```
In [0]:
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
# import dask.dataframe as dd
import numpy as np
from matplotlib import pyplot as plt
import matplotlib as mpl
from scipy import stats
from joblib import Parallel, delayed
from tqdm import tqdm notebook as tqdm
import qc
from scipy.io import wavfile #convert dataframe to sound
from IPython.core.display import HTML
from sklearn.metrics import mean absolute error
import librosa
from catboost import CatBoostRegressor,Pool
from sklearn.externals import joblib
```

Importing the data after EDA and Feature Engineering

In [0]:

```
import pickle
with open('y_train', 'rb') as f:
    y_train = pickle.load(f)

with open('x_train', 'rb') as f:
    x_train = pickle.load(f)

with open('x_test', 'rb') as f:
    x_test = pickle.load(f)
```

Dividing the data into train and CV for cross validating the error

```
In [0]:
```

```
# Divide the data into cv and train
from sklearn.model_selection import train_test_split
x_train,x_cv,y_train,y_cv = train_test_split(x_train,y_train,test_size = 0.1,random_state= 42)
```

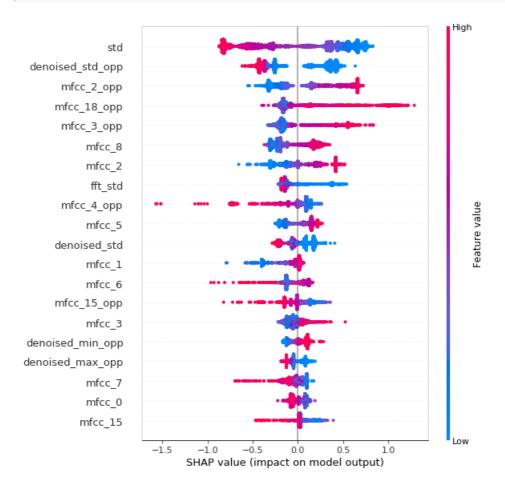
LGBM

```
In [436]:
```

```
'max bin': 500,
          'reg alpha': 0,
          'reg_lambda': 0,
          'n_jobs': 1
trn_data = lgb.Dataset(x_train, label=y_train)
val_data = lgb.Dataset(x_train, label=y_train) # Validation is not running for more iteration
hence have to keep x train only here
lgbm model = lgb.train(params, trn data, 430, valid sets = [trn data, val data], verbose eval=1000,
early stopping rounds = 1000)
4
Training until validation scores don't improve for 1000 rounds.
Did not meet early stopping. Best iteration is:
[430] training's l1: 1.90933 valid 1's l1: 1.90933
In [0]:
cv_pred_lgb = lgbm_model.predict(x_cv)
In [246]:
cv pred lgb[:10]
Out[246]:
array([ 2.07934204, 10.40320467, 6.94327691, 3.02479537, 2.56770003,
        7.28860105, 9.67783177, 6.83171589, 1.35346442, 4.48759473])
In [247]:
y cv[:10].values
Out[247]:
array([[ 1.37129712],
       [ 8.27259972],
       [ 8.60729916],
       [ 1.30829737],
       [ 1.47749618],
       [11.52579582],
       [ 9.97139798],
      [ 5.53919854],
       [ 1.8124981 ],
       [ 0.34519822]])
In [0]:
#check MAE for the CV by LGBM
y cv org = y cv.values
y_cv_pred = cv_pred_lgb[:]
lgb result cv = []
for index in range(0,len(cv_pred_lgb)):
 lgb_result_cv.append((y_cv_pred[index] - y_cv_org[index]) * (y_cv_pred[index] - y_cv_org[index]))
sum_lgb_cv = sum(lgb_result_cv)
sum_lgb_cv_mean = sum_lgb_cv / len(cv_pred_lgb)
In [249]:
print(sum_lgb_cv_mean) # This is the MAE on CV data and it's looking good
# 6.01725782 at 512
# 6.00538636 at 500
#6.00431808 at 450
# 6.04327404 at 400
# 6.00064977 at 430
# 433 6.00587812
```

[6.00064977]

In [0]:



CatModel

In [437]:

```
from catboost import CatBoostRegressor, Pool
cat model = CatBoostRegressor(
            iterations=1200, learning rate=0.018999, verbose=32, eval metric='MAE', task type='GPU'
# clf = CatBoostRegressor(n estimators=8000, verbose=1000, objective="MAE",
boosting type="Ordered", task type="GPU", learning rate=0.04)
cat model.fit(x train,y train)
#0.95 previously with 30k
0: learn: 3.0182080 total: 27.3ms remaining: 32.7s
32: learn: 2.4058942 total: 828ms remaining: 29.3s
64: learn: 2.1784222 total: 1.56s remaining: 27.3s
96: learn: 2.0891010 total: 2.28s remaining: 26s
128: learn: 2.0442392 total: 3s remaining: 24.9s
160: learn: 2.0170533 total: 3.71s remaining: 24s
192: learn: 1.9975570 total: 4.44s remaining: 23.1s
224: learn: 1.9817937 total: 5.15s remaining: 22.3s
256: learn: 1.9683053 total: 5.84s remaining: 21.4s
288: learn: 1.9567136 total: 6.54s remaining: 20.6s
320: learn: 1.9460469 total: 7.22s remaining: 19.8s
352: learn: 1.9364790 total: 7.92s remaining: 19s
```

```
384: learn: 1.9258085 total: 8.62s remaining: 18.2s
416: learn: 1.9167980 total: 9.35s remaining: 17.6s
448: learn: 1.9068044 total: 10s remaining: 16.8s
480: learn: 1.8972855 total: 10.7s remaining: 16s
512: learn: 1.8881666 total: 11.4s remaining: 15.3s
544: learn: 1.8783269 total: 12.1s remaining: 14.5s
576: learn: 1.8694957 total: 12.8s remaining: 13.8s
608: learn: 1.8599568 total: 13.5s remaining: 13.1s
640: learn: 1.8509963 total: 14.2s remaining: 12.4s
672: learn: 1.8419957 total: 14.9s remaining: 11.6s
704: learn: 1.8334088 total: 15.6s remaining: 10.9s
736: learn: 1.8258503 total: 16.3s remaining: 10.2s
768: learn: 1.8169122 total: 16.9s remaining: 9.5s
800: learn: 1.8103068 total: 17.7s remaining: 8.79s
832: learn: 1.8027500 total: 18.3s remaining: 8.08s
864: learn: 1.7951070 total: 19s remaining: 7.38s
896: learn: 1.7889291 total: 19.8s remaining: 6.67s
928: learn: 1.7814416 total: 20.4s remaining: 5.96s
960: learn: 1.7745809 total: 21.2s remaining: 5.26s
992: learn: 1.7680718 total: 21.9s remaining: 4.55s
1024: learn: 1.7612609 total: 22.5s remaining: 3.85s
1056: learn: 1.7554470 total: 23.3s remaining: 3.15s
1088: learn: 1.7486837 total: 24s remaining: 2.44s
1120: learn: 1.7421579 total: 24.6s remaining: 1.74s
1152: learn: 1.7355475 total: 25.4s remaining: 1.03s
1184: learn: 1.7301652 total: 26.1s remaining: 330ms
1199: learn: 1.7277503 total: 26.4s remaining: Ous
```

Out[437]:

<catboost.core.CatBoostRegressor at 0x7f0ebe6ea3c8>

In [289]:

```
#Check MAE on CV using catBoost model
cv pred cat = cat model.predict(x cv)
cat result cv = []
for index in range(0,len(cv pred cat)):
 cat_result_cv.append((cv_pred_cat[index] - y_cv_org[index]) * (cv_pred_cat[index] - y_cv_org[index]
x]))
sum cat cv = sum(cat result cv)
sum cat mean cv = sum cat cv / len(cv pred cat)
print(sum cat mean cv)
# at 512 5.9686735
# at 510 5.96824669
# at 511 5.96744135
# at 600 5.96284639
# at 650 5.95921433
# at 800 5.95560438
# at 1200 and learning 0.016 5.91783832
# at 1200 and learning 0.017 5.90141135
#at 1200 and learning 0.019 5.85995924
# at 1200 at 0.018999 5.8362926 //least
# at 1200 .020 5.92093588
# at 500 5.96865411
# at 430 6.00145801
# at 470 5.998312
```

[5.8362926]

In [0]:

```
#Merging both the models and checking the score on cv
```

In [0]:

```
cat pred = cat model.predict(x cv)
lgbm pred = lgbm model.predict(x cv)
cat arr = []
```

```
for index in cat_pred:
    cat_arr.append(index)

lgbm_arr = []
for index in lgbm_pred:
    lgbm_arr.append(index)
```

In [0]:

```
res_list = []
for i in range(0, len(cat_arr)):
    res_list.append((((cat_arr[i]) * 0.8) + ((lgbm_arr[i])* 0.2)))
```

In [73]:

```
#Check MAE on CV using both the models

cat_result_cv = []
for index in range(0,len(res_list)):
   cat_result_cv.append((res_list[index] - y_cv_org[index]) * (res_list[index] - y_cv_org[index]))

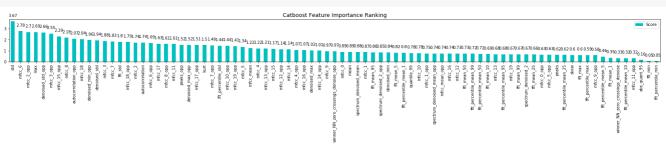
sum_cat_cv = sum(cat_result_cv)

sum_cat_mean_cv = sum_cat_cv / len(res_list)
print(sum_cat_mean_cv)
```

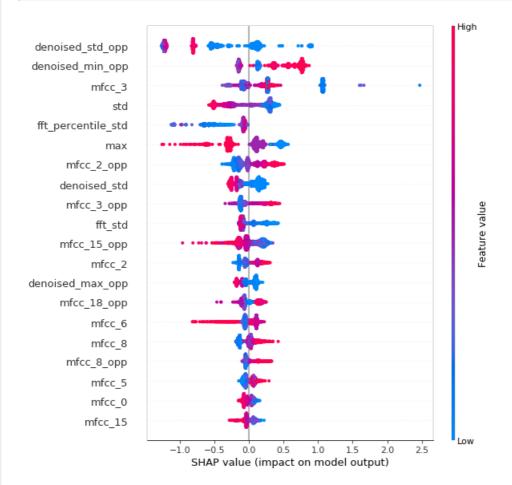
[5.96480534]

importance from the catBoost using Shap values

In [0]:



check based on shap graph CAT



Random Forest

```
In [0]:
```

```
# this not looking good we'll try by stacking another model
```

In [0]:

In [300]:

```
#random Forest
regr_grid = GridSearchCV(RandomForestRegressor(), param_grid=parameter_grid,n_jobs = -1,cv=10, retu
rn_train_score=True)
regr_grid.fit(x_train,y_train)
print(regr_grid.best_params_)
```

```
{'max_depth': 5, 'n_estimators': 80}
```

```
In [438]:
```

```
rf_model = RandomForestRegressor(max_depth=5, random_state=42,n_estimators=75)
rf_model.fit(x_train,y_train)
```

Out[438]:

In [342]:

```
regr_pred_cv = rf_model.predict(x_cv)
y_cv_org = y_cv.values
y_cv_pred = regr_pred_cv[:]

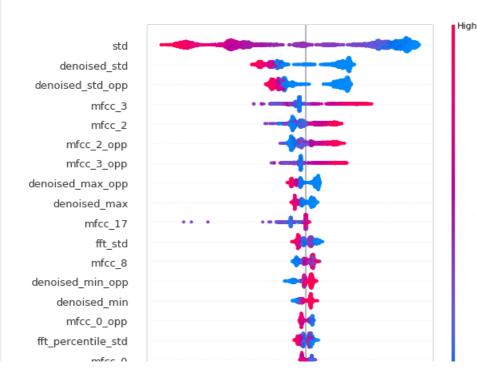
rf_result_cv = []
for index in range(0,len(y_cv_pred)):
    rf_result_cv.append((y_cv_pred[index] - y_cv_org[index]) * (y_cv_pred[index] - y_cv_org[index]))

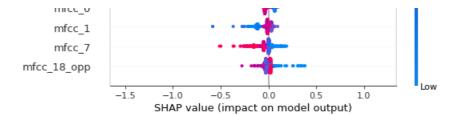
sum_rf_cv = sum(rf_result_cv)
sum_rf_cv_mean = sum_rf_cv / len(y_cv_pred)
print(sum_rf_cv_mean)
# w/o max_depth and n_estimator 6.53059592
# at 5 and 80 depth 6.20147728'
#81 6.20312337
# 75 6.18789375
# at 85 6.20858538
```

[6.18789375]

In [0]:

Feature value





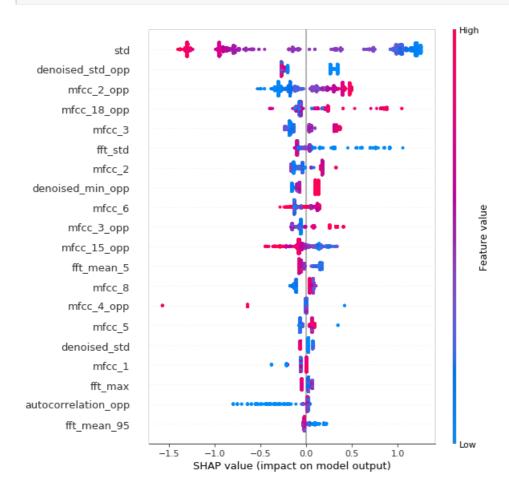
XGboost

```
In [343]:
from xgboost import XGBRegressor
parameter_grid = {'n_estimators': [50,60,70,80,90,100],
                   'max depth': [2,3,5,6,7]
xgb_grid = GridSearchCV(XGBRegressor(random_state=42), param_grid=parameter_grid,n_jobs = -1,cv=10,
return_train_score=True)
xgb grid.fit(x train,y train)
print(xgb_grid.best_params_)
[10:22:10] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated i
n favor of reg:squarederror.
{'max_depth': 2, 'n_estimators': 50}
In [439]:
xgb_boost = XGBRegressor(max_depth=2, random_state=42,n_estimators=51)
xgb_boost.fit(x_train,y_train)
[12:21:42] WARNING: /workspace/src/objective/regression obj.cu:152: reg:linear is now deprecated i
n favor of reg:squarederror.
Out[439]:
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=2, min_child_weight=1, missing=None, n_estimators=51,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=42,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
In [359]:
xgb pred cv = xgb boost.predict(x cv)
y_cv_org = y_cv.values
y cv pred = xgb pred cv[:]
xgb_result_cv = []
for index in range(0,len(y_cv_pred)):
  xgb_result_cv.append((y_cv_pred[index] - y_cv_org[index]) * (y_cv_pred[index] - y_cv_org[index]))
sum_xgb_cv = sum(xgb_result_cv)
sum_xgb_cv_mean = sum_xgb_cv / len(y_cv_pred)
print(sum xgb cv mean)
# at 50 6.17116169
# at 51 6.15943022
```

[6.15943022]

```
In [0]:
```

```
explainer = shap.TreeExplainer(xgb_boost)
shap_values = explainer.shap_values(x_train)
shap.summary_plot(shap_values, x_train)
```



Stacking Models

```
In [0]:
```

```
original_cv = []
for values in y_cv_org:
    original_cv.append(values[0])
```

In [0]:

```
#catboost prediction
cat_arr = cat_model.predict(x_cv)  # best cv score 5.96480534
#1gbm
lgbm_arr = lgbm_model.predict(x_cv)  # best cv score 6.00064977
#XG boost
xgb_pred_cv = xgb_boost.predict(x_cv)  # best cv score 6.15943022
#random forest
rf_arr = rf_model.predict(x_cv)  # best cv score 6.18789375

res_list = []
# best is cat
for i in range(0, len(cat_arr)):
    res_list.append((((cat_arr[i]) * 0.8) + ((lgbm_arr[i]) * 0.1) + (xgb_pred_cv[i] * 0.05) + (rf_arr[i] * 0.05)))
```

In [387]:

```
#Check MAE on CV using all 4 models
# res_list is the predicted values
```

```
stack result cv = []
for index in range(0,len(res list)):
 stack_result_cv.append((res_list[index] - original_cv[index]) * (res_list[index] - original_cv[index])
dex]))
sum stack cv = sum(stack result cv)
sum_stack_mean_cv = sum_stack_cv / len(res_list)
print(sum_stack_mean_cv)
# 5.88478023613998 on cat 0.5 lgbm 0.2 xgb 0.2 rf 0.1
# 5.960521842132663 on 0.25 all
# 5.906810735767607 on cat 0.7 lgbm 0.25 xgb 0.15 rf 0.2
# 5.838706569077672 on cat 0.8 lgbm 0.1 xgb 0.05 rf 0.05
```

5.881337367701245

after stacking am getting "MAE" on cv is 5.8813 </i>

Predictions for test data

```
In [01:
```

```
#catboost prediction
cat_arr = cat_model.predict(x_test) # best cv score 5.96480534
#1qbm
lgbm_arr = lgbm_model.predict(x_test) # best cv score 6.00064977
#XG boost
xgb_pred_cv = xgb_boost.predict(x_test) # best cv score 6.15943022
#random forest
rf_arr = rf_model.predict(x_test) # best cv score 6.18789375
res list = []
# best is cat
for i in range(0, len(cat_arr)):
   res_list.append((((cat_arr[i]) * 0.75) + ((lgbm_arr[i]) * 0.1) + (xgb_pred_cv[i] * 0.1) + (rf_ar
r[i] * 0.05)))
In [0]:
data = pd.read csv('sample submission.csv')
In [0]:
data['time to failure'] = res list
In [01:
data.to_csv('sample_submission_final_.csv')
In [0]:
```