Earthquake prediction model in Python

AI_Phases 4

Team Members:

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III Year CSE

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Get our environment set up

- The first thing we'll need to do is load in the libraries and dataset we'll be using. We'll be working with a dataset containing information on earthquakes that occured between 1965 and 2016.
- We have gathered this dataset from the publicly available domain Kaggle. We have used the ? Significant Earthquakes, 1965-2016? dataset from Kaggle in the CSV format. It includes a record of the date, time, location, depth, magnitude, and source of every earthquake with a reported magnitude 5.5 or higher since 1965.
-
```
# modules we'll use
import pandas as pd
import numpy as np
import seaborn as sns
import datetime

# read in our data
earthquakes = pd.read_csv("../input/earthquake-database/database.csv")

# set seed for reproducibility
np.random.seed(0)
```

1) Check the data type of our date column

- We are working with the "Date" column from the earthquakes dataframe. We investigate this column now and see if it looks like it contains dates and what the dtype of the column is.
-
```
# TODO: Your code here!
earthquakes['Date'].head()
```
-
```
0    01/02/1965
1    01/04/1965
2    01/05/1965
3    01/08/1965
4    01/09/1965
Name: Date, dtype: object
```

2) Convert our date columns to datetime

- Most of the entries in the "Date" column follow the same format: "month/day/four-digit year". However, the entry at index 3378 follows a completely different pattern. We run the code cell below to see this.earthquakes[3378:3383]

	Date	Time	Latitude	Longitude	\
3378	1975-02-23T02:58:41.000Z	1975-02-23T02:58:41.000Z	8.017	124.075	
3379	02/23/1975	03:53:36	-21.727	-71.356	
3380	02/23/1975	07:34:11	-10.879	166.667	
3381	02/25/1975	05:20:05	-7.388	149.798	
3382	02/26/1975	04:48:55	85.047	97.969	

	Type	Depth	Depth Error	Depth Seismic Stations	Magnitude	\
3378	Earthquake	623.0	NaN	NaN	5.6	
3379	Earthquake	33.0	NaN	NaN	5.6	
3380	Earthquake	33.0	NaN	NaN	5.5	
3381	Earthquake	33.0	NaN	NaN	5.5	
3382	Earthquake	33.0	NaN	NaN	5.6	

	Magnitude Type	...	Magnitude Seismic Stations	Azimuthal Gap	\
3378	MB	...	NaN	NaN	
3379	MB	...	NaN	NaN	
3380	MS	...	NaN	NaN	
3381	MB	...	NaN	NaN	
3382	MS	...	NaN	NaN	

	Horizontal Distance	Horizontal Error	Root Mean Square	ID	\
3378	NaN	NaN	NaN	USP0000A09	
3379	NaN	NaN	NaN	USP0000A0A	
3380	NaN	NaN	NaN	USP0000A0C	
3381	NaN	NaN	NaN	USP0000A12	
3382	NaN	NaN	NaN	USP0000A1H	

	Source	Location Source	Magnitude Source	Status
3378	US	US	US	Reviewed
3379	US	US	US	Reviewed
3380	US	US	US	Reviewed
3381	US	US	US	Reviewed
3382	US	US	US	Reviewed

[5 rows x 21 columns]

This does appear to be an issue with data entry: ideally, all entries in the column have the same format. We can get an idea of how widespread this issue is by checking the length of each entry in the "Date" column.

```
date_lengths = earthquakes.Date.str.len()
date_lengths.value_counts()
```

```
10      23409
24          3
Name: Date, dtype: int64
```

Looks like there are two more rows that has a date in a different format. We Run the code cell below to obtain the indices corresponding to those rows and print the data.

```
indices = np.where([date_lengths == 24])[1]
print('Indices with corrupted data:', indices)
earthquakes.loc[indices]
```

```
Indices with corrupted data: [ 3378  7512 20650]
```

	Date	Time	Latitude
3378	1975-02-23T02:58:41.000Z	1975-02-23T02:58:41.000Z	8.017
7512	1985-04-28T02:53:41.530Z	1985-04-28T02:53:41.530Z	-32.998
20650	2011-03-13T02:23:34.520Z	2011-03-13T02:23:34.520Z	36.344

	Longitude	Type	Depth	Depth Error	Depth Seismic Stations
3378	124.075	Earthquake	623.0	NaN	NaN
7512	-71.766	Earthquake	33.0	NaN	NaN
20650	142.344	Earthquake	10.1	13.9	289.0

	Magnitude	Magnitude Type	...	Magnitude Seismic Stations
3378	5.6	MB	...	NaN
7512	5.6	MW	...	NaN
20650	5.8	MWC	...	NaN

	Azimuthal Gap	Horizontal Distance	Horizontal Error	Root Mean Square
3378	NaN	NaN	NaN	NaN
7512	NaN	NaN	NaN	1.30
20650	32.3	NaN	NaN	1.06

	ID	Source	Location Source	Magnitude Source	Status
3378	USP0000A09	US	US	US	Reviewed
7512	USP0002E81	US	US	HRV	Reviewed
20650	USP000HWQP	US	US	GCMT	Reviewed

[3 rows x 21 columns]

Given all of this information, we create a new column "date_parsed" in the earthquakes dataset that has correctly parsed dates in it.

We have now converted all the date columns into datetime.

```
# TODO: Your code here
earthquakes.loc[3378, "Date"] = "02/23/1975"
earthquakes.loc[7512, "Date"] = "04/28/1985"
earthquakes.loc[20650, "Date"] = "03/13/2011"
earthquakes['date_parsed'] = pd.to_datetime(earthquakes['Date'], format="%m/%d/%Y")
```

3) Select the day of the month

Create a Pandas Series day_of_month_earthquakes containing the day of the month from the "date_parsed" column.

```
# try to get the day of the month from the date column
day_of_month_earthquakes = earthquakes['date_parsed'].dt.day
```

4) Plot the day of the month to check the date parsing

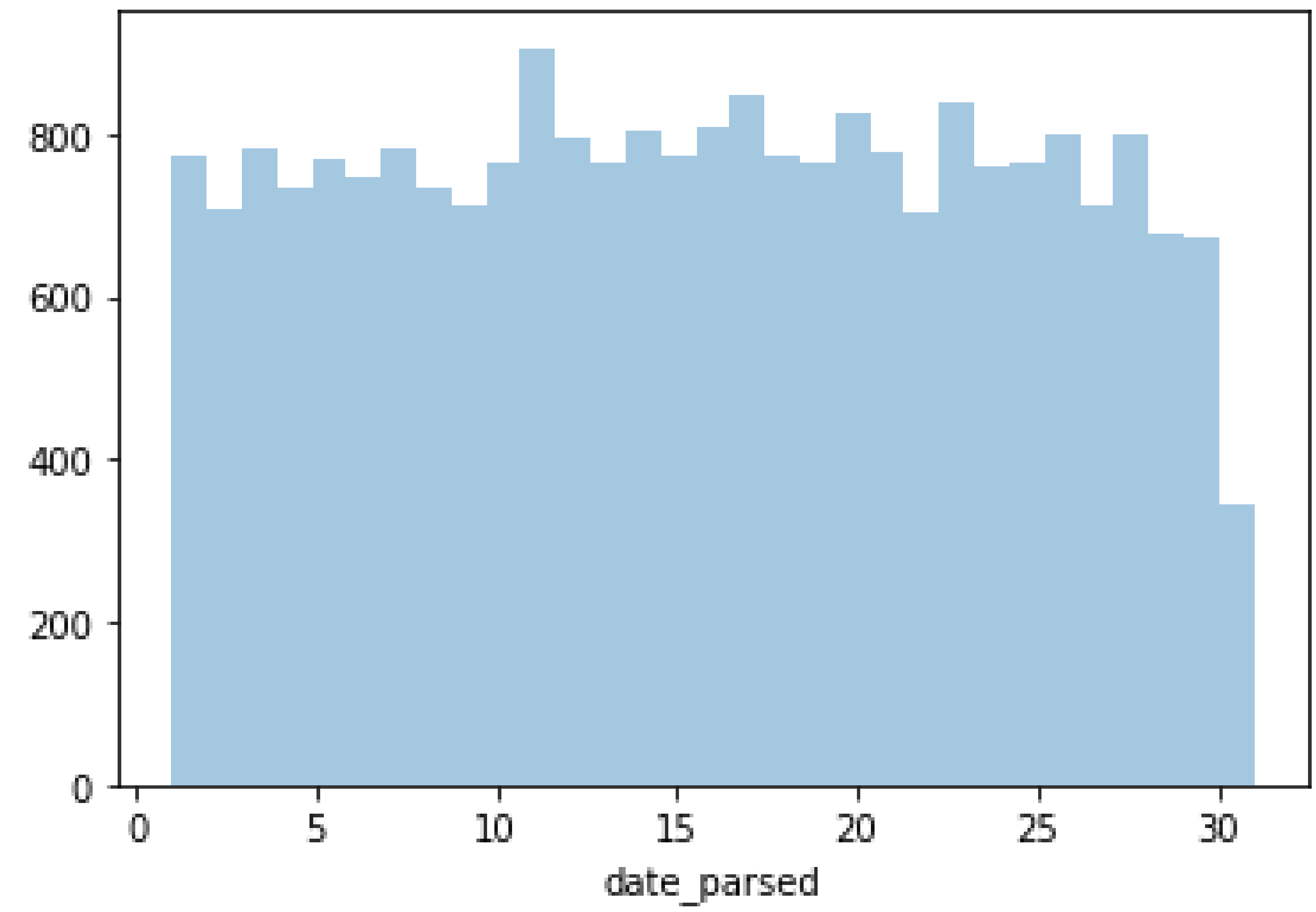
Plot the days of the month from your earthquake dataset.

```
# TODO: Your code here!
# remove na's
day_of_month_earthquakes = day_of_month_earthquakes.dropna()

# plot the day of the month
sns.distplot(day_of_month_earthquakes, kde=False, bins=31)
```

/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for

histograms).
 warnings.warn(msg, FutureWarning)

<AxesSubplot:xlabel='date_parsed'>



Now we have visualized a graph that shows the days of the month. This data parsing is just for visualizing the data. When training, we import and use the dataset as it is.

Import Libraries and Dataset

Here we import the other neccessary libraries for further data visualization and import the dataset as well

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

```
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  ...   Magnitude Source     Status
0  01/02/1965  13:44:18  ...             ISCGEM  Automatic
1  01/04/1965  11:29:49  ...             ISCGEM  Automatic
2  01/05/1965  18:05:58  ...             ISCGEM  Automatic
3  01/08/1965  18:49:43  ...             ISCGEM  Automatic
4  01/09/1965  13:32:50  ...             ISCGEM  Automatic

[5 rows x 21 columns]
```

```
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

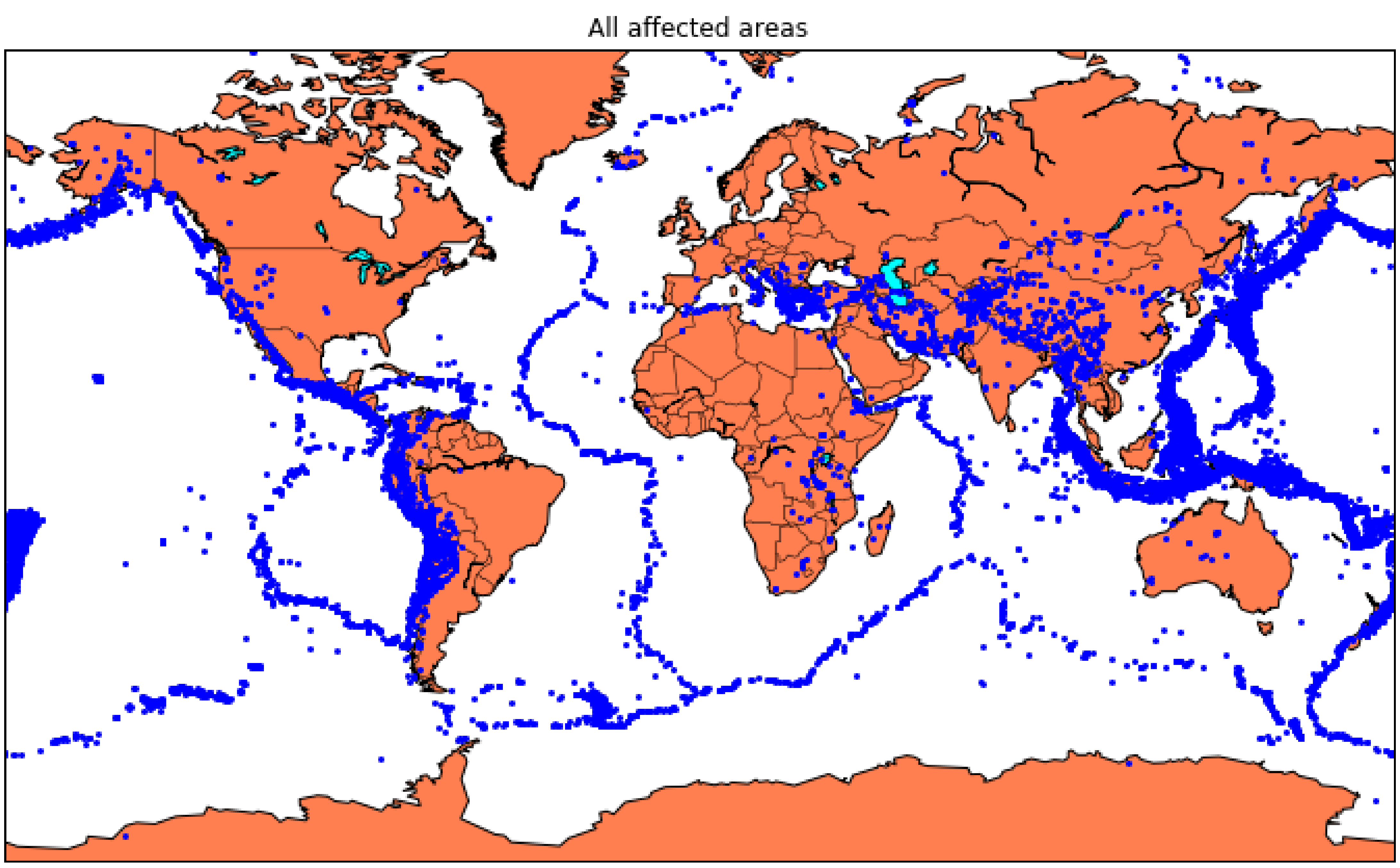
Visualization

- 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']]
```

```python
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)
```

Training using RandomForest

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.

```python
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]])
```

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

```
0.8614799631765803
```

```python
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
```

Building the 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: 1.000000 using {'activation': 'relu', 'batch_size': 10, 'epochs': 10, 'loss': 'squared_hinge', 'neurons':
16, 'optimizer': 'Adadelta'}
0.936562 (0.000858) 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'}
0.646286 (0.411324) with: {'activation': 'relu', 'batch_size': 10, 'epochs': 10, 'loss': 'squared_hinge',
'neurons': 16, 'optimizer': 'SGD'}
1.000000 (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 [==============================] - 3s 134us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 2/20
18727/18727 [==============================] - 2s 122us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 3/20
18727/18727 [==============================] - 2s 118us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 4/20
18727/18727 [==============================] - 2s 120us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 5/20
18727/18727 [==============================] - 2s 121us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 6/20
18727/18727 [==============================] - 3s 135us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 7/20
18727/18727 [==============================] - 2s 124us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 8/20
18727/18727 [==============================] - 2s 119us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 9/20
18727/18727 [==============================] - 2s 118us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
Epoch 10/20
18727/18727 [==============================] - 2s 120us/step - loss: 0.5000 - acc: 0.0189 -
val_loss: 0.5000 - val_acc: 0.0186
```

```
Epoch 11/20
18727/18727 [==============================] - 2s 123us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 12/20
18727/18727 [==============================] - 2s 118us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 13/20
18727/18727 [==============================] - 2s 121us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 14/20
18727/18727 [==============================] - 2s 119us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 15/20
18727/18727 [==============================] - 2s 125us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 16/20
18727/18727 [==============================] - 2s 121us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 17/20
18727/18727 [==============================] - 2s 124us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 18/20
18727/18727 [==============================] - 2s 120us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 19/20
18727/18727 [==============================] - 2s 120us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
Epoch 20/20
18727/18727 [==============================] - 3s 135us/step - loss: 0.5000 - acc: 0.0189 - val_loss: 0.5000 - val_acc: 0.0186
```

```
<keras.callbacks.History at 0x7838b345a358>
```

```python
[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 22us/step
Evaluation result on Test Data : Loss = 0.5, accuracy = 0.018581802648440837
```

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 that could be done with a user interface.

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