
Unique values in X60: 2
Unique values in X61: 2
Unique values in X62: 2
Unique values in X63: 2
Unique values in X64: 2
Unique values in X65: 2
Unique values in X66: 2
Unique values in X67: 2
Unique values in X68: 2
Unique values in X69: 2
Unique values in X70: 2
Unique values in X71: 2
Unique values in X73: 2
Unique values in X74: 2
Unique values in X75: 2
Unique values in X76: 2
Unique values in X77: 2
Unique values in X78: 2
Unique values in X79: 2
Unique values in X80: 2
Unique values in X81: 2
Unique values in X82: 2
Unique values in X83: 2
Unique values in X84: 2
Unique values in X85: 2
Unique values in X86: 2
Unique values in X87: 2
Unique values in X88: 2
Unique values in X89: 2
Unique values in X90: 2
Unique values in X91: 2
Unique values in X92: 2
```

```
Unique values in X94: 2
Unique values in X95: 2
Unique values in X96: 2
Unique values in X97: 2
Unique values in X98: 2
Unique values in X99: 2
Unique values in X100: 2
Unique values in X101: 2
Unique values in X102: 2
Unique values in X103: 2
Unique values in X104: 2
Unique values in X105: 2
Unique values in X106: 2
Unique values in X108: 2
Unique values in X109: 2
Unique values in X110: 2
Unique values in X111: 2
Unique values in X112: 2
Unique values in X113: 2
Unique values in X114: 2
Unique values in X115: 2
Unique values in X116: 2
Unique values in X117: 2
Unique values in X118: 2
Unique values in X119: 2
Unique values in X120: 2
Unique values in X122: 2
Unique values in X123: 2
Unique values in X124: 2
Unique values in X125: 2
Unique values in X126: 2
Unique values in X127: 2
Unique values in X128: 2
Unique values in X129: 2
Unique values in X130: 2
Unique values in X131: 2
Unique values in X132: 2
Unique values in X133: 2
Unique values in X134: 2
Unique values in X135: 2
Unique values in X136: 2
Unique values in X137: 2
Unique values in X138: 2
Unique values in X139: 2
Unique values in X140: 2
Unique values in X141: 2
Unique values in X142: 2
Unique values in X143: 2
```

```
Unique values in X144: 2
Unique values in X145: 2
Unique values in X146: 2
Unique values in X147: 2
Unique values in X148: 2
Unique values in X150: 2
Unique values in X151: 2
Unique values in X152: 2
Unique values in X153: 2
Unique values in X154: 2
Unique values in X155: 2
Unique values in X156: 2
Unique values in X157: 2
Unique values in X158: 2
Unique values in X159: 2
Unique values in X160: 2
Unique values in X161: 2
Unique values in X162: 2
Unique values in X163: 2
Unique values in X164: 2
Unique values in X165: 2
Unique values in X166: 2
Unique values in X167: 2
Unique values in X168: 2
Unique values in X169: 2
Unique values in X170: 2
Unique values in X171: 2
Unique values in X172: 2
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Unique values in X186: 2
Unique values in X187: 2
Unique values in X189: 2
Unique values in X190: 2
Unique values in X191: 2
Unique values in X192: 2
Unique values in X194: 2
```

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Unique values in X195: 2
Unique values in X196: 2
Unique values in X197: 2
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Unique values in X203: 2
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```

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Unique values in X298: 2
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Unique values in X378: 2
Unique values in X379: 2
Unique values in X380: 2
Unique values in X382: 2
Unique values in X383: 2
Unique values in X384: 2
Unique values in X385: 2
```

[54]:
```
check_unique_values(Final_X_test)
```

```
Unique values in X0: 49
Unique values in X1: 27
Unique values in X2: 45
Unique values in X3: 7
Unique values in X4: 4
Unique values in X5: 32
Unique values in X6: 12
Unique values in X8: 25
Unique values in X10: 2
```

```
Unique values in X12: 2
Unique values in X13: 2
Unique values in X14: 2
Unique values in X15: 2
Unique values in X16: 2
Unique values in X17: 2
Unique values in X18: 2
Unique values in X19: 2
Unique values in X20: 2
Unique values in X21: 2
Unique values in X22: 2
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Unique values in X26: 2
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Unique values in X110: 2
Unique values in X111: 2
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Unique values in X253: 2
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Unique values in X255: 2
Unique values in X256: 2
Unique values in X257: 1
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Unique values in X259: 2
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```
Unique values in X262: 2
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```

```
Unique values in X366: 2
Unique values in X367: 2
Unique values in X368: 2
Unique values in X369: 1
Unique values in X370: 2
Unique values in X371: 2
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Unique values in X373: 2
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Unique values in X378: 2
Unique values in X379: 2
Unique values in X380: 2
Unique values in X382: 2
Unique values in X383: 2
Unique values in X384: 2
Unique values in X385: 2
```

[55]:
```
### Dimensionality Reduction Using PCA
```

[56]:
```
pca = PCA(n_components=0.95)
```

[57]:
```
pca.fit(Final_X_train)
```

[57]:
```
PCA(n_components=0.95)
```

[58]:
```
Final_X_train_transformed = pca.transform(Final_X_train)
```

[59]:
```
Final_X_train_transformed.shape
```

[59]:
```
(4209, 6)
```

[60]:
```
Final_X_test_transformed=pca.transform(Final_X_test)
```

[61]:
```
Final_X_test_transformed.shape
```

[61]:
```
(4209, 6)
```

[62]:
```
#Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(Final_X_train_transformed,
 ↪y_train, test_size=0.3, random_state=42)
```

0.0.6 Model Building and Evaluation

[63]:
```
# Building model using XGBoost on train data
```

[64]:
```
xgbr = xgb.XGBRegressor(objective='reg:linear', colsample_bytree=0.5,␣
↪learning_rate=0.2, max_depth=7, n_estimators=30)
```

[65]:
```
xgbr.fit(X_train, y_train)
```

[65]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=0.5, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.2, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=7, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=30, n_jobs=None,
             num_parallel_tree=None, objective='reg:linear', …)
```

[66]:
```
preds = xgbr.predict(X_test)
```

[67]:
```
rmse = np.sqrt(mean_squared_error(y_test, preds))
```

[68]:
```
# Displaying model performance metrics
print("RMSE: %f" % (rmse))
print('r2_score: ', r2_score(y_test, preds))
```

```
RMSE: 11.291051
r2_score:  0.286889583619657
```

Visualizing the Distribution of Actual and Predicted Values

[69]:
```
# Creating a DataFrame for actual and predicted values
data = {'Actual': y_test, 'Predicted': preds}
df = pd.DataFrame(data)
```

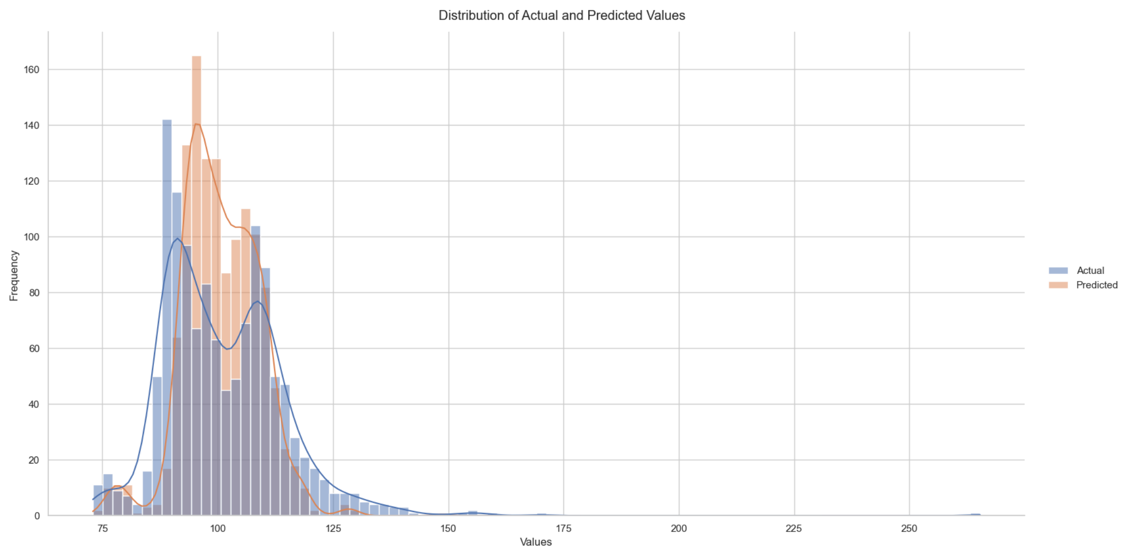
[70]:
```
# Setting the style and context for Seaborn
sns.set(style="whitegrid")
plt.figure(figsize=(12, 8))
```

[70]:
```
<Figure size 1200x800 with 0 Axes>
```

```
<Figure size 1200x800 with 0 Axes>
```

[71]:
```
# Creating the distribution plot
plot = sns.displot(data=df, kde=True, height=8, aspect=2)
```

```
plot.set_axis_labels("Values", "Frequency")
plot.fig.suptitle('Distribution of Actual and Predicted Values', y=1.02)
# Show the plot
plt.show()
```



0.0.7 Hyperparameter Tuning using Grid Search

[72]:
```
param_grid = {
    'learning_rate': [0.1, 0.2, 0.3],
    'max_depth': [5, 6, 7],
    'n_estimators': [20, 30, 40]
}
```

[73]:
```
grid_search = GridSearchCV(estimator=xgbr, param_grid=param_grid, cv=3,␣
 ↪n_jobs=-1, verbose=2)
```

[74]:
```
grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
```

[74]:
```
GridSearchCV(cv=3,
             estimator=XGBRegressor(base_score=None, booster=None,
                                    callbacks=None, colsample_bylevel=None,
                                    colsample_bynode=None, colsample_bytree=0.5,
                                    device=None, early_stopping_rounds=None,
                                    enable_categorical=False, eval_metric=None,
                                    feature_types=None, gamma=None,
                                    grow_policy=None, importance_type=None,
```

```
                                 interaction_constraints=None,
                                 learning_rate=0.2, max…
                                 max_cat_threshold=None,
                                 max_cat_to_onehot=None, max_delta_step=None,
                                 max_depth=7, max_leaves=None,
                                 min_child_weight=None, missing=nan,
                                 monotone_constraints=None,
                                 multi_strategy=None, n_estimators=30,
                                 n_jobs=None, num_parallel_tree=None,
                                 objective='reg:linear', …),
             n_jobs=-1,
             param_grid={'learning_rate': [0.1, 0.2, 0.3],
                         'max_depth': [5, 6, 7], 'n_estimators': [20, 30, 40]},
             verbose=2)
```

[75]:
```
# Getting the best parameters from grid search
best_params = grid_search.best_params_
print("Best parameters:", best_params)
```

```
Best parameters: {'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 40}
```

[76]:
```
# Building the model with the best parameters
best_xgbr = xgb.XGBRegressor(objective='reg:linear', colsample_bytree=0.5,␣
 ↪learning_rate=best_params['learning_rate'],max_depth=best_params['max_depth'],n_estimators=
```

[77]:
```
best_xgbr.fit(X_train, y_train)
```

[77]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=0.5, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=7, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=40, n_jobs=None,
             num_parallel_tree=None, objective='reg:linear', …)
```

[78]:
```
# Making predictions on the validation set with the best model
best_preds = best_xgbr.predict(X_test)
```

[79]:
```
best_rmse = np.sqrt(mean_squared_error(y_test, best_preds))
```

[80]:
```
# Displaying the model performance after tuning
print("Best RMSE after tuning: %f" % (best_rmse))
print('Best r2_score after tuning: ', r2_score(y_test, best_preds))
```

```
Best RMSE after tuning: 11.252240
Best r2_score after tuning:  0.2917834921180851
```

After tuning the model we got the best RMSE, which is 11.25

0.0.8 Predictions on Test Data

[81]:
```python
# Predict on test data using the best model
test_preds = best_xgbr.predict(Final_X_test_transformed)
```

[82]:
```python
# Displaying the predictions on the test data
print("Predictions on the test data:")
print(test_preds)
```

```
Predictions on the test data:
[ 79.98787  105.03395   95.04669  … 103.711685 104.94805  101.07462 ]
```

[83]:
```python
# Creating a DataFrame with the ID column and predictions
output_df = pd.DataFrame({'ID': test_df['ID'], 'y': test_preds})
```

[84]:
```python
output_df
```

[84]:
```
        ID           y
0        1   79.987869
1        2  105.033951
2        3   95.046692
3        4   91.216881
4        5  102.211876
…     …          …
4204  8410  107.010094
4205  8411   97.876816
4206  8413  103.711685
4207  8414  104.948051
4208  8416  101.074623

[4209 rows x 2 columns]
```

[85]:
```python
# Saving the DataFrame to a CSV file
output_df.to_csv('Prediction.csv', index=False)
```

Now, we will further attempt to reduce the RMSE by employing K-Fold Cross-Validation with RandomizedSearchCV to identify the best parameters.

[86]:
```python
# Again checking the shapes of transformed train data and target variable
print("Shape of Final_X_train_transformed:", Final_X_train_transformed.shape)
print("Shape of y_train:", y_train_copy.shape)
```

```
Shape of Final_X_train_transformed: (4209, 6)
Shape of y_train: (4209,)
```

0.0.9 Kfold Cross Validation with RandomizedSearchCV to find the best parameters

[87]:
```
# Set a random seed for reproducibility
random_state = 4242
```

[88]:
```
# Splitting the data into training and validation sets
X_train, X_valid, y_train, y_valid =
↪train_test_split(Final_X_train_transformed, y_train_copy, test_size=0.2,
↪random_state=4242)
```

[89]:
```
# Define a custom scoring function to calculate RMSE
def rmse_scorer(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))
```

[90]:
```
# Define the parameter grid for random search
param_dist = {
    'learning_rate': [0.02, 0.05, 0.1, 0.2],
    'max_depth': [4, 5, 6, 7],
    'n_estimators': [10, 20, 30, 40],
    'colsample_bytree': [0.45, 0.50, 0.6, 0.7, 1.0]
}
```

[91]:
```
# Create the XGBoost model
xgbr = xgb.XGBRegressor(objective='reg:linear')
```

[92]:
```
# Perform K-fold cross-validation with random search
kf = KFold(n_splits=13, shuffle=True, random_state=4242)
```

[93]:
```
random_search = RandomizedSearchCV(estimator=xgbr,
↪param_distributions=param_dist, n_iter=40, cv=kf, n_jobs=-1,
↪scoring=make_scorer(rmse_scorer, greater_is_better=False), random_state=4242)
```

[94]:
```
random_search.fit(X_train, y_train)
```

[94]:
```
RandomizedSearchCV(cv=KFold(n_splits=13, random_state=4242, shuffle=True),
                   estimator=XGBRegressor(base_score=None, booster=None,
                                          callbacks=None,
                                          colsample_bylevel=None,
                                          colsample_bynode=None,
                                          colsample_bytree=None, device=None,
                                          early_stopping_rounds=None,
                                          enable_categorical=False,
                                          eval_metric=None, feature_types=None,
                                          gamma=None, grow_policy=None,
                                          importance_type=…
                                          monotone_constraints=None,
                                          multi_strategy=None,
```

```
                                    n_estimators=None, n_jobs=None,
                                    num_parallel_tree=None,
                                    objective='reg:linear', …),
                   n_iter=40, n_jobs=-1,
                   param_distributions={'colsample_bytree': [0.45, 0.5, 0.6,
                                                             0.7, 1.0],
                                        'learning_rate': [0.02, 0.05, 0.1, 0.2],
                                        'max_depth': [4, 5, 6, 7],
                                        'n_estimators': [10, 20, 30, 40]},
                   random_state=4242,
                   scoring=make_scorer(rmse_scorer, greater_is_better=False))
```

[95]:
```
# Get the best parameters from random search
best_params = random_search.best_params_
print("Best parameters:", best_params)
```

```
Best parameters: {'n_estimators': 40, 'max_depth': 5, 'learning_rate': 0.2,
'colsample_bytree': 1.0}
```

[96]:
```
# Train the final model with the best parameters
xgbr_best = xgb.XGBRegressor(objective='reg:linear', **best_params)
```

[97]:
```
xgbr_best.fit(X_train, y_train, eval_metric="rmse", eval_set=[(X_train,␣
 ↪y_train), (X_valid, y_valid)], early_stopping_rounds=1, verbose=True)
```

```
[0]     validation_0-rmse:12.14276      validation_1-rmse:11.11439
[1]     validation_0-rmse:11.61985      validation_1-rmse:10.58670
[2]     validation_0-rmse:11.23708      validation_1-rmse:10.22761
[3]     validation_0-rmse:10.88403      validation_1-rmse:9.91344
[4]     validation_0-rmse:10.63431      validation_1-rmse:9.69145
[5]     validation_0-rmse:10.47990      validation_1-rmse:9.58799
[6]     validation_0-rmse:10.26181      validation_1-rmse:9.49428
[7]     validation_0-rmse:10.09721      validation_1-rmse:9.41754
[8]     validation_0-rmse:10.00043      validation_1-rmse:9.34202
[9]     validation_0-rmse:9.89744       validation_1-rmse:9.27018
[10]    validation_0-rmse:9.82136       validation_1-rmse:9.26285
[11]    validation_0-rmse:9.71762       validation_1-rmse:9.24684
[12]    validation_0-rmse:9.61939       validation_1-rmse:9.22065
[13]    validation_0-rmse:9.53394       validation_1-rmse:9.19613
[14]    validation_0-rmse:9.39030       validation_1-rmse:9.20527
```

[97]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=1.0, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.2, max_bin=None,
```

```
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=5, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=40, n_jobs=None,
              num_parallel_tree=None, objective='reg:linear', …)
```

[98]:
```
# Make predictions on the training set
preds_train = xgbr_best.predict(X_train)
```

[99]:
```
# Make predictions on the validation set
preds_valid = xgbr_best.predict(X_valid)
```

[100]:
```
# Calculate RMSE for the training set
rmse_train = rmse_scorer(y_train, preds_train)
print("RMSE on the training set:", rmse_train)
```

```
RMSE on the training set: 9.533944047798038
```

[101]:
```
# Calculate RMSE for the validation set
rmse_valid = rmse_scorer(y_valid, preds_valid)
print("RMSE on the validation set:", rmse_valid)
```

```
RMSE on the validation set: 9.196126721821981
```

0.0.10 Predictions on Test Data Using XgBoost

[102]:
```
# Make predictions on the test set
preds_test = xgbr_best.predict(Final_X_test_transformed)
```

[103]:
```
# Display the predictions on the test data
print("Predictions on the test data:")
print(preds_test)
```

```
Predictions on the test data:
[ 80.018326  97.78724   97.737816 … 104.67179  108.53205   98.01387 ]
```

[104]:
```
# Creating a DataFrame with the ID column and predictions
FinalOutput = pd.DataFrame()
FinalOutput['ID'] = id_test
FinalOutput['y'] = preds_test
```

[105]:
```
# Saving the final predictions to a CSV file
FinalOutput.to_csv('Finalpredictions.csv', index=False)
```

[106]:
```
# Displaying the first 30 rows of the final predictions
FinalOutput.head(30)
```

[106]:

	ID	y
0	1	80.018326
1	2	97.787239
2	3	97.737816
3	4	86.885231
4	5	106.913811
5	8	93.962547
6	10	93.150291
7	11	94.715431
8	12	114.863129
9	14	96.264915
10	15	114.549004
11	16	104.512589
12	17	100.101540
13	19	95.390556
14	20	99.948204
15	21	100.372787
16	22	117.756950
17	23	100.101540
18	26	97.845894
19	28	104.686066
20	29	100.101540
21	33	100.101540
22	35	101.978271
23	41	100.101540
24	42	103.070137
25	43	111.051109
26	45	98.807396
27	46	102.356476
28	51	95.801765
29	53	97.737816