CSCI E-103

Data Engineering for Analytics to Solve Business Challenges

Operationalizing Data Pipelines

Lecture 07

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Harvard Extension, Fall 2025

Logistics

- Assignment-1: Spark
  - Grades out, let us know if you didn’t receive yours
- Assignment-2: ETL and Exploratory Data Analysis (EDA)
  - Grades will be out soon
- Assignment-3: Batch & Streaming
- Quiz-1
- Case Study-1: Data Architectures (will release towards EoW)
  - Please check your groups and company to research
  - A suggested template deck is provided for organizing your material

Agenda

- Operationalizing a Pipeline from PoC to Production
- Requirements - functional & non-functional
- Data Lake Guiding Principles
- Data Pipeline Components
- Data checks
  - Ex. Missing Data, Duplicates, Late data, Upstream error
- Data profiling, data quality, PII data masking
- Data Governance
- Data Scaling
- Pipeline Automation
- Data Security
- Disaster Recovery

- Lab
  - Architecture considerations & Data checks
  - Delta Live Tables (DLT) - Simplifying ETL of data pipelines while hardening for production

Clear Requirements for a high quality data product/service

Functional Requirements

*Specifies **What** The System Should Do*

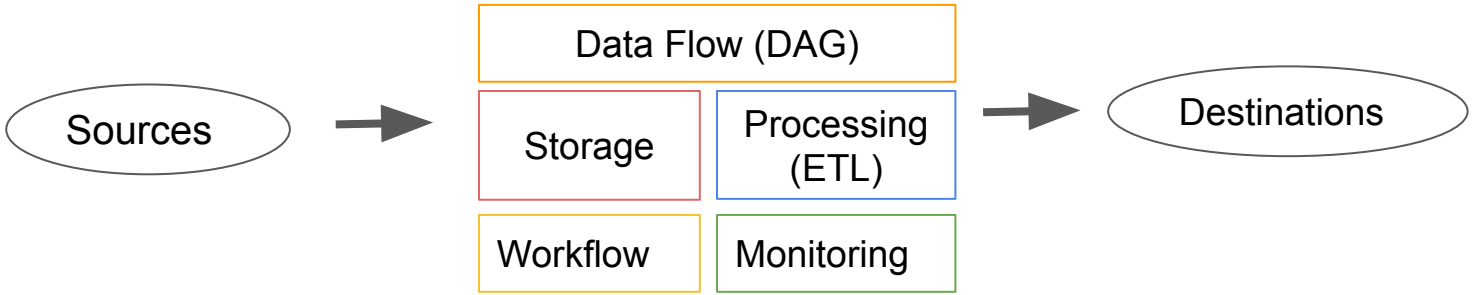
- Business Rules
- Transaction corrections, adjustments and cancellations
- Administrative functions
- Authentication
- Authorization levels
- Audit Tracking
- External Interfaces
- Certification Requirements
- Reporting Requirements
- Historical Data

Non-Functional Requirements

*Specifies **How** The System Performs A Certain Function*

- Performance – for example Response Time, Throughput, Utilization, Static Volumetric
- Scalability
- Capacity
- Availability
- Reliability
- Recoverability
- Maintainability & Serviceability
- Security & Regulatory
- Manageability
- Environmental
- Data Integrity
- Usability & Interoperability

Components of a Data Pipeline



- Sources/Destinations
- Data Flow graph captures data dependencies and movement
- Storage
- ETL or ELT
- Workflow controls Scheduling & Orchestration
- Monitoring for operational continuity and data drift
  - Robustness - notification, retries, auto heal ex. Scale, Failures
  - Metrics - performance, data characteristics, KPIs

Guiding Principles for an effective Data Lakehouse

Link

1. Curate Data and Offer Trusted Data-as-Products
2. Remove Data Silos and Minimize Data Movement
3. Democratize Value Creation through Self-Service Experience
4. Adopt an Organization-wide Data Governance Strategy
5. Encourage the Use of Open Interfaces and Open Formats
6. Build to Scale and Optimize for Performance & Cost

1. Curate Data and Offer Trusted Data-as-Products

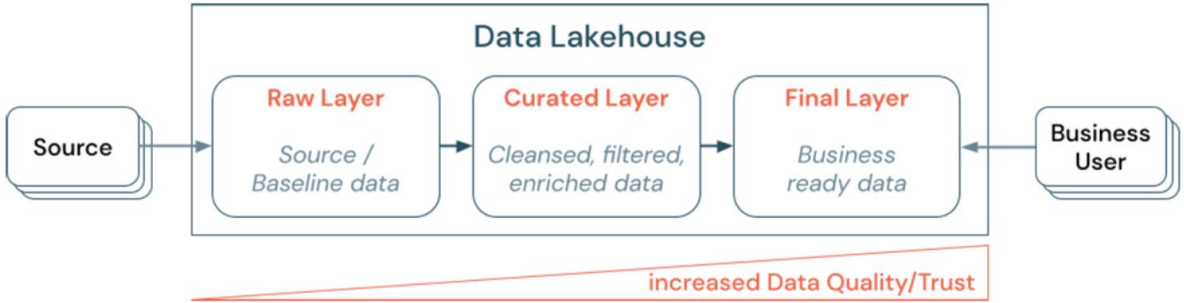


Figure 1: Data quality, as well as trust in data, increase as data progresses through the layers.

- Multi-Hop Architecture
  - Bronze - Raw
    - Usually necessary for rebuilding/re-processing
  - Silver - Harmonized
    - Provides a sound, reliable foundation for analyses and reports across all roles and functions
  - Gold - Curated, Prepares data around security needs (Eg. anonymization, pre-aggregated)
    - Aggregated
    - **Business Ready** - Semantic, Marts/Cubes

2. Remove Data Silos and Minimize Data Movement

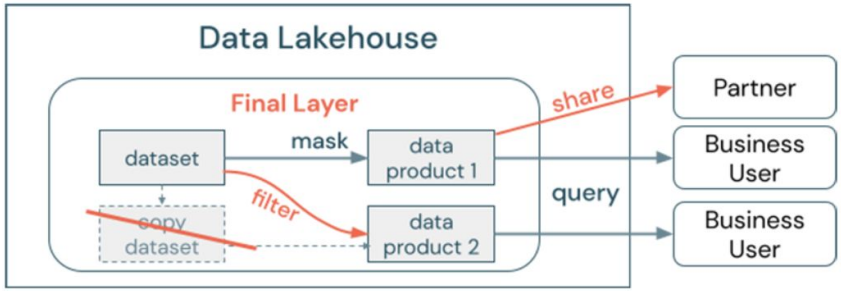


Figure 2: Lakehouses have capabilities that allows business user to query data, as well as share it with partners.

- Data movement introduces fragility, quality concerns, latency, cost
- Avoid data duplication that introduces operational dependencies
- Data sync
  - Clone (shallow, deep)
  - Sharing
  - Federation
  - Views/materialized views
  - Delta time travel

3. Democratize Value Creation through Self-Service Experience

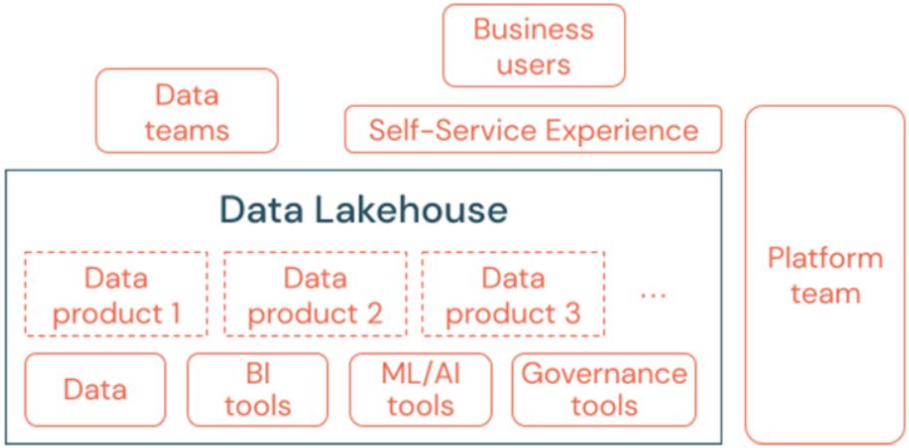


Figure 3: Lakehouse allows data teams to build data products that can be used through a self-service experience.

- Data driven decision making
- Centralized -> Decentralized decision making
- Teams need access to the right data along with the right tooling
- Self Service requires effective Guardrails

4. Adopt an Organization-wide Data Governance Strategy

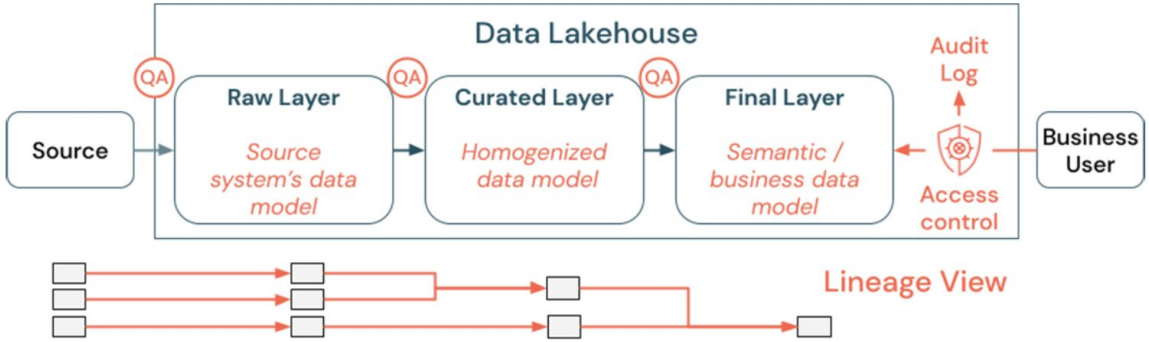


Figure 4: Lakehouse governance not only has strong access controls in place, but also can track data lineage.

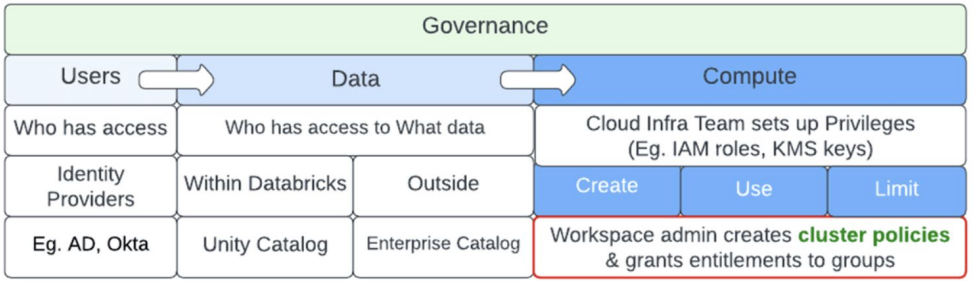


Figure 1: Governance of Data Platforms

- Data Quality
  - Constraints to ensure quality
  - Data timeliness via SLAs
- Data Catalog
  - Data Discovery, Metadata, Lineage
- Access Control
  - Row/column level access
  - Masking/anonymization
  - Adit Logs

5. Encourage the Use of Open Interfaces and Open Formats

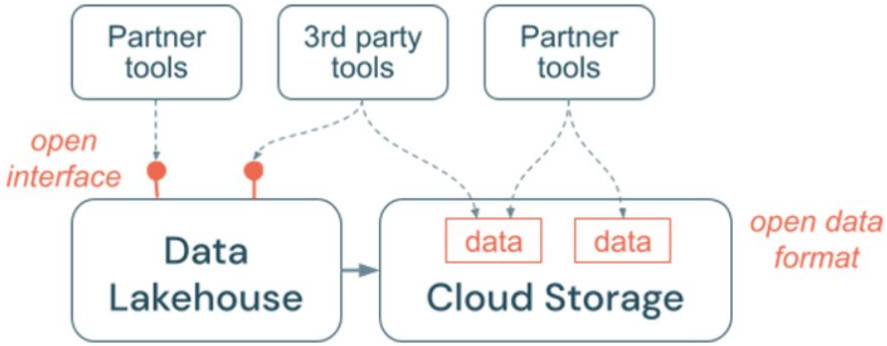


Figure 5: Lakehouse is built on open sources and open interfaces for easier integration with third party tools.

- Interoperability of systems
  - opens an ecosystem of partners who can quickly leverage the open interfaces to integrate their tools
- No vendor lock-in
  - increases the longevity and portability of the data
- Lower Cost
  - access the data directly on the cloud storage without the need to pipe it through a proprietary platform that can incur high egress and computation costs.

6. Build to Scale and Optimize for Performance & Cost

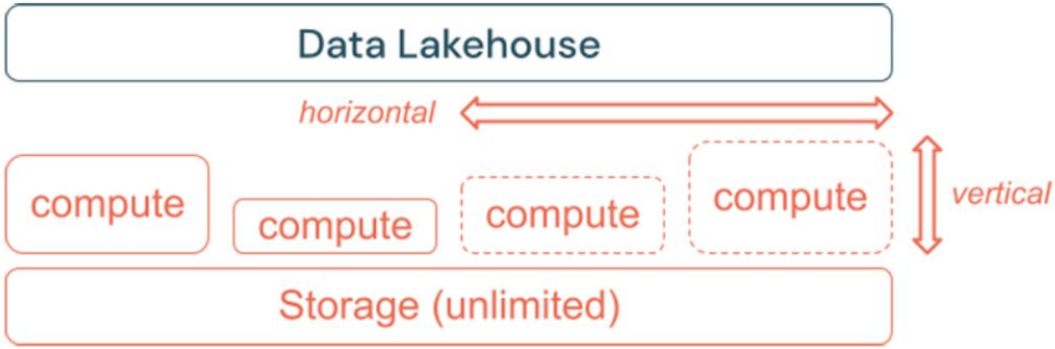
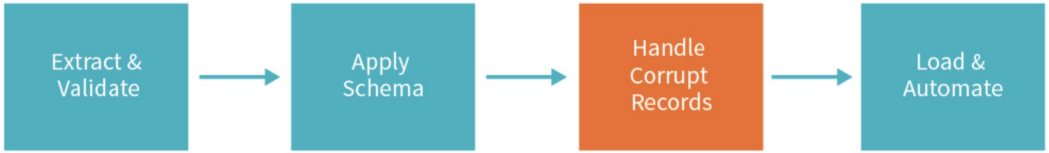


Figure 6: Lakehouse detaching storage form compute as well as leverage elastic compute for better scalability.

- Scaling
  - Vertical Scaling
  - Horizontal Scaling
- Price-Performance
  - Cost Vs Performance
- Storage Vs Compute
  - Decoupled architectures

Data Checks



- Data Checks
  - Missing information
  - Incomplete information
  - Schema mismatch
  - Differing formats or data types
  - User errors when writing data producers

ParseMode	Behavior
PERMISSIVE	Includes corrupt records in a "_corrupt_record" column (by default)
DROPMALFORMED	Ignores all corrupted records
FAILFAST	Throws an exception when it meets corrupted records

- Bad Records or Files
  - files may not be readable (for instance, they could be missing, inaccessible or corrupted)
  - even if the files are processable, some records are bad (for example, due to syntax errors and schema mismatch)
    - Use the **badRecordsPath** option in a file-based data source

```
data = """{"a": 1, "b":2, "c":3}|{"a": 1, "b":2, "c":3}|{"a": 1, "b, "c":10}""".split('|')

corruptDF = (spark.read.option("mode", "DROPMALFORMED").json(sc.parallelize(data)))

corruptDF = (spark.read.option("mode", "PERMISSIVE") .option("Corrupt", "_corrupt_record").json(sc.parallelize(data)))

corruptDF = (spark.read.option("badRecordsPath",  myBadRecords).json(sc.parallelize(data)))
```

Data manipulation functions

- Duplicate Data
  - user 1 performs a write operation on Delta table A.
  - At the same time, user 2 performs an append operation on Delta table A.
  - dedupedDF = duplicateDF.dropDuplicates(["id", "favorite_color"])
- Strategies for Imputing missing values
  - **Dropping these records:** Works when you do not need to use the information for downstream workloads
    - corruptDroppedDF = corruptDF.dropna("any")
  - **Adding a placeholder (e.g. `-1`):** Allows you to see missing data later on without violating a schema
  - **Basic imputing:** Allows you to have a "best guess" of what the data could have been, often by using the mean of non-missing data
    - corruptImputedDF = corruptDF.na.fill({"temperature": 68, "wind": 6})
  - **Advanced imputing:** using more advanced strategies such as clustering machine learning algorithms

Function	Use
`explode()`	Returns a new row for each element in the given array or map
`pivot()`	Pivots a column of the current DataFrame and perform the specified aggregation
`cube()`	Create a multi-dimensional cube for the current DataFrame using the specified columns, so we can run aggregation on them
`rollup()`	Create a multi-dimensional rollup for the current DataFrame using the specified columns, so we can run aggregation on them

Data Quality

- Constraints
  - Docs
  - ```
    ALTER TABLE default.people10m ADD CONSTRAINT dateWithinRange CHECK (birthDate > '1900-01-01');
    ```
- Schema Enforcement
- Generated Columns

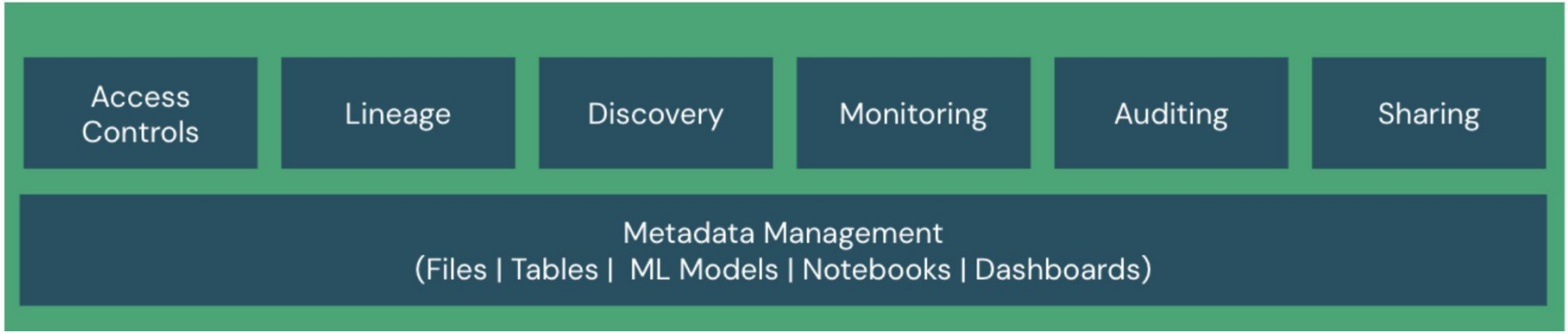
  Docs

```
CREATE TABLE default.people10m (
  id INT,
  gender STRING,
  birthDate TIMESTAMP,
  dateOfBirth DATE GENERATED ALWAYS AS (CAST(birthDate AS DATE)),
  salary INT
)
USING DELTA
PARTITIONED BY (gender)
```
```

Data Governance

Touches every aspect of data not just security

- For All your Data
  - structured/semi/Un-structured
- And All your Data Assets
  - Model
  - Dashboard
  - Services & Products



Scalability Vs Elasticity Vs Availability

Both **scalability** and **elasticity** help to improve availability and performance when demand is changing

A system is said to be **scalable** if it can increase its workload and throughput when additional resources are added.

Elasticity is the degree to which a system can adapt to workload changes by provisioning and deprovisioning resources in an on-demand manner, such that at each point in time the available resources match the current demand as closely as possible. The need is to avoid over/under provisioning.

Reliability - correct behavior

Availability - service is up

Scaling is of 2 types

- **Scale Up** - vertical scaling - bigger nodes
- **Scale Out** - horizontal scaling - more nodes - Autoscaling

Lakeflow helps you get great data

Ingest

All your data in one place

Connect

Transform

Efficiently clean, reshape and join data

Declarative Pipelines

Orchestrate

Run workloads in production

Jobs

Launched this year

Task Types

- Power BI (Preview)
- dbt Platform (Preview)
- dbt Core (GA)
- Clean Rooms (GA)
- AI/BI Dashboard (GA)
- Lakeflow Connect (GA)

Advanced Control Flow

- For each Task (GA)
- Conditional Task (GA)
- Partial runs (GA)
- SQL Task Values (GA)
- Backfill runs (Preview)

Scalability

- Serverless Compute (GA)
- Higher task limits (GA)

Triggers

- File Trigger (GA)
- Table Update Trigger (GA)
- Periodic Triggers (GA)

Monitoring

- Jobs system table (GA)
- Pipelines system table (GA)
- Unified tagging, listand search (GA)

Analytics projects require collaboration

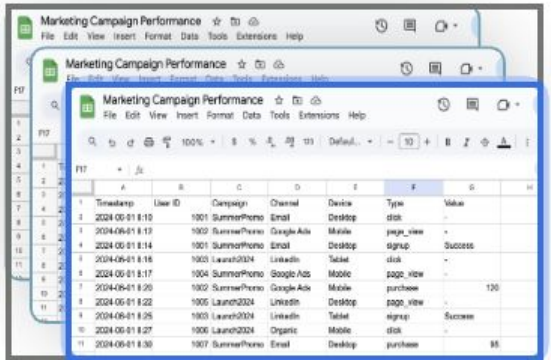
Data Intelligence Platform

Lakeflow

Data Engineers

?

Spreadsheets



Business Analysts

Lakeflow Designer