Earthquake prediction using python phase 3

Introduction:

Earthquake is a natural phenomenon whose occurrence predictability is still a hot topic in academia. This is because of the destructive power it holds. In this article, we'll learn how to analyze and visualize earthquake data with Python and Matplotlib.

Data Collection: Gather relevant data such as seismic wave patterns, geological information, historical earthquake occurrences, etc. This data can be sourced from geological surveys and seismic monitoring stations.
Preprocessing: Preprocess the data to remove noise and transform it into a usable format. This may include normalization, feature extraction, and filling or removing missing values.
Feature Engineering: Identify significant features or variables that are likely to have an impact on earthquake prediction. This may include the velocity of seismic waves, the depth of seismic activity, and the location of faults.
Model Selection: Select appropriate machine learning models for prediction. Common algorithms used in earthquake prediction include Support Vector Machines (SVM), Neural Networks, Random Forests, and Gradient Boosting.
Training: Split the data into training and testing sets, then train the selected model on the training data. Hyperparameter tuning and cross-validation can help in selecting the best model.
Prediction: Use the trained model to predict the likelihood of an earthquake in the given area. The output can be a binary classification (earthquake/no earthquake) or a continuous value representing the probability.
Evaluation: Evaluate the model using metrics like accuracy, precision, recall, and F1 score to assess its effectiveness in predicting earthquakes.
Deployment: If the model proves effective, it can be deployed in real-time systems to provide warnings and help in disaster preparedness.
Continuous Monitoring and Updating: Continuously monitor and update the model with new data to ensure its effectiveness in predicting earthquakes.
It's worth mentioning that predicting earthquakes with high accuracy is still a challenging task. Machine learning models can provide insights and predictions, but they must be used with caution and in conjunction with other scientific methods.

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Development

2.1 **Dataset**

In [2]:

```
data = pd.read_csv('../content.-Earthquake-Prediction/train.csv',
dtype={'acoustic_data': np.int16, 'time_to_failure': np.float64})
def calc_change_rate(x):
    change = (np.diff(x) / x[:-1]).values
    change = change[np.nonzero(change)[0]]
    change = change[~np.isnan(change)]
    change = change[change != -np.inf]
    change = change[change != np.inf]
    return np.mean(change)

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]

def featuresx(x_data, X, segment):
    X.loc[segment, 'ave'] = x_data.mean()
    X.loc[segment, 'std'] = x_data.std()
    X.loc[segment, 'max'] = x_data.max()
    X.loc[segment, 'min'] = x_data.min()

    X.loc[segment, 'q01'] = np.quantile(x_data,0.01)
    X.loc[segment, 'q05'] = np.quantile(x_data,0.05)
```

```
    X.loc[segment, 'q95'] = np.quantile(x_data,0.95)
    X.loc[segment, 'q99'] = np.quantile(x_data,0.99)

    X.loc[segment, 'mean_change_abs'] = np.mean(np.diff(x_data))
    X.loc[segment, 'mean_change_rate'] = calc_change_rate(x_data)
    X.loc[segment, 'abs_max'] = np.abs(x_data).max()
    X.loc[segment, 'abs_min'] = np.abs(x_data).min()

    X.loc[segment, 'max_to_min'] = x_data.max() / np.abs(x_data.min())
    X.loc[segment, 'max_to_min_diff'] = x_data.max() -
np.abs(x_data.min())
    X.loc[segment, 'count_big'] = len(x_data[np.abs(x_data) > 500])
    X.loc[segment, 'sum'] = x_data.sum()

    X.loc[segment, 'abs_trend'] = add_trend_feature(x_data,
abs_values=True)
    X.loc[segment, 'abs_mean'] = np.abs(x_data).mean()
    X.loc[segment, 'abs_std'] = np.abs(x_data).std()
    X.loc[segment, 'abs_median'] = np.median(np.abs(x_data))

    X.loc[segment, 'trend'] = add_trend_feature(x_data)
    X.loc[segment, 'mad'] = x_data.mad()
    X.loc[segment, 'kurt'] = x_data.kurtosis()
    X.loc[segment, 'skew'] = x_data.skew()
    X.loc[segment, 'med'] = x_data.median()

    X.loc[segment, 'abs_q95'] = np.quantile(np.abs(x_data),0.95)
    X.loc[segment, 'abs_q99'] = np.quantile(np.abs(x_data),0.99)
```

```
    X.loc[segment, 'F_test'], X.loc[segment, 'p_test'] = 
stats.f_oneway(x_data[:30000],x_data[30000:60000],x_data[60000:90000],
x_data[90000:120000],x_data[120000:])
    X.loc[segment, 'av_change_abs'] = np.mean(np.diff(x_data))

    return X

def feature_extraction(data,segments):
    X = pd.DataFrame(index=range(segments), dtype=np.float64)
    y = pd.DataFrame(index=range(segments), 
dtype=np.float64,columns=['time_to_failure'])
    for segment in tqdm(range(segments)):
        seg = data.iloc[segment*rows:segment*rows+rows]
        x_data = pd.Series(seg['acoustic_data'].values)
        y_data = seg['time_to_failure'].values[-1]

        y.loc[segment,'time_to_failure'] = y_data

        X = featuresx(x_data, X, segment)

    return X, y

from tqdm import tqdm
rows = 150_000
segments = int(np.floor(data.shape[0] / rows))

X,y = feature_extraction(data, segments)

y=y.values.flatten()
```

```
print(X.shape)

print(y.shape)

Output

0it [00:00, ?it/s](0, 0)

(0,)
```

2.1.1 Train-test split

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,

test_size=0.2,shuffle=True, random_state=102)

print(X_train.shape)

print(X_test.shape)

print(y_train.shape)

print(y_test.shape)

Output
```

(3355, 30)
(839, 30)
(3355,)
(839,)

2.2 Data Exploration

n=1000
y1_acoustic_data=data['acoustic_data'][::n]
y2_time_to_failure=data['time_to_failure'][::n]
print(data[0:10*n:n])

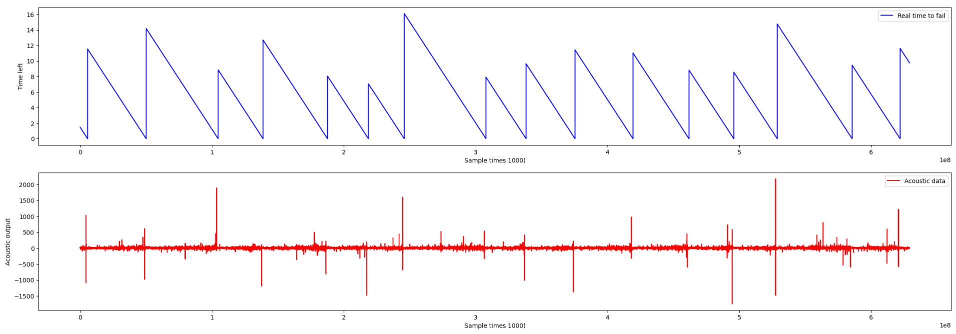
#plotting the graphs of all the deta
fig, ax = plt.subplots(2, 1, figsize=(27,9))
ax[0].plot(y2_time_to_failure, color='b')
ax[0].legend(['Real time to fail'])
ax[0].set_ylabel('Time left')
ax[0].set_xlabel('Sample times 1000)')
ax[1].plot(y1_acoustic_data, color='r')
ax[1].legend(['Acoustic data'])
ax[1].set_ylabel('Acoustic output')

ax[1].set_xlabel('Sample times 1000)')
acoustic_data time_to_failure

Output

0	**12**	**1.469100**
1000	**6**	**1.469099**
2000	**3**	**1.469098**
3000	**29**	**1.469097**
4000	**13**	**1.469096**
5000	**6**	**1.468099**
6000	**9**	**1.468098**
7000	**0**	**1.468097**
8000	**-1**	**1.468096**
9000	**9**	**1.466999**

Text(0.5, 0, 'Sample times 1000)')



2.3 Data Preparation

from sklearn import preprocessing
scaler = preprocessing.StandardScaler().fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

3. Training and Results

from sklearn.linear_model import LinearRegression
# define the model
model = LinearRegression()
# fit the model
model.fit(X_train, y_train)
# predict
predictions=model.predict(X_test)
#accuracy
score=model.score(X_test, y_test)
print(score)
mse = mean_squared_error(y_test, predictions)
print(mse)

Output
0.4534023803770155
7.017008736175641

```
#define and fit model
nsvm = NuSVR(kernel='linear')
nsvm.fit(X_train, y_train)
```

```
# predict
predictions=nsvm.predict(X_test)
# accuracy
score=nsvm.score(X_test, y_test)
print(score)
mse = mean_squared_error(y_test, predictions)
print(mse)
```

Output
0.44697377313180875
7.099536708456553

```
#define and fit model
svm = NuSVR(kernel='rbf')
svm.fit(X_train, y_train)

# predict
predictions=svm.predict(X_test)
# accuracy
score=svm.score(X_test, y_test)
print(score)
mse = mean_squared_error(y_test, predictions)
print(mse)
```

Output
0.4540831746662992
7.008268962521417

```
from sklearn.tree import DecisionTreeRegressor

tree = DecisionTreeRegressor(max_depth=3)
tree.fit(X_train, y_train)
predictions = tree.predict(X_test)
score=tree.score(X_test, y_test)
print(score)
mse = mean_squared_error(y_test, predictions)
print(mse)
```

Output
0.4421844511602614
7.161020170711448

4. Discussion and Conclusion

```
submission =
pd.read_csv('../input/LANL-Earthquake-Prediction/sample_submission.csv',
index_col='seg_id')
X_test = pd.DataFrame(dtype=np.float64, index=submission.index)

for seg_id in tqdm(X_test.index):
    seg = pd.read_csv('../content.Earthquake-Prediction/test/' + seg_id + '.csv')

    x = pd.Series(seg['acoustic_data'].values)
    X_test = featuresx(x, X_test, seg_id)

print(x.shape)
print(X_test.shape)

X_test = scaler.transform(X_test)
submission['time_to_failure'] = svm.predict(X_test)
submission.to_csv('submission.csv')

print(submission)
```

Output

```
100%
2624/2624 [06:09<00:00, 6.53it/s]
(150000,)
(2624, 30)
           time_to_failure
seg_id
seg_00030f        4.342878
seg_0012b5        6.150087
seg_00184e        5.998249
seg_003339        7.985206
seg_0042cc        7.101499
...                    ...
seg_ff4236        5.610940
seg_ff7478        6.446504
seg_ff79d9        4.966563
seg_ffbd6a        2.149476
seg_ffe7cc        9.163199

[2624 rows x 1 columns]
```

Conclusion

We also learned to work with big data, which leads into not being able to plot everything or make a useful table to see what you doing. This had made the understanding of the deta much harder. Furthermore our results are all under 50% which is not good, but we did not do the project to achieve a certain performance but to learn with the concept of machine learning.