# EARTHQUAKE PREDICTION USING PYTHON

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## PHASE 4 PROJECT

# Earthquake Prediction

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 occuring.

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 |

| | 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 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 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')
```

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 |

| | Date | Time | Latitude | Longitude | Depth | Magnitude |
|---|---|---|---|---|---|---|
| **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 |

# Visualization

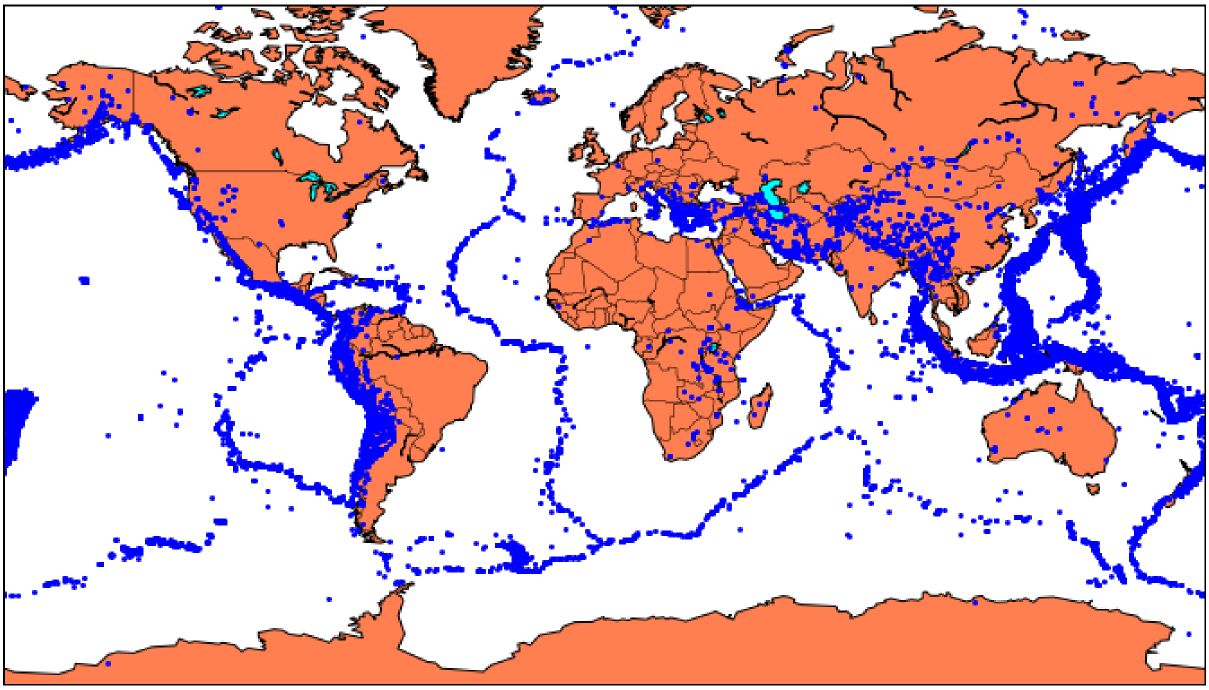
Here, all the earthquakes from the database in visualized on to the world map which shows clear representation of the locations where frequency of the earthquake will be more.

```
from mpl_toolkits.basemap import Basemap

m = Basemap(projection='mill',llcrnrlat=-80,urcrnrlat=80, llcrnrlon=-
180,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)
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()
/opt/conda/lib/python3.6/site-
packages/mpl_toolkits/basemap/__init__.py:1704:
MatplotlibDeprecationWarning: The axesPatch function was deprecated in
version 2.1. Use Axes.patch instead.
  limb = ax.axesPatch
/opt/conda/lib/python3.6/site-
packages/mpl_toolkits/basemap/__init__.py:1707:
MatplotlibDeprecationWarning: The axesPatch function was deprecated in
version 2.1. Use Axes.patch instead.
  if limb is not ax.axesPatch:
```




## 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%.

```
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,
random_state=42)
print(X_train.shape, X_test.shape, y_train.shape, X_test.shape)
(18727, 3) (4682, 3) (18727, 2) (4682, 3)
/opt/conda/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in favor of
the model_selection module into which all the refactored classes and
functions are moved. Also note that the interface of the new CV iterators
```

```
are different from that of this module. This module will be removed in
0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

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)
/opt/conda/lib/python3.6/site-
packages/sklearn/ensemble/weight_boosting.py:29: DeprecationWarning:
numpy.core.umath_tests is an internal NumPy module and should not be
imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
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
```

## 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.

```
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', 
'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.

```
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.

```
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))
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
<keras.callbacks.History at 0x78dfa2107ef0>
[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.

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