EarthQuake Analysis

Introduction

Creating a big data analytics pipeline, using big data technologies like PySpark, MLlib, Power BI and MongoDB.

Problem Statement

Create a model to predict the possibility of earth quakes based on sampledata from 1965-2016.

Working with earthquake data that will be transformed into summary tables. Then use these tables to train predictive models and predict future earthquakes. Write the final datasets to Mongodb. After that analyze the data by building reports and dashboards in Power BI Desktop

Dataset Details

Csv files.

Dabase.csv: This file will bethe source file containing earth quake details

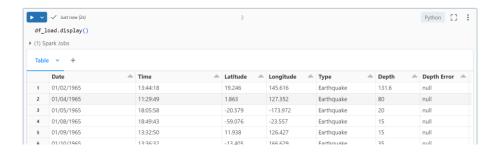
Steps Performed

- 1.Load the dataset containing earthquake details
- 2.Drop the columns which are not required
- 3. Created a year column from date
- 4.Build the quakes frequency dataframe using the year field and counts for each year
- 5. Check the schema and convert some fields from string to numeric
- 6.Create avg magnitude and max magnitude fields and add to df_quake_freq
- 7. Write the dataframes to mongodb

Details

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

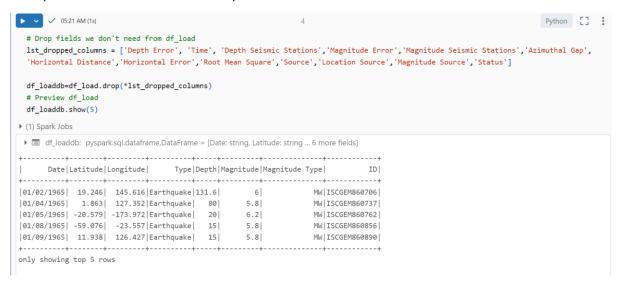
1.Load the dataset containing earthquake details



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



3.Create a year column from date

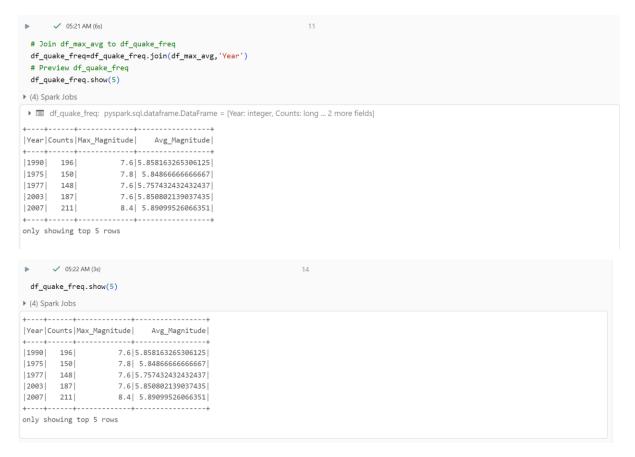


4. Build the quakes frequency data frame using the year field and counts for each year

5. Check the schema and convert some fields from string to numeric

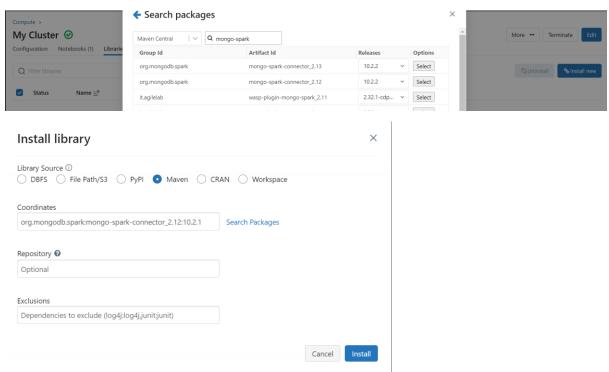


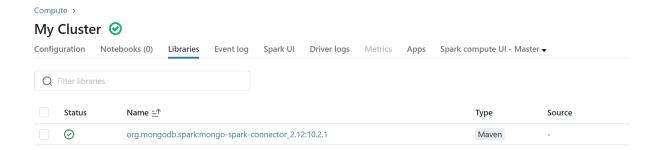
6.Create avg magnitude and max magnitude fields and join to df_quake_freq



7. Write the data frames to mongo Db

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





Write from databricks to mongodb

```
# 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://
.option("database","Quake")\
.option("collection","quakes")\
.save()

* (1) Spark Jobs

* Job 32 <u>View</u> (Stages: 1/1)
Stage 48 1/1 succeeded <u>View</u>
```

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

Mongodb:



Machine Learning

8.Load the Query.csv file which was stored in the HDFS which 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 2017-01-02T00:13:06.3002,-36.0365,51.9288,10,5.7,mwb,,26,14.685,1.37,us,us10007p5d,2017-03-27T23:53:17.0402, "Southwest Indian Ridge",earthquake,10.3,1.7,0.068,21,reviewed,us,us

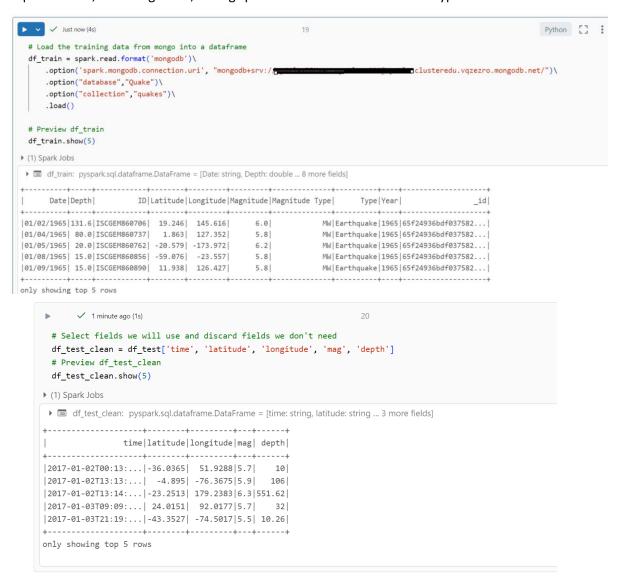
Section: Machine Learning with Spark

```
# Load the test data file into a dataframe

df_test = (spark.read

| .format("csv")
| .option("header", "true")
| .load("dbfs:/FileStore/ProjectPyspark/query.csv")
| .format("csv")
| .format("c
```

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



10.Create testing and training dataframes

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

Random Forest Regressor

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)
  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)
                                                                                                                               Python []
  # Select features to parse into our model and then create the feature vector
  assembler = VectorAssembler(inputCols=['Latitude', 'Longitude', 'Depth'], outputCol='features')
  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)
 ▶ ■ pred_results: pyspark.sql.dataframe.DataFrame = [Latitude: double, Longitude: double ... 4 more fields]
```

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

```
# 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)

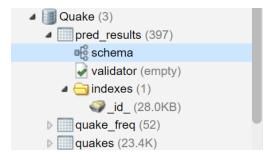
(1) Spark Jobs

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

12.Create the prediction Dataset

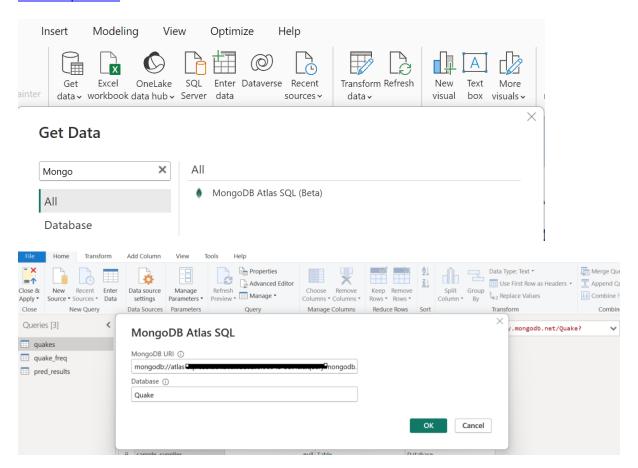
```
Python []
Just now (1s)
  # Create the prediction dataset
  df_pred_results = pred_results['Latitude', 'Longitude', 'prediction']
  # Rename the prediction field
  df_pred_results = df_pred_results.withColumnRenamed('prediction', 'Pred_Magnitude')
  # Add more columns to our prediction dataset
  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|
|-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
\left|\, -43.3527 \right| \ \ -74.5017 \left|\, 5.9204458792780486 \right| 2017 \left|\, 0.40307689171713734 \right|
+-----
only showing top 5 rows
```

13.Load the Prediction dataset to Mongodb

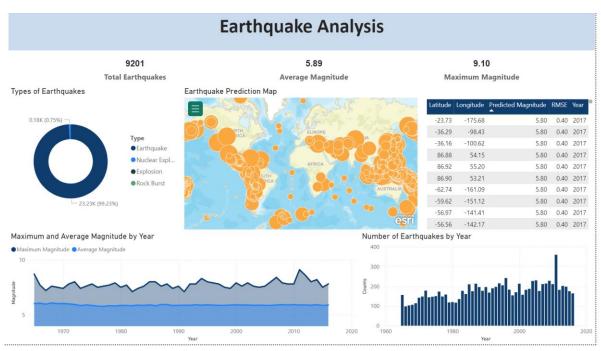


14. Connect the tables from MongoDB using Power BI

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.



Earthquake Analysis - Detail Danger Extreme Danger 7.60 10.00 Earthquake MWC USP000C41F ☐ Moderate 15.00 Earthquake MW ☐ Normal USP000381S 1987 09/03/1987 Danger 158.51 7.40 33.00 Earthquake MW -58.89 1965 08/02/1965 Danger -56.05 157.92 7.30 10.00 Earthquake MW ISCGEM854292 ISCGEM787884 1971 01/03/1971 Danger -55.92 -2.67 7.10 15.00 Earthquake MW 9201 2008 04/12/2008 Danger -55.66 158.45 7.10 16.00 Earthquake MWC USP000G3Q9 **Total Earthquakes** 2015 12/04/2015 Danger -47.62 85.09 7.10 35.00 Earthquake MWW US100043Z2 2001 12/12/2001 Danger -42.81 7.10 10.00 Earthquake MWC USP000AUFX 5.89 7.20 24.00 Earthquake MWW USP000HSFQ 2011 01/02/2011 Danger -38.36 -73.33 Average Magnitude 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 7.40 33.00 Earthquake MW USP0002CD3 9.10 1985 03/03/1985 Danger 8.00 33.00 Earthquake MW **Maximum Magnitude** ISCGEM782010 1971 07/09/1971 Danger -32.60 -71.08 7.80 60.30 Earthquake MW 1978 02/09/1978 Danger -177.36 7.20 33.00 Earthquake MS USP0000SWB -30.68 2001 06/03/2001 Danger -29.67 -178.63 7.20 178.10 Farthquake 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 Danner -2654 -7056 7.40 14.80 Farthquake MW IISP0001YTI