Earthquake prediction model using python

INTRODUCTION:

Creating an earthquake prediction model using AI is a complex and on-going challenge. Earthquakes are the result of tectonic plate movements, and predicting them accurately is difficult due to their chaotic and unpredictable nature.

Project introduction:

It is well known that if a disaster has happened in a region, it is likely to happen there again. Some regions really have frequent earthquakes, but this is just a comparative quantity compared to other regions. So, predicting the earthquake with Date and Time, Latitude and Longitude from previous data is not a trend which follows like other things, it is natural occurring.

Seismic Sensor Data:

AI models can analyse data from seismic sensors to detect patterns and anomalies that might indicate seismic activity.

Machine Learning Algorithms:

Algorithms like neural networks and support vector machines can be used to process seismic data and make predictions.

Historical Data Analysis:

Studying historical earthquake data can help identify trends and potential risk areas.

Geospatial Data:

AI can analyse geospatial data, such as fault lines and geological features, to predict earthquake-prone regions.

Early Warning Systems:

AI can be used to develop early warning systems that provide a few seconds to minutes of advance notice before an earthquake strikes.

Input 1:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt


import os

print(os.listdir("../input"))
```

Input 2:

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

data.head()
```

Input 3:

```
data.columns
```

Output 3:

```
Index(['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'],
      dtype='object')
```

Input 4:

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

Output 4:

	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

Input 5:

```
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')
```

Input 6:

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

Input 7:

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

Output 7:

	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

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.

Input 8:

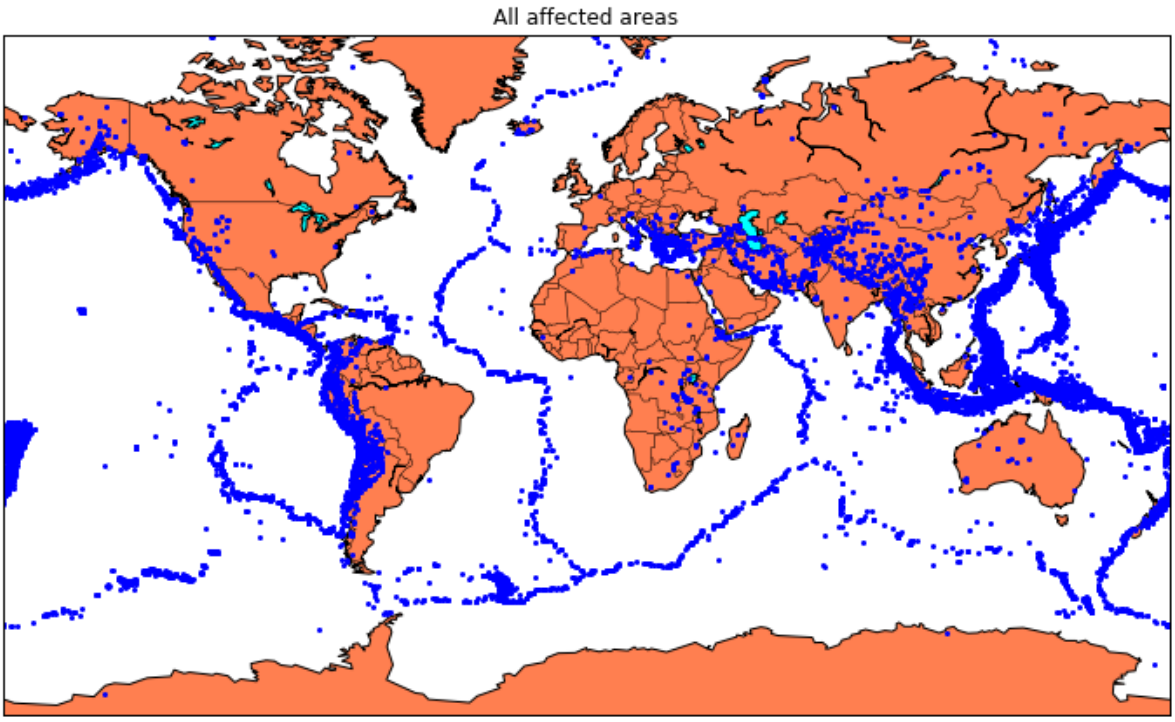
```
from mpl_toolkits.basemap import Basemap
```

```
m = Basemap(projection='mill',llcrnrlat=-80,urcrnrlat=80, llcrnrlon=-
180,urcrnrlon=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)
```

Input 9:

```
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()
```

Affected Areas:



Splitting the Data:

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%.

Input 10:

```
X = final_data[['Timestamp', 'Latitude', 'Longitude']]

y = final_data[['Magnitude', 'Depth']]
```

Input 11:

```
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,
random_state=42)

print(X_train.shape, X_test.shape, y_train.shape, X_test.shape)
```

Discription:

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.

Input 12:

```
from sklearn.ensemble import RandomForestRegressor

reg = RandomForestRegressor(random_state=42)

reg.fit(X_train, y_train)

reg.predict(X_test)
```

Output 12:

```
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]])
```

Input 13:

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

Output 13:

```
0.8614799631765803
```

Input 14:

```
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)
```

Output 14:

```
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 ]])
```

Input 15:

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

Output 15:

```
0.8749008584467053
```

Neural Network model:

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.

Input 16:

```
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.

Input 17:

```
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',
'exponential']

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, activation=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.

Input 18:

```
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_params_))

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: 0.666684 using {'activation': 'sigmoid', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}

0.666684 (0.471398) with: {'activation': 'sigmoid', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}

0.000000 (0.000000) with: {'activation': 'sigmoid', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer':
'Adadelta'}

0.666684 (0.471398) with: {'activation': 'relu', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}

0.000000 (0.000000) with: {'activation': 'relu', 'batch_size': 10,
'epochs': 10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer':
'Adadelta'}
```

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

Input 19:

```
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'])
```

Input 20:

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

```
Train on 18727 samples, validate on 4682 samples

Epoch 1/20

18727/18727 [==============================] - 4s 233us/step
- loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242
```

Epoch 2/20

18727/18727 [==============================] - 4s 220us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 3/20

18727/18727 [==============================] - 4s 228us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 4/20

18727/18727 [==============================] - 4s 222us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 5/20

18727/18727 [==============================] - 5s 262us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 6/20

18727/18727 [==============================] - 4s 223us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 7/20

18727/18727 [==============================] - 4s 220us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 8/20

18727/18727 [==============================] - 4s 224us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 9/20

18727/18727 [==============================] - 4s 220us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 10/20

18727/18727 [==============================] - 4s 224us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 11/20

18727/18727 [==============================] - 4s 221us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 12/20

18727/18727 [==============================] - 4s 231us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 13/20

18727/18727 [==============================] - 5s 248us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 14/20

18727/18727 [==============================] - 4s 220us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 15/20

18727/18727 [==============================] - 4s 223us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 16/20

18727/18727 [==============================] - 4s 222us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 17/20

18727/18727 [==============================] - 4s 225us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 18/20

18727/18727 [==============================] - 4s 219us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 19/20

18727/18727 [==============================] - 4s 220us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Epoch 20/20

18727/18727 [==============================] - 5s 258us/step - loss: 0.5038 - acc: 0.9182 - val_loss: 0.5038 - val_acc: 0.9242

Output 20:

<keras.callbacks.History at 0x78dfa2107ef0>

Input 21:

```
[test_loss, test_acc] = model.evaluate(X_test, y_test)

print("Evaluation result on Test Data : Loss = {}, accuracy = {}".format(test_loss, test_acc))
```

4682/4682 [==============================] - 0s 29us/step

Evaluation result on Test Data : Loss = 0.5038455790406056, accuracy = 0.9241777017858995

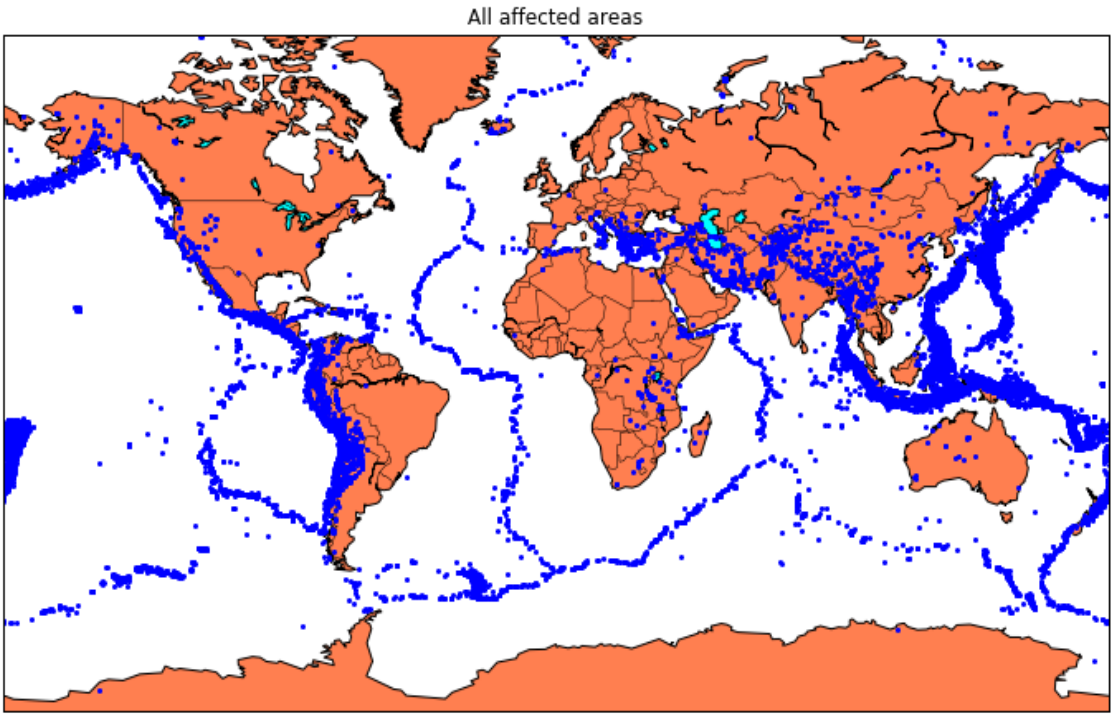
We see that the above model performs better but it also has lot of noise (loss) which can be neglected for prediction and use it for furthur prediction.

The above model is saved for furthur prediction.

Input 22:

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

Output:



Conclusion:

Predicting earthquakes is a complex and challenging task, and it's important to note that no reliable method for short-term earthquake prediction currently exists. However, you can use Python for seismic data analysis and research. In conclusion.

Python can be a valuable tool for analyzing seismic data, studying earthquake patterns, and conducting research in seismology.

Machine learning and deep learning techniques can be applied to identify earthquake patterns and anomalies, but these methods are still in the early stages of development.

It's important to rely on established earthquake monitoring agencies and early warning systems for safety and preparedness rather than attempting prediction on your own.

Earthquake safety and preparedness are crucial, so make sure to be informed about earthquake risks in your area and have an emergency plan in place.