Mercedes-Benz Greener Manufacturing

Business Problem

1.1 Description

Description

Since 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.

In this competition, Daimler is challenging Kagglers to tackle the curse of dimensionality and reduce the time that cars spend on the test bench. Competitors will work with a dataset representing different permutations of Mercedes-Benz car features to predict the time it takes to pass testing. Winning algorithms will contribute to speedier testing, resulting in lower carbon dioxide emissions without reducing Daimler's standards.

Problem Statemtent:

To predict the target variable y lie time in seconds that the car needs to pass the testing.

Source: [https://www.kaggle.com/c/mercedes-benz-greener-manufacturing (https://www.kaggle.com/c/mercedes-benz-greener-manufacturing)](https://www.kaggle.com/c/mercedes-benz-greener-manufacturing)

Real World / Business Objectives and Constraints:

1---->> Predict time in seconds with high value of R^2 (Coefficient of determination).

2---->> No strict latency constraints.

This 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. The target variable y is the time in seconds that the car needs to pass the test. Our job is to predict the time it takes to pass testing.

Machine Learning Problem Formulation

Data Description:

This 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.

The ground truth is labeled 'y' and represents the time (in seconds) that the car took to pass testing for each variable.

File descriptions:

Variables with letters are categorical. Variables with 0/1 are binary values.

train.csv - the training set test.csv - the test set, you must predict the 'y' variable for the 'ID's in this file sample_submission.csv - a sample submission file in the correct format

[https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/data (https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/data)](https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/data)

Type of Machine Learning Problem:

It is a Regression problem where y belongs to real value. A regression problem requires the prediction of a quantity. A regression can have real valued or discrete input variables. A problem with multiple input variables is often called a multivariate regression problem.

Performance Metric

Source: https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/overview/evaluation (https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/overview/evaluation)

Metric(s):

R^2 (Coefficient of determination).

https://en.wikipedia.org/wiki/Coefficient_of_determination (https://en.wikipedia.org/wiki/Coefficient_of_determination)

Importing libraries:

In [2]:

```
import pandas as pd
from datetime import datetime
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
import xgboost as xgb
color = sns.color_palette()
from statsmodels.formula.api import ols
from scipy import stats

from sklearn.linear_model import BayesianRidge,ElasticNet,Lasso,SGDRegressor,Ridge
from sklearn.ensemble import GradientBoostingRegressor,RandomForestRegressor
from sklearn.model_selection import cross_val_score,GridSearchCV,train_test_split
from sklearn.svm import LinearSVR,SVR
import xgboost as xgb
from sklearn.metrics import r2_score

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import warnings
warnings.filterwarnings("ignore")

from sklearn.model_selection import train_test_split

from sklearn import linear_model

from sklearn.tree import DecisionTreeRegressor

from sklearn.model_selection import cross_val_score

import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBRegressor


from sklearn.random_projection import GaussianRandomProjection
from sklearn.random_projection import SparseRandomProjection
from sklearn.decomposition import PCA
from sklearn.decomposition import FastICA
from sklearn.decomposition import TruncatedSVD
```

```
C:\Users\hp\Anaconda3\lib\site-packages\sklearn\ensemble\weight_boosting.py:
29: DeprecationWarning: numpy.core.umath_tests is an internal NumPy module a
nd should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

Data loading

In [52]:

```
df=pd.read_csv('train.csv')
```

Exploratory Data Analysis

https://www.kaggle.com/sudalairajkumar/simple-exploration-notebook-mercedes (https://www.kaggle.com/sudalairajkumar/simple-exploration-notebook-mercedes)

In [53]:

```
df.shape
```

Out[53]:

```
(4209, 378)
```

In [54]:

```
df.head()
```

Out[54]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	X11	X12	X13	X14	X15	X16	X17	X
0	0	130.81	k	v	at	a	d	u	j	o	0	0	0	1	0	0	0	0	
1	6	88.53	k	t	av	e	d	y	l	o	0	0	0	0	0	0	0	0	
2	7	76.26	az	w	n	c	d	x	j	x	0	0	0	0	0	0	0	1	
3	9	80.62	az	t	n	f	d	x	l	e	0	0	0	0	0	0	0	0	
4	13	78.02	az	v	n	f	d	h	d	n	0	0	0	0	0	0	0	0	

The target variable is continuous. From X0 to X8 is categorical. The others is looks like a binary nominal data type.

In [55]:

```
numerical_features = df.select_dtypes(include=[np.number]).columns
categorical_features = df.select_dtypes(include=[np.object]).columns

print('Numerical feature size: {}'.format(len(numerical_features)))
print('Categorical feature size: {} '.format(len(categorical_features)))
```

```
Numerical feature size: 370
Categorical feature size: 8
```

Explore the number of unique values in each categorical variable.

In [56]:

```
df[['X0', 'X1' ,  'X2', 'X3', 'X4', 'X5', 'X6', 'X8']].apply(lambda x : len(x.unique()))
```

Out[56]:

```
X0    47
X1    27
X2    44
X3     7
X4     4
X5    29
X6    12
X8    25
dtype: int64
```

In [57]:

```
missing_df = df.isnull().sum(axis=0).reset_index()
missing_df.columns = ['column_name', 'missing_count']
missing_df = missing_df.ix[missing_df['missing_count']>0]
missing_df = missing_df.sort_values(by='missing_count')
missing_df
```

Out[57]:

column_name	missing_count

Good to see that there are no missing values in the dataset :)

Integer Columns Analysis:

In [58]:

```
unique_values_dict = {}
for col in df.columns:
    if col not in ["ID", "y", "X0", "X1", "X2", "X3", "X4", "X5", "X6", "X8"]:
        unique_value = str(np.sort(df[col].unique()).tolist())
        tlist = unique_values_dict.get(unique_value, [])
        tlist.append(col)
        unique_values_dict[unique_value] = tlist[:]
for unique_val, columns in unique_values_dict.items():
    print("Columns containing the unique values : ",unique_val)
    print(columns)
    print("--------------------------------------------------")
```

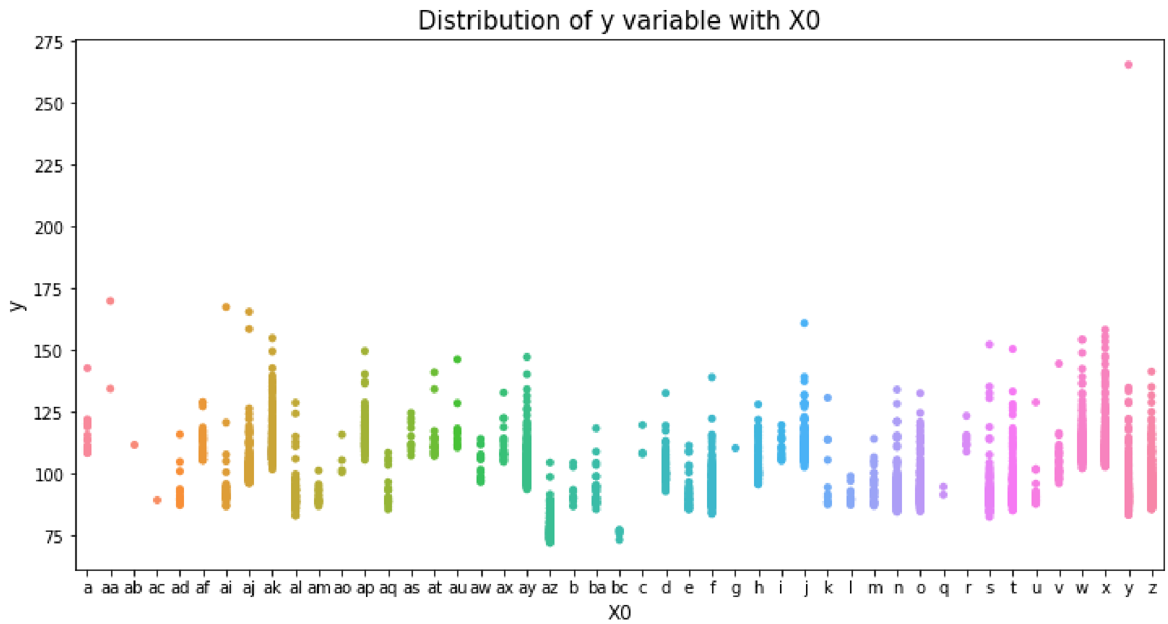
```
Columns containing the unique values :  [0, 1]
['X10', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X18', 'X19', 'X20', 'X2
1', 'X22', 'X23', 'X24', 'X26', 'X27', 'X28', 'X29', 'X30', 'X31', 'X32', 'X
33', 'X34', 'X35', 'X36', 'X37', 'X38', 'X39', 'X40', 'X41', 'X42', 'X43',
'X44', 'X45', 'X46', 'X47', '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', 'X94', 'X95', 'X96', 'X97', 'X98', 'X99', 'X10
0', 'X101', 'X102', 'X103', 'X104', 'X105', 'X106', 'X108', 'X109', 'X110',
'X111', 'X112', 'X113', 'X114', 'X115', 'X116', 'X117', 'X118', 'X119', 'X12
0', 'X122', 'X123', 'X124', 'X125', 'X126', 'X127', 'X128', 'X129', 'X130',
'X131', 'X132', 'X133', 'X134', 'X135', 'X136', 'X137', 'X138', 'X139', 'X14
0', 'X141', 'X142', 'X143', 'X144', 'X145', 'X146', 'X147', 'X148', 'X150',
'X151', 'X152', 'X153', 'X154', 'X155', 'X156', 'X157', 'X158', 'X159', 'X16
0', 'X161', 'X162', 'X163', 'X164', 'X165', 'X166', 'X167', 'X168', 'X169',
'X170', 'X171', 'X172', 'X173', 'X174', 'X175', 'X176', 'X177', 'X178', 'X17
9', 'X180', 'X181', 'X182', 'X183', 'X184', 'X185', 'X186', 'X187', 'X189',
'X190', 'X191', 'X192', 'X194', 'X195', 'X196', 'X197', 'X198', 'X199', 'X20
0', 'X201', 'X202', 'X203', 'X204', 'X205', 'X206', 'X207', 'X208', 'X209',
'X210', 'X211', 'X212', 'X213', 'X214', 'X215', 'X216', 'X217', 'X218', 'X21
9', 'X220', 'X221', 'X222', 'X223', 'X224', 'X225', 'X226', 'X227', 'X228',
'X229', 'X230', 'X231', 'X232', 'X234', 'X236', 'X237', 'X238', 'X239', 'X24
0', 'X241', 'X242', 'X243', 'X244', 'X245', 'X246', 'X247', 'X248', 'X249',
'X250', 'X251', 'X252', 'X253', 'X254', 'X255', 'X256', 'X257', 'X258', 'X25
9', 'X260', 'X261', 'X262', 'X263', 'X264', 'X265', 'X266', 'X267', 'X269',
'X270', 'X271', 'X272', 'X273', 'X274', 'X275', 'X276', 'X277', 'X278', 'X27
9', 'X280', 'X281', 'X282', 'X283', 'X284', 'X285', 'X286', 'X287', 'X288',
'X291', 'X292', 'X294', 'X295', 'X296', 'X298', 'X299', 'X300', 'X301', 'X30
2', 'X304', 'X305', 'X306', 'X307', 'X308', 'X309', 'X310', 'X311', 'X312',
'X313', 'X314', 'X315', 'X316', 'X317', 'X318', 'X319', 'X320', 'X321', 'X32
2', 'X323', 'X324', 'X325', 'X326', 'X327', 'X328', 'X329', 'X331', 'X332',
'X333', 'X334', 'X335', 'X336', 'X337', 'X338', 'X339', 'X340', 'X341', 'X34
2', 'X343', 'X344', 'X345', 'X346', 'X348', 'X349', 'X350', 'X351', 'X352',
'X353', 'X354', 'X355', 'X356', 'X357', 'X358', 'X359', 'X360', 'X361', 'X36
2', 'X363', 'X364', 'X365', 'X366', 'X367', 'X368', 'X369', 'X370', 'X371',
'X372', 'X373', 'X374', 'X375', 'X376', 'X377', 'X378', 'X379', 'X380', 'X38
2', 'X383', 'X384', 'X385']
--------------------------------------------------
Columns containing the unique values :  [0]
['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293', 'X29
7', 'X330', 'X347']
--------------------------------------------------
```

So all the integer columns are binary with some columns have only one unique value 0. Possibly we could exclude those columns in our modeling activity.

Now let us explore the categorical columns present in the dataset.

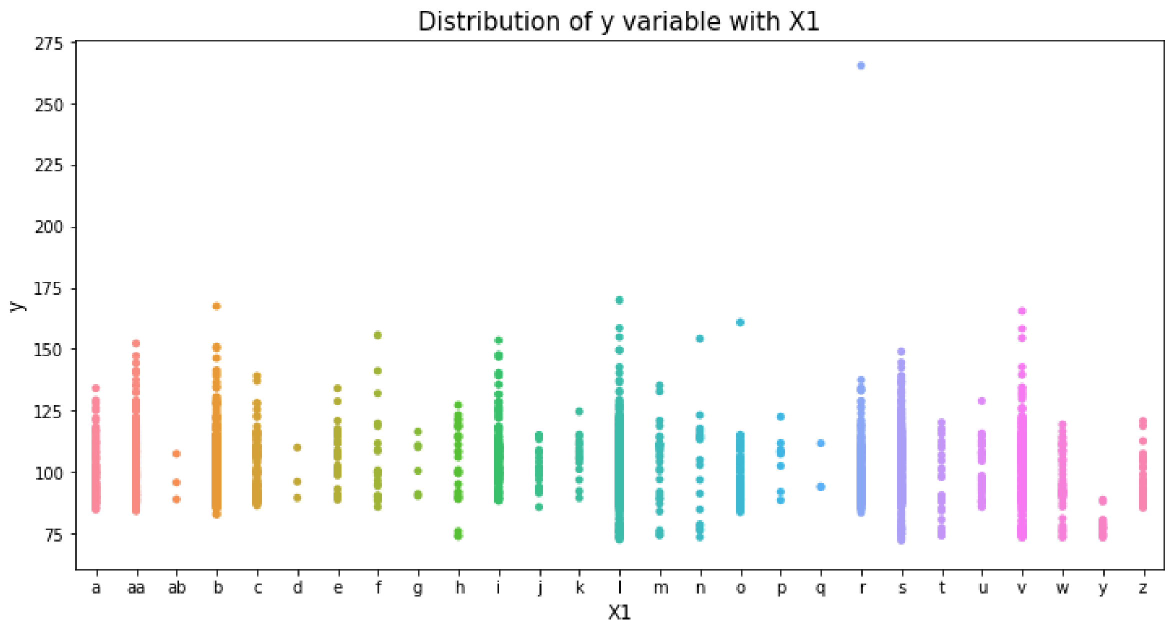
In [9]:

```
var_name = "X0"
col_order = np.sort(df[var_name].unique()).tolist()
plt.figure(figsize=(12,6))
sns.stripplot(x=var_name, y='y', data=df, order=col_order)
plt.xlabel(var_name, fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Distribution of y variable with "+var_name, fontsize=15)
plt.show()
```



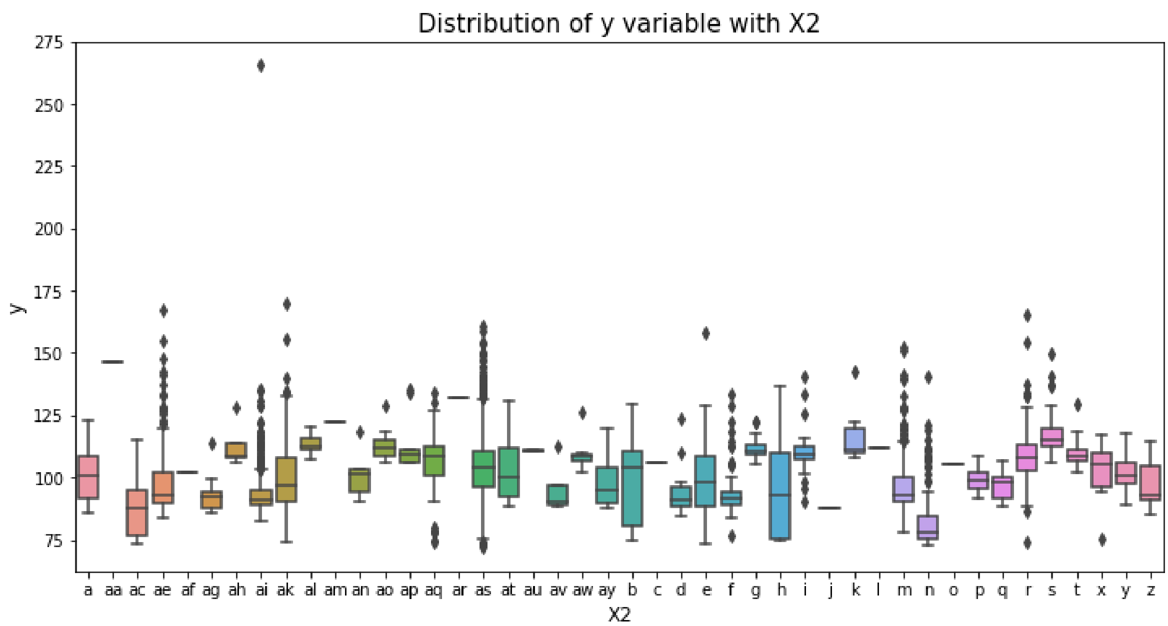
In [10]:

```
var_name = "X1"
col_order = np.sort(df[var_name].unique()).tolist()
plt.figure(figsize=(12,6))
sns.stripplot(x=var_name, y='y', data=df, order=col_order)
plt.xlabel(var_name, fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Distribution of y variable with "+var_name, fontsize=15)
plt.show()
```



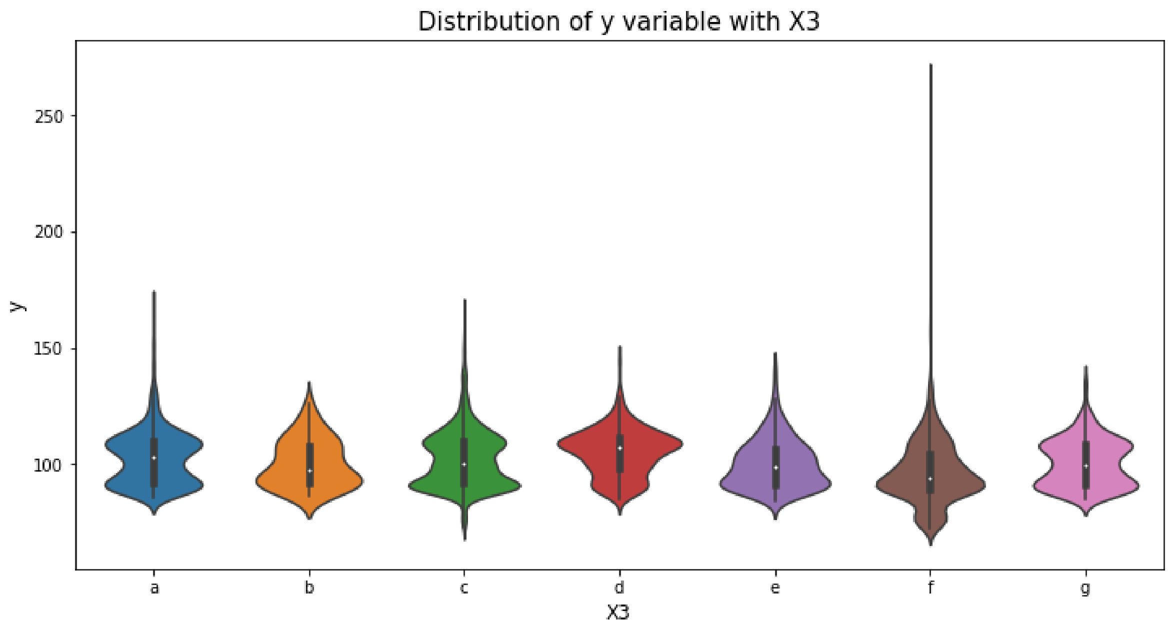
In [11]:

```
var_name = "X2"
col_order = np.sort(df[var_name].unique()).tolist()
plt.figure(figsize=(12,6))
sns.boxplot(x=var_name, y='y', data=df, order=col_order)
plt.xlabel(var_name, fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Distribution of y variable with "+var_name, fontsize=15)
plt.show()
```



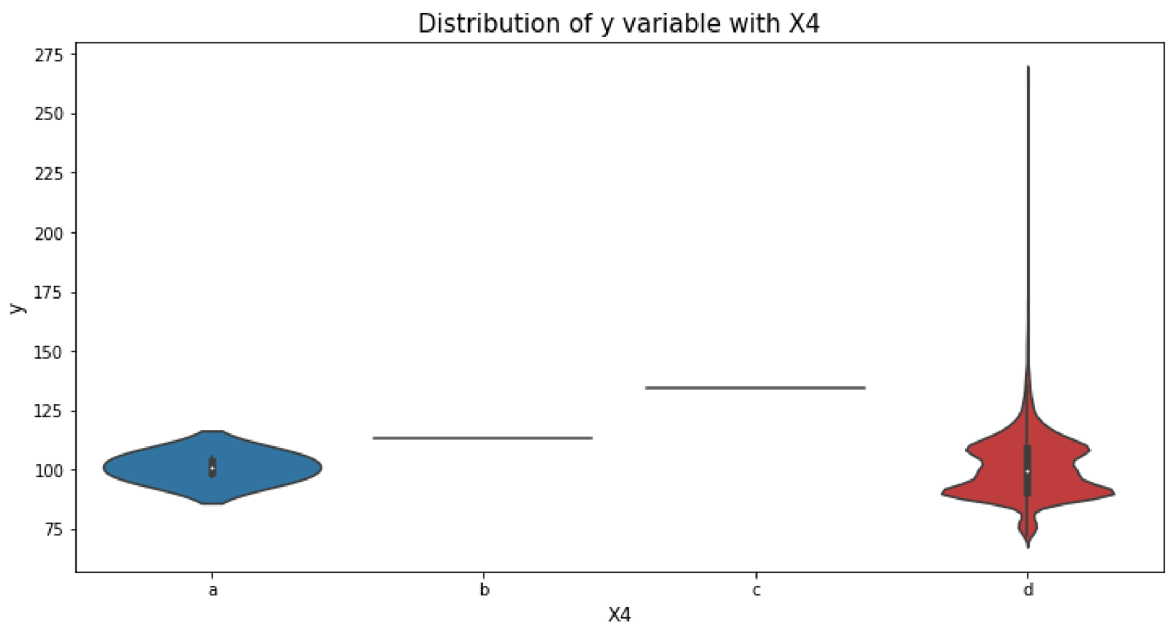
In [12]:

```
var_name = "X3"
col_order = np.sort(df[var_name].unique()).tolist()
plt.figure(figsize=(12,6))
sns.violinplot(x=var_name, y='y', data=df, order=col_order)
plt.xlabel(var_name, fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Distribution of y variable with "+var_name, fontsize=15)
plt.show()
```



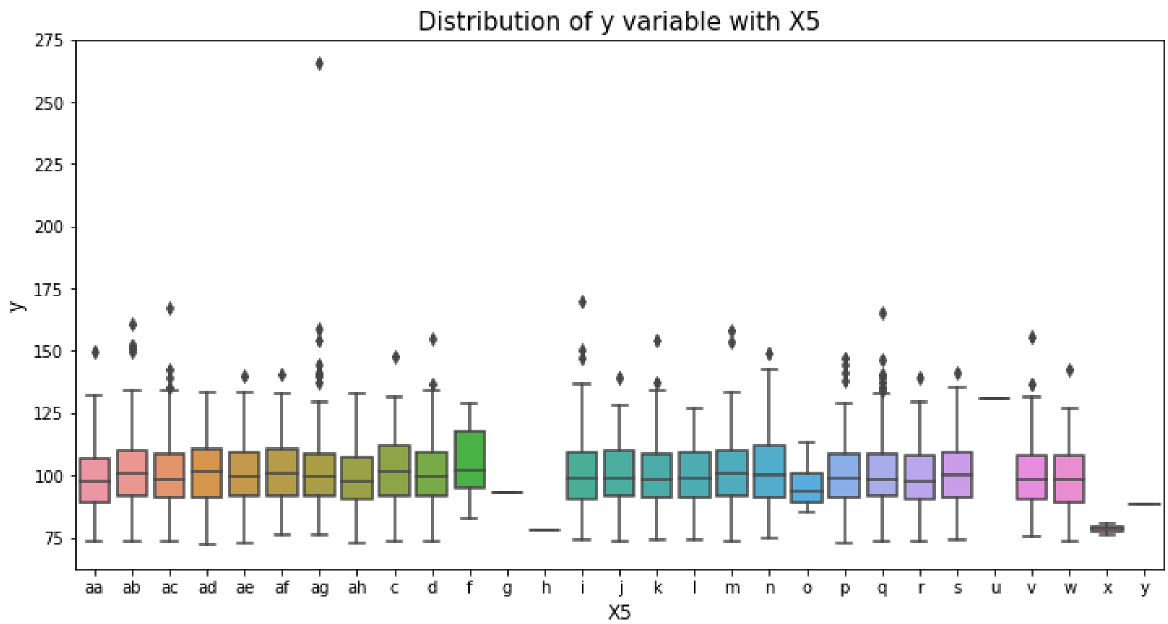
In [13]:

```
var_name = "X4"
col_order = np.sort(df[var_name].unique()).tolist()
plt.figure(figsize=(12,6))
sns.violinplot(x=var_name, y='y', data=df, order=col_order)
plt.xlabel(var_name, fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Distribution of y variable with "+var_name, fontsize=15)
plt.show()
```



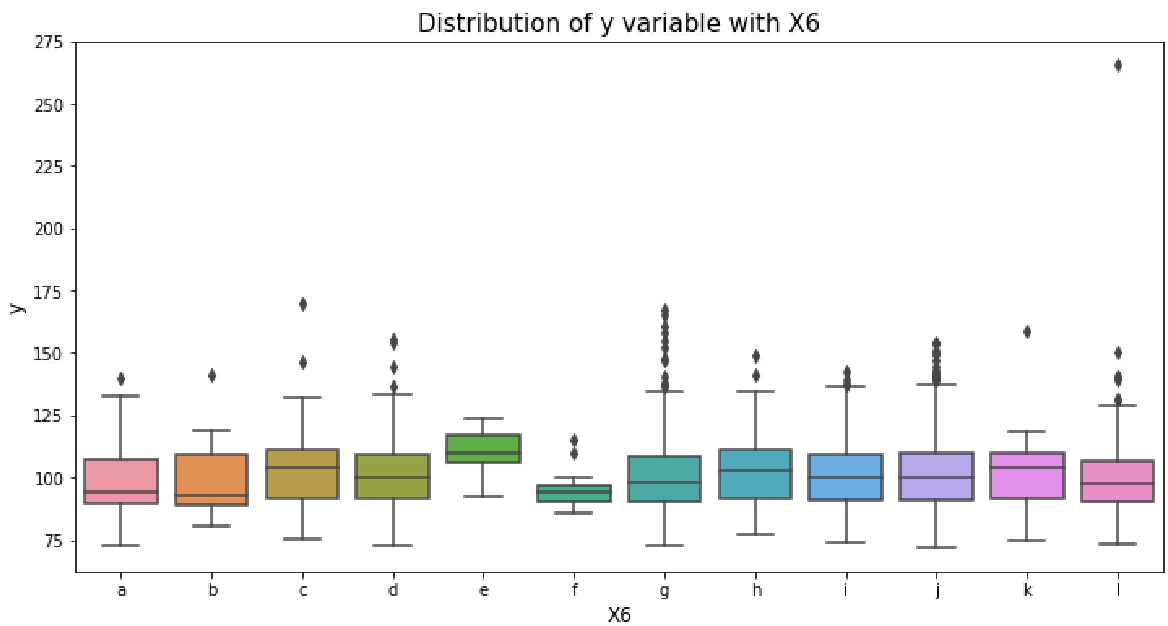
In [14]:

```
var_name = "X5"
col_order = np.sort(df[var_name].unique()).tolist()
plt.figure(figsize=(12,6))
sns.boxplot(x=var_name, y='y', data=df, order=col_order)
plt.xlabel(var_name, fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Distribution of y variable with "+var_name, fontsize=15)
plt.show()
```



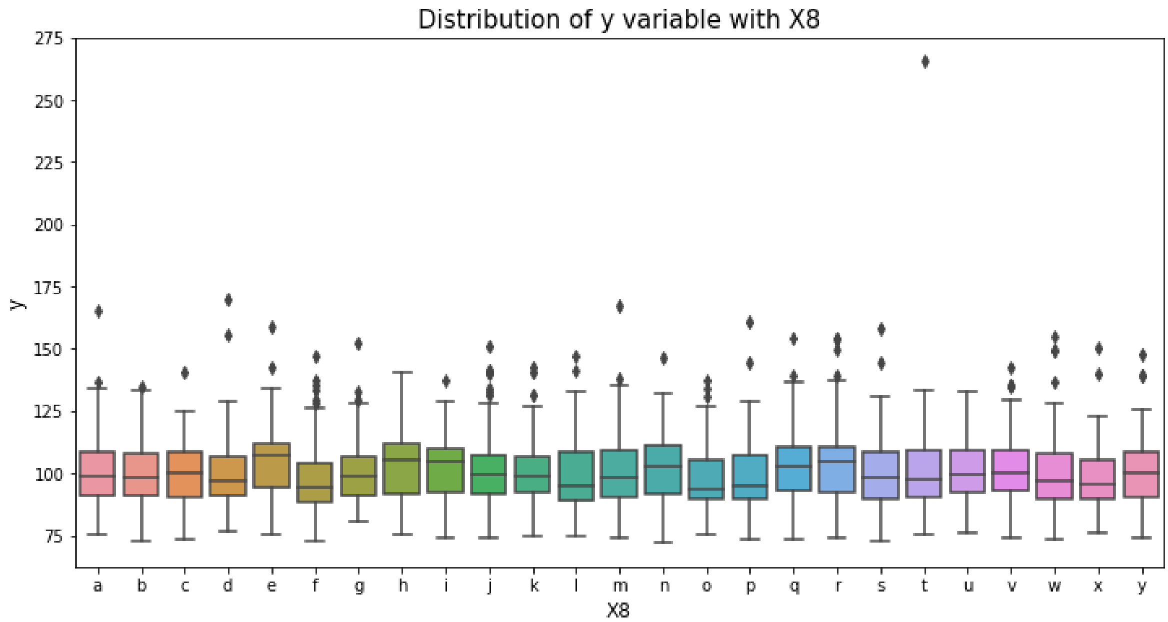
In [15]:

```
var_name = "X6"
col_order = np.sort(df[var_name].unique()).tolist()
plt.figure(figsize=(12,6))
sns.boxplot(x=var_name, y='y', data=df, order=col_order)
plt.xlabel(var_name, fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Distribution of y variable with "+var_name, fontsize=15)
plt.show()
```



In [16]:

```
var_name = "X8"
col_order = np.sort(df[var_name].unique()).tolist()
plt.figure(figsize=(12,6))
sns.boxplot(x=var_name, y='y', data=df, order=col_order)
plt.xlabel(var_name, fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Distribution of y variable with "+var_name, fontsize=15)
plt.show()
```



Binary Variables:

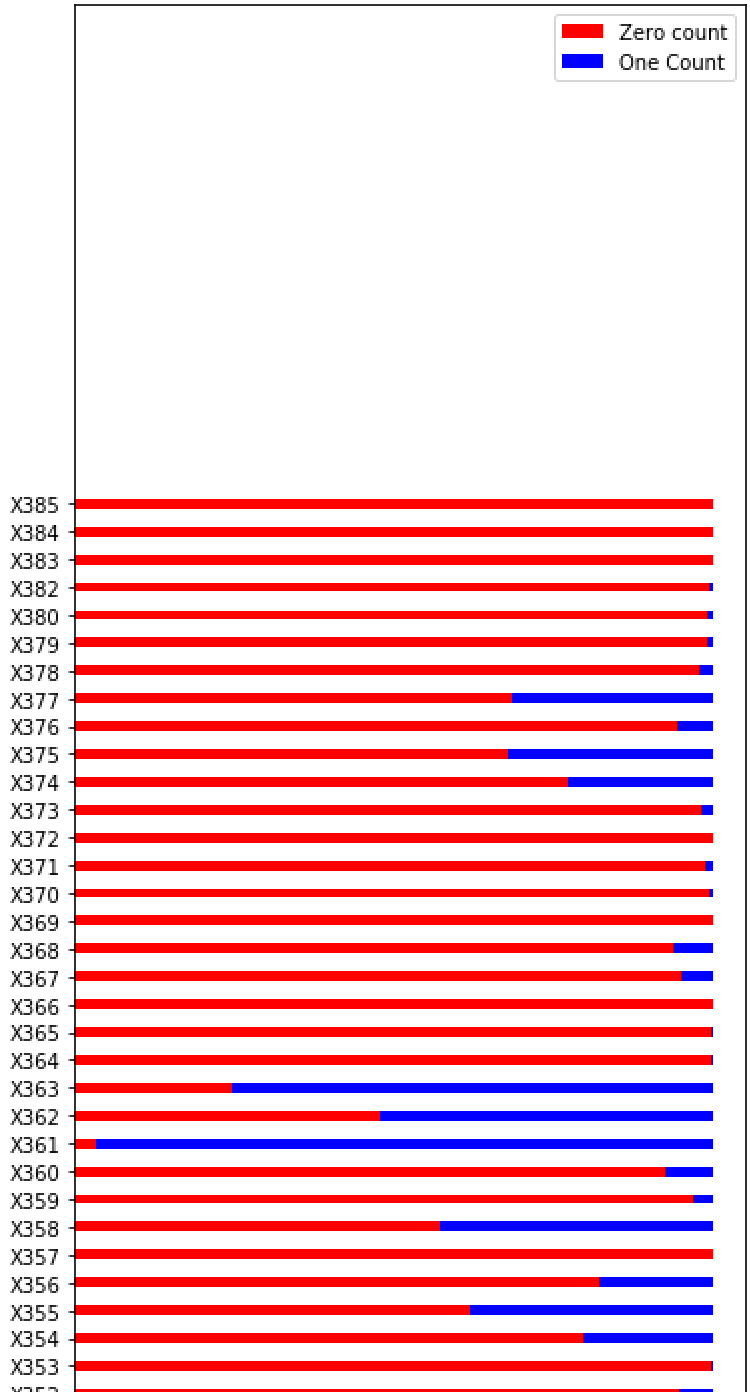
Now we can look into the binary variables. There are quite a few of them as we have seen before. Let us start with getting the number of 0's and 1's in each of these variables.

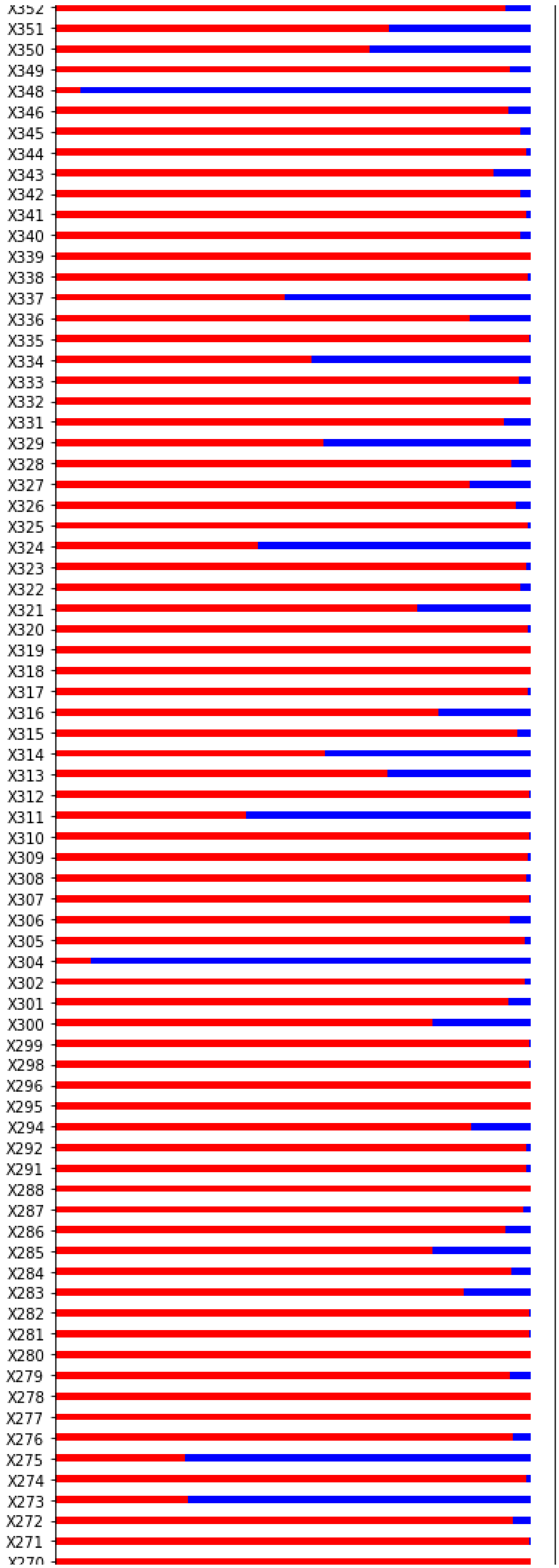
In [17]:

```
zero_count_list = []
one_count_list = []
cols_list = unique_values_dict['[0, 1]']
for col in cols_list:
    zero_count_list.append((df[col]==0).sum())
    one_count_list.append((df[col]==1).sum())

N = len(cols_list)
ind = np.arange(N)
width = 0.35

plt.figure(figsize=(6,100))
p1 = plt.barh(ind, zero_count_list, width, color='red')
p2 = plt.barh(ind, one_count_list, width, left=zero_count_list, color="blue")
plt.yticks(ind, cols_list)
plt.legend((p1[0], p2[0]), ('Zero count', 'One Count'))
plt.show()
```

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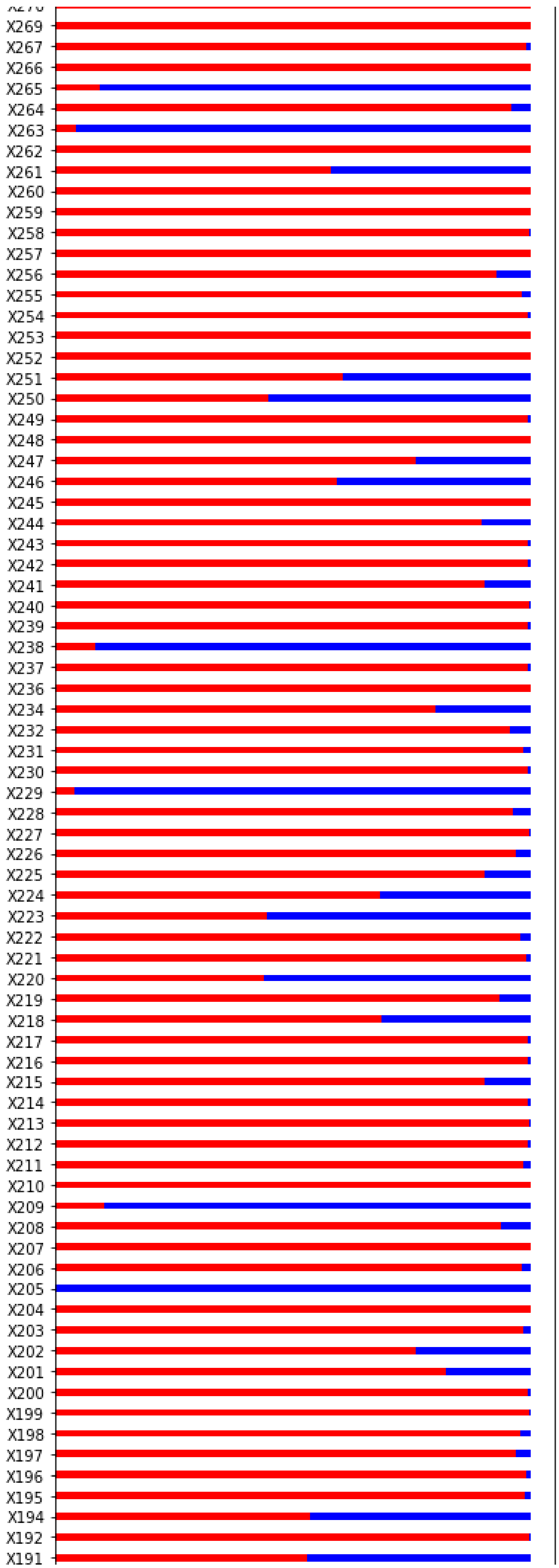
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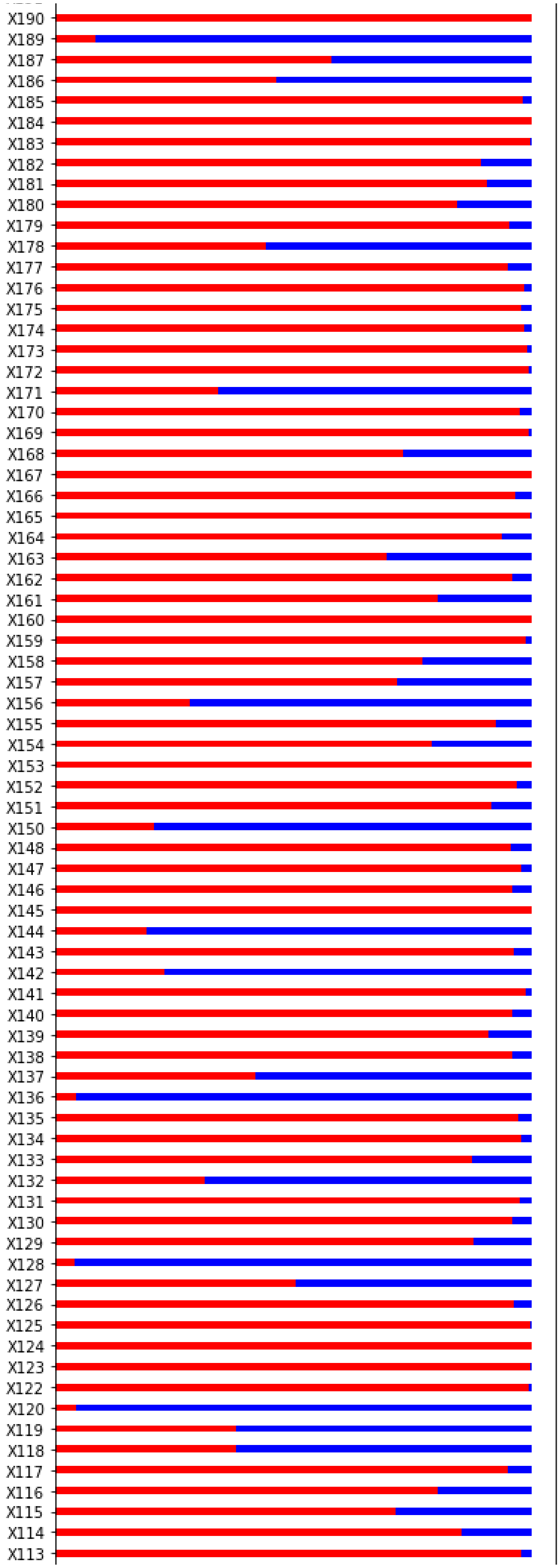
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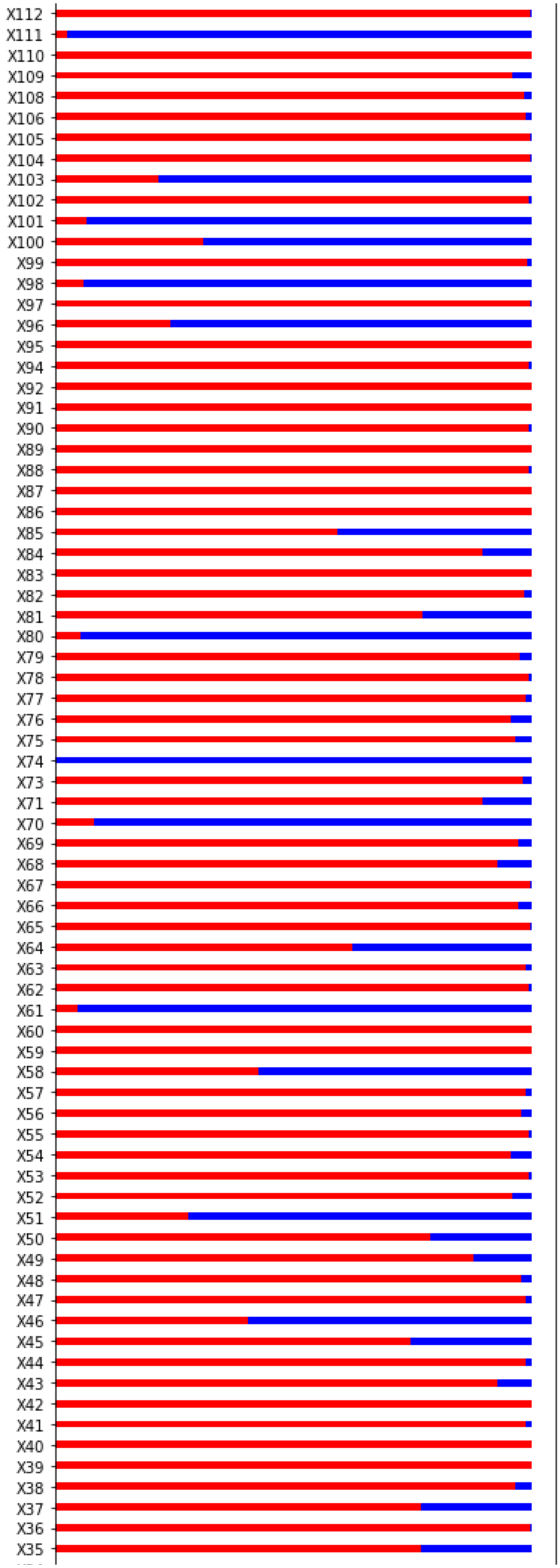
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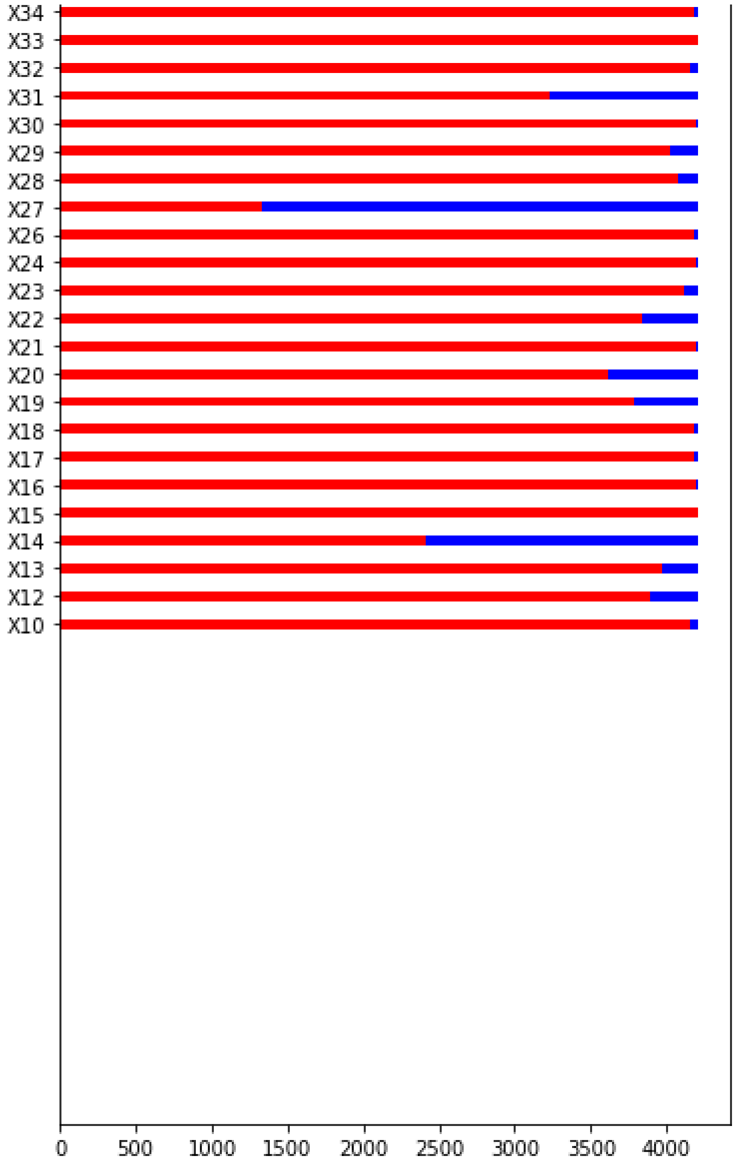
X36
X35



Target variable:

In [18]:

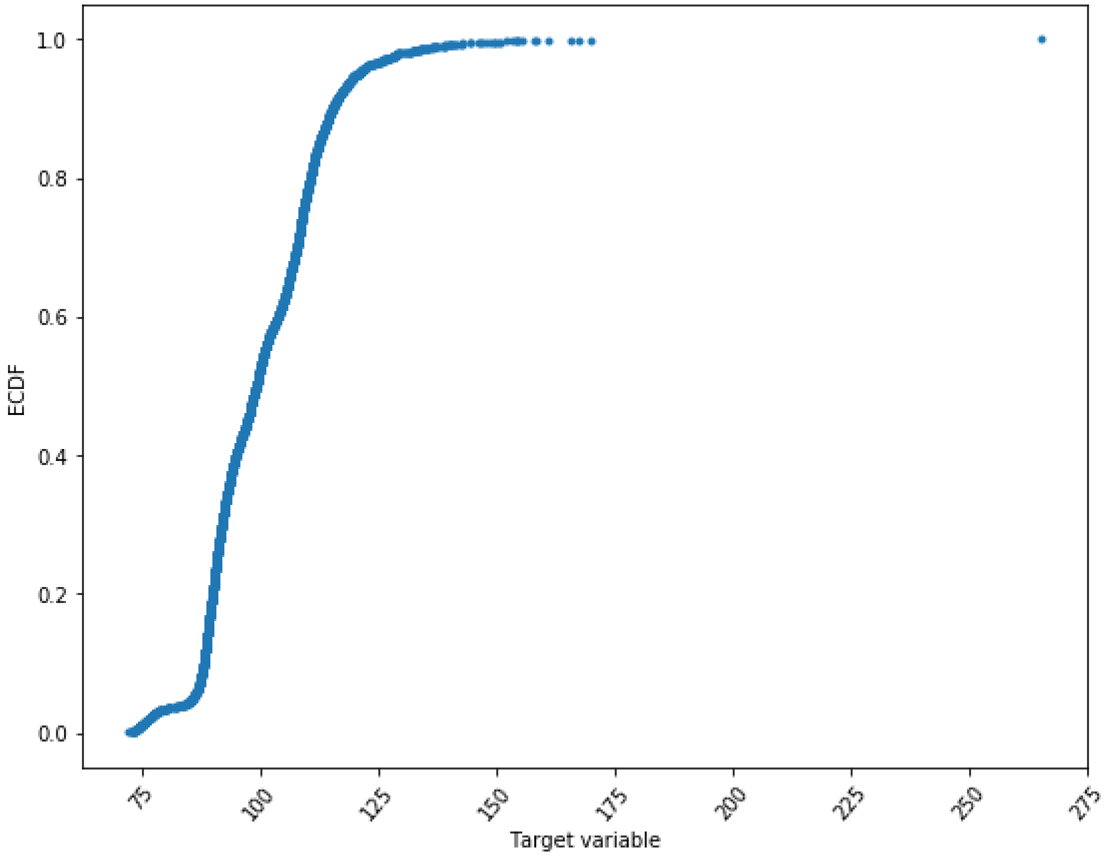
```
df.y.describe()
```

Out[18]:

```
count    4209.000000
mean      100.669318
std        12.679381
min        72.110000
25%        90.820000
50%        99.150000
75%       109.010000
max       265.320000
Name: y, dtype: float64
```

In [19]:

```
def ecdf(data):
    return np.sort(data), np.arange(1, len(data)+1) / len(data)

x1, y1 = ecdf(df.y)
plt.figure(figsize=(9, 7))
plt.xlabel('Target variable')
plt.ylabel('ECDF')
plt.plot(x1, y1, marker='.', linestyle='none')
plt.xticks(rotation=50)
plt.show()
```

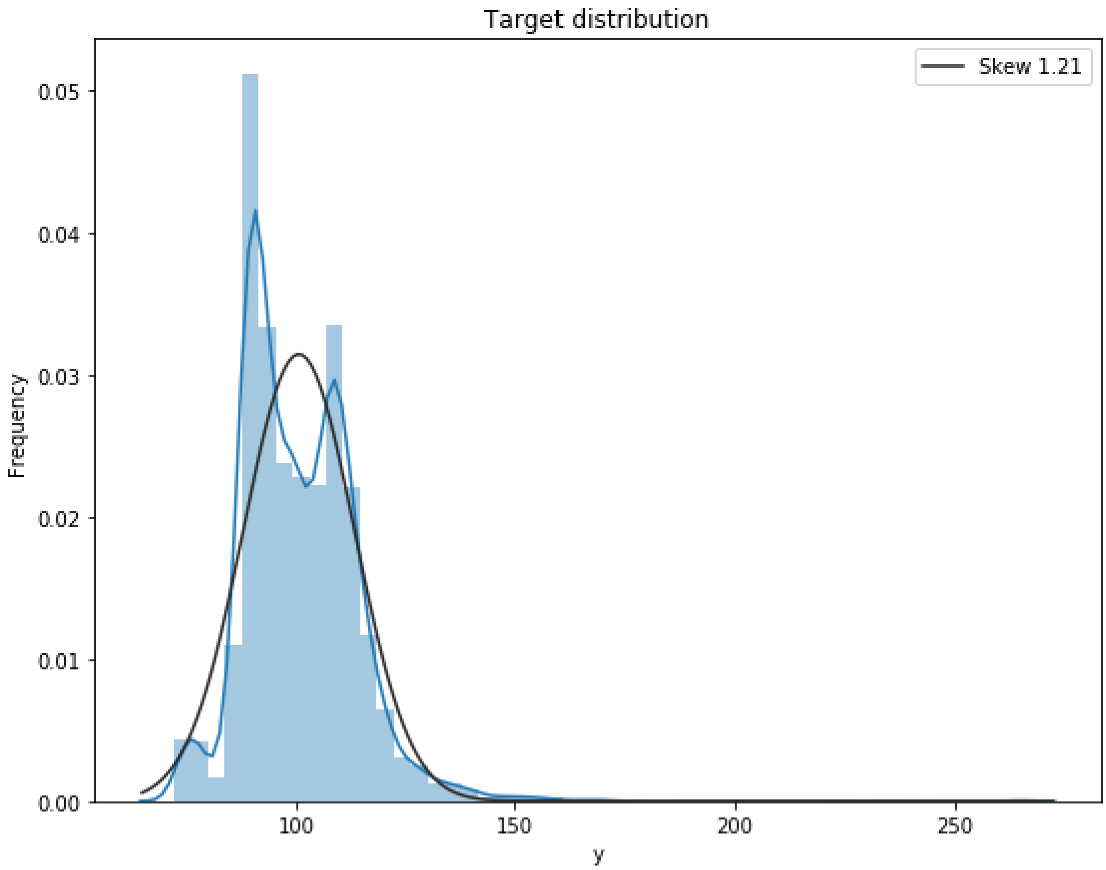


In [20]:

```
plt.figure(figsize=(9, 7))
sns.distplot(df['y'] , fit=stats.norm);
plt.legend(['Skew {:.2f}'.format(df['y'].skew())], loc='best')
plt.ylabel('Frequency')
plt.title('Target distribution')
```

Out[20]:

```
Text(0.5,1,'Target distribution')
```

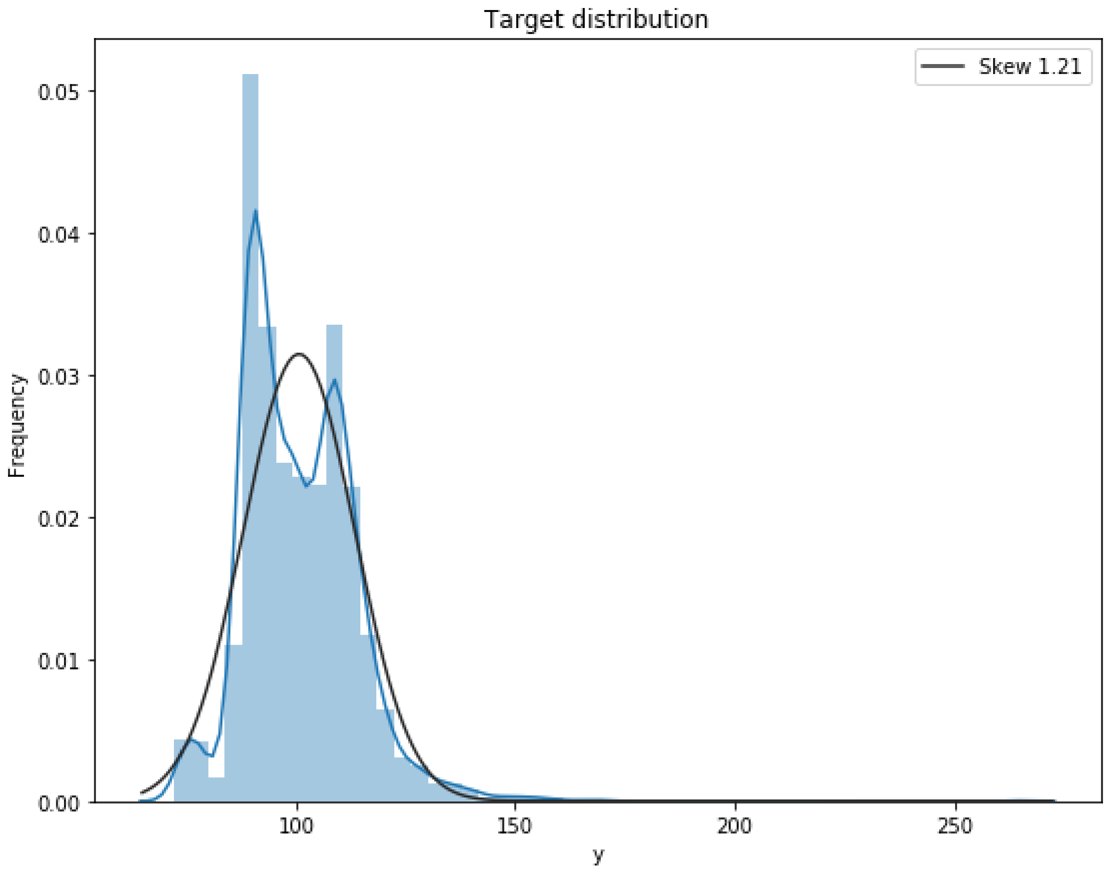


In [21]:

```
plt.figure(figsize=(9, 7))
sns.distplot(df['y'] , fit=stats.norm);
plt.legend(['Skew {:.2f}'.format(df['y'].skew())], loc='best')
plt.ylabel('Frequency')
plt.title('Target distribution')
```

Out[21]:

```
Text(0.5,1,'Target distribution')
```



Little bit right skewed.

Let us find the outlier values

In [60]:

```
print((df.loc[df.y>150,'y'].values))
df=df[df.y<150]
print("Removing outliers based on above information and setting 150 as a threshold value .
print(df.shape)
```

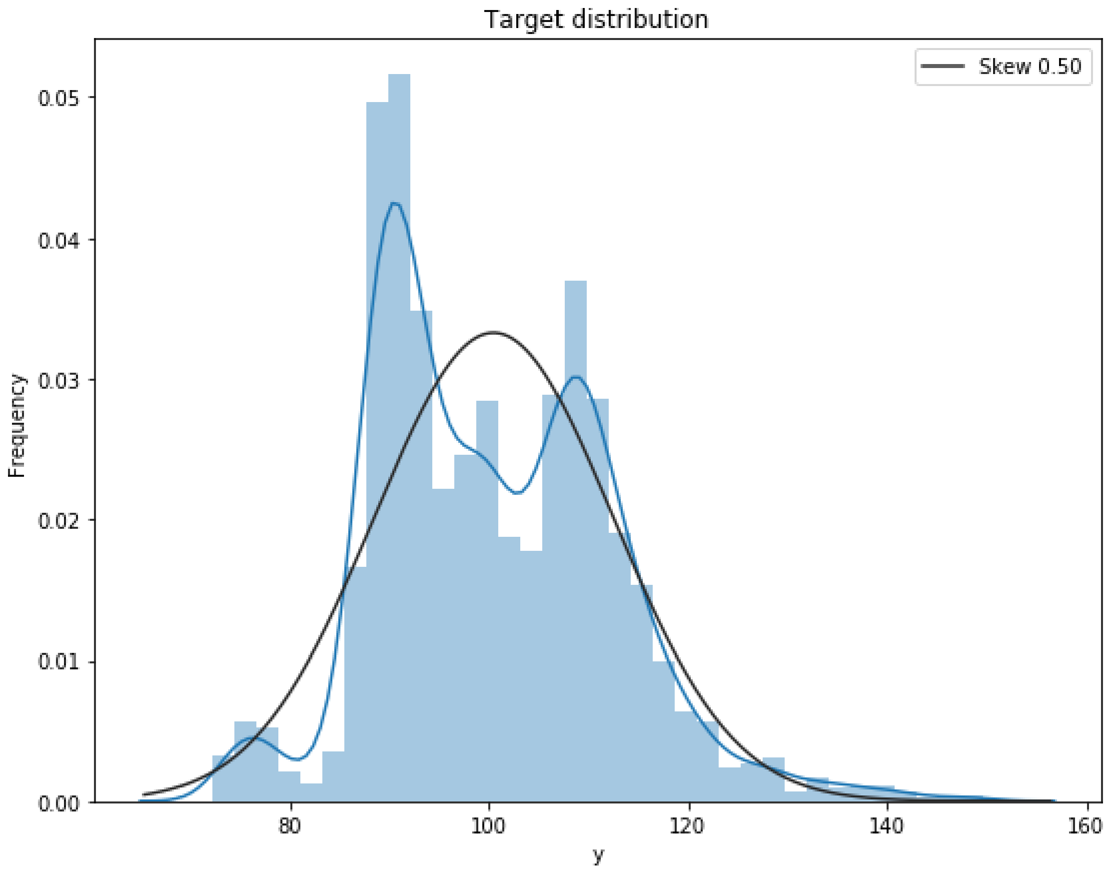
```
[150.43 169.91 154.87 265.32 158.53 154.43 160.87 150.89 152.32 167.45
 154.16 158.23 153.51 165.52 155.62]
Removing outliers based on above information and setting 150 as a threshold
value . . . . . . . . . . . . . . . . . . . . .
(4194, 378)
```

In [61]:

```
plt.figure(figsize=(9, 7))
sns.distplot(df['y'] , fit=stats.norm);
plt.legend(['Skew {:.2f}'.format(df['y'].skew())], loc='best')
plt.ylabel('Frequency')
plt.title('Target distribution')
```

Out[61]:

```
Text(0.5,1,'Target distribution')
```



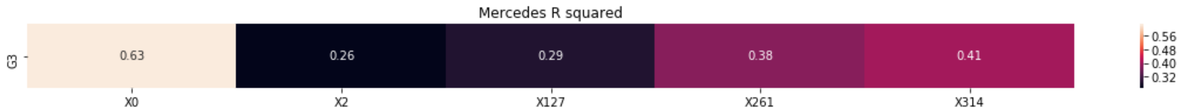
It looks much better.

Predictor features:

Explore the association between the target and the predictor variables:

In [62]:

```
# r squared method
def get_r2(x, y, data):
    formula = '{} ~ C({})'.format(y, x)
    return ols(formula, data).fit().rsquared

r2 = pd.DataFrame(index=['G3'])

for i in df.columns:
    if i not in ['ID', 'y']:
        score = get_r2(i, 'y', df)
        if score >= 0.2:
            r2.loc[:, i] = get_r2(i, 'y', df)

r2.fillna(np.nan, inplace=True)

plt.figure(figsize=(20, 1))
plt.title('Mercedes R squared')
sns.heatmap(r2, annot=True,fmt='.2f')
plt.show()
```



The X0 have a best relationship with the target. (64%).

In [63]:

```
df.shape
```

Out[63]:

```
(4194, 378)
```

E.D.A CONCLUSION:

Columns containing the unique values : [0] WE HAVE TO REMOVE THESE COLUMNS WHICH CONTAINING ONLY ZEROS

['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293', 'X297', 'X330', 'X339', 'X347']

We also try to remove the outliers.

DATA PREPERATION:

In [64]:

```
df.drop(['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293', 'X297', 'X33
```

In [65]:

```
df.shape
```

Out[65]:

```
(4194, 365)
```

In [89]:

```
def outliers_iqr(ys):
    quartile_1, quartile_3 = np.percentile(ys, [20, 80])
    iqr = quartile_3 - quartile_1
    lower_bound = quartile_1 - (iqr * 1.5)
    upper_bound = quartile_3 + (iqr * 1.5)
    return np.where((ys > upper_bound) | (ys < lower_bound))
drop=[]
drop = drop.append(outliers_iqr(df.y[df.y<150]))
drop
```

In [91]:

```
drop
```

In [80]:

```
df.drop(X_train.index[ 216,  678, 1031, 1135, 1340, 2346, 2365, 2874, 2892, 3077]), inplace
```

```
  File "<ipython-input-80-8fc758ab471a>", line 1
    df.drop(X_train.index[ 216,  678, 1031, 1135, 1340, 2346, 2365, 2874, 28
92, 3077]), inplace=True)

^
SyntaxError: invalid syntax
```

In [29]:

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

In [30]:

```
df.head()
```

Out[30]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X
0	0	130.81	32	23	16	0	3	24	9	14	0	0	1	0	0	0	0	1	
1	6	88.53	32	21	18	4	3	28	11	14	0	0	0	0	0	0	0	1	
2	7	76.26	20	24	33	2	3	27	9	23	0	0	0	0	0	0	1	0	
3	9	80.62	20	21	33	5	3	27	11	4	0	0	0	0	0	0	0	0	
4	13	78.02	20	23	33	5	3	12	3	13	0	0	0	0	0	0	0	0	

In [31]:

```
y=df['y']
```

In [32]:

```
df.drop(['y'], axis=1,inplace=True)
```

In [33]:

```
df.shape
```

Out[33]:

```
(4182, 364)
```

Random Train and Test split(80:20)

In [34]:

```
X_train, X_test, Y_train, Y_test = train_test_split(df, y, test_size=0.2, random_state=42)
```

In [35]:

```
print("No. of datapoints in X_train :",len(X_train))
print("No. of datapoints in X_test :",len(X_test))
print("Shape of Y_train :",Y_train.shape)
print("Shape of Y_test :",Y_test.shape)
```

```
No. of datapoints in X_train : 3345
No. of datapoints in X_test : 837
Shape of Y_train : (3345,)
Shape of Y_test : (837,)
```

Let us explore the X0, X2 and the X5 unique values. We append the differences to lists.

In [36]:

```
x0_new_to_train = [i for i in X_test.X0.unique() if i not in X_train.X0.unique()]
x2_new_to_train = [i for i in X_test.X2.unique() if i not in X_train.X2.unique()]
x5_new_to_train = [i for i in X_test.X5.unique() if i not in X_train.X5.unique()]

print(x0_new_to_train)
print(x2_new_to_train)
print(x5_new_to_train)
```

```
[]
[]
[]
```

In [37]:

```
x0_new_to_test = [i for i in X_train.X0.unique() if i not in X_test.X0.unique()]
x2_new_to_test = [i for i in X_train.X2.unique() if i not in X_test.X2.unique()]
x5_new_to_test = [i for i in X_train.X5.unique() if i not in X_test.X5.unique()]

print(x0_new_to_test)
print(x2_new_to_test)
print(x5_new_to_test)
```

```
[23, 37, 1, 11, 24, 3, 2, 28]
[40, 3, 18, 19, 5, 29, 36, 31, 14, 34, 22, 9]
[24, 27, 11, 12, 28]
```

We change that values.

In [38]:

```
X_train.X0 = X_train.X0.apply(lambda x : X_train.X0.mode()[0] if x in x0_new_to_test else x
X_train.X2 = X_train.X2.apply(lambda x : X_train.X2.mode()[0] if x in x2_new_to_test else x
X_train.X5 = X_train.X5.apply(lambda x : X_train.X5.mode()[0] if x in x5_new_to_test else x

X_test.X0 = X_test.X0.apply(lambda x : X_test.X0.mode()[0] if x in x0_new_to_train else x)
X_test.X2 = X_test.X2.apply(lambda x : X_test.X2.mode()[0] if x in x2_new_to_train else x)
X_test.X5 = X_test.X5.apply(lambda x : X_test.X5.mode()[0] if x in x5_new_to_train else x)
```

In [39]:

```
X_train.drop(['ID'], axis=1, inplace=True)
X_test.drop(['ID'], axis=1, inplace=True)
```

In [40]:

```
X_train.shape
```

Out[40]:

```
(3345, 363)
```

In [41]:

```
col = [k for k in X_train.columns if k not in {"y","X0","X1","X2","X3","X4","X5","X6","X8"}
```

In [42]:

```
    n_comp=10
    tsvd = TruncatedSVD(n_components=n_comp, random_state=420)
    tsvd_results_train = tsvd.fit_transform(X_train[col])
    tsvd_results_test = tsvd.transform(X_test[col])
    # PCA
    pca = PCA(n_components=n_comp, random_state=420)
    pca2_results_train = pca.fit_transform(X_train[col])
    pca2_results_test = pca.transform(X_test[col])
    # ICA
    ica = FastICA(n_components=n_comp, random_state=420)
    ica2_results_train = ica.fit_transform(X_train[col])
    ica2_results_test = ica.transform(X_test[col])
    # GRP
    grp = GaussianRandomProjection(n_components=n_comp, eps=0.1, random_state=420)
    grp_results_train = grp.fit_transform(X_train[col])
    grp_results_test = grp.transform(X_test[col])
    # SRP
    srp = SparseRandomProjection(n_components=n_comp, dense_output=True, random_state=420)
    srp_results_train = srp.fit_transform(X_train[col])
    srp_results_test = srp.transform(X_test[col])
    for i in range(1, n_comp + 1):
        X_train['tsvd_' + str(i)] = tsvd_results_train[:, i - 1]
        X_test['tsvd_' + str(i)] = tsvd_results_test[:, i - 1]
        X_train['pca_' + str(i)] = pca2_results_train[:, i - 1]
        X_test['pca_' + str(i)] = pca2_results_test[:, i - 1]
        X_train['ica_' + str(i)] = ica2_results_train[:, i - 1]
        X_test['ica_' + str(i)] = ica2_results_test[:, i - 1]
        X_train['grp_' + str(i)] = grp_results_train[:, i - 1]
        X_test['grp_' + str(i)] = grp_results_test[:, i - 1]
        X_train['srp_' + str(i)] = srp_results_train[:, i - 1]
        X_test['srp_' + str(i)] = srp_results_test[:, i - 1]
```

In [43]:

```
X_train.shape
```

Out[43]:

```
(3345, 413)
```

In [44]:

```
X_train.head(3)
```

Out[44]:

	X0	X1	X2	X3	X4	X5	X6	X8	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20
821	19	1	32	6	3	5	0	2	0	0	0	0	0	0	0	0	0	0
2847	40	1	15	2	3	20	6	21	0	0	0	1	0	0	0	0	0	0
1195	43	20	15	2	3	1	6	14	0	0	0	1	0	0	0	0	0	0

In [45]:

```
X_test.shape
```

Out[45]:

```
(837, 413)
```

Decision Tree Regression with hyperparameter tuning:

[https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html (https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html)](https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html)

In [159]:

```
hyper =  [1, 5, 10, 50, 100, 500, 1000]
param_grid = {'max_depth' :hyper}
lasso_model = DecisionTreeRegressor()
grid_search = GridSearchCV(lasso_model,param_grid, cv=5,scoring='r2')
grid_search.fit(X_train, Y_train)
print("Best SGDR alpha: ", grid_search.best_params_)
print("Best SGDR score: ", grid_search.best_score_)
```

```
Best SGDR alpha:  {'max_depth': 5}
Best SGDR score:  0.6169689489084359
```

In [160]:

```
madel2=DecisionTreeRegressor(max_depth=5)
madel2.fit(X_train, Y_train)
pred2 = madel2.predict(X_test)
acc2 = r2_score(Y_test, pred2)
print('\nThe R2 score for DEPTH = %f ON TEST DATA is %f%%' % (5, acc2))
```

```

The R2 score for DEPTH = 5.000000 ON TEST DATA is 0.599141%
```

XGB Regression with hyperparameter tuning:

[https://xgboost.readthedocs.io/en/latest/parameter.html (https://xgboost.readthedocs.io/en/latest/parameter.html)](https://xgboost.readthedocs.io/en/latest/parameter.html)

In [47]:

```
x_cfl=XGBRegressor()
prams={

'learning_rate':[0.01,0.03,0.05,0.1,0.15,0.2],
     'n_estimators':[100,200,500,1000,2000],
     'max_depth':[3,5,8,10],
    'colsample_bytree':[0.1,0.3,0.5,1],
    'subsample':[0.1,0.3,0.5,1]

}
first_xgb=GridSearchCV(x_cfl,prams,verbose=10,n_jobs=-1,scoring='r2')
first_xgb.fit(X_train, Y_train)
```

```
Fitting 3 folds for each of 1920 candidates, totalling 5760 fits
```

In [48]:

```
print (first_xgb.best_params_)
```

```
{'colsample_bytree': 0.5, 'learning_rate': 0.03, 'max_depth': 3, 'n_estimato
rs': 200, 'subsample': 1}
```

In [50]:

```
madel3=XGBRegressor(colsample_bytree=0.5,n_estimators=200,max_depth=3,learning_rate=.03,sub
madel3.fit(X_train, Y_train)
pred3 = madel3.predict(X_test)
acc3 = r2_score(Y_test, pred3)
print('\nThe R2 score of XGBRegressor ON TEST DATA is %f%%' % (acc3))
```

```
The R2 score of XGBRegressor ON TEST DATA is 0.609613%
```

Lasso Regression with hyperparameter tuning:

Because of anonymized set of variables, we'll use LASSO regression.

"LASSO regression (Least Absolute Shrinkage and Selection Operator) is a type of regression analysis in which both variable selection and regulization occurs simultaneously. This method uses a penalty which affects they value of coefficients of regression. As penalty increases more coefficients are becomes zero and vice Versa. It uses L1 normalisation technique in which tuning parameter is used as amount of shrinkage. As tuning parameter increase then bias increases and as is decreases then variance increases. If it is constant then no coefficients are zero and as is tends to infinity then all the coefficients will be zero."

So we don't reduce the dimensions, we confide in Lasso variable selection.

https://en.wikipedia.org/wiki/Lasso_(statistics) (https://en.wikipedia.org/wiki/Lasso_(statistics))

https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Lasso.html (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Lasso.html)

In [161]:

```
hyper = []
i = 0.0000001
while(i<=1000000000):
    hyper.append(np.round(i,7))
    i *= 10

lasso_grid = {"alpha" : hyper}
lasso_model = Lasso(fit_intercept=True,normalize=True)
grid_search = GridSearchCV(lasso_model, lasso_grid, cv=5, scoring='r2')
grid_search.fit(X_train, Y_train)
print("Best lasso alpha: ", grid_search.best_params_)
print("Best lasso score: ", grid_search.best_score_)
```

```
Best lasso alpha:  {'alpha': 0.01}
Best lasso score:  0.611276230109042
```

In [162]:

```
madel1=Lasso(alpha=0.01,fit_intercept=True,normalize=True)
madel1.fit(X_train, Y_train)
pred1 = madel1.predict(X_test)
acc = r2_score(Y_test, pred1)
print('\nThe R2 score for ALPHA = %f ON TEST DATA is %f%%' % (.01, acc))
```

```

The R2 score for ALPHA = 0.010000 ON TEST DATA is 0.584410%
```

In [171]:

```
# Creating table using PrettyTable library
from prettytable import PrettyTable

ptable = PrettyTable()
# Names of models
names =['Lasso Regression','Decision Tree Regression','XGB Regression']

#alpha=[0.001, 0.001]

Coefficient_of_determination = [0.584410,0.599141,0.608679]

Coefficient_of_determination1 = [0.51797,0.53522,0.54570]

Coefficient_of_determination2 = [0.52655,0.54524,0.55275]



# Adding columns

ptable.add_column("MODEL",names)

#ptable.add_column("Hyperparameter",alpha)
ptable.add_column("R^2",Coefficient_of_determination)
ptable.add_column("R^2(KAGGLE_SCORE_PUBLIC)",Coefficient_of_determination1)
ptable.add_column("R^2(KAGGLE_SCORE_PRIVATE)",Coefficient_of_determination2)
print(ptable)
```

```
+--------------------------+----------+--------------------------+----------
-----------------+
|          MODEL           |   R^2    | R^2(KAGGLE_SCORE_PUBLIC) | R^2(KAGGL
E_SCORE_PRIVATE) |
+--------------------------+----------+--------------------------+----------
-----------------+
|     Lasso Regression     | 0.58441  |         0.51797          |
0.52655          |
| Decision Tree Regression | 0.599141 |         0.53522          |
0.54524          |
|      XGB Regression      | 0.608679 |          0.5457          |
0.55275          |
+--------------------------+----------+--------------------------+----------
-----------------+
```

RESULT:

In 1st approach we got (Private Score:0.5457) AND (Public Score:0.55275) On kaggle.

---SECOND APPROACH---

SECOND APPROACH WITH DIFFERENT FEATURE ENGINEERING TO INCREASE SCORE R^2(Coef. of

determination)

AGAIN LODAING THE DATA

In [3]:

```
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
df = train
```

370 numerical features and 8 categorical features

In [5]:

```
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
df_num = df.select_dtypes(include=numerics)       #  numeric dataframe
objects = ['O']
df_cat = df.select_dtypes(include=objects)
print(df_num.shape,df_cat.shape)
print(df_cat.columns,'\n','-------------------------------------------------------------
```

```
(4209, 370) (4209, 8)
Index(['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8'], dtype='object')
 ----------------------------------------------------------------------------
-----
 Index(['ID', 'y', 'X10', 'X11', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17',
       ...
       'X375', 'X376', 'X377', 'X378', 'X379', 'X380', 'X382', 'X383', 'X38
4',
       'X385'],
      dtype='object', length=370)
```

A separate dataframe to study only categorical features and there mutual relationship and also the one with target column y.

In [6]:

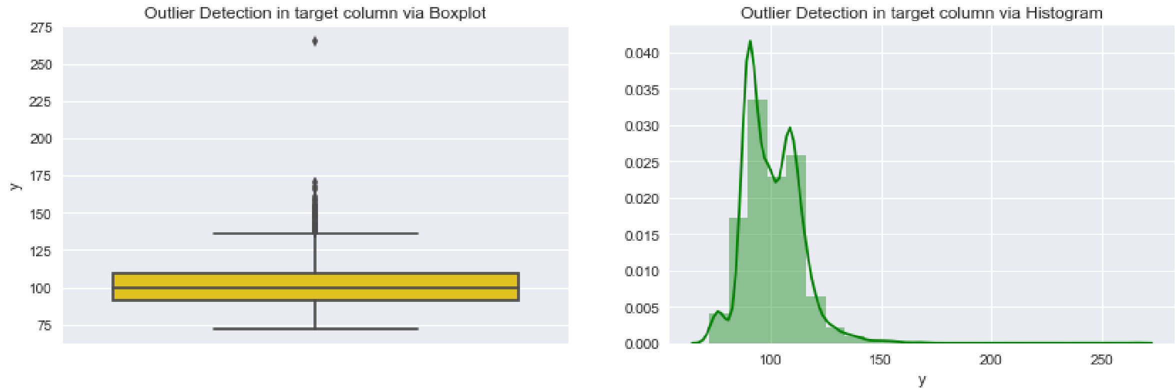
```
temp=df.y.values
df_cat['y']=temp
print(df_cat.head())
```

```
   X0 X1  X2 X3 X4 X5 X6 X8       y
0   k  v  at  a  d  u  j  o  130.81
1   k  t  av  e  d  y  l  o   88.53
2  az  w   n  c  d  x  j  x   76.26
3  az  t   n  f  d  x  l  e   80.62
4  az  v   n  f  d  h  d  n   78.02
```

Again outlier detection and removal .... A bit cleaning....

In [7]:

```
sns.set(rc={'figure.figsize':(14,9)})
plt.subplot(221)
plt.title("Outlier Detection in target column via Boxplot")
plt.ylabel("Values of y")
plt.grid(True)
sns.boxplot(y=df["y"],color='gold')
plt.subplot(222)
plt.title("Outlier Detection in target column via Histogram")
plt.grid(True)
ax = sns.distplot(df.y,color='green',bins=22)
plt.show()
```



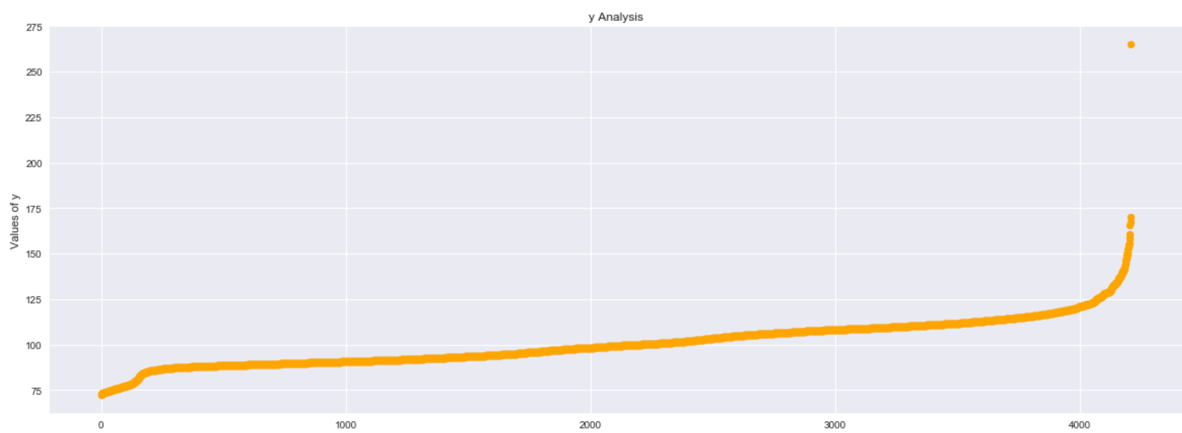
This clearly shows the outliers are above a value of approx. 137.5. Well we will remove outliers after 150.

In [8]:

```
sns.set(rc={'figure.figsize':(20,7)})
plt.title("y Analysis")
plt.ylabel("Values of y")
plt.scatter(range(df.shape[0]),np.sort(df.y.values),color='orange')
```

Out[8]:

```
<matplotlib.collections.PathCollection at 0x2a388d566a0>
```



A very distinct and conspicuous point around 275 in boxplot and also the green area in histogram. This noise has to removed.

In [9]:

```
print((df.loc[df.y>150,'y'].values))
df=df[df.y<150]
print("Removing outliers based on above information and setting 150 as a threshold value .
print(df.shape)
df_cat=df_cat[df_cat.y<150]
df_num=df_num[df_num.y<150]
```

```
[150.43 169.91 154.87 265.32 158.53 154.43 160.87 150.89 152.32 167.45
 154.16 158.23 153.51 165.52 155.62]
Removing outliers based on above information and setting 150 as a threshold
value . . . . . . . . . . . . . . . . . . . .
(4194, 378)
```

Further data cleaning . . . Removing the features from the main dataframe that are involving zero variance or are having constant value inorder to remove redundancy and increase model performance later. Also checking the individual correlation of the features and getting some idea about individual feature importance. There are total 13 variables with zero variance , therefore they must be dropped. Checking for duplicate features in this large set. Feature selection multiple times ..... Removing columns with zero ovariance

Removing columns with only zero value

In [10]:

```
temp = []
for i in df_num.columns:
    if df[i].var()==0:
        temp.append(i)
print(len(temp))
print(temp)
```

```
13
['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293', 'X29
7', 'X330', 'X339', 'X347']
```

Again setting a threshold of 0.01 for variance for each column and removing them too. The removed columns are also being removed from all the temporary dataframes.

In [11]:

```
count=0
low_var_col=[]
for i in test.columns:
    if test[i].dtype == 'int64':
        if test[i].var()<0.01:
            low_var_col.append(i)
            count+=1
print(count)

df.drop(low_var_col,axis=1,inplace=True)
df_num.drop(low_var_col,axis=1,inplace=True)
test.drop(low_var_col,axis=1,inplace=True)
```

```
146
```

Turn out to be there are 146 columns for removal purpose.

Updating the df_num dataframe after droping the features from original dataframe df.

In [12]:

```
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
df_num = df.select_dtypes(include=numerics)
```

Getting the dictionary of important correlated features with target column y

Some important feature correlations with the target variable.

Taking 0.25 as threshold on grounds of experimental changes . .

In [13]:

```

_num.columns:
/':
df[i].corr(df.y)>0.25 or df[i].corr(df.y)<-0.25:
dic[i]=df[i].corr(df.y)
rtant Features with there respective correlations are ",'\n','------------------------------
```

```
Important Features with there respective correlations are 
 ---------------------------------------------------------
 {'X28': -0.261548387853112, 'X29': -0.3979846718424932, 'X54': -0.393622636
88450944, 'X76': -0.39362263688450944, 'X80': -0.2566304628986176, 'X118':
0.2911340078121633, 'X119': 0.2911340078121633, 'X127': -0.5359508861669307,
'X136': 0.39362263688450944, 'X162': -0.3809601526804208, 'X166': -0.3469061
103890677, 'X178': -0.3105490342608788, 'X185': -0.25654857309239765, 'X23
2': -0.3979846718424932, 'X234': -0.27530886410908445, 'X250': -0.3231881489
6929704, 'X261': 0.6184684577479749, 'X263': 0.3979846718424932, 'X272': -0.
36779944561534245, 'X275': 0.29297093005751373, 'X276': -0.3766313433180077
4, 'X279': -0.3979846718424932, 'X313': -0.3453785698372581, 'X314': 0.63719
78536813558, 'X316': -0.2747484119054767, 'X328': -0.3839243197734775, 'X34
8': -0.25754835598033654, 'X378': -0.27115936517391354}
```

This states that X29, X54, X76, X127, X136, X162, X166, X178, X232, X250, X261, X263, X272, X276, X279, X313, X314, X328 are important features later we will select using some selection techniques.

But , YOU MUST SEE THAT SOME FEATURES ARE HAVING SAME CORRELATIONS THAT COULD INDICATE THE POSSIBLE DUPLICATE FEATURES. Lets check them too . .

In [14]:

```
print(df.X119.corr(df.X118),'\n', df.X29.corr(df.X54) ,'\n', df.X54.corr(df.X76) ,'\n', df.
```

```
0.9999999999999999
 0.9971247031088819
 1.0
 -1.0
```

This shows that are dataframe is containing some duplicate features which are having correlation of approx. 1. We will remove this redundancy also using some feature selection . . .

Duplicate features.

In [15]:

```
# Dublicate features
d = {}; done = []
cols = df.columns.values
for c in cols: d[c]=[]
for i in range(len(cols)):
    if i not in done:
        for j in range(i+1, len(cols)):
            if all(df[cols[i]] == df[cols[j]]):
                done.append(j)
                d[cols[i]].append(cols[j])
dub_cols = []
for k in d.keys():
    if len(d[k]) > 0:
        dub_cols += d[k]
print('Dublicates:','\n', dub_cols)
```

```
Dublicates:
 ['X232', 'X279', 'X35', 'X37', 'X113', 'X134', 'X147', 'X222', 'X76', 'X32
4', 'X84', 'X244', 'X119', 'X146', 'X226', 'X326', 'X360', 'X247']
```

Checking correlations among a set of duplicate features and preparing pairs who are highly correlated.

Again, correlation threshold of 0.9 has been judged and taken after multiple experiments .....

In [16]:

```
corrs=[]
high_corr=[]
for i in range(0,len(dub_cols)):
    for j in range(i+1,len(dub_cols)):
        if df[dub_cols[i]].corr(df[dub_cols[j]]) >=0.90:
            corrs.append(df[dub_cols[i]].corr(df[dub_cols[j]]))
            high_corr.append((dub_cols[i],dub_cols[j]))
print(corrs)
print("\n")
print(high_corr)
```

```
[1.0, 0.9971247031088819, 0.9971247031088819, 0.9999999999999999, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0]


[('X232', 'X279'), ('X232', 'X76'), ('X279', 'X76'), ('X35', 'X37'), ('X11
3', 'X134'), ('X113', 'X147'), ('X113', 'X222'), ('X134', 'X147'), ('X134',
'X222'), ('X147', 'X222'), ('X84', 'X244'), ('X226', 'X326')]
```

In [17]:

```
df.drop(['X279','X76','X37','X134','X147','X222','X244','X326'] , axis=1 , inplace=True)
test.drop(['X279','X76','X37','X134','X147','X222','X244','X326'] , axis=1 , inplace=True)
df_num.drop(['X279','X76','X37','X134','X147','X222','X244','X326'] , axis=1 , inplace=True
```

Label encoding the categorical features

This dataset has some real problem with the number of categories.

There are different number of categories in train and test datset. Encountered

In [18]:

```
from sklearn import preprocessing
categorical=[]
for i in df.columns:
    if df[i].dtype=='object':
        le = preprocessing.LabelEncoder()
        le.fit(list(df[i].values) + list(test[i].values))
        print("Categories in the encoded order from 1 to the size of "+i+" are : ")
        print(le.classes_)
        print("--------------------------------------------------------------------------")
        df[i] = le.transform(list(df[i].values))
        test[i] = le.transform(list(test[i].values))
        categorical.append(i)
```

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

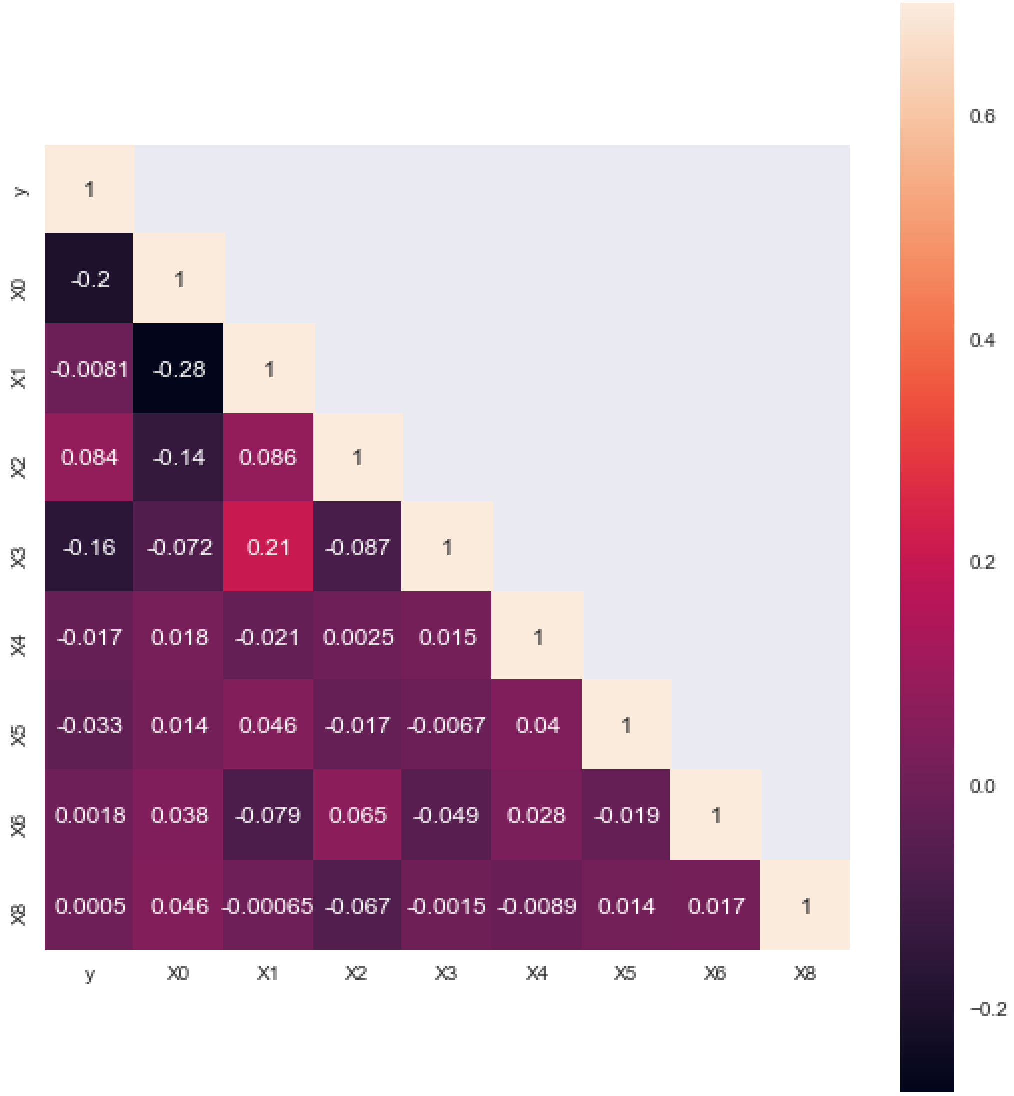
Now, finding correlations of each category with other . The increasing or decreasing class encoded value can be found from the categories written in the encoded order above.

In [19]:

```
correlation_map = df[df.columns[1:10]].corr()
obj = np.array(correlation_map)
obj[np.tril_indices_from(obj)] = False
fig,ax= plt.subplots()
fig.set_size_inches(9,10)
sns.heatmap(correlation_map, mask=obj,vmax=.7, square=True,annot=True)
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2a388062198>
```

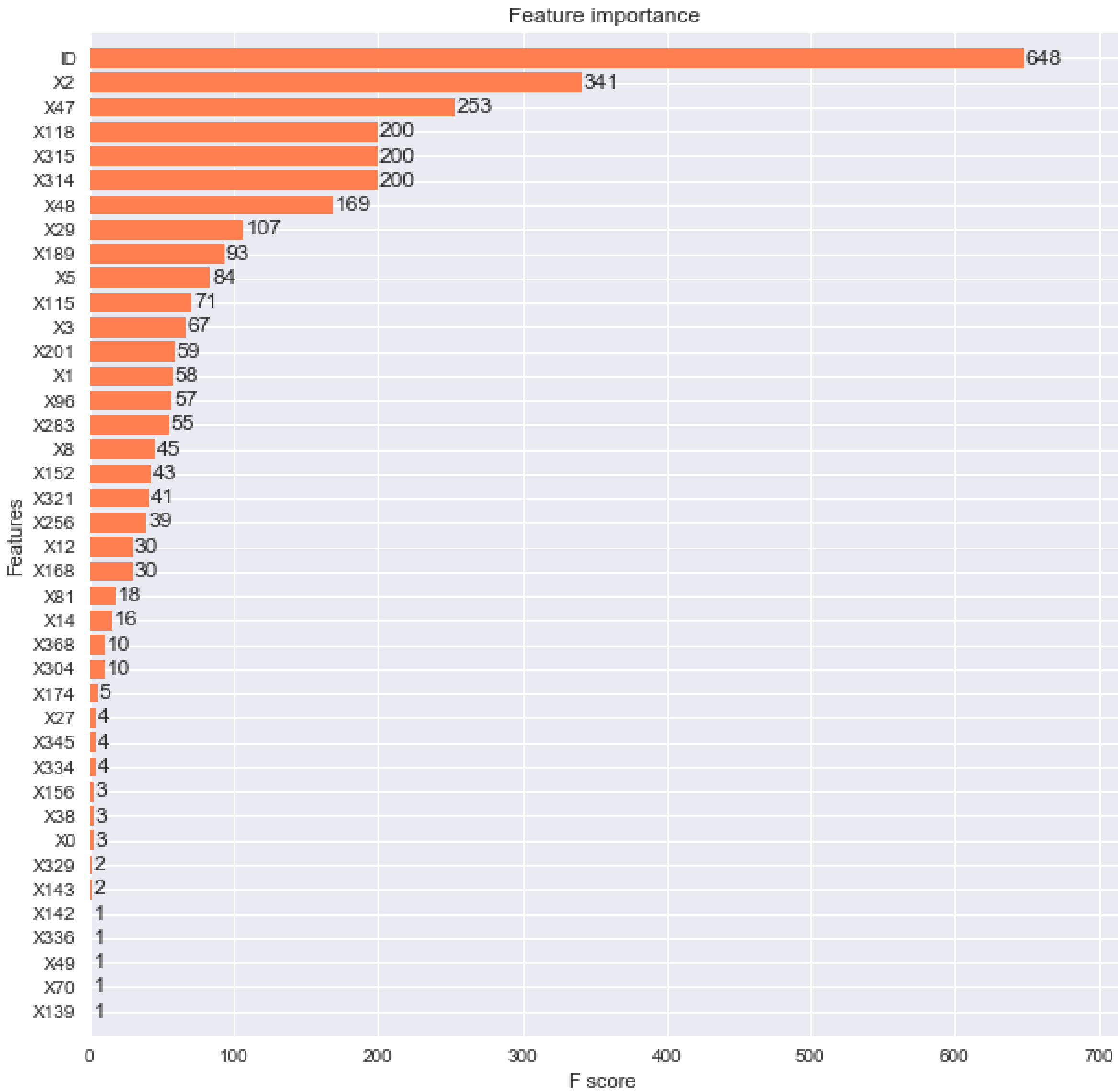


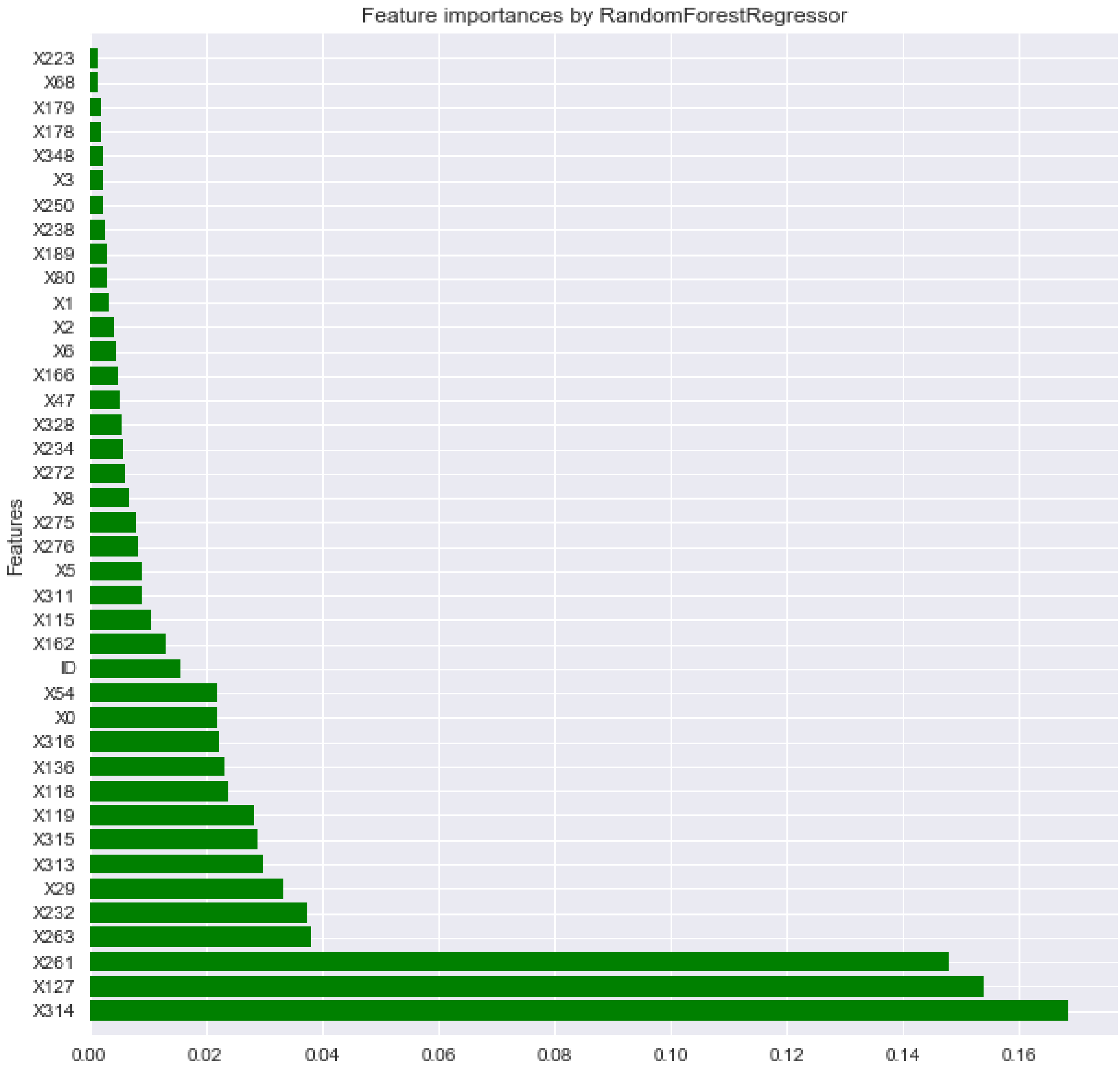
Preparing the data for feature importance

In [20]:

```
import xgboost as xgb
train_y = df["y"].values
train_X = df.drop(['y'], axis=1)

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

xgb_params = {
    'n_trees': 520,
    'eta': 0.0045,
    'max_depth': 4,
    'subsample': 0.98,
    'objective': 'reg:linear',
    'eval_metric': 'rmse',
    'base_score': np.mean(train_y), # base prediction = mean(target)
    'silent': 1
}

final = xgb.DMatrix(train_X, train_y, feature_names=train_X.columns.values)
model = xgb.train(dict(xgb_params), final, num_boost_round=200, feval=xgb_r2_score, maximiz

fig, ax = plt.subplots(figsize=(10,10))
xgb.plot_importance(model, max_num_features=40, height=0.8, ax=ax, color = 'coral')
print("Feature Importance by XGBoost")
plt.show()

from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(n_estimators=200, max_depth=10, min_samples_leaf=4, max_featu
model.fit(train_X, train_y)
feat_names = train_X.columns.values

importances = model.feature_importances_
std = np.std([tree.feature_importances_ for tree in model.estimators_], axis=0)
indices = np.argsort(importances)[::-1][:40]

plt.subplots(figsize=(10,10))
plt.title("Feature importances by RandomForestRegressor")
plt.ylabel("Features")
plt.barh(range(len(indices)), importances[indices], color="green", align="center")
plt.yticks(range(len(indices)), feat_names[indices], rotation='horizontal')
plt.ylim([-1, len(indices)])
plt.show()
```

```
Feature Importance by XGBoost
```


Feature importance
Features
ID 648
X2 341
X47 253
X118 200
X315 200
X314 200
X48 169
X29 107
X189 93
X5 84
X115 71
X3 67
X201 59
X1 58
X96 57
X283 55
X8 45
X152 43
X321 41
X256 39
X12 30
X168 30
X81 18
X14 16
X368 10
X304 10
X174 5
X27 4
X345 4
X334 4
X156 3
X38 3
X0 3
X329 2
X143 2
X142 1
X336 1
X49 1
X70 1
X139 1
0
100
200
300
400
500
600
700
F score



There seems a difference between the feature importances by the two models. You can check above, RandomForest is giving the feature importance more on the basis of the important correlations of target wrt numerical features that we have already figured out above.

Lets do some Feature Engineering . . .

Feature Engineering with interaction variable:

In [21]:

```
df['X314_plus_X315'] = df.apply(lambda row: row.X314 + row.X315, axis=1)
test['X314_plus_X315'] = test.apply(lambda row: row.X314 + row.X315, axis=1)
```

In [22]:

```
print("Correalation between X314_plus_X315 and y is :  ",df.y.corr(df['X314_plus_X315']))
print("Which makes it pretty much high !! Awesome !!")
```

```
Correalation between X314_plus_X315 and y is :   0.6990819224017311
Which makes it pretty much high !! Awesome !!
```

In [23]:

```
df['X118_plus_X314_plus_X315'] = df.apply(lambda row: row.X118 + row.X314 + row.X315, axis=
test['X118_plus_X314_plus_X315'] = test.apply(lambda row: row.X118 + row.X314 + row.X315, a
print("Correalation between X118_plus_X314_plus_X315 and y is :  ",df.y.corr(df['X118_plus_
print("Which makes it pretty much high !! Awesome !!")
```

```
Correalation between X118_plus_X314_plus_X315 and y is :   0.683726622379975
5
Which makes it pretty much high !! Awesome !!
```

In [24]:

```
df["X10_plus_X54"] = df.apply(lambda row: row.X10 + row.X54, axis=1)
test["X10_plus_X54"] = test.apply(lambda row: row.X10 + row.X54, axis=1)
print("Correalation between X10_plus_X54 and y is :  ",df.y.corr(df['X10_plus_X54']))
```

```
Correalation between X10_plus_X54 and y is :   -0.3597138023478578
```

In [25]:

```
df["X10_plus_X29"] = df.apply(lambda row: row.X10 + row.X29, axis=1)
test["X10_plus_X29"] = test.apply(lambda row: row.X10 + row.X29, axis=1)
print("Correalation between X10_plus_X29 and y is :  ",df.y.corr(df['X10_plus_X29']))
```

```
Correalation between X10_plus_X29 and y is :   -0.3633528870084599
```

Updating the dataframe for feature importance , the one we used above.

In [26]:

```
train_X['X314_plus_X315']=df['X314_plus_X315']
train_X['X118_plus_X314_plus_X315']=df['X118_plus_X314_plus_X315']
train_X["X10_plus_X54"] = df["X10_plus_X54"]
train_X["X10_plus_X29"] = df["X10_plus_X29"]
```

In [27]:

```
corr_val=[]
same_features=[]
for i in range(0,len(df_num.columns)-1):
    for j in range(i+1,len(df_num.columns)):
        temp_corr=df[df_num.columns[i]].corr(df[df_num.columns[j]])
        if temp_corr>=0.95 or temp_corr<=-0.95:
            same_features.append((df_num.columns[i],df_num.columns[j]))
            corr_val.append(temp_corr)
print(len(corr_val))
print(same_features)
```

```
63
[('X19', 'X215'), ('X29', 'X54'), ('X29', 'X136'), ('X29', 'X162'), ('X29',
'X232'), ('X29', 'X263'), ('X29', 'X328'), ('X31', 'X35'), ('X48', 'X113'),
('X48', 'X198'), ('X49', 'X129'), ('X52', 'X61'), ('X52', 'X120'), ('X54',
'X136'), ('X54', 'X162'), ('X54', 'X232'), ('X54', 'X263'), ('X54', 'X328'),
('X58', 'X137'), ('X58', 'X324'), ('X61', 'X120'), ('X66', 'X111'), ('X71',
'X84'), ('X80', 'X348'), ('X96', 'X363'), ('X108', 'X371'), ('X113', 'X19
8'), ('X118', 'X119'), ('X118', 'X311'), ('X119', 'X311'), ('X126', 'X264'),
('X128', 'X130'), ('X136', 'X162'), ('X136', 'X232'), ('X136', 'X263'), ('X1
36', 'X328'), ('X137', 'X324'), ('X138', 'X140'), ('X138', 'X146'), ('X140',
'X146'), ('X142', 'X158'), ('X152', 'X226'), ('X155', 'X360'), ('X156', 'X15
7'), ('X162', 'X232'), ('X162', 'X263'), ('X162', 'X328'), ('X178', 'X250'),
('X185', 'X378'), ('X186', 'X194'), ('X186', 'X362'), ('X194', 'X362'), ('X2
02', 'X247'), ('X208', 'X368'), ('X228', 'X229'), ('X232', 'X263'), ('X232',
'X328'), ('X246', 'X358'), ('X261', 'X314'), ('X263', 'X328'), ('X331', 'X35
2'), ('X331', 'X367'), ('X334', 'X337')]
```

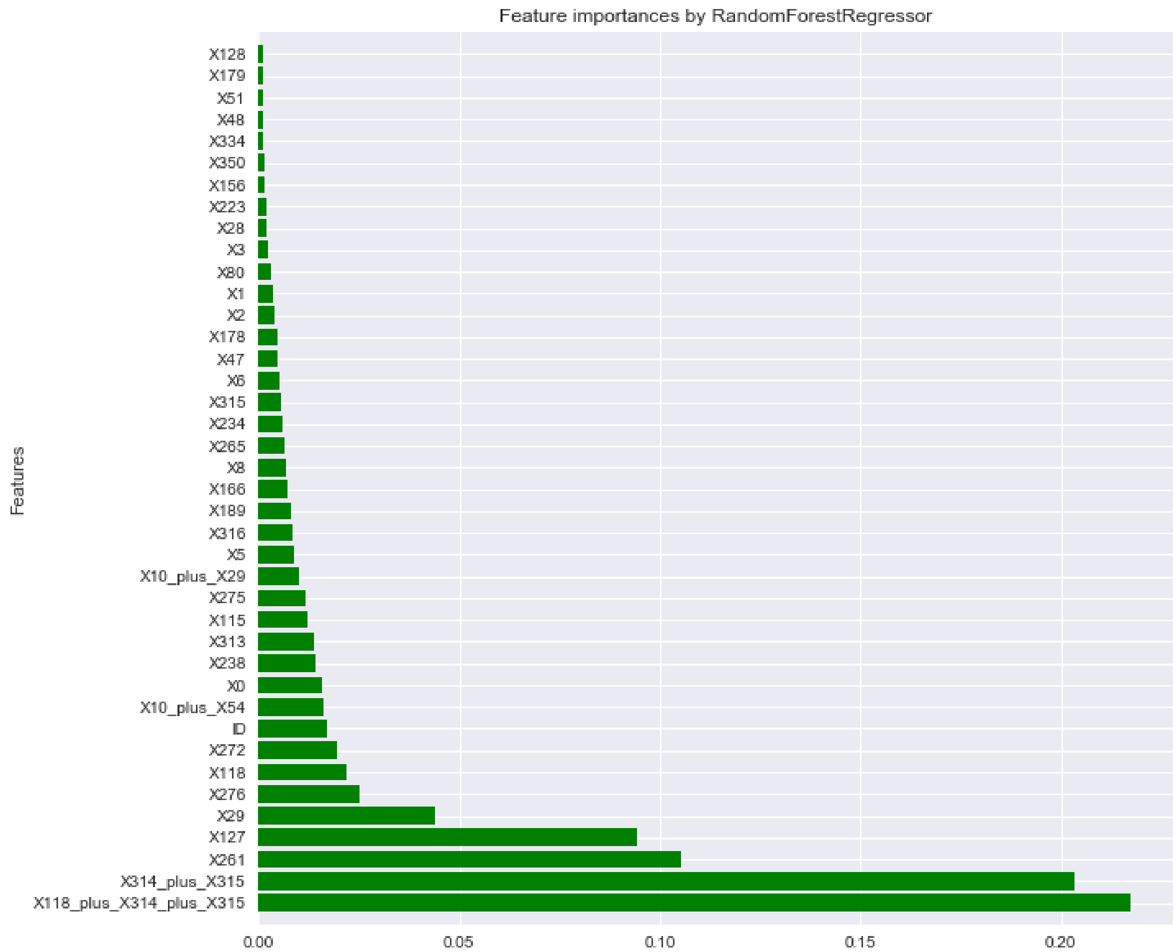
In [28]:

```
booler = np.ones(400)
for i in same_features:
    if booler[int(i[1][1:])]==1:
        booler[int(i[1][1:])]=0
        df_num.drop(i[1],axis=1,inplace=True)
        df.drop(i[1],axis=1,inplace=True)
        test.drop(i[1],axis=1,inplace=True)
        train_X.drop(i[1],axis=1,inplace=True)
    elif booler[int(i[0][1:])]==1:
        booler[int(i[0][1:])]=0
        df_num.drop(i[0],axis=1,inplace=True)
        df.drop(i[0],axis=1,inplace=True)
        test.drop(i[0],axis=1,inplace=True)
        train_X.drop(i[0],axis=1,inplace=True)
```

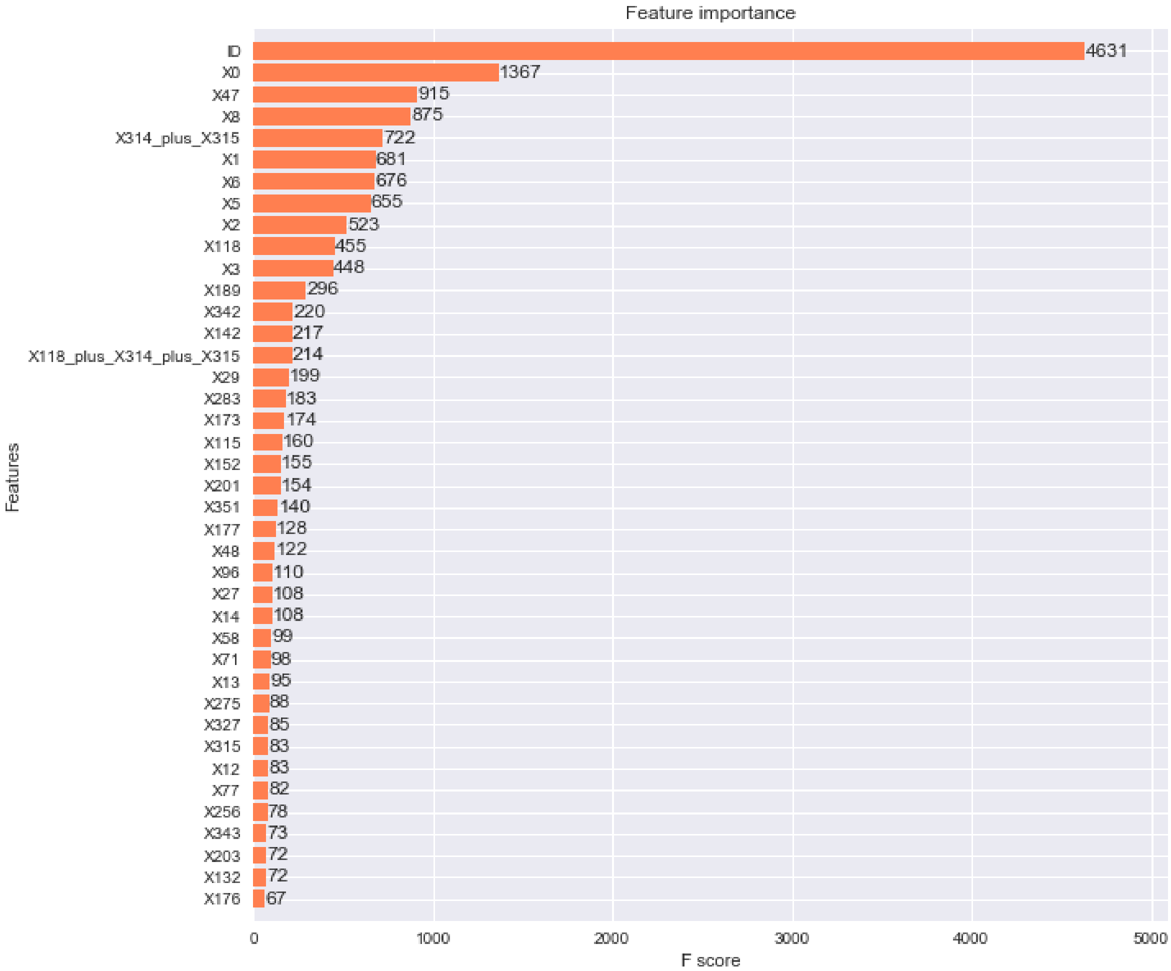
That look great the new features engineered have outperformed the existing features in the data in the RandomForrest feature importance plot.

In [29]:

```
model = RandomForestRegressor(n_estimators=200, max_depth=10, min_samples_leaf=4, max_featu
model.fit(train_X, train_y)
feature_names = train_X.columns.values

importances = model.feature_importances_
std = np.std([tree.feature_importances_ for tree in model.estimators_], axis=0)
indices = np.argsort(importances)[::-1][:40]

plt.subplots(figsize=(10,10))
plt.title("Feature importances by RandomForestRegressor")
plt.ylabel("Features")
plt.barh(range(len(indices)), importances[indices], color="green", align="center")
plt.yticks(range(len(indices)), feature_names[indices], rotation='horizontal')
plt.ylim([-1, len(indices)])
plt.show()

final = xgb.DMatrix(train_X, train_y, feature_names=train_X.columns.values)
model = xgb.train(dict(xgb_params), final, num_boost_round=1350, feval=xgb_r2_score, maximi

fig, ax = plt.subplots(figsize=(10,10))
xgb.plot_importance(model, max_num_features=40, height=0.8, ax=ax,color = 'coral')
print("Feature Importance by XGBoost")
plt.show()
```




```
Feature Importance by XGBoost
```



In [30]:

```
print(train_X.shape , test.shape)
```

```
(4194, 185) (4209, 185)
```

In [31]:

```
list(set(train_X.columns)-set(test.columns))
```

Out[31]:

```
[]
```

In [32]:

```
port xgboost as xgb
om sklearn.metrics import r2_score
om sklearn.model_selection import train_test_split

train, x_valid, y_train, y_valid = train_test_split(train_X, train_y, test_size=0.2, random_

train = xgb.DMatrix(x_train, label=y_train)
valid = xgb.DMatrix(x_valid, label=y_valid)
test = xgb.DMatrix(test)

_params = {
  'n_trees': 500,
  'eta': 0.0050,
  'max_depth': 3,
  'subsample': 0.95,
  'objective': 'reg:linear',
  'eval_metric': 'rmse',
  'base_score': np.mean(train_y), # base prediction = mean(target)
  'silent': 1


f xgb_r2_score(preds, dtrain):
  labels = dtrain.get_label()
  return 'r2', r2_score(labels, preds)

tchlist = [(d_train, 'train'), (d_valid, 'valid')]

f = xgb.train(xgb_params, d_train, 1050 , watchlist, early_stopping_rounds=70, feval=xgb_r2_
```

```
[430]	train-rmse:7.32642	valid-rmse:7.3009	train-r2:0.628808
valid-r2:0.621208
[440]	train-rmse:7.31506	valid-rmse:7.2932	train-r2:0.629958
valid-r2:0.622006
[450]	train-rmse:7.30447	valid-rmse:7.28584	train-r2:0.63103
valid-r2:0.622769
[460]	train-rmse:7.29431	valid-rmse:7.27881	train-r2:0.632055
valid-r2:0.623497
[470]	train-rmse:7.28489	valid-rmse:7.27304	train-r2:0.633004
valid-r2:0.624093
[480]	train-rmse:7.27597	valid-rmse:7.2677	train-r2:0.633903
valid-r2:0.624645
[490]	train-rmse:7.26759	valid-rmse:7.26285	train-r2:0.634745
valid-r2:0.625146
[500]	train-rmse:7.25984	valid-rmse:7.25776	train-r2:0.635524
valid-r2:0.625671
[510]	train-rmse:7.2522	valid-rmse:7.25387	train-r2:0.636291
valid-r2:0.626073
[520]	train-rmse:7.24474	valid-rmse:7.24966	train-r2:0.637039
```

In [33]:

```
train = xgb.DMatrix(train_X, label=train_y)
_valid = xgb.DMatrix(x_valid, label=y_valid)
test = xgb.DMatrix(test)

o_params = {
  'n_trees': 500,
  'eta': 0.0050,
  'max_depth': 3,
  'subsample': 0.95,
  'objective': 'reg:linear',
  'eval_metric': 'rmse',
  'base_score': np.mean(train_y),
  'silent': 1


f xgb_r2_score(preds, dtrain):
  labels = dtrain.get_label()
  return 'r2', r2_score(labels, preds)

tchlist = [(d_train, 'train')]

f = xgb.train(xgb_params, d_train, 1050 , watchlist, early_stopping_rounds=70, feval=xgb_r2_
```

```
[850]   train-rmse:7.09965      train-r2:0.649575
[860]   train-rmse:7.09602      train-r2:0.649933
[870]   train-rmse:7.09259      train-r2:0.650272
[880]   train-rmse:7.08914      train-r2:0.650612
[890]   train-rmse:7.08581      train-r2:0.65094
[900]   train-rmse:7.08269      train-r2:0.651247
[910]   train-rmse:7.07998      train-r2:0.651514

[920]   train-rmse:7.07696      train-r2:0.651811
[930]   train-rmse:7.07449      train-r2:0.652055
[940]   train-rmse:7.07169      train-r2:0.65233
[950]   train-rmse:7.06866      train-r2:0.652628
[960]   train-rmse:7.06601      train-r2:0.652888
[970]   train-rmse:7.06292      train-r2:0.653192
[980]   train-rmse:7.05994      train-r2:0.653484
[990]   train-rmse:7.05692      train-r2:0.653781
[1000]  train-rmse:7.05387      train-r2:0.65408
[1010]  train-rmse:7.05111      train-r2:0.654351
[1020]  train-rmse:7.0482       train-r2:0.654636
[1030]  train-rmse:7.04512      train-r2:0.654937
[1040]  train-rmse:7.04201      train-r2:0.655242
```

In [34]:

```
Answer = clf.predict(d_test)

submission = pd.read_csv('sample_submission.csv')
submission['y'] = Answer
submission.to_csv('sample_submission24.csv', index=False)
submission.head(5)
```

Out[34]:

	ID	y
0	1	85.353653
1	2	108.338951
2	3	80.733643
3	4	79.036476
4	5	114.450714

RESULT:

In 2rd approach we got (Private Score:0.55282) AND (Public Score:0.55709) On kaggle

---THIRD APPROACH---

THIRD APPROACH COMBINING FEATURE ENGINEERING OF 1st AND SECOND INCREASE SCORE R^2(Coef. of determination)

In [35]:

```
print(train_X.shape , test.shape)
```

```
(4194, 185) (4209, 185)
```

In [36]:

```
Y_train=train_y
```

In [37]:

```
X_train=train_X
X_test=test
```

In [ ]:

```
X_train=train_X
X_test=test
```

In [38]:

```
col = [k for k in X_train.columns if k not in {"y","X0","X1","X2","X3","X4","X5","X6","X8"}
```

In [40]:

```
    n_comp=3
    tsvd = TruncatedSVD(n_components=n_comp, random_state=420)
    tsvd_results_train = tsvd.fit_transform(X_train[col])
    tsvd_results_test = tsvd.transform(X_test[col])
    # PCA
    pca = PCA(n_components=n_comp, random_state=420)
    pca2_results_train = pca.fit_transform(X_train[col])
    pca2_results_test = pca.transform(X_test[col])
    # ICA
    ica = FastICA(n_components=n_comp, random_state=420)
    ica2_results_train = ica.fit_transform(X_train[col])
    ica2_results_test = ica.transform(X_test[col])
    # GRP
    grp = GaussianRandomProjection(n_components=n_comp, eps=0.1, random_state=420)
    grp_results_train = grp.fit_transform(X_train[col])
    grp_results_test = grp.transform(X_test[col])
    # SRP
    srp = SparseRandomProjection(n_components=n_comp, dense_output=True, random_state=420)
    srp_results_train = srp.fit_transform(X_train[col])
    srp_results_test = srp.transform(X_test[col])
    for i in range(1, n_comp + 1):
        X_train['tsvd_' + str(i)] = tsvd_results_train[:, i - 1]
        X_test['tsvd_' + str(i)] = tsvd_results_test[:, i - 1]
        X_train['pca_' + str(i)] = pca2_results_train[:, i - 1]
        X_test['pca_' + str(i)] = pca2_results_test[:, i - 1]
        X_train['ica_' + str(i)] = ica2_results_train[:, i - 1]
        X_test['ica_' + str(i)] = ica2_results_test[:, i - 1]
        X_train['grp_' + str(i)] = grp_results_train[:, i - 1]
        X_test['grp_' + str(i)] = grp_results_test[:, i - 1]
        X_train['srp_' + str(i)] = srp_results_train[:, i - 1]
        X_test['srp_' + str(i)] = srp_results_test[:, i - 1]
```

In [41]:

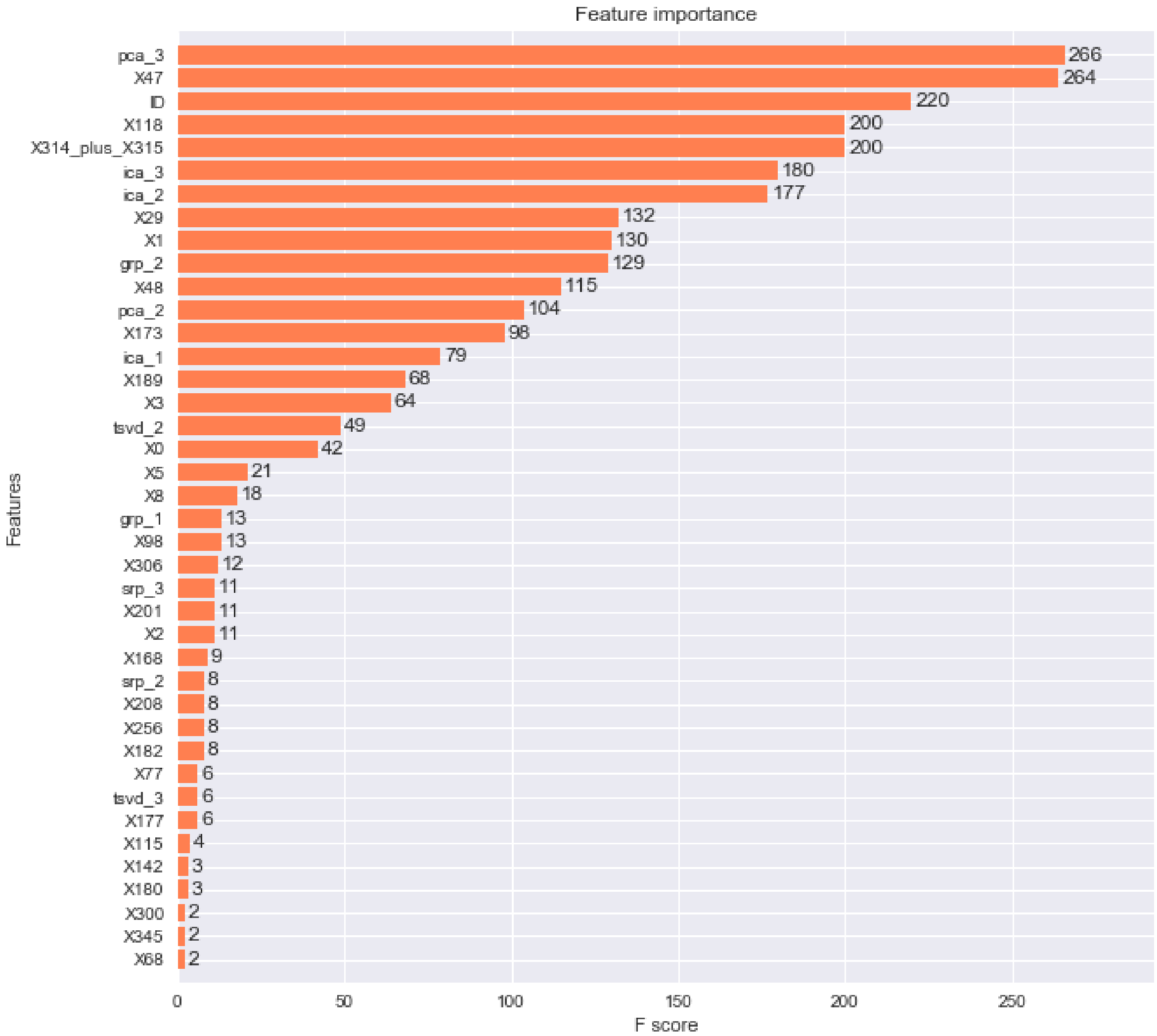
```
print(train_X.shape , test.shape)
```

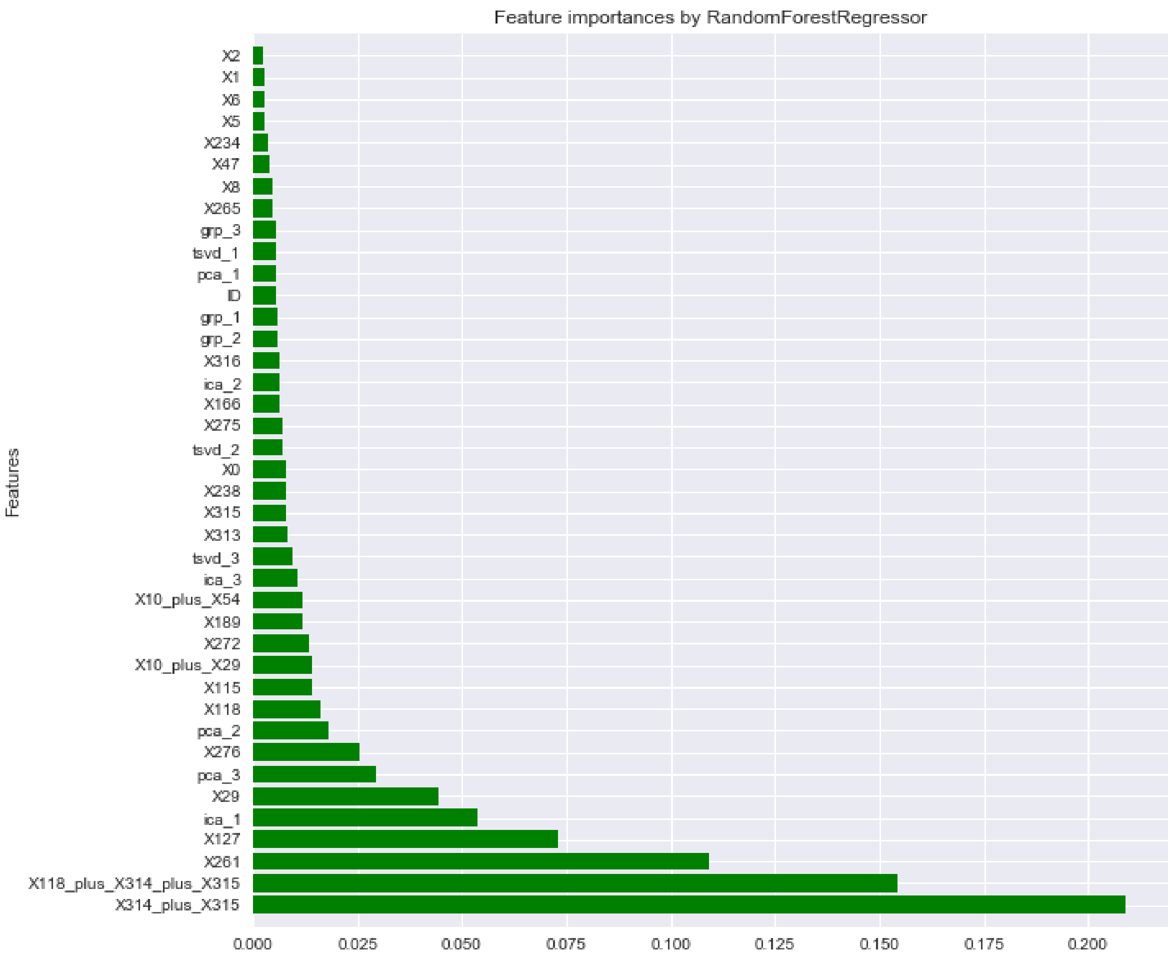
```
(4194, 200) (4209, 200)
```

In [42]:

```
import xgboost as xgb
train_y = Y_train
train_X = X_train

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

xgb_params = {
    'n_trees': 520,
    'eta': 0.0045,
    'max_depth': 4,
    'subsample': 0.98,
    'objective': 'reg:linear',
    'eval_metric': 'rmse',
    'base_score': np.mean(train_y), # base prediction = mean(target)
    'silent': 1
}

final = xgb.DMatrix(train_X, train_y, feature_names=train_X.columns.values)
model = xgb.train(dict(xgb_params), final, num_boost_round=200, feval=xgb_r2_score, maximiz

fig, ax = plt.subplots(figsize=(10,10))
xgb.plot_importance(model, max_num_features=40, height=0.8, ax=ax, color = 'coral')
print("Feature Importance by XGBoost")
plt.show()

from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(n_estimators=200, max_depth=10, min_samples_leaf=4, max_featu
model.fit(train_X, train_y)
feat_names = train_X.columns.values

importances = model.feature_importances_
std = np.std([tree.feature_importances_ for tree in model.estimators_], axis=0)
indices = np.argsort(importances)[::-1][:40]

plt.subplots(figsize=(10,10))
plt.title("Feature importances by RandomForestRegressor")
plt.ylabel("Features")
plt.barh(range(len(indices)), importances[indices], color="green", align="center")
plt.yticks(range(len(indices)), feat_names[indices], rotation='horizontal')
plt.ylim([-1, len(indices)])
plt.show()
```

```
Feature Importance by XGBoost
```


Feature importance
pca_3
X47
ID
X118
X314_plus_X315
ica_3
ica_2
X29
X1
grp_2
X48
pca_2
X173
ica_1
X189
X3
tsvd_2
X0
X5
X8
grp_1
X98
X306
srp_3
X201
X2
X168
srp_2
X208
X256
X182
X77
tsvd_3
X177
X115
X142
X180
X300
X345
X68
266
264
220
200
200
180
177
132
130
129
115
104
98
79
68
64
49
42
21
18
13
13
12
11
11
11
9
8
8
8
8
6
6
6
4
3
3
2
2
2
Features
0
50
100
150
200
250
F score


Feature importances by RandomForestRegressor
X2
X1
X6
X5
X234
X47
X8
X265
grp_3
tsvd_1
pca_1
ID
grp_1
grp_2
X316
ica_2
X166
X275
tsvd_2
X0
X238
X315
X313
tsvd_3
ica_3
X10_plus_X54
X189
X272
X10_plus_X29
X115
X118
pca_2
X276
pca_3
X29
ica_1
X127
X261
X118_plus_X314_plus_X315
X314_plus_X315
Features
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200

In [43]:

```
port xgboost as xgb
om sklearn.metrics import r2_score
om sklearn.model_selection import train_test_split

train, x_valid, y_train, y_valid = train_test_split(train_X, train_y, test_size=0.2, random_

train = xgb.DMatrix(x_train, label=y_train)
valid = xgb.DMatrix(x_valid, label=y_valid)
test = xgb.DMatrix(test)

_params = {
  'n_trees': 500,
  'eta': 0.0050,
  'max_depth': 3,
  'subsample': 0.95,
  'objective': 'reg:linear',
  'eval_metric': 'rmse',
  'base_score': np.mean(train_y), # base prediction = mean(target)
  'silent': 1


f xgb_r2_score(preds, dtrain):
  labels = dtrain.get_label()
  return 'r2', r2_score(labels, preds)

tchlist = [(d_train, 'train'), (d_valid, 'valid')]

f = xgb.train(xgb_params, d_train, 1050 , watchlist, early_stopping_rounds=70, feval=xgb_r2_
```

```
[0]	train-rmse:11.9877	valid-rmse:11.8273	train-r2:0.006234
valid-r2:0.005918
Multiple eval metrics have been passed: 'valid-r2' will be used for early
stopping.

Will train until valid-r2 hasn't improved in 70 rounds.
[10]	train-rmse:11.6245	valid-rmse:11.4687	train-r2:0.065538
valid-r2:0.065295
[20]	train-rmse:11.2861	valid-rmse:11.1354	train-r2:0.11915
valid-r2:0.118826
[30]	train-rmse:10.9706	valid-rmse:10.825	train-r2:0.167707
valid-r2:0.167268
[40]	train-rmse:10.6767	valid-rmse:10.536	train-r2:0.21171
valid-r2:0.211147
[50]	train-rmse:10.4032	valid-rmse:10.2678	train-r2:0.251576
valid-r2:0.250795
[60]	train-rmse:10.1502	valid-rmse:10.0204	train-r2:0.287529
valid-r2:0.286456
[70]	train-rmse:9.91438	valid-rmse:9.79002	train-r2:0.320256
```

In [44]:

```
train = xgb.DMatrix(train_X, label=train_y)
_valid = xgb.DMatrix(x_valid, label=y_valid)
test = xgb.DMatrix(test)

p_params = {
  'n_trees': 500,
  'eta': 0.0050,
  'max_depth': 3,
  'subsample': 0.95,
  'objective': 'reg:linear',
  'eval_metric': 'rmse',
  'base_score': np.mean(train_y),
  'silent': 1


f xgb_r2_score(preds, dtrain):
  labels = dtrain.get_label()
  return 'r2', r2_score(labels, preds)

tchlist = [(d_train, 'train')]

f = xgb.train(xgb_params, d_train, 1050 , watchlist, early_stopping_rounds=70, feval=xgb_r2_
```

```
[250]   train-rmse:7.75763      train-r2:0.581612
[260]   train-rmse:7.71028      train-r2:0.586703
[270]   train-rmse:7.66685      train-r2:0.591347
[280]   train-rmse:7.62727      train-r2:0.595555
[290]   train-rmse:7.591        train-r2:0.599392
[300]   train-rmse:7.55749      train-r2:0.602922
[310]   train-rmse:7.52679      train-r2:0.606141
[320]   train-rmse:7.49886      train-r2:0.609059
[330]   train-rmse:7.47331      train-r2:0.611718
[340]   train-rmse:7.44972      train-r2:0.614165
[350]   train-rmse:7.42829      train-r2:0.616382
[360]   train-rmse:7.4085       train-r2:0.618424
[370]   train-rmse:7.39036      train-r2:0.62029
[380]   train-rmse:7.37373      train-r2:0.621997
[390]   train-rmse:7.35819      train-r2:0.623589
[400]   train-rmse:7.34355      train-r2:0.625085
[410]   train-rmse:7.33008      train-r2:0.626459
[420]   train-rmse:7.31715      train-r2:0.627776
[430]   train-rmse:7.30503      train-r2:0.629008
```

In [45]:

```
Answer = clf.predict(d_test)
submission = pd.read_csv('sample_submission.csv')
submission['y'] = Answer
submission.to_csv('sample_submission26.csv', index=False)
submission.head(5)
```

Out[45]:

	ID	y
0	1	84.695724
1	2	104.191376
2	3	81.343300
3	4	80.838570
4	5	116.667526

In 3rd approach we got (Private Score:0.55077) AND (Public Score:0.55744) On kaggle

STEPS FOLLOWED:

1----->> Exploratory Data Analysis:

```
        A: Data Loading and Cleaning.

        B: Explore the categorical  and binary variable columns present in the datas
    et.
```

2----->> Data Preperation:

```
        A: Find the outlier values and drop them.

        B: Drop the columns having ony single value.

        C: Convert each catagorical value into labels.

        D: Random train test split (80:20) ratio.

        E: We did SVD,PCA,GRP,SRP,ICA and take 3 components from each as a feature.

        F: We also did interactive variable feature engineering.
```

2----->> Machine Learning Models.

```
        A: Lasso Regression with hyperparameter tuning:

        B: Decision Tree Regression with hyperparameter tuning

        C: XGB Regression with hyperparameter tuning:
```

OBSERVATIONS:

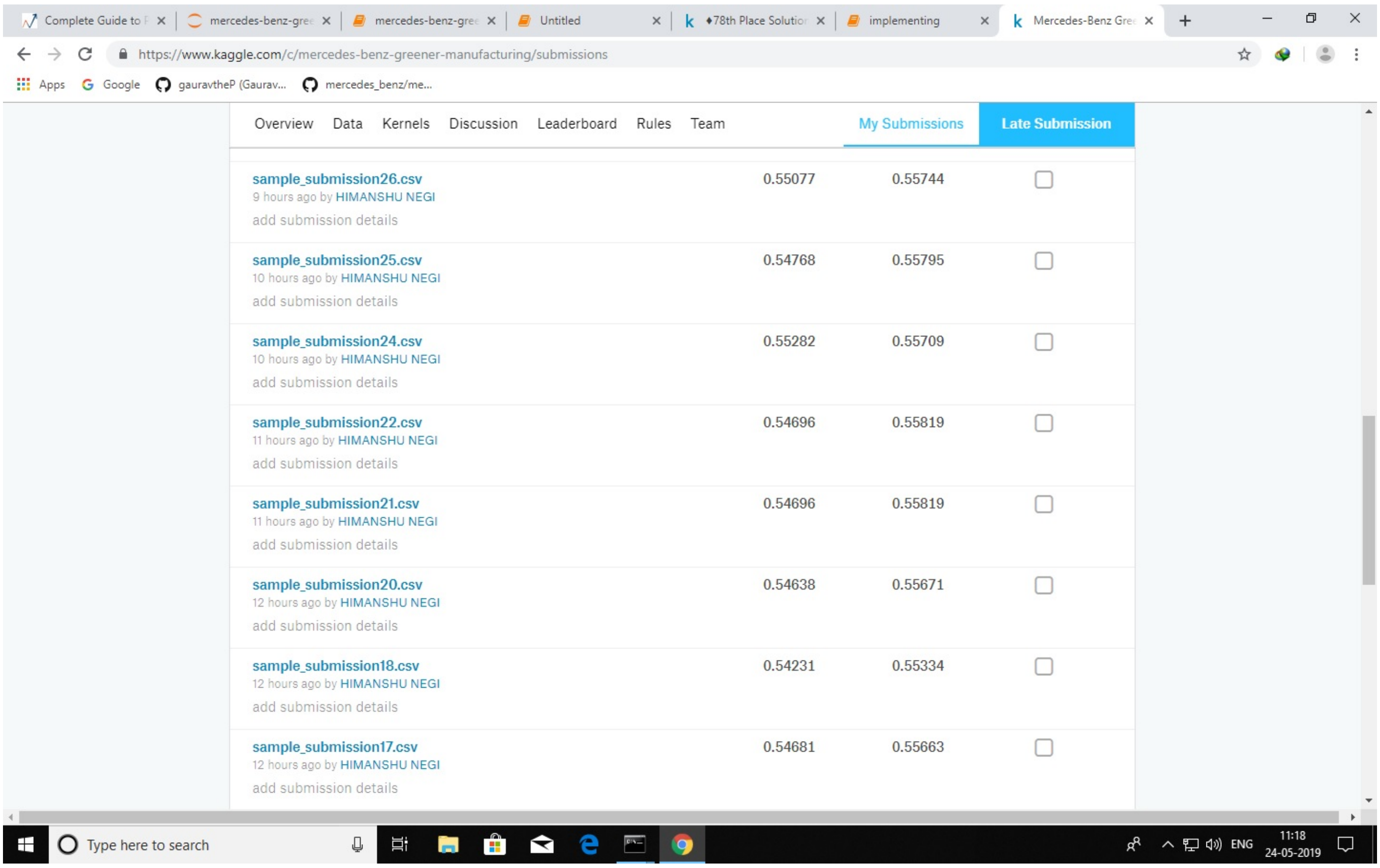
```
        A: As we apply above 3 regression models we come to know that if we use mo
del in productionization Lasso Regression
           IS best among above as of time complexity and R^2 MATRIX.

        B: If we only care about R^2 matrix then XGB is best.

        C: If we take model which have balance between XGB nad LASSO REGRESSION th
en we can go for decision tree.

        D: We observe that with simple feature engineering like with interaction v
ariable we are getting best score.
```

NOTE: 1 WE CAN IMPROVE OUR MODEL BY DO SOME MORE FEATURE ENGINEERING AND ALSO WITH OTHER REGRESSION #### MODELS AND OTHER ADVANCE TECHNIQUE.

2 HERE OUR GOAL IS TO TAKE SOME HANDS ON REAL MACHINE LEARNING INDUSTRY PROBLEMS AND NOT TO #### MAKE BEST MODEL .

3 We tried different approaches like feature engineering to improve our performance metric.

.



KAGGLE SCORE RESULT:

In [53]:

```
# Creating table using PrettyTable library
from prettytable import PrettyTable

ptable = PrettyTable()
# Names of models
names =['1st_approach','2nd_approach','3rd_approach']

#alpha=[0.001, 0.001]

Private_Score = [0.54570,0.55282,0.55077]

Public_Score = [0.55275,0.55709,0.55744]

Feature_engineering =['SVD,PCA,GRP,SRP,ICA','Interaction_variable','Combine_of_1st_2nd_appr

# Adding columns

ptable.add_column("APPROACH_NO",names)

#ptable.add_column("Hyperparameter",alpha)
ptable.add_column("Private_Score",Private_Score)
ptable.add_column("Public_Score ",Public_Score)
ptable.add_column("Feature_engineering ",Feature_engineering)

print(ptable)
```

```
+--------------+--------------+--------------+---------------------------
-+
| APPROACH_NO  | Private_Score | Public_Score  |     Feature_engineering     
|
+--------------+--------------+--------------+---------------------------
-+
| 1st_approach |    0.5457    |    0.55275    |     SVD,PCA,GRP,SRP,ICA     
|
| 2nd_approach |   0.55282    |    0.55709    |     Interaction_variable    
|
| 3rd_approach |   0.55077    |    0.55744    | Combine_of_1st_2nd_approach 
|
+--------------+--------------+--------------+---------------------------
-+
```

Link to see score:

https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/submissions?sortBy=date&group=all&page=1&pageSize=20&turbolinks%5BrestorationIdentifier%5D=92824c66-5757-4047-ba2b-d2e3200e4b69 (https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/submissions?sortBy=date&group=all&page=1&pageSize=20&turbolinks%5BrestorationIdentifier%5D=92824c66-5757-4047-ba2b-d2e3200e4b69)

In [ ]: