

# Modernizing Banking ETL and Analytics with Delta Live Tables

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Jian Zhou, Navy Federal Credit Union  
Ricardo Portilla, Databricks



# Introduction

Ricardo Portilla

- Industry Principal Architect, 6 years Databricks
- Previously led Market Surveillance at FINRA
- [Open source creator](#) and industry SME



2005



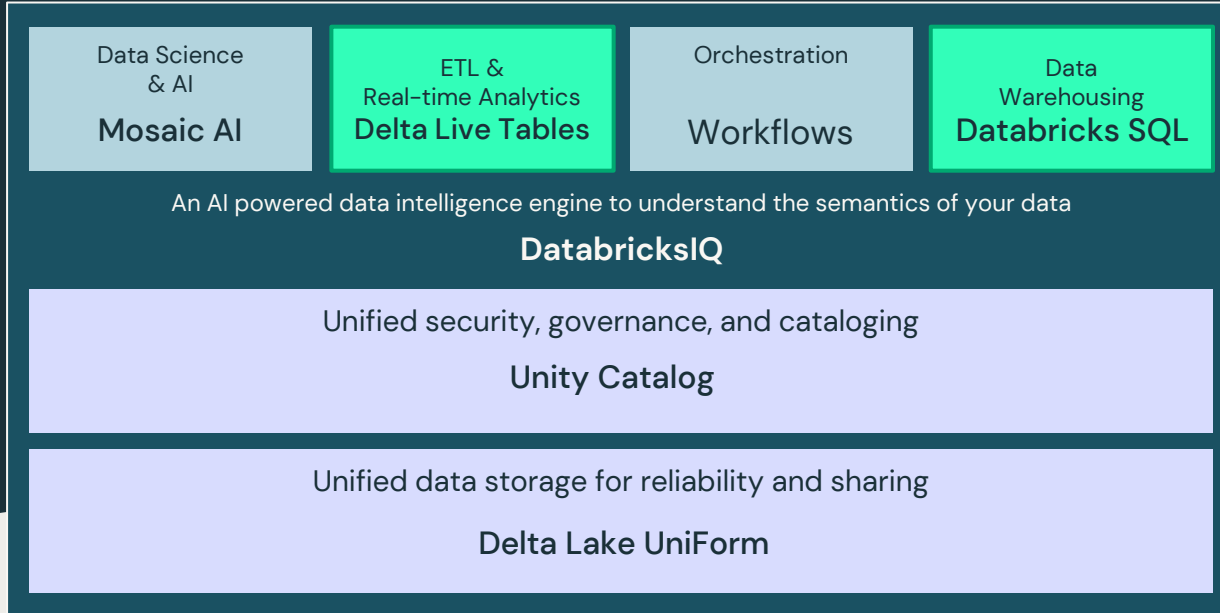
2007



2010



# Databricks Data Intelligence Platform

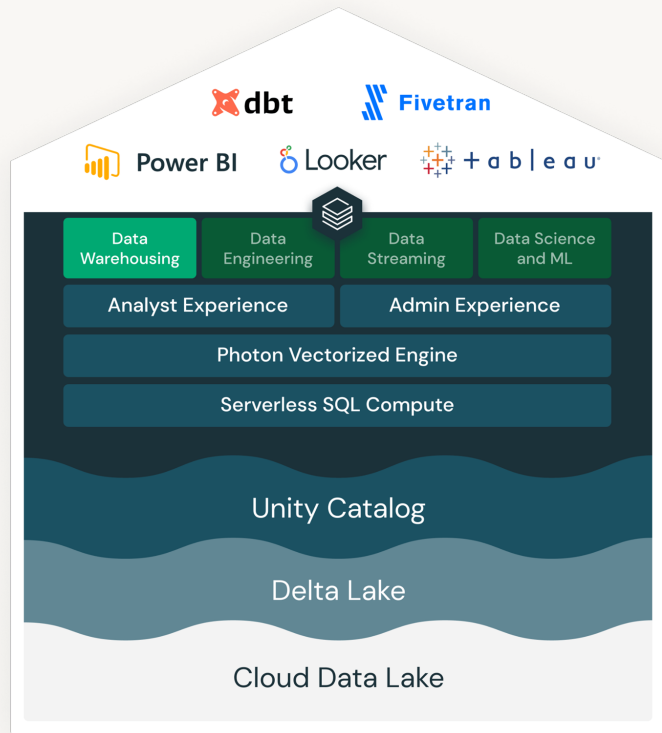


## Open Data Lake

All Raw Data  
(Logs, Texts, Audio, Video, Images)

# The best data warehouse is a lakehouse

Powered by Databricks SQL



Seamless Integration with the Ecosystem

Ease of Use

Real-world Performance

Centralized Governance

Open and Reliable Data Lake as the Foundation



# Introduction

Jian (Miracle) Zhou

- Sr. Manager, Digital Data Engineering
- Navy Federal Credit Union
- <https://www.linkedin.com/in/miraclezhou/>



The image features a clear, light blue sky as a background. Scattered across the sky are several white, low-poly clouds. These clouds are rendered with a faceted, geometric style, giving them a soft, crystalline appearance. The clouds vary in size and are positioned at different heights and depths, creating a sense of a bright, airy atmosphere. The largest cloud is on the right side, while smaller ones are scattered towards the left and top of the frame.

June 2023



A screenshot of a web browser displaying the Navy Federal Credit Union website. The browser's address bar shows the URL "https://digitalomni.navyfederal.org/nfcu-onl...". The website header features the "NAVY FEDERAL Credit Union" logo on the left and a list of military branches on the right: ARMY, MARINE CORPS, NAVY, AIR FORCE, SPACE FORCE, COAST GUARD, and VETERANS. Below the header is a navigation menu with links for "Accounts", "Move Money", "Cards", "Statements", and "My MakingCents", with "My MakingCents" being the active page. The main content area displays the "my MakingCents" logo and the tagline "Smart Money Strategies".





Micro-Wave

- Wave 2a
- Wave 2b
- Wave 2c

9/21/2023

10/25/2023



63,033

Sessions

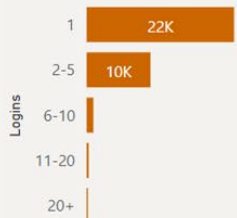
33,275

Unique Members

1.89

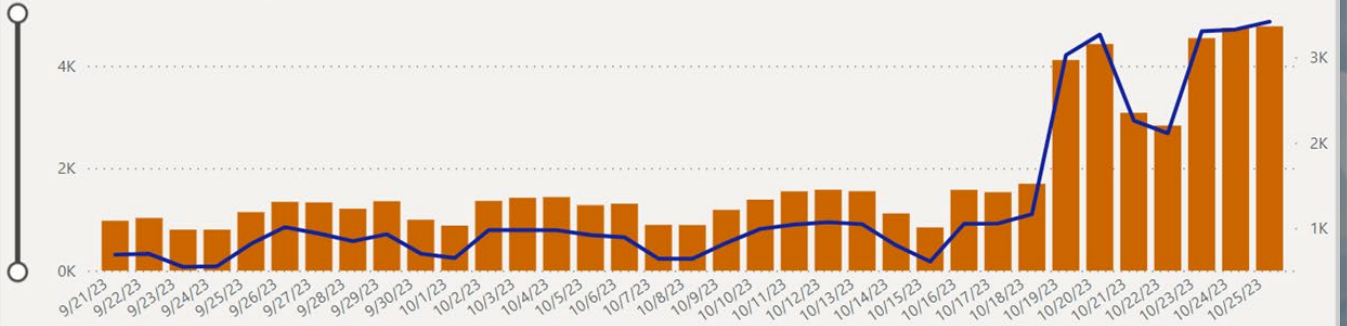
Sessions per Member

### Distinct Members by Logins

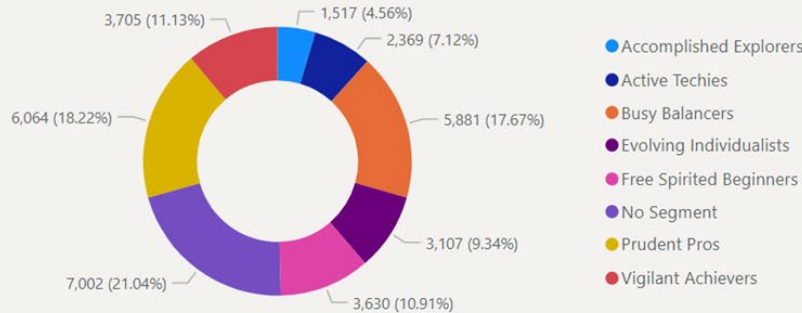


### Sessions & Unique Members - Online Wave 2

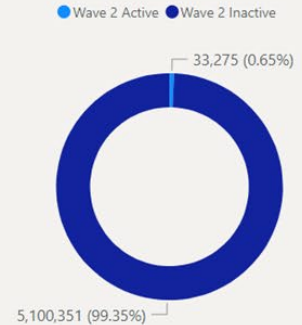
Wave 2 Sessions Wave 2 Unique Members



### Sessions & Unique Members - Online Wave 2



### Wave 2 Activity





- Micro-Wave
- Wave 2a
- Wave 2b
- Wave 2c

## Sessions & Unique Members - Online Wave 2

### Omnichannel | Real Time Online v7 Activity

Refreshed: 10/27/2023 11:58:27 AM



Select Options

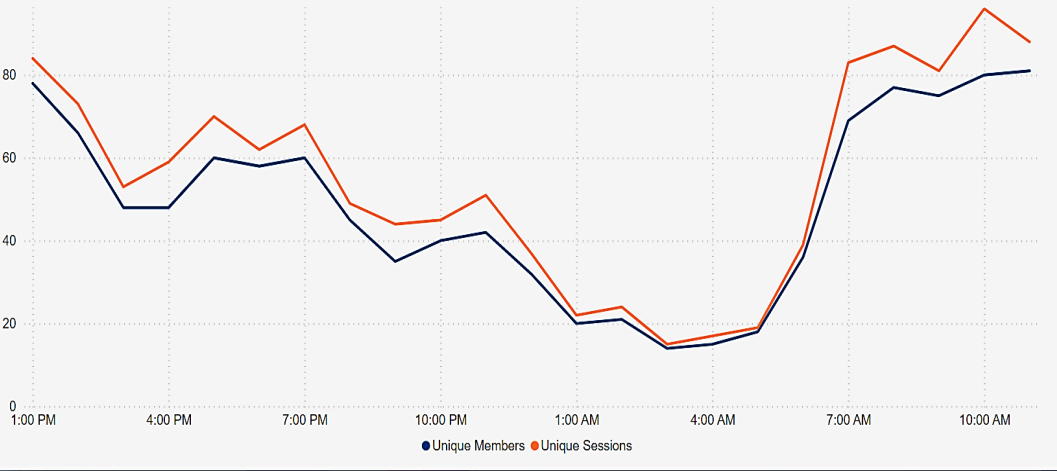
Wave 3a Unique Members & Sessions

Current Day

Unique Members  
476

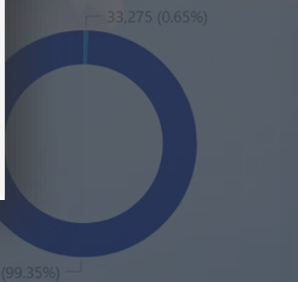
Sessions  
608

Unique Members & Sessions in last 24 hours (Duration by the hour in EST time)



Wave 2 Active ● Wave 2 Inactive

33,275 (0.65%)

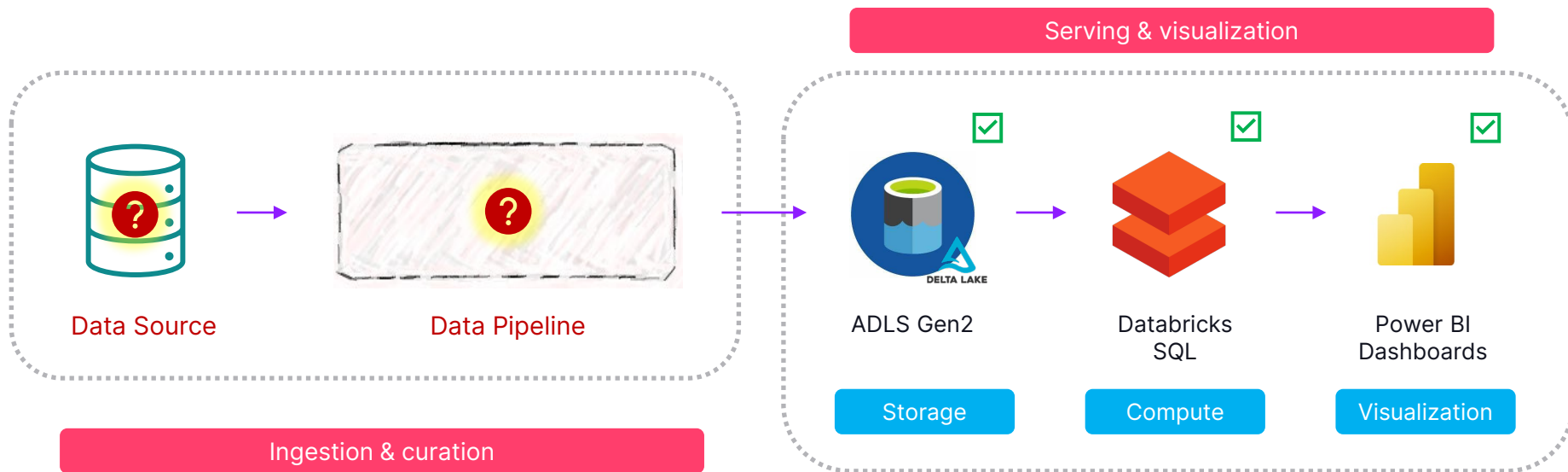


MISSION:

**NEAR REAL-TIME INSIGHTS**  
**IN 6 WEEKS**

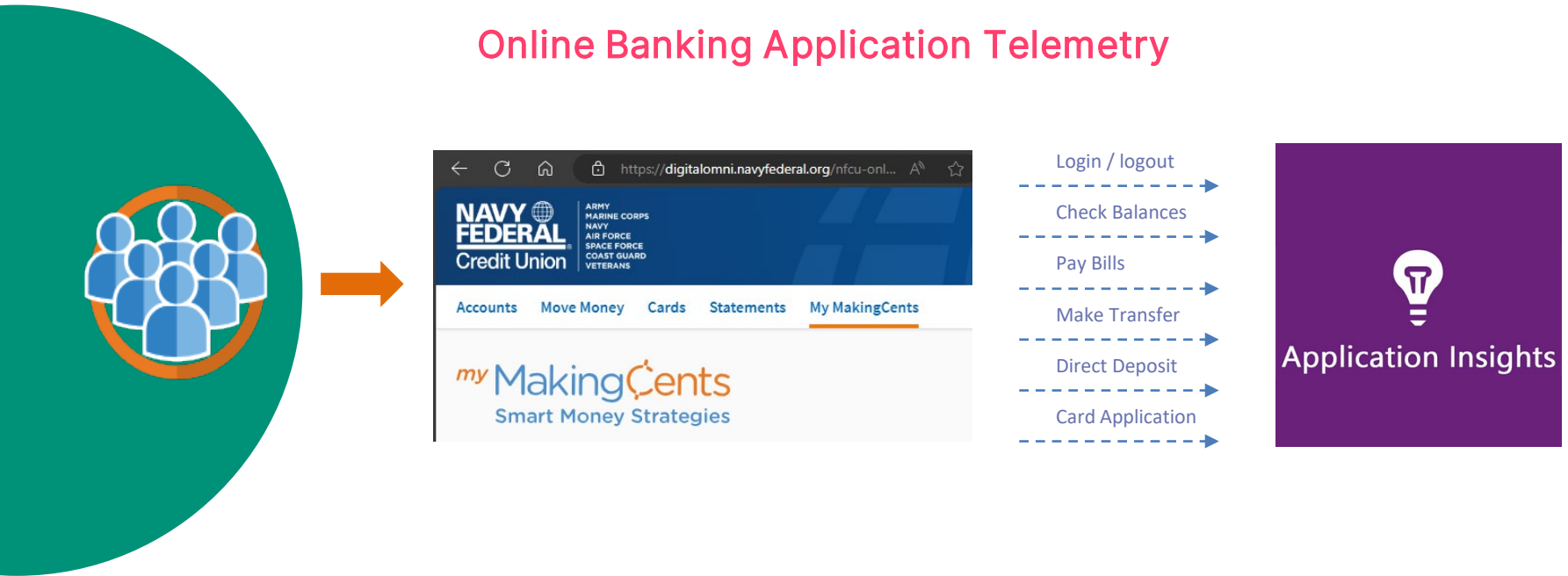


# Our dataflow pattern



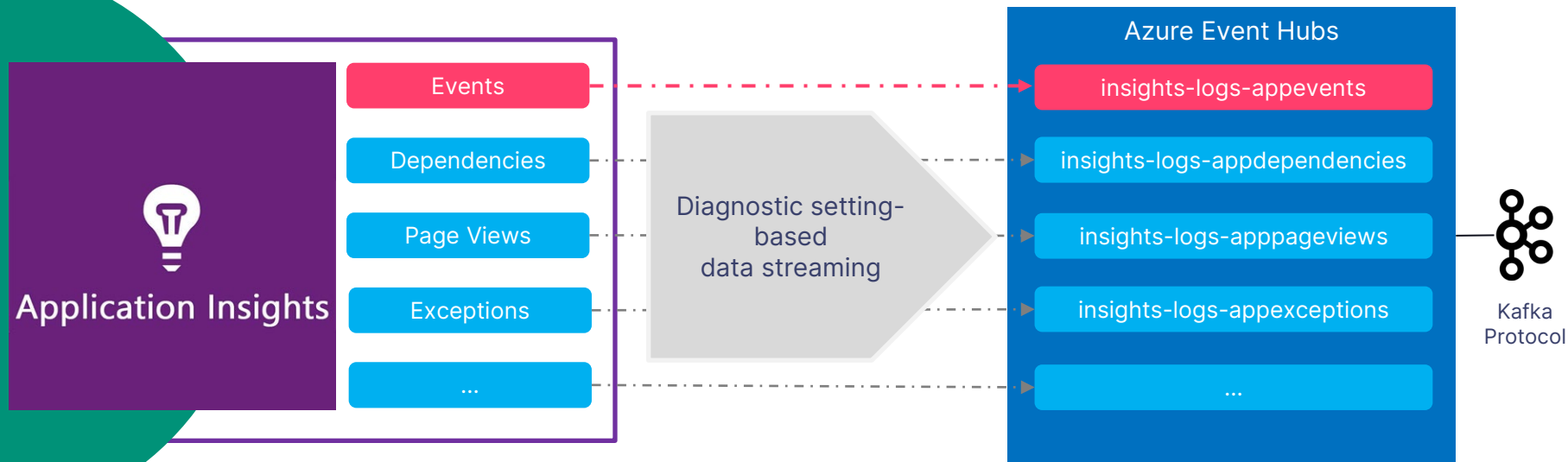
# The data source

## Online Banking Application Telemetry

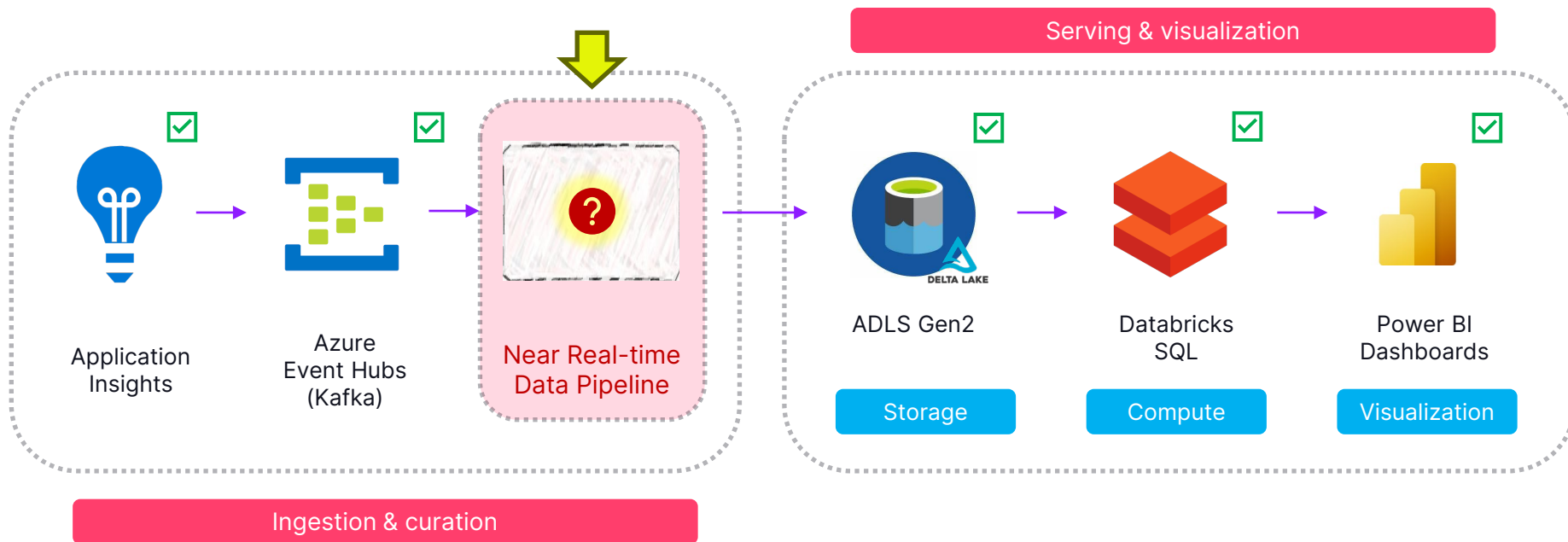


Since the initial rollout, Online v7 has logged over 8.5 billion events in Application Insights (as of April 2024)

# Turn on the telemetry firehose



# NRT Pipeline



# The input

- Semi-structured JSON documents
- App events embedded in an array
  - 140+ event types
  - 100+ event attributes
- There are **duplicates!**

```
{
  "records": [
    {
      "time": "2024-04-08T14:00:03.3500000Z",
      "OperationId": "1f85fe13fa9cc460463b008bf94ca156",
      "SessionId": "40cf0031-a1db-426e-850b-1940a290b6a4",
      "Properties": {
        "activity": "login",
        "channel": "web",
        "ipAddress": "20.84.33.69"
      }
    }
    {
      "time": "2024-04-08T14:02:05.3110000Z",
      "OperationId": "88a4321463a92645bb5224238d5b7967",
      "SessionId": "40cf0031-a1db-426e-850b-1940a290b6a4",
      "Properties": {
        "activity": "ingestion",
        "channel": "web",
        "ipAddress": "20.84.33.69",
        "paymentOrderStatus": "SUCCESS"
      }
    }
  ]
}
```

App event 1

App event 2

A sample message from Event Hubs



# The output

```
1 select *
2 from appevents_login
3 where channel is not null
4 order by event_date desc
5 limit 10;
```

dev data sample

Results ▾ +

	event_date	event_time	channel	is	guid
1	2023-10-24	2023-10-24 04:21:35.330	web	25198494-626f-4d20-a02a-df4b70d41689	a4e699a6-672c-4c5b-9fe6-7b68692d...
2	2023-10-24	2023-10-24 12:23:14.715	mobile	8a791733-9125-47b7-8469-4611b9db6627	d729140c-2813-4f44-8e97-b6fb2bd1...
3	2023-10-24	2023-10-24 12:25:08.771	web	62b346c3-4763-435f-a38f-d8a916fe0739	1d69c2ec-52ea-4996-af65-c5a73c799
4	2023-10-24	2023-10-24 13:24:56.989	web	f5322ccc-688f-4d71-82ab-48ca3d84d7f5	efaa771c-ec38-4e9b-8d05-949867b9f
5	2023-10-24	2023-10-24 14:01:44.380	mobile	577a90f4-181f-402f-9a05-102445258fd3	d5123f7a-4201-4093-ae86-09ddf013'
6	2023-10-24	2023-10-24 12:41:03.562	web	949bbd15-dacd-4191-80b9-f134190df2fd	c1f6d04f-dfad-4671-ac4d-2af914c27c

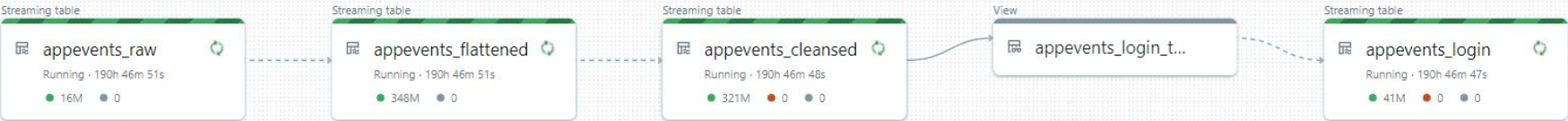
Persist

Flatten

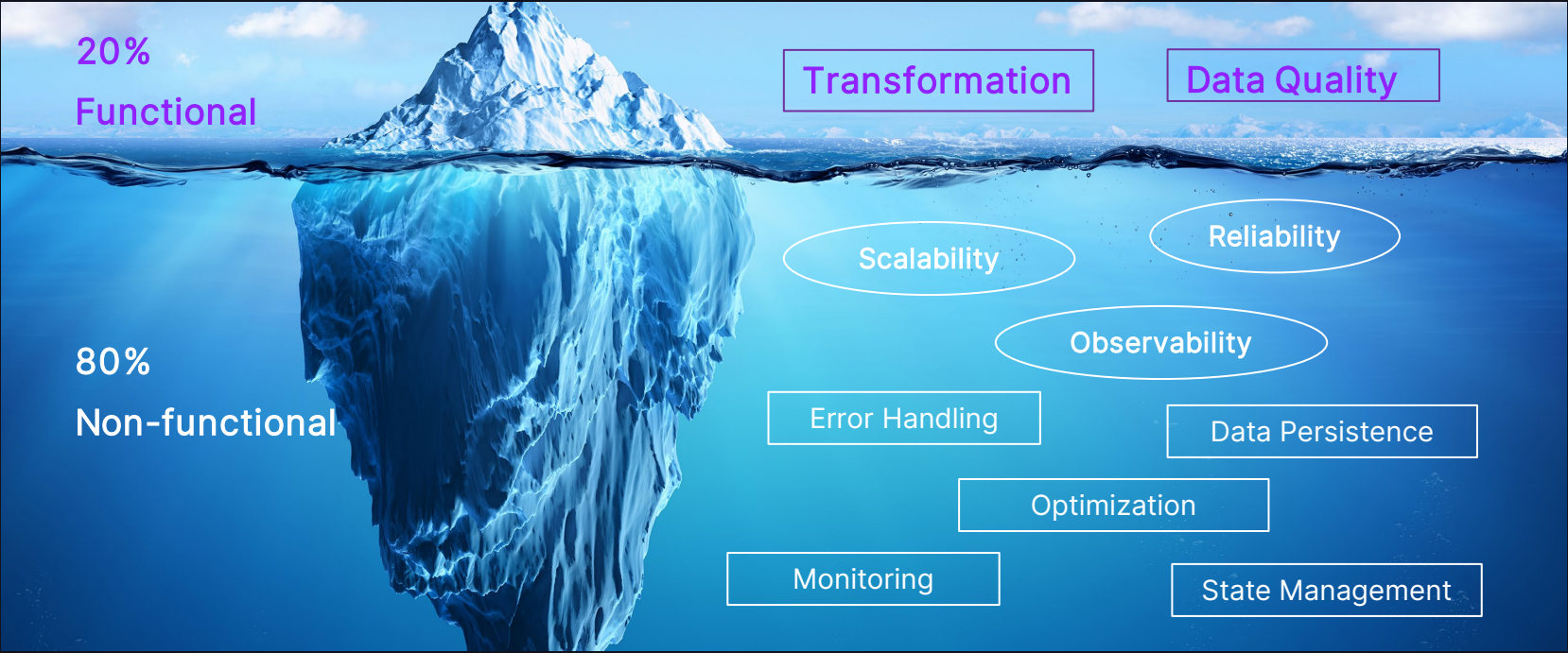
De-dupe

Tailor

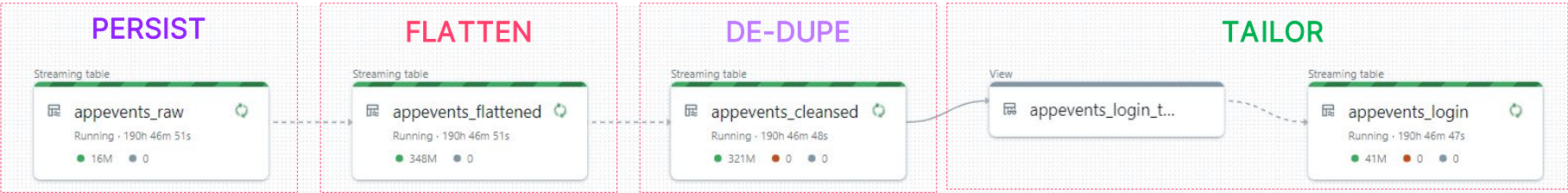
# The pipeline



# The iceberg of data engineering



# Simplicity



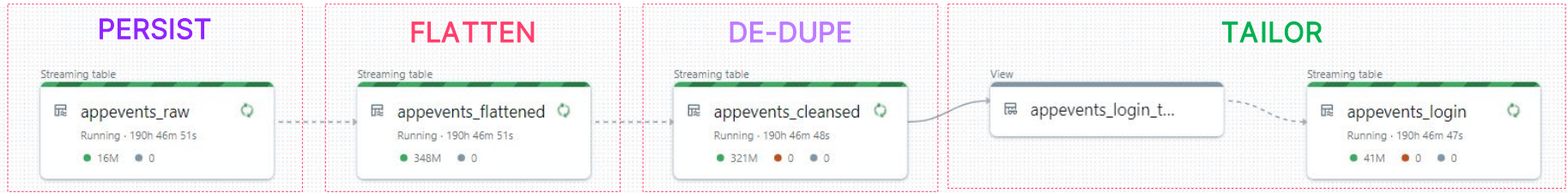


# Simplicity



```
@dlt.table()
@dlt.expect_or_drop(
    "valid records",
    "...")
def appevents_raw():
    options = get_kafka_config_options(
        spark,
        dbutils.secrets)
    return (spark
            .readStream
            .format("kafka")
            .options(**options)
            .load()
            .transform(parse_raw_appevents)
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dlt.create_streaming_table(
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dlt.apply_changes(
    target = "appevents_cleansed",
    source = "appevents_flattened",
    keys = ["event_date", ...],
    sequence_by = col("time"),
    except_column_list = [],
    stored_as_scd_type = 1
)
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@dlt.view
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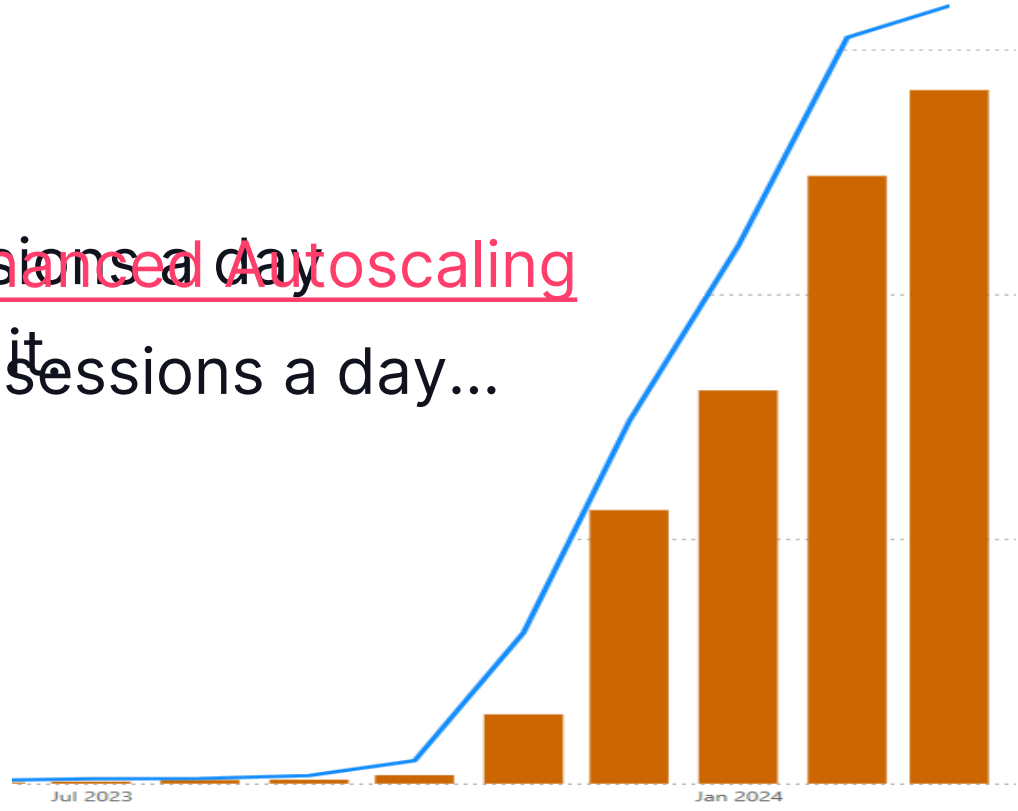
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)
```

3 queries. 2 CDC calls. ~100% for functional requirement.

# Scalability

We returned ~~<1,000~~ Enhanced Autoscaling sessions a day and forgot about it to ~~>1,000,000~~ of sessions a day...



# Reliability

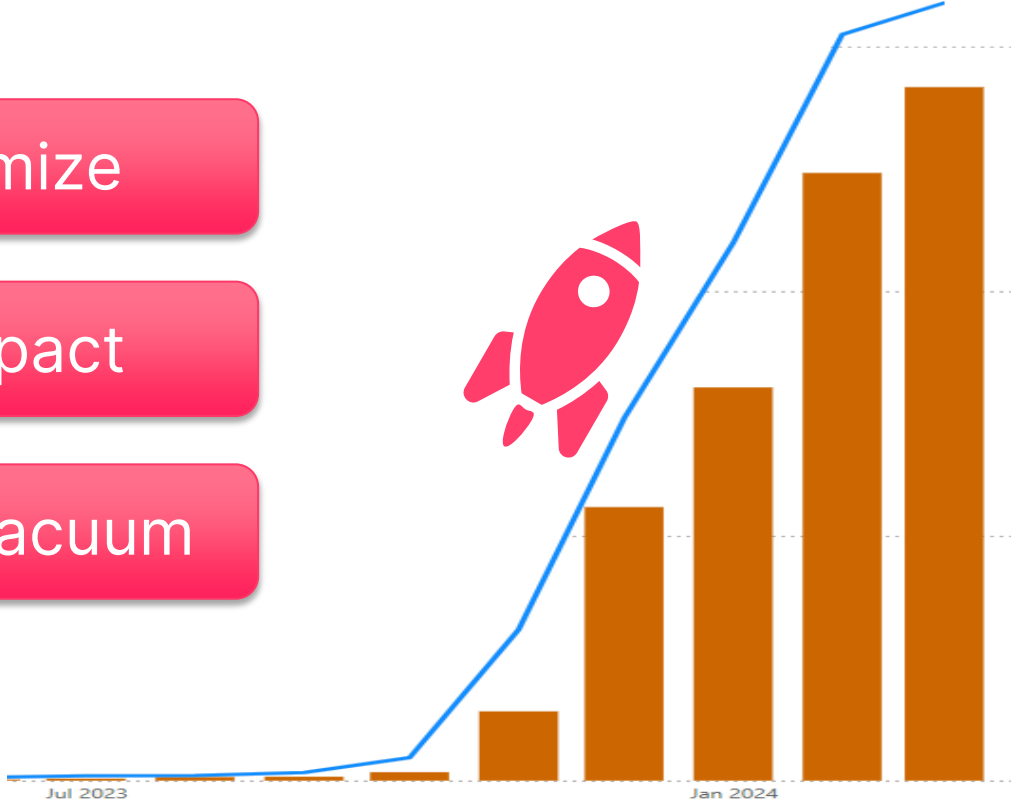
**24\*7**  
continuous streaming  
for 9 month

**9 billion**  
events processed

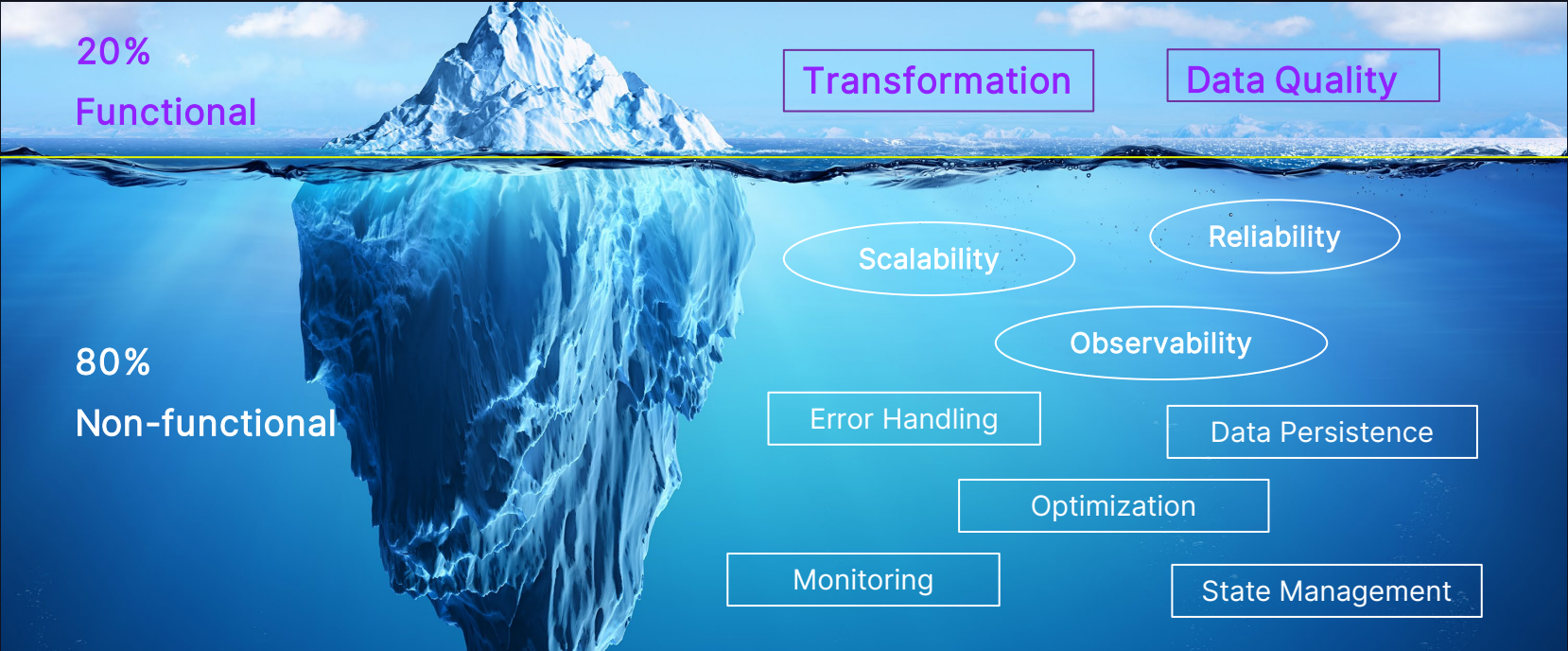
**100%**  
self-recovery from  
cloud failures

# Performance

- Auto-Optimize
- Auto-Compact
- Scheduled Vacuum



# Where DLT shines



- Time



Engineers



DLT



+ Scale





# Power BI + Databricks SQL

```
1 WITH CTE AS
2 (SELECT .. FROM appevents_login /* JOIN...WHERE... */) -- omitted for simplicity
3 SELECT
4   Flag
5   , COUNT( DISTINCT GUID_V7_Member_ID ) AS `Unique Member Count`
6   , COUNT( DISTINCT Login_Session_ID ) AS `Unique Session Count`
7 FROM CTE
8 GROUP BY Flag
9
10
```

#	Flag	Unique Member Count	Unique Session Count
1	0	525163	653996
2	1	1403	1815

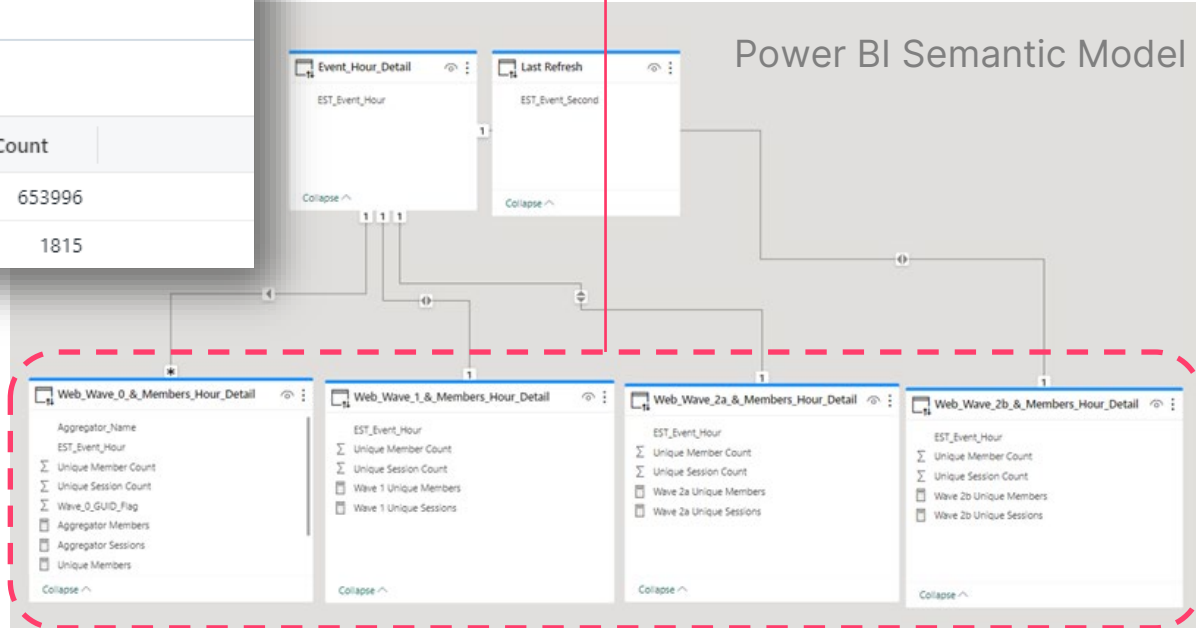
Databricks SQL

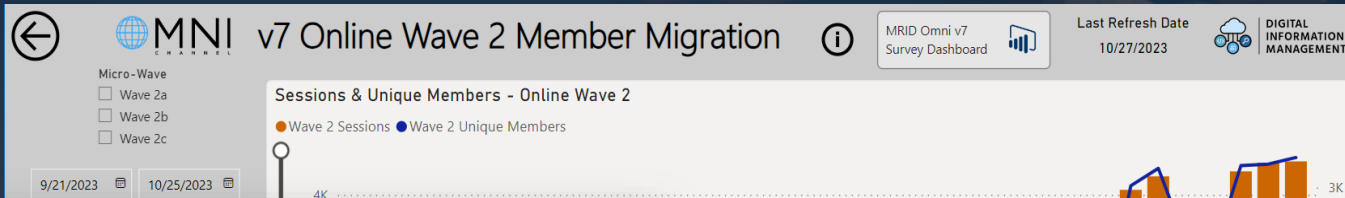
Power BI  
On-premises  
Data Gateway



Direct Query  
(real-time)

Power BI Semantic Model





Omnichannel | Real Time Online v7 Activity

Refreshed: 10/27/2023 11:58:27 AM



Current Day

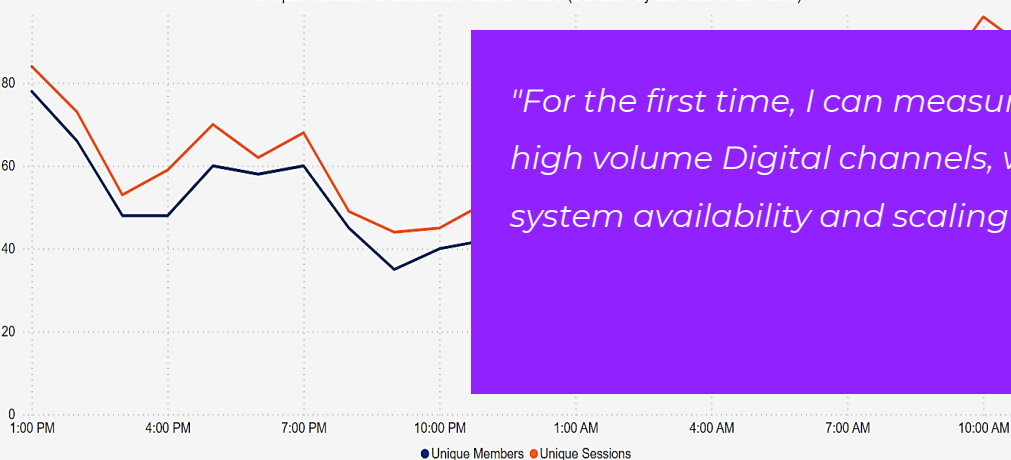
Unique Members  
476

Sessions  
608

Select Options

Wave 3a Unique Members & Sessions

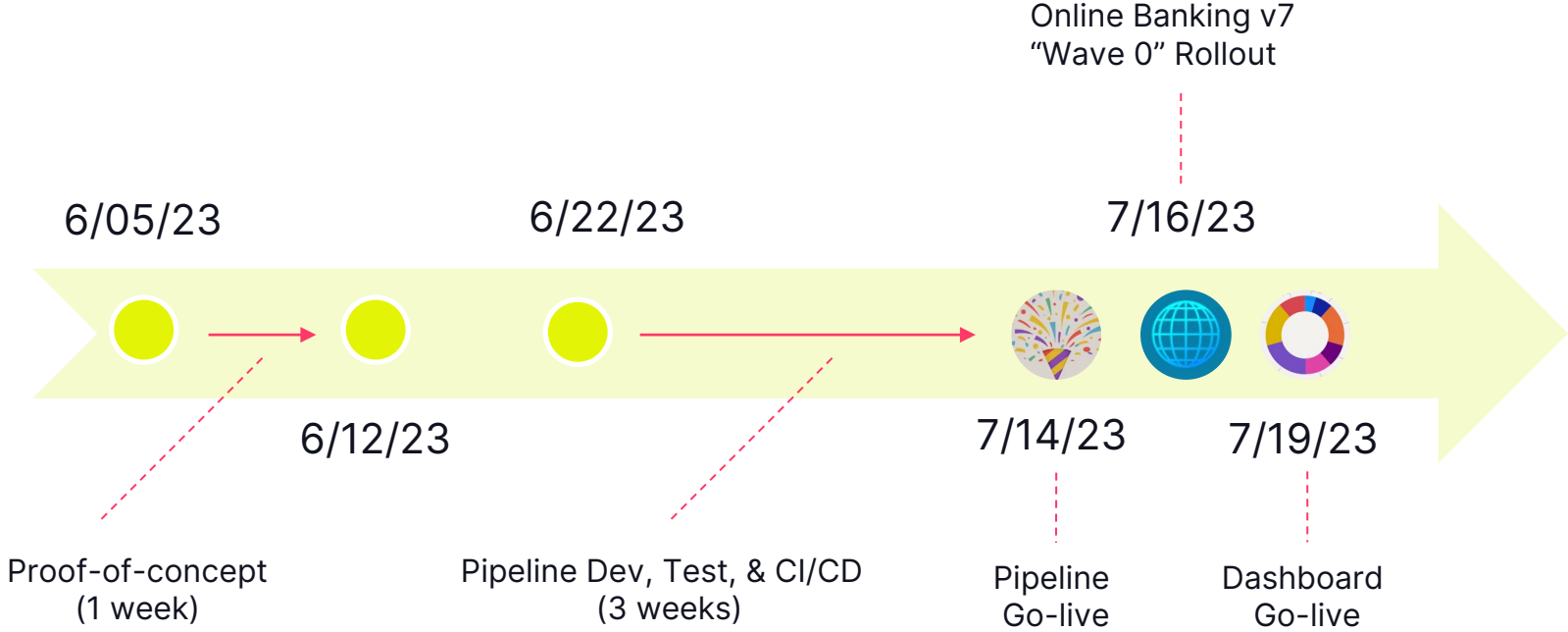
Unique Members & Sessions in last 24 hours (Duration by the hour in EST time)



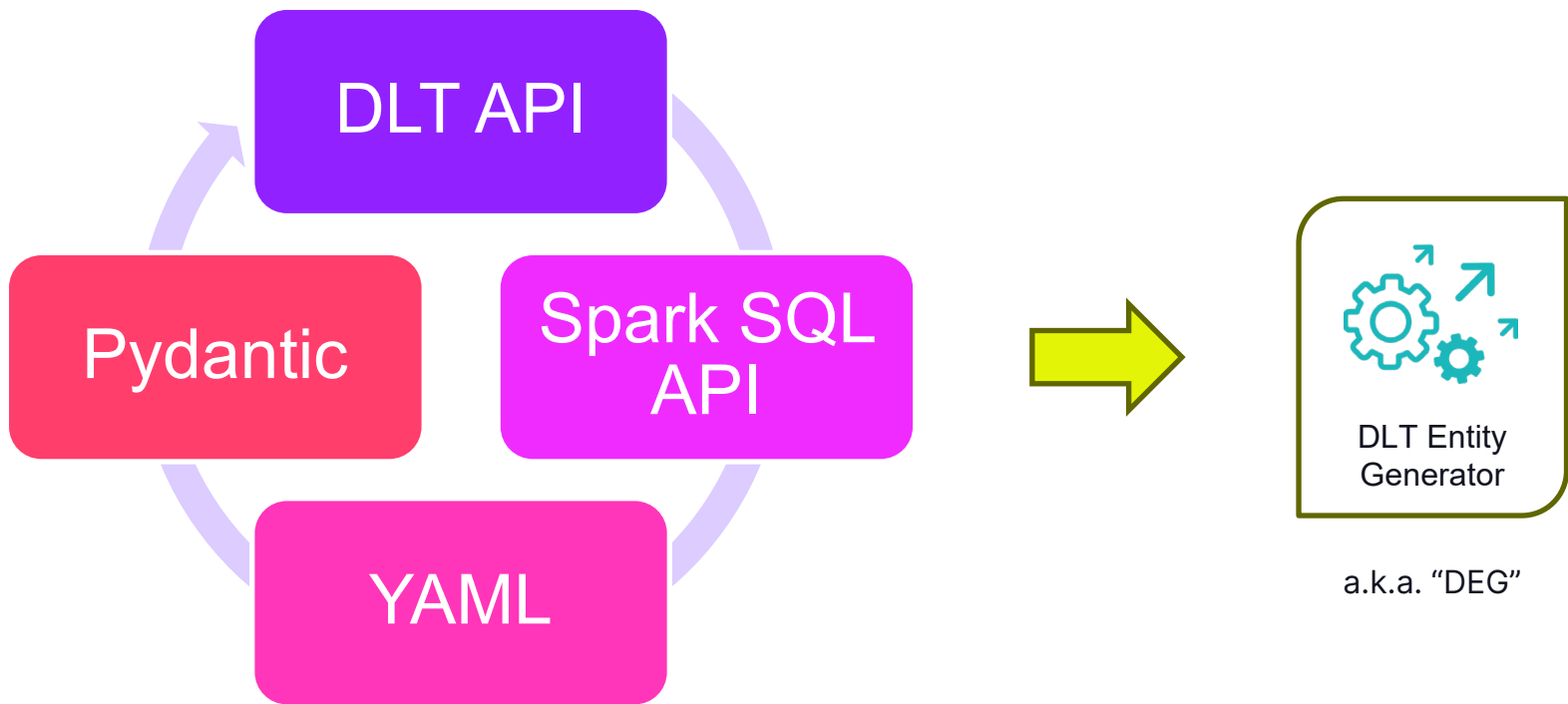
"For the first time, I can measure real time member activities across our high volume Digital channels, which allows for quick decision making on system availability and scaling in real time."

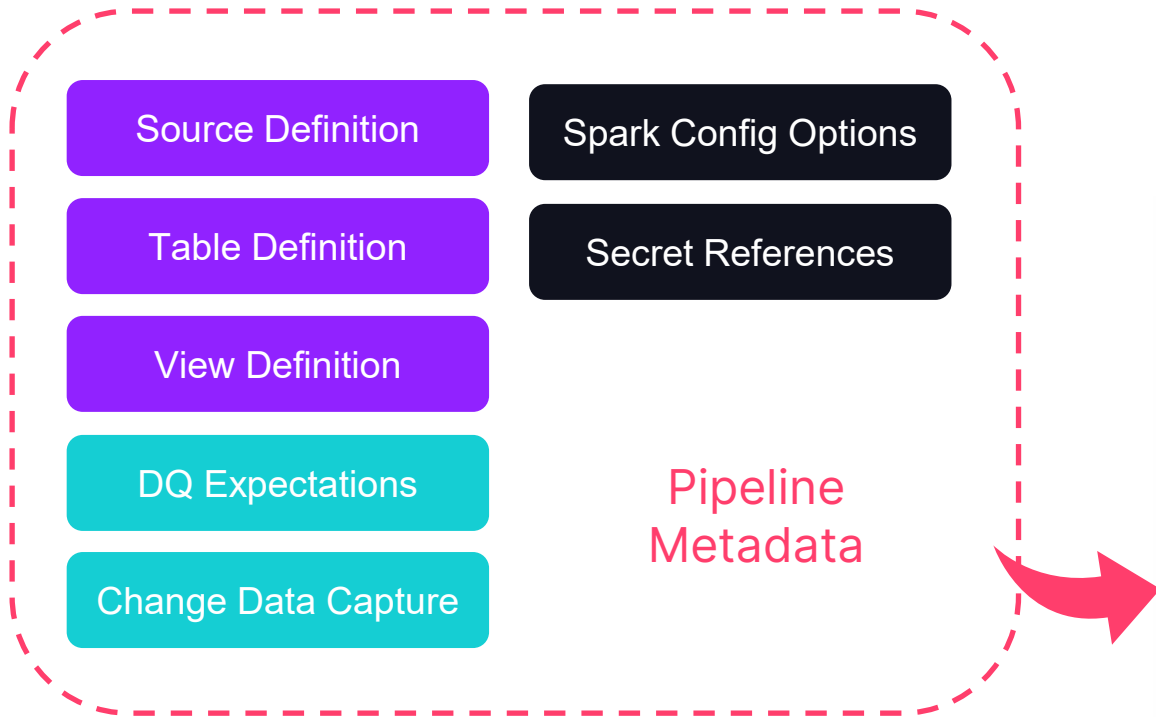
- Gautam N., VP Digital Engineering

# Speed to market

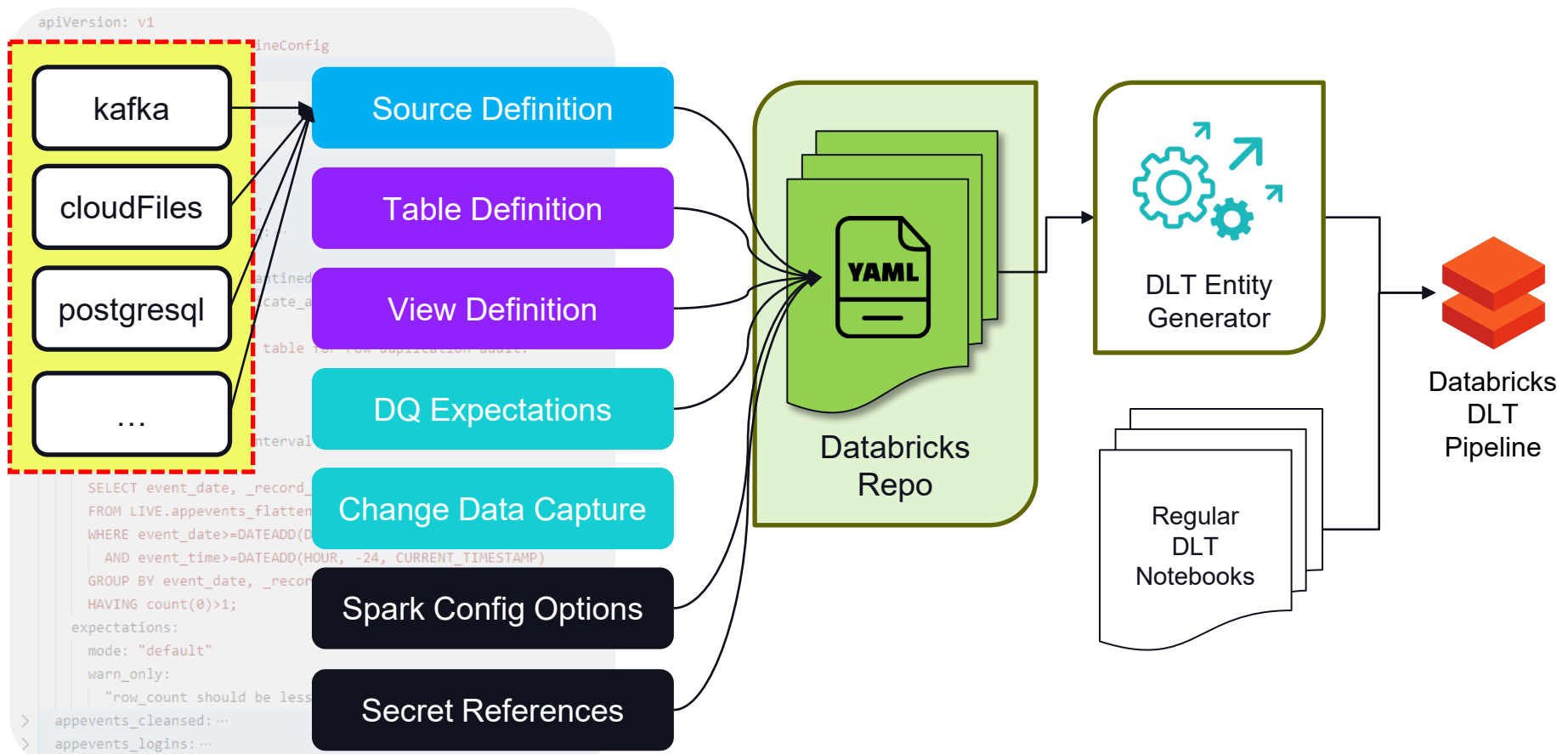


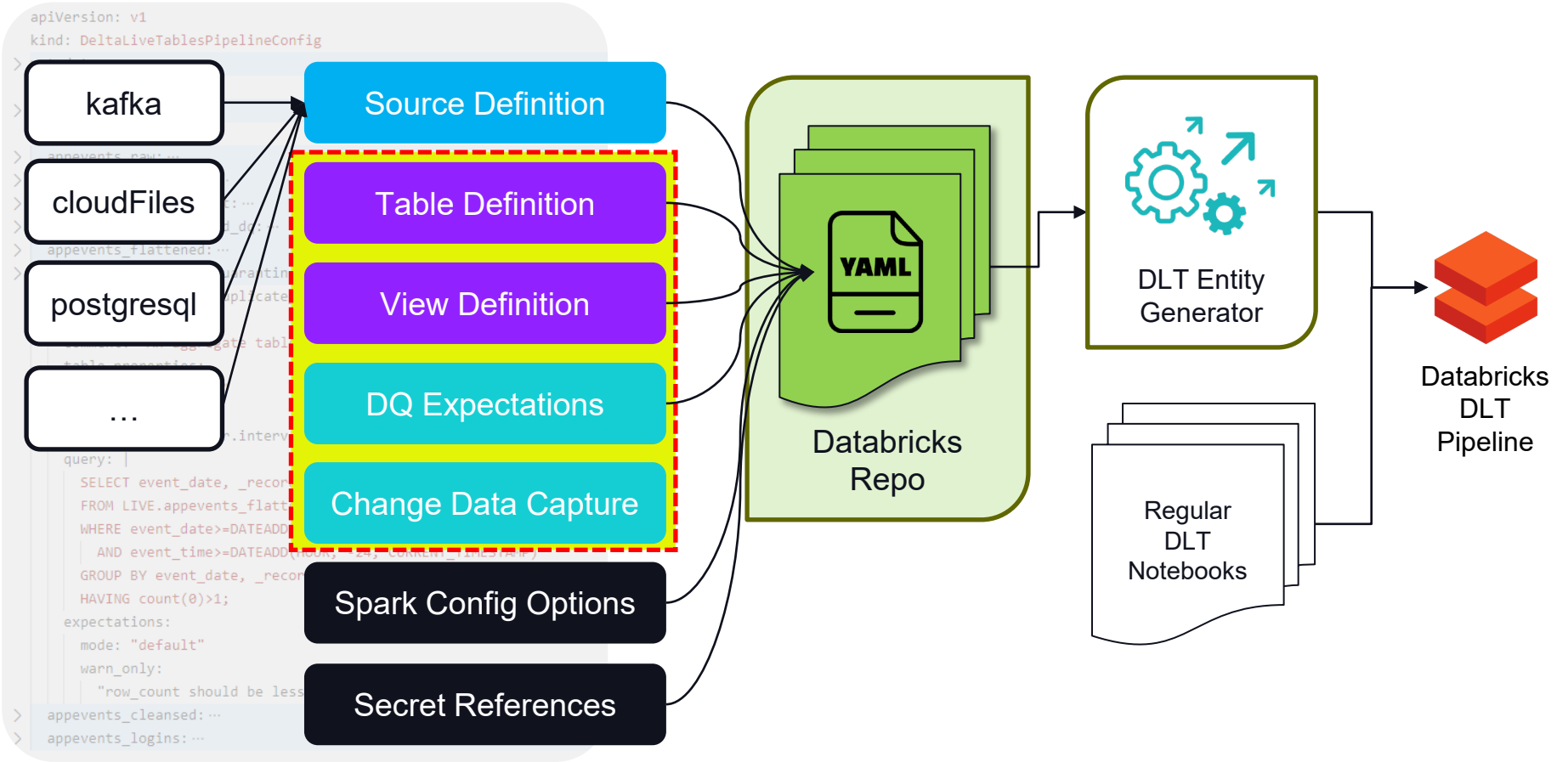
# METADATA-DRIVEN PIPELINE DEVELOPMENT



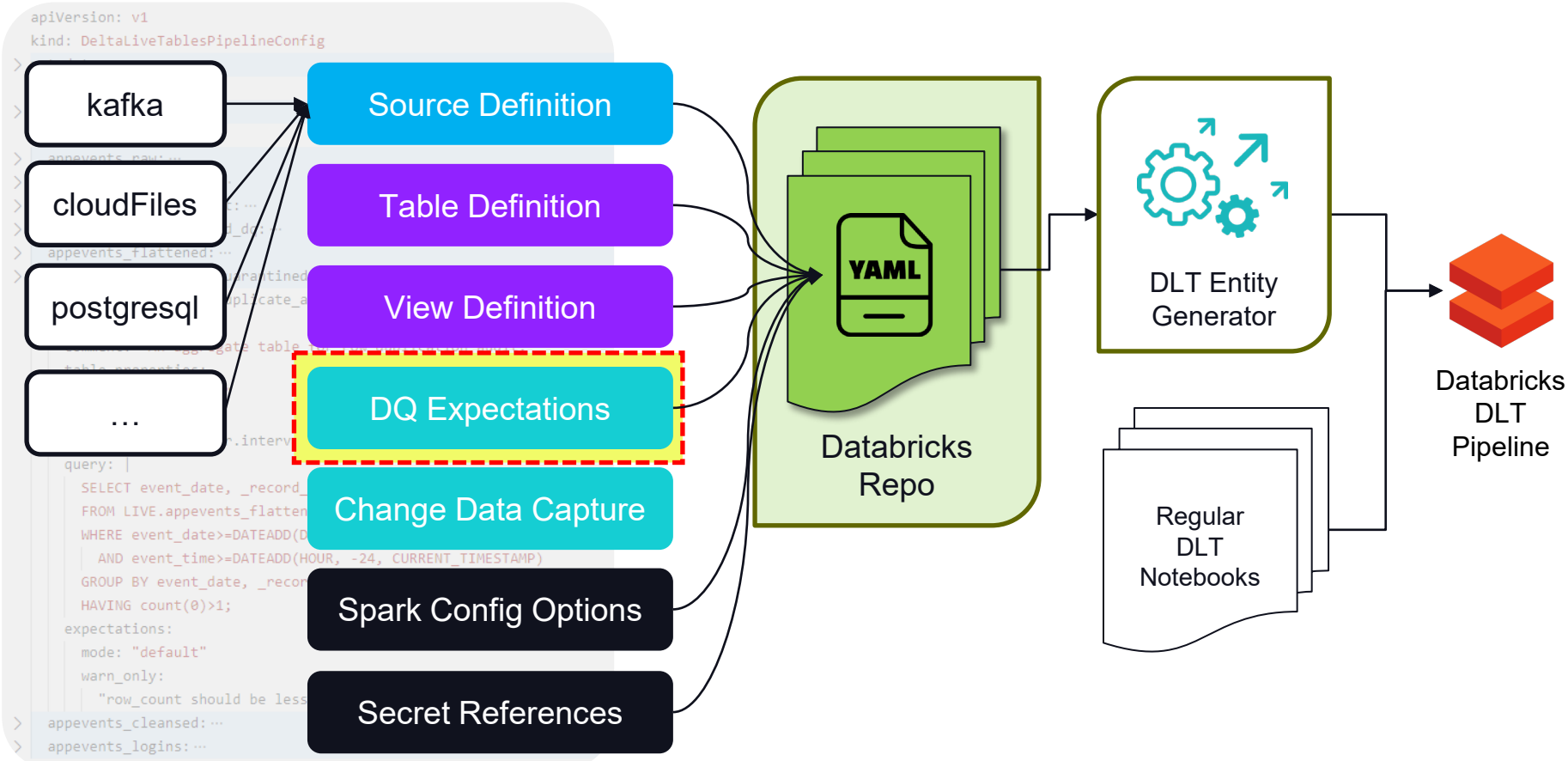


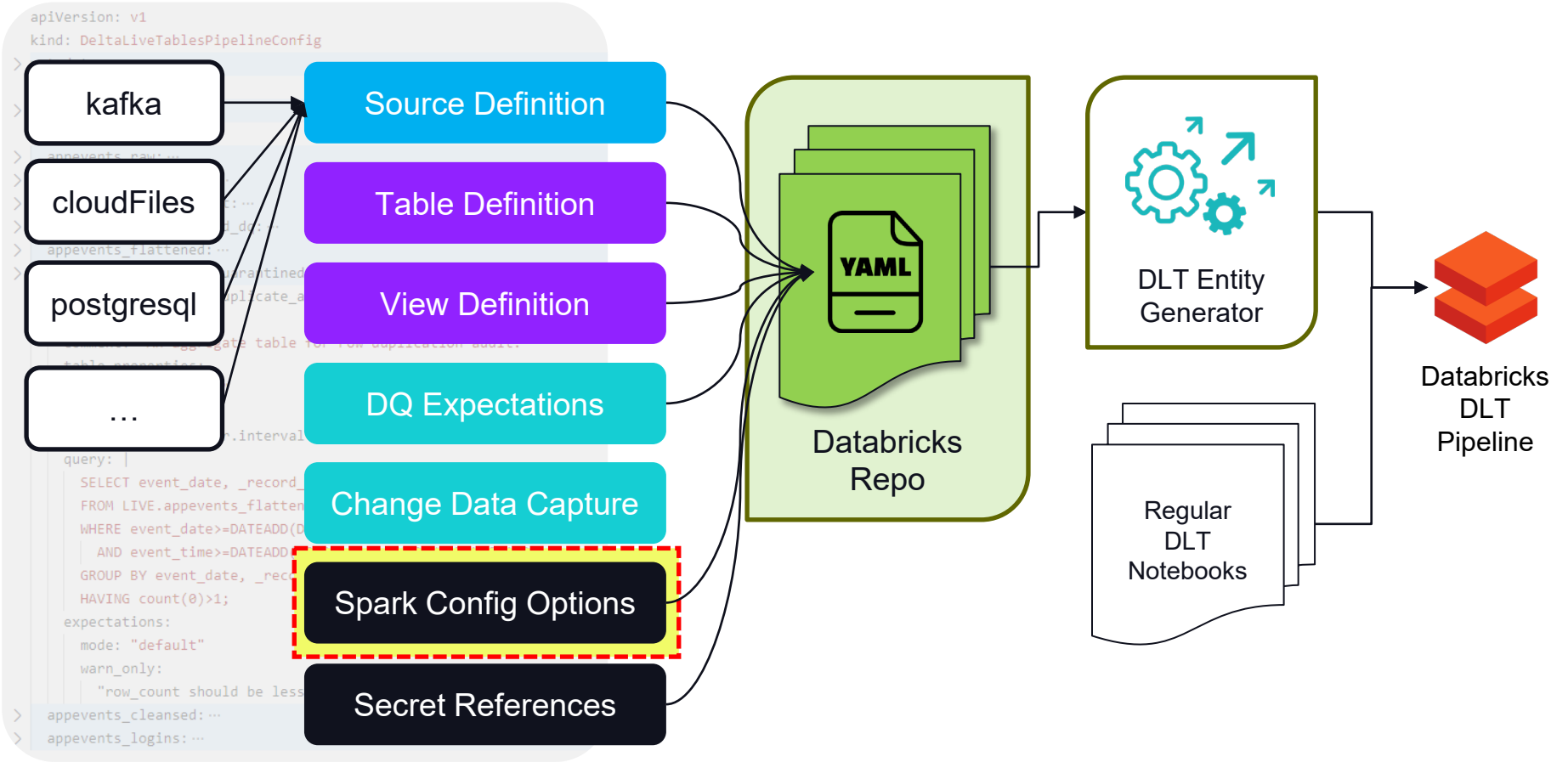
```
apiVersion: v1
kind: DeltaLiveTablesPipelineConfig
> metadata: ...
sources:
> appevents_source: ...
live_table_queries:
> appevents_raw: ...
> vw_appevents_raw_dq: ...
> appevents_raw_dq_audit: ...
> vw_appevents_flattened_dq: ...
> appevents_flattened: ...
> appevents_flattened_quarantined: ...
  appevents_flattened_duplicate_audit:
    type: "table"
    comment: "An aggregate table for row duplication audit."
    table_properties:
      "quality": "audit"
    spark_conf:
      "pipelines.trigger.interval" : "1 hour"
    query: |
      SELECT event_date, _record_hash_sha256, count(0) as row_count
      FROM LIVE.appevents_flattened
      WHERE event_date>=DATEADD(DAY, -1, CURRENT_DATE)
        AND event_time>=DATEADD(HOUR, -24, CURRENT_TIMESTAMP)
      GROUP BY event_date, _record_hash_sha256
      HAVING count(0)>1;
    expectations:
      mode: "default"
      warn_only:
        "row_count should be less than 2": "row_count<2"
> appevents_cleansed: ...
> appevents_logins: ...
```

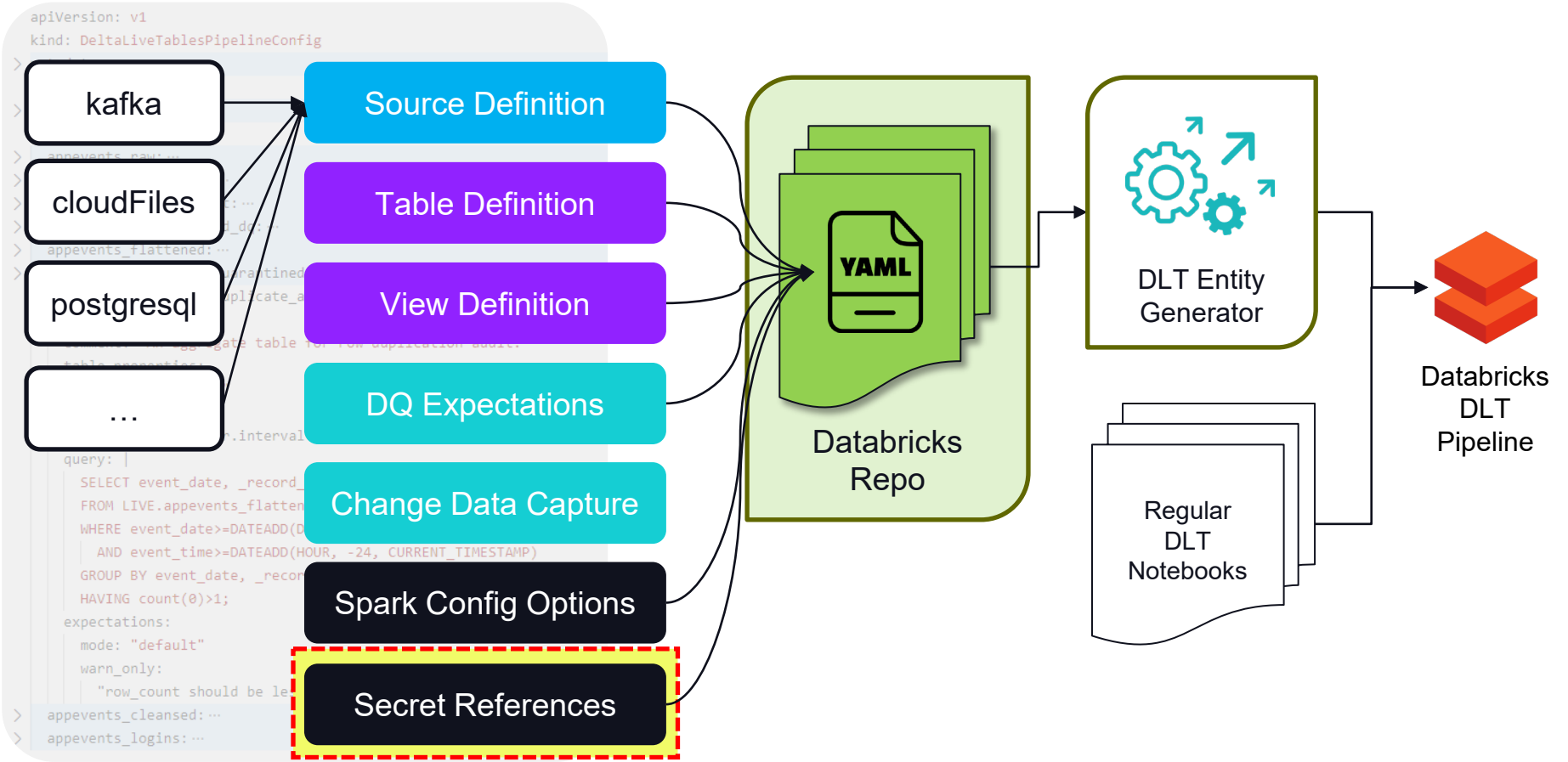


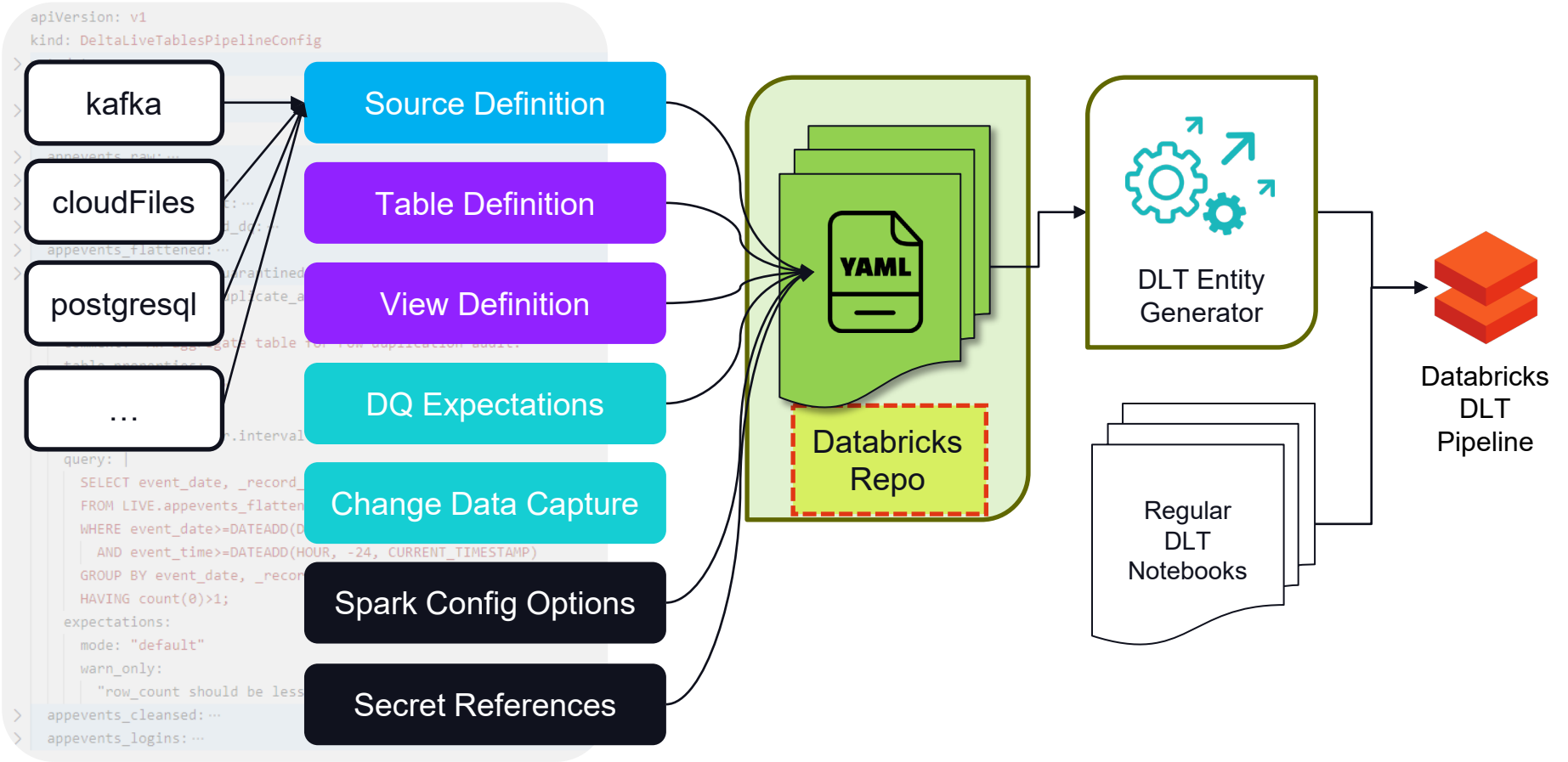


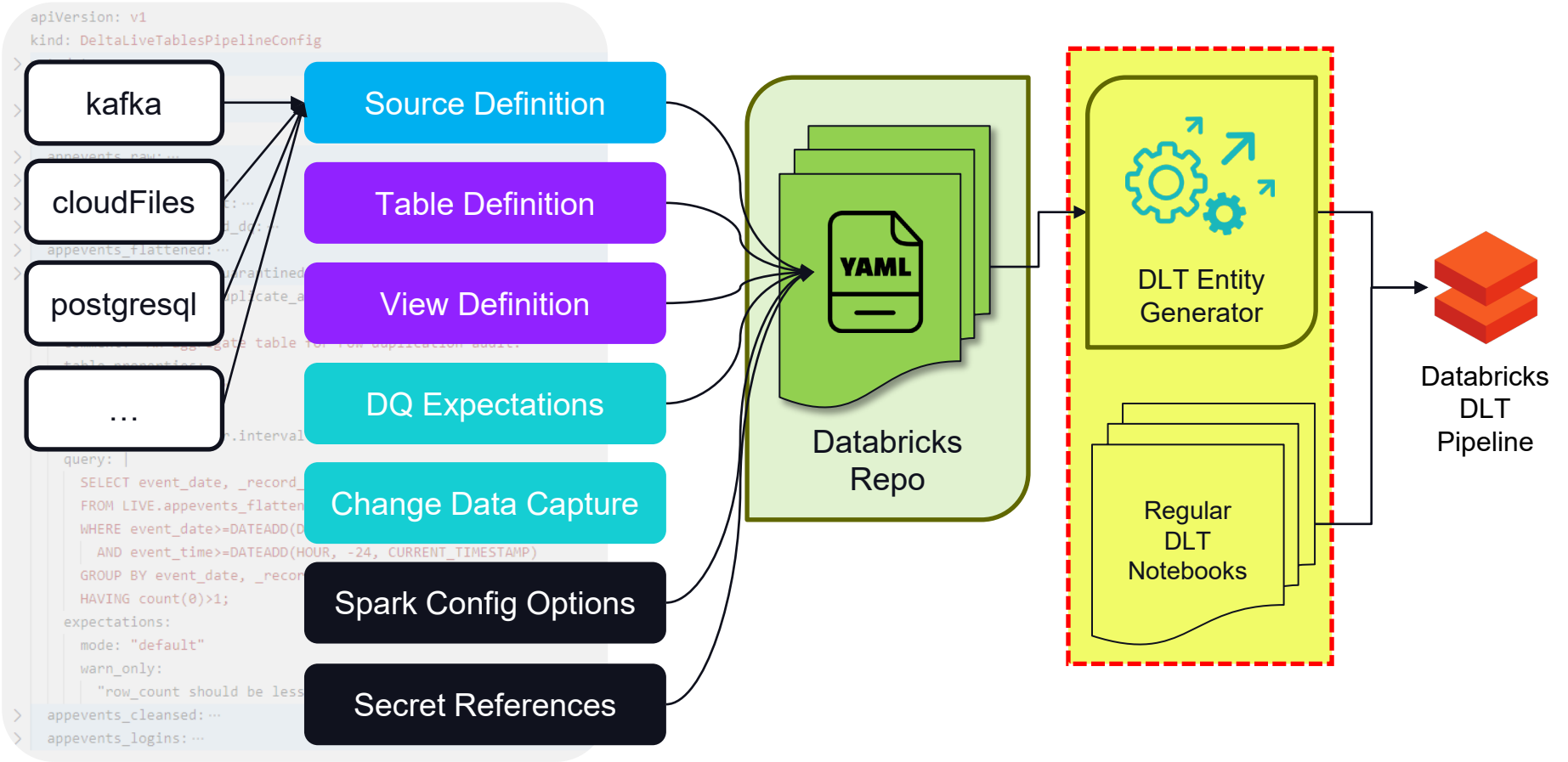




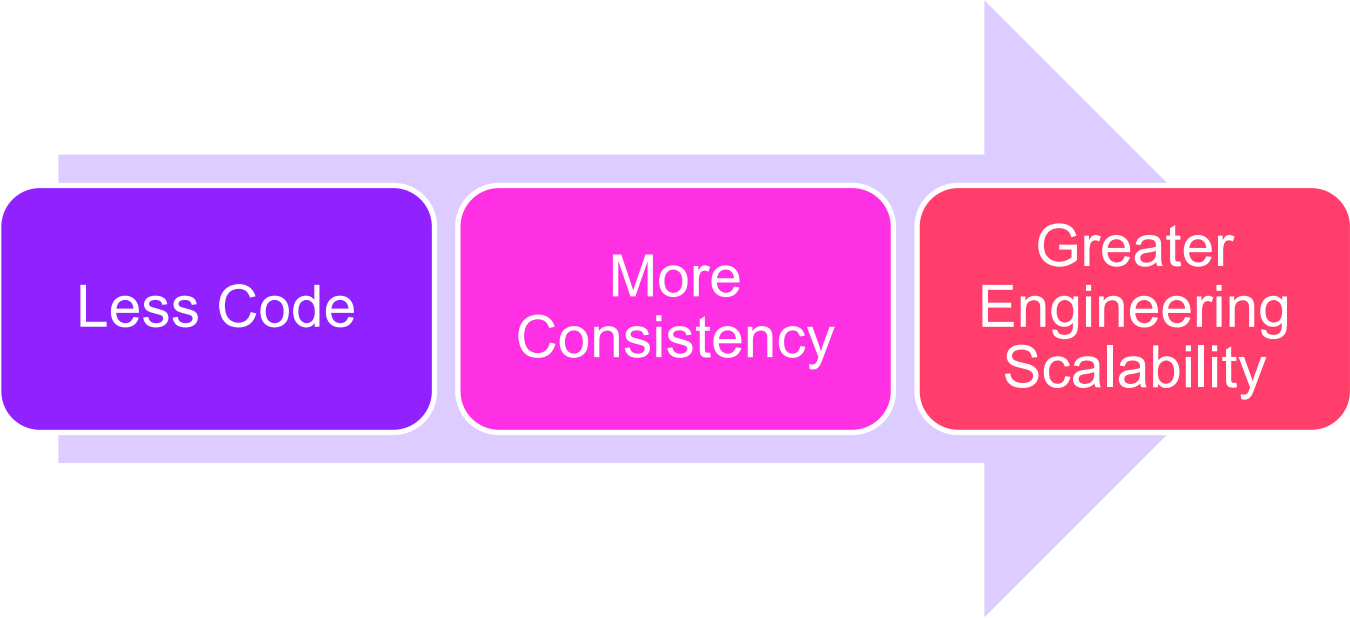








# Metadata-driven solution for engineering scalability



# SUMMARY

DLT isn't a silver bullet, but it worked for our use case wonderfully.

- **Simple** declarative programming model → speed to market
- Built-in **scalability, reliability, and optimization** → simplified operations
- **Programmability** → engineering creativity & scalability



# QUESTIONS?



# THANK YOU!

