Earthquake Prediction

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What is this competition all about?

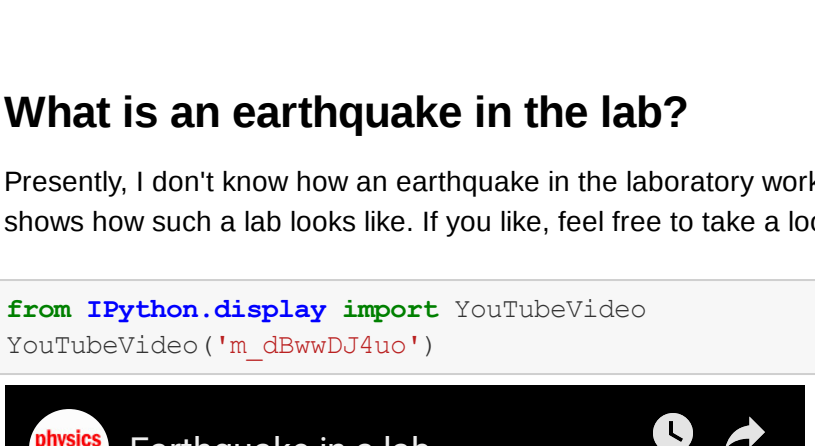
- Given seismic signals we are asked to predict the time until the onset of laboratory earthquakes.
- The training data is a single sequence of signal and seems to come from one experiment alone.
- In contrast the test data consists of several different sequences, called segments, that may correspond to different experiments. The regular pattern we might find in the train set does not match those of the test segments.
- For each test data segment with its corresponding seg_id we are asked to predict it's single time until the lab earthquake takes place.

What is an earthquake in the lab?

Presently, I don't know how an earthquake in the laboratory works. So I've googled around and found this video that shows how such a lab looks like. If you like, feel free to take a look at it. I'm still on my journey to understand the problem.

In [0]:
```
from IPython.display import YouTubeVideo
YouTubeVideo('m_dBwwDJ4uo')
```

Out[0]:



In the end we can see that the probes that are used are put under some kind of **normal pressure but there is a shear stress working on it as well**. Then, after some time, the probe splits. If you take a look at the additional material given, you can see that we have:

3 kind of plates

- 2 plates left and right that are under normal pressure: Forces are acting with 90 degree on the plate, pushing the two plates together.
- In the middle we find a third plate which is separated by some granular material. This plate moves downwards with constant velocity.

I'm not sure if I understand this right, but it seems that this granular material is the "rock" that can split and load again to produce this kind of lab earthquakes in repetitive cycles. Even though the train set contains continuous data it contains several such splits (earthquakes).

Loading Packages

In [0]:
```
# access kaggle datasets
!pip install kaggle

# math operations
!pip install numpy==1.15.0

# machine learning
!pip install catboost
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.6/dist-packages (1.5.2)
Requirement already satisfied: urllib3<1.23.0,>=1.15 in /usr/local/lib/python3.6/dist-packages
(from kaggle) (1.22)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.6/dist-packages (from kaggl
e) (1.11.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.6/dist-packages (from kaggle)
(2018.11.29)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.6/dist-packages (from
kaggle) (2.5.3)
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e) (2.18.4)
Requirement already satisfied: tqdm in /usr/local/lib/python3.6/dist-packages (from kaggle)
(4.28.1)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.6/dist-packages (from
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Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages
(from requests->kaggle) (3.0.4)
Requirement already satisfied: idna<2.7,>=2.5 in /usr/local/lib/python3.6/dist-packages (from
requests->kaggle) (2.6)
Requirement already satisfied: Unidecode>=0.04.16 in /usr/local/lib/python3.6/dist-packages (f
rom python-slugify->kaggle) (1.0.23)
Requirement already satisfied: numpy==1.15.0 in /usr/local/lib/python3.6/dist-packages (1.15.
0)
Requirement already satisfied: catboost in /usr/local/lib/python3.6/dist-packages (0.12.2)
Requirement already satisfied: numpy>=1.11.1 in /usr/local/lib/python3.6/dist-packages (from c
atboost) (1.15.0)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from catboost)
(1.11.0)
Requirement already satisfied: enum34 in /usr/local/lib/python3.6/dist-packages (from catboos
t) (1.1.6)
Requirement already satisfied: pandas>=0.19.1 in /usr/local/lib/python3.6/dist-packages (from
catboost) (0.22.0)
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pan
das>=0.19.1->catboost) (2018.9)
Requirement already satisfied: python-dateutil>=2 in /usr/local/lib/python3.6/dist-packages (f
rom pandas>=0.19.1->catboost) (2.5.3)
```

In [0]:
```
# data preprocessing
import pandas as pd

# math operations
import numpy as np

# machine learning
from catboost import CatBoostRegressor, Pool

# data scaling
from sklearn.preprocessing import StandardScaler

# hyperparameter optimization
from sklearn.model_selection import GridSearchCV

# support vector machine model
from sklearn.svm import NuSVR, SVR

# kernel ridge model
from sklearn.kernel_ridge import KernelRidge

# data visualization
import matplotlib.pyplot as plt
```

Import Dataset from Kaggle

In [0]:
```
# Colab's file access feature
from google.colab import files

# retrieve uploaded file
uploaded = files.upload()

# print results
for fn in uploaded.keys():
  print('User uploaded file "{name}" with length {length} bytes'.format(
      name=fn, length=len(uploaded[fn])))

# then move kaggle.json into the folder where the API expects to find it.
!mkdir -p ~/.kaggle/ && mv kaggle.json ~/.kaggle/ && chmod 600 ~/.kaggle/kaggle.json
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving kaggle.json to kaggle.json
User uploaded file "kaggle.json" with length 62 bytes
```

In [0]:
```
# list competitions
!kaggle competitions list
```

```
ref                                           deadline             category         reward
teamCount  userHasEntered
--------------------------------------------  -------------------  ---------------  ---------
---------  --------------
digit-recognizer                              2030-01-01 00:00:00  Getting Started  Knowledge
2617           False
titanic                                       2030-01-01 00:00:00  Getting Started  Knowledge
9973            True
house-prices-advanced-regression-techniques   2030-01-01 00:00:00  Getting Started  Knowledge
4136            True
imagenet-object-localization-challenge        2029-12-31 07:00:00  Research         Knowledge
33           False
competitive-data-science-predict-future-sales 2019-12-31 23:59:00  Playground           Kudos
2293            True
two-sigma-financial-news                      2019-07-15 23:59:00  Featured          $100,000
2897           False
LANL-Earthquake-Prediction                    2019-06-03 23:59:00  Research           $50,000
1012            True
tmdb-box-office-prediction                    2019-05-30 23:59:00  Playground       Knowledge
56           False
dont-overfit-ii                               2019-05-07 23:59:00  Playground            Swag
183           False
gendered-pronoun-resolution                   2019-04-22 23:59:00  Research           $25,000
115           False
histopathologic-cancer-detection              2019-03-30 23:59:00  Playground       Knowledge
571           False
petfinder-adoption-prediction                 2019-03-28 23:59:00  Featured           $25,000
1024           False
vsb-power-line-fault-detection                2019-03-21 23:59:00  Featured           $25,000
830            True
microsoft-malware-prediction                  2019-03-13 23:59:00  Research           $25,000
1558           False
humpback-whale-identification                 2019-02-28 23:59:00  Featured           $25,000
1777           False
elo-merchant-category-recommendation          2019-02-26 23:59:00  Featured           $50,000
3612           False
quora-insincere-questions-classification      2019-02-26 23:59:00  Featured           $25,000
4037           False
ga-customer-revenue-prediction                2019-02-15 23:59:00  Featured           $45,000
1104           False
reducing-commercial-aviation-fatalities       2019-02-12 23:59:00  Playground            Swag
160            True
pubg-finish-placement-prediction              2019-01-30 23:59:00  Playground            Swag
1534           False
```

In [0]:
```
# download earthquake dataset
!kaggle competitions download -c LANL-Earthquake-Prediction
```

```
sample_submission.csv: Skipping, found more recently modified local copy (use --force to force
download)
test.zip: Skipping, found more recently modified local copy (use --force to force download)
train.csv.zip: Skipping, found more recently modified local copy (use --force to force downloa
d)
```

In [0]:
```
# unzip training data for usage
!ls
!unzip train.csv.zip
!ls
```

```
catboost_info  sample_submission.csv  train.csv
sample_data    test.zip               train.csv.zip
Archive:  train.csv.zip
replace train.csv? [y]es, [n]o, [A]ll, [N]one, [r]ename: y
  inflating: train.csv
catboost_info  sample_submission.csv  train.csv
sample_data    test.zip               train.csv.zip
```

Exploratory Data Analysis

Let's get familiar with the data!

Training data

The total size of the train data is almost 9 GB and we don't want to wait too long just for a first impression, let's load only some rows:

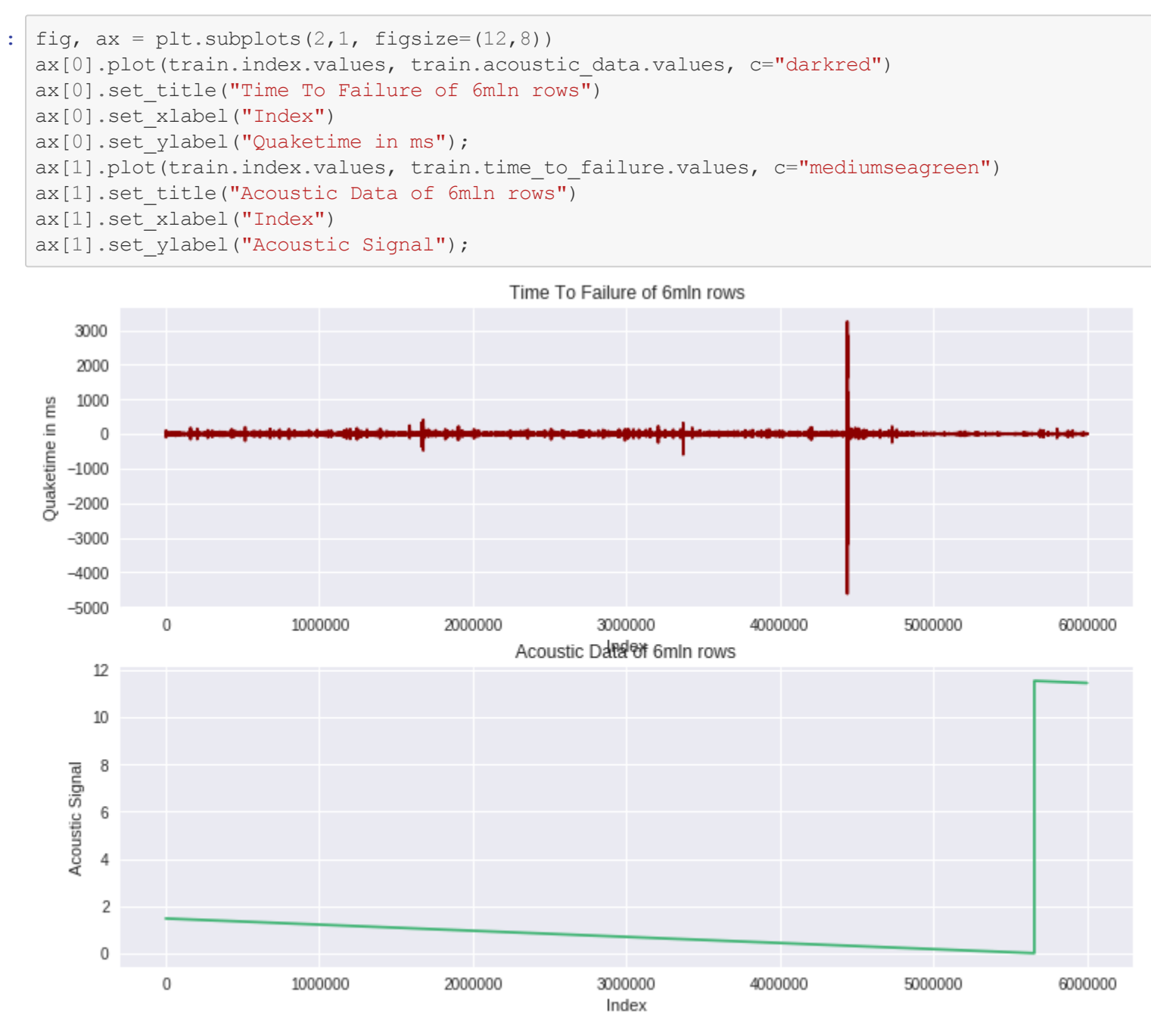
In [0]:
```
# extract training data into a dataframe for further manipulation
train = pd.read_csv('train.csv', nrows=6000000, dtype={'acoustic_data': np.int16, 'time_to_failu
re': np.float64})

# print first 10 entries
train.head(10)
```

Out[0]:

	acoustic_data	time_to_failure
0	12	1.4691
1	6	1.4691
2	8	1.4691
3	5	1.4691
4	8	1.4691
5	8	1.4691
6	9	1.4691
7	7	1.4691
8	-5	1.4691
9	3	1.4691

We see two columns: **acoustic_data** and **time_to_failure.** The former is the seismic singal and the latter corresponds to the the time (in seconds) until the next laboratory earthquake takes place.

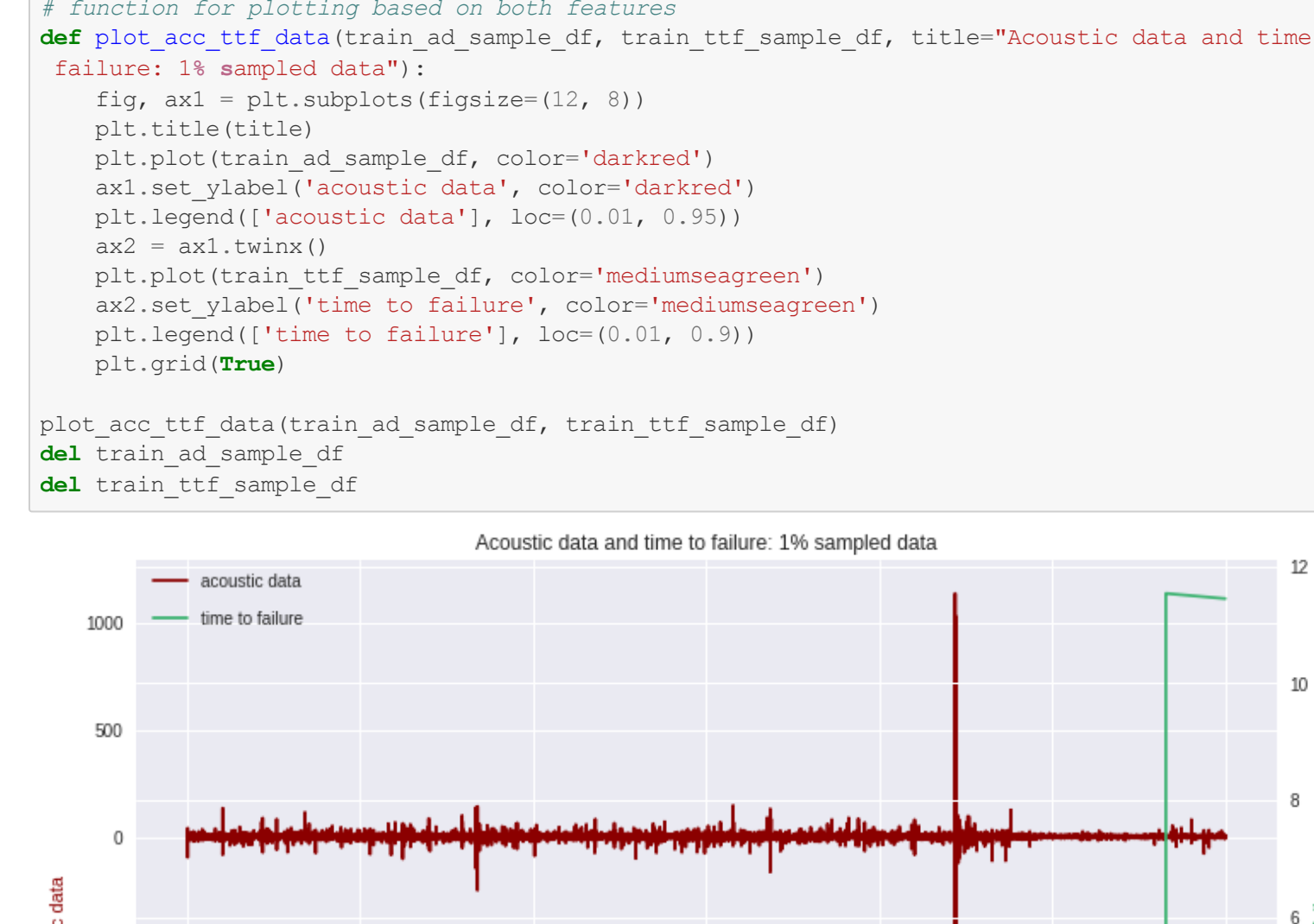
In [0]:
```
fig, ax = plt.subplots(2,1, figsize=(12,8))
ax[0].plot(train.index.values, train.acoustic_data.values, c="darkred")
ax[0].set_title("Time To Failure of 6mln rows")
ax[0].set_xlabel("Index")
ax[0].set_ylabel("Quaketime in ms");
ax[1].plot(train.index.values, train.time_to_failure.values, c="mediumseagreen")
ax[1].set_title("Acoustic Data of 6mln rows")
ax[1].set_xlabel("Index")
ax[1].set_ylabel("Acoustic Signal");
```



Observations:

- We can see only one time in 6mln rows when quaketime goes to 0. This is a timepoint where an earthquake in the lab occurs.
- There are many small oscillations until a heavy peak of the signal occurs. Then it takes some time with smaller oscillations and the earthquake occurs.

In [0]:
```
# visualize 1% of samples data, first 100 datapoints
train_ad_sample_df = train['acoustic_data'].values[::100]
train_ttf_sample_df = train['time_to_failure'].values[::100]

# function for plotting based on both features
def plot_acc_ttf_data(train_ad_sample_df, train_ttf_sample_df, title="Acoustic data and time to
 failure: 1% sampled data"):
    fig, ax1 = plt.subplots(figsize=(12, 8))
    plt.title(title)
    plt.plot(train_ad_sample_df, color='darkred')
    ax1.set_ylabel('acoustic data', color='darkred')
    plt.legend(['acoustic data'], loc=(0.01, 0.95))
    ax2 = ax1.twinx()
    plt.plot(train_ttf_sample_df, color='mediumseagreen')
    ax2.set_ylabel('time to failure', color='mediumseagreen')
    plt.legend(['time to failure'], loc=(0.01, 0.9))
    plt.grid(True)

plot_acc_ttf_data(train_ad_sample_df, train_ttf_sample_df)
del train_ad_sample_df
del train_ttf_sample_df
```



Feature Engineering

In [0]:
```
## Feature Engineering and signifiance of these statistical features

# let's create a function to generate some statistical features based on the training data
def gen_features(X):
    strain = []
    strain.append(X.mean())
    strain.append(X.std())
    strain.append(X.min())
    strain.append(X.max())
    strain.append(X.kurtosis())
    strain.append(X.skew())
    strain.append(np.quantile(X,0.01))
    strain.append(np.quantile(X,0.05))
    strain.append(np.quantile(X,0.95))
    strain.append(np.quantile(X,0.99))
    strain.append(np.abs(X).max())
    strain.append(np.abs(X).mean())
    strain.append(np.abs(X).std())
    return pd.Series(strain)
```

In [0]:
```
train = pd.read_csv('train.csv', iterator=True, chunksize=150_000, dtype={'acoustic_data': np.in
t16, 'time_to_failure': np.float64})

X_train = pd.DataFrame()
y_train = pd.Series()
for df in train:
    ch = gen_features(df['acoustic_data'])
    X_train = X_train.append(ch, ignore_index=True)
    y_train = y_train.append(pd.Series(df['time_to_failure'].values[-1]))
```

In [0]:
```
X_train.describe()
```

Out[0]:

	0	1	2	3	4	5	6	7	
count	4195.000000	4195.000000	4195.000000	4195.000000	4195.000000	4195.000000	4195.000000	4195.000000	4195
mean	4.519475	6.547788	-149.190942	163.522288	68.297997	0.125830	-11.224603	-2.184779	11
std	0.256049	8.503939	265.087984	272.930331	70.532565	0.477901	14.106852	2.346558	2
min	3.596313	2.802720	-5515.000000	23.000000	0.648602	-4.091826	-336.000000	-39.000000	9
25%	4.349497	4.478637	-154.000000	92.000000	28.090227	-0.040779	-14.000000	-3.000000	10
50%	4.522147	5.618798	-111.000000	123.000000	45.816625	0.085620	-10.000000	-2.000000	11
75%	4.693350	6.880904	-79.000000	170.000000	78.664202	0.253930	-6.000000	-1.000000	12
max	5.391993	153.703569	-15.000000	5444.000000	631.158927	4.219429	-2.000000	0.000000	50

Implement Catboost Model

In [0]:
```
# model #1 - Catboost

train_pool = Pool(X_train, y_train)
m = CatBoostRegressor(iterations=10000, loss_function='MAE', boosting_type='Ordered')
m.fit(X_train, y_train, silent=True)
m.best_score_
```

Out[0]:
```
{'learn': {'MAE': 1.7804224713035586}}
```

Not a great score, given the leaderboard's top 5 are in the mid 1.3 to 1.4

Implement Support Vector Machine + Radial Basis Function Kernel

In [0]:
```
# model #2 - Support Vector Machine w/ RBF + Grid Search

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.svm import NuSVR, SVR


scaler = StandardScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)

parameters = [{'gamma': [0.001, 0.005, 0.01, 0.02, 0.05, 0.1],
               'C': [0.1, 0.2, 0.25, 0.5, 1, 1.5, 2]}]
               #'nu': [0.75, 0.8, 0.85, 0.9, 0.95, 0.97]}]

reg1 = GridSearchCV(SVR(kernel='rbf', tol=0.01), parameters, cv=5, scoring='neg_mean_absolute_er
ror')
reg1.fit(X_train_scaled, y_train.values.flatten())
y_pred1 = reg1.predict(X_train_scaled)

print("Best CV score: {:.4f}".format(reg1.best_score_))
print(reg1.best_params_)
```

```
Best CV score: -2.1722
{'C': 2, 'gamma': 0.02}
```