In [1]:
```
from google.colab import drive
drive.mount('/content/drive/')
```

```
Drive already mounted at /content/drive/; to attempt to forcibly remoun
t, call drive.mount("/content/drive/", force_remount=True).
```

Mercedes-Benz Greener Manufacturing

- The first automobile, the Benz Patent Motor Car in 1886, Mercedes-Benz has stood for important automotive innovations. These include, for example, the passenger safety cell with 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 car makers. Daimler's Mercedes-Benz cars are leaders 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 each and every unique car configuration before they hit the road, Daimler's engineers have developed a robust testing system. But, optimizing the speed of their testing system for so many possible feature combinations is complex and time-consuming without a powerful algorithmic approach. As one of the world's biggest manufacturers of premium cars, safety and efficiency are paramount on Daimler's production lines.

Other aspect of the problem statement are

- If car take more time during testing it will effect on price of the car because Daimler's is spending there electricity, man-power,warehouse cost and other material. So more the test time more will be the cost of car.
- Other problem Co2 emmision will also increase more is testing machine take more time.

About Data

1. Dataset contains an anonymized set of variables, each representing a custom feature in a Mercedes car. For example, a variable could be 4WD, added air suspension, or a head-up display.
2. There is 8 catagorial feature, 1 ID feature, 368 are binary feature, and y column which is time in sec.

Performance metrics

1. R^2 (Coefficient of determination)

Business Constraints

1. There no constraint related to test time prediction but still predicting queries should not take must seconds because if it take 40–60 sec to predict then it has no use

Data Collection

1. Kaggle provides a ZIP file which contain Train.csv, Test.csv and Submission.csv https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/data

Loading data

In [2]:
```
from zipfile import ZipFile
file_name='/content/drive/My Drive/case/mercedes-benz-greener-manufactu
ring.zip'
with ZipFile(file_name,'r') as Zip:
  Zip.extractall()
```

In [3]:
```
file_name='train.csv.zip'
```

```
with ZipFile(file_name,'r') as Zip:
  Zip.extractall()
```

In [4]:
```
file_name='test.csv.zip'
with ZipFile(file_name,'r') as Zip:
  Zip.extractall()
```

In [5]:
```
import pandas as pd
import numpy as np
```

Importing train data

In [6]:
```
train_data=pd.read_csv('train.csv')
print('Train data shape : ',train_data.shape)
train_data.head(2)
```

```
Train data shape :  (4209, 378)
```

Out[6]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	X11	X12	X13	X14	X15	X16	X17	X18
0	0	130.81	k	v	at	a	d	u	j	o	0	0	0	1	0	0	0	0	1
1	6	88.53	k	t	av	e	d	y	l	o	0	0	0	0	0	0	0	0	1

2 rows × 378 columns

In [7]:
```
print('max of time  : ',max(train_data.y),'  , min of time   :  ',min(t
rain_data.y))
```

```
max of time  :  265.32   , min of time   :   72.11
```

In [8]:
```
test_data=pd.read_csv('test.csv')
print('Test data shape : ',test_data.shape)
test_data.head(2)
```

```
Test data shape :  (4209, 377)
```

Out[8]:

	ID	X0	X1	X2	X3	X4	X5	X6	X8	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19
0	1	az	v	n	f	d	t	a	w	0	0	0	0	0	0	0	0	0	0
1	2	t	b	ai	a	d	b	g	y	0	0	0	0	0	0	0	0	0	1

2 rows × 377 columns

Checking duplicate row

In [22]:
```
train_data.duplicated('ID').sum()
```

Out[22]: 0

Observation

1. There is no duplicated customer or ID

Importing test data

In [23]:
```
test_data=pd.read_csv('test.csv')
test_data.shape
```

Out[23]: (4209, 377)

Checking null value or not

In [25]:
```
train_data.isnull().sum().sum()
```

Out[25]: 0

Observation

1. No missing value present

In [26]:
```
print('Time median : ',train_data.y.median(),' | Time mean : ',train_da
ta.y.mean())
```

```
Time median :  99.09  | Time mean :  100.43993800667607
```

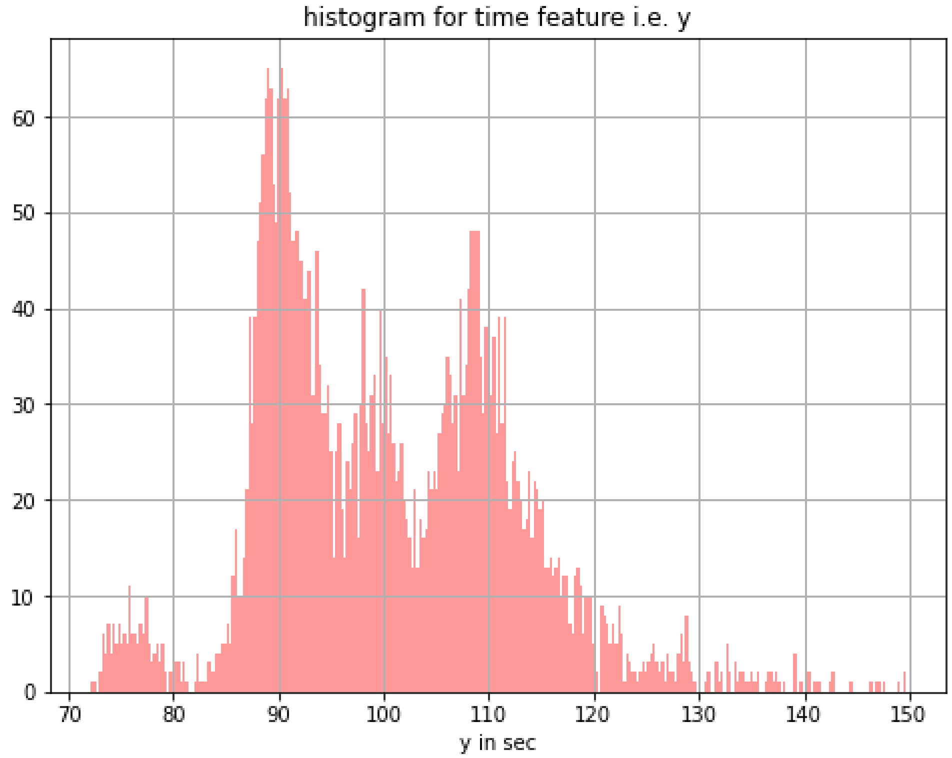
Let’s find some pattern in the data

In [27]:
```
import matplotlib.pyplot as plt
import seaborn as sb
```

Analysis of target variable y

In [28]:
```
plt.figure(figsize=(8,6))
plt.title('histogram for time feature i.e. y')
sb.distplot(train_data.y, bins=300, kde=False,color='red')
plt.xlabel('y in sec')
plt.grid(linewidth=1,)
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2551: F
utureWarning: `distplot` is a deprecated function and will be removed i
n a future version. Please adapt your code to use either `displot` (a f
igure-level function with similar flexibility) or `histplot` (an axes-l
evel function for histograms).
  warnings.warn(msg, FutureWarning)
```



Observation

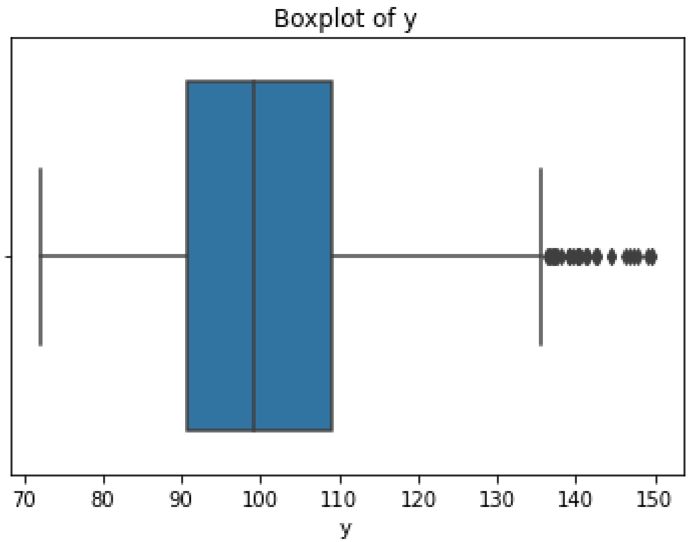
1. Maximum y lies between 80 to 120
2. y is skewed

In [29]:
```
plt.title('Boxplot of y')
sb.boxplot(train_data.y)
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: Futur
eWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing ot
her arguments without an explicit keyword will result in an error or mi
```

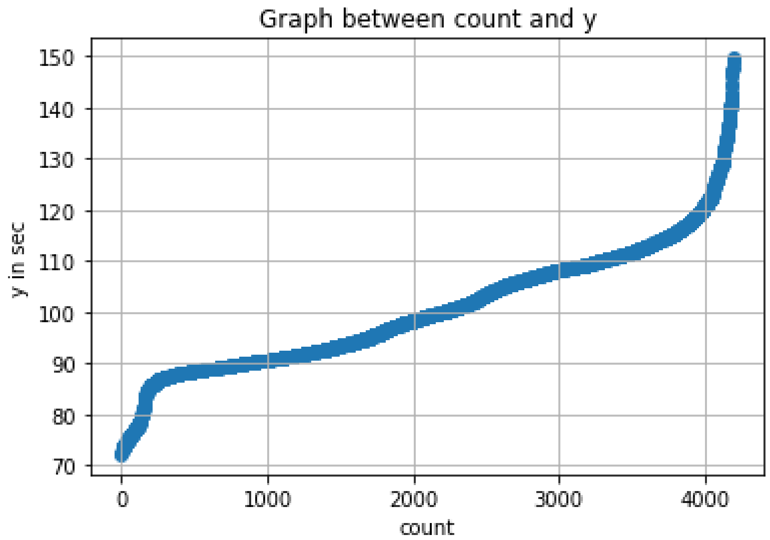
```
sinterpretation.
  FutureWarning
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f022d832ba8>



In [30]:

```
plt.title('Graph between count and y')# count =[1,2,3,4,...........420
9]
plt.scatter(range(len(train_data)),np.sort(train_data.y))
plt.xlabel('count')
plt.ylabel('y in sec')
plt.grid()
```



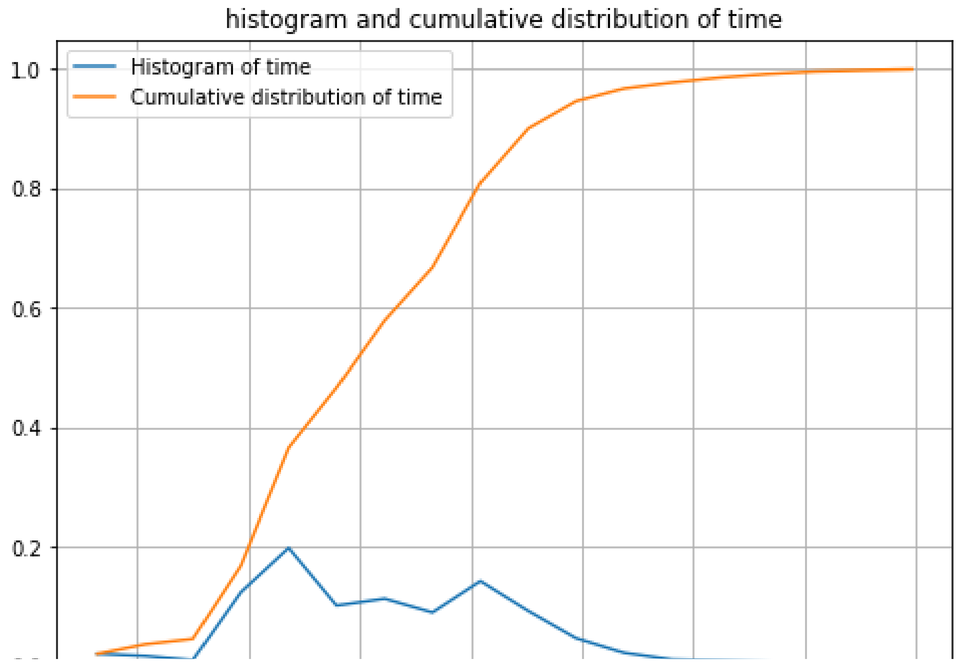
Observation

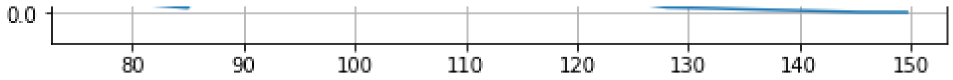
1. There is one point which is far from other points.

In [31]:
```
counts, bin_edges = np.histogram(train_data.y, bins=18,density = True,)
pdf = counts/(sum(counts))
print('pdf : ',pdf,'\n');
print('bin edge : ',bin_edges,'\n')
cdf = np.cumsum(pdf)
plt.figure(figsize=(8,6))
plt.plot(bin_edges[1:],pdf,label='Histogram of time')
plt.plot(bin_edges[1:], cdf,label='Cumulative distribution of time')
plt.title('histogram and cumulative distribution of time')
plt.legend()
plt.grid()
c=0
q=[]
for i in pdf:
 c=c+i
```

```
 q.append(c)
print('outlier : ',q)
```

```
pdf :  [0.01955174 0.0159752  0.00906056 0.12327134 0.19766333 0.1008
5837
 0.11230329 0.08917501 0.1416309  0.09155937 0.04577969 0.02122079
 0.01001431 0.00834526 0.0059609  0.00405341 0.00190749 0.00166905]

bin edge :  [ 72.11        76.41666667  80.72333333  85.03        89.
33666667
  93.64333333  97.95       102.25666667 106.56333333 110.87
 115.17666667 119.48333333 123.79       128.09666667 132.40333333
 136.71       141.01666667 145.32333333 149.63      ]

outlier :  [0.01955174058178347, 0.03552694325226514, 0.0445875059608
965, 0.16785884597043377, 0.3655221745350502, 0.46638054363376247, 0.
5786838340486411, 0.6678588459704344, 0.8094897472579874, 0.9010491177
873152, 0.9468288030519789, 0.9680495946590366, 0.9780639008106818,
0.9864091559370528, 0.9923700524558893, 0.996423462088698, 0.99833094
89747257, 0.9999999999999999]
```





Observation

1. We can consider that y>150 be outlier.
2. Almost 99.83368% data cover before 150 #### Approach Removing row y<150

In [32]:
```
train_data=train_data[train_data.y<150]
```

Analysis of categorical feature

In [33]:
```
for j,i in enumerate(range(2,9)):
  print('Unique value in X'+str(j),' :')
  print(train_data.iloc[:,i].unique())
  print('No. of unique value : ',train_data.iloc[:,i].unique().shape[0
],'\n')
print('Unique value in X8 :')
print(train_data.iloc[:,9].unique())
print('No. of unique value : ',train_data.iloc[:,9].unique().shape[0],'
\n')
```

```
Unique value in 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']
No. of unique value :  47

Unique value in 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']
No. of unique value :  27
```

```
Unique value in 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' 'h' 'x' 'au' 't' 'a
n'
 'z' 'ah' 'p' 'am' 'j' 'q' 'af' 'l' 'aa' 'c' 'o' 'ar']
No. of unique value :  44

Unique value in X3  :
['a' 'e' 'c' 'f' 'd' 'b' 'g']
No. of unique value :  7

Unique value in X4  :
['d' 'b' 'c' 'a']
No. of unique value :  4

Unique value in 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']
No. of unique value :  29

Unique value in X6  :
['j' 'l' 'd' 'h' 'i' 'a' 'g' 'c' 'k' 'e' 'f' 'b']
No. of unique value :  12

Unique value in 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']
No. of unique value :  25
```

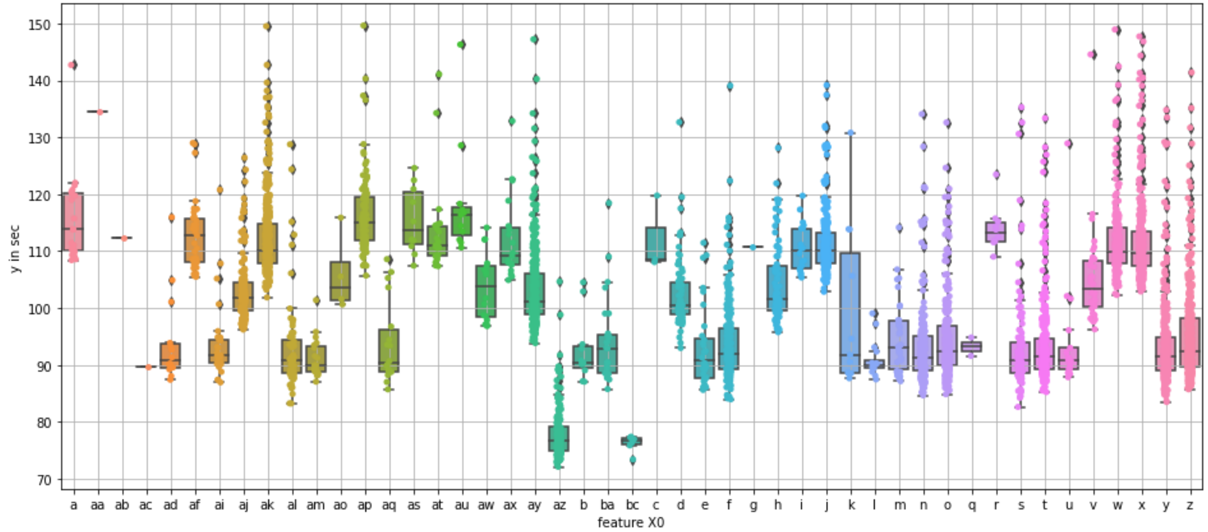
In [34]:

```
print('Time median : ',train_data.y.median(),' | Time mean : ',train_da
ta.y.mean())
```

```
Time median :  99.09  | Time mean :  100.43993800667607
```

X0 feature preprocessing

In [35]:
```
plt.figure(figsize=(16,7))
sb.stripplot(x='X0', y='y', data=train_data, order=np.sort(train_data.X
0.unique()).tolist())
sb.boxplot(x='X0', y='y', data=train_data, order=np.sort(train_data.X0.
unique()).tolist())
plt.xlabel('feature X0')
plt.ylabel('y in sec')
plt.grid()
```



Observation

This feature is well spread. It mean that all unique item’s lies in some specific range. e.g. all ‘a’ have time greater than 110 ,similarly ‘aa’ have time greater than 135,all ‘az’ time lie below 110 because of this we can guess or predict approx time easily. E.g. if my query point have ‘a’ then i don’t know the exact value but i know that will be more than 110 sec

Approach

We can put each unique iteam into sets by looking median.

Train

In [36]:
```
def X0_pre(train):
  f1=[]
  f2=[]
  f3=[]
  for i in train.X0.unique():
    a=train_data[train.X0==i].y.median()
    b=train_data[train.X0==i].shape[0]
    if 107<=a :
        f1.append(i)
    if 97<=a and a<107:
        f2.append(i)
    if a<97:
        f3.append(i)

  f=[f1,f2,f3]
  d0={}
  c=0
  for i in f:
    for j in i:
      d0[j]=c
    c=c+1
  X0=[]
  for i in train.X0:
    X0.append(d0[i])
  return d0,X0
```

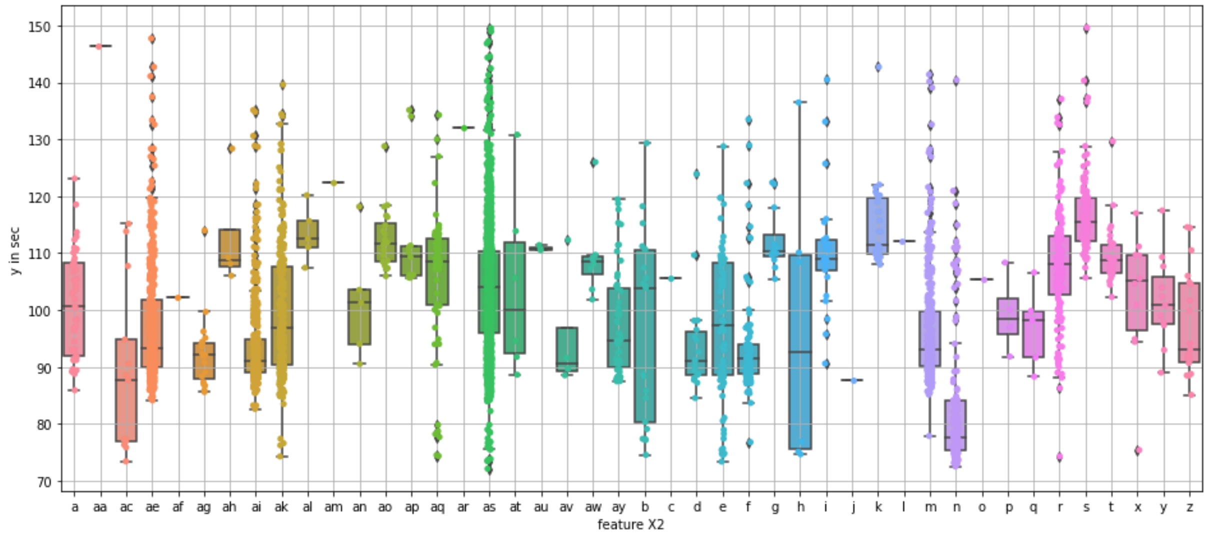
In [37]:
```
tr_df=pd.DataFrame(train_data.y,columns=['y'])
```

In [38]:
```
D,X=X0_pre(train_data)
```

In [39]:
```
tr_df['X0_n']=X
```

X2 feature preprocessing

In [40]:
```
plt.figure(figsize=(16,7))
sb.stripplot(x='X2', y='y', data=train_data, order=np.sort(train_data.X2.unique()).tolist())
sb.boxplot(x='X2', y='y', data=train_data, order=np.sort(train_data.X2.unique()).tolist())
plt.xlabel('feature X2')
plt.ylabel('y in sec')
plt.grid()
```



In [41]:
```
train_data[(train_data.X0=='a') & (train_data.y>=100)].shape
```

Out[41]: (21, 378)

Observation

ak,as,ae are the unique value which do not have specific range of time and ak,as,ae cover 69% of total data

In [42]:
```
def X2_pre(train_data):
  f1=[]
  f2=[]
  f3=[]
  for i in train_data.X2.unique():
    a=train_data[train_data.X2==i].y.median()
    b=train_data[train_data.X2==i].shape[0]
    if 107<=a :
      f1.append(i)
    if 98<=a and a<107:
      f2.append(i)
    if a<98:
      f3.append(i)
  f=[f1,f2,f3]
  d2={}
  c=0
  for i in f:
    for j in i:
      d2[j]=c
    c=c+1
  X2=[]
  for i in train_data.X2:
    X2.append(d2[i])
  return d2,X2
```

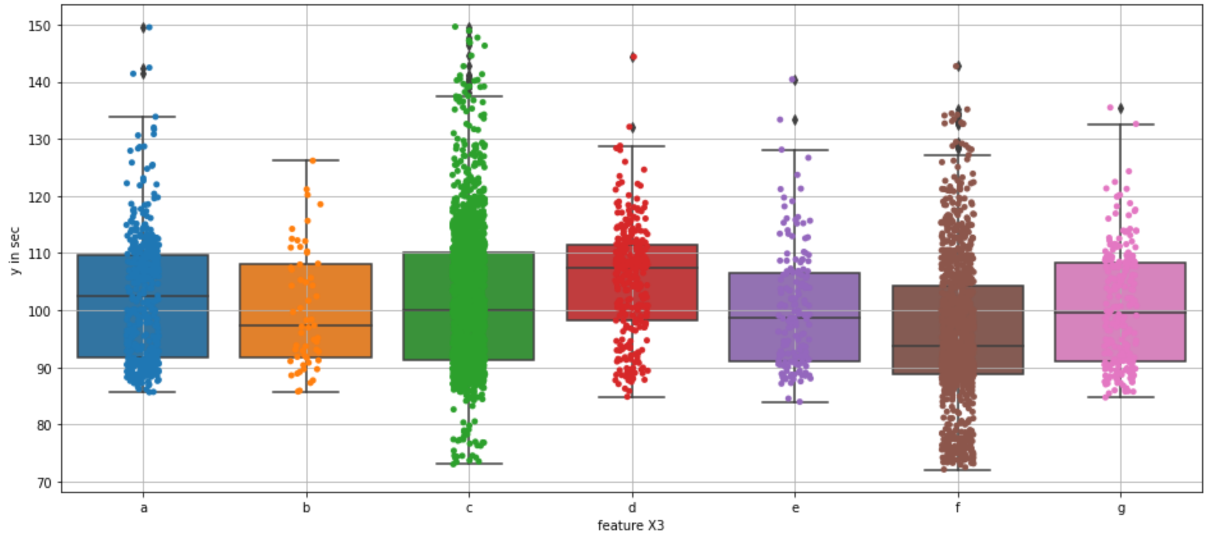
In [43]:
```
D2,X2=X2_pre(train_data)
```

In [44]:
```
tr_df['X2_n']=X2
```

X3 feature

In [45]:
```
plt.figure(figsize=(16,7))
sb.stripplot(x='X3', y='y', data=train_data, order=np.sort(train_data.X
3.unique()).tolist())
sb.boxplot(x='X3', y='y', data=train_data, order=np.sort(train_data.X3.
unique()).tolist())
```

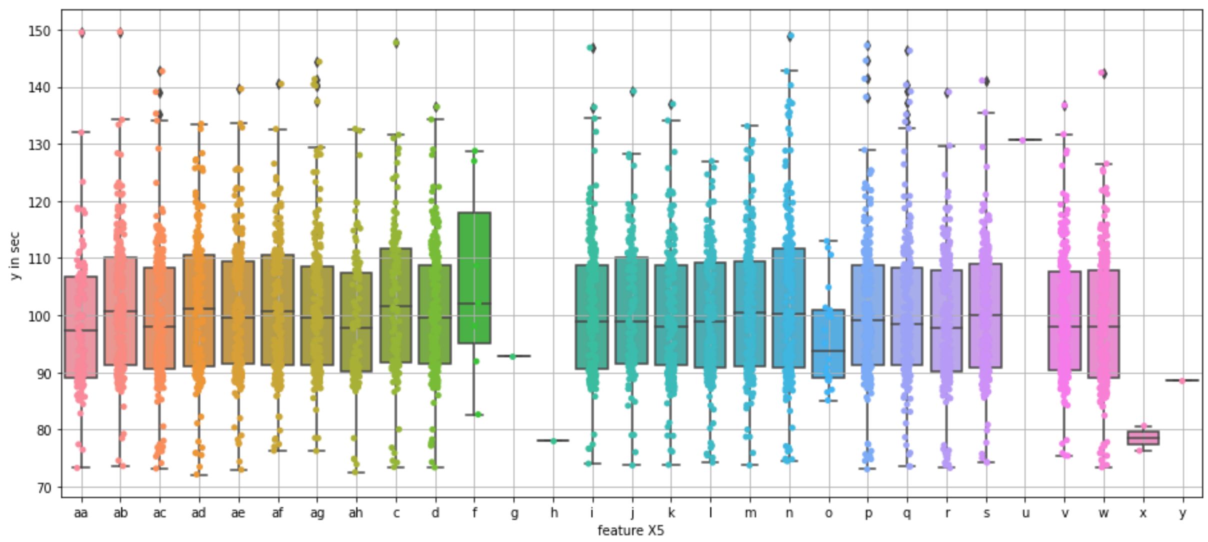
```
plt.xlabel('feature X3')
plt.ylabel('y in sec')
plt.grid()
```



X5 feature

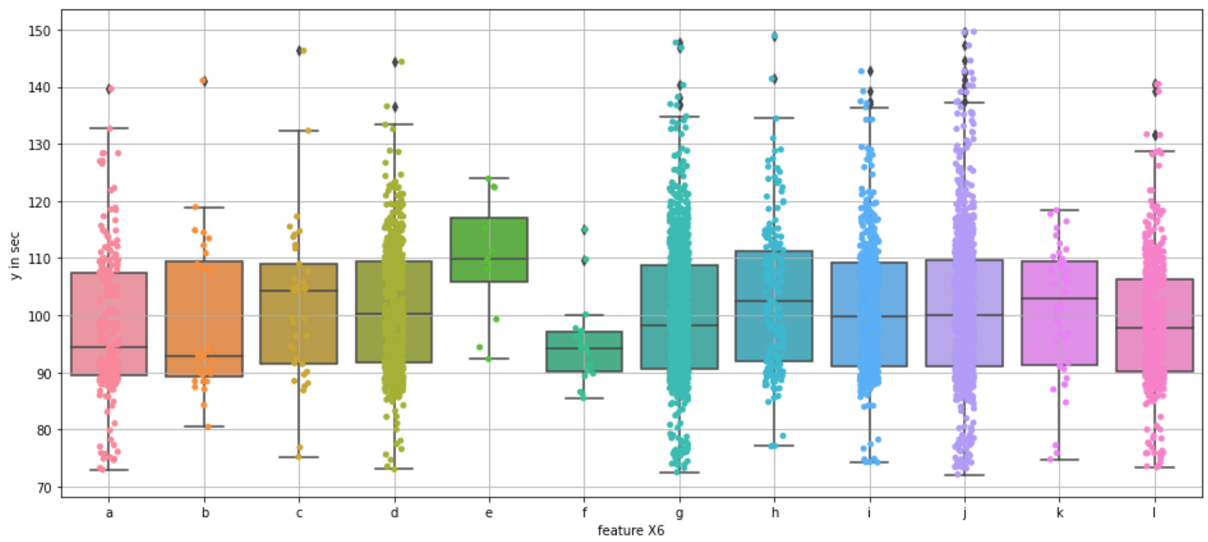
In [46]:

```
plt.figure(figsize=(16,7))
sb.stripplot(x='X5', y='y', data=train_data, order=np.sort(train_data.X
5.unique()).tolist())
sb.boxplot(x='X5', y='y', data=train_data, order=np.sort(train_data.X5.
unique()).tolist())
plt.xlabel('feature X5')
plt.ylabel('y in sec')
plt.grid()
```



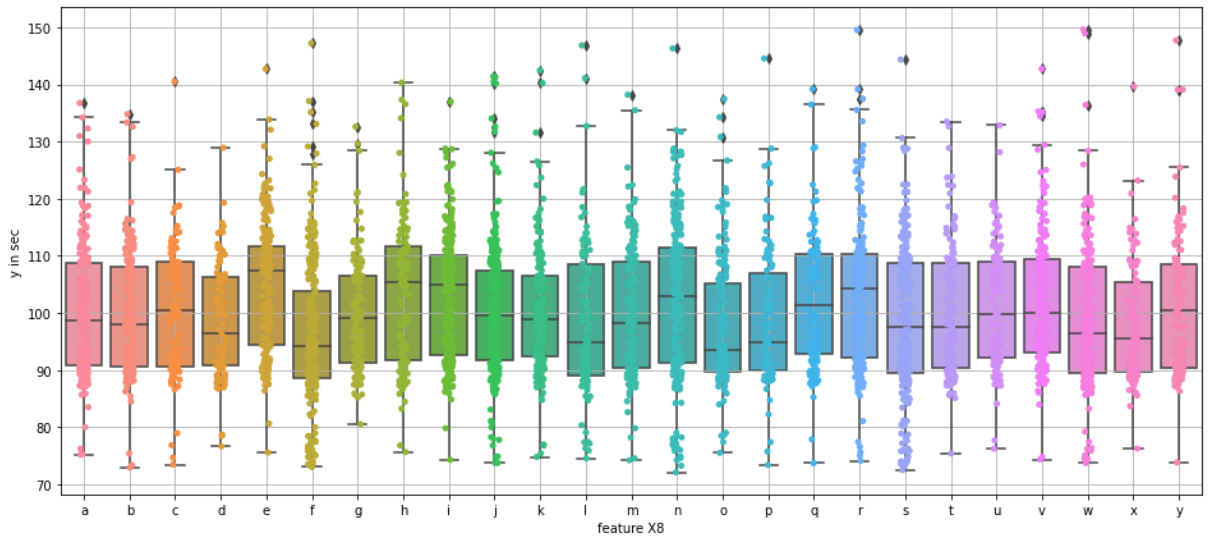
X6 feature

In [47]:
```
plt.figure(figsize=(16,7))
sb.stripplot(x='X6', y='y', data=train_data, order=np.sort(train_data.X
6.unique()).tolist())
sb.boxplot(x='X6', y='y', data=train_data, order=np.sort(train_data.X6.
unique()).tolist())
plt.xlabel('feature X6')
plt.ylabel('y in sec')
plt.grid()
```



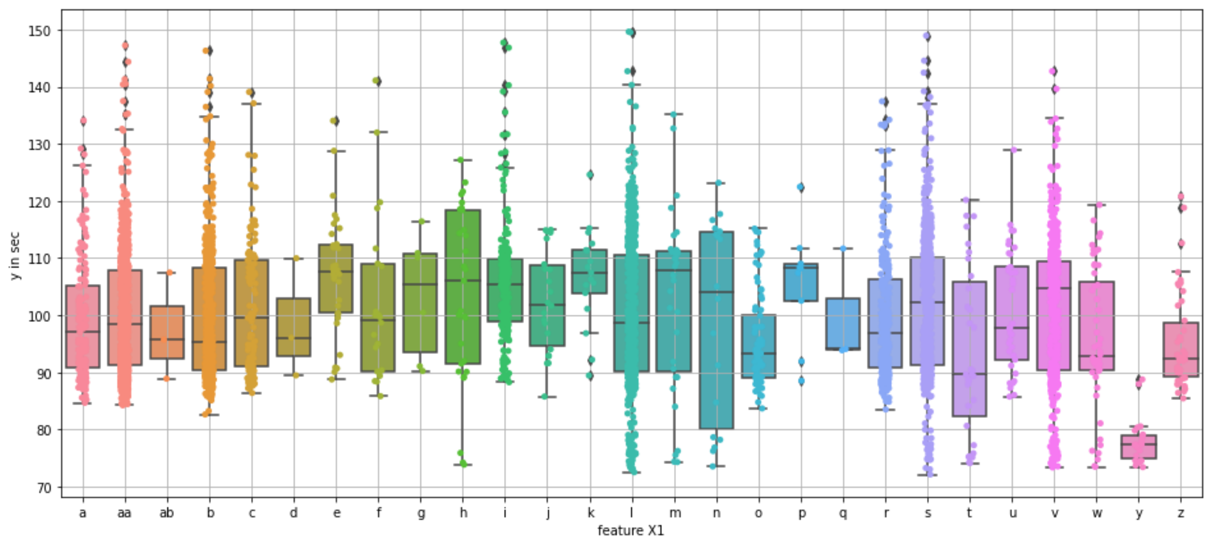
X8 feature

In [48]:
```
plt.figure(figsize=(16,7))
sb.stripplot(x='X8', y='y', data=train_data, order=np.sort(train_data.X
8.unique()).tolist())
sb.boxplot(x='X8', y='y', data=train_data, order=np.sort(train_data.X8.
unique()).tolist())
plt.xlabel('feature X8')
plt.ylabel('y in sec')
plt.grid()
```



X1 feature

In [49]:
```
plt.figure(figsize=(16,7))
sb.stripplot(x='X1', y='y', data=train_data, order=np.sort(train_data.X
1.unique()).tolist())
sb.boxplot(x='X1', y='y', data=train_data, order=np.sort(train_data.X1.
unique()).tolist())
plt.xlabel('feature X1')
plt.ylabel('y in sec')
plt.grid()
```



Observation

1. The feature X3,X1,X5,X6,X8,X4 can not be converted into a different sets because the unique value does not lies into a specific range. It means there is no set pattern. For eg in plot X1 : 'b' value can lies from 83 to 140+ similarly 'c' value can lies from 86 to 138 that's why we put value into sets according to the value ranges.
2. The feature X3,X1,X5,X6,X8,X4,X2 are less informative as compare to X0

Label Encoding for all categorical feature

In [50]:

```
import joblib
from sklearn.preprocessing import LabelEncoder
for i in ['X0','X1','X2','X3','X4','X5','X6','X8']:
    lab = LabelEncoder()
    lab.fit(pd.concat([train_data[i],test_data[i]]))
    joblib.dump(lab,i)
```

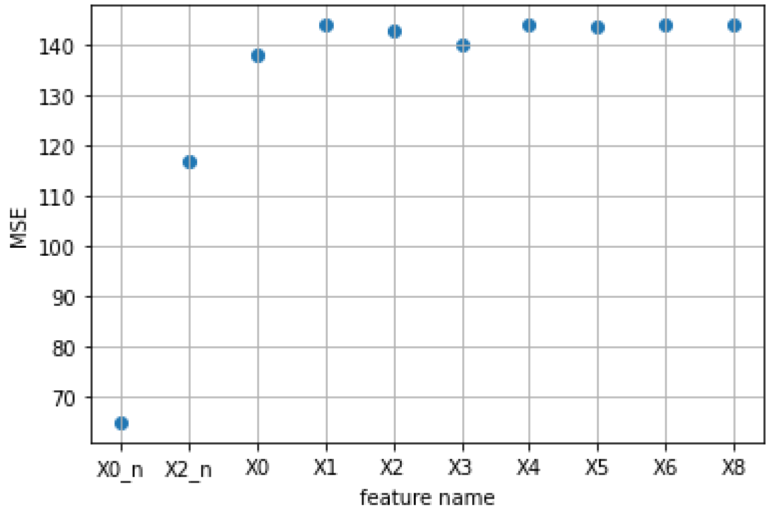
In [51]:
```
for i in ['X0','X1','X2','X3','X4','X5','X6','X8']:
  pre_enc=joblib.load(i)
  tr_df[i]=pre_enc.transform(train_data[i])
```

Checking Correlation

In [52]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score,mean_squared_error
```

In [53]:
```
mse=[]
for i in tr_df.columns:
  if i!='y':
    lin=LinearRegression()
    lin.fit(tr_df[[i]],tr_df.y)
    mse.append(mean_squared_error(tr_df.y,lin.predict(tr_df[[i]])))
```

In [54]:
```
plt.scatter(tr_df.columns[1:],mse)
plt.xlabel('feature name')
plt.ylabel('MSE')
plt.grid()
```



Observation

1. We can see 'X0_n' is most correlated with targert variable because it's MSE value is much lower in comparision with other feature.

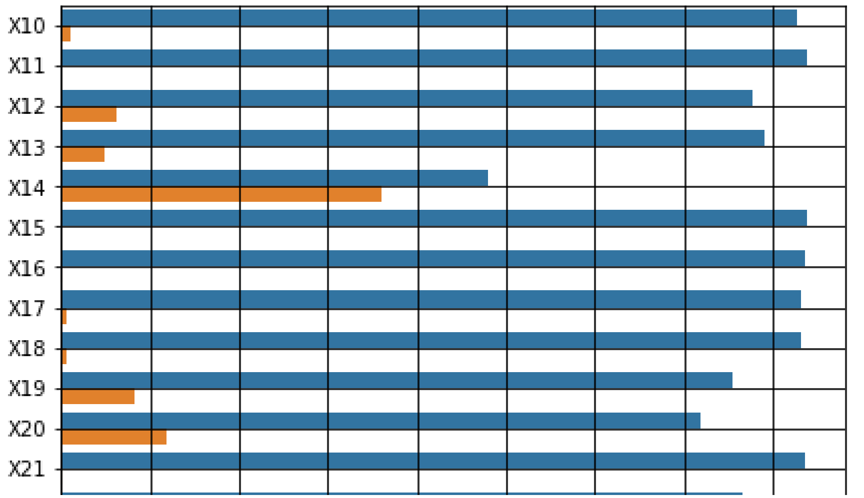
Binary feature

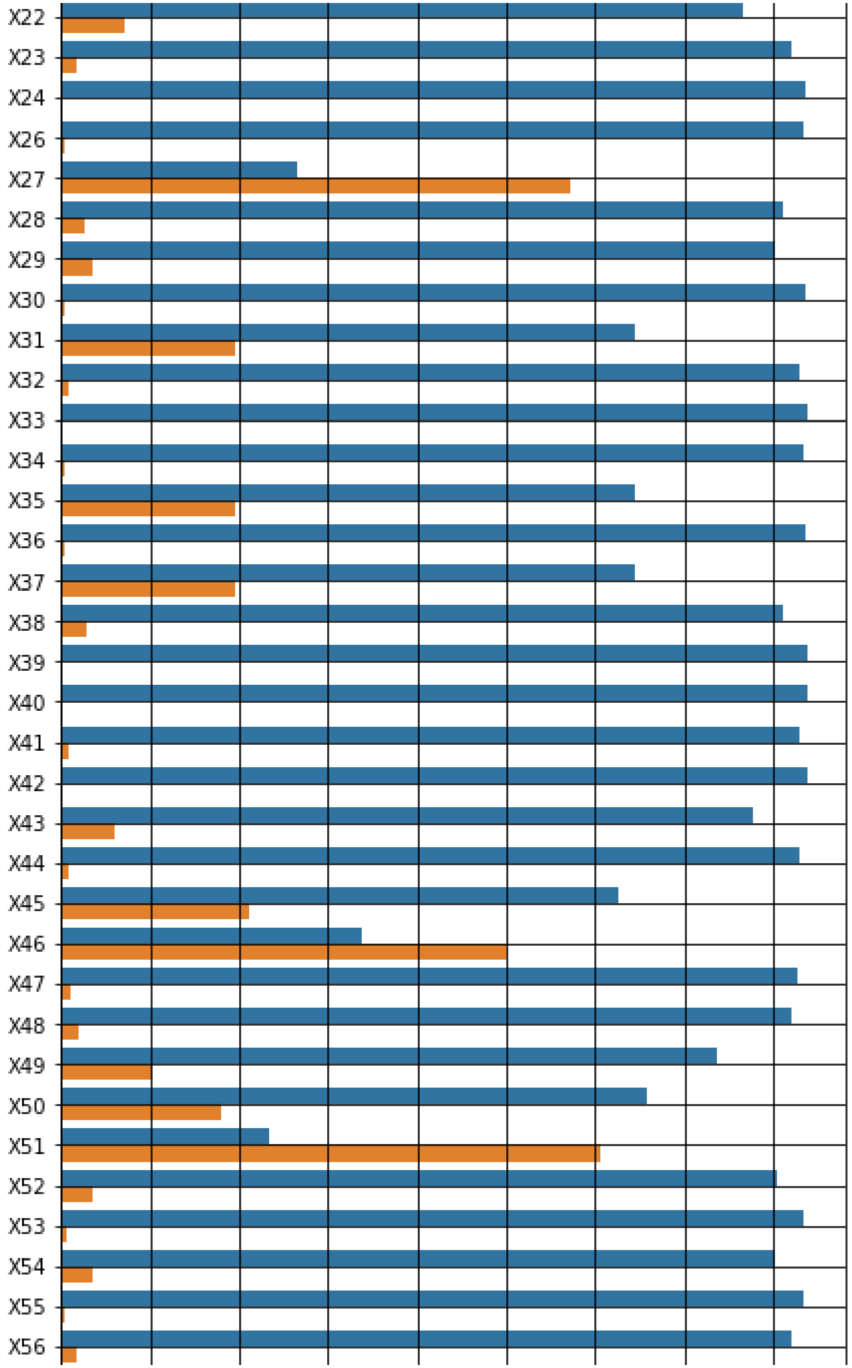
In [55]:
```
print('Total no. of binary feature : ',len(train_data.iloc[:,10:].colum
ns.tolist()))
```

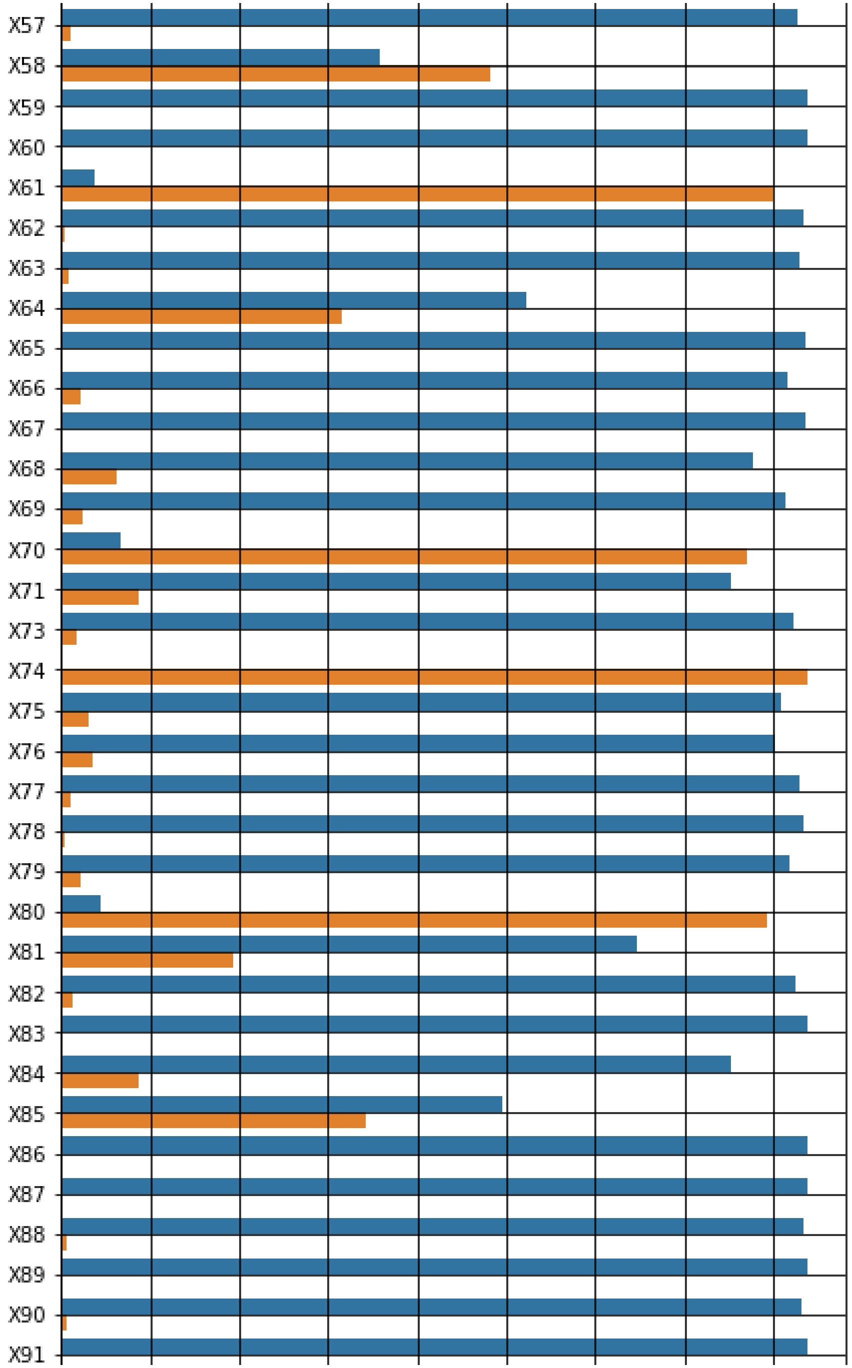
```
Total no. of binary feature :  368
```

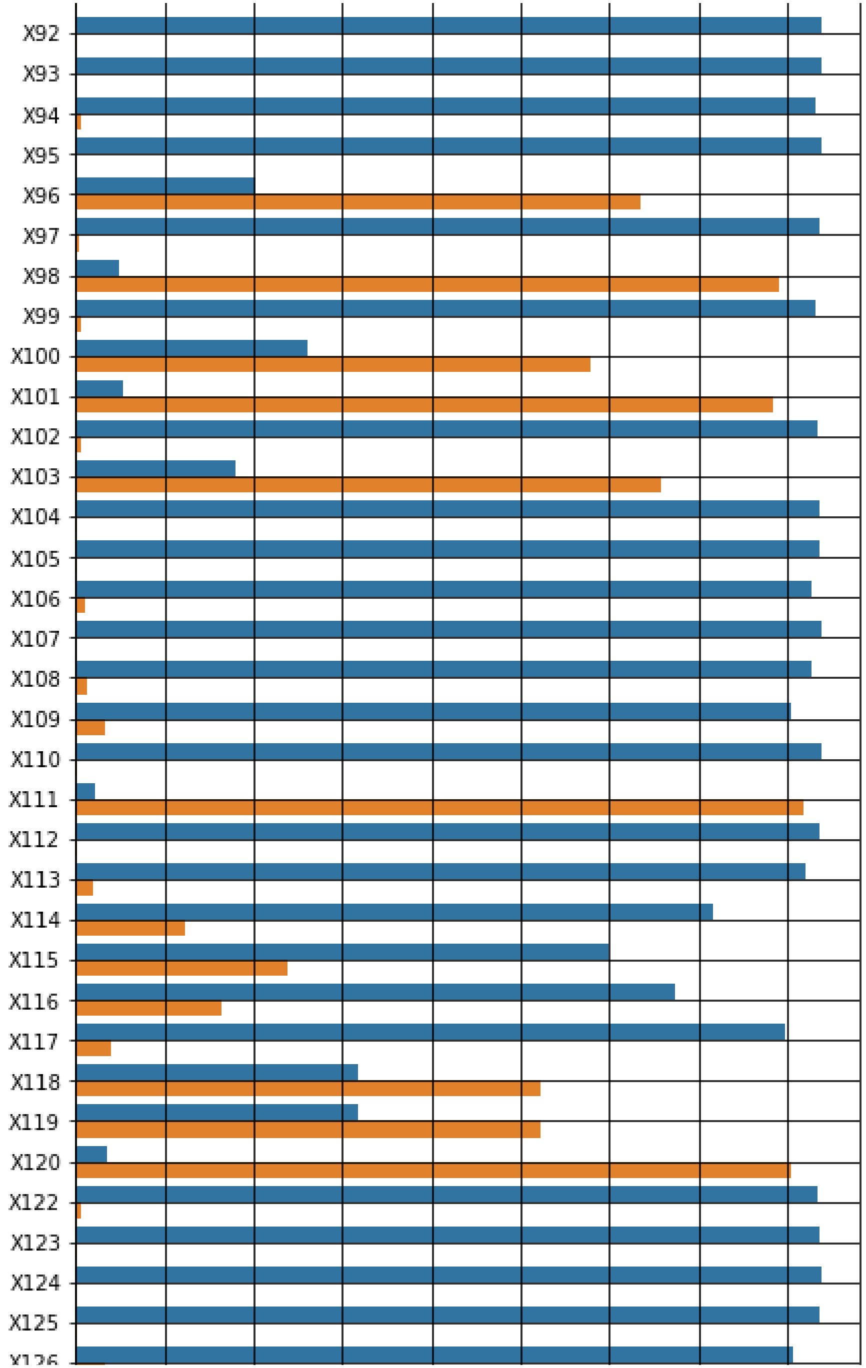
In [56]:
```
plt.figure(figsize=(7,136))
po=sb.countplot(y='variable',hue='value',data=pd.melt(train_data.iloc
[:,10:]))
plt.savefig('/content/drive/My Drive/poo.png')
plt.grid(color='black')
plt.legend()
```

Out[56]:
```
<matplotlib.legend.Legend at 0x7f022ebe9fd0>
```

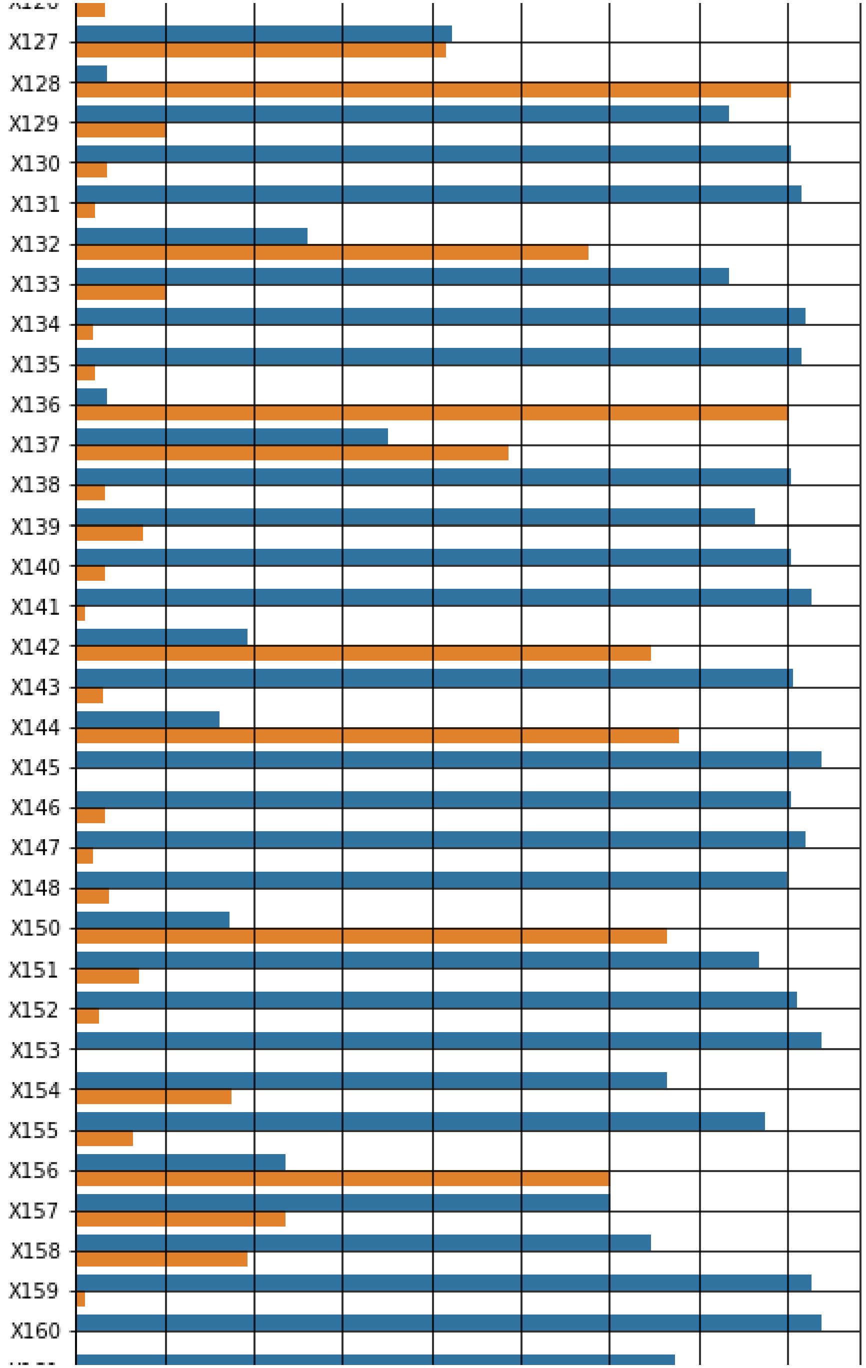


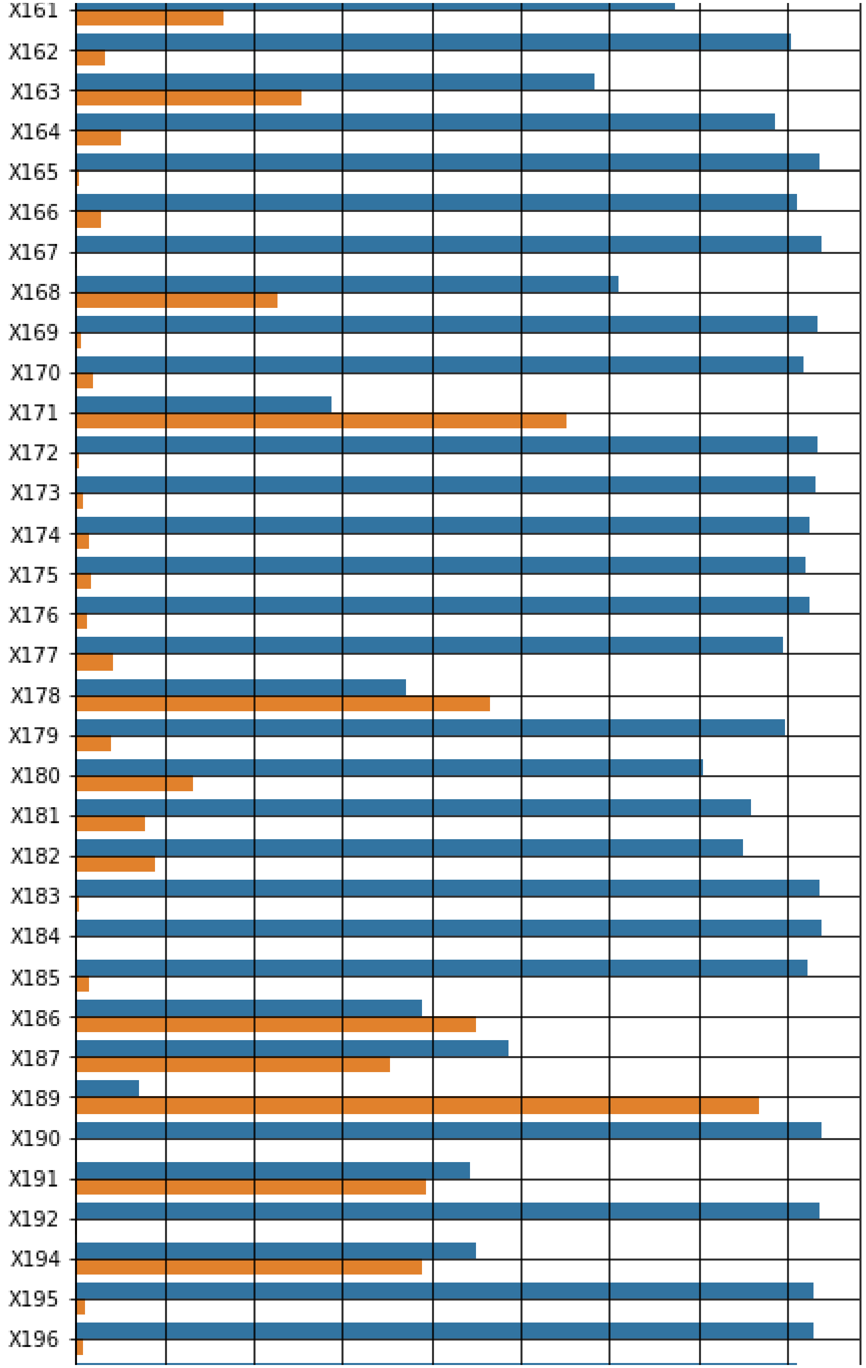

X22
X23
X24
X26
X27
X28
X29
X30
X31
X32
X33
X34
X35
X36
X37
X38
X39
X40
X41
X42
X43
X44
X45
X46
X47
X48
X49
X50
X51
X52
X53
X54
X55
X56

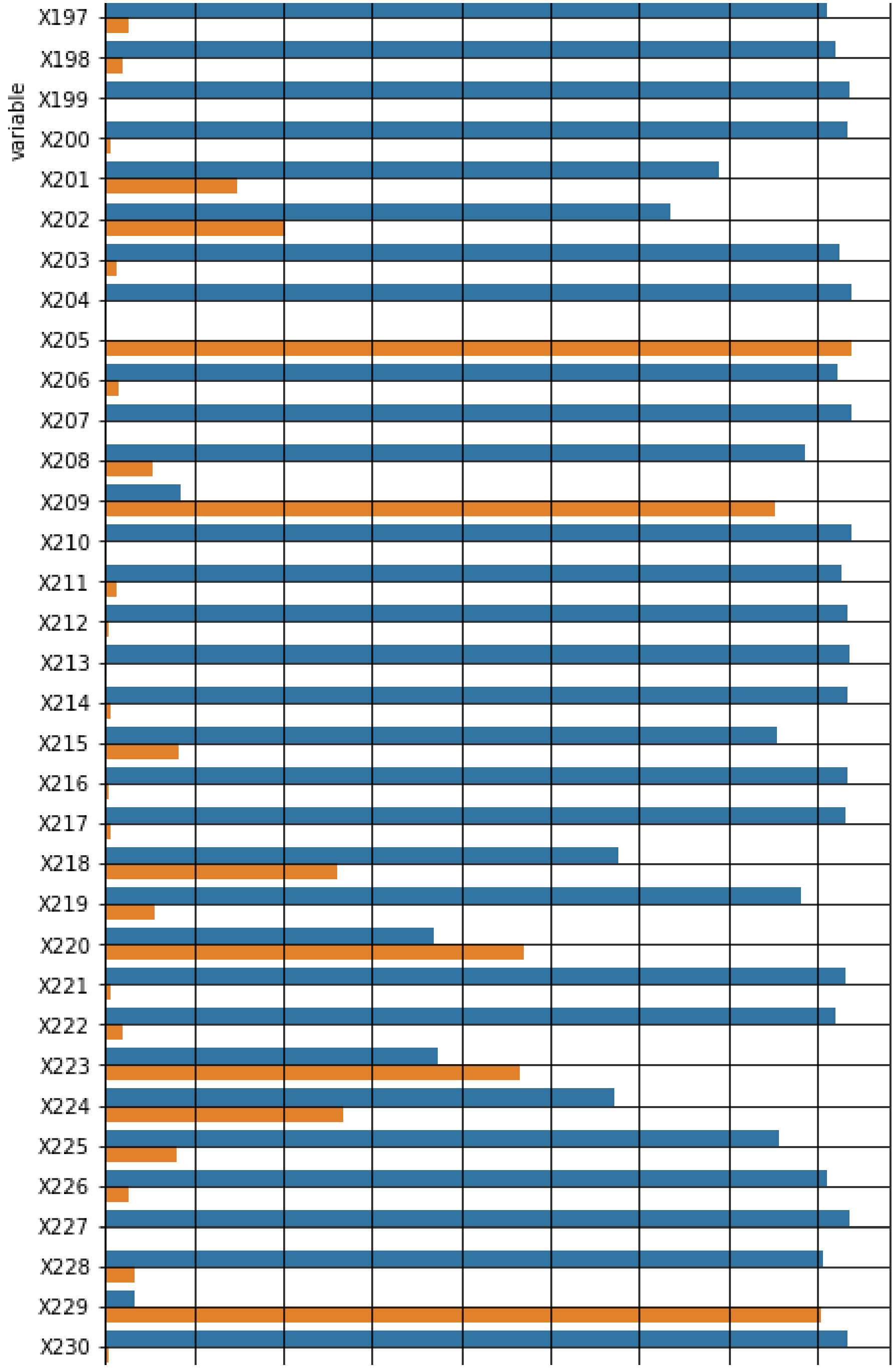

X57
X58
X59
X60
X61
X62
X63
X64
X65
X66
X67
X68
X69
X70
X71
X73
X74
X75
X76
X77
X78
X79
X80
X81
X82
X83
X84
X85
X86
X87
X88
X89
X90
X91

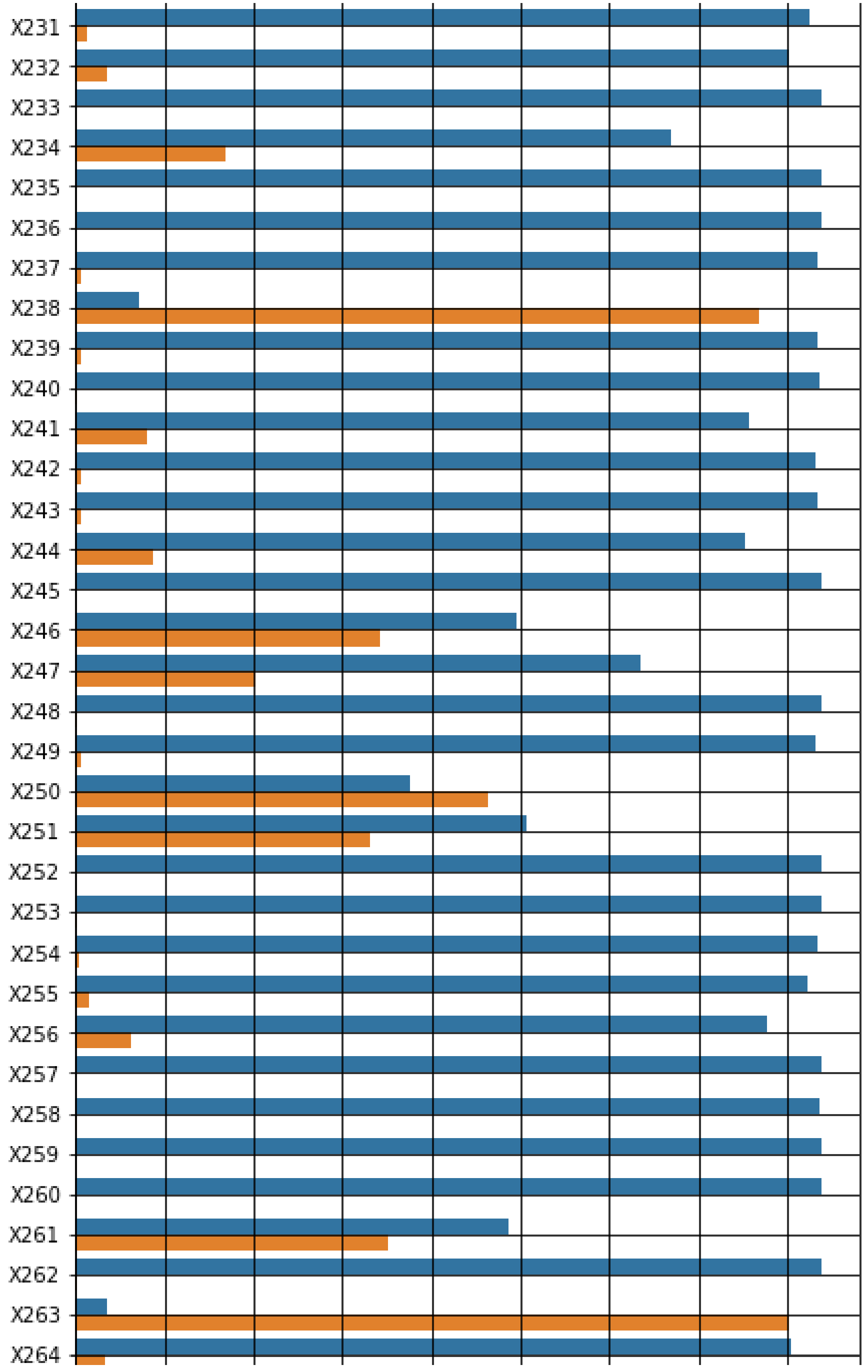


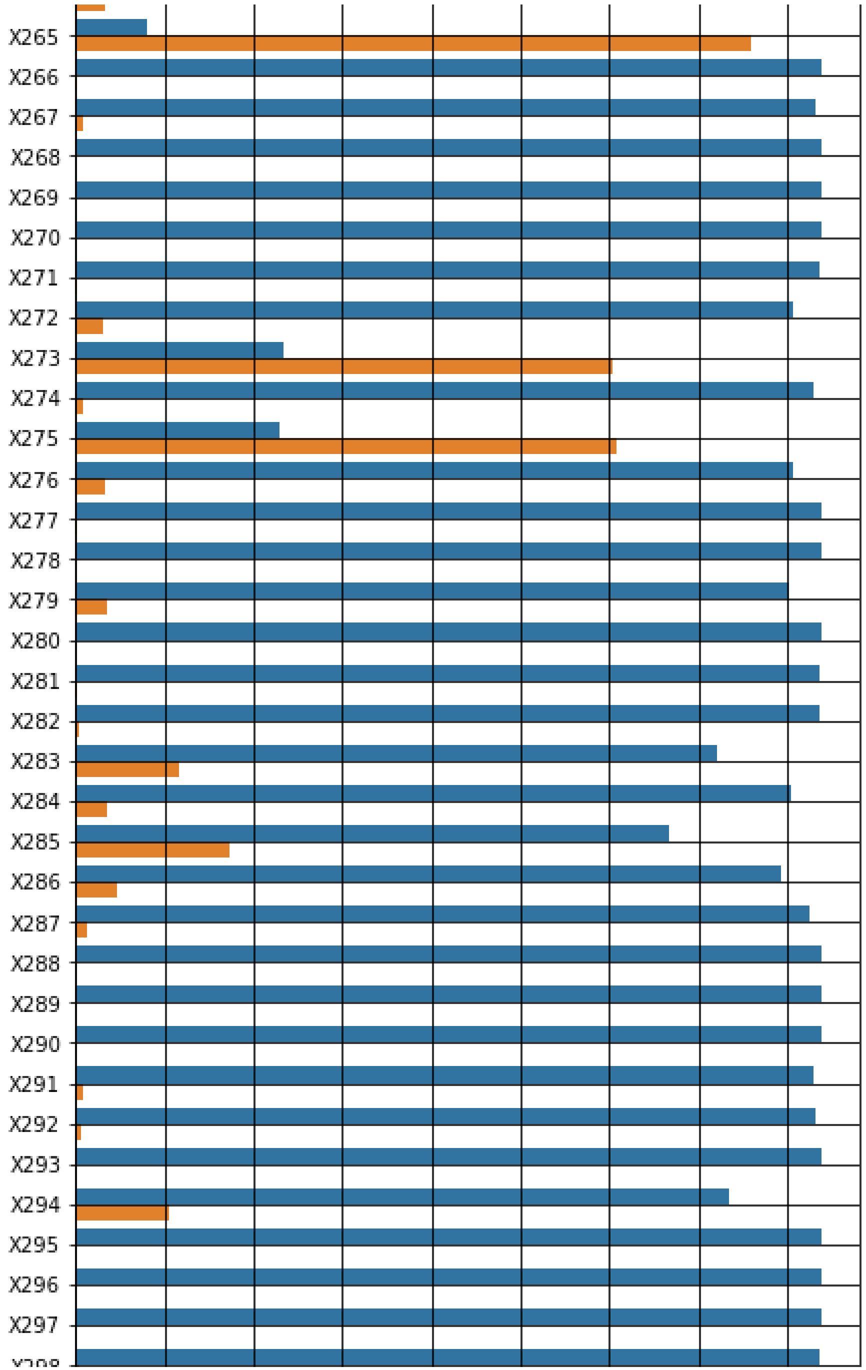
X92
X93
X94
X95
X96
X97
X98
X99
X100
X101
X102
X103
X104
X105
X106
X107
X108
X109
X110
X111
X112
X113
X114
X115
X116
X117
X118
X119
X120
X122
X123
X124
X125

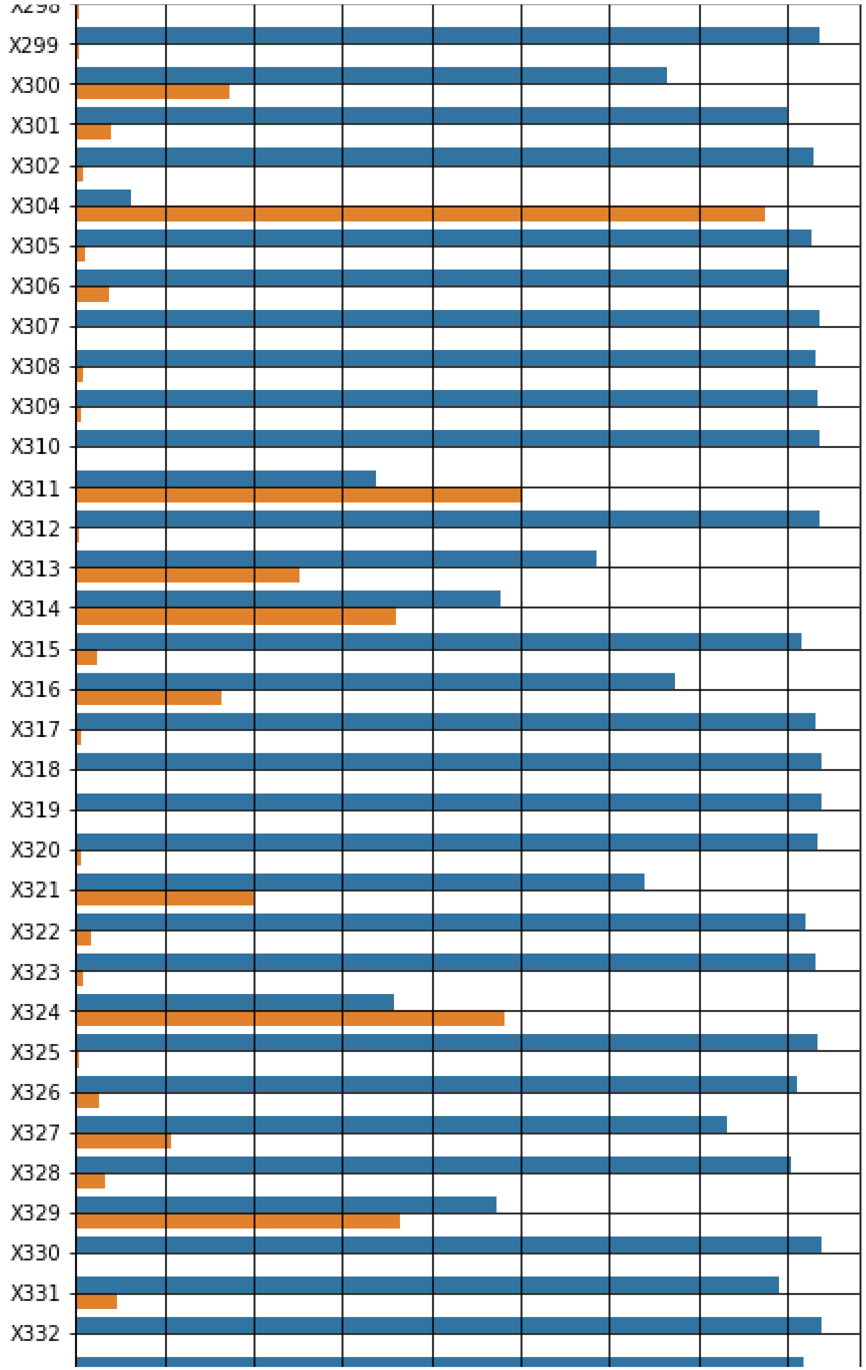

X127
X128
X129
X130
X131
X132
X133
X134
X135
X136
X137
X138
X139
X140
X141
X142
X143
X144
X145
X146
X147
X148
X150
X151
X152
X153
X154
X155
X156
X157
X158
X159
X160

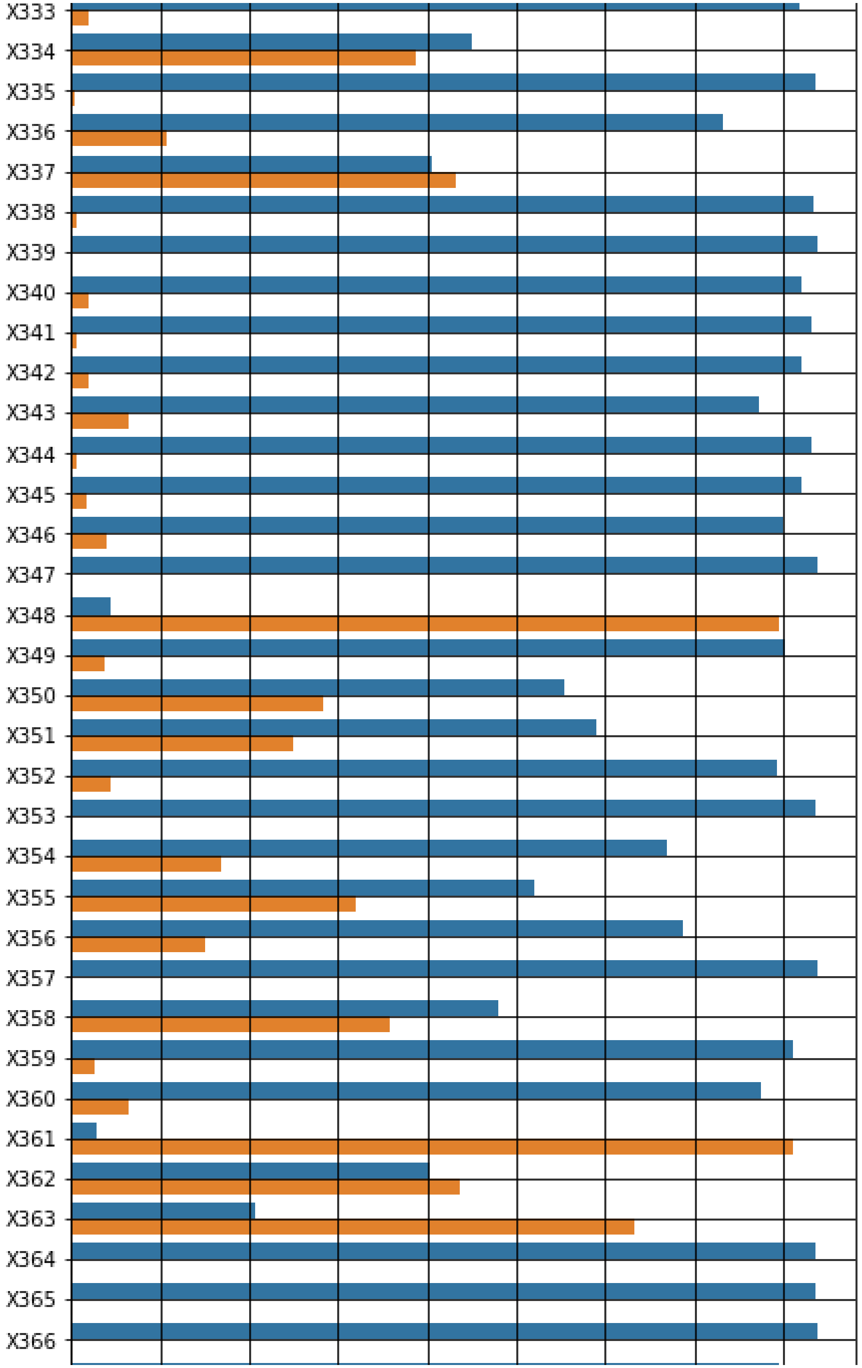

X161
X162
X163
X164
X165
X166
X167
X168
X169
X170
X171
X172
X173
X174
X175
X176
X177
X178
X179
X180
X181
X182
X183
X184
X185
X186
X187
X189
X190
X191
X192
X194
X195
X196

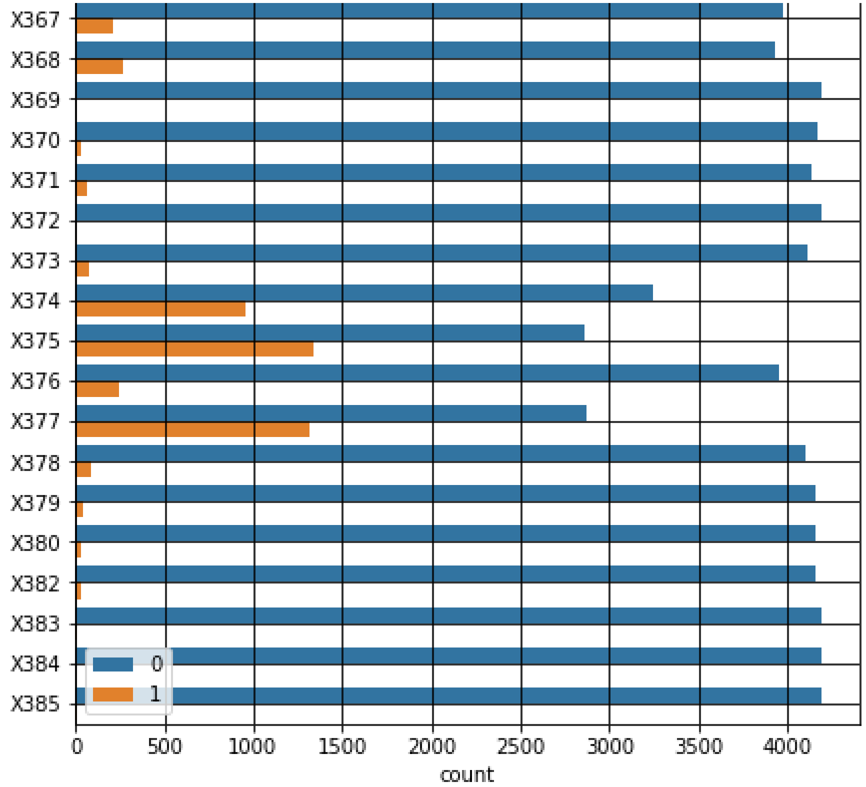

variable
X197
X198
X199
X200
X201
X202
X203
X204
X205
X206
X207
X208
X209
X210
X211
X212
X213
X214
X215
X216
X217
X218
X219
X220
X221
X222
X223
X224
X225
X226
X227
X228
X229
X230


X231
X232
X233
X234
X235
X236
X237
X238
X239
X240
X241
X242
X243
X244
X245
X246
X247
X248
X249
X250
X251
X252
X253
X254
X255
X256
X257
X258
X259
X260
X261
X262
X263
X264


X265
X266
X267
X268
X269
X270
X271
X272
X273
X274
X275
X276
X277
X278
X279
X280
X281
X282
X283
X284
X285
X286
X287
X288
X289
X290
X291
X292
X293
X294
X295
X296
X297


X298
X299
X300
X301
X302
X304
X305
X306
X307
X308
X309
X310
X311
X312
X313
X314
X315
X316
X317
X318
X319
X320
X321
X322
X323
X324
X325
X326
X327
X328
X329
X330
X331
X332


X333
X334
X335
X336
X337
X338
X339
X340
X341
X342
X343
X344
X345
X346
X347
X348
X349
X350
X351
X352
X353
X354
X355
X356
X357
X358
X359
X360
X361
X362
X363
X364
X365
X366



All unique feature from X10 to X378

In [57]:
```
def rem_zero(train):
  inn=[]
  out=[]
  for i in train.iloc[:,10:].columns:
    td=train[i].unique().tolist()
    if len(td)>=2:
      inn.append(i)
    else:
      out.append(i)
  return inn,out
```

In [58]:
```
n,o=rem_zero(train_data)
```

In [59]:
```
print('The features contain only 0   : ',o,' : lenght : ',len(o),'\n')
print('The features contain only 0|1 : ',n, ' : lenght : ',len(n))
```

```
The features contain only 0   :  ['X11', 'X93', 'X107', 'X233', 'X235',
'X268', 'X289', 'X290', 'X293', 'X297', 'X330', 'X339', 'X347']  : leng
ht :  13

The features contain only 0|1 :  ['X10', 'X12', 'X13', 'X14', 'X15', 'X
16', 'X17', 'X18', 'X19', 'X20', 'X21', 'X22', 'X23', 'X24', 'X26', 'X2
7', 'X28', 'X29', 'X30', 'X31', 'X32', 'X33', 'X34', 'X35', 'X36', 'X3
7', 'X38', 'X39', 'X40', 'X41', 'X42', 'X43', 'X44', 'X45', 'X46', 'X4
7', 'X48', 'X49', 'X50', 'X51', 'X52', 'X53', 'X54', 'X55', 'X56', 'X5
7', 'X58', 'X59', 'X60', 'X61', 'X62', 'X63', 'X64', 'X65', 'X66', 'X6
7', 'X68', 'X69', 'X70', 'X71', 'X73', 'X74', 'X75', 'X76', 'X77', 'X7
8', 'X79', 'X80', 'X81', 'X82', 'X83', 'X84', 'X85', 'X86', 'X87', 'X8
8', 'X89', 'X90', 'X91', 'X92', 'X94', 'X95', 'X96', 'X97', 'X98', 'X9
9', 'X100', 'X101', 'X102', 'X103', 'X104', 'X105', 'X106', 'X108', 'X1
09', 'X110', 'X111', 'X112', 'X113', 'X114', 'X115', 'X116', 'X117', 'X
118', 'X119', 'X120', 'X122', 'X123', 'X124', 'X125', 'X126', 'X127',
'X128', 'X129', 'X130', 'X131', 'X132', 'X133', 'X134', 'X135', 'X136',
'X137', 'X138', 'X139', 'X140', 'X141', 'X142', 'X143', 'X144', 'X145',
'X146', 'X147', 'X148', 'X150', 'X151', 'X152', 'X153', 'X154', 'X155',
'X156', 'X157', 'X158', 'X159', 'X160', 'X161', 'X162', 'X163', 'X164',
'X165', 'X166', 'X167', 'X168', 'X169', 'X170', 'X171', 'X172', 'X173',
'X174', 'X175', 'X176', 'X177', 'X178', 'X179', 'X180', 'X181', 'X182',
'X183', 'X184', 'X185', 'X186', 'X187', 'X189', 'X190', 'X191', 'X192',
'X194', 'X195', 'X196', 'X197', 'X198', 'X199', 'X200', 'X201', 'X202',
'X203', 'X204', 'X205', 'X206', 'X207', 'X208', 'X209', 'X210', 'X211',
'X212', 'X213', 'X214', 'X215', 'X216', 'X217', 'X218', 'X219', 'X220',
'X221', 'X222', 'X223', 'X224', 'X225', 'X226', 'X227', 'X228', 'X229',
'X230', 'X231', 'X232', 'X234', 'X236', 'X237', 'X238', 'X239', 'X240',
'X241', 'X242', 'X243', 'X244', 'X245', 'X246', 'X247', 'X248', 'X249',
'X250', 'X251', 'X252', 'X253', 'X254', 'X255', 'X256', 'X257', 'X258',
'X259', 'X260', 'X261', 'X262', 'X263', 'X264', 'X265', 'X266', 'X267',
'X269', 'X270', 'X271', 'X272', 'X273', 'X274', 'X275', 'X276', 'X277',
'X278', 'X279', 'X280', 'X281', 'X282', 'X283', 'X284', 'X285', 'X286',
'X287', 'X288', 'X291', 'X292', 'X294', 'X295', 'X296', 'X298', 'X299',
```

```
'X300', 'X301', 'X302', 'X304', 'X305', 'X306', 'X307', 'X308', 'X309',
'X310', 'X311', 'X312', 'X313', 'X314', 'X315', 'X316', 'X317', 'X318',
'X319', 'X320', 'X321', 'X322', 'X323', 'X324', 'X325', 'X326', 'X327',
'X328', 'X329', 'X331', 'X332', 'X333', 'X334', 'X335', 'X336', 'X337',
'X338', 'X340', 'X341', 'X342', 'X343', 'X344', 'X345', 'X346', 'X348',
'X349', 'X350', 'X351', 'X352', 'X353', 'X354', 'X355', 'X356', 'X357',
'X358', 'X359', 'X360', 'X361', 'X362', 'X363', 'X364', 'X365', 'X366',
'X367', 'X368', 'X369', 'X370', 'X371', 'X372', 'X373', 'X374', 'X375',
'X376', 'X377', 'X378', 'X379', 'X380', 'X382', 'X383', 'X384', 'X385']
  : lenght :  355
```

Observation

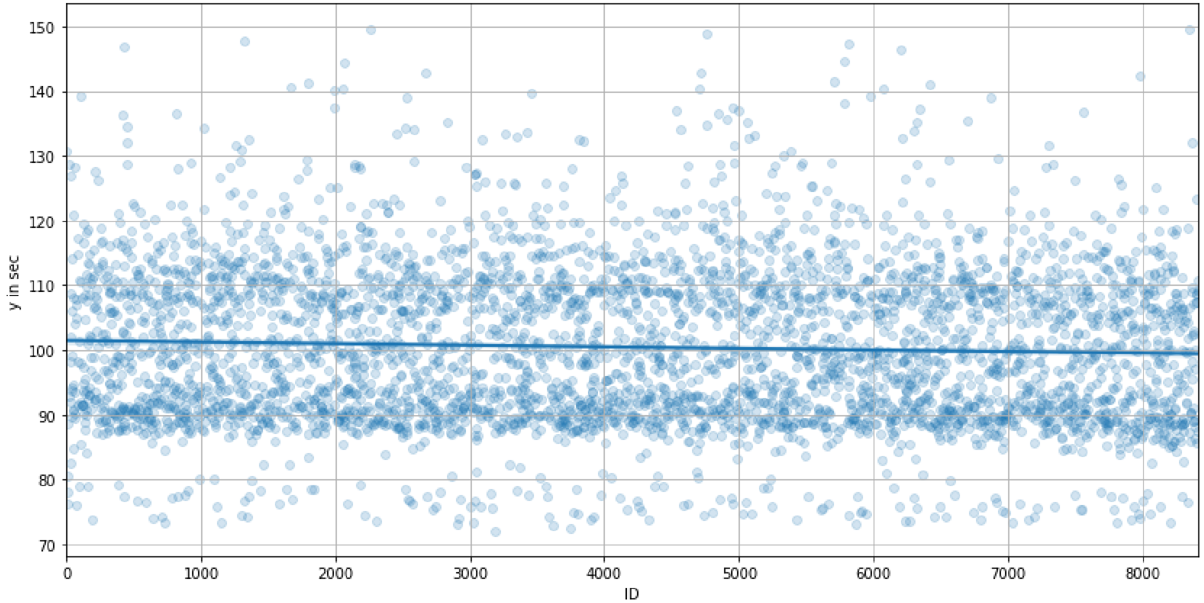
1. There are 13 features which have all-zero value. Which means no customer has used those products for there car. #### Approach We can remove all zero feature because it do not contain any information.

Removing zero columns

In [60]:
```
bin_data=train_data.loc[:,n]
```

ID feature preprocessing

In [61]:
```
plt.figure(figsize=(14,7))
sb.regplot(x='ID', y='y', data=train_data,scatter_kws={'alpha':0.2},)
plt.xlabel('ID')
plt.ylabel('y in sec')
plt.grid()
```



Observation

1. The linear fitting line(dark blue line) is going down as ID value increase, Which means as ID increase than time taken by a car is also reducing(slightly). #### Approach So we can give less weightage to new id. Which means ID 1st will get more weightage in compare to 10th ID.

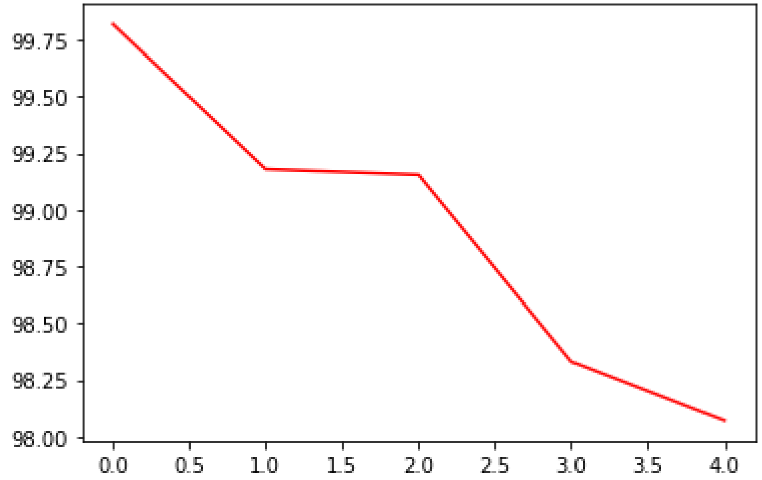
Smoothing the plot b/w target valriable and ID

In [62]:
```
median=[]
c=0
d=2000
for i in range(0,8400,2000):
  median.append(np.median(train_data[(train_data.ID>=c) & (train_data.I
D<=d)].y))
```

```
  c=c+2000
  d=d+2000
```

In [63]:
```
plt.plot(median,'red')
```

Out[63]: [<matplotlib.lines.Line2D at 0x7f02283c72b0>]



Observation

1. We use avg. method to smooth the traget variable.

In [64]:
```
def rec_id(train):
  ip=[]
  for i in train.ID:
    if i==0:
      ip.append(.35)
    else:
      ip.append(1/(np.log(i)+3))
  return ip
```

In [65]:
```
tr_df['ID']=rec_id(train_data)
```

In [66]:
```
data_tr=pd.concat([tr_df,bin_data],axis=1)
```

Clustering of X0

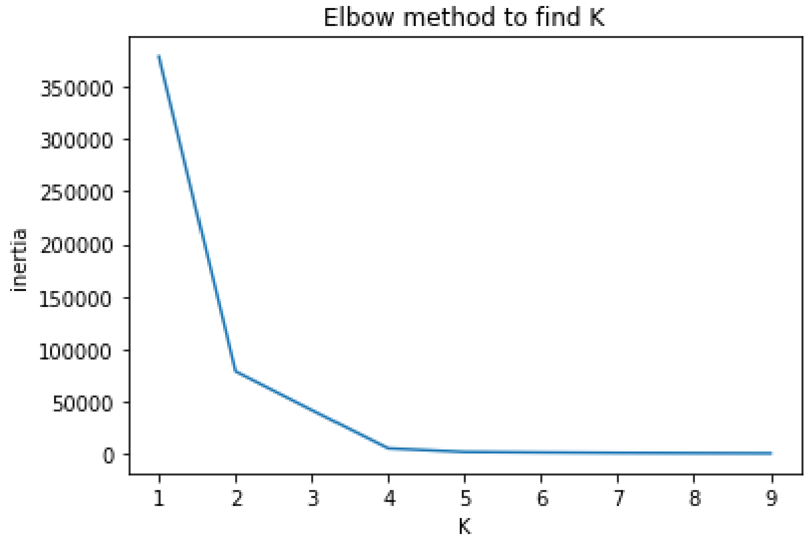
In [67]:
```
from sklearn.cluster import KMeans
```

In [68]:
```
def clust(data,n):
  pf=pd.DataFrame()
  pf['X']=data.X0
  pf['y']=data.y
  encod=data.groupby('X0')['y'].median()
  clust = KMeans(n,random_state=0)
  labels = clust.fit_predict(encod[data['X0'].values].values.reshape(-1
,1))
  pf['label']=labels
  lo=clust.inertia_
  return pf,lo
```

In [69]:
```
sse=[]
for i in [1,2,3,4,5,6,7,8,9]:
  a,b=clust(train_data,i)
  sse.append(b)
```

In [70]:
```
plt.plot(range(1,10),sse)
plt.title('Elbow method to find K')
plt.xlabel('K')
plt.ylabel('inertia')
```

Out[70]:
```
Text(0, 0.5, 'inertia')
```



Observation

1. Best number cluster should be 4

In [98]:
```
d,_=clust(train_data,4)
```

In [99]:
```
data_tr['X0_clus']=d.label
```

In [100]:
```
for i in [0,1,2,3]:
  print('Cluster',i,' median : ',np.median(data_tr[data_tr['X0_clus']==
i].y))
  print('Total percent of data in ',i,' : ',data_tr[data_tr['X0_clus']=
=i].shape[0]/data_tr.shape[0],'\n')
```

```
Cluster 0  median :  91.63
Total percent of data in  0  :  0.4971387696709585

Cluster 1  median :  110.59
Total percent of data in  1  :  0.30090605627086314
```

```
Cluster 2  median :  76.81
Total percent of data in  2  :  0.043156890796375774

Cluster 3  median :  101.355
Total percent of data in  3  :  0.15879828326180256
```

Observation

1. Max-m number point belongs to cluster 0 with 49.7%

Feature importance

In [101]:

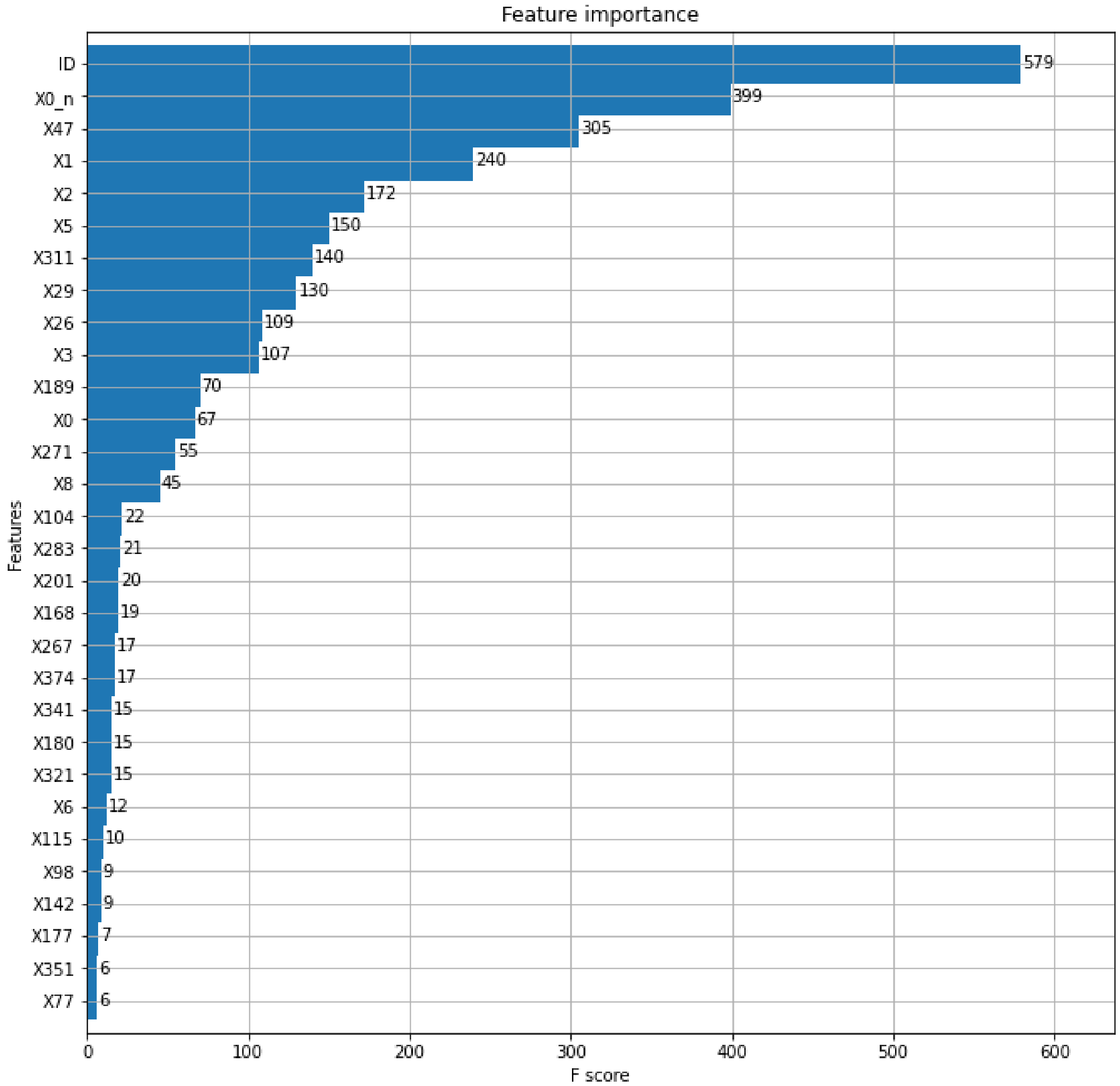
```
X=data_tr.drop('y',axis=1)
y=data_tr.y
```

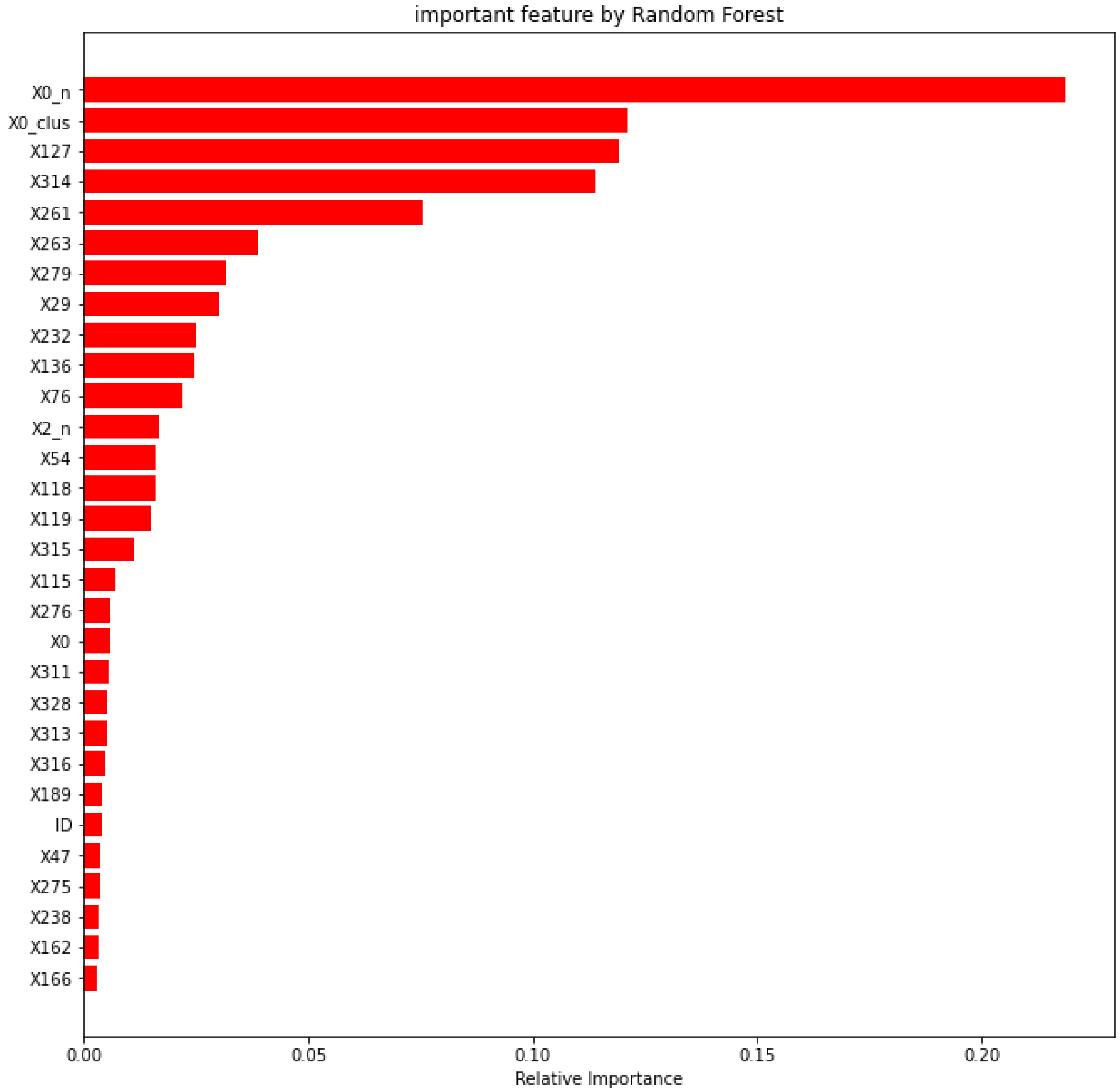
In [102]:

```
def r2_score(pre, final):
    l = dtrain.get_label()
    return 'r2', r2_score(l, pre)

X=data_tr.drop('y',axis=1)
y=data_tr.y
import xgboost as xgb
params = {'n_trees': 550,'max_depth': 4, 'eta': 0.0045,'eval_metric':
'rmse','subsample': 0.98,'objective': 'reg:linear','base_score': np.mea
n(y)}
f = xgb.DMatrix(X, y, feature_names=X.columns.values)
model = xgb.train(dict(params), f, num_boost_round=200,)
fig, ax = plt.subplots(figsize=(11,11))
xgb.plot_importance(model, max_num_features=30, height=1.2, ax=ax)
print("important feature by XGBoost")

from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(n_estimators=200, max_depth=5, max_featur
```

```
es=0.2, min_samples_leaf=4, random_state=0)
model.fit(X, y)
features = X.columns
importances = model.feature_importances_
indices = (np.argsort(importances))[-30:]
plt.figure(figsize=(11,11))
plt.title('important feature by Random Forest')
plt.barh(range(len(indices)), importances[indices], color='r', align='c
enter')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```

```
[05:18:47] WARNING: /workspace/src/objective/regression_obj.cu:152: r
eg:linear is now deprecated in favor of reg:squarederror.
important feature by XGBoost
```


Feature importance
ID
X0_n
X47
X1
X2
X5
X311
X29
X26
X3
X189
X0
X271
X8
X104
X283
X201
X168
X267
X374
X341
X180
X321
X6
X115
X98
X142
X177
X351
X77
579
399
305
240
172
150
140
130
109
107
70
67
55
45
22
21
20
19
17
17
15
15
15
12
10
9
9
7
6
6
Features
0
100
200
300
400
500
600
F score



Making new feature

In [103]:
```
data_tr['X118_plus_X314_plus_X315'] = data_tr.apply(lambda row: row.X11
```

```
8 + row.X314 + row.X315, axis=1)
```

In [104]:
```
data_tr['X314_plus_X315'] = data_tr.apply(lambda row: row.X314 + row.X3
15, axis=1)
```

Correlation of these features with target variable

In [105]:
```
for i in ['X118_plus_X314_plus_X315','X314_plus_X315']:
  lr=LinearRegression()
  lr.fit(data_tr[[i]],data_tr.y)
  print('MSE with feature '+str(i),mean_squared_error(data_tr.y,lr.pred
ict(data_tr[[i]])))
```

```
MSE with feature X118_plus_X314_plus_X315 76.59726836063406
MSE with feature X314_plus_X315 73.5430546149692
```

Observation

These feature MSE value near to 'X0_n' feature.

Feature.. MSE

1. X0_n 64.85
2. X118_plus_X314_plus_X315....................... 76.59
3. X314_plus_X315.. 73.54

Prediction function

In [141]:
```
def final(test,model,feature,algo):
  df_test=pd.DataFrame()
  d0,X0=X0_pre(train_data)
  uni=list(d0.keys())
  X_0=[]
```

```
  for i in test_data.X0:
    if i in uni:
      X_0.append(d0[i])
    else:
      X_0.append(0)
  df_test['X0_n']=X_0
  #
  d2,X2=X2_pre(train_data)
  uni=list(d2.keys())
  X_2=[]
  for i in test_data.X2:
    if i in uni:
      X_2.append(d2[i])
    else:
      X_2.append(0)
  df_test['X2_n']=X_2
  #label encoding
  for i in ['X0','X1','X2','X3','X4','X5','X6','X8']:
    pre_te_enc=joblib.load(i)
    df_test[i]=pre_te_enc.transform(test[i])
  #binary
  n,o=rem_zero(train_data)
  bin_df=test.loc[:,n]
  #ID
  df_test['ID']=rec_id(test)
  data_te=pd.concat([df_test,bin_df],axis=1)
  #cluster
  dc,_=clust(train_data,4)
  data_te['X0_clus']=test['X0'].map(dc.groupby('X')['label'].median())
  col_name=data_te.columns
  if algo!='xg boost':
    data_te = np.where(np.isnan(data_te.values), 0, data_te.values)
    data_te=pd.DataFrame(data_te,columns=col_name)
  #adding
  data_te['X118_plus_X314_plus_X315'] = data_te.apply(lambda row: row.X
118 + row.X314 + row.X315, axis=1)
  data_te['X314_plus_X315'] = data_te.apply(lambda row: row.X314 + row.
X315, axis=1)
  #prediction
```

```
    data_te=data_te.loc[:,feature]
    pre=(model.predict(data_te))
    return data_te,pre
```

In [106]:

```

```

Model

Linear Regression

In [107]:

```
from sklearn.linear_model import LinearRegression,Lasso,Ridge,SGDRegres
sor
from sklearn.model_selection import train_test_split,GridSearchCV,cross
_val_score
from sklearn.metrics import r2_score
```

Cross val score

In [108]:

```
p_dic={}
p=[]
for k in [0.18,0.24,0.36,0.44]:
  f=[]
  c=0
  for i in data_tr.columns:
    if i!='y':
      lin=LinearRegression()
      lin.fit(data_tr[[i]],data_tr.y)
      score=r2_score(data_tr.y,lin.predict(data_tr[[i]]))
      if score>k:
        f.append(i)
        c+=1

  df_xp=data_tr.loc[:,f]
```

```
  df_yp=data_tr.y

  cvs=cross_val_score(LinearRegression(),df_xp,df_yp,cv=3,scoring='r2')
  print('Total features : ',c,'and Avg. R2 score : ',np.median(np.sort(
cvs)))
  p_dic[np.median(np.sort(cvs))]=f
f=p_dic[np.sort(list(p_dic.keys()))[-1]]
```

```
Total features :  7 and Avg. R2 score :  0.61041428021907
Total features :  6 and Avg. R2 score :  0.6092491164851499
Total features :  5 and Avg. R2 score :  0.5481394694488149
Total features :  3 and Avg. R2 score :  0.5460957707675663
```

In [109]:

```
df_xp=data_tr.loc[:,f]
df_yp=data_tr.y
```

Model

In [110]:

```
lr=LinearRegression()
lr.fit(df_xp,df_yp)
```

Out[110]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=False)
```

In [111]:

```
r2_score(df_yp,lr.predict(df_xp))## train data prediction
```

Out[111]:

```
0.6174936067592987
```

In [112]:

```
data_te,pred=final(test_data,lr,f,'linear regression')## test data pred
iction
```

Summary

In [113]:

```
from prettytable import PrettyTable
```

```
report = PrettyTable()
report.field_names = ["Model", "hyper parameter", "R2 score",'Kaggle pr
ivate score']
report.add_row(["Linear Regression", 'Nan', 0.6174,0.5407])
print(report)
```

```
+-------------------+-----------------+----------+--------------------
-+
|       Model       | hyper parameter | R2 score | Kaggle private score
|
+-------------------+-----------------+----------+--------------------
-+
| Linear Regression |       Nan       |  0.6174  |        0.5407
|
+-------------------+-----------------+----------+--------------------
-+
```

Ridge Regression

Cross val score

In [114]:
```
p_dic={}
p=[]
for k in [0.13,.18,0.24,0.36,0.44]:
  f=[]
  c=0
  for i in data_tr.columns:
    if i!='y':
      lin=Ridge()
      lin.fit(data_tr[[i]],data_tr.y)
      score=r2_score(data_tr.y,lin.predict(data_tr[[i]]))
      if score>k:
        f.append(i)
        c+=1

  df_xp=data_tr.loc[:,f]
```

```
  df_yp=data_tr.y

  cvs=cross_val_score(Ridge(),df_xp,df_yp,cv=3,scoring='r2')
  print('Total features : ',c,'and Avg. R2 score : ',np.median(np.sort(
cvs)))
  p_dic[np.median(np.sort(cvs))]=f
f=p_dic[np.sort(list(p_dic.keys()))[-1]]
```

```
Total features :  18 and Avg. R2 score :  0.6112983471067194
Total features :  7 and Avg. R2 score :  0.6098326140927799
Total features :  6 and Avg. R2 score :  0.6086570164670546
Total features :  5 and Avg. R2 score :  0.5479842656066667
Total features :  3 and Avg. R2 score :  0.5461047328111706
```

In [115]:
```
df_xp=data_tr.loc[:,f]
df_yp=data_tr.y
```

Finding best param

In [116]:
```
para=[{'alpha':[0.001,0.01,1,6,10,20,100]}]
gsv=GridSearchCV(estimator=Ridge(),scoring='r2',param_grid=para)
gsv.fit(df_xp,df_yp)
print('Best param : ',gsv.best_params_)
```

```
Best param :  {'alpha': 6}
```

In [117]:
```
df_xp=data_tr.loc[:,f]
df_yp=data_tr.y
```

Model

In [118]:
```
rid=Ridge(alpha=6)
```

In [119]:
```
rid.fit(df_xp,df_yp)
```

```
Out[119]: Ridge(alpha=6, copy_X=True, fit_intercept=True, max_iter=None, normaliz
e=False,
      random_state=None, solver='auto', tol=0.001)
```

```
In [120]: r2_score(df_yp,rid.predict(df_xp))## train data prediction
```

```
Out[120]: 0.6229736438324186
```

```
In [121]: data_te,pred=final(test_data,rid,f,'ridge')## test data prediction
```

Summary

```
In [122]: report.add_row(["Ridge Regression", 'aplha = 6', 0.6229,0.54108])
print(report)
```

```
+-------------------+-----------------+----------+---------------------
-+
|       Model       | hyper parameter | R2 score | Kaggle private score
|
+-------------------+-----------------+----------+---------------------
-+
| Linear Regression |       Nan       |  0.6174  |        0.5407
|
|  Ridge Regression |    aplha = 6    |  0.6229  |       0.54108
|
+-------------------+-----------------+----------+---------------------
-+
```

Decision tree

```
In [123]: from sklearn.tree import DecisionTreeRegressor
```

Finding best param

In [124]:
```
para=[{'max_depth':[1,2,3,5,10,50,100,200,500]}]
gsv=GridSearchCV(estimator=DecisionTreeRegressor(),scoring='r2',param_g
rid=para)
gsv.fit(X,y)
print('Best param : ',gsv.best_params_)
```

```
Best param :  {'max_depth': 3}
```

In [125]:
```
dt=DecisionTreeRegressor(max_depth=3)
```

In [126]:
```
dt.fit(X,y)
```

Out[126]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=3,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecate
d',
                      random_state=None, splitter='best')
```

In [127]:
```
r2_score(y,dt.predict(X))## train data prediction
```

Out[127]:
```
0.630212526041533
```

In [128]:
```
data_te,pred=final(test_data,dt,X.columns,'random forest')## test data
 prediction
```

Summary

In [133]:
```
report.add_row(["Decision Tree", 'depth = 3',0.6302,0.54791])
print(report)
```

```
+-------------------+----------------+----------+---------------------
-+
|       Model       | hyper parameter | R2 score | Kaggle private score
|
```

```
+------------------+----------------+----------+--------------------
-+
| Linear Regression |       Nan       |  0.6174  |         0.5407
|
|  Ridge Regression |    aplha = 6    |  0.6229  |        0.54108
|
|   Decision Tree   |    depth = 3    |  0.6302  |        0.54791
|
|   Decision Tree   |    depth = 3    |  0.6302  |        0.54791
|
+------------------+----------------+----------+--------------------
-+
```

Xg Boost

In [134]:
```
X=data_tr.drop('y',axis=1)
y=data_tr.y
```

In [135]:
```
from xgboost import XGBRegressor
import warnings
warnings.filterwarnings('ignore')
```

In [136]:
```
xgbr=XGBRegressor()
prams={
 'learning_rate':[.01,.04,.1],
 'n_estimators':[400,500,600,700,800],
 'colsample_bytree':[0.35,.55,0.65,0.75],
 'subsample':[0.35,.55,0.65,0.85,1],
 'gamma':[.15,.65,.85,],
 'colsample_bylevel':[.45,.65,.75,.95]
 }
gsv=GridSearchCV(xgbr,prams,scoring='r2',cv=4)
#gsv.fit(X, y)
```

In [137]:
```
#print(tp.best_params_)
```

In [138]:
```
xg=XGBRegressor(learning_rate=.01,max_depth=3,n_estimators=600,colsampl
e_bytree=.55,subsample=.85,gamma=.65,colsample_bylevel=.95)
xg.fit(X,y)
```

```
[05:19:28] WARNING: /workspace/src/objective/regression_obj.cu:152: re
g:linear is now deprecated in favor of reg:squarederror.
```

Out[138]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=0.95,
             colsample_bynode=1, colsample_bytree=0.55, gamma=0.65,
             importance_type='gain', learning_rate=0.01, max_delta_step
=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimator
s=600,
             n_jobs=1, nthread=None, objective='reg:linear', random_sta
te=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=0.85, verbosity=1)
```

In [277]:
```
joblib.dump(xg,'model')
```

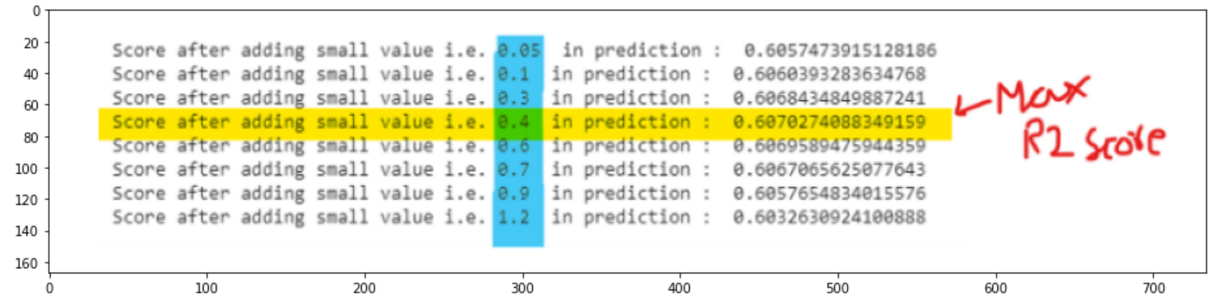
Out[277]:
```
['model']
```

In [139]:
```
r2_score(y,xg.predict(X))## train data prediction
```

Out[139]:
```
0.6553283609988065
```

In [152]:
```
plt.figure(figsize=(16,9))
plt.imshow(plt.imread('constant.png'))
```

Out[152]:
```
<matplotlib.image.AxesImage at 0x7f0219390c50>
```



Observation

We can see by adding small contant in predict value we got some increment in R2 score

In [153]:
```
r2_score(y,xg.predict(X)+0.4)## train data prediction
```

Out[153]:
```
0.6555987797628255
```

In [156]:
```
data_te,pred=final(test_data,xg,X.columns,'xg boost')## test data predi
ction
```

Summary

In [157]:
```
report.add_row(["Xg boost", 'learning_rate=.01, n_estimators=600, colsa
mple_bytree=.55, subsample=.85, gamma=.65, colsample_bylevel=.95', 0.65
53,0.55329])
print(report)
```

```
+------------------+----------------------------------------------------
-----------------------------------------------------+----------+-
--------------------+
|      Model       |                                                 hype
r parameter                                           | R2 score |
Kaggle private score |
+------------------+----------------------------------------------------
-----------------------------------------------------+----------+-
--------------------+
```

```
| Linear Regression |
  Nan                                                     |  0.6174  |
       0.5407        |
|  Ridge Regression |                                                        a
plha = 6                                                  |  0.6229  |
      0.54108        |
|   Decision Tree   |                                                        d
epth = 3                                                  |  0.6302  |
      0.54791        |
|   Decision Tree   |                                                        d
epth = 3                                                  |  0.6302  |
      0.54791        |
|      Xg boost     | learning_rate=.01, n_estimators=600, colsample_by
tree=.55, subsample=.85, gamma=.65, colsample_bylevel=.95 |  0.6553  |
      0.55329        |
+-------------------+---------------------------------------------------
----------------------------------------------------------+----------+-
---------------------+
```

Final submission Kaggle

In [100]:
```
final=pd.DataFrame()
final['ID']=test_data.ID
final['y']=pred
```

In [101]:
```
test=pd.merge(test_data,final,on='ID')
```

Final Observation Why X0 work better

1. We notice that in train data whose car testing time was less than 80 in that 95.77% have X0 feature value as 'az', 100% have X27,X10 feature value as 1,0 resp. Similarly in prediction whose car testing time was less than 80 in that 96.15% have X0 feature as 'az', 100% have X27,X10 feature value as 1,0 resp.

2. We notice that in train data whose car testing time between 90 and 100 in that 72.1 % have X0 feature value as ['y','z','t','o','f','n','s','al','e']. Similarly in prediction whose car testing time between 90 and 100 in that 84.4 % have X0 feature value as ['y','z','t','o','f','n','s','al','e'].
3. We notice that in train data whose car testing time between 100 and 120 in that 79.4 % have X0 feature value as ['ak','x','ay','w' ,'j','aj','ap','h','d','v']. Similarly in prediction whose car testing time between 100 and 120 in that 89.3 % have X0 feature value as ['ak','x','ay','w' ,'j','aj','ap','h','d','v'].

kaggle leaderboard

1. private 0.55329
2. public 0.55621

In [158]:
```
print('XG boost result for test dataset : ',pred+.4)
```

```
XG boost result for test dataset :  [ 85.68865  102.376595  85.50872
...  93.08515  110.703636  92.89591 ]
```

In [ ]: