Cloud Data Lakes

Amir H. Payberah
payberah@kth.se
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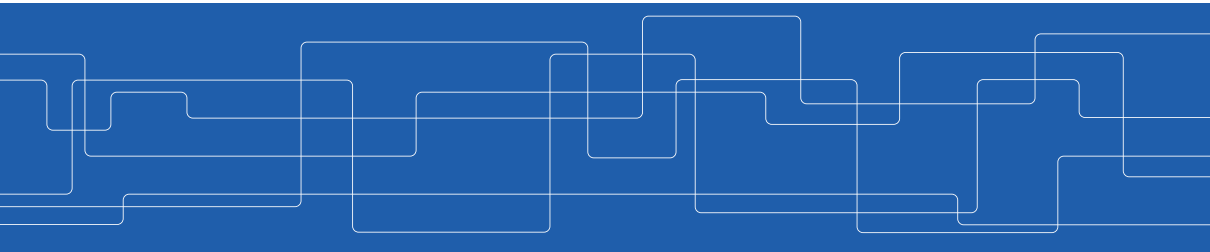
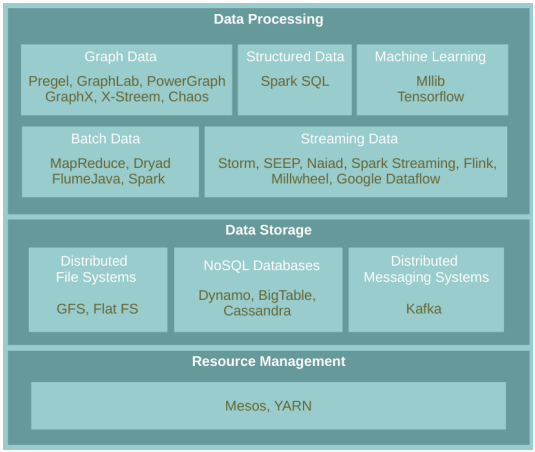


The Course Web Page

https://id2221kth.github.io

https://tinyurl.com/y4qph82u

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

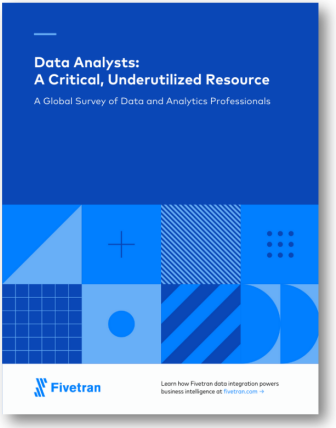
What Are The Challenges?

The Biggest Challenges With Data Today

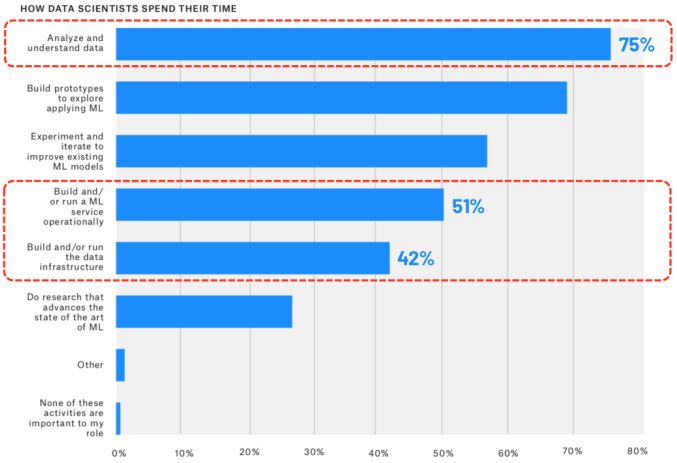
- Data quality
- Staleness
- Data volume
- Scale

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



Kaggle Data Analyst Survey

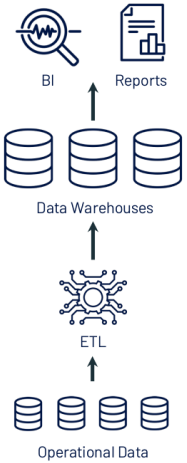


Getting high-quality, timely data is hard!

The Evolution of Data Management

Data Warehouses (1980s)

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



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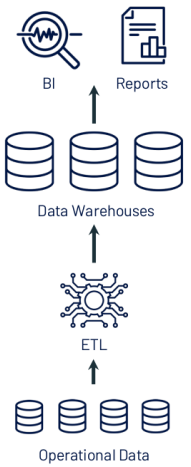

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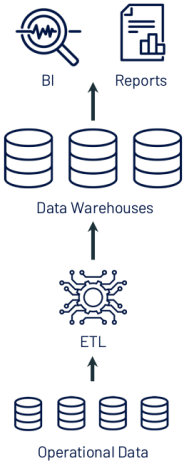
- Powerful management features such as ACID transactions and time travel



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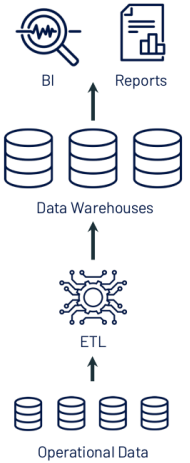

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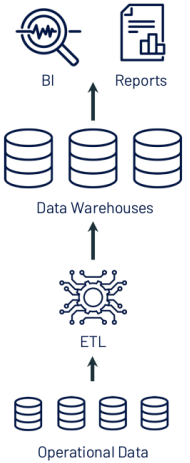

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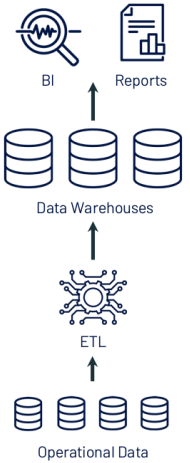
- No support for data science and ML.



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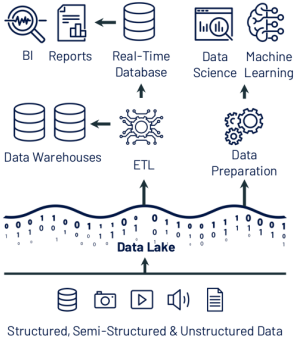

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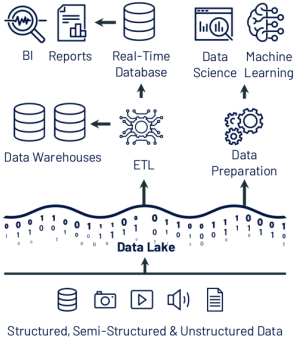

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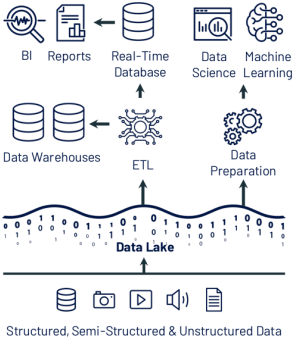
- Directly readable in ML libraries (e.g., TensorFlow and PyTorch) due to open file format.



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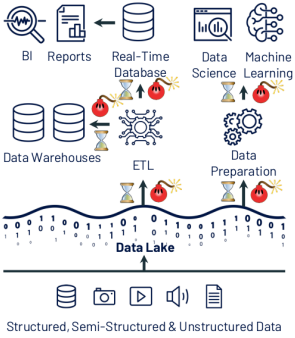

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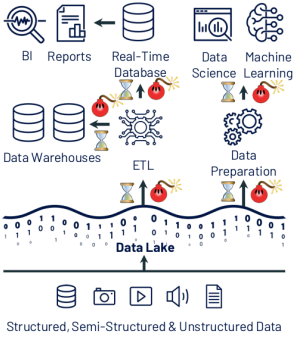

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- Data reliability suffers:
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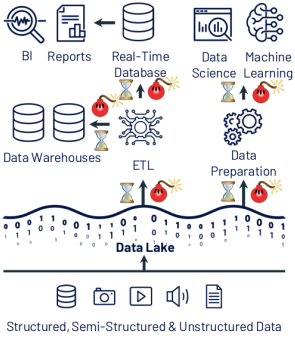
- Timeliness suffers and high cost:
  - Extra ETL steps before data is available in data warehouses.
  - Continuous ETL, duplicated storage



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- Data Lake stores all data irrespective of the source and its structure whereas Data Warehouse stores data in quantitative metrics with their attributes.
- Data Lake is a storage repository that stores huge structured, semi-structured and unstructured data while Data Warehouse is blending of technologies and component that allows the strategic use of data.

Data Lake vs. Data Warehouse (2/2)

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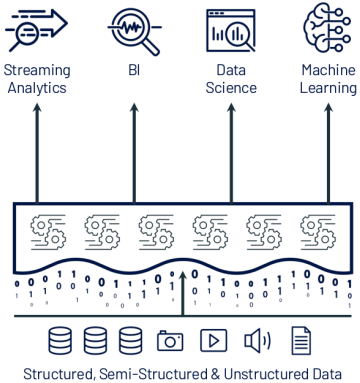
- Data Lake uses the ELT process while the Data Warehouse uses ETL process.
- Data Lake is ideal for those who want in-depth analysis whereas Data Warehouse is ideal for operational users.

Lakehouse

Lakehouse Vision



Single platform for every use case

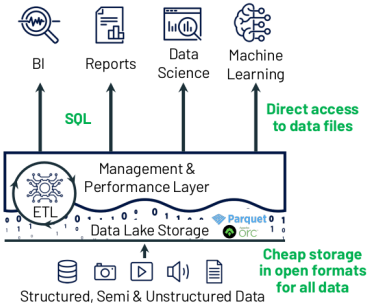
Management features (transactions, versioning, etc.)

Data lake storage for all data

- 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.



Lakehouse Systems

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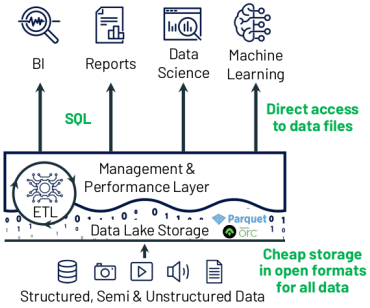
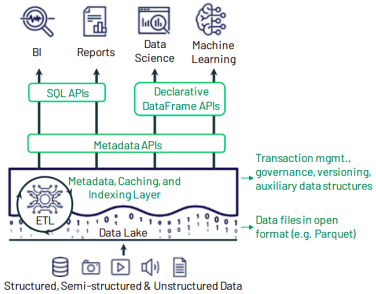
- Can we get state-of-the-art performance and governance features with this design?



Key Technologies Enabling Lakehouse

- Metadata layers for Data Lakes



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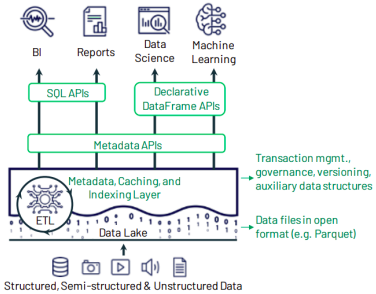

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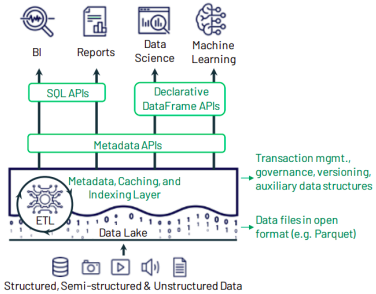

Metadata Layers for Data Lakes (1/2)

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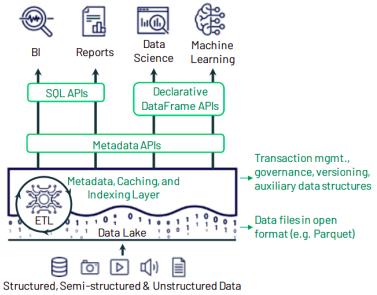
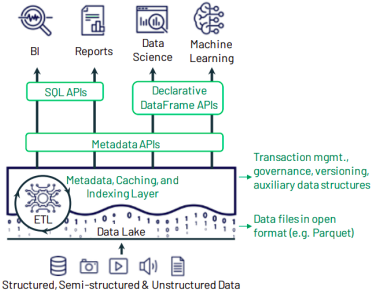


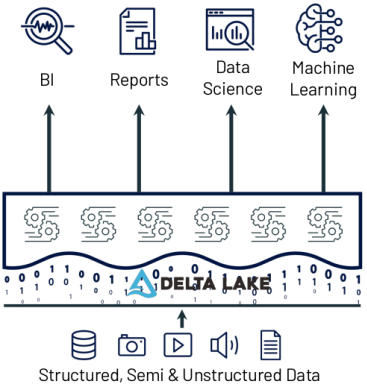
Metadata Layers for Data Lakes (1/2)

- Add transactions, versioning, and more ...
- Track which files are part of a table version to offer rich management features like transactions.
  - Clients can then access the underlying files at high speed.
  - Optimistic concurrency.



Metadata Layers for Data Lakes (2/2)

- Implemented in multiple systems, such as Delta Lake.



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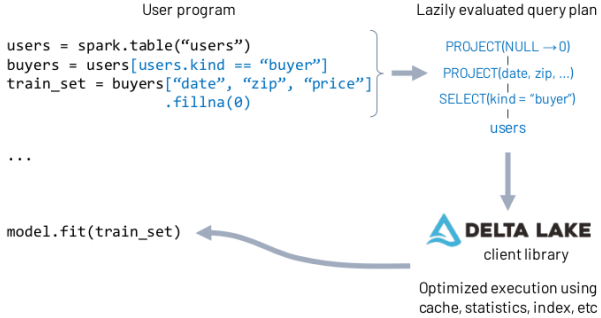
  - Auxiliary data structures like statistics and indexes
  - Vectorized execution engines for modern CPUs

Declarative Access for Data Science and ML

- ML frameworks already support reading Parquet, ORC, etc.



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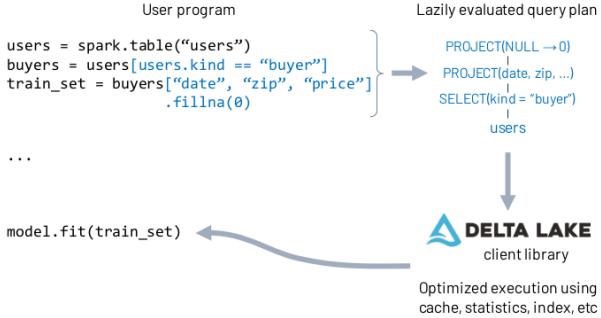

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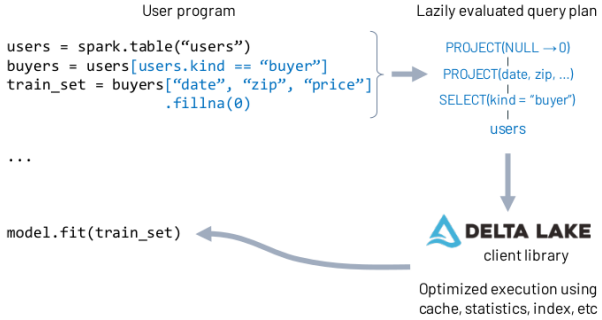
- Example: Spark DataFrame API compiles to relational algebra.




DELTA LAKE

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- Provides ACID transactions.
- Provides scalable metadata handling.
- Provides time travel and versioning.
- Unifies streaming and batch data processing.

Delta Lake (2/2)

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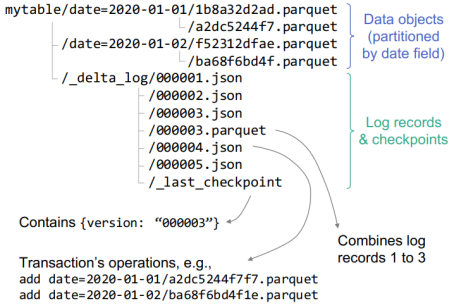
- A Delta Lake table is a directory (e.g., `mytable`) that holds data objects and a log of transaction operations.



Diving into Delta Lake

- Transaction log
- Schema enforcement and evolution

Transaction Log

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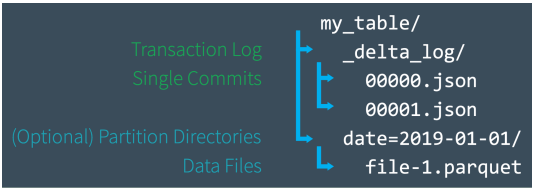
- Delta Lake uses the DeltaLog for many features including ACID transactions, scalable metadata handling, time travel, etc.
- Before apply any operation on a Delta Lake table, Spark checks the table DeltaLog to see what new transactions have posted to the table.

The Transaction Log Structure (1/2)

- When a user creates a Delta Lake table, that table's DeltaLog is automatically created in the `_delta_log` subdirectory.



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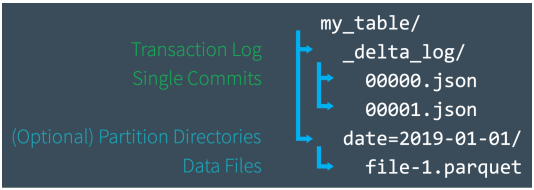

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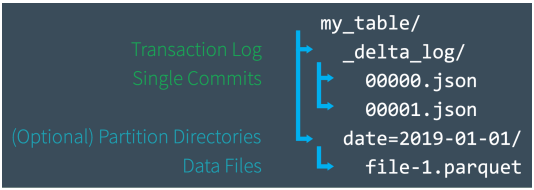

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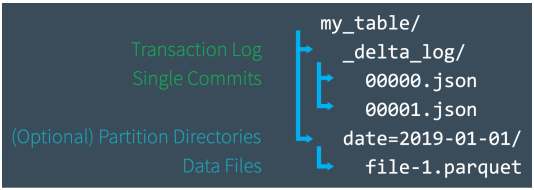
- Additional changes to the table generate subsequent JSON files in ascending numerical order, e.g., `000001.json`, 000002.json, and so on.



The Transaction Log Structure (2/2)

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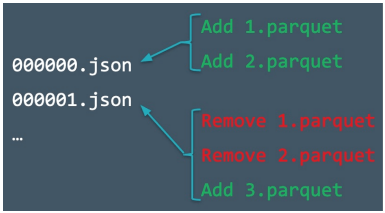

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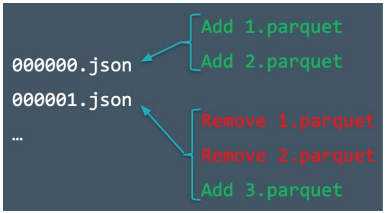

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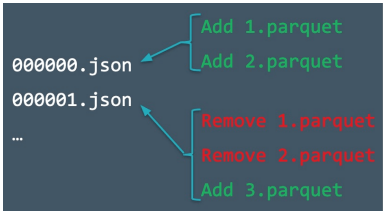

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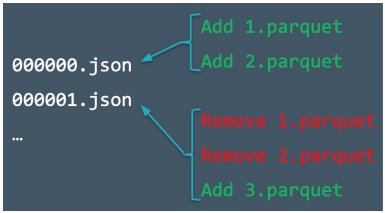
- Then, assume remove those files and add `3.parquet` instead.
- Those actions would be recorded as the next commit in the DeltaLog, as `000001.json`.



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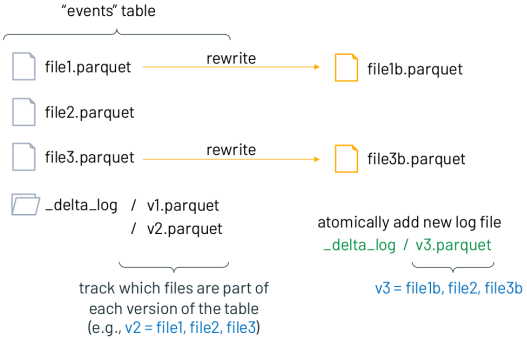

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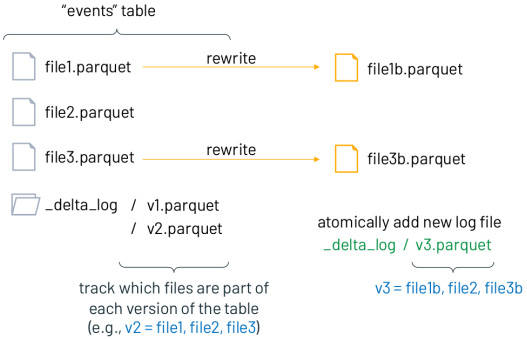

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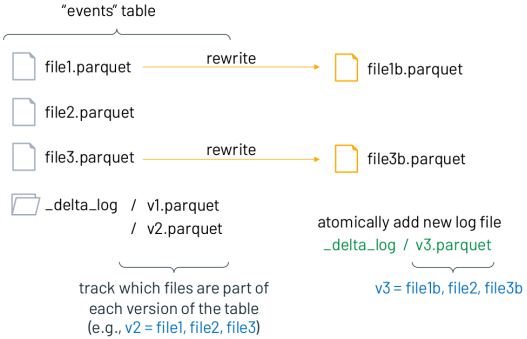

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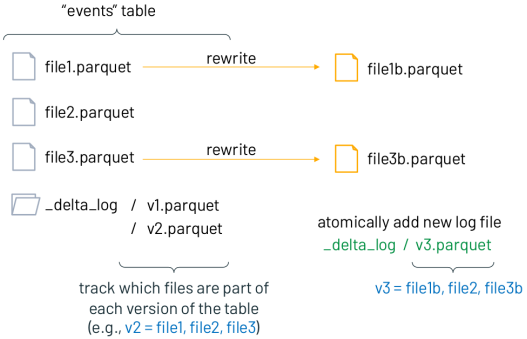

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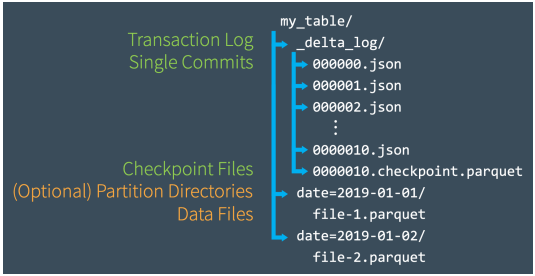

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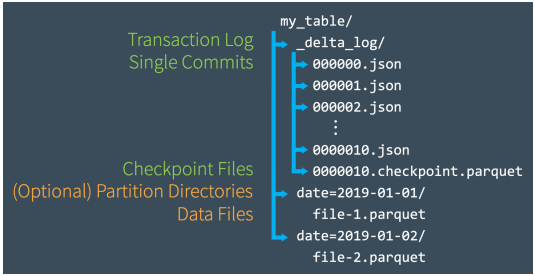

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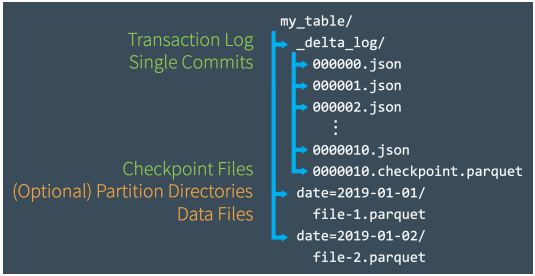

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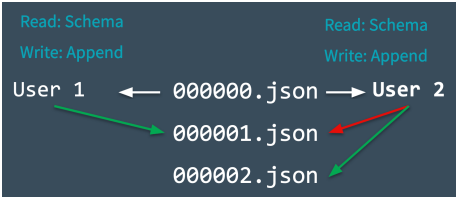

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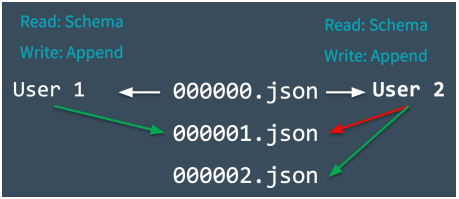

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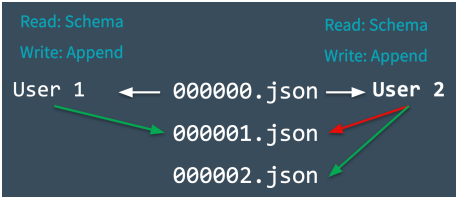

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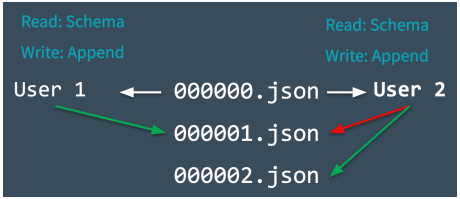

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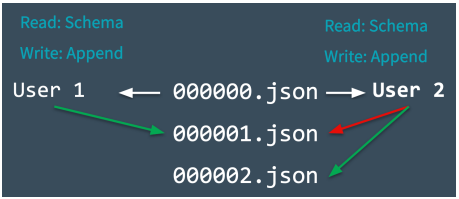

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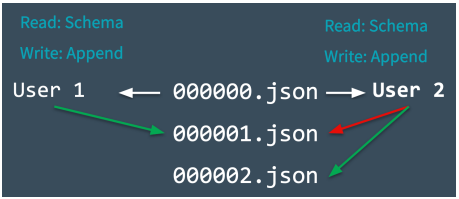

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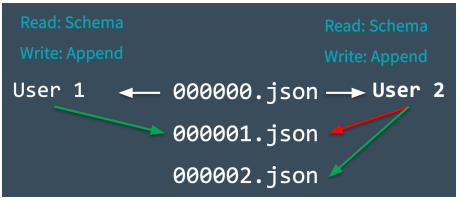

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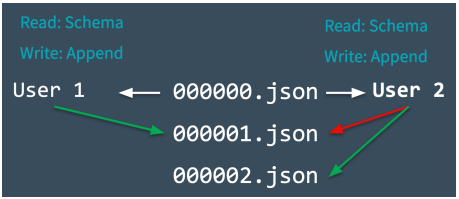

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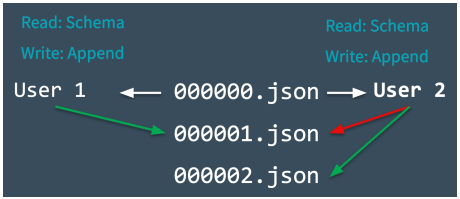

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- This ability is known as time travel or data versioning.

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- 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.

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

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- The schema enforcement will raise an exception and prevent the write operation from taking place.

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- Spark can be used in case sensitive or insensitive (default) mode.
- Parquet is case sensitive when storing and returning column information.
- Delta Lake is case-preserving, but insensitive when storing the schema.

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- Also can use `spark.databricks.delta.schema.autoMerge = True` to Spark configuration.
- Use with caution, as schema enforcement will no longer warn you about unintended schema mismatches.

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- The following types of schema changes are eligible:
  - Adding new columns (this is the most common scenario).
  - Changing of data types from non-nullable to nullable.
  - Upcasts from ByteType $\rightarrow$ ShortType $\rightarrow$ IntegerType.

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- Typically when overwriting.
- The following types of schema changes are eligible:
  - Dropping a column.
  - Changing an existing column's data type (in place).
  - Renaming column names that differ only by case (e.g., Foo and foo).

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’’)`.

```
// 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

- You can modify your existing Structured Streaming jobs to write to and read from a Delta Lake table by setting the format to ‘‘delta’’.

```
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).
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// org.apache.spark.sql.AnalysisException: A schema mismatch detected when writing
// to the Delta table (Table ID: 48bfa949-5a09-49ce-96cb-34090ab7d695).
```

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)
```

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  2. Copy all of the rows that are affected into a DataFrame, then perform the data modification.
  3. Insert the previously noted DataFrame's rows into the new table.
  4. Remove the old table and rename the new table to the old table name.

Transforming Existing Data - Updating Data (2/2)

- In Spark 3.0 and Delta Lake, you can simply run the `update` command instead.

```
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

- With data protection policies like the EU's General Data Protection Regulation (GDPR) coming into force, it is more important now than ever to be able to delete user data from all tables.

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

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

Transforming Existing Data - Upserting Data to a Table

- Replicating row changes made in an table to another table.
- Assume, we have another table of new loan information, some of which are new loans and others of which are updates to existing loans.
- Also, assume this changes table has the same schema as the `loan_delta` table.

```
deltaTable.alias("t")
    .merge(loanUpdates.alias("s"), "t.loan_id = s.loan_id")
    .whenMatched.updateAll()
    .whenNotMatched.insertAll()
    .execute()
```

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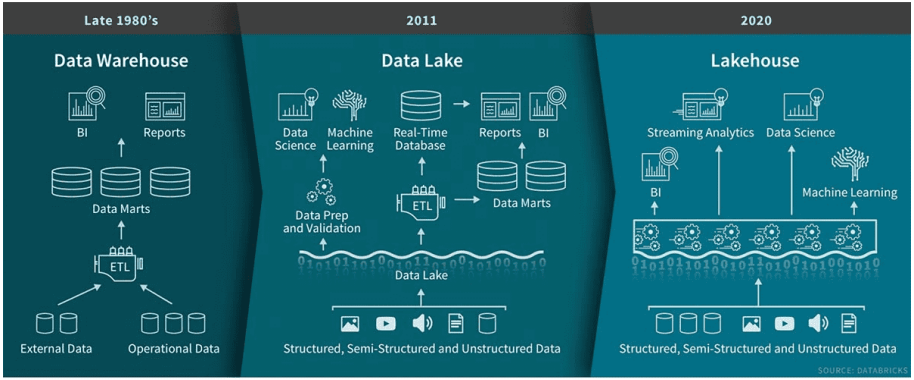
Late 1980's
Data Warehouse
BI
Reports
Data Marts
ETL
External Data
Operational Data
2011
Data Lake
Data Science
Machine Learning
Real-Time Database
Reports
BI
Data Prep and Validation
ETL
Data Marts
Data Lake
Structured, Semi-Structured and Unstructured Data
2020
Lakehouse
Streaming Analytics
Data Science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

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Questions?

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