Lakehouse Tutorial

Lakehouse

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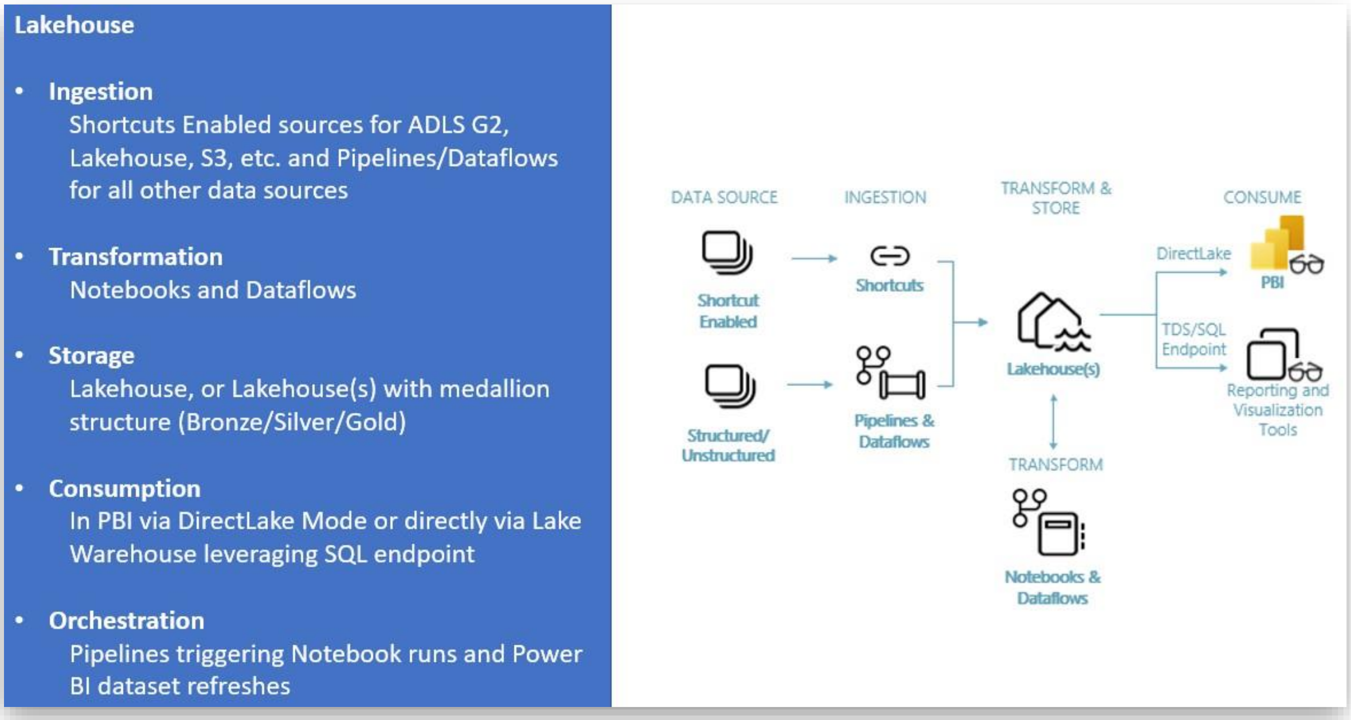


Lakehouse

- **Ingestion**
  Shortcuts Enabled sources for ADLS G2, Lakehouse, S3, etc. and Pipelines/Dataflows for all other data sources
- **Transformation**
  Notebooks and Dataflows
- **Storage**
  Lakehouse, or Lakehouse(s) with medallion structure (Bronze/Silver/Gold)
- **Consumption**
  In PBI via DirectLake Mode or directly via Lake Warehouse leveraging SQL endpoint
- **Orchestration**
  Pipelines triggering Notebook runs and Power BI dataset refreshes

Contents

Introduction

What is Fabric?

Fabric provides a one-stop shop for all the analytical needs for every enterprise. It covers the complete spectrum of services including data movement, data lake, data engineering, data integration and data science, real time analytics, and business intelligence. With Fabric, there is no need to stitch together different services from multiple vendors. Instead, the customer enjoys an end-to-end, highly integrated, single comprehensive product that is easy to understand, onboard, create and operate. There is no other product on the market that offers the breadth, depth, and level of integration that Fabric offers. Additionally, Microsoft Purview is included by default in every tenant to meet compliance and governance needs.

To get an overview of the components and concepts of Fabric read Fabric - Overview and Concepts.

The purpose of this tutorial

While many concepts in Fabric may be familiar to data and analytics professionals it can be challenging to apply those concepts in a new environment. This tutorial has been designed to walk step-by-step through an end-to-end scenario from data acquisition to data consumption to build a basic understanding of the Fabric UX, the various workloads and their integration points, and the Fabric professional and citizen developer experiences.

The tutorials are not intended to be a reference architecture, an exhaustive list of features and functionality, or a recommendation of specific best practices.

The lakehouse end-to-end scenario

Traditionally, organizations have been building modern data warehouses for their transactional and structured data processing/analytics needs and data lakehouses for big data (semi/unstructured data) processing/analytics needs. These two systems ran in parallel, creating silos, data duplicity and increased total cost of ownership.

Fabric with its unification of data store and standardization on Delta Lake format allows you to eliminate silos, remove data duplicity, and drastically reduce total cost of ownership.

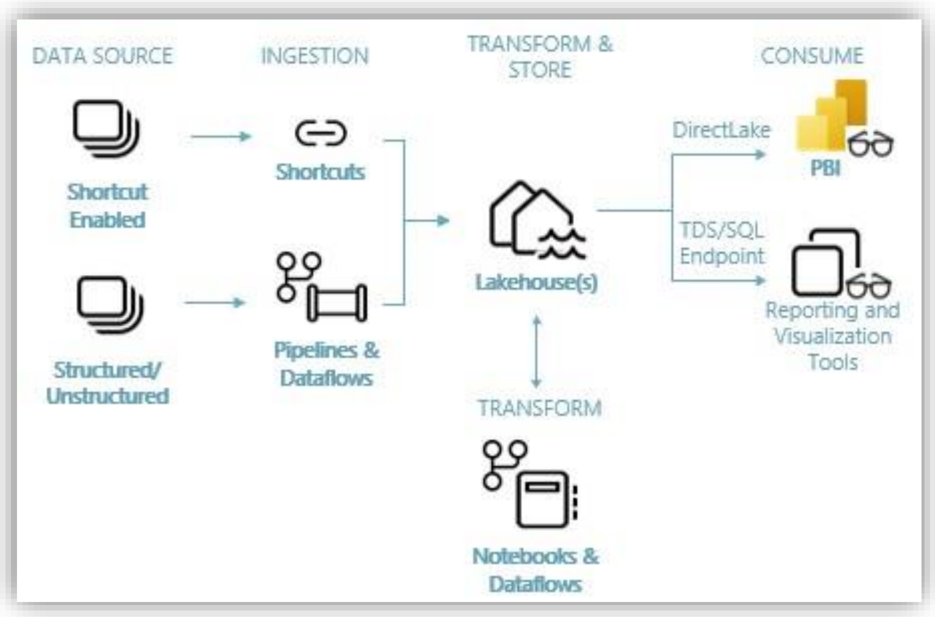
With the flexibility Fabric provides, you can implement either lakehouse or data warehouse architectures or combine these two together to get the best of both the worlds in simple implementation. In this tutorial, you are going to take an example of retail organization and build its lakehouse from start to finish. The same approach can be taken to implement a lakehouse for any organization from any industry.

In this tutorial, you will take on the role of a developer at the fictional Wide World Importers company from retail domain and complete the following steps:

- Sign into your Power BI online account, or if you don't have an account yet, sign up for a free trial.
- Build and implement an end-to-end lakehouse for your organization:
    - Create a Fabric workspace
    - Quickly create a lakehouse – an optional module to implement medallion architecture (Bronze, Silver, and Gold)
    - Ingest, Transform and load data into the lakehouse – bronze, silver and gold zones as delta lake tables for medallion architecture
    - Explore OneLake, OneCopy of your data across lake mode and warehouse mode
    - Connect to your lakehouse using TDS/SQL endpoint
    - Create Power BI report using DirectLake – to analyze sales data across different dimensions
    - Orchestrate and schedule data ingestion and transformation flow with Pipeline

- Cleanup resources by deleting the workspace and other items

The lakehouse end-to-end architecture



Data Sources – Fabric makes it easy and quick to connect to Azure Data Services, other cloud platforms, and on-premises data sources to ingest data from.

Ingestion – With 200+ native connectors as part of the Fabric pipeline and with drag and drop data transformation with dataflow, you can quickly build insights for your organization. Shortcut is a new feature in Fabric that provides a way to connect to existing data without having to copy or move it.

Transform and Store – Fabric standardizes on Delta Lake format, that means all the engines of Fabric can read and work on the same dataset stored in OneLake – no need for data duplicity. This storage allows you to build lakehouses using a medallion architecture or data mesh based on your organizational need. For transformation, you can choose either low-code or no-code experience with pipelines/dataflows or notebook/Spark for a code first experience.

Consume – Data from Lakehouse can be consumed by Power BI, industry leading business intelligence tool, for reporting and visualization. Each Lakehouse comes with a built-in TDS/SQL endpoint for easily connecting to and querying data in the Lakehouse tables from other reporting tools, when needed. When a Lakehouse is created a secondary item, called a Warehouse, will be automatically generated at the same time with the same name as the Lakehouse and this Warehouse item provides you with the TDS/SQL endpoint.

The sample data

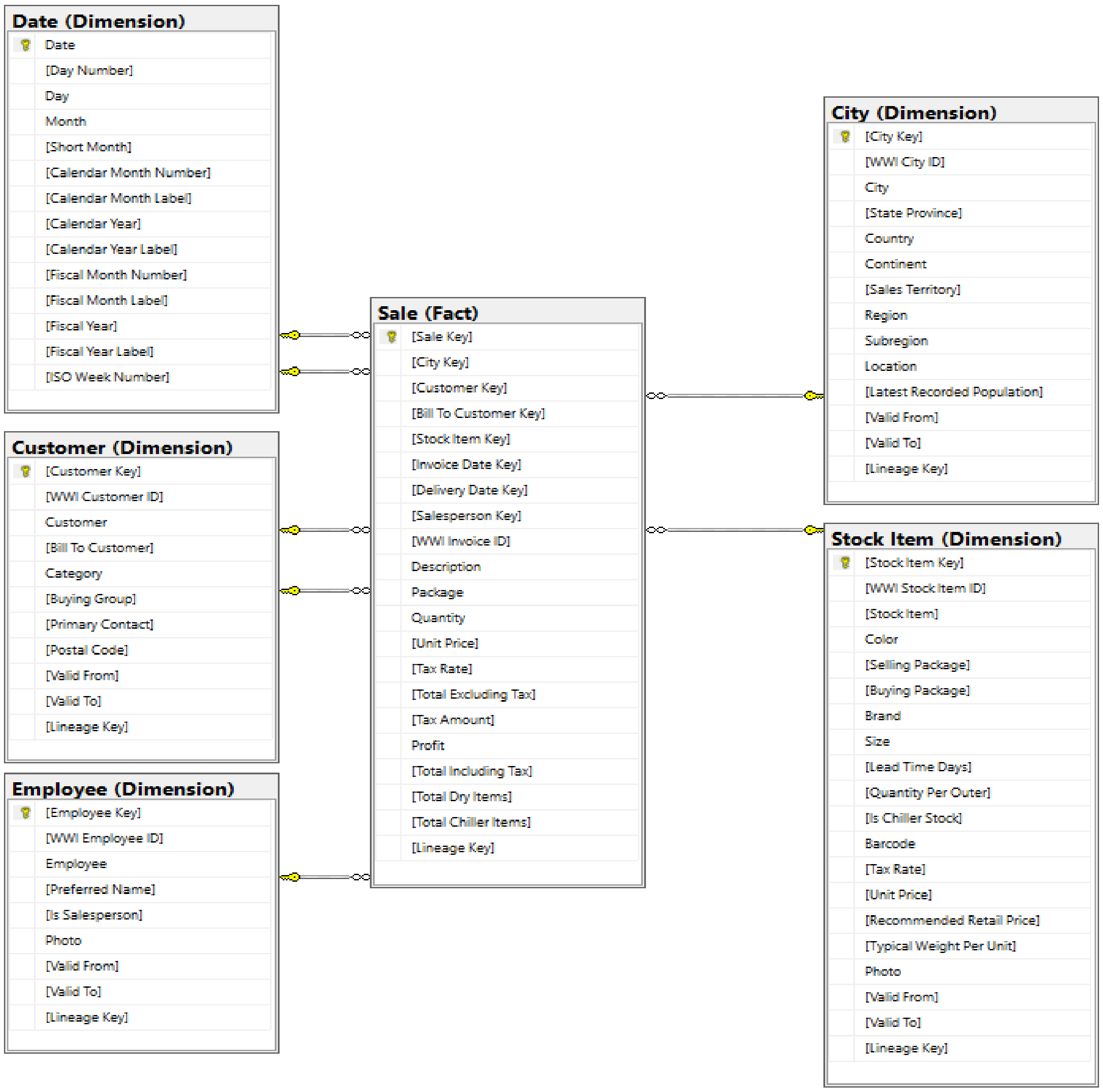
For sample data, we are going to use Wide World Importers (WWI) sample database. For our lakehouse end-to-end scenario, we have generated sufficient data for a sneak peek into the scale and performance capabilities of the Fabric platform.

Wide World Importers (WWI) is a wholesale novelty goods importer and distributor operating from the San Francisco Bay area. As a wholesaler, WWI's customers are mostly companies who resell to individuals. WWI sells to retail customers across the United States including specialty stores, supermarkets, computing stores, tourist attraction shops, and some individuals. WWI also sells to other wholesalers via a network of agents who promote the products on WWI's behalf. You can learn more about their company profile and operation here.

Typically, you would bring data from transactional systems (or line of business applications) into a lakehouse, however for simplicity of this tutorial, we are going to use the dimensional model provided by WWI as our initial data source. We are going to use it as the source to ingest the data into a lakehouse and transform it through different stages (Bronze, Silver, and Gold) of a medallion architecture.

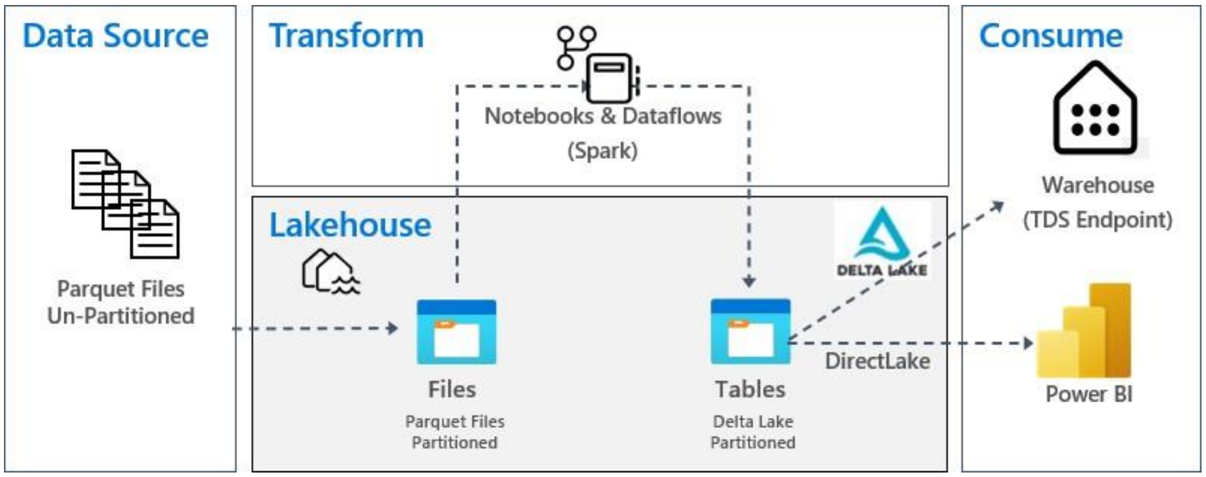
The data model

While the WWI dimensional model contains multiple fact tables, for simplicity in explanation we will focus on the Sale Fact table and its related dimensions only, as below, to demonstrate this end-to-end lakehouse scenario:



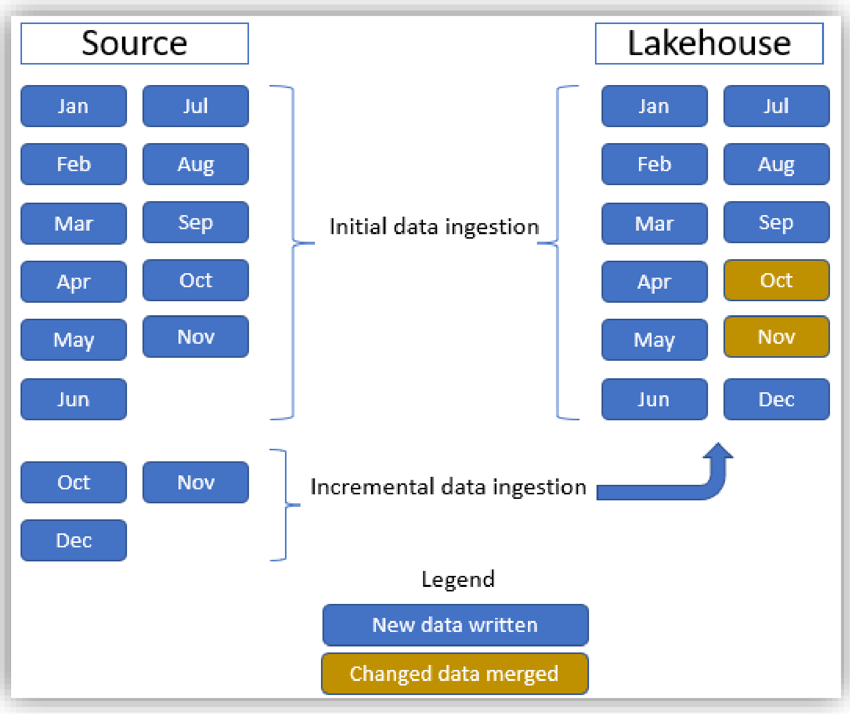
End-to-end data and transformation flow

Earlier, we described the Wide World Importers (WWI) sample data which we are going to leverage in building this end to end lakehouse. For this implementation, this sample data is in an Azure Data storage account in Parquet file format for all the tables, however in your real-world implementation data would likely come from varieties of sources and in a variety of formats.



Data Source – source data is in Parquet file format in an un-partitioned structure, stored in a folder for each table. For the purpose of this tutorial, we will set up pipeline to copy/ingest the complete historical or onetime data to the lakehouse.

To demonstrate process and capabilities for subsequent incremental data load, we will have an optional module at the end of this tutorial. In that module, we use a fact table (Sale) which has one parent folder with all the historical data for 11 months (one subfolder for each month) and another folder for just incremental data for 3 months (one subfolder for each month). During initial data ingestion, 11 months of data is ingested or written into the lakehouse table. However, when the incremental data arrives, it has updated data for Oct and Nov and new data for Dec, so Oct and Nov data are merged and new data for Dec is written into lakehouse table as depicted in figure below.



Lakehouse – For this implementation and for the simplicity's sake, we are going to create one lakehouse, ingest data into Files section of the lakehouse and then create delta lake tables in the Tables section of the lakehouse.

You will find an optional module at the end of this tutorial which covers creating the lakehouse with medallion architecture (Bronze, Silver, and Gold) and talks about its recommended approach.

Transform – For data preparation and transformation, we are going to demonstrate the use of Notebooks/Spark for code first users as well as demonstrate Pipelines/Dataflow for low-code/no-code users.

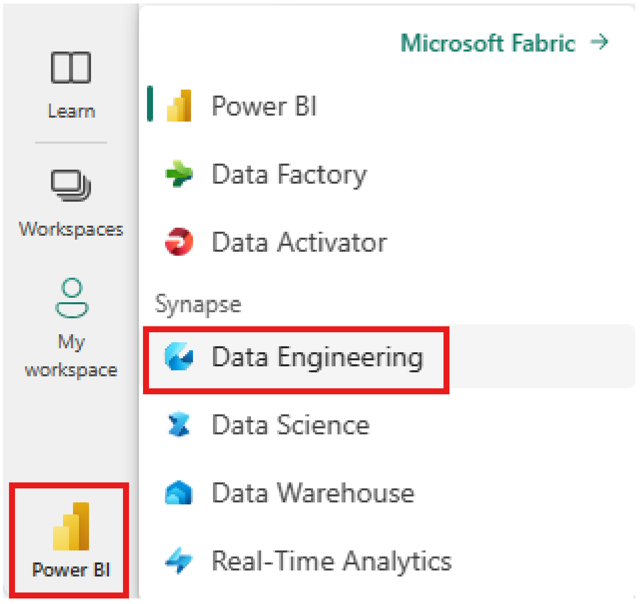
Consume – To demonstrate data consumption you will learn how you can use the DirectLake feature of Power BI to create reports/dashboards and directly query data from the lakehouse. Further, to demonstrate how you can make your data available to third party reporting tools, you can use TDS/SQL endpoint to connect to Warehouse and run SQL-based queries for analytics.

Module 1: Build your first Lakehouse in Fabric

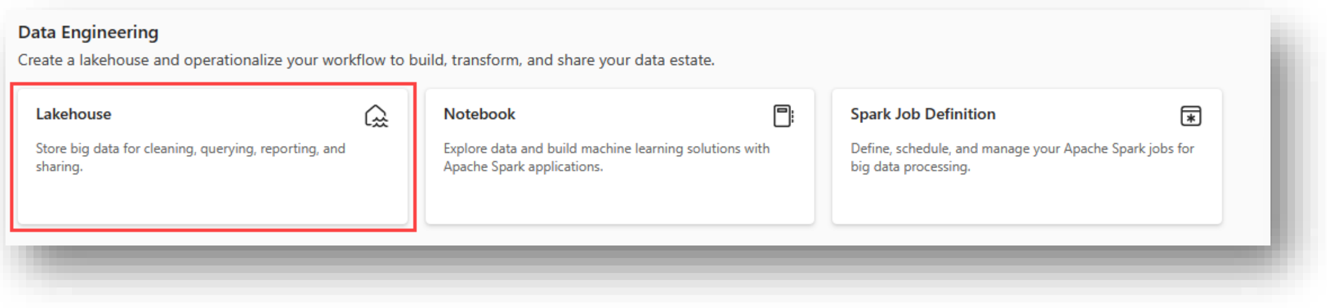
The intent of this module is to quickly build end to end journey of building a lakehouse, ingesting data for a table, applying transformation whenever required and then using ingested data into the lakehouse delta table for creating reports.

Create a lakehouse

1. In the Power BI service select **Workspaces** in the left-hand menu.
2. Search for your workspace by typing in the search textbox at the top and click on your workspace to open it.
3. From the workload switcher located at the bottom left of the screen, select **Data engineering**.



4. In the **Data Engineering** section, select **Lakehouse** to create a lakehouse.



Data Engineering

Create a lakehouse and operationalize your workflow to build, transform, and share your data estate.

Lakehouse

Store big data for cleaning, querying, reporting, and sharing.

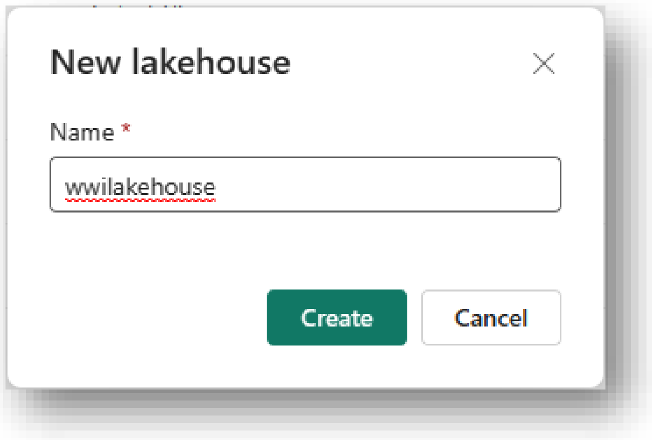
Notebook

Explore data and build machine learning solutions with Apache Spark applications.

Spark Job Definition

Define, schedule, and manage your Apache Spark jobs for big data processing.

5. Enter **wwilakehouse** in the **Name** box.



New lakehouse

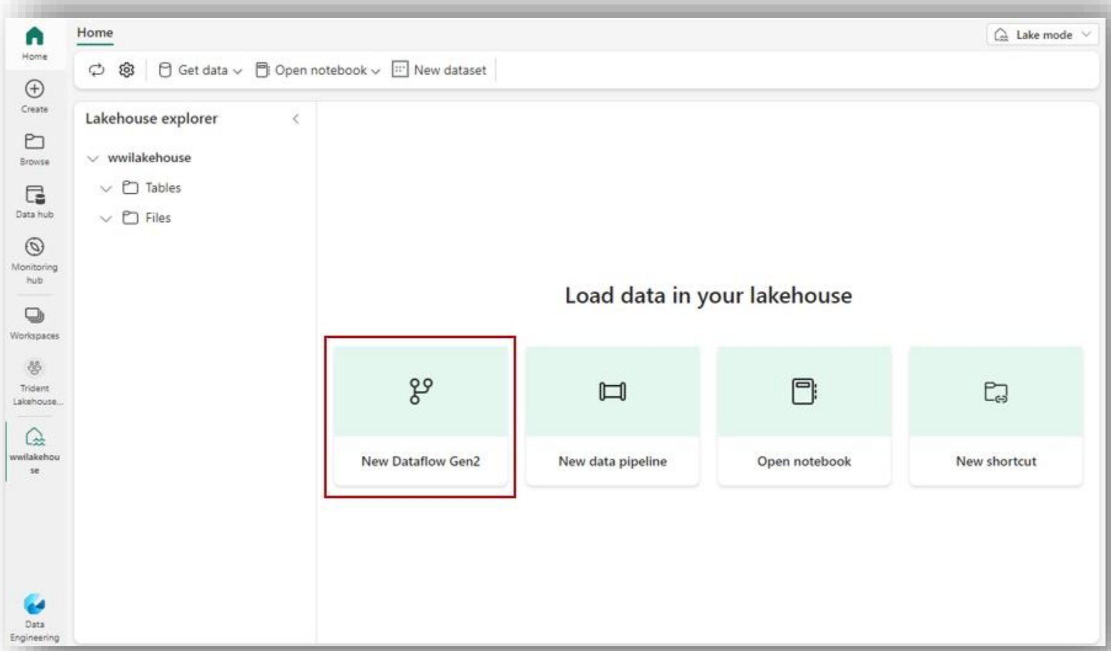
Name *

wwilakehouse

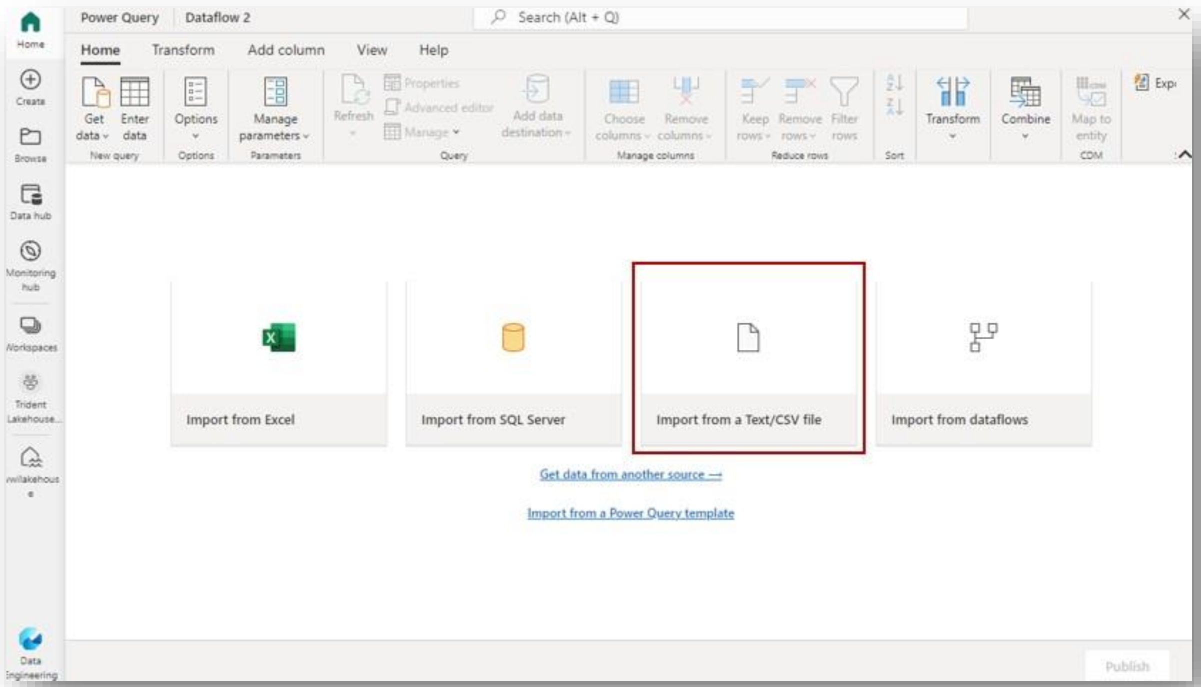
6. Click **Create**. The new lakehouse will be created and automatically opened.

Data Ingestion

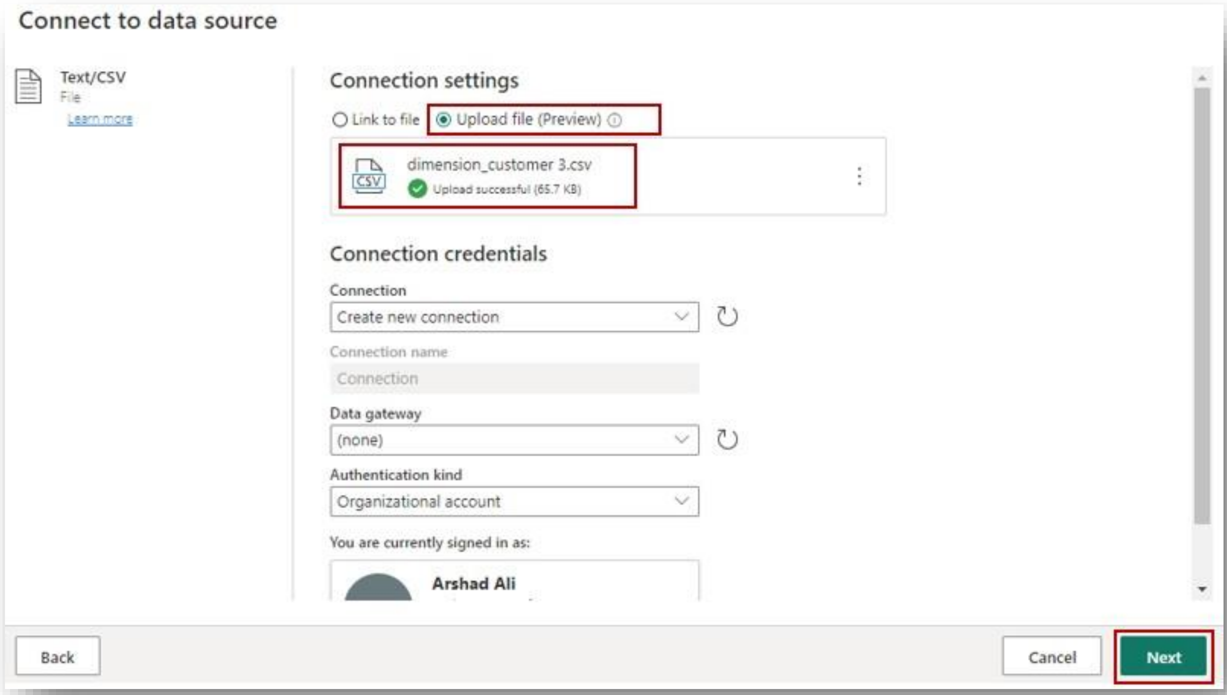
1. Download the ‘dimension_customer.csv’ file found in Data folder.
2. In the lakehouse view, you will see options to load data into lakehouse. Click on **New Dataflow Gen2**.



3. On the new dataflow page, click on **Import from a Text/CSV file**.



4. On the **Connect to data source** wizard, click on **Upload file** radio button and then drag and drop the data file that you downloaded in step 1 of this module. Once the file is uploaded, click **Next**.


Connect to data source

Text/CSV
File
Learn more

Connection settings

Link to file [✓ Upload file (Preview)]

dimension_customer 3.csv
Upload successful (65.7 KB)

Connection credentials

Connection: Create new connection

Connection name: Connection

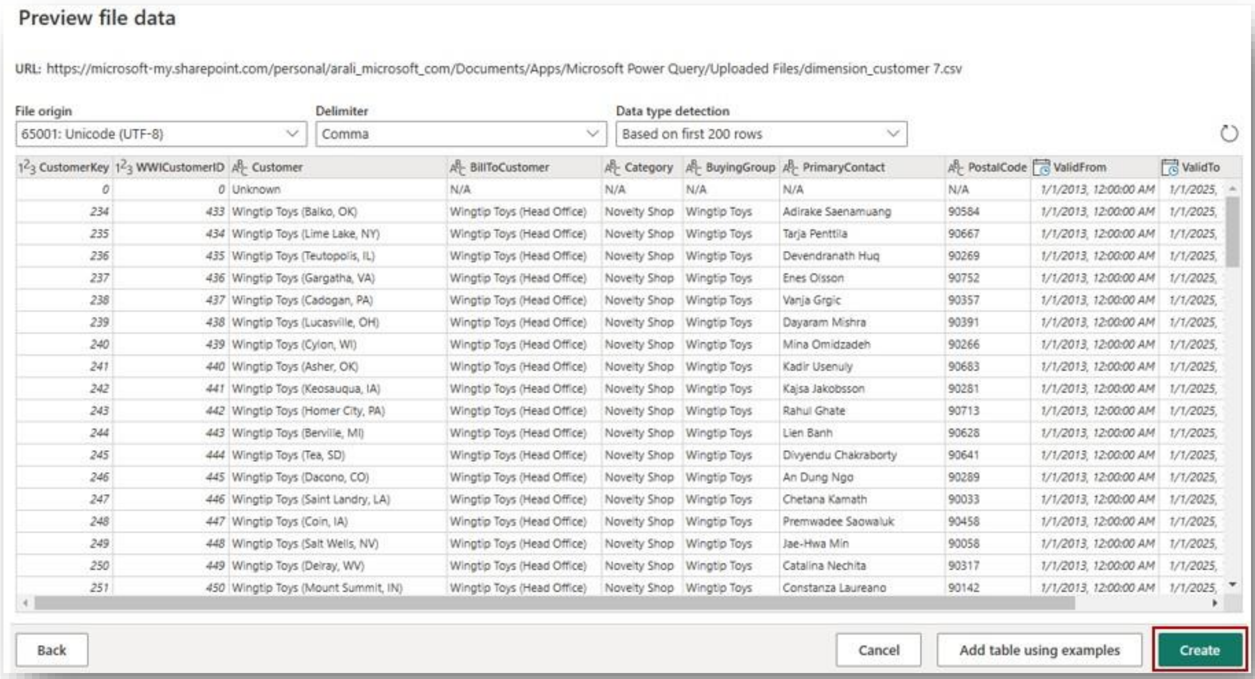
Data gateway: (none)

Authentication kind: Organizational account

You are currently signed in as:

Arshad Ali

5. Clicking **Next** on the previous screen will open the **Preview file data** page, click on **Create** to proceed and return back to dataflow canvas.



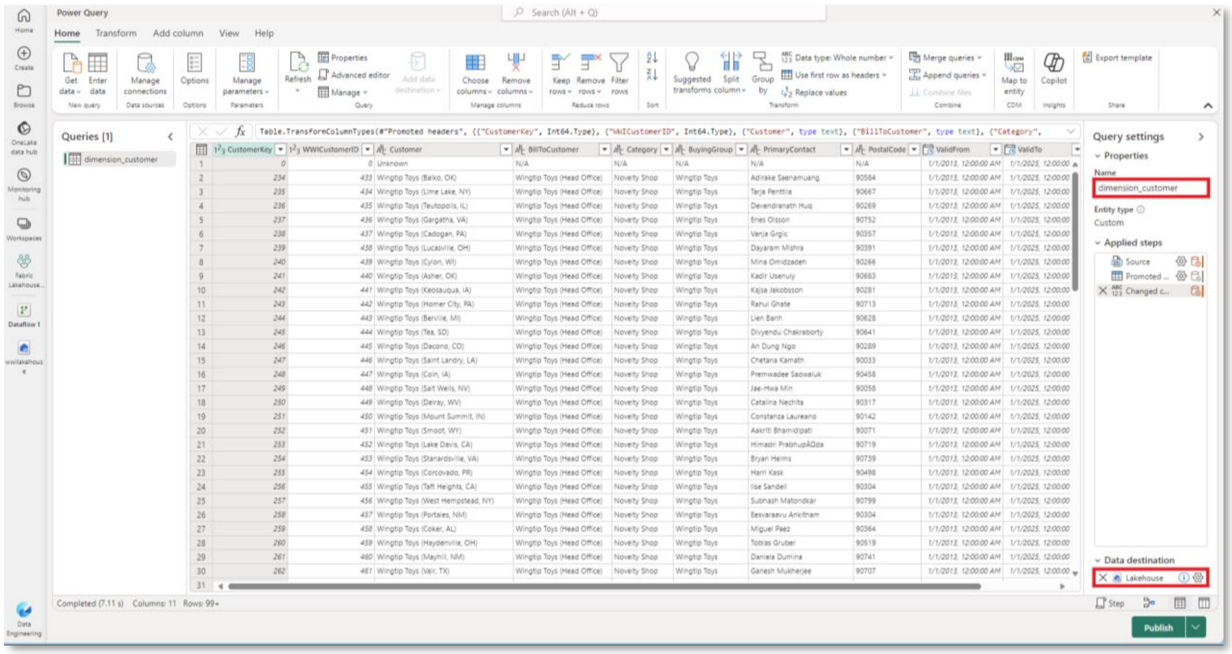
Preview file data

URL: https://microsoft-my.sharepoint.com/personal/arali_microsoft_com/Documents/Apps/Microsoft Power Query/Uploaded Files/dimension_customer 7.csv

File origin: 65001: Unicode (UTF-8)
Delimiter: Comma
Data type detection: Based on first 200 rows

CustomerKey	WWICustomerID	Customer	BillToCustomer	Category	BuyingGroup	PrimaryContact	PostalCode	ValidFrom	ValidTo
0	0	Unknown	N/A	N/A	N/A	N/A	N/A	1/1/2013, 12:00:00 AM	1/1/2025,
234	433	Wingtip Toys (Balko, OK)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Adirake Saenamuang	90584	1/1/2013, 12:00:00 AM	1/1/2025,
235	434	Wingtip Toys (Lime Lake, NY)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Tarja Penttila	90667	1/1/2013, 12:00:00 AM	1/1/2025,
236	435	Wingtip Toys (Teutopolis, IL)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Devendranath Huq	90269	1/1/2013, 12:00:00 AM	1/1/2025,
237	436	Wingtip Toys (Gargatha, VA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Enes Olsson	90752	1/1/2013, 12:00:00 AM	1/1/2025,
238	437	Wingtip Toys (Cadogan, PA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Vanja Grgic	90357	1/1/2013, 12:00:00 AM	1/1/2025,
239	438	Wingtip Toys (Lucasville, OH)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Dayaram Mishra	90391	1/1/2013, 12:00:00 AM	1/1/2025,
240	439	Wingtip Toys (Cylon, WI)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Mina Omidzadeh	90266	1/1/2013, 12:00:00 AM	1/1/2025,
241	440	Wingtip Toys (Asher, OK)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Kadir Usenuly	90683	1/1/2013, 12:00:00 AM	1/1/2025,
242	441	Wingtip Toys (Keosauqua, IA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Kajsa Jakobsson	90281	1/1/2013, 12:00:00 AM	1/1/2025,
243	442	Wingtip Toys (Homer City, PA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Rahul Ghate	90713	1/1/2013, 12:00:00 AM	1/1/2025,
244	443	Wingtip Toys (Berville, MI)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Lien Banh	90628	1/1/2013, 12:00:00 AM	1/1/2025,
245	444	Wingtip Toys (Tea, SD)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Divyendu Chakraborty	90641	1/1/2013, 12:00:00 AM	1/1/2025,
246	445	Wingtip Toys (Dacono, CO)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	An Dung Ngo	90289	1/1/2013, 12:00:00 AM	1/1/2025,
247	446	Wingtip Toys (Saint Landry, LA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Chetana Kamath	90033	1/1/2013, 12:00:00 AM	1/1/2025,
248	447	Wingtip Toys (Coin, IA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Premwadee Saowaluk	90458	1/1/2013, 12:00:00 AM	1/1/2025,
249	448	Wingtip Toys (Salt Wells, NV)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Jae-Hwa Min	90058	1/1/2013, 12:00:00 AM	1/1/2025,
250	449	Wingtip Toys (Delray, WV)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Catalina Nechita	90317	1/1/2013, 12:00:00 AM	1/1/2025,
251	450	Wingtip Toys (Mount Summit, IN)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Constanza Laureano	90142	1/1/2013, 12:00:00 AM	1/1/2025,

6. In the **Name** property of the query settings pane, enter **dimension_customer**. Next, select the gear in the **Data destination** property at the bottom of the query settings pane.



```
Table.TransformColumnTypes(#"Promoted headers", {{"CustomerKey", Int64.Type}, {"WWICustomerID", Int64.Type}, {"Customer", type text}, {"BillToCustomer", type text}, {"Category",
```

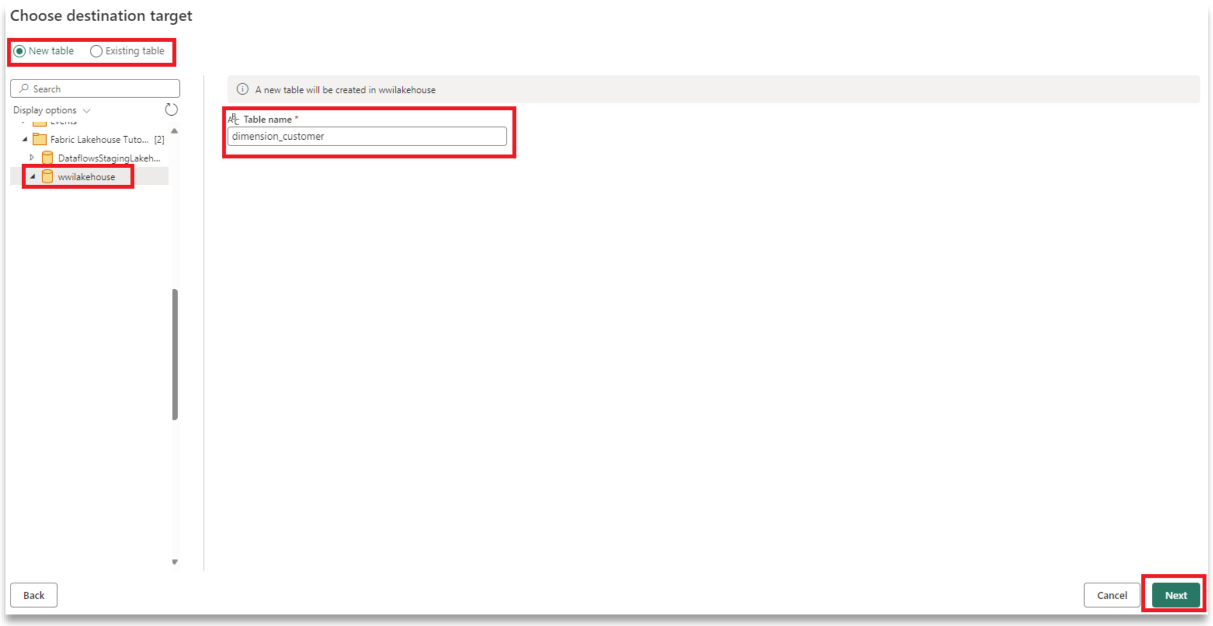
	CustomerKey	WWICustomerID	Customer	BillToCustomer	Category	BuyingGroup	PrimaryContact	PostalCode	ValidFrom	ValidTo
1	0	0	Unknown	N/A	N/A	N/A	N/A	N/A	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
2	234	433	Wingtip Toys (Balko, OK)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Adirake Saenamuang	90584	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
3	235	434	Wingtip Toys (Lime Lake, NY)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Tarja Penttila	90667	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
4	236	435	Wingtip Toys (Teutopolis, IL)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Devendranath Huq	90269	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
5	237	436	Wingtip Toys (Gargatha, VA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Enes Olsson	90752	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
6	238	437	Wingtip Toys (Cadogan, PA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Vanja Grgic	90357	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
7	239	438	Wingtip Toys (Lucasville, OH)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Dayaram Mishra	90391	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
8	240	439	Wingtip Toys (Cylon, WI)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Mina Omidzadeh	90266	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
9	241	440	Wingtip Toys (Asher, OK)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Kadir Usenuly	90683	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
10	242	441	Wingtip Toys (Keosauqua, IA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Kajsa Jakobsson	90281	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
11	243	442	Wingtip Toys (Homer City, PA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Rahul Ghate	90713	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
12	244	443	Wingtip Toys (Berville, MI)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Lien Banh	90628	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
13	245	444	Wingtip Toys (Tea, SD)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Divyendu Chakraborty	90641	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
14	246	445	Wingtip Toys (Dacono, CO)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	An Dung Ngo	90289	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
15	247	446	Wingtip Toys (Saint Landry, LA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Chetana Kamath	90033	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
16	248	447	Wingtip Toys (Coin, IA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Premwadee Saowaluk	90458	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
17	249	448	Wingtip Toys (Salt Wells, NV)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Jae-Hwa Min	90058	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
18	250	449	Wingtip Toys (Delray, WV)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Catalina Nechita	90317	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
19	251	450	Wingtip Toys (Mount Summit, IN)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Constanza Laureano	90142	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
20	252	451	Wingtip Toys (Smoot, WY)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Aakriti Bhamidipati	90071	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
21	253	452	Wingtip Toys (Lake Davis, CA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Himadri PrabhupÃda	90719	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
22	254	453	Wingtip Toys (Stanardsville, VA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Bryan Helms	90739	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
23	255	454	Wingtip Toys (Corcovado, PR)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Harri Kask	90498	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
24	256	455	Wingtip Toys (Taft Heights, CA)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Ilse Sandell	90304	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
25	257	456	Wingtip Toys (West Hempstead, NY)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Subhash Matondkar	90799	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
26	258	457	Wingtip Toys (Portales, NM)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Eesvaraavu Ankitham	90304	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
27	259	458	Wingtip Toys (Coker, AL)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Miguel Paez	90364	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
28	260	459	Wingtip Toys (Haydenville, OH)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Tobias Gruber	90519	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
29	261	460	Wingtip Toys (Mayhill, NM)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Daniela Dumina	90741	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
30	262	461	Wingtip Toys (Vair, TX)	Wingtip Toys (Head Office)	Novelty Shop	Wingtip Toys	Ganesh Mukherjee	90707	1/1/2013, 12:00:00 AM	1/1/2025, 12:00:00
31										

Completed (7.11 s) Columns: 11 Rows: 99+

Query settings
Properties
Name: dimension_customer
Entity type: Custom
Applied steps: Source; Promoted ...; Changed c...
Data destination: Lakehouse

7. If necessary, on the **Connect to data destination** screen, sign into your account. Click **Next**.
8. Navigate to the **wwilakehouse** in your workspace.
9. If the **dimension_customer** table does not exist, select the **New table** setting and enter the Table name of **dimension_customer**. If the table already exists, select the **Existing table** setting and select **dimension_customer** from the table list in the object explorer. Select **Next**.

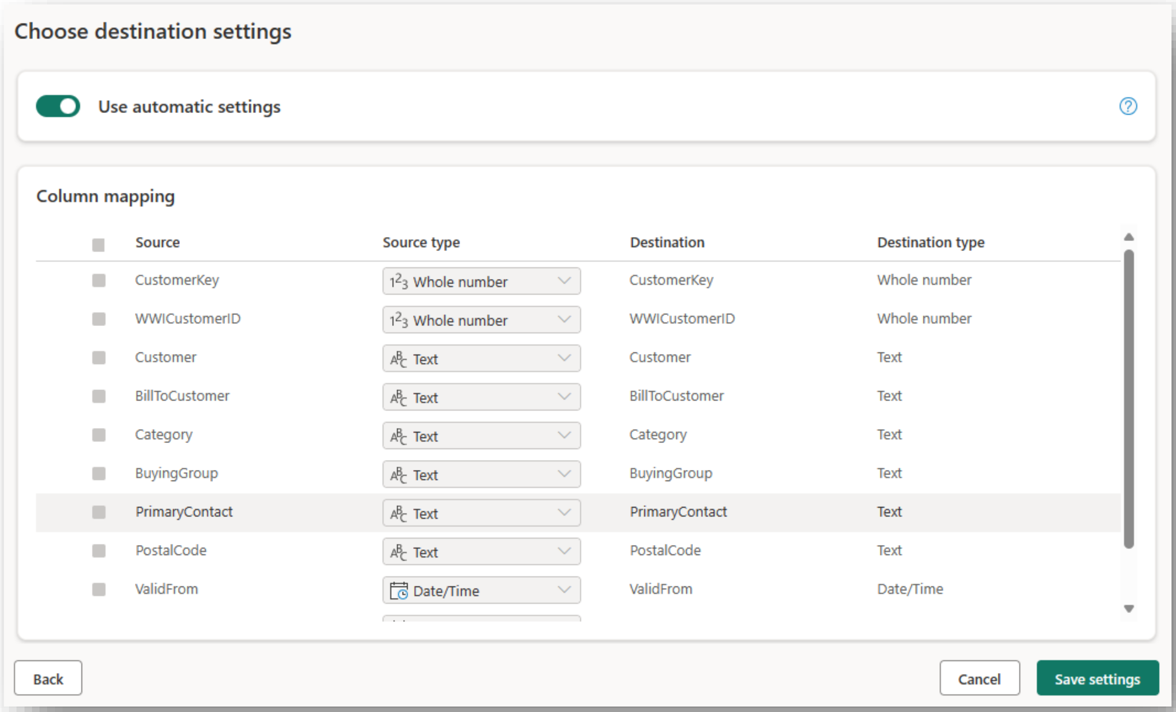
   Note – UI adds <space>Number at the end of the table name by default. Table names must be lower case and must not contain space. Please name it appropriately and remove any space from the table name.



A new table will be created in wwilakehouse

Table name *: dimension_customer

10. On the **Choose destination settings**, ensure **Use automatic settings** is enabled and click on **Save Settings**.



Choose destination settings

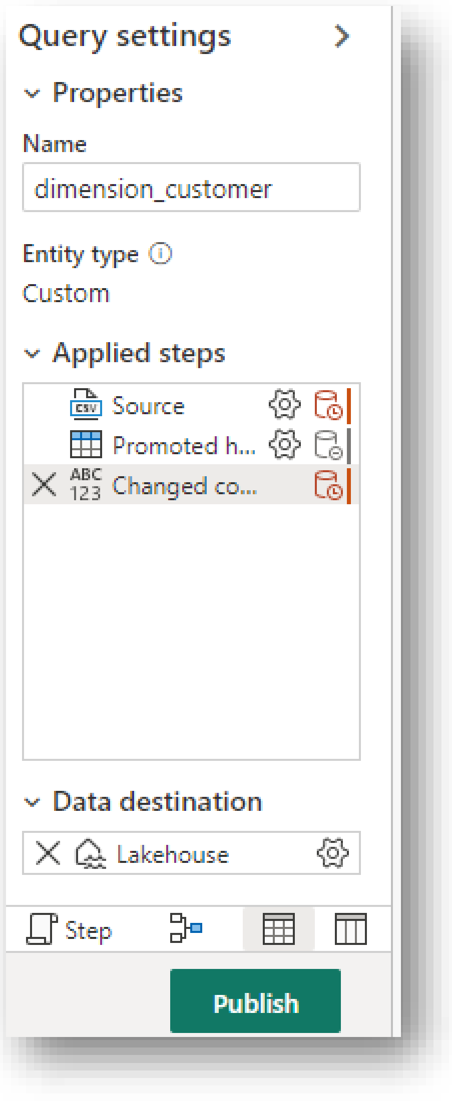
Use automatic settings

Column mapping

Source	Source type	Destination	Destination type
CustomerKey	Whole number	CustomerKey	Whole number
WWICustomerID	Whole number	WWICustomerID	Whole number
Customer	Text	Customer	Text
BillToCustomer	Text	BillToCustomer	Text
Category	Text	Category	Text
BuyingGroup	Text	BuyingGroup	Text
PrimaryContact	Text	PrimaryContact	Text
PostalCode	Text	PostalCode	Text
ValidFrom	Date/Time	ValidFrom	Date/Time

Classified as Microsoft Confidential

11. This will return you to the canvas of the dataflow. You can easily and quickly transform the data based on your business requirements using this nice and intuitive graphical user interface. For the purpose of this module, we will not make any changes here. To proceed, click on **Publish** at bottom right of the screen.



Query settings

Properties

Name: dimension_customer

Entity type: Custom

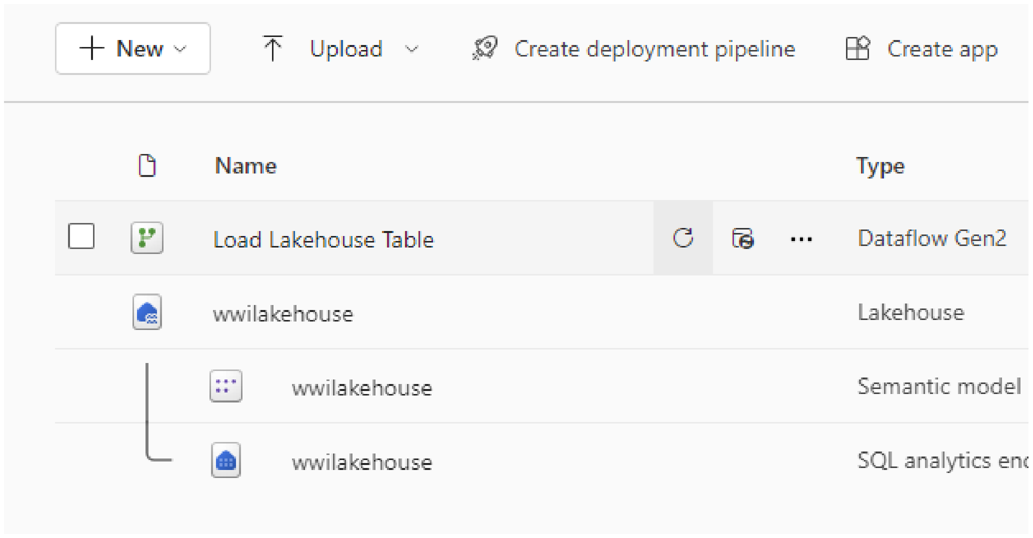
Applied steps

- Source
- Promoted h...
- Changed co...

Data destination

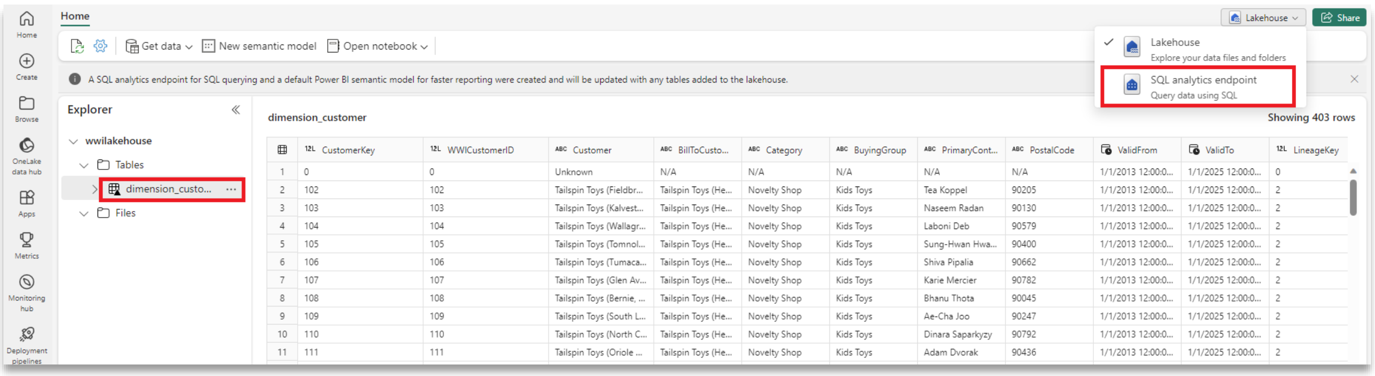
Lakehouse

12. A spinning circle next to the dataflow's name will indicate publishing is in progress on the artifact view. When this is completed, click on the ellipsis and select **Properties** to rename the dataflow. For the purpose of this module, Change the name to **Load Lakehouse Table** and select **Save**.
13. Next to the name of the data flow in the artifact view, there is an icon (**Refresh now**) to refresh the dataflow. Click on it to kick off execution of dataflow and to move the data from the source file to lakehouse table. While it's in progress, you will see a spinning circle under **Refreshed** column in the artifact view.



Name	Type
Load Lakehouse Table	Dataflow Gen2
wwilakehouse	Lakehouse
wwilakehouse	Semantic model
wwilakehouse	SQL analytics end

14. Once the dataflow's refresh is completed, you can go to the lakehouse, and you will notice **dimension_customer** delta table has been created. When you click on it, you should be able to preview its data. Further, you can use the SQL endpoint of the lakehouse to query the data with SQL statements in warehouse mode. Click on **SQL endpoint** under **Lake mode** on top right of the screen.



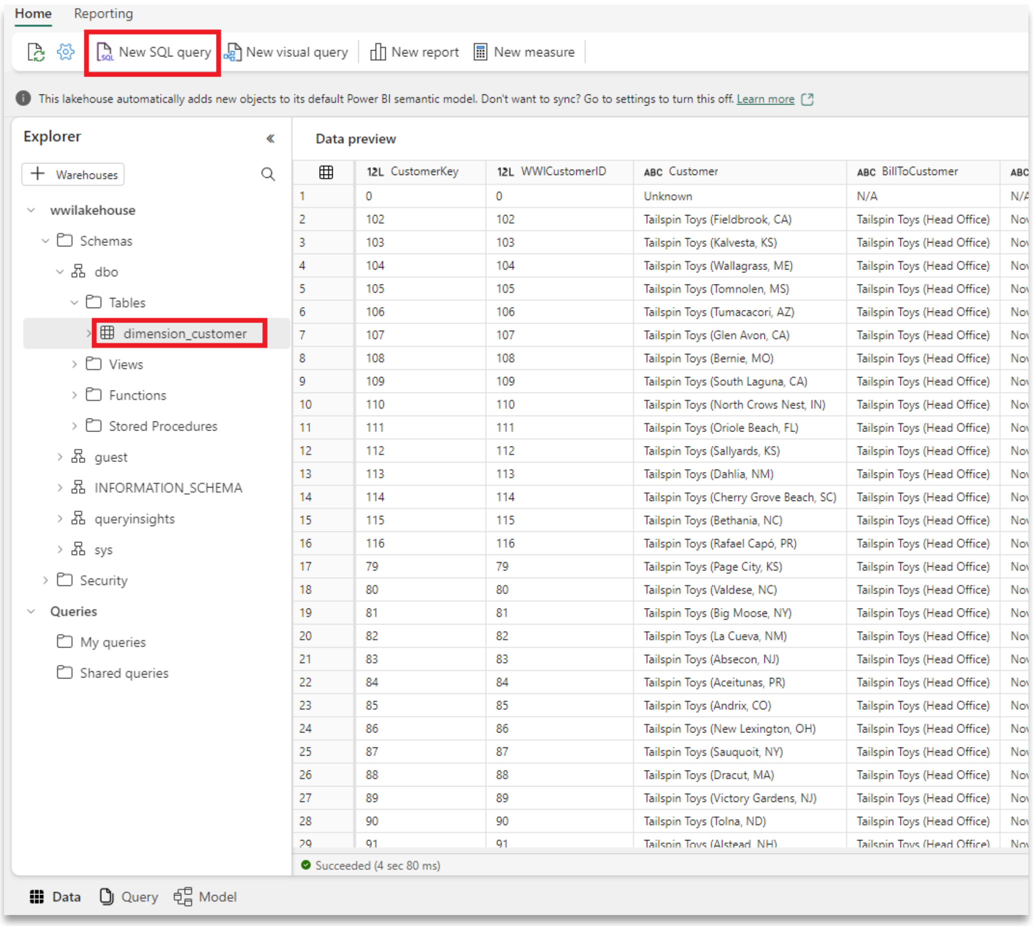
A SQL analytics endpoint for SQL querying and a default Power BI semantic model for faster reporting were created and will be updated with any tables added to the lakehouse.

dimension_customer

Showing 403 rows

	CustomerKey	WWICustomerID	Customer	BillToCusto...	Category	BuyingGroup	PrimaryCont...	PostalCode	ValidFrom	ValidTo	LineageKey
1	0	0	Unknown	N/A	N/A	N/A	N/A	N/A	1/1/2013 12:00:0...	1/1/2025 12:00:0...	0
2	102	102	Tailspin Toys (Fieldbr...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Tea Koppel	90205	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
3	103	103	Tailspin Toys (Kalvest...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Naseem Radan	90130	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
4	104	104	Tailspin Toys (Wallagr...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Laboni Deb	90579	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
5	105	105	Tailspin Toys (Tomnol...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Sung-Hwan Hwa...	90400	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
6	106	106	Tailspin Toys (Tumaca...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Shiva Pipalia	90662	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
7	107	107	Tailspin Toys (Glen Av...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Karie Mercier	90782	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
8	108	108	Tailspin Toys (Bernie, ...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Bhanu Thota	90045	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
9	109	109	Tailspin Toys (South L...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Ae-Cha Joo	90247	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
10	110	110	Tailspin Toys (North C...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Dinara Saparkyzy	90792	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2
11	111	111	Tailspin Toys (Oriole ...	Tailspin Toys (He...	Novelty Shop	Kids Toys	Adam Dvorak	90436	1/1/2013 12:00:0...	1/1/2025 12:00:0...	2

15. In the warehouse mode, you can click on **dimension_customer** table to preview its data and/or click on **New SQL query** to write your SQL statements.



This lakehouse automatically adds new objects to its default Power BI semantic model. Don't want to sync? Go to settings to turn this off. Learn more

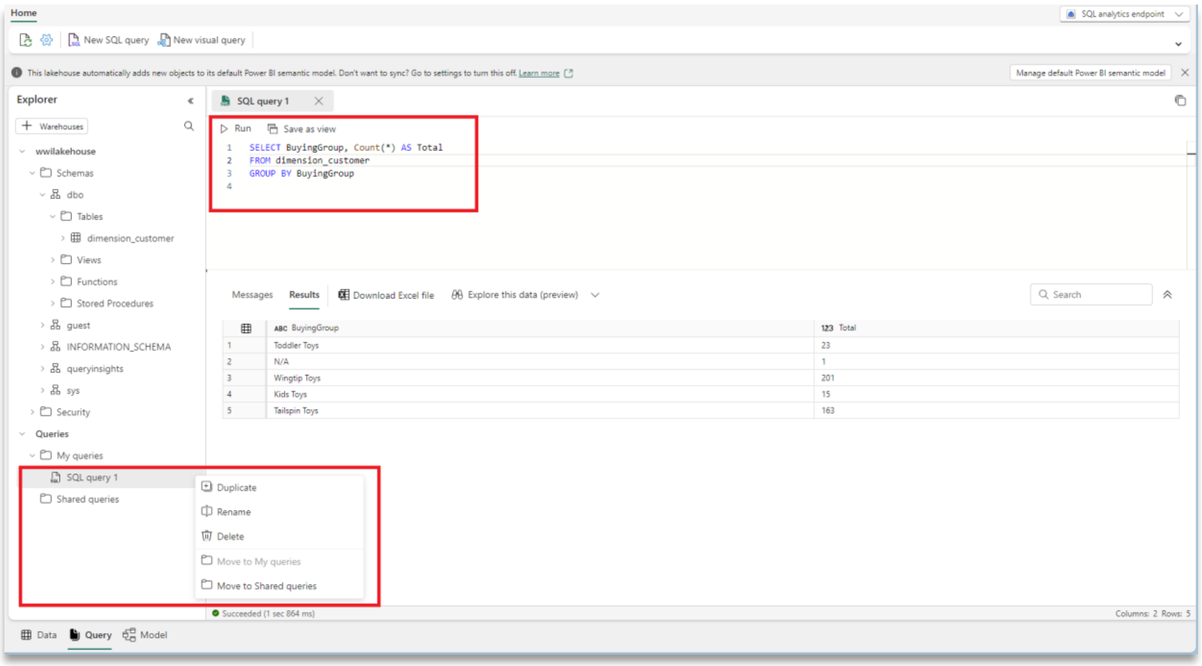
	12L CustomerKey	12L WWICustomerID	ABC Customer	ABC BillToCustomer	ABC
1	0	0	Unknown	N/A	N/A
2	102	102	Tailspin Toys (Fieldbrook, CA)	Tailspin Toys (Head Office)	No
3	103	103	Tailspin Toys (Kalvesta, KS)	Tailspin Toys (Head Office)	No
4	104	104	Tailspin Toys (Wallagrass, ME)	Tailspin Toys (Head Office)	No
5	105	105	Tailspin Toys (Tomnolen, MS)	Tailspin Toys (Head Office)	No
6	106	106	Tailspin Toys (Tumacacori, AZ)	Tailspin Toys (Head Office)	No
7	107	107	Tailspin Toys (Glen Avon, CA)	Tailspin Toys (Head Office)	No
8	108	108	Tailspin Toys (Bernie, MO)	Tailspin Toys (Head Office)	No
9	109	109	Tailspin Toys (South Laguna, CA)	Tailspin Toys (Head Office)	No
10	110	110	Tailspin Toys (North Crows Nest, IN)	Tailspin Toys (Head Office)	No
11	111	111	Tailspin Toys (Oriole Beach, FL)	Tailspin Toys (Head Office)	No
12	112	112	Tailspin Toys (Sallyards, KS)	Tailspin Toys (Head Office)	No
13	113	113	Tailspin Toys (Dahlia, NM)	Tailspin Toys (Head Office)	No
14	114	114	Tailspin Toys (Cherry Grove Beach, SC)	Tailspin Toys (Head Office)	No
15	115	115	Tailspin Toys (Bethania, NC)	Tailspin Toys (Head Office)	No
16	116	116	Tailspin Toys (Rafael Capó, PR)	Tailspin Toys (Head Office)	No
17	79	79	Tailspin Toys (Page City, KS)	Tailspin Toys (Head Office)	No
18	80	80	Tailspin Toys (Valdese, NC)	Tailspin Toys (Head Office)	No
19	81	81	Tailspin Toys (Big Moose, NY)	Tailspin Toys (Head Office)	No
20	82	82	Tailspin Toys (La Cueva, NM)	Tailspin Toys (Head Office)	No
21	83	83	Tailspin Toys (Absecon, NJ)	Tailspin Toys (Head Office)	No
22	84	84	Tailspin Toys (Aceitunas, PR)	Tailspin Toys (Head Office)	No
23	85	85	Tailspin Toys (Andrix, CO)	Tailspin Toys (Head Office)	No
24	86	86	Tailspin Toys (New Lexington, OH)	Tailspin Toys (Head Office)	No
25	87	87	Tailspin Toys (Sauquoit, NY)	Tailspin Toys (Head Office)	No
26	88	88	Tailspin Toys (Dracut, MA)	Tailspin Toys (Head Office)	No
27	89	89	Tailspin Toys (Victory Gardens, NJ)	Tailspin Toys (Head Office)	No
28	90	90	Tailspin Toys (Tolna, ND)	Tailspin Toys (Head Office)	No
29	91	91	Tailspin Toys (Alstead, NH)	Tailspin Toys (Head Office)	No

Succeeded (4 sec 80 ms)

16. Here is a sample query to aggregate the row count based on buyinggroup column of the **dimension_customer** table and its output. SQL query files are saved automatically for future references, and you can rename or delete these files appropriately based on your need.

    To run the script, click on the **Run** icon at the top of the script file.

```sql
SELECT BuyingGroup, Count(*) AS Total
FROM dimension_customer
GROUP BY BuyingGroup
```



```sql
SELECT BuyingGroup, Count(*) AS Total
FROM dimension_customer
GROUP BY BuyingGroup
```

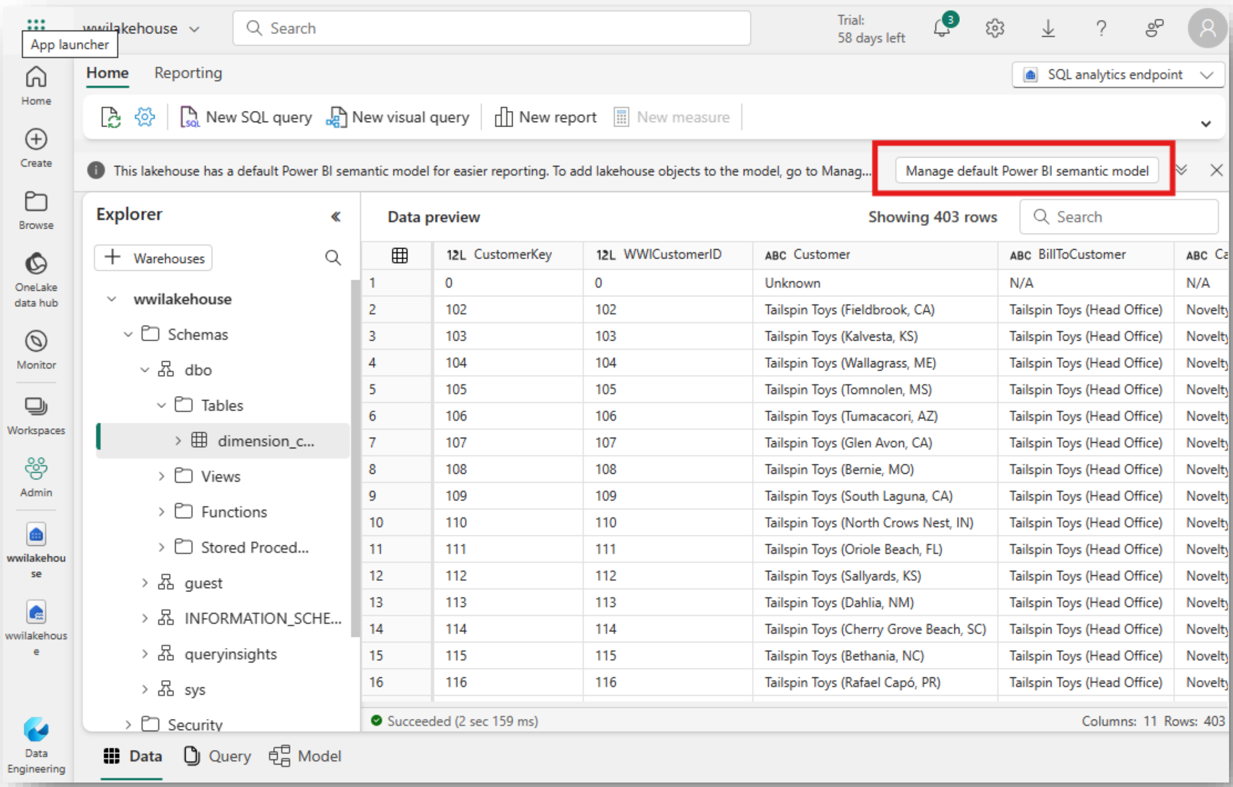
	BuyingGroup	Total
1	Toddler Toys	23
2	N/A	1
3	Wingtip Toys	201
4	Kids Toys	15
5	Tailspin Toys	163

Add table to the semantic model

In Microsoft Fabric, Power BI semantic models are a logical description of an analytical domain, with metrics, business friendly terminology, and representation, to enable deeper analysis. This semantic model is typically a star schema with facts that represent a domain, and dimensions that allow you to analyze, or slice and dice the domain to drill down, filter, and calculate different analyses.

Now that you've ingested data into a lakehouse table, we'll add that table to the **default semantic model** for the lakehouse.

1. From the SQL analytics Data view of the dimension_customer table, click **Manage default Power BI semantic model** button on the upper right.

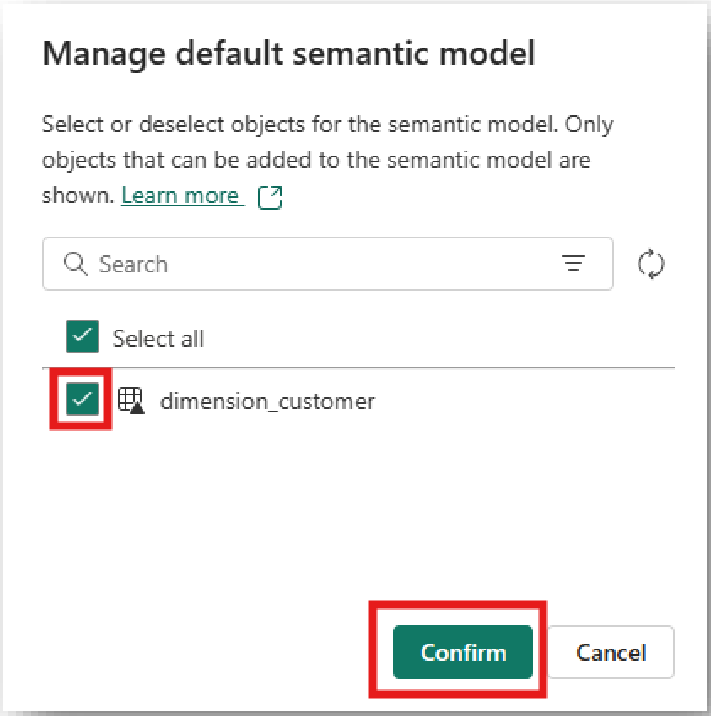


This lakehouse has a default Power BI semantic model for easier reporting. To add lakehouse objects to the model, go to Manag...

	12L CustomerKey	12L WWICustomerID	ABC Customer	ABC BillToCustomer	ABC Ca
1	0	0	Unknown	N/A	N/A
2	102	102	Tailspin Toys (Fieldbrook, CA)	Tailspin Toys (Head Office)	Novelty
3	103	103	Tailspin Toys (Kalvesta, KS)	Tailspin Toys (Head Office)	Novelty
4	104	104	Tailspin Toys (Wallagrass, ME)	Tailspin Toys (Head Office)	Novelty
5	105	105	Tailspin Toys (Tomnolen, MS)	Tailspin Toys (Head Office)	Novelty
6	106	106	Tailspin Toys (Tumacacori, AZ)	Tailspin Toys (Head Office)	Novelty
7	107	107	Tailspin Toys (Glen Avon, CA)	Tailspin Toys (Head Office)	Novelty
8	108	108	Tailspin Toys (Bernie, MO)	Tailspin Toys (Head Office)	Novelty
9	109	109	Tailspin Toys (South Laguna, CA)	Tailspin Toys (Head Office)	Novelty
10	110	110	Tailspin Toys (North Crows Nest, IN)	Tailspin Toys (Head Office)	Novelty
11	111	111	Tailspin Toys (Oriole Beach, FL)	Tailspin Toys (Head Office)	Novelty
12	112	112	Tailspin Toys (Sallyards, KS)	Tailspin Toys (Head Office)	Novelty
13	113	113	Tailspin Toys (Dahlia, NM)	Tailspin Toys (Head Office)	Novelty
14	114	114	Tailspin Toys (Cherry Grove Beach, SC)	Tailspin Toys (Head Office)	Novelty
15	115	115	Tailspin Toys (Bethania, NC)	Tailspin Toys (Head Office)	Novelty
16	116	116	Tailspin Toys (Rafael Capó, PR)	Tailspin Toys (Head Office)	Novelty

Succeeded (2 sec 159 ms)   Columns: 11 Rows: 403

2. The **Manage default semantic model** dialog will appear. Select the dimension_customer table and click **Confirm**.

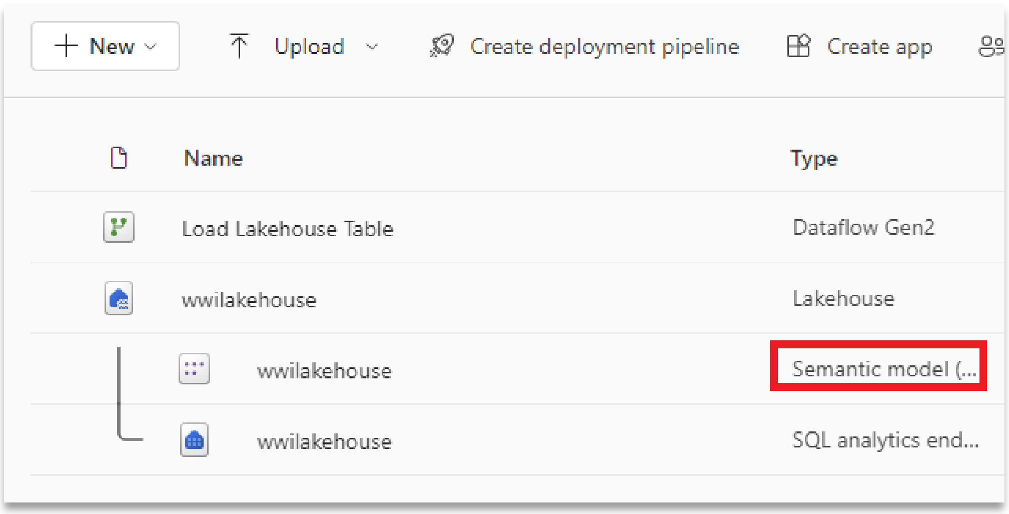


Manage default semantic model

Select or deselect objects for the semantic model. Only objects that can be added to the semantic model are shown. Learn more

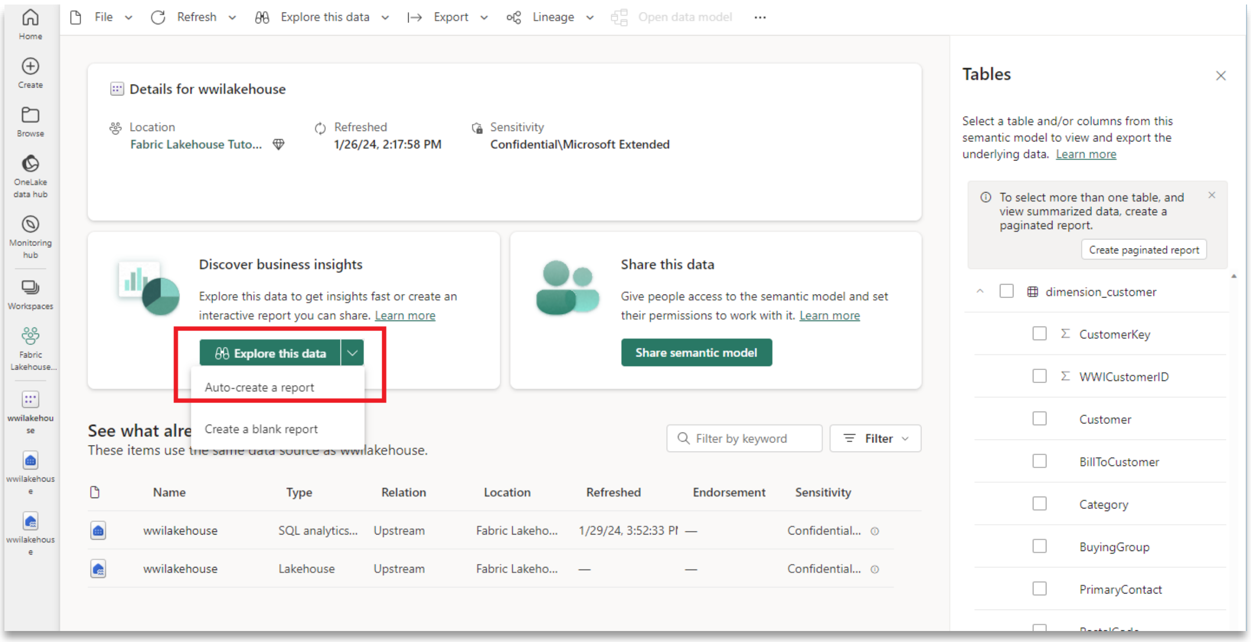
Building a report

1. In the artifact view of the workspace, click on **wwilakehouse** default semantic model, which gets created automatically with the same name of the lakehouse when you create a lakehouse.



Name	Type
Load Lakehouse Table	Dataflow Gen2
wwilakehouse	Lakehouse
wwilakehouse	Semantic model (...
wwilakehouse	SQL analytics end...

2. On the semantic model screen, you can view all the tables. You will have options to create reports either from scratch, paginated report or let Power BI do magic for you by automatically creating a report based on your data. For the purpose of this module, click on **Auto-create a report** under **Explore this data**. In the next module, we will create a report from scratch.



Location: Fabric Lakehouse Tuto...
Refreshed: 1/26/24, 2:17:58 PM
Sensitivity: Confidential\Microsoft Extended

Explore this data to get insights fast or create an interactive report you can share. Learn more

Give people access to the semantic model and set their permissions to work with it. Learn more

These items use the same data source as wwilakehouse.

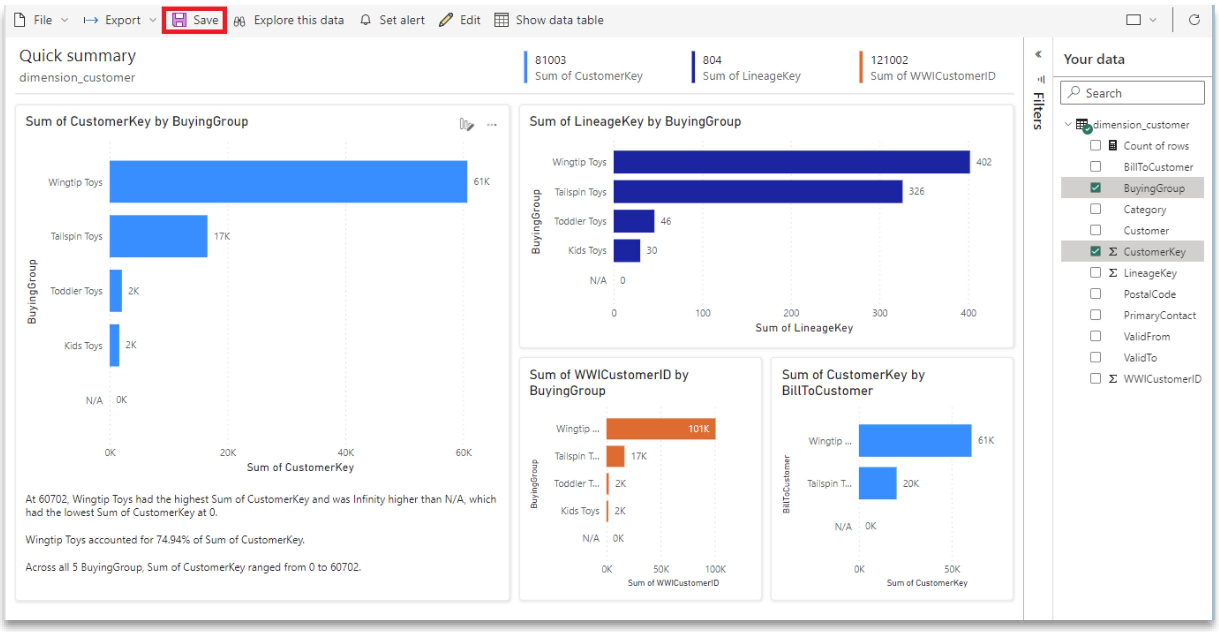
Select a table and/or columns from this semantic model to view and export the underlying data. Learn more

To select more than one table, and view summarized data, create a paginated report.

Name	Type	Relation	Location	Refreshed	Endorsement	Sensitivity
wwilakehouse	SQL analytics...	Upstream	Fabric Lakeho...	1/29/24, 3:52:33 PI	—	Confidential...
wwilakehouse	Lakehouse	Upstream	Fabric Lakeho...	—	—	Confidential...

3. Since the table is a dimension and there are no measures in it, Power BI smartly creates a measure for the row sum and aggregates it across different columns and creates different charts as below.

   You can save this report for the future by clicking on **Save** button at the top ribbon and giving it a name. You can further make changes to this report to meet your requirement by including or excluding additional tables or columns.



At 60702, Wingtip Toys had the highest Sum of CustomerKey and was Infinity higher than N/A, which had the lowest Sum of CustomerKey at 0.

Wingtip Toys accounted for 74.94% of Sum of CustomerKey.

Across all 5 BuyingGroup, Sum of CustomerKey ranged from 0 to 60702.

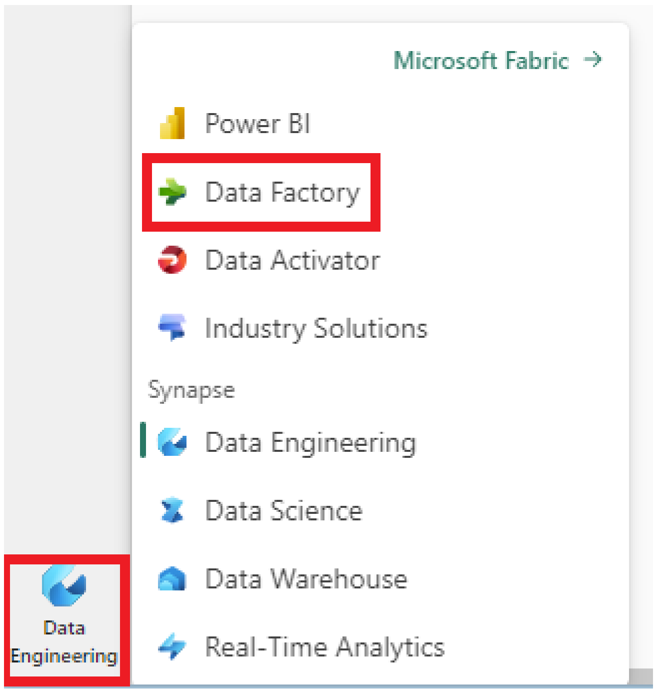
Module 2: Ingest, Prep and Analyze

This module is going to build on the work you completed in the previous module and ingest additional tables (dimensions and fact) of the dimensional model of Wide World Importers (WWI) as mentioned in the Introduction section of this document. Next, you will use notebooks with Spark runtime to transform and prepare the data. Finally, you will create Power BI data model and create a report from scratch.

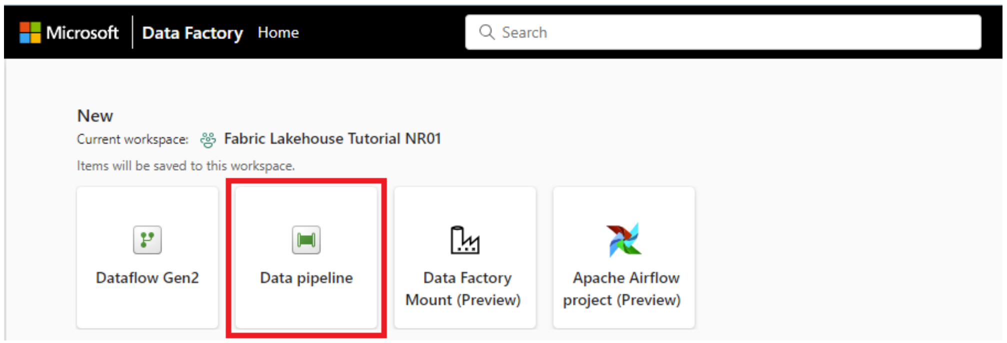
Data Ingestion

In this section, you will use **Copy data activity** of **Data Factory pipeline** to ingest sample data from source (Azure storage account) to the **Files** section of the lakehouse you created earlier.

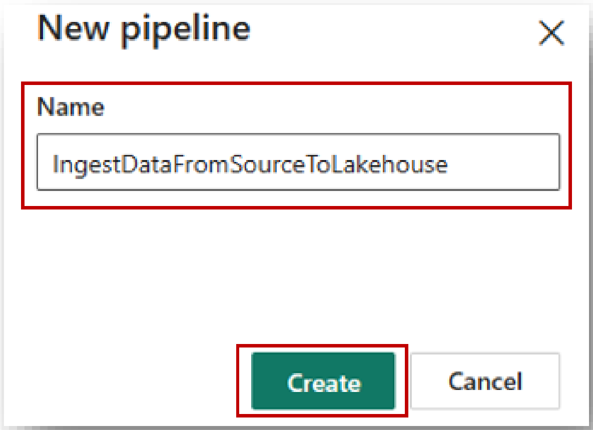
1. On the bottom left of the screen, click on the workload switcher, and then select **Data Factory**.



2. Click on **Data pipeline** under **New** to create a new data pipeline.

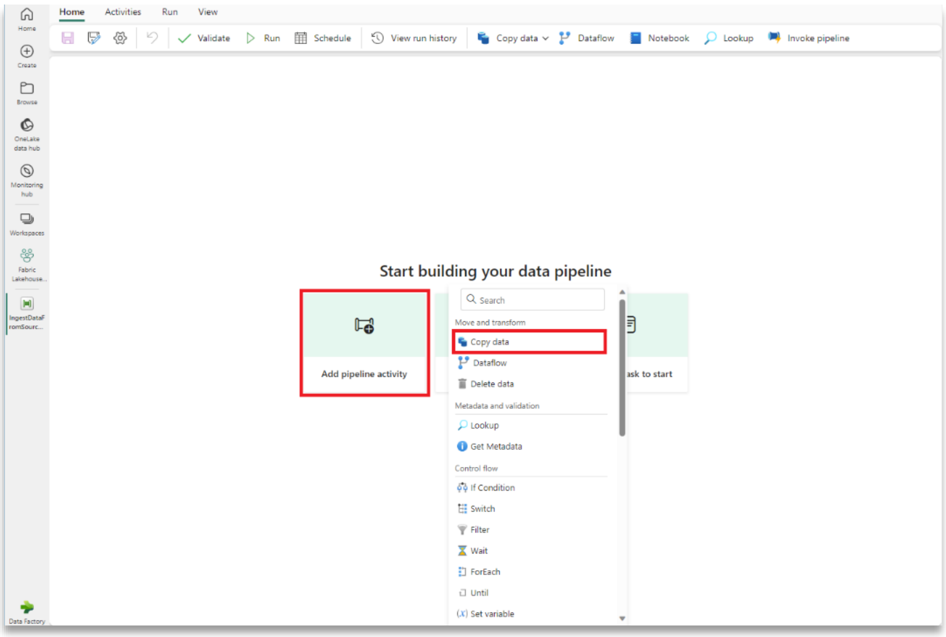

Microsoft
Data Factory
Home
Search
New
Current workspace: Fabric Lakehouse Tutorial NR01
Items will be saved to this workspace.
Dataflow Gen2
Data pipeline
Data Factory Mount (Preview)
Apache Airflow project (Preview)

3. For the **New pipeline**, specify the name as **IngestDataFromSourceToLakehouse** and click on **Create**. This will create a new data factory pipeline and open it on the screen to work on it.

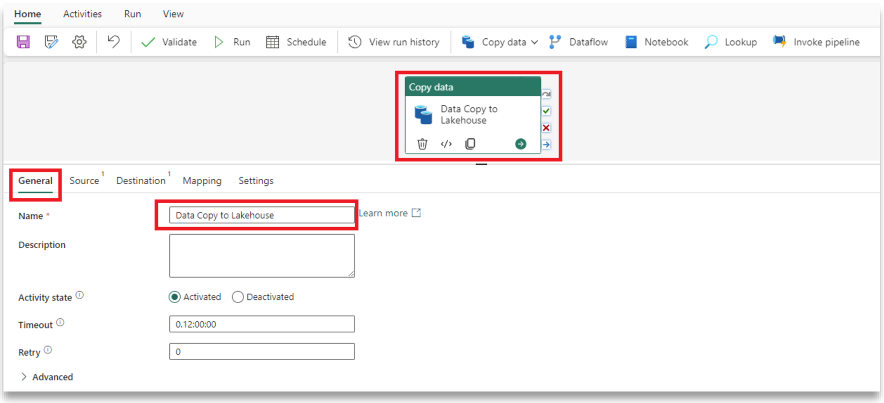


Name: IngestDataFromSourceToLakehouse

4. On the newly created data factory pipeline, click **Add pipeline activity** to add an activity to the pipeline and click on **Copy data**. This will add copy data activity to the pipeline canvas.

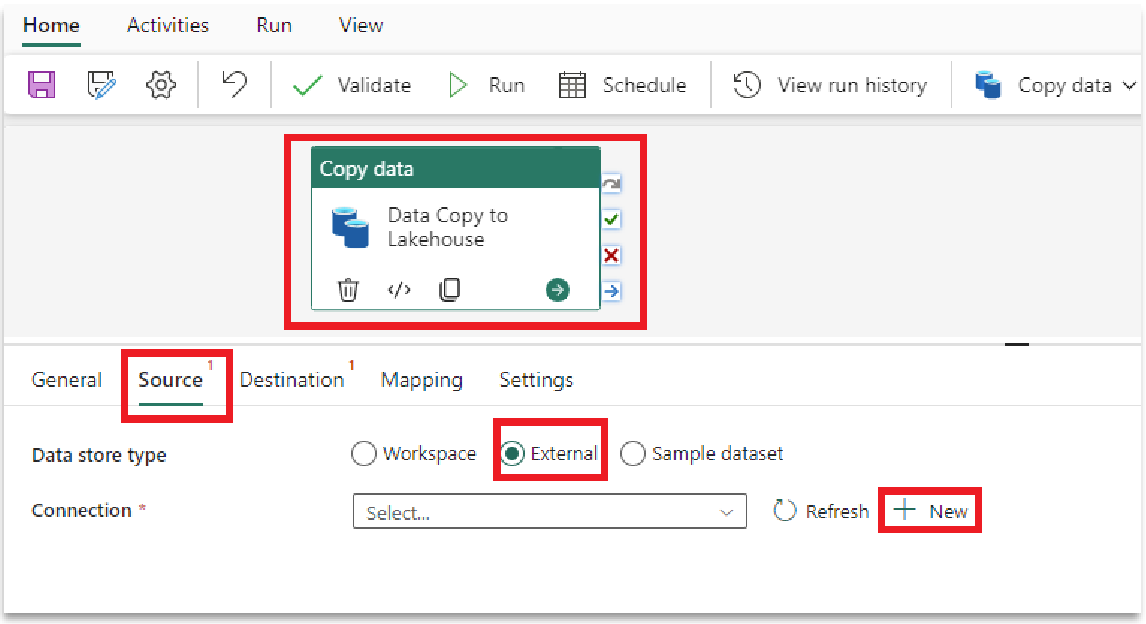


5. Select the newly added copy data activity to the canvas, which will show activity properties at the bottom. Under **General** tab, specify the name for the copy data activity **Data Copy to Lakehouse**.



Name *: Data Copy to Lakehouse
Description:
Activity state: [✓ Activated] Deactivated
Timeout: 0.12:00:00
Retry: 0

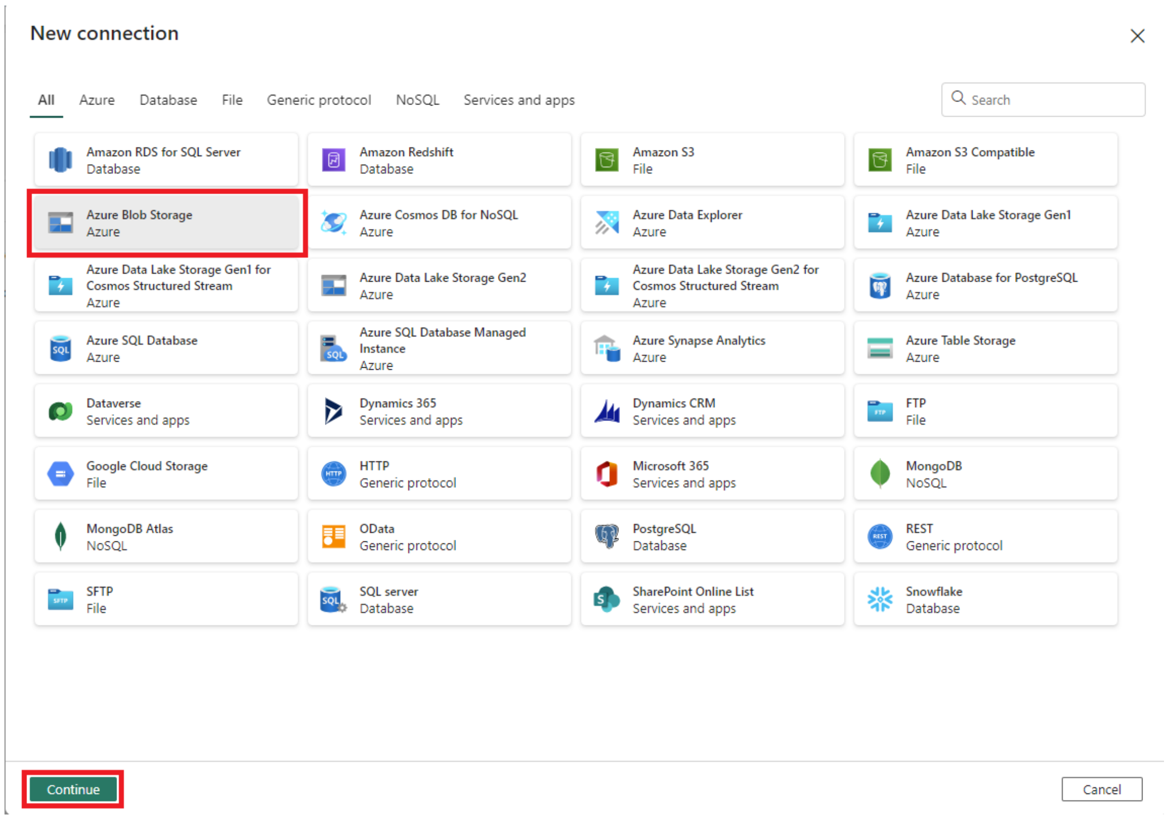
6. Under **Source** tab of the selected copy data activity, select **External** as **Data store type** and then click on **+ New** to create a new connection to data source.



Data store type: Workspace [✓ External] Sample dataset

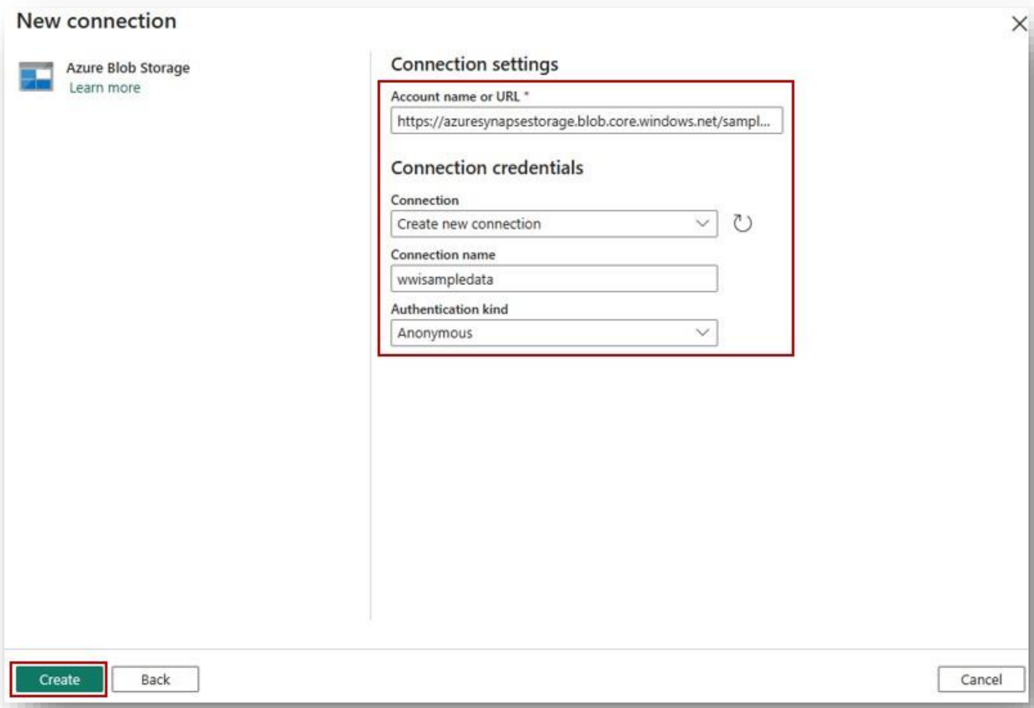
Connection *: Select...

7. For this tutorial, all the sample data is available in a public container of Azure blob storage so you will connect to this container to copy data from. On the **New connection** wizard, select **Azure Blob Storage** and then click on **Continue**.


New connection
All
Azure
Database
File
Generic protocol
NoSQL
Services and apps
Search
Amazon RDS for SQL Server Database
Amazon Redshift Database
Amazon S3 File
Amazon S3 Compatible File
Azure Blob Storage Azure
Azure Cosmos DB for NoSQL Azure
Azure Data Explorer Azure
Azure Data Lake Storage Gen1 Azure
Azure Data Lake Storage Gen1 for Cosmos Structured Stream Azure
Azure Data Lake Storage Gen2 Azure
Azure Data Lake Storage Gen2 for Cosmos Structured Stream Azure
Azure Database for PostgreSQL Azure
Azure SQL Database Azure
Azure SQL Database Managed Instance Azure
Azure Synapse Analytics Azure
Azure Table Storage Azure
Dataverse Services and apps
Dynamics 365 Services and apps
Dynamics CRM Services and apps
FTP File
Google Cloud Storage File
HTTP Generic protocol
Microsoft 365 Services and apps
MongoDB NoSQL
MongoDB Atlas NoSQL
OData Generic protocol
PostgreSQL Database
REST Generic protocol
SFTP File
SQL server Database
SharePoint Online List Services and apps
Snowflake Database
Continue
Cancel

8. On the next screen of the **New connection** wizard, please specify these details and click on **Create** to create the connection to the data source.

Account name or URI	https://azuresynapsestorage.blob.core.windows.net/sampledata
Connection	**Create new connection**
Connection name	**wwisampledata**
Authentication kind	**Anonymous**


New connection

Azure Blob Storage
Learn more

Connection settings

Account name or URL *
https://azuresynapsestorage.blob.core.windows.net/sampl...

Connection credentials

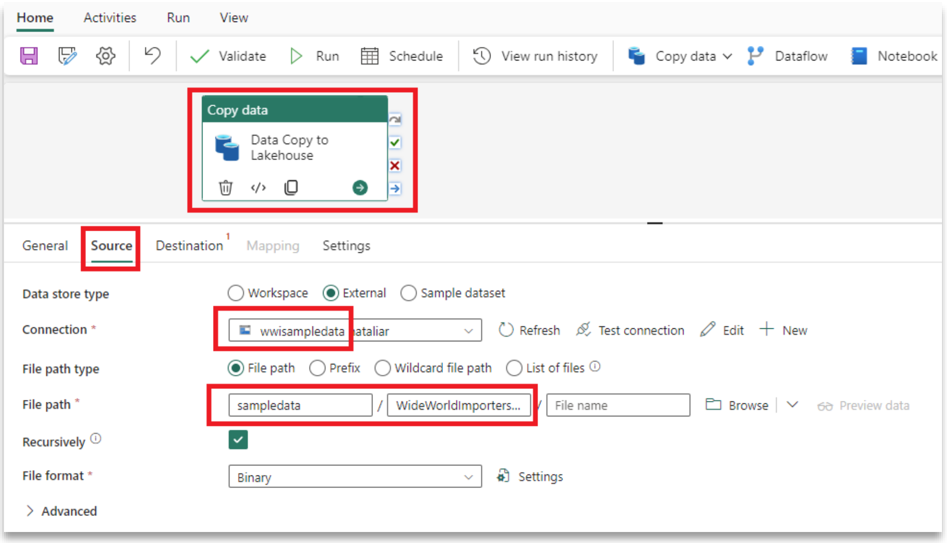
Connection: Create new connection

Connection name: wwisampledata

Authentication kind: Anonymous

9. Once the new connection is created, you will return to **Source** tab of the copy data activity and newly created connection will be selected by default. Please specify these properties before moving to the destination settings.

Data store type	**External**
Connection	**wwisampledata**
File path type	**File path**
File path	Container name (first text box) – **sampledata** Directory name (second text box) – **WideWorldImportersDW/parquet**
Recursively	**Checked**
File Format	**Binary**



Data store type: Workspace [✓ External] Sample dataset

Connection *: wwisampledata

File path type: [✓ File path] Prefix Wildcard file path List of files

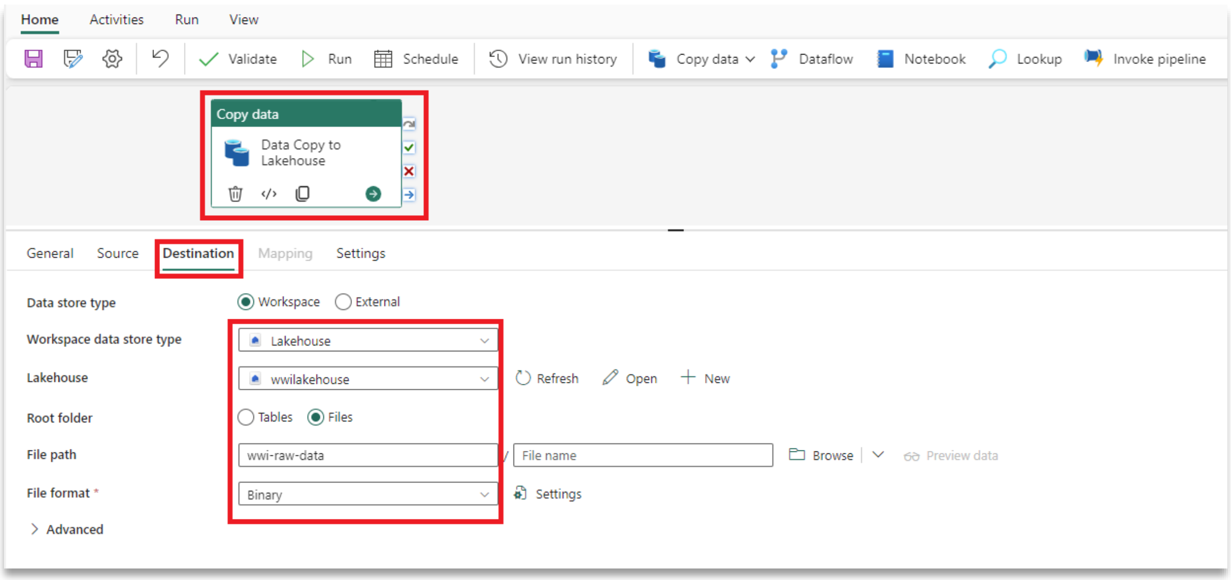
File path *: sampledata / WideWorldImporters... / File name

Recursively: ✓

File format *: Binary

10. Under **Destination** tab of the selected copy data activity, please specify these properties:

Data store type	**Workspace**
Workspace data store type	**Lakehouse**
Lakehouse	**Wwilakehouse**
Root Folder	**Files**
File path	Directory name (first text box) – **wwi-raw-data**
File Format	**Binary**



Data store type: [✓ Workspace] External

Workspace data store type: Lakehouse

Lakehouse: wwilakehouse — Refresh, Open, New

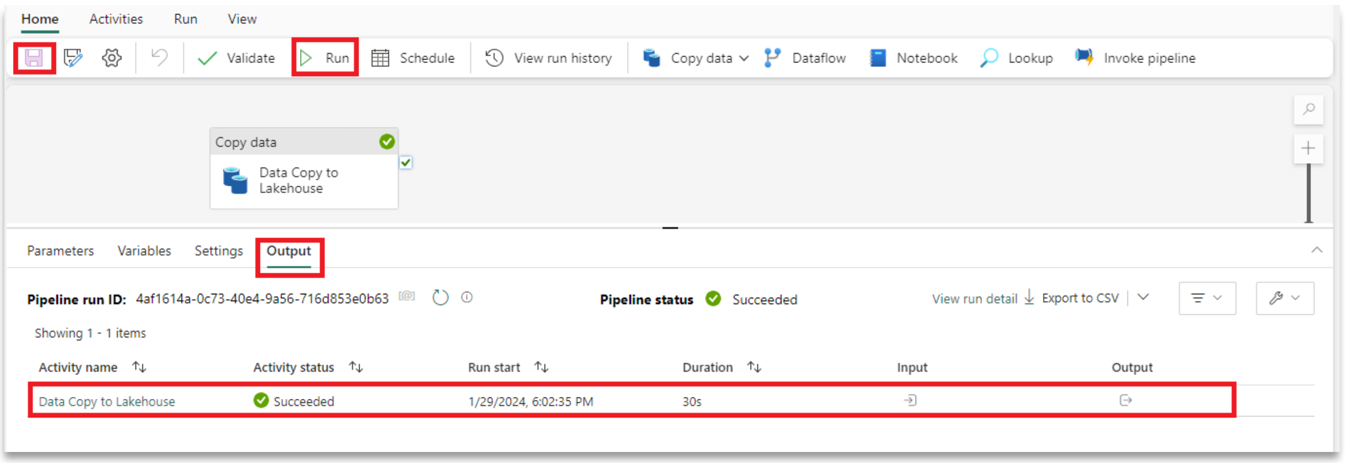
Root folder: Tables [✓ Files]

File path: wwi-raw-data / File name — Browse, Preview data

File format *: Binary — Settings

> Advanced

11. At this time, you have completed configuring copy data activity. Click on **Save** button under **Home** to save all these details and click on **Run** to kick off execution of this pipeline and its activity. You can also schedule pipelines to refresh data at defined intervals to meet your business requirements, however for this module, we will run the pipeline once by clicking on **Run** button. This will trigger data copy from the underlying data source to the specified lakehouse and might take up to a minute to complete. You can monitor the execution of the pipeline and its activity under **Output** tab which appears when you click anywhere on the canvas. Optionally, you can click on the activity name **"Data Copy to Lakehouse"** to look at the details of data transfer.



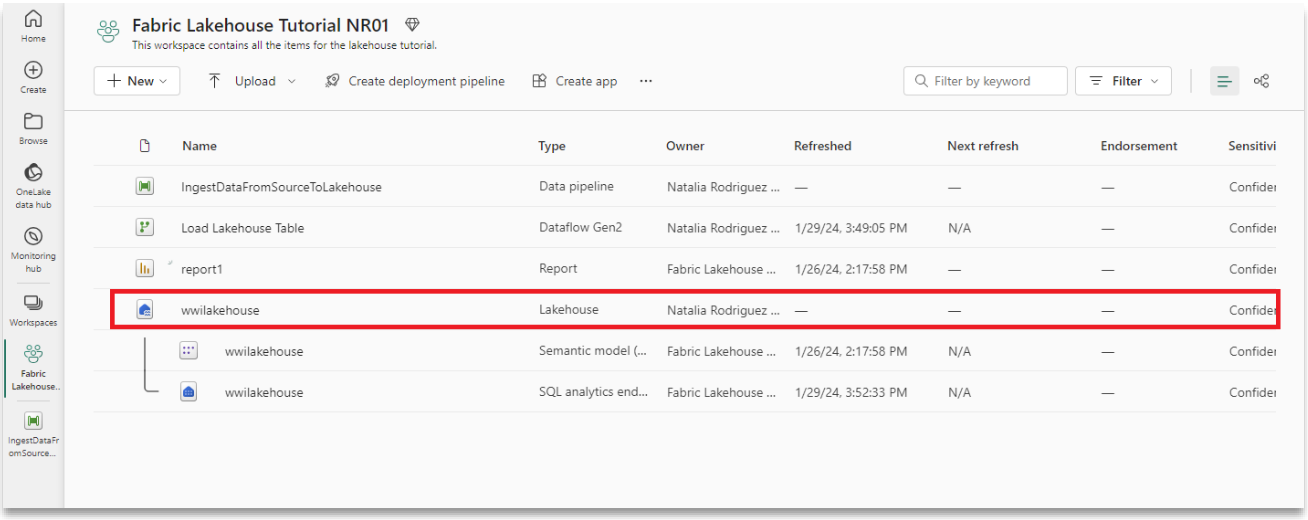
Pipeline run ID: 4af1614a-0c73-40e4-9a56-716d853e0b63

Pipeline status Succeeded

Showing 1 - 1 items

Activity name	Activity status	Run start	Duration	Input	Output
Data Copy to Lakehouse	Succeeded	1/29/2024, 6:02:35 PM	30s		

12. Once the data copy is completed, go to items view of the workspace and click on **wwilakehouse** to launch **Lakehouse explorer** of this selected lakehouse.

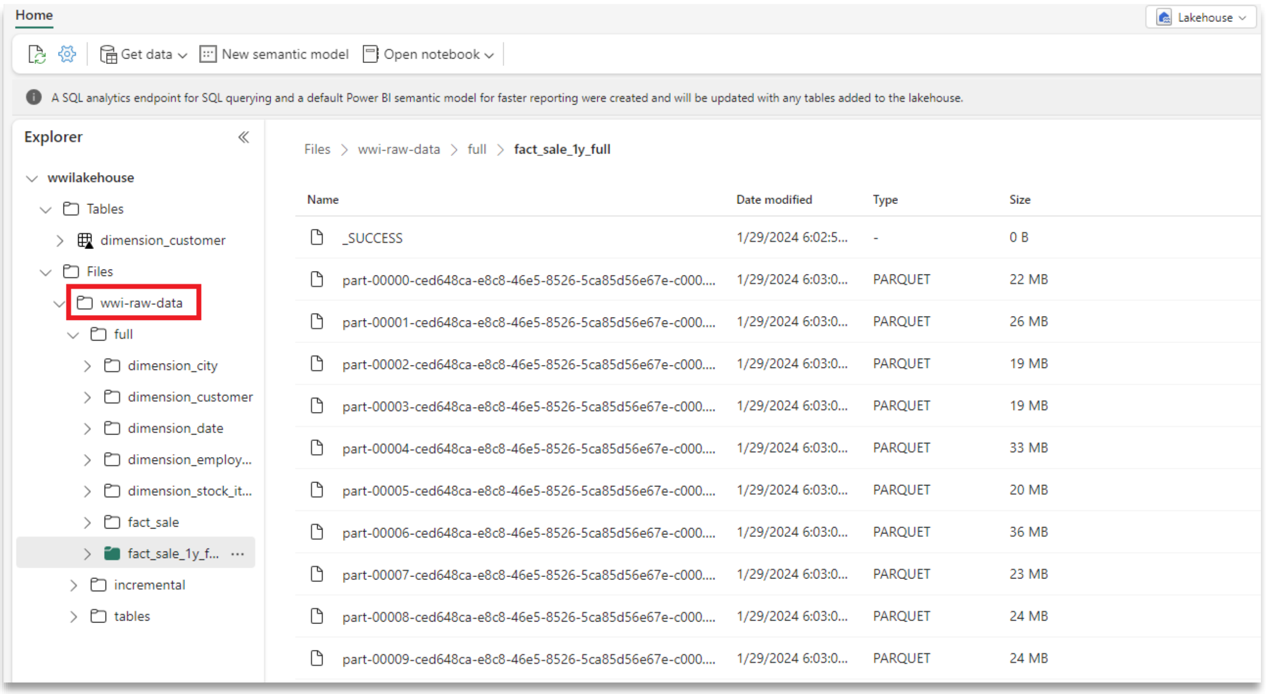


Fabric Lakehouse Tutorial NR01

This workspace contains all the items for the lakehouse tutorial.

Name	Type	Owner	Refreshed	Next refresh	Endorsement	Sensitivi
IngestDataFromSourceToLakehouse	Data pipeline	Natalia Rodriguez ...	—	—	—	Confide
Load Lakehouse Table	Dataflow Gen2	Natalia Rodriguez ...	1/29/24, 3:49:05 PM	N/A	—	Confide
report1	Report	Fabric Lakehouse ...	1/26/24, 2:17:58 PM	—	—	Confide
wwilakehouse	Lakehouse	Natalia Rodriguez ...	—	—	—	Confide
wwilakehouse	Semantic model (...	Fabric Lakehouse ...	1/26/24, 2:17:58 PM	N/A	—	Confide
wwilakehouse	SQL analytics end...	Fabric Lakehouse ...	1/29/24, 3:52:33 PM	N/A	—	Confide

13. In the **Lakehouse explorer** view, you would notice a new folder **wwi-raw-data** has been created and data for all the tables have been copied here.



A SQL analytics endpoint for SQL querying and a default Power BI semantic model for faster reporting were created and will be updated with any tables added to the lakehouse.

Explorer: wwilakehouse > Tables > dimension_customer; Files > wwi-raw-data > full > dimension_city, dimension_customer, dimension_date, dimension_employ..., dimension_stock_it..., fact_sale, fact_sale_1y_f...; incremental; tables

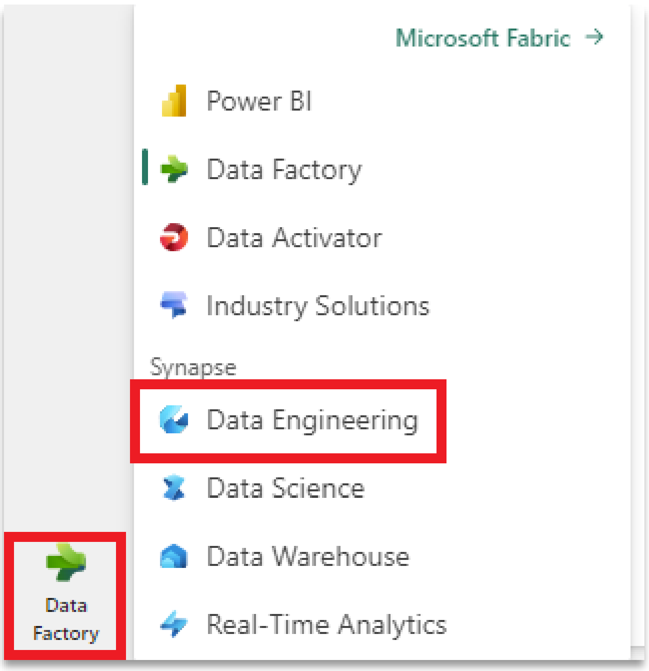
Files > wwi-raw-data > full > fact_sale_1y_full

Name	Date modified	Type	Size
_SUCCESS	1/29/2024 6:02:5...	-	0 B
part-00000-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	22 MB
part-00001-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	26 MB
part-00002-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	19 MB
part-00003-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	19 MB
part-00004-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	33 MB
part-00005-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	20 MB
part-00006-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	36 MB
part-00007-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	23 MB
part-00008-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	24 MB
part-00009-ced648ca-e8c8-46e5-8526-5ca85d56e67e-c000....	1/29/2024 6:03:0...	PARQUET	24 MB

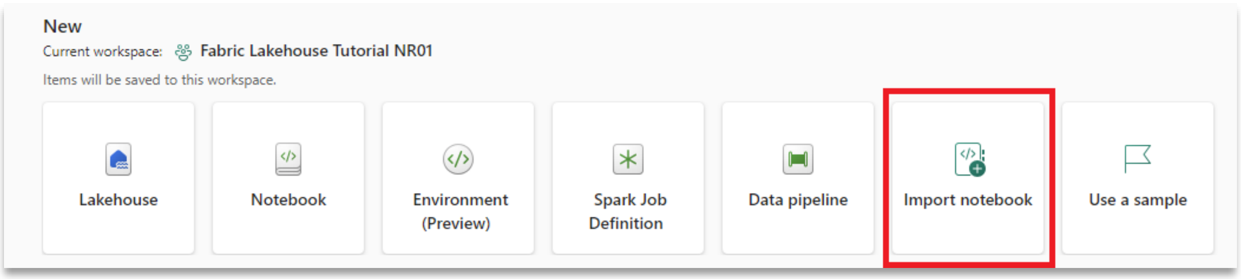
Data Preparation

Now since we have raw data already ingested from source to the **Files** section of the lakehouse, you can take this data, transform, and prepare it to create delta tables.

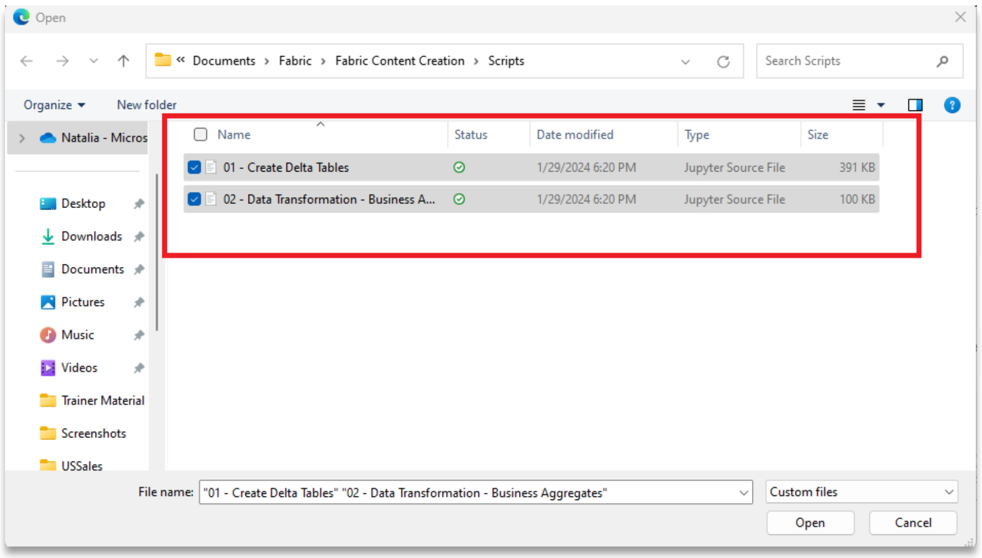
1. Download the set of notebooks found in the Scripts folder
2. From the workload switcher located at the bottom left of the screen, select **Data engineering**.



3. Select **Import notebook** from the **New** section at the top of the landing page.



4. Select **Upload** from the **Import status** pane that opens on the right side of the screen.
5. Select all the notebooks that were downloaded and/or unzipped in step 1 of this section.
6. Select **Open**. A notification indicating the status of the import will appear in the top right corner of the browser window.



Open

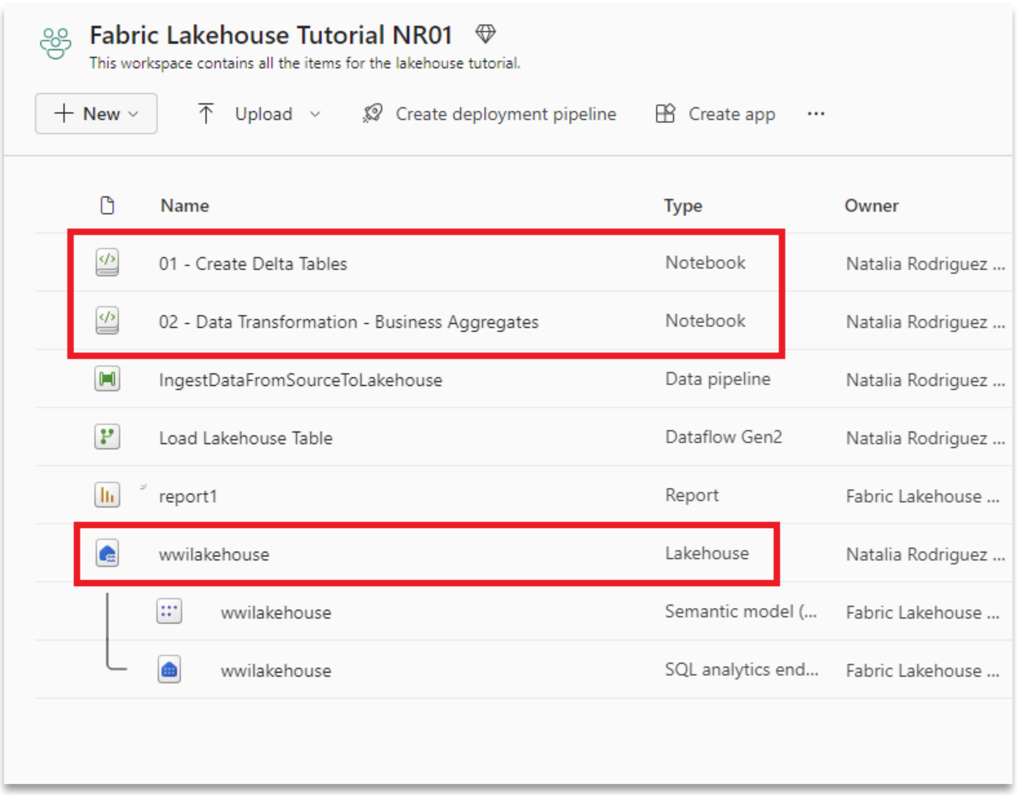
Documents › Fabric › Fabric Content Creation › Scripts

Name	Status	Date modified	Type	Size
01 - Create Delta Tables	✓	1/29/2024 6:20 PM	Jupyter Source File	391 KB
02 - Data Transformation - Business A...	✓	1/29/2024 6:20 PM	Jupyter Source File	100 KB

File name: "01 - Create Delta Tables" "02 - Data Transformation - Business Aggregates"

Custom files

7. After the import of notebooks is successful, you can go to items view of the workspace and see these newly imported notebooks. Click on **wwilakehouse** lakehouse to open it.

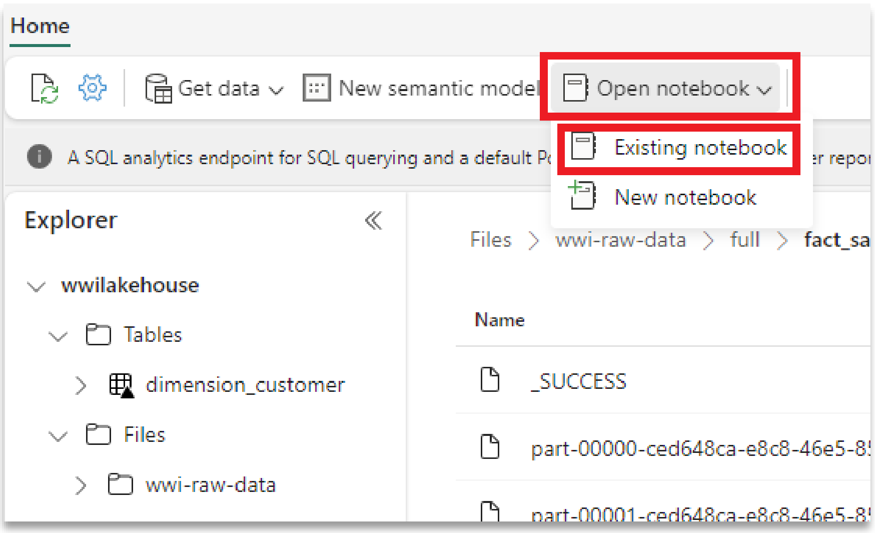


Fabric Lakehouse Tutorial NR01

This workspace contains all the items for the lakehouse tutorial.

Name	Type	Owner
01 - Create Delta Tables	Notebook	Natalia Rodriguez ...
02 - Data Transformation - Business Aggregates	Notebook	Natalia Rodriguez ...
IngestDataFromSourceToLakehouse	Data pipeline	Natalia Rodriguez ...
Load Lakehouse Table	Dataflow Gen2	Natalia Rodriguez ...
report1	Report	Fabric Lakehouse ...
wwilakehouse	Lakehouse	Natalia Rodriguez ...
wwilakehouse	Semantic model (...	Fabric Lakehouse ...
wwilakehouse	SQL analytics end...	Fabric Lakehouse ...

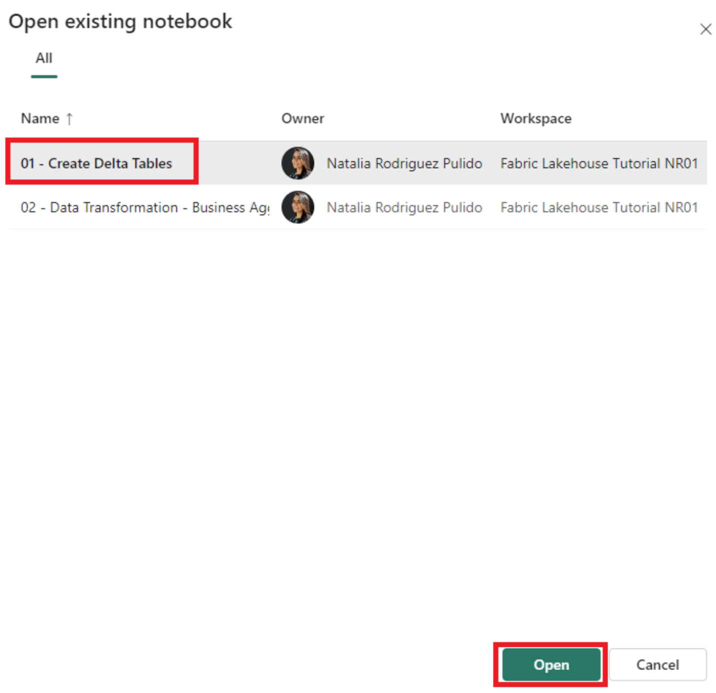
8. Once the **wwilakehouse** lakehouse is opened, click on **Open notebook** > **Existing notebook** on the ribbon at the top.



A SQL analytics endpoint for SQL querying and a default P

Name
_SUCCESS
part-00000-ced648ca-e8c8-46e5-8
part-00001-ced648ca-e8c8-46e5-8

9. From the list of existing notebooks, select the **01 - Create Delta Tables** notebook and click on **Open** button.



Name ↑	Owner	Workspace
01 - Create Delta Tables	Natalia Rodriguez Pulido	Fabric Lakehouse Tutorial NR01
02 - Data Transformation - Business Agi	Natalia Rodriguez Pulido	Fabric Lakehouse Tutorial NR01

10. Once the notebook is opened, in the **Lakehouse explorer** you will notice the notebook is already linked to your opened lakehouse.

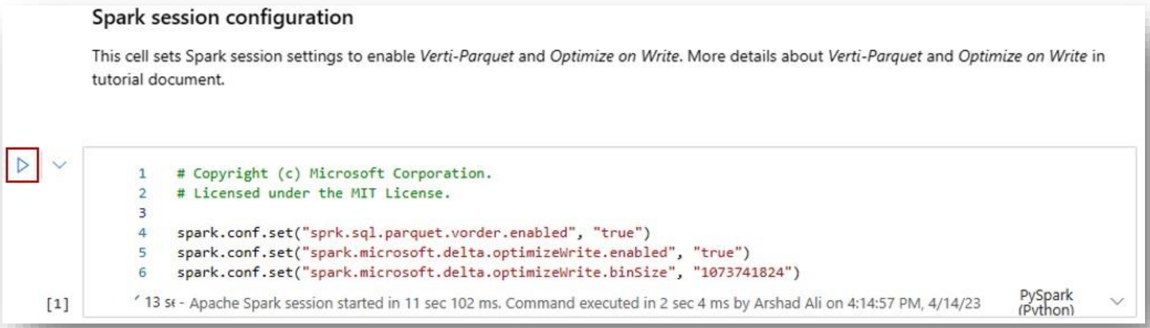
Note
Fabric provides these unique capabilities for writing optimized delta lake files:

- V-Order – Fabric includes Microsoft 's unique V-Order IP. V-Order transparently optimizes the Delta Lake files in a way that is highly optimized by Fabric compute engines, often resulting in 3x-4x compression improvement and up to 10x performance acceleration over Delta Lake files not optimized using VertiParquet while still maintaining full Delta Lake format compliance.

- Optimize write – Apache Spark performs most efficiently when using standardized larger file sizes. The relation between the file size, the number of files, the number of Spark workers and Spark's configurations play a critical role in performance. Ingestion workloads into Delta Lake tables may have the inherited characteristic of constantly writing lots of small files; this scenario is commonly known as the "small files problem". To overcome this problem, Spark in Fabric includes an Optimize Write feature that reduces the number of files written and aims to increase individual file size of the written data. It dynamically optimizes partitions while generating files with a default 128 MB size. The target file size may be changed per workload requirements using configurations.

11. Before you write data as delta lake tables in the **Tables** section of the lakehouse, you are going to use two features (**V-Order** and **Optimize Write**) of Fabric for optimized data writing and for subsequent better reading performance. To enable these features in your session you can set these configurations in the first cell of your notebook - eventually these features will be by default enabled for the Spark session.

    To start execution, click **Run All** under **Home** at the top to start execution of the notebook and all its cells in the sequence or click **Run** icon on the left of the cell or hit **SHIFT+ENTER** while control is in the cell to execute code from that specific cell.



Spark session configuration

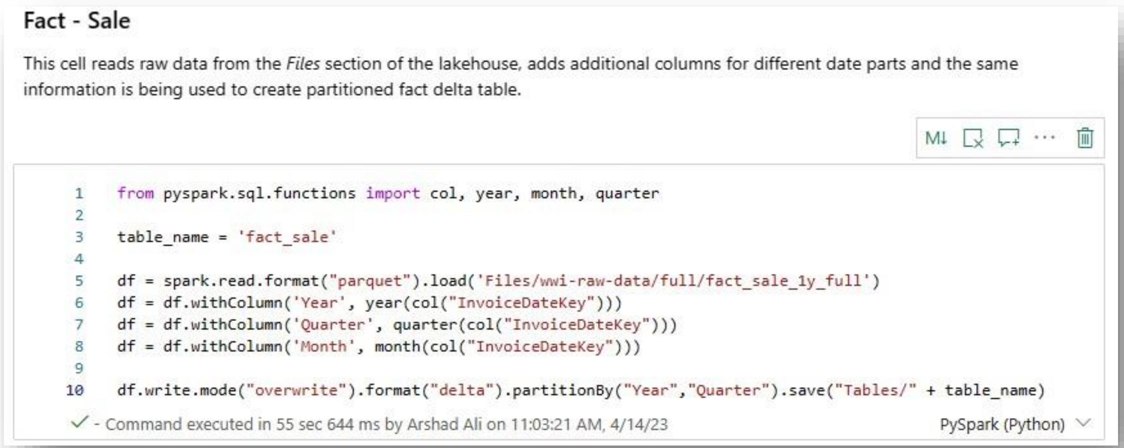
This cell sets Spark session settings to enable *Verti-Parquet* and *Optimize on Write*. More details about *Verti-Parquet* and *Optimize on Write* in tutorial document.

```
# Copyright (c) Microsoft Corporation.
# Licensed under the MIT License.

spark.conf.set("sprk.sql.parquet.vorder.enabled", "true")
spark.conf.set("spark.microsoft.delta.optimizeWrite.enabled", "true")
spark.conf.set("spark.microsoft.delta.optimizeWrite.binSize", "1073741824")
```

[1] 13 se - Apache Spark session started in 11 sec 102 ms. Command executed in 2 sec 4 ms by Arshad Ali on 4:14:57 PM, 4/14/23

The first thing you would have noticed when executing this cell is that you didn't have to specify the underlying Spark pool or cluster details as Fabric provides it through the concepts of Live Pool i.e., every Fabric workspace comes pre-wired with a default Spark pool, called Live Pool. This means that when users create notebooks, they don't have to worry about specifying any Spark configurations or cluster details (or something like that) and when they execute their first command in the notebooks the live pool kicks in and is up in a few seconds after establishing their Spark session and starts executing the code in the cell. Subsequent code execution is almost instantaneous in this notebook as long as the Spark session is active.

12. Next, you will read raw data from the **Files** section of the lakehouse, add additional columns for different date parts as part of the transformation. Finally, you will use partitionBy Spark API to partition the data before writing it as delta table based on the newly created data part columns (Year and Quarter).


Fact - Sale

This cell reads raw data from the *Files* section of the lakehouse, adds additional columns for different date parts and the same information is being used to create partitioned fact delta table.

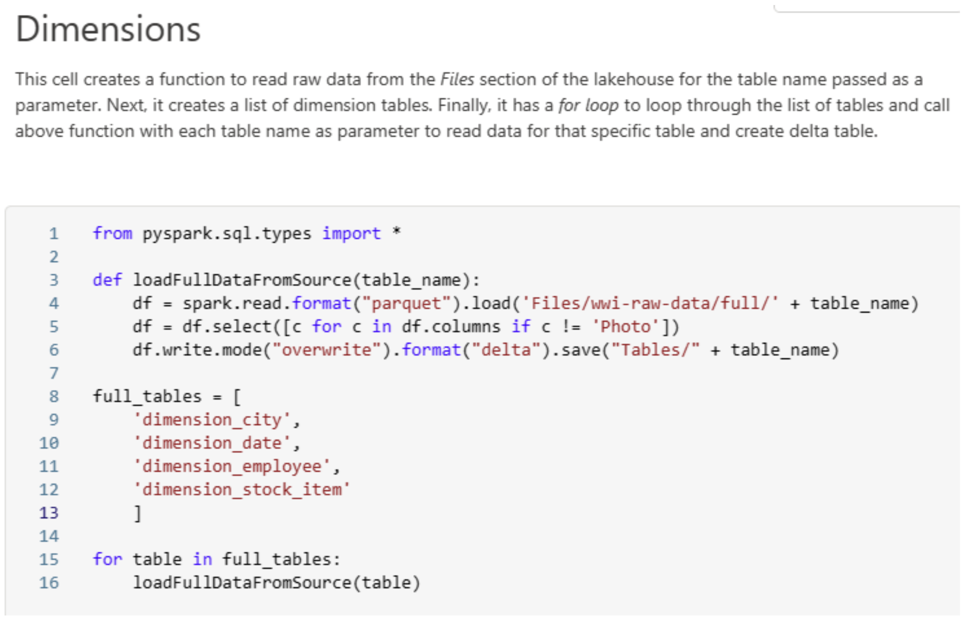
```python
from pyspark.sql.functions import col, year, month, quarter

table_name = 'fact_sale'

df = spark.read.format("parquet").load('Files/wwi-raw-data/full/fact_sale_1y_full')
df = df.withColumn('Year', year(col("InvoiceDateKey")))
df = df.withColumn('Quarter', quarter(col("InvoiceDateKey")))
df = df.withColumn('Month', month(col("InvoiceDateKey")))

df.write.mode("overwrite").format("delta").partitionBy("Year","Quarter").save("Tables/" + table_name)
```

✓ - Command executed in 55 sec 644 ms by Arshad Ali on 11:03:21 AM, 4/14/23

PySpark (Python)

```
from pyspark.sql.functions import col, year, month, quarter

table_name = 'fact_sale'

df = spark.read.format("parquet").load('Files/wwi-raw-data/full/fact_sale_1y_full')
df = df.withColumn('Year', year(col("InvoiceDateKey")))
df = df.withColumn('Quarter', quarter(col("InvoiceDateKey")))
df = df.withColumn('Month', month(col("InvoiceDateKey")))

df.write.mode("overwrite").format("delta").partitionBy("Year","Quarter").save("Tables/" + table_name)
```

13. After fact data load, you can move on to loading data for the rest of the dimensions. The following cell creates a function to read raw data from the **Files** section of the lakehouse for each of table names passed as a parameter. Next, it creates a list of dimension tables. Finally, it has a for loop to loop through the list of tables and call created function with each table name as parameter to read data for that specific table and create delta table respectively.

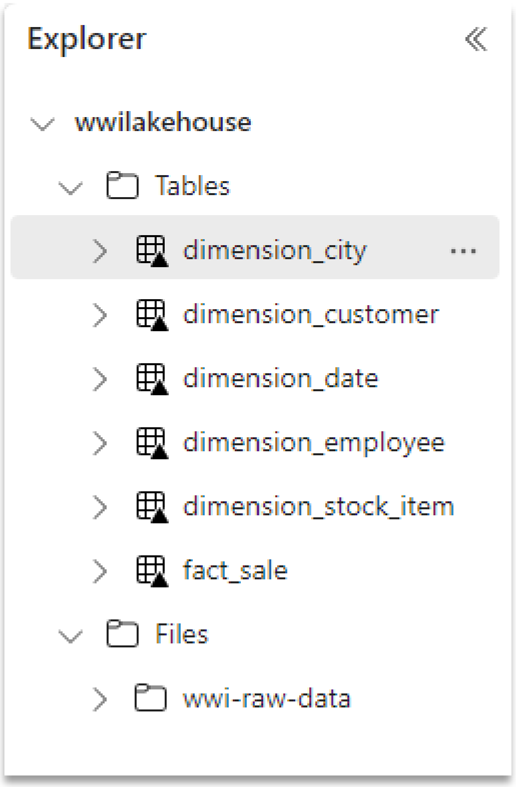

Dimensions

This cell creates a function to read raw data from the *Files* section of the lakehouse for the table name passed as a parameter. Next, it creates a list of dimension tables. Finally, it has a *for loop* to loop through the list of tables and call above function with each table name as parameter to read data for that specific table and create delta table.

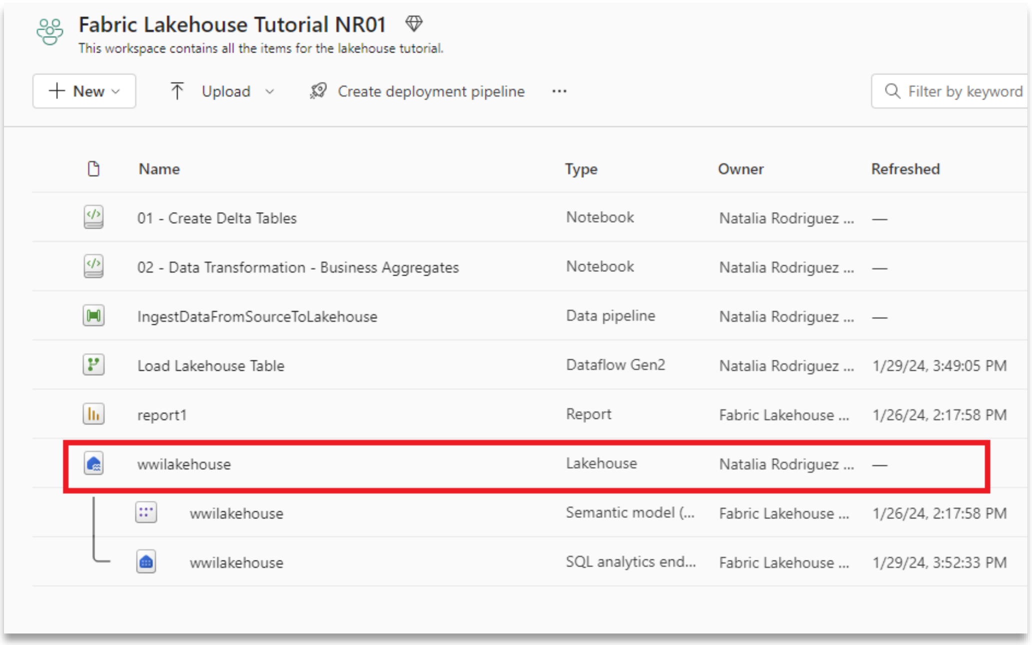
```python
from pyspark.sql.types import *

def loadFullDataFromSource(table_name):
    df = spark.read.format("parquet").load('Files/wwi-raw-data/full/' + table_name)
    df = df.select([c for c in df.columns if c != 'Photo'])
    df.write.mode("overwrite").format("delta").save("Tables/" + table_name)

full_tables = [
    'dimension_city',
    'dimension_date',
    'dimension_employee',
    'dimension_stock_item'
    ]

for table in full_tables:
    loadFullDataFromSource(table)
```

```
from pyspark.sql.types import *

def loadFullDataFromSource(table_name):
            df = spark.read.format("parquet").load('Files/wwi-raw-data/full/' +
       table_name)
  df = df.select([c for c in df.columns if c != 'Photo'])
            df.write.mode("overwrite").format("delta").save("Tables/" + table_name)

full_tables = [
            'dimension_city',
            'dimension_date',
            'dimension_employee',
            'dimension_stock_item'
            ]

for table in full_tables:
            loadFullDataFromSource(table)
```

14. You can validate created tables by right clicking and selecting refresh on **wwilakehouse** lakehouse and you will notice these created tables.



15. Please go the items view of the workspace again and click on **wwilakehouse** lakehouse to open it.

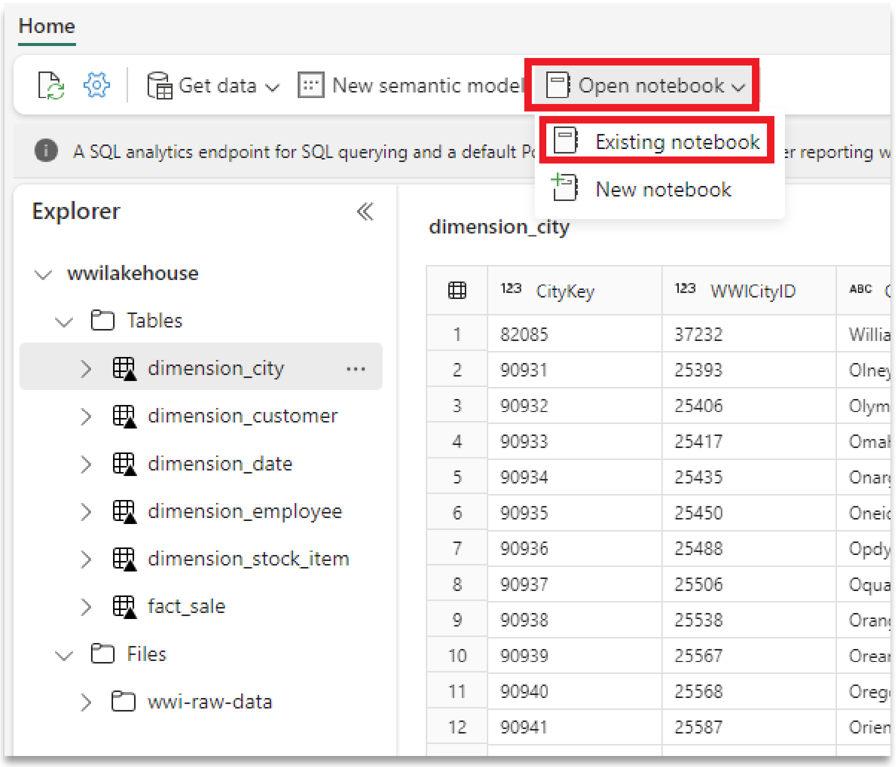


Fabric Lakehouse Tutorial NR01

This workspace contains all the items for the lakehouse tutorial.

Name	Type	Owner	Refreshed
01 - Create Delta Tables	Notebook	Natalia Rodriguez ...	—
02 - Data Transformation - Business Aggregates	Notebook	Natalia Rodriguez ...	—
IngestDataFromSourceToLakehouse	Data pipeline	Natalia Rodriguez ...	—
Load Lakehouse Table	Dataflow Gen2	Natalia Rodriguez ...	1/29/24, 3:49:05 PM
report1	Report	Fabric Lakehouse ...	1/26/24, 2:17:58 PM
wwilakehouse	Lakehouse	Natalia Rodriguez ...	—
wwilakehouse	Semantic model (...	Fabric Lakehouse ...	1/26/24, 2:17:58 PM
wwilakehouse	SQL analytics end...	Fabric Lakehouse ...	1/29/24, 3:52:33 PM

16. Now, open the second notebook. In the lakehouse view, click on **Open notebook** > **Existing notebook** on the ribbon at the top.



A SQL analytics endpoint for SQL querying and a default P

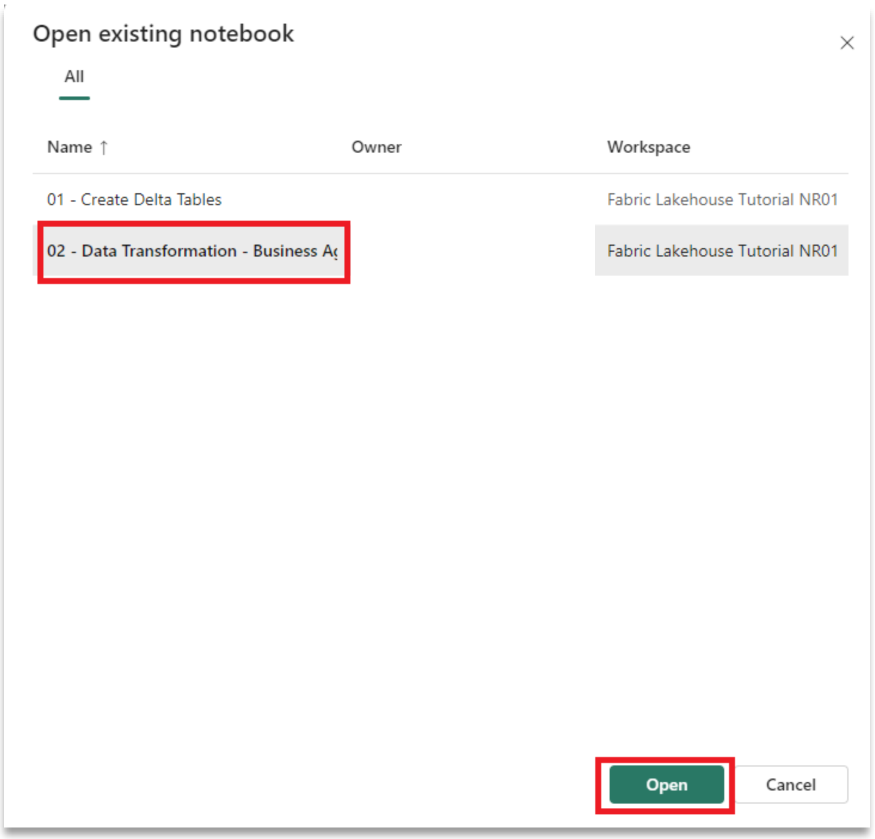
er reporting w

dimension_city

	CityKey	WWICityID
1	82085	37232
2	90931	25393
3	90932	25406
4	90933	25417
5	90934	25435
6	90935	25450
7	90936	25488
8	90937	25506
9	90938	25538
10	90939	25567
11	90940	25568
12	90941	25587

17. From the list of existing notebooks, select the **02 - Data Transformation - Business** notebook to open it.

18. Once the notebook is opened, in the **Lakehouse explorer** you will notice the notebook is already linked to your opened lakehouse.
19. An organization might have a group of data engineers working with Scala/Python while there might be other groups of data engineers preferring to work with SQL (Spark SQL or T-SQL) and all these while working on the


Open existing notebook

All

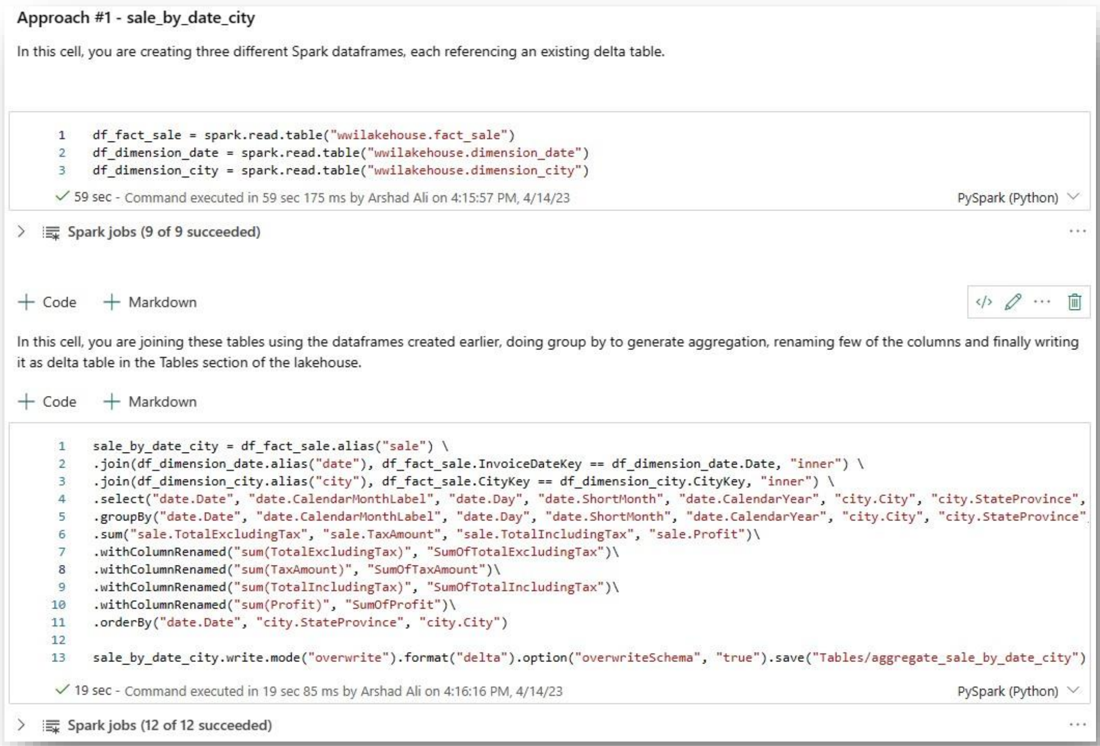
Name ↑	Owner	Workspace
01 - Create Delta Tables		Fabric Lakehouse Tutorial NR01
02 - Data Transformation - Business A(		Fabric Lakehouse Tutorial NR01

same copy of the data. Fabric makes it possible for these different groups, with varied experience and preference, to work and collaborate.

You are going to learn two different approaches, as below, to transform and generate business aggregates, and as a developer you can pick the one suitable for you or mix and match these approaches based on your preference without compromising on the performance:

- Approach #1 – Use PySpark to join and aggregates data for generating business aggregates. This approach would be preferable to someone with a programming (Python or PySpark) background.
- Approach #2 – Use Spark SQL to join and aggregates data for generating business aggregates. This approach would be preferable to someone with SQL background, transitioning to Spark.

20. **Approach #1** – Use PySpark to join and aggregates data for generating business aggregates. In the below code, you are creating three different Spark dataframes, each referencing an existing delta table. Then, you are joining these tables using the dataframes, doing group by to generate aggregation, renaming few of the columns and finally writing it as delta table in the **Tables** section of the lakehouse to persist with the data.



Approach #1 - sale_by_date_city

In this cell, you are creating three different Spark dataframes, each referencing an existing delta table.

```
df_fact_sale = spark.read.table("wwilakehouse.fact_sale")
df_dimension_date = spark.read.table("wwilakehouse.dimension_date")
df_dimension_city = spark.read.table("wwilakehouse.dimension_city")
```

✓ 59 sec - Command executed in 59 sec 175 ms by Arshad Ali on 4:15:57 PM, 4/14/23 PySpark (Python)

Spark jobs (9 of 9 succeeded)

In this cell, you are joining these tables using the dataframes created earlier, doing group by to generate aggregation, renaming few of the columns and finally writing it as delta table in the Tables section of the lakehouse.

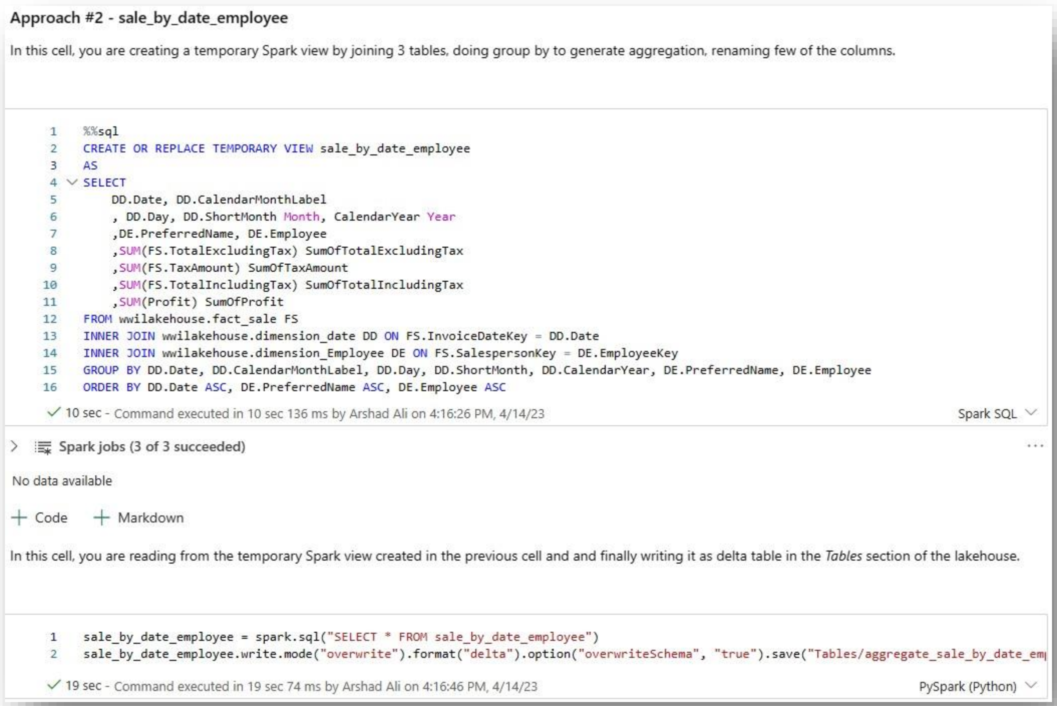
```
sale_by_date_city = df_fact_sale.alias("sale") \
.join(df_dimension_date.alias("date"), df_fact_sale.InvoiceDateKey == df_dimension_date.Date, "inner") \
.join(df_dimension_city.alias("city"), df_fact_sale.CityKey == df_dimension_city.CityKey, "inner") \
.select("date.Date", "date.CalendarMonthLabel", "date.Day", "date.ShortMonth", "date.CalendarYear", "city.City", "city.StateProvince",
.groupBy("date.Date", "date.CalendarMonthLabel", "date.Day", "date.ShortMonth", "date.CalendarYear", "city.City", "city.StateProvince"
.sum("sale.TotalExcludingTax", "sale.TaxAmount", "sale.TotalIncludingTax", "sale.Profit")\
.withColumnRenamed("sum(TotalExcludingTax)", "SumOfTotalExcludingTax")\
.withColumnRenamed("sum(TaxAmount)", "SumOfTaxAmount")\
.withColumnRenamed("sum(TotalIncludingTax)", "SumOfTotalIncludingTax")\
.withColumnRenamed("sum(Profit)", "SumOfProfit")\
.orderBy("date.Date", "city.StateProvince", "city.City")

sale_by_date_city.write.mode("overwrite").format("delta").option("overwriteSchema", "true").save("Tables/aggregate_sale_by_date_city")
```

✓ 19 sec - Command executed in 19 sec 85 ms by Arshad Ali on 4:16:16 PM, 4/14/23 PySpark (Python)

Spark jobs (12 of 12 succeeded)

```
df_fact_sale = spark.read.table("wwilakehouse.fact_sale")
df_dimension_date = spark.read.table("wwilakehouse.dimension_date")
df_dimension_city = spark.read.table("wwilakehouse.dimension_city")

sale_by_date_city = df_fact_sale.alias("sale") \
.join(df_dimension_date.alias("date"), df_fact_sale.InvoiceDateKey == df_dimension_date.Date, "inner") \
.join(df_dimension_city.alias("city"), df_fact_sale.CityKey == df_dimension_city.CityKey, "inner") \
.select("date.Date", "date.CalendarMonthLabel", "date.Day", "date.ShortMonth", "date.CalendarYear", "city.City", "city.StateProvince",
"city.SalesTerritory", "sale.TotalExcludingTax", "sale.TaxAmount", "sale.TotalIncludingTax", "sale.Profit")\
.groupBy("date.Date", "date.CalendarMonthLabel", "date.Day", "date.ShortMonth", "date.CalendarYear", "city.City", "city.StateProvince",
"city.SalesTerritory")\
.sum("sale.TotalExcludingTax", "sale.TaxAmount", "sale.TotalIncludingTax", "sale.Profit")\
.withColumnRenamed("sum(TotalExcludingTax)", "SumOfTotalExcludingTax")\
.withColumnRenamed("sum(TaxAmount)", "SumOfTaxAmount")\
.withColumnRenamed("sum(TotalIncludingTax)", "SumOfTotalIncludingTax")\
.withColumnRenamed("sum(Profit)", "SumOfProfit")\
.orderBy("date.Date", "city.StateProvince", "city.City")

sale_by_date_city.write.mode("overwrite").format("delta").option("overwriteSchema", "true").save("Tables/aggregate_sale_by_date_city")
```

21. **Approach #2** – Use Spark SQL to join and aggregates data for generating business aggregates. In the below code, you are creating a temporary Spark view by joining 3 tables, doing group by to generate aggregation, renaming few of the columns. Finally, you are reading from the temporary Spark view and finally writing it as delta table in the Tables section of the lakehouse to persist with the data.



Approach #2 - sale_by_date_employee

In this cell, you are creating a temporary Spark view by joining 3 tables, doing group by to generate aggregation, renaming few of the columns.

```
%%sql
CREATE OR REPLACE TEMPORARY VIEW sale_by_date_employee
AS
SELECT
    DD.Date, DD.CalendarMonthLabel
    , DD.Day, DD.ShortMonth Month, CalendarYear Year
    ,DE.PreferredName, DE.Employee
    ,SUM(FS.TotalExcludingTax) SumOfTotalExcludingTax
    ,SUM(FS.TaxAmount) SumOfTaxAmount
    ,SUM(FS.TotalIncludingTax) SumOfTotalIncludingTax
    ,SUM(Profit) SumOfProfit
FROM wwilakehouse.fact_sale FS
INNER JOIN wwilakehouse.dimension_date DD ON FS.InvoiceDateKey = DD.Date
INNER JOIN wwilakehouse.dimension_Employee DE ON FS.SalespersonKey = DE.EmployeeKey
GROUP BY DD.Date, DD.CalendarMonthLabel, DD.Day, DD.ShortMonth, DD.CalendarYear, DE.PreferredName, DE.Employee
ORDER BY DD.Date ASC, DE.PreferredName ASC, DE.Employee ASC
```

✓ 10 sec - Command executed in 10 sec 136 ms by Arshad Ali on 4:16:26 PM, 4/14/23 Spark SQL

Spark jobs (3 of 3 succeeded)

No data available

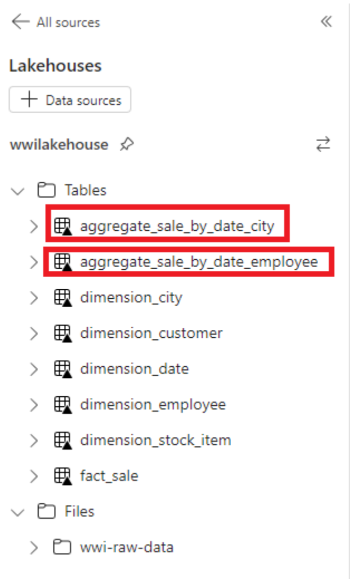
In this cell, you are reading from the temporary Spark view created in the previous cell and and finally writing it as delta table in the *Tables* section of the lakehouse.

```
sale_by_date_employee = spark.sql("SELECT * FROM sale_by_date_employee")
sale_by_date_employee.write.mode("overwrite").format("delta").option("overwriteSchema", "true").save("Tables/aggregate_sale_by_date_em
```

✓ 19 sec - Command executed in 19 sec 74 ms by Arshad Ali on 4:16:46 PM, 4/14/23 PySpark (Python)

```
%%sql
CREATE OR REPLACE TEMPORARY VIEW sale_by_date_employee
AS
SELECT
      DD.Date, DD.CalendarMonthLabel
 , DD.Day, DD.ShortMonth Month, CalendarYear Year
     ,DE.PreferredName, DE.Employee
     ,SUM(FS.TotalExcludingTax) SumOfTotalExcludingTax
     ,SUM(FS.TaxAmount) SumOfTaxAmount
     ,SUM(FS.TotalIncludingTax) SumOfTotalIncludingTax
     ,SUM(Profit) SumOfProfit
FROM wwilakehouse.fact_sale FS
INNER JOIN wwilakehouse.dimension_date DD ON FS.InvoiceDateKey = DD.Date
INNER JOIN wwilakehouse.dimension_Employee DE ON FS.SalespersonKey = DE.EmployeeKey
GROUP BY DD.Date, DD.CalendarMonthLabel, DD.Day, DD.ShortMonth, DD.CalendarYear, DE.PreferredName, DE.Employee
ORDER BY DD.Date ASC, DE.PreferredName ASC, DE.Employee ASC


sale_by_date_employee = spark.sql("SELECT * FROM sale_by_date_employee")
sale_by_date_employee.write.mode("overwrite").format("delta").option("overwriteSchema",
"true").save("Tables/aggregate_sale_by_date_employee")
```

22. You can validate created tables by right clicking and selecting refresh on **wwilakehouse** lakehouse and you will notice these aggregate tables appear.



If you notice both these above approaches (1 and 2) produce a similar outcome, however based on developer background and preference, one approach can be picked up over the other without any need for the developer to learn a new technology and compromising on the performance.

Further, you would have noticed that you are writing data as delta lake files and then the automatic table discovery and registration feature of Fabric picks it up and registers it in the metastore. That means, you don't need to explicitly call CREATE TABLE statement to create tables to use with SQL.

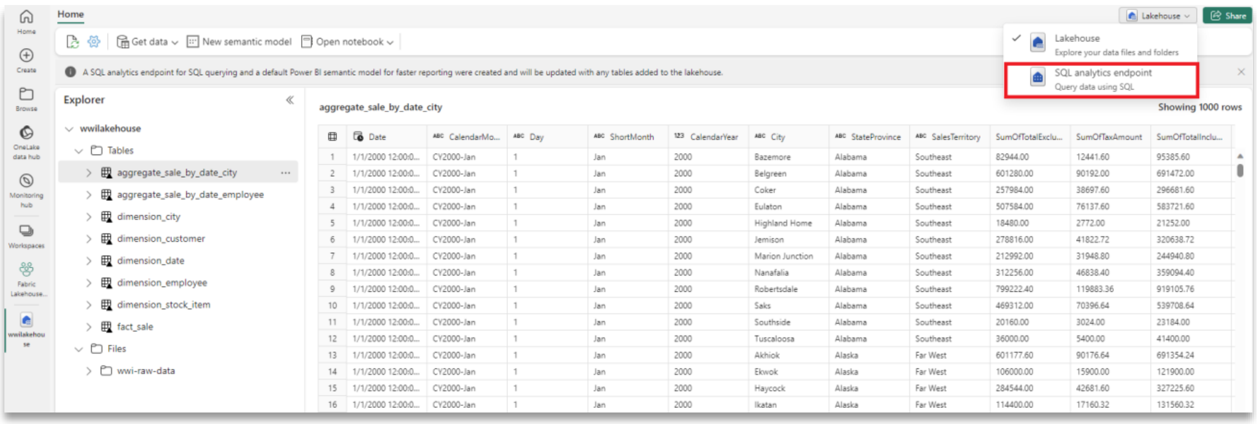
Building a report

Power BI is natively integrated in the whole Fabric experience and this native integration brings unique mode of accessing the data, called DirectLake, from the lakehouse to provide the most performant query and reporting experience. DirectLake mode is a groundbreaking new engine capability to analyze very large datasets in Power BI. The technology is based on the idea of loading parquet-formatted files directly from a data lake without having to query a data warehouse or lakehouse endpoint and without having to import or duplicate data into a Power BI dataset. DirectLake is a fast path to load the data from the data lake straight into the Power BI engine, ready for analysis.

In traditional DirectQuery mode, the Power BI engine queries the data directly from the data source every time it is queried and hence query performance depends on the speed data can be retrieved from the data source. It avoids having to copy the data i.e., any changes at the source are immediately reflected in the query results while in the import mode, on the other hand, performance is much better because the data is readily available in memory without having to query the data source each time, but the Power BI engine must first copy the data into the dataset at refresh time. Any changes at the source are only picked up during the next data refresh.

DirectLake mode now eliminates this import requirement by loading the data files directly into memory. Because there is no explicit import process, it is possible to pick up any changes at the source as they occur, thus combining the advantages of DirectQuery and import mode while avoiding their disadvantages. DirectLake mode is therefore the ideal choice for analyzing very large datasets as well as datasets with frequent updates at the source.

1. Please go the **wwilakehouse** lakehouse, click **SQL analytics endpoint** under **Lakehouse** on top right of the screen to open warehouse mode of the selected lakehouse.



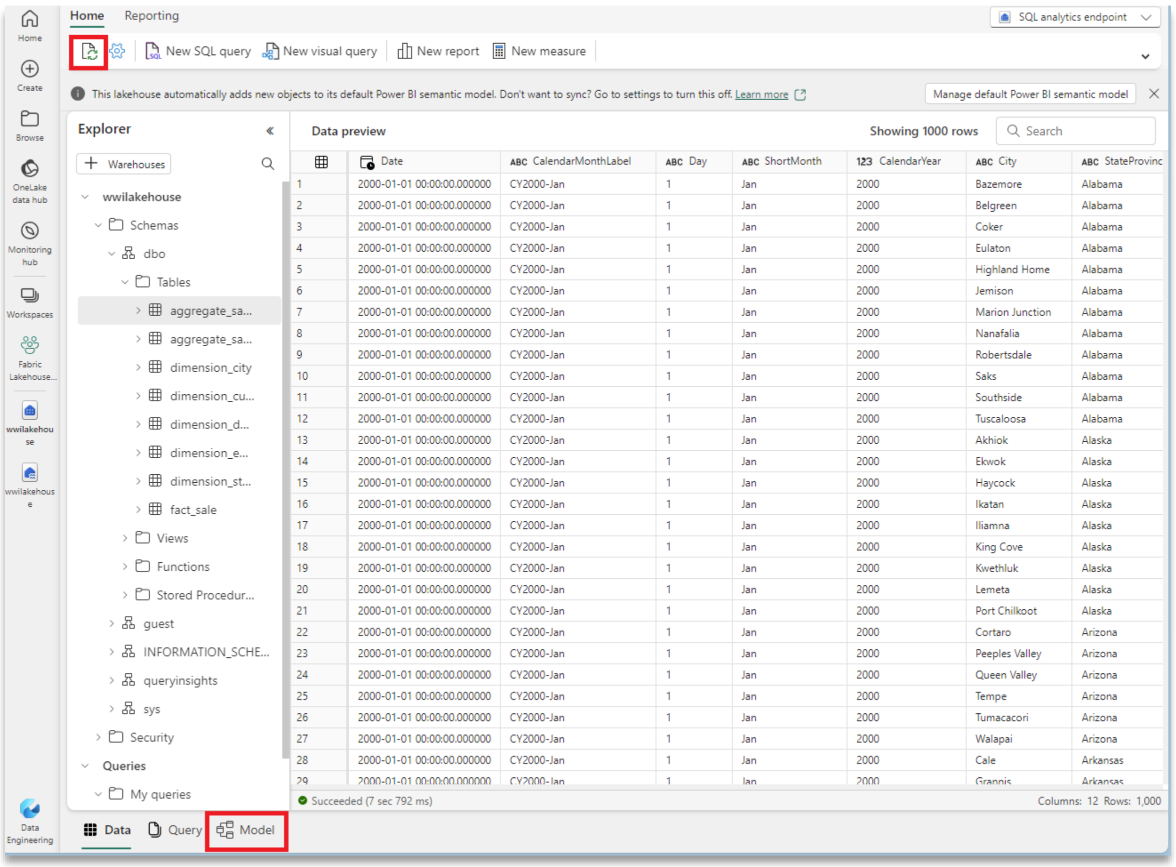
A SQL analytics endpoint for SQL querying and a default Power BI semantic model for faster reporting were created and will be updated with any tables added to the lakehouse.

aggregate_sale_by_date_city

Showing 1000 rows

	Date	CalendarMo...	Day	ShortMonth	CalendarYear	City	StateProvince	SalesTerritory	SumOfTotalExclu...	SumOfTaxAmount	SumOfTotalInclu...
1	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Bazemore	Alabama	Southeast	82944.00	12441.60	95385.60
2	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Belgreen	Alabama	Southeast	601280.00	90192.00	691472.00
3	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Coker	Alabama	Southeast	257984.00	38697.60	296681.60
4	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Eulaton	Alabama	Southeast	507584.00	76137.60	583721.60
5	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Highland Home	Alabama	Southeast	18480.00	2772.00	21252.00
6	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Jemison	Alabama	Southeast	278816.00	41822.72	320638.72
7	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Marion Junction	Alabama	Southeast	212992.00	31948.80	244940.80
8	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Nanafalia	Alabama	Southeast	312256.00	46838.40	359094.40
9	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Robertsdale	Alabama	Southeast	799222.40	119883.36	919105.76
10	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Saks	Alabama	Southeast	469312.00	70396.64	539708.64
11	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Southside	Alabama	Southeast	20160.00	3024.00	23184.00
12	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Tuscaloosa	Alabama	Southeast	36000.00	5400.00	41400.00
13	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Akhiok	Alaska	Far West	601177.60	90176.64	691354.24
14	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Ekwok	Alaska	Far West	106000.00	15900.00	121900.00
15	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Haycock	Alaska	Far West	284544.00	42681.60	327225.60
16	1/1/2000 12:00:0...	CY2000-Jan	1	Jan	2000	Ikatan	Alaska	Far West	114400.00	17160.32	131560.32

2. Once you are in warehouse mode you should be able to see all the tables you created. If you don't see them yet, please click on the **Refresh** icon at the top. Next, click on **Model** tab at the bottom to open the default Power BI dataset.



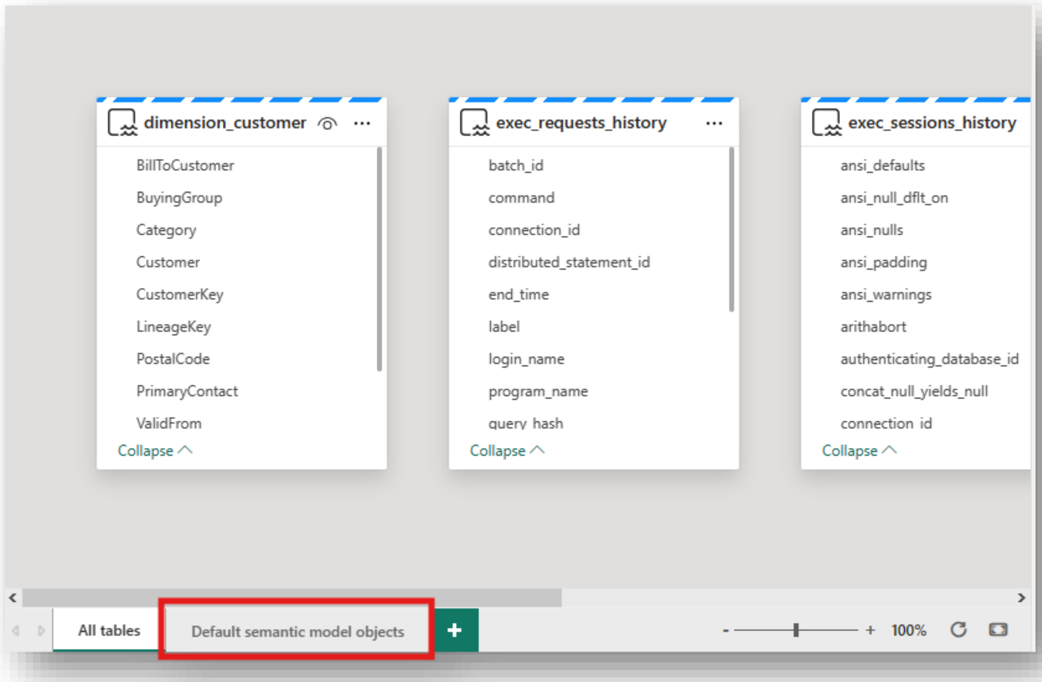
This lakehouse automatically adds new objects to its default Power BI semantic model. Don't want to sync? Go to settings to turn this off. Learn more

	Date	CalendarMonthLabel	Day	ShortMonth	CalendarYear	City	StateProvinc
1	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Bazemore	Alabama
2	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Belgreen	Alabama
3	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Coker	Alabama
4	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Eulaton	Alabama
5	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Highland Home	Alabama
6	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Jemison	Alabama
7	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Marion Junction	Alabama
8	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Nanafalia	Alabama
9	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Robertsdale	Alabama
10	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Saks	Alabama
11	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Southside	Alabama
12	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Tuscaloosa	Alabama
13	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Akhiok	Alaska
14	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Ekwok	Alaska
15	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Haycock	Alaska
16	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Ikatan	Alaska
17	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Iliamna	Alaska
18	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	King Cove	Alaska
19	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Kwethluk	Alaska
20	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Lemeta	Alaska
21	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Port Chilkoot	Alaska
22	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Cortaro	Arizona
23	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Peeples Valley	Arizona
24	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Queen Valley	Arizona
25	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Tempe	Arizona
26	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Tumacacori	Arizona
27	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Walapai	Arizona
28	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Cale	Arkansas
29	2000-01-01 00:00:00.000000	CY2000-Jan	1	Jan	2000	Grannis	Arkansas

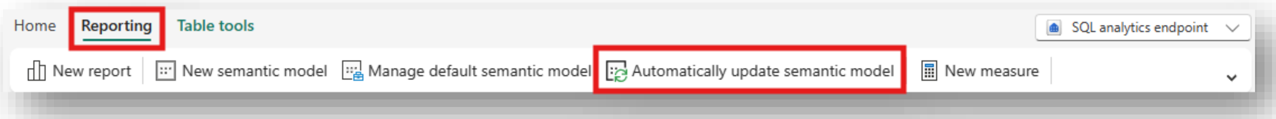
Succeeded (7 sec 792 ms)

Columns: 12 Rows: 1,000

3. You need to add the newly created tables to the default semantic model. Click on the **Default semantic model objects** at the bottom of the page.

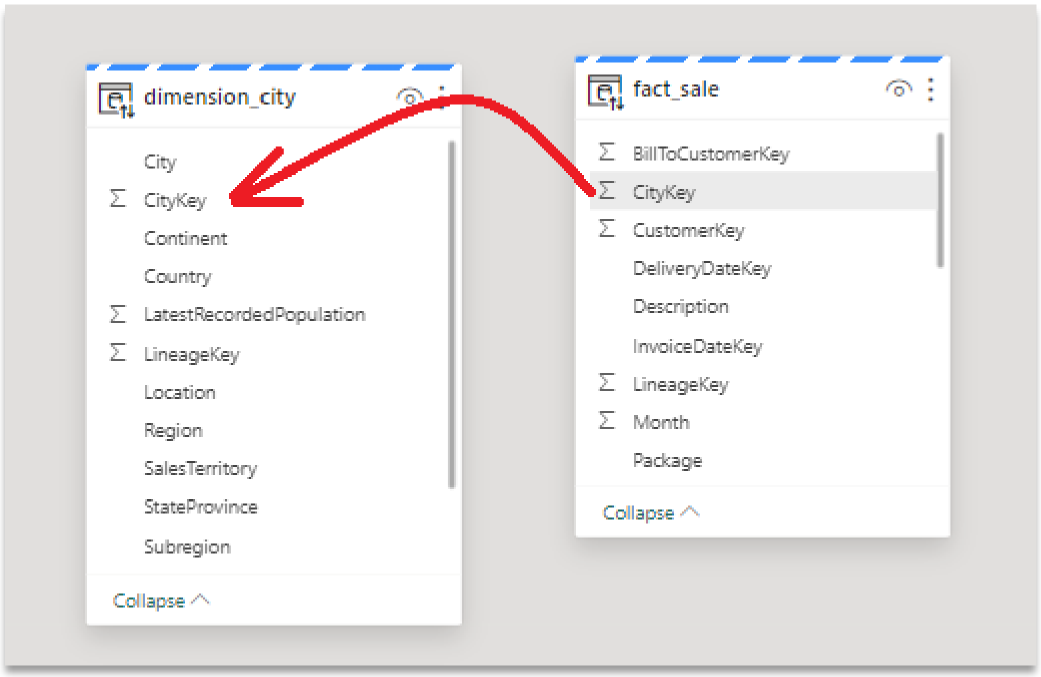


4. At the top of the page, go to the **Reporting** section, and click on **Automatically update semantic model**. This will automatically add any new tables created in this lakehouse to the default semantic model going forward. Allow a few moments for the new tables to be added to the semantic model.



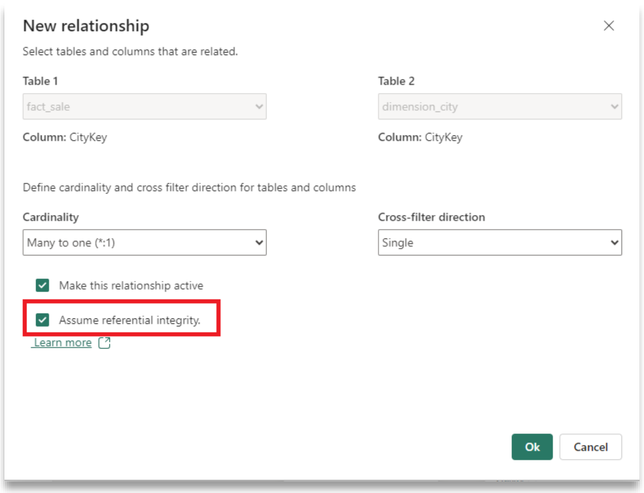
Note: *You can also select the **Manage default semantic model** option to specify which tables will be part of the default semantic model (but you don't need to do this now).*

5. For this data model, you need to define the relationship between different tables so that you can create reports and visualizations based on data coming across different tables. From the **fact_sale** table, drag the **CityKey** field and drop it on the **CityKey** field in the **dimension_city** table to create a relationship. Check the "Assume referential integrity" and click on ***Confirm*** to establish the relationship. **Note** – When defining relationships, please make sure you have many to one relationship from the fact to the dimension and not vice versa.



6. On the **New Relationship** settings:
    a. Table 1 will be populated with fact_sale and the column of CityKey.

b. Table 2 will be populated with dimension_city and the column of CityKey.
c. Cardinality: **Many to one (*:1)**
d. Cross filter direction: **Single**
e. Leave the box next to **Make this relationship active** checked.
f. Check the box next to **Assume referential integrity.**
g. Select **Confirm.**



New relationship

Select tables and columns that are related.

Table 1: fact_sale
Column: CityKey

Table 2: dimension_city
Column: CityKey

Define cardinality and cross filter direction for tables and columns

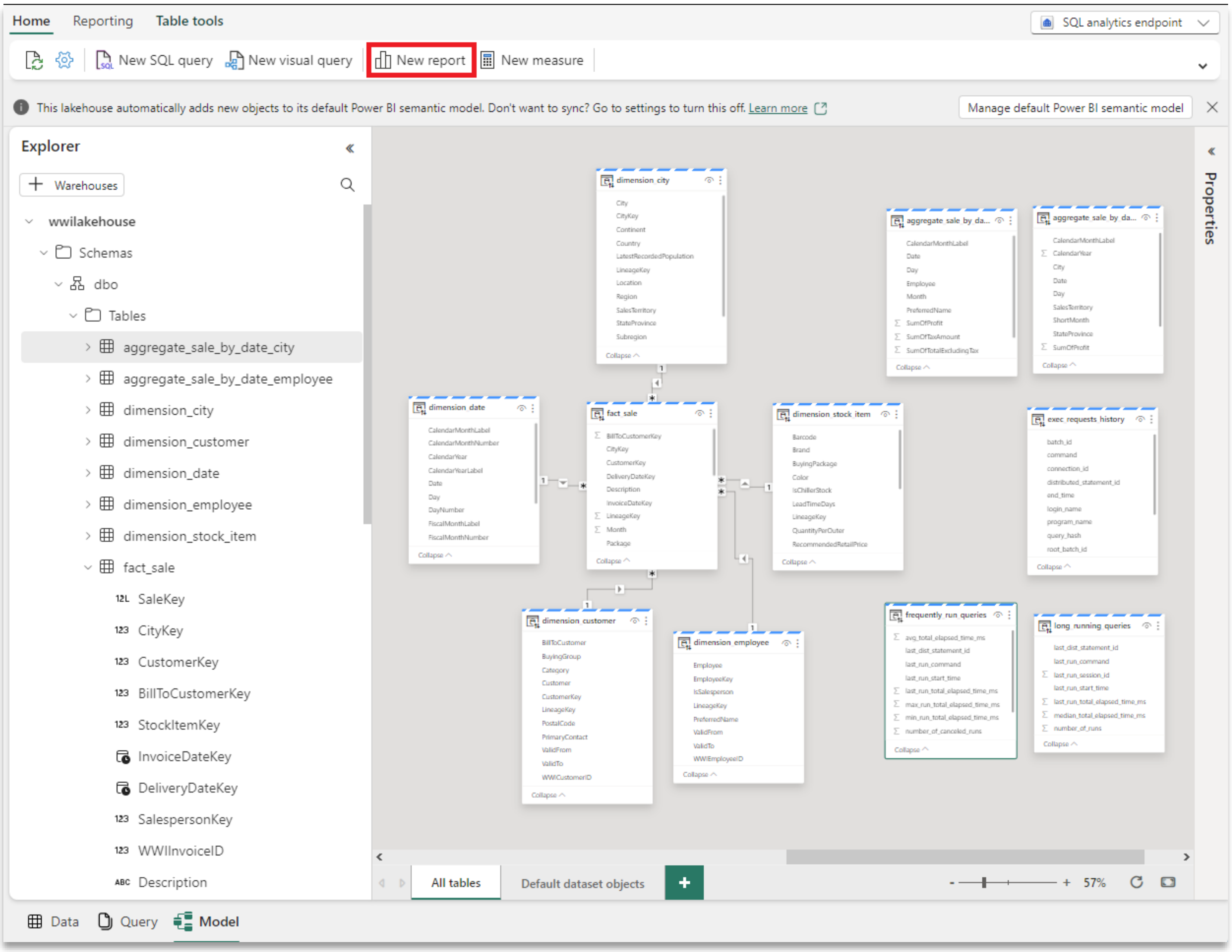
Cardinality: Many to one (*:1)

Cross-filter direction: Single

✓ Make this relationship active

✓ Assume referential integrity.

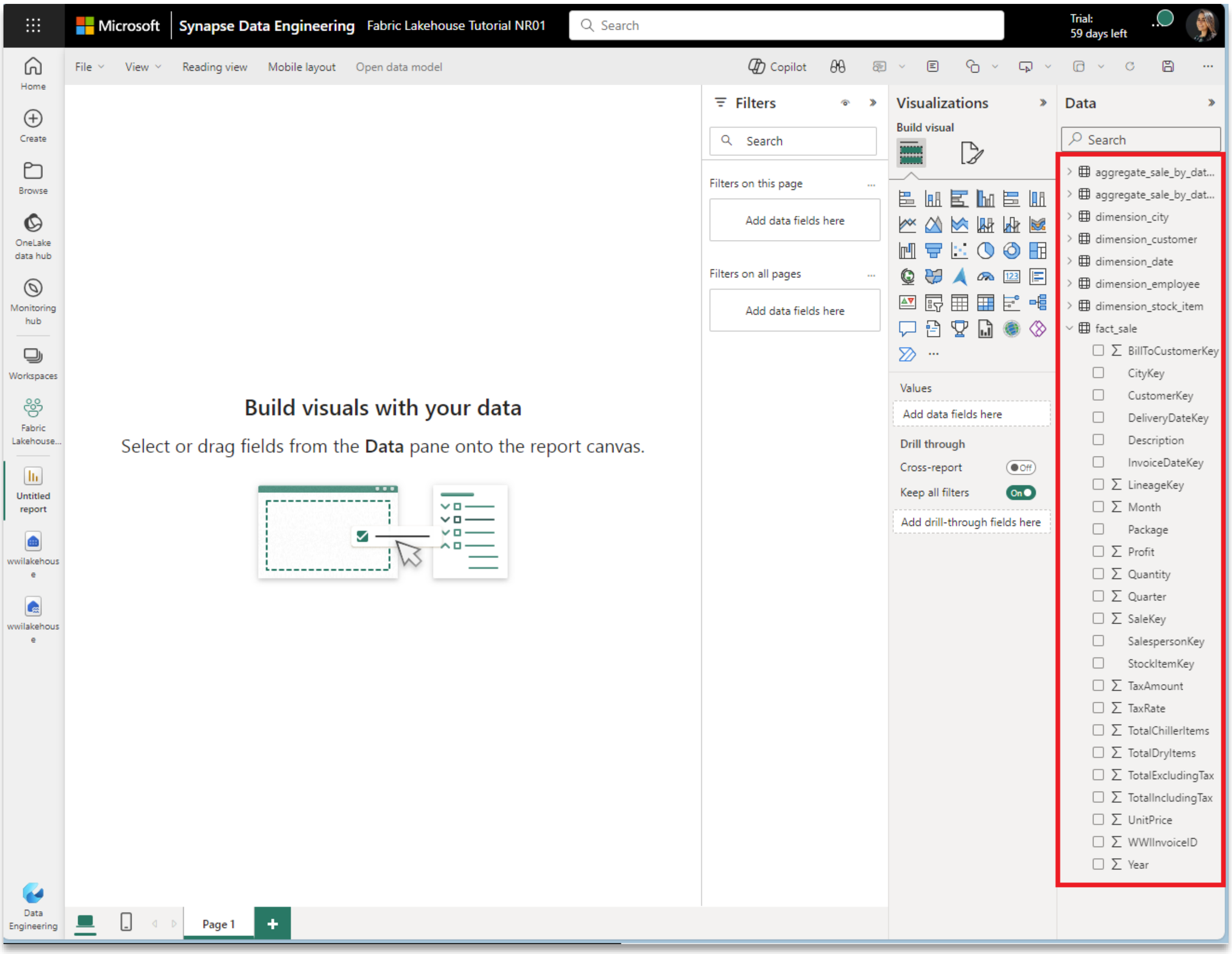
h. Similarly, you need to add these relationships as well:
- StockItemKey(fact_sale) – StockItemKey(dimension_stock_item)
- Salespersonkey(fact_sale) – EmployeeKey(dimension_employee)
- CustomerKey(fact_sale) – CustomerKey(dimension_customer)
- InvoiceDateKey(fact_sale) – Date(dimension_date)



This lakehouse automatically adds new objects to its default Power BI semantic model. Don't want to sync? Go to settings to turn this off. Learn more

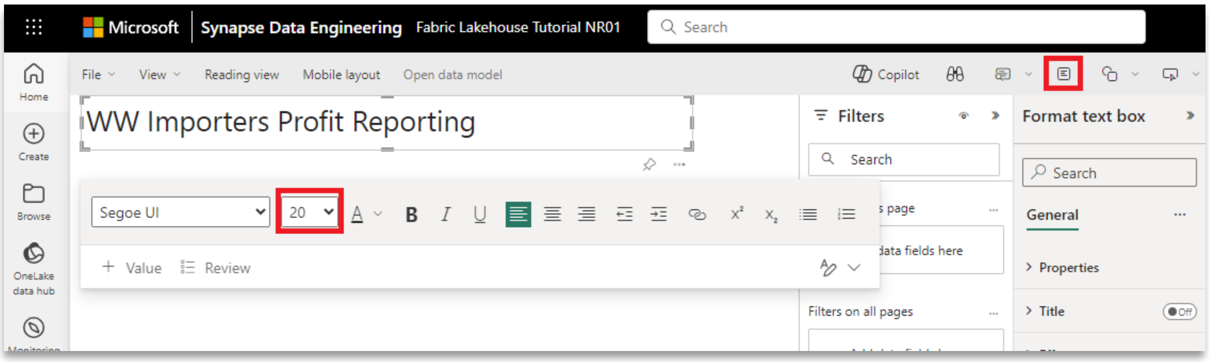
After adding these above relationships, your data model is ready, as above, for reporting. Click on ***New report*** to start creating reports/dashboards in Power BI.

7. On the Power BI report canvas, you can create reports to meet your business requirements by dragging required columns from the **Data** pane to the canvas and using one or more of available visualizations.

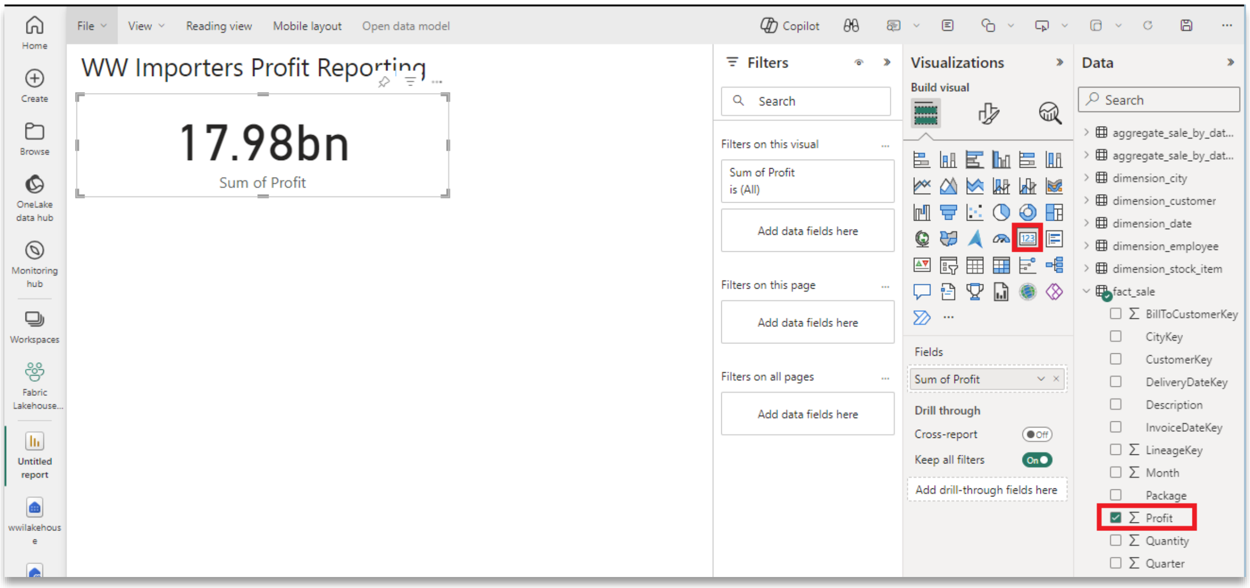


- aggregate_sale_by_dat...
- aggregate_sale_by_dat...
- dimension_city
- dimension_customer
- dimension_date
- dimension_employee
- dimension_stock_item
- fact_sale
  - BillToCustomerKey
  - CityKey
  - CustomerKey
  - DeliveryDateKey
  - Description
  - InvoiceDateKey
  - LineageKey
  - Month
  - Package
  - Profit
  - Quantity
  - Quarter
  - SaleKey
  - SalespersonKey
  - StockItemKey
  - TaxAmount
  - TaxRate
  - TotalChillerItems
  - TotalDryItems
  - TotalExcludingTax
  - TotalIncludingTax
  - UnitPrice
  - WWIInvoiceID
  - Year

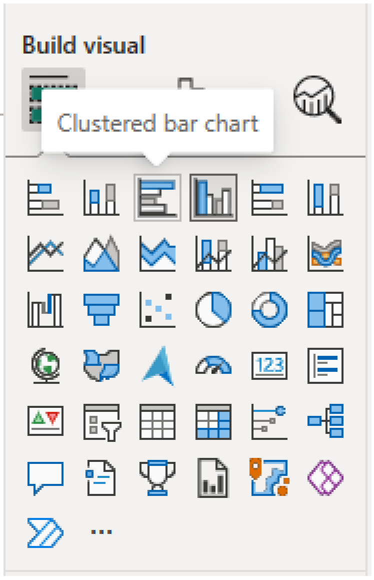
8. Add a title:
    a. In the Ribbon, click the Text Box icon
    b. Type in **WW Importers Profit Reporting**
    c. Highlight the text and increase size to 20 and place in the upper left of the report page



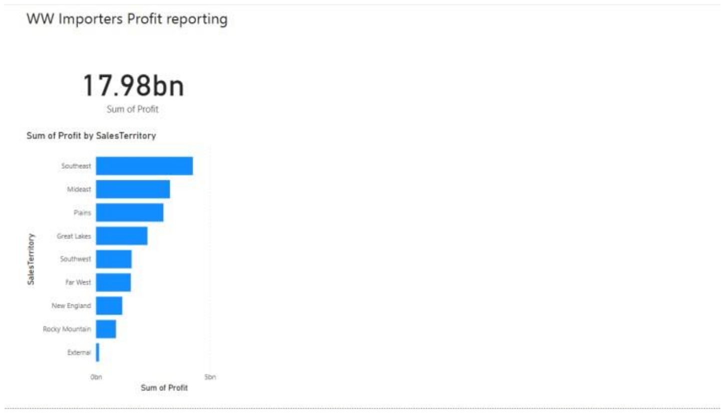
9. Add a Card
    a. On the **Data** pane, expand **fact_sales** and check the box next to **Profit**. This will create a column chart and add the field to the Y-axis.
    b. With the bar chart selected, click the Card visual in the visualization pane. This will convert the visual to a card.
    c. Place the card under the title



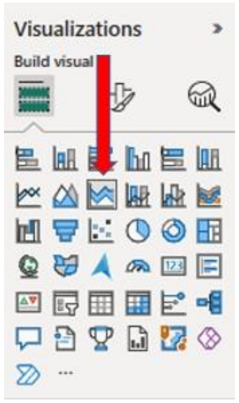
10. Add a Bar chart
    a. On the **Data** pane, expand **fact_sales** and check the box next to **Profit**. This will create a column chart and add the field to the Y-axis.
    b. On the **Data** pane, expand **dimension_city** and check the box for **SalesTerritory** This will add the field to the X-axis.
    c. With the bar chart selected, click on the Clustered Bar Chart visual in the visualization pane. This will convert the column chart into a bar chart.



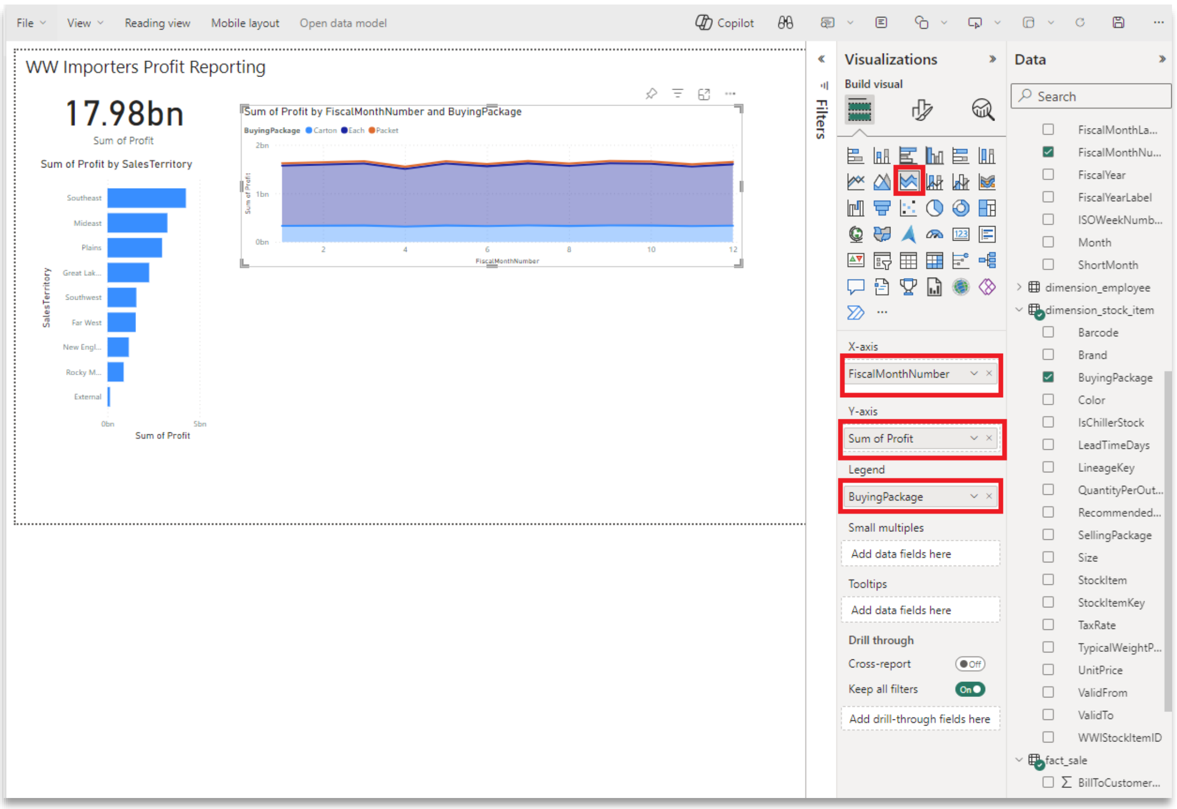
    d. Resize the Bar chart to fill in the area under the title and Card



11. Click anywhere on the blank canvas (or press the Esc key) so the bar chart visual is no longer selected.
12. Build a stacked area chart visual:
    a. On the **Visualizations** pane, select the **Stacked area chart** visual.

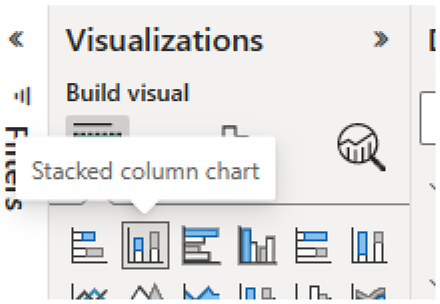


    b. Reposition and resize the stacked area chart to the right of the card and bar chart visuals created in the previous steps.
    c. On the **Data** pane, expand **fact_sales** and check the box next to **Profit.** Expand dimension_date and check the box next to **FiscalMonthNumber**. This will create a filled line chart showing profit by fiscal month.
    d. On the **Data** pane, expand **dimension_stock_item** and drag **BuyingPackage** into the Legend field well. This will add a line for each of the Buying Packages.



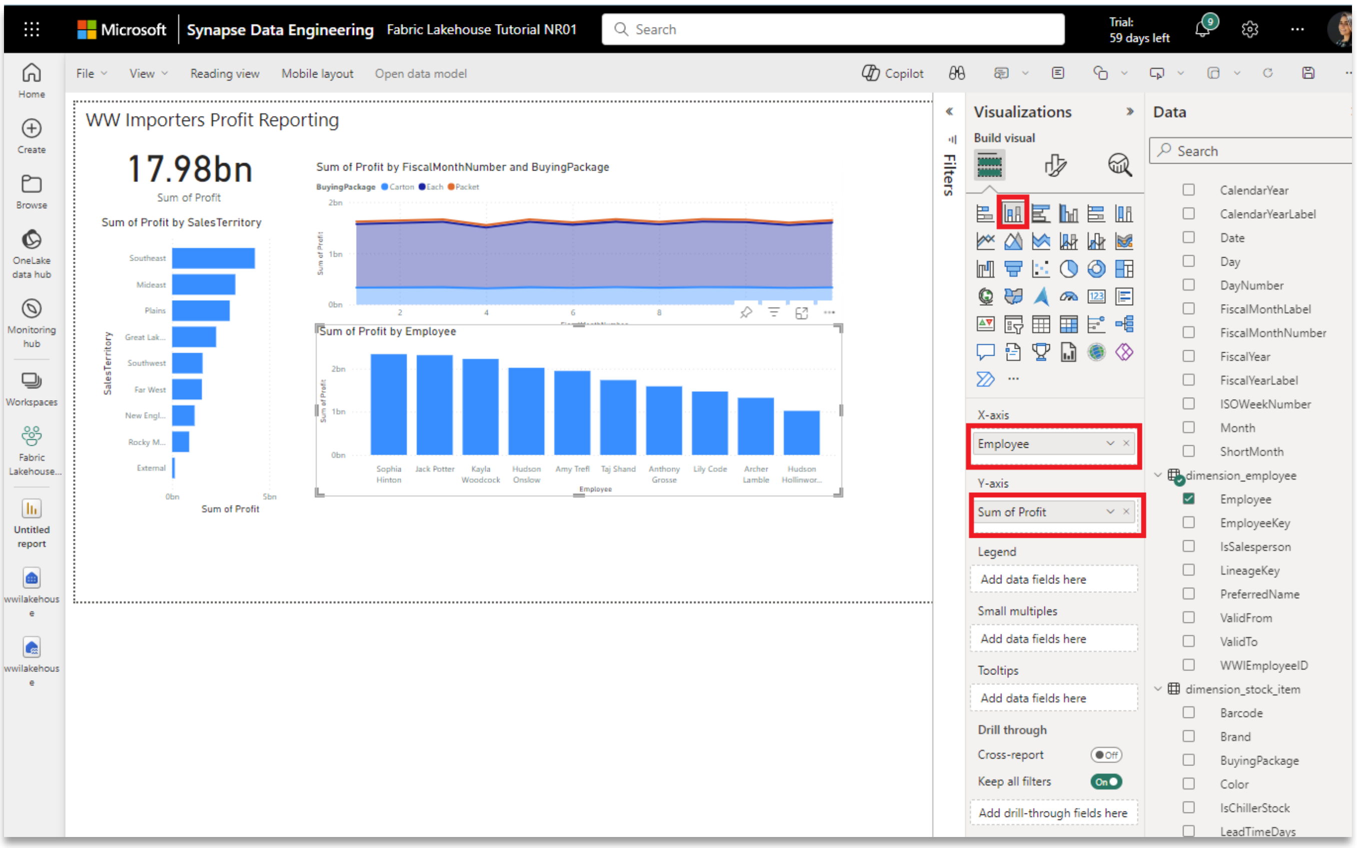
X-axis: FiscalMonthNumber
Y-axis: Sum of Profit
Legend: BuyingPackage

13. Click anywhere on the blank canvas (or press the Esc key) so the stacked area chart visual is no longer selected.
14. Build a column chart:
    a. On the **Visualizations** pane, select the **Stacked column chart** visual.

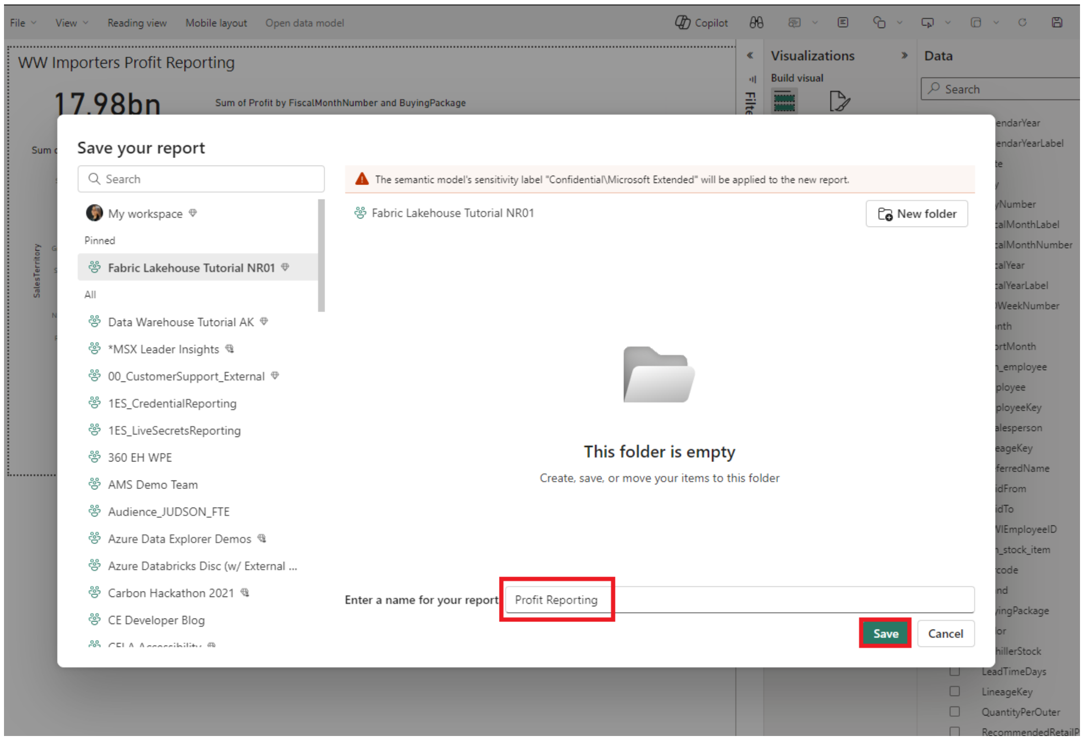


b. On the **Data** pane, expand **fact_sales** and check the box next to **Profit**. This will add the field to the Y-axis.

c. On the **Data** pane, expand **dimension_employee** and check the box next to **Employee**. This will add the field to the X-axis.



15. Click anywhere on the blank canvas (or press the Esc key) so the LINE chart visual is no longer selected.
16. From the ribbon, select **File > Save**.
17. Enter the name of your report as **Profit Reporting**.
18. Select **Save**



The semantic model's sensitivity label "Confidential\Microsoft Extended" will be applied to the new report.

Fabric Lakehouse Tutorial NR01

Enter a name for your report: Profit Reporting