

Project 1 - Mercedes-Benz Greener Manufacturing

November 15, 2022

1 Import Packages

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

from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()

from sklearn.model_selection import train_test_split

from sklearn.decomposition import PCA

import xgboost,time
from sklearn.metrics import r2_score
from sklearn.model_selection import GridSearchCV

import warnings
warnings.filterwarnings('ignore')
```

2 Import Data

```
[2]: train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

3 Check Data

```
[3]: train.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]: test.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]: train.dtypes
```

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

```
[6]: test.dtypes
```

```
[6]: ID      int64
     X0      object
     X1      object
     X2      object
     X3      object
     ...
     X380    int64
     X382    int64
     X383    int64
     X384    int64
     X385    int64
     Length: 377, dtype: object
```

4 Dropping irrelevant column

```
[7]: train = train.drop('ID',axis =1)
     test= test.drop('ID',axis=1)
```

```
[8]: train.head()
```

```
[8]:
```

	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	...	X375	X376	X377	X378	X379	\
0	130.81	k	v	at	a	d	u	j	o	0	...	0	0	1	0	0	
1	88.53	k	t	av	e	d	y	l	o	0	...	1	0	0	0	0	
2	76.26	az	w	n	c	d	x	j	x	0	...	0	0	0	0	0	
3	80.62	az	t	n	f	d	x	l	e	0	...	0	0	0	0	0	
4	78.02	az	v	n	f	d	h	d	n	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 377 columns]

```
[9]: test.head()
```

```
[9]:
```

	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	

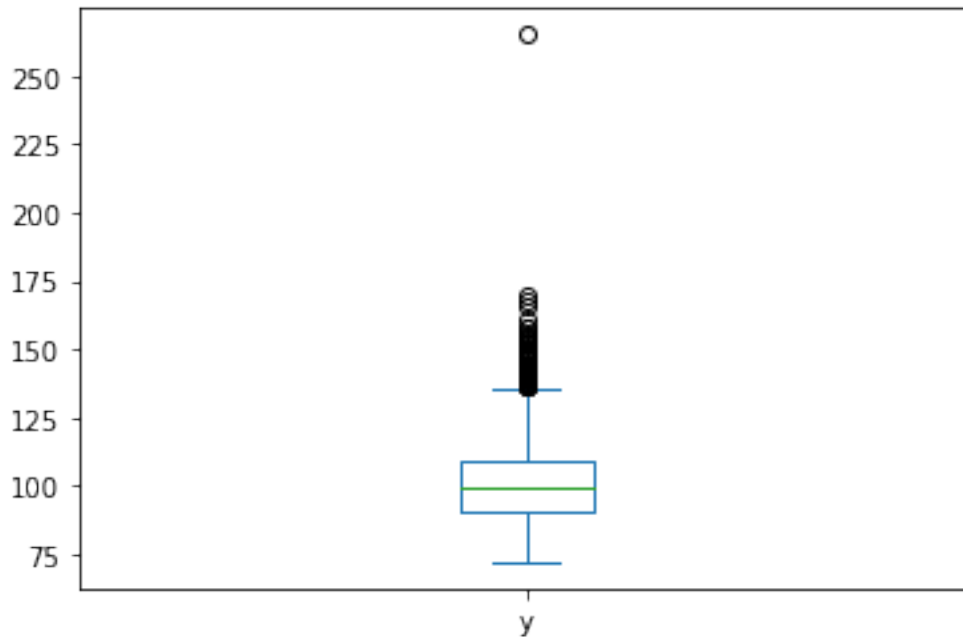
	X380	X382	X383	X384	X385
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

[5 rows x 376 columns]

5 Treat Target Column Outliers

```
[10]: train['y'].plot.box()
```

```
[10]: <AxesSubplot:>
```



```
[11]: Q1 = train['y'].quantile(0.25)
      Q3 = train['y'].quantile(0.75)

      IQR = Q3 - Q1

      lower_range = Q1 - 1.5 * IQR
      upper_range = Q3 + 1.5 * IQR

      print(lower_range)
```

```
print(upper_range)
```

```
63.534999999999975  
136.295000000000002
```

```
[12]: outlier_index = train[(train.y > upper_range)].index  
      outlier_index
```

```
[12]: Int64Index([ 43, 203, 216, 253, 342, 420, 429, 681, 846, 883, 889,  
                900, 995, 998, 1033, 1036, 1060, 1141, 1203, 1205, 1269, 1279,  
                1349, 1459, 1730, 2240, 2263, 2348, 2357, 2376, 2414, 2470, 2496,  
                2735, 2736, 2852, 2887, 2888, 2905, 2983, 3028, 3090, 3133, 3177,  
                3215, 3442, 3744, 3773, 3980, 4176],  
                dtype='int64')
```

6 Drop Outliers from Train

```
[13]: train = train.drop(outlier_index)
```

```
[14]: train.shape
```

```
[14]: (4159, 377)
```

7 Separating categorical and numerical data types.

```
[15]: df_num_train = train.select_dtypes(exclude = np.object)  
      df_cat_train = train.select_dtypes(include = np.object)  
  
      df_num_test = test.select_dtypes(exclude = np.object)  
      df_cat_test = test.select_dtypes(include = np.object)
```

```
[16]: print('Shape of Cat. Test Data:',df_cat_test.shape)  
      print('Shape of Num. Test Data:',df_num_test.shape)  
      print('Shape of Cat. Train Data:',df_cat_train.shape)  
      print('Shape of Num. Train Data:',df_num_train.shape)
```

```
Shape of Cat. Test Data: (4209, 8)  
Shape of Num. Test Data: (4209, 368)  
Shape of Cat. Train Data: (4159, 8)  
Shape of Num. Train Data: (4159, 369)
```

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

```
[17]:
```

	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	...	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	0	1	...	0	0	1	
2	0	0	0	0	1	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	0	1	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 368 columns]

```
[18]: df_cat_train.head()
```

```
[18]:
```

	X0	X1	X2	X3	X4	X5	X6	X8
0	k	v	at	a	d	u	j	o
1	k	t	av	e	d	y	l	o
2	az	w	n	c	d	x	j	x
3	az	t	n	f	d	x	l	e
4	az	v	n	f	d	h	d	n

8 If for any column(s), Variance = 0, then remove those variable(s).

```
[19]: # for train data
for i in df_num_train.columns :
    if df_num_train.var()[i] == 0:
        df_num_train.drop(i,axis=1,inplace=True)

# for test data
for i in df_num_test.columns :
    if df_num_test.var()[i] == 0:
        df_num_test.drop(i,axis=1,inplace=True)
```

```
[20]: print('Shape of Num. Test Data:',df_num_test.shape)
print('Shape of Num. Train Data:',df_num_train.shape)
```

```
Shape of Num. Test Data: (4209, 363)
Shape of Num. Train Data: (4159, 356)
```

9 Check for null and unique values for test and train sets.

Concat. df_cat & df_num

```
[21]: newtrain = pd.concat([df_num_train,df_cat_train],axis=1)
      newtest = pd.concat([df_num_test,df_cat_test],axis=1)
```

```
[22]: print('Shape of New Test Data:',newtest.shape)
      print('Shape of New Train Data:',newtrain.shape)
```

Shape of New Test Data: (4209, 371)

Shape of New Train Data: (4159, 364)

Check for null values

```
[23]: for i in newtrain.columns :
      if newtrain[i].isna().value_counts() is True:
          print(newtrain[i])

      for i in newtest.columns :
          if newtest[i].isna().value_counts() is True:
              print(newtest[i])
```

So no null values

Check for unique values

```
[24]: for i in newtrain.columns :
      print(i,':',end=" ")
      print(newtrain[i].unique())
```

y : [130.81 88.53 76.26 ... 85.71 108.77 87.48]

X10 : [0 1]

X12 : [0 1]

X13 : [1 0]

X14 : [0 1]

X15 : [0 1]

X16 : [0 1]

X17 : [0 1]

X18 : [1 0]

X19 : [0 1]

X20 : [0 1]

X21 : [1 0]

X22 : [0 1]

X23 : [0 1]

X24 : [0 1]

X26 : [0 1]

X27 : [0 1]

X28 : [0 1]

X29 : [0 1]
X30 : [0 1]
X31 : [1 0]
X32 : [0 1]
X33 : [0 1]
X34 : [0 1]
X35 : [1 0]
X36 : [0 1]
X37 : [1 0]
X38 : [0 1]
X39 : [0 1]
X40 : [0 1]
X41 : [0 1]
X42 : [0 1]
X43 : [0 1]
X44 : [0 1]
X45 : [0 1]
X46 : [1 0]
X47 : [0 1]
X48 : [0 1]
X49 : [0 1]
X50 : [0 1]
X51 : [0 1]
X52 : [0 1]
X53 : [0 1]
X54 : [0 1]
X55 : [0 1]
X56 : [0 1]
X57 : [0 1]
X58 : [1 0]
X59 : [0 1]
X60 : [0 1]
X61 : [0 1]
X62 : [0 1]
X63 : [0 1]
X64 : [0 1]
X65 : [0 1]
X66 : [0 1]
X67 : [0 1]
X68 : [1 0]
X69 : [0 1]
X70 : [1 0]
X71 : [0 1]
X73 : [0 1]
X74 : [1 0]
X75 : [0 1]
X76 : [0 1]
X77 : [0 1]

X78 : [0 1]
X79 : [0 1]
X80 : [0 1]
X81 : [0 1]
X82 : [0 1]
X83 : [0 1]
X84 : [0 1]
X85 : [1 0]
X86 : [0 1]
X87 : [0 1]
X88 : [0 1]
X89 : [0 1]
X90 : [0 1]
X91 : [0 1]
X92 : [0 1]
X94 : [0 1]
X95 : [0 1]
X96 : [0 1]
X97 : [0 1]
X98 : [0 1]
X99 : [0 1]
X100 : [0 1]
X101 : [0 1]
X102 : [0 1]
X103 : [0 1]
X104 : [0 1]
X105 : [0 1]
X106 : [0 1]
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X113 : [0 1]
X114 : [1 0]
X115 : [0 1]
X116 : [1 0]
X117 : [0 1]
X118 : [1 0]
X119 : [1 0]
X120 : [1 0]
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X129 : [0 1]
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X148 : [0 1]
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X156 : [1 0]
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X178 : [0 1]
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X270 : [0 1]
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X279 : [0 1]
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X370 : [0 1]
X371 : [0 1]
X372 : [0 1]
X373 : [0 1]
X374 : [0 1]
X375 : [0 1]
X376 : [0 1]
X377 : [1 0]
X378 : [0 1]
X379 : [0 1]
X380 : [0 1]
X382 : [0 1]
X383 : [0 1]

```

X384 :[0 1]
X385 :[0 1]
X0 :['k' 'az' 't' 'al' 'o' 'w' 'j' 'h' 's' 'n' 'ay' 'f' 'x' 'y' 'aj' 'ak' 'am'
      'z' 'q' 'at' 'ap' 'v' 'af' 'a' 'e' 'ai' 'd' 'aq' 'c' 'aa' 'ba' 'as' 'i'
      'r' 'b' 'ax' 'bc' 'u' 'ad' 'au' 'm' 'l' 'aw' 'ao' 'ac' 'g' 'ab']
X1 :['v' 't' 'w' 'b' 'r' 'l' 's' 'aa' 'c' 'a' 'e' 'h' 'z' 'j' 'o' 'u' 'p' 'n'
      'i' 'y' 'd' 'f' 'm' 'k' 'g' 'q' 'ab']
X2 :['at' 'av' 'n' 'e' 'as' 'aq' 'r' 'ai' 'ak' 'm' 'a' 'k' 'ae' 's' 'f' 'd'
      'ag' 'ay' 'ac' 'ap' 'g' 'i' 'aw' 'y' 'b' 'ao' 'al' 'x' 'au' 't' 'an' 'z'
      'ah' 'p' 'am' 'h' 'j' 'q' 'af' 'l' 'c' 'o' 'ar']
X3 :['a' 'e' 'c' 'f' 'd' 'b' 'g']
X4 :['d' 'b' 'c' 'a']
X5 :['u' 'y' 'x' 'h' 'g' 'f' 'j' 'i' 'd' 'c' 'af' 'ag' 'ab' 'ac' 'ad' 'ae'
      'ah' 'l' 'k' 'n' 'm' 'p' 'q' 's' 'r' 'v' 'w' 'o' 'aa']
X6 :['j' 'l' 'd' 'h' 'i' 'a' 'g' 'c' 'k' 'e' 'f' 'b']
X8 :['o' 'x' 'e' 'n' 's' 'a' 'h' 'p' 'm' 'k' 'd' 'i' 'v' 'j' 'b' 'q' 'w' 'g'
      'y' 'l' 'f' 'u' 'r' 't' 'c']

```

```

[25]: for i in newtest.columns :
        print(i,':',end="")
        print(newtest[i].unique())

```

```

X10 :[0 1]
X11 :[0 1]
X12 :[0 1]
X13 :[0 1]
X14 :[0 1]
X15 :[0 1]
X16 :[0 1]
X17 :[0 1]
X18 :[0 1]
X19 :[0 1]
X20 :[0 1]
X21 :[0 1]
X22 :[0 1]
X23 :[0 1]
X24 :[0 1]
X26 :[0 1]
X27 :[1 0]
X28 :[1 0]
X29 :[1 0]
X30 :[0 1]
X31 :[1 0]
X32 :[0 1]
X33 :[0 1]
X34 :[0 1]
X35 :[1 0]
X36 :[0 1]

```

X37 : [1 0]
X38 : [0 1]
X39 : [0 1]
X40 : [0 1]
X41 : [0 1]
X42 : [0 1]
X43 : [1 0]
X44 : [0 1]
X45 : [0 1]
X46 : [1 0]
X47 : [0 1]
X48 : [0 1]
X49 : [0 1]
X50 : [0 1]
X51 : [0 1]
X52 : [0 1]
X53 : [0 1]
X54 : [1 0]
X55 : [0 1]
X56 : [0 1]
X57 : [0 1]
X58 : [0 1]
X59 : [0 1]
X60 : [0 1]
X61 : [1 0]
X62 : [0 1]
X63 : [0 1]
X64 : [0 1]
X65 : [0 1]
X66 : [0 1]
X67 : [0 1]
X68 : [0 1]
X69 : [0 1]
X70 : [1 0]
X71 : [0 1]
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X378 : [1 0]
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X380 : [0 1]
X382 : [0 1]
X383 : [0 1]
X384 : [0 1]

```

X385 :[0 1]
X0 :['az' 't' 'w' 'y' 'x' 'f' 'ap' 'o' 'ay' 'al' 'h' 'z' 'aj' 'd' 'v' 'ak'
      'ba' 'n' 'j' 's' 'af' 'ax' 'at' 'aq' 'av' 'm' 'k' 'a' 'e' 'ai' 'i' 'ag'
      'b' 'am' 'aw' 'as' 'r' 'ao' 'u' 'l' 'c' 'ad' 'au' 'bc' 'g' 'an' 'ae' 'p'
      'bb']
X1 :['v' 'b' 'l' 's' 'aa' 'r' 'a' 'i' 'p' 'c' 'o' 'm' 'z' 'e' 'h' 'w' 'g' 'k'
      'y' 't' 'u' 'd' 'j' 'q' 'n' 'f' 'ab']
X2 :['n' 'ai' 'as' 'ae' 's' 'b' 'e' 'ak' 'm' 'a' 'aq' 'ag' 'r' 'k' 'aj' 'ay'
      'ao' 'an' 'ac' 'af' 'ax' 'h' 'i' 'f' 'ap' 'p' 'au' 't' 'z' 'y' 'aw' 'd'
      'at' 'g' 'am' 'j' 'x' 'ab' 'w' 'q' 'ah' 'ad' 'al' 'av' 'u']
X3 :['f' 'a' 'c' 'e' 'd' 'g' 'b']
X4 :['d' 'b' 'a' 'c']
X5 :['t' 'b' 'a' 'z' 'y' 'x' 'h' 'g' 'f' 'j' 'i' 'd' 'c' 'af' 'ag' 'ab' 'ac'
      'ad' 'ae' 'ah' 'l' 'k' 'n' 'm' 'p' 'q' 's' 'r' 'v' 'w' 'o' 'aa']
X6 :['a' 'g' 'j' 'l' 'i' 'd' 'f' 'h' 'c' 'k' 'e' 'b']
X8 :['w' 'y' 'j' 'n' 'm' 's' 'a' 'v' 'r' 'o' 't' 'h' 'c' 'k' 'p' 'u' 'd' 'g'
      'b' 'q' 'e' 'l' 'f' 'i' 'x']

```

10 Apply label encoder

```

[26]: # for train data
      for i in df_cat_train.columns:
          df_cat_train[i] = labelencoder.fit_transform(df_cat_train[i])
      df_cat_train

```

```

[26]:
      X0  X1  X2  X3  X4  X5  X6  X8
0      32  23  16   0   3  24   9  14
1      32  21  18   4   3  28  11  14
2      20  24  33   2   3  27   9  23
3      20  21  33   5   3  27  11   4
4      20  23  33   5   3  12   3  13
...
4204    8  20  15   2   3   0   3  16
4205   31  16  39   3   3   0   7   7
4206    8  23  37   0   3   0   6   4
4207    9  19  24   5   3   0  11  20
4208   46  19   2   2   3   0   6  22

[4159 rows x 8 columns]

```

```

[27]: ## for test data
      for i in df_cat_test.columns:
          df_cat_test[i] = labelencoder.fit_transform(df_cat_test[i])
      df_cat_test

```

```
[27]:
```

	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
...
4204	6	9	17	5	3	1	9	4
4205	42	1	8	3	3	1	9	24
4206	47	23	17	5	3	1	3	22
4207	7	23	17	0	3	1	2	16
4208	42	1	8	2	3	1	6	17

[4209 rows x 8 columns]

```
[28]: newtrain1 = pd.concat([df_num_train,df_cat_train],axis=1)
newtest1 = pd.concat([df_num_test,df_cat_test],axis=1)
```

11 Divide Data into features and target

```
[29]: features = newtrain1.drop('y',axis=1)
target = newtrain1['y']
# X_test = newtest1
```

12 Train & Validation Split

```
[30]: X_train, X_test, y_train, y_test = train_test_split(features, target,
    ↳train_size = 0.70, random_state = 3)
print('Shape of X_train:',X_train.shape)
print('Shape of y_train:',y_train.shape)
print('Shape of X_test:',X_test.shape)
print('Shape of y_test:',y_test.shape)
```

```
Shape of X_train: (2911, 363)
Shape of y_train: (2911,)
Shape of X_test: (1248, 363)
Shape of y_test: (1248,)
```


13 Perform Dimensionality Reduction (PCA)

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

```
[32]: pca.fit(X_train)
```

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

```
[33]: pca.explained_variance_ratio_
```

```
[33]: array([0.38545701, 0.21176206, 0.13354339, 0.11817431, 0.09057302,  
        0.01645431])
```

```
[34]: np.sum(pca.explained_variance_ratio_)
```

```
[34]: 0.9559640947644873
```

```
[35]: X_train_transformed = pca.transform(X_train)  
      X_test_transformed = pca.transform(X_test)
```

```
[36]: pd.DataFrame(X_train_transformed)
```

```
[36]:
```

	0	1	2	3	4	5
0	23.561022	15.422601	-9.550391	-3.074573	3.436354	4.176733
1	-3.825024	0.776333	1.042777	-12.679915	-0.189836	3.678164
2	-14.442352	-5.225660	12.982459	-10.424020	9.888473	6.303518
3	-2.813386	3.263954	-0.921325	11.784038	7.090589	-3.781918
4	3.144741	-9.597645	12.576378	-5.245294	-8.473391	0.034307
...
2906	19.399721	-7.716407	-10.862942	-0.190089	1.057341	-1.199447
2907	5.954690	14.740205	-10.709911	2.746565	-6.159345	1.491938
2908	20.931689	-8.400373	-9.206365	-3.825675	9.945546	-2.348915
2909	-14.709168	-11.149776	3.800036	9.644795	-4.540294	5.558305
2910	21.838512	-7.953137	-4.700524	-9.153851	5.653786	0.459855

```
[2911 rows x 6 columns]
```

14 xgboost

```
[37]: xgb_clf = xgboost.XGBRegressor(colsample_bytree= 0.7,  
                                     learning_rate= 0.03,  
                                     max_depth= 5,  
                                     min_child_weight= 4,  
                                     n_estimators= 200,  
                                     nthread= 4,
```

```
subsample= 0.9)
```

```
[38]: start = time.time()

xgb_clf.fit(X_train,y_train)

end = time.time()
time_elapsed = end - start
print('Time taken:',time_elapsed)

y_pred = xgb_clf.predict(X_test)
```

Time taken: 3.322930097579956

15 Check R Squared

```
[39]: r2_score(y_test,y_pred)
```

```
[39]: 0.6334253267224981
```