Snowpark Performance Scaling Test (Azure + Snowflake)

Introduction

In this performance-based assignment, the objective was to evaluate how scaling Snowflake Virtual Warehouses affects query execution time when processing large datasets using Snowpark for Python in Azure.

The test was carried out in a controlled environment using the database MY_PRACTICE_DB, schema PUBLIC, and a performance warehouse WH_ASSIGN2. The process covered warehouse configuration, dataset generation, Snowpark connection from Azure, performance testing, and monitoring through query history.

Step 1 — Create and Configure Virtual Warehouse

A dedicated warehouse named **WH_ASSIGN2** was created exclusively for the Snowpark performance test.

- The warehouse was configured as **STANDARD** type with auto-suspend (60 seconds) and auto-resume enabled.
- **Multi-cluster scaling** was set with a minimum of 1 and a maximum of 3 clusters to allow elasticity during heavy processing.
- After creation, the configuration was verified using SHOW WAREHOUSES and DESCRIBE WAREHOUSE WH ASSIGN2.
- The database context was switched to MY_PRACTICE_DB and schema to PUBLIC for further operations.

```
2025-10-16 11:00am
task1
                                                 Assignment_2
                                                                          assignment_3
                                                                                                   2025-10-17 11:22am
                                                                                                                            Users and roles
                                                                                                                          ACCOUNTADMIN
    MY_PRACTICE_DB.PUBLIC V
                                                                                                                                            [ O
    CREATE OR REPLACE WAREHOUSE wh_assign2
      WAREHOUSE_SIZE = 'LARGE'
      WAREHOUSE_TYPE = 'STANDARD'
      MIN_CLUSTER_COUNT = 1
      MAX_CLUSTER_COUNT = 3
      SCALING_POLICY = 'STANDARD'
      AUTO_SUSPEND = 60
      AUTO_RESUME = TRUE;
    SHOW WAREHOUSES.
    DESCRIBE WAREHOUSE wh_assign2;
```

Step 2 — Create Database, Schema, and Large Sample Table

To simulate a real-time data environment, a large event dataset was generated.

- A new table named BIG_EVENTS was created under MY PRACTICE DB.PUBLIC.
- This table was populated using Snowflake's internal generator function, producing 10 million records with random event timestamps, user IDs, and unique payload hash values.
- The warehouse WH_ASSIGN2 was later scaled up to XLARGE size to efficiently handle large data volume operations.
- Verification confirmed that the data was successfully generated and stored in the table.

```
MY_PRACTICE_DB_PUBLIC V Settings V

MY_PRACTICE_DB_PUBLIC V Settings V

SHOW WAREHOUSES;
DESCRIBE WAREHOUSE wh_assign2;
use database MY_PRACTICE_DB;
use schema PUBLIC;

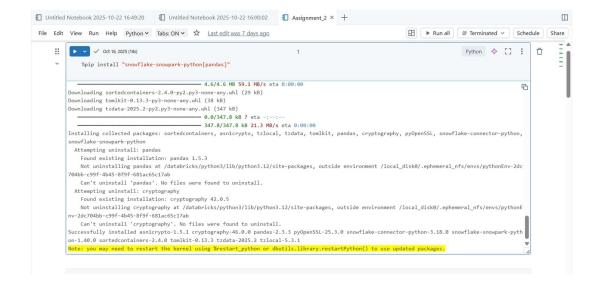
CREATE OR REPLACE TABLE big_events AS
SELECT
SEO4() AS id,
UNIFORM(0, 10000, RANDOM()), CURRENT_TIMESTAMP()) AS event_ts,
UNIFORM(1, 1000000, RANDOM())::NUMBER(12,0) AS user_id,
MD5(TO_VARCHAR(SEO4())) AS payLoad_hash
FROM TABLE(GENERATOR(ROWCOUNT => 10000000));

ALTER WAREHOUSE WH_ASSIGN2 SET WAREHOUSE_SIZE = 'XLARGE';
```

Step 3 — Connect from Azure using Snowpark and Execute Aggregation **Job**

Using Snowpark for Python, a connection was established from Azure to Snowflake.

- The Snowpark session was configured with account credentials, warehouse (WH_ASSIGN2), and the MY_PRACTICE_DB.PUBLIC schema.
- A Snowpark DataFrame was created to read data from the BIG EVENTS table.
- An aggregation operation was performed to count the number of events per user and store the output into a new table named **BIG EVENTS AGG**.
- The total execution time was recorded to measure job performance.
- Initial runtime on a smaller warehouse size served as a baseline for comparison.



```
Python 💠 [] : 🗓
Dot 16, 2025 (1s)
       from snowflake.snowpark import Session
        import time
        # --- Snowflake connection configuration ---
        connection_parameters = {
            "account":"tprtvog-tg33465",
            "user": "shivashankari",
            "password": "Shivashankari_04",
           "role": "ACCOUNTADMIN",
                                                      # or another valid role
           "warehouse": "wh_assign2",
"database": "MY_PRACTICE_DB",
                                                 # your test warehouse
            "schema": "PUBLIC"
        # --- Create a Snowpark session ---
        session = Session.builder.configs(connection_parameters).create()
        print("Connected to Snowflake!")
   Connected to Snowflake!
```

```
# V V Oct 16, 2025 (1s)

from snowflake.snowpark.functions import col, count

start = time.time()

# Load the big table

df = session.table("BIG_EVENTS")

# Group by USER_ID and count events

agg_df = df.group_by(col("USER_ID")).agg(count("*").alias("EVENT_COUNT")))

# Write the results into a new table

agg_df.write.save_as_table("BIG_EVENTS_AGG", mode="overwrite")

end = time.time()

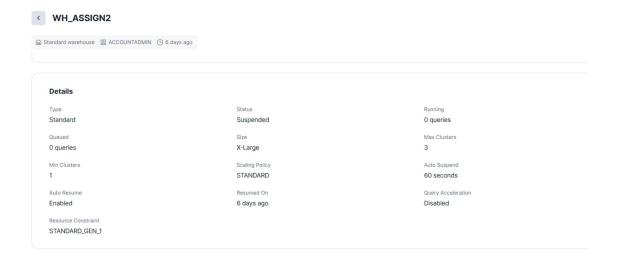
print(f"Snowpark job completed in {end - start:.2f} seconds")

Snowpark job completed in 0.78 seconds
```

Step 4 — Scale Warehouse and Re-run Aggregation

To observe the performance impact, the same Snowpark job was re-executed after scaling the warehouse.

- The WH_ASSIGN2 warehouse was resized to LARGE and then resumed for computation.
- The same aggregation logic was executed again using the same dataset and environment.
- The runtime was measured and compared across different warehouse sizes.



Step 5 — Monitor Query Performance using Snowflake Query History

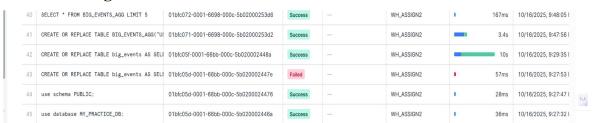
The **Snowflake Query History** feature was used to analyze and confirm performance changes.

- Queries containing BIG_EVENTS were filtered to review runtime, warehouse name, and execution start time.
- The metrics verified that queries executed under **larger warehouse sizes** completed much faster than smaller configurations.
- The improvement in performance directly reflected the benefits of Snowflake's scaling architecture.

Before Scaling:

	SQL TEXT	QUERY ID	STATUS	USER	WAREHOUSE	DURATION	STARTED
29	SELECT query_id, warehouse_name, total_ela	01bfc077-0001-66bb-000c-5b020002453a	Success	-	WH_ASSIGN2	1 312ms	10/16/2025, 9:53:24
30	SELECT * FROM BIG_EVENTS_AGG LIMIT 5	01bfc076-0001-6698-000c-5b020002542a	Success	_	WH_ASSIGN2	135ms	10/16/2025, 9:52:55
31	CREATE OR REPLACE TABLE BIG_EVENTS_AGG("US	01bfc076-0001-66bb-000c-5b0200024532	Success	-	WH_ASSIGN2	601ms	10/16/2025, 9:52:54
32	SELECT * FROM BIG_EVENTS_AGG LIMIT 5	01bfc076-0001-66bb-000c-5b020002452e	Success	-	WH_ASSIGN2	205ms	10/16/2025, 9:52:51
33	CREATE OR REPLACE TABLE BIG_EVENTS_AGG("US	01bfc076-0001-6698-000c-5b020002541e	Success	_	WH_ASSIGN2	729ms	10/16/2025, 9:52:30
34	SELECT * FROM BIG_EVENTS_AGG LIMIT 5	01bfc076-0001-66bb-000c-5b0200024522	Success	_	WH_ASSIGN2	120ms	10/16/2025, 9:52:17
35	CREATE OR REPLACE TABLE BIG_EVENTS_AGG("US	01bfc076-0001-6698-000c-5b020002541a	Success	_	WH_ASSIGN2	■ 776ms	10/16/2025, 9:52:16
36	SELECT * FROM BIG_EVENTS_AGG LIMIT 5	01bfc075-0001-6698-000c-5b0200025412	Success	_	WH_ASSIGN2	8 304ms	10/16/2025, 9:51:45

After Scaling:



Conclusion

The experiment successfully demonstrated how **warehouse scaling** in Snowflake enhances performance when handling large datasets with Snowpark.

Through this case study, we:

- Created and configured WH_ASSIGN2 warehouse for testing.
- Generated a large dataset (BIG_EVENTS) under MY_PRACTICE_DB.PUBLIC.
- Connected from Azure using Snowpark for Python.
- Executed and re-ran aggregation jobs at different warehouse sizes.
- Verified faster execution through query history analysis.

This exercise confirmed that increasing warehouse size in Snowflake provides significant performance improvement for large-scale Snowpark data transformations executed from Azure.