Cloud Data Lakes

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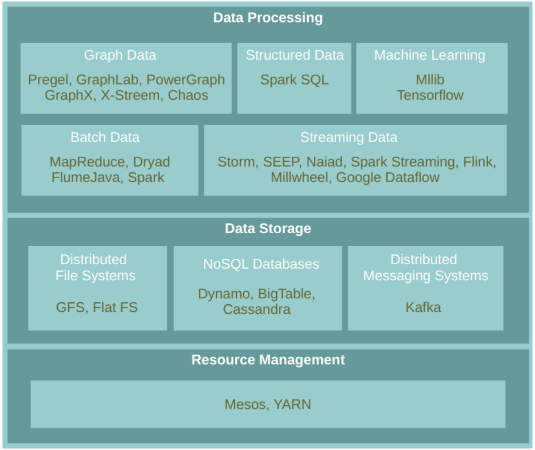
The Course Web Page

https://id2221kth.github.io

The Questions-Answers Page

https://tinyurl.com/bdenpwc5

Where Are We?



Data Processing
Graph Data
Pregel, GraphLab, PowerGraph
GraphX, X-Streem, Chaos
Structured Data
Spark SQL
Machine Learning
Mllib
Tensorflow
Batch Data
MapReduce, Dryad
FlumeJava, Spark
Streaming Data
Storm, SEEP, Naiad, Spark Streaming, Flink,
Millwheel, Google Dataflow
Data Storage
Distributed
File Systems
GFS, Flat FS
NoSQL Databases
Dynamo, BigTable,
Cassandra
Distributed
Messaging Systems
Kafka
Resource Management
Mesos, YARN

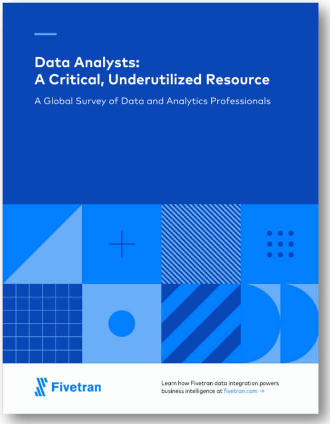
What Are The Challenges?

The Biggest Challenges With Data Today

- Data quality
- Staleness
- Data volume
- Scale

Fivetran Data Analyst Survey

- 60% reported data quality as top challenge.
- 86% of analysts had to use stale data, with 41% using data that is > 2 months old.
- 90% regularly had unreliable data sources over the last 12 months

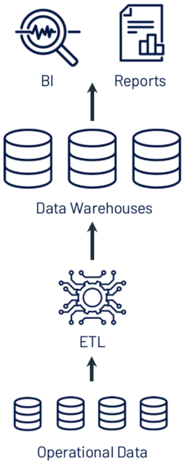


Getting high-quality, timely data is hard!

The Evolution of Data Management

Data Warehouses (1980s)

- ETL (Extract, Transform, Load) data directly from operational database systems.



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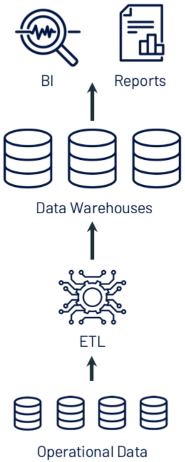

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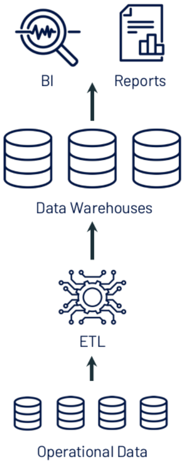

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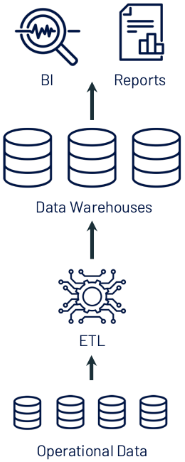

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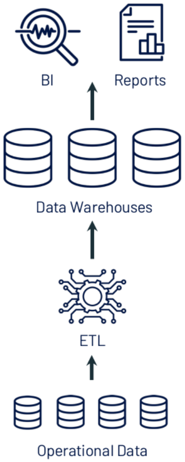

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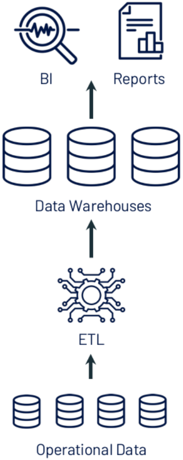

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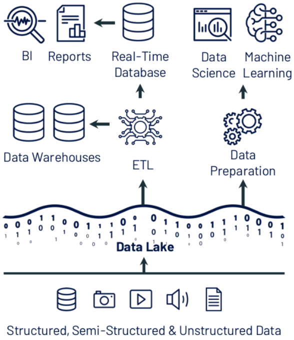

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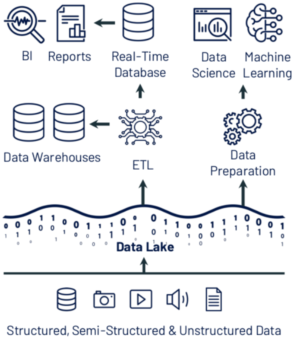

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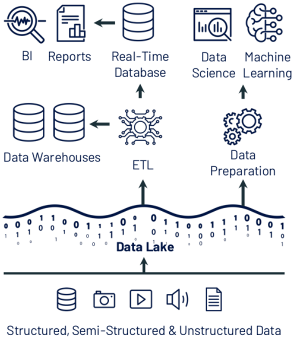
- Directly readable in ML libraries (e.g., TensorFlow and PyTorch) due to open file format.



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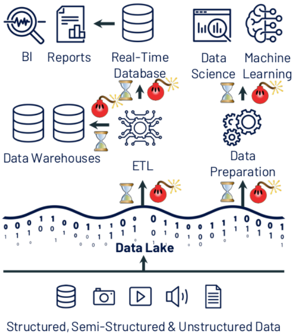

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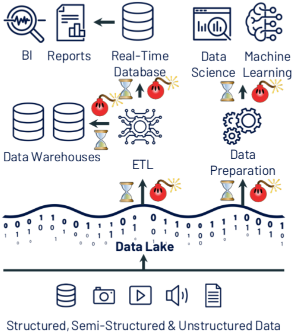

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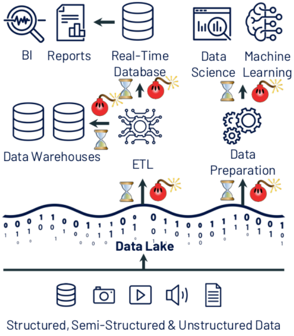
- Timeliness suffers and high cost:
  - Extra ETL steps before data is available in data warehouses.
  - Continuous ETL, duplicated storage



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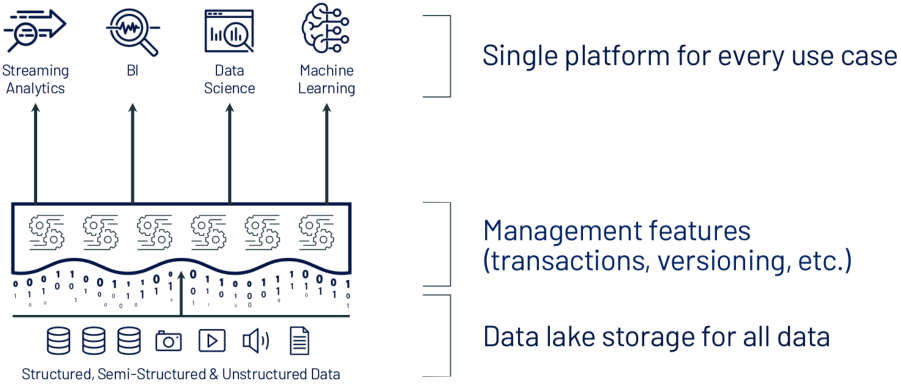
- Data Lake defines the schema after data is stored whereas Data Warehouse defines the schema before data is stored.
- Data Lake uses the ELT process while the Data Warehouse uses ETL process.

Lakehouse

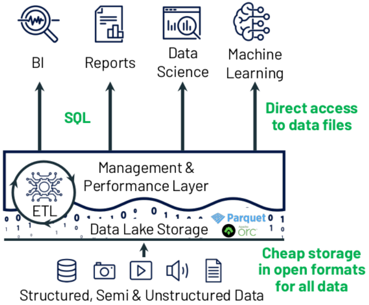
Lakehouse Vision



- Lakehouse systems combine the benefits of Data Warehouses and Data Lakes while simplifying enterprise data architectures.

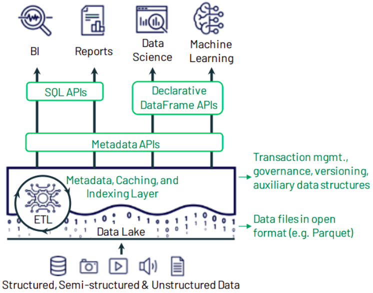
Lakehouse Systems

- Implement Data Warehouse management and performance features on top of directly-accessible data in open formats.



Key Technologies Enabling Lakehouse

- Metadata layers for Data Lakes



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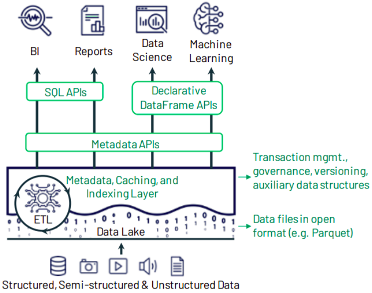

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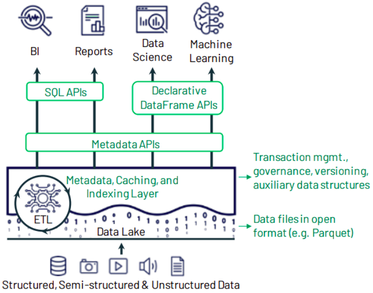
- Declarative access for data science and ML



Metadata Layers for Data Lakes

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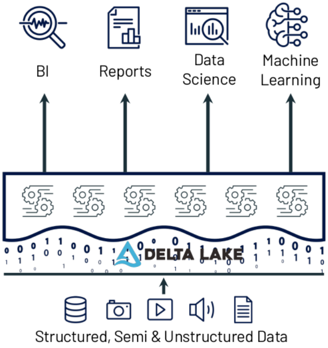

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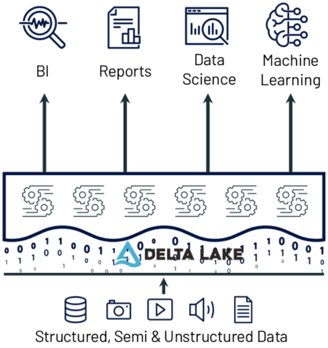

Metadata Layers for Data Lakes

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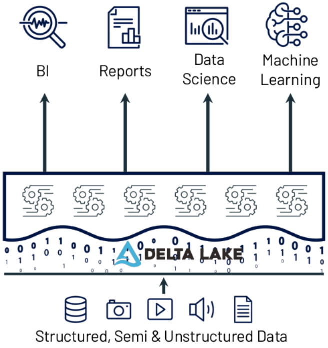
- Implemented in multiple systems, such as Delta Lake.



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  - Auxiliary data structures like statistics and indexes

Declarative Access for Data Science and ML

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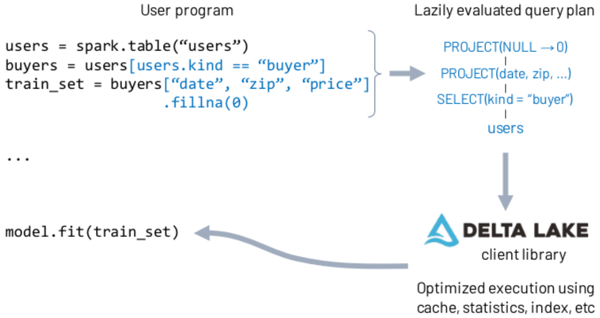

Declarative Access for Data Science and ML

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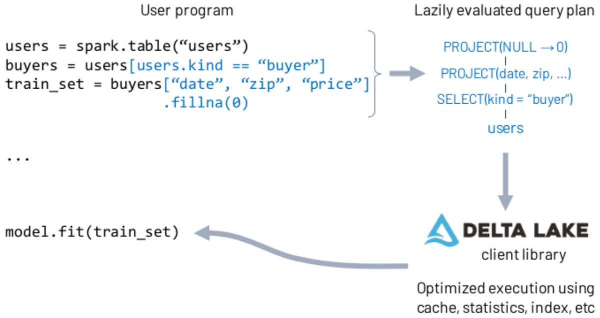
- Example: Spark DataFrame API compiles to relational algebra.



DELTA LAKE

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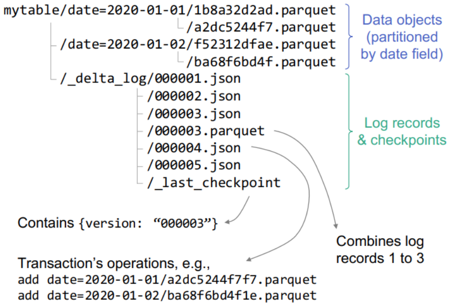
- Unifies streaming and batch data processing.

Delta Lake Table

- Delta Lake Table is a directory (e.g., `mytable`) that holds data objects and a log of transaction operations.



DeltaLog

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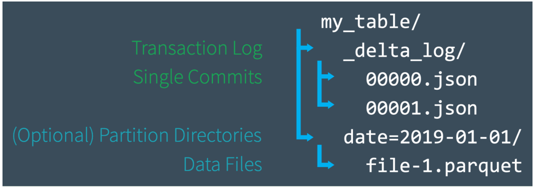
- Delta Lake uses the DeltaLog for many features including ACID transactions, scalable metadata handling, time travel, etc.

DeltaLog Structure (1/2)

- When a user creates a Delta Lake Table, its DeltaLog is automatically created in the `_delta_log` subdirectory.



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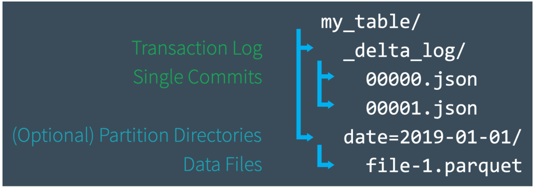

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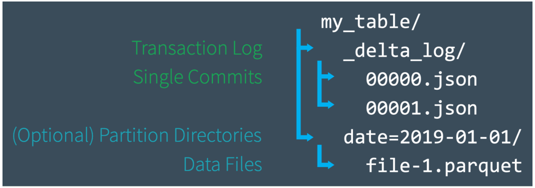

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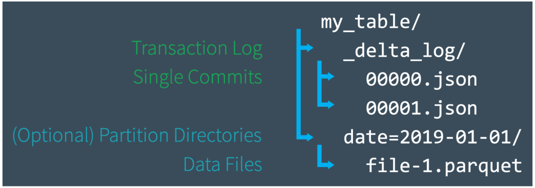
- Additional changes to the table generate subsequent JSON files in ascending numerical order, e.g., `000001.json`, 000002.json, and so on.



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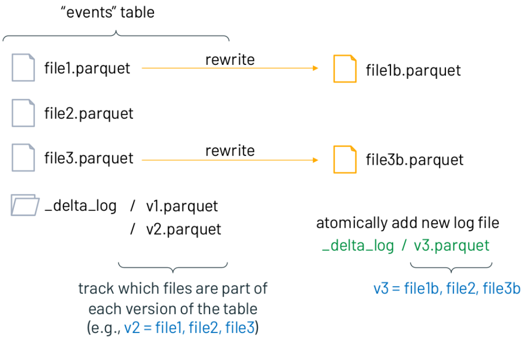
- Then, assume remove those files and add `3.parquet` instead.
- Those actions would be recorded as the next commit in the DeltaLog, as `000001.json`.

Delta Lake Transaction Example

- Query: delete all events data about customer no. 17



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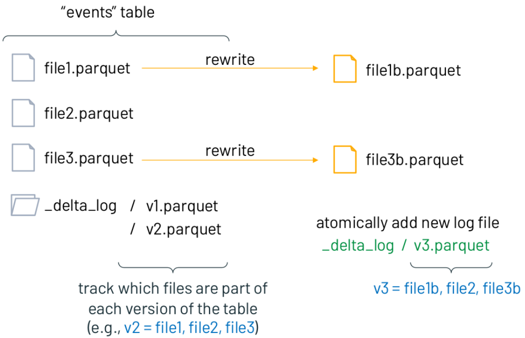

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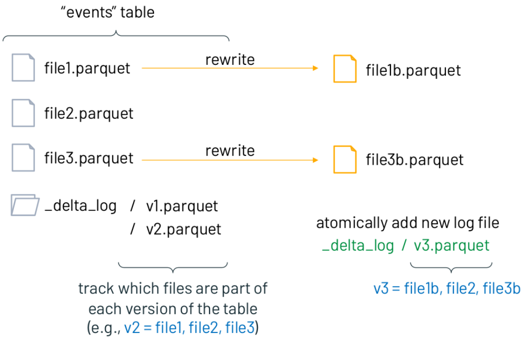

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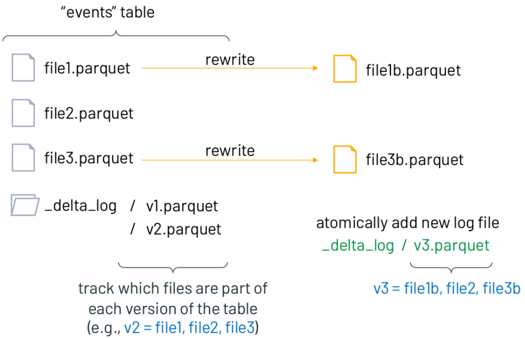

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  - If a client reads v3 of log, it sees file1b, file2, file3b (all deleted)

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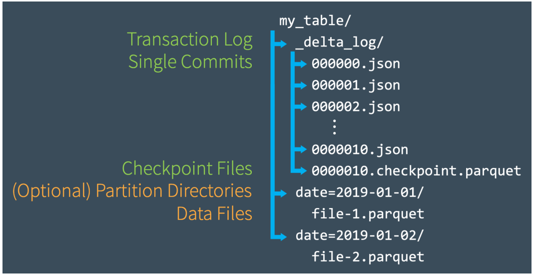
- Commit info: information around commit for auditing

Quickly Recomputing State With Checkpoint Files

- Delta Lake automatically generates checkpoint files every 10 commits in the same `_delta_log` subdirectory.



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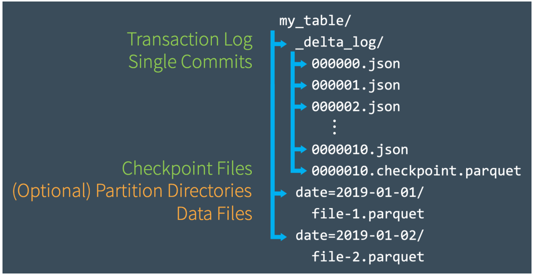

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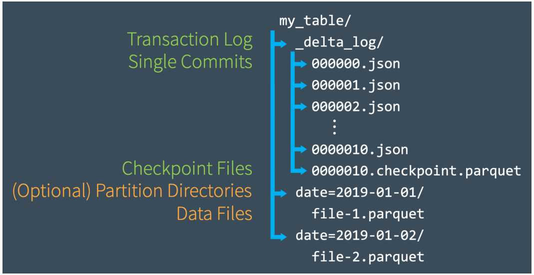
- They are in native Parquet format that is quick and easy for Spark to read.



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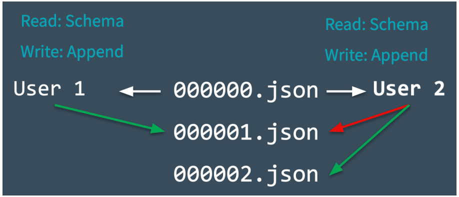
  2. Record reads/writes.
  3. Attempt a commit.
  4. If someone else wins, check whether anything you read has changed.
  5. Repeat.

Optimistic Concurrency Control (2/2)

- Two users read from the same table, then each attempts to add some data to it.



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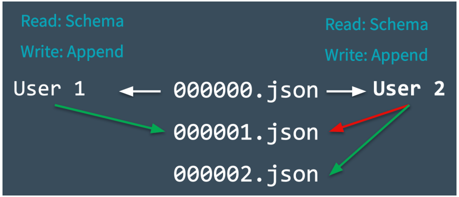

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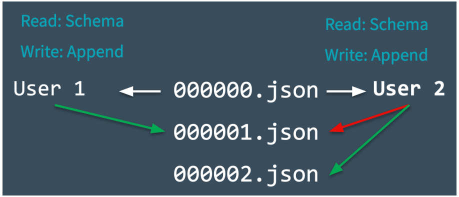

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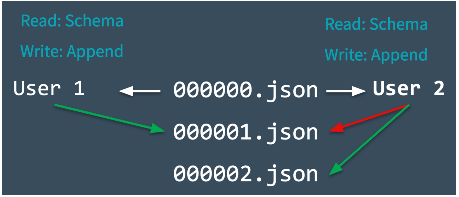
- However, Delta Lake does not throw an error for user 2 and handles this conflict optimistically.



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- This ability is known as time travel or data versioning.

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- It is is useful for governance, audit and compliance purposes.
- It can also be used to trace the origin of an inadvertent change or a bug in a pipeline back to the exact action that caused it.

Schema Enforcement and Evolution

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Schema Enforcement and Evolution

- Data is always evolving and accumulating.
- So, structure of data evolves over time.
- With Delta Lake, as the data changes, incorporating new dimensions is easy.
- Schema enforcement: prevents users from accidentally polluting their tables with mistakes or garbage data.
- Schema evolution: enables automatic addition of columns when desired.

Understanding Table Schemas

- Spark DataFrames contain the schema.
- With Delta Lake, the table's schema is saved in JSON format inside the DeltaLog.

```
schemaString: {"type":"struct","fields":[
  {"name":"loan_id","type":"long","nullable":false,"metadata":{}},
  {"name":"funded_amnt","type":"integer","nullable":true,"metadata":{}},
  {"name":"paid_amnt","type":"double","nullable":true,"metadata":{}},
  {"name":"addr_state","type":"string","nullable":true,"metadata":{}}
]}
```

Schema Enforcement

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- As well, Delta Lake raises an exception to let the user know about the mismatch.

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- Rule 2: cannot have column data types that differ from the column data types in the target table.
- Rule 3: Can not contain column names that differ only by case.

Schema Evolution

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- Most commonly used operations for append and overwrite.

Delta Lake and Spark

Loading Data into a Delta Lake Table (1/2)

- All you need to migrate any of the structured data formats (e.g., Parquet) to Delta Lake is to use `format("delta")`.

```scala
// Configure source data and Delta Lake path
val sourcePath = "loan-risks.snappy.parquet"
val deltaPath = "loans_delta"

// Create the Delta table with the same loans data
spark.read.format("parquet").load(sourcePath).write.format("delta").save(deltaPath)

// Create a view on the data called loans_delta
spark.read.format("delta").load(deltaPath).createOrReplaceTempView("loans_delta")
```

Loading Data into a Delta Lake Table (2/2)

```
// Read and explore the data
spark.sql("SELECT count(*) FROM loans_delta").show()

+--------+
|count(1)|
+--------+
|   14705|
+--------+

// First 3 rows of loans table
spark.sql("SELECT * FROM loans_delta LIMIT 3").show()

+-------+-----------+---------+----------+
|loan_id|funded_amnt|paid_amnt|addr_state|
+-------+-----------+---------+----------+
|      0|       1000|   182.22|        CA|
|      1|       1000|   361.19|        WA|
|      2|       1000|   176.26|        TX|
+-------+-----------+---------+----------+
```

Loading Data Streams into a Delta Lake Table

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```
import org.apache.spark.sql.streaming._

// Streaming DataFrame with new loans data
val newLoanStreamDF = ...

// Directory for streaming checkpoints
val checkpointDir = ...

val streamingQuery = newLoanStreamDF.writeStream
.format("delta")
.option("checkpointLocation", checkpointDir)
.trigger(Trigger.ProcessingTime("10 seconds"))
.start(deltaPath)
```

Schema Enforcement

- All writes to a Delta Lake table can verify whether the data being written has a schema compatible with that of the table.

```
val loanUpdates = Seq(
   (1111111L, 1000, 1000.0, "TX", false),
   (2222222L, 2000, 0.0, "CA", true))
 .toDF("loan_id", "funded_amnt", "paid_amnt", "addr_state", "closed")

loanUpdates.write.format("delta").mode("append").save(deltaPath)

// The exception message:
// This write will fail with the following error message:
// org.apache.spark.sql.AnalysisException: A schema mismatch detected when writing
// to the Delta table (Table ID: 48bfa949-5a09-49ce-96cb-34090ab7d695).
```

Schema Enforcement

- All writes to a Delta Lake table can verify whether the data being written has a schema compatible with that of the table.
- If it is not compatible, Spark will throw an error before any data is written and committed to the table.

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```

Schema Evolution

- A new column can be explicitly added by setting the option `mergeSchema` to `true`.

```
loanUpdates.write.format("delta").mode("append")
  .option("mergeSchema", "true")
  .save(deltaPath)
```

Transforming Existing Data - Updating Data

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- They ensure ACID guarantees.
- Assume we want to change all `addr_state = 'OR'` to `addr_state = 'WA'` in a table.

```
import io.delta.tables.DeltaTable
import org.apache.spark.sql.functions._

val deltaTable = DeltaTable.forPath(spark, deltaPath)

deltaTable.update(
    col("addr_state") === "OR",
    Map("addr_state" -> lit("WA")))
```

Transforming Existing Data - Deleting Data

- Deleting user data from all tables.

```
val deltaTable = DeltaTable.forPath(spark, deltaPath)

deltaTable.delete("funded_amnt >= paid_amnt")
```

Auditing Data Changes with Operation History

- All of the changes are recorded as commits in the table's DeltaLog.
- Every operation is automatically versioned.
- You can query the table's operation history.

```
deltaTable
    .history(3)
    .select("version", "timestamp", "operation", "operationParameters")
    .show(false)
```

Querying Previous Snapshots of a Table with Time Travel

- You can query previous versioned snapshots of a table by using the `DataFrameReader` options `versionAsOf` and `timestampAsOf`.

```
spark.read.format("delta")
    .option("timestampAsOf", "2020-01-01") // timestamp after table creation
    .load(deltaPath)

spark.read.format("delta")
    .option("versionAsOf", "4")
    .load(deltaPath)
```

Summary

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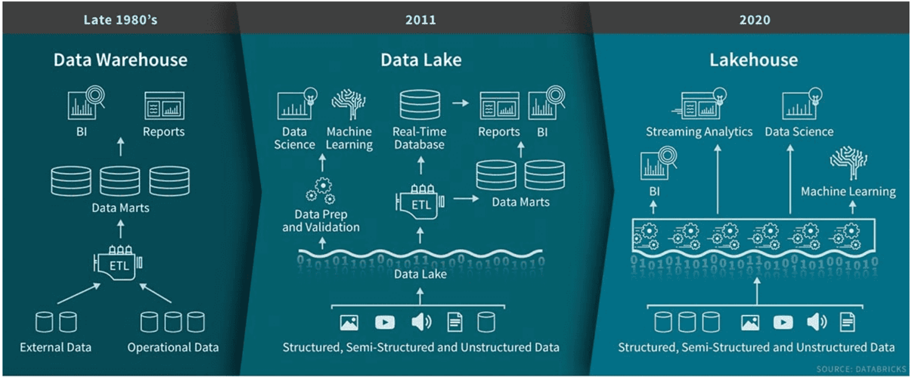

Late 1980's
2011
2020
Data Warehouse
BI
Reports
Data Marts
ETL
External Data
Operational Data
Data Lake
Data Science
Machine Learning
Real-Time Database
Reports
BI
Data Prep and Validation
ETL
Data Marts
Data Lake
Structured, Semi-Structured and Unstructured Data
Lakehouse
Streaming Analytics
Data Science
BI
Machine Learning
Structured, Semi-Structured and Unstructured Data
SOURCE: DATABRICKS

References

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- M. Armbrust et al., "Lakehouse: A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics", CIDR 2021
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Questions?

Acknowledgements

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