

# Mercedes-Benz Greener Manufacturing

January 28, 2021

## 0.1 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.

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.
- Find the datasets here.

## 0.2 Importing packages

```
[68]: import pandas as pd
import numpy as np

from sklearn.decomposition import PCA
from sklearn import preprocessing

import matplotlib.pyplot as plt
%matplotlib inline
```

## 0.3 Loading train and test

```
[69]: train = pd.read_csv("train.csv")
test =pd.read_csv("test.csv")
```

```
[70]: display(train.head())
display(train.sample(3))
display(test.head())
```

	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]

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	\
3400	6785	108.83	ak	v	r	c	d	r	i	i	...	0	0	1	0	
497	958	110.20	a	v	k	d	d	d	e	e	...	0	1	0	0	
2936	5889	98.94	aj	s	as	c	d	p	l	a	...	1	0	0	0	

	X379	X380	X382	X383	X384	X385
3400	0	0	0	0	0	0
497	0	0	0	0	0	0
2936	0	0	0	0	0	0

[3 rows x 378 columns]

	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]

```
[71]: train.shape, test.shape
```

```
[71]: ((4209, 378), (4209, 377))
```

```
[72]: display(train.describe())
display(test.describe())
```

	ID	y	X10	X11	X12	\
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	
mean	4205.960798	100.669318	0.013305	0.0	0.075077	
std	2437.608688	12.679381	0.114590	0.0	0.263547	
min	0.000000	72.110000	0.000000	0.0	0.000000	
25%	2095.000000	90.820000	0.000000	0.0	0.000000	
50%	4220.000000	99.150000	0.000000	0.0	0.000000	
75%	6314.000000	109.010000	0.000000	0.0	0.000000	
max	8417.000000	265.320000	1.000000	0.0	1.000000	

  

	X13	X14	X15	X16	X17	...	\
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	
mean	0.057971	0.428130	0.000475	0.002613	0.007603	...	
std	0.233716	0.494867	0.021796	0.051061	0.086872	...	
min	0.000000	0.000000	0.000000	0.000000	0.000000	...	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	...	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	...	
75%	0.000000	1.000000	0.000000	0.000000	0.000000	...	
max	1.000000	1.000000	1.000000	1.000000	1.000000	...	

  

	X375	X376	X377	X378	X379	\
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	

mean	0.318841	0.057258	0.314802	0.020670	0.009503
std	0.466082	0.232363	0.464492	0.142294	0.097033
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	1.000000	0.000000	1.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	X380	X382	X383	X384	X385
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	0.008078	0.007603	0.001663	0.000475	0.001426
std	0.089524	0.086872	0.040752	0.021796	0.037734
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

[8 rows x 370 columns]

	ID	X10	X11	X12	X13	\
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	
mean	4211.039202	0.019007	0.000238	0.074364	0.061060	
std	2423.078926	0.136565	0.015414	0.262394	0.239468	
min	1.000000	0.000000	0.000000	0.000000	0.000000	
25%	2115.000000	0.000000	0.000000	0.000000	0.000000	
50%	4202.000000	0.000000	0.000000	0.000000	0.000000	
75%	6310.000000	0.000000	0.000000	0.000000	0.000000	
max	8416.000000	1.000000	1.000000	1.000000	1.000000	

	X14	X15	X16	X17	X18	...	\
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	...	
mean	0.427893	0.000713	0.002613	0.008791	0.010216	...	
std	0.494832	0.026691	0.051061	0.093357	0.100570	...	
min	0.000000	0.000000	0.000000	0.000000	0.000000	...	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	...	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	...	
75%	1.000000	0.000000	0.000000	0.000000	0.000000	...	
max	1.000000	1.000000	1.000000	1.000000	1.000000	...	

	X375	X376	X377	X378	X379	\
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	
mean	0.325968	0.049656	0.311951	0.019244	0.011879	
std	0.468791	0.217258	0.463345	0.137399	0.108356	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	1.000000	0.000000	1.000000	0.000000	0.000000	

max	1.000000	1.000000	1.000000	1.000000	1.000000
	X380	X382	X383	X384	X385
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	0.008078	0.008791	0.000475	0.000713	0.001663
std	0.089524	0.093357	0.021796	0.026691	0.040752
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

[8 rows x 369 columns]

```
[73]: train.isnull().any()
```

```
[73]: ID      False
      y      False
      X0     False
      X1     False
      X2     False
      ...
      X380   False
      X382   False
      X383   False
      X384   False
      X385   False
      Length: 378, dtype: bool
```

```
[74]: test.isnull().any()
```

```
[74]: ID      False
      X0     False
      X1     False
      X2     False
      X3     False
      ...
      X380   False
      X382   False
      X383   False
      X384   False
      X385   False
      Length: 377, dtype: bool
```

```
[75]: display(test.dtypes.head(15))
      display(test.dtypes.tail(15))
```

```
ID      int64
```

```
X0      object
X1      object
X2      object
X3      object
X4      object
X5      object
X6      object
X8      object
X10     int64
X11     int64
X12     int64
X13     int64
X14     int64
X15     int64
dtype: object

X370    int64
X371    int64
X372    int64
X373    int64
X374    int64
X375    int64
X376    int64
X377    int64
X378    int64
X379    int64
X380    int64
X382    int64
X383    int64
X384    int64
X385    int64
dtype: object
```

## 0.4 exploring Train data

```
[76]: y_train = train["y"].values
      y_train
```

```
[76]: array([130.81,  88.53,  76.26, ..., 109.22,  87.48, 110.85])
```

```
[77]: features = [col for col in train.columns if 'X' in col]
      len(features)
```

```
[77]: 376
```

```
[78]: train[features].dtypes.value_counts()
```

```
[78]: int64      368
      object      8
      dtype: int64
```

## 0.5 Exploring test data

```
[79]: test_features = [col for col in test.columns if 'X' in col]
      len(test_features)
```

```
[79]: 376
```

```
[80]: test[test_features].dtypes.value_counts()
```

```
[80]: int64      368
      object      8
      dtype: int64
```

```
[ ]:
```

```
[81]: #removing unusable columns from train and test

usable_columns = list(set(train.columns)-set(["ID","y"]))

y_train = train["y"].values
id_test = test["ID"].values
print("y_train:",y_train)
print("id_test:",id_test)
print("y_train_shape:",y_train.shape)
print("id_test_shape:",id_test.shape)
```

```
y_train: [130.81  88.53  76.26 ... 109.22  87.48 110.85]
id_test: [   1    2    3 ... 8413 8414 8416]
y_train_shape: (4209,)
id_test_shape: (4209,)
```

```
[82]: X_train = train[usable_columns]
      X_test = test[usable_columns]
      print("X_train:",X_train.columns)
      print("X_test:",X_test.columns)
      print("X_train shape:",X_train.shape)
      print("X_test shape:",X_test.shape)
```

```
X_train: Index(['X184', 'X291', 'X131', 'X243', 'X126', 'X251', 'X105', 'X316',
               'X247',
               'X30',
               ...
```

```

        'X195', 'X364', 'X15', 'X123', 'X130', 'X230', 'X124', 'X59', 'X206',
        'X106'],
        dtype='object', length=376)
X_test: Index(['X184', 'X291', 'X131', 'X243', 'X126', 'X251', 'X105', 'X316',
              'X247',
              'X30',
              ...
              'X195', 'X364', 'X15', 'X123', 'X130', 'X230', 'X124', 'X59', 'X206',
              'X106'],
              dtype='object', length=376)
X_train shape: (4209, 376)
X_test shape: (4209, 376)

```

```

[83]: if X_train.isnull().any() is True:
        print("Missing values in X_Train")
    else:
        print("no Missing values in X_train")

```

no Missing values in X\_train

```

[84]: if X_test.isnull().any() is True:
        print("Missing values in X_Train")
    else:
        print("no Missing values in X_test")

```

no Missing values in X\_test

## 0.6 Dropping the Zero variance columns from train and test data

```

[85]: for column in usable_columns:
        cardinality = len(np.unique(X_train[column]))
        if cardinality ==1:
            X_train.drop(column,axis=1)
            X_test.drop(column,axis=1)
    X_train.head()

```

```

[85]:
   X184  X291  X131  X243  X126  X251  X105  X316  X247  X30  ...  X195  X364  \
0      1      0      1      0      0      0      0      1      0      0  ...      0      0
1      0      0      0      0      0      0      0      1      0      0  ...      0      0
2      0      0      0      0      0      0      0      0      0      0  ...      0      0
3      0      1      0      0      0      0      0      0      0      0  ...      0      0
4      0      0      0      0      0      0      0      0      0      0  ...      0      0

   X15  X123  X130  X230  X124  X59  X206  X106
0      0      0      0      0      0      0      0      0
1      0      0      0      0      0      0      0      0

```



2	0	0	0	0	0	0	1	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0

[5 rows x 376 columns]

## 0.7 Label encoding to categorical variables in test and train data

```
[86]: for f in ["X0", "X1", "X2", "X3", "X4", "X5", "X6", "X8"]:
        lbl = preprocessing.LabelEncoder()
        lbl.fit(list(X_train[f].values))
        X_train[f] = lbl.transform(list(X_train[f].values))
```

<ipython-input-86-2a0d19a9992f>:4: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
X\_train[f] = lbl.transform(list(X\_train[f].values))

```
[87]: X_train[["X0", "X1", "X2", "X3", "X4", "X5", "X6", "X8"]].dtypes
```

```
[87]: X0      int64
      X1      int64
      X2      int64
      X3      int64
      X4      int64
      X5      int64
      X6      int64
      X8      int64
      dtype: object
```

```
[88]: for g in ["X0", "X1", "X2", "X3", "X4", "X5", "X6", "X8"]:
        lbl1 = preprocessing.LabelEncoder()
        lbl1.fit(list(X_test[g].values))
        X_test[g] = lbl1.transform(list(X_test[g].values))
```

<ipython-input-88-07fe900192b5>:4: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
X\_test[g] = lbl1.transform(list(X\_test[g].values))

```
[89]: X_test[["X0", "X1", "X2", "X3", "X4", "X5", "X6", "X8"]].dtypes
```

```
[89]: X0      int64
      X1      int64
      X2      int64
      X3      int64
      X4      int64
      X5      int64
      X6      int64
      X8      int64
      dtype: object
```

```
[90]: X_train[features].dtypes.value_counts()
```

```
[90]: int64      376
      dtype: int64
```

```
[91]: X_test[features].dtypes.value_counts()
```

```
[91]: int64      376
      dtype: int64
```

```
[92]: from sklearn.preprocessing import StandardScaler

      sc = StandardScaler()

      X_train = sc.fit_transform(X_train)
      X_test = sc.transform(X_test)
```

```
[93]: pca1 = PCA()
      pca1_final_train = pca1.fit_transform(X_train)
      pca1_final_test = pca1.fit_transform(X_test)
```

```
[94]: print(pca1.explained_variance_ratio_)
```

```
[6.63394212e-02 5.03269345e-02 4.57153414e-02 3.75767070e-02
 3.18215977e-02 2.89246157e-02 2.51539240e-02 2.06618035e-02
 1.84389008e-02 1.79941209e-02 1.68205036e-02 1.61593234e-02
 1.58080558e-02 1.53189418e-02 1.51697469e-02 1.48712835e-02
 1.46491490e-02 1.36706593e-02 1.31243083e-02 1.28159562e-02
 1.25472520e-02 1.22316005e-02 1.14636195e-02 1.06621052e-02
 9.67132370e-03 9.09804809e-03 9.05450395e-03 8.58955625e-03
 8.49807882e-03 8.31369273e-03 8.10555591e-03 7.92646977e-03
 7.30411059e-03 7.17049852e-03 6.99520860e-03 6.87960083e-03
 6.70708936e-03 6.35045290e-03 6.21684912e-03 6.06173183e-03
 5.87784265e-03 5.75928614e-03 5.67072824e-03 5.37815991e-03
 5.18551283e-03 5.09914357e-03 5.01372028e-03 4.84597228e-03]
```

4.67574449e-03 4.58177883e-03 4.53613387e-03 4.36279045e-03  
 4.33359558e-03 4.26094041e-03 4.23135429e-03 4.17207207e-03  
 4.05056371e-03 4.02800841e-03 3.97633339e-03 3.89846715e-03  
 3.81368647e-03 3.74904277e-03 3.73049306e-03 3.69950969e-03  
 3.62449006e-03 3.60826517e-03 3.46398321e-03 3.40205604e-03  
 3.35923344e-03 3.32238906e-03 3.22194444e-03 3.17971188e-03  
 3.15114993e-03 3.14859055e-03 3.07143844e-03 3.05622002e-03  
 3.01935139e-03 3.00581114e-03 2.90315855e-03 2.90148089e-03  
 2.86918224e-03 2.84286136e-03 2.80118531e-03 2.77532741e-03  
 2.75806525e-03 2.68062792e-03 2.66159817e-03 2.64169140e-03  
 2.62149485e-03 2.60461639e-03 2.58901057e-03 2.54777747e-03  
 2.52455614e-03 2.50312014e-03 2.47790123e-03 2.45632139e-03  
 2.42385499e-03 2.40341530e-03 2.38204128e-03 2.34435082e-03  
 2.33722011e-03 2.29535619e-03 2.25916618e-03 2.25113681e-03  
 2.21760645e-03 2.18768291e-03 2.15668943e-03 2.14209412e-03  
 2.12964433e-03 2.08171443e-03 2.06922156e-03 2.04137843e-03  
 2.02718273e-03 1.99616414e-03 1.97482821e-03 1.95440912e-03  
 1.91671559e-03 1.89835378e-03 1.88365323e-03 1.83200252e-03  
 1.81174526e-03 1.80074982e-03 1.78799974e-03 1.76729831e-03  
 1.73806047e-03 1.67993706e-03 1.66760993e-03 1.64904824e-03  
 1.61420926e-03 1.56399350e-03 1.55951636e-03 1.52990956e-03  
 1.51798411e-03 1.51053990e-03 1.48201907e-03 1.45012409e-03  
 1.42269722e-03 1.41740901e-03 1.34942658e-03 1.32982925e-03  
 1.31730047e-03 1.29728201e-03 1.27387802e-03 1.25805131e-03  
 1.21467877e-03 1.18829574e-03 1.17352838e-03 1.16402666e-03  
 1.14774792e-03 1.11971082e-03 1.09620645e-03 1.06937874e-03  
 1.04238715e-03 1.03367002e-03 1.02671001e-03 1.00237228e-03  
 9.71584996e-04 9.47448343e-04 9.40929300e-04 9.17184858e-04  
 9.01195503e-04 8.70954039e-04 8.57174008e-04 8.26585188e-04  
 8.20212515e-04 8.14160456e-04 7.91832057e-04 7.82846854e-04  
 7.43804208e-04 7.33137596e-04 7.23818969e-04 7.12469091e-04  
 6.96603045e-04 6.65611928e-04 6.58911313e-04 6.41618882e-04  
 6.30206647e-04 6.09402723e-04 6.03204337e-04 5.91160828e-04  
 5.61739453e-04 5.52532993e-04 5.29381571e-04 5.24810515e-04  
 5.19344346e-04 4.97522524e-04 4.87987631e-04 4.74308543e-04  
 4.60371283e-04 4.54883297e-04 4.41691403e-04 4.27752279e-04  
 4.21717140e-04 4.02499320e-04 3.99374354e-04 3.85228354e-04  
 3.69257900e-04 3.55037601e-04 3.42081001e-04 3.35866730e-04  
 3.25836751e-04 3.15929689e-04 2.97158501e-04 2.92186567e-04  
 2.82878040e-04 2.76896256e-04 2.60324878e-04 2.57209562e-04  
 2.53843395e-04 2.44354895e-04 2.37555222e-04 2.27268498e-04  
 2.19007219e-04 2.10417753e-04 2.05524021e-04 1.95790941e-04  
 1.86775801e-04 1.78488532e-04 1.72505451e-04 1.66758532e-04  
 1.55709304e-04 1.49328344e-04 1.44247245e-04 1.33549250e-04  
 1.28522759e-04 1.25949014e-04 1.18713064e-04 1.12713875e-04  
 1.08179073e-04 1.05109773e-04 1.03987183e-04 9.86569143e-05  
 9.30648764e-05 8.92241671e-05 7.95452024e-05 7.44589218e-05  
 7.27134971e-05 6.19355711e-05 5.93551256e-05 5.16258290e-05

```
[96]: print(pca.explained_variance_ratio_)
```

## 0.8 Predicting test\_df values using XGBoost.

```
[97]: import xgboost as xgb
      from sklearn.metrics import r2_score
      from sklearn.model_selection import train_test_split
```

```
[98]: X_train,X_valid,y_train,y_valid =
      ↪train_test_split(pca2_result_train,y_train,test_size=0.20,random_state=21)
```

```
[99]: d_train = xgb.DMatrix(X_train, label=y_train)
      d_valid = xgb.DMatrix(X_valid, label=y_valid)
      d_test = xgb.DMatrix(pca2_result_test)
```

```
[100]: params = {}
      params["objective"] = 'reg:linear'
      params["eta"] = 0.02
      params["max_depth"] = 6
      params["subsample"] = 0.7
      params["colsample_size"] = 0.7

      def xgb_r2_score(preds,dtrain):
          labels = dtrain.get_label()
          return "r2",r2_score(labels,preds)

      watchlist = [(d_train,"train"),(d_valid,"valid")]

      clf = xgb.train(params,d_train,1000,watchlist,early_stopping_rounds=50,feval=
      ↪xgb_r2_score,maximize =True, verbose_eval=10)
```

```
[17:39:51] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.3.0/src/objective/regression_obj.cu:170: reg:linear is now
deprecated in favor of reg:squarederror.
```

```
[17:39:51] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.3.0/src/learner.cc:541:
Parameters: { colsample_size } might not be used.
```

This may not be accurate due to some parameters are only used in language bindings but

passed down to XGBoost core. Or some parameters are not used but slip through this

verification. Please open an issue if you find above cases.

```
[0]      train-rmse:98.98949      train-r2:-58.55114      valid-rmse:98.90655
      valid-r2:-66.25152
```

```
[10]     train-rmse:81.15344      train-r2:-39.02448      valid-rmse:81.02206
      valid-r2:-44.12928
```

[20]	train-rmse:66.62598 valid-r2:-29.36654	train-r2:-25.97734	valid-rmse:66.46175
[30]	train-rmse:54.79835 valid-r2:-19.48905	train-r2:-17.24933	valid-rmse:54.59275
[40]	train-rmse:45.18819 valid-r2:-12.88948	train-r2:-11.40971	valid-rmse:44.94870
[50]	train-rmse:37.38238 valid-r2:-8.47320	train-r2:-7.49270	valid-rmse:37.12124
[60]	train-rmse:31.07233 valid-r2:-5.52118	train-r2:-4.86759	valid-rmse:30.79905
[70]	train-rmse:26.00524 valid-r2:-3.55451	train-r2:-3.10992	valid-rmse:25.73918
[80]	train-rmse:21.92440 valid-r2:-2.23339	train-r2:-1.92124	valid-rmse:21.68717
[90]	train-rmse:18.68536 valid-r2:-1.35099	train-r2:-1.12185	valid-rmse:18.49268
[100]	train-rmse:16.11051 valid-r2:-0.75528	train-r2:-0.57736	valid-rmse:15.97890
[110]	train-rmse:14.11708 valid-r2:-0.35794	train-r2:-0.21116	valid-rmse:14.05445
[120]	train-rmse:12.54812 valid-r2:-0.09039	train-r2:0.04309	valid-rmse:12.59403
[130]	train-rmse:11.33759 valid-r2:0.08925	train-r2:0.21882	valid-rmse:11.50994
[140]	train-rmse:10.41561 valid-r2:0.21033	train-r2:0.34070	valid-rmse:10.71759
[150]	train-rmse:9.69779 valid-r2:0.29170	train-r2:0.42845	valid-rmse:10.15040
[160]	train-rmse:9.15309 valid-r2:0.34697	train-r2:0.49085	valid-rmse:9.74635
[170]	train-rmse:8.73508 valid-r2:0.38360	train-r2:0.53629	valid-rmse:9.46903
[180]	train-rmse:8.39644 valid-r2:0.40859	train-r2:0.57155	valid-rmse:9.27509
[190]	train-rmse:8.14885 valid-r2:0.42581	train-r2:0.59644	valid-rmse:9.13906
[200]	train-rmse:7.93635 valid-r2:0.43769	train-r2:0.61722	valid-rmse:9.04401
[210]	train-rmse:7.76197 valid-r2:0.44373	train-r2:0.63385	valid-rmse:8.99529
[220]	train-rmse:7.60846 valid-r2:0.44794	train-r2:0.64819	valid-rmse:8.96121
[230]	train-rmse:7.49517 valid-r2:0.44965	train-r2:0.65859	valid-rmse:8.94731
[240]	train-rmse:7.39046 valid-r2:0.45065	train-r2:0.66806	valid-rmse:8.93924
[250]	train-rmse:7.28970 valid-r2:0.45125	train-r2:0.67705	valid-rmse:8.93430

```

[260]   train-rmse:7.19950      train-r2:0.68500      valid-rmse:8.92014
valid-r2:0.45299
[270]   train-rmse:7.11905      train-r2:0.69200      valid-rmse:8.92622
valid-r2:0.45225
[280]   train-rmse:7.04576      train-r2:0.69831      valid-rmse:8.93590
valid-r2:0.45105
[290]   train-rmse:6.96334      train-r2:0.70532      valid-rmse:8.94407
valid-r2:0.45005
[300]   train-rmse:6.88008      train-r2:0.71233      valid-rmse:8.94884
valid-r2:0.44947
[310]   train-rmse:6.80763      train-r2:0.71835      valid-rmse:8.95748
valid-r2:0.44840

```

```
[ ]:
```

```

[101]: p_test = clf.predict(d_test)
       p_test

```

```

[101]: array([ 82.744354, 105.80603 ,  82.08374 , ..., 102.205154, 105.8811  ,
              95.3124  ], dtype=float32)

```

## 0.9 Creating a result dataframe

```

[102]: sub = pd.DataFrame()
       sub["ID"] = id_test
       sub["y"] = p_test
       sub.to_csv("xgb.csv", index=False)

```

---