Data Analysis

Analysis of Global Land Average Temperature Trends

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Project Overview:

Analysis of Global Land Average Temperature Trends

Our project is to implement data analysis using Spark SQL on Azure Databricks and process data for errors, seasonality, and anomalies. Some say climate change is the biggest threat of our age while others say it's a myth based on dodgy science. The goal of this project is to analyze the Global Land Average Temperature dataset to understand long-term temperature trends, detect anomalies, and identify potential factors contributing to climate change.

Project Requirements:

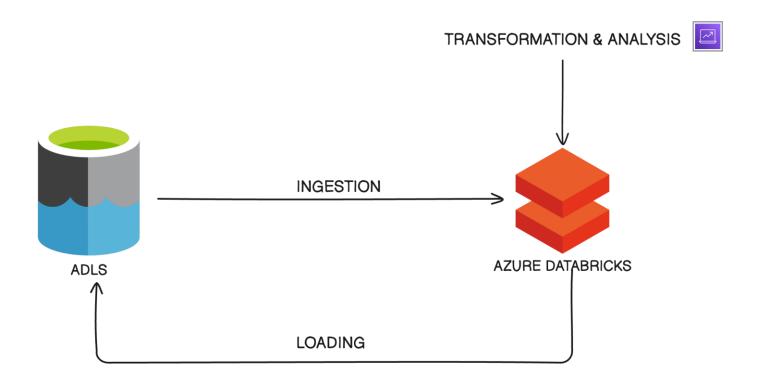
- 1. **Data Source:** We need access to data that needs to be analysed. This could be stored in various formats such as CSV, Parquet, JSON, or in a database.
- Azure Databricks Environment: Set up an Azure Databricks workspace and create a cluster with appropriate configurations based on the size of your data and computational requirements.
- 3. **PySparkSQL**: PySparkSQL, which is the Python API for Spark SQL. This includes understanding how to create SparkSession, loading data, performing data transformations, and executing SQL queries.
- 4. **Data Preparation:** Data often requires preprocessing before analysis. This may involve handling missing values, converting data types, filtering out irrelevant data, and ensuring the data is properly formatted for analysis.

5. Data Analysis:

- Utilize PySparkSQL queries to analyze the temperature data for long-term trends, seasonal variations, and anomalies.
- Aggregate the data to calculate statistical metrics such as average temperature by year or decade.

6. Visualization: Visualize the results of the analysis using plots, charts, and maps to convey insights effectively.

Architecture:



Azure Resources Used for this Project:

AZURE TOOLS:

- Azure Data Lake Storage: Azure Data Lake Storage (ADLS) is a scalable and secure cloud-based storage solution provided by Microsoft Azure. It's designed for big data analytics workloads and is optimized for storing large amounts of structured, semistructured, and unstructured data.
- Azure Databricks: Azure Databricks is a fast, easy, and collaborative Apache Spark-based
 analytics platform optimized for Azure. It provides a fully managed, cloud-based environment
 that integrates seamlessly with other Azure services, allowing data engineers, data
 scientists, and analysts to collaborate on big data and machine learning projects.

AZURE TECHNOLOGIES:

- Pyspark: PySpark is the Python API for Apache Spark, a distributed computing
 framework for processing large datasets. It allows developers to write Spark applications
 using Python programming language, leveraging Spark's distributed computing
 capabilities.
- Spark SQL: Spark SQL is a module in Apache Spark for processing structured data using SQL and DataFrame API. It provides a unified interface for querying structured data sources, enabling seamless integration of SQL queries with Spark's distributed processing engine.

How it Works:

1. Data Ingestion:

Load the dataset into Azure Databricks storage (e.g., Azure Blob Storage).

2. Data Exploration and Cleaning:

- Explore the structure and contents of the dataset to understand its schema and characteristics.
- Perform data cleaning steps to handle missing values, outliers, and inconsistencies.

3. Data Analysis:

- Utilize PySparkSQL queries to analyze the data for errors, seasonality, and anomalies.
- Aggregate the data to calculate statistics such as average.

4. Error Detection:

Utilize Spark SQL queries or built-in functions to detect errors in your data. This could involve identifying inconsistencies, duplicates, or unexpected values.

5. Seasonality Analysis:

Use Spark SQL functions or libraries like PySpark's pandas or numpy to analyze seasonality patterns in your data. This could involve time series analysis, trend detection, or Fourier transforms.

6. Anomaly Detection:

Implement anomaly detection algorithms using Spark SQL or PySpark libraries.

7. Visualization:

Visualize the results of the analysis using plots, charts, or dashboards to communicate insights effectively.

About Dataset:

Climate Change: Earth Surface Temperature Data

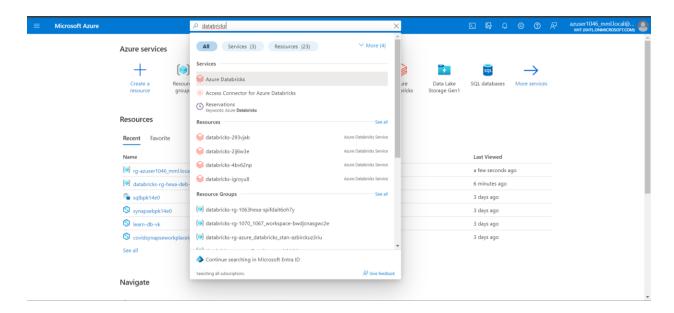
The Berkeley Earth Surface Temperature Study combines 1.6 billion temperature reports from 16 pre-existing archives. It is nicely packaged and allows for slicing into interesting subsets (for example by country). They publish the source data and the code for the transformations they applied. They also use methods that allow weather observations from shorter time series to be included, meaning fewer observations need to be thrown away.

Early data was collected by technicians using mercury thermometers, where any variation in the visit time impacted measurements. In the 1940s, the construction of airports caused many weather stations to be moved. In the 1980s, there was a move to electronic thermometers that are said to have a cooling bias. Our Dataset contains columns Date, Average Temperature, Average Temperature Uncertainty, Country.

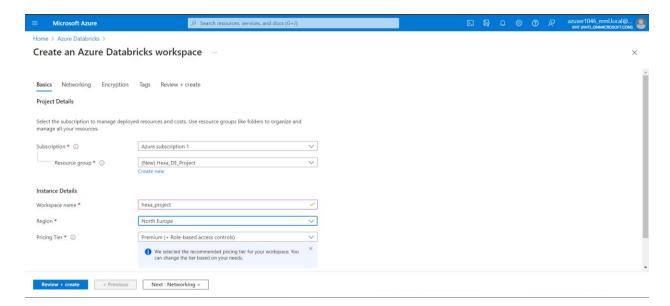
```
■ GlobalLandTemperaturesByCountry.csv X
D: > Hexaware > Data_Engineering-Batch > Data_Engineering_Projects > Datasets > GlobalLandTemperatures > 🖩 GlobalLandTemperaturesByCountry.csv
     1 Date, AverageTemperature, AverageTemperatureUncertainty, Country
          .
1743-11-01,4.383999999999995,2.294,Åland
         1743-12-01,,,Åland
          1744-01-01,,,Åland
     6 1744-03-01,,,Åland
          1744-04-01,1.53,4.68,Åland
        1744-05-01,6.702000000000001,1.789,Åland
        1744-06-01,11.609000000000002,1.577,Åland
1744-07-01,15.342,1.41,Åland
    11 1744-08-01,,,Åland
         1744-09-01,11.702,1.517,Åland
    13 1744-10-01,5.477,1.862,Åland
    14 1744-11-01,3.407,1.425,Åland
          1744-12-01,-2.181,1.641,Åland
    16 1745-01-01,-3.85,1.841,Åland
    17 1745-02-01,-6.57499999999998,1.36,Åland
18 1745-03-01,-4.195,1.213,Åland
    19 1745-04-01,-0.966000000000002,1.172,Åland
          1745-05-01,,,Åland
    21 1745-06-01,,,Åland
    22 1745-07-01,,,Åland
23 1745-08-01,,,Åland
    24 1745-09-01,,,Åland
         1745-10-01,,,Åland
    26 1745-11-01,,,Åland
    27 1745-12-01,,,Åland
28 1746-01-01,,,Åland
    29 1746-02-01,,,Åland
        1746-03-01,,,Åland
1746-04-01,,,Åland
     32 1746-05-01,,,Åland
          1746-06-01,,,Åland
     35 1746-08-01,,,Åland
          1746-09-01,,,Åland
     37 1746-10-01,,,Åland
```

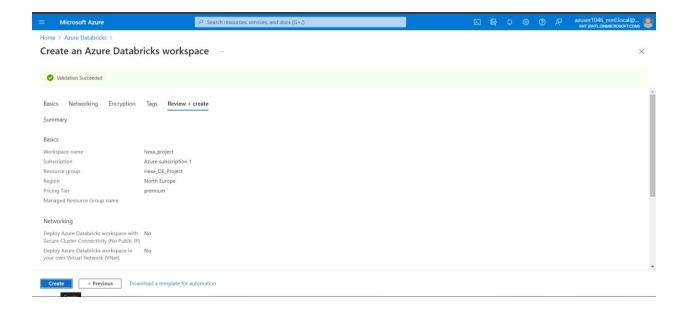
Tasks Performed:

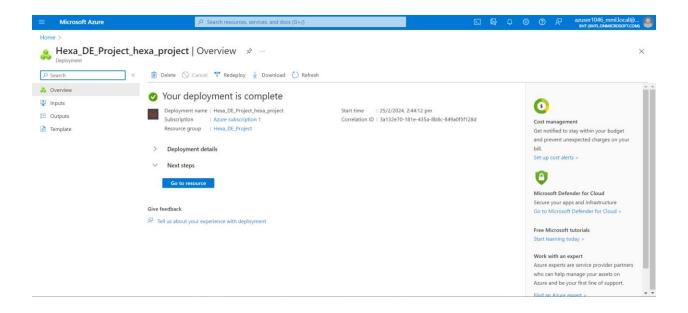
Search for Azure Databricks in the resources:



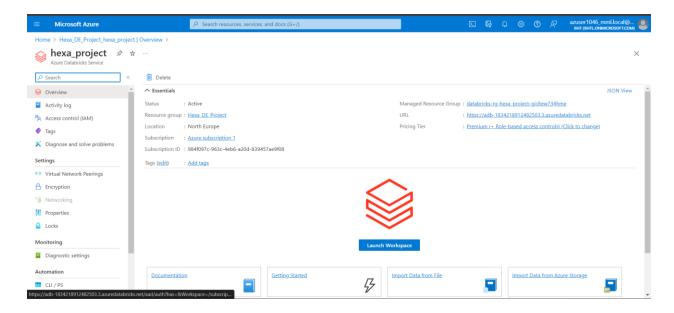
Created Azure Databricks Workspace:



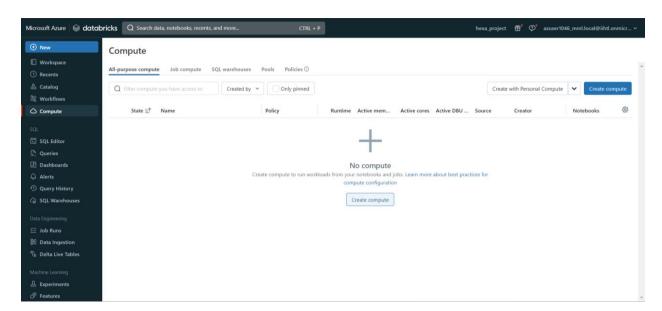




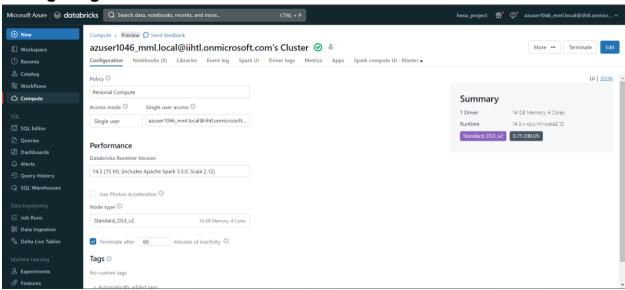
Launch Databricks Workspace:



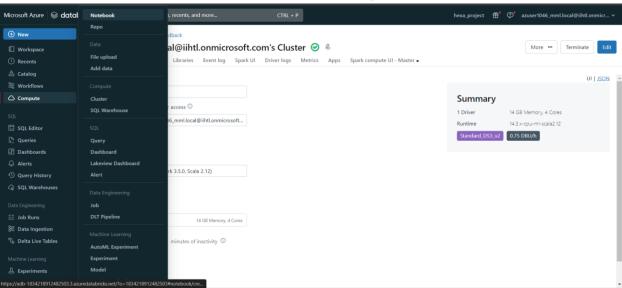
Created Cluster in Azure Databricks workspace:



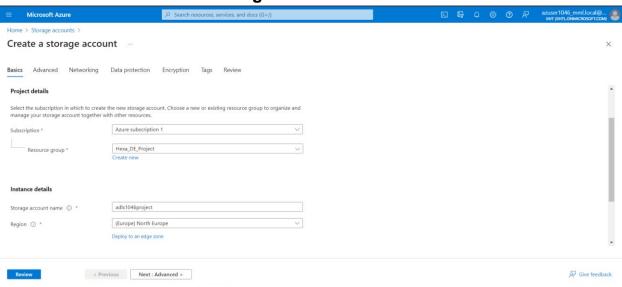
Configuring the Cluster:

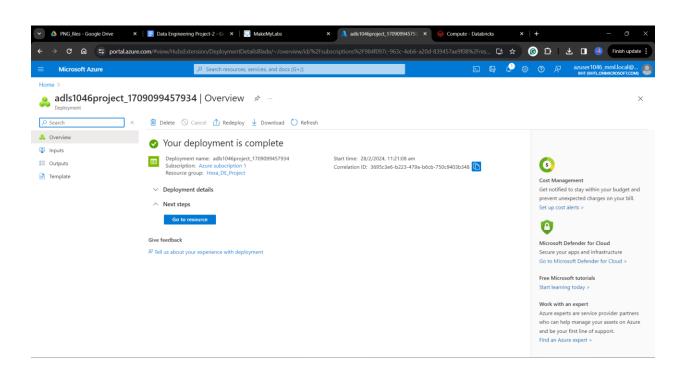


Created Notebook in Azure Databricks workspace:

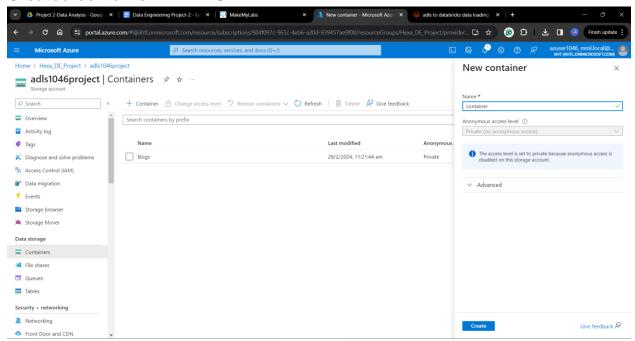


Created Azure Data Lake Storage account

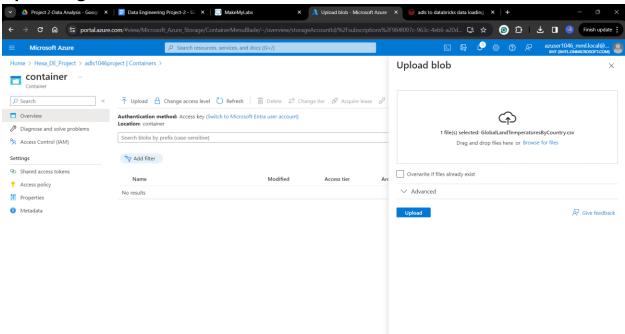




Created container in ADLS



Uploading Dataset in the ADLS

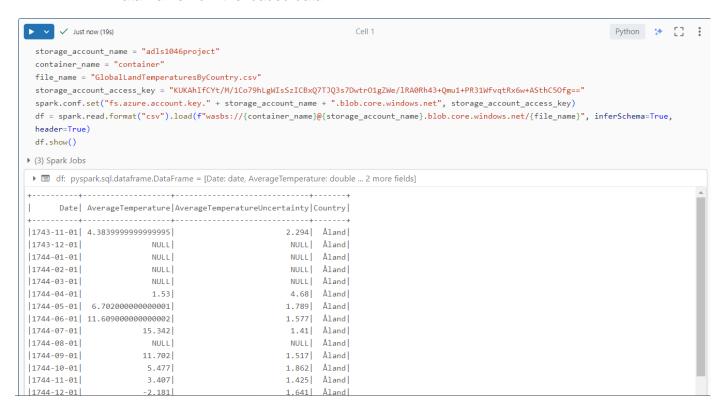


Data Preparation:

 Loaded the global temperature data into Spark DataFrame from our data source Azure Blob Storage.

Load Data from Data Sources:

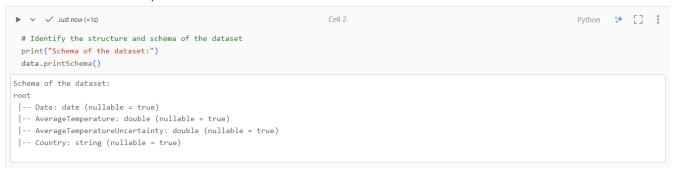
- For Azure Blob Storage: Use the spark.read.format("csv").load("wasbs://<container-name>@<storageaccount-name>.blob.core.windows.net/<path>") method to load CSV files from Azure Blob Storage.
- Once the data is loaded and formatted, created a Spark DataFrame to represent the data in a structured format for further analysis.
- Used the **spark.createDataFrame()** method or DataFrame APIs to create the DataFrame from the loaded data.



Data Exploration:

To explore our data using Spark SQL, We followed these steps:

- 1. Load the data into Spark DataFrame.
- 2. Used Spark SQL queries to explore the data, including identifying the structure, schema, and basic statistics.



```
# Use Spark SQL queries to explore the data
# Example 1: Count the number of records in the dataset
record_count = spark.sql("SELECT COUNT(*) AS record_count FROM climate_data").collect()[0]["record_count"]
print("Number of records in the dataset:", record_count)

Number of records in the dataset: 577462
```

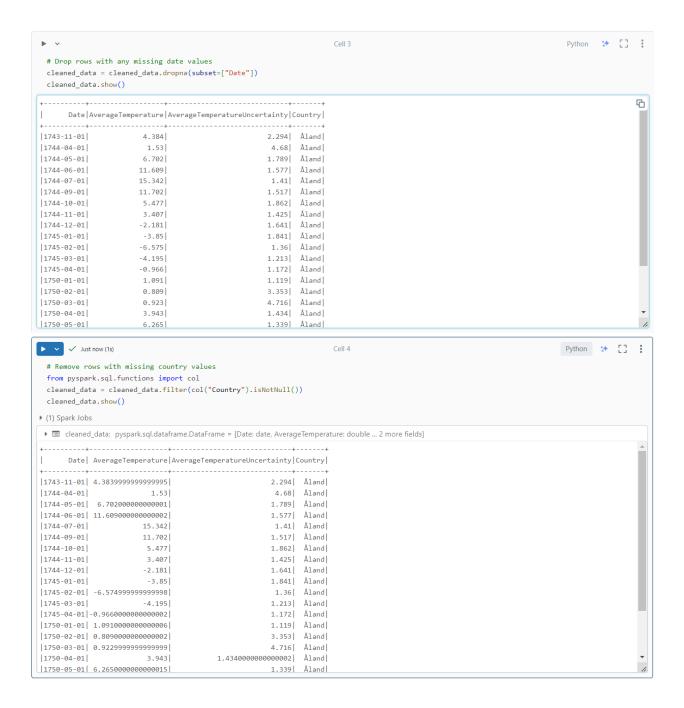


```
Python 💝 📋 :
 # Example 4: Calculate the average value of a numerical column
 print("Average value of a of temperature of the year:")
 avg_temp = spark.sql("SELECT DATE_PART('YEAR', Date), AVG(AverageTemperature) AS avg_temp FROM climate_data GROUP BY DATE_PART('YEAR', Date)
 ORDER BY DATE_PART('YEAR', Date)")
 avg_temp.show()
▶ (2) Spark Jobs
• avg_temp: pyspark.sql.dataframe.DataFrame = [date_part(YEAR, Date): integer, avg_temp: double]
Average value of a of temperature of the year:
                                                                                                                                         4
|date_part(YEAR, Date)| avg_temp|
               1743 | 5.18414 |
1744 | 9.8378975 |
                1745 1.38712500000000004
                1746
                                 NULL
                                  NULL
                1747
                1748
                                  NULL
                1749
                                  NULL
                1750 9.129352727272728
                1751 9.167387499999998
               1752 | 4.413386666666668|
                1753 8.870820754716977
               1754 8.822018957345971
                1755 | 8.530536277602524 |
                1756 9.17988625592417
                1757 8.993332283464566
                1758 8.13037054263566
                 17E0 0 2612E771604020
```

Data Cleaning:

 Used Spark SQL queries or DataFrame operations to perform data cleaning operations to inspect the data and to handle missing values, and any inconsistencies in the data.

```
Cell 2
  # Handle missing values
  # Drop rows with any missing temperature values
  cleaned_data = data.dropna(subset=["AverageTemperature"])
 cleaned_data.show()
| Date|AverageTemperature|AverageTemperatureUncertainty|Country|
|1743-11-01| 4.384|
                                            1.53|
6.702|
11.609|
15.342|
11.702|
5.477|
3.407|
-2.181|
1744-04-01
                                                  4.68| Åland|
1744-05-01
                                                 1.789| Åland|
                                                1.577 | Åland|
1744-06-01
                                                1.41| Åland|
1.517| Åland|
1744-07-01
1744-09-01
|1744-10-01|
                                                1.862| Åland|
                                                 1.425| Åland|
11744-11-01
1744-12-01
                                                 1.641 Åland
                                                1.841 | Åland|
|1745-01-01|
                     -3.85
1745-02-01
                     -6.575
                                                  1.36 | Åland|
1745-03-01
                     -4.195
                                                 1.213 | Åland
                    -0.966
1745-04-01
                                                1.172 | Åland|
|1750-01-01|
                      1.091
                                                 1.119 | Åland|
                    0.809
                                                11750-02-01
                    0.923
|1750-03-01|
                                                 4.716 | Åland|
 |1750-04-01|
                      3.943
                                                 1.434 | Åland|
                                                  1.339| Åland|
1750-05-01
                      6.265
```



```
Python 😘 🚼 :
                                                                    Cell 5
 # Drop irrelevant columns
 cleaned_data = cleaned_data.drop("AverageTemperatureUncertainty")
 cleaned data.show()
11744-05-01
                       6.702 Åland
                  6.702| Aland|
11.609| Åland|
15.342| Åland|
                                                                                                                                           6
11744-06-01
1744-07-01
                     11.702| Åland|
5.477| Åland|
|1744-09-01|
|1744-10-01|
1744-11-01
                      3.407| Åland|
                     -2.181| Åland|
1744-12-01
1745-01-01
                      -3.85| Åland|
                     -6.575| Åland|
1745-02-01
1745-03-01
                      -4.195| Åland|
1745-04-01
                      -0.966 | Åland|
|1750-01-01|
                      1.091| Åland|
|1750-02-01|
                      0.809| Åland|
1750-03-01
                      0.923 | Åland
                      3.943| Åland|
1750-04-01
                      6.265| Åland|
11750-05-01
1750-06-01
                     12.408 | Åland
|1750-07-01|
                      16.683| Åland|
only showing top 20 rows
```

Error Detection:

Utilized Spark SQL queries or built-in functions to detect errors in your data. This
involved identifying inconsistencies, duplicates, or unexpected values.

```
# Check for missing values in relevant columns (e.g., Country, AverageTemperature)
 missing_values = data.filter((col("Country").isNull()) | (col("AverageTemperature").isNull()))
 if missing_values.count() > 0:
     print("Missing values found in the dataset:")
     missing_values.show()
 else:
     print("No missing values found in the dataset.")
Missing values found in the dataset:
     Date | AverageTemperature | AverageTemperatureUncertainty | Country |
+-----
11743-12-01
                    nu111
                                               null| Åland|
                  null|
1744-01-01
                                              null| Åland|
1744-02-01
                                              null Åland
1744-03-01
                   null
                                              null| Åland|
                                              null Åland
1744-08-01
                    null
|1745-05-01|
                   null
                                              null| Åland|
|1745-06-01|
                   null
                                              null| Åland|
1745-07-01
                   null
                                               null Åland
1745-08-01
                   null
                                               null Åland
1745-09-01
                   null
                                               null Åland
1745-10-01
                   null
                                               null Åland
1745-11-01
                    null
                                               null Aland
1745-12-01
                    null
                                               null Aland
                    null
1746-01-01
                                               null Aland
|1746-02-01|
                    null
                                               null Åland
|1746-03-01|
                      null|
                                               null Åland
1746-04-01
                                               null| Åland|
                      null
```

```
# Check for duplicates
duplicate_count = data.groupBy(data.columns).count().filter("count > 1").count()
if duplicate_count > 0:
    print("Duplicates found in the dataset.")
else:
    print("No duplicates found in the dataset.")

No duplicates found in the dataset.
```

```
# Check for outliers or unrealistic values in AverageTemperature
 # you can set a threshold to identify outliers
 min threshold = -30
 max threshold = 50
 outliers = data.filter((col("AverageTemperature") < min_threshold) | (col("AverageTemperature") > max_threshold))
 if outliers.count() > 0:
    print("Outliers found in the AverageTemperature column:")
    print("No outliers found in the AverageTemperature column.")
Outliers found in the AverageTemperature column:
Date|AverageTemperature|AverageTemperatureUncertainty|Country|
|1831-02-01|
                     -31.28
                                                  4.364 Denmark
                 -31.259
1832-02-01
                                                  3.57 Denmark
                  -31.572
-31.831
1834-01-01
                                                   3.27 Denmark
                                                 3.245 Denmark
1835-02-01
                   -32.625
-31.057
1836-02-01
                                                  3.677 Denmark
1838-01-01
                                                  3.493 Denmark
1839-01-01
                    -31.251
                                                  3.188 Denmark
|1839-12-01|
                    -31.045
                                                  2.886 Denmark
1840-01-01
                    -31.082
                                                  3.549 Denmark
|1841-01-01|
                     -31.097
                                                   2.931|Denmark|
1844-02-01
                    -31.911
                                                   3.263 Denmark
|1845-02-01|
                     -31.081
                                                   3.222 Denmark
|1845-12-01|
                     -31.152
                                                   3.11 Denmark
```

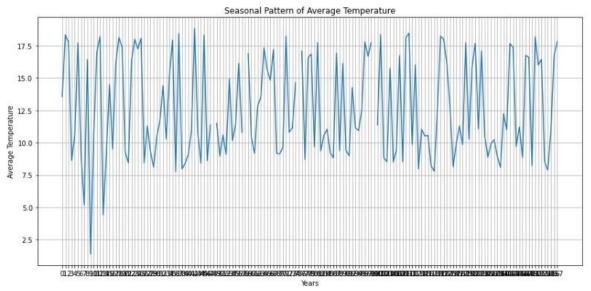
Seasonality Analysis:

• Use Spark SQL functions or libraries like PySpark's pandas or numpy to analyze seasonality patterns in your data.

```
Python 😘 []
 # Ensure 'Date' column is of type DateType
 data = data.withColumn("Date", data["Date"].cast("date"))
| Date | AverageTemperature | AverageTemperatureUncertainty | Country |
+-----
|1743-11-01| 4.384|
                                           2.294 | Åland|
                  null|
null|
null|
null|
1.53|
1743-12-01
                                             null| Åland|
1744-01-01
                                              null Åland
1744-02-01
                                             null| Åland|
1744-03-01
                                              null Åland
|1744-04-01|
                                              4.68| Åland|
1744-05-01
                   6.702
                                             1.789 | Åland|
                 11.609
1744-06-01
                                             1.577 | Åland|
                 15.342
1744-07-01
                                              1.41 Åland
1744-08-01
                    null
                                              null| Åland|
1744-09-01
                   11.702
                                             1.517 | Åland|
|1744-10-01|
                    5.477
                                              1.862| Åland|
1744-11-01
                    3.407
                                             1.425| Åland|
|1744-12-01|
                    -2.181
                                              1.641 | Åland|
1745-01-01
                    -3.85
                                             1.841 Åland
1745-02-01
                    -6.575
                                              1.36 | Åland|
1745-03-01
                    -4.195
                                              1.213 | Åland|
1745-04-01
                    -0.966
                                              1.172| Åland|
```

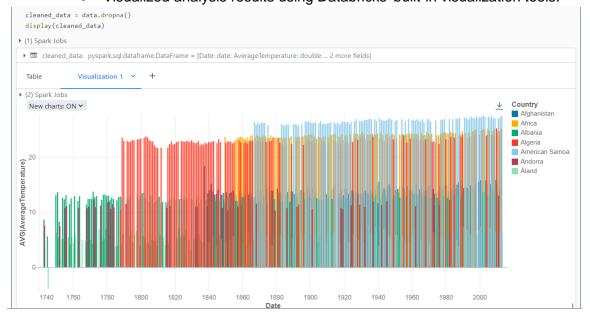
```
# Convert Spark DataFrame to Pandas DataFrame for visualization
yearly_avg_temp_pandas = yearly_avg_temp.toPandas()

# Plot the seasonal pattern of average temperature
plt.figure(figsize=(12, 6))
plt.plot(yearly_avg_temp_pandas["AvgTemperature"])
plt.title("Seasonal Pattern of Average Temperature")
plt.xlabel("Years")
plt.ylabel("Years")
plt.ylabel("Average Temperature")
plt.xticks(range(len(yearly_avg_temp_pandas)))
plt.grid(True)
plt.tight_layout()
plt.show()
```



Visualization:

• Visualized analysis results using Databricks' built-in visualization tools.

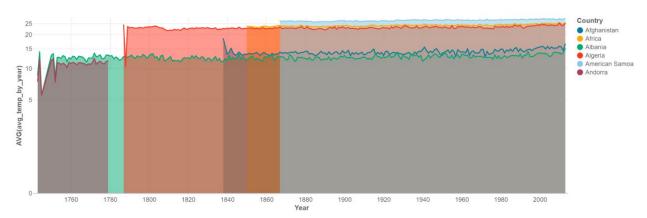


Data Analysis:

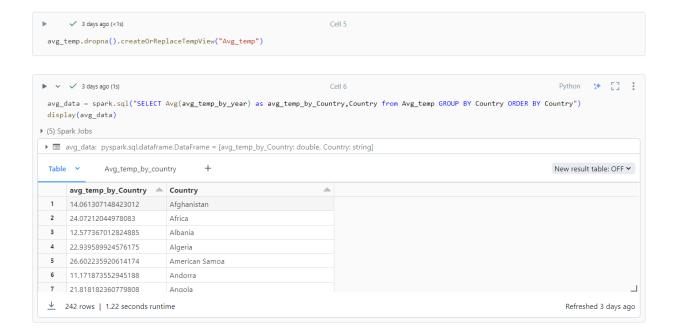
- Utilized PySparkSQL queries to analyze the data for errors, seasonality, and anomalies.
- Aggregate the data to calculate statistics such as average.

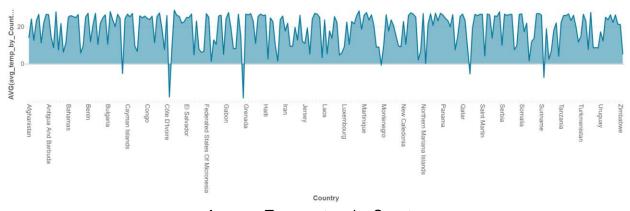






Average temperature by year





Average Temperature by Country

Conclusion:

In conclusion, the project successfully achieved its objectives of analyzing the Global Land Average Temperature dataset using PySpark on Azure Databricks. By leveraging distributed computing capabilities and advanced analytics techniques, the project provided actionable insights into temperature trends and anomalies, contributing to efforts to understand and address climate change.

The project demonstrates the power of using cloud-based data analytics platforms like Azure Databricks and PySpark for processing and analyzing large-scale environmental datasets, enabling data-driven decision-making and fostering scientific research in climate science and related fields.

Reference : https://learn.microsoft.com/en-us/azure/storage/blobs/create-data-lake-storage-account

https://learn.microsoft.com/en-in/azure/synapse-analytics/get-started-create-workspace https://blog.arinti.be/databricks-importing-data-from-a-blob-storage-2b8dc700d029 https://docs.databricks.com/en/_extras/notebooks/source/data-import/azure-blob-store.html