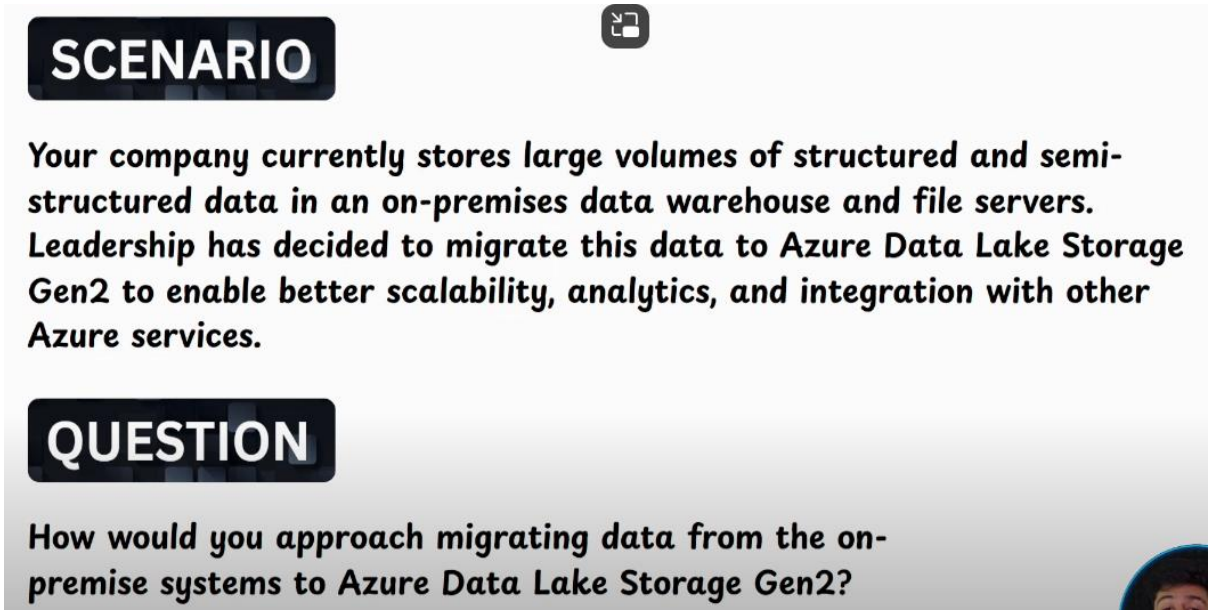
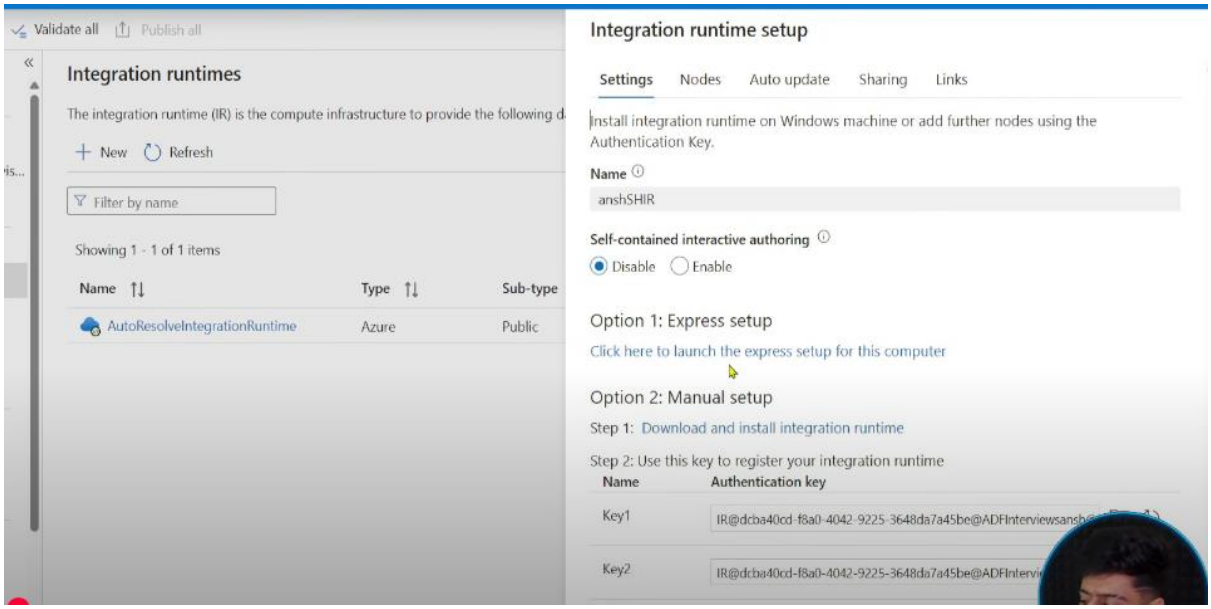
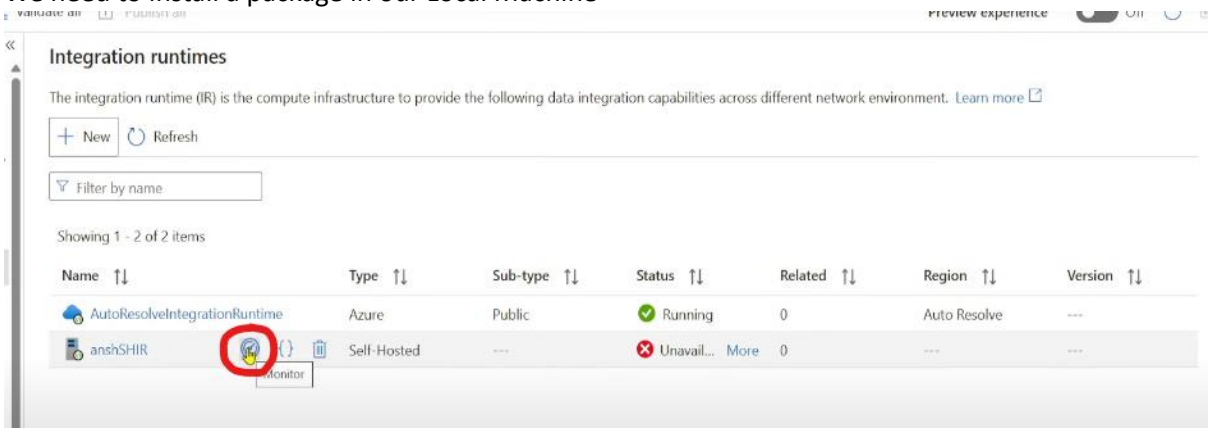
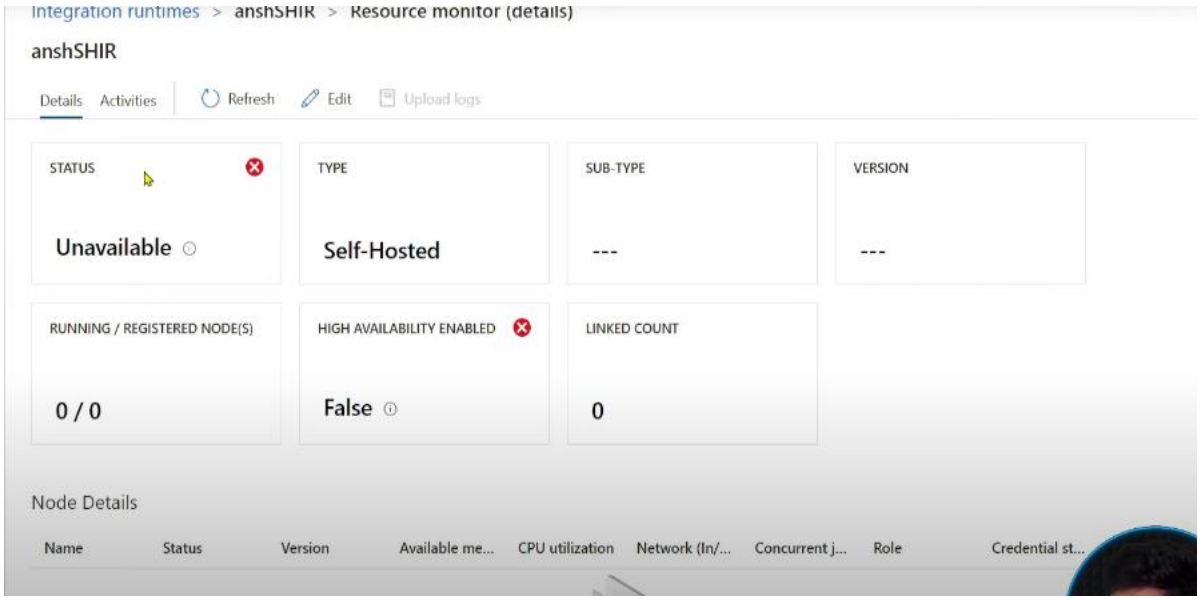


Use Self Hosted IR

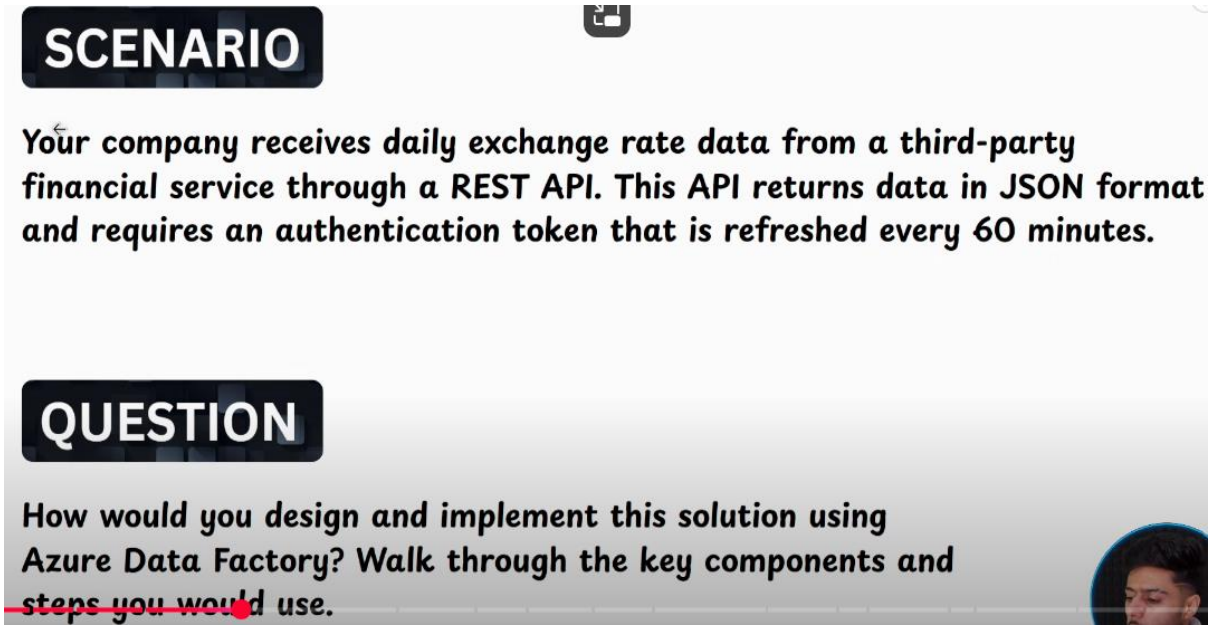


We need to install a package in our Local Machine

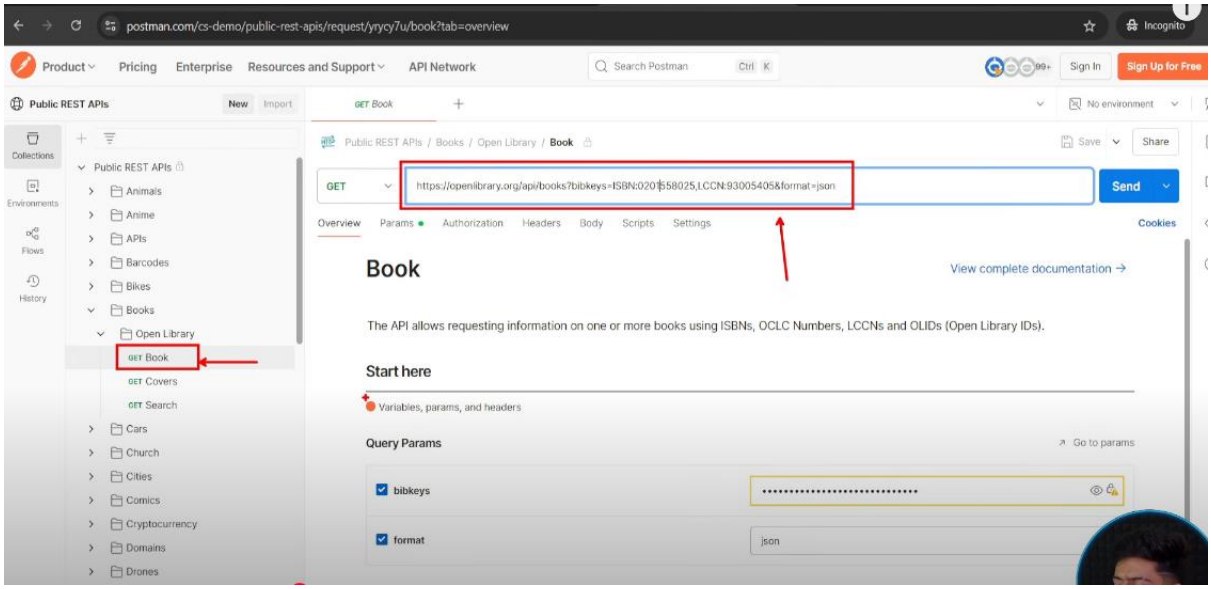




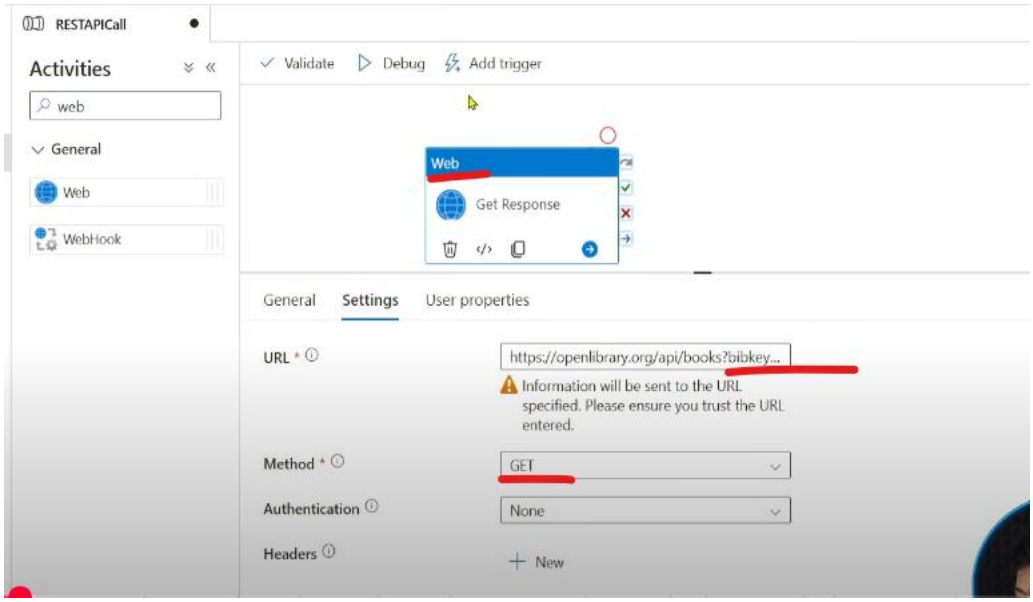
So start installing using Manual setup (advisable), post installing provide the key.
In real world, we create VMs as our IR(instead of downloading in local machine, download the IR in VM), in case of throttling(CPU utilisation is 80-90%) scale up VM. Easy to scaleup VM instead of local.
Post that create a LS for the datastore using SHIR.

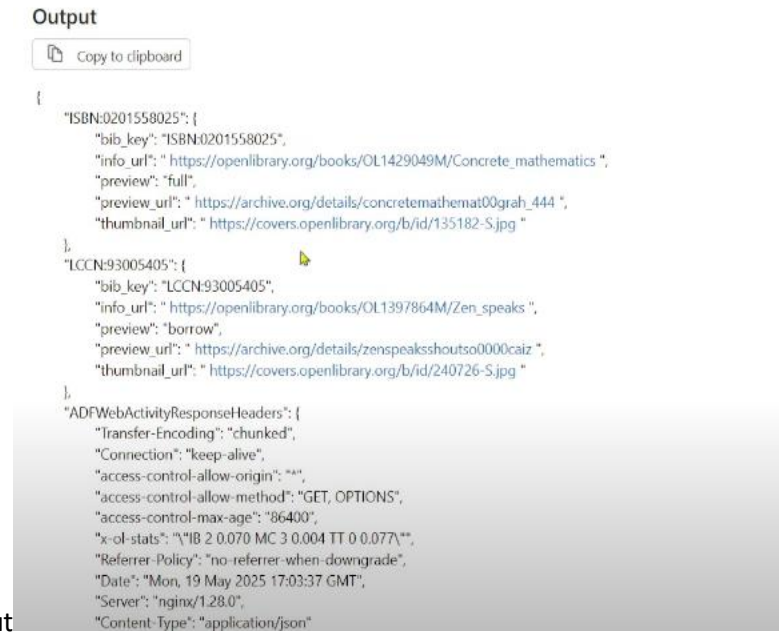


Sample API from Postman



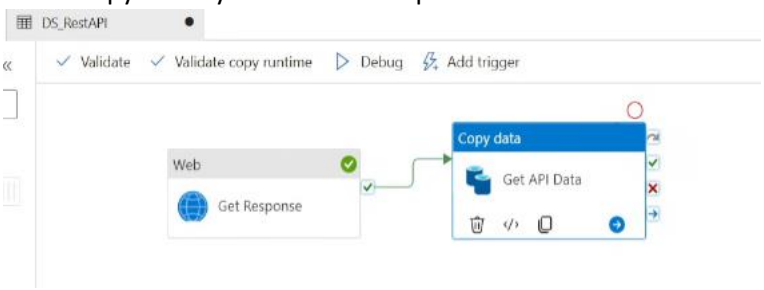
Query parameters: used for authentication of API



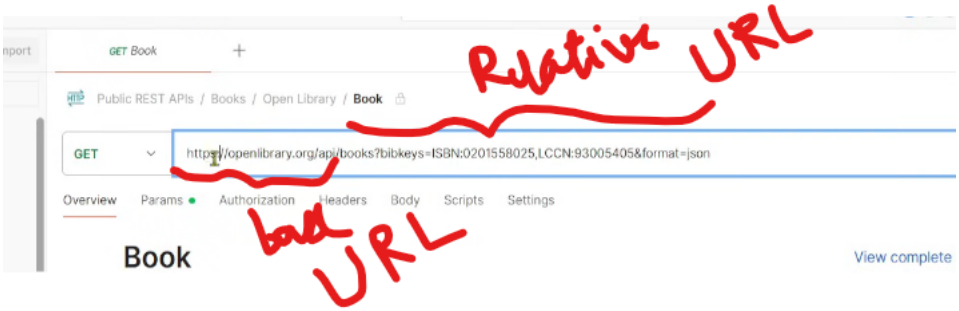


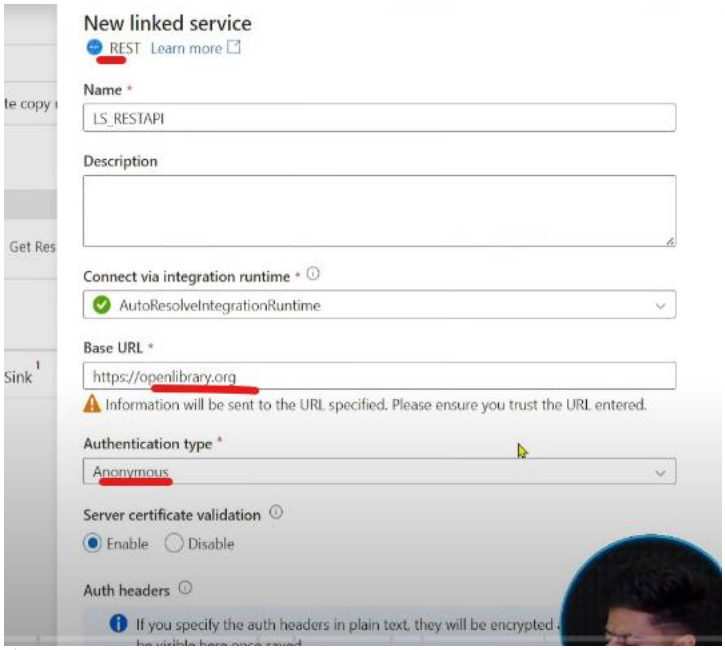
Debug to see output

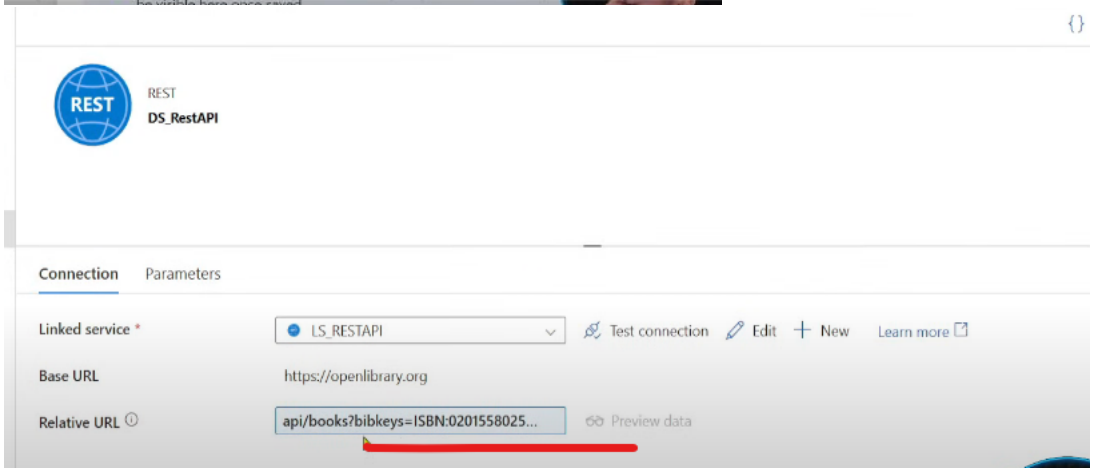
Use a Copy activity to store the response



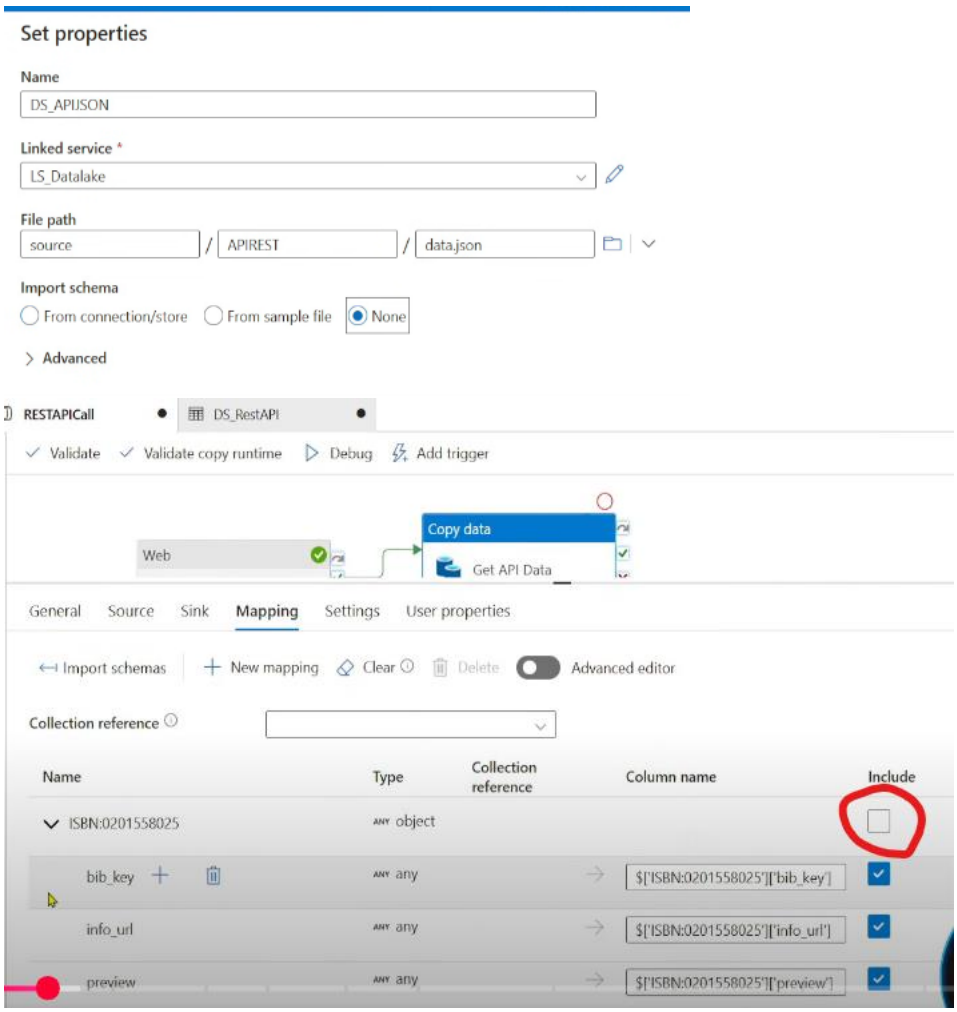
Source → REST dataset with REST LS



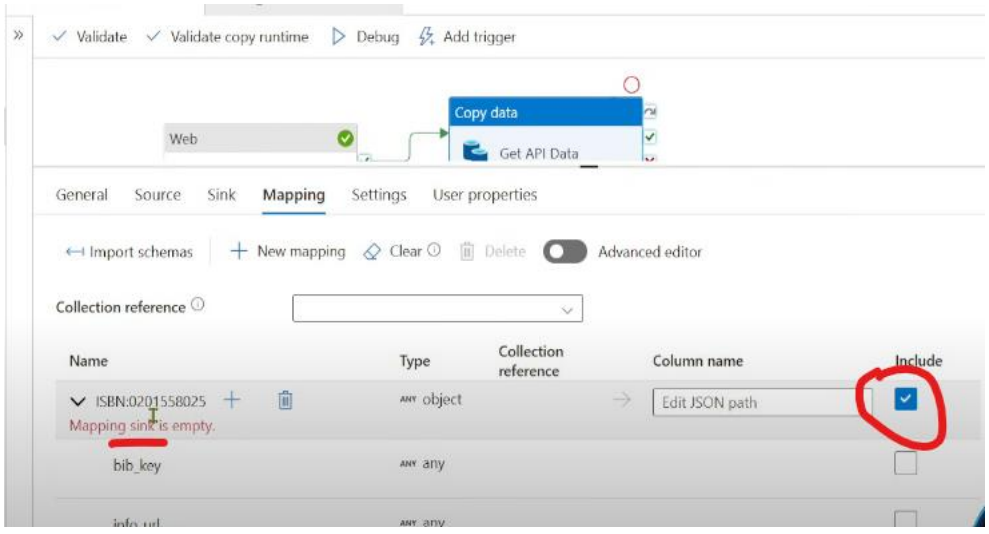




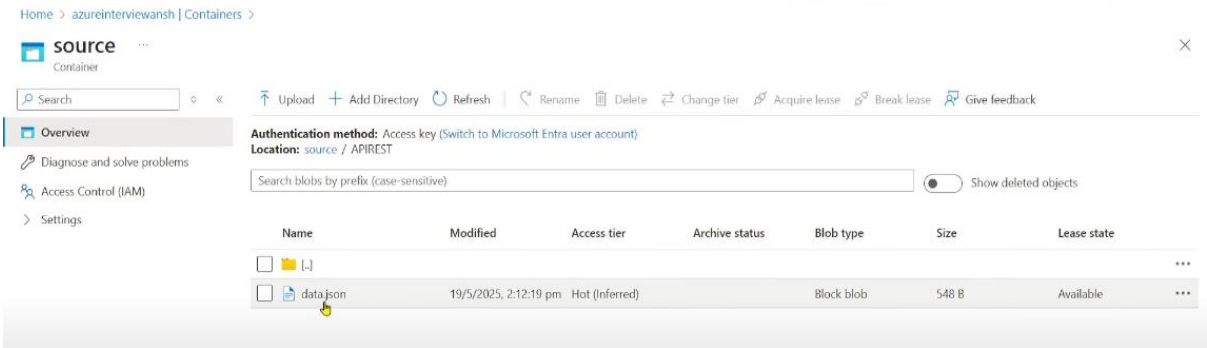
Sink → ADLS in JSON format



Include the parent object



Now click on Import Schemas again → Now debug the pipeline



Additional: Now let's consider if the output of Web activity is in csv format(not in json format) → Always use HTTP connection instead of REST in case of Delimited text
Because HTTP has an option of choosing Format (REST doesnot have)

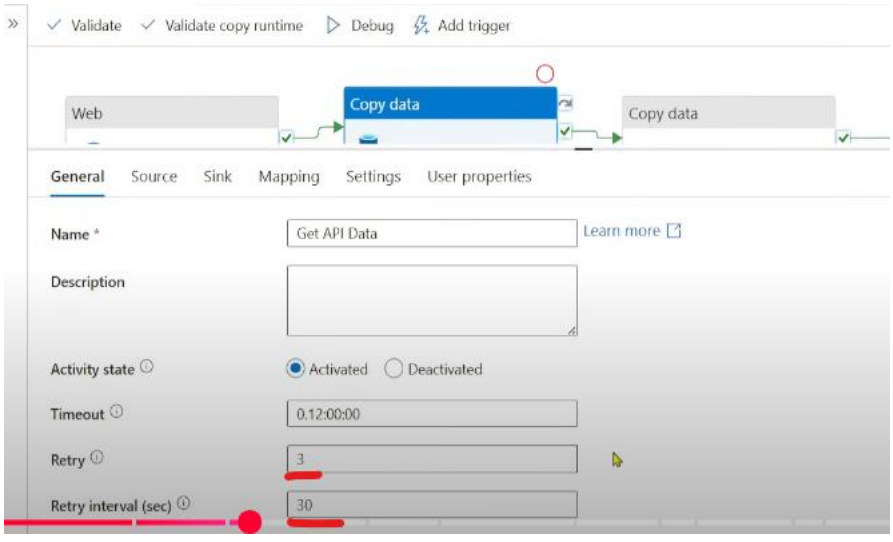
SCENARIO

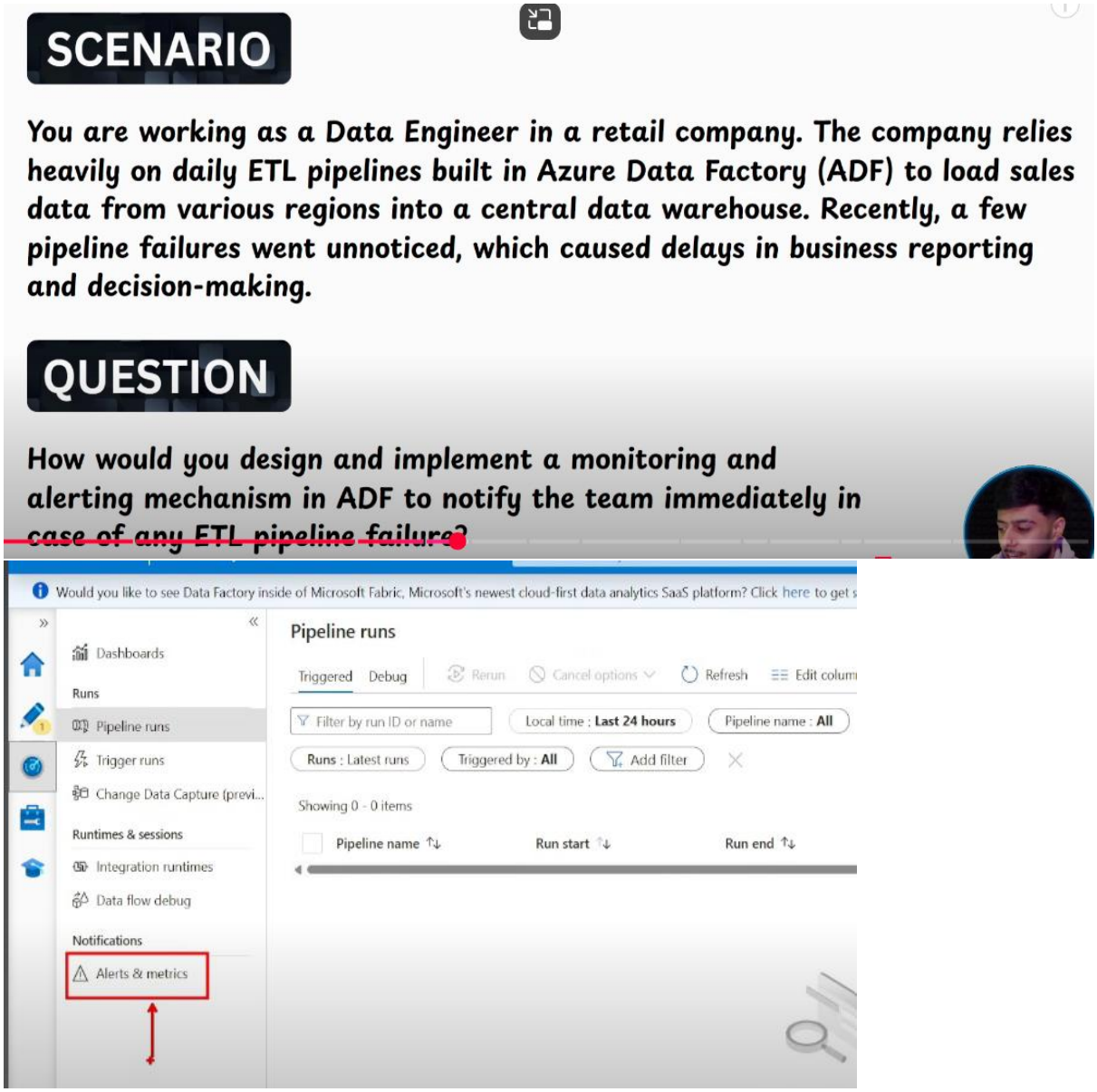
You're working on an ELT pipeline in a cloud-based data platform (like Azure Data Factory, AWS Glue, or Databricks). One of the pipeline activities is an API call to fetch data from a third-party service. This API is known to occasionally fail due to temporary network glitches or rate limiting issues.

QUESTION

How would you design this pipeline activity to handle intermittent failures gracefully without rerunning the entire pipeline?

Make pipeline robust enough to retry from the failed activity





Setup Alerts & metrics

SCENARIO

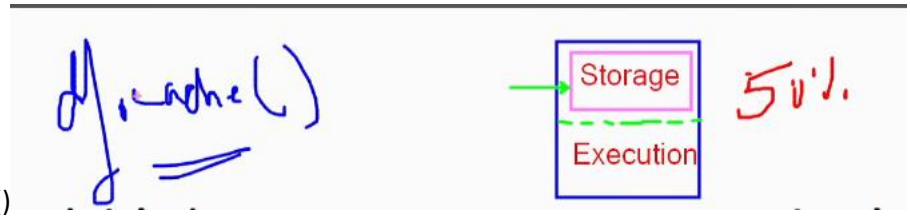
You're working on a PySpark job that processes customer transaction data from multiple sources. The initial steps involve heavy transformations like joins, filters, and aggregations, and the intermediate result is reused in multiple parts of the pipeline—first for generating KPIs, then for writing different outputs to Delta tables, and finally for some visualizations.

QUESTION

Given that the same intermediate DataFrame is reused in multiple stages, how would you optimize performance in this situation?

Whenever we create a dataframe, executor doesn't hold the dataframe in the execution memory for long time, it will eliminate dataframe immediately if it is assigned a different task or need to create a new df from an existing df.

Use cache() or persist()



Execution memory will be cleaned everytime there is a new job, so it will follow the DAG and start from the first step, so its better to store in storage memory.

Make sure to use unpersist() post completion.

SCENARIO

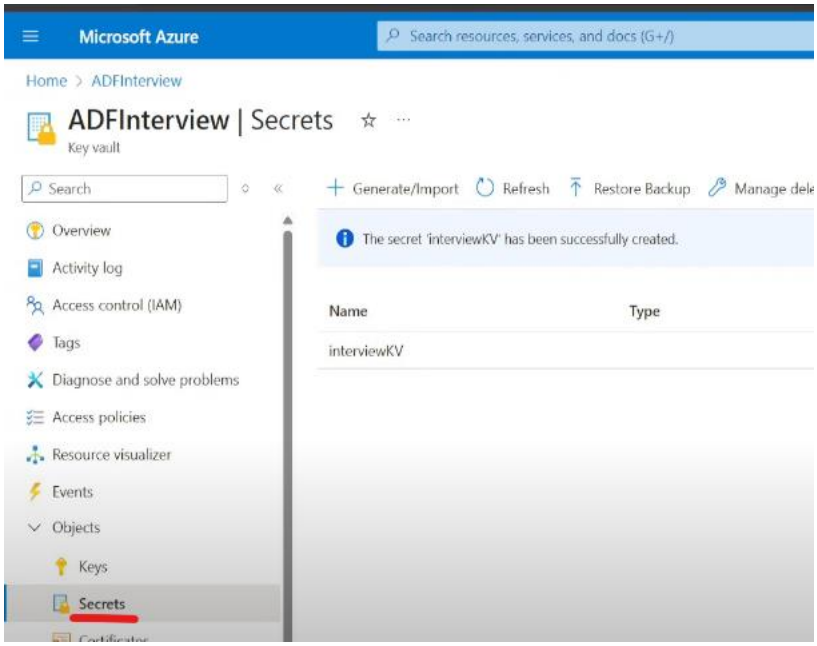
You're working on an Azure Data Factory (ADF) pipeline that involves calling a REST API through a Web Activity. This API requires an access key for authentication.

To follow best practices, your team has decided to store the API key securely using Azure Key Vault instead of hardcoding it in the pipeline.

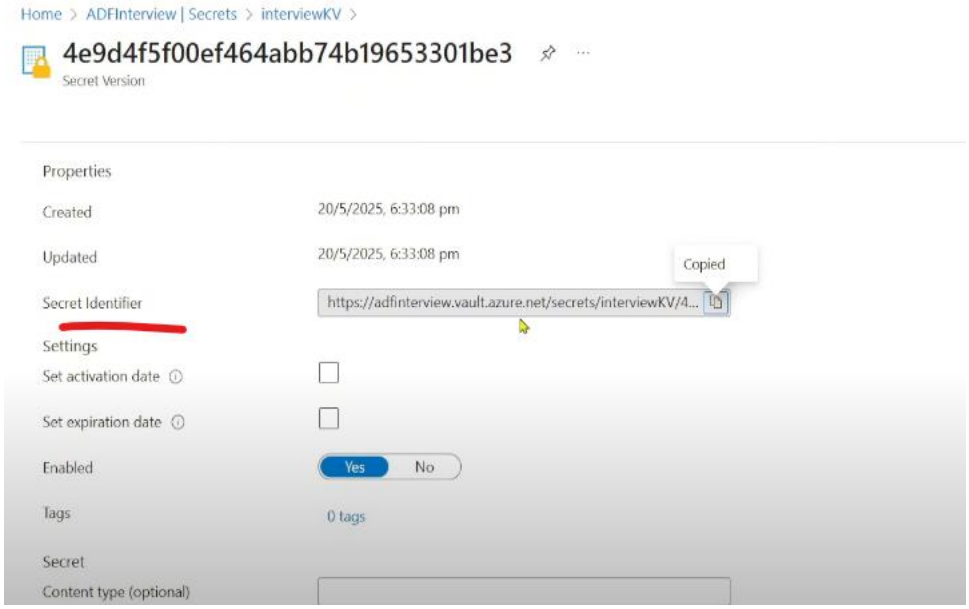
QUESTION

How would you implement the above scenario end-to-end in Azure Data Factory? Walk me through each step you would take, from creating the Key Vault to using its secret in the Web Activity, and ensuring secure handling of the output.

Create AKV → Grant KV Administrator role→ create secret

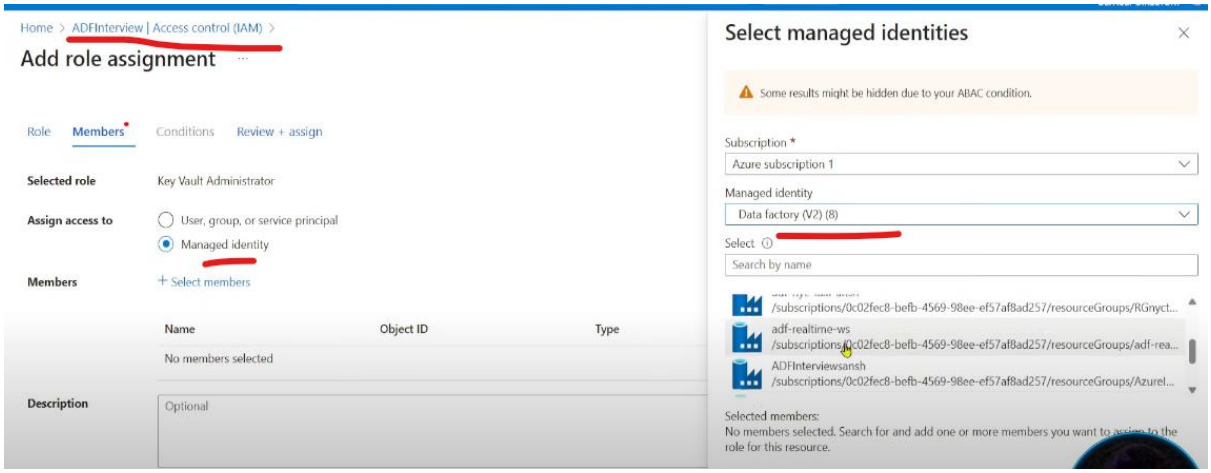


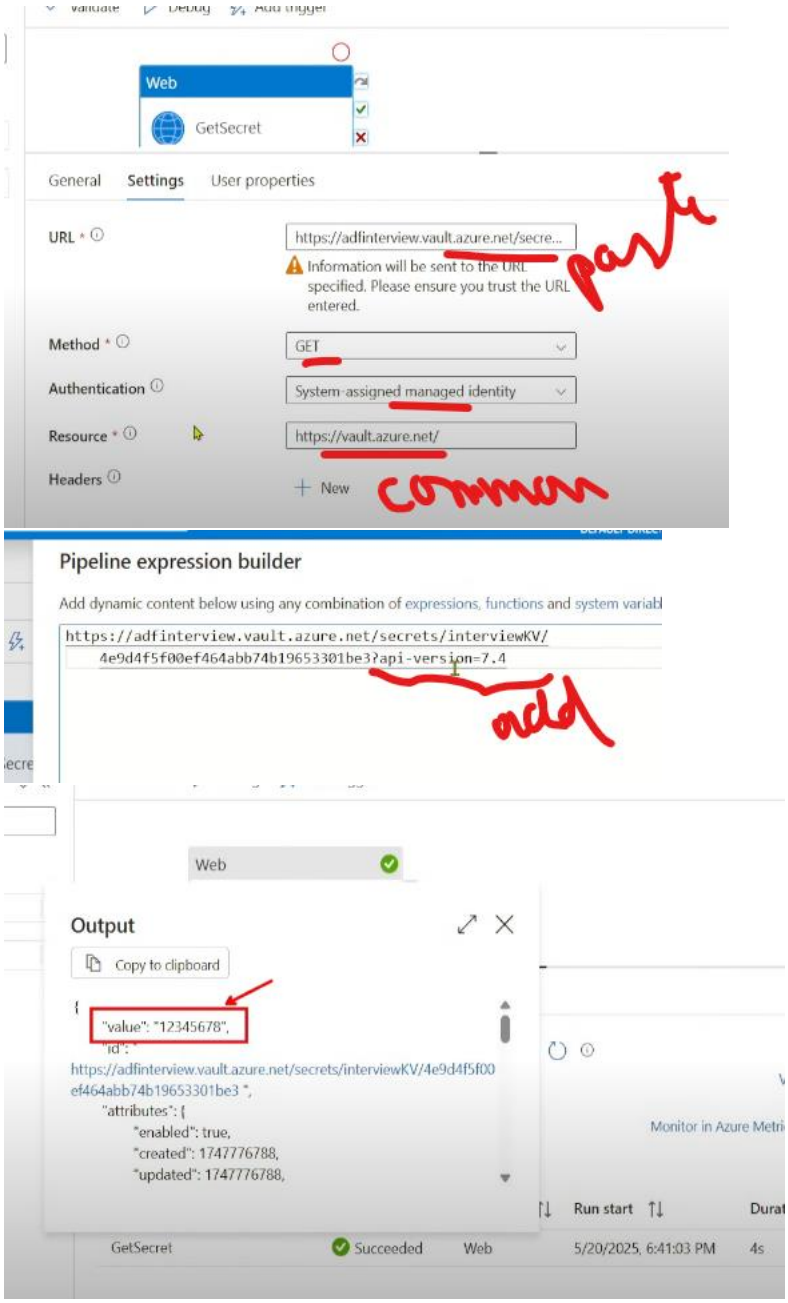
I want to fetch this info using Web activity



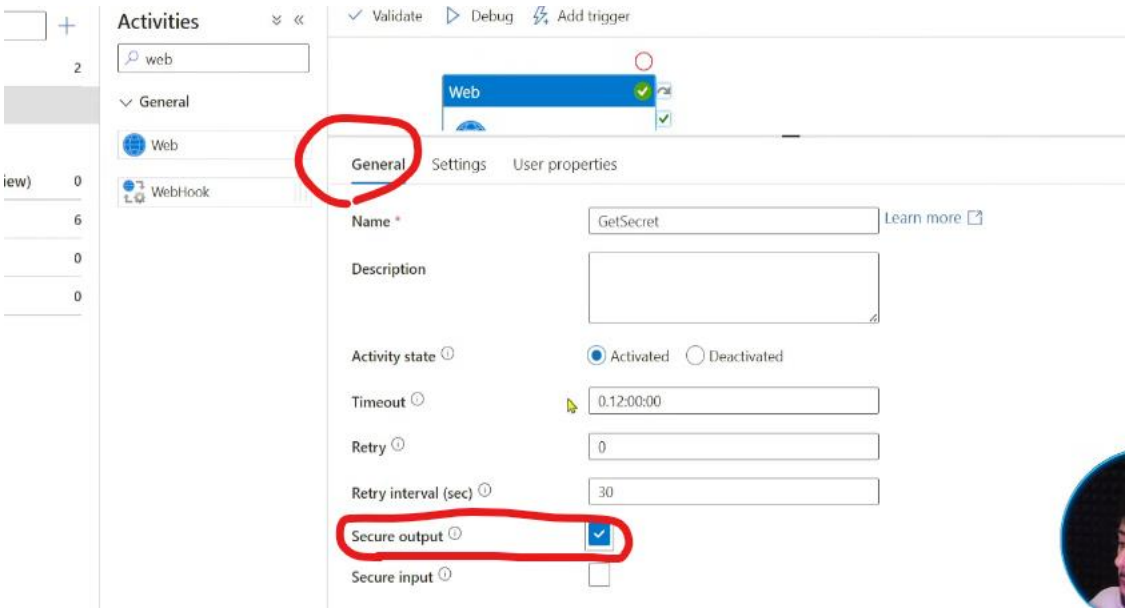
Copy the secret identifier

Grant ADF access to AKV (Go to AKV→ IAM → KV Administrator role→ Managed Identity)

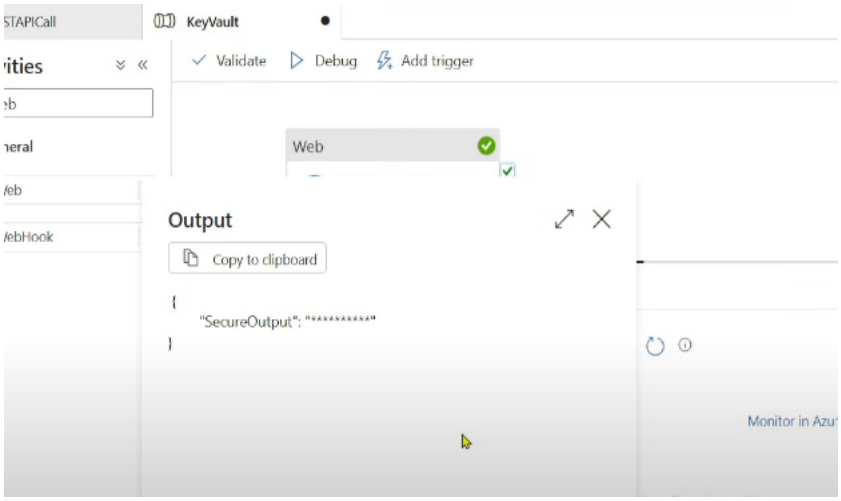




We can see the value, ideally we should not



Enable secure output



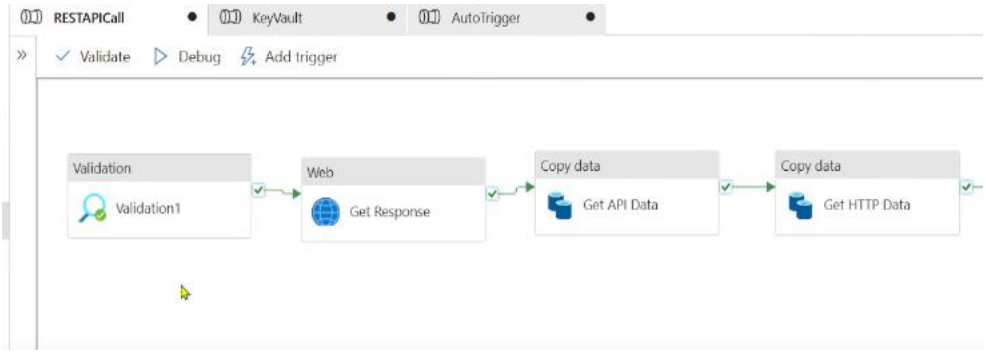
SCENARIO

The company receives daily sales data files from multiple regional branches. These files are uploaded at random times throughout the day to a specific folder in an Azure Data Lake Storage Gen2 account.
Your goal is to ensure that as soon as a new file arrives in this folder, an Azure Data Factory (ADF) pipeline is triggered automatically

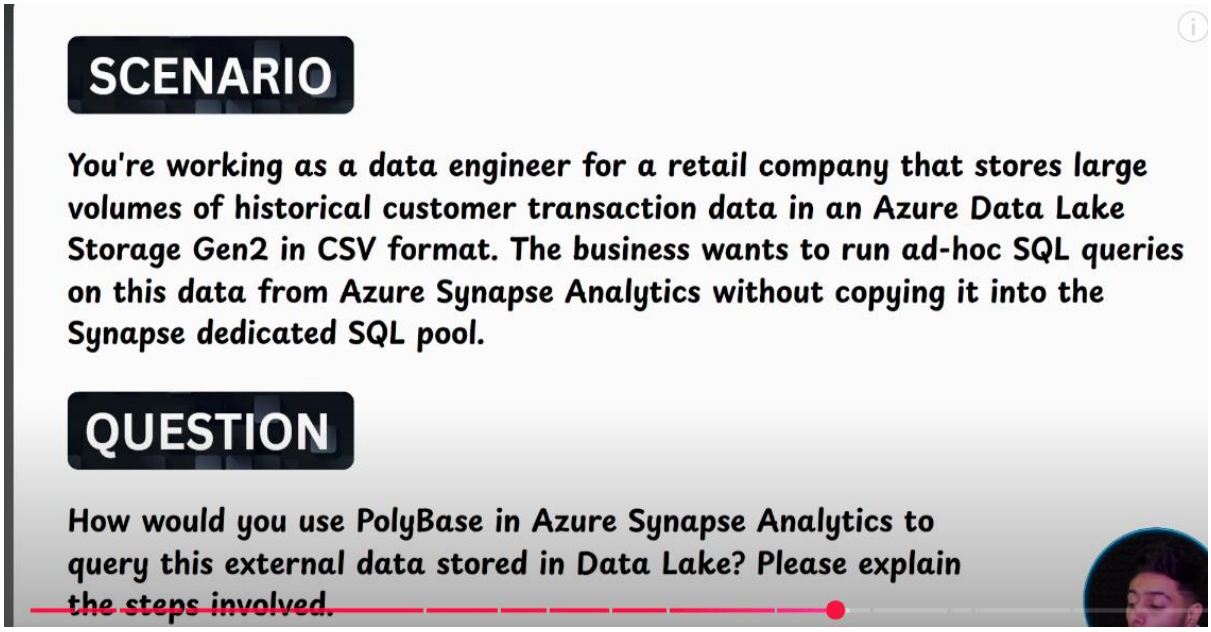
QUESTION

How would you design a solution in Azure Data Factory (or Synapse) to automatically trigger the pipeline whenever a new file is added to the specified folder in Azure Data Lake Storage Gen2?

M1 : Use Storage Events Trigger
M2 : Use Validation activity



Validation activity will be continuously searching for the file and then run the subsequent steps



In serverless SQL pool, we use Polybase
Step 1: Create Master key for database
Step 2: Create credential
Step 3: Create External Data Source
Step 4: Create External File Format
Step 5: Create External Table

SCENARIO

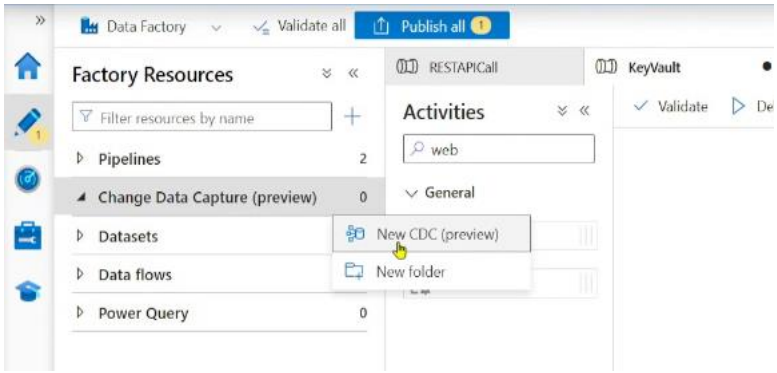
You are responsible for designing a Synapse Pipeline to incrementally load data from the Azure SQL source into the Data Lake using Parquet format, without loading the entire dataset each time.
The company also wants the solution to be efficient and cost-effective.

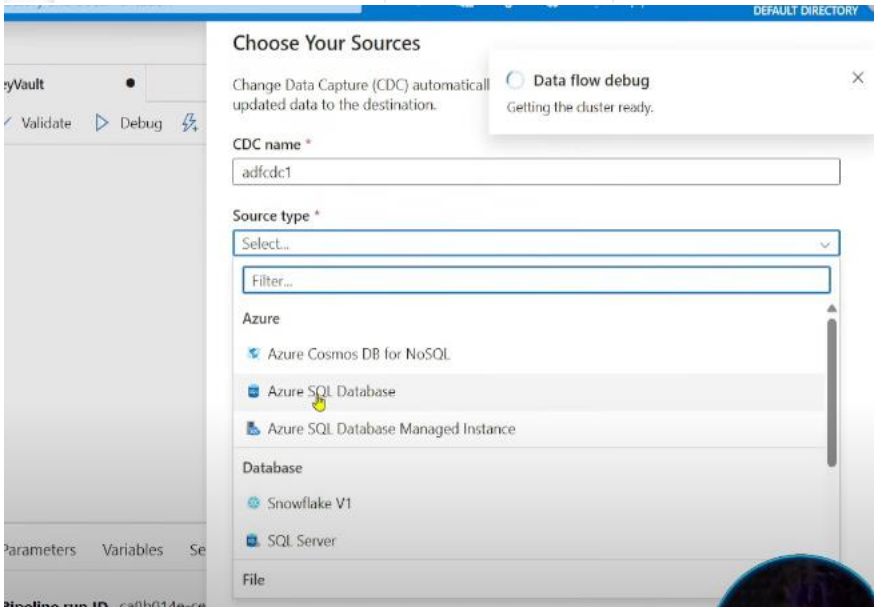
QUESTION

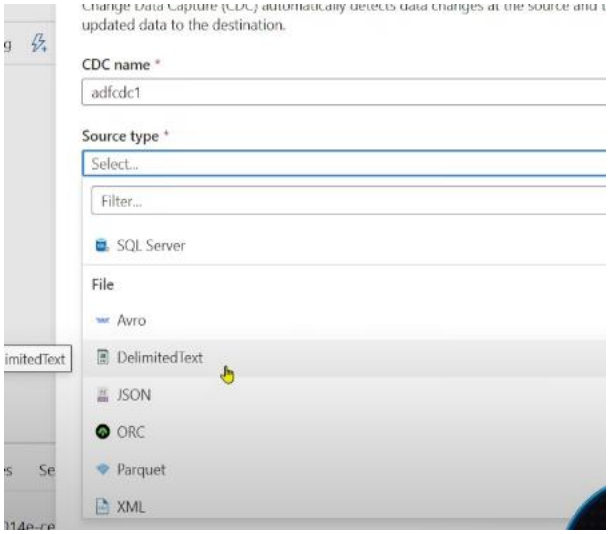
How would you implement incremental loading in Synapse Pipelines in this scenario?

1. **Watermarking approach**
2. **CDC (Change Data Capture)**

CDC as of now works when we have SQL db as a source

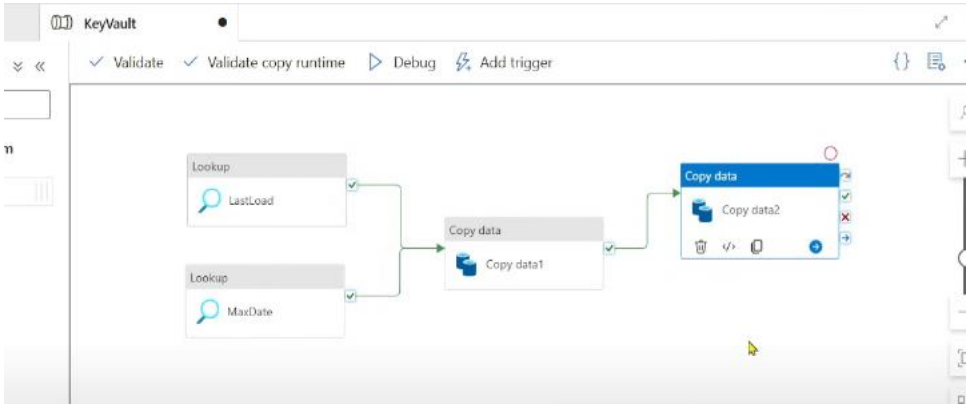






Enable CDC in the DB
Enable CDC in the Table
Connect the Table

Watermarking



Instead of Stored Procedure, store the data in file

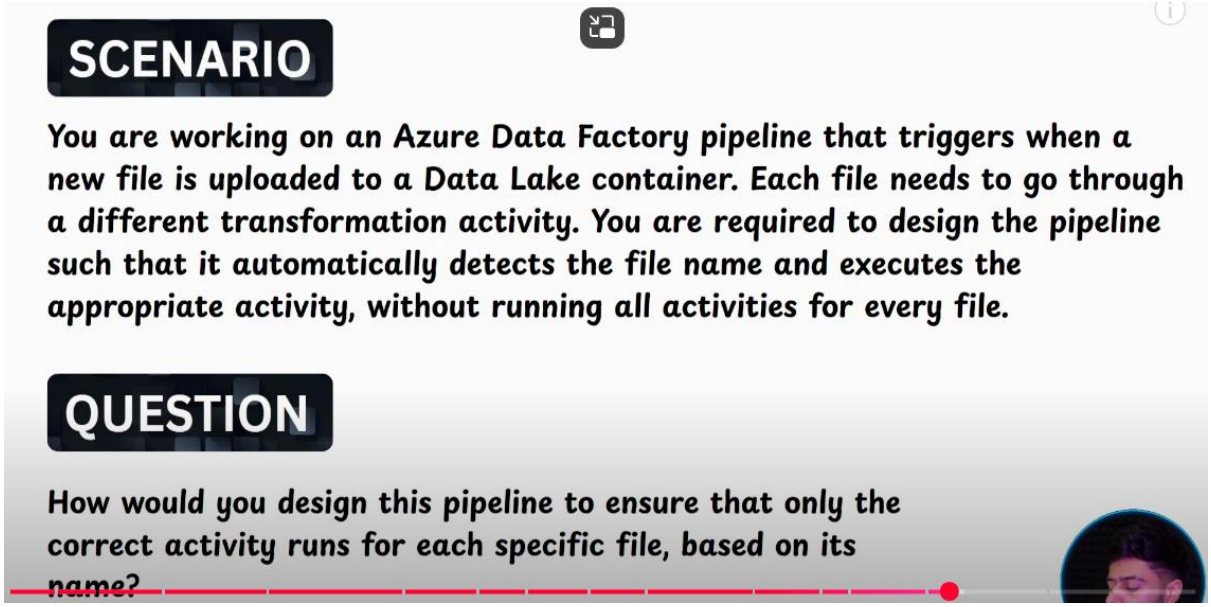
SCENARIO

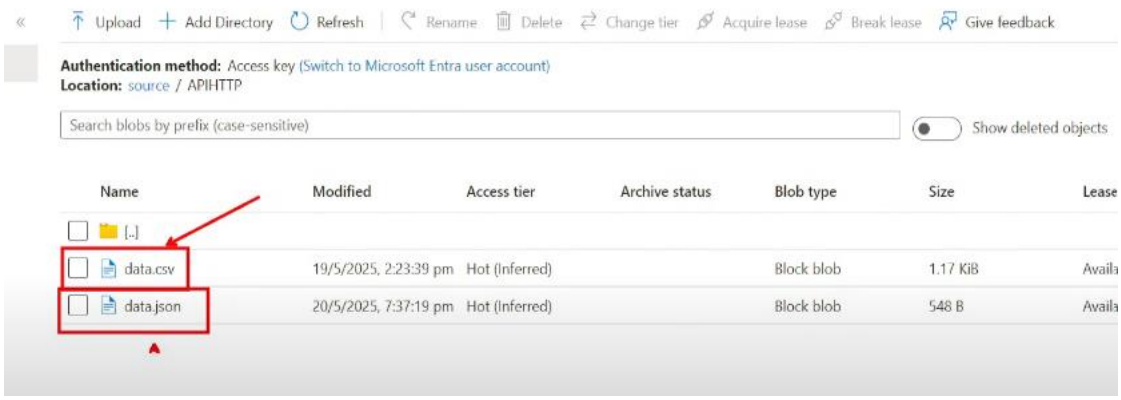
You're working on a data transformation job in Spark where large datasets from different sources are being joined and aggregated. The data volume varies significantly based on the day and data source.Initially, you tuned the join strategy and number of partitions manually, but you observed that the job still fails sometimes due to skewed data or inefficient joins. You enabled broadcast joins, but it's hard to predict the right size threshold.

QUESTION

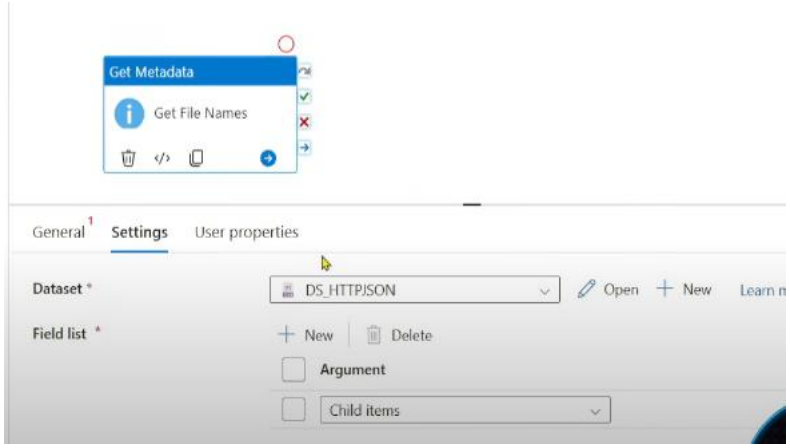
How can Adaptive Query Execution (AQE) help in this scenario?
What specific features of AQE would address the issues mentioned, and how would you enable them in Spark?

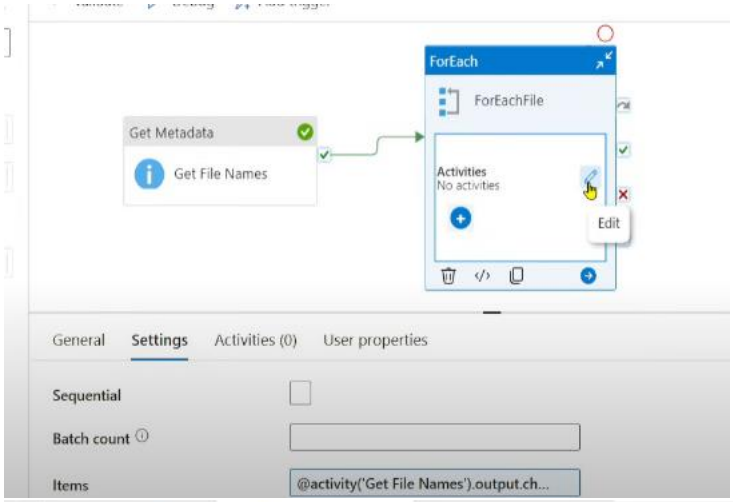
AQE : calculates query statistics during runtime based on that it addresses the manual threshold for broadcast join
(Before AQE, LP→PP) With AQE, LP→PP→Query statistics
Addresses skewness, Dynamically coalesces the partitions

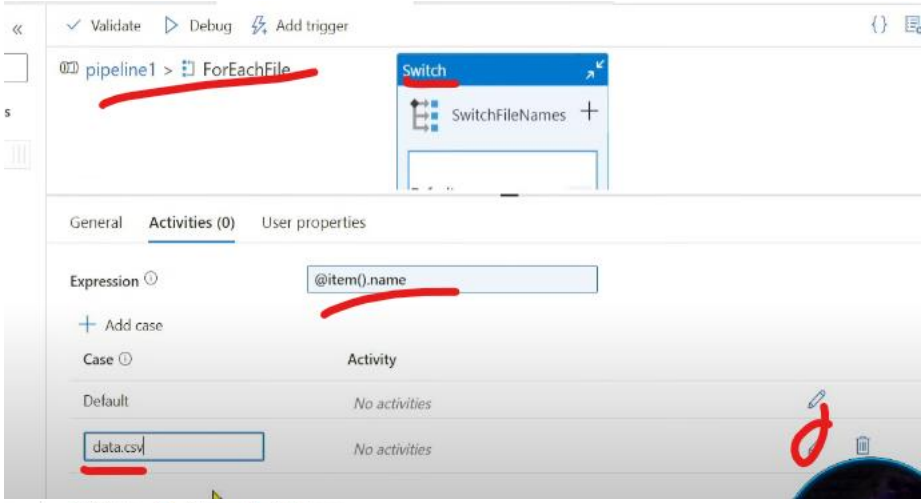


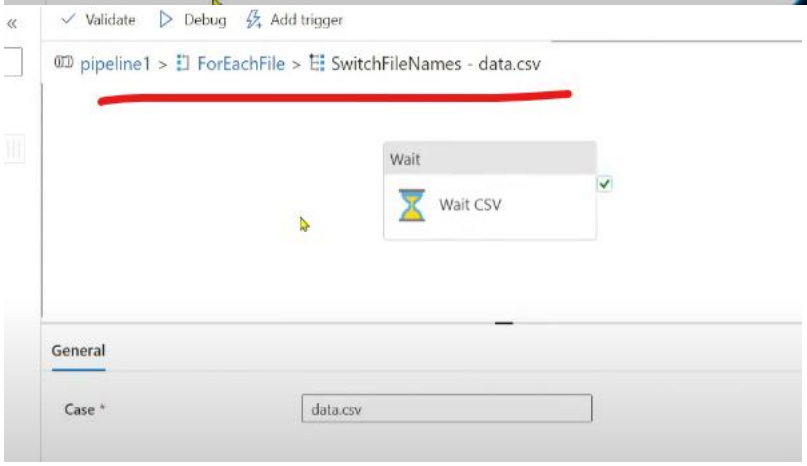


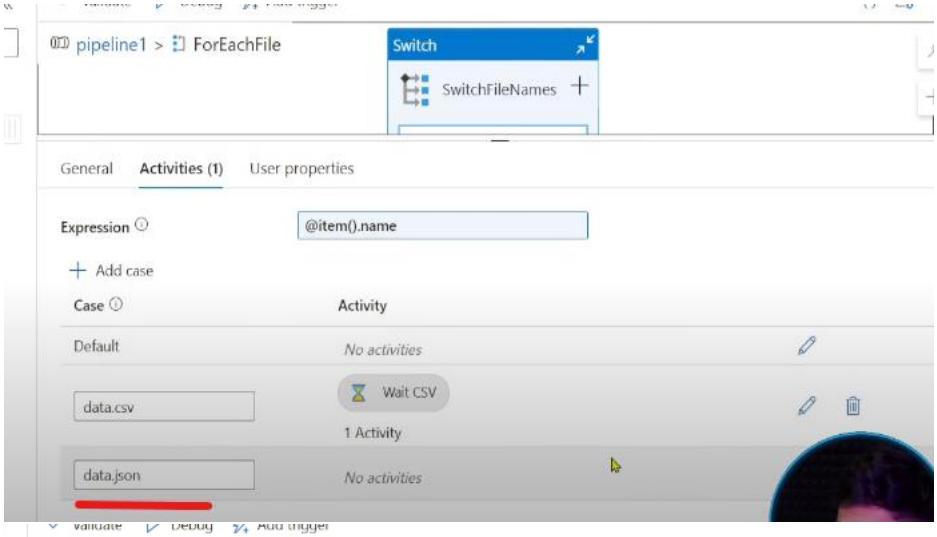
Want to perform different sets of activities for each of these files

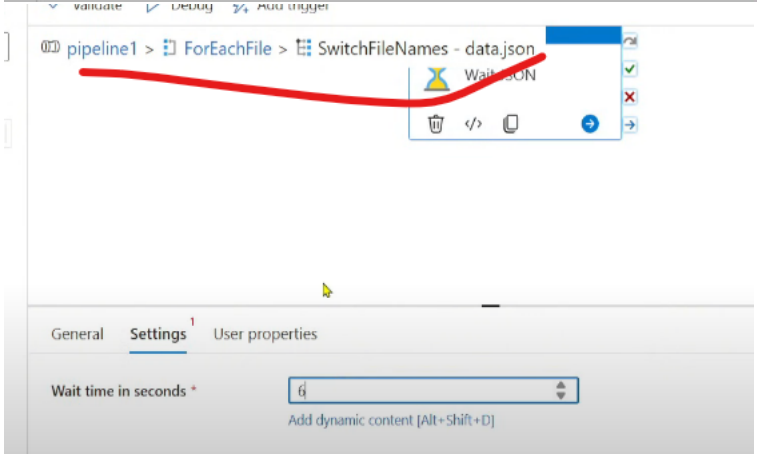



ForEach
ForEachFile
Get Metadata
Get File Names
Activities
No activities
Edit
General
Settings
Activities (0)
User properties
Sequential
Batch count
Items
@activity('Get File Names').output.ch...

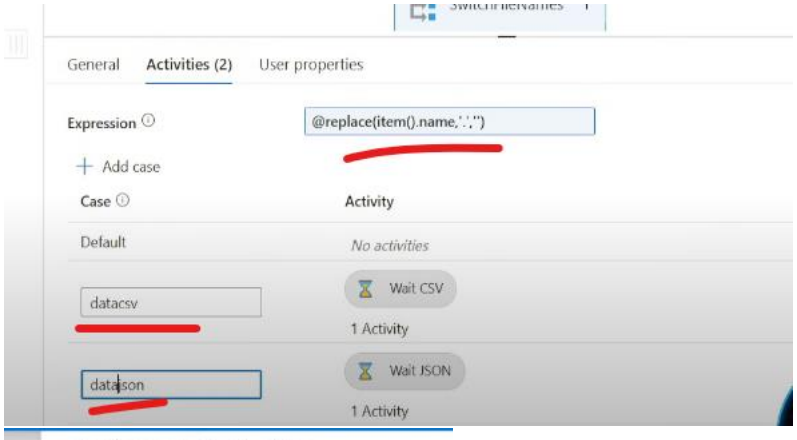

Validate
Debug
Add trigger
pipeline1 > ForEachFile
Switch
SwitchFileNames
General
Activities (0)
User properties
Expression
@item().name
Add case
Case
Activity
Default
No activities
data.csv
No activities

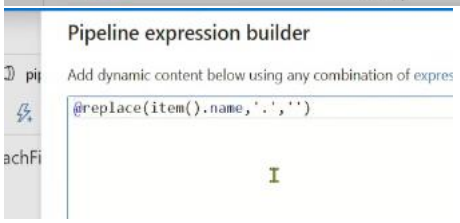

Validate
Debug
Add trigger
pipeline1 > ForEachFile > SwitchFileNames - data.csv
Wait
Wait CSV
General
Case *
data.csv

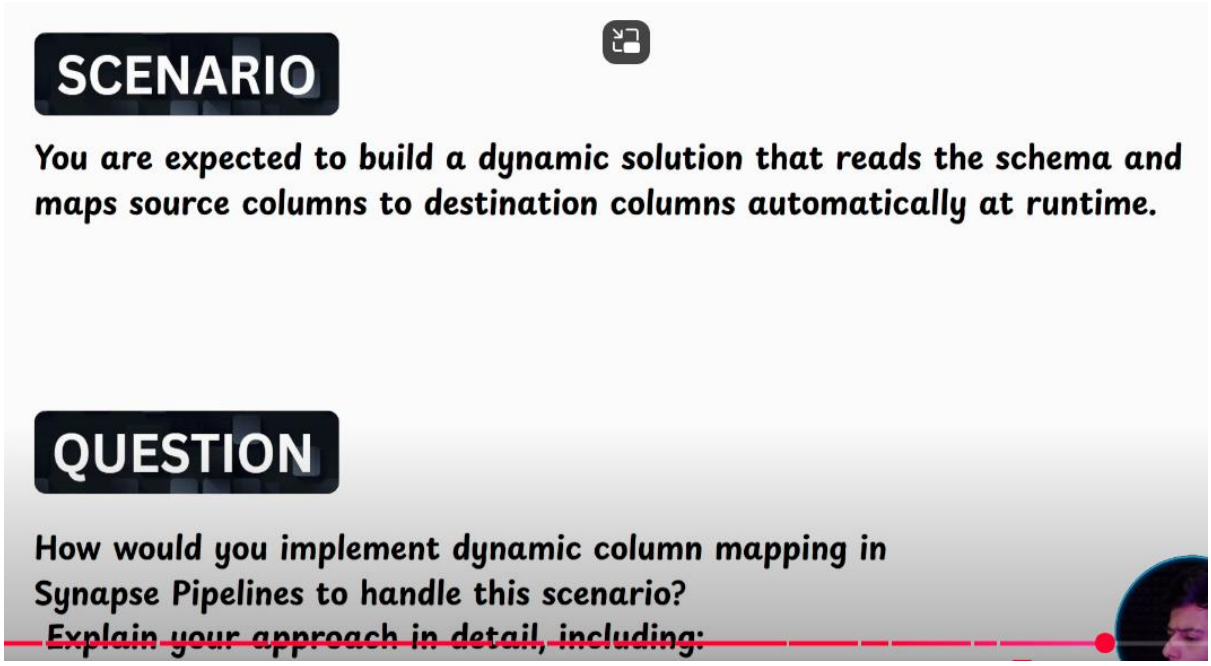




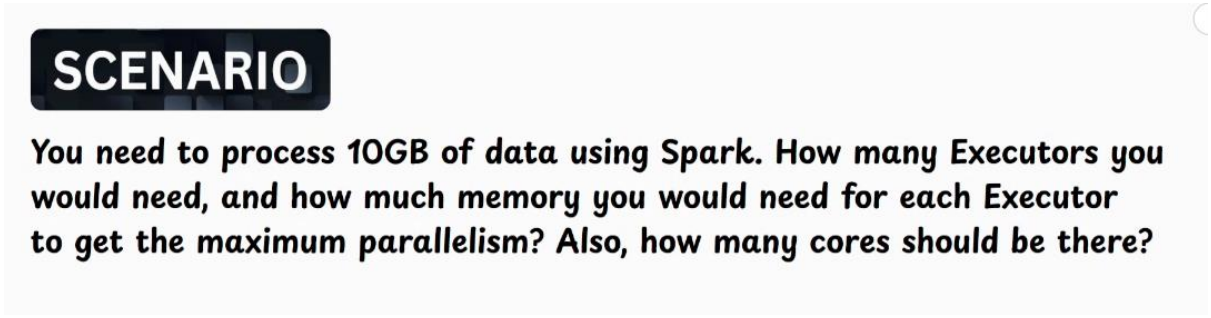
We cant use . in case conditions



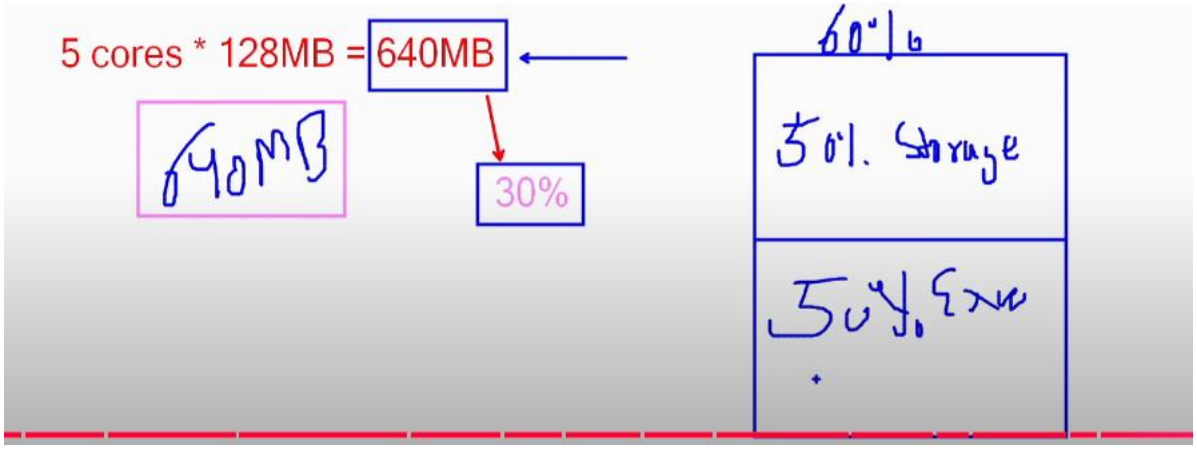




Copy the translator code



S1: 10GB → 80 partitions
S2: Leverage max parallelism→ 80 partitions → 80 cores
S3: No of cores→ 5 per executor → 80/5 → 16 executor
S4: Memory for each Executor → In each executor 5 cores, each core will process 1 partition sized 128MB i.e. 128*5 = 640MB
640MB is not the total memory, 640MB is required just to execute the task, we get 30% memory to execute the task.



Spark pool memory is 60%, 40% off heap.
Out of 60%, 50% is storage memory/caching & 50% is execution memory.

So 640MB is equivalent to 50% execution memory.
So we multiply 640 with 3.5-4 to get the total executor memory

Total Executor memory = 2.6 GB