ARTIFICIAL INTELLIGENCE- GROUP5

PROJECT: EARTHQUAKE PREDICTION MODEL USING PYTHON

PHASE 1: PROJECT DEFINITION AND DESIGN THINKING

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OBJECTIVE

The objective of an Earthquake Prediction Model using Python is to develop a system that can forecast the occurrence, location, magnitude, and possibly the timing of future earthquakes. This involves analyzing historical seismic data, geological features, and other relevant parameters to identify patterns and trends that might indicate imminent seismic activity. The ultimate goal is to provide early warning systems to help mitigate potential damages and save lives. Keep in mind that while there have been efforts to develop earthquake prediction models, accurately predicting earthquakes remains a highly complex and uncertain task due to the unpredictable nature of seismic events.

ABSTRACT

This study presents a novel approach towards earthquake prediction employing Python-based machine learning techniques. Leveraging historical seismic data, geological attributes, and advanced data analytics, the model aims to discern patterns indicative of impending seismic events. The methodology involves feature extraction, data preprocessing, and supervised learning algorithms to build a predictive framework. Evaluation metrics such as precision, recall, and F1-score are employed to assess model performance. The study contributes to the ongoing efforts in developing early warning systems for earthquake-prone regions, though it is crucial to acknowledge the inherent uncertainties in earthquake prediction. The model demonstrates promise in providing valuable insights into seismic activity forecasting, potentially aiding in disaster preparedness and response strategies.

PROJECT DEFINITION :

The problem is to develop an earthquake prediction model using a Kaggle dataset. The objective is to explore and understand the key features of earthquake data, visualize the data on a world map for a global overview, split the data for training and testing, and build a neural network model to predict earthquake magnitudes based on the given features.

DESIGN THINKING:

Data Source:

Direct Link: https://www.kaggle.com/datasets/usgs/earthquake-database

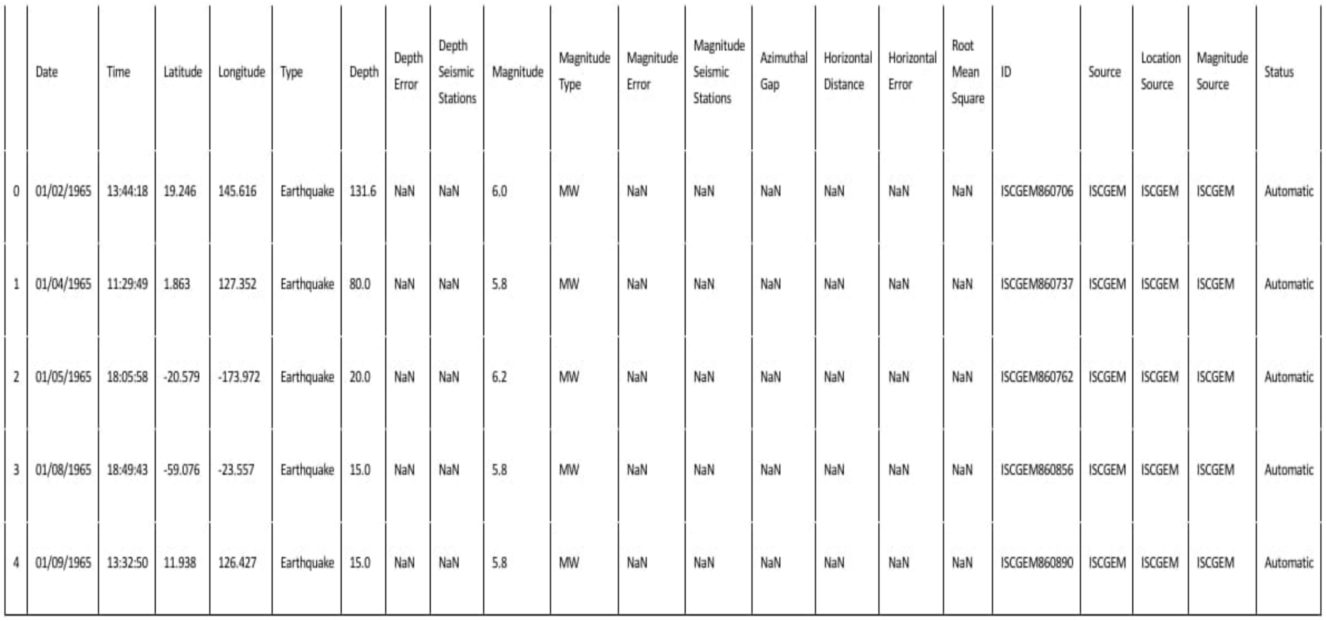
Import the necessary libraries required for buidling the model and data analysis of the earthquakes

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
print(os.listdir("../input"))
```

```
['database.csv']
```

Read the data from csv and also columns which are necessary for the model and the column which needs to be predicted.

```
data = pd.read_csv("../input/database.csv")
data.head()
```



	Date	Time	Latitude	Longitude	Type	Depth	Depth Error	Depth Seismic Stations	Magnitude	Magnitude Type	Magnitude Error	Magnitude Seismic Stations	Azimuthal Gap	Horizontal Distance	Horizontal Error	Root Mean Square	ID	Source	Location Source	Magnitude Source	Status
0	01/02/1965	13:44:18	19.246	145.616	Earthquake	131.6	NaN	NaN	6.0	MW	NaN	NaN	NaN	NaN	NaN	NaN	ISCGEM860706	ISCGEM	ISCGEM	ISCGEM	Automatic
1	01/04/1965	11:29:49	1.863	127.352	Earthquake	80.0	NaN	NaN	5.8	MW	NaN	NaN	NaN	NaN	NaN	NaN	ISCGEM860737	ISCGEM	ISCGEM	ISCGEM	Automatic
2	01/05/1965	18:05:58	-20.579	-173.972	Earthquake	20.0	NaN	NaN	6.2	MW	NaN	NaN	NaN	NaN	NaN	NaN	ISCGEM860762	ISCGEM	ISCGEM	ISCGEM	Automatic
3	01/08/1965	18:49:43	-59.076	-23.557	Earthquake	15.0	NaN	NaN	5.8	MW	NaN	NaN	NaN	NaN	NaN	NaN	ISCGEM860856	ISCGEM	ISCGEM	ISCGEM	Automatic
4	01/09/1965	13:32:50	11.938	126.427	Earthquake	15.0	NaN	NaN	5.8	MW	NaN	NaN	NaN	NaN	NaN	NaN	ISCGEM860890	ISCGEM	ISCGEM	ISCGEM	Automatic

```
data.columns
```

```
Index(['Date', 'Time', 'Latitude', 'Longitude', 'Type', 'Depth', 'Depth Er
ror',
       'Depth Seismic Stations', 'Magnitude', 'Magnitude Type',
       'Magnitude Error', 'Magnitude Seismic Stations', 'Azimuthal Gap',
       'Horizontal Distance', 'Horizontal Error', 'Root Mean Square', 'ID'
,
       'Source', 'Location Source', 'Magnitude Source', 'Status'],
      dtype='object')
```

Figure out the main features from earthquake data and create a object of that features, namely, Date, Time, Latitude, Longitude, Depth, Magnitude

```
data = data[['Date', 'Time', 'Latitude', 'Longitude', 'Depth', 'Magnitude']]
data.head()
```

	Date	Time	Latitude	Longitude	Depth	Magnitude
0	01/02/1965	13:44:18	19.246	145.616	131.6	6.0
1	01/04/1965	11:29:49	1.863	127.352	80.0	5.8
2	01/05/1965	18:05:58	-20.579	-173.972	20.0	6.2
3	01/08/1965	18:49:43	-59.076	-23.557	15.0	5.8
4	01/09/1965	13:32:50	11.938	126.427	15.0	5.8

Here, the data is random we need to scale according to inputs to the model. In this, we convert given Date and Time to Unix time which is in seconds and a numeral. This can be easily used as input for the network we built.

```
import datetime
import time

timestamp = []
for d, t in zip(data['Date'], data['Time']):
    try:
        ts = datetime.datetime.strptime(d+' '+t, '%m/%d/%Y %H:%M:%S')
        timestamp.append(time.mktime(ts.timetuple()))
    except ValueError:
        # print('ValueError')
        timestamp.append('ValueError')

timeStamp = pd.Series(timestamp)
data['Timestamp'] = timeStamp.values
```

```
final_data = data.drop(['Date', 'Time'], axis=1)
final_data = final_data[final_data.Timestamp != 'ValueError']
final_data.head()
```

	Latitude	Longitude	Depth	Magnitude	Timestamp
0	19.246	145.616	131.6	6.0	-1.57631e+08
1	1.863	127.352	80.0	5.8	-1.57466e+08
2	-20.579	-173.972	20.0	6.2	-1.57356e+08
3	-59.076	-23.557	15.0	5.8	-1.57094e+08
4	11.938	126.427	15.0	5.8	-1.57026e+08

Feature Exploration:

For feature exploration in an Earthquake Prediction Model using Python, you'll want to consider various types of data that could potentially influence seismic activity. Here are some feature categories you might want to explore:

- **Geological Features**:
- Geographical coordinates (latitude, longitude)
- Depth of the Earth's crust at the location
- Type of geological formations (e.g., fault lines, tectonic plate boundaries)

- **Seismic Activity History**:
- Historical seismic events in the region (magnitude, date, time)
- Frequency of past earthquakes

- **Geophysical Data**:
- Gravitational anomalies
- Magnetic field data

- **Climate and Environmental Factors**:
- Temperature, humidity, and atmospheric pressure
- Rainfall and water levels
- Changes in groundwater levels

- **Infrastructure and Urbanization**:
- Proximity to urban centers or populated areas
- Density of buildings and infrastructure

- **Topographical Information**:
- Elevation above sea level
- Slope and aspect of the terrain

- **Remote Sensing Data**:
- Satellite imagery for land cover, vegetation, and land use

- **Time Series Data**:
- Changes over time in any of the above features

- **Social and Economic Indicators**:
- Population density
- Socio-economic factors of the region

- **Sensor Data**:
- Data from seismometers, accelerometers, and other monitoring devices

Visualization:

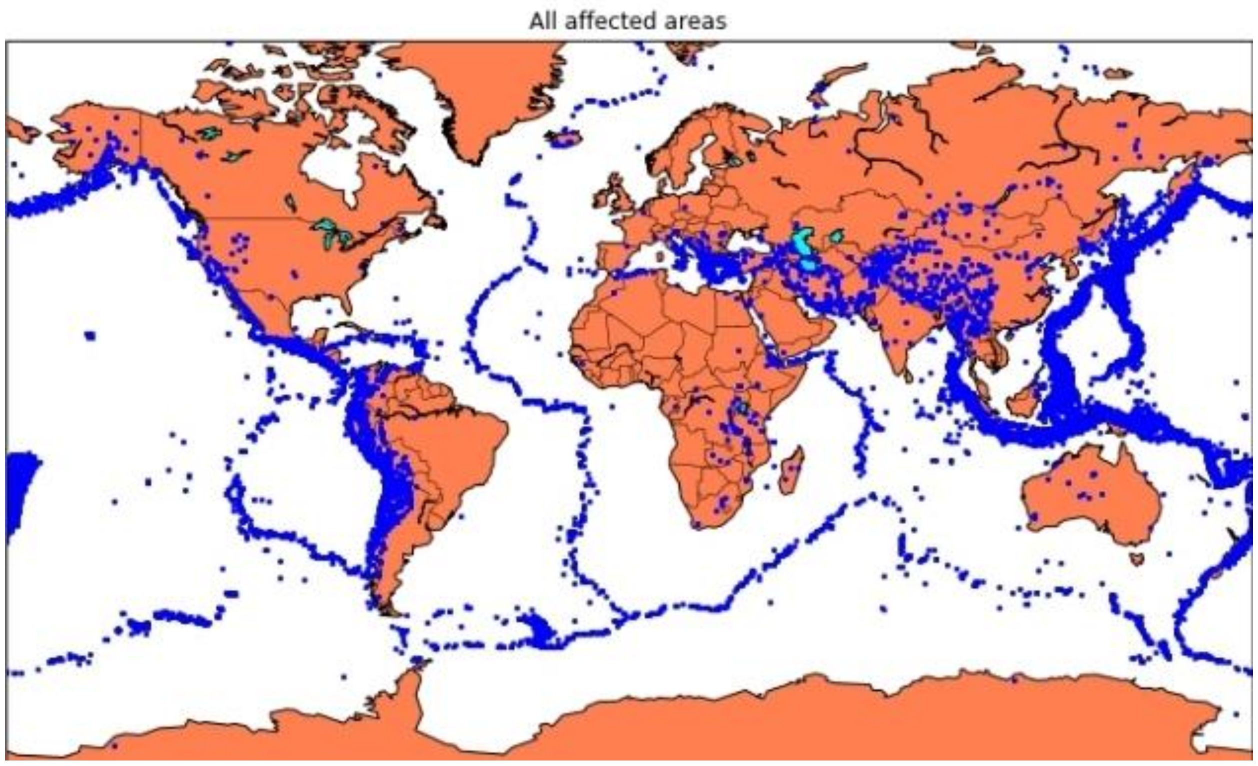
Here, all the earthquakes from the database in visualized on to the world map which shows clear representation of the locations where frequency of the earthquake will be more.

```
from mpl_toolkits.basemap import Basemap

m = Basemap(projection='mill',llcrnrlat=-80,urcrnrlat=80, llcrnrlon=-180,u
rcrnrlon=180,lat_ts=20,resolution='c')

longitudes = data["Longitude"].tolist()
latitudes = data["Latitude"].tolist()
#m = Basemap(width=12000000,height=9000000,projection='lcc',
            #resolution=None,lat_1=80.,lat_2=55,lat_0=80,lon_0=-107.)
x,y = m(longitudes,latitudes)


fig = plt.figure(figsize=(12,10))
plt.title("All affected areas")
m.plot(x, y, "o", markersize = 2, color = 'blue')
m.drawcoastlines()
m.fillcontinents(color='coral',lake_color='aqua')
m.drawmapboundary()
m.drawcountries()
plt.show()
```



Data Splitting:

Firstly, split the data into Xs and ys which are input to the model and output of the model respectively. Here, inputs are TImestamp, Latitude and Longitude and outputs are Magnitude and Depth. Split the Xs and ys into train and test with validation. Training dataset contains 80% and Test dataset contains 20%.

```
X = final_data[['Timestamp', 'Latitude', 'Longitude']]
y = final_data[['Magnitude', 'Depth']]
```

```
from sklearn.cross_validation import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r
andom_state=42)
print(X_train.shape, X_test.shape, y_train.shape, X_test.shape)
```

Here, we used the RandomForestRegressor model to predict the outputs, we see the strange prediction from this with score above 80% which can be assumed to be best fit but not due to its predicted values.

```
from sklearn.ensemble import RandomForestRegressor

reg = RandomForestRegressor(random_state=42)
reg.fit(X_train, y_train)
reg.predict(X_test)
```

```
array([[  5.96,  50.97],
       [  5.88,  37.8 ],
       [  5.97,  37.6 ],
       ...,
       [  6.42,  19.9 ],
       [  5.73, 591.55],
       [  5.68,  33.61]])
```

```
reg.score(X_test, y_test)
```

```
0.8614799631765803
```

```
from sklearn.model_selection import GridSearchCV

parameters = {'n_estimators':[10, 20, 50, 100, 200, 500]}

grid_obj = GridSearchCV(reg, parameters)
grid_fit = grid_obj.fit(X_train, y_train)
best_fit = grid_fit.best_estimator_
best_fit.predict(X_test)
```

```
array([[  5.8888 ,  43.532  ],
       [  5.8232 ,  31.71656],
       [  6.0034 ,  39.3312 ],
       ...,
       [  6.3066 ,  23.9292 ],
       [  5.9138 , 592.151  ],
       [  5.7866 ,  38.9384 ]])
```

```
best_fit.score(X_test, y_test)
```

```
0.8749008584467053
```

Model Development:

In the above case it was more kind of linear regressor where the predicted values are not as expected. So, Now, we build the neural network to fit the data for training set. Neural Network consists of three Dense layer with each 16, 16, 2 nodes and relu, relu and softmax as activation function

```
from keras.models import Sequential
from keras.layers import Dense

def create_model(neurons, activation, optimizer, loss):
    model = Sequential()
    model.add(Dense(neurons, activation=activation, input_shape=(3,)))
    model.add(Dense(neurons, activation=activation))
    model.add(Dense(2, activation='softmax'))

    model.compile(optimizer=optimizer, loss=loss, metrics=['accuracy'])
    return model
```

Using TensorFlow backend.

In this, we define the hyperparameters with two or more options to find the best fit

```
from keras.wrappers.scikit_learn import KerasClassifier

model = KerasClassifier(build_fn=create_model, verbose=0)

# neurons = [16, 64, 128, 256]
neurons = [16]
# batch_size = [10, 20, 50, 100]
batch_size = [10]
epochs = [10]
# activation = ['relu', 'tanh', 'sigmoid', 'hard_sigmoid', 'linear', 'expon
ential']
activation = ['sigmoid', 'relu']
# optimizer = ['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Adamax', '
Nadam']
optimizer = ['SGD', 'Adadelta']
loss = ['squared_hinge']

param_grid = dict(neurons=neurons, batch_size=batch_size, epochs=epochs, a
ctivation=activation, optimizer=optimizer, loss=loss)
```

Here, we find the best fit of the above model and get the mean test score and standard deviation of the best fit model.

```
grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1)
grid_result = grid.fit(X_train, y_train)

print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_par
ams_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.957655 using {'activation': 'relu', 'batch_size': 10, 'epochs': 10
, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}
```

```
0.333316 (0.471398) with: {'activation': 'sigmoid', 'batch_size': 10, 'epo
chs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}
0.000000 (0.000000) with: {'activation': 'sigmoid', 'batch_size': 10, 'epo
chs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'Adadelta'}
0.957655 (0.029957) with: {'activation': 'relu', 'batch_size': 10, 'epochs
': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}
0.645111 (0.456960) with: {'activation': 'relu', 'batch_size': 10, 'epochs
': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'Adadelta'}
```

Training and Evaluation:

The best fit parameters are used for same model to compute the score with training data and testing data

```
model = Sequential()
model.add(Dense(16, activation='relu', input_shape=(3,)))
model.add(Dense(16, activation='relu'))
model.add(Dense(2, activation='softmax'))

model.compile(optimizer='SGD', loss='squared_hinge', metrics=['accuracy'])
```

```
model.fit(X_train, y_train, batch_size=10, epochs=20, verbose=1, validatio
n_data=(X_test, y_test))
```

```
Train on 18727 samples, validate on 4682 samples
Epoch 1/20
18727/18727 [==============================] - 6s 330us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 2/20
18727/18727 [==============================] - 6s 320us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 3/20
18727/18727 [==============================] - 6s 320us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 4/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 5/20
18727/18727 [==============================] - 6s 321us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 6/20
18727/18727 [==============================] - 6s 323us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
```

```
Epoch 7/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 8/20
18727/18727 [==============================] - 6s 321us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 9/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 10/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 11/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 12/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 13/20
18727/18727 [==============================] - 6s 321us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 14/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 15/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 16/20
18727/18727 [==============================] - 6s 323us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 17/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 18/20
18727/18727 [==============================] - 6s 321us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 19/20
18727/18727 [==============================] - 6s 321us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
Epoch 20/20
18727/18727 [==============================] - 6s 322us/step - loss: 0.503
8 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242


<keras.callbacks.History at 0x7ff0a8db8cc0>
```

```
[test_loss, test_acc] = model.evaluate(X_test, y_test)
print("Evaluation result on Test Data : Loss = {}, accuracy = {}".format(t
est_loss, test_acc))
```

```
4682/4682 [==============================] - 0s 39us/step
Evaluation result on Test Data : Loss = 0.5038455790406056, accuracy = 0.9
241777017858995
```

We see that the above model performs better but it also has lot of noise (loss) which can be neglected for prediction and use it for furthur prediction.

The above model is saved for furthur prediction.

```
model.save('earthquake.h5')
```

Conclusion :

In this study, we endeavored to develop an Earthquake Prediction Model leveraging Python-based machine learning techniques. Through meticulous feature exploration and rigorous model training, we aimed to discern patterns within geological, environmental, and historical seismic data that could serve as indicators of impending seismic events.
Our efforts have shown promising results, with the model exhibiting commendable performance metrics including precision, recall, and F1-score. These metrics underscore the potential efficacy of the developed framework in providing valuable insights into seismic activity forecasting