* ***RVS college of Engineering***
* ***Phase :3***
* ***Name:A Shivanithi***

***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***

***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***

***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: 0.957655 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, ‘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’}***

***0.957655 (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’}***

***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 [==============================] – 6s 330us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 2/20***

***18727/18727 [==============================] – 6s 320us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 3/20***

***18727/18727 [==============================] – 6s 320us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 4/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 5/20***

***18727/18727 [==============================] – 6s 321us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 6/20***

***18727/18727 [==============================] – 6s 323us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 7/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 8/20***

***18727/18727 [==============================] – 6s 321us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 9/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 10/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 11/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 12/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 13/20***

***18727/18727 [==============================] – 6s 321us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 14/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 15/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 16/20***

***18727/18727 [==============================] – 6s 323us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 17/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 18/20***

***18727/18727 [==============================] – 6s 321us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 19/20***

***18727/18727 [==============================] – 6s 321us/step – loss: 0.5038 – acc: 0.9182 – val\_loss: 0.5038 – val\_acc: 0.9242***

***Epoch 20/20***

***18727/18727 [==============================] – 6s 322us/step – loss: 0.5038 – 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(test\_loss, test\_acc))***

***4682/4682 [==============================] – 0s 39us/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’)***

# **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.

In [1]:

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.

In [2]:

data = pd.read\_csv("../input/database.csv")

data.head()

Out[2]:

|  | 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 |

In [3]:

data.columns

Out[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')

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

In [4]:

data = data[['Date', 'Time', 'Latitude', 'Longitude', 'Depth', 'Magnitude']]

data.head()

Out[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 |

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.

In [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')

In [6]:

timeStamp = pd.Series(timestamp)

data['Timestamp'] = timeStamp.values

In [7]:

final\_data = data.drop(['Date', 'Time'], axis=1)

final\_data = final\_data[final\_data.Timestamp != 'ValueError']

final\_data.head()

Out[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.

In [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)

In [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()

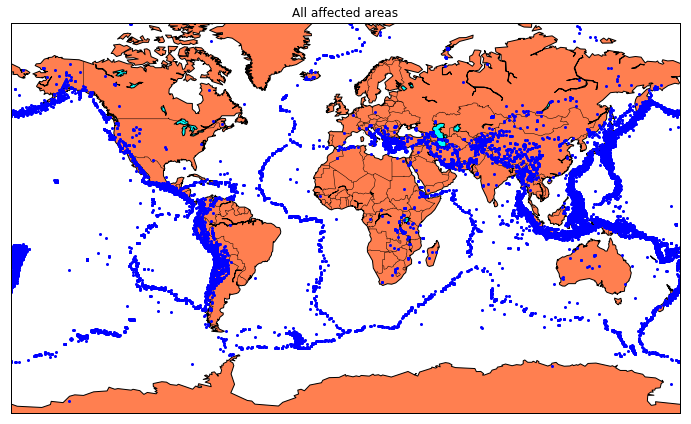
plt.show()

/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%.

In [10]:

X = final\_data[['Timestamp', 'Latitude', 'Longitude']]

y = final\_data[['Magnitude', 'Depth']]

In [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)

(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.

In [12]:

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

Out[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]])

In [13]:

reg.score(X\_test, y\_test)

Out[13]:

0.8614799631765803

In [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)

Out[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 ]])

In [15]:

best\_fit.score(X\_test, y\_test)

Out[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.

In [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.

In [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.

In [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: 0.957655 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, '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'}

0.957655 (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'}

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

In [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'])

In [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 [==============================] - 6s 330us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 2/20

18727/18727 [==============================] - 6s 320us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 3/20

18727/18727 [==============================] - 6s 320us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 4/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 5/20

18727/18727 [==============================] - 6s 321us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 6/20

18727/18727 [==============================] - 6s 323us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 7/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 8/20

18727/18727 [==============================] - 6s 321us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 9/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 10/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 11/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 12/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 13/20

18727/18727 [==============================] - 6s 321us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 14/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 15/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 16/20

18727/18727 [==============================] - 6s 323us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 17/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 18/20

18727/18727 [==============================] - 6s 321us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 19/20

18727/18727 [==============================] - 6s 321us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Epoch 20/20

18727/18727 [==============================] - 6s 322us/step - loss: 0.5038 - acc: 0.9182 - val\_loss: 0.5038 - val\_acc: 0.9242

Out[20]:

<keras.callbacks.History at 0x7ff0a8db8cc0>

In [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 39us/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.

In [22]:

model.save('earthquake.h5')