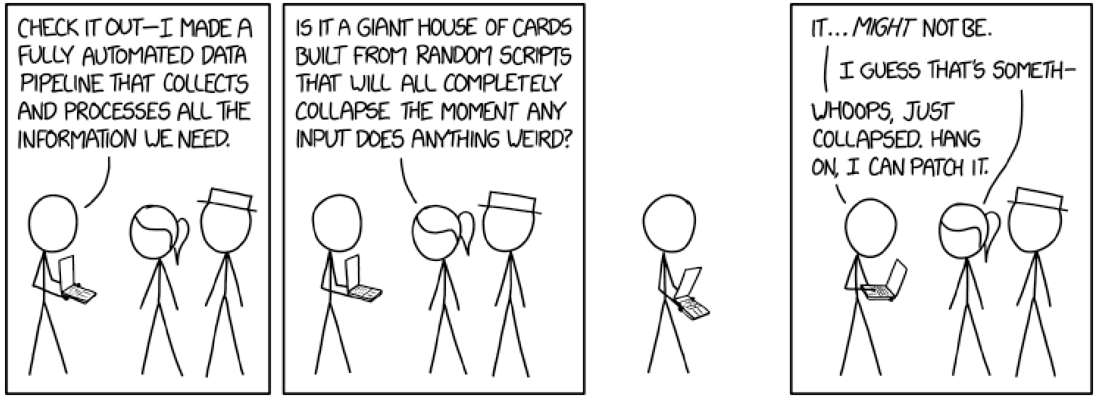
BIG DATA AND CLOUD PLATFORMS

Data pipelines on cloud (Storage)

Data pipeline

Data pipeline

- *"A sequence of operations to transform and consume raw data"*



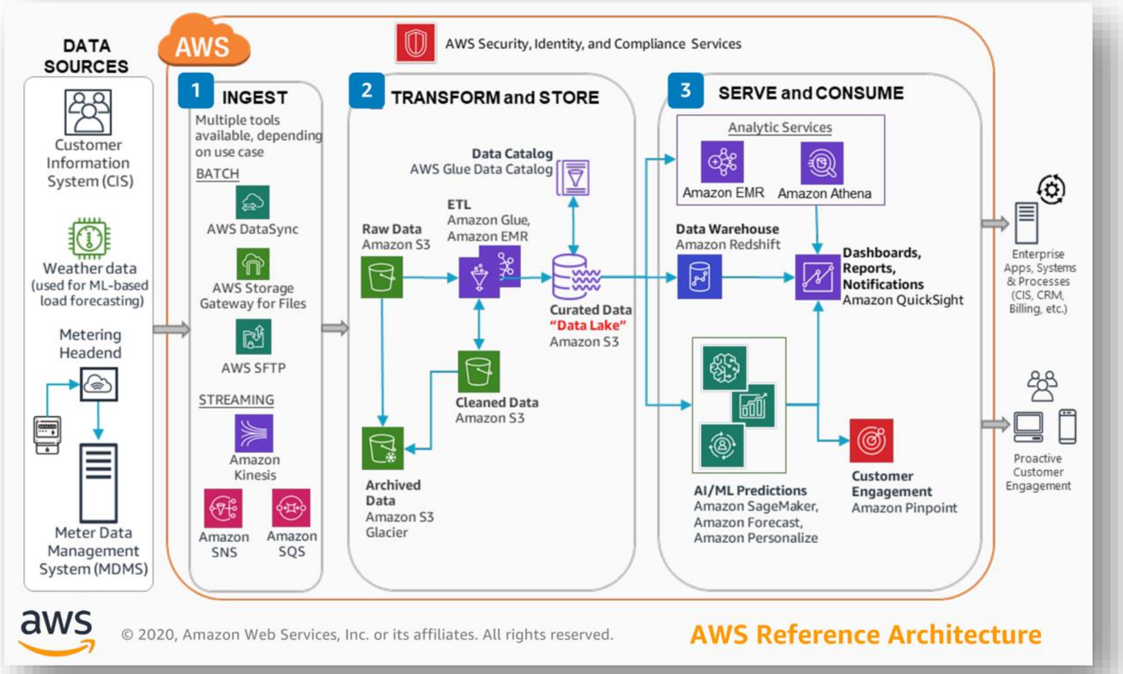
https://xkcd.com/2054/

Quemy, Alexandre. "Data Pipeline Selection and Optimization." *DOLAP*. 2019.

Data pipeline - AWS

Three main categories

- Ingest
  - Gateway, DataSync (batch)
  - Kinesis, SNS, SQS (stream)
- Transform and store
  - S3 and Glacier (storage)
  - Glue (ETL)
- Serve and consume
  - EMR (Hadoop-like cluster)
  - Athena (serverless query service to analyze data in Amazon S3)
  - (Many) Machine learning services

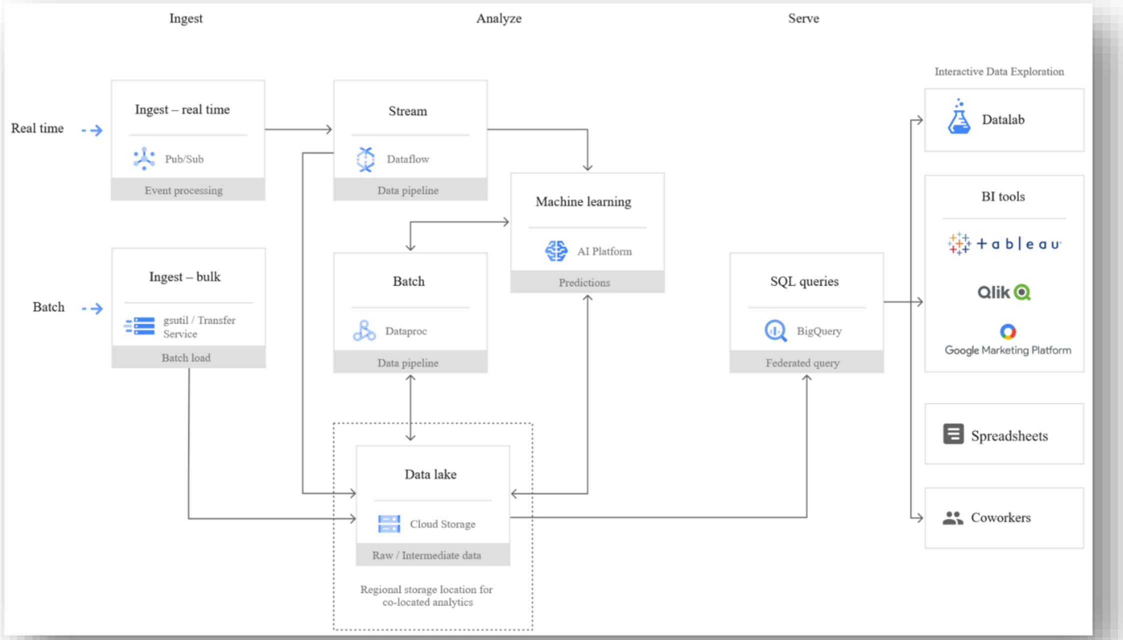


https://console.aws.amazon.com/console

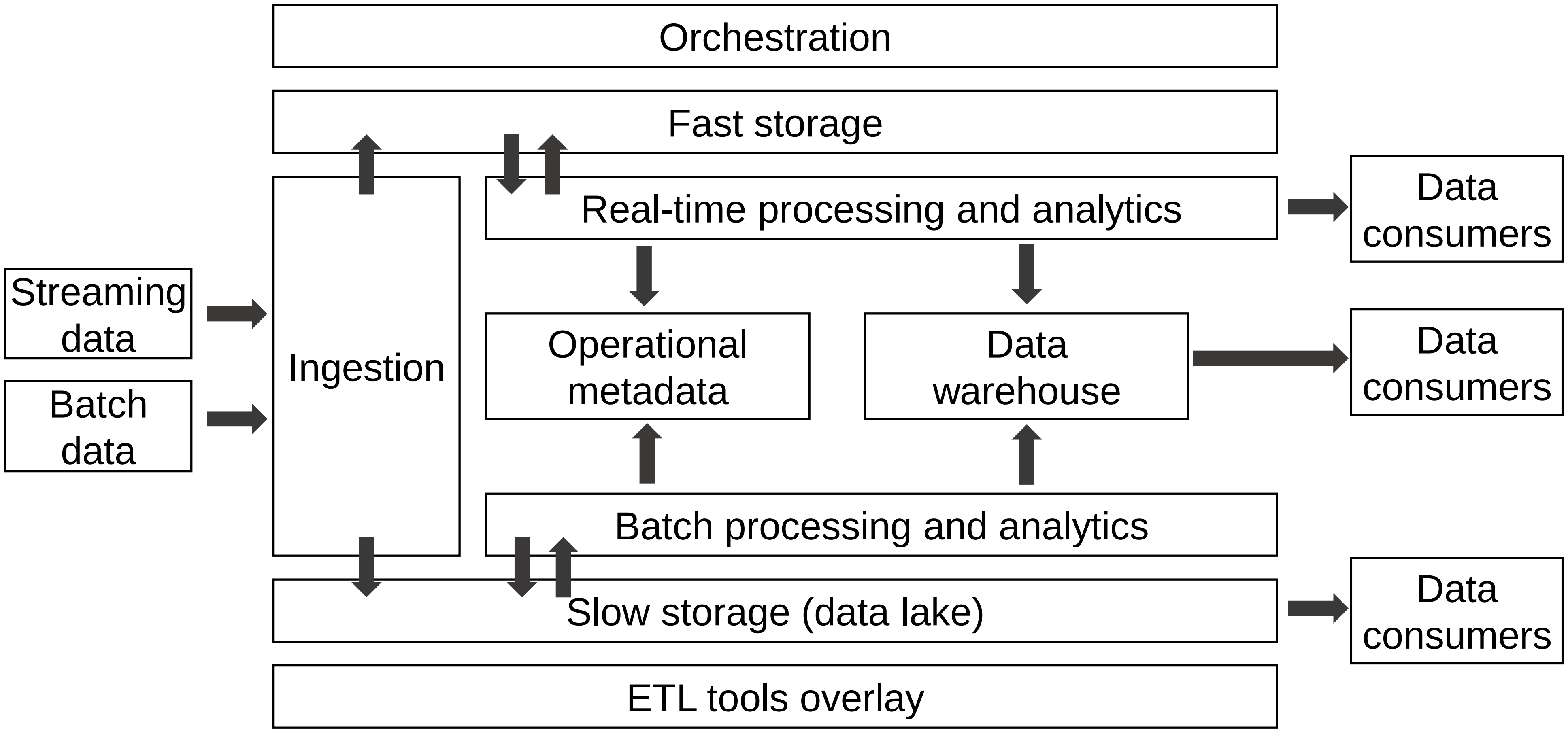
Data pipeline - Google cloud

Three main categories

- Ingest
  - Transfer service (batch)
  - Pub/Sub (stream)
- Analyze
  - Dataproc (batch)
  - Dataflow (stream)
  - Cloud storage (storage)
  - Machine learning services
- Serve
  - BigQuery (query service)



A tentative organization



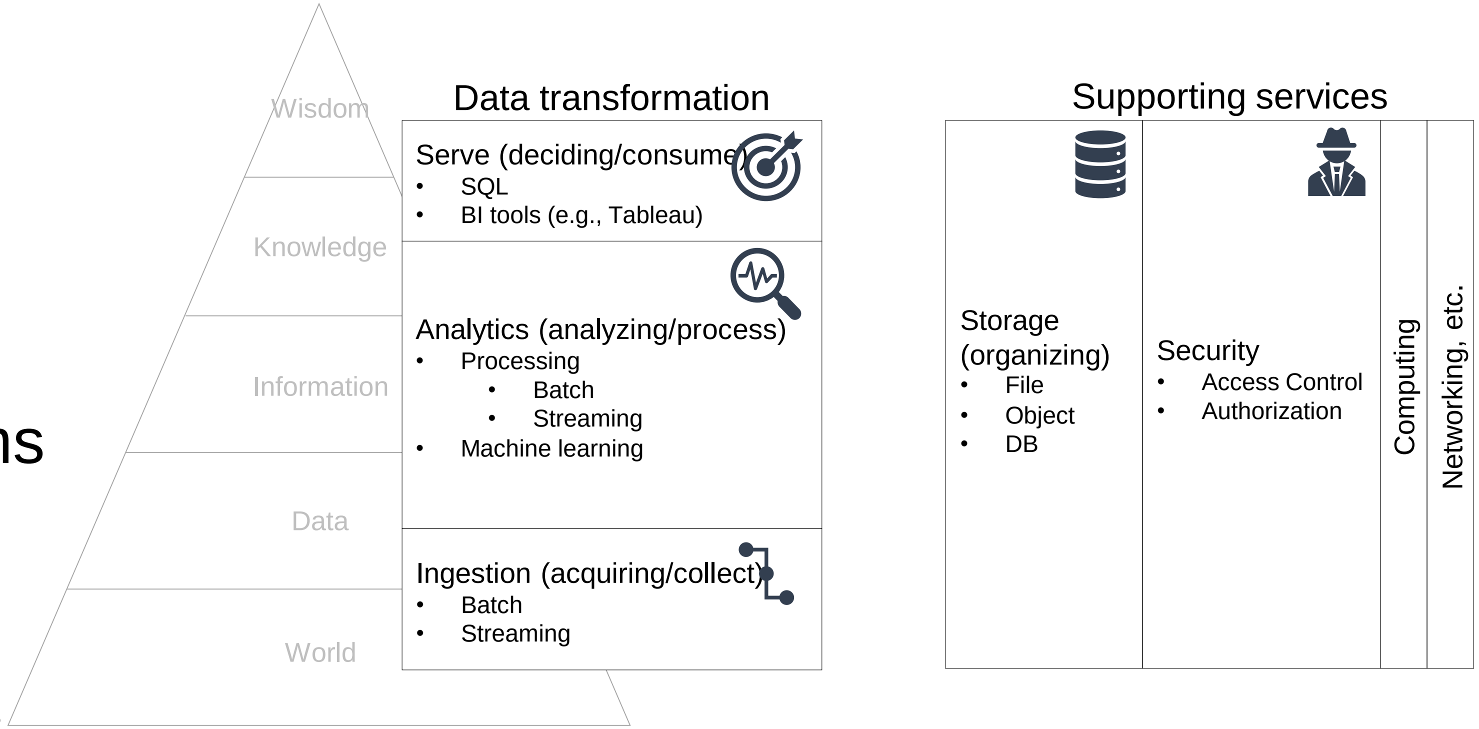
A tentative organization

We have services

- To transform data
- To support the transformation

The (DIKW) pyramid abstracts many techniques and algorithms

- Standardization
- Integration
- Orchestration
- Accessibility through APIs

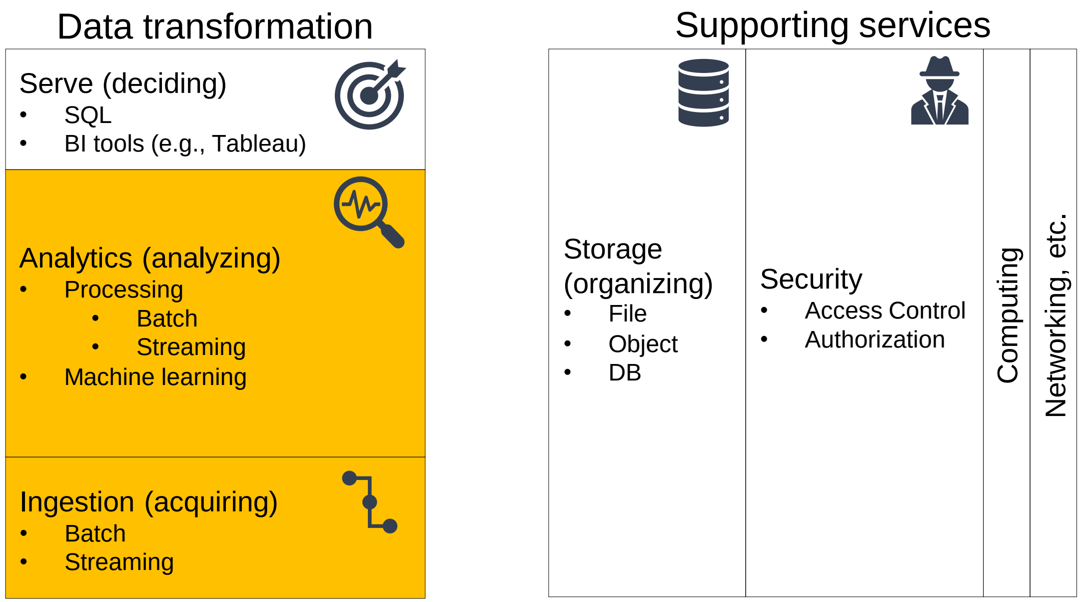


A tentative organization

This is not a sharp taxonomy

Ingestion vs Analytics

- Data streams are used for ingestion
- ... and (event) processing

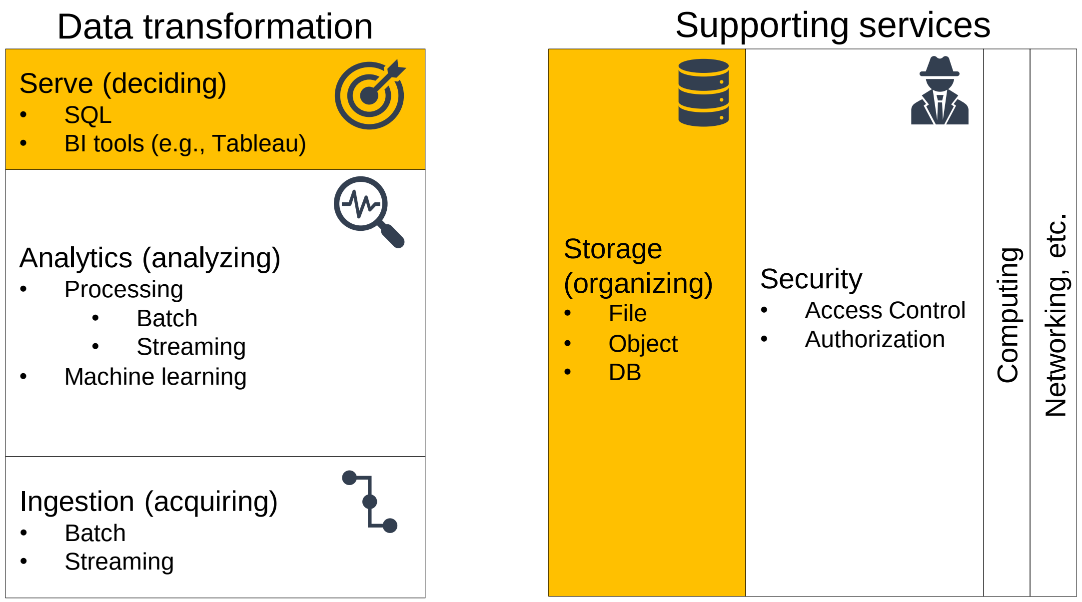


A tentative organization

This is not a sharp taxonomy

Storage vs Serving

- Databases are storage
- ... with processing capability
- ... and with serving capability



Data transformation

Serve (deciding)
- SQL
- BI tools (e.g., Tableau)

Analytics (analyzing)
- Processing
  - Batch
  - Streaming
- Machine learning

Ingestion (acquiring)
- Batch
- Streaming

Supporting services

Storage (organizing)
- File
- Object
- DB

Security
- Access Control
- Authorization

Computing

Networking, etc.

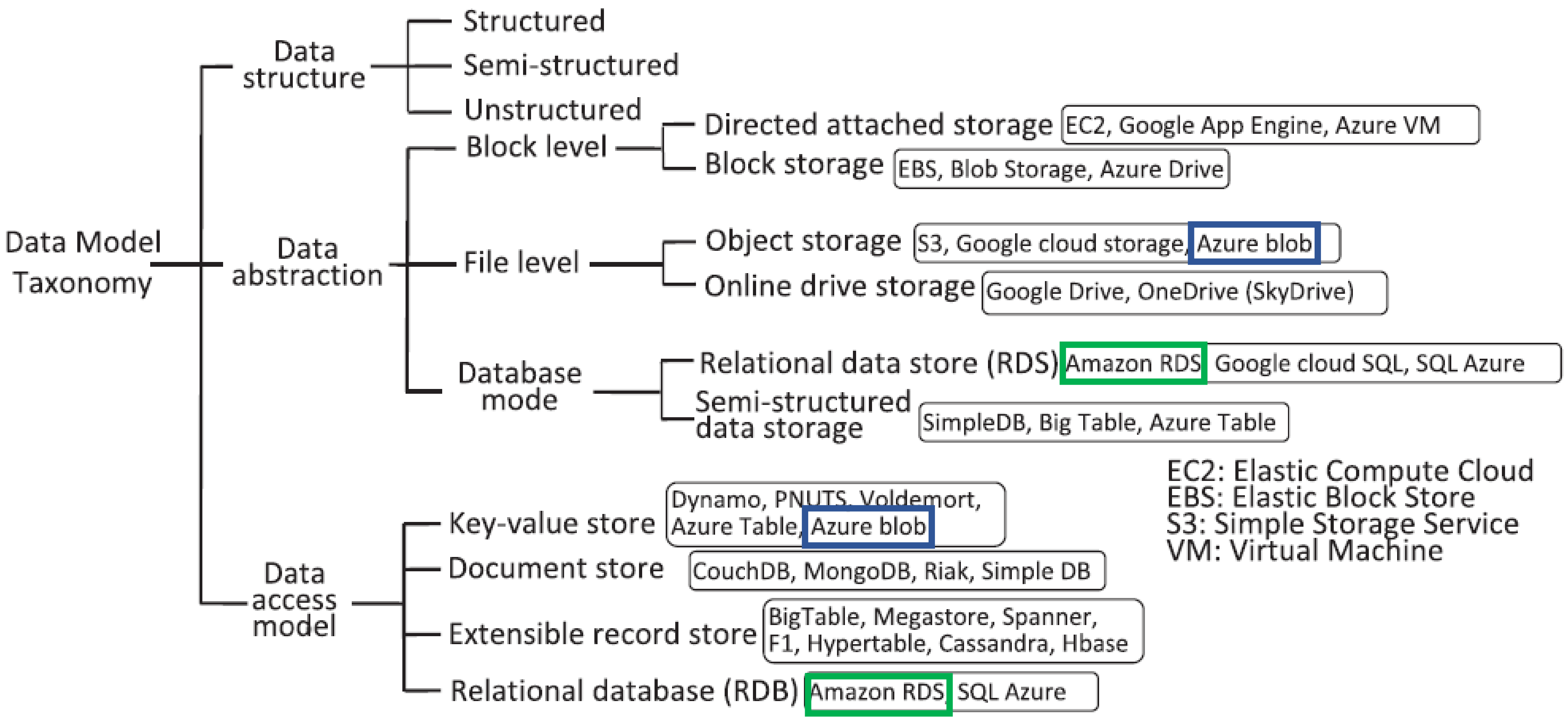
Storage

Goal: persisting data

Which storage do we choose?

- **Storage model** (or data model) ~= variety
  - How data are organized/accessed in a storage system
    - Structured vs unstructured
    - Data access model (key-value, column, etc.)
- Access **frequency**
- **Analyses** to be performed

Storage models



Mansouri, Yaser, Adel Nadjaran Toosi, and Rajkumar Buyya. "Data storage management in cloud environments: Taxonomy, survey, and future directions." ACM Computing Surveys (CSUR) 50.6 (2017): 1-51.

Storage models (AWS)

Data structure: structured

Data abstraction: database

Data access model: relational

Relational

- Store data with predefined schemas and relationships between them
- Support ACID transactions
- Maintain referential integrity

Database type	Use cases	AWS service
Relational	Traditional applications, ERP, CRM, e-commerce	Amazon Aurora, Amazon RDS, Amazon Redshift
Key-value	High-traffic web apps, e-commerce systems, gaming applications	Amazon DynamoDB
In-memory	Caching, session management, gaming leaderboards, geospatial applications	Amazon ElastiCache for Memcached, Amazon ElastiCache for Redis
Document	Content management, catalogs, user profiles	Amazon DocumentDB (with MongoDB compatibility)
Wide column	High scale industrial apps for equipment maintenance, fleet management, and route optimization	Amazon Keyspaces (for Apache Cassandra)
Graph	Fraud detection, social networking, recommendation engines	Amazon Neptune
Time series	IoT applications, DevOps, industrial telemetry	Amazon Timestream
Ledger	Systems of record, supply chain, registrations, banking transactions	Amazon QLDB

https://aws.amazon.com/products/databases/

Storage models (AWS)

Data structure: semi/unstructured

Data abstraction: database

Data access model: *

- **Key/value:** store and retrieve large volumes of data
- **Document :** store semi-structured data as JSON-like documents
- **Columnar:** use tables but unlike a relational database, columns can vary from row to row in the same table
- **Graph:** navigate and query relationships between highly connected datasets
- **... and more**

Database type	Use cases	AWS service
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https://aws.amazon.com/products/databases/

Storage models (Google Cloud)

	Cloud Datastore	Bigtable	Cloud Storage	Cloud SQL	Cloud Spanner	BigQuery
Type	NoSQL document	NoSQL wide column	Blobstore	Relational SQL for OLTP	Relational SQL for OLTP	Relational SQL for OLAP
Transactions	Yes	Single-row	No	Yes	Yes	No
Complex queries	No	No	No	Yes	Yes	Yes
Capacity	Terabytes+	Petabytes+	Petabytes+	Terabytes	Petabytes	Petabytes+
Unit size	1 MB/entity	~10 MB/cell ~100 MB/row	5 TB/object	Determined by DB engine	10,240 MiB/ row	10 MB/row

	Cloud Datastore	Cloud Bigtable	Cloud Storage	Cloud SQL	Cloud Spanner	BigQuery
Type	NoSQL document	NoSQL wide column	Blobstore	Relational SQL for OLTP	Relational SQL for OLTP	Relational SQL for OLAP
Best for	Semi-structured application data, durable key-value data	"Flat" data, Heavy read/write, events, analytical data	Structured and unstructured binary or object data	Web frameworks, existing applications	Large-scale database applications (> ~2 TB)	Interactive querying, offline analytics
Use cases	Getting started, App Engine applications	AdTech, Financial and IoT data	Images, large media files, backups	User credentials, customer orders	Whenever high I/O, global consistency is needed	Data warehousing

https://cloud.google.com/products/databases

Storage models (AWS)

Data structure: unstructured

Data abstraction: file (or database)

Data access model: key-value

File system (EFS), **object storage** (S3) (or **DB K-V**; e.g., DynamoDB)

- Handle unstructured data
- ... organized as files (or blob)
- ... accessed using a key-value

Differ in the supported features

- E.g., maximum item size (DynamoDB: 400KB, S3: 5TB)
- E.g., indexes, querying mechanisms, latency, etc.

AWS S3

Simple Storage Service (S3)

- Serverless storage, save data as **objects** within **buckets**
- An **object** is composed of a file and any metadata that describes that file (e.g., **object key**)
- **Buckets** are logical containers for objects
  - You can have one or more buckets in your account
  - Control access for each bucket individually
  - Choose the geographical region where Amazon S3 will store the bucket and its contents

Benefits

- Unified data architecture
  - Build a multi-tenant environment, where many users can bring their own data
  - Improve both cost and data governance over traditional solutions
- Decoupling of storage from compute and data processing
  - You can cost-effectively store all data types in their native formats
  - Then, launch transformations as you need

Storage: access frequency (AWS)

24 storage (AWS S3) **classes**

- **Standard**: general purpose
- **Infrequent** (rapid) **access**
- **One Zone-IA**: lower-cost option for infrequently accessed data that do not require high availability and resilience
- **Glacier**: low-cost storage class for data archiving, three retrieval options that range from a few minutes to hours
- **Deep Glacier**: long-term retention for data accessed once or twice in a year. E.g., retain data sets for 10 years or longer
- **Intelligent-Tiering**: move objects between access tiers when access patterns change

	S3 Standard	S3 Intelligent-Tiering*	S3 Standard-IA	S3 One Zone-IA†	S3 Glacier	S3 Glacier Deep Archive
Designed for durability	99.999999999% (11 9's)	99.999999999% (11 9's)	99.999999999% (11 9's)	99.999999999% (11 9's)	99.999999999% (11 9's)	99.999999999% (11 9's)
Designed for availability	99.99%	99.9%	99.9%	99.5%	99.99%	99.99%
Availability SLA	99.9%	99%	99%	99%	99.9%	99.9%
Availability Zones	≥3	≥3	≥3	1	≥3	≥3
Minimum capacity charge per object	N/A	N/A	128KB	128KB	40KB	40KB
Minimum storage duration charge	N/A	30 days	30 days	30 days	90 days	180 days
Retrieval fee	N/A	N/A	per GB retrieved	per GB retrieved	per GB retrieved	per GB retrieved
First byte latency	milliseconds	milliseconds	milliseconds	milliseconds	select minutes or hours	select hours
Storage type	Object	Object	Object	Object	Object	Object
Lifecycle transitions	Yes	Yes	Yes	Yes	Yes	Yes

https://aws.amazon.com/s3/storage-classes/

Storage: access frequency (AWS)

Lifecycle configuration

- A set of rules that define actions that Amazon S3 applies to a group of objects

Two types of actions:

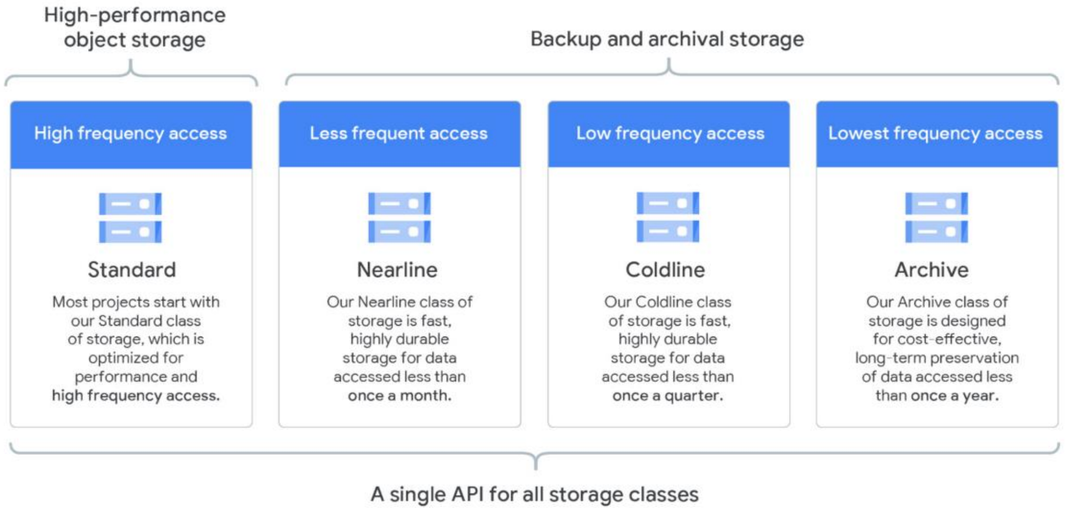
- **Transition:** when objects transition to another storage class. E.g., archive objects to the S3 Glacier storage class one year after creating them
- **Expiration**: when objects expire. Amazon S3 deletes expired objects on your behalf

Transition

	S3 Standard	S3 Intelligent-Tiering*	S3 Standard-IA	S3 One Zone-IA†	S3 Glacier	S3 Glacier Deep Archive
Designed for durability	99.999999999 (11 9's)	(11 9's)	(11 9's)	(11 9's)	(11 9's)	99.999999999% (11 9's)
Designed for availability	99.99%	99.9%	99.9%	99.5%	99.99%	99.99%
Availability SLA	99.9%	99%	99%	99%	99.9%	99.9%
Availability Zones	≥3	≥3	≥3	1	≥3	≥3
Minimum capacity charge per object	N/A	N/A	128KB	128KB	40KB	40KB
Minimum storage duration charge	N/A	30 days	30 days	30 days	90 days	180 days
Retrieval fee	N/A	N/A	per GB retrieved	per GB retrieved	per GB retrieved	per GB retrieved
First byte latency	milliseconds	milliseconds	milliseconds	milliseconds	select minutes or hours	select hours
Storage type	Object	Object	Object	Object	Object	Object
Lifecycle transitions	Yes	Yes	Yes	Yes	Yes	Yes

https://docs.aws.amazon.com/AmazonS3/latest/userguide/object-lifecycle-mgmt.html

Storage: access frequency (Google Cloud)



Retention Period

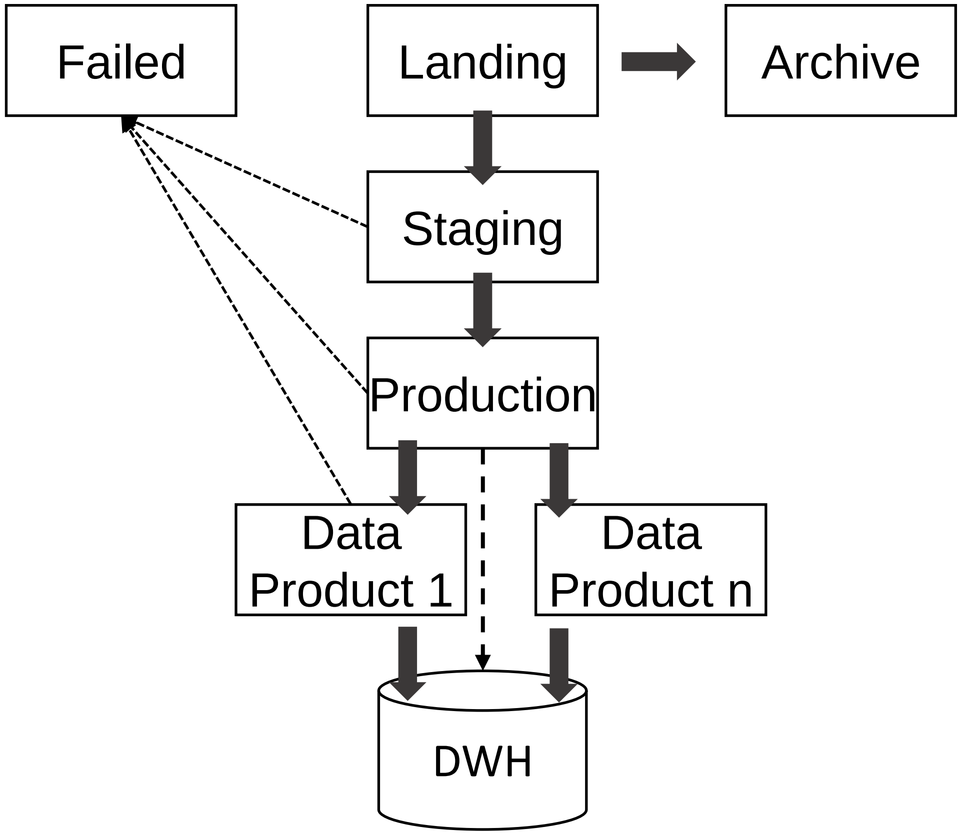
Access Frequency	<1 mo	1–3 mo	3–12 mo	>12 mo
>12/yr	Standard	Standard	Standard	Standard
4–12/yr	Standard	Nearline	Nearline	Nearline
1–4/yr	Standard	Nearline	Coldline	Coldline
<1/yr	Standard	Nearline	Coldline	Archive

https://cloud.google.com/blog/products/storage-data-transfer/archive-storage-class-for-coldest-data-now-available

Organizing the data lake

Having consistent principles on how to organize your data is important

- To build standardized pipelines with the same design with regard to where read/write data
- Standardization makes it easier to manage your pipelines at scale
- Helps data users search for data in the storage and understand exactly to find what they need
- Decoupling storage from processing



Organizing the data lake

Landing area (LA)

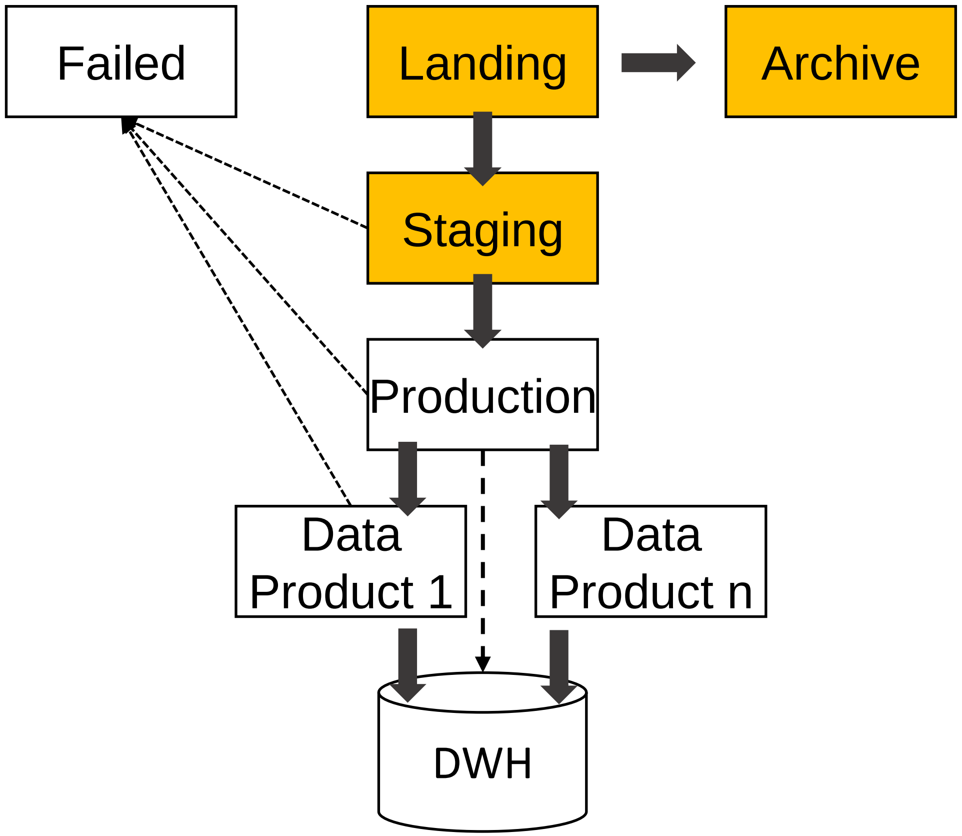
- Save raw data from ingestion
- Transient, data is not stored for long term

Staging area (SA)

- Raw data goes through a set of common transformations: ensuring basic quality and making sure it conforms to existing schemas for this data source and then data is saved into SA

Archive area (A)

- After saving into SA, raw data from LA should be copied into the archive to reprocess any given batch of data by simply copying it from AA into LA
- Useful for debugging and testing



Organizing the data lake

Production area (PA)

- Apply the business logic to data from SA

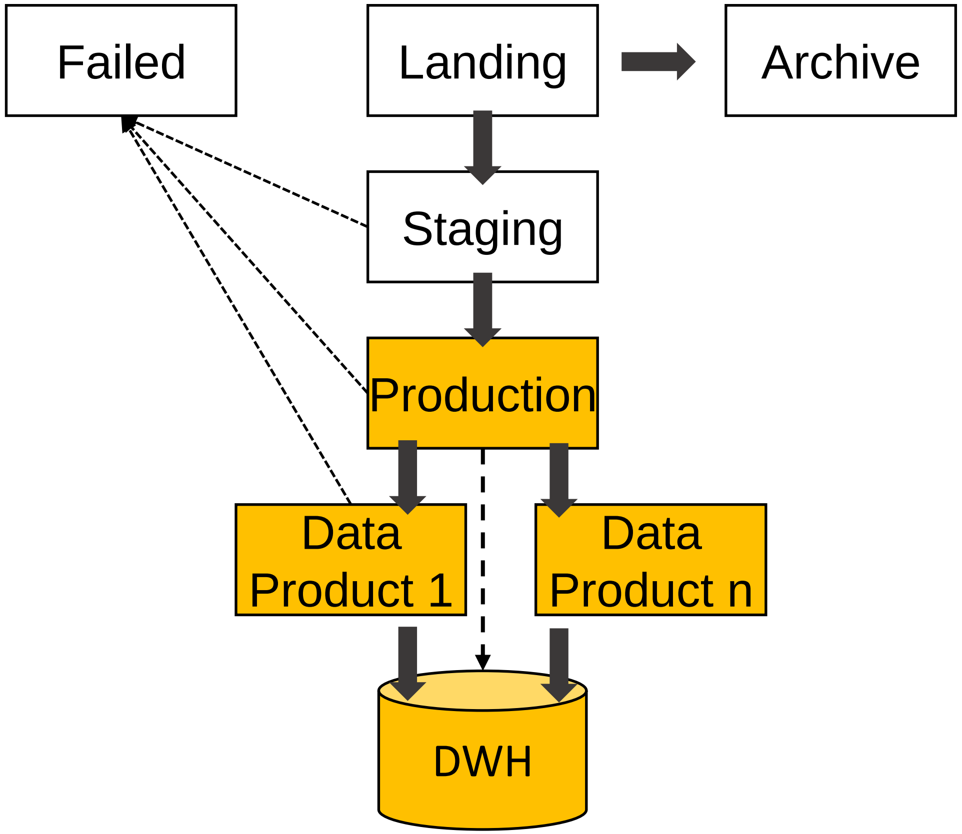
Pass-through job

- Copy data from SA to PA and then into DWH without applying any business logic
- Optional, but having a data set in the data warehouse and PA that is an exact replica can be helpful when debugging any issues with the business logic

Cloud data warehouse (DWH)

Failed area (FA)

- You need to be able to deal with all kinds of errors and failures
- There might be bugs in the pipeline code, cloud resources may fail



Organizing the data lake

Area	Permissions	Tier
Landing	Ingestion applications can write Scheduled pipelines can read Data consumers can’t access	Hot
Staging	Scheduled pipelines can read/write Selected data consumers can read	Hot
Production	Scheduled pipelines can read/write Selected data consumers can read	Hot
Archive	Scheduled pipelines can write Dedicated data reprocessing pipelines can read	Cold or archive
Failed	Scheduled pipelines can write Dedicated data reprocessing pipelines can read Data consumers don’t have access	Hot

Organizing the data lake

Use folders to organize data inside areas into a logical structure

- Namespace
  - Logically group multiple pipelines together.
- Pipeline name
  - Each data pipeline should have a name that reflects its purpose. For example
    - A pipeline that takes data from the LA, applies common processing steps, and saves data into SA
    - You will also have one for archiving data into AA
- Data source name
  - Ingestion layer will assign a name to each data source you bring into the platform
- BatchId
  - Unique identifier for any batch of data that is saved into LA
  - E.g., Since only ingestion can write to LA, it is its responsibility to generate this identifier
  - A common choice for this type of an identifier is a Universally Unique Identifier (UUID)

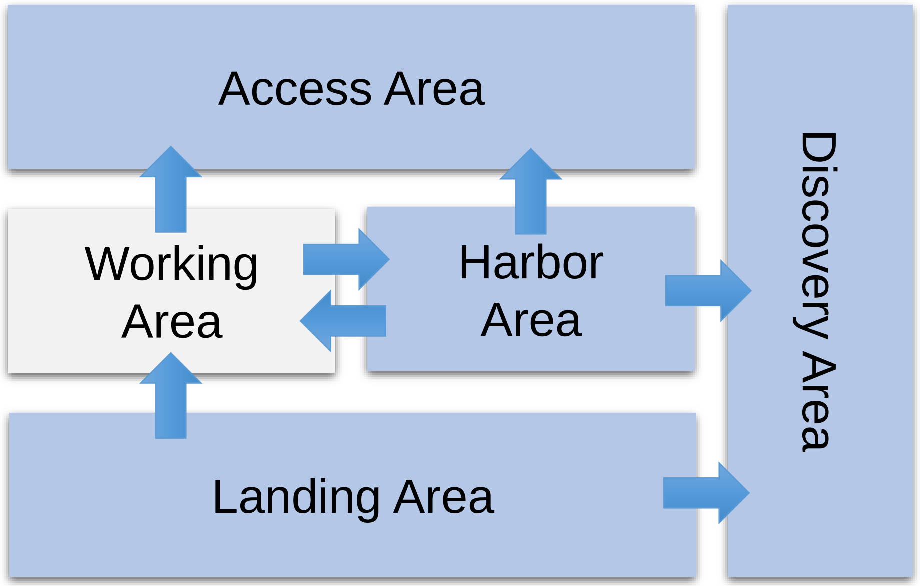
Different areas will have slightly different folder structures

- /landing/ETL/sales_oracle_ingest/customers/01DFTFX89YDFAXREPJTR94

Organizing the data lake

However, alternative organizations are available

"A data lake is a central repository system for storage, processing, and analysis of raw data, in which the data is **kept in its original format** and is processed to be queried only when needed. It can store a **varied amount of formats** in big data ecosystems, from unstructured, semi-structured, to structured data sources." – *Couto et al.*, 2019



Data Lakehouse

Combine the key benefits of data lakes and data warehouses

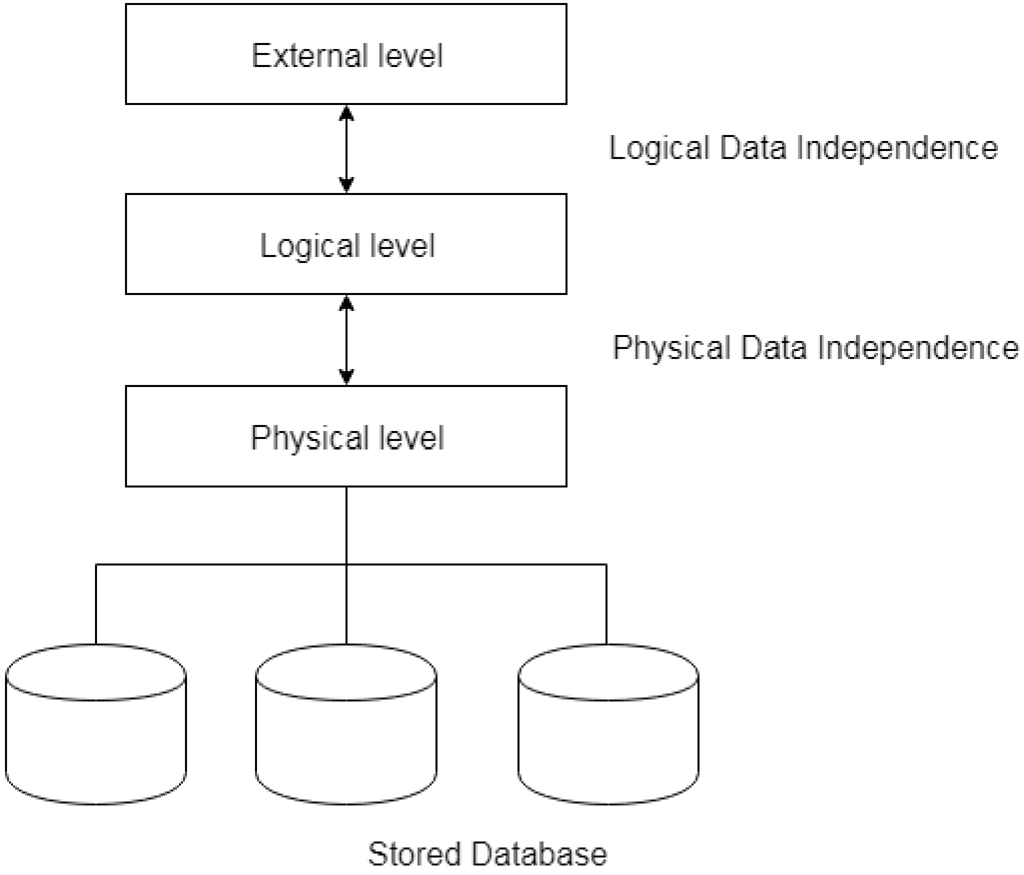
- Low-cost storage in an open format accessible by a variety of systems from the former
- Powerful management and optimization features from the latter
    - ACID transactions, data versioning, auditing, indexing, caching, and query optimization.

Key question: can we combine these benefits in an effective way?

- Direct access means that they **give up some aspects of data independence**, which has been a cornerstone of relational DBMS design
- **Lakehouses are an especially good fit for cloud environments with separate compute and storage**: different computing applications can run on-demand on completely separate computing nodes (e.g., a GPU cluster for ML) while directly accessing the same storage data

Data Independence

- Data independence can be explained using the three-schema architecture
- Data independence refers characteristic of being able to modify the schema at one level of the database system without altering the schema at the next higher level



Data Lakehouse

1st generation systems: data warehousing started with helping business leaders get analytical insights

- Data in these warehouses would be written with schema-on-write, which ensured that the data model was optimized for downstream BI consumption
- Several challenges
  - They typically coupled compute and storage into an on-premises appliance
    - This forced enterprises to provision and pay for the peak of user load and data under management, very costly
  - More and more datasets were completely unstructured, which DWHs could not store and query at all

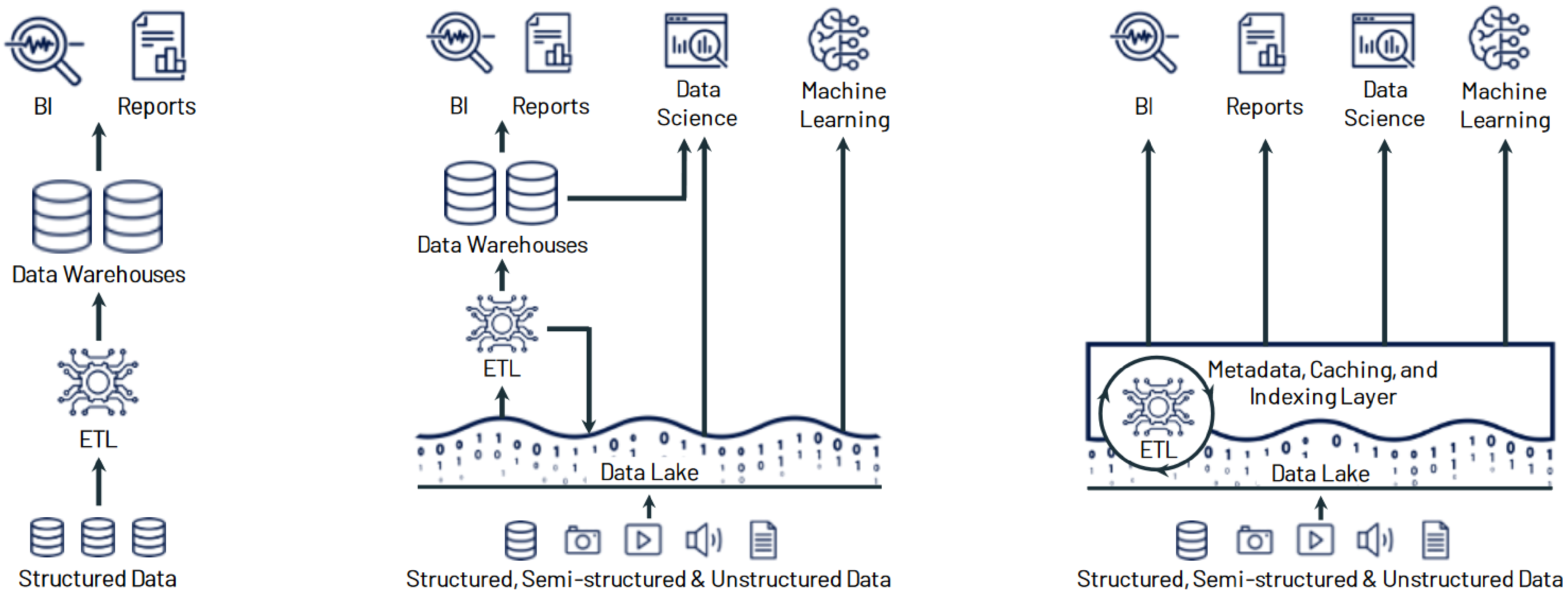
Armbrust, Michael, et al. "Lakehouse: a new generation of open platforms that unify data warehousing and advanced analytics." *CIDR*. 2021.

Data Lakehouse

2nd generation: offloading all the raw data into data lakes

- The data lake is schema-on-read and stores any data at low cost, but on the other hand, punted the problem of data quality and governance
- In this architecture, a small subset of data in the lake would later be ETLed to a downstream data warehouse
- The use of open formats also made data lake data directly accessible to a wide range of other analytics engines, such as machine learning systems
- From 2015 onwards, cloud data lakes, such as S3, ADLS and GCS, started replacing HDFS
  - Superior durability (often >10 nines), geo-replication, and most importantly, extremely low cost

Data Lakehouse



Data Lakehouse

While the cloud data lake and warehouse architecture is ostensibly cheap, a two-tier architecture is highly complex for users

- Data is first ETLed into lakes, and then again ELTed into warehouses
- Enterprise use cases now include advanced analytics such as machine learning, for which neither data lakes nor warehouses are ideal
- (Some) main problems:
  - **Reliability**. Keeping the data lake and warehouse consistent is difficult and costly
  - Data **staleness**. The data in the warehouse is stale compared to that of the data lake, with new data frequently taking days to load
  - **Limited support for advanced analytics**. Businesses want to ask predictive questions using their warehousing data, e.g., “which customers should I offer discounts to?” None of the leading machine learning systems directly work well on top of warehouses
    - Process large datasets using complex non-SQL code

Dataset Search for Data Discovery, Augmentation, and Explanation

Is there a real need for many unstructured and integrated dataset?

- Recent years have seen an explosion in our ability to collect and catalog immense amounts of data about our environment, society, and populace
- Governments, and organizations are increasingly making structured data available on the Web and in various repositories and data lakes
- **This opportunity is often missed due to a central technical barrier**: it is currently nearly impossible for domain experts to weed through the vast amount of available information to discover datasets that are needed for their specific application

Juliana Freire, keynote @ EDBT 2023

Data Lakehouse

Main features

- **Store data in a low-cost object store** using a standard file format such as Apache Parquet
- **Implement a transactional metadata layer** on top of the object store that defines which objects are part of a table version
- **Implement management features** within the metadata layer

Challenges:

- The metadata layer is insufficient to achieve good SQL performance
  - **Data warehouses use several techniques to get state-of-the-art performance**
    - Storing hot data on fast devices such as SSDs, maintaining statistics, building efficient indexes, etc.
  - **In a Lakehouse it is not possible to change the format**, but it is possible to implement other optimizations that leave the data files unchanged

Delta Lake

Challenges:

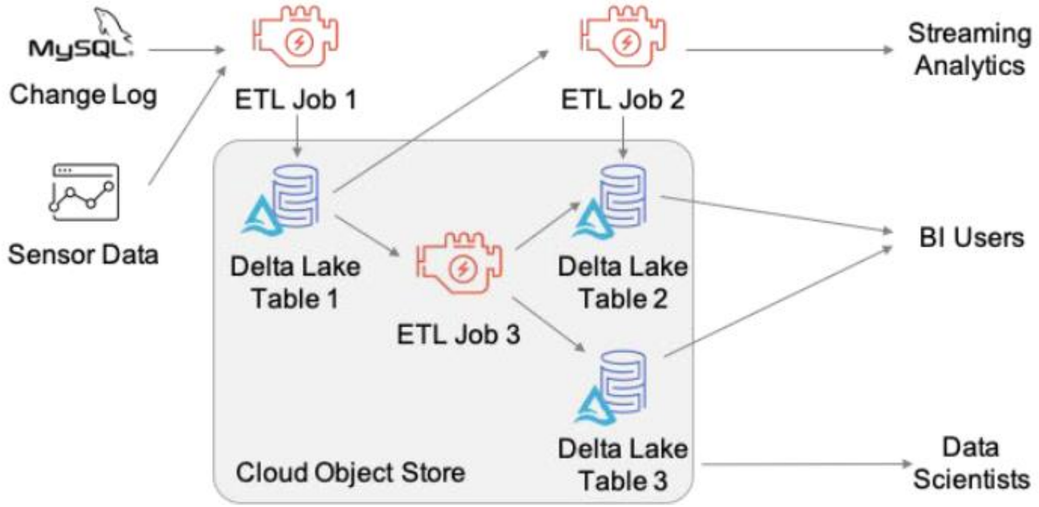
- Most **cloud object stores are merely key-value stores**, with no cross-key consistency
- **Multi-object updates are not atomic**, there is no isolation between queries
    - If a query needs to update multiple objects in the table readers will see partial updates as the query updates each object individually
- For large tables with millions of objects, **metadata operations are expensive**. The latency of cloud object stores is so much higher that these data skipping checks can take longer than the actual query

Armbrust, Michael, et al. "Delta lake: high-performance ACID table storage over cloud object stores." Proceedings of the VLDB Endowment 13.12 (2020): 3411-3424.

Delta Lake

Delta Lake uses a **transaction log** that is compacted **into Apache Parquet** for significantly faster metadata operations for large tabular datasets

- E.g., quickly search billions of table partitions for those relevant to a query
- The log is stored in the **_delta_log** subdirectory within the table
- It contains
  - Sequence of JSON objects with increasing, zero-padded numerical IDs to store the log records
  - Occasional checkpoints for specific log objects that summarize the log up to that point



Delta Lake

Each log record object (e.g., 000003.json) contains an array of actions to apply to the previous version of the table to generate the next one

Examples of actions are:

- Change Metadata
- Add or Remove Files

It is necessary to compress the log periodically into checkpoints

- Checkpoints store all the non-redundant actions in the table's log up to a certain log record ID, in Parquet format
- Some sets of actions are redundant and can be removed Read the _last_checkpoint object in the table's log directory, if it exists, to obtain a recent checkpoint ID.

Delta Lake

Example of a write transaction

- Identify a log record ID (i.e., looking forward from the last checkpoint ID). The transaction will then read the data at table version r (if needed) and attempt to write log record r + 1
- Read data at table version r, if required combine previous checkpoint and further log records
- Write any new data objects that the transaction aims to add to the table into new files in the correct data directories, generating the object names using GUIDs.
  - This step can happen in parallel
  - At the end, these objects are ready to reference in a new log record.
- Attempt to write the transaction's log record into the r + 1 .json log object, if no other client has written this object. **This step needs to be atomic**. If the step fails, the transaction can be retried; depending on the query's semantics
- Optionally, write a new .parquet checkpoint for log record r + 1

Creating the r + 1 .json record, needs to be atomic: only 1 client should succeed. Not all large-scale storage systems have an atomic put operation

- Google Cloud Storage and Azure Blob Store support atomic put-if-absent operations
- HDFS, we use atomic renames to rename a temporary file to the target name
- Amazon S3 need ad-hoc protocols

Lakehouse

(SQL) Format-independent optimizations are

- **Caching**: When using a transactional metadata layer such as Delta Lake, it is safe for a Lakehouse system to cache files from the cloud object store on faster storage devices such as SSDs and RAM on the processing nodes
- **Auxiliary data**: maintain column min-max statistics for each data file in the table within the same Parquet file used to store the transaction log, which enables data skipping optimizations when the base data is clustered by particular columns
- **Data layout**:
  - Record ordering: which records are clustered together and hence easiest to read together, e.g. ordering records using individual dimensions or space-filling curves such as Z-order
  - Compression strategies differently for various groups of records, or other strategies

Offer a declarative version of the DataFrame APIs which maps data preparation computations into Spark SQL query plans and can benefit from logical optimizations