STAR LION COLLEGE OF ENGINEERING AND TECHNOLODGY

Program : Earthquake Prediction model using python
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EARTHQUAKE PREDICTION USING PYTHON MODEL

Earthquake Prediction System :

Earthquakes were once thought to result from supernatural forces in the prehistoric era. Aristotle was the first to identify earthquakes as a natural occurrence and to provide some potential explanations for them in a truly scientific manner.

One of nature's most destructive dangers is earthquakes. Strong earthquakes frequently have negative effects.

A lot of devastating earthquakes occasionally occur in nations like Japan, the USA, China, and nations in the middle and far east. Several major and medium-sized earthquakes have also occurred in India, which have resulted in significant property damage and fatalities.

One of the most catastrophic earthquakes ever recorded occurred in Maharastra early on September 30, 1993. One of the main goals of researchers studying earthquake seismology is to develop effective predicting methods for the occurrence of the next severe earthquake event that may allow us to reduce the death toll and property damage.

Most earthquakes, or 90%, are natural and result from tectonic activity. 10% of the remaining characteristics are associated with volcanism, man-made consequences, or other variables. Natural earthquakes are those that occur naturally and are typically far more powerful than other kinds of earthquakes.

The continental drift theory and the plate-tectonic theory are the two hypotheses that deal with earthquakes.

Random Forest :

It is a type of machine learning algorithm that is very famous nowadays. It generates a random decision tree and combines it into a single forest.

It features a decision model to increase accuracy. These trees divide the predictor space using a series of binary splits ("splits") on distinct variables. The tree's "root" node represents the entire predictor space.

The final division of the predictor space is made up of the "terminal nodes," which are nodes that are not split. Depending on the value of one of the predictor variables, each nonterminal node divides into two descendant nodes, one on the left and one on the right. If a continuous predictor variable is smaller than a split point, the points to the left will be the smaller predictor points, and the points to the right will be the larger predictor points.

The values of a categorical predictor variable Xi come from a small number of categories. To divide a node into its two descendants, a tree must analyze every possible split on each predictor variable and select the “best” split based on some criteria. A common splitting criterion in the context of regression is the mean squared residual at the node.

It is also a classification technique that uses ensemble learning.

The random forest generates a root node feature by randomly dividing, which is the primary distinction between it and the decision tree.

To enhance its accuracy, the Random forest chooses a random feature.

The random forest approach is faster than the bagging and boosting method. In some circumstances, the neural network Support Vector Machine performs better when using the random forest.

Support Vector Classifier :

There is a computer algorithm known as a support vector machine (SVM) that learns to name objects. For instance, by looking at hundreds or thousands of reports of both fraudulent and legitimate credit card activity, an SVM can learn to identify fraudulent credit card activity.

A vast collection of scanned photos of handwritten zeros, ones, and other numbers can also be used to train an SVM to recognize handwritten numerals.

Additionally, SVMs have been successfully used in a growing number of biological applications.

The automatic classification of microarray gene expression profiles is a typical use of support vector machines in the biomedical field.

Theoretically, an SVM can examine the gene expression profile derived from a tumor sample or from peripheral fluid and arrive at a diagnosis or prognosis.

An SVM could theoretically analyze the gene expression profile obtained from a tumor sample or from peripheral fluid and determine a diagnosis or prognosis.

An SVM is essentially a mathematical construct that serves as a method (or recipe) for maximizing a specific mathematical function with regard to a given set of data. But it’s not necessary to read an equation to understand the fundamental concepts behind the SVM algorithm.

In fact, I contend that in order to comprehend the core of SVM classification, one only needs to understand four fundamental ideas: the separating hyperplane, the maximum-margin hyperplane, the soft margin, and the kernel function.

The SVM algorithm's apparent ability to solely handle binary classification issues is its most glaring flaw, according to the information provided thus far.

We can distinguish between ALL and AML, but how do we distinguish between the many other types of cancer classes? It is simple to generalize to multiclass classification and can be done in a number of different ways. The most straightforward method may be to train several one-versus-all classifiers.

Gradient Boosting Algorithm :

To provide a more precise estimate of the response variable, gradient boosting machines, or simply GBMs, use a learning process that sequentially fits new models. This algorithm's fundamental notion is to build the new base learners to have as much in common as possible with the ensemble's overall negative gradient of the loss function.

The loss functions used can be chosen at random. However, for the sake of clarity, let's assume that the learning process yields successive error-fitting if the error function is the traditional squared-error loss.

In general, it is up to the researcher to decide on the loss function, and there is a wealth of previously determined loss functions and the option of developing one's own task-specific loss.

Due to their high degree of adaptability, GBMs can be easily tailored to any specific data-driven activity. It adds a great deal of flexibility to the model design, making the selection of the best loss function a question of trial and error.

But because boosting methods are very easy to use, it is possible to test out various model architectures. Additionally, the GBMs have demonstrated a great deal of success in a variety of machine learning and data mining problems in addition to practical applications.

Ensemble models are a helpful practical tool for various predictive tasks from the perspective of neurorobotics since they regularly deliver findings with a better degree of accuracy than traditional single-strong machine learning models.

To detect and identify human movement and activity, for instance, the ensemble models can effectively map the EMG and EEG sensor readings. These models, however, can also be incredibly insightful for memory simulations and models of brain development.

In contrast to artificial neural networks, which store learned patterns in the connections between virtual neurons, in boosted ensembles the base-learners act as the memory medium and successively build the acquired patterns, thereby enhancing the level of pattern detail.

Since the ensemble formation models and network growth strategies can be combined, advances in boosted ensembles can be useful in the field of brain simulation.

The ability to build ensembles with various graph properties and topologies, such as small-world networks, which are present in biological neural networks, will be possible in particular if the base learners are thought of as the network's nodes, which in the context of the connectome will mean the neurons.

It is crucial to first establish the technique and computational framework for these models before moving forward with sophisticated neurorobotics applications of boosted ensemble models.

Steps to Implement :

1. **Import the modules and all the libraries we would require in this project.**

```
import numpy as np#importing the numpy module
import pandas as pd#importing the pandas module
from sklearn.model_selection import train_test_split#importing the train test split module
import pickle #import pickle
from sklearn import metrics #import metrics
from sklearn.ensemble import RandomForestClassifier#import the Random Forest Classifier
```

2. Here we are reading the dataset and we are creating a function to do some data processing on our dataset. Here we are using the numpy to convert the data into an array.

```
dataframe= pd.read_csv("dataset.csv")#here we are reading the dataset
dataframe= np.array(dataframe)#converting the dataset into an numpy array
print(dataframe)#printing the dataframe
```

3. Here we are dividing our dataset into X and Y where x is the independent variable whereas y is the dependent variable. Then we are using the test train split function to divide the X and Y into training and testing datasets. We are taking the percentage of 80 and 20% for training and testing respectively.

```
x_set = dataframe[:, 0:-1]#getting the x dataset
```



```
y_set = dataframe[:, -1]#getting the y dataset
y_set = y_set.astype('int')#converting the y_set into int
x_set = x_set.astype('int')#converting the x_set into int
x_train, x_test, y_train, y_test = train_test_split(x_set, y_set, test_size=0.2, random_state=0)
```

4. Here we are creating our RandomForestClassifier and we are passing our training dataset to our model to train it. Also then we are passing our testing dataset to predict the dataset.

```
Random_forest_classifier = RandomForestClassifier()#creating the model
random_forest_classifier.fit(x_train, y_train)#fitting the model with training dataset
y_pred = random_forest_classifier.predict(X_test)#predicting the result using test set
print(metrics.accuracy_score(y_test, y_pred))#printing the accuracy score
```

5. In this piece of code, we are creating our instance for Gradient Boosting Classifier. The maximum Depth of this Gradient Boosting algorithm is 3. After creating the instance, we pass our training data to the classifier to fit our training data into the algorithm. This is a part of training.

Once we are done with training, we pass the testing data, and we make our predictions on testing data and store it in another variable. After training and testing, it's time to print the score. For this, we are using the accuracy score function, and we are passing the predicted values and the original values to the function, and it is printing the accuracy.

```
#importing the descision tree classifier from the sklearn tree
tree = GradientBoostingClassifier() #making an instance the descision tree with maxdepth = 3 as passing the input
clf = tree.fit(X_train,y_train) #here we are passing our training and the testing data to the tree and fitting it
```



```
y_pred = clf.predict(X_test) #predicting the value by passing the x_test datset to the tree
accuracy_score(y_pred,y_test)# here we are printing the accuracy score of the prediction and the testing data
```

6. Here, we are doing the same thing as above. The only difference is that this time, we are using Support Vector Classifier. So, we are creating an instance of Support Vector Classifier and setting the gamma function to "auto". After that, we pass the training data to the classifier.

After training the model, we pass the testing data to our model and predict the accuracy score using the accuracy score function.

```
#importing the descision tree classifier from the sklearn tree
tree = SVC(gamma='auto') #making an instance the support vector tree
clf = tree.fit(X_train,y_train) #here we are passing our training and the testing data to the tree and fitting it
```

y_pred = clf.predict(X_test) #predicting the value by passing the x_test datset to the tree

accuracy_score(y_pred,y_test)# here we are printing the accuracy score of the prediction and the testing data

```
jupyter earthquake_prediction Last Checkpoint: 09/08/2022 (autosaved)                Logout
File  Edit  View  Insert  Cell  Kernel  Widgets  Help          Not Trusted | Python 3 (ipykernel) O
                                                                Run  Code

         [[ 22  94  10]
          [ 27  75   5]
          [ 34  76  10]
          ...
          [ 31  76   5]
          [ 23  70  10]
          [ 37  72 125]] [4 2 2 ... 3 4 4]
         0.5625

In [2]:  from sklearn.svm import SVC#importing the SVC from sklearn.svm library which will be used in this project
         from sklearn.ensemble import RandomForestClassifier#importing the Random Forest Classifier library which will be used in this pro
         from sklearn.ensemble import GradientBoostingClassifier#importing the Gradient Boosting Classifier library which will be used in

In [5]:  #importing the descision tree classifier from the sklearn tree
         tree = GradientBoostingClassifier() #making an instance the descision tree with maxdepth = 3 as passing the input
         clf = tree.fit(X_train,y_train) #here we are passing our training and the testing data to the tree and fitting it
         y_pred = clf.predict(X_test) #predicting the value by passing the x_test datset to the tree
         accuracy_score(y_pred,y_test)# here we are printing the accuracy score of the prediction and the testing data

Out[5]:  0.5808823529411765

In [6]:  #importing the descision tree classifier from the sklearn tree
         tree = SVC(gamma='auto') #making an instance the descision tree with maxdepth = 3 as passing the input
         clf = tree.fit(X_train,y_train) #here we are passing our training and the testing data to the tree and fitting it
         y_pred = clf.predict(X_test) #predicting the value by passing the x_test datset to the tree
         accuracy_score(y_pred,y_test)# here we are printing the accuracy score of the prediction and the testing data

Out[6]:  0.5680147058823529
```

EXTRACT, TRANSFORM, LOAD (ETL) :

Once we have successfully running PySpark in Jupyter

Notebook now we can load the dataset from the local directory.

```
In [3]: # Load the dataset
        df_load = spark.read.csv(r"C:\Users\Intel X Nvidia\Downloads\database.csv", header=True)
        # Preview df_load
        df_load.take(1)

Out[3]: [Row(Date='01/02/1965', Time='13:44:18', Latitude='19.246', Longitude='145.616', Type='Earthquake', Depth='131.6', Depth Error=
        None, Depth Seismic Stations=None, Magnitude='6', Magnitude Type='MW', Magnitude Error=None, Magnitude Seismic Stations=None, A
        zimuthal Gap=None, Horizontal Distance=None, Horizontal Error=None, Root Mean Square=None, ID='ISCGEM860706', Source='ISCGEM',
        Location Source='ISCGEM', Magnitude Source='ISCGEM', Status='Automatic')]
```

After we load the dataset we can preview the column using df.take() this function help to show us the specific row. In the output, we can see the dataset contains many columns hence we don’t need to use all the columns. So we drop column we don’t need using df.drop().

```
In [4]: # Drop fields we don't need from df_load
        lst_dropped_columns = ['Depth Error', 'Time', 'Depth Seismic Stations','Magnitude Error','Magnitude Seismic Stations','Azimuthal
            'Root Mean Square','Source','Location Source','Magnitude Source','Status']

        df_load = df_load.drop(*lst_dropped_columns)
        # Preview df_load
        df_load.show(5)
```

```
+----------+--------+---------+----------+-----+---------+--------------+------------+
|      Date|Latitude|Longitude|      Type|Depth|Magnitude|Magnitude Type|          ID|
+----------+--------+---------+----------+-----+---------+--------------+------------+
|01/02/1965|  19.246|  145.616|Earthquake|131.6|        6|            MW|ISCGEM860706|
|01/04/1965|   1.863|  127.352|Earthquake|   80|      5.8|            MW|ISCGEM860737|
|01/05/1965| -20.579| -173.972|Earthquake|   20|      6.2|            MW|ISCGEM860762|
|01/08/1965| -59.076|  -23.557|Earthquake|   15|      5.8|            MW|ISCGEM860856|
|01/09/1965|  11.938|  126.427|Earthquake|   15|      5.8|            MW|ISCGEM860890|
+----------+--------+---------+----------+-----+---------+--------------+------------+
only showing top 5 rows
```

Now we can see only the columns that we need to operate, the dataset is much cleaner now. After we sorting the column now the thing we need to do is append the “Year” column into the dataframe. Before we add it to the dataframe we need to convert the type of “Date” column into “the timestamp” because the original type of “Date” is an “object” which is “object” type cannot be extracted. So we can simply do this:

```
In [5]: # Create a year field and add it to the dataframe
        df_load = df_load.withColumn('Year', year(to_timestamp('Date', 'dd/MM/yyyy')))
        # Preview df_load
        df_load.show(5)
```

```
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|      Date|Latitude|Longitude|      Type|Depth|Magnitude|Magnitude Type|          ID|Year|
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|01/02/1965|  19.246|  145.616|Earthquake|131.6|        6|            MW|ISCGEM860706|1965|
|01/04/1965|   1.863|  127.352|Earthquake|   80|      5.8|            MW|ISCGEM860737|1965|
|01/05/1965| -20.579| -173.972|Earthquake|   20|      6.2|            MW|ISCGEM860762|1965|
|01/08/1965| -59.076|  -23.557|Earthquake|   15|      5.8|            MW|ISCGEM860856|1965|
|01/09/1965|  11.938|  126.427|Earthquake|   15|      5.8|            MW|ISCGEM860890|1965|
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
only showing top 5 rows
```

After we add the "Year" column into the dataframe now we can count how many quakes occurred in each year. We can use groupBy() and count():

```
In [6]: # Build the quakes frequency dataframe using the year field and counts for each year
df_quake_freq = df_load.groupBy('Year').count().withColumnRenamed('count', 'Counts')
# Preview df_quake_freq
df_quake_freq.show(5)
```

```
+----+------+
|Year|Counts|
+----+------+
|1990|   196|
|1975|   150|
|1977|   148|
|2003|   187|
|2007|   211|
+----+------+
only showing top 5 rows
```

Based on the dataframe we can see that the year column is not sorted sequentially, later we can handle this.

After we count the quakes based on a year now we can check the type of every data in

a column like this:

As we can see from the output most of the type of the co

```
In [7]: # Preview df_load schema
df_load.printSchema()
```

```
root
 |-- Date: string (nullable = true)
 |-- Latitude: string (nullable = true)
 |-- Longitude: string (nullable = true)
 |-- Type: string (nullable = true)
 |-- Depth: string (nullable = true)
 |-- Magnitude: string (nullable = true)
 |-- Magnitude Type: string (nullable = true)
 |-- ID: string (nullable = true)
 |-- Year: integer (nullable = true)
```

As we can see from the output most of the type of the column is a string which is cannot be joined. For that, we need to convert some columns we need from strings into numeric types using cast().

```
In [8]: # Cast some fields from string into numeric types
        df_load = df_load.withColumn('Latitude', df_load['Latitude'].cast(DoubleType()))\
            .withColumn('Longitude', df_load['Longitude'].cast(DoubleType()))\
            .withColumn('Depth', df_load['Depth'].cast(DoubleType()))\
            .withColumn('Magnitude', df_load['Magnitude'].cast(DoubleType()))

        # Preview of df_load
        df_load.show(5)
```

```
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|      Date|Latitude|Longitude|      Type|Depth|Magnitude|Magnitude Type|          ID|Year|
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|01/02/1965|  19.246|  145.616|Earthquake|131.6|      6.0|            MW|ISCGEM860706|1965|
|01/04/1965|   1.863|  127.352|Earthquake| 80.0|      5.8|            MW|ISCGEM860737|1965|
|01/05/1965| -20.579| -173.972|Earthquake| 20.0|      6.2|            MW|ISCGEM860762|1965|
|01/08/1965| -59.076|  -23.557|Earthquake| 15.0|      5.8|            MW|ISCGEM860856|1965|
|01/09/1965|  11.938|  126.427|Earthquake| 15.0|      5.8|            MW|ISCGEM860890|1965|
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
only showing top 5 rows
```

```
In [9]: # Preview df_load schema
        df_load.printSchema()
```

```
root
 |-- Date: string (nullable = true)
 |-- Latitude: double (nullable = true)
 |-- Longitude: double (nullable = true)
 |-- Type: string (nullable = true)
 |-- Depth: double (nullable = true)
 |-- Magnitude: double (nullable = true)
 |-- Magnitude Type: string (nullable = true)
 |-- ID: string (nullable = true)
 |-- Year: integer (nullable = true)
```

```
In [10]: # Create avg magnitude and max magnitude fields and add to df_quake_freq
         df_max = df_load.groupBy('Year').max('Magnitude').withColumnRenamed('max(Magnitude)', 'Max_Magnitude')
         df_avg = df_load.groupBy('Year').avg('Magnitude').withColumnRenamed('avg(Magnitude)', 'Avg_Magnitude')
```

```
In [11]: # Join df_max, and df_avg to df_quake_freq
         df_quake_freq = df_quake_freq.join(df_avg, ['Year']).join(df_max, ['Year'])
         df_quake_freq = df_quake_freq.orderBy(asc('Year'))
         df_quake_freq.show(5)
```

```
+----+------+-----------------+-------------+
|Year|Counts|    Avg_Magnitude|Max_Magnitude|
+----+------+-----------------+-------------+
|1965|   156| 6.009615384615388|          8.7|
|1966|    98| 6.060714285714285|          7.7|
|1967|   103|5.962135922330985|          7.2|
|1968|   106| 6.070754716981133|          7.6|
|1969|   114| 6.015789473684214|          7.5|
+----+------+-----------------+-------------+
only showing top 5 rows
```

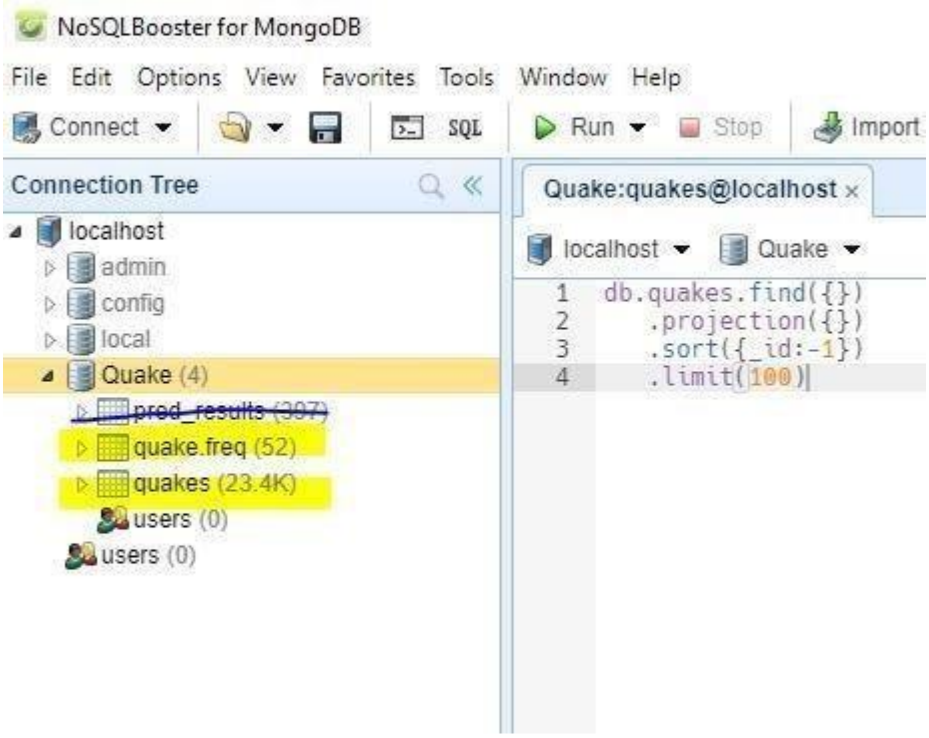
After we converting the string columns into numeric now we can join the df_max and the df_avg into a new variable called df_quake_freq.

```
In [12]: # Remove nulls
         df_load.dropna()
         df_quake_freq.dropna()

Out[12]: DataFrame[Year: int, Counts: bigint, Avg_Magnitude: double, Max_Magnitude: double]

In [13]: # Preview dataframes
         df_load.show(5)

+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|      Date|Latitude|Longitude|      Type|Depth|Magnitude|Magnitude Type|          ID|Year|
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|01/02/1965|  19.246|  145.616|Earthquake|131.6|      6.0|            MW|ISCGEM860706|1965|
|01/04/1965|   1.863|  127.352|Earthquake| 80.0|      5.8|            MW|ISCGEM860737|1965|
|01/05/1965| -20.579| -173.972|Earthquake| 20.0|      6.2|            MW|ISCGEM860762|1965|
|01/08/1965| -59.076|  -23.557|Earthquake| 15.0|      5.8|            MW|ISCGEM860856|1965|
|01/09/1965|  11.938|  126.427|Earthquake| 15.0|      5.8|            MW|ISCGEM860890|1965|
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
only showing top 5 rows

In [14]: df_quake_freq.show(5)

+----+------+-----------------+-------------+
|Year|Counts|    Avg_Magnitude|Max_Magnitude|
+----+------+-----------------+-------------+
|1965|   156| 6.009615384615388|          8.7|
|1966|    98| 6.060714285714285|          7.7|
|1967|   103|5.9621359223300985|          7.2|
|1968|   106| 6.070754716981133|          7.6|
|1969|   114| 6.015789473684214|          7.5|
+----+------+-----------------+-------------+
only showing top 5 rows
```

After we removed the nulls now the data is ready to use, the next thing we need to do is save the data into MongoDB.

```
In [15]: # Build the tables/collections in mongodb
         # Write df_load to mongodb
         df_load.write.format('mongo')\
             .mode('overwrite')\
             .option('spark.mongodb.output.uri', 'mongodb://127.0.0.1:27017/Quake.quakes').save()

In [16]: # Write df_quake_freq to mongodb
         df_quake_freq.write.format('mongo')\
             .mode('overwrite')\
             .option('spark.mongodb.output.uri', 'mongodb://127.0.0.1:27017/Quake.quake.freq' ).save()
```

To make sure the dataframe is saved properly into MongoDB, we can open the NoSQLBooster and expand the Quake database, if you see this, it means the data is already stored successfully, ignore pred_results in this step.



After the training data is already saved the next thing we can do is load the test data. You can download the test data from here. The file name is query.csv, its contents are the same as the training data but the difference is its scope only for 2017.

Okay, once you have downloaded the file you now can load the test and training data

with the Jupyter Notebook.

In [18]:
```python
# Load the test data file into a dataframe
df_test = spark.read.csv(r"C:\Users\Intel X Nvidia\Downloads\query.csv", header=True)
# Preview df_test
df_test.take(1)
```

Out[18]:
```
[Row(time='2017-01-02T00:13:06.300Z', latitude='-36.0365', longitude='51.9288', depth='10', mag='5.7', magType='mwb', nst=None,
gap='26', dmin='14.685', rms='1.37', net='us', id='us10007p5d', updated='2017-03-27T23:53:17.040Z', place='Southwest Indian Rid
ge', type='earthquake', horizontalError='10.3', depthError='1.7', magError='0.068', magNst='21', status='reviewed', locationSou
rce='us', magSource='us')]
```

In [19]:
```python
# Load the training data from mongo into a dataframe
df_train = spark.read.format('mongo')\
    .option('spark.mongodb.input.uri', 'mongodb://127.0.0.1:27017/Quake.quakes').load()

# Preview df_train
df_train.show(5)
```

```
+----------+-----+------------+--------+---------+---------+--------------+----------+----+--------------------+
|      Date|Depth|          ID|Latitude|Longitude|Magnitude|Magnitude Type|      Type|Year|                 _id|
+----------+-----+------------+--------+---------+---------+--------------+----------+----+--------------------+
|01/02/1965|131.6|ISCGEM860706|  19.246|  145.616|      6.0|            MW|Earthquake|1965|[6139c28b50a0ee1a...|
|01/04/1965| 80.0|ISCGEM860737|   1.863|  127.352|      5.8|            MW|Earthquake|1965|[6139c28b50a0ee1a...|
|01/05/1965| 20.0|ISCGEM860762| -20.579| -173.972|      6.2|            MW|Earthquake|1965|[6139c28b50a0ee1a...|
|01/08/1965| 15.0|ISCGEM860856| -59.076|  -23.557|      5.8|            MW|Earthquake|1965|[6139c28b50a0ee1a...|
|01/09/1965| 15.0|ISCGEM860890|  11.938|  126.427|      5.8|            MW|Earthquake|1965|[6139c28b50a0ee1a...|
+----------+-----+------------+--------+---------+---------+--------------+----------+----+--------------------+
only showing top 5 rows
```

select the columns we wanted and rename After test and
training data are loaded, the next thing we can do is them.

```
In [20]: # Select fields we will use and discard fields we don't need
df_test_clean = df_test['time', 'latitude', 'longitude', 'mag', 'depth']
# Preview df_test_clean
df_test_clean.show(5)
```

```
+-------------------+--------+---------+---+------+
|               time|latitude|longitude|mag| depth|
+-------------------+--------+---------+---+------+
|2017-01-02T00:13:...|-36.0365|  51.9288|5.7|    10|
|2017-01-02T13:13:...|  -4.895| -76.3675|5.9|   106|
|2017-01-02T13:14:...|-23.2513| 179.2383|6.3|551.62|
|2017-01-03T09:09:...| 24.0151|  92.0177|5.7|    32|
|2017-01-03T21:19:...|-43.3527| -74.5017|5.5| 10.26|
+-------------------+--------+---------+---+------+
only showing top 5 rows
```

```
In [21]: # Rename fields
df_test_clean = df_test_clean.withColumnRenamed('time', 'Date')\
    .withColumnRenamed('latitude', 'Latitude')\
    .withColumnRenamed('longitude', 'Longitude')\
    .withColumnRenamed('mag', 'Magnitude')\
    .withColumnRenamed('depth', 'Depth')

# Preview df_test_clean
df_test_clean.show(5)
```

```
+-------------------+--------+---------+---------+------+
|               Date|Latitude|Longitude|Magnitude| Depth|
+-------------------+--------+---------+---------+------+
|2017-01-02T00:13:...|-36.0365|  51.9288|      5.7|    10|
|2017-01-02T13:13:...|  -4.895| -76.3675|      5.9|   106|
|2017-01-02T13:14:...|-23.2513| 179.2383|      6.3|551.62|
|2017-01-03T09:09:...| 24.0151|  92.0177|      5.7|    32|
|2017-01-03T21:19:...|-43.3527| -74.5017|      5.5| 10.26|
+-------------------+--------+---------+---------+------+
only showing top 5 rows
```

As you can see how we are doing the same set of processes as we did previously to the training data, so now we check and convert the type of fields in test data from the string into numeric.

```
In [22]: # Preview Schema
         df_test_clean.printSchema()

root
 |-- Date: string (nullable = true)
 |-- Latitude: string (nullable = true)
 |-- Longitude: string (nullable = true)
 |-- Magnitude: string (nullable = true)
 |-- Depth: string (nullable = true)
```

```
In [23]: # Cast some string fields into numeric fields
         df_test_clean = df_test_clean.withColumn('Latitude', df_test_clean['Latitude'].cast(DoubleType()))\
             .withColumn('Longitude', df_test_clean['Longitude'].cast(DoubleType()))\
             .withColumn('Depth', df_test_clean['Depth'].cast(DoubleType()))\
             .withColumn('Magnitude', df_test_clean['Magnitude'].cast(DoubleType()))
```

```
In [24]: df_test_clean.printSchema()

root
 |-- Date: string (nullable = true)
 |-- Latitude: double (nullable = true)
 |-- Longitude: double (nullable = true)
 |-- Magnitude: double (nullable = true)
 |-- Depth: double (nullable = true)
```

After all the columns we need are converted to numeric, now we can create a training and testing dataframe, and remove all the missing values within using dropna().

```
In [25]: # Create training and testing dataframes
         df_testing = df_test_clean['Latitude', 'Longitude', 'Magnitude', 'Depth']
         df_training = df_train['Latitude', 'Longitude', 'Magnitude', 'Depth']
```

```
In [26]: # Preview df_training
         df_training.show(5)
```

```
+--------+---------+---------+-----+
|Latitude|Longitude|Magnitude|Depth|
+--------+---------+---------+-----+
|  19.246|  145.616|      6.0|131.6|
|   1.863|  127.352|      5.8| 80.0|
| -20.579| -173.972|      6.2| 20.0|
| -59.076|  -23.557|      5.8| 15.0|
|  11.938|  126.427|      5.8| 15.0|
+--------+---------+---------+-----+
only showing top 5 rows
```

```
In [27]: # Preview df_testing
         df_testing.show(5)
```

```
+--------+---------+---------+------+
|Latitude|Longitude|Magnitude| Depth|
+--------+---------+---------+------+
|-36.0365|  51.9288|      5.7|  10.0|
|  -4.895| -76.3675|      5.9| 106.0|
|-23.2513| 179.2383|      6.3|551.62|
| 24.0151|  92.0177|      5.7|  32.0|
|-43.3527| -74.5017|      5.5| 10.26|
+--------+---------+---------+------+
only showing top 5 rows
```

```
In [28]: # Drop record with null values from out dataframes
         df_testing = df_testing.dropna()
         df_training = df_training.dropna()
```

Once we have removed all the nulls and the dataframe is tidy now we can move to the machine learning session.

MACHINE LEARNING :

Now we move to the machine learning session, in this process, we will import some

necessary libraries to create the model.

```
In [29]: from pyspark.ml import Pipeline
         from pyspark.ml.regression import RandomForestRegressor
         from pyspark.ml.feature import VectorAssembler
         from pyspark.ml.evaluation import RegressionEvaluator
```

After we imported the libraries we needed we can create the model.

```
In [30]: # Select feature to parse into our model and then create the feature vector
         assembler = VectorAssembler(inputCols=['Latitude', 'Longitude', 'Depth'], outputCol='features')

         # Create the model
         model_reg = RandomForestRegressor(featuresCol='features', labelCol='Magnitude')

         # Chain the assembler with the model in a pipeline
         pipeline = Pipeline(stages=[assembler, model_reg])

         # Train the Model
         model = pipeline.fit(df_training)

         # Make the prediction
         pred_results = model.transform(df_testing)
```

```
In [31]: # Preview pred_results dataframe
         pred_results.show(5)

+--------+--------+---------+------+--------------------+-----------------+
|Latitude|Longitude|Magnitude| Depth|            features|       prediction|
+--------+--------+---------+------+--------------------+-----------------+
|-36.0365|  51.9288|      5.7|  10.0|[-36.0365,51.9288...|5.845803808668242|
|  -4.895| -76.3675|      5.9| 106.0|[-4.895,-76.3675,...|5.882302317310106|
|-23.2513| 179.2383|      6.3|551.62|[-23.2513,179.238...|5.905875451821726|
| 24.0151|  92.0177|      5.7|  32.0|[24.0151,92.0177,...|5.881770835768791|
|-43.3527| -74.5017|      5.5| 10.26|[-43.3527,-74.501...|5.954785795157244|
+--------+--------+---------+------+--------------------+-----------------+
only showing top 5 rows
```

As we can see from the syntax above to make a prediction we need to aggregate latitude, longitude, and depth data into one vector and stored it into a new column called features. After that, the results of the prediction are stored automatically in the prediction column. We can compare the magnitude prediction with the magnitude from the test data, the difference is tolerable. To verify this model is reliable we need to test the accuracy using RMSE. If the RMSE is below 0.5 it means the model is a good fit and we can use it to predict.

After we calculate the RMSE the result is 0.402274 which means the model is a good

fit and reliable.

Now the next thing we can do is creating a dataset for prediction, drop the column we don't need, and rename some columns.

DATA VISUALIZATION :

```
In [32]: # Evaluate the model
         # RMSE should be less than 0.5 for the model to be useful
         evaluator = RegressionEvaluator(labelCol='Magnitude', predictionCol='prediction', metricName='rmse')
         rmse = evaluator.evaluate(pred_results)
         print('Root Mean Squared Error (RMSE) on test data = %g' % rmse)

         Root Mean Squared Error (RMSE) on test data = 0.402274
```

Now is the interesting part because we can see our model through plots. Before we start to create the plot we need to import some libraries. One of the libraries is Bokeh which is an important part to visualize the model.

```
In [34]: # Create the prediction dataset
         df_pred_results = pred_results['Latitude', 'Longitude', 'prediction']

         # Rename the prediction field
         df_pred_results = pred_results.withColumnRenamed('prediction', 'Pred_Magnitude')

         # Add more columns to our prediction dataset
         df_pred_results = df_pred_results.withColumn('Year', lit(2017))\
             .withColumn('RMSE', lit(rmse))

         # Discard column that we don't need ('features' is vector so it will cause error when load into mongodb)
         columns_to_drop = ['Magnitude', 'Depth', 'features']
         df_pred_results = df_pred_results.drop(*columns_to_drop)

         # Preview df_pred_results
         df_pred_results.show(5)

         +--------+---------+-----------------+----+------------------+
         |Latitude|Longitude|   Pred_Magnitude|Year|              RMSE|
         +--------+---------+-----------------+----+------------------+
         |-36.0365|  51.9288|5.845803808668242|2017|0.40227436189606913|
         |  -4.895| -76.3675|5.882302317310106|2017|0.40227436189606913|
         |-23.2513| 179.2383|5.905875451821726|2017|0.40227436189606913|
         | 24.0151|  92.0177|5.881770835768791|2017|0.40227436189606913|
         |-43.3527| -74.5017|5.954785795157244|2017|0.40227436189606913|
         +--------+---------+-----------------+----+------------------+
         only showing top 5 rows
```

```
In [38]: import pandas as pd
         from bokeh.io import output_notebook, output_file
         from bokeh.plotting import figure, show, ColumnDataSource
         from bokeh.models.tools import HoverTool
         import math
         from math import pi
         from bokeh.palettes import Category20c
         from bokeh.transform import cumsum
         from bokeh.tile_providers import CARTODBPOSITRON, get_provider, Vendors
         from bokeh.themes import built_in_themes
         from bokeh.io import curdoc
         from pymongo import MongoClient
         import warnings
         warnings.filterwarnings('ignore')
         from pyspark.sql.functions import desc
```

After the libraries are imported, the next thing we can do is create a custom read function. This part is important to read data from MongoDB.

```
In [39]: # Create a custom read function to read data from mongodb into a dataframe
def read_mongo(host='127.0.0.1', port=27017, username=None, password=None, db='Quake', collection='pred_results'):

    mongo_uri = 'mongodb://{}:{}/{}.{}'.format(host, port, db, collection)

    # Connect to mongodb
    conn = MongoClient(mongo_uri)
    db = conn[db]

    # Select all records from the collection
    cursor = db[collection].find()

    # Create the dataframe
    df = pd.DataFrame(list(cursor))

    # Delete the _id field
    del df['_id']

    return df
```

```
In [40]: # Load the datasets from mongodb
df_quakes = read_mongo(collection='quakes')
df_quake_freq = read_mongo(collection='quake.freq')
df_quake_pred = read_mongo(collection='pred_results')
```

Data from 2016

Then type output_notebook to verify the BokehJS is loaded in Jupyter Notebook.

```
In [41]: df_quakes_2016 = df_quakes[df_quakes['Year'] == 2016]
# Preview df_quakes_2016
df_quakes_2016.head()
```

Out[41]:

	Date	Latitude	Longitude	Type	Depth	Magnitude	Magnitude Type	ID	Year
22943	01/01/2016	-50.5575	139.4489	Earthquake	10.00	6.3	MWW	US10004ANT	2016.0
22944	01/01/2016	-28.6278	-177.2810	Earthquake	34.00	5.8	MWW	US10004AQY	2016.0
22945	01/02/2016	44.8069	129.9406	Earthquake	585.47	5.8	MWW	US10004ATB	2016.0
22946	01/03/2016	24.8036	93.6505	Earthquake	55.00	6.7	MWW	US10004B2N	2016.0
22947	01/05/2016	30.6132	132.7337	Earthquake	4.71	5.8	MWW	US10004BEN	2016.0

Okay, after we create the dataset from 2016 the next thing we can do now is creating a function to style our plot. To style the plots you can simply do this:

Styling plots

After we created a custom style function, now we can create the Geo Map plot. Using Geo Map we can see our model applied on

```
In [42]: # Show plots embedded in Jupyter Notebook
         output_notebook()
```

BokehJS 2.3.3 successfully loaded.

```
In [43]: # Create custom style function to style our plots
         def style(p):
             # Title
             p.title.align = 'center'
             p.title.text_font_size = '20pt'
             p.title.text_font = 'serif'

             # Axis titles
             p.xaxis.axis_label_text_font_size = '14pt'
             p.xaxis.axis_label_text_font_style = 'bold'
             p.yaxis.axis_label_text_font_size = '14pt'
             p.yaxis.axis_label_text_font_style = 'bold'

             # Tick labels
             p.xaxis.major_label_text_font_size = '12pt'
             p.yaxis.major_label_text_font_size = '12pt'

             # Plot the legend in the top left corner
             p.legend.location = 'top_left'

             return p
```

the earth map. The syntax is quite long so I will quote the code below:

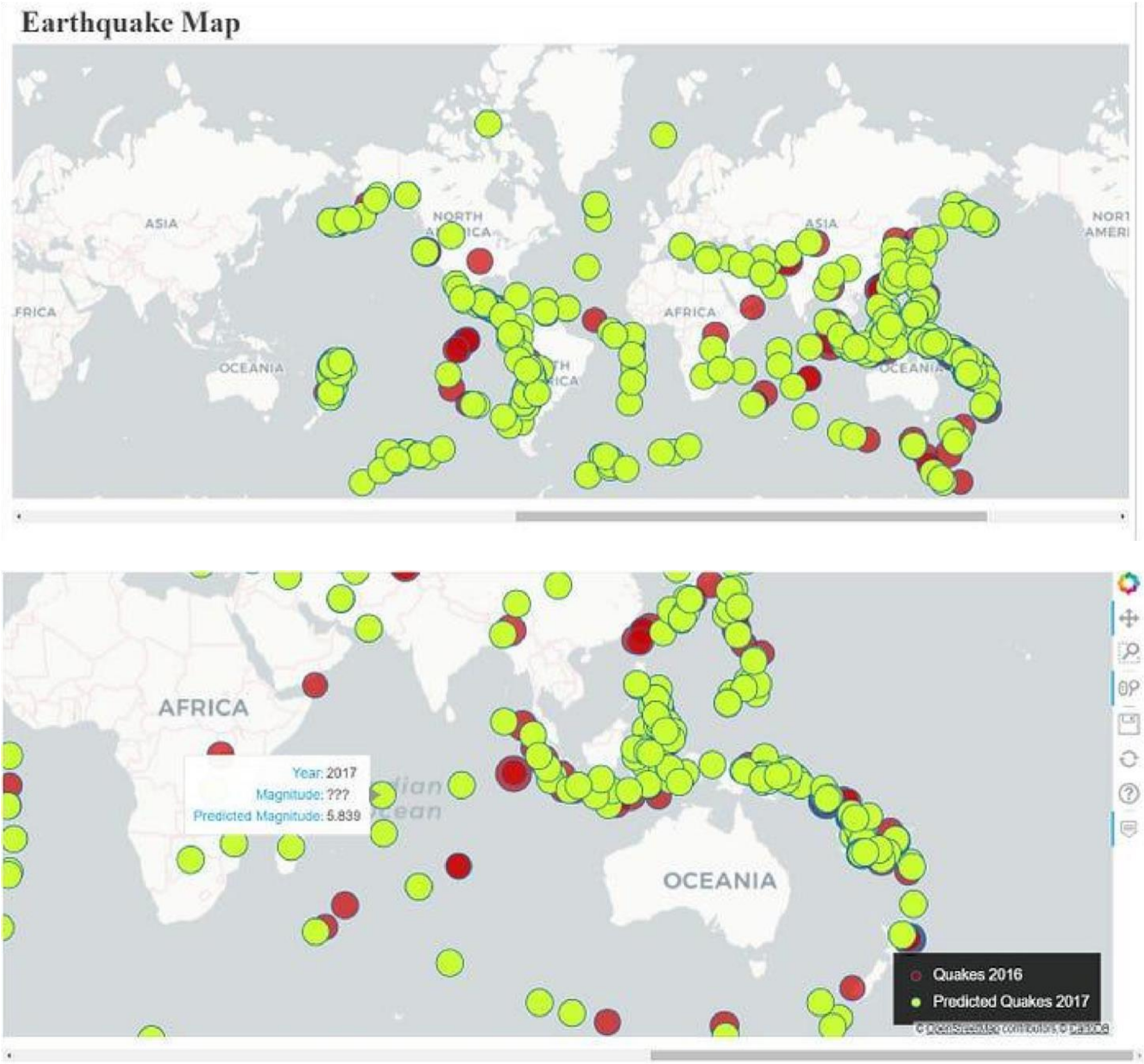
```
# Create the Geo Map plot
def plotMap():
 lat = df_quakes_2016['Latitude'].values.tolist()
lon = df_quakes_2016['Longitude'].values.tolist()

 pred_lat = df_quake_pred['Latitude'].values.tolist()
```

```
 pred_lon =
df_quake_pred['Longitude'].values.tolist()     lst_lat
= []  lst_lon = []  lst_pred_lat = []  lst_pred_lon =
[]

i=0
j=0
 # Convert lat and lon values into merc_projection format
for i in range (len(lon)):
 r_major = 6378137.000
x    = r_major * math.radians(lon[i])
scale  =  x/lon[i]  y =  180.0/math.pi  *
math.log(math.tan(math.pi/4.0 +  lat[i]
* (math.pi/180.0)/2.0)) * scale

lst_lon.append(x)
lst_lat.append(y)
i += 1
 # Convert predicted lat and long values into
merc_projection format  for j in range (len(pred_lon)):
 r_major = 6378137.000
x    = r_major * math.radians(pred_lon[j])
scale  =  x/pred_lon[j]  y =  180.0/math.pi  *
math.log(math.tan(math.pi/4.0 +  pred_lat[j]
* (math.pi/180.0)/2.0)) * scale
lst_pred_lon.append(x)  lst_pred_lat.append(y)
j += 1    df_quakes_2016['coords_x'] = lst_lat
df_quakes_2016['coords_y'] = lst_lon
df_quake_pred['coords_x'] =
lst_pred_lat  df_quake_pred['coords_y']
= lst_pred_lon

 # Scale the circles
 df_quakes_2016['Mag_Size'] = df_quakes_2016['Magnitude'] * 4
df_quake_pred['Mag_Size'] = df_quake_pred['Pred_Magnitude'] *
4
 #  Create  datasources  for  our  ColumnDataSource
object   lats = df_quakes_2016['coords_x'].tolist()
longs = df_quakes_2016['coords_y'].tolist()  mags =
df_quakes_2016['Magnitude'].tolist()      years   =
df_quakes_2016['Year'].tolist()       mag_size    =
df_quakes_2016['Mag_Size'].tolist()
```

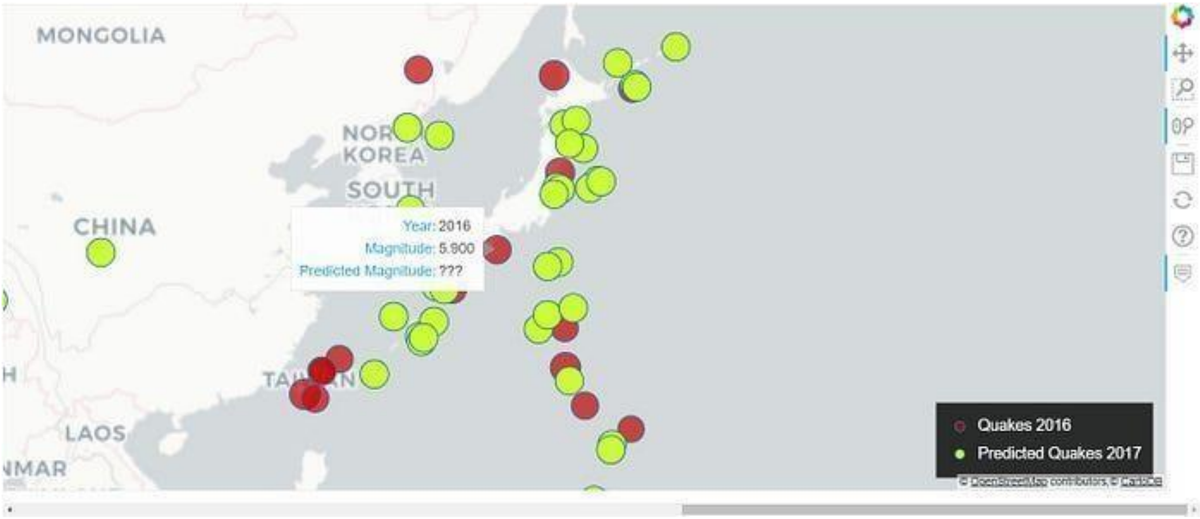
```
 pred_lats = df_quake_pred['coords_x'].tolist()
pred_longs = df_quake_pred['coords_y'].tolist()
pred_mags =
df_quake_pred['Pred_Magnitude'].tolist()  pred_year
= df_quake_pred['Year'].tolist()  pred_mag_size =
df_quake_pred['Mag_Size'].tolist()
 #   Create   column
datasource    cds   =
ColumnDataSource(
data=dict( lat=lats,
lon=longs, mag=mags,
year=years,
mag_s=mag_size
 )
 )
 pred_cds = ColumnDataSource(
data=dict(
pred_lat=pred_lats,
pred_long=pred_longs,
pred_mag=pred_mags,
year=pred_year,
pred_mag_s=pred_mag_size
 )
 )

 # Tooltips
 TOOLTIPS = [
 ("Year", " @year"),
 ("Magnitude", " @mag"),
 ("Predicted Magnitude", " @pred_mag")
]

 # Create figure
 p = figure(title = 'Earthquake Map',  plot_width=2300,
plot_height=450,  x_range=(-
2000000, 6000000),  y_range=(-1000000,
7000000),  tooltips=TOOLTIPS)

 p.circle(x='lon', y='lat', size='mag_s',
fill_color='#cc0000', fill_alpha=0.7,
source=cds, legend='Quakes 2016')

 # Add circles for our predicted earthquakes
 p.circle(x='pred_long', y='pred_lat',
size='pred_mag_s', fill_color='#ccff33', fill_alpha=7.0,
source=pred_cds, legend='Predicted Quakes 2017')

 tile_provider = get_provider(Vendors.CARTODBPOSITRON)
```

```
p.add tile(tile provider)

# Style the map plot
# Title
p.title.align=’center’
p.title.text font size=’20pt’
p.title.text font=’serif’

# Legend
p.legend.location=’bottom right’
p.legend.background fill color=’black’
p.legend.background fill alpha=0.8
p.legend.click policy=’hide’
p.legend.label text color=’white’
p.xaxis.visible=False
p.yaxis.visible=False
p.axis.axis label=None
p.axis.visible=False
p.grid.grid line color=None


show(p)

plotMap()
```

After you running the syntax now you see the output of the map with the dots. The green dots represent the predicted quakes of 2017 and the red dots for quakes of the year 2016.


Earthquake Map
ASIA
OCEANIA
AFRICA
Year: 2017
Magnitude: ???
Predicted Magnitude: 5.839
OCEANIA
Quakes 2016
Predicted Quakes 2017

Quake Map

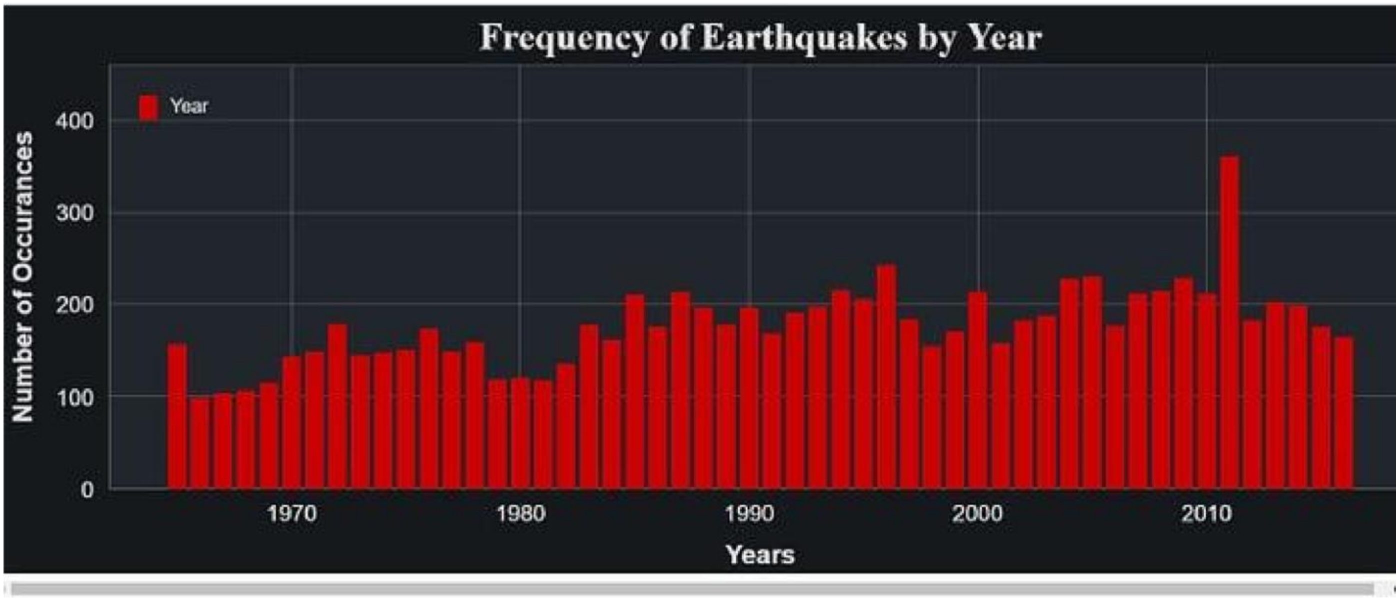


Okay after we creating the geo map, the next thing we can do is creating a bar chart. In this

bar chart, we will visualize how the frequency of quakes every year.

```python
# Create the Bar Chart
def plotBar():
    # Load the datasource
    cds = ColumnDataSource(data=dict(
        yrs = df_quake_freq['Year'].values.tolist(),
        numQuakes = df_quake_freq['Counts'].values.tolist()
    ))

    # Tooltip
    TOOLTIPS =[
        ('Year', ' @yrs'),
        ('Number of earthquakes', ' @numQuakes')
    ]

    # Create a figure
    barChart = figure(title='Frequency of Earthquakes by Year',
                      plot_height=400,
                      plot_width=1150,
                      x_axis_label='Years',
                      y_axis_label='Number of Occurances',
                      x_minor_ticks=2,
                      y_range=(0, df_quake_freq['Counts'].max() +100),
                      toolbar_location=None,
                      tooltips=TOOLTIPS)

    # Create a vertical bar
    barChart.vbar(x='yrs', bottom=0, top='numQuakes',
                  color='#cc0000', width=0.75,
                  legend='Year', source=cds)

    # Style the bar chart
    barChart = style(barChart)

    show(barChart)

    return barChart

plotBar()
```

Frequency of Earthquakes by Year

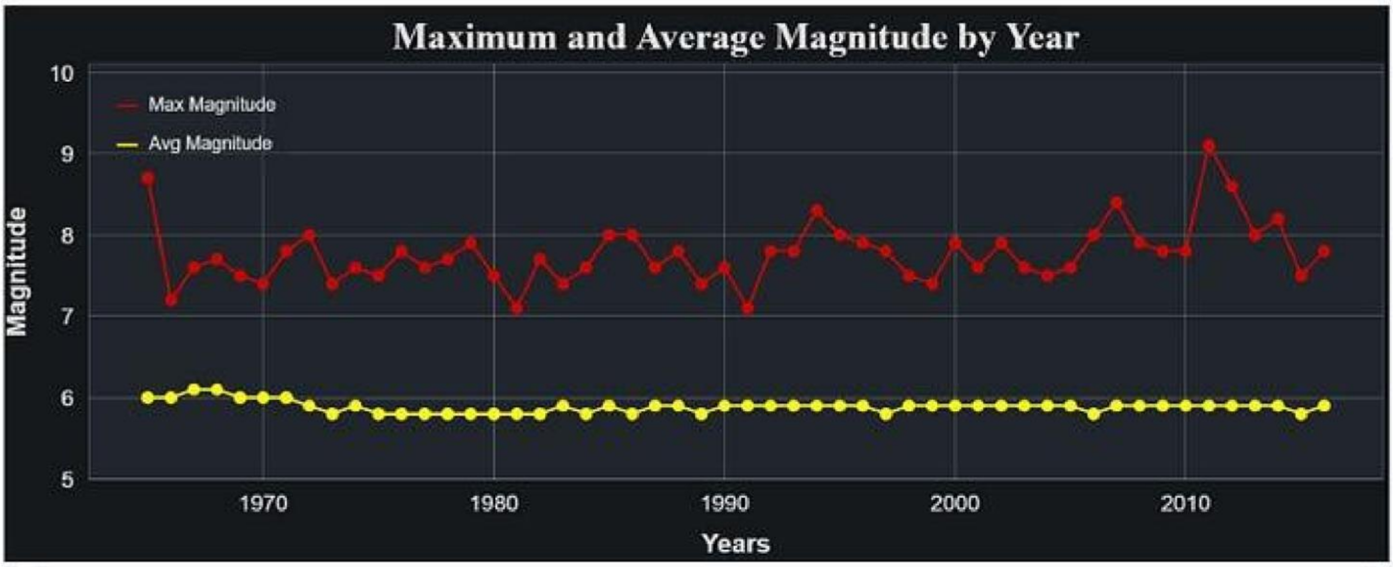


The bar chart tells us how is the trend of earthquakes every year, based on the graphic we can see 2010 is the year of the highest number of earthquakes occurrences.

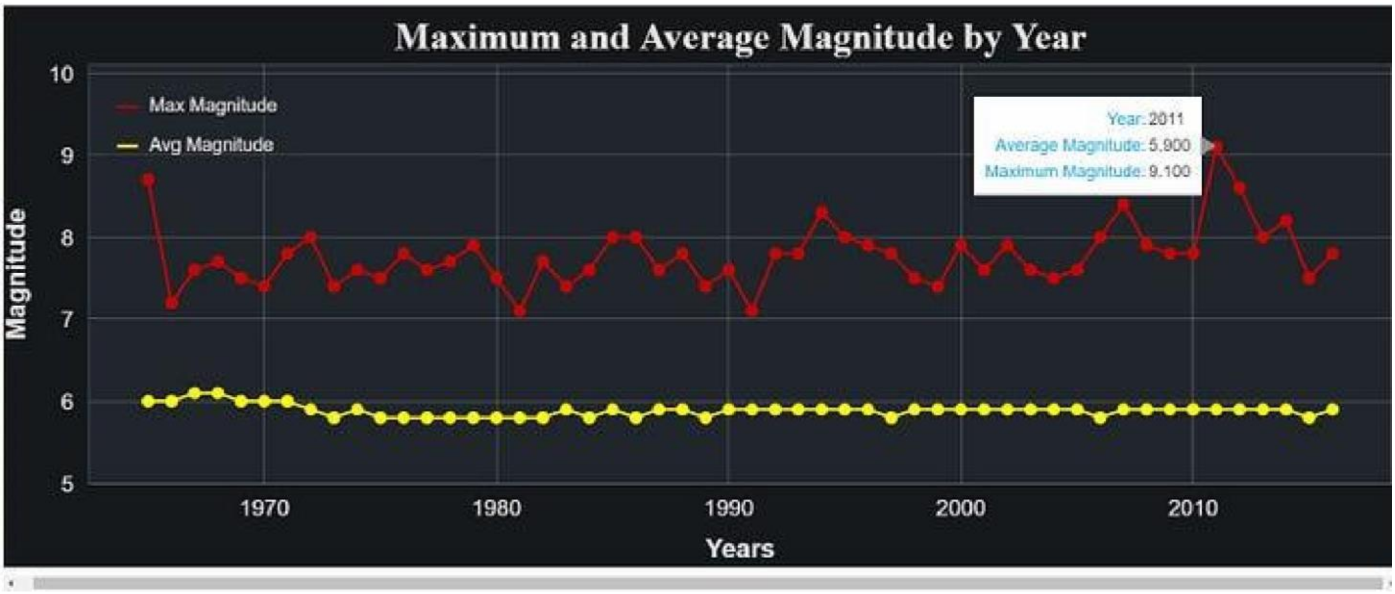
After we create the bar chart for quakes frequency, now we will create the line chart to know the trend of magnitude by year.

```
In [46]: # Create a magnitude plot
def plotMagnitude():
    # Load the datasource
    cds = ColumnDataSource(data=dict(
        yrs = df_quake_freq['Year'].sort_values().values.tolist(),
        avg_mag = df_quake_freq['Avg_Magnitude'].round(1).values.tolist(),
        max_mag = df_quake_freq['Max_Magnitude'].values.tolist()
    ))

    # Tooltip
    TOOLTIPS = [
        ('Year', ' @yrs'),
        ('Average Magnitude', ' @avg_mag'),
        ('Maximum Magnitude', ' @max_mag')
    ]

    # Create the figure
    mp = figure(title='Maximum and Average Magnitude by Year',
                plot_width=1150, plot_height=400,
                x_axis_label='Years',
                y_axis_label='Magnitude',
                x_minor_ticks=2,
                y_range=(5, df_quake_freq['Max_Magnitude'].max() + 1),
                toolbar_location=None,
                tooltips=TOOLTIPS)

    # Max Magnitude
    mp.line(x='yrs', y='max_mag', color='#cc0000', line_width=2, legend='Max Magnitude', source=cds)
    mp.circle(x='yrs', y='max_mag', color='#cc0000', size=8, fill_color='#cc0000', source=cds)

    # Average Magnitude
    mp.line(x='yrs', y='avg_mag', color='yellow', line_width=2, legend='Avg Magnitude', source=cds)
    mp.circle(x='yrs', y='avg_mag', color='yellow', size=8, fill_color='yellow', source=cds)

    mp = style(mp)

    show(mp)

    return mp

plotMagnitude()
```

Creating a m



Maximum and Average Magnitude



Trend by Year

Seismology and Deep Learning

Within the past few years, there has been rapid growth in the seismic data quantity. This makes it challenging for modern seismology to analyze and process the data. Most of the popular techniques for earthquake prediction use the old seismic data, which was small. With the advancement in machine learning and deep learning, it is possible to extract useful information and train models on large datasets.

Once we train a deep learning model with large amounts of data, it can acquire their knowledge by extracting features from raw data to recognize natural objects and make expert-level decisions in various disciplines. Besides the advancement in computational power, it has become straightforward to train large models. These advantages make deep learning suitable for applications in real-time seismology and earthquake prediction.

For the task of the earthquake prediction, the deep learning models which perform better than other models are CNN and LSTM:

Convolution Neural Network

“In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.

They have applications in image and video recognition, recommender systems, image classification, medical image analysis, natural language processing, brain-computer interfaces, and financial time series”. (Source: Wikipedia)

A convolutional neural network consists of an input layer, hidden layers and an output layer. A typical CNN consists of:

Convolution Layer: Convolutional layers convolve the input and pass its result to the next layer.

Pooling Layer: Pooling layers reduce the data’s dimensions by combining the outputs of neuron clusters at one layer into a single neuron in the next layer.

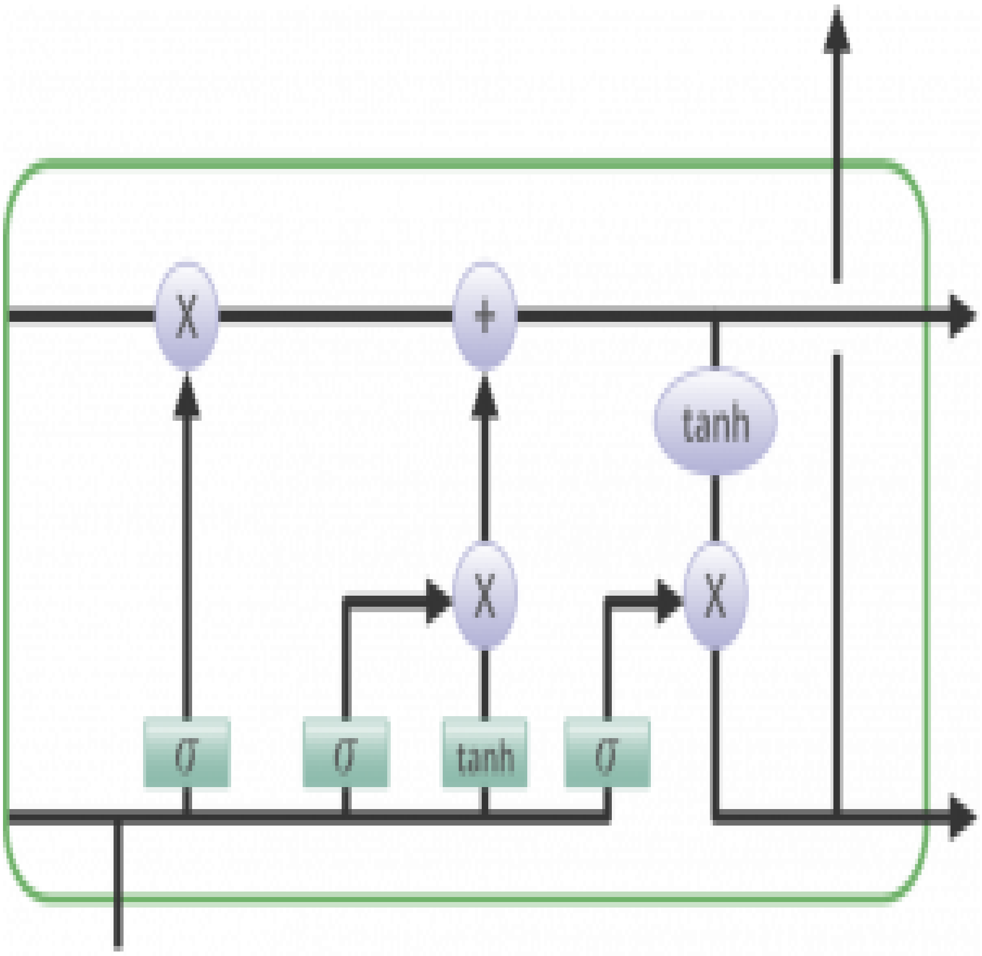
Fully Connected Layer: Fully connected layers connect every neuron in one layer to every neuron in another layer.

Long Short Term Memory :

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning.

LSTM networks are well-suited to classifying, processing and making predictions based on time series data since there can be lags of unknown duration between important events in a time series.

A standard LSTM unit comprises a cell, an input gate, an output gate and a forget gate.



Available Datasets:

STanford EArthquake Dataset (STEAD)

The data set in its current state contains two categories:

(1) local earthquake waveforms (recorded at "local" distances within 350 km of earthquakes), and

(2) seismic noise waveforms that are free of earthquake signals.

Together these data comprise ~1.2 million time-series or more than 19,000 hours of seismic signal recordings.

STEAD includes two main classes of earthquake and non-earthquake signals recorded by seismic instruments.

The seismic data is in the form of individual NumPy arrays containing three waveforms (each waveform has 6000 samples).

LANL Earthquake prediction data :

This data comes from a well-known experimental set-up used to study earthquake physics. The acoustic_data input signal is used to predict the time remaining before the next laboratory earthquake (time_to_failure).

The data contains data training and testing. The data is structured as follows:

csv – A single, continuous training segment of experimental data.

test – A folder containing many small segments of test data.

Conclusion :

Deep learning is a set of powerful machine learning algorithms and concepts that have seen groundbreaking success for the last ten years.

The main benefit of deep neural networks is their ability to learn complex, nonlinear hypotheses through data without explicitly modelling features.

This property of deep learning makes it possible to design and train the robust earthquake prediction model.