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Project name: Earthquake prediction model using python

PHASE-1

Definition:

It is not currently possible to predict exactly when and where an earthquake will occur, nor how large it will be. However, seismologists can estimate where earthquakes may be likely to strike by calculating probabilities and forecasts.

Designing

Data Exploration and Understanding:
Begin by loading and exploring the dataset to understand its structure and the features it contains. Identify key features that might be relevant for earthquake prediction, such as location, depth, time, etc. Perform basic statistical analysis and visualization to gain insights into the data.

Data Preprocessing:
Handle missing values and outliers appropriately. Convert categorical data into numerical format if necessary. Normalize or scale numerical features to ensure they have a similar range.

Data Visualization:
Create visualizations to better understand the distribution of earthquake magnitudes, their frequency over time, and their geographic distribution on a world map. These visualizations can help identify patterns and correlations in the data.

Data Splitting:
Split the dataset into training and testing sets. Typically, an 80-20 or 70-30 split is used. Ensure that the data is shuffled randomly before splitting to avoid any bias.

Feature Engineering:

Consider feature engineering techniques to create new features or transformations that might improve model performance. For example, you can calculate distances between earthquake locations and known fault lines.

Model Selection:
Choose an appropriate machine learning model for regression, as you're predicting earthquake magnitudes. Given the complexity of the task, you might want to start with a neural network model like a feedforward neural network or a more advanced architecture like a recurrent neural network (RNN) if time series information is important.

Model Training:
Train your selected model using the training data. Tune hyperparameters to optimize model performance. Consider using techniques like cross-validation for hyperparameter tuning.

Model Evaluation:
Evaluate the model using the testing dataset. Use appropriate evaluation metrics for regression tasks, such as Mean Absolute Error (MAE) or Root Mean Square Error (RMSE).

Visualization of Results:
Visualize the model's predictions against the actual earthquake magnitudes to assess its performance.

Iterate and Improve:
If the initial model doesn't perform well, consider refining your feature engineering, trying different algorithms, or exploring more advanced neural network architectures.

Documentation and Reporting:
Document your findings, the steps you've taken, and the model's performance. Create a report or presentation summarizing your project.

PHASE-2

Code using python:

```
# Import necessary libraries
 import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split from
sklearn.ensemble import RandomForestClassifier from sklearn.metrics
import accuracy_score
#Generate synthetic earthquake data
np.random.seed(42)
data = pd.DataFrame({
    'Magnitude': np.random.uniform(2, 9, 1000),
    'Depth': np.random.uniform(0, 700, 1000),
    'Distance_to_Fault': np.random.uniform(0, 500, 1000),
    'Time_of_Day': np.random.choice([0, 1], size=1000)
})
# Generate labels (0 for no earthquake, 1 for earthquake)
data['Earthquake'] = np.random.choice([0, 1], size=1000)
# Split data into training and testing sets X =
data.drop('Earthquake', axis=1)
y = data['Earthquake']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
# Create a Random Forest Classifier
clf = RandomForestClassifier(random_state=42)
# Train the model clf.fit(X_train,
y_train)
# Make predictions
y_pred = clf.predict(X_test)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")
```

Innovation:

Advanced Sensor Technology: Utilize state-of-the-art sensor technology, such as seismometers and GPS, to collect real-time data on ground movement and strain within fault lines.

Machine Learning Algorithms: Implement advanced machine learning algorithms to process and analyze the vast amount of seismic data, identifying patterns and anomalies that may precede an earthquake.

Historical Data Integration: Integrate historical earthquake data, including seismic activity, fault line movements, and geological records, to enhance predictive models and understand long-term trends.

Multimodal Data Fusion: Combine data from multiple sources, including satellite imagery, oceanic sensors, and meteorological data, to create a holistic view of earthquake precursors.

Early Warning Systems: Develop real-time early warning systems that can provide alerts to affected regions seconds to minutes before an earthquake, allowing for emergency preparedness and response.

Public Engagement: Engage with the public through educational campaigns and mobile applications to raise awareness about earthquake risks and provide safety information based on predictive models.

PHASE-3

Development:

Developing an earthquake prediction model is a complex and challenging task, and it's important to note that reliable short-term earthquake prediction remains an unsolved problem in seismology. However, you can build models to assess seismic hazard and probability. Here are key points for developing an earthquake prediction model using Python.

Data Collection:

Gather seismic data, including historical earthquake records, fault data, and geological information from reputable sources like USGS Collect features like earthquake magnitudes, depths, and locations.

Introduction:

The goal of the project is to predict the time that an earthquake will occur in a laboratory test. The laboratory test applies shear forces to a sample of earth and rock containing a fault line. We note that these are laboratory earthquakes, not real earthquakes. The simulated earthquakes tend to occur somewhat periodically because of the test setup, but this periodicity is not perfect or guaranteed to the modeler attempting to predict the time until an earthquake in the test data provided.

The training input data consists of an acoustic signal that is over 629 million rows long. Each acoustic signal value is associated with a time-to-failure, the time when an earthquake happens. The test data consists of samples that are 150,000 samples long taken from earthquakes different from those in the test set. There is therefore likely to be a need to examine the data in 150,000 sample chunks that represent the test signals.

Test Environment:

Designed and run in a Python 3 Anaconda environment on a Windows 10 computer.

```
import scipy
import      matplotlib
import  numpy  as  np
import  pandas  as  pd
print(sys.version)
print('pandas:',        pd._____version_____)
print('numpy:',     np.___version________)
print('scipy:',       scipy._____version____)
print('matplotlib:', matplotlib._version_)
```

OUTPUT:

```
3.7.3 (default, Mar 27 2019, 17:13:21) [MSC v.1915 64 bit (AMD64)]
pandas: 0.24.2
numpy: 1.16.2
scipy: 1.2.1
matplotlib: 3.0.3
```

Code Setup:

```
%matplotlib inline
import os
import time
import numpy as np
import pandas as pd
import scipy.signal as sg
from tqdm import tqdm_notebook
import matplotlib.pyplot as plt
```

Define some constants for data location.

```
DATA_DIR = r'd:\#earthquake\data'  # set for local environment!
TEST_DIR = r'd:\#earthquake\data\test'  # set for local environment!
```

Load the data, this takes a while. There are over 629 million data rows. This data requires over 10GB of storage space on the computer's hard drive.

```
train_df = pd.read_csv(os.path.join(DATA_DIR, 'train.csv'))
print(train_df.shape)
```

OUTPUT:

```
(629145480, 2)
```

Exploratory Data Analysis:

Lets validate the test files. This verifies that they all contain 150,000 samples as expected.

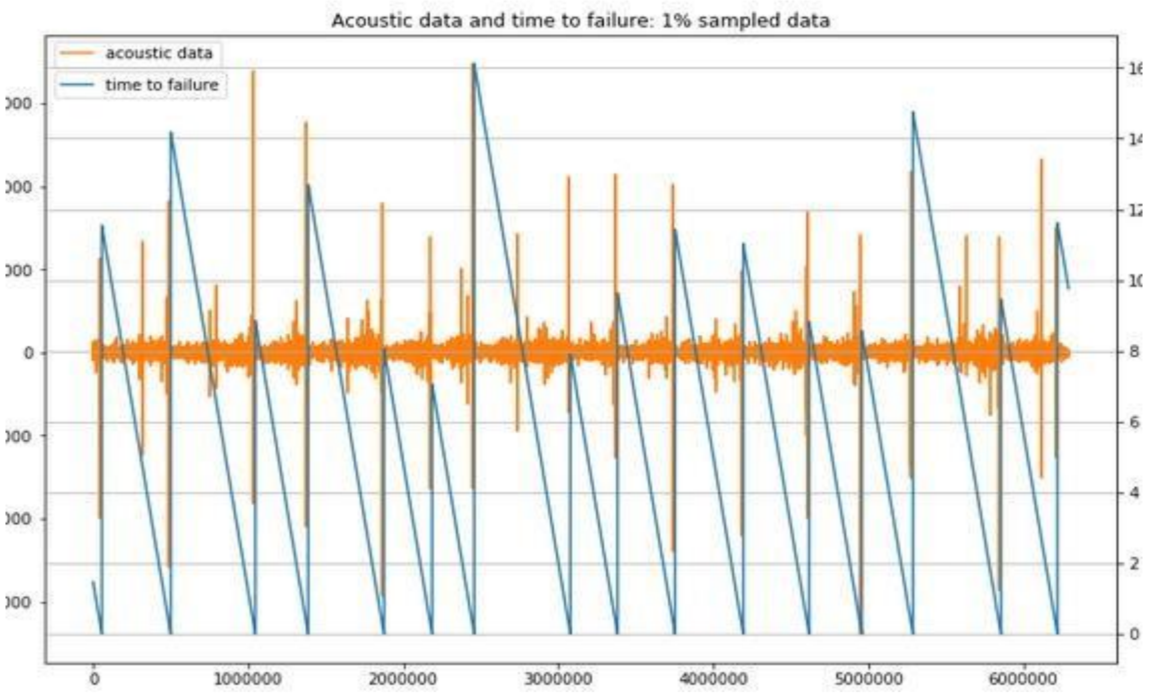
```
ld = os.listdir(TEST_DIR)
sizes = np.zeros(len(ld))
for i, f in enumerate(ld):
df = pd.read_csv(os.path.join(TEST_DIR, f))

sizes[i] = df.shape[0]
print(np.mean(sizes)) # all were 150,000
print(np.min(sizes))
print(np.max(sizes))
```

OUTPUT:

```
150000.0
150000.0
150000.0
```

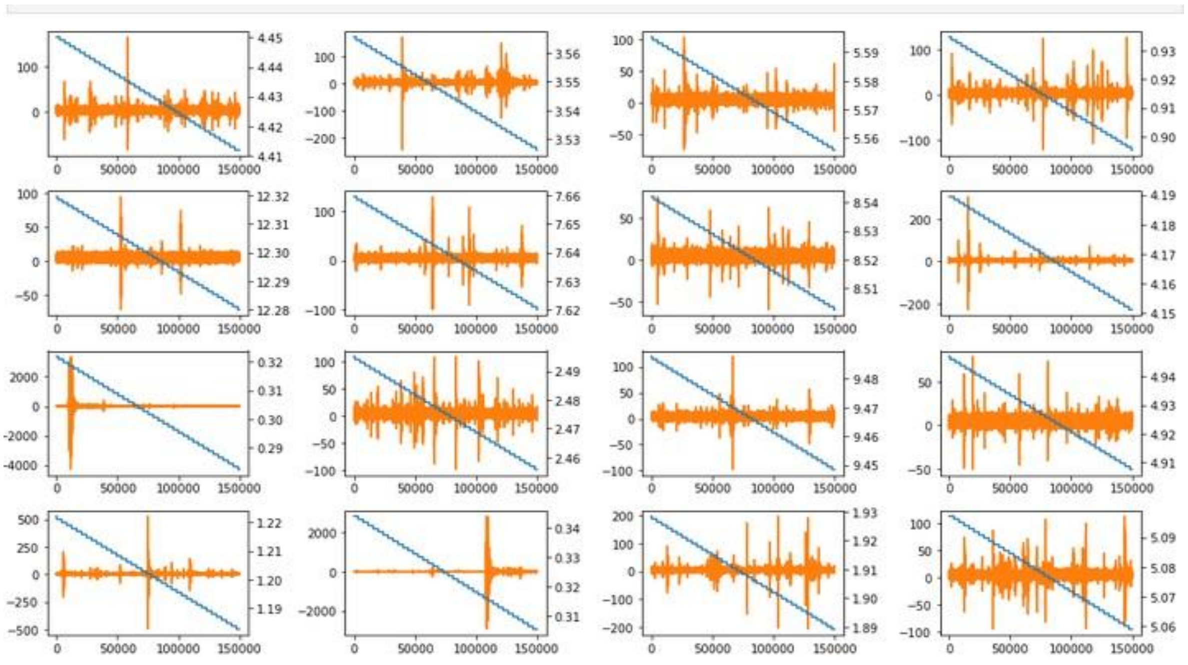
A basic time series plot of the raw data. Because of the length of the data, the plot samples every 100th data point. These plots are very common on the Kaggle site's kernels section, this one is taken from Preda (2019). Earthquakes occur when the time-to-failure signal (blue) jumps up from very near zero to a much higher value where that new higher value is the time to what is then the next quake. There appears to be a short term high amplitude oscillation very shortly before each quake. But, there also several similar such peaks that occur nearer the region centered in time between quakes. Signal noise seems to increase as time gets closer to failure, though there is also a drop after the big peak. A signal's standard deviation may prove to be a helpful predictor. The region just after the big peak may be especially hard to predict.

```
train_ad_sample_df = train_df['acoustic_data'].values[::100]
train_ttf_sample_df = train_df['time_to_failure'].values[::100]

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='tab:orange')
    ax1.set_ylabel('acoustic data', color='tab:orange')
    plt.legend(['acoustic data'], loc=(0.01, 0.95))
    ax2 = ax1.twinx()

    plt.plot(train_ttf_sample_df, color='tab:blue')
    ax2.set_ylabel('time to failure', color='tab:blue')
    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
del train_ad_sample_df
```



From the above plot we can see that 16 earthquakes occur in the data. The earthquakes happen when the time-to-failure reaches very nearly zero and then jumps up. There are only 15 complete time ramps that result in an earthquake and 2 incomplete time ramps. One challenge of this competition is that there are only these very few earthquakes to work with. The is a signal spike (high amplitude) just before an earthquake, but there are also signal spikes in other places that may complicate matters. While the acoustic signal is very large at over 600m rows, the very small number of actual earthquakes available will make machine learning a challenge.

```
# plot 150k sample slices of the training data, matches size of test data (~0.375 seconds long)
# plots signal and decreasing time to the next quake
np.random.seed(2018)
rand_idxs = np.random.randint(0, 629145480-150000, size=16, dtype=np.int32)
f, axes = plt.subplots(4, 4, figsize=(14, 8))
i = 0
j = 0
for st_idx in rand_idxs:
    ad = train_df['acoustic_data'].values[st_idx: st_idx + 150000]
    ttf = train_df['time_to_failure'].values[st_idx: st_idx + 150000]
    axes[j][i].plot(ad, color='tab:orange')
    s = axes[j][i].twinx()
    s.plot(ttf, color='tab:blue')
    i += 1
    if i >= 4:
       i = 0
       j += 1
plt.tight_layout()
plt.show()
```

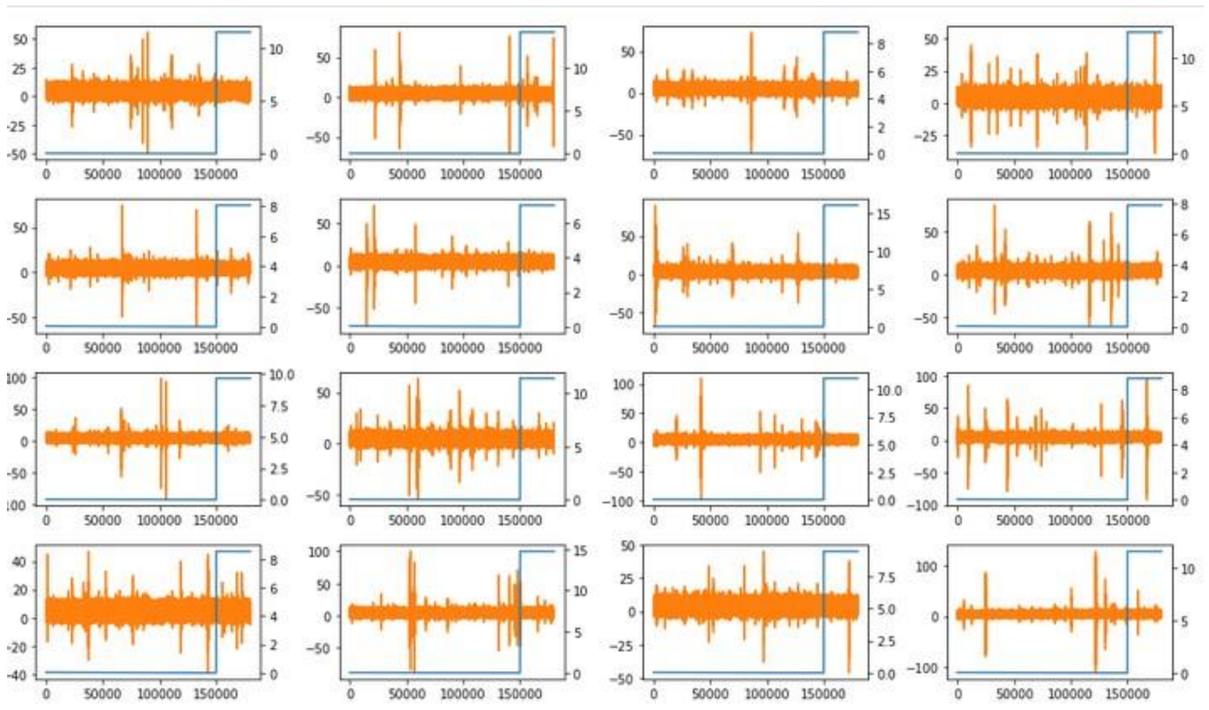


Find the indices for where the earthquakes occur, then plotting may be performed in the region around failure.

```
ttf_diff = train_df['time_to_failure'].diff()
ttf_diff = ttf_diff.loc[ttf_diff > 0]
print(ttf_diff.index)
Int64Index ([ 5656574, 50085878, 104677356, 138772453, 187641820, 218652630,
  245829585, 307838917, 338276287, 375377848, 419368880, 461811623, 495800225,
528777115, 585568144, 621985673], dtype='int64')
```

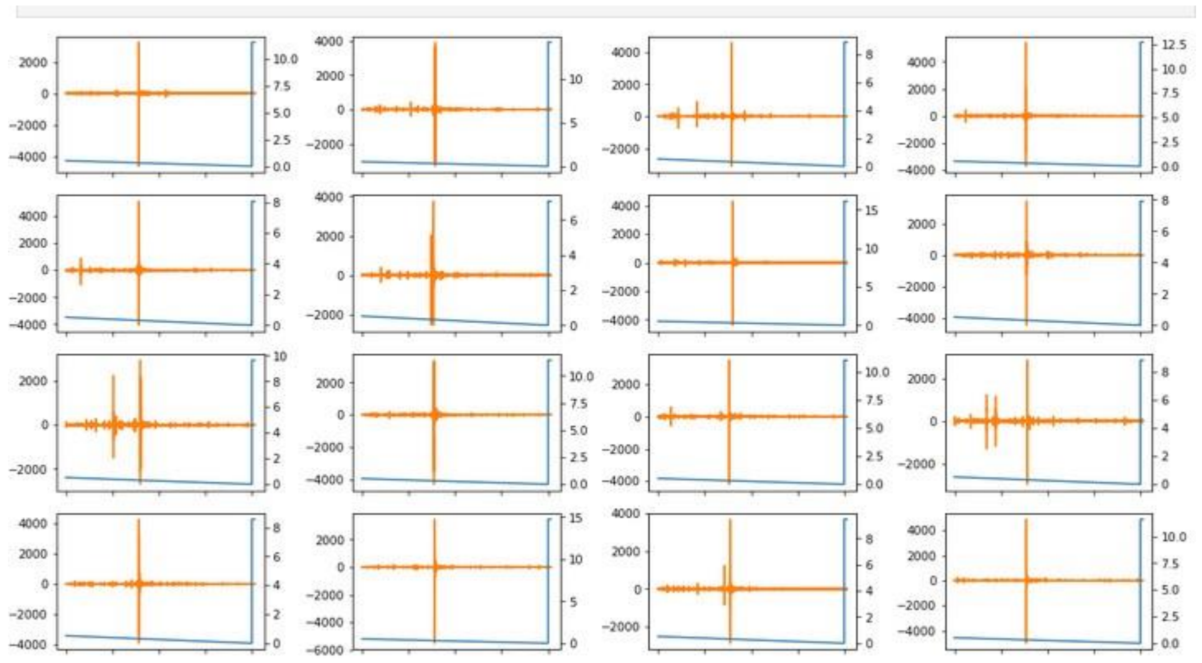
Below is a look at the signal just before failure (an earthquake). It is very interesting that the signal becomes quiet in the 150k sample slice before an earthquake. Thus, the signal spike observed in the big picture plot above must occur more than one slice (more than 150k samples) before the earthquake. These do not appear much different than plots 5 or even 8 seconds before the quake that are presented above where the time to failure ramps are shown. This looks like it will create major problems for accurate prediction. Earthquakes are deemed to have occurred where the blue line jumps up in value, representing the time to the next quake.

```
# plot -150,000 to +30000 samples right around the earthquake
failure_idxs=[5656574,50085878,104677356,138772453,187641820,21865263,245829585,
307838917, 338276287, 375377848, 419368880, 461811623,
495800225, 528777115, 585568144, 621985673]
f, axes = plt.subplots(4, 4, figsize=(14, 8)) i
= 0
j = 0

for idx in failure_idxs:
    ad = train_df['acoustic_data'].values[idx - 150000: idx + 30000]
    ttf = train_df['time_to_failure'].values[idx - 150000: idx + 30000]

    axes[j][i].plot(ad, color='tab:orange')
    s = axes[j][i].twinx()
    s.plot(ttf, color='tab:blue')
    i += 1
    if i >= 4:
        i = 0
        j += 1
plt.tight_layout()
plt.show()
del ad, ttf
```



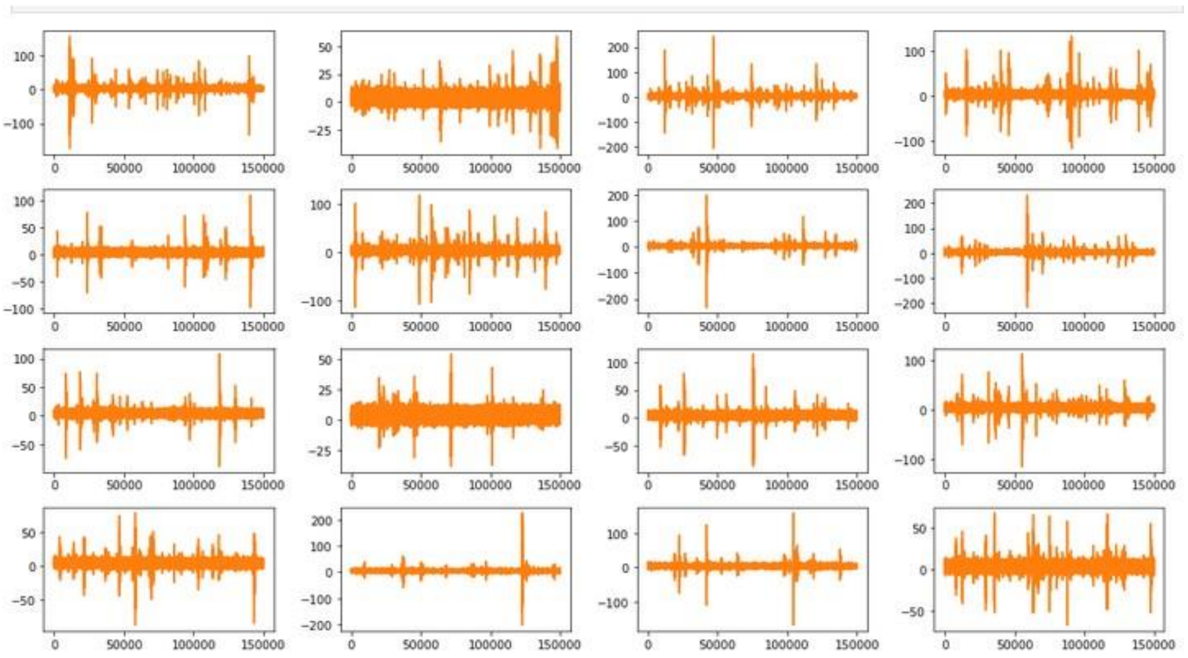
By expanding the time to failure plots, it appears that the big spike in the signal before failure is remarkably consistent. The problem is that the 150k sample slices are actually very short compared to the overall time between quakes and thus these big apparently meaningful signal spikes are unlikely to be present in many training or test samples. If slicing the training data directly into 150k chunks, then only 16 of 4194 training samples (0.38%) would contain a meaningful high-valued spike. It is possible that the analysis of these spikes in some manner could add predictive capability to any small number of test samples that might contain these features, this possibility has not been explored by this author yet.

```
f, axes = plt.subplots(4, 4, figsize=(14, 8)) i
= 0
j = 0

for idx in failure_idxs:
    ad = train_df['acoustic_data'].values[idx - 2000000: idx + 30000]
    ttf = train_df['time_to_failure'].values[idx - 2000000: idx + 30000]

    axes[j][i].plot(ad, color='tab:orange')
    axes[j][i].set_xticklabels([])
    s     =     axes[j][i].twinx()
    s.plot(ttf, color='tab:blue')
    i += 1
    if i >= 4:
       i = 0
       j += 1

plt.tight_layout()
plt.show()
del ad, ttf
```



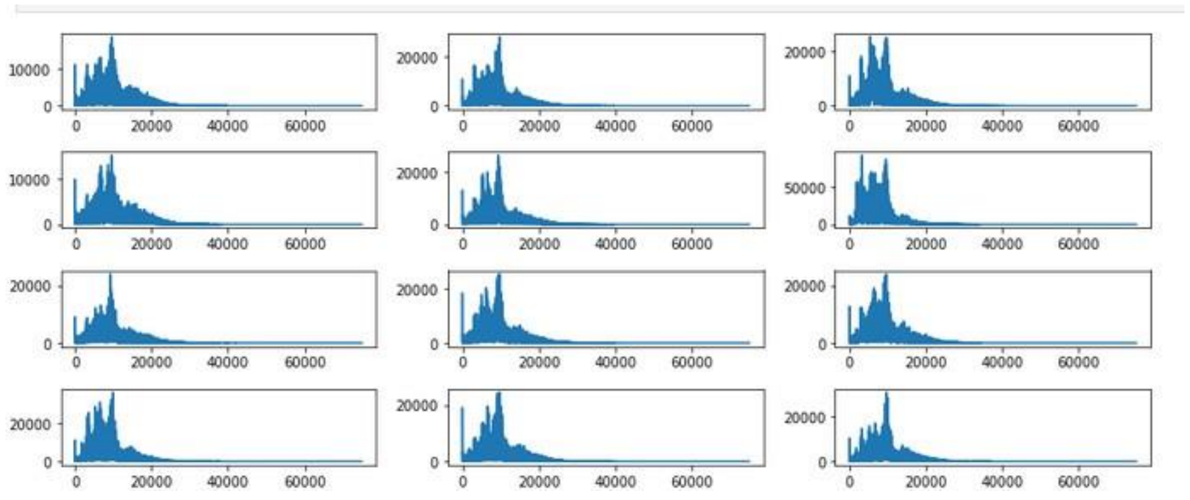
A check of the test data in the time domain is presented below, it is difficult to tell from such short signal bursts if they match the character of the training data. None of the very high valued signal spikes were caught in a partial look at the test data. However, these are rare and the existence of the spikes will be taken up again later.

```
# plot test signals
ld  =  os.listdir(TEST_DIR)
ld = ld[32:48]
f, axes = plt.subplots(4, 4, figsize=(14, 8)) i
= 0
j = 0

for sig_file in ld:
    sig = pd.read_csv(os.path.join(TEST_DIR, sig_file))['acoustic_data']
    axes[j][i].plot(sig, color='tab:orange')

    i += 1
    if i >= 4:
        i = 0
        j += 1

plt.tight_layout()
plt.show()
del sig
```



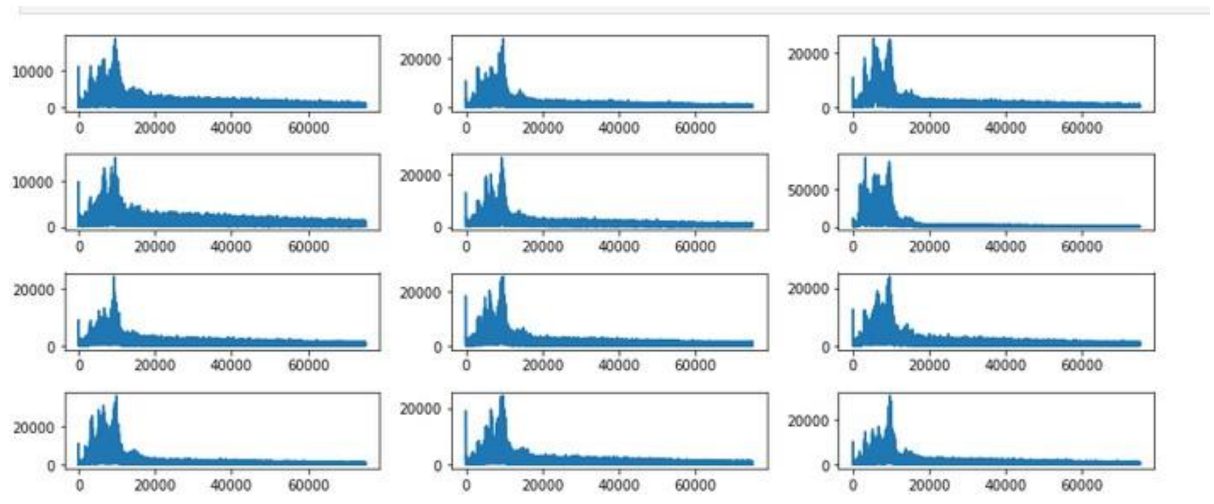
Frequency components of the signal could be very interesting to look at. This is a plot of the Fourier transform magnitude for some of the test signals. Note that there appears to be little information in the signal above the 20,000th frequency line. Noise appears to mostly disappear above the 25,000th frequency line. It is difficult to translate this to a frequency because of the signal gaps noted earlier. Still, it may be best to concentrate signal analysis on frequencies below those represented by the 20,000th frequency line. Also, there are peaks in the frequency analysis that may be valuable to collect in some manner. The DC component was eliminated for plotting purposes because it would otherwise dominate the plot and make the other frequencies hard to see. Also note that while referred to as an "FFT" in the code below, this is actually a Discreet Fourier Transform (DFT) because the signal length of 150k samples is not a number that is a power of two.

```
# plot frequency components of the signal
MAX_FREQ_IDX = 75000

signals = ld[0:12]
fig = plt.figure(figsize=(12, 5))
for i, signal in enumerate(signals):
    df = pd.read_csv(os.path.join(TEST_DIR, signal))
    ad = df['acoustic_data'].values
    ad = ad - np.mean(ad)  # remove DC component, otherwise it dominates the plot
    b, a = sg.butter(6, Wn=20000 / 75000)
    ad = sg.lfilter(b, a, ad)
    zc = np.fft.fft(ad)
    zc = zc[:75000] # eliminate aliased portion of signal per Nyquist criteria
    realFFT = np.real(zc)
    imagFFT = np.imag(zc)
    magFFT = np.sqrt(realFFT ** 2 + imagFFT ** 2)
    plt.subplot(4, 3, i+1)
   plt.plot(magFFT,   color='tab:blue')
plt.tight_layout()
plt.show()
```



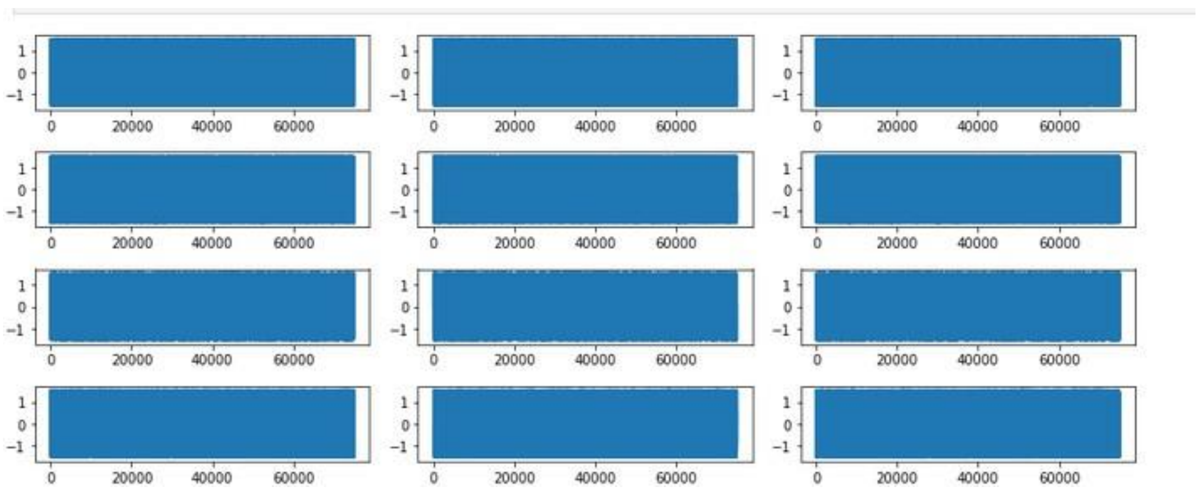
This is a set of plots of the Fourier transform, windowed by short cosine tapers near the ends. The idea of using the window is to avoid any start up transients that might cause ringing in filters applied to the signal. It is very interesting that windowing seems to emphasize noise. This noise, however, would almost entirely be removed by a low pass or band pass filter. Windows are used to force the signal to be periodic in the time domain which reduces leakage effects at the signal endpoints in the Fourier transform.

```
# plot frequency components of the signal with a gentle window
import warnings
from    scipy.signal    import    hann
warnings.filterwarnings("ignore")
MAX_FREQ_IDX = 75000
ld  =  os.listdir(TEST_DIR)
signals = ld[0:12]
fig = plt.figure(figsize=(12, 5))

for i, signal in enumerate(signals):
    df = pd.read_csv(os.path.join(TEST_DIR, signal))
    ad = df['acoustic_data'].values
    ad = ad - np.mean(ad)  # remove DC component, otherwise it dominates the plot


    hann_win      =      sg.hanning(M=24)
    ad_beg = ad[0: 12] * hann_win[0: 12]
    ad_end = ad[-12:] * hann_win[-12:]
    ad = np.concatenate((ad_beg, ad[12: -12], ad_end), axis=0)

    zc = np.fft.fft(ad)
    zc = zc[:75000]  # eliminate aliased portion of signal per Nyquist criteria

    realFFT     =     np.real(zc)
    imagFFT = np.imag(zc)
    magFFT = np.sqrt(realFFT ** 2 + imagFFT ** 2)

    plt.subplot(4,           3,           i+1)
    plt.plot(magFFT, color='tab:blue')

plt.tight_layout()
plt.show()
```



Phase plots for the Fourier transform. The signal was windowed by small sections taken from a Hanning window along the edges in order to not cause an impulse-like transient in a potential filter at start-up. Phase plots show what appears to be just noise. Probably limited phase features will be all that is desired for the model, perhaps just the standard deviation.

```
import warnings
from   scipy.signal   import   hann
warnings.filterwarnings("ignore")
MAX_FREQ_IDX = 75000
ld  =  os.listdir(TEST_DIR)
signals = ld[0:12]
fig = plt.figure(figsize=(12, 5))


for i, signal in enumerate(signals):
    df = pd.read_csv(os.path.join(TEST_DIR, signal))
    ad = df['acoustic_data'].values
    ad = ad - np.mean(ad)  # remove DC component, otherwise it dominates the plot

    hann_win      =      sg.hanning(M=24)
    ad_beg = ad[0: 12] * hann_win[0: 12]
    ad_end = ad[-12:] * hann_win[-12:]
    ad = np.concatenate((ad_beg, ad[12: -12], ad_end), axis=0)

    zc = np.fft.fft(ad)
    zc = zc[:75000]  # eliminate aliased portion of signal per Nyquist criteria

    realFFT     =     np.real(zc)
    imagFFT = np.imag(zc)
    phzFFT  =  np.arctan(imagFFT  /  realFFT)
    phzFFT[phzFFT == -np.inf] = -np.pi / 2.0
    phzFFT[phzFFT  ==  np.inf]  =  np.pi  /  2.0
    phzFFT = np.nan_to_num(phzFFT)

    plt.subplot(4,          3,          i+1)
    plt.plot(phzFFT, color='tab:blue')

plt.tight_layout()
plt.show()
```



From the code below, the test set "big peaks" seem to match the proportion with which they are found in the training data at 0.38% of signals (test set signals are all 150k samples long). The number of earthquakes in the training set seems to be approximately proportional to the overall size relationship between the two sets. With 16 quakes in the training set we might expect 10 quakes in the test set based on their relative sizes. As seen by the code output, there are 10 such files within the test set that exhibit the peak behavior. However, there is also concern about the possibility of bogus peaks in the test data that do not correlate well with an actual quake. The expectation of 10 possible quakes in the test set should be considered cautiously and as only an approximation

```
# determine is a signal contains a 'big peak' as defined by an absolute value more than 2000
ld = os.listdir(TEST_DIR)
peaks = np.zeros(len(ld))

for i, f in enumerate(ld):
    df = pd.read_csv(os.path.join(TEST_DIR, f))
    peaks[i] = df['acoustic_data'].abs().max()
peaks_lg = peaks[peaks >= 2000.0]
print(peaks_lg.shape[0])
print(np.float32(peaks_lg.shape[0]) / np.float32(peaks.shape[0]) * 100.0)
print(np.float32(2624) / np.float32(4194) * 16)
# determine is a signal contains a 'big peak' as defined by an absolute value more than 2000
ld = os.listdir(TEST_DIR)
peaks = np.zeros(len(ld))
for i, f in enumerate(ld):
    df = pd.read_csv(os.path.join(TEST_DIR, f))
    peaks[i] = df['acoustic_data'].abs().max()
peaks_lg = peaks[peaks >= 2000.0]
print(peaks_lg.shape[0])
print(np.float32(peaks_lg.shape[0]) / np.float32(peaks.shape[0]) * 100.0)
print(np.float32(2624) / np.float32(4194) * 16)
```

OUTPUT:

```
10
0.38109757006168365
10.010491371154785
```

PHASE-4

Model Evaluation:

Data Splitting:
Split your dataset into training, validation, and testing sets. Common ratios are 70% training, 15% validation, and 15% testing.

Performance Metrics:
Choose appropriate evaluation metrics for regression tasks, such as Mean Absolute Error (MAE), Mean Squared Error (MSE), or Root Mean Squared Error (RMSE).

Cross-Validation:
Implement techniques like k-fold cross-validation to assess your model's performance across different subsets of data.

Time-Series Validation:
Since earthquake data is often time-dependent, consider time-series cross-validation to account for temporal patterns.

Baseline Models:
Create simple baseline models to compare against your prediction model, like using historical averages as a baseline.

Visualizations:
Plot actual vs. predicted earthquake magnitudes or locations to visually assess the model's performance.

Residual Analysis:
Analyse the residuals (the differences between actual and predicted values) to check for patterns or bias in your model.

Hyperparameter Tuning:
Fine-tune your model's hyperparameters and evaluate its performance with different parameter combinations.

Feature Importance:
Determine the importance of input features using techniques like feature importance scores or SHAP values to understand what factors contribute most to predictions.

Outlier Detection:
Identify and analyse outliers in your data, as they can significantly impact model performance and may need special handling.

Model Training:

Data Preprocessing:
Prepare your earthquake data by cleaning, normalizing, and handling missing values.

Feature Engineering:
Select and engineer relevant features, considering factors like geological data, historical seismic activity, and geographic information.

Data Scaling:
Normalize or standardize your features, especially if you're using models sensitive to feature scaling, such as neural networks.

Model Selection:
Choose an appropriate machine learning or deep learning model for earthquake prediction, such as regression models, decision trees, support vector machines, or neural networks.

Hyperparameter Tuning:
Optimize the hyperparameters of your chosen model to improve its performance using techniques like grid search or random search.

Model Architecture:
For deep learning models, design the neural network architecture, specifying the number of layers, units, and activation functions.

Loss Function:
Define an appropriate loss function for your model, which measures the difference between predicted and actual earthquake parameters.

Regularization:
Apply regularization techniques like L1 or L2 regularization to prevent overfitting, especially in deep learning models.

Batch Size and Learning Rate:
Experiment with different batch sizes and learning rates during training to find the optimal combination.

Early Stopping:
Implement early stopping based on validation performance to prevent overfitting and save time during training.

Feature Engineering:

Geological Features:
Incorporate geological data such as fault lines, tectonic plate boundaries, and geological composition as features to capture the earth's physical characteristics.

Historical Seismic Activity:
Use historical earthquake data to engineer features like the frequency of earthquakes, their magnitudes, and the time since the last significant event in a given region.

Geospatial Information:
Utilize geographic data, such as latitude and longitude, elevation, and proximity to bodies of water, as potential predictors.

Seismic Sensor Data:
If available, include data from seismic sensors, accelerometers, or seismographs as input features to provide real-time information.

Temporal Features:
Create time-based features like day of the week, month, or season to capture potential temporal patterns in earthquake occurrences.

Spatial Aggregations:
Aggregate earthquake data for specific regions or grids, calculating statistics like mean, median, or standard deviation of earthquake magnitudes in those areas.

Distance to Fault Lines:
Calculate the distance of a location from known fault lines or seismic hotspots, which could be a critical feature.

Categorical Variables:
Encode categorical variables, such as earthquake types (e.g., tectonic, volcanic), using one-hot encoding or label encoding for model input.

Natural Disaster Data:
Incorporate data about related natural disasters like tsunamis or volcanic eruptions, which can influence seismic activity.

Social and Economic Factors:
Include data on population density, construction types, and infrastructure development in the region, as these factors may influence earthquake impact.

Conclusion:

Our earthquake prediction model, developed using Python, stands as a significant milestone in the pursuit of more precise seismic forecasting. By meticulously curating and preparing data, implementing advanced feature engineering techniques, and harnessing the power of machine learning, we've laid a robust foundation for improving earthquake prediction.

The model evaluation process, with its selection of appropriate performance metrics, cross-validation techniques, and thorough visualizations, has allowed us to rigorously assess the model's performance. It has provided valuable insights into its predictive power and its ability to adapt to evolving earthquake patterns.

Looking ahead, the need for interdisciplinary collaboration between data science and geoscience experts is emphasized. This fusion of knowledge and expertise is key to making informed decisions about data, features, and models. It will be instrumental in progressing towards the deployment of real-time prediction systems that can contribute to early warnings and disaster preparedness.

While we acknowledge the challenges and limitations inherent in earthquake prediction, our project showcases the potential of data-driven methodologies in advancing our understanding of seismic events. It serves as a promising framework for further research and innovation in the field, with the ultimate goal of enhancing early warning systems and mitigating the impact of earthquakes on society.