Project 02: Customer Behavior Analysis Documentation

1. Project Overview

What is ETL?

ETL stands for Extract, Transform, Load and is a critical process in data integration and analytics pipelines. The purpose of ETL is to collect data from various sources, transform it into a usable format, and load it into a storage system for analysis and reporting. Here's a breakdown of each step:

- **Extract**: Collecting raw data from multiple sources (e.g., databases, APIs, or files).
- **Transform**: Cleaning, filtering, and formatting the extracted data to align with business requirements.
- **Load**: Storing the processed data into a data warehouse, database, or storage system for further use.

Objective:

To automate the ETL (Extract, Transform, Load) workflow for an Online Retail Analysis project using Azure Data Factory, Azure Databricks, and Azure Git. This project utilizes the Medallion Architecture, which includes Bronze, Silver, and Gold layers, to prepare data for predictive analysis.

Dataset:

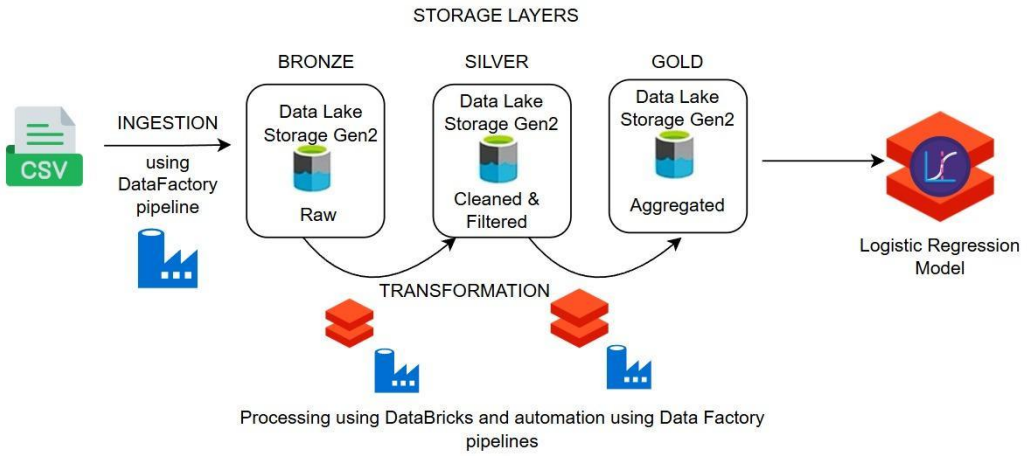
The dataset, **"Online Retail.xlsx"**, contains transactional data from a UK-based online retail company. It includes the following columns:

- **InvoiceNo**: Unique identifier for each transaction.
- **StockCode**: Unique identifier for each product.
- **Description**: Product name or description.
- **Quantity**: Number of products sold per transaction.
- **InvoiceDate**: Date and time of the transaction.
- **UnitPrice**: Price per unit of the product.
- **CustomerID**: Unique identifier for each customer.
- **Country**: Country of the customer.

The dataset will be used for customer behavior analysis, focusing on metrics like purchase patterns, sessionized interactions, and churn prediction.

For a detailed walkthrough of the project, please refer to the project explanation video.

Architecture:



=> Setting Up the Environment:-

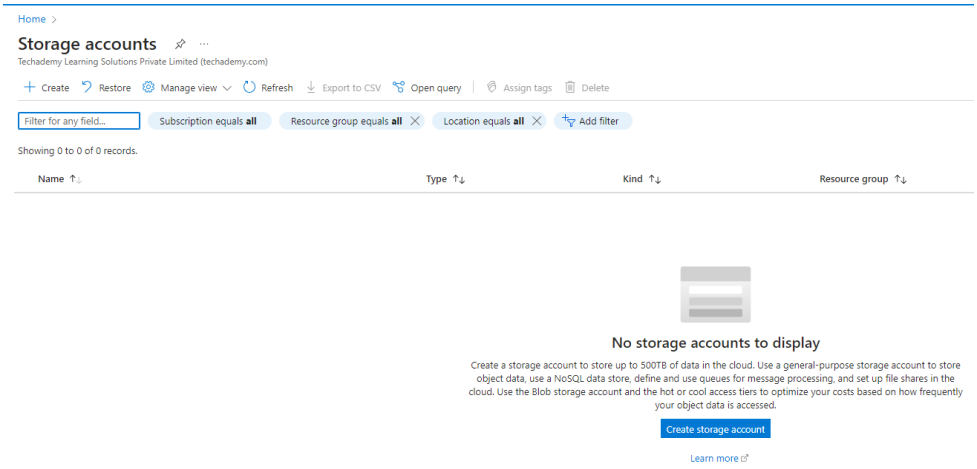
1. Create Storage Account, Containers, and Upload Raw Data

Purpose:

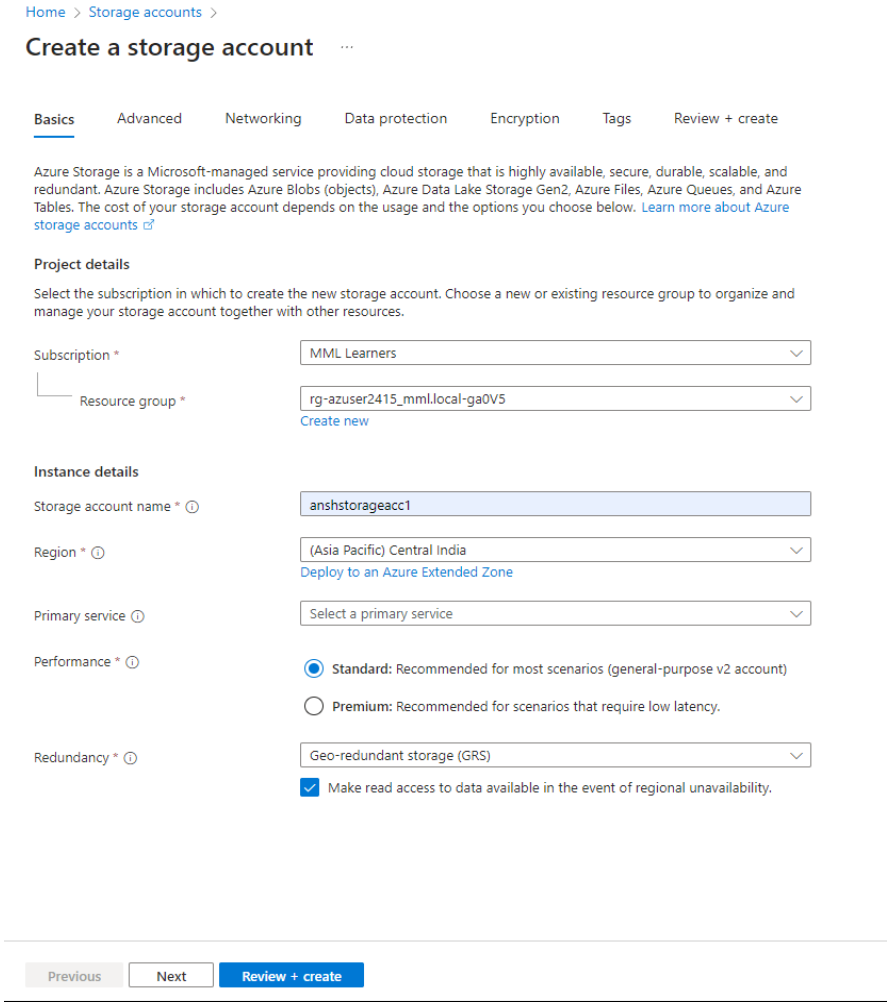
- **The storage account serves as the Azure Data Lake Gen2, providing distributed data storage for the ETL process.**
- **Containers help organize data based on the Medallion Architecture.**

Steps:

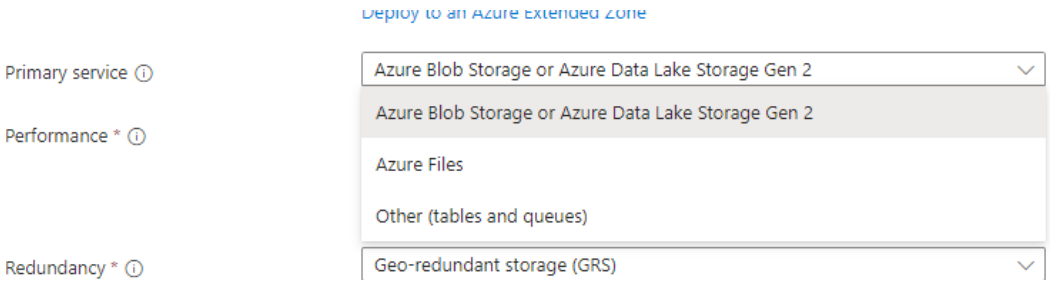
1. **Navigate to Storage Accounts > New Storage Account.**



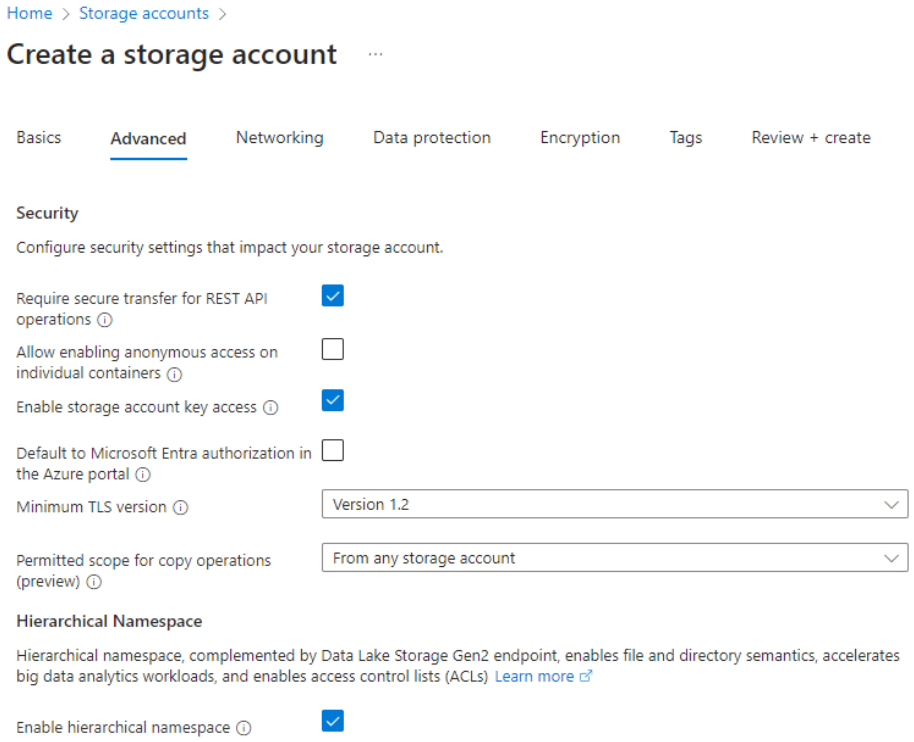
2. **Fill in required details (e.g., subscription, resource group) and click Review + Create.**



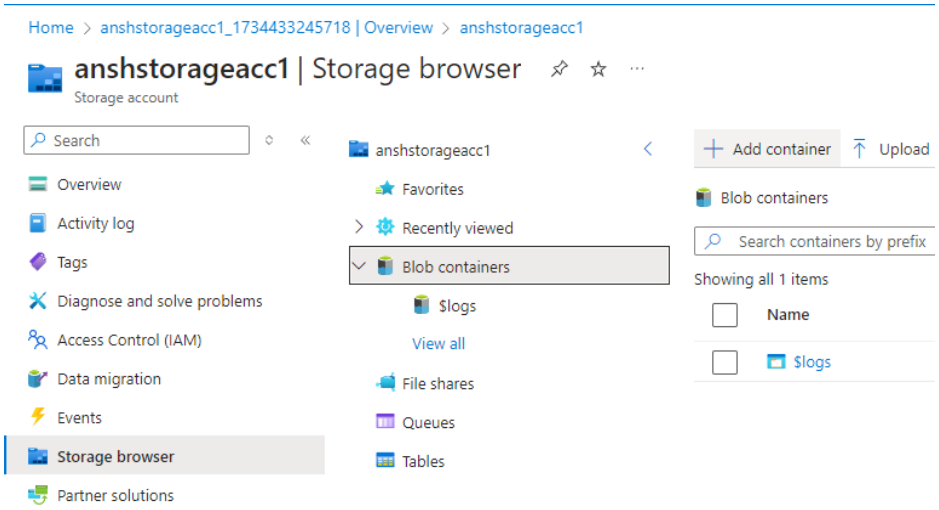
3. **Under the Basic tab, select Data Lake Storage Gen2.**



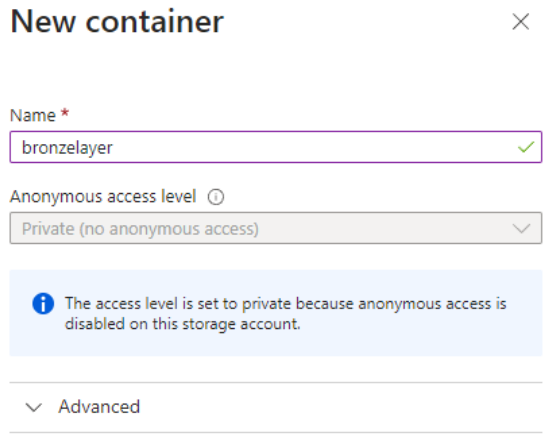
4. **Enable Hierarchical namespace under the Advanced tab.**

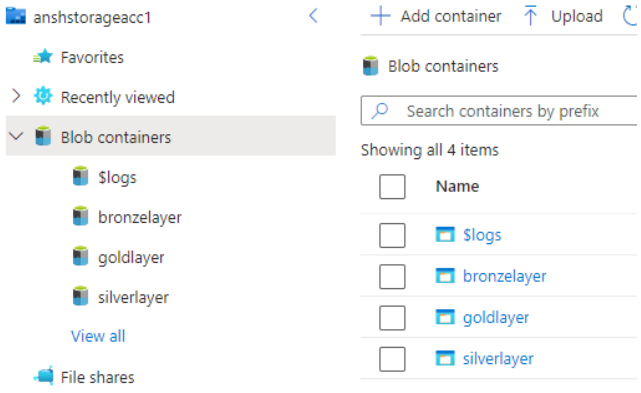


5. **Once deployed, go to Storage Browser > Blob Containers > Add Container.**

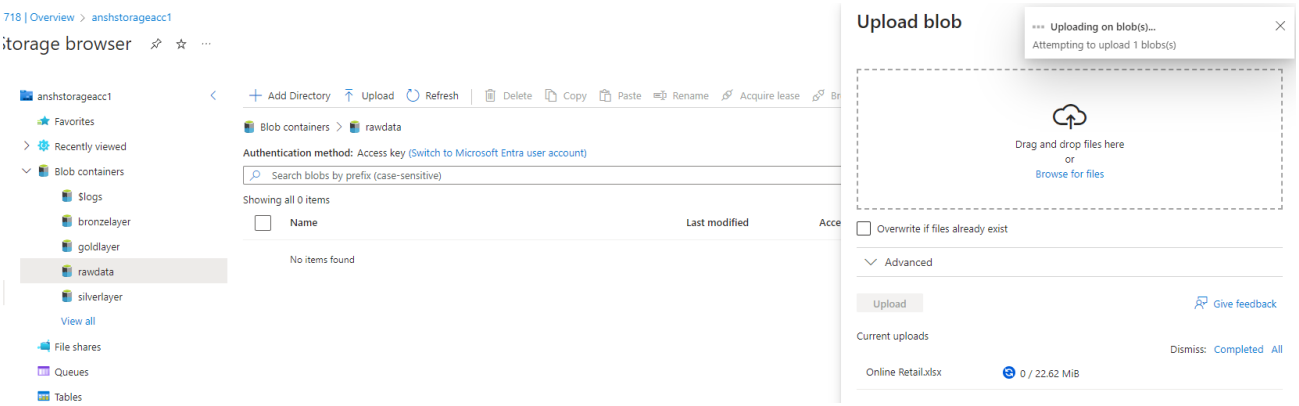


6. **Create four containers:**
    - **One for each layer: `bronze`, `silver`, and `gold`.**

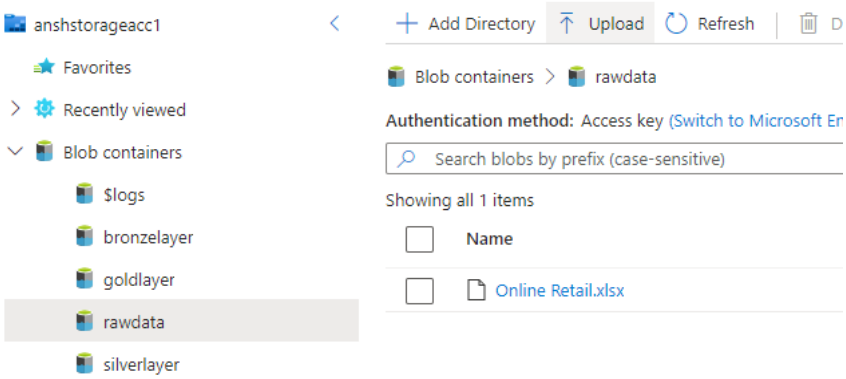




    - **One for raw data (`rawdata`).**



7. **Upload raw data files to the `rawdata` container.**



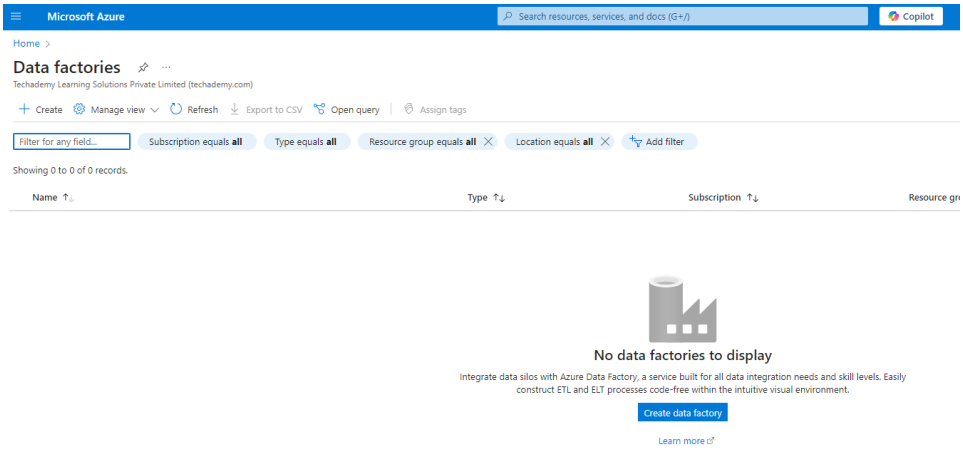
2. Create Data Factory

Purpose:

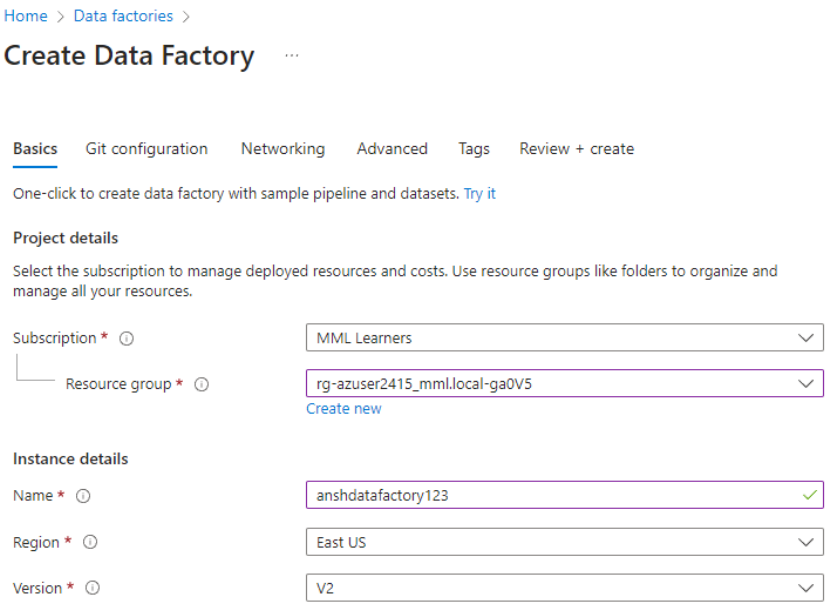
- **Azure Data Factory orchestrates the ETL workflow by automating data ingestion, transformations, and movement between layers.**

Steps:

1. **Go to Azure Data Factories > Create a data factory.**



2. **Provide a unique name for your data factory and click Review + Create.**



3. **After deployment, the Data Factory is ready to create pipelines for automation.**

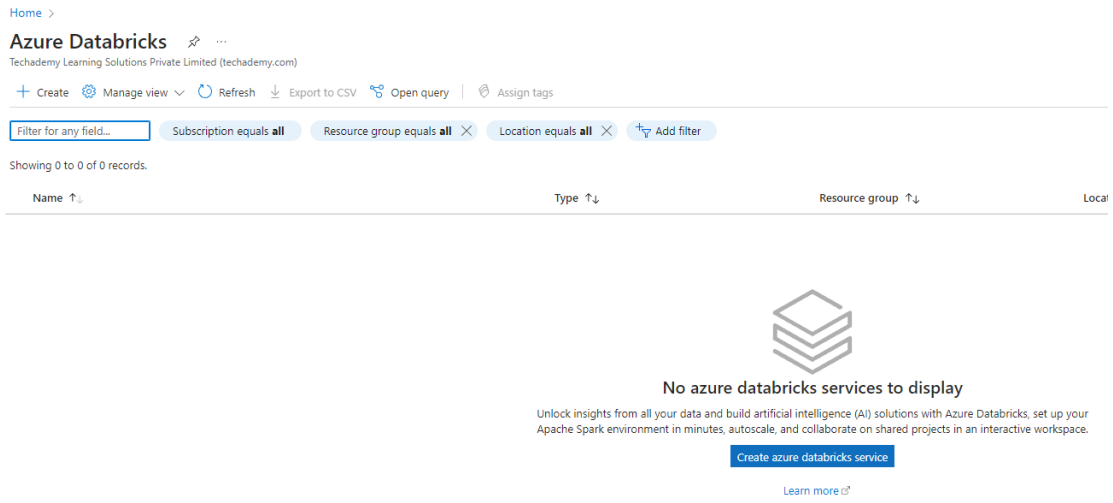
3. Create Databricks Workspace

Purpose:

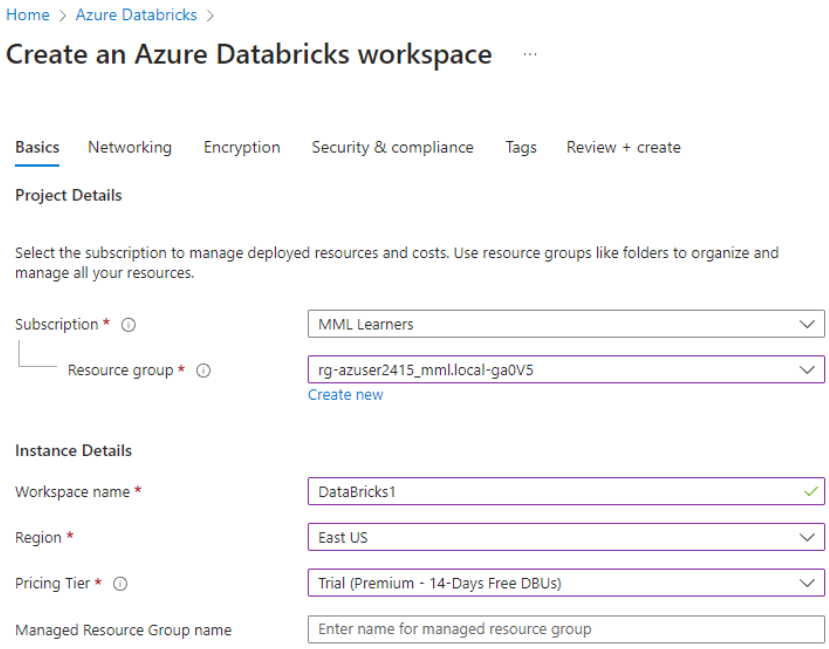
- **Azure Databricks enables scalable data transformations and advanced analytics using Spark.**

Steps:

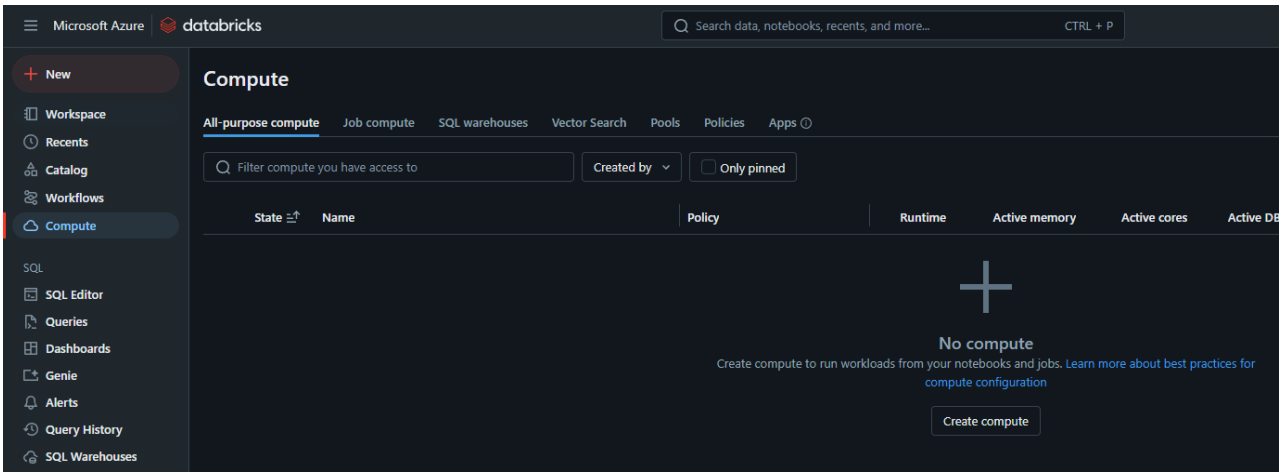
1. **Navigate to Azure Databricks > Create Azure Databricks Service.**



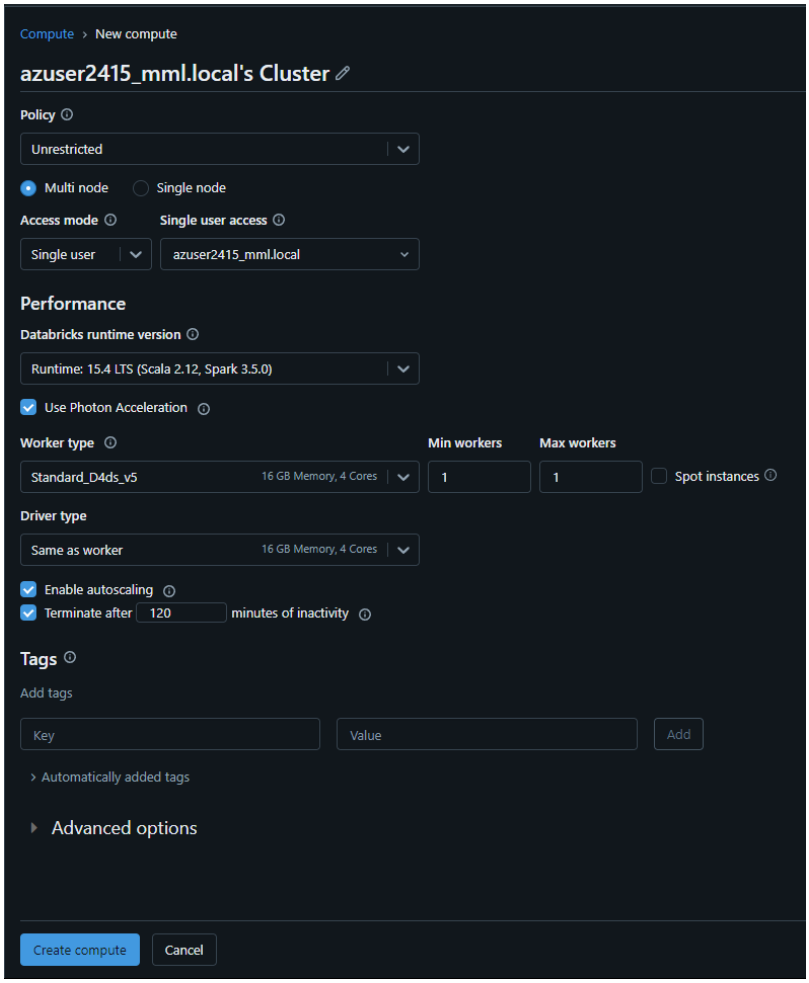
2. **Enter details (e.g., subscription, resource group) and click Review + Create.**



3. **Once deployed, launch the workspace.**



4. **Go to Compute > Create Compute to set up a cluster.**



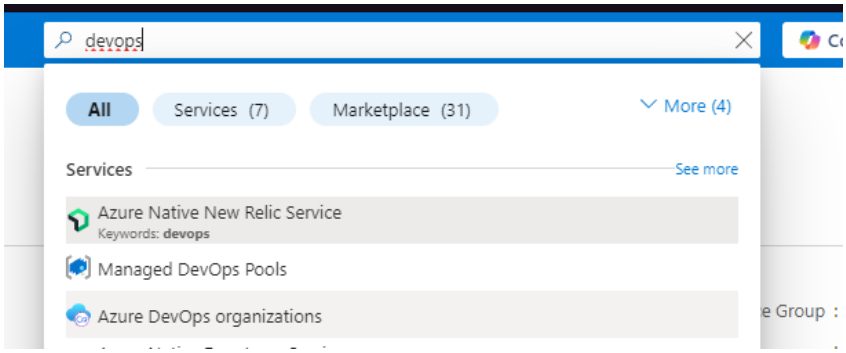
4. Set Up Azure Git Repository

Purpose:

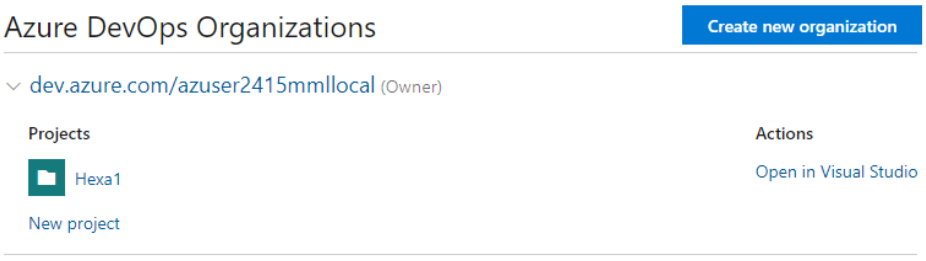
- **Azure Git repository provides version control and collaboration.**
- **The repository integrates with Databricks to enable seamless notebook management.**

Steps:

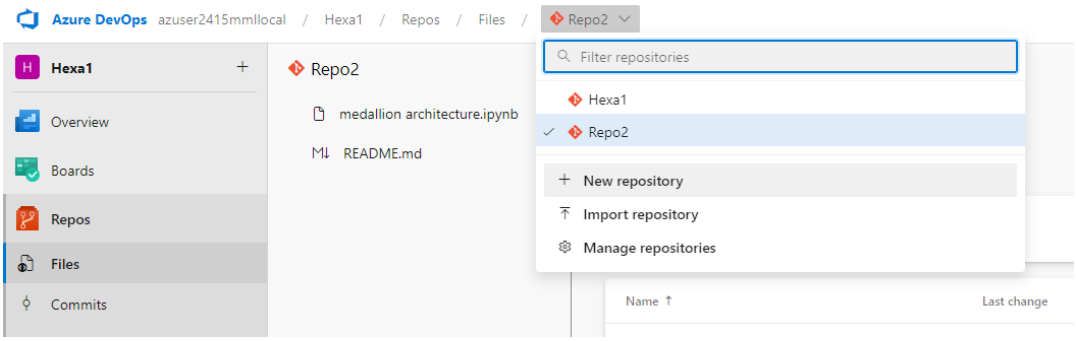
1. **Search for Azure DevOps and navigate to My Azure DevOps Organizations.**

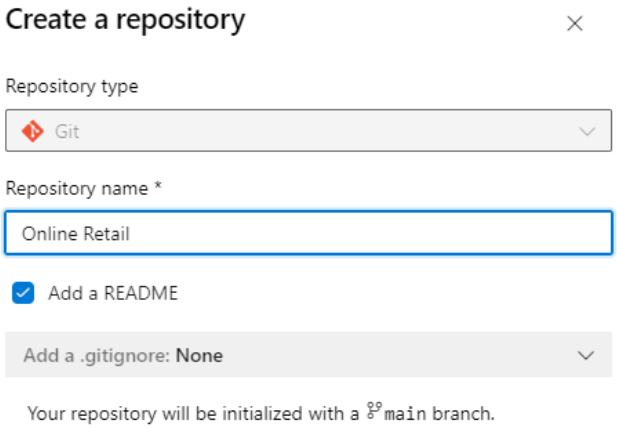


2. **Select or create an organization.**

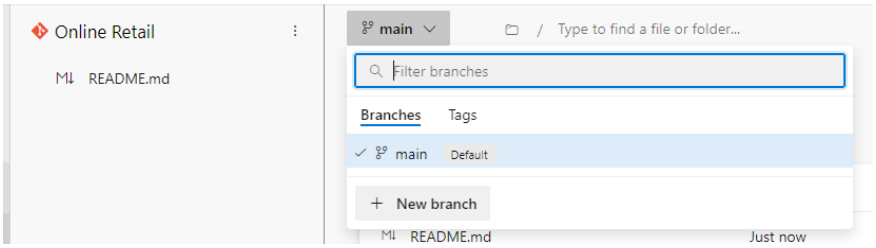


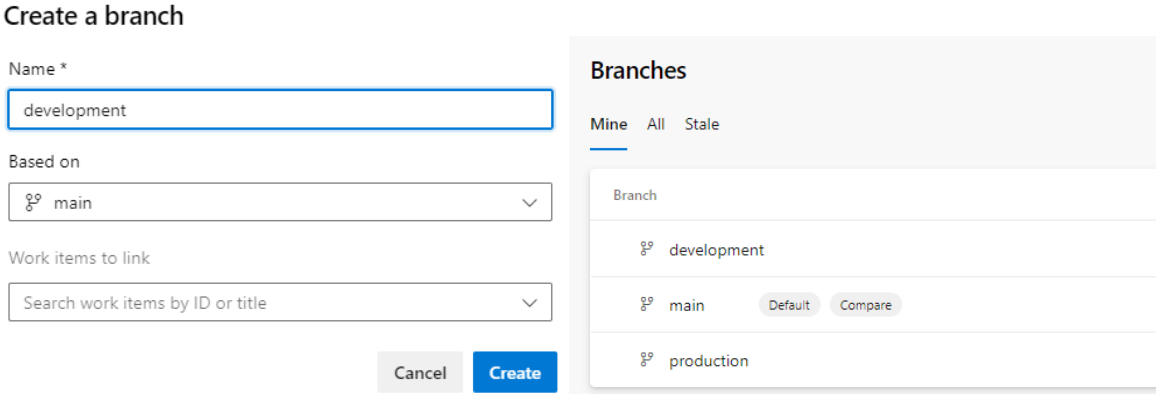
3. **Go to Repos > New Repository and name it (e.g., `Online Retail Analysis`).**



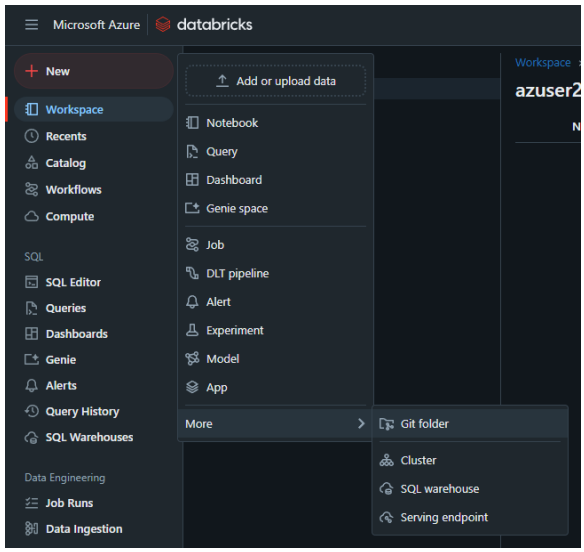


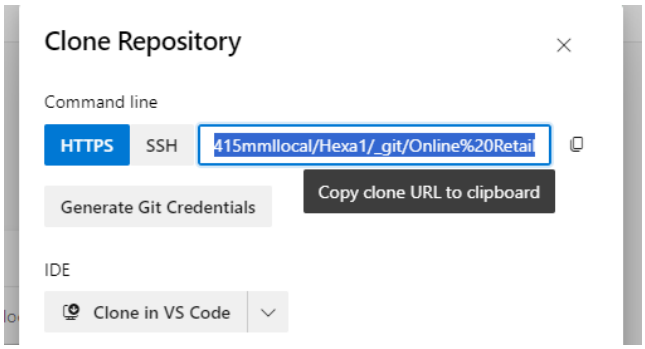
4. **Create two additional branches: `development` and `production`.**



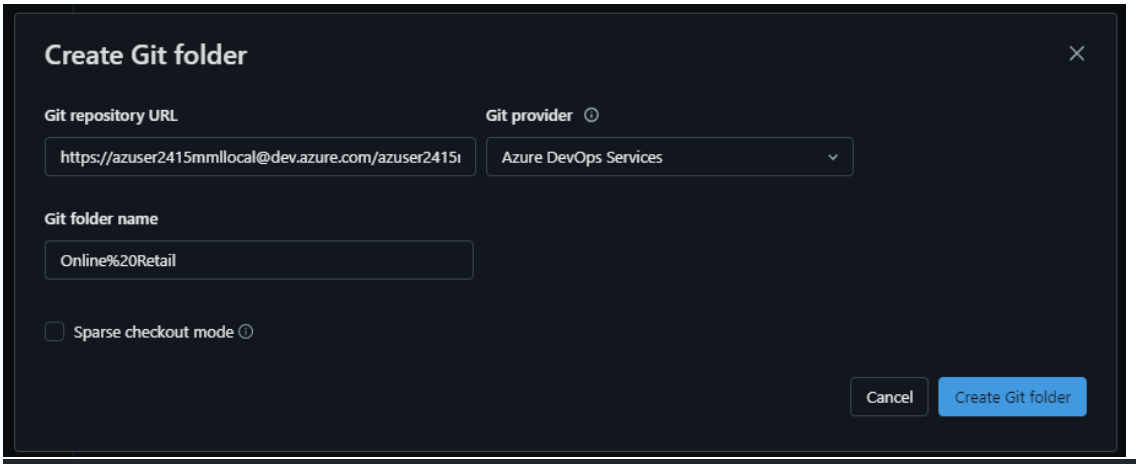


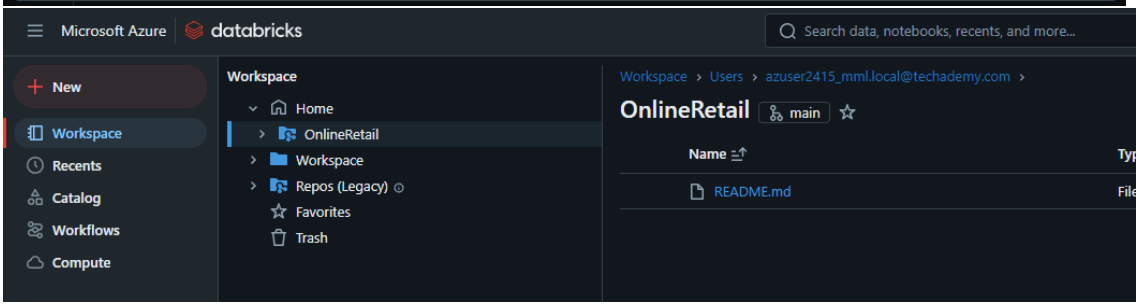
5. **In Databricks, go to Workspace > More > Git Integration.**





6. **Copy the repository URL from Azure DevOps and paste it into the Git configuration in Databricks.**





5. Configure CI/CD Pipelines

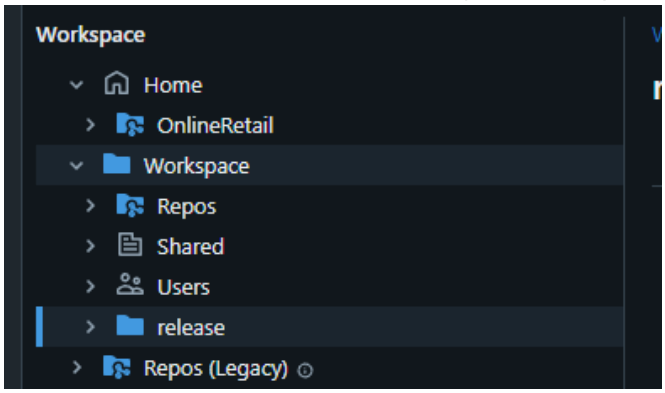
Purpose:

- **Automates code deployment and ensures the latest changes are available in production and the release folder.**
- **Simplifies collaboration and reduces manual intervention.**

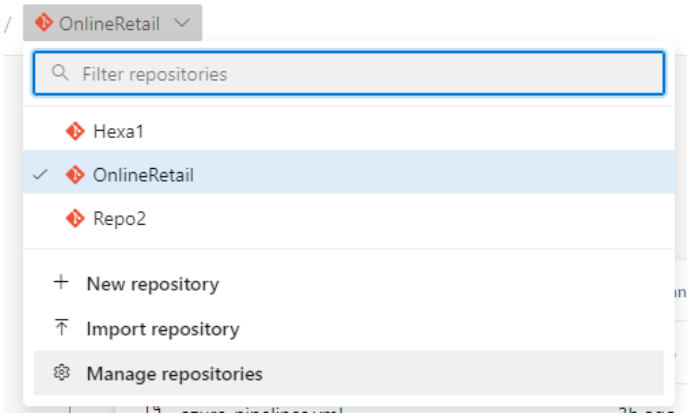
Steps:

1. **Set up two CI/CD pipelines:**
    - **Pipeline 1: Automatically merges changes from the `main` branch to the `production` branch.**
    - **Pipeline 2: Updates a `release` folder in the Databricks workspace with the latest code from the `main` branch.**
2. **Use Azure DevOps to configure the pipelines with a YAML script that includes tasks like:**
    - **Checking out the repository.**
    - **Installing the Databricks CLI.**
    - **Merging branches.**
    - **Deploying updates to the `release` folder.**

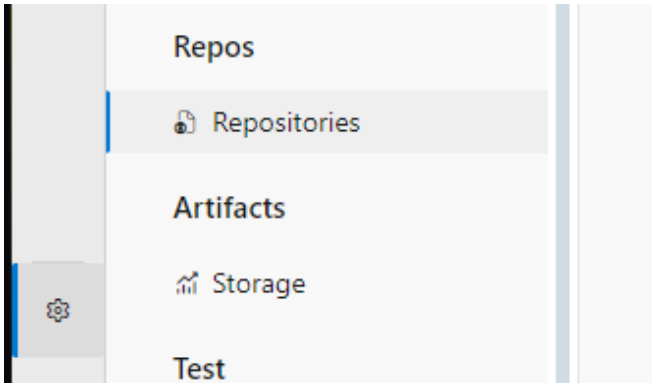
1. Create a folder called release inside your workspace



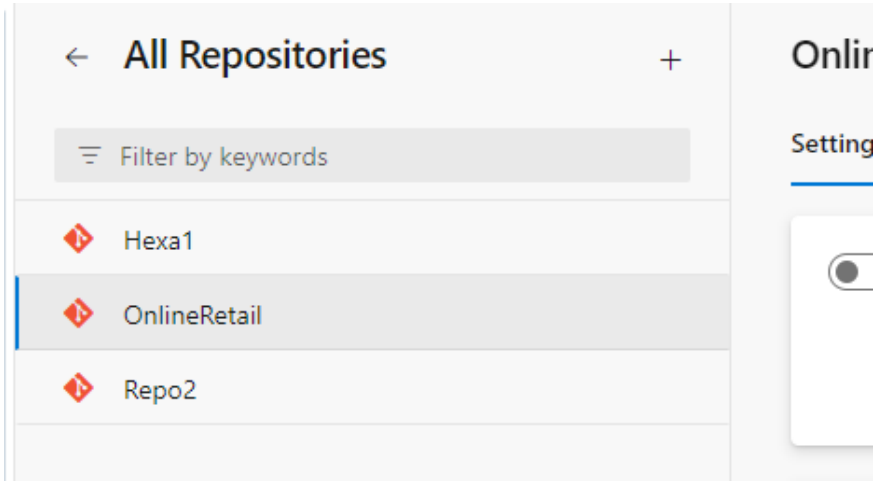
2. Inside your Repo tab go to Manage Repositories



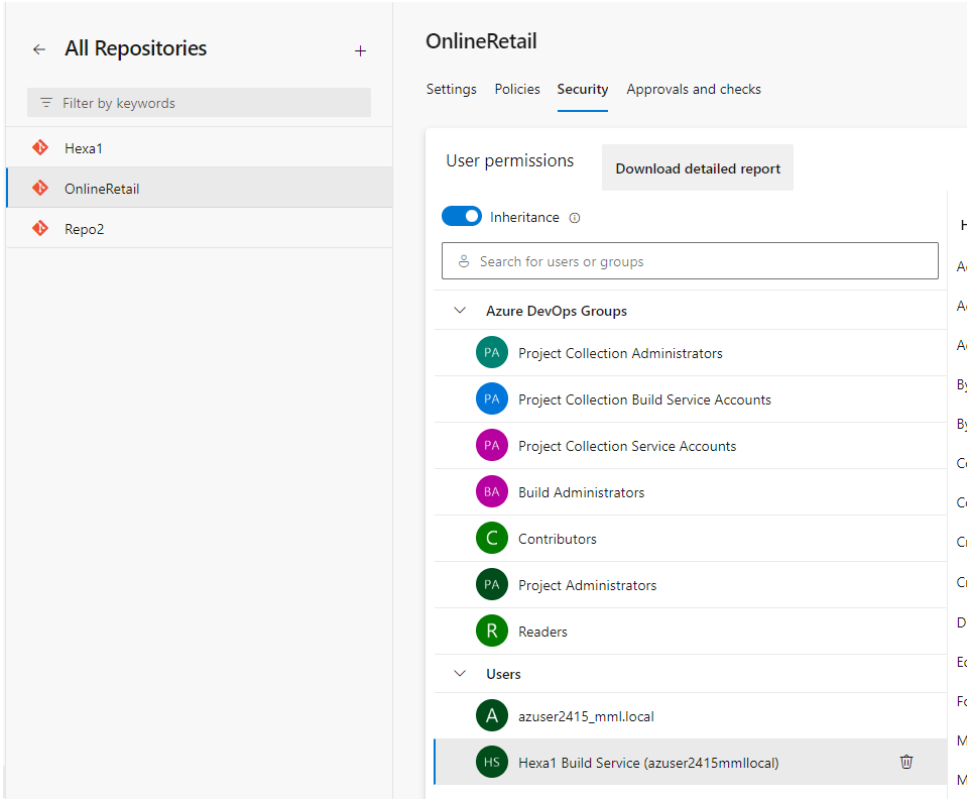
3. Alternatively you can also go to Project Settings on bottom left > Repository side tab



4. Pick your repository from menu



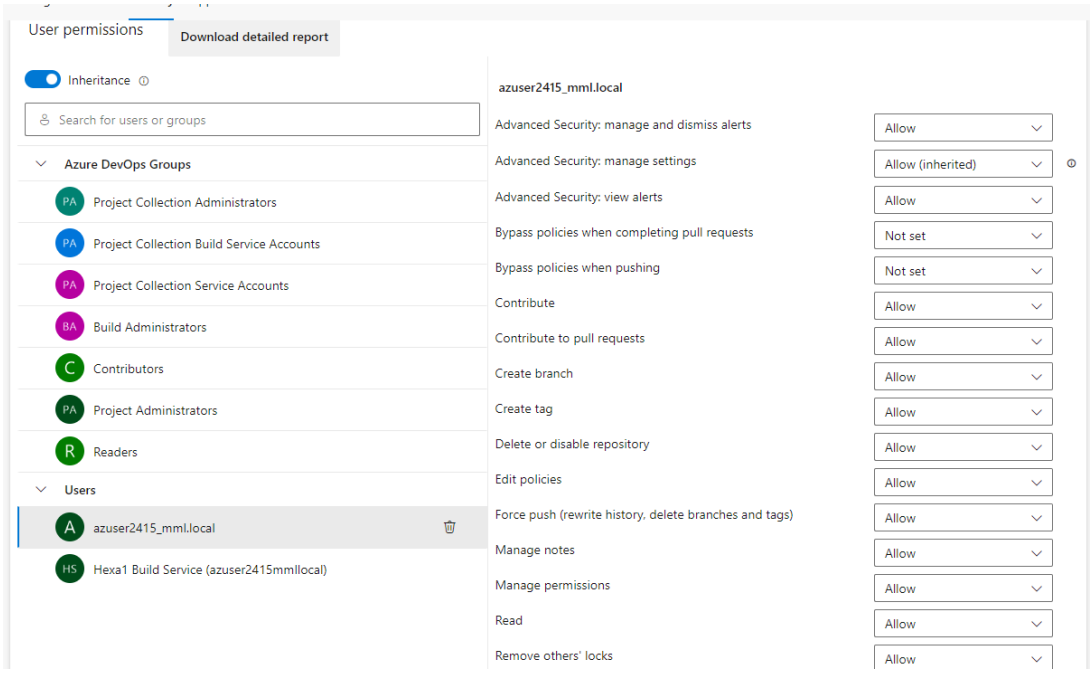
5. Go to Security tab and under Users go to Build Services



the bottom most option here

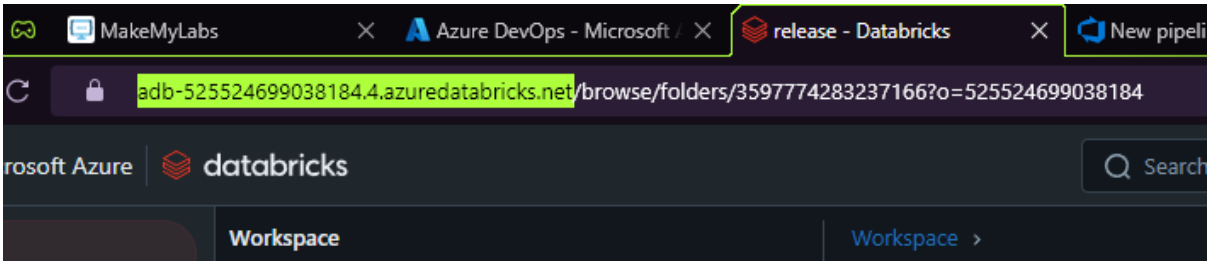
6. There are 3 settings : ‘Contribute’ , ‘Contribute to pull requests’ , ‘Create branch’. Make sure they are all set to Allow

7. Now go to under users title go to your <username> tab just above this Build Service and make sure these 3 settings are set as allow there as well

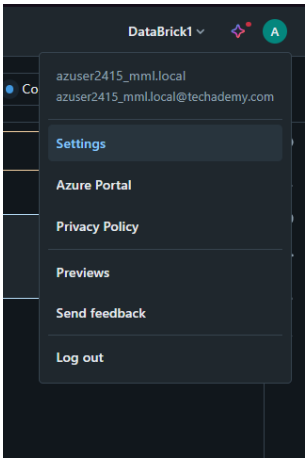


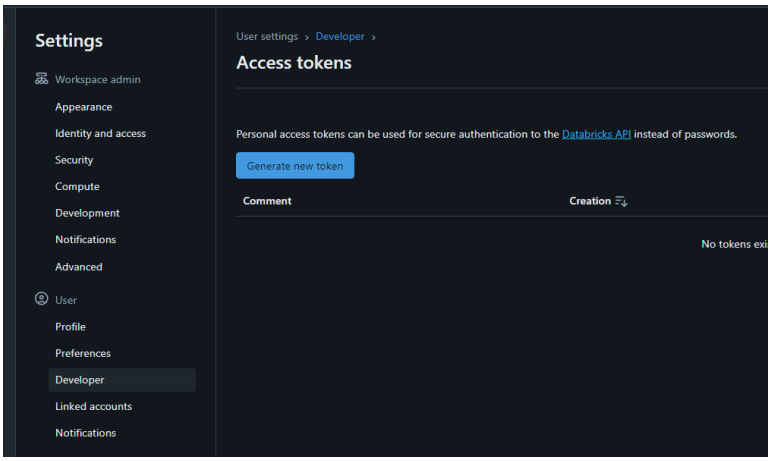
8. We need to save 2 variables in a variable group databricksHost and databricksToken. This is like username and password to log into databricks

9. To get the databricksHost > The url of our page upuntil .net is our databricksHost

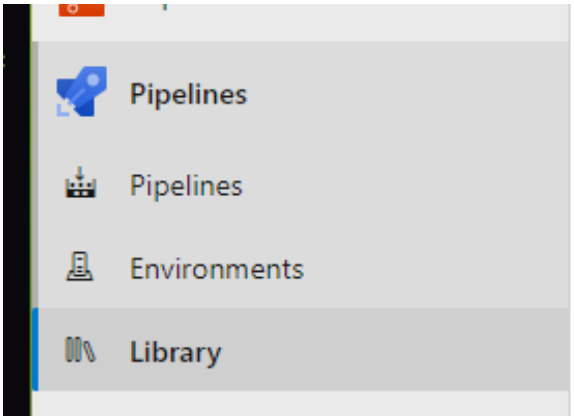


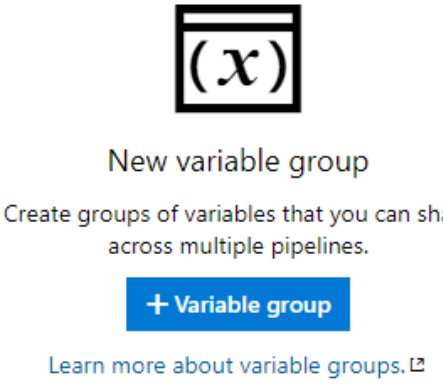
10. To get databricksToken, Go to settings > Developer > Generate new token



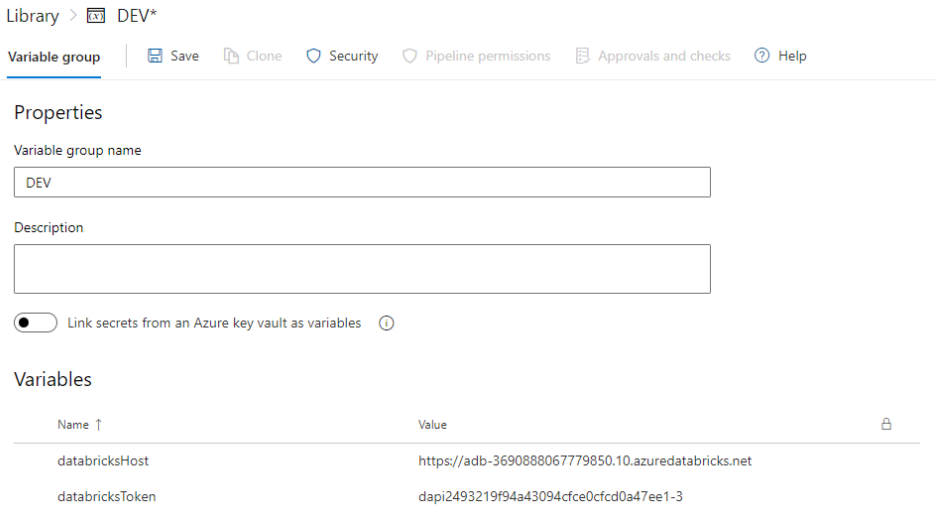


11. Now we need to create variable groups
    Go to Pipeline side tab > Library > New Variable Group



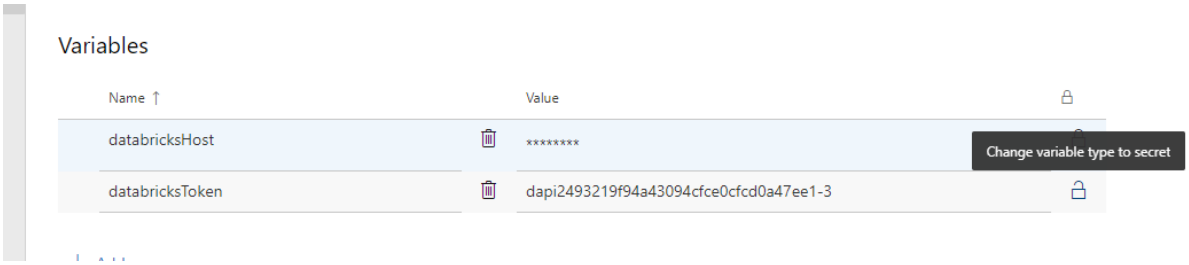


12. Add the group name and variable names and values

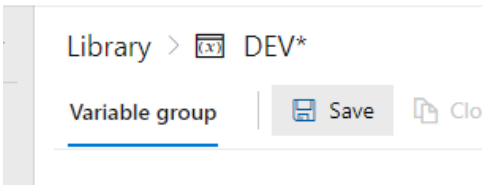


13. The name DEV is from what we defined in our yaml script

14. You can also turn them Mask /invisible

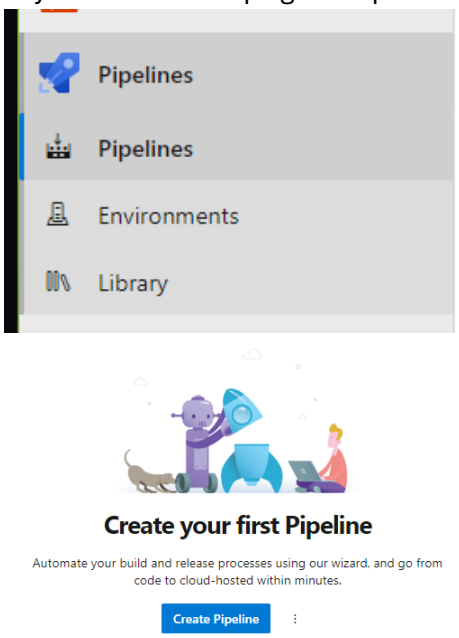


15. Save

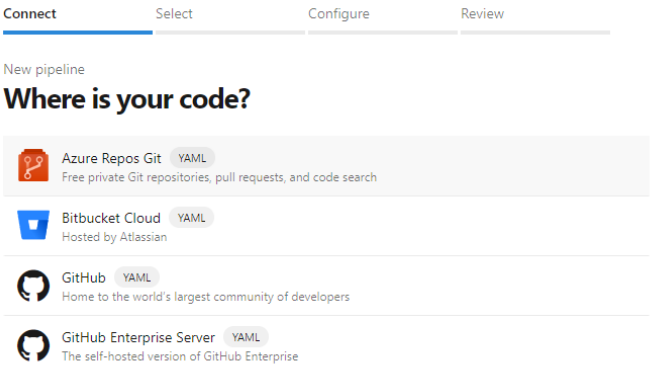


16. Using the Variable Group we created earlier we will be creating pipeline following these steps

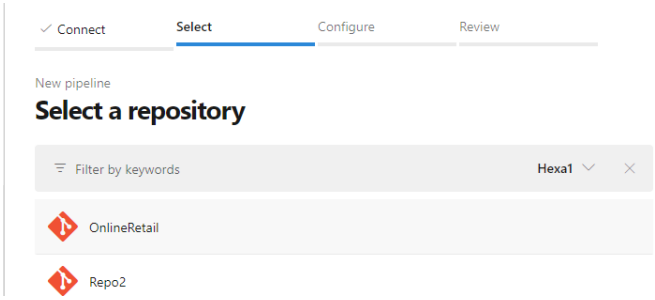
17. In your Azure DevOps go to Pipeline side tab



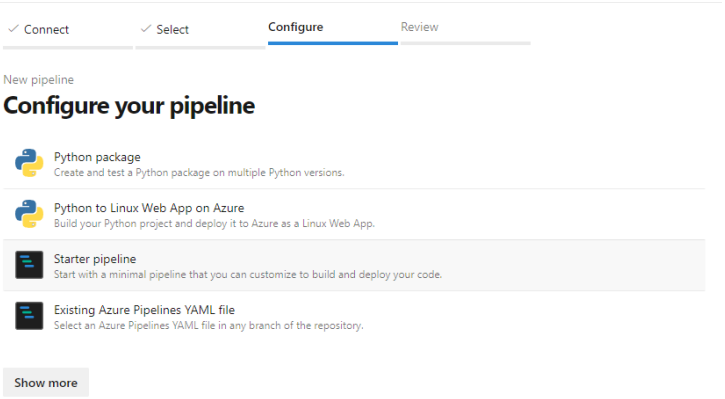
18. Choose azure repo



19. Select Repo



20. Starter Pipeline



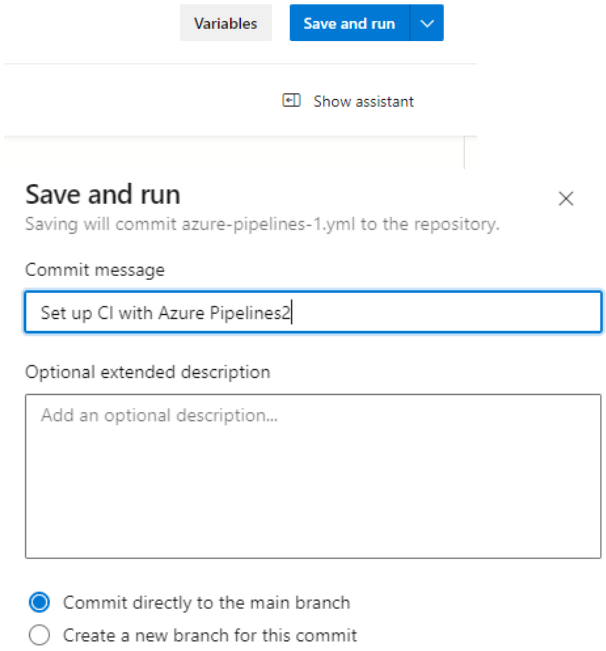
21. In the YAML script write this

```
pool:
  vmImage: ubuntu-latest

variables:
- group: 'DEV'
- name: branchName
  value: $(Build.SourceBranch)
- name: FolderName
  value: release

steps:

# Step 1: Checkout Repository with Persisted Credentials
- checkout: self
  displayName: 'Checkout Repository'
  fetchDepth: 0
  persistCredentials: true  # Ensures authentication token is used
for git commands

# Step 2: Set Git Identity for Commit
- script: |
    git config --global user.email "ci-pipeline@yourdomain.com"
    git config --global user.name "CI Pipeline"
  displayName: 'Set Git Identity'

# Step 3: Install Databricks CLI
- script: |
    pip install databricks-cli
  displayName: "Install Databricks CLI"

# Step 4: Configure Databricks CLI
- script: |
    echo "$(databricksHost)
    $(databricksToken)" | databricks configure --token
  displayName: 'Configure Databricks CLI'
```

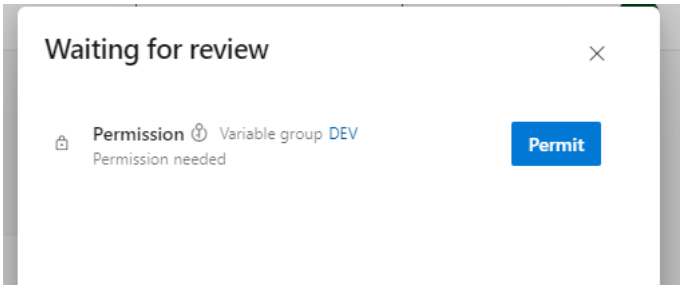
```
# Step 5: Test Databricks CLI Connection
- script: |
    databricks workspace ls
  displayName: 'Test Databricks CLI Connection'

# Step 6: Fetch All Branches and Checkout Prod Branch
- script: |
    git fetch --all
    git checkout prod || git checkout -b prod
  displayName: 'Fetch and Checkout Prod Branch'

# Step 7: Merge Main into Prod
- script: |
    git merge origin/main --no-ff --commit -m "Merge changes from
main branch"
  displayName: 'Merge Main into Prod'

# Step 8: Push Changes to Prod Branch
- script: |
    git push origin prod
  displayName: 'Push Changes to Prod Branch'

# Step 9: Publish Updated Prod Branch Files as Pipeline Artifact
- task: PublishPipelineArtifact@1
  inputs:
    targetPath: '$(Build.Repository.LocalPath)/'
    artifact: 'Databricks'
    publishLocation: 'pipeline'
  displayName: 'Publish Prod Branch Files as Artifact'

# Step 10: Download Pipeline Artifact
- task: DownloadPipelineArtifact@2
  inputs:
    source: current
    artifact: 'Databricks'
    downloadPath: $(System.ArtifactsDirectory)/databricks
  displayName: 'Download Prod Files Artifact'

# Step 11: List Downloaded Files
- script: |
    ls $(System.ArtifactsDirectory)/databricks
  displayName: 'List Downloaded Artifacts'

# Step 12: Delete Old Release Folder in Databricks
- script: |
    FOLDER=/$(FolderName)
    echo "Folder to delete: $FOLDER"
    databricks workspace rm $FOLDER --recursive
  displayName: 'Delete Old Release Folder'

# Step 13: Deploy New Release to Databricks
```

```
  - script: |
      FOLDER=/$(FolderName)
      echo "Folder for new release: $FOLDER"
      databricks workspace import_dir
  $(System.ArtifactsDirectory)/databricks $FOLDER --exclude-hidden-
  files
    displayName: 'Deploy New Release to Databricks'
```

22. Now Save and Run after Reviewing your YAML

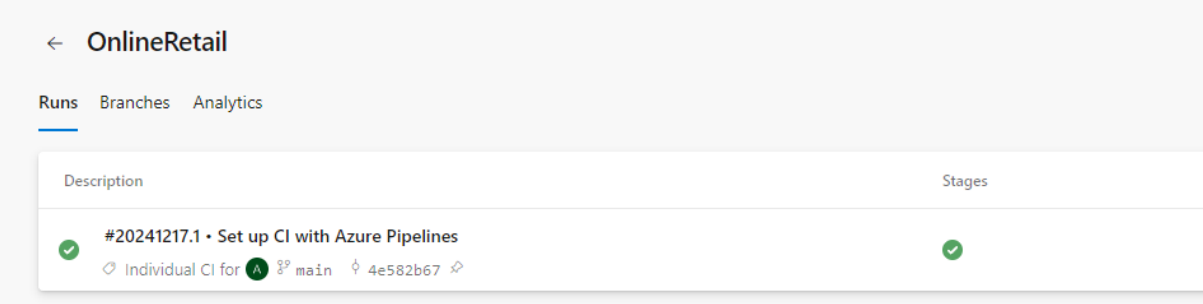


23. Permit if asked

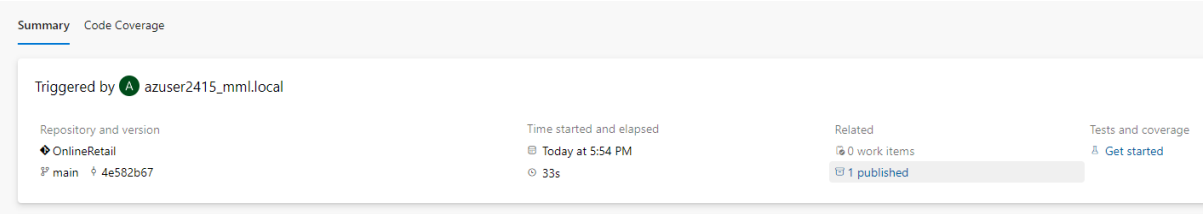


24. Now you have a pipeline to pull and merge changes from main branch to production branch whenever any changes occur in main branch and it also delivers the latest code from main branch to the release folder in our workspace

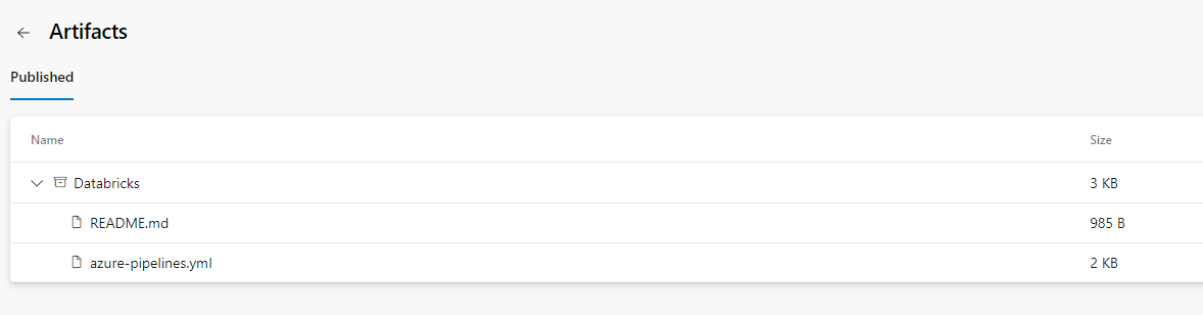
25. Refresh your databricks page and you will see that the pipeline is running



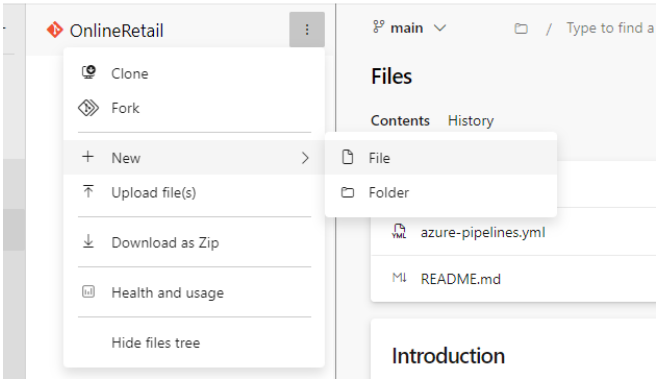
26. Now you can see it says 1 published

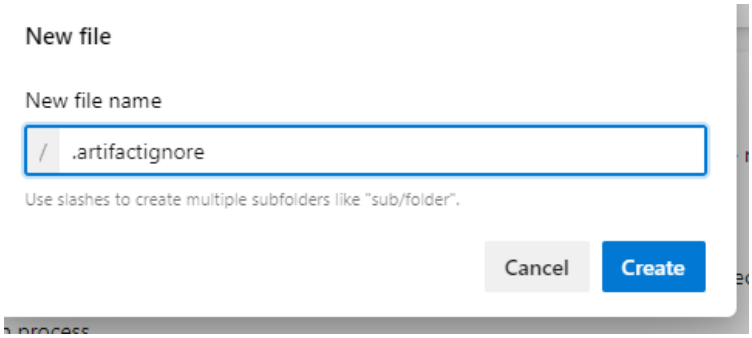


27. Click on it and see the artifacts it created

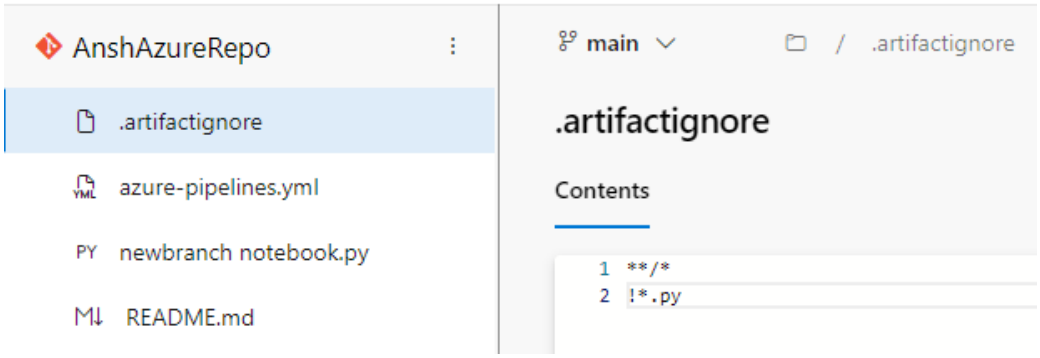


28. It has created an artifact for all items in repo even the YAML file which we do not want
    So in our repo we can create .artifactignore file





29. In the .artifactignore file write
    **/*
    !*.py

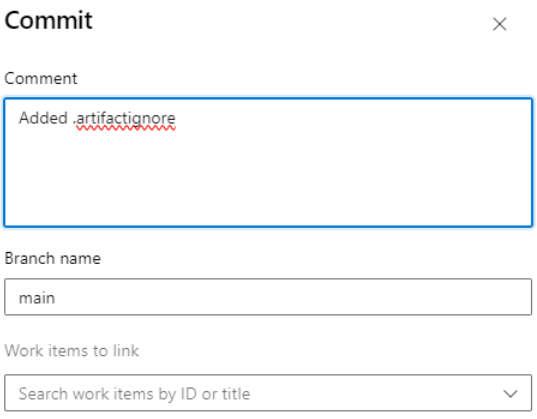


**/* means to take everything in repo

!*.py means ignore the ones which are .py files

Essentially meaning add all files of directory which are not .py files into the .artifactignore

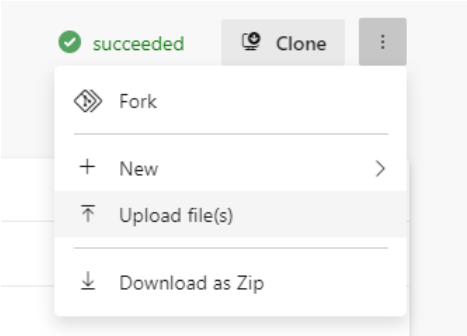
30. Commit



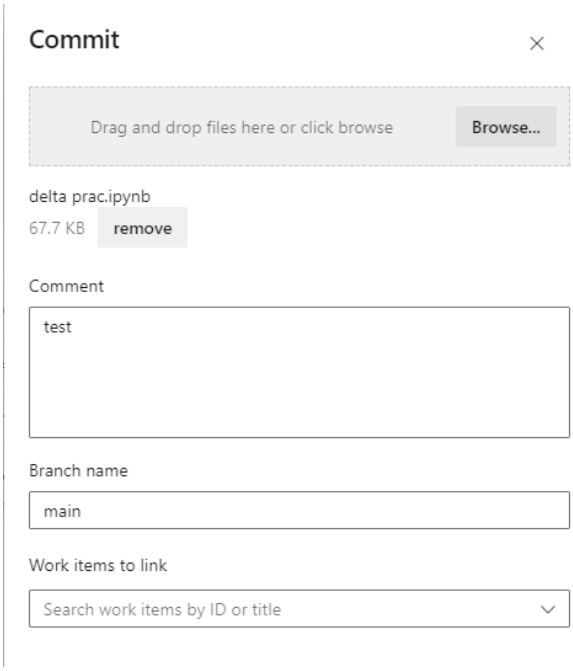
3. **Save and run the pipeline to verify its functionality.**

As a test uploading a random notebook to main branch to test the working of pipeline

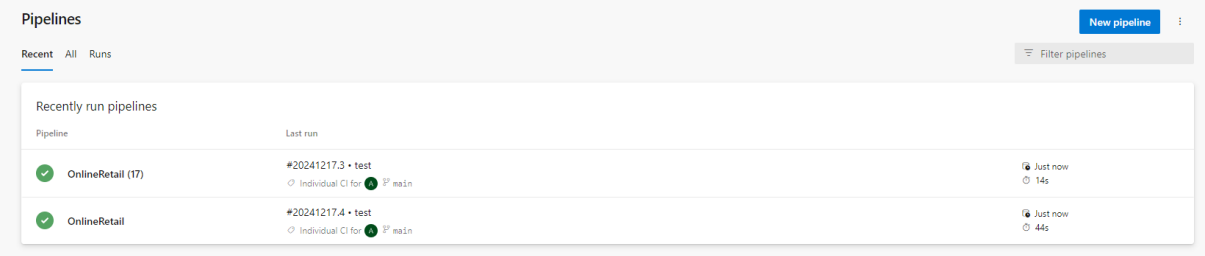
1. Uploading notebook to main branch



2. Committing changes

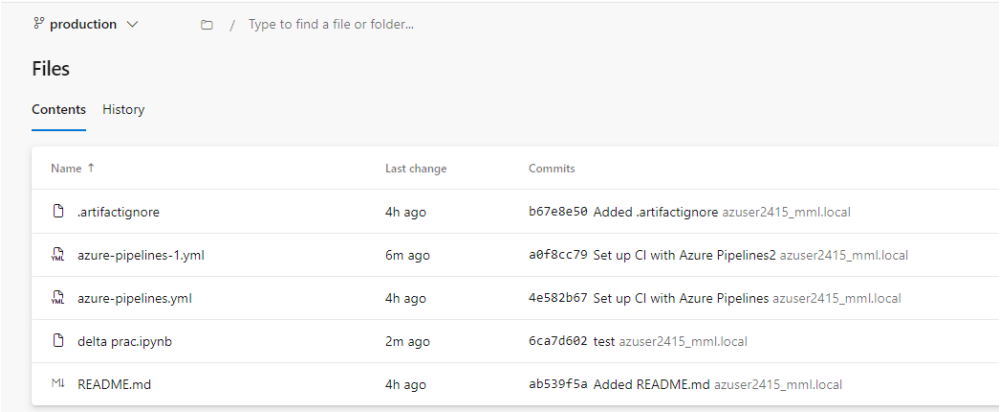


3. Go to pipeline tab to check the pipelines

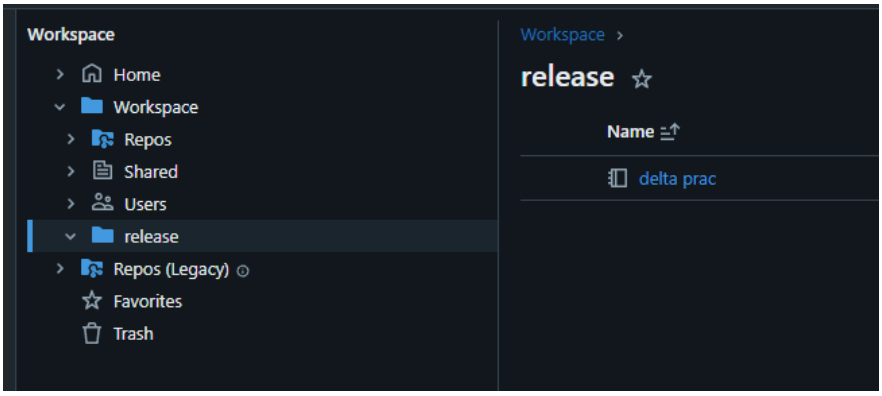


Both have executed successfully

4. Check for changes to be reflected in production branch



5. Check for updates to be reflected in the release folder



We have confirmed that the pipeline is running perfectly. We should go ahead and delete the test notebook we added.

Now our all our environment is setup and ready to perform tasks

=> <u>Data Work</u>:-

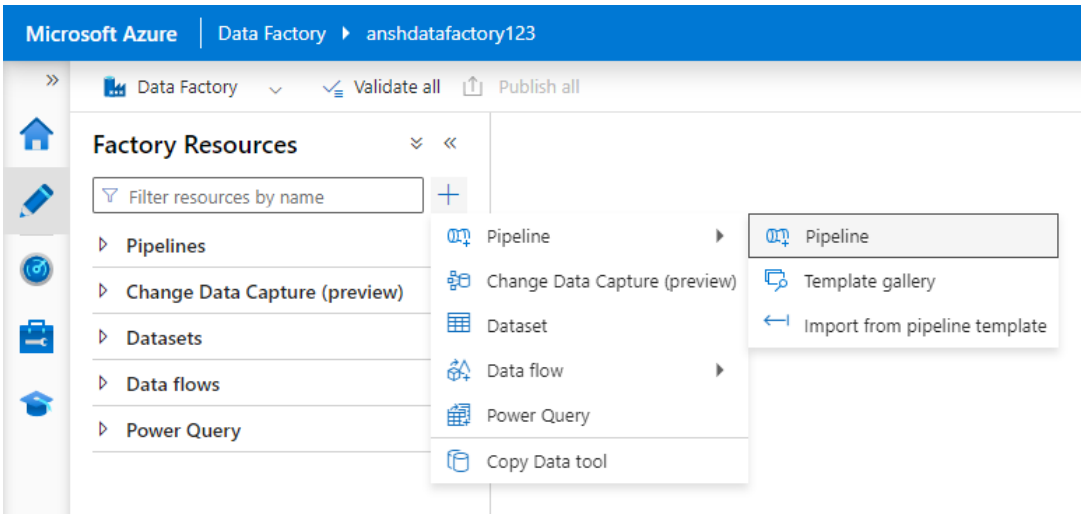
6. Bronze Pipeline (Raw Data Ingestion)

Purpose:

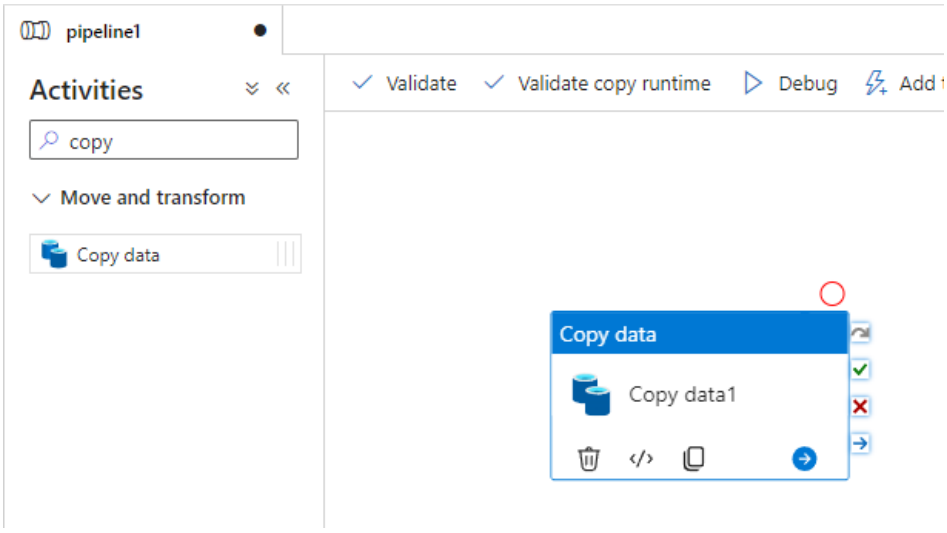
- **The Bronze layer stores raw data with minimal processing, acting as the single source of truth.**
- **Automating this process ensures data consistency and repeatability.**

Steps:

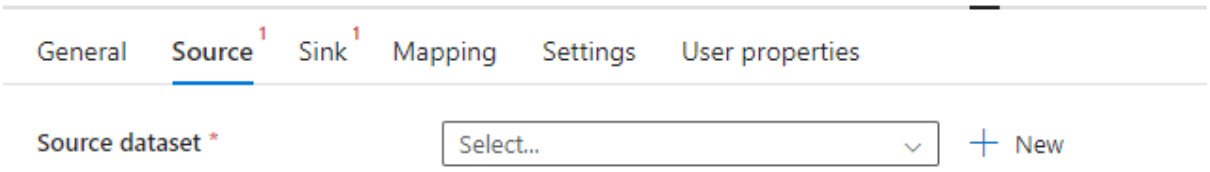
1. **Open Azure Data Factory and create a new pipeline.**



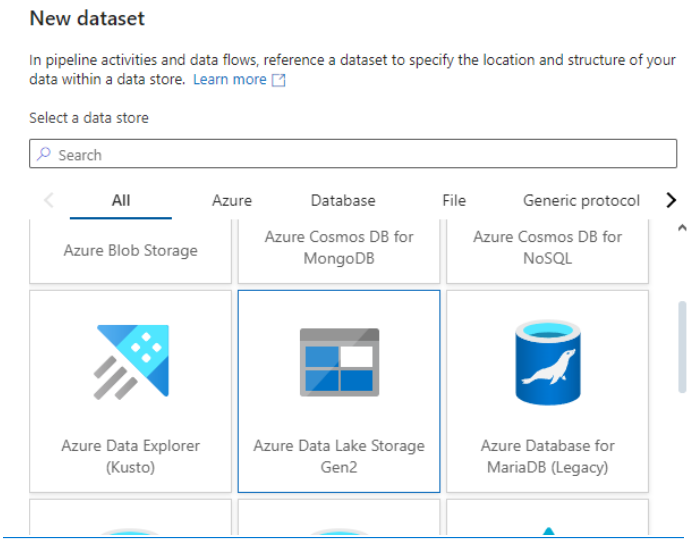
2. **Use the Copy Data activity to transfer raw data from the `rawdata` container to the `bronze` container.**

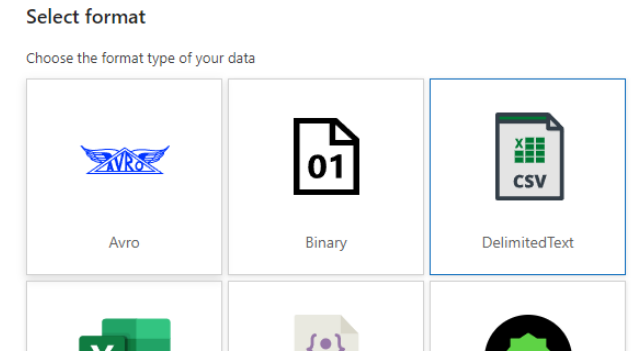


3. **Configure the source as the raw data container and the sink as the bronze container.**

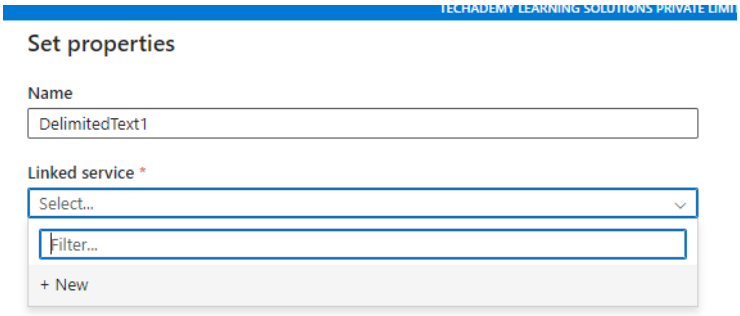


4. **Select Data Lake Storage Gen2 > DelimitedText (csv) which is our file type**

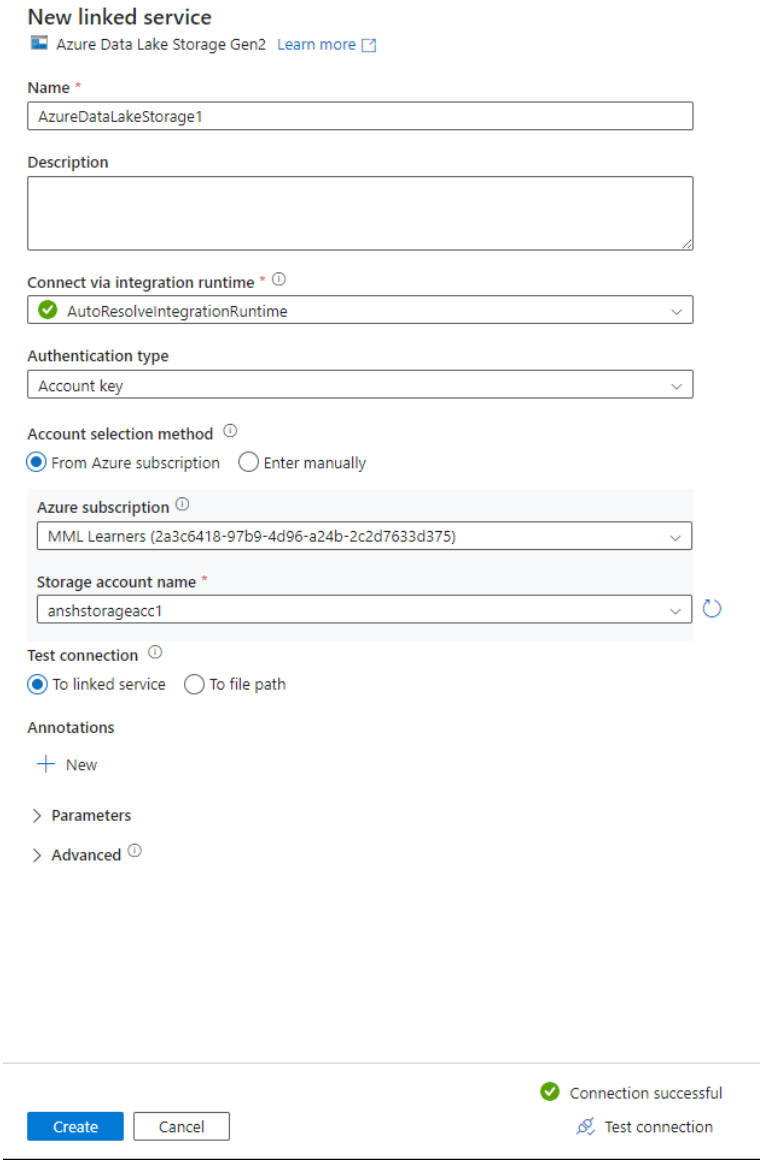




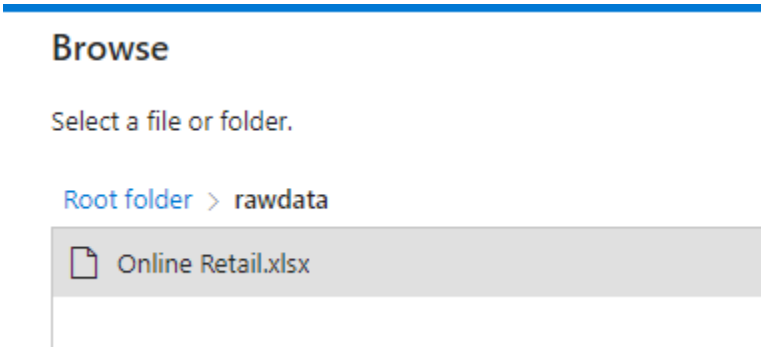
5. **Now we need to create a new Linked Service**

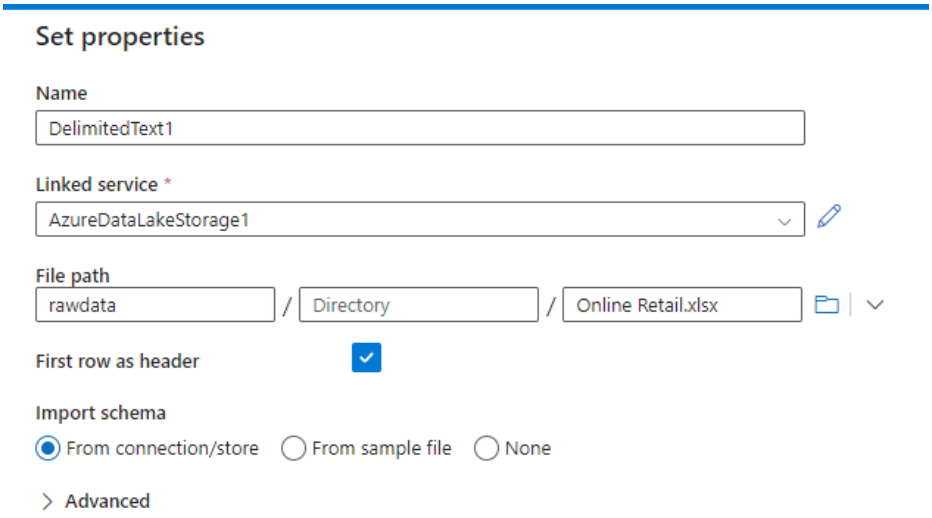


6. **Select your azure subscription and storage account name and test connection on bottom right. Then click on create**

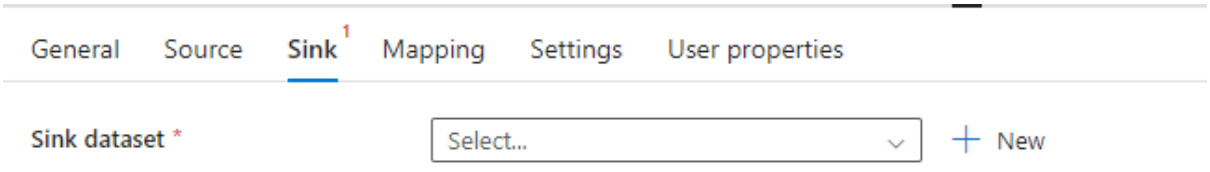


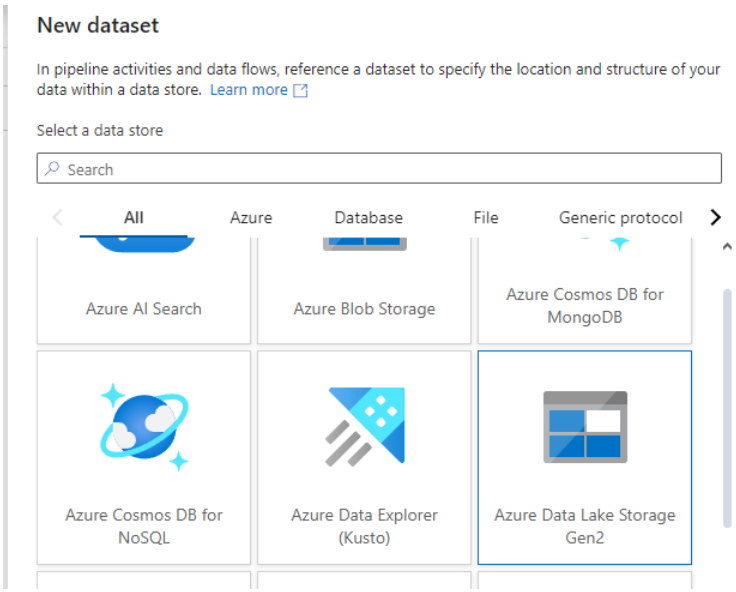
7. **Next you need to browse for your file**



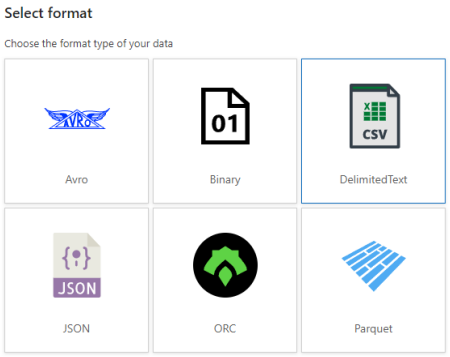


8. **Now you source is done we need to select sink**
   Go to the sink tab > New > Data Lake Storage Gen2

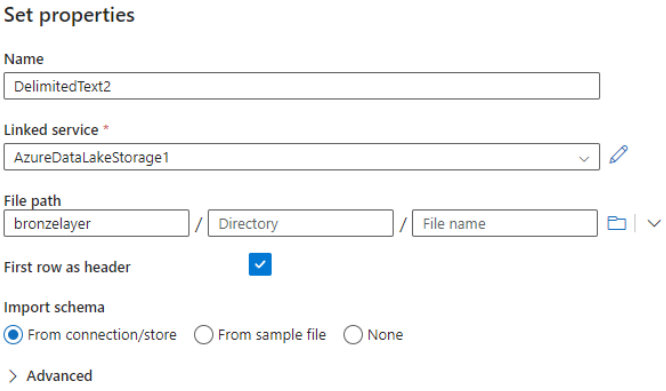




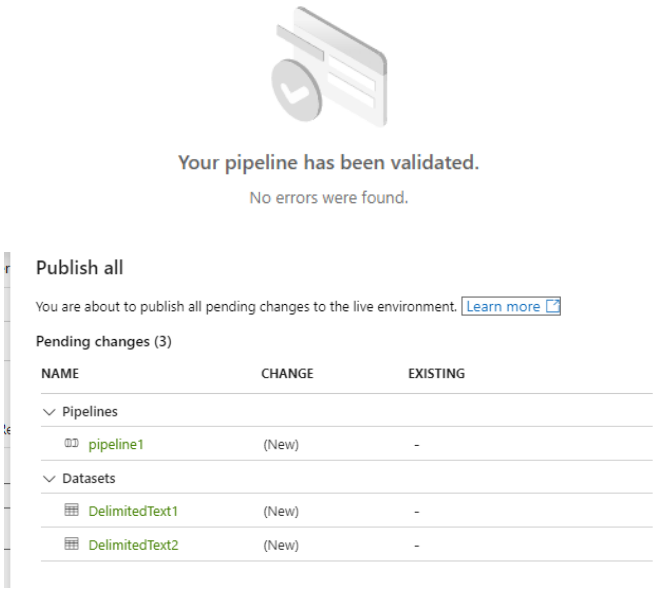
9. **We will not be converting our data to parquet files at this stage. It will be performed later in a silver layer. Currently our goal is to save the raw data in the Bronze Layer Container.**
   Select the DelimitedText option again.



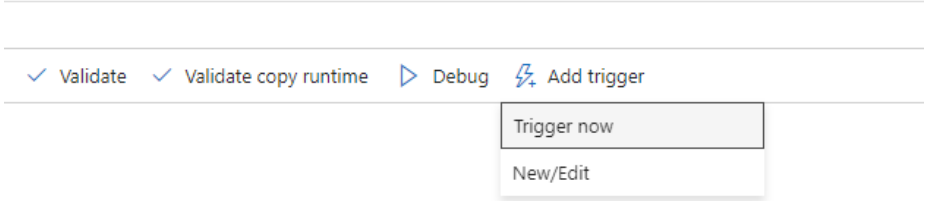
10. **Select the bronzelayer container as the sink path**



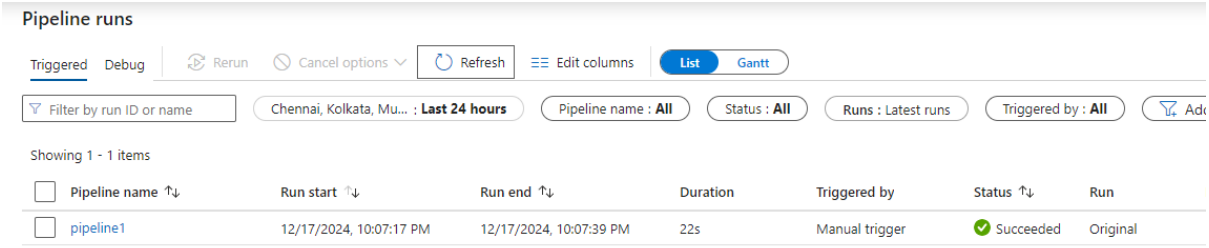
11. Test, Validate and publish the pipeline.



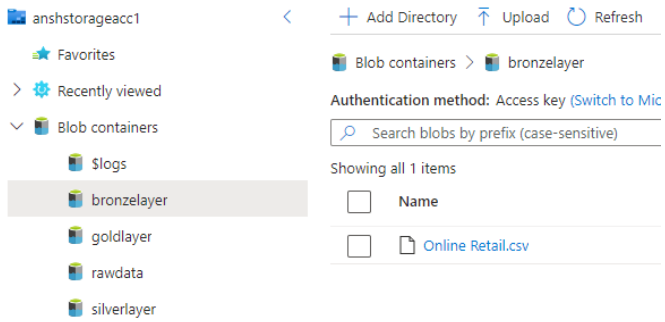
12. Trigger the pipeline



13. You can check the pipeline in the Monitor side tab



14. Check your bronzelayer container. The raw files are uploaded there



7. Silver Layer (Data Cleaning)

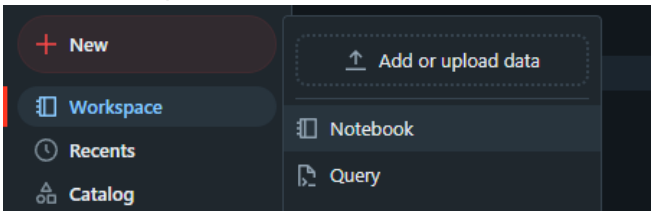
Purpose:

- **The Silver layer provides cleaned and enriched data, enabling downstream processes to work with consistent datasets.**

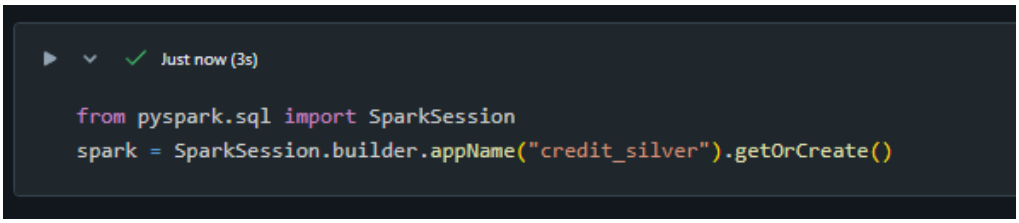
Steps:

Now that we have our containers ready, we need an Azure Databricks Workspace for ETL transformations

1. Launch the Azure Databricks workspace we created earlier
2. Go to your repo folder and switch to development branch
3. In the development branch click +New > Notebook



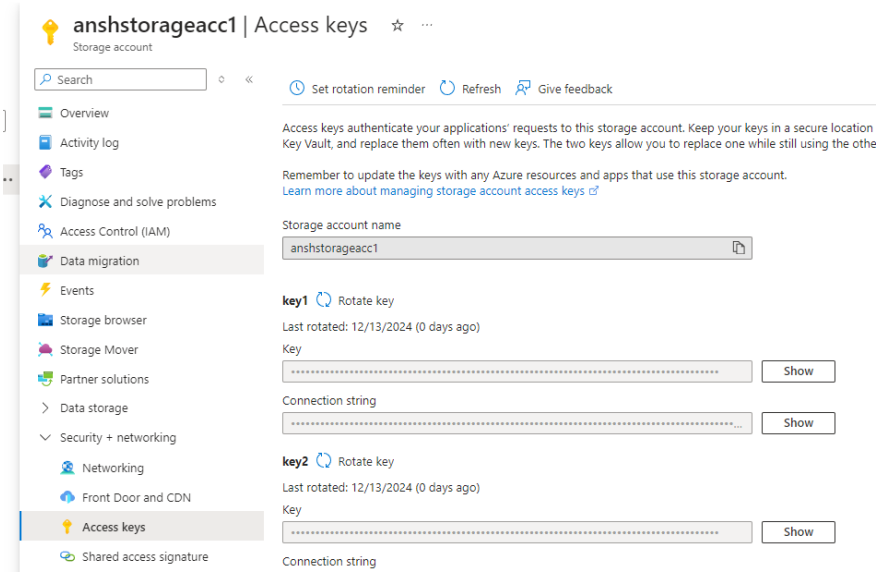
1. Create a spark session



EXTRACTION:

2. Mount your bronzelayer container to your workspace
   define your source
   source="wasbs://{container_name}@{storage_account}.blob.core.windows.net/",
   Mounting point
   mount_point="/path "
   Configurations
   extra_configs={f"fs.azure.account.key.{storage_account}.blob.core.windows.net":"{access_key_of_storage_account}"}

   To grab the access key go to your storage account > Security + Networking > Access Keys



Rotate the key once to make sure it is fresh and click on show in key 1 to copy


```
dbutils.fs.mount(
    source="wasbs://bronzelayer@anshstorageacc1.blob.core.windows.net/",
    mount_point="/mnt/bronze",
    extra_configs={f"fs.azure.account.key.anshstorageacc1.blob.core.windows.net":"yjYkxy/4lM16tOdGB95ttNjLhXoQ4ljG9n4iajm4ayIRTX8hY+hFB4pTAXYirbgAD7DXMSZ5pRCH+ASt
)
```

3. Read the data from the container

```
df=spark.read.csv('dbfs:/mnt/bronze/Online Retail.csv', header=True, inferSchema=True)
```

(2) Spark Jobs

Table +

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
1	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	01-12-2010 08:26	2.55	17850	United Kingdom
2	536365	71053	WHITE METAL LANTERN	6	01-12-2010 08:26	3.39	17850	United Kingdom
3	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	01-12-2010 08:26	2.75	17850	United Kingdom
4	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	01-12-2010 08:26	3.39	17850	United Kingdom
5	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	01-12-2010 08:26	3.39	17850	United Kingdom
6	536365	22752	SET 7 BABUSHKA NESTING BOXES	2	01-12-2010 08:26	7.65	17850	United Kingdom
7	536365	21730	GLASS STAR FROSTED T-LIGHT HOLDER	6	01-12-2010 08:26	4.25	17850	United Kingdom
8	536366	22633	HAND WARMER UNION JACK	6	01-12-2010 08:28	1.85	17850	United Kingdom
9	536366	22632	HAND WARMER RED POLKA DOT	6	01-12-2010 08:28	1.85	17850	United Kingdom
10	536367	84879	ASSORTED COLOUR BIRD ORNAMENT	32	01-12-2010 08:34	1.69	13047	United Kingdom
11	536367	22745	POPPY'S PLAYHOUSE BEDROOM	6	01-12-2010 08:34	2.1	13047	United Kingdom
12	536367	22748	POPPY'S PLAYHOUSE KITCHEN	6	01-12-2010 08:34	2.1	13047	United Kingdom
13	536367	22749	FELTCRAFT PRINCESS CHARLOTTE DOLL	8	01-12-2010 08:34	3.75	13047	United Kingdom
14	536367	22310	IVORY KNITTED MUG COSY	6	01-12-2010 08:34	1.65	13047	United Kingdom
15	536367	84969	BOX OF 6 ASSORTED COLOUR TEASPOONS	6	01-12-2010 08:34	4.25	13047	United Kingdom

TRANSFORMATION:

4. Printing the schema of df

```
df.printSchema()
```

```
root
 |-- InvoiceNo: string (nullable = true)
 |-- StockCode: string (nullable = true)
 |-- Description: string (nullable = true)
 |-- Quantity: integer (nullable = true)
 |-- InvoiceDate: string (nullable = true)
 |-- UnitPrice: double (nullable = true)
 |-- CustomerID: integer (nullable = true)
 |-- Country: string (nullable = true)
```

The InvoiceDate column is of string data type

5. converting the InvoiceDate column into a date and time format

```
from pyspark.sql.functions import to_timestamp

# Convert InvoiceDate to a datetime column
df = df.withColumn("InvoiceDate", to_timestamp("InvoiceDate", "dd-MM-yyyy HH:mm"))

df.printSchema()
df.select("InvoiceDate").show(5, truncate=False)
```

```
root
 |-- InvoiceNo: string (nullable = true)
 |-- StockCode: string (nullable = true)
 |-- Description: string (nullable = true)
 |-- Quantity: integer (nullable = true)
 |-- InvoiceDate: timestamp (nullable = true)
 |-- UnitPrice: double (nullable = true)
 |-- CustomerID: integer (nullable = true)
 |-- Country: string (nullable = true)

+-------------------+
|InvoiceDate        |
+-------------------+
|2010-12-01 08:26:00|
|2010-12-01 08:26:00|
|2010-12-01 08:26:00|
|2010-12-01 08:26:00|
|2010-12-01 08:26:00|
+-------------------+
only showing top 5 rows
```

6. Checking for number of rows with unique combinations of InvoiceNo and StockCode, taking the combination as a unique identifier

```
# Count rows with unique combinations of InvoiceNo and StockCode
unique_count = df.select("InvoiceNo", "StockCode").distinct().count()
print(f"Number of unique rows with distinct combinations of InvoiceNo and StockCode: {unique_count}")
```

▸ (3) Spark Jobs

```
Number of unique rows with distinct combinations of InvoiceNo and StockCode: 531225
```

7. Checking how many null values are present in each row

```
from pyspark.sql.functions import col, sum, when

null_counts = df1.select(
    [
        sum(when(col(c).isNull(), 1).otherwise(0)).alias(c)
        for c in df1.columns
    ]
)

null_counts.display()
```

```
+---------+---------+-----------+--------+-----------+---------+----------+-------+
|InvoiceNo|StockCode|Description|Quantity|InvoiceDate|UnitPrice|CustomerID|Country|
+---------+---------+-----------+--------+-----------+---------+----------+-------+
|        0|        0|       1454|       0|          0|        0|    135080|      0|
+---------+---------+-----------+--------+-----------+---------+----------+-------+
```

8. Dropping any rows with NULL values

```
df = df.dropna()
```

▸ df: pyspark.sql.dataframe.DataFrame =

```
# Count rows with unique combinations of InvoiceNo and StockCode after dropping NULL values
unique_count = df.select("InvoiceNo", "StockCode").distinct().count()
print(f"Number of unique rows with distinct combinations of InvoiceNo and StockCode: {unique_count}")
```

▸ (3) Spark Jobs

```
Number of unique rows with distinct combinations of InvoiceNo and StockCode: 396681
```

9. **Filtering the dataset**

Removing rows where Quantity is 0 or less

```
from pyspark.sql.functions import col

# Removing rows where Quantity is 0 or less
df_filtered = df.filter(col("Quantity") > 0)
```

10. Removing rows where UnitPrice is 0 or less

```
# Removing rows where UnitPrice is 0 or less
df_filtered = df_filtered.filter(col("UnitPrice") > 0)
```

11. Filter out rows where Quantity is not an integer (or is a decimal value)

```
# Filter out rows where Quantity is not an integer (or is a decimal value)
df_filtered = df_filtered.filter(col("Quantity") % 1 == 0)
```

12. Since this dataset stores each item of an invoice in a separate row. Keeping only 1 record for each order of a customer at a given datetime, so we can later find which customers have reordered in the future

```
df_unique = df_filtered.dropDuplicates(["CustomerID", "InvoiceDate"])
df_unique.orderBy("InvoiceNo").show()
```

(2) Spark Jobs

df_unique: pyspark.sql.dataframe.DataFrame = [InvoiceNo: string, StockCode: string ... 6 more fields]

InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
536365	85123A	WHITE HANGING HEA...	6	2010-12-01 08:26:00	2.55	17850	United Kingdom
536366	22633	HAND WARMER UNION...	6	2010-12-01 08:28:00	1.85	17850	United Kingdom
536367	84879	ASSORTED COLOUR B...	32	2010-12-01 08:34:00	1.69	13047	United Kingdom
536369	21756	BATH BUILDING BLO...	3	2010-12-01 08:35:00	5.95	13047	United Kingdom
536370	22728	ALARM CLOCK BAKEL...	24	2010-12-01 08:45:00	3.75	12583	France
536371	22086	PAPER CHAIN KIT 5...	80	2010-12-01 09:00:00	2.55	13748	United Kingdom
536372	22632	HAND WARMER RED P...	6	2010-12-01 09:01:00	1.85	17850	United Kingdom
536373	85123A	WHITE HANGING HEA...	6	2010-12-01 09:02:00	2.55	17850	United Kingdom

13. Getting a count of number of unique orders for each customer

```
from pyspark.sql.functions import count

# Group by CustomerID and count the occurrences
df_customer_multiple = df_unique.groupBy("CustomerID") \
                                .agg(count("CustomerID").alias("customer_count"))
```

```
df_customer_multiple.show(10)
```

▸ (3) Spark Jobs

```
+----------+--------------+
|CustomerID|customer_count|
+----------+--------------+
|     15727|             7|
|     17389|            34|
|     16503|             4|
|     14570|             2|
|     17420|             3|
|     13285|             4|
|     13623|             5|
|     15447|             1|
|     16386|             2|
|     14450|             3|
+----------+--------------+
only showing top 10 rows
```

14. Now we can join this df to our df_filtered, this results in a new column which shows how many times a customer placed an order in our original df

```
# Perform a left join between df_filtered and df_customer_multiple on CustomerID
df_filtered_with_flag = df_filtered.join(df_customer_multiple, on="CustomerID", how="left")
```

```
df_filtered_with_flag.show()
```

▸ (4) Spark Jobs

```
+----------+---------+---------+--------------------+--------+-------------------+---------+--------------+--------------+
|CustomerID|InvoiceNo|StockCode|         Description|Quantity|        InvoiceDate|UnitPrice|       Country|customer_count|
+----------+---------+---------+--------------------+--------+-------------------+---------+--------------+--------------+
|     17850|   536365|   85123A|WHITE HANGING HEA...|       6|2010-12-01 08:26:00|     2.55|United Kingdom|            33|
|     17850|   536365|    71053| WHITE METAL LANTERN|       6|2010-12-01 08:26:00|     3.39|United Kingdom|            33|
|     17850|   536365|   84406B|CREAM CUPID HEART...|       8|2010-12-01 08:26:00|     2.75|United Kingdom|            33|
|     17850|   536365|   84029G|KNITTED UNION FLA...|       6|2010-12-01 08:26:00|     3.39|United Kingdom|            33|
|     17850|   536365|   84029E|RED WOOLLY HOTTIE...|       6|2010-12-01 08:26:00|     3.39|United Kingdom|            33|
|     17850|   536365|    22752|SET 7 BABUSHKA NE...|       2|2010-12-01 08:26:00|     7.65|United Kingdom|            33|
|     17850|   536365|    21730|GLASS STAR FROSTE...|       6|2010-12-01 08:26:00|     4.25|United Kingdom|            33|
|     17850|   536366|    22633|HAND WARMER UNION...|       6|2010-12-01 08:28:00|     1.85|United Kingdom|            33|
|     17850|   536366|    22632|HAND WARMER RED P...|       6|2010-12-01 08:28:00|     1.85|United Kingdom|            33|
|     13047|   536367|    84879|ASSORTED COLOUR B...|      32|2010-12-01 08:34:00|     1.69|United Kingdom|             9|
|     13047|   536367|    22745|POPPY'S PLAYHOUSE...|       6|2010-12-01 08:34:00|      2.1|United Kingdom|             9|
|     13047|   536367|    22748|POPPY'S PLAYHOUSE...|       6|2010-12-01 08:34:00|      2.1|United Kingdom|             9|
|     13047|   536367|    22749|FELTCRAFT PRINCES...|       8|2010-12-01 08:34:00|     3.75|United Kingdom|             9|
|     13047|   536367|    22310|IVORY KNITTED MUG...|       6|2010-12-01 08:34:00|     1.65|United Kingdom|             9|
|     13047|   536367|    84969|BOX OF 6 ASSORTED...|       6|2010-12-01 08:34:00|     4.25|United Kingdom|             9|
|     13047|   536367|    22623|BOX OF VINTAGE JI...|       3|2010-12-01 08:34:00|     4.95|United Kingdom|             9|
```

15. Making a new column Flag_reorder where the value is 1 if the customer has reordered or else 0 if the customer never reordered from the store

```
from pyspark.sql.functions import when

# Assuming customer_count is a column in df_filtered_with_flag
df_filtered_with_flag = df_filtered_with_flag.withColumn(
    "Flag_reorder", when(col("customer_count") == 1, 0).otherwise(1)
)

df_filtered_with_flag.show()
```

LOAD:

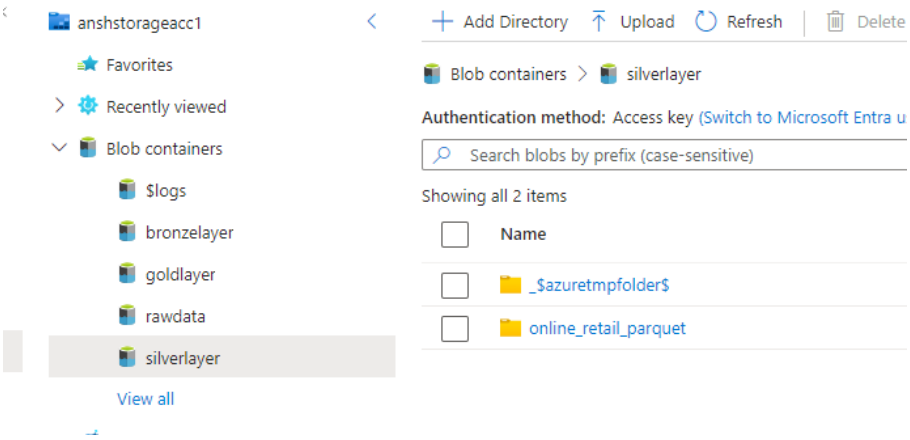
16. Saving the data into silverlayer container
    Mounting the container

```
#Saving this data in our silver layer container
#mounting
dbutils.fs.mount(
    source="wasbs://silverlayer@anshstorageacc1.blob.core.windows.net/",
    mount_point="/mnt/silver",
    extra_configs={f"fs.azure.account.key.anshstorageacc1.blob.core.windows.net":"yjYkxy/4lM16tOdGB95ttNjLhXoQ4ljG9n4iajm4ayIRTX8hY+hFB4pTAXYirbgAD7DXMSZ5pRCH+AStqwkNgw=="}
)
```

```
True
```

17. Writing the data in form of parquet files

```
1  df_filtered_with_flag.write.format("parquet").mode("overwrite").save("/mnt/silver/online_retail_parquet")
```



8. Gold Layer (Data Aggregation)

Purpose:

- **The Gold layer stores business-ready data for analytics and reporting.**

Steps:

Gold Layer (Data Enrichment and Aggregation) In the Gold layer, the data is enriched with business-level aggregations and summaries.

Now create a new notebook for Gold Layer

1. Create your spark session

```
from pyspark.sql import SparkSession
spark = SparkSession.builder.appName("credit_gold").getOrCreate()
```

EXTRACTION:

2. Mount your silverlayer container (if required)

```
%fs ls dbfs:/mnt/silver/
```

Table

	path	name	size	modificationTime
1	dbfs:/mnt/silver/online_retail_parqu...	online_retail_parqu...	0	0

LOAD:

3. Load the data from your silverlayer container

```
# Read the Parquet file into a DataFrame
df = spark.read.format("parquet").load("dbfs:/mnt/silver/online_retail_parquet/")
```

```
df.show(10)
```

(1) Spark Jobs

CustomerID	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Country	customer_count	Flag_reorder
18119	537567	90178A	AMBER CHUNKY GLAS...	1	2010-12-07 11:59:00	11.95	United Kingdom	1	0
18119	537567	21864	UNION JACK FLAG P...	1	2010-12-07 11:59:00	2.1	United Kingdom	1	0
18119	537567	21916	SET 12 RETRO WHIT...	1	2010-12-07 11:59:00	0.42	United Kingdom	1	0
18119	537567	21866	UNION JACK FLAG L...	1	2010-12-07 11:59:00	1.25	United Kingdom	1	0
18119	537567	21916	SET 12 RETRO WHIT...	1	2010-12-07 11:59:00	0.42	United Kingdom	1	0
18119	537567	20751	FUNKY WASHING UP ...	1	2010-12-07 11:59:00	2.1	United Kingdom	1	0
18119	537567	21327	SKULLS WRITING SET	1	2010-12-07 11:59:00	1.65	United Kingdom	1	0
18119	537567	21328	BALLOONS WRITING...	1	2010-12-07 11:59:00	1.65	United Kingdom	1	0
18119	537567	21865	PINK UNION JACK ...	1	2010-12-07 11:59:00	2.1	United Kingdom	1	0
18119	537567	21867	PINK UNION JACK ...	1	2010-12-07 11:59:00	1.25	United Kingdom	1	0

TRANSFORMATION:

4. Performing Aggregations:
   Since each item of invoices are listed as a separate row we need to group the rows by InvoiceID

```
from pyspark.sql.functions import first

df_grouped = df.groupBy("InvoiceNo").agg(
    first("CustomerID").alias("CustomerID"),
    first("Country").alias("Country"),
    first("customer_count").alias("customer_count"),
    first("Flag_reorder").alias("Flag_reorder")
)

df_grouped.show()
```

```
+---------+----------+--------------+--------------+------------+
|InvoiceNo|CustomerID|       Country|customer_count|Flag_reorder|
+---------+----------+--------------+--------------+------------+
|   541783|     16618|United Kingdom|             5|           1|
|   544303|     18116|United Kingdom|             8|           1|
|   537691|     13842|United Kingdom|             9|           1|
|   541518|     12451|   Switzerland|             5|           1|
|   550831|     13534|United Kingdom|            22|           1|
|   550617|     13376|United Kingdom|             3|           1|
|   562204|     16324|United Kingdom|             3|           1|
|   554792|     12547|         Spain|             2|           1|
|   553390|     17841|United Kingdom|           124|           1|
|   552191|     16832|United Kingdom|             3|           1|
|   554072|     13555|United Kingdom|             4|           1|
|   553658|     16818|United Kingdom|            11|           1|
```

5. Now we also need a df with only data of individual customers

```
df_customer_only = df.groupBy("CustomerID").agg(
    first("Country").alias("Country"),
    first("customer_count").alias("customer_count"),
    first("Flag_reorder").alias("Flag_reorder")
)

df_customer_only.show()
```

```
+----------+--------------+--------------+------------+
|CustomerID|       Country|customer_count|Flag_reorder|
+----------+--------------+--------------+------------+
|     18119|United Kingdom|             1|           0|
|     13211|United Kingdom|             3|           1|
|     14560|United Kingdom|            22|           1|
|     16686|United Kingdom|             7|           1|
|     12455|        Cyprus|             6|           1|
|     18138|United Kingdom|             1|           0|
|     16940|United Kingdom|             3|           1|
|     18210|United Kingdom|             6|           1|
```

6. Finding out customer retention rate

```
from pyspark.sql.functions import col

#Customers who have placed only 1 order
customers_one = df.filter(col("Flag_reorder") == 0).count()
print(f"Number of customers with only 1 order placed: {customers_one}")

#Customers who have placed multiple orders
customers_multi = df.filter(col("Flag_reorder") == 1).count()
print(f"Number of customers with multiple orders placed: {customers_multi}")
```

```
Number of customers with only 1 order placed: 1495
Number of customers with multiple orders placed: 2843
```

Counting the number of customer with only 1 order and number of customers with multiple orders placed

7. **Customer Retention Rate:**

The customer retention rate measures the percentage of customers a business retains over a specific period. It indicates how good the business is at keeping its customers returning for future purchases or interactions.

Retention_rate = (Customers with multiple orders/Customers with single order)*100

```
#Percentage of returning customers
percentage = (customers_multi / (customers_one + customers_multi)) * 100
print(f"Customer Retention rate : {percentage:.2f}%")
```

```
Customer Retention rate : 65.54%
```

The Customer Retention Rate for the store in the past 1 year time period is 65.54%

8. **Customer Churn Rate**

Customer churn rate, also known as customer attrition rate, is a metric that measures the percentage of customers who stop using a company's product or service over a given period of time. It is commonly used by businesses to evaluate customer retention and satisfaction.

The formula for calculating the churn rate is:

Churn Rate = (Number of customers lost/Total Numbe of customers)*100

```
churn_rate = (customers_one / (customers_one + customers_multi)) * 100
print(f"The Churn Rate for the store is : {churn_rate:.2f}%")
```

```
The Churn Rate for the store is : 34.46%
```

The Churn Rate for the store in the past 1 year time period is 34.46%

LOAD:

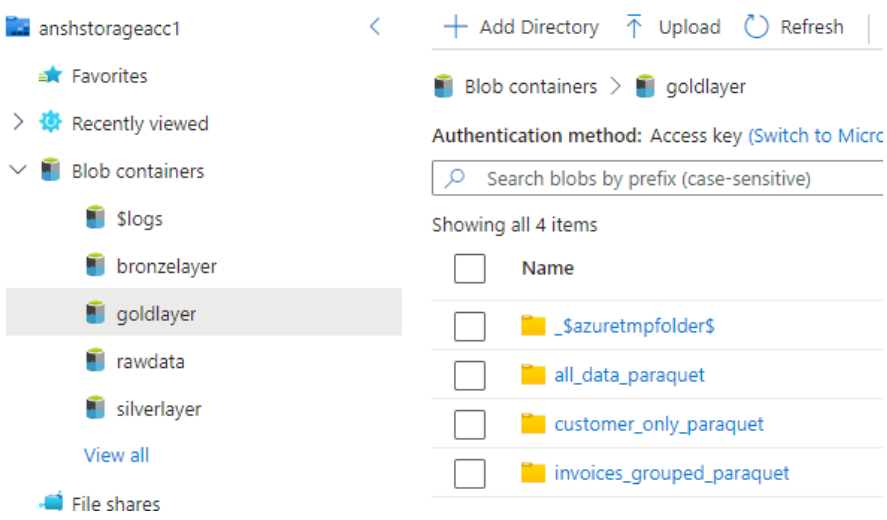
9. Mounting the goldlayer storage

```
#Saving this data in our gold layer container
#mounting
dbutils.fs.mount(
    source="wasbs://goldlayer@anshstorageacc1.blob.core.windows.net/",
    mount_point="/mnt/gold",
    extra_configs={f"fs.azure.account.key.anshstorageacc1.blob.core.windows.net":"bD2ueNu8QSJAFB2nDoa/PKCR7WsHsJHEAxwNP4nsO0izZ/gpKYv3UGpl0RgAtZojcW3Z1m4dn3eK+ASttqwPAA=="}
)
```

```
True
```

10. Saving all 3 data frames so that the which ever df is required can be used by analytics

```
df.write.format("parquet").mode("overwrite").save("/mnt/gold/all_data_paraquet")
df_grouped.write.format("parquet").mode("overwrite").save("/mnt/gold/invoices_grouped_paraquet")
df_customer_only.write.format("parquet").mode("overwrite").save("/mnt/gold/customer_only_paraquet")
```



9. Logistic Regression Model

Purpose:

- **Predicts customer churn likelihood, aiding in strategic decision-making.**

Steps:

Creating a logistic regression model to predict if a customer will be returning customer or a one time customer only

1. Creating spark session

```
03:53 PM (<1s)

1  from pyspark.sql import SparkSession
2  spark = SparkSession.builder.appName("logistic_regression").getOrCreate()
```

2. Loading the data
   Mount the container if required, here since we already have the container mounted in our databricks workspace we can directly load

```
1  %fs ls dbfs:/mnt/gold
```

Table

	path	name	size	modificationTime
1	dbfs:/mnt/gold/all_data_paraquet/	all_data_paraquet/	0	0
2	dbfs:/mnt/gold/customer_only_paraquet/	customer_only_paraquet/	0	0
3	dbfs:/mnt/gold/invoices_grouped_paraqu...	invoices_grouped_paraqu...	0	0

```
1  # Read the Parquet file into a DataFrame
2  data = spark.read.format("parquet").load("dbfs:/mnt/gold/all_data_paraquet/")
```

```
1  data.show(5)
```

(1) Spark Jobs

```
+----------+---------+---------+--------------------+--------+-------------------+---------+--------------+--------------+------------+
|CustomerID|InvoiceNo|StockCode|         Description|Quantity|        InvoiceDate|UnitPrice|       Country|customer_count|Flag_reorder|
+----------+---------+---------+--------------------+--------+-------------------+---------+--------------+--------------+------------+
|     18119|   537567|   90178A|AMBER CHUNKY GLAS...|       1|2010-12-07 11:59:00|    11.95|United Kingdom|             1|           0|
|     18119|   537567|    21864|UNION JACK FLAG P...|       1|2010-12-07 11:59:00|      2.1|United Kingdom|             1|           0|
|     18119|   537567|    21916|SET 12 RETRO WHIT...|       1|2010-12-07 11:59:00|     0.42|United Kingdom|             1|           0|
|     18119|   537567|    21866|UNION JACK FLAG L...|       1|2010-12-07 11:59:00|     1.25|United Kingdom|             1|           0|
|     18119|   537567|    21916|SET 12 RETRO WHIT...|       1|2010-12-07 11:59:00|     0.42|United Kingdom|             1|           0|
+----------+---------+---------+--------------------+--------+-------------------+---------+--------------+--------------+------------+
```

3. Getting schema

```
1  data.printSchema()
```

```
root
 |-- CustomerID: integer (nullable = true)
 |-- InvoiceNo: string (nullable = true)
 |-- StockCode: string (nullable = true)
 |-- Description: string (nullable = true)
 |-- Quantity: integer (nullable = true)
 |-- InvoiceDate: timestamp (nullable = true)
 |-- UnitPrice: double (nullable = true)
 |-- Country: string (nullable = true)
 |-- customer_count: long (nullable = true)
 |-- Flag_reorder: integer (nullable = true)
```

4. Dropping the columns "InvoiceNo", "Description", "InvoiceDate", "customer_count" as we will not be using them as features for Logistic Regression model

```
2  data = data.drop("InvoiceNo", "Description", "InvoiceDate", "customer_count")
3  data.show()
```

```
+----------+---------+--------+---------+--------------+------------+
|CustomerID|StockCode|Quantity|UnitPrice|       Country|Flag_reorder|
+----------+---------+--------+---------+--------------+------------+
|     18119|   90178A|       1|    11.95|United Kingdom|           0|
|     18119|    21864|       1|      2.1|United Kingdom|           0|
|     18119|    21916|       1|     0.42|United Kingdom|           0|
|     18119|    21866|       1|     1.25|United Kingdom|           0|
|     18119|    21916|       1|     0.42|United Kingdom|           0|
|     18119|    20751|       1|      2.1|United Kingdom|           0|
|     18119|    21327|       1|     1.65|United Kingdom|           0|
|     18119|    21328|       1|     1.65|United Kingdom|           0|
|     18119|    21865|       1|      2.1|United Kingdom|           0|
```

5. Getting a count for the number of distinct values in country

```
1  count = data.select("Country").distinct().count()
2  print(count)
```

```
▸ (3) Spark Jobs
37
```

Since there are 37 unique countries performing onehotencoder will massively increase the complexity of our dataset. So we will only be performing Indexing

6. Performing Indexing for the columns Country and StockCode as they are string values. We need to pass integer or numeric values for Vectorization

```
indexer_country = StringIndexer(inputCol="Country", outputCol="CountryIndex", handleInvalid="skip")
indexer_stockcode = StringIndexer(inputCol="StockCode", outputCol="StockCodeIndex", handleInvalid="skip")

assembler=VectorAssembler(inputCols=[
 'CustomerID',
 'Quantity',
 'UnitPrice',
 'CountryIndex',
 'StockCodeIndex'],outputCol='features')
```

7.
```
from pyspark.ml.classification import LogisticRegression
from pyspark.ml import Pipeline
```
```
log_reg=LogisticRegression(featuresCol='features',labelCol='Flag_reorder')
```

8. Creating a pipeline to ensure the transformations to data happens in the correct order in a sequential manner

```
pipeline=Pipeline(stages=[indexer_country,indexer_stockcode,assembler,log_reg])
```

9. Splitting our data into train and test dataset in the ratio of 70% : 30%

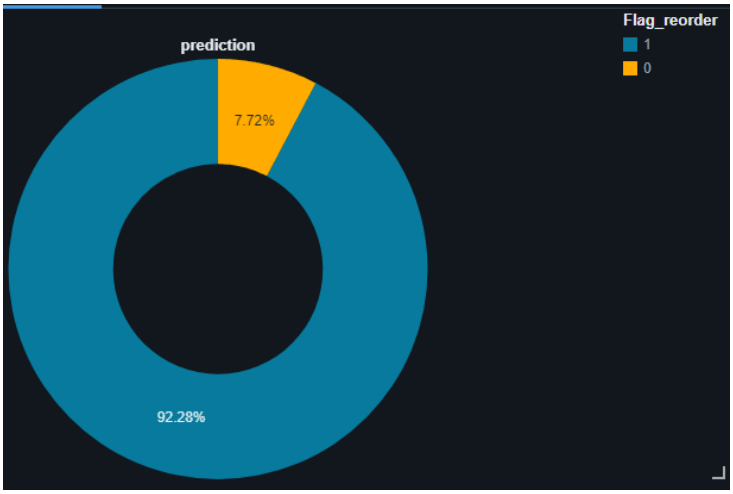
```
1  train,test=data.randomSplit([0.7,.3])
```
```
test:  pyspark.sql.dataframe.DataFrame = [CustomerID: integer, StockCode: string ... 4 more fields]
train:  pyspark.sql.dataframe.DataFrame = [CustomerID: integer, StockCode: string ... 4 more fields]
```

10. Training the model on train dataset

```
model=pipeline.fit(train)
```

11. Performing a test of model on the test dataset

```
result=model.transform(test)
display(result.select('Flag_reorder','prediction'))
```



12. Getting the accuracy for the model

```
from pyspark.ml.evaluation import BinaryClassificationEvaluator
eval_re=BinaryClassificationEvaluator(rawPredictionCol='prediction',labelCol='Flag_reorder')
```

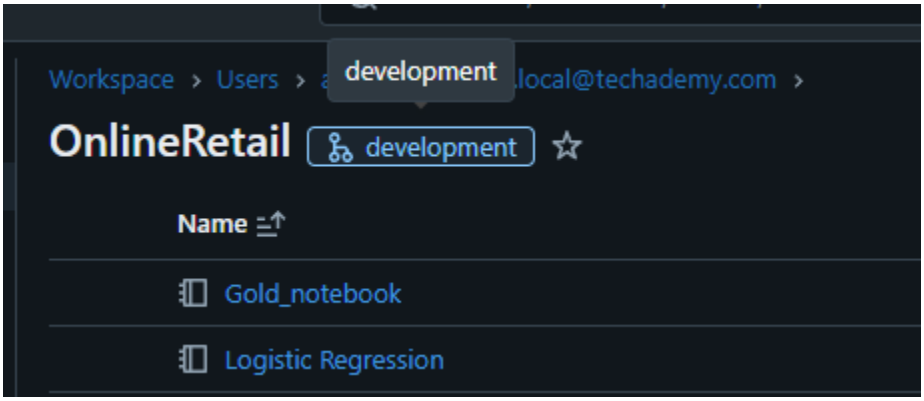
```
1  AUC=eval_re.evaluate(result)
2  AUC
```

▸ (4) Spark Jobs

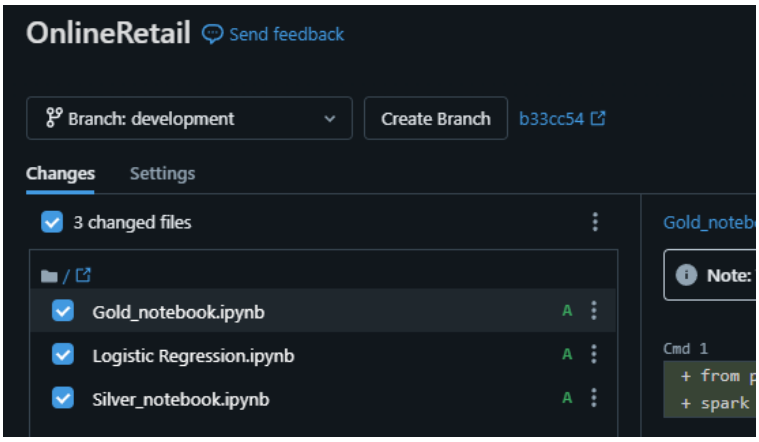
```
0.5
```

10. Pushing the changes into the Development branch

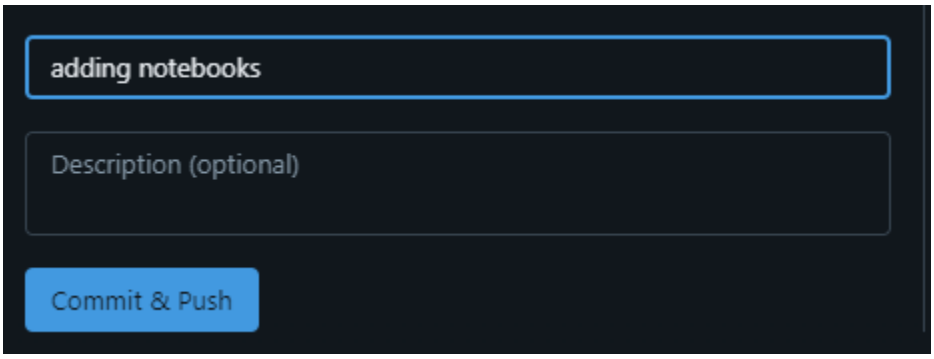
1. **You should be in the development branch if our repo in your databricks workspace**
2. **Click on the branch icon**



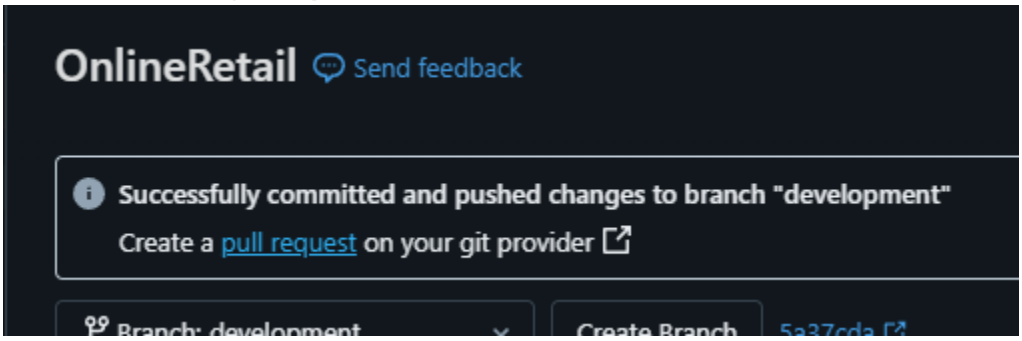
3. **You can see that it notices 3 new notebook additions**



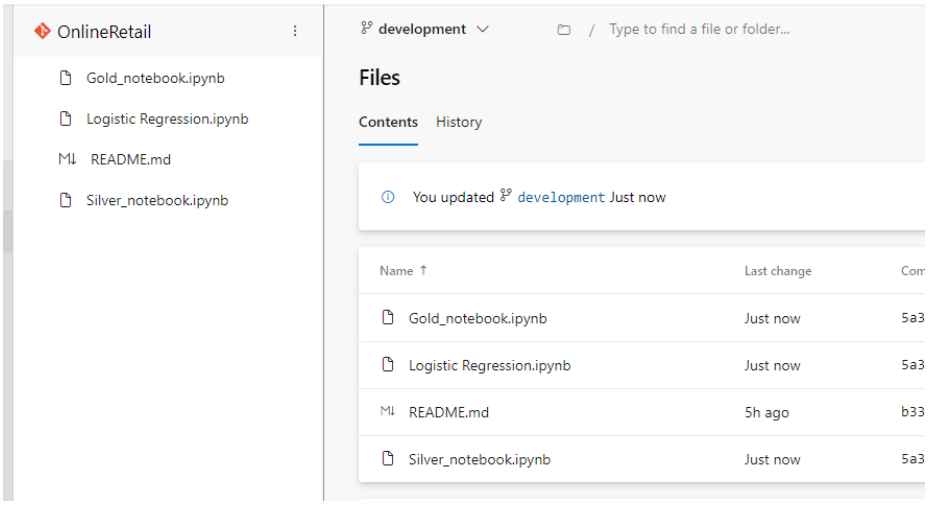
4. **Select the Commit & Push button**



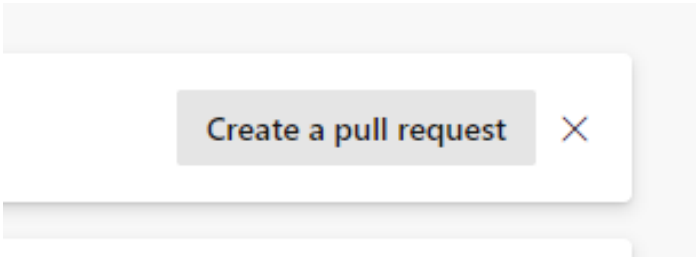
5. **Push successfully completed**



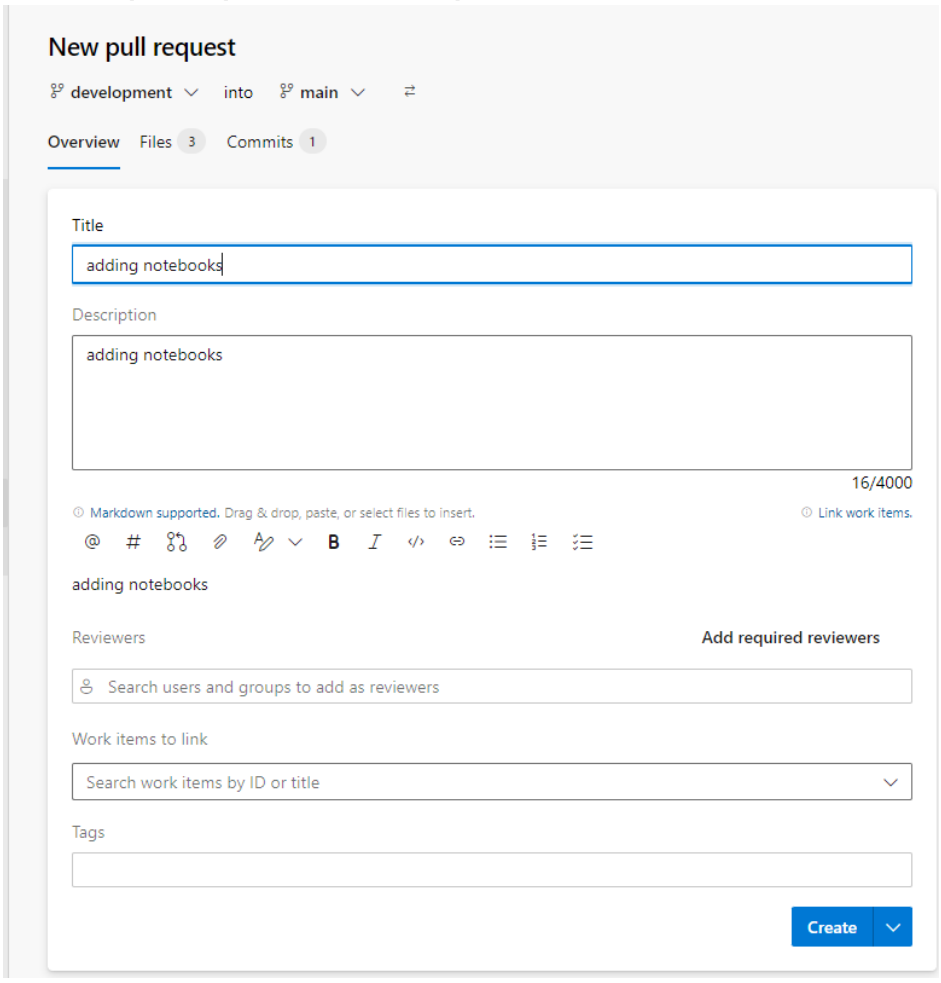
6. **You can see the changes in the repo by selecting the development branch in Azure Git repo**



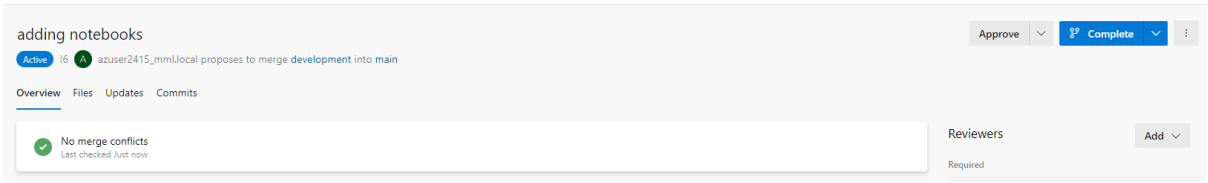
7. **You will not see an option to create a pull request**



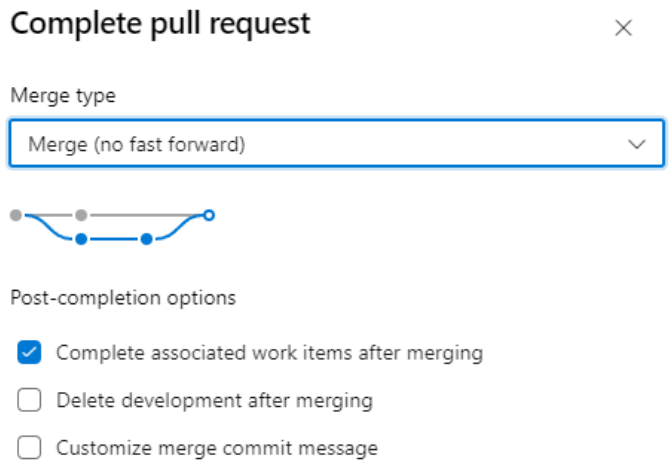
8. Create a pull request from development to main branch



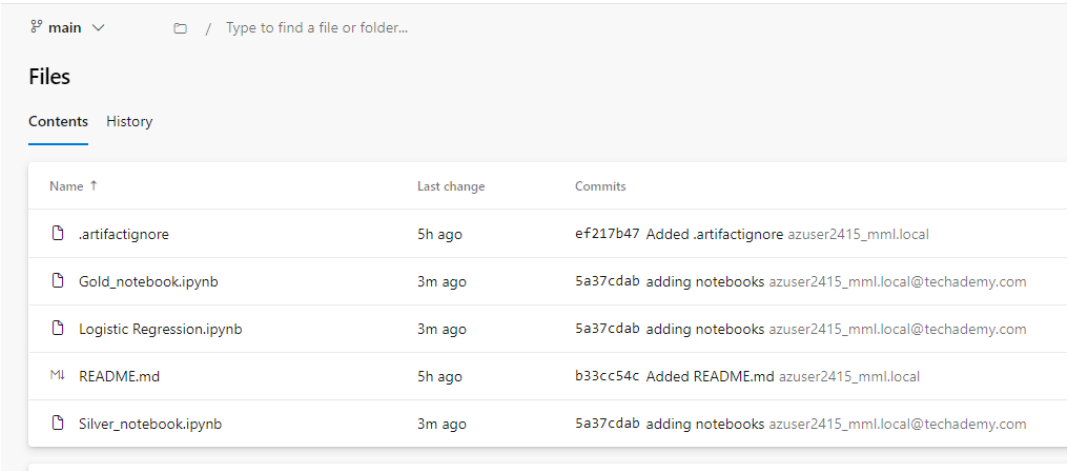
9. Review and Complete the pull request



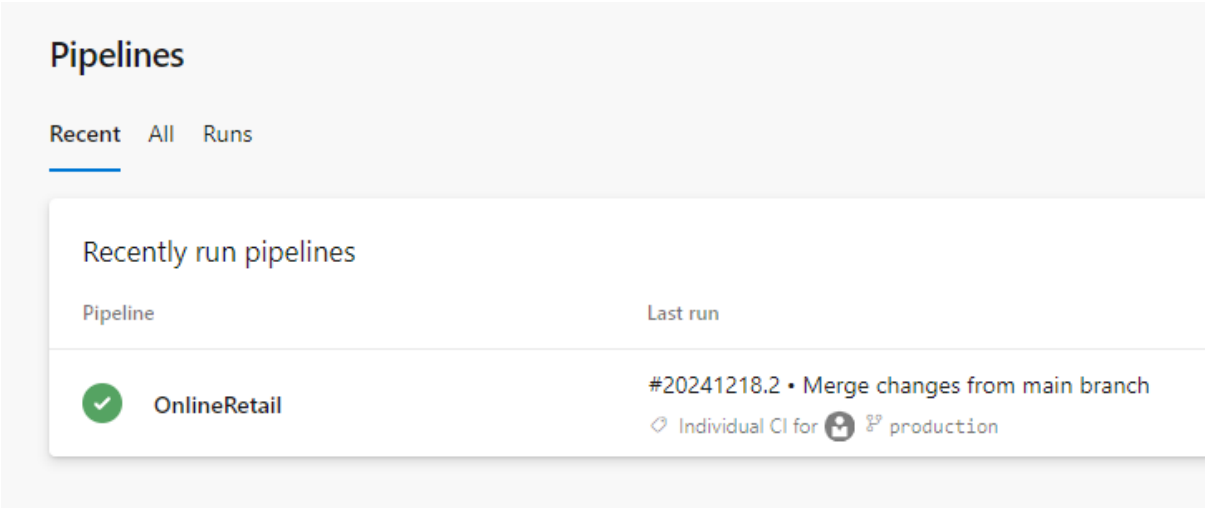
10. Do not check the delete development branch at the moment and complete the merge



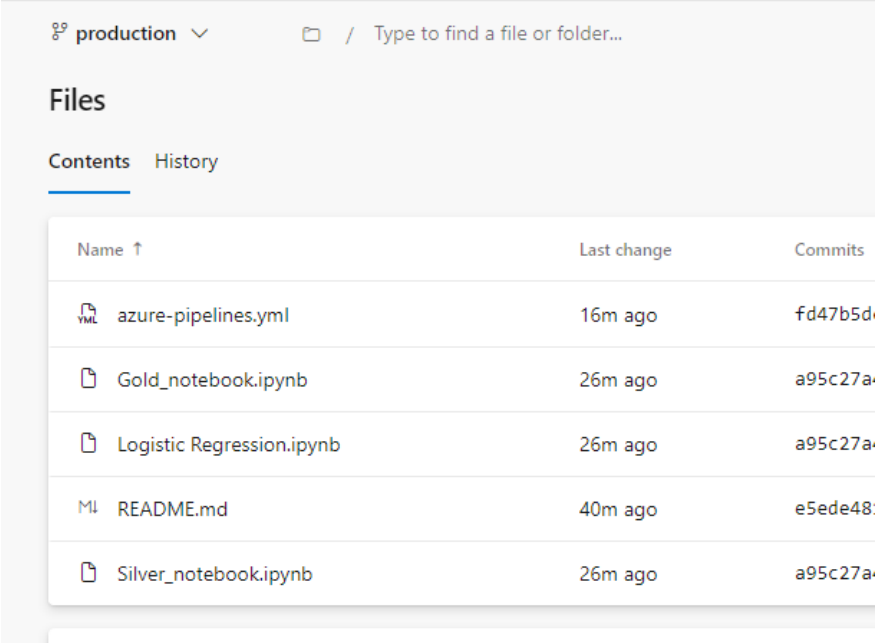
11. Now your main branch should also contain the notebooks we created earlier



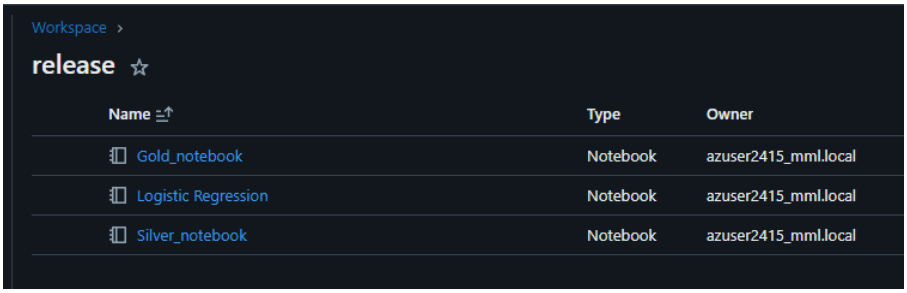
12. You pipeline should have been automatically triggered as well



13. The pipeline changes can be observed in both the production branch

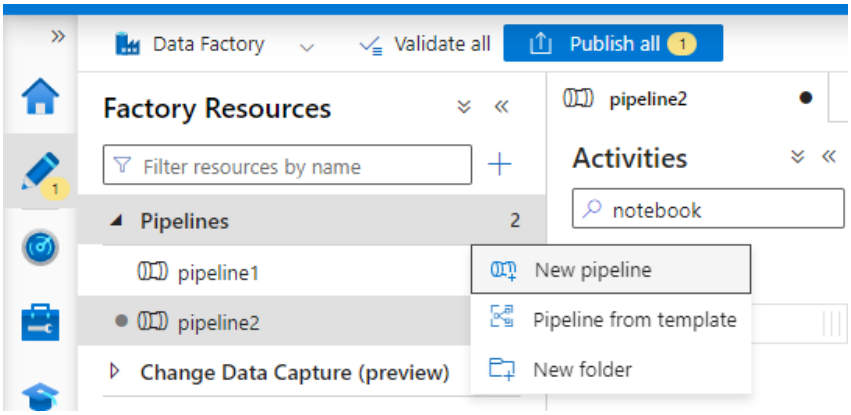


as well as the release folder in our repo clone

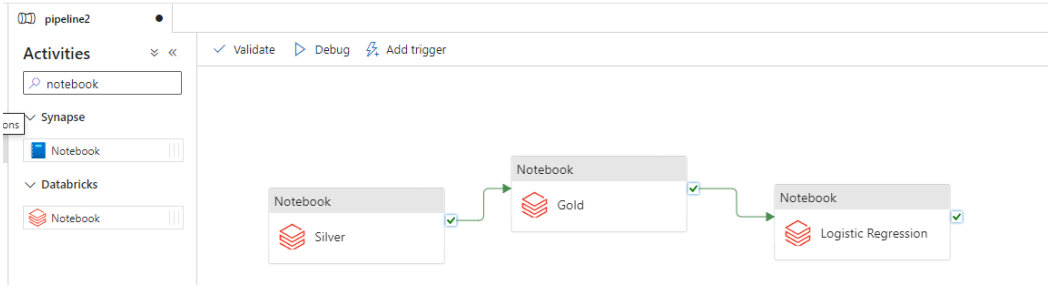


11. Creating a pipeline for automating notebooks

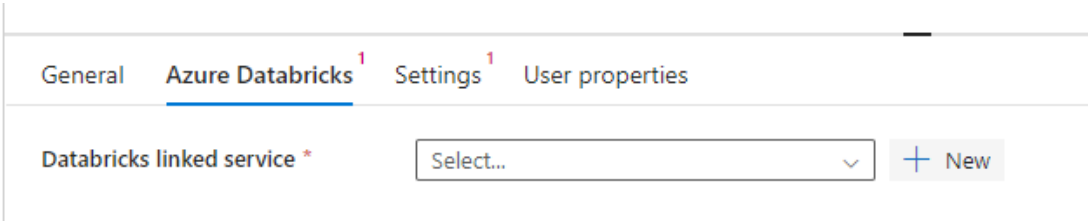
1. **Go to your Azure DataFactory > Author > Pipeline > New**



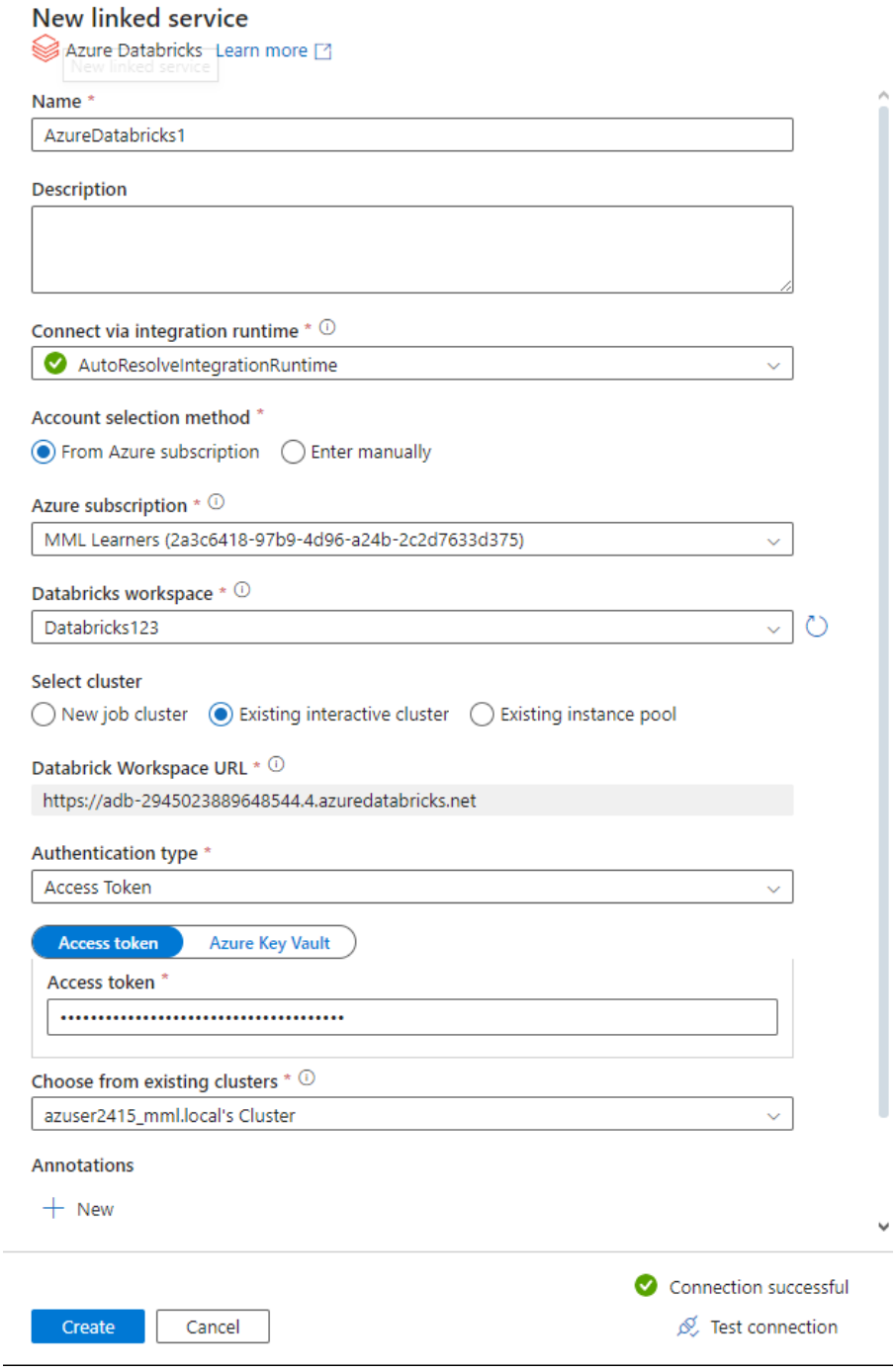
2. **From activities drag 3 notebook activities, one for each notebook and link then on condition "on success"**



3. **In Silver Notebook's Azure Databrick tab, create a new linked service**

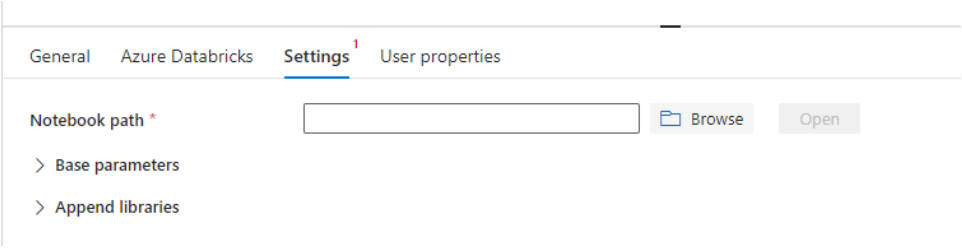


4. **Select your azure subscription and workspace**
   choose Existing interactive cluster and grab an access token like we did before
   After entering the access token select the cluster from drop down menu

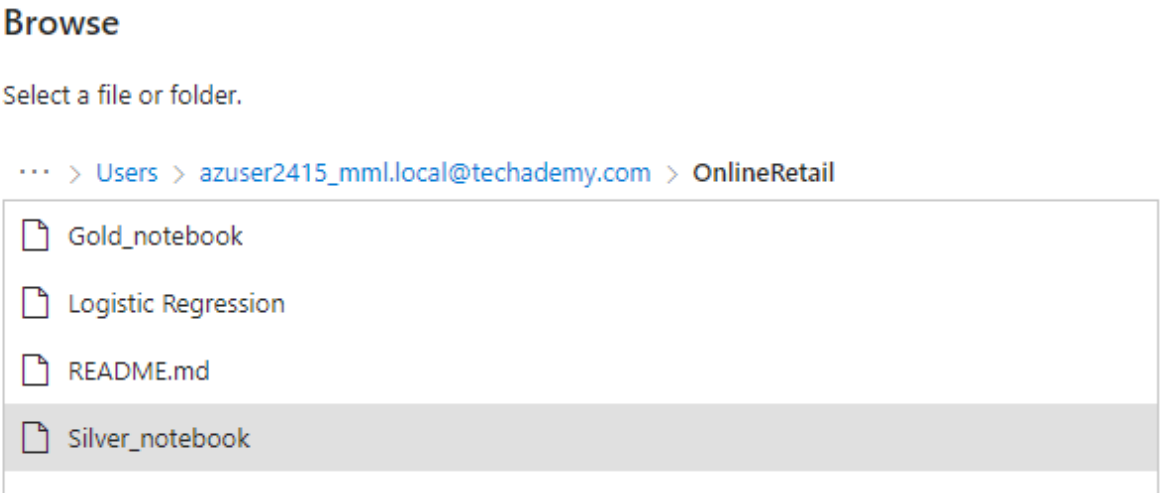


5. **Then click on create**

6. **Next in the Settings tab browse for notebook path**

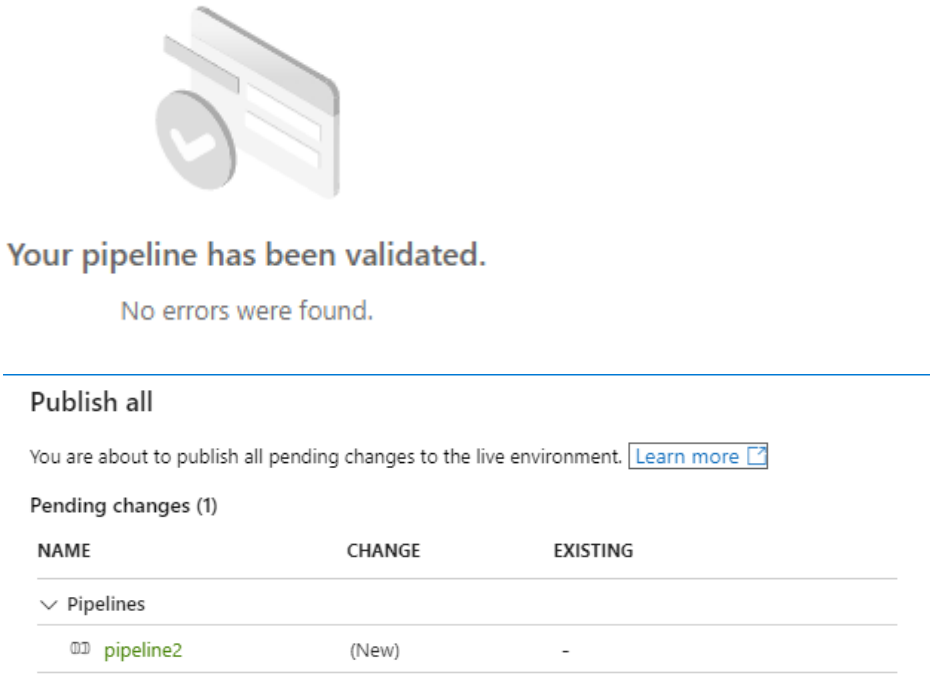


7. **Browse and select your silver notebook**



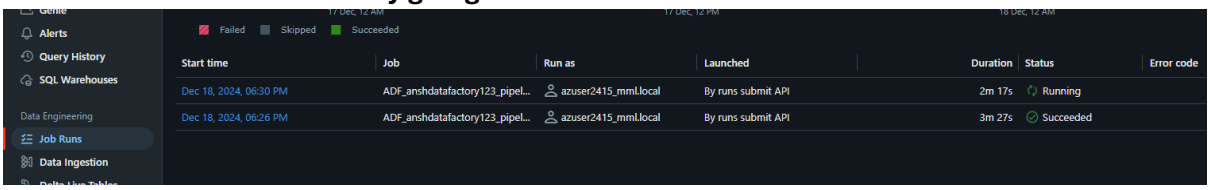
8. **Follow the same steps for gold notebook and logistic regression notebook as well**

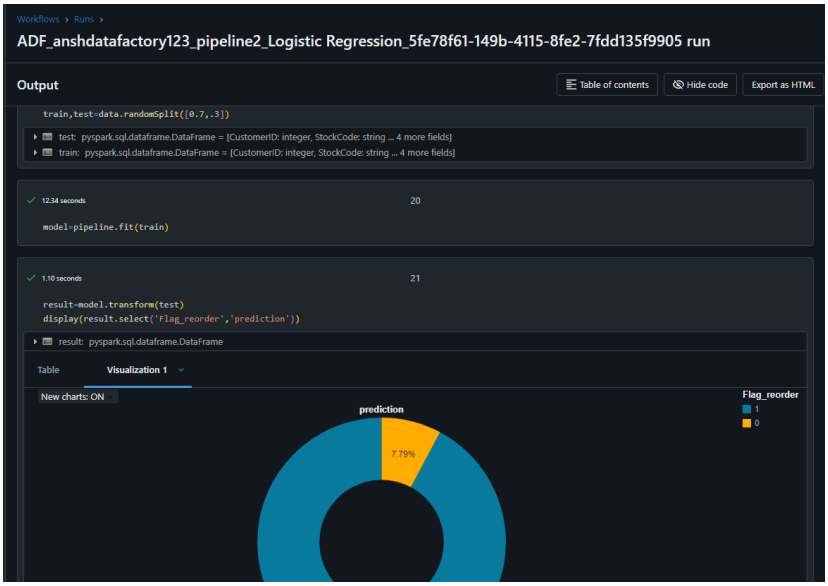
9. **Next Validate and Publish the pipeline**



10. **Trigger the pipeline**

11. **You can view the execution by going to databricks > Job Runs side tab**





12. We have successfully completed execution of all 3 notebooks

Start time	Job	Run as	Launched	Duration	Status
Dec 18, 2024, 06:32 PM	ADF_anshdatafactory123_pipel...	azuser2415_mml.local	By runs submit API	47s	Succeeded
Dec 18, 2024, 06:30 PM	ADF_anshdatafactory123_pipel...	azuser2415_mml.local	By runs submit API	2m 23s	Succeeded
Dec 18, 2024, 06:26 PM	ADF_anshdatafactory123_pipel...	azuser2415_mml.local	By runs submit API	3m 27s	Succeeded

Showing 1 - 2 items

Pipeline name	Run start	Run end	Duration	Triggered by	Status
pipeline2	12/18/2024, 6:26:27 PM	12/18/2024, 6:33:59 PM	7m 33s	Manual trigger	Succeeded
pipeline1	12/18/2024, 12:25:04 PM	12/18/2024, 12:25:23 PM	19s	Manual trigger	Succeeded

12. Results

1. **Bronze Layer (Raw Data Ingestion):**
    - Successfully ingested raw transactional data from Online Retail.xlsx into Azure Data Lake using Data Factory.
    - Verified raw data consistency and ensured schema alignment for further transformations.
2. **Silver Layer (Data Cleaning & Transformation):**
    - Cleaned the dataset by handling missing values, removing duplicates, and filtering invalid transactions (e.g., negative quantities).
    - Sessionized customer interactions to better understand user behavior and interaction duration.
3. **Gold Layer (Aggregation & Metrics):**
    - Created aggregated customer activity metrics, such as total purchases, average spending, and frequency of transactions.
    - Generated business-ready insights, including customer segmentation and purchasing trends.
4. **Predictive Model (Churn Prediction):**
    - Implemented a logistic regression model in Databricks to predict the likelihood of customer churn.
    - Achieved high accuracy and interpretability, identifying key features influencing customer retention.
5. **CI/CD Integration:**
    - Successfully integrated the project with Azure Git for version control.
    - Automated deployment processes with CI/CD workflows, ensuring seamless updates to the production environment.

13. Conclusion

1. The project provides a scalable and efficient ETL workflow for customer behavior analysis using the Medallion architecture (Bronze, Silver, Gold layers).
2. Key business insights, such as customer purchase trends and churn likelihood, empower data-driven decision-making for improving customer retention.
3. The use of Azure Data Factory and Databricks ensures seamless orchestration and powerful transformations, enabling efficient data processing and predictive analytics.
4. By incorporating CI/CD pipelines, the workflow achieves operational reliability and streamlined deployment across environments.
5. The methodology can be extended to similar retail datasets, offering a robust framework for customer analytics in other industries.