2110531 - Data Science and Data Engineering Tools

Big Data Architecture

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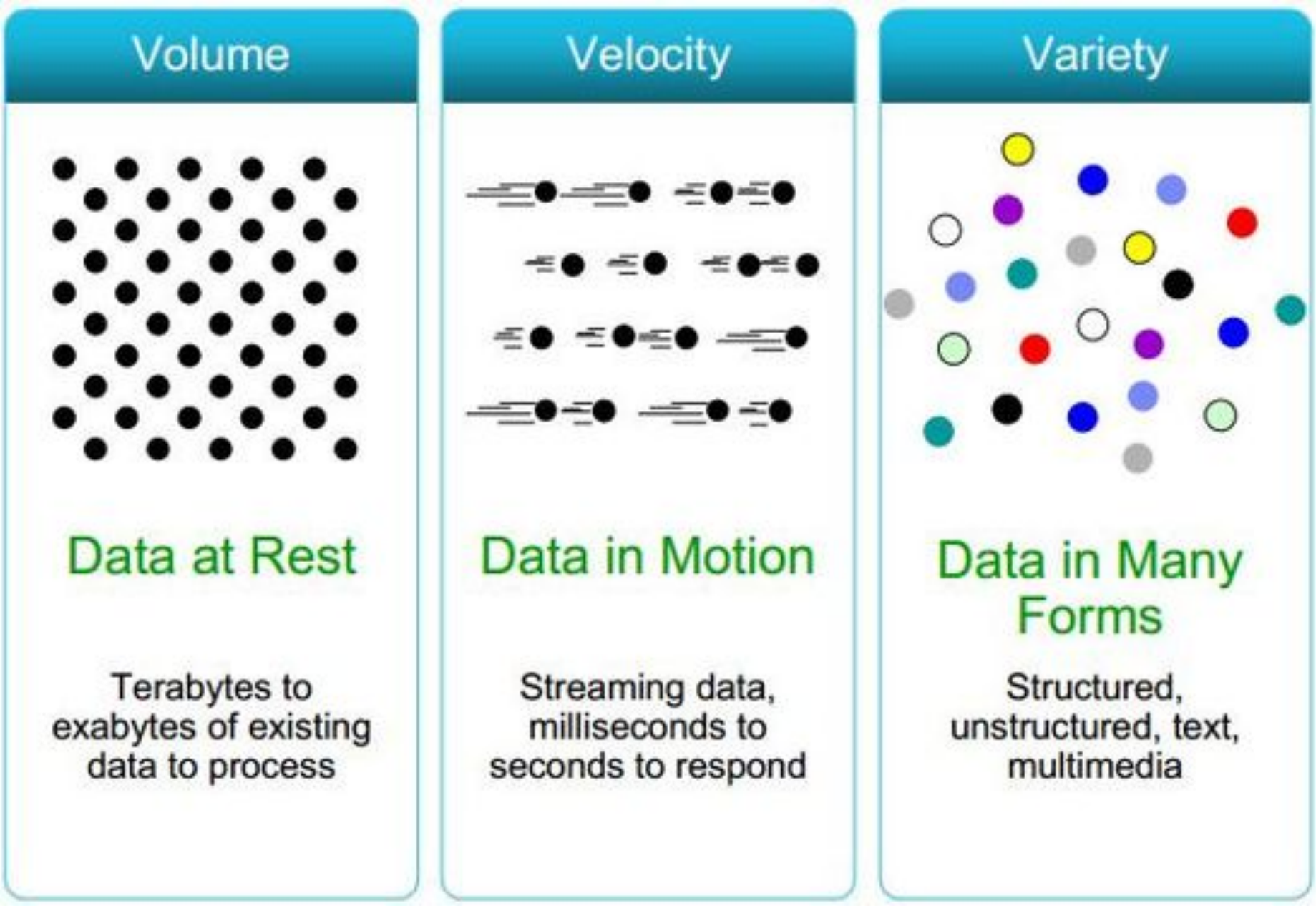
CHULA ENGINEERING
Foundation toward Innovation

Back to Basic - Data Characteristics - 3V



Source: IBM

MACHINE LEARNING, ARTIFICIAL INTELLIGENCE, AND DATA (MAD) LANDSCAPE 2021

INFRASTRUCTURE

STORAGE
HADOOP
DATA LAKES
DATA WAREHOUSES
STREAMING / IN-MEMORY
RDBMS
NoSQL DATABASES
NewSQL DATABASES
REAL TIME DATABASES
GRAPH DBs
MPP DBs
ETL / ELT / DATA TRANSFORMATION
REVERSE ETL
DATA INTEGRATION
DATA GOVERNANCE & ACCESS
PRIVACY & SECURITY
DATA OBSERVABILITY
DATA QUALITY
MGMT / MONITORING
SERVER-LESS
CLUSTER SVCS

ANALYTICS

BI PLATFORMS
VISUALIZATION
DATA ANALYST PLATFORMS
AUGMENTED ANALYTICS
DATA CATALOG AND DISCOVERY
METRICS STORE
LOG ANALYTICS
QUERY ENGINE
SEARCH

MACHINE LEARNING & ARTIFICIAL INTELLIGENCE

DATA SCIENCE NOTEBOOKS
DATA SCIENCE PLATFORMS
ML PLATFORMS
DATA GENERATION & LABELLING
MODEL BUILDING
FEATURE STORE
DEPLOY-MENT & PRO-DUCTION
MODEL MONITORING & OBSERVA-BILITY
COMPUTER VISION
SPEECH
NLP
SYNTHETIC MEDIA
HORIZONTAL AI
GPU DBS & CLOUD
AI HARDWARE

APPLICATIONS – ENTERPRISE

SALES
MARKETING - B2B
MARKETING - B2C
CUSTOMER EXPERIENCE / SERVICE
HUMAN CAPITAL
LEGAL
REGTECH & COMPLIANCE
FINANCE
AUTOMATION & RPA
SECURITY
PARTNERSHIPS

APPLICATIONS – INDUSTRY

ADVERTISING
EDUCATION
REAL ESTATE
GOV'T & INTELLIGENCE
COMMERCE
FINANCE - LENDING
INSURANCE
FINANCE - INVESTING
HEALTHCARE
LIFE SCIENCES
TRANSPORTATION
AGRICULTURE
INDUSTRIAL
OTHER

OPEN SOURCE

FRAMEWORKS
FORMAT
QUERY / DATA FLOW
DATA ACCESS
DATABASES
ORCHESTRATION
INFRA-STRUCTURE
DATA OPS
STREAMING & MESSAGING
STAT TOOLS & LANGUAGES
ML OPS & INFRA
AI / MACHINE LEARNING / DEEP LEARNING
SEARCH
LOGGING & MONITORING
VISUALIZATION
COLLABORATION
SECURITY

DATA SOURCES & APIs

DATA MARKETPLACES & DISCOVERY
FINANCIAL & ECONOMIC DATA
AIR / SPACE / SEA
PEOPLE / ENTITIES
LOCATION INTELLIGENCE
OTHER

DATA RESOURCES

DATA SERVICES
INCUBATORS & SCHOOLS
RESEARCH

Version 3.0 - November 2021

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FIRSTMARK
EARLY STAGE VENTURE CAPITAL


INFRASTRUCTURE
STORAGE
amazon S3
Azure Storage
IBM Storage
PURESTORAGE
wasabi
COHESITY
VAST
CLUMIO
HADOOP
CLOUDERA
Pivotal
jethro
Cloud Platform
arm
DATA LAKES
databricks
Azure Data Lake Storage
dremio
aws Lake Formation
IBM Power Systems
Qubole
DATA WAREHOUSES
amazon REDSHIFT
FIREBOLT
Pivotal
Infoworks
Kyligence
Yellowbrick
STREAMING / IN-MEMORY
amazon Kinesis
databricks
Cloud Platform
striim
GIGASPACES
GridGain
hazelcast
kx
Materialize
ESTUARY
RDBMS
ORACLE
NoSQL DATABASES
amazon DynamoDB
amazon DocumentDB
Azure CosmosDB
ORACLE
mongoDB
MarkLogic
Couchbase
DATASTAX
AEROSPIKE
redislabs
SCYLLA.
ArangoDB
CRATE.IO
NewSQL DATABASES
SAP
Amazon Aurora
NUODB
Pivotal
Clustrix
Cockroach Labs
splice
VOLTDB
TiDB
PingCAP
REAL TIME DATABASES
SingleStore
imply
ROCKSET
ClickHouse
Altinity
Rill
GRAPH DBs
neo4j
Amazon Neptune
IBM
ORACLE
OrientDB
InfiniteGraph
Objectivity
TigerGraph
TerminusDB
MPP DBs
TERADATA
VERTICA
Exasol
ETL / ELT / DATA TRANSFORMATION
dbt
talend
alteryx
Fivetran
Stitch
MATILLION
pentaho
TRIFACTA
Paxata
StreamSets
tamr
Airbyte
Meltano
Rivery
REVERSE ETL
Census
hightouch
Grouparoo
rudderstack
Flywheel Software
POLYTOMIC
DATA INTEGRATION
Data Services
segment
Informatica
MuleSoft
TEALIUM
snaplogic
Qlik Data Catalyst
tray.io
xplenty
ATTUNITY
ZALONI
import.io
Infoworks
SNOWPLOW
flatfile
DATA GOVERNANCE & ACCESS
Informatica
SailPoint
IBM
Alation
collibra
dremio
IMMUTA
OKERA
data.world
atlan
PRIVACY & SECURITY
VERY GOOD SECURITY
PRIVAGERA
Cyral
Transcend
skyflow
Duality
Privacy Dynamics
Ketch
DATA OBSERVABILITY
datakin
MONTE CARLO
MANTA
Collibra
DATA QUALITY
talend
SODA
Bigeye
SUPERCONDUCTIVE
Collibra
Anomalo
precisely
MGMT / MONITORING
Cloudwatch
New Relic
DATADOG
splunk>
APPDYNAMICS
rubrik
dynatrace
solarwinds
WAVEFRONT
actifio
Cribl
Moogsoft
chronosphere
unravel
pagerduty
SCALYR
zenoss
ScienceLogic
MAGNITUDE
VEEAM
Grafana Labs
OpsRamp
honeycomb.io
SERVER-LESS
nuclio
CLUSTER SVCS
AmazonECS
IBM
AmazonEKS
Cluster Server
D2 IQ
Colled
anyscale
packet
CYCLECLOUD

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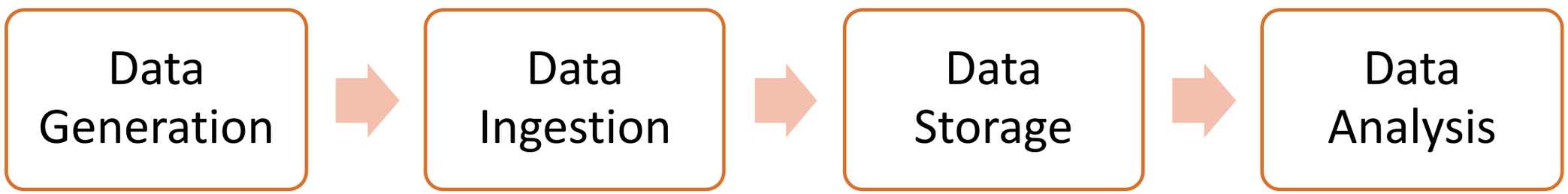
Data Pipeline Analogy

Data Science Lifecycle



- Various data sources
- Real time and batch

- Data collection
- Data transportation
- Data pre-processing

- Relational vs NoSQL
- CAP theorem

- Data manipulation
- Data exploration
- ML / prediction
- Data visualization

- Transactional Databases
- Mobile Applications
- IOT / Sensors

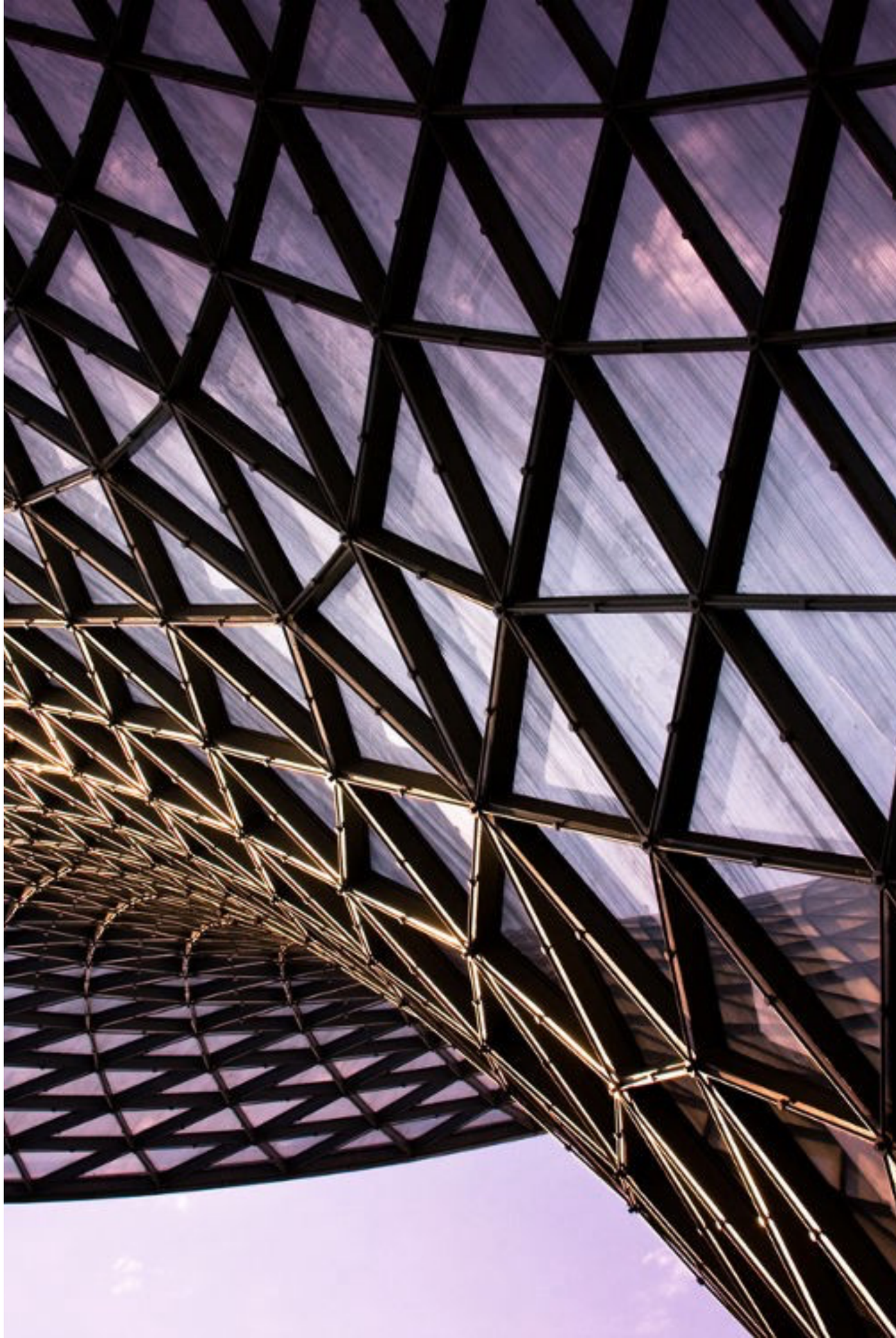
- Message Oriented Middleware (Kafka, MQ)
- ETL tools

- HDFS, MongoDB, Cassandra, Redis
- Arrow, Presto, Drill

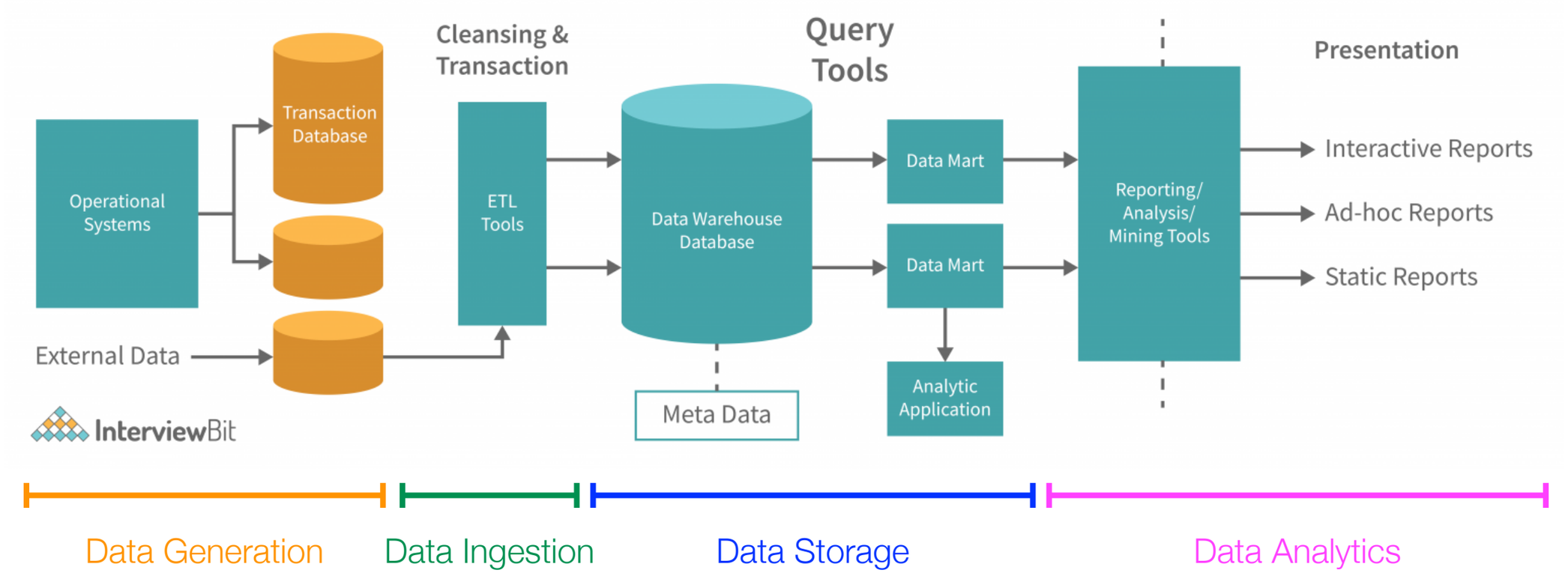
- Pandas, Spark, Flink
- ML algorithms
- Power BI, Tableau

Architectural Patterns

Common design patterns being used in data science

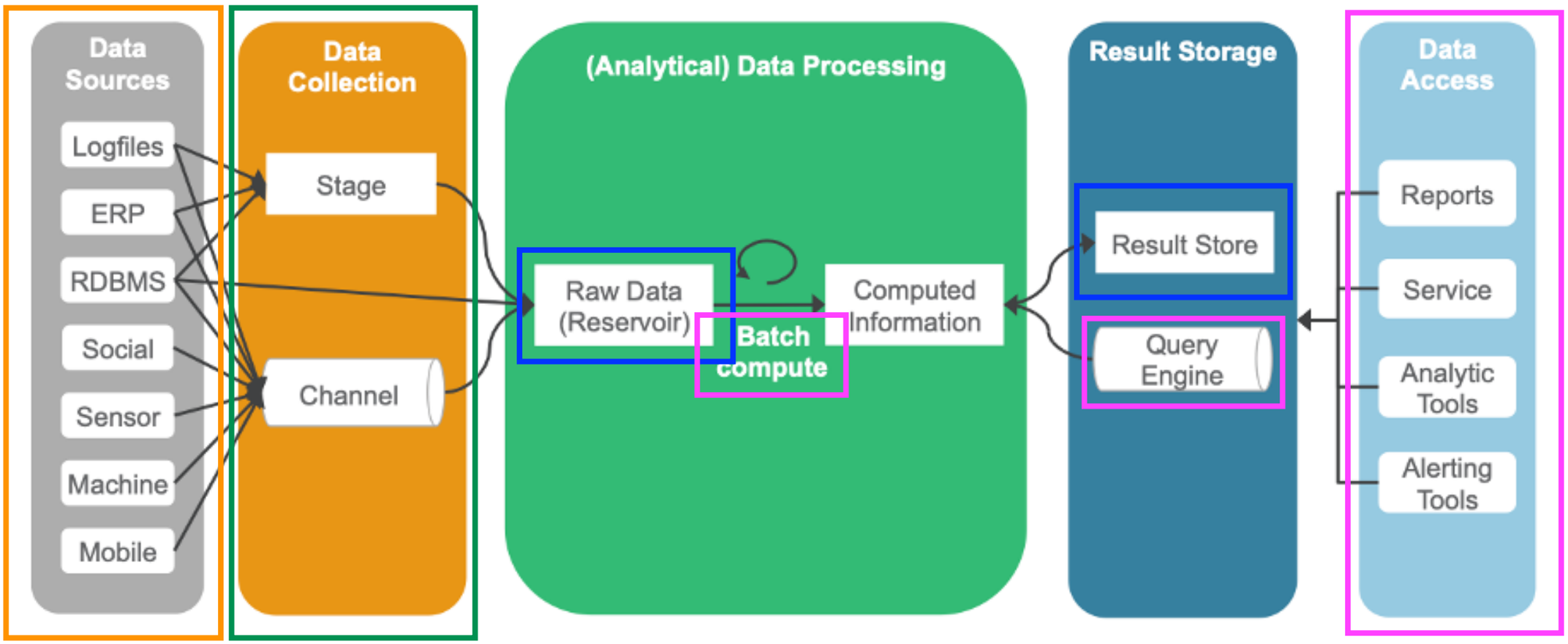


Data Warehouse
Pre-Big-Data Era Data Analytics



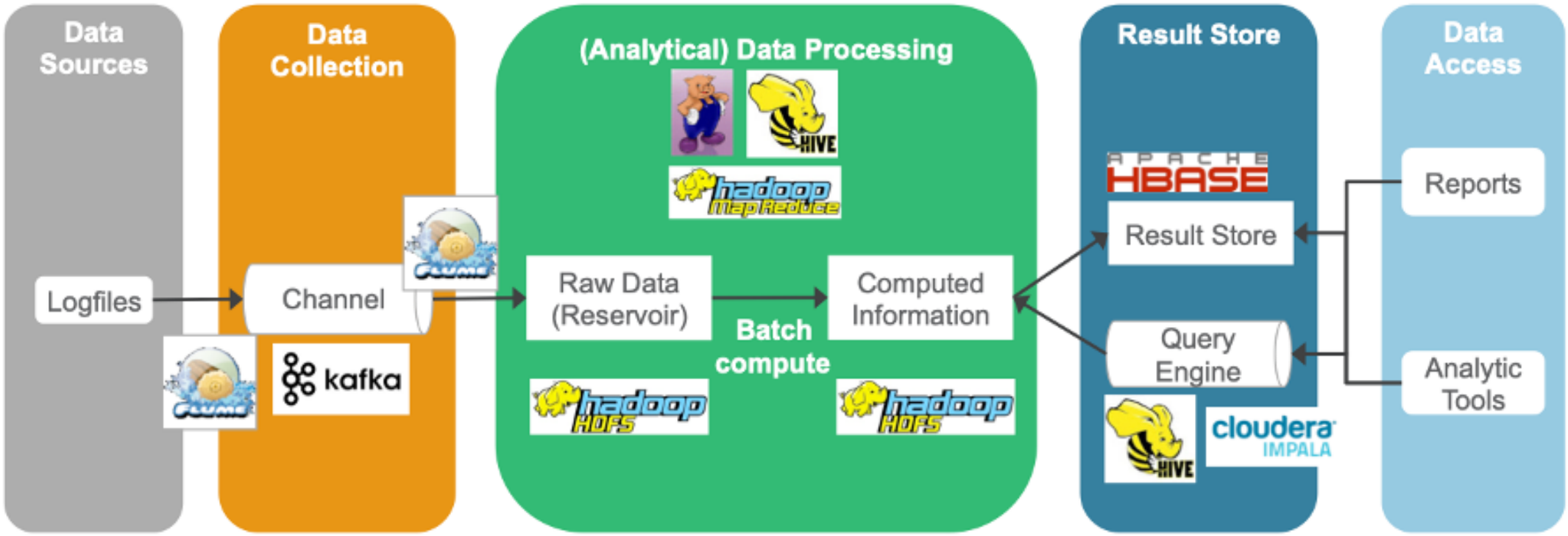
Source: “Data Warehouse Architecture – Detailed Explanation”, https://www.interviewbit.com/blog/data-warehouse-architecture/

Simple Big Data Analytic Architecture

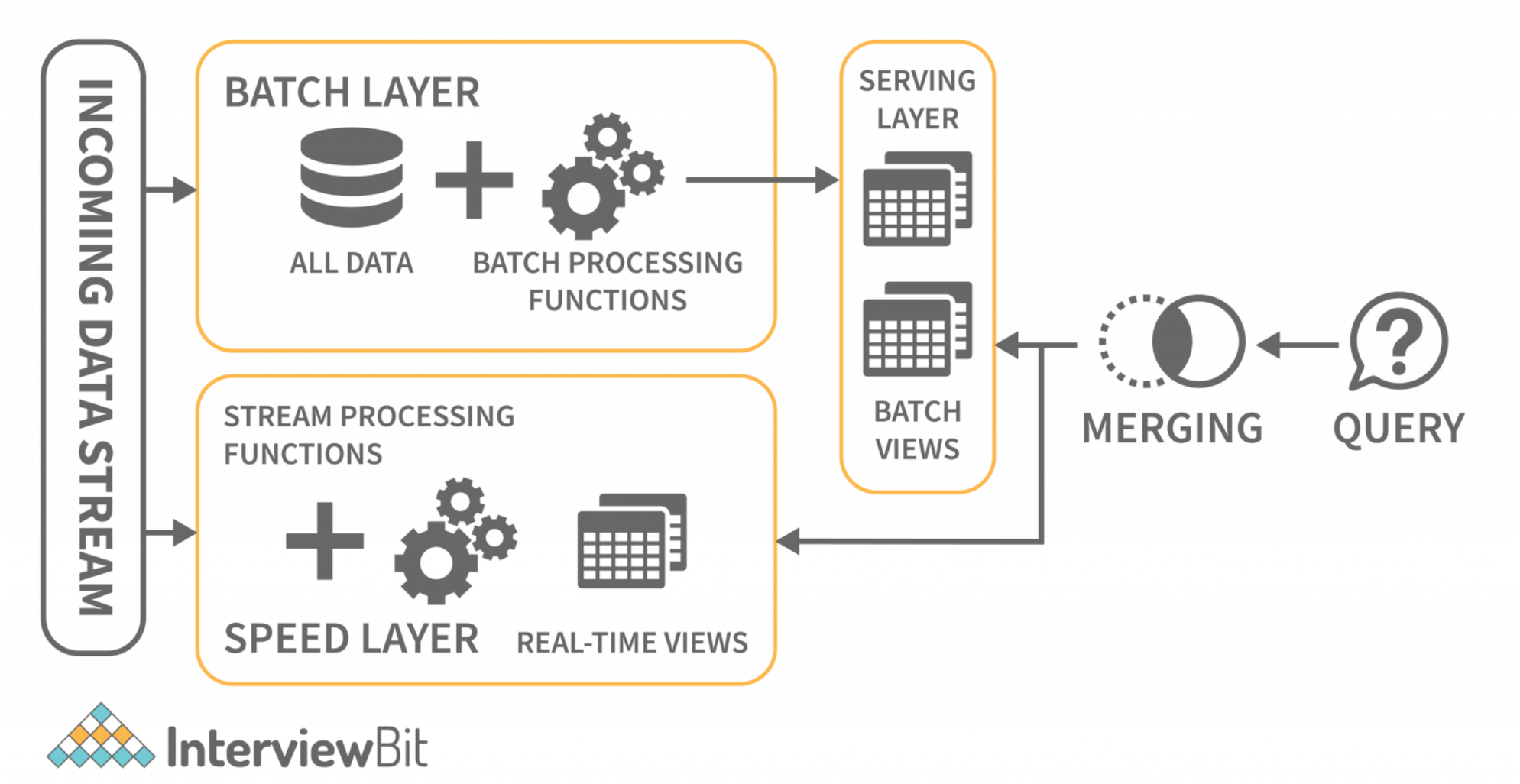


Data Generation Data Ingestion Data Storage Data Analytics

Example: Facebook Data Pipeline (early days)



Lambda Architecture (Nathan Marz)



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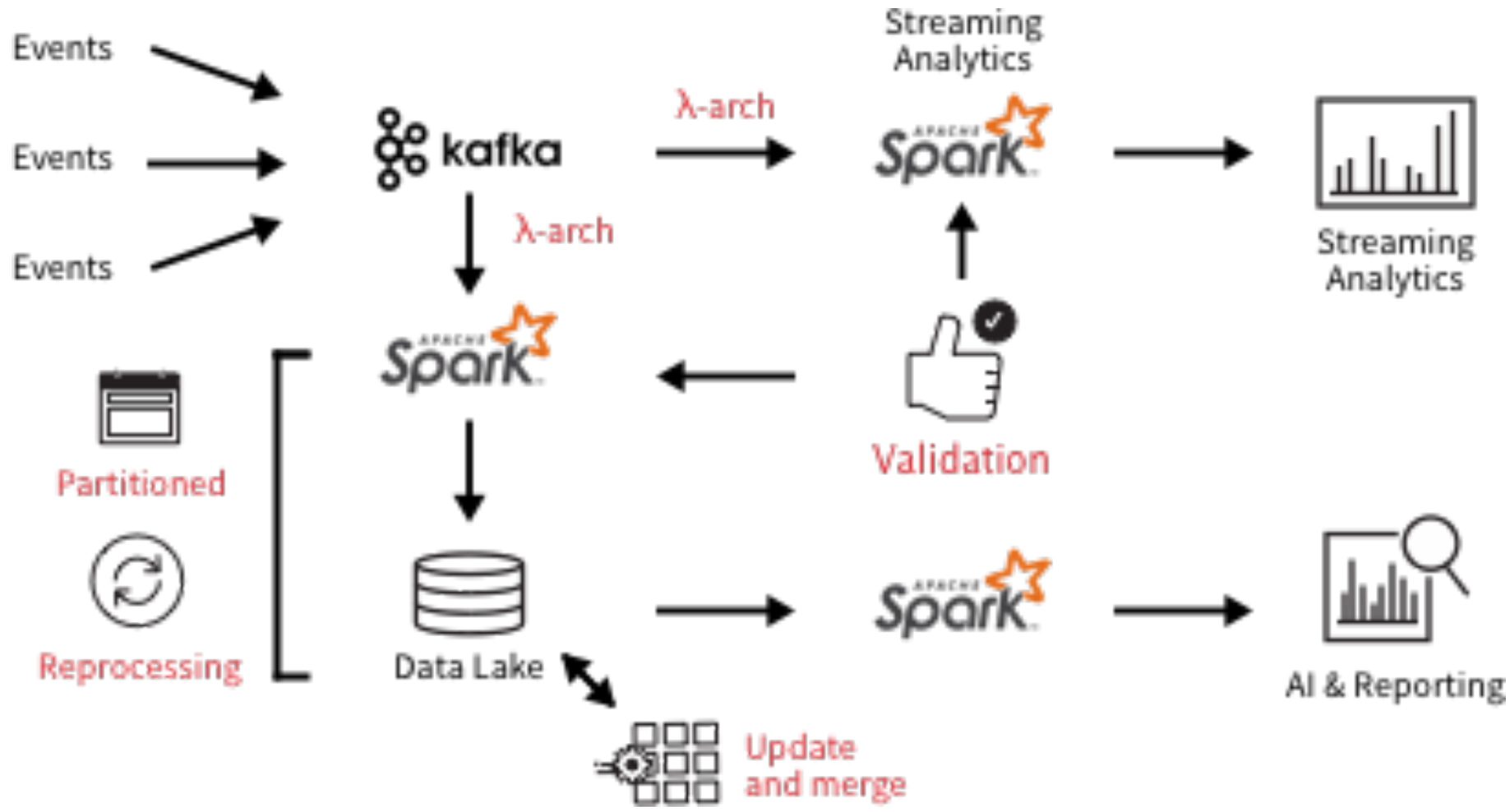
Lambda Architecture in Practice

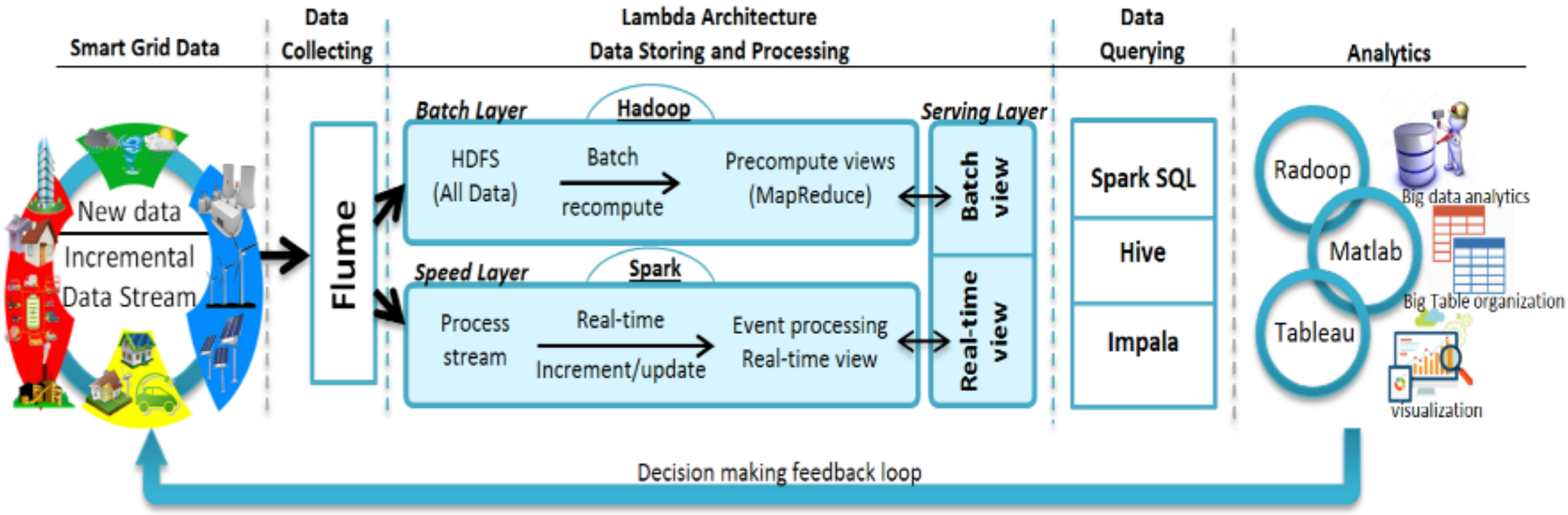


https://www.databricks.com/blog/2020/11/20/delta-vs-lambda-why-simplicity-trumps-complexity-for-data-pipelines.html

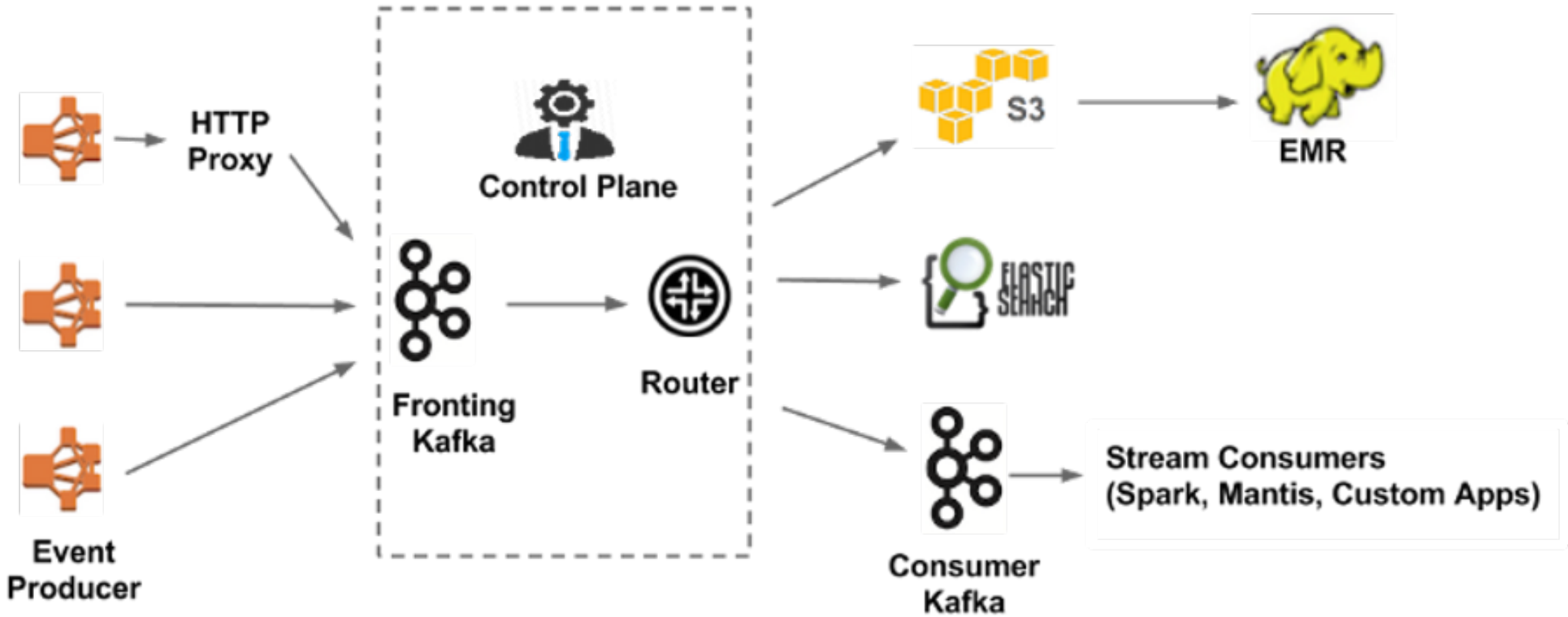
Principles of Lambda Architecture

- Assume on a data model with an append-only, immutable data source that serves as a system of record
- Intended for ingesting and processing timestamped events that are appended to existing events rather than overwriting them
- Balance latency, throughput, and fault-tolerance
  - Batch processing to provide comprehensive and accurate views of batch data
  - Real-time stream processing to provide views of online data

Example: Smart Grid Architecture

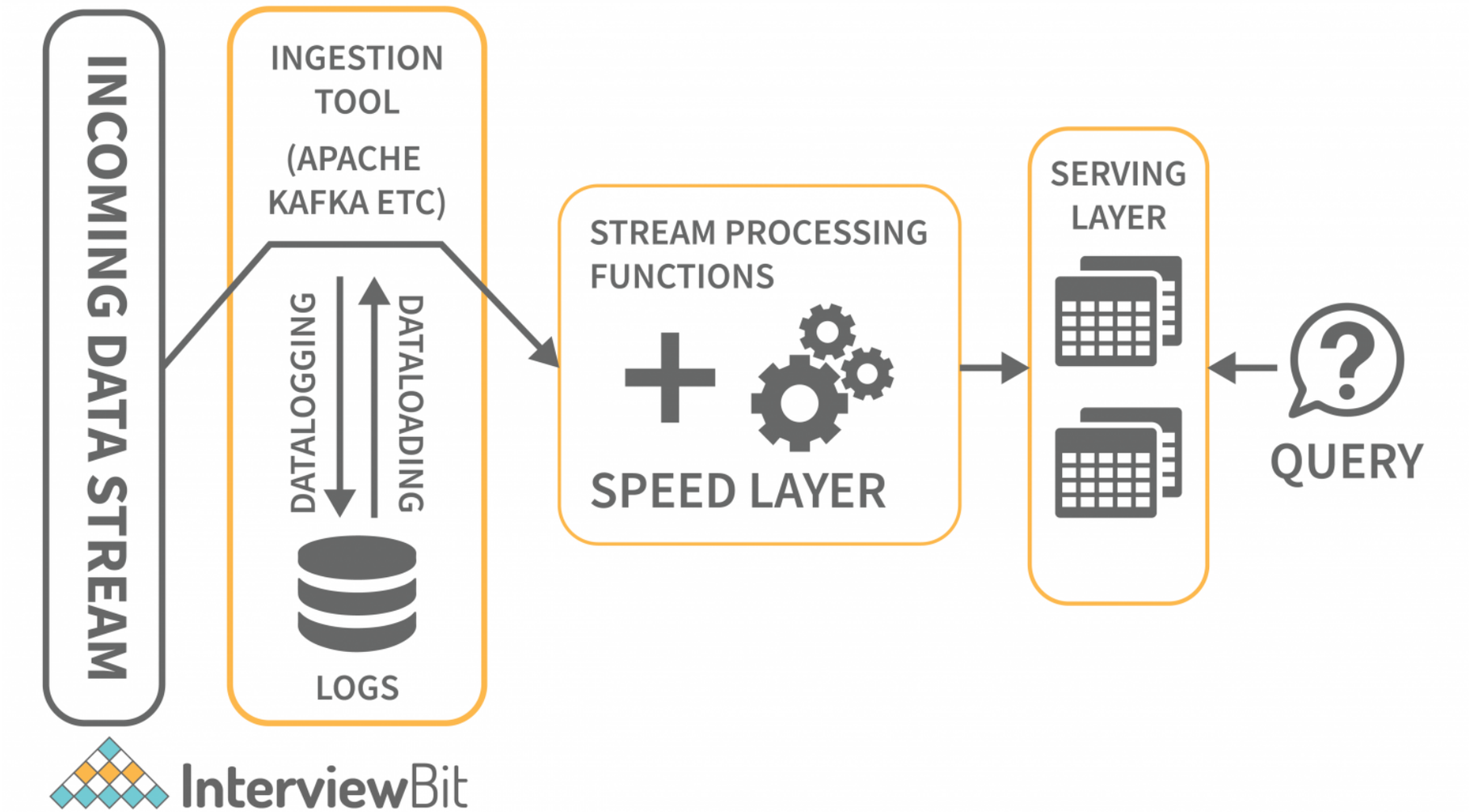


Example: Netflix's Keystone Architecture



Source: https://towardsdatascience.com/scalable-efficient-big-data-analytics-machine-learning-pipeline-architecture-on-cloud-4d59efc092b5

Kappa Architecture (Jay Krepsen)

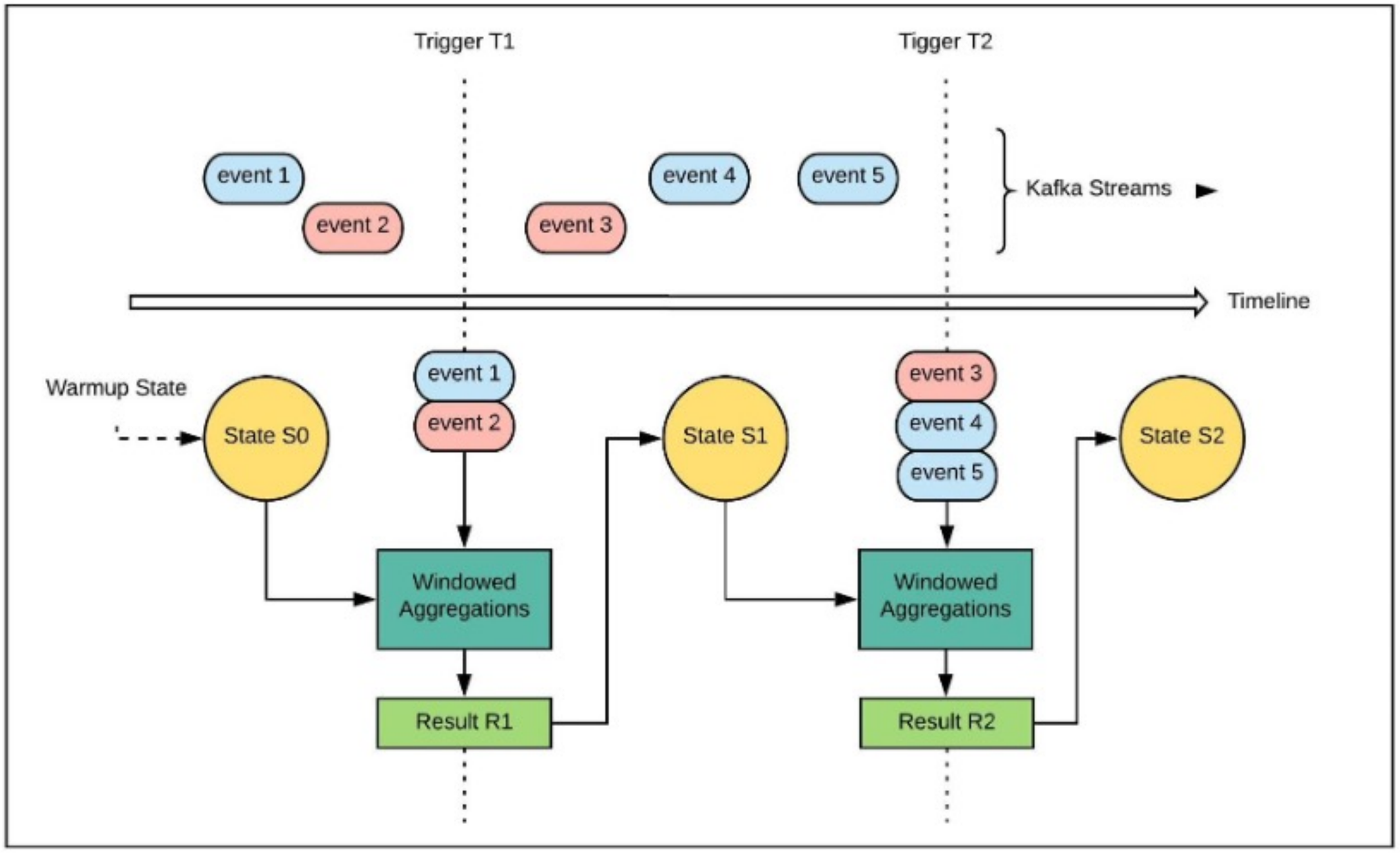


Source: “Data Warehouse Architecture – Detailed Explanation”, https://www.interviewbit.com/blog/data-warehouse-architecture/

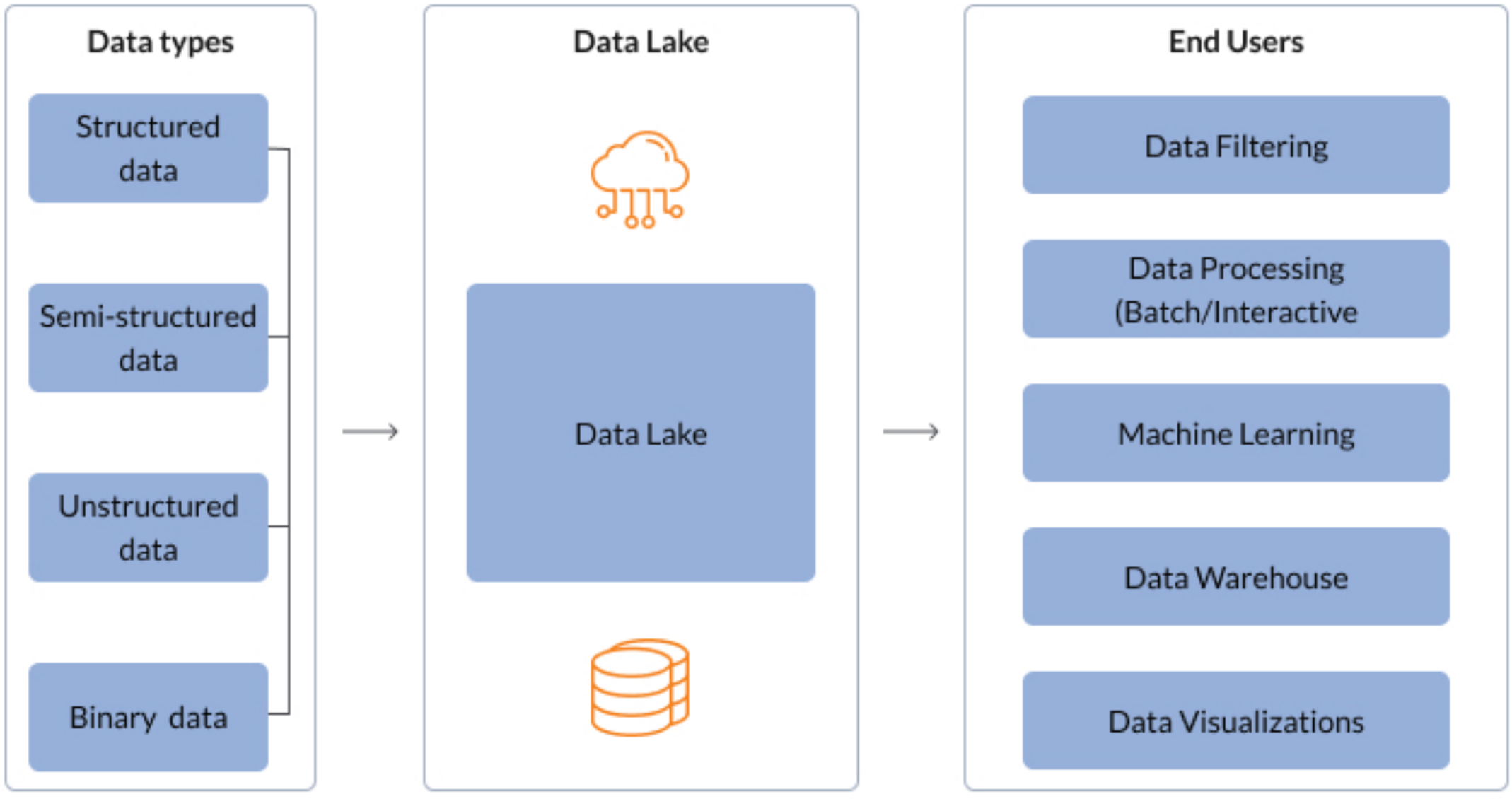
Principles of Kappa Architecture

- Real-time data or “stream” is everything, batch is just a subset of stream
- Raw data is never changed
- Multiple views can be defined on one raw data stream
- Single and unified data processing framework (for both real-time and batch
- Handle late data arrival and failure recovery can be done by reprocessing or “replaying” historical data (because raw data is never changed)

Example: Uber Real-Time Dynamic Pricing

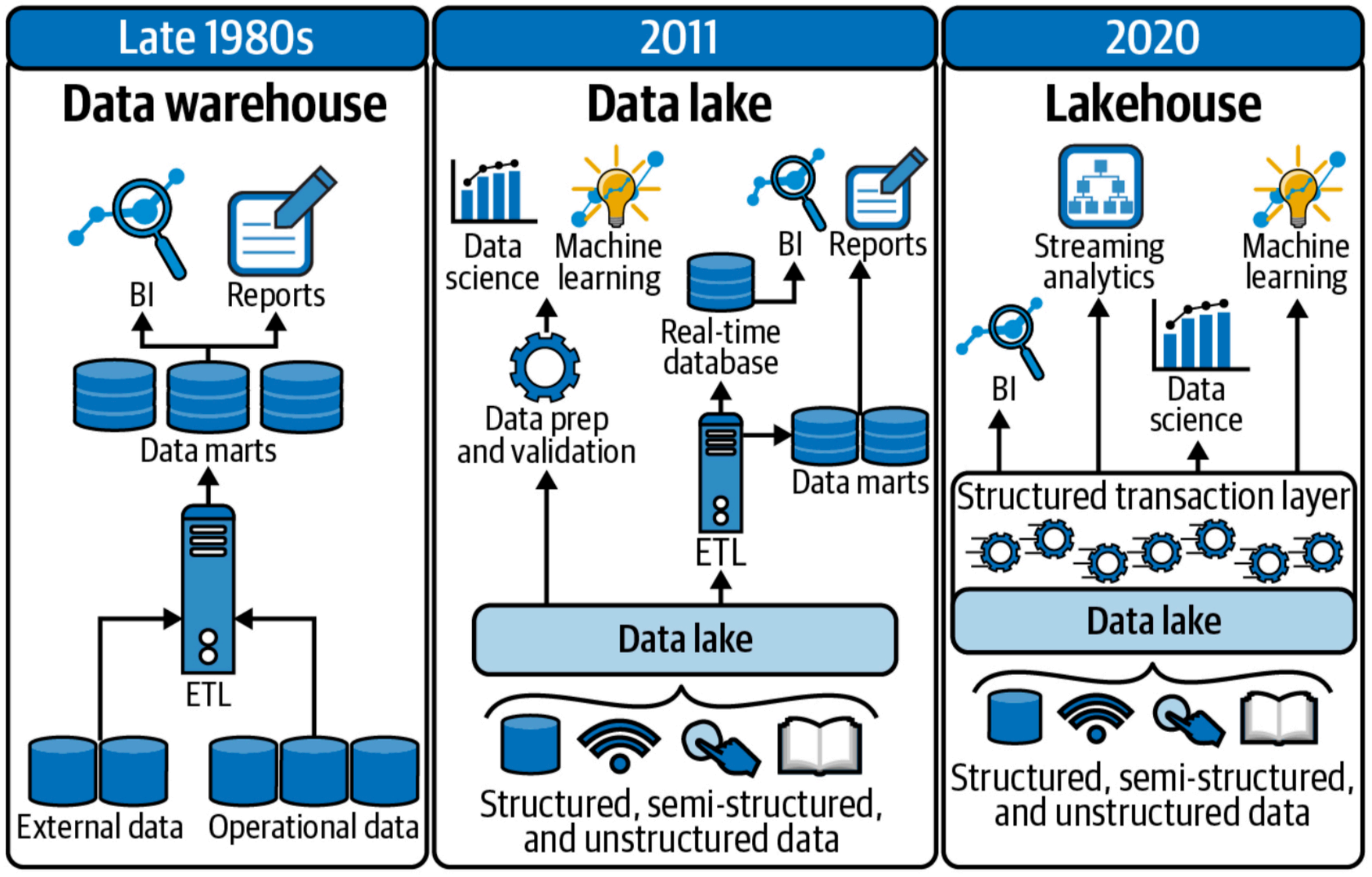


Data Lake Architecture



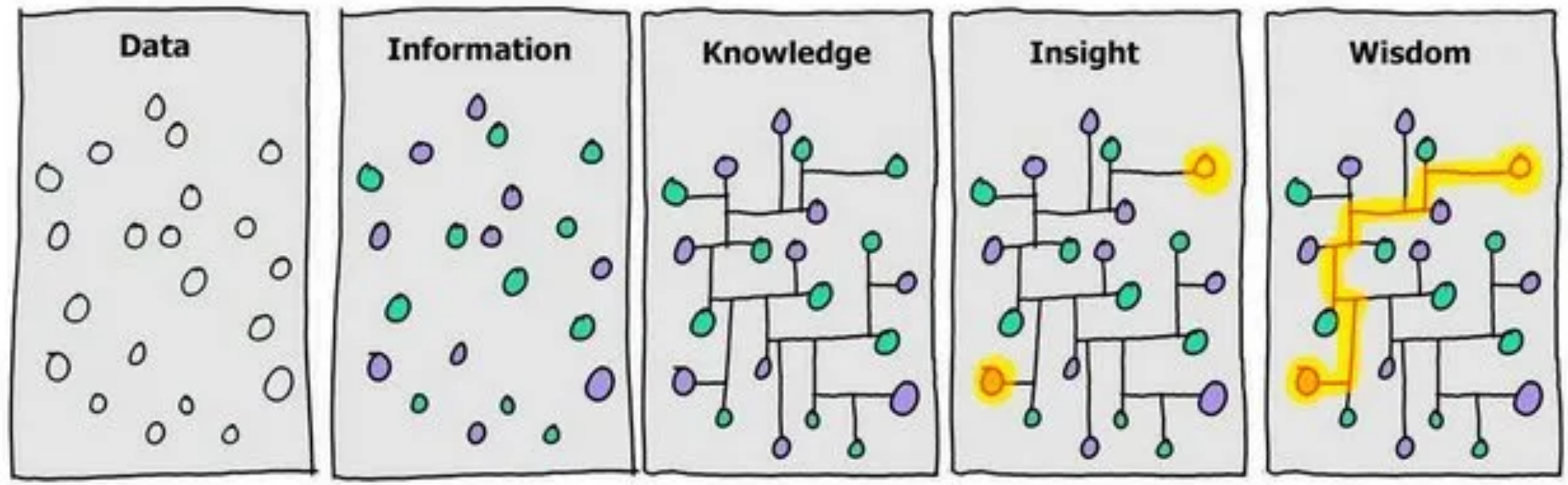
Source: https://www.n-ix.com/data-lake-vs-data-warehouse/

Data Lakehouse Architecture



Source: Alice LaPlante, “The Modern Cloud Data Platform”

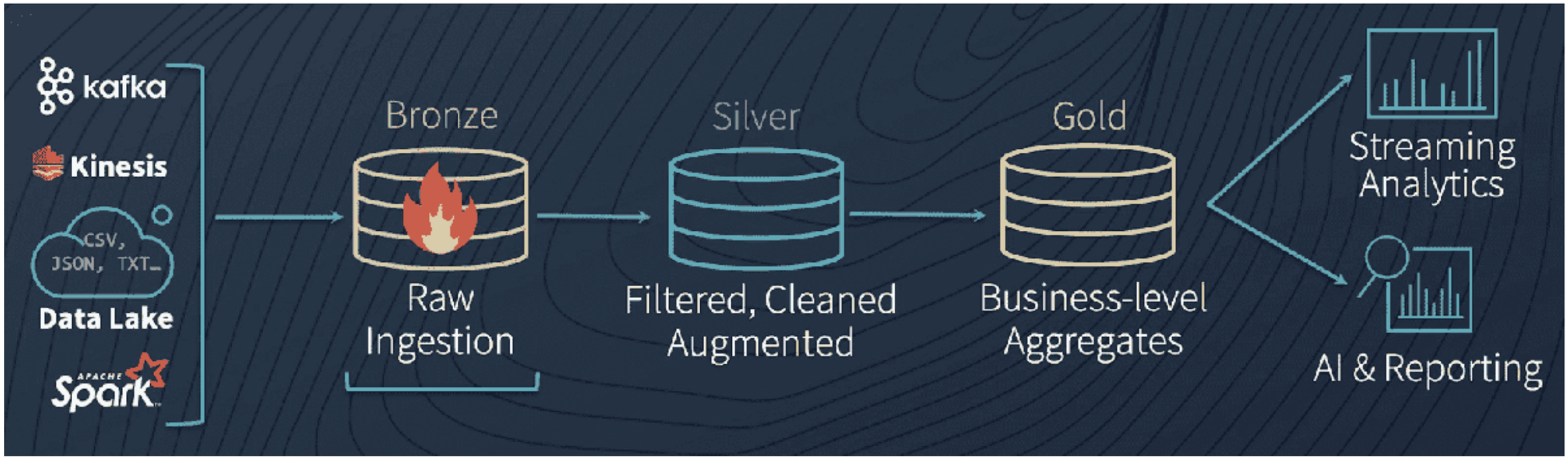
Data Evolution



Bronze	Silver	Gold

Visualization / BI Tools	Personalization AI/ML

Delta Lake Architecture



Source: https://www.databricks.com/blog/2020/11/20/delta-vs-lambda-why-simplicity-trumps-complexity-for-data-pipelines.html

- All the processing and enrichment of data from Bronze (raw data) to Silver (cleansed, filtered) to Gold (structured and ready to be used by analytics, reporting, and data science) happens within Delta Lake

Principles of Delta Lake Architecture

- Lambda architecture is complex and requires data validation between real-time and batch processing paths

- Kappa architecture does not perform well when large amount of historical data playback is required

- Delta Lake architecture focuses on simplicity by processing data in the data store from bronze to silver to gold

- Single source of truth as there is only one path

Key Benefits of Delta Lake Architecture

- Recording all changes and commits in transaction log ensures data integrity and reliability

- Each write creates a new data version, old version can be view and revert (rollback)

- Built-in data governance including ACID transaction control, schema enforcement, etc.

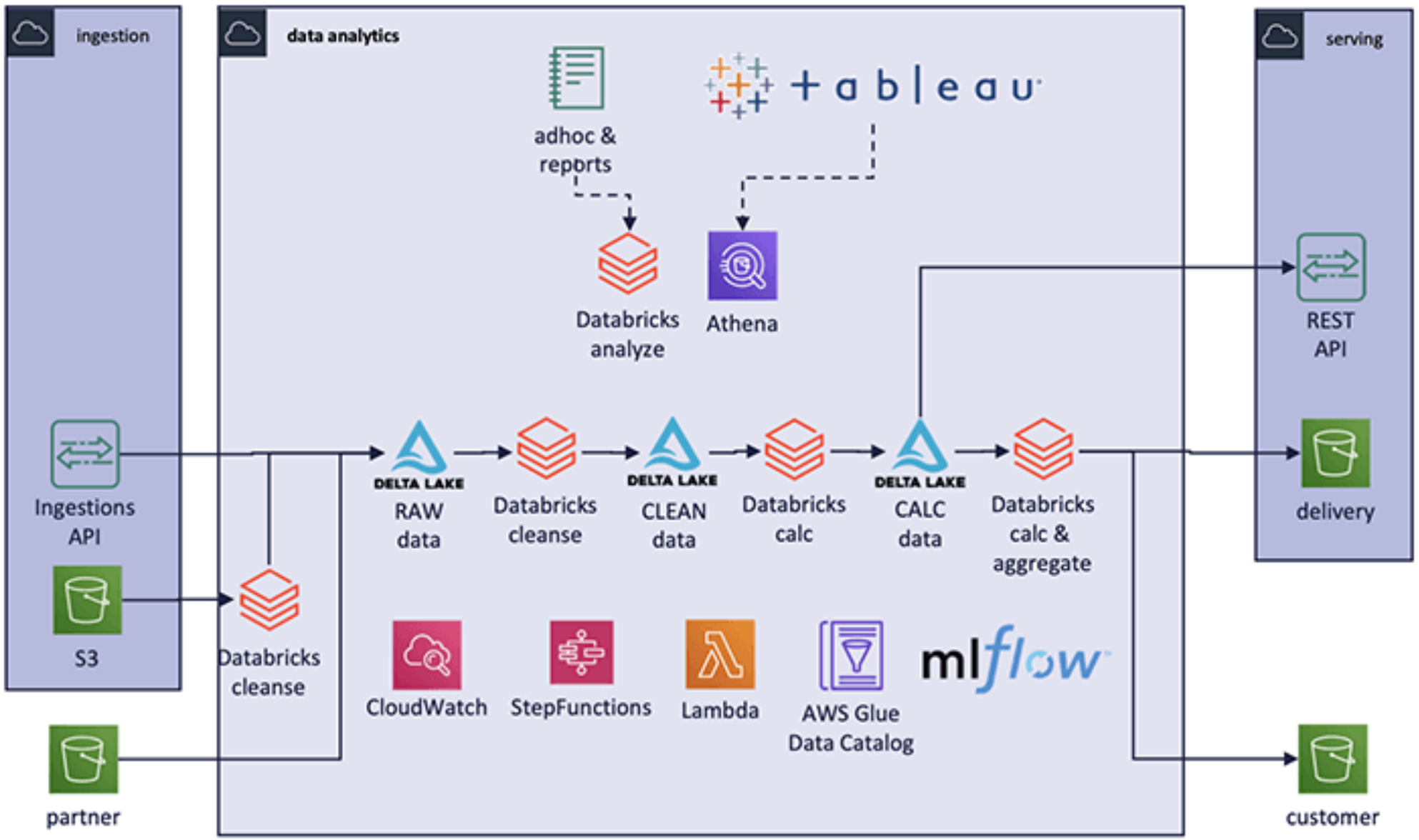
- Unifying batch and stream processing simplifies data pipeline development and maintenance

https://streamsets.com/blog/delta-lake-architecture-bridge-between-data-lakes-data-warehouses/

Example: wetter.com

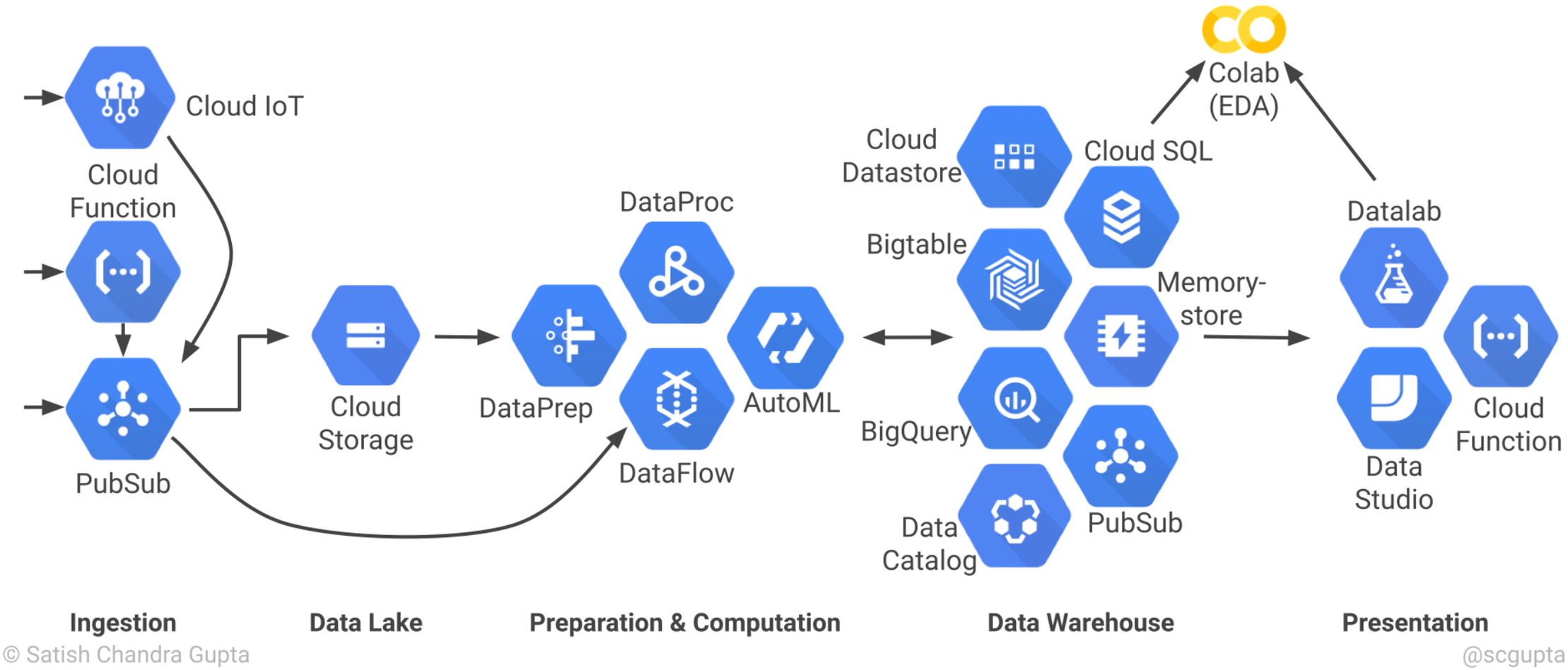
- Germany weather portal with up to 20 million monthly unique users
- Monetize data by selling data-products to business customers
- Decode the interrelation between weather, consumer behavior and many other factors used by clients in retail, FMCG, e-commerce, tourism, food and advertising
- Switch from multiple steps Spark/S3 data pipeline to Delta Lake architecture

Example: wetter.com



https://www.databricks.com/blog/2020/11/13/how-to-evaluate-data-pipelines-for-cost-to-performance.html

Cloud Serverless Architecture



Source: https://towardsdatascience.com/scalable-efficient-big-data-analytics-machine-learning-pipeline-architecture-on-cloud-4d59efc092b5

Key Takeaways

- Big Data is just a foundation for data processing; data analytics is also important as it creates business values

- Architectural design patterns can provide templates or guidelines to big data pipeline solutions

- Lambda Architecture is one of the most popular architecture as it can support both batch and real-time data processing

- Data Lakehouse is an emerging architecture, combining best features from data lake (flexibility, low-cost) and data warehouse (structured, governance)

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