

@ADVANALYTICSUK

# WHO AM I



- 17+ Years Experience
- Data Engineering Consultant
- Intensive Software & Data Engineering Experience
- Microsoft AI MVP
- Public Speaker
- **Community Organiser**



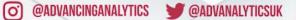












# WHO AM I



- SQL Server DBA/Developer
- 20 years + experience
- Microsoft Data Platform MVP
- User Group Leader
- **SQLBits Organiser**















# WHO AM I



- 9+ Years Experience
- Data Engineering Consultant
- **Database Engineer**
- Public Speaker
- Data Bristol Organiser
- Pydata Bristol Organiser





















# **AGENDA**

- **ACID Transactions**
- Parquet/Delta Storage vs Storage Structures
- Partitioning Delta vs SQL
- Z-ordering vs Clustered Indexing and Column Store Indexing
- Delta History and Time Travel vs SQL Temporal Tables
- Delta Vacuum vs Data Retention
- Identity Columns, Primary & Foreign Keys
- Security (Unity Catalog) vs SQL Security
- Databricks Clusters vs SQL Engine











# ATOMICITY, CONSISTENCY, ISOLATION, AND DURABILITY

Atomicity: The Transaction can be treated as a single

unit that can succeed or fail

Consistency: The data must be consistent before and after

the Transaction

Isolation: The Transaction is independent and can be

attempted without interference

Durability: A successful transaction persists if the system

fails



# ATOMICITY, CONSISTENCY, ISOLATION, AND DURABILITY

SQL Server uses a single write ahead transaction log per database. Databrick gains the functionality of a log file from delta format.

	Atomicity	Consistency	Isolation	Durability
Parquet	×	×	×	×
Delta Format	<b>√</b>		<b>√</b>	
Simple Recovery	<b>✓</b>	<b>✓</b>	<b>✓</b>	<b>✓</b>
Full Recovery	<b>√</b>		<b>√</b>	<b>✓</b>

#### Isolation

SQL Server	Delta Format	
Read	Write	
Uncommitted	Serializable	
Repeatable Read	×	
Snapshot	×	
Serializable	Serializable	





# ATOMICITY, CONSISTENCY, ISOLATION, AND DURABILITY

Databricks uses Delta format to get ACID properties Delta format is open source!







We have to persist data to disk

- Data stored in files
- SQL Server exclusively access the files

	SQL Server	Delta Format	Parquet
File Structure	*.MDF, *.NDF	*.parquet	*.parquet
Log File Structure	*.LDF	/_delta_log /000000.json	







	SQL Server
File Structure	MDF, NDF
Log File Structure	LDF

Many tables to a file

[Person].[Address]
[Person].[Person]
[Production].[Product]
[Sales].[Customer]

LDF

MDF

We can have multiple tables in the same file



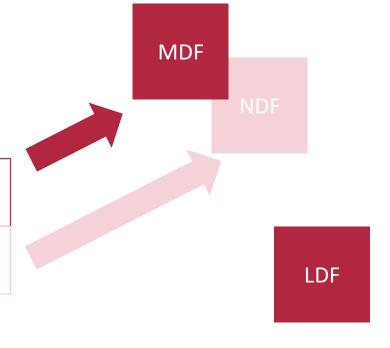


	SQL Server
File Structure	MDF, NDF
Log File Structure	LDF

- Many tables to a files
- Multiple files

[Person].[Address]
[Person].[Person]

[Production].[Product]
[Sales].[Customer]



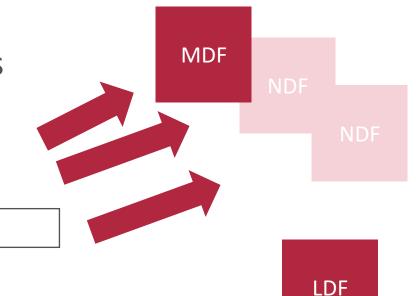
- We can have multiple tables in the same file
- We can have tables in different files groups



	SQL Server
File Structure	MDF, NDF
Log File Structure	LDF

- Many tables to a files
- Multiple files
- Many files to a table

[Person].[Address]



- We can have multiple tables in the same file
- We can have tables in different files groups
- We can have one table per file group unless the table has been partitioned
- If additional log files are used, they are still shared

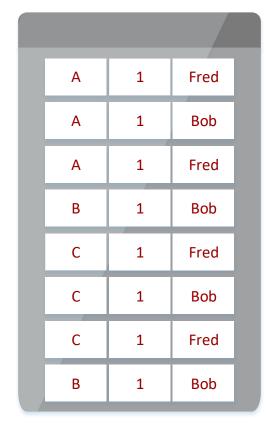




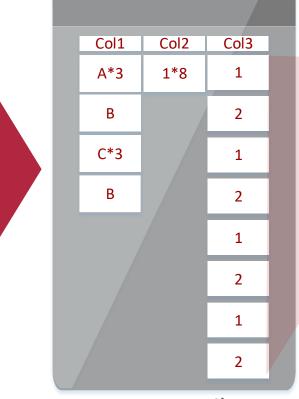
#### **WHAT IS PARQUET?**

Open source, column-oriented data file format

**Metadata** – Schema, Structure, Dictionaries







Parquet File



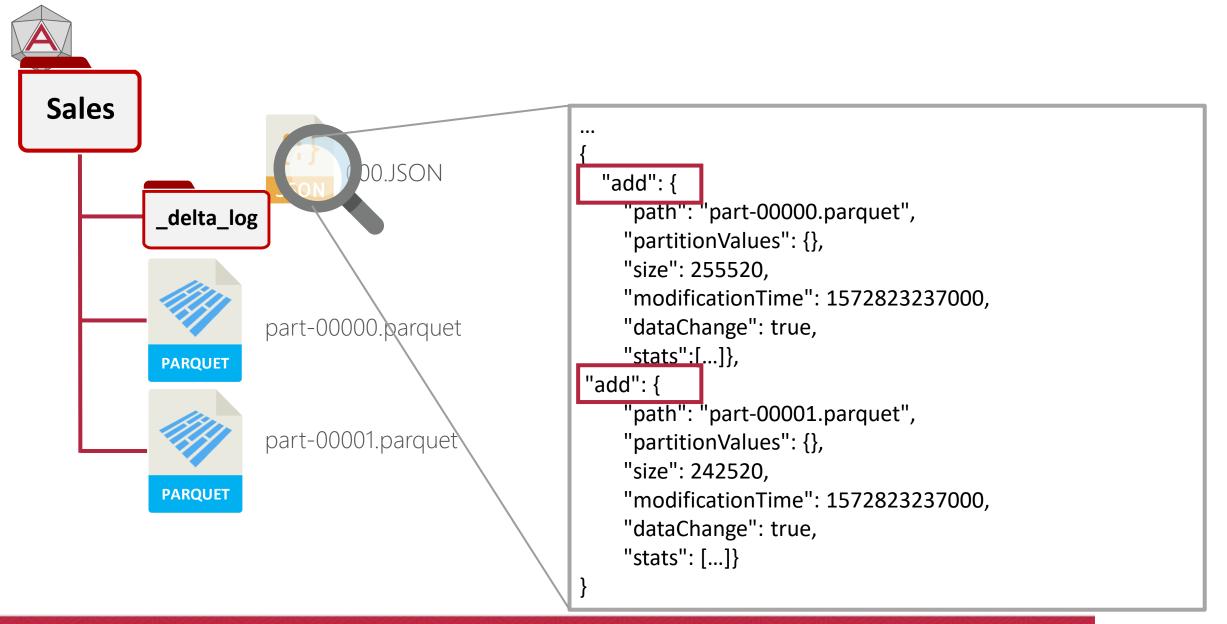




### **DELTA FEATURES**

- ACID Transactions
- Scalable Metadata
- Time Travelling
- Audit History
- Batch & Streaming Support
- Schema Enforcement
- Schema Evolution
- Familiar SQL Commands
- Open Format
- Compatible with Spark









### **STORAGE STRUCTURES**

Within these files, SQL Server has three types of storage structures that are Heap, clustered and column store indexes

- Heap
- Clustered Index
- Column store Index

This are where the data is physically stored on Disk





SQL Server allow us to have a transactional copy of the data as a non-clustered index that can optimise reads.

In contrast, we would create copy with a subset in Databricks!

	SQL Server	Delta	Parquet
Data Structure	Heap, B Tree, Clustered Column Store, Order Clustered Column Store	Columnal	Columnal
Secondary Data Copies	Non Clustered Index, Non Clustered Column Store		





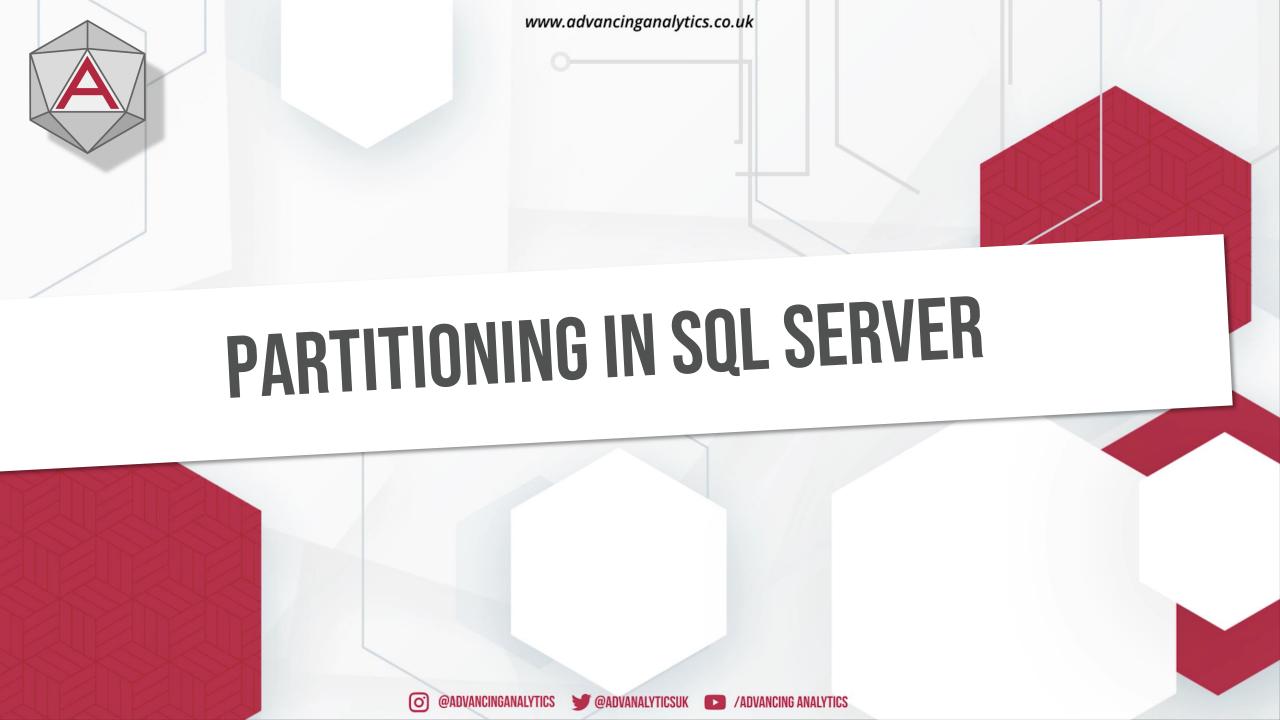
#### WHAT PROBLEM ARE WE TRYING TO SOLVE?

 Chunking data into logical buckets for reading and writing without having to work with the entire dataset

 Large Data Set can have issues at scale with data manipulation and storage size









### PARTITION VIEW AND TABLE PARTITION

SQL Server has two type of partitioning.

- Partition Table
- Partition Views

Partition Tables are tables partitioned on a key across multiple files.

Partition views can be place over tables to partition different keys.





# **PARTITION VIEW AND TABLE PARTITION**

Table File Structure View a b **One Table** One Table to multiple Files e e **One View to multiple Tables** Each table will have its own file group W



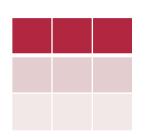


# PARTITION VIEW AND TABLE PARTITION

View

Table

File Structure

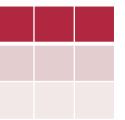










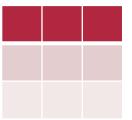








0











Delta data is stored as multiple small files when loaded.

Delta Partitioning divides those data file into useful slices so they can be retrieved quickly and effectively.

	path	name	size	
1	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Exported/_delta_log/	_delta_log/	0	
2	$dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow\_TripData/Exported/part-00000-829f8ebc-6be6-4491-a1ba-f9bb93311d5f-c000.snappy.parquet$	part-00000-829f8ebc-6be6-4491-a1ba-f9bb93311d5f-c000.snappy.parquet	161807024	
3	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Exported/part-00001-a95fa1fc-a3c5-4249-b09b-a2e475442757-c000.snappy.parquet	part-00001-a95fa1fc-a3c5-4249-b09b-a2e475442757-c000.snappy.parquet	154872635	
4	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Exported/part-00002-459fd8dc-f4ce-4dcf-8fd9-d87bdf2f9c25-c000.snappy.parquet	part-00002-459fd8dc-f4ce-4dcf-8fd9-d87bdf2f9c25-c000.snappy.parquet	153406419	
5	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Exported/part-00003-2f681144-3098-4adf-a917-b5800c8557d5-c000.snappy.parquet	part-00003-2f681144-3098-4adf-a917-b5800c8557d5-c000.snappy.parquet	154855624	
6	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Exported/part-00004-e30f11fb-008d-4029-87bd-7953f9346e20-c000.snappy.parquet	part-00004-e30f11fb-008d-4029-87bd-7953f9346e20-c000.snappy.parquet	147625269	
7	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Exported/part-00005-b470a4e3-a8fb-413e-85c4-320e8d82ca3e-	part-00005-b470a4e3-a8fb-413e-85c4-320e8d82ca3e-c000.snappy.parquet	144943806	





### **WRITING DELTA PARTITION**

```
# Define DataFrame over root entity folder
( df.write
    .format("delta")
    .mode("overwrite")
    .partitionBy("<ColumnName>")
    .save("deltaFilePath")
)
```

To write delta partition you use the .partitionBy() command

	path	name $ riangle$	size 📤
1	$dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow\_TripData/Partitioned/PULocationID=1/$	PULocationID=1/	0
2	$dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow\_TripData/Partitioned/PULocationID=10/$	PULocationID=10/	0
3	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Partitioned/PULocationID=100/	PULocationID=100/	0
4	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Partitioned/PULocationID=101/	PULocationID=101/	0
5	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Partitioned/PULocationID=102/	PULocationID=102/	0
6	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Partitioned/PULocationID=104/	PULocationID=104/	0
7	dbfs:/mnt/deltalake/MasteringDelta/NYCTaxi/Yellow_TripData/Partitioned/PULocationID=105/	PULocationID=105/	0





# **DEMO**

- Storage
- Partitions



#### WHAT PROBLEM ARE WE TRYING TO SOLVE?

Improve performance when reading data

 We don't want to have to scan the entire dataset to find rows that match our query

 Ordering data on a granular row by row level for more optimal reading









# "Sort the data on specific columns before writing to files, to optimize data skipping"

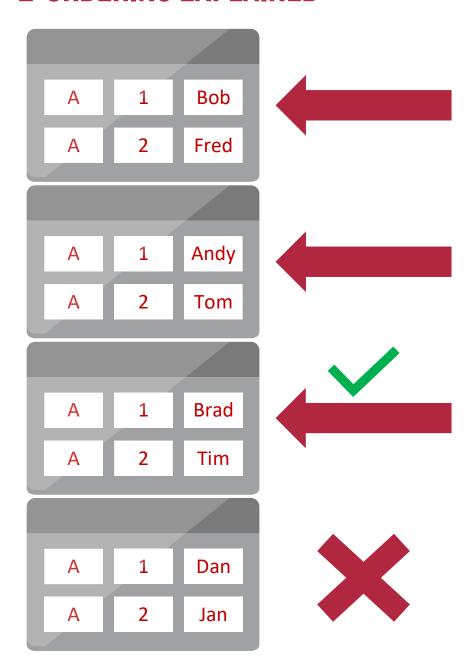
```
--Optimize an entire table OPTIMIZE [database].[table] ZORDER BY [ColumnName]
```



Z-Order can be expense, as with any sort-based Operation. It is sometimes better to perform this as an out-of-hours maintenance operation



#### **Z-ORDERING EXPLAINED**



**SELECT** count(\*) **FROM** Employees WHERE Name = 'Brad'

- The small files are not ordered
- SQL statement to query data
- Data skipping will look at all files until it finds what it's looking for



#### **Z-ORDERING EXPLAINED**

#### **SELECT** count(\*) **FROM** Employees WHERE Name = 'Brad'



Andy Tom

Brad

Tim

Dan Jan

**OPTIMZE ZORDER BY** 

Andy 1 Bob 1 Α 1 Brad Α Dan

2 Fred 1 Jan Tim 2 Α Tom Α

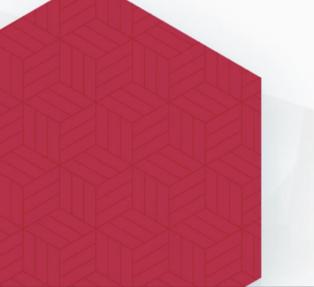
Z-Order as similar to a clustered index - organising your data on disk to maximise queries for specific columns

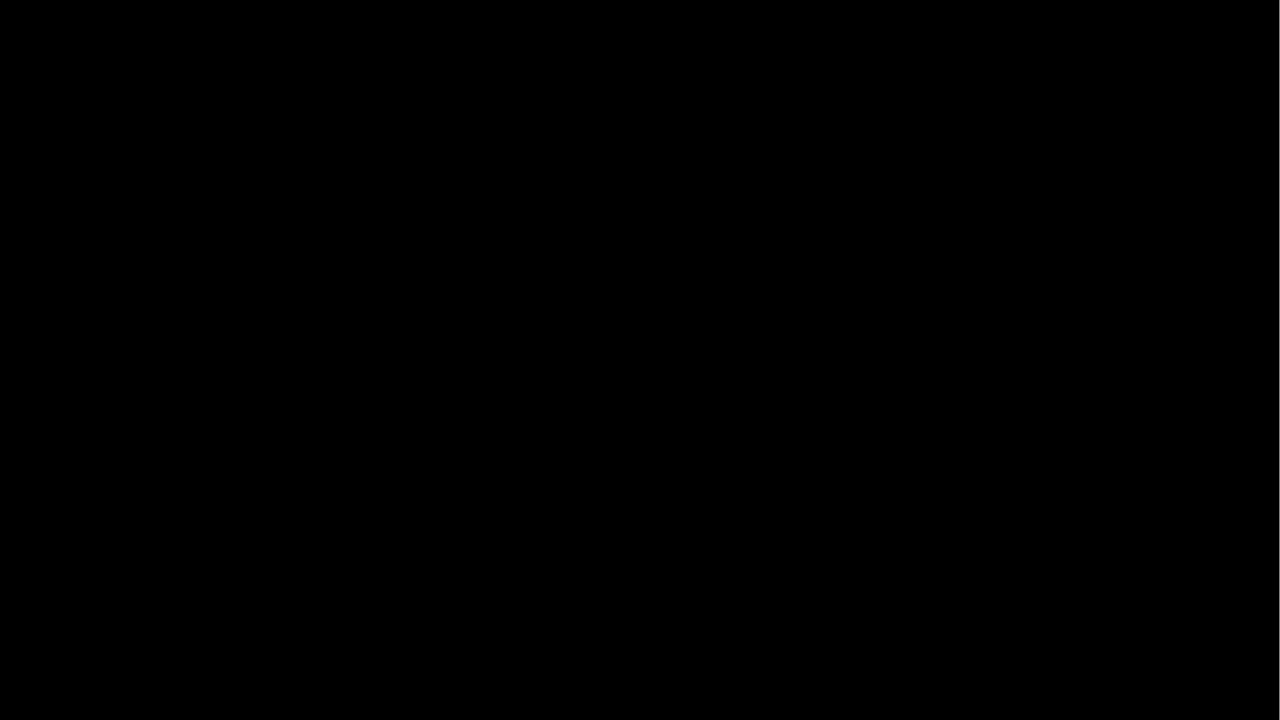




# **DEMO**

Z-ordering







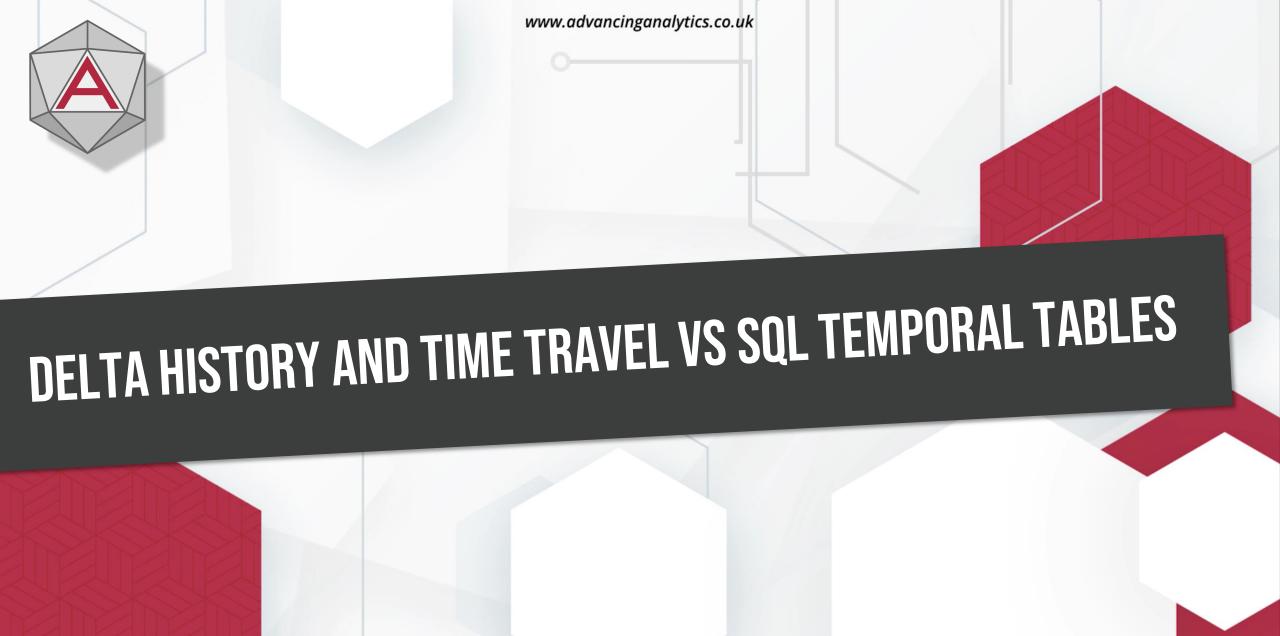


The order of the data is set by the Clustered Index

Index Maintenance

- Rebuilds
- Reorganization





#### WHAT PROBLEM ARE WE TRYING TO SOLVE?

- Keeping a history of changes for data
- Being able to query against point in time







- Delta Lake allow you to query older version/snapshots of a Delta table using Time Travel.
- Delta Lake stored a 30-days version history by default.
- Useful for debugging, auditing, rolling back for data quality or to reproduce experiments.
- Can query an older versions using Python or SQL syntax.



# **DELTA TIME TRAVEL**

```
-- SQL syntax
SELECT count(*)
FROM
<databaseName>.<tableName>
VERSION AS OF 0
```

	version $lacktriangle$	timestamp	
3			
4	4	2021-08-09T10:48:28.000+0000	
5	3	2021-08-09T10:47:53.000+0000	
6	2	2021-08-09T10:45:52.000+0000	
7	1	2021-08-09T10:45:49.000+0000	
8	0	2021-08-09T10:45:29.000+0000	





### **DEMO**

- History
- Versions







#### **TEMPORAL TABLES**

- Allow you to keep history of data changes
- Used for auditing
- Retention



#### **CREATING A TEMPORAL TABLE**

```
CREATE TABLE dbo.TmprlEmployee
        [EmployeeID] int IDENTITY NOT NULL PRIMARY KEY CLUSTERED
        , [Name] nvarchar(100) NOT NULL
        , [Position] varchar(100) NOT NULL
        , [Department] varchar(100) NOT NULL
        , [ValidFrom] datetime2 GENERATED ALWAYS AS ROW START
        , [ValidTo] datetime2 GENERATED ALWAYS AS ROW END
        , PERIOD FOR SYSTEM_TIME (ValidFrom, ValidTo)
10
11
12
       -- Set the history table, this is automatically created
      WITH (SYSTEM_VERSIONING = ON (HISTORY_TABLE = dbo.TmprlEmployeeHistory,
13
           HISTORY RETENTION PERIOD = 6 MONTHS ));
14
```





#### **INSERTING INTO A TEMPORAL TABLE**

```
INSERT INTO TmprlEmployee
([Name], Position, Department)

VALUES
('Fred Flintstone' ,'Team Leader', 'Cave Building'),
('Barney Rubble' ,'Assistant', 'Cave Building')

7
```





#### **INSERTING INTO A TEMPORAL TABLE**

- [6] 1 -- We can see the new record
  - 2 SELECT \* FROM TmprlEmployee
  - 3 -- but there is nothing in the history table because currently nothing has changed
  - 4 SELECT \* FROM TmprlEmployeeHistory

(2 rows affected)

(0 rows affected)

Total execution time: 00:00:00.016



	EmployeeID 🗸	Name 🗸	Position 🗸	Department 🗸	ValidFrom 🗸	ValidTo 🗸
1	1	Fred Flintstone	Team Leader	Cave Building	2023-09-29 18:08:40.5018095	9999-12-31 23:59:59.9999999
2	2	Barney Rubble	Assistant	Cave Building	2023-09-29 18:08:40.5018095	9999-12-31 23:59:59.9999999





#### **UPDATING A TEMPORAL TABLE**

```
1   UPDATE TmprlEmployee
2   SET Position = 'Manager'
3   WHERE [EmployeeID] = 1
4
```





#### **UPDATING A TEMPORAL TABLE**



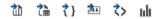
- 1 -- We can see the new record
- 2 SELECT \* FROM TmprlEmployee
- 3 -- but there is nothing in the history table because currently nothing has changed
- 4 SELECT \* FROM TmprlEmployeeHistory

 $\wedge$ 

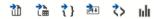
(2 rows affected)

(1 row affected)

Total execution time: 00:00:00.013



	EmployeeID 🗸	Name 🗸	Position 🗸	Department 🗸	ValidFrom 🗸	ValidTo 🗸
1	1	Fred Flintstone	Manager	Cave Building	2023-10-01 12:54:53.6886117	9999-12-31 23:59:59.9999999
2	2	Barney Rubble	Assistant	Cave Building	2023-09-29 18:08:40.5018095	9999-12-31 23:59:59.9999999



	EmployeeID 🗸	Name 🗸	Position 🗸	Department 🗸	ValidFrom 🗸	ValidTo 🗸
1	1	Fred Flintstone	Team Leader	Cave Building	2023-09-29 18:08:40.5018095	2023-10-01 12:54:53.6886117





#### **DELETING FROM A TEMPORAL TABLE**

```
1 -- Now what happens if we remove a record
2 DELETE FROM TmprlEmployee
3 WHERE employeeid = 2
4
```





#### **DELETING FROM A TEMPORAL TABLE**

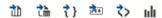


- -- the current table is showing the new from date
- SELECT \* FROM TmprlEmployee
- 3 -- and the history table is showing the old record
- 4 SELECT \* FROM TmprlEmployeeHistory



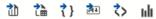
(2 rows affected)

Total execution time: 00:00:00.012



	EmployeeID	~	Name 🗸	Position 🗸	Department 🗸	ValidFrom ~	ValidTo 🗸
1	1		Fred Flintstone	Manager	Cave Building	2023-10-01 12:54:53.6886117	9999-12-31 23:59:59.9999999

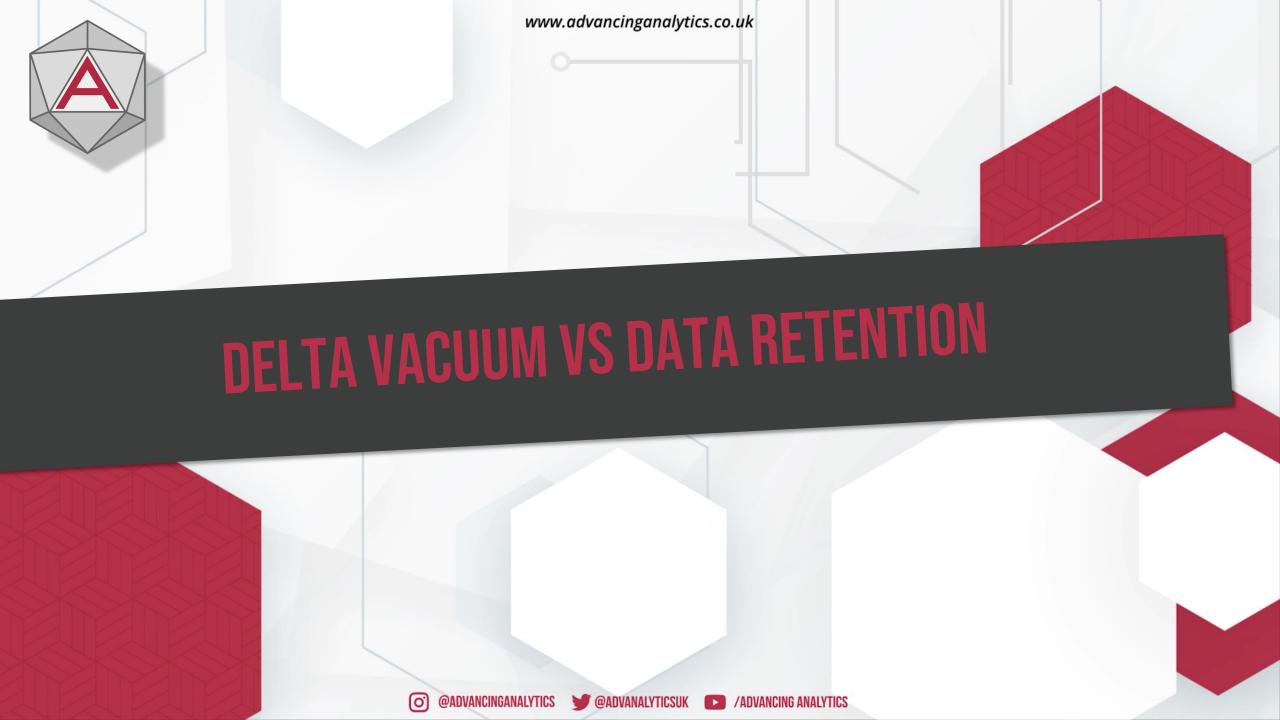
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	EmployeeID 🗸	Name 🗸	Position 🗸	Department 🗸	ValidFrom 🗸	ValidTo 🗸
1	1	Fred Flintstone	Team Leader	Cave Building	2023-09-29 18:08:40.5018095	2023-10-01 12:54:53.6886117
2	2	Barney Rubble	Assistant	Cave Building	2023-09-29 18:08:40.5018095	2023-10-01 12:56:35.2509339

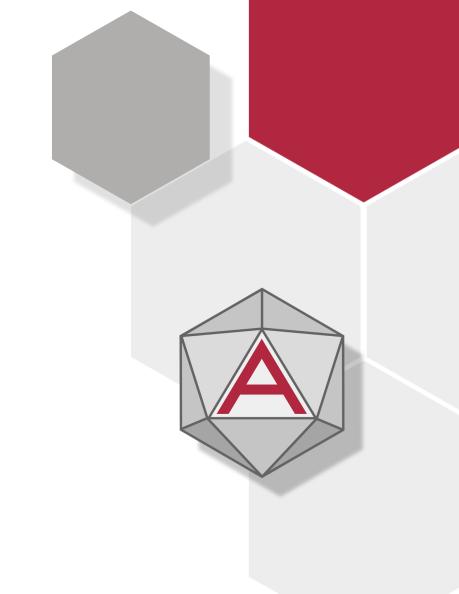






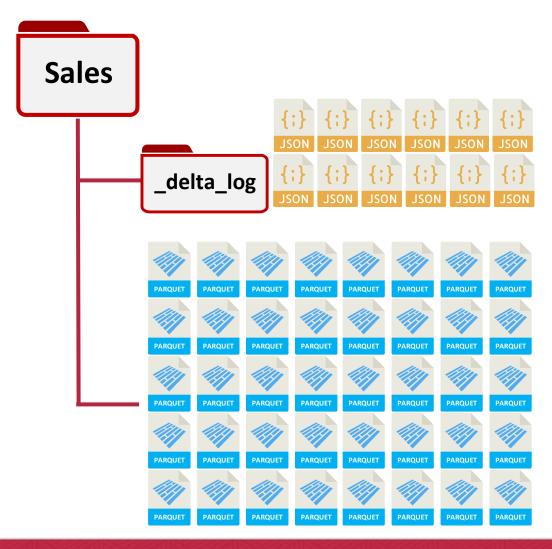
#### WHAT PROBLEM ARE WE TRYING TO SOLVE?

 Removing historical information that is no longer required









To remove obsolete history files, Delta has the **VACUUM** command

This command physically deletes data files older than a specified date

You CANNOT time travel past dates where history has been vacuumed



#### Vacuuming in SQL:

```
--Vacuum Table using defaults
VACUUM [database].[table]

--Vacuum using path not Hive table
VACUUM '/mnt/lake/BASE/myTable/'

--VACUUM for a non-default time period
VACUUM [database].[table] RETAIN 168 HOURS

--TEST THE VACUUM BEFORE YOU RUN IT
VACUUM [database].[table] RETAIN 168 HOURS DRY RUN
```

#### Using the python deltaTable object:

```
# Vacuum Table using defaults
deltaTable.vacuum()

# Vacuum Table for files older than 7 days (168 hours)
deltaTable.vacuum(168)
```





# **DEMO**

Vacuum











#### **DATA RETENTION**

- Audit logs
- Change Data Capture (CDC)
- Temporal Tables









#### WHAT PROBLEM ARE WE TRYING TO SOLVE?

- How can we keep referential integrity?
- How can we join data together across data?







#### WHAT IS DATABRICKS UNITY CATALOG?

Unity Catalog provides centralized access control, auditing, lineage, and data discovery capabilities across Databricks workspaces.

- Define once, secure everywhere
- Standards-compliant security model
- Built-in auditing and lineage
- Data discovery
- System tables

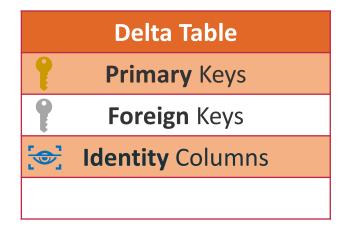




















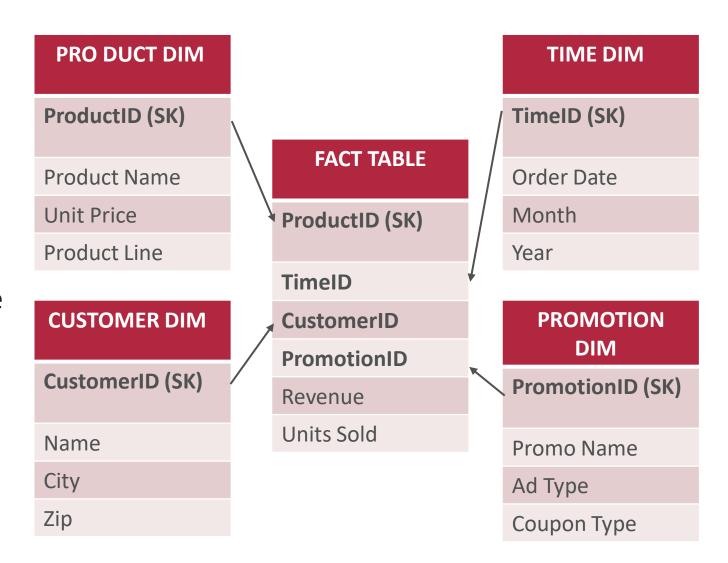
### DELTA CONSTRAINTS - DATABRICKS ONLY

- Primary Keys and Foreign Keys
- Identity Columns (Surrogate Keys)





- Traditionally used when created SK (Surrogate Keys ) for Star Schemas
- This was long awaited, but tricky for Databricks to implement due to the nature of distributed compute (unlike SQL Server)
- With <u>Databricks Runtime 10.4 LTS</u> we finally had <u>identity columns</u>









# PRIMARY AND FOREIGN KEYS

A primary key a constraint that enforces uniqueness,

This can be a single column or multiple columns.

A foreign Key is constraint that is linked

to a primary key constraint.

This link enforces that the value in

the foreign key must exist in the primary key.









# **SQL SERVER SECURITY**

- SQL Server has an object level security model.
- Data must be accessed via the SQL Server.
- SQL Server holds a file lock at all time.

We have AD/AAD with users, groups, Manage Identities and SQL Auth!



Application hold file locks at all time



Application hold file all time





#### **PREVIOUSLY**

 Secured Data on ADLS instance via Access Control Lists (ACLs)

 Couldn't sync AD (Active Directory) groups to Databricks





### **SECURITY IN UNITY CATLOG**

Unity Catalog gives you the ability to choose between centralized and distributed governance models:

- In the centralized governance model, your governance administrators are owners of the metastore and can take ownership of any object and grant and revoke permissions.
- In a distributed governance model, the catalog or a set of catalog's is the data domain

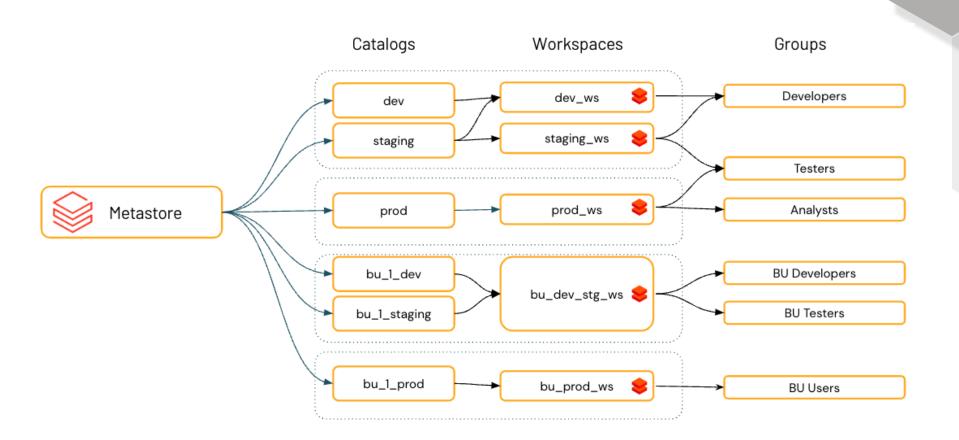




## **SECURITY IN UNITY CATLOG** Metastore External Storage Catalog Share Recipient Provider Connection credential location Schema Table View Volume Function Model



# **SECURITY IN UNITY CATLOG**









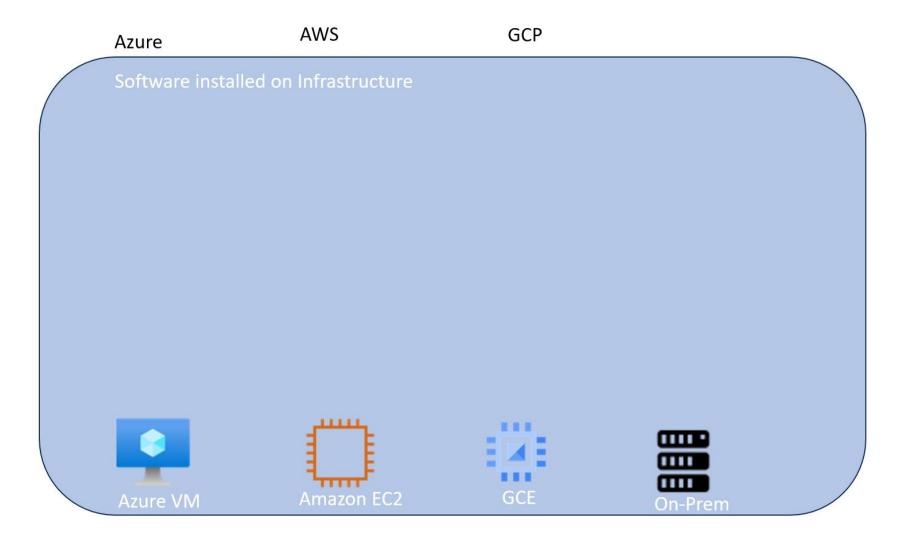
## WHAT PROBLEM ARE WE TRYING TO SOLVE?

What compute engine are we using?



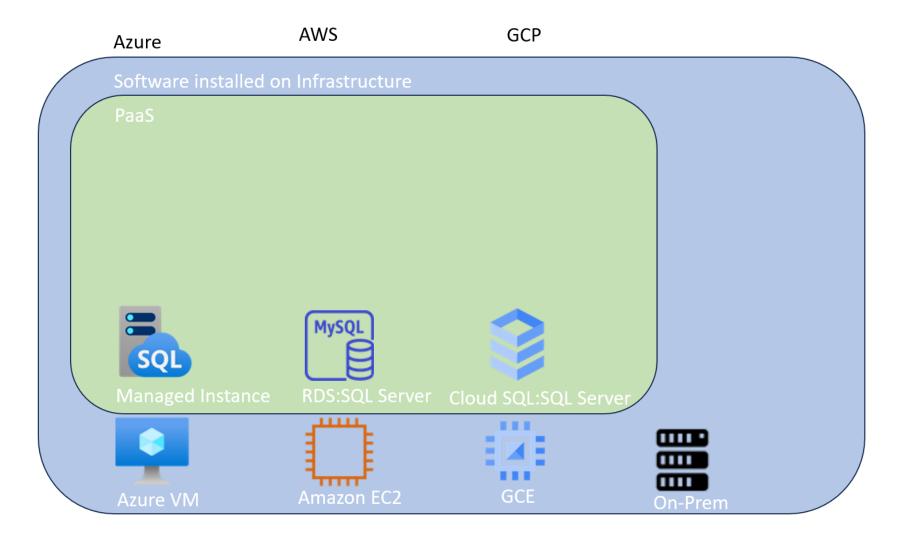


# **SQL SERVER AND IT DEPLOYMENT**



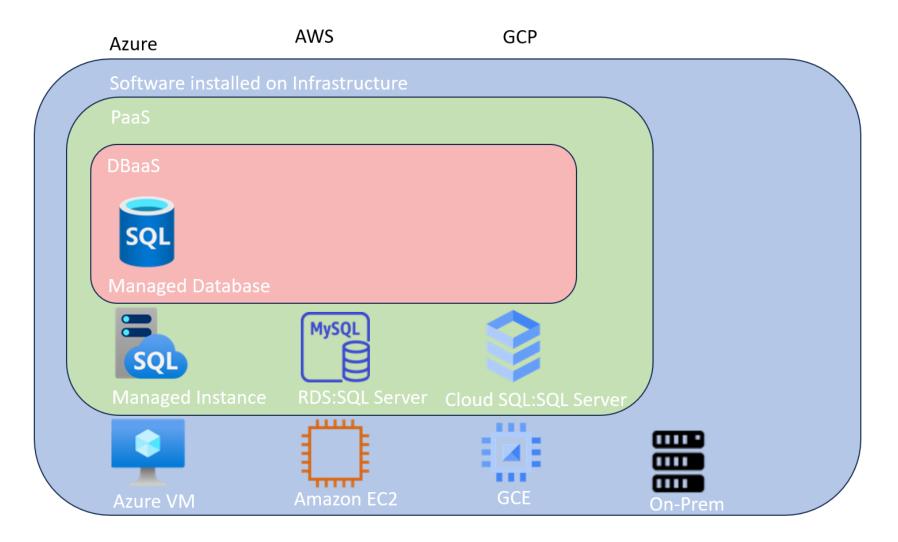


# **SQL SERVER AND IT DEPLOYMENT**





# **SQL SERVER AND IT DEPLOYMENT**

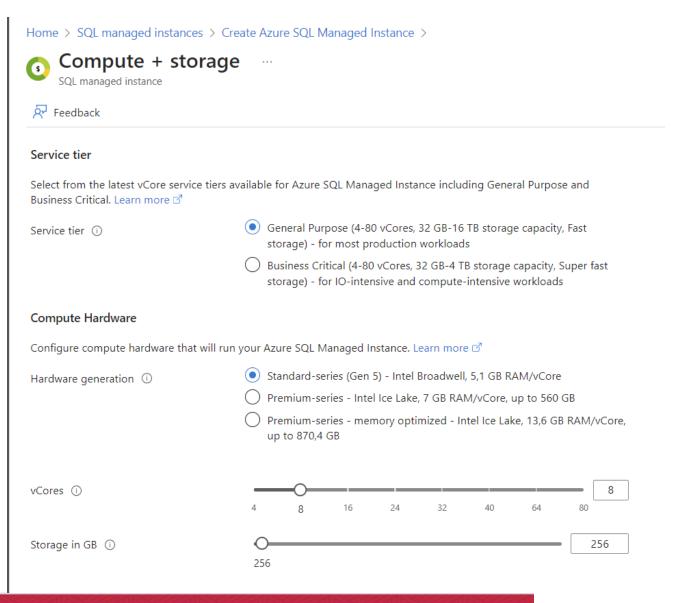






## Managed Instance:

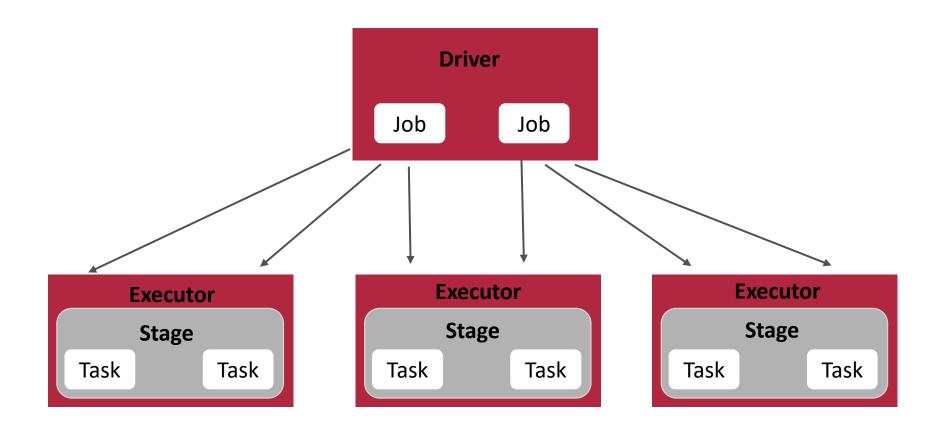
- Standard
- Premium
- Memory Optimized Premium







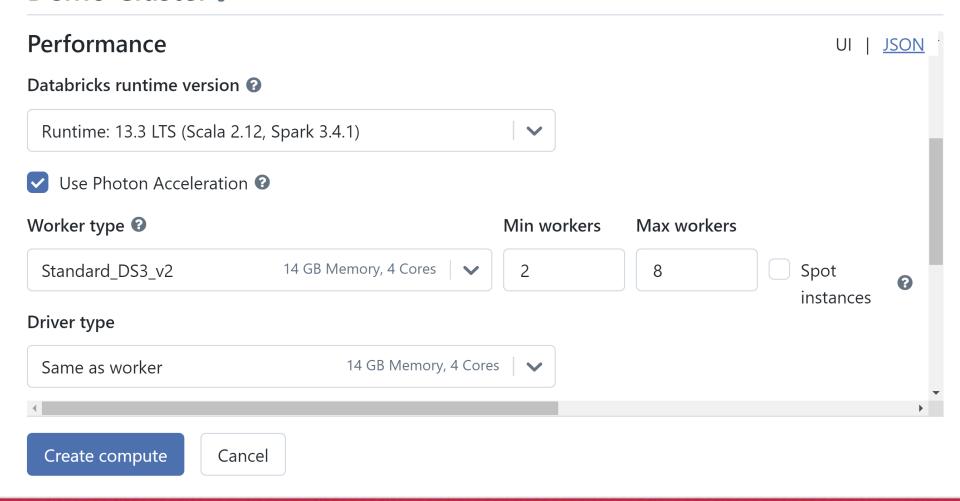








#### Demo Cluster 🕖





## **SUMMARY**

- We have ACID transactions and Partitioning in both
- They have different approaches to storage
- Ordering data on a granular row by row level for more optimal reading available in both: Clustered Indexes, Z-Ordering
- Replay history is achievable in both but very different
- Compute is very different in both, with Databricks being more complex
- Similarities in security approaches but still very different



