Earthquake_Prediction_Model

May 11, 2023

1 Problem Statement :Earthquake Prediction Model

1.1 Description:

It is well known that if a disaster occurs in one region, it is likely to happen again. Some regions have frequent earthquakes, but this is only a comparative amount compared to other regions. So, predicting the earthquake with date and time, latitude and longitude from previous data is not a trend that follows like other things, it happens naturally.

2 1. Importing Libraries

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

3 2. Dataset information

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[ ]:
```
df=pd.read_csv("/content/drive/MyDrive/Colab Notebooks/DS_PROJECT/
 ↪Earthquake_Prediction_Model/database.csv")
df.head()
```

[ ]:

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

```
   Depth Seismic Stations  Magnitude Magnitude Type  ...  \
0                     NaN        6.0             MW  ...
1                     NaN        5.8             MW  ...
2                     NaN        6.2             MW  ...
3                     NaN        5.8             MW  ...
4                     NaN        5.8             MW  ...

   Magnitude Seismic Stations  Azimuthal Gap  Horizontal Distance  \
0                         NaN            NaN                  NaN
1                         NaN            NaN                  NaN
2                         NaN            NaN                  NaN
3                         NaN            NaN                  NaN
4                         NaN            NaN                  NaN

   Horizontal Error  Root Mean Square            ID  Source Location Source  \
0               NaN               NaN  ISCGEM860706  ISCGEM          ISCGEM
1               NaN               NaN  ISCGEM860737  ISCGEM          ISCGEM
2               NaN               NaN  ISCGEM860762  ISCGEM          ISCGEM
3               NaN               NaN  ISCGEM860856  ISCGEM          ISCGEM
4               NaN               NaN  ISCGEM860890  ISCGEM          ISCGEM

  Magnitude Source     Status
0           ISCGEM  Automatic
1           ISCGEM  Automatic
2           ISCGEM  Automatic
3           ISCGEM  Automatic
4           ISCGEM  Automatic

[5 rows x 21 columns]
```

[ ]:
```
df.columns.unique()
```

[ ]:
```
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')
```

- **Now let's see the main characteristics of earthquake data and create an object of these characteristics, namely, date, time, latitude, longitude, depth, magnitude:**

[ ]:
```
df = df[['Date', 'Time', 'Latitude', 'Longitude', 'Depth', 'Magnitude']]
df.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
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
Date         0
Time         0
Latitude     0
Longitude    0
Depth        0
Magnitude    0
dtype: int64
```

- **No Null value present**
- **Since the data is random, so we need to scale it based on the model inputs. In this, we convert the given date and time to Unix time which is in seconds and a number. This can be easily used as an entry for the network we have built:**

[ ]:
```
import datetime
import time

timestamp = []
for d, t in zip(df['Date'], df['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)
df['Timestamp'] = timeStamp.values
final_data = df.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 -157630542.0
1     1.863    127.352   80.0        5.8 -157465811.0
2   -20.579   -173.972   20.0        6.2 -157355642.0
3   -59.076    -23.557   15.0        5.8 -157093817.0
4    11.938    126.427   15.0        5.8 -157026430.0
```

4 3. Data Visualization

- **Now, before we create the earthquake prediction model, let's visualize the data on a world map that shows a clear representation of where the earthquake frequency**

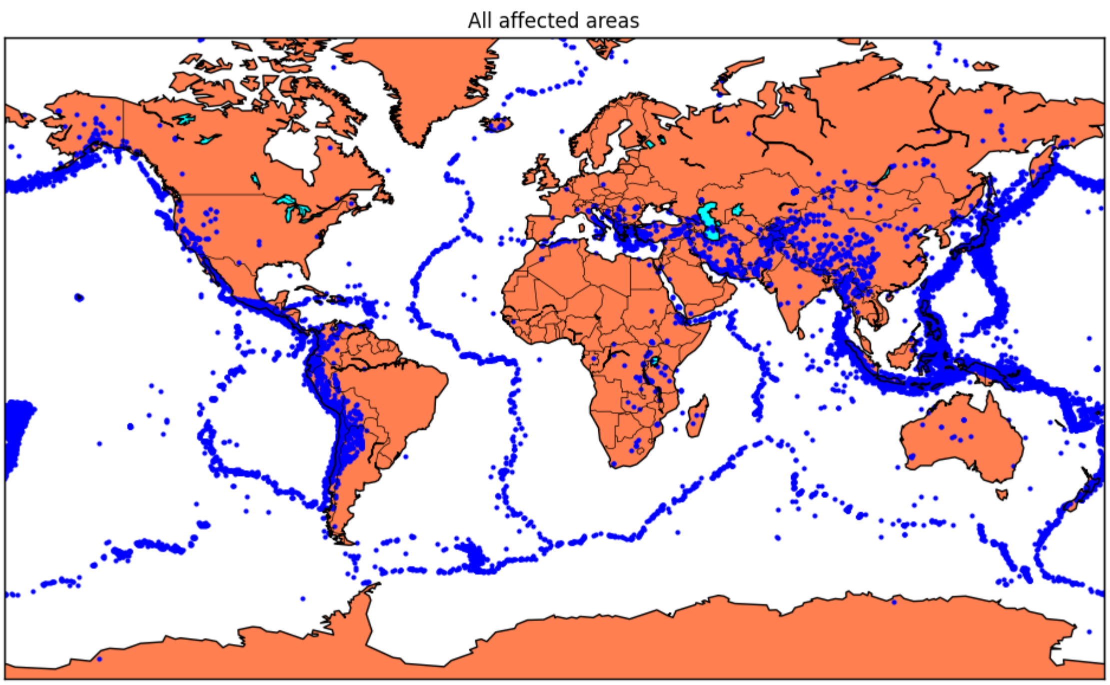
will be more:

```
[ ]: !pip install basemap
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: basemap in /usr/local/lib/python3.10/dist-
packages (1.3.7)
Requirement already satisfied: basemap-data<1.4,>=1.3.2 in
/usr/local/lib/python3.10/dist-packages (from basemap) (1.3.2)
Requirement already satisfied: pyshp<2.4,>=1.2 in
/usr/local/lib/python3.10/dist-packages (from basemap) (2.3.1)
Requirement already satisfied: matplotlib<3.8,>=1.5 in
/usr/local/lib/python3.10/dist-packages (from basemap) (3.7.1)
Requirement already satisfied: pyproj<3.6.0,>=1.9.3 in
/usr/local/lib/python3.10/dist-packages (from basemap) (3.5.0)
Requirement already satisfied: numpy<1.25,>=1.22 in
/usr/local/lib/python3.10/dist-packages (from basemap) (1.22.4)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.8,>=1.5->basemap)
(1.0.7)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
packages (from matplotlib<3.8,>=1.5->basemap) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.8,>=1.5->basemap)
(4.39.3)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.8,>=1.5->basemap)
(1.4.4)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.8,>=1.5->basemap)
(23.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
packages (from matplotlib<3.8,>=1.5->basemap) (8.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.8,>=1.5->basemap)
(3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.8,>=1.5->basemap)
(2.8.2)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-
packages (from pyproj<3.6.0,>=1.9.3->basemap) (2022.12.7)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.7->matplotlib<3.8,>=1.5->basemap) (1.16.0)
```

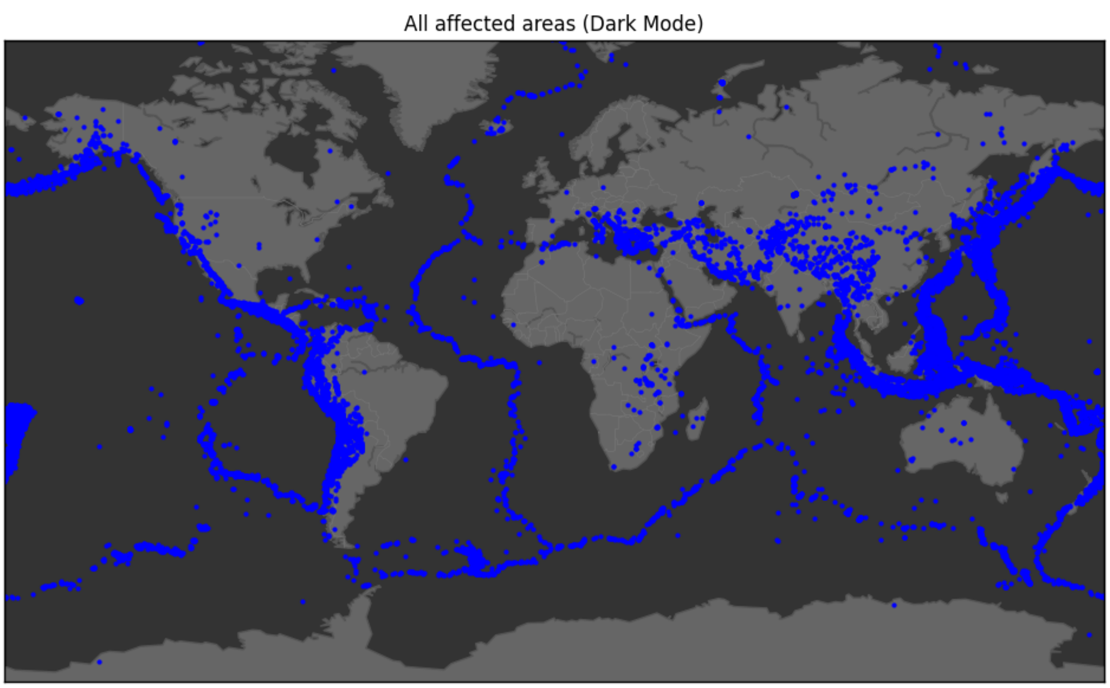
```
[ ]: from mpl_toolkits.basemap import Basemap
```

```
m = Basemap(projection='mill',llcrnrlat=-80,urcrnrlat=80,␣
↪llcrnrlon=-180,urcrnrlon=180,lat_ts=20,resolution='c')

longitudes = df["Longitude"].tolist()
latitudes = df["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()
```



[ ]:
```
from mpl_toolkits.basemap import Basemap
import matplotlib.pyplot as plt

# Create Basemap object with projection and limits
m = Basemap(projection='mill',llcrnrlat=-80,urcrnrlat=80,␣
↪llcrnrlon=-180,urcrnrlon=180,lat_ts=20,resolution='c')
```

```
# Get longitudes and latitudes from DataFrame
longitudes = df["Longitude"].tolist()
latitudes = df["Latitude"].tolist()

# Convert longitudes and latitudes to map coordinates
x,y = m(longitudes,latitudes)

# Create figure and set title
fig = plt.figure(figsize=(12,10))
plt.title("All affected areas (Dark Mode)")

# Set colors for map elements
m.drawcoastlines(color='#555555')
m.drawmapboundary(fill_color='#333333')
m.fillcontinents(color='#666666',lake_color='#333333')
m.drawcountries(color='#777777')

# Plot data points on map
m.plot(x, y, "o", markersize = 2, color = 'blue')

# Show map
plt.show()
```



5 4. Data Splitting

- **Now, to create the earthquake prediction model, we need to divide the data into Xs and ys which respectively will be entered into the model as inputs to receive the output from the model.**
- **Here the inputs are TImestamp, Latitude and Longitude and the outputs are Magnitude and Depth. I'm going to split the xs and ys into train and test with validation. The training set contains 80% and the test set contains 20%:**

[ ]:
```python
X = final_data[['Timestamp', 'Latitude', 'Longitude']] #independent
y = final_data[['Magnitude', 'Depth']] #dependent
```

[ ]:
```python
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,␣
↪random_state=42)
print(X_train.shape, X_test.shape, y_train.shape, X_test.shape)
```

```
(18727, 3) (4682, 3) (18727, 2) (4682, 3)
```

6 5. Neural Network For Earthquake Prediction

- **Now I will create a neural network to fit the data from the training set. Our neural network will consist of three dense layers each with 16, 16, 2 nodes and reread. Relu and softmax will be used as activation functions:**

[ ]:
```python
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
```

- **Now I'm going to define the hyperparameters with two or more options to find the best fit:**

[ ]:
```python
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)
```

```
<ipython-input-20-e86ab04a3ebc>:3: DeprecationWarning: KerasClassifier is
deprecated, use Sci-Keras (https://github.com/adriangb/scikeras) instead. See
https://www.adriangb.com/scikeras/stable/migration.html for help migrating.
  model = KerasClassifier(build_fn=create_model, verbose=0)
```

- **Now we need to find the best fit of the above model and get the mean test score and standard deviation of the best fit model**

[ ]:
```
X_train = np.asarray(X_train).astype(np.float32)
y_train = np.asarray(y_train).astype(np.float32)
```

[ ]:
```
from sklearn.model_selection import GridSearchCV
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: 0.787987 using {'activation': 'relu', 'batch_size': 10, 'epochs': 10,
'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}
0.213027 (0.394294) with: {'activation': 'sigmoid', 'batch_size': 10, 'epochs':
10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}
0.600000 (0.489898) with: {'activation': 'sigmoid', 'batch_size': 10, 'epochs':
10, 'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'Adadelta'}
0.787987 (0.394680) with: {'activation': 'relu', 'batch_size': 10, 'epochs': 10,
'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'SGD'}
0.600271 (0.464062) with: {'activation': 'relu', 'batch_size': 10, 'epochs': 10,
'loss': 'squared_hinge', 'neurons': 16, 'optimizer': 'Adadelta'}
```

- **In the step below, the best-fit parameters are used for the same model to calculate the score with the training data and the test data:**

[ ]:
```
X_test = np.asarray(X_test).astype(np.float32)
y_test = np.asarray(y_test).astype(np.float32)
```

[ ]:
```
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,␣
↪validation_data=(X_test, y_test))

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

```
Epoch 1/20
469/469 [==============================] - 3s 5ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 2/20
469/469 [==============================] - 2s 5ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 3/20
469/469 [==============================] - 2s 4ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 4/20
469/469 [==============================] - 2s 5ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 5/20
469/469 [==============================] - 2s 3ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 6/20
469/469 [==============================] - 2s 3ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 7/20
469/469 [==============================] - 2s 5ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 8/20
469/469 [==============================] - 2s 5ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 9/20
469/469 [==============================] - 2s 4ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 10/20
469/469 [==============================] - 2s 3ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 11/20
469/469 [==============================] - 1s 3ms/step - loss: 0.5038 -
```

```
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 12/20
469/469 [==============================] - 2s 3ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 13/20
469/469 [==============================] - 1s 3ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 14/20
469/469 [==============================] - 1s 3ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 15/20
469/469 [==============================] - 2s 3ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 16/20
469/469 [==============================] - 3s 6ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 17/20
469/469 [==============================] - 3s 6ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 18/20
469/469 [==============================] - 2s 5ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 19/20
469/469 [==============================] - 2s 4ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
Epoch 20/20
469/469 [==============================] - 1s 3ms/step - loss: 0.5038 -
accuracy: 0.9814 - val_loss: 0.5038 - val_accuracy: 0.9814
147/147 [==============================] - 0s 2ms/step - loss: 0.5038 -
accuracy: 0.9814
Evaluation result on Test Data : Loss = 0.5038455724716187, accuracy =
0.9814181923866272
```

7 Conclusion:

So we can see in the above output that our neural network model for earthquake prediction performs well.

8 Reference:

- Aman Kharwal (Medium.com)
- Image Resource (Data Flair)

9 Thank You