EarthQuake Prediction

April 4, 2019

1 LANL Earthquake Prediction

1.0.1 1.1 Description

Forecasting earthquakes is one of the most important problems in Earth science because of their devastating consequences. Current scientific studies related to earthquake forecasting focus on three key points: when the event will occur, where it will occur, and how large it will be.

The goal of the challenge is to capture the physical state of the laboratory fault and how close it is from failure from a snapshot of the seismic data it is emitting. You will have to build a model that predicts the time remaining before failure from a chunk of seismic data, like we have done in our first paper above on easier data.

The input is a chunk of 0.0375 seconds of seismic data (ordered in time), which is recorded at 4MHz, hence 150'000 data points, and the output is time remaining until the following lab earthquake, in seconds.

The seismic data is recorded using a piezoceramic sensor, which outputs a voltage upon deformation by incoming seismic waves. The seismic data of the input is this recorded voltage, in integers.

Both the training and the testing set come from the same experiment. There is no overlap between the training and testing sets, that are contiguous in time.

Time to failure is based on a measure of fault strength (shear stress, not part of the data for the competition). When a labquake occurs this stress drops unambiguously.

The data is recorded in bins of 4096 samples. Within those bins seismic data is recorded at 4MHz, but there is a 12 microseconds gap between each bin, an artifact of the recording device.

1.1 Problem Statement:

To predict the time remaining before laboratory earthquakes occur from real-time seismic data.

1.2 Sources https://www.kaggle.com/c/LANL-Earthquake-Prediction https://www.kaggle.com/c/LANL-Earthquake-Prediction/discussion

2. Machine Learning problem

1.1.1 2.1 Data

train.csv - A single, continuous training segment of experimental data.

1.1.2 2.1.1 Data Overview

train.csv contains 2 columns: acoustic_data - the seismic signal [int16] time_to_failure - the time (in seconds) until the next laboratory earthquake [float64] Number of rows in Train.csv = 629145480

1.1.3 2.2.1 Type of Machine Leaning Problem

It is a Regression problem, for a given chunk of seismic data we need to predict the time remaining before laboratory earthquakes occur

2.2.2 Performance Metric Source: https://www.kaggle.com/c/LANL-Earthquake-Prediction#evaluation Metric(s): Mean Absolute Error

1.2 Exploratory Data Analysis

In [1]:
```
import numpy as np
import pandas as pd
from scipy.signal import hann
from tqdm import tqdm_notebook
from scipy.signal import convolve
import matplotlib.pyplot as pl5t
from scipy.signal import hilbert
import os
#print(os.listdir("/"))
import matplotlib.pyplot as plt
from tqdm import tqdm
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error
from scipy.stats import kurtosis
import matplotlib.pyplot as plt
from sklearn.model_selection import GridSearchCV
from scipy.stats import skew
from scipy.stats import norm
from sklearn.linear_model import LinearRegression

from scipy.signal import lfilter
import scipy.signal
from sklearn.svm import SVR
from sklearn.svm import NuSVR
from sklearn.model_selection import GridSearchCV
from sklearn.decomposition import TruncatedSVD
import xgboost as xgb
import catboost as cb
from catboost import CatBoostRegressor,Pool
```

In [2]:
```
#reading the data
train = pd.read_csv('train.csv', dtype={'acoustic_data': np.int16, 'time_to_failure': n
```

```
In [99]: train.shape
```

```
Out[99]: (629145480, 2)
```

There are 6.2 billion datapoints

```
In [98]: # to show all the decimal points
         pd.options.display.precision = 15
         train.head()
```

Out[98]:

	acoustic_data	time_to_failure
0	12	1.4690999832
1	6	1.4690999821
2	8	1.4690999810
3	5	1.4690999799
4	8	1.4690999788

We can see that for each sample the time to failure decreases by 1.1e-9

```
In [42]: train.describe()
```

Out[42]:

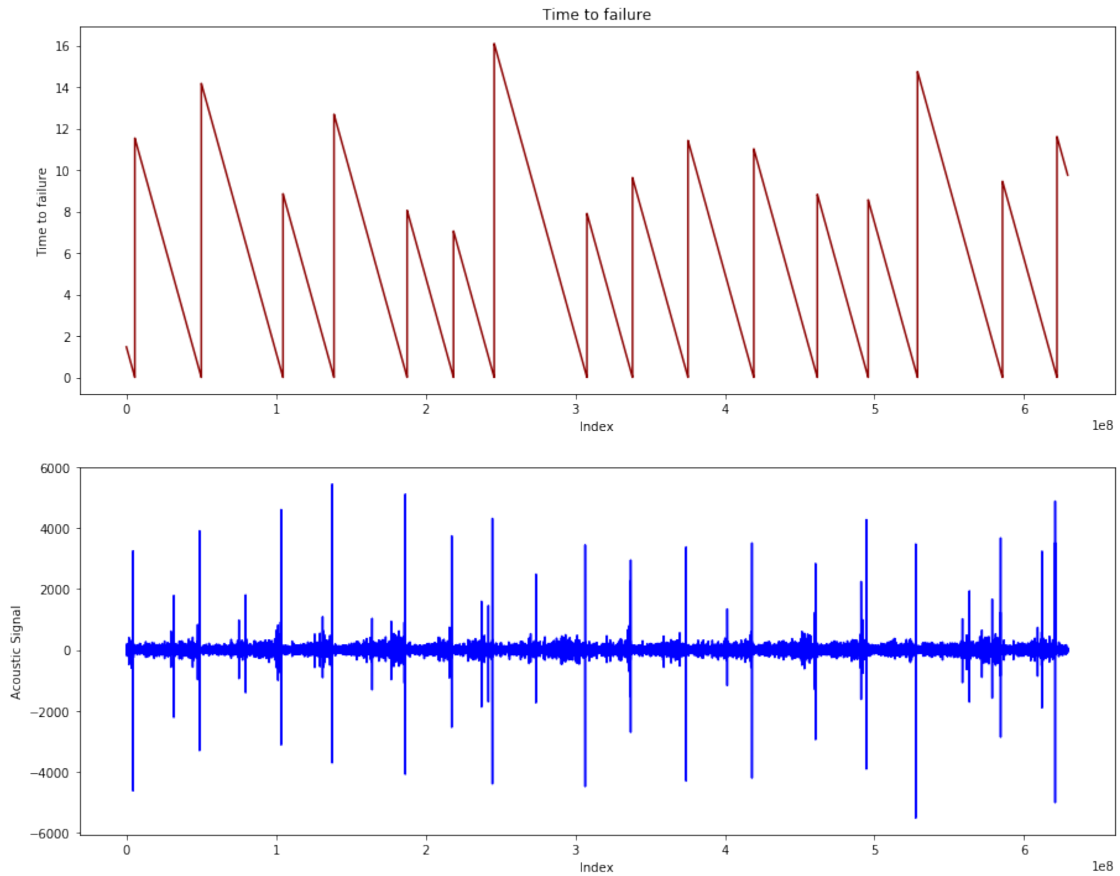
	acoustic_data	time_to_failure
count	6.291455e+08	6.291455e+08
mean	4.519468e+00	5.678292e+00
std	1.073571e+01	3.672697e+00
min	-5.515000e+03	9.550396e-05
25%	2.000000e+00	2.625997e+00
50%	5.000000e+00	5.349798e+00
75%	7.000000e+00	8.173396e+00
max	5.444000e+03	1.610740e+01

75% of the acoustic data is below 7 and the max value is 5.4e+03, i e only few values are approximately 5.4e+03

1.2.1 Visualizing Train data

1.2.2 Number of occurences of Earthquake

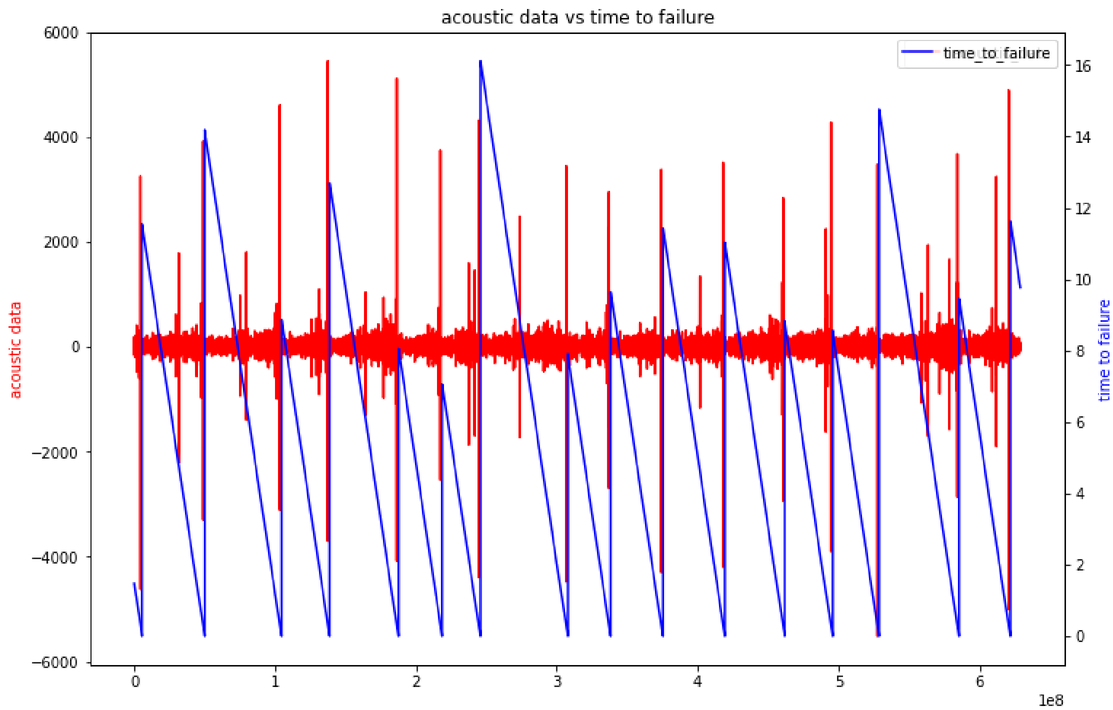
```
In [5]: #plotting the train data
        fig, ax = plt.subplots(2,1, figsize=(15,12))
        ax[0].plot(train.index.values, train.time_to_failure.values, c="darkred")
        ax[0].set_title("Time to failure")
        ax[0].set_xlabel("Index")
        ax[0].set_ylabel("Time to failure");
        ax[1].plot(train.index.values, train.acoustic_data.values, c="blue")
        #ax[1].set_title("Index")
        ax[1].set_xlabel("Index")
        ax[1].set_ylabel("Acoustic Signal")
        plt.show()
```



It is given that the earthquake occurs when the time_to_failure hits 0, hence we can count that there are 16 occurences of earthquake in the whole training data

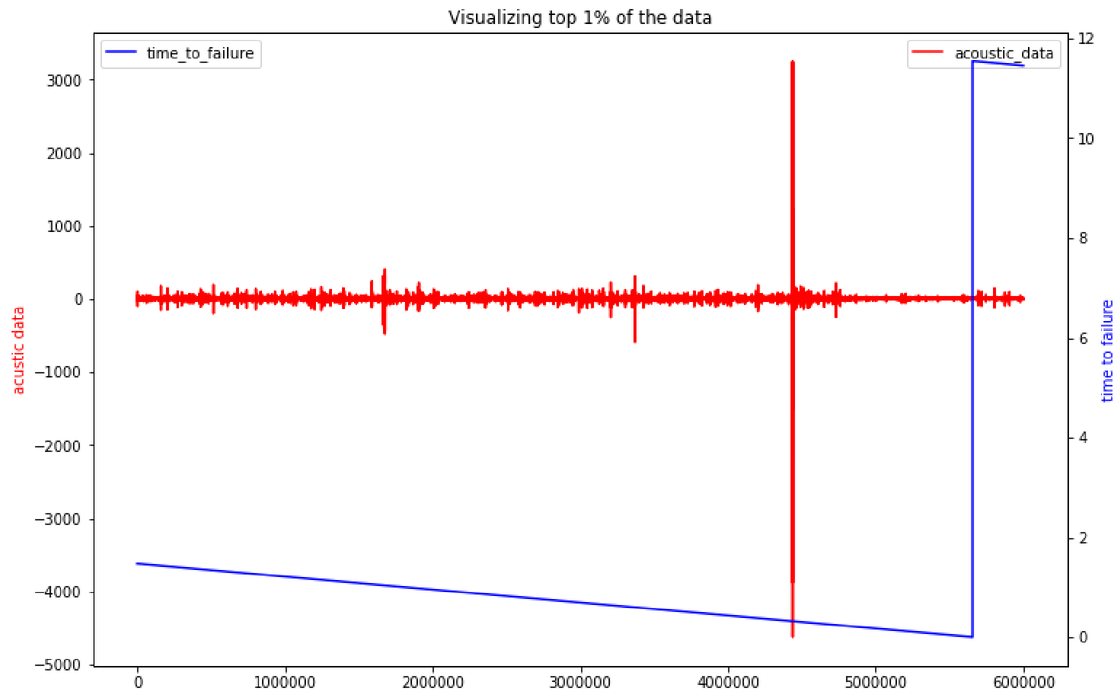
1.2.3 Relationship between time to failure and acoustic data

```
In [4]: #plotting acoustic data vs time to failure
        fig, ax1 = plt.subplots(figsize=(12, 8))
        plt.plot(train.acoustic_data,color='r')
        plt.legend()
        ax1.set_ylabel('acoustic data',color='r')
        ax2=ax1.twinx()
        ax2.set_ylabel('time to failure',color='b')
        plt.plot(train.time_to_failure,color='b')
        plt.title('acoustic data vs time to failure')
        plt.legend()
        plt.show()
```



The acoustic data has a peak just before time to failure hits zero. We can verify it by zooming into the plot.

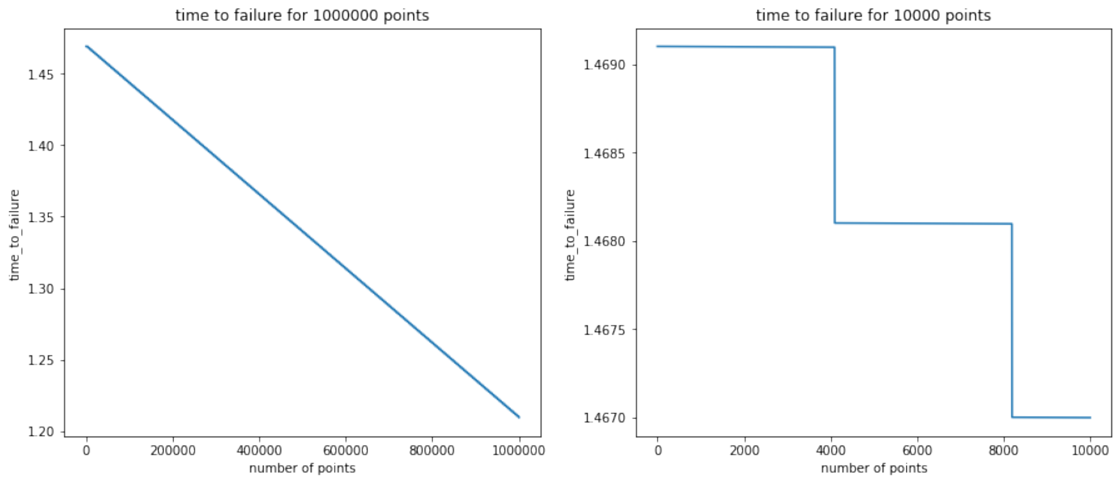
```
In [5]: #plotting only top 1% of the value
        fig, ax1 = plt.subplots(figsize=(12, 8))
        plt.plot(train.acoustic_data[0:6000000],color='r')
        plt.legend()
        ax1.set_ylabel('acustic data',color='r')
        ax2=ax1.twinx()
        ax2.set_ylabel('time to failure',color='b')
        plt.plot(train.time_to_failure[0:6000000],color='b')
        plt.title('Visualizing top 1% of the data')
        plt.legend()
        plt.show()
```



If we zoom into the data we can see that the acoustic data has a peak just before the earthquake occurs and the whole training data follows the same pattern

1.2.4 Is time to failure continously Decreasing

```
In [3]: #plotting time to failure for fewer data
        fig = plt.figure(figsize=(15, 6))
        plt.subplot(1,2,1)

        plt.plot(train.time_to_failure[0:1000000])
        plt.title('time to failure for 1000000 points')
        plt.xlabel('number of points')
        plt.ylabel('time_to_failure')

        plt.subplot(1,2,2)
        plt.plot(train.time_to_failure[0:10000])
        plt.xlabel('number of points')
        plt.ylabel('time_to_failure')
        plt.title('time to failure for 10000 points')

        plt.show()
```



If we plot the data for 1000000 points we can see that the graph is continously decreasing but if we zoom into it we can see that the time_to_failure stops decreasing for a while when it reaches ~4000 samples. It is due to the fact that the data is recorded in bins of 4096 samples and the recording device stops for 12 microseconds after each bin.

1.2.5 Visualizing Test Data

```
In [36]: #Reading the test data
         from tqdm.auto import tqdm
         submission = pd.read_csv('sample_submission.csv', index_col='seg_id')
         test = pd.DataFrame(dtype=np.float64, index=submission.index)
         whole_test=[]
         for seg_id in tqdm(test.index):
             seg = pd.read_csv('Untitled Folder/' + seg_id + '.csv')
             for i in seg['acoustic_data'].values:
                 whole_test.append(i)
```

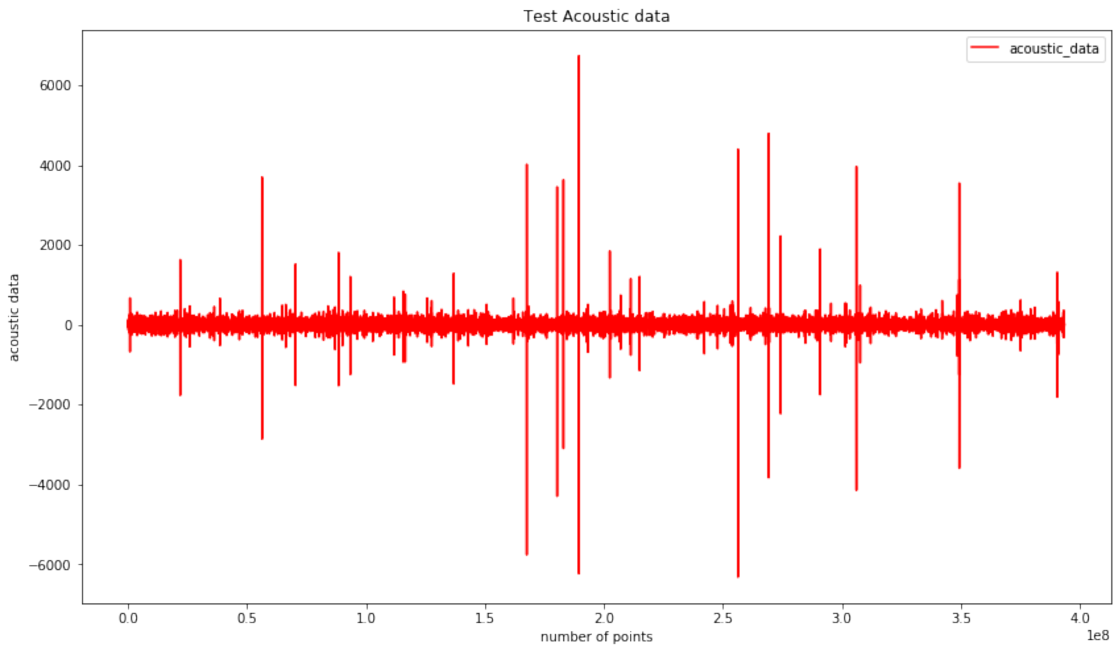
```
HBox(children=(IntProgress(value=0, max=2624), HTML(value='')))
```

```
In [40]: #total number of datapoints in test
         len(whole_test)
```

```
Out[40]: 393600000
```

```
In [39]: #plotting test data
         fig = plt.figure(figsize=(14, 8))

         plt.plot(whole_test,color='r',label='acoustic_data')
         plt.title('Test Acoustic data')
         plt.xlabel('number of points')
         plt.ylabel('acoustic data')
```

```
plt.legend()
plt.show()
```



Checking for Null values

```
In [41]: train.isnull().any().any()
```

```
Out[41]: False
```

There are no null values in the whole training data

```
In [46]: #n = 100  # the larger n is, the smoother curve will be
         #b = [1.0 / n] * n
         #a = 1
         #x = lfilter(b,a,train.acoustic_data)
```

```
In [8]: #http://gilestrolab.github.io/pyrem/pyrem.univariate.html
        #http://pyeeg.sourceforge.net/
        #returns acivity, mobility and complexity of the signal
        def hjorth(a):

            first_deriv = np.diff(a)
            second_deriv = np.diff(a,2)

            var_zero = np.mean(a ** 2)
            var_d1 = np.mean(first_deriv ** 2)
```

```
    var_d2 = np.mean(second_deriv ** 2)

    activity = var_zero
    mobility = np.sqrt(var_d1 / var_zero)
    complexity = np.sqrt(var_d2 / var_d1) / mobility

    return activity, mobility, complexity

#returns the coefficient of linear regression
def add_trend_feature(arr, abs_values=False):
    idx = np.array(range(len(arr)))
    if abs_values:
        arr = np.abs(arr)
    lr = LinearRegression()
    lr.fit(idx.reshape(-1, 1), arr)
    return lr.coef_[0]
```

1.2.6 Featurizing the data

```
In [9]: # Create a training file with simple features

        rows = 150000
        segments = int(np.floor(train.shape[0] / rows))
        X_train = pd.DataFrame(index=range(segments), dtype=np.float64,
                               columns=['peak_count','peak_std','peak_mean','trend','hjorth_0'
                                        'std', 'max', 'min','skew','kurt','max/min','max-min',
                                        'percentile_99.99','percentile_99.95','Rmean','Rstd','
                                        'percentile_99.9' ,'Moving_avg_10_mean','Moving_avg_50
                                        'exp_Moving_avg_10_mean','Moving_avg_500_mean','Moving
                                        'exp_Moving_avg_500_mean','exp_Moving_avg_5000_mean',
                                        'percentile_99','consec_diff_mean','std_f_10000','std_
                                        'iqr','Moving_avg_500_std','Moving_avg_5000_std','Movi
                                        'exp_Moving_avg_50000_mean','Moving_avg_50000_mean','s
                                        'Hilbert_mean','Hann_window_mean','Moving_avg_50_std',
        #
        y_train = pd.DataFrame(index=range(segments), dtype=np.float64,
                               columns=['time_to_failure'])

In [101]: X_train.shape

Out[101]: (4194, 48)

In [10]: import warnings
         warnings.filterwarnings("ignore")

         from tqdm.auto import tqdm
         for segment in tqdm(range(segments)):
             seg = train.iloc[segment*rows:segment*rows+rows]
             x = seg['acoustic_data'].values
```

```
#fourier transform
z = np.fft.fft(x)
dfx=pd.DataFrame(x,columns=['acoustic_data'])
y = seg['time_to_failure'].values[-1]
y_train.loc[segment, 'time_to_failure'] = y
imagFFT = np.imag(z)


X_train.loc[segment, 'trend']=add_trend_feature(x, abs_values=False)
#activity,mobility and complexity
X_train.loc[segment, 'hjorth_0'] =hjorth(x)[0]
X_train.loc[segment, 'hjorth_1'] =hjorth(x)[1]
X_train.loc[segment, 'hjorth_2'] =hjorth(x)[2]
#X_train.loc[segment, 'dfa'] =dfa(x, Ave=None, L=None)

#returns the peak of the signal
peaks=scipy.signal.find_peaks(x,100)[1]['peak_heights']
X_train.loc[segment, 'peak_count']=len(peaks)
X_train.loc[segment, 'peak_std']=np.std(peaks)
X_train.loc[segment, 'peak_mean']=np.mean(peaks)

# considering the real part of fft
realFFT = np.real(z)

X_train.loc[segment, 'Rmean'] = realFFT.mean()
X_train.loc[segment, 'Rstd'] = realFFT.std()
X_train.loc[segment, 'Rmax'] = realFFT.max()
X_train.loc[segment, 'Rmin'] = realFFT.min()

#statistical features
X_train.loc[segment, 'ave'] = x.mean()
X_train.loc[segment, 'std'] = x.std()
X_train.loc[segment, 'max'] = x.max()
X_train.loc[segment, 'min'] = x.min()
X_train.loc[segment, 'skew'] =skew(x)
X_train.loc[segment, 'kurt'] = kurtosis(x)
X_train.loc[segment, 'median'] = np.median(x)
X_train.loc[segment, 'percentile_0.01'] = np.percentile(x,0.01)
X_train.loc[segment, 'percentile_99.99'] = np.percentile(x,99.99)
X_train.loc[segment, 'percentile_99.95'] = np.percentile(x,99.95)
X_train.loc[segment, 'percentile_0.05'] = np.percentile(x,0.05)
X_train.loc[segment, 'percentile_99.9'] = np.percentile(x,99.9)
X_train.loc[segment, 'percentile_99'] = np.percentile(x,99)
X_train.loc[segment, 'std_f_10000'] = x[0:10000].std()
X_train.loc[segment, 'std_l_10000'] = x[40000:50000].std()
X_train.loc[segment, 'std_f_50000'] = x[0:50000].std()
X_train.loc[segment, 'std_l_50000'] = x[100000:150000].std()
X_train.loc[segment, 'max/min'] = x.max()/x.min()
```

```
        X_train.loc[segment, 'max-min'] = x.max()-x.min()
        X_train.loc[segment, 'iqr'] = np.subtract(*np.percentile(x, [75, 25]))

        #moving and exponential moving averages
        X_train.loc[segment, 'Moving_avg_50_std'] = dfx['acoustic_data'].rolling(window=50
        X_train.loc[segment, 'Moving_avg_10_std'] = dfx['acoustic_data'].rolling(window=10
        X_train.loc[segment, 'Moving_avg_500_std'] = dfx['acoustic_data'].rolling(window=5
        X_train.loc[segment, 'Moving_avg_5000_std'] = dfx['acoustic_data'].rolling(window=
        X_train.loc[segment, 'Moving_avg_50000_std'] = dfx['acoustic_data'].rolling(windo
        X_train.loc[segment, 'Hilbert_mean'] = np.abs(hilbert(x)).mean()
        X_train.loc[segment, 'Hann_window_mean'] = (convolve(x, hann(150), mode='same') /
        X_train.loc[segment, 'Moving_avg_50_mean'] = dfx['acoustic_data'].rolling(window=5
        X_train.loc[segment, 'Moving_avg_10_mean'] = dfx['acoustic_data'].rolling(window=1
        X_train.loc[segment, 'Moving_avg_500_mean'] = dfx['acoustic_data'].rolling(window=
        X_train.loc[segment, 'Moving_avg_5000_mean'] = dfx['acoustic_data'].rolling(windo
        X_train.loc[segment, 'Moving_avg_50000_mean'] = dfx['acoustic_data'].rolling(windo
        ewma = pd.Series.ewm
        X_train.loc[segment, 'exp_Moving_avg_50_mean'] = (ewma(dfx['acoustic_data'], span=
        X_train.loc[segment, 'exp_Moving_avg_10_mean'] = (ewma(dfx['acoustic_data'], span=
        X_train.loc[segment, 'exp_Moving_avg_500_mean'] = (ewma(dfx['acoustic_data'], span
        X_train.loc[segment, 'exp_Moving_avg_5000_mean'] = (ewma(dfx['acoustic_data'], spa
        X_train.loc[segment, 'exp_Moving_avg_50000_mean'] = (ewma(dfx['acoustic_data'], sp

        #taking the difference between consecutive samples and mean.
        cc=dfx['acoustic_data']- dfx['acoustic_data'].shift(-1)
        cv=cc.fillna(dfx['acoustic_data'].tail(1))
        X_train.loc[segment, 'consec_diff_mean'] = cv.mean()
```

```
HBox(children=(IntProgress(value=0, max=4194), HTML(value='')))
```

In [11]:
```
X_train.head()
```

Out[11]:

```
   peak_count   peak_std   peak_mean         trend   hjorth_0  hjorth_1  \
0         1.0   0.000000  104.000000 -3.268300e-06  49.875673  0.480837
1        13.0  23.206049  127.307692  9.090424e-07  65.745180  0.453286
2         6.0  13.148722  110.666667  3.962182e-06  72.616993  0.440686
3        11.0  37.245666  144.181818  1.637207e-06  68.454693  0.448160
4         7.0  10.669430  127.857143 -6.668392e-07  77.401387  0.416186

   hjorth_2       ave       std    max  ...  exp_Moving_avg_50000_mean  \
0  2.949767  4.884113  5.101089  104.0  ...                   4.953219
1  2.918704  4.725767  6.588802  181.0  ...                   4.720102
2  2.950026  4.906393  6.967374  140.0  ...                   4.842499
3  2.924000  4.902240  6.922282  197.0  ...                   4.887399
4  3.172026  4.908720  7.301086  145.0  ...                   4.923698
```

```
   Moving_avg_50000_mean  std_f_50000  std_l_50000  Hilbert_mean  \
0               4.930208     6.488487     3.664627      7.027028
1               4.719066     7.305160     5.493016      7.380383
2               4.907583     6.104775     8.603610      8.016930
3               4.876404     6.238047     5.652385      7.606850
4               4.940916     5.323776     7.694429      7.895403

   Hann_window_mean  Moving_avg_50_std  Moving_avg_10_std  median  std_l_10000
0          4.883327           4.011743           3.507118     5.0     4.653028
1          4.725049           4.379248           3.761435     5.0     5.287957
2          4.905511           4.849219           4.080841     5.0     5.318101
3          4.901428           4.475839           3.788192     5.0     5.079281
4          4.908115           4.700727           3.835604     5.0     4.607163

[5 rows x 50 columns]
```

In [12]:
```python
#since peak_std and peak_mean will be null if there are no peaks in the signal
print(X_train.isnull().any().any())
#filling null values with zero
X_train2=X_train.fillna(0)
```

```
True
```

In [13]:
```python
X_train2.head()
```

Out[13]:
```
   peak_count  peak_std   peak_mean         trend   hjorth_0  hjorth_1  \
0         1.0  0.000000  104.000000 -3.268300e-06  49.875673  0.480837
1        13.0 23.206049  127.307692  9.090424e-07  65.745180  0.453286
2         6.0 13.148722  110.666667  3.962182e-06  72.616993  0.440686
3        11.0 37.245666  144.181818  1.637207e-06  68.454693  0.448160
4         7.0 10.669430  127.857143 -6.668392e-07  77.401387  0.416186

   hjorth_2       ave       std   max  ...  exp_Moving_avg_50000_mean  \
0  2.949767  4.884113  5.101089  104.0  ...                   4.953219
1  2.918704  4.725767  6.588802  181.0  ...                   4.720102
2  2.950026  4.906393  6.967374  140.0  ...                   4.842499
3  2.924000  4.902240  6.922282  197.0  ...                   4.887399
4  3.172026  4.908720  7.301086  145.0  ...                   4.923698

   Moving_avg_50000_mean  std_f_50000  std_l_50000  Hilbert_mean  \
0               4.930208     6.488487     3.664627      7.027028
1               4.719066     7.305160     5.493016      7.380383
2               4.907583     6.104775     8.603610      8.016930
3               4.876404     6.238047     5.652385      7.606850
4               4.940916     5.323776     7.694429      7.895403

   Hann_window_mean  Moving_avg_50_std  Moving_avg_10_std  median  std_l_10000
```

0	4.883327	4.011743	3.507118	5.0	4.653028
1	4.725049	4.379248	3.761435	5.0	5.287957
2	4.905511	4.849219	4.080841	5.0	5.318101
3	4.901428	4.475839	3.788192	5.0	5.079281
4	4.908115	4.700727	3.835604	5.0	4.607163

[5 rows x 50 columns]

In [90]:
```
#standardizing the data
scaler = StandardScaler()
scaler.fit(X_train2)
X_train_scaled = scaler.transform(X_train2)
#X_test_scaled = scaler.transform(X_train2[3701:])
```

Tried denoising the data using a filter but the results were same.

1.3 Machine Learning Models

In [192]:
```
# utility function to plot the output
def plot_op(y_predicted):
    plt.figure(figsize=(12,6))
    plt.plot(y_train,label='Time to Failure')
    plt.plot(y_predicted,label='Predicted Time to Failure')
    plt.xlabel('index')
    plt.ylabel('Time to failure')
    plt.legend()
    plt.title('Predictions')
    plt.show()

#to plot feature importances of respective models
def plot_importance(clf):
    fig, ax = plt.subplots(figsize=(15, 10))

    my_dict={}
    #getting feature names and score
    for a,b in zip(X_train.columns,clf.feature_importances_):
        my_dict[a]=b
    import collections
    #to get top 10 features
    c = collections.Counter(my_dict)
    g=c.most_common(10)
    keys=[]
    values=[]
    for i in range(len(g)):
        keys.append(g[i][0])
        values.append(g[i][1])
    plt.bar(keys,values)
    plt.title('feature importances')
```

```
plt.xlabel('features')
plt.show()
```

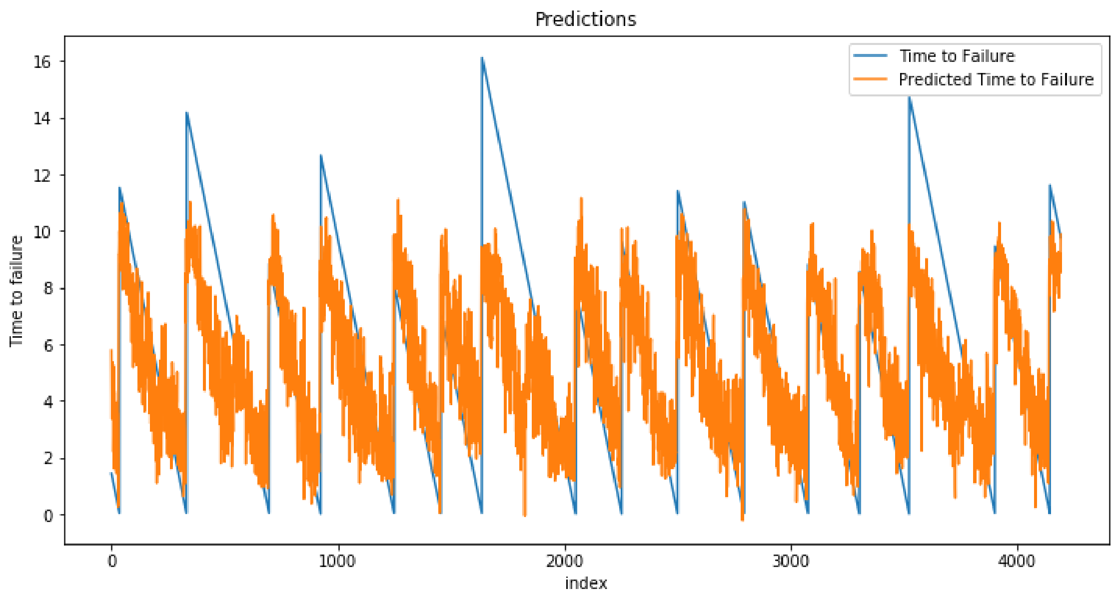
1.3.1 SVM

```
In [86]: #finding the hyperparameters using gridsearchcv
         alphalist=np.concatenate([np.linspace(0.001, 1, 50), np.linspace(1, 100, 10)]).tolist
         grid={"C":alphalist}
         svm=SVR(degree=3, tol=0.001, shrinking=True, verbose=False, max_iter=-1)
         clf1=GridSearchCV(svm,grid,cv=5,n_jobs=-1,scoring='neg_mean_absolute_error',verbose=1
         clf1.fit(X_train_scaled,y_train.values.flatten())
         print('The best parameters are :',clf1.best_params_)
         print('The best score is:',clf1.best_score_)
```

```
Fitting 5 folds for each of 60 candidates, totalling 300 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 24 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    3.1s
[Parallel(n_jobs=-1)]: Done 152 tasks      | elapsed:   24.4s
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:   48.9s finished


The best parameters are : {'C': 0.775734693877551}
The best score is: -2.2334527116874776
```

```
In [235]: #predicting and plotting on train data
          svm=SVR(kernel='rbf', degree=3, tol=0.001,C=0.776,  shrinking=True, cache_size=200, 
          svm.fit(X_train_scaled, y_train.values.flatten())
          y_pred_svm=svm.predict(X_train_scaled)
          score_svm = mean_absolute_error(y_train.values.flatten(), y_pred_svm)
          print('Mean Absolute Error on test data is: {0:.3f}'.format(score_svm))
          plot_op(y_pred_svm)
```

```
Mean Absolute Error on test data is: 2.084
```



The model predicts well but does not fit to the peak points

1.3.2 XGBOOST

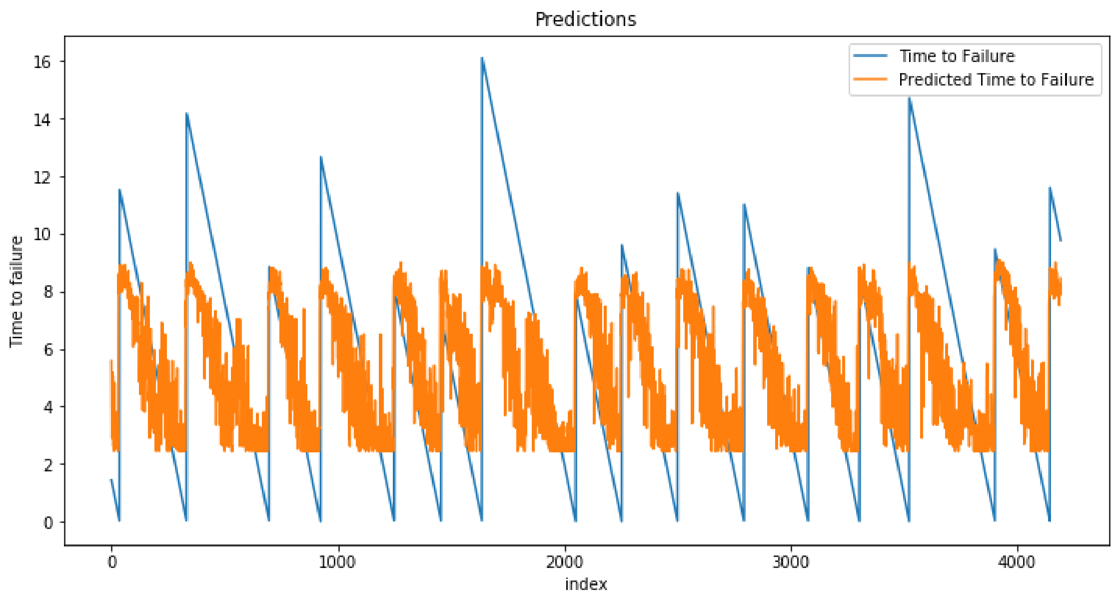
In [199]:
```
#finding the hyperparameters using gridsearchcv
grid={'n_estimators':[int(i) for i in np.linspace(1, 100, 50).tolist()], 'max_depth'
#train_pool = Pool(X_train_scaled,train_y)
xg = xgb.XGBRegressor(verbose=10,n_jobs=-1)
clf5=GridSearchCV(xg,grid,cv=5,n_jobs=-1,scoring='neg_mean_absolute_error',verbose=1
clf5.fit(X_train_scaled,y_train.values.flatten())
print('The best parameters are :',clf5.best_params_)
print('The best score is:',clf5.best_score_)
```

```
Fitting 5 folds for each of 500 candidates, totalling 2500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 24 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done 547 tasks      | elapsed:   10.1s
[Parallel(n_jobs=-1)]: Done 825 tasks      | elapsed:   19.1s
[Parallel(n_jobs=-1)]: Done 1175 tasks      | elapsed:   37.1s
[Parallel(n_jobs=-1)]: Done 1625 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 2175 tasks      | elapsed:  2.0min


The best parameters are : {'n_estimators': 25, 'max_depth': 2}
The best score is: -2.2120059371338825
```

```
[Parallel(n_jobs=-1)]: Done 2500 out of 2500 | elapsed:  2.8min finished
```

In [236]:
```
#predicting on training data to visualize the output
import xgboost as xgb
xg = xgb.XGBRegressor(verbose=10,n_jobs=-1,n_estimators=25, max_depth=2)

xg.fit(X_train_scaled,y_train.values.flatten())
y_pred_xgb=xg.predict(X_train_scaled)
score_xgb = mean_absolute_error(y_train.values.flatten(), y_pred_xgb)
print('Mean Absolute Error is: {0:.3f}'.format(score_xgb))
plot_op(y_pred_xgb)
```

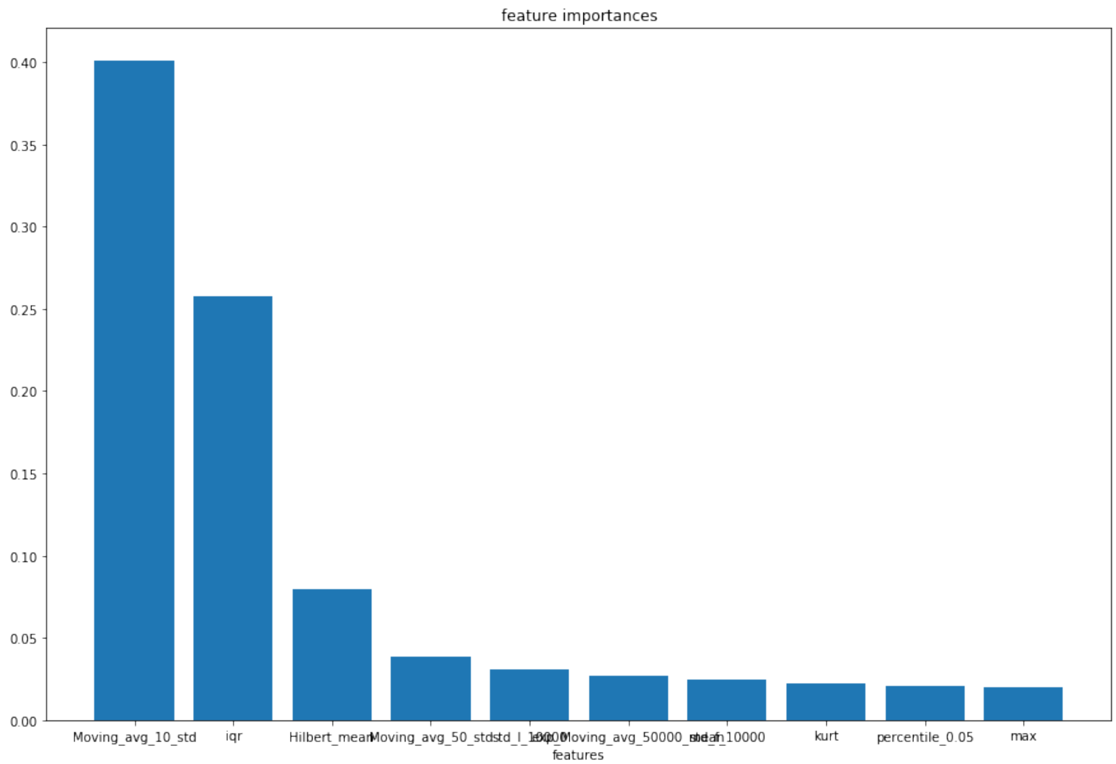
```
Mean Absolute Error is: 2.118
```



We can see that the model is not able to find the peak points

Feature Importances

In [202]:
```
plot_importance(xg)
```

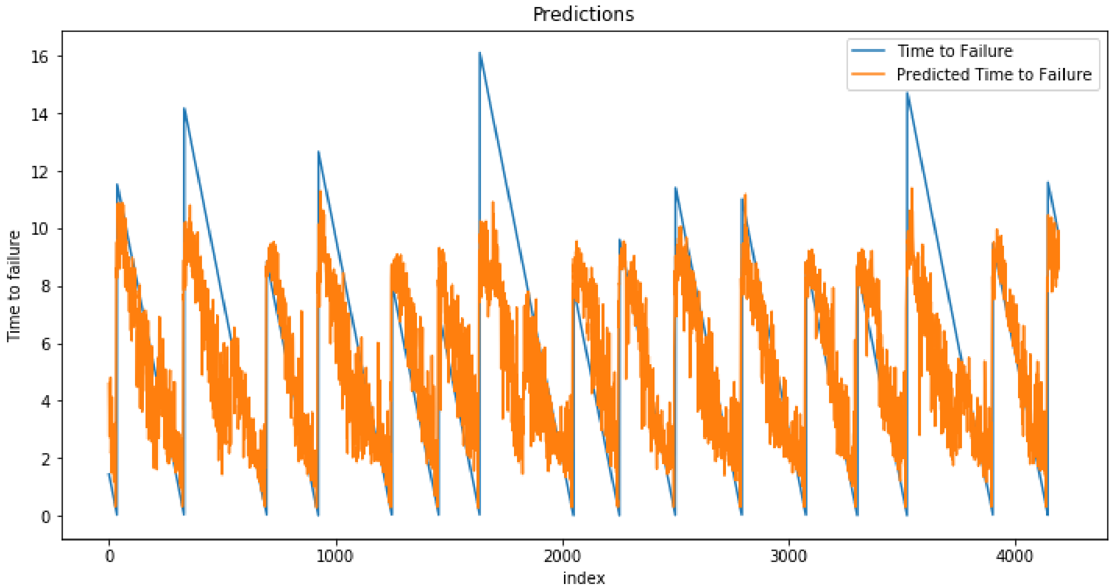


Moving_avg_std_10 is the most important feature followed by iqr

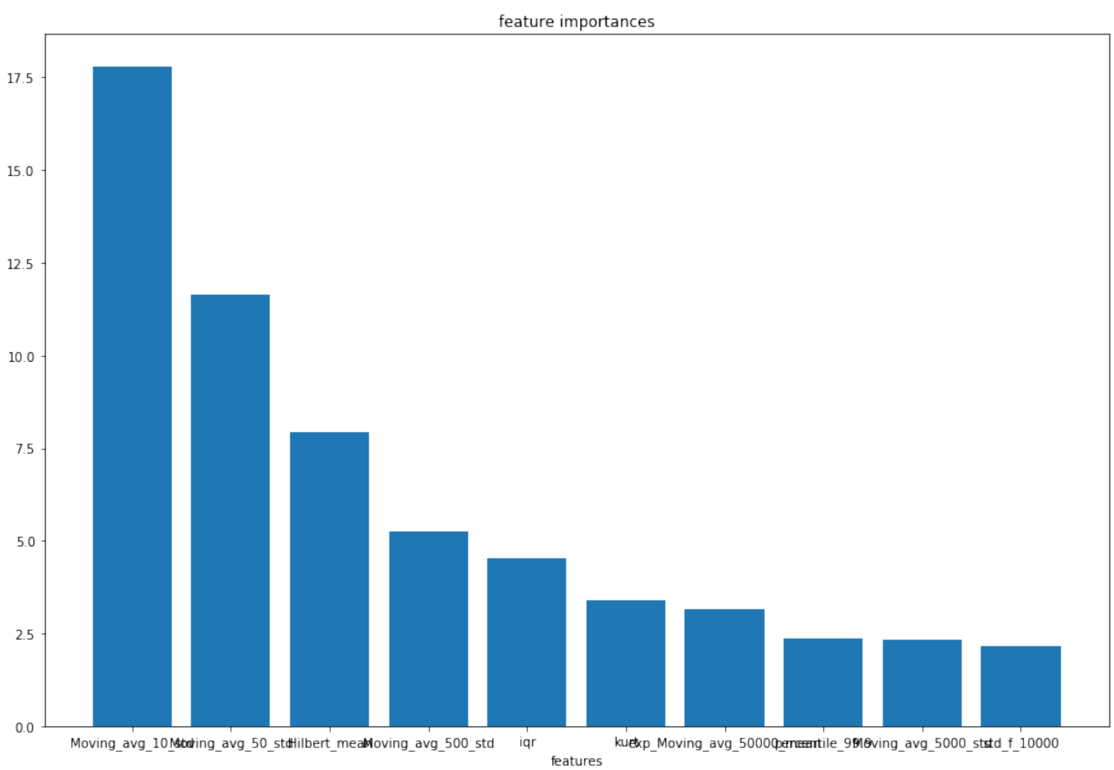
1.3.3 CatBoost Model

```
In [238]: train_pool = Pool(X_train_scaled,y_train)
          cat_model = CatBoostRegressor(
                                          boosting_type='Ordered',
                                          loss_function='MAE',
                                           iterations= 4000
                                         )

          cat_model.fit(X_train_scaled,y_train,silent=True)
          y_pred_cat=cat_model.predict(X_train_scaled)
          score_cat = mean_absolute_error(y_train.values.flatten(), y_pred_cat)
          #print(f'Score: {score:0.3f}')
          print('Mean Absolute Error is: {0:.3f}'.format(score_cat))
          plot_op(y_pred_cat)
```

```
Mean Absolute Error is: 1.824
```




```
In [194]: plot_importance(cat_model)
```



1.3.4 Random Forest

```
In [158]: from sklearn.ensemble import RandomForestRegressor
          #finding the hyperparameters using gridsearchcv
          grid={'n_estimators':[int(i) for i in np.linspace(1, 100, 30).tolist()], 'max_depth'

          rf = RandomForestRegressor(n_jobs=-1, verbose=10)
          clf6=GridSearchCV(rf,grid,cv=10,n_jobs=-1,scoring='neg_mean_absolute_error',verbose=
          clf6.fit(X_train_scaled,y_train.values.flatten())
          print('The best parameters are :',clf6.best_params_)
          print('The best score is:',clf6.best_score_)
```

```
Fitting 10 folds for each of 180 candidates, totalling 1800 fits
```

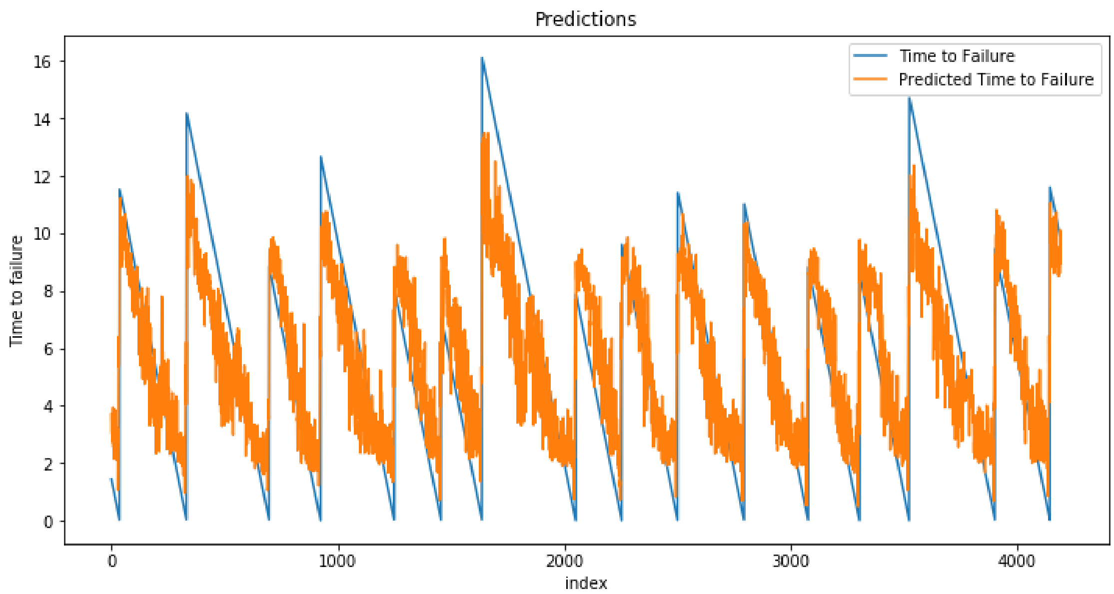
```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 24 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    2.7s
[Parallel(n_jobs=-1)]: Done 152 tasks      | elapsed:    7.1s
[Parallel(n_jobs=-1)]: Done 402 tasks      | elapsed:   19.4s
[Parallel(n_jobs=-1)]: Done 752 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 1202 tasks      | elapsed:  2.9min
[Parallel(n_jobs=-1)]: Done 1752 tasks      | elapsed:  5.7min
[Parallel(n_jobs=-1)]: Done 1800 out of 1800 | elapsed:  6.1min finished
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 24 concurrent workers.
[Parallel(n_jobs=-1)]: Done   3 out of  38 | elapsed:    0.2s remaining:    1.9s
[Parallel(n_jobs=-1)]: Done   7 out of  38 | elapsed:    0.2s remaining:    0.8s
[Parallel(n_jobs=-1)]: Done  11 out of  38 | elapsed:    0.2s remaining:    0.4s
[Parallel(n_jobs=-1)]: Done  15 out of  38 | elapsed:    0.2s remaining:    0.3s
```

```
building tree 1 of 38
building tree 2 of 38
building tree 3 of 38
building tree 4 of 38
building tree 5 of 38
building tree 6 of 38
building tree 7 of 38
building tree 8 of 38
building tree 9 of 38
building tree 10 of 38
building tree 11 of 38
building tree 12 of 38building tree 13 of 38
building tree 14 of 38
building tree 15 of 38
building tree 16 of 38
building tree 17 of 38
building tree 18 of 38
building tree 19 of 38
building tree 20 of 38
```

```
building tree 21 of 38
building tree 22 of 38

building tree 23 of 38
building tree 24 of 38
building tree 25 of 38
building tree 26 of 38
building tree 27 of 38
building tree 28 of 38
building tree 29 of 38building tree 30 of 38building tree 31 of 38
building tree 32 of 38


building tree 33 of 38building tree 34 of 38

building tree 35 of 38building tree 36 of 38
building tree 37 of 38

building tree 38 of 38
The best parameters are : {'n_estimators': 38, 'max_depth': 9}
The best score is: -2.3093861535788998


[Parallel(n_jobs=-1)]: Done  19 out of  38 | elapsed:    0.2s remaining:    0.2s
[Parallel(n_jobs=-1)]: Done  23 out of  38 | elapsed:    0.2s remaining:    0.1s
[Parallel(n_jobs=-1)]: Done  27 out of  38 | elapsed:    0.3s remaining:    0.1s
[Parallel(n_jobs=-1)]: Done  31 out of  38 | elapsed:    0.3s remaining:    0.1s
[Parallel(n_jobs=-1)]: Done  35 out of  38 | elapsed:    0.3s remaining:    0.0s
[Parallel(n_jobs=-1)]: Done  38 out of  38 | elapsed:    0.3s finished
```

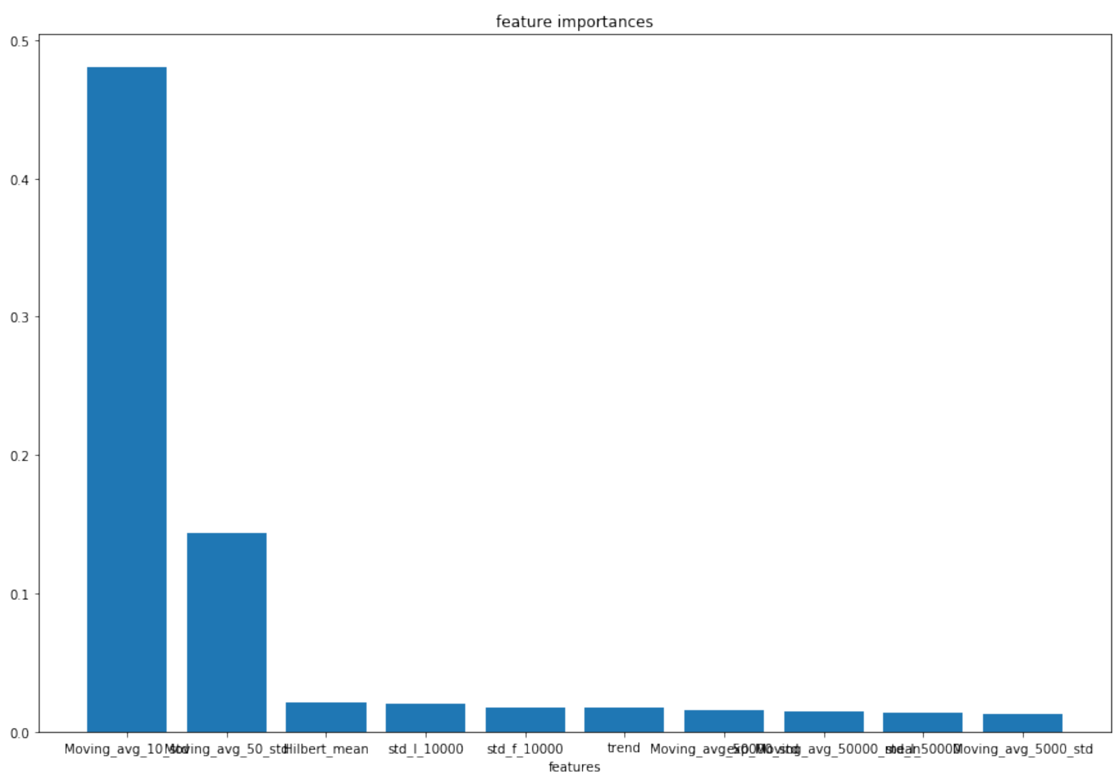
In [159]:
```
rf = RandomForestRegressor(n_jobs=-1,n_estimators=38, max_depth=9)
rf.fit(X_train_scaled,y_train.values.flatten())
y_pred_rf=rf.predict(X_train_scaled)
score_rf = mean_absolute_error(y_train.values.flatten(), y_pred_rf)
#print(f'Score: {score:0.3f}')
print('Mean Absolute Error is: {0:.3f}'.format(score_xgb))
plot_op(y_pred_rf)
```

```
Mean Absolute Error is: 2.061
```



Feature Importance

```
In [195]: plot_importance(rf)
```

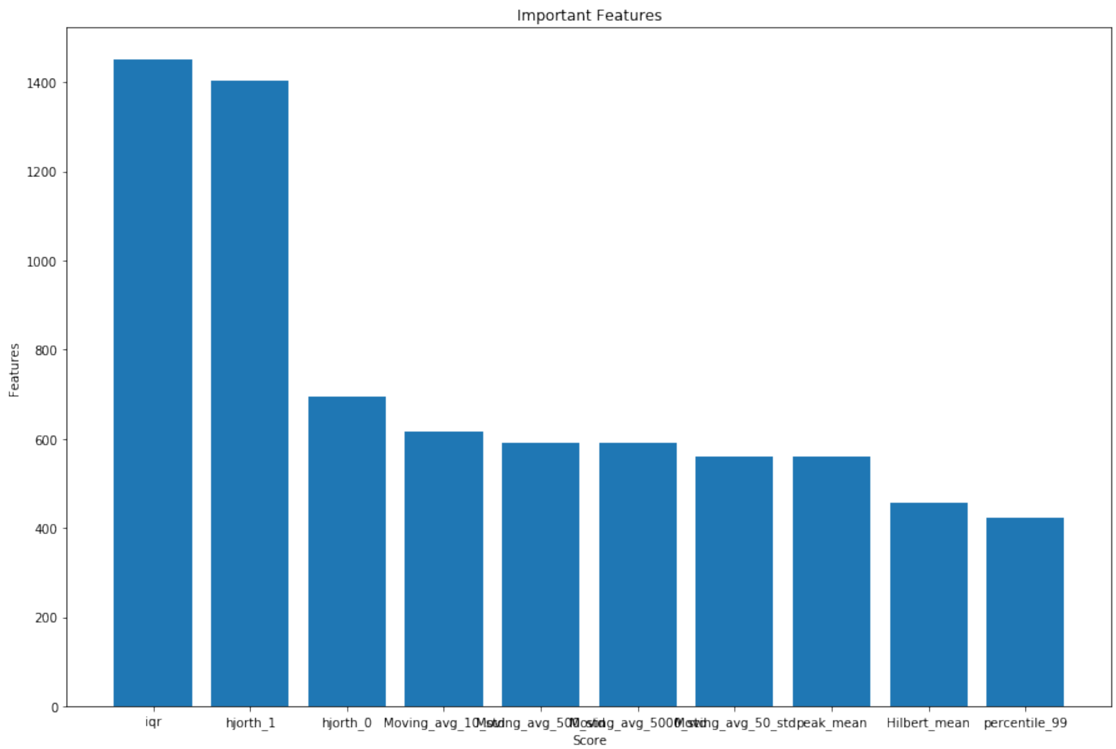


1.4 Feature Selection

In [162]:
```
import sklearn
#normalising, since sklearns selectkbest does not work with negative features
scaler = sklearn.preprocessing.MinMaxScaler()
X_train_norm=scaler.fit_transform(X_train2)
#converting to dataframe
X_train_norm=pd.DataFrame(X_train_norm,columns=X_train.columns)
```

In [184]:
```
#using sklearns selectkbest
fig, ax = plt.subplots(figsize=(15, 10))
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
X = X_train_norm
y = y_train.values.flatten().tolist()
#  extracting top 10 features
bestfeatures = SelectKBest(score_func=sklearn.feature_selection.f_regression, k=10)
fit = bestfeatures.fit(X,y)
scores_df = pd.DataFrame(fit.scores_)
columns_df = pd.DataFrame(X.columns)
#concat two dataframes for better visualization
topfeatures = pd.concat([columns_df,scores_df],axis=1)
topfeatures.columns = ['features','Score']

topfeatures=topfeatures.sort_values(by='Score',ascending=False)
print(topfeatures[0:10])
print('-----------------------------------------------------------------------------
print('-----------------------------------------------------------------------------
plt.bar(topfeatures.features[0:10],topfeatures.Score[0:10])
plt.ylabel('Features')
plt.title('Important Features')
plt.xlabel('Score')
plt.show()
```

```
              features        Score
36                 iqr  1450.318911
5             hjorth_1  1402.870727
4             hjorth_0   695.818758
47   Moving_avg_10_std   616.268155
37  Moving_avg_500_std   590.588305
38 Moving_avg_5000_std   590.221087
46   Moving_avg_50_std   559.393004
2            peak_mean   558.887042
44        Hilbert_mean   456.747846
32      percentile_99   423.174034
--------------------------------------------------------------------------------------------
--------------------------------------------------------------------------------------------
```



using only top features

In [186]:
```
X_train2.columns[[36,5,4,47,37,38,46,2,44,32]]
```

Out[186]:
```
Index(['iqr', 'hjorth_1', 'hjorth_0', 'Moving_avg_10_std',
       'Moving_avg_500_std', 'Moving_avg_5000_std', 'Moving_avg_50_std',
       'peak_mean', 'Hilbert_mean', 'percentile_99'],
      dtype='object')
```

In [187]:
```
#considering top features
X_train4=X_train2[['iqr', 'hjorth_1', 'hjorth_0', 'Moving_avg_10_std',
       'Moving_avg_500_std', 'Moving_avg_5000_std', 'Moving_avg_50_std',
       'peak_mean', 'Hilbert_mean', 'percentile_99']]
```

In [188]:
```
#since peak_std and peak_mean will be null if there are no peaks in the signal
print(X_train4.isnull().any().any())
#filling null values with zero
X_train_top=X_train4.fillna(0)

#standardizing the data
scaler = StandardScaler()
scaler.fit(X_train_top)
X_train_scaled_top = scaler.transform(X_train_top)
```

```
False
```

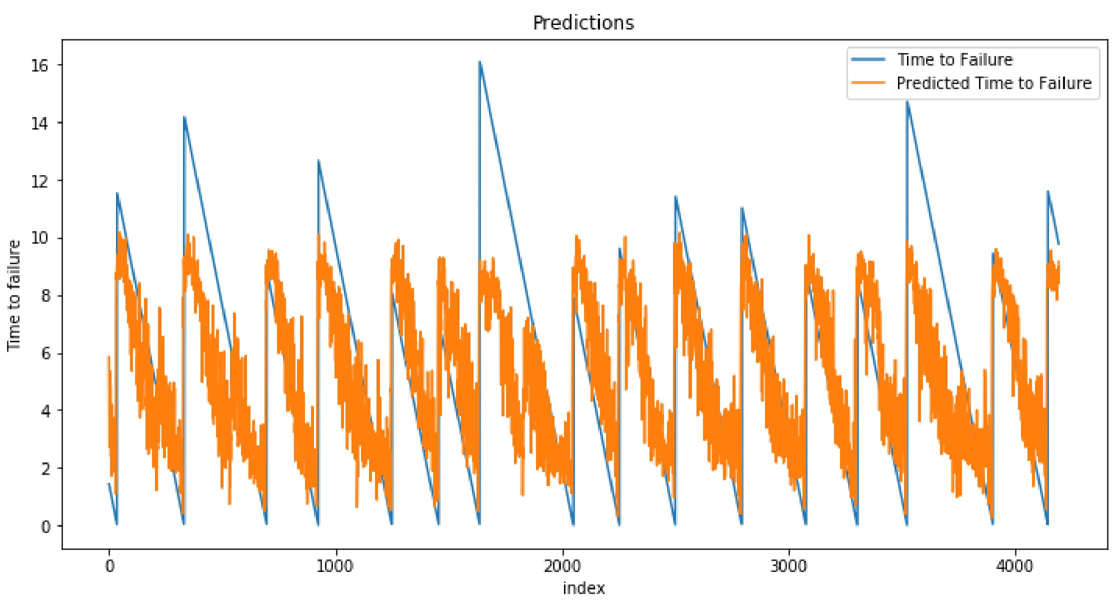
1.4.1 SVM

```
In [190]: #finding the hyperparameters using gridsearchcv
          alphalist=np.concatenate([np.linspace(0.001, 1, 50), np.linspace(1, 100, 10)]).tolis
          grid={"C":alphalist}
          svm=SVR(degree=3, tol=0.001, shrinking=True, verbose=False, max_iter=-1)
          clf1=GridSearchCV(svm,grid,cv=5,n_jobs=-1,scoring='neg_mean_absolute_error',verbose=
          clf1.fit(X_train_scaled_top,y_train.values.flatten())
          print('The best parameters are :',clf1.best_params_)
          print('The best score is:',clf1.best_score_)
```

```
Fitting 5 folds for each of 60 candidates, totalling 300 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 24 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    1.5s
[Parallel(n_jobs=-1)]: Done 152 tasks      | elapsed:   13.0s
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:   24.7s finished


The best parameters are : {'C': 1.0}
The best score is: -2.168056875251725
```

```
In [240]: #predicting and plotting on train data
          svm=SVR(kernel='rbf', degree=3, tol=0.001,C=1,  shrinking=True, cache_size=200, verbo
          svm.fit(X_train_scaled_top, y_train.values.flatten())
          y_pred_svm=svm.predict(X_train_scaled_top)
          score_svm = mean_absolute_error(y_train.values.flatten(), y_pred_svm)
          print('Mean Absolute Error on test data is: {0:.3f}'.format(score_svm))
          plot_op(y_pred_svm)
```

```
Mean Absolute Error on test data is: 2.084
```



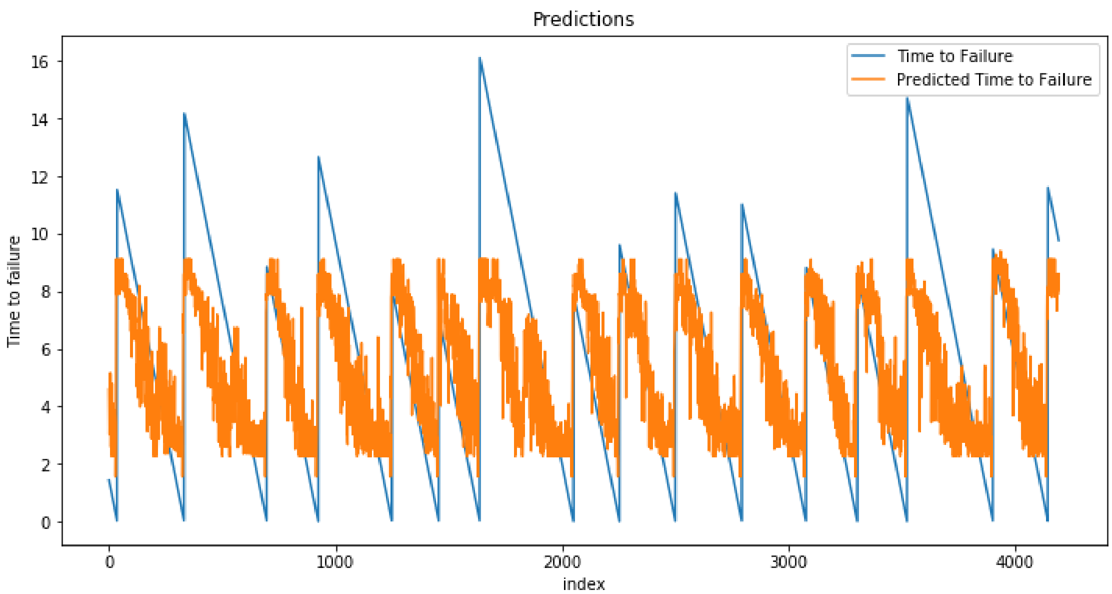
1.4.2 XGBoost

```
In [204]: #finding the hyperparameters using gridsearchcv
          grid={'n_estimators':[int(i) for i in np.linspace(1, 100, 50).tolist()], 'max_depth'
          xg = xgb.XGBRegressor(verbose=10,n_jobs=-1)
          clf7=GridSearchCV(xg,grid,cv=5,n_jobs=-1,scoring='neg_mean_absolute_error',verbose=1
          clf7.fit(X_train_scaled_top,y_train.values.flatten())
          print('The best parameters are :',clf7.best_params_)
          print('The best score is:',clf7.best_score_)
```

```
Fitting 5 folds for each of 500 candidates, totalling 2500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 24 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    3.4s
[Parallel(n_jobs=-1)]: Done 183 tasks      | elapsed:    4.4s
[Parallel(n_jobs=-1)]: Done 683 tasks      | elapsed:    8.0s
[Parallel(n_jobs=-1)]: Done 1383 tasks      | elapsed:   17.1s
[Parallel(n_jobs=-1)]: Done 1904 tasks      | elapsed:   27.8s


The best parameters are : {'n_estimators': 25, 'max_depth': 3}
The best score is: -2.1865879084428785


[Parallel(n_jobs=-1)]: Done 2500 out of 2500 | elapsed:   46.1s finished
```

```
In [241]: #predicting on training data to visualize the output
          import xgboost as xgb
          xg = xgb.XGBRegressor(verbose=10,n_jobs=-1,n_estimators=25, max_depth=3)

          xg.fit(X_train_scaled_top,y_train.values.flatten())
          y_pred_xgb=xg.predict(X_train_scaled_top)
          score_xgb = mean_absolute_error(y_train.values.flatten(), y_pred_xgb)
          #print(f'Score: {score:0.3f}')
          print('Mean Absolute Error is: {0:.3f}'.format(score_xgb))
          plot_op(y_pred_xgb)
```

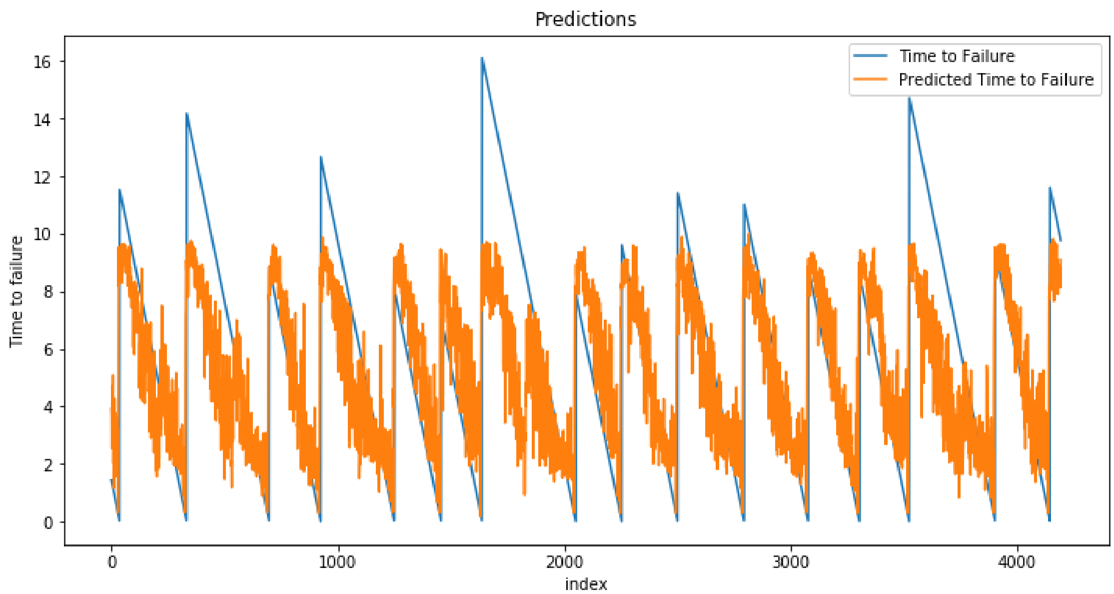
```
Mean Absolute Error is: 2.086
```



CatBoost Model

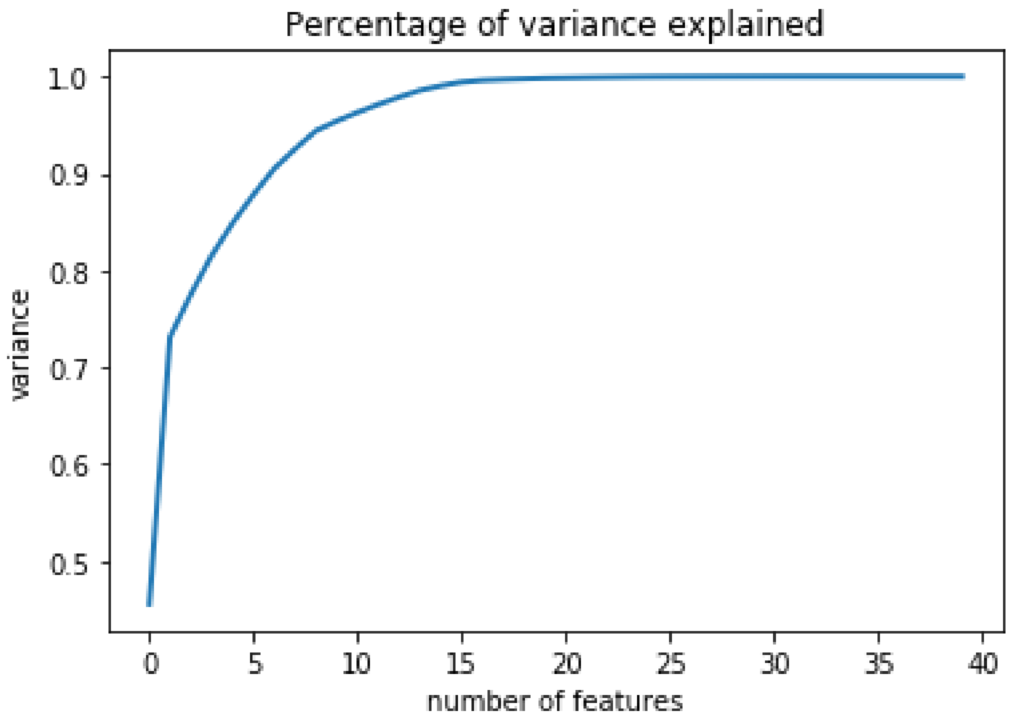
In [210]:
```
train_pool = Pool(X_train_scaled,y_train)
cat_model = CatBoostRegressor(
                                    boosting_type='Ordered',
                                    loss_function='MAE',

                                     iterations= 3000
                                   )

cat_model.fit(X_train_scaled_top,y_train,silent=True)
y_pred_cat=cat_model.predict(X_train_scaled_top)
score_cat = mean_absolute_error(y_train.values.flatten(), y_pred_cat)
#print(f'Score: {score:0.3f}')
print('Mean Absolute Error is: {0:.3f}'.format(score_cat))
#CatBoostRegressor.plot_importance(cat_model)
#1.765
plot_op(y_pred_cat)
```

```
Mean Absolute Error is: 1.960
```



1.5 Truncated SVD

In [211]:
```
#applying truncated svd with n_components =40
tsvd =TruncatedSVD(algorithm="randomized",n_components=40, n_iter=7,\
                   random_state=42,tol=0.0)
X_reduced = tsvd.fit_transform(X_train_scaled)

#plotting the percentage of the variance explained by the features
percentage_variance_explained=tsvd.explained_variance_/sum(tsvd.explained_variance_)
cum_variance_explained=np.cumsum(percentage_variance_explained)
plt.plot(cum_variance_explained,linewidth='2')
plt.xlabel("number of features")
plt.ylabel("variance")
plt.title("Percentage of variance explained")
plt.show()
```



In [212]:
```
tsvd =TruncatedSVD(algorithm="randomized",n_components=15, n_iter=7,\
                   random_state=42,tol=0.0)
tsvd_reduced = tsvd.fit_transform(X_train_scaled)
```

SVM

In [213]:
```
#finding the hyperparameters using gridsearchcv
alphalist=np.concatenate([np.linspace(0.001, 1, 50), np.linspace(1, 100, 10)]).tolis
grid={"C":alphalist}
svm=SVR(degree=3, tol=0.001, shrinking=True, verbose=False, max_iter=-1)
clf8=GridSearchCV(svm,grid,cv=5,n_jobs=-1,scoring='neg_mean_absolute_error',verbose=
clf8.fit(tsvd_reduced,y_train.values.flatten())
print('The best parameters are :',clf8.best_params_)
print('The best score is:',clf8.best_score_)
```

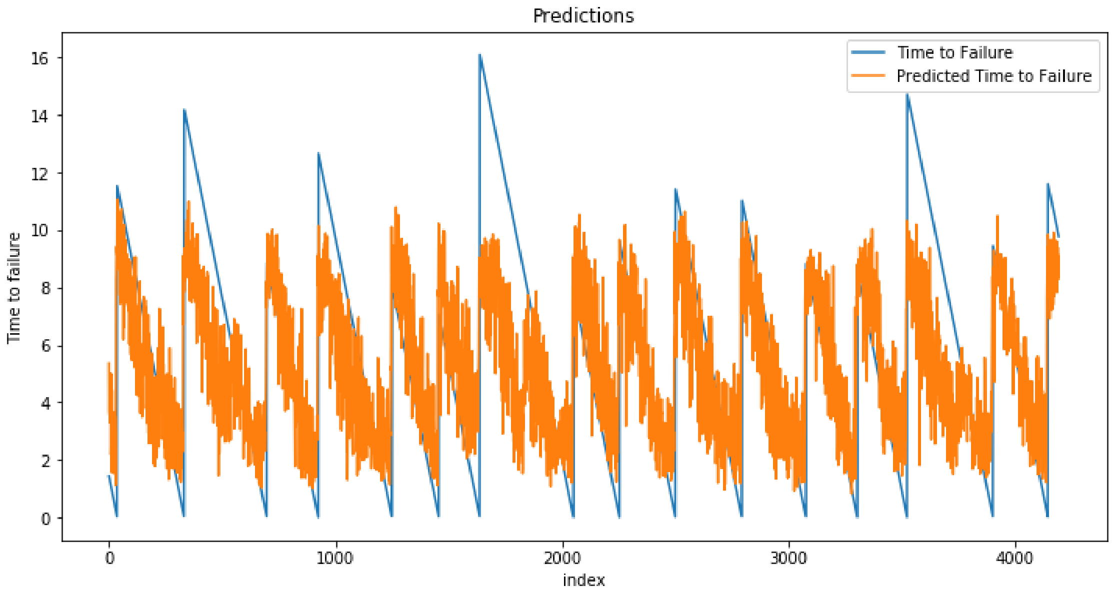
```
Fitting 5 folds for each of 60 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 24 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    1.6s
[Parallel(n_jobs=-1)]: Done 152 tasks      | elapsed:   14.5s
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:   36.1s finished
```

```
The best parameters are : {'C': 0.7349591836734695}
The best score is: -2.2871278122619496
```

```
In [214]: #predicting and plotting on train data
          svm=SVR(kernel='rbf', degree=3, tol=0.001,C=0.735,  shrinking=True, cache_size=200, v
          svm.fit(tsvd_reduced, y_train.values.flatten())
          y_pred_svm=svm.predict(tsvd_reduced)
          score_svm = mean_absolute_error(y_train.values.flatten(), y_pred_svm)
          print('Mean Absolute Error on test data is: {0:.3f}'.format(score_svm))
          plot_op(y_pred_svm)
```

```
Mean Absolute Error on test data is: 2.051
```



XGBoost

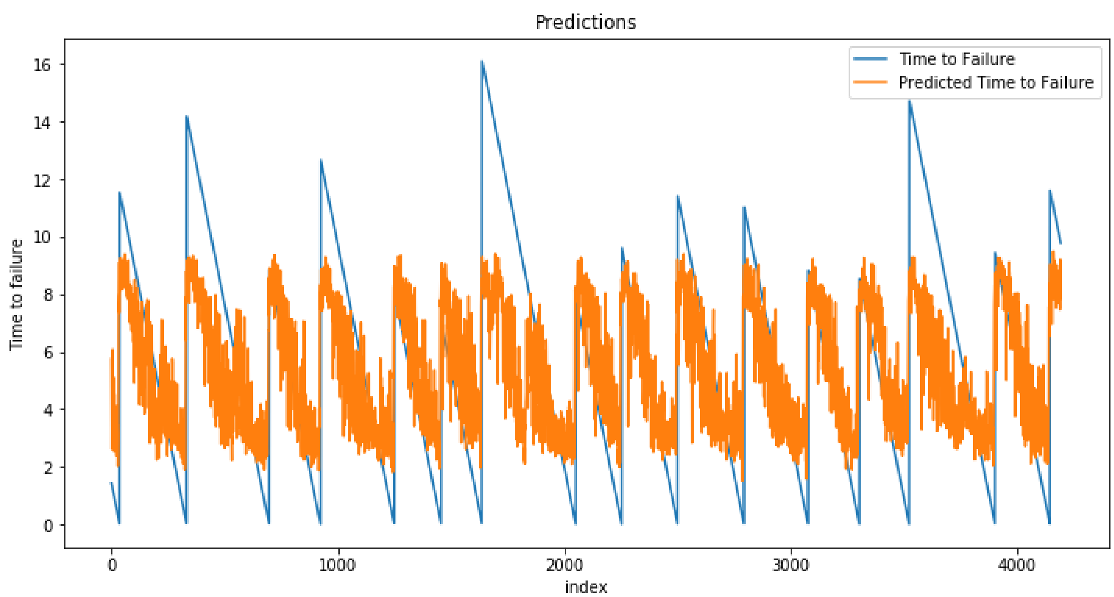
```
In [215]: #finding the hyperparameters using gridsearchcv
          grid={'n_estimators':[int(i) for i in np.linspace(1, 100, 50).tolist()], 'max_depth'

          xg = xgb.XGBRegressor(verbose=10,n_jobs=-1)
          clf9=GridSearchCV(xg,grid,cv=5,n_jobs=-1,scoring='neg_mean_absolute_error',verbose=1)
          clf9.fit(tsvd_reduced,y_train.values.flatten())
          print('The best parameters are :',clf9.best_params_)
          print('The best score is:',clf9.best_score_)
```

```
Fitting 5 folds for each of 500 candidates, totalling 2500 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 24 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.0s
[Parallel(n_jobs=-1)]: Done 931 tasks      | elapsed:   11.4s
[Parallel(n_jobs=-1)]: Done 1251 tasks      | elapsed:   18.0s
[Parallel(n_jobs=-1)]: Done 1601 tasks      | elapsed:   27.5s
[Parallel(n_jobs=-1)]: Done 2051 tasks      | elapsed:   45.6s


The best parameters are : {'n_estimators': 27, 'max_depth': 3}
The best score is: -2.2477934711856675


[Parallel(n_jobs=-1)]: Done 2500 out of 2500 | elapsed:  1.2min finished
```

```
In [216]: #predicting on training data to visualize the output
          import xgboost as xgb
          xg = xgb.XGBRegressor(verbose=10,n_jobs=-1,n_estimators=27, max_depth=3)

          xg.fit(tsvd_reduced,y_train.values.flatten())
          y_pred_xgb=xg.predict(tsvd_reduced)
          score_xgb = mean_absolute_error(y_train.values.flatten(), y_pred_xgb)

          print('Mean Absolute Error is: {0:.3f}'.format(score_xgb))
          plot_op(y_pred_xgb)
```

```
Mean Absolute Error is: 2.121
```



Submitting results

In [55]:
```
submission = pd.read_csv('sample_submission.csv', index_col='seg_id')
X_test = pd.DataFrame(columns=X_train.columns, dtype=np.float64, index=submission.inde
```

In [228]:
```
submission.head()
```

Out[228]:

	time_to_failure
seg_id	
seg_00030f	0
seg_0012b5	0
seg_00184e	0
seg_003339	0
seg_0042cc	0

In [229]:
```
for seg_id in tqdm(X_test.index):

    seg = pd.read_csv('Untitled Folder/' + seg_id + '.csv')
    x = seg['acoustic_data'].values
    z = np.fft.fft(x)
    dfx=pd.DataFrame(x,columns=['acoustic_data'])


    #returns the peak of the signal
    peaks=scipy.signal.find_peaks(x,100)[1]['peak_heights']
    X_test.loc[seg_id, 'peak_count']=len(peaks)
    X_test.loc[seg_id, 'peak_std']=np.std(peaks)
    X_test.loc[seg_id, 'peak_mean']=np.mean(peaks)


    X_test.loc[seg_id, 'trend']=add_trend_feature(x, abs_values=False)
    #X_train.loc[segment, 'dfa'] = dfa(x, Ave=None, L=None)
    X_test.loc[seg_id, 'hjorth_0'] =hjorth(x)[0]
    X_test.loc[seg_id, 'hjorth_1'] =hjorth(x)[1]
    X_test.loc[seg_id, 'hjorth_2'] =hjorth(x)[2]
    #X_train.loc[segment, 'dfa'] =dfa(x, Ave=None, L=None)

    realFFT = np.real(z)
    imagFFT = np.imag(z)
    X_test.loc[seg_id, 'Rmean'] = realFFT.mean()
    X_test.loc[seg_id, 'Rstd'] = realFFT.std()
    X_test.loc[seg_id, 'Rmax'] = realFFT.max()
    X_test.loc[seg_id, 'Rmin'] = realFFT.min()
    X_test.loc[seg_id, 'ave'] = x.mean()
    X_test.loc[seg_id, 'std'] = x.std()
    X_test.loc[seg_id, 'max'] = x.max()
    X_test.loc[seg_id, 'min'] = x.min()
    X_test.loc[seg_id, 'skew'] =skew(x)
    X_test.loc[seg_id, 'kurt'] = kurtosis(x)
```

```
        X_train.loc[segment, 'median'] = np.median(x)#not useful
        X_test.loc[seg_id, 'percentile_0.01'] = np.percentile(x,0.01)
        X_test.loc[seg_id, 'percentile_99.99'] = np.percentile(x,99.99)
        X_test.loc[seg_id, 'percentile_99.95'] = np.percentile(x,99.95)
        X_test.loc[seg_id, 'percentile_0.05'] = np.percentile(x,0.05)
        X_test.loc[seg_id, 'percentile_99.9'] = np.percentile(x,99.9)
        X_test.loc[seg_id, 'percentile_99'] = np.percentile(x,99)
        X_test.loc[seg_id, 'std'] = x.std()

        X_test.loc[seg_id, 'std_f_10000'] = x[0:10000].std()

        X_test.loc[seg_id, 'std_l_10000'] = x[140000:150000].std()
        X_test.loc[seg_id, 'std_f_50000'] = x[0:50000].std()
        X_test.loc[seg_id, 'std_l_50000'] = x[100000:150000].std()
        X_test.loc[seg_id, 'iqr'] = np.subtract(*np.percentile(x, [75, 25]))
        X_test.loc[seg_id, 'Moving_avg_50_std'] = dfx['acoustic_data'].rolling(window=50)
        X_test.loc[seg_id, 'Moving_avg_10_std'] = dfx['acoustic_data'].rolling(window=10)
        X_test.loc[seg_id, 'Moving_avg_500_std'] = dfx['acoustic_data'].rolling(window=50
        X_test.loc[seg_id, 'Moving_avg_5000_std'] = dfx['acoustic_data'].rolling(window=5
        X_test.loc[seg_id, 'Moving_avg_50000_std'] = dfx['acoustic_data'].rolling(window=
        X_test.loc[seg_id, 'Hilbert_mean'] = np.abs(hilbert(x)).mean()
        X_test.loc[seg_id, 'Hann_window_mean'] = (convolve(x, hann(150), mode='same') / s


        X_test.loc[seg_id, 'max/min'] = x.max()/x.min()
        X_test.loc[seg_id, 'max-min'] = x.max()-x.min()
        X_test.loc[seg_id, 'Moving_avg_10_mean'] = dfx['acoustic_data'].rolling(window=10
        X_test.loc[seg_id, 'Moving_avg_50_mean'] = dfx['acoustic_data'].rolling(window=50
        X_test.loc[seg_id, 'Moving_avg_500_mean'] = dfx['acoustic_data'].rolling(window=5
        X_test.loc[seg_id, 'Moving_avg_5000_mean'] = dfx['acoustic_data'].rolling(window=
        X_test.loc[seg_id, 'Moving_avg_50000_mean'] = dfx['acoustic_data'].rolling(window
        ewma = pd.Series.ewm

        X_test.loc[seg_id, 'exp_Moving_avg_50_mean'] = (ewma(dfx['acoustic_data'], span=5
        X_test.loc[seg_id, 'exp_Moving_avg_10_mean'] = (ewma(dfx['acoustic_data'], span=1
        X_test.loc[seg_id, 'exp_Moving_avg_500_mean'] = (ewma(dfx['acoustic_data'], span=
        X_test.loc[seg_id, 'exp_Moving_avg_5000_mean'] = (ewma(dfx['acoustic_data'], span
        X_test.loc[seg_id, 'exp_Moving_avg_50000_mean'] = (ewma(dfx['acoustic_data'], spa

        cc=dfx['acoustic_data']- dfx['acoustic_data'].shift(-1)
        cv=cc.fillna(dfx['acoustic_data'].tail(1))
        X_test.loc[seg_id, 'consec_diff_mean'] = cv.mean()
```

```
HBox(children=(IntProgress(value=0, max=2624), HTML(value='')))
```

```
In [244]: X_test1=X_test[['iqr', 'hjorth_1', 'hjorth_0', 'Moving_avg_10_std',
                  'Moving_avg_500_std', 'Moving_avg_5000_std', 'Moving_avg_50_std',
                  'peak_mean', 'Hilbert_mean', 'percentile_99']]
```

```
In [230]: #since peak_std and peak_mean will be null if there are no peaks in the signal
          print(X_test.isnull().any().any())
          #filling null values with zero
          X_test=X_test.fillna(0)
```

```
True
```

```
In [245]: #standardizing the data
          scaler = StandardScaler()
          scaler.fit(X_test1)
          X_test_scaled = scaler.transform(X_test1)
```

```
In [246]: #pred_stack=(xg.predict(X_test_scaled)+svm.predict(X_test_scaled)+cat_model.predict(
          pred_stack=(xg.predict(X_test_scaled)+svm.predict(X_test_scaled))/2
```

```
In [247]: submission['time_to_failure'] = pred_stack
          submission.to_csv('stacked2modelsubmissionon4.csv')
```

```
In [60]: #score=1.474
         X_test_scaled = scaler.transform(X_test)
         submission['time_to_failure'] = cat_model.predict(X_test_scaled)
         submission.to_csv('catmodel_10000_denoised_submission3.csv')
```

```
In [31]: #score=1.53
         #overfit
         X_test_scaled = scaler.transform(X_test)
         submission['time_to_failure'] = xgb.predict(X_test_scaled)
         submission.to_csv('xgb_submission.csv')
```

1.6 Conclusion

Objective:To predict the time remaining before laboratory earthquakes occur from real-time seismic data.

1. We are given a dataset with 629145480 rows and 2 columns: acoustic_data, time_to_failure, where time_to_failure is the time remaining for next earthquake.
2. We visualize the train and test data to get the pattern and observer that the there is a spike in siesmic data before earthquake occurs and there are a total of 16 earthquakes in train data.
3. We tried to denoise the signal, use Wavelet decomposition features and then apply the models, but the results did not improve.
4. We then featurize the data using simple statistical features like mean,std,moving averages etc and also signal processing features like fft, peaks, hjorth parameters.

5. Apply various machine learning models and find the right hyperparameter using gridsearchcv, compare the cross validation result and plot the corresponding feature importances.
6. Since not all features contribute to the model, we use feature selection to get the top 10 features.
7. We use sklearns selectkbest to find the top 10 features and then apply models on it and compare them and we get a slight improvement from that of considering all features
8. We use truncated svd to check the variance explained by features and get the top features which covers 95% variance and then apply models and compare them.

In [1]:
```
from prettytable import PrettyTable

x=PrettyTable()

x.field_names=['Feature Selection','Algorithm','C','max_depth','n_estimators','MAE']
x.add_row([" - ","XGB",'-',2, 25, 2.21])
x.add_row([" - ","SVM",0.775,'-', '-',2.23])
x.add_row([" - ","RF",'-',9, 38,2.30])
x.add_row(["SelectKbest","xg",'-' ,3,25,2.18])
x.add_row(["SelectKbest","SVM",1,'-', '-',2.16])
x.add_row(["tsvd","xg",'-', 3,27,2.24])
x.add_row(["tsvd","svm",0.73,'-','-',2.28])


print(x)
```

```
+-------------------+-----------+-------+-----------+--------------+------+
| Feature Selection | Algorithm |   C   | max_depth | n_estimators | MAE  |
+-------------------+-----------+-------+-----------+--------------+------+
|         -         |    XGB    |   -   |     2     |      25      | 2.21 |
|         -         |    SVM    | 0.775 |     -     |      -       | 2.23 |
|         -         |     RF    |   -   |     9     |      38      | 2.3  |
|    SelectKbest    |     xg    |   -   |     3     |      25      | 2.18 |
|    SelectKbest    |    SVM    |   1   |     -     |      -       | 2.16 |
|        tsvd       |     xg    |   -   |     3     |      27      | 2.24 |
|        tsvd       |    svm    |  0.73 |     -     |      -       | 2.28 |
+-------------------+-----------+-------+-----------+--------------+------+
```

We get a MAE of 2.16 with top 10 features using sklearns selectkbest

In [ ]: