databricks

eBook

Big Book of Data Warehousing and BI

Contents

Data is vital to the success of every company. As organizations increasingly rely on data, maintaining efficient data management and governance becomes more crucial. Addressing this, the Databricks Data Intelligence Platform enables effective data management, utilization and access to data and AI. Built on the lakehouse architecture, it merges the best features of data lakes and data warehouses, reducing costs and speeding up data and AI initiatives. The platform provides unified governance for data and AI, along with a versatile query engine for ETL, SQL, machine learning and BI.

Introduction to the Data Intelligence Platform

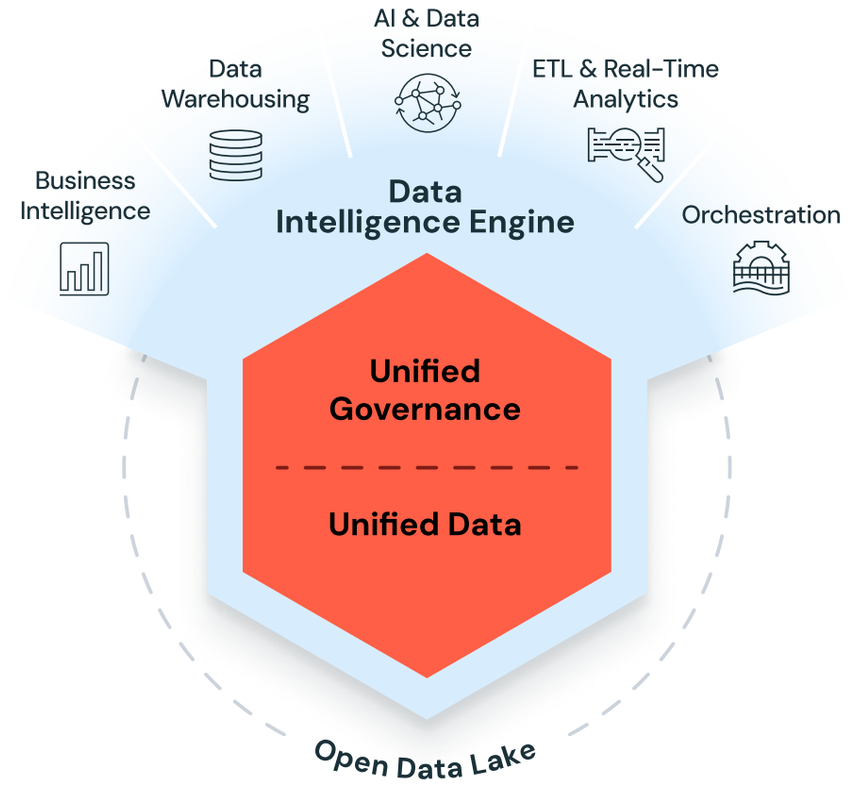
The Databricks Data Intelligence Platform enables organizations to effectively manage, utilize and access all their data and AI. The platform — built on the lakehouse architecture, with a unified governance layer across data and AI and a single unified query engine that spans ETL, SQL, AI and BI — combines the best elements of data lakes and data warehouses to help reduce costs and deliver faster data and AI initiatives.

By combining generative AI with the unification benefits of a lakehouse, the Data Intelligence Platform offers a Data Intelligence Engine called DatabricksIQ that understands the unique semantics of your enterprise data. DatabricksIQ automatically analyzes all aspects of data, including its content, metadata and usage patterns (such as queries, reports and lineage). This comprehensive analysis enables the platform to continually learn, enhance and add new capabilities, optimizing data management and AI applications. Through this deep understanding of data, the Databricks Data Intelligence Platform enables:

- **Natural Language Access:** Leveraging AI models, the Data Intelligence Platform enables working with data in natural language, tailored to each organization's jargon and acronyms. The platform observes how data is used in existing workloads to learn the organization's terms and offers a tailored natural language interface to all users — from nonexperts to data engineers.
- **Semantic Cataloging and Discovery:** Generative AI can understand each organization's data model, metrics and KPIs to offer unparalleled discovery features or automatically identify discrepancies in how data is being used.
- **Automated Management and Optimization:** AI models can optimize data layout, partitioning and indexing based on data usage, reducing the need for manual tuning and knob configuration.

Enhanced Governance and Privacy: Data Intelligence Platforms can automatically detect, classify and prevent misuse of sensitive data, while simplifying management using natural language.

First-Class Support for AI Workloads: Data Intelligence Platforms can enhance any enterprise AI application by allowing it to connect to the relevant business data and leverage the semantics learned by the platform (metrics, KPIs, etc.) to deliver accurate results. AI application developers no longer have to "hack" intelligence together through brittle prompt engineering.



The Databricks Platform also simplifies the development of enterprise AI applications. The platform makes it easy for enterprises to build AI applications that understand their data. The Databricks Platform offers multiple capabilities to directly integrate enterprise data into AI systems, including:

- End-to-end RAG (retrieval augmented generation) to build high-quality conversational agents on your custom data
- Training custom models either from scratch on an organization's data, or by continued pretraining of existing models such as MPT and Llama 2, to further enhance AI applications with deep understanding of a target domain
- Efficient and secure serverless inference on your enterprise data, with unified governance and quality monitoring functionality
- End-to-end MLOps based on the popular MLflow open source project, with all produced data automatically actionable, tracked and monitorable in the lakehouse

This how-to reference guide showcases data warehousing best practices on the Databricks Data Intelligence Platform through end-to-end use cases from real-world examples. Discover how the platform helps businesses of all sizes translate raw data into actionable data using SQL — from data ingestion to data processing, AI and LLMs, analytics and BI. We'll arm you with reference architectures and code samples so you can explore all aspects of the data lifecycle on the Data Intelligence Platform.

To learn more about Databricks SQL, read our eBook Why the Data Lakehouse Is Your Next Data Warehouse.

SECTION

02

Data Warehousing Built With Intelligence and Automation

Success in lakehouse-based data and AI initiatives hinges on a simplified data architecture, data quality and governance, and scalability and performance. These pillars collectively provide the foundation upon which organizations build their data strategies, guiding them through the intricate maze of modern data management and analytics.

Simplified Data Architecture

The data lakehouse architecture solves the problems of data silos while incorporating the capabilities of a data warehouse. The approach starts by centralizing data within a cloud-based data lake. This foundation, supported by **Delta Lake**, allows analytics and AI use cases to operate on a single data source — reducing storage expenses and streamlining data engineering. The lakehouse architecture integrates a unified governance and security structure with **Unity Catalog**, ensuring granular data control and timely access for respective teams.

The lakehouse architecture's holistic approach encompasses the entire data lifecycle, transformation and impact across various analytics and AI workloads. Because all workloads share the same data while adhering to uniform security and governance policies, you can feel confident knowing you can rely on the accuracy of the data. Functional silos diminish, paving the way for seamless collaboration and, consequently, enhanced productivity in delivering data products.

These are some of the additional benefits of a simplified data architecture:

- Built on open source and standards, a lakehouse removes data silos, simplifying the data landscape and facilitating data and AI operations
- One platform serves integration, storage, processing, governance, sharing, analytics and AI. It offers a unified approach for handling both structured and unstructured data, a complete view of data lineage and provenance, and a consolidated toolset for Python and SQL, notebooks, IDEs, batch, streaming and all primary cloud providers.
- Automated optimization for performance and storage delivers optimal TCO, setting performance benchmarks for data warehousing and AI — including advanced processes like large language models (LLMs)

Data Governance and Quality

Data, being fundamental to organizations, requires stringent quality and governance, especially with increasing volumes and variety. Organizations must prioritize accuracy, reliability and compliance to maximize their lakehouse's potential. Subpar data quality can distort insights, while weak governance can lead to regulatory and security lapses. The Databricks Data Intelligence Platform, with its Unity Catalog, addresses these issues, providing an integrated framework for managing and improving the quality of data across its lifecycle. With governance on the lakehouse architecture, you can:

- Discover, classify and consolidate data and AI assets from various platforms on any cloud, enhancing data exploration and insight extraction using natural language, all from a single access point
- Simplify access management through a unified interface, ensuring consistent and secure access across clouds and platforms, with enhanced fine-grained control and scalable low-code policies
- Harness AI to automate data and ML model monitoring, receive proactive alerts for issues, streamline debugging, and achieve holistic observability of your lakehouse operations using built-in system tables
- Efficiently share data and AI assets across clouds, regions and platforms using open source Delta Sharing in Unity Catalog, enabling secure collaboration and value creation without the need for complex processes or costly replication

Scalability and Performance

With growing data volumes, a lakehouse architecture distributes computing features, independent of storage, aiming to maintain consistent performance at optimal costs. The Databricks Data Intelligence Platform is designed for elasticity, allowing organizations to scale their data operations as needed. Scalability extends across various dimensions:

SERVERLESS

The Databricks Platform utilizes serverless cloud-based computing resources, enabling workloads to adjust and scale elastically based on the required computing capacity. Such dynamic resource allocation guarantees rapid data processing and analysis, even during peak demand.

CONCURRENCY

Leveraging serverless compute and AI-driven optimizations, the Databricks Platform facilitates concurrent data processing and query execution. This ensures that multiple users and teams can undertake analytics tasks concurrently without performance constraints.

STORAGE

The platform seamlessly integrates with data lakes, facilitating the cost-effective storage of extensive data volumes while ensuring data availability and reliability. It also optimizes data storage for enhanced performance, reducing storage expenses.

Scalability, though essential, is complemented by performance. In this regard, the Databricks Data Intelligence Platform stands out, offering a variety of AI-driven optimizations:

OPTIMIZED QUERY PROCESSING

The platform utilizes machine learning optimization techniques to accelerate query execution. It leverages automatic indexing, caching and predicate pushdown to ensure queries are processed efficiently, resulting in rapid insights.

AUTOSCALING

The Databricks Platform intelligently scales serverless resources to match your workloads, ensuring that you pay only for the compute you use, all while maintaining optimal query performance.

PHOTON

The new native massively parallel processing (MPP) engine on the Databricks Platform provides extremely fast query performance at low cost — from data ingestion, ETL, streaming, data science and interactive queries — directly on your data lake. Photon is compatible with Apache Spark™ APIs — no code changes and no lock-in.

DELTA LAKE

Delta Lake with Unity Catalog and Photon offers the best price/performance out of the box without manual tuning. The Databricks Platform uses AI models to solve common challenges with data storage, so you get faster performance without having to manually manage tables, even as they change over time.

- Predictive I/O for updates optimizes your query plans and data layout for peak performance, intelligently balancing read vs. write performance. So you can get more from your data without needing to decide between strategies like copy-on-write vs. merge-on-read.
- Liquid clustering delivers the performance of a well-tuned, well-partitioned table without the traditional headaches that come with partitioning, such as worrying about whether you can partition high-cardinality columns or expensive rewrites when changing partition columns. The result is lightning-fast, well-clustered tables with minimal configuration.
- Predictive optimization automatically optimizes your data for the best performance and price. It learns from your data usage patterns, builds a plan for the right optimizations to perform and then runs those optimizations on hyper-optimized serverless infrastructure.

Having established the foundation of the lakehouse architecture, it's pertinent to explore the delivery of data warehouse and analytics capabilities on Databricks with appropriate data structures and management functionalities facilitated by Databricks SQL (DB SQL).

Databricks SQL Serverless: The best data warehouse for a lakehouse architecture

Databricks SQL was introduced to enhance data warehousing capabilities and offer premier SQL support on the Databricks Data Intelligence Platform. It streamlines SQL-based data transformation, exploration and analysis, catering to users of diverse technical backgrounds. From BI analysts and data architects to analytics engineers, its intuitive SQL interface facilitates queries and complex data operations without necessitating specialized programming. This broadened data access fosters an organization-centric culture, empowering more teams to base decisions on data insights.

Databricks SQL distinguishes itself with its ability to handle massive data sets with speed and efficiency. Utilizing Databricks' next-gen engine, Photon with AI-driven optimizations, ensures rapid data processing and analysis, notably decreasing query execution durations. High performance is crucial for organizations facing data challenges, guaranteeing insights from an extensive variety of data sets. Moreover, Databricks SQL champions collaboration, providing a workspace where data professionals can instantaneously share queries, outcomes and understandings. This shared setting promotes knowledge exchange and hastens resolution, allowing organizations to capitalize on their teams' collective intelligence.

Additionally, Databricks SQL incorporates advanced provisions for data governance, security and compliance, empowering organizations to uphold data quality, implement access restrictions, oversee data activities, safeguard sensitive data and adhere to regulatory standards. To sum up, Databricks SQL provides:

- **Faster Time to Insights**
  Use plain English to access data, and it will automatically create the SQL queries for you. This makes it faster to refine your queries and is available to everyone in the enterprise.
- **Best Price/Performance**
  Serverless compute combined with AI-optimized processing achieves top-tier performance and scale at lower costs, without the need for cloud infrastructure management
- **Unified Governance**
  Establish one unified governance layer across all data and AI assets no matter where they live
- **Reduce Complexity**
  Unify all your data, analytics and AI on one platform that supports SQL and Python, notebooks and IDEs, batch and streaming, and all major cloud providers
- **Rich Ecosystem**
  Utilize SQL and favorite tools such as Power BI, Tableau, dbt and Fivetran with Databricks for BI, data ingestion and transformation

Conclusion

The Databricks Data Intelligence Platform represents a significant advancement in the realm of data warehousing and analytics. It addresses the critical need for efficient data warehousing workloads in today's data-driven business landscape. The platform's simplified data architecture centralizes data with complete end-to-end data warehouse capabilities, leading to cost savings and speeding up time to turn raw data into actionable insights at scale — and unify batch and streaming. Moreover, it ensures data quality and governance through the Unity Catalog, enabling organizations to easily discover, secure and manage all their data with fine-grained governance with data lineage across clouds.

Scalability and performance are key foundational differentiators of the Databricks Platform, with serverless computing, concurrency support and optimized storage strategies. AI-driven optimizations enhance query processing, improve performance and optimize data for best performance and price, making data analysis faster and more cost-effective.

Databricks SQL further enhances the platform's capabilities by providing premier SQL support, facilitating data transformation and analysis for many users. It promotes collaboration, data governance and a rich ecosystem of tools, breaking down data silos and enabling your organization to harness the full potential of your data. Now, let's take a look at a few use cases for running your data warehousing and BI workloads on the Databricks Platform.

LEARN MORE

- → Why the Data Lakehouse Is Your Next Data Warehouse: 2nd Edition
- → What's new in Databricks SQL?
- → Introducing Lakehouse Federation Capabilities in Unity Catalog
- → Introducing AI Functions: Integrating Large Language Models with Databricks SQL

SECTION

03

Data Warehousing Best Practices on the Lakehouse

SECTION 3.1

Data Warehousing Modeling Techniques and Their Implementation on the Lakehouse

Using Data Vaults and Star Schemas on the Lakehouse

by Soham Bhatt and Deepak Sekar

The lakehouse is a new data platform paradigm that combines the best features of data lakes and data warehouses. It is designed as a large-scale enterprise-level data platform that can house many use cases and data products. It can serve as a single unified enterprise data repository for all of your:

- data domains,
- real-time streaming use cases,
- data marts,
- disparate data warehouses,
- data science feature stores and data science sandboxes, and
- departmental self-service analytics sandboxes.

Given the variety of the use cases, different data organizing principles and modeling techniques may apply to different projects on a lakehouse. Technically, the lakehouse architecture can support many different data modeling styles. In this article, we aim to explain the implementation of the Bronze/Silver/Gold data organizing principles of the lakehouse and how different data modeling techniques fit in each layer.

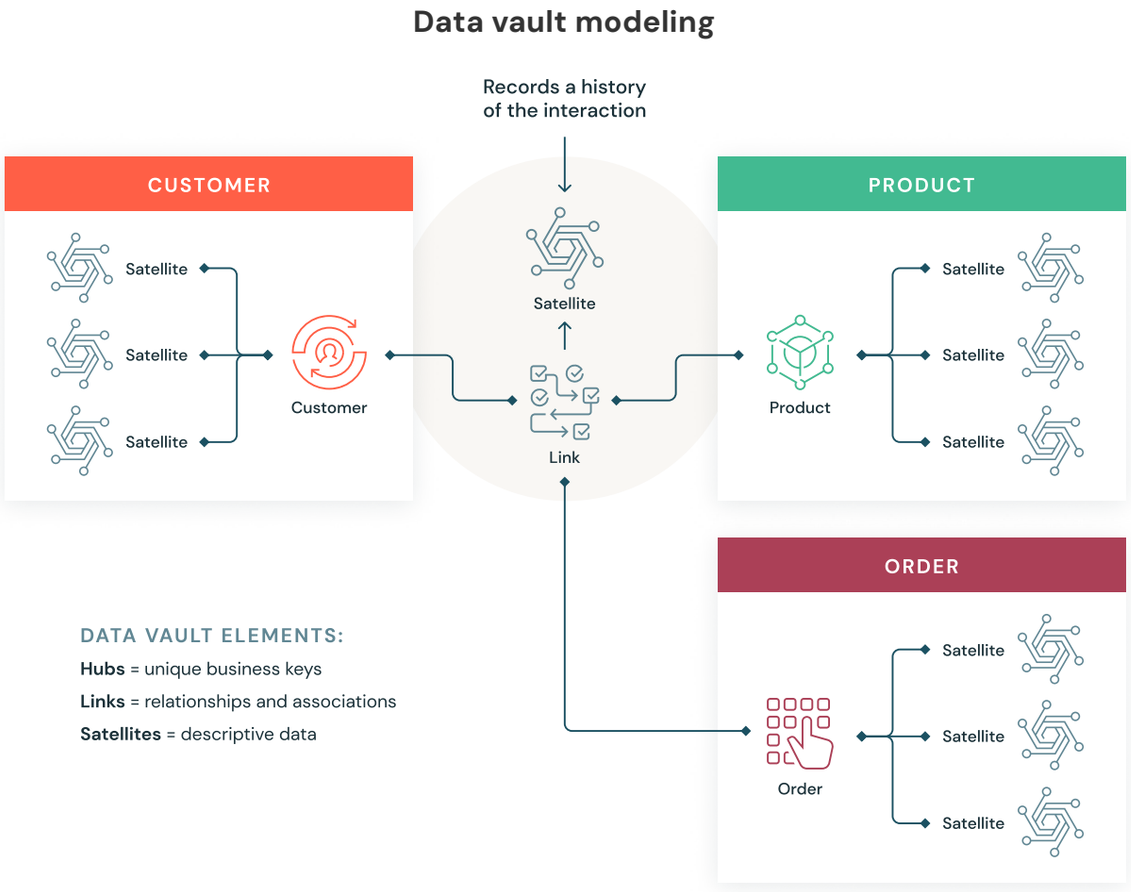
What is a Data Vault?

A Data Vault is a more recent data modeling design pattern used to build data warehouses for enterprise-scale analytics compared to Kimball and Inmon methods.

Data Vaults organize data into three different types: hubs, links, and satellites. Hubs represent core business entities, links represent relationships between hubs, and satellites store attributes about hubs or links.

Data Vault focuses on agile data warehouse development where scalability, data integration/ETL and development speed are important. Most customers have a landing zone, Vault zone and a data mart zone which correspond to the Databricks organizational paradigms of Bronze, Silver and Gold layers. The Data Vault modeling style of hub, link and satellite tables typically fits well in the Silver layer of the lakehouse architecture.

Learn more about Data Vault modeling at Data Vault Alliance.

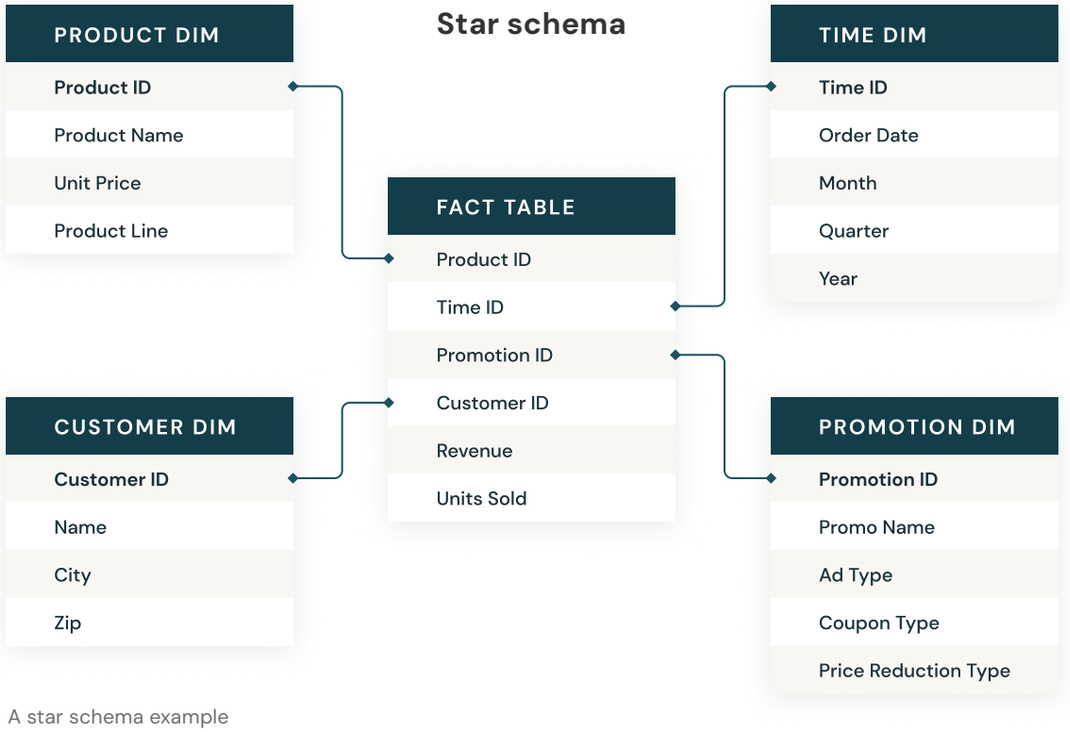


A diagram showing how Data Vault modeling works, with hubs, links, and satellites connecting to one another.

What is Dimensional Modeling?

Dimensional modeling is a bottom-up approach to designing data warehouses in order to optimize them for analytics. Dimensional models are used to denormalize business data into dimensions (like time and product) and facts (like transactions in amounts and quantities), and different subject areas are connected via conformed dimensions to navigate to different fact tables.

The most common form of dimensional modeling is the star schema. A star schema is a multi-dimensional data model used to organize data so that it is easy to understand and analyze, and very easy and intuitive to run reports on. Kimball-style star schemas or dimensional models are pretty much the gold standard for the presentation layer in data warehouses and data marts, and even semantic and reporting layers. The star schema design is optimized for querying large data sets.

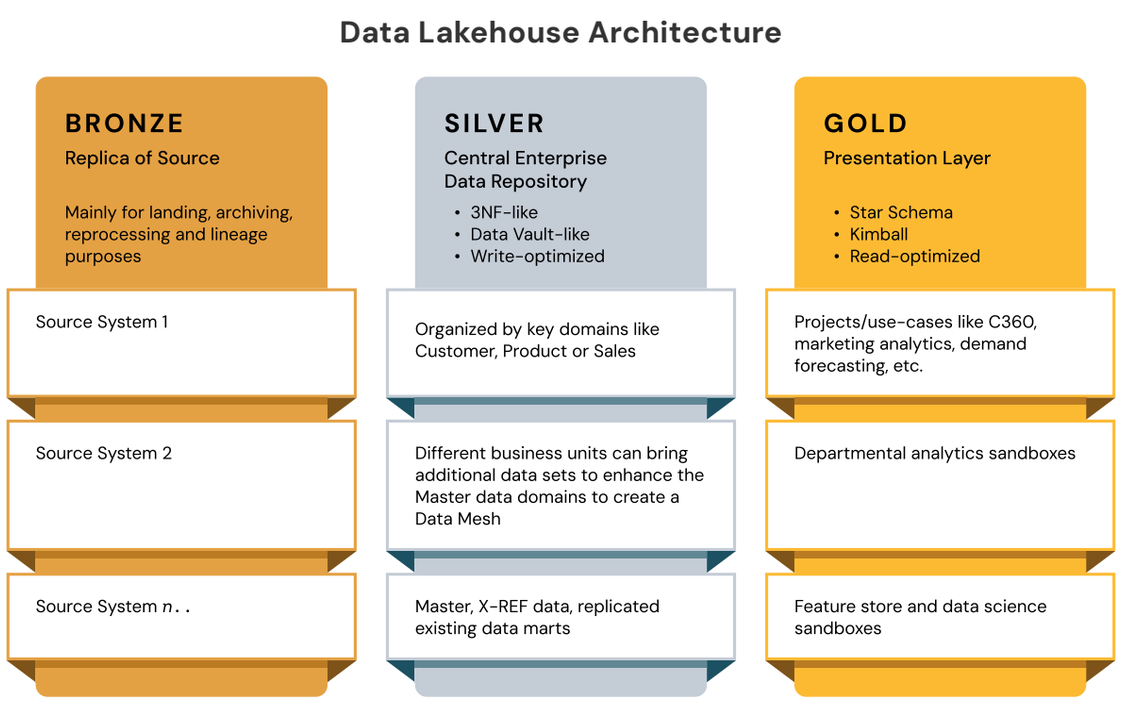


A star schema example

Both normalized Data Vault (write-optimized) and denormalized dimensional models (read-optimized) data modeling styles have a place in the Databricks Data Intelligence Platform. The Data Vault's hubs and satellites in the Silver layer are used to load the dimensions in the star schema, and the Data Vault's link tables become the key driving tables to load the fact tables in the dimension model. Learn more about dimensional modeling from the Kimball Group.

Data organization principles in each layer of the lakehouse

A modern lakehouse is an all-encompassing enterprise-level data platform. It is highly scalable and performant for all kinds of different use cases such as ETL, BI, data science and streaming that may require different data modeling approaches. Let's see how a typical lakehouse is organized:



A diagram showing characteristics of the Bronze, Silver and Gold layers of the data lakehouse architecture.

Bronze Layer — the Landing Zone

The Bronze layer is where we land all the data from source systems. The table structures in this layer correspond to the source system table structures "as-is," aside from optional metadata columns that can be added to capture the load date/time, process ID, etc. The focus in this layer is on change data capture (CDC), and the ability to provide an historical archive of source data (cold storage), data lineage, auditability, and reprocessing if needed — without rereading the data from the source system.

In most cases, it's a good idea to keep the data in the Bronze layer in Delta format, so that subsequent reads from the Bronze layer for ETL are performant — and so that you can do updates in Bronze to write CDC changes. Sometimes, when data arrives in JSON or XML formats, we do see customers landing it in the original source data format and then stage it by changing it to Delta format. So sometimes, we see customers manifest the logical Bronze layer into a physical landing and staging zone.

Storing raw data in the original source data format in a landing zone also helps with consistency wherein you ingest data via ingestion tools that don't support Delta as a native sink or where source systems dump data onto object stores directly. This pattern also aligns well with the autoloader ingestion framework wherein sources land the data in landing zone for raw files and then Databricks AutoLoader converts the data to Staging layer in Delta format.

Silver Layer — the Enterprise Central Repository

In the Silver layer of the lakehouse architecture, the data from the Bronze layer is matched, merged, conformed and cleaned ("just-enough") so that the Silver layer can provide an "enterprise view" of all its key business entities, concepts and transactions. This is akin to an Enterprise Operational Data Store (ODS) or a Central Repository or Data domains of a Data Mesh (e.g. master customers, products, non-duplicated transactions and cross-reference tables). This enterprise view brings the data from different sources together, and enables self-service analytics for ad-hoc reporting, advanced analytics and ML. It also serves as a source for departmental analysts, data engineers and data scientists to further create data projects and analysis to answer business problems via enterprise and departmental data projects in the Gold layer.

In the lakehouse data engineering paradigm, typically the (Extract-Load-Transform) ELT methodology is followed vs. traditional Extract-Transform-Load(ETL). ELT approach means only minimal or "just-enough" transformations and data cleansing rules are applied while loading the Silver layer. All the "enterprise level" rules are applied in the Silver layer vs. project-specific transformational rules, which are applied in the Gold layer. Speed and agility to ingest and deliver the data in the lakehouse is prioritized here.

From a data modeling perspective, the Silver layer has more 3rd-Normal Form like data models. Data Vault-like write-performant data architectures and data models can be used in this layer. If using a Data Vault methodology, both the raw Data Vault and Business Vault will fit in the logical Silver layer of the lake — and the Point-In-Time (PIT) presentation views or materialized views will be presented in the Gold layer.

Gold Layer — the Presentation Layer

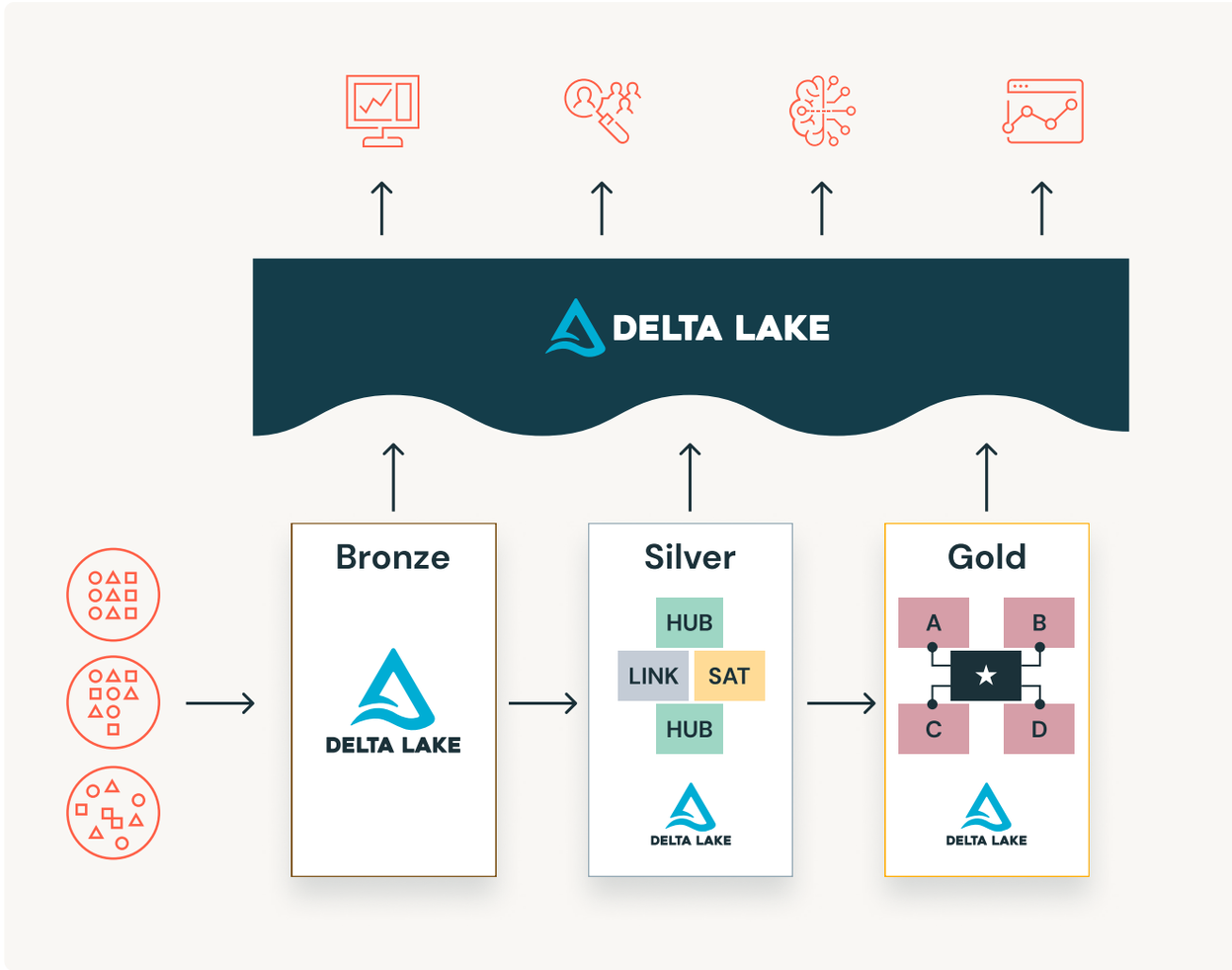
In the Gold layer, multiple data marts or warehouses can be built as per dimensional modeling/Kimball methodology. As discussed earlier, the Gold layer is for reporting and uses more denormalized and read-optimized data models with fewer joins compared to the Silver layer. Sometimes tables in the Gold layer can be completely denormalized, typically if the data scientists want it that way to feed their algorithms for feature engineering.

ETL and data quality rules that are "project-specific" are applied when transforming data from the Silver layer to Gold layer. Final presentation layers such as data warehouses, data marts or data products like customer analytics, product/quality analytics, inventory analytics, customer segmentation, product recommendations, marketing/sales analytics, etc., are delivered in this layer. Kimball style star-schema based data models or Inmon style Data marts fit in this Gold layer of the lakehouse. Data Science Laboratories and Departmental Sandboxes for self-service analytics also belong in the Gold layer.

The Lakehouse Data Organization Paradigm

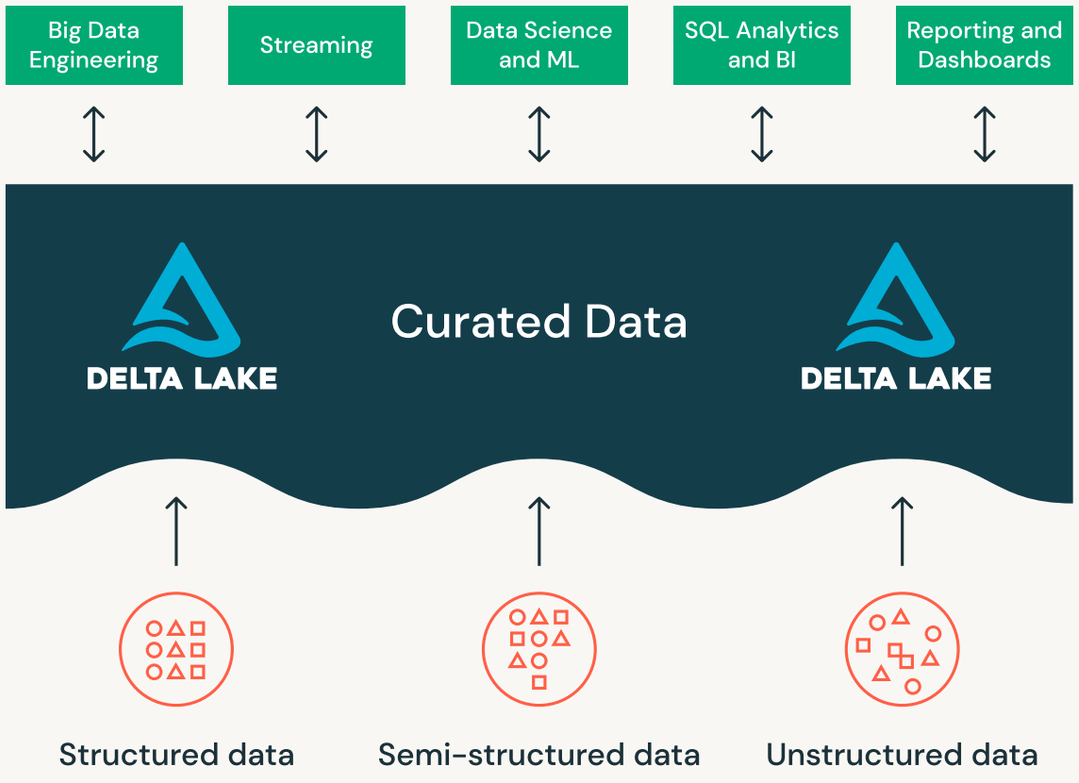
To summarize, data is curated as it moves through the different layers of a data lakehouse architecture.

- The Bronze layer uses the data models of source systems. If data is landed in raw formats, it is converted to DeltaLake format within this layer.
- The Silver layer for the first time brings the data from different sources together and conforms it to create an Enterprise view of the data — typically using a more normalized, write-optimized data models that are typically 3rd-Normal Form-like or Data Vault-like.
- The Gold layer is the presentation layer with more denormalized or flattened data models than the Silver layer, typically using Kimball-style dimensional models or star schemas. The Gold layer also houses departmental and data science sandboxes to enable self-service analytics and data science across the enterprise. Providing these sandboxes and their own separate compute clusters prevents the Business teams from creating their own copies of data outside of the Lakehouse.



This lakehouse data organization approach is meant to break data silos, bring teams together, and empower them to do ETL, streaming, and BI and AI on one platform with proper governance. Central data teams should be the enablers of innovation in the organization, speeding up the onboarding of new self-service users, as well as the development of many data projects in parallel — rather than the data modeling process becoming the bottleneck. The Databricks Unity Catalog provides search and discovery, governance and lineage on the lakehouse to ensure good data governance cadence.

Build your Data Vaults and star schema data warehouses with Databricks SQL today. →



How data is curated as it moves through the various lakehouse architecture layers.

LEARN MORE

- → Five Simple Steps for Implementing a Star Schema in Databricks With Delta Lake
- → Best practices to implement a Data Vault model in Databricks Lakehouse
- → Dimensional Modeling Best Practice & Implementation on Modern Lakehouse
- → Identity Columns to Generate Surrogate Keys Are Now Available in a Lakehouse Near You!
- → Load an EDW Dimensional Model in Real Time With Databricks Lakehouse

SECTION 3.2

Dimensional Modeling Best Practice and Implementation on a Modern Lakehouse Architecture

by Leo Mao, Abhishek Dey, Justin Breese and Soham Bhatt

A large number of our customers are migrating their legacy data warehouses to Databricks Lakehouse as it enables them to modernize not only their Data Warehouse but they also instantly get access to a mature Streaming and Advanced Analytics platform. Lakehouse can do it all as it is one platform for all your streaming, ETL, BI, and AI needs — and it helps your business and Data teams collaborate on one platform.

As we help customers in the field, we find that many are looking for best practices around proper data modeling and physical data model implementations in Databricks.

In this article, we aim to dive deeper into the best practice of dimensional modeling on the Databricks Data Intelligence Platform and provide a live example of a physical data model implementation using our table creation and DDL best practices.

Here are the high-level topics we will cover in this blog:

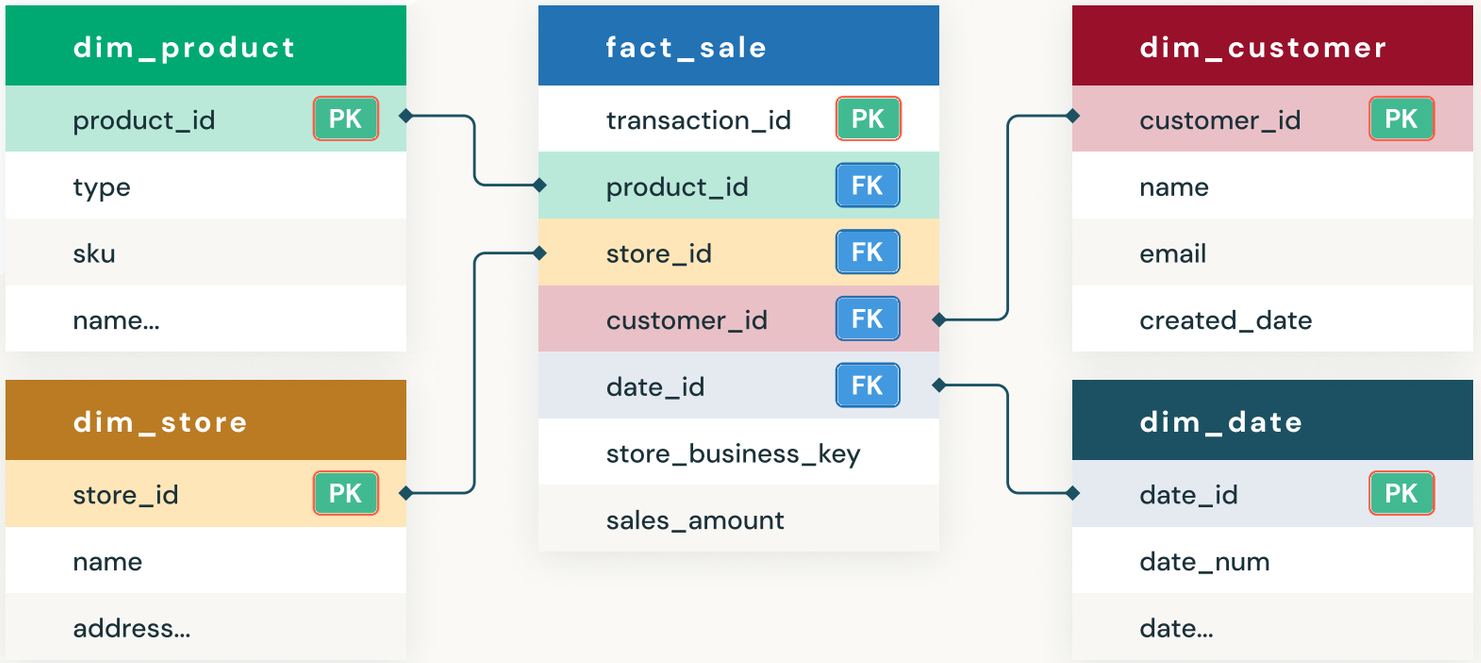
- The Importance of Data Modeling
- Common Data Modeling Techniques
- Data Warehouse Modeling DDL Implementation
- Best Practice and Recommendation for Data Modeling on the Lakehouse

The importance of Data Modeling for Data Warehouse

Data Models are front and center of building a Data Warehouse. Typically the process starts with defending the Semantic Business Information Model, then a Logical data Model, and finally a Physical Data Model (PDM). It all starts with a proper Systems Analysis and Design phase where a Business Information model and process flows are created first and key business entities, attributes and their interactions are captured as per the business processes within the organization. The Logical Data Model is then created depicting how the entities are related to each other and this is a Technology agnostic model. Finally a PDM is created based on the underlying technology platform to ensure that the writes and reads can be performed efficiently. As we all know, for Data Warehousing, Analytics-friendly modeling styles like Star-schema and Data Vault are quite popular.

Best practices for creating a Physical Data Model in Databricks

Based on the defined business problem, the aim of the data model design is to represent the data in an easy way for reusability, flexibility, and scalability. Here is a typical star-schema data model that shows a Sales fact table that holds each transaction and various dimension tables such as customers, products, stores, date etc. by which you slice-and-dice the data. The dimensions can be joined to the fact table to answer specific business questions such as what are the most popular products for a given month or which stores are best performing ones for the quarter. Let's see how to get it implemented in Databricks.



Dimensional model on the lakehouse architecture

Note each dimension table has **__START_AT** and **__END_AT** columns to support SCD Type 2, which are not displayed here because of limited space.

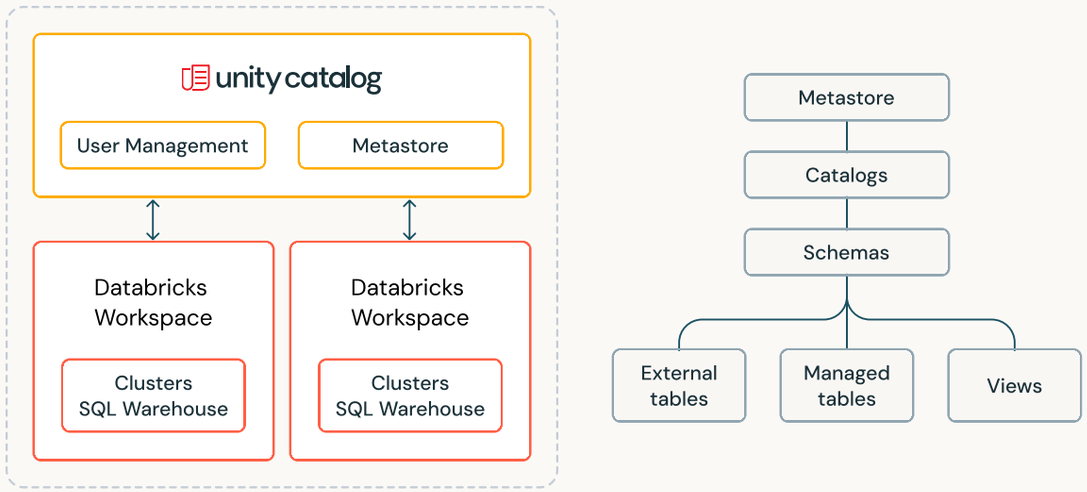
Data Warehouse Modeling DDL Implementation on Databricks

In the following sections, we would demonstrate the below using our examples.

- Creating 3-level Catalog, Database and Table
- Primary Key, Foreign Key definitions
- Identity columns for Surrogate keys
- Column constraints for Data Quality
- Index, optimize and analyze
- Advanced techniques

1. Unity Catalog - 3 level namespace

Unity Catalog is a Databricks Governance layer which lets Databricks admins and data stewards manage users and their access to data centrally across all of the workspaces in a Databricks account using one Metastore. Users in different workspaces can share access to the same data, depending on privileges granted centrally in Unity Catalog. Unity Catalog has 3 level Namespace (catalog.schema(database).table) that organizes your data. Learn more about Unity Catalog here.



Here is how to set up the catalog and schema before we create tables within the database. For our example, we create a catalog **US_Stores** and a schema (database) **Sales_DW** as below, and use them for the later part of the section.

```
CREATE CATALOG IF NOT EXISTS US_Stores;
USE CATALOG US_Stores;
CREATE SCHEMA IF NOT EXISTS Sales_DW;
USE SCHEMA Sales_DW;
```

Setting up the Catalog and Database

Here is an example on querying the **fact_sales** table with a 3 level namespace.

```
SELECT *
FROM US_Stores.Sales_DW.fact_sales
```

▸ (2) Spark Jobs

Table | Data Profile

	transaction_id	date_id	customer_id	product_id	store_id	store_business_key	sales_amount
1	10001	20211001	1	1	1	PER01	50
2	10004	20211003	2	1	2	BNE02	60
3	10005	20211003	3	2	1	PER01	79
4	10002	20211002	2	1	2	BNE02	79
5	10003	20211002	1	2	2	BNE02	79

Showing all 5 rows.

Example of querying table with catalog.database.tablename

2. Primary Key, Foreign Key definitions

Primary and Foreign Key definitions are very important when creating a data model. Having the ability to support the PK/FK definition makes defining the data model super easy in Databricks. It also helps analysts quickly figure out the join relationships in Databricks SQL Warehouse so that they can effectively write queries. Like most other Massively Parallel Processing (MPP), EDW, and Cloud Data Warehouses, the PK/FK constraints are informational only. Databricks does not support enforcement of the PK/FK relationship, but gives the ability to define it to make the designing of Semantic Data Model easy.

Here is an example of creating the **dim_store** table with **store_id** as an Identity Column and it's also defined as a Primary Key at the same time.

```
-- Store dimension
CREATE OR REPLACE TABLE dim_store(
  store_id BIGINT GENERATED ALWAYS AS IDENTITY PRIMARY KEY,
  business_key STRING,
  name STRING,
  email STRING,
  city STRING,
  address STRING,
  phone_number STRING,
  created_date TIMESTAMP,
  updated_date TIMESTAMP,
  start_at TIMESTAMP,
  end_at TIMESTAMP
);
```

DDL Implementation for creating store dimension with Primary Key Definitions

After the table is created, we can see that the primary key (store_id) is created as a constraint in the table definition below.

Describe Dim Store table information

```
DESC TABLE EXTENDED US_Stores.Sales_DW.dim_store
```

Table | Data Profile

	col_name	data_type
20	Owner	leo.mao@databricks.com
21	Is_managed_location	true
22	Table Properties	[delta.minReaderVersion=1,delta.minWriterVersion=6]
23		
24	# Constraints	
25	dim_store_pk	PRIMARY KEY (`store_id`)

Showing all 25 rows.

Primary Key store_id shows as table constraint

Here is an example of creating the **fact_sales** table with **transaction_id** as a Primary Key, as well as foreigh keys that are referencing the dimension tables.

```
-- Fact Sales
CREATE OR REPLACE TABLE fact_sales(
  transaction_id BIGINT PRIMARY KEY,
  date_id BIGINT NOT NULL CONSTRAINT dim_date_fk FOREIGN KEY REFERENCES dim_date,
  customer_id BIGINT NOT NULL CONSTRAINT dim_customer_fk FOREIGN KEY REFERENCES
dim_customer,
  product_id BIGINT NOT NULL CONSTRAINT dim_product_fk FOREIGN KEY REFERENCES
dim_product,
  store_id BIGINT NOT NULL CONSTRAINT dim_store_fk FOREIGN KEY REFERENCES dim_
store,
  store_business_key STRING,
  sales_amount DOUBLE
);
```

DDL Implementation for creating sales fact with Foreign Key definitions

After the fact table is created, we could see that the primary key **(transaction_id)** and foreign keys are created as constraints in the table definition below.

Describe Fact Sales Table Info

```
DESC TABLE EXTENDED US_Stores.Sales_DW.fact_sales
```

Table | Data Profile

	col_name	data_type
20	# Constraints	
21	dim_product_fk	FOREIGN KEY (`product_id`) REFERENCES `us_stores`.`sales_dw`.`dim_product` (`product_id`)
22	dim_date_fk	FOREIGN KEY (`date_id`) REFERENCES `us_stores`.`sales_dw`.`dim_date` (`date_id`)
23	dim_customer_fk	FOREIGN KEY (`customer_id`) REFERENCES `us_stores`.`sales_dw`.`dim_customer` (`customer_id`)
24	dim_store_fk	FOREIGN KEY (`store_id`) REFERENCES `us_stores`.`sales_dw`.`dim_store` (`store_id`)
25	fact_sales_pk	PRIMARY KEY (`transaction_id`)

Showing all 25 rows.

Fact table definition with primary key and foreign keys referencing dimensions

3. Identity columns for Surrogate keys

An identity column is a column in a database that automatically generates a unique ID number for each new row of data. These are commonly used to create surrogate keys in the data warehouses. Surrogate keys are system-generated, meaningless keys so that we don't have to rely on various Natural Primary Keys and concatenations on several fields to identify the uniqueness of the row. Typically these surrogate keys are used as Primary and Foreign keys in data warehouses. Details on Identity columns are discussed in this blog. Below is an example of creating an identity column customer_id, with automatically assigned values starting with 1 and increment by 1.

```
-- Customer dimension
CREATE OR REPLACE TABLE dim_customer(
  customer_id BIGINT GENERATED ALWAYS AS IDENTITY (START WITH 1 INCREMENT BY 1)
PRIMARY KEY,
  name STRING,
  email STRING,
  address STRING,
  created_date TIMESTAMP,
  updated_date TIMESTAMP,
  start_at TIMESTAMP,
  end_at TIMESTAMP
);
```

DDL Implementation for creating customer dimension with identity column

4. Column constraints for Data Quality

In addition to Primary and Foreign key informational constraints, Databricks also supports column-level Data Quality Check constraints which are enforced to ensure the quality and integrity of data added to a table. The constraints are automatically verified. Good examples of these are NOT NULL constraints and column value constraints. Unlike the other Cloud Data Warehouse, Databricks went further to provide column value check constraints, which are very useful to ensure the data quality of a given column. As we could see below, the **valid_sales_amount** check constraint will verify that all existing rows satisfy the constraint (i.e. **sales amount** > 0) before adding it to the table. More information can be found here.

Here are examples to add constraints for dim_store and fact_sales respectively to make sure store_id and sales_amount have valid values.

```
-- Add constraint to dim_store to make sure column store_id is between 1 and 9998
ALTER TABLE US_Stores.Sales_DW.dim_store ADD CONSTRAINT valid_store_id CHECK
(store_id > 0 and store_id < 9999);

-- Add constraint to fact_sales to make sure column sales_amount has a valid value
ALTER TABLE US_Stores.Sales_DW.fact_sales ADD CONSTRAINT valid_sales_amount CHECK
(sales_amount > 0);
```

Add column constraint to existing tables to ensure data quality

5. Index, Optimize, and Analyze

Traditional Databases have b-tree and bitmap indexes, Databricks has much advanced form of indexing - multi-dimensional Z-order clustered indexing and we also support Bloom filter indexing. First of all, the Delta file format uses Parquet file format, which is a columnar compressed file format so it's already very efficient in column pruning and on top of it using z-order indexing gives you the ability to sift through petabyte scale data in seconds. Both Z-order and Bloom filter indexing dramatically reduce the amount of data that needs to be scanned in order to answer highly selective queries against large Delta tables, which typically translates into orders-of-magnitude runtime improvements and cost savings. Use Z-order on your Primary Keys and foreign keys that are used for the most frequent joins. And use additional Bloom filter indexing as needed.

```
-- Optimise fact_sales table by customer_id and product_id for better query and
join performance
OPTIMIZE US_Stores.Sales_DW.fact_sales
ZORDER BY (customer_id, product_id);
```

Optimize fact_sales on customer_id and product_id for better performance

```
-- Create a bloomfilter index to enable data skipping on store_business_key
CREATE BLOOMFILTER INDEX
ON TABLE US_Stores.Sales_DW.fact_sales
FOR COLUMNS(store_business_key)
```

Create a Bloomfilter Index to enable data skipping on a given column

And just like any other Data warehouse, you can ANALYZE TABLE to update statistics to ensure the Query optimizer has the best statistics to create the best query plan.

```
-- collect stats for all columns for better performance
ANALYZE TABLE US_Stores.Sales_DW.fact_sales COMPUTE STATISTICS FOR ALL COLUMNS;
```

Collect stats for all the columns for better query execution plan

6. Advanced Techniques

While Databricks support advanced techniques like Table Partitioning, please use these feature sparingly, only when you have many Terabytes of compressed data - because most of the time our OPTIMIZE and Z-ORDER indexes will give you the best file and data pruning which makes partitioning a table by date or month almost a bad practice. It is however a good practice to make sure that your table DDLs are set for auto optimization and auto compaction. These will ensure your frequently written data in small files are compacted into bigger columnar compressed formats of Delta.

Are you looking to leverage a visual data modeling tool? Our partner erwin Data Modeler by Quest can be used to reverse engineer, create and implement Star-schema, Data Vaults, and any Industry Data Models in Databricks with just a few clicks.

Databricks Notebook Example

With the Databricks Platform, one can easily design and implement various data models with ease. To see all of the above examples in a complete workflow, please look at this example.

Please also check out our related blog:

Five Simple Steps for Implementing a Star Schema in Databricks With Delta Lake →

SECTION 3.3

Loading a Data Warehouse Data Model in Real Time With the Databricks Data Intelligence Platform

Dimensional modeling implementation on the modern lakehouse using Delta Live Tables

by Leo Mao, Soham Bhatt and Abhishek Dey

Dimensional modeling is one of the most popular data modeling techniques for building a modern data warehouse. It allows customers to quickly develop facts and dimensions based on business needs for an enterprise. When helping customers in the field, we found many are looking for best practices and implementation reference architecture from Databricks.

In this article, we aim to dive deeper into the best practice of dimensional modeling on the lakehouse architecture and provide a live example to load an EDW dimensional model in real-time using Delta Live Tables.

Here are the high-level steps we will cover in this blog:

- Define a business problem
- Design a dimensional model
- Best practices and recommendations for dimensional modeling
- Implementing a dimensional model on a lakehouse architecture
- Conclusion

Define a business problem

Dimensional modeling is business-oriented; it always starts with a business problem. Before building a dimensional model, we need to understand the business problem to solve, as it indicates how the data asset will be presented and consumed by end users. We need to design the data model to support more accessible and faster queries.

The Business Matrix is a fundamental concept in Dimensional Modeling, below is an example of the business matrix, where the columns are shared dimensions and rows represent business processes. The defined business problem determines the grain of the fact data and required dimensions. The key idea here is that we could incrementally build additional data assets with ease based on the Business Matrix and its shared or conformed dimensions.

Shared Dimensions →

Business Processes ↓	Date	Customer	Product	Vendor	Promotion	Reseller	Sales Territory	Employee	Account	Organization
Internet Sales	✓	✓	✓	✓	✓		✓			
Reseller Sales	✓		✓		✓	✓	✓	✓		
General Ledger	✓								✓	✓
Sales Plan	✓		✓				✓			
Inventory	✓		✓	✓					✓	
Customer Surveys	✓	✓								
Customer Service Calls	✓	✓	✓					✓		

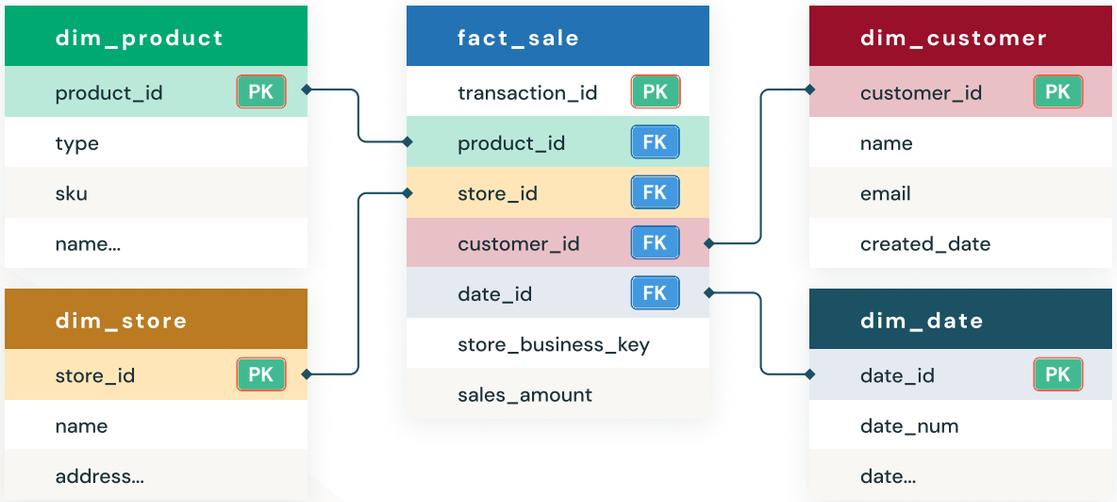
A Business Matrix with Shared Dimensions and Business Processes

Here we assume that the business sponsor would like to team to build a report to give insights on:

- What are the top selling products so they can understand product popularity
- What are the best performing stores to learn good store practices

Design a dimensional model

Based on the defined business problem, the data model design aims to represent the data efficiently for reusability, flexibility and scalability. Here is the high-level data model that could solve the business questions above.



Dimensional model on the lakehouse architecture

Note each dimension table has **__START_AT** and **__END_AT** columns to support SCD Type 2, which are not displayed here because of limited space.

The design should be easy to understand and efficient with different query patterns on the data. From the model, we designed the sales fact table to answer our business questions; as you can see, other than the foreign keys (FKs) to the dimensions, it only contains the numeric metrics used to measure the business, e.g. sales_amount.

We also designed dimension tables such as Product, Store, Customer, Date that provide contextual information on the fact data. Dimension tables are typically joined with fact tables to answer specific business questions, such as the most popular products for a given month, which stores are the best-performing ones for the quarter, etc.

Best practices and recommendations for dimensional modeling

With the Databricks Data Intelligence Platform, one can easily design and implement dimensional models, and simply build the facts and dimensions for the given subject area.

Below are some of the best practices recommended while implementing a dimensional model:

- One should denormalize the dimension tables. Instead of the third normal form or snowflake type of model, dimension tables typically are highly denormalized with flattened many-to-one relationships within a single dimension table.
- Use conformed dimension tables when attributes in different dimension tables have the same column names and domain contents. This advantage is that data from different fact tables can be combined in a single report using conformed dimension attributes associated with each fact table.
- A usual trend in dimension tables is around tracking changes to dimensions over time to support as-is or as-was reporting. You can easily apply the following basic techniques for handling dimensions based on different requirements.
  - The type 1 technique overwrites the dimension attribute's initial value.
  - With the type 2 technique, the most common SCD technique, you use it for accurate change tracking over time.

  This can be easily achieved out of the box with Delta Live Tables implementation.
  - One can easily perform SCD type 1 or SCD type 2 using Delta Live Tables using APPLY CHANGES INTO
- Primary + Foreign Key **Constraints** allow end users like yourselves to understand relationships between tables.
- **Usage of IDENTITY Columns** automatically generates unique integer values when new rows are added. Identity columns are a form of surrogate keys. Refer to the blog link for more details.
- **Enforced CHECK Constraints** to never worry about data quality or data correctness issues sneaking up on you.

Implementing a dimensional model on a lakehouse architecture

Now, let us look at an example of Delta Live Tables based dimensional modeling implementation:

The example code below shows us how to create a dimension table (dim_store) using SCD Type 2, where change data is captured from the source system.

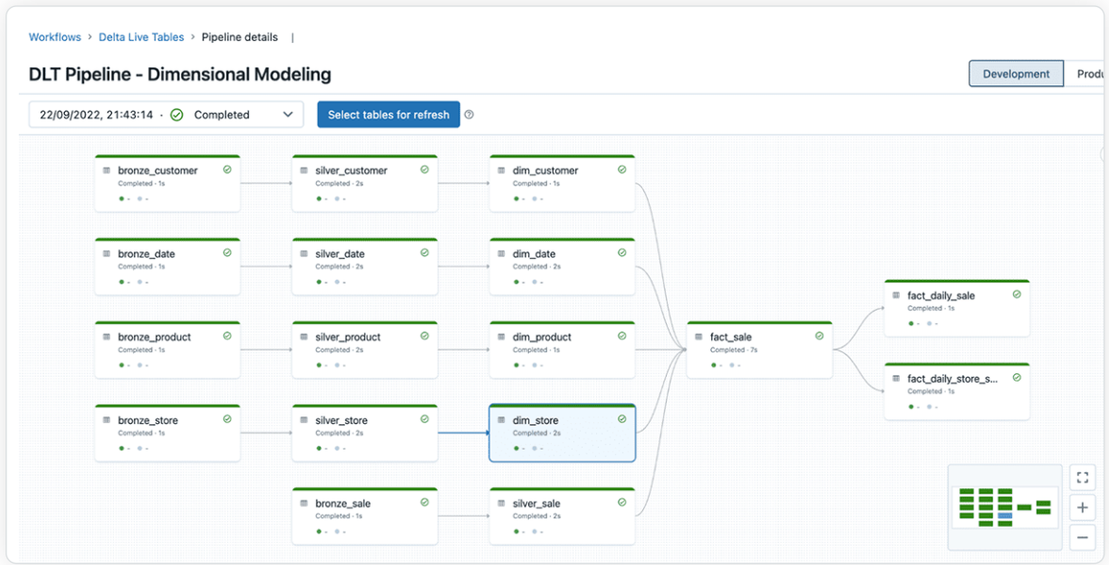
```
-- create the gold table
CREATE INCREMENTAL LIVE TABLE dim_store
TBLPROPERTIES (“quality” = “gold”)
COMMENT “Slowly Changing Dimension Type 2 for store dimension in the gold layer”;

-- store all changes as SCD2
APPLY CHANGES INTO live.dim_store
FROM STREAM(live.silver_store)
  KEYS (store_id)
  SEQUENCE BY updated_date
  COLUMNS * EXCEPT (_rescued_data, input_file_name)
  STORED AS SCD TYPE 2;
```

The example code below shows us how to create a fact table (fact_sale), with the constraint of valid_product_id we are able to ensure all fact records that are loaded have a valid product associated with it.

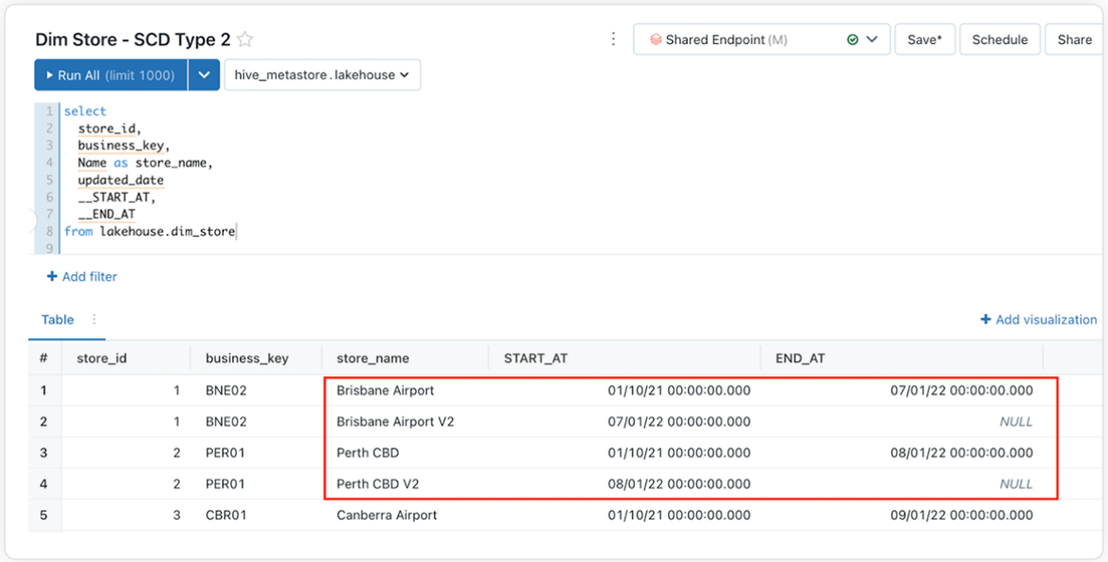
```
-- create the fact table for sales in gold layer
CREATE STREAMING LIVE TABLE fact_sale (
  CONSTRAINT valid_store_business_key EXPECT (store_business_key IS NOT NULL) ON
VIOLATION DROP ROW,
  CONSTRAINT valid_product_id EXPECT (product_id IS NOT NULL) ON VIOLATION DROP
ROW
)
TBLPROPERTIES (“quality” = “gold”, “ignoreChanges” = “true”)
COMMENT “sales fact table in the gold layer” AS
  SELECT
    sale.transaction_id,
    date.date_id,
    customer.customer_id,
    product.product_id AS product_id,
    store.store_id,
    store.business_key AS store_business_key,
    sales_amount
  FROM STREAM(live.silver_sale) sale
  INNER JOIN live.dim_date date
  ON to_date(sale.transaction_date, ‘M/d/yy’) = to_date(date.date, ‘M/d/yyyy’)
  -- only join with the active customers
  INNER JOIN (SELECT * FROM live.dim_customer WHERE __END_AT IS NULL) customer
  ON sale.customer_id = customer.customer_id
  -- only join with the active products
  INNER JOIN (SELECT * FROM live.dim_product WHERE __END_AT IS NULL) product
  ON sale.product = product.SKU
  -- only join with the active stores
  INNER JOIN (SELECT * FROM live.dim_store WHERE __END_AT IS NULL) store
  ON sale.store = store.business_key
```

The Delta Live Tables pipeline example could be found here. Please refer to Delta Live Tables quickstart on how to create a Delta Live Tables pipeline. As seen below, DLT offers full visibility of the ETL pipeline and dependencies between different objects across Bronze, Silver and Gold layers following the lakehouse medallion architecture.



End to End DLT Pipeline

Here is an example of how the dimension table dim_store gets updated based on the incoming changes. Below, the Store Brisbane Airport was updated to Brisbane Airport V2, and with the out-of-box SCD Type 2 support, the original record ended on Jan 07 2022, and a new record was created which starts on the same day with an open end date (NULL) - which indicates the latest record for the Brisbane airport.



#	store_id	business_key	store_name	START_AT	END_AT
1	1	BNE02	Brisbane Airport	01/10/21 00:00:00.000	07/01/22 00:00:00.000
2	1	BNE02	Brisbane Airport V2	07/01/22 00:00:00.000	*NULL*
3	2	PER01	Perth CBD	01/10/21 00:00:00.000	08/01/22 00:00:00.000
4	2	PER01	Perth CBD V2	08/01/22 00:00:00.000	*NULL*
5	3	CBR01	Canberra Airport	01/10/21 00:00:00.000	09/01/22 00:00:00.000

SCD Type 2 for Store Dimension

For more implementation details, please refer to here for the full notebook example.

Conclusion

In this blog, we learned about dimensional modeling concepts in detail, best practices, and how to implement them using Delta Live Tables.

Learn more about dimensional modeling at Kimball Technology.

SECTION 3.4

What's New With Databricks SQL?

AI-driven optimizations, lakehouse federation, and more for enterprise-grade BI

by Alex Lichen, Miranda Luna, Can Efeoglu and Cyrielle Simeone

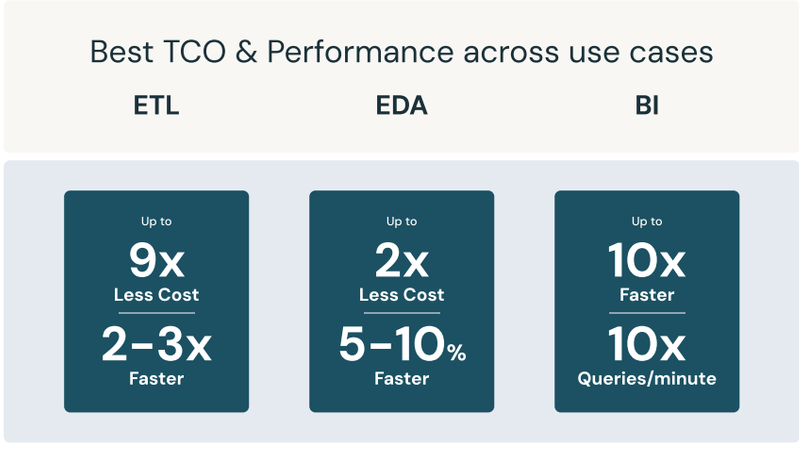
At this year's Data + AI Summit, Databricks SQL continued to push the boundaries of what a data warehouse can be, leveraging AI across the entire product surface to extend our leadership in performance and efficiency, while still simplifying the experience and unlocking new opportunities for our customers. In parallel, we continue to deliver improvements to our core data warehousing capabilities to help you unify your data stack under the lakehouse architecture on the Databricks Data Intelligence Platform.

In this blog post, we are thrilled to share the highlights of what's new and coming next in Databricks SQL:

- AI-driven performance optimizations like Predictive I/O that deliver leading performance and cost-savings, without manual tuning required.
- New user experiences with AI Functions, SQL Warehouses in Notebooks, new Dashboards, and Python User Defined Functions.
- Rich external data source support with Lakehouse Federation.
- New ways to access your data with the SQL Statement Execution API.
- Simple and efficient data processing with Streaming Tables, Materialized Views and Workflows integration.
- Intelligent assistance powered by DatabricksIQ, our knowledge engine.
- Enhanced administration tools with Databricks SQL System Tables and Live Query Profile.
- Additional features for our partner integrations with Fivetran, dbt labs and PowerBI

The AI-optimized warehouse: Ready for all your workloads — no tuning required

We believe that the best data warehouse is a lakehouse; therefore, we continue to extend our leadership in ETL workloads and harnessing the power of AI. Databricks SQL now also delivers industry-leading performance for your EDA and BI workloads, while improving cost savings — with no manual tuning.



Say goodbye to manually creating indexes. With Predictive I/O for reads (GA) and updates (Public Preview), Databricks SQL now analyzes historical read and write patterns to intelligently build indexes and optimize workloads. Early customers have benefited from a remarkable 35x improvement in point lookup efficiency, impressive performance boosts of 2-6x for MERGE operations and 2-10x for DELETE operations.

With Predictive Optimizations (Public Preview), Databricks will seamlessly optimize file sizes and clustering by running OPTIMIZE, VACUUM, ANALYZE and CLUSTERING commands for you. With this feature, Anker Innovations benefited from a 2.2x boost to query performance while delivering 50% savings on storage costs.

> **Databricks' Predictive Optimizations intelligently optimized our Unity Catalog storage, which saved us 50% in annual storage costs while speeding up our queries by >2x. It learned to prioritize our largest and most-accessed tables. And, it did all of this automatically, saving our team valuable time.**
>
> — ANKER INNOVATIONS

Tired of managing different warehouses for smaller and larger workloads or fine tuning scaling parameters? Intelligent Workload Management is a suite of features that keeps queries fast while keeping cost low. By analyzing real time patterns, Intelligent Workload Management ensures that your workloads have the optimal amount of compute to execute incoming SQL statements without disrupting already running queries.

With AI-powered optimizations, Databricks SQL provides industry leading TCO and performance for any kind of workload, without any manual tuning needed. To learn more about available optimization previews, watch Reynold Xin's keynote and Databricks SQL Serverless Under the Hood: How We Use ML to Get the Best Price/Performance from the Data+AI Summit.

Unlock siloed data with Lakehouse Federation

Today's organizations face challenges in discovering, governing and querying siloed data sources across fragmented systems. With Lakehouse Federation, data teams can use Databricks SQL to discover, query and manage data in external platforms including MySQL, PostgreSQL, Amazon Redshift, Snowflake, Azure SQL Database, Azure Synapse, Google's BigQuery (coming soon) and more.

Furthermore, Lakehouse Federation seamlessly integrates with advanced features of Unity Catalog when accessing external data sources from within Databricks. Enforce row and column level security to restrict access to sensitive information. Leverage data lineage to trace the origins of your data and ensure data quality and compliance. To organize and manage data assets, easily tag federated catalog assets for simple data discovery.

Finally, to accelerate complicated transformations or cross-joins on federated sources, Lakehouse Federation supports Materialized Views for better query latencies.

For more details, watch our dedicated session Lakehouse Federation: Access and Governance of External Data Sources from Unity Catalog from the Data+AI Summit.

Develop on the lakehouse architecture with the SQL Statement Execution API

The SQL Statement Execution API enables access to your Databricks SQL warehouse over a REST API to query and retrieve results. With HTTP frameworks available for almost all programming languages, you can easily connect to a diverse array of applications and platforms directly to a Databricks SQL Warehouse.

The Databricks SQL Statement Execution API is available with the Databricks Premium and Enterprise tiers. To learn more, watch our session, follow our tutorial (AWS | Azure), read the documentation (AWS | Azure), or check our repository of code samples.

Streamline your data processing with Streaming Tables, Materialized Views, and DB SQL in Workflows

With Streaming Tables, Materialized Views, and DB SQL in Workflows, any SQL user can now apply data engineering best practices to process data. Efficiently ingest, transform, orchestrate, and analyze data with just a few lines of SQL.

Streaming Tables are the ideal way to bring data into "Bronze" tables. With a single SQL statement, scalably ingest data from various sources such as cloud storage (S3, ADLS, GCS), message buses (EventHub, Kafka, Kinesis), and more. This ingestion occurs incrementally, enabling low-latency and cost-effective pipelines, without the need for managing complex infrastructure.

```
CREATE STREAMING TABLE web_clicks
AS
SELECT *
FROM STREAM
  read_files('s3://mybucket')
```

Materialized Views reduce cost and improve query latency by pre-computing slow queries and frequently used computations, and are incrementally refreshed to improve overall latency. In a data engineering context, they are used for transforming data. But they are also valuable for analyst teams in a data warehousing context because they can be used to (1) speed up end-user queries and BI dashboards, and (2) securely share data. In just four lines of code, any user can create a materialized view for performant data processing.

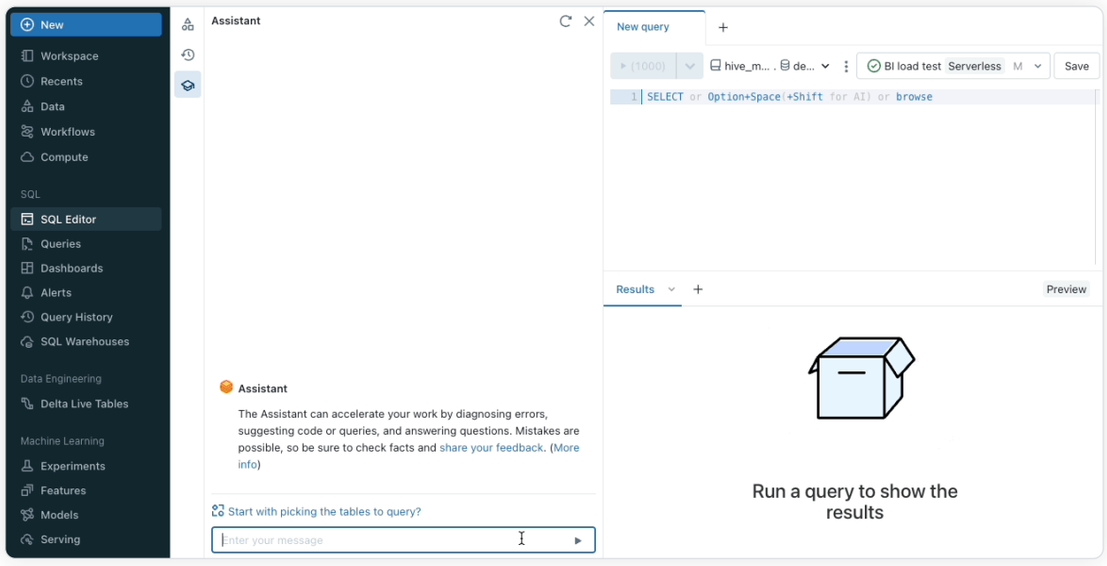
```
CREATE MATERIALIZED VIEW customer_orders
AS
SELECT
  customers.name,
  sum(orders.amount),
  orders.orderdate
FROM orders
  LEFT JOIN customers ON
    orders.custkey = customers.c_custkey
GROUP BY
  name,
  orderdate;
```

Need orchestration with DB SQL? Workflows now allows you to schedule SQL queries, dashboards and alerts. Easily manage complex dependencies between tasks and monitor past job executions with the intuitive Workflows UI or via API.

Streaming Tables and Materialized Views are now in public preview. To learn more, read our dedicated blog post. To enroll in the public preview for both, enroll in this form. Workflows in DB SQL is now generally available, and you can learn more by reading the documentation (AWS | Azure).

Databricks Assistant: Write better and faster SQL with natural language

Databricks Assistant is a context-aware AI assistant embedded inside Databricks Notebooks and the SQL Editor. Databricks Assistant can take a natural language question and suggest a SQL query to answer that question. When trying to understand a complex query, users can ask the Assistant to explain it using natural language, enabling anyone to understand the logic behind query results.



Databricks Assistant uses a number of signals to provide more accurate, relevant results. It uses context from code cells, libraries, popular tables, Unity Catalog schemas and tags to map natural language questions into queries and code.

In the future, we will be adding integration with DatabricksIQ to provide even more context for your requests.

Manage your data warehouse with confidence

Administrators and IT teams need the tools to understand data warehouse usage. With System Tables, Live Query Profile, and Statement Timeouts, admins can monitor and fix problems when they occur, ensuring that your data warehouse runs efficiently.

Gain deeper visibility and insights into your SQL environment with System Tables. System Tables are Databricks-provided tables that contain information about past statement executions, costs, lineage, and more. Explore metadata and usage metrics to answer questions like “What statements were run and by whom?”, “How and when did my warehouses scale?” and “What was I billed for?”. Since System Tables are integrated within Databricks, you have access to native capabilities such as SQL alerts and SQL dashboards to automate the monitoring and alerting process.

As of today, there are three System Tables currently in public preview: Audit Logs, Billable Usage System Table, and Lineage Sytem Table (AWS | Azure). Additional system tables for warehouse events and statement history are coming soon.

For example, to compute the monthly DBUs used per SKU, you can query the Billiable Usage System Tables.

```
SELECT sku_name, usage_date, sum(usage_quantity) as `DBUs`
    FROM system.billing.usage
WHERE
    month(usage_date) = month(NOW())
    AND year(usage_date) = year(NOW())
GROUP BY sku_name, usage_date
```

With Live Query Profile, users gain real-time insights into query performance to help optimize workloads on the fly. Visualize query execution plans and assess live query task executions to fix common SQL mistakes like exploding joins or full table scans. Live Query Profile allows you to ensure that running queries on your data warehouse are optimized and running efficiently. Learn more by reading the documentation (AWS | Azure).

Looking for automated controls? Statement Timeouts allow you to set a custom workspace or query level timeout. If a query's execution time exceeds the timeout threshold, the query will be automatically halted. Learn more by reading the documentation (AWS | Azure)

Compelling new experiences in DBSQL

Over the past year, we've been hard at work to add new, cutting-edge experiences to Databricks SQL. We're excited to announce new features that put the power of AI in SQL users hands such as, enabling SQL warehouses throughout the entire Databricks platform; introducing a new generation of SQL dashboards; and bringing the power of Python into Databricks SQL.

Democratize unstructured data analysis with AI Functions

With AI Functions, DB SQL is bringing the power of AI into the SQL warehouse. Effortlessly harness the potential of unstructured data by performing tasks such as sentiment analysis, text classification, summarization, translation and more. Data analysts can apply AI models via self-service, while data engineers can independently build AI-enabled pipelines.

Using AI Functions is quite simple. For example, consider a scenario where a user wants to classify the sentiment of some articles into Frustrated, Happy, Neutral, or Satisfied.

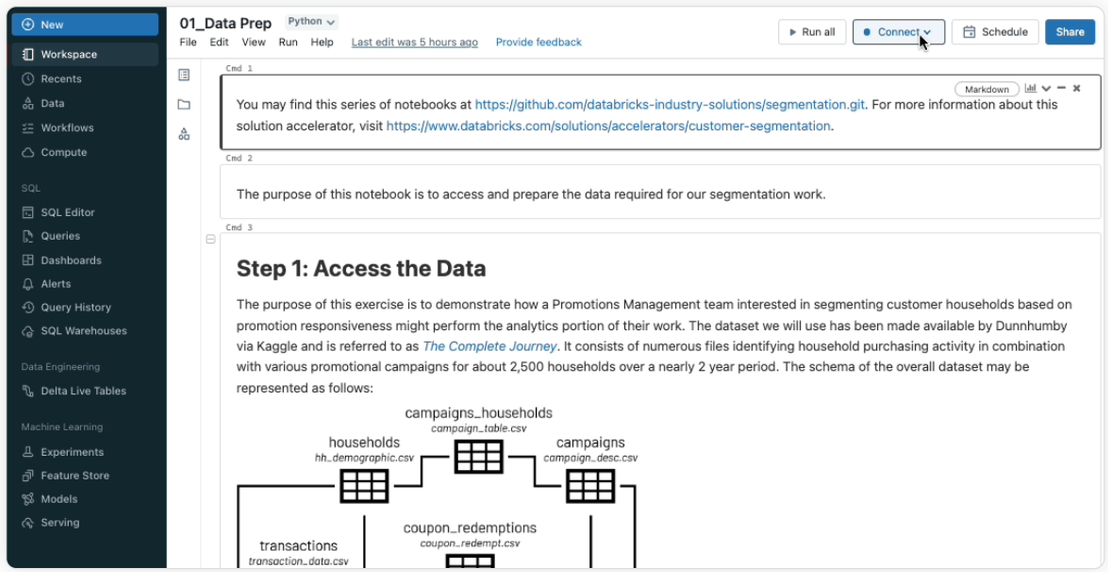
```
-- create a udf for sentiment classification
CREATE FUNCTION classify_sentiment(text STRING)
  RETURNS STRING
  RETURN ai_query(
    'Dolly', -- the name of the model serving endpoint
    named_struct(
      'prompt',
      CONCAT('Classify the following text into one of four categories [Frustrated,
Happy, Neutral, Satisfied]:\n',
        text),
      'temperature', 0.5),
    'returnType', 'STRING');
```

```
-- use the udf
SELECT classify_sentiment(text) AS sentiment
FROM reviews;
```

AI Functions are now in Public Preview. To sign up for the Preview, fill out the form here. To learn more, you can also read our detailed blog post or review the documentation (AWS | Azure).

Bring the power of SQL warehouses to notebooks

Databricks SQL warehouses are now public preview in notebooks, combining the flexibility of notebooks with the performance and TCO of Databricks SQL Serverless and Pro warehouses. To enable SQL warehouses in notebooks, simply select an available SQL warehouse from the notebooks compute dropdown.



Connecting serverless SQL warehouses from Databricks notebooks

Find and share insights with a new generation of dashboards

Discover a revamped dashboarding experience directly on the lakehouse architecture. Users can simply select a desired dataset and build stunning visualizations with a SQL-optional experience. Say goodbye to managing separate queries and dashboard objects - an all-in-one content model simplifies the permissions and management process. Finally, publish a dashboard to your entire organization, so that any authenticated user in your identity provider can access the dashboard via a secure web link, even if they don't have Databricks access.

New Databricks SQL Dashboards are currently in Private Preview. Contact your account team to learn more.

Leverage the flexibility of Python in SQL

Bring the flexibility of Python into Databricks SQL with Python user-defined functions (UDFs). Integrate machine learning models or apply custom redaction logic for data processing and analysis by calling custom Python functions directly from your SQL query. UDFs are reusable functions, enabling you to apply consistent processing to your data pipelines and analysis.

For instance, to redact email and phone numbers from a file, consider the following CREATE FUNCTION statement.

```
CREATE FUNCTION redact(a STRING)
RETURNS STRING
LANGUAGE PYTHON
AS $$
import json
keys = [“email”, “phone”]
obj = json.loads(a)
for k in obj:
  if k in keys:
    obj[k] = “REDACTED”
return json.dumps(obj)
$$;
```

Learn more about enrolling in the private preview here.

Integrations with your data ecosystem

At Data+AI Summit, Databricks SQL announced new integrations for a seamless experience with your tools of choice.

Databricks + Fivetran

We're thrilled to announce the general availability of Fivetran access in Partner Connect for all users including non-admins with sufficient privileges to a catalog. This innovation makes it 10x easier for all users to ingest data into Databricks using Fivetran. This is a huge win for all Databricks customers as they can now bring data into the lakehouse architecture from hundreds of connectors Fivetran offers, like Salesforce and PostgreSQL. Fivetran now fully supports serverless warehouses as well!

Learn more by reading the blog post here.

Databricks + dbt Labs

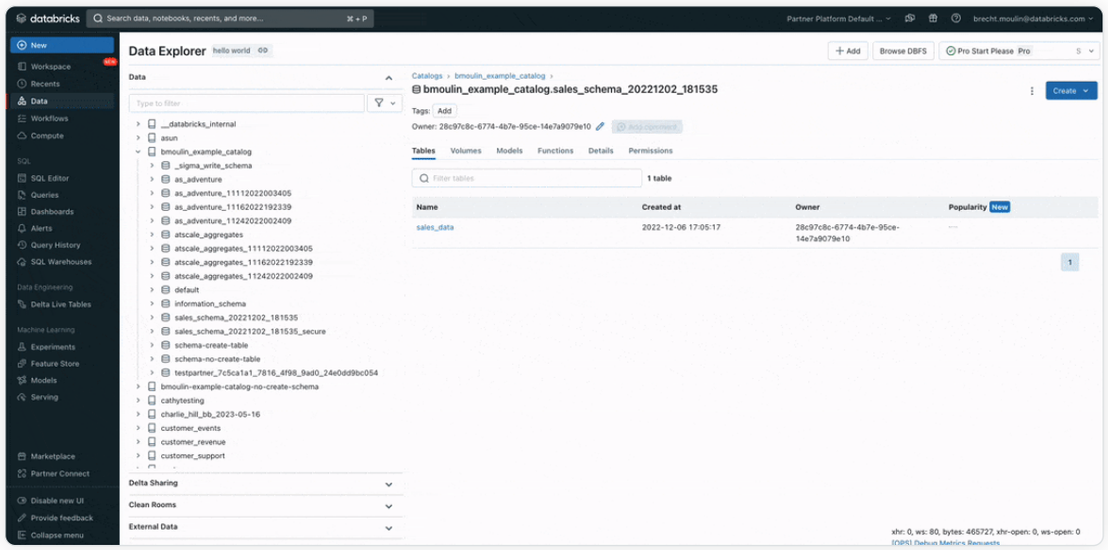
Simplify real-time analytics engineering on the lakehouse architecture with Databricks and dbt Labs. The combination of dbt's highly popular analytics engineering framework with the Databricks Platform provides powerful capabilities:

- dbt + Streaming Tables: Streaming ingestion from any source is now built-in to dbt projects. Using SQL, analytics engineers can define and ingest cloud/streaming data directly within their dbt pipelines.
- dbt + Materialized Views: Building efficient pipelines becomes easier with dbt, leveraging Databricks' powerful incremental refresh capabilities. Users can use dbt to build and run pipelines backed by MVs, reducing infrastructure costs with efficient, incremental computation.

To learn more, read the detailed blog post.

Databricks + PowerBI: Publish to PowerBI Workspaces

Publish datasets from your Databricks workspace to PowerBI Online workspace with a few clicks! No more managing odbc/jdbc connections — simply select the dataset you want to publish. Simply select the datasets or schema you want to publish and select your PBI workspace! This makes it easier for BI admins and report creators to support PowerBI workspaces without also having to use Power BI Desktop.



Getting Started with Databricks SQL

Follow the guide (AWS | Azure | GCP) on how to setup a SQL warehouse to get started with Databricks SQL today! Databricks SQL Serverless is currently available with a 20%+ promotional discount, visit our pricing page to learn more.

You can also watch **Databricks SQL: Why the Best Serverless Data Warehouse is a Lakehouse** and **What's New in Databricks SQL — With Live Demos** for a complete overview.

SECTION 3.5

Distributed Data Governance and Isolated Environments With Unity Catalog

by Max Nienu, Zeashan Pappa, Paul Roome and Sachin Thakur

Effective data governance is essential for any organization that relies on data, analytics and AI for its operations. In many organizations, there is a growing recognition of the value proposition of centralized data governance. However, even with the best intentions, implementing centralized governance can be challenging without the proper organizational processes and resources. The role of Chief Data Officer (CDO) is still emerging in many organizations, leaving questions about who will define and execute data governance policies across the organization.

As a result, the responsibility for defining and executing data governance policies across the organization is often not centralized, leading to policy variations or governing bodies across lines of business, sub-units, and other divisions within an organization. For simplicity, we can call this pattern distributed governance, where there is a general agreement on the distinctions between these governing units but not necessarily a central data governance function.

In this blog, we'll explore implementing a distributed governance model using Databricks Unity Catalog, which provides a unified governance solution for data, analytics, and AI in the lakehouse.

Evolution of Data Governance in Databricks

Before the introduction of Unity Catalog, the concept of a workspace was monolithic, with each workspace having its own metastore, user management, and Table ACL store. This led to intrinsic data and governance isolation boundaries between workspaces and duplication of effort to address consistency across them.

To handle this, some customers resorted to running pipelines or code to synchronize their metastores and ACLs, while others set up their own self-managed metastores to use across workspaces. However, these solutions added more overhead and maintenance costs forcing upfront architecture decisions on how to partition data across the organization, creating data silos.

Data Governance with Unity Catalog

To overcome these limitations, Databricks developed Unity Catalog, which aims to make it easy to implement data governance while maximizing the ability to collaborate on and share data. The first step in achieving this was implementing a common namespace that permits access to any data within an organization.

This approach may seem like a challenge to the distributed governance pattern mentioned earlier but Unity Catalog offers new isolation mechanisms within the namespace that organizations have traditionally addressed using multiple Hive metastores. These isolation mechanisms enable groups to operate independently with minimal or no interaction and also allow them to achieve isolation in other scenarios, such as production vs development environments.

Hive Metastore versus Unity Catalog in Databricks

With Hive, a metastore was a service boundary, meaning that having different metastores meant different hosted underlying Hive services and different underlying databases. Unity Catalog is a platform service within the Databricks Data Intelligence Platform, so there are no service boundaries to consider.

Unity Catalog provides a common namespace that allows you to govern and audit your data in one place.

When using Hive, it was common to use multiple metastores, each with its own namespace, to achieve isolation between development and production environments, or to allow for the separation of data between operating units.

In Unity Catalog, these requirements are solved through dynamic isolation mechanisms on namespaces that don't compromise the ability to share and collaborate on data and don't require hard one-way upfront architecture decisions.

Working across different teams and environments

When using a data platform, there is often a strong need to have isolation boundaries between environments like dev/prod and between business groups, teams, or operating units of your organization.

Let's begin by defining isolation boundaries in a data platform such as Databricks:

- Users should only gain access to data based on agreed access rules
- Data can be managed by designated people or teams
- Data should be physically separated in storage
- Data should only be accessed in designated environments

Users should only gain access to data based on agreed access rules

Organizations usually have strict requirements around data access based on some organizational/regulatory requirements which is fundamental to keeping data secure. Typical examples include employee salary information or credit card payment information.

Access to this type of information is typically tightly controlled and audited periodically. Unity Catalog provides organizations granular control over data assets within the catalog to meet these industry standards. With the controls, Unity Catalog provides users will only see and query the data they are entitled to see and query.

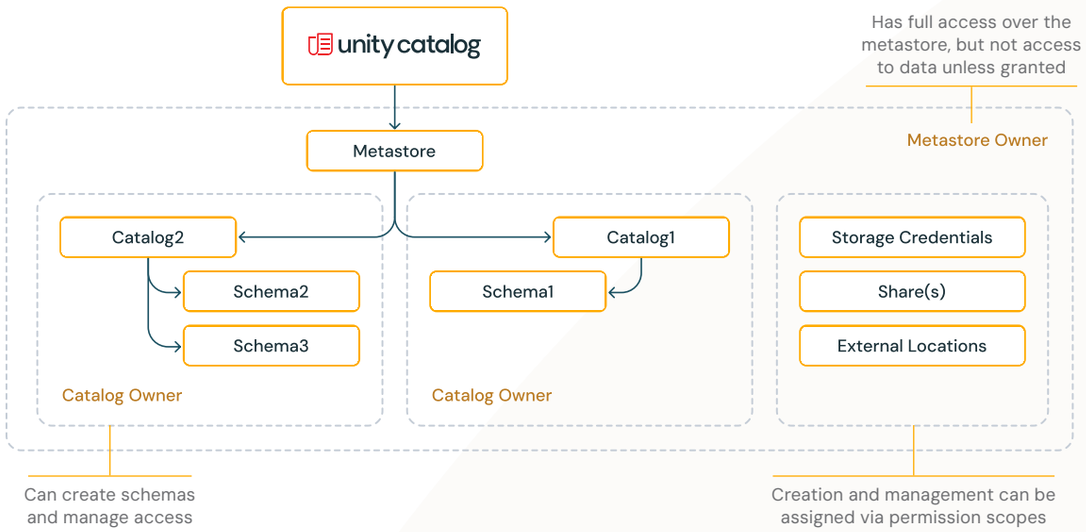
Data can be managed by designated people or teams

Unity Catalog gives you the ability to choose from centralized governance or distributed governance models.

In the centralized governance model, your governance administrators are owners of the metastore and can take ownership of any object and set ACLs and policy.

In a distributed governance model, you would consider a catalog or set of catalogs to be a data domain. The owner of that catalog can create and own all assets and manage governance within that domain. Therefore the owners of domains can operate independently of other owners in other domains.

We strongly recommend setting a group to be the owner or service principal for both of these options if management is done through tooling.



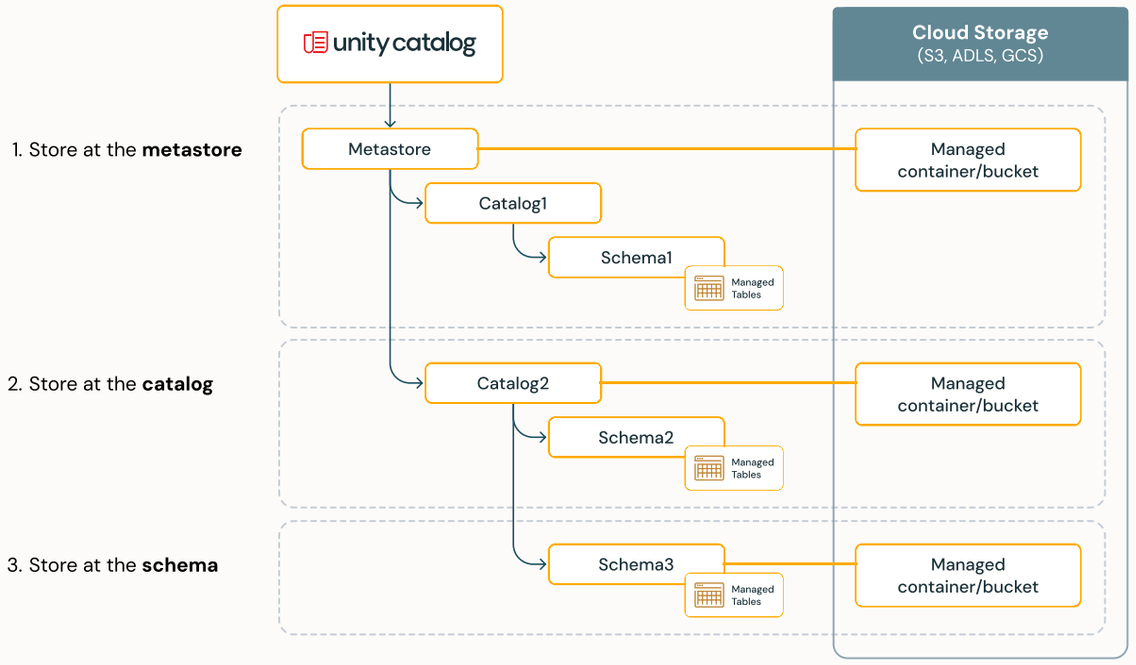
Data should be physically separated in storage

By default, when creating a UC metastore, the Databricks Account Admin provides a single cloud storage location and credential as the default location for managed tables.

Organizations that require physical isolation of data, for regulatory reasons, or for example across SDLC scopes, between business units, or even for cost allocation purposes, should consider managed data source features at the catalog and schema level.

Unity Catalog allows you to choose the defaults for how data is separated in storage. By default, all data is stored at the metastore. With feature support for managed data sources on catalogs and schemas, you can physically isolate data storage and access, helping your organization achieve their governance and data management requirements.

When creating managed tables, the data will then be stored using the schema location (if present) followed by the catalog location (if present), and will only use the metastore location if the prior two locations have not been set.

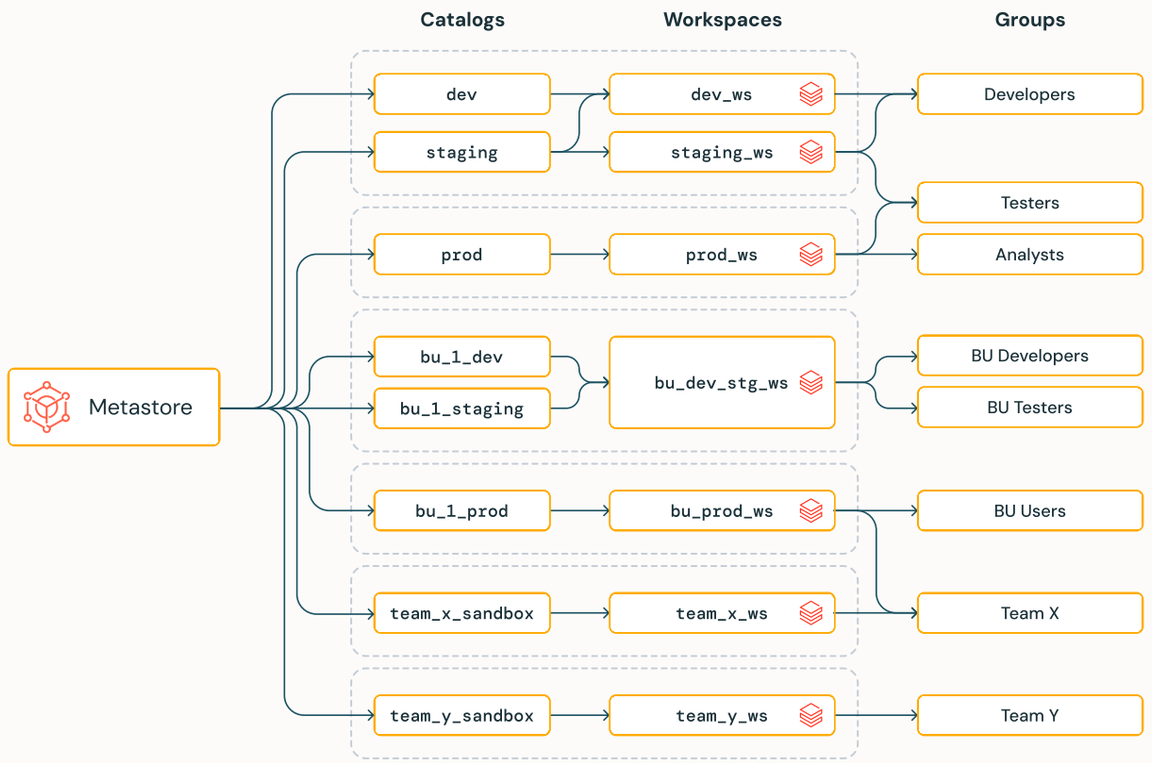


databricks

Data should only be accessed in designated environments, based on the purpose of that data

Oftentimes, organizational and compliance requirements maintain that you need to keep certain data accessible only in certain environments versus others. An example of this could be dev and production, or HIPAA or PII environments that contain PII data for analysis and have special access rules around who can access the data and the environments that allow access to that data. Sometimes requirements dictate that certain data sets or domains cannot be crossed or combined together.

In Databricks, we consider a workspace to be an environment. Unity Catalog has a feature that allows you to 'bind' catalogs to workspace. These environment-aware ACLs give you the ability to ensure that only certain catalogs are available within a workspace, regardless of a user's individual ACLs. This means that the metastore admin, or the catalog owner can define the workspaces that a data catalog can be accessed from. This can be controlled via our UI or via API/ terraform for easy integrations. We even recently published a blog on how to control Unity Catalog via terraform to help fit your specific governance model.



Access to data and availability of data can be isolated across workspaces and groups. Users can only access certain catalogs in certain environments.

Conclusion

With Unity Catalog at the center of your lakehouse architecture, you can achieve a flexible and scalable governance implementation without sacrificing your ability to manage and share data effectively. With Unity Catalog, you can overcome the limitations and constraints of your existing Hive metastore, enabling you to more easily isolate and collaborate on data according to your specific business needs. Follow the Unity Catalog guides (AWS, Azure) to get started. Download this free ebook on Data, analytics and AI governance to learn more about best practices to build an effective governance strategy for your data lakehouse.

SECTION 3.6

The Hitchhiker's Guide to Data Privilege Model and Access Control in Unity Catalog

Distill concepts within the Unity Catalog privilege model in a simple, digestible way, to support different access needs and patterns

by Som Natarajan and Vuong Nguyen

As the volume, velocity and variety of data grows, organizations are increasingly relying on staunch data governance practices to ensure their core business outcomes are adequately met. Unity Catalog is a fine-grained governance solution for data and AI powering the Databricks Data Intelligence Platform. It helps simplify the security and governance of your enterprise data assets by providing a centralized mechanism to administer and audit data access.

Taking a journey down memory lane, before Unity Catalog unified the permission model for files, tables and added support for all languages, customers were implementing fine-grained data access control on Databricks using the legacy workspace-level Table ACL (TACL), which were essentially restricted to certain cluster configurations and worked only for Python and SQL. Both Unity Catalog and TACL let you control access to securable objects like catalogs, schemas (databases), tables, views, but there are some nuances in how each access model works.

A good understanding of the object access model is essential for implementing data governance at scale using Unity Catalog. Even more so, if you have already implemented the Table ACL model and are looking to upgrade to Unity Catalog to take advantage of all the newest features, such as multi-language support, centralized access control and data lineage.

The Axioms of Unity Catalog access model

- Unity Catalog privileges are defined at metastore — Unity Catalog permissions always refer to account-level identities, while TACL permissions defined within the hive_metastore catalog always refer to the local identities in the workspace
- Privilege inheritance — Objects in Unity Catalog are hierarchical and privileges are inherited downward. The highest level object that privileges are inherited from is the catalog
- Object ownership is important — Privileges can only be granted by a metastore admin, the owner of an object, or the owner of the catalog or schema that contains the object. Only the owner of an object, or the owner of the catalog or schema that contains it can drop the object
- USE privileges for boundaries — USE CATALOG/SCHEMA is required to interact with objects within a catalog/schema. However, USE privilege does not allow one to browse the object metadata that is housed within the catalog/schema
- Permissions on derived objects are simplified — Unity Catalog only requires the owner of a view to have SELECT privilege, along with USE SCHEMA on the views' parent schema and USE CATALOG on the parent catalog. In contrast with TACL, a view's owner needs to be an owner of all referenced tables and views

Some more complex axioms

- Secure by default — only clusters with Unity-Catalog specific access modes (shared or single-user) can access Unity Catalog data. With TACL, all users have access to all data on non-shared clusters
- Limitation of single-user clusters — Single users clusters do not support dynamic views. Users must have SELECT on all referenced tables and views to read from a view
- No support for ANY FILE or ANONYMOUS FUNCTIONs: Unity Catalog does not support these permissions, as they could be used to circumvent access control restrictions by allowing an unprivileged user to run privileged code

Interesting patterns

There are many governance patterns that can be achieved using the Unity Catalog access model.

Example 1 - Consistent permissions across workspaces

Connecting serverless SQL Warehouses from Databricks notebooks

Axiom 1 allows product team to define permissions for their data product within their own workspace, and having those reflected and enforced across all other workspaces, no matter where their consumers are coming from

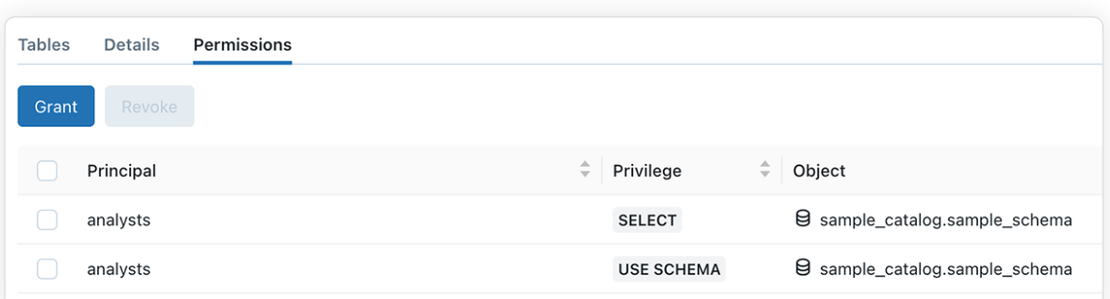
Example 2 - Setting boundary for data sharing

Axiom 2 allows catalog/schema owners to set up default access rules for their data. For example the following commands enable the machine learning team to create tables within a schema and read each other's tables:

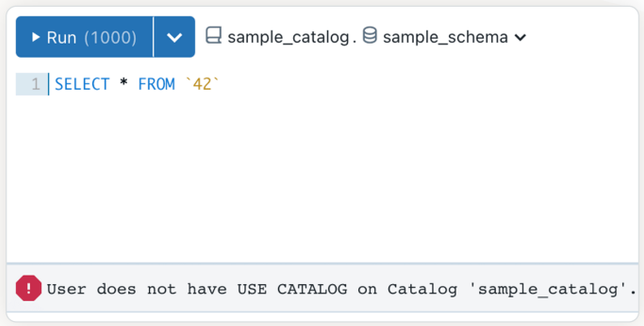
```
CREATE CATALOG ml;
CREATE SCHEMA ml.sandbox;
GRANT USE_CATALOG ON CATALOG ml TO ml_users;
GRANT USE_SCHEMA ON SCHEMA ml.sandbox TO ml_users;
GRANT CREATE TABLE ON SCHEMA ml.sandbox TO ml_users;
GRANT SELECT ON SCHEMA ml.sandbox TO ml_users;
```

More interestingly, axiom 4 now allows catalog/schema owners to limit how far individual schema and table owners can share data they produce. A table owner granting SELECT to another user does not allow that user read access to the table unless they also have been granted USE CATALOG privileges on its parent catalog as well as USE SCHEMA privileges on its parent schema.

In the below example, sample_catalog is owned by user A, user B created a sample_schema schema, and table 42. Even though USE SCHEMA and SELECT permission is granted to the analysts team, they still cannot query the table, due to permission boundary set by user A



Permission page showing analysts group having SELECT and USE SCHEMA permission on sample_catalog.sample_schema

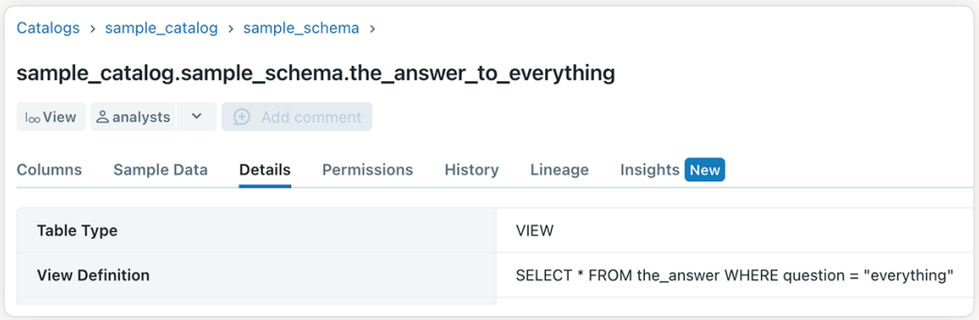


Query page with an error message

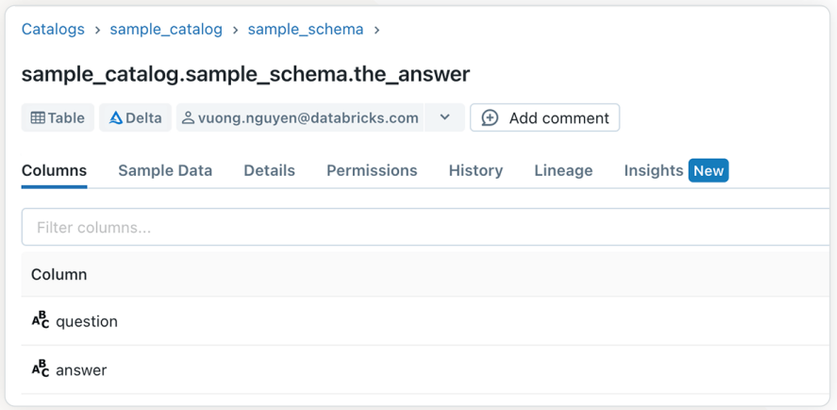
Example 3 - Easier sharing of business logic

Data consumers have a need to share their workings and transformation logic, and a reusable way of doing it is by creating and sharing views to other consumers.

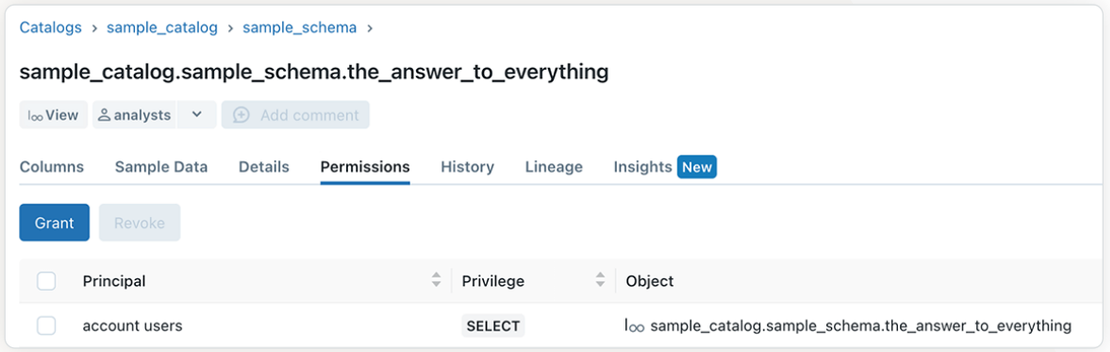
Axiom 5 unlocks the ability for data consumers to do this seamlessly, without requiring manual back and forth with the table owners.



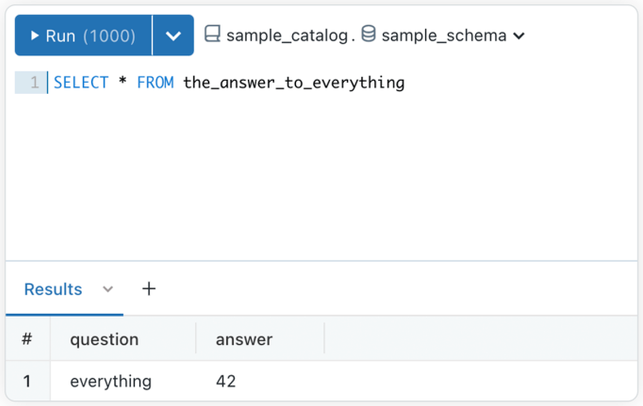
Definition of the view



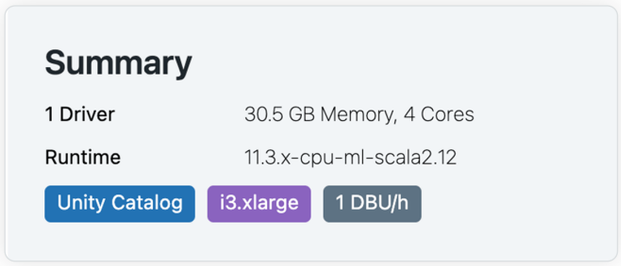
Ownership of the table



Permission page showing a view owned by analysts group, and account users group having SELECT permission



Query page showing the result of the answer to everything



Cluster summary indicating Unity Catalog support

Example 4 - No more data leakage

Thanks to axiom 6, data owners can be certain that there will be no unauthorized access to their data due to cluster misconfiguration. Any cluster that is not configured with the correct access mode will not be able to access data in Unity Catalog.

Users can check that their clusters can access Unity Catalog data thanks to this handy tooltip on the Create Clusters page

Now that data owners can understand the data privilege model and access control, they can leverage Unity Catalog to simplify access policy management at scale.

There are upcoming features that will further empower data administrators and owners to author even more complex access policy:

- **Row filtering and column masking:** Use standard SQL functions to define row filters and column masks, allowing fine-grained access controls on rows and columns.
- **Attribute Based Access Controls:** Define access policies based on tags (attributes) of your data assets.

SECTION

04

Analytics Use Cases on Databricks

SECTION 4.1

How to Build a Marketing Analytics Solution Using Fivetran and dbt on Databricks

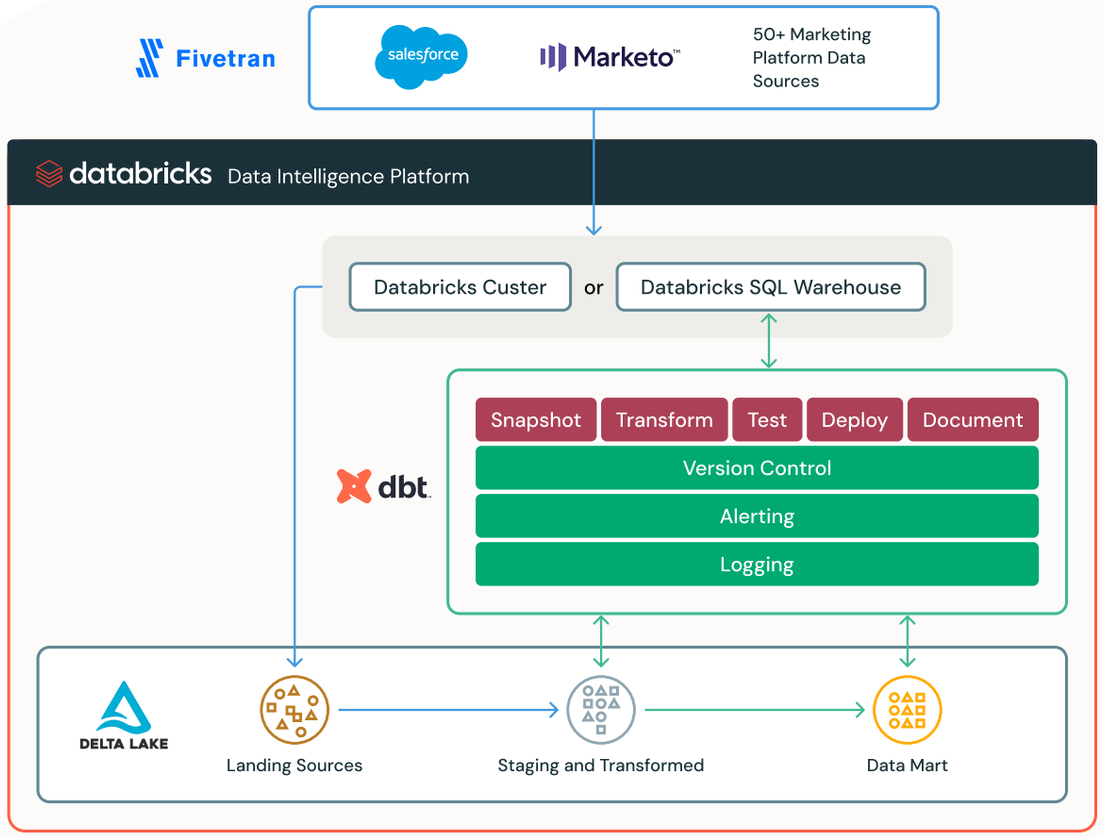
by Tahir Fayyaz, Bilal Aslam and Robert Saxby

Marketing teams use many different platforms to drive marketing and sales campaigns, which can generate a significant volume of valuable but disconnected data. Bringing all of this data together can help to drive a large return on investment, as shown by Publicis Groupe who were able to increase campaign revenue by as much as 50%.

Databricks, which unifies data warehousing and AI use cases on a single platform, is the ideal place to build a marketing analytics solution: we maintain a single source of truth, and unlock AI/ML use cases. We also leverage two Databricks partner solutions, Fivetran and dbt, to unlock a wide range of marketing analytics use cases including churn and lifetime value analysis, customer segmentation, and ad effectiveness.

Fivetran allows you to easily ingest data from 50+ marketing platforms into Delta Lake without the need for building and maintaining complex pipelines. If any of the marketing platforms' APIs change or break, Fivetran will take care of updating and fixing the integrations so your marketing data keeps flowing in.

dbt is a popular open source framework that lets lakehouse users build data pipelines using simple SQL. Everything is organized within directories, as plain text, making version control, deployment, and testability simple. Once the data is ingested into Delta Lake, we use dbt to transform, test and document the data. The transformed marketing analytics data mart built on top of the ingested data is then ready to be used to help drive new marketing campaigns and initiatives.



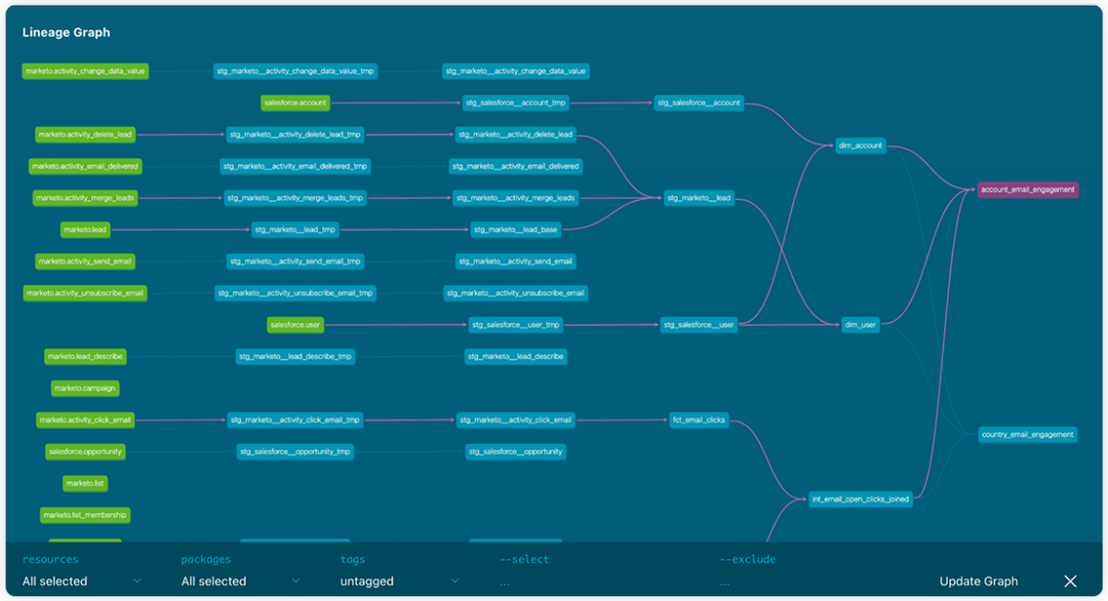
Fivetran and dbt can read and write to Delta Lake using a Databricks cluster or Databricks SQL warehouse

Both Fivetran and dbt are a part of Databricks Partner Connect, a one-stop portal to discover and securely connect data, analytics and AI tools directly within the Databricks Platform. In just a few clicks you can configure and connect these tools (and many more) directly from within your Databricks workspace.

How to build a marketing analytics solution

In this hands-on demo, we will show how to ingest Marketo and Salesforce data into Databricks using Fivetran and then use dbt to transform, test, and document your marketing analytics data model.

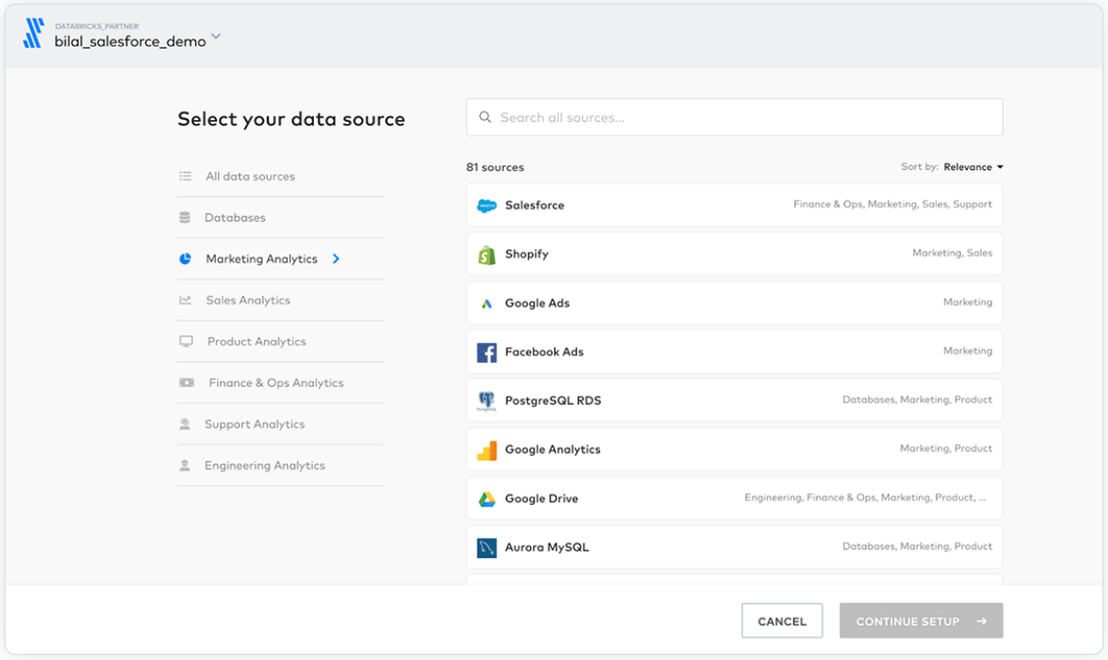
All the code for the demo is available on Github in the workflows-examples repository.



dbt lineage graph showing data sources and models

The final dbt model lineage graph will look like this. The Fivetran source tables are in green on the left and the final marketing analytics models are on the right. By selecting a model, you can see the corresponding dependencies with the different models highlighted in purple.

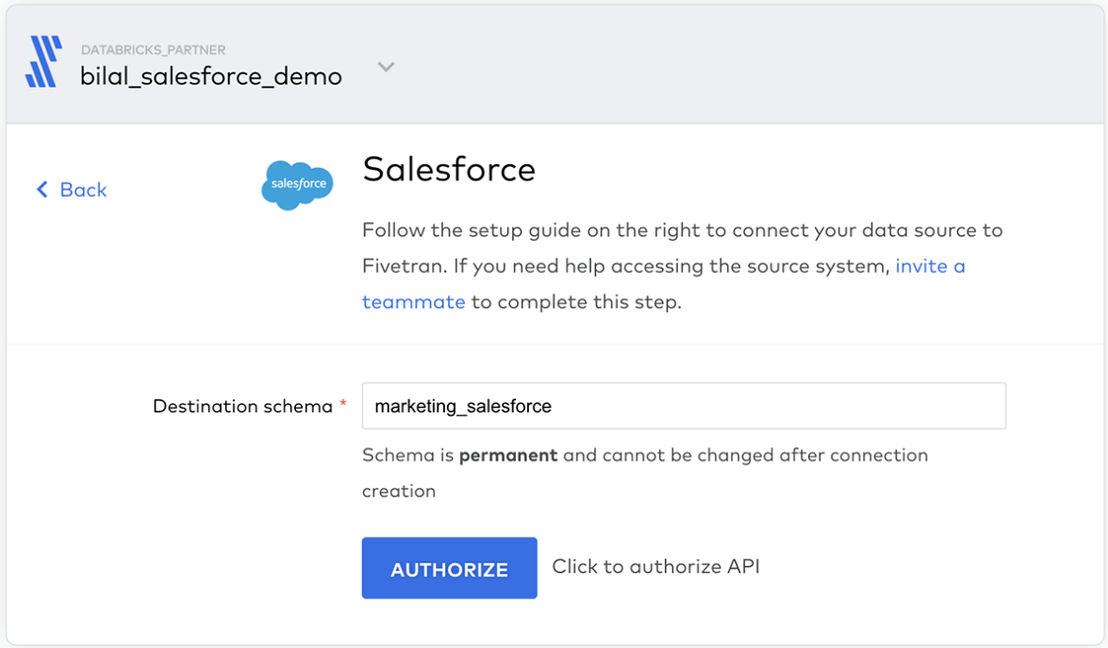
Data ingestion using Fivetran



Fivetran has many marketing analytics data source connectors

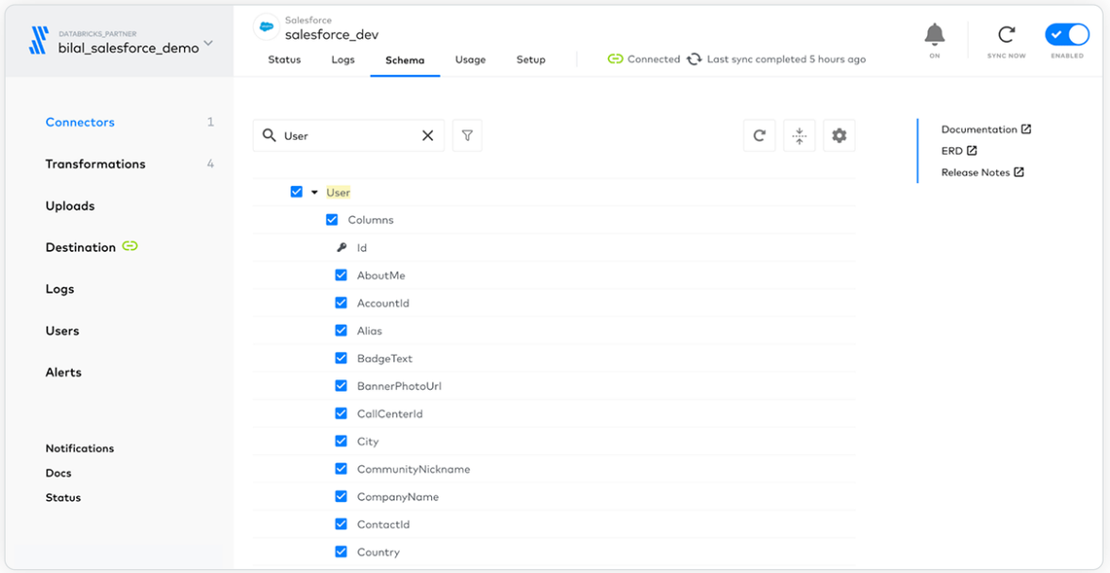
databricks

Create new Salesforce and Marketo connections in Fivetran to start ingesting the marketing data into Delta Lake. When creating the connections Fivetran will also automatically create and manage a schema for each data source in Delta Lake. We will later use dbt to transform, clean and aggregate this data.



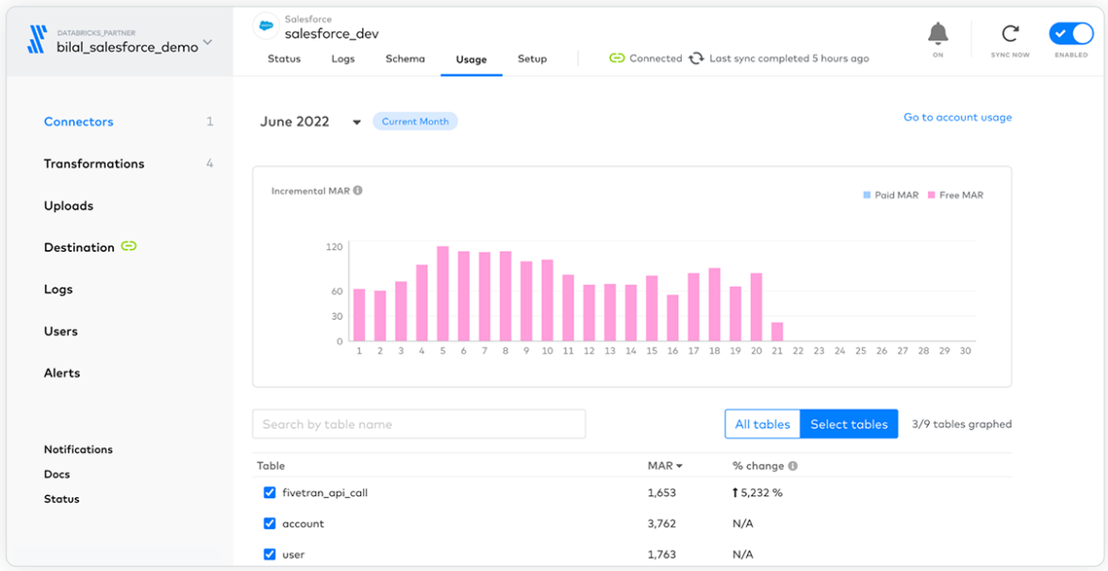
Define a destination schema in Delta Lake for the Salesforce data source

For the demo name the schemas that will be created in Delta Lake marketing_salesforce and marketing_marketo. If the schemas do not exist Fivetran will create them as part of the initial ingestion load.



Select which data source objects to synchronize as Delta Lake tables

You can then choose which objects to sync to Delta Lake, where each object will be saved as individual tables. Fivetran also makes it simple to manage and view what columns are being synchronized for each table:



Fivetran monitoring dashboard to monitor monthly active rows synchronized

Additionally, Fivetran provides a monitoring dashboard to analyze how many monthly active rows of data are synchronized daily and monthly for each table, among other useful statistics and logs.

Data modeling using dbt

Now that all the marketing data is in Delta Lake, you can use dbt to create your data model by following these steps

Setup dbt project locally and connect to Databricks SQL

Set up your local dbt development environment in your chosen IDE by following the set-up instructions for dbt Core and dbt-databricks.

Scaffold a new dbt project and connect to a Databricks SQL Warehouse using dbt init, which will ask for following information.

```
$ dbt init
Enter a name for your project (letters, digits, underscore):
Which database would you like to use?
[1] databricks
[2] spark

Enter a number: 1
host (yourorg.databricks.com):
http_path (HTTP Path):
token (dapiXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX):
schema (default schema that dbt will build objects in):
threads (1 or more) [1]:
```

Once you have configured the profile you can test the connection using:

```
$ dbt debug
```

Install Fivetran dbt model packages for staging

The first step in using the Marketo and Salesforce data is to create the tables as sources for our model. Luckily, Fivetran has made this easy to get up and running with their pre-built Fivetran dbt model packages. For this demo, let's make use of the `marketo_source` and `salesforce_source` packages.

To install the packages just add a **`packages.yml`** file to the root of your dbt project and add the `marketo-source`, `salesforce-source` and the `fivetran-utils` packages:

```
packages:
  - package: dbt-labs/spark_utils
    version: 0.3.0
  - package: fivetran/marketo_source
    version: [">=0.7.0", "=0.4.0", "

To download and use the packages run
```

```
$ dbt deps
```

You should now see the Fivetran packages installed in the packages folder.

Update dbt_project.yml for Fivetran dbt models

There are a few configs in the `dbt_project.yml` file that you need to modify to make sure the Fivetran packages work correctly for Databricks.

The `dbt_project.yml` file can be found in the root folder of your dbt project.

spark_utils overriding dbt_utils macros

The Fivetran dbt models make use of macros in the `dbt_utils` package but some of these macros need to be modified to work with Databricks which is easily done using the `spark_utils` package.

It works by providing shims for certain `dbt_utils` macros which you can set using the dispatch config in the `dbt_project.yml` file and with this dbt will first search for macros in the `spark_utils` package when resolving macros from the `dbt_utils` namespace.

```
dispatch:
 - macro_namespace: dbt_utils
   search_order: ['spark_utils', 'dbt_utils']
```

Variables for the marketo_source and salesforce_source schemas

The Fivetran packages require you to define the catalog (referred to as database in dbt) and schema of where the data lands when being ingested by Fivetran.

Add these variables to the `dbt_project.yml` file with the correct catalog and schema names. The default catalog is `hive_metastore` which will be used if `_database` is left blank. The schema names will be what you defined when creating the connections in Fivetran.

```
vars:
 marketo_source:
   marketo_database: # leave blank to use the default hive_metastore catalog
   marketo_schema: marketing_marketo
 salesforce_source:
   salesforce_database: # leave blank to use the default hive_metastore catalog
   salesforce_schema: marketing_salesforce
```

Target schema for Fivetran staging models

To avoid all the staging tables that are created by the Fivetran source models being created in the default target schema it can be useful to define a separate staging schema.

In the `dbt_project.yml` file add the staging schema name and this will then be suffixed to the default schema name.

```
models:
 marketo_source:
   +schema: your_staging_name # leave blank to use the default target_schema
 salesforce_source:
   +schema: your_staging_name # leave blank to use the default target_schema
```

Based on the above, if your target schema defined in `profiles.yml` is **`mkt_analytics`**, the schema used for `marketo_source` and `salesforce_source` tables will be **`mkt_analytics_your_staging_name`**.

Disable missing tables

At this stage you can run the Fivetran model packages to test that they work correctly.

```
dbt run -select marketo_source
```

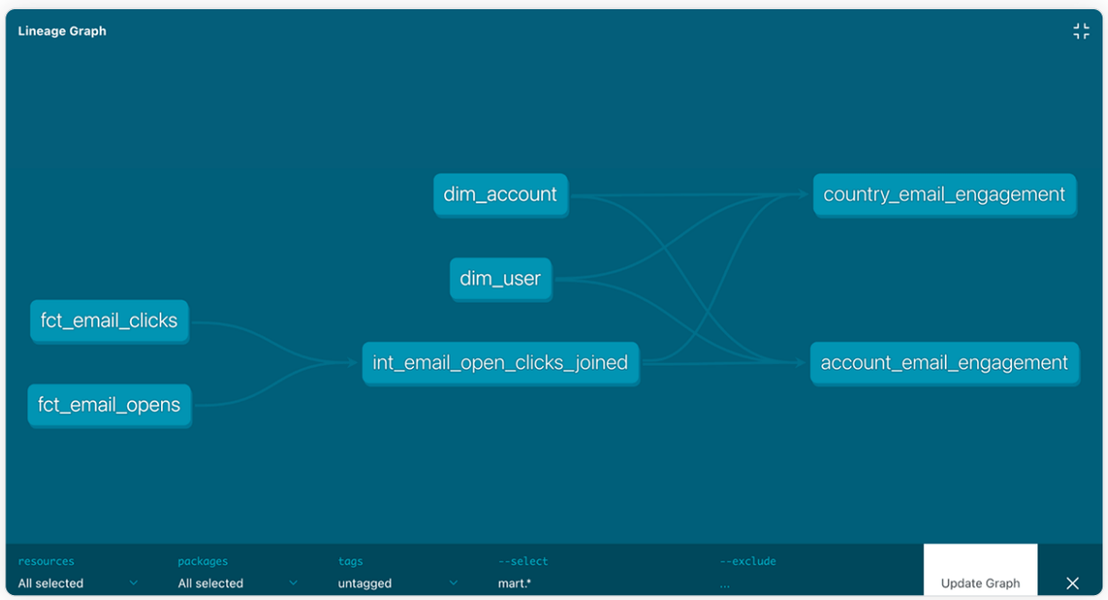
```
dbt run -select marketo_source
```

If any of the models fail due to missing tables, because you chose not to sync those tables in Fivetran, then in your source schema you can disable those models by updating the **`dbt_project.yml`** file.

For example if the email bounced and email template tables are missing from the Marketo source schema you can disable the models for those tables by adding the following under the models config:

```
models:
 marketo_source:
   +schema: your_staging_name
   tmp:
     stg_marketo__activity_email_bounced_tmp:
       +enabled: false
     stg_marketo__email_template_history_tmp:
       +enabled: false
   stg_marketo__activity_email_bounced:
     +enabled: false
   stg_marketo__email_template_history:
     +enabled: false
```

Developing the marketing analytics models



dbt lineage graph showing the star schema and aggregate tables data model

Now that the Fivetran packages have taken care of creating and testing the staging models you can begin to develop the data models for your marketing analytics use cases which will be a star schema data model along with materialized aggregate tables.

For example, for the first marketing analytics dashboard, you may want to see how engaged certain companies and sales regions are by the number of email campaigns they have opened and clicked.

To do so, you can join Salesforce and Marketo tables using the Salesforce user email, Salesforce `account_id` and Marketo `lead_id`.

The models will be structured under the mart folder in the following way.

```
marketing_analytics_demo
|-- dbt_project.yml
|-- packages.yml
|-- models
      |-- mart
            |-- core
            |-- intermediate
            |-- marketing_analytics
```

You can view the code for all the models on Github in the /models/mart directory and below describes what is in each folder along with an example.

Core models

The core models are the facts and dimensions tables that will be used by all downstream models to build upon.

The dbt SQL code for the `dim_user` model:

```
with salesforce_users as (
   select
       account_id,
       email
   from {{ ref('stg_salesforce__user') }}
   where email is not null and account_id is not null
),
marketo_users as (
   select
       lead_id,
       email
   from {{ ref('stg_marketo__lead') }}
),
joined as (
   select
     lead_id,
     account_id
   from salesforce_users
     left join marketo_users
     on salesforce_users.email = marketo_users.email
)

select * from joined
```

You can also add documentation and tests for the models using a yaml file in the folder.

There are 2 simple tests in the `core.yml` file that have been added

```
version: 2

models:
 - name: dim_account
   description: “The Account Dimension Table”
   columns:
     - name: account_id
       description: “Primary key”
       tests:
         - not_null
 - name: dim_user
   description: “The User Dimension Table”
   columns:
     - name: lead_id
       description: “Primary key”
       tests:
         - not_null
```

Intermediate models

Some of the final downstream models may rely on the same calculated metrics and so to avoid repeating SQL you can create intermediate models that can be reused.

The dbt SQL code for `int_email_open_clicks_joined` model:

```
with opens as (
        select *
        from {{ ref('fct_email_opens') }}
), clicks as (
        select *
        from {{ ref('fct_email_clicks') }}
), opens_clicks_joined as (

    select
      o.lead_id as lead_id,
      o.campaign_id as campaign_id,
      o.email_send_id as email_send_id,
      o.activity_timestamp as open_ts,
      c.activity_timestamp as click_ts
    from opens as o
      left join clicks as c
      on o.email_send_id = c.email_send_id
      and o.lead_id = c.lead_id

)

select * from opens_clicks_joined
```

Marketing Analytics models

These are the final marketing analytics models that will be used to power the dashboards and reports used by marketing and sales teams.

The dbt SQL code for `country_email_engagement` model:

```
with accounts as (
        select
        account_id,
        billing_country
        from {{ ref('dim_account') }}
), users as (
        select
        lead_id,
        account_id
        from {{ ref('dim_user') }}
), opens_clicks_joined as (

    select * from {{ ref('int_email_open_clicks_joined') }}

), joined as (

        select *
        from users as u
        left join accounts as a
        on u.account_id = a.account_id
        left join opens_clicks_joined as oc
        on u.lead_id = oc.lead_id

)

select
        billing_country as country,
        count(open_ts) as opens,
        count(click_ts) as clicks,
        count(click_ts) / count(open_ts) as click_ratio
from joined
group by country
```

Run and test dbt models

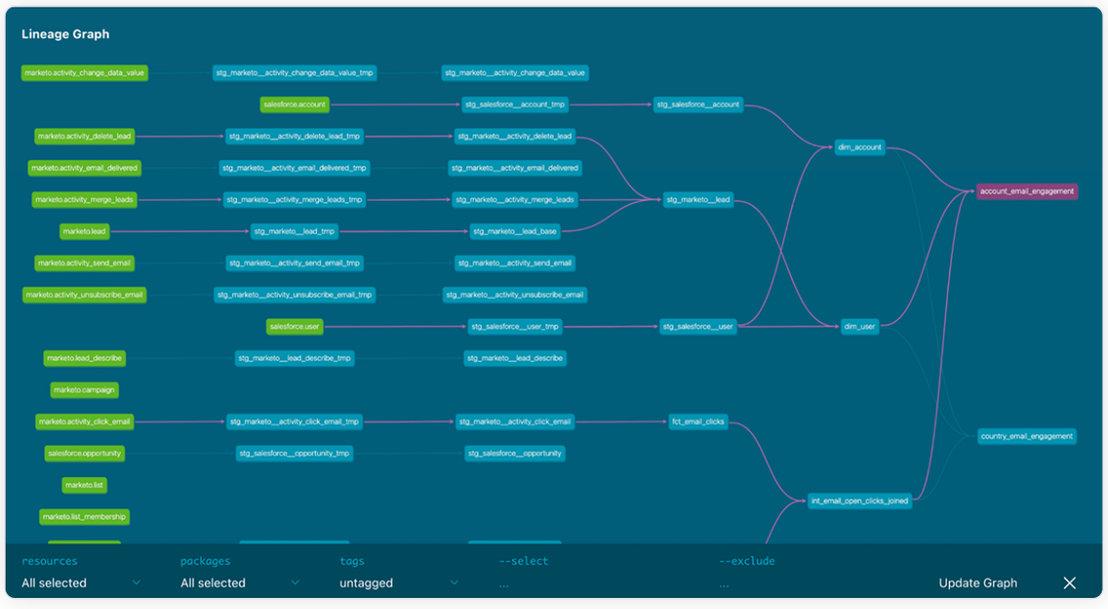
Now that your model is ready you can run all the models using

```
dbt run
```

And then run the tests using

```
dbt test
```

View the dbt docs and lineage graph



dbt lineage graph for the marketing analytics model

Once your models have run successfully you can generate the docs and lineage graph using

```
$ dbt docs generate
```

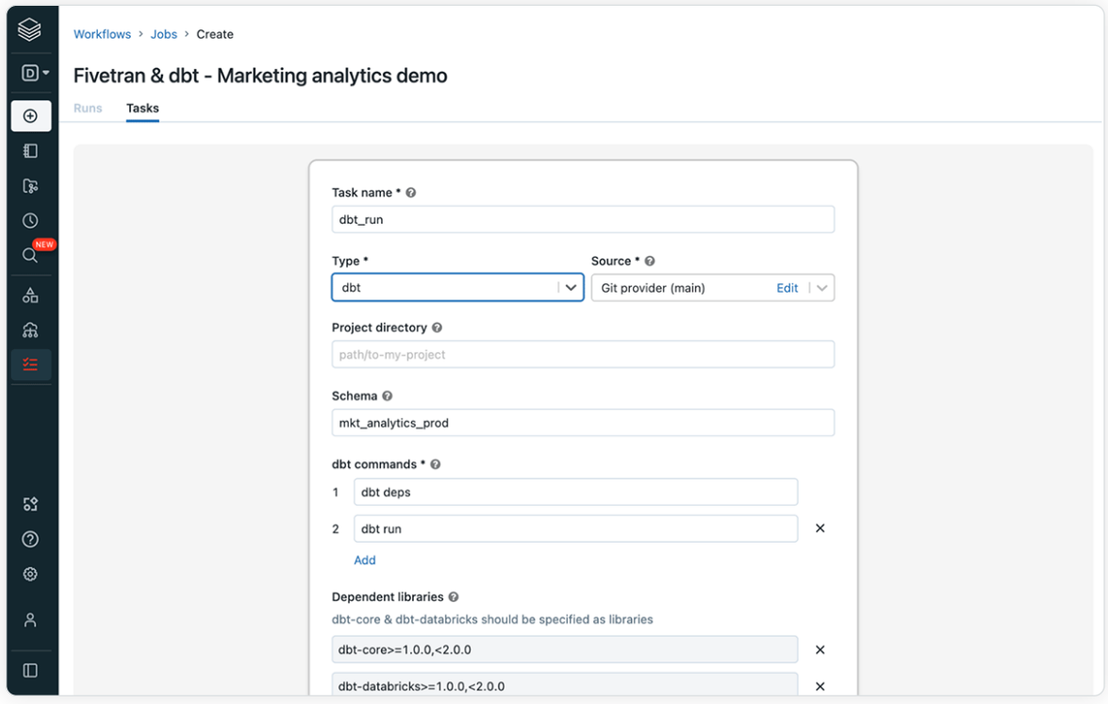
To then view them locally run

```
$ dbt docs serve
```

Deploying dbt models to production

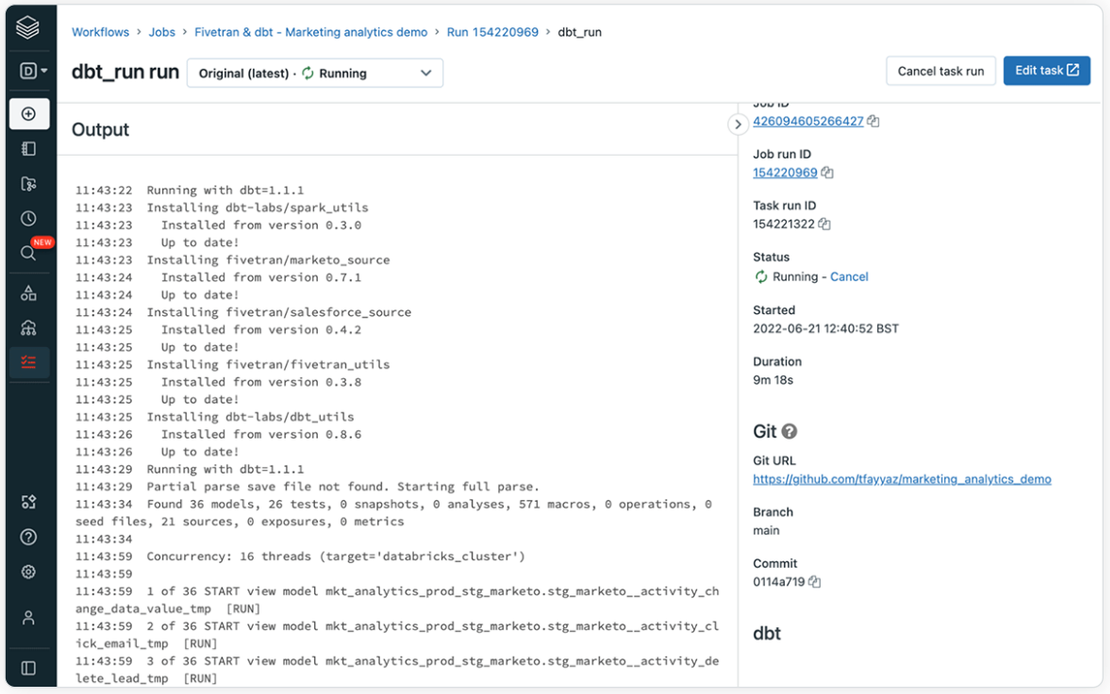
Once you have developed and tested your dbt model locally you have multiple options for deploying into production one of which is the new dbt task type in Databricks Workflows (private preview).

Your dbt project should be managed and version controlled in a Git repository. You can create a dbt task in your Databricks Workflows job pointing to the Git repository.



Using a dbt task type in Databricks Workflows to orchestrate dbt

As you are using packages in your dbt project the first command should be dbt deps followed by dbt run for the first task and then dbt test for the next task.



Viewing the dbt logs for each dbt run

For each run you can see the logs for each dbt command helping you debug and fix any issues.

Powering your marketing analytics with Fivetran and dbt

As shown here, using Fivetran and dbt alongside the Databricks Data Intelligence Platform allows you to easily build a powerful marketing analytics solution that is easy to set up, manage and flexible enough to suit any of your data modeling requirements.

To get started with building your own solution, visit the documentation for integrating Fivetran and dbt with Databricks and re-use the marketing_analytics_demo project example to quickly get started.

The dbt task type in Databricks Workflows is in private preview. To try the dbt task type, please reach out to your Databricks account executive.

SECTION 4.2

Claims Automation on Databricks

Smart claims increases efficiency by automating all aspects of claims processing from ingestion, analysis, and decision-making.

by Anindita Mahapatra and Marzi Rasooli

According to the latest reports from global consultancy EY, the future of insurance will become increasingly **data-driven**, and **analytics enabled**. The recent focus on the cloud has improved access to advanced technological infrastructure, but most organizations still need help implementing and leveraging these capabilities. It's time to shift the focus on operationalizing services to realize value.

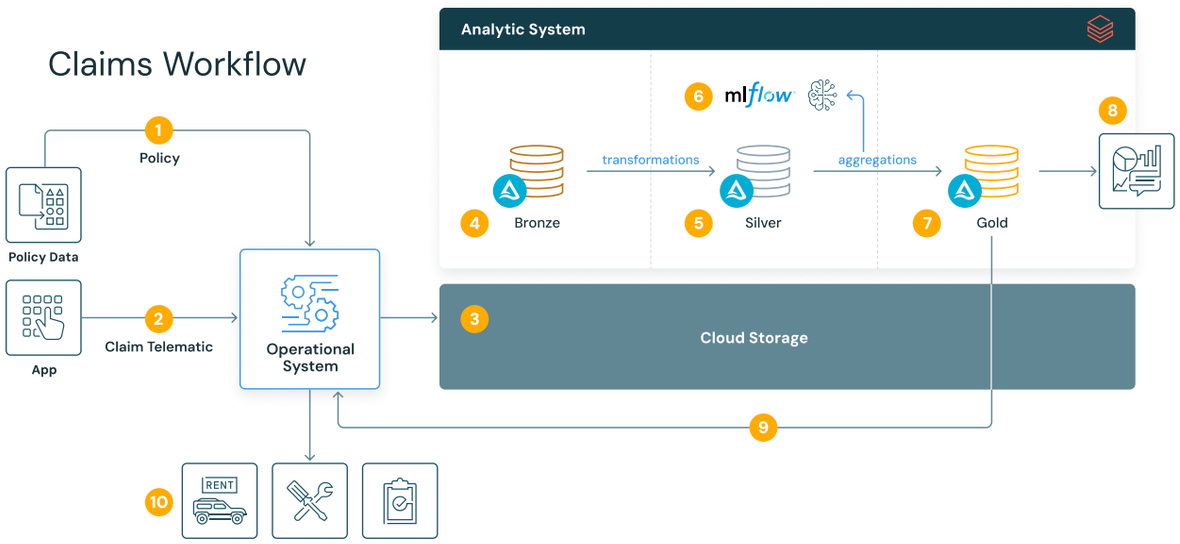
In today's economic circumstances, insurance companies face an ever-increasing number of challenges. Insurers are being forced to leverage data to their advantage and **innovate** at an accelerated pace. For personal P&C insurers, this means an increased focus on **personalization** and customer retention. Brand loyalty is at an all-time low, with customers continuously shopping for more competitive rates and better overall experiences, which increases the risk of churn. An increase in fraudulent claims further erodes profit margins. Insurers need to find additional ways to reduce costs and better manage risks.

Automating and optimizing the claims-handling process is one area that can significantly reduce costs through time saved and lesser reliance on human capital. Furthermore, effectively leveraging insights from data and advanced analytics can substantially reduce the overall exposure to risk.

The motivation behind the "Smart Claims" solution accelerator is simple — improve the claims handling process to enable faster settlement, lower processing costs, and deliver quicker insights about potentially fraudulent claims, with the lakehouse. Implementing the lakehouse paradigm simplifies the current architectural landscape and sets the scene for future expansion across the organization. The accompanying assets can be found here.

Reference Architecture and Workflow

A typical claims workflow involves some level of orchestration between operational systems such as Guidewire and analytical systems like Databricks. The diagram below shows an example of such a workflow for an automotive insurer.



Smart Claims Reference Architecture and Workflow

Automating and optimizing the claims handling process requires a deep understanding of customer interaction with operational systems and the various sources of information available for analysis.

In this example, we assume that customers primarily interact through a mobile application, and from there, they can submit claims and monitor the status of existing cases. This touch point offers vital information about customer behavior. Another important source of information is IoT devices installed in customer vehicles. Telematics data can be streamed to the operational and analytical systems, providing valuable insights into customer-driving behavior and patterns. Other external data sources may include weather and road conditions data that supplement the traditional data categories such as vehicle characteristics (make, model, year), driver characteristics and exposure/coverage (limits, deductibles)

Access to additional data sources can become increasingly important, especially in the absence of data from traditional sources such as credit bureaus. Credit scores from bureaus usually form the basis for risk modeling, assessing the exposure for drivers, which ultimately impacts their premiums. On the other hand, data from mobile applications and IoT devices provide a more personalized view of customer behavior, which could be used to create a more accurate indicator of the risk associated with a given party. This alternative, **behavioral-based** approach to risk modeling and pricing is essential for delivering a hyper-personalized customer experience.

The lakehouse architecture powered by the Databricks Data Intelligence Platform is the only platform that combines all the required features and services to support a future-proof claims-handling process. From streaming to machine learning and reporting, Databricks offers the best platform to build an end-to-end solution for the insurance industry of tomorrow.

The following steps capture the overall flow:

- Policy data is ingested.
- Telematics data is continuously ingested from IoT sensors. A claimant submits claims data via a mobile app.
- All the operational data is ingested into cloud storage.
- This is incrementally loaded as 'Raw data' into Delta Bronze tables
- The data is wrangled and refined via various data transformations
- Data is scored using the trained model
- The predictions are loaded to a Gold table
- The Claims Dashboard is refreshed for visualization
- The resulting insights are fed back to the operational system. This provides the feedback loop of pulling data from Guidewire and passing 'Next Best Action' back to Guidewire in real time to know which claims should be prioritized.
- The Claims Decisioning workflows use these generated insights to route the case appropriately. (Eg. approve repair expenses, rental reimbursement, or alert authorities)

How the lakehouse paradigm aids Smart Claims

The lakehouse architecture enables all data personas (data engineers, data scientists, analytic engineers, and BI analysts) to work collaboratively on a single platform. Supporting all big-data workloads and paradigms (e.g., batch processing, streaming, DataOps, ML, MLOps, and BI) in a single, collaborative platform greatly simplifies the overall architecture, improves stability, and reduces cost significantly.

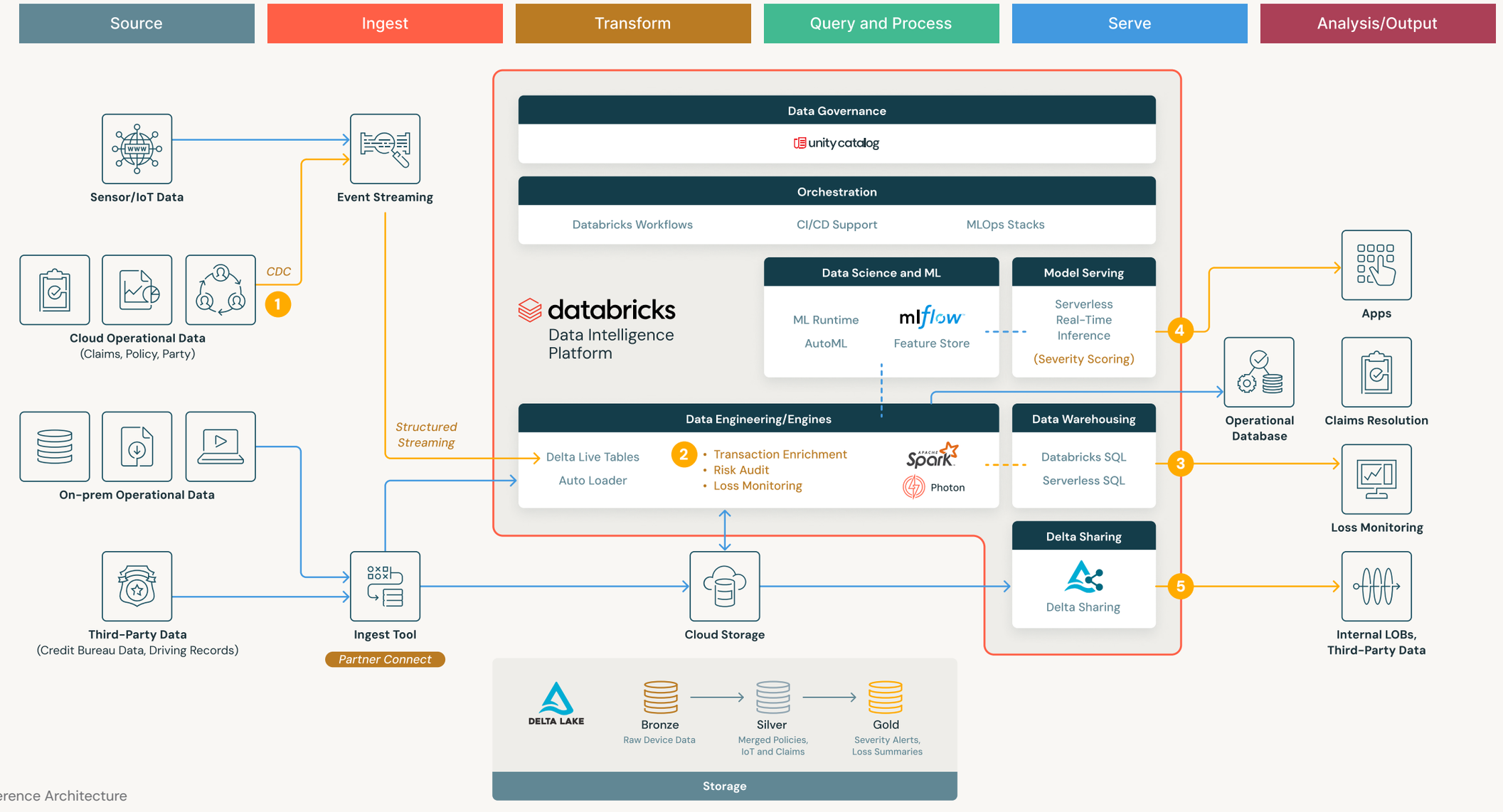
Databricks Delta Live Tables (DLT) pipelines offer a simple, declarative framework to develop and implement workloads quickly. It also provides native support for data quality management with granular constraints to guarantee the integrity of outputs.

ML and AI workloads can easily be created and managed with MLflow for reproducibility and auditability. MLFlow simplifies the entire model lifecycle, from experimenting through model deployment, serving, and archiving. ML can be run on all types of data including unstructured data beyond text (images, audio, video, etc). In this solution, we will use computer vision capabilities to assess damage to the vehicle.

Finally, Databricks SQL provides a fast and efficient engine to query curated and aggregated data. These insights can then be packaged and served through interactive Dashboards within minutes.

Unity Catalog provides a multi-cloud, centralized governance solution for all data and AI assets including files, tables, machine learning models and dashboards with built-in search, discovery, automated workload lineage.

The diagram below shows a reference architecture for the lakehouse in the context of typical insurance use cases:



Insurance Reference Architecture

Data Ingestion using DLT and Multitask Workflows

Automating the claims-handling process starts with optimizing the ingestion and data engineering workflow. The figure below offers a summary of the typical data sources encountered including structured, semi-structured and unstructured. Some sources are slower-moving, while others update more rapidly. Additionally, some sources might be additive, requiring appending, while others offer incremental updates and must be treated as slow-changing dimensions.

Volume	Velocity	Variety
High • Telematic data	**Near Real Time** • Telematic data	**Structured** • Policy, policy-holder, telematic
Medium • Claim data	**Streaming** • Claim data, accident data	**Semi-Structured** • Claim data
Low • Policy, policy-holder data • Accident data	**Batch** • Policy, policy-holder data	**Unstructured** • Accident data • Image, video and text

Sample Datasets used in Claims Processing

DLT can simplify and operationalize the data processing pipeline. The framework offers support for Auto Loader to facilitate ingestion from streaming sources, efficient auto-scaling to handle sudden changes in data volumes, and resiliency via a restart of task failure.

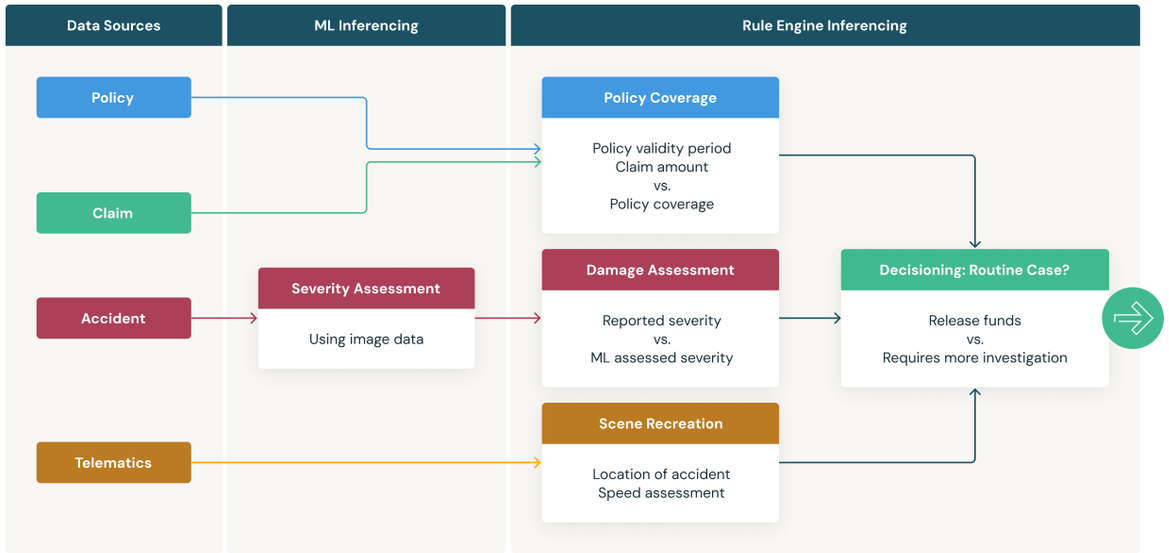
Databricks Workflows can accommodate multiple tasks and workloads (e.g., notebooks, DLT, ML, SQL). Workflows support repair-and-run and compute sharing across tasks - enabling robust, scalable, cost-effective workloads. Additionally, Workflow can easily be automated through schedules or programmatic invoking via REST APIs.

Insight Generation using ML and Dynamic Rules Engine

Leveraging ML is essential to uncovering previously unknown patterns, highlighting new insights, and flagging suspicious activity. However, combining ML and traditional rules-based approaches can be even more powerful.

Within the claims-handling process, ML can be used for several use cases. One example would be using computer vision and ML for assessing and scoring images submitted with vehicle insurance claims. Models can be trained to focus on the validity and severity of damages. Here, MLFlow can be crucial in simplifying the model training and serving process with its end-to-end MLOps capabilities. MLFlow offers a serverless model serving through REST APIs. Trained models can be operationalized and put into production with the click of a button.

On the other hand, rules engines offer flexible ways of defining known operational characteristics and statistical checks, which can be automated and applied without requiring human interaction. Flags are raised whenever data does not comply with preset expectations and are sent for human review and investigation. Incorporating such an approach with ML-based workflows offers additional oversight and significantly reduces the time claims investigators require to dissect and review flagged cases.



ML and Rule Engine Inferencing

Insight visualization using Dashboards

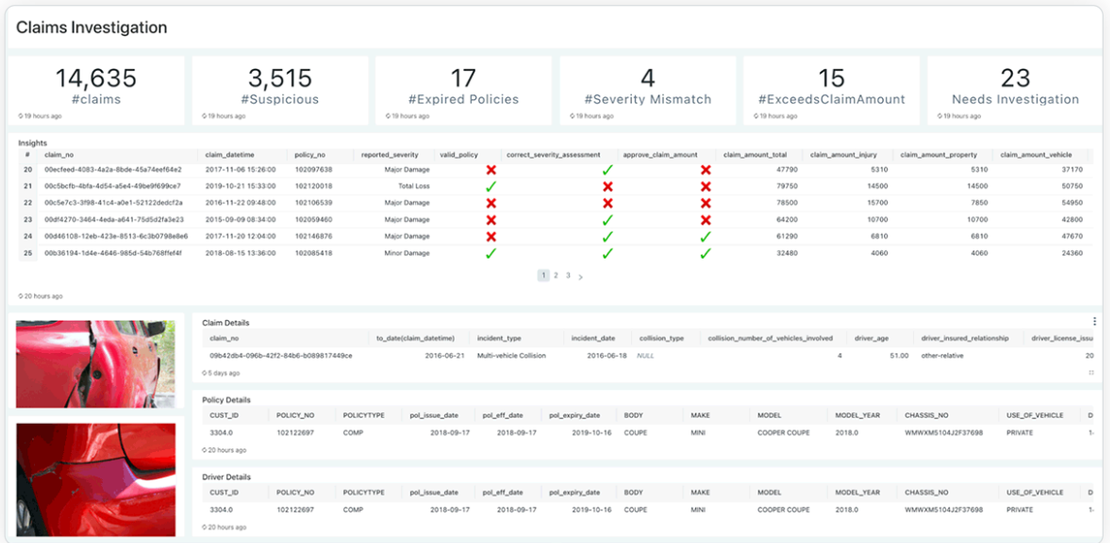
In this example, we created two dashboards to capture critical business insights. The dashboards include the following:

- A **Loss Summary** dashboard for a high-level view of the overall business operations; and
- A **Claims Investigation** dashboard with a granular view of claims details to understand the specifics of a given case.

Analyzing recent trends can further aid in reviewing similar cases such as :

- Loss Ratio is computed by insurance claims paid plus adjustment expenses divided by total earned premiums. E.g. typical average Loss Ratio (all coverages combined, Bodily Injury, and Physical Damage) for personal auto should be around 65%
- Summary visualization captures count of incident type by damage severity
- Trend lines over various features/dimensions
- Geographic distribution of policies

The Claims Investigation dashboard facilitates faster investigation by providing all relevant information around a claim allowing the human investigator to drill down to a specific claim to see details such as images of the damaged vehicle, Claim, Policy and Driver details, Telematic data draws the path taken by the vehicle, Reported data is contrasted with assessed data insights.



Claim Investigation Dashboard

Provides recent claims that are auto-scored in the pipeline using ML inferencing and rule engine

- A green tick is used to denote auto-assessment matches claims description
- A red cross indicates a mismatch that warrants further manual investigation

Summary

Innovation and personalization are essential for insurance firms to differentiate themselves from the competition. Databricks provides a data intelligence platform for insurers to enable and accelerate innovation with an open, secure, extensible architecture that easily integrates with third-party tools and services. This Solution Accelerator demonstrates how the paradigm can be applied to claims handling. Further, the Databricks ecosystem offers a range of capabilities to enable data teams and business stakeholders to collaborate and generate and share insights that support business decisions and drive tangible value to the bottom line.

The technical assets, including pipeline configurations, models, and sample data used in this example, can be accessed here or directly on Git.

SECTION 4.3

Design Patterns for Batch Processing in Financial Services

Laying the foundation for automating workflows

by Eon Retief

Introduction

Financial services institutions (FSIs) around the world are facing unprecedented challenges ranging from market volatility and political uncertainty to changing legislation and regulations. Businesses are forced to accelerate digital transformation programs; automating critical processes to reduce operating costs and improve response times. However, with data typically scattered across multiple systems, accessing the information required to execute on these initiatives tends to be easier said than done.

Architecting an ecosystem of services able to support the plethora of data-driven use cases in this digitally transformed business can, however, seem to be an impossible task. This blog will focus on one crucial aspect of the modern data stack: batch processing. A seemingly outdated paradigm, we'll see why batch processing remains a vital and highly viable component of the data architecture. And we'll see how Databricks can help FSIs navigate some of the crucial challenges faced when building infrastructure to support these scheduled or periodic workflows.

Why batch ingestion matters

Over the last two decades, the global shift towards an instant society has forced organizations to rethink the operating and engagement model. A digital-first strategy is no longer optional but vital for survival. Customer needs and demands are changing and evolving faster than ever. This desire for instant gratification is driving an increased focus on building capabilities that support real-time processing and decisioning. One might ask whether batch processing is still relevant in this new dynamic world.

While real-time systems and streaming services can help FSIs remain agile in addressing the volatile market conditions at the edge, they do not typically meet the requirements of back-office functions. Most business decisions are not reactive but rather, require considered, strategic reasoning. By definition, this approach requires a systematic review of aggregate data collected over a period of time. Batch processing in this context still provides the most efficient and cost-effective method for processing large, aggregate volumes of data. Additionally, batch processing can be done offline, reducing operating costs and providing greater control over the end-to-end process.

The world of finance is changing, but across the board incumbents and startups continue to rely heavily on batch processing to power core business functions. Whether for reporting and risk management or anomaly detection and surveillance, FSIs require batch processing to reduce human error, increase the speed of delivery, and reduce operating costs.

Getting started

Starting with a 30,000-ft view, most FSIs will have a multitude of data sources scattered across on-premises systems, cloud-based services and even third-party applications. Building a batch ingestion framework that caters for all these connections require complex engineering and can quickly become a burden on maintenance teams. And that's even before considering things like change data capture (CDC), scheduling, and schema evolution. In this section, we will demonstrate how the lakehouse architecture for financial services and its ecosystem of partners can be leveraged to address these key challenges and greatly simplify the overall architecture.

The lakehouse architecture is designed to provide a unified platform that supports all analytical and scientific data workloads. Figure 1 shows the reference architecture for a decoupled design that allows easy integration with other platforms that support the modern data ecosystem. The lakehouse makes it easy to construct ingestion and serving layers that operate irrespective of the data's source, volume, velocity, and destination.

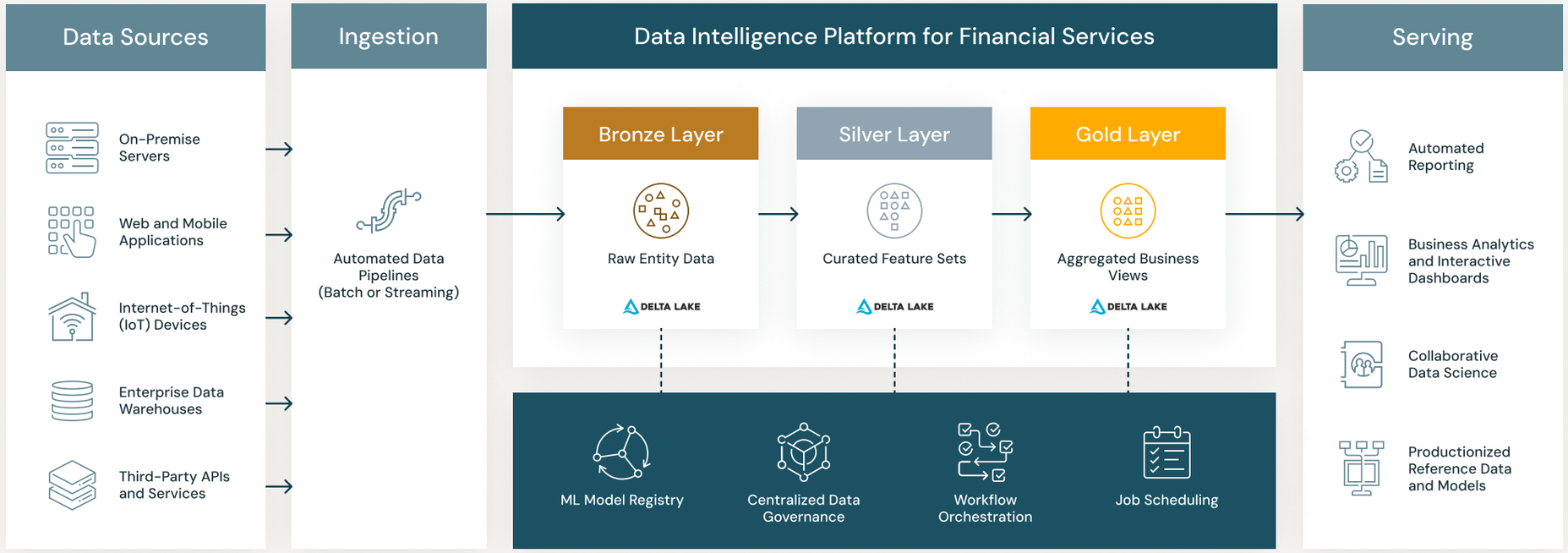


Figure 1 — Reference architecture of the lakehouse for financial services.

To demonstrate the power and efficiency of the LFS, we turn to the world of insurance. We consider the basic reporting requirements for a typical claims workflow. In this scenario, the organization might be interested in the key metrics driven by claims processes. For example:

- Number of active policies
- Number of claims
- Value of claims
- Total exposure
- Loss ratio

Additionally, the business might want a view of potentially suspicious claims and a breakdown by incident type and severity. All these metrics are easily calculable from two key sources of data: 1) the book of policies and 2) claims filed by customers. The policy and claims records are typically stored in a combination of enterprise data warehouses (EDWs) and operational databases. The main challenge becomes connecting to these sources and ingesting data into our lakehouse, where we can leverage the power of Databricks to calculate the desired outputs.

Luckily, the flexible design of the LFS makes it easy to leverage best-in-class products from a range of SaaS technologies and tools to handle specific tasks. One possible solution for our claims analytics use case would be to use Fivetran for the batch ingestion plane. Fivetran provides a simple and secure platform for connecting to numerous data sources and delivering data directly to the Databricks Data Intelligence Platform. Additionally, it offers native support for CDC, schema evolution and workload scheduling. In Figure 2, we show the technical architecture of a practical solution for this use case.

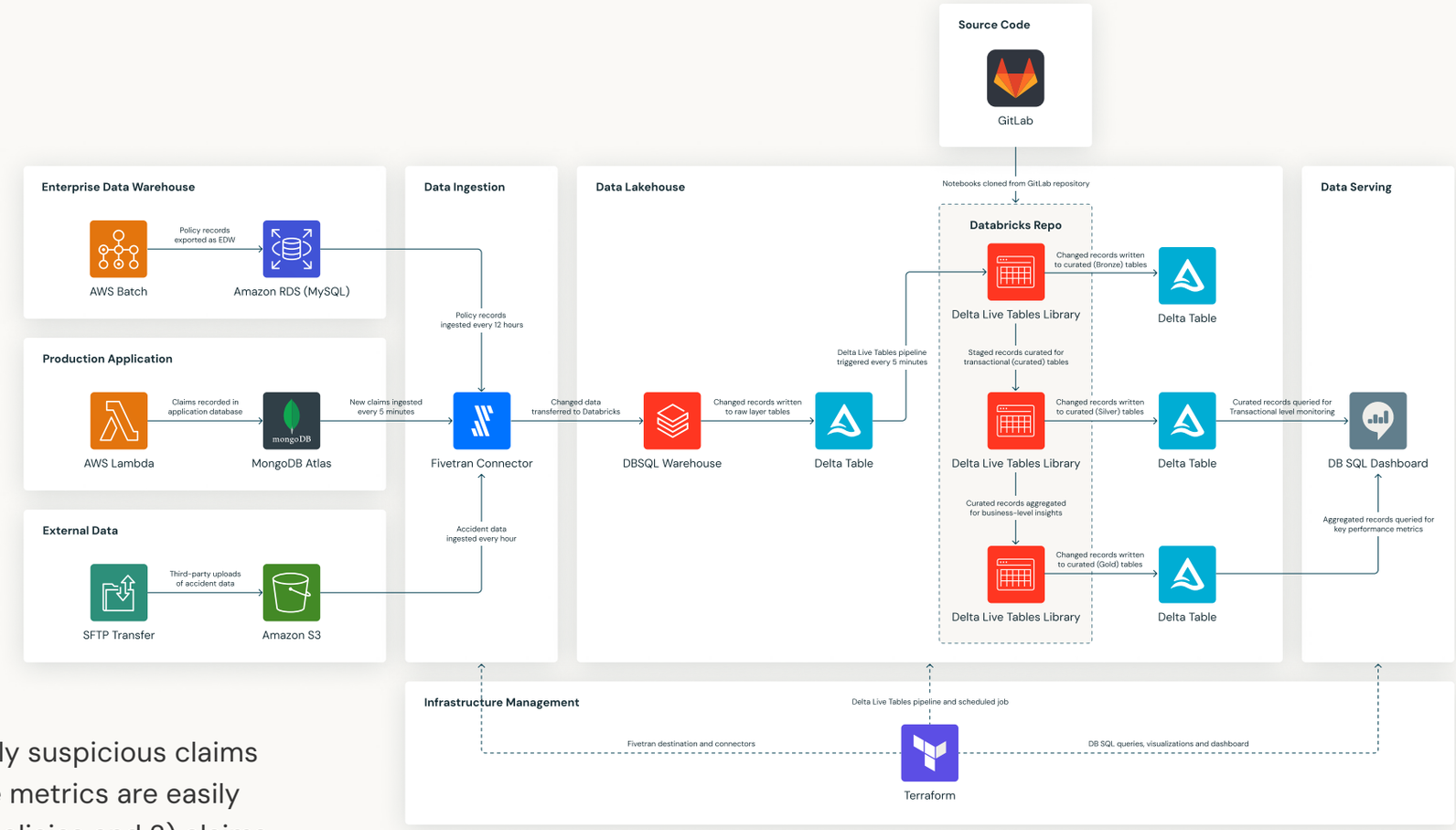


Figure 2 — Technical architecture for a simple insurance claims workflow.

Once the data is ingested and delivered to the LFS, we can use Delta Live Tables (DLT) for the entire engineering workflow. DLT provides a simple, scalable declarative framework for automating complex workflows and enforcing data quality controls. The outputs from our DLT workflow, our curated and aggregated assets, can be interrogated using Databricks SQL (DB SQL). DB SQL brings data warehousing to the LFS to power business-critical analytical workloads. Results from DB SQL queries can be packaged in easy-to-consume dashboards and served to business users.

Step 1: Creating the ingestion layer

Setting up an ingestion layer with Fivetran requires a two-step process. First, configuring a so-called destination where data will be delivered, and second, establishing one or more connections with the source systems. The Partner Connect interface takes care of the first step with a simple, guided interface to connect Fivetran with a Databricks warehouse. Fivetran will use the warehouse to convert raw source data to Delta tables and store the results in the Databricks Data Intelligence Platform. Figures 3 and 4 show steps from the Partner Connect and Fivetran interfaces to configure a new destination.

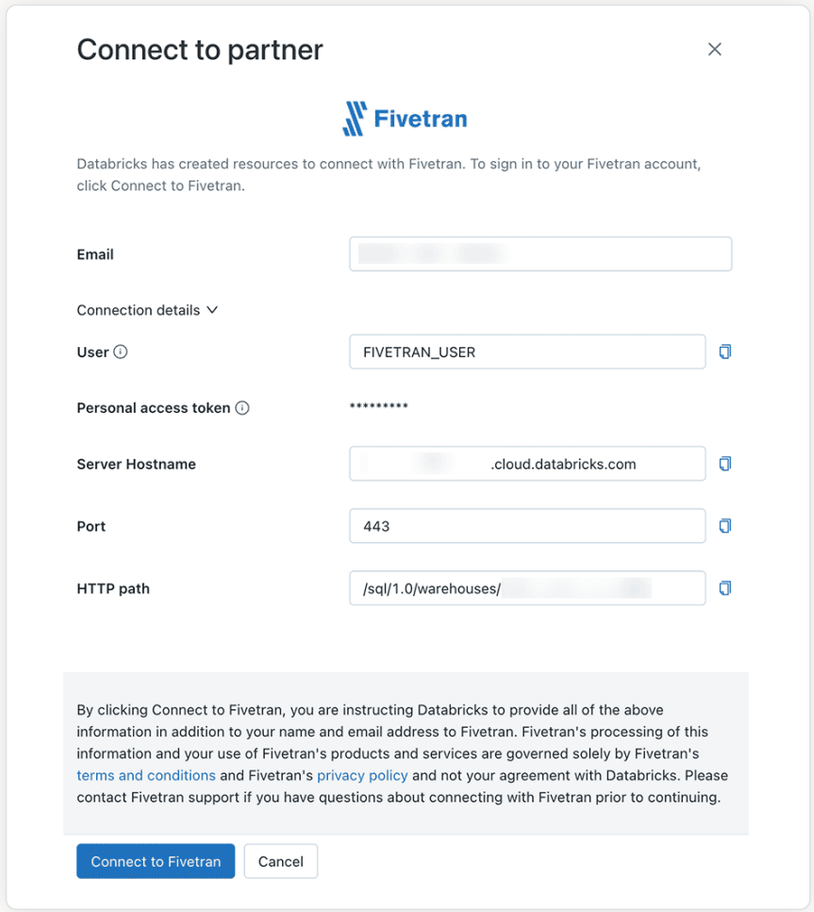


Figure 3 — Databricks Partner Connect interface for creating a new connection.

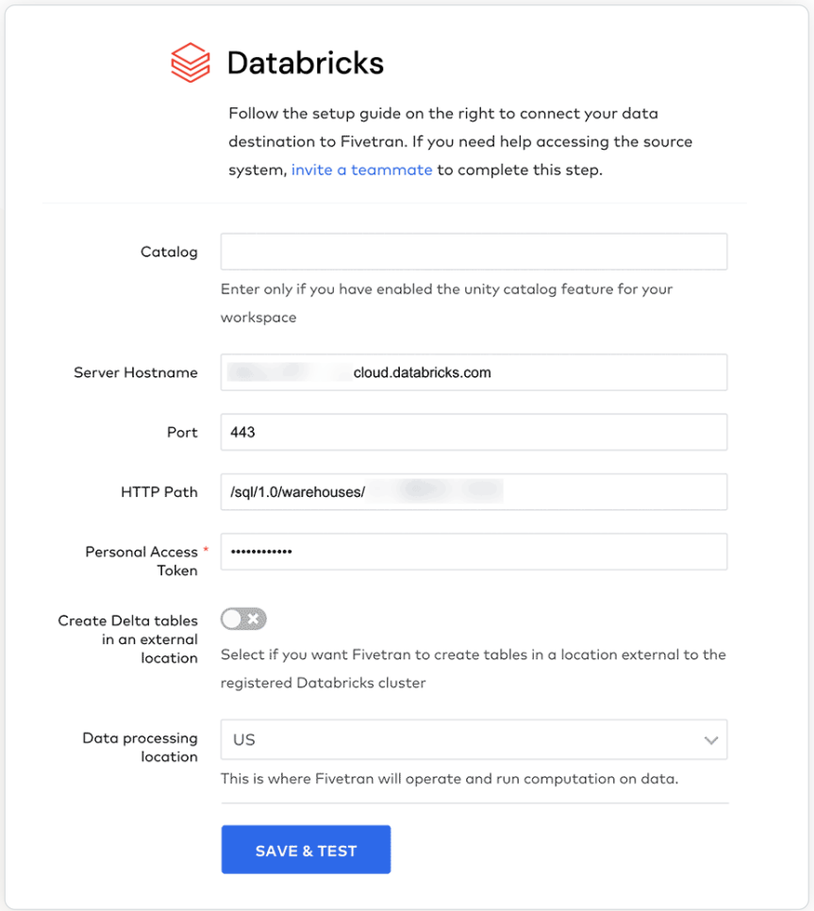


Figure 4 — Fivetran interface for confirming a new destination.

For the next step, we move to the Fivetran interface. From here, we can easily create and configure connections to several different source systems (please refer to the official documentation for a complete list of all supported connections). In our example, we consider three sources of data: 1) policy records stored in an Operational Data Store (ODS) or Enterprise Data Warehosue (EDW), 2) claims records stored in an operational database, and 3) external data delivered to blob storage. As such, we require three different connections to be configured in Fivetran. For each of these, we can follow Fivetran's simple guided process to set up a connection with the source system. Figures 5 and 6 show how to configure new connections to data sources.

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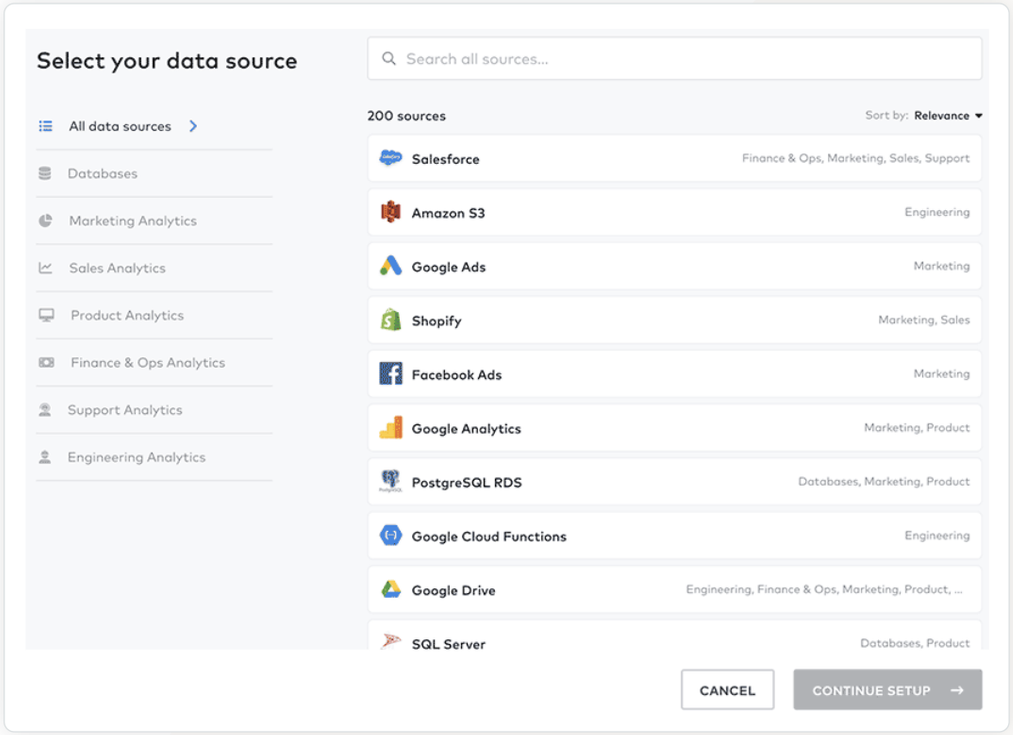


Figure 5 — Fivetran interface for selecting a data source type.

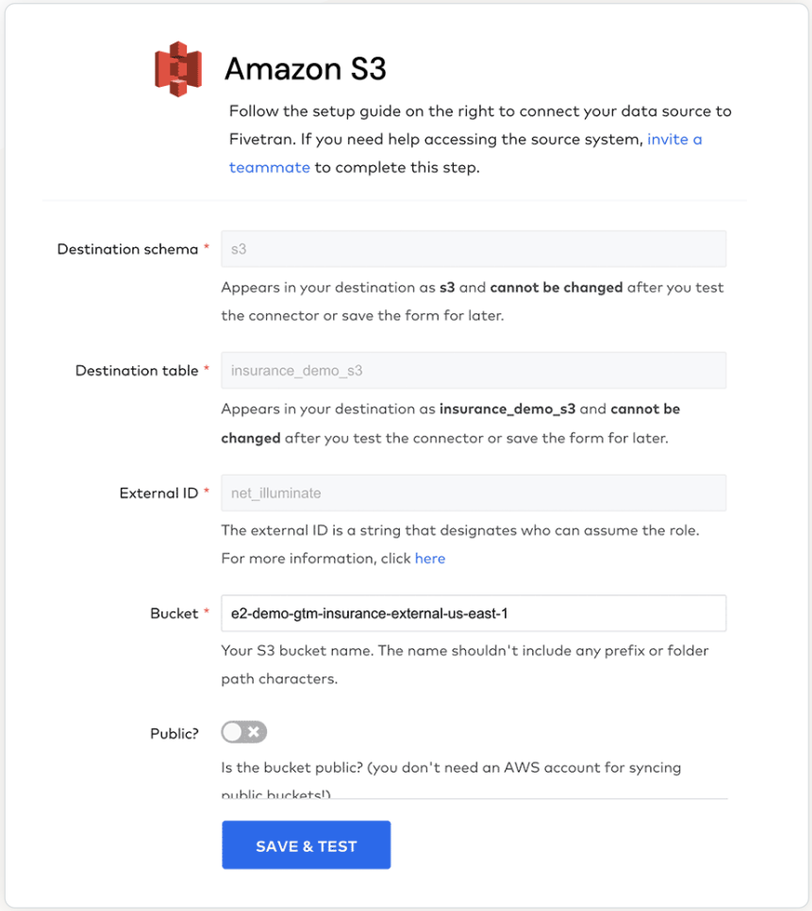


Figure 6 — Fivetran interface for configuring a data source connection.

Connections can further be configured once they have been validated. One important option to set is the frequency with which Fivetran will interrogate the source system for new data. In Figure 7, we can see how easy Fivetran has made it to set the sync frequency with intervals ranging from 5 minutes to 24 hours.

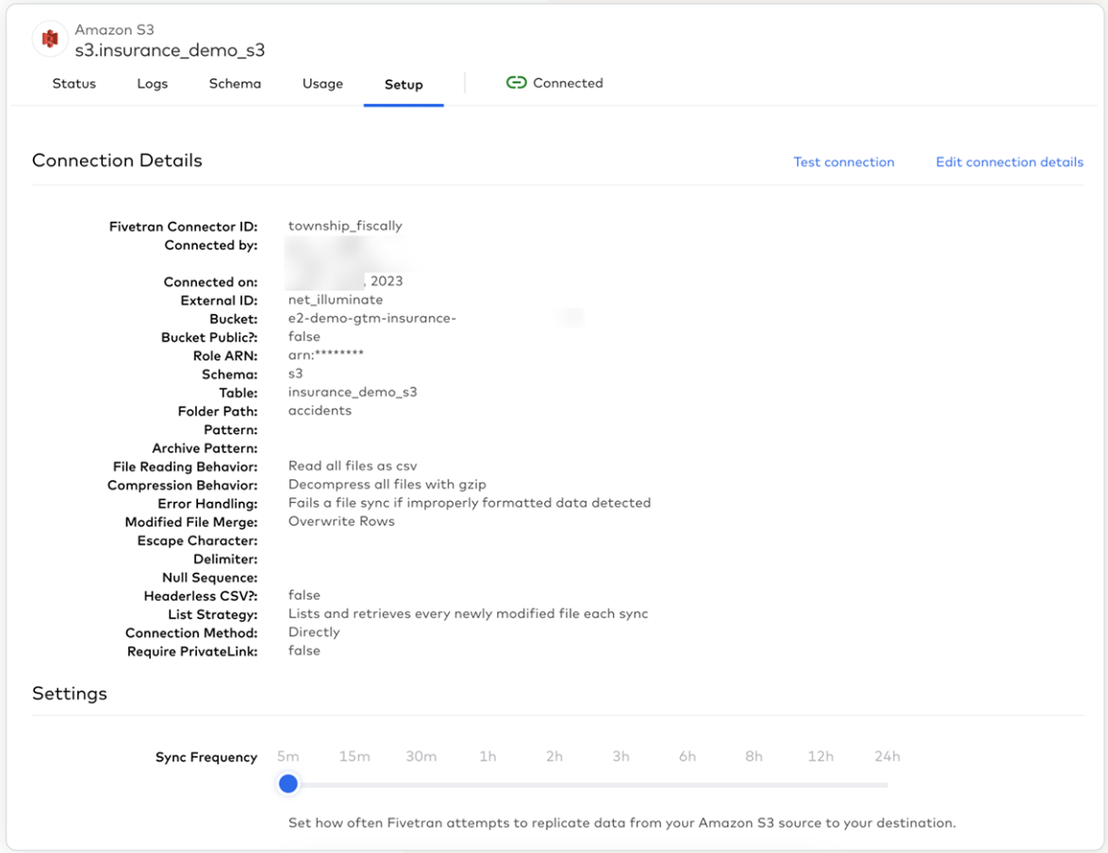


Figure 7 — Overview of configuration for a Fivetran connector.

Fivetran will immediately interrogate and ingest data from source systems once a connection is validated. Data is stored as Delta tables and can be viewed from within Databricks through the Catalog Explorer. By default, Fivetran will store all data under the Hive metastore. A new schema is created for each new connection, and each schema will contain at least two tables: one containing the data and another with logs from each attempted ingestion cycle (see Figure 8).

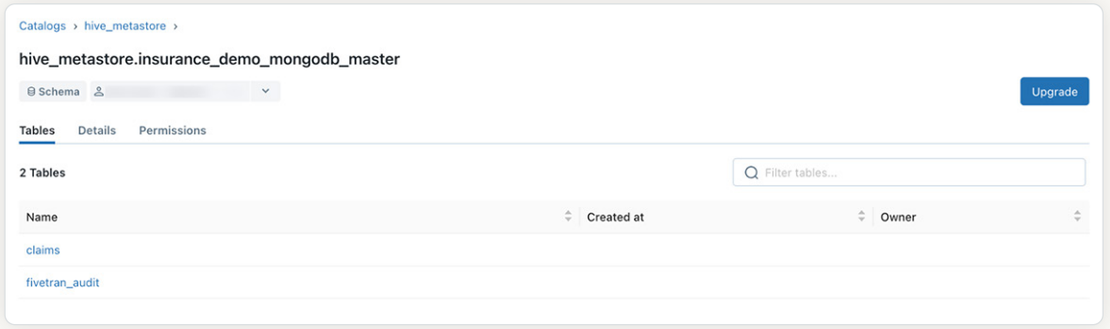


Figure 8 — Summary of tables created by Fivetran in the Databricks Warehouse for an example connection.

Having the data stored in Delta tables is a significant advantage. Delta Lake natively supports granular data versioning, meaning we can time travel through each ingestion cycle (see Figure 9). We can use DB SQL to interrogate specific versions of the data to analyze how the source records evolved.

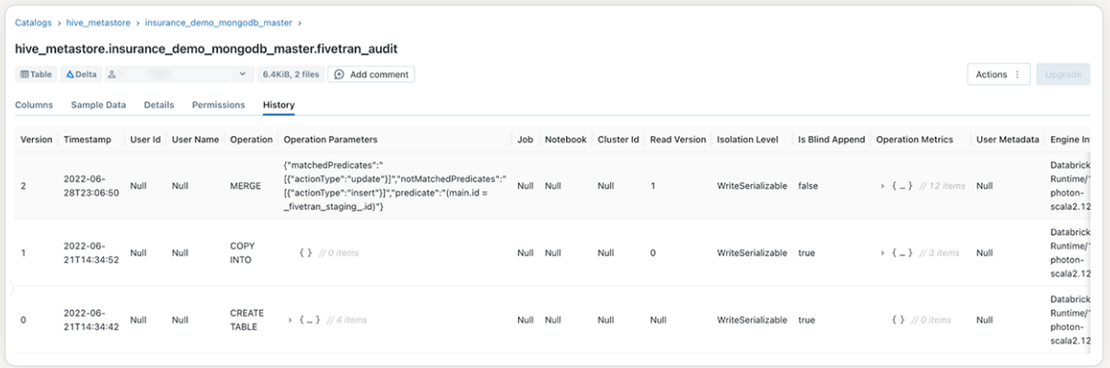


Figure 9 — View of the history showing changes made to the Fivetran audit table.

databricks

It is important to note that if the source data contains semi-structured or unstructured values, those attributes will be flattened during the conversion process. This means that the results will be stored in grouped text-type columns, and these entities will have to be dissected and unpacked with DLT in the curation process to create separate attributes.

Step 2: Automating the workflow

With the data in the lakehouse, we can use Delta Live Tables (DLT) to build a simple, automated data engineering workflow. DLT provides a declarative framework for specifying detailed feature engineering steps. Currently, DLT supports APIs for both Python and SQL. In this example, we will use Python APIs to build our workflow.

The most fundamental construct in DLT is the definition of a table. DLT interrogates all table definitions to create a comprehensive workflow for how data should be processed. For instance, in Python, tables are created using function definitions and the `dlt.table` decorator (see example of Python code below). The decorator is used to specify the name of the resulting table, a descriptive comment explaining the purpose of the table, and a collection of table properties.

```
@dlt.table(
   name             = “curated_claims”,
   comment          = “Curated claim records”,
   table_properties = {
       “layer”: “silver”,
       “pipelines.autoOptimize.managed”: “true”,
       “delta.autoOptimize.optimizeWrite”: “true”,
       “delta.autoOptimize.autoCompact”: “true”
   }
)
def curate_claims():
   # Read the staged claim records into memory
   staged_claims = dlt.read(“staged_claims”)
   # Unpack all nested attributes to create a flattened table structure
   curated_claims = unpack_nested(df = staged_claims, schema = schema_claims)

   ...
```

Instructions for feature engineering are defined inside the function body using standard PySpark APIs and native Python commands. The following example shows how PySpark joins claims records with data from the policies table to create a single, curated view of claims.

```
    ...

    # Read the staged claim records into memory
    curated_policies = dlt.read("curated_policies")
    # Evaluate the validity of the claim
    curated_claims = curated_claims \
        .alias("a") \
        .join(
            curated_policies.alias("b"),
            on   = F.col("a.policy_number") == F.col("b.policy_number"),
            how = "left"
        ) \
        .select([F.col(f"a.{c}") for c in curated_claims.columns] + [F.col(f"b.
{c}").alias(f"policy_{c}") for c in ("effective_date", "expiry_date")]) \
        .withColumn(
            # Calculate the number of months between coverage starting and the
claim being filed
            "months_since_covered", F.round(F.months_between(F.col("claim_date"),
F.col("policy_effective_date")))
        ) \
        .withColumn(
            # Check if the claim was filed before the policy came into effect
            "claim_before_covered", F.when(F.col("claim_date") < F.col("policy_
effective_date"), F.lit(1)).otherwise(F.lit(0))
        ) \
        .withColumn(
            # Calculate the number of days between the incident occurring and the
claim being filed
            "days_between_incident_and_claim", F.datediff(F.col("claim_date"),
F.col("incident_date"))
        )

    # Return the curated dataset
    return curated_claims
```

One significant advantage of DLT is the ability to specify and enforce data quality standards. We can set expectations for each DLT table with detailed data quality constraints that should be applied to the contents of the table. Currently, DLT supports expectations for three different scenarios:

Decorator	Description
`expect`	Retain records that violate expectations
`expect_or_drop`	Drop records that violate expectations
`expect_or_fail`	Halt the execution if any record(s) violate constraints

Expectations can be defined with one or more data quality constraints. Each constraint requires a description and a Python or SQL expression to evaluate. Multiple constraints can be defined using the `expect_all`, `expect_all_or_drop`, and `expect_all_or_fail` decorators. Each decorator expects a Python dictionary where the keys are the constraint descriptions, and the values are the respective expressions. The example below shows multiple data quality constraints for the retain and drop scenarios described above.

```
@dlt.expect_all({
    "valid_driver_license": "driver_license_issue_date > (current_date() -
cast(cast(driver_age AS INT) AS INTERVAL YEAR))",
    "valid_claim_amount": "total_claim_amount > 0",
    "valid_coverage": "months_since_covered > 0",
    "valid_incident_before_claim": "days_between_incident_and_claim > 0"
})
@dlt.expect_all_or_drop({
    "valid_claim_number": "claim_number IS NOT NULL",
    "valid_policy_number": "policy_number IS NOT NULL",
    "valid_claim_date": "claim_date < current_date",
    "valid_incident_date": "incident_date < current_date",
    "valid_incident_hour": "incident_hour between 0 and 24",
    "valid_driver_age": "driver_age > 16",
    "valid_effective_date": "policy_effective_date < current_date()",
    "valid_expiry_date": "policy_expiry_date <= current_date()"
})
def curate_claims():
    ...
```

We can use more than one Databricks Notebook to declare our DLT tables. Assuming we follow the medallion architecture, we can, for example, use different notebooks to define tables comprising the Bronze, Silver and Gold layers. The DLT framework can digest instructions defined across multiple notebooks to create a single workflow; all inter-table dependencies and relationships are processed and considered automatically. Figure 10 shows the complete workflow for our claims example. Starting with three source tables, DLT builds a comprehensive pipeline that delivers thirteen tables for business consumption.

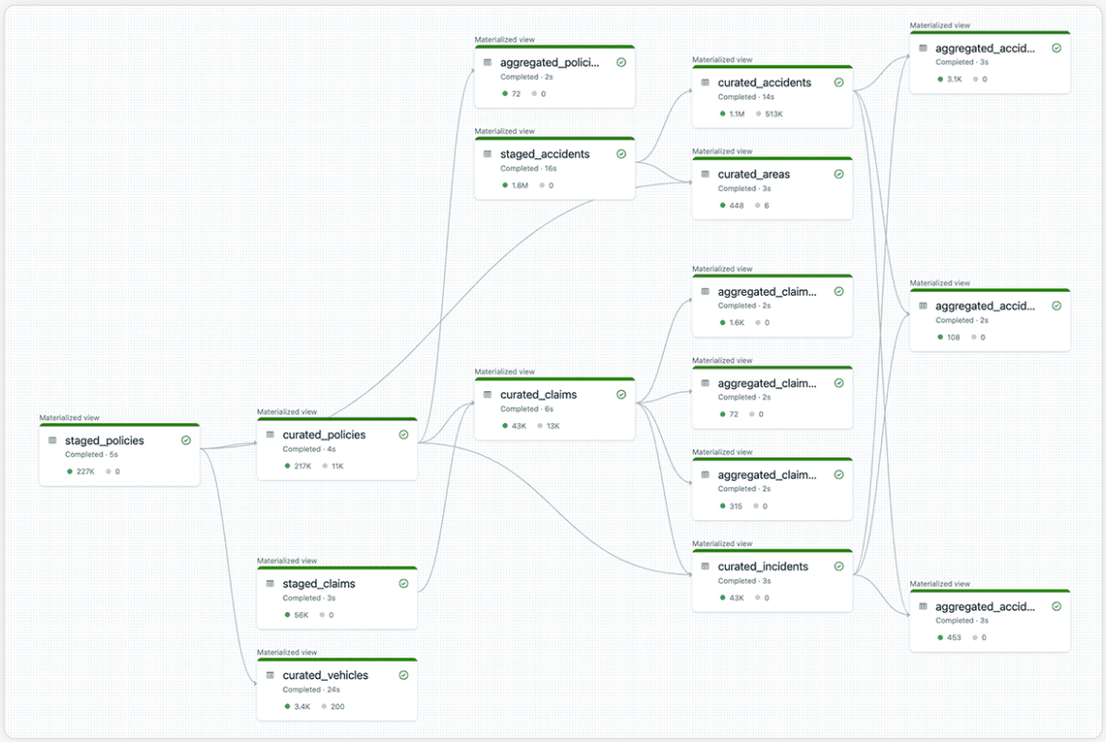


Figure 10 — Overview of a complete Delta Live Tables (DLT) workflow.

Results for each table can be inspected by selecting the desired entity. Figure 11 provides an example of the results of the curated claims table. DLT provides a high-level overview of the results from the data quality controls:

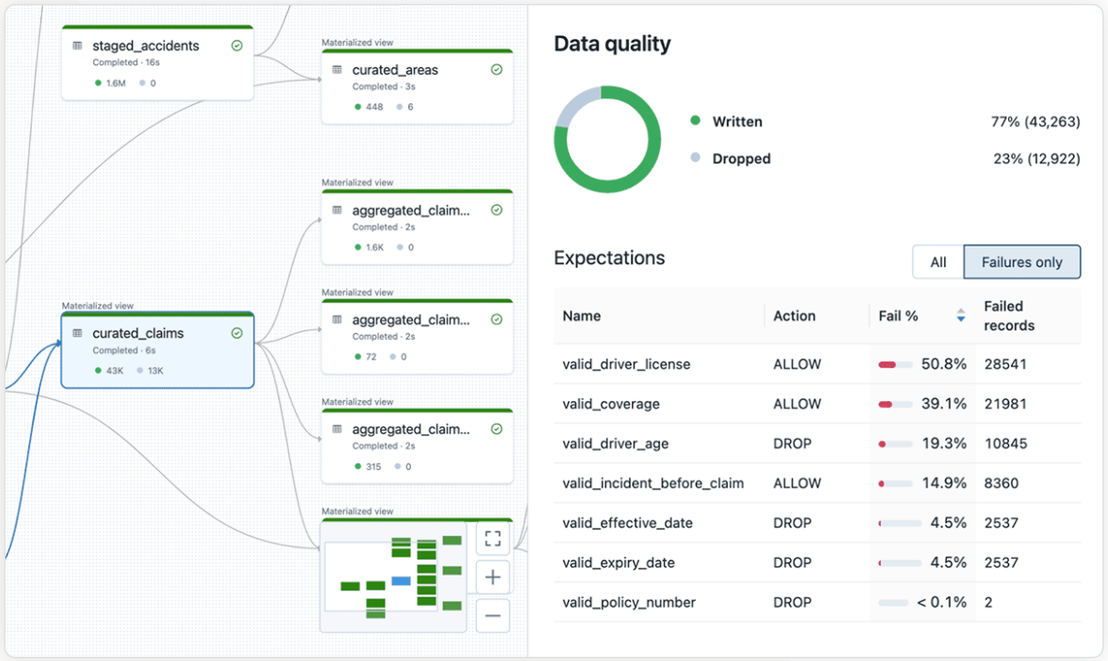


Figure 11 — Example of detailed view for a Delta Live Tables (DLT) table entity with the associated data quality report.

Results from the data quality expectations can be analyzed further by querying the event log. The event log contains detailed metrics about all expectations defined for the workflow pipeline. The query below provides an example for viewing key metrics from the last pipeline update, including the number of records that passed or failed expectations:

```
SELECT
  row_expectations.dataset AS dataset,
  row_expectations.name AS expectation,
  SUM(row_expectations.passed_records) AS passing_records,
  SUM(row_expectations.failed_records) AS failing_records
FROM
  (
    SELECT
      explode(
        from_json(
          details :flow_progress :data_quality :expectations,
          "array<struct<name: string, dataset: string, passed_records: int,
failed_records: int>>"
        )
      ) row_expectations
    FROM
      event_log_raw
    WHERE
      event_type = 'flow_progress'
      AND origin.update_id = '${latest_update.id}'
  )
GROUP BY
  row_expectations.dataset,
  row_expectations.name;
```

Again, we can view the complete history of changes made to each DLT table by looking at the Delta history logs (see Figure 12). It allows us to understand how tables evolve over time and investigate complete threads of updates if a pipeline fails.

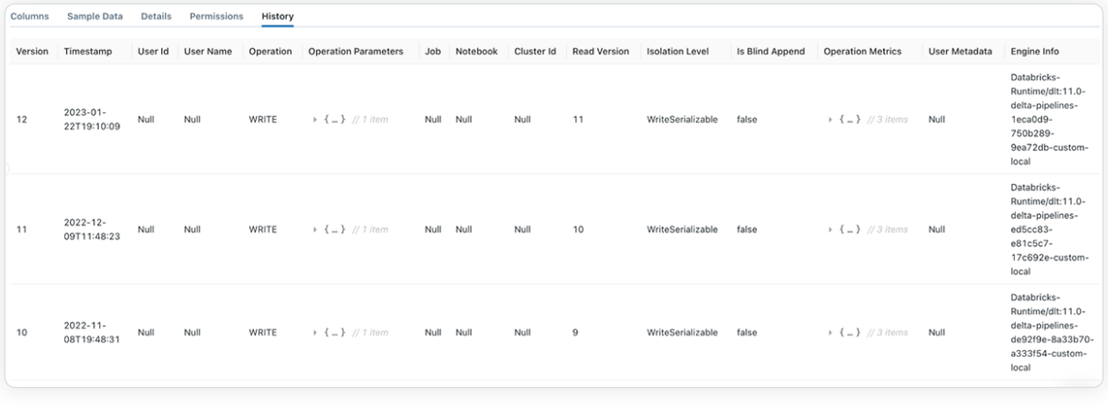


Figure 12 — View the history of changes made to a resulting Delta Live Tables (DLT) table entity.

We can further use change data capture (CDC) to update tables based on changes in the source datasets. DLT CDC supports updating tables with slow-changing dimensions (SCD) types 1 and 2.

We have one of two options for our batch process to trigger the DLT pipeline. We can use the Databricks Auto Loader to incrementally process new data as it arrives in the source tables or create scheduled jobs that trigger at set times or intervals. In this example, we opted for the latter with a scheduled job that executes the DLT pipeline every five minutes.

Operationalizing the outputs

The ability to incrementally process data efficiently is only half of the equation. Results from the DLT workflow must be operationalized and delivered to business users. In our example, we can consume outputs from the DLT pipeline through ad hoc analytics or prepacked insights made available through an interactive dashboard.

Ad hoc analytics

Databricks SQL (or DB SQL) provides an efficient, cost-effective data warehouse on top of the lakehouse architecture. It allows us to run our SQL workloads directly against the source data with up to 12x better price/performance than its alternatives.

We can leverage DB SQL to perform specific ad hoc queries against our curated and aggregated tables. We might, for example, run a query against the curated policies table that calculates the total exposure. The DB SQL query editor provides a simple, easy-to-use interface to build and execute such queries (see example below).

```
SELECT
  round(curr.total_exposure, 0) AS total_exposure,
  round(prev.total_exposure, 0) AS previous_exposure
FROM
  (
    SELECT
      sum(sum_insured) AS total_exposure
    FROM
      insurance_demo_lakehouse.curated_policies
    WHERE
      expiry_date > '{{ date.end }}'
      AND (effective_date <= '{{ date.start }}'
        OR (effective_date BETWEEN '{{ date.start }}' AND '{{ date.end }}'))
  ) curr
  JOIN
  (
    SELECT
      ...
```

We can also use the DB SQL query editor to run queries against different versions of our Delta tables. For example, we can query a view of the aggregated claims records for a specific date and time (see example below). We can further use DB SQL to compare results from different versions to analyze only the changed records between those states.

```
SELECT
  *
FROM
  insurance_demo_lakehouse.aggregated_claims_weekly TIMESTAMP AS OF '2022-06-
05T17:00:00';
```

DB SQL offers the option to use a serverless compute engine, eliminating the need to configure, manage or scale cloud infrastructure while maintaining the lowest possible cost. It also integrates with alternative SQL workbenches (e.g., DataGrip), allowing analysts to use their favorite tools to explore the data and generate insights.

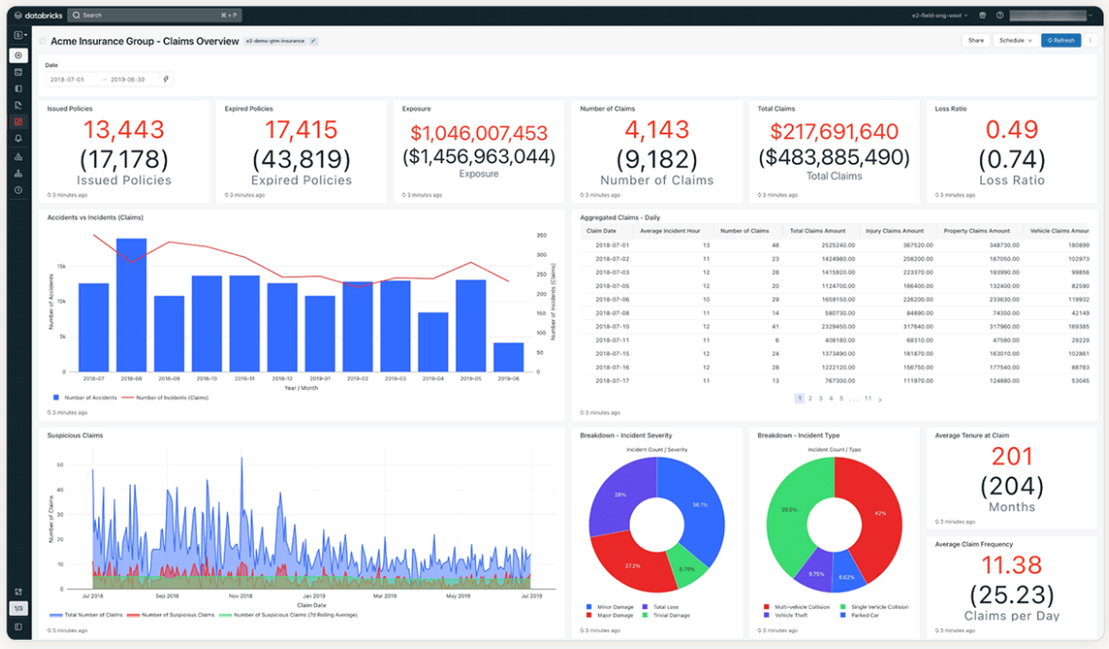


Figure 13 — Example operational dashboard built on a set of resulting Delta Live Tables (DLT) table entities.

For our use case, we created a dashboard with a collection of key metrics, rolling calculations, high-level breakdowns, and aggregate views. The dashboard provides a complete summary of our claims process at a glance. We also added the option to specify specific date ranges. DB SQL supports a range of query parameters that can substitute values into a query at runtime. These query parameters can be defined at the dashboard level to ensure all related queries are updated accordingly.

DB SQL integrates with numerous third-party analytical and BI tools like Power BI, Tableau and Looker. Like we did for Fivetran, we can use Partner Connect to link our external platform with DB SQL. This allows analysts to build and serve dashboards in the platforms that the business prefers without sacrificing the performance of DB SQL and the Databricks Data Intelligence Platform.

Conclusion

As we move into this fast-paced, volatile modern world of finance, batch processing remains a vital part of the modern data stack, able to hold its own against the features and benefits of streaming and real-time services. We've seen how we can use the lakehouse architecture for financial services and its ecosystem of partners to architect a simple, scalable, and extensible framework that supports complex batch-processing workloads with a practical example in insurance claims processing. With Delta Live Tables (DLT) and Databricks SQL (DB SQL), we can build a data platform with an architecture that scales infinitely, is easy to extend to address changing requirements, and will withstand the test of time.

To learn more about the sample pipeline described, including the infrastructure setup and configuration used, please refer to this GitHub repository or watch this demo video.

SECTION

05

Success Stories: Real Results on Databricks

SECTION 5.1

InMobi: Driving Meaningful Connections Between Customers and Brands

When it comes to advertising, consumers want to see content that's relevant and personalized — especially if it's appearing on their mobile devices, where time is a valuable resource — so it's important to instantly capture the consumer's attention and drive engagement. InMobi does this by using real-time customer data to deliver targeted mobile advertising and lock screen experiences. But as data processing requirements increased to 20+ terabytes per hour, the cost of running their multicloud data warehouse skyrocketed, while its proprietary nature created silos that hindered collaboration and data sharing.

InMobi migrated from their multicloud data warehouse to Databricks to unify their various workloads (data warehousing, AI and analytics), streamline operations and free up their engineers to work on more valuable tasks, helping them to achieve better operational agility and efficiency. Since moving to the lakehouse, the company has not only significantly reduced their total cost of ownership (TCO) compared to when they used a multicloud data warehouse — they have also improved productivity across the organization, resulting in faster time-to-market of new products.

Our focus to optimize price/performance was met head-on by Databricks. The lakehouse helped us reduce costs without sacrificing performance across mixed workloads, allowing us to optimize data and AI operations today and into the future.

— MOHIT SAXENA
Co-founder and Group CTO,
InMobi

32%
LowerTCO compared to their multicloud data warehouse

15%
Faster queries compared to their multicloud data warehouse

20%
Improved performance of supplier reporting

databricks

Complex legacy infrastructure and multicloud data warehouse unwieldy to manage

InMobi is all about targeted advertising and helping brands reach and engage consumers in a meaningful and cost-effective way. But to accurately deliver relevant ads, you need data — a lot of it. Over time, they extended their on-premises Hadoop system by adding multiple cloud data warehouses to address various problems. However, as the amount of data the company needed to process increased exponentially (20TB of data per hour), InMobi continued to build on top of their legacy system, resulting in a multicloud data warehouse that had a host of challenges: It was overly complex, had outages, was extremely costly as they scaled, and led to data silos that limited data sharing and collaboration. The team at InMobi realized that if they continued with this system in place, it would slow down their ability to innovate and keep precious engineering resources locked into maintenance mode.

> **"The data infrastructure that we built worked, but it created significant complexity and overhead that pulled our focus away from our own core products," said Madhan Sundaram, Senior Director of Platform Engineering at InMobi. "We needed our talented engineers to create more value for our customers, and to do that, we needed a simpler and more unified system."**

What InMobi wanted was a single system that could solve multiple problems. To accomplish this goal, the company needed to consolidate their disjointed systems into a single platform to free up engineers to focus on higher-value tasks such as developing ML and large language models. That's why the team looked to the Databricks Data Intelligence Platform to unify their data warehousing and AI workloads on a single platform.

Migration to lakehouse results in unified data, analytics and AI

Although InMobi has a team of fully capable engineers, they learned a valuable lesson in productivity and operational agility. "We found that we were spending more time maintaining our environment, which was hurting our ability to support and collaborate with the business," explained Sundaram. "We wanted to be more strategic and identify ways to operationalize data more efficiently." After careful evaluation of their current multicloud data warehouse and the prospects of building in-house, they determined that the Databricks Data Intelligence Platform clearly aligned best with their goals — to improve developer productivity through reduced infrastructure complexity while achieving the best possible price/performance.

Once they made their selection, the team partnered with Databricks to start the migration planning process. With over a decade of customizations built on top of existing systems and over 1 petabyte of data, InMobi knew the migration was going to be complex. On the ETL side alone, there were 150 pipelines and eight teams involved with migrating from open source Apache Spark™. They also needed to migrate approximately 300 reporting dashboards to ensure there was no disruption of information delivery to suppliers and customers. To help navigate this process, Databricks worked closely with InMobi — which had allocated two in-house engineers per team to provide support — and Databricks' implementation partner Celebal Technologies on the optimizations needed for a seamless migration.

As a result, Databricks was able to help InMobi migrate from their multicloud data warehouse to the lakehouse with ease. "Databricks gives us the edge in terms of being able to utilize industry-first features that help us establish technical differentiation," said Sundaram. "Their expertise came through during the migration as they helped us optimize our compute resources for cost and performance. The ownership that Databricks took to drive the optimizations and how transparent and educational they were was commendable."

Bringing more personalized mobile ads to customers everywhere

Now, with a unified, more streamlined lakehouse architecture, InMobi is able to take full advantage of their robust customer data to deliver smarter, more personalized mobile advertising. Various teams leverage Databricks notebooks for ad hoc analysis, Power BI for visualizations on top of Databricks SQL — the serverless data warehouse on the lakehouse — and MLflow to build their next-generation AI platform. They've also found great success with Delta Live Tables for anomaly detection, with a 50% improvement in SLAs and an 80% reduction in costs. Data silos and data discoverability are no longer an issue either, thanks to Unity Catalog. With Unity Catalog, they can now govern access at the table and column levels, while ensuring complete data lineage is captured to ensure they have visibility into where data comes from and whether it's stale or not.

With a platform designed to meet their analytics and AI needs, the InMobi team is diving into new technologies, including large language models (LLMs), to help deliver insights to their customers more efficiently. "We've started to look at implementing LLMs to make it easier for our end users to ask a question and find the information they need. The lakehouse architecture will make this effort easier, as jobs will run automatically under the hood. This will give our teams the ability to simply ask a question without any expertise and get the contextual answers they want at their fingertips," explained Sundaram.

In terms of business impact, there've been a number of measurable improvements across the board after the migration. Not only are infrastructure costs 34% lower than before, but there is also a 15% boost in query speeds and 20% fewer job failures compared to their previous data environment, all contributing to 20% better performance of reporting and insights delivery to end users. The TCO is 32% lower compared to when they used a multicloud data warehouse, and there's been a 24% cost reduction in running their ETL pipelines as well. More qualitatively, the team is seeing overall better reliability — with systems more stable than ever — and experiencing a positive reputation boost with their customers.

"Our rate of experimentation has improved tremendously," said Mohit Saxena, Co-founder and Group CTO at InMobi. "Databricks has simplified collaboration, and the unified approach that the lakehouse offers allows us to be more efficient, productive and compliant when delivering new features and products."

By moving to a unified platform on the Databricks Data Intelligence Platform, InMobi can now focus on innovating in the mobile advertising space to deliver real-time personalization that drives value for both InMobi's customers as well as their internal end users.

Read More Success Stories

SECTION 5.2

Akamai: Delivering Real-Time Analytics at Scale With Delta Lake

Akamai runs a pervasive, highly distributed content delivery network (CDN). Its CDN uses approximately 345,000 servers in more than 135 countries and over 1,300 networks worldwide to route internet traffic for some of the largest enterprises in media, commerce, finance, retail and many other industries. About 30% of the internet's traffic flows through Akamai servers. Akamai also provides cloud security solutions.

In 2018, the company launched a web security analytics tool that offers Akamai customers a single, unified interface for assessing a wide range of streaming security events and perform analysis of those events. The web analytics tool helps Akamai customers to take informed actions in relation to security events in real time. Akamai is able to stream massive amounts of data and meet the strict SLAs it provides to customers by leveraging Delta Lake and the Databricks Data Intelligence Platform for the web analytics tool.

Delta Lake allows us to not only query the data better but to also acquire an increase in the data volume. We've seen an 80% increase in traffic and data in the last year, so being able to scale fast is critical.

— TOMER PATEL
Engineering Manager,
Akamai

<1
Minute ingestion time, reduced from 15 min

>85%
Of queries have a response time of 7 seconds or less

Ingesting and streaming enormous amounts of data

Akamai's web security analytics tool ingests approximately 10GB of data related to security events per second. Data volume can increase significantly when retail customers conduct a large number of sales — or on big shopping days like Black Friday or Cyber Monday. The web security analytics tool stores several petabytes of data for analysis purposes. Those analyses are performed to protect Akamai's customers and provide them with the ability to explore and query security events on their own.

The web security analytics tool initially relied on an on-premises architecture running Apache Spark™ on Hadoop. Akamai offers strict service level agreements (SLAs) to its customers of 5 to 7 minutes from when an attack occurs until it is displayed in the tool. The company sought to improve ingestion and query speed to meet those SLAs. "Data needs to be as real-time as possible so customers can see what is attacking them," says Tomer Patel, Engineering Manager at Akamai. "Providing queryable data to customers quickly is critical. We wanted to move away from on-prem to improve performance and our SLAs so the latency would be seconds rather than minutes."

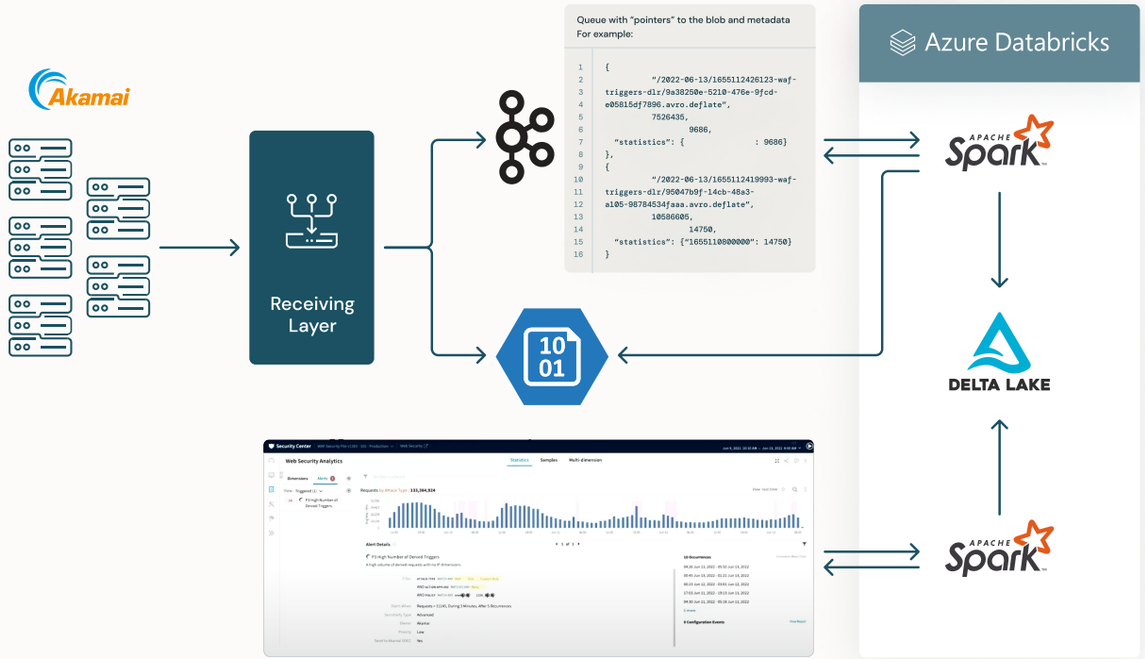
After conducting proofs of concept with several companies, Akamai chose to base its streaming analytics architecture on Spark and the Databricks Data Intelligence Platform. "Because of our scale and the demands of our SLA, we determined that Databricks was the right solution for us," says Patel. "When we consider storage optimization, and data caching, if we went with another solution, we couldn't achieve the same level of performance."

Improving speed and reducing costs

Today, the web security analytics tool ingests and transforms data, stores it in cloud storage, and sends the location of the file via Kafka. It then uses a Databricks Job as the ingest application. Delta Lake, the open source storage format at the base of the Databricks Data Intelligence Platform, supports real-time querying on the web security analytics data. Delta Lake also enables Akamai to scale quickly. "Delta Lake allows us to not only query the data better but to also acquire an increase in the data volume," says Patel. "We've seen an 80% increase in traffic and data in the last year, so being able to scale fast is critical."

Akamai also uses Databricks SQL (DBSQL) and Photon, which provide extremely fast query performance. Patel added that Photon provided a significant boost to query performance. Overall, Databricks' streaming architecture combined with DBSQL and Photon enables Akamai to achieve real-time analytics, which translates to real-time business benefits.

Patel says he likes that Delta Lake is open source, as the company has benefitted from a community of users working to improve the product. "The fact that Delta Lake is open source and there's a big community behind it means we don't need to implement everything ourselves," says Patel. "We benefit from fixed bugs that others have encountered and from optimizations that are contributed to the project." Akamai worked closely with Databricks to ensure Delta Lake can meet the scale and performance requirements Akamai defined. These improvements have been contributed back to the project (many of which were made available as part of Delta Lake 2.0), and so any user running Delta Lake now benefits from the technology being tested at such a large scale in a real-world production scenario.



Meeting aggressive requirements for scale, reliability and performance

Using Spark Structured Streaming on the Databricks Data Intelligence Platform enables the web security analytics tool to stream vast volumes of data and provide low-latency, real-time analytics-as-a-service to Akamai's customers. That way Akamai is able to make available security event data to customers within the SLA of 5 to 7 minutes from when an attack occurs. "Our focus is performance, performance, performance," says Patel. "The platform's performance and scalability are what drives us."

Using the Databricks Data Intelligence Platform, it now takes under 1 minute to ingest the security event data. "Reducing ingestion time from 15 minutes to under 1 minute is a huge improvement," says Patel. "It benefits our customers because they can see the security event data faster and they have a view of what exactly is happening as well as the capability to filter all of it."

Akamai's biggest priority is to provide customers with a good experience and fast response times. To date, Akamai has moved about 70% of security event data from its on-prem architecture to Databricks, and the SLA for customer query and response time has improved significantly as a result. "Now, with the move to Databricks, our customers experience much better response time, with over 85% of queries completing under 7 seconds." Providing that kind of real-time data means Akamai can help its customers stay vigilant and maintain an optimal security configuration.

Read More Success Stories

SECTION 5.3

Quartile: Becoming the Largest e-Commerce Ad Platform

Quartile is the world's largest e-commerce cross-channel advertising platform, serving over 5,000 connected ad accounts from more than 10 channels. Built on six patented machine learning technologies, the platform automates and optimizes e-commerce advertising on Google, Facebook, Amazon, Instacart, Walmart and more. Quartile pairs leading technology with marketing experts who create strategies that are tailored to their customers' business goals. Thousands of sellers worldwide trust Quartile's funnel optimization approach to unlock the full potential of their selling and advertising across multiple channels, entirely integrated and at scale.

The Databricks Data Intelligence Platform has been enabling our technology teams to keep improving our time to market on new solutions and delighting customers with quality data sets. Becoming the largest e-commerce cross-channel ad platform would be much harder without Databricks and the lakehouse architecture.

— DANIEL KNIJNIK
CEO,
Quartile

80%
Reduction in data storage from traditional databases

10x faster
45 minutes to optimize bidding, down from 7.5 hours

databricks

Size of data and performance needed to scale

Quartile faced challenges in storing and processing data for multiple advertising channels due to crucial needs in reporting and consolidating sales data, including over 60 days of attribution. The previous architecture couldn't keep up with the size of data Quartile was processing. The team was batch processing over 10TB of data on a single job, which applied all transformations required for data reporting, causing server unavailability and late deliveries of data points. This process alone, which is responsible for improving the performance of ads, had severe performance problems, such as individual jobs running up to 7.5 hours every day.

Technology evolution, from legacy to modern data stack

As part of the evolution of the company, Quartile's data architecture has reached new levels of maturity, growing from traditional SQL databases running on Azure cloud to a new solution with the Databricks Data Intelligence Platform as the foundation. This modernization has had direct impact in several areas of the company and clear benefits for Quartile's customers: with Delta Lake there has been more data reliability, faster performance and reduced costs. When migrating the data from a traditional SQL database to Databricks, they saw a considerable reduction in data volume, mainly due to the optimizations of Delta with version control and Parquet compacting, resulting in storage reduction from 90TB to about 18TB.

The lakehouse architecture has enabled Quartile's data stack to evolve. This has been accomplished through several processes: by leveraging Databricks Auto Loader for incremental and efficient processing of new data files as they arrive in cloud storage; by using Delta Lake for its open format storage layer, which delivers reliability, security and performance on the data lake; by using Databricks SQL, which continues to bring data engineers and data analysts closer with easy-to-build queries and dashboards; and with Databricks Workflows, which connects all of the pieces together in a stable and scalable way.

To provide the best experience for customers, Quartile needs to be able to retrieve accurate data. This is an important challenge that is easier to handle with Spark User-Defined Functions, as the company uses the power of parallelism to break down processing into as many parts as needed. For their solution to scale, they utilize Terraform for deploying all workspaces, easily spinning up new clusters and jobs as well as ensuring the correct standards are being followed across the company.

Helping their partners run ads better

It is critical that Quartile's customers have a centralized solution in which they can analyze their sales, costs and other metrics related to their campaigns. At Quartile, they take advantage of the solid data engineering work and integrate Databricks with Power BI for embedding the dashboards directly in their portal. This helps provide a single place for clients to both configure marketing campaigns across several channels as well as follow up on performance changes while still maintaining a smaller data storage footprint that is 80% less expensive compared to the data stored in traditional data warehouses by leveraging Delta Lake's file format on object storage. The ability to combine data from all different channels has already helped several of their customers — SmartyPants, as an example, has grown over 100% since they partnered with Quartile.

But that's not all. Quartile has also patented algorithms for improving the performance of ads, which are implemented utilizing the machine learning persona in Databricks. The ability of having a central lakehouse architecture to build their entire data stack has made the lives of Quartile's developers much simpler, allowing them to focus on developing innovative solutions and bringing increasingly better results for their customers. As another example, OfficeSupply has had excellent results during their first year of working with Quartile, with a 67% increase in Google Ads revenue and a 103% increase in Google Shopping clicks for trademark terms by improving the performance of individual jobs — they used to take 7.5 hours but now run in 45 minutes on the lakehouse architecture.

Looking ahead, Quartile is continuing to partner with Databricks to build their modern data stack, integrating and testing newer solutions. This includes Delta Live Tables for higher data quality checks, Delta Sharing to send customers their own data, and Data Marketplace to enable clients to get started quickly. Quartile has a bold target to develop the first cross-channel learning for an ads optimization algorithm in this space, and Databricks will be the center of these innovations.

About Databricks

Databricks is the data and AI company. More than 10,000 organizations worldwide — including Comcast, Condé Nast, Grammarly and over 50% of the Fortune 500 — rely on the Databricks Data Intelligence Platform to unify and democratize data, analytics and AI. Databricks is headquartered in San Francisco, with offices around the globe, and was founded by the original creators of Lakehouse, Apache Spark™, Delta Lake and MLflow.

To learn more, follow Databricks on Twitter, LinkedIn and Facebook.

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