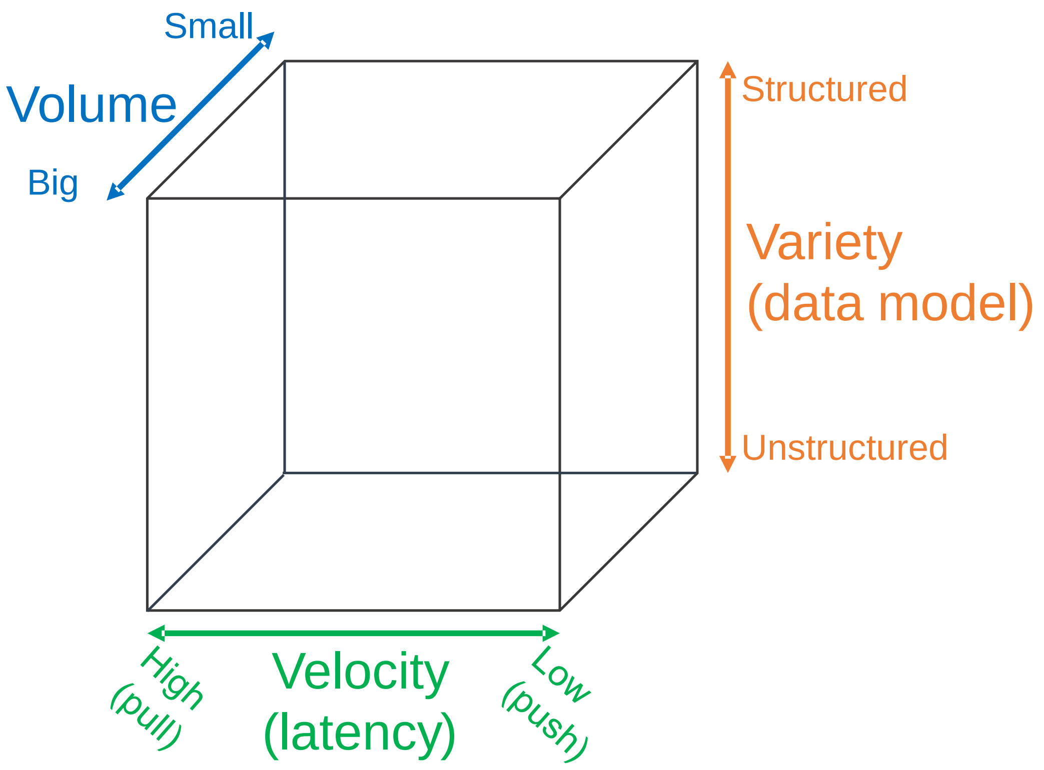
BIG DATA AND CLOUD PLATFORMS

Building data pipelines

Reference scenario

The big-data cube

- Volume: small to big
- Variety: structure to unstructured
- Velocity: pull to push

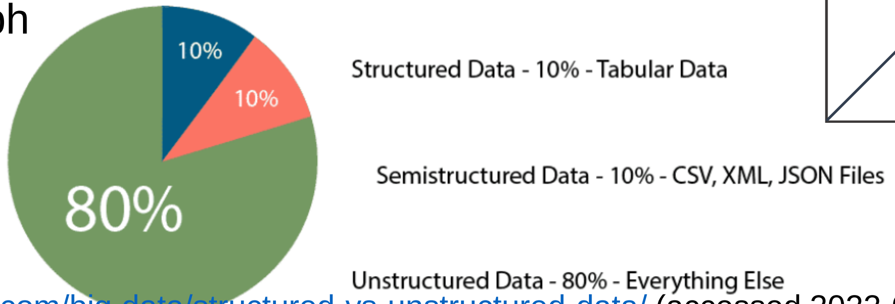


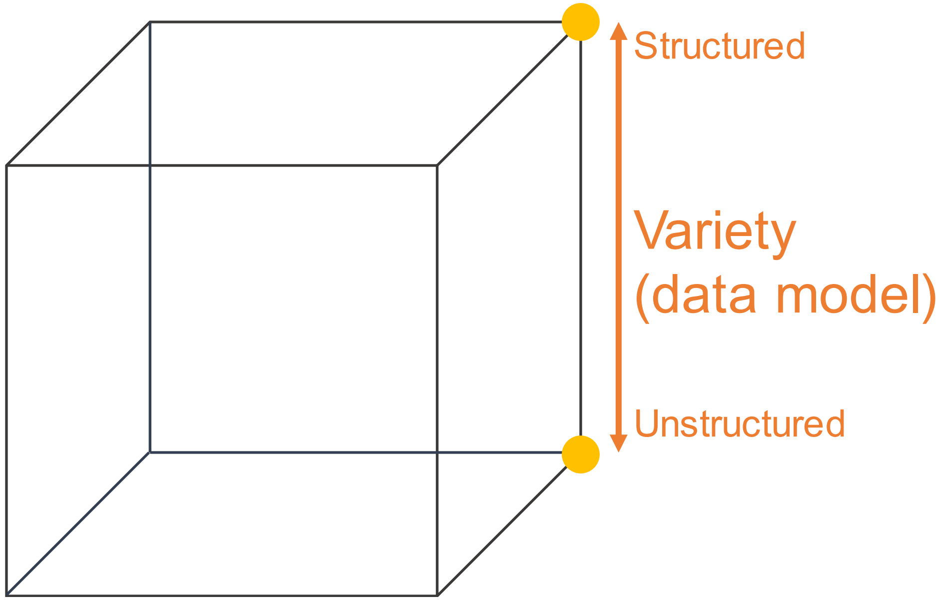
Meijer, Erik. "Your mouse is a database." *Communications of the ACM* 55.5 (2012): 66-73.

Reference scenario

Variety

- **Structured**
  - Relational tuples with FK/PK relationships
- **Unstructured**
  - Key-value
  - Columnar
  - Document-based
  - Graph
  - ...





https://www.datamation.com/big-data/structured-vs-unstructured-data/ (accessed 2022-08-01)

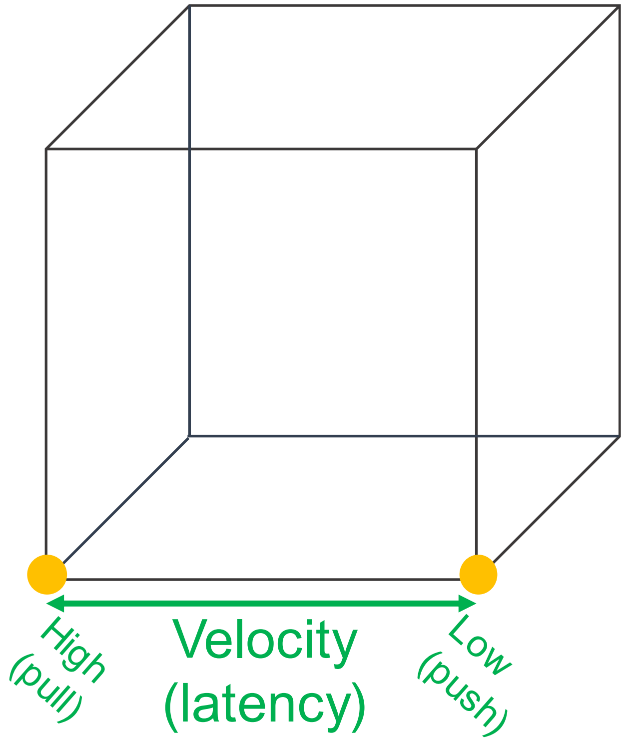
Reference scenario

Velocity (latency)

- **High**: clients synchronously pulling data from sources
- **Low**: sources asynchronously pushing data to clients

Velocity (speed; dual to latency)

- **High**: processing in real-time (milliseconds) or near-real time (minutes)
- **Low**: processing can take hours



Reference scenario

Collecting data

- **Scheduled Batch**
  - Large volume of data processed on a regular scheduled basis
  - Velocity is very predictable
- **Periodic**:
  - Data processed at irregular times (e.g., after collecting a certain ---large--- amount of data)
  - Velocity is less predictable
- **Near real-time**
  - Streaming data processed in small individual batches collected and processed within minutes
  - Velocity is a huge concern
- **Real-time**
  - Streaming data collected and processed in very small individual batches within milliseconds
  - Velocity is the paramount concern

Processing data

- **Batch and periodic**
  - Once data has been collected, processing can be done in a controlled environment
  - There is time to plan for the appropriate resources
- **Near real-time and real-time**
  - Collection of the data leads to an immediate need for processing
  - Depending on the complexity of the processing (cleansing, scrubbing, curation), this can slow down the velocity of the solution significantly
  - Plan accordingly

Reference scenario

Acceleration

- The rate at which large collections of data can be ingested, processed, and analyzed
- Acceleration is not constant, it comes in bursts
- Take Twitter as an example
  - Hashtags can become hugely popular and appear hundreds of times in just seconds
  - … or slow down to one tag an hour
- Your system must be able to efficiently handle the peak as well as the lows

Reference scenario

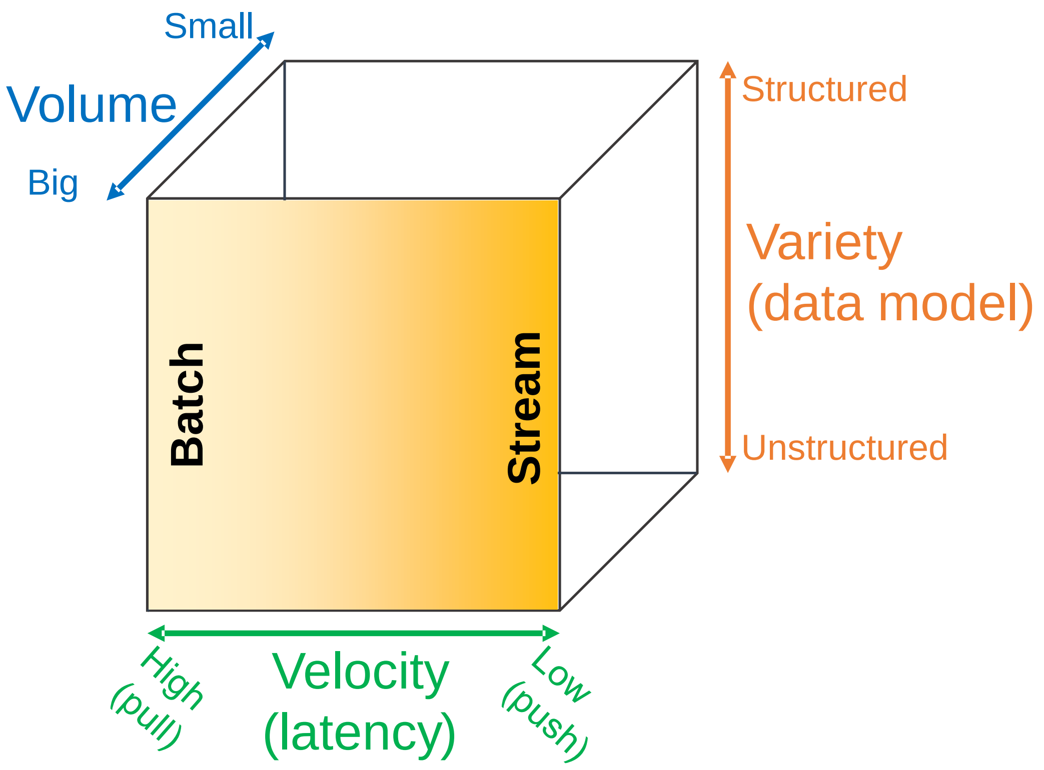
Plus other Vs

- **Veracity**: data trustworthiness/quality
- **Value**: ability to extract meaningful information
- …

Our focus

- (Un)Structured big-data batch
- (Un)Structured big-data streams

Goal: keep in mind the cube to categorize the services



Reference scenario

Scenario 1

- My business has a set of 15 JSON data files that are each about 2.5 GB in size.
- They are placed on a file server once an hour, and they must be ingested as soon as they arrive in this location.
- Data must be combined with all transactions from financial dashboard for this same period, then compared to the recommendations from marketing engine
- All data is fully cleansed.
- The results from this time period must be made available to decision makers by 10 minutes after the hour in the form of financial dashboards.

Which Vs are involved?

Reference scenario

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Which Vs are involved?

- Volume This scenario describes huge JSON files to be combined with transactional data and marketing data.
- Velocity "Wait - now hurry up!" Wait to collect data for a full hour and then produce meaningful results in 10 minutes (is it batch or stream processing?)
- Variety three data source types: log files, transactional data, and recommendation information
- Value populate dashboards that are used by decision makers as soon as they are made available. The value is reached because it requires an understanding of what the organization is trying to accomplish

Reference scenario

Scenario 2

- My business compiles data generated by hundreds of corporations.
- This data is delivered to us in very large files, transactional updates, and even data streams.
- The data must be cleansed and prepared to ensure that rogue inputs do not skew the results.
- Knowing the data source for each record is vital to the work we do.
- A large portion of the data gathered is irrelevant to our analysis, so this data must be eliminated.
- The final requirement is that all data must be combined and loaded into our data warehouse, where it will be analyzed.

Which Vs are involved?

Reference scenario

Scenario 2

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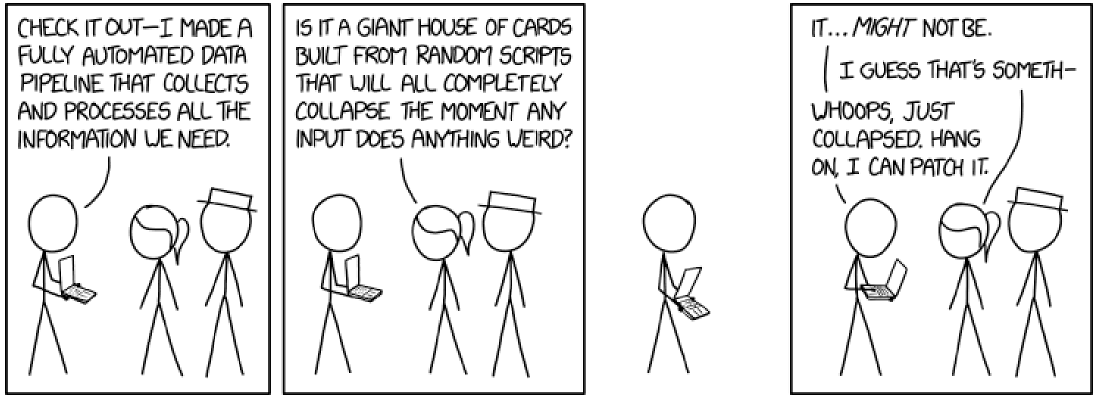
Which Vs are involved?

- Volume The data is delivered in very large files, transactional updates, and even in data streams
- Variety The business will need to combine the data from all three sources into a single data warehouse.
- Veracity The data is known to be suspect. The data must be cleansed and prepared to ensure that rogue inputs do not skew the results. Knowing the data source for each record is vital to the work we do.

Data pipeline

Data pipeline

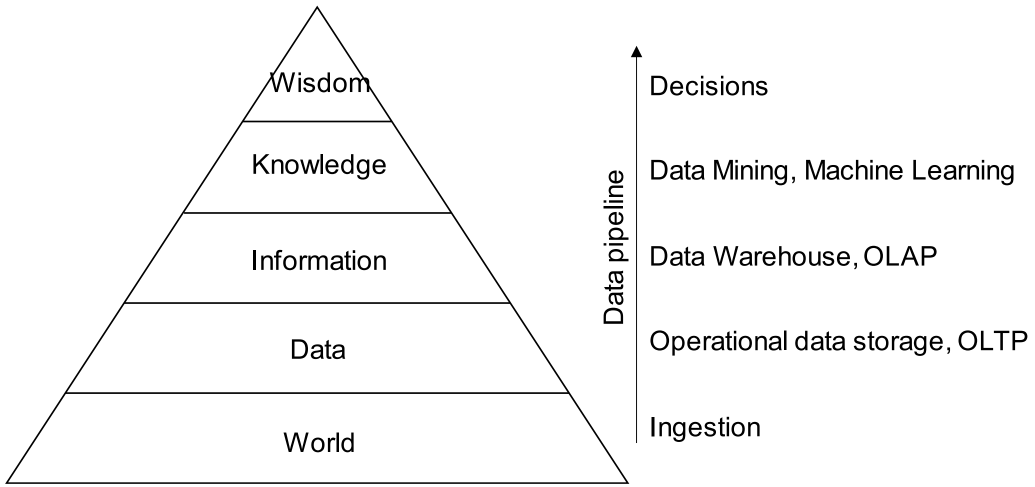
"A succession of operations to transform and consume raw data"



https://xkcd.com/2054/

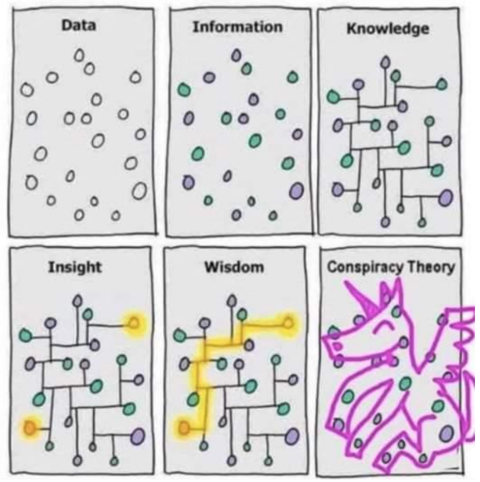
Quemy, Alexandre. "Data Pipeline Selection and Optimization." *DOLAP*. 2019.

Data pipeline



DIKW hierarchy

- Layers representing structural relationships between data, information, knowledge, and wisdom



Ackoff, Russell L. "From data to wisdom." Journal of applied systems analysis 16.1 (1989): 3-9.

Data pipelines on cloud

The pyramid abstracts tons of techniques, algorithms, etc.

To provide them as services, architecting data pipelines on cloud requires

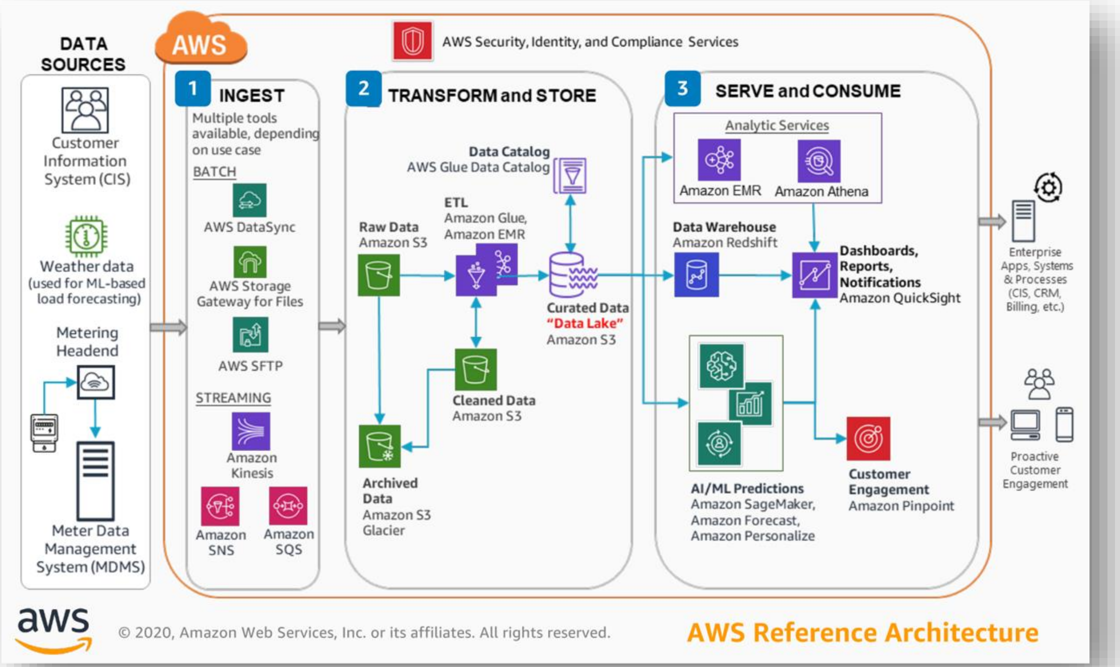
- Standardization (of common services)
- Integration
- Orchestration
- Accessibility through simple APIs

Let us look to data pipelines on different cloud services providers

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

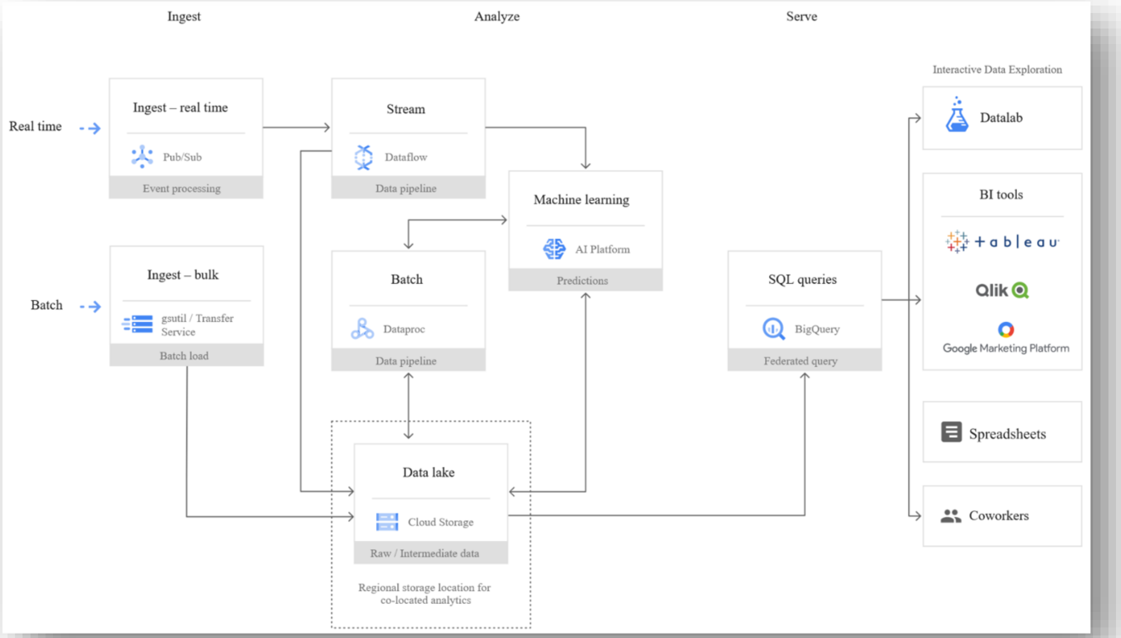


https://console.aws.amazon.com/console

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 ization

Two main ways to consume data:
- Querying produces results that are great for quick analysis by data analysts.
- BI tools produce visualizations that are grouped into reports and dashboards to help users explore data and determine the best actions to take

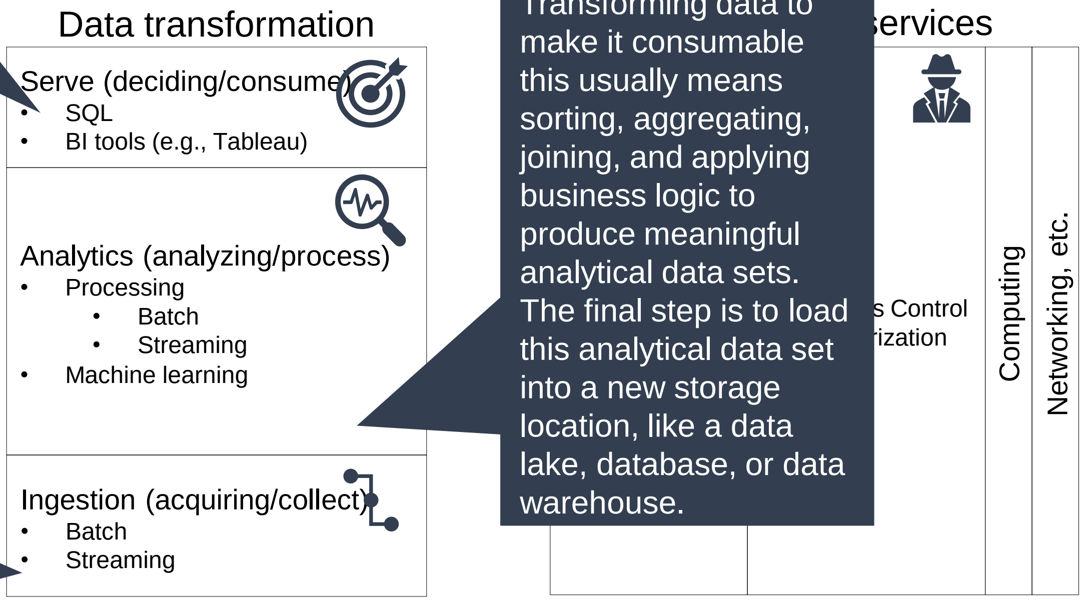
Common points

We have services
- Which transforms data
  - Recall the DIKW p
- Which supports data

Collecting raw data from
- transactions
- logs
- IoT devices is a challenge.

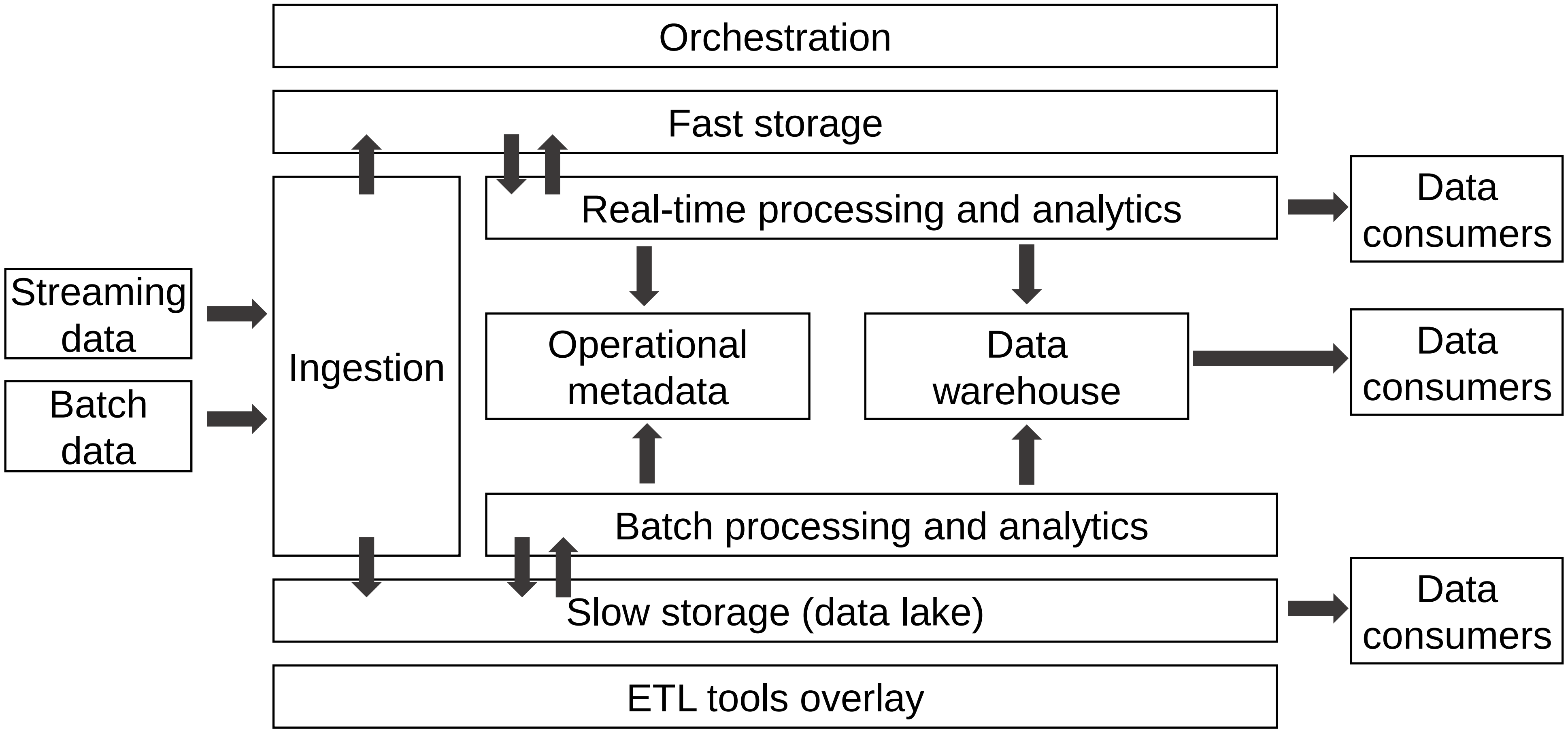
A good data analysis solution allows developers to ingest a wide variety of data at any speed, from batch to streaming

Data pipelines are ba
- Ingesting data
- Analyzing data
- Serving data



Transforming data to make it consumable this usually means sorting, aggregating, joining, and applying business logic to produce meaningful analytical data sets. The final step is to load this analytical data set into a new storage location, like a data lake, database, or data warehouse.

A tentative organization

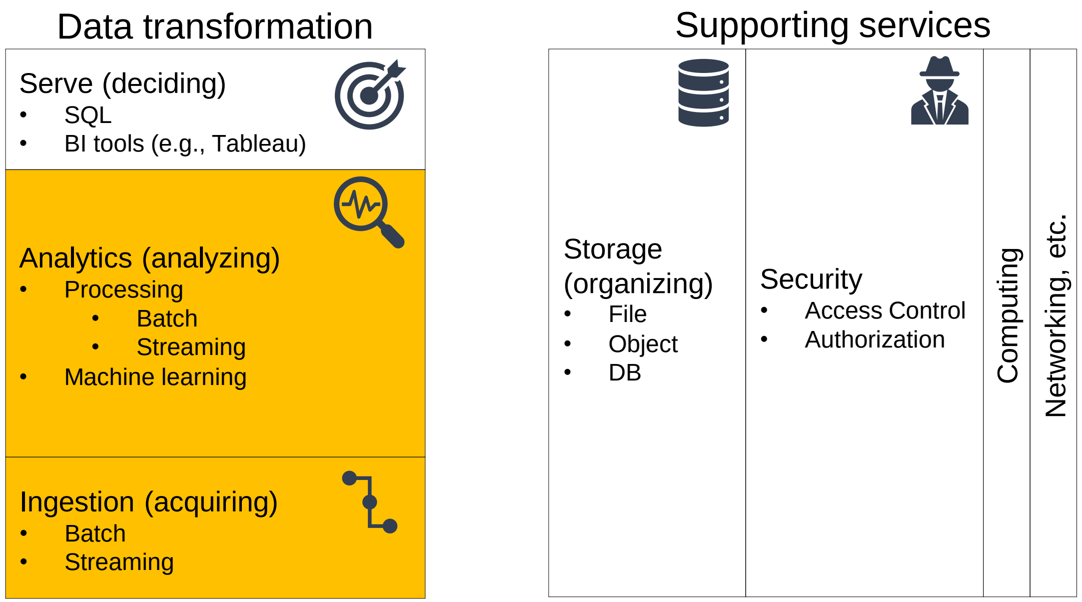


A tentative organization

This is not a sharp taxonomy

Ingestion vs Analytics

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

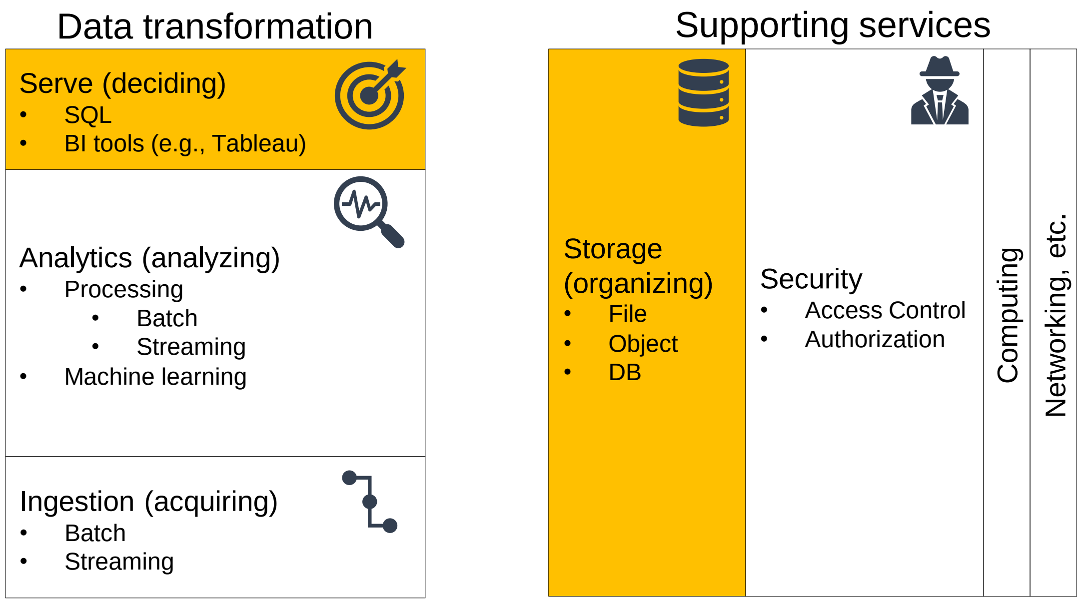


A tentative organization

This is not a sharp taxonomy

Storage vs Serving

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



A tentative organization

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.

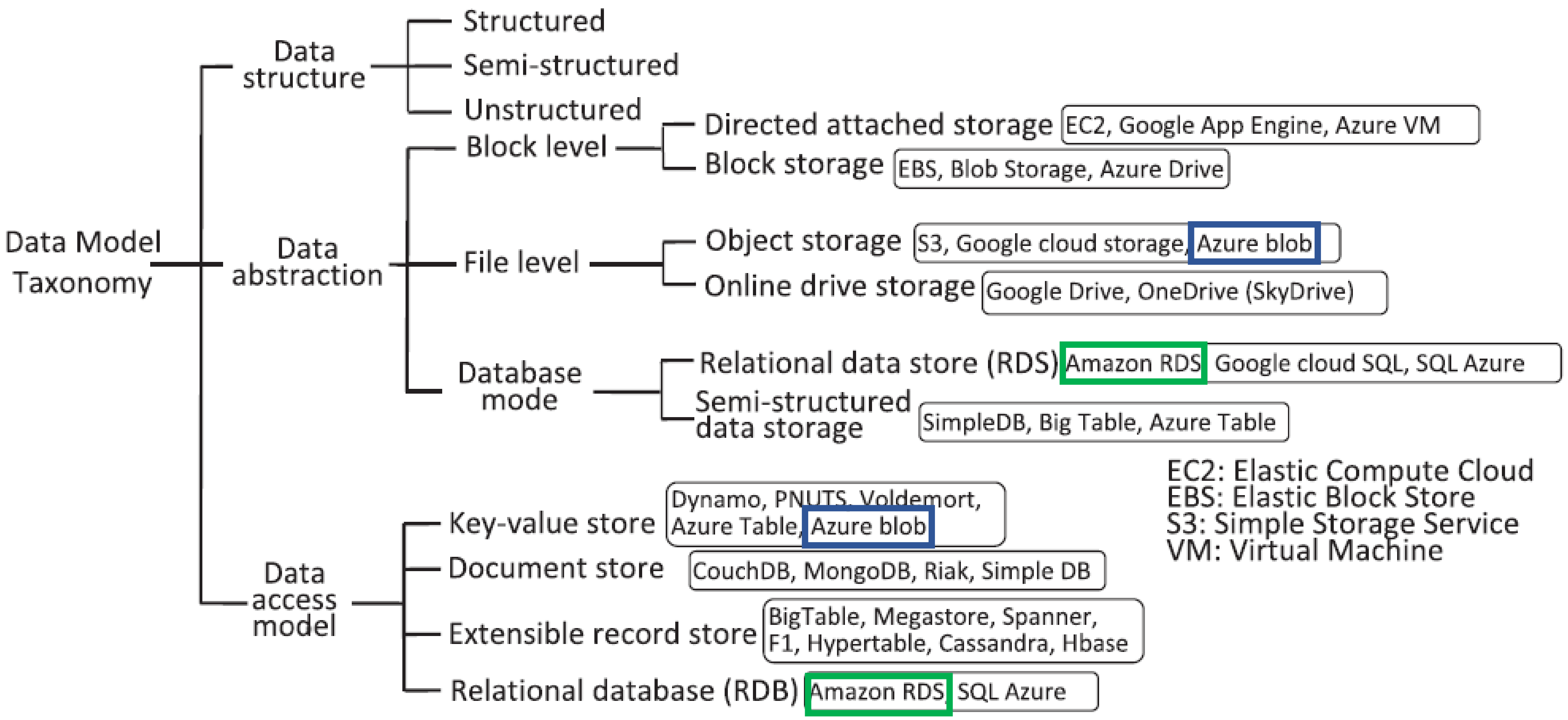
Storage

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**

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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)

- Amazon S3 stores data as **objects** within **buckets**.
- An **object** is composed of a file and any metadata that describes that file
  - Once objects have been stored in an Amazon S3 bucket, they are given an **object key**. Use this, along with the bucket name, to access the object.
- **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

- Centralized data architecture (create a single—trustworthy—dataset)
  - Build a multi-tenant environment, where many users can bring their own data
  - Improve both cost and data governance over traditional solutions
  - Although this may require an additional step to load your data into S3
- Decoupling of storage from compute and data processing.
  - You can cost-effectively store all data types in their native formats
  - Then, launch as many virtual servers needed or analytics tools needed to process your data

Storage: access frequency (AWS)

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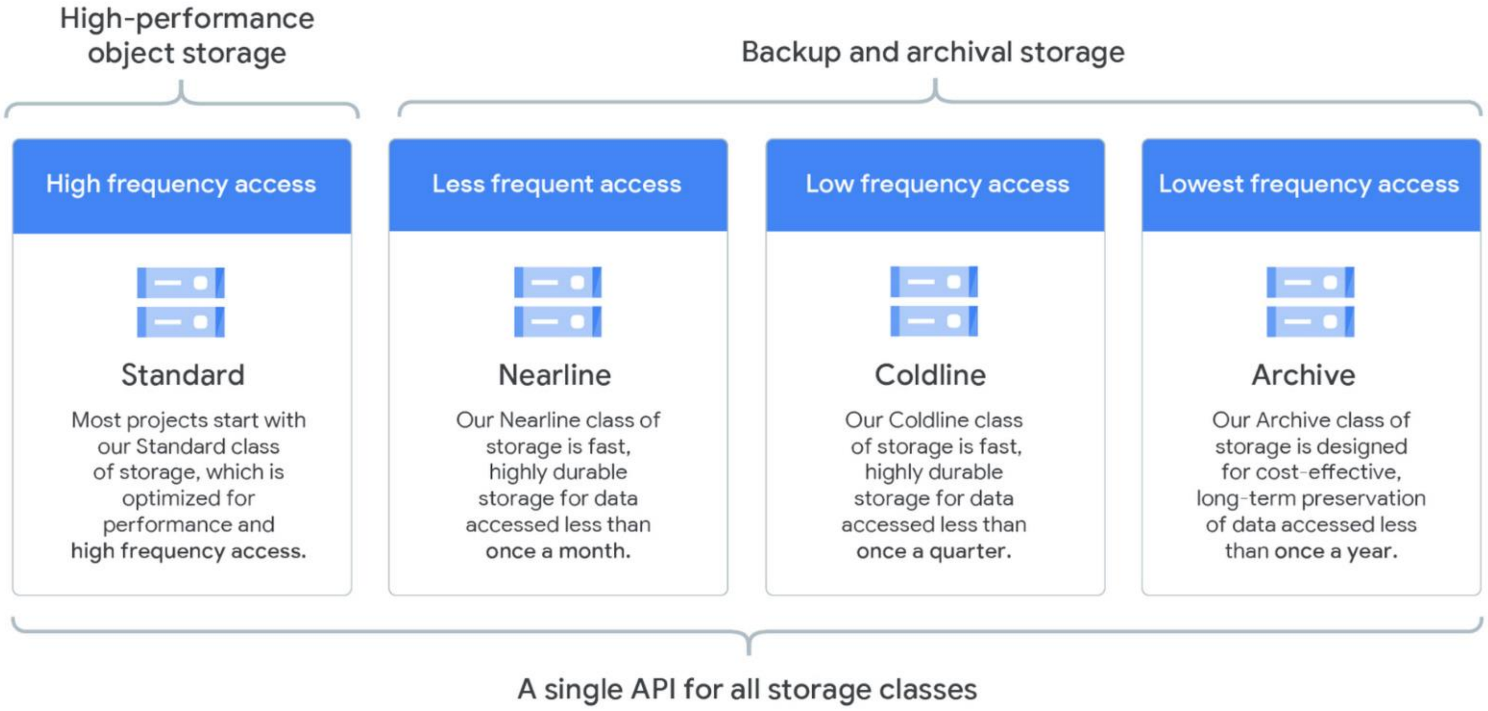
https://docs.aws.amazon.com/AmazonS3/latest/userguide/object-lifecycle-mgmt.html

Storage: access frequency (Google Cloud)



Retention Period

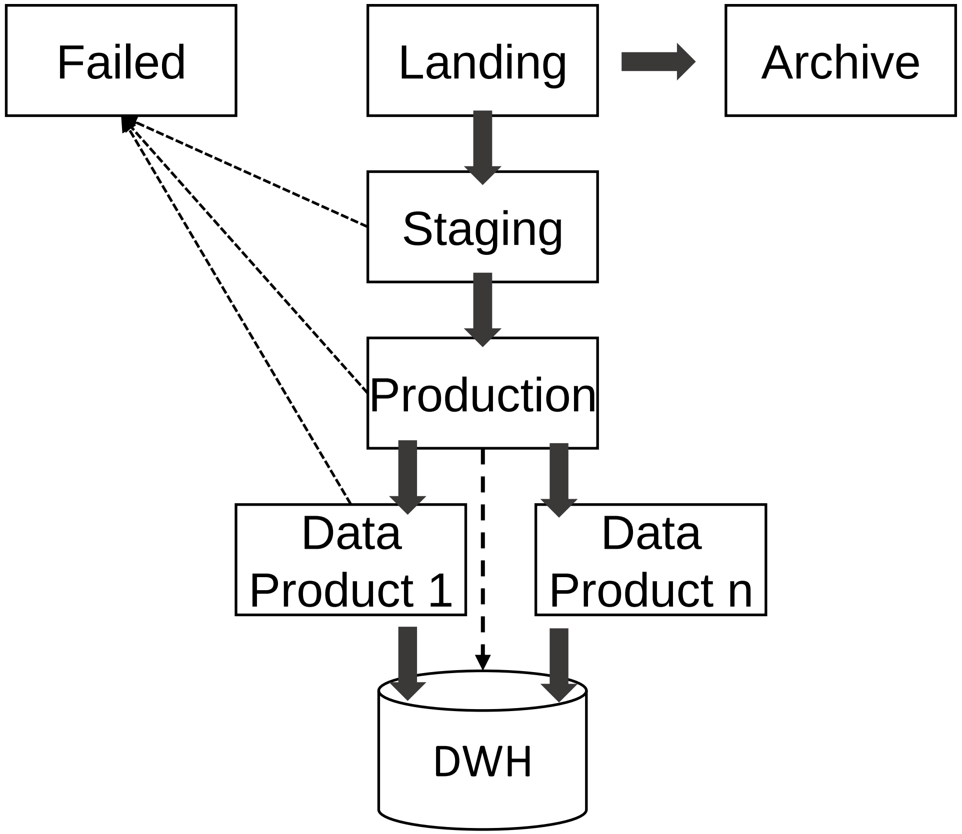
Access Frequency	<1 mo	1–3 mo	3–12 mo	>12 mo
>12/yr	Standard	Standard	Standard	Standard
4–12/yr	Standard	Nearline	Nearline	Nearline
1–4/yr	Standard	Nearline	Coldline	Coldline
<1/yr	Standard	Nearline	Coldline	Archive

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

Organizing the data lake

Having a 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)

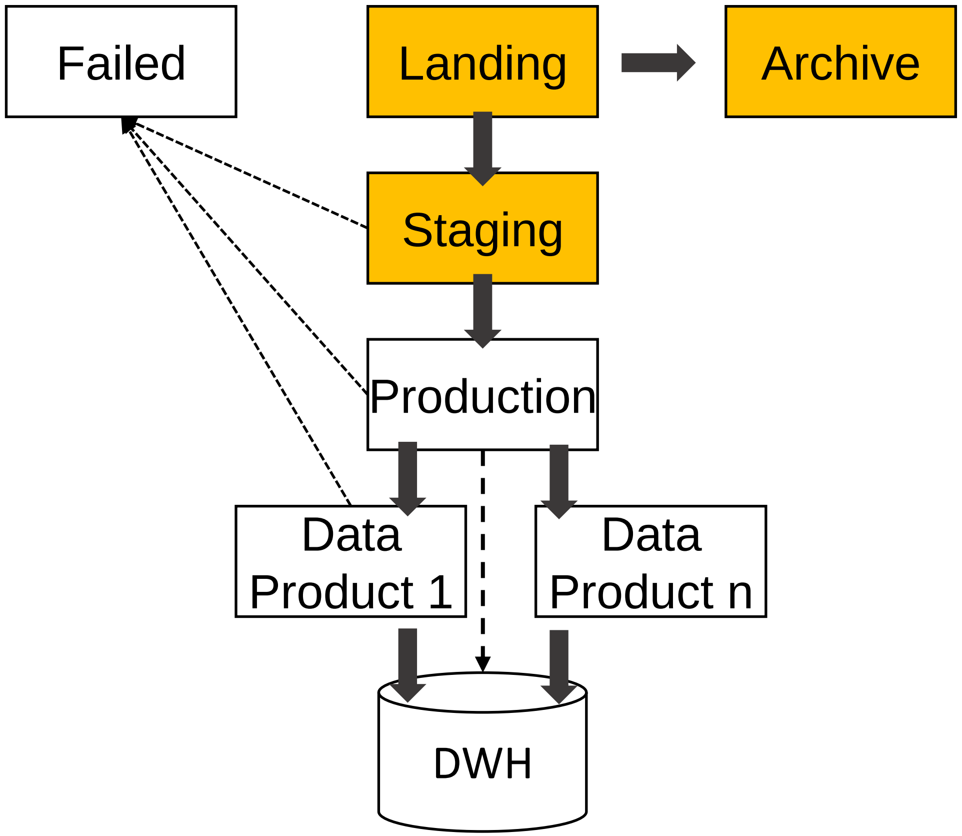
- Save raw data from ingestion
- Transient, data is not stored for long term

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

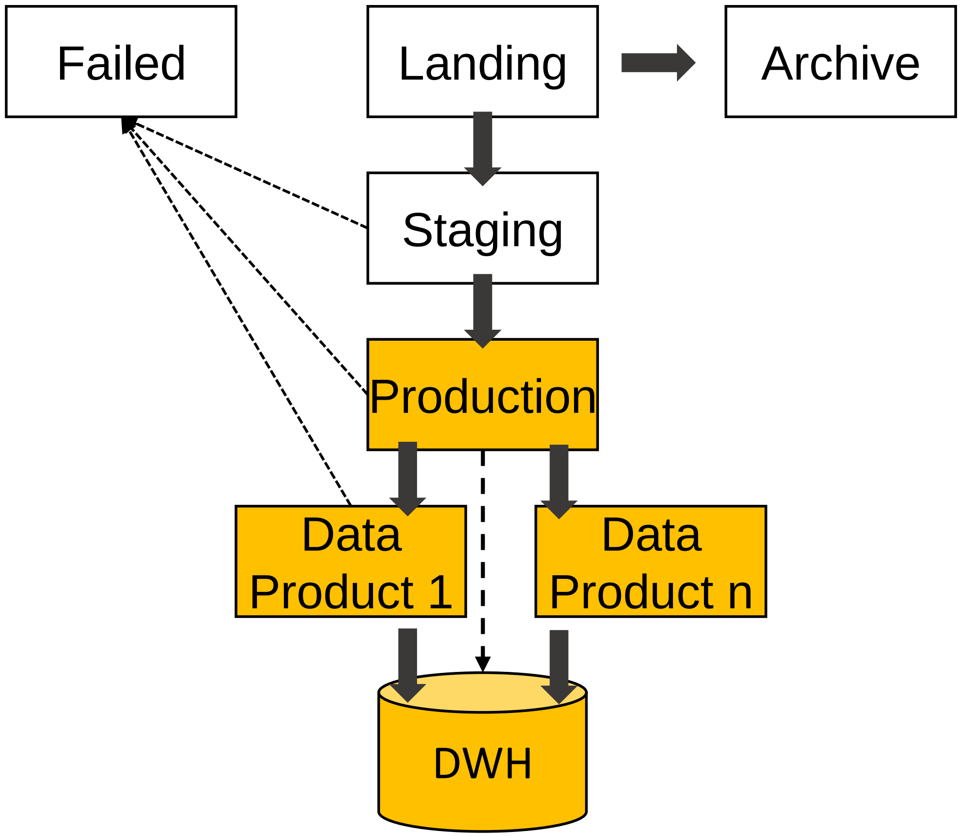
Pass-through job

- 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