Mercedes-Benz Greener Manufacturing Case Study

Data Source: [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)

Problem Statment: Can you cut the time a Mercedes-Benz spends on the test bench?

1. 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.
2. 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.
3. In this competition, Daimler is challenging to reduce the time that cars spend on the test bench.

Data Description:

1. 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.
2. The ground truth is labeled ‘y’ and represents the time (in seconds) that the car took to pass testing for each variable.
3. File descriptions: Variables with letters are categorical. Variables with 0/1 are binary values.
4. train.csv - the training set
5. test.csv - the test set, you must predict the 'y' variable for the 'ID's in this file
6. sample_submission.csv - a sample submission file in the correct format

Data Analysis

In [1]:

```
# Importing all necessary modules.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
import xgboost as xgb
from sklearn.base import BaseEstimator,TransformerMixin,ClassifierMixin
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA, FastICA
from sklearn.decomposition import TruncatedSVD
from sklearn.random_projection import GaussianRandomProjection
from sklearn.random_projection import SparseRandomProjection
from sklearn.linear_model import ElasticNetCV, LassoLarsCV
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.pipeline import make_pipeline, make_union
from sklearn.utils import check_array
from sklearn.metrics import r2_score
# keras
from keras.models import Sequential, load_model
from keras.layers import Dense, Dropout, BatchNormalization, Activation
from keras.wrappers.scikit_learn import KerasRegressor
from keras.callbacks import EarlyStopping, ModelCheckpoint

# model evaluation
from sklearn.model_selection import cross_val_score, KFold, train_test_split
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.feature_selection import SelectFromModel

# To make Results reproducible
seed = 40

import warnings
warnings.filterwarnings('ignore')
color = sns.color_palette()
%matplotlib inline
```

```
Using TensorFlow backend.
```

In [2]:

```
train_df = pd.read_csv("train.csv")
test_df = pd.read_csv("test.csv")
print("Train shape : ", train_df.shape)
print("Test shape : ", test_df.shape)
```

```
Train shape :  (4209, 378)
Test shape :  (4209, 377)
```

In [3]:

```
train_df.head()
```

Out[3]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	0	130.81	k	v	at	a	d	u	j	o	...	0	0	1	0	0	0	0	0	0	0
1	6	88.53	k	t	av	e	d	y	l	o	...	1	0	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	1	0	0	0
3	9	80.62	az	t	n	f	d	x	l	e	...	0	0	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	0	0

5 rows × 378 columns

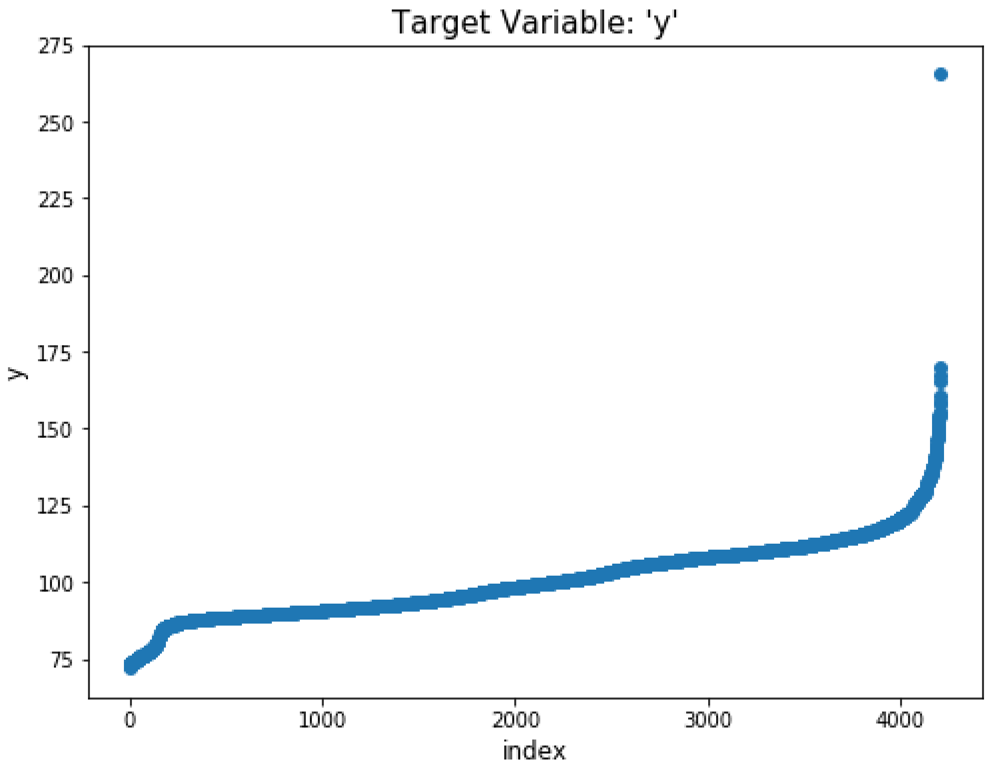
Features of Data:

1. **ID** : ID column of data.
2. **y** : Target Variable.
3. **X0-X385** : Data columns.

Target Variable(y):

"y" is the variable we need to predict. So let us do perform analysis on this variable.

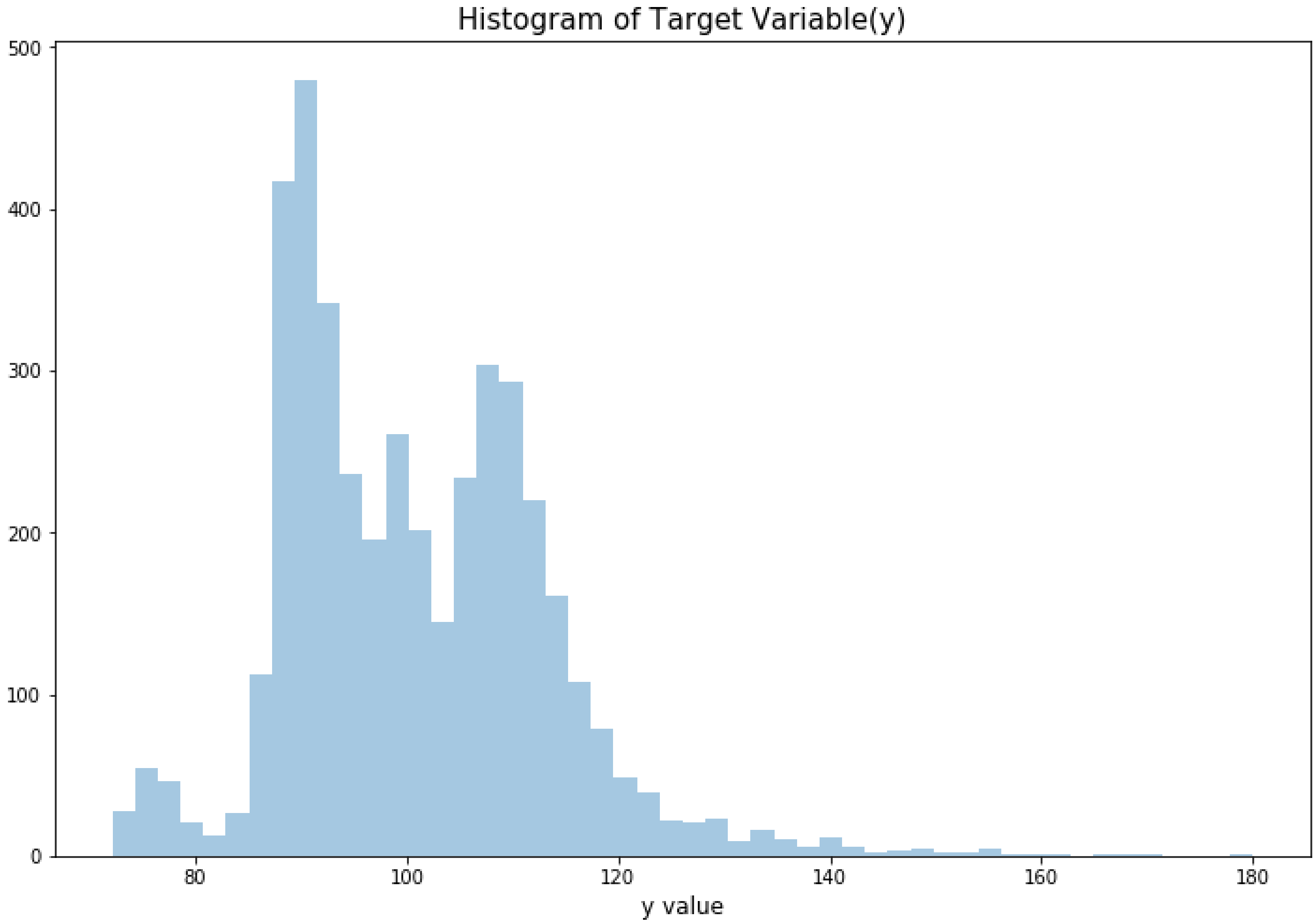
In [4]:
```
plt.figure(figsize=(8,6))
plt.scatter(range(train_df.shape[0]), np.sort(train_df.y.values))
plt.xlabel('index', fontsize=12)
plt.ylabel('y', fontsize=12)
plt.title("Target Variable: 'y'",fontsize=15)
plt.show()
```



Value of "y" is fairly spread across the range between 70-200

In [5]:
```
ulimit = 180
train_df['y'].ix[train_df['y']>ulimit] = ulimit

plt.figure(figsize=(12,8))
sns.distplot(train_df.y.values, bins=50, kde=False)
plt.xlabel('y value', fontsize=12)
plt.title("Histogram of Target Variable(y)",fontsize=15)
plt.show()
```



In [6]:

```
print('min: {} max: {} mean: {} std: {}'.format(min(train_df['y'].values), max(train_df['y'].values), train_df[
print('Count of values above 180: {}'.format(np.sum(train_df['y'].values > 180)))
```

```
min: 72.11 max: 180.0 mean: 100.64904727963888 std: 12.481281731120474
Count of values above 180: 0
```

Observations of Target Variable y:

1. **We can observe that most of the values lies between 90-120. So avg production time is 90-120.**
2. So we have a pretty **standard distribution** here, which is centred around almost exactly 100.
3. The fact that ID is not equal to the row ID seems to suggest that the **train and test sets are randomly sampled**.

Variables/Feature Analysis.

In [7]:

```
dtype_df = train_df.dtypes.reset_index()
dtype_df.columns = ["Count", "Column Type"]
dtype_df.groupby("Column Type").aggregate('count').reset_index()
```

Out[7]:

	Column Type	Count
0	int64	369
1	float64	1
2	object	8

So majority of the columns are integers with 8 categorical features and 1 float feature (target variable)

In [8]:

```
dtype_df.ix[:10,:]
```

Out[8]:

	Count	Column Type
0	ID	int64
1	y	float64
2	X0	object
3	X1	object
4	X2	object
5	X3	object
6	X4	object
7	X5	object
8	X6	object
9	X8	object
10	X10	int64

X0 to X8 are the categorical columns.

Check for the missing values.

In [9]:

```
missing_df = train_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[9]:

column_name	missing_count

We don't have any missing values.

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

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

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

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

In [11]:
```
counts = [[], [], []]
for c in cols:
    typ = train_df[c].dtype
    uniq = len(np.unique(train_df[c]))
    if uniq == 1: counts[0].append(c)
    elif uniq == 2 and typ == np.int64: counts[1].append(c)
    else: counts[2].append(c)

print('Constant features: {} Binary features: {} Categorical features: {}\n'.format(*[len(c) for c in counts]))

print('Constant features:', counts[0])
print('Categorical features:', counts[2])
```

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

Constant features: ['X11', 'X93', 'X107', 'X233', 'X235', 'X268', 'X289', 'X290', 'X293', 'X297', 'X330', 'X34
7']
Categorical features: ['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8']
```

In [12]:

```python
unique_values_dict = {}
for col in train_df.columns:
    if col not in ["ID", "y", "X0", "X1", "X2", "X3", "X4", "X5", "X6", "X8"]:
        unique_value = str(np.sort(train_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', 'X21', 'X22', 'X23', 'X24', 'X26', 'X
27', 'X28', 'X29', 'X30', 'X31', 'X32', 'X33', 'X34', 'X35', 'X36', 'X37', 'X38', 'X39', 'X40', 'X41', 'X4
2', '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', 'X7
4', 'X75', 'X76', 'X77', 'X78', 'X79', 'X80', 'X81', 'X82', 'X83', 'X84', 'X85', 'X86', 'X87', 'X88', 'X89',
'X90', 'X91', 'X92', 'X94', 'X95', 'X96', 'X97', 'X98', 'X99', 'X100', 'X101', 'X102', 'X103', 'X104', 'X10
5', 'X106', 'X108', 'X109', 'X110', 'X111', 'X112', 'X113', 'X114', 'X115', 'X116', 'X117', 'X118', 'X119',
'X120', 'X122', 'X123', 'X124', 'X125', 'X126', 'X127', 'X128', 'X129', 'X130', 'X131', 'X132', 'X133', 'X13
4', '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', 'X16
2', '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', 'X19
0', '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', 'X21
8', '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', 'X24
7', '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', 'X27
5', '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', 'X30
7', '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', 'X33
5', 'X336', 'X337', 'X338', 'X339', 'X340', 'X341', 'X342', 'X343', 'X344', 'X345', 'X346', 'X348', 'X349',
'X350', 'X351', 'X352', 'X353', 'X354', 'X355', 'X356', 'X357', 'X358', 'X359', 'X360', 'X361', 'X362', 'X36
3', 'X364', 'X365', 'X366', 'X367', 'X368', 'X369', 'X370', 'X371', 'X372', 'X373', 'X374', 'X375', 'X376',
'X377', 'X378', 'X379', 'X380', 'X382', 'X383', 'X384', 'X385']
--------------------------------------------------
Columns containing the unique values :  [0]
```

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

Categorical features.

In [13]:

```
# Let's print some categorical feature rows.
cat_feat = counts[2]
train_df[cat_feat].head()
```

Out[13]:

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

Features:

1. Constant features: 12
2. Binary features: 356
3. Categorical features: 8

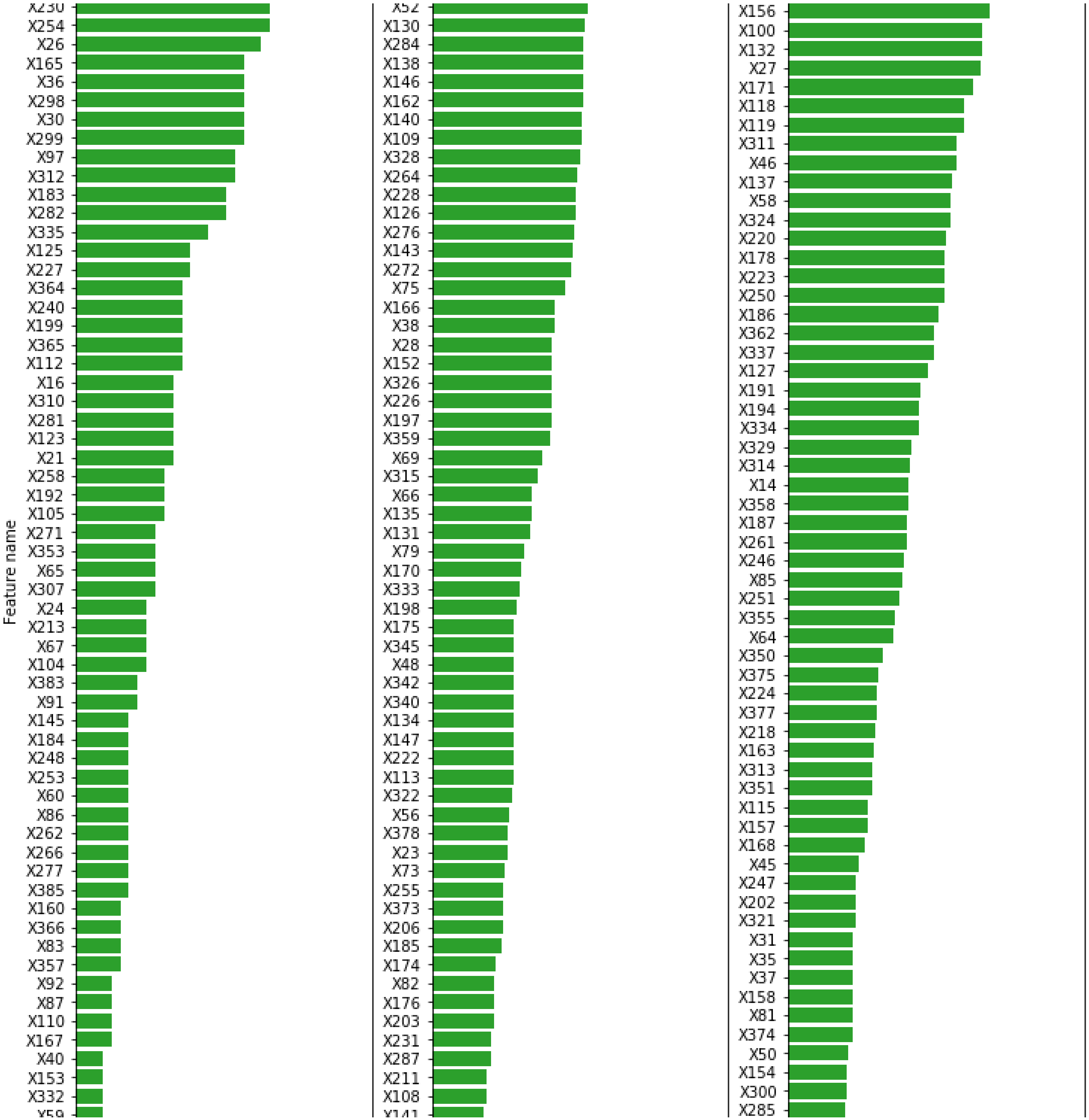
We have 12 features which only have a single value in them - these are pretty useless for supervised algorithms, and should probably be dropped.

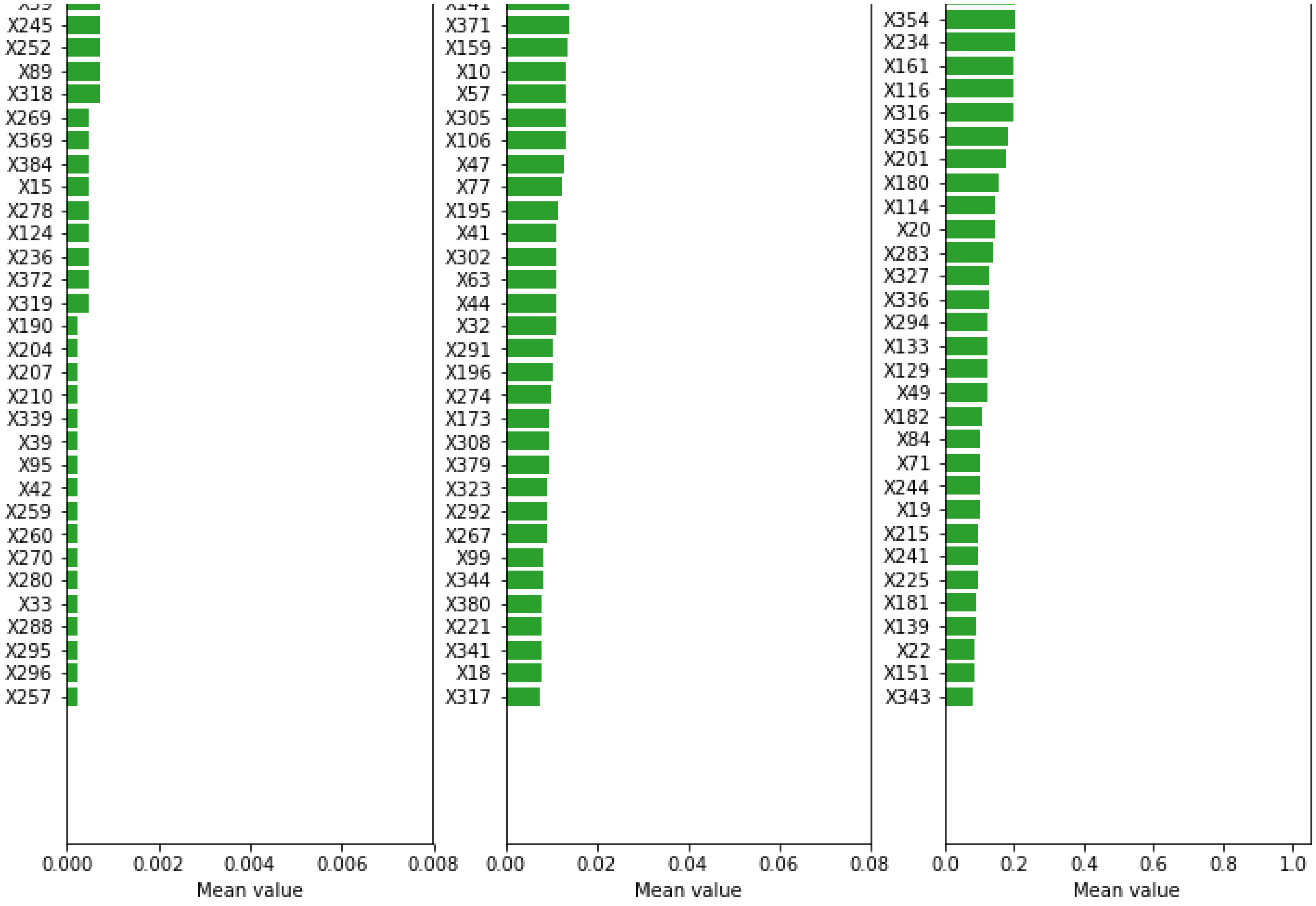
In [14]:

```python
binary_means = [np.mean(train_df[c]) for c in counts[1]]
binary_names = np.array(counts[1])[np.argsort(binary_means)]
binary_means = np.sort(binary_means)

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

Mean values of binary variables


Feature name
X230
X254
X26
X165
X36
X298
X30
X299
X97
X312
X183
X282
X335
X125
X227
X364
X240
X199
X365
X112
X16
X310
X281
X123
X21
X258
X192
X105
X271
X353
X65
X307
X24
X213
X67
X104
X383
X91
X145
X184
X248
X253
X60
X86
X262
X266
X277
X385
X160
X366
X83
X357
X92
X87
X110
X167
X40
X153
X332
X59
X52
X130
X284
X138
X146
X162
X140
X109
X328
X264
X228
X126
X276
X143
X272
X75
X166
X38
X28
X152
X326
X226
X197
X359
X69
X315
X66
X135
X131
X79
X170
X333
X198
X175
X345
X48
X342
X340
X134
X147
X222
X113
X322
X56
X378
X23
X73
X255
X373
X206
X185
X174
X82
X176
X203
X231
X287
X211
X108
X141
X156
X100
X132
X27
X171
X118
X119
X311
X46
X137
X58
X324
X220
X178
X223
X250
X186
X362
X337
X127
X191
X194
X334
X329
X314
X14
X358
X187
X261
X246
X85
X251
X355
X64
X350
X375
X224
X377
X218
X163
X313
X351
X115
X157
X168
X45
X247
X202
X321
X31
X35
X37
X158
X81
X374
X50
X154
X300
X285



From above plot we can understand the general mean values of all Binary features.

Machine Learning Algorithms.

We can solve Regression problem to optimize the Production Time Feature (i.e. Target Variable = y).

Baseline Model 1: xgboost model

To analyse Important Variables

In [15]:

```
# Data Preprocessing.

# LabelEncoder: Used to Encode labels with value between 0 and n_classes-1.

for f in ["X0", "X1", "X2", "X3", "X4", "X5", "X6", "X8"]:
        lbl = preprocessing.LabelEncoder()
        lbl.fit(list(train_df[f].values)) # Fit label encoder
        train_df[f] = lbl.transform(list(train_df[f].values)) # Transform labels to normalized encoding.

# Dropping ID feature & creating saperate Input/Output training data.
train_y = train_df['y'].values
train_X = train_df.drop(["ID", "y"], axis=1)

# Reference : https://xgboost.readthedocs.io/en/latest/python/python_intro.html
def xgb_r2_score(preds, dtrain):
    labels = dtrain.get_label()
    return 'r2', r2_score(labels, preds)

xgb_params = {
    'eta': 0.05,
    'max_depth': 6,
    'subsample': 0.7,
    'colsample_bytree': 0.7,
    'objective': 'reg:linear',
    'silent': 1
}
dtrain = xgb.DMatrix(train_X, train_y, feature_names=train_X.columns.values)
model = xgb.train(dict(xgb_params, silent=0), dtrain, num_boost_round=100, feval=xgb_r2_score, maximize=True)
```

```
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=4
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 6 extra nodes, 0 pruned node
s, max_depth=2
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
```

```
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 6 extra nodes, 0 pruned node
s, max_depth=2
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 10 extra nodes, 0 pruned node
s, max_depth=4
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 10 extra nodes, 0 pruned node
s, max_depth=4
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 8 extra nodes, 0 pruned node
s, max_depth=4
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 10 extra nodes, 0 pruned node
s, max_depth=4
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 10 extra nodes, 0 pruned node
s, max_depth=4
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 18 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 10 extra nodes, 0 pruned node
s, max_depth=3
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 12 extra nodes, 0 pruned node
s, max_depth=4
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 20 extra nodes, 0 pruned node
s, max_depth=6
```

```
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 20 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 16 extra nodes, 0 pruned node
s, max_depth=4
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 18 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 34 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 30 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 42 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 48 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 48 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 40 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 62 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 60 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 60 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 54 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 70 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 64 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 58 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 62 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 72 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 94 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 76 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 54 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 106 extra nodes, 0 pruned nod
```

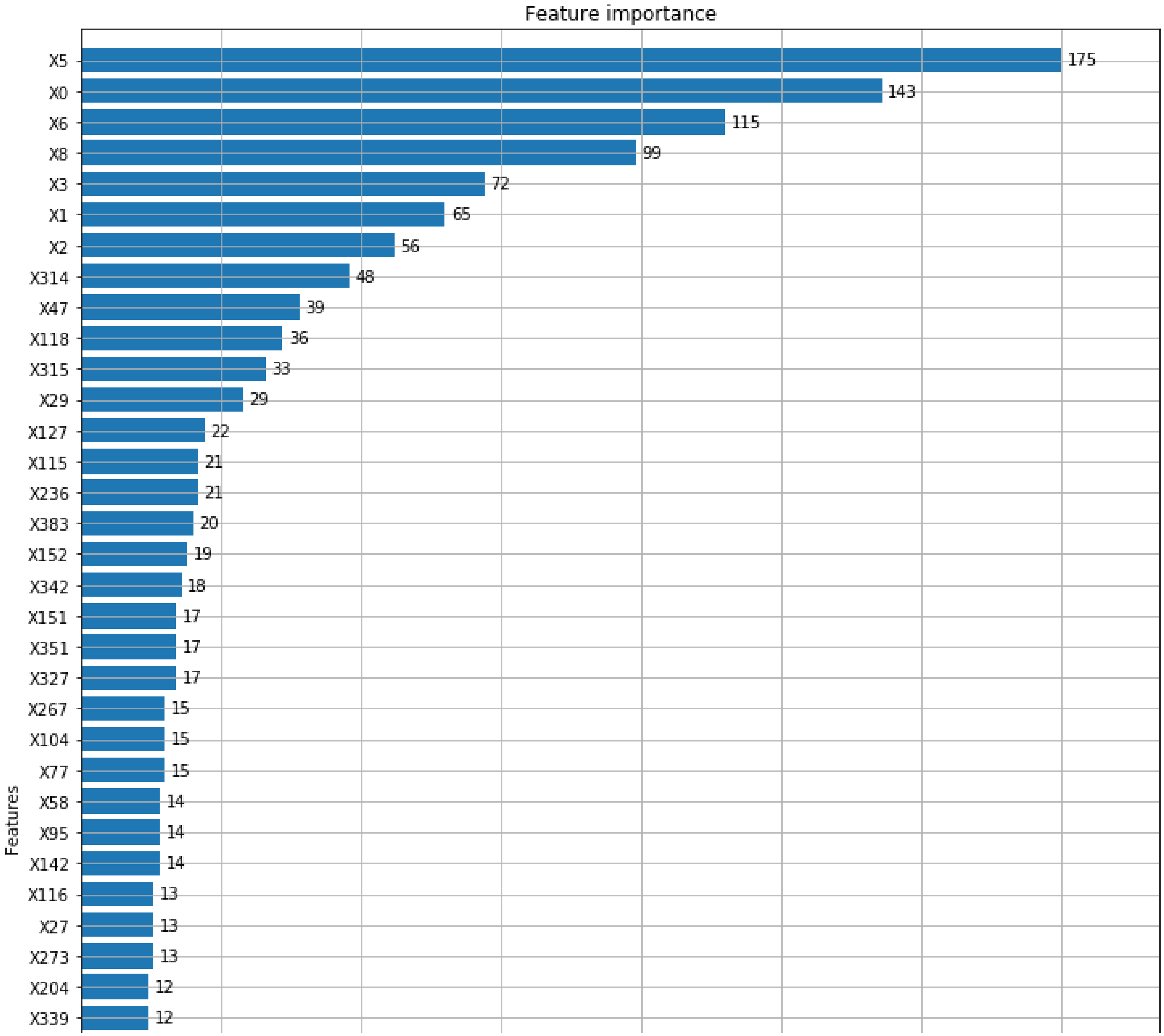
```
es, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 78 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 54 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 42 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 64 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 64 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 102 extra nodes, 0 pruned nod
es, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 66 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 58 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 58 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 50 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 66 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 50 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 46 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 70 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 56 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 70 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 62 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 66 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 44 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 48 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 32 extra nodes, 0 pruned node
s, max_depth=6
```

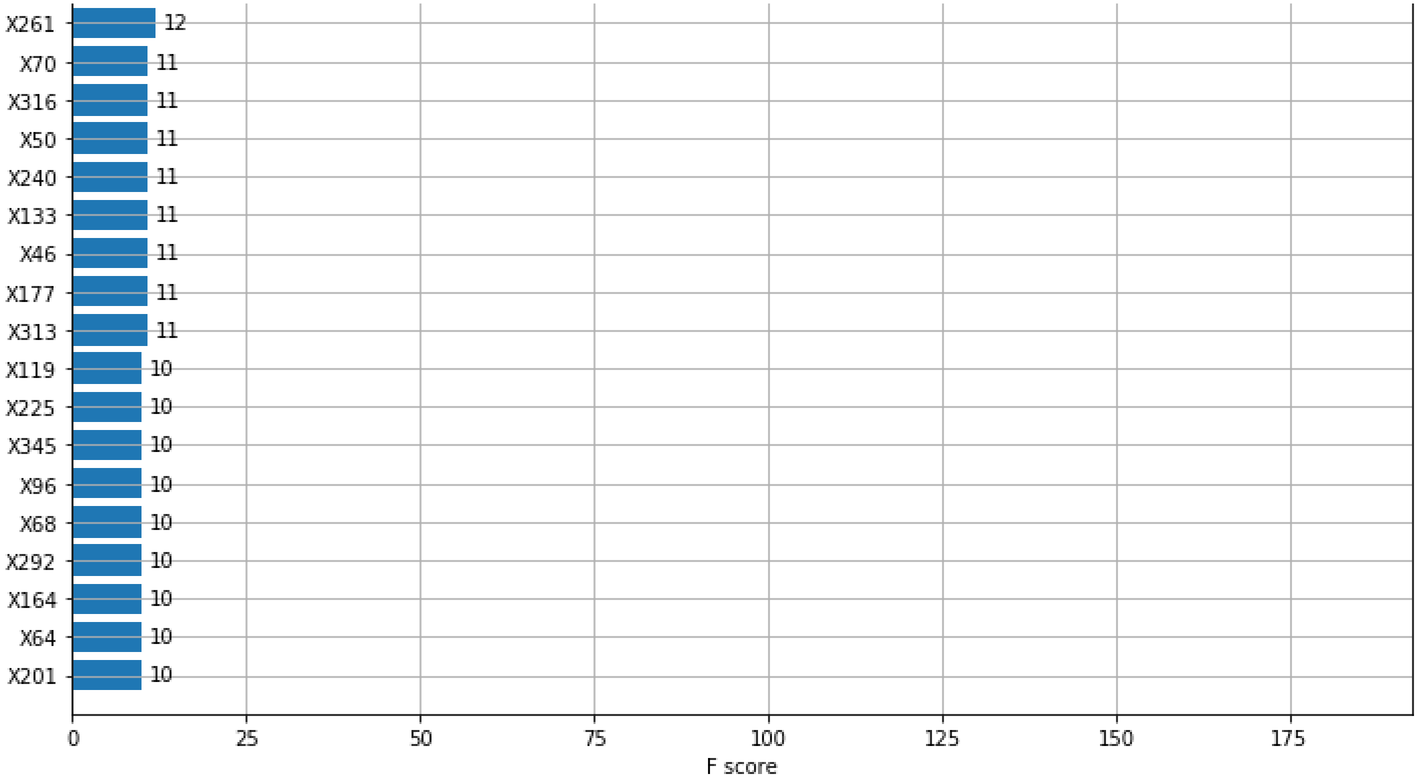
```
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 38 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 36 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 78 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 30 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 28 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 44 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 46 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 66 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 32 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 44 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 48 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 64 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 34 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 60 extra nodes, 0 pruned node
s, max_depth=6
```

```
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 88 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 20 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 46 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 36 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 24 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 46 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 72 extra nodes, 0 pruned node
s, max_depth=6
```

```
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 44 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 42 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 86 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 62 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 82 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 90 extra nodes, 0 pruned node
s, max_depth=6
[10:41:50] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 30 extra nodes, 0 pruned node
s, max_depth=6
[10:41:51] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 50 extra nodes, 0 pruned node
s, max depth=6
```

```
In [16]: # plot the important features #
         fig, ax = plt.subplots(figsize=(12,18))
         xgb.plot_importance(model, max_num_features=50, height=0.8, ax=ax)
         plt.show()
```





Observations:

1. **Categorical features X5,X0,X8,X6,X1,X2,X3 are highly important in prediction of XGBoost model.** *
2. **Binary features are less important comparitively.**
3. **We have dropped ID feature as it is not important.**

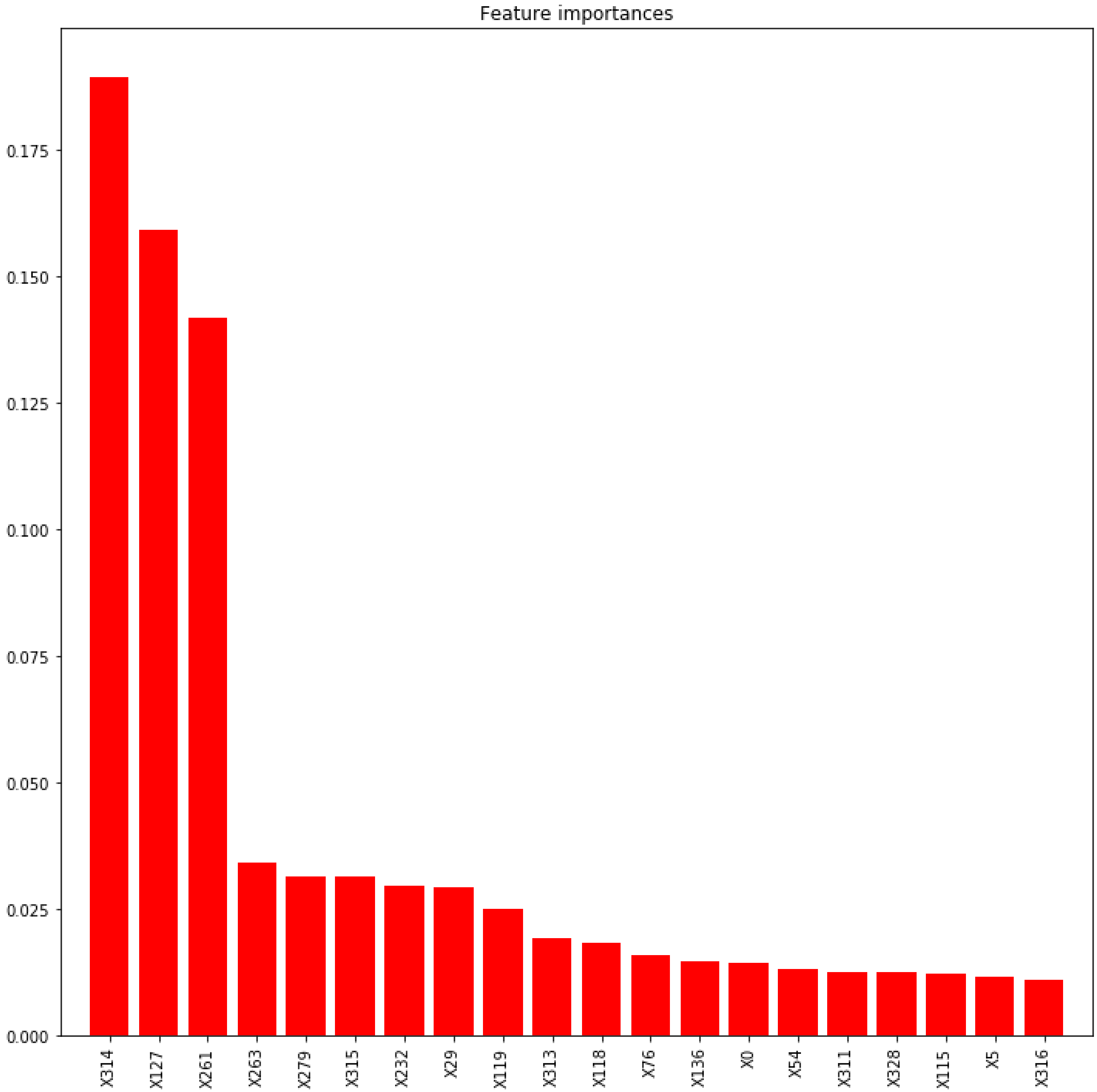
Baseline Model 2: Random Forest model

In [17]:

```
from sklearn import ensemble
model = ensemble.RandomForestRegressor(n_estimators=200, max_depth=10, min_samples_leaf=4, max_features=0.2, n_
model.fit(train_X, train_y)
feat_names = train_X.columns.values

## plot the importances ##
importances = model.feature_importances_
std = np.std([tree.feature_importances_ for tree in model.estimators_], axis=0)
indices = np.argsort(importances)[::-1][:20]

plt.figure(figsize=(12,12))
plt.title("Feature importances")
plt.bar(range(len(indices)), importances[indices], color="r", align="center")
plt.xticks(range(len(indices)), feat_names[indices], rotation='vertical')
plt.xlim([-1, len(indices)])
plt.show()
```


Feature importances
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
X314
X127
X261
X263
X279
X315
X232
X29
X119
X313
X118
X76
X136
X0
X54
X311
X328
X115
X5
X316

Observations:

1. **Binary features X314,X127,X261 are highly important in the prediction of Random forest model.*
2. **Categorical features are less important comparitively.**
3. **We have dropped ID feature as it is not important.**

XGboost Regression model.

Creating the components using various dimensionality reduction techniques.

In [19]:
```
# Reference : https://www.analyticsvidhya.com/blog/2018/08/dimensionality-reduction-techniques-python/

from sklearn.decomposition import PCA, FastICA, TruncatedSVD
# Dimensionality reduction techniques
n_comp = 15

# tSVD
tsvd = TruncatedSVD(n_components=n_comp, random_state=420)
tsvd_results_train = tsvd.fit_transform(train_X)
tsvd_results_test = tsvd.transform(test)
# PCA
pca = PCA(n_components=n_comp, random_state=42)
pca2_results_train = pca.fit_transform(train_X)
pca2_results_test = pca.transform(test)

# ICA
ica = FastICA(n_components=n_comp, random_state=42)
ica2_results_train = ica.fit_transform(train_X)
ica2_results_test = ica.transform(test)

# Append decomposition components to datasets
for i in range(1, n_comp+1):
    train['tsvd_' + str(i)] = tsvd_results_train[:,i-1]
    test['tsvd_' + str(i)] = tsvd_results_test[:, i-1]

    train['pca_' + str(i)] = pca2_results_train[:,i-1]
    test['pca_' + str(i)] = pca2_results_test[:, i-1]

    train['ica_' + str(i)] = ica2_results_train[:,i-1]
    test['ica_' + str(i)] = ica2_results_test[:, i-1]

y_mean = np.mean(y_train)
```

In [20]:
```
# Reference : https://www.analyticsvidhya.com/blog/2016/03/complete-guide-parameter-tuning-xgboost-with-codes-py

import xgboost as xgb

# Prepare dict of params for xgboost model.
xgb_params = {
    'n_trees': 500,
    'eta': 0.005,
    'max_depth':6,
    'subsample': 0.5,
    'objective': 'reg:linear',
    'eval_metric': 'rmse',
    'base_score': y_mean, # base prediction = mean(target)
    'silent': 1}


# Creating DMatrices for Xgboost training
dtrain = xgb.DMatrix(train, y_train)
dtest = xgb.DMatrix(test)

# xgboost, cross-validation
cv_result = xgb.cv(xgb_params,dtrain,num_boost_round=700,verbose_eval=50,show_stdv=False)

num_boost_rounds = len(cv_result)
print(num_boost_rounds)

# Train model
model = xgb.train(dict(xgb_params, silent=0), dtrain, num_boost_round=num_boost_rounds)
```

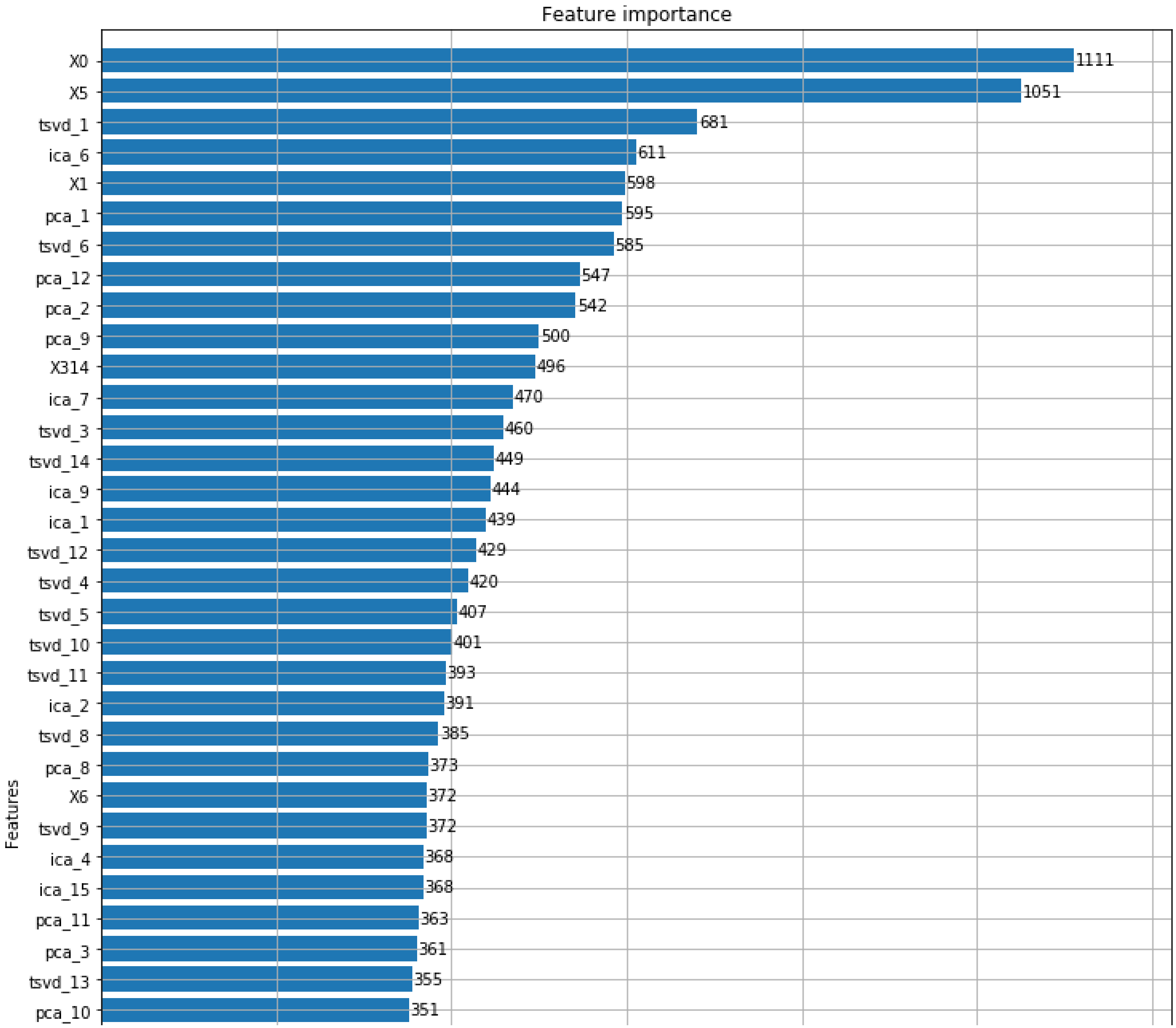
```
[0]     train-rmse:12.3841      test-rmse:12.385
[50]    train-rmse:10.7518      test-rmse:10.8754
[100]   train-rmse:9.57748      test-rmse:9.84481
[150]   train-rmse:8.73635      test-rmse:9.16087
[200]   train-rmse:8.13691      test-rmse:8.72088
[250]   train-rmse:7.70472      test-rmse:8.44323
[300]   train-rmse:7.3866       test-rmse:8.27705
[350]   train-rmse:7.14044      test-rmse:8.18174
[400]   train-rmse:6.93932      test-rmse:8.12804
[450]   train-rmse:6.77325      test-rmse:8.09886
[500]   train-rmse:6.63014      test-rmse:8.084
[550]   train-rmse:6.51027      test-rmse:8.07597
[600]   train-rmse:6.40507      test-rmse:8.07439
```

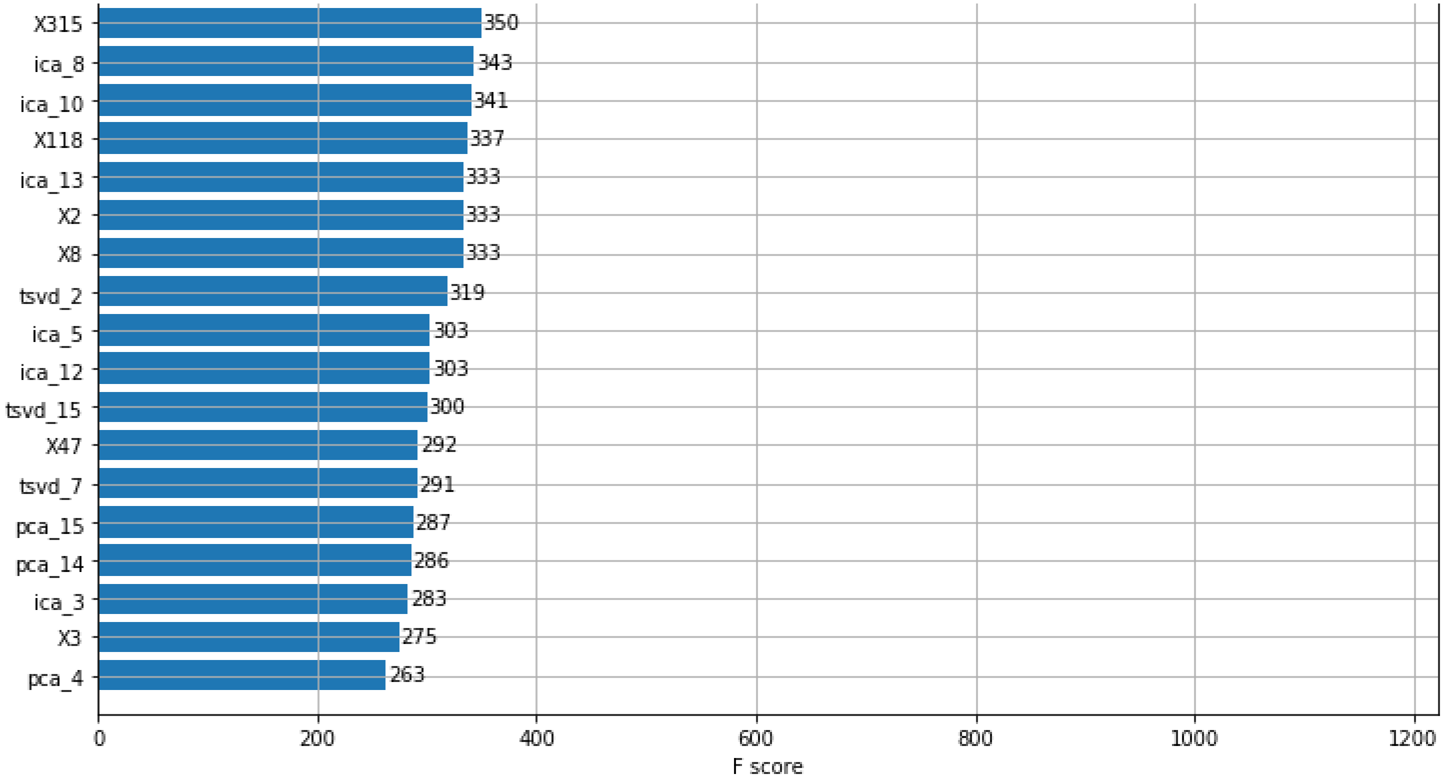
```
[650]	train-rmse:6.30951	test-rmse:8.07828
[699]	train-rmse:6.22381	test-rmse:8.08397
700
[04:52:04] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 64 extra nodes, 0 pruned node
s, max_depth=6
[04:52:04] /workspace/src/tree/updater_prune.cc:74: tree pruning end, 1 roots, 68 extra nodes, 0 pruned node
```

Observations:

1. **After 700 num_boost_round: 1. train-rmse:6.22381 2. test-rmse:8.08397**
2. We have pretty decent values of Train & Test error parameter(RMSE).
3. Model is performing nicely & not overfitting.

In [21]:
```
# Plot the important features #
fig, ax = plt.subplots(figsize=(12,18))
xgb.plot_importance(model, max_num_features=50, height=0.8, ax=ax)
plt.show()
```





Observations:

1. Categorical features **X0 & X5 are highly important** in the prediction of our XGBoost model.
2. **TSVD,PCA & ICA generated features are also contributing effectively in the prediction.**
3. We can also **drop the features that are less important** to increase the model effectivity/time to predict target Variable.

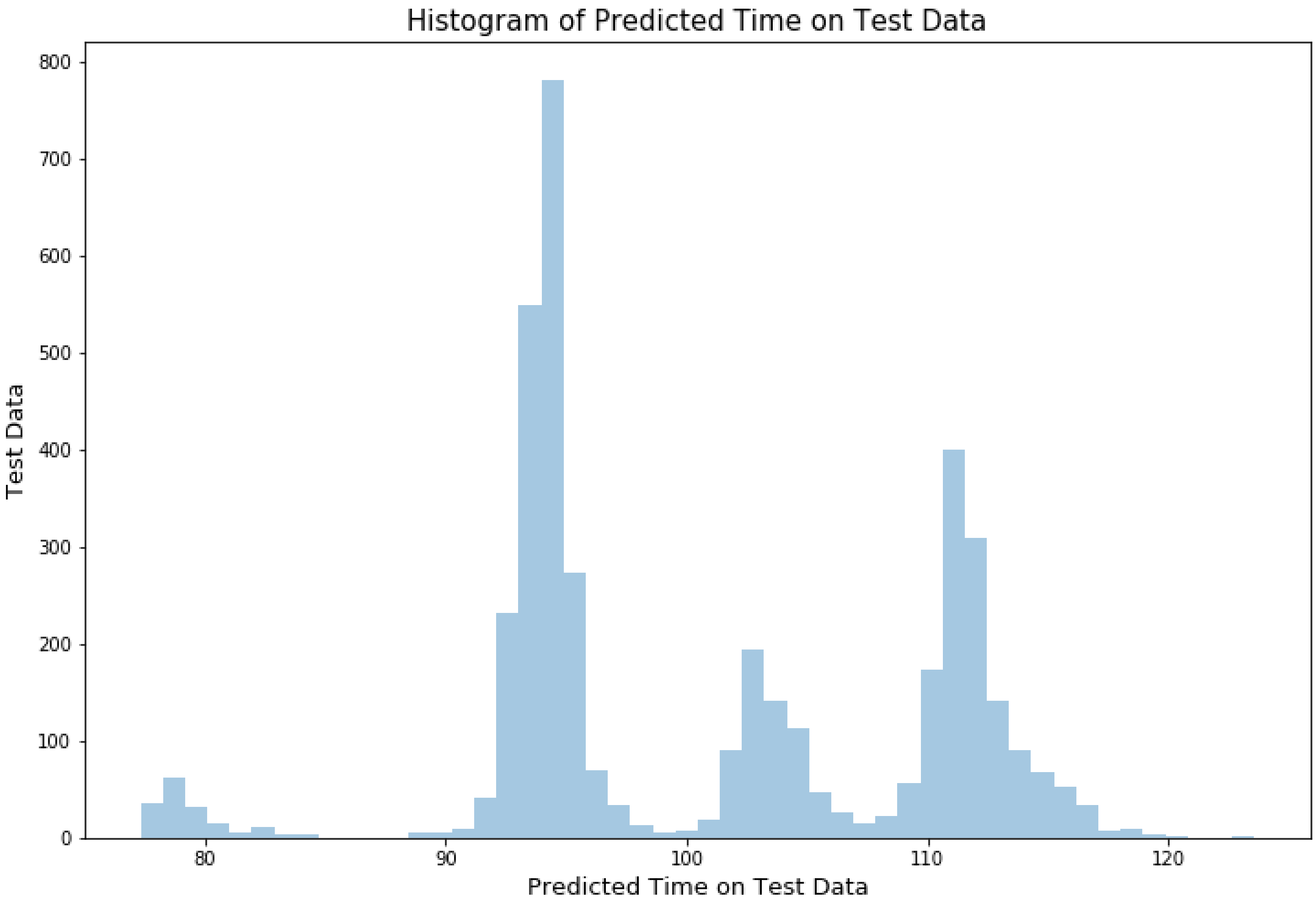
In [22]:
```
# check f2-score (to get higher score - increase num_boost_round in previous cell)
from sklearn.metrics import r2_score

# now fixed, correct calculation
print(r2_score(dtrain.get_label(), model.predict(dtrain)))
```

```
0.718001643662283
```

r2_score = 0.718

In [23]:
```
test = pd.read_csv('test.csv')
y_pred = model.predict(dtest)
output = pd.DataFrame({'id': test['ID'].astype(np.int32), 'y': y_pred})
output.to_csv('XGB_test_results.csv', index=False)
output = pd.DataFrame({'id': test['ID'].astype(np.int32), 'y': y_pred})
plt.figure(figsize=(12,8))
sns.distplot(output.y.values, bins=50, kde=False)
plt.xlabel('Predicted Time on Test Data', fontsize=13)
plt.ylabel('Test Data', fontsize=13)
plt.title('Histogram of Predicted Time on Test Data', fontsize=15)
plt.show()
```



Stacked Regression model.

In [16]:

```
class StackingEstimator(BaseEstimator, TransformerMixin):

    def __init__(self, estimator):
        self.estimator = estimator


    def fit(self, X, y=None, **fit_params):
        self.estimator.fit(X, y, **fit_params)
        return self

    def transform(self, X):
        X = check_array(X)
        X_transformed = np.copy(X)
        # add class probabilities as a synthetic feature
        if issubclass(self.estimator.__class__, ClassifierMixin) and hasattr(self.estimator, 'predict_proba'):
            X_transformed = np.hstack((self.estimator.predict_proba(X), X))

        # add class prodiction as a synthetic feature
        X_transformed = np.hstack((np.reshape(self.estimator.predict(X), (-1, 1)), X_transformed))

        return X_transformed
```

In [17]:

```
# Import the data
train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")

print("Train shape : ", train.shape)
print("Test shape : ", test.shape)
```

```
Train shape :  (4209, 378)
Test shape :  (4209, 377)
```

In [18]:
```
# Data Preprocessing.

# LabelEncoder: Used to Encode labels with value between 0 and n_classes-1.

for c in train.columns:
    if train[c].dtype == 'object':
        lbl = LabelEncoder()
        lbl.fit(list(train[c].values) + list(test[c].values))# Fit label encoder
        train[c] = lbl.transform(list(train[c].values))# Transform labels to normalized encoding.
        test[c] = lbl.transform(list(test[c].values))# Transform labels to normalized encoding.

# Dropping ID feature & creating saperate Input/Output training data.
train_y = train['y'].values
y_mean = np.mean(train_y)
id_test = test['ID'].values
train = train.drop(["ID"], axis=1)
test = test.drop(["ID"], axis=1)
# Reference : https://xgboost.readthedocs.io/en/latest/python/python_intro.html
def xgb_r2_score(preds, dtrain):
    labels = dtrain.get_label()
    return 'r2', r2_score(labels, preds)

# Save columns list before adding the decomposition components

usable_columns = list(set(train.columns) - set(['y']))
```

Creating the components using various dimensionality reduction techniques.

In [19]:

```python
# Dimensionality reduction techniques
n_comp = 15

# tSVD
tsvd = TruncatedSVD(n_components=n_comp, random_state=420)
tsvd_results_train = tsvd.fit_transform(train.drop(["y"], axis=1))
tsvd_results_test = tsvd.transform(test)
# PCA
pca = PCA(n_components=n_comp, random_state=42)
pca2_results_train = pca.fit_transform(train.drop(["y"], axis=1))
pca2_results_test = pca.transform(test)

# ICA
ica = FastICA(n_components=n_comp, random_state=42)
ica2_results_train = ica.fit_transform(train.drop(["y"], axis=1))
ica2_results_test = ica.transform(test)

# GRP
grp = GaussianRandomProjection(n_components=n_comp, eps=0.1, random_state=42)
grp_results_train = grp.fit_transform(train.drop(["y"], axis=1))
grp_results_test = grp.transform(test)

# SRP
srp = SparseRandomProjection(n_components=n_comp, dense_output=True, random_state=42)
srp_results_train = srp.fit_transform(train.drop(["y"], axis=1))
srp_results_test = srp.transform(test)

# Append decomposition components to datasets
for i in range(1, n_comp+1):

    train['tsvd_' + str(i)] = tsvd_results_train[:,i-1]
    test['tsvd_' + str(i)] = tsvd_results_test[:, i-1]

    train['pca_' + str(i)] = pca2_results_train[:,i-1]
    test['pca_' + str(i)] = pca2_results_test[:, i-1]

    train['ica_' + str(i)] = ica2_results_train[:,i-1]
    test['ica_' + str(i)] = ica2_results_test[:, i-1]

    train['grp_' + str(i)] = grp_results_train[:, i-1]
    test['grp_' + str(i)] = grp_results_test[:, i-1]
```

```
    train['srp_' + str(i)] = srp_results_train[:, i-1]
    test['srp_' + str(i)] = srp_results_test[:,i-1]
```

In [20]:

```
# final_train and final_test are data to be used only the stacked model (does not contain PCA, SVD... arrays)

final_train = train[usable_columns].values
final_test = test[usable_columns].values

# Reference : https://www.analyticsvidhya.com/blog/2016/03/complete-guide-parameter-tuning-xgboost-with-codes-py

import xgboost as xgb

# Prepare dict of params for xgboost model.
xgb_params = {
    'n_trees': 500,
    'eta': 0.005,
    'max_depth':5,
    'subsample': 0.9,
    'objective': 'reg:linear',
    'eval_metric': 'rmse',
    'base_score': y_mean, # base prediction = mean(target)
    'silent': 1}


# Creating DMatrices for Xgboost training
dtrain = xgb.DMatrix(train.drop(["y"], axis=1), train_y)
dtest = xgb.DMatrix(test)

# xgboost, cross-validation
cv_result = xgb.cv(xgb_params,dtrain,num_boost_round=1000,verbose_eval=50,show_stdv=False)

num_boost_rounds = len(cv_result)
print(num_boost_rounds)

# Train model
model = xgb.train(dict(xgb_params, silent=0), dtrain, num_boost_round=num_boost_rounds)
y_pred = model.predict(dtest)
```

```
[0]     train-rmse:12.6392      test-rmse:12.638
[50]    train-rmse:11.0477      test-rmse:11.1558
[100]   train-rmse:9.90336      test-rmse:10.161
[150]   train-rmse:9.10037      test-rmse:9.5143
[200]   train-rmse:8.53487      test-rmse:9.10244
[250]   train-rmse:8.13785      test-rmse:8.84734
[300]   train-rmse:7.84902      test-rmse:8.69675
```

```
[350]	train-rmse:7.63858	test-rmse:8.60636
[400]	train-rmse:7.46158	test-rmse:8.55571
[450]	train-rmse:7.31058	test-rmse:8.53298
[500]	train-rmse:7.1737	test-rmse:8.52107
[550]	train-rmse:7.05194	test-rmse:8.51768
[600]	train-rmse:6.94264	test-rmse:8.52118
[650]	train-rmse:6.84518	test-rmse:8.52708
[700]	train-rmse:6.74954	test-rmse:8.5383
[750]	train-rmse:6.6645	test-rmse:8.54567
[800]	train-rmse:6.57573	test-rmse:8.55308
[850]	train-rmse:6.49414	test-rmse:8.5616
```

In [21]:

```python
# Train the stacked models then predict the test data !!
from sklearn.pipeline import make_pipeline, make_union
Stacked_pipeline = make_pipeline(
    StackingEstimator(estimator=LassoLarsCV(normalize=True)),
    StackingEstimator(estimator=GradientBoostingRegressor(learning_rate=0.001,loss="huber",max_features=0.55,
                                                          min_samples_leaf=18,
                                                          min_samples_split=14, subsample=0.7)),
    LassoLarsCV())



Stacked_pipeline.fit(final_train, train_y)
predictions = Stacked_pipeline.predict(final_test)

# R2 Score on the entire Train data when averaging

print('R2 score on train data:')
print(r2_score(train_y,Stacked_pipeline.predict(final_train)*0.2855 + model.predict(dtrain)*0.7145))

# Average the preditionon test data  of both models then save it on a csv file.

sub = pd.DataFrame()
sub['ID'] = id_test
sub['y'] = y_pred*0.75 + predictions*0.25
sub.to_csv('stacked_model_pred.csv', index=False)
```

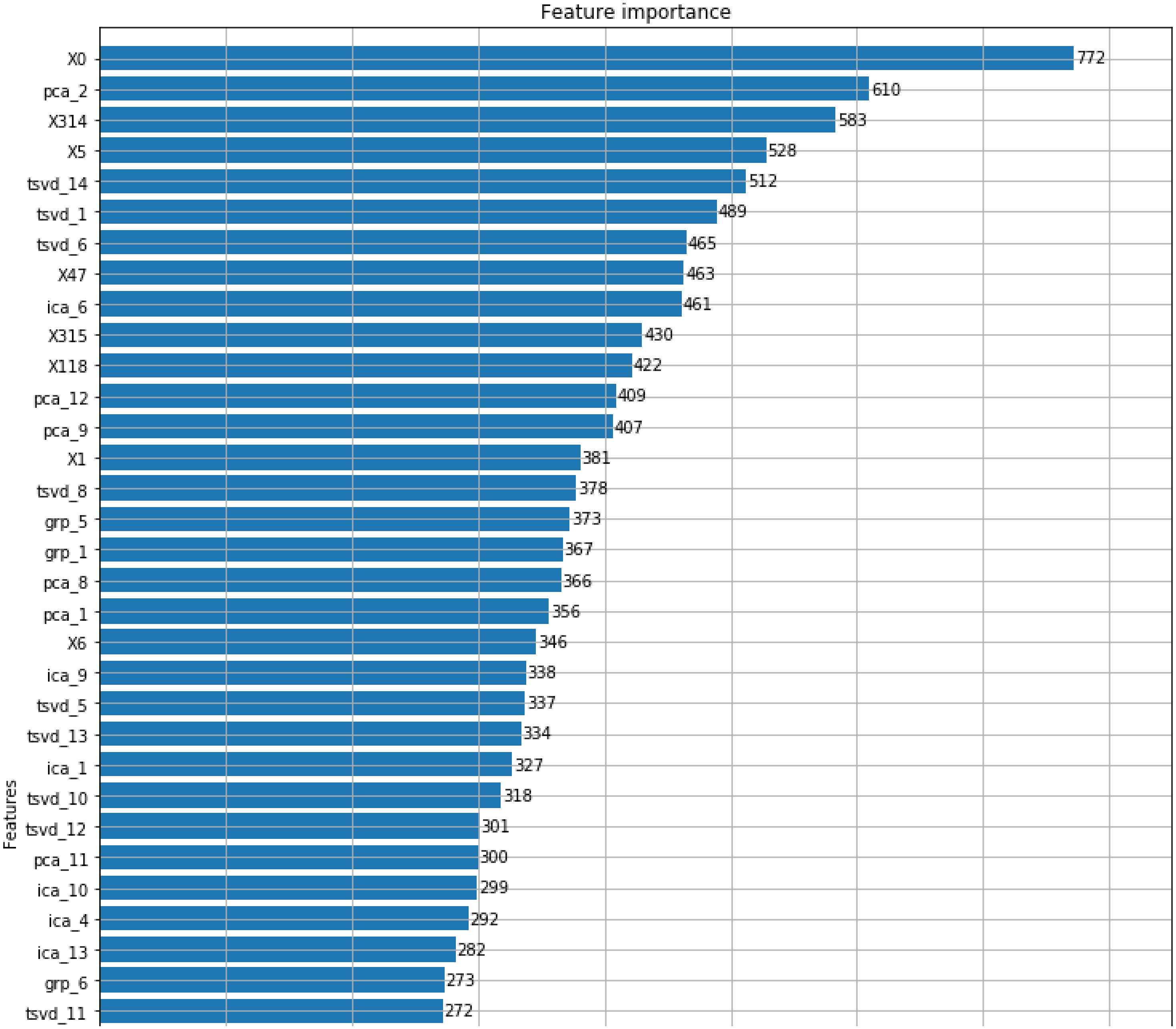
```
R2 score on train data:
0.6805083932610694
```

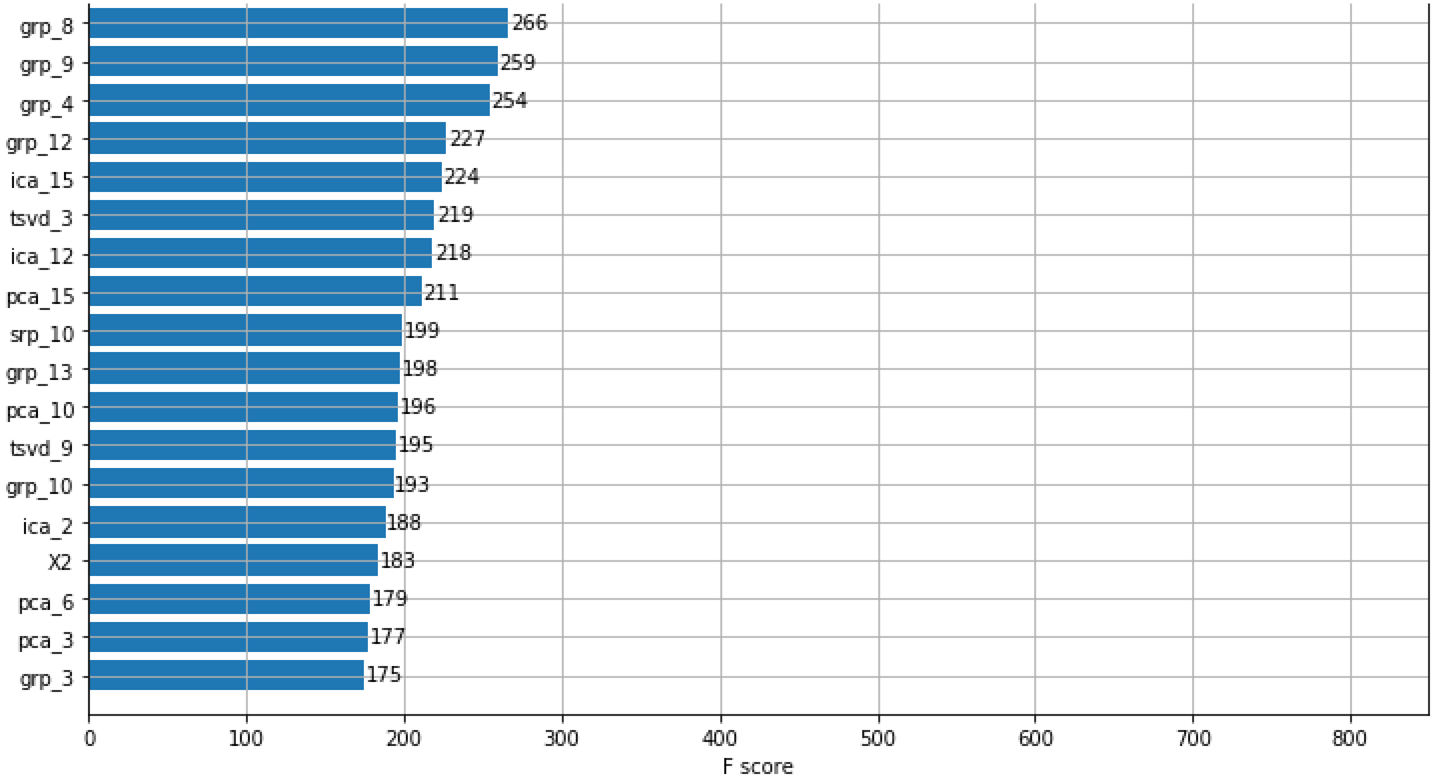
Observations:

Observations:

1. **After 1000 num_boost_round: 1. train-rmse:6.28061 2. test-rmse:8.58585**
2. We have pretty decent values of Train & Test error parameter(RMSE).
3. Model is performing nicely & not overfitting.
4. **R2 score on train data: 0.6805083932610694**

In [22]:
```
# Plot the important features #
fig, ax = plt.subplots(figsize=(12,18))
xgb.plot_importance(model, max_num_features=50, height=0.8, ax=ax)
plt.show()
```





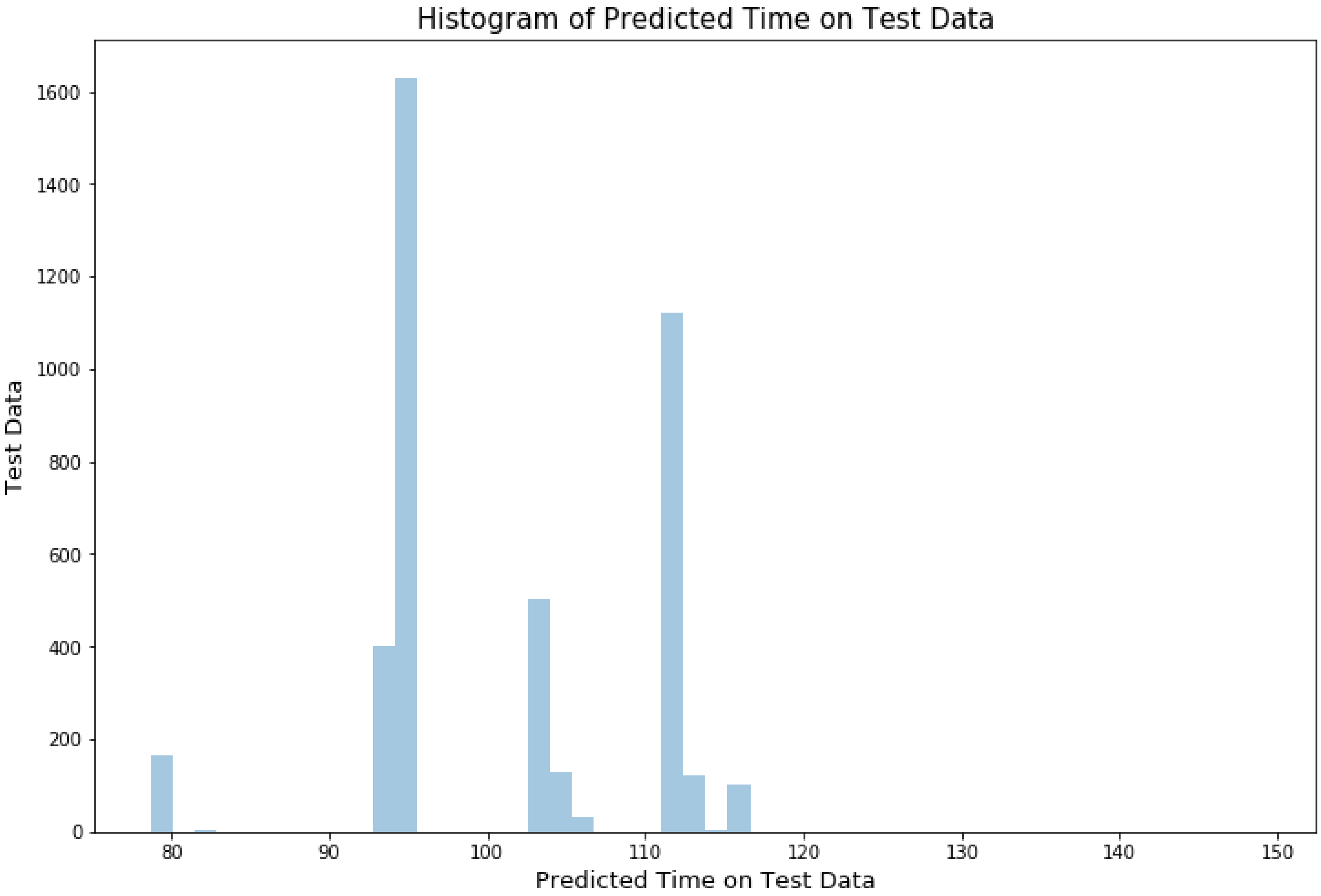
Observations:

1. Categorical features **X0 & X5 are highly important** in the prediction of our XGBoost model.
2. **TSVD,PCA & ICA generated features are also contributing effectively in the prediction.**
3. We can also **drop the features that are less important** to increase the model effectivity/time to predict target Variable.

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

output = pd.DataFrame({'id': test['ID'].astype(np.int32), 'y': predictions})

plt.figure(figsize=(12,8))
sns.distplot(output.y.values, bins=50, kde=False)
plt.xlabel('Predicted Time on Test Data', fontsize=13)
plt.ylabel('Test Data', fontsize=13)
plt.title('Histogram of Predicted Time on Test Data', fontsize=15)
plt.show()
```



Deep Learning Algorithms.

We can solve Regression problem to optimize the Production Time Feature (i.e. Target Variable = y).

Baseline Model: MLP using Keras

In [19]:
```
# Data preprocessing.

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

# removing the outliers.
train = train.loc[train['y'] < 200, :]

# seperating label and features.
y_train = train['y']

train = train.drop(["ID", "y"], axis=1)

test = test.drop(["ID"], axis=1)

# label encoding the categorical features for dimension reduction.
for c in train.columns:
    if train[c].dtype == 'object':
        lbl = LabelEncoder()
        lbl.fit(list(train[c].values) + list(test[c].values))
        train[c] = lbl.transform(list(train[c].values))
        test[c] = lbl.transform(list(test[c].values))
```

In [20]:
```
print(train.shape)
print(test.shape)
```

```
(4208, 376)
(4209, 376)
```

In [21]:
```
from keras import optimizers

adam = optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay=0.0)

# Define custom R2 metrics for Keras backend.
from keras import backend as K

def r2_keras(y_true, y_pred):
    SS_res = K.sum(K.square(y_true - y_pred))
    SS_tot = K.sum(K.square(y_true - K.mean(y_true)))
    return (1 - SS_res / (SS_tot + K.epsilon()))

# Reference:https://stackoverflow.com/questions/45250100/kerasregressor-coefficient-of-determination-r2-score
```

In [22]:
```
# Initialize input dimensions variable.
input_dims = train.shape[1]
```

In [23]:

```
# Architecture of MLP.

def nn_model():
    model = Sequential()
    # Input layer.
    model.add(Dense(input_dims, input_dim=input_dims))
    model.add(BatchNormalization())
    model.add(Activation('relu'))
    model.add(Dropout(0.4))
    # hidden layer1
    model.add(Dense(input_dims))
    model.add(BatchNormalization())
    model.add(Activation('relu'))
    model.add(Dropout(0.4))
    # hidden layer2
    model.add(Dense(input_dims//2))
    model.add(BatchNormalization())
    model.add(Activation('relu'))
    model.add(Dropout(0.4))
    # hidden layer3
    model.add(Dense(input_dims//4, activation='relu'))

    # Output layer (y_pred)
    model.add(Dense(1, activation='linear'))

    return model


model = nn_model()
print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 376)               141752    
_________________________________________________________________
batch_normalization_1 (Batch (None, 376)               1504      
_________________________________________________________________
activation_1 (Activation)    (None, 376)               0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 376)               0         
_________________________________________________________________
```

```
dense_2 (Dense)              (None, 376)               141752    
_________________________________________________________________
batch_normalization_2 (Batch (None, 376)               1504      
_________________________________________________________________
activation_2 (Activation)    (None, 376)               0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 376)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 188)               70876     
_________________________________________________________________
batch_normalization_3 (Batch (None, 188)               752       
_________________________________________________________________
activation_3 (Activation)    (None, 188)               0         
_________________________________________________________________
dropout_3 (Dropout)          (None, 188)               0         
_________________________________________________________________
dense_4 (Dense)              (None, 94)                17766     
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 95        
=================================================================
Total params: 376,001
Trainable params: 374,121
Non-trainable params: 1,880
_________________________________________________________________
None
```

In [26]:

```
filepath="weights_baseline_mlp.best.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_r2_keras', verbose=1, save_best_only=True, mode='max')
callbacks_list = [checkpoint]
```

In [27]:
```python
# Fitting the model on the training data.
model.compile(loss='mean_squared_error', optimizer=adam, metrics=[r2_keras])
history = model.fit(train, y_train, nb_epoch = 200, batch_size=50, shuffle=True,verbose=1,
                    validation_split=0.3,callbacks=callbacks_list)
```

```
0.7293 - val_r2_keras: 0.4032

Epoch 00074: val_r2_keras did not improve from 0.55457
Epoch 75/200
2945/2945 [==============================] - 0s 169us/step - loss: 40.0958 - r2_keras: 0.7366 - val_loss: 7
7.2276 - val_r2_keras: 0.4299

Epoch 00075: val_r2_keras did not improve from 0.55457
Epoch 76/200
2945/2945 [==============================] - 0s 165us/step - loss: 39.5970 - r2_keras: 0.7457 - val_loss: 6
9.2608 - val_r2_keras: 0.4950

Epoch 00076: val_r2_keras did not improve from 0.55457
Epoch 77/200
2945/2945 [==============================] - 0s 167us/step - loss: 39.6753 - r2_keras: 0.7451 - val_loss: 8
7.5152 - val_r2_keras: 0.3521

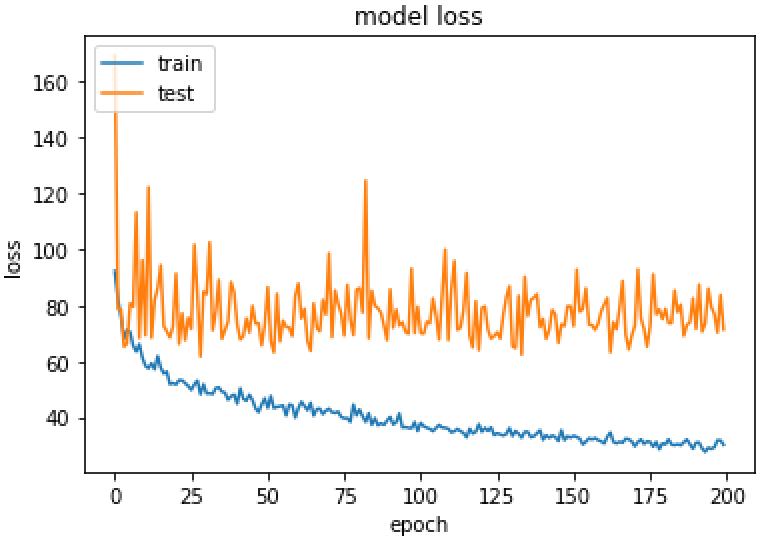
Epoch 00077: val_r2_keras did not improve from 0.55457
Epoch 78/200
2945/2945 [==============================] - 0s 169us/step - loss: 38.3412 - r2_keras: 0.7555 - val_loss: 7
```

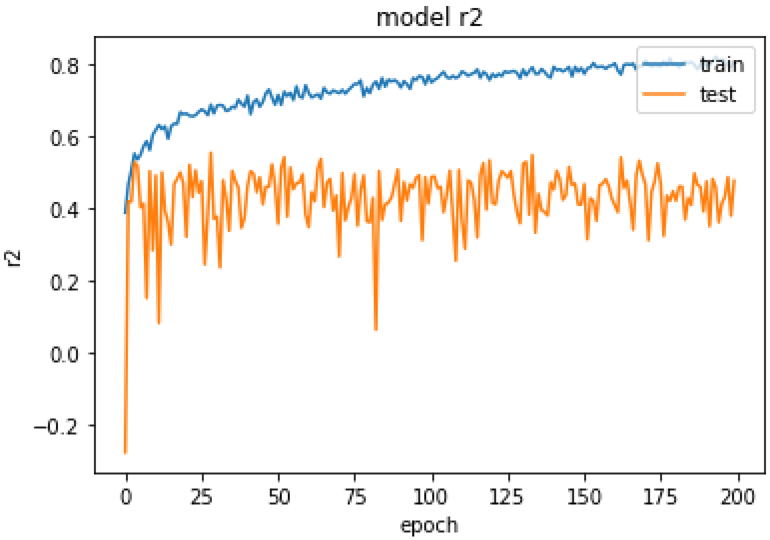
After 29 epochs:

1. *Training Data: *
    - A. **mean_squared_error loss: 48.2294**
    - B. **r2 metric: 0.6881**
2. *Validation Data: *
    - A. **mean_squared_error loss: 61.74**
    - B. **r2 metric: 0.5546**

In [28]:
```
# Plot Loss & R2 metric.
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

plt.plot(history.history['r2_keras'])
plt.plot(history.history['val_r2_keras'])
plt.title('model r2')
plt.ylabel('r2')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.show()
```





Observations:

1. We can easily see that model is predicting the Target variable brillianlty.
2. The Loss & R2 metric graphs converge after few epochs.
3. **No Overfitting.**

In [29]:

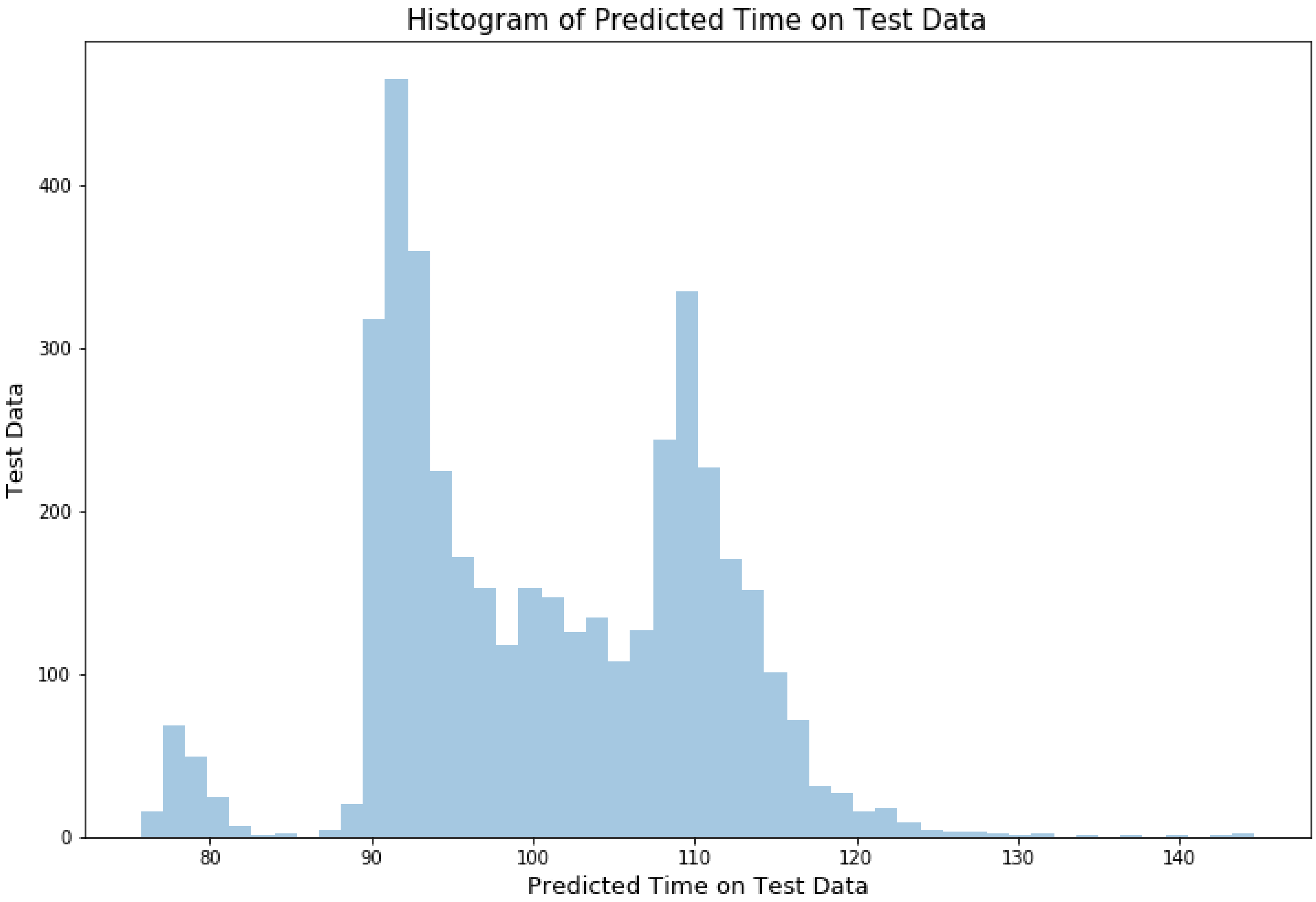
```
# Passing the Test data through the trained model & storing the results on disk.

Dtest = pd.read_csv('test.csv')
# predict results
res = model.predict(test).ravel()
print(res)

# create df and convert it to csv
output = pd.DataFrame({'id': Dtest["ID"], 'y': res})
output.to_csv('keras-baseline.csv', index=False)
```

```
[ 85.117355  94.5353    79.48812  ...  96.592606 107.8587    95.03621 ]
```

In [30]:
```
plt.figure(figsize=(12,8))
sns.distplot(output.y.values, bins=50, kde=False)
plt.xlabel('Predicted Time on Test Data', fontsize=13)
plt.ylabel('Test Data', fontsize=13)
plt.title('Histogram of Predicted Time on Test Data', fontsize=15)
plt.show()
```



Observations:

1. The distribution of the Predicted Time (y) on Test Data is almost similar to the input data distribution.

Final Model: MLP using Keras.

In [26]:
```
# Data preprocessing.

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

# removing the outliers.
train = train.loc[train['y'] < 200, :]

# seperating label and features
y_train = train['y']
train = train.drop(["ID", "y"], axis=1)
test = test.drop(["ID"], axis=1)
y_mean = np.mean(y_train)
# label encoding the categorical features for dimension reduction
for c in train.columns:
    if train[c].dtype == 'object':
        lbl = LabelEncoder()
        lbl.fit(list(train[c].values) + list(test[c].values))
        train[c] = lbl.transform(list(train[c].values))
        test[c] = lbl.transform(list(test[c].values))
```

In [27]:
```
# Dimensionality reduction techniques

n_comp = 15

# tSVD
tsvd = TruncatedSVD(n_components=n_comp, random_state=42)
tsvd_results_train = tsvd.fit_transform(train)
tsvd_results_test = tsvd.transform(test)
# PCA
pca = PCA(n_components=n_comp, random_state=42)
pca2_results_train = pca.fit_transform(train)
pca2_results_test = pca.transform(test)

# ICA
ica = FastICA(n_components=n_comp, random_state=42)
ica2_results_train = ica.fit_transform(train)
ica2_results_test = ica.transform(test)

# GRP
grp = GaussianRandomProjection(n_components=n_comp, eps=0.1, random_state=42)
grp_results_train = grp.fit_transform(train)
grp_results_test = grp.transform(test)

# SRP
srp = SparseRandomProjection(n_components=n_comp, dense_output=True, random_state=42)
srp_results_train = srp.fit_transform(train)
srp_results_test = srp.transform(test)

# Append decomposition components to datasets
for i in range(1, n_comp+1):
    train['tsvd_' + str(i)] = tsvd_results_train[:,i-1]
    test['tsvd_' + str(i)] = tsvd_results_test[:, i-1]

    train['pca_' + str(i)] = pca2_results_train[:,i-1]
    test['pca_' + str(i)] = pca2_results_test[:, i-1]

    train['ica_' + str(i)] = ica2_results_train[:,i-1]
    test['ica_' + str(i)] = ica2_results_test[:, i-1]

    train['grp_' + str(i)] = grp_results_train[:,i-1]
    test['grp_' + str(i)] = grp_results_test[:, i-1]
```

```
    train['srp_' + str(i)] = srp_results_train[:,i-1]
    test['srp_' + str(i)] = srp_results_test[:, i-1]
```

In [28]:

```
# Define custom R2 metrics for Keras backend
from keras import backend as K

def r2_keras(y_true, y_pred):
    SS_res =  K.sum(K.square( y_true - y_pred ))
    SS_tot = K.sum(K.square( y_true - K.mean(y_true) ) )
    return ( 1 - SS_res/(SS_tot + K.epsilon()) )

# Reference:https://stackoverflow.com/questions/45250100/kerasregressor-coefficient-of-determination-r2-score
```

In [29]:
```
# Model architecture definition.
def model():
    model = Sequential()
    #input layer
    model.add(Dense(input_dims, input_dim=input_dims))
    model.add(BatchNormalization())
    model.add(Activation('relu'))
    model.add(Dropout(0.4))
    # hidden layer1
    model.add(Dense(input_dims))
    model.add(BatchNormalization())
    model.add(Activation('relu'))
    model.add(Dropout(0.4))
    # hidden layer2
    model.add(Dense(input_dims//2))
    model.add(BatchNormalization())
    model.add(Activation('relu'))
    model.add(Dropout(0.4))
    # hidden layer3
    model.add(Dense(input_dims//4, activation='relu'))

    # output layer (y_pred)
    model.add(Dense(1, activation='linear'))

    # compile this model
    model.compile(loss='mean_squared_error',optimizer='adam',metrics=[r2_keras])

    # Visualize NN architecture
    print(model.summary())
    return model
```

In [30]:

```
# Initialize input dimension
input_dims = train.shape[1]

# To make Results reproducible
np.random.seed(seed)

# Initialize estimator, wrap model in KerasRegressor.
# Reference : https://stackoverflow.com/questions/44132652/keras-how-to-perform-a-prediction-using-kerasregress

estimator = KerasRegressor(build_fn=model,nb_epoch=150,batch_size=20,verbose=1)
```

In [31]:

```
filepath="weights_final_mlp.best.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_r2_keras', verbose=1, save_best_only=True, mode='max')
callbacks_list = [checkpoint]
```

In [32]:

```
# Fit the estimator.
history = estimator.fit(train,y_train,epochs=200,validation_split=0.3,verbose=2,shuffle=True,callbacks=callbacks
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 451)               203852
_________________________________________________________________
batch_normalization_1 (Batch (None, 451)               1804
_________________________________________________________________
activation_1 (Activation)    (None, 451)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 451)               0
_________________________________________________________________
dense_2 (Dense)              (None, 451)               203852
_________________________________________________________________
batch_normalization_2 (Batch (None, 451)               1804
_________________________________________________________________
activation_2 (Activation)    (None, 451)               0
_________________________________________________________________
dropout_2 (Dropout)          (None, 451)               0
_________________________________________________________________
```

After 88 epochs:

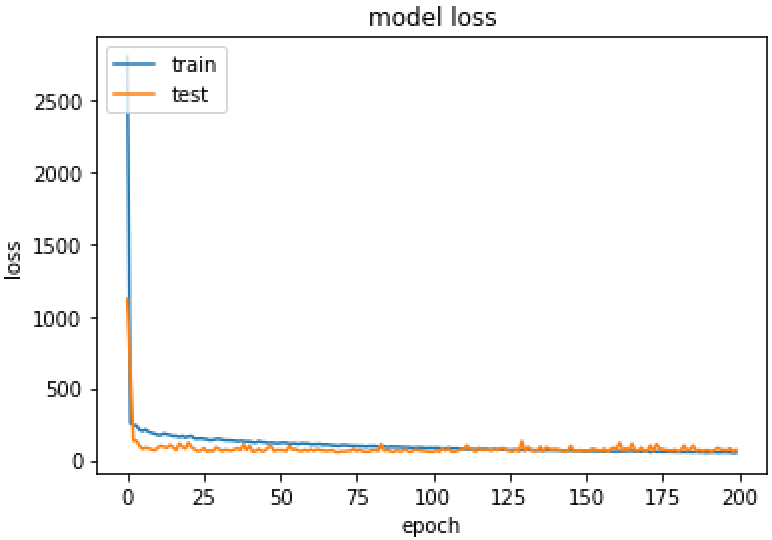
1. *Training Data: *

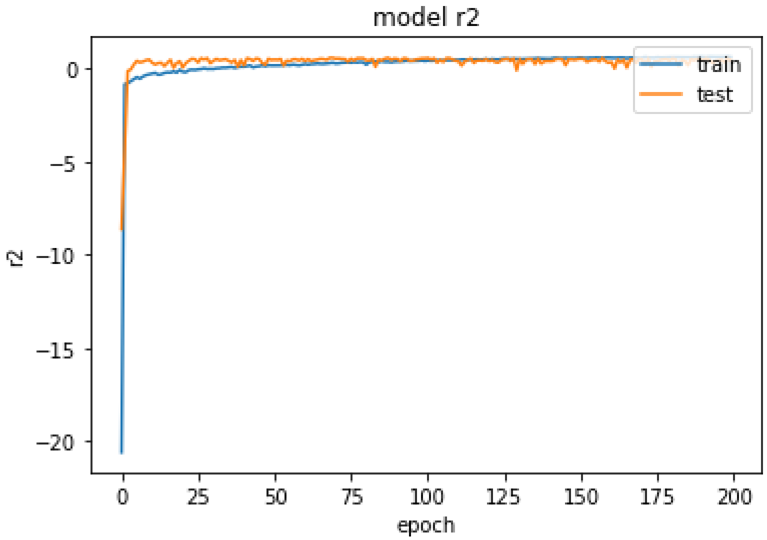
    A. **mean_squared_error loss: 92.732**
    B. **r2 metric: 0.3655**
2. *Validation Data: *
    A. **mean_squared_error loss: 57.118**
    B. **r2 metric: 0.57795**

In [33]:

```
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

plt.plot(history.history['r2_keras'])
plt.plot(history.history['val_r2_keras'])
plt.title('model r2')
plt.ylabel('r2')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')
plt.show()
```





Observations:

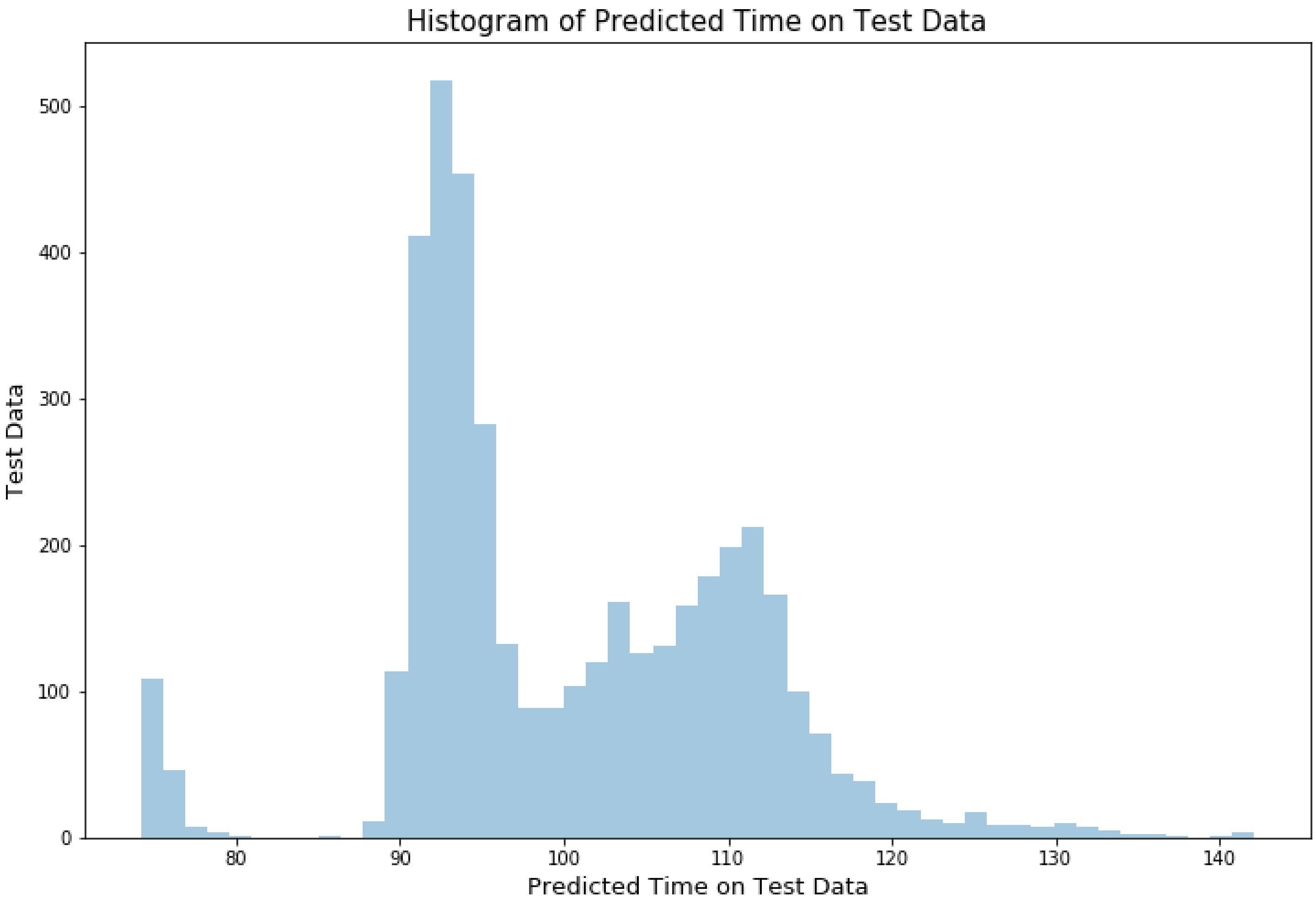
1. We can easily see that model is predicting the Target variable brillianlty.
2. The Loss & R2 metric graphs converge after few epochs.
3. **No Overfitting.**

In [34]:
```
Dtest = pd.read_csv('test.csv')
# predict results
res = estimator.predict(test).ravel()
print(res)

# create df and convert it to csv
output = pd.DataFrame({'id': Dtest["ID"], 'y': res})
output.to_csv('Keras_final.csv', index=False)
```

```
4209/4209 [==============================] - 0s 84us/step
[ 76.85151   92.717636  74.61126  ...  93.58735  108.86175   92.010956]
```

In [35]:
```
plt.figure(figsize=(12,8))
sns.distplot(output.y.values, bins=50, kde=False)
plt.xlabel('Predicted Time on Test Data', fontsize=13)
plt.ylabel('Test Data', fontsize=13)
plt.title('Histogram of Predicted Time on Test Data', fontsize=15)
plt.show()
```



```
### Observations:

1. The distribution of the Predicted Time (y) on Test Data is shifted left compared to the input data
distribution.
```

In [1]:
```
# Model performance table
```

In [3]:
```
from prettytable import PrettyTable


x = PrettyTable()
x.field_names = ["Model","Train Error/Loss RMSE","Test Error/Loss RMSE","R2 Metric"]
x.add_row(["XGBoost Model",6.22,8.08,0.53])
x.add_row(["Stacking Model",6.28,8.58,0.68])
x.add_row(["DL MLP Model",9.62,7.55,0.58])
print(x)
```

```
+----------------+----------------------+----------------------+-----------+
|     Model      | Train Error/Loss RMSE | Test Error/Loss RMSE | R2 Metric |
+----------------+----------------------+----------------------+-----------+
| XGBoost Model  |         6.22         |         8.08         |    0.53   |
| Stacking Model |         6.28         |         8.58         |    0.68   |
|  DL MLP Model  |         9.62         |         7.55         |    0.58   |
+----------------+----------------------+----------------------+-----------+
```

In [ ]:
```
#Existing approaches & my Improvements on them

# 1)https://github.com/subhadipml/Mercedes-Benz-Greener-Manufacturing/blob/master/Mercedes-Benz%20Greener%20Manu
# 2)https://www.kaggle.com/deadskull7/78th-place-solution-private-lb-0-55282-top-2
# Both solutions had more or less the same approach where categorical columns were encoded using label encoding
# used as dimensionality reduction technique in the first solution and finally XGBoost regressor algorithm was c

# I applied Xgboost model ,Random forest model,Stacked model & Deep learning MLP models on the data ,I managed t
# overfitting and in order to improve the scores by training the model rigorously & extensive hyperparameter tur
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In [ ]:

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#Future Work

# 1)Feature engineering was a success and it yielded good results. Hence,there can be a scope of improvement if
# 2)Finally, this regression problem can also be solved using advanced Artificial Deep Learning Neural Networks
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In [ ]:

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#References

# 1)https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/discussion/37700
# 2)https://www.kaggle.com/deadskull7/78th-place-solution-private-lb-0-55282-top-2
# 3)https://blog.cambridgespark.com/hyperparameter-tuning-in-xgboost-4ff9100a3b2f
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Conclusion:

1. **We have taken the Mercedes-Benz Greener Manufacturing data.**
2. **We have trained Machine Learning & Deep Learning models on the data.**
3. **Stacking model gives best performence (i.e R^2=0.68).**