Project -2
Data Analysis

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Data Engineering Batch

Analysis of Global Land Average Temperature Trends

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.

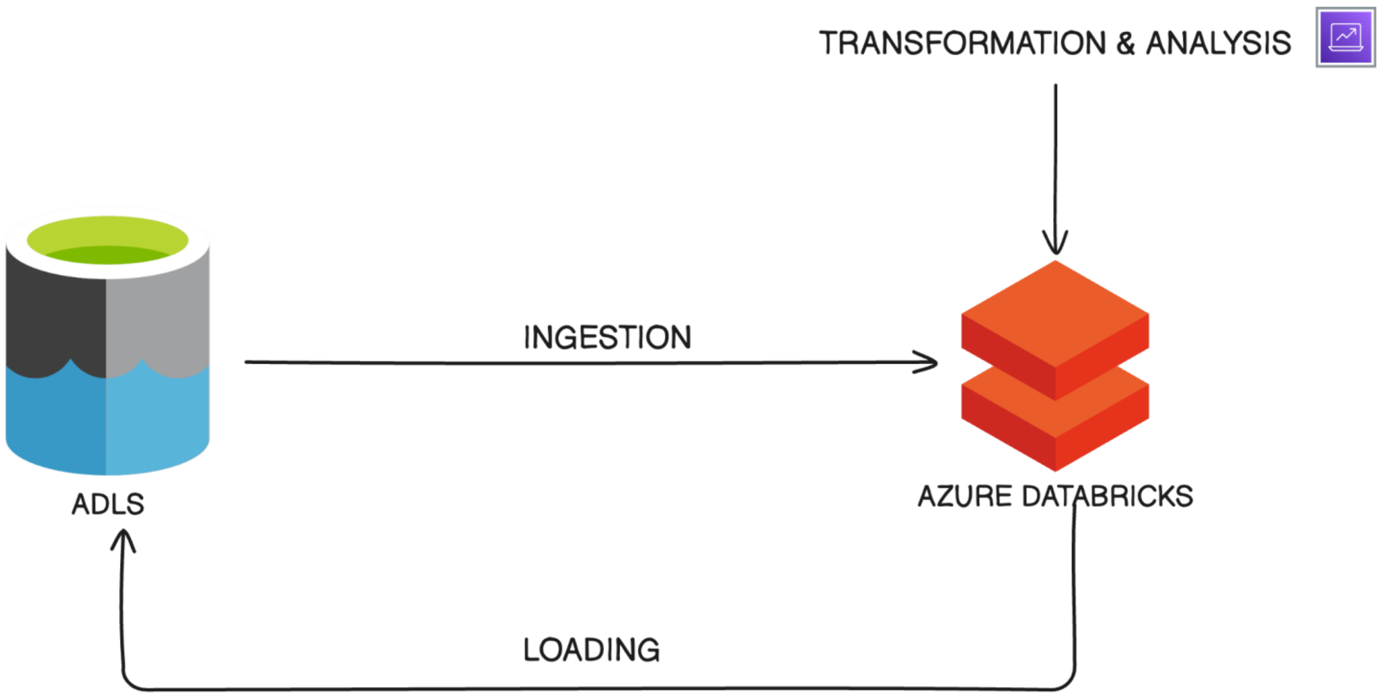
2. **Azure Databricks Environment:** Set up an Azure Databricks workspace and create a cluster with appropriate configurations based on the size of your data and computational requirements.

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, semi-structured, 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.

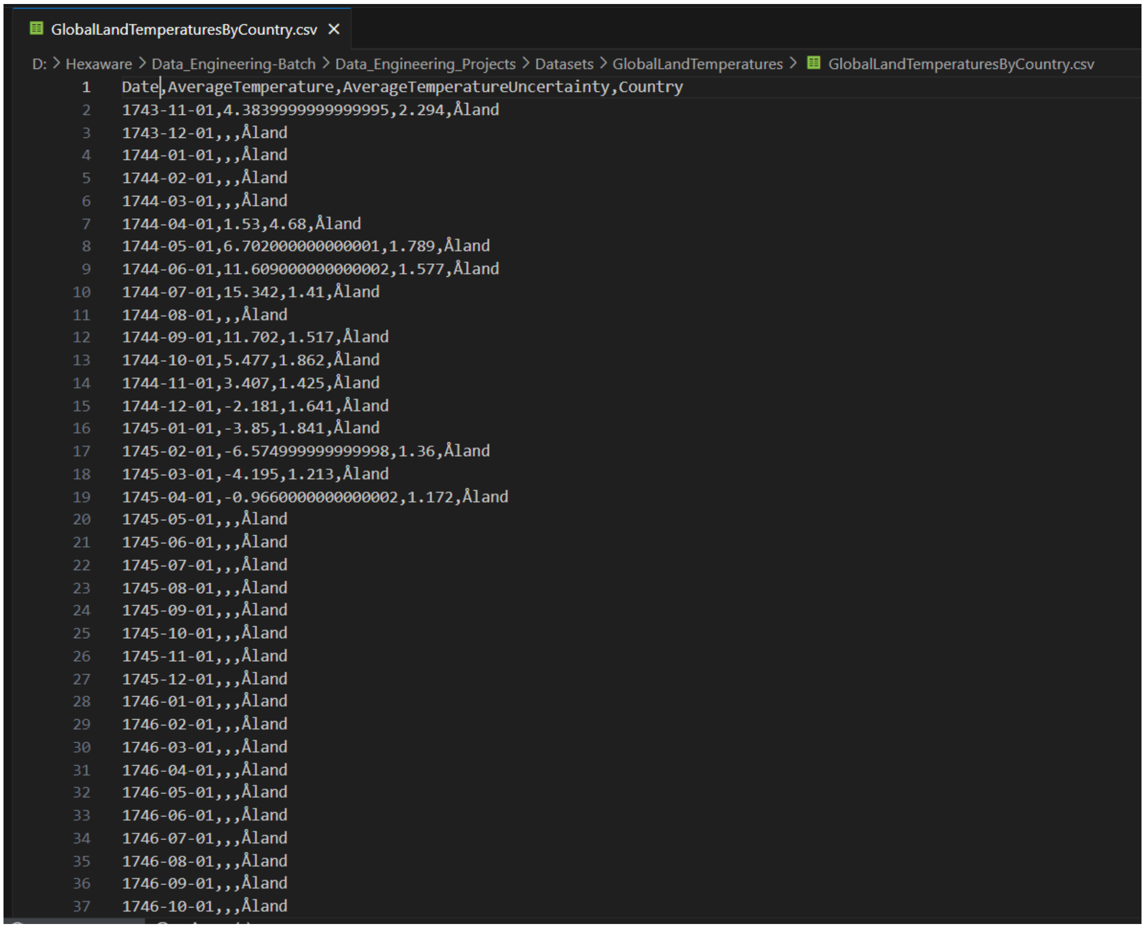
About Dataset :

Climate Change: Earth Surface Temperature Data

Exploring global temperatures since 1750

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.

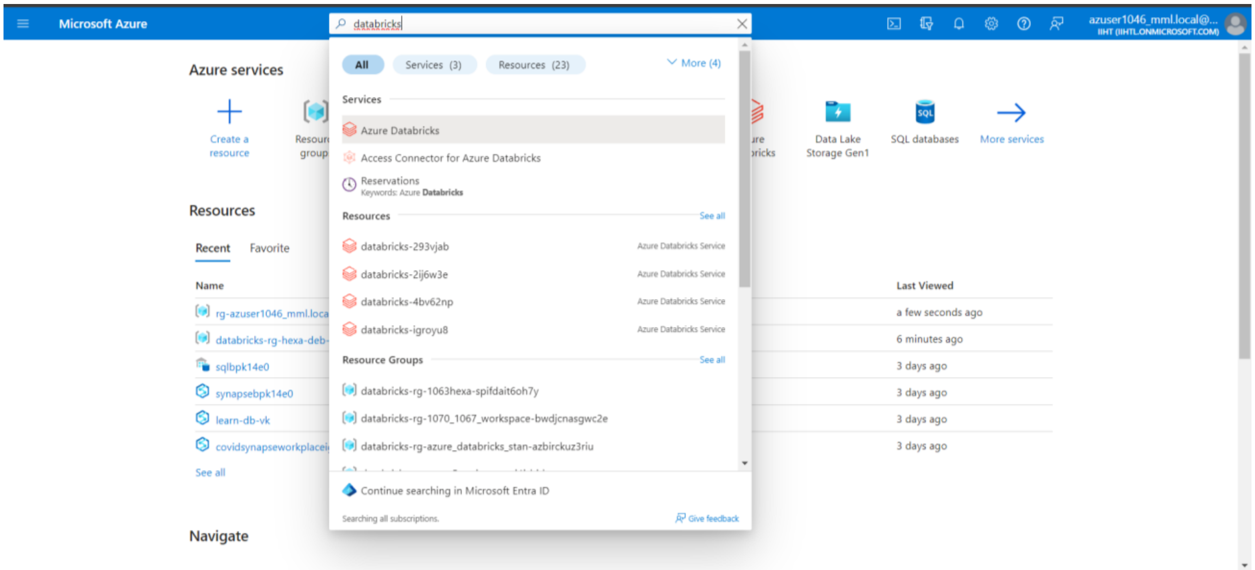
Early data was collected by technicians using mercury thermometers, where any variation in the visit time impacted measurements. In the 1940s, the construction of airports caused many weather stations to be moved. In the 1980s, there was a move to electronic thermometers that are said to have a cooling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



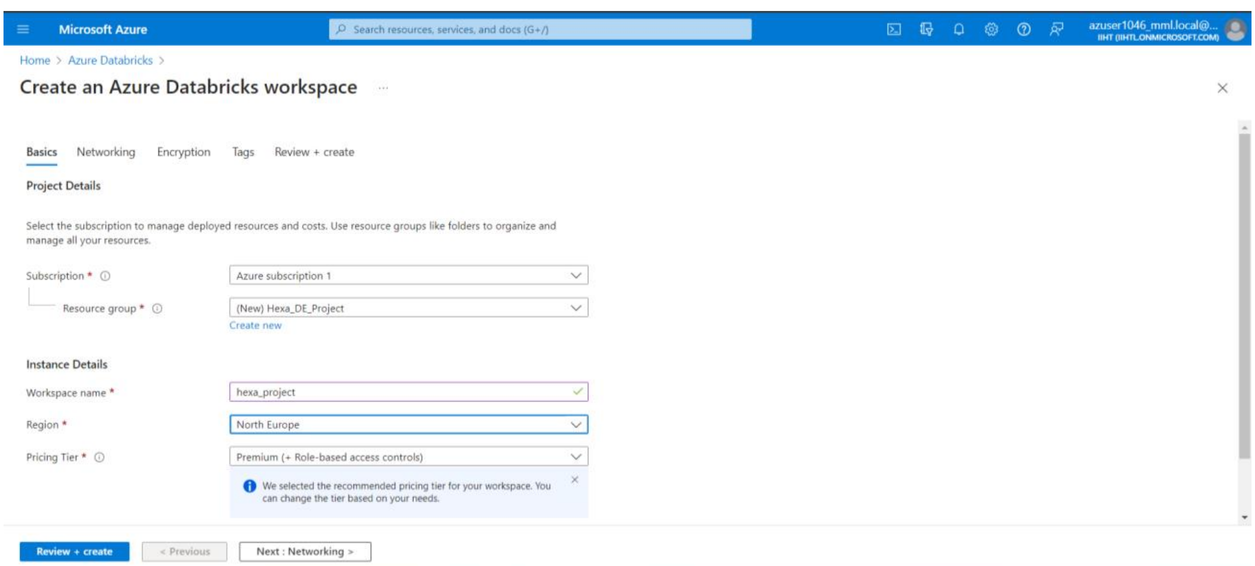

```
Date,AverageTemperature,AverageTemperatureUncertainty,Country
1743-11-01,4.3839999999999995,2.294,Åland
1743-12-01,,,Åland
1744-01-01,,,Åland
1744-02-01,,,Åland
1744-03-01,,,Åland
1744-04-01,1.53,4.68,Åland
1744-05-01,6.702000000000001,1.789,Åland
1744-06-01,11.609000000000002,1.577,Åland
1744-07-01,15.342,1.41,Åland
1744-08-01,,,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,-6.574999999999998,1.36,Åland
1745-03-01,-4.195,1.213,Åland
1745-04-01,-0.9660000000000002,1.172,Åland
1745-05-01,,,Åland
1745-06-01,,,Åland
1745-07-01,,,Åland
1745-08-01,,,Åland
1745-09-01,,,Åland
1745-10-01,,,Åland
1745-11-01,,,Åland
1745-12-01,,,Åland
1746-01-01,,,Åland
1746-02-01,,,Åland
1746-03-01,,,Åland
1746-04-01,,,Åland
1746-05-01,,,Åland
1746-06-01,,,Åland
1746-07-01,,,Åland
1746-08-01,,,Åland
1746-09-01,,,Åland
1746-10-01,,,Åland
```

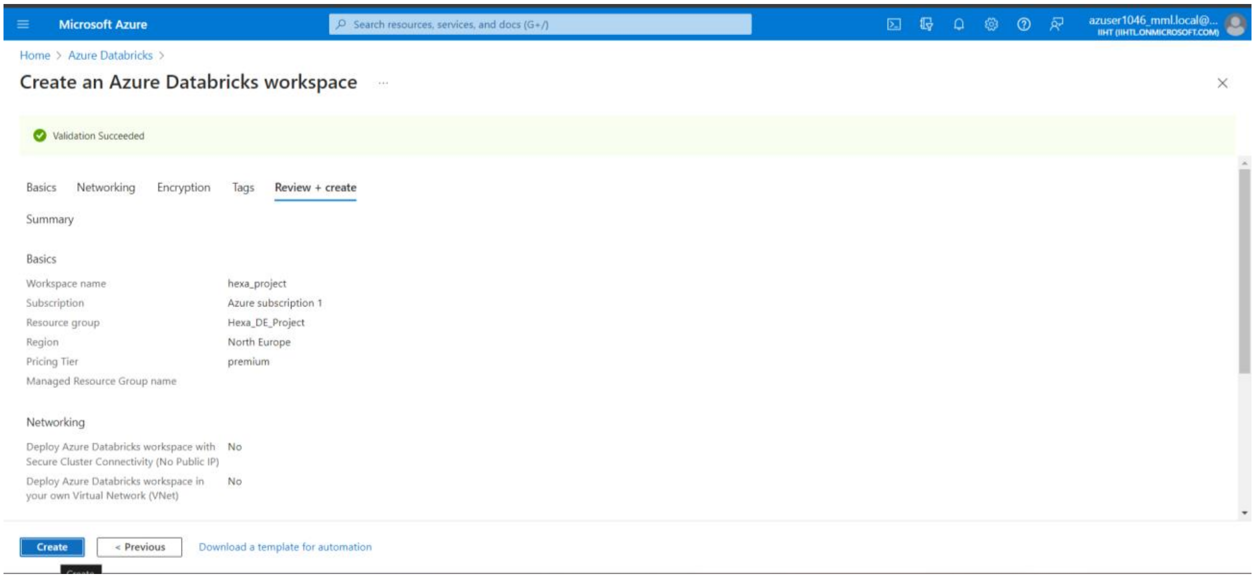
Tasks Performed :

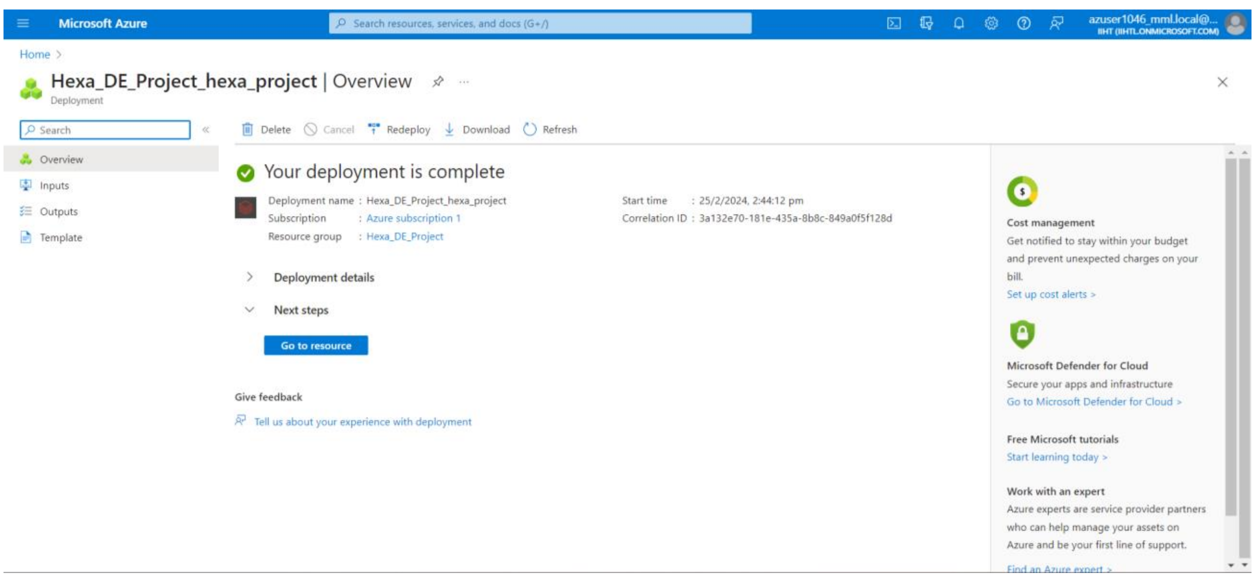
Search for Azure Databricks in the resources :



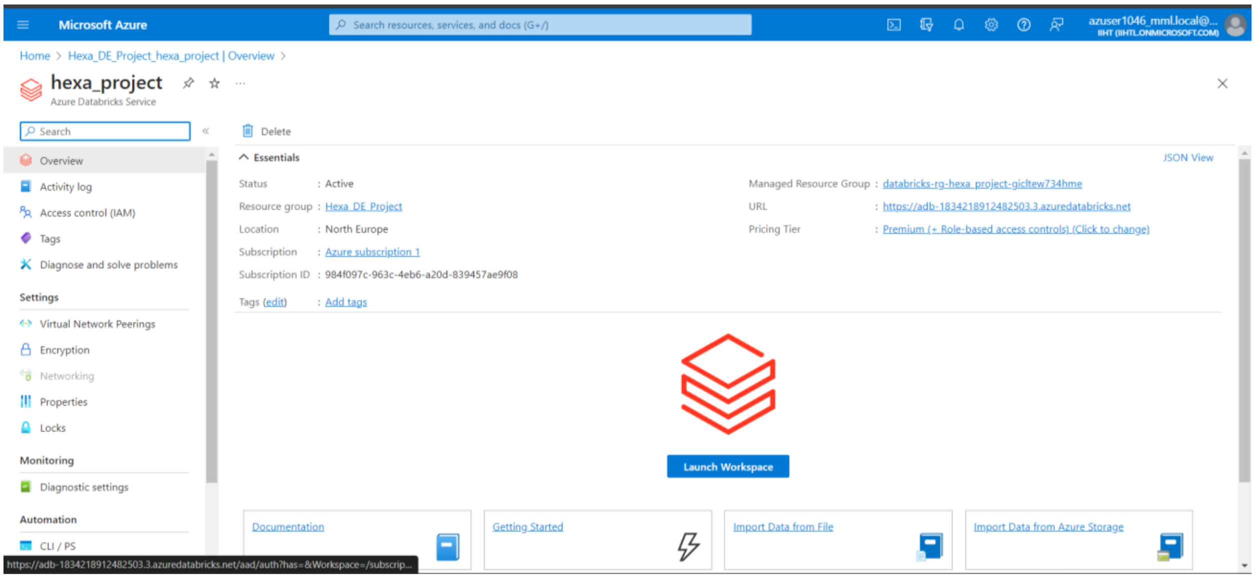
Created Azure Databricks Workspace :



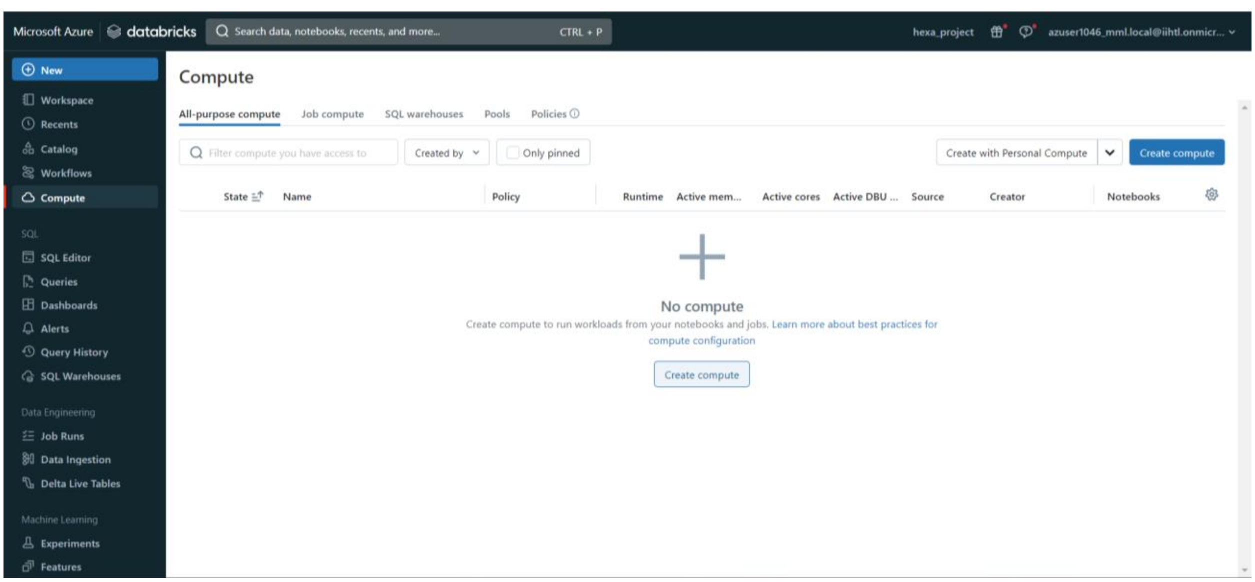

Microsoft Azure
Search resources, services, and docs (G+/)
azuser1046_mml.local@...
IIHT (IIHTL.ONMICROSOFT.COM)
Home > Azure Databricks >
Create an Azure Databricks workspace
Validation Succeeded
Basics
Networking
Encryption
Tags
Review + create
Summary
Basics
Workspace name hexa_project
Subscription Azure subscription 1
Resource group Hexa_DE_Project
Region North Europe
Pricing Tier premium
Managed Resource Group name
Networking
Deploy Azure Databricks workspace with Secure Cluster Connectivity (No Public IP) No
Deploy Azure Databricks workspace in your own Virtual Network (VNet) No
Create
< Previous
Download a template for automation


Microsoft Azure
Search resources, services, and docs (G+/)
azuser1046_mml.local@...
IIHT (IIHTL.ONMICROSOFT.COM)
Home >
Hexa_DE_Project_hexa_project | Overview
Deployment
Search
Overview
Inputs
Outputs
Template
Delete
Cancel
Redeploy
Download
Refresh
Your deployment is complete
Deployment name : Hexa_DE_Project_hexa_project
Subscription : Azure subscription 1
Resource group : Hexa_DE_Project
Start time : 25/2/2024, 2:44:12 pm
Correlation ID : 3a132e70-181e-435a-8b8c-849a0f5f128d
Deployment details
Next steps
Go to resource
Give feedback
Tell us about your experience with deployment
Cost management
Get notified to stay within your budget and prevent unexpected charges on your bill.
Set up cost alerts >
Microsoft Defender for Cloud
Secure your apps and infrastructure
Go to Microsoft Defender for Cloud >
Free Microsoft tutorials
Start learning today >
Work with an expert
Azure experts are service provider partners who can help manage your assets on Azure and be your first line of support.
Find an Azure expert >

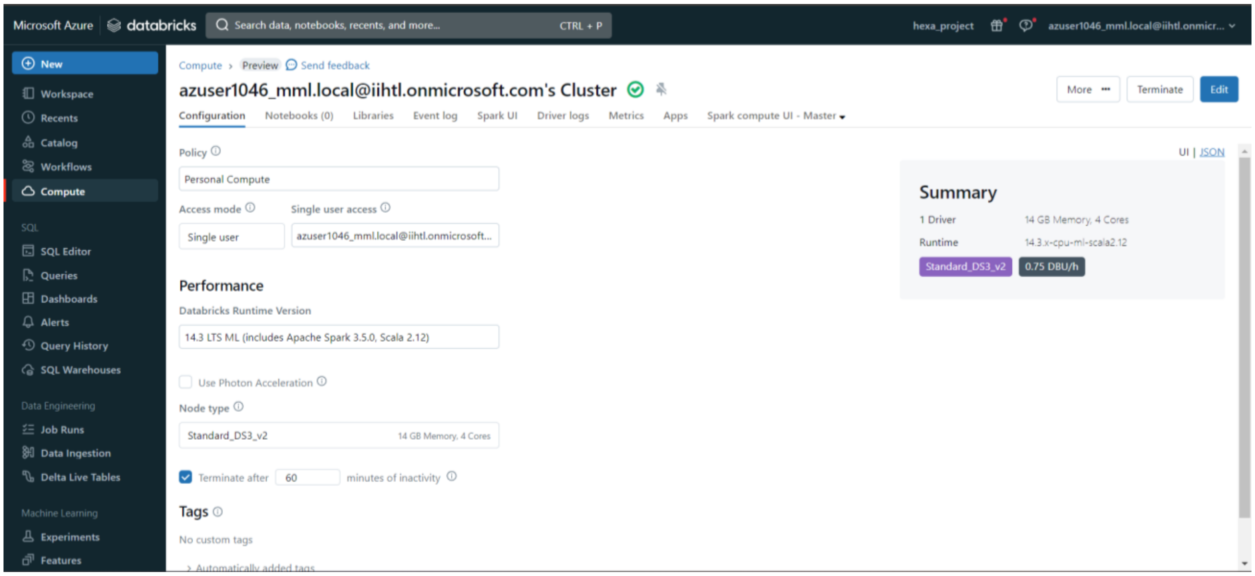
Launch Databricks Workspace :



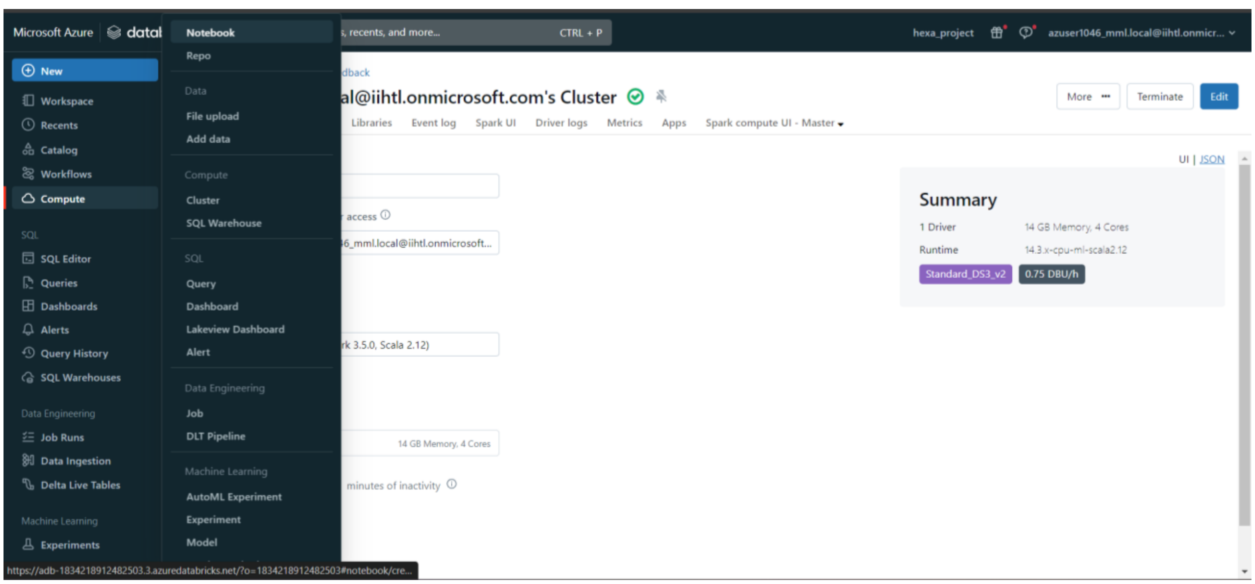
Created Cluster in Azure Databricks workspace :



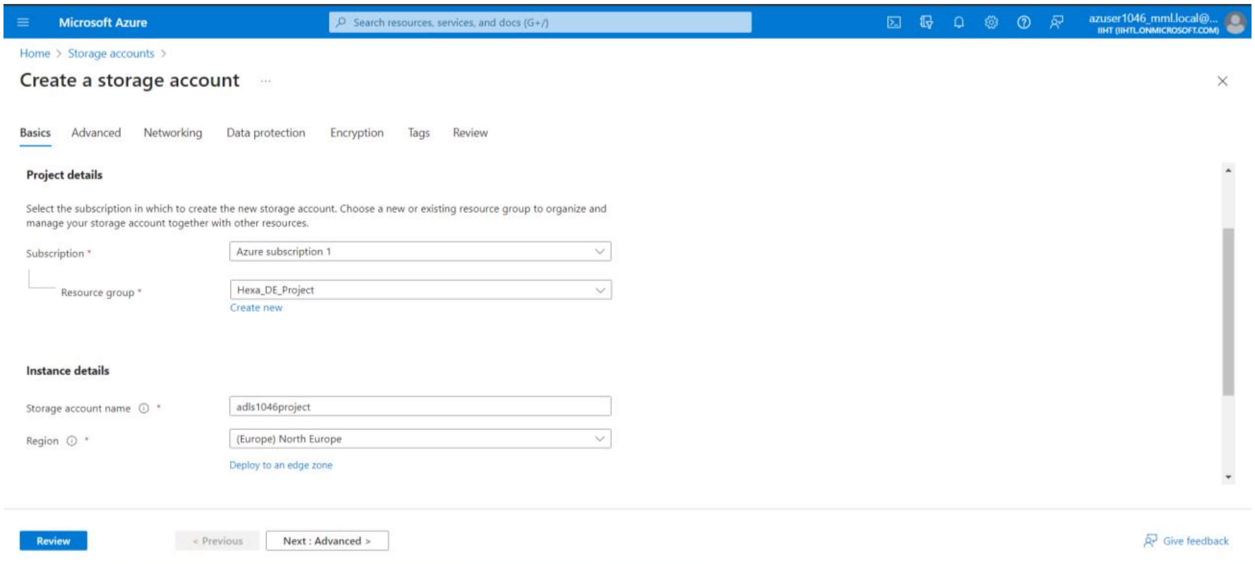
Configuring the Cluster :

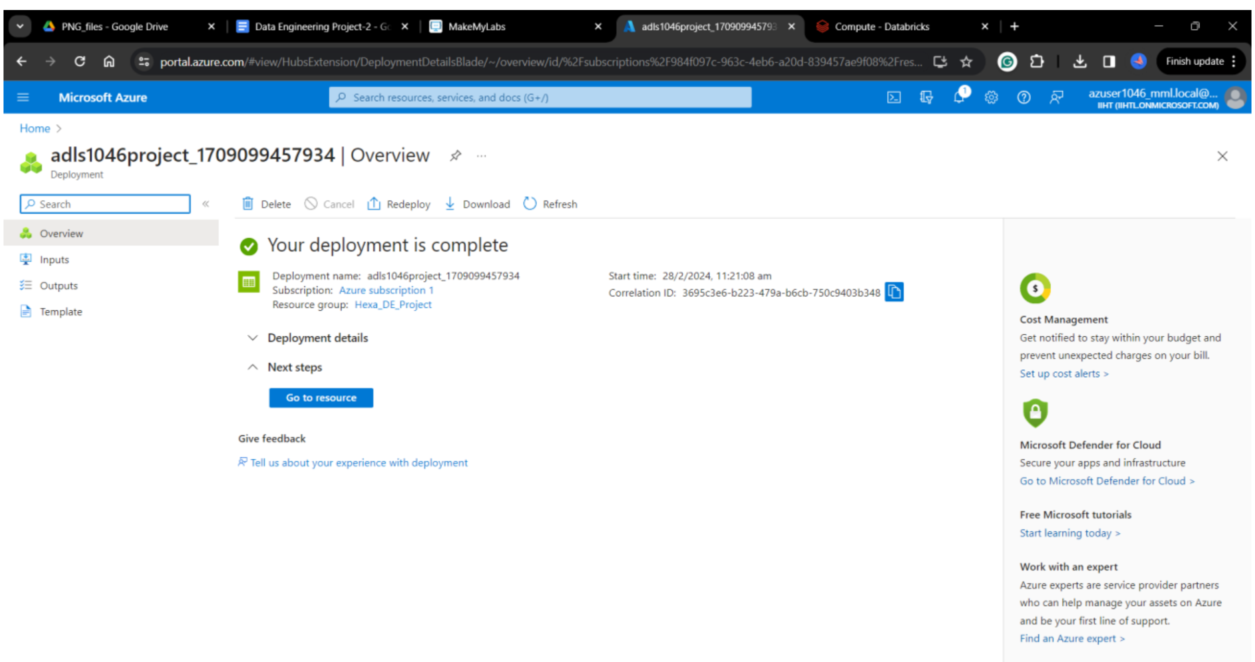


Created Notebook in Azure Databricks workspace :

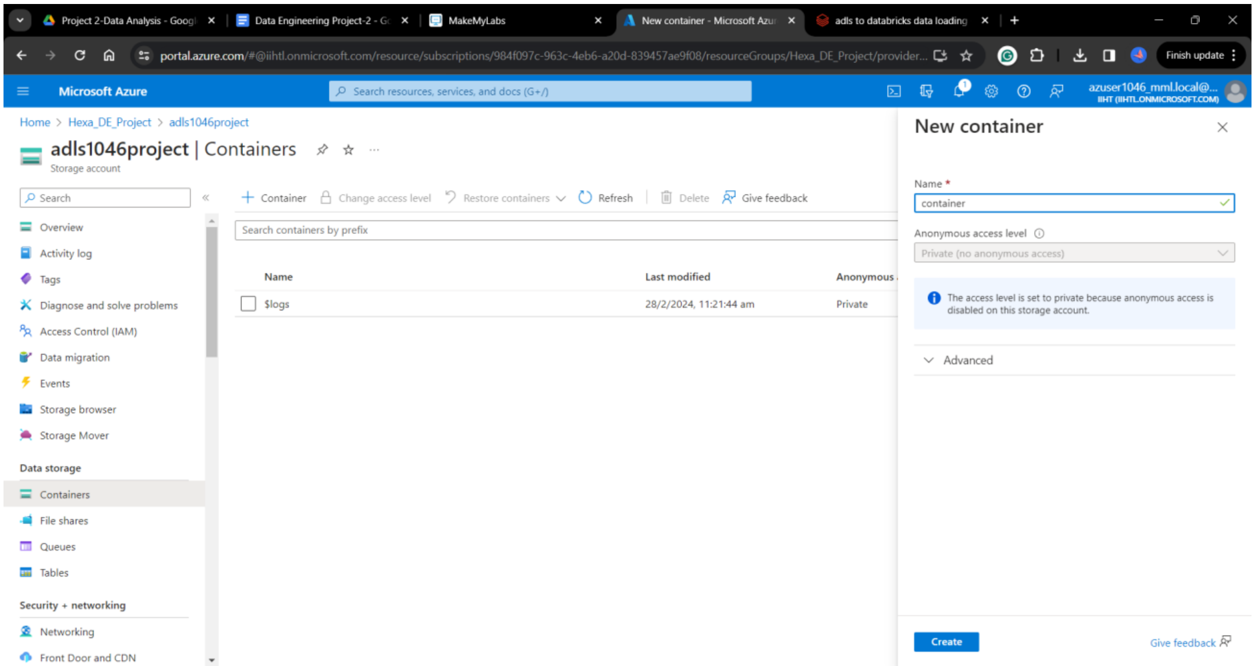


Created Azure Data Lake Storage account

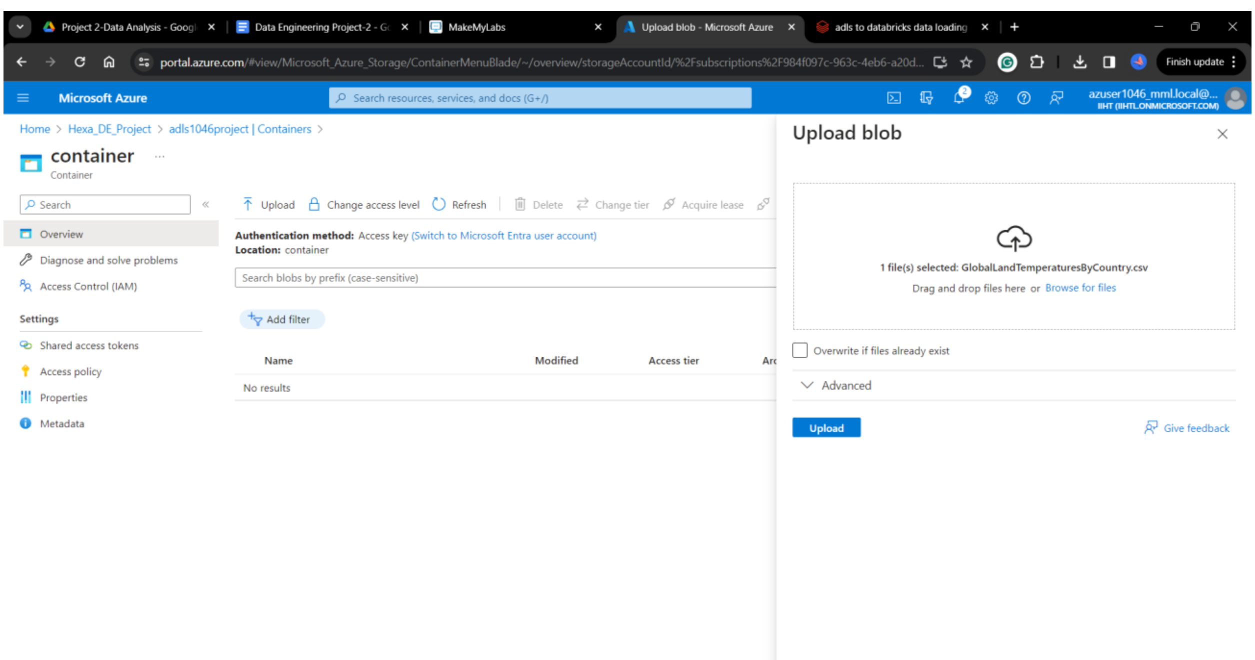




Created container in ADLS



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>@<storage-account-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.

Just now (19s) Cell 1 Python

```python
storage_account_name = "adls1046project"
container_name = "container"
file_name = "GlobalLandTemperaturesByCountry.csv"
storage_account_access_key = "KUKAhIfCYt/M/1Co79hLgWIsSzICBxQ7TJQ3s7DwtrO1gZWe/lRA0Rh43+Qmu1+PR31WfvqtRx6w+ASthC5Ofg=="
spark.conf.set("fs.azure.account.key." + storage_account_name + ".blob.core.windows.net", storage_account_access_key)
df = spark.read.format("csv").load(f"wasbs://{container_name}@{storage_account_name}.blob.core.windows.net/{file_name}", inferSchema=True,
header=True)
df.show()
```

(3) Spark Jobs

df: pyspark.sql.dataframe.DataFrame = [Date: date, AverageTemperature: double ... 2 more fields]

```
+----------+------------------+-----------------------------+-------+
|      Date|AverageTemperature|AverageTemperatureUncertainty|Country|
+----------+------------------+-----------------------------+-------+
|1743-11-01| 4.383999999999995|                        2.294|  Åland|
|1743-12-01|              NULL|                         NULL|  Åland|
|1744-01-01|              NULL|                         NULL|  Åland|
|1744-02-01|              NULL|                         NULL|  Åland|
|1744-03-01|              NULL|                         NULL|  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|
|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|
```

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.

Just now (<1s) Cell 2 Python

```python
# Identify the structure and schema of the dataset
print("Schema of the dataset:")
data.printSchema()
```

```
Schema of the dataset:
root
 |-- Date: date (nullable = true)
 |-- AverageTemperature: double (nullable = true)
 |-- AverageTemperatureUncertainty: double (nullable = true)
 |-- Country: string (nullable = true)
```

Cell 4 Python

```python
# 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
```

Just now (2s) Cell 6 Python

```python
# Example 3: Display distinct values in a particular column
print("Distinct Countries:")
spark.sql("SELECT DISTINCT Country FROM climate_data").show()
```

(2) Spark Jobs

```
Distinct Countries:
+--------------+
|       Country|
+--------------+
|      Anguilla|
|         Åland|
|   Afghanistan|
|        Africa|
|       Algeria|
|     Argentina|
|        Angola|
|  Baker Island|
|       Albania|
|       Bahamas|
|American Samoa|
|       Andorra|
|    Antarctica|
|         Aruba|
|    Azerbaijan|
|       Armenia|
|          Asia|
```

Just now (3s) Cell 7 Python

```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:
+--------------------+------------------+
|date_part(YEAR, Date)|          avg_temp|
+--------------------+------------------+
|                1743|           5.18414|
|                1744|         9.8378975|
|                1745|1.3871250000000004|
|                1746|              NULL|
|                1747|              NULL|
|                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|
```

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

```python
# 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|                        2.294|  Åland|
|1744-04-01|              1.53|                         4.68|  Åland|
|1744-05-01|             6.702|                        1.789|  Åland|
|1744-06-01|            11.609|                        1.577|  Åland|
|1744-07-01|            15.342|                         1.41|  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|
|1750-01-01|             1.091|                        1.119|  Åland|
|1750-02-01|             0.809|                        3.353|  Åland|
|1750-03-01|             0.923|                        4.716|  Åland|
|1750-04-01|             3.943|                        1.434|  Åland|
|1750-05-01|             6.265|                        1.339|  Åland|
```

Cell 3 Python

```python
# Drop rows with any missing date values
cleaned_data = cleaned_data.dropna(subset=["Date"])
cleaned_data.show()
```

```
+----------+------------------+-----------------------------+-------+
|      Date|AverageTemperature|AverageTemperatureUncertainty|Country|
+----------+------------------+-----------------------------+-------+
|1743-11-01|             4.384|                        2.294|  Åland|
|1744-04-01|              1.53|                         4.68|  Åland|
|1744-05-01|             6.702|                        1.789|  Åland|
|1744-06-01|            11.609|                        1.577|  Åland|
|1744-07-01|            15.342|                         1.41|  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|
|1750-01-01|             1.091|                        1.119|  Åland|
|1750-02-01|             0.809|                        3.353|  Åland|
|1750-03-01|             0.923|                        4.716|  Åland|
|1750-04-01|             3.943|                        1.434|  Åland|
|1750-05-01|             6.265|                        1.339|  Åland|
```

Just now (1s) Cell 4 Python

```python
# Remove rows with missing country values
from pyspark.sql.functions import col
cleaned_data = cleaned_data.filter(col("Country").isNotNull())
cleaned_data.show()
```

(1) Spark Jobs

cleaned_data: pyspark.sql.dataframe.DataFrame = [Date: date, AverageTemperature: double ... 2 more fields]

```
+----------+-------------------+-----------------------------+-------+
|      Date| AverageTemperature|AverageTemperatureUncertainty|Country|
+----------+-------------------+-----------------------------+-------+
|1743-11-01| 4.3839999999999995|                        2.294|  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|
|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| -6.574999999999998|                         1.36|  Åland|
|1745-03-01|             -4.195|                        1.213|  Åland|
|1745-04-01|-0.9660000000000002|                        1.172|  Åland|
|1750-01-01| 1.0910000000000006|                        1.119|  Åland|
|1750-02-01| 0.8090000000000002|                        3.353|  Åland|
|1750-03-01| 0.9229999999999999|                        4.716|  Åland|
|1750-04-01|              3.943|           1.4340000000000002|  Åland|
|1750-05-01| 6.2650000000000015|                        1.339|  Åland|
```

Cell 5 Python

```
# Drop irrelevant columns
cleaned_data = cleaned_data.drop("AverageTemperatureUncertainty")
cleaned_data.show()
```

```
|1744-05-01|             6.702|  Åland|
|1744-06-01|            11.609|  Åland|
|1744-07-01|            15.342|  Åland|
|1744-09-01|            11.702|  Åland|
|1744-10-01|             5.477|  Åland|
|1744-11-01|             3.407|  Åland|
|1744-12-01|            -2.181|  Åland|
|1745-01-01|             -3.85|  Åland|
|1745-02-01|            -6.575|  Åland|
|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|
|1750-04-01|             3.943|  Åland|
|1750-05-01|             6.265|  Åland|
|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|
+----------+------------------+-----------------------------+-------+
|1743-12-01|              null|                         null|  Åland|
|1744-01-01|              null|                         null|  Åland|
|1744-02-01|              null|                         null|  Åland|
|1744-03-01|              null|                         null|  Åland|
|1744-08-01|              null|                         null|  Åland|
|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|  Åland|
|1745-12-01|              null|                         null|  Åland|
|1746-01-01|              null|                         null|  Åland|
|1746-02-01|              null|                         null|  Åland|
|1746-03-01|              null|                         null|  Åland|
|1746-04-01|              null|                         null|  Åland|
```

Cell 3

```
# 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:")
    outliers.show()
else:
    print("No outliers found in the AverageTemperature column.")
```

```
Outliers found in the AverageTemperature column:
+----------+------------------+-----------------------------+-------+
|      Date|AverageTemperature|AverageTemperatureUncertainty|Country|
+----------+------------------+-----------------------------+-------+
|1823-02-01|           -31.746|                        3.438|Denmark|
|1831-02-01|            -31.28|                        4.364|Denmark|
|1832-02-01|           -31.259|                         3.57|Denmark|
|1834-01-01|           -31.572|                         3.27|Denmark|
|1835-02-01|           -31.831|                        3.245|Denmark|
|1836-02-01|           -32.625|                        3.677|Denmark|
|1838-01-01|           -31.057|                        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|
|1848-02-01|           -31.245|                        3.602|Denmark|
```

Seasonality Analysis:

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

Cell 2 Python

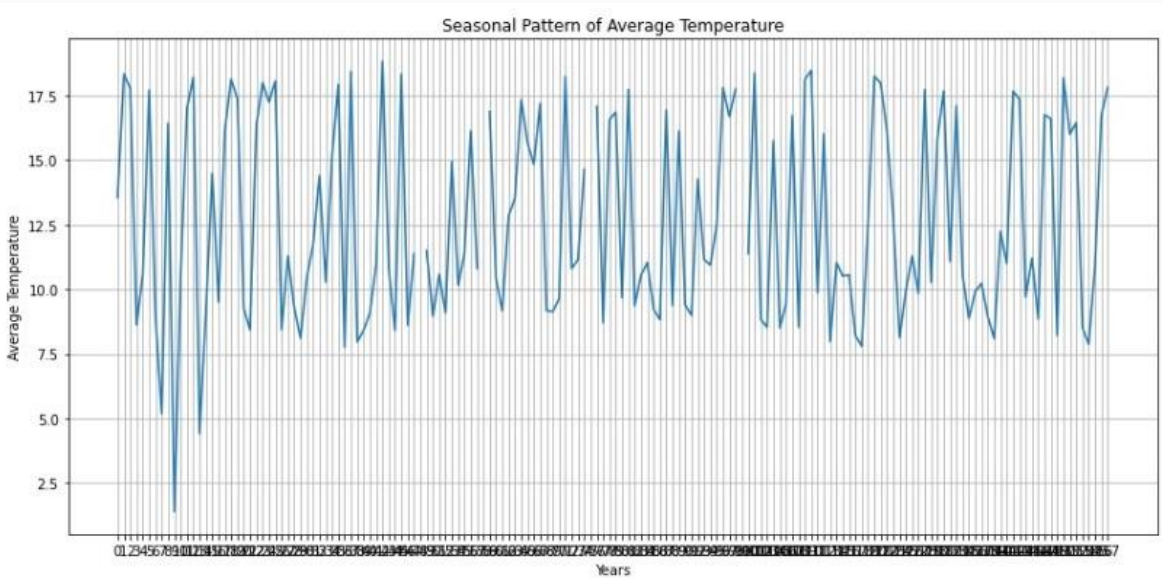
```
# Ensure 'Date' column is of type DateType
data = data.withColumn("Date", data["Date"].cast("date"))
data.show()
```

```
+----------+------------------+-----------------------------+-------+
|      Date|AverageTemperature|AverageTemperatureUncertainty|Country|
+----------+------------------+-----------------------------+-------+
|1743-11-01|             4.384|                        2.294|  Åland|
|1743-12-01|              null|                         null|  Åland|
|1744-01-01|              null|                         null|  Åland|
|1744-02-01|              null|                         null|  Åland|
|1744-03-01|              null|                         null|  Åland|
|1744-04-01|              1.53|                         4.68|  Åland|
|1744-05-01|             6.702|                        1.789|  Åland|
|1744-06-01|            11.609|                        1.577|  Åland|
|1744-07-01|            15.342|                         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|
```

Cell 6

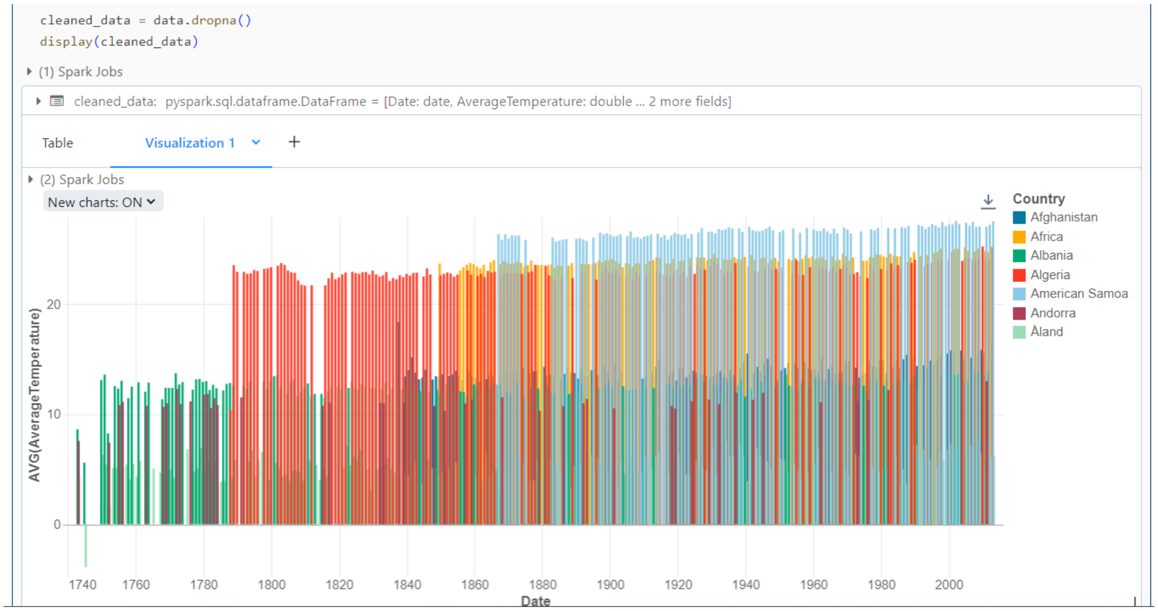
```
# Convert Spark DataFrame to Pandas DataFrame for visualization
yearly_avg_temp_pandas = yearly_avg_temp.toPandas()

# 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("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.

```
3 days ago (1s)                Cell 3                Python

print("Total Countries:")
spark.sql("SELECT Count(DISTINCT Country) as Total_Countries FROM climate_data").show()

(3) Spark Jobs

Distinct Countries:
+---------------+
|Total_Countries|
+---------------+
|            243|
+---------------+
```

▶ ✓ 3 days ago (1s) Cell 4

```
avg_temp = spark.sql("SELECT DATE_PART('YEAR', dt) as Year, AVG(AverageTemperature) AS avg_temp_by_year,Country FROM climate_data GROUP BY
DATE_PART('YEAR', dt), Country ORDER BY Country,Year")
display(avg_temp.dropna())
```

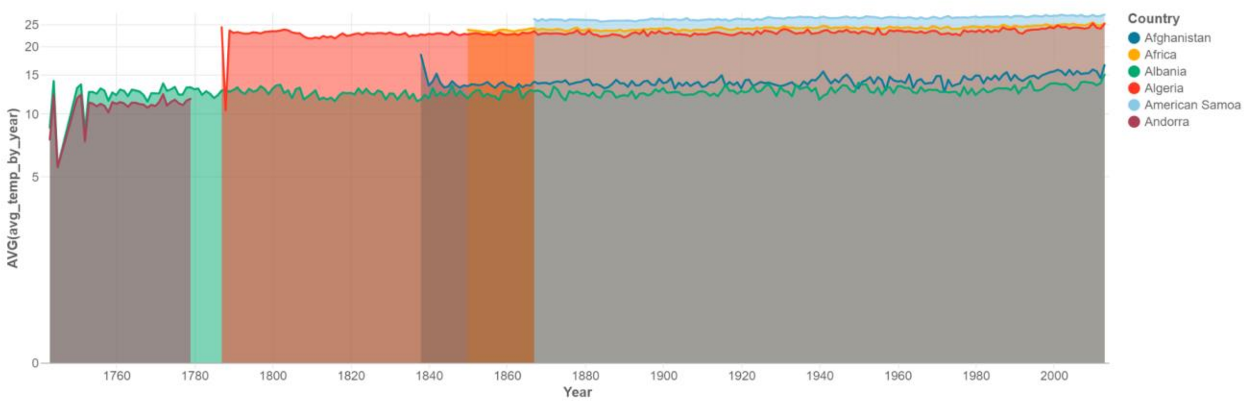
▸ (2) Spark Jobs

▸ avg_temp: pyspark.sql.dataframe.DataFrame = [Year: integer, avg_temp_by_year: double ... 1 more field]

Table | Avg_Temp_by_Year | + | New result table: OFF

	Year	avg_temp_by_year	Country
1	1838	18.379571428571428	Afghanistan
2	1840	13.413454545454545	Afghanistan
3	1841	13.9976	Afghanistan
4	1842	15.15466666666667	Afghanistan
5	1843	13.75625	Afghanistan
6	1844	13.148750000000001	Afghanistan
7	1845	13.305833333333332	Afghanistan

10,000 rows | Truncated data | 1.19 seconds runtime   Refreshed 3 days ago



Average temperature by year

▶ ✓ 3 days ago (<1s) Cell 5

```
avg_temp.dropna().createOrReplaceTempView("Avg_temp")
```

▶ ✓ 3 days ago (1s) Cell 6 Python

```
avg_data = spark.sql("SELECT Avg(avg_temp_by_year) as avg_temp_by_Country,Country from Avg_temp GROUP BY Country ORDER BY Country")
display(avg_data)
```

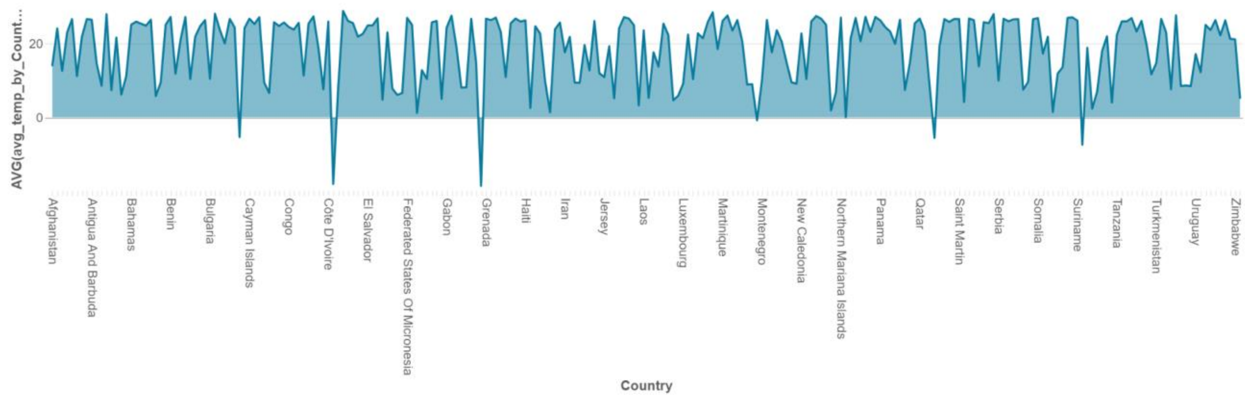
▸ (5) Spark Jobs

▸ avg_data: pyspark.sql.dataframe.DataFrame = [avg_temp_by_Country: double, Country: string]

Table | Avg_temp_by_country | + | New result table: OFF

	avg_temp_by_Country	Country
1	14.061307148423012	Afghanistan
2	24.07212044978083	Africa
3	12.577367012824885	Albania
4	22.939589924576175	Algeria
5	26.602235920614174	American Samoa
6	11.171873552945188	Andorra
7	21.818182360779808	Angola

242 rows | 1.22 seconds runtime   Refreshed 3 days ago



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.

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