Earthquake prediction model by using python

Phase 3: Topic:Loading and Preprocessing the Earthquake Prediction Model By using Python

Introduction:

- Machine learning has the ability to advance our knowledge of earthquakes and enable more accurate forecasting and catastrophe respon.
- It's crucial to remember that developing accurate and dependable prediction models for earthquakes still needs more study as it is a complicated and difficult topic.
- In order to anticipate earthquakes, machine learning may be used to examine seismic data trends. Seismometers capture seismic data, which may be used to spot changes to the earth's surface, like seismic waves brought on by earthquakes.
- Machine learning algorithms may utilize these patterns to forecast the risk of an earthquake happening in a certain region by studying these patterns and learning to recognize key traits that are linked to seismic activity.
- So we will be predicting the earthquake and Time, Latitude, and Longitude from previous data is not a trend that follows like other things. It is naturally occurring

- earthquake

The data are from an experiment conducted on rock in a double direct shear geometry subjected to bi-axial loading, a classic laboratory earthquake model.

Two fault gouge layers are sheared simultaneously while subjected to a constant normal load and a prescribed shear velocity. The laboratory faults fail in repetitive cycles of stick and slip that is meant to mimic the cycle of loading and failure on tectonic faults. While the experiment is considerably simpler than a fault in Earth, it shares many physical characteristics.

Los Alamos' initial work showed that the prediction of laboratory earthquakes from continuous seismic data is possible in the case of quasi-periodic laboratory seismic cycles.

Competition

In this competition, the team has provided a much more challenging dataset with considerably more aperiodic earthquake failures.
Objective of the competition is to predict the failures for each test set.

Prepare the data analysis

Load packages

Here we define the packages for data manipulation, feature engineering and model training.

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In [1]:

linkcode

```
import gc
import os
import time
import logging
import datetime
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
import xgboost as xgb
import lightgbm as lgb
from scipy import stats
from scipy.signal import hann
from tqdm import tqdm_notebook
import matplotlib.pyplot as plt
from scipy.signal import hilbert
from scipy.signal import convolve
from sklearn.svm import NuSVR, SVR
from catboost import CatBoostRegressor
from sklearn.kernel_ridge import KernelRidge
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import mean_absolute_error
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import KFold,StratifiedKFold, R
epeatedKFold
warnings.filterwarnings("ignore")
```

Load the data

Let's see first what files we have in input directory.

unfold_lessHide code

```
In [2]:
IS_LOCAL = False
if(IS_LOCAL):
PATH="../input/LANL/"
else:
PATH="../input/"
```

```
os.listdir(PATH)
```

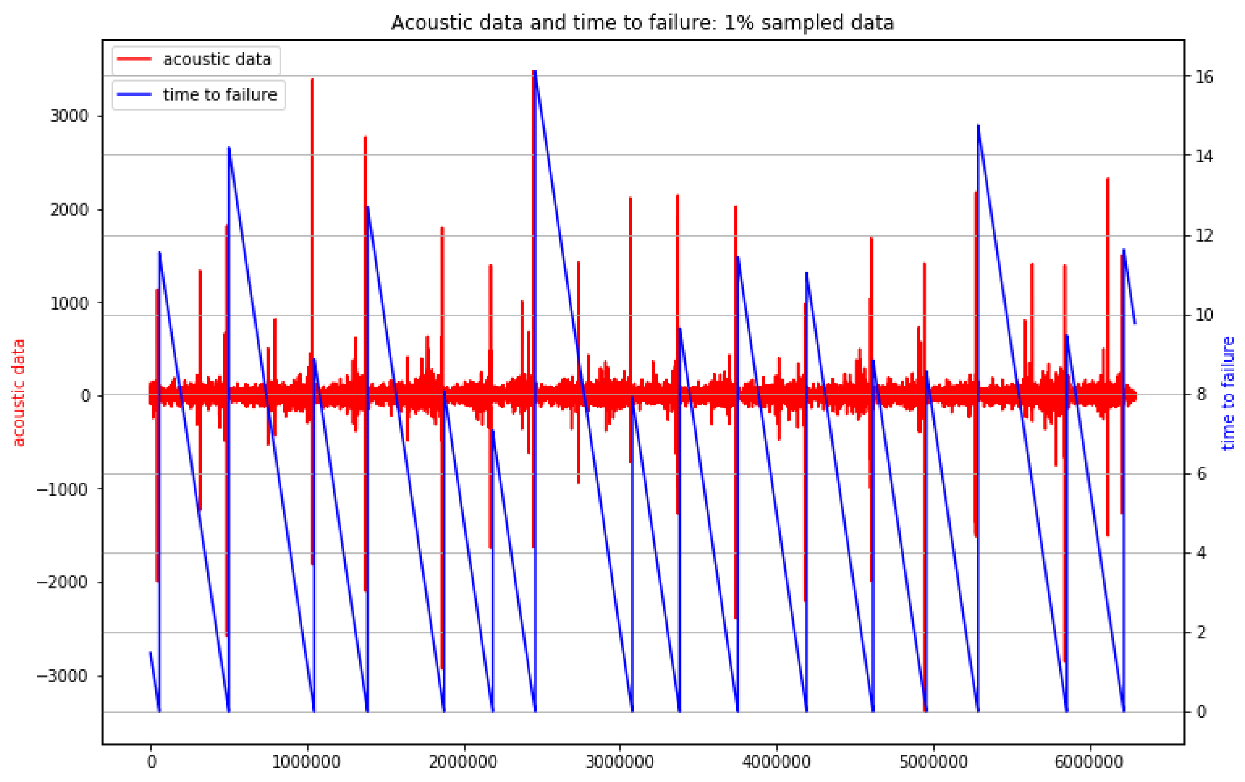
Out[2]:

```
['test', 'sample_submission.csv', 'train.csv']
```

```
print("There are {} files in test folder".format(len(os.list
dir(os.path.join(PATH, 'test' )))))
```

```
CPU times: user 2min 20s, sys: 14.1 s, total: 2min 34s
Wall time: 2min 35s
```

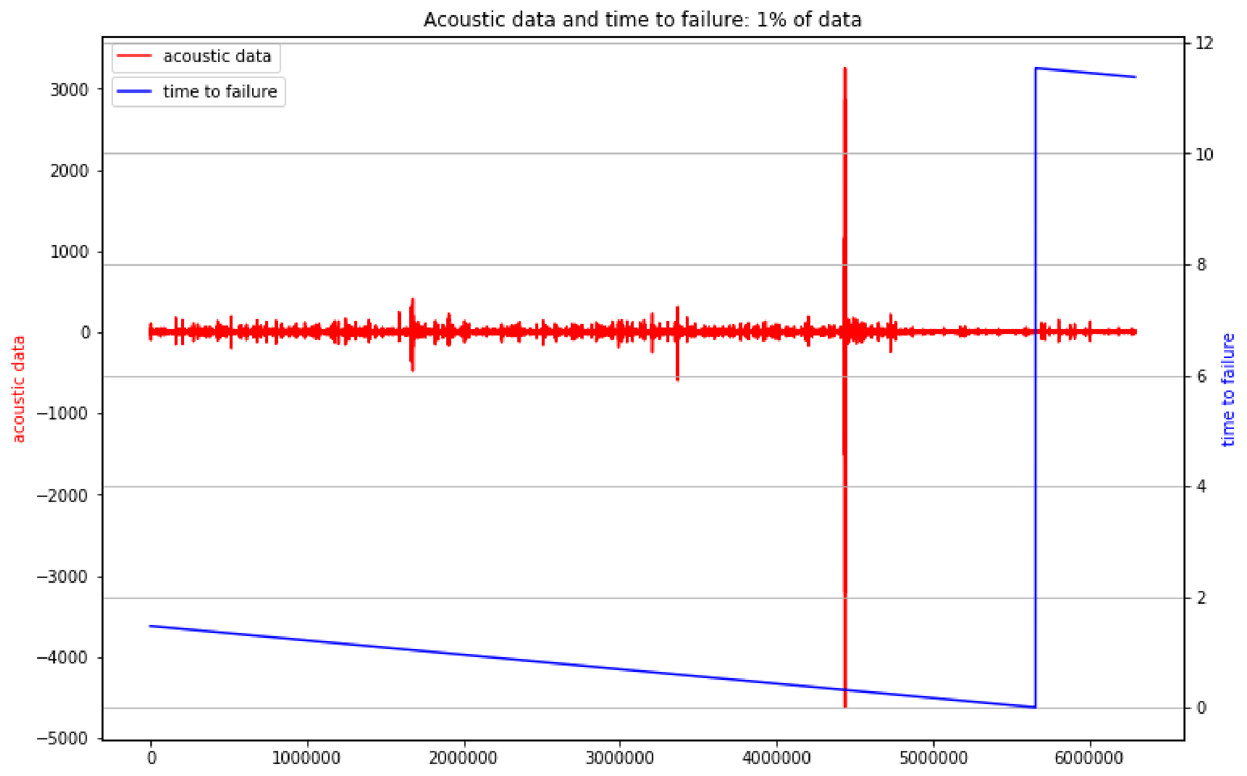
```
pd.options.display.precision = 15
train_df.head(10)
```



```
train_ad_sample_df = train_df['acoustic_data'].values[:62914
55]
train_ttf_sample_df = train_df['time_to_failure'].values[:62
91455]
plot_acc_ttf_data(train_ad_sample_df, train_ttf_sample_df, t
itle="Acoustic data and time to failure: 1% of data")
del train_ad_sample_df
del train_ttf_sample_df
```

Features engineering

The test segments are 150,000 each.
We split the train data in segments of the same dimmension with the test sets.



```
train_X = pd.DataFrame(index=range(segments), dtype=np.float
64)
```

```
train_y = pd.DataFrame(index=range(segments), dtype=np.float
64, columns=['time_to_failure'])
total_mean = train_df['acoustic_data'].mean()
total_std = train_df['acoustic_data'].std()
total_max = train_df['acoustic_data'].max()
total_min = train_df['acoustic_data'].min()
total_sum = train_df['acoustic_data'].sum()
total_abs_sum = np.abs(train_df['acoustic_data']).sum()
```

unfold_moreShow hidden code

```
train_X = pd.DataFrame(index=range(segments), dtype=np.float64)
train_y = pd.DataFrame(index=range(segments), dtype=np.float64, columns=['time_to_fai
lure'])
total_mean = train_df['acoustic_data'].mean()
total_std = train_df['acoustic_data'].std()
total_max = train_df['acoustic_data'].max()
total_min = train_df['acoustic_data'].min()
total_sum = train_df['acoustic_data'].sum()
total_abs_sum = np.abs(train_df['acoustic_data']).sum()
```

```
oof = np.zeros(len(scaled_train_X))
predictions = np.zeros(len(scaled_test_X))
feature_importance_df = pd.DataFrame()
#run model
for fold_, (trn_idx, val_idx) in enumerate(folds.split(scaled_train_X,train_y.values)
):
    strLog = "fold {}".format(fold_)
    print(strLog)

    X_tr, X_val = scaled_train_X.iloc[trn_idx], scaled_train_X.iloc[val_idx]
    y_tr, y_val = train_y.iloc[trn_idx], train_y.iloc[val_idx]

    model = lgb.LGBMRegressor(**params, n_estimators = 20000, n_jobs = -1)
    model.fit(X_tr,
              y_tr,
              eval_set=[(X_tr, y_tr), (X_val, y_val)],
              eval_metric='mae',
              verbose=1000,
              early_stopping_rounds=500)
    oof[val_idx] = model.predict(X_val, num_iteration=model.best_iteration_)
    #feature importance
    fold_importance_df = pd.DataFrame()
    fold_importance_df["Feature"] = train_columns
    fold_importance_df["importance"] = model.feature_importances_[:len(train_columns)
]
    fold_importance_df["fold"] = fold_ + 1
    feature_importance_df = pd.concat([feature_importance_df, fold_importance_df], ax
is=0)
    #predictions
    predictions += model.predict(scaled_test_X, num_iteration=model.best_iteration_)
/ folds.n_splits
fold 0
Training until validation scores don't improve for 500 rounds.
[1000]  training's l1: 1.95653  valid_1's l1: 2.25767
[2000]  training's l1: 1.56603  valid_1's l1: 2.13002
[3000]  training's l1: 1.33595  valid_1's l1: 2.10806
[4000]  training's l1: 1.16028  valid_1's l1: 2.10499
Early stopping, best iteration is:
[3692]  training's l1: 1.21055  valid_1's l1: 2.1045
fold 1
Training until validation scores don't improve for 500 rounds.
[1000]  training's l1: 1.94954  valid_1's l1: 2.27403
[2000]  training's l1: 1.55888  valid_1's l1: 2.14423
[3000]  training's l1: 1.33327  valid_1's l1: 2.12142
[4000]  training's l1: 1.15832  valid_1's l1: 2.11415
Early stopping, best iteration is:
[4353]  training's l1: 1.10461  valid_1's l1: 2.11341
fold 2
Training until validation scores don't improve for 500 rounds.
[1000]  training's l1: 1.95751  valid_1's l1: 2.28141
[2000]  training's l1: 1.57091  valid_1's l1: 2.11881
[3000]  training's l1: 1.34303  valid_1's l1: 2.08681
[4000]  training's l1: 1.16558  valid_1's l1: 2.08075
[5000]  training's l1: 1.01986  valid_1's l1: 2.08095
Early stopping, best iteration is:
[4543]  training's l1: 1.08318  valid_1's l1: 2.08006
fold 3
Training until validation scores don't improve for 500 rounds.
[1000]  training's l1: 1.97583  valid_1's l1: 2.13799
[2000]  training's l1: 1.57798  valid_1's l1: 2.03289
[3000]  training's l1: 1.34362  valid_1's l1: 2.02755
Early stopping, best iteration is:
[3226]  training's l1: 1.29993  valid_1's l1: 2.02722
fold 4
Training until validation scores don't improve for 500 rounds.
[1000]  training's l1: 1.94634  valid_1's l1: 2.26153
[2000]  training's l1: 1.55907  valid_1's l1: 2.11486
[3000]  training's l1: 1.33059  valid_1's l1: 2.09017
[4000]  training's l1: 1.15548  valid_1's l1: 2.08648
Early stopping, best iteration is:
[3918]  training's l1: 1.16854  valid_1's l1: 2.08631
```

Necessary step to follow:

1.Import Libraries:

Start by importing the necessary libraries:

Program:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

2.Load the Dataset:

Load your dataset into a Pandas DataFrame. You can typically find house price datasets in CSV format, but you can adapt this code to other formats as needed.

Program:

```
df = pd.read_csv(' E:\USA_Housing.csv ')
Pd.read()
```

3. Exploratory Data Analysis (EDA):

Perform EDA to understand your data better. This includes checking for missing values, exploring the data's statistics, and visualizing it to identify patterns.

Program:

```
# Check for missing values
print(df.isnull().sum())
# Explore statistics
print(df.describe())
# Visualize the data (e.g., histograms, scatter plots, etc.)
```

Feature Engineering:

Depending on your dataset, you may need to create new features or transform existing ones. This can involve one-hot encoding categorical variables, handling date/time data, or scaling numerical features.

Program:

```
# Example: One-hot encoding for categorical variables
df = pd.get_dummies(df, columns=[' Avg. Area Income ', ' Avg. Area
House Age '])
```

5. Split the Data:

Split your dataset into training and testing sets. This helps you evaluate your model's performance later.

```
X = df.drop('price', axis=1) # Features
y = df['price'] # Target variable
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
```

6. Feature Scaling:

Apply feature scaling to normalize your data, ensuring that all features have similar scales. Standardization (scaling to mean=0 and std=1) is a common choice.

Program:

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Importance of loading and processing dataset:

Loading and preprocessing the dataset is an important first step in building any machine learning model. However, it is especially important for house price prediction models, as house price datasets are often complex and noisy.

By loading and preprocessing the dataset, we can ensure that the machine learning algorithm is able to learn from the data effectively and accurately.

Challenges involved in loading and preprocessing a house price dataset;

There are a number of challenges involved in loading and preprocessing a house price dataset, including:

 Handling missing values:

House price datasets often contain missing values, which can be due to a variety of factors, such as human error or incomplete data collection. Common methods for handling missing values include dropping the rows with missing values, imputing the missing values with the mean or median of the feature, or using a more sophisticated method such as multiple imputation.

 Encoding categorical variables:

House price datasets often contain categorical features, such as the type of house, the neighborhood, and the school district. These features need to be encoded before they can be used by machine learning models. One common way to encode categorical variables is to use one-hot encoding.

 Scaling the features:

It is often helpful to scale the features before training a machine learning model. This can help to improve the performance of the model and make it more robust to outliers. There are a variety of ways to scale the features, such as min-max scaling and standard scaling.

 Splitting the dataset into training and testing sets:

Once the data has been pre-processed, we need to split the dataset into training and testing sets. The training set will be used to train the model, and the testing set will be used to evaluate the performance of the model on unseen data. It is important to split the dataset in a way that is representative of the real world distribution of the data.

How to overcome the challenges of loading and preprocessing a house price dataset:

There are a number of things that can be done to overcome the challenges of loading and preprocessing a house price dataset, including:

 Use a data preprocessing library:

There are a number of libraries available that can help with data preprocessing tasks, such as handling missing values, encoding categorical variables, and scaling the features.

 Carefully consider the specific needs of your model:

The best way to preprocess the data will depend on the specific machine learning algorithm that you are using. It is important to carefully consider the requirements of the algorithm and to preprocess the data in a way that is compatible with the algorithm.

Validate the preprocessed data:

It is important to validate the preprocessed data to ensure that it is in a format that can be used by the machine learning algorithm and that it is of high quality. This can be done by inspecting the data visually or by using statistical methods.

1.Loading the dataset:

 Loading the dataset using machine learning is the process of bringing the data into the machine learning environment so that it can be used to train and evaluate a model.

 The specific steps involved in loading the dataset will vary depending on the machine learning library or framework that is being used. However, there are some general steps that are common to most machine learning frameworks:

2.Identify the dataset:

The first step is to identify the dataset that you want to load. This

dataset may be stored in a local file, in a database, or in a cloud storage

service.

b.Load the dataset:

Once you have identified the dataset, you need to load it into the

machine learning environment. This may involve using a built-in

function in the machine learning library, or it may involve writing your

own code.

c.Preprocess the dataset:

Once the dataset is loaded into the machine learning environment,

you may need to preprocess it before you can start training and

evaluating your model. This may involve cleaning the data, transforming

the data into a suitable format, and splitting the data into training and

test sets.

Preprocess the

dataset

Load the dataset

Identify the

dataset

Loading the

dataset

Here, how to load a dataset using machine learning in Python

CONCLUSION:

When comparing two models, both the mean squared error (MSE) and R-squared (R2) score can be used to evaluate the performance of the models.

In general, a model with a lower MSE and a higher R2 score is considered a better model. This is because the MSE measures the average difference between the predicted and actual values, and a lower MSE indicates that the model is making more accurate predictions. The R2 score measures the proportion of the variance in the target variable that is explained by the model, and a higher R2 score indicates that the model is able to explain more of the variability in the target variable.

From the results of this project we can conclude that random forest is the most accurate model for predicting the magnitude of Earthquake compared to all other models used in this project.

However, it's important to keep in mind that the relative importance of MSE and R2 score may vary depending on the specific problem and the context in which the models are being used. For example, in some cases, minimizing the MSE may be more important than maximizing the R2 score, or vice versa. It's also possible that one model may perform better on one metric and worse on another, so it's important to consider both metrics together when evaluating the performance of the models.