EarthQuake Analysis

Introduction

This project aims to develop a big data analytics solution for earthquake prediction using various big data technologies, including PySpark, MLlib, Power BI, and MongoDB. By leveraging these tools, our goal is to establish a comprehensive framework for processing earthquake data, training predictive models, and visualizing insights through reports and dashboards.

Problem Statement

The primary objective of this project is to create a predictive model to forecast the likelihood of earthquakes based on historical earthquake data spanning from 1965 to 2016

We will initially work with sample data to develop and validate the model. The process encompasses the following steps:

Data Preprocessing: Transforming raw earthquake data into summary tables suitable for model training.

Model Training: Utilizing MLlib to train predictive models based on historical earthquake data.

Prediction: Using trained models to predict future earthquakes.

Data Storage: Writing the final datasets to MongoDB for storage and retrieval.

Data Analysis and Visualization: Building reports and dashboards in Power BI Desktop to analyze and visualize insights derived from the earthquake data.

Dataset Details

Database.csv : This file will be the source file containing earth quake details

Steps Performed

A. Data Loading and Data Pre-Processing

1.Load the dataset containing earthquake details

2.Drop the columns which are not required

3.Extract the year component from the date field in the dataframe and create a new column to store the year information

4.Build the quakes frequency dataframe using the year field and counts for each year

5.Check the schema and convert relevant fields from string to numeric datatype as necessary

6.Calculate the average and maximum magnitude of earthquakes add to df_quake_freq

7.Write dataframes to mongodb

B. Model Training

Utilizing PySpark's MLlib to train machine learning models, such as random forests on the pre-processed earthquake data and then evaluate model performance using appropriate metrics, such as accuracy, precision, and recall.

8.Load the earthquake test data

9.Load the training data from mongodb and Perform the data cleansing activity

10.Create testing and training dataframes

11.Import the relevant modules for machine learning ,create model and evaluate it

C. Prediction

Use the trained models to predict the likelihood of future earthquakes based on input data.

12.Create the prediction Dataset

D. Data Storage

13.Load the Prediction dataset to Mongodb

E. Data Analysis and Visualization

14. Connect Power BI to the MongoDB instance containing the prediction tables

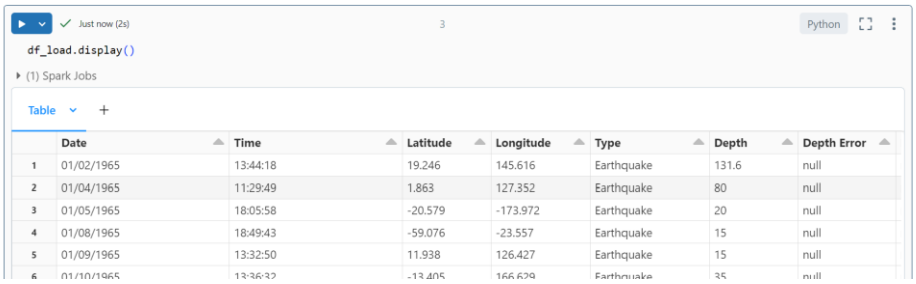
15. Create a report in Power BI which will showcase the different metrics and predictions.

Implementation Details

A. Data Loading and Data Pre-Processing

Dataset containing earth quake details are uploaded into Filestore of databricks /dbfs/FileStore/ProjectPyspark

1.Load the dataset containing earthquake details



Sample data:

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, Azimuthal Gap=None,

Horizontal Distance=None, Horizontal Error=None, Root Mean Square=None, ID='ISCGEM860706', Source='ISCGEM', Location Source='ISCGEM', Magnitude Source='ISCGEM', Status='Automatic'

2.Drop the columns which are not required

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

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

```
(1) Spark Jobs
df_loaddb:  pyspark.sql.dataframe.DataFrame = [Date: string, Latitude: string ... 6 more fields]
+----------+--------+---------+----------+-----+---------+--------------+------------+
|      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
```

3.Extract the year component from the date field in the dataframe and create a new column to store the year information

```
#Create a year column and add to dataframe
df_loaddb = df_loaddb.withColumn('Year',year(to_timestamp('Date','dd/MM/yyyy')))
df_loaddb.show(5)
```

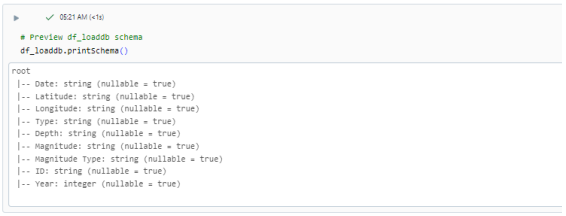
```
(1) Spark Jobs
df_loaddb:  pyspark.sql.dataframe.DataFrame = [Date: string, Latitude: string ... 7 more fields]
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|      Date|Latitude|Longitude|      Type|Depth|Magnitude|Magnitude Type|          ID|Year|
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|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
```

4.Group the dataframe by the year field and calculate the count of earthquakes for each year to create a summary dataframe

```
# Build the quakes frequency dataframe using the year field and counts for each year
df_quake_freq = df_loaddb.groupBy("Year").count().withColumnRenamed("count","Counts")
# Preview df_quake_freq
df_quake_freq.show(5)
```

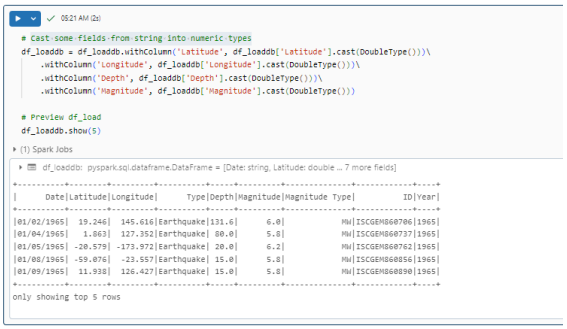
```
(2) Spark Jobs
df_quake_freq:  pyspark.sql.dataframe.DataFrame = [Year: integer, Counts: long]
+----+------+
|Year|Counts|
+----+------+
|1990|   196|
|1975|   150|
|1977|   148|
|2003|   187|
|2007|   211|
+----+------+
only showing top 5 rows
```

5.Check the schema and convert relevant fields from string to numeric datatype as necessary.



```
# Preview df_loaddb schema
df_loaddb.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)
```



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

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

(1) Spark Jobs

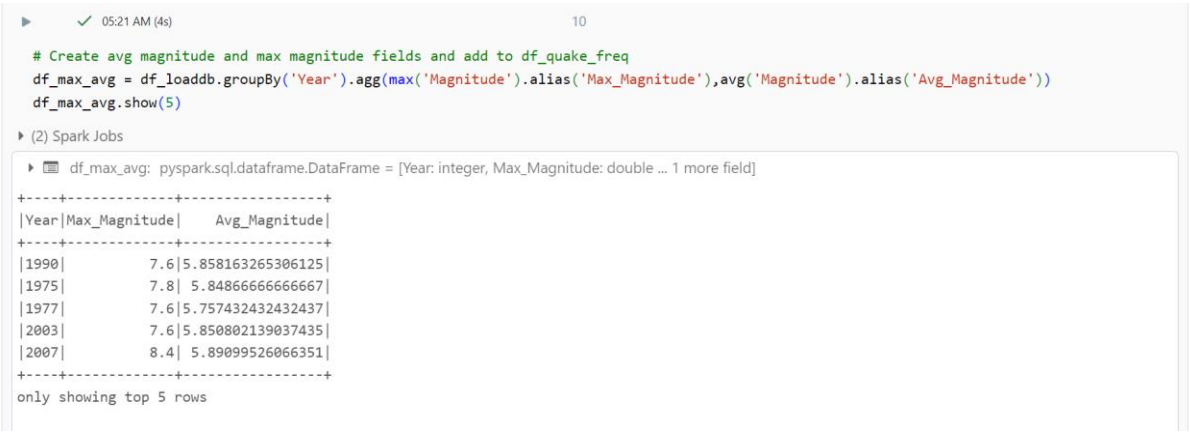
df_loaddb: pyspark.sql.dataframe.DataFrame = [Date: string, Latitude: double ... 7 more fields]

```
+----------+--------+---------+----------+-----+---------+--------------+------------+----+
|      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
```

```
# Preview df_loaddb schema
df_loaddb.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)
```

6.Calculate the average and maximum magnitude of earthquakes and for each year and add these fields to the earthquake frequency DataFrame



05:21 AM (4s) 10

```
# Create avg magnitude and max magnitude fields and add to df_quake_freq
df_max_avg = df_loaddb.groupBy('Year').agg(max('Magnitude').alias('Max_Magnitude'),avg('Magnitude').alias('Avg_Magnitude'))
df_max_avg.show(5)
```

(2) Spark Jobs

df_max_avg: pyspark.sql.dataframe.DataFrame = [Year: integer, Max_Magnitude: double ... 1 more field]

```
+----+-------------+-----------------+
|Year|Max_Magnitude|    Avg_Magnitude|
+----+-------------+-----------------+
|1990|          7.6|5.858163265306125|
|1975|          7.8| 5.84866666666667|
|1977|          7.6|5.757432432432437|
|2003|          7.6|5.850802139037435|
|2007|          8.4| 5.89099526066351|
+----+-------------+-----------------+
only showing top 5 rows
```

05:21 AM (6s) 11

```
# Join df_max_avg to df_quake_freq
df_quake_freq=df_quake_freq.join(df_max_avg,'Year')
# Preview df_quake_freq
df_quake_freq.show(5)
```

(4) Spark Jobs

df_quake_freq: pyspark.sql.dataframe.DataFrame = [Year: integer, Counts: long ... 2 more fields]

```
+----+------+-------------+-----------------+
|Year|Counts|Max_Magnitude|    Avg_Magnitude|
+----+------+-------------+-----------------+
|1990|   196|          7.6|5.858163265306125|
|1975|   150|          7.8| 5.84866666666667|
|1977|   148|          7.6|5.757432432432437|
|2003|   187|          7.6|5.850802139037435|
|2007|   211|          8.4| 5.89099526066351|
+----+------+-------------+-----------------+
only showing top 5 rows
```

05:22 AM (3s) 14

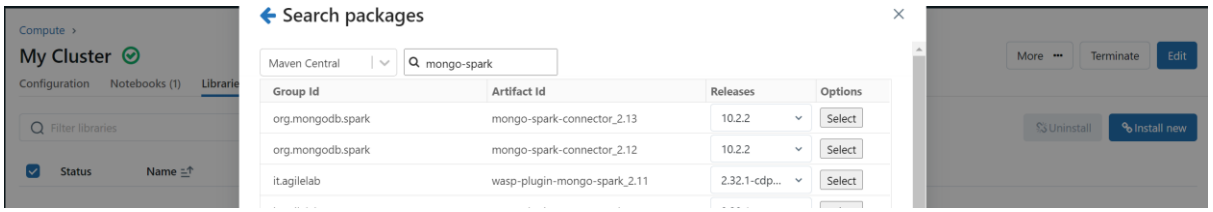
```
df_quake_freq.show(5)
```

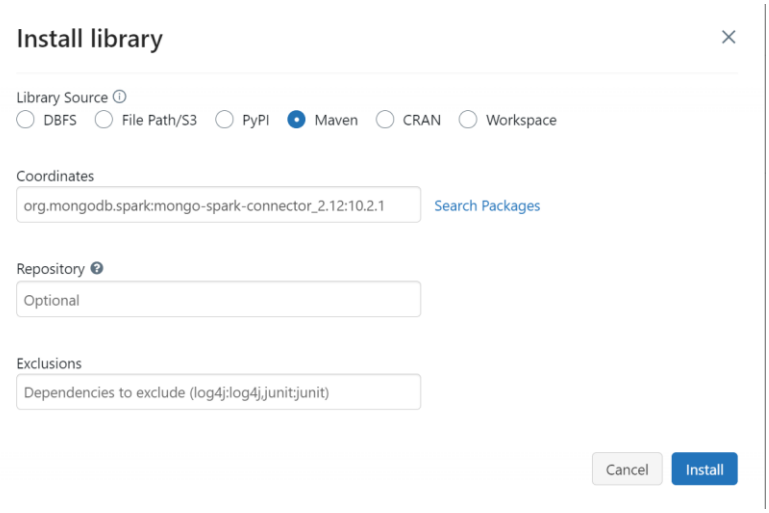
(4) Spark Jobs

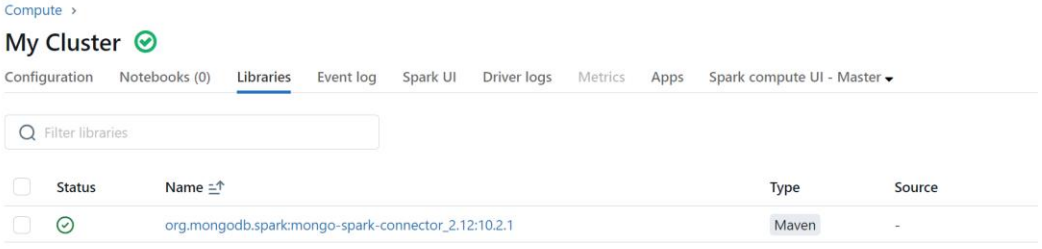
```
+----+------+-------------+-----------------+
|Year|Counts|Max_Magnitude|    Avg_Magnitude|
+----+------+-------------+-----------------+
|1990|   196|          7.6|5.858163265306125|
|1975|   150|          7.8| 5.84866666666667|
|1977|   148|          7.6|5.757432432432437|
|2003|   187|          7.6|5.850802139037435|
|2007|   211|          8.4| 5.89099526066351|
+----+------+-------------+-----------------+
only showing top 5 rows
```

7.Write data frames to MongoDb

To establish a connection from databricks to mongodb we need to install mongo-spark connector library.





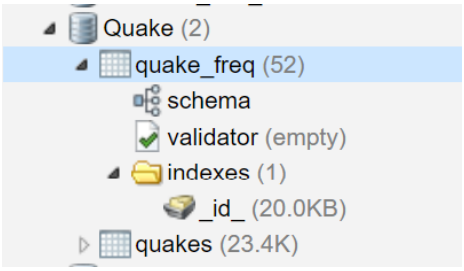


Write dataframe containing earthquake details and the earthquake frequency summary dataframe to MongoDB

```
✓ 3 minutes ago (2m)                                                    15

# Build the tables/collections in mongodb
# Write df_loaddb to mongodb
df_loaddb.write.format('mongodb')\
    .mode('overwrite')\
    .option("spark.mongodb.connection.uri", "mongodb+srv://[redacted]clusteredu.vqzezro.mongodb.net/")\
    .option("database","Quake")\
    .option("collection","quakes")\
    .save()

▾ (1) Spark Jobs
  ▾ Job 32 View (Stages: 1/1)
      Stage 48  1/1 succeeded  View
```

```
✓ Just now (5s)                                                         16                    Python

# Write df_quake_freq to mongodb
df_quake_freq.write.format('mongodb')\
    .mode('overwrite')\
    .option('spark.mongodb.connection.uri', "mongodb+srv://[redacted]clusteredu.vqzezro.mongodb.net/")\
    .option("database","Quake")\
    .option("collection","quake_freq")\
    .save()
```

Mongodb:



Machine Learning

B. Model Training

8.Load the Load the Earthquake Test Data.

Query.csv file stored in the HDFS contains the earthquake test data

Sample

```
time,latitude,longitude,depth,mag,magType,nst,gap,dmin,rms,net,id,updated,place,type,horizontalError,depthError,magError,magNst,status,locationSource,magSource
2017-01-02T00:13:06.300Z,-36.0365,51.9288,10,5.7,mwb,,26,14.685,1.37,us,us10007p5d,2017-03-27T23:53:17.040Z,"Southwest Indian Ridge",earthquake,10.3,1.7,0.068,21,reviewed,us,us
```

Section: Machine Learning with Spark

```
✓ Just now (2s)                                                         18                    Python

# Load the test data file into a dataframe
df_test = (spark.read
    .format("csv")
    .option("header","true")
    .load("dbfs:/FileStore/ProjectPyspark/query.csv")
    )
# Preview df_test
df_test.take(1)

▸ (2) Spark Jobs
  ▸ df_test: pyspark.sql.dataframe.DataFrame = [time: string, latitude: string ... 20 more fields]
[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 Ridge', type='earthquake', horizontalError='10.3', depthError='1.7', magError='0.068', magNst='21', status='reviewed', locationSource='us', magSource='us')]
```

9.Load the training data from mongodb and Perform the data cleansing activity such as selecting only required fields,Renaming fields,casting specific fields to the desired datatype

Just now (4s) 19 Python

```
# Load the training data from mongo into a dataframe
df_train = spark.read.format('mongodb')\
    .option('spark.mongodb.connection.uri', "mongodb+srv://[redacted]clusteredu.vqzezro.mongodb.net/")\
    .option("database","Quake")\
    .option("collection","quakes")\
    .load()

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

(1) Spark Jobs

df_train: pyspark.sql.dataframe.DataFrame = [Date: string, Depth: double ... 8 more fields]

```
+----------+-----+-----------+--------+---------+---------+--------------+----------+----+--------------------+
|      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|65f24936bdf037582...|
|01/04/1965| 80.0|ISCGEM860737|   1.863|  127.352|      5.8|            MW|Earthquake|1965|65f24936bdf037582...|
|01/05/1965| 20.0|ISCGEM860762| -20.579| -173.972|      6.2|            MW|Earthquake|1965|65f24936bdf037582...|
|01/08/1965| 15.0|ISCGEM860856| -59.076|  -23.557|      5.8|            MW|Earthquake|1965|65f24936bdf037582...|
|01/09/1965| 15.0|ISCGEM860890|  11.938|  126.427|      5.8|            MW|Earthquake|1965|65f24936bdf037582...|
+----------+-----+-----------+--------+---------+---------+--------------+----------+----+--------------------+
only showing top 5 rows
```

1 minute ago (1s) 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)
```

(1) Spark Jobs

df_test_clean: pyspark.sql.dataframe.DataFrame = [time: string, latitude: string ... 3 more fields]

```
+--------------------+--------+---------+---+------+
|                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
```

Just now (1s) 25 Python

```
df_test_clean.show()
```

(1) Spark Jobs

```
+--------------------+--------+---------+---------+------+
|                Date|Latitude|Longitude|Magnitude| Depth|
+--------------------+--------+---------+---------+------+
|2017-01-02T00:13:...|-36.0365|  51.9288|      5.7|  10.0|
|2017-01-02T13:13:...|  -4.895| -76.3675|      5.9| 106.0|
|2017-01-02T13:14:...|-23.2513| 179.2383|      6.3|551.62|
|2017-01-03T09:09:...| 24.0151|  92.0177|      5.7|  32.0|
|2017-01-03T21:19:...|-43.3527| -74.5017|      5.5| 10.26|
```

10.Create testing and training dataframes

```
Just now (<1s)                                                    26                    Python
# Create training and testing dataframes
df_testing = df_test_clean['Latitude', 'Longitude', 'Magnitude', 'Depth']
df_training = df_train['Latitude', 'Longitude', 'Magnitude', 'Depth']

df_testing:  pyspark.sql.dataframe.DataFrame
        Latitude: double
        Longitude: double
        Magnitude: double
        Depth: double
df_training:  pyspark.sql.dataframe.DataFrame
        Latitude: double
        Longitude: double
        Magnitude: double
        Depth: double
```

11.Import the relevant modules for machine learning and create model and evaluate it

RandomForestRegressor
VectorAssembler
RegressionEvaluator

Select features to parse into model and then create the feature vector. After that create and train the model and make the predictions.

```
06:38 AM (1s)                                                     30
from pyspark.ml import Pipeline
from pyspark.ml.regression import RandomForestRegressor
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.evaluation import RegressionEvaluator
```

```
3 minutes ago (17s)                                               31                    Python
# Select features 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)

(8) Spark Jobs
pred_results:  pyspark.sql.dataframe.DataFrame = [Latitude: double, Longitude: double ... 4 more fields]
```

```
Just now (1s)                                                     32                    Python
# Preview pred_results dataframe
pred_results.show(5)

(1) Spark Jobs
+--------+---------+---------+------+-------------------+-----------------+
|Latitude|Longitude|Magnitude| Depth|           features|       prediction|
+--------+---------+---------+------+-------------------+-----------------+
|-36.0365|  51.9288|      5.7|  10.0|[-36.0365,51.9288...| 5.850136724800972|
|  -4.895| -76.3675|      5.9| 106.0|[-4.895,-76.3675,...| 5.869637793167875|
|-23.2513| 179.2383|      6.3|551.62|[-23.2513,179.238...| 5.896591561887881|
| 24.0151|  92.0177|      5.7|  32.0|[24.0151,92.0177,...| 5.931774818629581|
|-43.3527| -74.5017|      5.5| 10.26|[-43.3527,-74.501...|5.9204458792780486|
+--------+---------+---------+------+-------------------+-----------------+
only showing top 5 rows
```

Evaluate the model.rmse and it should be less than 0.5 for the model to be useful

```
Just now (1s)                                                    33

# 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)

(1) Spark Jobs

Root Mean Squared Error (RMSE) on test data = 0.403077
```

C. Prediction

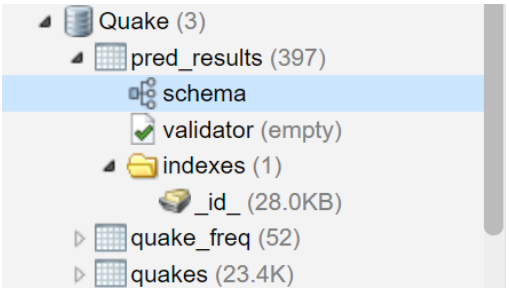
12.Create the prediction Dataset

```
Just now (1s)                                                    35                                    Python

# Create the prediction dataset
df_pred_results = pred_results['Latitude', 'Longitude', 'prediction']

# Rename the prediction field
df_pred_results = df_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))

# Preview df_pred_results
df_pred_results.show(5)

(1) Spark Jobs

df_pred_results:  pyspark.sql.dataframe.DataFrame = [Latitude: double, Longitude: double ... 3 more fields]

+--------+---------+------------------+----+------------------+
|Latitude|Longitude|    Pred_Magnitude|Year|              RMSE|
+--------+---------+------------------+----+------------------+
|-36.0365|  51.9288| 5.850136724800972|2017|0.40307689171713734|
|  -4.895| -76.3675| 5.869637793167875|2017|0.40307689171713734|
|-23.2513| 179.2383| 5.896591561887881|2017|0.40307689171713734|
| 24.0151|  92.0177| 5.931774818629581|2017|0.40307689171713734|
|-43.3527| -74.5017|5.9204458792780486|2017|0.40307689171713734|
+--------+---------+------------------+----+------------------+
only showing top 5 rows
```

D. Data Storage

13.Load the Prediction dataset to Mongodb

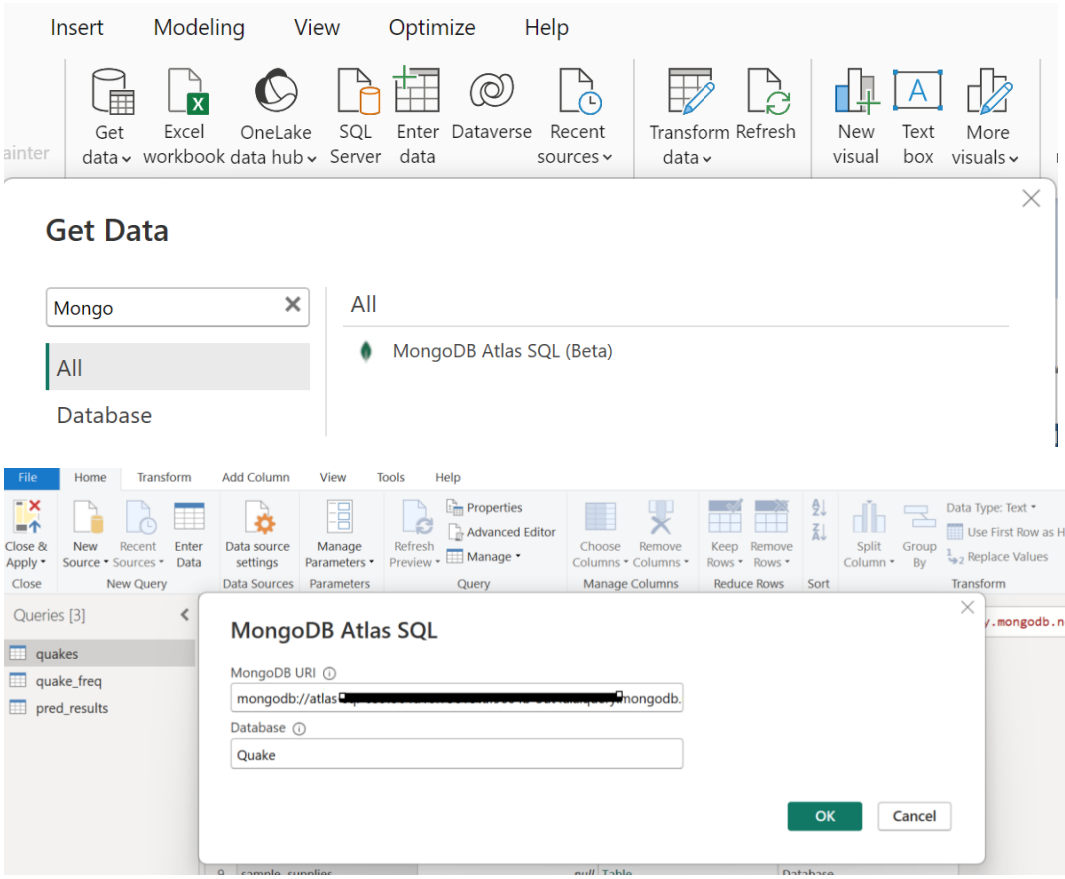
```
Just now (4s)                                                    36                                    Python

# Load the prediction dataset into mongodb
# Write df_pred_results

df_pred_results.write.format('mongodb')\
    .mode('overwrite')\
    .option("spark.mongodb.connection.uri", "mongodb+srv:/[redacted]clusteredu.vqzezro.mongodb.net/")\
    .option("database","Quake")\
    .option("collection","pred_results")\
    .save()

(1) Spark Jobs
```



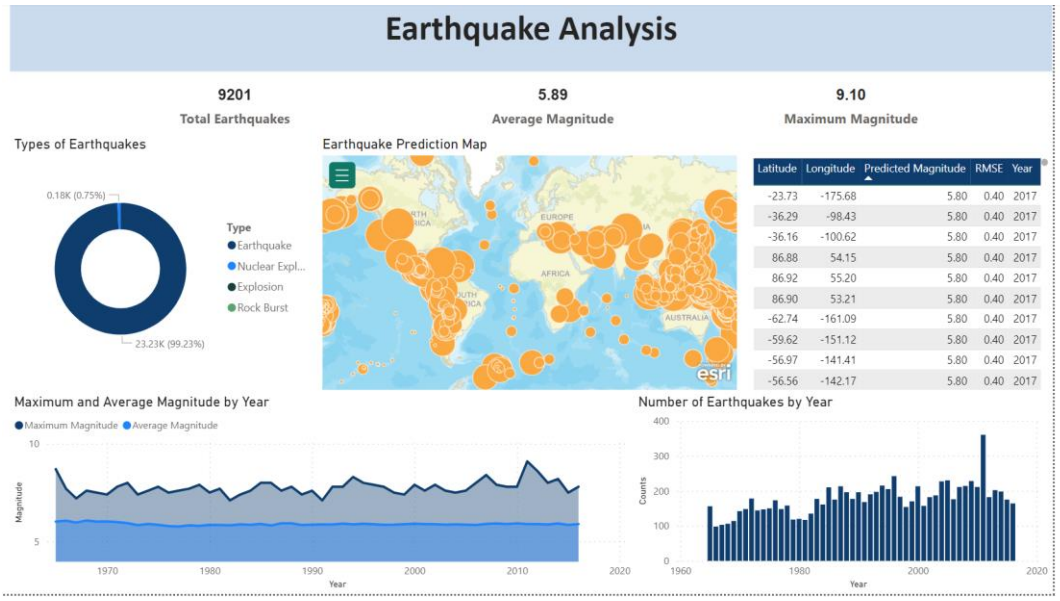
E. Data Analysis and Visualization

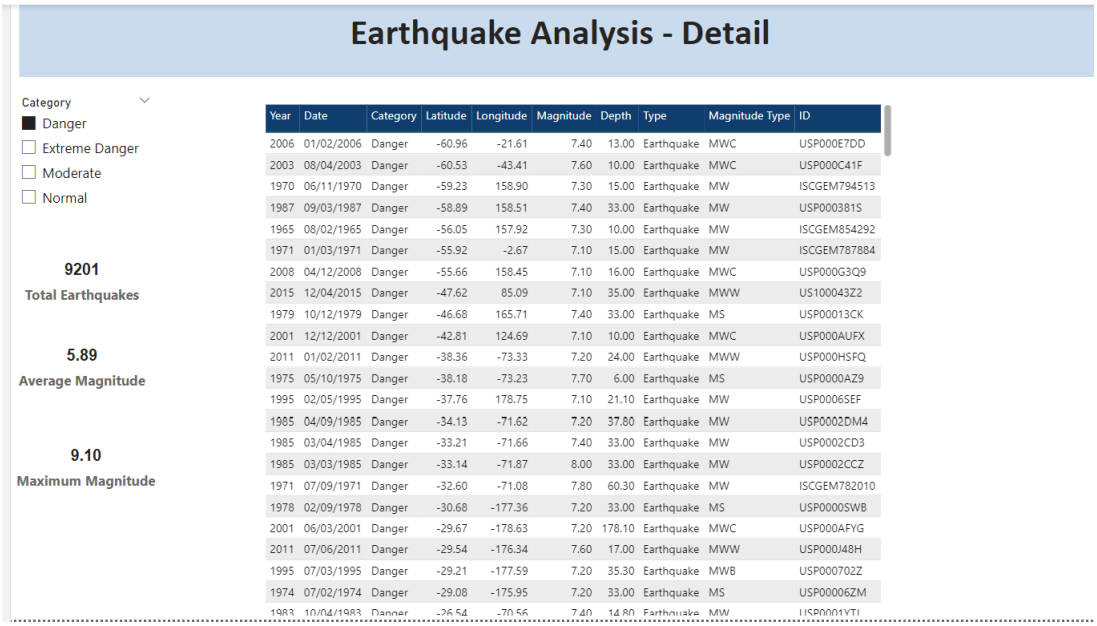
14.Connect Power BI to the MongoDB instance containing the prediction tables

https://www.mongodb.com/docs/atlas/data-federation/query/sql/powerbi/connect/#std-label-sql-connect-powerbi



15.Create a report in Power BI which will showcase the different metrics and predictions.





Conclusion

In this project, we have developed a comprehensive big data analytics pipeline for earthquake prediction using PySpark, MLlib, Power BI, and MongoDB. The pipeline encompasses various stages, including data loading, preprocessing, model training, prediction, data storage, and analysis/visualization.