The **Data Lakehouse** for Simpler, Faster and More Integrated Data Analysis and Data Science

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DSPT Webinar

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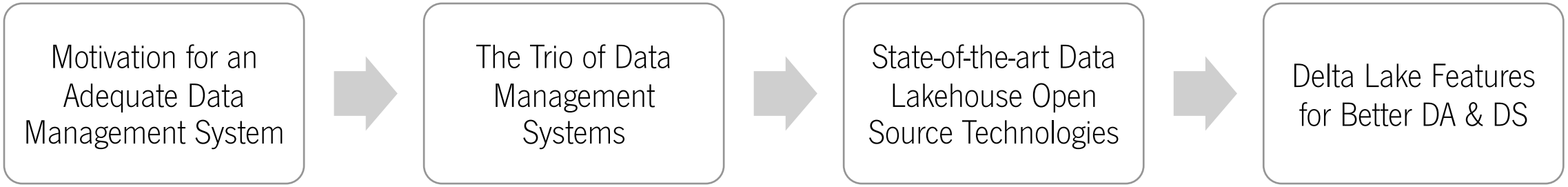
Agenda

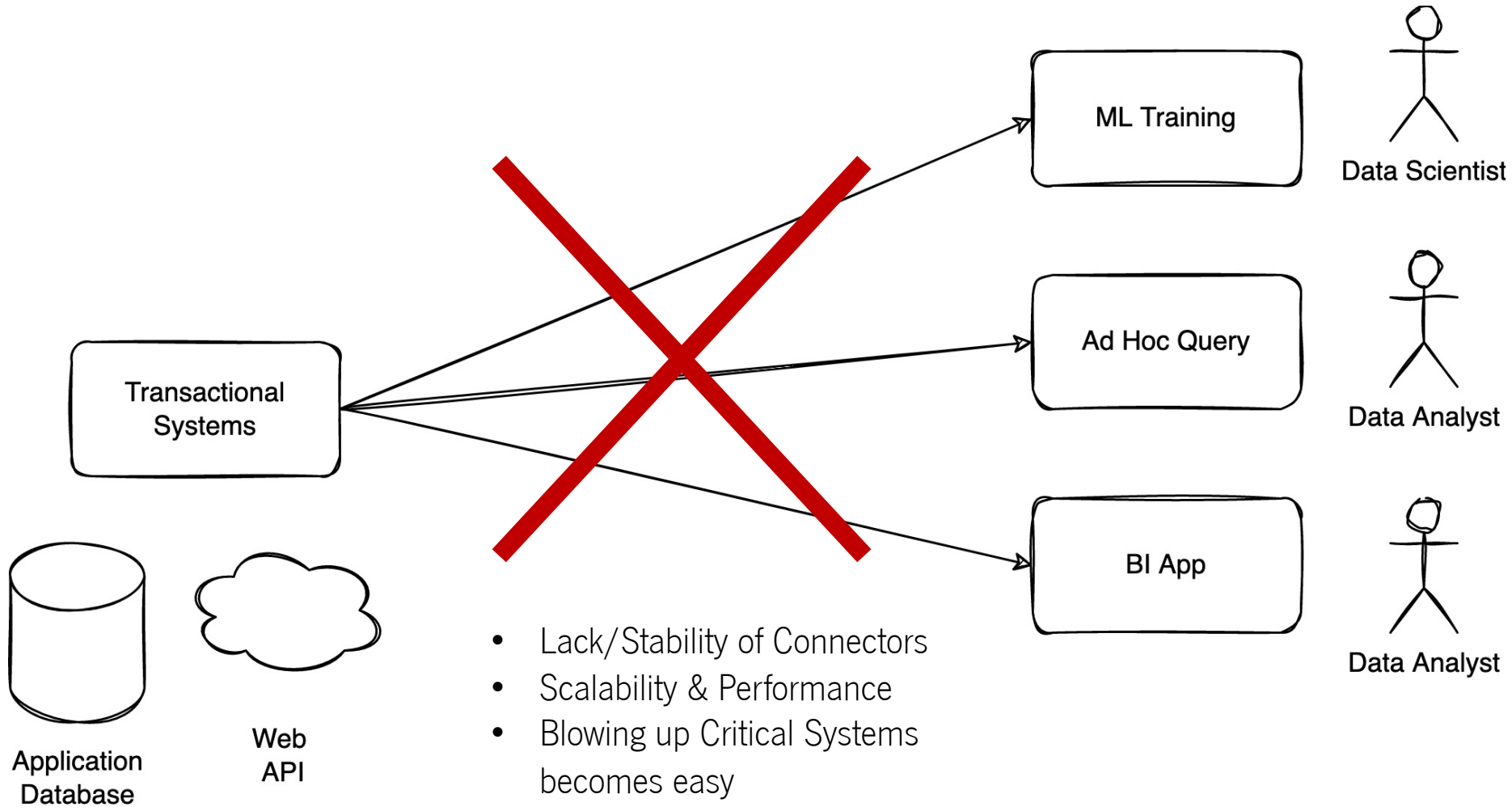

Motivation for an Adequate Data Management System
The Trio of Data Management Systems
State-of-the-art Data Lakehouse Open Source Technologies
Delta Lake Features for Better DA & DS

Disclaimer

These are my opinions and interpretations of the state of the art… does not mean I'm wrong or right! Use it as food for though… or ammo for discussion :P

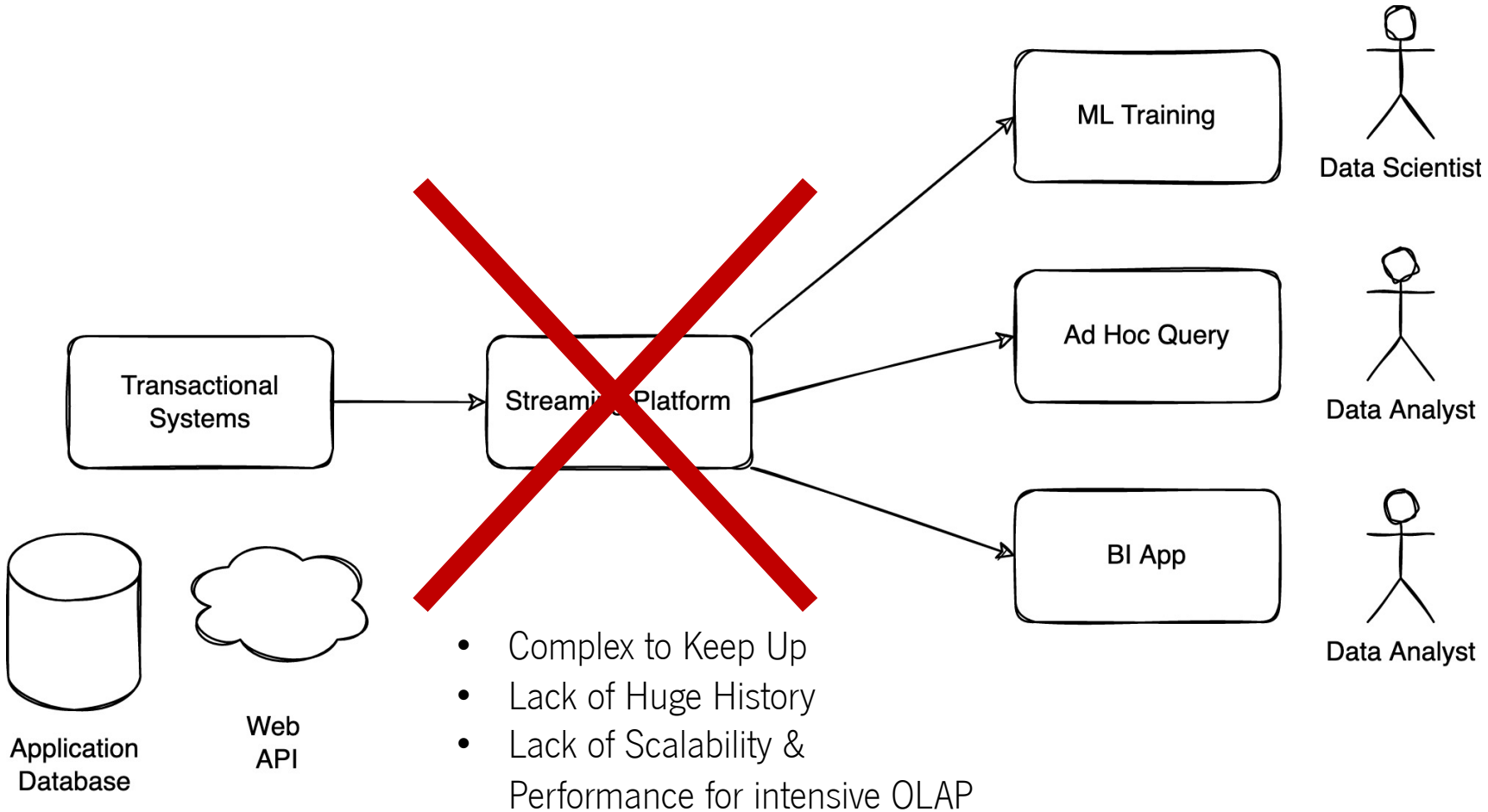
Motivation for an Adequate Data Management System

”Give me access to the Source” Pattern



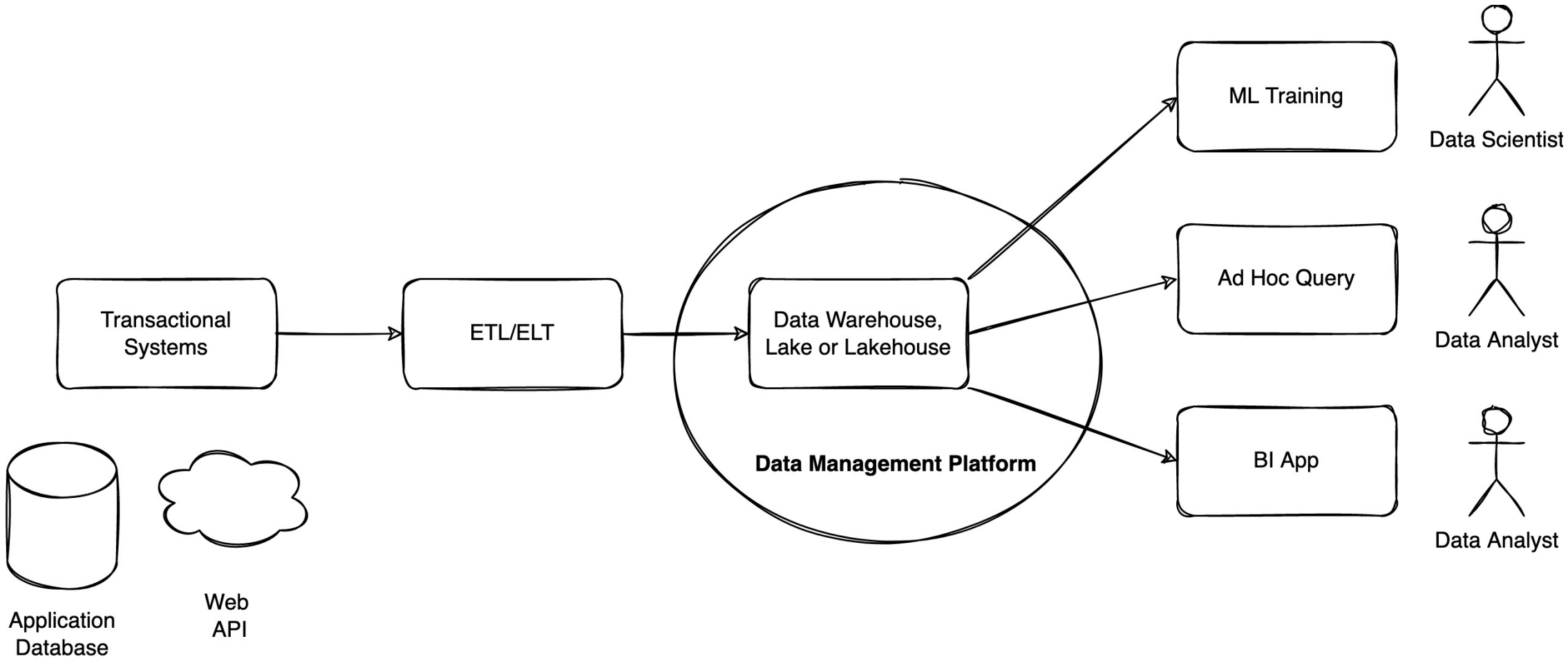
- Lack/Stability of Connectors
- Scalability & Performance
- Blowing up Critical Systems becomes easy

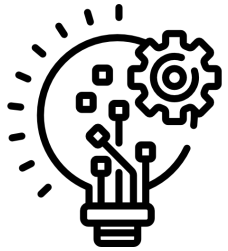
The “Streaming, Streaming, Streaming!!!” Pattern



- Complex to Keep Up
- Lack of Huge History
- Lack of Scalability & Performance for intensive OLAP

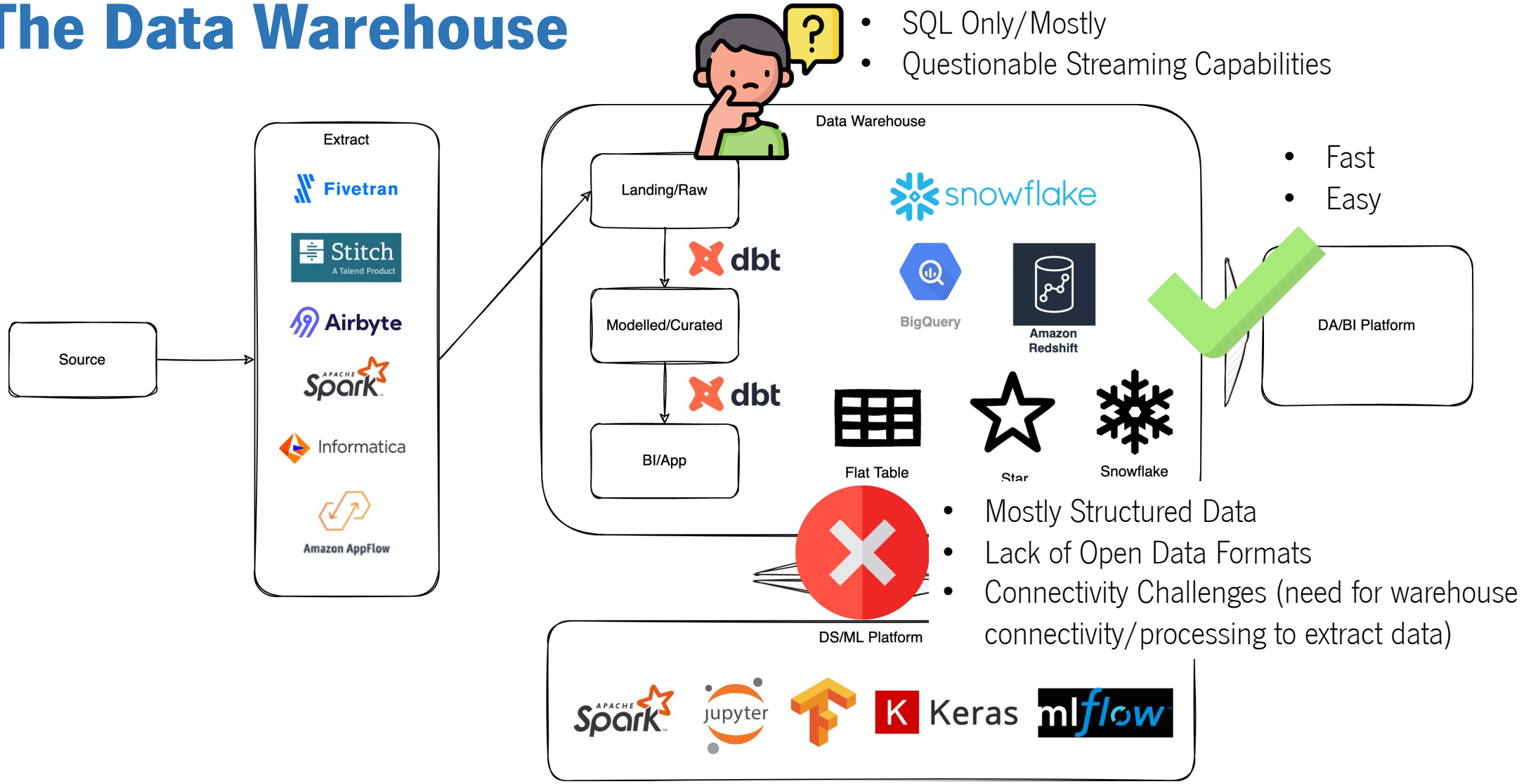
The Data Management Platform





The Trio of Data Management Platforms

The Data Warehouse



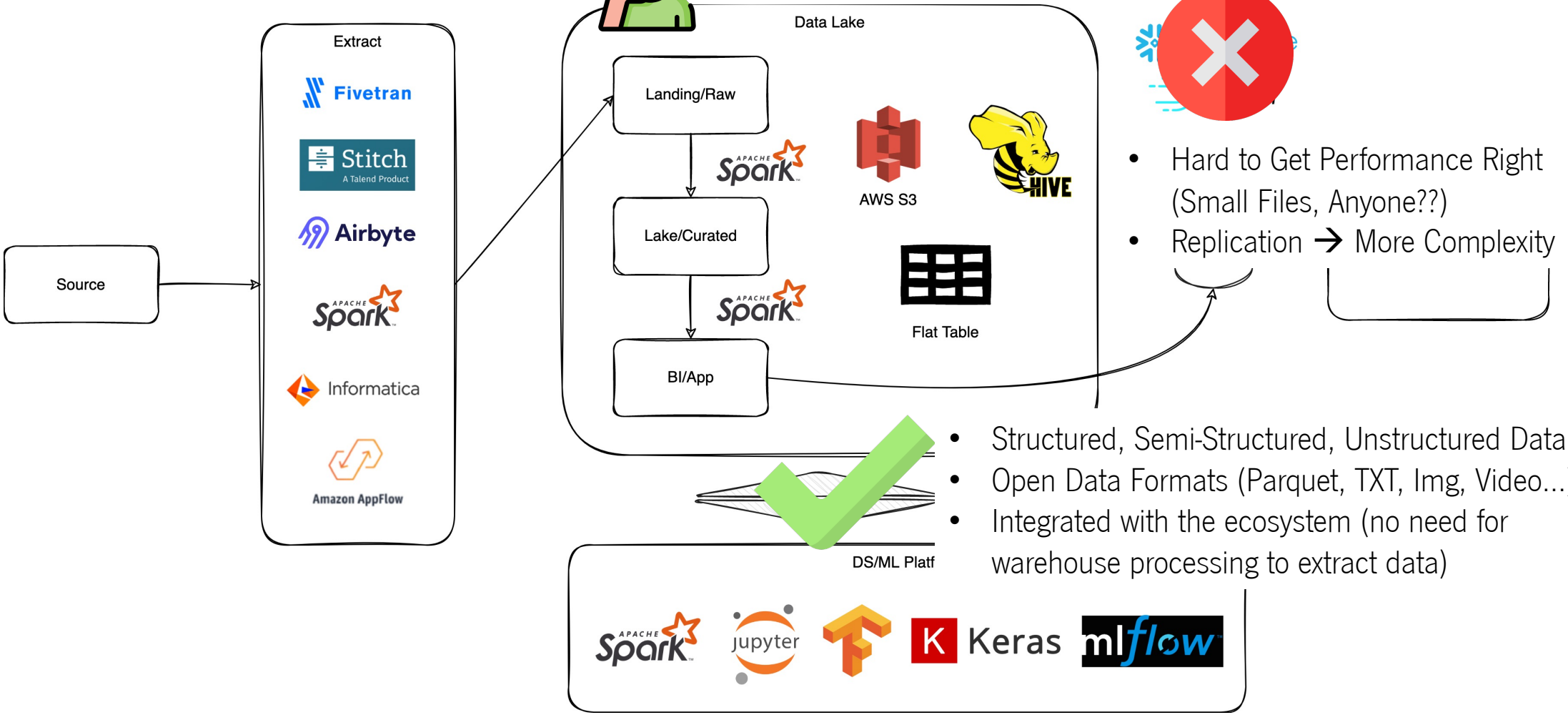
- SQL Only/Mostly
- Questionable Streaming Capabilities

- Fast
- Easy

- Mostly Structured Data
- Lack of Open Data Formats
- Connectivity Challenges (need for warehouse connectivity/processing to extract data)

The Data Lake

- Good to have Python, Scala, Java, SQL, but...
- Lack of ACID Transactions
- Lack of proper Schema Mngmt & DML

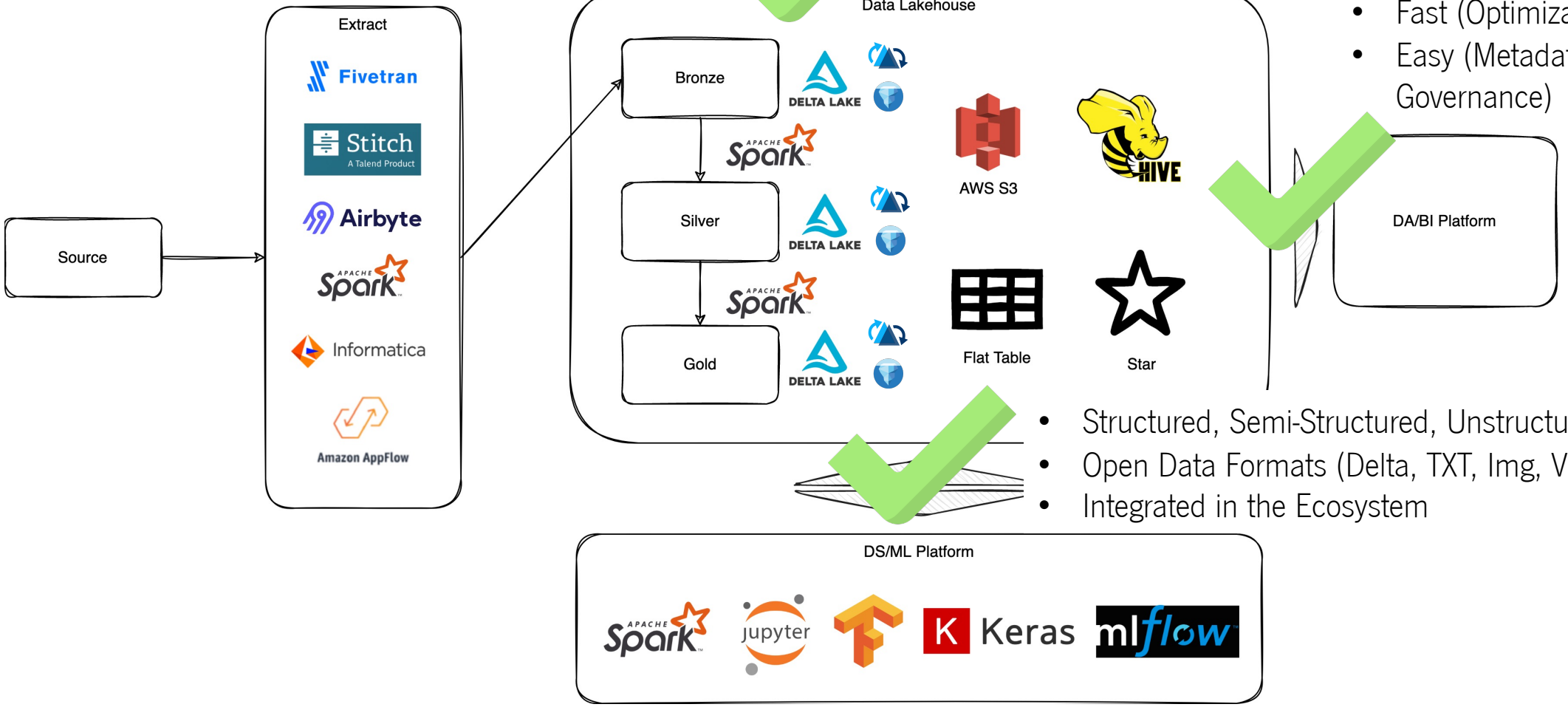


- Hard to Get Performance Right (Small Files, Anyone??)
- Replication → More Complexity

- Structured, Semi-Structured, Unstructured Data
- Open Data Formats (Parquet, TXT, Img, Video...)
- Integrated with the ecosystem (no need for warehouse processing to extract data)

The Data Lakehouse

- Python, Scala, Java, SQL...
- ACID Transactions
- Proper Schema Mngmt & DML

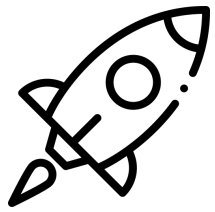


- Fast (Optimizations)
- Easy (Metadata & Governance)

- Structured, Semi-Structured, Unstructured Data
- Open Data Formats (Delta, TXT, Img, Video...)
- Integrated in the Ecosystem

Wrapping it Up

	Data Warehouse	*Data Lake*	*Data Lakehouse*
The Good	• BI/OLAP Speed • Easiness of Management and Access	• Handling All Volumes, Varieties and Velocities of Data • Several Programming Languages • Good Data Science Integration	• All the Benefits of the Data Warehouse and Data Lakehouse
The Bad	• Unstructured Data Handling • Streaming Capabilities are Questionable • SQL Only/Mostly	• Lack of ACID • Lack of proper DML • Lack of proper Schema Mngmt.	• *(Not so bad)* Performance is influenced by the querying processing technology (e.g., Spark, Presto, etc....)
The Ugly	• An "Alien" to the Data Science Ecosystem	• Replication into BI/OLAP oriented Stores (e.g., DW) • Complexity of the Replication	• ???



State-of-the-art Data Lakehouse Open-Source Technologies

- Open-Sourced by **Uber**
- *"Hadoop Upserts Deletes and Incrementals"*
- "Hudi brings transactions, record-level updates/deletes and change streams to data lakes"
- *Can use Parquet underneath*
- https://hudi.apache.org

- Open-Sourced by **Netflix**
- *"The open table format for analytic datasets"*
- "Iceberg is a high-performance format for huge analytic tables. Iceberg brings the reliability and simplicity of SQL tables to big data..."
- *Can use Parquet underneath*
- https://iceberg.apache.org

- Open-Sourced by **Databricks**
- *"Build Lakehouses with Delta Lake"*
- *"Delta Lake is an open-source storage framework that enables building a Lakehouse architecture with compute engines..."*
- *Parquet only underneath*
- https://delta.io

Delta Lake Features For Better DA & DS

ACID Transactions

- Readers see a consistent snapshot view of the data since the start of the query…
  - Even if the table was modified since then
- Multiple Writers can write to the same table partition concurrently and:
  - Always see a consistent snapshot view of the data
  - A serial order for these writes is ensured (isolation)
- General Steps:
  - Read latest state of the table to identify the files that need to be modified
  - Stage the new files to write
  - Validate if there are no conflicts and commit.

my_table/

_delta_log/

000000.json — *Add 2.parquet*

000001.json — *Remove 1.parquet*

…

000010.checkpoint.parquet

sales_date=2022-04-18/

sales_date=2022-04-19/

sales_date=2022-04-20/

Sources:
https://docs.delta.io/latest/concurrency-control.html
https://databricks.com/blog/2019/08/21/diving-into-delta-lake-unpacking-the-transaction-log.html

Comprehensive Data Manipulation Language (DML)

```
DELETE FROM dummy_table WHERE date < ‘2022-04-25’
DELETE FROM delta.`/foo/bar` WHERE date < ‘2022-04-25’
```

```
UPDATE dummy_table SET month = ‘January' WHERE month = ‘Jan’;
```

```
MERGE INTO dummy_table
USING new_data
ON dummy_table.id = new_date.id
WHEN MATCHED THEN
   UPDATE SET dummy_table.id = new_date.id, dummy_table.firstName = new_date.firstName, ...
WHEN NOT MATCHED THEN
   INSERT (...) VALUES (...)
```

Source: https://docs.delta.io/latest/

Schema Enforcement & Evolution

Fail if schema does not match ... **OR**

```
> df.write...option("mergeSchema", "true")
```

OR (to set it across the Spark Session)

```
> spark.conf.set("spark.databricks.delta.schema.autoMerge.enabled", "true")
```

OR (for overwrites)

```
> df.write.option("overwriteSchema", "true")
```

Source: https://docs.delta.io/latest/

Constraints

NOT NULL

```
> CREATE TABLE dummy_table (
        dummy_id INT NOT NULL,
        ...
)
> ALTER TABLE table CHANGE COLUMN dummy_name DROP NOT NULL;
```

CHECK CONSTRAINTS

```
> ALTER TABLE dummy_table ADD CONSTRAINT c CHECK (date > '2022-04-25')
```

Source: https://docs.delta.io/latest/

Unified Batch & Streaming

Read the Stream

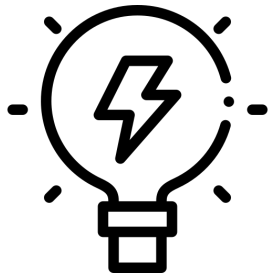
```
events = spark.readStream.format("delta").load("/foo/bar")
```

Transform

…

Write the Stream

```
events
  .writeStream
  .format("delta")
  .outputMode("append")
  .option("checkpointLocation", "/.../_checkpoints/...")
  .toTable(”table")
```



Tip of the day!

Batch = Streaming

```
.trigger(Trigger.Once())
```

Source: https://docs.delta.io/latest/

Audit History

```
DESCRIBE HISTORY delta.'/foo/bar/' -- full history
DESCRIBE HISTORY '/data/events/' LIMIT 1 -- last version only
DESCRIBE HISTORY eventsTable -- use table name
```

OR

```
from delta.tables import *
delta_table = DeltaTable.forPath(spark, '/foo/bar')
all_history_df = deltaTable.history()
last_version_df = deltaTable.history(1)
```

***Git Log* for your Data!**

```
+-------+-------------------+------+--------+---------+--------------------+----+--------+--------------------+
|version|          timestamp|userId|userName|operation| operationParameters| job|clusterId|operationMetrics    |
+-------+-------------------+------+--------+---------+--------------------+----+--------+--------------------+
|      5|2019-07-29 14:07:47|  null|    null|   DELETE|[predicate -> ["(...|null|    null| [numTotalRows -> ...|
|      4|2019-07-29 14:07:41|  null|    null|   UPDATE|[predicate -> (id...|null|    null| [numTotalRows -> ...|
|      3|2019-07-29 14:07:29|  null|    null|   DELETE|[predicate -> ["(...|null|    null| [numTotalRows -> ...|
|      2|2019-07-29 14:06:56|  null|    null|   UPDATE|[predicate -> (id...|null|    null| [numTotalRows -> ...|
|      1|2019-07-29 14:04:31|  null|    null|   DELETE|[predicate -> ["(...|null|    null| [numTotalRows -> ...|
```

Source: https://docs.delta.io/latest/

Time Travel

```
df1 = spark.read.format("delta").option("timestampAsOf", timestamp_string)...
df2 = spark.read.format("delta").option("versionAsOf", version)...
```

Use it for Fixing Problems (re-insert deleted user events)

```
df = spark.read.format("delta") \
  .option("timestampAsOf", yesterday) \
  .load("/foo/bar") \

df.where("user = 'dummy_user'") \
  .write.format("delta") \
  .mode("append") \
  .save("/foo/bar")
```

***Git Reset* for your Data!**

Source: https://docs.delta.io/latest/

Time Travel for Analytics

```
df = spark.read.format("delta”) \
  .option("timestampAsOf", last_week) \
  .load("/foo/bar”)

last_week_count = df.select(”user") \
  .distinct() \
  .count()

count = spark.read.format("delta") \
  .load("/foo/bar”) \
  .select(”user") \
  .distinct() \
  .count()

new_customers_count = count - last_week_count
```

Feature Store

(Customer, Product, Product Images Metadata, Stores...)

Reproducible Experiments

Read Changes

between 2 versions with ***Except***

Source: https://docs.delta.io/latest/

Compactation & Other Optimizations

Optimize the layout of data (compact small files into larger ones)

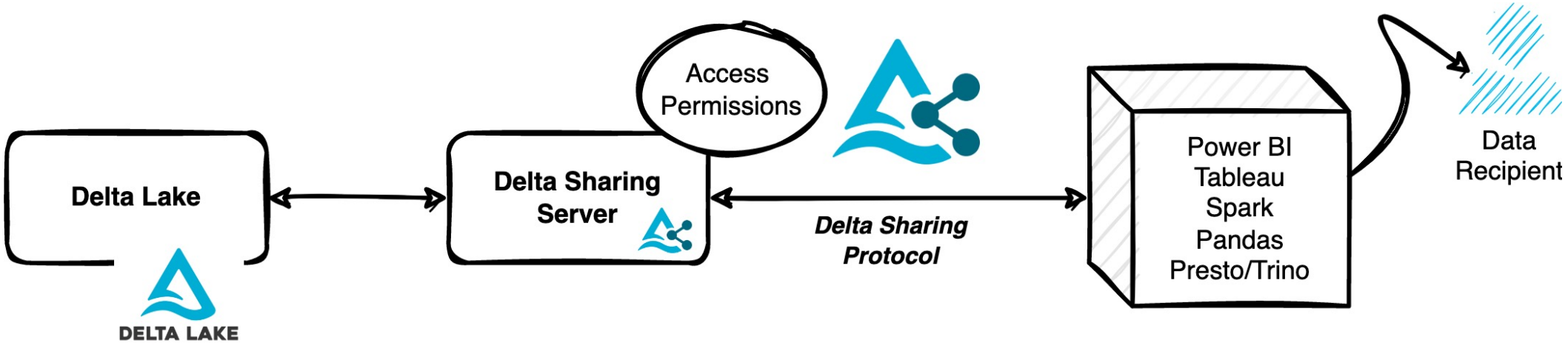
```
OPTIMIZE table
OPTIMIZE delta.`/foo/bar`

-- only optimize a subset of the table
OPTIMIZE table WHERE date >= '2022-04-25'
```

Data Skipping

- Used at query time to **skip unnecessary data**
- **Min** and **Max** values for each column **collected automatically** when writing
  - for *x* configurable number of columns
- Best Performance when used in combination with **"ordering before writing" pattern**

Source: https://docs.delta.io/latest/

Delta Sharing



> spark.read.format("deltaSharing").load(table_path)

> delta_sharing.load_as_pandas(...)

Source: https://delta.io/sharing/

Thank You!

Ask me anything ☺

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