

# Incremental View Maintenance (IVM)

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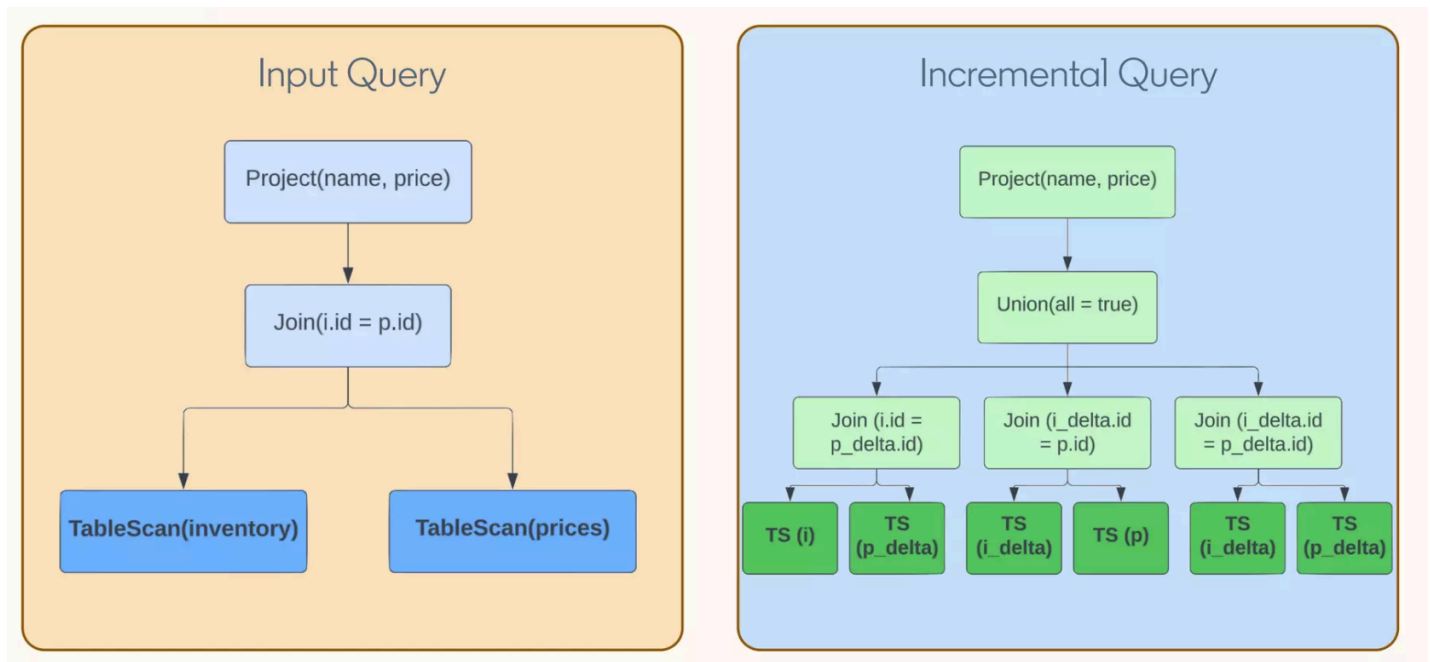
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## Context

Incremental View Maintenance is a super clever incremental data processing technique that applies the same differential calculus principles we learnt in school towards processing SQL queries efficiently:

$dy/dt$  = small approximate change

The idea is, (almost) any SQL query plan can be rewritten to be expressed as a full + diff - the trick is to knowing what the diff is since last run:



Once you figure out how to rewrite the query - e.g. for Spark SQL, you can use `coral-incremental` (see below). Others, like DBSP, parse the AST and implement the processing logic using a novel

**Circuit** (like electrical circuits) abstraction - [crates/dbsp/src/circuit/](https://crates.io/crates/dbsp/src/circuit/):

**Table 1: Implementation of SQL relational set operators as circuits computing on  $\mathbb{Z}$ -sets.**

Operation	SQL example	DBSP circuit	Details
Composition	<code>SELECT ... FROM (SELECT ... FROM I)</code>	$I \rightarrow [C_I] \rightarrow [C_O] \rightarrow 0$	$C_I$ circuit for inner query, $C_O$ circuit for outer query.
Union	<code>(SELECT * FROM I1) UNION (SELECT * FROM I2)</code>	$I1 \rightarrow \oplus \rightarrow [distinct] \rightarrow 0$ $I2 \rightarrow \oplus$	<i>distinct</i> eliminates duplicates. An implementation of UNION ALL does not need the <i>distinct</i> .
Projection	<code>SELECT DISTINCT I.c FROM I</code>	$I \rightarrow [\pi_c] \rightarrow [distinct] \rightarrow 0$	Project each row with its weight unchanged. Add up weights of identical rows.
Filtering	<code>SELECT * FROM I WHERE P(...)</code>	$I \rightarrow [\sigma_P] \rightarrow 0$	P is a predicate applied to each row. Select each row separately. If the row is selected, preserve the weight, else make the weight 0.
Cartesian product	<code>SELECT I1.*, I2.* FROM I1, I2</code>	$I1 \rightarrow \times \rightarrow 0$ $I2 \rightarrow \times$	The weight of the pair (a,b) is the product of the weights of a and b.
Equi-join	<code>SELECT I1.*, I2.* FROM I1 JOIN I2 ON I1.c1 = I2.c2</code>	$I1 \rightarrow [\sigma_{c1=c2}] \rightarrow 0$ $I2 \rightarrow [\sigma_{c1=c2}]$	Multiply the weights of the rows that appear in the output.
Intersection	<code>(SELECT * FROM I1) INTERSECT (SELECT * FROM I2)</code>	$I1 \rightarrow \bowtie \rightarrow 0$ $I2 \rightarrow \bowtie$	Special case of equi-join when both relations have the same schema.
Difference	<code>SELECT * FROM I1 EXCEPT SELECT * FROM I2</code>	$I1 \rightarrow \oplus \rightarrow [distinct] \rightarrow 0$ $I2 \rightarrow \ominus \rightarrow \oplus$	<i>distinct</i> removes rows with negative weights from the result.

With Delta Lake or Iceberg, you basically time-travel and load the (n-1)th and nth version of the table into a temporary view, which becomes the `dy/dt` you inject into the incrementalized query.

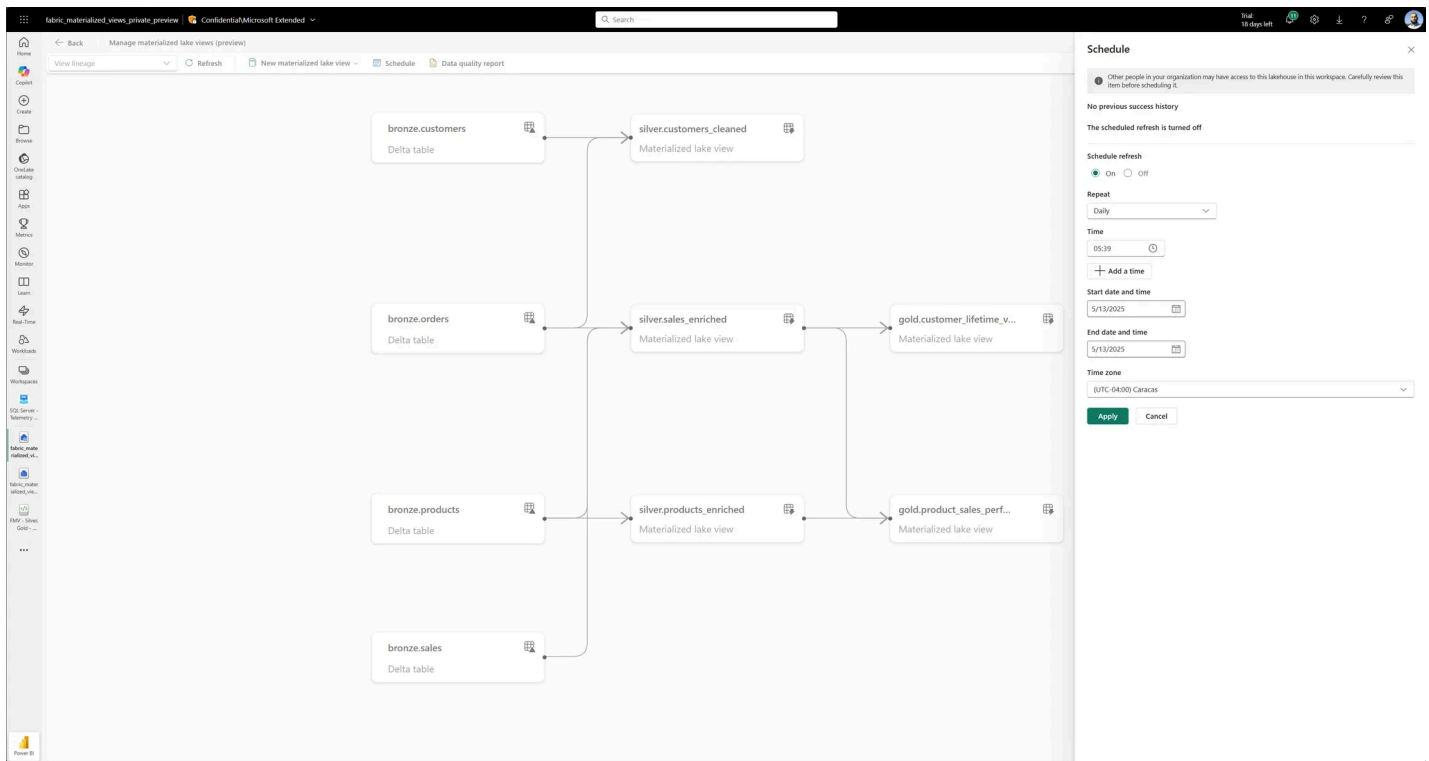
Or, you can use the [Delta Lake Change Data Feed \(CDF\)](#), which contains the same incremental commit information.

Sometimes it's cheaper to just do a full recomputation, so you need a Cost-based optimizer that makes a decision. If your pipeline runs as a Microbatch Stream continuously, it's probably always cheaper to run incrementally though.

You can implement this pretty easily as a plugin in dbt Labs (see example below with coral) or Tobiko's SQL Mesh (doesn't exist yet) to hook into the Spark engine that does the heavy lifting of time-travel loads and state persistence into stream checkpoints.

## Reference code

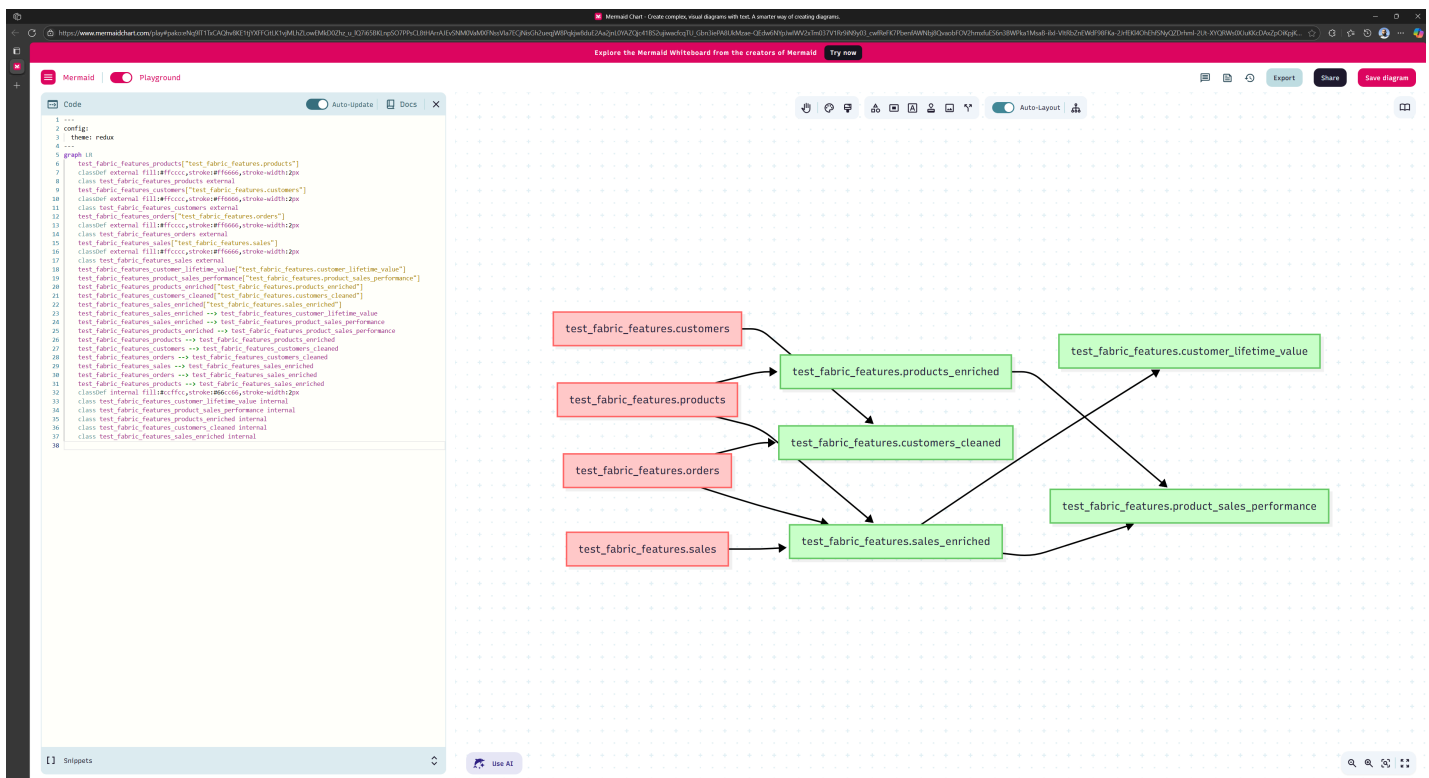
Currently we try to test the Fabric native IVM engine. In Fabric UI, the Directed Acyclic Graph looks like this:



## [A good mermaid visualization website](#)

See:

- To run an end-to-end demo of ivm capabilities locally:  
`com.microsoft.azurearcdata.sparkmsit.etl.drivers.demos.DemoIncrementalViewMaintenance`
- Graphviz based DAG creation:  
`com.microsoft.azurearcdata.sparkmsit.etl.FabricMaterializedViewIntegrationTest`



## Products

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- [BigQuery Materialized View](#)
- [Clickhouse Materialized View](#)
- [Databricks Enzyme](#)
- [Databricks Materialized View](#)
- [Fabric Kusto Materialized View](#)
- [Fabric Spark Materialized View](#)
- [Feldera](#)
- [Firebolt Materialized View](#)
- [Materialize](#)
- [Snowflake Dynamic table](#)
- [Snowflake Materialized View](#)
- [SQL Server Indexed View](#)

## OSS Implementations on top of Spark

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- [Coral DBT](#)
- [Coral Incremental](#)
- [OSS Spark Declarative Pipelines](#) (No IVM yet)

## Academic Papers/Blogs/Videos

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- [DBSP: Incremental Computation on Streams and Its Applications to Databases](#)
- [DBSP: Automatic Incremental View Maintenance for Rich Query Languages](#)
- [DBSP: Taking the short path to streaming on the GPU with DBSP](#)
- [DBSP: Python package for any DataFrame](#)
- [DBSP: Notebook demo of academic paper](#)
- [Everything You Need to Know About Incremental View Maintenance](#)
- [Databricks Enzyme](#)
- [Coral Deck](#)
- [Coral Demo](#)
- [SPIP: Declarative Pipeline Framework for Apache Spark](#)