Azure End-to-End Data Engineering Project

1. Data Sources

- There are two types of data sources shown:
- Logs, files, and media (unstructured) – represented by an icon of a document.
- Business/custom apps (structured) – represented by a device icon.
- These sources feed data into the pipeline.

2. Ingest Layer – Azure Data Factory

- The first processing step is Azure Data Factory.
- ADF ingests both structured and unstructured data and orchestrates the pipeline.

3. Storage Layer – Azure Blob Storage

- Next, the ingested data moves into Azure Blob Storage, a scalable data lake/storage layer.
- This is marked with a Step 1 label above it.
- Another green circle numbered 2 shows the movement from ADF to Blob Storage.

4. Prep and Train Layer – Azure Databricks

- From Blob Storage, data flows to Azure Databricks, where it can be processed using:
- Python
- Scala
- Spark SQL
- This step is also marked with a green circle with the number 2.
- Databricks is the main compute engine for transformation, training, or ETL operations.

5. Data Warehouse Layer – Azure SQL Data Warehouse (Synapse Dedicated SQL Pool)

- Processed data from Databricks flows into an Azure SQL Data Warehouse.
- A path labelled PolyBase shows that data can also be loaded directly from Blob Storage into the warehouse.
- A green circle numbered 3 marks this step.

6. Model and Serve Layer – Azure Analysis Services

- From the data warehouse, models can be built and served using Azure Analysis Services (AAS).
- A green circle numbered 4 marks this step.

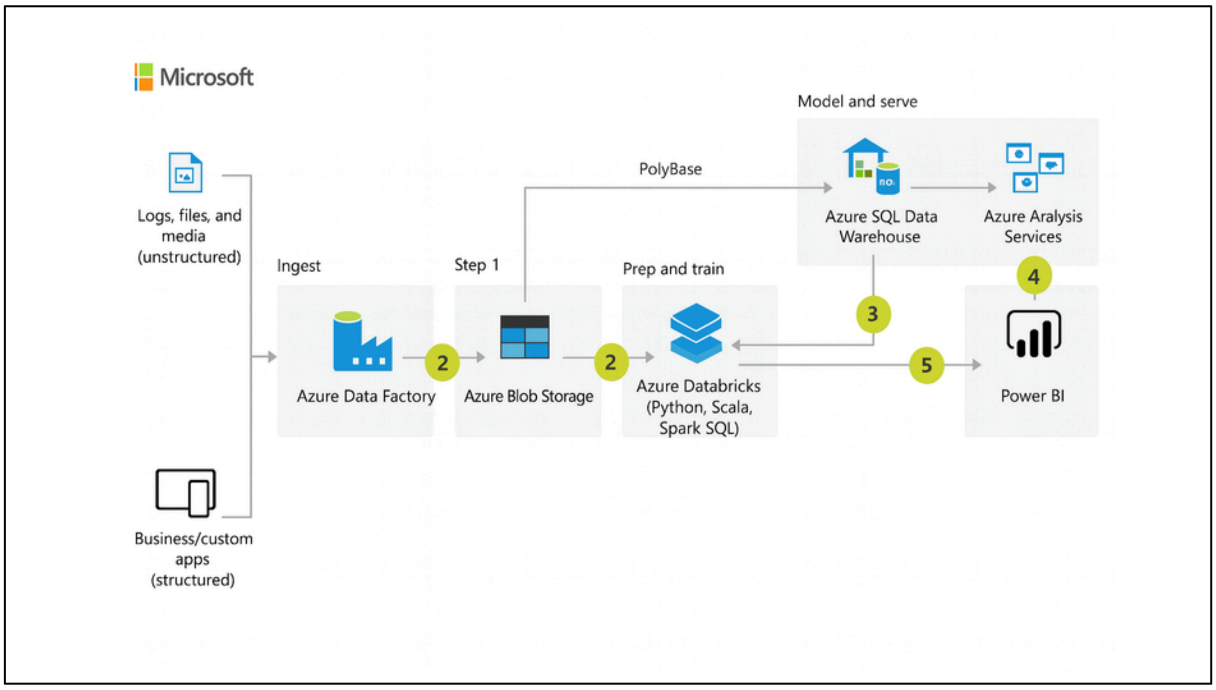
7. Reporting Layer – Power BI

- Finally, Power BI is used to create reports and dashboards.
- Two arrows point to Power BI:
- From Analysis Services
- From Databricks directly (marked with a green circle numbered 5)

Overall Flow Summary

ADF → Blob Storage → Databricks → SQL Data Warehouse → Analysis Services → Power BI

- The diagram shows a typical Azure pipeline where:
- ADF orchestrates
- Blob stores
- Databricks transforms
- SQL DW warehouses
- AAS models
- Power BI visualizes



What is Data Engineering? Data engineering refers to designing and building systems that collect, process, store, and analyze data at different scales. This data usually comes from different sources at different times, hence the need to ensure proper cleaning and transformation before making it available to data scientists and analysts. The common task for data engineers involves creating data pipelines to allow streaming data for different use cases. The standard data pipeline phases
include:

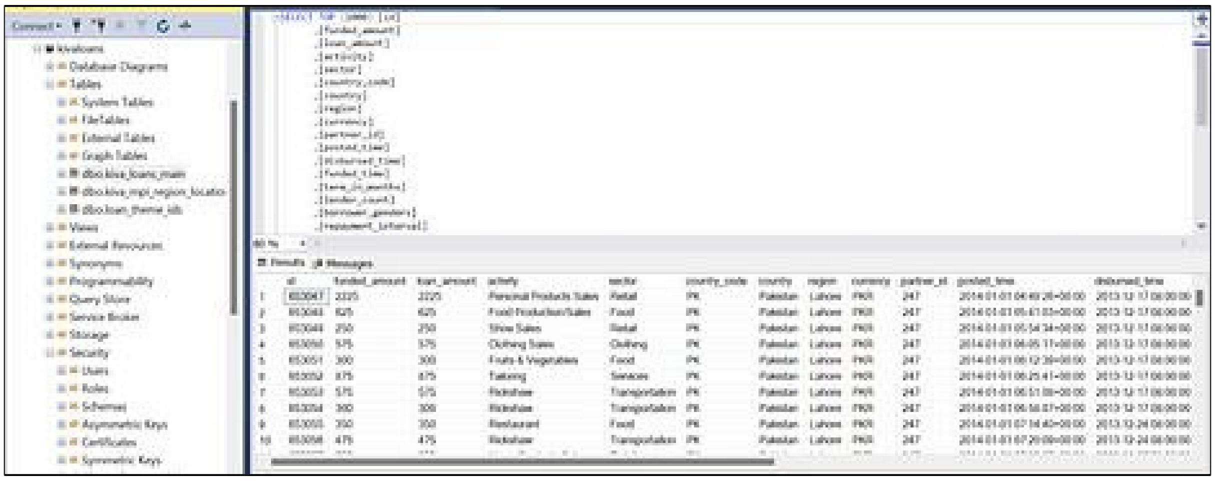
1. Ingestion: This phase involves gathering data from various sources.

2. Processing: This stage involves processing the data to desired data sets for different use cases.

3. Storing: The processed data is then stored for easy retrieval from the database.

4. Access: The stored data is accessible to users for different use cases.

Azure End-to-End Data Engineering I will use Microsoft Azure to demonstrate a real-world application of data engineering. I will also use an open-source dataset from the Kaggle competition “Data Science for Good: Kiva Crowd funding This data is in CSV format; hence, you need to load the data into the database for storage. I assumed I would be receiving data daily to add to the different tables in the database. I used the SQL server database as the data source for the project.



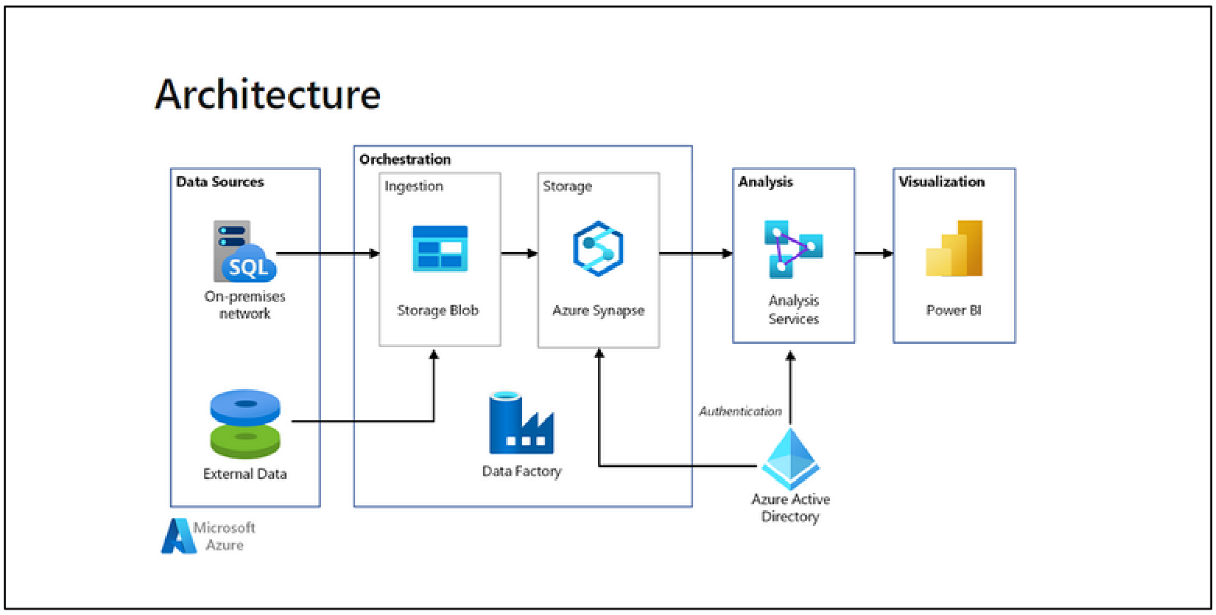
```
SELECT TOP (1000) [id]
      ,[funded_amount]
      ,[loan_amount]
      ,[activity]
      ,[sector]
      ,[country_code]
      ,[country]
      ,[region]
      ,[currency]
      ,[partner_id]
      ,[posted_time]
      ,[disbursed_time]
      ,[funded_time]
      ,[term_in_months]
      ,[lender_count]
      ,[borrower_genders]
      ,[repayment_interval]
```

	id	funded_amount	loan_amount	activity	sector	country_code	country	region	currency	partner_id	posted_time	disbursed_time
1	653047	2225	2225	Personal Products Sales	Retail	PK	Pakistan	Lahore	PKR	247	2014-01-01 04:49:26+00:00	2013-12-17 08:00:00
2	653048	625	625	Food Production/Sales	Food	PK	Pakistan	Lahore	PKR	247	2014-01-01 05:41:03+00:00	2013-12-17 08:00:00
3	653049	250	250	Shoe Sales	Retail	PK	Pakistan	Lahore	PKR	247	2014-01-01 05:54:34+00:00	2013-12-17 08:00:00
4	653050	575	575	Clothing Sales	Clothing	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:05:11+00:00	2013-12-17 08:00:00
5	653051	300	300	Fruits & Vegetables	Food	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:12:39+00:00	2013-12-17 08:00:00
6	653052	875	875	Tailoring	Services	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:25:41+00:00	2013-12-17 08:00:00
7	653053	575	575	Rickshaw	Transportation	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:51:08+00:00	2013-12-17 08:00:00
8	653054	300	300	Rickshaw	Transportation	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:56:07+00:00	2013-12-17 08:00:00
9	653055	350	350	Restaurant	Food	PK	Pakistan	Lahore	PKR	247	2014-01-01 07:14:40+00:00	2013-12-24 08:00:00
10	653058	475	475	Rickshaw	Transportation	PK	Pakistan	Lahore	PKR	247	2014-01-01 07:29:09+00:00	2013-12-24 08:00:00

Kiva is an online crowdfunding organization that offers loan services to underserved and unbanked populations worldwide. Some of the use cases of these loans include starting a business, paying school fees, and investing in farming. The datasets available at Kiva show the loans issued to borrowers between January 2014 and July 2017. This information will be valuable in defining some Key Performance Indicators (KPIs) to evaluate the organization’s performance over time.

The Data Architecture

I used data stored on our On-prem SQL server database. The project aimed to create a data pipeline that migrated the data into the cloud from the SQL server. Therefore, I would trigger this pipeline to run daily when new data is added to the database.



1. On-prem SQL Server Database: I used data stored in our local SQL database in the project.

2. Azure Data Factory: ADF is the ETL tool used for data ingestion. I connected the ADF to the SQL server to copy the required tables to the cloud.

3. Azure Data Lake Gen 2: This is where all the data are stored.

4. Azure Databricks: Azure Databricks transformed the data into the required format.

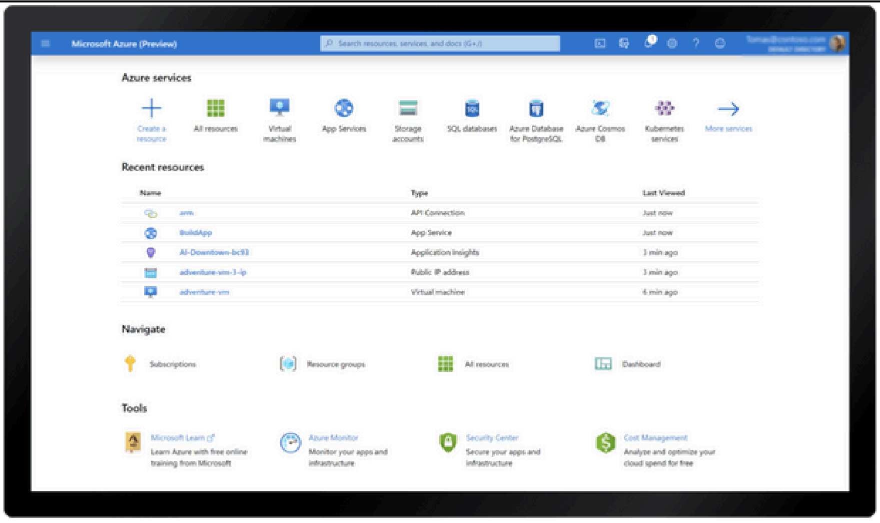
5. Azure Synapse Analytics: This tool will load the Azure SQL database data.

6. Power BI: To load data from Azure Synapse Analytics and Create reports for business use cases.

7. Azure Active Directory and Azure Key Vault: To enhance security access to the different data in the cloud.

Environment

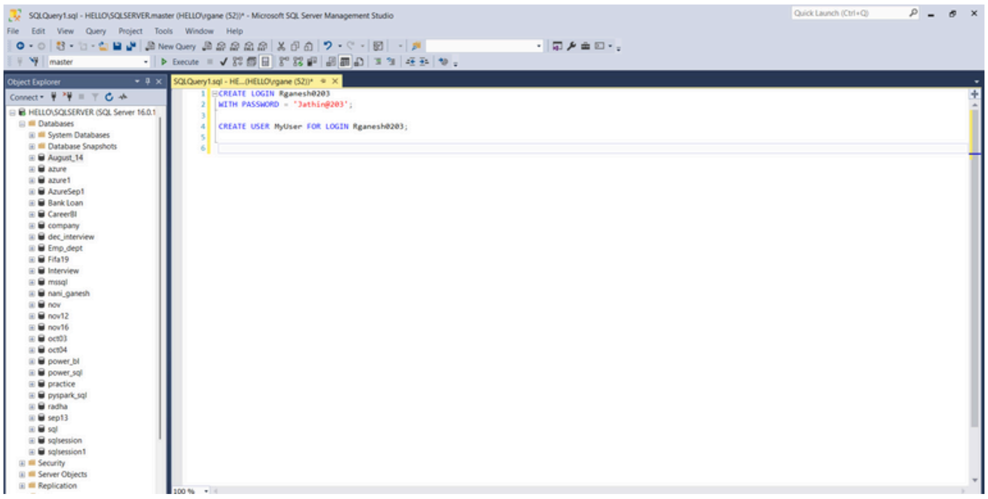
Set-up One requires a Microsoft Azure account for this project. Microsoft offers beginners a free 30-day trial period to access the Azure portal. Inside the portal, you need to create a resource group with a unique name. Furthermore, you need to create different resources in the resource group to enable the execution of the different data pipeline runs.



Name	Type	Last Viewed
arm	API Connection	Just now
BuildApp	App Service	Just now
AI-Downtown-bc93	Application Insights	3 min ago
adventure-vm-3-ip	Public IP address	3 min ago
adventure-vm	Virtual machine	6 min ago

Data Source

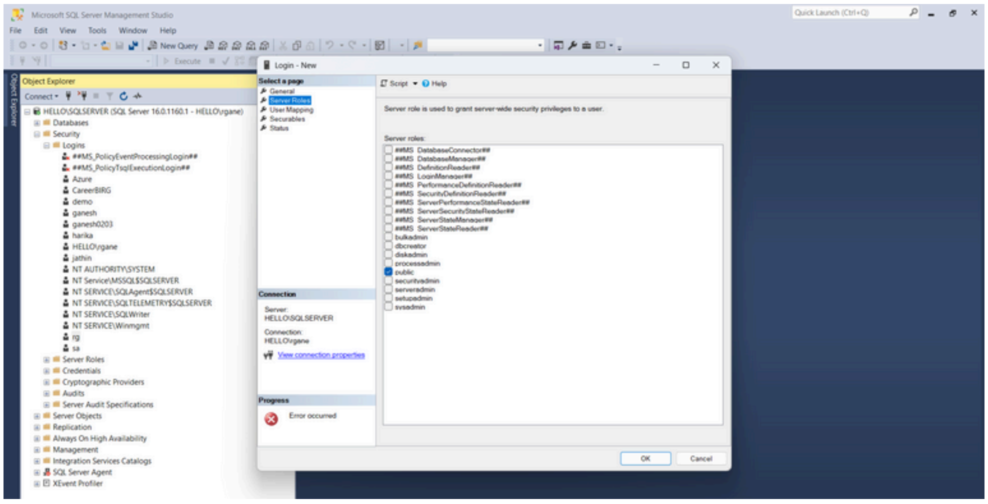
In this project, I created a username and password to allow access to the Azure database. Besides, I stored the username and password in the Azure Key vault for secure login to access the data.



```sql
CREATE LOGIN Rganesh0203
WITH PASSWORD = 'Jathin@203';

CREATE USER MyUser FOR LOGIN Rganesh0203;
```

SQLQuery1.sql - HELLO\SQLSERVER.master (HELLO\rgane (52))* - Microsoft SQL Server Management Studio
Object Explorer
SQLQuery1.sql - HE...(HELLO\rgane (52))*
Execute
100 %

Ialso granted the user access to the database to read all the tables with the prefix 'dbo' since I will read the tables with the 'dbo' schema to Azure. To check the user permissions, expand the security panel on the left side under the particular database, expand the user, and refresh to show the new user created. Right-click on the user name, under the properties, grant the 'db_datareader' for the database role membership.



Login - New

Server role is used to grant server-wide security privileges to a user.

Server roles:

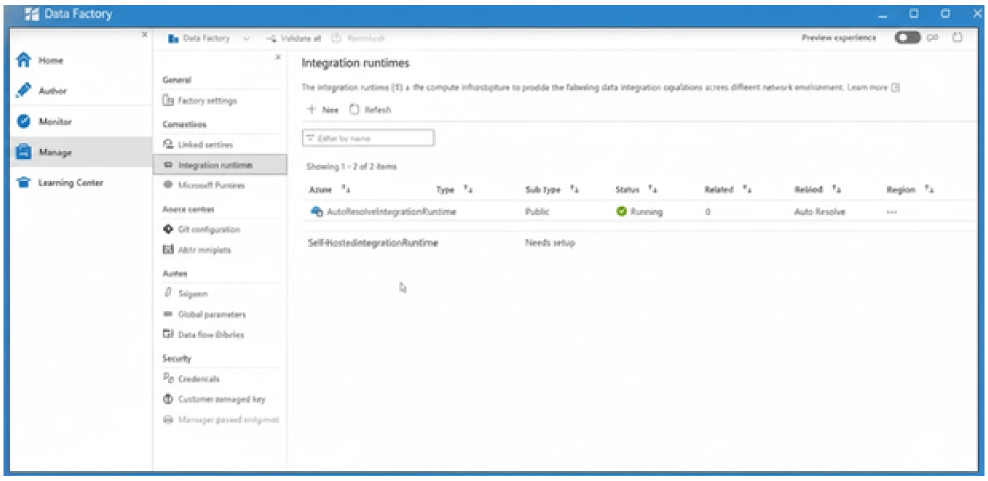
- [ ] ##MS_DatabaseConnector##
- [ ] ##MS_DatabaseManager##
- [ ] ##MS_DefinitionReader##
- [ ] ##MS_LoginManager##
- [ ] ##MS_PerformanceDefinitionReader##
- [ ] ##MS_SecurityDefinitionReader##
- [ ] ##MS_ServerPerformanceStateReader##
- [ ] ##MS_ServerSecurityStateReader##
- [ ] ##MS_ServerStateManager##
- [ ] ##MS_ServerStateReader##
- [ ] bulkadmin
- [ ] dbcreator
- [ ] diskadmin
- [ ] processadmin
- [x] public
- [ ] securityadmin
- [ ] serveradmin
- [ ] setupadmin
- [ ] sysadmin

Connection
Server: HELLO\SQLSERVER
Connection: HELLO\rgane

Progress
Error occurred

Data Ingestion Using Azure Data Factory

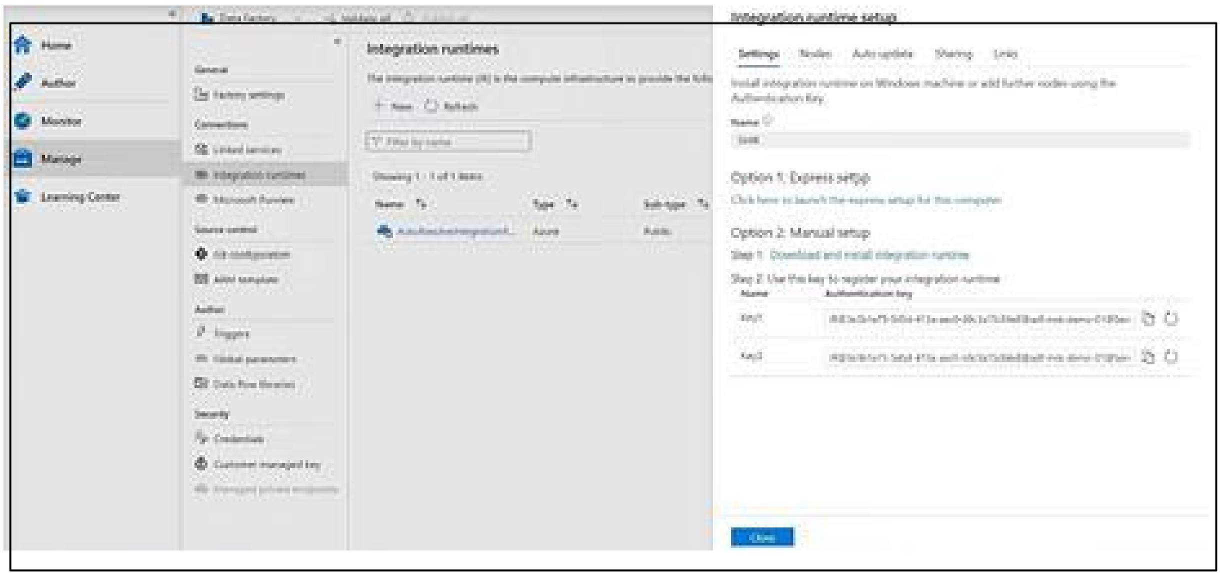
Creating a Connection Between SQL Server and Azure Data Factory
Since there was no relationship between Azure Data Factory and the SQL server database, I needed to install a Self-Hosted Integration Runtime to create the link. Under the manage tab in the ADF, select integration runtime. Under this option, there will be an Auto Resolve Integration Run time already running. This Auto Resolve Integration Runtime is usually used to connect to cloud-based resources. However, I needed to create an integration runtime to connect to the on-prem SQL database.



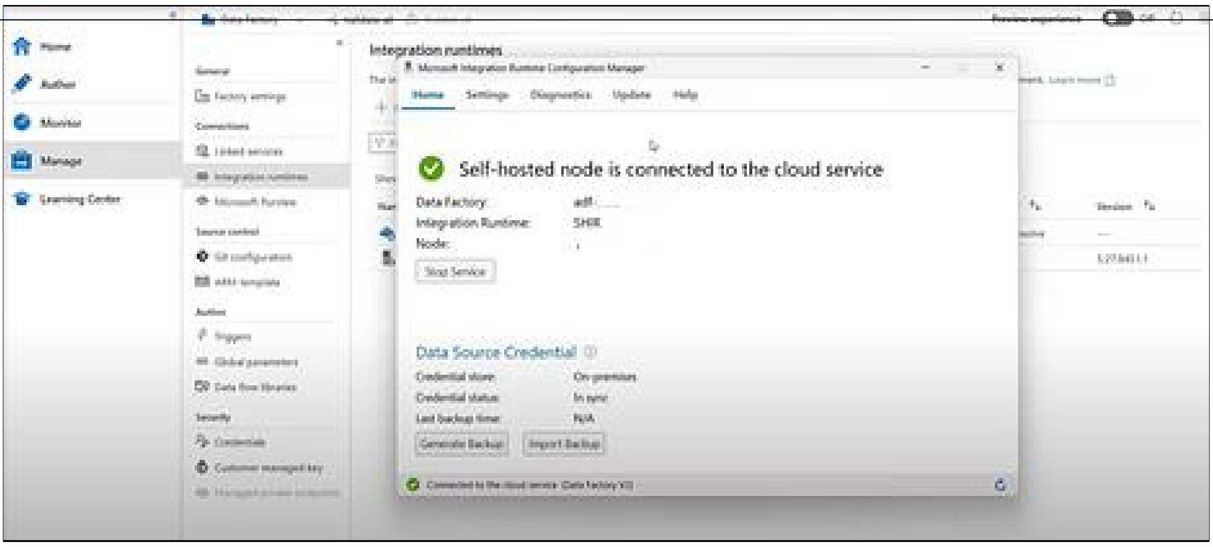
Showing 1 - 2 of 2 items

Azure	Type	Sub type	Status	Related	Reload	Region
AutoResolveIntegrationRuntime		Public	Running	0	Auto Resolve	---
SelfHostedIntegrationRuntime		Needs setup				

To create the SHIR, select the new button and select Azure, Self-Hosted setup, give a descriptive name, and create the runtime. For this project, I used the express setup option since I was installing it on my machine only. However, one can use the manual setup option when installing the SHIR on multiple machines for the same project.



On successful installation, run the newly installed Microsoft Integration Runtime Configuration Manager to confirm if the connection is established. A successful installation should show the connection as:



Self-hosted node is connected to the cloud service

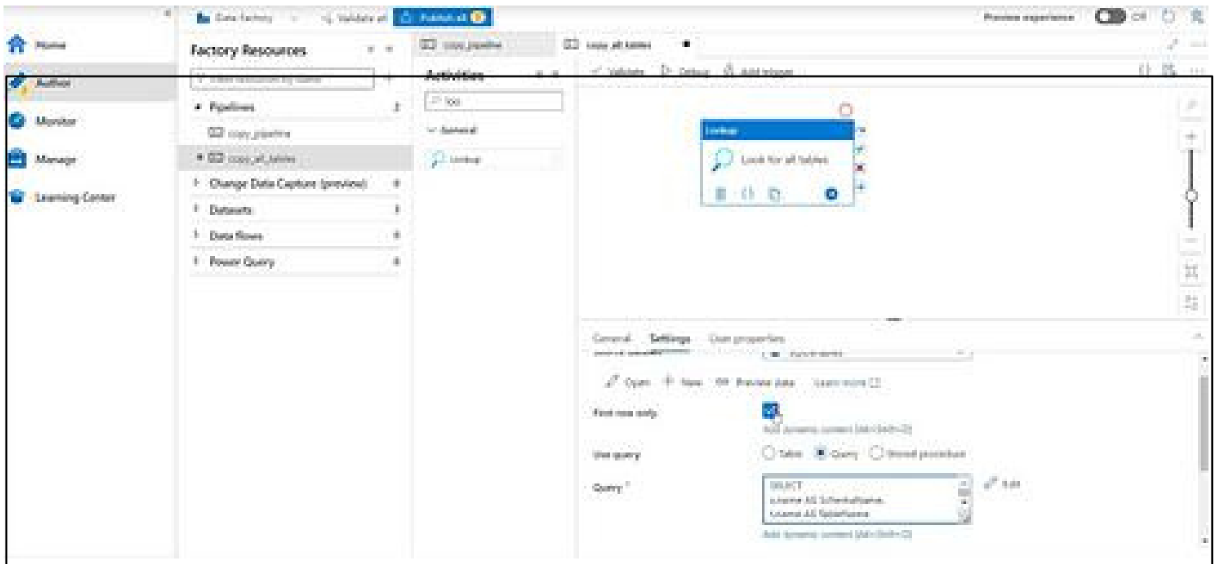
Data Factory: adf-
Integration Runtime: SHIR
Node:

Data Source Credential

Credential store: On-premises
Credential status: In sync
Last backup time: N/A

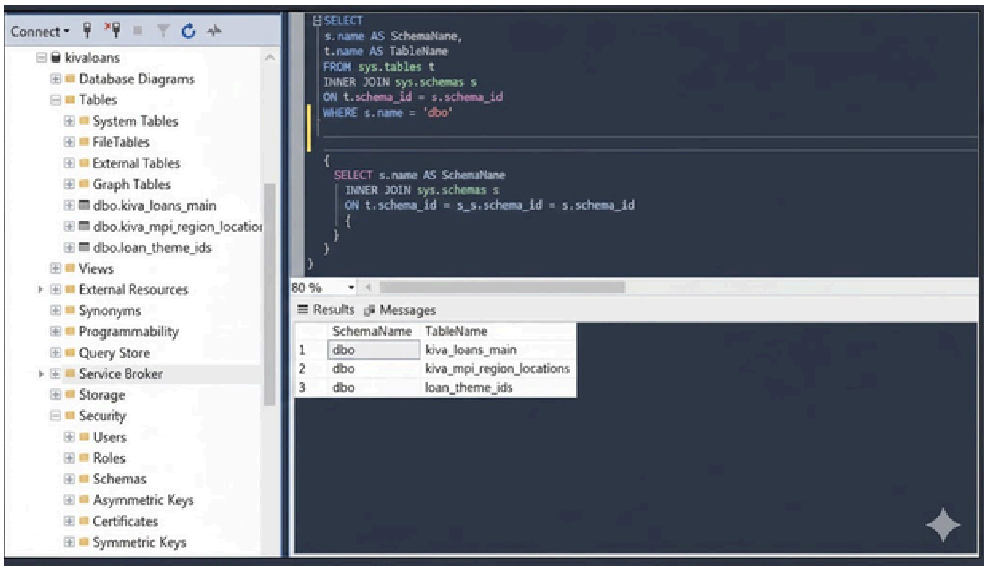
Connected to the cloud service (Data Factory V2)

Data Ingestion
For this project, I was interested in creating a pipeline that would read all the tables in the SQL server and load them in Azure Data Lake Gen 2. I created three storage containers, (gold, silver, and bronze) where the bronze container will store the raw data as it was from the source. The silver container would contain data from level 1 transformation from the bronze container while the gold container would contain the cleaned and transformed data from the silver container. To create a pipeline to read all the tables in the database, I used the lookup activity to look up all the tables from the SQL database. In this lookup activity, I use a query to list the tables to ingest in Azure Data Lake Gen 2.



First row only ✓
Use query: ○ Table [✓ Query] ○ Stored procedure
Query:
```
SELECT
s.name AS SchemaName,
t.name AS TableName,
```

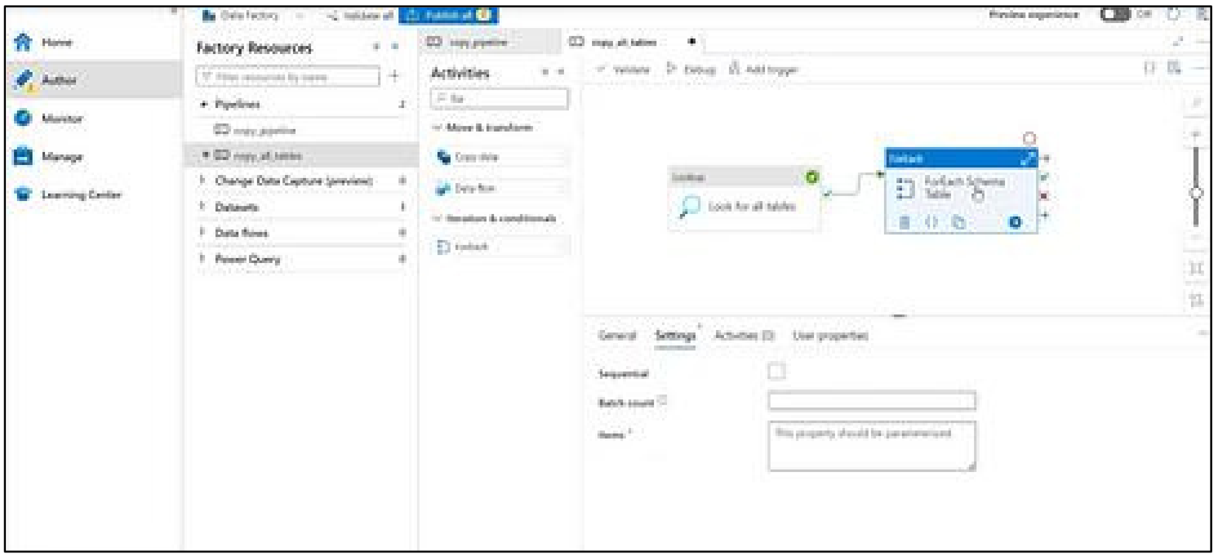
This query would list the tables available in the database with the given schema name.



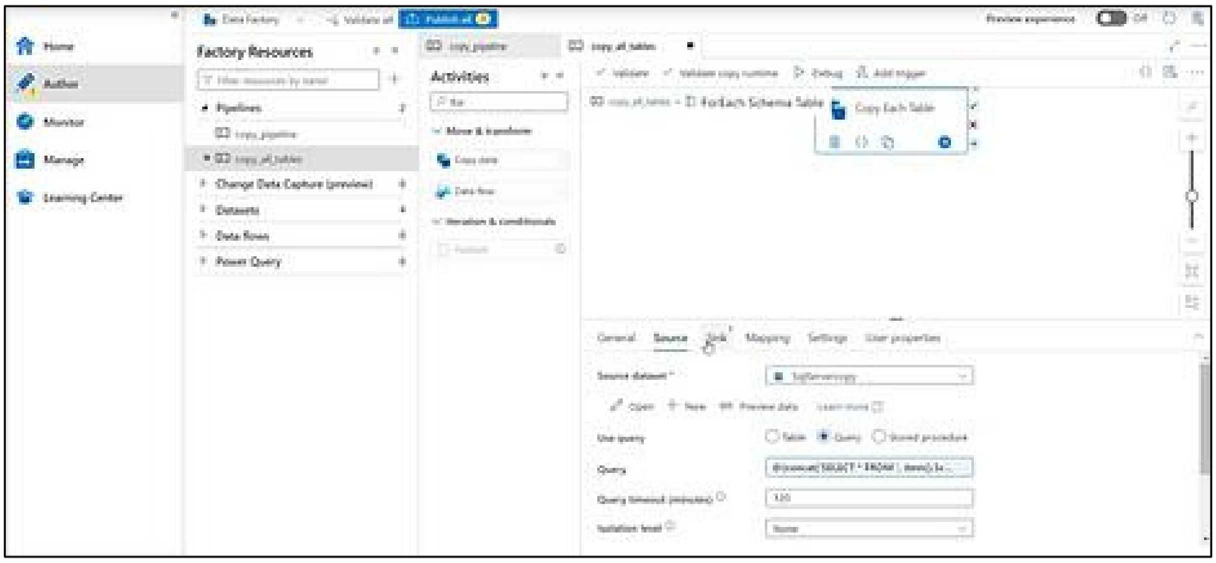
```
SELECT
s.name AS SchemaNane,
t.name AS TableNane
FROM sys.tables t
INNER JOIN sys.schemas s
ON t.schema_id = s.schema_id
WHERE s.name = 'dbo'

{
  SELECT s.name AS SchemaNane
   INNER JOIN sys.schemas s
   ON t.schema_id = s_s.schema_id = s.schema_id
   {
  }
 }
}
```

	SchemaName	TableName
1	dbo	kiva_loans_main
2	dbo	kiva_mpi_region_locations
3	dbo	loan_theme_ids

Thereafter, I created a ForEach item in the pipeline to iterate from the Lookup activity to copy all the tables. The ForEach item would loop through all the tables and copy the items listed from the lookup table.



Under the ForEach item, I created the Copy data item to copy data from the source. I configured the source of the data and the sink to save the data as CSV files. I also specified the path of the datasets so that each copied table would be stored separately in a folder and a path with the file name. Furthermore, the data ingestion pipeline was used to read and store the data from the SQL server to the bronze container, where the data was in the raw format.



Source dataset *: SqlServerCopy

Use query: ( ) Table [✓ Query] ( ) Stored procedure

Query: @{concat('SELECT * FROM ', item().Ia...

Query timeout (minutes): 120

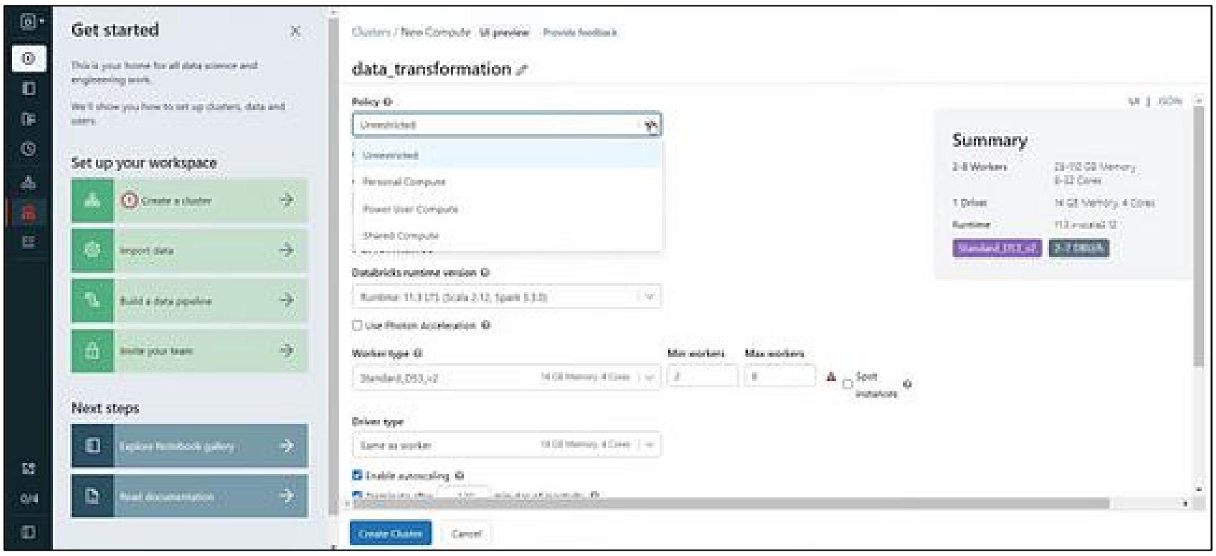
Isolation level: None

After the successful configuration of the pipeline, I ran using the debug option to test whether it was working without any errors. Besides, I used the add trigger option to run the pipeline and tested with the current time. Since the pipeline was meant to fetch the tables from the on-prem SQL server every time it runs, every successful run would overwrite the existing folder in the bronze container. At the end of the data ingestion, the data was now stored in the bronze container ready for transformation.

Data Transformation Using Azure Databricks

Storage

Mount After loading data from the SQL server to the bronze container, I performed two levels of transformations of the datasets into cleaner versions. However, I needed to create a compute cluster to allow different jobs to run in the notebooks. To create the compute cluster, launch the Azure Databricks studio, click on the compute tab, and configure the compute instance according to your needs. I selected a single user since I was the only one using the cluster in the resource and selected the other default options. It is also important to note that I enabled 'credential passthrough for user-level data access' to allow Azure Databricks to connect to Azure Data Lake Gen 2.



Clusters / New Compute

data_transformation

Policy: Unrestricted

Databricks runtime version: Runtime: 11.3 LTS (Scala 2.12, Spark 3.3.0)

Use Photon Acceleration: ☐

Worker type: Standard_DS3_v2 — 14 GB Memory, 4 Cores

Min workers: 2

Max workers: 8

Spot instances: ☐

Driver type: Same as worker — 14 GB Memory, 4 Cores

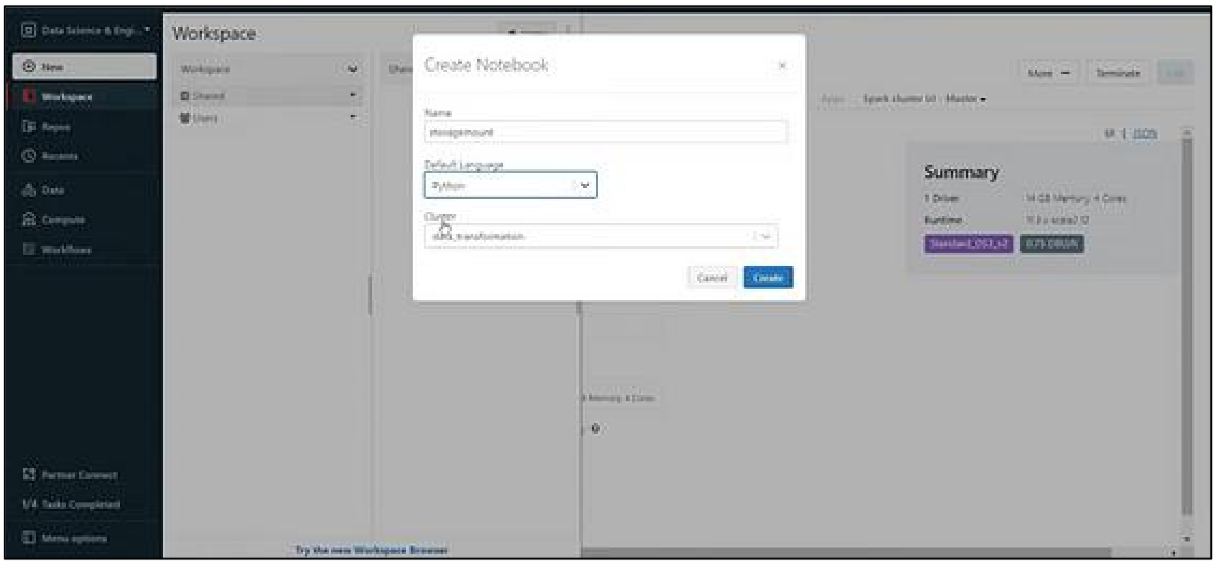
Enable autoscaling: ✓

Summary

2-8 Workers	28-112 GB Memory, 8-32 Cores
1 Driver	14 GB Memory, 4 Cores
Runtime	11.3.x-scala2.12

Standard_DS3_v2 · 2-7 DBU/h

In the Databricks workspace, create a notebook called 'storagemount' to mount the storage account in Azure Databricks. This option will allow accessing the files in the storage account.



Create Notebook

Name: storagemount

Default Language: Python

Cluster: data_transformation

To mount the storage using credential passthrough, there are codes from this webpage (https://learn.microsoft.com/en-us/azure/databricks/archive/credential-passthrough/adls-passthrough), and made some changes according to my configuration.

```
configs = {
  "fs.azure.account.auth.type": "CustomAccessToken",
  "fs.azure.account.custom.token.provider.class":
spark.conf.get("spark.databricks.passthrough.adls.gen2.tokenProviderClassName")
}
#Optionally, you can add <directory-name> to the source URI of your mount point.
dbutils.fs.mount(

  source = "abfss://bronze@kivaloansfolder.dfs.core.windows.net/",
  mount_point = "/mnt/bronze",
  extra_configs = configs)
```

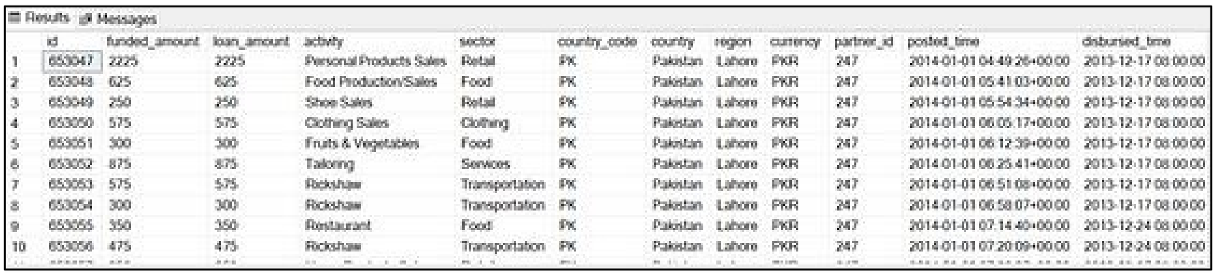
For this code, update the container and storage account names to match what is on the resource group. Also, change the mount point name with that of the container.
Similarly, I mounted both the silver and gold containers. This option allowed accessing data from these different containers. Furthermore, I could access the data by giving the full path forthe containers since I had allowed credential passthrough.

```
configs = {
  "fs.azure.account.auth.type": "CustomAccessToken",
  "fs.azure.account.custom.token.provider.class":
spark.conf.get("spark.databricks.passthrough.adls.gen2.tokenProviderClassName")
}
#Optionally, you can add <directory-name> to the source URI of your mount point.
dbutils.fs.mount(

  source = "abfss://silver@kivaloansfolder.dfs.core.windows.net/",
  mount_point = "/mnt/silver",
  extra_configs = configs)
```

```
configs = {
  "fs.azure.account.auth.type": "CustomAccessToken",
  "fs.azure.account.custom.token.provider.class":
spark.conf.get("spark.databricks.passthrough.adls.gen2.tokenProviderClassName")
}
#Optionally, you can add <directory-name> to the source URI of your mount point.
dbutils.fs.mount(
  source = "abfss://gold@kivaloansfolder.dfs.core.windows.net/",
  mount_point = "/mnt/gold",
  extra_configs = configs)
```

Level 1 Data Transformation

Since the data looked relatively clean in the database, I focused the first level of transformation on changing the date format from date-time to date type. At this level, I wanted the transformation to apply to all the tables and the columns of the date data type.



	id	funded_amount	loan_amount	activity	sector	country_code	country	region	currency	partner_id	posted_time	disbursed_time
1	653047	2225	2225	Personal Products Sales	Retail	PK	Pakistan	Lahore	PKR	247	2014-01-01 04:49:26+00:00	2013-12-17 08:00:00
2	653048	625	625	Food Production/Sales	Food	PK	Pakistan	Lahore	PKR	247	2014-01-01 05:41:03+00:00	2013-12-17 08:00:00
3	653049	250	250	Shoe Sales	Retail	PK	Pakistan	Lahore	PKR	247	2014-01-01 05:54:34+00:00	2013-12-17 08:00:00
4	653050	575	575	Clothing Sales	Clothing	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:05:17+00:00	2013-12-17 08:00:00
5	653051	300	300	Fruits & Vegetables	Food	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:12:39+00:00	2013-12-17 08:00:00
6	653052	875	875	Tailoring	Services	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:25:41+00:00	2013-12-17 08:00:00
7	653053	575	575	Rickshaw	Transportation	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:51:08+00:00	2013-12-17 08:00:00
8	653054	300	300	Rickshaw	Transportation	PK	Pakistan	Lahore	PKR	247	2014-01-01 06:58:07+00:00	2013-12-17 08:00:00
9	653055	350	350	Restaurant	Food	PK	Pakistan	Lahore	PKR	247	2014-01-01 07:14:40+00:00	2013-12-24 08:00:00
10	653056	475	475	Rickshaw	Transportation	PK	Pakistan	Lahore	PKR	247	2014-01-01 07:20:09+00:00	2013-12-24 08:00:00

First, I created another notebook named 'bronze_to_silver' for this first transformation. I created an array to list the table names in the bronze container. This code iterates through the bronze container to get the directory name and append the directory name to the table name array.

```
table_name = []
for i in dbutils.fs.ls('mnt/bronze/dbo/'):
  table_name.append(i.name.split('/')[0])
```

The code below generates the input path for all the tables iteratively and then loads as a data frame. The code declares the variable column, which gets the column names from the data frame as a list. I ensured that the file type was specified as CSV and the header was set as true to return the tables with header names. The next loop in the code checks if any column name has the name 'date' or 'time' and then converts it to the date format only. The last part of the code generates the output path in the silver container using the table name and writing the transformed data in the data lake. I specified the file type as CSV and used the overwrite option to rewrite any data in the silver container with the new version.

```
frompyspark.sql.functions import from_utc_timestamp, date_format
frompyspark.sql.types import StructType, StructField, StringType, TimestampType

foriintable_name:

  input_path = '/mnt/bronze/dbo/' + i + '/' + i +'.csv'
  df=spark.read.format('csv').option('header', 'true').load(input_path)

  forcol in df.columns:

    if"date" in col or "time" in col:
      df = df.withColumn(col, date_format(from_utc_timestamp(df[col].cast(TimestampType()),
"UTC"), "yyyy-MM-dd"))

  output_path = '/mnt/silver/dbo/' + i + '/'
  df.write.format('csv').mode("overwrite").option('header', 'true').save(output_path)
```

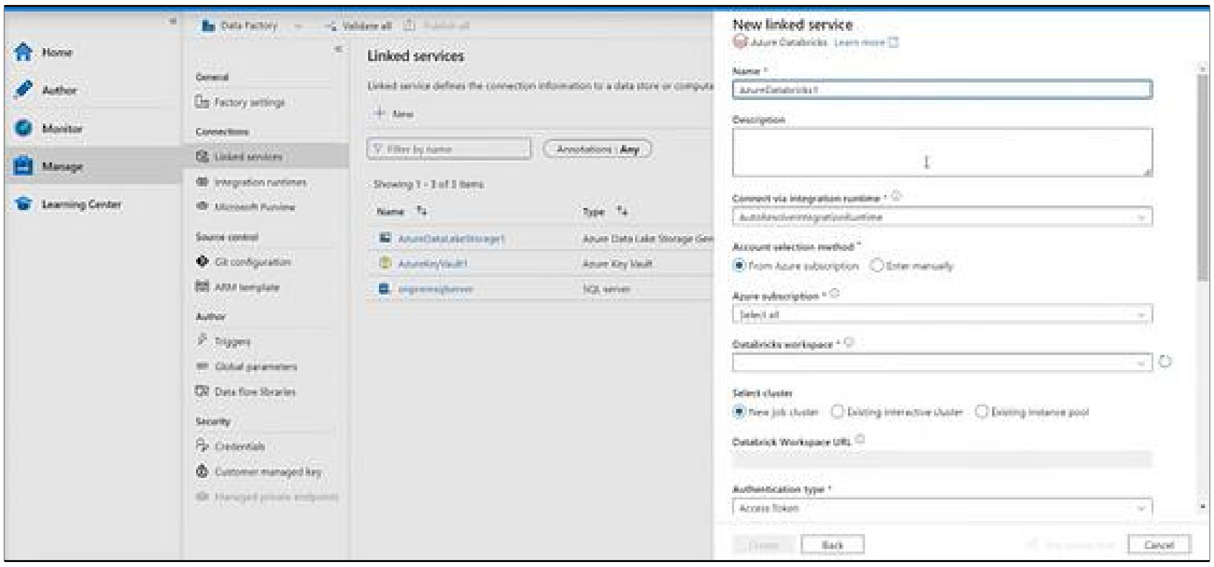
Level 2 Data Transformation After performing the first level of transformation to the data, the data in the silver container appeared cleaner but required further transformation to be ready for different use cases. Thus, I performed another transformation from data in the silver container by changing the column names to lowercase. This transformation was to ensure there is a uniform naming convention for the data across the different tables. The transformed data was then stored in different folders in the gold container with respective table names.
I created another notebook and named it 'silver_to_gold.' Similarly, I created an array listing table names in the silver container. This code iterates through the silver container to get the directory name and append the directory name to the table name array.

```
table_name = []
for i in dbutils.fs.ls('mnt/silver/dbo/'):
  table_name.append(i.name.split('/')[0])
```

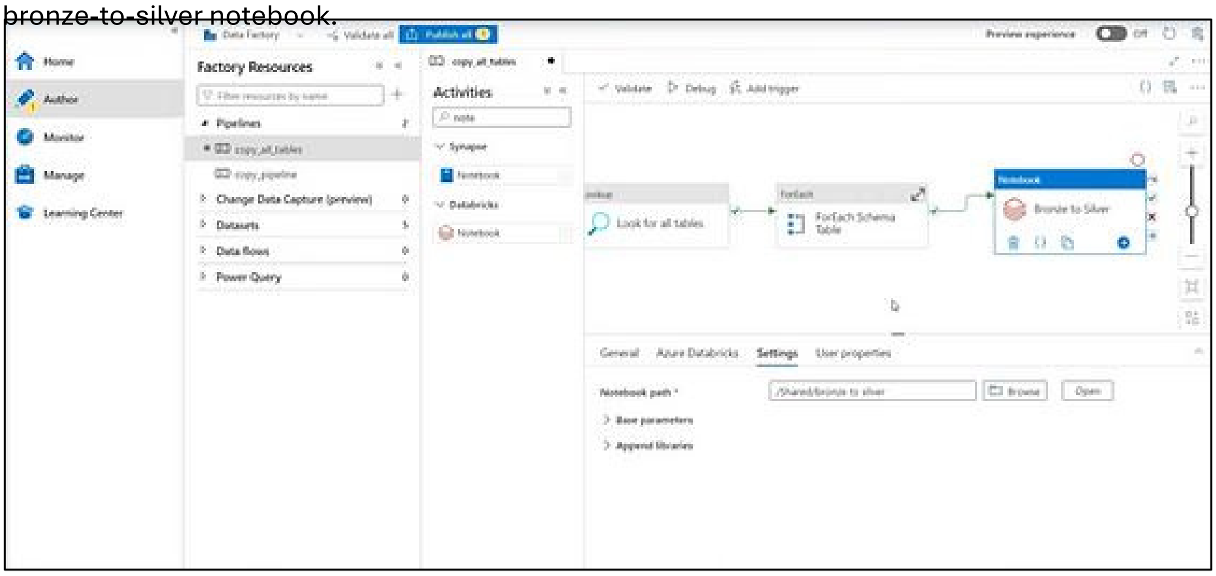
The code below generates the input path for all the tables iteratively and then loads as a data frame. The code declares the variable column_names, which gets the column names from the data frame as a list. I ensured that the file type was specified as CSV and the header was set as true to return the tables with header names. The next loop in the code iterates through the column names and changes to lowercase. The last part of the code generates the output path in the gold container using the table name and writing the transformed data in the data lake. I specified the file type as CSV and used the overwrite option to rewrite any data in the gold container with the new version.

```
forname in table_name:
  input_path = '/mnt/silver/dbo/' + name # Fix the input_path variable
  print(input_path)
  df=spark.read.format('csv').option('header', 'true').load(input_path)

  #Get the list of column names
  column_names = df.columns
  forold_col_name in column_names:

    #Change the column names to lowercase
    new_col_name = old_col_name.lower()

    #Change the column name using withColumnRenamed
    df= df.withColumnRenamed(old_col_name, new_col_name)

  output_path = '/mnt/gold/dbo/' + name + '/'
  df.write.format('csv').mode("overwrite").option('header', 'true').save(output_path)
```

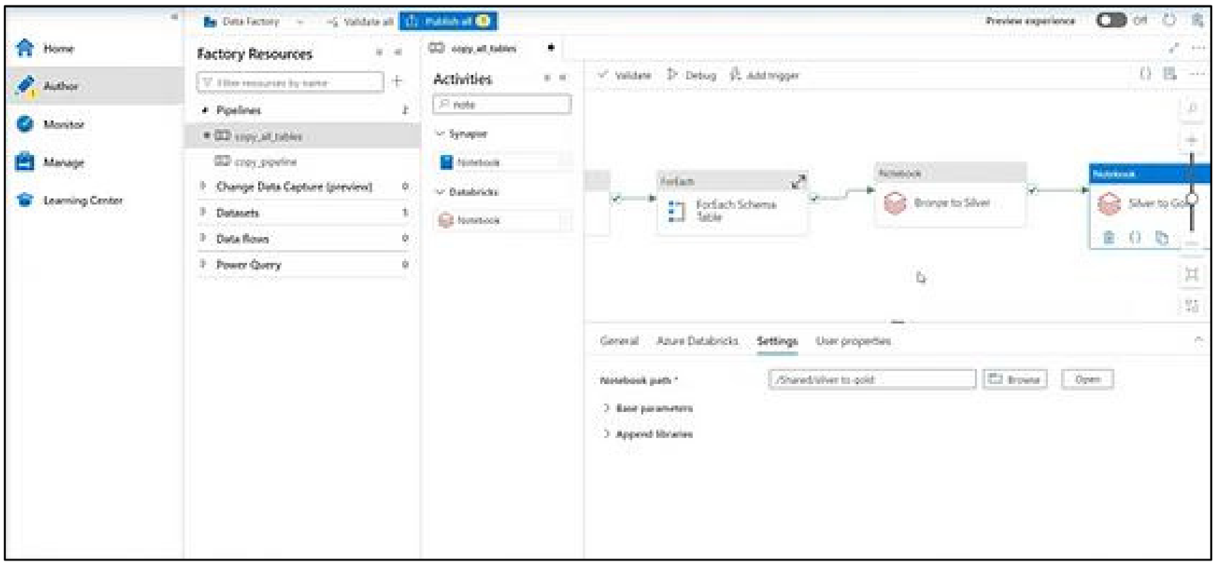
Data Transformation Pipeline Since the two notebooks perform the necessary transformation for data, I needed to add them to the Azure Data Factory pipeline to transform the data when triggered with daily additional data. To achieve the connection between Azure Databricks and Azure Data Factory, I created a new linked service and used an access token to authenticate the linked service.


New linked service
Azure Databricks
Name *: AzureDatabricks1
Description:
Connect via integration runtime *: AutoResolveIntegrationRuntime
Account selection method *: [✓ From Azure subscription] Enter manually
Azure subscription *: Select all
Databricks workspace *:
Select cluster: [✓ New job cluster] Existing interactive cluster Existing instance pool
Databrick Workspace URL:
Authentication type *: Access Token

After creating the linked service, I selected the author tab and looked for the pipeline I had created earlier to add the two notebooks. I added the Azure Databricks notebook item from this tab to add the new activity for the bronze to the silver notebook. I specified the path of the notebook and connected the output of the ForEach activity to the bronze-to-silver notebook. This link ensured the notebook would only run if the ForEach activity were successful. Similarly, I added another notebook item for the silver-to-gold activity to run after the successful run of the bronze-to-silver notebook.



General Azure Databricks Settings User properties
Notebook path *: /Shared/bronze to silver
Base parameters
Append libraries

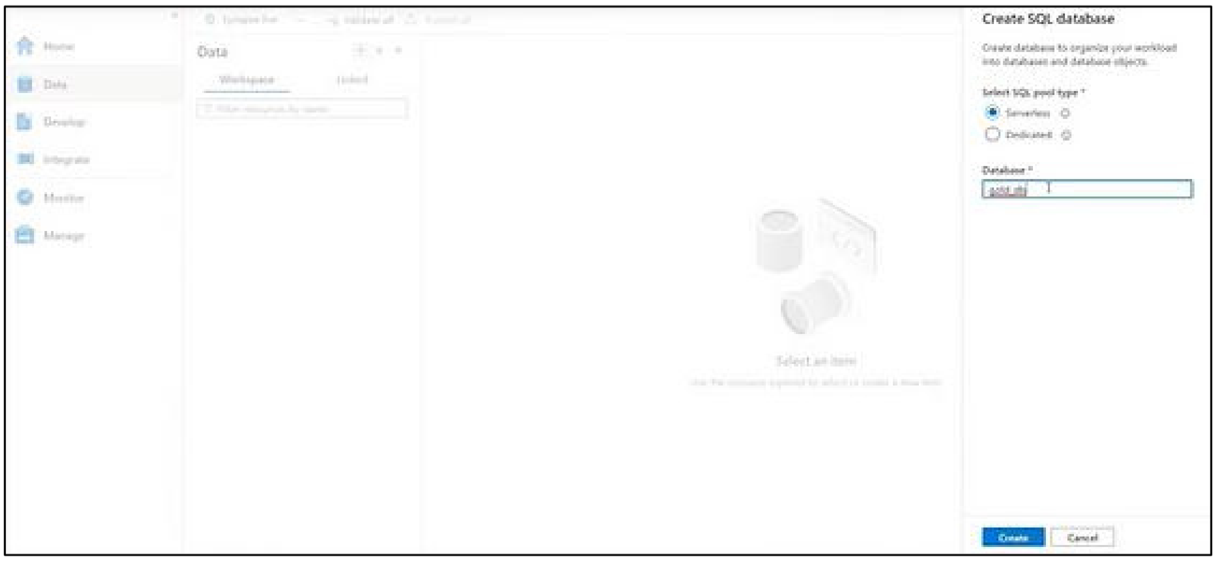


Notebook path * /Shared/silver to gold

I published all the changes and used the debug option to run the pipeline. Similarly, I added a new trigger to run the pipeline to confirm if it properly worked, where I confirmed each activity ran successfully from data ingestion to processing.

Data Loading Using Azure Synapse

With the transformed data in the gold container, I needed to load the data in the Azure SQL database for access and reporting. Therefore, I created a serverless database to store the dataand named the database ‘gold_db.’ The Azure Synapse Analytics workspace is linked to the Azure Data Lake Gen 2; hence, one can find data from the different containers in the linked datasets.


Create SQL database

Create database to organize your workload into databases and database objects.

Select SQL pool type *

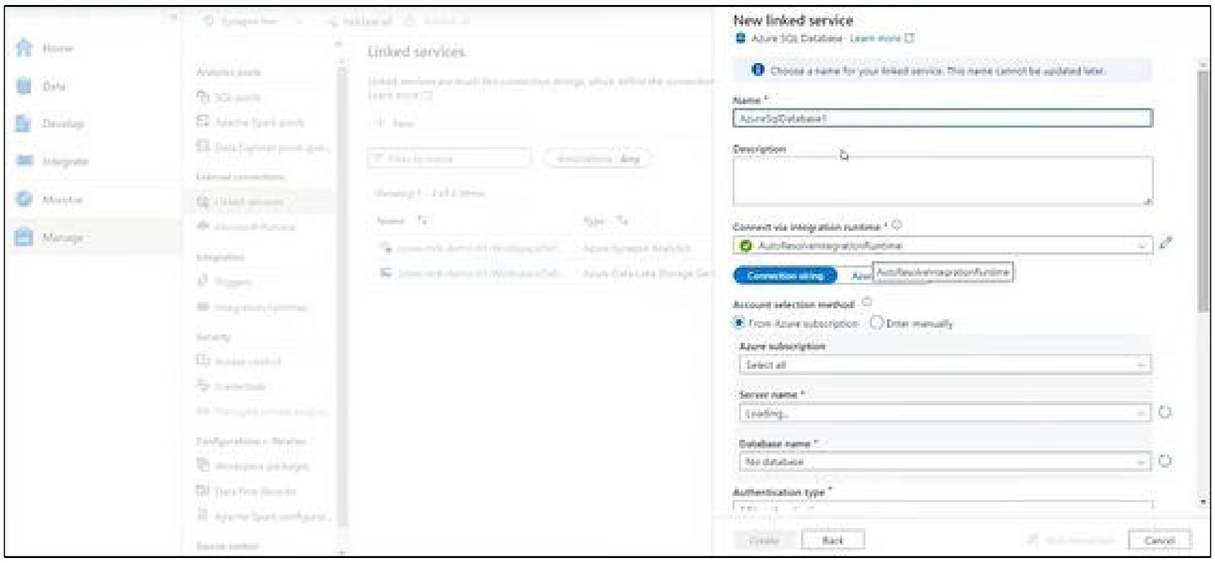
[✓ Serverless] Dedicated

Database * gold_db

Since there were different tables in the gold container, I needed to create views for the Azure SQL database. Therefore, I created a stored procedure using a new SQL script to create views of the different tables.

```
USE gold_db
GO
CREATE OR ALTER PROC CreateSQLServerlessView_gold @Viewname nvarchar(100)
AS
BEGIN

DECLARE @statement VARCHAR(MAX)


 SET @statement = N'CREATE OR ALTER VIEW ' + @Viewname + ' AS
  SELECT *
  FROM
   OPENROWSET(
   BULK ''https://kivaloansstg.dfs.core.windows.net/gold/dbo/' + @Viewname + '/'',
   FORMAT = ''CSV''
  ) AS [result]
  '

EXEC (@statement)

END
GO
```

Ialso needed to create a pipeline to use the stored procedure (SQL query) to create views in the SQL serverless database. Under the manage tab, I made a new linked service for the 'Azure SQL Database' to access the serverless SQL database. Note the integration runtime is automatically selected as "AutoResolveIntegrationRuntime' since it is a cloud-based resource. Configure the account selection manually and use the 'System Assigned Managed Identity' authentication type.



New linked service

Azure SQL Database · Learn more

Choose a name for your linked service. This name cannot be updated later.

Name *: AzureSqlDatabase1

Description

Connect via integration runtime *: AutoResolveIntegrationRuntime

Account selection method: (● From Azure subscription) ○ Enter manually

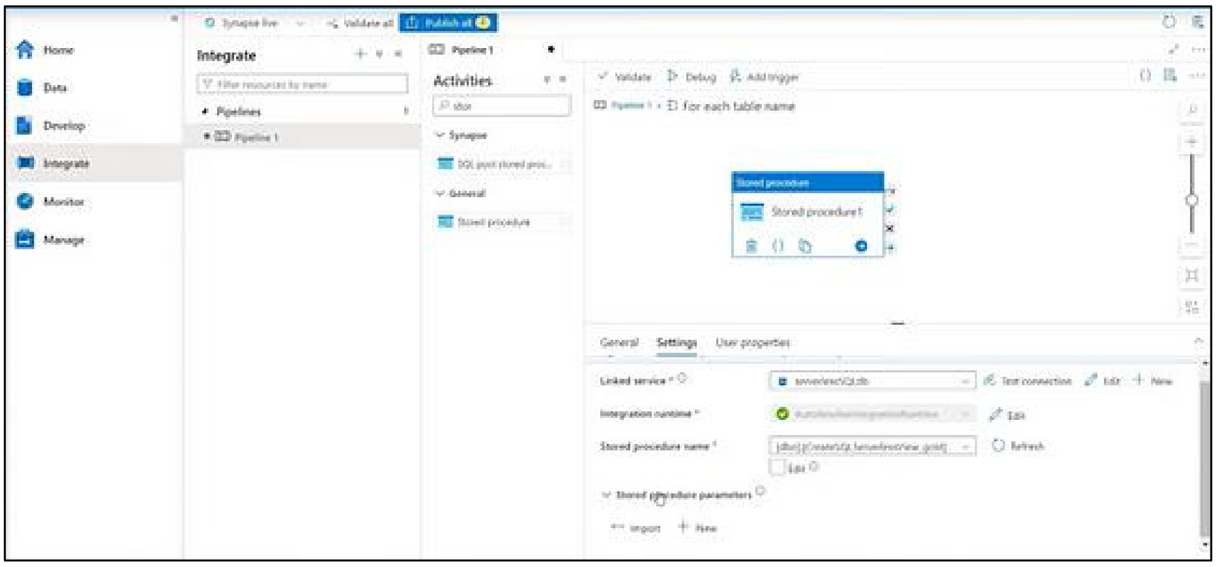
Azure subscription: Select all

Server name *: Loading...

Database name *: No database

Authentication type *

After creating the linked service, I made a new pipeline and added the 'Get Metadata' item to get the table names from the gold container. Similarly, I added a 'ForEach' item to get each item from the metadata and selected the stored procedure name from the existing list.



Pipeline 1 › For each table name

Stored procedure: Stored procedure1

General | Settings | User properties

Linked service *: serverlessSQLdb

Integration runtime *: AutoResolveIntegrationRuntime

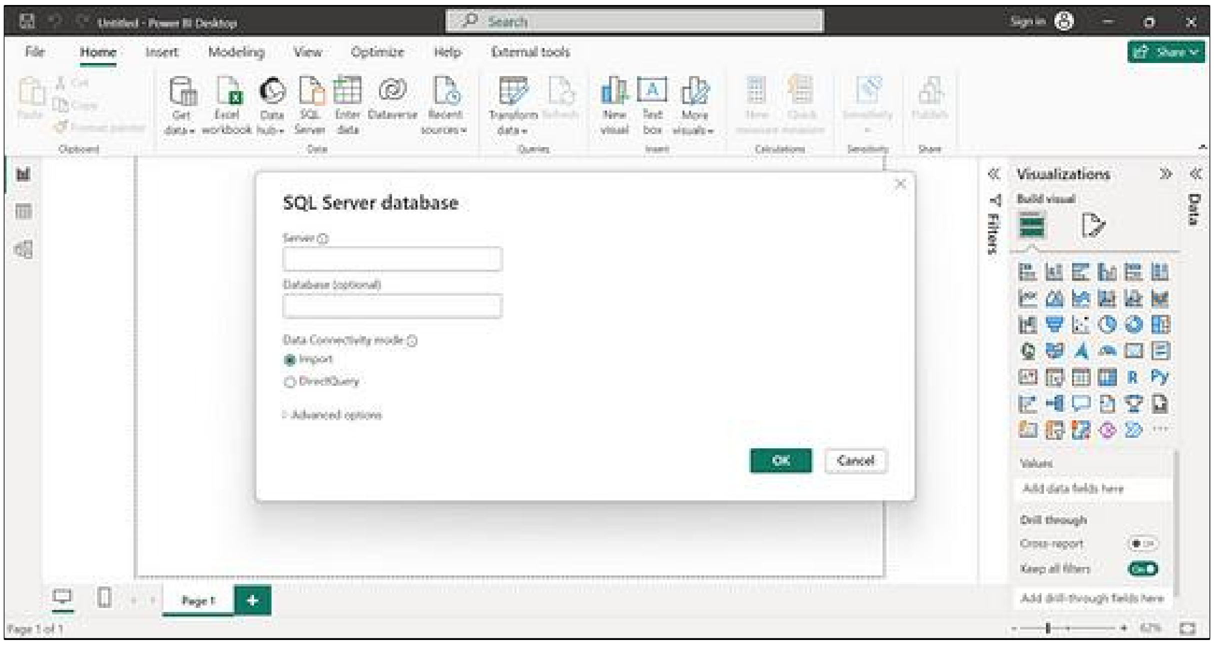
Stored procedure name *: [dbo].[CreateSQLServerlessView_gold]

Stored procedure parameters

After that, I published all the changes and ran the pipeline using the debug option. This option added the different views from the tables in the gold container to the Azure SQL database.

Data Reporting using Power BI

In this last section of the project, I explain how I used Power BI to connect to the Azure Synapse SQL serverless database, fetched the views in the database, and created an interactive dashboard to report some of the KPIs for Kiva. I used the 'Get data' option on the Power BI ribbon for this scenario and selected Azure. Under the Azure data source, I selected 'Azure Synapse Analytics SQL' and hit the connect button. This action prompts one to input the server name and database.



SQL Server database

Server

Database (optional)

Data Connectivity mode

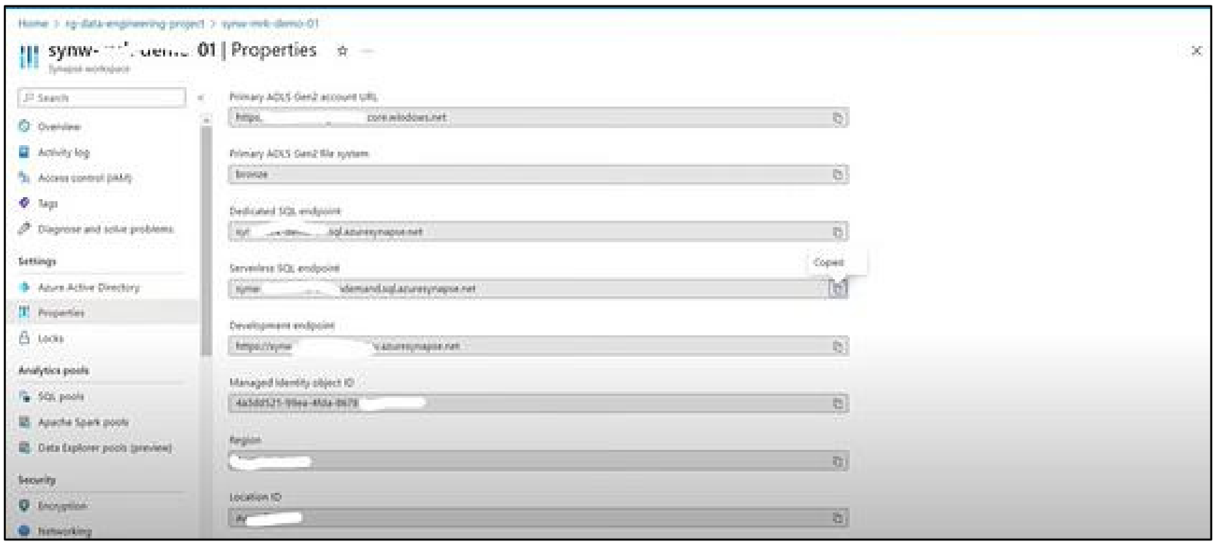
[✓ Import]

DirectQuery

Advanced options

OK Cancel

One can get the server's name by navigating to the Azure Synapse Analytics workspace, under the properties tab, and copying the 'Serverless SQL endpoint' as the server name. I also maintained the import data connectivity mode to load the data/tables in Power BI.



Home > rg-data-engineering-project > synw-mk-demo-01

synw-[illegible] 01 | Properties

Synapse workspace

Primary ADLS Gen2 account URL: https.[redacted]core.windows.net

Primary ADLS Gen2 file system: bronze

Dedicated SQL endpoint: syt[redacted]sql.azuresynapse.net

Serverless SQL endpoint: synw[redacted]ondemand.sql.azuresynapse.net

Copied

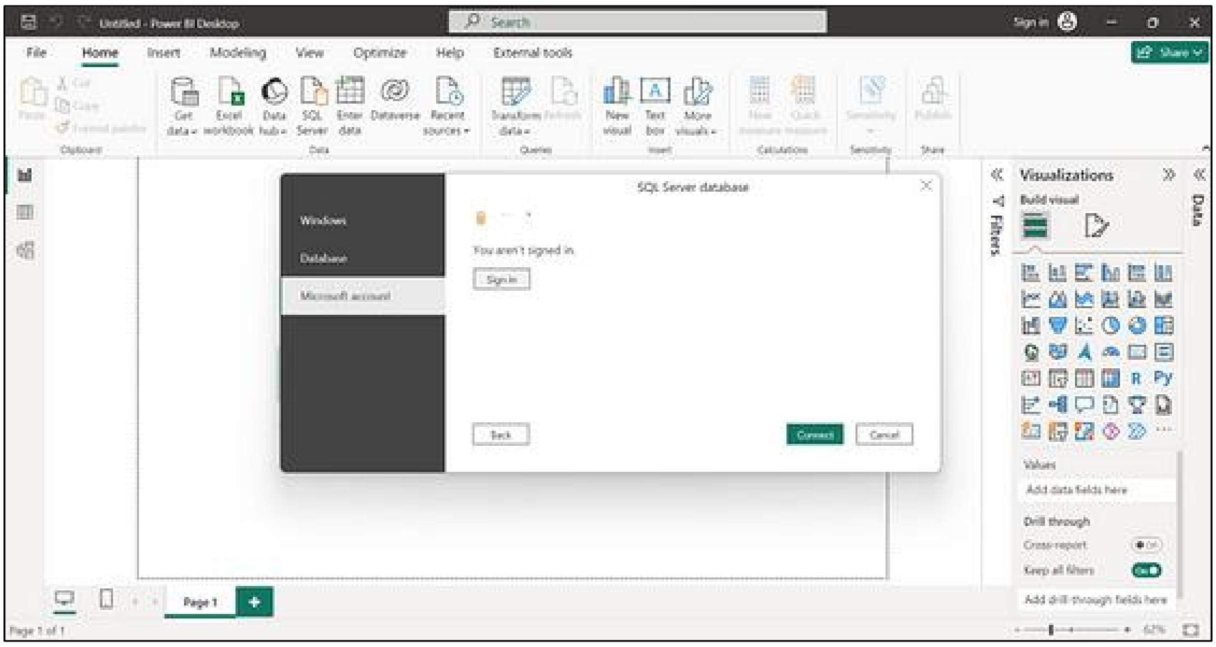
Development endpoint: https://synw[redacted].azuresynapse.net

Managed Identity object ID: 4a3dd521-99ea-4fda-8678[redacted]

Region: [redacted]

Location ID: [redacted]

I used my Microsoft account to sign in and connect to the database.



SQL Server database

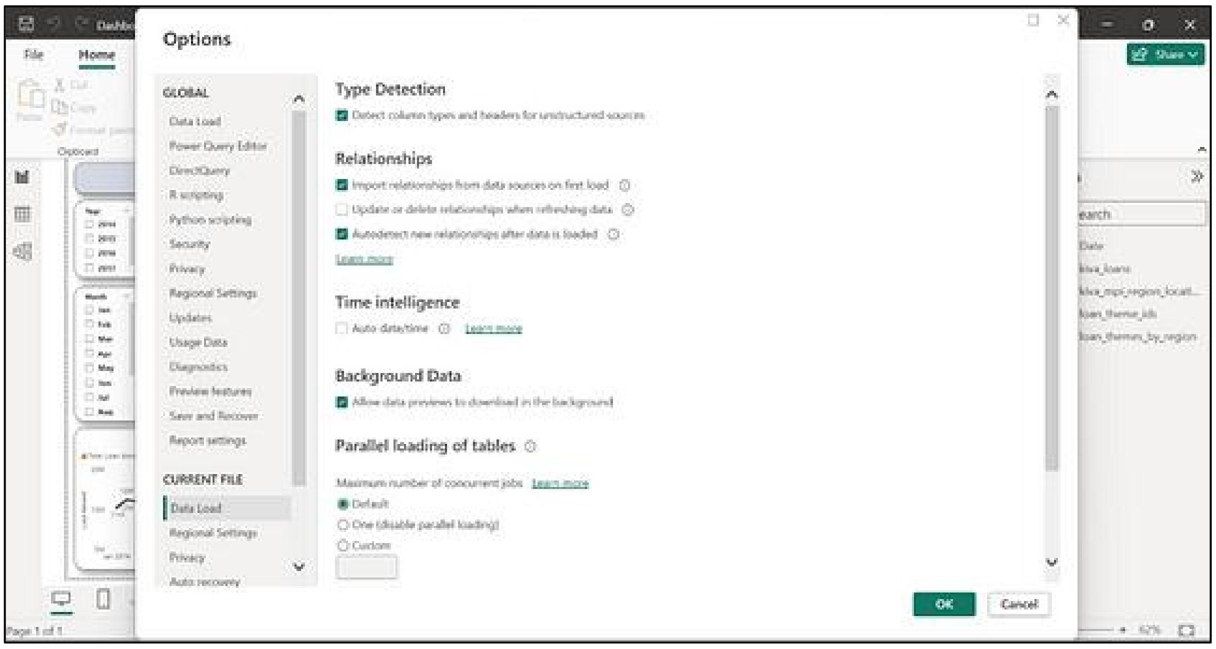
Windows
Database
Microsoft account

You aren't signed in

Sign in

Back
Connect
Cancel

This action connected to the database and fetched the different views in the Azure SQL database as tables. I noticed an error in importing the files due to a conflict between the date format in the tables and my settings in Power BI. Therefore, I disabled the 'Time Intelligence' option under the 'Options' menu for the current file.



Options

Type Detection

- [✓] Detect column types and headers for unstructured sources

Relationships

- [✓] Import relationships from data sources on first load
- [ ] Update or delete relationships when refreshing data
- [✓] Autodetect new relationships after data is loaded

Learn more

Time intelligence

- [ ] Auto date/time Learn more

Background Data

- [✓] Allow data previews to download in the background

Parallel loading of tables

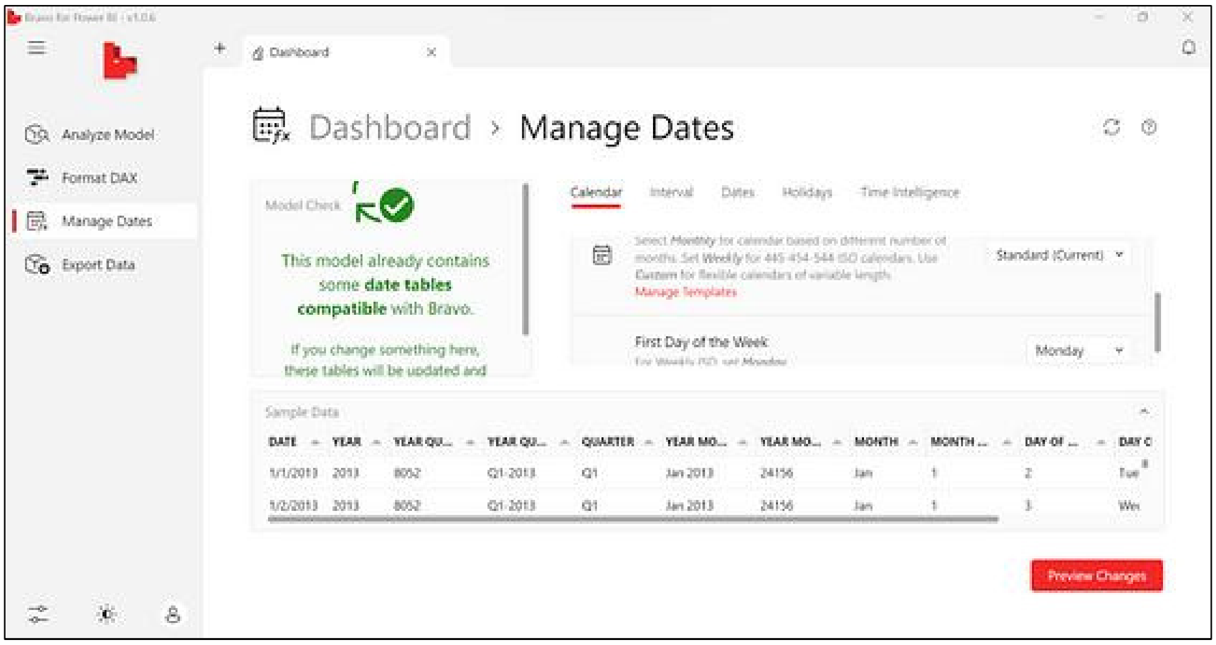
Maximum number of concurrent jobs Learn more

- [✓ Default]
- One (disable parallel loading)
- Custom

OK
Cancel

I performed some transformations on the tables using Power Query to ensure each column was of the right data type. I also converted the date column of the main table to the appropriate data type.

Since I was to use the dates to filter the data for some insights, I created the date table separately using Bravo, an external tool for Power BI. Bravo generates the dates automatically and creates the date table.


Dashboard › Manage Dates

Model Check

This model already contains some **date tables compatible** with Bravo.

If you change something here, these tables will be updated and

Calendar | Interval | Dates | Holidays | Time Intelligence

Select *Monthly* for calendar based on different number of months. Set *Weekly* for 445-454-544 ISO calendars. Use *Custom* for flexible calendars of variable length.
Manage Templates

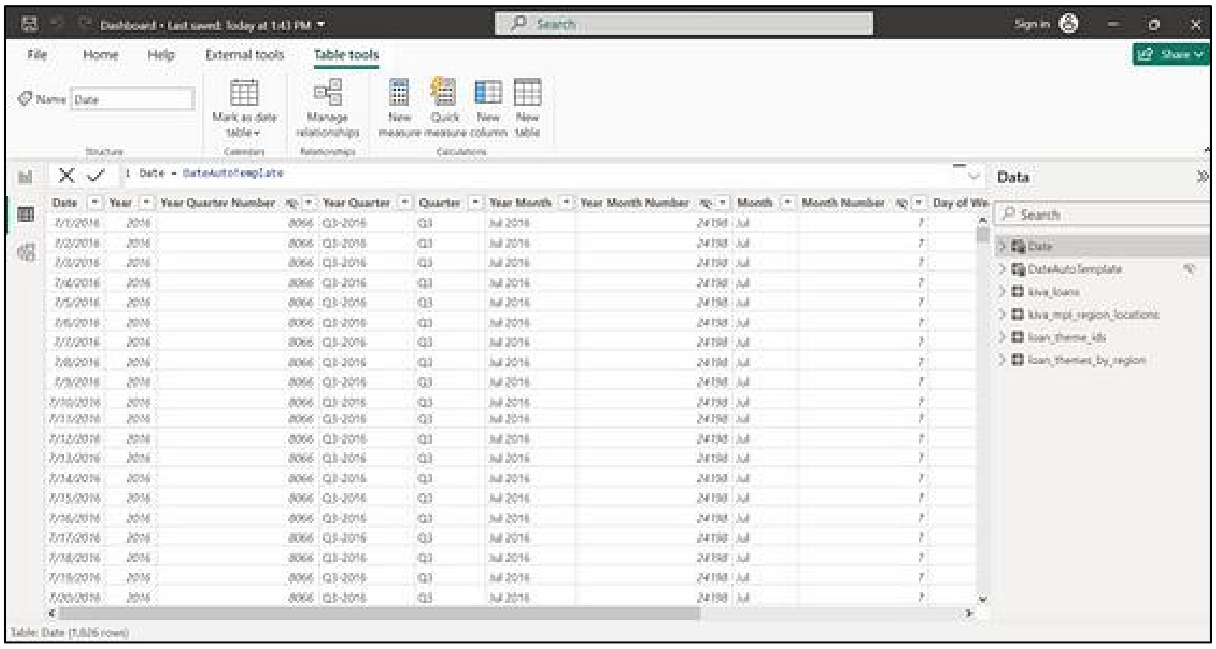
Standard (Current)

First Day of the Week — Monday

Sample Data

DATE	YEAR	YEAR QU...	YEAR QU...	QUARTER	YEAR MO...	YEAR MO...	MONTH	MONTH ...	DAY OF ...	DAY C
1/1/2013	2013	8052	Q1-2013	Q1	Jan 2013	24156	Jan	1	2	Tue
1/2/2013	2013	8052	Q1-2013	Q1	Jan 2013	24156	Jan	1	3	We

The resulting data table is shown below. The other tables remained the same.



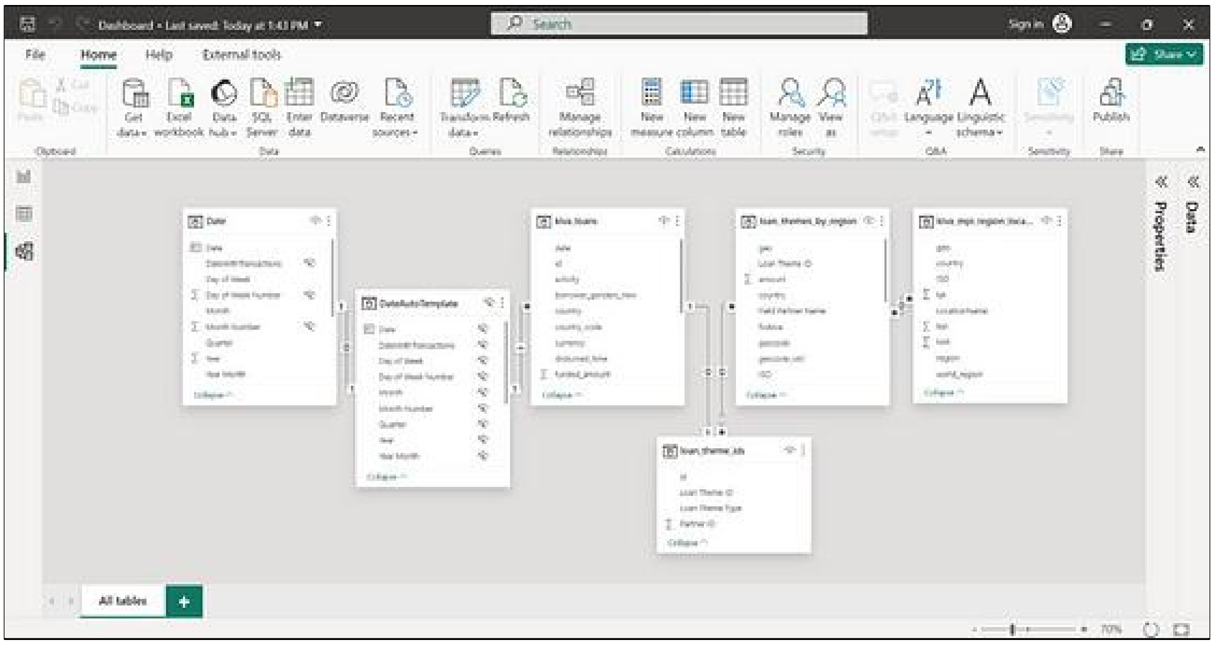
Name: Date

```
1 Date = DateAutoTemplate
```

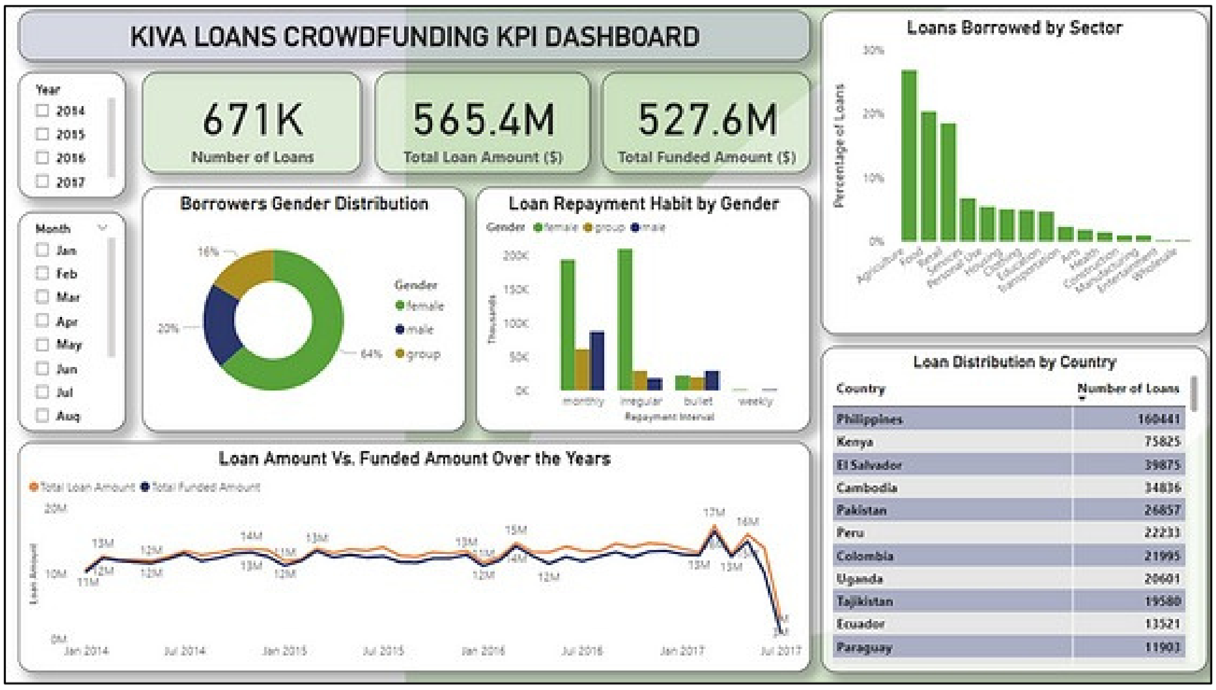
Date	Year	Year Quarter Number	Year Quarter	Quarter	Year Month	Year Month Number	Month	Month Number	Day of We
7/1/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/2/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/3/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/4/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/5/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/6/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/7/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/8/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/9/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/10/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/11/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/12/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/13/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/14/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/15/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/16/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/17/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/18/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/19/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	
7/20/2016	2016	8066	Q3-2016	Q3	Jul 2016	24198	Jul	7	

Table: Date (1,826 rows)

Before analyzing and building the visuals, I checked the modeling tab to ensure the tables had proper relations. One must manually create the relationship between the new date table and the date column of the ‘kiva_loans’table.



After confirming the tables had the appropriate relationships, I created the dashboard below for reporting.



Country	Number of Loans
Philippines	160441
Kenya	75825
El Salvador	39875
Cambodia	34836
Pakistan	26857
Peru	22233
Colombia	21995
Uganda	20601
Tajikistan	19580
Ecuador	13521
Paraguay	11903

According to this dashboard, I used three cards to display the important metrics. Using the unique ID from the ‘kiva_loans’ table, I got the count of the total number of loans disbursed by Kiva. Besides, the total loan and total funded amounts are $565.4 million and $527.6 million, respectively. I also included a bar chart to show the percentage of loans borrowed by sector. This chart shows the sector where the loan borrowers intended to use the loans. Additionally, I included a doughnut chart to show the gender distribution of the borrowers. To achieve this chart, applied conditional formatting to the column borrowers’ gender and categorized the ‘male’ as male, ‘female’ as ‘female’, and any other combination as a group. Therefore, the chart shows females were the most borrowers while people in group borrowers were the least.

I also included a clustered column chart to show the loan repayment habits of the borrowers based on gender. The chart indicates most of the borrowers' monthly repayments. However, some borrowers made irregular repayments making it the second-most repayment routine. Still, the bullet and weekly repayment intervals were the least preferred repayment intervals by the borrowers. I also included a table to show the loan distribution by country. The table is in descending order and shows the top two countries, the Philippines and Kenya. The line chart shows the total loan amount vs the funded amount from January 2014 to July 2017. There is a significant trend and difference between these two metrics over the years and different months.
From the data table, I included the 'Year' and 'Month' slicers to help filter the dashboard according to specific periods. This approach would allow users to check the different metrics and compare the trends throughout the various months.

Pipeline Testing

I tested this pipeline by adding 10 random rows to the main table and triggering the pipeline to run. I also created a scheduled trigger to run once daily as I added ten rows of data in the original table for five days. After the successful run of each trigger, I refreshed the Power BI report, which changed to reflect the new data according to the number of loans added. This approach showed the data engineering pipeline worked as scheduled.

Conclusion

According to this project, I have showcased how I used Microsoft Azure to create an end-to-end data engineering pipeline. This pipeline used data from the on-premise SQL server database and loaded the data in Azure Data Lake Gen 2 storage. I performed the necessary transformations using Azure Databricks and loaded the data in Azure SQL Database. Using two levels of transformations, I ensured the data was clean and ready for different use cases. Thus, I extracted the data using Power BI and created a report for presentation to relevant stakeholders. This report represents a practical use case of Azure in data engineering in gathering data and making it ready and reliable for use.