Engineering challenges of a data lake

by Nicola Orecchini, 19/07/2025

Agenda

- A data lake architecture
- Storage layer
  - Data Layout
- Pipeline
  - Writing algorithms
- Engineering challenges
  - Late Arriving Data
  - Accumulated Data
- Takeaways
- Annex

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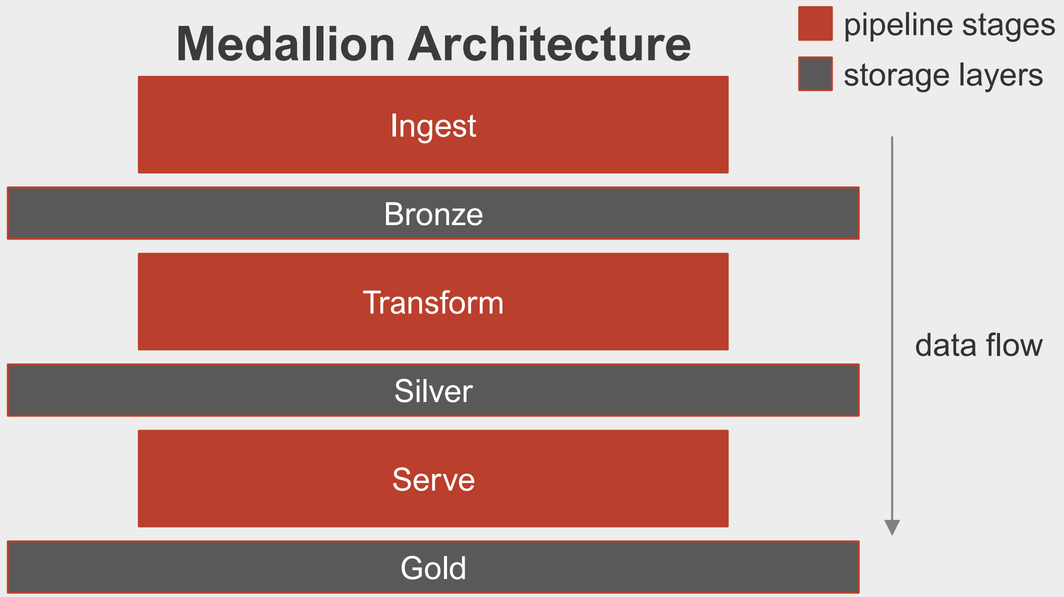
The medallion architecture is a way to decompose the old 'monolithic ETL script' model in a layered, modular approach

Traditional ETL pipeline

```
--Extract and transform sales data for reporting
WITH
raw_sales AS (SELECT…
FROM …
WHERE …),
enriched_sales AS (SELECT…
FROM …
LEFT JOIN … ON …
WHERE …),
--Final select (used for reporting)
SELECT…
FROM aggregated_sales a
LEFT JOIN region_mapping r
ON …
WHERE…
ORDER BY …;
```

- A single **monolithic** SQL script or notebook
- Filled with **nested subqueries** and **views**
- Hard to debug, test, or scale
- Everything runs in a **tight sequence**, one giant transformation pipeline
- **Difficult to reuse** or reason about **intermediate steps**

Medallion Architecture



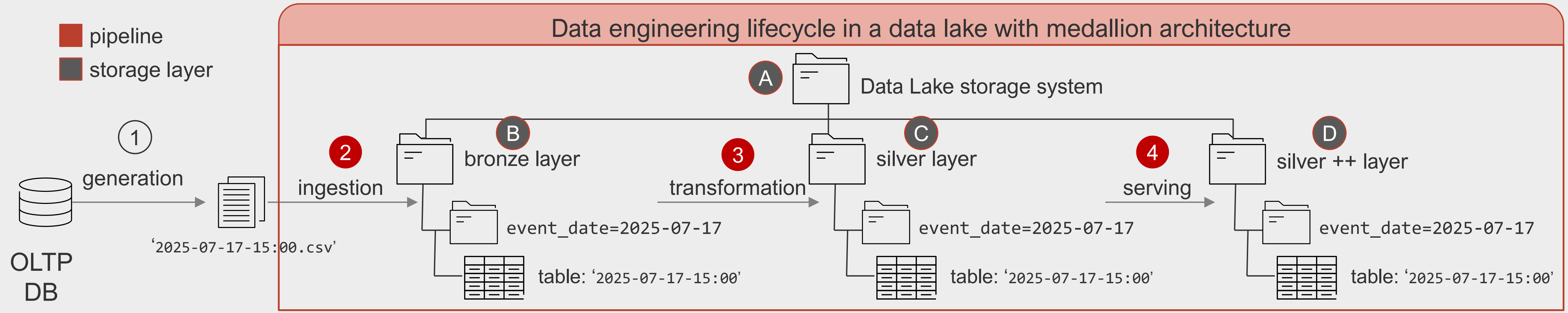
ETL is broken down into **3 standalone, idempotent processing jobs**:

1. **Ingest** → writes to bronze/
2. **Transform** → reads from bronze/, writes to silver/
3. **Serve** → reads from silver/, writes to gold/

Each stage is:

- **Modular** (can be tested and deployed separately)
- **Idempotent** (can be rerun without side effects)
- **Folder-based** (uses file/table boundaries like bronze/, silver/)
- **Decoupled** (can run independently or be orchestrated in parallel/asynchronously)

Building a data lake with a medallion architecture means implementing a **pipeline** & designing the **storage layer**



1. An operational system produces data in the form of `csv` files (illustrative)

2. First thing first: you copy the received data as they are into a local staging area, the "bronze layer", without applying any transformation to them

3. You apply transformations to the data (e.g., data quality checks), and store the result in a "silver layer"

4. The improved version of data is now ready to be "incorporated" into a final dataset, stored in a "silver ++" level. This step is responsible of incorporating the extracted & transformed data into the existing dataset

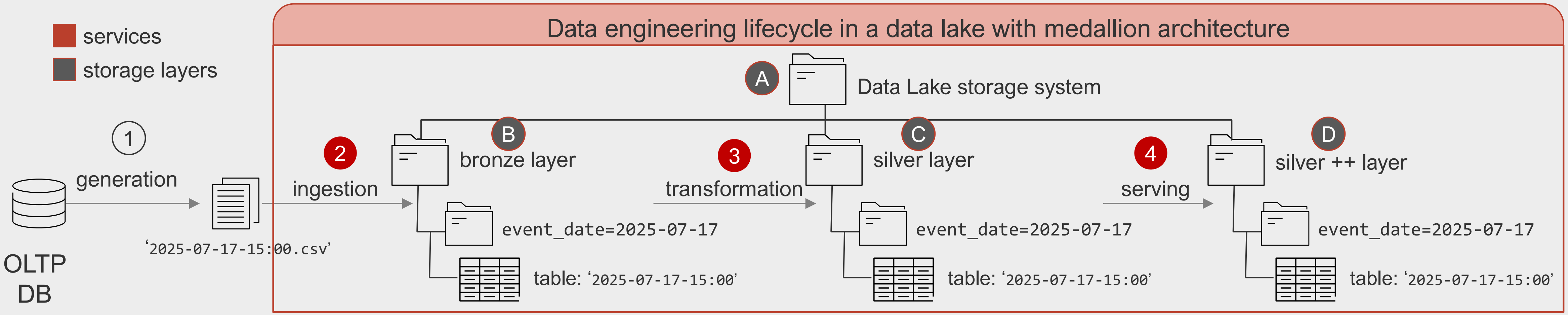
A The storage component organizes files in folders, leveraging some data layout (e.g., partitioning, liquid clustering, a mix, etc.)

B

C

D

During the design, some key considerations have shaped the architecture of the data lake



A

Data layout

- What are the **most frequent queries** that will be performed on the data?
- How to **organize data on the disk** to guarantee maximum **efficiency** of such **queries**? Partitioning? Liquid clustering?
- Do we store the complete history of data in each layer?

2

Data source type

- How will the pipeline **receive data from** the **source** systems? Will the pipeline receive snapshots of data, delta data or events? How often?
- Is it possible that the source could produce **late arriving data?**

2 3 4

Pipeline characteristics

- What are minimum **SLA** the **pipeline** must **guarantee**? (e.g., idempotency, …)
- How does **each step read input from the previous**? **Icrementally** (i.e., only new data), or **fully** (i.e., all data)? It may seem a dumb question, but if you read incrementally then you could have challenges with **late arriving data**

4

Writing algorithms

- How will we have to **write the incoming data**? Overwrite the existing dataset? Maintain history?

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When you have a large dataset stored on disk as a single Parquet file, filtering it can be costly

```sql
SELECT *
FROM orders
WHERE 2025-07-18 <= date <= 2025-07-19
```

orders

Order ID	Item	Date
1001	T-shirt	2025-07-15
1002	Coffee Mug	2025-07-16
1003	Laptop Case	2025-07-16
1004	Notebook	2025-07-17
1005	Water Bottle	2025-07-18
1006	Headphones	2025-07-19
1007	Phone Stand	2025-07-20

To execute this query, the Spark engine has to read the entire orders table, as it doesn't know where records with the requested *date* are

Source: https://delta.io/blog/liquid-clustering/

To solve this challenge, you need a data layout, a way to organize your data in the storage. The traditional data layout is *partitioning*[1]

Order ID	Item	Date
1001	T-shirt	2025-07-15
1002	Coffee Mug	2025-07-16
1003	Laptop Case	2025-07-16
1004	Notebook	2025-07-17
1005	Water Bottle	2025-07-18
1006	Headphones	2025-07-19
1007	Phone Stand	2025-07-20

You split your dataset into smaller chunks based on the values in a specific column (e.g., *date*)

Order ID	Item	Date
1001	T-shirt	2025-07-15

Order ID	Item	Date
1002	Coffee Mug	2025-07-16
1003	Laptop Case	2025-07-16

Order ID	Item	Date
1004	Notebook	2025-07-17

Order ID	Item	Date
1005	Water Bottle	2025-07-18

Order ID	Item	Date
1007	Phone Stand	2025-07-20

Then, you physically organize the dataset in **folders on disk**

- each chunk gets its own folder

```
spark-warehouse/order_data
    event_date=2025-07-15
        part-00001.snappy.parquet
    event_date=2025-07-16
        part-00002.snappy.parquet
        part-00003.snappy.parquet
    event_date=2025-07-17
...
```

Now, queries on the *date* column will run faster, because of **partition pruning**: Spark will read only files in relevant folders

Pros:

✓ **reduce volume of data read by queries** (partition pruning), but only if you know exactly which queries will run frequently on the dataset

✓ **optimize disk or cloud I/O**

Cons:

× **not flexible**: you need to decide which column to partition on

× if you want to **change partition column**, you have to rewrite the entire dataset

1. The word *partitioning*, in Spark, can be used with 2 different meanings. One is the one we're describing, the other refers to distributed computing. See Annex for a summary slide on this ambiguity

Source: https://delta.io/blog/liquid-clustering/

If you use partitioning, be sure to do it on a column that then you use in queries

```sql
SELECT *
FROM sales
WHERE 2025-07-18 <= event_date <= 2025-07-19
```

full dataset partitioned by `sale_rep_name`

- sale_rep_name='Jack Lemon'
- sale_rep_name='Johnson Righeira'
- sale_rep_name='Manu Chao'

To execute the above query, Spark would need to go through all files

```sql
SELECT *
FROM sales
WHERE 2025-07-18 <= event_date <= 2025-07-19
```

full dataset partitioned by `event_date`

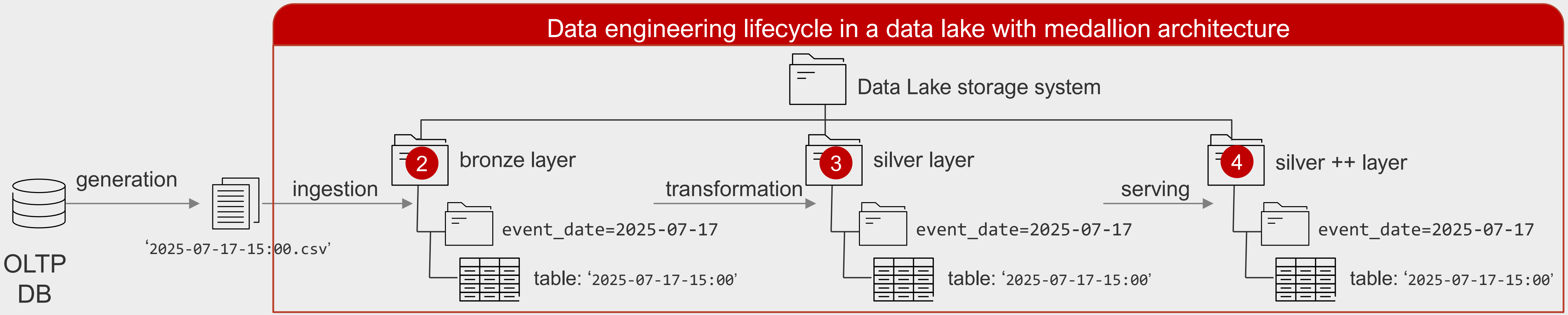
- event_date=2025-07-17
- event_date=2025-07-18
- event_date=2025-07-19

Partition pruning: Spark just looks into the relevant folders

Choose the key to partition data as the key that will be most frequently used in queries

An alternative to partitioning is Liquid Clustering

For our pipeline, the best data layout was selected for each layer of the medallion architecture



2

Bronze layer

The data stored in the bronze layer will be the input for the *transformation* phase. And what does this phase do? In few words,

3

Silver layer

The data stored in the bronze layer will be the input for the *transformation* phase. And what does this phase do? In few words,

4

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In any ETL pipeline, there is a point where you have to combine new incoming data into an existing dataset

`new incoming data`

Order ID	Item	Date
1001	T-shirt	2025-07-15
1002	Coffee Mug	2025-07-16
1003	Laptop Case	2025-07-16
1004	Notebook	2025-07-17
1005	Water Bottle	2025-07-18
1006	Headphones	2025-07-19
1007	Phone Stand	2025-07-20

`existing dataset`

Order ID	Item	Date
1001	T-shirt	2025-07-15
1002	Coffee Mug	2025-07-16
1003	Laptop Case	2025-07-16
1004	Notebook	2025-07-17
1005	Water Bottle	2025-07-18

There are multiple ways of doing it: Full vs Incremental

- new data
- old data
- inactive data

Full

Discard the current destination table and create a new one from the entire new incoming data

Incremental

Insert only a subset of incoming data into the destination table, while leaving the rest untouched.
There are many possibilities, and we report 3 of the most used

Full refresh

`new incoming`

ID	Value	Date
1	F	02-07-25
2	G	02-07-25
3	H	02-07-25
4	I	02-07-25
5	L	02-07-25

`destination`

ID	Value	Date
1	A	01-07-25
2	B	01-07-25
3	C	01-07-25
4	D	01-07-25
5	E	01-07-25

`updated destination`

ID	Value	Date
1	F	02-07-25
2	G	02-07-25
3	H	02-07-25
4	I	02-07-25
5	L	02-07-25

Overwrites the entire dataset:

1. discard all records in `destination`
2. insert in `destination` all records coming from `new incoming`

Warning: rebuilding the whole table can take time and cost more money. However, if the table is not large the operation can be still affordable (a few million rows or less)

Append

`new incoming`

ID	Value	Date
1	A	01-07-25
2	B	01-07-25
3	C	01-07-25
4	D	02-07-25
5	E	02-07-25
6	F	03-07-25

`destination`

ID	Value	Date
1	A	01-07-25
2	B	01-07-25
3	C	01-07-25
4	D	02-07-25

`updated destination`

ID	Value	Date
1	A	01-07-25
2	B	01-07-25
3	C	01-07-25
4	D	02-07-25
4	D	02-07-25
5	E	02-07-25
6	F	03-07-25

Insert all or some of the new incoming records into the destination table:

1. apply any filters on `updates` to **get only new records***
2. insert records from step 1 into `destination`

Warning: depending on the filters applied in step 1, `destination could` have duplicates (e.g., id=4 in the example is duplicated, because in step 1 the filter was something like `where date >= 02-07-25`)

Upsert

`new incoming`

ID	Value1	Value2
2	new	new
3	new	new
99	x	y

`destination`

ID	Value1	Value2
1	old	old
2	old	old
3	old	old

`updated destination`

ID	Value1	Value2
1	old	old
2	new	new
3	new	new
99	x	y

Solves the problem of duplicate records of Append. If the unique key already exists in the destination table, updates the record; if the records don't exist, inserts them:

1. apply any filters on updates to **get only new & updated records***
2. get updated records ids: ids that are both in `new incoming` and in `destination`
3. get new record ids: ids of step 1 – ids of step 2
4. update records from step 2 and insert records from step 3

Slowly Changing Dimension

`new incoming`

ID	Key	Start
2	X	2025
3	Y	2025
99	Z	2025

`destination`

ID	Key	Start	End	Active
1	A	2020	2999	Y
2	B	2020	2999	Y
3	C	2020	2999	Y

`updated destination`

ID	Key	Start	End	Active
1	A	2020	2999	Y
2	B	2020	2024	N
3	C	2020	2024	N
2	X	2025	2999	Y
3	Y	2025	2999	Y
99	Z	2025	2999	Y

A mix of Append and Upsert. Here, the goal is to maintain the history. new records. The process goes on similar to Upsert, with the difference that, at step 4,

1. **new records***: rows are inserted and marked as "active"
2. changed records: old version is maintained and marked as "inactive; new version is inserted and marled as "actrive"

* see next slides to understand what we mean by "new records"
Source: https://medium.com/refined-and-refactored/dbt-incremental-choosing-the-right-strategy-p1-6113d51898ec

Here are some tested patterns you can use for each scenario

Full

```sql
--Insert Overwrite Pattern
INSERT OVERWRITE TABLE
vendite_silver
SELECT *
FROM vendite_bronze
```

All patterns guarantee idempotency

Upsert

```sql
--Merge Pattern
MERGE INTO target USING
updates
ON target.id = updates.id
WHEN MATCHED THEN UPDATE
WHEN NOT MATCHED THEN INSERT
```

```sql
--Delete-Write Pattern
DELETE FROM target
WHERE last_updated = '2025-07-
17’
INSERT INTO target
SELECT * FROM updates
WHERE last_updated >= '2025-
07-17'
```

Slowly Changing Dimension

```sql
--SCD Type 2 Pattern
MERGE INTO dim_clienti AS
target
USING updates
ON target.cod_fisc =
updates.cod_fisc AND
target.fine_validità = ‘2999-
12-31’

WHEN MATCHED AND
target.indirizzo <>
updates.indirizzo THEN
    UPDATE SET fine_validità =
current_date()

WHEN NOT MATCHED THEN
    INSERT (cod_fis, ind,
iniz_val, fine_val)
    VALUES (...)
```

When you use Upsert or SCD, you need to define what «new records» are

In the example patterns, we just put a dummy date for the sake of simplicity. In reality, you need to calculate this date from your existing dataset

There are multiple ways:

- selecting the max date of your existing dataset
- selecting mthe max date of the new incoming dataset
- selecting the timestamp at which the pipeline is running

Selecting the best way depends of course on the business logic you want to accomplish, as well as what guarantees you want to give your pipeline. But we will discuss the latter later on

```
--Delete-Write Pattern
DELETE FROM target
WHERE last_updated = SELECT(
    MAX(last_updated)
    FROM target)
INSERT INTO target
SELECT * FROM updates
WHERE last_updated >= SELECT(
    MAX(last_updated)
    FROM target)
```

When you use Upsert or SCD, a deduplication algorithm must be implemented

Both Upsert and SCD algorithms work with an assumption:

If the value of an existing record has changed, then there must be 1 and only 1 new version of it to replace it

Why? Because if there were 2 or more new versions, which one should the algorithm use to update the record?

new incoming

ID	Value	Start
2	X	2025
2	Y	2025
99	Z	2025

There are two records with ID 2. Which one do we need to use to replace the old value for ID 2?

destination

ID	Value	Start	End	Active
1	A	2020	2999	Y
2	B	2020	2999	Y
3	C	2020	2999	Y

So, if for whatever reason you find 2 or more "new versions" of an old record, you must set up a **deduplication algorithm** to make sure there's exactly 1 new version to feed into the upsert/SCD algorithm.

For example, the deduplication logic could be: take the most recent record, and, in case of tie, choose one randomly

Selecting the best writing algorithm: 4 factors to consider

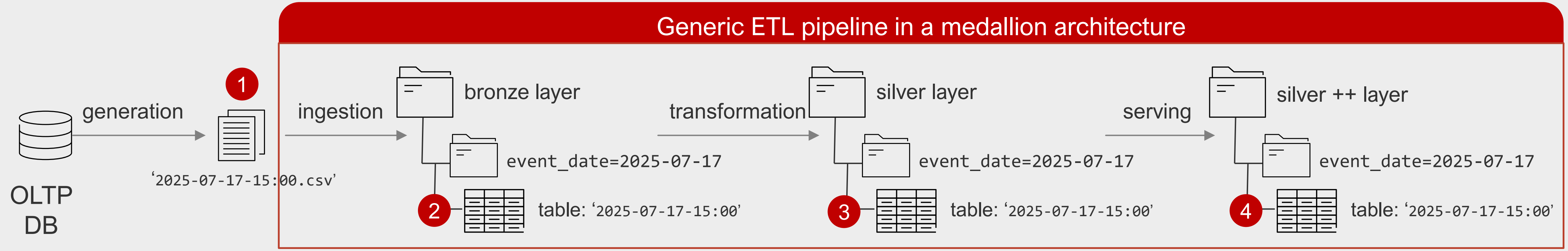
Factor	Possibilities	
Incoming dataset type	**Snapshot** You receive each time the whole dataset	**Delta** You receive each time only records generated from the last ingestion
Incoming dataset size	**Small** Few million rows	**Large** Millions/billions rows
Transformations performed on data	**Simple** Schema/format checks, nulls, deduplication	**Computationally expensive** Regex expressions, UDFs
Business requirements	**Keep history**	**Discard history**

Suitable writing algorithms*

- Full refresh
- Append
- Upsert
- SCD

*generally speaking. Choice of the proper algorithm always needs to be evaluated taking into account the broader context

In our pipeline, writing algorithms are implemented on the serve phase



1

Order ID	Item	Generation Time
1001	T-shirt	2025-07-15
1002	Coffee Mug	2025-07-16
1003	Laptop Case	2025-07-16
1004	Notebook	2025-07-17
1005	NULL	2025-07-17

2

Order ID	Item	Generation Time
1001	T-shirt	2025-07-15
1002	Coffee Mug	2025-07-16
1003	Laptop	2025-07-16
1004	Notebook	2025-07-17
1005	NULL	2025-07-17

3

Order ID	Item	Generation Time
1001	T-shirt	2025-07-15
1002	Coffee Mug	2025-07-16
1003	LaptopCase	2025-07-16
1004	Notebook	2025-07-17

4

Order ID	Item	Generation Time	Processing Time

new data   old data

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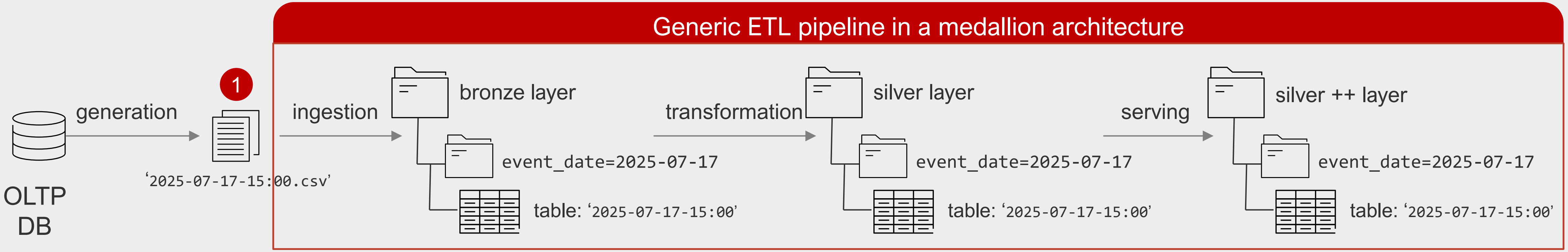
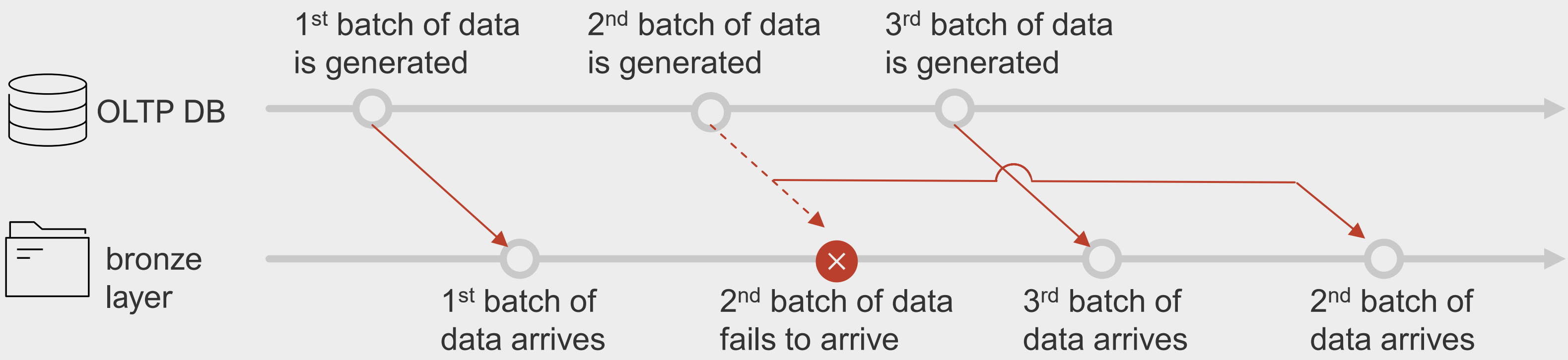
Sometimes the source system can play tricks



1 Due to **network latency** or **instability**, the 2nd batch of data arrives at the ingestion folder later than expected, after the 3rd batch has already arrived

This isn't necessarily a problem, but in some situations it can be. If for example the pipeline is designed to run once a day, this could potentially cause misalignment



How does the pipeline handle late arriving data?

incoming | existing | upsert (simplified) | existing updated

01/07

incoming

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01

existing

Order ID	Item	Date

Date to filter calculated as:
SELECT MAX(Date) FROM existing

upsert (simplified)

```
INSERT INTO existing
SELECT * FROM incoming
WHERE date > '2025-07-01'
```

existing updated

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01

02/07

existing

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01

upsert (simplified)

```
INSERT INTO existing
SELECT * FROM incoming
WHERE date > '2025-07-01'
```

existing updated

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01

03/07

incoming

Order ID	Item	Date
1003	Laptop Case	2025-07-03
1004	Notebook	2025-07-03

existing

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01

upsert (simplified)

```
INSERT INTO existing
SELECT * FROM incoming
WHERE date > '2025-07-01'
```

existing updated

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01
1003	Laptop Case	2025-07-03
1004	Notebook	2025-07-03

04/07

incoming

Order ID	Item	Date
1005	Kettlebell	2025-07-02
1006	Headphones	2025-07-02
1007	Phone Stand	2025-07-04

Records from 07-02 are late arriving data

existing

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01
1003	Laptop Case	2025-07-03
1004	Notebook	2025-07-03

upsert (simplified)

```
INSERT INTO existing
SELECT * FROM incoming
WHERE date > '2025-07-03'
```

The most recent date in existing is 07-03, so the query filters incoming > 07-03

existing updated

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01
1003	Laptop Case	2025-07-03
1004	Notebook	2025-07-03
1007	Phone Stand	2025-07-04

Records from 07-02 are missing!

Solution: filter on *Tech Date*, the date the file arrives in pipeline

01/07

incoming

ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01

existing

ID	Item	Bus Date	Tech Date

Date to filter calculated as:
SELECT MAX(Tech Date) FROM existing

upsert (simplified)

```
INSERT INTO existing
SELECT * FROM incoming
WHERE tech_date > '2025-
07-01'
```

existing updated

ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01

02/07

existing

ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01

upsert (simplified)

```
INSERT INTO existing
SELECT * FROM incoming
WHERE tech_date > '2025-
07-01'
```

existing updated

ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01

03/07

incoming

ID	Item	Bus Date	Tech Date
1003		2025-07-03	2025-07-03
1004		2025-07-03	2025-07-03

existing

ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01

upsert (simplified)

```
INSERT INTO existing
SELECT * FROM incoming
WHERE tech_date > '2025-
07-01'
```

existing updated

ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01
1003		2025-07-03	2025-07-03
1004		2025-07-03	2025-07-03

04/07

incoming

ID	Item	Bus Date	Tech Date
1005		2025-07-02	2025-07-04
1006		2025-07-02	2025-07-04
1007		2025-07-04	2025-07-04

Records from 07-02 are late arriving data

existing

ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01
1003		2025-07-03	2025-07-03
1004		2025-07-03	2025-07-03

upsert (simplified)

```
INSERT INTO existing
SELECT * FROM incoming
WHERE tech_date > '2025-
07-03'
```

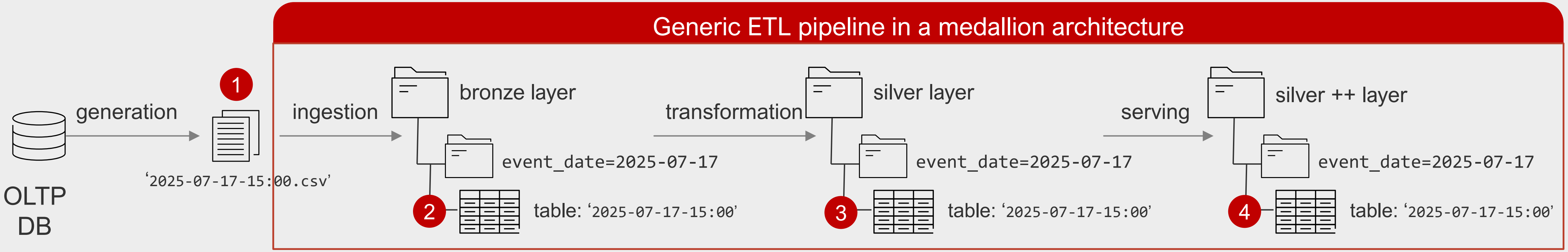
The most recent Tech Date in existing is 07-03, so the query filters incoming with Tech Date > 07-03

existing updated

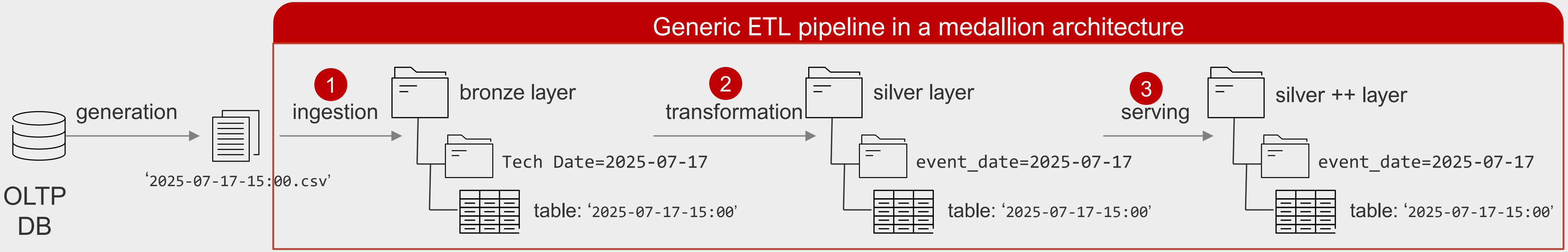
ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01
1003		2025-07-03	2025-07-03
1004		2025-07-03	2025-07-03
1005		2025-07-02	2025-07-04
1006		2025-07-02	2025-07-04
1007		2025-07-04	2025-07-04

Records from 07-02 are now present

In our pipeline, late arriving data can only affect the ingest phase, as it's the only that takes data from the source



This has an impact on the architecture: data must be partitioned by *Tech Date*



1

```sql
SELECT * FROM
landing_layer
WHERE date > '2025-07-01'
```

2

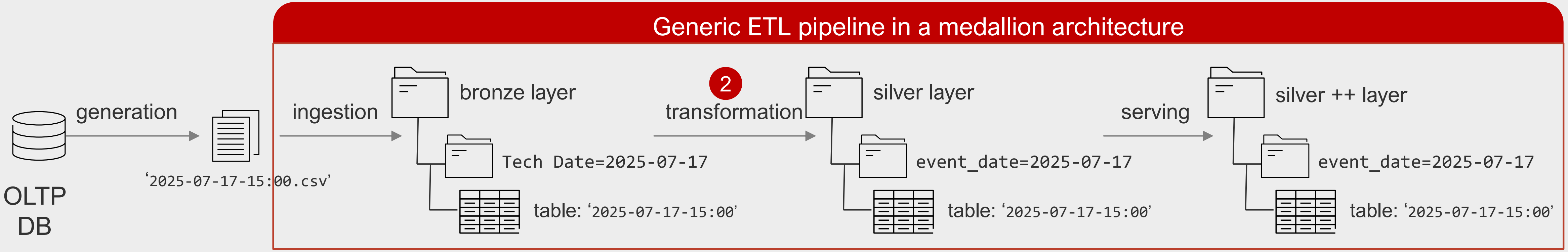
```sql
SELECT * FROM
bronze_layer
WHERE date > '2025-07-01'
```

3

```sql
SELECT * FROM
silver_layer
WHERE date > '2025-07-01'
```

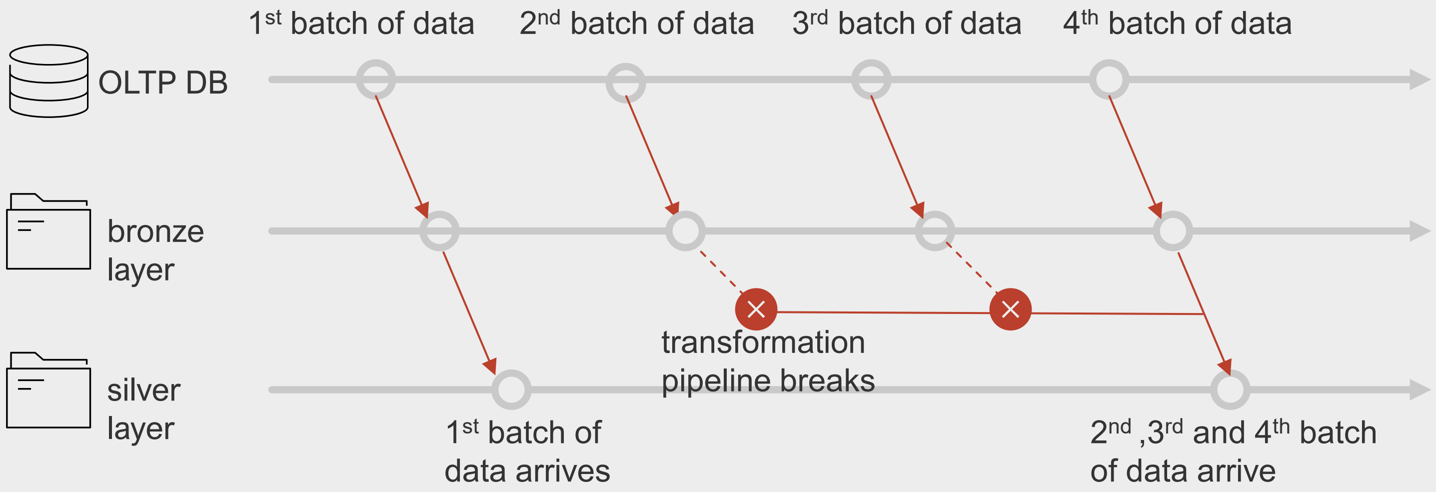
Agenda

If a step of our pipeline breaks while all the preceding continue to work, data will accumulate



2 Due to a **failure** of the **transformation step of the pipeline** (e.g., bug), the 2nd and 3rd batch of data aren't processed, and accumulate in the bronze layer. At the 4th batch, the pipeline is back again, only to find the accumulated data in the bronze layer

This isn't necessarily a problem, but in some situations it can be. If for example the pipeline is designed to run **sequentially each day**, having multiple days of data to process could cause misalignment



Imagine a step supposed to run once a day breaks. How does the step behave when it comes up again?

incoming | existing | pipeline filter step | existing updated

01/07

incoming

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01

existing

Order ID	Item	Date

Date to filter calculated as:
SELECT MAX(Date) FROM existing

pipeline filter step

```
SELECT * FROM
previous_step
WHERE date > '2025-07-01'
```

existing updated

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01

02/07

incoming

Order ID	Item	Date
1005	Kettlebell	2025-07-02
1006	Headphones	2025-07-02

Pipeline step is down

03/07

incoming

Order ID	Item	Date
1005	Kettlebell	2025-07-02
1006	Headphones	2025-07-02
1003	Laptop Case	2025-07-03
1004	Notebook	2025-07-03

Pipeline step is down

04/07

incoming

Order ID	Item	Date
1005	Kettlebell	2025-07-02
1006	Headphones	2025-07-02
1003	Laptop Case	2025-07-03
1004	Notebook	2025-07-03
1007	Phone Stand	2025-07-04

existing

Order ID	Item	Date
1001	T-shirt	2025-07-01
1002	Coffee Mug	2025-07-01

pipeline filter step

```
SELECT * FROM
previous_step
WHERE date > '2025-07-01'
```

When the step of the pipeline is up again, it will find accumulated data to process. **Can the step consider the data as one single batch and process them together?**

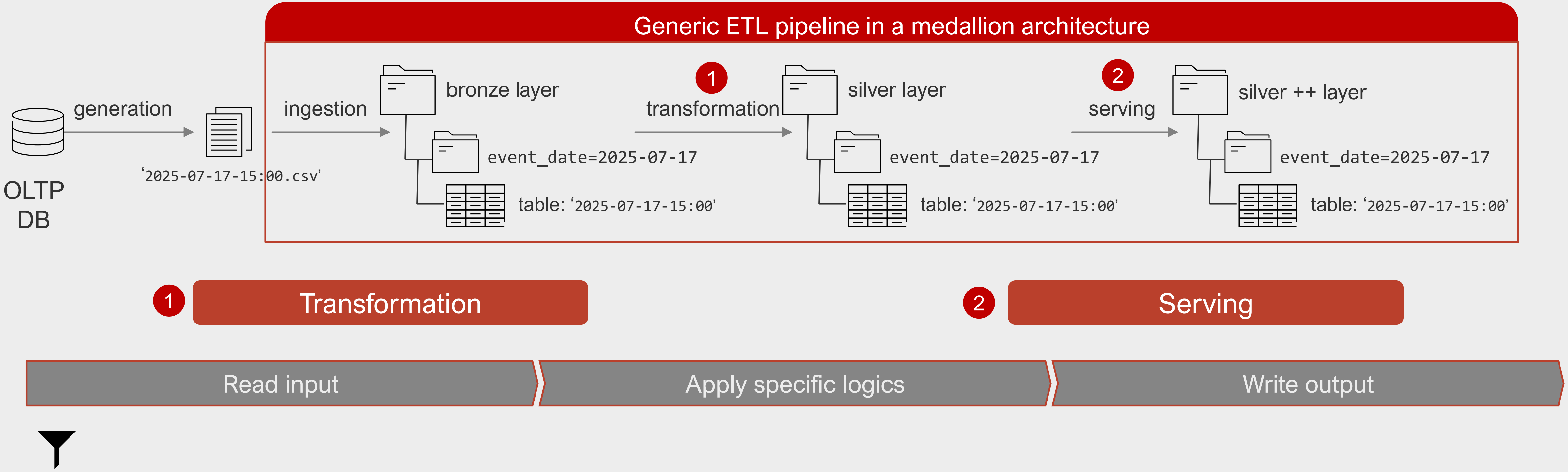
existing updated

ID	Item	Bus Date	Tech Date
1001		2025-07-01	2025-07-01
1002		2025-07-01	2025-07-01
1003		2025-07-03	2025-07-03
1004		2025-07-03	2025-07-03
1005		2025-07-02	2025-07-04
1006		2025-07-02	2025-07-04

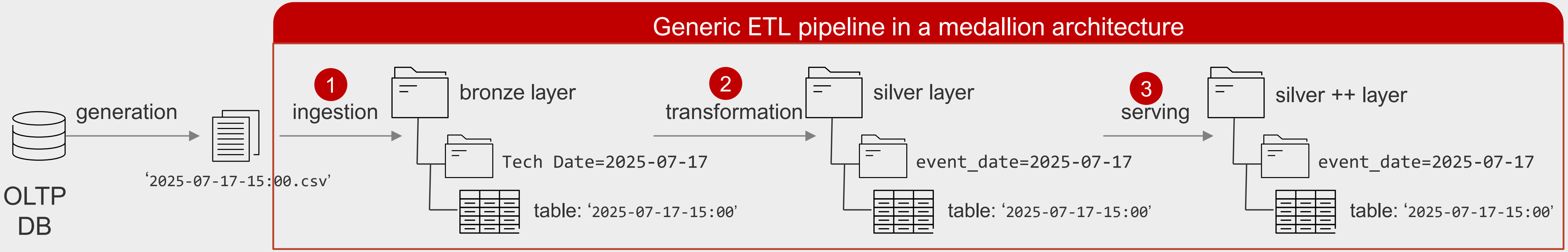
In presence of accumulated data, the pipeline must behave as if there were no interruption: process each «unit» singularly

processing units

In our pipeline, this problem can affect all steps, as they all are independent



This has an impact on the architecture: data must be partitioned by *Tech Date*



1

```sql
SELECT * FROM
landing_layer
WHERE date > '2025-07-01'
```

2

```sql
SELECT * FROM
bronze_layer
WHERE date > '2025-07-01'
```

3

```sql
SELECT * FROM
silver_layer
WHERE date > '2025-07-01'
```

Agenda

A data lake architecture

Storage layer

- Data Layout

Pipeline

- Writing algorithms

Engineering challenges

- Late Arriving Data
- Accumulated Data

Takeaways

Annex

Why stressing so much the filtering part? 2 reasons

1. The field on which you filter impacts how you partition

2. The field on which you filter impacts how you handle late arriving data

Thanks for reading

Disclaimer

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nicola.orecchini@gmail.com

Rookie Data Engineer

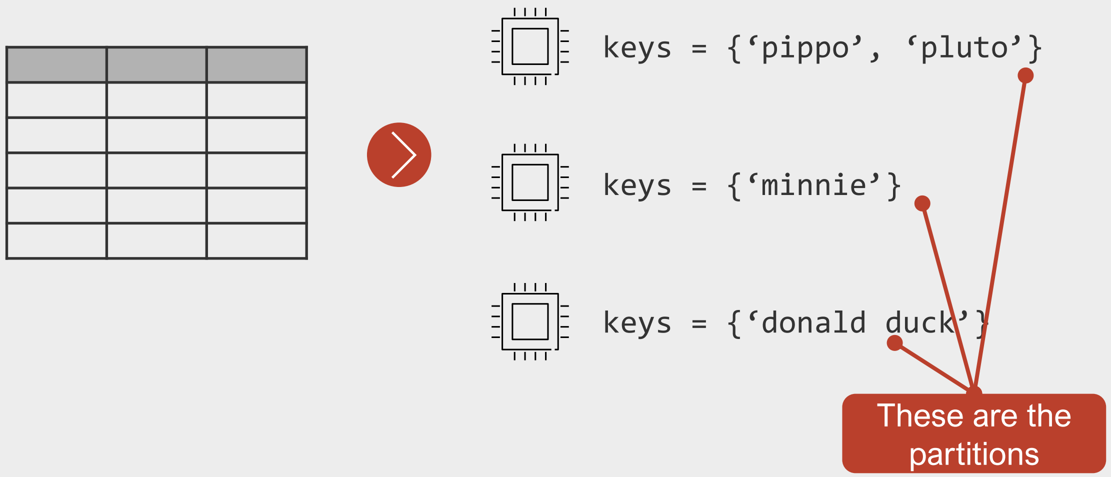
Agenda

Notice that, in the Spark world, the term “Partition” is used with 2 very different meanings

today we focus on this meaning: from now on, we’ll use only «partition» to refer to it

Partition (**logical**, on RAM memory)

- It refers to splitting a dataset into **chunks**, i.e. logical groupings, on the RAM
- Useful for:
  - **parallelizing** the **processing** of the dataset (each partition is processed by only 1 executor)
  - **distributing** work across the cluster to **reduce memory requirements** of each node (*horizontal scalability*)



Partition (**physical**, on disk)

- It refers to physically organizing data in **folders** (e.g., by creating groups of rows based on the value of a specific key)
- Useful for:
  - **reducing volume of data** read by queries (*partition pruning*)
  - **optimizing disk** or cloud **I/O**