Getting Started with Snowflake - Zero to Snowflake

Overview

Welcome to Snowflake! This entry-level guide designed for database and data warehouse administrators and architects will help you navigate the Snowflake interface and introduce you to some of our core capabilities. Sign up for a free 30-day trial of Snowflake and follow along with this lab exercise. Once we cover the basics, you'll be ready to start processing your own data and diving into Snowflake's more advanced features like a pro.

Prerequisites:

- Use of the Snowflake free 30-day trial environment
- Basic knowledge of SQL, database concepts, and objects
- Familiarity with CSV comma-delimited files and JSON semi-structured data

What You'll Learn:

- How to create stages, databases, tables, views, and virtual warehouses.
- How to load structured and semi-structured data.
- How to perform analytical queries on data in Snowflake, including joins between tables.
- How to clone objects.
- How to undo user errors using Time Travel.
- How to create roles and users, and grant them privileges.
- How to securely and easily share data with other accounts.
- How to consume datasets in the Snowflake Data Marketplace.

Prepare Your Lab Environment

If you haven't already, register for a Snowflake free 30-day trial. The rest of the sections in this lab assume you are using a new Snowflake account created by registering for a trial.

The Snowflake edition (Standard, Enterprise, Business Critical, etc.) and cloud provider (AWS, Azure, GCP), and Region (US East, EU, etc.) you use for this lab do not matter. However, we suggest you select the region that is physically closest to you and Enterprise, our most popular offering, as your Snowflake edition.

After registering, you will receive an email with an activation link and URL for accessing your Snowflake account.

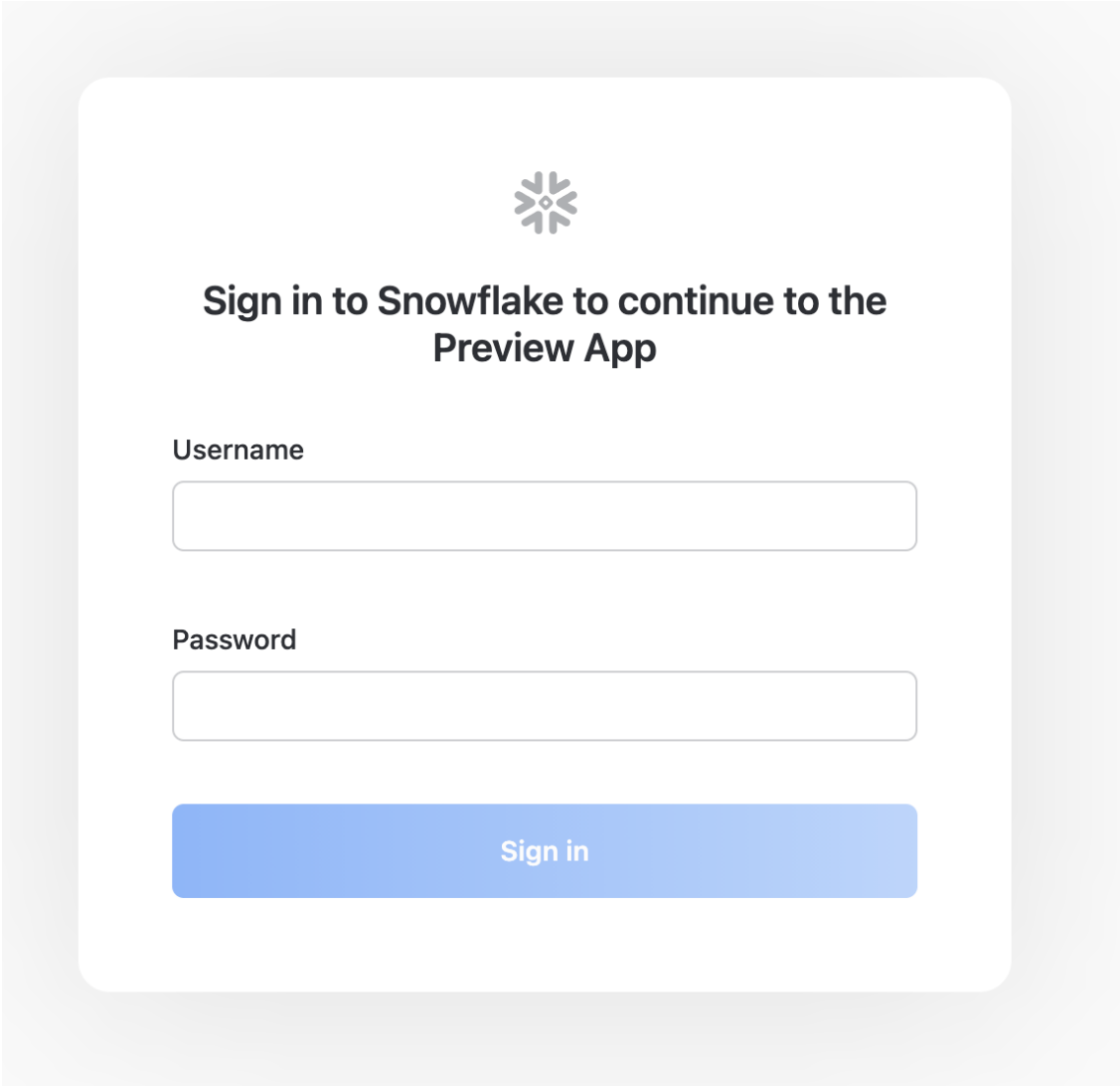
The Snowflake User Interface & Lab Story

Negative : **About the screenshots, sample code, and environment** Screenshots in this lab depict examples and results that may vary slightly from what you see when you complete the exercises.

Logging into the Snowflake User Interface (UI)

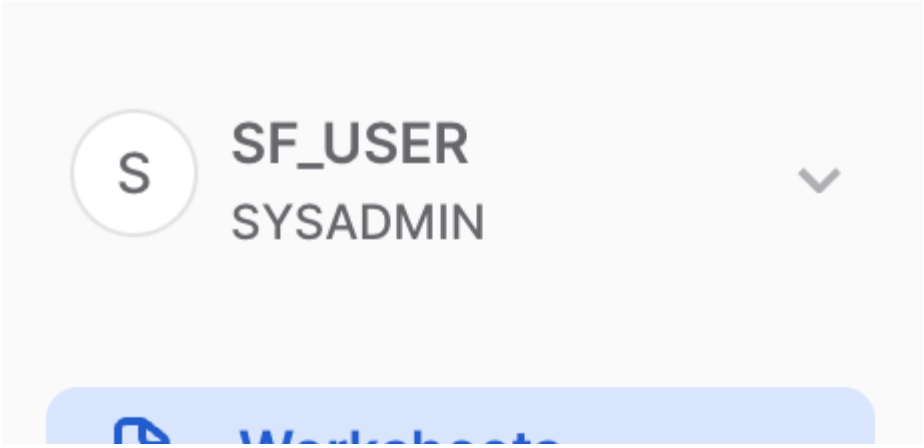
Open a browser window and enter the URL of your Snowflake 30-day trial environment that was sent with your registration email.

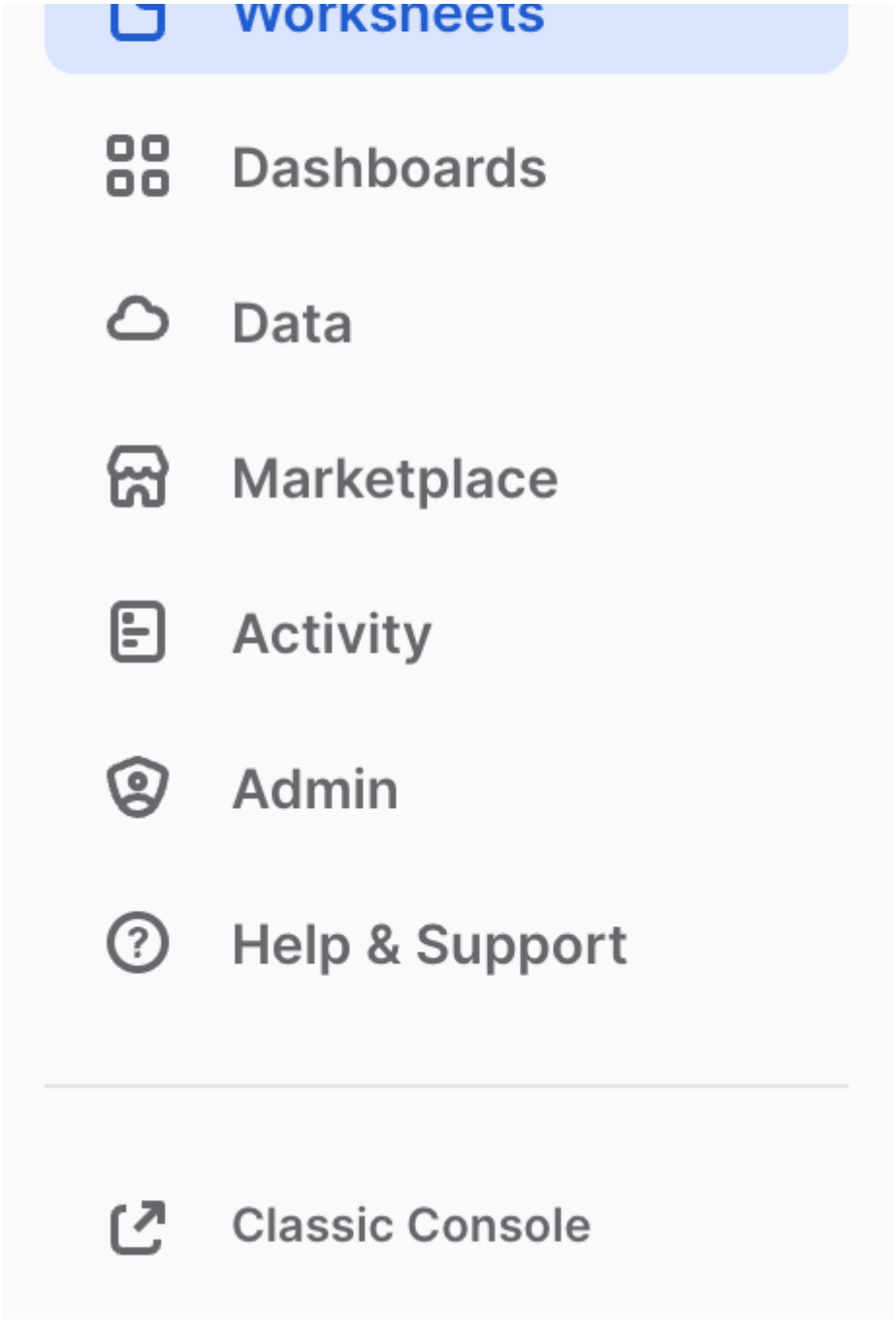
You should see the following login dialog. Enter the username and password that you specified during the registration:



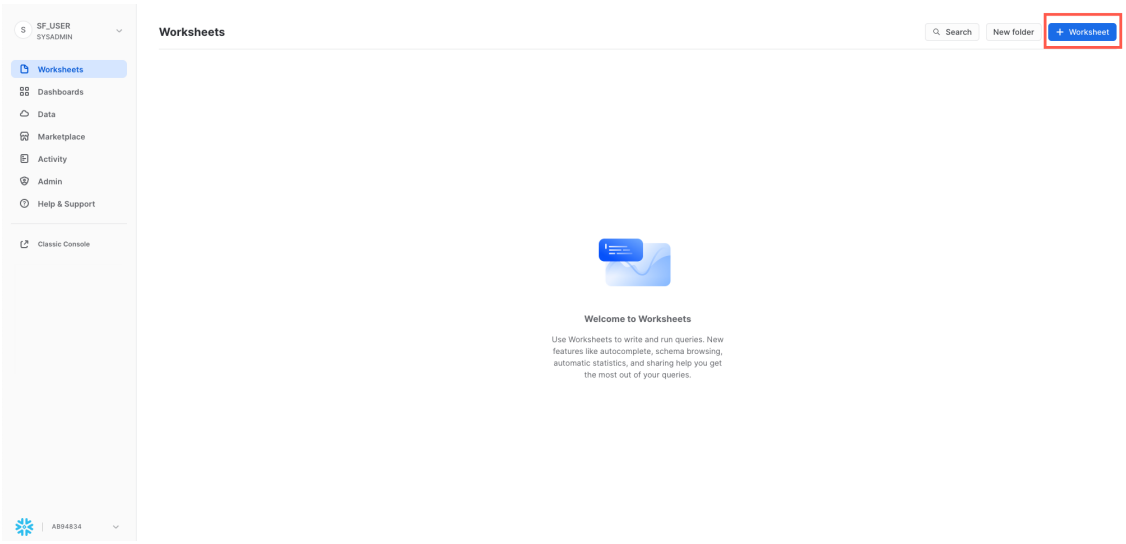
Navigating the Snowflake UI

Let's get you acquainted with Snowflake! This section covers the basic components of the user interface. We will move from top to bottom on the left-hand side margin.

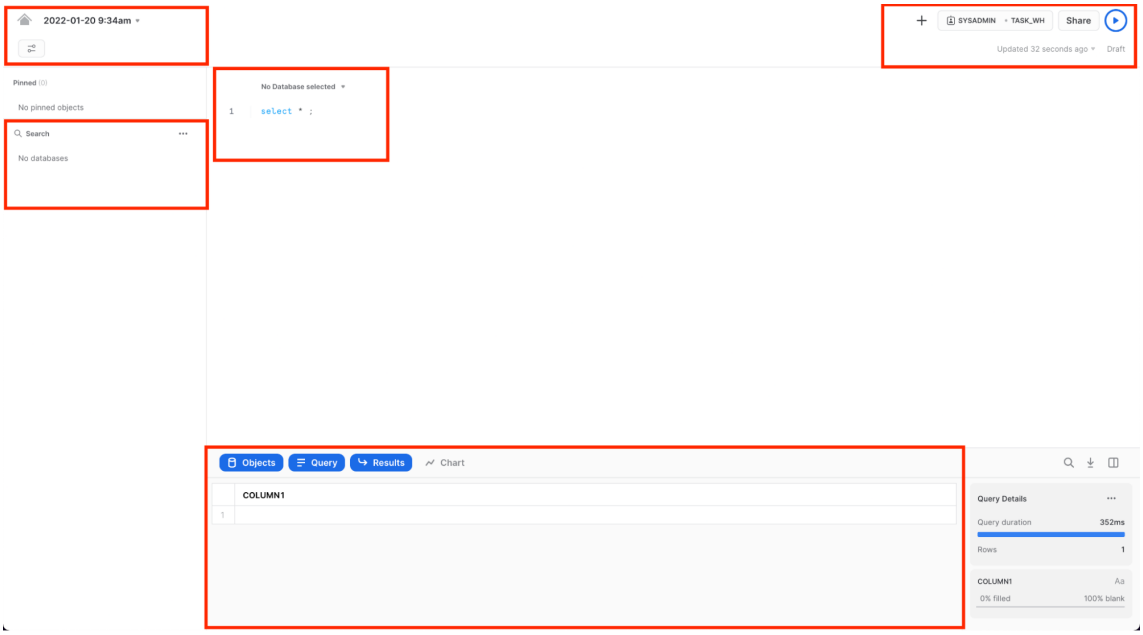



Worksheets
Dashboards
Data
Marketplace
Activity
Admin
Help & Support
Classic Console

Worksheets



The **Worksheets** tab provides an interface for submitting SQL queries, performing DDL and DML operations, and viewing results as your queries or operations complete. A new worksheet is created by clicking **+ Worksheet** on the top right.



The top left corner contains the following:

- **Home** icon: Use this to get back to the main console/close the worksheet.
- **Worksheet_name** drop-down: The default name is the timestamp when the worksheet was created. Click the timestamp to edit the worksheet name. The drop-down also displays additional actions you can perform for the worksheet.
- **Manage filters** button: Custom filters are special keywords that resolve as a subquery or list of values.

The top right corner contains the following:

- **+** button: This creates a new worksheet.

- **Context** box: This lets Snowflake know which role and warehouse to use during this session. It can be changed via the UI or SQL commands.
- **Share** button: Open the sharing menu to share to other users or copy the link to the worksheet.
- **Play/Run** button: Run the SQL statement where the cursor currently is or multiple selected statements.

The middle pane contains the following:

- Drop-down at the top for setting the database/schema/object context for the worksheet.
- General working area where you enter and execute queries and other SQL statements.

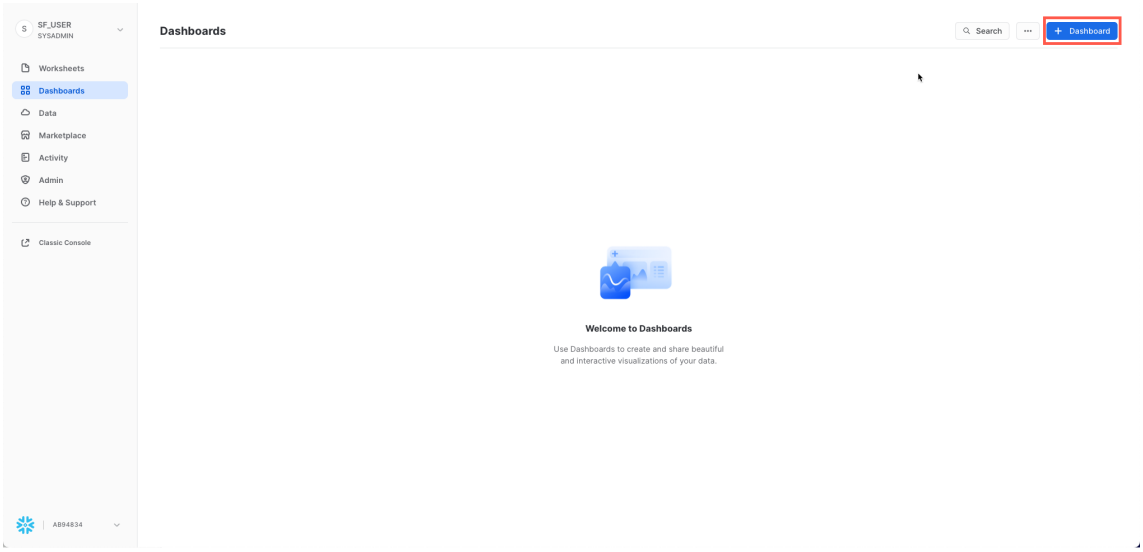
The middle-left panel contains the database objects browser which enables you to explore all databases, schemas, tables, and views accessible by the role currently in use for the worksheet.

The bottom pane displays the results of queries and other operations. Also includes 4 options (**Object**, **Query**, **Result**, **Chart**) that open/close their respective panels on the UI. **Chart** opens a visualization panel for the returned results. More on this later.

The various panes on this page can be resized by adjusting their sliders. If you need more room in the worksheet, collapse the database objects browser in the left panel. Many of the screenshots in this guide keep this panel closed.

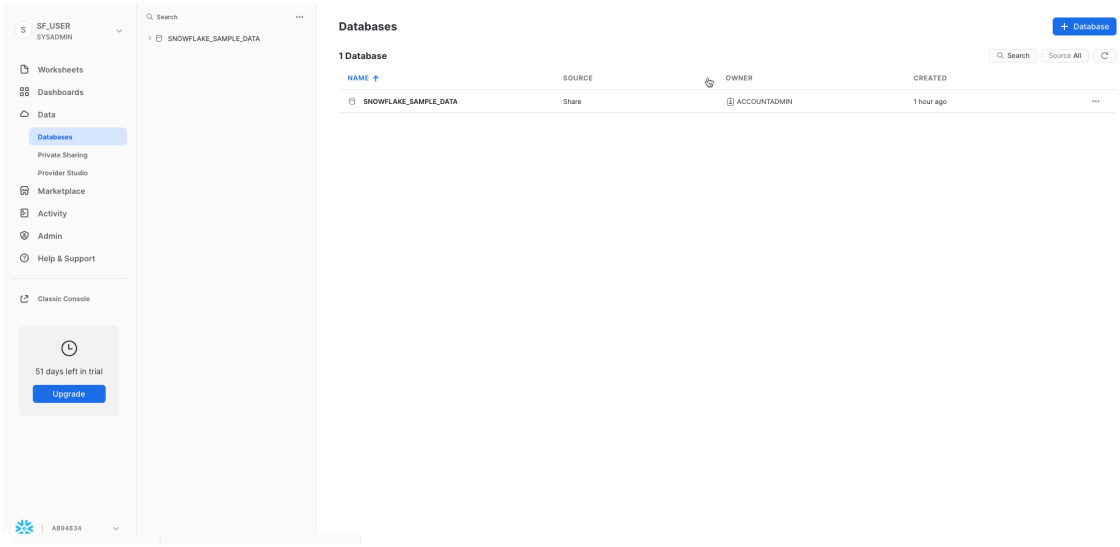
Negative : **Worksheets vs the UI** Most of the exercises in this lab are executed using pre-written SQL within this worksheet to save time. These tasks can also be done via the UI, but would require navigating back-and-forth between multiple UI tabs.

Dashboards



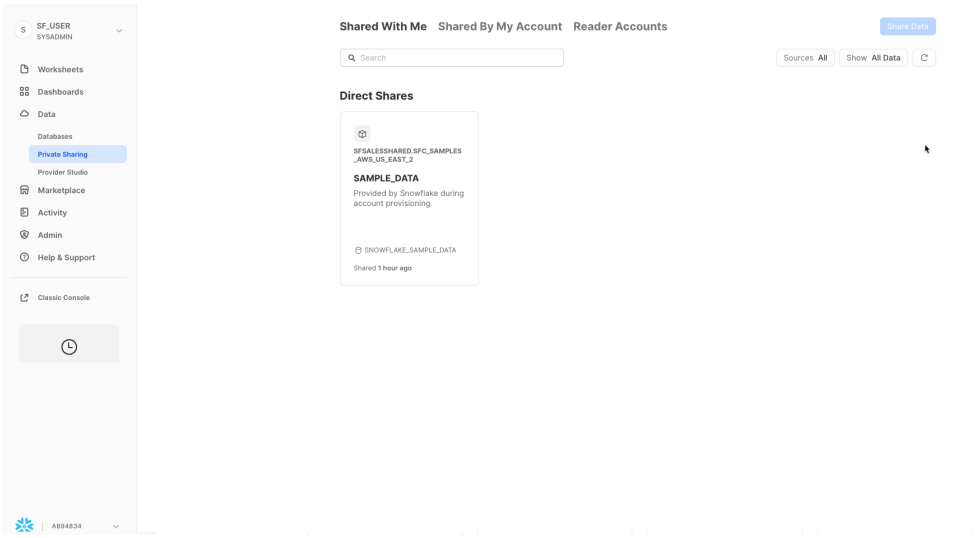
The **Dashboards** tab allows you to create flexible displays of one or more charts (in the form of tiles, which can be rearranged). Tiles and widgets are produced by executing SQL queries that return results in a worksheet. Dashboards work at a variety of sizes with minimal configuration.

Databases



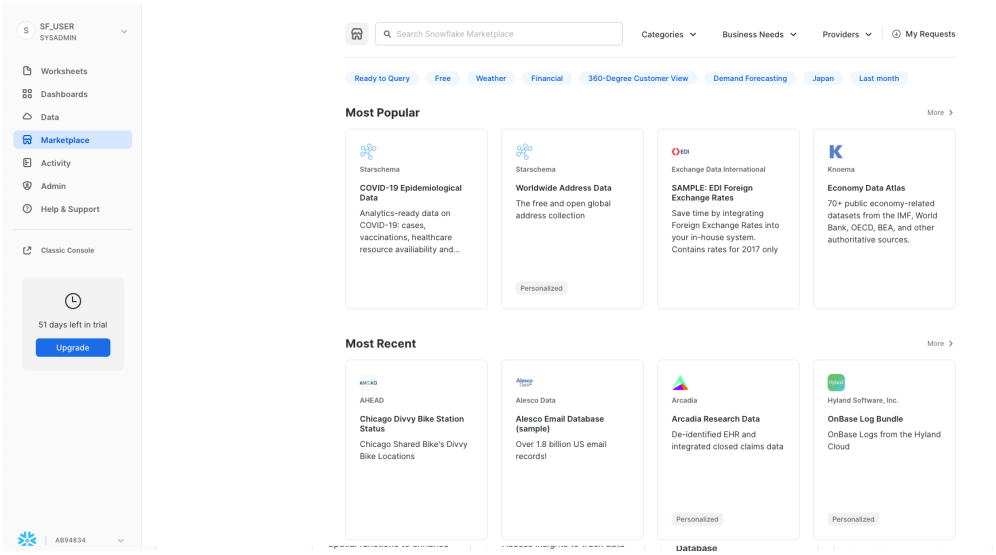
Under **Data**, the **Databases** tab shows information about the databases you have created or have permission to access. You can create, clone, drop, or transfer ownership of databases, as well as load data in the UI. Notice that a database already exists in your environment. However, we will not be using it in this lab.

Private Shared Data



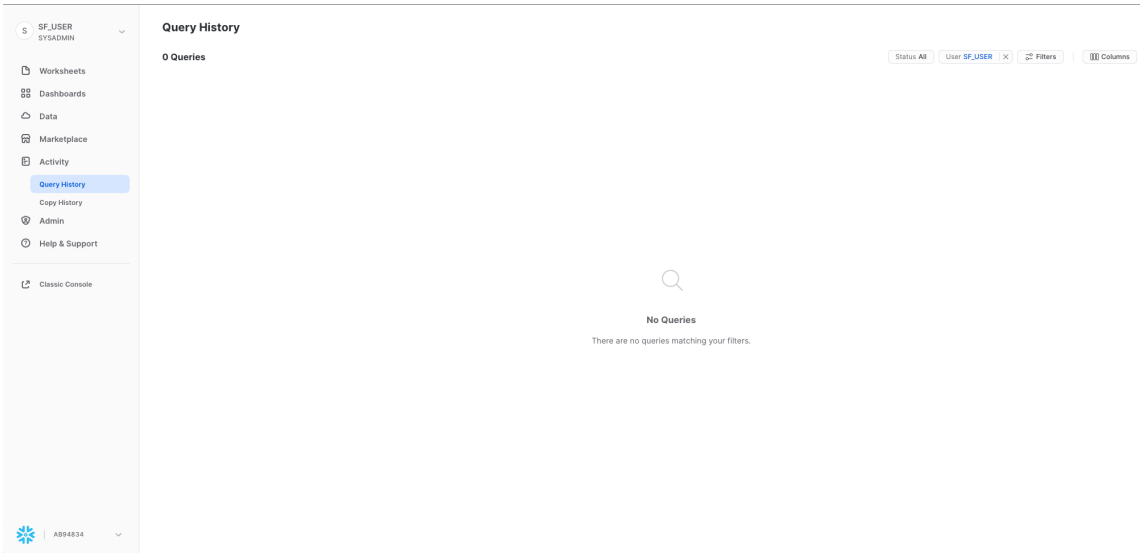
Also under **Data**, the **Private Shared Data** tab is where data sharing can be configured to easily and securely share Snowflake tables among separate Snowflake accounts or external users, without having to create a copy of the data. We will cover data sharing in Section 10.

Marketplace



The **Marketplace** tab is where any Snowflake customer can browse and consume data sets made available by providers. There are two types of shared data: Public and Personalized. Public data is free data sets available for querying instantaneously. Personalized data requires reaching out to the provider of data for approval of sharing data.

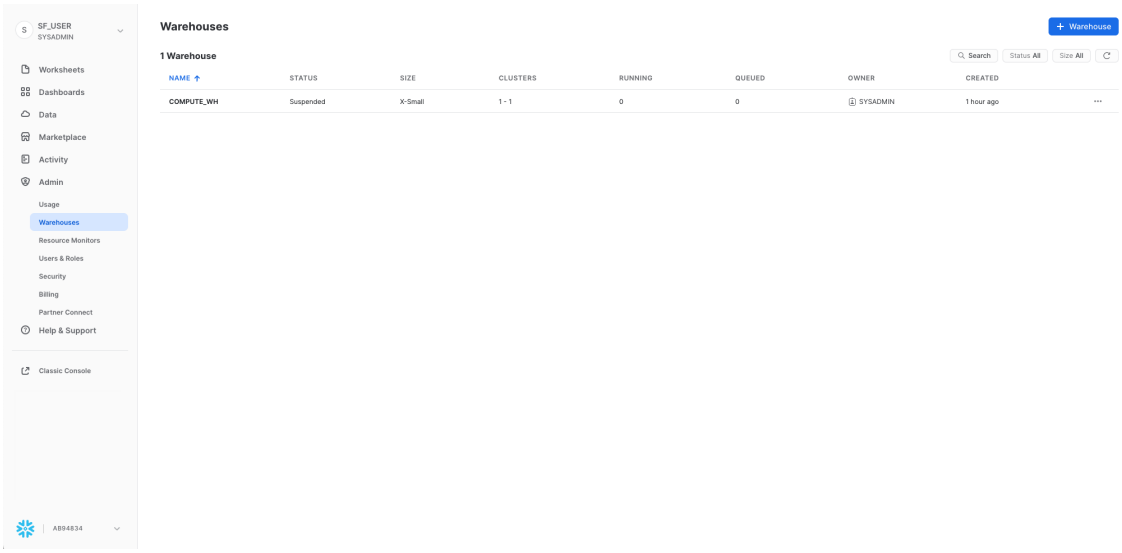
Query History



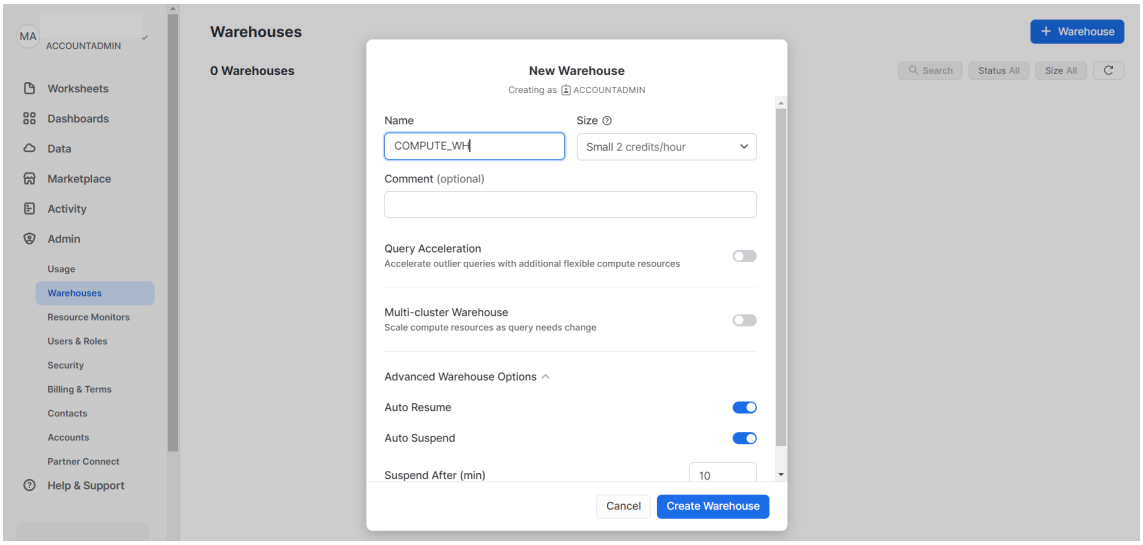
Under **Activity** there are two tabs **Query History** and **Copy History**:

- **QuerHistory** is where previous queries are shown, along with filters that can be used to hone results (user, warehouse, status, query tag, etc.). View the details of all queries executed in the last 14 days from your Snowflake account. Click a query ID to drill into it for more information.
- **Copy History** shows the status of copy commands run to ingest data into Snowflake.

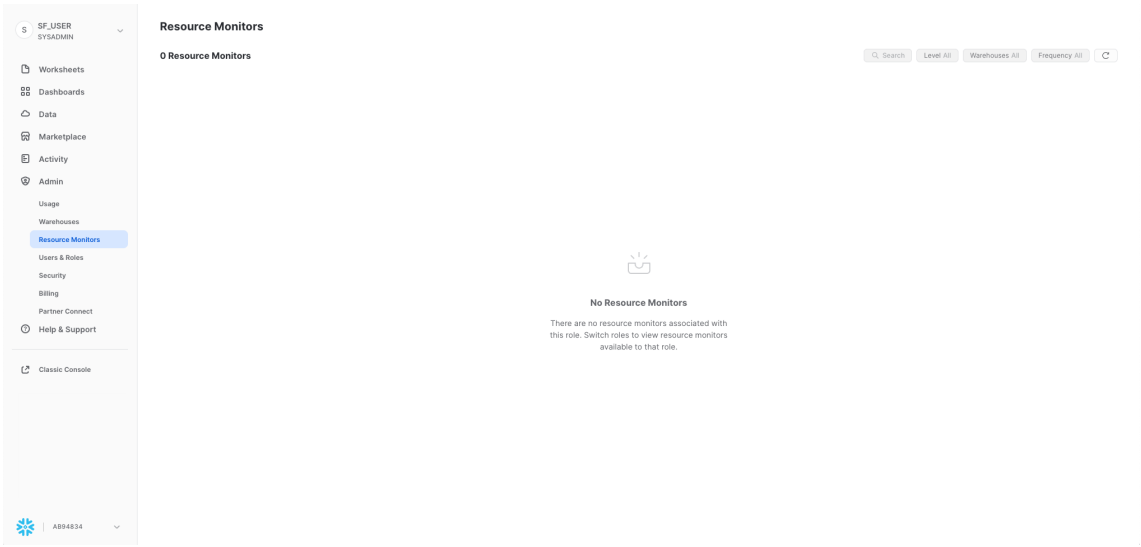
Warehouses



Under **Admin**, the **Warehouses** tab is where you set up and manage compute resources known as virtual warehouses to load or query data in Snowflake. If you don't see a warehouse called COMPUTE_WH in your environment, you can create it as shown below:

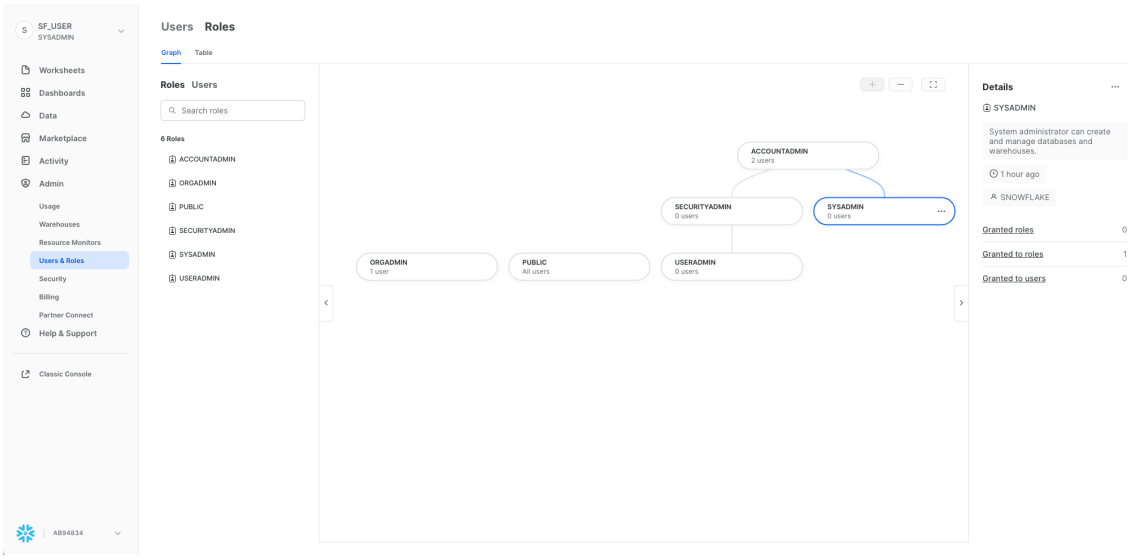


Resource Monitors



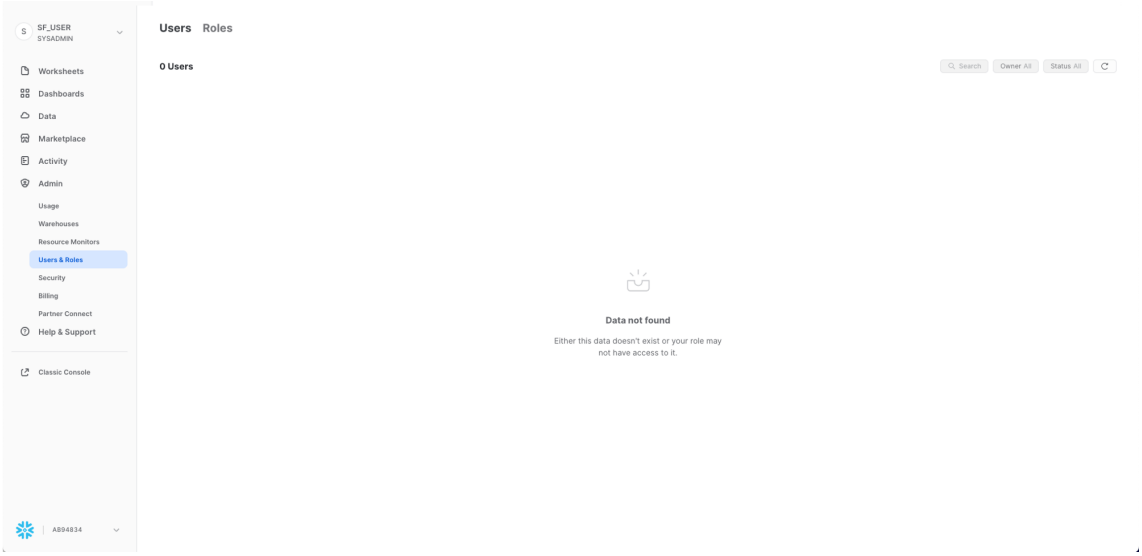
Under **Admin**, the **Resource Monitors** tab shows all the resource monitors that have been created to control the number of credits that virtual warehouses consume. For each resource monitor, it shows the credit quota, type of monitoring, schedule, and actions performed when the virtual warehouse reaches its credit limit.

Roles

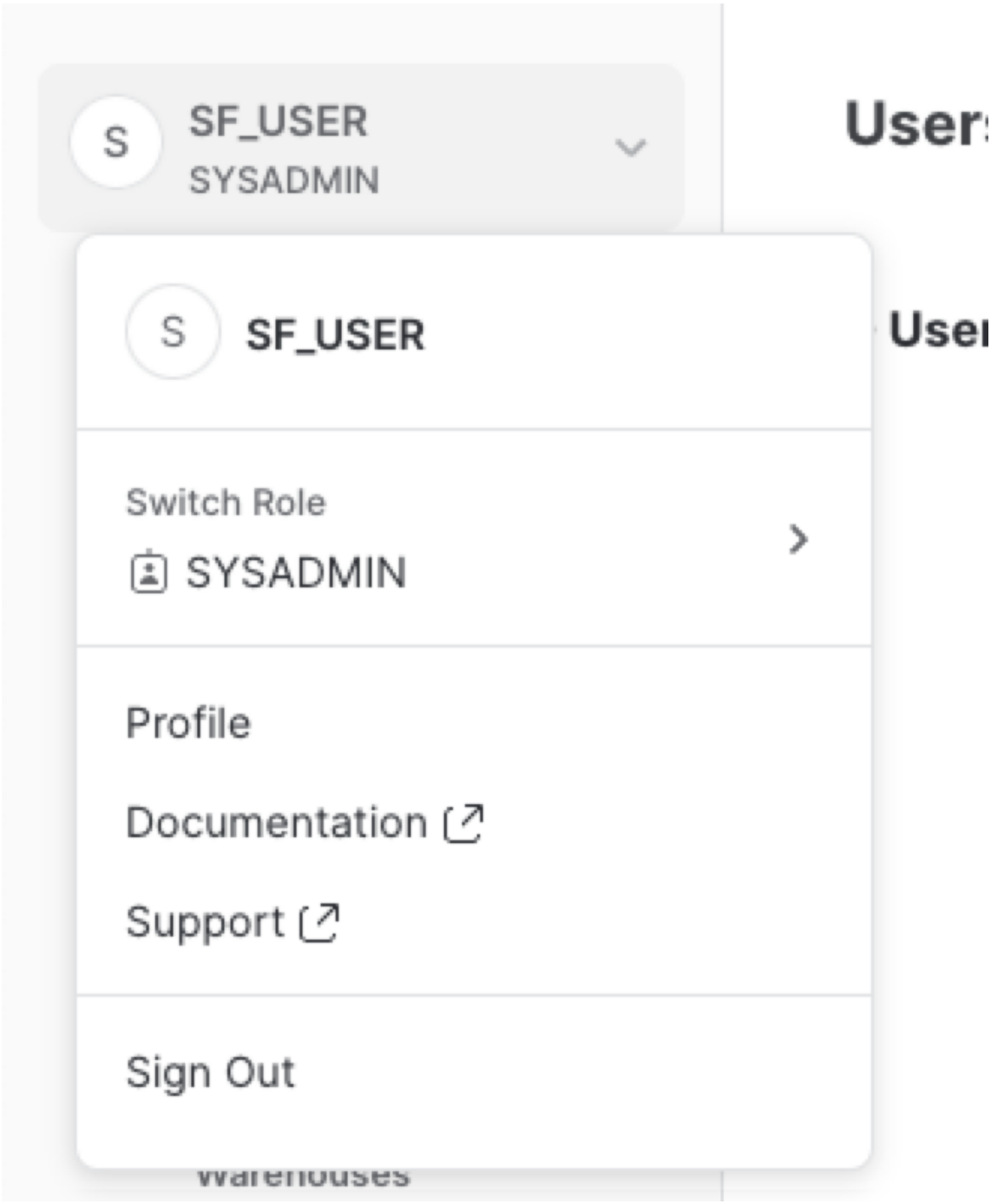


Under **Admin**, the **Roles** sub-tab of the **Users and Roles** tab shows a list of the roles and their hierarchies. Roles can be created, reorganized, and granted to users in this tab. The roles can also be displayed in tabular/list format by selecting the **Table** sub-tab.

Users



Also under **Admin** tab, the **Users** sub-tab of the **Users and Roles** tab shows a list of users in the account, default roles, and owner of the users. For a new account, no records are shown because no additional roles have been created. Permissions granted through your current role determine the information shown for this tab. To see all the information available on the tab, switch your role to ACCOUNTADMIN.



Clicking on your username in the top right of the UI allows you to change your password, roles, and preferences. Snowflake has several system defined roles. You are currently in the default role of `SYSADMIN` and will stay in this role for the majority of the lab.

Negative : **SYSADMIN** The `SYSADMIN` (aka System Administrator) role has privileges to create warehouses, databases, and other objects in an account.

The Lab Story

This lab is based on the analytics team at Citi Bike, a real, citywide bike sharing system in New York City, USA. The team wants to run analytics on data from their internal transactional systems to better understand their riders and how to best serve them.

We will first load structured `.csv` data from rider transactions into Snowflake. Later we will work with open-source, semi-structured JSON weather data to determine if there is any correlation between the number of bike rides and the weather.

Preparing to Load Data

Let's start by preparing to load the structured Citi Bike rider transaction data into Snowflake.

This section walks you through the steps to:

- Create a database and table.
- Create an external stage.
- Create a file format for the data.

Negative : **Getting Data into Snowflake** There are many ways to get data into Snowflake from many locations including the COPY command, Snowpipe auto-ingestion, external connectors, or third-party ETL/ELT solutions.

For the purposes of this lab, we use the COPY command and AWS S3 storage to load data manually. In a real-world scenario, you would more likely use an automated process or ETL solution.

The data we will be using is bike share data provided by Citi Bike NYC. The data has been exported and pre-staged for you in an Amazon AWS S3 bucket in the US-EAST region. The data consists of information about trip times, locations, user type, gender, age, etc. On AWS S3, the data represents 61.5M rows, 377 objects, and 1.9GB compressed.

Below is a snippet from one of the Citi Bike CSV data files:

```
"tripduration","starttime","stoptime","start station id","start station name","start
station latitude","start station longitude","end station id","end station name","end
station latitude","end station
longitude","bikeid","name_localizedValue0","usertype","birth year","gender"
196,"2018-01-01 00:01:51","2018-01-01 00:05:07",315,"South St & Gouverneur Ln",
40.70355377,-74.00670227,259,"South St & Whitehall St",
40.70122128,-74.01234218,18534,"Annual Membership","Subscriber",1997,1
207,"2018-01-01 00:02:44","2018-01-01 00:06:11",3224,"W 13 St & Hudson St",
40.73997354103409,-74.00513872504234,470,"W 20 St & 8 Ave",
40.74345335,-74.00004031,19651,"Annual Membership","Subscriber",1978,1
613,"2018-01-01 00:03:15","2018-01-01 00:13:28",386,"Centre St & Worth St",
40.71494807,-74.00234482,2008,"Little West St & 1 Pl",
40.70569254,-74.01677685,21678,"Annual Membership","Subscriber",1982,1
```

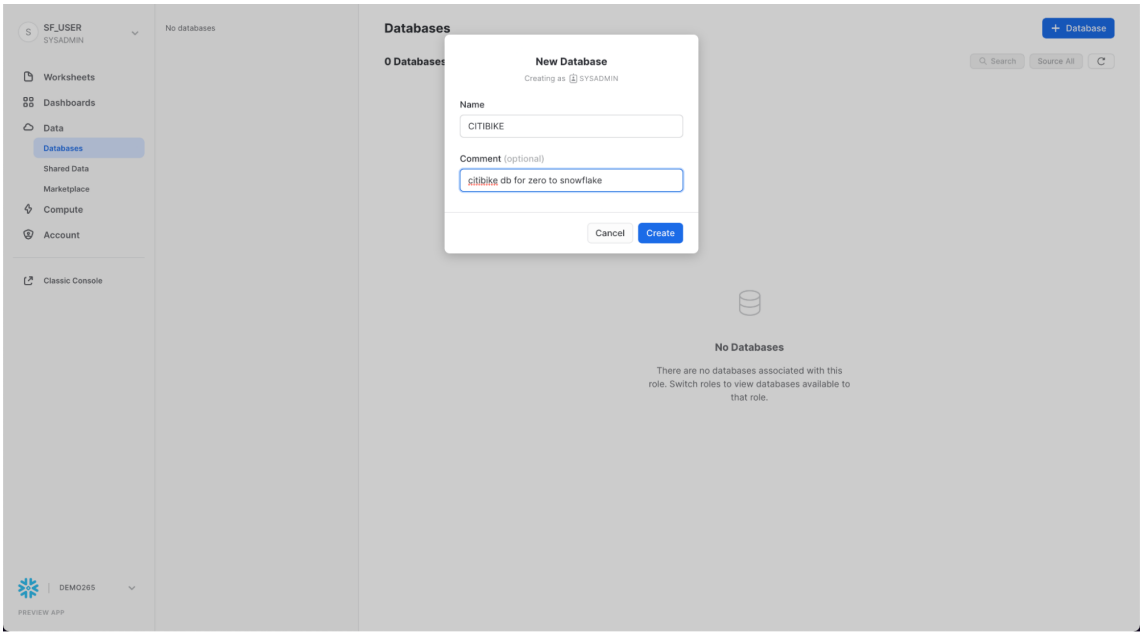
It is in comma-delimited format with a single header line and double quotes enclosing all string values, including the field headings in the header line. This will come into play later in this section as we configure the Snowflake table to store this data.

Create a Database and Table

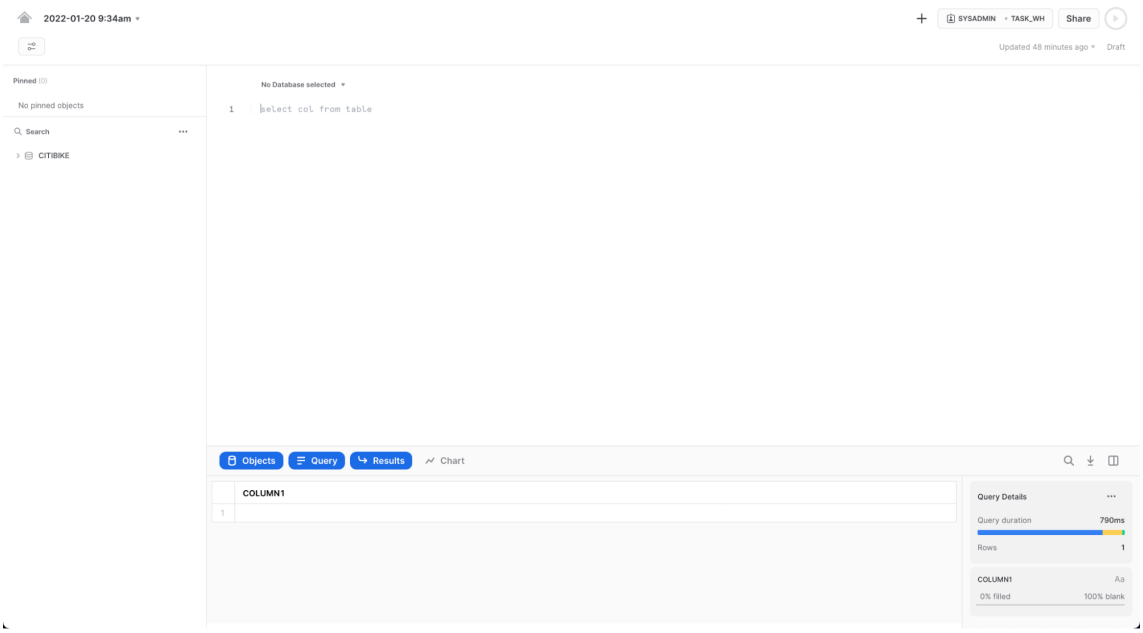
First, let's create a database called `CITIBIKE` to use for loading the structured data.

Ensure you are using the sysadmin role by selecting **Switch Role** > **SYSADMIN**.

Navigate to the **Databases** tab. Click **Create**, name the database `CITIBIKE` , then click **CREATE**.



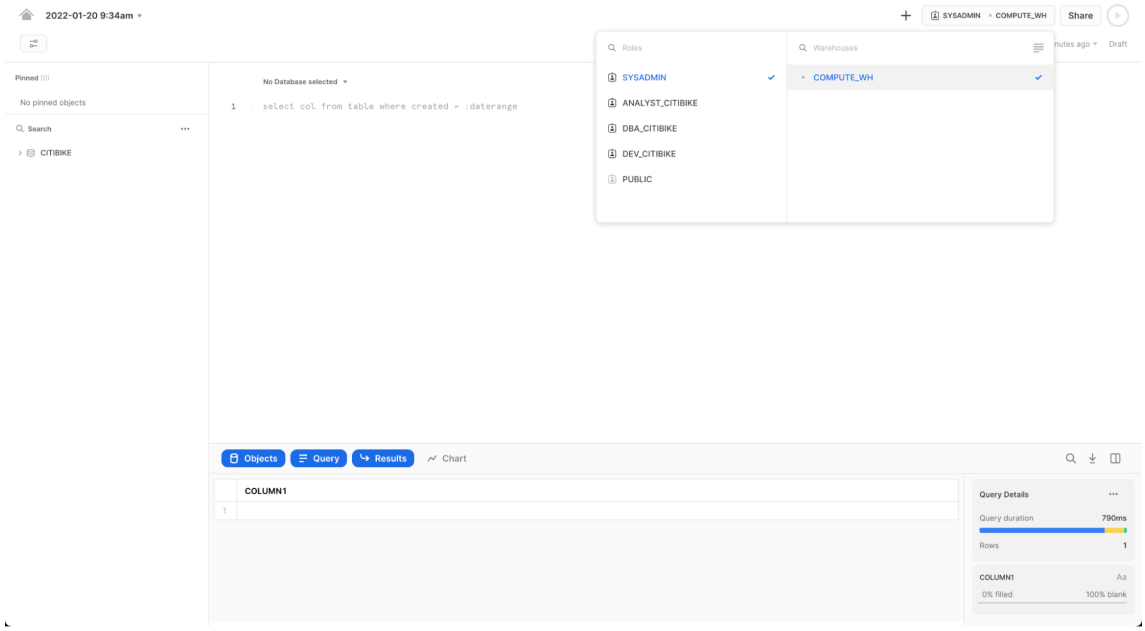
Now navigate to the **Worksheets** tab. You should see the worksheet we created in step 3.



We need to set the context appropriately within the worksheet. In the upper right corner of the worksheet, click the box next to the **+** to show the context menu. Here we control the elements you can see and run from each worksheet. We are using the UI here to set the context. Later in the lab, we will accomplish the same thing via SQL commands within the worksheet.

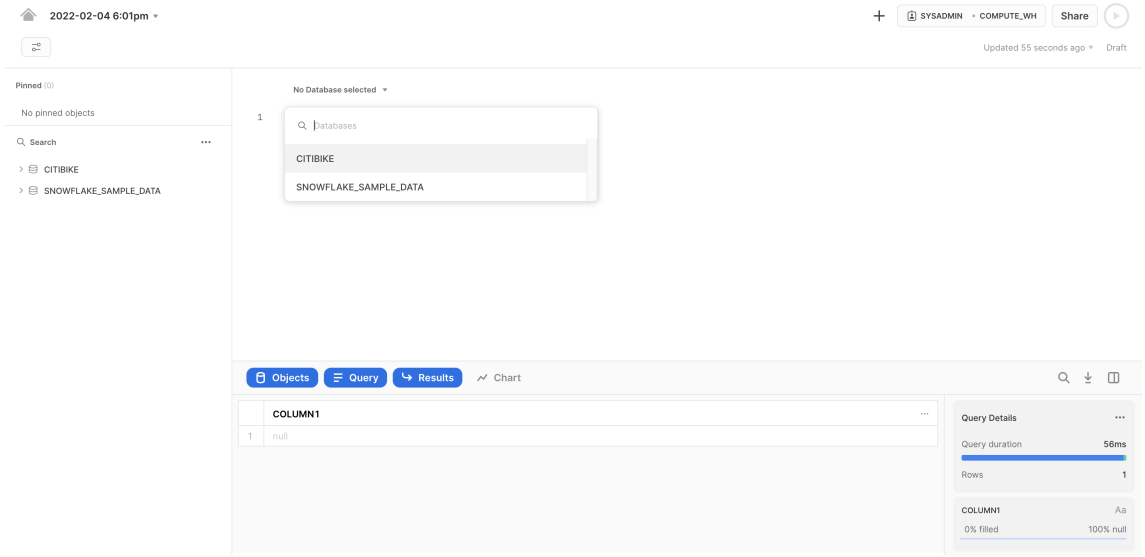
Select the following context settings:

Role: `SYSADMIN` Warehouse: `COMPUTE_WH`



Next, in the drop-down for the database, select the following context settings:

Database: `CITIBIKE` Schema = `PUBLIC`



Negative : **Data Definition Language (DDL) operations are free!** All the DDL operations we have done so far do not require compute resources, so we can create all our objects for free.

To make working in the worksheet easier, let's rename it. In the top left corner, click the worksheet name, which is the timestamp when the worksheet was created, and change it to `CITIBIKE_ZERO_TO_SNOWFLAKE`.

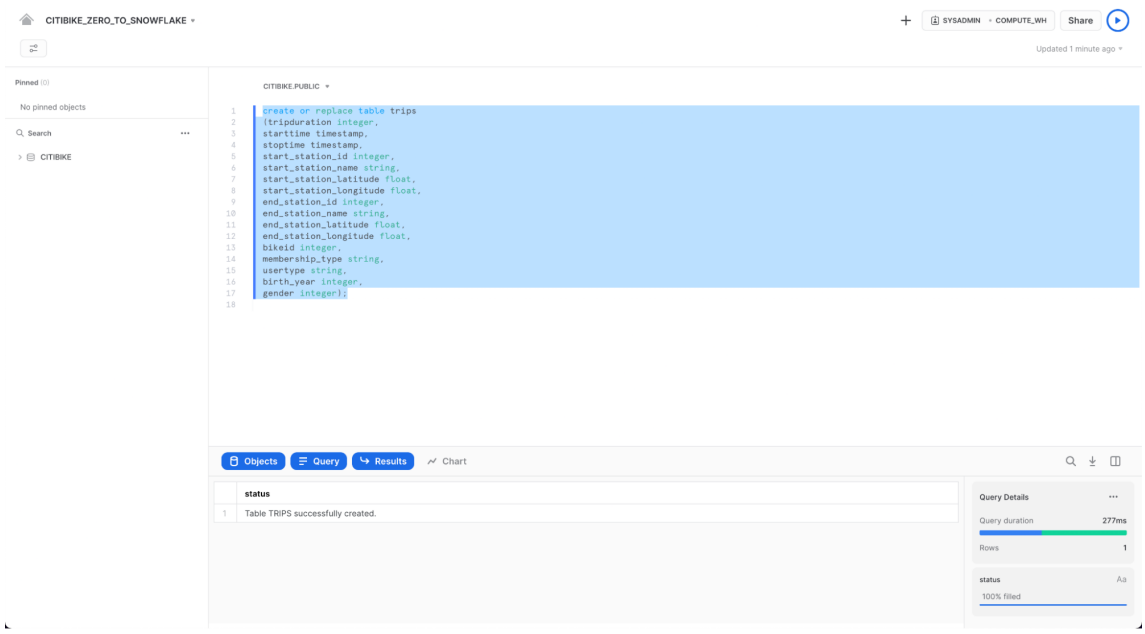
Next we create a table called `TRIPS` to use for loading the comma-delimited data. Instead of using the UI, we use the worksheet to run the DDL that creates the table. Copy the following SQL text into your worksheet:

```
create or replace table trips
(tripduration integer,
starttime timestamp,
stoptime timestamp,
start_station_id integer,
start_station_name string,
start_station_latitude float,
start_station_longitude float,
end_station_id integer,
end_station_name string,
end_station_latitude float,
end_station_longitude float,
bikeid integer,
membership_type string,
usertype string,
birth_year integer,
gender integer);
```

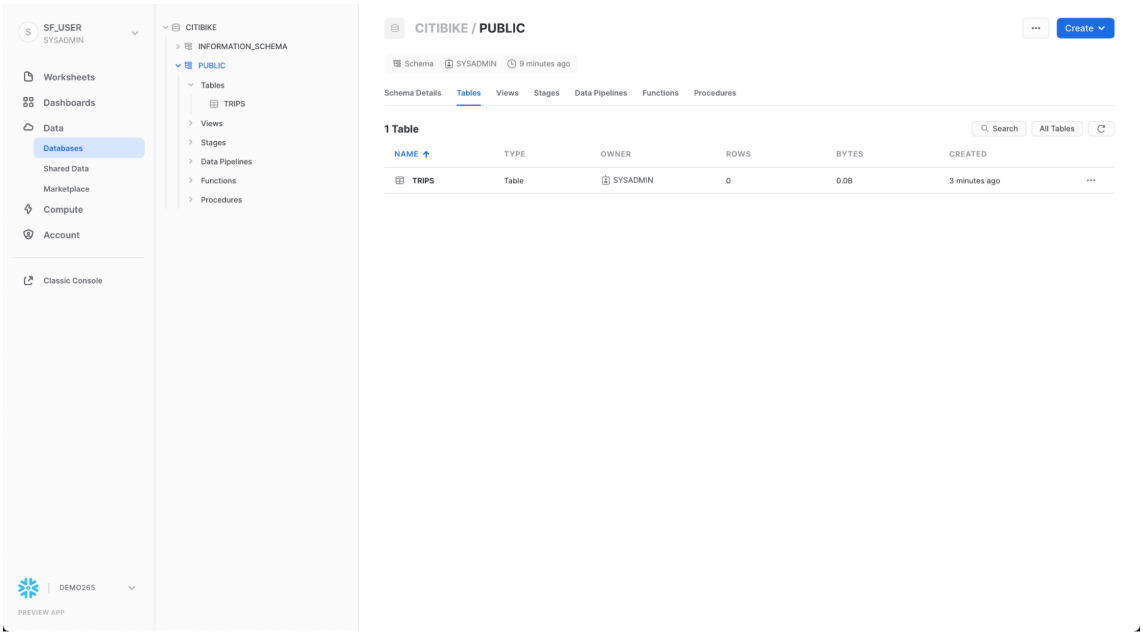
Negative : **Many Options to Run Commands.** SQL commands can be executed through the UI, via the **Worksheets** tab, using our SnowSQL command line tool, with a SQL editor of your choice via ODBC/JDBC, or through our other connectors (Python, Spark, etc.). As mentioned earlier, to save time, we are performing most of the operations in this lab via pre-written SQL executed in the worksheet as opposed to using the UI.

Run the query by placing your cursor anywhere in the SQL text and clicking the blue **Play/Run** button in the top right of the worksheet. Or use the keyboard shortcut [Ctrl]/[Cmd]+[Enter].

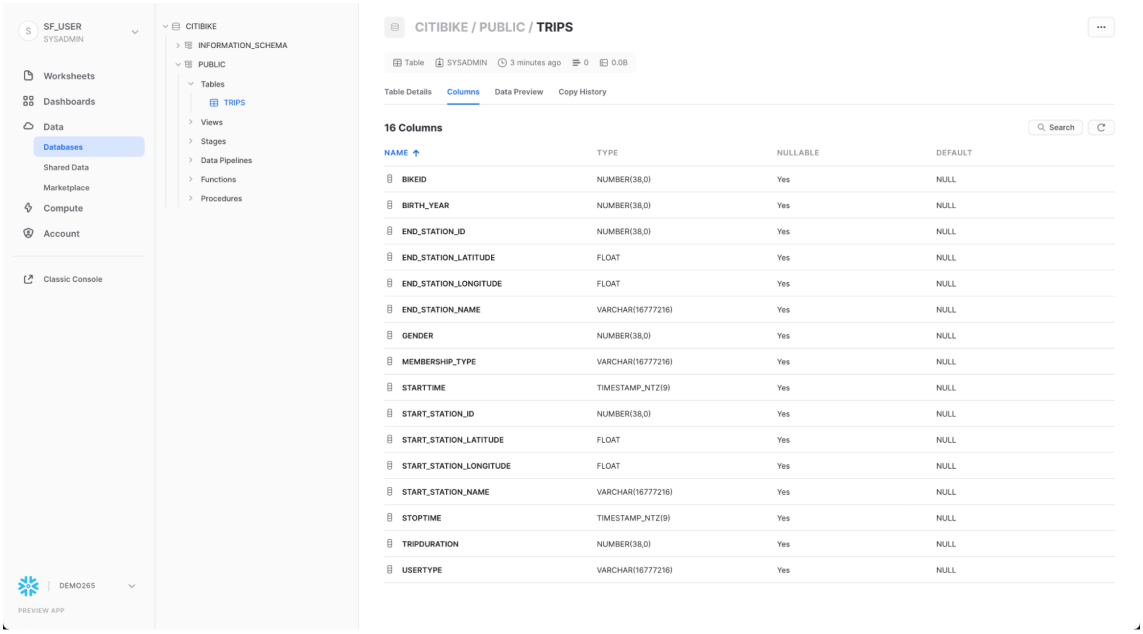
Verify that your TRIPS table has been created. At the bottom of the worksheet you should see a Results section displaying a "Table TRIPS successfully created" message.



Navigate to the **Databases** tab by clicking the **HOME** icon in the upper left corner of the worksheet. Then click **Data** > **Databases**. In the list of databases, click `CITIBIKE` > `PUBLIC` > **TABLES** to see your newly created `TRIPS` table. If you don't see any databases on the left, expand your browser because they may be hidden.



Click `TRIPS` and the **Columns** tab to see the table structure you just created.

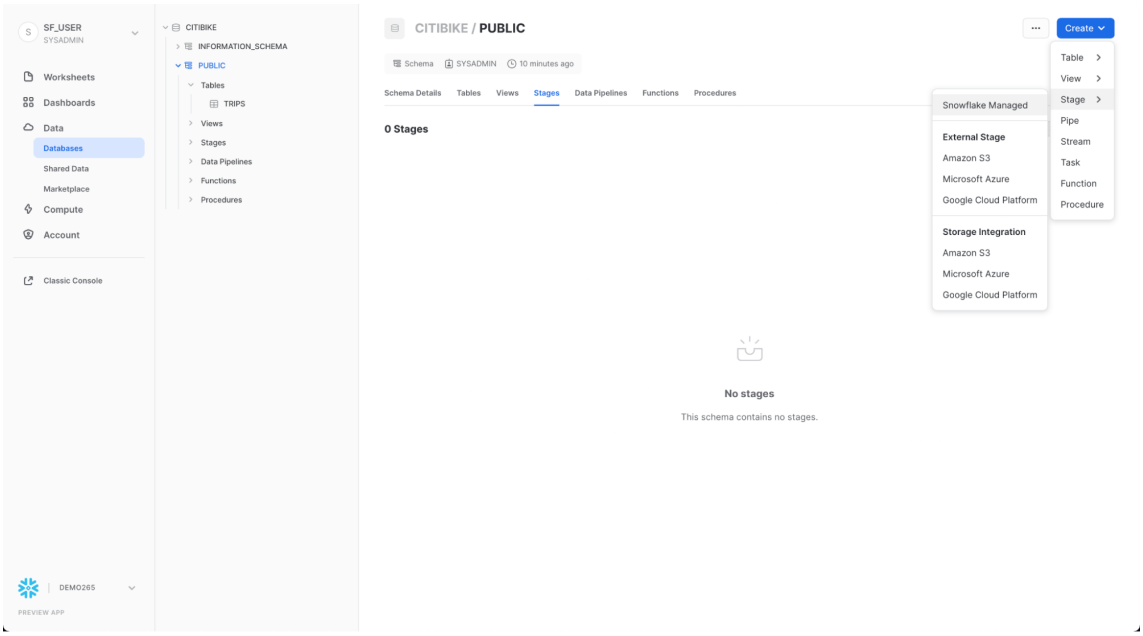


Create an External Stage

We are working with structured, comma-delimited data that has already been staged in a public, external S3 bucket. Before we can use this data, we first need to create a Stage that specifies the location of our external bucket.

Positive : For this lab we are using an AWS-East bucket. To prevent data egress/transfer costs in the future, you should select a staging location from the same cloud provider and region as your Snowflake account.

From the **Databases** tab, click the `CITIBIKE` database and `PUBLIC` schema. In the **Stages** tab, click the **Create** button, then **Stage** > **Amazon S3**.



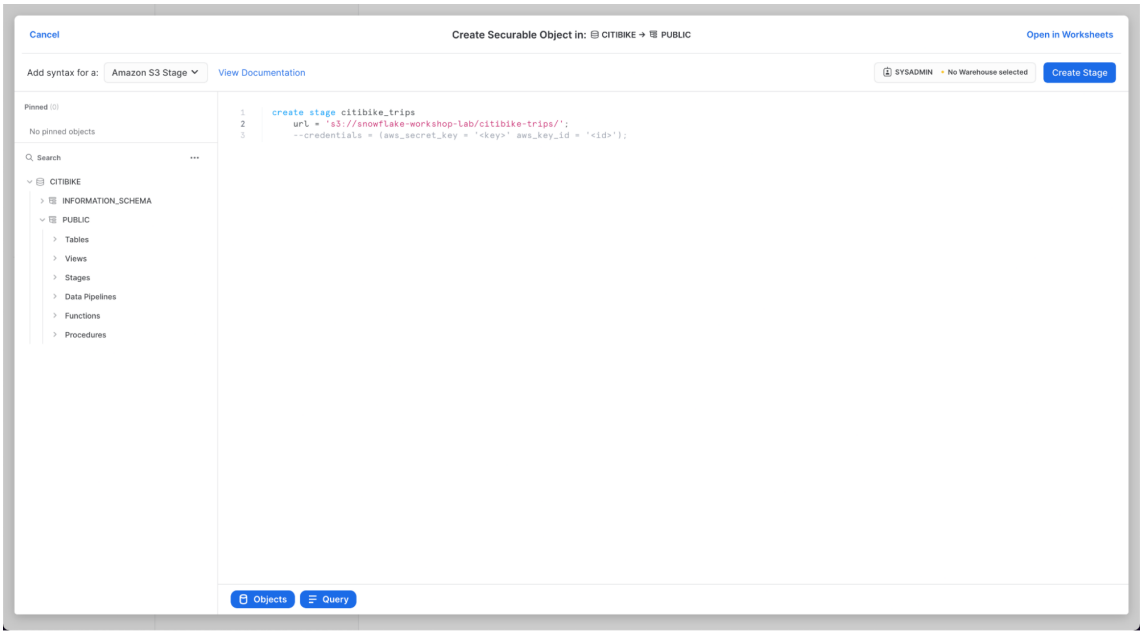
In the "Create Securable Object" dialog that opens, replace the following values in the SQL statement:

`stage_name` : `citibike_trips`

`url` : `s3://snowflake-workshop-lab/citibike-trips-csv/`

Note: Make sure to include the final forward slash (`/`) at the end of the URL or you will encounter errors later when loading data from the bucket. Also ensure you have removed 'credentials = (...)' statejment which is not required. The create stage command should resemble that show above exactly.

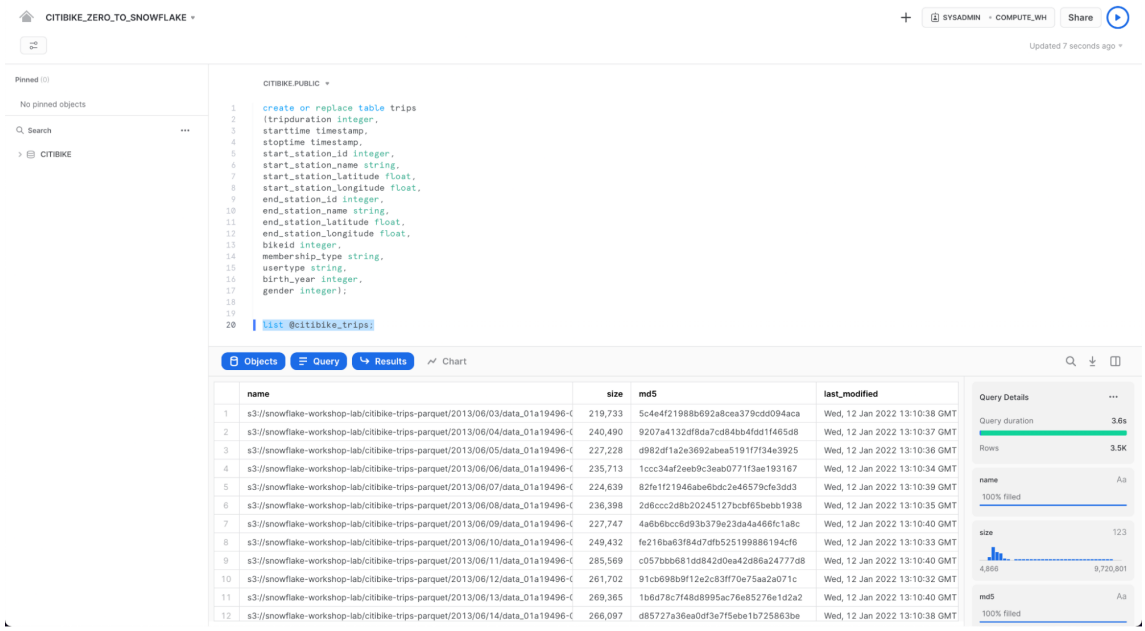
Positive : The S3 bucket for this lab is public so you can leave the credentials options in the statement empty. In a real-world scenario, the bucket used for an external stage would likely require key information.



Now let's take a look at the contents of the `citibike_trips` stage. Navigate to the **Worksheets** tab and execute the following SQL statement:

```
list @citibike_trips;
```

In the results in the bottom pane, you should see the list of files in the stage:

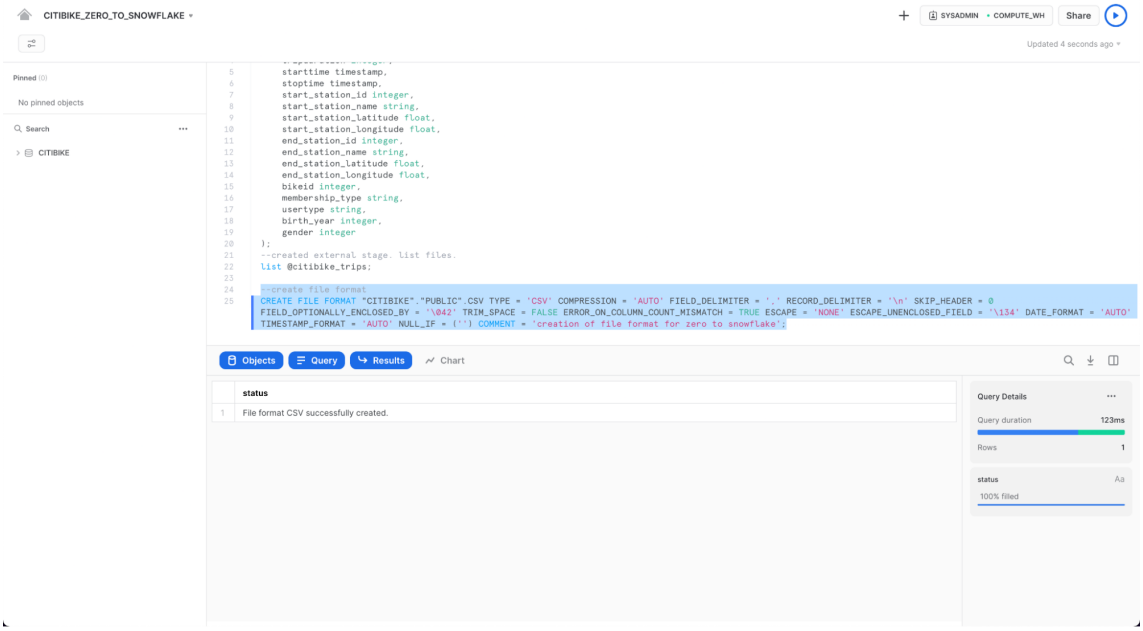


Create a File Format

Before we can load the data into Snowflake, we have to create a file format that matches the data structure.

In the worksheet, run the following command to create the file format:

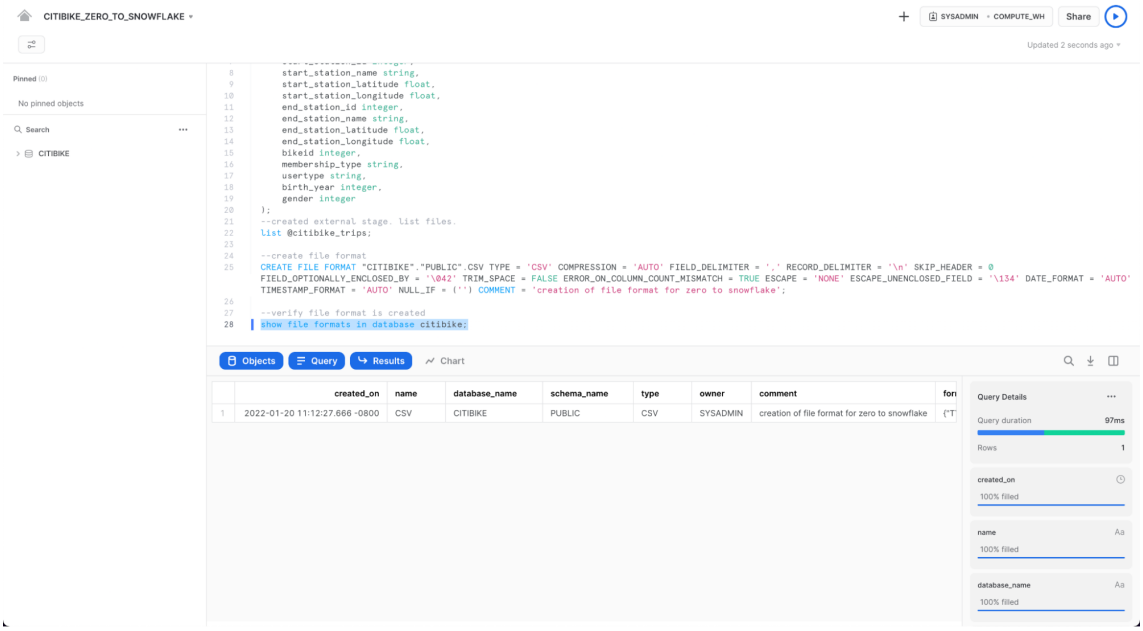
```
--create file format

create or replace file format csv type='csv'
  compression = 'auto' field_delimiter = ',' record_delimiter = '\n'
  skip_header = 0 field_optionally_enclosed_by = '\042' trim_space = false
  error_on_column_count_mismatch = false escape = 'none' escape_unenclosed_field =
'\134'
  date_format = 'auto' timestamp_format = 'auto' null_if = ('') comment = 'file format
for ingesting data for zero to snowflake';
```



Verify that the file format has been created with the correct settings by executing the following command:

```
--verify file format is created

show file formats in database citibike;
```

The file format created should be listed in the result:



Loading Data

In this section, we will use a virtual warehouse and the COPY command to initiate bulk loading of structured data into the Snowflake table we created in the last section.

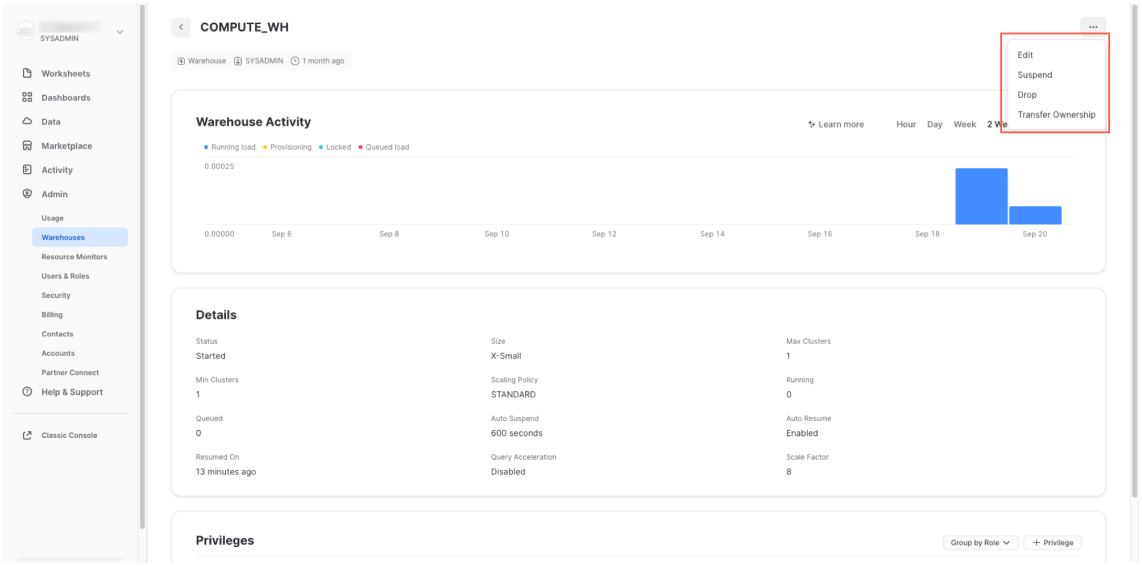
Resize and Use a Warehouse for Data Loading

Compute resources are needed for loading data. Snowflake's compute nodes are called virtual warehouses and they can be dynamically sized up or out according to workload, whether you are loading data, running a query, or performing a DML operation. Each workload can have its own warehouse so there is no resource contention.

Navigate to the **Warehouses** tab (under **Admin**). This is where you can view all of your existing warehouses, as well as analyze their usage trends.

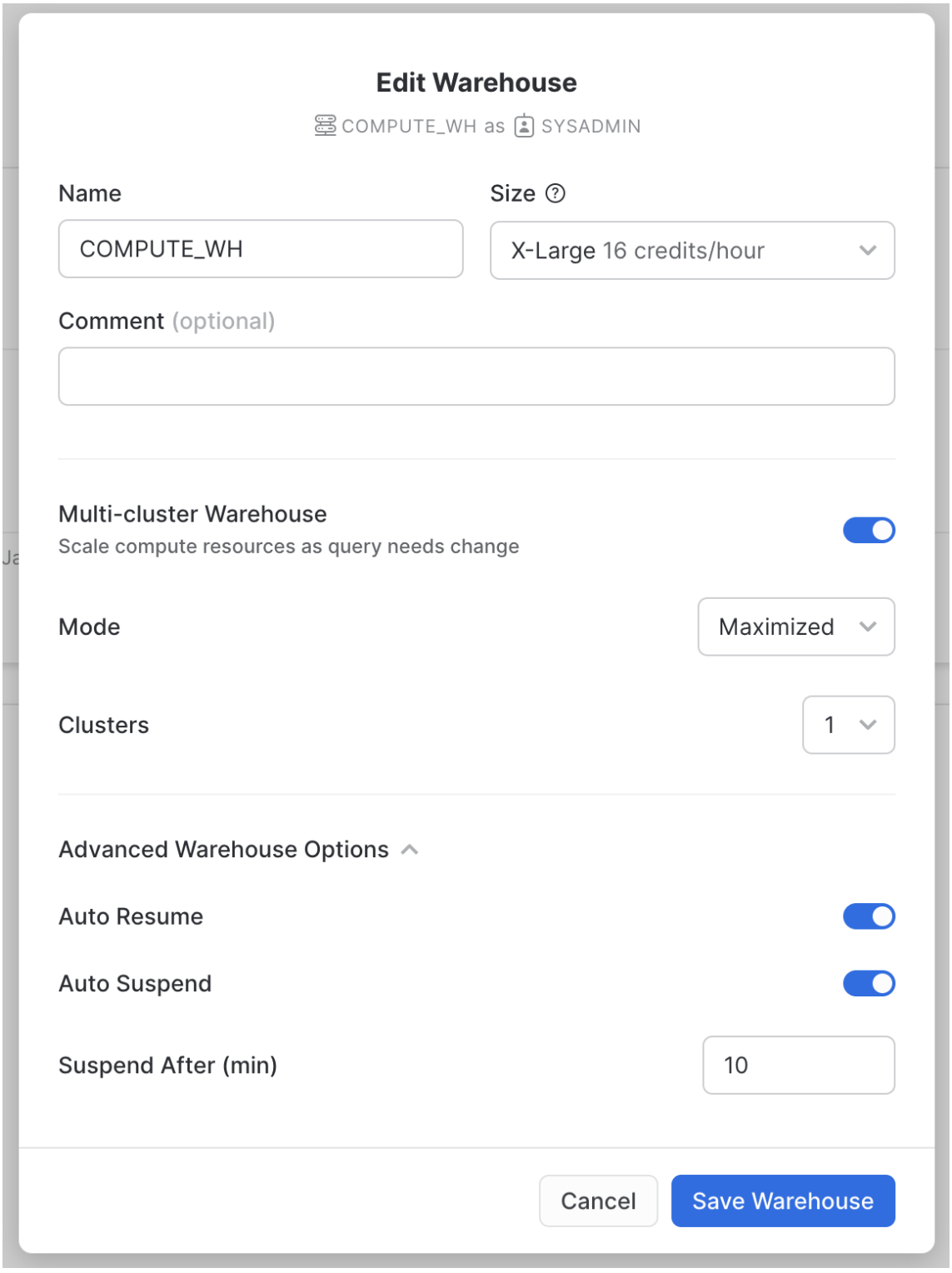
Note the **+ Warehouse** option in the upper right corner of the top. This is where you can quickly add a new warehouse. However, we want to use the existing warehouse COMPUTE_WH included in the 30-day trial environment.

Click the row of the `COMPUTE_WH` warehouse. Then click the **...** (dot dot dot) in the upper right corner text above it to see the actions you can perform on the warehouse. We will use this warehouse to load the data from AWS S3.



Click **Edit** to walk through the options of this warehouse and learn some of Snowflake's unique functionality.

Positive : If this account isn't using Snowflake Enterprise Edition (or higher), you will not see the **Mode** or **Clusters** options shown in the screenshot below. The multi-cluster warehouses feature is not used in this lab, but we will discuss it as a key capability of Snowflake.



- The **Size** drop-down is where the capacity of the warehouse is selected. For larger data loading operations or more compute-intensive queries, a larger warehouse is recommended. The sizes translate to the underlying compute resources provisioned from the cloud provider (AWS, Azure, or GCP) where your Snowflake account is hosted. It also determines the number of credits consumed by the warehouse for each full hour it runs. The larger the size, the more compute resources from the cloud provider are allocated to

the warehouse and the more credits it consumes. For example, the `4X-Large` setting consumes 128 credits for each full hour. This sizing can be changed up or down at any time with a simple click.

- If you are using Snowflake Enterprise Edition (or higher) and the **Multi-cluster Warehouse** option is enabled, you will see additional options. This is where you can set up a warehouse to use multiple clusters of compute resources, up to 10 clusters. For example, if a `4X-Large` multi-cluster warehouse is assigned a maximum cluster size of 10, it can scale out to 10 times the compute resources powering that warehouse...and it can do this in seconds! However, note that this will increase the number of credits consumed by the warehouse to 1280 if all 10 clusters run for a full hour (128 credits/hour x 10 clusters). Multi-cluster is ideal for concurrency scenarios, such as many business analysts simultaneously running different queries using the same warehouse. In this use case, the various queries are allocated across multiple clusters to ensure they run quickly.
- Under **Advanced Warehouse Options**, the options allow you to automatically suspend the warehouse when not in use so no credits are needlessly consumed. There is also an option to automatically resume a suspended warehouse so when a new workload is sent to it, it automatically starts back up. This functionality enables Snowflake's efficient "pay only for what you use" billing model which allows you to scale your resources when necessary and automatically scale down or turn off when not needed, nearly eliminating idle resources.

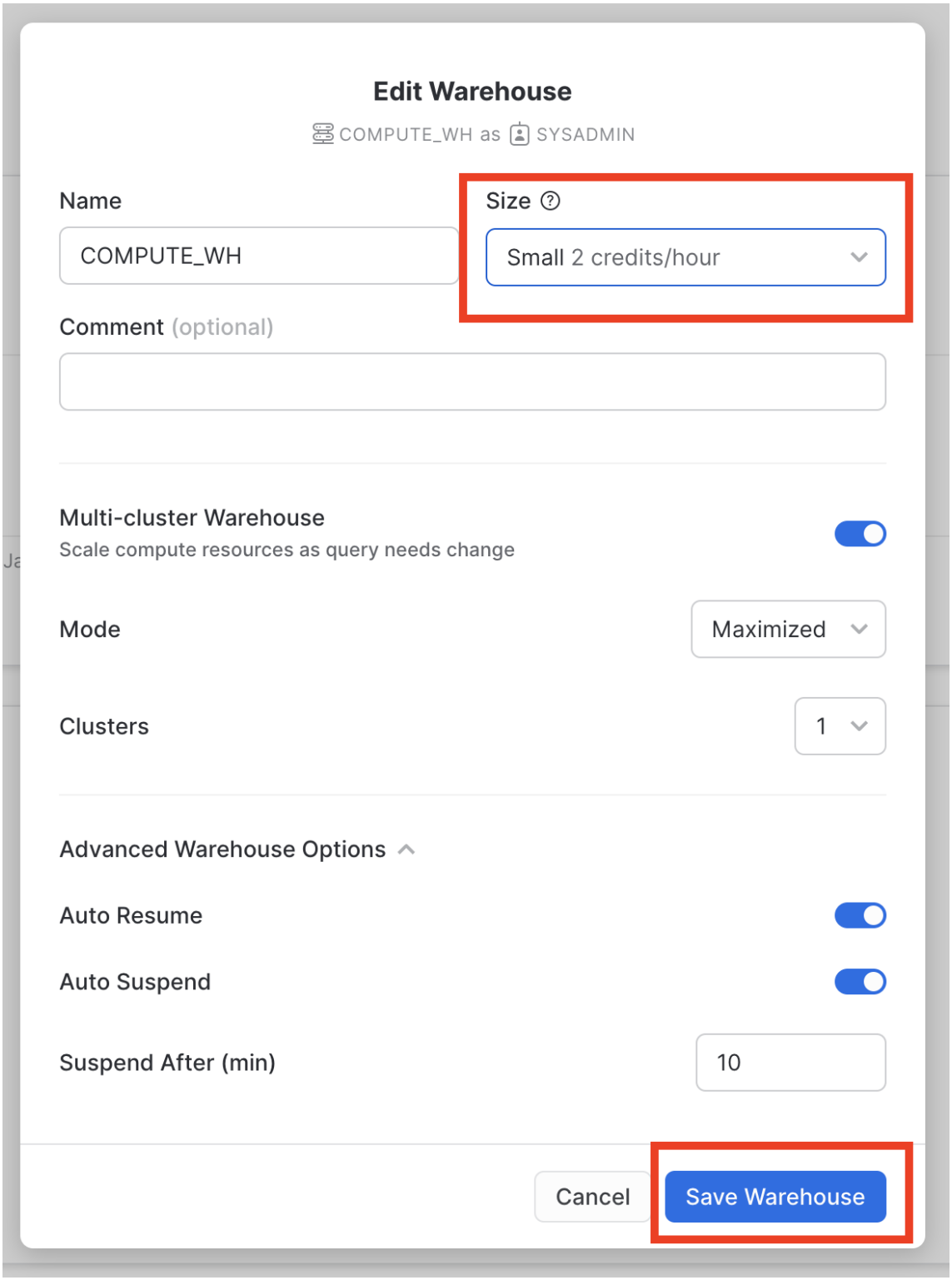
Negative : **Snowflake Compute vs Other Data Warehouses** Many of the virtual warehouse and compute capabilities we just covered, such as the ability to create, scale up, scale out, and auto-suspend/resume virtual warehouses are easy to use in Snowflake and can be done in seconds. For on-premise data warehouses, these capabilities are much more difficult, if not impossible, as they require significant physical hardware, over-provisioning of hardware for workload spikes, and significant configuration work, as well as additional challenges. Even other cloud-based data warehouses cannot scale up and out like Snowflake without significantly more configuration work and time.

Warning - Watch Your Spend! During or after this lab, you should be careful about performing the following actions without good reason or you may burn through your $400 of free credits more quickly than desired:

- Do not disable auto-suspend. If auto-suspend is disabled, your warehouses continues to run and consume credits even when not in use.
- Do not use a warehouse size that is excessive given the workload. The larger the warehouse, the more credits are consumed.

We are going to use this virtual warehouse to load the structured data in the CSV files (stored in the AWS S3 bucket) into Snowflake. However, we are first going to change the size of the warehouse to increase the compute resources it uses. After the load, note the time taken and then, in a later step in this section, we will re-do the same load operation with an even larger warehouse, observing its faster load time.

Change the **Size** of this data warehouse from `X-Small` to `Small`. then click the **Save Warehouse** button:

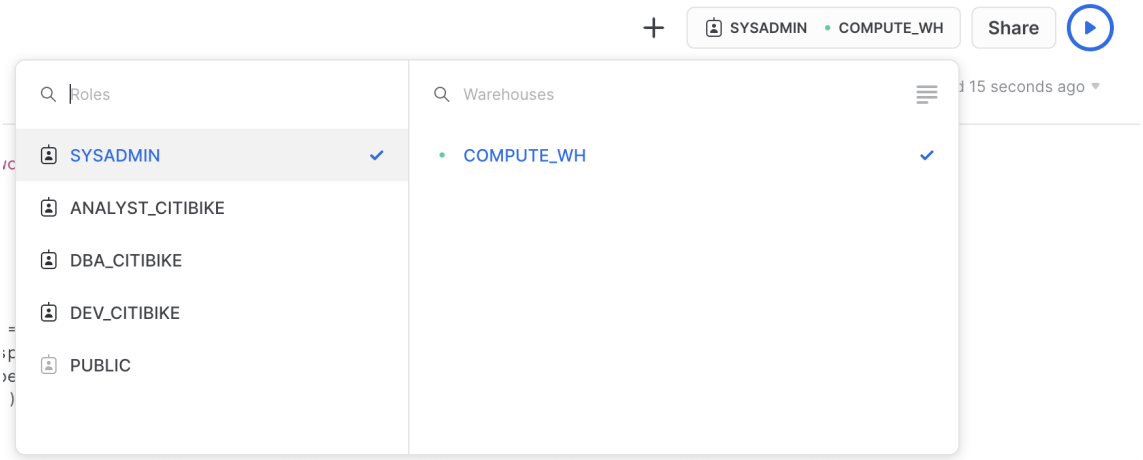


Load the Data

Now we can run a COPY command to load the data into the `TRIPS` table we created earlier.

Navigate back to the `CITIBIKE_ZERO_TO_SNOWFLAKE` worksheet in the **Worksheets** tab. Make sure the worksheet context is correctly set:

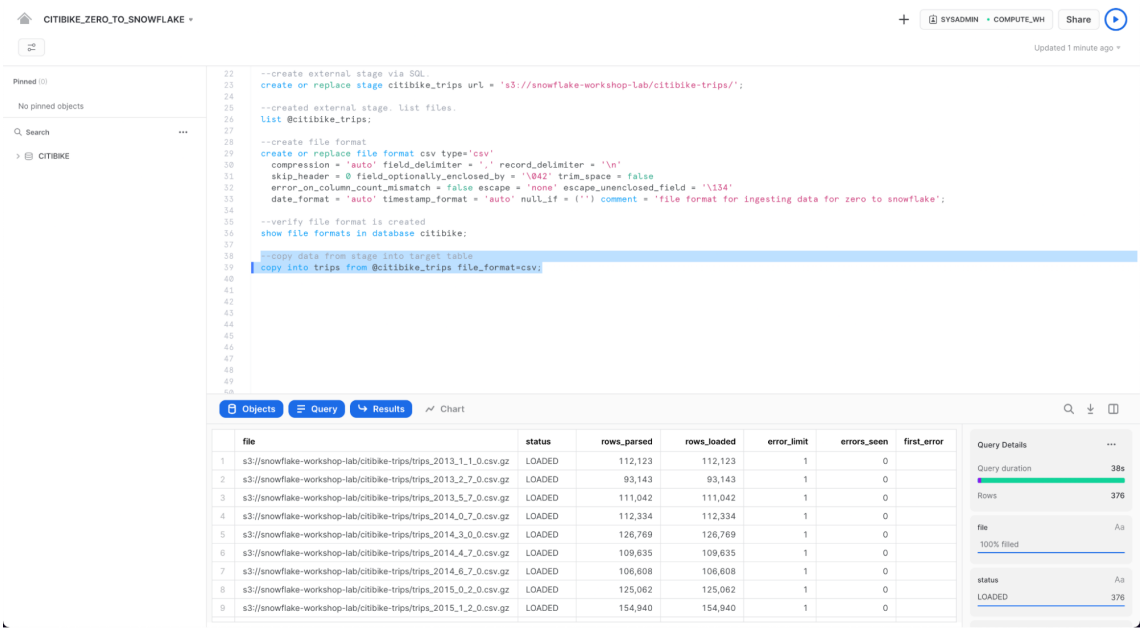
Role: `SYSADMIN` Warehouse: `COMPUTE_WH` Database: `CITIBIKE` Schema = `PUBLIC`



Execute the following statements in the worksheet to load the staged data into the table. This may take up to 30 seconds.

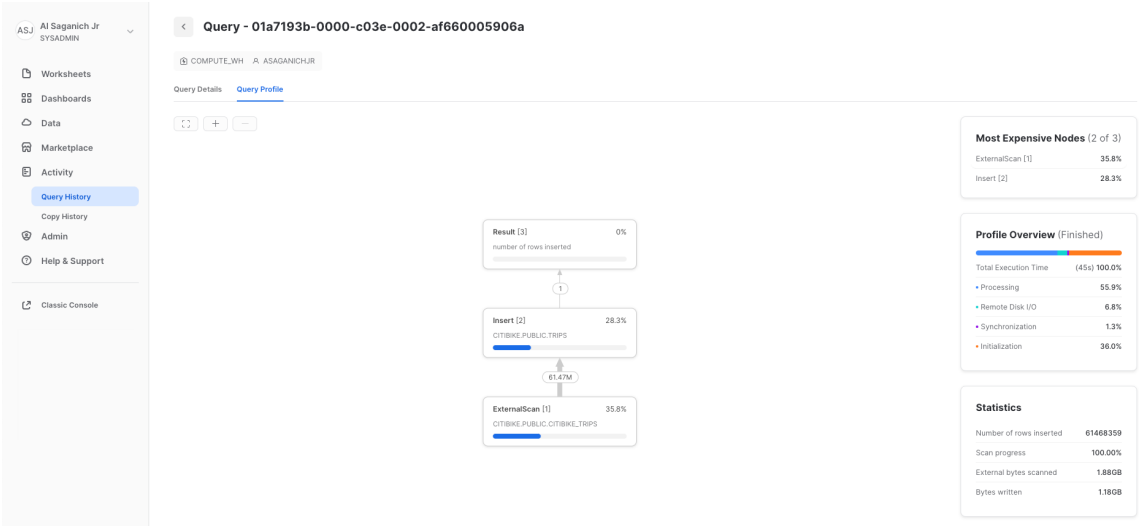
```
copy into trips from @citibike_trips file_format=csv PATTERN = '.*csv.*' ;
```

In the result pane, you should see the status of each file that was loaded. Once the load is done, in the **Query Details** pane on the bottom right, you can scroll through the various statuses, error statistics, and visualizations for the last statement executed:



Next, navigate to the **Query History** tab by clicking the **Home** icon and then **Activity** > **Query History**. Select the query at the top of the list, which should be the COPY INTO statement that was last executed. Select the **Query**

Profile tab and note the steps taken by the query to execute, query details, most expensive nodes, and additional statistics.



Now let's reload the `TRIPS` table with a larger warehouse to see the impact the additional compute resources have on the loading time.

Go back to the worksheet and use the TRUNCATE TABLE command to clear the table of all data and metadata:

```
truncate table trips;
```

Verify that the table is empty by running the following command:

```
--verify table is clear
select * from trips limit 10;
```

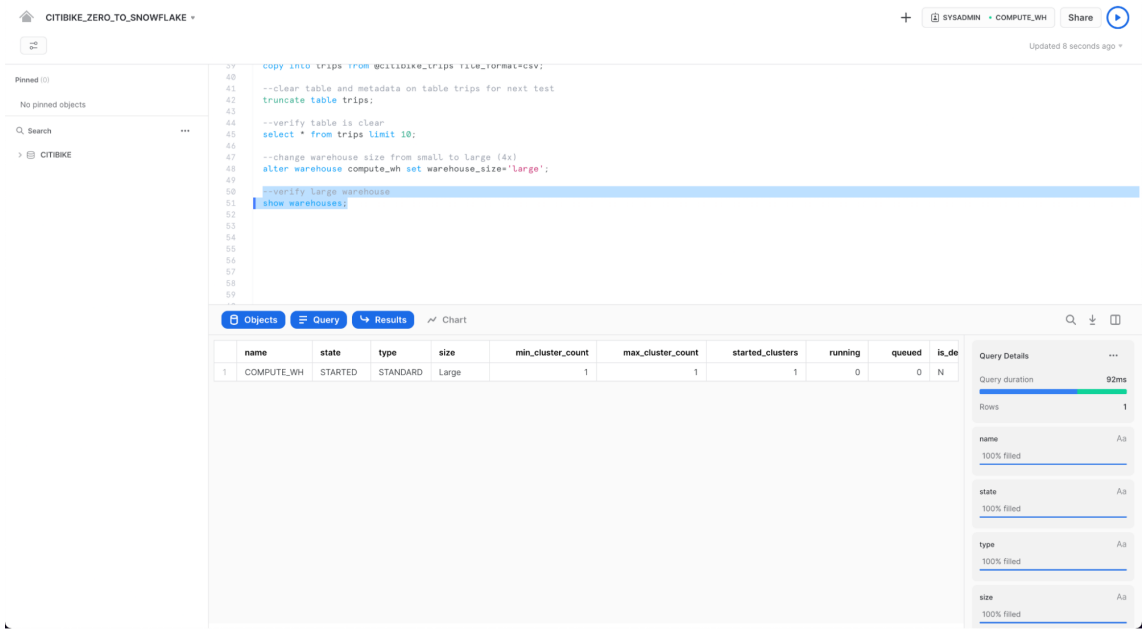
The result should show "Query produced no results".

Change the warehouse size to `large` using the following ALTER WAREHOUSE:

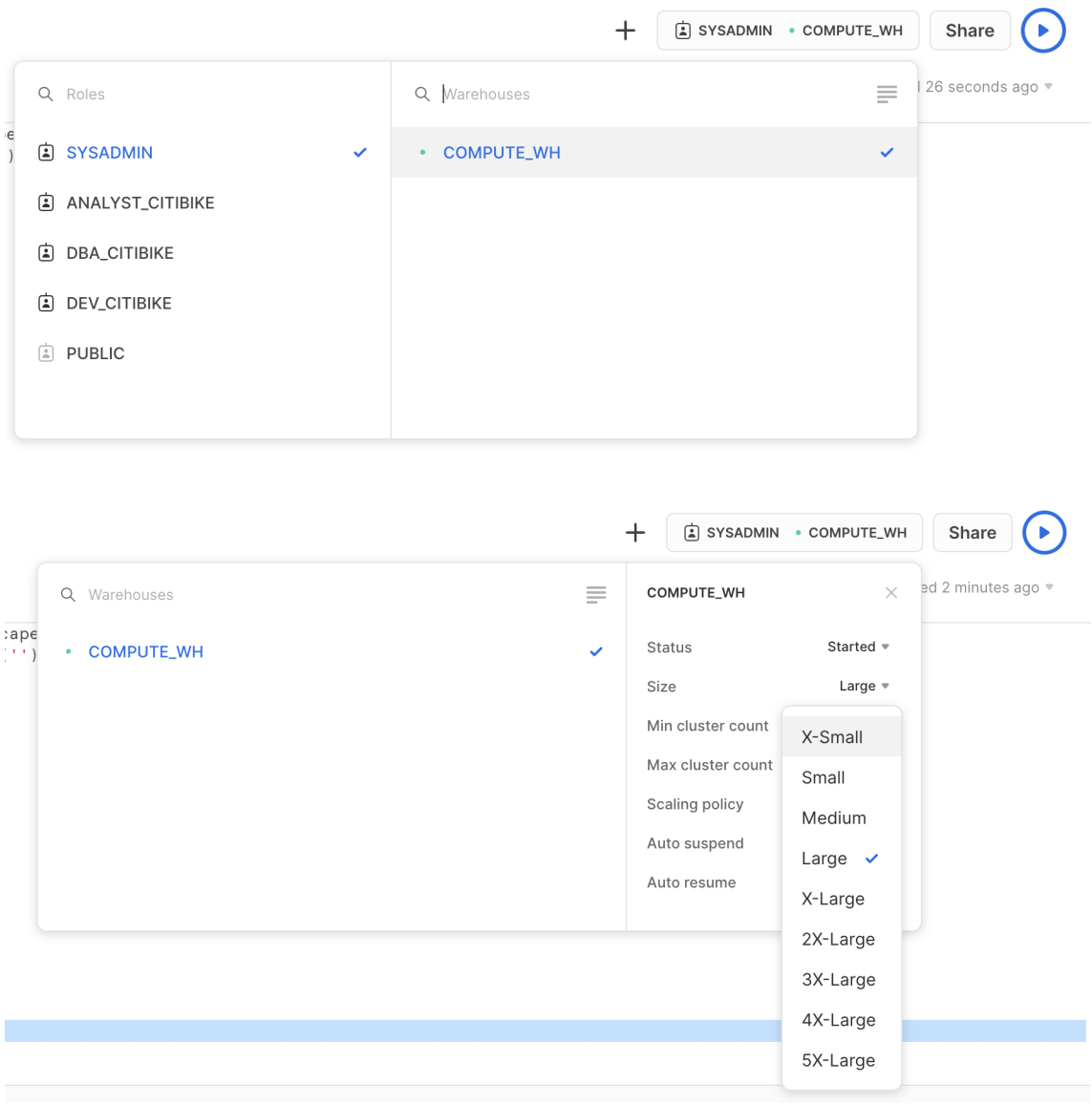
```
--change warehouse size from small to large (4x)
alter warehouse compute_wh set warehouse_size='large';
```

Verify the change using the following SHOW WAREHOUSES:

```
--load data with large warehouse
show warehouses;
```

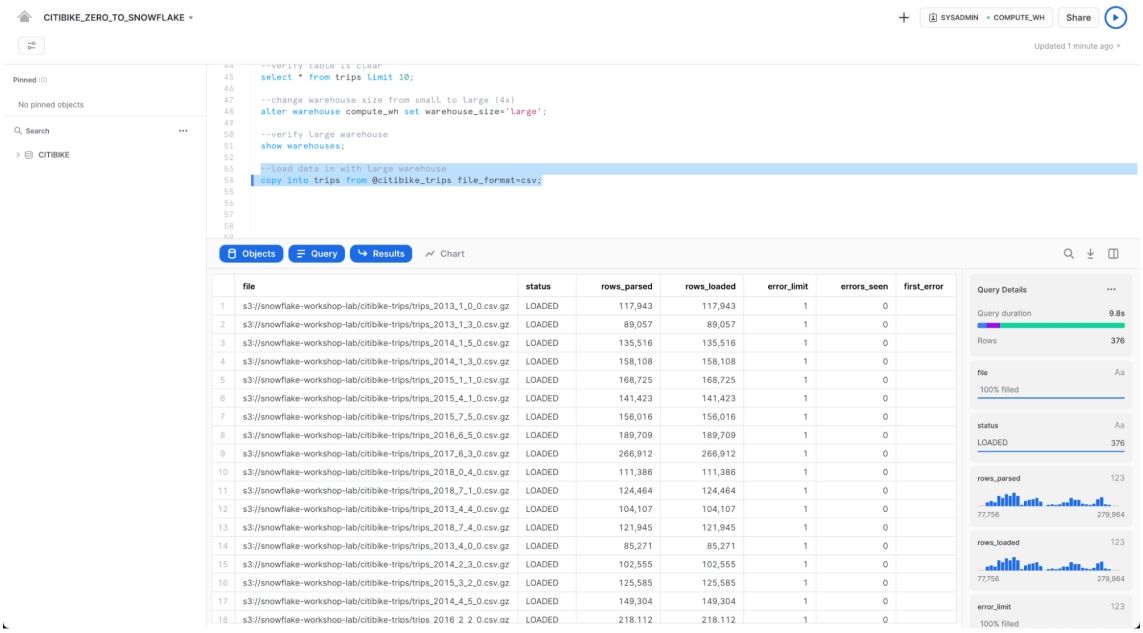


The size can also be changed using the UI by clicking on the worksheet context box, then the **Configure** (3-line) icon on the right side of the context box, and changing `Small` to `Large` in the **Size** drop-down:



Execute the same COPY INTO statement as before to load the same data again:

```
copy into trips from @citibike_trips
file_format=CSV;
```



Once the load is done, navigate back to the **Queries** page (**Home** icon > **Activity** > **Query History**). Compare the times of the two COPY INTO commands. The load using the `Large` warehouse was significantly faster.

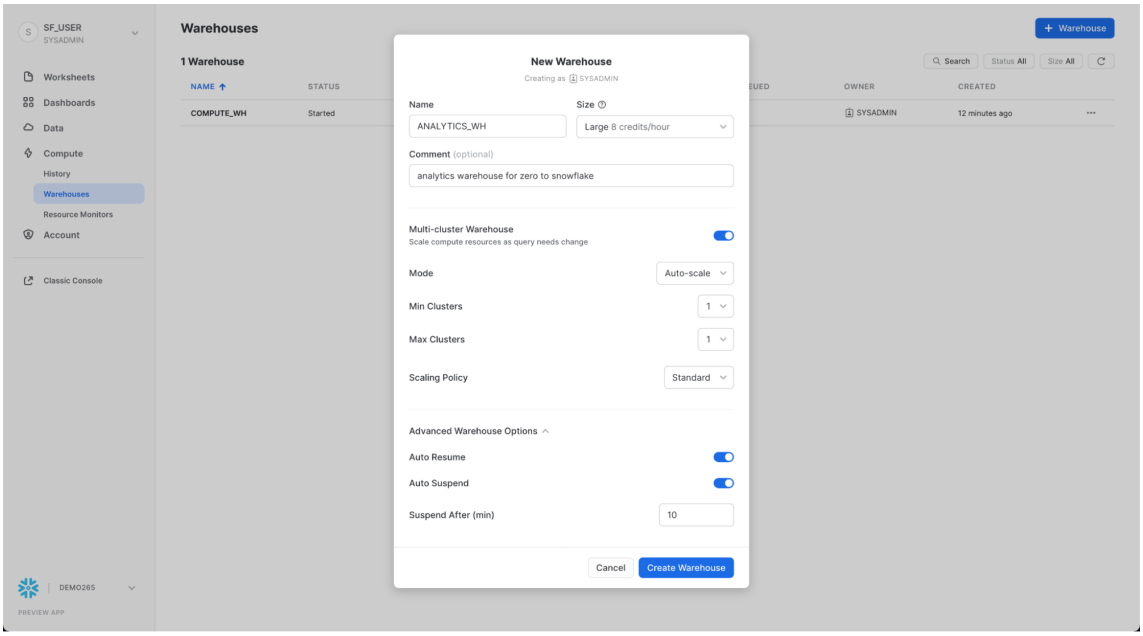
Create a New Warehouse for Data Analytics

Going back to the lab story, let's assume the Citi Bike team wants to eliminate resource contention between their data loading/ETL workloads and the analytical end users using BI tools to query Snowflake. As mentioned earlier, Snowflake can easily do this by assigning different, appropriately-sized warehouses to various workloads. Since Citi Bike already has a warehouse for data loading, let's create a new warehouse for the end users running analytics. We will use this warehouse to perform analytics in the next section.

Navigate to the **Admin** > **Warehouses** tab, click **+ Warehouse**, and name the new warehouse `` and set the size to `Large`.

If you are using Snowflake Enterprise Edition (or higher) and **Multi-cluster Warehouses** is enabled, you will see additional settings:

- Make sure **Max Clusters** is set to `1`.
- Leave all the other settings at their defaults.



Click the **Create Warehouse** button to create the warehouse.

Working with Queries, the Results Cache, & Cloning

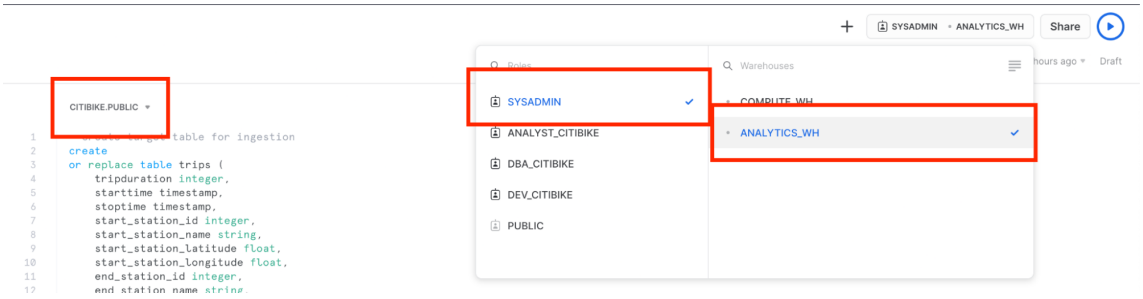
In the previous exercises, we loaded data into two tables using Snowflake's COPY bulk loader command and the `COMPUTE_WH` virtual warehouse. Now we are going to take on the role of the analytics users at Citi Bike who need to query data in those tables using the worksheet and the second warehouse `ANALYTICS_WH`.

Negative : **Real World Roles and Querying** Within a real company, analytics users would likely have a different role than SYSADMIN. To keep the lab simple, we are going to stay with the SYSADMIN role for this section. Additionally, querying would typically be done with a business intelligence product like Tableau, Looker, PowerBI, etc. For more advanced analytics, data science tools like Datarobot, Dataiku, AWS Sagemaker or many others can query Snowflake. Any technology that leverages JDBC/ODBC, Spark, Python, or any of the other supported programmatic interfaces can run analytics on the data in Snowflake. To keep this lab simple, all queries are being executed via the Snowflake worksheet.

Execute Some Queries

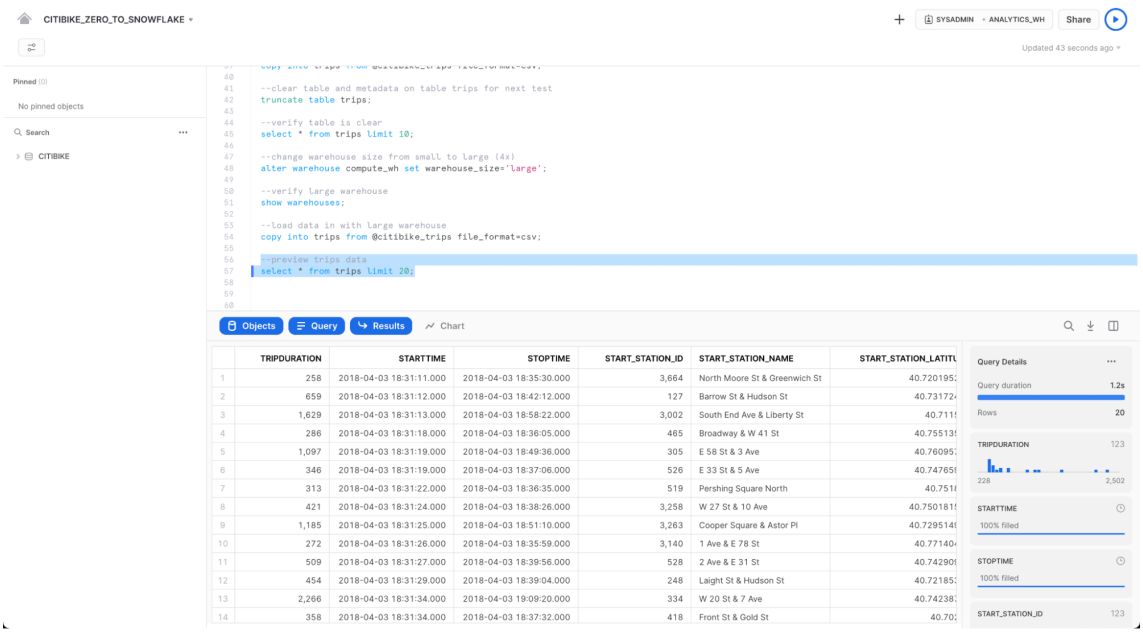
Go to the **CITIBIKE_ZERO_TO_SNOWFLAKE** worksheet and change the warehouse to use the new warehouse you created in the last section. Your worksheet context should be the following:

Role: `SYSADMIN` Warehouse: `ANALYTICS_WH (L)` Database: `CITIBIKE` Schema = `PUBLIC`



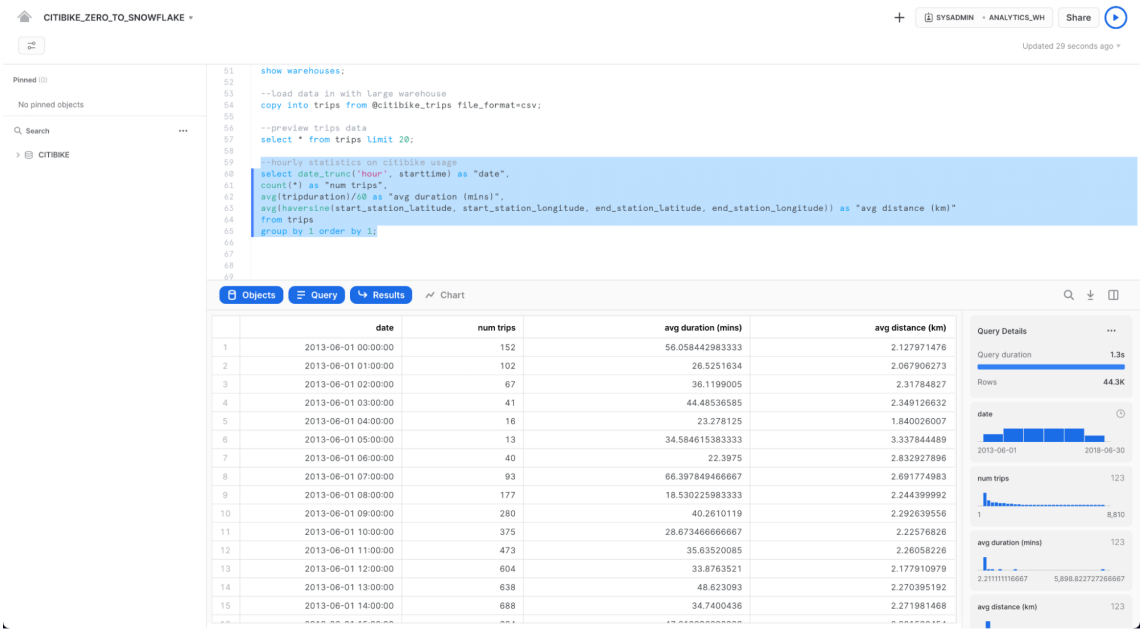
Run the following query to see a sample of the `trips` data:

```
select * from trips limit 20;
```



Now, let's look at some basic hourly statistics on Citi Bike usage. Run the query below in the worksheet. For each hour, it shows the number of trips, average trip duration, and average trip distance.

```
select date_trunc('hour', starttime) as "date",
count(*) as "num trips",
avg(tripduration)/60 as "avg duration (mins)",
avg(haversine(start_station_latitude, start_station_longitude, end_station_latitude,
end_station_longitude)) as "avg distance (km)"
from trips
group by 1 order by 1;
```



	date	num trips	avg duration (mins)	avg distance (km)
1	2013-06-01 00:00:00	152	56.058442983333	2.127971476
2	2013-06-01 01:00:00	102	26.5251634	2.067906273
3	2013-06-01 02:00:00	67	36.1199005	2.31784827
4	2013-06-01 03:00:00	41	44.48536585	2.349126632
5	2013-06-01 04:00:00	16	23.278125	1.840026007
6	2013-06-01 05:00:00	13	34.584615383333	3.337844489
7	2013-06-01 06:00:00	40	22.3975	2.832927896
8	2013-06-01 07:00:00	93	66.397849466667	2.691774983
9	2013-06-01 08:00:00	177	18.530225983333	2.244399992
10	2013-06-01 09:00:00	280	40.2610119	2.292639556
11	2013-06-01 10:00:00	375	28.673466666667	2.22576826
12	2013-06-01 11:00:00	473	35.63520085	2.26058226
13	2013-06-01 12:00:00	604	33.8763521	2.177910979
14	2013-06-01 13:00:00	638	48.623093	2.270395192
15	2013-06-01 14:00:00	688	34.7400436	2.271981468

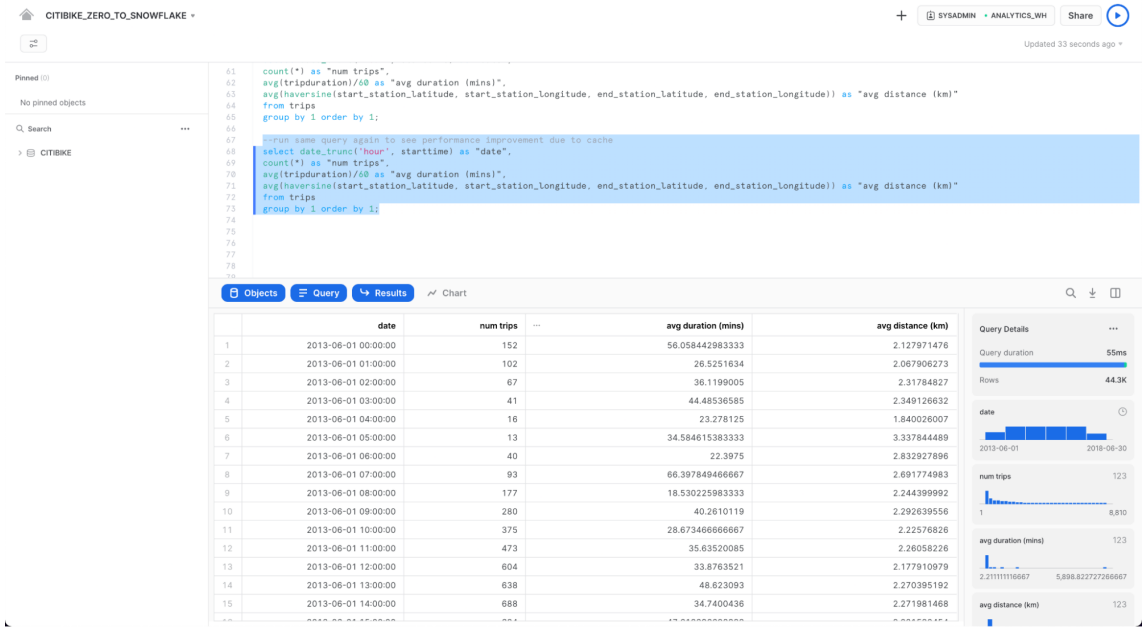
Use the Result Cache

Snowflake has a result cache that holds the results of every query executed in the past 24 hours. These are available across warehouses, so query results returned to one user are available to any other user on the system who executes the same query, provided the underlying data has not changed. Not only do these repeated queries return extremely fast, but they also use no compute credits.

Let's see the result cache in action by running the exact same query again.

```
select date_trunc('hour', starttime) as "date",
count(*) as "num trips",
avg(tripduration)/60 as "avg duration (mins)",
avg(haversine(start_station_latitude, start_station_longitude, end_station_latitude,
end_station_longitude)) as "avg distance (km)"
from trips
group by 1 order by 1;
```

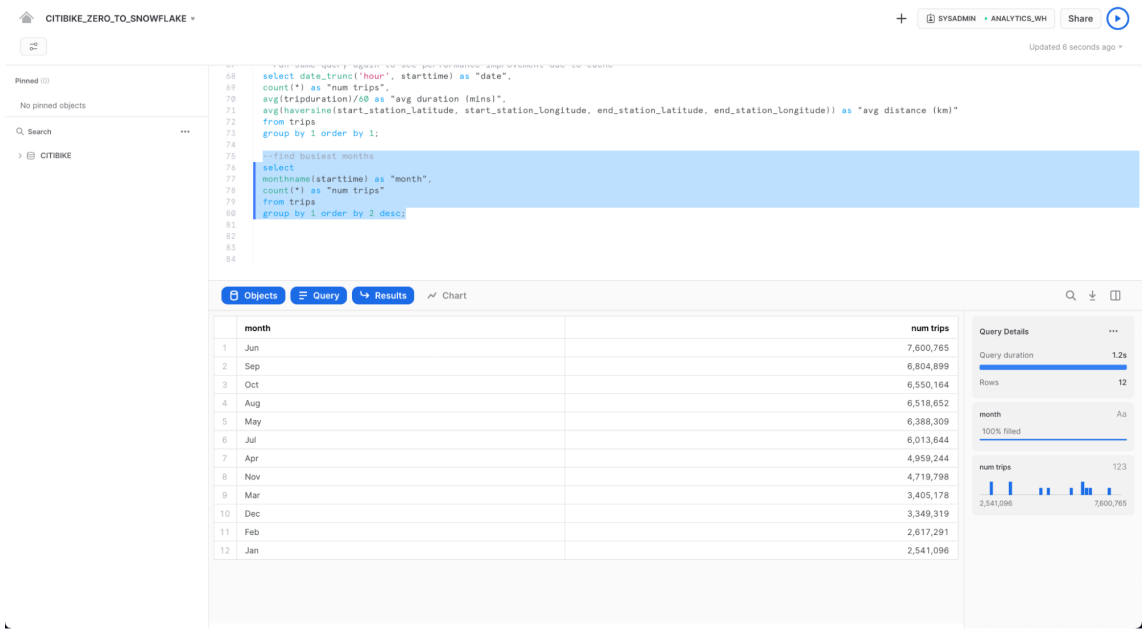
In the **Query Details** pane on the right, note that the second query runs significantly faster because the results have been cached.



Execute Another Query

Next, let's run the following query to see which months are the busiest:

```
select
monthname(starttime) as "month",
count(*) as "num trips"
from trips
group by 1 order by 2 desc;
```



Clone a Table

Snowflake allows you to create clones, also known as "zero-copy clones" of tables, schemas, and databases in seconds. When a clone is created, Snowflake takes a snapshot of data present in the source object and makes it available to the cloned object. The cloned object is writable and independent of the clone source. Therefore, changes made to either the source object or the clone object are not included in the other.

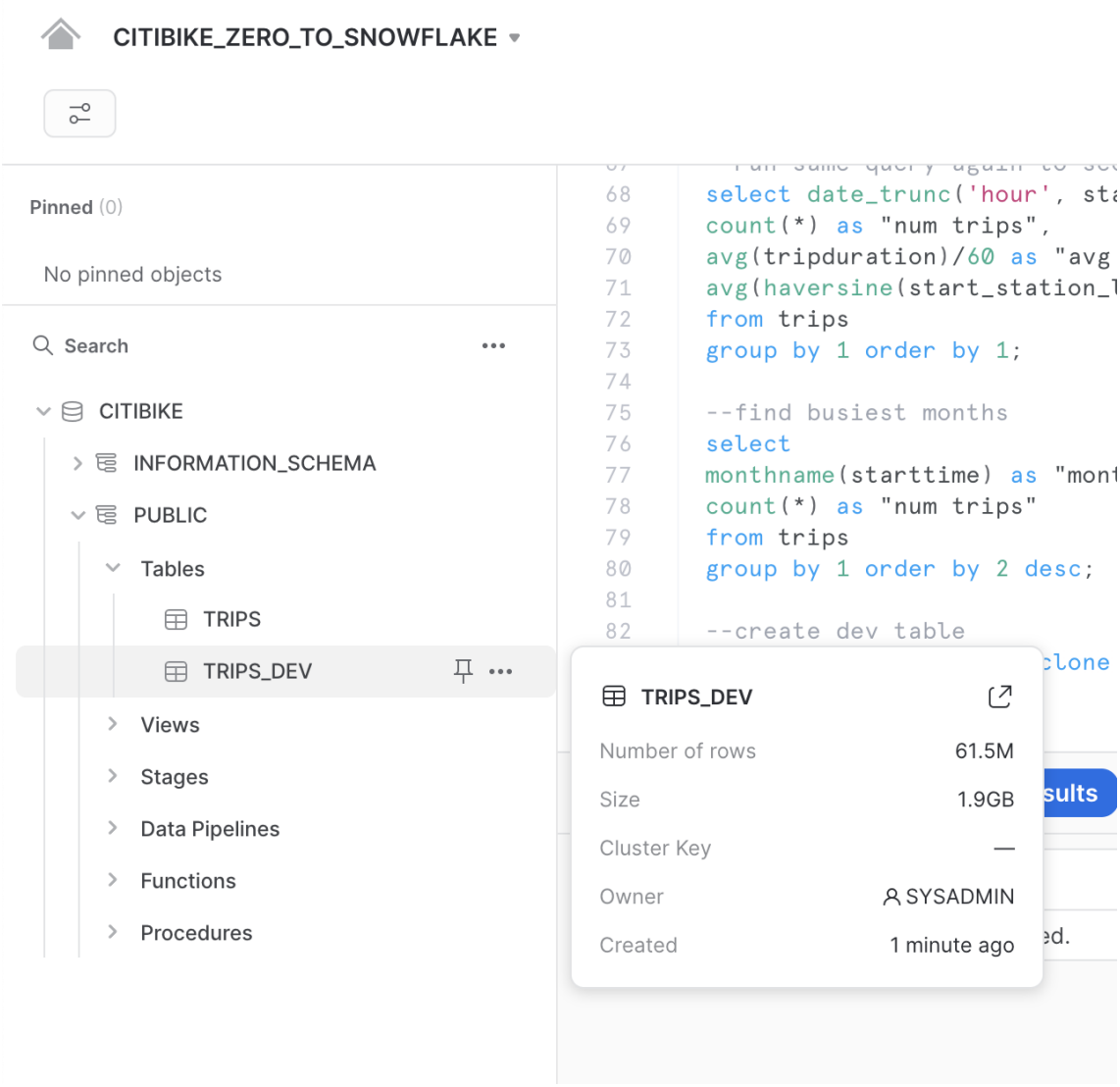
A popular use case for zero-copy cloning is to clone a production environment for use by Development & Testing teams to test and experiment without adversely impacting the production environment and eliminating the need to set up and manage two separate environments.

Negative : **Zero-Copy Cloning** A massive benefit of zero-copy cloning is that the underlying data is not copied. Only the metadata and pointers to the underlying data change. Hence, clones are “zero-copy" and storage requirements are not doubled when the data is cloned. Most data warehouses cannot do this, but for Snowflake it is easy!

Run the following command in the worksheet to create a development (dev) table clone of the `trips` table:

```
create table trips_dev clone trips;
```

Click the three dots (**...**) in the left pane and select **Refresh**. Expand the object tree under the `CITIBIKE` database and verify that you see a new table named `trips_dev` . Your Development team now can do whatever they want with this table, including updating or deleting it, without impacting the `trips` table or any other object.



Working with Semi-Structured Data, Views, & Joins

Positive : This section requires loading additional data and, therefore, provides a review of data loading while also introducing loading semi-structured data.

Going back to the lab's example, the Citi Bike analytics team wants to determine how weather impacts ride counts. To do this, in this section, we will:

- Load weather data in semi-structured JSON format held in a public S3 bucket.
- Create a view and query the JSON data using SQL dot notation.
- Run a query that joins the JSON data to the previously loaded `TRIPS` data.
- Analyze the weather and ride count data to determine their relationship.

The JSON data consists of weather information provided by *MeteoStat* detailing the historical conditions of New York City from 2016-07-05 to 2019-06-25. It is also staged on AWS S3 where the data consists of 75k rows, 36 objects, and 1.1MB compressed. If viewed in a text editor, the raw JSON in the GZ files looks like:

Negative : **SEMI-STRUCTURED DATA** Snowflake can easily load and query semi-structured data such as JSON, Parquet, or Avro without transformation. This is a key Snowflake feature because an increasing amount of business-relevant data being generated today is semi-structured, and many traditional data warehouses cannot easily load and query such data. Snowflake makes it easy!

Create a New Database and Table for the Data

First, in the worksheet, let's create a database named `WEATHER` to use for storing the semi-structured JSON data.

```
create database weather;
```

Execute the following USE commands to set the worksheet context appropriately:

```
use role sysadmin;

use warehouse compute_wh;

use database weather;

use schema public;
```

Positive : **Executing Multiple Commands** Remember that you need to execute each command individually. However, you can execute them in sequence together by selecting all of the commands and then clicking the **Play/Run** button (or using the keyboard shortcut).

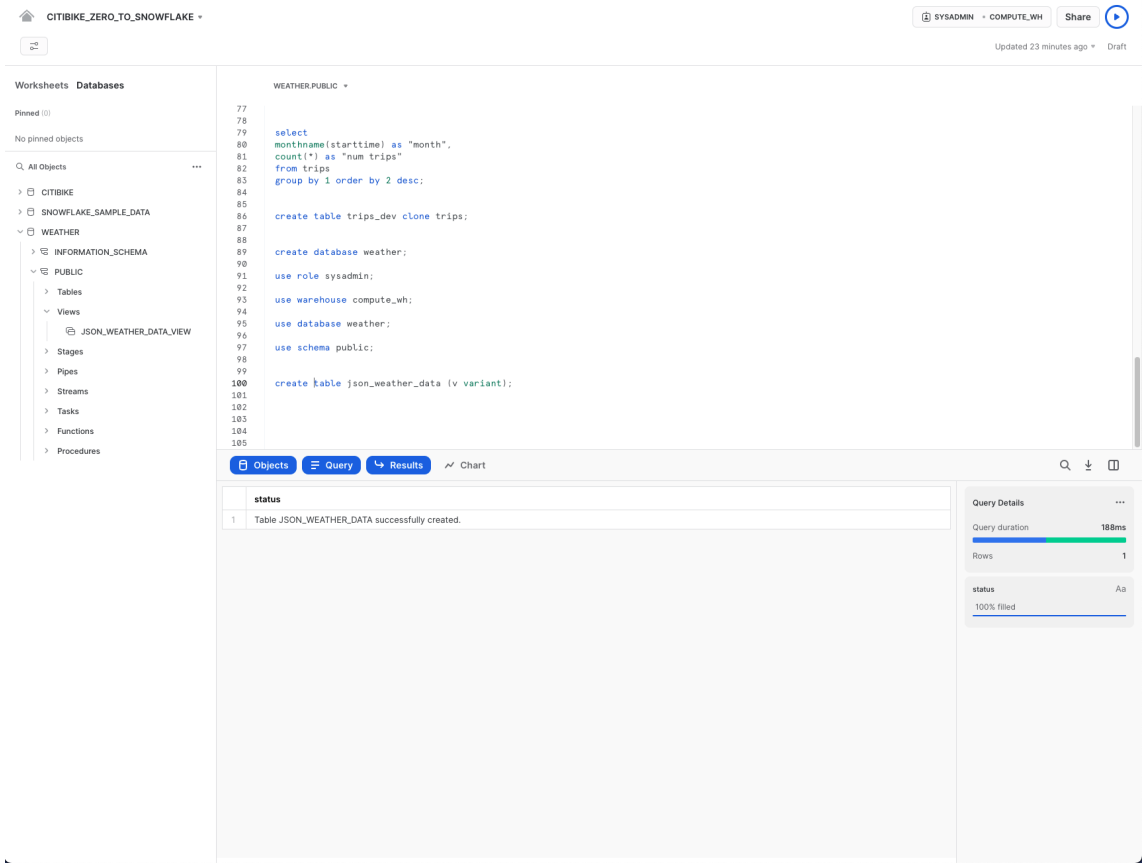
Next, let's create a table named `JSON_WEATHER_DATA` to use for loading the JSON data. In the worksheet, execute the following CREATE TABLE command:

```
create table json_weather_data (v variant);
```

Note that Snowflake has a special column data type called `VARIANT` that allows storing the entire JSON object as a single row and eventually query the object directly.

Negative : **Semi-Structured Data Magic** The VARIANT data type allows Snowflake to ingest semi-structured data without having to predefine the schema.

In the results pane at the bottom of the worksheet, verify that your table, `JSON_WEATHER_DATA`, was created:



Create Another External Stage

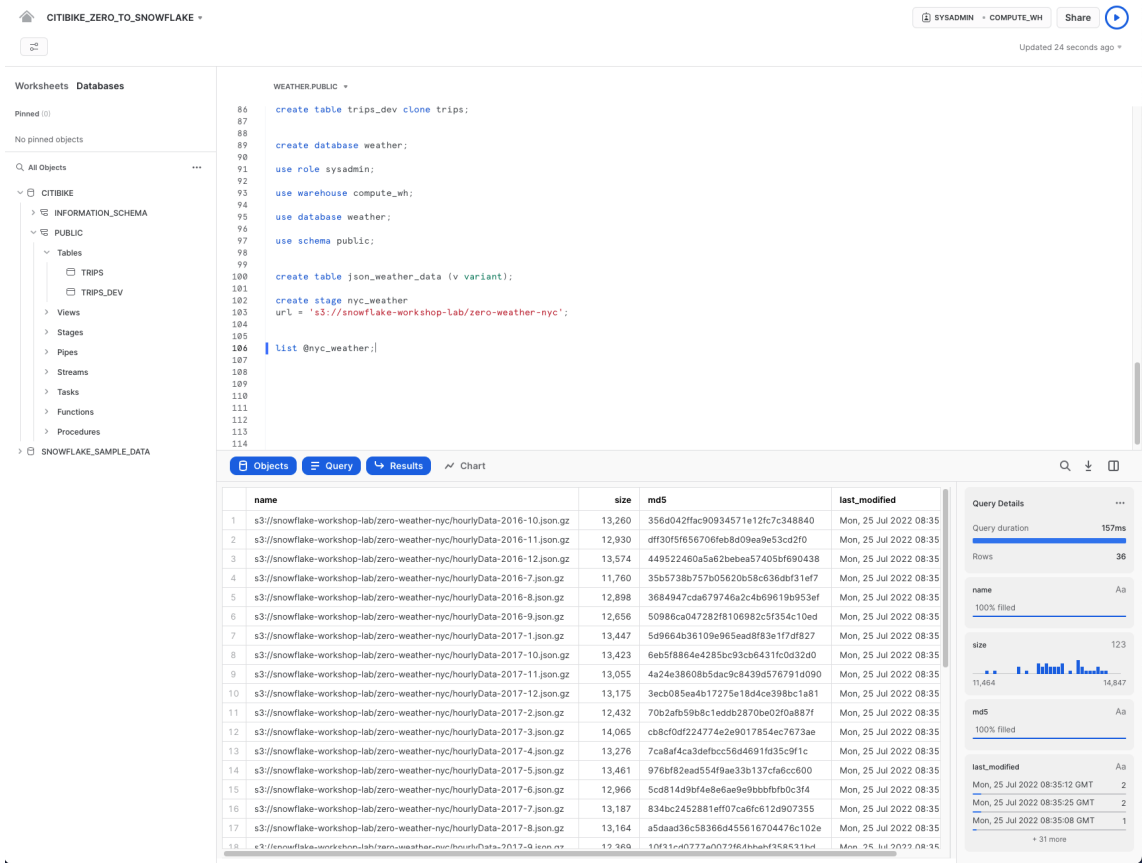
In the `CITIBIKE_ZERO_TO_SNOWFLAKE` worksheet, use the following command to create a stage that points to the bucket where the semi-structured JSON data is stored on AWS S3:

```
create stage nyc_weather
url = 's3://snowflake-workshop-lab/zero-weather-nyc';
```

Now let's take a look at the contents of the `nyc_weather` stage. Execute the following LIST command to display the list of files:

```
list @nyc_weather;
```

In the results pane, you should see a list of `.gz` files from S3:



Load and Verify the Semi-structured Data

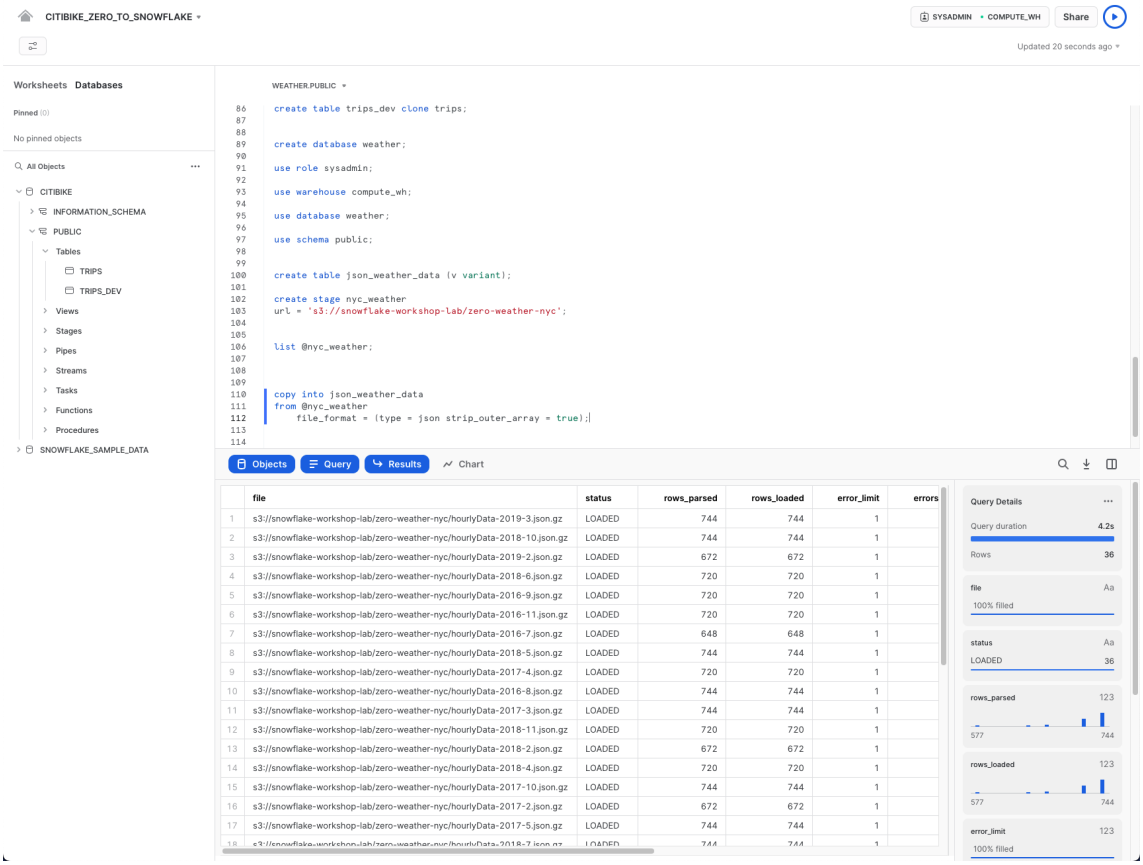
In this section, we will use a warehouse to load the data from the S3 bucket into the `JSON_WEATHER_DATA` table we created earlier.

In the `CITIBIKE_ZERO_TO_SNOWFLAKE` worksheet, execute the COPY command below to load the data.

Note that you can specify a `FILE FORMAT` object inline in the command. In the previous section where we loaded structured data in CSV format, we had to define a file format to support the CSV structure. Because the JSON data here is well-formed, we are able to simply specify the JSON type and use all the default settings:

```
copy into json_weather_data
from @nyc_weather
    file_format = (type = json strip_outer_array = true);
```

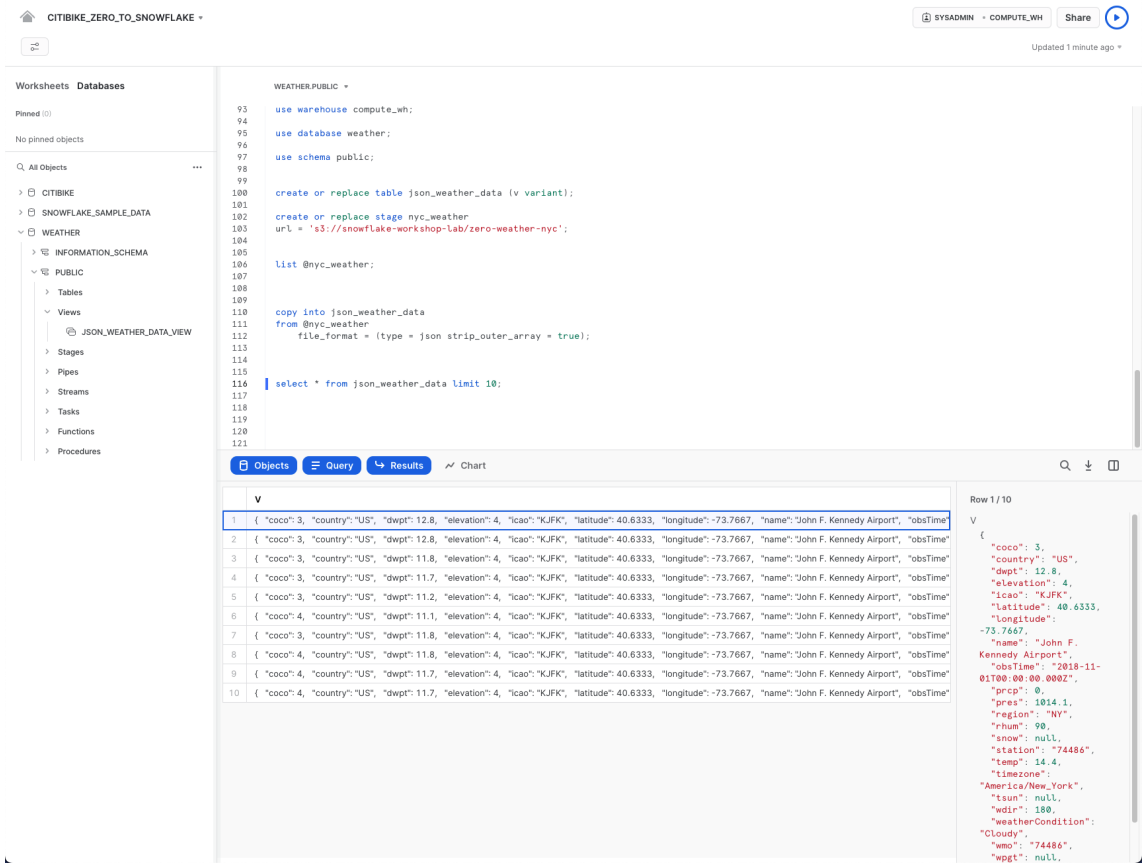
Verify that each file has a status of `LOADED`:



Now, let's take a look at the data that was loaded:

```
select * from json_weather_data limit 10;
```

Click any of the rows to display the formated JSON in the right panel:



To close the display in the panel and display the query details again, click the **X** (Close) button that appears when you hover your mouse in the right corner of the panel.

Create a View and Query Semi-Structured Data

Next, let's look at how Snowflake allows us to create a view and also query the JSON data directly using SQL.

Negative : **Views & Materialized Views** A view allows the result of a query to be accessed as if it were a table. Views can help present data to end users in a cleaner manner, limit what end users can view in a source table, and write more modular SQL. Snowflake also supports materialized views in which the query results are stored as though the results are a table. This allows faster access, but requires storage space. Materialized views can be created and queried if you are using Snowflake Enterprise Edition (or higher).

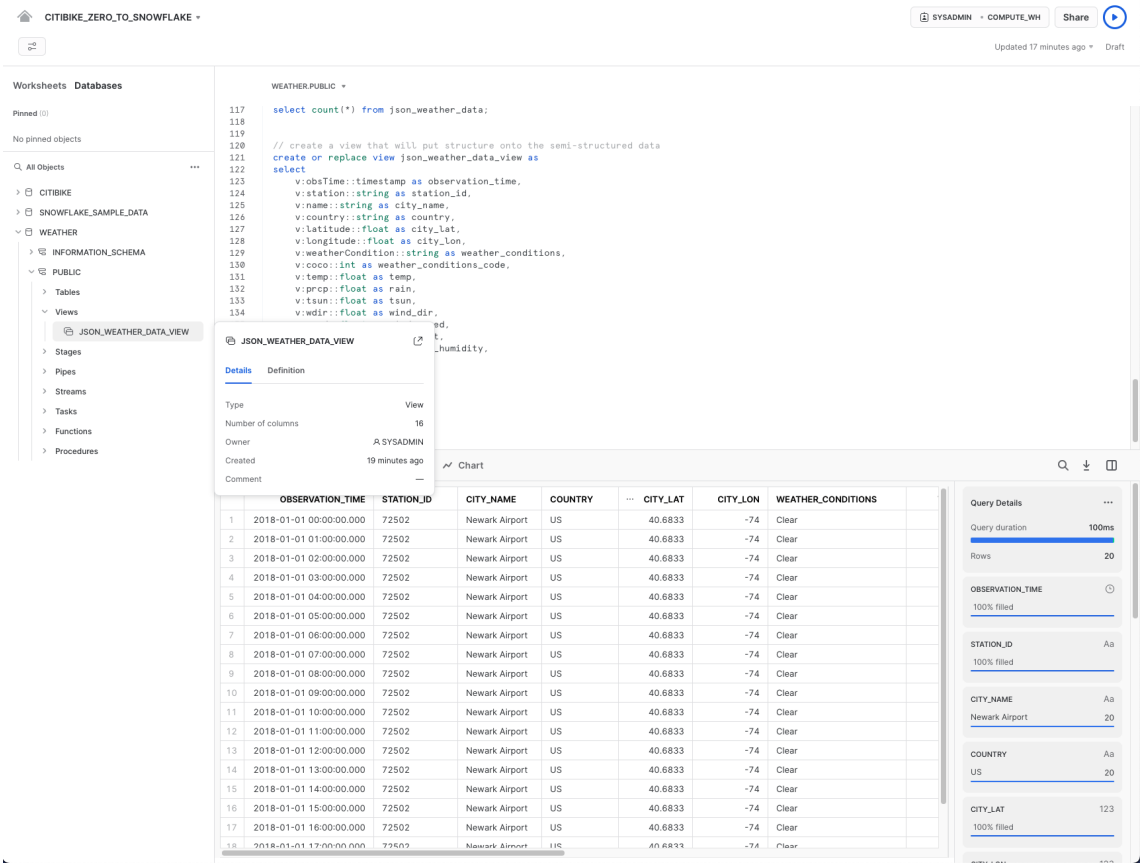
Run the following command to create a columnar view of the semi-structured JSON weather data so it is easier for analysts to understand and query. The `72502` value for `station_id` corresponds to Newark Airport, the closest station that has weather conditions for the whole period.

```
// create a view that will put structure onto the semi-structured data
create or replace view json_weather_data_view as
select
    v:obsTime::timestamp as observation_time,
    v:station::string as station_id,
    v:name::string as city_name,
    v:country::string as country,
    v:latitude::float as city_lat,
    v:longitude::float as city_lon,
```

```
    v:weatherCondition::string as weather_conditions,
    v:coco::int as weather_conditions_code,
    v:temp::float as temp,
    v:prcp::float as rain,
    v:tsun::float as tsun,
    v:wdir::float as wind_dir,
    v:wspd::float as wind_speed,
    v:dwpt::float as dew_point,
    v:rhum::float as relative_humidity,
    v:pres::float as pressure
from
    json_weather_data
where
    station_id = '72502';
```

SQL dot notation `v:temp` is used in this command to pull out values at lower levels within the JSON object hierarchy. This allows us to treat each field as if it were a column in a relational table.

The new view should appear as `JSON_WEATHER_DATA` under `WEATHER` > `PUBLIC` > **Views** in the object browser on the left. You may need to expand or refresh the objects browser in order to see it.

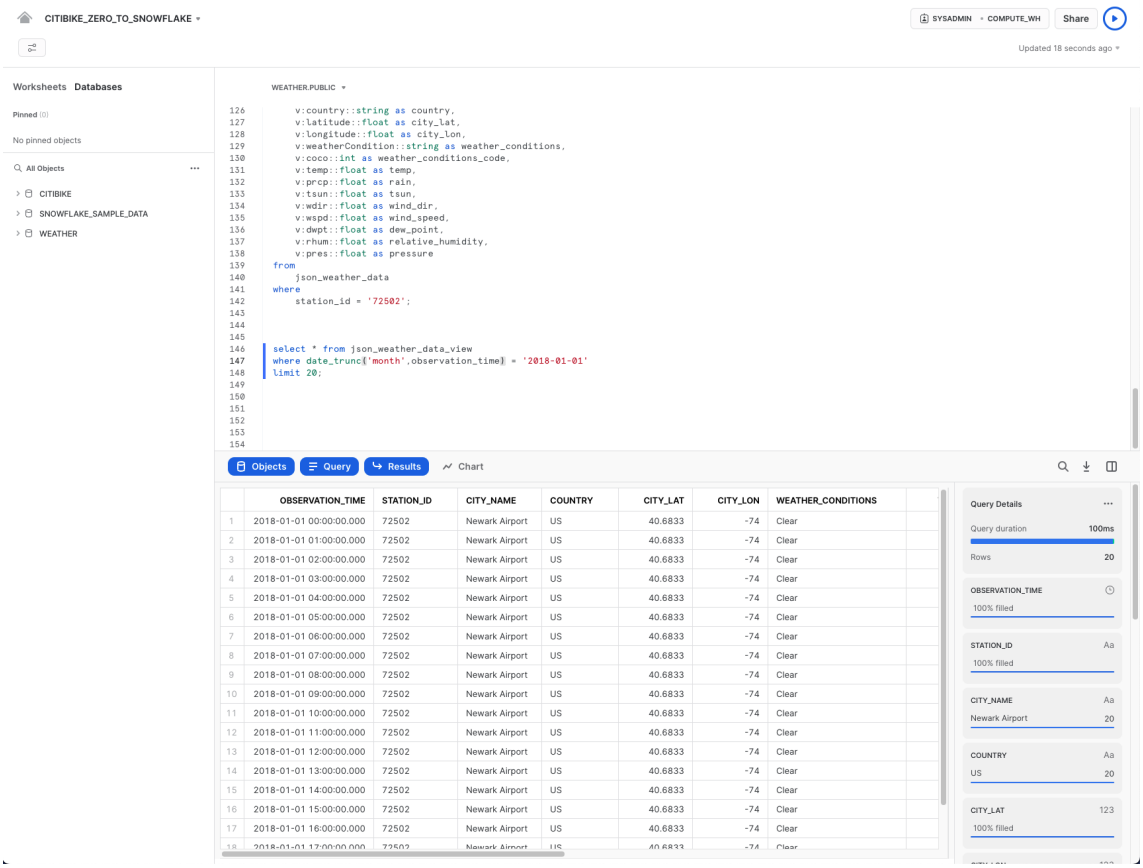


Verify the view with the following query:

```
select * from json_weather_data_view
where date_trunc('month',observation_time) = '2018-01-01'
```

```
limit 20;
```

Notice the results look just like a regular structured data source. Your result set may have different `observation_time` values:



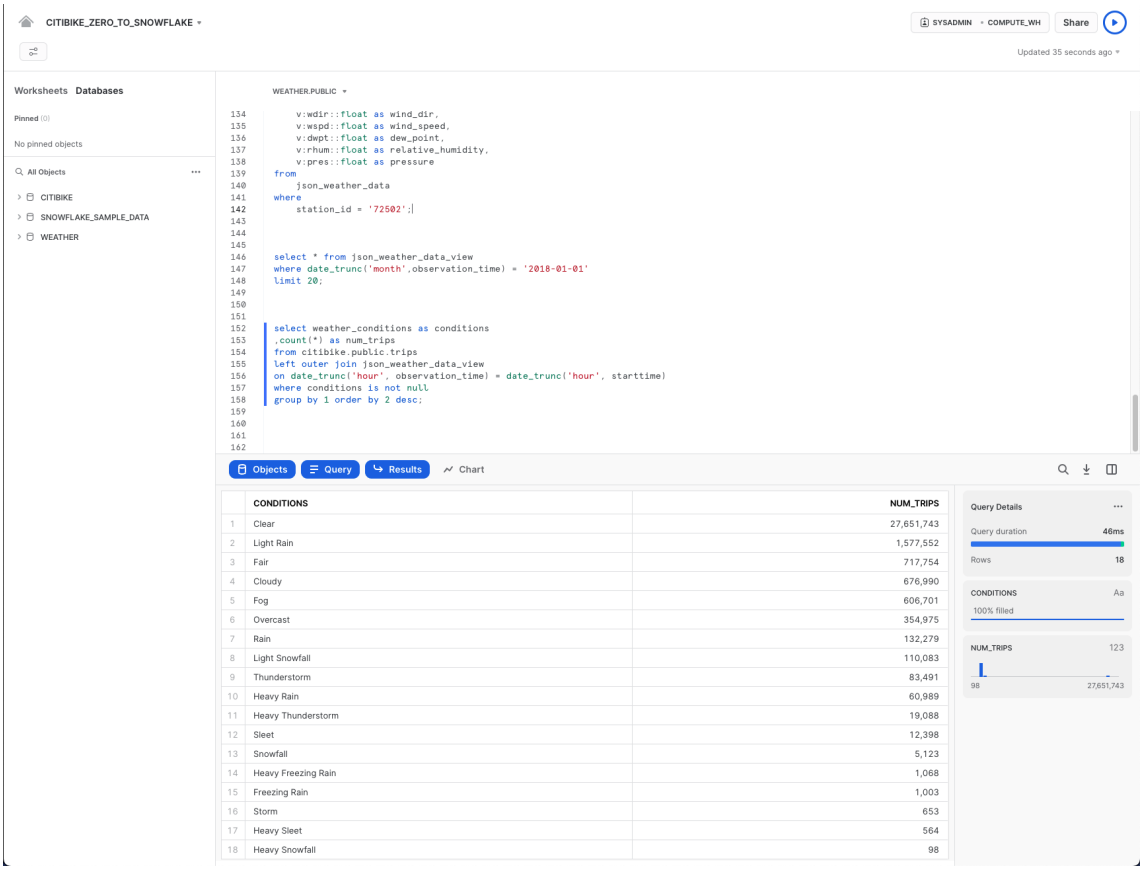
Use a Join Operation to Correlate Against Data Sets

We will now join the JSON weather data to our `CITIBIKE.PUBLIC.TRIPS` data to answer our original question of how weather impacts the number of rides.

Run the query below to join `WEATHER` to `TRIPS` and count the number of trips associated with certain weather conditions:

Positive : Because we are still in the worksheet, the `WEATHER` database is still in use. You must, therefore, fully qualify the reference to the `TRIPS` table by providing its database and schema name.

```
select weather_conditions as conditions
,count(*) as num_trips
from citibike.public.trips
left outer join json_weather_data_view
on date_trunc('hour', observation_time) = date_trunc('hour', starttime)
where conditions is not null
group by 1 order by 2 desc;
```



The initial goal was to determine if there was any correlation between the number of bike rides and the weather by analyzing both ridership and weather data. Per the results above we have a clear answer. As one would imagine, the number of trips is significantly higher when the weather is good!

Using Time Travel

Snowflake's powerful Time Travel feature enables accessing historical data, as well as the objects storing the data, at any point within a period of time. The default window is 24 hours and, if you are using Snowflake Enterprise Edition, can be increased up to 90 days. Most data warehouses cannot offer this functionality, but - you guessed it - Snowflake makes it easy!

Some useful applications include:

- Restoring data-related objects such as tables, schemas, and databases that may have been deleted.
- Duplicating and backing up data from key points in the past.
- Analyzing data usage and manipulation over specified periods of time.

Drop and Undrop a Table

First let's see how we can restore data objects that have been accidentally or intentionally deleted.

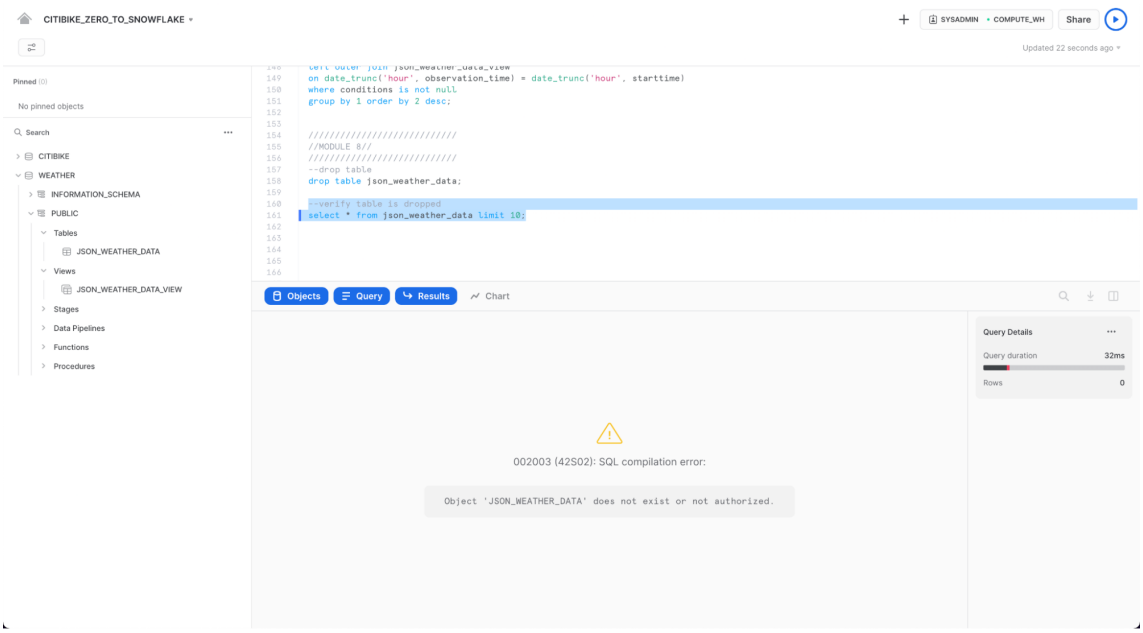
In the `CITIBIKE_ZERO_TO_SNOWFLAKE` worksheet, run the following DROP command to remove the `JSON_WEATHER_DATA` table:

```
drop table json_weather_data;
```

Run a query on the table:

```
select * from json_weather_data limit 10;
```

In the results pane at the bottom, you should see an error because the underlying table has been dropped:

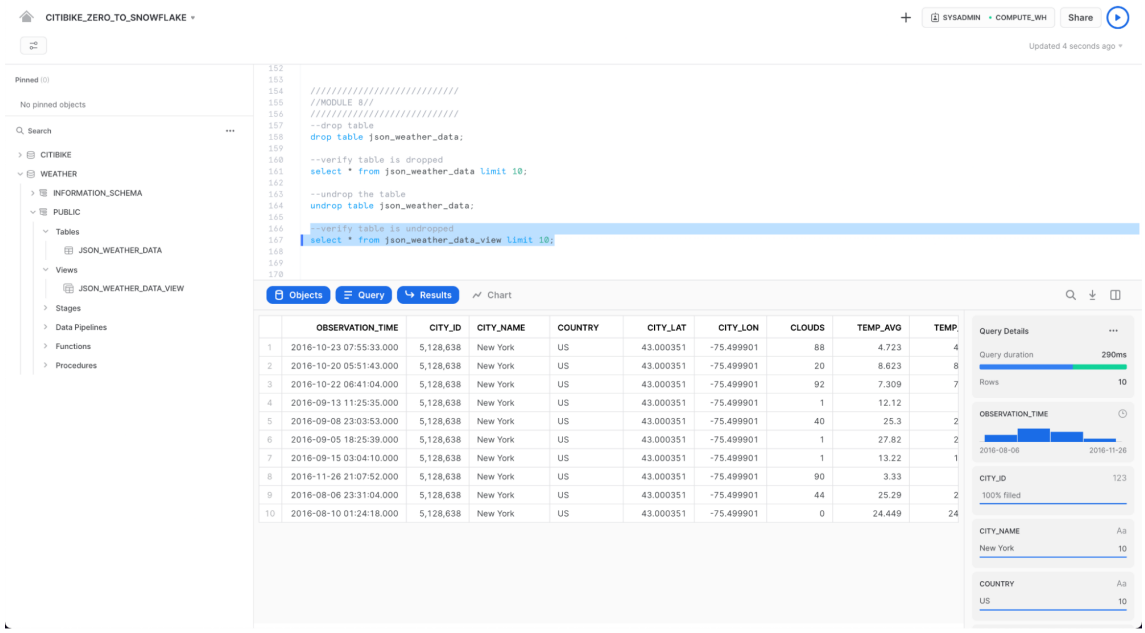


Now, restore the table:

```
undrop table json_weather_data;
```

The json_weather_data table should be restored. Verify by running the following query:

```
--verify table is undropped

select * from json_weather_data_view limit 10;
```



Roll Back a Table

Let's roll back the `TRIPS` table in the `CITIBIKE` database to a previous state to fix an unintentional DML error that replaces all the station names in the table with the word "oops".

First, run the following SQL statements to switch your worksheet to the proper context:

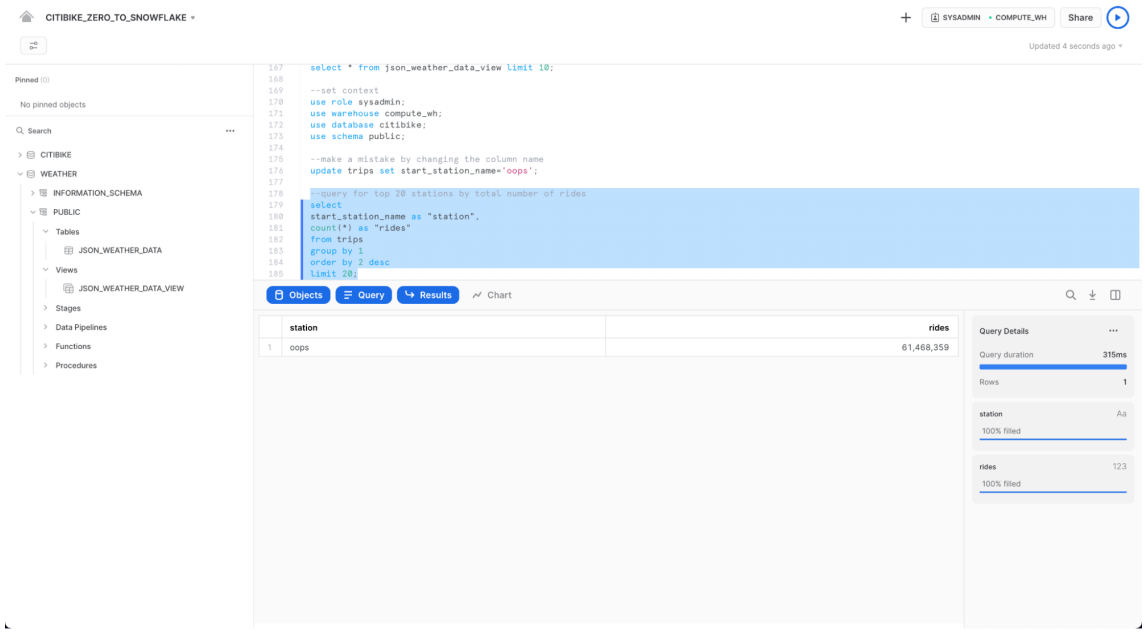
```
use role sysadmin;

use warehouse compute_wh;

use database citibike;

use schema public;
```

Run the following command to replace all of the station names in the table with the word "oops":

```
update trips set start_station_name = 'oops';
```

Now, run a query that returns the top 20 stations by number of rides. Notice that the station names result contains only one row:

```
select
start_station_name as "station",
count(*) as "rides"
from trips
group by 1
order by 2 desc
limit 20;
```



Normally we would need to scramble and hope we have a backup lying around.

In Snowflake, we can simply run a command to find the query ID of the last UPDATE command and store it in a variable named `$QUERY_ID`.

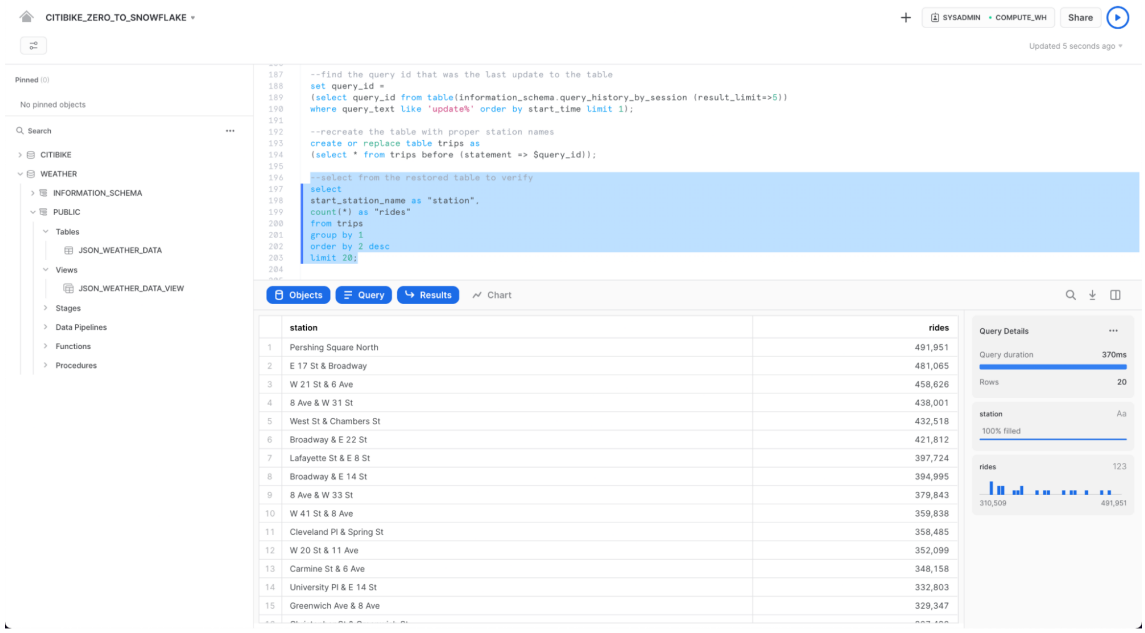
```
set query_id =
(select query_id from table(information_schema.query_history_by_session
(result_limit=>5))
where query_text like 'update%' order by start_time desc limit 1);
```

Use Time Travel to recreate the table with the correct station names:

```
create or replace table trips as
(select * from trips before (statement => $query_id));
```

Run the previous query again to verify that the station names have been restored:

```
select
start_station_name as "station",
count(*) as "rides"
from trips
group by 1
order by 2 desc
limit 20;
```



Working with Roles, Account Admin, & Account Usage

In this section, we will explore aspects of Snowflake's access control security model, such as creating a role and granting it specific permissions. We will also explore other usage of the ACCOUNTADMIN (Account Administrator) role, which was briefly introduced earlier in the lab.

Continuing with the lab story, let's assume a junior DBA has joined Citi Bike and we want to create a new role for them with less privileges than the system-defined, default role of SYSADMIN.

Negative : **Role-Based Access Control** Snowflake offers very powerful and granular access control that dictates the objects and functionality a user can access, as well as the level of access they have.

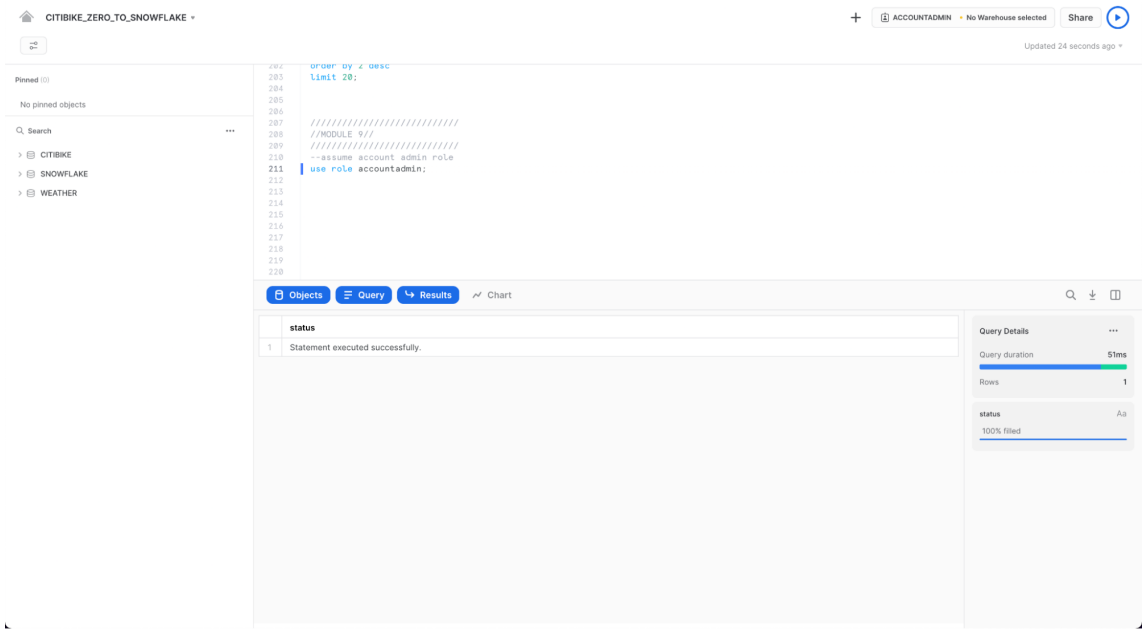
Create a New Role and Add a User

In the `CITIBIKE_ZERO_TO_SNOWFLAKE` worksheet, switch to the ACCOUNTADMIN role to create a new role. ACCOUNTADMIN encapsulates the SYSADMIN and SECURITYADMIN system-defined roles. It is the top-level role in the account and should be granted only to a limited number of users.

In the `CITIBIKE_ZERO_TO_SNOWFLAKE` worksheet, run the following command:

```
use role accountadmin;
```

Notice that, in the top right of the worksheet, the context has changed to ACCOUNTADMIN:



Before a role can be used for access control, at least one user must be assigned to it. So let's create a new role named `JUNIOR_DBA` and assign it to your Snowflake user. To complete this task, you need to know your username, which is the name you used to log in to the UI.

Use the following commands to create the role and assign it to you. Before you run the GRANT ROLE command, replace `YOUR_USERNAME_GOES_HERE` with your username:

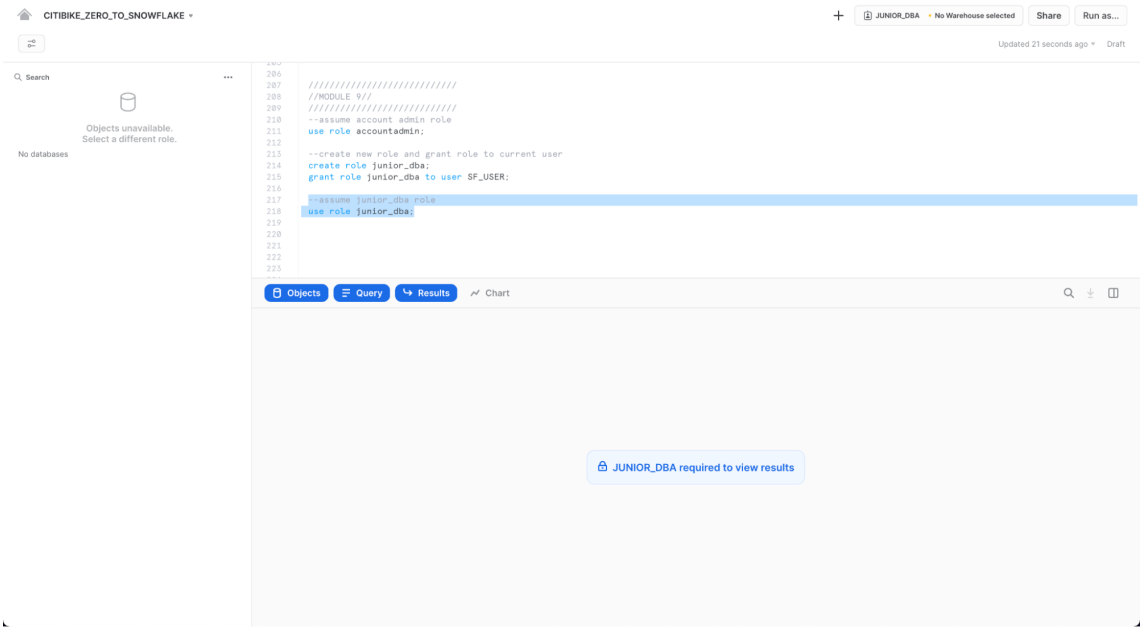
```
create role junior_dba;

grant role junior_dba to user YOUR_USERNAME_GOES_HERE;
```

Positive : If you try to perform this operation while in a role such as SYSADMIN, it would fail due to insufficient privileges. By default (and design), the SYSADMIN role cannot create new roles or users.

Change your worksheet context to the new `JUNIOR_DBA` role:

```
use role junior_dba;
```

In the top right of the worksheet, notice that the context has changed to reflect the `JUNIOR_DBA` role.



Also, the warehouse is not selected because the newly created role does not have usage privileges on any warehouse. Let's fix it by switching back to ADMIN role and grant usage privileges to `COMPUTE_WH` warehouse.

```
use role accountadmin;

grant usage on warehouse compute_wh to role junior_dba;
```

Switch back to the `JUNIOR_DBA` role. You should be able to use `COMPUTE_WH` now.

```
use role junior_dba;

use warehouse compute_wh;
```

Finally, you can notice that in the database object browser panel on the left, the `CITIBIKE` and `WEATHER` databases no longer appear. This is because the `JUNIOR_DBA` role does not have privileges to access them.

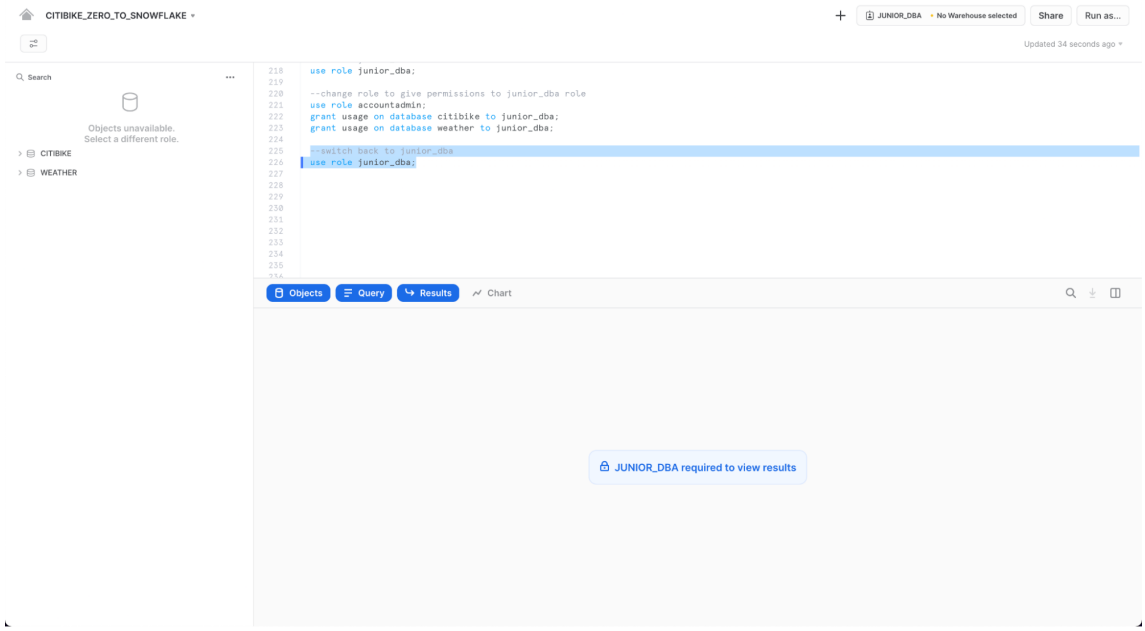
Switch back to the ACCOUNTADMIN role and grant the `JUNIOR_DBA` the USAGE privilege required to view and use the `CITIBIKE` and `WEATHER` databases:

```
use role accountadmin;

grant usage on database citibike to role junior_dba;

grant usage on database weather to role junior_dba;
```

Switch to the `JUNIOR_DBA` role:

```
use role junior_dba;
```

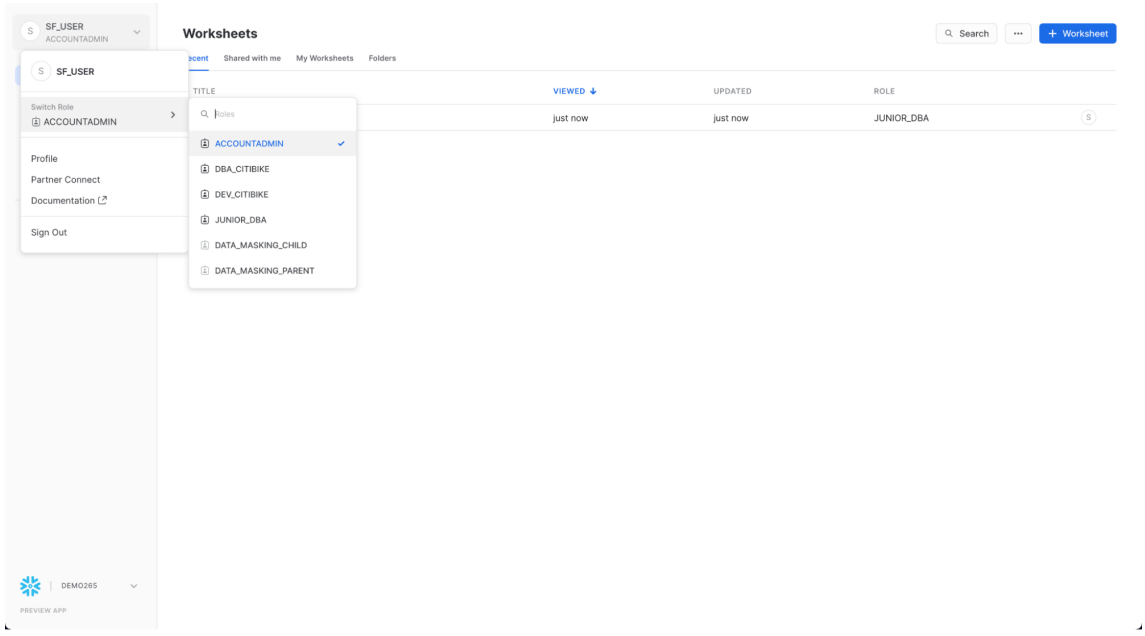
Notice that the `CITIBIKE` and `WEATHER` databases now appear in the database object browser panel on the left. If they don't appear, try clicking **...** in the panel, then clicking **Refresh**.



View the Account Administrator UI

Let's change our access control role back to `ACCOUNTADMIN` to see other areas of the UI accessible only to this role. However, to perform this task, use the UI instead of the worksheet.

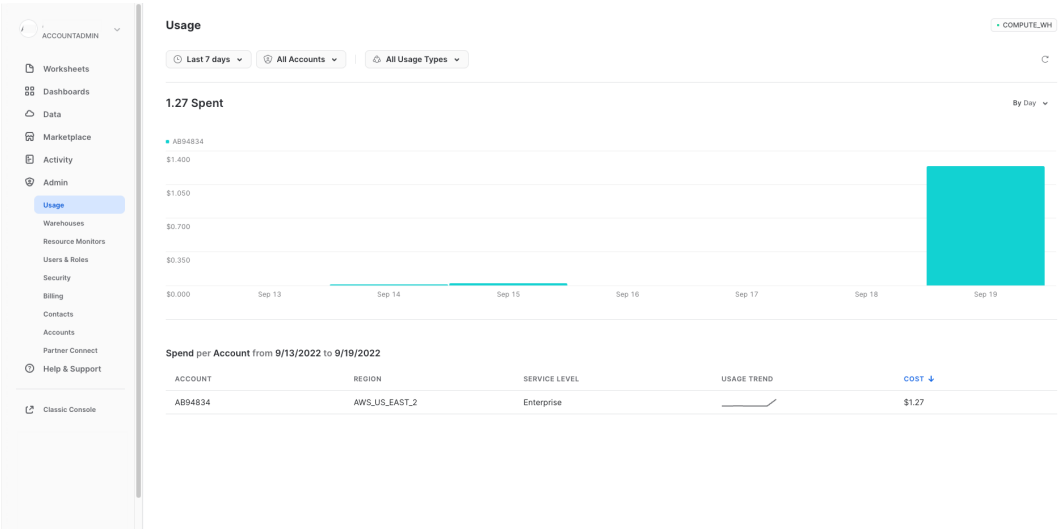
First, click the **Home** icon in the top left corner of the worksheet. Then, in the top left corner of the UI, click your name to display the user preferences menu. In the menu, go to **Switch Role** and select ACCOUNTADMIN.



Negative : **Roles in User Preference vs Worksheet** Why did we use the user preference menu to change the role instead of the worksheet? The UI session and each worksheet have their own separate roles. The UI session role controls the elements you can see and acceess in the UI, whereas the worksheet role controls only the objects and actions you can access within the role.

Notice that once you switch the UI session to the ACCOUNTADMIN role, new tabs are available under **Admin**.

Usage

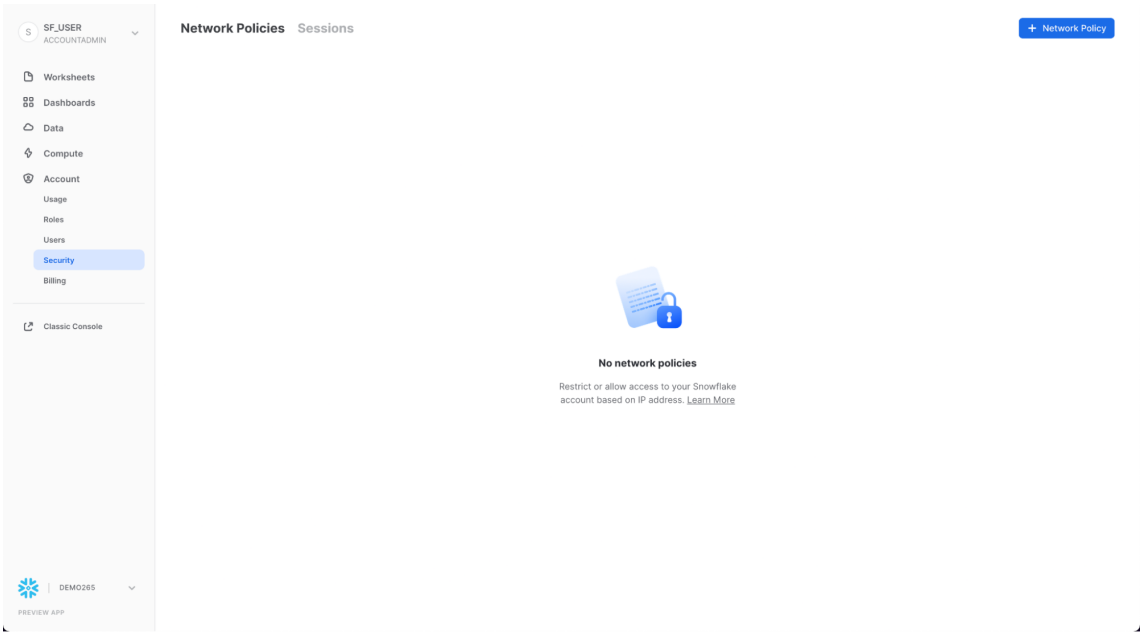


The **Usage** tab shows the following, each with their own page:

- **Organization**: Credit usaged across all the accounts in your organization.
- **Consumption**: Credits consumed by the virtual warehouses in the current account.
- **Storage**: Average amount of data stored in all databases, internal stages, and Snowflake Failsafe in the current account for the past month.
- **Transfers**: Average amount of data transferred out of the region (for the current account) into other regions for the past month.

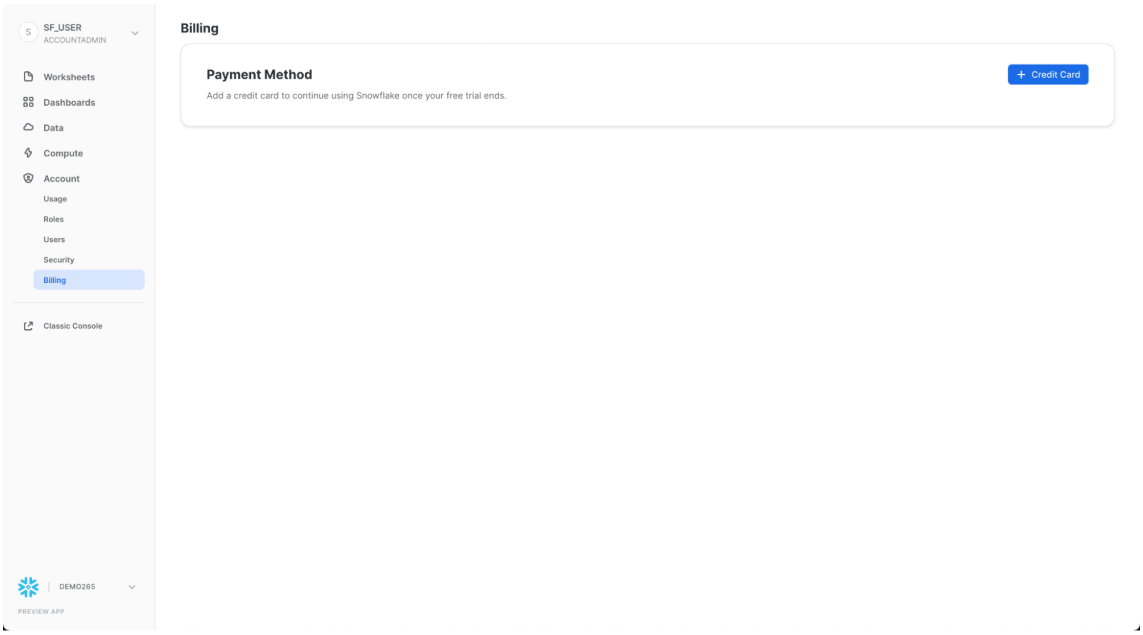
The filters in the top right corner of each page can be used to break down the usage/consumption/etc. visualizations by different measures.

Security



The **Security** tab contains network policies created for the Snowflake account. New network policies can be created by selecting "+ Network Policy" at the top right hand side of the page.

Billing



The **Billing** tab contains the payment method for the account:

- If you are a Snowflake contract customer, the tab shows the name associated with your contract information.
- If you are an on-demand Snowflake customer, the tab shows the credit card used to pay month-to-month, if one has been entered. If no credit card is on file, you can add one to continue using Snowflake when your trial ends.

For the next section, stay in the ACCOUNTADMIN role for the UI session.

Sharing Data Securely & the Data Marketplace

Snowflake enables data access between accounts through the secure data sharing features. Shares are created by data providers and imported by data consumers, either through their own Snowflake account or a provisioned Snowflake Reader account. The consumer can be an external entity or a different internal business unit that is required to have its own unique Snowflake account.

With secure data sharing:

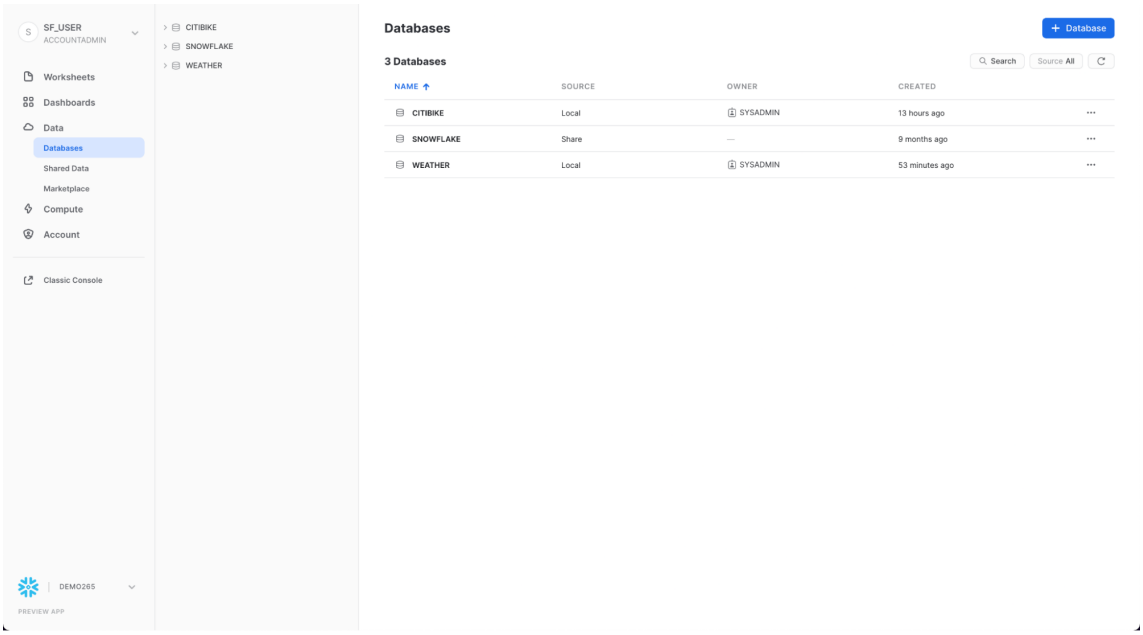
- There is only one copy of the data that lives in the data provider's account.
- Shared data is always live, real-time, and immediately available to consumers.
- Providers can establish revocable, fine-grained access to shares.
- Data sharing is simple and safe, especially compared to older data sharing methods, which were often manual and insecure, such as transferring large `.csv` files across the internet.

Snowflake uses secure data sharing to provide account usage data and sample data sets to all Snowflake accounts. In this capacity, Snowflake acts as the data provider of the data and all other accounts.

Secure data sharing also powers the Snowflake Data Marketplace, which is available to all Snowflake customers and allows you to discover and access third-party datasets from numerous data providers and SaaS vendors. Again, in this data sharing model, the data doesn't leave the provider's account and you can use the datasets without any transformation.

View Existing Shares

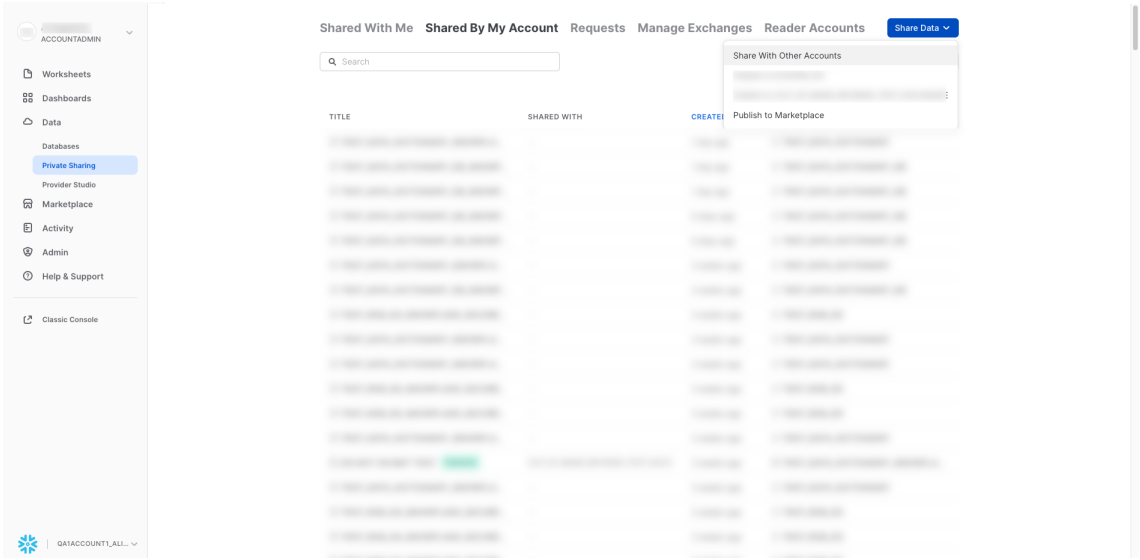
In the home page, navigate to **Data** > **Databases**. In the list of databases, look at the **SOURCE** column. You should see two databases with `Local` in the column. These are the two databases we created previously in the lab. The other database, `SNOWFLAKE`, shows `Share` in the column, indicating it's shared from a provider.



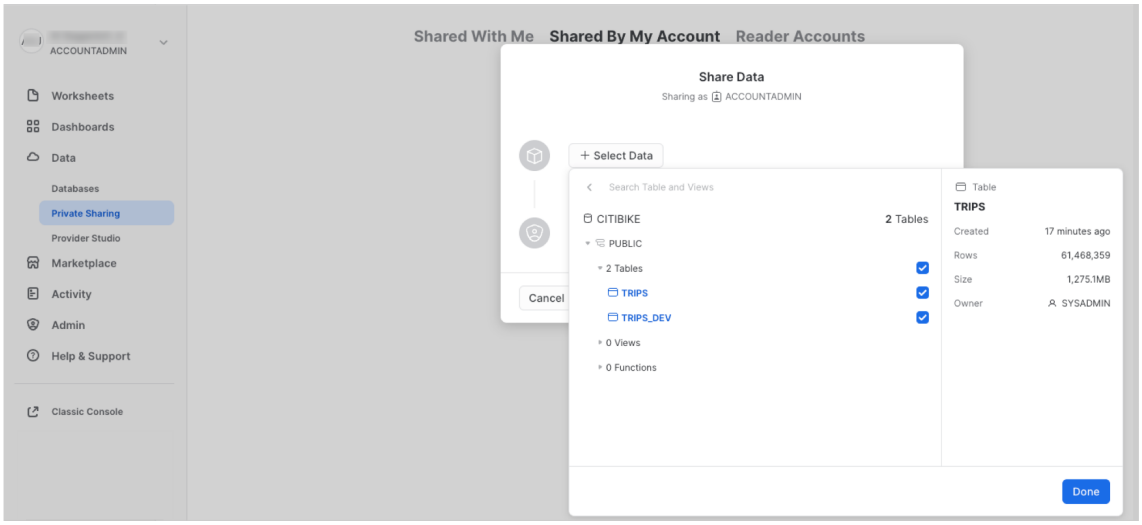
Create an Outbound Share

Let's go back to the Citi Bike story and assume we are the Account Administrator for Snowflake at Citi Bike. We have a trusted partner who wants to analyze the data in our `TRIPS` database on a near real-time basis. This partner also has their own Snowflake account in the same region as our account. So let's use secure data sharing to allow them to access this information.

Navigate to **Data** > **Shared Data**, then click **Shared by My Account** at the top of the tab. Click the **Share Data** button in the top right corner and select **Share with Other Accounts**:



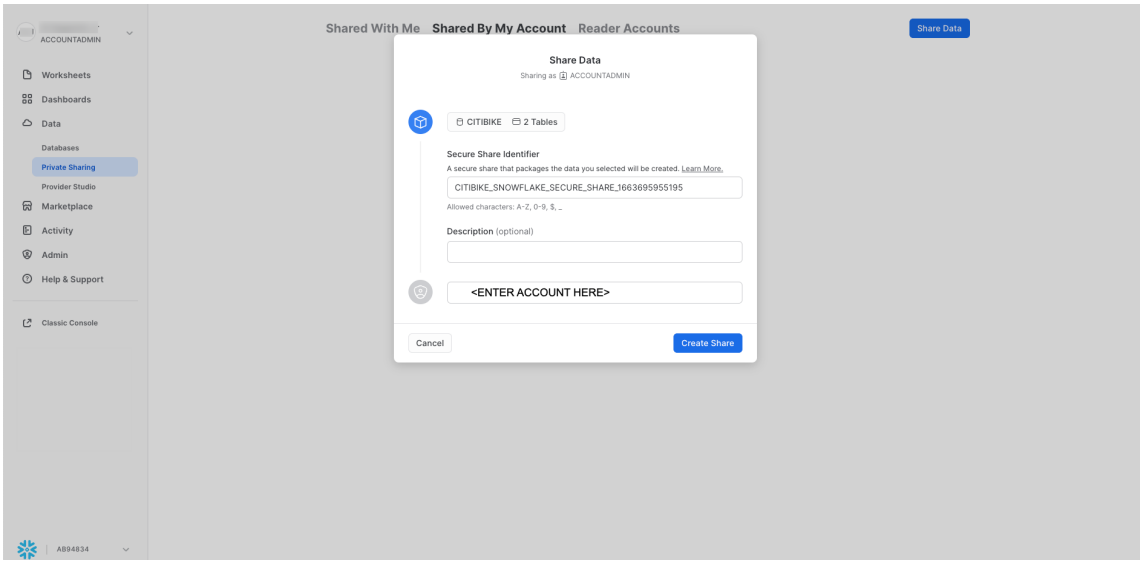
Click **+ Data** and navigate to the `CITIBIKE` database and `PUBLIC` schema. Select the 2 tables we created in the schema and click the **Done** button:



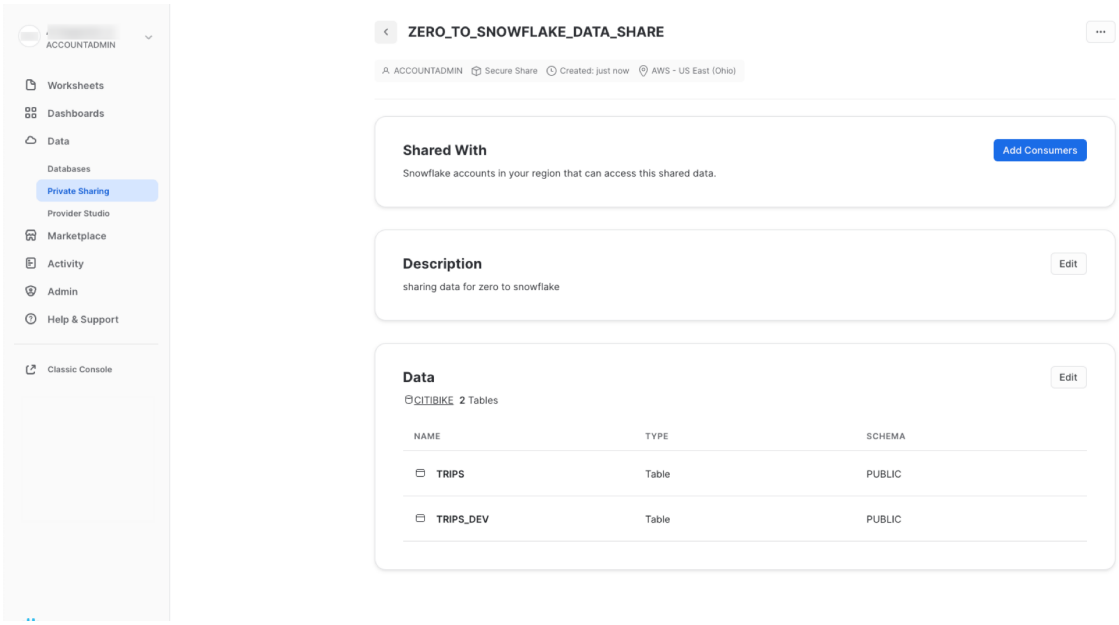
The default name of the share is a generic name with a random numeric value appended. Edit the default name to a more descriptive value that will help identify the share in the future (e.g. `ZERO_TO_SNOWFLAKE_SHARED_DATA`). You can also add a comment.

In a real-world scenario, the Citi Bike Account Administrator would next add one or more consumer accounts to the share, but we'll stop here for the purposes of this lab.

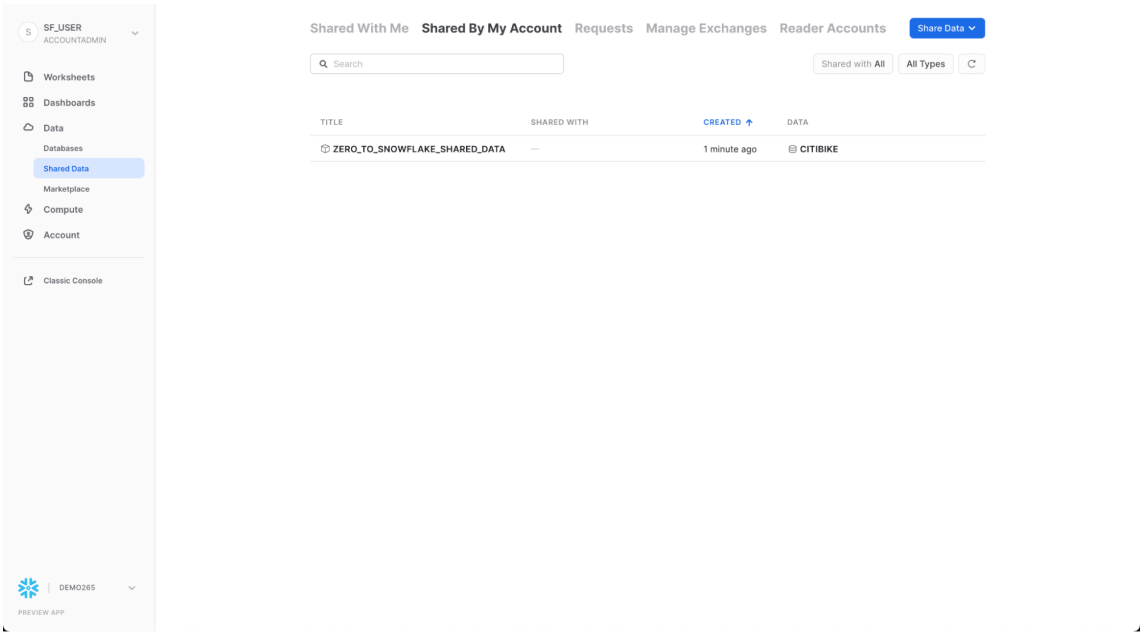
Click the **Create Share** button at the bottom of the dialog:



The dialog closes and the page shows the secure share you created:



You can add consumers, add/change the description, and edit the objects in the share at any time. In the page, click the **<** button next to the share name to return to the **Share with Other Accounts** page:

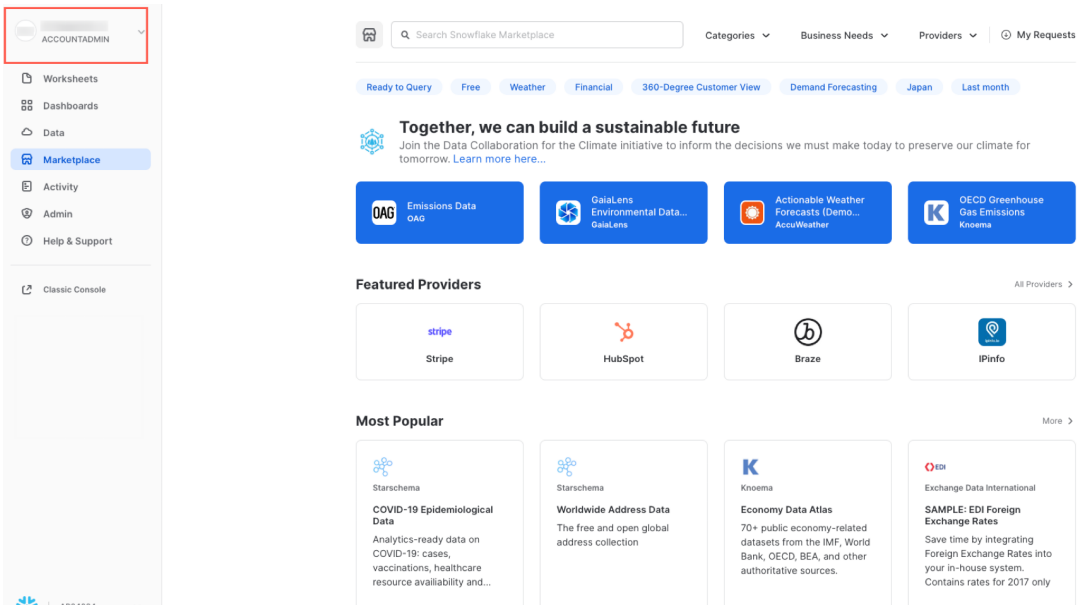


We've demonstrated how it only takes seconds to give other accounts access to data in your Snowflake account in a secure manner with no copying or transferring of data required!

Snowflake provides several ways to securely share data without compromising confidentiality. In addition to tables, you can share secure views, secure UDFs (user-defined functions), and other secure objects. For more details about using these methods to share data while preventing access to sensitive information, see the [Snowflake documentation].

Snowflake Data Marketplace

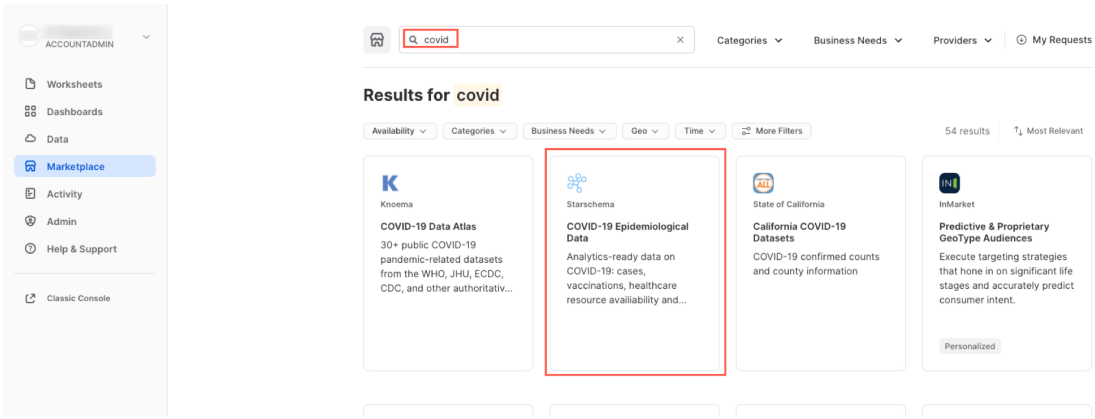
Make sure you're using the ACCOUNTADMIN role and, navigate to the **Marketplace**:



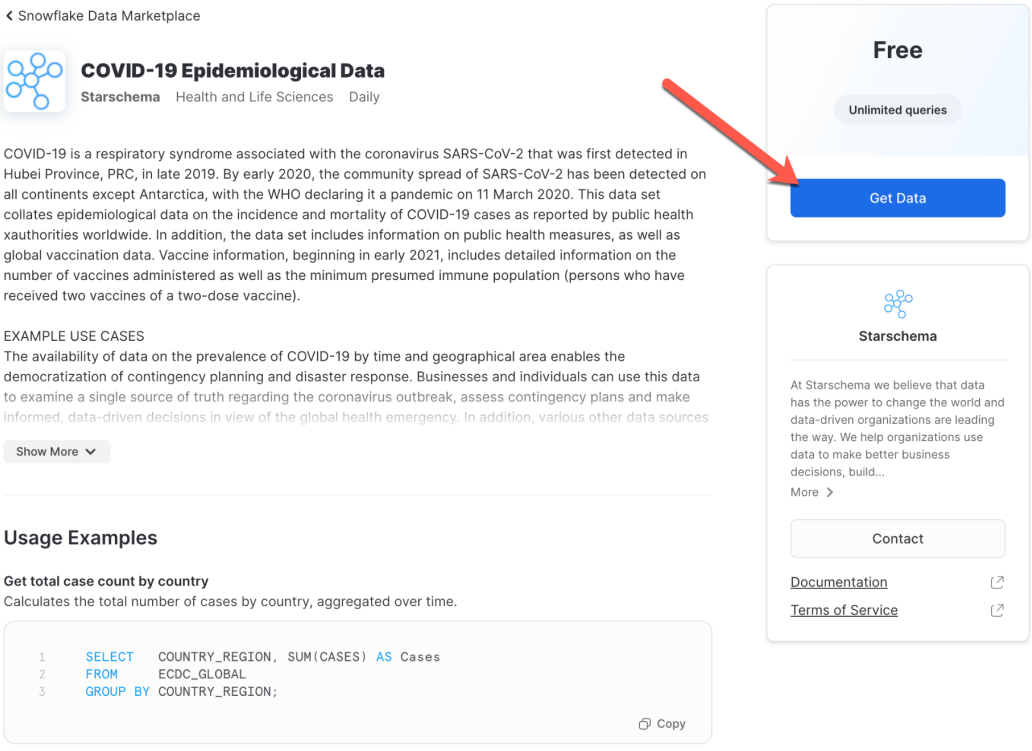
Find a listing

The search box at the top allows you to search for a listings. The drop-down lists to the right of the search box let you filter data listings by Provider, Business Needs, and Category.

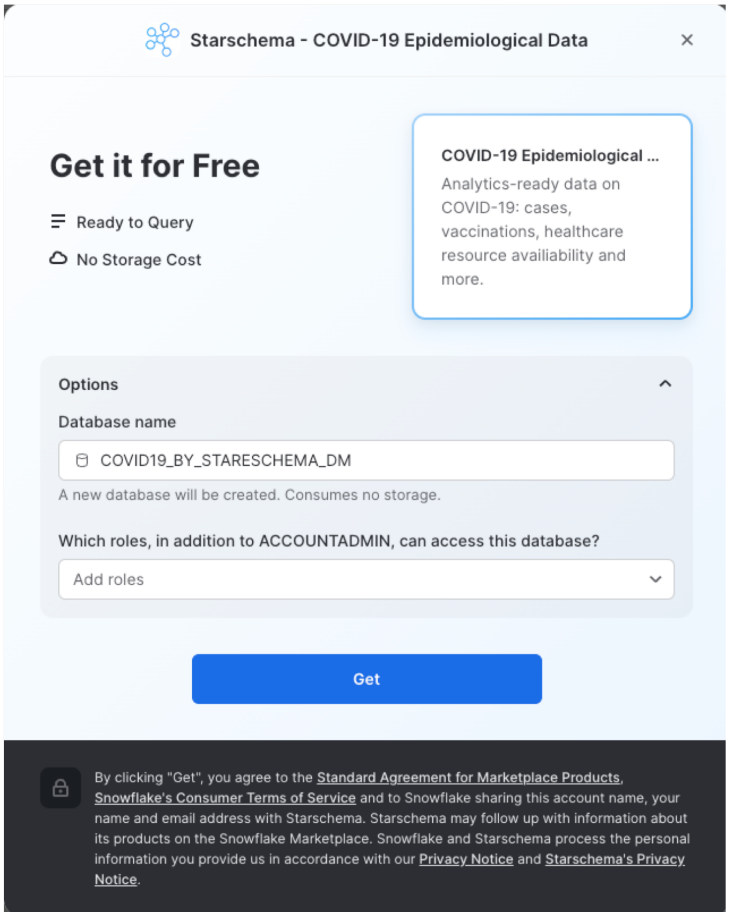
Type `COVID` in the search box, scroll through the results, and select **COVID-19 Epidemiological Data** (provided by Starschema).



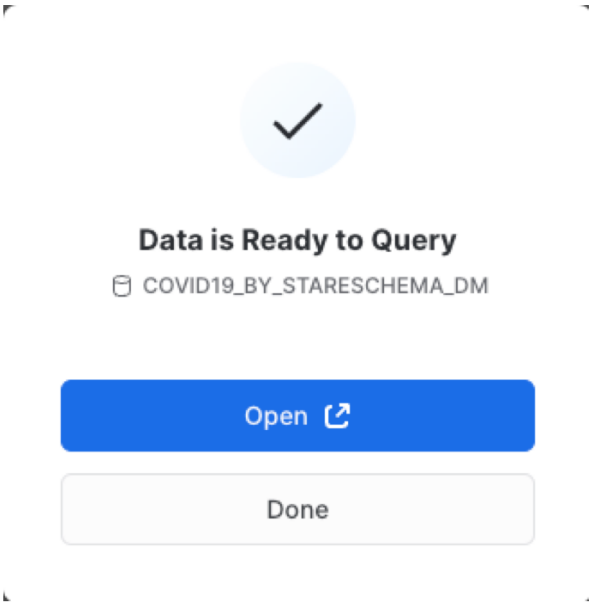
In the **COVID-19 Epidemiological Data** page, you can learn more about the dataset and see some usage example queries. When you're ready, click the **Get Data** button to make this information available within your Snowflake account:



Review the information in the dialog and glick **Get** again:

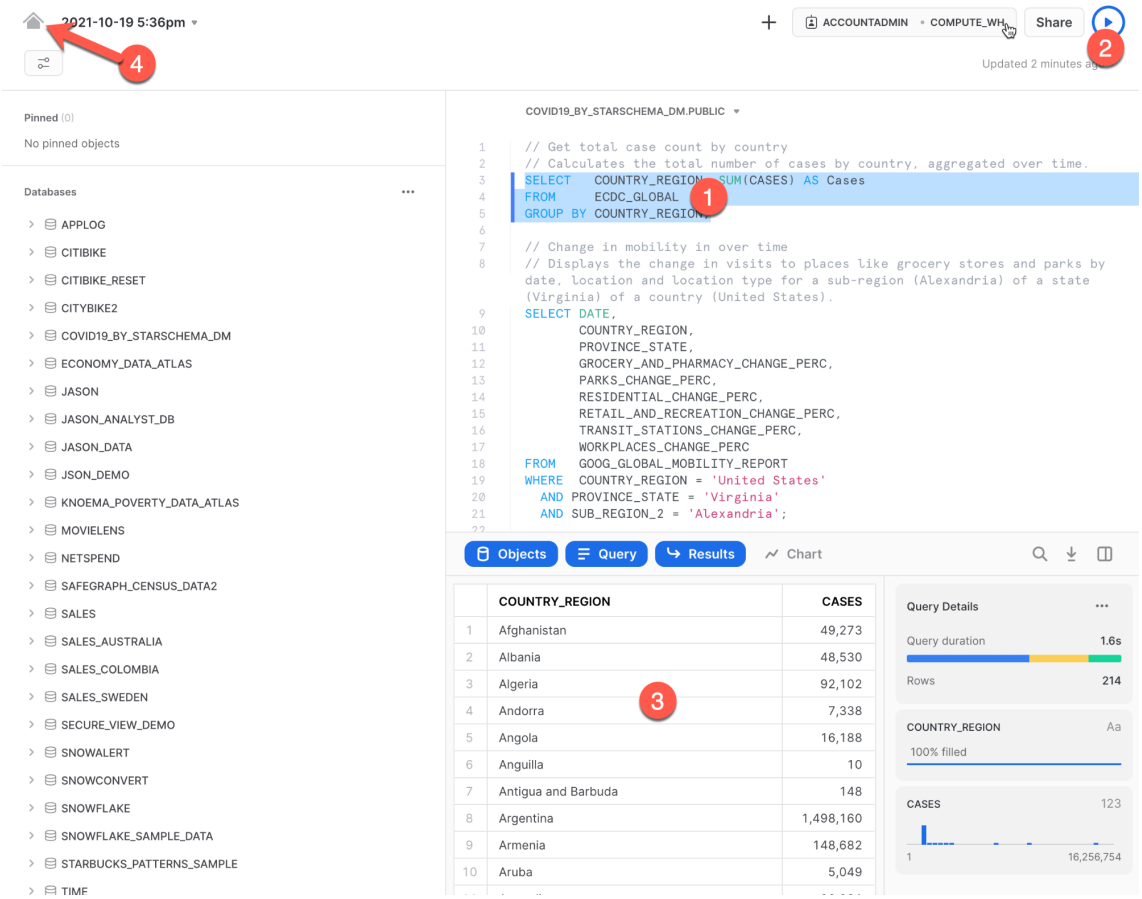


You can now click **Done** or choose to run the sample queries provided by Starschema:



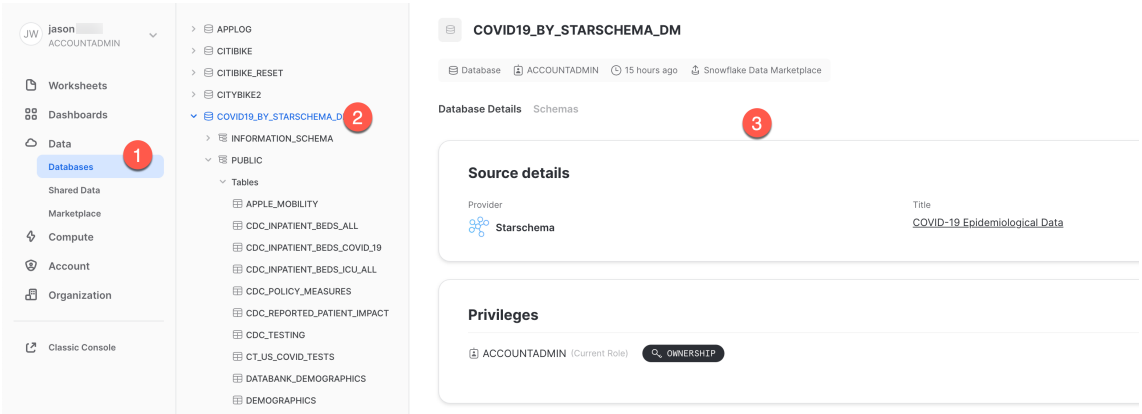
If you chose **Open**, a new worksheet opens in a new browser tab/window:

1. Select the query you want to run (or place your cursor in the query text).
2. Click the **Run/Play** button (or use the keyboard shortcut).
3. You can view the data results in the bottom pane.
4. When you are done running the sample queries, click the **Home** icon in the upper left corner.



Next:

1. Click **Data** > **Databases**
2. Click the `COVID19_BY_STARSCHEMA_DM` database.
3. You can see details about the schemas, tables, and views that are available to query.



That's it! You have now successfully subscribed to the COVID-19 dataset from Starschema, which is updated daily with global COVID data. Notice we didn't have to create databases, tables, views, or an ETL process. We simply searched for and accessed shared data from the Snowflake Data Marketplace.

Resetting Your Snowflake Environment

If you would like to reset your environment by deleting all the objects created as part of this lab, run the SQL statements in a worksheet.

First, ensure you are using the ACCOUNTADMIN role in the worksheet:

```
use role accountadmin;
```

Then, run the following SQL commands to drop all the objects we created in the lab:

```
drop share if exists zero_to_snowflake_shared_data;
-- If necessary, replace "zero_to_snowflake-shared_data" with the name you used for
the share

drop database if exists citibike;

drop database if exists weather;

drop warehouse if exists analytics_wh;

drop role if exists junior_dba;
```

Conclusion & Next Steps

Congratulations on completing this introductory lab exercise! You've mastered the Snowflake basics and are ready to apply these fundamentals to your own data. Be sure to reference this guide if you ever need a refresher.

We encourage you to continue with your free trial by loading your own sample or production data and by using some of the more advanced capabilities of Snowflake not covered in this lab.

What we've covered:

- How to create stages, databases, tables, views, and virtual warehouses.
- How to load structured and semi-structured data.
- How to perform analytical queries on data in Snowflake, including joins between tables.
- How to clone objects.
- How to undo user errors using Time Travel.
- How to create roles and users, and grant them privileges.
- How to securely and easily share data with other accounts.
- How to consume datasets in the Snowflake Data Marketplace.

Getting Started with SnowSQL

Overview

SnowSQL is the software CLI tool used to interact with Snowflake. Using SnowSQL, you can control all aspects of your Snowflake Data Cloud, including uploading data, querying data, changing data, and deleting data. This guide will review SnowSQL and use it to create a database, load data, and learn helpful commands to manage your tables and data directly from your CLI.

What You'll Learn

- how to create a Snowflake account
- how to install SnowSQL locally
- how to set up a cloud database and table
- how to create a virtual warehouse
- how to migrate sample data to the cloud
- how to query cloud data
- how to insert additional data
- how to drop database objects and close SnowSQL connection

Be sure to check the needed computing requirements before beginning. Also, download the sample files to complete this tutorial and note the folder location for later use.

What You'll Need

- Local [Browser and OS Requirements]
- Download the [Sample Data Files]

What You'll Build

- A connection to cloud host and manage data with SnowSQL.

Set up SnowSQL

First, you'll get a Snowflake account and get comfortable navigating in the web console. After downloading the SnowSQL installer, you'll install and confirm your success.

Create a Snowflake Account

Snowflake lets you try out their services for free with a trial account.

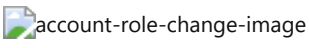
Access Snowflake's Web Console

```
https://<account-name>.snowflakecomputing.com/console/login
```

Log in to the web interface on your browser. The URL contains your [account name] and potentially the region.

Increase Your Account Permission

The Snowflake web interface has a lot to offer, but for now, we'll just switch the account role from the default `SYSADMIN` to `ACCOUNTADMIN`. This increase in permissions will allow the user account to create objects.


account-role-change-image

Download the SnowSQL Installer

SnowSQL can be downloaded and installed on Linux, Windows, or Mac. Download the SnowSQL Installer for Windows from here:

`https://sfc-repo.snowflakecomputing.com/snowsql/bootstrap/1.2/windows_x86_64/snowsql-1.2.21-windows_x86_64.msi`

Install SnowSQL Locally

- Double-click the installer file and walk through the wizard prompts.
- Confirm the install was successful by checking the version `$ snowsql -v`.
- Reboot your machine and check again if necessary.

After completing these steps, you'll be ready to use SnowSQL to make a database in the next section.

Create a Database

With your account active and SnowSQL installed, you'll use the terminal to sign in and create the needed objects for cloud storage.

Sign in From the Terminal

```
snowsql -a <account-name> -u <username>
```

The `-a` flag represents the Snowflake account, and the `-u` represents the username.

Create a Database and Schema

```
create or replace database sf_tuts;
```

The command [create or replace database] makes a new database and auto-creates the schema 'public.' It'll also make the new database active for your current session.

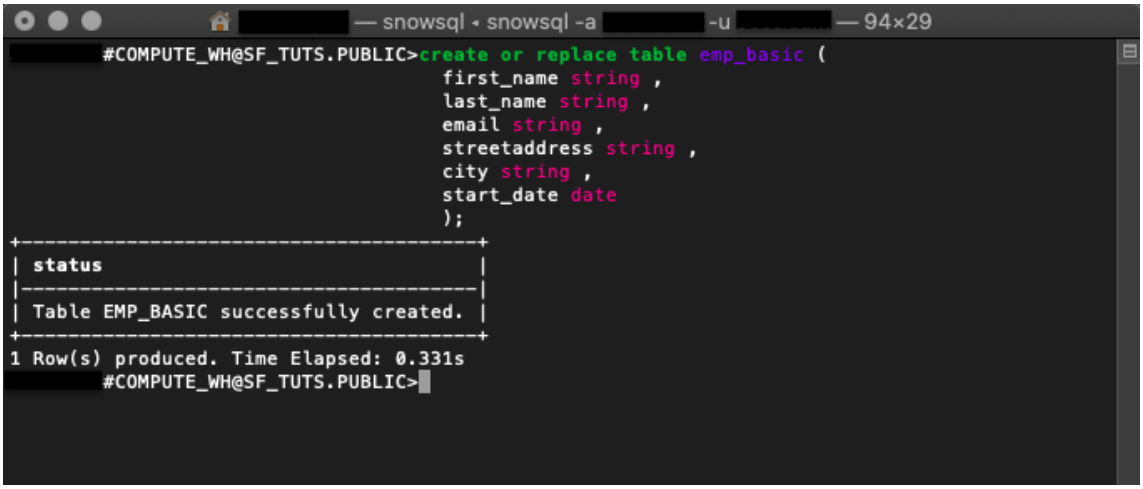
To check which database is in use for your current session, execute:

```
select current_database(),
current_schema();
```

Generate a Table

```
create or replace table emp_basic (
  first_name string ,
  last_name string ,
  email string ,
  streetaddress string ,
  city string ,
  start_date date
  );
```

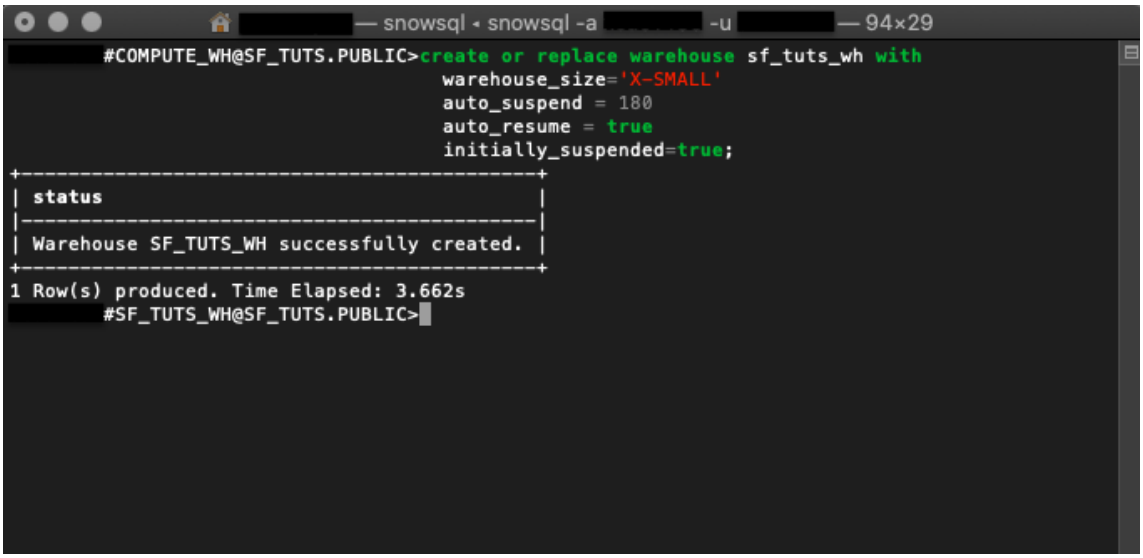
Running [create or replace table] will build a new table based on the parameters specified. This example reflects the same columns in the sample CSV employee data files.



Make a Virtual Warehouse

```
create or replace warehouse sf_tuts_wh with
  warehouse_size='X-SMALL'
  auto_suspend = 180
  auto_resume = true
  initially_suspended=true;
```

After creation, this virtual warehouse will be active for your current session and begin running once the computing resources are needed.



With the database objects ready, you'll employ SnowSQL to move the sample data onto the `emp_basic` table.

Upload Data

In this section, you'll stage your sample CVS employee files and execute a SQL command to copy the data onto your table.

If you have not already done so, you can download the sample files here:

Download Sample Data

Stage Files With PUT

Linux

```
put file:///tmp/employees0*.csv @<database-name>.<schema-name>.%<table-name>;
```

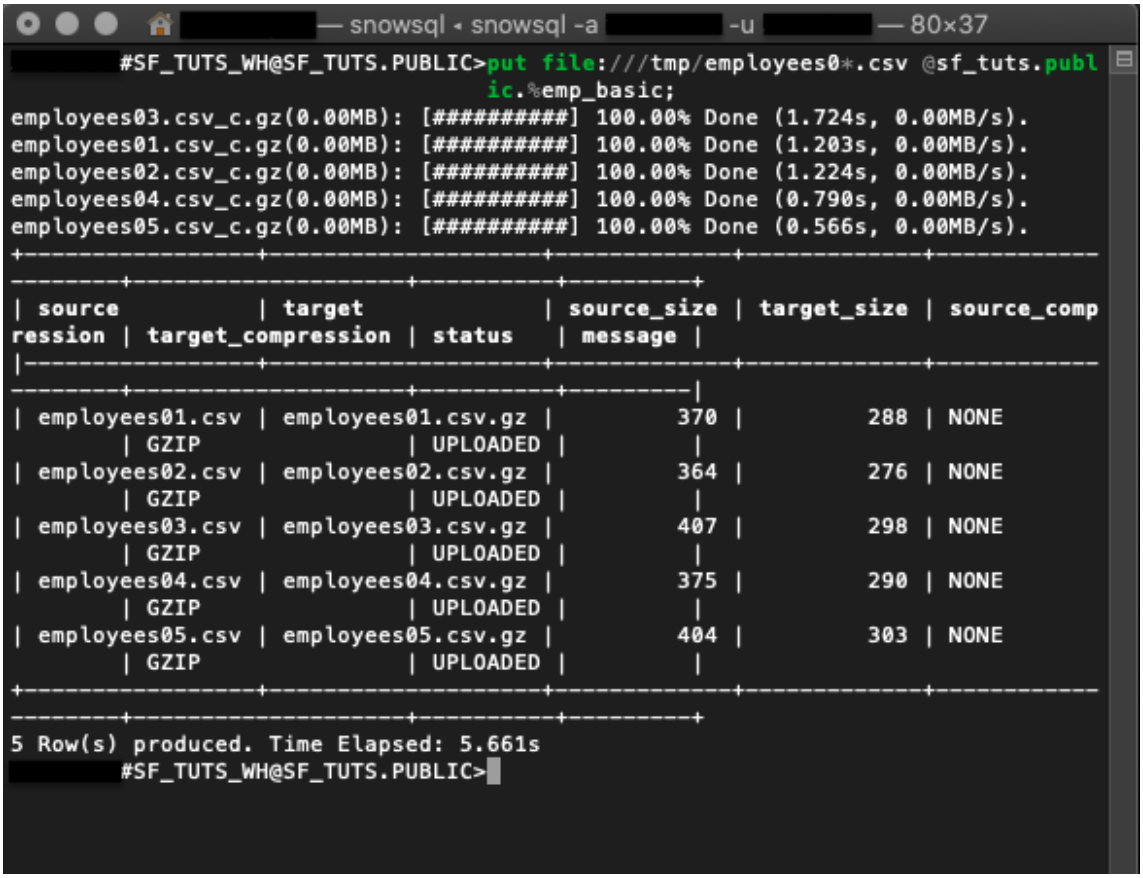
Windows

```
put file://c:\temp\employees0*.csv @sf_tuts.public.%emp_basic;
```

- `file` specifies the *local* file path of the files to be staged. File paths are OS-specific.
- `@<database-name>.<schema-name>.%<table-name>` is the specific database, schema, and table the staged files are headed.
- The `@` sign before the database and schema name `@sf_tuts.public` indicates that the files are being uploaded to an internal stage, rather than an external stage. The `%` sign before the table name `%emp_basic` indicates that the internal stage being used is the stage for the table. For more details about stages, see Staging Data Files from a Local File System.

```
put file:///tmp/employees0*.csv @sf_tuts.public.%emp_basic;
```

Here is a PUT call to stage the sample employee CSV files from a macOS `file:///tmp/` folder onto the `emp_basic` table within the `sf_tuts` database.



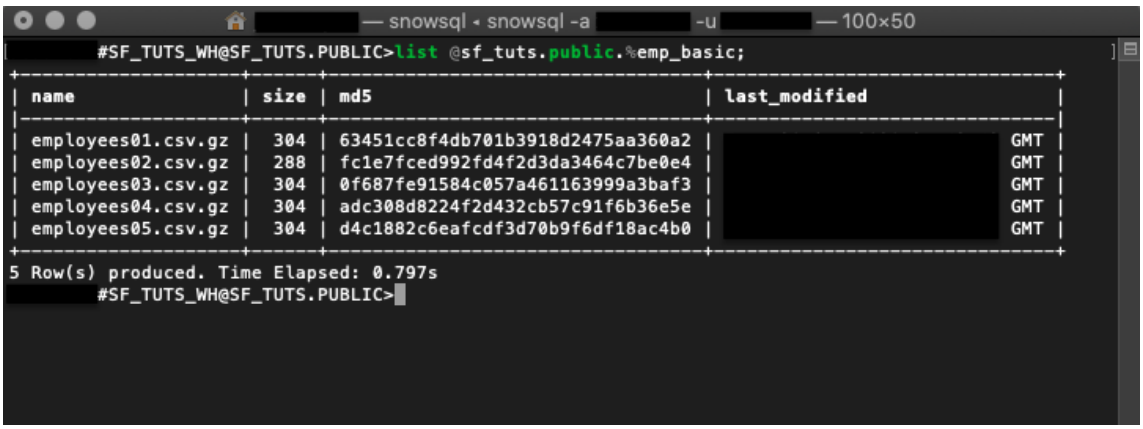
LIST Staged Files

```
list @<database-name>.<schema-name>.%<table-name>;
```

To check your staged files, run the `list` command.

```
list @sf_tuts.public.%emp_basic;
```

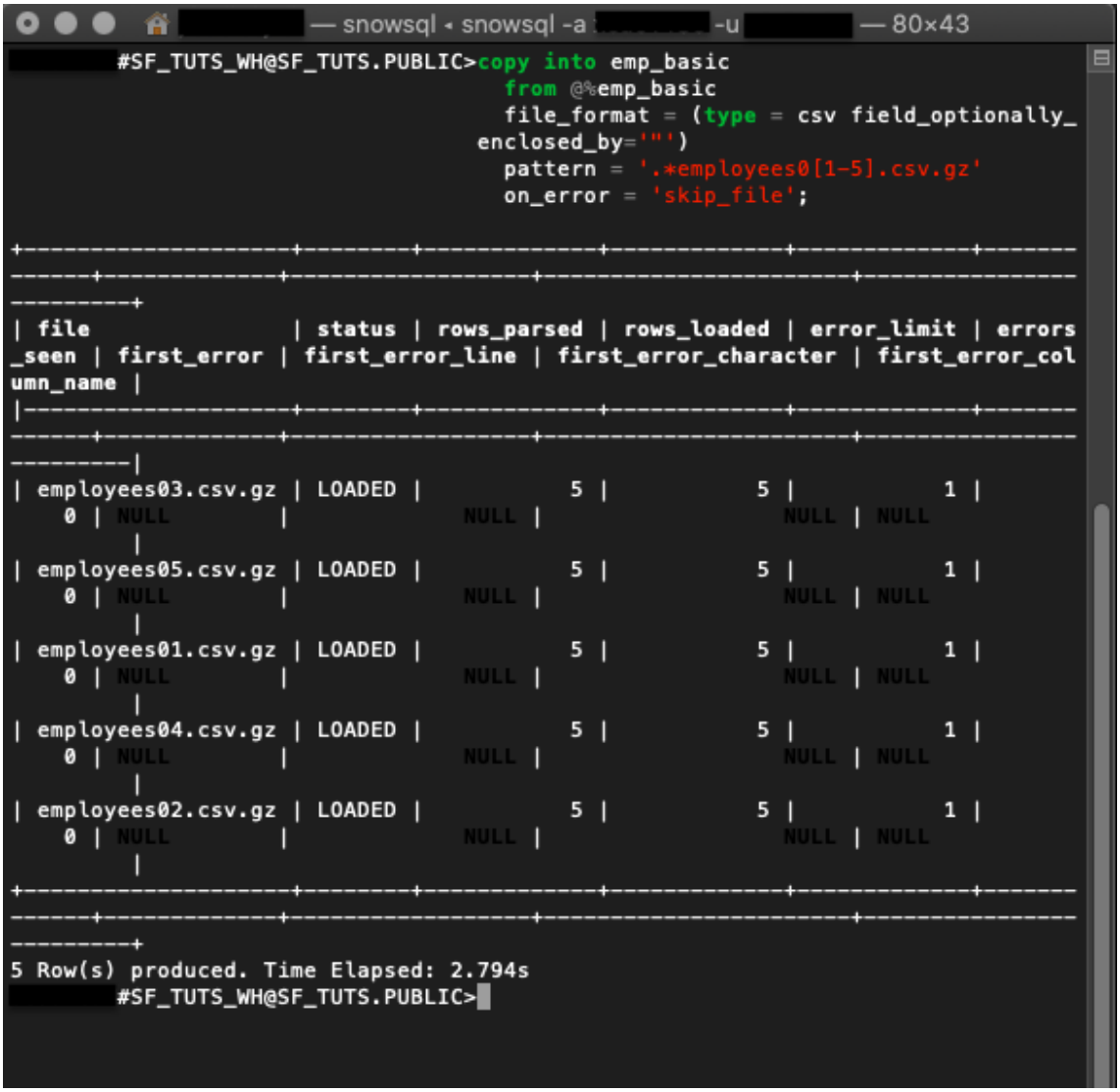
The example command above is to output the staged files for the `emp_basic` table.



[COPY INTO] Your Table

```
copy into emp_basic
  from @%emp_basic
  file_format = (type = csv field_optionally_enclosed_by='"')
  pattern = '.*employees0[1-5].csv.gz'
  on_error = 'skip_file';
```

After getting the files staged, the data is copied into the `emp_basic` table. This DML command also auto-resumes the virtual warehouse made earlier.



The output indicates if the data was successfully copied and records any errors.

Query Data

With your data in the cloud, you need to know how to query it. We'll go over a few calls that will put your data on speed-dial.

- The `select` command followed by the wildcard `*` returns all rows and columns in `<table-name>`.

```
select * from emp_basic;
```

Here is an example command to `select` everything on the `emp_basic` table.

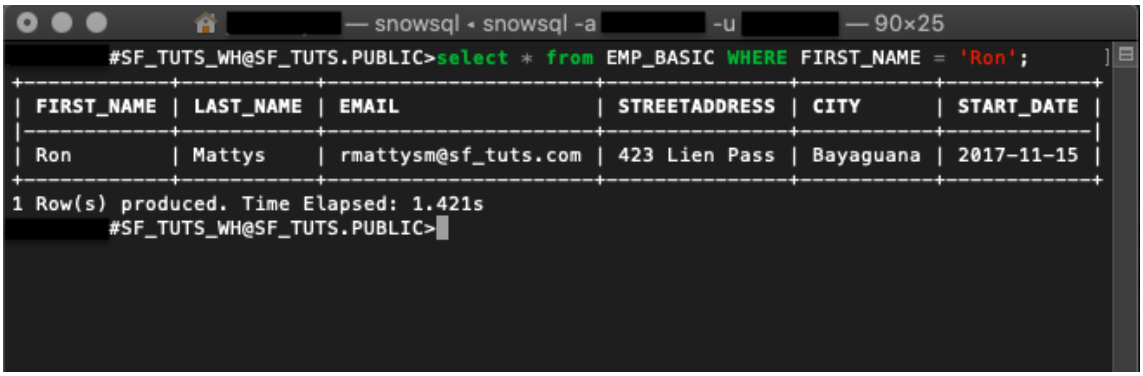
```
#SF_TUTS_WH@SF_TUTS.PUBLIC>select * from EMP_BASIC;
+------------+------------+--------------------------+--------------------------+-------------------+------------+
| FIRST_NAME | LAST_NAME  | EMAIL                    | STREETADDRESS            | CITY              | START_DATE |
|------------+------------+--------------------------+--------------------------+-------------------+------------|
| Althea     | Featherstone | afeatherstona@sf_tuts.com | 8172 Browning Street, Apt B | Calatrava       | 2017-07-12 |
| Hollis     | Anneslie   | hanneslieb@sf_tuts.com   | 3248 Roth Park           | Aleysk            | 2017-11-16 |
| Betti      | Cicco      | bciccoc@sf_tuts.com      | 121 Victoria Junction    | Sinegor'ye        | 2017-06-22 |
| Brendon    | Durnall    | bdurnalld@sf_tuts.com    | 26814 Weeping Birch Place | Sabadell         | 2017-11-14 |
| Kylila     | MacConnal  | kmacconnale@sf_tuts.com  | 04 Valley Edge Court     | Qingshu           | 2017-06-22 |
| Arlene     | Davidovits | adavidovitsk@sf_tuts.com | 7571 New Castle Circle   | Meniko            | 2017-05-03 |
| Violette   | Shermore   | vshermorel@sf_tuts.com   | 899 Merchant Center      | Troitsk           | 2017-01-19 |
| Ron        | Mattys     | rmattysm@sf_tuts.com     | 423 Lien Pass            | Bayaguana         | 2017-11-15 |
| Shurlocke  | Oluwatoyin | soluwatoyinn@sf_tuts.com | 40637 Portage Avenue     | Seměnovskoye      | 2017-09-12 |
| Granger    | Bassford   | gbassfordo@sf_tuts.co.uk | 6 American Ash Circle    | Kardítsa          | 2016-12-30 |
| Lem        | Boissier   | lboissier@sf_tuts.com    | 3002 Ruskin Trail        | Shikārpur         | 2017-08-25 |
| Iain       | Hanks      | ihanks1@sf_tuts.com      | 2 Pankratz Hill          | Monte-Carlo       | 2017-12-10 |
| Avo        | Laudham    | alaudham2@sf_tuts.com    | 6948 Debs Park           | Pražmów           | 2017-10-18 |
| Emili      | Cornner    | ecornner3@sf_tuts.com    | 177 Magdeline Avenue     | Norrköping        | 2017-08-13 |
| Harrietta  | Goolding   | hgoolding4@sf_tuts.com   | 450 Heath Trail          | Osielsko          | 2017-11-27 |
| Wallis     | Sizey      | wsizeyf@sf_tuts.com      | 36761 American Lane      | Taibao            | 2016-12-30 |
| Di         | McGowran   | dmcgowrang@sf_tuts.com   | 1856 Maple Lane          | Banjar Bengkelgede | 2017-04-22 |
| Carson     | Bedder     | cbedderh@sf_tuts.co.au   | 71 Clyde Gallagher Place | Leninskoye        | 2017-03-29 |
| Dana       | Avory      | davoryi@sf_tuts.com      | 2 Holy Cross Pass        | Wenlin            | 2017-05-11 |
| Ronny      | Talmadge   | rtalmadgej@sf_tuts.co.uk | 588 Chinook Street       | Yawata            | 2017-06-02 |
| Nyssa      | Dorgan     | ndorgan5@sf_tuts.com     | 7 Tomscot Way            | Pampas Chico      | 2017-04-13 |
| Catherin   | Devereu    | cdevereu6@sf_tuts.co.au  | 535 Basil Terrace        | Magapit           | 2016-12-17 |
| Grazia     | Glaserman  | gglaserman7@sf_tuts.com  | 162 Debra Lane           | Shiquanhe         | 2017-06-06 |
| Ivett      | Casemore   | icasemore8@sf_tuts.com   | 84 Holmberg Pass         | Campina Grande    | 2017-03-29 |
| Cesar      | Hovie      | chovie9@sf_tuts.com      | 5 7th Pass               | Miami             | 2016-12-21 |
+------------+------------+--------------------------+--------------------------+-------------------+------------+
25 Row(s) produced. Time Elapsed: 2.603s
#SF_TUTS_WH@SF_TUTS.PUBLIC>
```

Sifting through everything on your table may not be the best use of your time. Getting specific results are simple, with a few functions and some query syntax.

- [WHERE] is an additional clause you can add to your select query.

```
select * from emp_basic where first_name = 'Ron';
```

This query returns a list of employees by the `first_name` of 'Ron' from the `emp_basic` table.

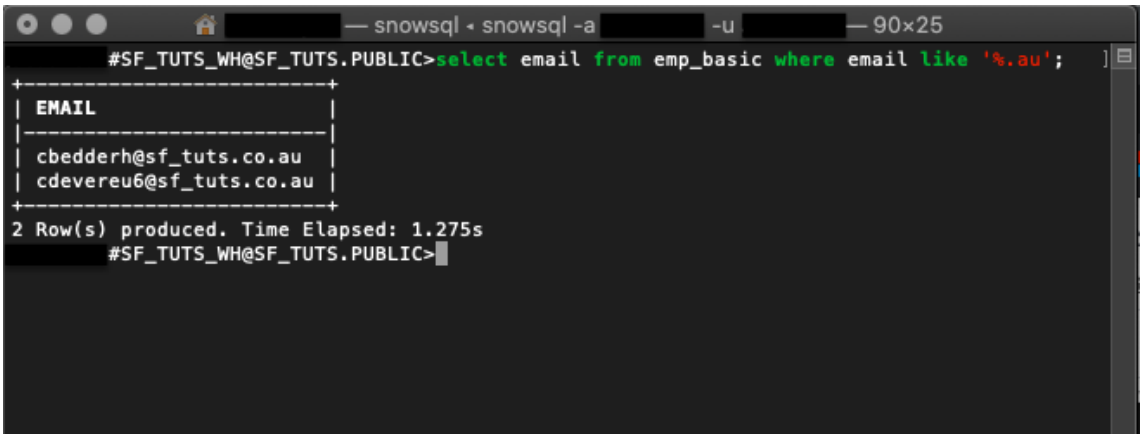


```
#SF_TUTS_WH@SF_TUTS.PUBLIC>select * from EMP_BASIC WHERE FIRST_NAME = 'Ron';
+------------+-----------+---------------------+---------------+-----------+------------+
| FIRST_NAME | LAST_NAME | EMAIL               | STREETADDRESS | CITY      | START_DATE |
|------------+-----------+---------------------+---------------+-----------+------------|
| Ron        | Mattys    | rmattysm@sf_tuts.com | 423 Lien Pass | Bayaguana | 2017-11-15 |
+------------+-----------+---------------------+---------------+-----------+------------+
1 Row(s) produced. Time Elapsed: 1.421s
#SF_TUTS_WH@SF_TUTS.PUBLIC>
```

- [LIKE] function supports wildcard `%` and `_`.

```
select email from emp_basic where email like '%.au';
```

The like function checks all emails in the `emp_basic` table for `au` and returns a record.



Snowflake supports many [functions], [operators], and [commands]. However, if you need more specific tasks performed, consider setting up an [external function].

Manage and Delete Data

Often data isn't static. We'll review a few common ways to maintain your cloud database.

If HR updated the CSV file after hiring another employee, downloading, staging, and copying the whole CSV would be tedious. Instead, simply insert the new employee information into the targeted table.

Insert Data

[INSERT] will update a table with additional values.

```
insert into emp_basic values
  ('Clementine','Adamou','cadamou@sf_tuts.com','10510 Sachs Road','Klenak','2017-9-
22') ,
  ('Marlowe','De Anesy','madamouc@sf_tuts.co.uk','36768 Northfield
Plaza','Fangshan','2017-1-26');
```

Drop Objects

In the command displayed, `insert` is used to add two new employees to the `emp_basic` table.

- [DROP] objects no longer in use.

```
drop database if exists sf_tuts;

drop warehouse if exists sf_tuts_wh;
```

After practicing the basics covered in this tutorial, you'll no longer need the `sf-tuts` database and warehouse. To remove them altogether, use the `drop` command.

- Close Your Connection with `!exit` or `!disconnect`

For security reasons, it's best not to leave your terminal connection open unnecessarily. Once you're ready to close your SnowSQL connection, simply enter `!exit`.

Conclusion

Use SnowSQL for Your Application

You've created a Snowflake account, set up a cloud database with compute resources, and migrated data to the cloud with SnowSQL. Nice work! There are many advantages to using the cloud. Now that you know how easy getting started with Snowflake is, it's time to consider your next steps.

With your firm grasp of loading data with SnowSQL, start using it to run your application. Continue by [developing an application] with SnowSQL to learn how to connect your data to a Python application. If you already have application data, consider migrating it to the cloud with the same steps we used to complete the `emp_basic` table. Snowflake's tools and documentation are extensive and give you the power of cloud computing.

What we've covered

- SnowSQL setup
- Uploading data using SnowSQL
- Querying data using SnowSQL
- Managing and deleting data using SnowSQL

Extract Attributes from DICOM Files using a Java UDF

Overview

This lab is designed to help you understand the capabilities included in Snowflake's support for unstructured data and Snowpark. Although this guide is specific to processing DICOM files, you can apply this pattern of processing natively in Snowflake to many types of unstructured data. All source code for this guide can be found on Github.

What You'll Need

- Snowflake account
- [SnowSQL] installed

What You'll Learn

- How to access DICOM files in cloud storage from Snowflake
- How to extract attributes from DICOM files natively using a Java User-Defined Function (UDF)

What You'll Build

- An external stage to access files in S3 from Snowflake
- A user-defined function using Snowflake's engine to process files

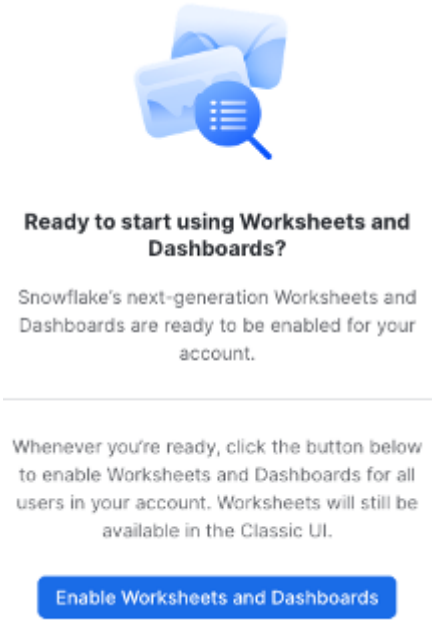
Prepare Your Environment

If you haven't already, register for a Snowflake free 30-day trial. The Snowflake edition (Standard, Enterprise, Business Critical, e.g.), cloud provider (AWS, Azure, e.g.), and Region (US East, EU, e.g.) do not matter for this lab. We suggest you select the region which is physically closest to you and the Enterprise Edition, our most popular offering. After registering, you will receive an email with an activation link and your Snowflake account URL.

Navigating to Snowsight

For this lab, you will use the latest Snowflake web interface, Snowsight.

1. Log into your Snowflake trial account
2. Click on **Snowsight** Worksheets tab. The new web interface opens in a separate tab or window.
3. Click **Worksheets** in the left-hand navigation bar. The **Ready to Start Using Worksheets and Dashboards** dialog opens.
4. Click the **Enable Worksheets and Dashboards button**.



Access the Data

Let's start by accessing DICOM files from Snowflake. Snowflake supports two types of stages for storing data files used for loading and unloading:

- [Internal] stages store the files internally within Snowflake.
- [External] stages store the files in an external location (i.e. S3 bucket) that is referenced by the stage. An external stage specifies location and credential information, if required, for the bucket.

For this lab, we will use an external stage, but processing and analysis workflows demonstrated in this lab can also be done using an internal stage.

Create a Database, Warehouse, and Stage

Let's create a database, warehouse, and stage that will be used for processing the files. We will use the UI within the Worksheets tab to run the DDL that creates the database and schema. Copy the commands below into your trial environment, and execute each individually.

```
use role sysadmin;

create or replace database dicom;
create or replace warehouse quickstart;

use database dicom;
use schema public;
use warehouse quickstart;

create or replace stage dicom_external
url="s3://sfquickstarts/Extract DICOM Attributes/DICOM/"
directory = (enable = TRUE);
```

Verify if the DICOM files are accessible in your external stage by entering the following command on your Snowflake worksheet.

```
ls @dicom_external;
```

You should now see an identical list of files from the S3 bucket. Make sure you see 24 files.

```
14
15    ls @dicom_external;
```

Objects | Query | Results | Chart

	name	size
1	s3://sfquickstarts/Extract DICOM Attributes/DICOM/ID_0000_AGE_0060_CONTRAS	528,130
2	s3://sfquickstarts/Extract DICOM Attributes/DICOM/ID_0001_AGE_0069_CONTRAS	528,118
3	s3://sfquickstarts/Extract DICOM Attributes/DICOM/ID_0002_AGE_0074_CONTRAS	527,528
4	s3://sfquickstarts/Extract DICOM Attributes/DICOM/ID_0003_AGE_0075_CONTRAS	527,402
5	s3://sfquickstarts/Extract DICOM Attributes/DICOM/ID_0004_AGE_0056_CONTRAS	528,158
6	s3://sfquickstarts/Extract DICOM Attributes/DICOM/ID_0005_AGE_0048_CONTRAS	527,660
7	s3://sfquickstarts/Extract DICOM Attributes/DICOM/ID_0006_AGE_0075_CONTRAS	527,402

Extract Attributes from DICOM Files

In this section, we want to extract attributes from the DICOM files. The entities extracted are going to be fields like manufacturer, patient position, and study date. The goal is to have these fields to enrich the file-level metadata for analytics.

Creating a Java UDF in Snowflake

The Java code to parse DICOM files requires some dependencies. Instead of downloading those jar files and uploading to an internal stage, you can create an external stage and reference them when creating a UDF inline.

```
-- Create stage to store the jar file
create or replace stage jars_stage_internal;

-- Create external stage to import jars from S3
create or replace stage jars_stage
 url = "s3://sfquickstarts/Common JARs/"
 directory = (enable = true auto_refresh = false);

-- Create a java function to parse DICOM files
create or replace function read_dicom(file string)
returns String
language java
imports = ('@jars_stage/dcm4che-core-5.24.2.jar', '@jars_stage/log4j-1.2.17.jar',
           '@jars_stage/slf4j-api-1.7.30.jar', '@jars_stage/slf4j-log4j12-1.7.30.jar',
           '@jars_stage/gson-2.8.7.jar')
HANDLER = 'DicomParser.Parse'
```

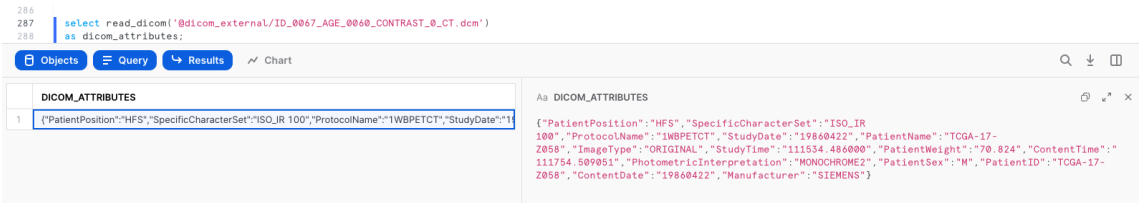
```
as
$$
import org.dcm4che3.data.Attributes;
import org.dcm4che3.data.Tag;
import org.dcm4che3.io.DicomInputStream;
import org.xml.sax.SAXException;

import java.io.*;
import java.util.HashMap;
import java.util.Map;

import com.google.gson.Gson;

import com.snowflake.snowpark_java.types.SnowflakeFile;

public class DicomParser {
    public static String Parse(String file_url) throws IOException {
     SnowflakeFile file = SnowflakeFile.newInstance(file_url);
String jsonStr = null;

        try {
            DicomInputStream dis = new DicomInputStream(file.getInputStream());
            DicomInputStream.IncludeBulkData includeBulkData =
DicomInputStream.IncludeBulkData.URI;
            dis.setIncludeBulkData(includeBulkData);
            Attributes attrs = dis.readDataset(-1, -1);

            Map<String, String> attributes = new HashMap<String, String>();
            attributes.put("PerformingPhysicianName",
attrs.getString(Tag.PerformingPhysicianName));
            attributes.put("PatientName",  attrs.getString(Tag.PatientName));
            attributes.put("PatientBirthDate",
attrs.getString(Tag.PatientBirthDate));
            attributes.put("Manufacturer",  attrs.getString(Tag.Manufacturer));
            attributes.put("PatientID",  attrs.getString(Tag.PatientID));
            attributes.put("PatientSex",  attrs.getString(Tag.PatientSex));
            attributes.put("PatientWeight",  attrs.getString(Tag.PatientWeight));
            attributes.put("PatientPosition",  attrs.getString(Tag.PatientPosition));
            attributes.put("StudyID",  attrs.getString(Tag.StudyID));
            attributes.put("PhotometricInterpretation",
attrs.getString(Tag.PhotometricInterpretation));
            attributes.put("RequestedProcedureID",
attrs.getString(Tag.RequestedProcedureID));
            attributes.put("ProtocolName",  attrs.getString(Tag.ProtocolName));
            attributes.put("ImagingFrequency",
attrs.getString(Tag.ImagingFrequency));
            attributes.put("StudyDate",  attrs.getString(Tag.StudyDate));
            attributes.put("StudyTime",  attrs.getString(Tag.StudyTime));
            attributes.put("ContentDate",  attrs.getString(Tag.ContentDate));
            attributes.put("ContentTime",  attrs.getString(Tag.ContentTime));
            attributes.put("InstanceCreationDate",
attrs.getString(Tag.InstanceCreationDate));
```

```
            attributes.put("SpecificCharacterSet",
attrs.getString(Tag.SpecificCharacterSet));
            attributes.put("StudyDescription",
attrs.getString(Tag.StudyDescription));
            attributes.put("ReferringPhysicianName",
attrs.getString(Tag.ReferringPhysicianName));
            attributes.put("ImageType",  attrs.getString(Tag.ImageType));
            attributes.put("ImplementationVersionName",
attrs.getString(Tag.ImplementationVersionName));
            attributes.put("TransferSyntaxUID",
attrs.getString(Tag.TransferSyntaxUID));

            Gson gsonObj = new Gson();
            jsonStr = gsonObj.toJson(attributes);
        }
        catch (Exception exception) {
            System.out.println("Exception thrown :" + exception.toString());
            throw exception;
        }

        return jsonStr;
    }
}
$$;
```

Invoking the Java UDF

The UDF can be invoked on any DICOM file with a simple SQL statement. First, make sure to refresh the directory table metadata for your external stage.

```
alter stage dicom_external refresh;

select read_dicom('@dicom_external/ID_0067_AGE_0060_CONTRAST_0_CT.dcm')
as dicom_attributes;
```



The output is key-value pairs extracted from `ID_0067_AGE_0060_CONTRAST_0_CT.dcm`.

```
{
  "PatientPosition": "HFS",
  "SpecificCharacterSet": "ISO_IR 100",
  "ProtocolName": "1WBPETCT",
  "StudyDate": "19860422",
  "PatientName": "TCGA-17-Z058",
  "ImageType": "ORIGINAL",
  "StudyTime": "111534.486000",
```

```
  "PatientWeight": "70.824",
  "ContentTime": "111754.509051",
  "PhotometricInterpretation": "MONOCHROME2",
  "PatientSex": "M",
  "PatientID": "TCGA-17-Z058",
  "ContentDate": "19860422",
  "Manufacturer": "SIEMENS"
}
```

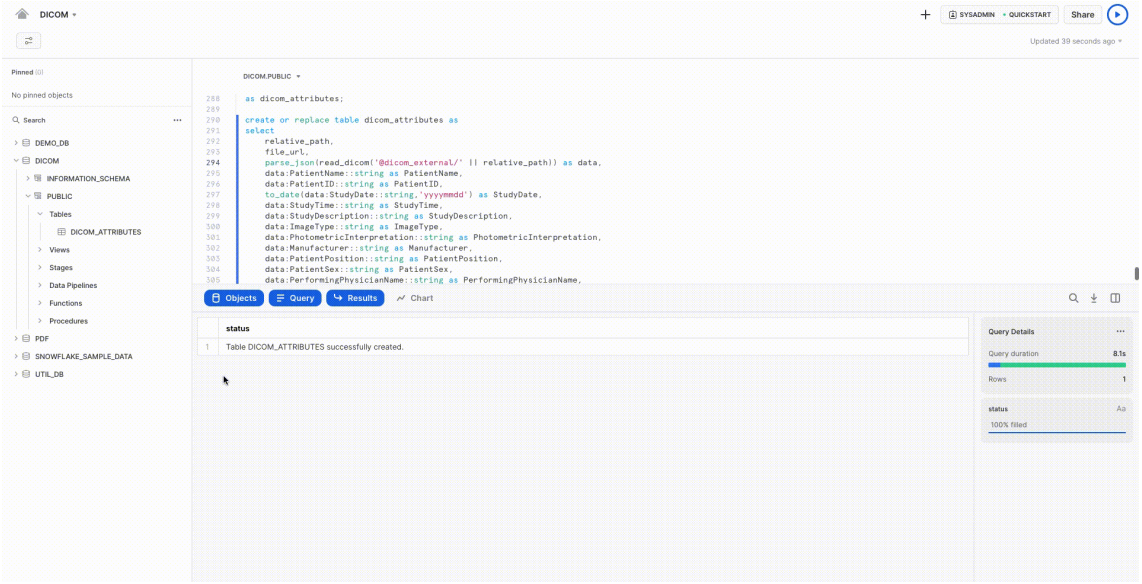
UDFs are account-level objects. So if a developer familiar with Java creates a UDF, an analyst in the same account with proper permissions can invoke the UDF in their queries.

Extracting and Storing Attributes

We want to store the extracted attributes as columns in a table for analysts to be able to query, analyze, and retrieve files. This can be done easily with Snowflake's native support for semi-structured data.

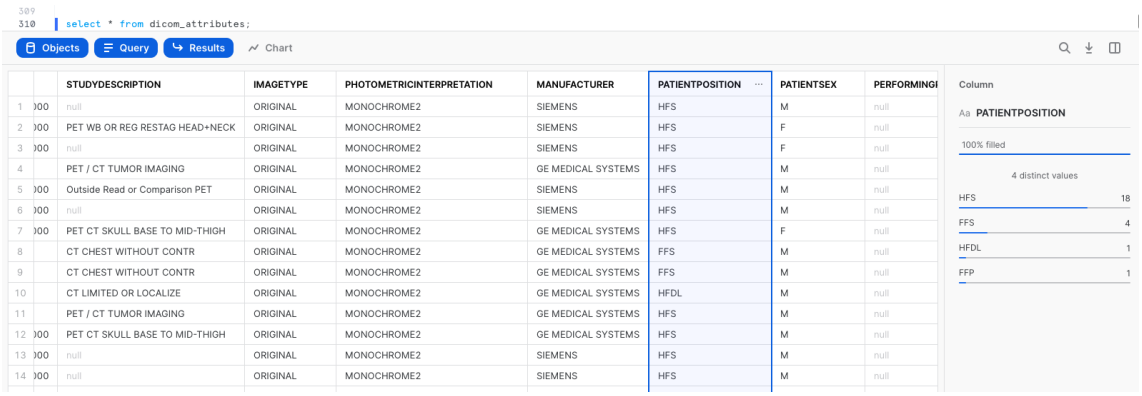
```
create or replace table dicom_attributes as
select
    relative_path,
    file_url,
    parse_json(read_dicom('@dicom_external/' || relative_path)) as data,
    data:PatientName::string as PatientName,
    data:PatientID::string as PatientID,
    to_date(data:StudyDate::string,'yyyymmdd') as StudyDate,
    data:StudyTime::string as StudyTime,
    data:StudyDescription::string as StudyDescription,
    data:ImageType::string as ImageType,
    data:PhotometricInterpretation::string as PhotometricInterpretation,
    data:Manufacturer::string as Manufacturer,
    data:PatientPosition::string as PatientPosition,
    data:PatientSex::string as PatientSex,
    data:PerformingPhysicianName::string as PerformingPhysicianName,
    data:ImagingFrequency::string as ImagingFrequency,
    data:ProtocolName::string as ProtocolName
from directory(@dicom_external);
```

If you collapse and expand the `DICOM` database in the Objects pane on the left, you should now see a table named `DICOM_ATTRIBUTES`. Click on that table, and below you should see a preview of the fields you have created along with icons to indicate the data type. You can also see a preview of the view by clicking on the button that looks like a magnifier glass.



One of the many new things you can do with Snowsight is quickly see summary statistics and distributions of field values in query results. For example, select the entire table `EXTRACTED_DICOM_ATTRIBUTES`. Then in the query results, click on the columns such as `MANUFACTURER`, `PATIENTPOSITION`, and `PATIENTSEX` to see the distribution of values in each column.

```
select * from dicom_attributes;
```



Conclusion

Congratulations! You used Snowflake to extract attributes from DICOM files.

What we've covered

- Accessing unstructured data with an **external stage**
- Processing unstructured data with a **Java UDF**

Analyze PDF Invoices using Java UDF and Snowsight

Overview

This lab is designed to help you understand the capabilities included in Snowflake's support for unstructured data and Snowpark. Although this guide is specific to processing PDF files, you can apply this pattern of processing natively in Snowflake to many types of unstructured data. All source code for this guide can be found on Github.

What You'll Need

- Snowflake account
- SnowSQL installed

What You'll Learn

- How to access PDF invoices in cloud storage from Snowflake
- How to extract text from PDFs natively using a Java User-Defined Function (UDF)

What You'll Build

- An external stage to access files in S3 from Snowflake
- A user-defined function using Snowflake's engine to process files

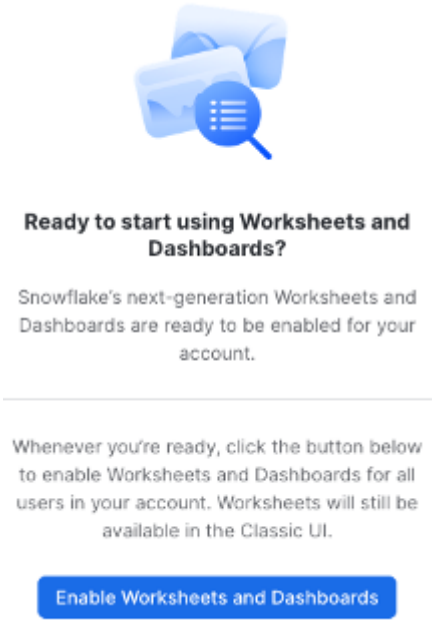
Prepare Your Environment

If you haven't already, register for a Snowflake free 30-day trial. The Snowflake edition (Standard, Enterprise, Business Critical, e.g.), cloud provider (AWS, Azure, e.g.), and Region (US East, EU, e.g.) do not matter for this lab. We suggest you select the region which is physically closest to you and the Enterprise Edition, our most popular offering. After registering, you will receive an email with an activation link and your Snowflake account URL.

Navigating to Snowsight

For this lab, you will use the latest Snowflake web interface, Snowsight.

1. Log into your Snowflake trial account
2. Click on **Snowsight** Worksheets tab. The new web interface opens in a separate tab or window.
3. Click **Worksheets** in the left-hand navigation bar. The **Ready to Start Using Worksheets and Dashboards** dialog opens.
4. Click the **Enable Worksheets and Dashboards button**.



Access the Data

Let's start by loading the PDF invoices into Snowflake. Snowflake supports two types of stages for storing data files used for loading and unloading:

- [Internal] stages store the files internally within Snowflake.
- [External] stages store the files in an external location (i.e. S3 bucket) that is referenced by the stage. An external stage specifies location and credential information, if required, for the bucket.

For this lab, we will use an external stage, but processing and analysis workflows demonstrated in this lab can also be done using an internal stage.

Create a Database, Warehouse, and Stage

Let's create a database, warehouse, and stage that will be used for loading and processing the PDFs. We will use the UI within the Worksheets tab to run the DDL that creates the database and schema. Copy the commands below into your trial environment, and execute each individually.

```
use role sysadmin;

create or replace database pdf;
create or replace warehouse quickstart;

use database pdf;
use schema public;
use warehouse quickstart;

create or replace stage pdf_external
url="s3://sfquickstarts/Analyze PDF Invoices/Invoices/"
directory = (enable = TRUE);
```

Verify if the PDF files are accessible in your external stage by entering the following command on your Snowflake worksheet.

```
ls @pdf_external;
```

You should now see an identical list of files from the S3 bucket. Make sure you see 300 files.

```
14
15  ls @pdf_external;
```

Objects | Query | Results | Chart

	name	... size
1	s3://sfquickstarts/Analyze PDF Invoices/Invoices/invoice1.pdf	13,636
2	s3://sfquickstarts/Analyze PDF Invoices/Invoices/invoice10.pdf	13,639
3	s3://sfquickstarts/Analyze PDF Invoices/Invoices/invoice100.pdf	13,653
4	s3://sfquickstarts/Analyze PDF Invoices/Invoices/invoice101.pdf	13,171
5	s3://sfquickstarts/Analyze PDF Invoices/Invoices/invoice102.pdf	12,962
6	s3://sfquickstarts/Analyze PDF Invoices/Invoices/invoice103.pdf	13,269
7	s3://sfquickstarts/Analyze PDF Invoices/Invoices/invoice104.pdf	12,683

Extract Text from PDFs

In this section, we want to extract attributes from the PDF invoices. The entities extracted are going to be fields like product names, unit cost, total cost, as well as business name. The goal is to have these fields to enrich the file-level metadata for analytics.

Creating a Java UDF in Snowflake

The Java code to parse PDFs requires some dependencies. Instead of downloading those jar files and uploading to an internal stage, you can create an external stage and reference them when creating a UDF inline.

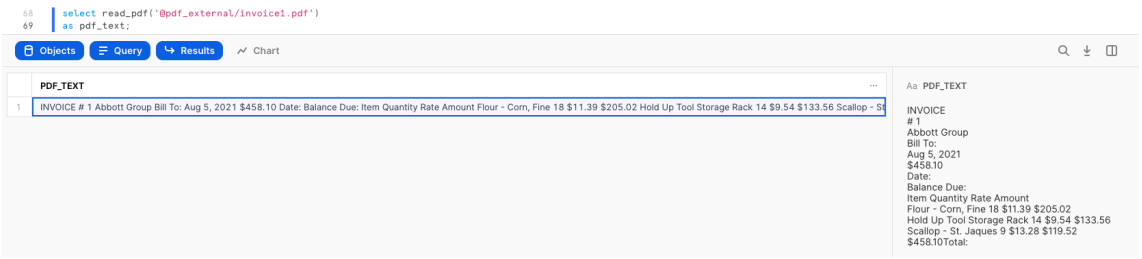
```
-- Create stage to store the JAR file
create or replace stage jars_stage_internal;

-- Create external stage to import PDFBox from S3
create or replace stage jars_stage
 url = "s3://sfquickstarts/Common JARs/"
 directory = (enable = true auto_refresh = false);

-- Create a java function to parse PDF files
create or replace function read_pdf(file string)
returns String
language java
imports = ('@jars_stage/pdfbox-app-2.0.24.jar')
```

```
HANDLER = 'PdfParser.ReadFile'
as
$$
import org.apache.pdfbox.pdmodel.PDDocument;
import org.apache.pdfbox.text.PDFTextStripper;
import org.apache.pdfbox.text.PDFTextStripperByArea;

import java.io.File;
import java.io.FileInputStream;
import java.io.IOException;
import java.io.InputStream;

import com.snowflake.snowpark_java.types.SnowflakeFile;

public class PdfParser {

    public static String ReadFile(String file_url) throws IOException {
SnowflakeFile file = SnowflakeFile.newInstance(file_url);
        try (PDDocument document = PDDocument.load(file.getInputStream())) {

            document.getClass();

            if (!document.isEncrypted()) {

                PDFTextStripperByArea stripper = new PDFTextStripperByArea();
                stripper.setSortByPosition(true);

                PDFTextStripper tStripper = new PDFTextStripper();

                String pdfFileInText = tStripper.getText(document);
                return pdfFileInText;
            }
        }

        return null;
    }
}
$$;
```

Invoking the Java UDF

The UDF can be invoked on any PDF file with a simple SQL statement. First, make sure to refresh the directory table metadata for your external stage.

```
alter stage pdf_external refresh;

select read_pdf('@pdf_external/invoice1.pdf')
as pdf_text;
```



The output is text values extracted from `invoice1.pdf`.

```
INVOICE
# 1
Abbott Group
Bill To:
Aug 5, 2021
$458.10
Date:
Balance Due:
Item Quantity Rate Amount
Flour - Corn, Fine 18 $11.39 $205.02
Hold Up Tool Storage Rack 14 $9.54 $133.56
Scallop - St. Jaques 9 $13.28 $119.52
$458.10Total:
```

UDFs are account-level objects. So if a developer familiar with Java creates a UDF, an analyst in the same account with proper permissions can invoke the UDF in their queries.

Extracting and Storing Fields

We want to store the extracted text as additional attributes for analysts to be able to select and retrieve the files of interest in their analysis, as well as perform some analytics on the attributes found.

We first need to create a table with the extracted text in its raw form. From this table, we can create views to parse the text into various fields for easier analysis.

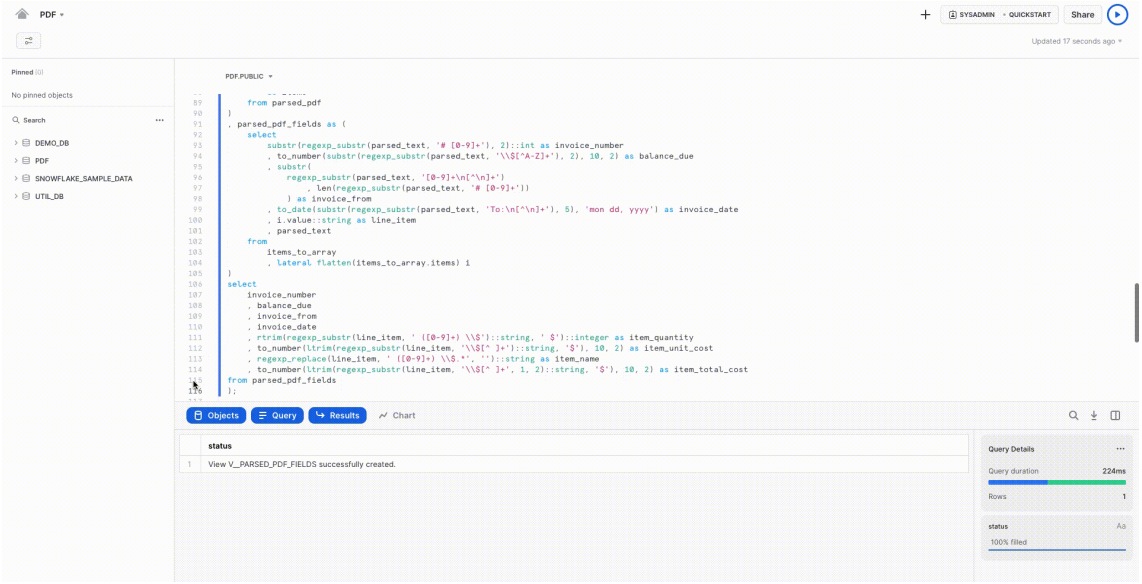
```
create or replace table parsed_pdf as
select
    relative_path
    , file_url
    , read_pdf('@pdf_external/' || relative_path) as parsed_text
from directory(@pdf_external);
```

Using Snowflake's string functions, we can parse out specific values as fields like balance due, item name, item quantity, and more.

```
create or replace view v__parsed_pdf_fields as (
with items_to_array as (
    select
        *
        , split(
            substr(
              regexp_substr(parsed_text, 'Amount\n(.*)\n(.*)\n(.*)'
```

```
              ), 8
            ), '\n'
          )
        as items
    from parsed_pdf
)
, parsed_pdf_fields as (
    select
        substr(regexp_substr(parsed_text, '# [0-9]+'), 2)::int as invoice_number
        , to_number(substr(regexp_substr(parsed_text, '\\$[^A-Z]+'), 2), 10, 2) as
balance_due
        , substr(
            regexp_substr(parsed_text, '[0-9]+\n[^\n]+')
                , len(regexp_substr(parsed_text, '# [0-9]+'))
            ) as invoice_from
        , to_date(substr(regexp_substr(parsed_text, 'To:\n[^\n]+'), 5), 'mon dd,
yyyy') as invoice_date
        , i.value::string as line_item
        , parsed_text
    from
        items_to_array
        , lateral flatten(items_to_array.items) i
)
select
    invoice_number
    , balance_due
    , invoice_from
    , invoice_date
    , rtrim(regexp_substr(line_item, ' ([0-9]+) \\$')::string, ' $')::integer as
item_quantity
    , to_number(ltrim(regexp_substr(line_item, '\\$[^ ]+')::string, '$'), 10, 2) as
item_unit_cost
    , regexp_replace(line_item, ' ([0-9]+) \\$.*', '')::string as item_name
    , to_number(ltrim(regexp_substr(line_item, '\\$[^ ]+', 1, 2)::string, '$'), 10, 2)
as item_total_cost
from parsed_pdf_fields
);
```

If you collapse and expand the `PDF` database in the Objects pane on the left, you should now see a view name `V__PARSED_PDF_FIELDS`. Click on that view, and below you should see a preview of the fields you have created along with icons to indicate the data type. You can also see a preview of the view by clicking on the button that looks like a magnifier glass.



Exploring Invoice Data

Now let's explore the data from the PDF invoices. What are the most purchased items based on quantity?

```
select
    sum(item_quantity)
    , item_name
from v__parsed_pdf_fields
group by item_name
order by sum(item_quantity) desc
limit 10;
```

```
117
118  --what are the 10 most purchased items?
119  select
120      sum(item_quantity)
121      , item_name
122  from v__parsed_pdf_fields
123  group by item_name
124  order by sum(item_quantity) desc
125  limit 10;
```

Objects | Query | Results | Chart

	SUM(ITEM_QUANTITY)	ITEM_NAME
1	203	Apron
2	178	Lettuce - California Mix
3	169	Bar Special K
4	159	Oil - Margarine
5	158	Flower - Commercial Bronze
6	155	Apple - Fuji
7	154	Wine - Rhine Riesling Wolf Blass
8	152	Garam Marsala
9	151	Phyllo Dough
10	146	Salmon - Smoked, Sliced

What are the items on which the most money was spent?

```
select
    sum(item_total_cost)
    , item_name
```

```
from v__parsed_pdf_fields
group by item_name
order by sum(item_total_cost) desc
limit 10;
```

```
126
127   --on which 10 items was the most money spent?
128   select
129       sum(item_total_cost)
130       , item_name
131   from v__parsed_pdf_fields
132   group by item_name
133   order by sum(item_total_cost) desc
134   limit 10;
```

Objects | Query | Results | Chart

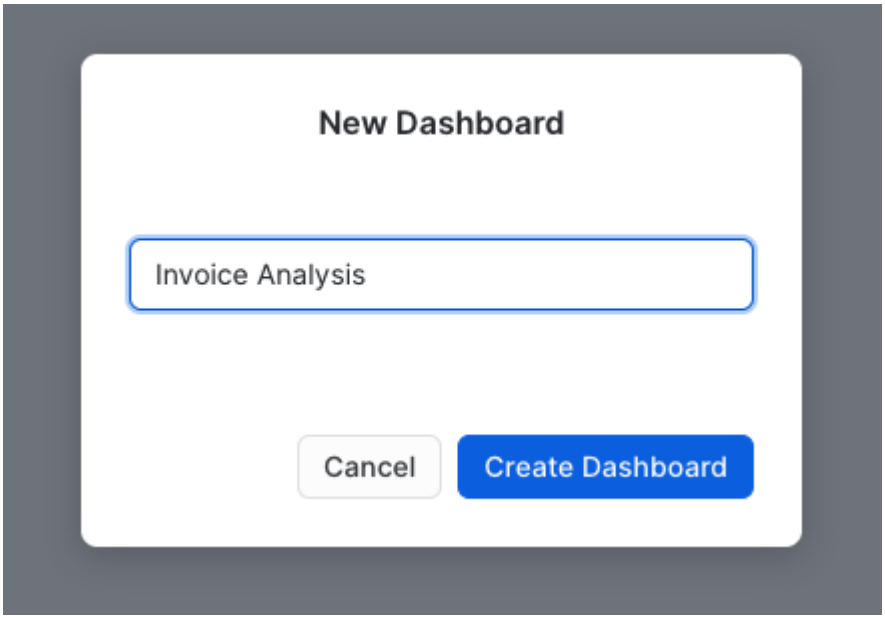
	SUM(ITEM_TOTAL_COST)	ITEM_NAME
1	3,214.68	Lettuce - California Mix
2	3,079.83	Oil - Margarine
3	2,644.85	Bar Special K
4	2,518.65	Pepper - Chili Powder
5	2,313.32	Phyllo Dough
6	2,173.98	Soup - Boston Clam Chowder
7	2,057.94	Sauce - Oyster
8	1,905.64	Cinnamon Rolls
9	1,865.92	Duck - Legs
10	1,825	Salmon - Smoked, Sliced

Analyze the Data with Snowsight

Now we can use Snowsight to visualize the data extracted from the PDF invoices.

Create a Dashboard

Let's use a dashboard as a collection of all of the visualizations we will create. Click on the Home button, then click on **Dashboards** in the pane on the left. Create a new dashboard by clicking the **+ Dashboard** button in the top-right. Name the dashboard `Invoice Analysis`, and click **Create Dashboard**.

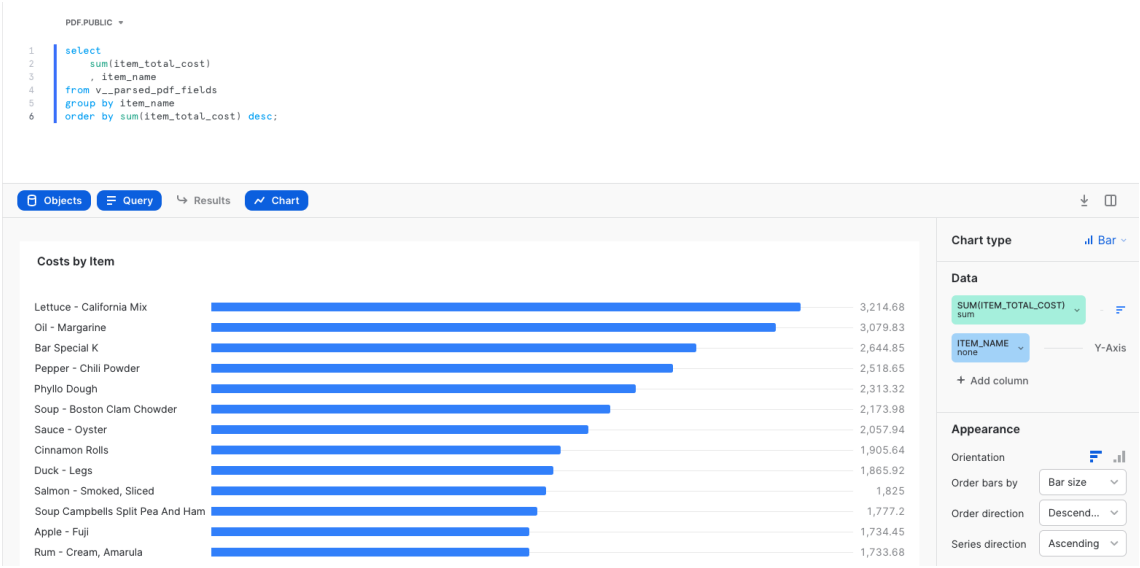


Now let's create the first tile on the Invoice Analysis dashboard by clicking the button **+ New Tile**. Give the tile a name by clicking on the timestamp at the top, and name it `Costs by Item`. In the canvas, copy/paste the SQL

below to query the data needed for the chart and run it.

```
select
    sum(item_total_cost)
    , item_name
from v__parsed_pdf_fields
group by item_name
order by sum(item_total_cost) desc;
```

Now click on **Chart**. Change the chart type from line to bar, X-Axis to `ITEM_NAME`, and orientation to horizontal. In this chart, you should see "Lettuce - California Mix" as the item on which the most money was spent, $3,214.68.



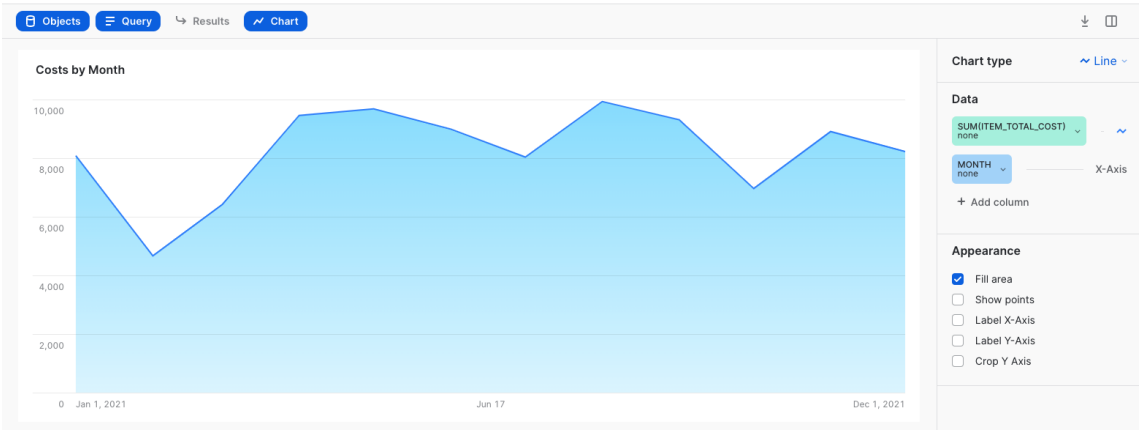
Now let's create another tile by clicking **Return to Invoice Analysis** in the top-left, then click on the **+** button, then **New Tile from Worksheet**. Name the tile `Costs by Month`. Now copy/paste and run this query.

```
select
    sum(item_total_cost)
    , date_trunc('month', invoice_date) as month
from v__parsed_pdf_fields
group by date_trunc('month', invoice_date);
```

Again, click **Chart**. You should see a line chart with `MONTH` on the x-axis and `SUM(ITEM_TOTAL_COST)` on the y-axis. Then click **Return to Invoice Analysis**. You should now see two tiles on your dashboard, which you can rearrange by clicking and dragging.

PDF.PUBLIC

```
select
    sum(item_total_cost)
    , date_trunc('month', invoice_date) as month
from v__parsed_pdf_fields
group by date_trunc('month', invoice_date);
```



Conclusion

Congratulations! You used Snowflake to analyze PDF invoices.

What we've covered

- Accessing unstructured data with an **external stage**
- Processing unstructured data with a **Java UDF**
- Visualize data with **Snowsight**

Getting Started with Time Travel

Overview

Panic hits when you mistakenly delete data. Problems can come from a mistake that disrupts a process, or worse, the whole database was deleted. Thoughts of how recent was the last backup and how much time will be lost might have you wishing for a rewind button. Straightening out your database isn't a disaster to recover from with Snowflake's Time Travel. A few SQL commands allow you to go back in time and reclaim the past, saving you from the time and stress of a more extensive restore.

We'll get started in the Snowflake web console, configure data retention, and use Time Travel to retrieve historic data. Before querying for your previous database states, let's review the prerequisites for this guide.

What You'll Learn

- Snowflake account and user permissions
- Make database objects
- Set data retention timelines for Time Travel
- Query Time Travel data
- Clone past database states
- Remove database objects
- Next options for data protection

What You'll Need

- A Snowflake Account

What You'll Build

- Create database objects with Time Travel data retention

Get Started With the Essentials

First things first, let's get your Snowflake account and user permissions primed to use Time Travel features.

Create a Snowflake Account

Snowflake lets you try out their services for free with a trial account. A **Standard** account allows for one day of Time Travel data retention, and an **Enterprise** account allows for 90 days of data retention. An **Enterprise** account is necessary to practice some commands in this tutorial.

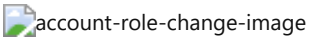
Access Snowflake's Web Console

`https://<account-name>.snowflakecomputing.com/console/login`

Log in to the web interface on your browser. The URL contains your [account name] and potentially the region.

Increase Your Account Permission

Snowflake's web interface has a lot to offer, but for now, switch the account role from the default `SYSADMIN` to `ACCOUNTADMIN`. You'll need this increase in permissions later.


account-role-change-image

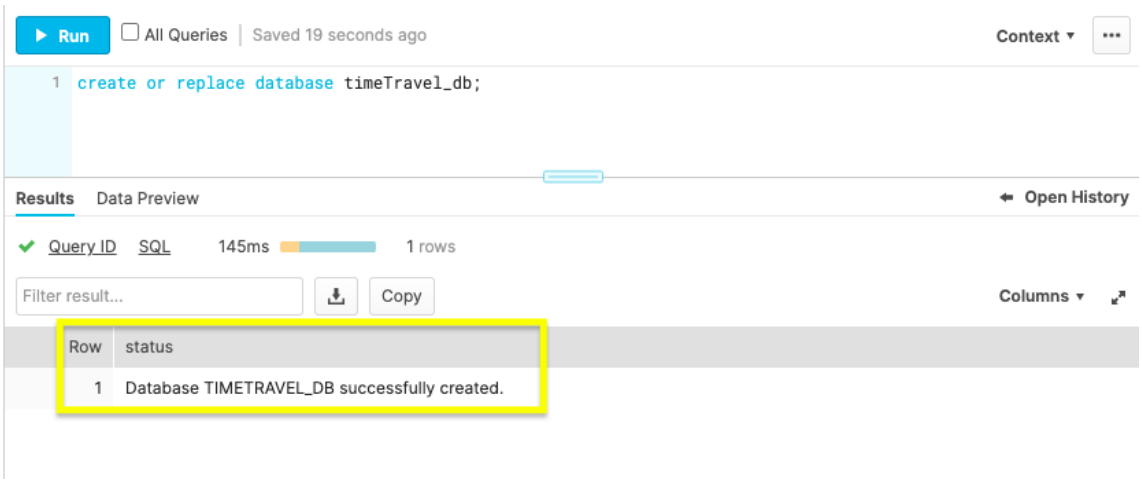
Now that you have the account and user permissions needed, let's create the required database objects to test drive Time Travel.

Generate Database Objects

Within the Snowflake web console, navigate to **Worksheets** and use a fresh worksheet to run the following commands.

Create Database

```
create or replace database timeTravel_db;
```



Use the above command to make a database called 'timeTravel_db'. The **Results** output will show a status message of `Database TIMETRAVEL_DB successfully created`.

Create Table

```
create or replace table timeTravel_table(ID int);
```

This command creates a table named 'timeTravel_table' on the timeTravel_db database. The **Results** output should show a status message of `Table TIMETRAVEL_TABLE successfully created`.

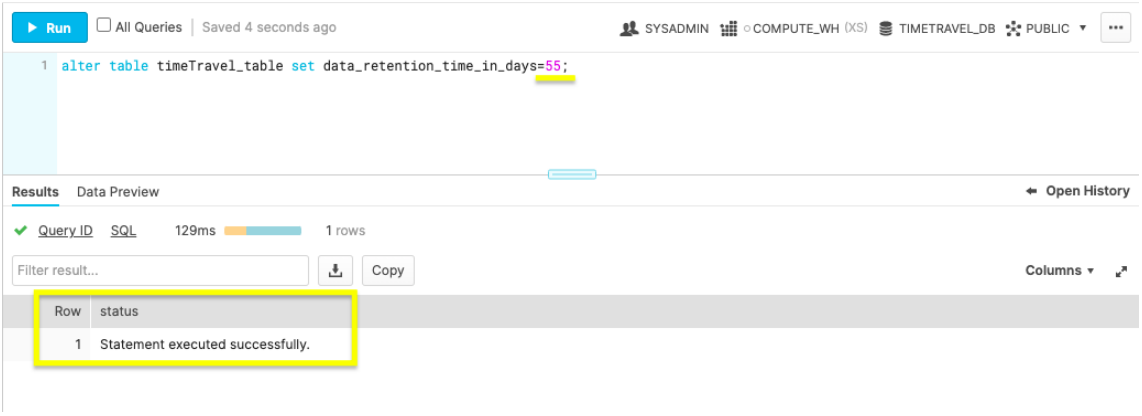
With the Snowflake account and database ready, let's get down to business by configuring Time Travel.

Prepare Your Database for Disaster

Be ready for anything by setting up data retention beforehand. The default setting is one day of data retention. However, if your one day mark passes and you need the previous database state back, you can't retroactively extend the data retention period. This section teaches you how to be prepared by preconfiguring Time Travel retention.

Alter Table

```
alter table timeTravel_table set data_retention_time_in_days=55;
```



The command above changes the table's data retention period to 55 days. If you opted for a **Standard** account, your data retention period is limited to the default of one day. An **Enterprise** account allows for 90 days of preservation in Time Travel.

Now you know how easy it is to [alter] your data retention, let's bend the rules of time by querying an old database state with Time Travel.

Query Your Time Travel Data

With your data retention period specified, let's turn back the clock with the `AT` and `BEFORE` [clauses].

At

```
select * from timeTravel_table at(timestamp => 'Fri, 23 Oct 2020 16:20:00
-0700'::timestamp);
```

Use `timestamp` to summon the database state **at** a specific date and time.

```
select * from timeTravel_table at(offset => -60*5);
```

Employ `offset` to call the database state **at** a time difference of the current time. Calculate the offset in seconds with math expressions. The example above states, `-60*5`, which translates to five minutes ago.

Before

```
select * from timeTravel_table before(statement => '<statement_id>');
```

If you're looking to restore a database state just **before** a transaction occurred, grab the transaction's statement id. Use the command above with your statement id to get the database state right before the transaction statement was executed.

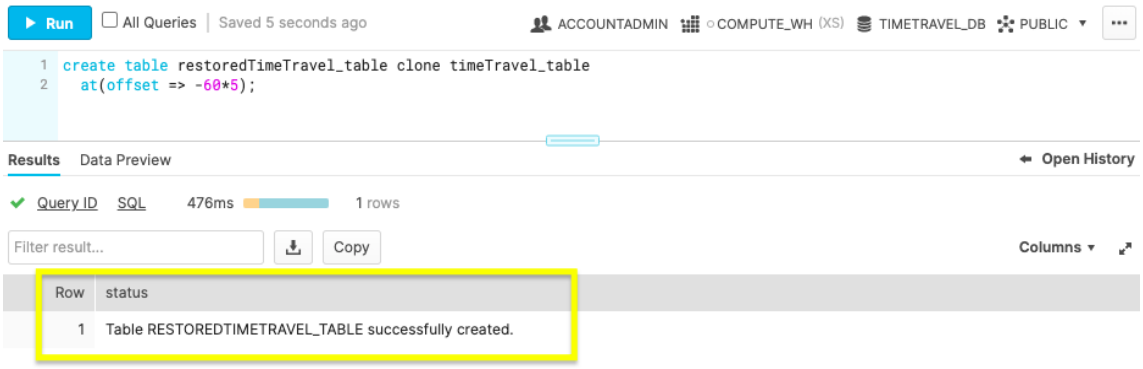
By practicing these queries, you'll be confident in how to find a previous database state. After locating the desired database state, you'll need to get a copy by cloning in the next step.

Clone Past Database States

With the past at your fingertips, make a copy of the old database state you need with the `clone` keyword.

Clone Table

```
create table restoredTimeTravel_table clone timeTravel_table
  at(offset => -60*5);
```



The command above creates a new table named `restoredTimeTravel_table` that is an exact copy of the table `timeTravel_table` from five minutes prior.

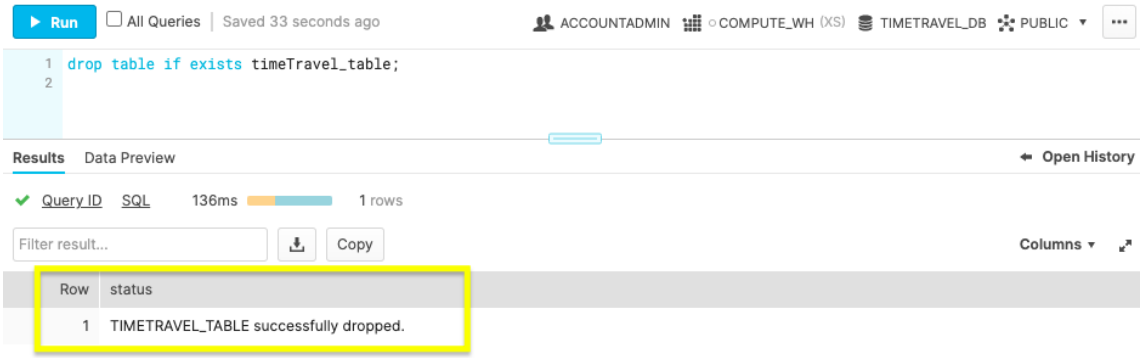
Cloning will allow you to maintain the current database while getting a copy of a past database state. After practicing the steps in this guide, remove the practice database objects in the next section.

Cleanup and Know Your Options

You've created a Snowflake account, made database objects, configured data retention, query old table states, and generate a copy of the old table state. Pat yourself on the back! Complete the steps to this tutorial by deleting the objects created.

Drop Table

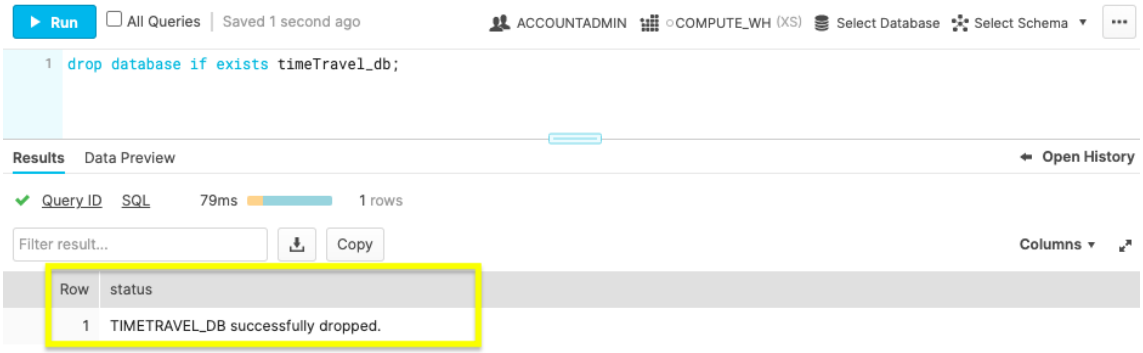
```
drop table if exists timeTravel_table;
```



By dropping the table before the database, the retention period previously specified on the object is honored. If a parent object(e.g., database) is removed without the child object(e.g., table) being dropped prior, the child's data retention period is null.

Drop Database

```
drop database if exists timeTravel_db;
```



With the database now removed, you've completed learning how to call, copy, and erase the past.

Building a Real-Time Data Vault in Snowflake

Overview

In this day and age, with the ever-increasing availability and volume of data from many types of sources such as IoT, mobile devices, and weblogs, there is a growing need, and yes, demand, to go from batch load processes to streaming or "real-time" (RT) loading of data. Businesses are changing at an alarming rate and are becoming more competitive all the time. Those that can harness the value of their data faster to drive better business outcomes will be the ones to prevail.

One of the benefits of using the Data Vault 2.0 architecture is that it was designed from inception not only to accept data loaded using traditional batch mode (which was the prevailing mode in the early 2000s when Dan Linstedt introduced Data Vault) but also to easily accept data loading in real or near-realtime (NRT). In the early 2000s, that was a nice-to-have aspect of the approach and meant the methodology was effectively future-proofed from that perspective. Still, few database systems had the capacity to support that kind of requirement. Today, RT or at least NRT loading is almost becoming a mandatory requirement for modern data platforms. Granted, not all loads or use cases need to be NRT, but most forward-thinking organizations need to onboard data for analytics in an NRT manner.

Those who have been using the Data Vault approach don't need to change much other than figure out how to engineer their data pipeline to serve up data to the Data Vault in NRT. The data models don't need to change; the reporting views don't need to change; even the loading patterns don't need to change. (NB: For those that aren't using Data Vault already, if they have real-time loading requirements, this architecture and method might be worth considering.)

Data Vault on Snowflake

Luckily, streaming data is one of the [use-cases] that Snowflake was built to support, so we have many features to help us achieve this goal.

Prerequisites

- A Snowflake account. Existing or if you are not(yet) a Snowflake user, you can always get a trial account
- Familiarity with Snowflake and Snowflake objects
- Understanding of Data Vault concepts and modelling techniques

What You'll Learn

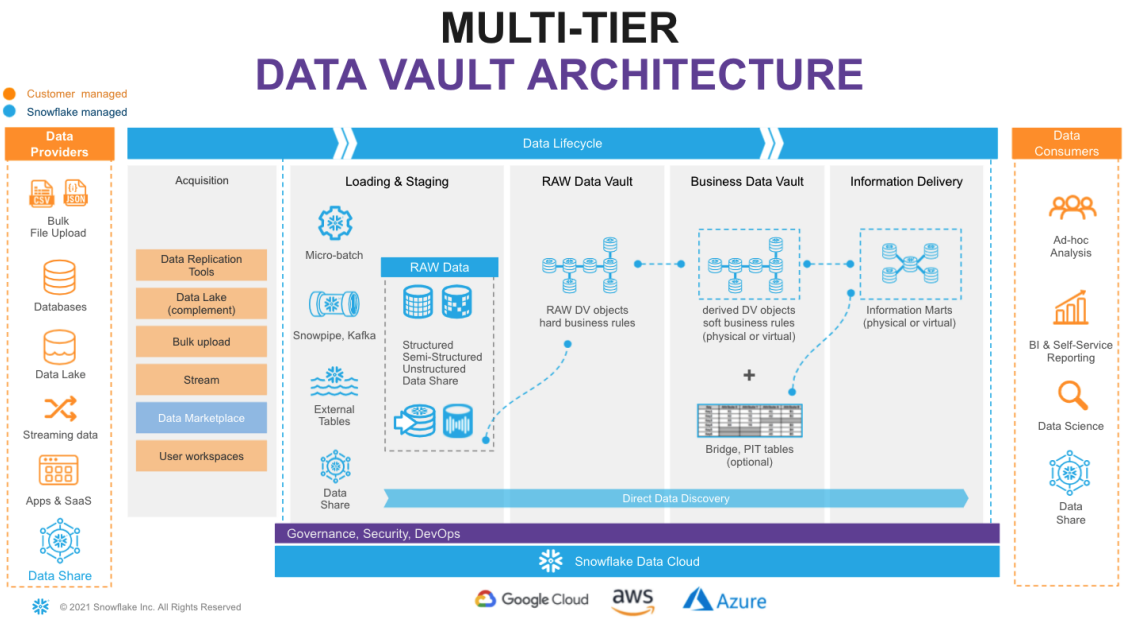
- how to use Data Vault on Snowflake
- how to build basic objects and write ELT code for it
- how to leverage [Snowpipe] and [Continous Data Pipelines] to automate data processing
- how to apply data virtualization to accellerate data access

What You'll Build

- a Data Vault environment on Snowflake, based on sample dataset
- data pipelines, leveraging streams, tasks and Snowpipe

Reference Architecture

Let's start with the overall architecture to put everything in context.



On the very left of figure above we have a list of **data providers** that typically include a mix of existing operational databases, old data warehouses, files, lakes as well as 3rd party apps. There is now also the possibility to leverage Snowflake Data Sharing/Marketplace as a way to tap into new 3rd party data assets to augment your data set.

On the very right we have our ultimate **data consumers**: business users, data scientists, IT systems or even other companies you decided to exchange your data with.

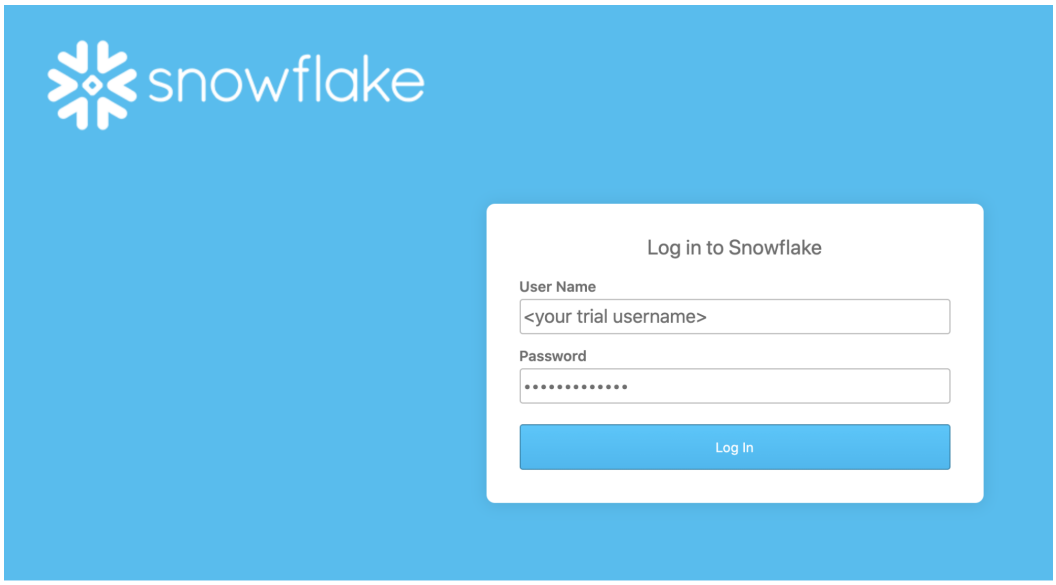
Architecturally, we will split the data lifecycle into following layers:

- **Data Acquisition:** extracting data from source systems and making it accessible for Snowflake.
- **Loading & Staging:** moving the source data into Snowflake. For this Snowflake has multiple options, including batch load, external tables and Snowpipe(our managed service for onboarding streaming data). Snowflake allows you to load and store structured and semi-structured in the original format whilst automatically optimizing the physical structure for efficient query access. The data is immutable and should be stored as it was received from source with no changes to the content. From a Data Vault perspective, functionally, this layer is also responsible for adding technical metadata (record source,, load date timestamp, etc.) as well as calculating business keys.
- **Raw Data Vault:** a data vault model with no soft business rules or transformations applied (only hard rules are allowed) loading all records received from source.
- **Business Data Vault:** data vault objects with soft business rules applied. The raw data vault data is getting augmented by the intelligence of the system. It is not a copy of the raw data vault, but rather a sparse addition with perhaps calculated satellites, mastered records,or maybe even commonly used aggregations. This could also optionally include PIT and Bridge tables helping to simplify access to bi-temporal view of the data. From a Snowflake perspective, raw and business data vaults could be separated by object naming convention or represented as different schemas or even different databases.
- **Information Delivery:** a layer of consumer-oriented models. This could be implemented as a set (or multiple sets) of views. It is common to see the use of dimensional models (star/snowflake) or denormalized flat tables (for example for data science or sharing) but it could be any other modeling stye (e.g., unified star

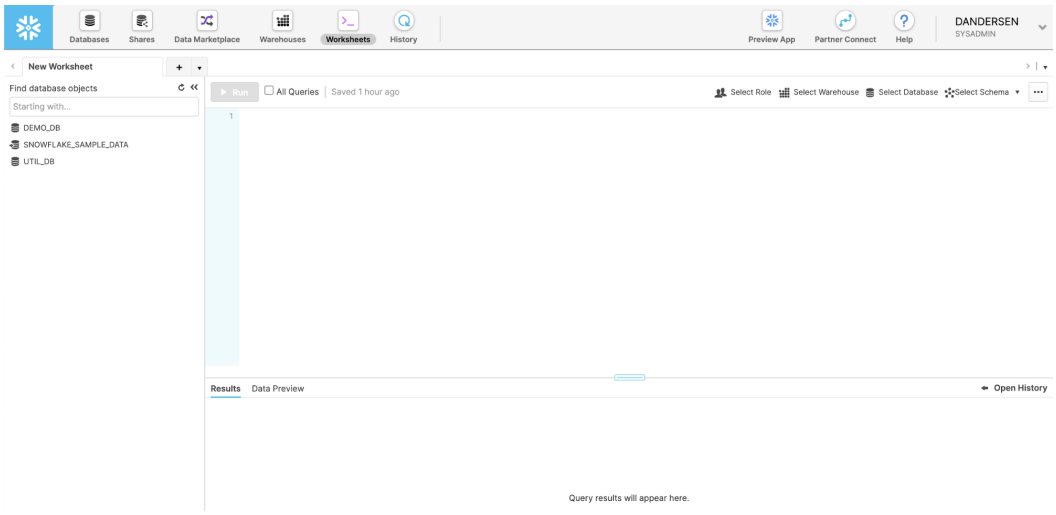
schema, supernova, key-value, document object mode, etc.) that fits best for your data consumer. Snowflake's scalability will support the required speed of access at any point of this data lifecycle. You should consider Business Vault and Information Delivery objects materialization as optional.

Environment setup

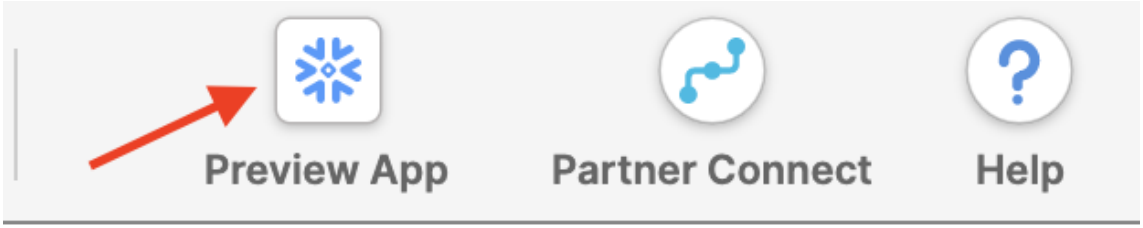
1. Login to your Snowflake trial account.



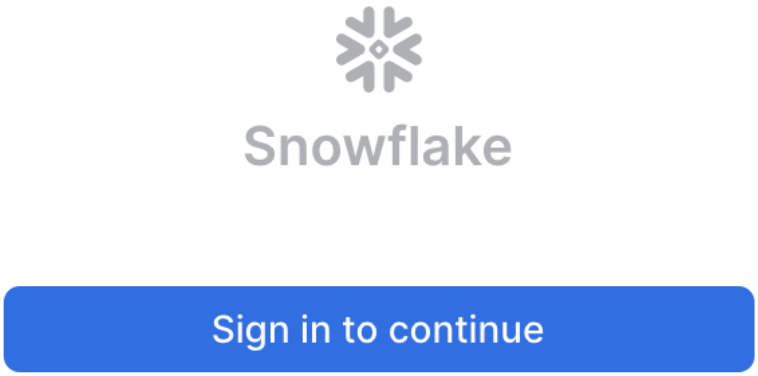
2. First page you are going to see would likely be [Snowflake Classic UI]:



To keep things interesting, for the purpose of this lab let's use [Snowflake New Web Interface] also known as Snowsight. However, you absolutely can continue using Classic UI as all steps in this guide are expressed in SQL and will work regardless what interface is used. To switch into Snowsight, let's click the **Preview** button in the top-right corner:

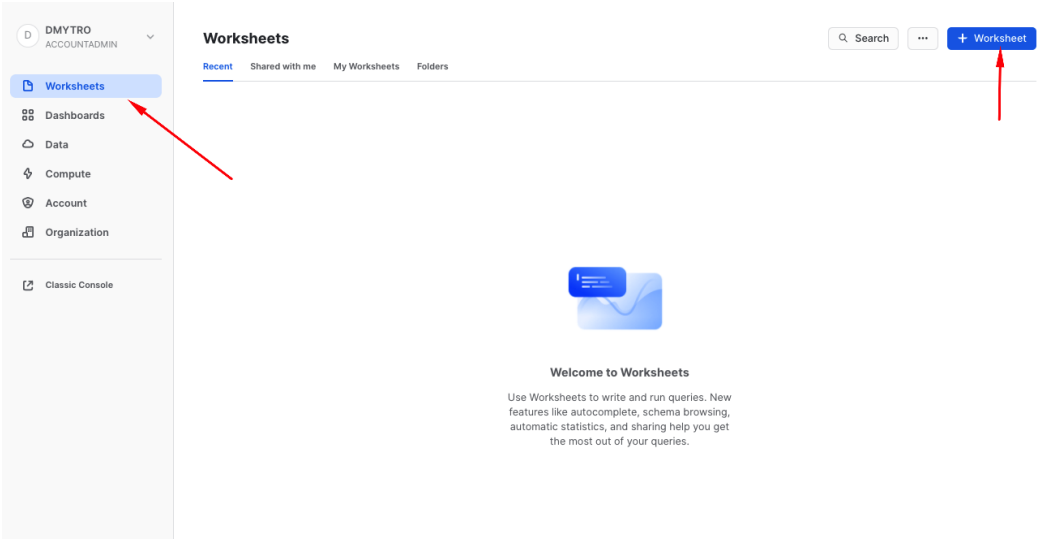


Click Sign in to continue. You will need to use the same user and password that you used to login to your Snowflake account the first time.

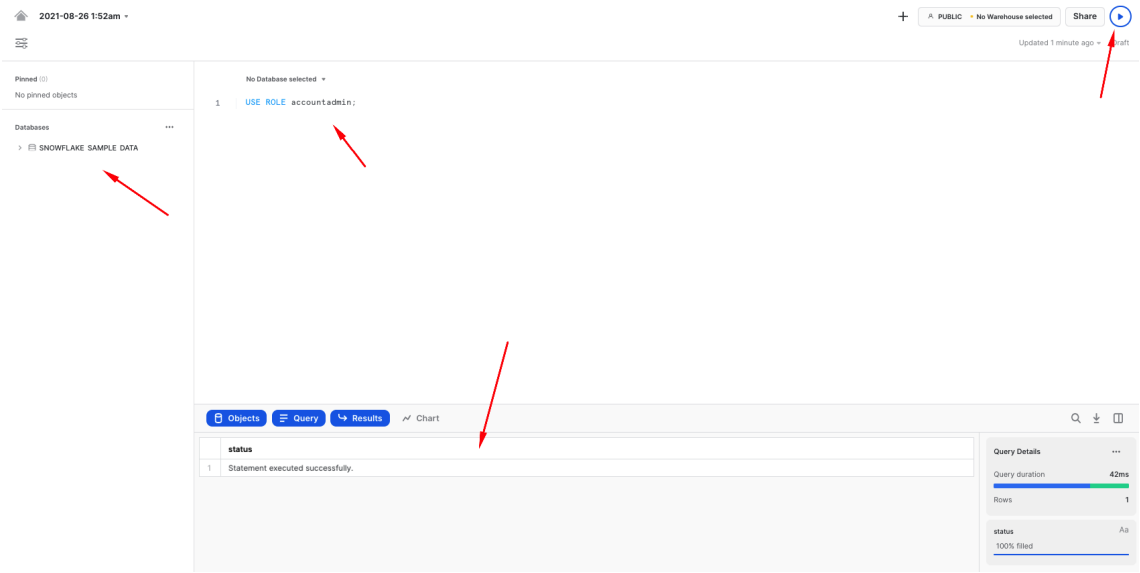


You're now in the new UI - Snowsight. It's pretty cool - with charting, dashboards, autocompletion and new capabilities that our engineering team will continue to add on weekly. Now, let's click on Worksheets...

3. Let's click on the worksheets -> **+ Worksheet**



And without going into too much details, this is a fairly intuitive SQL workbench. It has a section for code we are going to be copy-pasting, object tree on the left, the 'run' button and of course the result panel at the bottom with the simple charting functionality.

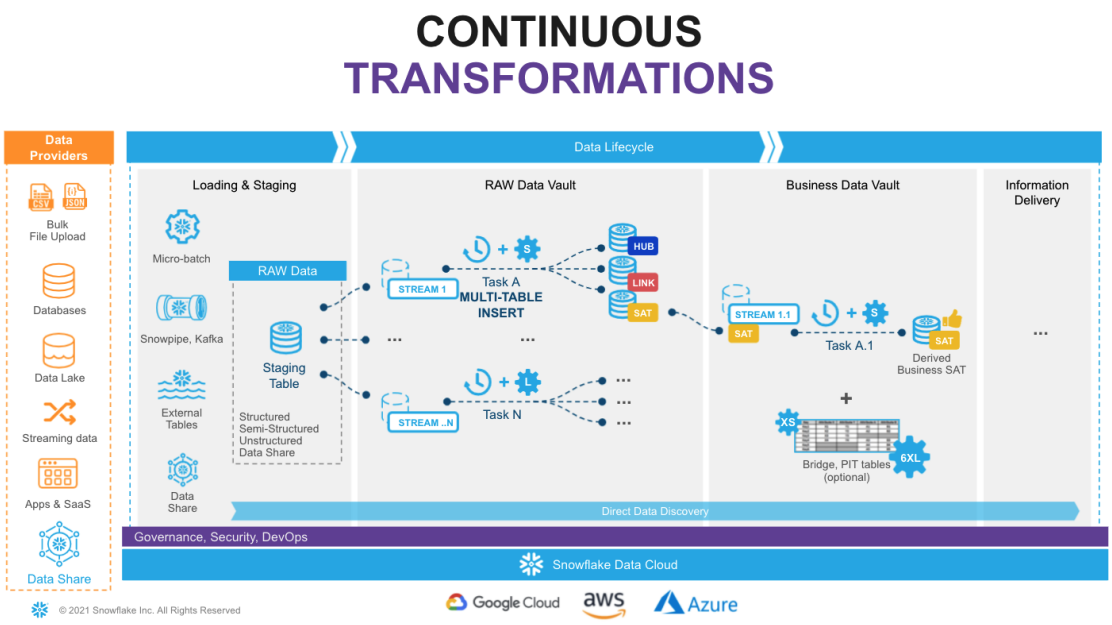


4. We are going to start by setting up basics for the lab environment. Creating a clean database and logically dividing it into four different schemas, representing each functional area mentioned in the reference architecture.

To keep things simple, we are going to use the ACCOUNTADMIN role. We also going to create two [Snowflake virtual warehouses] to manage compute - one for generic use during the course of this lab and the other one (dv_rdv_wh) that is going to be used by our data pipelines. You might notice that the code for two more virtual warehouses (dv_bdv_wh, dv_id_wh) is commented - again, this is just to keep things simple for the guide but we wanted to illustrate the fact you can have as many of virtual warehouses of any size and configuration as you needed. For example having separate ones to deal with different layers in our Data Vault architecture.

```
-----------------------------------------------------------------------
-- setting up the environment
-----------------------------------------------------------------------

USE ROLE accountadmin;

CREATE OR REPLACE DATABASE dv_lab;

USE DATABASE dv_lab;

CREATE OR REPLACE WAREHOUSE dv_lab_wh WITH WAREHOUSE_SIZE = 'XSMALL' MIN_CLUSTER_COUNT
= 1 MAX_CLUSTER_COUNT = 1 AUTO_SUSPEND = 60 COMMENT = 'Generic WH';
CREATE OR REPLACE WAREHOUSE dv_rdv_wh WITH WAREHOUSE_SIZE = 'XSMALL' MIN_CLUSTER_COUNT
= 1 MAX_CLUSTER_COUNT = 1 AUTO_SUSPEND = 60 COMMENT = 'WH for Raw Data Vault object
pipelines';
--CREATE OR REPLACE WAREHOUSE dv_bdv_wh WITH WAREHOUSE_SIZE = 'XSMALL'
MIN_CLUSTER_COUNT = 1 MAX_CLUSTER_COUNT = 1 AUTO_SUSPEND = 60 COMMENT = 'WH for
Business Data Vault object pipelines';
--CREATE OR REPLACE WAREHOUSE dv_id_wh  WITH WAREHOUSE_SIZE = 'XSMALL'
MIN_CLUSTER_COUNT = 1 MAX_CLUSTER_COUNT = 1 AUTO_SUSPEND = 60 COMMENT = 'WH for
information delivery object pipelines';

USE WAREHOUSE dv_lab_wh;

CREATE OR REPLACE SCHEMA l00_stg COMMENT = 'Schema for Staging Area objects';
CREATE OR REPLACE SCHEMA l10_rdv COMMENT = 'Schema for Raw Data Vault objects';
CREATE OR REPLACE SCHEMA l20_bdv COMMENT = 'Schema for Business Data Vault objects';
CREATE OR REPLACE SCHEMA l30_id  COMMENT = 'Schema for Information Delivery objects';
```

Data Pipelines: Design



Snowflake supports multiple options for engineering data pipelines. In this post we are going to show one of the most efficient ways to implement incremental NRT integration leveraging Snowflake [Continuous Data Pipelines]. Let's take a look at the architecture diagram above to understand how it works.

Snowflake has a special [stream] object that tracks all data changes on a table (inserts, updates, and deletes). This process is 100% automatic and unlike traditional databases will never impact the speed of data loading. The change log from a stream is automatically 'consumed' once there is a successfully completed DML operation using the stream object as a source.

So, loading new data into a staging table, would immediately be reflected in a stream showing the ['delta'] that requires processing.

The second component we are going to use is [tasks]. It is a Snowflake managed data processing unit that will wake up on a defined interval (e.g., every 1-2 min), check if there is any data in the associated stream and if so, will run SQL to push it to the Raw Data Vault objects. Tasks could be arranged in a [tree-like dependency graph], executing child tasks the moment the predecessor finished its part.

Last but not least, following Data Vault 2.0 best practices for NRT data integration (to load data in parallel) we are going to use Snowflake's [multi-table insert (MTI)] inside tasks to populate multiple Raw Data Vault objects by a single DML command. (Alternatively you can create multiple streams & tasks from the same table in stage in order to populate each data vault object by its own asynchronous flow.)

Next step, you assign tasks to one or many virtual warehouses. This means you always have enough [compute power] (XS to 6XL) to deal with any size workload, whilst the [multi-cluster virtual warehouse] option will automatically scale-out and load balance all the tasks as you introduce more hubs, links and satellites to your vault.

Talking about tasks, Snowflake just introduced another fantastic capability - serverless tasks. This enables you to rely on compute resources managed by Snowflake instead of user-managed virtual warehouses. These compute resources are automatically resized and scaled up and down by Snowflake as required by each workload. This feature will be out of scope for this guide, but serverless compute model could reduce compute costs, in some cases significantly, allowing you to process more data, faster with even less management.

As your raw vault is updated, streams can then be used to propagate those changes to Business Vault objects (such as derived Sats, PITS, or Bridges, if needed) in the next layer. This setup can be repeated to move data through all the layers in small increments very quickly and efficiently. All the way until it is ready to be accessed by data consumers (if materialization of the data is required for performance).

Following this approach will result in a hands-off production data pipeline that feeds your Data Vault architecture.

Sample data & staging area

Every Snowflake account provides access to [sample data sets]. You can find corresponding schemas in SNOWFLAKE_SAMPLE_DATA database in your object explorer. For this guide we are going to use a subset of objects from [TPC-H] set, representing **customers** and their **orders**. We also going to take some reference data about **nations** and **regions**.

Dataset	Description	Source	Load Scenario	Mechanism
Nation	Static ref data	snowflake.sample_data.tpch_sf10.nation	one-off CTAS	SQL
Region	Static ref data	snowflake.sample_data.tpch_sf10.region	one-off CTAS	SQL
Customer	Customer data	snowflake.sample_data.tpch_sf10.customer	incremental JSON files	Snowpipe

Orders	Orders data	snowflake.sample_data.tpch_sf10.orders	incremental CSV files	Snowpipe

1. Let's start with the static reference data:

```
-----------------------------------------------------------------------
-- setting up staging area
-----------------------------------------------------------------------

USE SCHEMA l00_stg;

CREATE OR REPLACE TABLE stg_nation
AS
SELECT src.*
     , CURRENT_TIMESTAMP()          ldts
     , 'Static Reference Data'      rscr
  FROM snowflake_sample_data.tpch_sf10.nation src;

CREATE OR REPLACE TABLE stg_region
AS
SELECT src.*
     , CURRENT_TIMESTAMP()          ldts
     , 'Static Reference Data'      rscr
  FROM snowflake_sample_data.tpch_sf10.region src;
```

2. Next, let's create staging tables for our data loading. This syntax should be very familiar with anyone working with databases before. It is ANSI SQL compliant DDL, with probably one key exception - for stg_customer we are going to load the full payload of JSON into raw_json column. For this, Snowflake has a special data type [VARIANT].

As we load data we also going to add some technical metadata, like load data timestamp, row number in a file.

```
CREATE OR REPLACE TABLE stg_customer
(
  raw_json                VARIANT
, filename                STRING   NOT NULL
, file_row_seq            NUMBER   NOT NULL
, ldts                    STRING   NOT NULL
, rscr                    STRING   NOT NULL
);

CREATE OR REPLACE TABLE stg_orders
(
  o_orderkey              NUMBER
, o_custkey               NUMBER
, o_orderstatus           STRING
, o_totalprice            NUMBER
, o_orderdate             DATE
, o_orderpriority         STRING
, o_clerk                 STRING
, o_shippriority          NUMBER
, o_comment               STRING
, filename                STRING   NOT NULL
```

```
, file_row_seq            NUMBER    NOT NULL
, ldts                    STRING    NOT NULL
, rscr                    STRING    NOT NULL
);
```

3. Tables we just created are going to be used by Snowpipe to drip-feed the data as it is lands in the stage. In order to easily detect and incrementally process the new portion of data we are going to create [streams] on these staging tables:

```
CREATE OR REPLACE STREAM stg_customer_strm ON TABLE stg_customer;
CREATE OR REPLACE STREAM stg_orders_strm ON TABLE stg_orders;
```

4. Next we are going to produce some sample data. And for the sake of simplicity we are going to take a bit of a shortcut here. We are going to generate data by unloading subset of data from our TPCH sample dataset into files and then use Snowpipe to load it back into our Data Vault lab, simulating the streaming feed. Let's start by creating two stages for each data class type (orders, customers data). In real-life scenarios these could be internal or external stages as well as these feeds could be sourced via Kafka connector. The world is your oyster.

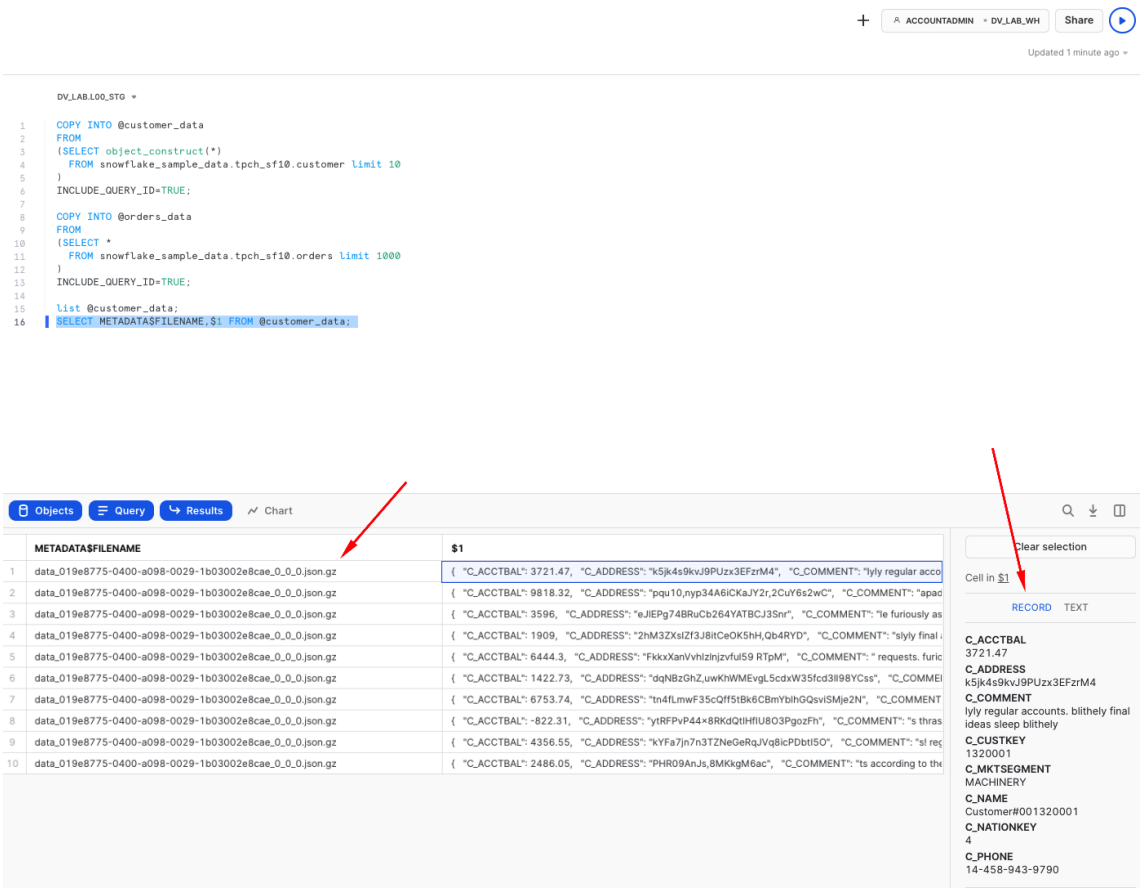
```
CREATE OR REPLACE STAGE customer_data FILE_FORMAT = (TYPE = JSON);
CREATE OR REPLACE STAGE orders_data   FILE_FORMAT = (TYPE = CSV) ;
```

5. Generate and unload sample data. There are couple of things going on. First, we are using [object_construct] as a quick way to create a object/document from all columns and subset of rows for customer data and offload it into customer_data stage. Orders data would be extracted into compressed CSV files. There are many additonal options in [COPY INTO stage] construct that would fit most requirements, but in this case we are using INCLUDE_QUERY_ID to make it easier to generate new incremental files as we are going to run these commands over and over again, without a need to deal with file overriding.

```
COPY INTO @customer_data
FROM
(SELECT object_construct(*)
  FROM snowflake_sample_data.tpch_sf10.customer limit 10
)
INCLUDE_QUERY_ID=TRUE;

COPY INTO @orders_data
FROM
(SELECT *
  FROM snowflake_sample_data.tpch_sf10.orders limit 1000
)
INCLUDE_QUERY_ID=TRUE;
```

You can now run the following to validate that the data is now stored in files:

```
list @customer_data;
SELECT METADATA$FILENAME,$1 FROM @customer_data;
```



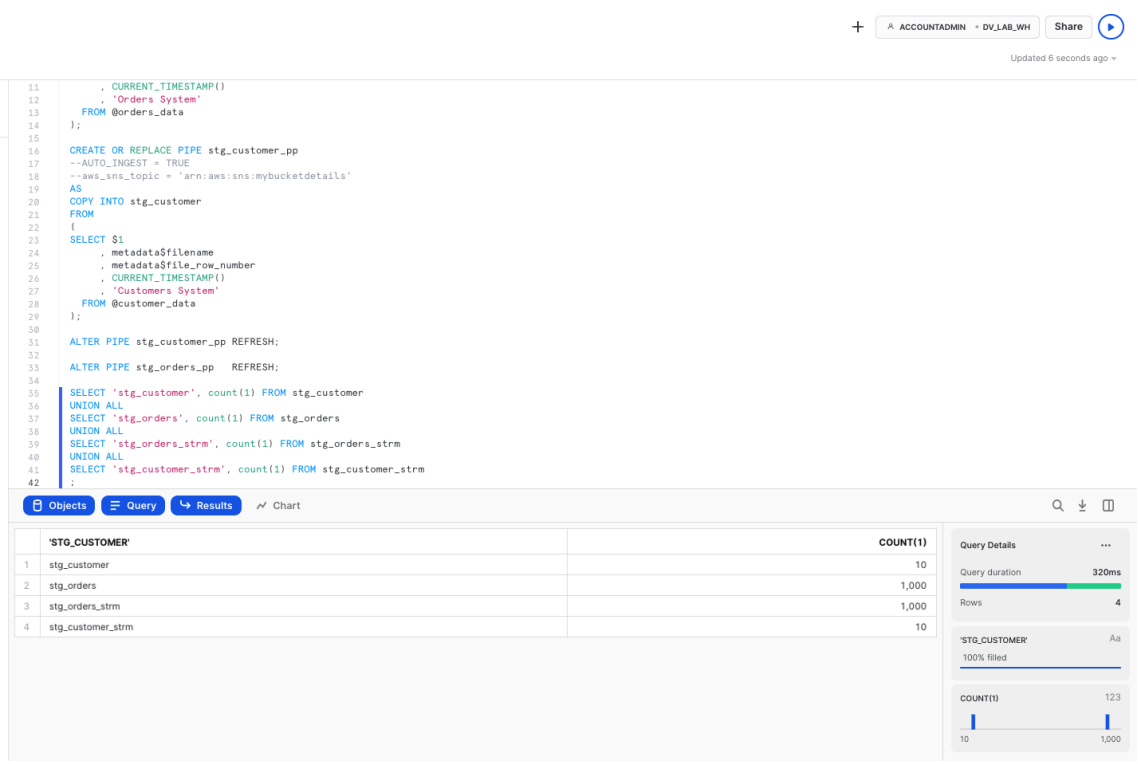
6. Next, we are going to setup Snowpipe to load data from files in a stage into staging tables. In this guide, for better transparency we are going to trigger Snowpipe explicitly to scan for new files, but in real projects you will likely going to enable AUTO_INGEST, connecting it with your cloud storage events (like AWS SNS) and process new files automatically.

```
CREATE OR REPLACE PIPE stg_orders_pp
AS
COPY INTO stg_orders
FROM
(
SELECT $1,$2,$3,$4,$5,$6,$7,$8,$9
      , metadata$filename
      , metadata$file_row_number
      , CURRENT_TIMESTAMP()
      , 'Orders System'
  FROM @orders_data
);

CREATE OR REPLACE PIPE stg_customer_pp
--AUTO_INGEST = TRUE
--aws_sns_topic = 'arn:aws:sns:mybucketdetails'
AS
COPY INTO stg_customer
FROM
```

```
(
SELECT $1
      , metadata$filename
      , metadata$file_row_number
      , CURRENT_TIMESTAMP()
      , 'Customers System'
  FROM @customer_data
);

ALTER PIPE stg_customer_pp REFRESH;

ALTER PIPE stg_orders_pp   REFRESH;
```

Once this done, you should be able to see data appearling in the target tables and the stream on these tables. As you would notice, number of rows in a stream is exactly the same as in the base table. This is because we didn't process/consumed the delta of that stream yet. Stay tuned!

```
SELECT 'stg_customer', count(1) FROM stg_customer
UNION ALL
SELECT 'stg_orders', count(1) FROM stg_orders
UNION ALL
SELECT 'stg_orders_strm', count(1) FROM stg_orders_strm
UNION ALL
SELECT 'stg_customer_strm', count(1) FROM stg_customer_strm
;
```



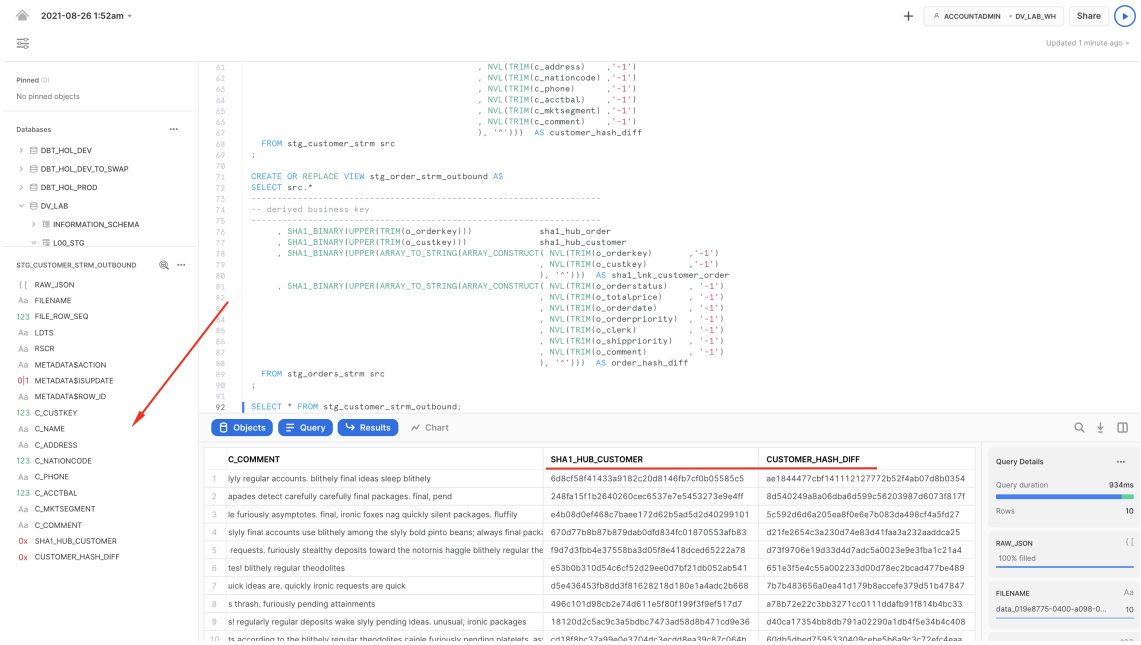
7. Finally, now that we established the basics and new data is knocking at our door (stream), let's see how we can derive some of the business keys for the Data Vault entites we are going to model. In this example, we

will model it as a view on top of the stream that should allow us to perform data parsing (raw_json -> columns) and business_key, hash_diff derivation on the fly. Another thing to notice here is the use of SHA1_BINARY as hasing function. For this lab, we are going to use fairly common SHA1 and its BINARY version from Snowflake arsenal of functions that use less bytes to encode value than STRING.

```
CREATE OR REPLACE VIEW stg_customer_strm_outbound AS
SELECT src.*
     , raw_json:C_CUSTKEY::NUMBER           c_custkey
     , raw_json:C_NAME::STRING              c_name
     , raw_json:C_ADDRESS::STRING           c_address
     , raw_json:C_NATIONKEY::NUMBER         C_nationcode
     , raw_json:C_PHONE::STRING             c_phone
     , raw_json:C_ACCTBAL::NUMBER           c_acctbal
     , raw_json:C_MKTSEGMENT::STRING        c_mktsegment
     , raw_json:C_COMMENT::STRING           c_comment
-----------------------------------------------------------------------
-- derived business key
-----------------------------------------------------------------------
     , SHA1_BINARY(UPPER(TRIM(c_custkey)))  sha1_hub_customer
     , SHA1_BINARY(UPPER(ARRAY_TO_STRING(ARRAY_CONSTRUCT(
                                            NVL(TRIM(c_name)       ,'-1')
                                          , NVL(TRIM(c_address)    ,'-1')
                                          , NVL(TRIM(c_nationcode) ,'-1')
                                          , NVL(TRIM(c_phone)      ,'-1')
                                          , NVL(TRIM(c_acctbal)    ,'-1')
                                          , NVL(TRIM(c_mktsegment) ,'-1')
                                          , NVL(TRIM(c_comment)    ,'-1')
                                          ), '^')))  AS customer_hash_diff
  FROM stg_customer_strm src
;

CREATE OR REPLACE VIEW stg_order_strm_outbound AS
SELECT src.*
-----------------------------------------------------------------------
-- derived business key
-----------------------------------------------------------------------
     , SHA1_BINARY(UPPER(TRIM(o_orderkey)))             sha1_hub_order
     , SHA1_BINARY(UPPER(TRIM(o_custkey)))              sha1_hub_customer
     , SHA1_BINARY(UPPER(ARRAY_TO_STRING(ARRAY_CONSTRUCT( NVL(TRIM(o_orderkey)
,'-1')
                                                        , NVL(TRIM(o_custkey)
,'-1')
                                                        ), '^')))  AS
sha1_lnk_customer_order
     , SHA1_BINARY(UPPER(ARRAY_TO_STRING(ARRAY_CONSTRUCT( NVL(TRIM(o_orderstatus)    ,
'-1')
                                                        , NVL(TRIM(o_totalprice)     ,
'-1')
                                                        , NVL(TRIM(o_orderdate)      ,
'-1')
                                                        , NVL(TRIM(o_orderpriority)  ,
'-1')
```

```
                                                    , NVL(TRIM(o_clerk)          ,
'-1')
                                                    , NVL(TRIM(o_shippriority)   ,
'-1')
                                                    , NVL(TRIM(o_comment)        ,
'-1')
                                                    ), '^')))  AS order_hash_diff
  FROM stg_orders_strm src
;
```

Finally let's query these views to validate the results:

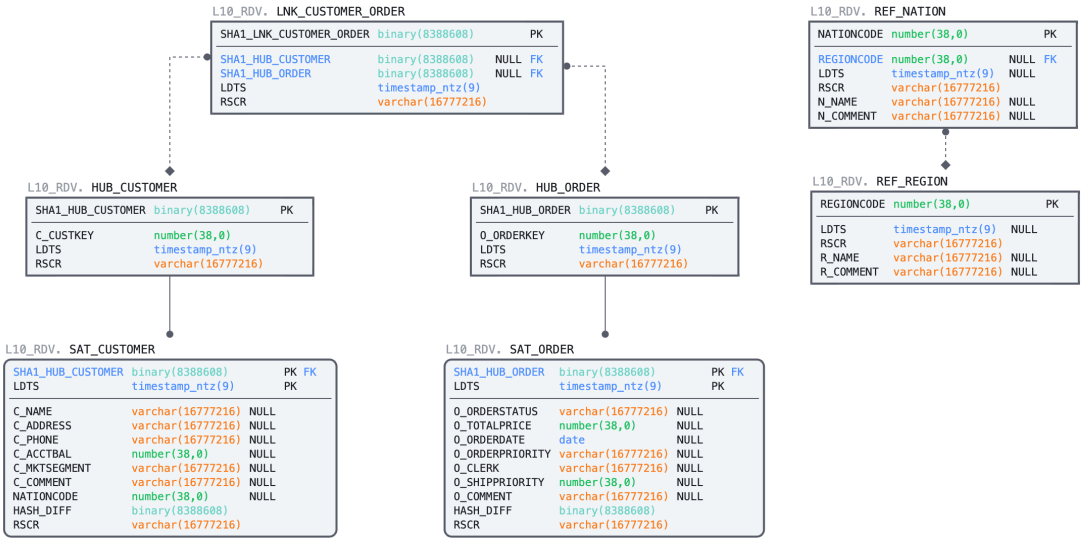


Well done! We build our staging/inbound pipeline, ready to accomodate streaming data and derived business keys that we are going to use in our Raw Data Vault. Let's move on to the next step!

Build: Raw Data Vault

In this section, we will start building structures and pipelines for **Raw Data Vault** area.

Here is the ER model of the objects we are going to deploy using the script below:



1. We'll start by deploying DDL for the HUBs, LINKs and SATellite tables. As you can imagine, this guide has no chance to go in the detail on data vault modelling process. This is something we usually highly recommend to establish by working with experts & partners from Data Vault Alliance.

```
-----------------------------------------------------------------------
-- setting up RDV
-----------------------------------------------------------------------

USE SCHEMA l10_rdv;

-- hubs

CREATE OR REPLACE TABLE hub_customer
(
  sha1_hub_customer       BINARY    NOT NULL
, c_custkey               NUMBER    NOT NULL
, ldts                    TIMESTAMP NOT NULL
, rscr                    STRING    NOT NULL
, CONSTRAINT pk_hub_customer        PRIMARY KEY(sha1_hub_customer)
);

CREATE OR REPLACE TABLE hub_order
(
  sha1_hub_order          BINARY    NOT NULL
, o_orderkey              NUMBER    NOT NULL
, ldts                    TIMESTAMP NOT NULL
, rscr                    STRING    NOT NULL
, CONSTRAINT pk_hub_order           PRIMARY KEY(sha1_hub_order)
```

```
);

-- sats

CREATE OR REPLACE TABLE sat_customer
(
  sha1_hub_customer      BINARY    NOT NULL
, ldts                   TIMESTAMP NOT NULL
, c_name                 STRING
, c_address              STRING
, c_phone                STRING
, c_acctbal              NUMBER
, c_mktsegment           STRING
, c_comment              STRING
, nationcode             NUMBER
, hash_diff              BINARY    NOT NULL
, rscr                   STRING    NOT NULL
, CONSTRAINT pk_sat_customer       PRIMARY KEY(sha1_hub_customer, ldts)
, CONSTRAINT fk_sat_customer       FOREIGN KEY(sha1_hub_customer) REFERENCES
hub_customer
);

CREATE OR REPLACE TABLE sat_order
(
  sha1_hub_order         BINARY    NOT NULL
, ldts                   TIMESTAMP NOT NULL
, o_orderstatus          STRING
, o_totalprice           NUMBER
, o_orderdate            DATE
, o_orderpriority        STRING
, o_clerk                STRING
, o_shippriority         NUMBER
, o_comment              STRING
, hash_diff              BINARY    NOT NULL
, rscr                   STRING    NOT NULL
, CONSTRAINT pk_sat_order PRIMARY KEY(sha1_hub_order, ldts)
, CONSTRAINT fk_sat_order FOREIGN KEY(sha1_hub_order) REFERENCES hub_order
);

-- links

CREATE OR REPLACE TABLE lnk_customer_order
(
  sha1_lnk_customer_order BINARY     NOT NULL
, sha1_hub_customer       BINARY
, sha1_hub_order          BINARY
, ldts                    TIMESTAMP  NOT NULL
, rscr                    STRING     NOT NULL
, CONSTRAINT pk_lnk_customer_order  PRIMARY KEY(sha1_lnk_customer_order)
, CONSTRAINT fk1_lnk_customer_order FOREIGN KEY(sha1_hub_customer) REFERENCES
hub_customer
, CONSTRAINT fk2_lnk_customer_order FOREIGN KEY(sha1_hub_order)    REFERENCES
```

```
hub_order
);

-- ref data

CREATE OR REPLACE TABLE ref_region
(
  regioncode            NUMBER
, ldts                  TIMESTAMP
, rscr                  STRING NOT NULL
, r_name                STRING
, r_comment             STRING
, CONSTRAINT PK_REF_REGION PRIMARY KEY (REGIONCODE)
)
AS
SELECT r_regionkey
     , ldts
     , rscr
     , r_name
     , r_comment
  FROM l00_stg.stg_region;

CREATE OR REPLACE TABLE ref_nation
(
  nationcode            NUMBER
, regioncode            NUMBER
, ldts                  TIMESTAMP
, rscr                  STRING NOT NULL
, n_name                STRING
, n_comment             STRING
, CONSTRAINT pk_ref_nation PRIMARY KEY (nationcode)
, CONSTRAINT fk_ref_region FOREIGN KEY (regioncode) REFERENCES ref_region(regioncode)
)
AS
SELECT n_nationkey
     , n_regionkey
     , ldts
     , rscr
     , n_name
     , n_comment
  FROM l00_stg.stg_nation;
```

2. Now we have source data waiting in our staging streams & views, we have target RDV tables. Let's connect the dots. We are going to create tasks, one per each stream so whenever there is new records coming in a stream, that delta will be incrementally propagated to all dependent RDV models in one go. To achieve that, we are going to use multi-table insert functionality as described in design section before. As you can see, tasks can be set up to run on a pre-defined frequency (every 1 minute in our example) and use dedicated virtual warehouse as a compute power (in our guide we are going to use same warehouse for all tasks, thou this could be as granular as needed). Also, before waking up a compute resource, tasks are going to check that there is data in a corresponding stream to process. Again, you are paying only for the compute when you actually use it.

```
CREATE OR REPLACE TASK customer_strm_tsk
  WAREHOUSE = dv_rdv_wh
  SCHEDULE = '1 minute'
WHEN
  SYSTEM$STREAM_HAS_DATA('L00_STG.STG_CUSTOMER_STRM')
AS
INSERT ALL
WHEN (SELECT COUNT(1) FROM hub_customer tgt WHERE tgt.sha1_hub_customer =
src_sha1_hub_customer) = 0
THEN INTO hub_customer
( sha1_hub_customer
, c_custkey
, ldts
, rscr
)
VALUES
( src_sha1_hub_customer
, src_c_custkey
, src_ldts
, src_rscr
)
WHEN (SELECT COUNT(1) FROM sat_customer tgt WHERE tgt.sha1_hub_customer =
src_sha1_hub_customer AND tgt.hash_diff = src_customer_hash_diff) = 0
THEN INTO sat_customer
(
  sha1_hub_customer
, ldts
, c_name
, c_address
, c_phone
, c_acctbal
, c_mktsegment
, c_comment
, nationcode
, hash_diff
, rscr
)
VALUES
(
  src_sha1_hub_customer
, src_ldts
, src_c_name
, src_c_address
, src_c_phone
, src_c_acctbal
, src_c_mktsegment
, src_c_comment
, src_nationcode
, src_customer_hash_diff
, src_rscr
)
SELECT sha1_hub_customer   src_sha1_hub_customer
```

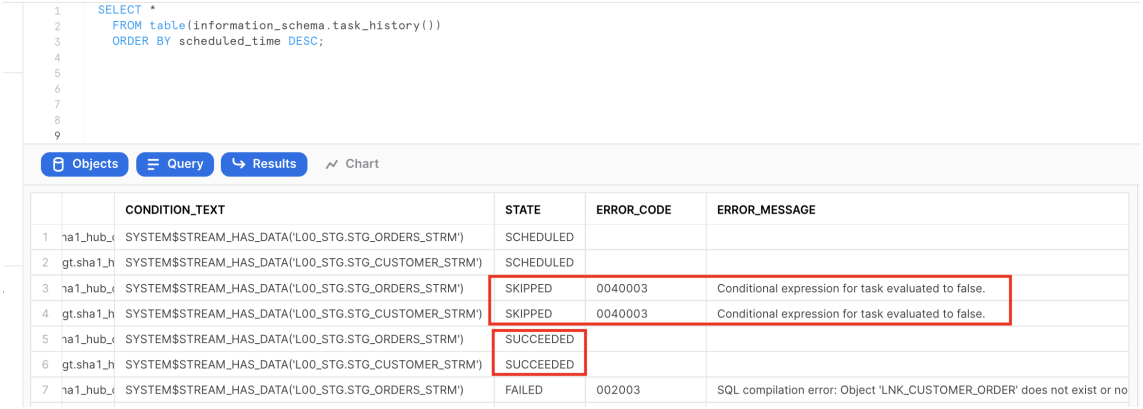
```
     , c_custkey           src_c_custkey
     , c_name              src_c_name
     , c_address           src_c_address
     , c_nationcode        src_nationcode
     , c_phone             src_c_phone
     , c_acctbal           src_c_acctbal
     , c_mktsegment        src_c_mktsegment
     , c_comment           src_c_comment
     , customer_hash_diff  src_customer_hash_diff
     , ldts                src_ldts
     , rscr                src_rscr
  FROM l00_stg.stg_customer_strm_outbound src
;


CREATE OR REPLACE TASK order_strm_tsk
  WAREHOUSE = dv_rdv_wh
  SCHEDULE = '1 minute'
WHEN
  SYSTEM$STREAM_HAS_DATA('L00_STG.STG_ORDERS_STRM')
AS
INSERT ALL
WHEN (SELECT COUNT(1) FROM hub_order tgt WHERE tgt.sha1_hub_order =
src_sha1_hub_order) = 0
THEN INTO hub_order
( sha1_hub_order
, o_orderkey
, ldts
, rscr
)
VALUES
( src_sha1_hub_order
, src_o_orderkey
, src_ldts
, src_rscr
)
WHEN (SELECT COUNT(1) FROM sat_order tgt WHERE tgt.sha1_hub_order = src_sha1_hub_order
AND tgt.hash_diff = src_order_hash_diff) = 0
THEN INTO sat_order
(
  sha1_hub_order
, ldts
, o_orderstatus
, o_totalprice
, o_orderdate
, o_orderpriority
, o_clerk
, o_shippriority
, o_comment
, hash_diff
, rscr
)
```

```
VALUES
(
  src_sha1_hub_order
, src_ldts
, src_o_orderstatus
, src_o_totalprice
, src_o_orderdate
, src_o_orderpriority
, src_o_clerk
, src_o_shippriority
, src_o_comment
, src_order_hash_diff
, src_rscr
)
WHEN (SELECT COUNT(1) FROM lnk_customer_order tgt WHERE tgt.sha1_lnk_customer_order =
src_sha1_lnk_customer_order) = 0
THEN INTO lnk_customer_order
(
  sha1_lnk_customer_order
, sha1_hub_customer
, sha1_hub_order
, ldts
, rscr
)
VALUES
(
  src_sha1_lnk_customer_order
, src_sha1_hub_customer
, src_sha1_hub_order
, src_ldts
, src_rscr
)
SELECT sha1_hub_order          src_sha1_hub_order
     , sha1_lnk_customer_order src_sha1_lnk_customer_order
     , sha1_hub_customer       src_sha1_hub_customer
     , o_orderkey              src_o_orderkey
     , o_orderstatus           src_o_orderstatus
     , o_totalprice            src_o_totalprice
     , o_orderdate             src_o_orderdate
     , o_orderpriority         src_o_orderpriority
     , o_clerk                 src_o_clerk
     , o_shippriority          src_o_shippriority
     , o_comment               src_o_comment
     , order_hash_diff         src_order_hash_diff
     , ldts                    src_ldts
     , rscr                    src_rscr
  FROM l00_stg.stg_order_strm_outbound src;

ALTER TASK customer_strm_tsk RESUME;
ALTER TASK order_strm_tsk    RESUME;
```

2. Once tasks are created and RESUMED (by default, they are initially suspended) let's have a look on the task execution history to see how the process will start.

```
SELECT *
  FROM table(information_schema.task_history())
  ORDER BY scheduled_time DESC;
```

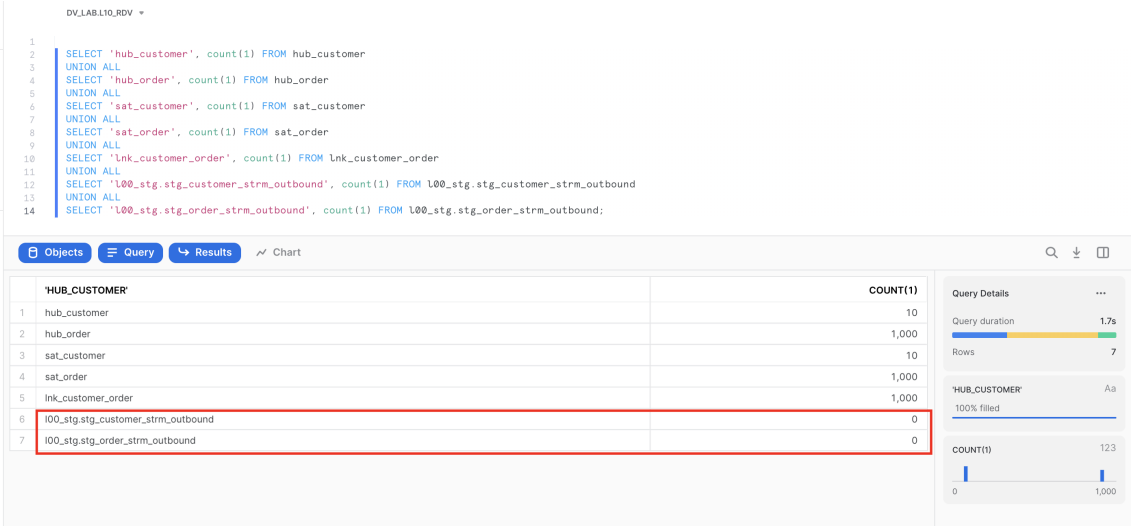
Notice how after successfull execution, next two tasks run were automatically SKIPPED as there were nothing in the stream and there nothing to do.



		CONDITION_TEXT	STATE	ERROR_CODE	ERROR_MESSAGE
1	ha1_hub_(	SYSTEM$STREAM_HAS_DATA('L00_STG.STG_ORDERS_STRM')	SCHEDULED		
2	gt.sha1_h	SYSTEM$STREAM_HAS_DATA('L00_STG.STG_CUSTOMER_STRM')	SCHEDULED		
3	ha1_hub_(	SYSTEM$STREAM_HAS_DATA('L00_STG.STG_ORDERS_STRM')	SKIPPED	0040003	Conditional expression for task evaluated to false.
4	gt.sha1_h	SYSTEM$STREAM_HAS_DATA('L00_STG.STG_CUSTOMER_STRM')	SKIPPED	0040003	Conditional expression for task evaluated to false.
5	ha1_hub_(	SYSTEM$STREAM_HAS_DATA('L00_STG.STG_ORDERS_STRM')	SUCCEEDED		
6	gt.sha1_h	SYSTEM$STREAM_HAS_DATA('L00_STG.STG_CUSTOMER_STRM')	SUCCEEDED		
7	ha1_hub_(	SYSTEM$STREAM_HAS_DATA('L00_STG.STG_ORDERS_STRM')	FAILED	002003	SQL compilation error: Object 'LNK_CUSTOMER_ORDER' does not exist or no

3. We can also check content and stats of the objects involved. Please notice that views on streams in our staging area are no longer returning any rows. This is because that delta of changes was consumed by a successfully completed DML transaction (in our case, embedded in tasks). This way you don't need to spend any time implementing incremental detection/processing logic on the application side.

```
SELECT 'hub_customer', count(1) FROM hub_customer
UNION ALL
SELECT 'hub_order', count(1) FROM hub_order
UNION ALL
SELECT 'sat_customer', count(1) FROM sat_customer
UNION ALL
SELECT 'sat_order', count(1) FROM sat_order
UNION ALL
SELECT 'lnk_customer_order', count(1) FROM lnk_customer_order
UNION ALL
SELECT 'l00_stg.stg_customer_strm_outbound', count(1) FROM
l00_stg.stg_customer_strm_outbound
UNION ALL
SELECT 'l00_stg.stg_order_strm_outbound', count(1) FROM
l00_stg.stg_order_strm_outbound;
```



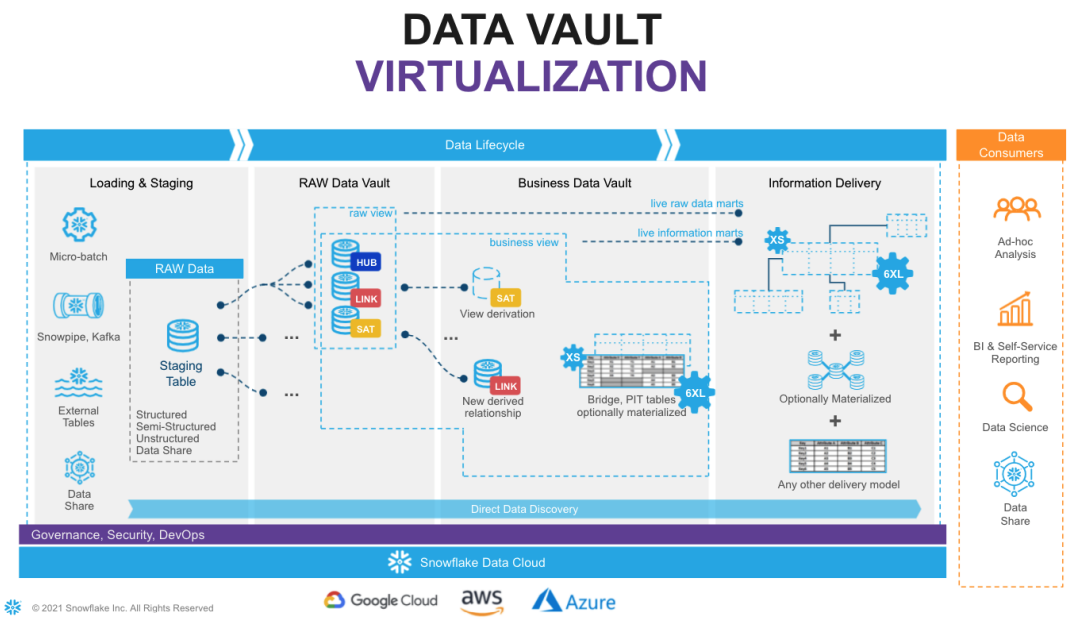
Great. We now have data in our **Raw Data Vault** core structures. Let's move on and talk about the concept of virtualization for building your near-real time Data Vault solution.

Views for Agile Reporting

One of the great benefits of having the compute power from Snowflake is that now it is totally possible to have most of your business vault and information marts in a Data Vault architecture be built exclusively from views. There are numerous customers using this approach in production today. There is no longer a need to have the argument that there are “too many joins” or that the response won’t be fast enough. The elasticity of the Snowflake virtual warehouses combined with our dynamic optimization engine have solved that problem.

If you really want to deliver data to the business users and data scientists in NRT, in our opinion using views is the only option. Once you have the streaming loads built to feed your Data Vault, the fastest way to make that data visible downstream will be views. Using views allows you to deliver the data faster by eliminating any latency that would be incurred by having additional ELT processes between the Data Vault and the data consumers downstream.

All the business logic, alignment, and formatting of the data can be in the view code. That means fewer moving parts to debug, and reduces the storage needed as well.



Looking at the diagram above you will see an example of how virtualization could fit in the architecture. Here, solid lines are representing physical tables and dotted lines - views. You incrementally ingest data into **Raw Data Vault** and all downstream transformations are applied as views. From a data consumer perspective when working with a virtualized information mart, the query always shows everything known by your data vault, right up to the point the query was submitted.

With Snowflake you have the ability to provide as much compute as required, on-demand, without a risk of causing performance impact on any surrounding processes and pay only for what you use. This makes materialization of transformations in layers like **Business Data Vault** and **Information delivery** an option rather than a must-have. Instead of "optimizing upfront" you can now make this decision based on the usage pattern characteristics, such as frequency of use, type of queries, latency requirements, readiness of the requirements etc.

Many modern data engineering automation frameworks are already actively supporting virtualization of logic. Several tools offer a low-code or configuration-like ability to switch between materializing an object as a view or a physical table, automatically generating all required DDL & DML. This could be applied on specific objects, layers or/and be environment specific. So even if you start with a view, you can easily refactor to use a table if user requirements evolve.

As said before, virtualization is not only a way to improve time-to-value and provide near real time access to the data, given the scalability and workload isolation of Snowflake, virtualization also is a design technique that could make your Data Vault excel: minimizing cost-of-change, accelerating the time-to-delivery and becoming an extremely agile, future proof solution for ever growing business needs.

Build: Business Data Vault

As a quick example of using views for transformations we just discussed, here is how enrichment of customer descriptive data could happen in Business Data Vault, connecting data received from source with some reference data.

1. Let's create a view that will perform these additional derivations on the fly. Assuming non-functional capabilities are satisflying our requirements, deploying (and re-deploying a new version) transformations in this way is super easy.

```
USE SCHEMA l20_bdv;

CREATE OR REPLACE VIEW sat_customer_bv
AS
SELECT rsc.sha1_hub_customer
     , rsc.ldts
     , rsc.c_name
     , rsc.c_address
     , rsc.c_phone
     , rsc.c_acctbal
     , rsc.c_mktsegment
     , rsc.c_comment
     , rsc.nationcode
     , rsc.rscr
     -- derived
     , rrn.n_name                    nation_name
     , rrr.r_name                    region_name
  FROM l10_rdv.sat_customer          rsc
  LEFT OUTER JOIN l10_rdv.ref_nation rrn
    ON (rsc.nationcode = rrn.nationcode)
  LEFT OUTER JOIN l10_rdv.ref_region rrr
    ON (rrn.regioncode = rrr.regioncode)
;
```

2. Now,let's imagine we have a heavier transformation to perform that it would make more sense to materialize it as a table. It could be more data volume, could be more complex logic, PITs, bridges or even an object that will be used frequently and by many users. For this case, let's first build a new business satellite that for illustration purposes will be deriving additional classification/tiering for orders based on the conditional logic.

```
CREATE OR REPLACE TABLE sat_order_bv
(
  sha1_hub_order         BINARY    NOT NULL
, ldts                   TIMESTAMP NOT NULL
, o_orderstatus          STRING
, o_totalprice           NUMBER
, o_orderdate            DATE
, o_orderpriority        STRING
, o_clerk                STRING
, o_shippriority         NUMBER
, o_comment              STRING
, hash_diff              BINARY    NOT NULL
, rscr                   STRING    NOT NULL
-- additional attributes
, order_priority_bucket  STRING
, CONSTRAINT pk_sat_order PRIMARY KEY(sha1_hub_order, ldts)
, CONSTRAINT fk_sat_order FOREIGN KEY(sha1_hub_order) REFERENCES l10_rdv.hub_order
)
AS
SELECT sha1_hub_order
     , ldts
     , o_orderstatus
```

```
     , o_totalprice
     , o_orderdate
     , o_orderpriority
     , o_clerk
     , o_shippriority
     , o_comment
     , hash_diff
     , rscr
     -- derived additional attributes
     , CASE WHEN o_orderpriority IN ('2-HIGH', '1-URGENT')             AND
o_totalprice >= 200000 THEN 'Tier-1'
            WHEN o_orderpriority IN ('3-MEDIUM', '2-HIGH', '1-URGENT') AND
o_totalprice BETWEEN 150000 AND 200000 THEN 'Tier-2'
            ELSE 'Tier-3'
       END order_priority_bucket
  FROM l10_rdv.sat_order;
```

3. What we are going to do from processing/orchestration perspective is extending our order processing pipeline so that when the task populates a **l10_rdv.sat_order** this will generate a new stream of changes and these changes are going to be propagated by a dependent task to **l20_bdv.sat_order_bv**. This is super easy to do as tasks in Snowflake can be not only schedule-based but also start automatically once the parent task is completed.

```
CREATE OR REPLACE STREAM l10_rdv.sat_order_strm ON TABLE l10_rdv.sat_order;

ALTER TASK l10_rdv.order_strm_tsk SUSPEND;

CREATE OR REPLACE TASK l10_rdv.hub_order_strm_sat_order_bv_tsk
  WAREHOUSE = dv_rdv_wh
  AFTER l10_rdv.order_strm_tsk
AS
INSERT INTO l20_bdv.sat_order_bv
SELECT
  sha1_hub_order
, ldts
, o_orderstatus
, o_totalprice
, o_orderdate
, o_orderpriority
, o_clerk
, o_shippriority
, o_comment
, hash_diff
, rscr
-- derived additional attributes
, CASE WHEN o_orderpriority IN ('2-HIGH', '1-URGENT')             AND o_totalprice >=
200000 THEN 'Tier-1'
       WHEN o_orderpriority IN ('3-MEDIUM', '2-HIGH', '1-URGENT') AND o_totalprice
BETWEEN 150000 AND 200000 THEN 'Tier-2'
       ELSE 'Tier-3'
  END order_priority_bucket
FROM sat_order_strm;
```

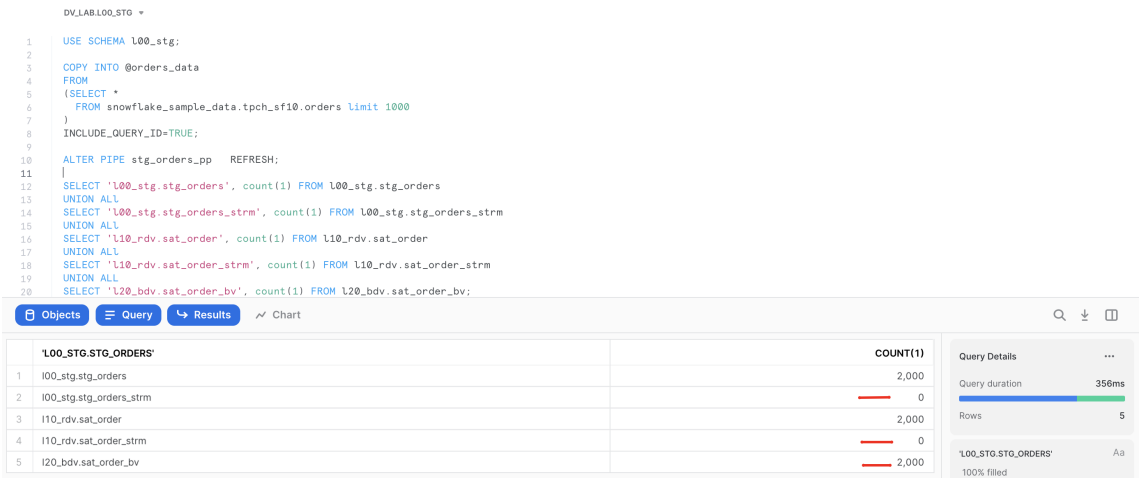
```
ALTER TASK l10_rdv.hub_order_strm_sat_order_bv_tsk RESUME;
ALTER TASK l10_rdv.order_strm_tsk RESUME;
```

4. Now, let's go back to our staging area to process another slice of data to test the task.

```
USE SCHEMA l00_stg;

COPY INTO @orders_data
FROM
(SELECT *
  FROM snowflake_sample_data.tpch_sf10.orders limit 1000
)
INCLUDE_QUERY_ID=TRUE;

ALTER PIPE stg_orders_pp   REFRESH;
```

5. Data is not automatically flowing through all the layers via asyncronous tasks. With the results you can validate:

```
SELECT 'l00_stg.stg_orders', count(1) FROM l00_stg.stg_orders
UNION ALl
SELECT 'l00_stg.stg_orders_strm', count(1) FROM l00_stg.stg_orders_strm
UNION ALl
SELECT 'l10_rdv.sat_order', count(1) FROM l10_rdv.sat_order
UNION ALl
SELECT 'l10_rdv.sat_order_strm', count(1) FROM l10_rdv.sat_order_strm
UNION ALL
SELECT 'l20_bdv.sat_order_bv', count(1) FROM l20_bdv.sat_order_bv;
```



Great. Hope this example illustrated few ways of managing **Business Data Vault** objects in our pipeline. Let's finally move into the **Information Delivery** layer.

Build: Information Delivery

When it comes to Information Delivery area we are not changing the meaning of data, but we may change format to simplify users to access and work with the data products/output interfaces. Different consumers may have different needs and preferences, some would prefer star/snowflake dimensional schemas, some would adhere to use flattened objects or even transform data into JSON/parquet objects.

1. First things we would like to add to simplify working with satellites is creating views that shows latest version for each key.

```
-----------------------------------------------------------------------
-- RDV curr views
-----------------------------------------------------------------------

USE SCHEMA l10_rdv;

CREATE VIEW sat_customer_curr_vw
AS
SELECT  *
FROM    sat_customer
QUALIFY LEAD(ldts) OVER (PARTITION BY sha1_hub_customer ORDER BY ldts) IS NULL;

CREATE OR REPLACE VIEW sat_order_curr_vw
AS
SELECT  *
FROM    sat_order
QUALIFY LEAD(ldts) OVER (PARTITION BY sha1_hub_order ORDER BY ldts) IS NULL;

-----------------------------------------------------------------------
-- BDV curr views
-----------------------------------------------------------------------

USE SCHEMA l20_bdv;

CREATE VIEW sat_order_bv_curr_vw
AS
SELECT  *
FROM    sat_order_bv
QUALIFY LEAD(ldts) OVER (PARTITION BY sha1_hub_order ORDER BY ldts) IS NULL;

CREATE VIEW sat_customer_bv_curr_vw
AS
SELECT  *
FROM    sat_customer_bv
QUALIFY LEAD(ldts) OVER (PARTITION BY sha1_hub_customer ORDER BY ldts) IS NULL;
```

2. Let's create a simple dimensional structure. Again, we will keep it virtual(as views) to start with, but you already know that depending on access characteristics required any of these could be selectively materialized.

```
USE SCHEMA l30_id;

-- DIM TYPE 1
```

```
CREATE OR REPLACE VIEW dim1_customer
AS
SELECT hub.sha1_hub_customer                        AS dim_customer_key
     , sat.ldts                                     AS effective_dts
     , hub.c_custkey                                AS customer_id
     , sat.rscr                                     AS record_source
     , sat.*
  FROM l10_rdv.hub_customer                         hub
     , l20_bdv.sat_customer_bv_curr_vw              sat
 WHERE hub.sha1_hub_customer                        = sat.sha1_hub_customer;

-- DIM TYPE 1
CREATE OR REPLACE VIEW dim1_order
AS
SELECT hub.sha1_hub_order                           AS dim_order_key
     , sat.ldts                                     AS effective_dts
     , hub.o_orderkey                               AS order_id
     , sat.rscr                                     AS record_source
     , sat.*
  FROM l10_rdv.hub_order                            hub
     , l20_bdv.sat_order_bv_curr_vw                 sat
 WHERE hub.sha1_hub_order                           = sat.sha1_hub_order;

-- FACT table

CREATE OR REPLACE VIEW fct_customer_order
AS
SELECT lnk.ldts                                     AS effective_dts
     , lnk.rscr                                     AS record_source
     , lnk.sha1_hub_customer                        AS dim_customer_key
     , lnk.sha1_hub_order                           AS dim_order_key
-- this is a factless fact, but here you can add any measures, calculated or derived
  FROM l10_rdv.lnk_customer_order                   lnk;
```

3. All good so far? Now lets try to query **fct_customer_order** and at least in my case this view was not returning any rows. Why? If you remember, when we were unloading sample data, we took a subset of random orders and a subset of random customers. Which in my case didn't have any overlap, therefore doing the inner join with dim1_order was resulting in all rows being eliminated from the resultset. Thankfully we are using Data Vault and all need to do is go and load full customer dataset. Just think about it, there is no need to reprocess any links or fact tables simply because customer/reference feed was incomplete. I am sure for those of you who were using different architectures for data engineering and warehousing have painful experience when such situations occur. So, lets go and fix it:

```
USE SCHEMA l00_stg;

COPY INTO @customer_data
FROM
(SELECT object_construct(*)
  FROM snowflake_sample_data.tpch_sf10.customer
  -- removed LIMIT 10
)
INCLUDE_QUERY_ID=TRUE;
```

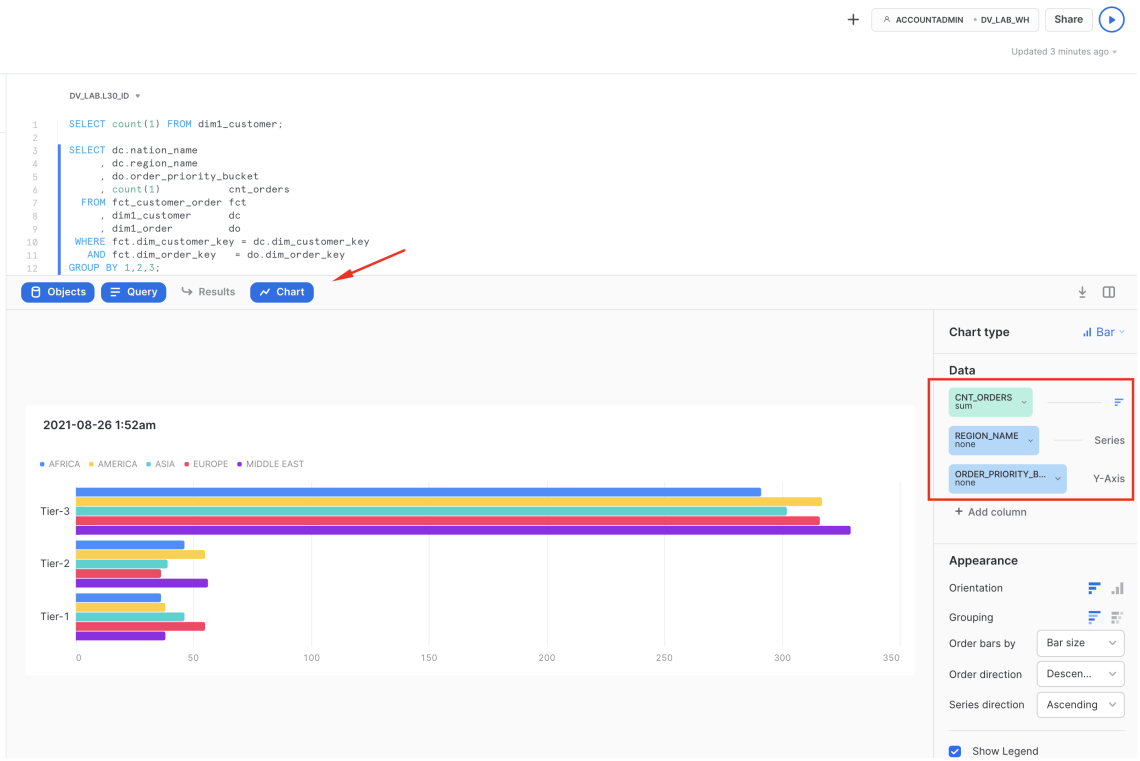
```
ALTER PIPE stg_customer_pp   REFRESH;
```

All you need to do now is just wait a few seconds whilst our continious data pipeline will automatically propagate new customer data into Raw Data Vault. Quick check for the records count in customer dimension now shows that there are 1.5Mn records:

```
USE SCHEMA l30_id;

SELECT COUNT(1) FROM dim1_customer;


COUNT(1)
------
1,500,000
```

4. Finally lets wear user's hat and run a query to break down orders by nation,region and order_priority_bucket (all attributes we derived in **Business Data Vault**). As we are using Snowsight, why not quickly creating a chart from this result set to better understand the data. For this simply click on the 'Chart' section on the bottom pane and put attributes/measures as it is snown on the screenshot below.

```
SELECT dc.nation_name
     , dc.region_name
     , do.order_priority_bucket
     , COUNT(1)                                 cnt_orders
  FROM fct_customer_order                       fct
     , dim1_customer                            dc
     , dim1_order                               do
 WHERE fct.dim_customer_key                     = dc.dim_customer_key
   AND fct.dim_order_key                        = do.dim_order_key
GROUP BY 1,2,3;
```



Voila! This concludes our journey for this guide. Hope you enjoyed it and lets summarise key points in the next section.

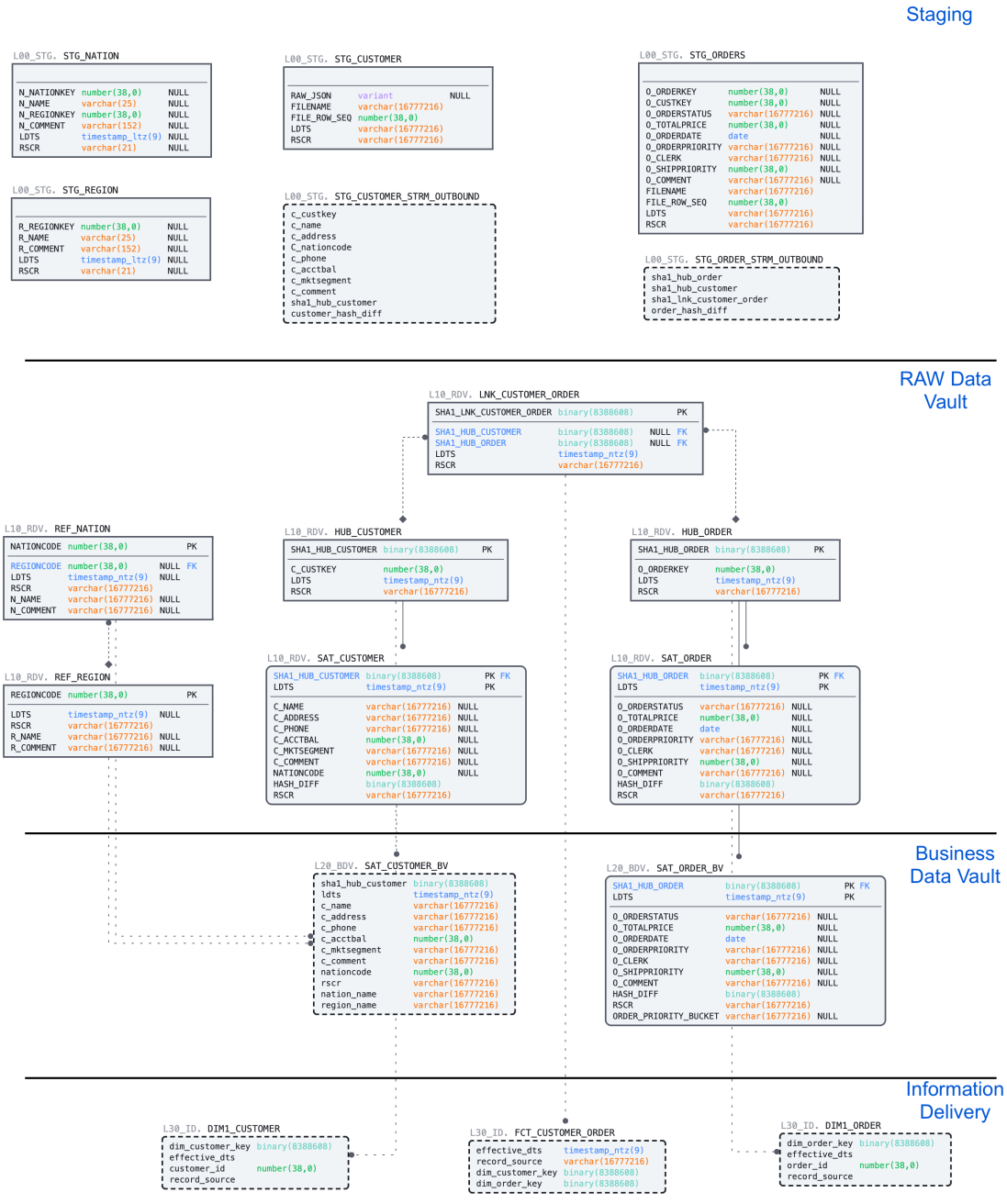
Conclusion

Simplicity of engineering, openness, scalable performance, enterprise-grade governance enabled by the core of the Snowflake platform are now allowing teams to focus on what matters most for the business and build truly agile, collaborative data environments. Teams can now connect data from all parts of the landscape, until there are no stones left unturned. They are even tapping into new datasets via live access to the Snowflake Data Marketplace. The Snowflake Data Cloud combined with a Data Vault 2.0 approach is allowing teams to democratize access to all their data assets at any scale. We can now easily derive more and more value through insights and intelligence, day after day, bringing businesses to the next level of being truly data-driven.

Delivering more usable data faster is no longer an option for today's business environment. Using the Snowflake platform, combined with the Data Vault 2.0 architecture it is now possible to build a world class analytics platform that delivers data for all users in near real-time.

What we've covered

- unloading and loading back data using COPY and Snowpipe
- engineering data pipelines using virtualization, streams and tasks
- building multi-layer Data Vault environment on Snowflake:



Call to action

- seeing is believing. Try it!
- we made examples limited in size, but feel free to scale the data volumes and virtual warehouse size to see scalability in action
- tap into numerous communities of practice for Data Engineering on Snowflake and Data Vault in particular
- talk to us about modernizing your data landscape! Whether it is Data Vault or not you have on your mind, we have the top expertise and product to meet your demand
- feedback is super welcome!
- Enjoy your journey!

Resource Optimization: Billing Metrics

Overview

This resource optimization guide represents one module of the four contained in the series. These guides are meant to help customers better monitor and manage their credit consumption. Helping our customers build confidence that their credits are being used efficiently is key to an ongoing successful partnership. In addition to this set of Snowflake Quickstarts for Resource Optimization, Snowflake also offers community support as well as Training and Professional Services offerings.

Billing Metrics

Billing queries are responsible for identifying total costs associated with the high level functions of the Snowflake Cloud Data Platform, which includes warehouse compute, snowpipe compute, and storage costs. If costs are noticeably higher in one category versus the others, you may want to evaluate what might be causing that.

These metrics also seek to identify those queries that are consuming the most amount of credits. From there, each of these queries can be analyze for their importance (do they need to be run as frequently, if at all) and explore if additional controls need to be in place to prevent excessive consumption (i.e. resource monitors, statement timeouts, etc.).

What You'll Learn

- how to identify and analyze Snowflake consumption across all services
- how to analyze most resource-intensive queries
- how to analyze serverless consumption

What You'll Need

- A Snowflake Account
- Access to view [Account Usage Data Share]

Related Materials

- Resource Optimization: Setup & Configuration
- Resource Optimization: Usage Monitoring
- Resource Optimization: Performance

Query Tiers

Each query within the Resource Optimization Snowflake Quickstarts will have a tier designation just to the right of its name as "(T*)". The following tier descriptions should help to better understand those designations.

Tier 1 Queries

At its core, Tier 1 queries are essential to Resource Optimization at Snowflake and should be used by each customer to help with their consumption monitoring - regardless of size, industry, location, etc.

Tier 2 Queries

Tier 2 queries, while still playing a vital role in the process, offer an extra level of depth around Resource Optimization and while they may not be essential to all customers and their workloads, it can offer further explanation as to any additional areas in which over-consumption may be identified.

Tier 3 Queries

Finally, Tier 3 queries are designed to be used by customers that are looking to leave no stone unturned when it comes to optimizing their consumption of Snowflake. While these queries are still very helpful in this process, they are not as critical as the queries in Tier 1 & 2.

Billing Metrics (T1)

TIER 1

Description:

Identify key metrics as it pertains to total compute costs from warehouses, serverless features, and total storage costs.

How to Interpret Results:

Where are we seeing most of our costs coming from (compute, serverless, storage)? Are seeing excessive costs in any of those categories that are above expectations?

Primary Schema:

Account_Usage

SQL

```
/* These queries can be used to measure where costs have been incurred by
   the different cost vectors within a Snowflake account including:
   1) Warehouse Costs
   2) Serverless Costs
   3) Storage Costs

   To accurately report the dollar amounts, make changes to the variables
   defined on lines 17 to 20 to properly reflect your credit price, the initial
   capacity purchased, when your contract started and the term (default 12 months)

   If unsure, ask your Sales Engineer or Account Executive
*/

USE DATABASE SNOWFLAKE;
USE SCHEMA ACCOUNT_USAGE;

SET CREDIT_PRICE = 4.00; --edit this number to reflect credit price
SET TERM_LENGTH = 12; --integer value in months
SET TERM_START_DATE = '2019-01-01';
SET TERM_AMOUNT = 100000.00; --number(10,2) value in dollars


WITH CONTRACT_VALUES AS (

      SELECT
                $CREDIT_PRICE::decimal(10,2) as CREDIT_PRICE
               ,$TERM_AMOUNT::decimal(38,0) as TOTAL_CONTRACT_VALUE
               ,$TERM_START_DATE::timestamp as CONTRACT_START_DATE
               ,DATEADD(month,$TERM_LENGTH,$TERM_START_DATE)::timestamp as
```

```
CONTRACT_END_DATE

),
PROJECTED_USAGE AS (

      SELECT
                  CREDIT_PRICE
                 ,TOTAL_CONTRACT_VALUE
                 ,CONTRACT_START_DATE
                 ,CONTRACT_END_DATE
                 ,(TOTAL_CONTRACT_VALUE)
                     /
                     DATEDIFF(day,CONTRACT_START_DATE,CONTRACT_END_DATE)  AS
DOLLARS_PER_DAY
                 , (TOTAL_CONTRACT_VALUE/CREDIT_PRICE)
                     /
                 DATEDIFF(day,CONTRACT_START_DATE,CONTRACT_END_DATE) AS CREDITS_PER_DAY
      FROM       CONTRACT_VALUES

)

--COMPUTE FROM WAREHOUSES
SELECT
          'WH Compute' as WAREHOUSE_GROUP_NAME
         ,WMH.WAREHOUSE_NAME
         ,NULL AS GROUP_CONTACT
         ,NULL AS GROUP_COST_CENTER
         ,NULL AS GROUP_COMMENT
         ,WMH.START_TIME
         ,WMH.END_TIME
         ,WMH.CREDITS_USED
         ,$CREDIT_PRICE
         ,($CREDIT_PRICE*WMH.CREDITS_USED) AS DOLLARS_USED
         ,'ACTUAL COMPUTE' AS MEASURE_TYPE
from     SNOWFLAKE.ACCOUNT_USAGE.WAREHOUSE_METERING_HISTORY WMH

UNION ALL

--COMPUTE FROM SNOWPIPE
SELECT
          'Snowpipe' AS WAREHOUSE_GROUP_NAME
         ,PUH.PIPE_NAME AS WAREHOUSE_NAME
         ,NULL AS GROUP_CONTACT
         ,NULL AS GROUP_COST_CENTER
         ,NULL AS GROUP_COMMENT
         ,PUH.START_TIME
         ,PUH.END_TIME
         ,PUH.CREDITS_USED
         ,$CREDIT_PRICE
         ,($CREDIT_PRICE*PUH.CREDITS_USED) AS DOLLARS_USED
         ,'ACTUAL COMPUTE' AS MEASURE_TYPE
from     SNOWFLAKE.ACCOUNT_USAGE.PIPE_USAGE_HISTORY PUH
```

```
UNION ALL

--COMPUTE FROM CLUSTERING
SELECT
         'Auto Clustering' AS WAREHOUSE_GROUP_NAME
        ,DATABASE_NAME || '.' || SCHEMA_NAME || '.' || TABLE_NAME AS WAREHOUSE_NAME
        ,NULL AS GROUP_CONTACT
        ,NULL AS GROUP_COST_CENTER
        ,NULL AS GROUP_COMMENT
        ,ACH.START_TIME
        ,ACH.END_TIME
        ,ACH.CREDITS_USED
        ,$CREDIT_PRICE
        ,($CREDIT_PRICE*ACH.CREDITS_USED) AS DOLLARS_USED
        ,'ACTUAL COMPUTE' AS MEASURE_TYPE
from    SNOWFLAKE.ACCOUNT_USAGE.AUTOMATIC_CLUSTERING_HISTORY ACH

UNION ALL

--COMPUTE FROM MATERIALIZED VIEWS
SELECT
         'Materialized Views' AS WAREHOUSE_GROUP_NAME
        ,DATABASE_NAME || '.' || SCHEMA_NAME || '.' || TABLE_NAME AS WAREHOUSE_NAME
        ,NULL AS GROUP_CONTACT
        ,NULL AS GROUP_COST_CENTER
        ,NULL AS GROUP_COMMENT
        ,MVH.START_TIME
        ,MVH.END_TIME
        ,MVH.CREDITS_USED
        ,$CREDIT_PRICE
        ,($CREDIT_PRICE*MVH.CREDITS_USED) AS DOLLARS_USED
        ,'ACTUAL COMPUTE' AS MEASURE_TYPE
from    SNOWFLAKE.ACCOUNT_USAGE.MATERIALIZED_VIEW_REFRESH_HISTORY MVH

UNION ALL

--COMPUTE FROM SEARCH OPTIMIZATION
SELECT
         'Search Optimization' AS WAREHOUSE_GROUP_NAME
        ,DATABASE_NAME || '.' || SCHEMA_NAME || '.' || TABLE_NAME AS WAREHOUSE_NAME
        ,NULL AS GROUP_CONTACT
        ,NULL AS GROUP_COST_CENTER
        ,NULL AS GROUP_COMMENT
        ,SOH.START_TIME
        ,SOH.END_TIME
        ,SOH.CREDITS_USED
        ,$CREDIT_PRICE
        ,($CREDIT_PRICE*SOH.CREDITS_USED) AS DOLLARS_USED
        ,'ACTUAL COMPUTE' AS MEASURE_TYPE
from    SNOWFLAKE.ACCOUNT_USAGE.SEARCH_OPTIMIZATION_HISTORY SOH
```

```
UNION ALL

--COMPUTE FROM REPLICATION
SELECT
         'Replication' AS WAREHOUSE_GROUP_NAME
        ,DATABASE_NAME AS WAREHOUSE_NAME
        ,NULL AS GROUP_CONTACT
        ,NULL AS GROUP_COST_CENTER
        ,NULL AS GROUP_COMMENT
        ,RUH.START_TIME
        ,RUH.END_TIME
        ,RUH.CREDITS_USED
        ,$CREDIT_PRICE
        ,($CREDIT_PRICE*RUH.CREDITS_USED) AS DOLLARS_USED
        ,'ACTUAL COMPUTE' AS MEASURE_TYPE
from    SNOWFLAKE.ACCOUNT_USAGE.REPLICATION_USAGE_HISTORY RUH

UNION ALL

--STORAGE COSTS
SELECT
         'Storage' AS WAREHOUSE_GROUP_NAME
        ,'Storage' AS WAREHOUSE_NAME
        ,NULL AS GROUP_CONTACT
        ,NULL AS GROUP_COST_CENTER
        ,NULL AS GROUP_COMMENT
        ,SU.USAGE_DATE
        ,SU.USAGE_DATE
        ,NULL AS CREDITS_USED
        ,$CREDIT_PRICE
        ,((STORAGE_BYTES + STAGE_BYTES +
FAILSAFE_BYTES)/(1024*1024*1024*1024)*23)/DA.DAYS_IN_MONTH AS DOLLARS_USED
        ,'ACTUAL COMPUTE' AS MEASURE_TYPE
from    SNOWFLAKE.ACCOUNT_USAGE.STORAGE_USAGE SU
JOIN    (SELECT COUNT(*) AS DAYS_IN_MONTH,TO_DATE(DATE_PART('year',D_DATE)||'-
'||DATE_PART('month',D_DATE)||'-01') as DATE_MONTH FROM
SNOWFLAKE_SAMPLE_DATA.TPCDS_SF10TCL.DATE_DIM GROUP BY
TO_DATE(DATE_PART('year',D_DATE)||'-'||DATE_PART('month',D_DATE)||'-01')) DA ON
DA.DATE_MONTH = TO_DATE(DATE_PART('year',USAGE_DATE)||'-
'||DATE_PART('month',USAGE_DATE)||'-01')

UNION ALL


SELECT
         NULL as WAREHOUSE_GROUP_NAME
        ,NULL as WAREHOUSE_NAME
        ,NULL as GROUP_CONTACT
        ,NULL as GROUP_COST_CENTER
        ,NULL as GROUP_COMMENT
        ,DA.D_DATE::timestamp as START_TIME
        ,DA.D_DATE::timestamp as END_TIME
```

```
        ,PU.CREDITS_PER_DAY AS CREDITS_USED
        ,PU.CREDIT_PRICE
        ,PU.DOLLARS_PER_DAY AS DOLLARS_USED
        ,'PROJECTED COMPUTE' AS MEASURE_TYPE
FROM    PROJECTED_USAGE PU
JOIN    SNOWFLAKE_SAMPLE_DATA.TPCDS_SF10TCL.DATE_DIM DA ON DA.D_DATE BETWEEN
PU.CONTRACT_START_DATE AND PU.CONTRACT_END_DATE

UNION ALL


SELECT
         NULL as WAREHOUSE_GROUP_NAME
        ,NULL as WAREHOUSE_NAME
        ,NULL as GROUP_CONTACT
        ,NULL as GROUP_COST_CENTER
        ,NULL as GROUP_COMMENT
        ,NULL as START_TIME
        ,NULL as END_TIME
        ,NULL AS CREDITS_USED
        ,PU.CREDIT_PRICE
        ,PU.TOTAL_CONTRACT_VALUE AS DOLLARS_USED
        ,'CONTRACT VALUES' AS MEASURE_TYPE
FROM    PROJECTED_USAGE PU
;
```

Screenshot

	WAREHOUSE_GROUP_NAME	WAREHOUSE_NAME	GROUP_CONTACT	GROUP_COST_CENTER	GROUP_COMMENT	START_TIME	END_TIME	CREDITS_USED	$CREDIT_PRICE	DOLLARS_USED	MEASURE_TYPE
1	WH Compute	COMPUTE_WH				2021-07-09 13:00:00.000 -0700	2021-07-09 14:00:00.000 -0700	0.399620556	4	1.598482224	ACTUAL COMPUTE
2	WH Compute	RESET_WH				2021-07-09 12:00:00.000 -0700	2021-07-09 13:00:00.000 -0700	0.000061389	4	0.000245556	ACTUAL COMPUTE
3	WH Compute	RESET_WH				2021-07-29 06:00:00.000 -0700	2021-07-29 07:00:00.000 -0700	2.752222222	4	11.008888888	ACTUAL COMPUTE
4	Storage	Storage				2021-03-21 00:00:00.000 -0700	2021-03-21 00:00:00.000 -0700		4	0.625538534603	ACTUAL COMPUTE
5	Storage	Storage				2020-10-10 00:00:00.000 -0700	2020-10-10 00:00:00.000 -0700		4	0.625538534601	ACTUAL COMPUTE
6	Storage	Storage				2020-08-25 00:00:00.000 -0700	2020-08-25 00:00:00.000 -0700		4	0.625538534603	ACTUAL COMPUTE
7	Storage	Storage				2020-11-10 00:00:00.000 -0800	2020-11-10 00:00:00.000 -0800		4	0.646389819087	ACTUAL COMPUTE
8	Storage	Storage				2021-07-04 00:00:00.000 -0700	2021-07-04 00:00:00.000 -0700		4	0.625538534829	ACTUAL COMPUTE
9	Storage	Storage				2021-05-19 00:00:00.000 -0700	2021-05-19 00:00:00.000 -0700		4	0.625538534829	ACTUAL COMPUTE
10	Storage	Storage				2020-12-26 00:00:00.000 -0800	2020-12-26 00:00:00.000 -0800		4	0.6255385346	ACTUAL COMPUTE
11	Storage	Storage				2021-08-06 00:00:00.000 -0700	2021-08-06 00:00:00.000 -0700		4	0.625539930966	ACTUAL COMPUTE
12	Storage	Storage				2021-02-12 00:00:00.000 -0800	2021-02-12 00:00:00.000 -0800		4	0.69256052045	ACTUAL COMPUTE
13	Storage	Storage				2021-07-20 00:00:00.000 -0700	2021-07-20 00:00:00.000 -0700		4	0.625539522069	ACTUAL COMPUTE

Most Expensive Queries (T2)

TIER 2

Description:

This query orders the most expensive queries from the last 30 days. It takes into account the warehouse size, assuming that a 1 minute query on larger warehouse is more expensive than a 1 minute query on a smaller warehouse

How to Interpret Results:

This is an opportunity to evaluate expensive queries and take some action. The admin could:

-look at the query profile

-contact the user who executed the query

-take action to optimize these queries

Primary Schema:

Account_Usage

SQL

```
WITH WAREHOUSE_SIZE AS
(
     SELECT WAREHOUSE_SIZE, NODES
       FROM (
              SELECT 'XSMALL' AS WAREHOUSE_SIZE, 1 AS NODES
              UNION ALL
              SELECT 'SMALL' AS WAREHOUSE_SIZE, 2 AS NODES
              UNION ALL
              SELECT 'MEDIUM' AS WAREHOUSE_SIZE, 4 AS NODES
              UNION ALL
              SELECT 'LARGE' AS WAREHOUSE_SIZE, 8 AS NODES
              UNION ALL
              SELECT 'XLARGE' AS WAREHOUSE_SIZE, 16 AS NODES
              UNION ALL
              SELECT '2XLARGE' AS WAREHOUSE_SIZE, 32 AS NODES
              UNION ALL
              SELECT '3XLARGE' AS WAREHOUSE_SIZE, 64 AS NODES
              UNION ALL
              SELECT '4XLARGE' AS WAREHOUSE_SIZE, 128 AS NODES
            )
),
QUERY_HISTORY AS
(
     SELECT QH.QUERY_ID
           ,QH.QUERY_TEXT
           ,QH.USER_NAME
           ,QH.ROLE_NAME
           ,QH.EXECUTION_TIME
           ,QH.WAREHOUSE_SIZE
      FROM SNOWFLAKE.ACCOUNT_USAGE.QUERY_HISTORY QH
     WHERE START_TIME > DATEADD(month,-2,CURRENT_TIMESTAMP())
)

SELECT QH.QUERY_ID
      ,'https://' || current_account() ||
'.snowflakecomputing.com/console#/monitoring/queries/detail?queryId='||QH.QUERY_ID AS
QU
      ,QH.QUERY_TEXT
      ,QH.USER_NAME
      ,QH.ROLE_NAME
      ,QH.EXECUTION_TIME as EXECUTION_TIME_MILLISECONDS
      ,(QH.EXECUTION_TIME/(1000)) as EXECUTION_TIME_SECONDS
      ,(QH.EXECUTION_TIME/(1000*60)) AS EXECUTION_TIME_MINUTES
      ,(QH.EXECUTION_TIME/(1000*60*60)) AS EXECUTION_TIME_HOURS
      ,WS.WAREHOUSE_SIZE
      ,WS.NODES
      ,(QH.EXECUTION_TIME/(1000*60*60))*WS.NODES as RELATIVE_PERFORMANCE_COST
```

```
FROM QUERY_HISTORY QH
JOIN WAREHOUSE_SIZE WS ON WS.WAREHOUSE_SIZE = upper(QH.WAREHOUSE_SIZE)
ORDER BY RELATIVE_PERFORMANCE_COST DESC
LIMIT 200
;
```

Average Cost per Query by Warehouse (T2)

TIER 2

Description:

This summarize the query activity and credit consumption per warehouse over the last month. The query also includes the ratio of queries executed to credits consumed on the warehouse

How to Interpret Results:

Highlights any scenarios where warehouse consumption is significantly out of line with the number of queries executed. Maybe auto-suspend needs to be adjusted or warehouses need to be consolidated.

Primary Schema:

Account_Usage

SQL

```
set credit_price = 4;  --edit this value to reflect your credit price

SELECT
    COALESCE(WC.WAREHOUSE_NAME,QC.WAREHOUSE_NAME) AS WAREHOUSE_NAME
    ,QC.QUERY_COUNT_LAST_MONTH
    ,WC.CREDITS_USED_LAST_MONTH
    ,WC.CREDIT_COST_LAST_MONTH
    ,CAST((WC.CREDIT_COST_LAST_MONTH / QC.QUERY_COUNT_LAST_MONTH) AS decimal(10,2) )
AS COST_PER_QUERY

FROM (
    SELECT
       WAREHOUSE_NAME
      ,COUNT(QUERY_ID) as QUERY_COUNT_LAST_MONTH
    FROM SNOWFLAKE.ACCOUNT_USAGE.QUERY_HISTORY
    WHERE TO_DATE(START_TIME) >= TO_DATE(DATEADD(month,-1,CURRENT_TIMESTAMP()))
    GROUP BY WAREHOUSE_NAME
      ) QC
JOIN (

    SELECT
        WAREHOUSE_NAME
        ,SUM(CREDITS_USED) as CREDITS_USED_LAST_MONTH
        ,SUM(CREDITS_USED)*($CREDIT_PRICE) as CREDIT_COST_LAST_MONTH
    FROM SNOWFLAKE.ACCOUNT_USAGE.WAREHOUSE_METERING_HISTORY
    WHERE TO_DATE(START_TIME) >= TO_DATE(DATEADD(month,-1,CURRENT_TIMESTAMP()))
    GROUP BY WAREHOUSE_NAME
  ) WC
```

```
    ON WC.WAREHOUSE_NAME = QC.WAREHOUSE_NAME

ORDER BY COST_PER_QUERY DESC
;
```

Screenshot

WAREHOUSE_NAME	QUERY_COUNT_LAST_MONTH	CREDITS_USED_LAST_MONTH	CREDIT_COST_LAST_MONTH	COST_PER_QUERY
DATALAKE_WH	53	8.392294444	33.569177776	0.63
COMPUTE_WH	234	10.023920556	40.095682224	0.17
RESET_WH	109	3.836485278	15.345941112	0.14
ANALYTICS_WH	189	2.526540556	10.106162224	0.05
LOAD_WH	219	2.752667501	11.010670004	0.05
TASK_WH	302	1.077893611	4.311574444	0.01
BI_MEDIUM_WH	2	0.000060000	0.000240000	0.00
BI_LARGE_WH	16734	0.481809443	1.927237772	0.00

AutoClustering Cost History (by Day by Object) (T3)

TIER 3

Description:

Full list of tables with auto-clustering and the volume of credits consumed via the service over the last 30 days, broken out by day.

How to Interpret Results:

Look for irregularities in the credit consumption or consistently high consumption

Primary Schema:

Account_Usage

SQL

```
SELECT TO_DATE(START_TIME) as DATE
,DATABASE_NAME
,SCHEMA_NAME
,TABLE_NAME
,SUM(CREDITS_USED) as CREDITS_USED


FROM "SNOWFLAKE"."ACCOUNT_USAGE"."AUTOMATIC_CLUSTERING_HISTORY"

WHERE START_TIME >= dateadd(month,-1,current_timestamp())
GROUP BY 1,2,3,4
ORDER BY 5 DESC
;
```

Screenshot

CLUSTERING_DATE	DATABASE_NAME	SCHEMA_NAME	TABLE_NAME	CREDITS_USED
2020-02-19	ASHISH_TEST_DB	PUBLIC	GENOTYPES_COPY	266.442864197
2020-04-28	PACIONE_TEST	PUBLIC	COLLAT_AMT_FACT_AC	118.290533383
2020-10-13	CARLINENG	TPCDS_UNCLUSTERED	AUTOCLUSTER_SOLD_DATE_ITEM	78.132147290
2020-10-13	CARLINENG	TPCDS_UNCLUSTERED	AUTOCLUSTER_TICKET_NUMBER	67.328296503
2020-10-13	CARLINENG	TPCDS_UNCLUSTERED	AUTOCLUSTER_SOLD_DATE	57.013410098
2020-01-08	GENOMES_STAGE	GENOME1K	GENOTYPES	29.637784249
2019-12-18	JCLARKE_DB	PUBLIC	SNOW121900_CBD	25.405727086
2020-06-18	SKIPSANDBOX	PUBLIC	WEB_SALES	18.709104655
2019-12-18	JCLARKE_DB	PUBLIC	SNOW121900_CBTS	11.821695786
2020-06-18	SKIPSANDBOX	PUBLIC	TEST_CLUSTER_IMPACT_ON_CARD_EST	9.956016226
2020-07-01	GEOSPATIAL	NASANEX	NEX_GDDP_ALL	8.324776052
2020-06-25	JCLARKE_DB	PUBLIC	C_TEST	4.867021840
2020-07-30	SKIPSANDBOX	PUBLIC	SEARCH OPTIMIZATION ON TABLE_ID:2778292	4.259085124
2020-04-28	NTIERNEY_TEST_DB	CLUSTER_TEST	V_ORDERS_CUSTOMER	3.167348136
2020-06-22	CARLOS_TEST_DB	PUBLIC	LINEITEM	2.060566449
2020-06-26	JCLARKE_DB	PUBLIC	C_TEST	1.202380758
2020-07-02	GEOSPATIAL	NASANEX	NEX_GDDP_ALL	0.698955203
2020-04-28	NTIERNEY_TEST_DB	CLUSTER_TEST	ORDERS	0.575332238
2020-06-23	CARLOS_TEST_DB	PUBLIC	LINEITEM	0.363553380
2020-09-23	CARLINENG	PUBLIC	ORDERS	0.212436370

Materialized Views Cost History (by Day by Object) (T3)

TIER 3

Description:

Full list of materialized views and the volume of credits consumed via the service over the last 30 days, broken out by day.

How to Interpret Results:

Look for irregularities in the credit consumption or consistently high consumption

Primary Schema:

Account_Usage

SQL

```
SELECT

TO_DATE(START_TIME) as DATE
,DATABASE_NAME
,SCHEMA_NAME
,TABLE_NAME
,SUM(CREDITS_USED) as CREDITS_USED

FROM "SNOWFLAKE"."ACCOUNT_USAGE"."MATERIALIZED_VIEW_REFRESH_HISTORY"

WHERE START_TIME >= dateadd(month,-1,current_timestamp())
GROUP BY 1,2,3,4
ORDER BY 5 DESC
;
```

Search Optimization Cost History (by Day by Object) (T3)

TIER 3

Description:

Full list of tables with search optimization and the volume of credits consumed via the service over the last 30 days, broken out by day.

How to Interpret Results:

Look for irregularities in the credit consumption or consistently high consumption

Primary Schema:

Account_Usage

SQL

```
TSELECT

TO_DATE(START_TIME) as DATE
,DATABASE_NAME
,SCHEMA_NAME
,TABLE_NAME
,SUM(CREDITS_USED) as CREDITS_USED

FROM "SNOWFLAKE"."ACCOUNT_USAGE"."SEARCH_OPTIMIZATION_HISTORY"

WHERE START_TIME >= dateadd(month,-1,current_timestamp())
GROUP BY 1,2,3,4
ORDER BY 5 DESC
;
```

Snowpipe Cost History (by Day by Object) (T3)

TIER 3

Description:

Full list of pipes and the volume of credits consumed via the service over the last 30 days, broken out by day.

How to Interpret Results:

Look for irregularities in the credit consumption or consistently high consumption

Primary Schema:

Account_Usage

SQL

```
SELECT

TO_DATE(START_TIME) as DATE
,PIPE_NAME
,SUM(CREDITS_USED) as CREDITS_USED

FROM "SNOWFLAKE"."ACCOUNT_USAGE"."PIPE_USAGE_HISTORY"

WHERE START_TIME >= dateadd(month,-1,current_timestamp())
GROUP BY 1,2
```

```
ORDER BY 3 DESC
;
```

Replication Cost History (by Day by Object) (T3)

TIER 3

Description:

Full list of replicated databases and the volume of credits consumed via the replication service over the last 30 days, broken out by day.

How to Interpret Results:

Look for irregularities in the credit consumption or consistently high consumption

Primary Schema:

Account_Usage

SQL

```
SELECT
TO_DATE(START_TIME) as DATE
,DATABASE_NAME
,SUM(CREDITS_USED) as CREDITS_USED
FROM "SNOWFLAKE"."ACCOUNT_USAGE"."REPLICATION_USAGE_HISTORY"
WHERE START_TIME >= dateadd(month,-1,current_timestamp())
GROUP BY 1,2
ORDER BY 3 DESC
;
```

Resource Optimization: Performance

Performance

The queries provided in this guide are intended to help you setup and run queries pertaining to identifying areas where poor performance might be causing excess consumption, driven by a variety of factors.

What You'll Learn

- how to identify areas in which performance can be improved
- how to analyze workloads with poor performance causing excess consumption
- how to identify warehouses that would benefit from scaling up or out

What You'll Need

- A Snowflake Account
- Access to view [Account Usage Data Share]

Related Materials

- Resource Optimization: Setup & Configuration
- Resource Optimization: Usage Monitoring
- Resource Optimization: Billing Metrics

Query Tiers

Each query within the Resource Optimization Snowflake Quickstarts will have a tier designation just to the right of its name as "(T*)". The following tier descriptions should help to better understand those designations.

Tier 1 Queries

At its core, Tier 1 queries are essential to Resource Optimization at Snowflake and should be used by each customer to help with their consumption monitoring - regardless of size, industry, location, etc.

Tier 2 Queries

Tier 2 queries, while still playing a vital role in the process, offer an extra level of depth around Resource Optimization and while they may not be essential to all customers and their workloads, it can offer further explanation as to any additional areas in which over-consumption may be identified.

Tier 3 Queries

Finally, Tier 3 queries are designed to be used by customers that are looking to leave no stone unturned when it comes to optimizing their consumption of Snowflake. While these queries are still very helpful in this process, they are not as critical as the queries in Tier 1 & 2.

Data Ingest with Snowpipe and "Copy" (T1)

TIER 1

Description:

This query returns an aggregated daily summary of all loads for each table in Snowflake showing average file size, total rows, total volume and the ingest method (copy or snowpipe)

How to Interpret Results:

With this high-level information you can determine if file sizes are too small or too big for optimal ingest. If you can map the volume to credit consumption you can determine which tables are consuming more credits per TB loaded.

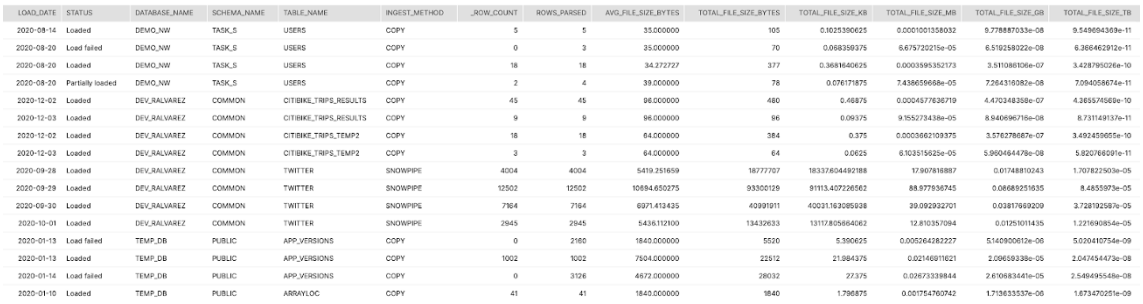
Primary Schema:

Account_Usage

SQL

```
SELECT
  TO_DATE(LAST_LOAD_TIME) as LOAD_DATE
  ,STATUS
  ,TABLE_CATALOG_NAME as DATABASE_NAME
  ,TABLE_SCHEMA_NAME as SCHEMA_NAME
  ,TABLE_NAME
  ,CASE WHEN PIPE_NAME IS NULL THEN 'COPY' ELSE 'SNOWPIPE' END AS INGEST_METHOD
  ,SUM(ROW_COUNT) as ROW_COUNT
  ,SUM(ROW_PARSED) as ROWS_PARSED
  ,AVG(FILE_SIZE) as AVG_FILE_SIZE_BYTES
  ,SUM(FILE_SIZE) as TOTAL_FILE_SIZE_BYTES
  ,SUM(FILE_SIZE)/POWER(1024,1) as TOTAL_FILE_SIZE_KB
  ,SUM(FILE_SIZE)/POWER(1024,2) as TOTAL_FILE_SIZE_MB
  ,SUM(FILE_SIZE)/POWER(1024,3) as TOTAL_FILE_SIZE_GB
  ,SUM(FILE_SIZE)/POWER(1024,4) as TOTAL_FILE_SIZE_TB
FROM "SNOWFLAKE"."ACCOUNT_USAGE"."COPY_HISTORY"
GROUP BY 1,2,3,4,5,6
ORDER BY 3,4,5,1,2
;
```

Screenshot



LOAD_DATE	STATUS	DATABASE_NAME	SCHEMA_NAME	TABLE_NAME	INGEST_METHOD	ROW_COUNT	ROWS_PARSED	AVG_FILE_SIZE_BYTES	TOTAL_FILE_SIZE_BYTES	TOTAL_FILE_SIZE_KB	TOTAL_FILE_SIZE_MB	TOTAL_FILE_SIZE_GB	TOTAL_FILE_SIZE_TB
2020-08-14	Loaded	DEMO_NW	TASK_S	USERS	COPY	5	5	35.000000	105	0.10253906	0.0001001358032	9.778887033e-08	9.549694369e-11
2020-08-20	Load failed	DEMO_NW	TASK_S	USERS	COPY	0	3	35.000000	70	0.068359375	6.675722215e-05	6.519258022e-08	6.366462912e-11
2020-08-20	Loaded	DEMO_NW	TASK_S	USERS	COPY	18	18	34.272727	377	0.3681640625	0.0003595352173	3.511086106e-07	3.428795026e-10
2020-08-20	Partially loaded	DEMO_NW	TASK_S	USERS	COPY	2	4	39.000000	78	0.07617187	7.438659668e-05	7.264316082e-08	7.094058674e-11
2020-12-02	Loaded	DEV_RALVAREZ	COMMON	CITIBIKE_TRIPS_RESULTS	COPY	45	45	96.000000	480	0.46875	0.0004577636719	4.470348358e-07	4.365574569e-10
2020-12-03	Loaded	DEV_RALVAREZ	COMMON	CITIBIKE_TRIPS_RESULTS	COPY	9	9	96.000000	96	0.09375	9.155273438e-05	8.940696716e-08	8.731149137e-11
2020-12-02	Loaded	DEV_RALVAREZ	COMMON	CITIBIKE_TRIPS_TEMP2	COPY	18	18	64.000000	384	0.375	0.0003662109375	3.576278687e-07	3.492459655e-10
2020-12-03	Loaded	DEV_RALVAREZ	COMMON	CITIBIKE_TRIPS_TEMP2	COPY	3	3	64.000000	64	0.0625	6.103515625e-05	5.960464478e-08	5.820766091e-11
2020-09-28	Loaded	DEV_RALVAREZ	COMMON	TWITTER	SNOWPIPE	4004	4004	5419.251659	18777707	18337.604492188	17.907816887	0.01748810243	1.707822503e-05
2020-09-29	Loaded	DEV_RALVAREZ	COMMON	TWITTER	SNOWPIPE	12502	12502	10694.650275	93300129	91113.407226562	88.977836745	0.08689251635	8.4855973e-05
2020-09-30	Loaded	DEV_RALVAREZ	COMMON	TWITTER	SNOWPIPE	7164	7164	6971.412435	40991911	40031.163085938	39.092932701	0.03817699209	3.728192587e-05
2020-10-01	Loaded	DEV_RALVAREZ	COMMON	TWITTER	SNOWPIPE	2945	2945	5436.112100	13432633	13117.805664062	12.810357094	0.01251011435	1.221690854e-05
2020-01-13	Load failed	TEMP_DB	PUBLIC	APP_VERSIONS	COPY	0	2160	1840.000000	5520	5.390625	0.005264282227	5.140900612e-06	5.020410754e-09
2020-01-13	Loaded	TEMP_DB	PUBLIC	APP_VERSIONS	COPY	1002	1002	7504.000000	22512	21.984375	0.02146911621	2.09659338e-05	2.047494473e-08
2020-01-14	Load failed	TEMP_DB	PUBLIC	APP_VERSIONS	COPY	0	3126	4672.000000	28032	27.375	0.02673339844	2.610683441e-05	2.548695548e-08
2020-01-10	Loaded	TEMP_DB	PUBLIC	ARRAYLOC	COPY	41	41	1840.000000	1840	1.796875	0.001754760742	1.713633537e-06	1.673470251e-09

Scale Up vs. Out (Size vs. Multi-cluster) (T2)

TIER 2

Description:

Two separate queries that list out the warehouses and times that could benefit from either a MCW setting OR scaling up to a larger size

How to Interpret Results:

Use this list to determine reconfiguration of a warehouse and the times or users that are causing contention on the warehouse

Primary Schema:

Account_Usage

SQL

```
--LIST OF WAREHOUSES AND DAYS WHERE MCW COULD HAVE HELPED
SELECT TO_DATE(START_TIME) as DATE
,WAREHOUSE_NAME
,SUM(AVG_RUNNING) AS SUM_RUNNING
,SUM(AVG_QUEUED_LOAD) AS SUM_QUEUED
FROM "SNOWFLAKE"."ACCOUNT_USAGE"."WAREHOUSE_LOAD_HISTORY"
WHERE TO_DATE(START_TIME) >= DATEADD(month,-1,CURRENT_TIMESTAMP())
GROUP BY 1,2
HAVING SUM(AVG_QUEUED_LOAD) >0
;

--LIST OF WAREHOUSES AND QUERIES WHERE A LARGER WAREHOUSE WOULD HAVE HELPED WITH
REMOTE SPILLING
SELECT QUERY_ID
,USER_NAME
,WAREHOUSE_NAME
,WAREHOUSE_SIZE
,BYTES_SCANNED
,BYTES_SPILLED_TO_REMOTE_STORAGE
,BYTES_SPILLED_TO_REMOTE_STORAGE / BYTES_SCANNED AS SPILLING_READ_RATIO
FROM "SNOWFLAKE"."ACCOUNT_USAGE"."QUERY_HISTORY"
WHERE BYTES_SPILLED_TO_REMOTE_STORAGE > BYTES_SCANNED * 5  -- Each byte read was
spilled 5x on average
ORDER BY SPILLING_READ_RATIO DESC
;
```

Screenshot

DATE	WAREHOUSE_NAME	SUM_RUNNING	SUM_QUEUED
2020-10-10	SGURSOY_MCW_CLUSTER	23.134146666	71.554796667
2020-10-06	DGARDNER_MCW_CLUSTER	30.532923333	108.237089999
2020-10-27	AP_WAREHOUSE	4.105586666	0.328790000
2020-10-06	VLAD	12.718840002	4.664140001

Warehouse Cache Usage (T3)

TIER 3

Description:

Aggregate across all queries broken out by warehouses showing the percentage of data scanned from the warehouse cache.

How to Interpret Results:

Look for warehouses that are used from querying/reporting and have a low percentage. This indicates that the warehouse is suspending too quickly

Primary Schema:

Account_Usage

SQL

```
SELECT WAREHOUSE_NAME
,COUNT(*) AS QUERY_COUNT
,SUM(BYTES_SCANNED) AS BYTES_SCANNED
,SUM(BYTES_SCANNED*PERCENTAGE_SCANNED_FROM_CACHE) AS BYTES_SCANNED_FROM_CACHE
,SUM(BYTES_SCANNED*PERCENTAGE_SCANNED_FROM_CACHE) / SUM(BYTES_SCANNED) AS
PERCENT_SCANNED_FROM_CACHE
FROM "SNOWFLAKE"."ACCOUNT_USAGE"."QUERY_HISTORY"
WHERE START_TIME >= dateadd(month,-1,current_timestamp())
AND BYTES_SCANNED > 0
GROUP BY 1
ORDER BY 5
;
```

Screenshot

WAREHOUSE_NAME	QUERY_COUNT	BYTES_SCANNED	BYTES_SCANNED_FROM_CACHE	PERCENT_SCANNED_FROM_CACHE
ADMIN_WH	2	3656736768	0	0
MRAINEY_WH	8	4075008	0	0
DEMO_WH	1	237568	0	0
SKUMAR_WH	2	115639296	1536	1.328268204e-05
SCWH	3	4732139520	2174976	0.0004596178939
REF_ER_WH	25	676613120	1774080	0.00262200059
MPROCTOR_XS_WH	8	10470936656	83157504	0.007941744538
ADHOC	60	5188376544	79983072	0.01541581867
MHENSON_WH	221	353100925440	6399581184	0.01812394339

Heavy Scanners (T3)

TIER 3

Description:

Ordered list of users that run queries that scan a lot of data.

How to Interpret Results:

This is a potential opportunity to train the user or enable clustering.

Primary Schema:

Account_Usage

SQL

```
select
  User_name
, warehouse_name
, avg(case when partitions_total > 0 then partitions_scanned / partitions_total else 0
end) avg_pct_scanned
from   snowflake.account_usage.query_history
where  start_time::date > dateadd('days', -45, current_date)
group by 1, 2
order by 3 desc
;
```

Full Table Scans by User (T3)

TIER 3

Description:

These queries are the list of users that run the most queries with near full table scans and then the list of the queries themselves.

How to Interpret Results:

This is a potential opportunity to train the user or enable clustering.

Primary Schema:

Account_Usage

SQL

```
--who are the users with the most (near) full table scans
SELECT USER_NAME
,COUNT(*) as COUNT_OF_QUERIES
FROM "SNOWFLAKE"."ACCOUNT_USAGE"."QUERY_HISTORY"
WHERE START_TIME >= dateadd(month,-1,current_timestamp())
AND PARTITIONS_SCANNED > (PARTITIONS_TOTAL*0.95)
AND QUERY_TYPE NOT LIKE 'CREATE%'
group by 1
order by 2 desc;

-- This gives all queries in the last month with nearly a full table scan :) > 95%,
ordered by the worst offending
SELECT *
FROM "SNOWFLAKE"."ACCOUNT_USAGE"."QUERY_HISTORY"
WHERE START_TIME >= dateadd(month,-1,current_timestamp())
AND PARTITIONS_SCANNED > (PARTITIONS_TOTAL*0.95)
AND QUERY_TYPE NOT LIKE 'CREATE%'
ORDER BY PARTITIONS_SCANNED DESC
LIMIT 50  -- Configurable threshold that defines "TOP N=50"
;
```

Top 10 Spillers Remote (T3)

TIER 3

Description:

Identifies the top 10 worst offending queries in terms of bytes spilled to remote storage.

How to Interpret Results:

These queries should most likely be run on larger warehouses that have more local storage and memory.

Primary Schema:

Account_Usage

SQL

```
select query_id, substr(query_text, 1, 50) partial_query_text, user_name,
warehouse_name, warehouse_size,
       BYTES_SPILLED_TO_REMOTE_STORAGE, start_time, end_time, total_elapsed_time/1000
total_elapsed_time
from   snowflake.account_usage.query_history
where  BYTES_SPILLED_TO_REMOTE_STORAGE > 0
and start_time::date > dateadd('days', -45, current_date)
order  by BYTES_SPILLED_TO_REMOTE_STORAGE desc
limit 10
;
```

AutoClustering History & 7-Day Average (T3)

TIER 3

Description:

Average daily credits consumed by Auto-Clustering grouped by week over the last year.

How to Interpret Results:

Look for anomalies in the daily average over the course of the year. Opportunity to investigate the spikes or changes in consumption.

Primary Schema:

Account_Usage

SQL

```
WITH CREDITS_BY_DAY AS (
SELECT TO_DATE(START_TIME) as DATE
,SUM(CREDITS_USED) as CREDITS_USED


FROM "SNOWFLAKE"."ACCOUNT_USAGE"."AUTOMATIC_CLUSTERING_HISTORY"

WHERE START_TIME >= dateadd(year,-1,current_timestamp())
GROUP BY 1
ORDER BY 2 DESC
  )

SELECT DATE_TRUNC('week',DATE)
```

```
,AVG(CREDITS_USED) as AVG_DAILY_CREDITS
FROM CREDITS_BY_DAY
GROUP BY 1
ORDER BY 1
;
```

Materialized Views History & 7-Day Average (T3)

TIER 3

Description:

Average daily credits consumed by Materialized Views grouped by week over the last year.

How to Interpret Results:

Look for anomalies in the daily average over the course of the year. Opportunity to investigate the spikes or changes in consumption.

Primary Schema:

Account_Usage

SQL

```
WITH CREDITS_BY_DAY AS (
SELECT TO_DATE(START_TIME) as DATE
,SUM(CREDITS_USED) as CREDITS_USED


FROM "SNOWFLAKE"."ACCOUNT_USAGE"."MATERIALIZED_VIEW_REFRESH_HISTORY"

WHERE START_TIME >= dateadd(year,-1,current_timestamp())
GROUP BY 1
ORDER BY 2 DESC
  )

SELECT DATE_TRUNC('week',DATE)
,AVG(CREDITS_USED) as AVG_DAILY_CREDITS
FROM CREDITS_BY_DAY
GROUP BY 1
ORDER BY 1
;
```

Search Optimization History & 7-Day Average (T3)

TIER 3

Description:

Average daily credits consumed by Search Optimization grouped by week over the last year.

How to Interpret Results:

Look for anomalies in the daily average over the course of the year. Opportunity to investigate the spikes or changes in consumption.

Primary Schema:

Account_Usage

SQL

```
WITH CREDITS_BY_DAY AS (
SELECT TO_DATE(START_TIME) as DATE
,SUM(CREDITS_USED) as CREDITS_USED


FROM "SNOWFLAKE"."ACCOUNT_USAGE"."SEARCH_OPTIMIZATION_HISTORY"

WHERE START_TIME >= dateadd(year,-1,current_timestamp())
GROUP BY 1
ORDER BY 2 DESC
  )

SELECT DATE_TRUNC('week',DATE)
,AVG(CREDITS_USED) as AVG_DAILY_CREDITS
FROM CREDITS_BY_DAY
GROUP BY 1
ORDER BY 1
;
```

Snowpipe History & 7-Day Average (T3)

TIER 3

Description:

Average daily credits consumed by Snowpipe grouped by week over the last year.

How to Interpret Results:

Look for anomalies in the daily average over the course of the year. Opportunity to investigate the spikes or changes in consumption.

Primary Schema:

Account_Usage

SQL

```
WITH CREDITS_BY_DAY AS (
SELECT TO_DATE(START_TIME) as DATE
,SUM(CREDITS_USED) as CREDITS_USED


FROM "SNOWFLAKE"."ACCOUNT_USAGE"."PIPE_USAGE_HISTORY"

WHERE START_TIME >= dateadd(year,-1,current_timestamp())
GROUP BY 1
ORDER BY 2 DESC
  )
```

```
SELECT DATE_TRUNC('week',DATE)
,AVG(CREDITS_USED) as AVG_DAILY_CREDITS
FROM CREDITS_BY_DAY
GROUP BY 1
ORDER BY 1
;
```

Replication History & 7-Day Average (T3)

TIER 3

Description:

Average daily credits consumed by Replication grouped by week over the last year.

How to Interpret Results:

Look for anomalies in the daily average over the course of the year. Opportunity to investigate the spikes or changes in consumption.

Primary Schema:

Account_Usage

SQL

```
WITH CREDITS_BY_DAY AS (
SELECT TO_DATE(START_TIME) as DATE
,SUM(CREDITS_USED) as CREDITS_USED


FROM "SNOWFLAKE"."ACCOUNT_USAGE"."REPLICATION_USAGE_HISTORY"

WHERE START_TIME >= dateadd(year,-1,current_timestamp())
GROUP BY 1
ORDER BY 2 DESC
  )

SELECT DATE_TRUNC('week',DATE)
,AVG(CREDITS_USED) as AVG_DAILY_CREDITS
FROM CREDITS_BY_DAY
GROUP BY 1
ORDER BY 1
;
```

Getting Started With Snowflake SQL API

Overview

Welcome! The Snowflake SQL API is a REST API that you can use to access and update data in a Snowflake database. You can use this API to execute [standard queries] and most [DDL] and [DML] statements.

This getting started guide will walk you through executing a SQL statement with the API and retrieving the results.

Prerequisites

- A familiarity with Snowflake
- A familiarity with SQL

What You'll Learn

- Perform simple queries
- Manage your deployment (e.g., provision users and roles, create tables, etc.)
- Submit one SQL statement for execution per API call.
- Check the status of the execution of a statement.
- Cancel the execution of a statement.

What You'll Need

- A Snowflake Account with an accessible warehouse, database, schema, and role
- SnowSQL 1.2.17 or higher
- Working Key-Pair authentication

What You'll Build

- An execution of a statement using the Snowflake SQL API

Introducing the API

Head to the SQL API by navigating to your version of the following URL, replacing `*account_locator*` with the account locator for your own Snowflake account:

```
https://*account_locator*.snowflakecomputing.com/api/v2
```

Negative : Note that the account locator might include additional segments for your region and cloud provider. See [Specifying Region Information in Your Account Hostname] for details.

Now let's break down the parts of the API before we begin using it. The API consists of the `/api/v2/statements/` resource and provides the following endpoints:

- `/api/v2/statements` : You'll use this endpoint to [submit a SQL statement for execution].
- `/api/v2/statements/*statementHandle*` : You'll use this endpoint to [check the status of the execution of a statement].
- `/api/v2/statements/*statementHandle*/cancel` : You'll use this endpoint to [cancel the execution of a statement].

In the steps to come, you shall use all these endpoints to familiarize yourself with the API.

Positive : You can use development tools and libraries for REST APIs (e.g., Postman) to send requests and handle responses.

Limitations of the SQL API

It's important to be aware of the [limitations that the SQL API] currently has. In particular noting that `GET` and `PUT` are not supported.

Assigning a Unique Request ID for Resubmitting Requests

In some cases, it might not be clear if Snowflake executed the SQL statement in an API request (e.g., due to a network error or a timeout). You might choose to resubmit the same request to Snowflake again in case Snowflake did not execute the statement.

If Snowflake already executed the statement in the initial request and you resubmit the request again, the statement is executed twice. For some types of requests, repeatedly executing the same statement can have unintended consequences (e.g., inserting duplicate data into a table).

To prevent Snowflake from executing the same statement twice when you resubmit a request, you can use a request ID to distinguish your request from other requests. Suppose you specify the same request ID in the initial request and in the resubmitted request. In that case, Snowflake does not execute the statement again if the statement has already executed successfully.

To specify a request ID, generate a universally unique identifier (UUID) and include this identifier in the `requestId` query parameter:

```
POST /api/v2/statements?requestId=<UUID> HTTP/1.1
```

If Snowflake fails to process a request, you can submit the same request again with the same request ID. Using the same request ID indicates to the server that you are submitting the same request again.

Now let's move on to additional information you need to include in requests: authentication parameters.

Authenticating to the Server

When you send a request, the request must include authentication information. There are two options for providing authentication: OAuth and JWT key pair authentication. You can use whichever one you have previously implemented or whichever one you are most comfortable with. This example will be detailing authentication with JWT.

If you haven't done so already, make sure you have [key pair authentication] working with Snowflake already.

You can test to make sure you can successfully connect to Snowflake Key Pairs using the following command:

```
$ snowsql -a <account> -u <user> --private-key-path <path to private key>
```

After you've verified you can connect to Snowflake using key-pair authentication, you'll need to generate a JWT token. This JWT token is time limited token which has been signed with your key and Snowflake will know that you authorized this token to be used to authenticate as you for the SQL API.

```
$ snowsql -a <account> -u <user> --private-key-path <path to private key> --generate-
jwt
<returns JWT token>
```

You'll need the JWT token generated to be used for using the SQL API. The following headers need be set in each API request that you send within your application code:

- `Authorization: Bearer *jwt_token*` where `*jwt_token*` is the generated JWT token from SnowSQL

- `X-Snowflake-Authorization-Token-Type: KEYPAIR_JWT`

Altogether, your request query and header will take the following form:

```
POST /api/v2/statements?requestId=<UUID> HTTP/1.1
Authorization: Bearer <jwt_token>
Content-Type: application/json
Accept: application/json
User-Agent: myApplication/1.0
X-Snowflake-Authorization-Token-Type: KEYPAIR_JWT
```

Now that you have been introduced to authentication and unique request IDs, you can now move to actually making a request to execute a SQL statement.

Submitting a Request to Execute a SQL Statement

To submit a SQL statement for execution, send a [POST request to the /api/v2/statements/ endpoint]:

```
POST /api/v2/statements?requestId=<UUID> HTTP/1.1
Authorization: Bearer <jwt_token>
Content-Type: application/json
Accept: application/json
User-Agent: myApplication/1.0
X-Snowflake-Authorization-Token-Type: KEYPAIR_JWT

(request body)
```

In the request URL, you can also set query parameters to:

- Execute the statement asynchronously: `async=true`

For the [body of the request], set the following fields:

- Set the `statement` field to the SQL statement that you want to execute.
- To specify the warehouse, database, schema, and role to use, set the `warehouse`, `database`, `schema`, and `role` fields.

Negative : Note: the values in these fields are case-sensitive.

- To set a timeout for the statement execution, set the `timeout` field to the maximum number of seconds to wait. If the `timeout` field is not set, the timeout specified by the [STATEMENT_TIMEOUT_IN_SECONDS] parameter is used.

```
POST /api/v2/statements HTTP/1.1
Authorization: Bearer <jwt_token>
Content-Type: application/json
Accept: application/json
User-Agent: myApplication/1.0
X-Snowflake-Authorization-Token-Type: KEYPAIR_JWT

{
"statement": "select * from T",
```

```
"timeout": 60,
"database": "<your_database>",
"schema": "<your_schema>",
"warehouse": "<your_warehouse>",
"role": "<your_role>"
}
```

Let's go over some specific fields in this request:

- The `statement` field specifies the SQL statement to execute.
- The `timeout` field specifies that the server allows 60 seconds for the statement to be executed.

If the statement was executed successfully, Snowflake returns the HTTP response code 200 and the first results in a [ResultSet] object. We'll go over how to check the status and retrieve the results after we look at including bind variables.

Now we'll look at how you can include bind variables (`?` placeholders) in the statement and set the `bindings` field to an object that specifies the corresponding Snowflake data types and values for each variable.

Using Bind Variables in a Statement

If you want to use bind variables (`?` placeholders) in the statement, use the `bindings` field to specify the values that should be inserted.

Set this field to a JSON object that specifies the [Snowflake data type] and value for each bind variable.

```
...
"statement": "select * from T where c1=?",
...
"bindings": {
"1": {
"type": "FIXED",
"value": "123"
}
},
...
```

Choose the binding type that corresponds to the type of the value that you are binding. For example, if the value is a string representing a date (e.g. `2021-04-15`) and you want to insert the value into a DATE column, use the `TEXT` binding type.

The following table specifies the values of the `type` field that you can use to bind to different [Snowflake data types] for this preview release.

- The first column on the left specifies the binding types that you can use.
- The rest of the columns specify the Snowflake data type of the column where you plan to insert the data.
- Each cell specifies the type of value that you can use with a binding type to insert data into a column of a particular Snowflake data type.

Negative : If the cell for a binding type and Snowflake data type is empty, you cannot use the specified binding type to insert data into a column of that Snowflake data type.

Binding types supported for different Snowflake data types¶

Snowflake Data Types	INT / NUMBER	FLOAT	VARCHAR	BINARY	BOOLEAN	DATE	TIME	TIMESTAMP_TZ	TIMESTAMP_LTZ	TIMESTAMP_NTZ
Binding Types										
FIXED	integer	integer	integer		0 (false) / nonzero (true)					
REAL	integer	int or float	int or float		0/non-0					
TEXT	integer	int or float	any text	hexdec	`"true"` / `"false"`	see notes below	see notes below	see notes below	see notes below	see notes below
BINARY			hexdec							
BOOLEAN			true/false, 0/1		true/false					
DATE			epoch (ms)			epoch (ms)		epoch (ms)	epoch (ms)	epoch (ms)
TIME			epoch (nano)				epoch (nano)			
TIMESTAMP_TZ			epoch (nano)			epoch (nano)	epoch (nano)	epoch (nano)		
TIMESTAMP_LTZ			epoch (nano)			epoch (nano)	epoch (nano)	epoch (nano)	epoch (nano)	epoch (nano)
TIMESTAMP_NTZ			epoch (nano)			epoch (nano)	epoch (nano)	epoch (nano)	epoch (nano)	epoch (nano)

For additional information on binding specific data types, see the documentation's section on [Using Bind Variables in a Statement]

If the value is in a format not supported by Snowflake, the API returns an error:

```
{
code: "100037",
message: "<bind type> value '<value>' is not recognized",
sqlState: "22018",
statementHandle: "<ID>"
}
```

Whether you use bind variables or not, you'll want to check the status of your statements. Let's look at that next.

Checking the Status of the Execution of the Statement

When you submit a SQL statement for execution, Snowflake returns a 202 response code if the execution of the statement has not yet been completed or if you submitted an asynchronous query.

In the body of the response, Snowflake includes a [QueryStatus] object. The `statementStatusUrl` field in this object specifies the URL to the [/api/v2/statements/ endpoint] that you can use to check the execution status:

```
{
"code": "090001",
"sqlState": "00000",
"message": "successfully executed",
"statementHandle": "e4ce975e-f7ff-4b5e-b15e-bf25f59371ae",
"statementStatusUrl": "/api/v2/statements/e4ce975e-f7ff-4b5e-b15e-bf25f59371ae"
}
```

As illustrated by the URL above, in requests to check the status of a statement and cancel the execution of a statement, you specify the statement handle (a unique identifier for the statement) as a path parameter in order to identify the statement to use.

Note that the `QueryStatus` object also provides the statement handle as a separate value in the `statementHandle` field.

To check the status of the execution of the statement, send a GET request using this URL:

```
GET /api/v2/statements/{statementHandle}
```

For example, the following request checks the execution status of the statement with the handle `e4ce975e-f7ff-4b5e-b15e-bf25f59371ae`:

```
GET /api/v2/statements/e4ce975e-f7ff-4b5e-b15e-bf25f59371ae HTTP/1.1
Authorization: Bearer <jwt_token>
Content-Type: application/json
Accept: application/json
User-Agent: myApplication/1.0
X-Snowflake-Authorization-Token-Type: KEYPAIR_JWT
```

If the statement has finished executing successfully, Snowflake returns the HTTP response code 200 and the first results in a [ResultSet] object. However, if an error occurred when executing the statement, Snowflake returns the HTTP response code 422 with a [QueryFailureStatus] object.

Once the statement has executed successfully, you can then retrieve the results, detailed in the next step.

Cancelling the Execution of a SQL Statement

To cancel the execution of a statement, send a POST request to the [cancel endpoint].

```
POST /api/v2/statements/{statementHandle}/cancel
```

Retrieving the Results

If you [submit a SQL statement for execution] or [check the status of statement execution], Snowflake returns a [ResultSet] object in the body of the response if the statement was executed successfully.

The following is an example of a `ResultSet` object that is returned for a query, truncated for brevity.

```
{
  "code" : "090001",
  "statementStatusUrl" : "/api/v2/statements/01a288b9-0603-af68-0000-328502422e7e?
requestId=f8ccd534-7cd5-4c06-b673-f25361e96d7f",
  "requestId" : "f8ccd534-7cd5-4c06-b673-f25361e96d7f",
  "sqlState" : "00000",
  "statementHandle" : "01a288b9-0603-af68-0000-328502422e7e",
  "message" : "Statement executed successfully.",
  "createdOn" : 1645742998434,
  "resultSetMetaData" : {
    "rowType" : [ {
      "name" : "HIGH_NDV_COLUMN",
      "database" : "",
      "schema" : "",
      "table" : "",
      "type" : "fixed",
      "scale" : 0,
      "precision" : 19,
      "byteLength" : null,
      "nullable" : false,
```

```
      "collation" : null,
      "length" : null
    }, {
      "name" : "LOW_NDV_COLUMN",
      "database" : "",
      "schema" : "",
      "table" : "",
      "type" : "fixed",
      "scale" : 0,
      "precision" : 2,
      "byteLength" : null,
      "nullable" : false,
      "collation" : null,
      "length" : null
    }, {
      "name" : "CONSTANT_COLUM",
      "database" : "",
      "schema" : "",
      "table" : "",
      "type" : "fixed",
      "scale" : 0,
      "precision" : 1,
      "byteLength" : null,
      "nullable" : false,
      "collation" : null,
      "length" : null
    } ],
    "numRows" : 100000000,
    "format" : "jsonv2",
    "partitionInfo" : [ {
      "rowCount" : 8192,
      "uncompressedSize" : 152879,
      "compressedSize" : 22412
    }, {
      "rowCount" : 53248,
      "uncompressedSize" : 1048161,
      "compressedSize" : 151251
    }, {
      "rowCount" : 86016,
      "uncompressedSize" : 1720329,
      "compressedSize" : 249447
    }, {
```


Notice that there is an `ARRAY` of `partitionInfo` objects. These partitions objects give you some information, such as rowCount and size, about the partitions that are available for retrieval. The API returns the data data inline in JSON of the first partition, or partition `0` with the response and we'll cover how to retrieve subsequent partitions in a later section.

Getting Metadata About the Result

It also includes, in the response the `rowType` which gives additional metadata about the datatypes and names of data returned from the query. This metadata is only included in the initial response, and no metadata is returned when retrieving subsequent partitions.

In the `ResultSet` object returned in the response, the `resultSetMetaData` field contains a [`ResultSet_resultSetMetaData`] object that describes the result set (for example, the format of the results, etc.).

In this object, the `rowType` field contains an array of [ResultSet_resultSetMetaData_rowType] objects. Each object describes a column in the results. The `type` field specifies the Snowflake data type of the column.

```
{
"resultSetMetaData": {
"rowType": [
{
"name":"ROWNUM",
"type":"FIXED",
"length":0,
"precision":38,
"scale":0,
"nullable":false
}, {
"name":"ACCOUNT_NAME",
"type":"TEXT",
"length":1024,
"precision":0,
"scale":0,
"nullable":false
}, {
"name":"ADDRESS",
"type":"TEXT",
"length":16777216,
"precision":0,
"scale":0,
"nullable":true
}, {
"name":"ZIP",
"type":"TEXT",
"length":100,
"precision":0,
"scale":0,
"nullable":true
}, {
"name":"CREATED_ON",
"type":"TIMESTAMP_NTZ",
"length":0,
"precision":0,
"scale":3,
"nullable":false
}
]
},
}
```

Retrieving Result Partitions

Partitions are [retrieved] using the `partition=n` query parameter at `/api/v2/statements/<handle>?partition=<partition_number>` endpoint. This can be used to iterate, or even retrieve in parallel, the results from the SQL API call.

```
GET /api/v2/statements/e4ce975e-f7ff-4b5e-b15e-bf25f59371ae?partition=1 HTTP/1.1
Authorization: Bearer <jwt_token>
Content-Type: application/json
Accept: application/json
User-Agent: myApplication/1.0
X-Snowflake-Authorization-Token-Type: KEYPAIR_JWT
```

The above query call, with `partition=1` returns just the data below. Notice that the `data` object does not contain any of the additional metadata about the result. Only the data, in gzipped format that needs to be uncompressed.

```
{"data": [
["32768","3","5"],
["32772","4","5"],
["32776","3","5"],
["32780","3","5"],
["32784","2","5"],
....
]}
```

Each array within the array contains the data for a row:

- The first element in each array is a JSON string containing a sequence ID that starts from 0.
- The rest of the elements in each array represent the data in a row.

The data in the result set is encoded in JSON v1.0, which means that all data is expressed as strings, regardless of the Snowflake data type of the column.

For example, the value `1.0` in a `NUMBER` column is returned as the string `" 1.0"`. As another example, timestamps are returned as the number of nanoseconds since the epoch. For example, the timestamp for Thursday, January 28, 2021 10:09:37.123456789 PM is returned as `"1611871777123456789"`.

You are responsible for converting the strings to the appropriate data types.

Helpful URLs to iterate and retrieve partitions

Since your results may contain significant number of partitions, the Snowflake SQL API provides a special header, `Link`, which assists in helping clients traverse and retrieve those results.

To get the next parition of results or other partitions, use the URLs provided in the [Link header] in the HTTP response. The `Link` header specifies the URLs for retrieving the first, next, previous, and last partitions of results:

```
HTTP/1.1 200 OK
Link: </api/v2/statements/01a288b9-0603-af68-0000-328502422e7e?requestId=918e2211-
d1d6-4c53-bec3-457d047651f7&partition=0>; rel="first"
,</api/v2/statements/01a288b9-0603-af68-0000-328502422e7e?requestId=51ad0c0a-e514-
4d8a-9cf2-cf537d439e39&partition=1>; rel="next"
,</api/v2/statements/01a288b9-0603-af68-0000-328502422e7e?requestId=c6a17bb3-7593-
489d-bbac-5e3b268bc6da&partition=47>; rel="last"
...
```

Getting Started with Snowpark Python

Overview

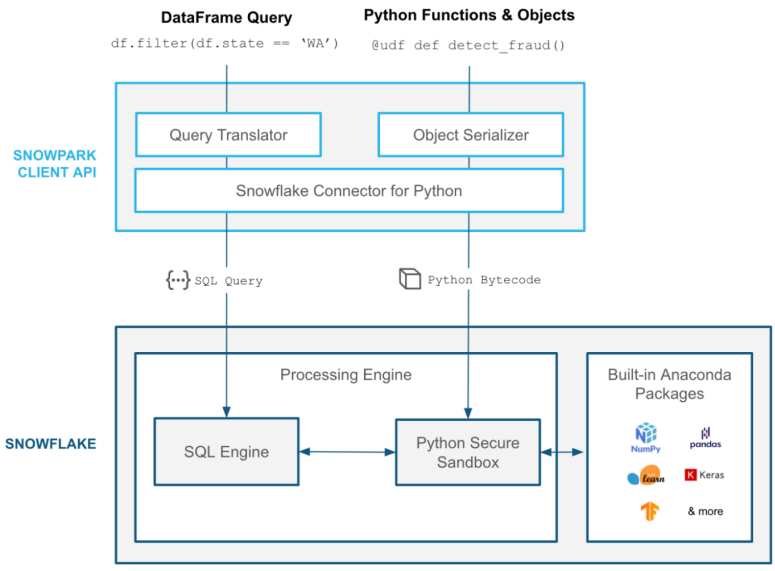
Python is the language of choice for Data Science and Machine Learning workloads. Snowflake has long supported Python via the Python Connector, allowing data scientists to interact with data stored in Snowflake from their preferred Python environment. This did, however, require data scientists to write verbose SQL queries. To provide a more friendly, expressive, and extensible interface to Snowflake, we built **Snowpark Python**, a native Python experience with a pandas and PySpark-like API for data manipulation. This includes a client-side API to allow users to write Python code in a Spark-like API without the need to write verbose SQL. Python UDF and Stored Procedure support also provides more general additional capabilities for compute pushdown.

Snowpark includes client-side APIs and server-side runtimes that extends Snowflake to popular programming languages including Scala, Java, and Python. Ultimately, this offering provides a richer set of tools for Snowflake users (e.g. Python's extensibility and expressiveness) while still leveraging all of Snowflake's core features, and the underlying power of SQL, and provides a clear path to production for machine learning products and workflows.

A key component of Snowpark for Python is that you can "Bring Your Own IDE"- anywhere that you can run a Python kernel, you can run client-side Snowpark Python. You can use it in your code development the exact same way as any other Python library or module. In this lab, we will be using Jupyter Notebooks, but you could easily replace Jupyter with any IDE of your choosing.

Throughout this lab, we will specifically explore the power of the Snowpark Python Dataframe API, as well as server-side Python runtime capabilities, and how Snowpark Python can enable and accelerate end-to-end Machine Learning workflows.

The source code for this lab is available on GitHub.



What You'll Learn

- How to create a DataFrame that loads data from a stage
- How to perform data and feature engineering using Snowpark DataFrame API
- How to bring a trained ML model into Snowflake as a UDF to score new data

What You'll Need

- A Snowflake Account with [Anaconda Integration enabled by ORGADMIN]
- if you do not already have a Snowflake account, you can register for a free trial account
- A Snowflake login with the `ACCOUNTADMIN` role. If you have this role in your corporate environment, you may choose to use it directly. If not, you will either need to (1) register for a free trial account above, (2) use a different role that has the ability to create and use a database, schema and tables, and UDFs (edit the `config.py` file and Jupyter notebooks to use this alternative role), OR (3) use an existing database and schema in which you can create tables and UDFs (edit the `config.py` file and notebook to use that role, database, and schema). If you're confused, it is best to just sign up for a free Enterprise-level trial account via the link above.
- Python 3.8
- Jupyter Notebook
- Snowpark Python 0.7.0 API (included in the Quickstart GitHub repo)

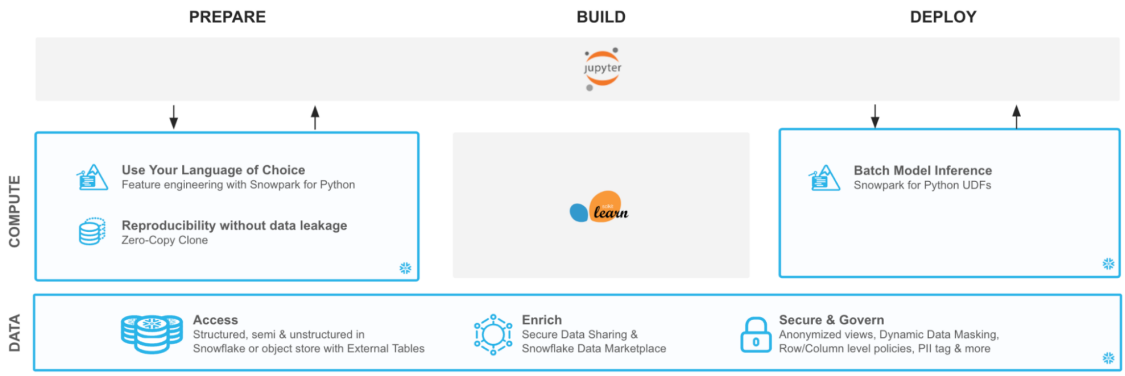
What You'll Build

You will build an end-to-end data science workflow leveraging Snowpark for Python to load, clean and prepare data and then deploy our trained model in Snowflake using Python UDF for inference.

Use-Case: Predicting Customer Churn

You are part of a team of data engineers and data scientists at a Telecom company that has been tasked to reduce customer churn using a machine learning based solution.

To build this, you have access to customer demographic and billing data. Using Snowpark, we will ingest, analyze and transform this data to train a model that will then be deployed inside Snowflake to score new data.



With Snowflake, it is easy to make all relevant data instantly accessible to your machine learning models whether it is for training or inference. For this guide, we are going to do all of our data and feature engineering with Snowpark for Python but users can choose to work with SQL or any of the other Snowpark supported languages including Java and Scala without the need for separate environments.

To streamline your path to production, we will learn how to bring trained models (whether trained inside Snowflake or in an external environment) to run directly inside Snowflake as a UDF bringing models where the data and data pipelines live.

Setup

Let's set up the Python environment necessary to run this lab:

First, clone the source code for this repo to your local environment (you can also download the code here and unzip the files into the location of your choosing in your local environment):

```
git clone git@github.com:fenago/getting-started-snowpark-python.git
cd getting-started-snowpark-python/customer-churn-prediction
```

Snowpark Python via Anaconda

If you are using Anaconda on your local machine, create a conda env for this lab:

```
conda env create -f jupyter_env.yml
conda activate getting_started_snowpark_python
```

Conda will automatically install `snowflake-snowpark-python==0.7.0` and all other dependencies for you.

Once Snowpark is installed, create a kernel for Jupyter:

```
python -m ipykernel install --user --name=getting_started_snowpark_python
```

Now, launch Jupyter Notebook on your local machine:

```
jupyter notebook
```

Open up the `config.py` file in Jupyter and modify with your account, username, and password information:

If your Snowflake URL is https://mycompany-sandpit.snowflakecomputing.com/console/login#/ , your username is `THOMAS` , and the role you will use is `ACCOUNTADMIN` , then you would fill it in like so:

```
snowflake_conn_prop = {

   "account": "mycompany-sandpit",

   "user": "THOMAS",

   "password": "YourPasswordHere",

   "role": "ACCOUNTADMIN",

   "database": "snowpark_quickstart",

   "schema": "TELCO",

   "warehouse": "sp_qs_wh",

}
```

Now, you are ready to get started with the notebooks. For each notebook, make sure that you select the `getting_started_snowpark_python` kernel when running. You can do this by navigating to: `Kernel -> Change Kernel` and selecting `getting_started_snowpark_python` after launching each Notebook.

Load Data Using Snowpark Python Client API

Persona: DBA/Platform Administrator/Data Engineer

What You'll Do:

- Establish the Snowpark Python session
- Create the database, schema, and warehouses needed for the remainder of the lab
- Load raw parquet data into Snowflake using Snowpark Python

Open up the `01-Load-Data-with-Snowpark` Jupyter notebook and run each of the cells to explore loading and transforming data with Snowpark Python.

Analyze Data Using Snowpark Python Dataframe API

Persona: Data Scientist

What You'll Do:

- Understand and analyze the data set
- Perform data and feature discovery

Open up the `02-Data-Analysis` Jupyter notebook and run each of the cells to explore data analysis using Snowpark Python.

Deploy Trained Models using Snowpark Python UDFs

Persona: Data Scientist/ML Engineer

What You'll Do:

- Perform feature selection, model training, and model seelction
- Deploy the model into Snowflake for inference using Snowpark Python UDFs

Open up the `03-Snowpark-UDF-Deployment` Jupyter notebook and run each of the cells to train a model and deploy it for in-Snowflake inference using Snowpark Python UDFs

Conclusion

Through this lab we were able to experience how Snowpark for Python enables you to use familiar syntax and constructs to process data where it lives with Snowflake's elastic, scalable and secure engine, accelerating the path to production for data pipelines and ML workflows. Here's what you were able to complete:

- Load data into a Snowpark DataFrame
- Clean and prepare data using the Snowpark DataFrame API
- Deploy a trained machine learning model in Snowflake as Python UDF

Getting Started with Snowpark and the Dataframe API

Overview

This project will demonstrate how to get started with Jupyter Notebooks on [Snowpark], a new product feature announced by Snowflake for [public preview]during the 2021 Snowflake Summit. With this tutorial you will learn how to tackle real world business problems as straightforward as ELT processing but also as diverse as math with rational numbers with unbounded precision, sentiment analysis and machine learning.

Snowpark not only works with Jupyter Notebooks but with a variety of IDEs. Instructions on how to set up your favorite development environment can be found in the Snowpark documentation under [Setting Up Your Development Environment for Snowpark].

Snowpark

Snowpark is a new developer framework of Snowflake. It brings deeply integrated, DataFrame-style programming to the languages developers like to use, and functions to help you expand more data use cases easily, all executed inside of Snowflake. Snowpark support starts with Scala API, Java UDFs, and External Functions.

With Snowpark, developers can program using a familiar construct like the DataFrame, and bring in complex transformation logic through UDFs, and then execute directly against Snowflake's processing engine, leveraging all of its performance and scalability characteristics in the Data Cloud.

Snowpark provides several benefits over how developers have designed and coded data driven solutions in the past:

1. Simplifies architecture and data pipelines by bringing different data users to the same data platform, and process against the same data without moving it around.

2. Accelerates data pipeline workloads by executing with performance, reliability, and scalability with Snowflake's elastic performance engine.
3. Eliminates maintenance and overhead with managed services and near-zero maintenance.
4. Creates a single governance framework and a single set of policies to maintain by using a single platform.
5. Provides a highly secure environment with administrators having full control over which libraries are allowed to execute inside the Java/Scala runtimes for Snowpark.

The following tutorial highlights these benefits and lets you experience Snowpark in your environment.

Prerequisites:

This repo is structured in multiple parts. Each part has a notebook with specific focus areas. All notebooks in this series require a Jupyter Notebook environment with a Scala kernel.

All notebooks will be fully self contained, meaning that all you need for processing and analyzing datasets is a Snowflake account. If you do not have a Snowflake account, you can sign up for a free trial. It doesn't even require a credit card.

- Use of the Snowflake free 30-day trial environment
- All notebooks in this series require a Jupyter Notebook environment with a Scala kernel.
    - If you do not already have access to that type of environment, Follow the instructions below to either run Jupyter locally or in the AWS cloud.
- Instructions on how to set up your favorite development environment can be found in the Snowpark documentation under [Setting Up Your Development Environment for Snowpark].

What you will learn

- Part 1

  The first notebook in this series provides a quick-start guide and an introduction to the Snowpark DataFrame API. The notebook explains the steps for setting up the environment (REPL), and how to resolve dependencies to Snowpark. After a simple "Hello World" example you will learn about the Snowflake DataFrame API, projections, filters, and joins.

- Part 2

  The second notebook in the series builds on the quick-start of the first part. Using the TPCH dataset in the sample database, it shows how to use aggregations and pivot functions in the Snowpark DataFrame API. Then it introduces UDFs and how to build a stand-alone UDF: a UDF that only uses standard primitives. From there, we will learn how to use third party Scala libraries to perform much more complex tasks like math for numbers with unbounded (unlimited number of significant digits) precision and how to perform sentiment analysis on an arbitrary string.

- Part 3

  The third notebook combines what you learned in part 1 and 2. It implements an end-to-end ML use case including data ingestion, ETL/ELT transformations, model training, model scoring, and result visualization.

Preparing your lab environment

Option 1: Running Jupyter locally

1. Clone the GitHub Lab repo:

```
git clone https://github.com/fenago/snowpark_on_jupyter.git
```

2. Starting your Local Jupyter environment

```
`jupyter lab`

The output should be similar to the following

    To access the server, open this file in a browser:
        file:///home/jovyan/.local/share/jupyter/runtime/jpserver-15-open.html
    Or copy and paste one of these URLs:
        http://162e383e431c:8888/lab?
token=bdaead06c9944057a86f9d8a823cebad4ce66799d855be5d
        http://127.0.0.1:8888/lab?
token=bdaead06c9944057a86f9d8a823cebad4ce66799d855be5d
```

8. Start a browser session (Chrome, ...). Paste the line with the local host address (127.0.0.1) printed in **your shell window** into the browser status bar and update the port (8888) to **your port** in case you have changed the port in the step above.

Positive : Once you have completed this step, you can move on to the Setup Credentials Section.

Setup Credentials

First, we have to set up the Jupyter environment for our notebook. The full instructions for setting up the environment are in the Snowpark documentation [Configure Jupyter].

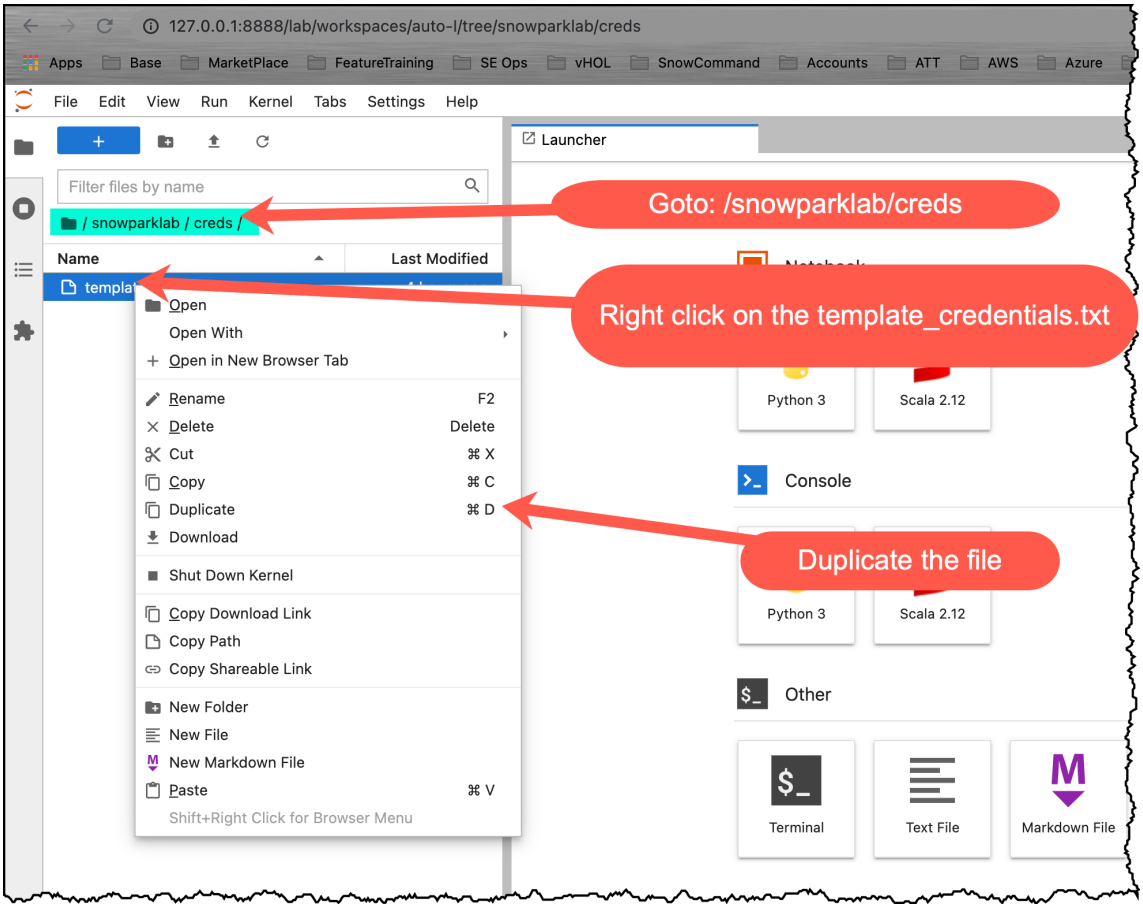
Setup your credentials file

To create a Snowflake session, we need to authenticate to the Snowflake instance. Though it might be tempting to just override the authentication variables with hard coded values in your Jupyter notebook code, it's not considered best practice to do so. If you share your version of the notebook, you might disclose your credentials by mistake to the recipient. Even worse, if you upload your notebook to a public code repository, you might advertise your credentials to the whole world. To prevent that, you should keep your credentials in an external file (like we are doing here).

Then, update your credentials in that file and they will be saved on your local machine. Even better would be to switch from user/password authentication to [private key authentication].

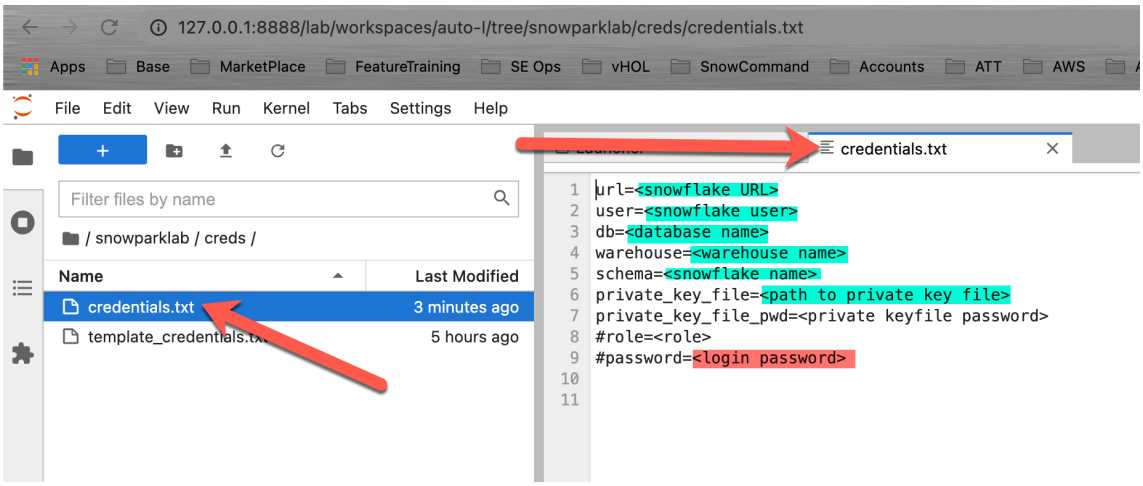
Positive : Put your key pair files into the same directory or update the location in your credentials file.

- Open your Jupyter environment in your web browser
- Navigate to the folder: /snowparklab/creds
- Duplicate the file **template_credentials.txt**



- Rename the duplicated file to **credentials.txt** (right click menu)
- Double click the **credential.txt** file to open and edit it in the Jupyter environment
- Update the file to your Snowflake environment connection parameters

Positive : You can comment out parameters by putting a # at the beginning of the line.

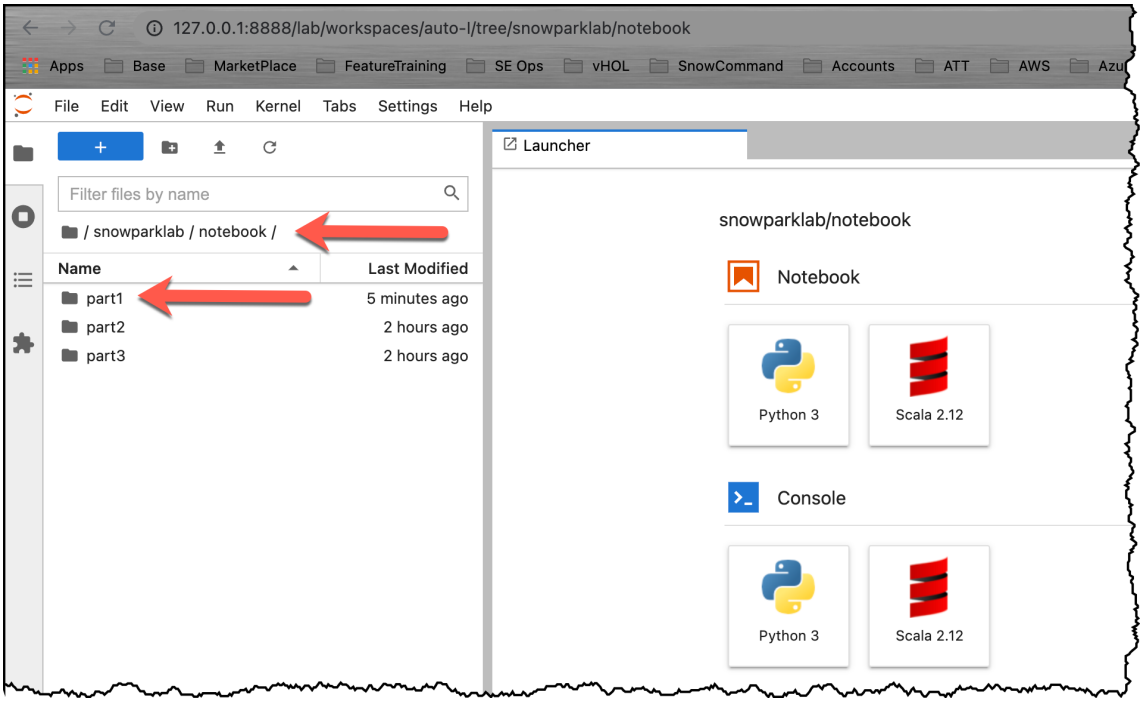


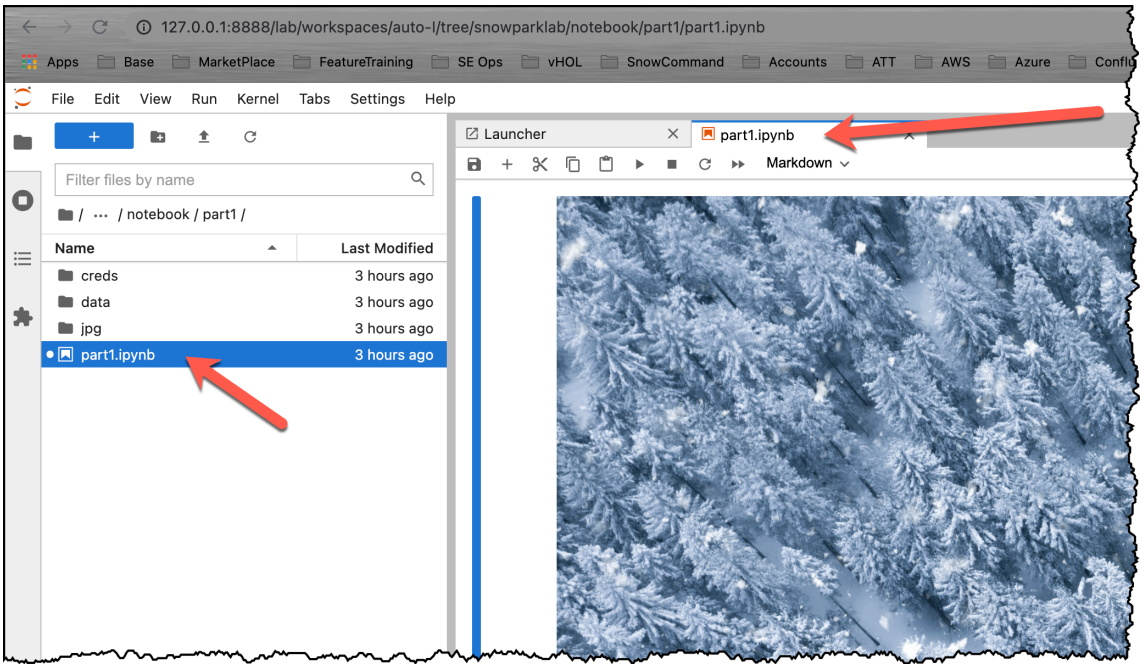
Part 1: Introduction to the Snowpark DataFrame API

This is the first notebook of a series to show how to use Snowpark on Snowflake. This notebook provides a quick-start guide and an introduction to the Snowpark DataFrame API. The notebook explains the steps for setting up the environment (REPL), and how to resolve dependencies to Snowpark. After a simple "Hello World" example you will learn about the Snowflake DataFrame API, projections, filters, and joins.

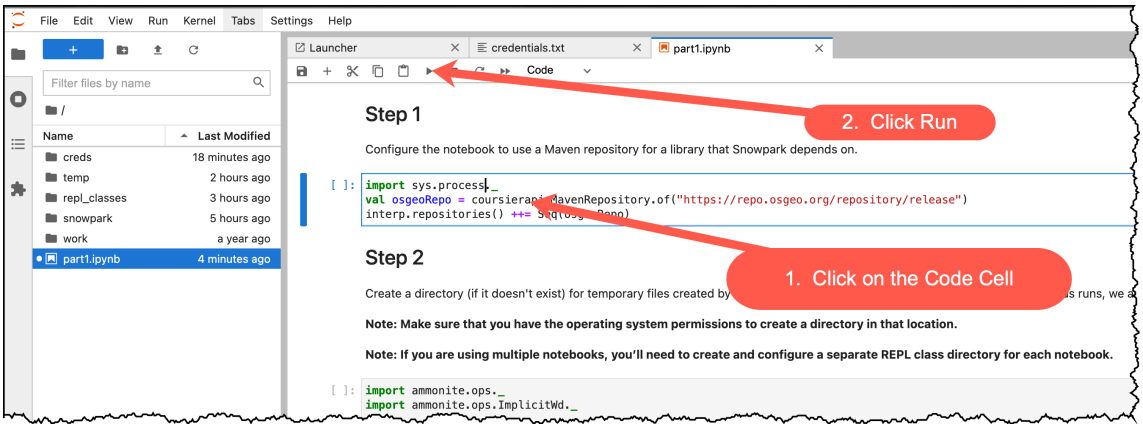
Open the Part 1 notebook

Open your Jupyter environment. Navigate to the folder snowparklab/notebook/part1 and Double click on the part1.ipynb to open it





Now read through and run each step in the notebook.



Positive : **Return here once you have finished the first notebook.**

Part 2: Aggregations, Pivots, and UDF's

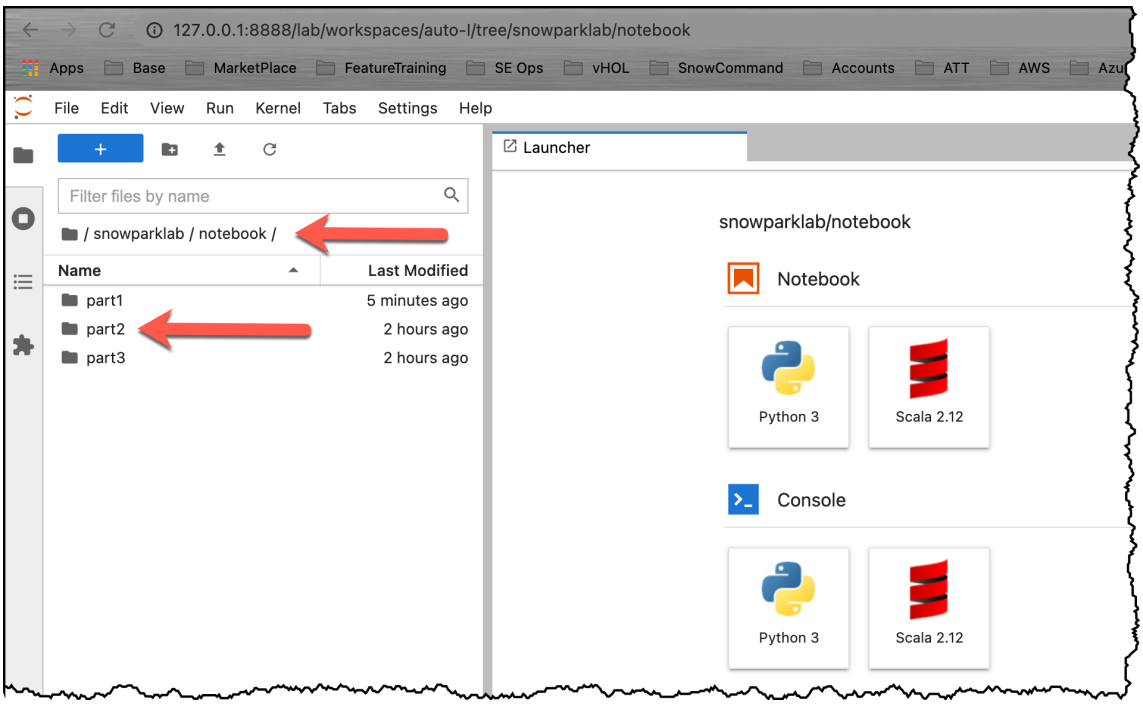
This is the second notebook in the series. It builds on the quick-start of the first part. Using the TPCH dataset in the sample database, we will learn how to use aggregations and pivot functions in the Snowpark DataFrame API. Then, it introduces user definde functions (UDFs) and how to build a stand-alone UDF: a UDF that only uses standard primitives. From there, we will learn how to use third party Scala libraries to perform much more complex tasks like math for numbers with unbounded (unlimited number of significant digits) precision and how to perform sentiment analysis on an arbitrary string.

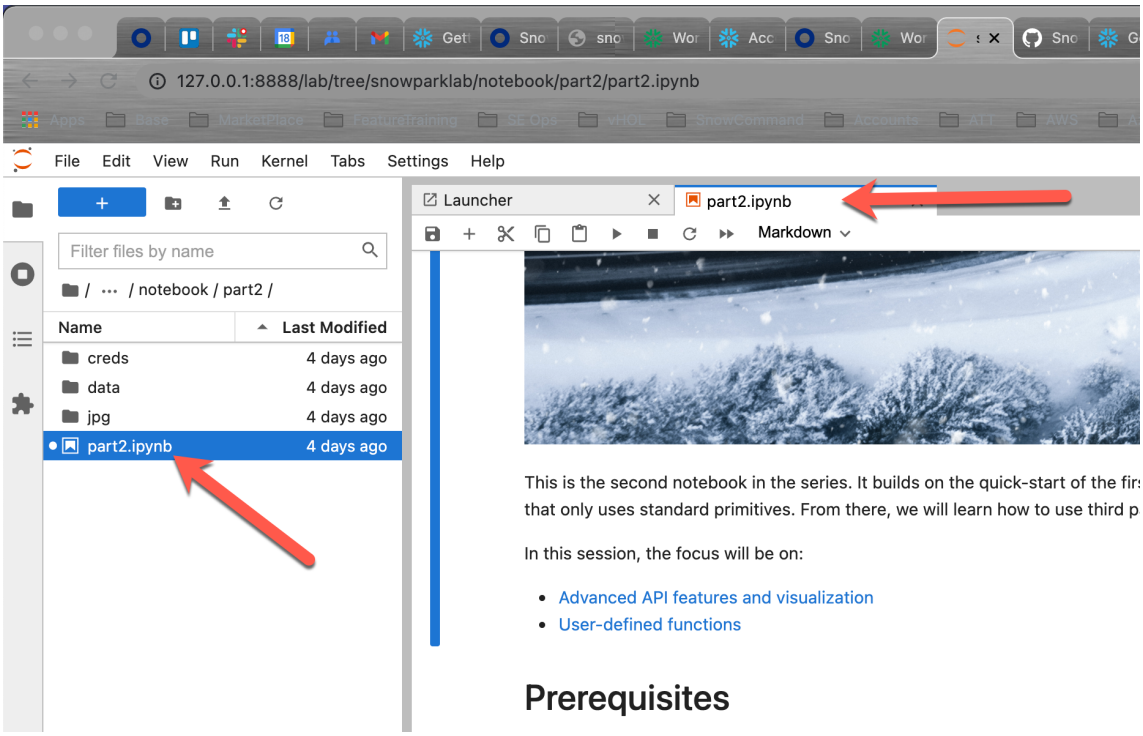
In this session, the focus will be on:

- Advanced API features and visualization
- User-defined functions

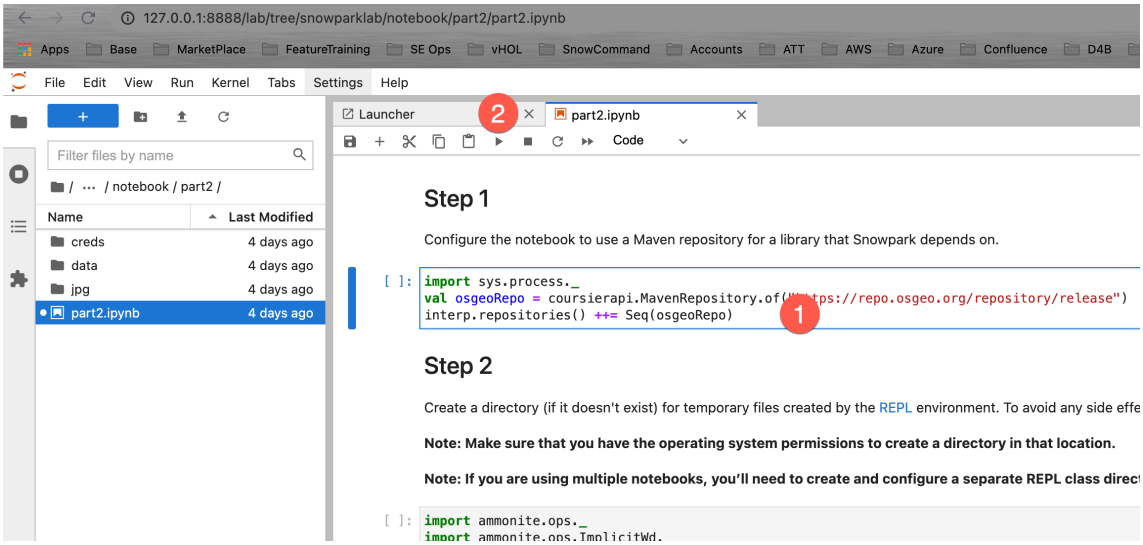
Open the Part 2 notebook

Open your Jupyter environment. Navigate to the folder snowparklab/notebook/part2 and Double click on the part2.ipynb to open it





Now read through and run each step in the notebook.



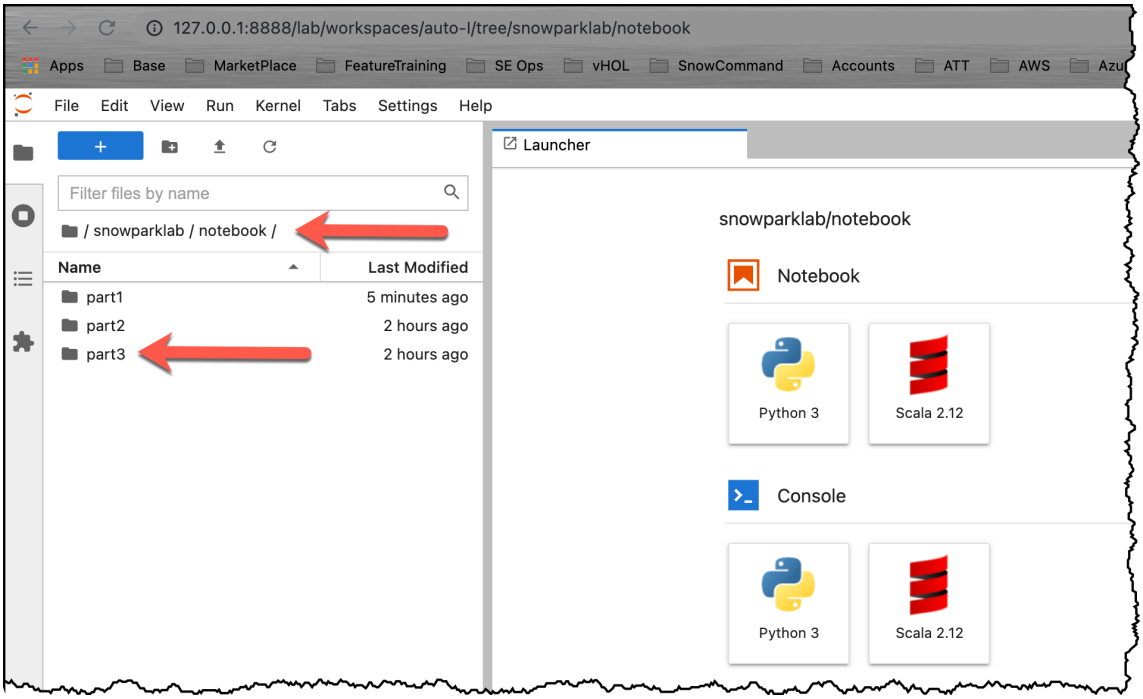
Positive : **Return here once you have finished the second notebook.**

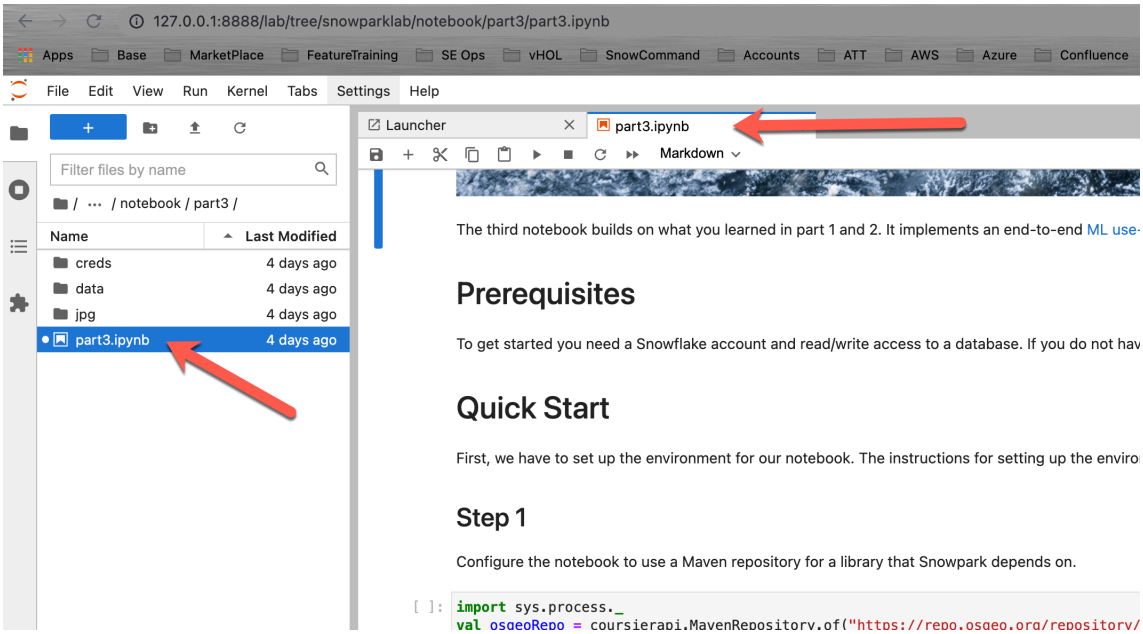
Part 3: Data Ingestion, transformation, and model training

The third notebook builds on what you learned in part 1 and 2. It implements an end-to-end ML use-case including data ingestion, ETL/ELT transformations, model training, model scoring, and result visualization.

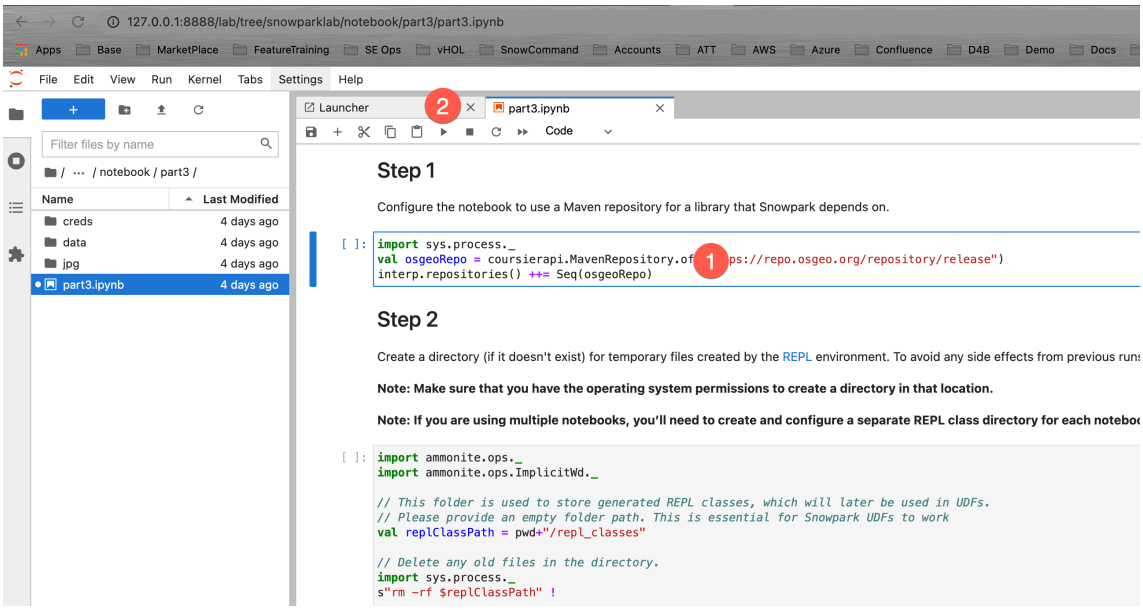
Open the Part 3 notebook

Open your Jupyter environment. Navigate to the folder snowparklab/notebook/part2 and Double click on the part2.ipynb to open it





Now read through and run each step in the notebook.



Positive : **Return here once you have finished the third notebook so you can read the conclusion & Next steps, and complete the guide.**

Conclusion & Next Steps

Snowpark is a brand new developer experience that brings scalable data processing to the Data Cloud. In Part1 of this series, we learned how to set up a Jupyter Notebook and configure it to use Snowpark to connect to the Data Cloud. Next, we built a simple Hello World! program to test connectivity using embedded SQL. Then we enhanced that program by introducing the Snowpark Dataframe API. Lastly we explored the power of the Snowpark Dataframe API using filter, projection, and join transformations.

We encourage you to continue with your free trial by loading your own sample or production data and by using some of the more advanced capabilities of Snowflake not covered in this lab.

What we've covered:

- Quick Start: Set up the environment
- Hello World: First steps
- Snowflake DataFrame API: Query the Snowflake Sample Datasets via Snowflake DataFrames
- Aggregations, Pivots, and UDF's using the Snowpark API
- Data Ingestion, transformation, and model training

Lab 12: Defining Virtual Warehouses

One of the first things you'll do when setting up your Snowflake environment is to establish your virtual warehouses. What this boils down to, essentially, is how much compute you want to use and how segregated that compute will be.

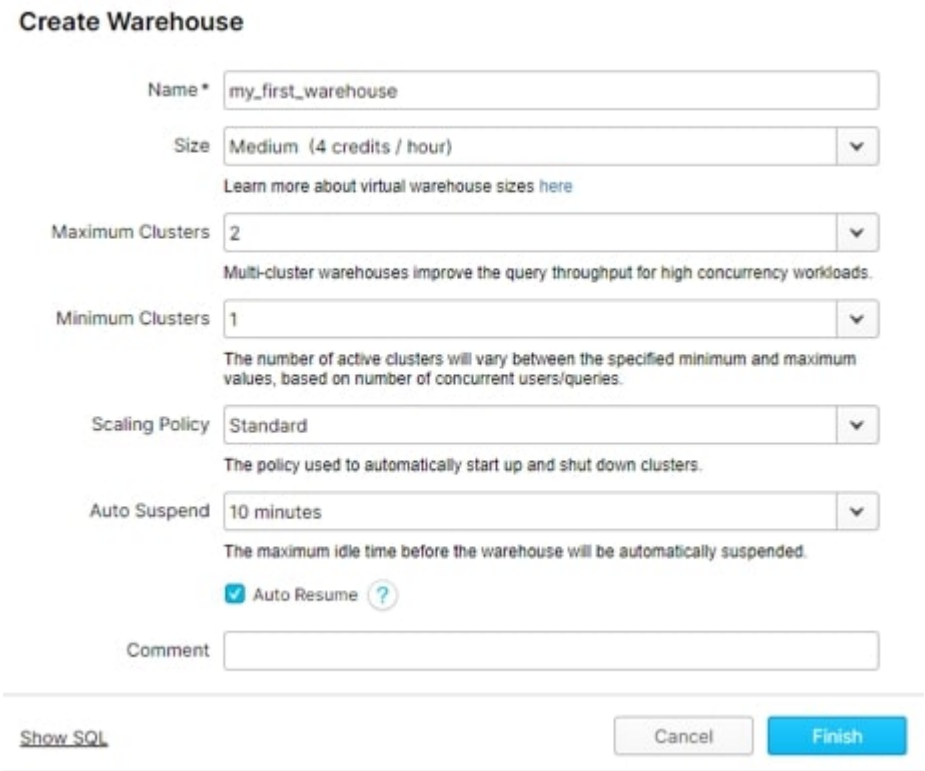
What Is a Virtual Warehouse?

Warehouses are required for queries, as well as for operations like loading data into tables. They come in a variety of T-shirt sizes ranging from extra small to 4XL, with each representing an increase in the hardware resources available for you to use.

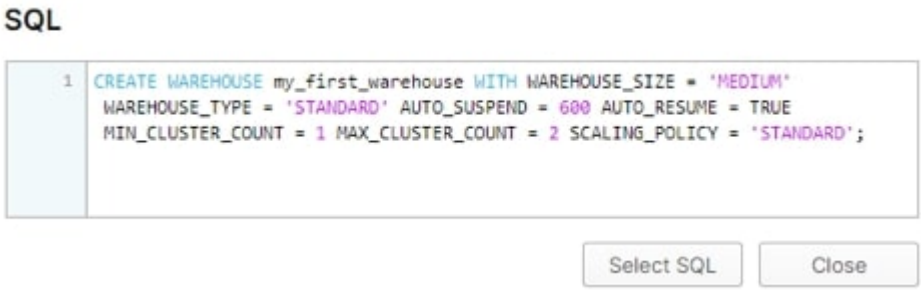
Warehouses can be started and stopped at any time. They can also be resized at any time, even while running, to accommodate the need for more or fewer compute resources, depending on the type of operations you are performing at that time.

If you are on the Enterprise or higher edition of Snowflake, the warehouses can also be configured to scale outwards by adding more servers to a cluster. Doing so provides a boost in parallel processing capabilities, which is useful when you have a surge in concurrent activity.

A warehouse can be created using the web interface by any Snowflake user with the appropriate rights. Simply select Warehouses from the menu ribbon and then click on the Create button. You'll see a dialog like this where you can define the name, size and other attributes about the warehouse:



You can also script a warehouse. You can use the **Show SQL** link on the above dialog to give you a headstart, as it will translate the information you enter and the selections you make into the SQL needed to create that warehouse:



But how many warehouses do I need? And when do you know to scale up vs. scale out a warehouse?

How Many Warehouses Do I Need?

Well, the good news is that creating warehouses doesn't cost you anything, so you can have as many as you need. I tend to say there are four different types of warehouses, and it's worth considering whether your organisation will need some, or all, of these. You can optionally combine types here, but as you'll see later in this article, they don't necessarily share the same setup, and if you do combine, you don't fully optimise. Below are the types of warehouses available:

- **Staging:** Used by any process that brings information into Snowflake
- **Integration**: Used when you want to transform and integrate information within Snowflake
- **Consumption**: Used by any process that extracts or uses information hosted within Snowflake; for example, Tableau connecting and gathering information for use by a dashboard
- **Labs**: Optional compute reserved exclusively for high-intensity requests from Data Scientists and Data Citizens within your organisation

How many of each warehouse type you need is influenced by several contributing factors:

- **Isolation of Workload**: If you want to load a lot of information into Snowflake from various sources in parallel---as might be the case with a nightly load---or maybe you want to reserve or secure compute for specific users, it can be useful to define multiple warehouses of either a staging or consumption type.
- **Usage Chargeback**: If your data analytics delivery model relies on funding from different departments, then creating separate consumption and/or lab warehouses for each consumer group can help you to track and chargeback as applicable.

If you're wondering what makes these warehouses different, let me elaborate.

Staging

A staging warehouse switches on for just long enough to stage information from a source:

```
 CREATE OR REPLACE WAREHOUSE "STG_XXXX"
 WITH WAREHOUSE_SIZE = 'X-SMALL'
 AUTO_SUSPEND = 60
 AUTO_RESUME = TRUE
 MIN_CLUSTER_COUNT = 1
 MAX_CLUSTER_COUNT = 1
 SCALING_POLICY = 'STANDARD'
 INITIALLY_SUSPENDED = TRUE
COMMENT = 'For the staging of information from XXXX source';
```

- Start with the smallest warehouse and scale up as needed to load information in a timely manner.

- Experiment with scaling outward to improve performance if you are on Enterprise edition and already beyond an XS T-shirt size.
- You might set up access rights for this type of warehouse to be sized up or down by your ELT platform as it needs the extra compute.

Integration

An integration warehouse stays on for longer and generally has a lot to do when transforming and integrating information:

```
CREATE OR REPLACE WAREHOUSE "INT_General"
    WITH WAREHOUSE_SIZE = 'SMALL'
    AUTO_SUSPEND = 300
    AUTO_RESUME = TRUE
    MIN_CLUSTER_COUNT = 1
    MAX_CLUSTER_COUNT = 2
    SCALING_POLICY = 'STANDARD'
    INITIALLY_SUSPENDED = TRUE
    COMMENT = 'For all data integration within the EDW';
```

- Start with a small warehouse and scale up as needed to integrate information in a timely manner.
- Review your cluster counts as you increase warehouse size, but consciously increment the maximum number of servers in the cluster to reach optimal processing capabilities. Don't just set it to the maximum available for that T-shirt size.
- If you see the warehouse suspending routinely during the integration process, increase the auto-suspend timeout.

You could combine staging and integration warehouse types and have just one type here; a lot of people do. I always consider the separation when those influencing factors I mentioned above come into play or where I may need to separate resources for data security purposes.

Consumption

Consumption warehouses are split either by function or department---whichever is a natural and required level of separation within your business. They should stay on for longer and only scale when resources are in high demand:

```
CREATE OR REPLACE WAREHOUSE "OUT_XXXX"
WITH WAREHOUSE_SIZE = 'X-SMALL'
AUTO_SUSPEND = 600
AUTO_RESUME = TRUE
MIN_CLUSTER_COUNT = 1
MAX_CLUSTER_COUNT = 1
SCALING_POLICY = 'ECONOMY'
INITIALLY_SUSPENDED = TRUE
COMMENT = 'VW for all data analytics delivered by XXXX';
```

- Start with the smallest warehouse and scale up by benchmarking performance from the BI tool or the process that is extracting information.
- Increase the auto-suspend timeout if the BI tool (or process) makes infrequent requests. This will maximise cache usage and result in a faster return of results for subsequent requests for similar information.

Labs

Labs are your secret weapon when a group wants dedicated resources and may put extraordinary load on Snowflake (which it can take), but maybe you want to keep a watchful eye on their usage.

The definition of the warehouse really depends upon their needs, but I also establish a `Resource Monitor` to monitor their consumption for me:

```
CREATE RESOURCE MONITOR "RM_LAB_OPERATIONS"
WITH CREDIT_QUOTA = 30, frequency = 'MONTHLY'
TRIGGERS
ON 80 PERCENT DO NOTIFY
ON 120 PERCENT DO SUSPEND;

ALTER WAREHOUSE "LAB_OPERATIONS SET RESOURCE_MONITOR = "RM_LAB_OPERATIONS";
```

You must be an account admin to establish these resource monitors, but doing so gives you an early indication of excessive usage. They can be set up to inform you and the users that they are approaching or exceeding the assigned quota. The monitor can be configured to solely notify, or it can take steps to restrict usage.

Tips for Naming Your Warehouses

When it comes to naming your warehouses, I always recommend these good habits:

- Distinguish which type of warehouse it is. I use the prefixes STG, INT, OUT and LAB.
- Keep your names short. When you select a warehouse in the context menu of a worksheet, you can only see the first 14 characters, so by keeping it short, you'll be able to see the full name.
- Don't include the size of the warehouse in the name. As we've already said, a warehouse can be scaled up or down at any time, and the interface tells you in other ways what size it is presently.
- Include a more verbose description of the warehouse purpose in the comments attribute. Hovering over a warehouse at different places in the web interface often pops up the comments in the accompanying tooltip, helping those with access to multiple warehouses decide on the most appropriate to use.

Lab 13: Table Types in Snowflake

Tables are database objects logically structured as a collection of rows and columns. All data in Snowflake is stored in database tables. Apart from standard database tables, Snowflake supports other table types that are especially useful for storing data that does not need to be maintained for extended periods of time.

When data is loaded into Snowflake, Snowflake reorganizes that data into its internal optimized, compressed, columnar format. Snowflake stores this optimized data in cloud storage.

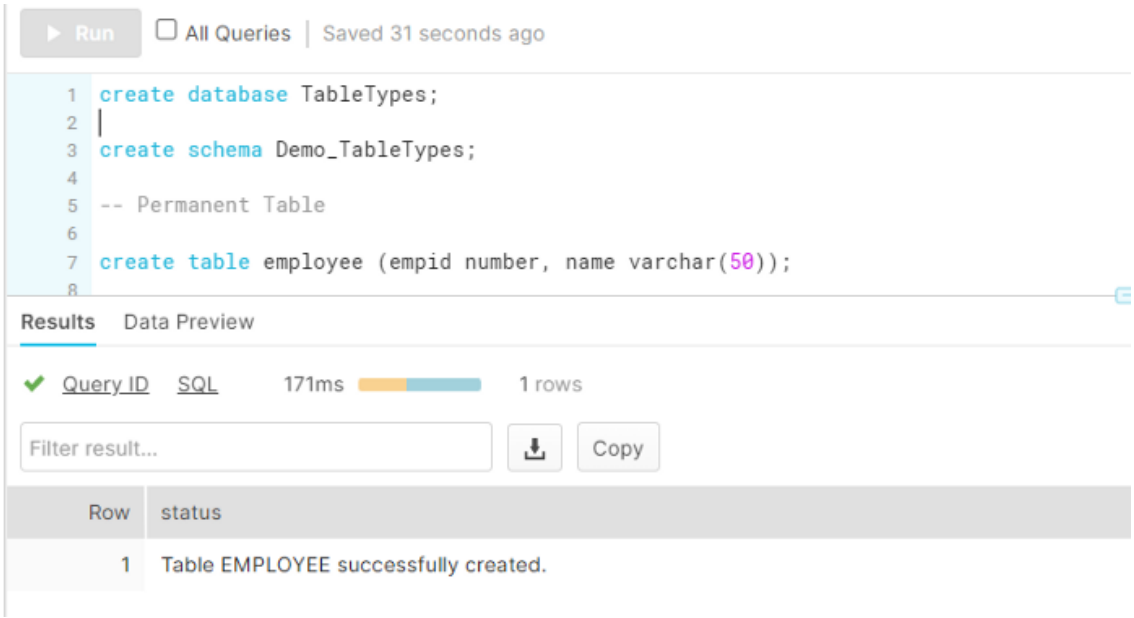
Snowflake supports different types of tables

- Permanent Table
- Transient Table
- Temporary Table
- External Table

Permanent Table:

These are the standard, regular database tables. Permanent tables are the default table type in Snowflake and do not need any additional syntax while creating to make them permanent.

```
create database TableTypes;
create schema Demo_TableTypes;
-- Permanent Table
create table employee (empid number, name varchar(50));
```



The data stored in permanent tables consumes space and contributes to the storage charges that Snowflake bills your account. It also comes with additional features like Time-Travel and Fail-Safe which helps in data availability and recovery.

Transient Table:

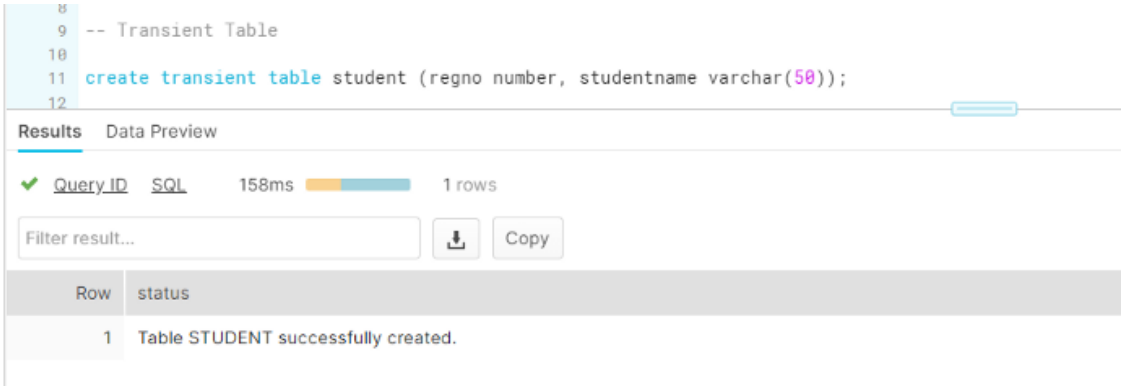
Transient tables in Snowflake are similar to permanent tables except that that they do not have a Fail-safe period and only have a very limited Time-Travel period. These are best suited in scenarios where the data in your table is not

critical and can be recovered from external means if required.

Transient tables, like permanent tables, contribute to your account's overall storage expenses. However, since Transient Tables do not use Fail-safe, there are no Fail-safe costs (i.e. the costs associated with maintaining the data required for Fail-safe disaster recovery).

To create a Transient table in Snowflake, You need to mention ***transient*** in the create table syntax.

```
create transient table student (regno number, studentname varchar(50));
```

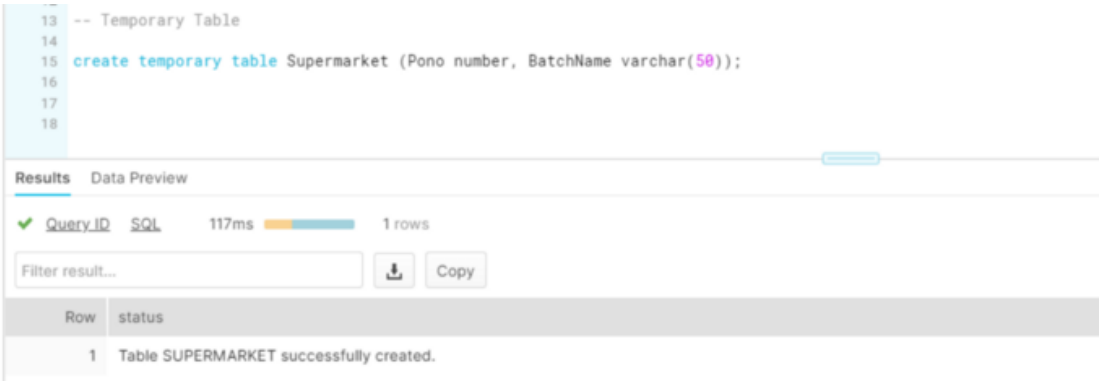


Temporary Table:

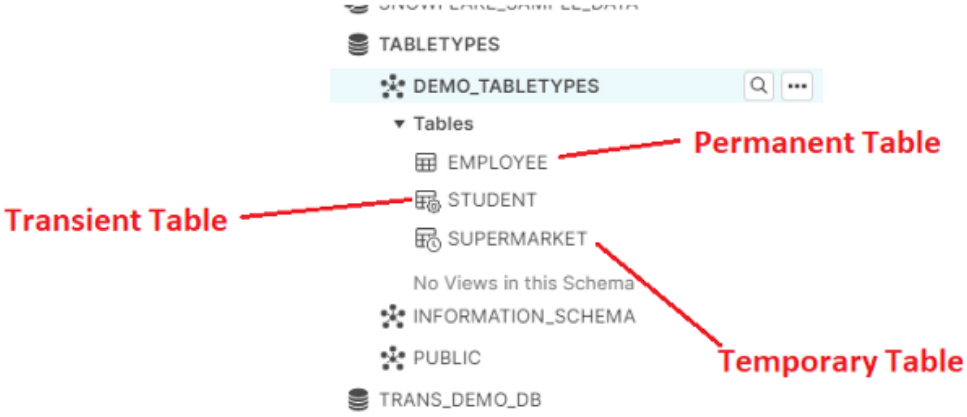
Snowflake supports creating temporary tables to store transient, non-permanent data. Temporary tables exist only within the session. They are created and persist only for the session remainder. They are not visible to other sessions or users and don't support standard features like cloning.

Therefore the data stored in the system is cleaned entirely and is not recoverable either by the user-created table or Snowflake.

```
-- Temporary Table
create temporary table Supermarket (Pono number, BatchName varchar(50));
```

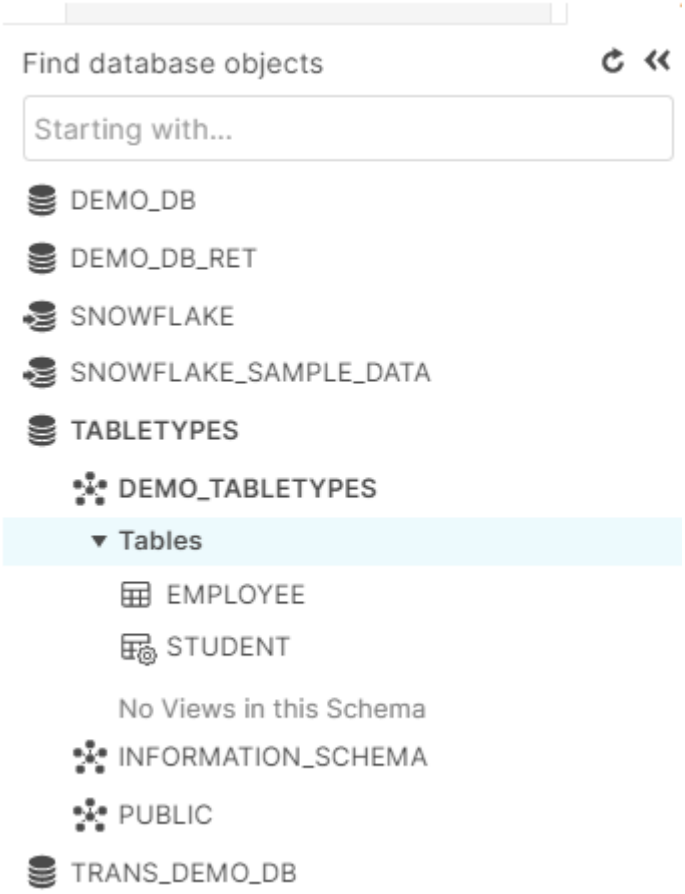


PFB the icon displayed for **different tables**,



Though Temporary tables are dropped at the end of the session, Snowflake recommends explicitly dropping these tables once they are no longer needed to prevent any unexpected storage changes when working with large temporary tables.

If logout the particular session and re login then particular temporary table will not be displayed.



As shown in **Figure 1.1**, the temporary table (SUPERMARKET) has been dropped after relogging in.

Next, will will cover how to differentiate Temporary Tables from Non-Temporary Tables.

Types of Table in Snowflake

In this section, we see about **How Snowflake behave when we create temporary table that has the same name as an existing table in the same schema?**

Before answering this question let's see how to find type of table present in database.

> *SHOW TABLES --- Lists the tables for which you have access privileges, including dropped tables that are still within the Time Travel retention period and, therefore, can be undropped.*

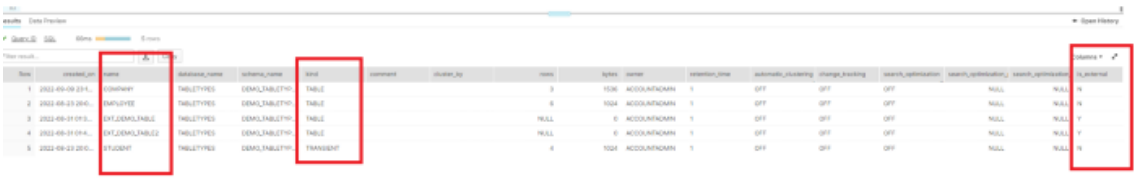
Syntax:

```
SHOW TABLES;
```

Example:

```
SHOW TABLES;
```

Output:



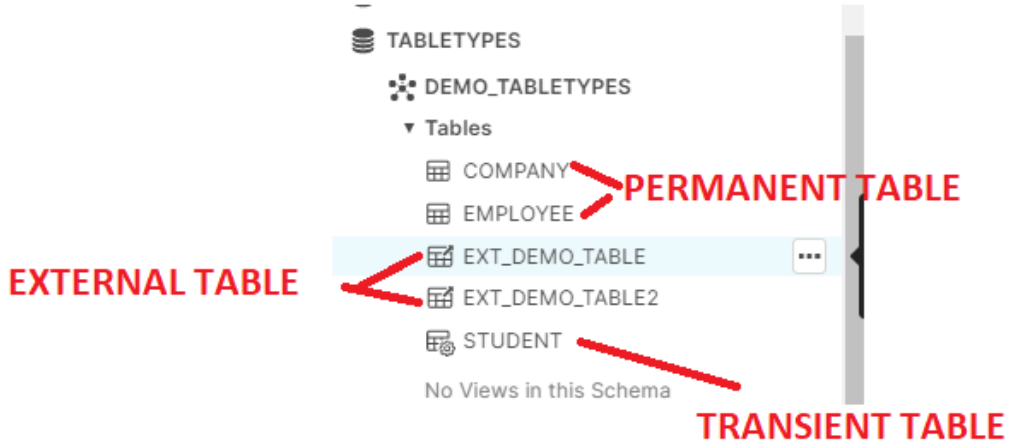
Scenario 1:

When you create a temporary table that has the same name as an existing table in the same schema ?

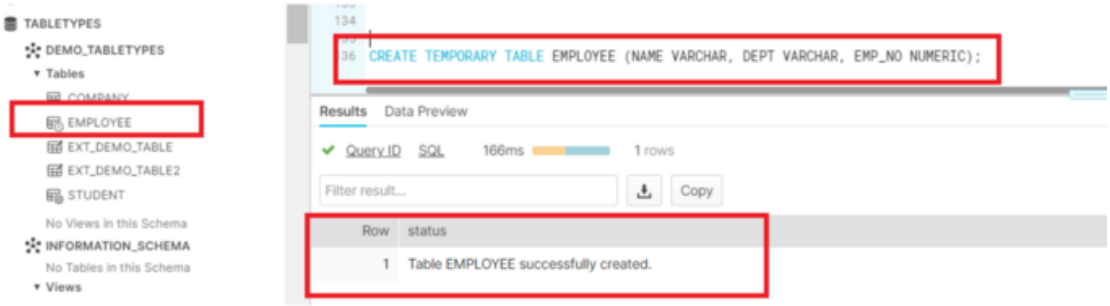
Snowflake supports creating a temporary table that has the same name as an existing permanent/transient table in the same schema. However, note that the temporary table takes precedence in the session over any other table with the same name in the same schema.

Temporary table take precedence and hides the existing non-temporary table.

Screenshot 1: Before creating temporary table in my database.



Screenshot 2: After creating temporary table in my database,



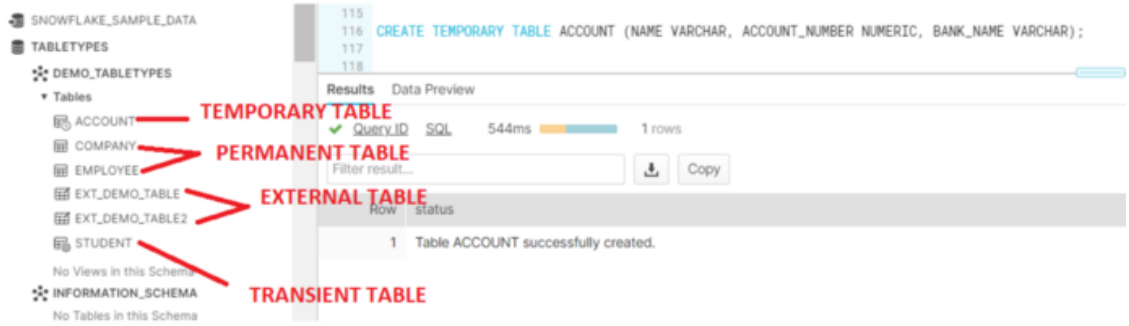
In above screenshot Temporary table take precedence and hides the existing permanent table.

Scenario 2:

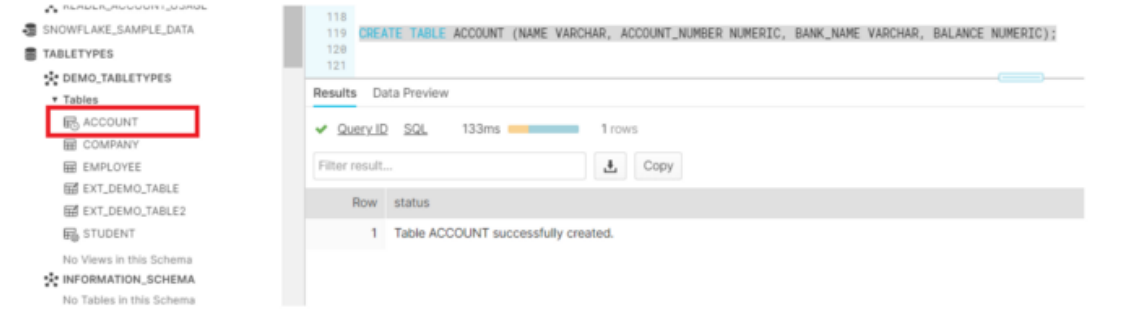
When you create a table that has the same name as an existing temporary table in the same schema ?

The newly-created table is hidden by the temporary table.

Screenshot 1: Before creating permanent table same name like temporary table name in my database.



Screenshot 2: After creating permanent table (Account) same name like temporary table (Account) name in my database.



In above screenshot Temporary table take precedence and hides the newly created permanent table.

All queries and other operations performed in the session on the table effect only the temporary table.

Comparison of Snowflake Table Types

The below table summarizes the differences between the three table types, particularly with regard to their impact on Time Travel and Fail-safe:

Table Type	Availability	Time-Travel Retention period in days	Fail-Safe period in days
Temporary	Remainder of session	0 or 1 (Default is 1)	0
Transient	Until explicitly dropped	0 or 1 (Default is 1)	0
Permanent (Standard Edition)	Until explicitly dropped	0 or 1 (Default is 1)	7
Permanent (Enterprise and higher Edition)	Until explicitly dropped	0 to 90 (default is configurable)	7

Lab 14: Loading JSON data into Snowflake

Have you ever faced any use case or scenario where you've to ***load JSON data into*** the **Snowflake**? We better know JSON data is one of the common data format to store and exchange information between systems. JSON is a relatively concise format. If we are implementing a database solution, it is very common that we will come across a system that provides data in JSON format. Snowflake has a very straight forward approach to load JSON data. In this blog, we will understand this approach in a step-wise manner.

1. Stage the JSON data

The JSON data looks like:

```
{
  "Name": "Aman Gupta",
  "family_detail": [
    {
      "Name": "Avinash Gupta",
      "Relationship": "Father",
    },
    {
      "Name": "Lata Gupta",
      "Relationship": "Mother",
    },
    {
      "Name": "Shrishti Gupta",
      "Relationship": "Sister",
    },
    {
      "Name": "Bobin Gupta",
      "Relationship": "Brother",
    }
  ]
}
```

Create `family.json` file with above content and save it. Also, update file path in below command.

In snowflake Staging the data means, make the data available in Snowflake ***stage***(intermediate storage) it can be **internal or external**. Staging JSON data in Snowflake is similar to staging any other files. Let's Staging JSON data file from a **local file system.**

```
CREATE OR REPLACE STAGE my_json_stage file_format = (type = json);
PUT file:///home/knoldus/Desktop/family.json @my_json_stage;
```

```
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>CREATE OR REPLACE STAGE my_json_stage file_format = (type = json);
+----------------------------------------------+
| status                                       |
|----------------------------------------------|
| Stage area MY_JSON_STAGE successfully created. |
+----------------------------------------------+
1 Row(s) produced. Time Elapsed: 0.236s
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>PUT file:///home/knoldus/Desktop/family.json @my_json_stage;
family.json_c.gz(0.00MB): [##########] 100.00% Done (0.297s, 0.00MB/s).
+-------------+---------------+-------------+-------------+--------------------+--------------------+----------+---------+
| source      | target        | source_size | target_size | source_compression | target_compression | status   | message |
|-------------+---------------+-------------+-------------+--------------------+--------------------+----------+---------|
| family.json | family.json.gz |         353 |         166 | NONE               | GZIP               | UPLOADED |         |
+-------------+---------------+-------------+-------------+--------------------+--------------------+----------+---------+
```

2. Load JSON data as raw into temporary table

To load the JSON data as raw, first, create a table with a column of VARIANT type. VARIANT can contain any type of data so it is suitable for loading JSON data.

```
CREATE TABLE relations_json_raw (
  json_data_raw VARIANT
);
```

Now let's **copy** the JSON file into **relations_json_raw** table.

```
COPY INTO relations_json_raw from @my_json_stage;
```

Note that a file format does not need to be specified because it is included in the stage definition.

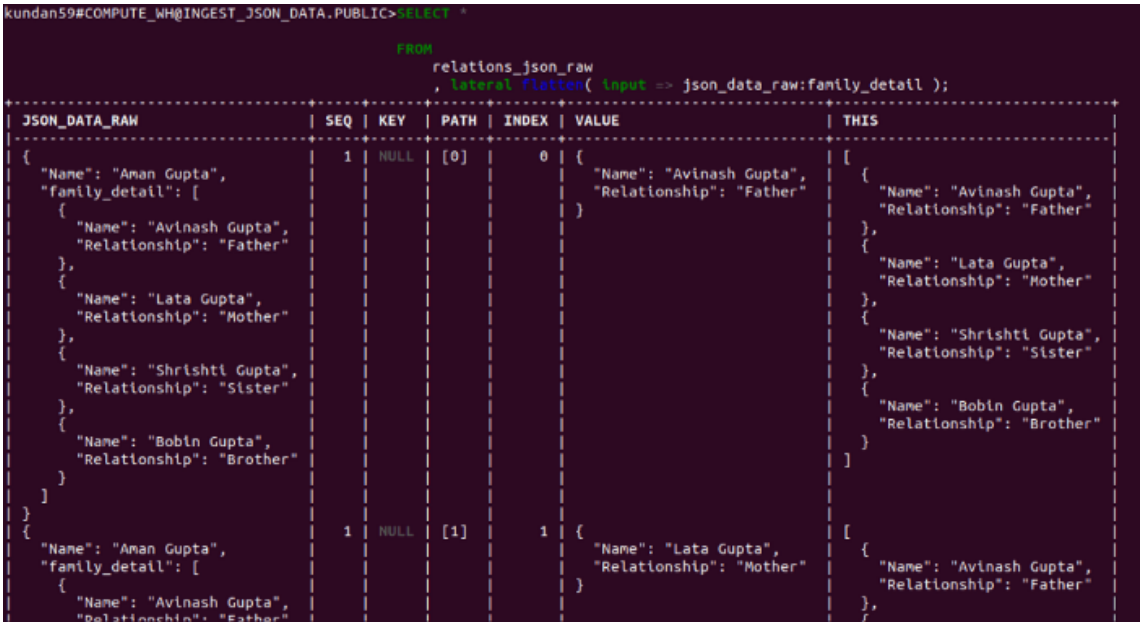
```
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>COPY INTO relations_json_raw from @my_json_stage;
+-----------------------------+--------+-------------+-------------+-------------+-------------+-------------+------------------+--------------+----------------------+
| file                        | status | rows_parsed | rows_loaded | error_limit | errors_seen | first_error | first_error_line | first_error_character | first_error_column_name |
|-----------------------------+--------+-------------+-------------+-------------+-------------+-------------+------------------+--------------+----------------------|
| my_json_stage/family.json.gz | LOADED |           1 |           1 |           1 |           0 | NULL        |             NULL |         NULL | NULL                 |
+-----------------------------+--------+-------------+-------------+-------------+-------------+-------------+------------------+--------------+----------------------+
```

3. Analyze and prepare raw JSON data

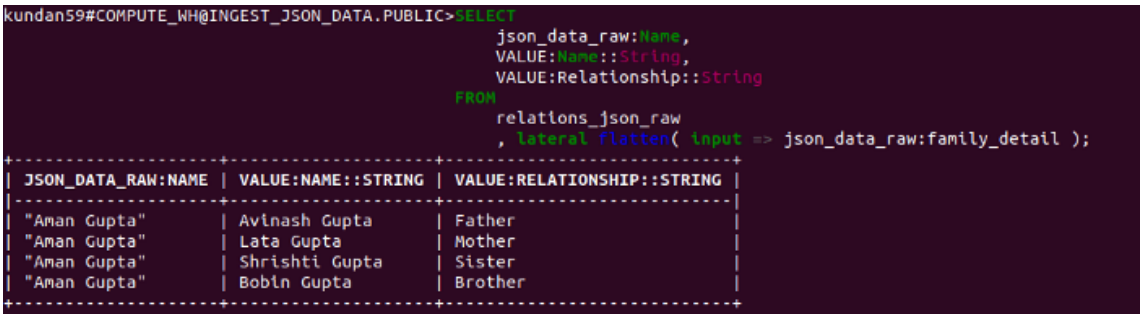
The next step would be **to analyze** the **loaded raw JSON data**. Determining what information needs to be extracted from JSON data. For example, in our case, we are interested to extract the name key and from the family_detail array object, we want to extract the name and relationship key from each JSON object. The below query will do that.

```
SELECT
    json_data_raw:Name,
    VALUE:Name::String,
    VALUE:Relationship::String
FROM
    relations_json_raw
    , lateral flatten( input => json_data_raw:family_detail );
```

The above query using **lateral join** and a **flatten functio**n. The flatten function returns a row for each JSON object from the family_detail array. and the lateral modifier joins the data with any information outside of the object, in our example candidate name that we are extracting with **json_data_raw: Name.**



```
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>SELECT *
                                        FROM
                                            relations_json_raw
                                            , lateral flatten( input => json_data_raw:family_detail );
+--------------------------------+-----+------+------+-------+-----------------------------+-----------------------------+
| JSON_DATA_RAW                  | SEQ | KEY  | PATH | INDEX | VALUE                       | THIS                        |
|--------------------------------+-----+------+------+-------+-----------------------------+-----------------------------|
| {                              |   1 | NULL | [0]  |     0 | {                           | [                           |
|   "Name": "Aman Gupta",        |     |      |      |       |   "Name": "Avinash Gupta",  |   {                         |
|   "family_detail": [           |     |      |      |       |   "Relationship": "Father"  |     "Name": "Avinash Gupta",|
|     {                          |     |      |      |       | }                           |     "Relationship": "Father"|
|       "Name": "Avinash Gupta", |     |      |      |       |                             |   },                        |
|       "Relationship": "Father" |     |      |      |       |                             |   {                         |
|     },                         |     |      |      |       |                             |     "Name": "Lata Gupta",   |
|     {                          |     |      |      |       |                             |     "Relationship": "Mother"|
|       "Name": "Lata Gupta",    |     |      |      |       |                             |   },                        |
|       "Relationship": "Mother" |     |      |      |       |                             |   {                         |
|     },                         |     |      |      |       |                             |     "Name": "Shrishti Gupta",|
|     {                          |     |      |      |       |                             |     "Relationship": "Sister"|
|       "Name": "Shrishti Gupta",|     |      |      |       |                             |   },                        |
|       "Relationship": "Sister" |     |      |      |       |                             |   {                         |
|     },                         |     |      |      |       |                             |     "Name": "Bobin Gupta",  |
|     {                          |     |      |      |       |                             |     "Relationship": "Brother"|
|       "Name": "Bobin Gupta",   |     |      |      |       |                             |   }                         |
|       "Relationship": "Brother"|     |      |      |       |                             | ]                           |
|     }                          |     |      |      |       |                             |                             |
|   ]                            |     |      |      |       |                             |                             |
| }                              |     |      |      |       |                             |                             |
| {                              |   1 | NULL | [1]  |     1 | {                           | [                           |
|   "Name": "Aman Gupta",        |     |      |      |       |   "Name": "Lata Gupta",     |   {                         |
|   "family_detail": [           |     |      |      |       |   "Relationship": "Mother"  |     "Name": "Avinash Gupta",|
|     {                          |     |      |      |       | }                           |     "Relationship": "Father"|
|       "Name": "Avinash Gupta", |     |      |      |       |                             |   },                        |
|       "Relationship": "Father" |     |      |      |       |                             |   {                         |
+--------------------------------+-----+------+------+-------+-----------------------------+-----------------------------+
```



```
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>SELECT
                                            json_data_raw:Name,
                                            VALUE:Name::String,
                                            VALUE:Relationship::String
                                        FROM
                                            relations_json_raw
                                            , lateral flatten( input => json_data_raw:family_detail );
+--------------------+--------------------+---------------------------+
| JSON_DATA_RAW:NAME | VALUE:NAME::STRING | VALUE:RELATIONSHIP::STRING |
|--------------------+--------------------+---------------------------|
| "Aman Gupta"       | Avinash Gupta      | Father                    |
| "Aman Gupta"       | Lata Gupta         | Mother                    |
| "Aman Gupta"       | Shrishti Gupta     | Sister                    |
| "Aman Gupta"       | Bobin Gupta        | Brother                   |
+--------------------+--------------------+---------------------------+
```

Load Data into target table

Now we have analyzed and extracted information. We can load the extracted data into the target table.

```
CREATE OR REPLACE TABLE candidate_family_detail AS
SELECT
    json_data_raw:Name AS candidate_name,
    VALUE:Name::String AS relation_name,
    VALUE:Relationship::String AS relationship

FROM
    relations_json_raw
    , lateral flatten( input => json_data_raw:family_detail );
```

```
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>CREATE OR REPLACE TABLE candidate_family_detail AS
                                            SELECT
                                                json_data_raw:Name AS candidate_name,
                                                VALUE:Name::String AS relation_name,
                                                VALUE:Relationship::String AS relationship
                                            FROM
                                                relations_json_raw
                                                , lateral flatten( input => json_data_raw:family_detail);
+-------------------------------------------------+
| status                                          |
|-------------------------------------------------|
| Table CANDIDATE_FAMILY_DETAIL successfully created. |
+-------------------------------------------------+
1 Row(s) produced. Time Elapsed: 1.798s
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>SELECT * from CANDIDATE_FAMILY_DETAIL;
+---------------+---------------+--------------+
| CANDIDATE_NAME | RELATION_NAME  | RELATIONSHIP |
|---------------+---------------+--------------|
| "Aman Gupta"   | Avinash Gupta  | Father       |
| "Aman Gupta"   | Lata Gupta     | Mother       |
| "Aman Gupta"   | Shrishti Gupta | Sister       |
| "Aman Gupta"   | Bobin Gupta    | Brother      |
+---------------+---------------+--------------+
```

If you don't want to do a "create table as", you can pre-create a table and then insert the JSON data into the table.

```
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>CREATE TABLE candidate_family_detail (
                                                candidate_name STRING,
                                                relation_name   STRING,
                                                relationship STRING
                                            );
+-------------------------------------------------+
| status                                          |
|-------------------------------------------------|
| Table CANDIDATE_FAMILY_DETAIL successfully created. |
+-------------------------------------------------+
1 Row(s) produced. Time Elapsed: 0.408s
```

```
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>INSERT INTO candidate_family_detail
                                            SELECT
                                                json_data_raw:Name AS candidate_name,
                                                VALUE:Name::String AS relation_name,
                                                VALUE:Relationship::String AS relationship

                                            FROM
                                                relations_json_raw
                                                , lateral flatten( input => json_data_raw:family_detail );
+------------------------+
| number of rows inserted |
|------------------------|
|                      4 |
+------------------------+
4 Row(s) produced. Time Elapsed: 2.193s
kundan59#COMPUTE_WH@INGEST_JSON_DATA.PUBLIC>SELECT * FROM candidate_family_detail;
+---------------+---------------+--------------+
| CANDIDATE_NAME | RELATION_NAME  | RELATIONSHIP |
|---------------+---------------+--------------|
| Aman Gupta     | Avinash Gupta  | Father       |
| Aman Gupta     | Lata Gupta     | Mother       |
| Aman Gupta     | Shrishti Gupta | Sister       |
| Aman Gupta     | Bobin Gupta    | Brother      |
+---------------+---------------+--------------+
4 Row(s) produced. Time Elapsed: 1.244s
```

Getting Started with Snowpipe

Overview

When building data applications, your users count on seeing the latest. Stale data is less actionable and could lead to costly errors. That's why continuously generated data is essential. Snowflake provides a data loading tool to drive updates, ensuring your databases are accurate by updating tables in micro-batches.

Let's look into how Snowpipe can be configured for continual loading. Then, we can review how you can efficiently perform basic management tasks. But first, If you're unfamiliar with Snowflake or loading database objects, check out these resources to get familiar with the topics ahead.

Prerequisites

- AWS S3 Service Documentation

What You'll Learn

- Snowpipe staging methods
- Configure security access for Snowflake and AWS
- Automate Snowpipe with AWS S3 event notifications
- Manage Snowpipe and remove
- Next steps with database automation

What You'll Need

- Create a Snowflake account with an **ACCOUNTADMIN** role
- AWS Account with access to a Snowflake supported region

What You'll Build

- Automated data loading with Snowpipe between AWS S3 bucket and Snowflake database.

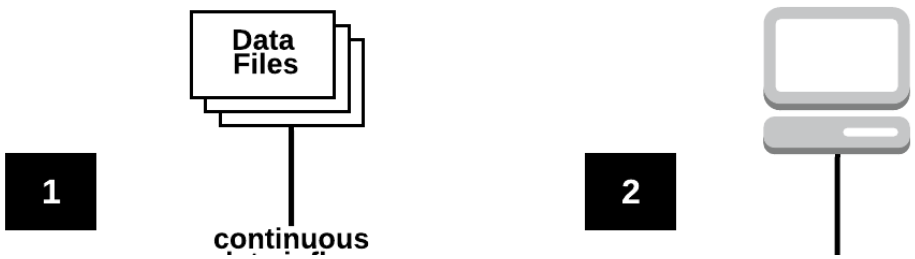
After ensuring the prerequisites detailed in this section, jump into the queueing data integration options with Snowpipe.

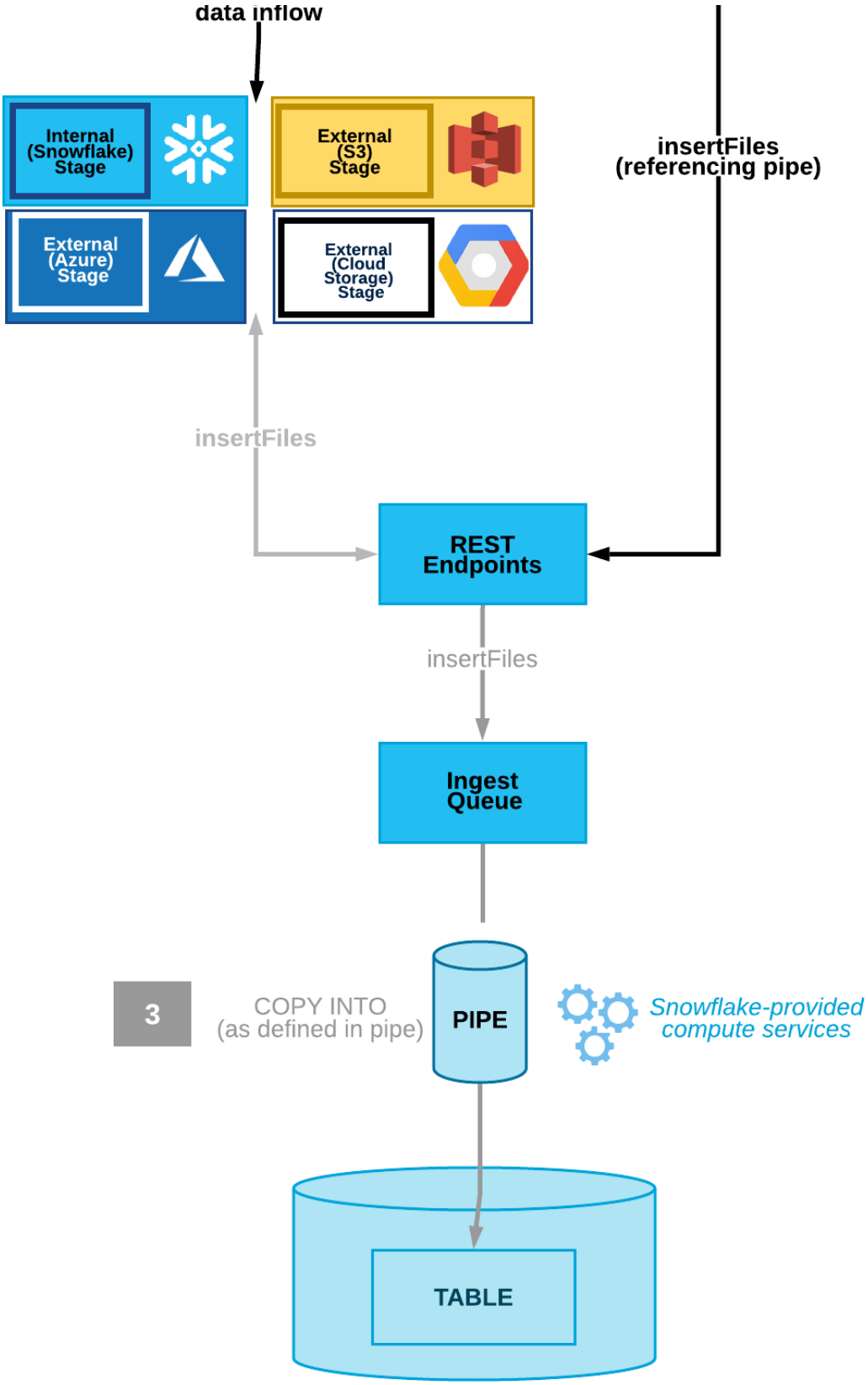
Choose the Data Ingestion Method

Snowpipe is an event based data ingest tool. Snowpipe provides two main methods for triggering a data loading event. This trigger could be a cloud storage notification (i.e. AWS S3 `ObjectCreated` event) or by directly calling the Snowpipe `insertFiles` REST API.

1. Cloud Storage Event Notifications (AWS S3, GCP CS, Azure Blob)
2. Snowpipe's REST API

This tutorial follows option 1, automating continuous data loading with cloud event notifications on AWS S3. In the next section, we'll configure your cloud notification preferences.




data inflow
Internal (Snowflake) Stage
External (S3) Stage
External (Azure) Stage
External (Cloud Storage) Stage
insertFiles (referencing pipe)
insertFiles
REST Endpoints
insertFiles
Ingest Queue
3
COPY INTO (as defined in pipe)
PIPE
Snowflake-provided compute services
TABLE

The image above reveals the two Snowpipe workflows. Option one shows continuous data loading with cloud storage event notifications. Option two illustrates queueing data with a REST API call to the `insertFiles` endpoint.

Configure Cloud Storage Event Notifications

Notifications from your cloud storage infrastructure are a straight-forward way to trigger Snowpipe for continuous loading.

Cloud Storage Platforms Snowpipe Supports

- Google Cloud Storage
- Microsoft Azure Blob Storage
- AWS S3

Choosing AWS S3 with Snowpipe integration allows you to decide between using an S3 event notification or Amazon's Simple Notification Service(SNS) to stage data for integration. Check if you currently have S3 event notifications that may conflict with a new notification. If so, you'll want to opt for SNS notifications. If not, the simple choice is to trigger continuous integration with S3 event notifications. Be aware that SNS network traffic travels outside of Amazon's VPC. If the potential security risk is an issue, consider employing AWS's PrivateLink service.

Let's go over the access requirements needed to begin using S3 event notifications to load new data seamlessly in micro-batches.

Configure Cloud Storage Permissions

To begin using AWS storage notifications for Snowpipe processing, you'll follow these steps within your AWS and Snowflake account to set up the security conditions.

1. Create IAM Policy for Snowflake's S3 Access

Snowflake needs IAM policy permission to access your S3 with `GetObject`, `GetObjectVersion`, and `ListBucket`. Log into your AWS console and navigate to the IAM service. Within the **Account settings**, confirm the **Security Token Service** list records your account's region as **Active**.

Navigate to **Policies** and use the JSON below to create a new IAM policy named 'snowflake_access'.

```
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [
                "s3:GetObject",
                "s3:GetObjectVersion"
            ],
            "Resource": "arn:aws:s3:::<bucket>/<prefix>/*"
        },
        {
            "Effect": "Allow",
            "Action": "s3:ListBucket",
            "Resource": "arn:aws:s3:::<bucket>",
            "Condition": {
                "StringLike": {
                    "s3:prefix": [
```

```
                "*"
            ]
        }
    }
  ]
}
```

Don't forget to replace the `<bucket>` and `<prefix>` with **your** AWS S3 bucket name and folder path prefix.

2. New IAM Role

On the AWS IAM console, add a new IAM role tied to the 'snowflake_access' IAM policy. Create the role with the following settings.

- **Trusted Entity**: Another AWS account
- **Account ID**:
- **Require External ID**: [x]
- **External ID**: 0000
- **Role Name**: snowflake_role
- **Role Description**: Snowflake role for access to S3 `<bucket>`
- **Policies**: snowflake_access

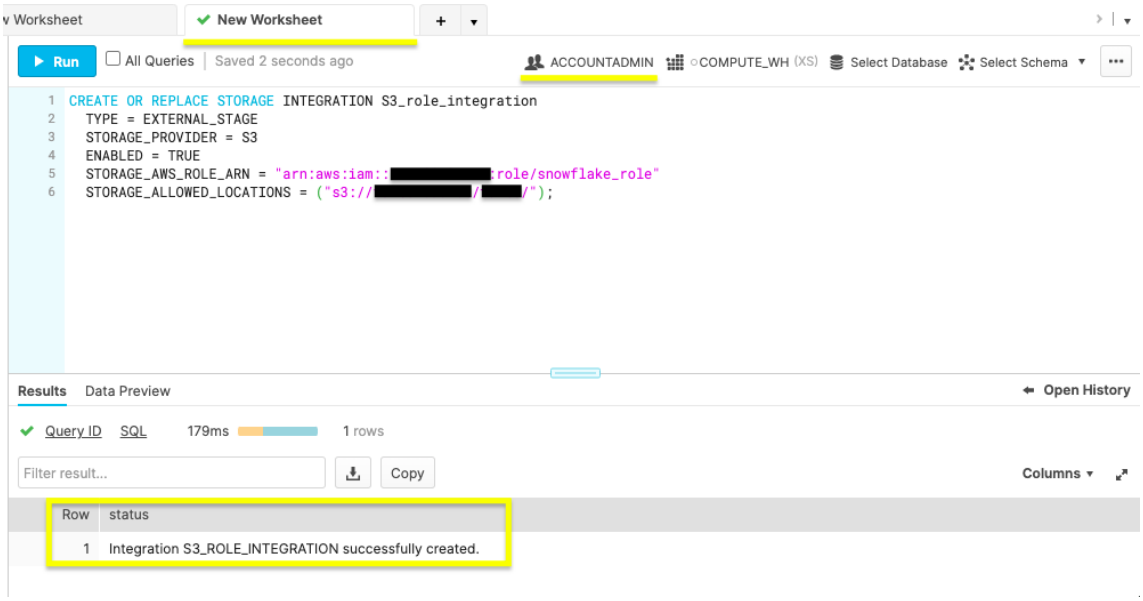
Create the role, then click to see the role's summary and record the **Role ARN**.

3. Integrate IAM user with Snowflake storage.

Within your Snowflake web console, you'll run a `CREATE STORAGE INTEGRATION` command on a worksheet.

```
CREATE OR REPLACE STORAGE INTEGRATION S3_role_integration
  TYPE = EXTERNAL_STAGE
  STORAGE_PROVIDER = S3
  ENABLED = TRUE
  STORAGE_AWS_ROLE_ARN = "arn:aws:iam::<role_account_id>:role/snowflake_role"
  STORAGE_ALLOWED_LOCATIONS = ("s3://<bucket>/<path>/");
```

Be sure to change the `<bucket>`, `<prefix>` and `<role_account_id>` is replaced with *your* AWS S3 bucket name, folder path prefix, and IAM role account ID.

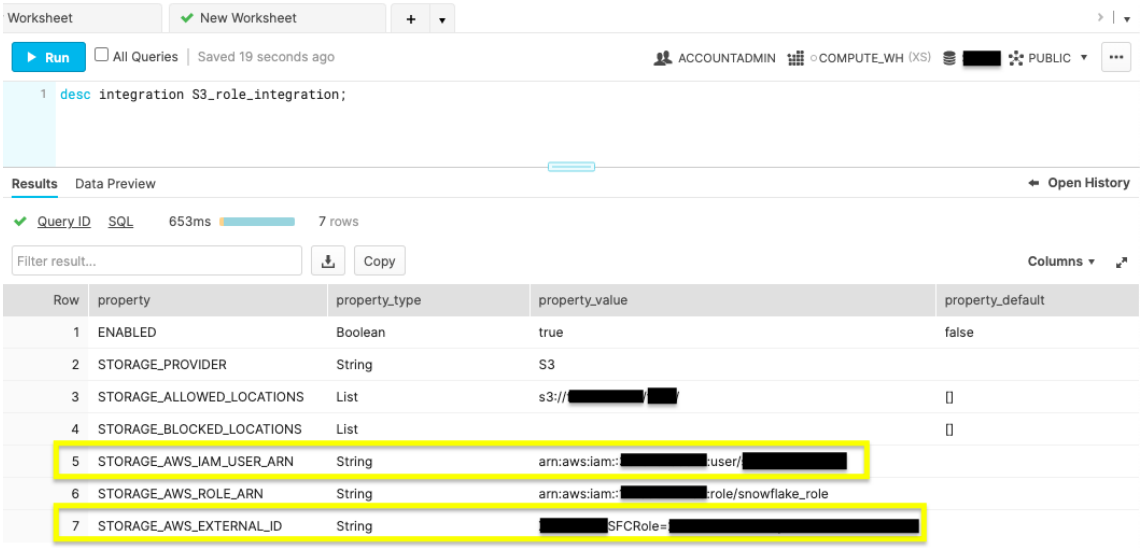


Note in the figure above the **ACCOUNTADMIN** role and status message of a successful creation.

4. Run storage integration description command.

```
desc integration S3_role_integration;
```

Run the above command to display your new integration's description.



Record the property values displayed for `STORAGE_AWS_IAM_USER_ARN` and `STORAGE_AWS_EXTERNAL_ID`.

5. IAM User Permissions

Navigate back to your AWS IAM service console. Within the **Roles**, click the 'snowflake_role'. On the **Trust relationships** tab, click **Edit trust relationship** and edit the file with the `STORAGE_AWS_IAM_USER_ARN` and `STORAGE_AWS_EXTERNAL_ID` retrieved in the previous step.

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Principal": {
        "AWS": "<STORAGE_AWS_IAM_USER_ARN>"
      },
      "Action": "sts:AssumeRole",
      "Condition": {
        "StringEquals": {
          "sts:ExternalId": "<STORAGE_AWS_EXTERNAL_ID>"
        }
      }
    }
  ]
}
```

Update Trust Policy after replacing the string values for *your* `STORAGE_AWS_IAM_USER_ARN` and `STORAGE_AWS_EXTERNAL_ID`.

After completing this section, your AWS and Snowflake account permissions are ready for Snowpipe. The next section provides the steps to perform automated micro-batching with cloud notifications triggering Snowpipe.

Create a pipe in Snowflake

Now that your AWS and Snowflake accounts have the right security conditions, complete Snowpipe setup with S3 event notifications.

1. Create a Database, Table, Stage, and Pipe

On a fresh Snowflake web console worksheet, use the commands below to create the objects needed for Snowpipe ingestion.

Create Database

```
create or replace database S3_db;
```

Execute the above command to create a database called 'S3_db'. The **Results** output will show a status message of `Database S3_DB successfully created`.

Create Table

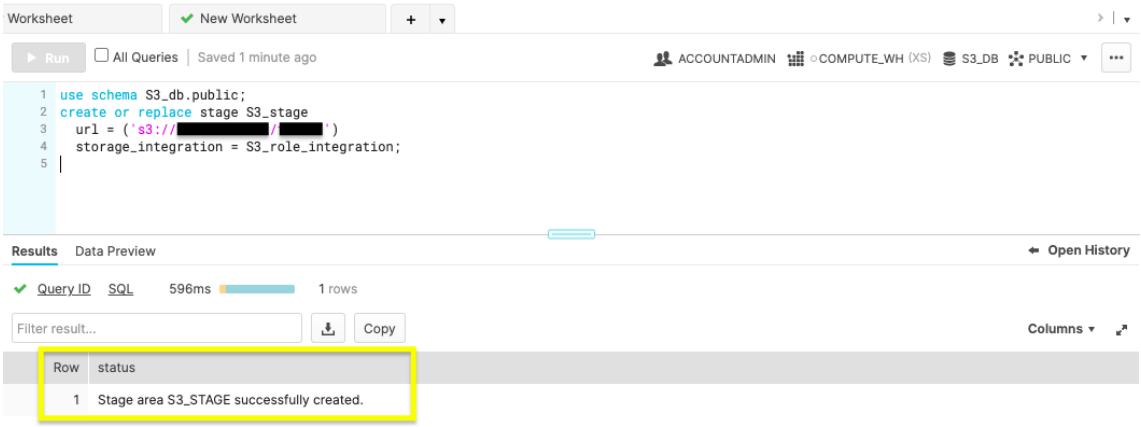
```
create or replace table S3_table(files string);
```

This command will make a table by the name of 'S3_table' on the S3_db database. The **Results** output will show a status message of `Table S3_TABLE successfully created`.

Create Stage

```
use schema S3_db.public;
create or replace stage S3_stage
  url = ('s3://<bucket>/<path>/')
  storage_integration = S3_role_integration;
```

To make the external [stage] needed for our S3 bucket, use this command. Be mindful to replace the `<bucket>` and `<path>` with your S3 bucket name and file path.



The figure above shows *Results* reading 'Stage area S3_STAGE successfully created'.

Create Pipe

The magic of automation is in the [create pipe] parameter, `auto_ingest=true`. With auto_ingest set to true, data stagged will automatically integrate into your database.

```
create or replace pipe S3_db.public.S3_pipe auto_ingest=true as
  copy into S3_db.public.S3_table
  from @S3_db.public.S3_stage;
```

Confirm you receive a status message of, 'Pipe S3_PIPE successfully created'.

2. Configure Snowpipe User Permissions

To ensure the Snowflake user associated with executing the Snowpipe actions had sufficient permissions, create a unique role to manage Snowpipe security privileges. Do not employ the user account you're currently utilizing, instead create a new user to assign to Snowpipe within the web console.

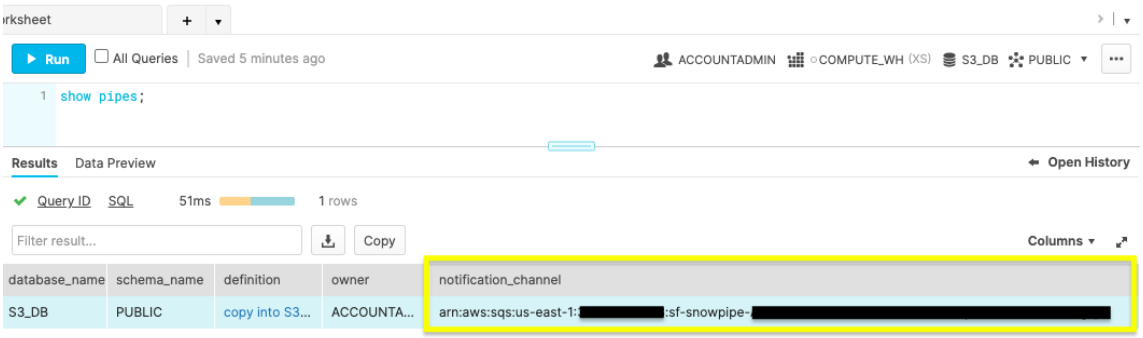
```
-- Create Role
use role securityadmin;
create or replace role S3_role;

-- Grant Object Access and Insert Permission
grant usage on database S3_db to role S3_role;
grant usage on schema S3_db.public to role S3_role;
grant insert, select on S3_db.public.S3_table to role S3_role;
grant usage on stage S3_db.public.S3_stage to role S3_role;

-- Bestow S3_pipe Ownership
grant ownership on pipe S3_db.public.S3_pipe to role S3_role;

-- Grant S3_role and Set as Default
grant role S3_role to user <username>;
alter user <username> set default_role = S3_role;
```

Create a new role named `S3_role` with *SECURITYADMIN* access. Give the `S3_role` usage permissions to the database objects, insert permission for the `S3_table` and ownership of `S3_pipe`. Lastly, set the S3_role as a Snowflake user's default. Confirm the statement was successful before creating the S3 event notification.

3. New S3 Event

Run the `show pipes` command to record the ARN listed in the 'notification_channel' column.

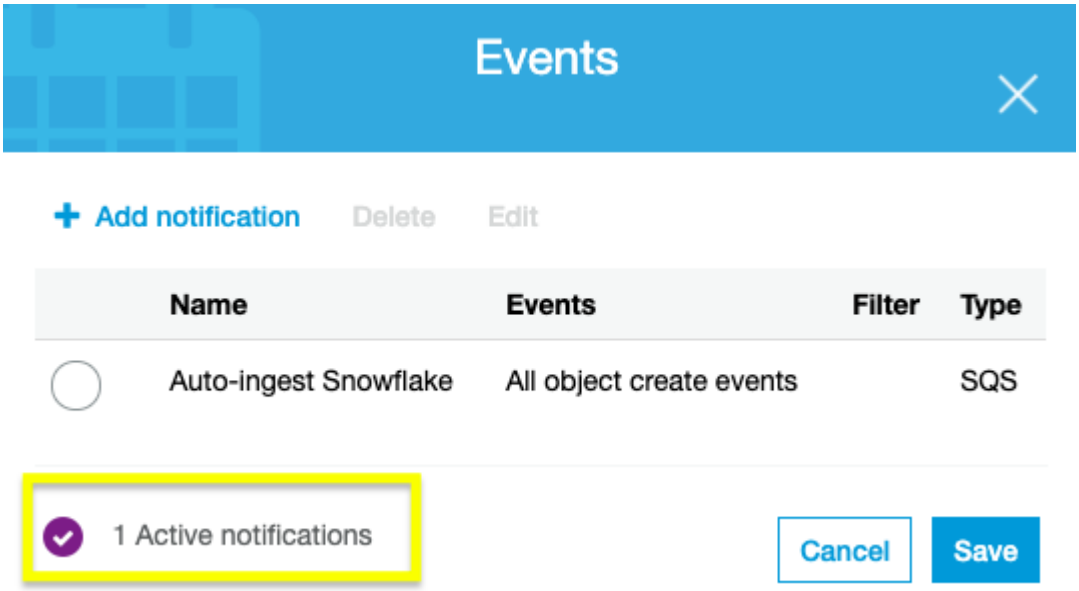
```
show pipes;
```



Copy the ARN because you'll need it to configure the S3 event notification.

Sign in to your AWS account and navigate to the S3 service console. Select the bucket being used for Snowpipe and go to the **Properties** tab. The **Events** card listed will allow you to **Add notification**. Create a notification with the values listed.

- **Name**: Auto-ingest Snowflake
- **Events**: All object create events
- **Send to**: SQS Queue
- **SQS**: Add SQS queue ARN
- **SQS queue ARN:**



Snowpipe's automated micro-batching is now active. Learn how to manage database integration in the next step.

Manage and Remove Pipes

Snowpipe is configured and now updates the Snowflake database when any object is created in the AWS S3 bucket. Let's review a few common commands to manage and remove Snowpipe.

ALTER PIPE

- Pause Snowpipe

```
ALTER PIPE … SET PIPE_EXECUTION_PAUSED = true
```

Before making configuration changes with `ALTER PIPE`, stop the Snowpipe process by pausing it by setting `PIPE_EXECUTION_PAUSED` to true. Once you're ready to start the pipe again, set this parameter to false.

- Check Snowpipe Status

```
SYSTEM$PIPE_STATUS
```

To check the status of the pipe, run the above command.

DROP PIPE

```
drop pipe S3_db.public.S3_pipe;
```

The `drop` command will delete your Snowpipe once you are finished with this tutorial.

SHOW PIPE

```
show pipes
```

Confirm the pipe was removed by displaying all of the pipes.

After wrapping up this section, you're ready to look ahead to using Snowpipe on your applications.

Conclusion

You've learned the benefits of continuous data loading and the different ways Snowpipe can be triggered to load new data. Plus, you can now configure cloud storage event notifications and manage Snowpipe.

Review the various ways to implement Snowpipe. If you're contemplating migrating an active database, select the staging method best for your architecture, and test the workflow on a small dataset. Experimenting will allow for an accurate cost-benefit analysis.

What we've covered

- Snowpipe Continuous Data Loading vs SnowPipe REST API
- Configuring AWS S3 event notifications for Snowpipe
- Creating, managing, and deleting pipes in Snowflake