Mercedes-Benz Greener Manufacturing

January 4, 2020

1 Project 1 - Submission

2 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.
```

2.1 Importing Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
import gc
import seaborn as sns
palette = sns.color_palette()
sns.set()
%matplotlib inline
```

2.2 Importing train data

[2]:
```
df_train = pd.read_csv('C:
↪\\Users\\DELL\\Desktop\\Machine-Learning\\Machine-Learning--Projects-master\\Projects\\Proj
↪for Submission\\Project 1 - Mercedes-Benz Greener Manufacturing\\Dataset for␣
↪the project\\train.csv')
```

2.3 Printing shape of data

[3]:
```
print('Size of training set: {} rows and {} columns'.format(*df_train.shape))
```

```
Size of training set: 4209 rows and 378 columns
```

2.4 Printing first 5 rows

[4]:
```
df_train.head()
```

[4]:
```
   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]
```

There are total 378 columns given. The feature names are not given. There are total 4209 rows are given means 4209 observations are given.

ID column is not of usual index, it is representing some other significant index. It might the case that from a same dataset, test and train data are splitted and hence ID are different numbers.

y column is might be the label column which are given in seconds as our aim is to reduce the time spent.

2.5 Exploratory Data Analysis

2.5.1 Data description

[5]:
```
df_train.describe()
```

[5]:
```
                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]
```

2.5.2 Checking for missing values

[6]:
```
df_train.isnull().sum()
```

[6]:
```
ID       0
y        0
X0       0
X1       0
X2       0
        ..
X380     0
X382     0
X383     0
X384     0
X385     0
Length: 378, dtype: int64
```

It seems there are no missing values

2.5.3 Checking the information of the data

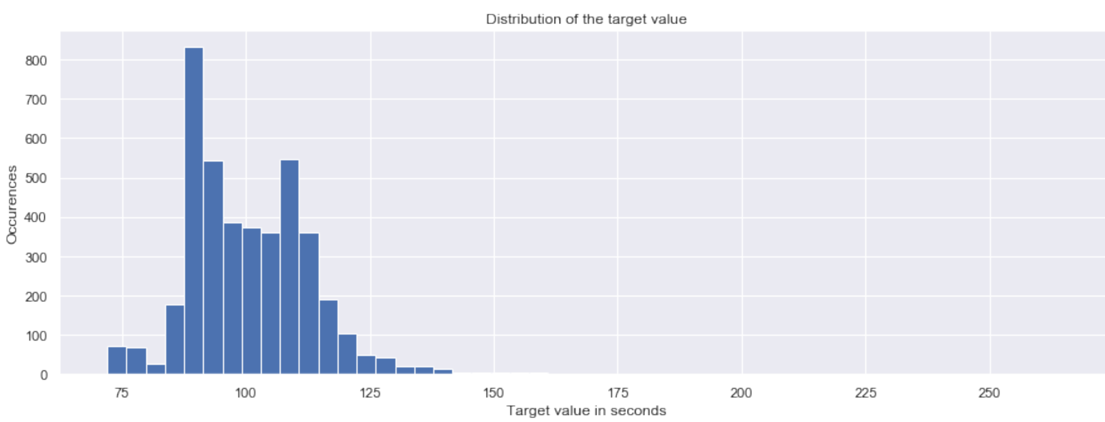
[7]:
```
df_train.info()
```

```
<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
```

2.5.4 Checking the distribution of label column y

[8]:
```
y_train = df_train['y'].values
plt.figure(figsize=(15, 5))
plt.hist(y_train, bins=50)
plt.xlabel('Target value in seconds')
plt.ylabel('Occurences')
plt.title('Distribution of the target value')

print('min: {} '.format(min(y_train)))
print('max: {} '.format(max(y_train)))
print('mean: {} '.format(y_train.mean()))
print('std: {} '.format(y_train.std()))

print('Count of values above 180: {}'.format(np.sum(y_train > 200)))
```

```
min: 72.11
max: 265.32
mean: 100.66931812782134
std: 12.6778749695168
Count of values above 180: 1
```



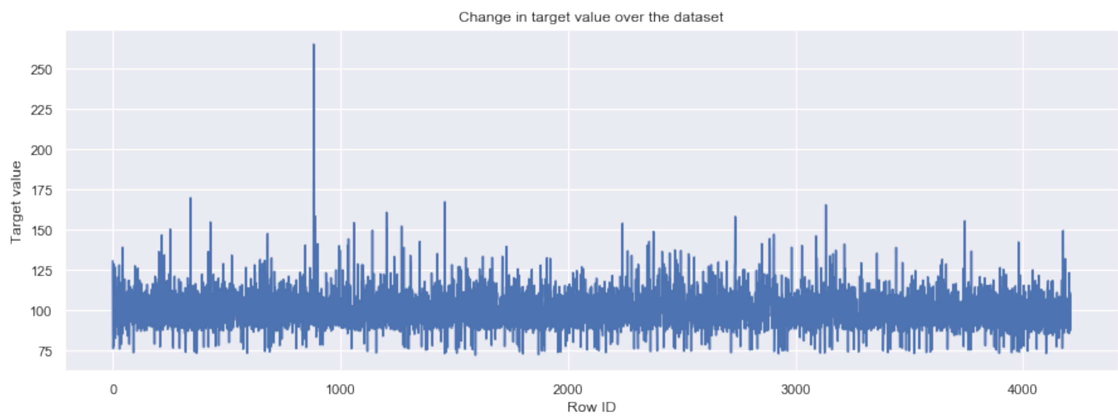
Distribution seems pretty much standard normal.

Distribution is centered around 100.

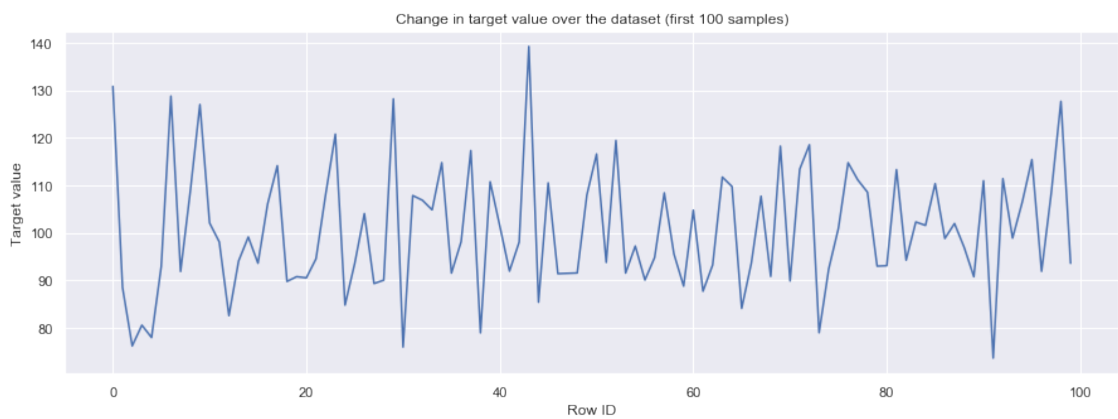
All the data points of label are below 180. It seems there is only one outlier here.

2.6 Is it a time series data ?

[9]:
```
plt.figure(figsize=(15, 5))
plt.plot(y_train)
plt.xlabel('Row ID')
plt.ylabel('Target value')
plt.title('Change in target value over the dataset')
plt.show()

plt.figure(figsize=(15, 5))
plt.plot(y_train[:100])
plt.xlabel('Row ID')
plt.ylabel('Target value')
plt.title('Change in target value over the dataset (first 100 samples)')
```



[9]: Text(0.5, 1.0, 'Change in target value over the dataset (first 100 samples)')



It seems pretty stationary. No pattern recognized.

At first glance, there doesn't seem to be anything overly suspicious here - looks like how a random sort would. We might take a closer look later but for now let's move on to the features.

2.7 Feature Analysis

[10]:
```python
column_names = df_train.columns
cols = [c for c in column_names if 'X' in c]
print('Number of features: {}'.format(len(cols)))

print('Feature types:')
df_train[cols].dtypes.value_counts()
```

```
Number of features: 376
Feature types:
```

[10]:
```
int64     368
object      8
dtype: int64
```

There are total 368 integer variables and 8 are string variables.

2.8 Finding the no. of different types of features.

[11]:
```python
counts = [[], [], []]
for c in cols:
    typ = df_train[c].dtype
    uniq = len(np.unique(df_train[c]))
    if uniq == 1: counts[0].append(c)
    elif uniq == 2 and typ == np.int64: counts[1].append(c)
    else: counts[2].append(c)
l = [len(c) for c in counts]
print('Constant features: {}'.format(l[0]))
print('Binary features: {}'.format(l[1]))
print('Categorical features: {}'.format(l[2]))
print("\n")
print('Constant features:', counts[0])
print('Categorical features:', counts[2])
```

```
Constant features: 12
Binary features: 356
Categorical features: 8
```

```
Constant features: ['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289',
'X290', 'X293', 'X297', 'X330', 'X347']
Categorical features: ['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8']
```

2.9 Checking column variance

[12]:
```
df_train[counts[0]].var()
```

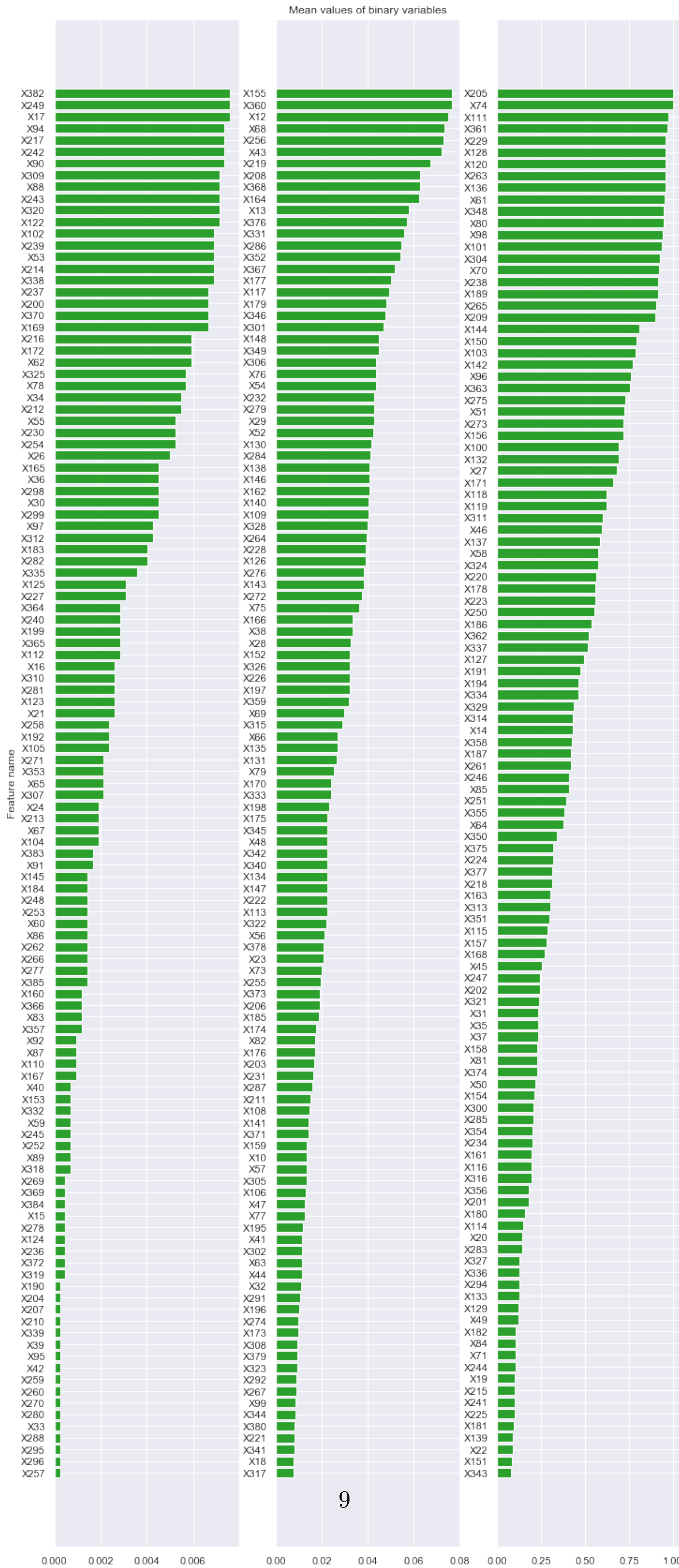
[12]:
```
X11     0.0
X93     0.0
X107    0.0
X233    0.0
X235    0.0
X268    0.0
X289    0.0
X290    0.0
X293    0.0
X297    0.0
X330    0.0
X347    0.0
dtype: float64
```

2.10 Constant features are zero-variance features.

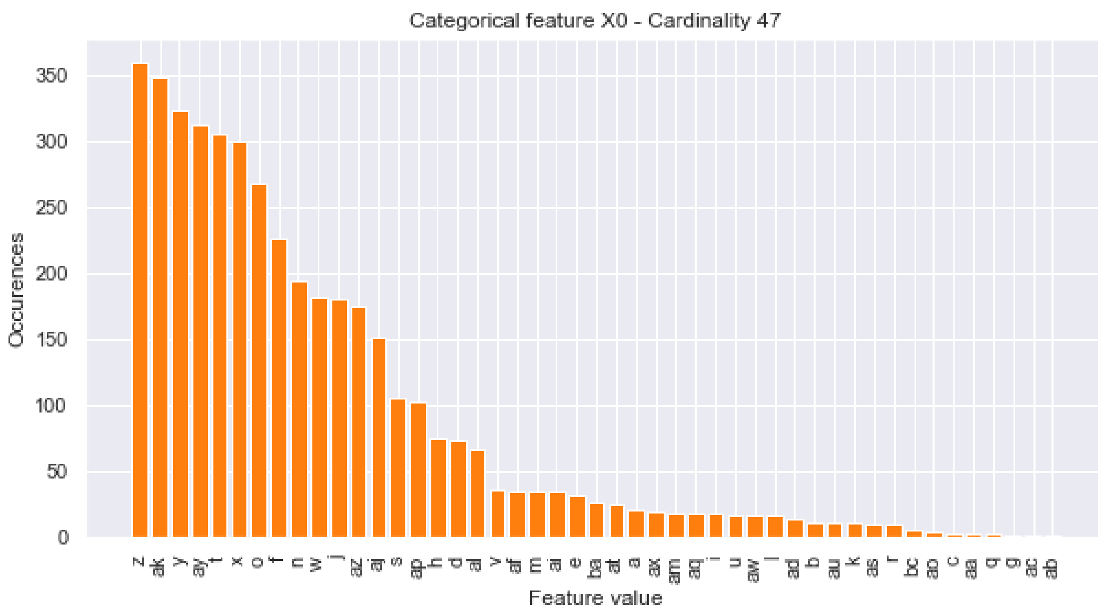
Interestingly, we have 12 features which only have a single value in them - these are pretty useless for supervised algorithms, and should probably be dropped.

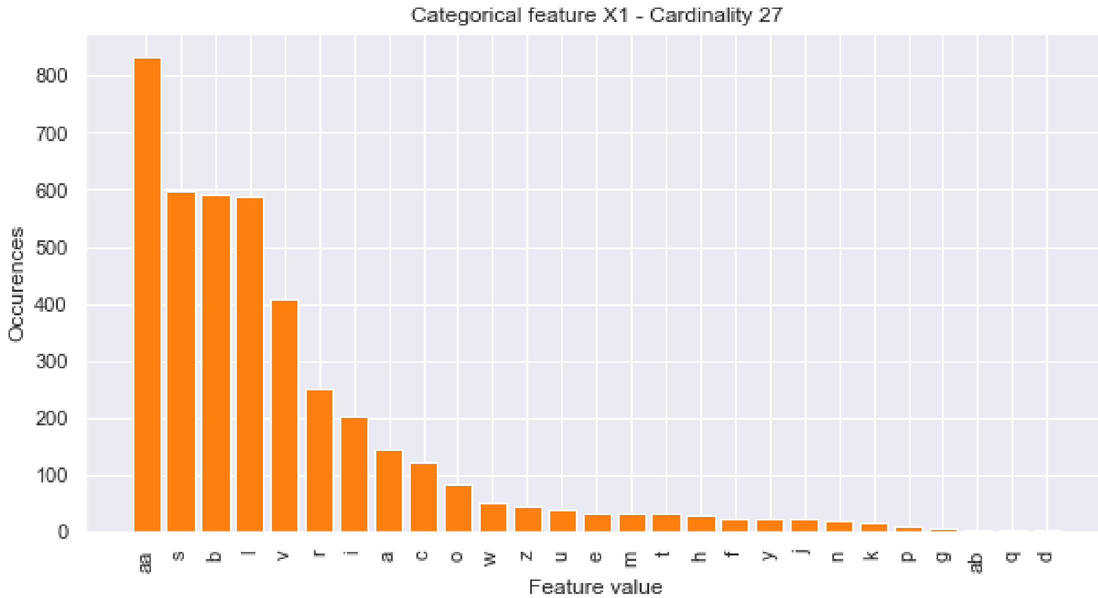
The rest of our dataset is made up of many binary features, and a few categorical features.

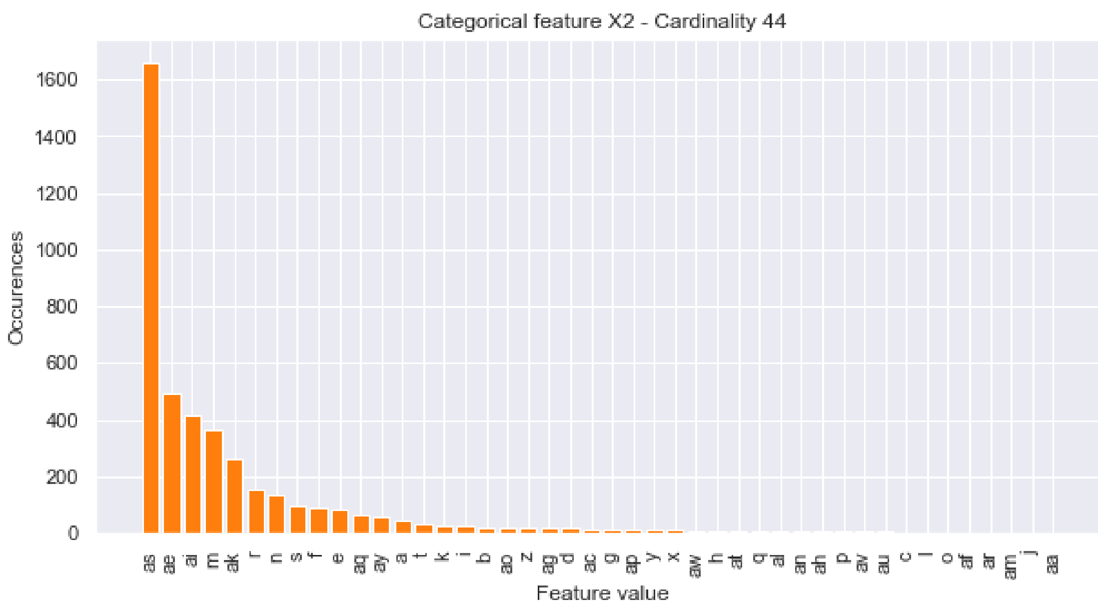
[13]:
```
binary_means = [np.mean(df_train[c]) for c in counts[1]]
binary_names = np.array(counts[1])[np.argsort(binary_means)]
binary_means = np.sort(binary_means)

fig, ax = plt.subplots(1, 3, figsize=(12,30))
ax[0].set_ylabel('Feature name')
ax[1].set_title('Mean values of binary variables')
for i in range(3):
    names, means = binary_names[i*119:(i+1)*119], binary_means[i*119:(i+1)*119]
    ax[i].barh(range(len(means)), means, color=palette[2])
    ax[i].set_xlabel('Mean value')
    ax[i].set_yticks(range(len(means)))
    ax[i].set_yticklabels(names, rotation='horizontal')
plt.show()
```

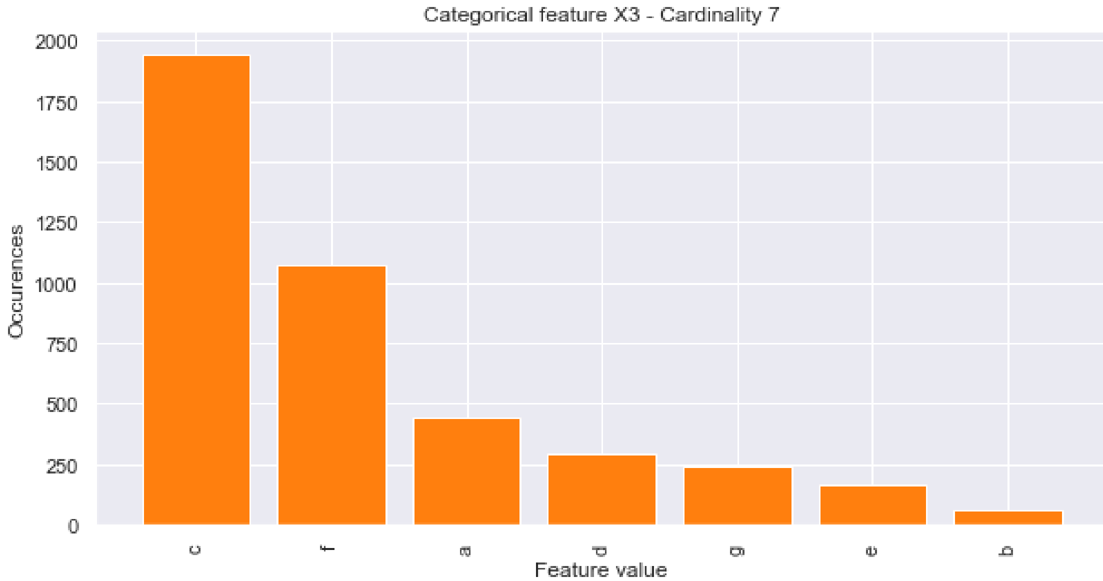

Mean values of binary variables
Feature name
Mean value
Mean value
Mean value
0.000 0.002 0.004 0.006
0.00 0.02 0.04 0.06 0.08
0.00 0.25 0.50 0.75 1.00
X382 X249 X17 X94 X217 X242 X90 X309 X88 X243 X320 X122 X102 X239 X53 X214 X338 X237 X200 X370 X169 X216 X172 X62 X325 X78 X34 X212 X55 X230 X254 X26 X165 X36 X298 X30 X299 X97 X312 X183 X282 X335 X125 X227 X364 X240 X199 X365 X112 X16 X310 X281 X123 X21 X258 X192 X105 X271 X353 X65 X307 X24 X213 X67 X104 X383 X91 X145 X184 X248 X253 X60 X86 X262 X266 X277 X385 X160 X366 X83 X357 X92 X87 X110 X167 X40 X153 X332 X59 X245 X252 X89 X318 X269 X369 X384 X15 X278 X124 X236 X372 X319 X190 X204 X207 X210 X339 X39 X95 X42 X259 X260 X270 X280 X33 X288 X295 X296 X257
X155 X360 X12 X68 X256 X43 X219 X208 X368 X164 X13 X376 X331 X286 X352 X367 X177 X117 X179 X346 X301 X148 X349 X306 X76 X54 X232 X279 X29 X52 X130 X284 X138 X146 X162 X140 X109 X328 X264 X228 X126 X276 X143 X272 X75 X166 X38 X28 X152 X326 X226 X197 X359 X69 X315 X66 X135 X131 X79 X170 X333 X198 X175 X345 X48 X342 X340 X134 X147 X222 X113 X322 X56 X378 X23 X73 X255 X373 X206 X185 X174 X82 X176 X203 X231 X287 X211 X108 X141 X371 X159 X10 X57 X305 X106 X47 X77 X195 X41 X302 X63 X44 X32 X291 X196 X274 X173 X308 X379 X323 X292 X267 X99 X344 X380 X221 X341 X18 X317
X205 X74 X111 X361 X229 X128 X120 X263 X136 X61 X348 X80 X98 X101 X304 X70 X238 X189 X265 X209 X144 X150 X103 X142 X96 X363 X275 X51 X273 X156 X100 X132 X27 X171 X118 X119 X311 X46 X137 X58 X324 X220 X178 X223 X250 X186 X362 X337 X127 X191 X194 X334 X329 X314 X14 X358 X187 X261 X246 X85 X251 X355 X64 X350 X375 X224 X377 X218 X163 X313 X351 X115 X157 X168 X45 X247 X202 X321 X31 X35 X37 X158 X81 X374 X50 X154 X300 X285 X354 X234 X161 X116 X316 X356 X201 X180 X114 X20 X283 X327 X336 X294 X133 X129 X49 X182 X84 X71 X244 X19 X215 X241 X225 X181 X139 X22 X151 X343

[14]:
```
for c in counts[2]:
    value_counts = df_train[c].value_counts()
    fig, ax = plt.subplots(figsize=(10, 5))
    plt.title('Categorical feature {} - Cardinality {}'.format(c, len(np.
 ↪unique(df_train[c]))))
    plt.xlabel('Feature value')
    plt.ylabel('Occurences')
    plt.bar(range(len(value_counts)), value_counts.values, color=palette[1])
    ax.set_xticks(range(len(value_counts)))
    ax.set_xticklabels(value_counts.index, rotation='vertical')
    plt.show()
```

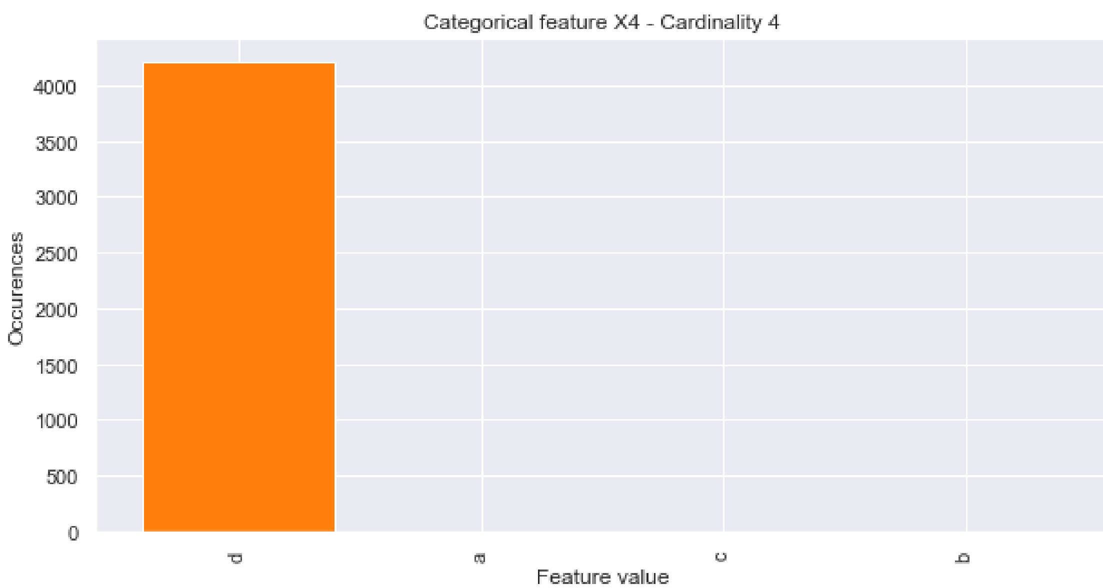



Categorical feature X1 - Cardinality 27
Occurences
Feature value
aa s b l v r i a c o w z u e m t h f y j n k p g ab q d

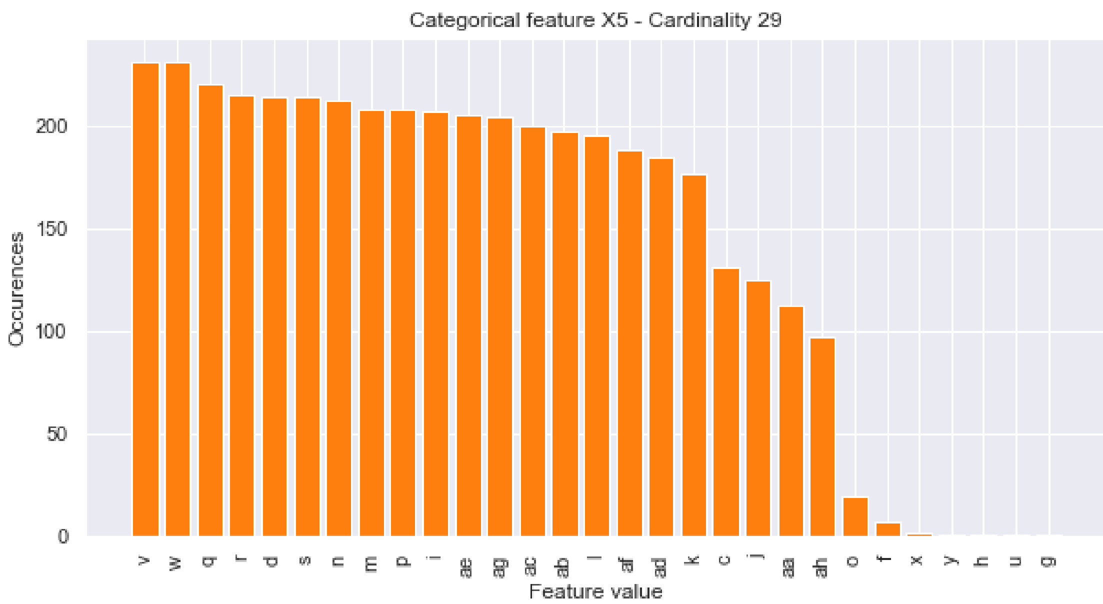

Categorical feature X2 - Cardinality 44
Occurences
Feature value

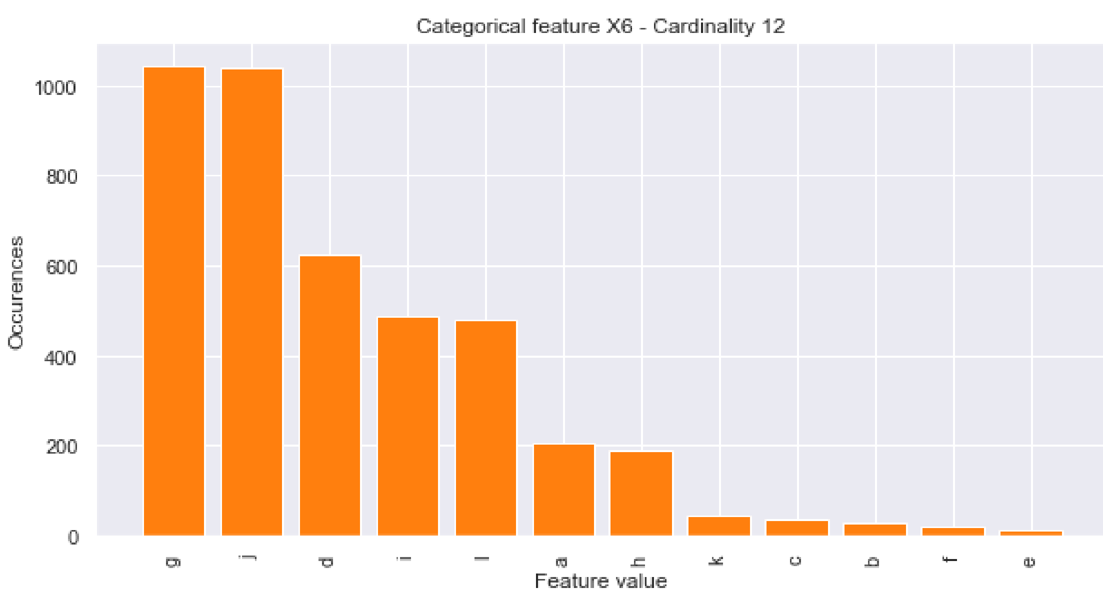


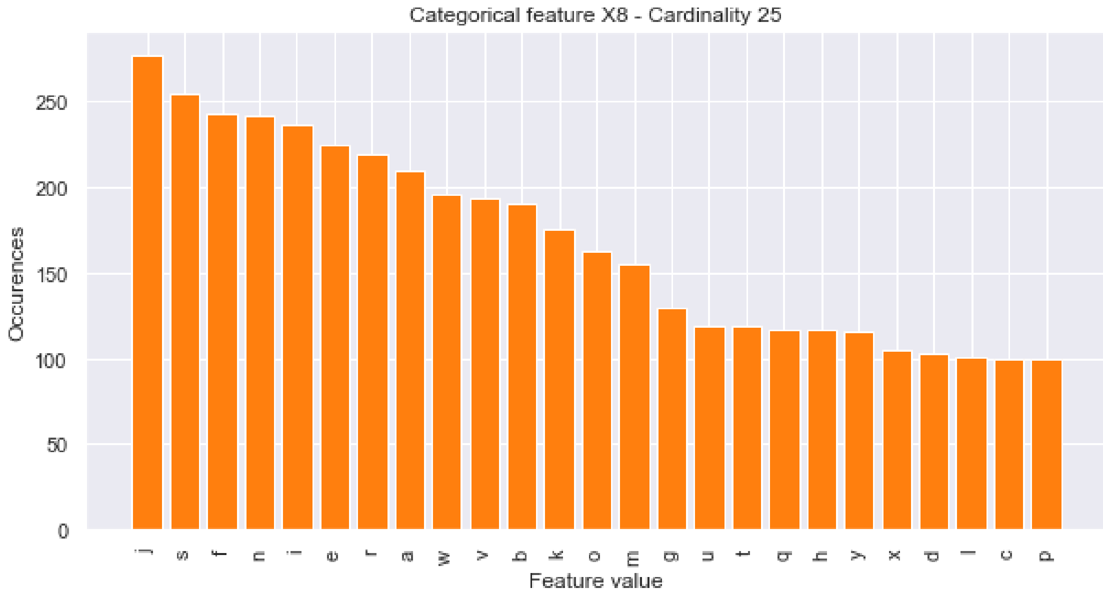
Categorical feature X3 - Cardinality 7
Occurences
2000
1750
1500
1250
1000
750
500
250
0
c
f
a
d
g
e
b
Feature value



Categorical feature X4 - Cardinality 4
Occurences
4000
3500
3000
2500
2000
1500
1000
500
0
d
a
c
b
Feature value


Categorical feature X5 - Cardinality 29
Occurences
0
50
100
150
200
v
w
q
r
d
s
n
m
p
i
ae
ag
ac
ab
l
af
ad
k
c
j
aa
ah
o
f
x
y
h
u
g
Feature value


Categorical feature X6 - Cardinality 12
Occurences
0
200
400
600
800
1000
g
j
d
i
l
a
h
k
c
b
f
e
Feature value



2.10.1 Importing test data

[15]:
```
df_test = pd.read_csv('C:
↪\\Users\\DELL\\Desktop\\Machine-Learning\\Machine-Learning--Projects-master\\Projects\\Proj
↪for Submission\\Project 1 - Mercedes-Benz Greener Manufacturing\\Dataset for␣
↪the project\\test.csv')
```

[16]:
```
df_test.columns
```

[16]:
```
Index(['ID', 'X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8', 'X10',
       …
       'X375', 'X376', 'X377', 'X378', 'X379', 'X380', 'X382', 'X383', 'X384',
       'X385'],
      dtype='object', length=377)
```

2.10.2 Dimensionality Reduction for both train and test data

[17]:
```
usable_columns = list(set(df_train.columns) - set(['ID', 'y']))

y_train = df_train['y'].values
id_test = df_test['ID'].values

x_train = df_train[usable_columns]
x_test = df_test[usable_columns]
```

```python
for column in usable_columns:
    cardinality = len(np.unique(x_train[column]))
    if cardinality == 1:
        x_train.drop(column, axis=1) # Column with only one value is useless so␣
 ↪we drop it
        x_test.drop(column, axis=1)
    if cardinality > 2: # Column is categorical
        mapper = lambda x: sum([ord(digit) for digit in x])
        x_train[column] = x_train[column].apply(mapper)
        x_test[column] = x_test[column].apply(mapper)

x_train[['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8']].head()
```

```
F:\anaconda\lib\site-packages\ipykernel_launcher.py:16: 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: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  app.launch_new_instance()
F:\anaconda\lib\site-packages\ipykernel_launcher.py:17: 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: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[17]:

	X0	X1	X2	X3	X4	X5	X6	X8
0	107	118	213	97	100	117	106	111
1	107	116	215	101	100	121	108	111
2	219	119	110	99	100	120	106	120
3	219	116	110	102	100	120	108	101
4	219	118	110	102	100	104	100	110

3 XGBoost Model Fitting

3.0.1 Importing libraries

[18]:

```python
import xgboost as xgb
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
```

3.0.2 Splitting train data into train and validation sets

[19]:
```
x_train, x_valid, y_train, y_valid = train_test_split(x_train, y_train,␣
↪test_size=0.2, random_state=4242)

d_train = xgb.DMatrix(x_train, label=y_train)
d_valid = xgb.DMatrix(x_valid, label=y_valid)

d_test = xgb.DMatrix(x_test)

params = {}
params['objective'] = 'reg:linear'
params['eta'] = 0.02
params['max_depth'] = 4

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)
```

```
[11:39:58] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[0]     train-rmse:99.1397      valid-rmse:98.2538      train-r2:-58.3426
valid-r2:-67.6247
Multiple eval metrics have been passed: 'valid-r2' will be used for early
stopping.

Will train until valid-r2 hasn't improved in 50 rounds.
[10]    train-rmse:81.1832      valid-rmse:80.2714      train-r2:-38.7928
valid-r2:-44.804
[20]    train-rmse:66.541       valid-rmse:65.5967      train-r2:-25.7332
valid-r2:-29.5876
[30]    train-rmse:54.6149      valid-rmse:53.6305      train-r2:-17.0092
valid-r2:-19.4459
[40]    train-rmse:44.9172      valid-rmse:43.8842      train-r2:-11.1814
valid-r2:-12.6899
[50]    train-rmse:37.0508      valid-rmse:35.9587      train-r2:-7.28831
valid-r2:-8.19158
[60]    train-rmse:30.6913      valid-rmse:29.5289      train-r2:-4.68723
valid-r2:-5.19837
[70]    train-rmse:25.5745      valid-rmse:24.3342      train-r2:-2.949
valid-r2:-3.20936
[80]    train-rmse:21.4844      valid-rmse:20.1622      train-r2:-1.78687
```

```
valid-r2:-1.88973
[90]    train-rmse:18.2427      valid-rmse:16.8438      train-r2:-1.00933
valid-r2:-1.01679
[100]   train-rmse:15.7022      valid-rmse:14.2284      train-r2:-0.488656
valid-r2:-0.439108
[110]   train-rmse:13.7342      valid-rmse:12.1909      train-r2:-0.138886
valid-r2:-0.056463
[120]   train-rmse:12.2363      valid-rmse:10.6426      train-r2:0.095993
valid-r2:0.194848
[130]   train-rmse:11.1155      valid-rmse:9.49485      train-r2:0.25401
valid-r2:0.359148
[140]   train-rmse:10.2883      valid-rmse:8.67363      train-r2:0.360921
valid-r2:0.46521
[150]   train-rmse:9.68714      valid-rmse:8.08715      train-r2:0.433418
valid-r2:0.535086
[160]   train-rmse:9.25779      valid-rmse:7.68483      train-r2:0.482529
valid-r2:0.580193
[170]   train-rmse:8.94881      valid-rmse:7.42454      train-r2:0.516494
valid-r2:0.608149
[180]   train-rmse:8.7327       valid-rmse:7.25769      train-r2:0.539565
valid-r2:0.625563
[190]   train-rmse:8.57747      valid-rmse:7.15337      train-r2:0.555789
valid-r2:0.636249
[200]   train-rmse:8.4698       valid-rmse:7.09427      train-r2:0.566871
valid-r2:0.642236
[210]   train-rmse:8.39459      valid-rmse:7.06157      train-r2:0.574529
valid-r2:0.645526
[220]   train-rmse:8.33815      valid-rmse:7.04293      train-r2:0.58023
valid-r2:0.647395
[230]   train-rmse:8.29572      valid-rmse:7.03983      train-r2:0.584491
valid-r2:0.647705
[240]   train-rmse:8.26076      valid-rmse:7.03841      train-r2:0.587987
valid-r2:0.647847
[250]   train-rmse:8.23444      valid-rmse:7.04347      train-r2:0.590608
valid-r2:0.647341
[260]   train-rmse:8.20804      valid-rmse:7.05177      train-r2:0.593229
valid-r2:0.646509
[270]   train-rmse:8.18605      valid-rmse:7.06035      train-r2:0.595406
valid-r2:0.645648
[280]   train-rmse:8.16704      valid-rmse:7.0707       train-r2:0.597282
valid-r2:0.644609
Stopping. Best iteration:
[235]   train-rmse:8.2763       valid-rmse:7.03728      train-r2:0.586435
valid-r2:0.64796
```

4 Predicting XGBoost Model on test data

[20]:
```
p_test = clf.predict(d_test)

predictions = pd.DataFrame()
predictions['ID'] = id_test
predictions['y'] = p_test
```

[21]:
```
predictions
```

[21]:
```
        ID           y
0        1   89.522064
1        2  105.298737
2        3   89.935326
3        4   77.471291
4        5  111.139229
…     …          …
4204  8410  102.779503
4205  8411   92.947731
4206  8413   92.751747
4207  8414  110.757317
4208  8416   92.762100

[4209 rows x 2 columns]
```

5 Done!