Taksh Shah

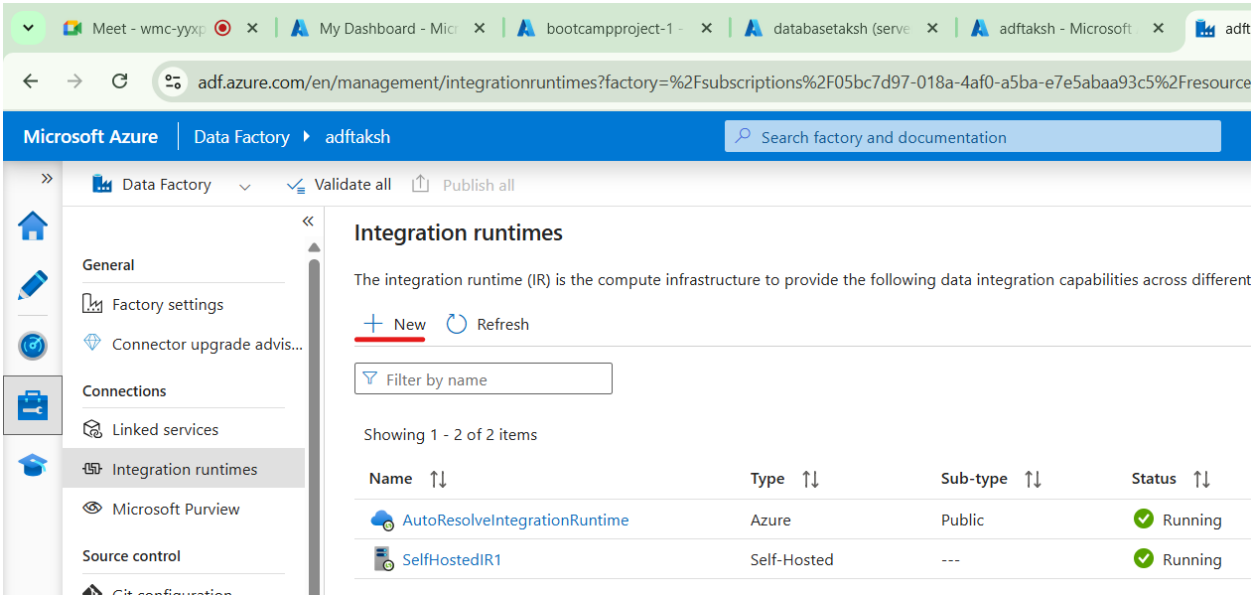
Project: Customer Account Analysis

Objective:

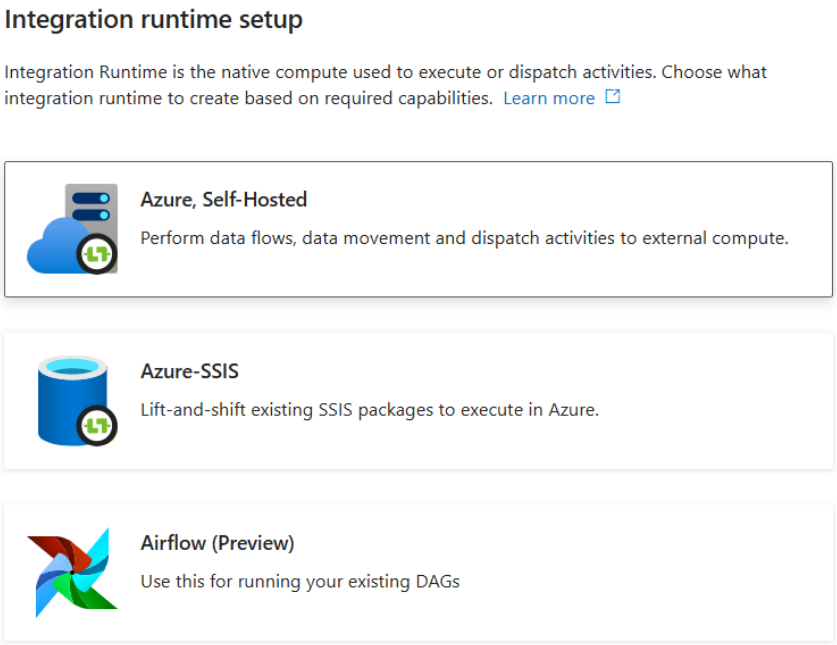
The project aims to design and implement a robust data pipeline for processing customer account data. This includes copying data from a backend team's storage account, performing necessary transformations using ADF and upserting (inserting or updating) data from a file stored in Azure Data Lake Storage ADLS Gen2 storage into sql database table. The pipeline aims to ensure efficient, accurate, and scalable data processing to support downstream analytics and reporting needs.

To begin with, in order to get data from a local system to adlsgen2 storage account on Microsoft Azure, we'll use self-hosted integration runtime (IR) to achieve this task. You can utilize virtual machine for this task as well, but we'll use self-hosted IR.

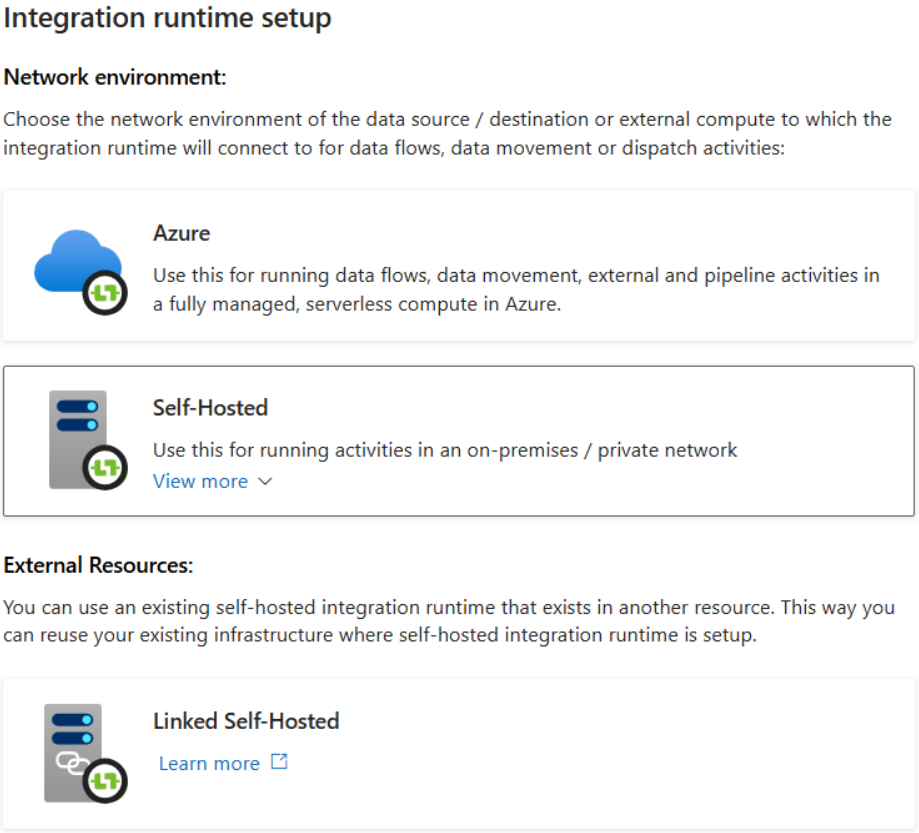
For that, go to this website: https://www.microsoft.com/en-us/download/details.aspx?id=39717 and download "IntegrationRuntime_5.50.9171.1.msi" into your local system(pc/laptop). Then, in your ADF (Azure Data Factory), go to manage -> integration runtimes and create a new IR.



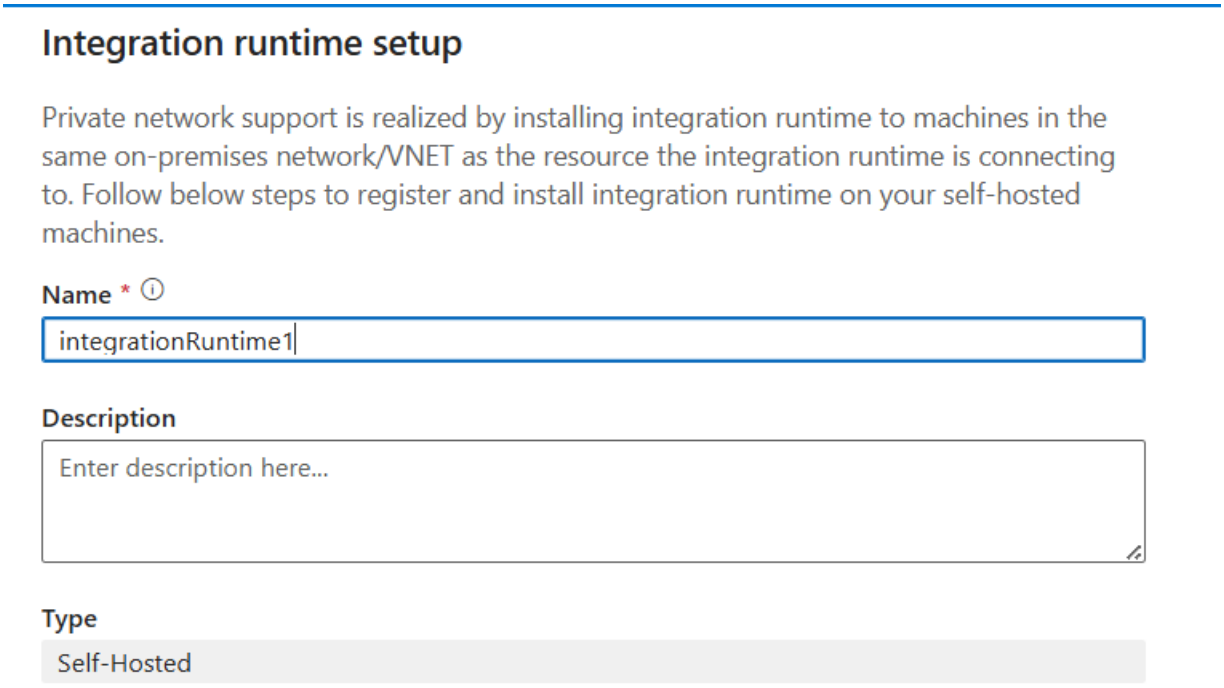
Then, select “Azure, Self-Hosted” option and select continue.



Again, select “Self-Hosted” and continue.



Now, give a name to your self-hosted IR and click create.

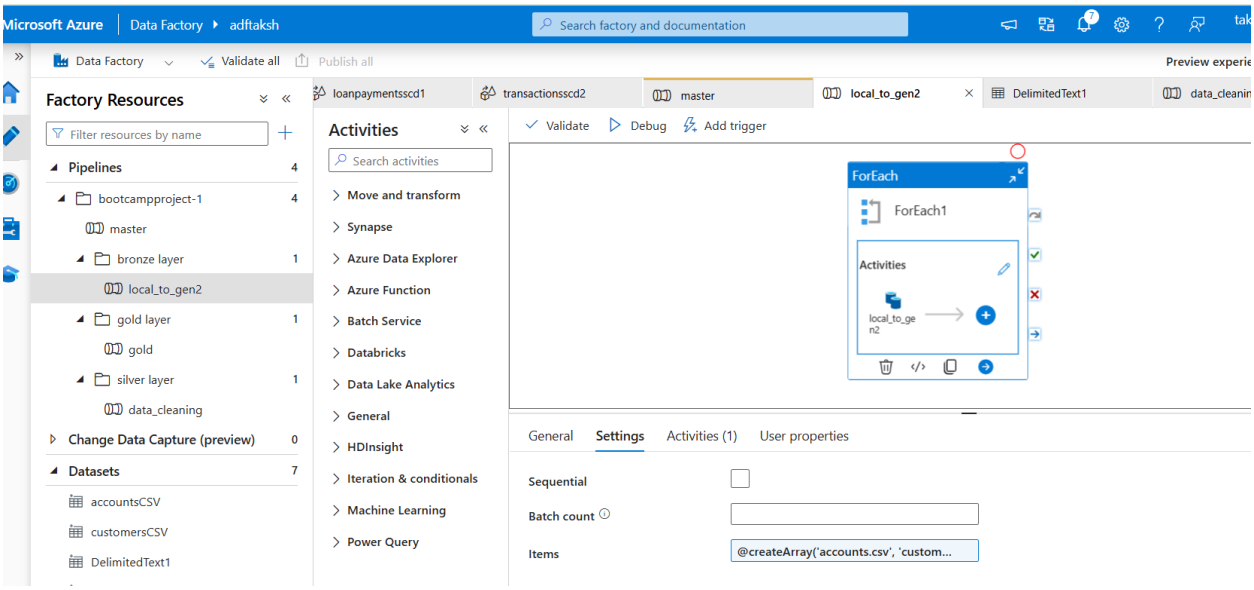


This will create your self-hosted IR and show 2 keys – key1 and key2 – copy key1 as we'll use it later. Now, let's setup the IR that we downloaded from the previously mentioned Microsoft website. Once you open its setup and install all the files, it'll then prompt you to enter a key for your IR – this is where we'll utilize the key1 that we had previously copied.

Bronze Layer Pipeline:

This pipeline will be responsible in copying the data from our local system to the adlsgen2 storage account. We have 5 csv files in our dataset namely 'accounts.csv', 'customers.csv', 'loan_payments.csv', 'loans.csv', 'transactions.csv'

Dataset link: https://www.kaggle.com/datasets/varunkumari/ai-bank-dataset



Bronze layer pipeline – for-each loop with a copy data activity

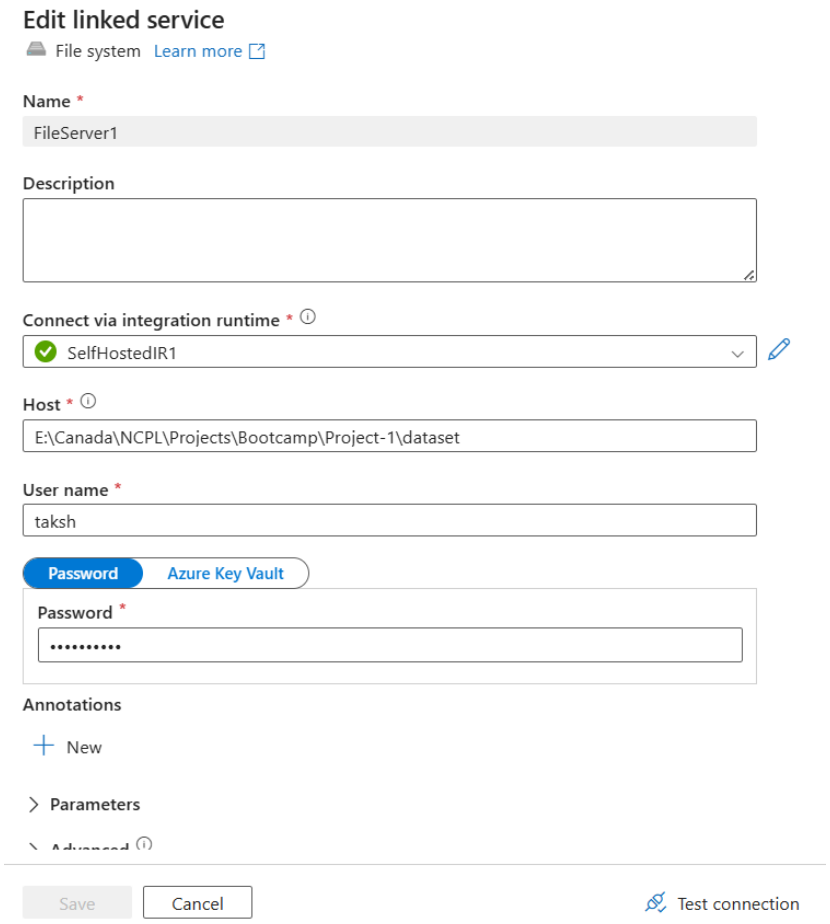
To build this pipeline, we'll use a copy data activity within a for-each loop, so instead of using the copy data activity multiple times to get all the files from the dataset into our storage account, a loop will prove more convenient and efficient to do the same task.

Create a for-each activity. Under its settings, in "items" field, we'll have to provide a value as it's a requirement. Now for-each loop takes input in the form of arrays, meaning we'll have to pass a value as an array. Since we want to get the files from our dataset folder present on our local system, we'll provide an array of the filenames to our loop, so it'll iterate through those names and then the copy data activity within the loop will copy all the files into our storage account. Use the following command as an input to the "items" field:

@createArray('accounts.csv', 'customers.csv', 'loan_payments.csv', 'loans.csv', 'transactions.csv')

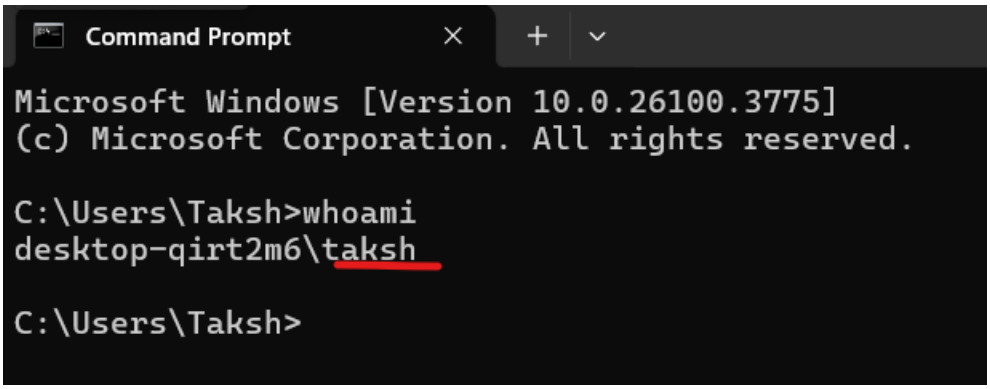
Now, let's create a copy-data activity within the for-each loop. Under "source", let's create a new dataset. Here, we'll have to create a new linked service for our file system. So we'll select source as "file system" as data is present in our local system and source will be adlsgen2 where

the data will be stored a CSV file. The image below shows what the linked service settings will look like.

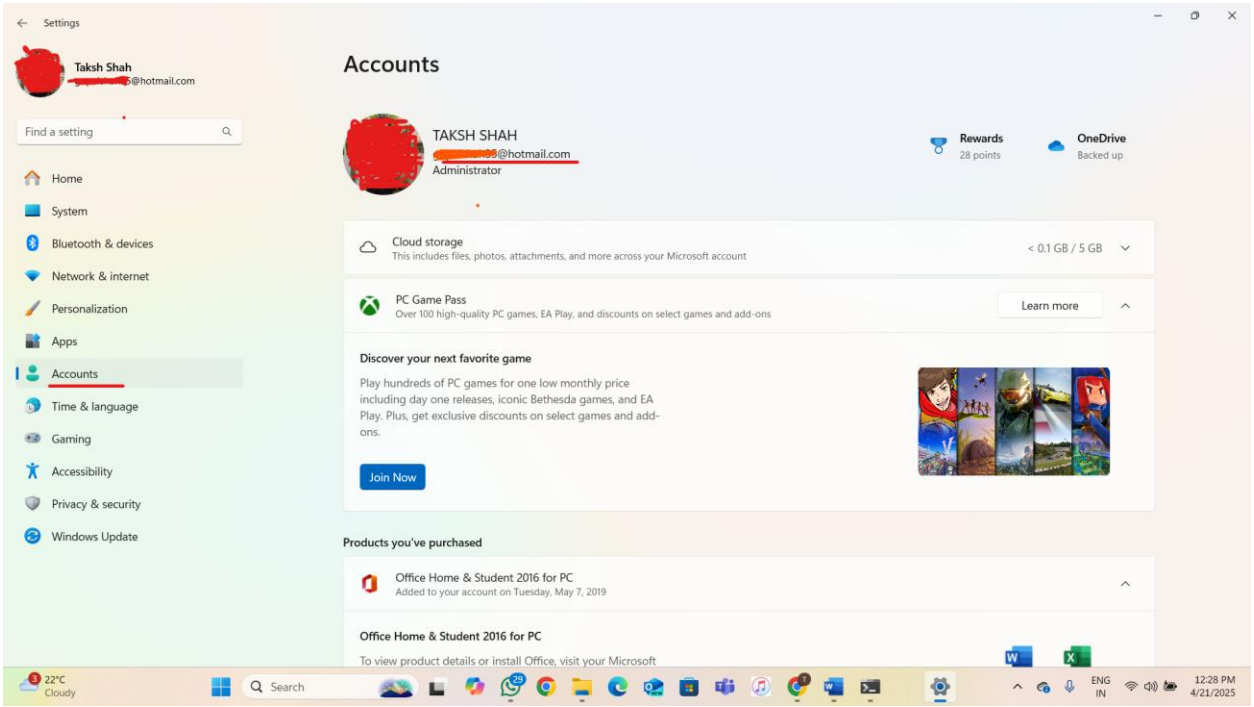


Here, “host” will be the path where the dataset is stored in the local system. Username and password – these credentials are crucial – they can be found as follows:

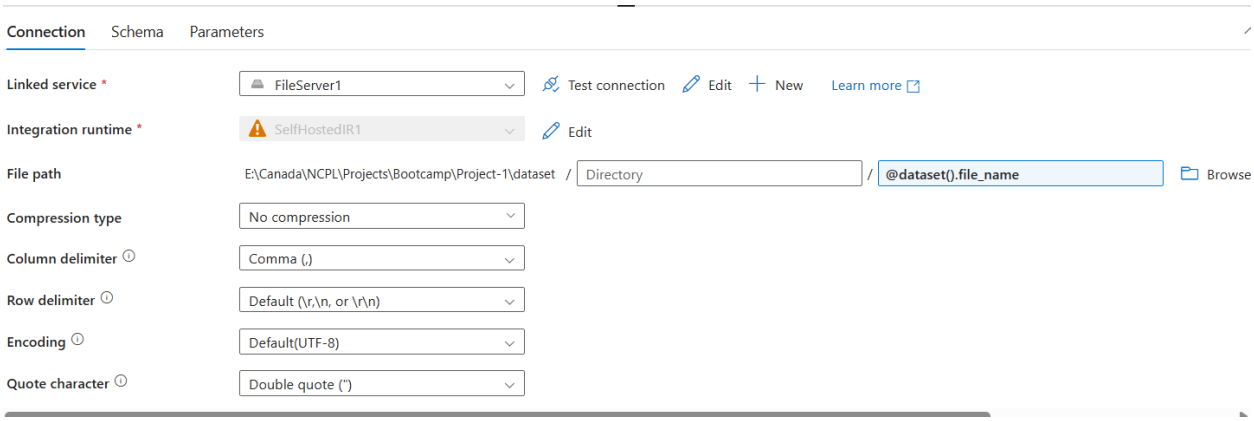
In your command prompt, write the command “whoami” to figure out the user name.



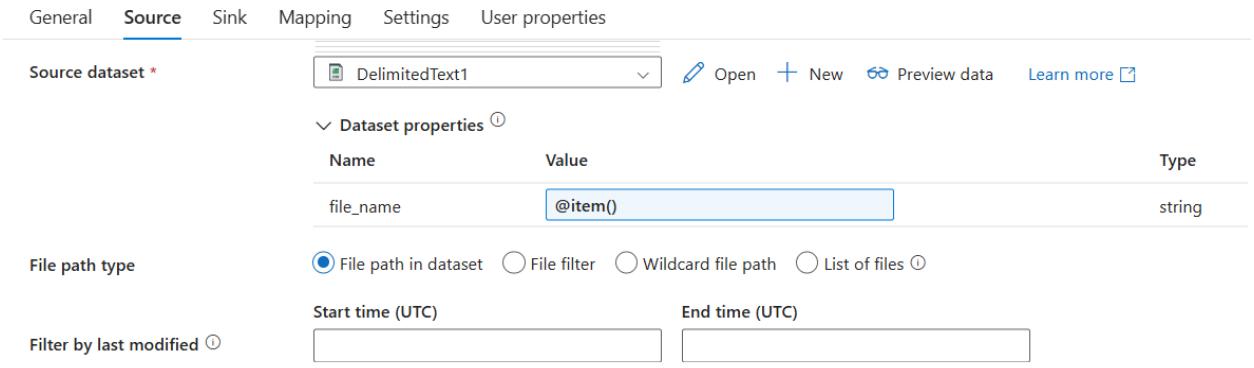
The password will be either of these 2 – your laptop/pc user password (ie, the password with which you login to your laptop/pc) OR the password of the email with which you’re currently signed into in your laptop/pc – this can be found in settings -> accounts if it’s a windows system.



Once your linked service is created, select the self-hosted integration runtime which we created earlier, provide file path as the location of the dataset folder and make sure to select first row as header option. Here, we’ll create a parameter called file_name which will be useful in iterating through all the files present in the dataset folder.



This completes the creation of our dataset for the copy data activity. Make sure to provide the value for file_name parameter which we created earlier.

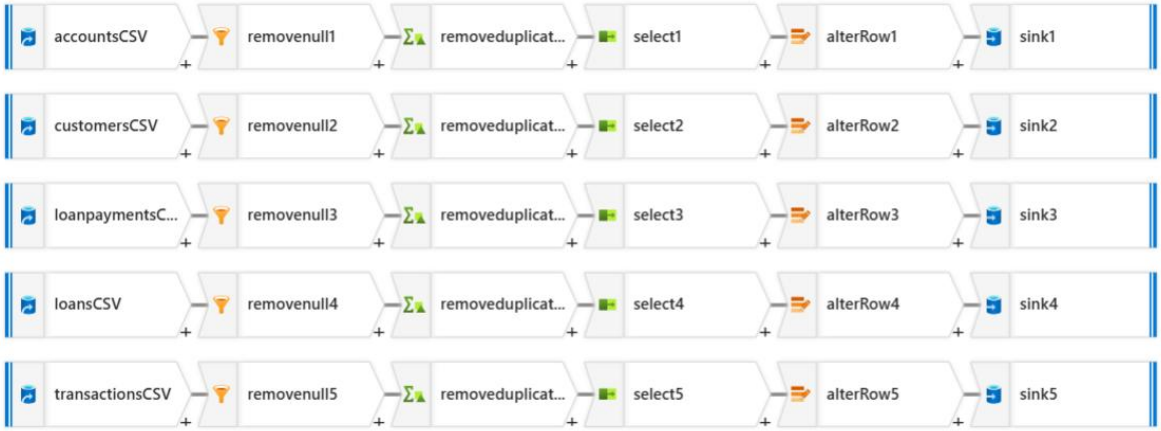


For the sink part of copy data activity, we'll create a new dataset. Linked service will be the one for adlsgen2 storage account with self-hosted IR. File path will be your container in the adlsgen2 storage account where you can create a folder called "bronze layer" and store the files. Make sure to select first row as header option. Under "sink" section, make sure to change file extension to ".csv". This marks the end of bronze layer pipeline.

Silver Layer Pipeline:

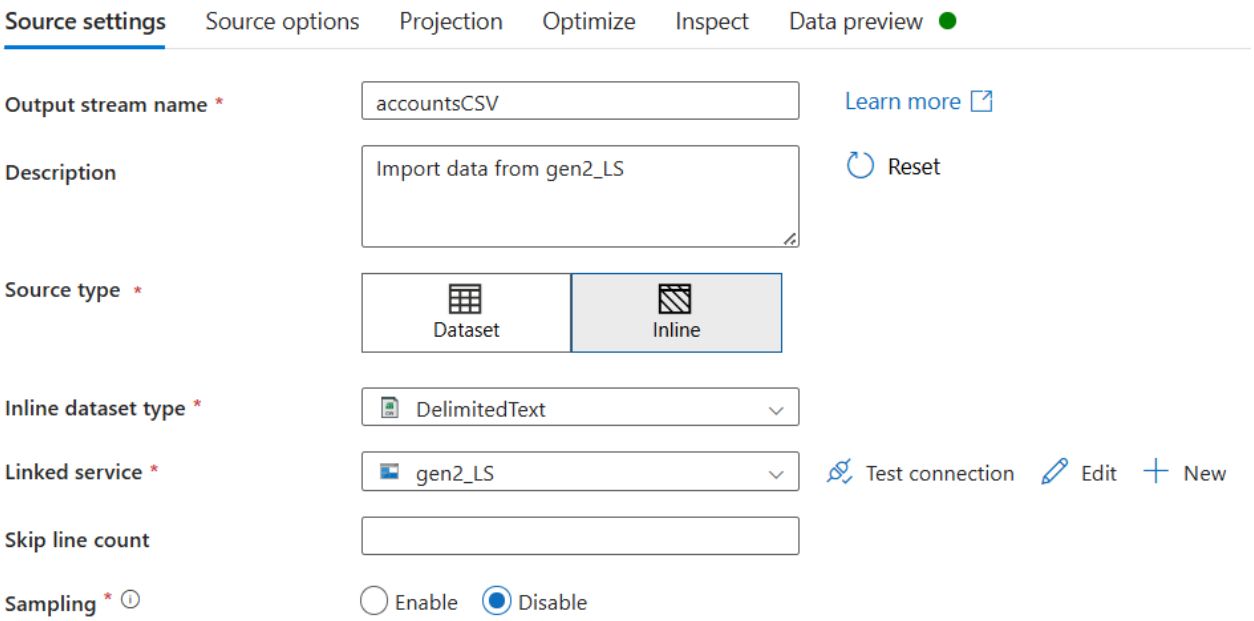
This pipeline will be responsible for cleaning the data that we just stored into our adlsgen2 storage account from the local system so that it can be used for processing and eventually storing the data into our sql database. We'll remove null values, remove duplicate values and rename the columns at this stage.

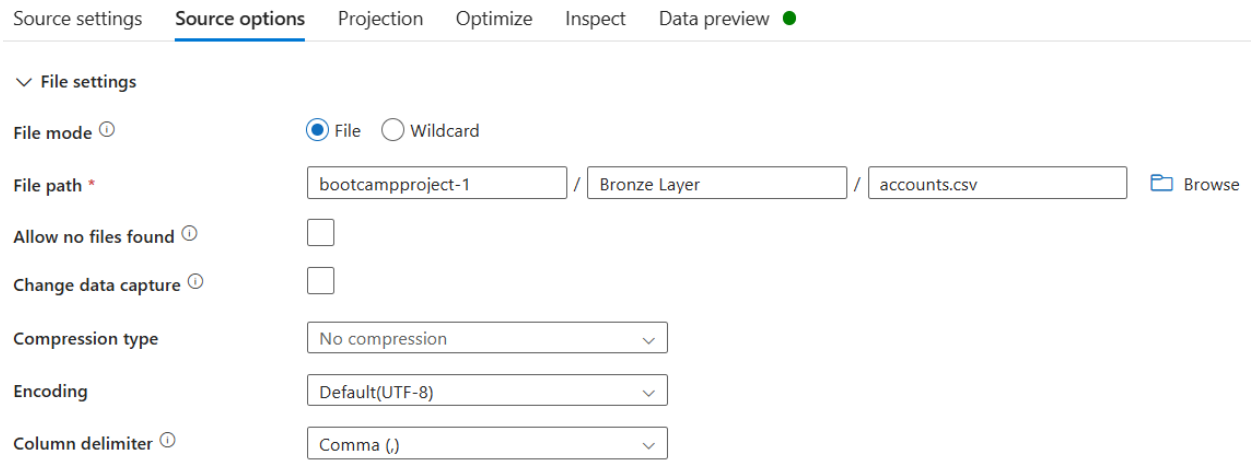
Here, we'll use a dataflow within which we'll use 5 sources – 1 for each file – and apply all the necessary transformations and eventually store the data back into our adlsgen2 account in a folder called "silver layer" and in delta format.



Silver layer pipeline – inside the dataflow

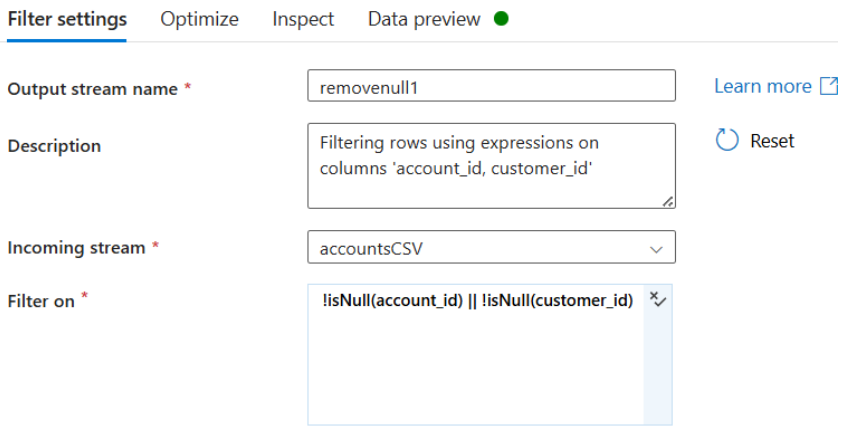
Let's take the first source to understand the pipeline – accountsCSV



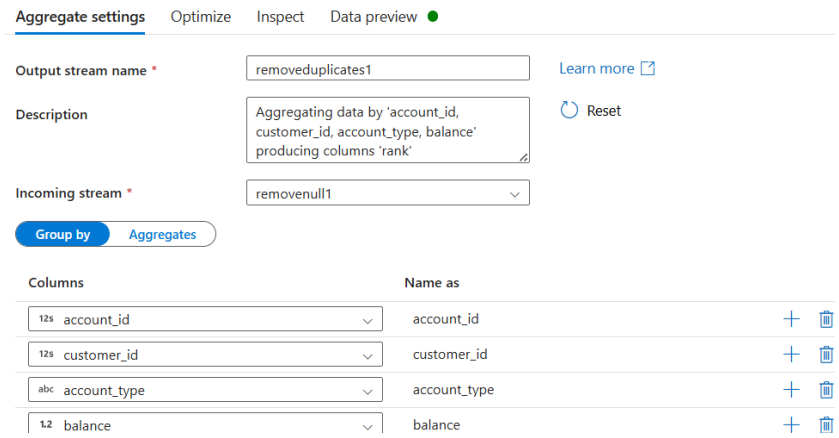


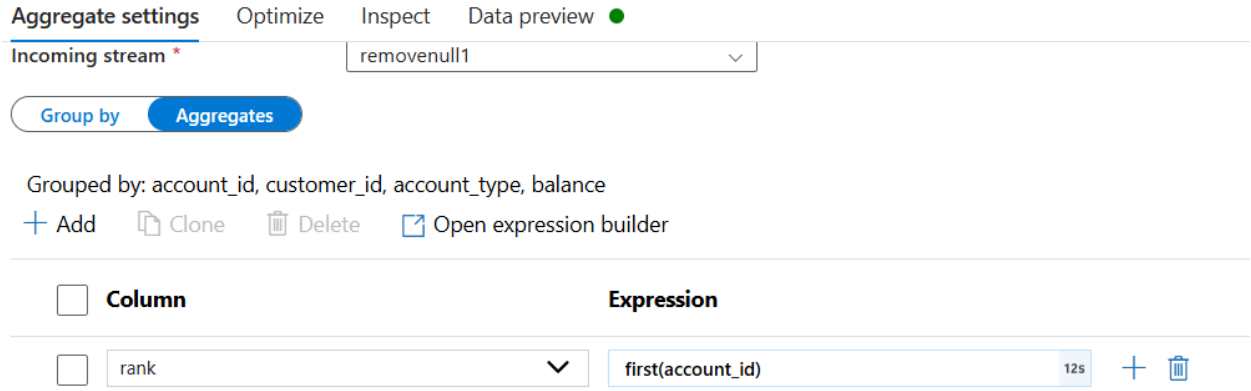
In source settings, make sure to select first row as header option.

The source is then connected to a filter transformation which will be used to check the data for null values. We're only checking account_id and customer_id columns here because any of these fields being empty suggests that the record may be null or doesn't exist.

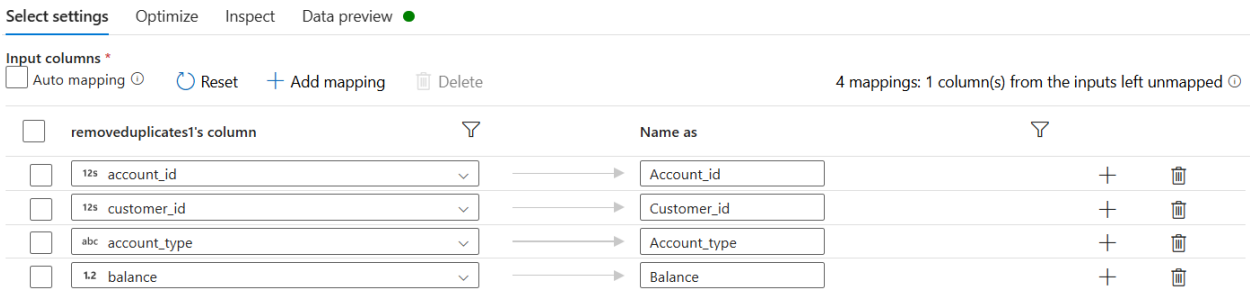


Next, we connect the filter transformation to an aggregate transformation which will be used to remove duplicate values. In "group by" section, we'll add all the columns of accountsCSV as we want to check for duplicates in each field. However, aggregate transformation requires us to provide atleast 1 column. To fulfil that requirement, we'll create a dummy column called "rank" whose expression will be first(account_id) – this basically means that it'll take the first occurring value in the column "account_id".



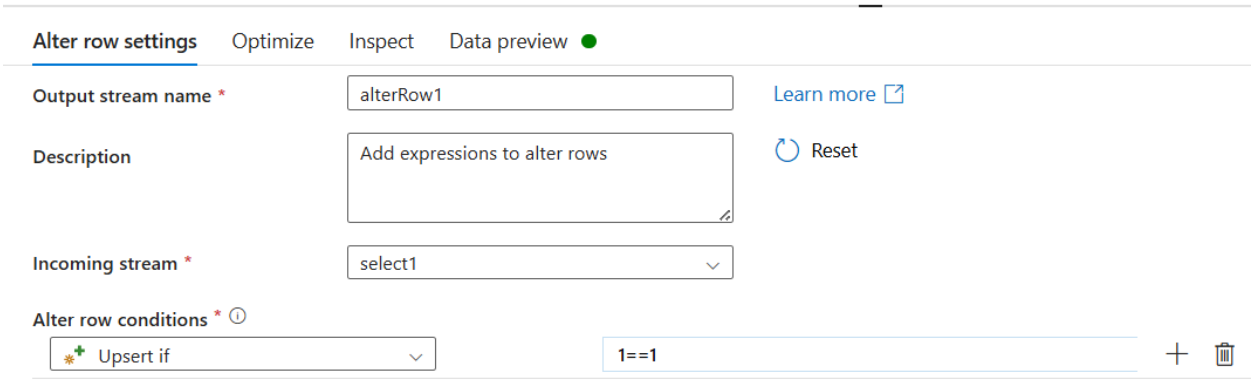


Next, connect the aggregate transformation to a select transformation which we'll use to drop the dummy "rank" column which we created in the last step and also rename the columns.



So, under select settings, simply delete the mapping of rank column and under "name as" section, you can rename the columns. We have simply capitalized the first letter of all the column names.

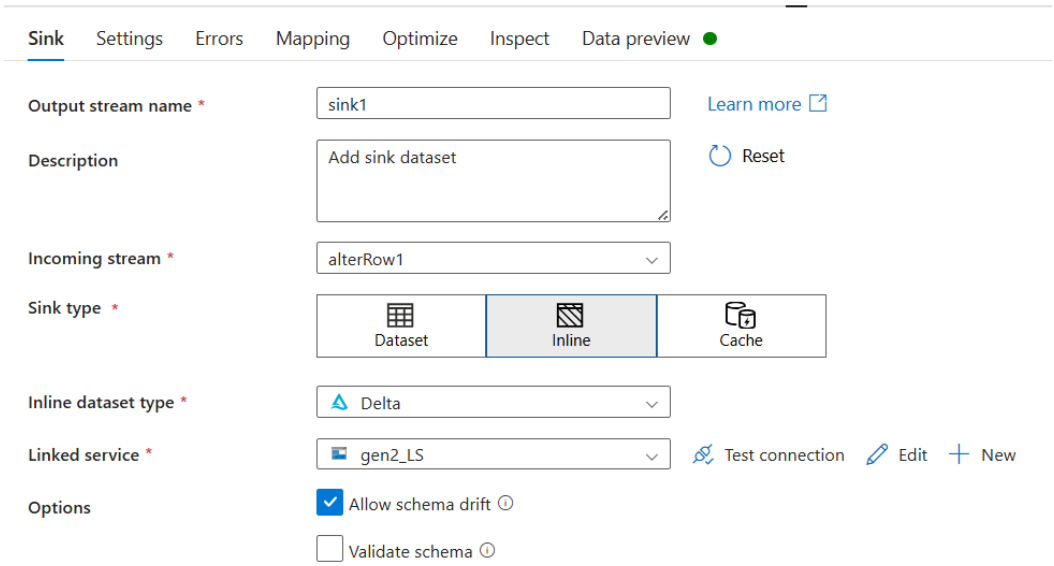
Now, we'll connect the select transformation to an alter row transformation.

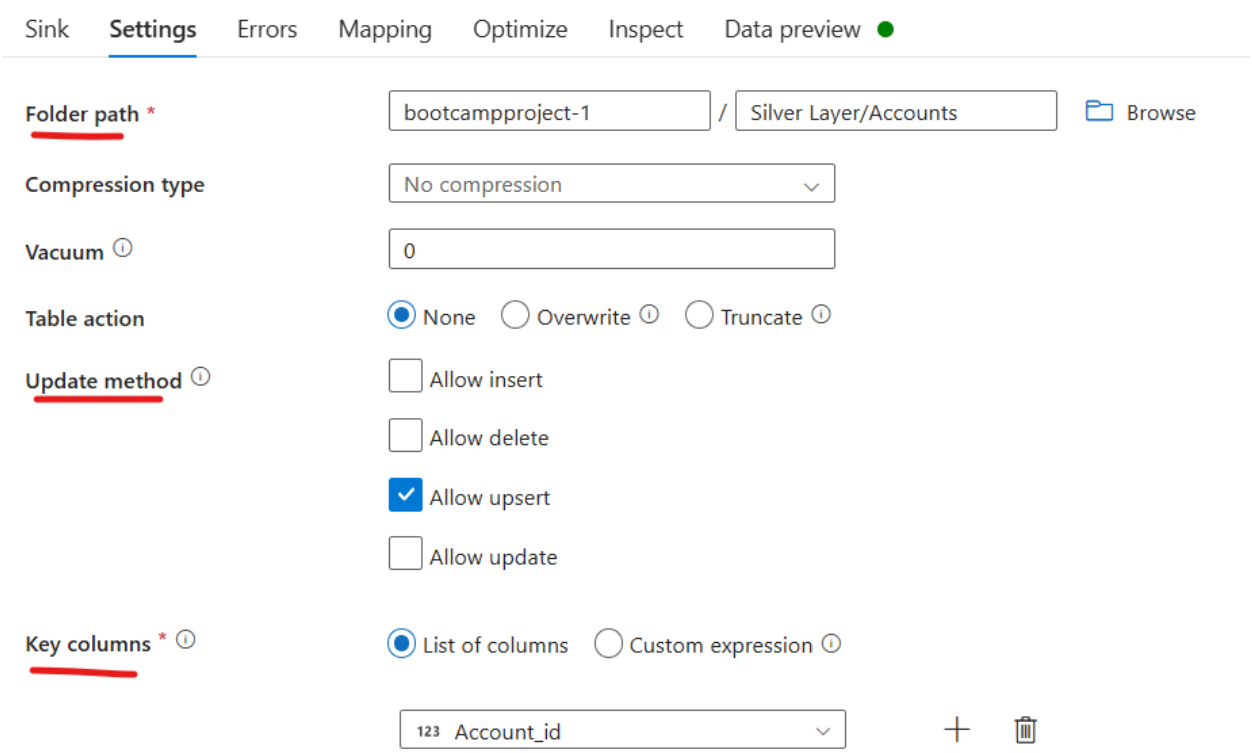


Here, we select the **"Upsert if"** option in the Alter Row transformation and set the condition to **1==1**, which effectively allows **all changes (inserts and updates)** to pass through. This is because, by the time data reaches this point in the Data Flow, all necessary transformations have already been applied. Our goal now is simply to allow those changes and persist the final data in **Delta format** in the **Silver layer** folder within the **ADLS Gen2** account.

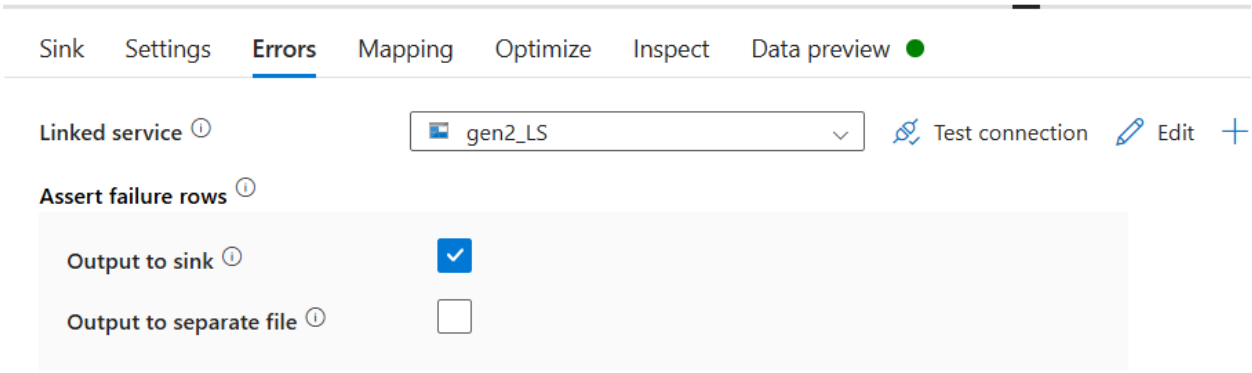
Using the Alter Row transformation here is essential: it enables **fine-grained control over row-level operations**, such as insert, update, delete, or upsert, and allows you to dynamically assign these actions based on conditions. In this case, we want to ensure that **new records are inserted** and **existing records are updated** appropriately before writing to the sink. This is why Alter Row is used—to direct the behavior of how each row is written to the target storage.

Finally, we connect the alter row transformation to a sink.





As per the above image, make sure to give path as the location where we want to store are cleaned data. We'll store that in a folder called "Silver Layer", but since we're storing the data in delta format, it'll also have a log file, so we'll create another folder for each csv file within the silver layer folder to avoid creating a mess and organize the data in a well-structured format. And make sure to select "allow upsert" as the update method and provide a key column for that particular dataset file.



In "errors" section, we just have to select the linked service for adlsgen2 account. Here, we don't need to select the linked service with self-hosted IR as we're moving data within cloud, not from local system to cloud. Similarly, we have to build the pipeline for all the other sources (1 for each csv file in the dataset).

Gold Layer Pipeline:

This pipeline will be useful in processing the data in SCDType-1 and SCDType-2 fashion and eventually store the data into an azure sql database.

First, we'll create 5 tables in our sql database – 3 for scdtype-1 and 2 for scdtype-2

We'll use accounts.csv, customers.csv, loan_payments.csv for scdtype-1 and loans.csv, transformations.csv for scdtype-2

The images of the code used to create all the tables are provided below:

```
create table accounts (
account_id int,
customer_id int,
account_type varchar(50),
balance decimal(8,2),
createdby varchar(50),
updatedby varchar(50),
createdate datetime,
updatedate datetime,
hashkey bigint
)
```

Accounts table

```
create table customers (
customer_id int,
first_name varchar(100),
last_name varchar(100),
address varchar(100),
city varchar(100),
state varchar(100),
zip varchar(50),
createdby varchar(50),
updatedby varchar(50),
createdate datetime,
updatedate datetime,
hashkey bigint
)
```

Customers table

```sql
create table loanpayments (
payment_id int,
loan_id int,
payment_date date,
payment_amount decimal(8,2),
createdby varchar(50),
updatedby varchar(50),
createdate datetime,
updatedate datetime,
hashkey bigint
)
```

Loanpayments table

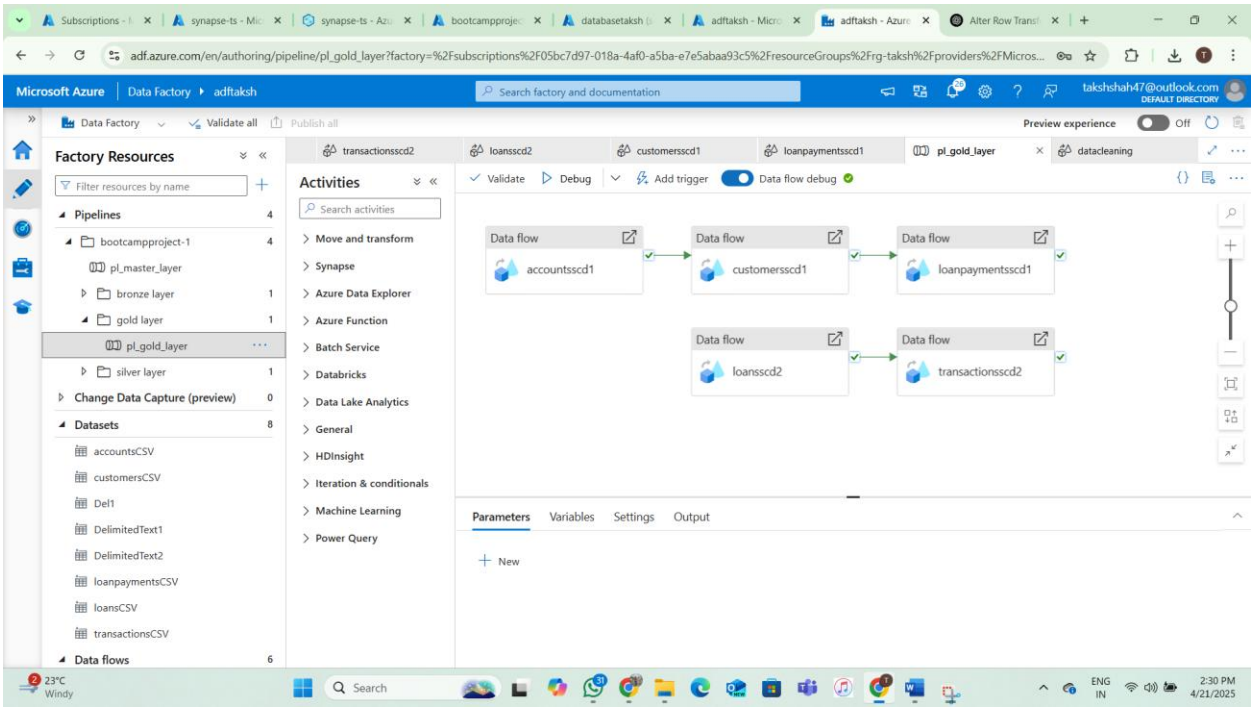
```sql
create table loans (
loan_id int,
customer_id int ,
loan_amount int,
interest_rate decimal(8,1),
loan_term int,
createdby varchar(100),
createddate datetime,
updatedby varchar(100),
updateddate datetime,
hashkey bigint,
isactive int,
)
```

Loans table

```sql
create table transactions (
transaction_id int,
account_id int,
transaction_date date,
transaction_amount decimal(8,2),
transaction_type varchar(100),
createdby varchar(100),
createddate datetime,
updatedby varchar(100),
updateddate datetime,
hashkey bigint,
isactive int,
)
```

Transactions table

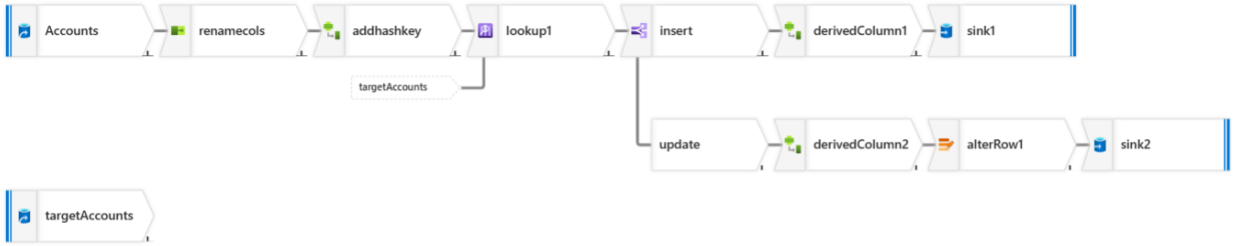
Once we've created these tables in our azure sql database, we're ready to begin developing the gold layer pipeline.



Gold layer pipeline

We'll utilize 5 dataflows here, 1 for each csv file in the dataset, where 3 of them will be used to implement scdtype-1 logic (accounts, customers, loanpayments) while the other 2 will be used for scdtype-2 logic (loans, transactions). We'll connect the 3 dataflows for scdtype-1 and 2 dataflows for scdtype-2 as show in the image above which will then be parallelly processed when the pipeline is run.

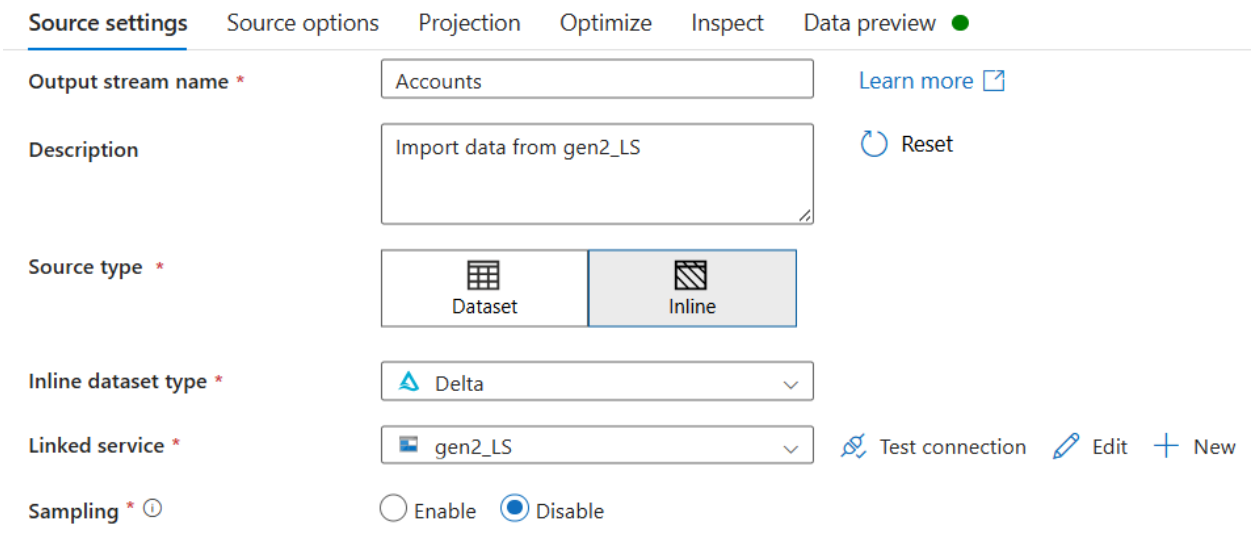
Let's take accountssscd1 dataflow – scdtype-1:



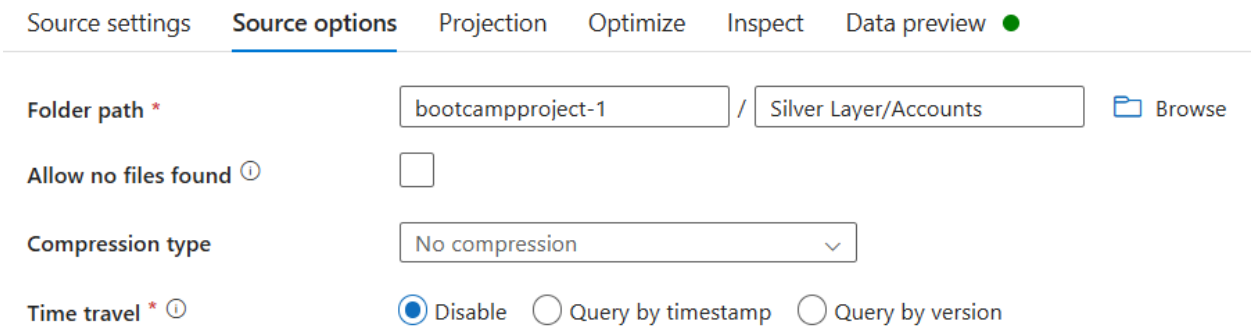
Dataflow for accountsscd1 – scdtype-1

The image above shows the dataflow for scdtype-1 that we have to build.

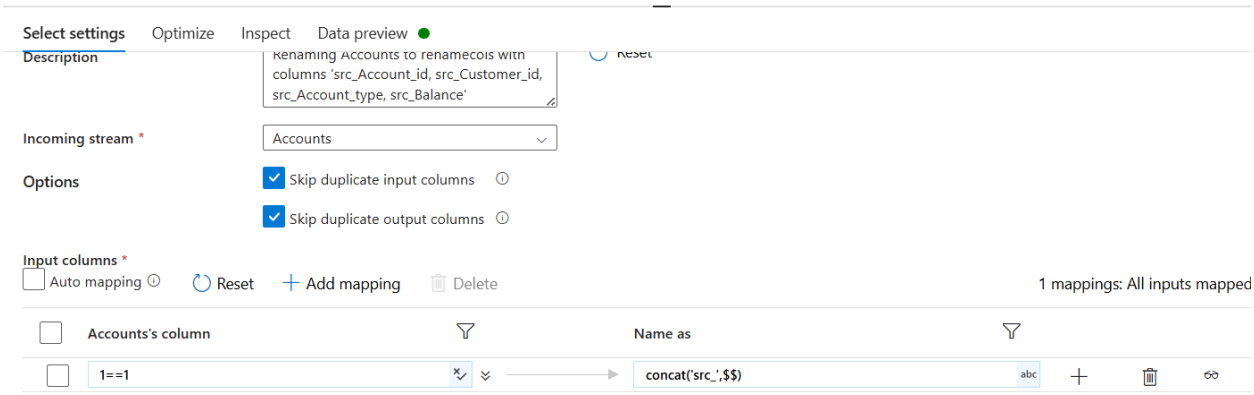
First, let's configure our source. The images are provided below which show the configuration.



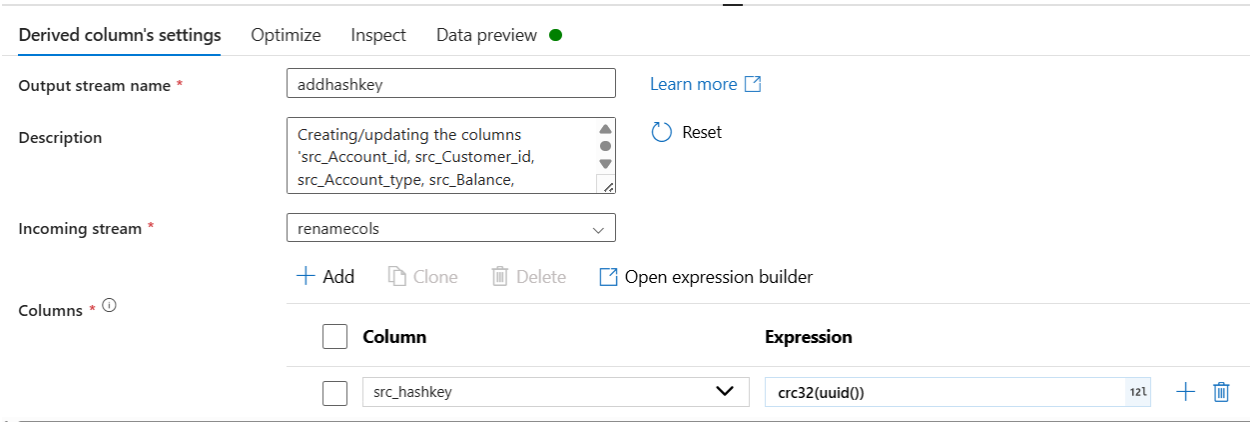
Here, inline dataset type is selected as "delta" because we had stored the cleaned data in delta format in our silver layer folder. Now we're using that data for scdtype-1 and scdtype-2 logic.



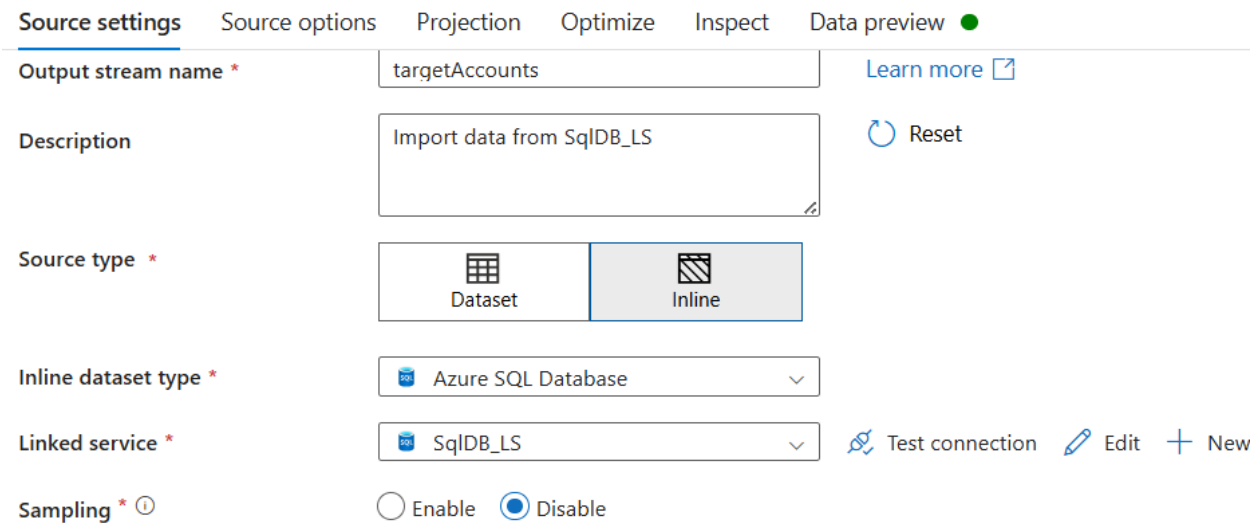
Then we connect the source to a select transformation, which is used to rename columns by concatenating "src_" to all the column names.

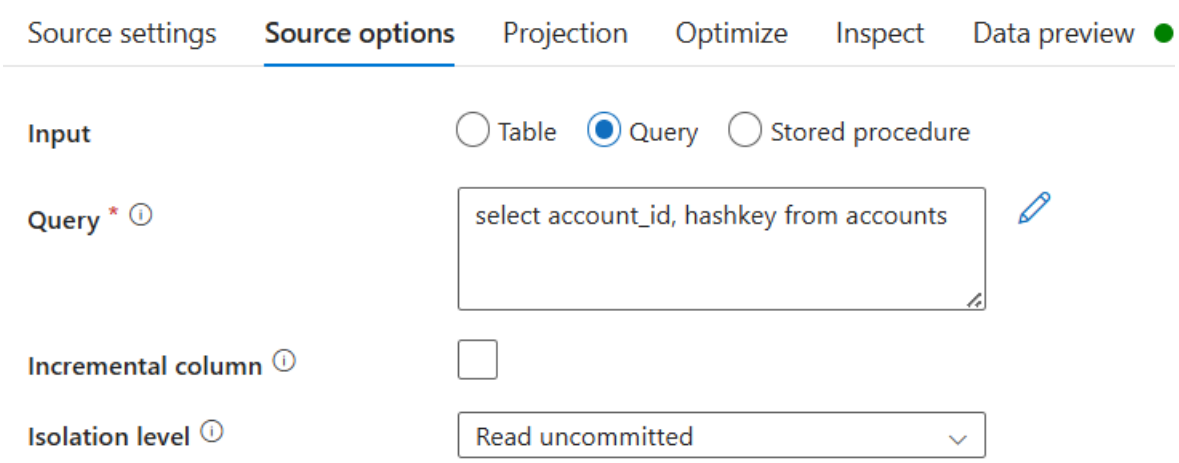


Next, we connect a derived column transformation to add a hashkey column called "src_hashkey" using a hash function called crc32() and calling another function within it called uuid() which helps in generating random hashkeys.



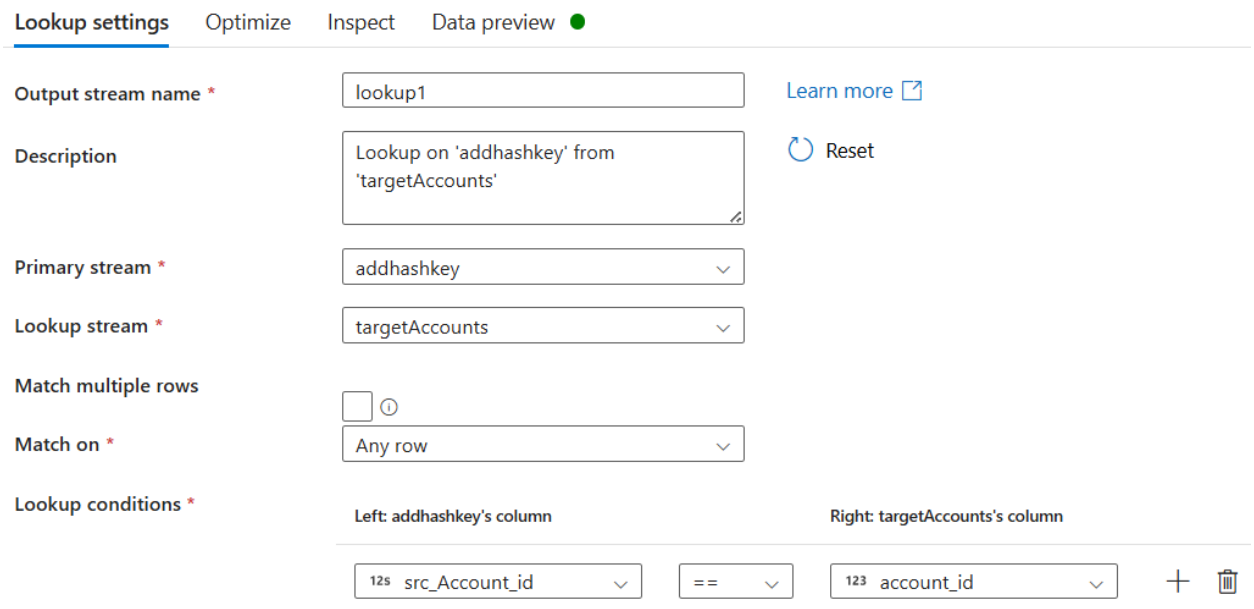
Then, we'll create our target (a second source) – where we want to store our data essentially – only this target will be used for a left join that we need to implement in our logic in the next step. Our target will be the azure sql database because that's where we'll eventually store the data.



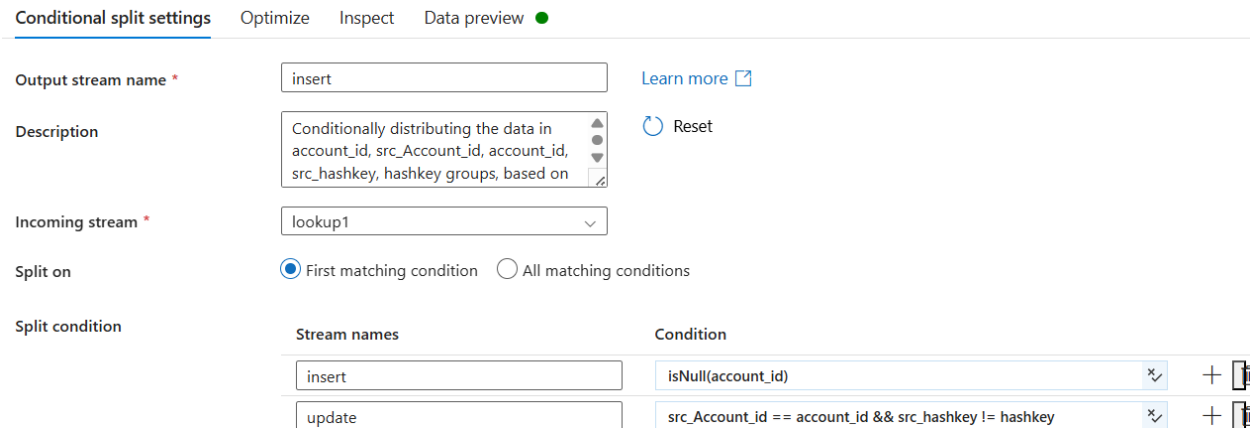


We only need to compare the key column and hashkey column with our source file so those are the only 2 columns needed in our target.

Now, we'll connect a lookup transformation to our derived column transformation to implement a left join between source and target on the column "account_id".



Next, we'll connect a conditional split to this lookup transformation which will help us to either insert or update data in our sink based on certain conditions.



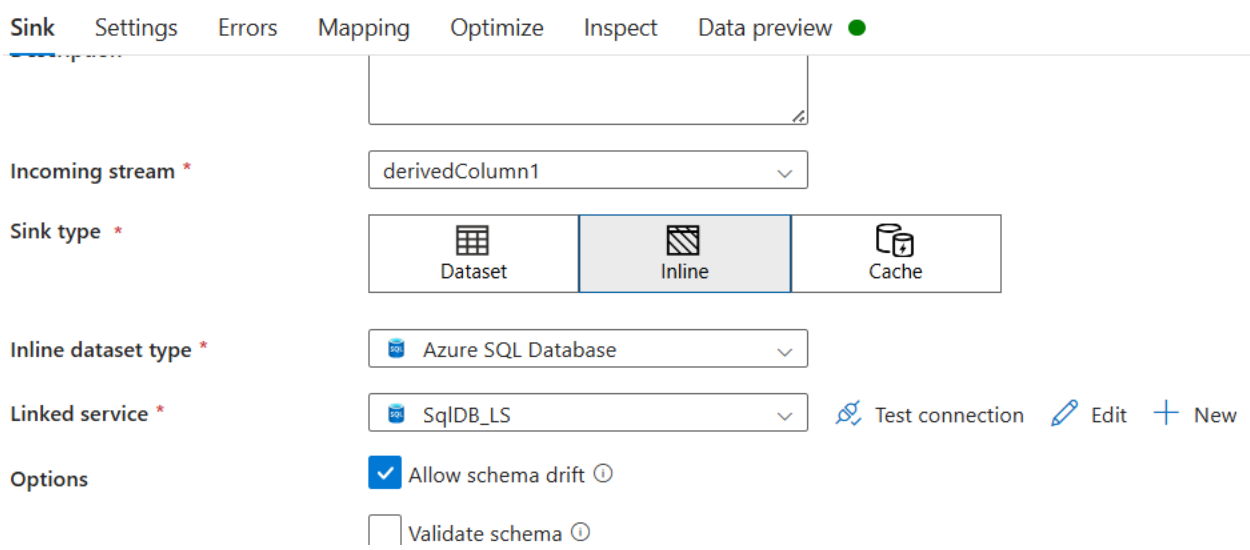
As shown in the image above, we'll add 2 conditional streams – insert and update. Condition for insert – if account_id is NULL in target/sink, that means our source file has an ID which does not exist in our target/sink, so it needs to be inserted.

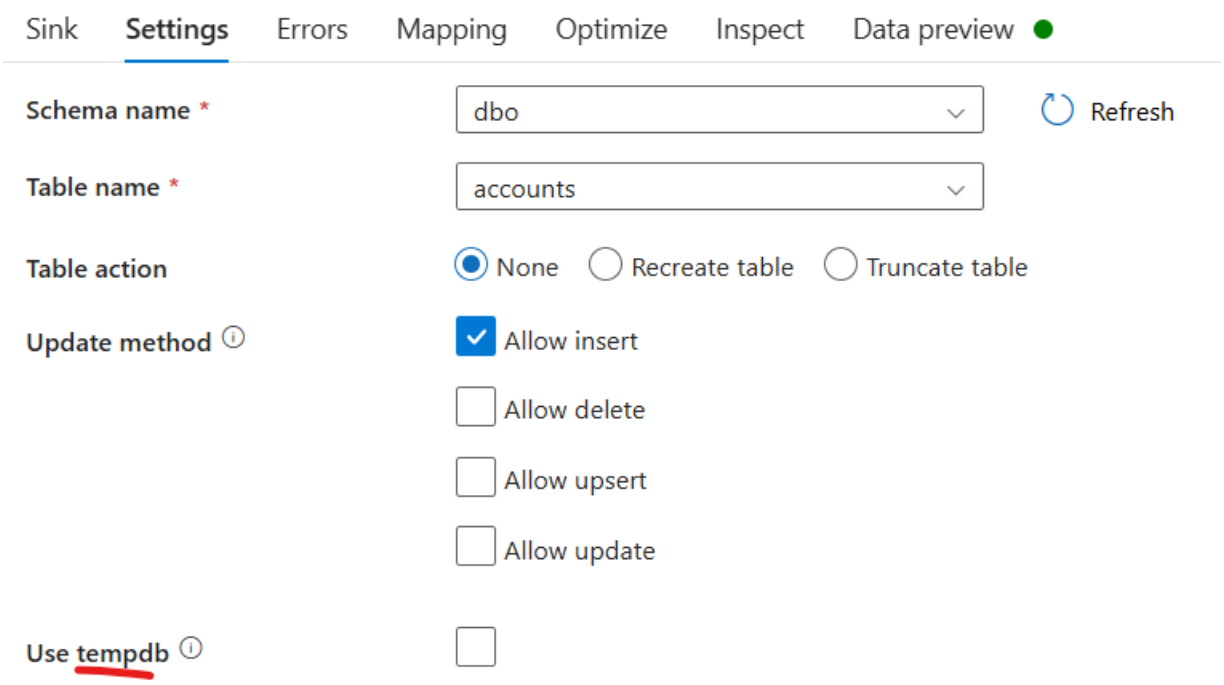
Condition for update – if an update needs to be made, that means a record must already exist in the target/sink, so we'll check if the IDs match or not. Also, hashkeys come into play here – if a change is made, the hashkey changes, so we have to ensure that hashkeys of source record and target record do not match.

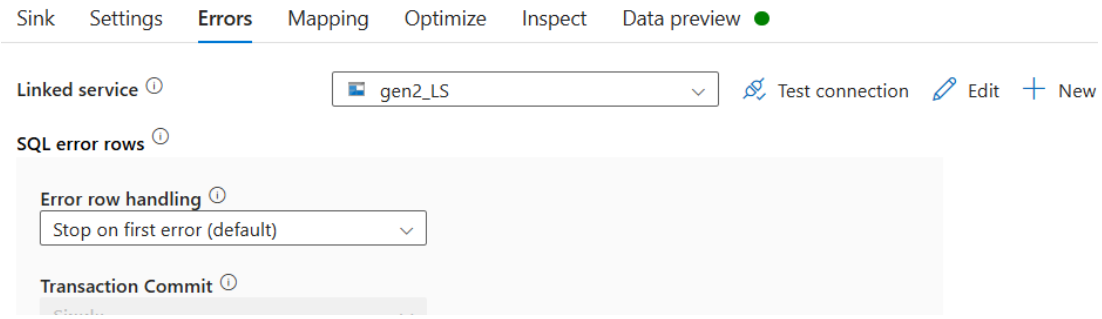
Insert stream:

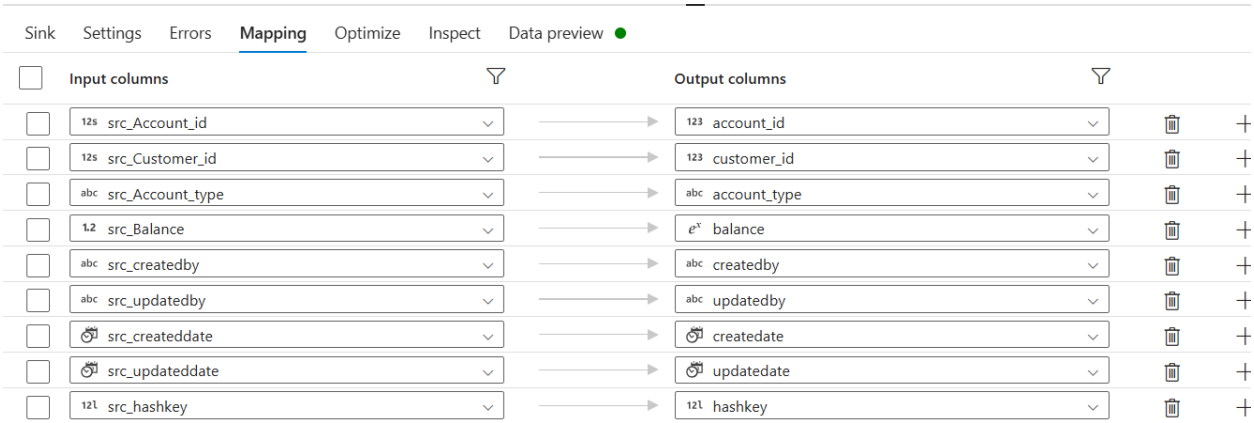
This stream is then connected to a derived column transformation which is used to enter the values of src_createdby, src_createddate, src_updatedby, src_updateddate columns (which we had created while creating the tables in our sql database) as 'dataflow', currentTimestamp(), 'dataflow', currentTimestamp() respectively. We write 'dataflow' just for us to understand in the output that a particular change was made from the insert stream part of our dataflow. CurrentTimestamp() function records the date and time of any changes that will be made.

Finally, it is connected to a sink – where we'll store our data – so this will be same as target, ie, sql database.


Sink
Settings
Errors
Mapping
Optimize
Inspect
Data preview
Incoming stream *
derivedColumn1
Sink type *
Dataset
Inline
Cache
Inline dataset type *
Azure SQL Database
Linked service *
SqlDB_LS
Test connection
Edit
New
Options
Allow schema drift
Validate schema


Sink
Settings
Errors
Mapping
Optimize
Inspect
Data preview
Schema name *
dbo
Refresh
Table name *
accounts
Table action
None
Recreate table
Truncate table
Update method
Allow insert
Allow delete
Allow upsert
Allow update
Use tempdb

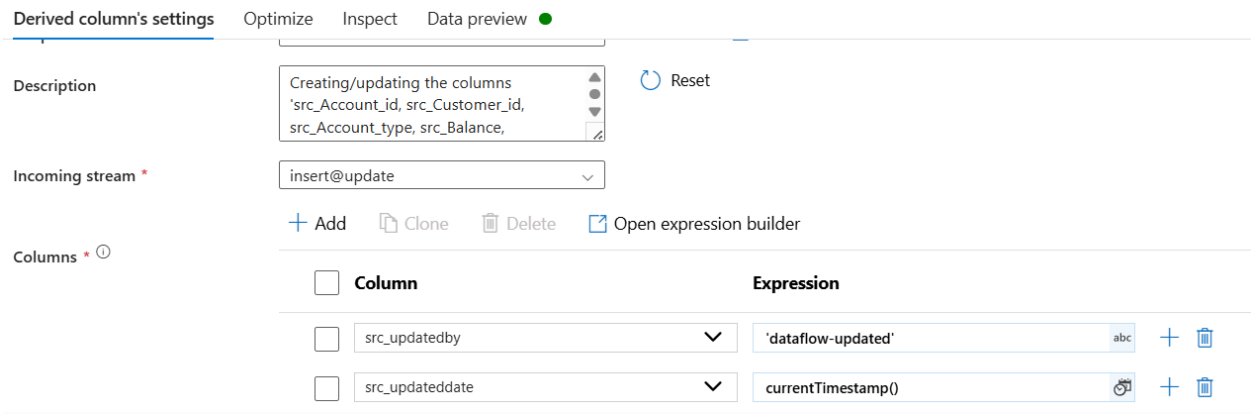

Sink
Settings
Errors
Mapping
Optimize
Inspect
Data preview
Linked service
gen2_LS
Test connection
Edit
New
SQL error rows
Error row handling
Stop on first error (default)
Transaction Commit



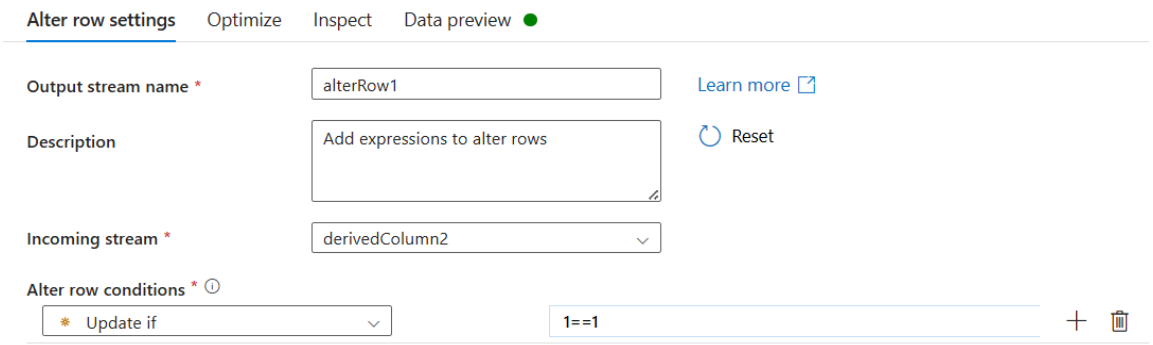
Under “mapping” section of the sink, first delete all the mappings, import schema and then reset mappings. Then map all the columns from source to target.

Update stream:

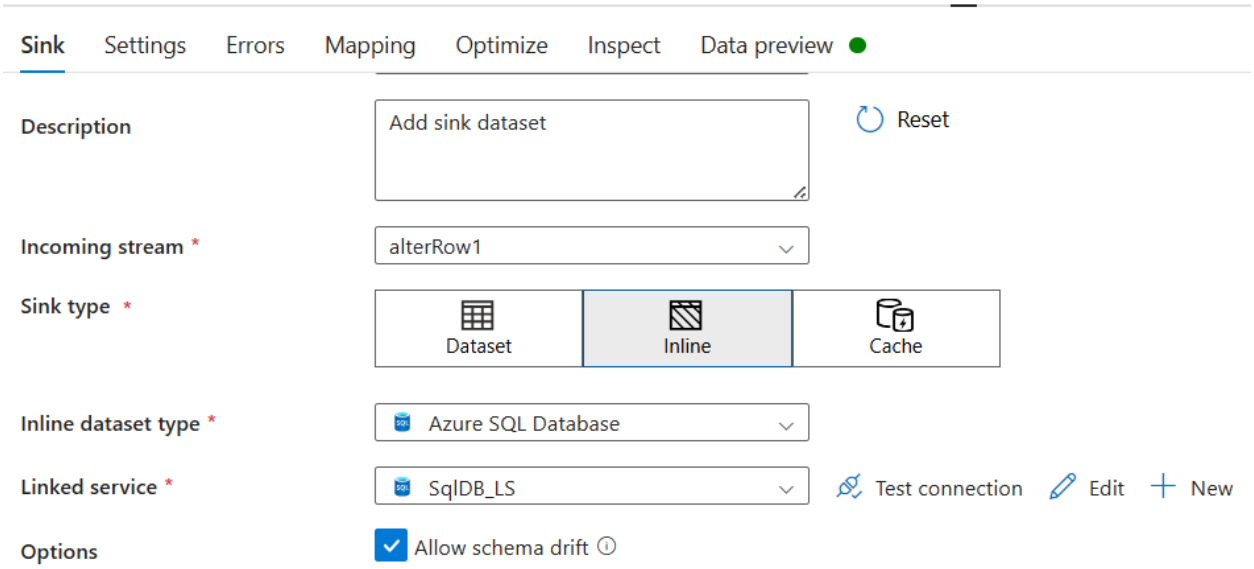
Similarly, update stream is connected to a derived column transformation to insert the values of src_updatedby and src_updateddate columns as ‘dataflow-updated’ and currentTimestamp() respectively. The logic behind this remains similar to that of what we did in insert stream. We don’t need src_createdby and src_createddate as this is the update stream so these values will not be changed here.

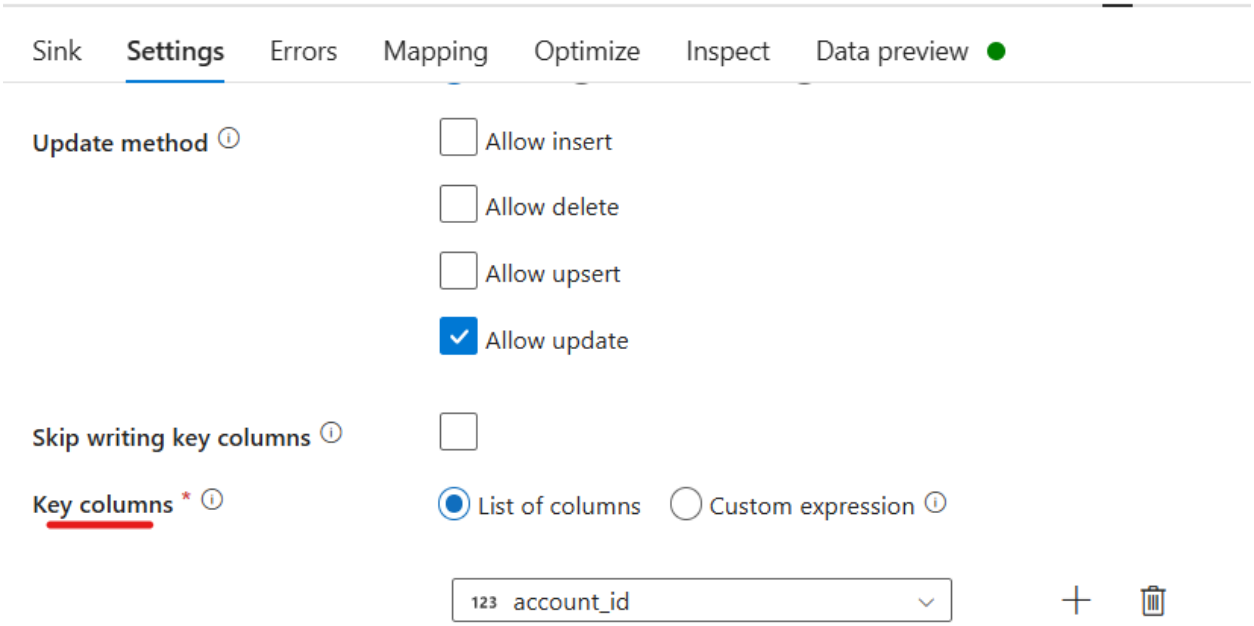


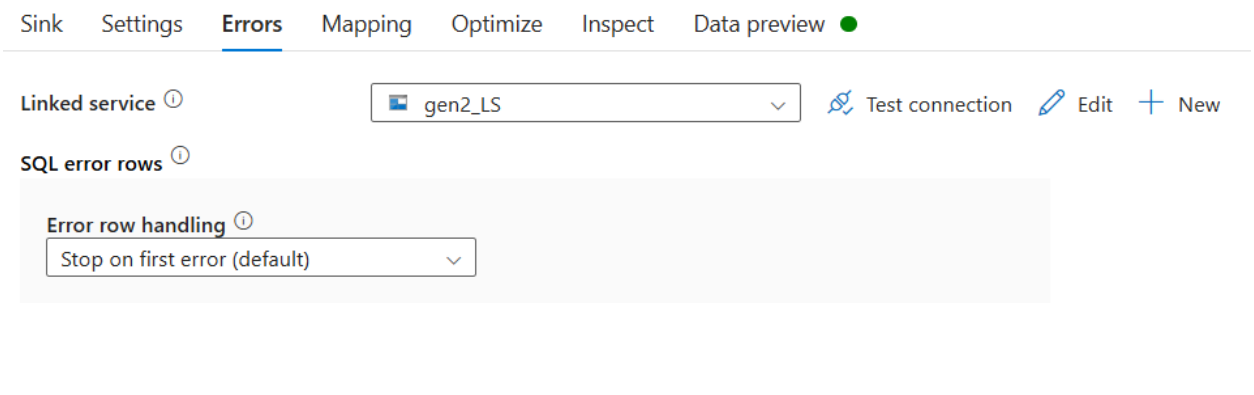
Next, we connect it to an alter row transformation to give it access to our sink, ie, the sql database so the dataflow can update the data.

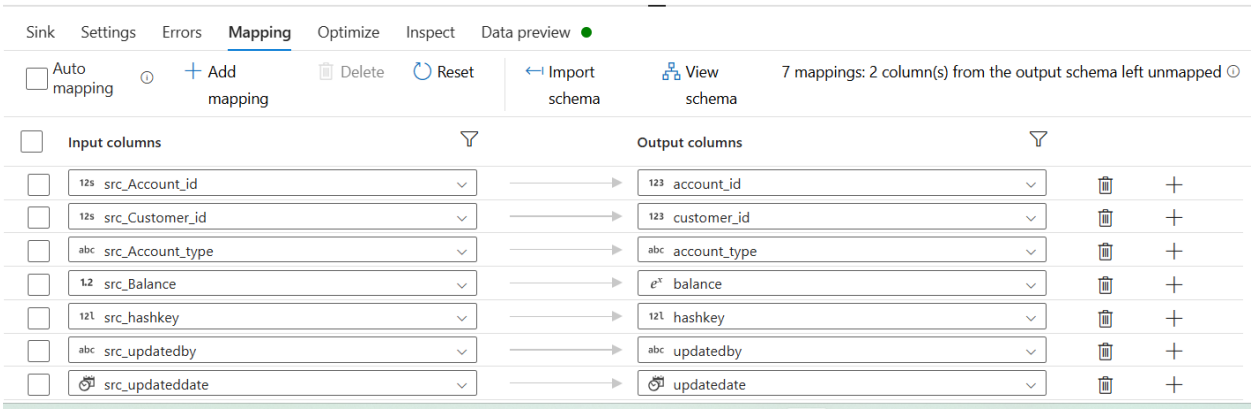


Finally, we connect it to a sink – same as target, ie, sql database.





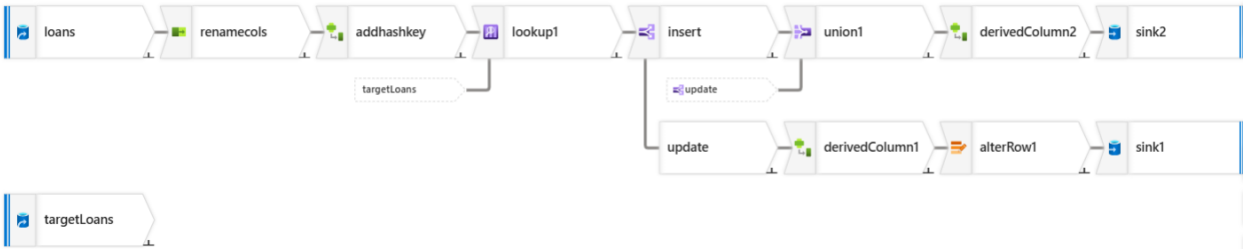




Similar to the insert sink mapping, we'll get rid of all the mappings, import schema and then reset the mappings and map all columns from source to target. Note that created_by and createddate columns are not needed here as those values are not affected in this stream.

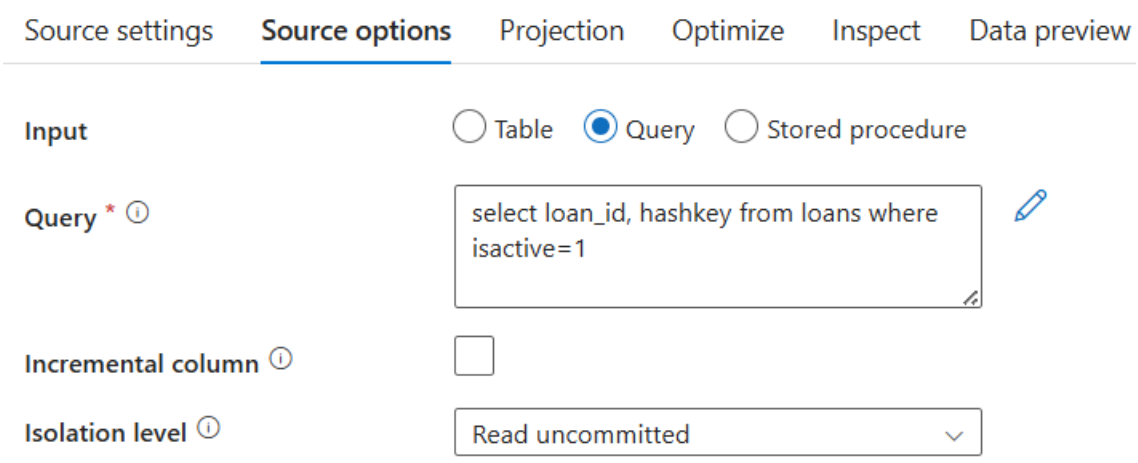
This marks the end of the scdtype-1 dataflow. Similarly, we can clone this dataflow and make necessary changes for the remaining 2 scdtype-1 dataflows.

Let's discuss scdtype-2 dataflow for loans.csv

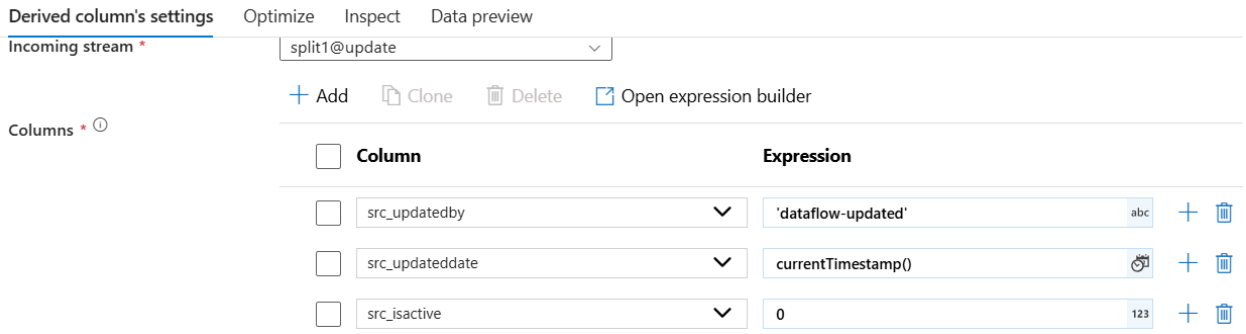


It is very similar to scdtype-1 dataflow, in fact, until the conditional split for insert and update streams, the logic remains the same. The changes are as follows:

In target, we select only those records of the key column and hashkey where isactive = 1

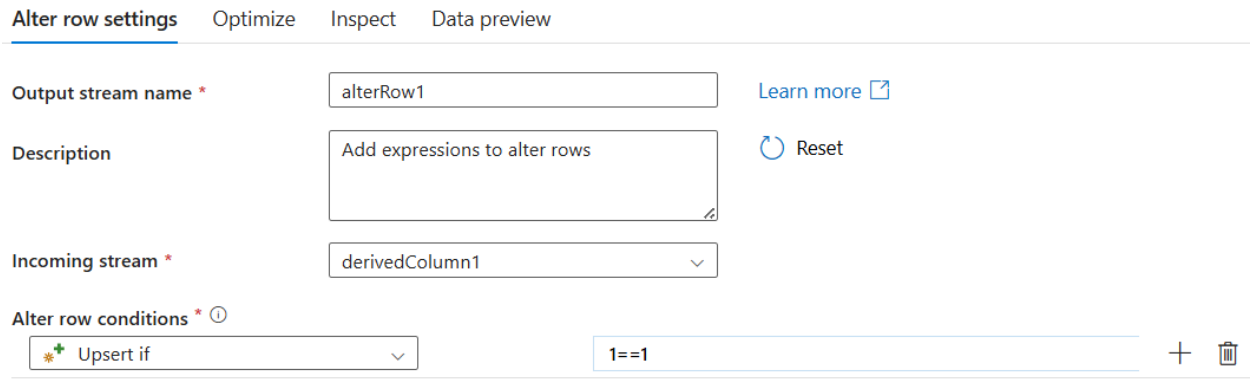


We first complete the update stream and then complete the insert stream.



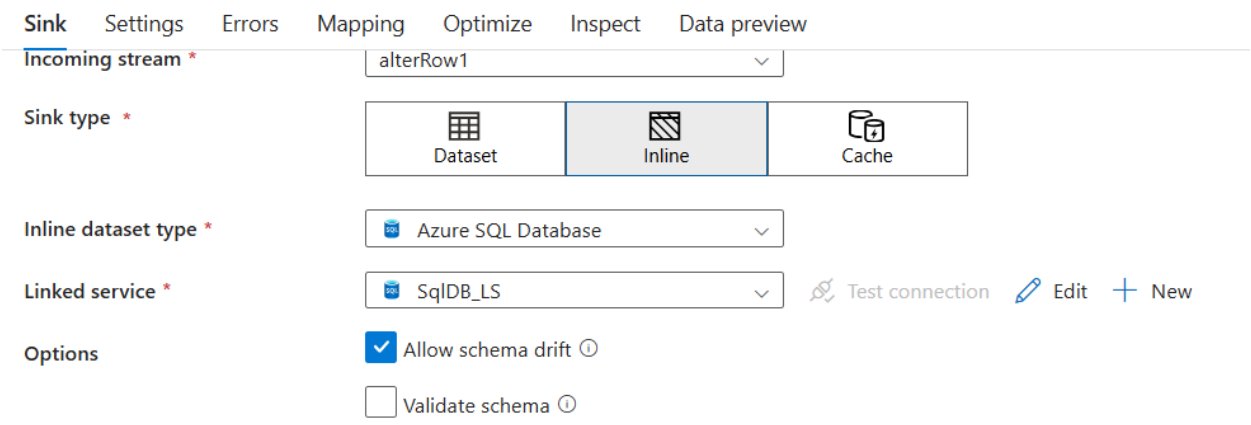
Derived column transformation of update stream

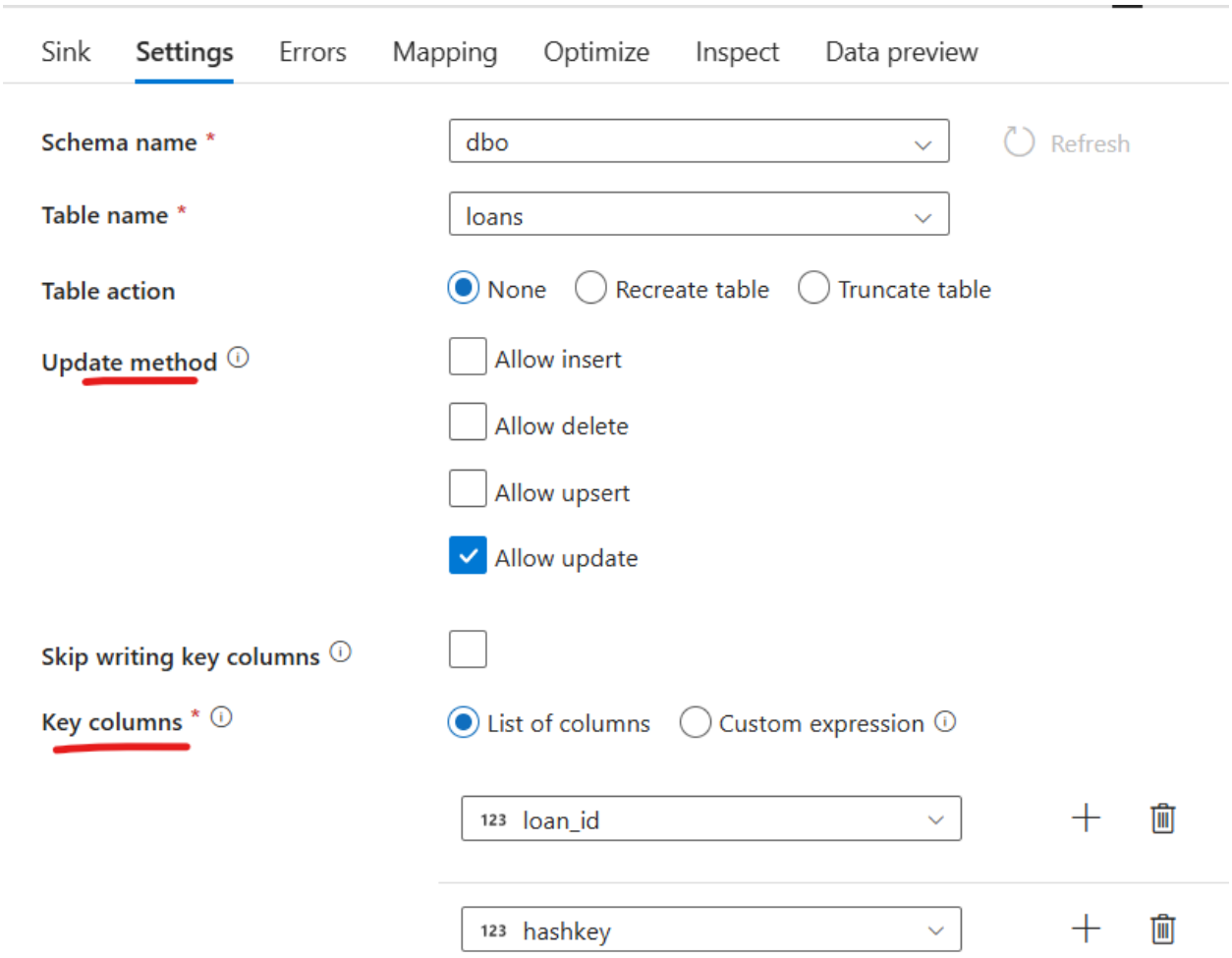
Here, we set the value for “src_isactive” column as zero because once a record is updated, THAT record will become inactive and a new record with the UPDATED DATA will be added in to the target/sink whose status will be active (ie,1 and remember that scdtype-2 logic stores historical data).



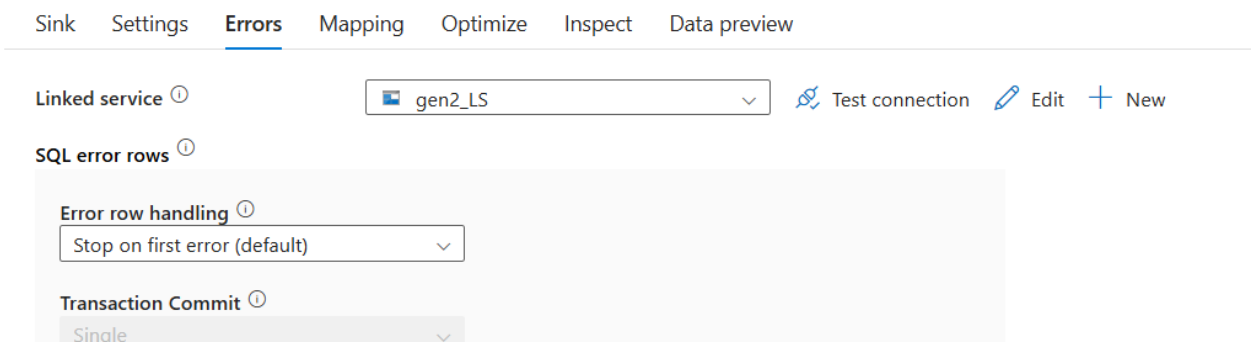
For scdtype-2 logic, we select “upsert if” in the alter row transformation of update stream because we’ll actually INSERT a new record with UPDATED data into our target/sink, and to do that we need to provide both insert and update permission – which is enabled by upsert.

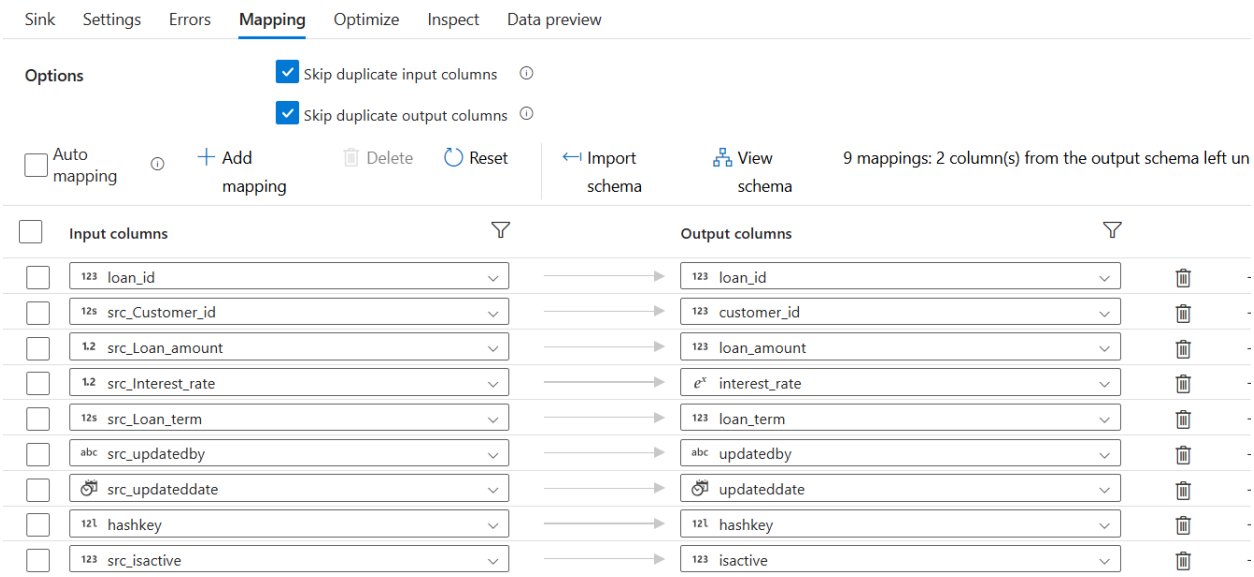
Then comes the update sink as follows:





Note that under sink settings, we'll select "allow update" as through update stream, we'll only be updating data but inserting the data in new record will be done by insert stream, where we'll unionize the output of update stream. Hence, its necessary to give permission to upsert in alter row transformation but only update permission in sink will do the job. Make sure to add the key columns loan_id and hashkey. We add the hashkey as a key column as well because we'll be storing historical (old) data as well, so both the id and hashkey are required to store the old data and once the data is updated, hashkey will change.

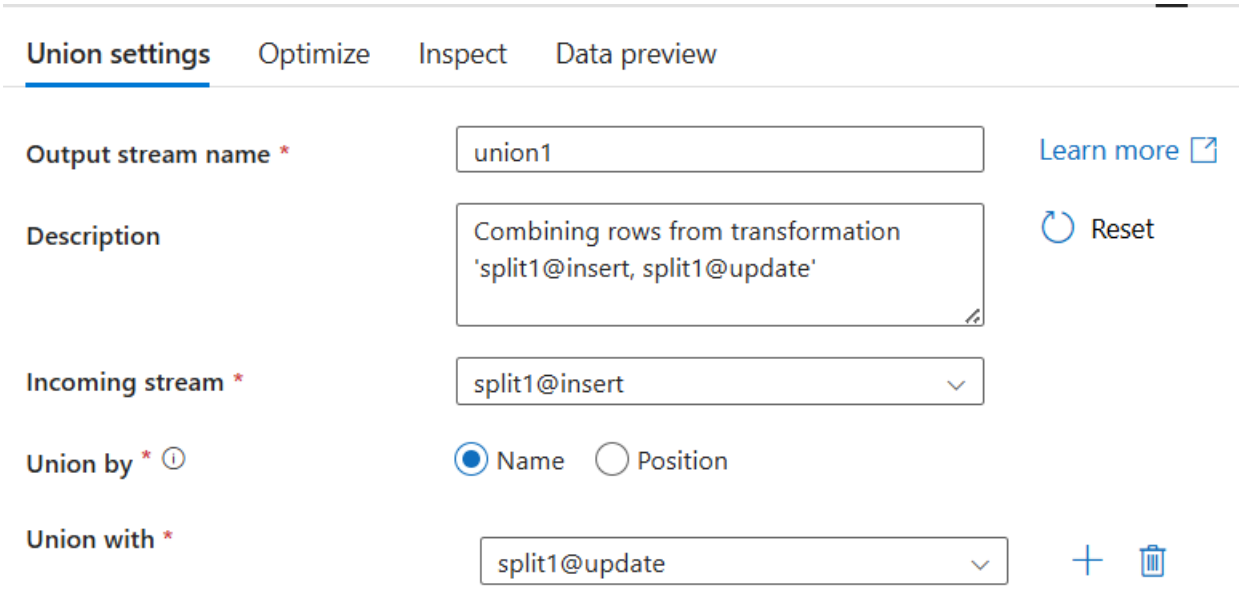




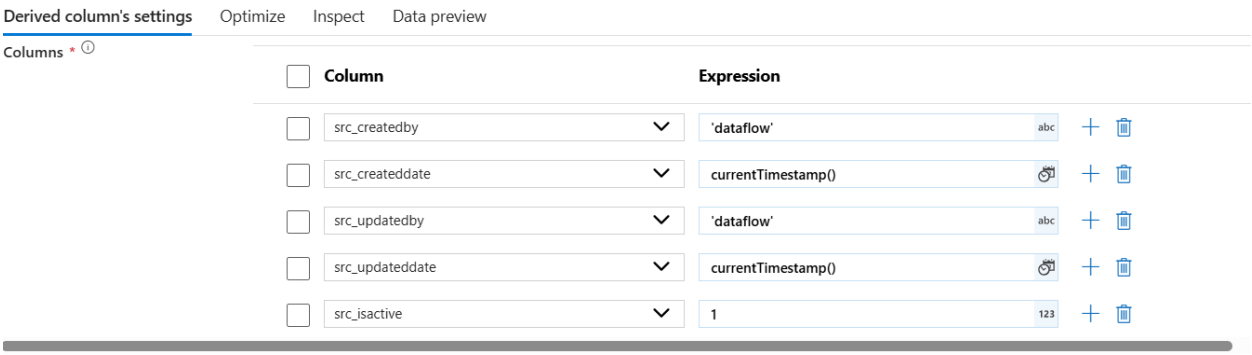
Similar to scdtype-1 mappings, we'll get rid of all the mappings initially and reset them after importing the schema and finally map all the columns from source to target. Here, the only exceptions will be key column (loan_id) and hashkey column will be mapped from target to target.

Insert stream for scdtype-2:

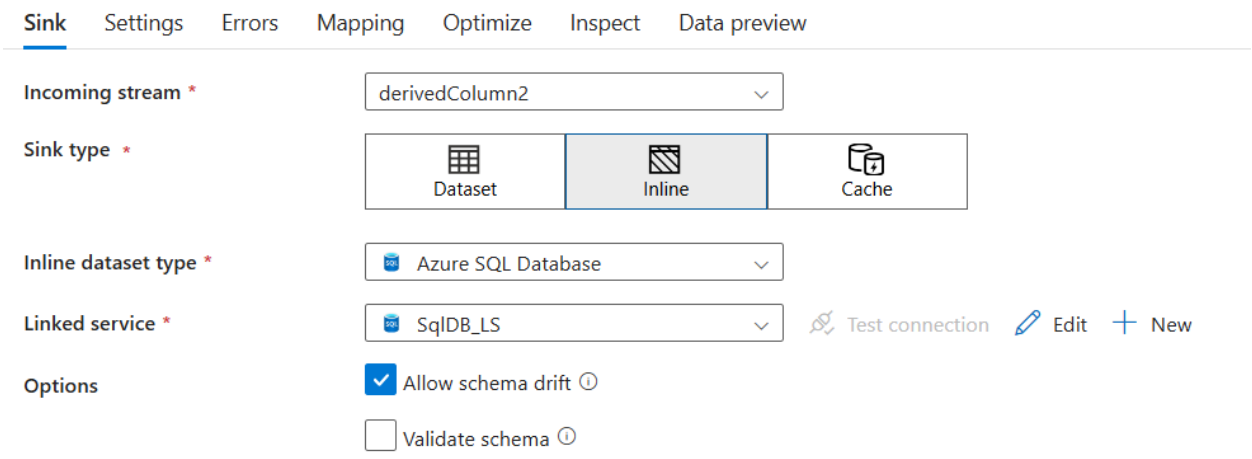
We'll first connect the split with a union transformation.

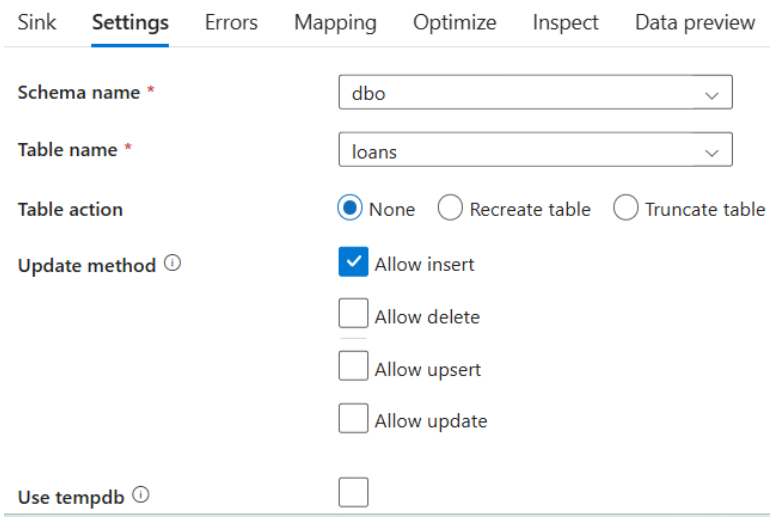


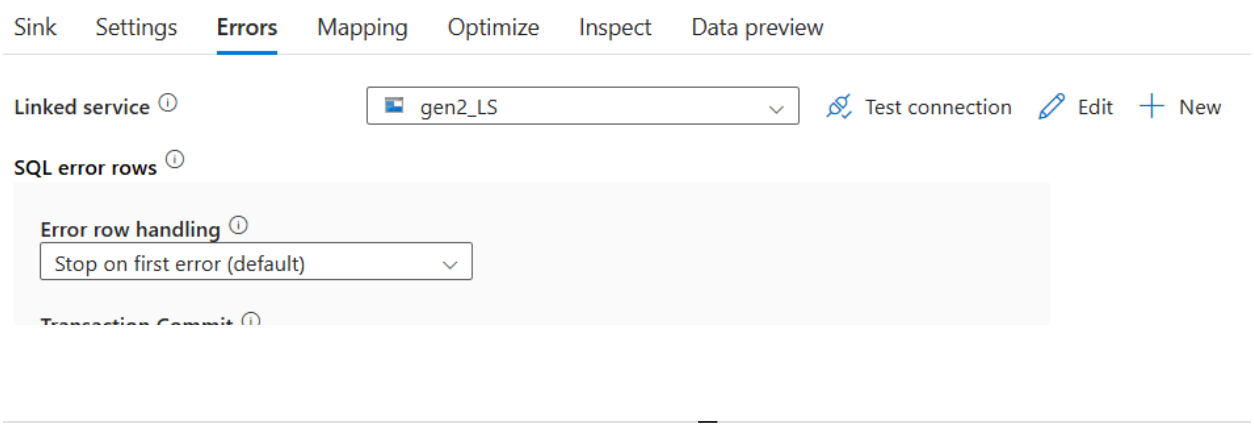
Then comes the derived column transformation. Here, src_isactive will be 1 because whenever a new record is inserted, it'll always be active(1) initially until a change is made to that record.

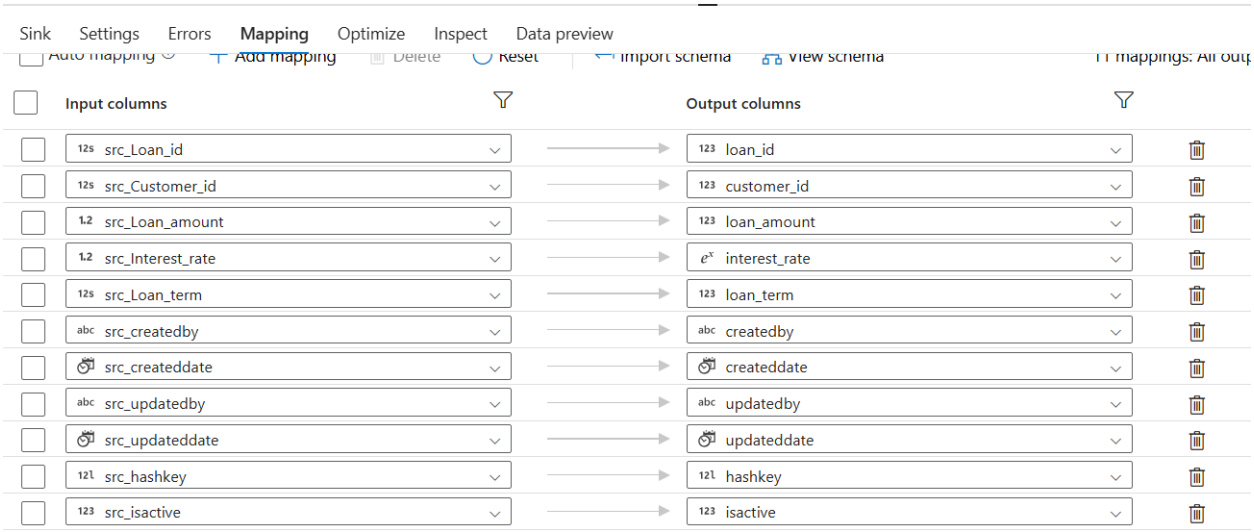


In the end comes the sink for input stream of scdtype-2









All columns are mapped from source to target.

This marks the end of scdtype-2 dataflow. Similary, this can be cloned to make the remaining scdtype-2 dataflow with necessary changes.

Finally, we connect everything in a master pipeline where we invoke the bronze layer pipeline followed by silver layer pipeline and finally gold layer pipeline and connect them in the same fashion.

In order to publish this project to github, create a new repository in github and connect it from the manage -> git configuration section in azure data factory in azure portal.