# Fabric I love you, I love you not

Riccardo Perico

BI & Power BI Engineer @Lucient Italia



# Sponsor











#### Bio





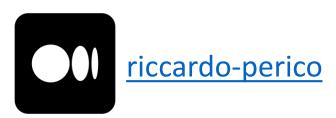








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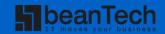




riccardo-perico











In this session I'll try not to "simply explain features", main goal is to give a feedback on them, based on my personal experience with Fabric doing tests and POCs.













## What to expect from this session?

- Discover things
- Enforce knowledge
- If you enter that door with doubts... will you get an answer?
   Maybe

Maybe not...

But I hope you'll get the right doubts

F

A













Maybe I'm wrong, or you've a different point of view...

Share your experience while we go, if you please















## I tried to keep my session as aligned as possible with all the recent announcements.

Please forgive me if I lost something.

I feel this session very ambitious,

I hope to met your expectations.



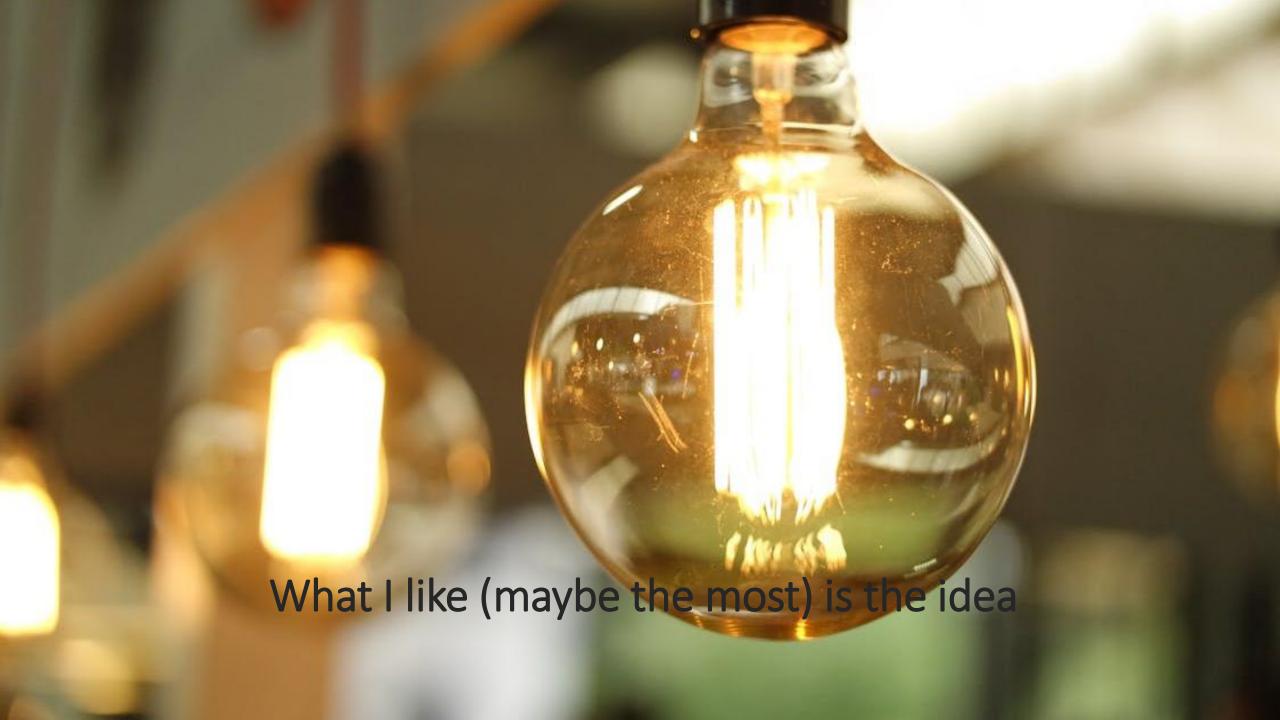




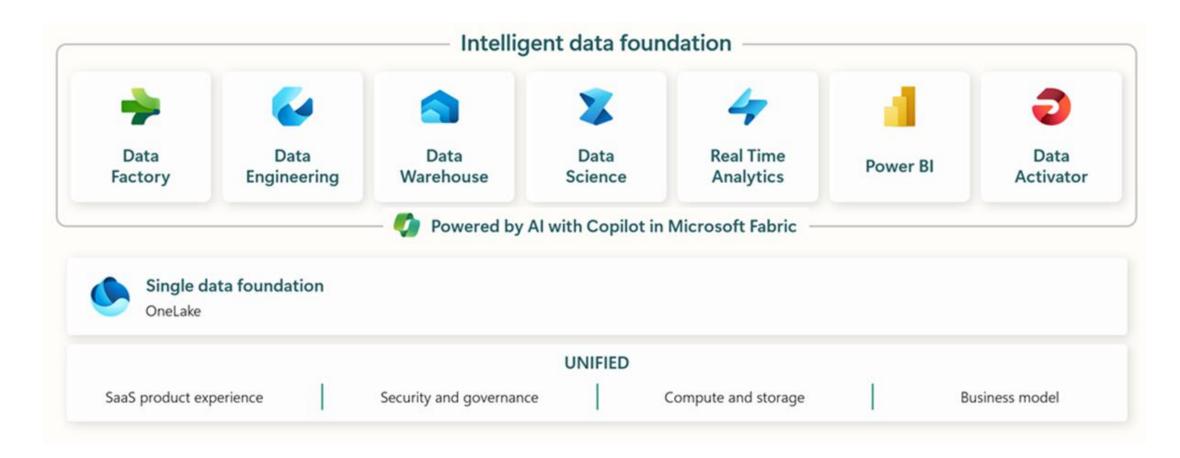








## The great unifier





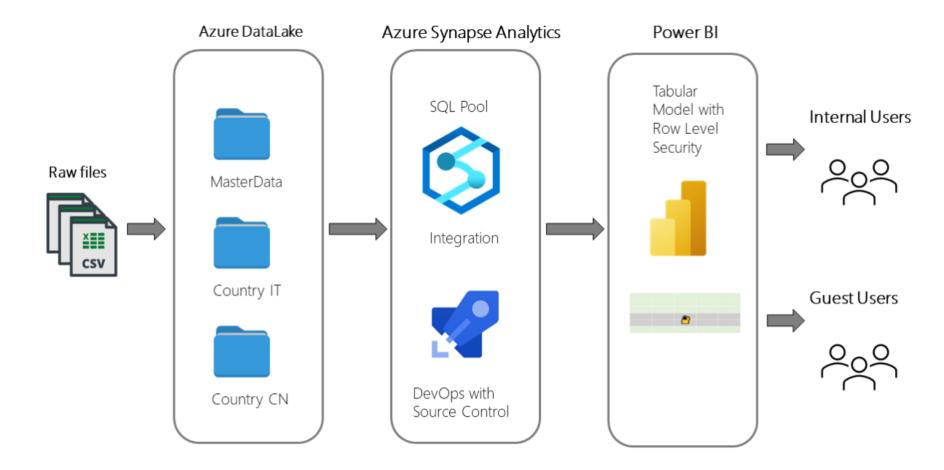








## As it is









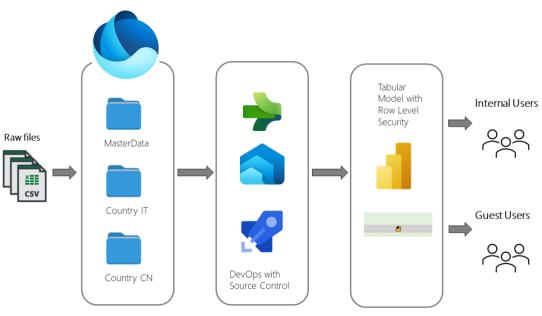




## To be

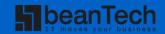
- From ADLS to OneLake folders
- Users can use Explorer Add-in
- From Synapse Pipelines to Data
   Pipeline
- From Dedicated SQL Pool to Warehouse
- From Power BI to Power BI
- Therefore... all-in one... Workspace















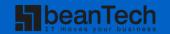
## OneLake idea is great

- If I'm the CDO, I can create a single repository
  - Structured
  - Unstrctured
- Tell all my platforms to read and write there
  - Fabric workload
  - ADF pipelines
  - Databricks
  - Snowflake
- Standard file format













## OneLake support for Import Mode Semantic Models



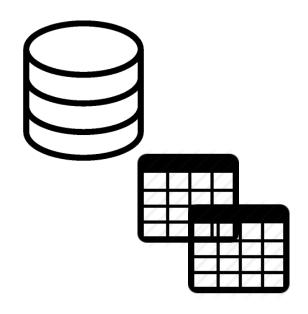


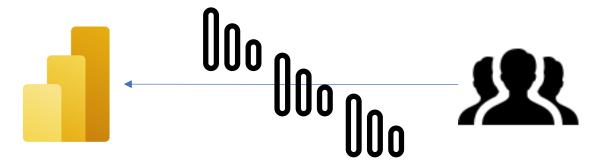






## The usecase







#### **Business Layer / Semantic Layer**

- + Cleansing
- + Naming Convention
- + Relationships
- + Calculated Columns
- + Calculated Tables

- Ask for CSV extract
- Use executeQueries API
- Go back to the source



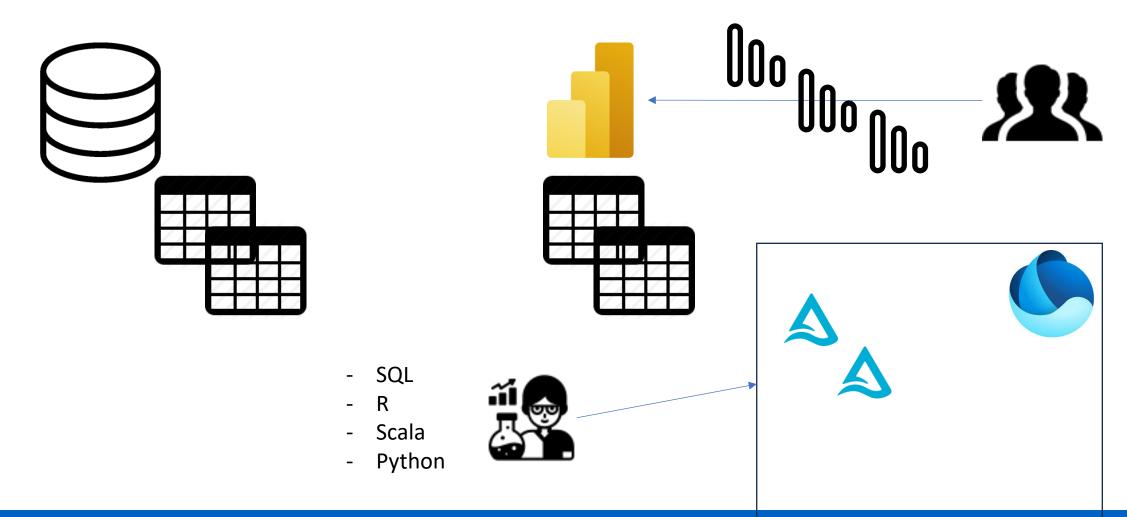








## A possible solution





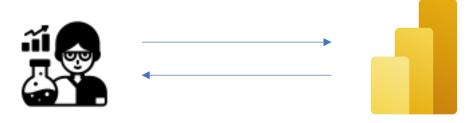








## Sempy to leverage the "Golden Model"



#### **Business Layer / Semantic Layer**

- + Cleansing
- + Naming Convention
- + Relationships
- + Calculated Columns
- + Calculated Tables
- + Measures

%pip install semantic-link

import sempy.fabric as fabric

dataset = "Retail Analysis Sample PBIX"

fabric.evaluate\_measure

(dataset, measure="Average Selling Area Size")











## Use cases for Sempy

- Data Analysts / Data Scientists searching for data already prepared
- Golden Model enrichment
- Improved data governance
- Strict data pipeline
- Programmatic interface for administrative tasks
  - Models and partitions refresh
  - Dataset migration to Direct Lake
  - Monitoring
  - Tenant management
  - API calls in Python (alternative to PowerShell)
  - •











## OneLake loves other platforms











## It's not a closed environment



- OneLake support for Iceberg
- OneLake Shortcuts over Snowflake
- Snowflake can store data in OneLake
- Snowflake can read data from OneLake



- "Mirrored" (federated) Azure
   Databricks Unity Catalog
- Federated Access OneLake from Databricks







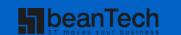




## One storage to rule them all







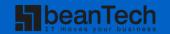
















## T-SQL is alive and well











#### Clone

- Metadata only copy (zero copy)
- Time travel back up to 30 days
- Good for development and testing
- Good for backup and restore
- Archiving system

```
CREATE TABLE
     dbo.nyctaxi clone
AS CLONE OF
     dbo.nyctaxi;
OPTION
      (FOR TIMESTAMP AS OF
     'yyyy-mm-
ddTHH:MM:SS.SSS');
```











## Time Travel (preview)

```
SELECT *
FROM dbo.Top10CustomersView

OPTION (
FOR TIMESTAMP AS OF '2024-04-24T20:59:06.097'
);
```











## Plan migration carefully











## Migration is not straight forward



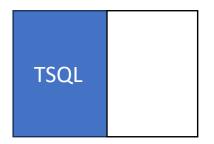


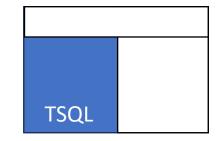






















## **Not Supported**

- SET XACT\_ABORT ON
- MERGE
- PRIMARY KEY
- UNIQUE
- IDENTITY
- SET IDENTITY\_INSERT
- Scalar Function
- TRUNCATE TABLE











## Latin1\_General\_100\_BIN2\_UTF8

**SELECT** \*

FROM dbo.MyTable;

<>

**SELECT** \*

FROM dbo.mytable;

**SELECT COUNT(\*)** 

FROM dbo.MyTable

WHERE Code = 'abc';

Id	Code
1	abc
2	abc
3	abc

Id	Code
1	Abc
2	abc
3	ABC











#### **NVARCHAR**

As of today, not supported.

Not a big deal since **Parquet manage automatically encoding** and collation is UTF-8.





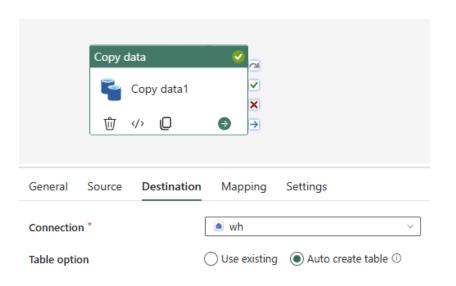






## View-table pipeline looses types

```
CREATE VIEW dbo. MyView AS
 SELECT
   AnIntField = CONVERT(int, t.F1)
   ,AString = CONVERT(varchar(20), t.F2)
   ,AndADateField = CONVERT(date, t.F3)
  FROM dbo.MyTable;
GO
                     CREATE TABLE dbo. MyNormalized Table
                              AnIntField int NULL,
                              Astring varchar (8000) NULL,
                              AndADateField date NULL
                     GO
```













## Workaround

**SELECT \*** 

INTO dbo.MyNormalizedTable

FROM dbo.MyView;











#### Or

CREATE TABLE dbo.MyNormalizedTable AS

**SELECT \*** 

FROM dbo.MyView;







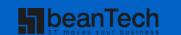




## Pump data before playing



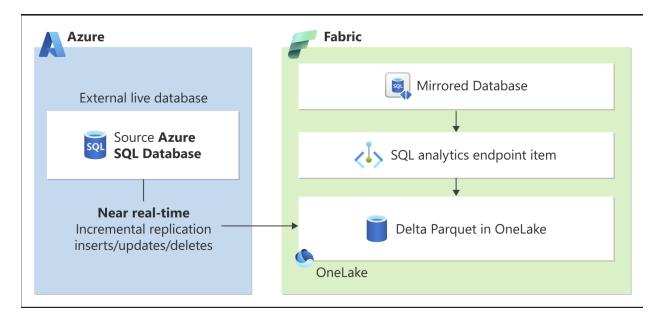


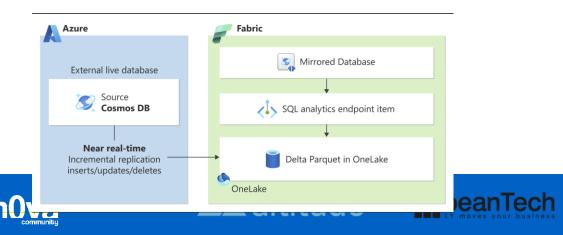


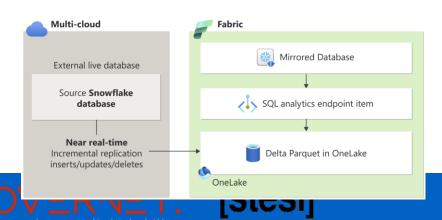




## Mirroring to Fabric







## Pros & Cons (On the SQL side)

- Managed ELT
- Near real-time replication
- Multi platform
- No extra cost 1TB per CU

- Preview feature
- No On-Prem SQL Server
- Public access only supported
- Cross tenant not supported
- ... it's not magic











#### Cons... continue

- A table cannot be mirrored if it does not have a primary key rowstore clustered index
- Following DDL operations aren't allowed on source tables
  - Switch/Split/Merge partition
  - Alter primary key
  - Drop table
  - Truncate table
  - Rename table
  - Alter column
- When there is DDL change, a complete data snapshot is restarted for the changed table, and data is reseeded













#### Snowflake has less limitations











#### Another definitive Great Unifier...











#### Simply unmatched, truly limitless: Announcing Azure Synapse Analytics

By Rohan Kumar, Corporate Vice President, Azure Data

Posted on November 4, 2019 3 min read



Big Data

Today, businesses are forced to maintain two types of analytical systems, data warehouses and data lakes. Data warehouses provide critical insights on business health. Data lakes can uncover important signals on customers, products, employees, and processes. Both are critical, yet operate independently of one another, which can lead to uninformed decisions. At the same time, businesses need to unlock insights from *all* their data to stay competitive and fuel innovation with purpose. Can a single cloud analytics service bridge this gap and enable the agility that businesses demand?

#### **Azure Synapse Analytics**

Today, we are announcing Azure Synapse Analytics, a limitless analytics service, that brings together enterprise data warehousing and Big Data analytics. It gives you the freedom to query data on your terms, using either serverless on-demand or provisioned resources, at scale. Azure Synapse brings these two worlds together with a unified experience to ingest, prepare, manage, and serve data for immediate business intelligence and machine learning needs.



#### **Explore**

Let us know what you think of Azure and what you would like to see in the future.

Provide feedback

Build your cloud computing and Azure skills with free courses by Microsoft Learn.

**Explore Azure learning** 











#### It seems a building site yet

- Tons of features every months
- Many features stay in preview for a very long time (even core)
  - GIT integration
  - Invoke Pipeline
  - Folders
  - Data Activator
  - Mirroring (only Snowflake GA)
  - PBIP and TMDL, New Card, Field Parameters...
- Flagship features only announced i.e. OneSecurity
- Security features premium+ (+F64)













## Database project support











#### **DACPACs**























# Lakehouse or not Lakehouse













### What experts say



#### Jovan Popovic

Principal Program Manager at Microsoft, working on Microsoft Fabric Warehouse. Worked on Azure Synapse, Azure SQL Azure SQL Managed Instance, and SQL Server.

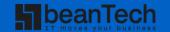
Published Aug 10, 2023

<u>Choosing between Lakehouse and Warehouse in Microsoft</u> Fabric (linkedin.com)

- Language preference for data management The choice between Lakehouse and Warehouse depends on the preferred programming languages of your team. This includes both syntax and functionalities that are available in the language that you choose. If your team leans towards PySpark or Scala for data management, Lakehouse is the natural choice. On the other hand, Warehouse caters to those who favor T-SQL. This distinction may be less relevant for visual, low-code, or citizen developers. However, it's important to consider the features associated with different languages. For instance, if you need ML/regular expressions, Lakehouse is the choice for you because these features are available in Python/Scala. On the other hand, if you need multi-table transactions, some enterprise data management features, or fine-grained permissions on every object in the database with GRANT/DENY, RLS, data masking you should choose T-SQL language in the Warehouse.
- Data format requirements If your data exists primarily in Delta format with relational structure, Warehouse seamlessly handles your needs. However, if you work with diverse formats like CSV, Parquet, or JSON, or you are using nonstructured data, Lakehouse proves to be the more versatile solution.
- Migration scenarios If your existing data solutions are implemented on SQL Server, Azure SQL, Synapse warehouse or other RDBMS systems, or involve a significant T-SQL code base that you wish to retain while transitioning to Fabric, the Warehouse is the preferable option. If you're migrating from a Spark/Databricks and have already implemented significant data processing logic in PySpark, Scala or SparkSQL notebooks, Lakehouse provides an easier path to migration within the Fabric ecosystem.



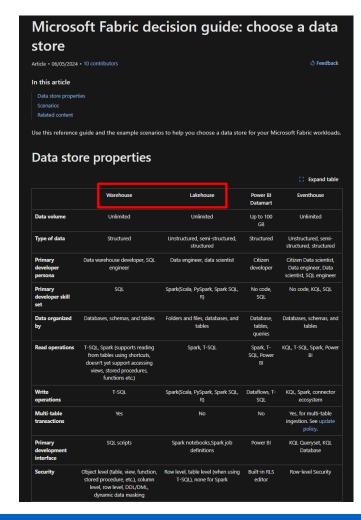








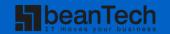
#### Even in official docs



<u>Fabric decision guide - choose a data store –</u> Microsoft Fabric | Microsoft Learn



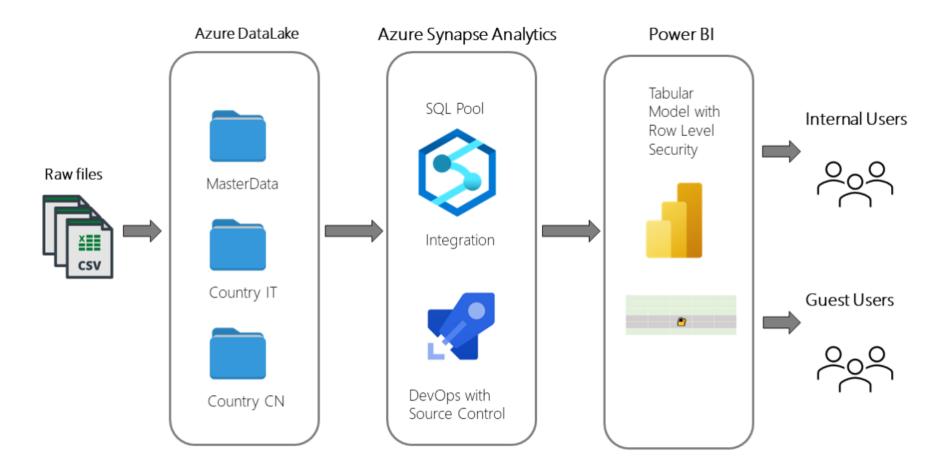








### Is it really a choice?













#### You'll likely need both...





- No Mirroring
- No cross-table transaction
- No T-SQL CRUD

- No Shortcut
- No OneLake interoperability
- No security features
  - ADLS firewalled access







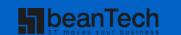




# Dealing with Delta in a different way



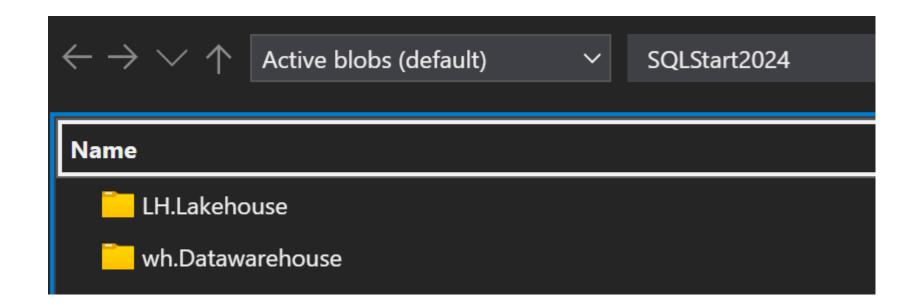








#### Under the hood













### Lakehouse style

```
df = spark.sql("SELECT 1 AS col")
for i in range(1, 11):
    df.write.format("delta").mode("append").
saveAsTable("TestVacumLH")
```

c _delta_log	6/9/2024 5:07:14 PM	Folder	11 item
part-00000-29e9efd5-5c0f-4bff-884b-06ee4a4bb9ee-c000.snappy.parquet	6/9/2024 5:07:26 PM	parquet	781 B
part-00000-3e33182e-74ad-4d19-91b1-8b2e6a5b74e2-c000.snappy.parquet	6/9/2024 5:07:28 PM	parquet	781 B
part-00000-47b3d85f-2df0-409b-8594-0ae8fb4ebdef-c000.snappy.parquet	6/9/2024 5:07:30 PM	parquet	781 B
part-00000-4d680093-de40-4e73-9218-bb7b55f690ad-c000.snappy.parquet	6/9/2024 5:07:15 PM	parquet	781 B
part-00000-5ec6b95a-7c36-4a86-a13a-33780505117b-c000.snappy.parquet	6/9/2024 5:07:32 PM	parquet	781 B
part-00000-5f6d19a6-4a95-4581-8184-b53d5e69558a-c000.snappy.parquet	6/9/2024 5:07:22 PM	parquet	781 B
part-00000-7438f8bc-418e-436a-bdc2-b4fd22cdffc3-c000.snappy.parquet	6/9/2024 5:07:18 PM	parquet	781 B
part-00000-8a391aab-84cc-4516-9ad7-ebcfcdf7ee16-c000.snappy.parquet	6/9/2024 5:07:24 PM	parquet	781 B
part-00000-b0f803f5-7e1f-4302-94a3-271cbbc7b3b3-c000.snappy.parquet	6/9/2024 5:07:34 PM	parquet	781 B
part-00000-e43b0ed5-9c09-4b99-b230-588fc0b30b68-c000.snappy.parquet	6/9/2024 5:07:20 PM	parquet	781 B

#### testvacumlh (file view) > delta log

Name	Date modified	Type	Size
🖰 0000000000000000000json	6/9/2024 5:07:15 PM	json	1 KB
000000000000000001,json	6/9/2024 5:07:18 PM	json	713 B
00000000000000000000000000000000000000	6/9/2024 5:07:20 PM	json	713 B
(h) 000000000000000003,json	6/9/2024 5:07:22 PM	json	713 B
000000000000000004.json	6/9/2024 5:07:24 PM	json	713 B
() 000000000000000005.json	6/9/2024 5:07:26 PM	json	713 B
① 00000000000000000ijson	6/9/2024 5:07:28 PM	json	713 B
000000000000000007.json	6/9/2024 5:07:30 PM	json	713 B
() 0000000000000000008.json	6/9/2024 5:07:32 PM	json	713 B
	6/9/2024 5:07:34 PM	json	713 B
temporary	6/9/2024 5:07:15 PM	Folder	0 item





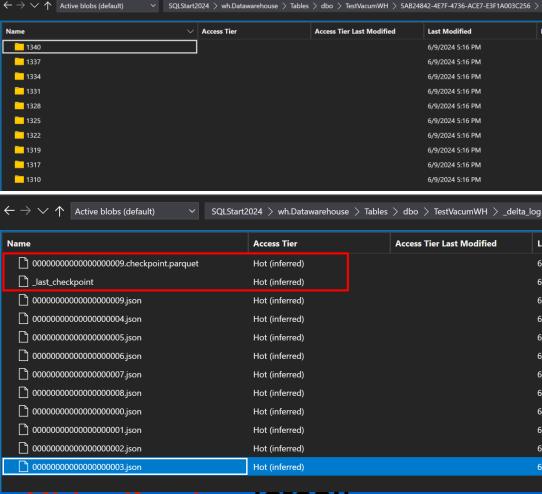






#### Warehouse style

```
SELECT 1 AS col
INTO dbo.TestVacumWH;
GO
DECLARE @i INT = 1;
WHILE @i < 10
BEGIN
    INSERT INTO
       dbo.TestVacumWH
    VALUES(1);
    SET @i = @i + 1;
END;
```













## Last checkpoint

```
"version": 11,
"size": 15,
"sizeInBytes": 13909,
"numOfAddedFiles": 10
```











## Checkpoint.parquet

```
{"txn":{"appId":"424c3456-c3dc-e5f8-530f-135019cd5974", "version":1530, "lastUpdated":null, "protocol":null, "metaData":null, "add":null, "remove":null}
{"txn":null, "protocol":null, "metaData":null, "add":{"path":"E7285DBA-A770-473F-8ED7-D7D849AF3BB3/0/1530/3893A81A-6437-43CB-B1FE-CB1D4BE98D84.parquet",
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{"txn":null, "protocol":null, "metaData":null, "add":{"path":"E7285DBA-A770-473F-8ED7-D7D849AF3BB3/0/1512/C34BE407-2192-4C72-920C-8FA21C85EC09.parquet",
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{"txn":null, "protocol":null, "metaData":null, "add":"E7285DBA-A770-473F-8ED7-D7D849AF3BB3/0/1504/32D7FE8B-3CDD-49FF-A0AE-FC2280D11C2E.parquet",
{"txn":null, "protocol":null, "metaData":"liminWriterVersion":1, "remove":null, "writerFeatures":null, "metaData":"liminWriterVersion":1, "remove":null, "writerFeatures":null, "metaData":"liminWriterVersion":1, "remove":null, "writerFeatures":null, "metaData":"liminWriterVersion":1, "remove":null, "remove":null, "protocol":null, "metaData":"liminWriterVersion":1, "remo
```



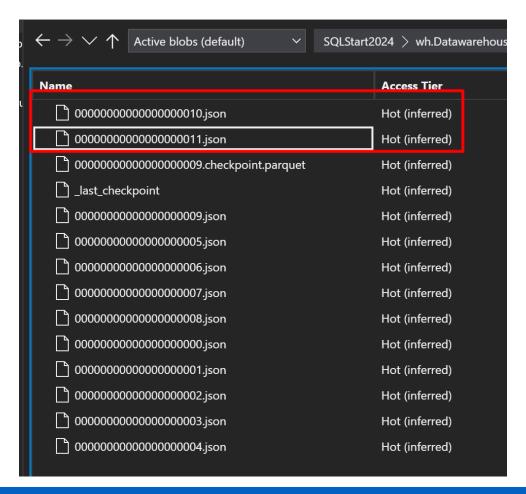








#### Later on...













#### WH - Automatic Data Compaction

lame	Access Tier	Access Tier Last Modified	Last Modified	∨ Blob Type	Content Type	Size
25259834-67A2-4751-8862-4651D0E84220.parc	Hot (inferred)		06/02/2024 09:52	Block Blob	application/octet-stream	40,01 MiB
126AAE70-7D44-4408-88F6-8D7AE0082097.par	Hot (inferred)		06/02/2024 09:52	Block Blob	application/octet-stream	46,59 MiB
1E043E48-202E-4A81-872B-D7FD57061F2C.parc	Hot (inferred)		06/02/2024 09:52	Block Blob	application/octet-stream	41,27 MiB
4A408569-8484-4A30-9BD1-9BA62AF3D885.pa	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	14,61 MiB
5AEA304A-8AFA-43FE-8970-8DF6DAAF63CD.pa	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	14,34 MiB
956D0660-AC72-48A0-889C-6E85C412E082.par	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	16,56 MiB
DA7641A3-7D9E-4DF8-8125-8A2487954808.par	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	11,39 Mil
028692F8-DC16-4417-B865-41C682E88252.parc	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	6,24 MiB
087C739E-0807-4E8F-95F2-D0A585983415.parc	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	6,05 MiB
36786AFA-C453-43E2-9E23-1C54794D6C87.parc	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	6,14 MiB
3988471F-76B7-44A8-8089-2850AC277D1B.pan	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	7,07 MiB
695E3C89-0F4A-4284-81FB-85315EA64B4C.parc	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	4,74 MiB
6D7E0EC9-BA19-4C2F-9B8E-01A94E715C2D.par	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	12,14 Mil
7345937E-0954-4458-81F8-45219F020588.parq	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	5,85 MiB
736CD976-865C-4840-A318-12FC93682679.par	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	5,74 MiB
747682B2-8448-409C-9A09-8EA4AF8A5F02.part	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	8,48 MiB
778CF681-36E6-4E23-B1F3-7A4D2EE93488.parc	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	5,84 MiB
7A018363-7248-49D3-AC46-1410E6C6BEE7.pan	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	8,55 MiB
A7598F85-9714-4600-9149-81E4A57A38DE.parc	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	5,37 MiB
☐ 0A5B1A55-280B-48D6-A0AC-B3682F02CECB.pai	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	50,04 Mi8
28300206-485A-4F28-8645-5F909D3A8809.parc	Hot (inferred)		06/02/2024 09:38	Block Blob	application/octet-stream	49,59 Mil
D 22404455 0500 4255 4555 250707000070	11 1 5 5 1		07/03/2034 00 30			20.20.12











## %%sql OPTIMIZE <table|fileOrFolderPath>;

```
₹ 00000000000000000010.checkpoi
      {"col":1}
      {"col":1}
      {"col":1}
      {"col":1}
      {"col":1}
      {"col":1}
      {"col":1}
      {"col":1}
      {"col":1}
      {"col":1}
 10
```













#### Burns as much as it can

Fabric SKU	Equivalent Premium SKU	Baseline Capacity Units (CU)	Burstable Scale Factor
F2		2	1x - 32x
F4		4	1x - 16x
F8		8	1x - 12x
F16		16	1x - 12x
F32		32	1x - 12x
F64	P1	64	1x - 12x
F128	P2	128	1x - 12x
F256	P3	256	1x - 12x
F512	P4	512	1x - 12x
F1024	P5	1024	1x - 12x
F2048		2048	1x - 12x



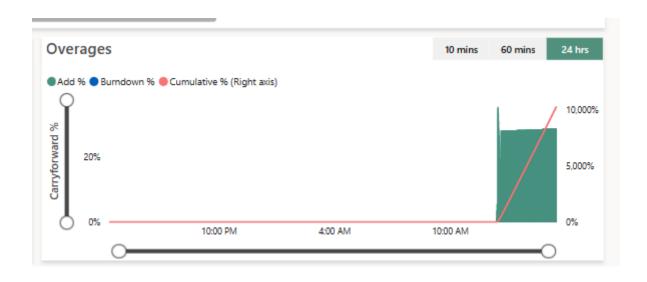








#### And then...













#### **Useful Links**

- Access Fabric data locally with OneLake file explorer
- Transitioning from ADLS to OneLake
- Datasets Execute Queries REST API (Power BI Power BI REST APIs)
- Exporting Power BI Reports And Sharing With Granular Access Control In Fabric
- Limitations for Fabric mirrored databases
- Create shortcuts to on-premises data
- Microsoft Idea Limit Bursting
- Apache XTable™ (Incubating)











## Questions?



## Thank You!

