

Data Integration Part 1

Resource naming throughout this lab

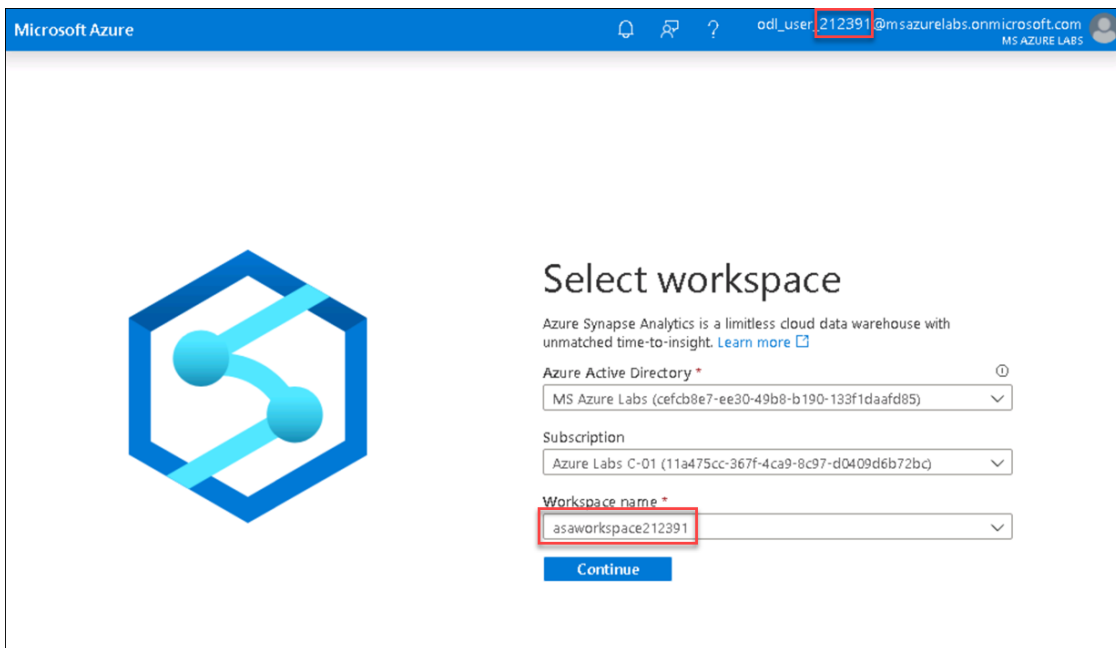
For the remainder of this guide, the following terms will be used for various ASA-related resources (make sure you replace them with actual names and values):

Azure Synapse Analytics Resource	To be referred to
Workspace resource group	WorkspaceResourceGroup
Workspace / workspace name	Workspace
Primary Storage Account	PrimaryStorage
Default file system container	DefaultFileSystem
SQL Pool	SqlPool01

Lab prerequisite

Start the SQL Pool in your lab environment.

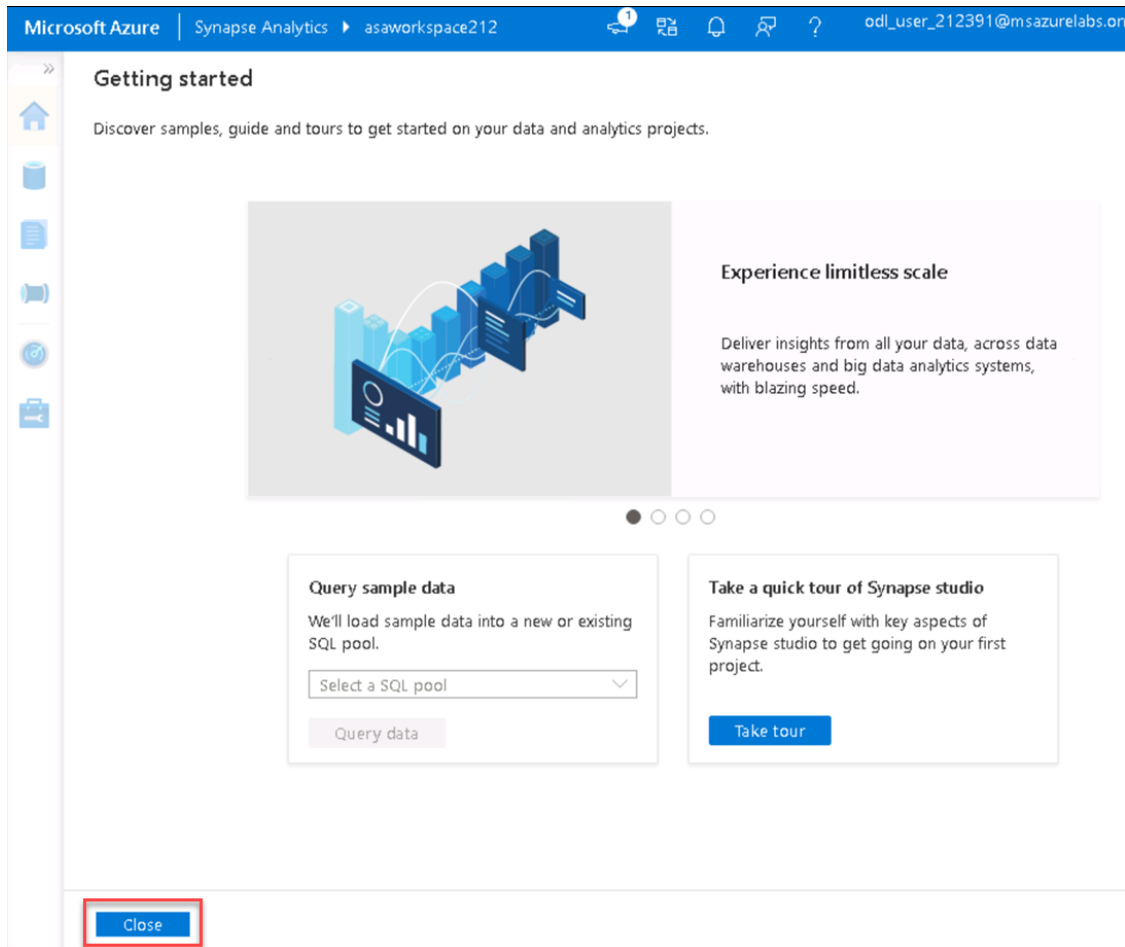
1. Open Synapse Studio (<https://web.azuresynapse.net/>). If you see a prompt to select your workspace, select the Azure subscription and workspace name used for the lab. When using a hosted lab environment, the workspace name will end with the same SUFFIX as your user name, as shown in the screenshot below. Make note of the suffix, as it is referenced throughout this and the remaining labs.



The username suffix and workspace suffix are highlighted.

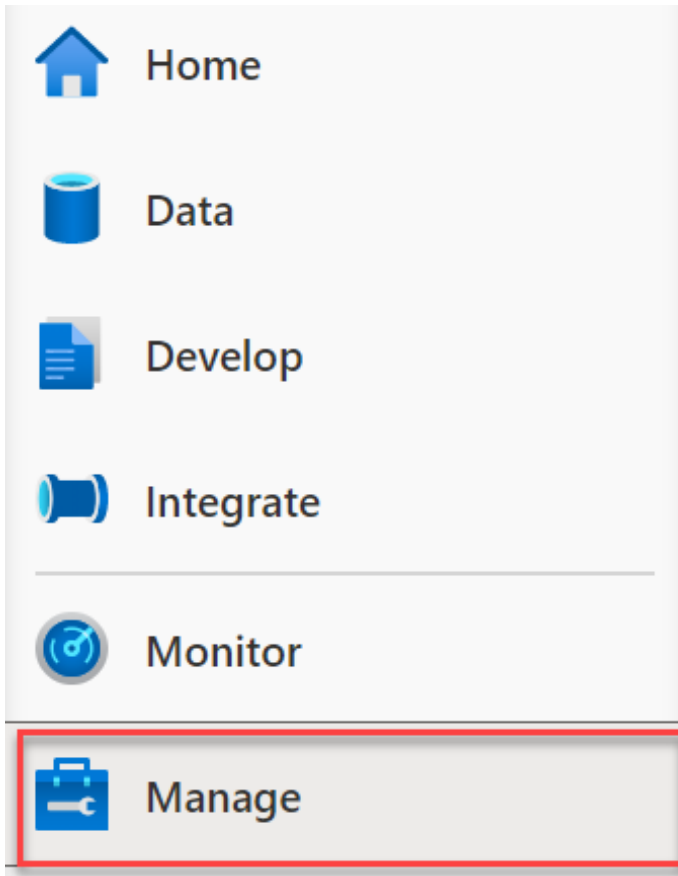
NOTE You may need to logout of whatever account you are already logged into before you can gain access to the target workspace. You can also attempt to utilize a new InPrivate browser window.

2. If this is your first time connecting to the Synapse Analytics workspace, you may see the *Getting started* prompt. Select **Close** to continue.



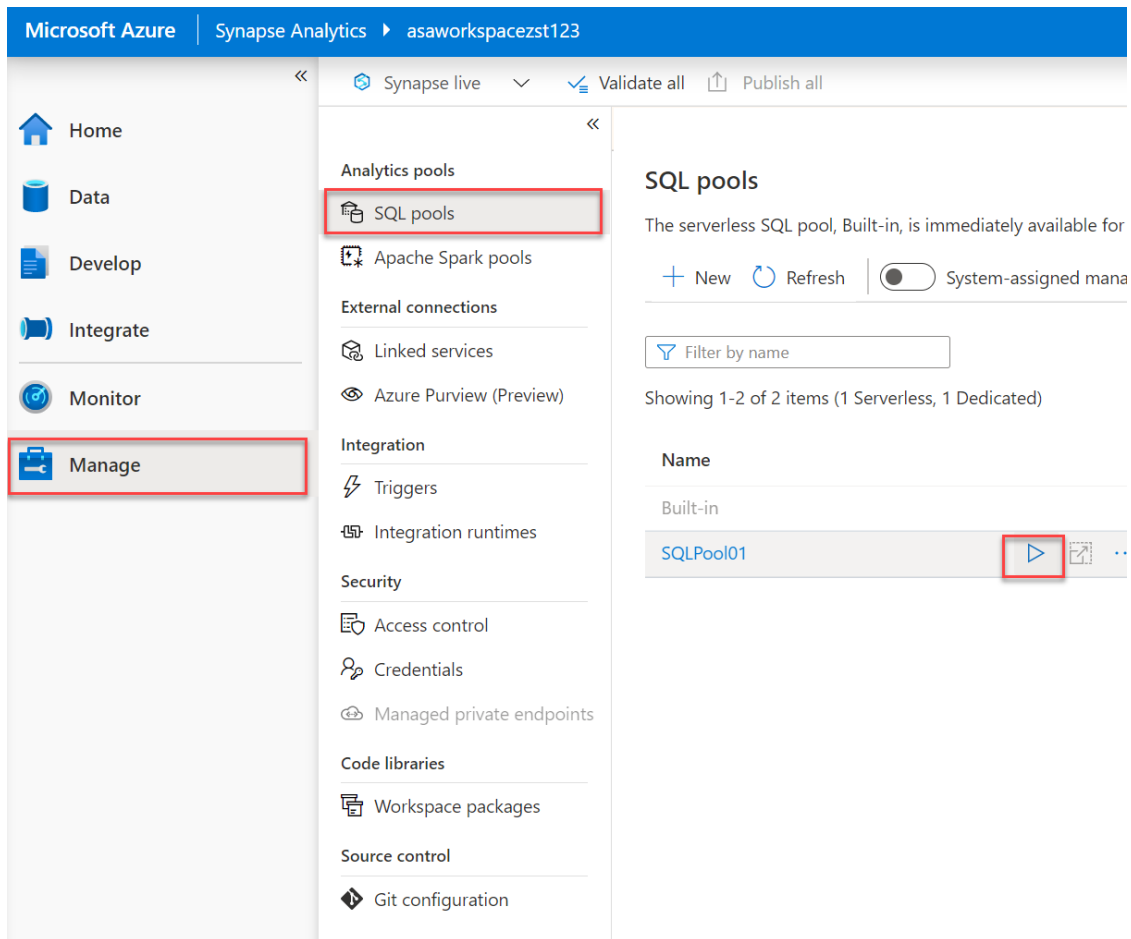
The Close button is highlighted on the Getting started dialog.

3. Once the Synapse Studio workspace is loaded, navigate to the **Manage** hub.



The Manage menu item is highlighted.

4. From the center menu, select **SQL pools** from beneath the **Analytics pools** heading. Locate SQLPool01, and select the **Resume** button.



The Manage menu item is selected, with SQL pools selected from the center menu. The resume button is selected next to the SQLPool01 item.

Exercise 1: Configure linked service and create datasets


Task 1: Create linked service

Our data sources for labs 1 and 2 include files stored in ADLS Gen2 and Azure Cosmos DB. The linked service for ADLS Gen2 already exists as it is the primary ADLS Gen2 account for the workspace.

1. After connecting to the Synapse Analytics workspace, navigate to the **Manage** hub.




DB account name select asacosmosdb{Suffix} and set the **Database name** value to CustomerProfile.

New linked service (Azure Cosmos DB (SQL API))

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


Name *

Description

Connect via integration runtime * 
  


☒ Connection string




☐ Azure Key Vault

Account selection method 

☒ From Azure subscription

☐ Enter manually


Azure subscription 

Azure Cosmos DB account name * 
  


Database name *

☒ Edit


Additional connection properties

 New

Annotations

 New

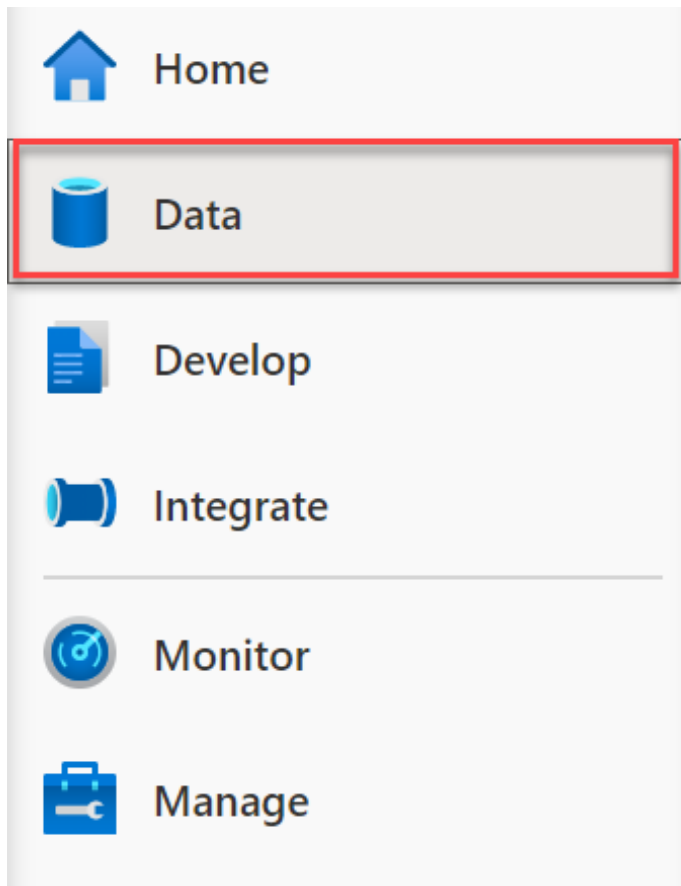
Parameters

Advanced 

New Azure Cosmos DB linked service.

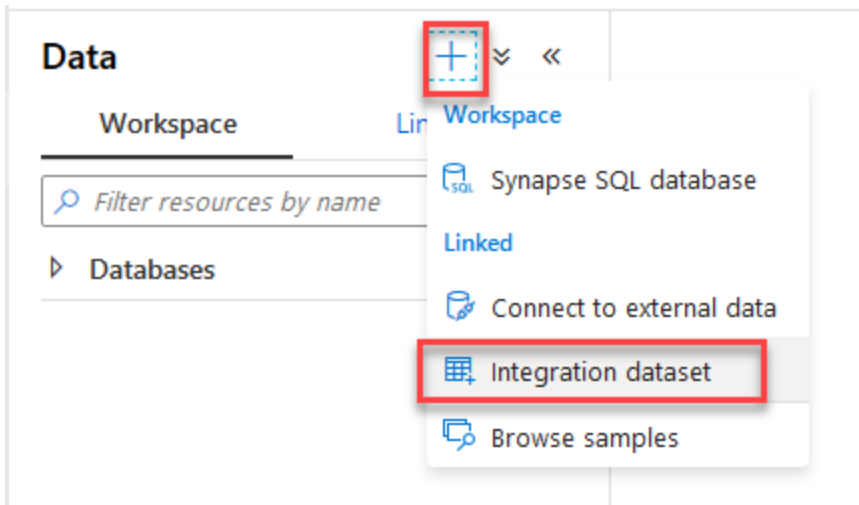
Task 2: Create datasets

1. Navigate to the **Data** hub.



The Data menu item is highlighted.

2. With the Workspace tab selected under Data, select + in the toolbar, then select **Integration dataset** to create a new dataset.



Create new Dataset.

3. Create a new **Azure Cosmos DB (SQL API)** dataset with the following characteristics:
 - **Name:** Enter asal400_customerprofile_cosmosdb.
 - **Linked service:** Select the Azure Cosmos DB linked service.
 - **Collection:** Select OnlineUserProfile01.

Set properties

i Choose a name for your dataset. This name can be updated at any time until it is published.

Name
asal400_customerprofile_cosmosdb

Linked service *
asacosmosdb01

[Edit connection](#)

Collection
OnlineUserProfile01

☐ Edit

Import schema
☒ From connection/store ☐ None

New Azure Cosmos DB dataset.

4. After creating the dataset, navigate to its **Connection** tab, then select **Preview data**.



Connection	Schema	Parameters
Linked service *	<div>asacosmosdb1</div>	<div>Test connection</div> <div>Edit</div> <div>+ New</div>
Collection	<div>OnlineUserProfile01</div>	<div>Refresh</div> <div>Preview data</div>
	<div>Edit</div>	

The preview data button on the dataset is highlighted.

5. Preview data queries the selected Azure Cosmos DB collection and returns a sample of the documents within. The documents are stored in JSON format and include a `userId` field, `cartId`, `preferredProducts` (an array of product IDs that may be empty), and `productReviews` (an array of written product reviews that may be empty). We will use this data in lab 2.

Preview data

Linked service: asacosmosdb01

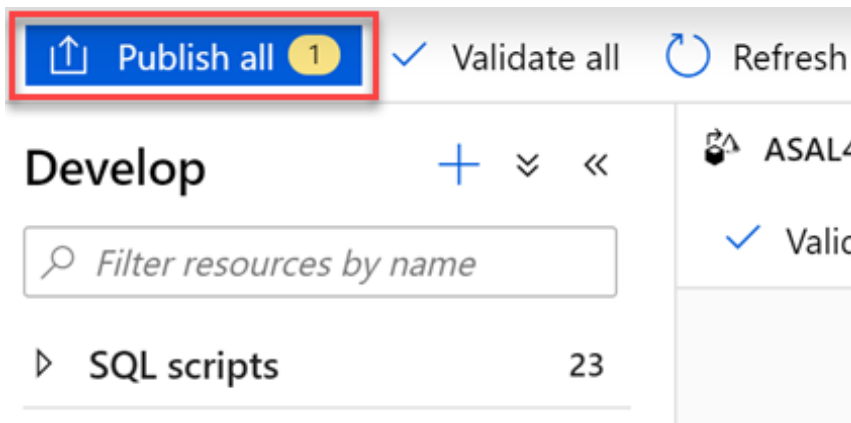
Object: OnlineUserProfile01

```
[
  {
    "userId": 9079954,
    "cartId": "406a06af-e54f-42e9-aad8-9a36f2c7f8ca",
    "preferredProducts": [],
    "productReviews": [
      {
        "productId": 3965,
        "reviewText": "It only works when I'm Bahrain.",
        "reviewDate": "2019-01-15T19:04:42.5554783+00:00"
      },
      {
        "productId": 1287,
        "reviewText": "This Harbors works so well. It imperfectly improves my baseball by a lot.",
        "reviewDate": "2017-04-23T19:54:59.273694+00:00"
      },
      {
        "productId": 169,
        "reviewText": "one of my hobbies is antique-shopping. and when i'm antique-shopping this works great.",
        "reviewDate": "2020-03-23T20:52:59.5875906+00:00"
      }
    ]
  },
  {
    "id": "441589f6-6754-4f75-a04a-23191dbf72de",
    "_rid": "OC8bALmbB4kBAAAAAAAAAA==",
    "_self": "dbs/OC8bAA==/colls/OC8bALmbB4k=/docs/OC8bALmbB4kBAAAAAAAAAA==/",
    "_etag": "\"2101cde1-0000-0200-0000-5e969f4b0000\"",
    "_attachments": "attachments/",
    "_ts": 1586929483
  }
],
{
  "userId": 9079747,
  "cartId": "5c4dc5dc-a585-41ec-8149-9133caa3a73a",
  "preferredProducts": [
    4235,
    3288,
    2756
  ],
  "productReviews": [
```

A preview of the Azure Cosmos DB data is displayed.

6. Select the **Schema** tab, then select **Import schema**. Synapse Analytics evaluates the JSON documents within the collection and infers the schema based on the nature of the data within. Since we are only storing one document type in this collection, you will see the inferred schema for all documents within.

- **Name:** Enter asal400_ecommerce_userprofiles_source.
 - **Linked service:** Select the asadata lakeXX linked service that already exists.
 - **File path:** Browse to the wwi-02/online-user-profiles-02 path.
 - **Import schema:** Select From connection/store.
9. Select **Publish all**, then **Publish** to save your new resources.



Publish all is highlighted.

Exercise 2: Explore source data in the Data hub

Understanding data through data exploration is one of the core challenges faced today by data engineers and data scientists as well. Depending on the underlying structure of the data as well as the specific requirements of the exploration process, different data processing engines will offer varying degrees of performance, complexity, and flexibility.

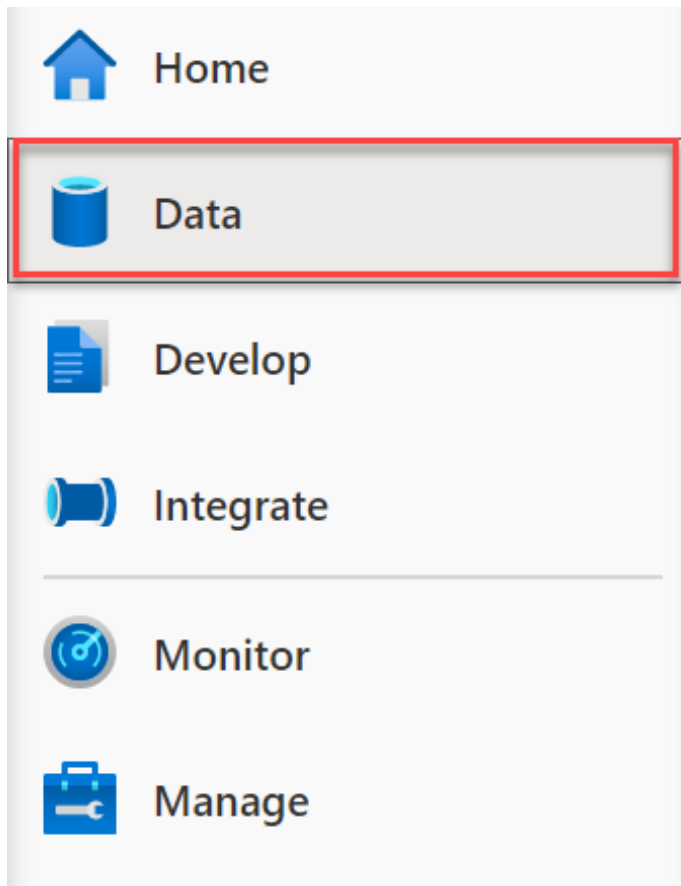
In Azure Synapse Analytics, you have the possibility of using either the Synapse serverless SQL engine, the big-data Spark engine, or both.

In this exercise, you will explore the data lake using both options.

Task 1: Query sales Parquet data with a serverless SQL pool

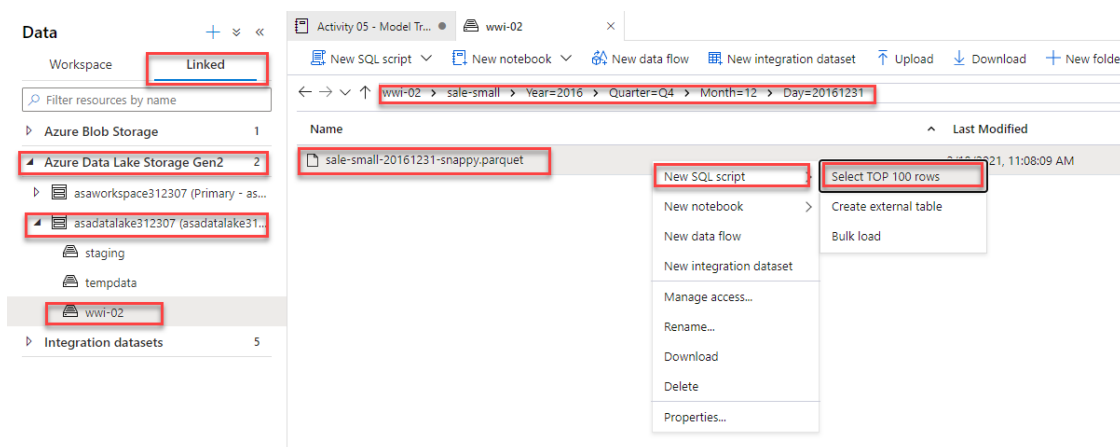
When you query Parquet files using a serverless SQL pool, you can explore the data with T-SQL syntax.

1. In Synapse Analytics Studio, navigate to the **Data** hub.



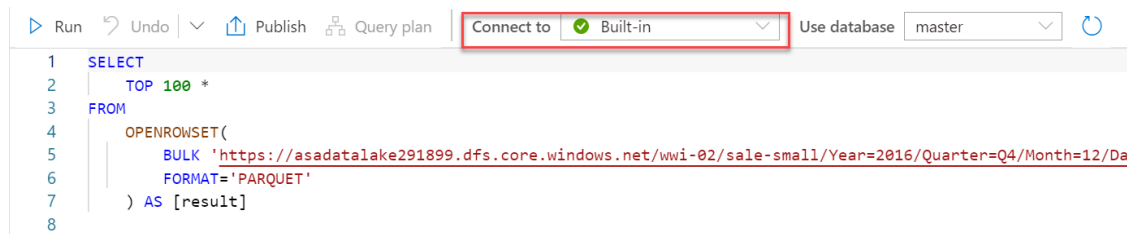
The Data menu item is highlighted.

2. Select the **Linked** tab and expand *Azure Data Lake Storage Gen2*. Expand the asaworkspaceXX primary ADLS Gen2 account and select wwi-02.
3. Navigate to the sale-small/Year=2016/Quarter=Q4/Month=12/Day=20161231 folder. Right-click on the sale-small-20161231-snappy.parquet file, select **New SQL script**, then **Select TOP 100 rows**.



The Data hub is displayed with the options highlighted.

4. Ensure **Built-in** is selected in the Connect to dropdown list above the query window, then run the query. Data is loaded by the Synapse SQL Serverless endpoint and processed as if it was coming from any regular relational database.



The serverless SQL connection is highlighted.

5. Modify the SQL query to perform aggregates and grouping operations to better understand the data. Replace the query with the following, making sure that the file path in OPENROWSET matches your current file path:

SELECT

```
TransactionDate, ProductId,
  CAST(SUM(ProfitAmount) AS decimal(18,2)) AS [(sum) Profit],
  CAST(AVG(ProfitAmount) AS decimal(18,2)) AS [(avg) Profit],
  SUM(Quantity) AS [(sum) Quantity]
```

FROM

```
OPENROWSET(
  BULK 'https://asadatalakeSUFFIX.dfs.core.windows.net/wwi-02/sale-
small/Year=2016/Quarter=Q4/Month=12/Day=20161231/sale-small-20161231-
snappy.parquet',
  FORMAT='PARQUET'
) AS [r] GROUP BY r.TransactionDate, r.ProductId;
```

```

1 SELECT
2     TransactionDate, ProductId,
3     CAST(SUM(ProfitAmount) AS decimal(18,2)) AS [(sum) Profit],
4     CAST(AVG(ProfitAmount) AS decimal(18,2)) AS [(avg) Profit],
5     SUM(Quantity) AS [(sum) Quantity]
6 FROM
7     OPENROWSET(
8         BULK 'https://asadatalake01.dfs.core.windows.net/wwi-02/sale-small/Year=2016/Quarter=Q4/Month=12/Day=20161231/sal
9         FORMAT='PARQUET'
10    ) AS [r] GROUP BY r.TransactionDate, r.ProductId;
11

```

Results Messages

View Table Chart Export results

Search

TRANSACTIONDATE	PRODUCTID	(SUM) PROFIT	(AVG) PROFIT	(SUM) QUANTITY
20161231	3	2770.53	5.95	1169
20161231	5	10799.35	19.96	1355
20161231	15	8053.50	16.34	1239
20161231	21	11670.75	23.63	1197
20161231	22	8461.56	16.24	1284
20161231	33	9165.84	17.80	1266
20161231	41	14511.84	29.14	1234
20161231	48	11758.50	25.40	1206
20161231	49	8202.20	16.01	1212

The T-SQL query above is displayed within the query window.

- Now let's figure out how many records are contained within the Parquet files for 2019 data. This information is important for planning how we optimize for importing the data into Azure Synapse Analytics. To do this, replace your query with the following (be sure to update the name of your data lake in BULK statement, by replacing [asadatalakeSUFFIX]):

```

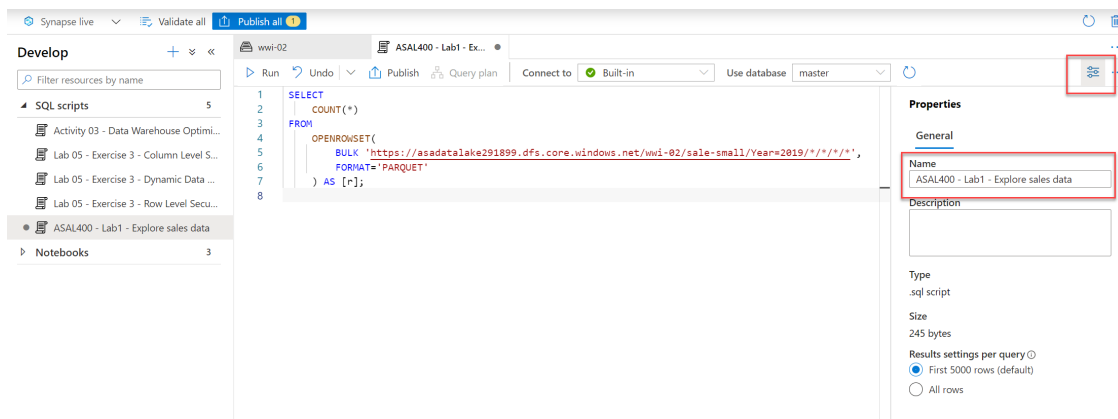
SELECT
    COUNT(*)
FROM
    OPENROWSET(
        BULK 'https://asadatalakeSUFFIX.dfs.core.windows.net/wwi-02/sale-
small/Year=2019/*/*/*/*',
        FORMAT='PARQUET'
    ) AS [r];

```

Notice how we updated the path to include all Parquet files in all subfolders of sale-small/Year=2019.

The output should be **339507246** records.

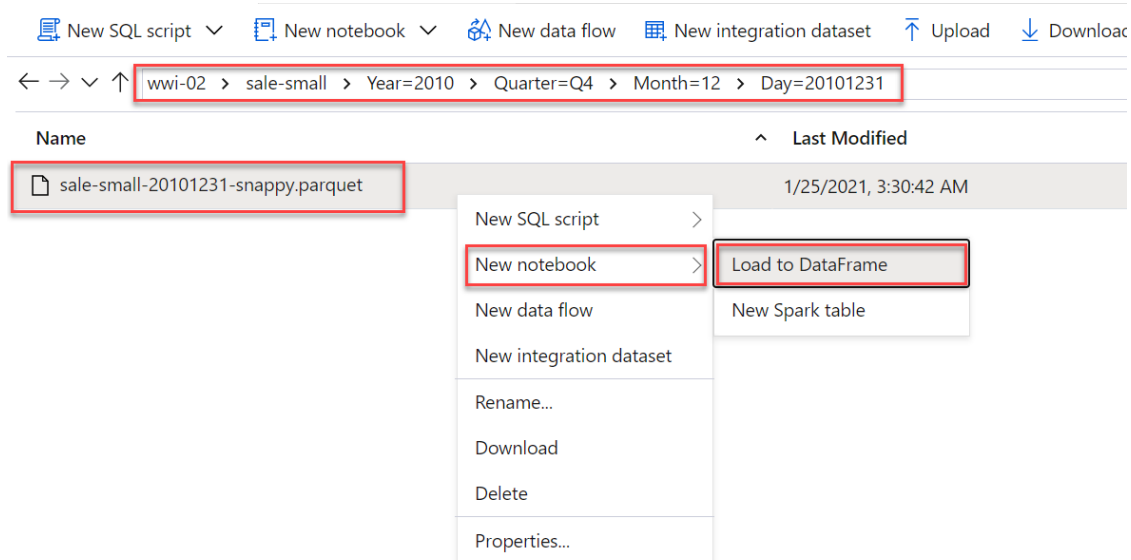
Optional: If you wish to keep this SQL script for future reference, select the Properties button, provide a descriptive name, such as ASAL400 - Lab1 - Explore sales data, then select **Publish all**.



The SQL Script properties is displayed with the new script name, and the Publish all button is highlighted.

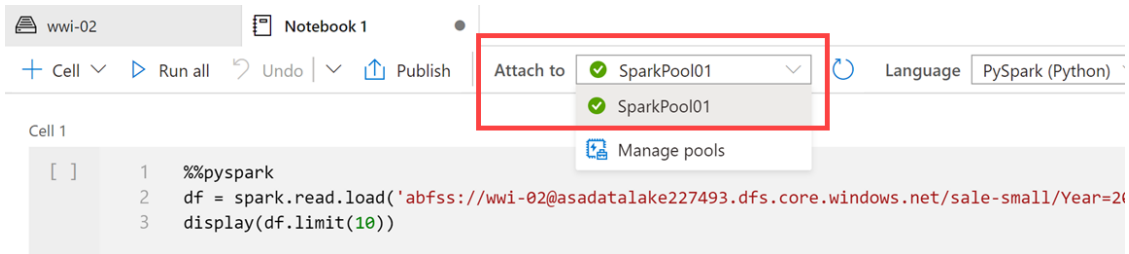
Task 2: Query sales Parquet data with Azure Synapse Spark

1. Navigate to the **Data** hub, browse to the data lake storage account folder sale-small/Year=2010/Quarter=Q4/Month=12/Day=20101231 if needed, then right-click the Parquet file and select New notebook, then Load to DataFrame.



The Parquet file is displayed with the New notebook menu item highlighted.

2. This will generate a notebook with PySpark code to load the data in a dataframe and display 100 rows with the header.
3. Attach the notebook to a Spark pool.



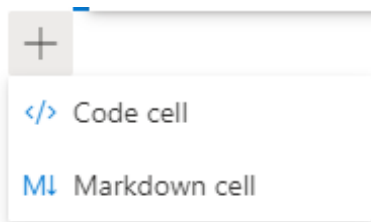
The Spark pool list is displayed.

4. Select **Run all** on the notebook toolbar to execute the notebook.

Note: The first time you run a notebook in a Spark pool, Synapse creates a new session. This can take approximately 3-5 minutes.

Note: To run just the cell, either hover over the cell and select the *Run cell* icon to the left of the cell, or select the cell then type **Ctrl+Enter** on your keyboard.

5. Create a new cell underneath by hovering over the **+** button and selecting the **Code cell** item. The **+** button is located beneath the notebook cell on the left. Alternatively, you can also expand the **+ Cell** menu in the Notebook toolbar and select the **Code cell** item.



The Add Code menu option is highlighted.

6. The Spark engine can analyze the Parquet files and infer the schema. To do this, enter the following in the new cell:

```
df.printSchema()
```

Your output should look like the following:

```
root
|-- TransactionId: string (nullable = true)
|-- CustomerId: integer (nullable = true)
|-- ProductId: short (nullable = true)
|-- Quantity: short (nullable = true)
|-- Price: decimal(29,2) (nullable = true)
|-- TotalAmount: decimal(29,2) (nullable = true)
|-- TransactionDate: integer (nullable = true)
|-- ProfitAmount: decimal(29,2) (nullable = true)
|-- Hour: byte (nullable = true)
|-- Minute: byte (nullable = true)
|-- StoreId: short (nullable = true)
```

7. Now let's use the dataframe to perform the same grouping and aggregate query we performed with the serverless SQL pool. Create a new cell and enter the following:

```
from pyspark.sql import SparkSession
from pyspark.sql.types import *
from pyspark.sql.functions import *

profitByDateProduct = (df.groupBy("TransactionDate", "ProductId")
    .agg(
        sum("ProfitAmount").alias("(sum)ProfitAmount"),
        round(avg("Quantity"), 4).alias("(avg)Quantity"),
        sum("Quantity").alias("(sum)Quantity"))
    .orderBy("TransactionDate"))
profitByDateProduct.show(100)
```

We import required Python libraries to use aggregation functions and types defined in the schema to successfully execute the query.

Task 3: Query user profile JSON data with Apache Spark in Azure Synapse Analytics

In addition to the sales data, we have customer profile data from an e-commerce system that provides top product purchases for each visitor of the site (customer) over the past 12 months. This data is stored within JSON files in the data lake. We will import this data in the next lab, but let's explore it while we're in the Spark notebook.

1. Create a new cell in the Spark notebook, enter the following code, replace <asadatalakeNNNNNN> with your data lake name (you can find this value in the first cell of the notebook), and execute the cell:

```
df = (spark.read \
    .option("inferSchema", "true") \
    .json("abfss://wwi-02@asadatalakeSUFFIX.dfs.core.windows.net/online-user-profiles-02/*.json", multiLine=True)
)

df.printSchema()
```

Your output should look like the following:

```
root
|-- topProductPurchases: array (nullable = true)
|   |-- element: struct (containsNull = true)
|   |   |-- itemsPurchasedLast12Months: long (nullable = true)
|   |   |-- productId: long (nullable = true)
|-- visitorId: long (nullable = true)
```

Notice that we are selecting all JSON files within the online-user-profiles-02 directory. Each JSON file contains several rows, which is why we specified the multiLine=True option. Also, we set the inferSchema option to true, which

instructs the Spark engine to review the files and create a schema based on the nature of the data.

2. We have been using Python code in these cells up to this point. If we want to query the files using SQL syntax, one option is to create a temporary view of the data within the dataframe. Execute the following in a new cell to create a view named `user_profiles`:

```
# create a view called user_profiles  
df.createOrReplaceTempView("user_profiles")
```

3. Create a new cell. Since we want to use SQL instead of Python, we use the `%%sql` magic to set the language of the cell to SQL. Execute the following code in the cell:

```
%%sql
```

```
SELECT * FROM user_profiles LIMIT 10
```

Notice that the output shows nested data for `topProductPurchases`, which includes an array of `productId` and `itemsPurchasedLast12Months` values. You can expand the fields by clicking the right triangle in each row.

Cell 6

1

%%sql

2

3

SELECT * FROM user_profiles LIMIT 10

Command executed in 7s 88ms by joel on 04-19-2020 12:35:36.277 -04:00

▶

Job execution Succeeded

Spark 2 executors 8 cores

View

Table

Chart

topProductPurchases	visitorId
▶ [{"schema":{"name":"itemsPurcha	9983082
▶ [{"schema":{"name":"itemsPurcha	9983083
▼ [{"schema":{"name":"itemsPurcha	9983084
▶ 0: [{"schema":{"name":"itemsPu	
▼ 1: [{"schema":{"name":"itemsPu	
▼ schema: [{"name":"itemsPurcl	
▼ 0: [{"name":"itemsPurchasec	
name: ""itemsPurchasedLas	
dataType: "{}"	
nullable: "true"	
▼ metadata: {"map":{}}	
map: "{}"	
▶ 1: [{"name":"productId","dat	
▼ values: "[44,4905]"	
0: "44"	
1: "4905"	
▶ 2: [{"schema":{"name":"itemsPu	
▶ 3: [{"schema":{"name":"itemsPu	
▶ 4: [{"schema":{"name":"itemsPu	
▶ [{"schema":{"name":"itemsPurcha	9983085

JSON nested output.

This makes analyzing the data a bit difficult. This is because the JSON file contents look like the following:

```
[
{
  "visitorId": 9529082,
  "topProductPurchases": [
```

```
{
  "productId": 4679,
  "itemsPurchasedLast12Months": 26
},
{
  "productId": 1779,
  "itemsPurchasedLast12Months": 32
},
{
  "productId": 2125,
  "itemsPurchasedLast12Months": 75
},
{
  "productId": 2007,
  "itemsPurchasedLast12Months": 39
},
{
  "productId": 1240,
  "itemsPurchasedLast12Months": 31
},
{
  "productId": 446,
  "itemsPurchasedLast12Months": 39
},
{
  "productId": 3110,
  "itemsPurchasedLast12Months": 40
},
{
  "productId": 52,
  "itemsPurchasedLast12Months": 2
},
{
  "productId": 978,
  "itemsPurchasedLast12Months": 81
},
{
  "productId": 1219,
  "itemsPurchasedLast12Months": 56
},
{
  "productId": 2982,
  "itemsPurchasedLast12Months": 59
}
]
},
{
  ...
},
{
```

```
    ...
}
```

- PySpark contains a special `explode` function, which returns a new row for each element of the array. This will help flatten the `topProductPurchases` column for better readability or for easier querying. Execute the following in a new cell:

```
from pyspark.sql.functions import udf, explode
```

```
flat=df.select('visitorId',explode('topProductPurchases').alias('topProductPurchases_flat'))
flat.show(100)
```

In this cell, we created a new dataframe named `flat` that includes the `visitorId` field and a new aliased field named `topProductPurchases_flat`. As you can see, the output is a bit easier to read and, by extension, easier to query.

```
[7] 1 flat=df.select('visitorId',explode('topProductPurchases').alias('topProductPurchases_flat'))
     2 flat.show(100)
```

visitorId	topProductPurchases_flat
9983082	[60, 1281]
9983082	[36, 4737]
9983082	[69, 3608]
9983082	[3, 2055]
9983082	[17, 812]
9983082	[24, 3475]
9983082	[20, 3182]
9983082	[93, 2380]
9983082	[42, 1104]
9983082	[60, 3857]
9983082	[28, 1244]
9983082	[18, 821]
9983082	[84, 1433]
9983082	[34, 818]
9983082	[42, 2428]

The improved output is displayed.

- Create a new cell and execute the following code to create a new flattened version of the dataframe that extracts the `topProductPurchases_flat.productId` and `topProductPurchases_flat.itemsPurchasedLast12Months` fields to create new rows for each data combination:

```
topPurchases =
(flat.select('visitorId','topProductPurchases_flat.productId','topProductPurchases_flat.itemsPurchasedLast12Months')
.orderBy('visitorId'))
```

```
topPurchases.show(100)
```

In the output, notice that we now have multiple rows for each `visitorId`.

```

1 from pyspark.sql.functions import count
2
3 topPurchases = flat.select('visitorId', 'topProductPurchases_flat.productId', 'topProductPurchases_flat.itemsPurchasedLast12Months') \
4
5 topPurchases.show(100)

```

visitorId	productId	itemsPurchasedLast12Months
9983082	1281	60
9983082	4737	36
9983082	3608	69
9983082	2055	3
9983082	812	17
9983082	3475	24
9983082	3182	20
9983082	2380	93
9983082	1104	42
9983082	3857	60
9983082	1244	28
9983082	821	18
9983082	1433	84
9983082	818	34
9983082	2428	42
9983082	763	34
9983082	2101	68
9983082	2400	85
9983083	4933	23
9983083	2035	51
9983083	1160	53
9983083	3657	50
9983084	1340	61

The visitorId rows are highlighted.

- Let's order the rows by the number of items purchased in the last 12 months. Create a new cell and execute the following code:

```
# Let's order by the number of items purchased in the last 12 months
sortedTopPurchases = topPurchases.orderBy("itemsPurchasedLast12Months")
```

```
sortedTopPurchases.show(100)
```

- How do we sort in reverse order? One might conclude that we could make a call like this: `topPurchases.orderBy("itemsPurchasedLast12Months desc")`. Try it in a new cell:

```
topPurchases.orderBy("itemsPurchasedLast12Months desc")
```

```

Cell 10
1 topPurchases.orderBy("itemsPurchasedLast12Months desc")

```

Command executed in 3s 488ms by joel on 09-10-2020 16:04:59.708 -04:00

```

AnalysisException: cannot resolve 'itemsPurchasedLast12Months desc' given input columns: [visitorId, productId, itemsPurchasedLast12Months];
'Sort ['itemsPurchasedLast12Months desc ASC NULLS FIRST], true
+- Sort [visitorId#394L ASC NULLS FIRST], true
+- Project [visitorId#394L, topProductPurchases_flat#442.productId AS productId#454L, topProductPurchases_flat#442.itemsPurchasedLast12Months
AS itemsPurchasedLast12Months#455L]
+- Project [visitorId#394L, topProductPurchases_flat#442]
+- Generate explode(topProductPurchases#393), false, [topProductPurchases_flat#442]
+- Relation[topProductPurchases#393,visitorId#394L] json
Traceback (most recent call last):
  File "/opt/spark/python/lib/pyspark.zip/pyspark/sql/dataframe.py", line 1098, in sort
    jdf = self._jdf.sort(self._sort_cols(cols, kwargs))
  File "/opt/spark/python/lib/py4j-0.10.7-src.zip/py4j/java_gateway.py", line 1257, in __call__
    answer, self.gateway_client, self.target_id, self.name)
  File "/opt/spark/python/lib/pyspark.zip/pyspark/sql/utils.py", line 75, in deco
    raise AnalysisException(s.split(': ', 1)[1], stackTrace)
pyspark.sql.utils.AnalysisException: cannot resolve 'itemsPurchasedLast12Months desc' given input columns: [visitorId, productId,
itemsPurchasedLast12Months].

```

An error is displayed.

Notice that there is an AnalysisException error, because `itemsPurchasedLast12Months desc` does not match up with a column name.

Why does this not work?

- The DataFrames API is built upon an SQL engine.
- There is a lot of familiarity with this API and SQL syntax in general.
- The problem is that `orderBy(. .)` expects the name of the column.
- What we specified was an SQL expression in the form of **requests desc**.
- What we need is a way to programmatically express such an expression.
- This leads us to the second variant, `orderBy(Column)` and more specifically, the class `Column`.

8. The **Column** class is an object that encompasses more than just the name of the column, but also column-level-transformations, such as sorting in a descending order. Execute the following code in a new cell:

```
sortedTopPurchases = (topPurchases
    .orderBy( col("itemsPurchasedLast12Months").desc() ))

sortedTopPurchases.show(100)
```

9. How many *types* of products did each customer purchase? To figure this out, we need to group by `visitorId` and aggregate on the number of rows per customer. Execute the following code in a new cell:

```
groupedTopPurchases = (sortedTopPurchases.select("visitorId")
    .groupBy("visitorId")
    .agg(count("*").alias("total")))
    .orderBy("visitorId" )

groupedTopPurchases.show(100)
```



```
1 # How many types of products did each customer purchase?
2 groupedTopPurchases = (sortedTopPurchases.select("visitorId")
3   .groupBy("visitorId")
4   .agg(count("*").alias("total"))
5   .orderBy("visitorId") )
6
7 groupedTopPurchases.show(100)
```

visitorId	total
9529082	11
9529083	14
9529084	15
9529085	16
9529086	4
9529087	18
9529088	16
9529089	14
9529090	18
9529091	15
9529092	2
9529093	2
9529094	12
9529095	8
9529096	2

The query output is displayed.

10. How many *total items* did each customer purchase? To figure this out, we need to group by visitorId and aggregate on the sum of itemsPurchasedLast12Months values per customer. Execute the following code in a new cell:

```
groupedTopPurchases =
(sortedTopPurchases.select("visitorId", "itemsPurchasedLast12Months")
  .groupBy("visitorId")
  .agg(sum("itemsPurchasedLast12Months").alias("totalItemsPurchased"))
  .orderBy("visitorId") )

groupedTopPurchases.show(100)
```

```
1 # How many total items did each customer purchase?
2 groupedTopPurchases = (sortedTopPurchases.select("visitorId","itemsPurchasedLast12Months")
3   .groupBy("visitorId")
4   .agg(sum("itemsPurchasedLast12Months").alias("totalItemsPurchased"))
5   .orderBy("visitorId") )
6
7 groupedTopPurchases.show(100)
```

visitorId	totalItemsPurchased
9529082	480
9529083	564
9529084	546
9529085	941
9529086	85
9529087	724
9529088	862
9529089	693
9529090	925
9529091	759
9529092	127
9529093	118
9529094	623
9529095	450
9529096	153
9529097	837
9529098	396
9529099	298
9529100	190

The query output is displayed.

Exercise 3: Import sales data with PolyBase and COPY using T-SQL

There are different options for loading large amounts and varying types of data into Azure Synapse Analytics, such as through T-SQL commands using a Synapse SQL Pool, and with Azure Synapse pipelines. In our scenario, Wide World Importers stores most of their raw data in a data lake and in different formats. Among the data loading options available to them, WWI's data engineers are most comfortable using T-SQL.

However, even with their familiarity with SQL, there are some things to consider when loading large or disparate file types and formats. Since the files are stored in ADLS Gen2, WWI can use either PolyBase external tables or the new COPY statement. Both options enable fast and scalable data load operations, but there are some differences between the two:

PolyBase	COPY
GA, stable	GA, stable
Needs CONTROL permission	Relaxed permission
Has row width limits	No row width limit
No delimiters within text	Supports delimiters in text
Fixed line delimiter	Supports custom column and row delimiters
Complex to set up in code	Reduces amount of code

WWI has heard that PolyBase is generally faster than COPY, especially when working with large data sets.

In this exercise, you will help WWI compare ease of setup, flexibility, and speed between these loading strategies.

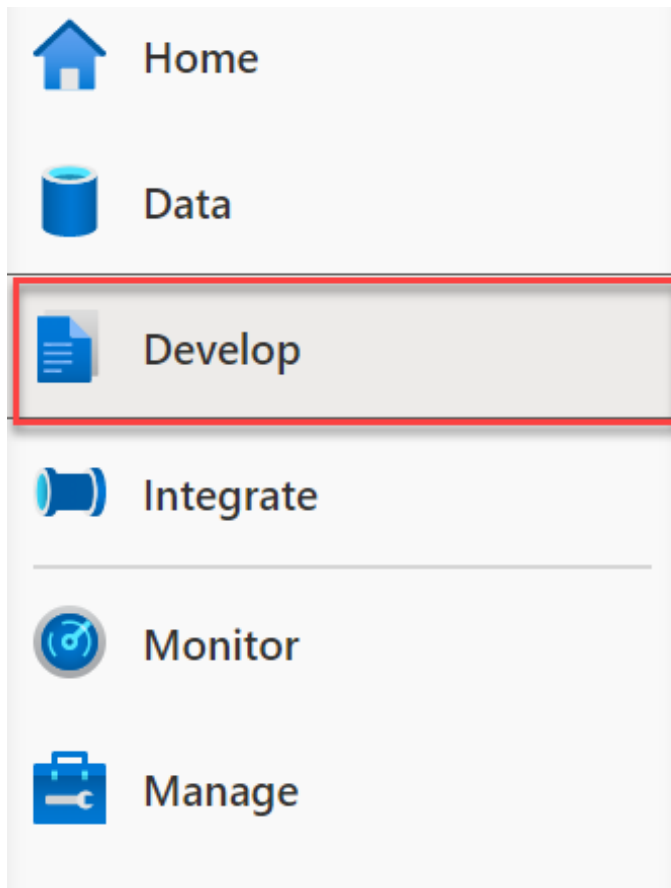
Task 1: Create staging tables

The Sale table has a columnstore index to optimize for read-heavy workloads. It is also used heavily for reporting and ad-hoc queries. To achieve the fastest loading speed and minimize the impact of heavy data inserts on the Sale table, WWI has decided to create a staging table for loads.

In this task, you will create a new staging table named SaleHeap in a new schema named wwi_staging. You will define it as a **heap** and use round-robin distribution. When WWI finalizes their data loading pipeline, they will load the data into SaleHeap, then insert from the heap table into Sale. Although this is a two-step process, the second step of inserting the rows to the production table does not incur data movement across the distributions.

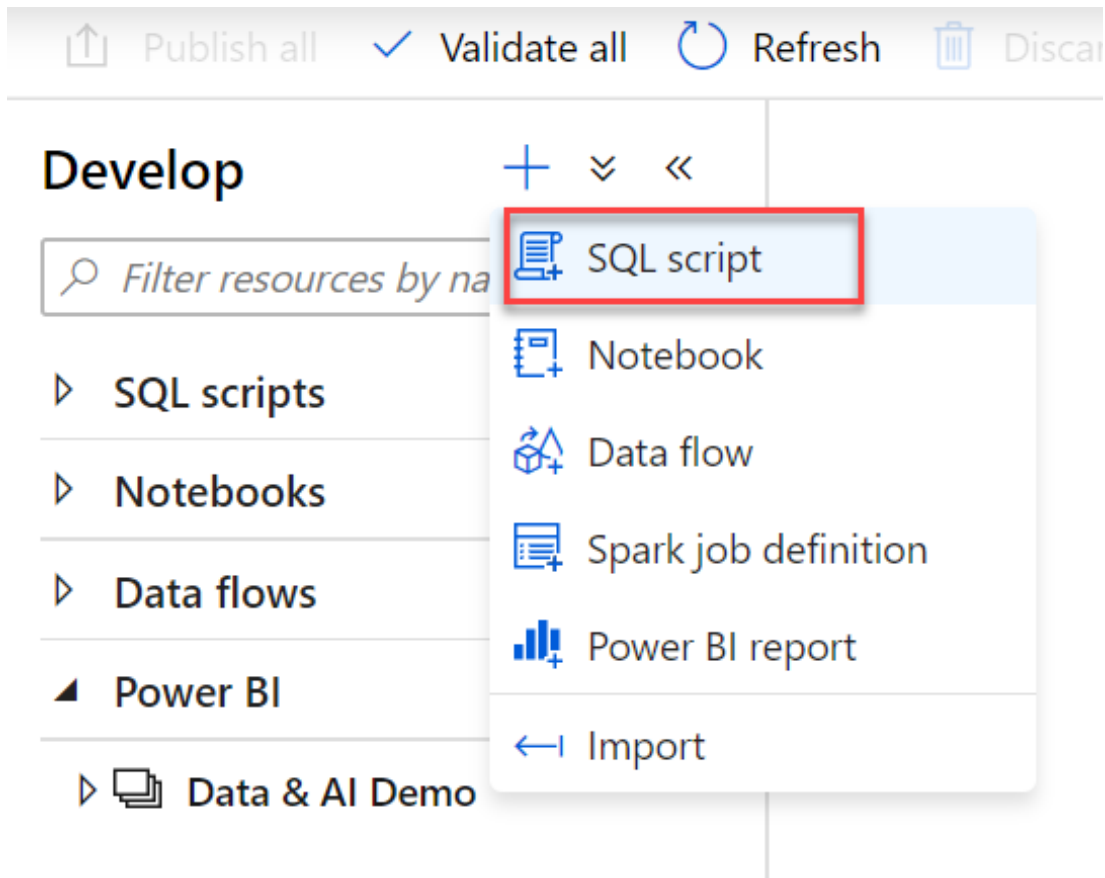
You will also create a new Sale clustered columnstore table within the wwi_staging to compare data load speeds.

1. Open Synapse Analytics Studio (<https://web.azuresynapse.net/>), and then navigate to the **Develop** hub.



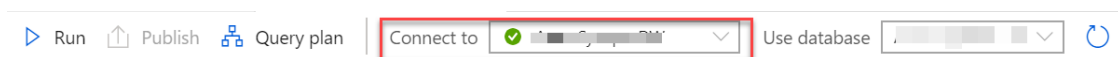
The Develop menu item is highlighted.

2. From the **Develop** menu, select the + button and choose **SQL Script** from the context menu.



The SQL script context menu item is highlighted.

3. In the toolbar menu, connect to the **SQL Pool** database to execute the query.

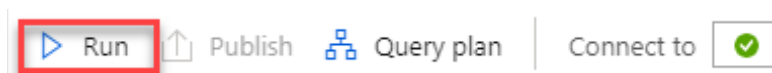


The connect to option is highlighted in the query toolbar.

4. In the query window, replace the script with the following to create the **wwi_staging** schema:

```
CREATE SCHEMA [wwi_staging]
```

5. Select **Run** from the toolbar menu to execute the SQL command.



The run button is highlighted in the query toolbar.

Note: If you receive the following error, continue to the next step: Failed to execute query. Error: There is already an object named 'wwi_staging' in the database. CREATE SCHEMA failed due to previous errors.

6. In the query window, replace the script with the following to create the heap table:

```

CREATE TABLE [wwi_staging].[SaleHeap]
(
    [TransactionId] [uniqueidentifier] NOT NULL,
    [CustomerId] [int] NOT NULL,
    [ProductId] [smallint] NOT NULL,
    [Quantity] [smallint] NOT NULL,
    [Price] [decimal](9,2) NOT NULL,
    [TotalAmount] [decimal](9,2) NOT NULL,
    [TransactionDate] [int] NOT NULL,
    [ProfitAmount] [decimal](9,2) NOT NULL,
    [Hour] [tinyint] NOT NULL,
    [Minute] [tinyint] NOT NULL,
    [StoreId] [smallint] NOT NULL
)
WITH
(
    DISTRIBUTION = ROUND_ROBIN,
    HEAP
)

```

7. Select **Run** from the toolbar menu to execute the SQL command.
8. In the query window, replace the script with the following to create the Sale table in the wwi_staging schema for load comparisons:

```

CREATE TABLE [wwi_staging].[Sale]
(
    [TransactionId] [uniqueidentifier] NOT NULL,
    [CustomerId] [int] NOT NULL,
    [ProductId] [smallint] NOT NULL,
    [Quantity] [smallint] NOT NULL,
    [Price] [decimal](9,2) NOT NULL,
    [TotalAmount] [decimal](9,2) NOT NULL,
    [TransactionDate] [int] NOT NULL,
    [ProfitAmount] [decimal](9,2) NOT NULL,
    [Hour] [tinyint] NOT NULL,
    [Minute] [tinyint] NOT NULL,
    [StoreId] [smallint] NOT NULL
)
WITH
(
    DISTRIBUTION = HASH ( [CustomerId] ),
    CLUSTERED COLUMNSTORE INDEX,
    PARTITION
    (
        [TransactionDate] RANGE RIGHT FOR VALUES (20100101, 20100201,
        20100301, 20100401, 20100501, 20100601, 20100701, 20100801, 20100901,
        20101001, 20101101, 20101201, 20110101, 20110201, 20110301, 20110401,
        20110501, 20110601, 20110701, 20110801, 20110901, 20111001, 20111101,
        20111201, 20120101, 20120201, 20120301, 20120401, 20120501, 20120601,

```

```

20120701, 20120801, 20120901, 20121001, 20121101, 20121201, 20130101,
20130201, 20130301, 20130401, 20130501, 20130601, 20130701, 20130801,
20130901, 20131001, 20131101, 20131201, 20140101, 20140201, 20140301,
20140401, 20140501, 20140601, 20140701, 20140801, 20140901, 20141001,
20141101, 20141201, 20150101, 20150201, 20150301, 20150401, 20150501,
20150601, 20150701, 20150801, 20150901, 20151001, 20151101, 20151201,
20160101, 20160201, 20160301, 20160401, 20160501, 20160601, 20160701,
20160801, 20160901, 20161001, 20161101, 20161201, 20170101, 20170201,
20170301, 20170401, 20170501, 20170601, 20170701, 20170801, 20170901,
20171001, 20171101, 20171201, 20180101, 20180201, 20180301, 20180401,
20180501, 20180601, 20180701, 20180801, 20180901, 20181001, 20181101,
20181201, 20190101, 20190201, 20190301, 20190401, 20190501, 20190601,
20190701, 20190801, 20190901, 20191001, 20191101, 20191201)
)
)

```

9. Select **Run** from the toolbar menu to execute the SQL command.

Task 2: Configure and run PolyBase load operation

PolyBase requires the following elements:

- An external data source that points to the abfss path in ADLS Gen2 where the Parquet files are located
 - An external file format for Parquet files
 - An external table that defines the schema for the files, as well as the location, data source, and file format
1. In the query window, replace the script with the following to create the external data source. Be sure to replace SUFFIX with the lab workspace id:

```

-- Replace SUFFIX with the Lab workspace id.
CREATE EXTERNAL DATA SOURCE ABSS
WITH
( TYPE = HADOOP,
  LOCATION = 'abfss://wwi-02@asadatalakeSUFFIX.dfs.core.windows.net'
);

```

2. Select **Run** from the toolbar menu to execute the SQL command.
3. In the query window, replace the script with the following to create the external file format and external data table. Notice that we defined TransactionId as an nvarchar(36) field instead of uniqueidentifier. This is because external tables do not currently support uniqueidentifier columns:

```

CREATE EXTERNAL FILE FORMAT [ParquetFormat]
WITH (
  FORMAT_TYPE = PARQUET,
  DATA_COMPRESSION = 'org.apache.hadoop.io.compress.SnappyCodec'
)
GO

```

```

CREATE SCHEMA [wwi_external];
GO

CREATE EXTERNAL TABLE [wwi_external].Sales
(
    [TransactionId] [nvarchar](36) NOT NULL,
    [CustomerId] [int] NOT NULL,
    [ProductId] [smallint] NOT NULL,
    [Quantity] [smallint] NOT NULL,
    [Price] [decimal](9,2) NOT NULL,
    [TotalAmount] [decimal](9,2) NOT NULL,
    [TransactionDate] [int] NOT NULL,
    [ProfitAmount] [decimal](9,2) NOT NULL,
    [Hour] [tinyint] NOT NULL,
    [Minute] [tinyint] NOT NULL,
    [StoreId] [smallint] NOT NULL
)
WITH
(
    LOCATION = '/sale-small%2FYear%3D2019',
    DATA_SOURCE = ABSS,
    FILE_FORMAT = [ParquetFormat]
)
GO

```

Note: The /sale-small/Year=2019/ folder's Parquet files contain **339,507,246 rows**.

4. Select **Run** from the toolbar menu to execute the SQL command.
5. In the query window, replace the script with the following to load the data into the wwi_staging.SalesHeap table:

```

INSERT INTO [wwi_staging].[SaleHeap]
SELECT *
FROM [wwi_external].[Sales]

```

6. Select **Run** from the toolbar menu to execute the SQL command. It will take a few minutes to execute this command. **Take note** of how long it took to execute this query.
7. In the query window, replace the script with the following to see how many rows were imported:

```

SELECT COUNT(1) FROM wwi_staging.SaleHeap(nolock)

```

8. Select **Run** from the toolbar menu to execute the SQL command. You should see a result of 339507246.

Task 3: Configure and run the COPY statement

Now let's see how to perform the same load operation with the COPY statement.

1. In the query window, replace the script with the following to truncate the heap table and load data using the COPY statement. Be sure to replace SUFFIX with the id from your workspace:

```
TRUNCATE TABLE wwi_staging.SaleHeap;  
GO
```

```
-- Replace SUFFIX with the id from your workspace.
```

```
COPY INTO wwi_staging.SaleHeap  
FROM 'https://asadatalakeSUFFIX.dfs.core.windows.net/wwi-02/sale-  
small%2FYear%3D2019'  
WITH (  
    FILE_TYPE = 'PARQUET',  
    COMPRESSION = 'SNAPPY'  
)  
GO
```

2. Select **Run** from the toolbar menu to execute the SQL command. It takes a few minutes to execute this command. **Take note** of how long it took to execute this query.
3. In the query window, replace the script with the following to see how many rows were imported:

```
SELECT COUNT(1) FROM wwi_staging.SaleHeap(nolock)
```

4. Select **Run** from the toolbar menu to execute the SQL command. You should see a result of 339507246.

Do the number of rows match for both load operations? Which activity was fastest? You should see that both copied the same amount of data in roughly the same amount of time.

Task 4: Load data into the clustered columnstore table

For both of the load operations above, we inserted data into the heap table. What if we inserted into the clustered columnstore table instead? Is there really a performance difference? Let's find out!

1. In the query window, replace the script with the following to load data into the clustered columnstore Sale table using the COPY statement. Be sure to replace SUFFIX with the id for your workspace:

```
-- Replace SUFFIX with the workspace default storage account name.  
COPY INTO wwi_staging.Sale  
FROM 'https://asadatalakeSUFFIX.dfs.core.windows.net/wwi-02/sale-  
small%2FYear%3D2019'  
WITH (  

```

```

FILE_TYPE = 'PARQUET',
COMPRESSION = 'SNAPPY'
)
GO

```

2. Select **Run** from the toolbar menu to execute the SQL command. It takes a few minutes to execute this command. **Take note** of how long it took to execute this query.
3. In the query window, replace the script with the following to see how many rows were imported:

```
SELECT COUNT(1) FROM wwi_staging.Sale(nolock)
```

4. Select **Run** from the toolbar menu to execute the SQL command.

What were the results? Did the load operation take more or less time writing to Sale table vs. the heap (SaleHeap) table?

In our case, the results are as follows:

PolyBase vs. COPY (DW2000) (*insert 2019 small data set (339,507,246 rows)*):

- COPY (Heap: **2:31**, clustered columnstore: **3:26**)
- PolyBase (Heap: **2:38**)

Task 5: Use COPY to load text file with non-standard row delimiters

One of the advantages COPY has over PolyBase is that it supports custom column and row delimiters.

WWI has a nightly process that ingests regional sales data from a partner analytics system and saves the files in the data lake. The text files use non-standard column and row delimiters where columns are delimited by a . and rows by a ,:

```
20200421.114892.130282.159488.172105.196533,20200420.109934.108377.122039.101
946.100712,20200419.253714.357583.452690.553447.653921
```

The data has the following fields: Date, NorthAmerica, SouthAmerica, Europe, Africa, and Asia. They must process this data and store it in Synapse Analytics.

1. In the query window, replace the script with the following to create the DailySalesCounts table and load data using the COPY statement. Be sure to replace <PrimaryStorage>` with the default storage account name for your workspace:

```

CREATE TABLE [wwi_staging].DailySalesCounts
(
    [Date] [int] NOT NULL,
    [NorthAmerica] [int] NOT NULL,
    [SouthAmerica] [int] NOT NULL,
    [Europe] [int] NOT NULL,
    [Africa] [int] NOT NULL,

```

```

        [Asia] [int] NOT NULL
    )
GO

-- Replace <PrimaryStorage> with the workspace default storage account
name.
COPY INTO wwi_staging.DailySalesCounts
FROM 'https://asadatalakeSUFFIX.dfs.core.windows.net/wwi-02/campaign-
analytics/dailycounts.txt'
WITH (
    FILE_TYPE = 'CSV',
    FIELDTERMINATOR='.',
    ROWTERMINATOR=','
)
GO

```

Notice the FIELDTERMINATOR and ROWTERMINATOR properties that help us correctly parse the file.

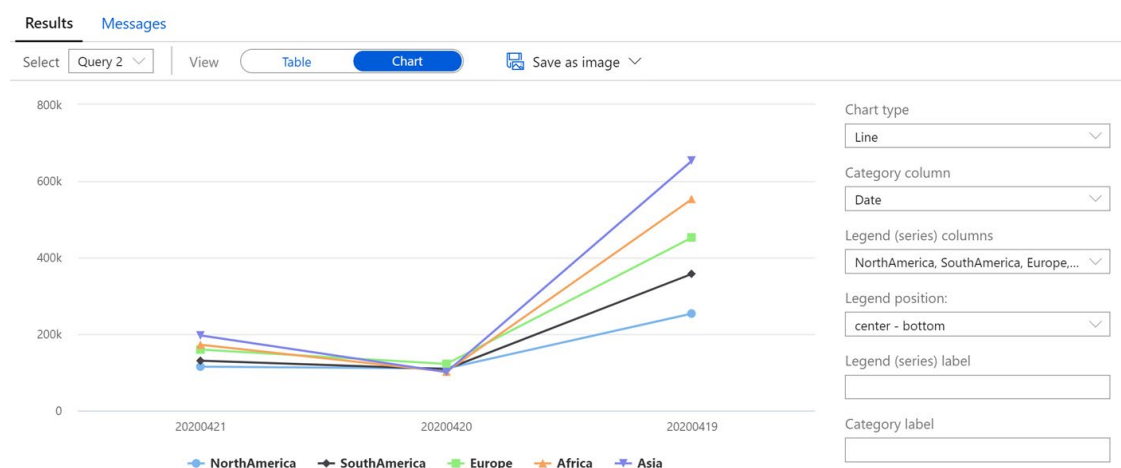
2. Select **Run** from the toolbar menu to execute the SQL command.
3. In the query window, replace the script with the following to view the imported data:

```

SELECT * FROM [wwi_staging].DailySalesCounts
ORDER BY [Date] DESC

```

4. Select **Run** from the toolbar menu to execute the SQL command.
5. Try viewing the results in a Chart and set the **Category column** to Date:



The results are displayed in a chart.

Task 6: Use PolyBase to load text file with non-standard row delimiters

Let's try this same operation using PolyBase.

1. In the query window, replace the script with the following to create a new external file format, external table, and load data using PolyBase:

```
CREATE EXTERNAL FILE FORMAT csv_dailysales
WITH (
    FORMAT_TYPE = DELIMITEDTEXT,
    FORMAT_OPTIONS (
        FIELD_TERMINATOR = '.',
        DATE_FORMAT = '',
        USE_TYPE_DEFAULT = False
    )
);
GO

CREATE EXTERNAL TABLE [wwi_external].DailySalesCounts
(
    [Date] [int] NOT NULL,
    [NorthAmerica] [int] NOT NULL,
    [SouthAmerica] [int] NOT NULL,
    [Europe] [int] NOT NULL,
    [Africa] [int] NOT NULL,
    [Asia] [int] NOT NULL
)
WITH
(
    LOCATION = '/campaign-analytics/dailycounts.txt',
    DATA_SOURCE = ABSS,
    FILE_FORMAT = csv_dailysales
)
GO
INSERT INTO [wwi_staging].[DailySalesCounts]
SELECT *
FROM [wwi_external].[DailySalesCounts]
```

2. Select **Run** from the toolbar menu to execute the SQL command.

You should see an error similar to: Failed to execute query. Error: HdfsBridge::recordReaderFillBuffer - Unexpected error encountered filling record reader buffer: HadoopExecutionException: Too many columns in the line..

Why is this? According to [PolyBase documentation](#):

The row delimiter in delimited-text files must be supported by Hadoop's LineRecordReader. That is, it must be either \r, \n, or \r\n. These delimiters are not user-configurable.

This is an example of where COPY's flexibility gives it an advantage over PolyBase.

Exercise 4: Import sales data with COPY using a pipeline

Now that WWI has gone through the process of loading data using PolyBase and COPY via T-SQL statements, it's time for them to experiment with loading sales data through a Synapse pipeline.

When moving data into a data warehouse, there is oftentimes a level of orchestration involved, coordinating movement from one or more data sources and sometimes some level of transformation. The transformation step can occur during (extract-transform-load - ETL) or after (extract-load-transform - ELT) data movement. Any modern data platform must provide a seamless experience for all the typical data wrangling actions like extractions, parsing, joining, standardizing, augmenting, cleansing, consolidating, and filtering. Azure Synapse Analytics provides two significant categories of features - data flows and data orchestrations (implemented as pipelines).

In this exercise, we will focus on the orchestration aspect. Lab 2 will focus more on the transformation (data flow) pipelines. You will create a new pipeline to import a large Parquet file, following best practices to improve the load performance.

Task 1: Configure workload management classification

When loading a large amount of data, it is best to run only one load job at a time for fastest performance. If this isn't possible, run a minimal number of loads concurrently. If you expect a large loading job, consider scaling up your SQL pool before the load.

Be sure that you allocate enough memory to the pipeline session. To do this, increase the resource class of a user which has permissions to rebuild the index on this table to the recommended minimum.

To run loads with appropriate compute resources, create loading users designated for running loads. Assign each loading user to a specific resource class or workload group. To run a load, sign in as one of the loading users, and then run the load. The load runs with the user's resource class.

1. In the query window, replace the script with the following to create a workload group, BigDataLoad, that uses workload isolation by reserving a minimum of 50% resources with a cap of 100%:

```
IF NOT EXISTS (SELECT * FROM sys.workload_management_workload_classifiers
WHERE group_name = 'BigDataLoad')
BEGIN
    CREATE WORKLOAD GROUP BigDataLoad WITH
    (
        MIN_PERCENTAGE_RESOURCE = 50 -- integer value
        ,REQUEST_MIN_RESOURCE_GRANT_PERCENT = 25 -- (guaranteed a
minimum of 4 concurrency)
        ,CAP_PERCENTAGE_RESOURCE = 100
    );
END
```

2. Select **Run** from the toolbar menu to execute the SQL command.
3. In the query window, replace the script with the following to create a new workload classifier, HeavyLoader that assigns the `asa.sql.import01` user we created in your environment to the BigDataLoad workload group. At the end, we select from `sys.workload_management_workload_classifiers` to view all classifiers, including the one we just created:

```
IF NOT EXISTS (SELECT * FROM sys.workload_management_workload_classifiers
WHERE [name] = 'HeavyLoader')
BEGIN
    CREATE WORKLOAD Classifier HeavyLoader WITH
    (
        Workload_Group = 'BigDataLoad',
        MemberName = 'asa.sql.import01',
        IMPORTANCE = HIGH
    );
END
```

```
SELECT * FROM sys.workload_management_workload_classifiers
```

4. Select **Run** from the toolbar menu to execute the SQL command. You should see the new classifier in the query results:

```
16 IF NOT EXISTS (SELECT * FROM sys.workload_management_workload_classifiers WHERE [name] = 'HeavyLoader')
17 BEGIN
18     CREATE WORKLOAD Classifier HeavyLoader WITH
19     (
20         Workload_Group = 'BigDataLoad',
21         MemberName = 'asa.sql.import01',
22         IMPORTANCE = HIGH
23     );
24 END
25
26 SELECT * FROM sys.workload_management_workload_classifiers
```

Results Messages

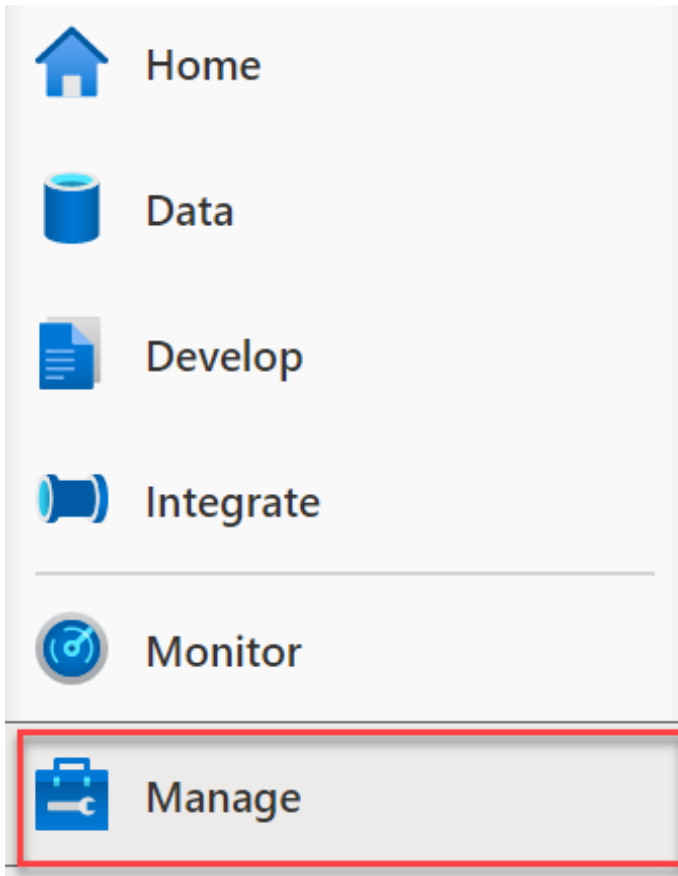
View Table Chart Export results

Search

CLASSIFIER_ID	NAME	GROUP_NAME	IMPORTANCE	CREATE_TIME	MODIFY_TIME	IS_ENABLED
9	staticrc50	staticrc50	normal	2020-04-10T08:3...	2020-04-10T08:3...	True
10	staticrc60	staticrc60	normal	2020-04-10T08:3...	2020-04-10T08:3...	True
11	staticrc70	staticrc70	normal	2020-04-10T08:3...	2020-04-10T08:3...	True
12	staticrc80	staticrc80	normal	2020-04-10T08:3...	2020-04-10T08:3...	True
14	HeavyLoader	BigDataLoad	high	2020-04-21T22:0...	2020-04-21T22:0...	True

The new workload classifier is highlighted.

5. Navigate to the **Manage** hub.



The Manage menu item is highlighted.

6. Locate and select a linked service named `sqlpool01_import01`. Notice that the user name for the SQL Pool connection is the `asa.sql.import01` user we added to the HeavyLoader classifier. We will use this linked service in our new pipeline to reserve resources for the data load activity.

Edit linked service (Azure Synapse Analytics (formerly SQL DW))

Name *
_import01

Description

Connect via integration runtime *
AutoResolveIntegrationRuntime

Connection string Azure Key Vault

Account selection method
☐ From Azure subscription ☒ Enter manually

Fully qualified domain name *
.database.windows.net

Database name *

Authentication type *
SQL authentication

User name *
asa.sql.import01

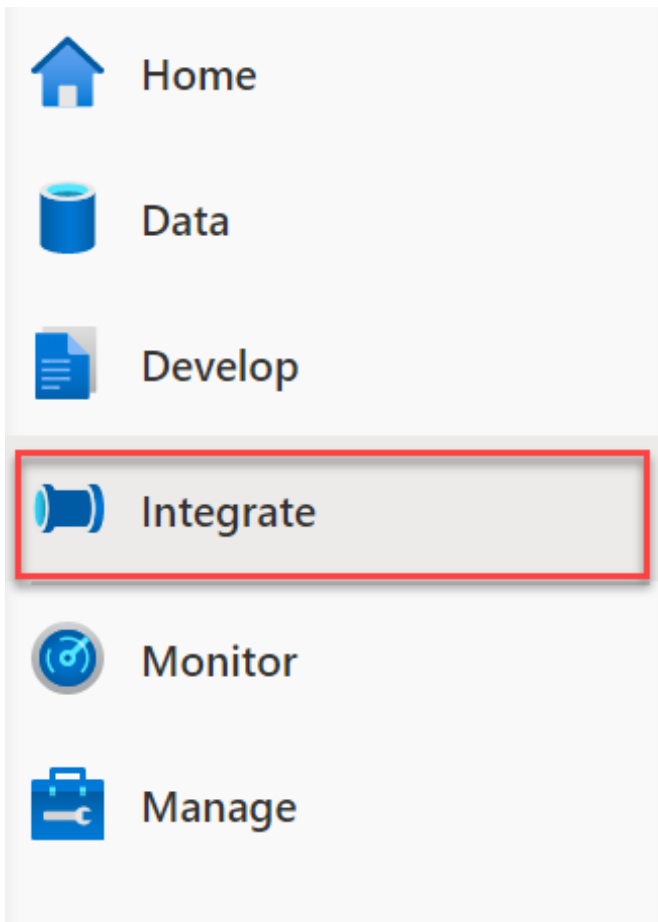
Password Azure Key Vault

AKV linked service *

The user name is highlighted.

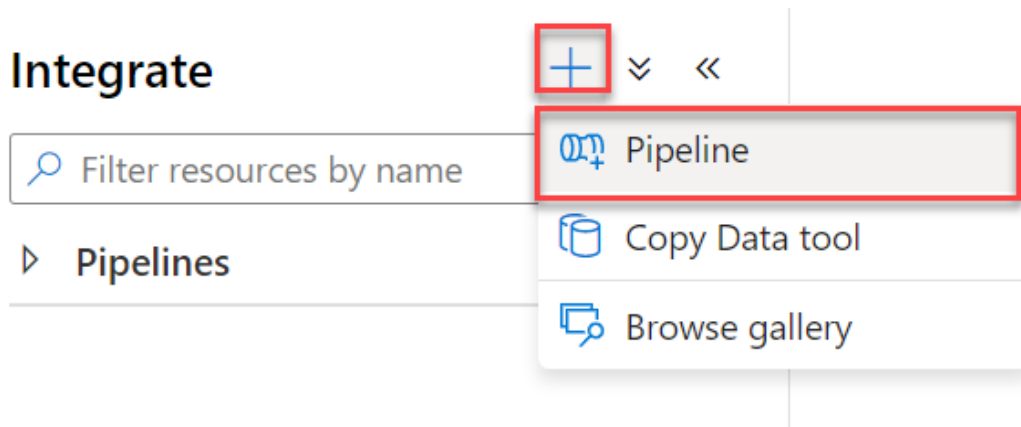
Task 2: Create pipeline with copy activity

1. Navigate to the **Integrate** hub.



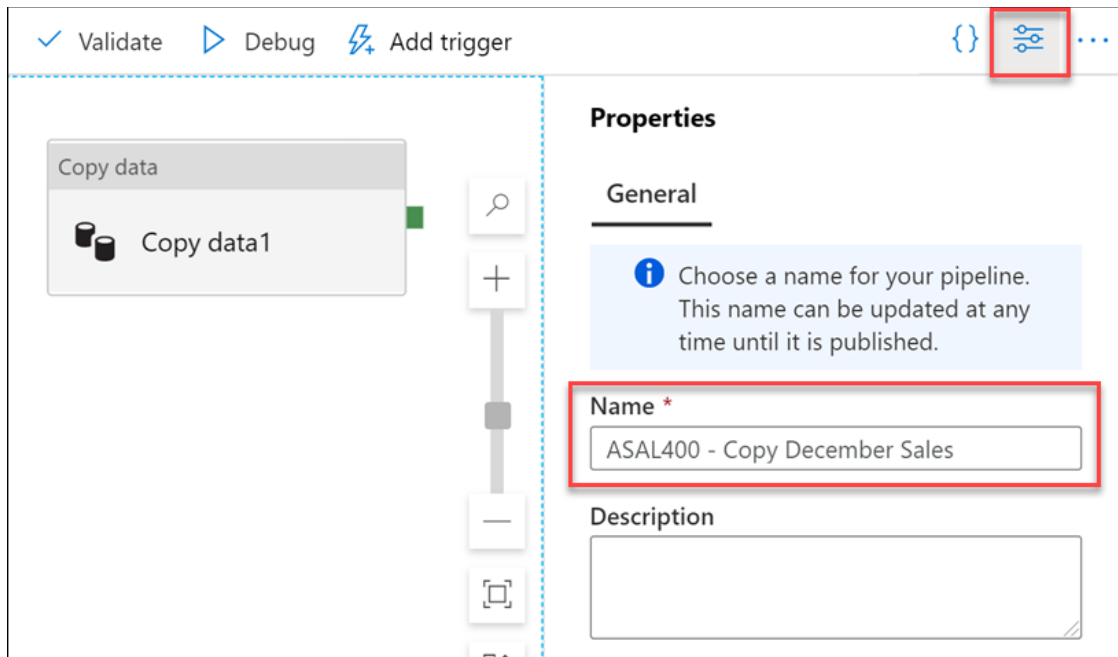
The Integrate hub is highlighted.

2. Select + then **Pipeline** to create a new pipeline.



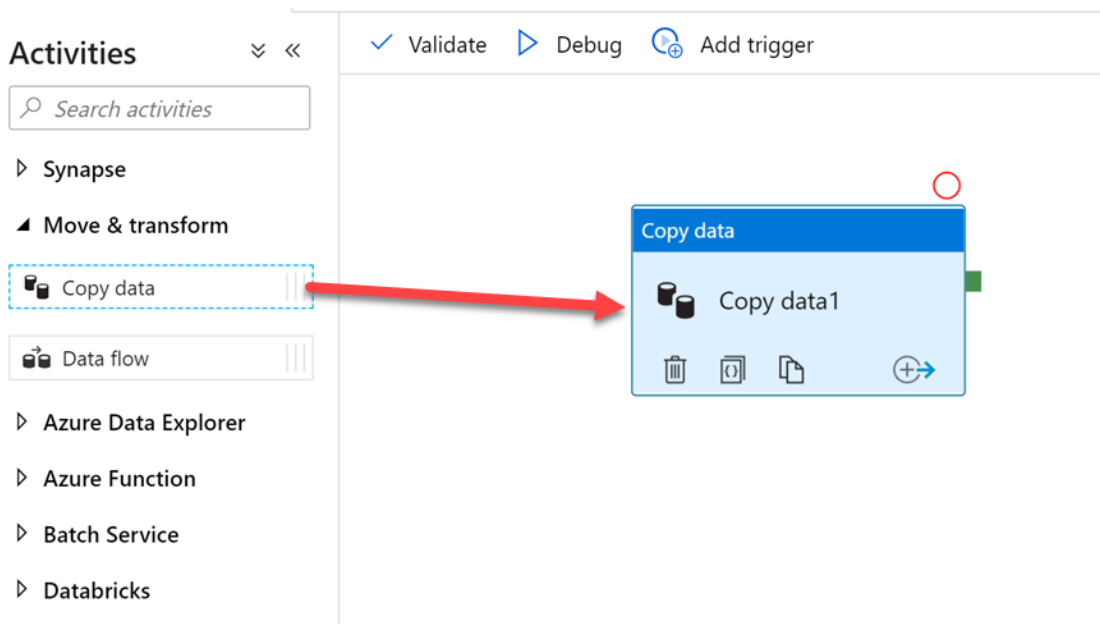
The new pipeline context menu item is selected.

3. In the **Properties** pane for the new pipeline, enter the following **Name**: ASAL400 - Copy December Sales.



The Name property is highlighted.

4. Expand **Move & transform** within the Activities list, then drag the **Copy data** activity onto the pipeline canvas.




Copy data is dragged to the canvas

5. Select the **Copy data** activity on the canvas and set the **Name** to Copy Sales.
6. Select the **Source** tab, then select **+ New** next to Source dataset.
7. Select the **Azure Data Lake Storage Gen2** data store, then select **Continue**.

8. Choose the **Parquet** format, then select **Continue**.
9. In the properties, set the name to **asal400_december_sales** and select the **asdatalakeSUFFIX** linked service. Browse to the `wwi-02/campaign-analytics/sale-20161230-snappy.parquet` file location, select **From sample file** for schema import. [Download this sample file](#) to your computer, then browse to it in the **Select file** field. Select **OK**.

Set properties

 Choose a name for your dataset. This name can be updated at any time until it is published.

Name


Linked service *

asdatalake01

Edit connection

File path


/ /



Import schema

☐ From connection/store ☒ From sample file ☐ None


Select file

 Advanced

The properties are displayed.


10. Select the **Sink** tab, then select **+ New** next to Sink dataset.
11. Select the **Azure Synapse Analytics** data store, then select **Continue**.
12. In the properties, set the name to **asal400_saleheap_asa** and select the **sqlpool01_import01** linked service that connects to Synapse Analytics with the `asa.sql.import01` user. For the table name, scroll the Table name dropdown and choose the **wwi_staging.SaleHeap** table then select **OK**.

Set properties

 Choose a name for your dataset. This name can be updated at any time until it is published.

Name


Linked service *

 _import01

▼

[Edit connection](#)

Table name



▼

☐ Edit

Import schema
☒ From connection/store ☐ None

▸ Advanced

The properties are displayed.

13. In the **Sink** tab, select the **Copy command** copy method and enter the following in the pre-copy script to clear the table before import: `TRUNCATE TABLE wwi_staging.SaleHeap.`

General Source **Sink** Mapping Settings User properties

Sink dataset * asal400_saleheap_asa [Open](#) [+ New](#) [Learn more](#)

Copy method ☐ PolyBase ☒ Copy command ☐ Bulk insert

Allow copy command ☒

Default values [+ New](#)

Additional options [+ New](#)

Table option ☒ None ☐ Auto create table

Pre-copy script

```
TRUNCATE TABLE wwi_staging.SaleHeap
```

Write batch timeout

Write batch size

Max concurrent connections

Disable performance metrics analytics ☐

The described settings are displayed.

14. Select the **Mapping** tab and select **Import schemas** to create mappings for each source and destination field.

General Source Sink **Mapping** Settings User properties

Import schemas [Preview source](#) [+ New mapping](#) [Clear](#) [Delete](#)

Source	Type	Destination	Type
TransactionId	UTF8	TransactionId	uniqueidentifier
CustomerId	INT32	CustomerId	int
ProductId	INT_16	ProductId	smallint
Quantity	INT_8	Quantity	smallint
Price	DECIMAL	Price	decimal
TotalAmount	DECIMAL	TotalAmount	decimal
TransactionDate	INT32	TransactionDate	int
ProfitAmount	DECIMAL	ProfitAmount	decimal
Hour	INT_8	Hour	tinyint
Minute	INT_8	Minute	tinyint
StoreId	INT_16	StoreId	smallint

The mapping is displayed.

15. Select **Settings** and set the **Data integration unit** to 8. This is required due to the large size of the source Parquet file.

General Source Sink Mapping **Settings** User properties

i You will be charged # of used DIUs * copy duration * \$0.25/DIU-hour. Local

Data integration unit 8 i

☐ Edit

Add dynamic content [Alt+P]

Degree of copy parallelism i

☒ Edit

Fault tolerance i

Enable staging i

The data integration unit value is set to 32.

16. Select **Publish all** to save your new resources.

Publish all 1 ☒ Validate all

Develop + ≡ «

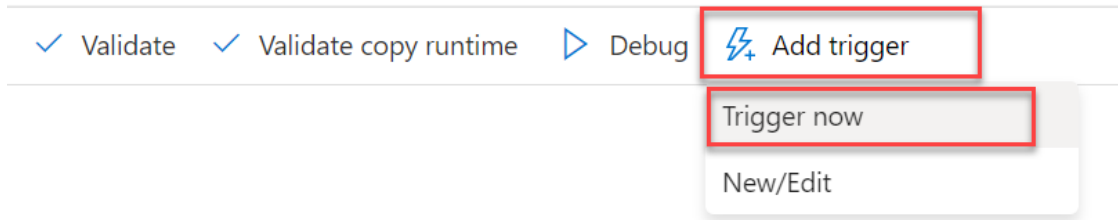
▶ SQL scripts 23

ASAL4

☒ Valid

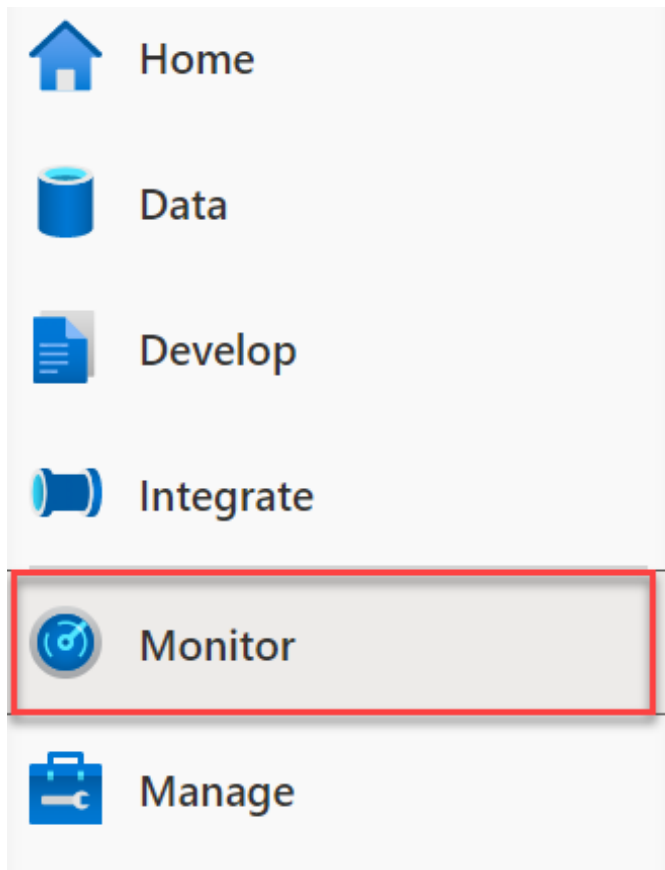
Publish all is highlighted.

17. Select **Add trigger**, then **Trigger now**. Select **OK** in the pipeline run trigger to begin.



Trigger now.

18. Navigate to the **Monitor** hub.



The Monitor hub menu item is selected.

19. Select **Pipeline Runs**. You can see the status of your pipeline run here. Note that you may need to refresh the view. Once the pipeline run is complete, you can query the `wwi_staging.SaleHeap` table to view the imported data.

Pipeline runs

Triggered

Debug

Rerun

Cancel

Refresh

Edit columns

List

Gantt

Search by run ID or name

Local time : Last 24 hours

Pipeline name : All

Status : All

Runs : Latest runs

Add filter

Showing 1 - 1 items

<div><input type="checkbox"/></div> Pipeline name	Run start <div><div></div><div></div></div>	Run end	Duration	Triggered by	Status	Run	Parameters
<div><input type="checkbox"/></div> ASAL400 - Copy December Sa...	1/30/21, 5:27:39 PM	1/30/21, 5:28:32 PM	00:00:53	Manual trigger	<div><div></div></div> Succeeded	Original	

The completed pipeline run is displayed.

20. Clean up! In a SQL script, execute the following:

```
DROP WORKLOAD CLASSIFIER HeavyLoader;
DROP WORKLOAD GROUP BigDataLoad;
```