Azure Databricks Assignment

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Practice of Loading Data:-

1. Load and Display Loan Table Data

data =spark.read.table("samples.nyctaxi.trips")

datatable

=spark.read.table("hive_metastore.default.loan")

datatable.display()

(1) Spark Jobs

datatable: pyspark.sql.dataframe.DataFrame = [Customer_ID: string, Age: long ... 13 more fields]

Table

	Customer_ID	Age	Gender	Occupation	Marital Status	Family Size	Income
1	IB14001	30	MALE	BANK MANAGER	SINGLE	4	50000
2	IB14008	44	MALE	PROFESSOR	MARRIED	6	51000
3	IB14012	30	FEMALE	DENTIST	SINGLE	3	58450
4	IB14018	29	MALE	TEACHER	MARRIED	5	45767
5	IB14022	34	MALE	POLICE	SINGLE	4	43521
6	IB14024	55	FEMALE	NURSE	MARRIED	6	34999
7	IB14025	39	FEMALE	TEACHER	MARRIED	6	46619
8	IB14027	51	MALE	SYSTEM MANAGER	MARRIED	3	49999
9	IB14029	24	FEMALE	TEACHER	SINGLE	3	45008
10	IB14031	37	FEMALE	SOFTWARE ENGINEER	MARRIED	5	55999
11	IB14032	24	MALE	DATA ANALYST	SINGLE	4	60111
12	IB14034	32	MALE	PRODUCT ENGINEER	MARRIED	6	null

---

2. Create RDDs and Load Delta Tables

to create rdds and dataframe from pyspark

import SparkContext from pyspark.sql import

SparkSession # Initialize SparkContext and

```
SparkSession sc = SparkContext.getOrCreate()

spark = SparkSession.builder.appName('pyspark

first program').getOrCreate()

data = spark.read.format("delta").load("dbfs:/databricks-datasets/nyctaxi-

withzipcodes/subsampled") datatable =

spark.read.format("delta").load("dbfs:/user/hive/warehouse/loan")

data.display() datatable.display()
```

(3) Spark Jobs

data: pyspark.sql.dataframe.DataFrame = [tpep_pickup_datetime: timestamp, tpep_dropoff_datetime: timestamp ... 4 more fields]

datatable: pyspark.sql.dataframe.DataFrame = [Customer_ID: string, Age: long ... 13 more fields]

Table

	tpep_pickup_datetime	tpep_dropoff_datetime	1.2 trip_distance	1.2 fare_amount	pickup_zip	dropof
1	2016-02-16T22:40:45.000+00:00	2016-02-16T22:59:25.000+00:00	5.35	18.5	10003	
2	2016-02-05T16:06:44.000+00:00	2016-02-05T16:26:03.000+00:00	6.5	21.5	10282	
3	2016-02-08T07:39:25.000+00:00	2016-02-08T07:44:14.000+00:00	0.9	5.5	10119	
4	2016-02-29T22:25:33.000+00:00	2016-02-29T22:38:09.000+00:00	3.5	13.5	10001	
5	2016-02-03T17:21:02.000+00:00	2016-02-03T17:23:24.000+00:00	0.3	3.5	10028	
6	2016-02-10T00:47:44.000+00:00	2016-02-10T00:53:04.000+00:00	0	5	10038	
7	2016-02-19T03:24:25.000+00:00	2016-02-19T03:44:56.000+00:00	6.57	21.5	10001	
8	2016-02-02T14:05:23.000+00:00	2016-02-02T14:23:07.000+00:00	1.08	11.5	10103	
9	2016-02-20T15:42:20.000+00:00	2016-02-20T15:50:40.000+00:00	0.8	7	10003	

Table

	Customer_ID	Age	Gender	Occupation	Marital Status	Family Size	Income
1	IB14001	30	MALE	BANK MANAGER	SINGLE	4	50000
2	IB14008	44	MALE	PROFESSOR	MARRIED	6	51000
3	IB14012	30	FEMALE	DENTIST	SINGLE	3	58450
4	IB14018	29	MALE	TEACHER	MARRIED	5	45767
5	IB14022	34	MALE	POLICE	SINGLE	4	43521
6	IB14024	55	FEMALE	NURSE	MARRIED	6	34999
7	IB14025	39	FEMALE	TEACHER	MARRIED	6	46619
8	IB14027	51	MALE	SYSTEM MANAGER	MARRIED	3	49999

Summary of Loading Data: -

In the first code block, I used PySpark to create a Spark session, which is essential for processing data in Databricks. I then loaded the loan data stored in a Delta format table from the Databricks

File System (DBFS) into a DataFrame using spark.read.format("delta"). Delta format offers several advantages such as ACID transactions and time travel, making it a reliable choice for working with large datasets in Databricks. After loading the data, I displayed it to visually inspect the information, which allows me to quickly understand the structure of the dataset.

In the second code block, I accessed two tables from the Databricks metastore using spark.table(). This method allows me to easily query tables that have already been registered in the metastore, which is a centralized place to manage metadata for structured data. The first table, loan_table, was loaded from the default schema (hive_metastore.default), while the second table, trips_table, came from the samples.nyctaxi schema. By displaying both tables, I can examine the content and start analyzing them for insights. These two tables represent two different kinds of data: financial data in the loan_table and transportation data in the trips_table.

This entire process showcases the simplicity and flexibility of working with various data formats (like Delta) and managing data in Databricks using PySpark, which is a powerful tool for big data analysis. With this setup, I can perform various analyses, transformations, and queries on the data to derive meaningful insights.

Practice on Delta Tables: -

1. Loading and Displaying Data from Delta Table in Azure

```
spark.table("default.export")

data =spark.read.format("delta").load("dbfs:/user/hive/warehouse/export")

data.show()
```

```
▸ data: pyspark.sql.dataframe.DataFrame = [id: long, firstName: string ... 6 more fields]
|  3|     Quyen|    Marlen|        Dome|     F|1970-10-11 04:00:00|957-57-8246| 53417|
|  4|   Coralie|  Antonina|     Marshal|     F|1990-04-11 04:00:00|963-39-4885| 94727|
|  5|    Terrie|      Wava|       Bonar|     F|1980-01-16 05:00:00|964-49-8051| 79908|
|  6|  Chassidy|Concepcion|Bourthouloume|    F|1990-11-24 05:00:00|954-59-9172| 64652|
|  7|      Geri|    Tambra|       Mosby|     F|1970-12-19 05:00:00|968-16-4020| 38195|
|  8|    Patria|     Nancy|     Arstall|     F|1985-01-02 05:00:00|984-76-3770|102053|
|  9|    Terese|  Alfredia|      Tocque|     F|1967-11-17 05:00:00|967-48-7309| 91294|
| 10|      Wava|   Lyndsey|     Jeandon|     F|1963-12-30 05:00:00|997-82-2946| 56521|
| 11|    Sophie|   Emerita|       Hearn|     F|1979-09-17 04:00:00|977-66-4483| 90920|
| 12|     Jodie|   Tabetha|     Laneham|     F|1959-01-31 05:00:00|923-24-9769| 90634|
| 13|  Marietta|     Mandi|     Yansons|     F|1974-02-19 04:00:00|900-34-8083| 93162|
| 14|   Caridad|     Maire|      Snelle|     F|1960-09-26 04:00:00|992-11-7062| 38859|
| 15|   Yasmine|       Meg|   Edworthye|     F|1960-01-29 05:00:00|922-12-9862| 76220|
| 16|      Chan|      Jani|      Hartas|     F|1986-12-05 05:00:00|995-51-3115| 75050|
| 17|Evangeline|   Wanetta|   Casserley|     F|1961-09-29 04:00:00|926-61-3526| 62814|
| 18|    Elnora|     Kecia|      Lipman|     F|1980-02-14 05:00:00|950-23-9739| 71350|
| 19|    Adelle|   Kathyrn|   Grigoriev|     F|1978-11-14 05:00:00|923-23-5984| 60600|
| 20|      Mica|    Zandra|    Challens|     F|1973-11-24 05:00:00|918-66-1232| 51071|
+---+----------+----------+------------+------+-------------------+-----------+------+
only showing top 20 rows
```

2. Writing DataFrame to Delta Tables in Azure Databricks

from pyspark.sql import SparkSession spark =

SparkSession.builder.appName('Delta Table Write').getOrCreate() data =

spark.createDataFrame([(1, "Alice", 1000), (2, "Bob", 2000),

(3, "Charlie", 3000)],["id", "name", "salary"])

Write the DataFrame as Delta tables

data.write.format('delta').saveAsTable("mydata_delta", mode="overwrite")

data.write.format('delta').saveAsTable("mydata")

3. Loading and Displaying Data from Delta Table in Databricks

spark.table("default.export") data =

spark.read.format("delta").load("dbfs:/user/hive/warehouse/export")

data.display()

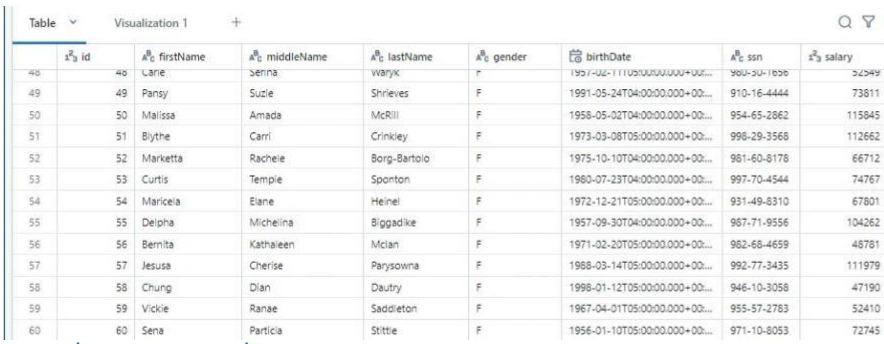
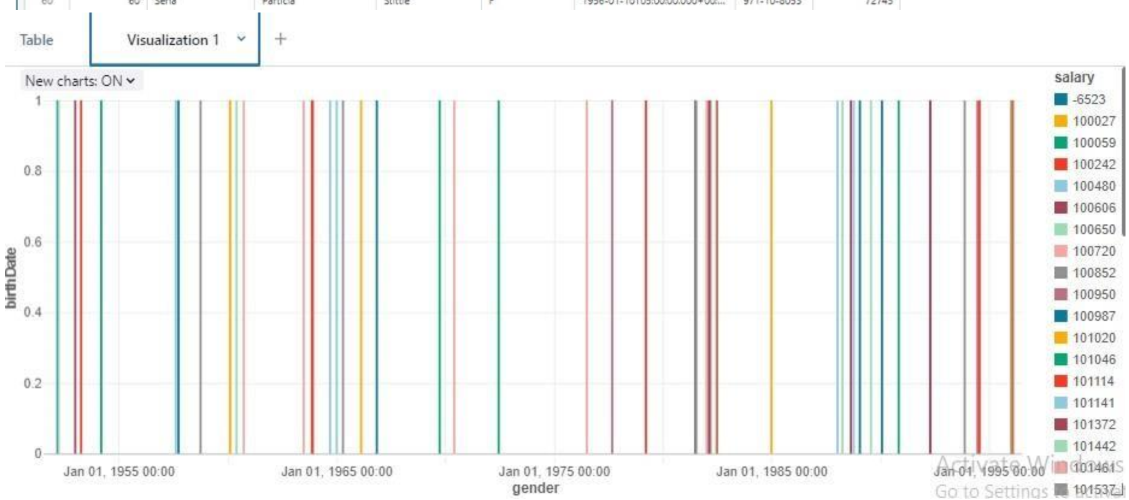


Table | Visualization 1 | +

	id	firstName	middleName	lastName	gender	birthDate	ssn	salary
48	48	Carie	Serina	Waryk	F	1957-02-11T05:00:00.000+00:...	980-30-1656	52549
49	49	Pansy	Suzie	Shrieves	F	1991-05-24T04:00:00.000+00:...	910-16-4444	73811
50	50	Malissa	Amada	McRill	F	1958-05-02T04:00:00.000+00:...	954-65-2862	115845
51	51	Blythe	Carri	Crinkley	F	1973-03-08T05:00:00.000+00:...	998-29-3568	112662
52	52	Marketta	Rachele	Borg-Bartolo	F	1975-10-10T04:00:00.000+00:...	981-60-8178	66712
53	53	Curtis	Tempie	Sponton	F	1980-07-23T04:00:00.000+00:...	997-70-4544	74767
54	54	Maricela	Elane	Heinel	F	1972-12-21T05:00:00.000+00:...	931-49-8310	67801
55	55	Delpha	Michelina	Biggadike	F	1957-09-30T04:00:00.000+00:...	987-71-9556	104262
56	56	Bernita	Kathaleen	Mclan	F	1971-02-20T05:00:00.000+00:...	982-68-4659	48781
57	57	Jesusa	Cherise	Parysowna	F	1988-03-14T05:00:00.000+00:...	992-77-3435	111979
58	58	Chung	Dian	Dautry	F	1998-01-12T05:00:00.000+00:...	946-10-3058	47190
59	59	Vickie	Ranae	Saddleton	F	1967-04-01T05:00:00.000+00:...	955-57-2783	52410
60	60	Sena	Particia	Stittle	F	1956-01-10T05:00:00.000+00:...	971-10-8053	72745



Summary on Delta Tables: -

In Azure Databricks, Delta tables are used to store data in a structured format that supports efficient querying and data management. The first block of code shows how to read data from an existing Delta table stored in the Databricks metastore or from a path in the DBFS (Databricks File System). Using the spark.read.format("delta") method, we load the data from the Delta table into a DataFrame and display it. This process allows us to view the content of the Delta table, which is stored in a structured format for analysis.

Next, we see how to create and write a new Delta table from a DataFrame. The data.write.format("delta").saveAsTable("mydata") command writes the data into a new Delta table named "mydata". This code demonstrates the ability to save a DataFrame into a Delta table, making it accessible for future queries and operations. We can specify the mode (like overwrite) to control how existing data is handled when writing the new data.

Finally, the data.display() method is used to show the contents of the newly written Delta table in a Databricks notebook. Overall, Delta tables provide a powerful and efficient way to store and manage data in Databricks, with built-in support for ACID transactions, versioning, and schema enforcement. This makes them ideal for data analysis and machine learning tasks where data integrity and fast querying are crucial.

Practice EDA Analysis: -

1. Reading and Displaying Data from the Loan Table in Databricks

```
data = spark.read.table("hive_metastore.default.loan") display(data)
```

(1) Spark Jobs

data: pyspark.sql.dataframe.DataFrame = [Customer_ID: string, Age: long ... 13 more fields]

Table

	Customer_ID	Age	Gender	Occupation	Marital Status	Family Size	Income
1	IB14001	30	MALE	BANK MANAGER	SINGLE	4	50000
2	IB14008	44	MALE	PROFESSOR	MARRIED	6	51000
3	IB14012	30	FEMALE	DENTIST	SINGLE	3	58450
4	IB14018	29	MALE	TEACHER	MARRIED	5	45767
5	IB14022	34	MALE	POLICE	SINGLE	4	43521
6	IB14024	55	FEMALE	NURSE	MARRIED	6	34999
7	IB14025	39	FEMALE	TEACHER	MARRIED	6	46619
8	IB14027	51	MALE	SYSTEM MANAGER	MARRIED	3	49999
9	IB14029	24	FEMALE	TEACHER	SINGLE	3	45008
10	IB14031	37	FEMALE	SOFTWARE ENGINEER	MARRIED	5	55999
11	IB14032	24	MALE	DATA ANALYST	SINGLE	4	60111
12	IB14034	32	MALE	PRODUCT ENGINEER	MARRIED	6	null

2. Getting Row Count and Schema Information of the Data

```
# Total row count data.count() # Schema information data.printSchema()
```

▸ (2) Spark Jobs

```
root
 |-- Customer_ID: string (nullable = true)
 |-- Age: long (nullable = true)
 |-- Gender: string (nullable = true)
 |-- Occupation: string (nullable = true)
 |-- Marital Status: string (nullable = true)
 |-- Family Size: long (nullable = true)
 |-- Income: long (nullable = true)
 |-- Expenditure: long (nullable = true)
 |-- Use Frequency: long (nullable = true)
 |-- Loan Category: string (nullable = true)
 |-- Loan Amount: string (nullable = true)
 |-- Overdue: long (nullable = true)
 |--  Debt Record: string (nullable = true)
 |--  Returned Cheque: long (nullable = true)
 |--  Dishonour of Bill: long (nullable = true)
```

---

3. Displaying Summary Statistics for 'Income' Column

```
# Summary statistics for 'Income'
data.describe(['Income']).show()
```

▸ (2) Spark Jobs

```
+-------+-----------------+
|summary|           Income|
+-------+-----------------+
|  count|              468|
|   mean|68339.49145299145|
| stddev|86796.49367750238|
|    min|            28366|
|    max|           930000|
+-------+-----------------+
```

---

4. Counting Rows Grouped by Gender

```
data.groupBy('gender').count().show()
```

▸ (2) Spark Jobs

gender	count
MALE	280
FEMALE	220

---

5. Displaying Top 5 Highest Incomes

Top 5 Highest Incomes data.orderBy(data.Income.desc()).limit(5).show()

▸ (1) Spark Jobs

Customer_ID	Age	Gender	Occupation	Marital Status	Family Size	Income	Expenditure	Use Frequency	Loan Category	Loan Amount	Overdue	Debt Record	Returned Cheque	Dishonour of Bill
IBI4157	35	MALE	BANK MANAGER	MARRIED	4	930000	35680	6	HOUSING	6,79,040	5	34,000	5	5
IB14107	44	FEMALE	ACCOUNT MANAGER	MARRIED	4	800000	15632	8	AUTOMOBILE	23,65,478	5	20,145	3	4
IB14163	44	FEMALE	ACCOUNT MANAGER	MARRIED	4	800000	15632	8	COMPUTER SOFTWARES	23,65,478	5	20,145	3	4
IB14256	44	FEMALE	ACCOUNT MANAGER	MARRIED	4	800000	15632	8	COMPUTER SOFTWARES	23,65,478	5	20,145	3	4
IB14128	46	FEMALE	CLERK	MARRIED	3	750000	25641	5	GOLD LOAN	2,14,569	4	16,324	3	4

---

6. Grouping Employees by Salary Buckets and Counting

Salary Distribution from pyspark.sql.functions import ceil, col

Add salary buckets data_with_buckets = data.withColumn('salary_bucket',

ceil(col('Income') / 20000) * 20000)

Count employees in each bucket

data_with_buckets.groupBy('salary_bucket').count().orderBy('salary_bucket').show()

▸ (2) Spark Jobs

▸ data_with_buckets: pyspark.sql.dataframe.DataFrame = [Customer_ID: string, Age: long ... 14 more fields]

```
+-------------+-----+
|salary_bucket|count|
+-------------+-----+
|         NULL|   32|
|        40000|   70|
|        60000|  200|
|        80000|  136|
|       100000|   55|
|       440000|    1|
|       700000|    1|
|       760000|    1|
|       800000|    3|
|       940000|    1|
+-------------+-----+
```

Summary of EDA Analysis: -

I worked on a dataset from the hive_metastore.default.loan table using PySpark in Databricks. First, I loaded the data into a Spark DataFrame and displayed it to get a view of the records. I calculated the total number of rows in the dataset with the count() function, which shows how many entries there are. Then, I examined the schema of the data to understand the structure of the table, such as the column names and data types.

I also performed summary statistics for the Income column, which gave me basic measures like the count, mean, and standard deviation. I grouped the data by gender to count how many records fall into each gender category. To further explore the data, I identified the top 5 highest incomes by sorting the data in descending order based on the Income column. Finally, I created salary buckets by dividing the Income into ranges and counted how many employees fall into each bucket, helping me understand the distribution of income within the dataset.

Practice on Visualization: -

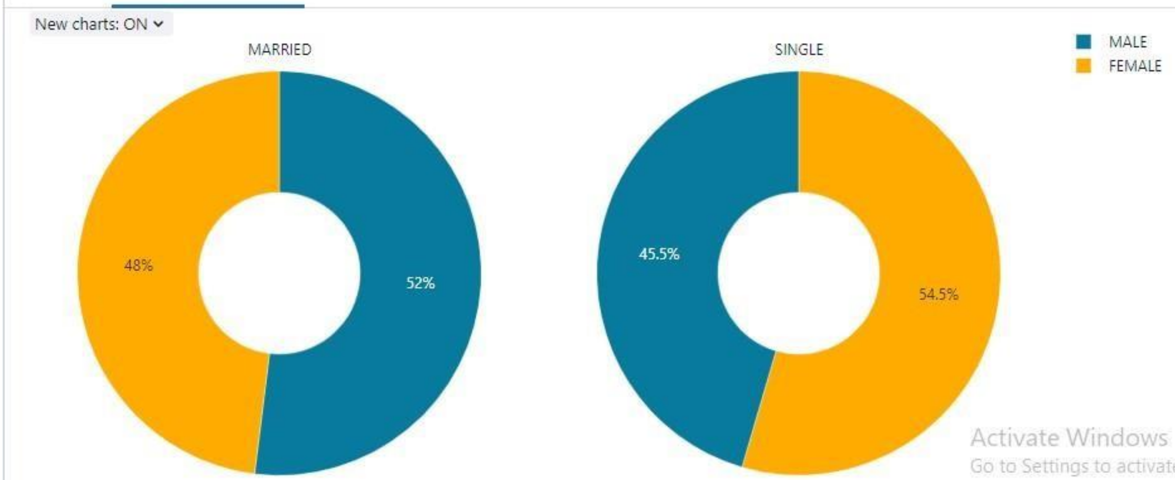
1. Loading and Displaying Data from the 'loan' Table

Table | Visualization 1 | +

	Customer_ID	Age	Gender	Occupation	Marital Status	Family Size	Income	Expenditure
1	IB14001	30	MALE	BANK MANAGER	SINGLE	4	50000	2
2	IB14008	44	MALE	PROFESSOR	MARRIED	6	51000	1
3	IB14012	30	FEMALE	DENTIST	SINGLE	3	58450	2
4	IB14018	29	MALE	TEACHER	MARRIED	5	45767	1
5	IB14022	34	MALE	POLICE	SINGLE	4	43521	1
6	IB14024	55	FEMALE	NURSE	MARRIED	6	34999	1
7	IB14025	39	FEMALE	TEACHER	MARRIED	6	46619	1
8	IB14027	51	MALE	SYSTEM MANAGER	MARRIED	3	49999	1
9	IB14029	24	FEMALE	TEACHER	SINGLE	3	45008	1
10	IB14031	37	FEMALE	SOFTWARE ENGINEER	MARRIED	5	55999	2
11	IB14032	24	MALE	DATA ANALYST	SINGLE	4	60111	2
12	IB14034	32	MALE	PRODUCT ENGINEER	MARRIED	6	null	2
13	IB14037	54	FEMALE	TEACHER	MARRIED	5	48099	1
14	IB14039	45	MALE	ACCOUNT MANAGER	MARRIED	7	45777	1

datatable: pyspark.sql.dataframe.DataFrame = [Customer_ID: string, Age: long ... 13 more fields]

Table | Visualization 1 | +



2. Loading and Displaying Data from 'export' Table and Delta Location

spark.table("default.export") data =

spark.read.format("delta").load("dbfs:/user/hive/warehouse/export")

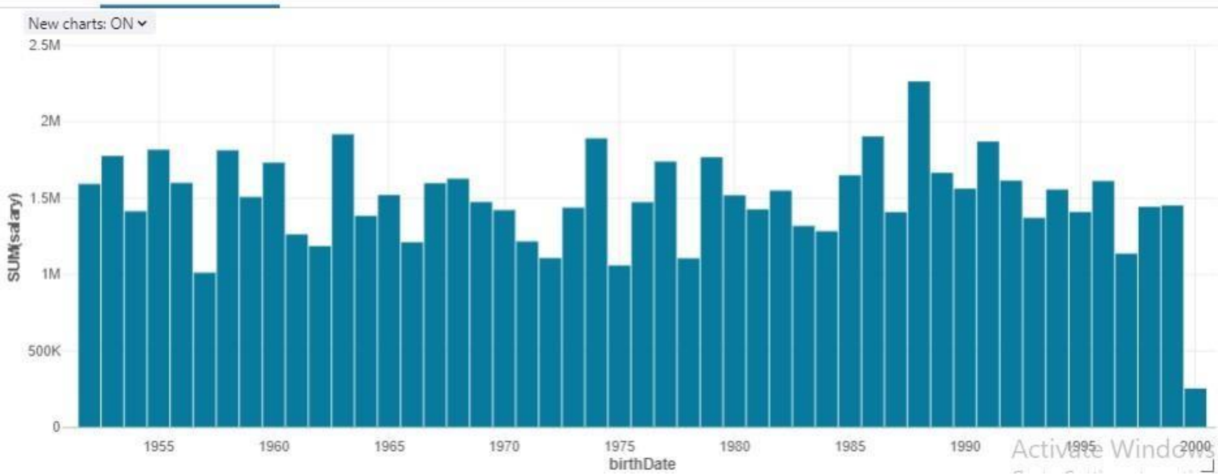
data.display()

Table | Visualization 1 | +

	id	firstName	middleName	lastName	gender	birthDate	ssn	salary
1	1	Pennie	Carry	Hirschmann	F	1955-07-02T04:00:00.000+00:...	981-43-9345	56172
2	2	An	Amira	Cowper	F	1992-02-08T05:00:00.000+00:...	978-97-8086	40203
3	3	Quyen	Marlen	Dome	F	1970-10-11T04:00:00.000+00:...	957-57-8246	53417
4	4	Coralie	Antonina	Marshal	F	1990-04-11T04:00:00.000+00:...	963-39-4685	94727
5	5	Terrie	Wava	Bonar	F	1980-01-16T05:00:00.000+00:...	964-49-8051	79908
6	6	Chassidy	Concepcion	Bourthouloume	F	1990-11-24T05:00:00.000+00:...	954-59-9172	64652
7	7	Geri	Tambra	Mosby	F	1970-12-19T05:00:00.000+00:...	968-16-4020	38195
8	8	Patria	Nancy	Arstall	F	1985-01-02T05:00:00.000+00:...	984-76-3770	102053
9	9	Terese	Alfredia	Tocque	F	1967-11-17T05:00:00.000+00:...	967-48-7309	91294
10	10	Wava	Lyndsey	Jeandon	F	1963-12-30T05:00:00.000+00:...	997-82-2946	56521
11	11	Sophie	Emerita	Hearn	F	1979-09-17T04:00:00.000+00:...	977-66-4483	90920
12	12	Jodie	Tabetha	Laneham	F	1959-01-31T05:00:00.000+00:...	923-24-9769	90634
13	13	Marietta	Mandi	Yansons	F	1974-02-19T04:00:00.000+00:...	900-34-8083	93162
14	14	Caridad	Maire	Snelle	F	1960-09-26T04:00:00.000+00:...	992-11-7062	38859
15	15	Yasmine	Meg	Edworthye	F	1960-01-29T05:00:00.000+00:...	922-12-9862	76220

data: pyspark.sql.dataframe.DataFrame = [id: long, firstName: string ... 6 more fields]

Table | Visualization 1 | +



Summary on Visualization: -

In Azure Databricks, data visualization using PySpark can help you easily interpret and present data insights. PySpark allows you to work with large datasets and perform complex transformations before visualizing the results. The display() function in Databricks provides a powerful way to visualize DataFrames directly in the notebook interface. When you load data into PySpark, whether from a table or a Delta file, you can quickly visualize it using Databricks' built-in visualization tools.

Visualizations like bar charts, line graphs, and scatter plots can be created with just a few clicks, providing an intuitive way to explore data patterns. You can create custom visualizations to examine trends over time, compare categories, or understand distributions. Databricks also supports interactive visualization, which means you can drill down into the data, filter values, and adjust axes for better clarity.

By using PySpark for data processing and Databricks for visualization, you can enhance your data exploration experience without switching tools or environments. This integration makes it easier to share insights with others and perform interactive analysis in real-time. Visualizations are crucial for communicating data findings in an understandable and impactful way.