EarthQuake Analysis

Introduction

This project aims to develop a big data analytics pipeline for earthquake prediction using various big data technologies, including PySpark, MLlib, Power BI, and MongoDB. By leveraging these tools, we aim to create a robust pipeline 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 pipeline involves 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

```
05:20 AM (17s)                                2

#Load the dataset
df_load= (spark.read
            .format("csv")
            .option("header","true")
            .load("dbfs:/FileStore/ProjectPyspark/database.csv")
            )

#Preview of load
df_load.count()

(3) Spark Jobs
df_load: pyspark.sql.dataframe.DataFrame = [Date: string, Time: string ... 19 more fields]
23412
```

```
Just now (2s)                                 3                    Python
df_load.display()
(1) Spark Jobs
```

Table

	Date	Time	Latitude	Longitude	Type	Depth	Depth Error
1	01/02/1965	13:44:18	19.246	145.616	Earthquake	131.6	null
2	01/04/1965	11:29:49	1.863	127.352	Earthquake	80	null
3	01/05/1965	18:05:58	-20.579	-173.972	Earthquake	20	null
4	01/08/1965	18:49:43	-59.076	-23.557	Earthquake	15	null
5	01/09/1965	13:32:50	11.938	126.427	Earthquake	15	null
6	01/10/1965	13:36:32	-13.405	166.629	Earthquake	35	null

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

```
05:21 AM (1s)    4    Python

# 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

```
05:21 AM (1s)    5

#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

```
05:21 AM (4s)    6

# 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.

```
05:21 AM (<1s)

# 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)
```

```
05:21 AM (2s)

# 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
```

```
05:21 AM (<1s)

# 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

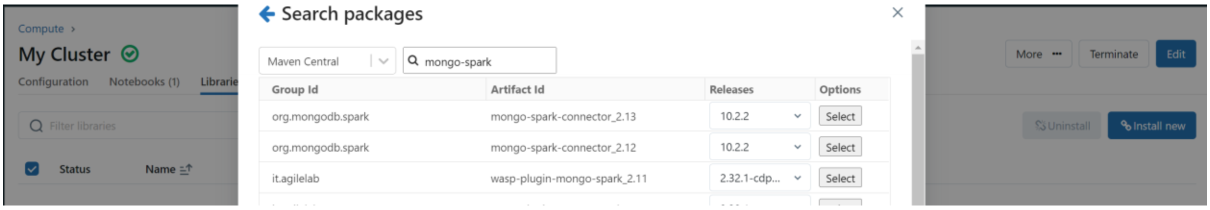
```
05:21 AM (4s)                                   10

# 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
```

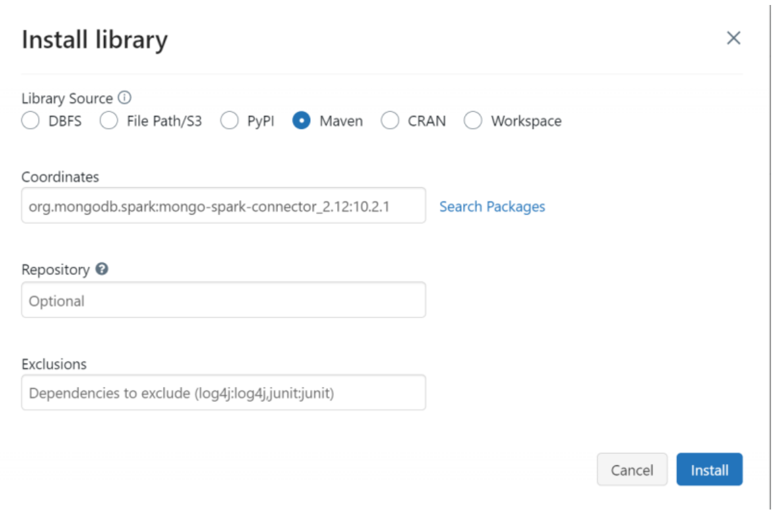
```
05:21 AM (6s)                                   11

# 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
```

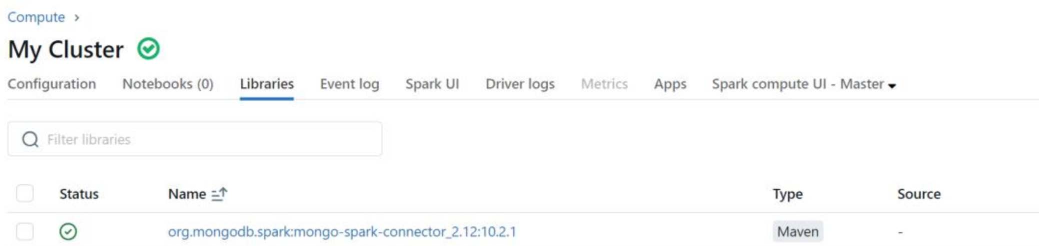
```
05:22 AM (3s)                                    14

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:

- Quake (2)
  - quake_freq (52)
    - schema
    - validator (empty)
    - indexes (1)
      - _id_ (20.0KB)
  - quakes (23.4K)

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

```
# 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.

```
from pyspark.ml import Pipeline
from pyspark.ml.regression import RandomForestRegressor
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.evaluation import RegressionEvaluator
```

```
# 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]
```

```
# 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

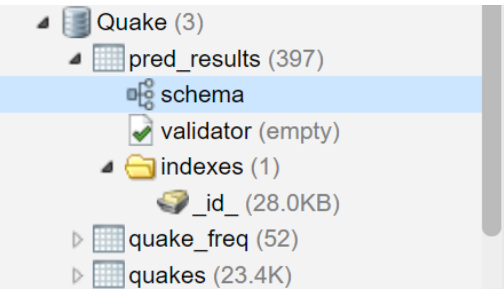
12.Create the prediction Dataset

```
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

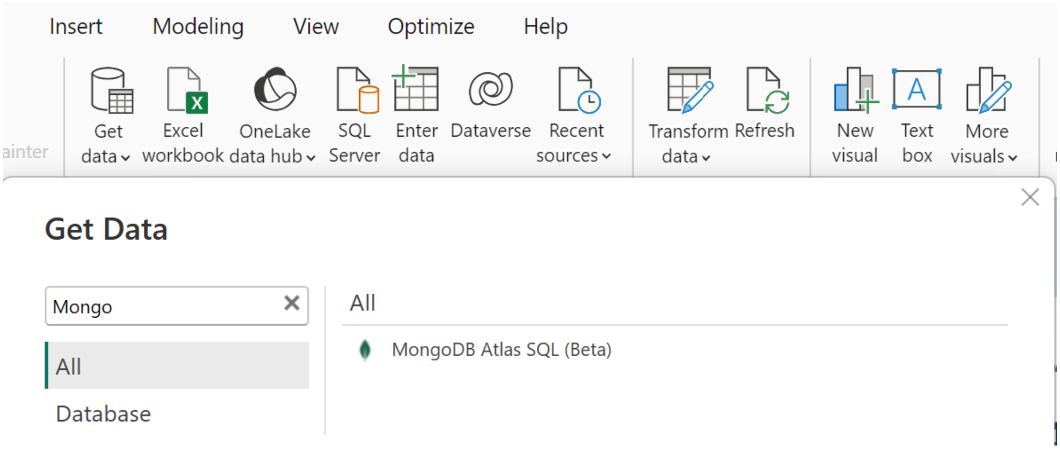
```
Just now (4s)                                    36                     Python

# 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]lusteredu.vqzezro.mongodb.net/")\
    .option("database","Quake")\
    .option("collection","pred_results")\
    .save()

(1) Spark Jobs
```

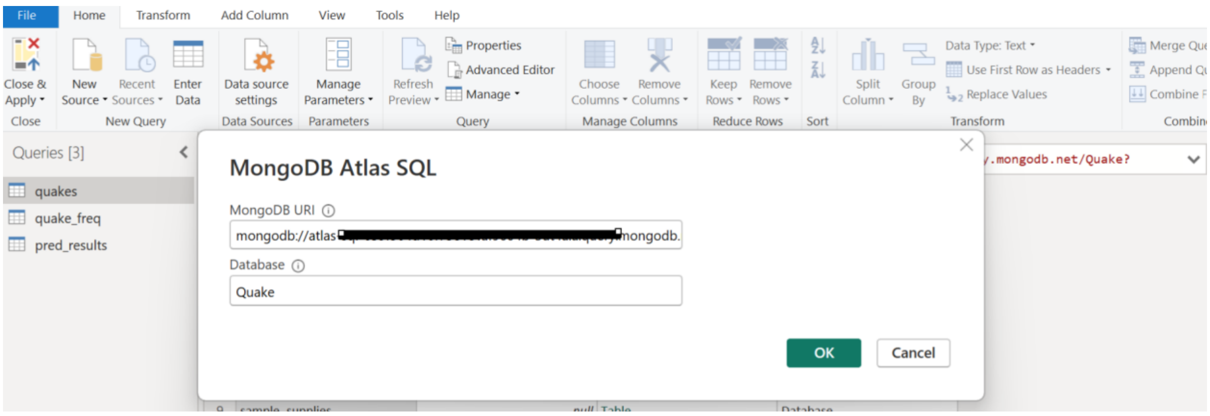


E. Data Analysis and Visualization

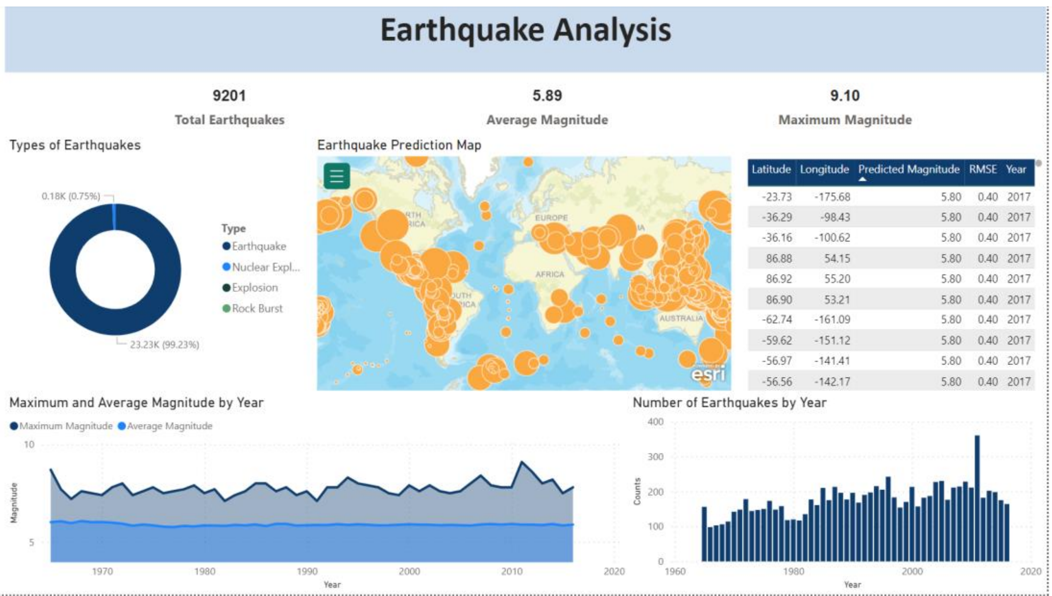
14.Connect Power BI to the MongoDB instance containing the prediction tables

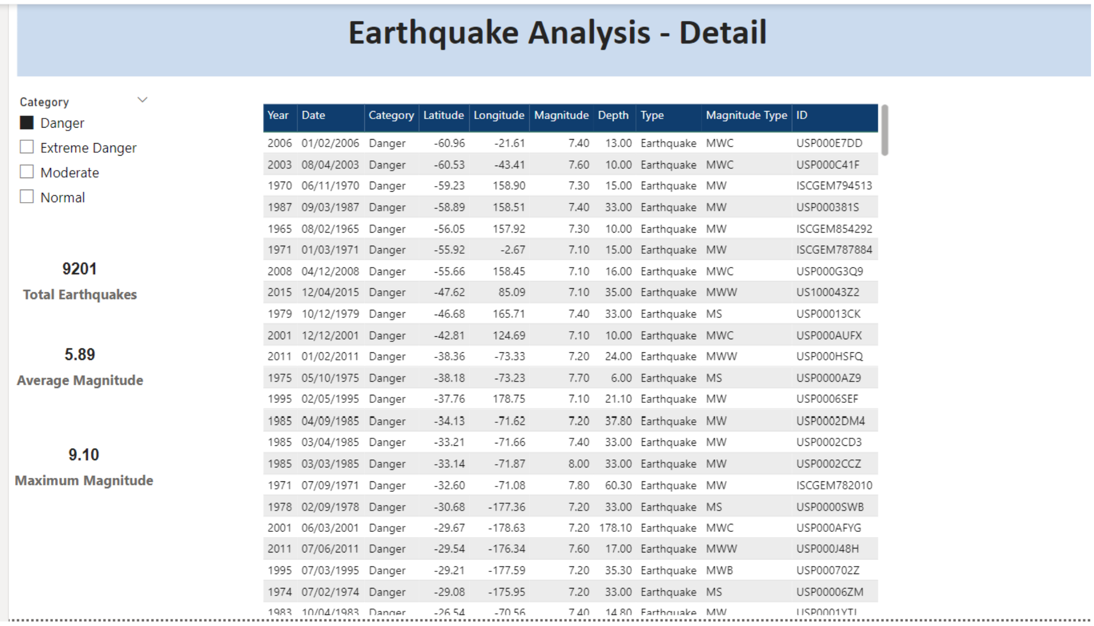
https://www.mongodb.com/docs/atlas/data-federation/query/sql/powerbi/connect/#std-label-sql-connect-powerbi





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





Year	Date	Category	Latitude	Longitude	Magnitude	Depth	Type	Magnitude Type	ID
2006	01/02/2006	Danger	-60.96	-21.61	7.40	13.00	Earthquake	MWC	USP000E7DD
2003	08/04/2003	Danger	-60.53	-43.41	7.60	10.00	Earthquake	MWC	USP000C41F
1970	06/11/1970	Danger	-59.23	158.90	7.30	15.00	Earthquake	MW	ISCGEM794513
1987	09/03/1987	Danger	-58.89	158.51	7.40	33.00	Earthquake	MW	USP000381S
1965	08/02/1965	Danger	-56.05	157.92	7.30	10.00	Earthquake	MW	ISCGEM854292
1971	01/03/1971	Danger	-55.92	-2.67	7.10	15.00	Earthquake	MW	ISCGEM787884
2008	04/12/2008	Danger	-55.66	158.45	7.10	16.00	Earthquake	MWC	USP000G3Q9
2015	12/04/2015	Danger	-47.62	85.09	7.10	35.00	Earthquake	MWW	US100043Z2
1979	10/12/1979	Danger	-46.68	165.71	7.40	33.00	Earthquake	MS	USP00013CK
2001	12/12/2001	Danger	-42.81	124.69	7.10	10.00	Earthquake	MWC	USP000AUFX
2011	01/02/2011	Danger	-38.36	-73.33	7.20	24.00	Earthquake	MWW	USP000HSFQ
1975	05/10/1975	Danger	-38.18	-73.23	7.70	6.00	Earthquake	MS	USP0000AZ9
1995	02/05/1995	Danger	-37.76	178.75	7.10	21.10	Earthquake	MW	USP0006SEF
1985	04/09/1985	Danger	-34.13	-71.62	7.20	37.80	Earthquake	MW	USP0002DM4
1985	03/04/1985	Danger	-33.21	-71.66	7.40	33.00	Earthquake	MW	USP0002CD3
1985	03/03/1985	Danger	-33.14	-71.87	8.00	33.00	Earthquake	MW	USP0002CCZ
1971	07/09/1971	Danger	-32.60	-71.08	7.80	60.30	Earthquake	MW	ISCGEM782010
1978	02/09/1978	Danger	-30.68	-177.36	7.20	33.00	Earthquake	MS	USP0000SWB
2001	06/03/2001	Danger	-29.67	-178.63	7.20	178.10	Earthquake	MWC	USP000AFYG
2011	07/06/2011	Danger	-29.54	-176.34	7.60	17.00	Earthquake	MWW	USP000J48H
1995	07/03/1995	Danger	-29.21	-177.59	7.20	35.30	Earthquake	MWB	USP000702Z
1974	07/02/1974	Danger	-29.08	-175.95	7.20	33.00	Earthquake	MS	USP00006ZM
1983	10/04/1983	Danger	-26.54	-70.56	7.40	14.80	Earthquake	MW	[illegible]

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.