Data Lake Analytics

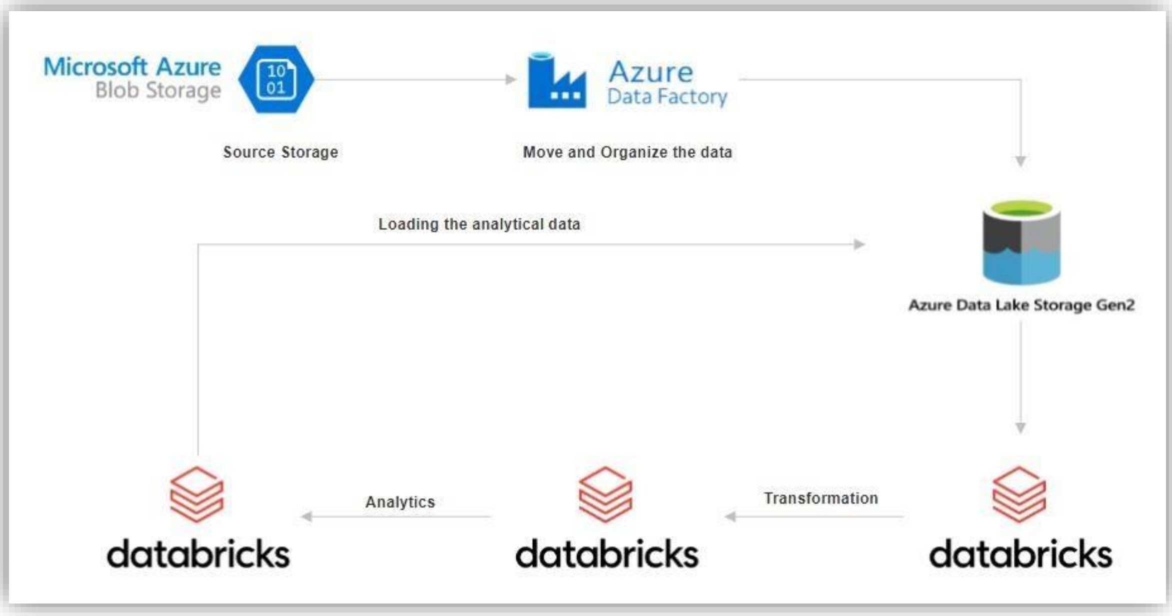
Project Overview

In today's data-driven world, the ability to efficiently process and analyse large volumes of data is crucial for businesses to gain insights and make informed decisions. This project aims to leverage the power of Azure Databricks and PySpark to perform data analytical tasks, including Extract, Transform, and Load (ETL) operations, on massive datasets.

About Project

This project revolves around the seamless orchestration of data movement, transformation, and analytics by integrating Azure Data Factory (ADF) and Azure Databricks. The workflow involves moving data from Azure Blob Storage to Azure Data Lake Storage Gen2 (ADLS Gen2) using ADF, mounting the ADLS Gen2 within Databricks notebooks for data transformations and analytics, and finally, persisting the analytical results back to ADLS Gen2.

Architectural Diagram



Key-Components/Requirements of the projects

1. <u>Azure Databricks:</u>

- Azure Databricks provides a cloud-based platform for big data analytics and machine learning. It offers a collaborative environment for data engineers, data scientists, and analysts to work together seamlessly.

- Databricks provides managed Spark clusters, eliminating the need for infrastructure management and allowing teams to focus on data processing tasks.

2. <u>PySpark</u>**:**

- PySpark is the Python API for Apache Spark, a powerful open-source framework for distributed data processing. PySpark simplifies development tasks by providing a Python interface to Spark's capabilities.

- With PySpark, developers can write concise and expressive code to perform complex data transformations, aggregations, and analytics on large datasets.

3. <u>Azure Data Factory:</u>

- Data Factory (ADF) allows users to create, schedule, and manage data pipelines that can move data between various supported data stores. ADF provides a scalable, fully managed platform for orchestrating and automating data workflows.

- It has It has many features such as data orchestration, seamless integration with Azure services, hybrid data integration, security, scalability, monitoring, metadata management, and cost management, enabling users to create, automate, and manage data pipelines for diverse data workflows.

Azure Resources Used for this Project

1. Azure Blob Storage

- This is where the raw data is stored. Azure Blob Storage integral to Microsoft Azure's storage service, is a cloud-based solution tailored for managing vast amounts of unstructured data, encompassing both text and binary data. Termed "Blob" for "Binary Large Object," it signifies a compilation of binary data treated as a singular entity within a database.

2. Azure Data Factory

- Here, we use azure data factory for moving and organizing the data from blob storage to azure data lake gen 2. It provides essential tools to create pipelines for the movement of data.
- It also provides Cloud-based service for orchestrating, automating data workflows, enabling seamless movement, transformation, and integration across diverse sources.

3. Azure Data Lake Storage Gen2

- This is where the raw data is loaded by ADF and then the analytical data is also moved and organized here. Azure Data Lake Storage Gen2 provides a scalable and secure platform for storing large volumes of data. It enables us to manage, access, and analyze data effectively.

4. Azure Databricks

- Azure Databricks are used to develop essential notebooks that contains the pyspark code which perform transformation and analytical operations on the data based on the business requirement.

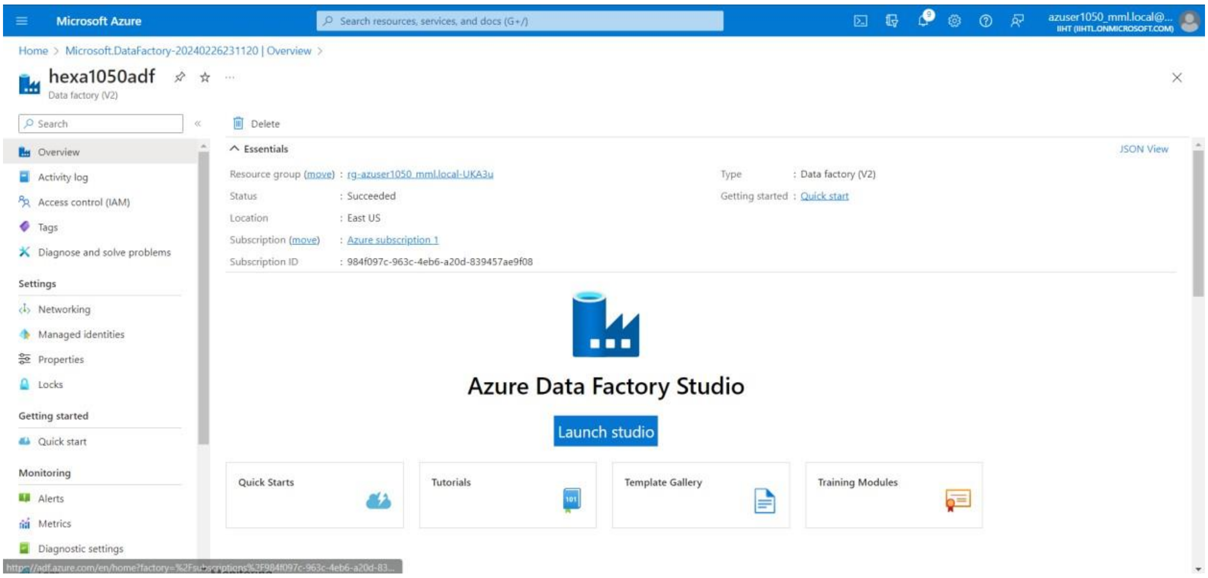
5. Databricks Cluster

- An Azure Databricks cluster process the data depending on the user instructions in the Azure Notebook. It serves as a computational resource facilitating the processing of extensive data and execution of analytics workloads through the Apache Spark platform within the Microsoft Azure cloud.
- Azure Databricks are used to develop essential notebooks that contains the pyspark code which perform transformation and analytical operations on the data based on the business requirement.

How It works

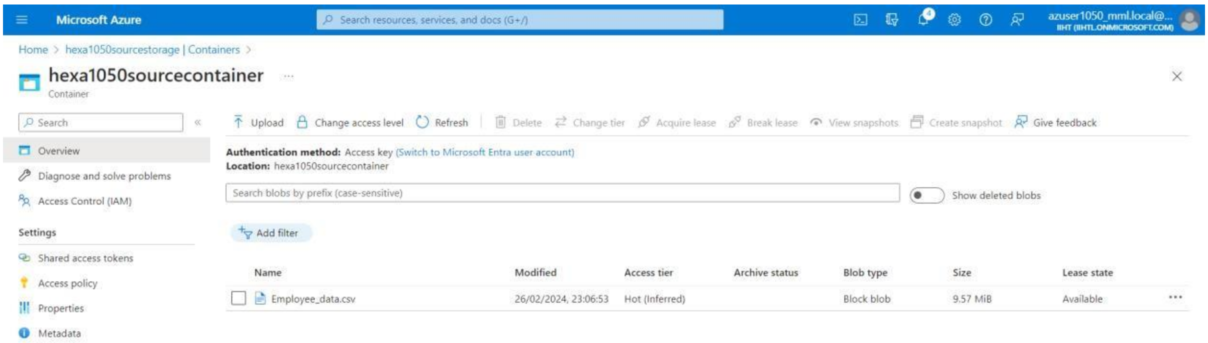
1. Setting Up Azure Databricks Factory:

- Sign in to the Azure portal and create an Azure Data Factory. Configure the settings, including pricing tier, region, and workspace name.

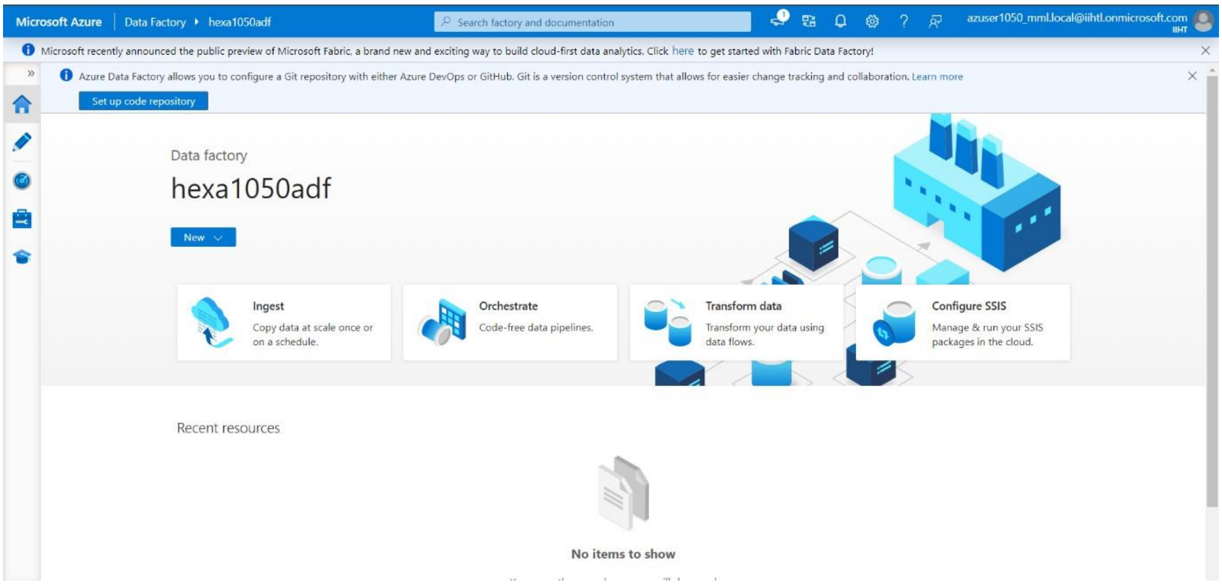


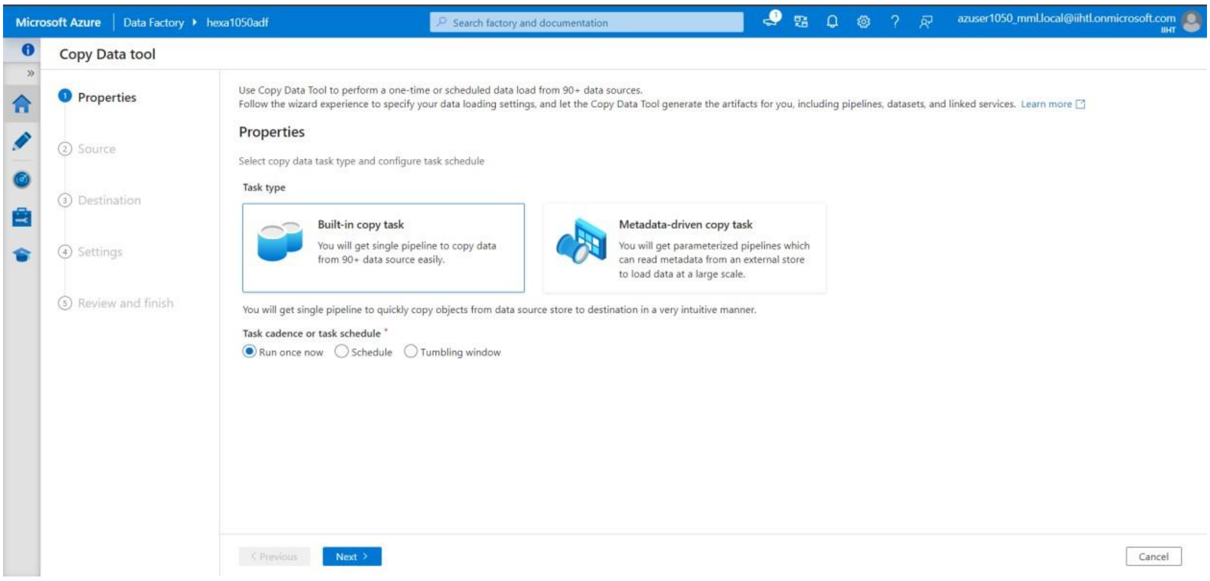
2. Movement of data:

- Raw data is stored in source storage (Azure Blob Storage)

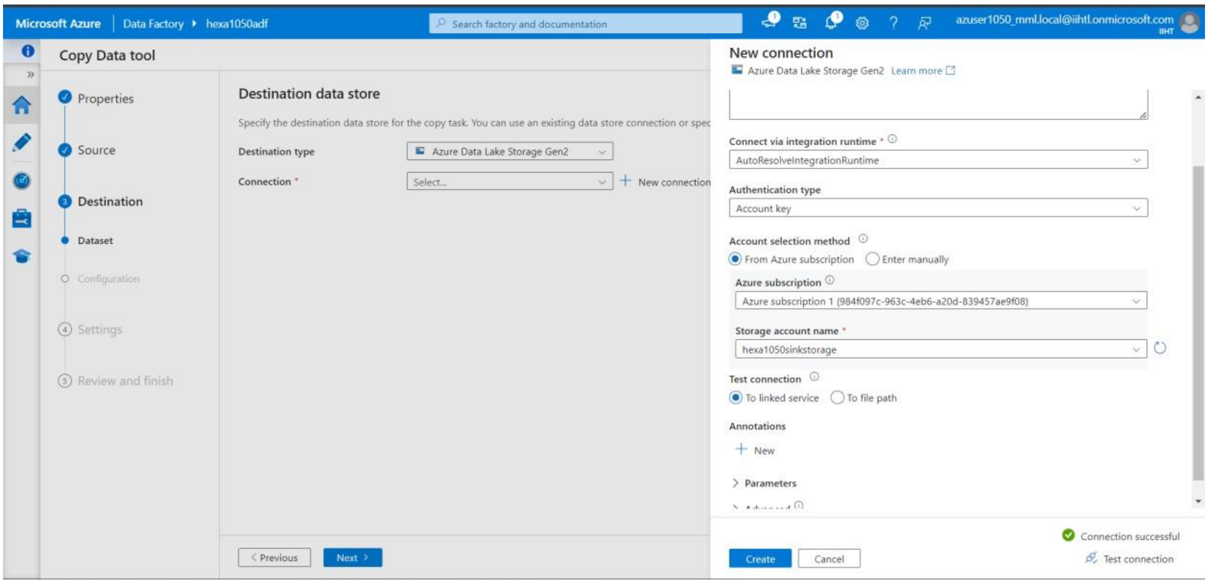


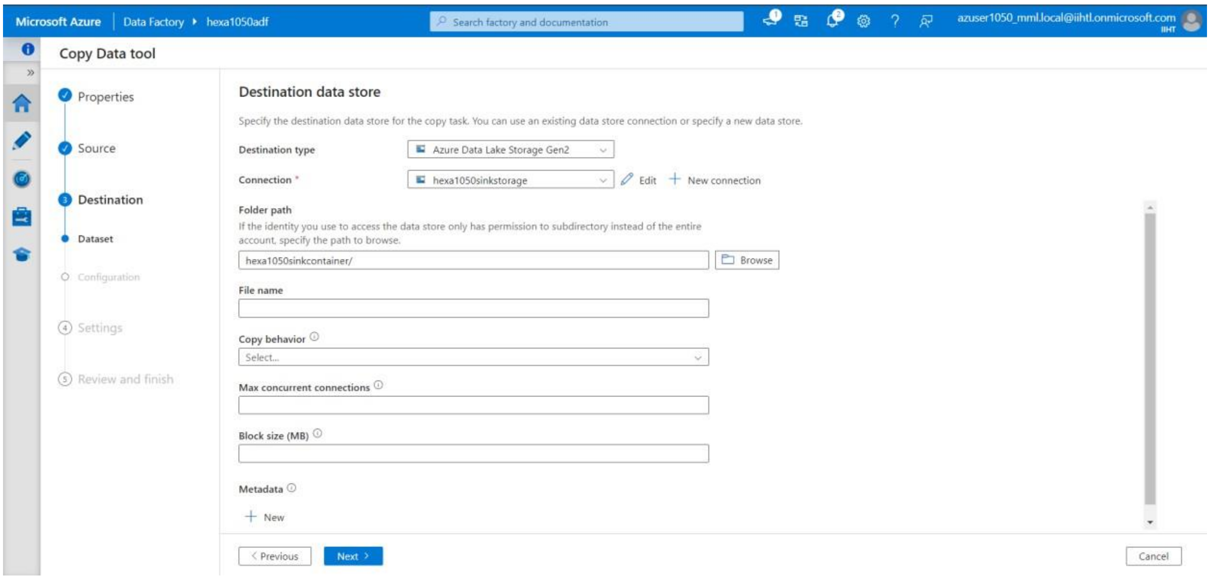
- Ingest the data from the source storage(blob storage) to sink storage(Azure data lake gen 2) by creating a pipeline in the azure data factory with the following properties.



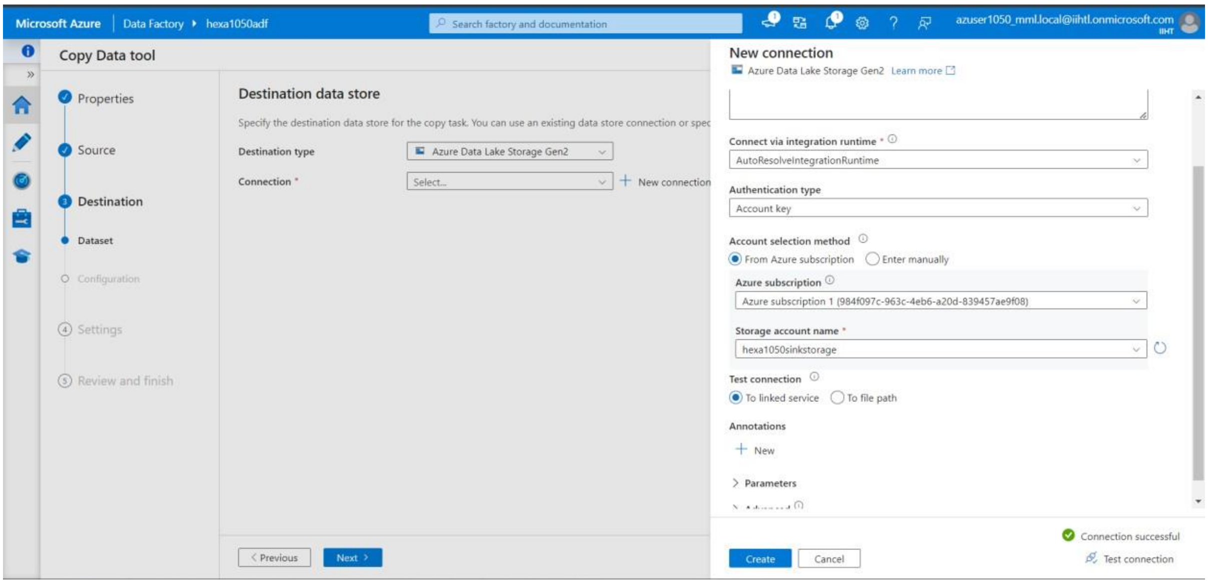


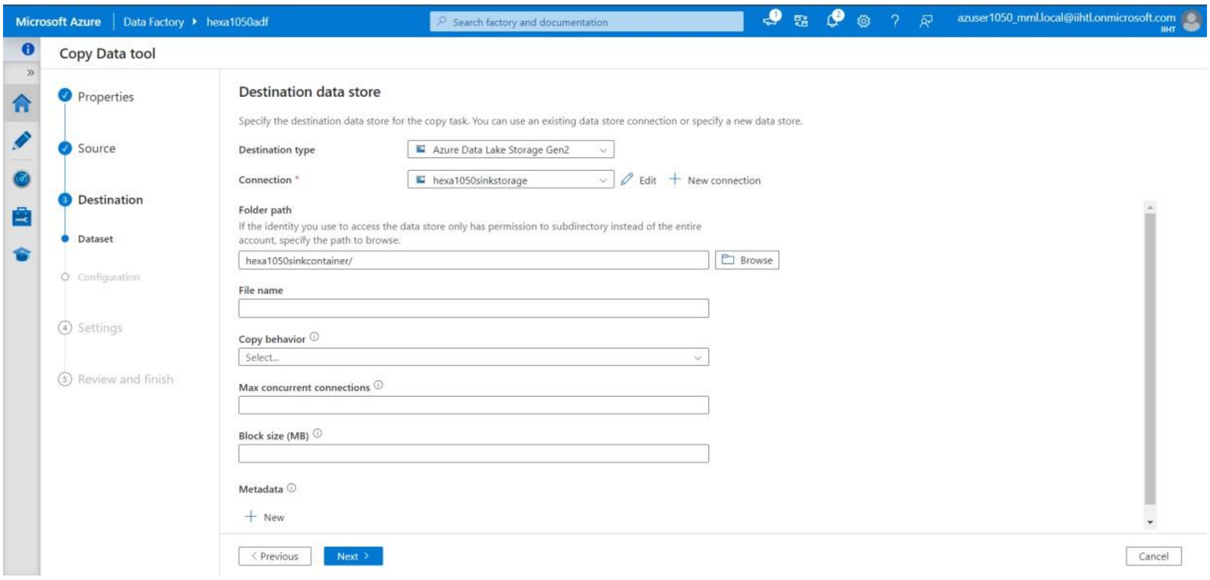
- Create the connection with the source storage and mention the right file path of the raw data.



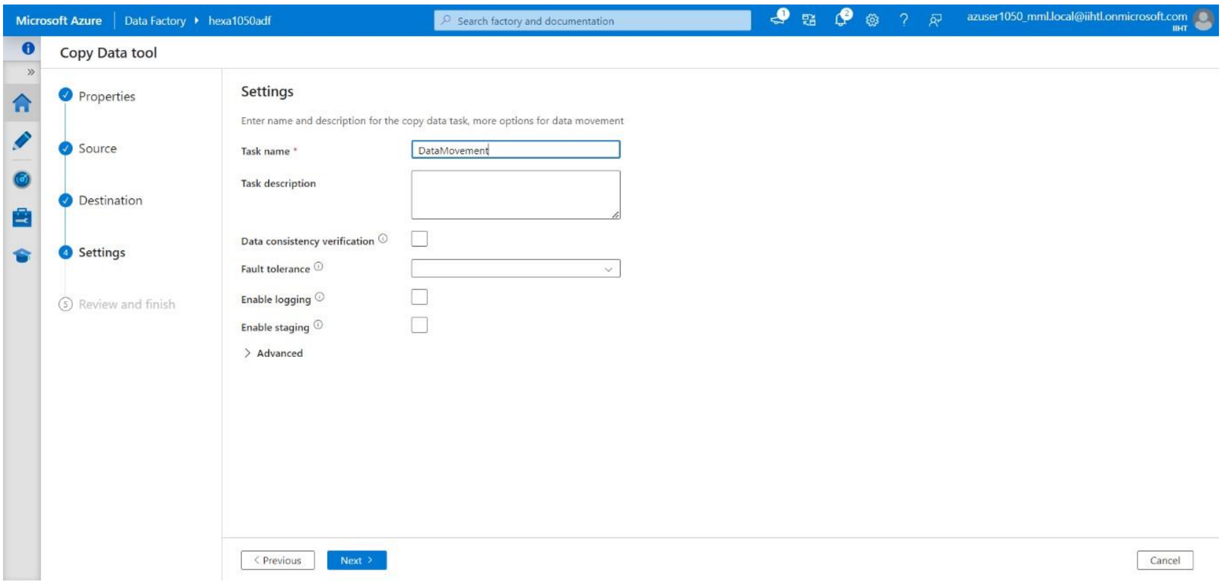


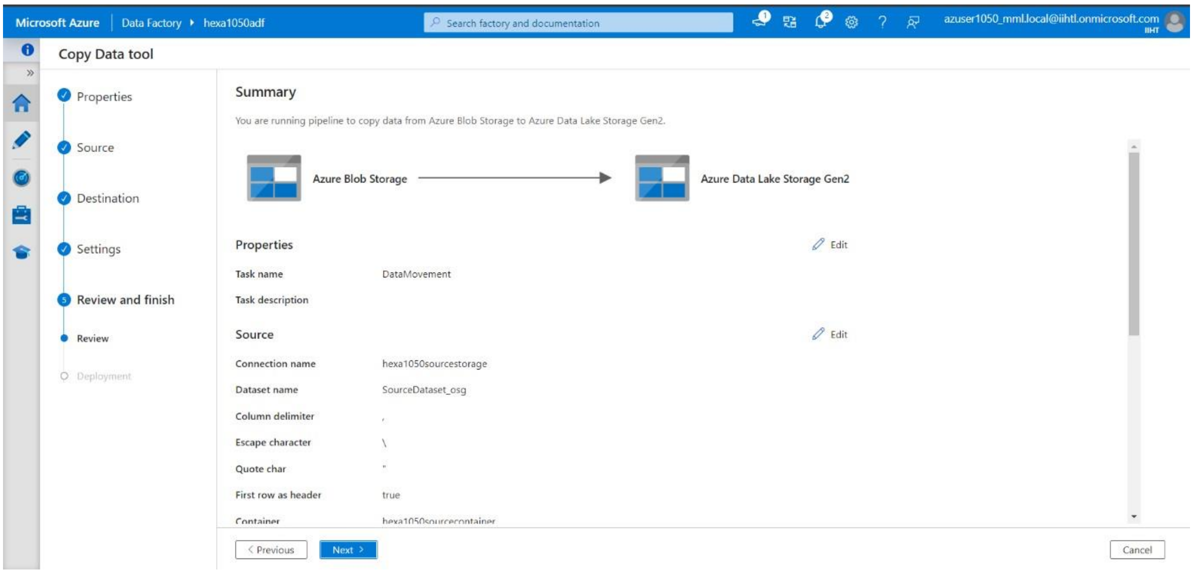
- Create connection with sink storage and mention the path or container destination where the data has to be copy from source storage.

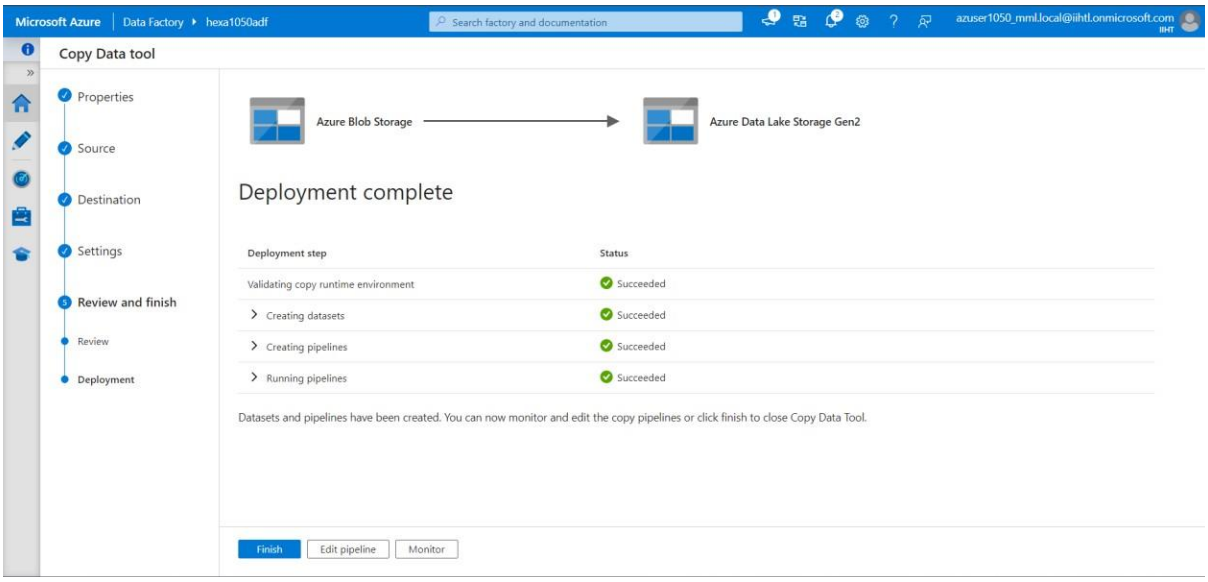




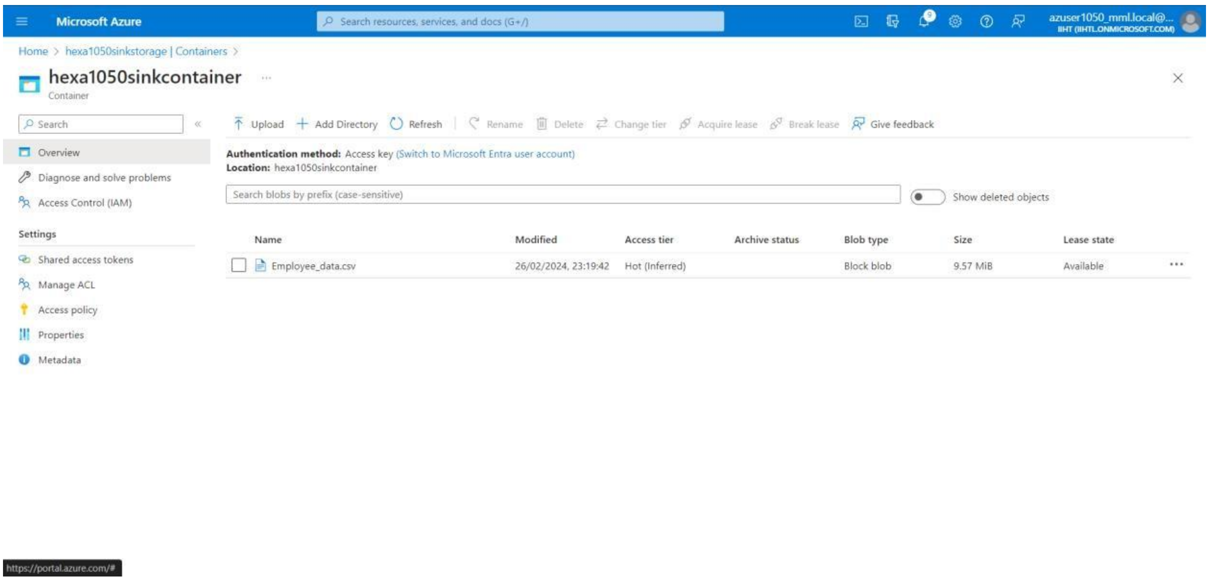
- Give pipeline details, review and start the copy process







- After the process gets finish we can see that the data in the source storage (blob storage) has copied to sink storage (Azure data lake)

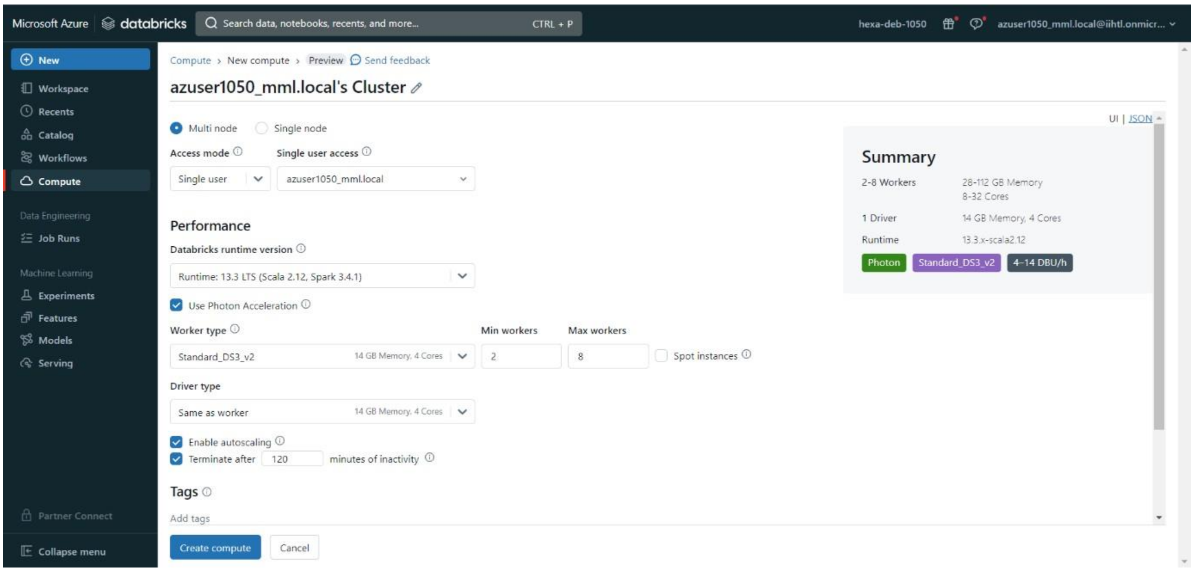


3. Developing Pyspark Notebook

- Create a new PySpark notebook within the Databricks workspace. Begin writing PySpark code to perform ETL operations, data transformations, and data analytical tasks

4. Create cluster and connecting it to notebook

- The cluster is created with autoscaling is enabled which automatically adjust cluster size to accommodate changes in workload demand, allowing for seamless scalability without manual intervention.



5. Importing Necessary libraries and Creating Spark Session

- Use SparkSession.builder to configure and create a SparkSession. specify the application name using .appName() and configure any additional Spark options using .config(). Finally, call .getOrCreate() to either create a new SparkSession

39 minutes ago (<1s) Cell 1

```
# Import the necessary modules
from pyspark.sql import SparkSession
from pyspark.sql.functions import trim, when, col, regexp_replace,sum, count, avg, min, max
from pyspark.sql.window import Window
```

46 minutes ago (<1s) Cell 2

```
# Create a SparkSession
spark = SparkSession.builder.appName("DataLakeAnalytics").getOrCreate()
```

6. Extracting Data from Source storage

- Connecting data source (Azure Blob Storage) by mounting it to the Databricks File System (DBFS) to simplify data access
- It helps to retrieve raw data for processing and analysis within the PySpark environment

43 minutes ago (11s) Cell 3

```
# 1) Extracting the data from Data lake
# Mounting the Data Lake with Azure databricks

dbutils.fs.mount(
    source = "wasbs://hexa1050sinkcontainer@hexa1050sinkstorage.blob.core.windows.net",
    mount_point="/mnt/blobStorage",
    extra_configs={"fs.azure.account.key.hexa1050sinkstorage.blob.core.windows.net":"FDVopi9Fy8FwvYxDFNCLDK1Yf/EoFaV0esH9nYNYXjATF7J/6kG
    +FKP6yvNsuGu/ptbbg1Nm1/MF+AStSwcMFw=="}
)
```

```
True
```

43 minutes ago (< 1s) Cell 4

```
# Listing the File information to get file path

dbutils.fs.ls('/mnt/blobStorage')
```

```
[FileInfo(path='dbfs:/mnt/blobStorage/Employee_data.csv', name='Employee_data.csv', size=10034689, modificationTime=1708969782000)]
```

43 minutes ago (12s) Cell 5

```
# Reading the data of Data lake and converting it to spark RDD

path = "dbfs:/mnt/blobStorage/Employee_data.csv"
RDD = spark.read.csv(path, header=True,inferSchema=True)
```

(2) Spark Jobs

RDD: pyspark.sql.dataframe.DataFrame = [EEID: integer, Full Name: string ... 10 more fields]

42 minutes ago (1s) Cell 6

```
RDD.display()
```

(1) Spark Jobs

Table + New result table: OFF

	EEID	Full Name	Job Title	Department	Gender	Ethnicity	Age
1	98278	Samaira Raj	Human Resources Manager	Human Resources	Male	White	46
2	19840	Lavanya Hayer	Data Analyst	Research and Development	Female	null	55
3	22487	Shayak Raval	Financial Analyst	Finance	Female	White	29
4	17160	Inaaya Bala	Software Engineer	Research and Development	Male	null	65
5	10385	Aarav Garde	Data Analyst	Research and Development	Male	White	56
6	28297	Romil Keer	Customer Service Representative	Customer Service	null	null	19
7	21123	Pranav Chadha	Human Resources Manager	Human Resources	Male	Hispanic	46

10,000 rows | Truncated data | 1.15 seconds runtime

Refreshed 42 minutes ago

7. Transforming the raw data

- Utilize PySpark DataFrame transformations and functions to cleanse, transform, and prepare the data for analysis.
- Implement business logic and data processing steps to transform raw dataset up to mark for data analysis purpose.

Transformations done:-

- Removing the Duplicate records

Just now (4s) Cell 7

```
# Removing the Duplicate data

print(RDD.count())
RDD=RDD.distinct()
print(RDD.count())
```

(5) Spark Jobs

RDD: pyspark.sql.dataframe.DataFrame = [EEID: integer, Full Name: string ... 10 more fields]

```
100000
99996
```

- Handling anonymous data

Just now (3s) Cell 8

```
# Removing the anonymous data

print(RDD.count())
RDD = RDD.na.drop("any",subset=["EEID"])
print(RDD.count())
```

(6) Spark Jobs

RDD: pyspark.sql.dataframe.DataFrame = [EEID: integer, Full Name: string ... 10 more fields]

```
99996
99984
```

- Removing Extra spaces and filling the null data with proper messages

42 minutes ago (<1s) Cell 9

```
# Removing Leading and Trailing spaces from the data

RDD = RDD.withColumn("Full Name", trim("Full Name"))
RDD = RDD.withColumn("Job Title", trim("Job Title"))
RDD = RDD.withColumn("Department", trim("Department"))
RDD = RDD.withColumn("Gender", trim("Gender"))
RDD = RDD.withColumn("Ethnicity", trim("Ethnicity"))
RDD = RDD.withColumn("Country", trim("Country"))
```

RDD: pyspark.sql.dataframe.DataFrame = [EEID: integer, Full Name: string ... 10 more fields]

42 minutes ago (<1s) Cell 10

```
# Filling the null values with proper message

RDD = RDD.na.fill(value="Not Known",subset=["Full Name"])
RDD = RDD.na.fill(value="Not Known",subset=["Job Title"])
RDD = RDD.na.fill(value="Not Known",subset=["Department"])
RDD = RDD.na.fill(value="Prefer Not to say",subset=["Gender"])
RDD = RDD.na.fill(value="Not Known",subset=["Ethnicity"])
RDD = RDD.na.fill(value="Not Known",subset=["Country"])
RDD = RDD.na.fill(value=0,subset=["Bonus %"])
RDD = RDD.withColumn('Hire Date',when(col('Hire Date').isNull(),('No data provided')).otherwise(col('Hire Date')))
RDD = RDD.withColumn('Exit Date',when(col('Exit Date').isNull(),('Currently Working')).otherwise(col('Exit Date')))
```

RDD: pyspark.sql.dataframe.DataFrame = [EEID: integer, Full Name: string ... 10 more fields]

- Handling the numerical columns and renaming USA to US to make dataset consistent

41 minutes ago (<1s) Cell 11

```
# Filling the numerical column's null values with proper average values

window_spec = Window.partitionBy()
RDD = RDD.withColumn('Age',when(col('Age').isNull(),avg(col('Age')).over(window_spec)).otherwise(col('Age')))

average_salaries = RDD.groupBy("Country", "Department").avg("Annual Salary")
RDD = RDD.join(average_salaries, ["Country", "Department"], "left").withColumnRenamed("avg(Annual Salary)", "Average Salary")
RDD = RDD.withColumn('Annual Salary', when(col('Annual Salary').isNull(), col('Average Salary'))
                    .otherwise(col('Annual Salary'))).drop("Average Salary")
```

average_salaries: pyspark.sql.dataframe.DataFrame = [Country: string, Department: string ... 1 more field]
RDD: pyspark.sql.dataframe.DataFrame = [Country: string, Department: string ... 10 more fields]

40 minutes ago (1s) Cell 12

```
# Renaming USA as US

RDD=RDD.withColumn('Country',when(RDD.Country=='USA',regexp_replace(RDD.Country,'USA','US')).otherwise(RDD.Country))
print(RDD.select("Country").distinct().collect())
```

(3) Spark Jobs

RDD: pyspark.sql.dataframe.DataFrame = [Country: string, Department: string ... 10 more fields]

```
[Row(Country='US'), Row(Country='UK'), Row(Country='Canada'), Row(Country='Australia')]
```

8. Data Analytics

- Data analytics is the collection, transformation, and organization of data in order to draw conclusions, make predictions, and drive informed decision making.

Analytics Performed

- Grouping the data based on country and department (count_df)

40 minutes ago (1s) Cell 14

```
# Employee count based on country and department

count_df = RDD.groupBy("Country", "Department").agg(
    count("EEID").alias("Total_employees"),
    sum(when(RDD["Gender"] == "Male", 1).otherwise(0)).alias("Male"),
    sum(when(RDD["Gender"] == "Female", 1).otherwise(0)).alias("Female"),
    sum(when(RDD["Gender"].isin("Male", "Female"), 0).otherwise(1)).alias("Prefer_not_to_say"),
    sum(when(RDD["Ethnicity"] == "Black", 1).otherwise(0)).alias("Black"),
    sum(when(RDD["Ethnicity"] == "White", 1).otherwise(0)).alias("White"),
    sum(when(RDD["Ethnicity"] == "Asian", 1).otherwise(0)).alias("Asian"),
    sum(when(RDD["Ethnicity"].isin("Black", "White", "Asian"), 0).otherwise(1)).alias("other_race"),
    sum(when(RDD["Age"] < 40, 1).otherwise(0)).alias("age_below_40"),
    sum(when(RDD["Age"] > 40, 1).otherwise(0)).alias("age_above_40")
).orderBy("Country", "Department")
count_df.display()
```

▸ (3) Spark Jobs

▸ count_df: pyspark.sql.dataframe.DataFrame = [Country: string, Department: string ... 10 more fields]

Table | New result table: OFF

	Country	Department	Total_employees	Male	Female	Prefer_not_to_say	Black	White	Asi
1	Australia	Customer Service	2387	792	791	804	426	511	45
2	Australia	Engineering	2499	878	850	771	471	507	49
3	Australia	Finance	2418	804	836	778	468	499	50
4	Australia	Human Resources	2541	861	851	829	481	528	49
5	Australia	IT	2484	817	864	803	520	500	46
6	Australia	Legal	2480	866	826	788	473	488	49
7	Australia	Marketing	2552	851	905	796	464	530	48

40 rows | 1.39 seconds runtime Refreshed 40 minutes ago

- Sorting the data by considering only working employees (working_employees_df)

▸ ✓ 33 minutes ago (2s) Cell 16

```python
# Fetching records of working employees

working_employees_df = RDD.filter(col("Exit Date") == "Currently Working")
working_employees_df = working_employees_df.drop("Exit Date")

working_employees_df.display()
```

▸ (5) Spark Jobs

▸ working_employees_df: pyspark.sql.dataframe.DataFrame = [Country: string, Department: string ... 9 more fields]

Table + New result table: OFF

	Country	Department	EEID	Full Name	Job Title	Gender	Ethnicity
1	Australia	Sales	45876	Jayant Devan	Sales Representative	Female	Black
2	Canada	IT	69030	Abram Mani	Software Engineer	Male	Hispanic
3	UK	Customer Service	39341	Kismat Keer	Customer Service Representative	Female	Asian
4	Canada	Engineering	86184	Stuvan Dutt	Software Engineer	Female	Black
5	US	Operations	78333	Ritvik Lanka	Customer Service Representative	Prefer Not to say	Not Known
6	UK	Engineering	75249	Arnav Mand	Project Manager	Male	Not Known
7	Australia	Marketing	47025	Samar Chowdhury	Marketing Specialist	Male	Not Known

10,000 rows | Truncated data | 1.58 seconds runtime Refreshed 33 minutes ago

- Sorting the data by considering only those employees who left the company (non_working_employees_df)

▸ ✓ 27 minutes ago (1s) Cell 18

```python
# Fetching records of non-working employees
non_working_employees_df = RDD.filter(col("Exit Date") != "Currently Working")

non_working_employees_df.display()
```

▸ (5) Spark Jobs

▸ non_working_employees_df: pyspark.sql.dataframe.DataFrame = [Country: string, Department: string ... 10 more fields]

Table + New result table: OFF

	Country	Department	EEID	Full Name	Job Title	Gender	Ethnicity
1	Canada	Marketing	46400	Riya Grover	Data Analyst	Female	Asian
2	UK	Engineering	61085	Ira Wable	Project Manager	Female	Asian
3	US	IT	92676	Parinaaz Karpe	Software Engineer	Female	Asian
4	Canada	Research and Development	38396	Taran Butala	Software Engineer	Female	White
5	Canada	Sales	22677	Samiha Vasa	Sales Representative	Female	Not Know
6	US	Customer Service	94951	Kabir Dey	Customer Service Representative	Prefer Not to say	Not Know
7	UK	Sales	30669	Tarini Brahmbhatt	Sales Representative	Male	White

10,000 rows | Truncated data | 1.36 seconds runtime Refreshed 27 minutes ago

- Making the statistical data of Annual salary and Bonus percentage in each country based on department (salaries_df)

12:01 AM (1s) Cell 20

```python
# Country and department wise salaries
salaries_df = RDD.groupBy("Country", "Department").agg(
    avg(RDD["Annual Salary"]).alias("Average_Salary"),
    min(RDD["Annual Salary"]).alias("Min_Salary"),
    max(RDD["Annual Salary"]).alias("Max_Salary"),
    avg(RDD["Bonus %"]).alias("Average_Bonus"),
    min(RDD["Bonus %"]).alias("Min_Bonus"),
    max(RDD["Bonus %"]).alias("Max_Bonus")
)

salaries_df.display()
```

(5) Spark Jobs

salaries_df: pyspark.sql.dataframe.DataFrame = [Country: string, Department: string ... 6 more fields]

Table + New result table: OFF

	Country	Department	Average_Salary	Min_Salary	Max_Salary	Average_Bonus	Min_Bonus	Max_Bonus
1	US	Marketing	79991.36395141699	40086.07	119939.58	4.877534412955467	0	10
2	US	Operations	79234.15896837942	40033.76	119974.62	5.003936758893281	0	10
3	US	Sales	79589.61770023788	40010.3	119984.9	5.02660190325139	0.01	10
4	UK	Legal	81114.15970008212	40056.76	119986.21	5.086400986031222	0	10
5	UK	IT	80053.21730563555	40055.65	119992.87	4.991616618675444	0	9.99
6	Canada	Engineering	79417.14880513234	40023.06	119980.68	5.043031275060145	0.01	10
7	US	IT	80151.04563575322	40030.79	119971.89	5.014553084347462	0	10

40 rows | 1.15 seconds runtime

Refreshed 20 minutes ago

9. Loading and organizing the analytical data to the azure data lake

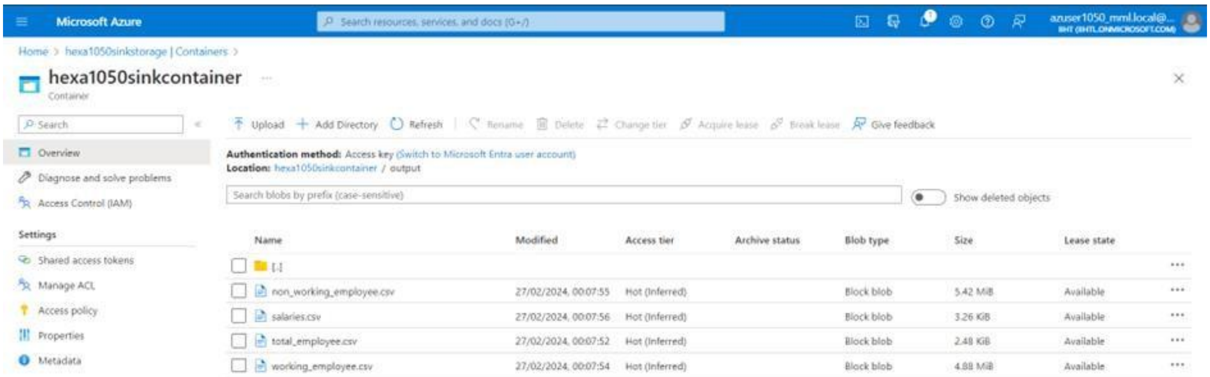
- By using the mount point load and organize the data into the data lake
- Use the appropriate folder path in the container for better organizing of analytical data and also use the appropriate names for the files

12:07 AM (6s) Cell 22

```
# writing the analytical data to the data lake

count_df = count_df.toPandas()
count_df.to_csv("/dbfs/mnt/blobStorage/output/total_employee.csv", index = False)

working_employees_df = working_employees_df.toPandas()
working_employees_df.to_csv("/dbfs/mnt/blobStorage/output/working_employee.csv", index = False)

non_working_employees_df = non_working_employees_df.toPandas()
non_working_employees_df.to_csv("/dbfs/mnt/blobStorage/output/non_working_employee.csv", index = False)

salaries_df = salaries_df.toPandas()
salaries_df.to_csv("/dbfs/mnt/blobStorage/output/salaries.csv", index = False)
```

(18) Spark Jobs

- We can see the analytical data files has been generated and organized in the appropriate output path in the azure data lake



10. Unmounting the azure data lake

12:10 AM (11s)

```
# Unmounting the Data lake

dbutils.fs.unmount("/mnt/blobStorage")
```

```
/mnt/blobStorage has been unmounted.
True
```

Analytical data stored in Sink storage

1. Grouped data based on country and department

	A	B	C	D	E	F	G	H	I	J	K	L
1	Country	Departme	Total_emp	Male	Female	Prefer_not	Black	White	Asian	other_race	age_below	age_above
2	Australia	Customer	2387	792	791	804	426	511	454	996	980	1356
3	Australia	Engineerin	2499	878	850	771	471	507	498	1023	1019	1427
4	Australia	Finance	2418	804	836	778	468	499	500	951	1008	1377
5	Australia	Human Re	2541	861	851	829	481	528	497	1035	1044	1436
6	Australia	IT	2484	817	864	803	520	500	466	998	990	1439
7	Australia	Legal	2480	866	826	788	473	488	499	1020	1007	1435
8	Australia	Marketing	2552	851	905	796	464	530	488	1070	1051	1451
9	Australia	Operation	2462	761	860	841	495	490	500	977	1015	1406
10	Australia	Research a	2488	820	833	835	477	492	511	1008	1030	1406
11	Australia	Sales	2610	899	888	823	519	487	520	1084	1107	1456
12	Canada	Customer	2552	856	843	853	509	510	504	1029	1082	1418
13	Canada	Engineerin	2494	846	812	836	498	504	532	960	1050	1398
14	Canada	Finance	2557	850	826	881	500	509	519	1029	1075	1439
15	Canada	Human Re	2509	843	862	804	490	503	510	1006	1037	1414
16	Canada	IT	2566	845	874	847	507	473	552	1034	1120	1395
17	Canada	Legal	2597	858	904	835	526	537	513	1021	1085	1478
18	Canada	Marketing	2512	826	869	817	511	484	557	960	1023	1440
19	Canada	Operation	2469	822	851	796	505	509	497	958	1071	1359
20	Canada	Research a	2579	794	875	910	537	541	518	983	1078	1454
21	Canada	Sales	2572	830	840	902	515	507	542	1008	1083	1443
22	UK	Customer	2497	859	842	796	492	493	502	1010	1006	1437
23	UK	Engineerin	2445	815	849	781	471	496	479	999	1030	1361
24	UK	Finance	2508	877	817	814	484	502	526	996	1041	1411
25	UK	Human Re	2535	818	847	870	506	505	510	1014	1042	1462
26	UK	IT	2431	807	806	818	493	435	504	999	993	1395
27	UK	Legal	2434	802	847	785	486	499	478	971	1041	1352

total_employee

2. Currently Working employees data

	A	B	C	D	E	F	G	H	I	J	K
1	Country	Departmei	EEID	Full Name	Job Title	Gender	Ethnicity	Age	Hire Date	Annual Sal	Bonus %
2	Australia	Sales	45876	Jayant Dev	Sales Repr	Female	Black	24	########	57866.08	4.18
3	Canada	IT	69030	Abram Ma	Software E	Male	Hispanic	44	########	48409.17	8.63
4	UK	Customer	39341	Kismat Kee	Customer	Female	Asian	40	########	110918.4	4.94
5	Canada	Engineerin	86184	Stuvan Dut	Software E	Female	Black	69	########	41516.36	5.26
6	US	Operation:	78333	Ritvik Lank	Customer	Prefer Not	Not Knowi	43	########	90268.73	8.09
7	UK	Engineerin	75249	Arnav Mar	Project Ma	Male	Not Knowi	67	########	111875.2	8.71
8	Australia	Marketing	47025	Samar Chc	Marketing	Male	Not Knowi	60	########	78734.94	9.19
9	Australia	Sales	12513	Ranbir Kib	Sales Repr	Prefer Not	Hispanic	30	########	53666.9	2.53
10	US	Operation:	18133	Anahi War	Customer	Prefer Not	Hispanic	40	########	68894.55	1.68
11	UK	Marketing	15031	Kartik Sara	Marketing	Prefer Not	Black	44	########	53166.22	9.55
12	Australia	Customer	54645	Tiya Gade	Customer	Prefer Not	Asian	40	########	43707.88	9.65
13	UK	Engineerin	31550	Siya Zacha	Data Analy	Female	Hispanic	62	########	84515.76	8.47
14	US	Operation:	65812	Piya Kuma	Operation:	Male	Black	24	########	62979.41	8.08
15	Canada	Sales	28607	Ivan Sarma	Sales Repr	Female	Hispanic	29	########	84558.07	2.3
16	Australia	Research a	42518	Yuvraj Gai	Software E	Male	Not Knowi	29	########	102204.7	9.71
17	UK	Human Re	31890	Ritvik Joha	Human Re	Male	Black	59	########	46455.5	9.76
18	US	Research a	40954	Seher Man	Data Analy	Female	Asian	28	########	83268.53	5.85
19	UK	Operation:	74888	Hunar Hor	Operation:	Prefer Not	Hispanic	31	########	65121.48	2.38
20	Canada	Finance	83192	Eva Sekhoi	Financial A	Female	White	39	########	81679.57	2.97
21	Australia	Operation:	20880	Priyansh B	Customer	Prefer Not	Hispanic	20	########	119436.5	4.13
22	Australia	Legal	43955	Kabir Bhat	Lawyer	Male	Black	22	########	46516.3	5.03
23	Canada	Human Re	69413	Rohan Das	Human Re	Female	Asian	37	########	65418.6	4.48
24	Canada	Marketing	58853	Shamik She	Marketing	Female	Asian	68	########	76597.36	0.01
25	UK	Sales	71315	Jivin Char	Sales Repr	Male	Hispanic	18	########	49709.96	3.72
26	UK	Engineerin	46232	Samiha Ma	Software E	Male	Black	58	########	93753.84	5.67
27	US	Operation:	78741	Bhamini Re	Customer	Prefer Not	Asian	40	########	76528.79	0.4

working_employee

3. Non-Working employees data

	A	B	C	D	E	F	G	H	I	J	K	L
1	Country	Departmer	EEID	Full Name	Job Title	Gender	Ethnicity	Age	Hire Date	Annual Sal	Bonus %	Exit Date
2	Canada	Marketing	46400	Riya Grove	Data Analy	Female	Asian	25	########	75499.29	3.83	########
3	UK	Engineerin	61085	Ira Wable	Project Ma	Female	Asian	18	########	110198.8	2.09	########
4	US	IT	92676	Parinaaz K	Software E	Female	Asian	44	########	41026.82	5.31	########
5	Canada	Research a	38396	Taran Buta	Software E	Female	White	68	########	105485.7	8.69	########
6	Canada	Sales	22677	Samiha Va	Sales Repr	Female	Not Known	70	########	104495.8	5.83	########
7	US	Customer	94951	Kabir Dey	Customer	Prefer Not	Not Known	40	########	49184.54	8.37	########
8	UK	Sales	30669	Tarini Brah	Sales Repr	Male	White	64	########	64526.56	9.09	########
9	UK	Sales	44291	Aradhya Cl	Sales Repr	Prefer Not	Not Known	29	########	71443.58	1.7	########
10	Canada	Research a	20783	Rasha Aur	Data Analy	Female	White	40	########	118531.4	2.32	########
11	Canada	Legal	38418	Ryan Sura	Lawyer	Prefer Not	Not Known	18	########	46707.41	4.8	########
12	US	Operation:	45764	Adira Sahn	Customer	Male	Not Known	26	########	78001.94	2.36	########
13	Australia	IT	86860	Navya She	Data Analy	Male	Hispanic	49	########	71266.08	4.21	########
14	US	Legal	45864	Farhan Bal	Lawyer	Male	White	22	########	116168	5.35	########
15	UK	Finance	31359	Anvi Ahluw	Accountan	Prefer Not	Asian	25	########	101659	9.25	########
16	UK	Operation:	27549	Emir Tailor	Operation:	Prefer Not	Black	64	########	68657.94	5.17	########
17	Australia	Human Re	80691	Indrans La	Human Re	Male	White	66	########	103161.8	0.66	########
18	Canada	Operation:	88868	Biju Sani	Operation:	Male	Hispanic	70	########	59208.66	7.47	########
19	UK	Finance	46756	Dhruv Cha	Financial A	Female	Not Known	32	########	82979.87	1.98	########
20	UK	Customer	19905	Miraan Ka	Customer	Female	Hispanic	50	########	82354.25	1.93	########
21	UK	Finance	81298	Jhanvi Edw	Accountan	Male	Hispanic	70	########	101083.8	0.45	########
22	Canada	Legal	98088	Ehsaan Lol	Lawyer	Male	Hispanic	18	########	86847.62	3.76	########
23	US	IT	99341	Navya Red	Data Analy	Female	Black	18	########	76176.64	7.18	########
24	Australia	Operation:	83584	Parinaaz K	Customer	Female	Hispanic	28	########	73740.33	4.41	########
25	Australia	Marketing	41923	Fateh Yogi	Marketing	Prefer Not	White	60	########	77113.86	0.31	########
26	Canada	Research a	94118	Tushar Bal	Data Analy	Male	Not Known	62	########	41376.64	2.14	########
27	UK	Human Re	45580	Prisha Sara	Human Re	Male	Hispanic	42	########	62170.93	9.64	########

non_working_employee

4. <u>Statistical data of Annual salary and Bonus percentage in each country based on department</u>

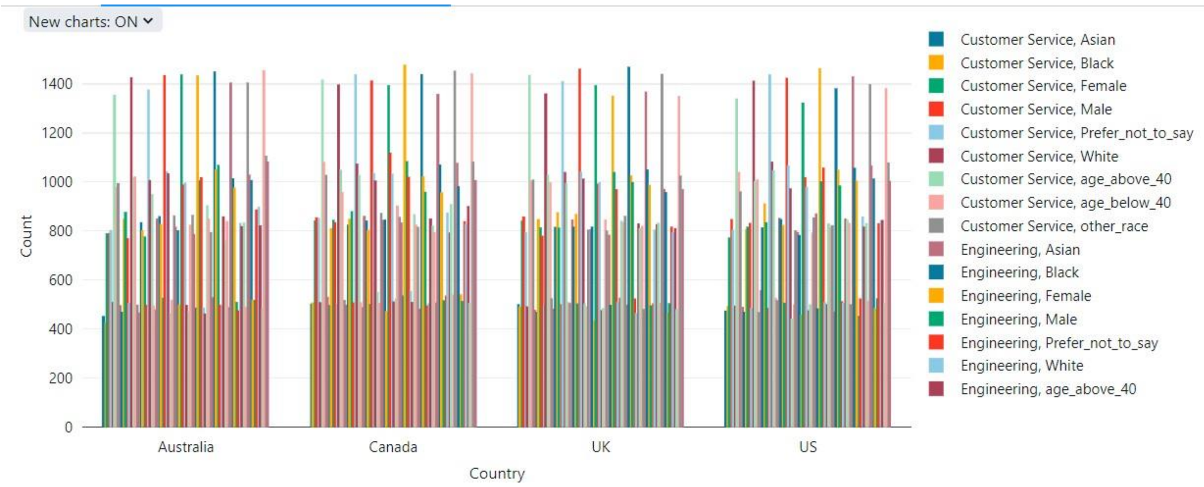
	A	B	C	D	E	F	G	H
1	Country	Departmei	Average_S	Min_Salary	Max_Salar	Average_B	Min_Bonu	Max_Bonus
2	US	Marketing	79991.36	40086.07	119939.6	4.877534	0	10
3	US	Operation:	79234.16	40033.76	119974.6	5.003937	0	10
4	US	Sales	79589.62	40010.3	119984.9	5.026602	0.01	10
5	UK	Legal	81114.16	40056.76	119986.2	5.086401	0	10
6	UK	IT	80053.22	40055.65	119992.9	4.991617	0	9.99
7	Canada	Engineerin	79417.15	40023.06	119980.7	5.043031	0.01	10
8	US	IT	80151.05	40030.79	119971.9	5.014553	0	10
9	UK	Finance	79955.71	40025.58	119986.3	4.954274	0.01	10
10	US	Human Re	80656.29	40009.99	119998.6	4.992073	0.01	10
11	Canada	Research a	79711.05	40025.73	119994.2	5.02575	0	10
12	Australia	Marketing	80797.67	40031.52	119990.5	4.978946	0	10
13	Australia	Research a	79737.21	40077.18	119988.6	4.945374	0	10
14	Canada	Marketing	80176.44	40001.64	119995.3	5.083193	0	10
15	US	Legal	79972.82	40009.73	119962.3	5.040385	0	10
16	US	Research a	80220.45	40012.07	119950.1	5.053296	0	10
17	UK	Human Re	79940.91	40028.45	119989.3	4.944592	0	10
18	Australia	IT	80731.98	40006.42	119993.5	5.055221	0	10
19	Australia	Sales	80398.31	40023.93	119983	4.992402	0	10
20	US	Customer	79833.69	40021.43	119992.7	5.050272	0.01	9.99
21	Canada	IT	79490.89	40003.06	119973.7	4.946629	0	9.99
22	Australia	Legal	79828.55	40022.34	119971.5	4.955532	0	9.99
23	Canada	Human Re	79651.17	40000.48	119994.2	4.955126	0	9.98
24	Canada	Operation:	79540.82	40083.11	119928.6	5.04373	0.01	10
25	Australia	Operation:	80474.08	40011.58	119999.6	5.065658	0.01	9.99
26	UK	Engineerin	80462.75	40048.92	119980	4.979211	0	10
27	Canada	Finance	79834.22	40003.3	119915.1	4.933844	0	10

salaries

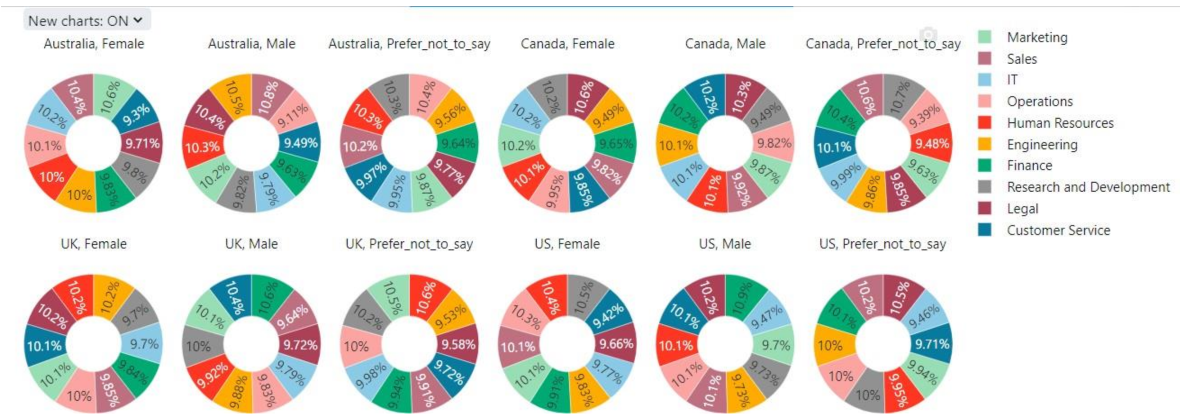
Data visualization on analytical data (truncated data is used)

1. Count_df:

- Bar graph of count_df with country at x-axis and count at y-axis

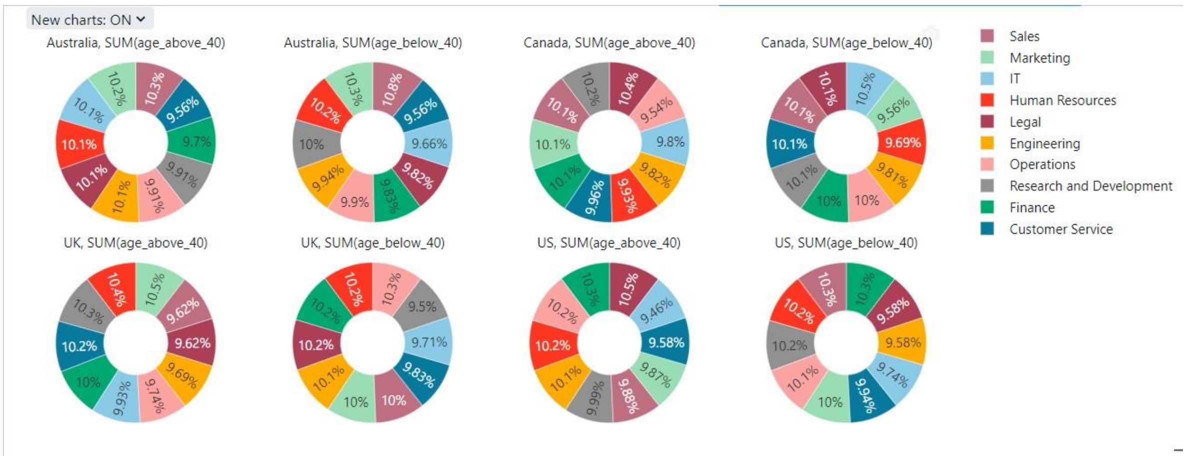


- Pie chart of Departmental Statistical data based on gender



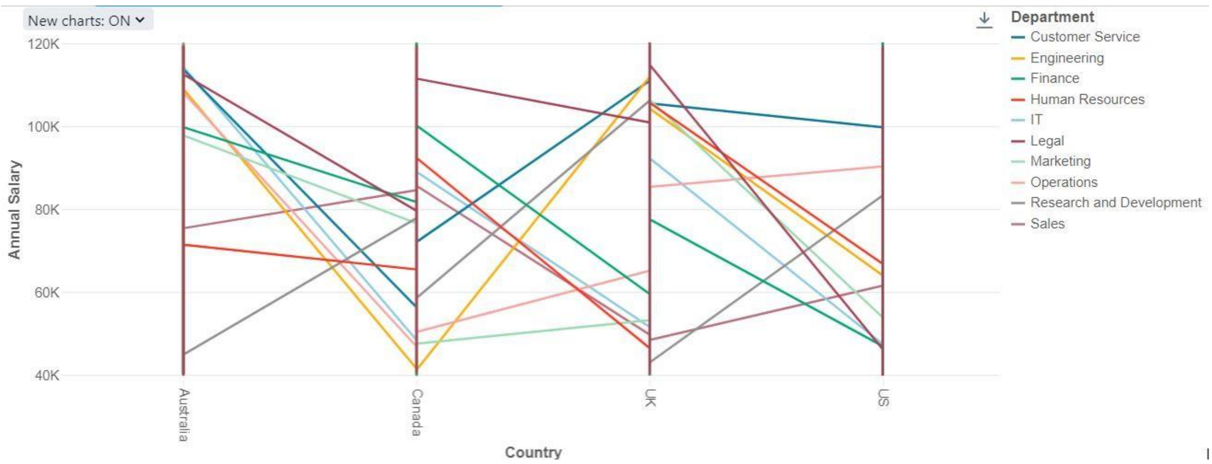
- Pie chart of Departmental Statistical data based on ethnicity

- Pie chart of Departmental Statistical data based on age

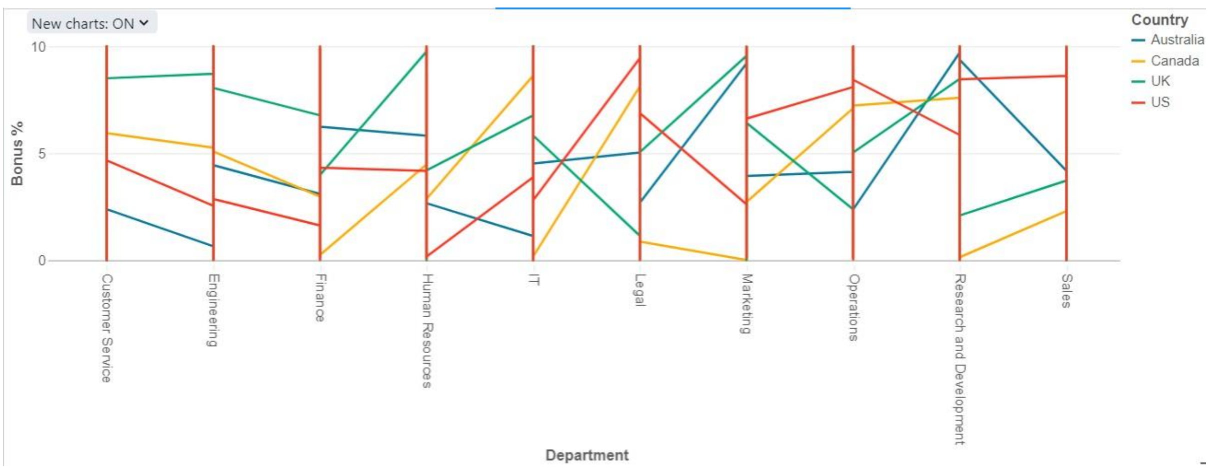


2. working_employee_df

- Representation of Departmental wise Annual Salary for each country

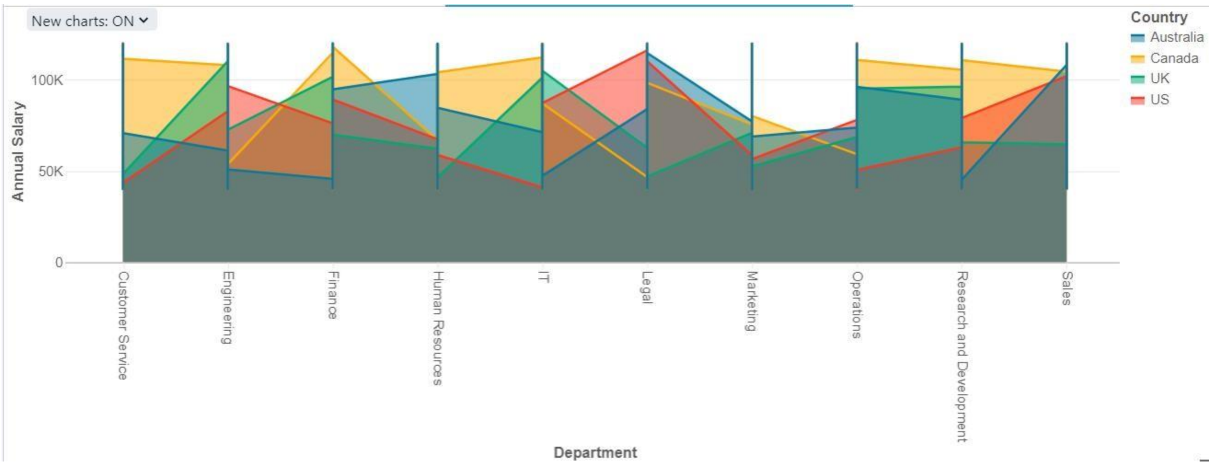


- Representation of Departmental wise Bonus percentage for each country

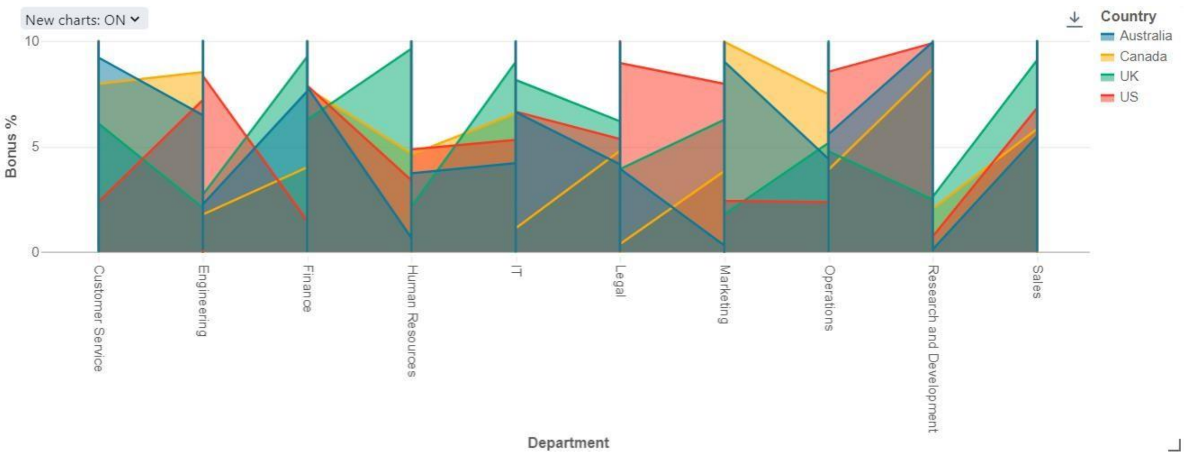


3. non_working_employee_df

- Representation of Departmental wise Annual Salary for each country

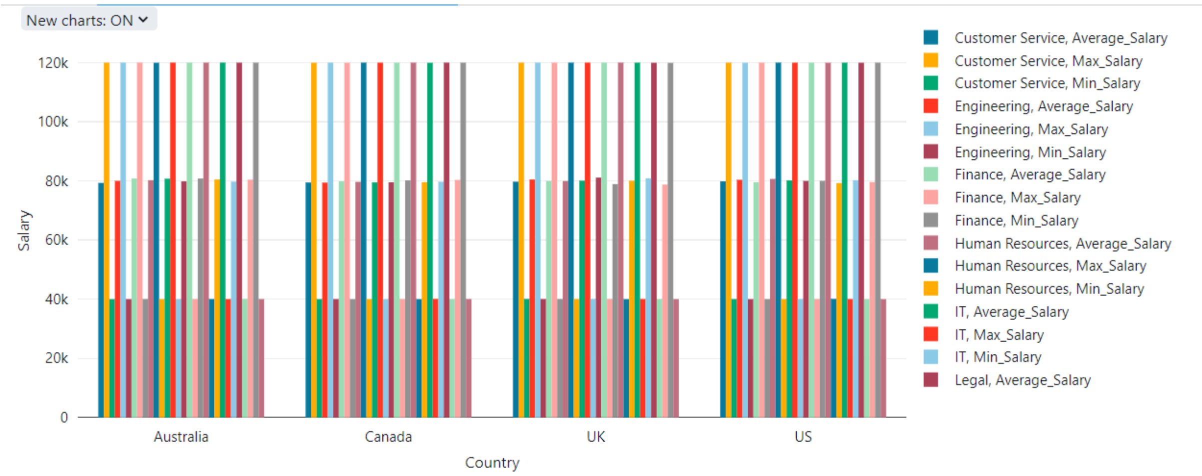


- Representation of Departmental wise Bonus percentage for each country

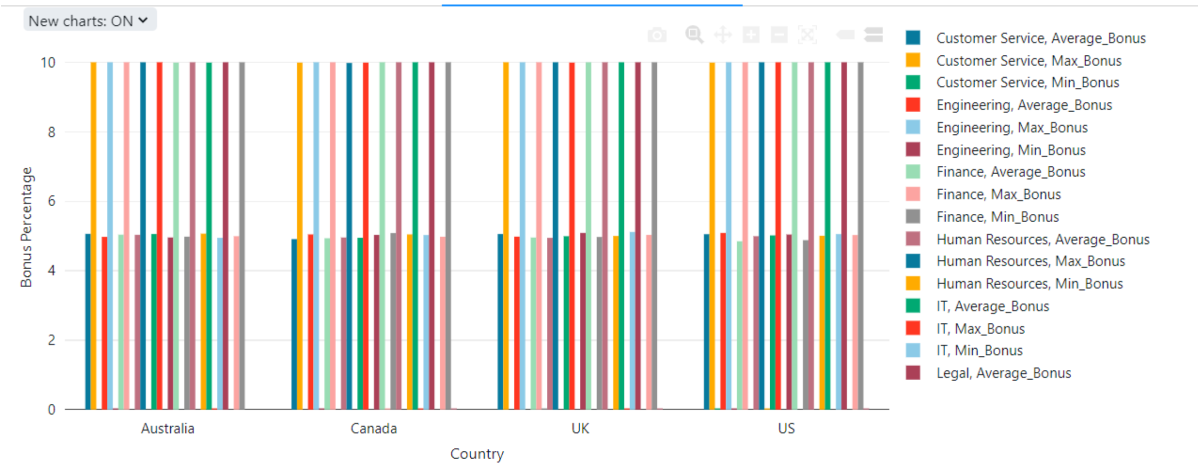


4. salaries_df

- Representation of Department wise Annual Salary for each country



- Representation of Department wise Bonus percentage for each country



Conclusion

In conclusion, this project showcases a cohesive data processing pipeline leveraging Azure Data Factory and Azure Databricks, seamlessly moving data from Azure Blob Storage to Azure Data Lake Storage Gen2 then processing the data by performing transformation and analytical operations through azure databricks, then loading and organizing the data back to Azure data lake storage.