Foundation of Data Engineering

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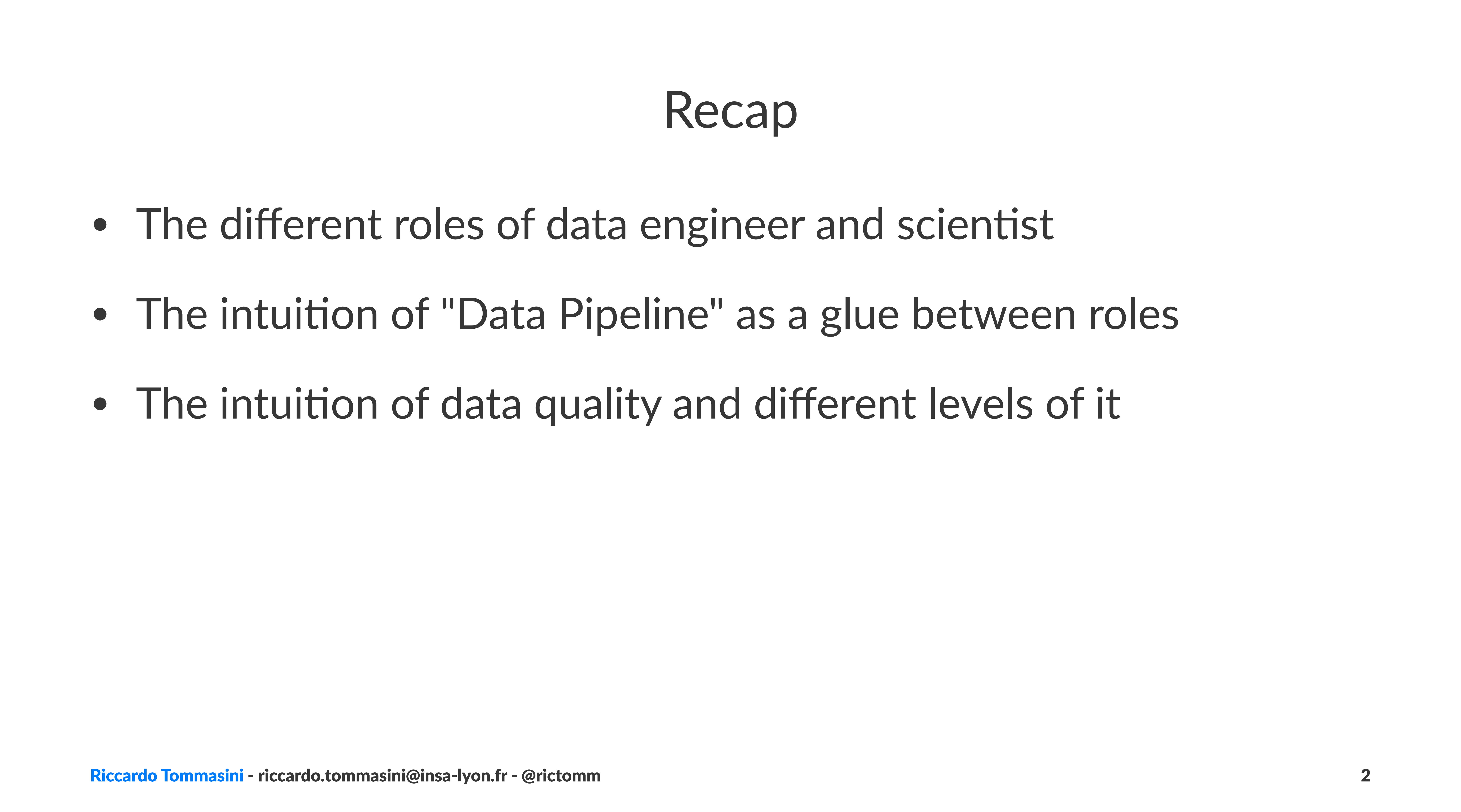
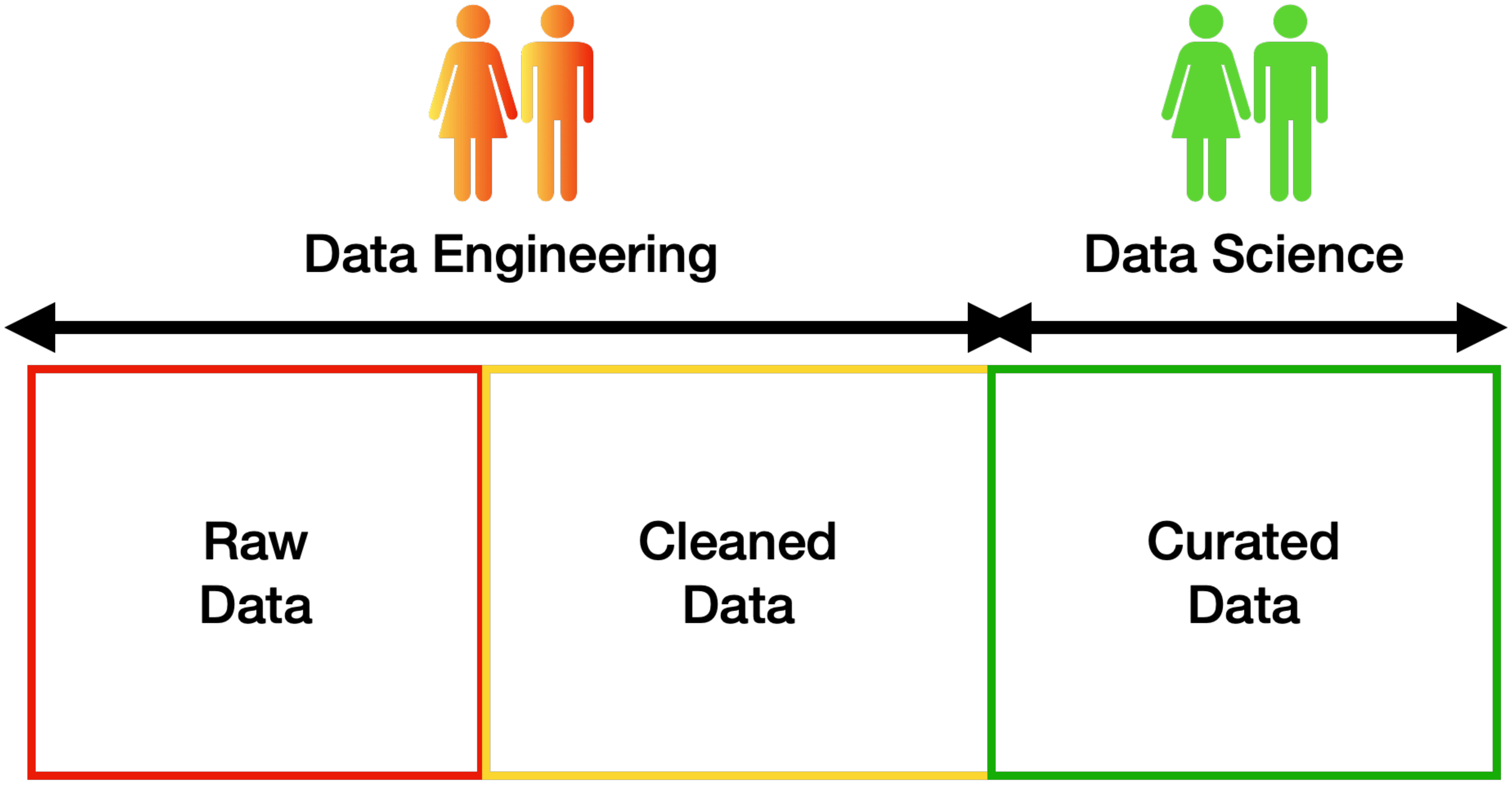


Recap

- The different roles of data engineer and scientist
- The intuition of "Data Pipeline" as a glue between roles
- The intuition of data quality and different levels of it

- However, the data pipeline has been quite an abstract concept so far
- We still miss the elements that implements the pipeline (Airflow)
- We did not discuss concrete problems like durability and distribution

A Conceptual View of a Data Pipeline

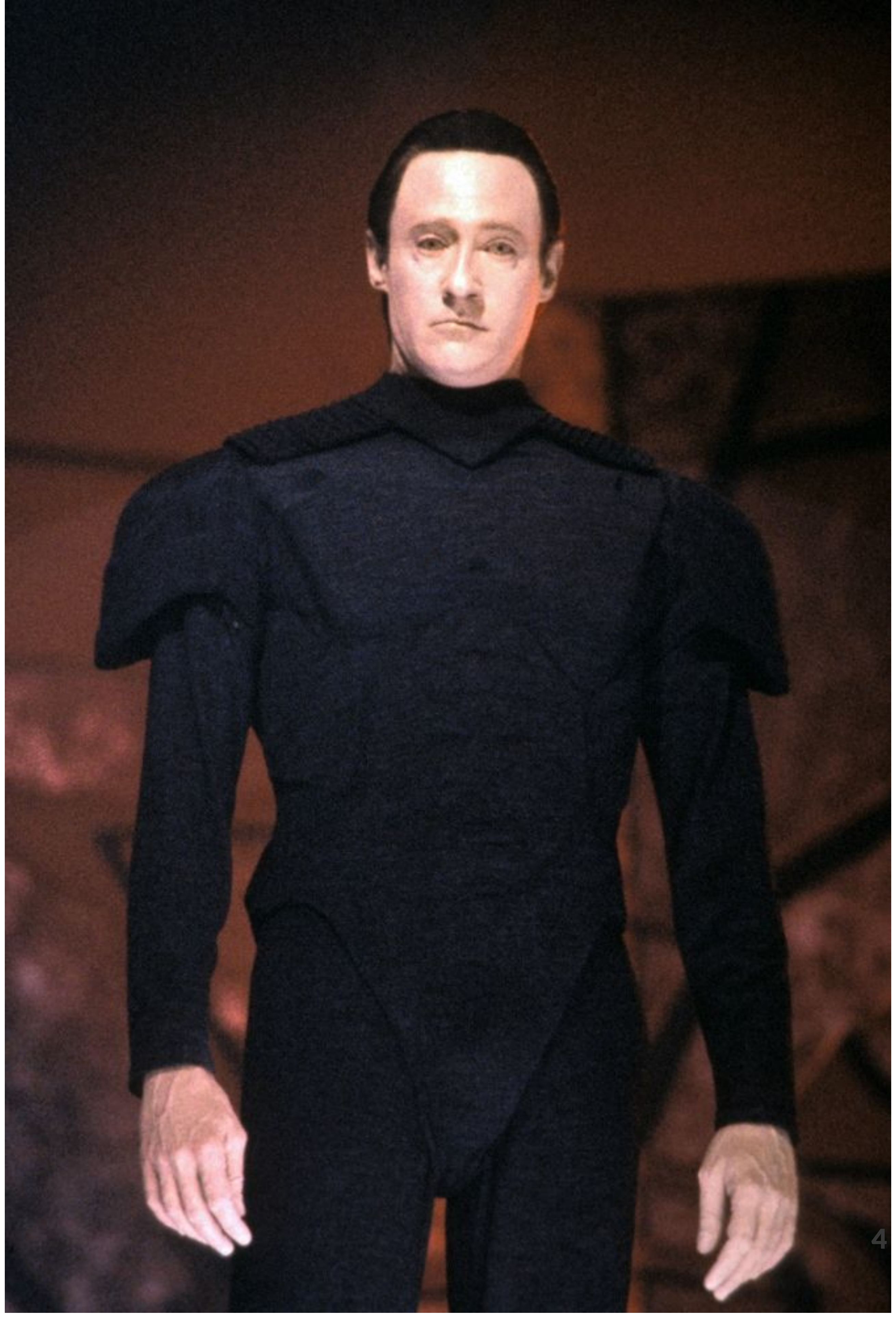


Data Modeling

It is the process of defining the structure of the data for the purpose of communicating[11] or to develop an information systems[12].

[11] between functional and technical people to show data needed for business processes

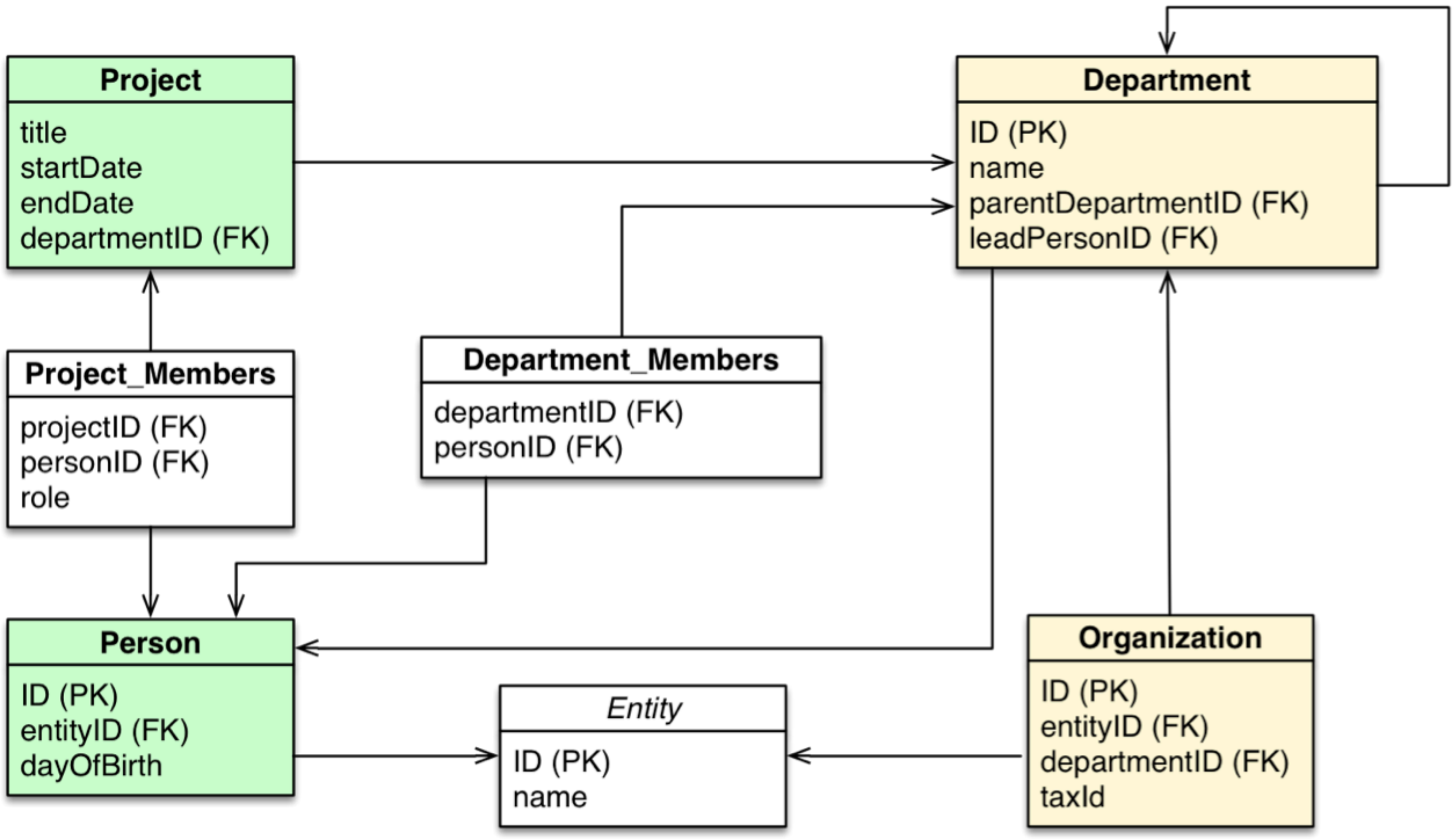
[12] between components of the information system, how data is stored and accessed.



What is a data model?

- A data model represents the structure and the integrity of the data elements of a (single) applications 2
- Data models provide a framework for data to be used within information systems by giving specific definitions and formats.
- The literature of data management is rich of data models that aim at providing increased expressiveness to the modeller and capturing a richer set of semantics.

Any Example?


Project
title
startDate
endDate
departmentID (FK)
Department
ID (PK)
name
parentDepartmentID (FK)
leadPersonID (FK)
Project_Members
projectID (FK)
personID (FK)
role
Department_Members
departmentID (FK)
personID (FK)
Person
ID (PK)
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name
Organization
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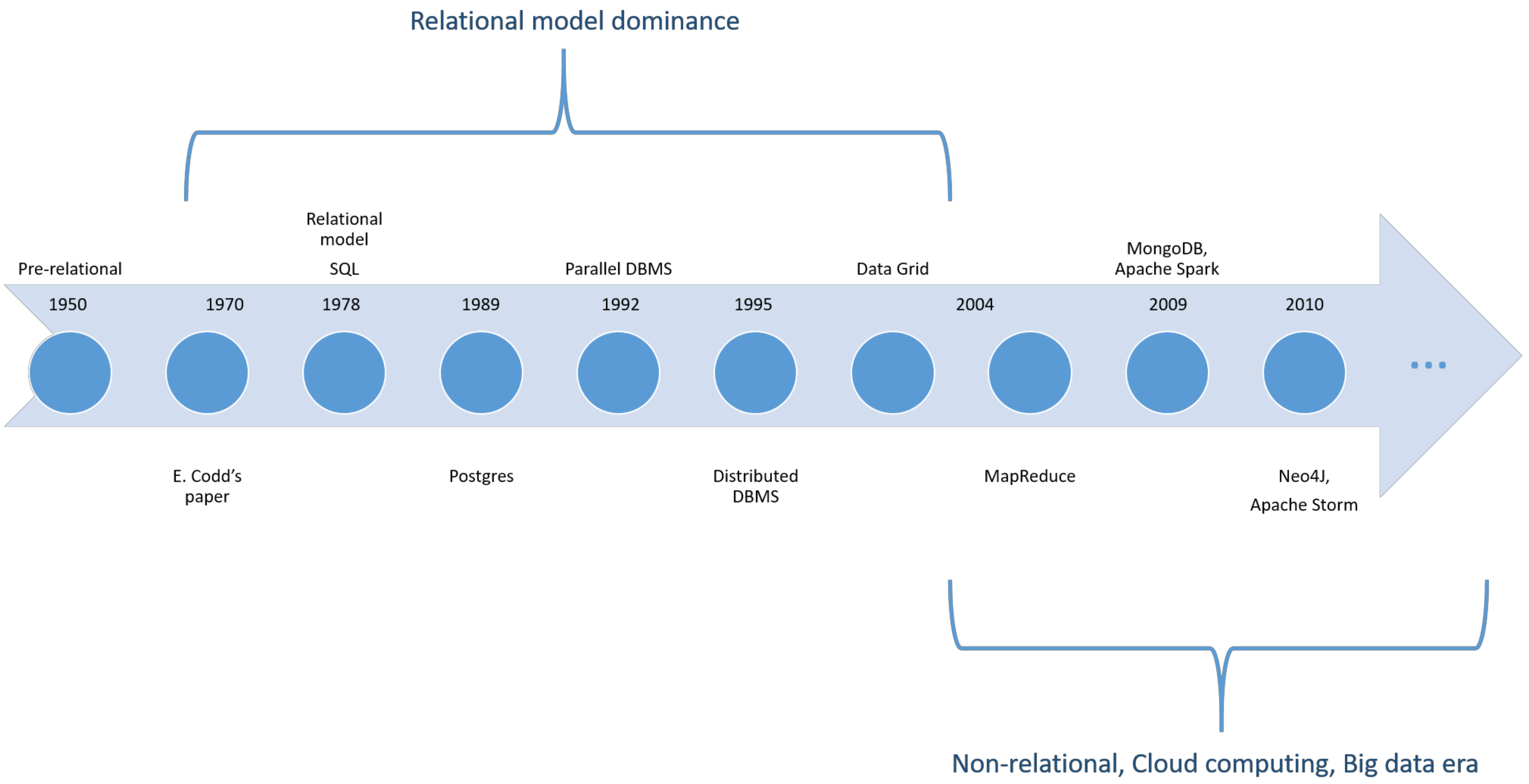
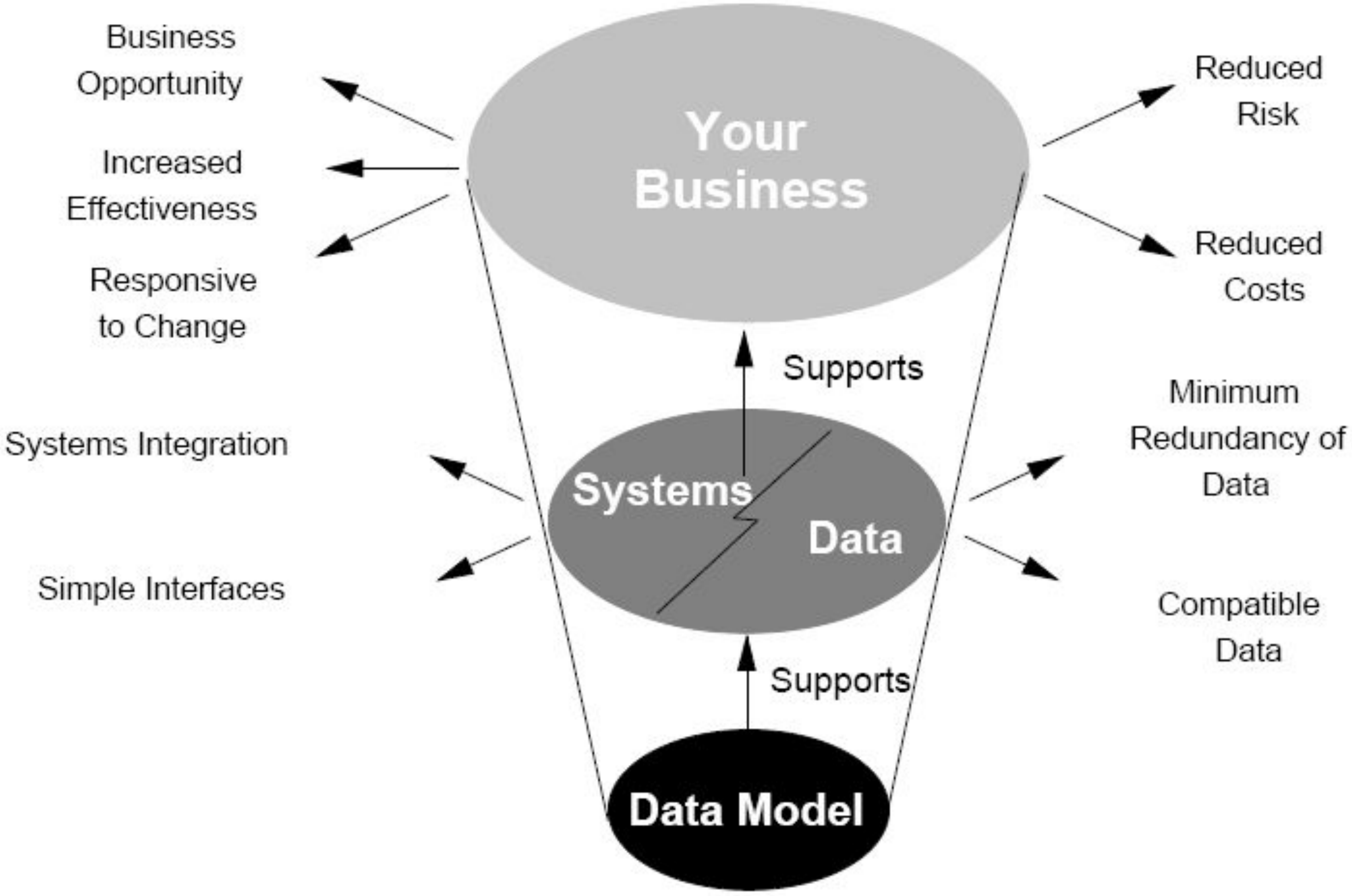
departmentID (FK)
taxId


Relational model dominance
Pre-relational
1950
1970
E. Codd's paper
Relational model
SQL
1978
1989
Postgres
Parallel DBMS
1992
1995
Distributed DBMS
Data Grid
2004
MapReduce
MongoDB, Apache Spark
2009
2010
Neo4J, Apache Storm
...
Non-relational, Cloud computing, Big data era

> Data models are perhaps the most important part of developing software. They have such a profound effect not only on how the software is written, but also on how we think about the problem that we are solving[13].
>
> — *Martin Kleppmann*

[13] Designing Data-Intensive Applications

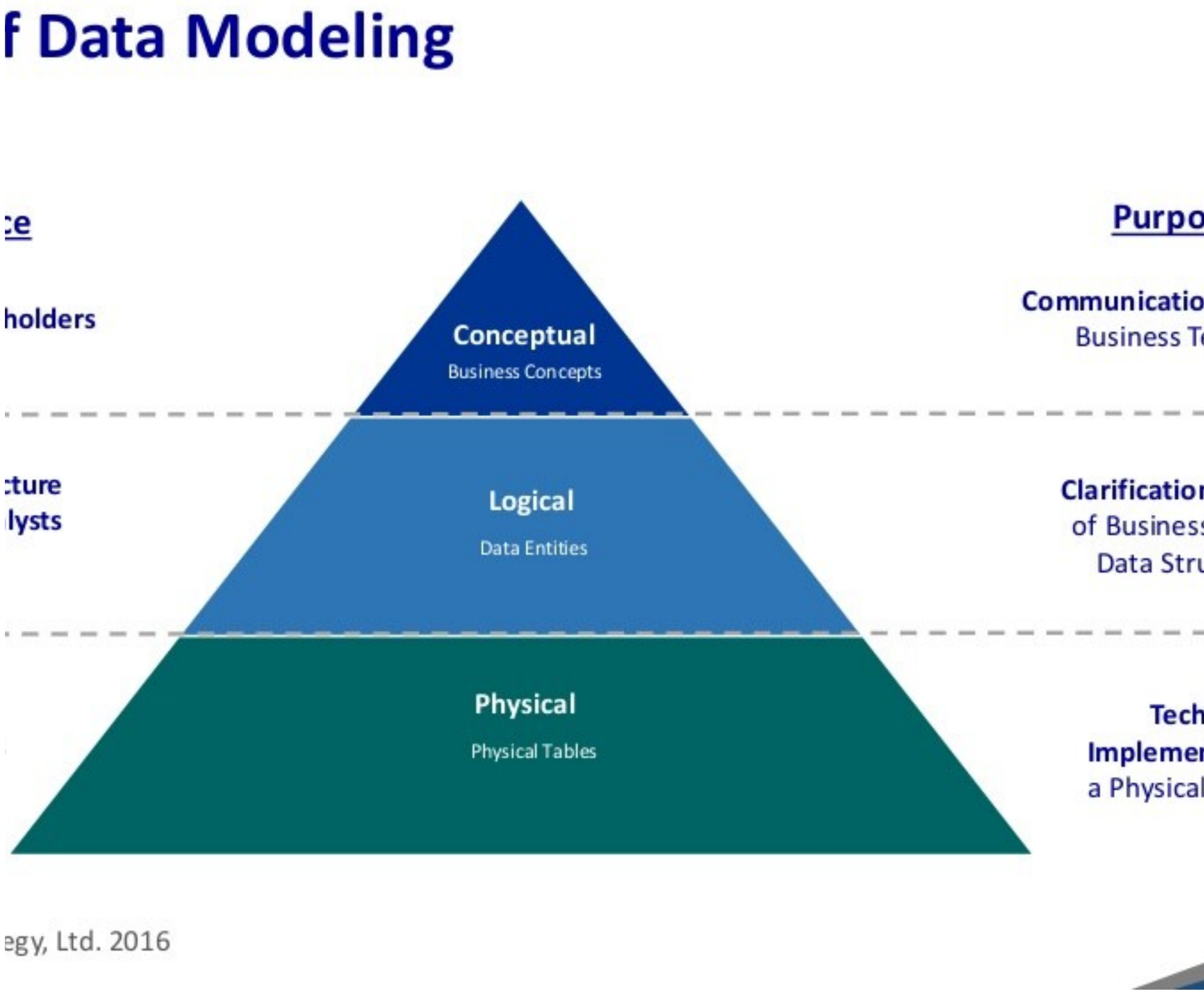

Business Opportunity
Increased Effectiveness
Responsive to Change
Your Business
Reduced Risk
Reduced Costs
Supports
Systems Integration
Simple Interfaces
Systems
Data
Minimum Redundancy of Data
Compatible Data
Supports
Data Model

Level of Data Modeling

Conceptual: The data model defines *WHAT* the system contains.

Logical: Defines *HOW* the system should be implemented regardless of the DBMS.

Physical: This Data Model describes *HOW* the information system will be implemented using a specific technology[14].



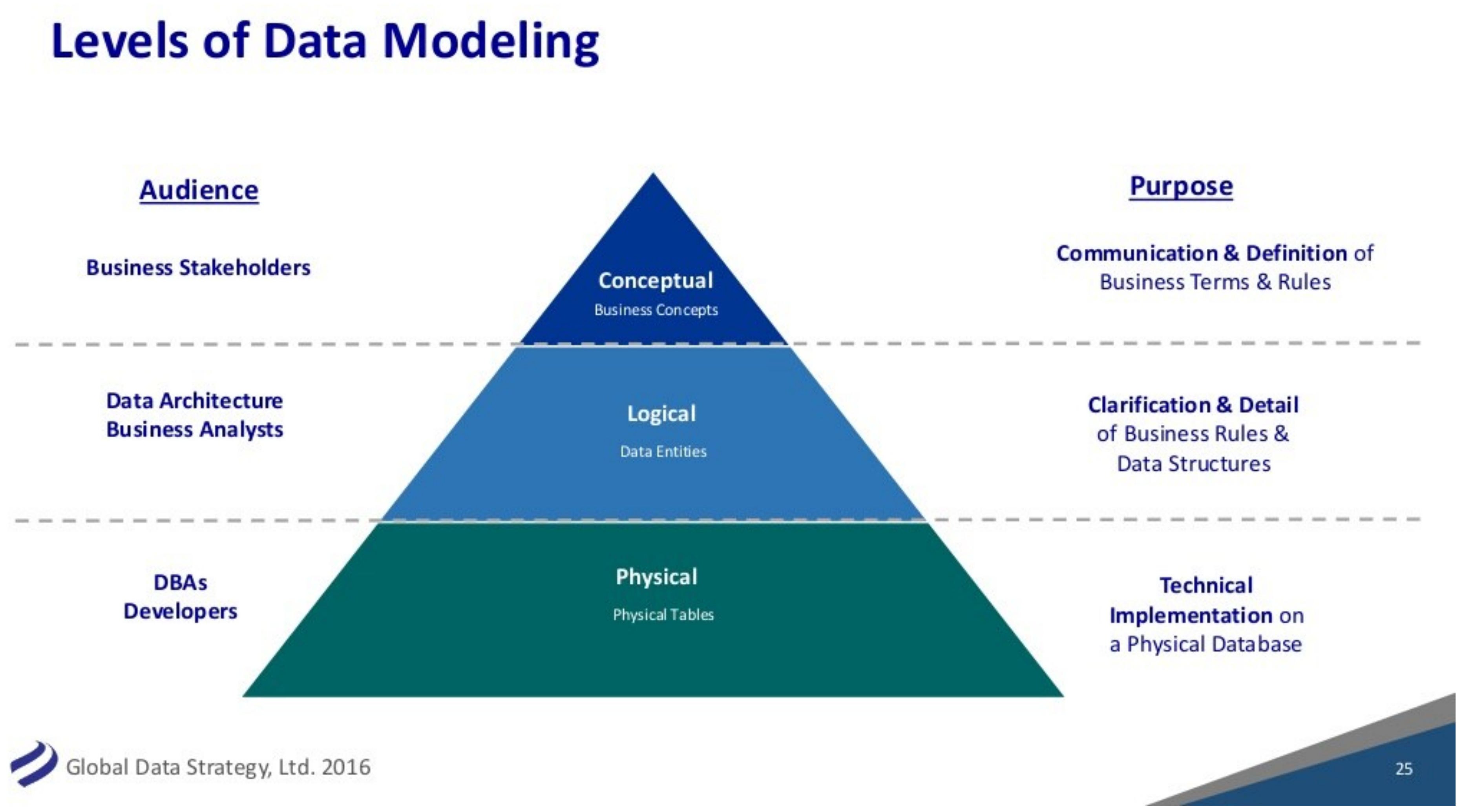
[14] physical

Conceptual model is typically created by Business stakeholders. The purpose is to organize, scope and define business concepts and rules. Definitions are most important this level.

Logical model is typically created by Data Architects. The purpose is to developed technical map of rules and data structures. Business rules, relationships, attribute become visible. Conceptual definitions become metadata.

Physical model is typically created by DBA and developers. The purpose is actual implementation of the database. Trade-offs are explored by in terms of data structures and algorithms.

A Closer Look[15]



Levels of Data Modeling

Audience

Business Stakeholders

Data Architecture
Business Analysts

DBAs
Developers

Purpose

Communication & Definition of Business Terms & Rules

Clarification & Detail of Business Rules & Data Structures

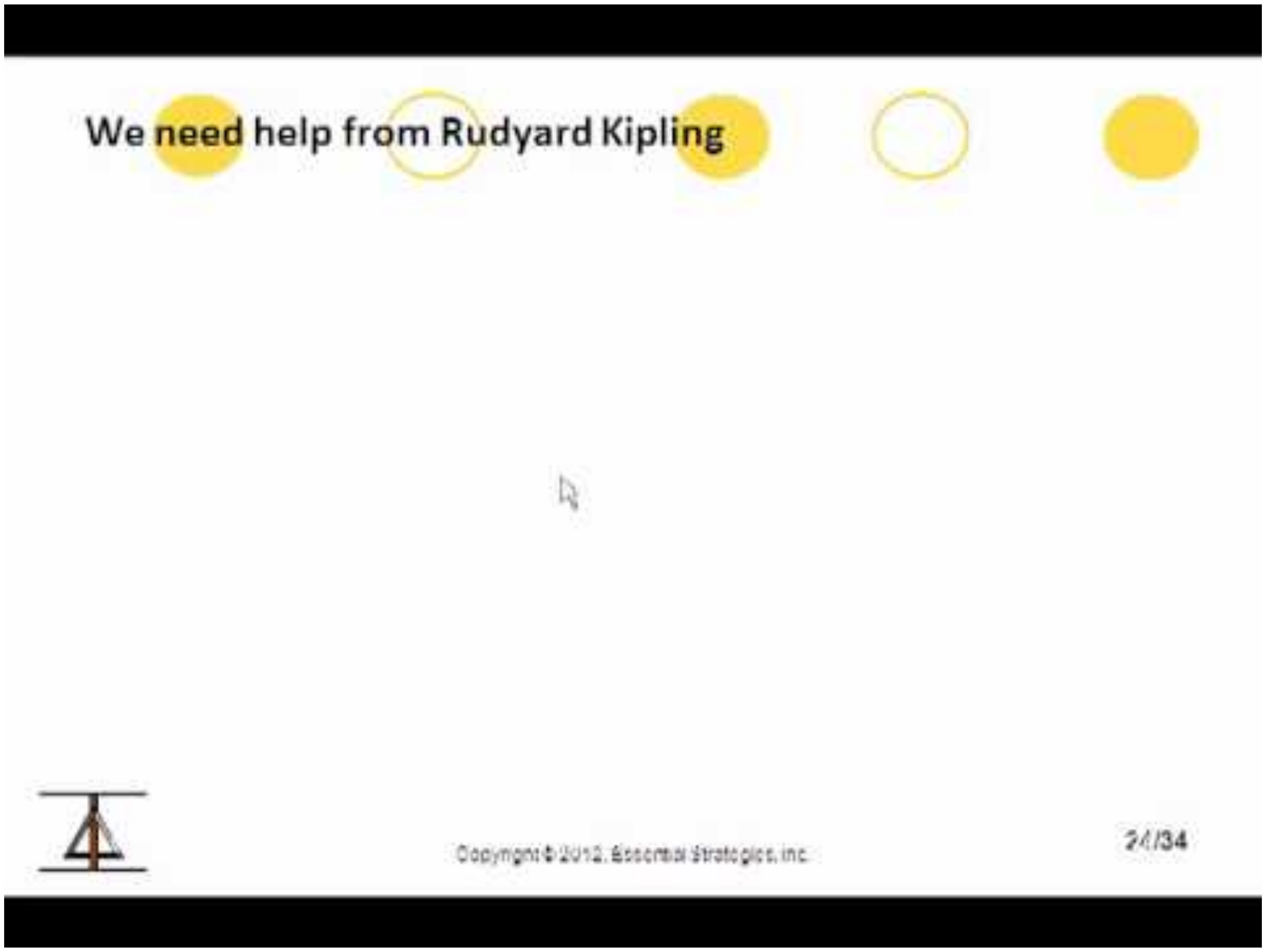
Technical Implementation on a Physical Database

Global Data Strategy, Ltd. 2016

25

[15] slides & video by Donna Burbank

The variety of data available today encourages the design and development of dedicated data models and query languages that can improve both BI as well as the engineering process itself.



We need help from Rudyard Kipling

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Conceptual

- Semantic Model (divergent)
  - Describes an enterprise in terms of the language it uses (the jargon).
  - It also tracks inconsistencies, i.e., semantic conflicts
- Architectural Model (convergent)
  - More fundamental, abstract categories across enterprise

Logical

Already bound to a technology, it typically refers already to implementation details

- Relational
- Hierarchical
- Key-Value
- Object-Oriented
- Graph

Since it has a physical bias, you might be tempted to confuse this with the physical model, but this is wrong.

Physical

The physical level describes how data are **Stored** on a device.

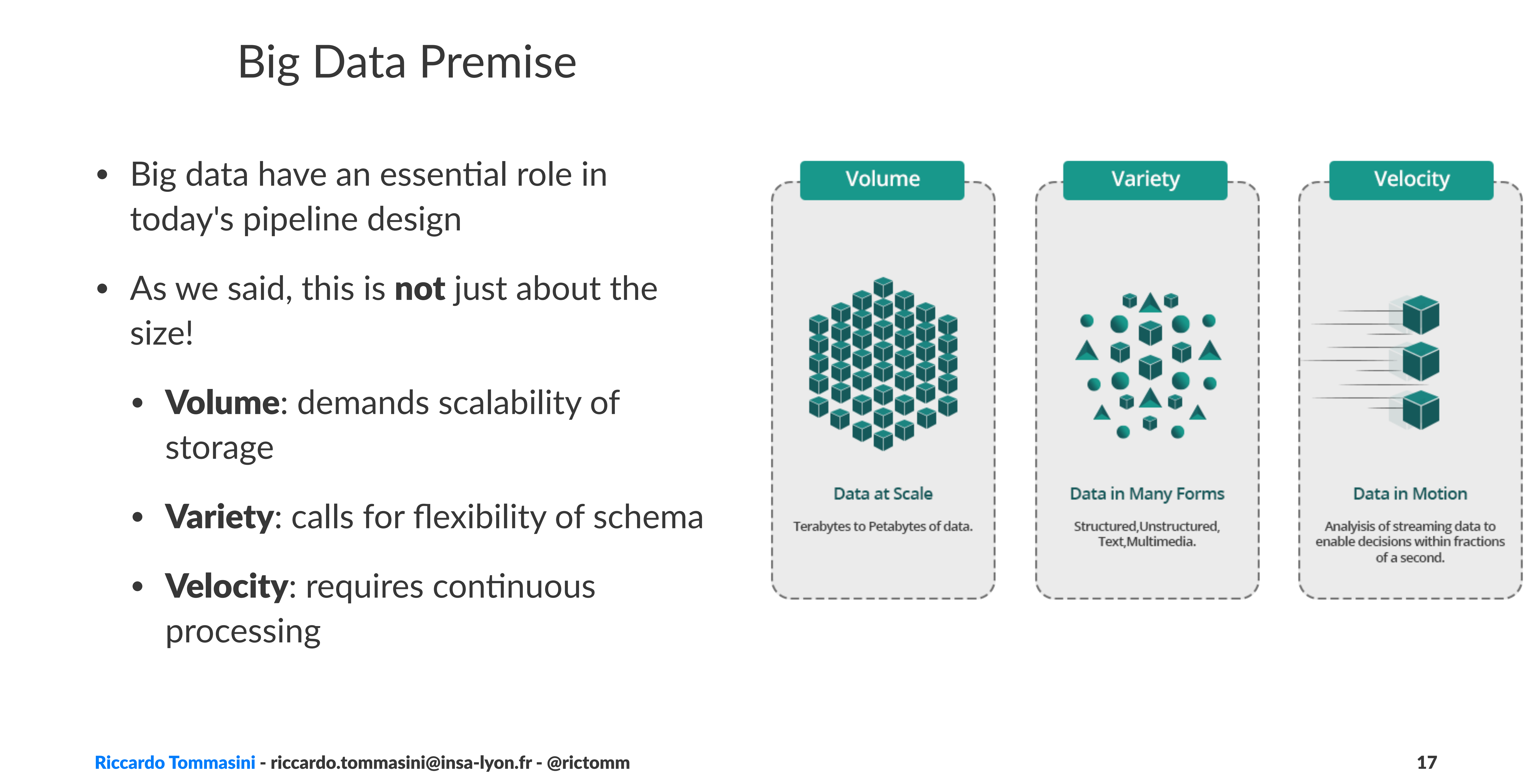
- Data formats
- Distribution
- Indexes
- Data Partitions
- Data Replications

...an you are in the Big Data World

Towards a Physical View

Before digging into the details of the physical view, we need to unveil two premises

- A Big Data Premise (Workload)
- A Distributed System Premise: CAP Theorem



Big Data Premise

- Big data have an essential role in today's pipeline design
- As we said, this is **not** just about the size!
  - **Volume**: demands scalability of storage
  - **Variety**: calls for flexibility of schema
  - **Velocity**: requires continuous processing

Volume

Data at Scale

Terabytes to Petabytes of data.

Variety

Data in Many Forms

Structured,Unstructured, Text,Multimedia.

Velocity

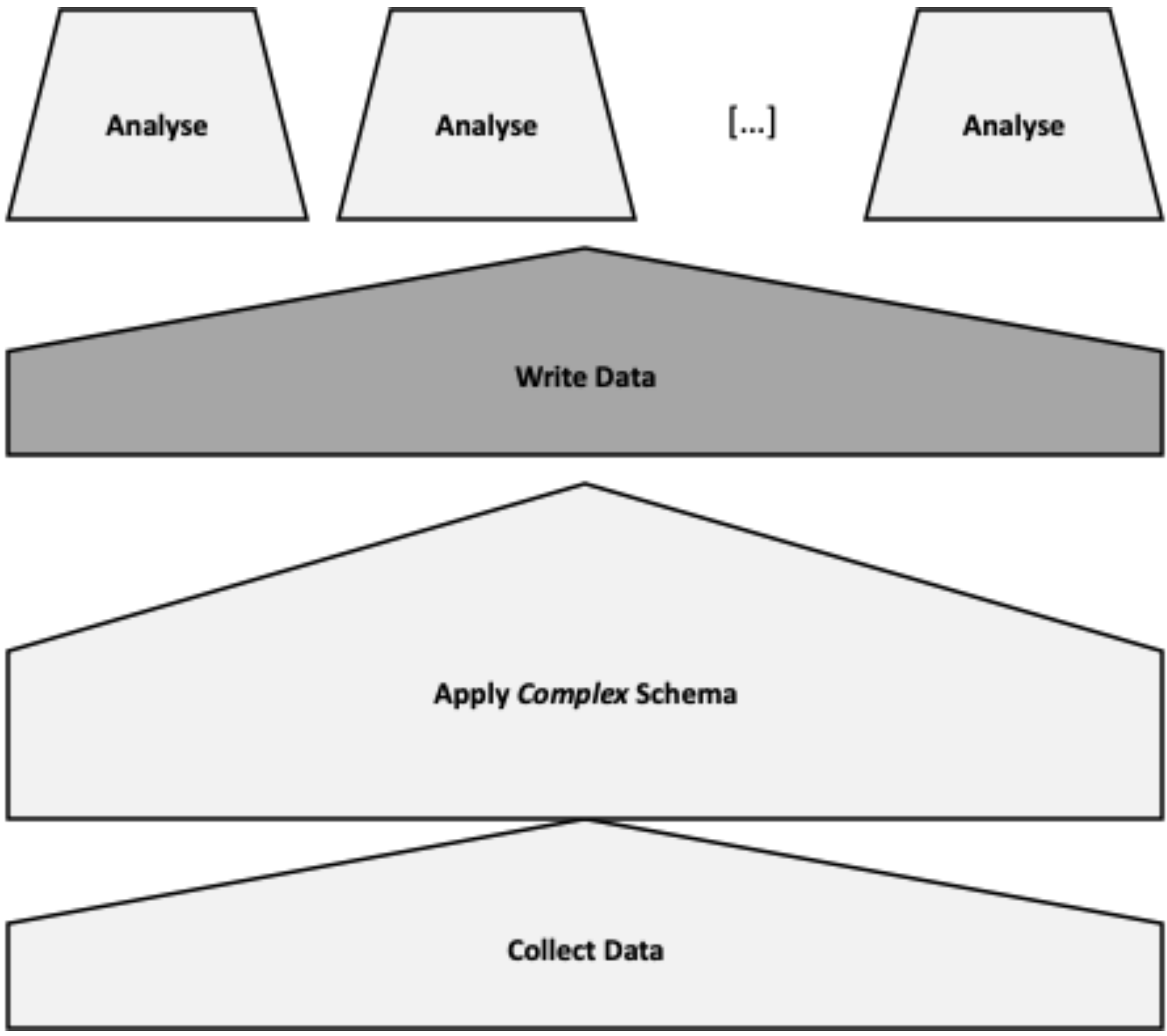
Data in Motion

Analyisis of streaming data to enable decisions within fractions of a second.

- Once again the big data challenges impact the design of our pipelines
- The are all relevant at many levels, but volume is the one that caused most of the changes
- we need to relax some aspects of the data systems

Traditional Data Modelling Workflow

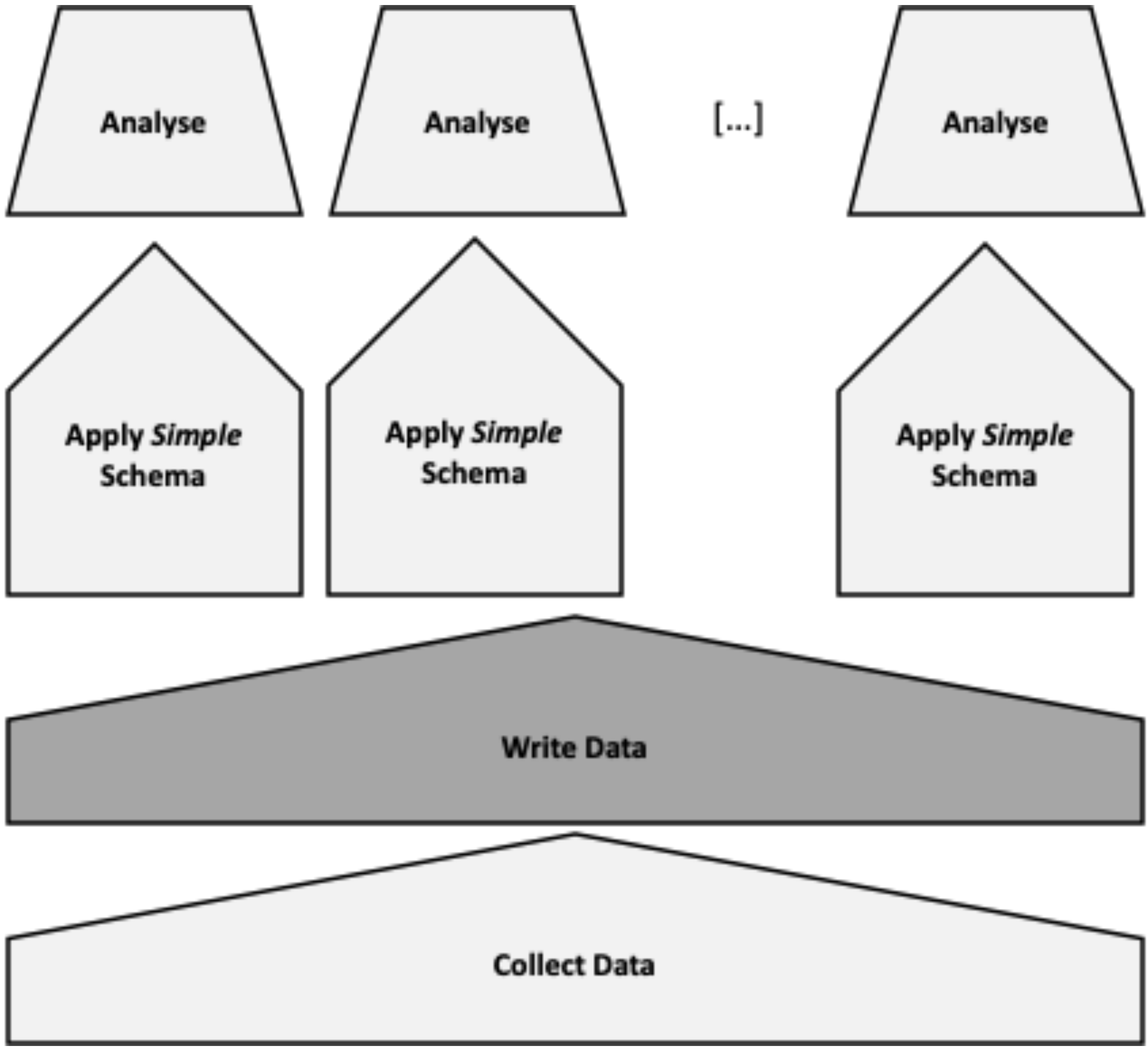
- Known as Schema on Write
- Focus on the modelling a schema that can accommodate all needs
- Bad impact on those analysis that were not envisioned



- Extract Transform Load
 - Some analyses may no longer be performed because the data were lost at writing time,

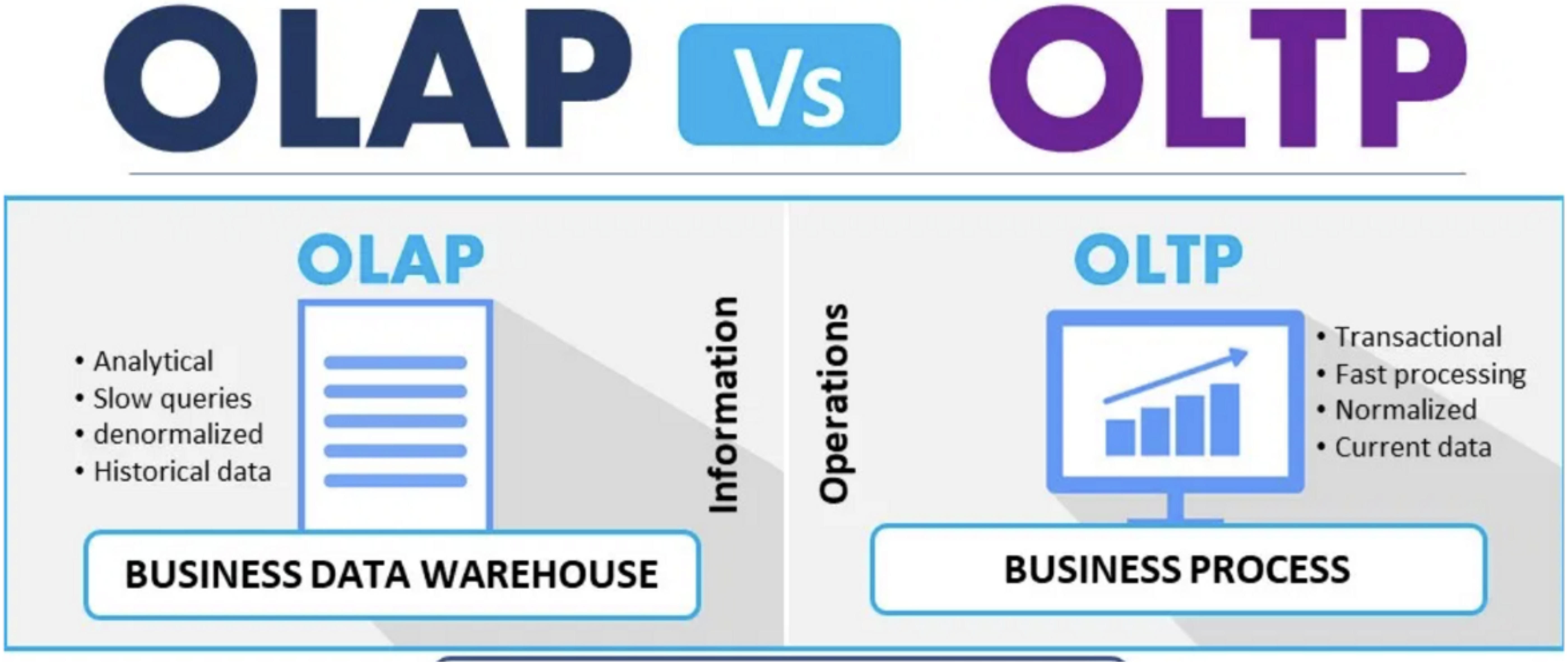
Schema on Read

- Load data first, ask question later
- All data are kept, the minimal schema need for an analysis is applied when needed
- New analyses can be introduced in any point in time



So, what’s a logical architecture for a data engineering pipeline?

Let's Talk about Workloads



OLAP Vs OLTP

OLAP

- Analytical
- Slow queries
- denormalized
- Historical data

BUSINESS DATA WAREHOUSE

Information

Operations

OLTP

- Transactional
- Fast processing
- Normalized
- Current data

BUSINESS PROCESS

- **OLTP** systems are usually expected to be **highly available** and to process transactions with low latency, since they are often critical to the operation of the business.
- **OLAP** queries are often written by business analysts, and feed into reports that help the management of a company make better decisions (business intelligence).

Online Transactional Processing

Because these applications are interactive, the access pattern became known as **online**

Transactional means allowing clients to make low-latency reads and writes—as opposed to batch processing jobs, which only run periodically (for example, once per day).

Refresh on ACID Properties

- ACID, which stands for Atomicity, Consistency, Isolation, and Durability[11]
- **Atomicity** refers to something that cannot be broken down into smaller parts.
  - It is not about concurrency (which comes with the I)
- **Consistency** (overused term), that here relates to the data *invariants* (integrity would be a better term IMHO)
- **Isolation** means that concurrently executing transactions are isolated from each other.
  - Typically associated with serializability, but there weaker options.
- **Durability** means (fault-tolerant) persistency of the data, once the transaction is completed.
- ^ The terms was coined in 1983 by Theo Härder and Andreas Reuter [16]

[11] between functional and technical people to show data needed for business processes

[16] Theo Härder and Andreas Reuter: “Principles of Transaction-Oriented Database Recovery,” ACM Computing Surveys, volume 15, number 4, pages 287–317, December 1983. doi:10.1145/289.291

Online Analytical Processing

An OLAP system allows a data analyst to look at different cross-tabs on the same data by interactively selecting the attributes in the cross-tab

Statistical analysis often requires grouping on multiple attributes.

Example

Consider this is a simplified version of the sales fact table joined with the dimension tables, and many attributes removed (and some renamed)

sales (item*name*, *color*, *clothes*size, quantity)

item_name	color	clothes_size	quantity
dress	dark	small	2
dress	dark	medium	6
...	...	...	...
pants	pastel	medium	0
pants	pastel	large	1
pants	white	small	3
pants	white	medium	0
shirt	white	medium	1
...	...	...	...
shirt	white	large	10
skirt	dark	small	2
skirt	dark	medium	5
...	...	...	...

Cross-tabulation of sales by item name and color

	dark	pastel	white	total
skirt	8	35	10	53
dress	20	11	5	36
shirt	22	4	46	72
pants	23	42	25	90
total	73	92	102	267

columns header: color
rows header: item name

Cheat Sheet of OLAP Operations[17]

- **Pivoting**: changing the dimensions used in a cross-tab
  - E.g. moving colors to column names
- **Slicing**: creating a cross-tab for fixed values only
  - E.g fixing color to white and size to small
  - Sometimes called dicing, particularly when values for multiple dimensions are fixed.
- **Rollup**: moving from finer-granularity data to a coarser granularity
  - E.g. aggregating away an attribute
  - E.g. moving from aggregates by day to aggregates by month or year
- **Drill down**: The opposite operation - that of moving from coarser granularity data to finer-granularity data

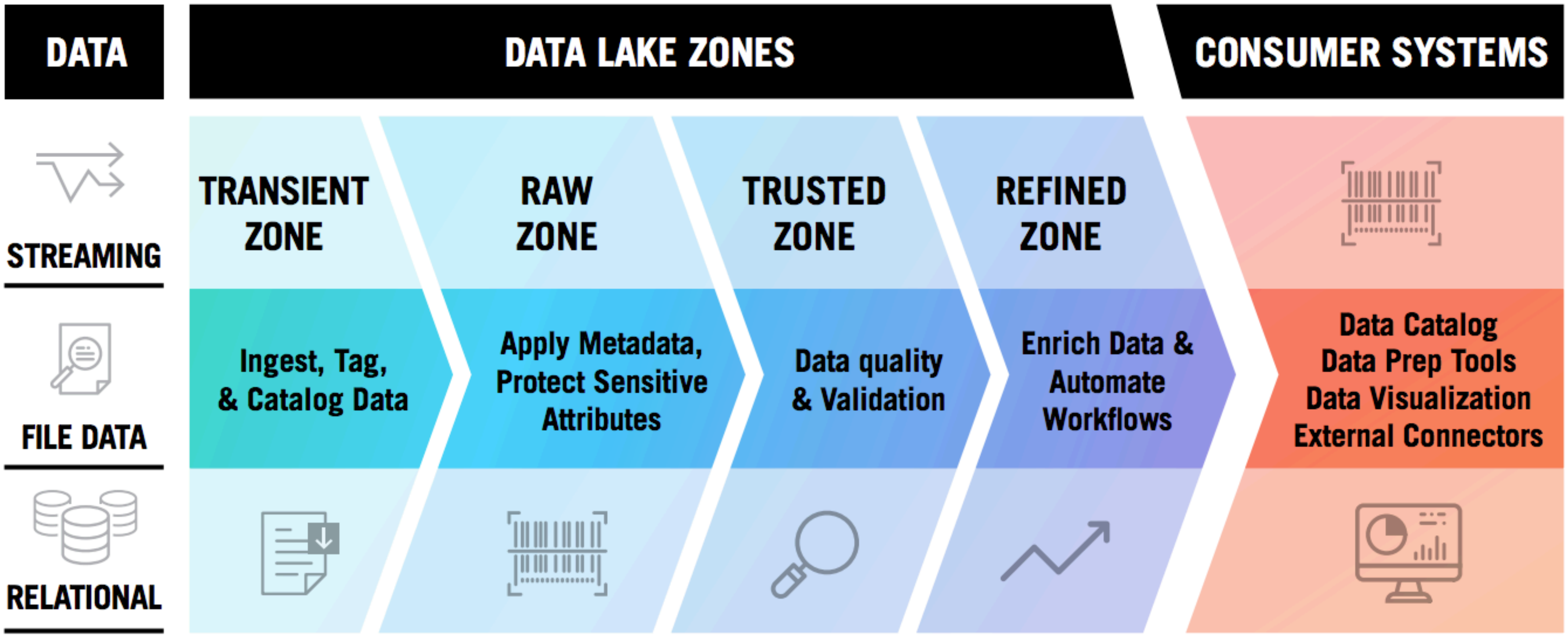
[17] Database System Concepts Seventh Edition Avi Silberschatz Henry F. Korth, S. Sudarshan McGraw-Hill ISBN 9780078022159 link

Summary OLTP vs OLAP[13]

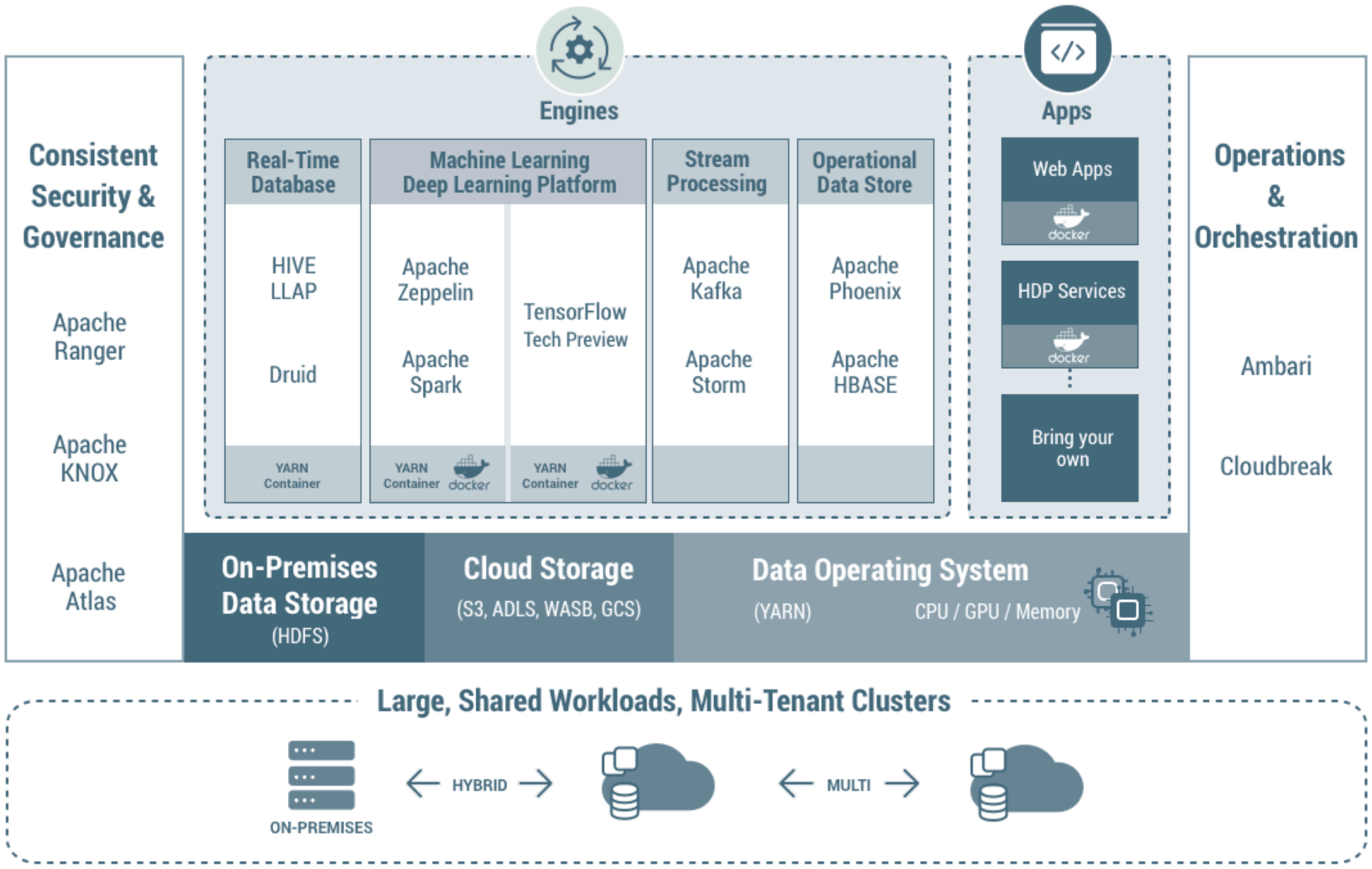
Property	OLTP	OLAP
Main read pattern	Small number of records per query, fetched by key	Aggregate over large number of records
Main write pattern	Random-access, low-latency writes from user input	Bulk import (ETL) or event stream
Primarily used by	End user/customer, via web application	Internal analyst, for decision support
What data represents	Latest state of data (current point in time)	History of events that happened over time
Dataset size	Gigabytes to terabytes	Terabytes to petabytes

[13] Designing Data-Intensive Applications

Data Lakes (Conceptual View)



Physical Architecture of a Big Data Platform



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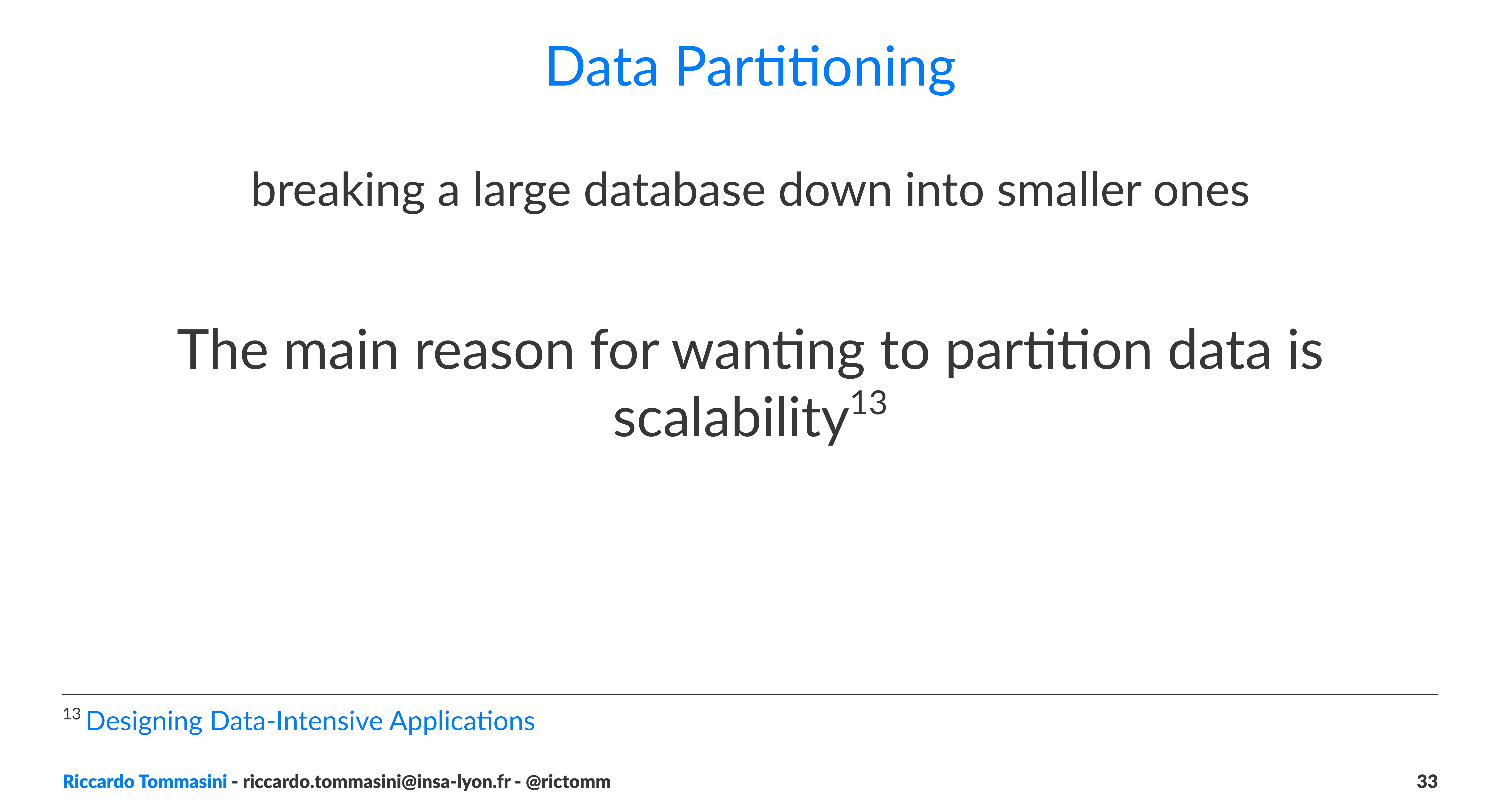
Distributed System Premise



Data Partitioning

breaking a large database down into smaller ones

The main reason for wanting to partition data is scalability[13]

[13] Designing Data-Intensive Applications

For very large datasets, or very high query throughput, that is not sufficient

- Different partitions can be placed on different nodes in a shared-nothing cluster
- Queries that operate on a single partition can be independently executed. Thus, throughput can be scaled by adding more nodes.

What to know

- If some partitions have more data or queries than others the partitioning is **skewed**
- A partition with disproportionately high load is called a **hot spot**
- For reaching maximum scalability (linear) partitions should be balanced

Let's consider some partitioning strategies, for simplicity we consider Key,Value data.

Partitioning Strategies

- **Round-robin** randomly assigns new keys to the partitions.
  - Ensures an even distribution of tuples across nodes;
- **Range partitioning** assigns a contiguous key range to each node.
  - Not necessarily balanced, because data may not be evenly distributed
- **Hash partitioning** uses a hash function to determine the target partition. - If the hash function returns i, then the tuple is placed

CAP Theorem (Brewer's Theorem)

It is impossible for a distributed computer system to simultaneously provide all three of the following guarantees:

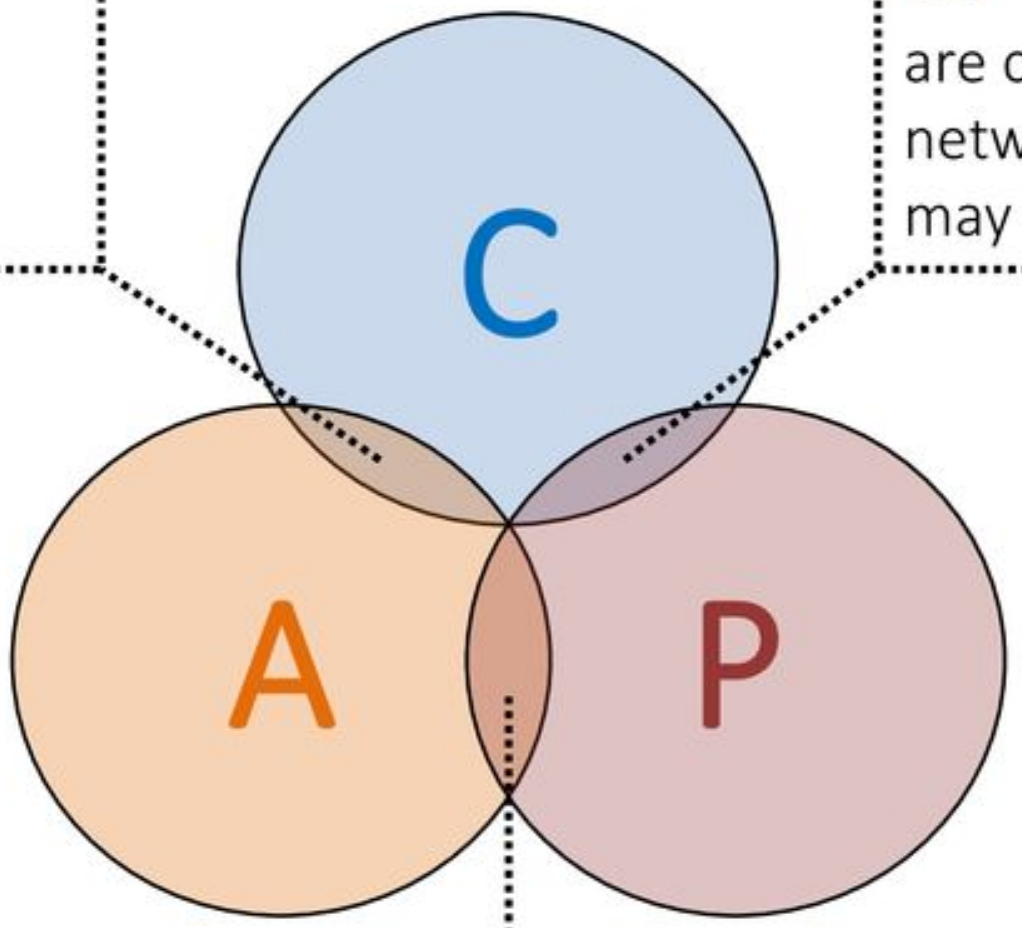
- **Consistency**: all nodes see the same data at the same time
- **Availability**: Node failures do not prevent other survivors from continuing to operate (a guarantee that every request receives a response whether it succeeded or failed)
- **Partition tolerance**: the system continues to operate despite arbitrary partitioning due to network failures (e.g., message loss)

A distributed system can satisfy any two of these guarantees at the same time but not all three.

CAP Systems

CA: Guarantees to give a correct response but only while network works fine (*Centralised / Traditional*)

CP: Guarantees responses are correct even if there are network failures, but response may fail (*Weak availability*)



(No intersection)

AP: Always provides a “best-effort” response even in presence of network failures (*Eventual consistency*)

The network is not reliable

In a distributed system, *_a network (of networks)_ * failures can, and will, occur.

Since We cannot neglect Partition Tolerance the remaining option is choosing between **Consistency** and **Availability**.

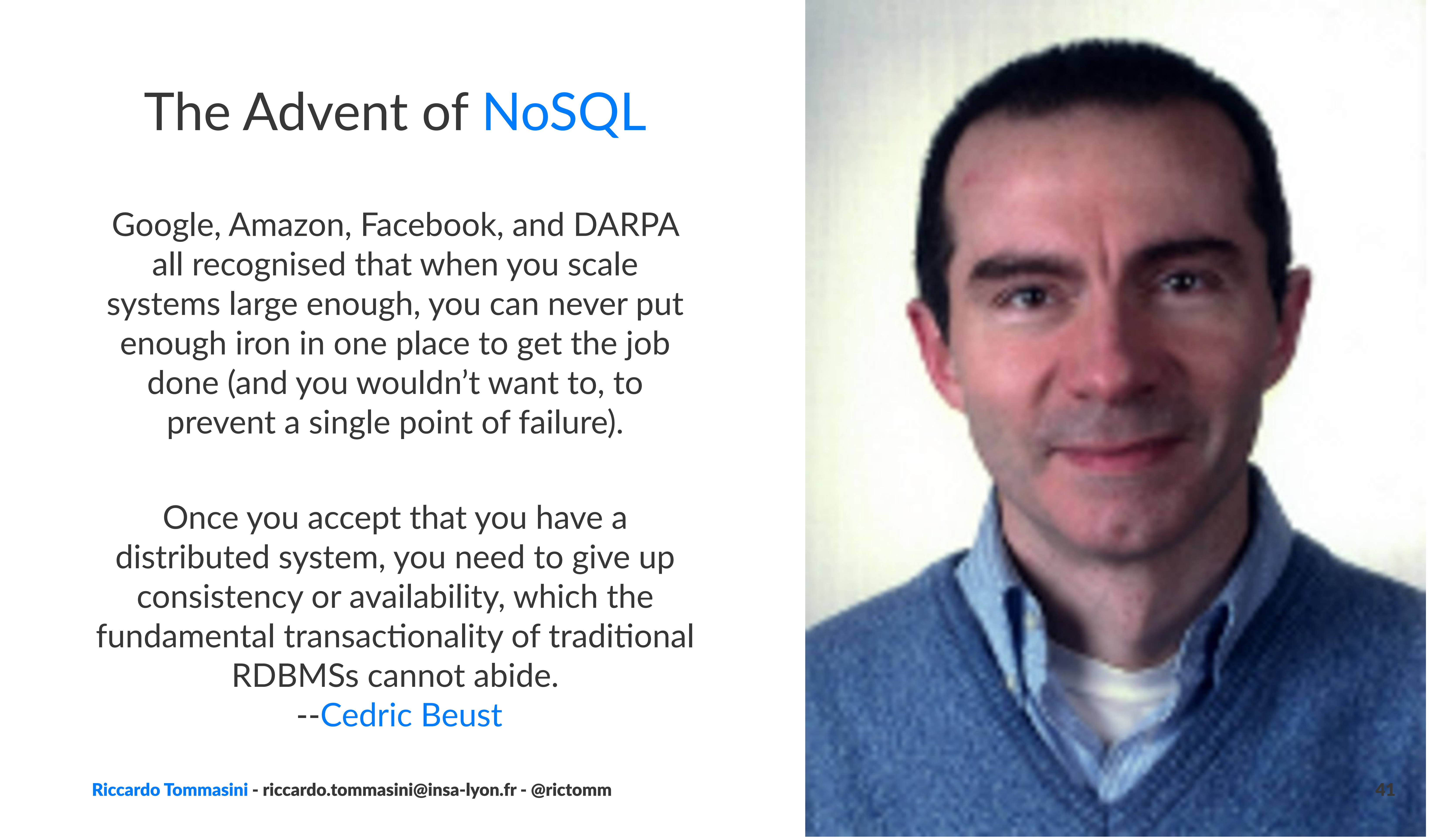
We cannot neglect Partition Tolerance

Not necessarily in a mutually exclusive manner:

- CP: A partitioned node returns
  - the correct value
  - a timeout error or an error, otherwise
- AP: A partitioned node returns the most recent version of the data, which could be stale.

Implications of CAP Theorem

- change the transactionality gurantees
- redesign the data workflow ()
- reimagine the data processing systems (noSQL)

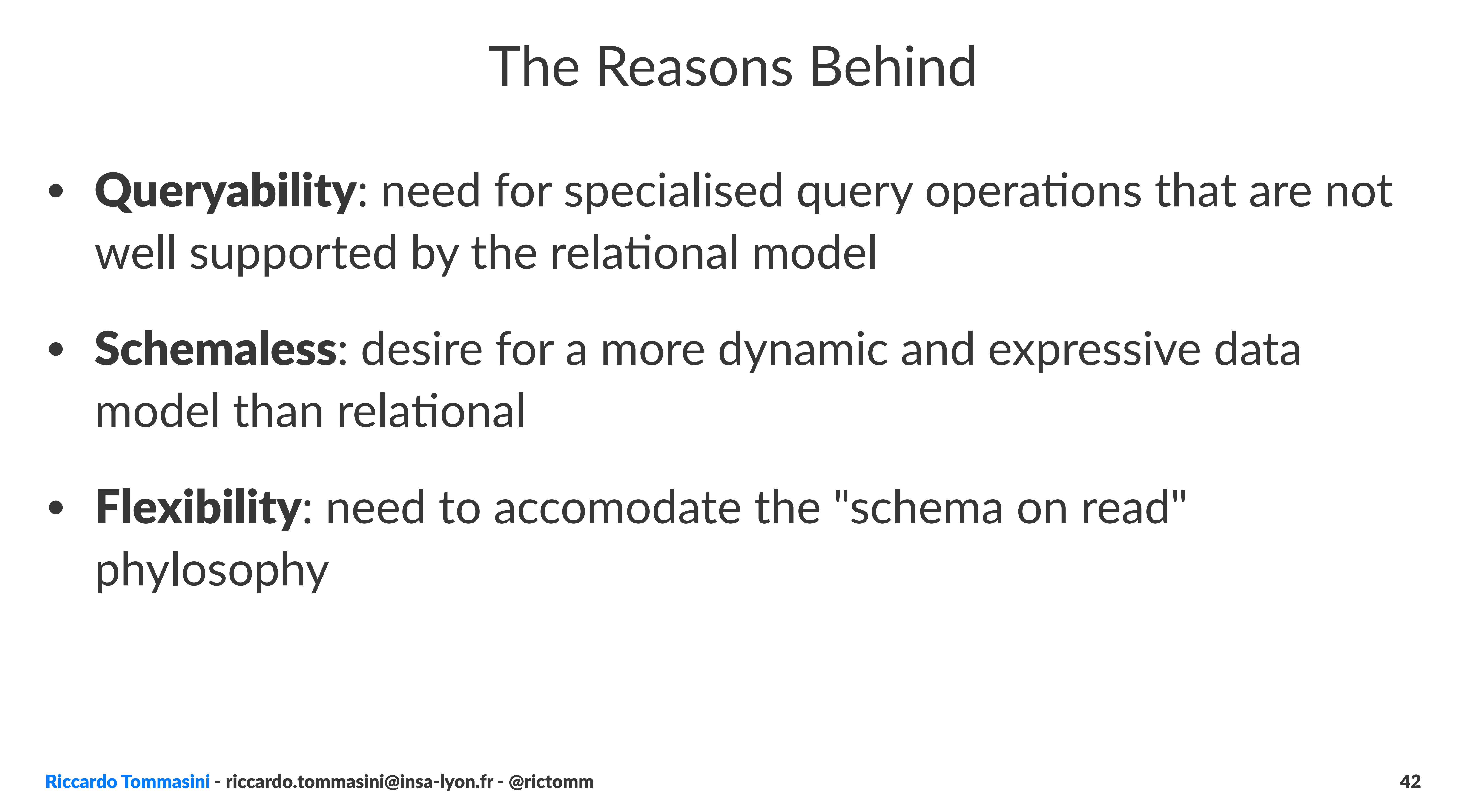


The Advent of NoSQL

Google, Amazon, Facebook, and DARPA all recognised that when you scale systems large enough, you can never put enough iron in one place to get the job done (and you wouldn't want to, to prevent a single point of failure).

Once you accept that you have a distributed system, you need to give up consistency or availability, which the fundamental transactionality of traditional RDBMSs cannot abide.
--Cedric Beust

The name "NoSQL" is unfortunate, since it doesn't actually refer to any particular technology—it was originally intended simply as a catchy Twitter hashtag for a meetup on open source, distributed, non-relational databases in 2009 Cf Pramod J. Sadalage and Martin Fowler: NoSQL Distilled. Addison-Wesley, August 2012. ISBN: 978-0-321-82662-6



The Reasons Behind

- **Queryability**: need for specialised query operations that are not well supported by the relational model
- **Schemaless**: desire for a more dynamic and expressive data model than relational
- **Flexibility**: need to accomodate the "schema on read" phylosophy

- **Big Data**: need for greater scalability than relational databases can easily achieve *in write*
- **Open Source:** a widespread preference for free and open source software

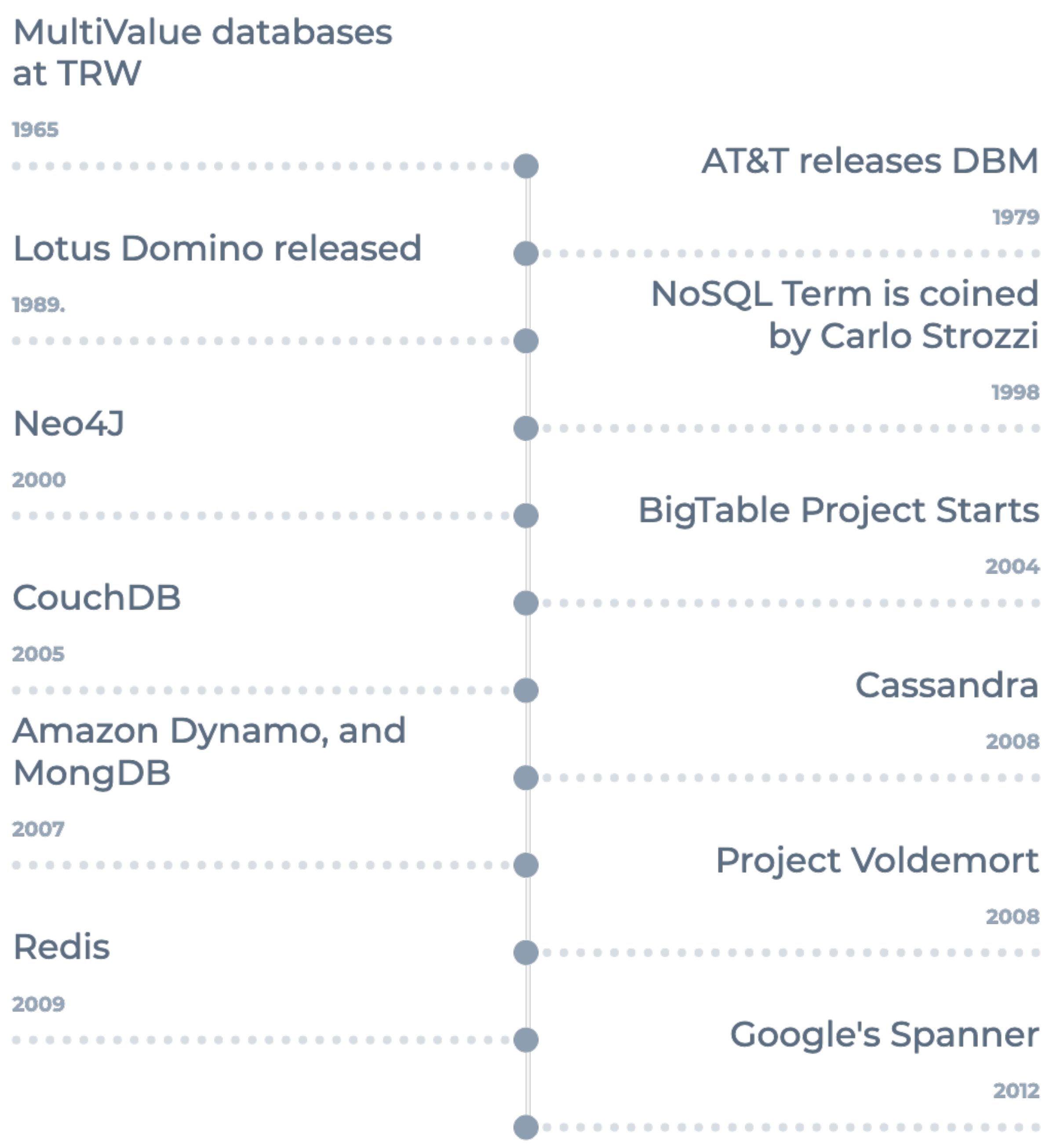
Object-Relational Mismatch

Most application development today is done in **object-oriented** programming languages

An **awkward translation** layer is required between the **objects** in the application code and the database model of **tables**, **rows**, and **columns**

Object-relational mapping (**ORM**) frameworks like **Hibernate** try to mild the mismatch, but they **can't completely hide** the differences

NoSQL Timeline



MultiValue databases at TRW

1965

AT&T releases DBM

1979

Lotus Domino released

1989.

NoSQL Term is coined by Carlo Strozzi

1998

Neo4J

2000

BigTable Project Starts

2004

CouchDB

2005

Cassandra

2008

Amazon Dynamo, and MongDB

2007

Project Voldemort

2008

Redis

2009

Google's Spanner

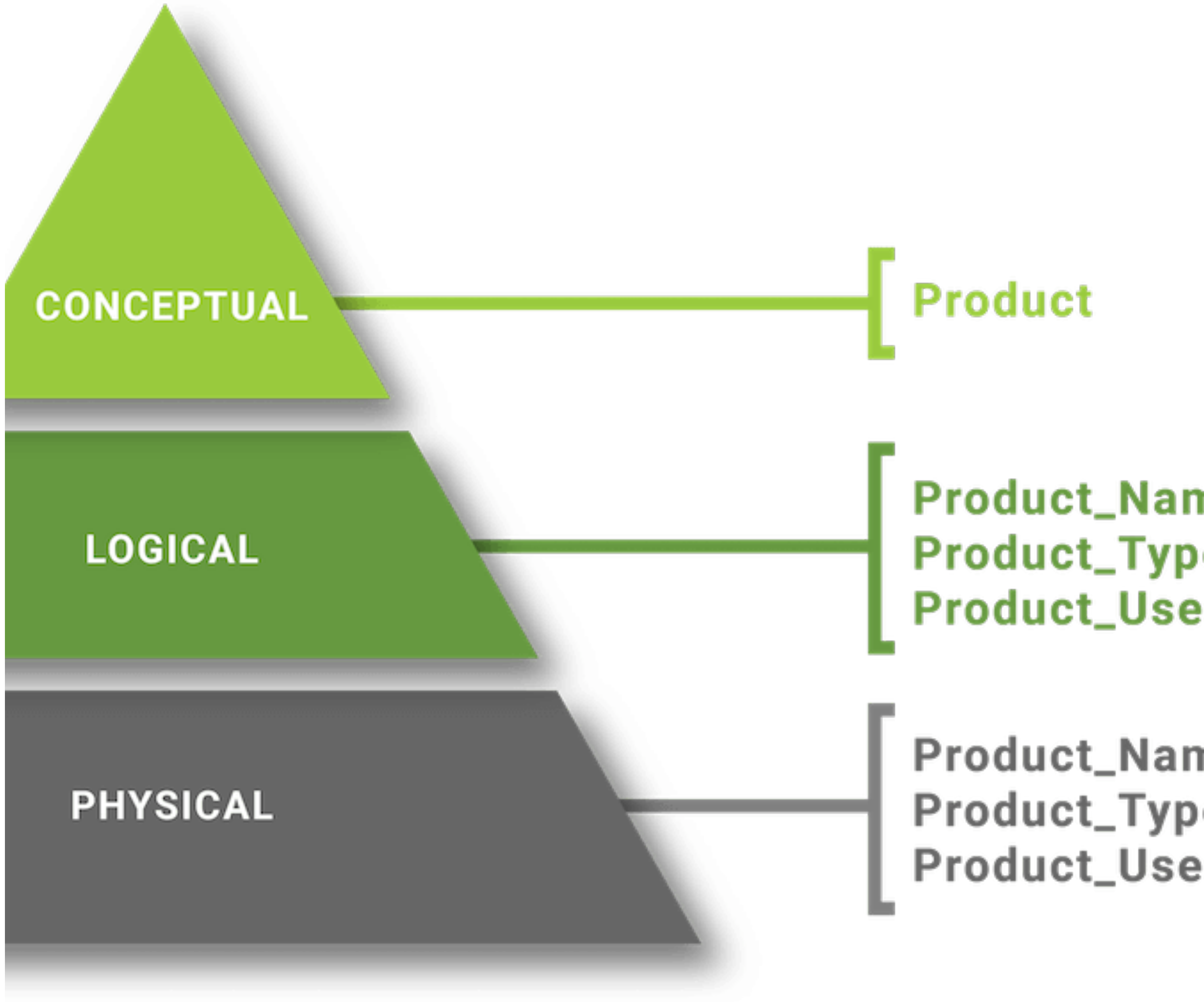
2012

the idea of NOSQL actually originates in the late 60s together with the raise of the raise of object-oriented languages, but become popular later.

Shall we rethink the three-layered modelling for Big Data?

Designing NoSQL Data Structures

- NoSQL data structures driven by application design.
  - Need to take into account necessary CRUD operations
- To embed or not to imbed. That is the question!
  - Rule of thumb is to imbed whenever possible.
- No modelling standards or CASE[case] tools!

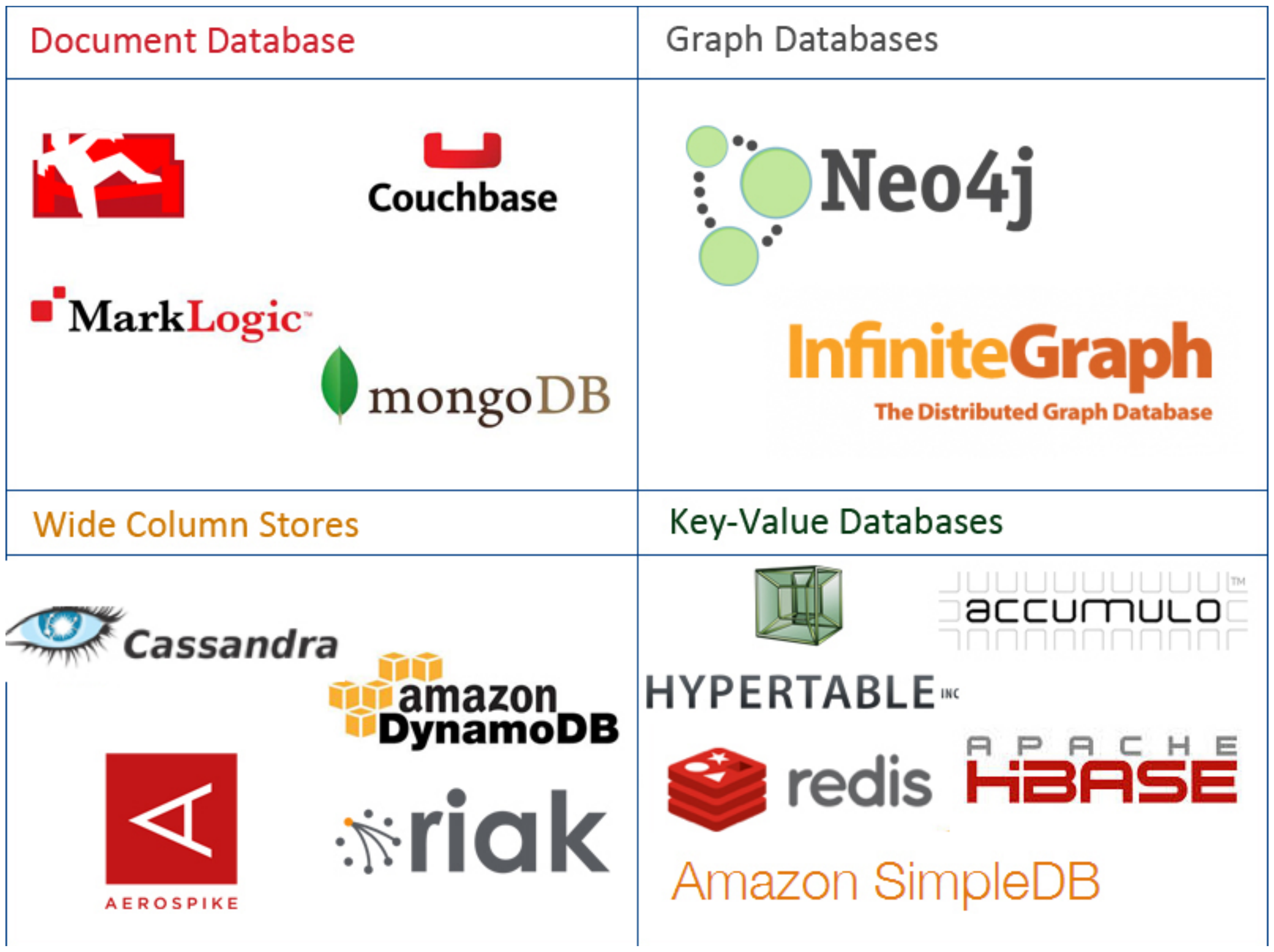


[case] computer aided software engineering

Data Modeling for Big Data

- **Conceptual Level** remains:
  - ER, UML diagram can still be used for no SQL as they output a model that encompasses the whole company.
- **Phsyical Level** remains: NoSQL solutions often expose internals for obtaining flexibility, e.g.,
  - Key-value stores API
  - Column stores
  - Log structures
- *Logical level no longer make sense. Schema on read focuses on the query side.*_

NoSQL Familty



Document Database	Graph Databases
Couchbase MarkLogic mongoDB	Neo4j InfiniteGraph The Distributed Graph Database
Wide Column Stores	**Key-Value Databases**
Cassandra amazon DynamoDB AEROSPIKE riak	accumulo HYPERTABLE INC redis APACHE HBASE Amazon SimpleDB

Kinds of NoSQL (2/4)

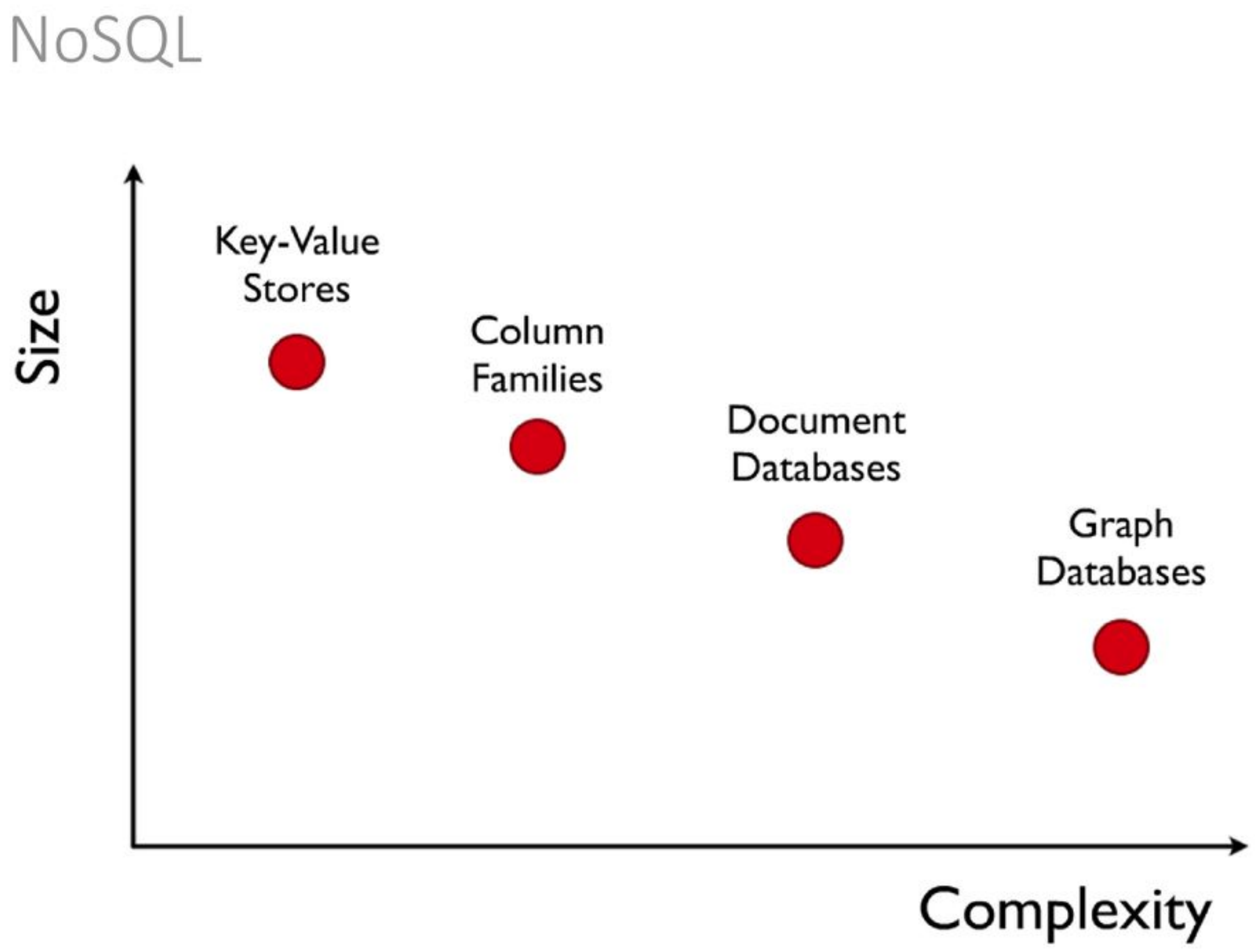
NoSQL solutions fall into four major areas:

- **Key-Value Store**
  - A key that refers to a payload (actual content / data)
  - Examples: MemcacheDB, Azure Table Storage, Redis, HDFS
- **Column Store**
  - Column data is saved together, as opposed to row data
  - Super useful for data analytics
  - Examples: Hadoop, Cassandra, Hypertable

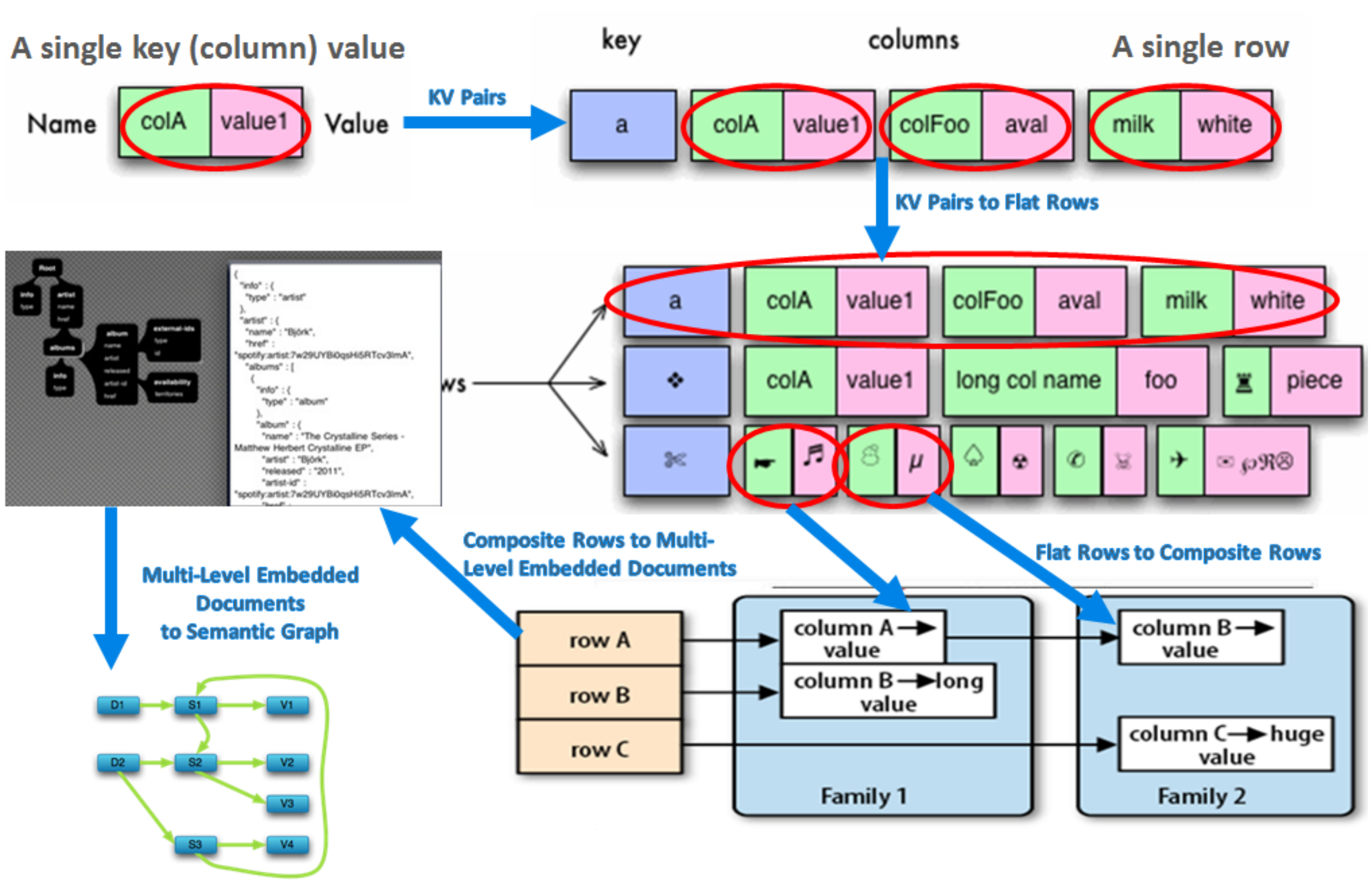
Kinds of NoSQL (4/4)

- **Document / XML / Object Store**
  - Key (and possibly other indexes) point at a serialized object
  - DB can operate against values in document
  - Examples: MongoDB, CouchDB, RavenDB
- **Graph Store**
  - Nodes are stored independently, and the relationship between nodes (edges) are stored with data
  - Examples: AllegroGraph, Neo4j

Complexity Across Families



Dependencies Across Families

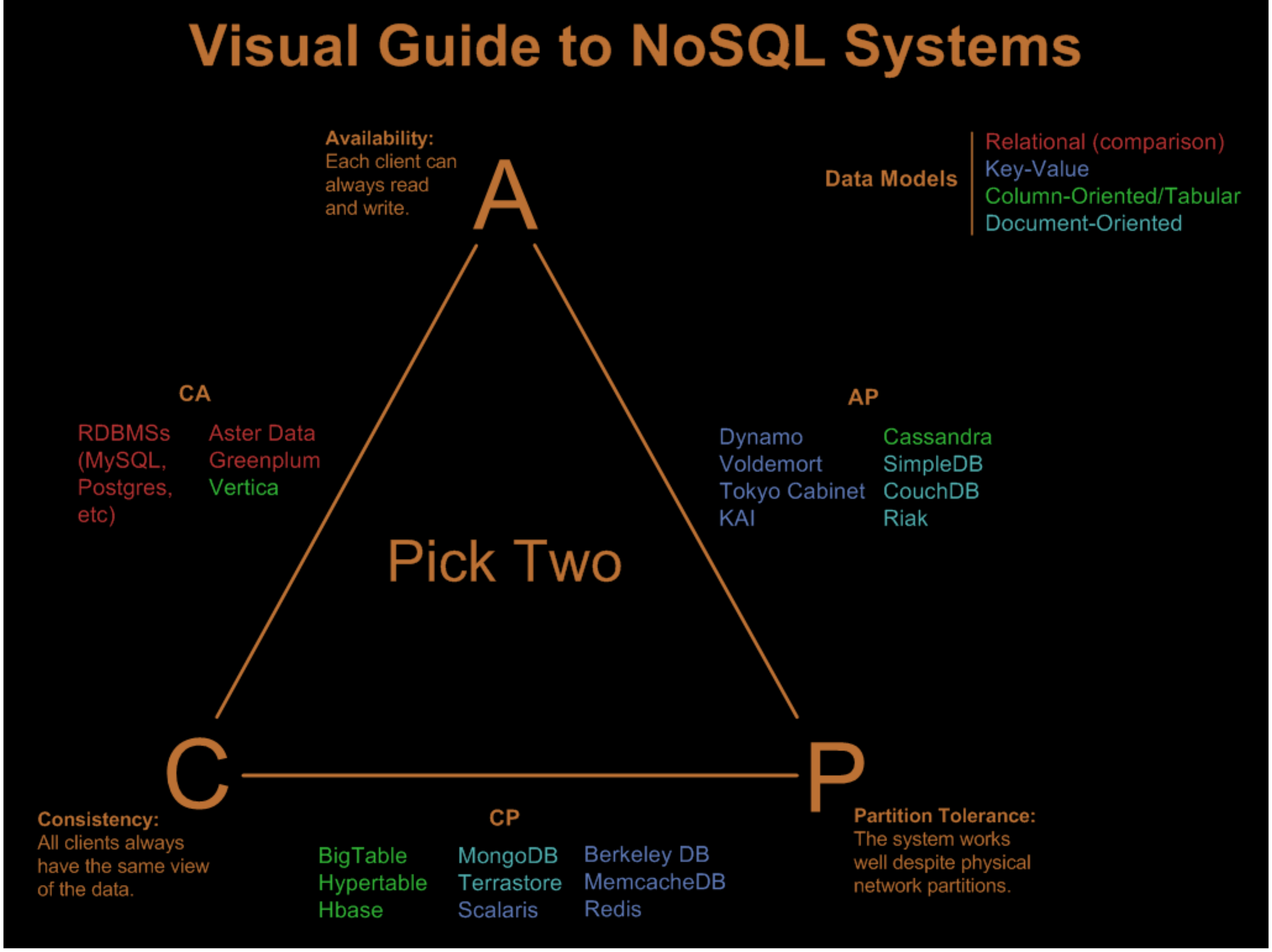


a natural evolutionary path exists from simple key-value stores to the highly complicated graph databases, as shown in the following diagram:

SQL vs NoSQL

SQL databases	**NoSQL databases**
Triggered the need of relational databases	Triggered by the storage needs of Web 2.0 companies such as Facebook,Google and Amazon.com
Well structured data	Not necessarily well structured – e.g., pictures, documents, web page description, video clips, etc.
Focus on data integrity	focuses on availability of data even in the presence of multiple failures
Mostly Centralised	spread data across many storage systems with a high degree of replication.
ACID properties should hold	ACID properties may not hold[^62]

NoSQL & CAP Theorem



Visual Guide to NoSQL Systems

Availability: Each client can always read and write.

A

Data Models

- Relational (comparison)
- Key-Value
- Column-Oriented/Tabular
- Document-Oriented

CA

RDBMSs (MySQL, Postgres, etc)

Aster Data
Greenplum
Vertica

AP

Dynamo
Voldemort
Tokyo Cabinet
KAI

Cassandra
SimpleDB
CouchDB
Riak

Pick Two

C

P

Consistency: All clients always have the same view of the data.

CP

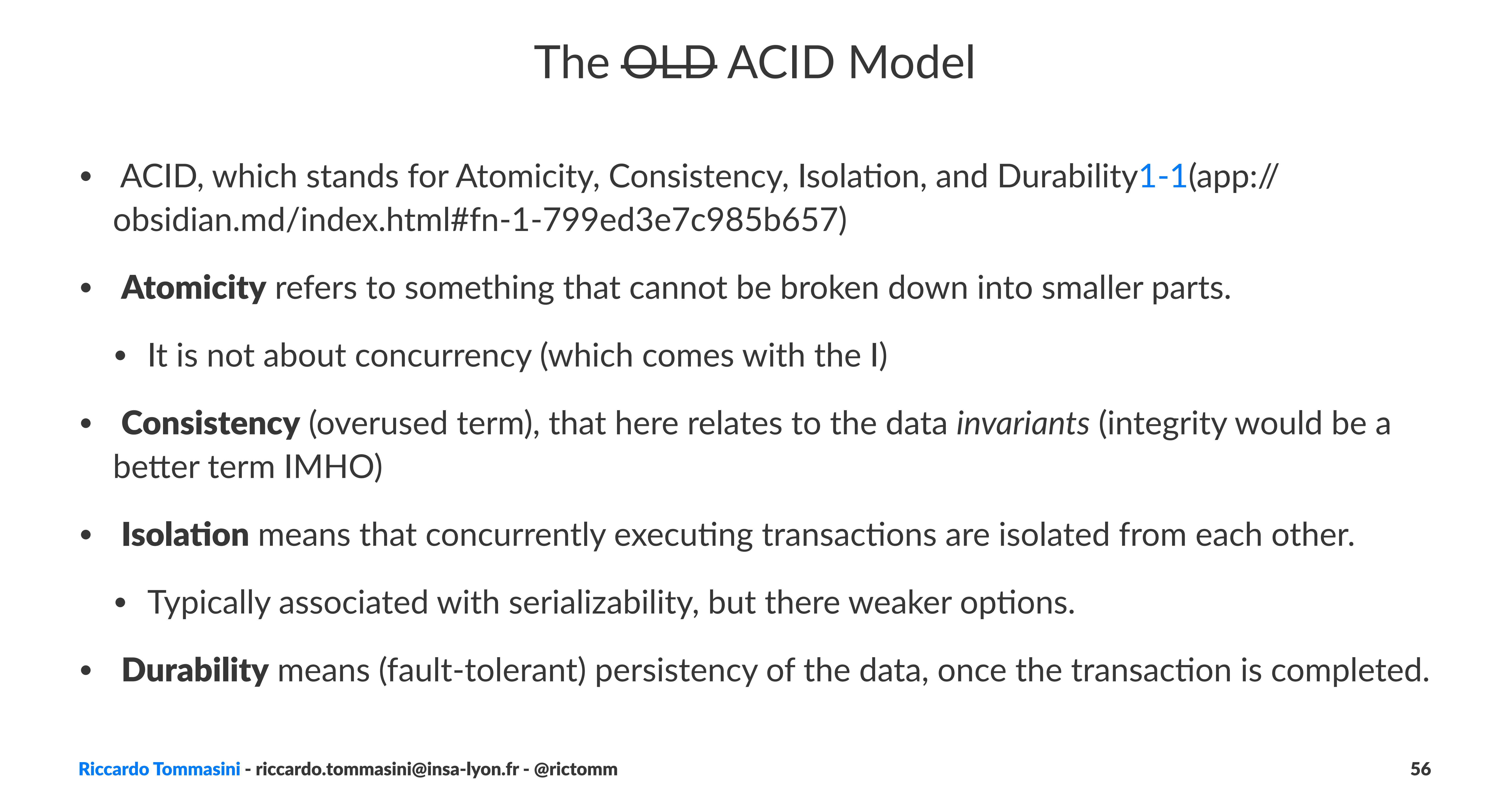
BigTable
Hypertable
Hbase

MongoDB
Terrastore
Scalaris

Berkeley DB
MemcacheDB
Redis

Partition Tolerance: The system works well despite physical network partitions.

img



The ~~OLD~~ ACID Model

- ACID, which stands for Atomicity, Consistency, Isolation, and Durability1-1(app://obsidian.md/index.html#fn-1-799ed3e7c985b657)
- **Atomicity** refers to something that cannot be broken down into smaller parts.
  - It is not about concurrency (which comes with the I)
- **Consistency** (overused term), that here relates to the data *invariants* (integrity would be a better term IMHO)
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The terms was coined in 1983 by Theo Härder and Andreas Reuter 6(app://obsidian.md/index.html#fn-6-799ed3e7c985b657)

Rationale to Change

- It’s ok to use stale data (Accounting systems do this all the time. It’s called “closing out the books.”) ;
- It’s ok to give approximate answers
- Use resource versioning -> say what the data really is about – no more, no less
    - the value of x is 5 at time T

The New BASE Model

BASE(Basically Available, Soft-State, Eventually Consistent)

- **Basic Availability**: fulfill request, even in partial consistency.
- **Soft State**: abandon the consistency requirements of the ACID model pretty much completely
- **Eventual Consistency**: delayed consistency, as opposed to immediate consistency of the ACID properties[67].
  - purely aliveness guarantee (reads eventually return the requested value); but
  - does not make safety guarantees, i.e.,
  - an eventually consistent system can return any value before it converges

[67] at some point in the future, data will converge to a consistent state;

ACID vs. BASE trade-off

No general answer to whether your application needs an ACID versus BASE consistency model.

Given **BASE** ’s loose consistency, developers **need to** be more knowledgeable and **rigorous** about **consistent** data if they choose a BASE store for their application.

Planning around **BASE** limitations can sometimes be a major **disadvantage** when compared to the simplicity of ACID transactions.

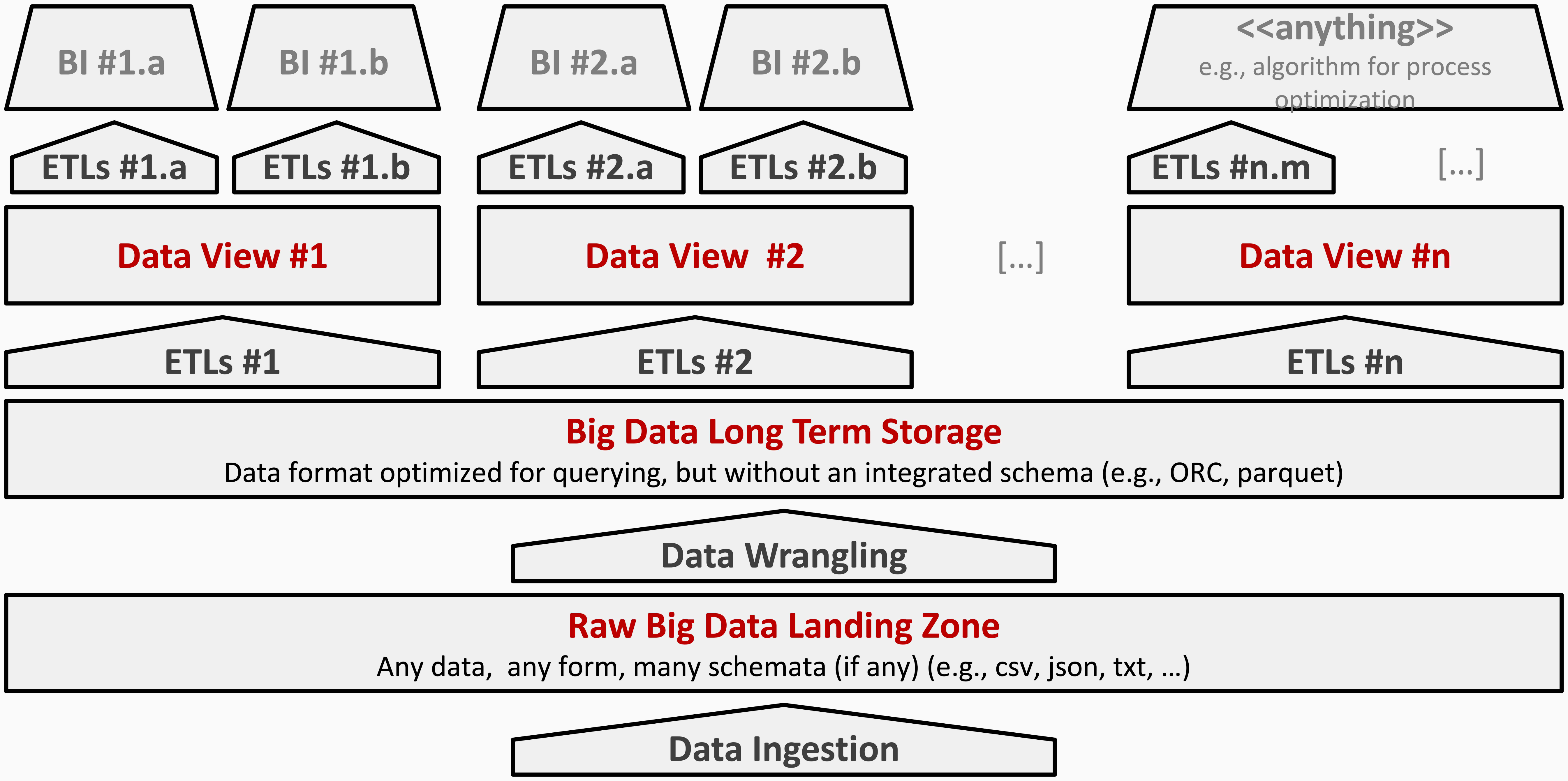
A fully **ACID** database is the perfect fit for use cases where data **reliability** and **consistency** are essential.

Extra Reads

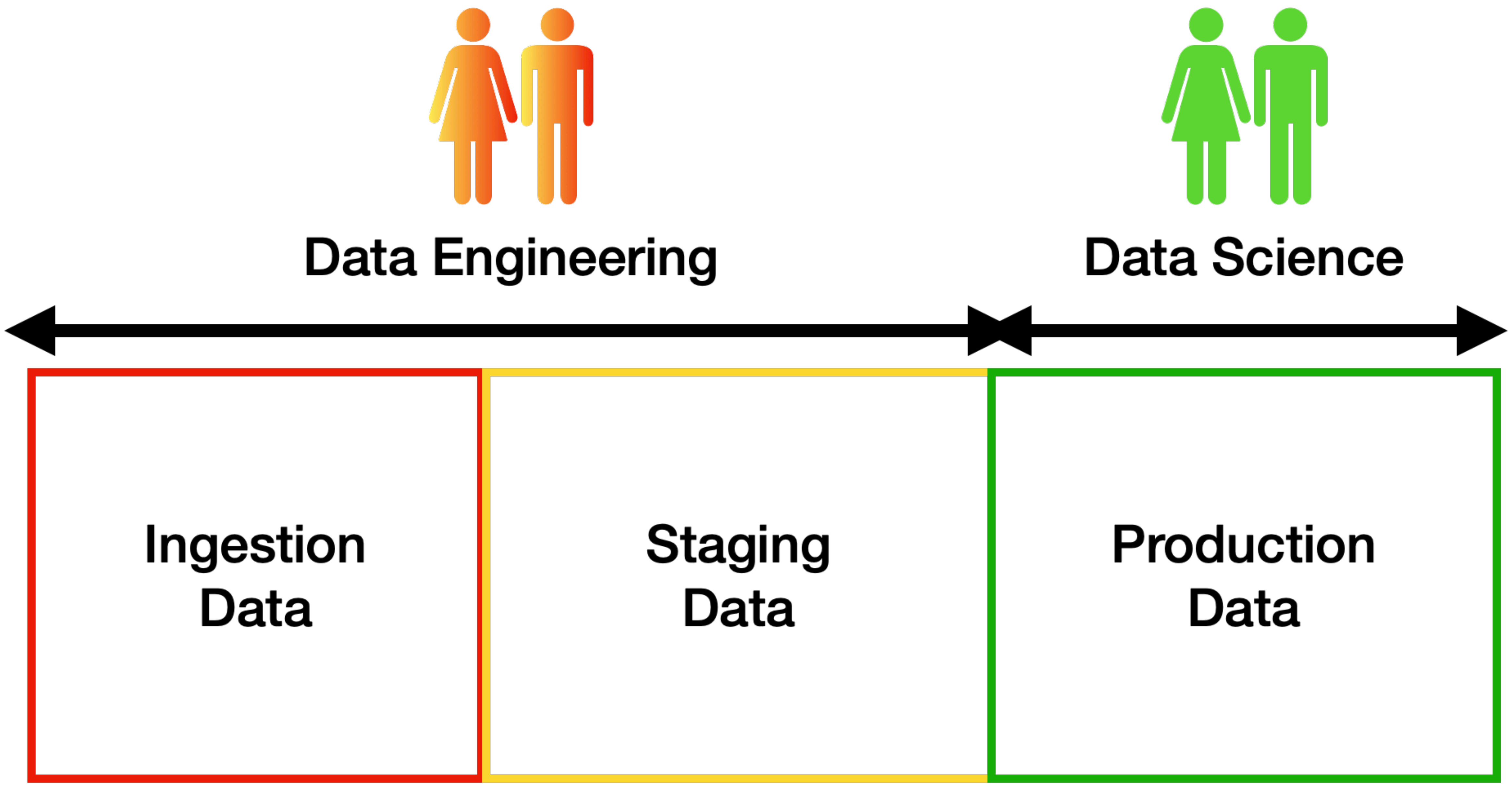
- History of Data Models by Ilya Katsov
- Life beyond Distributed Transactions

Refining the Initial View

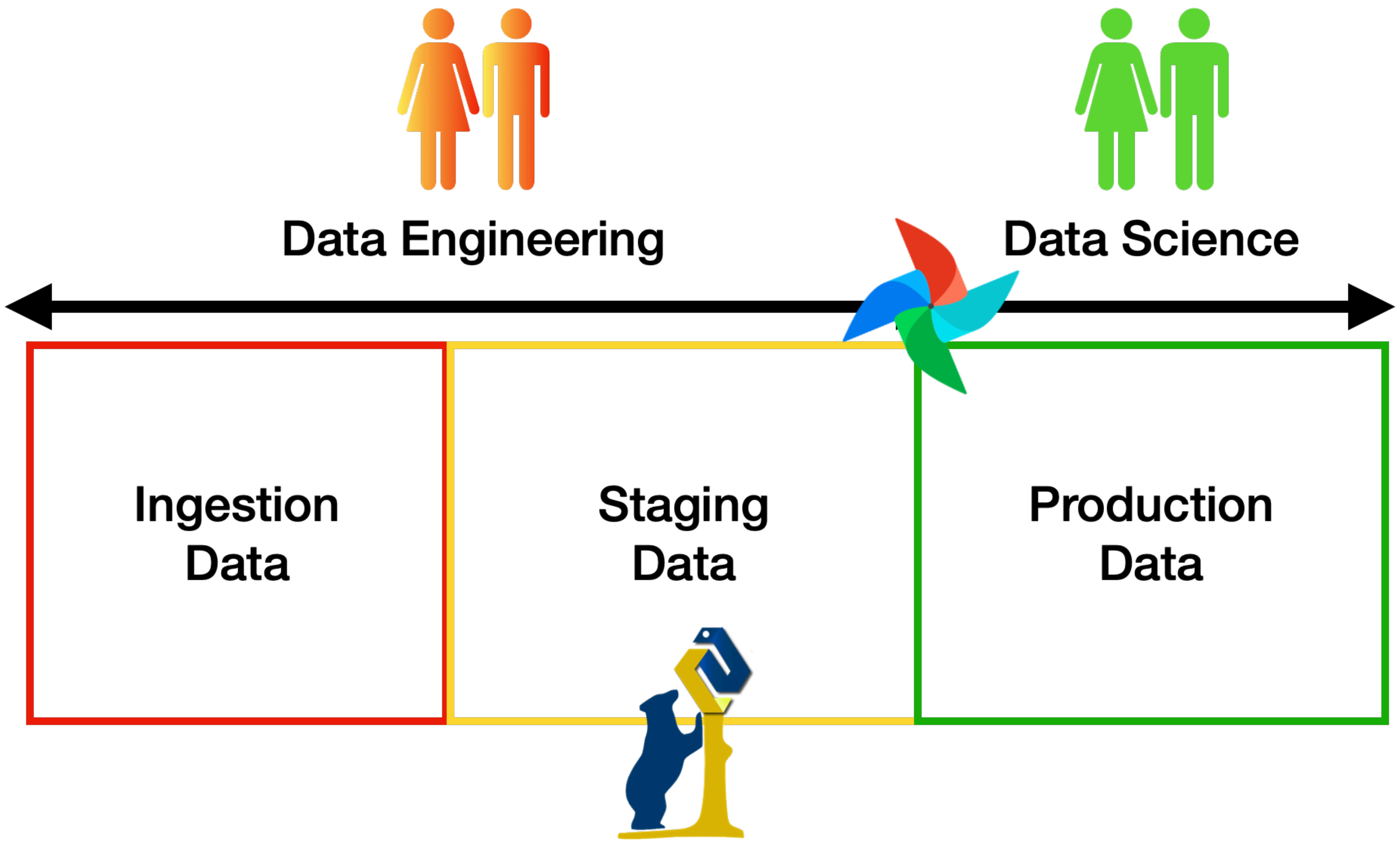
Logical architecture of a data engineering pipeline


BI #1.a
BI #1.b
BI #2.a
BI #2.b
<<anything>>
e.g., algorithm for process optimization
ETLs #1.a
ETLs #1.b
ETLs #2.a
ETLs #2.b
ETLs #n.m
[...]
Data View #1
Data View #2
[...]
Data View #n
ETLs #1
ETLs #2
ETLs #n
Big Data Long Term Storage
Data format optimized for querying, but without an integrated schema (e.g., ORC, parquet)
Data Wrangling
Raw Big Data Landing Zone
Any data, any form, many schemata (if any) (e.g., csv, json, txt, …)
Data Ingestion

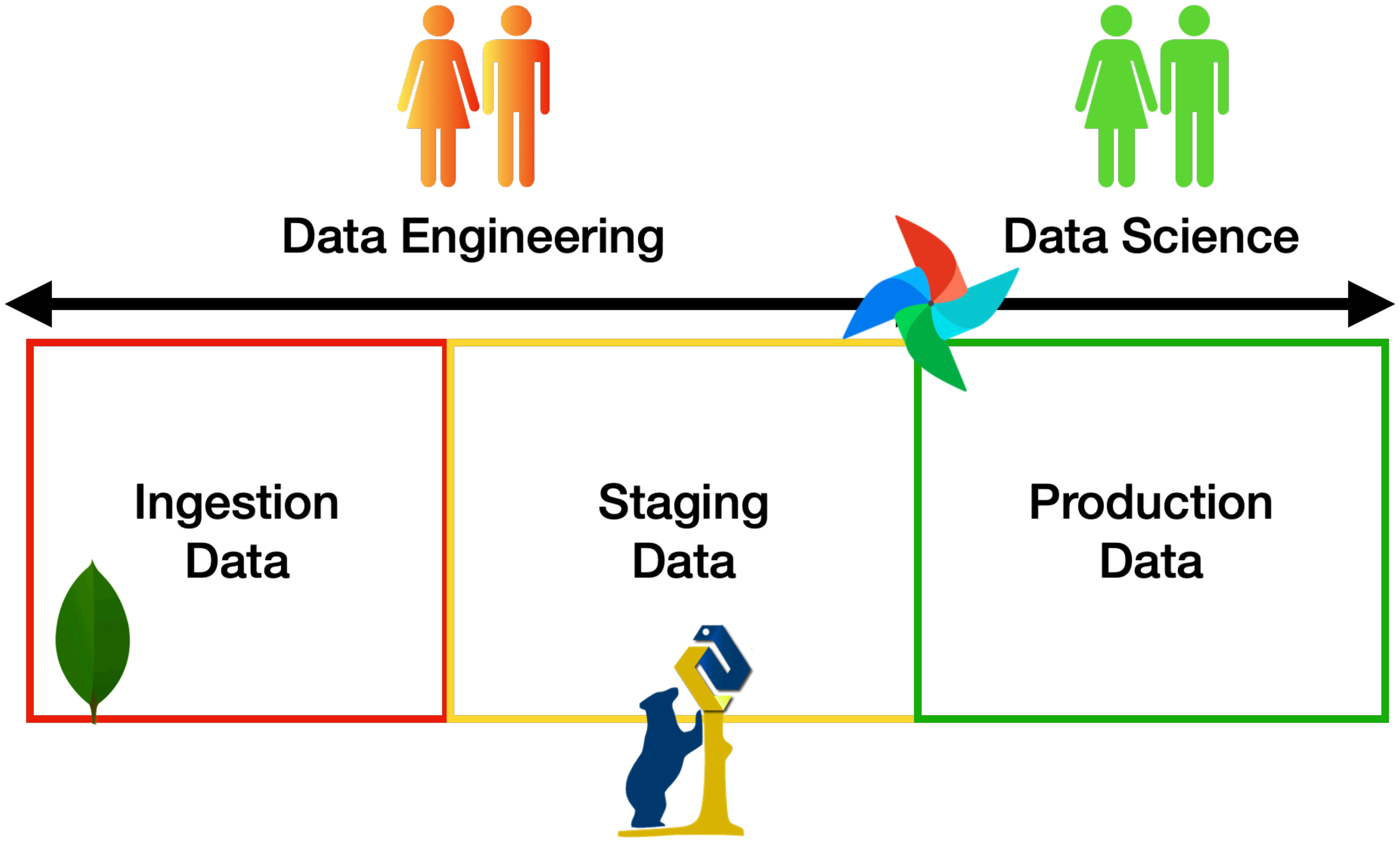
A Simplified view



Our Physical View



Our Physical View



Data Engineering

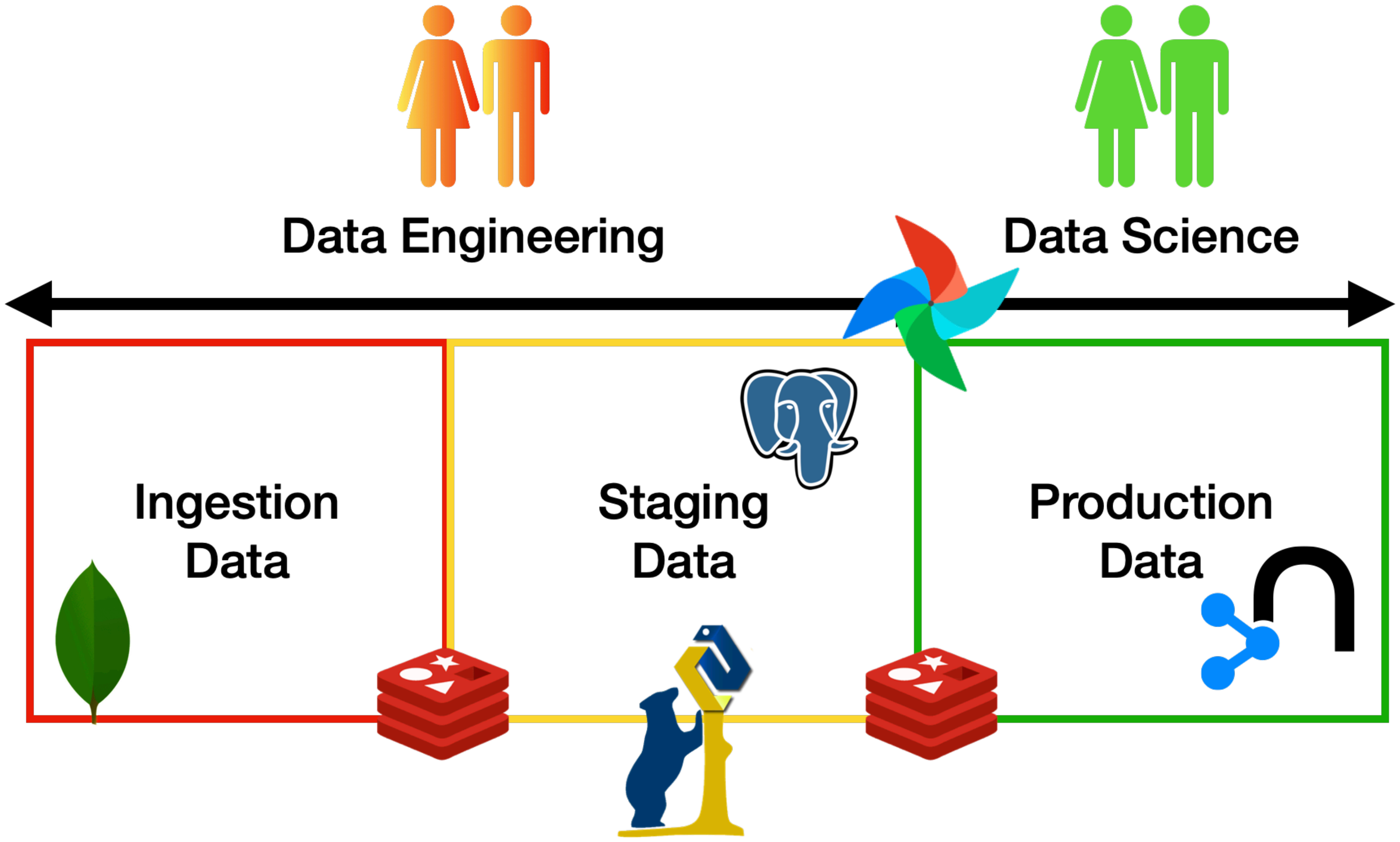
Data Science

Ingestion Data

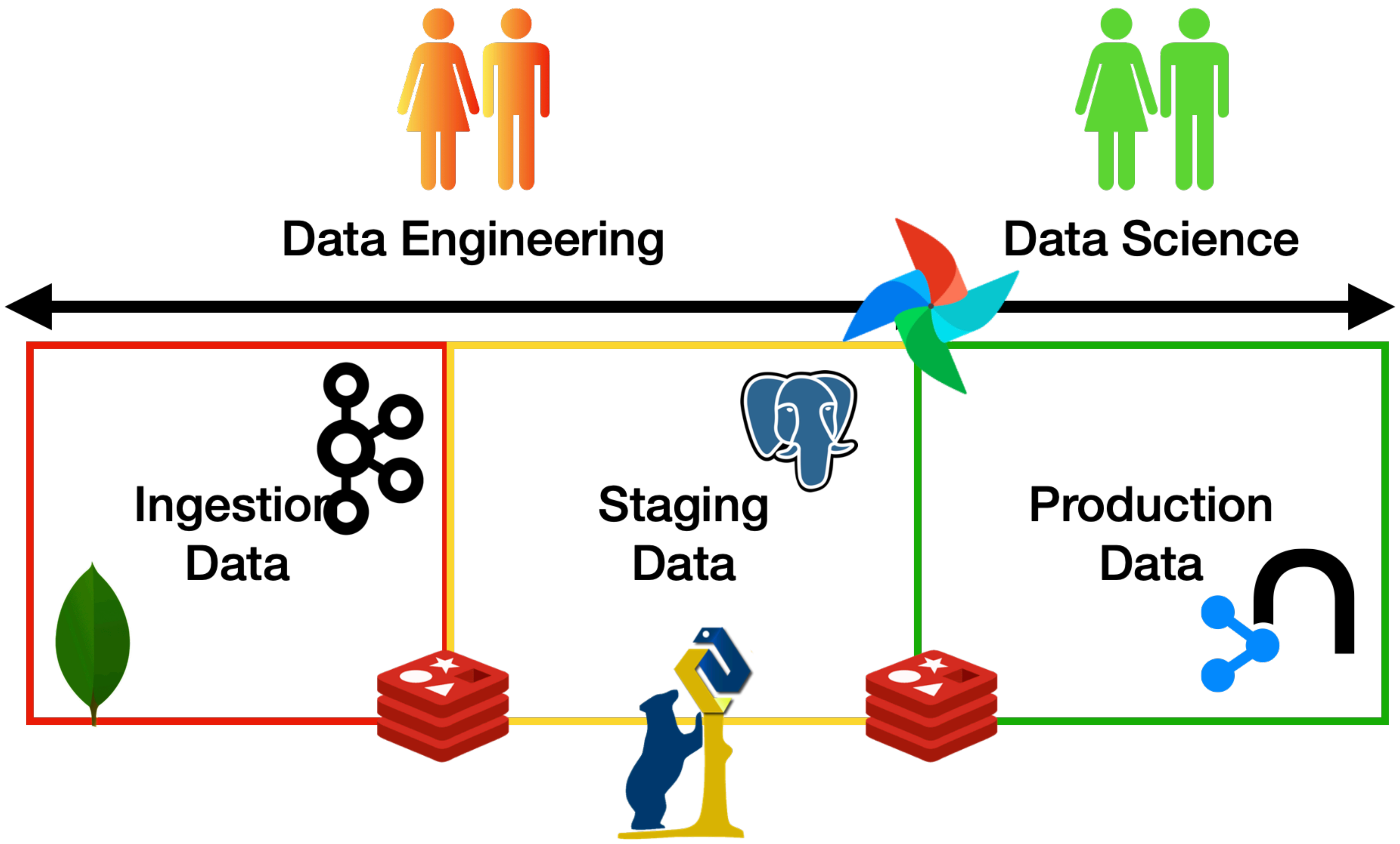
Staging Data

Production Data

Our Physical View



Our Physical View



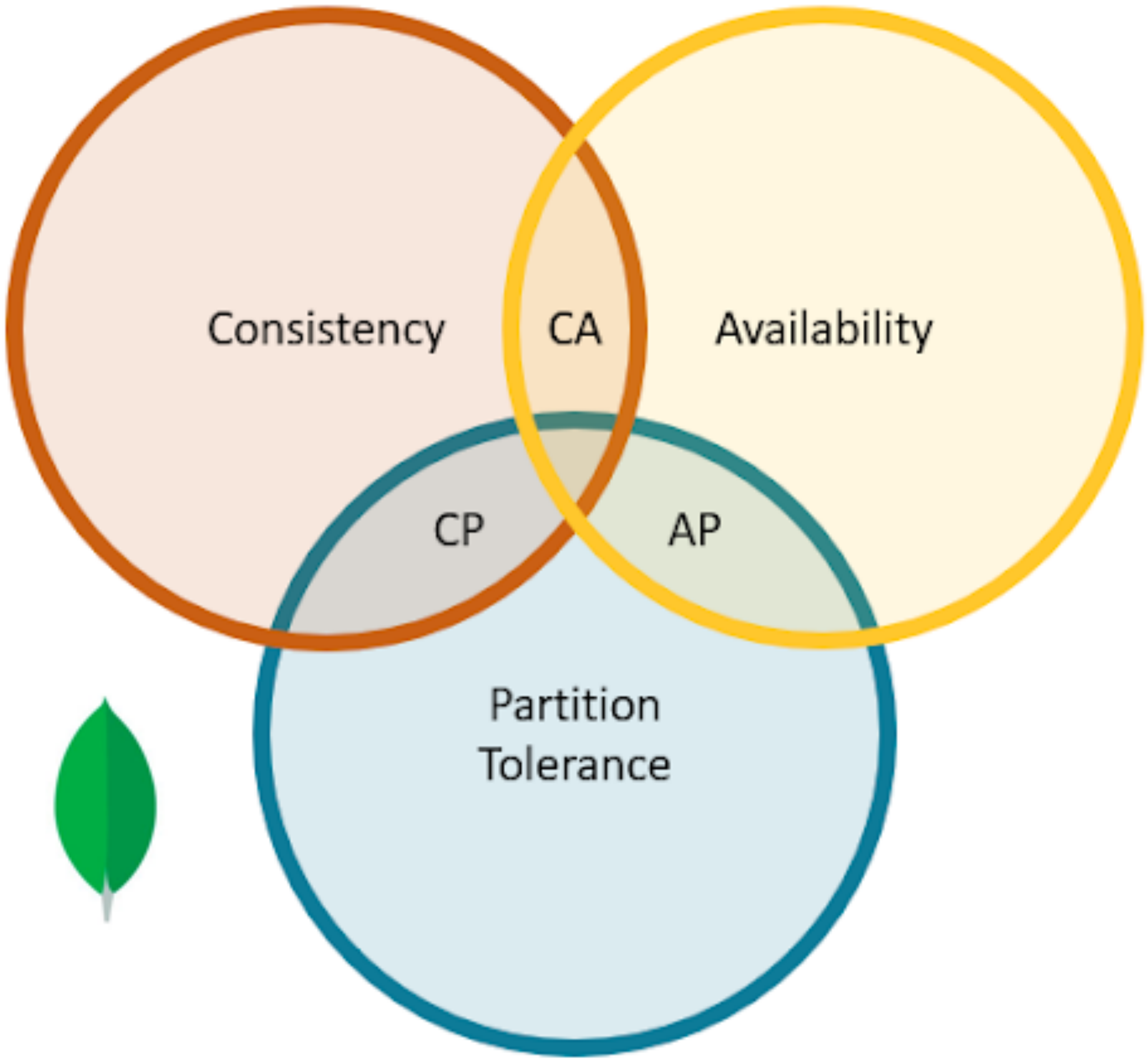
MongoDB

History and Motivation

- An open source and document-oriented database.
- Data is stored in JSON-like documents.
- Designed with both scalability and developer agility.
- Dynamic schemas.
- Automatic data sharding

What MongoDB is :

- An In-Memory Document Databases
- Strong consistency (**C**)
- *Tuneably* available (~~**A**~~)
- Horizontal Scalable (**P**)



What MongoDB is not

- Always Available[91]
- No Schemas
- No transactions
- No joins
- Max document size of 16MB[92]

[91] Larger documents handled with GridFS

[92] there will always be downtime when (i) the new leader is getting elected or (ii) the client driver disconnects from the leader

Use Cases

- SEGA Capture **game** events, scaling to meet high-write workloads.
- HSBC Financial Services: Risk Analytics & Reporting, Trade Repository
- BOSCH manufacturing, automotive, retail, and energy
- ThermoFisher SCIENTIFIC fast-changing sensor data captured from multiple devices and experiments

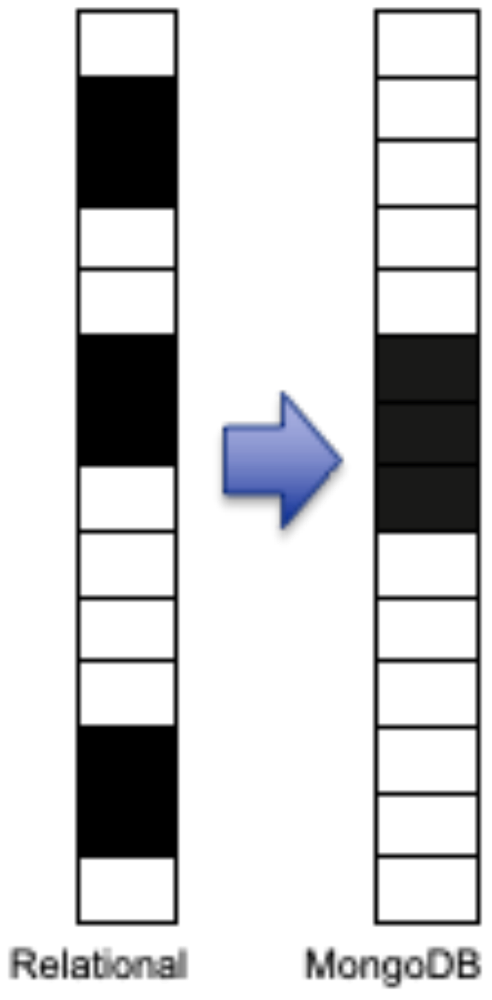
When to consider MongoDB

- When you don't need high availability of data
- when you need fast and instant data recovery
- when do not want to sustain schema migration costs

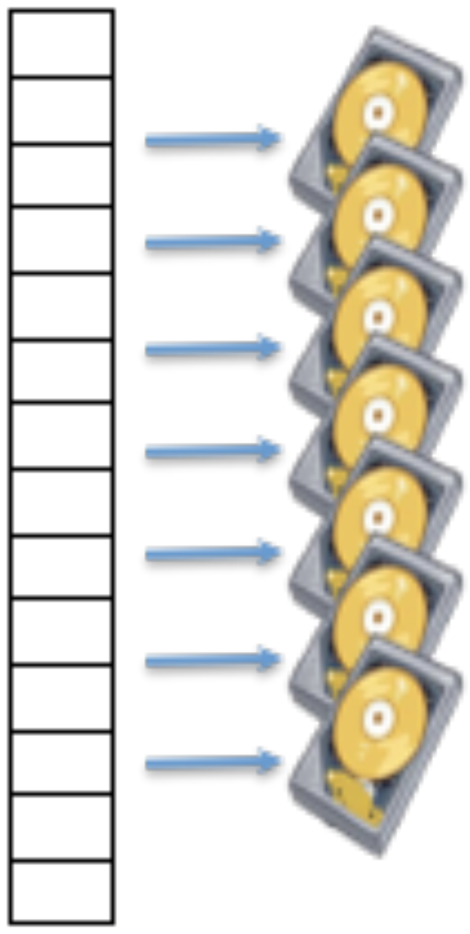
Advantages

- Full featured indexes
- Sophisticated query language
- Easy mapping to object-oriented code
- Native language drivers in all popular languages
- Simple to set up and manage
- Operates at in-memory speed wherever possible
- Auto-sharding built in
- Dynamically add / remove capacity with no downtime

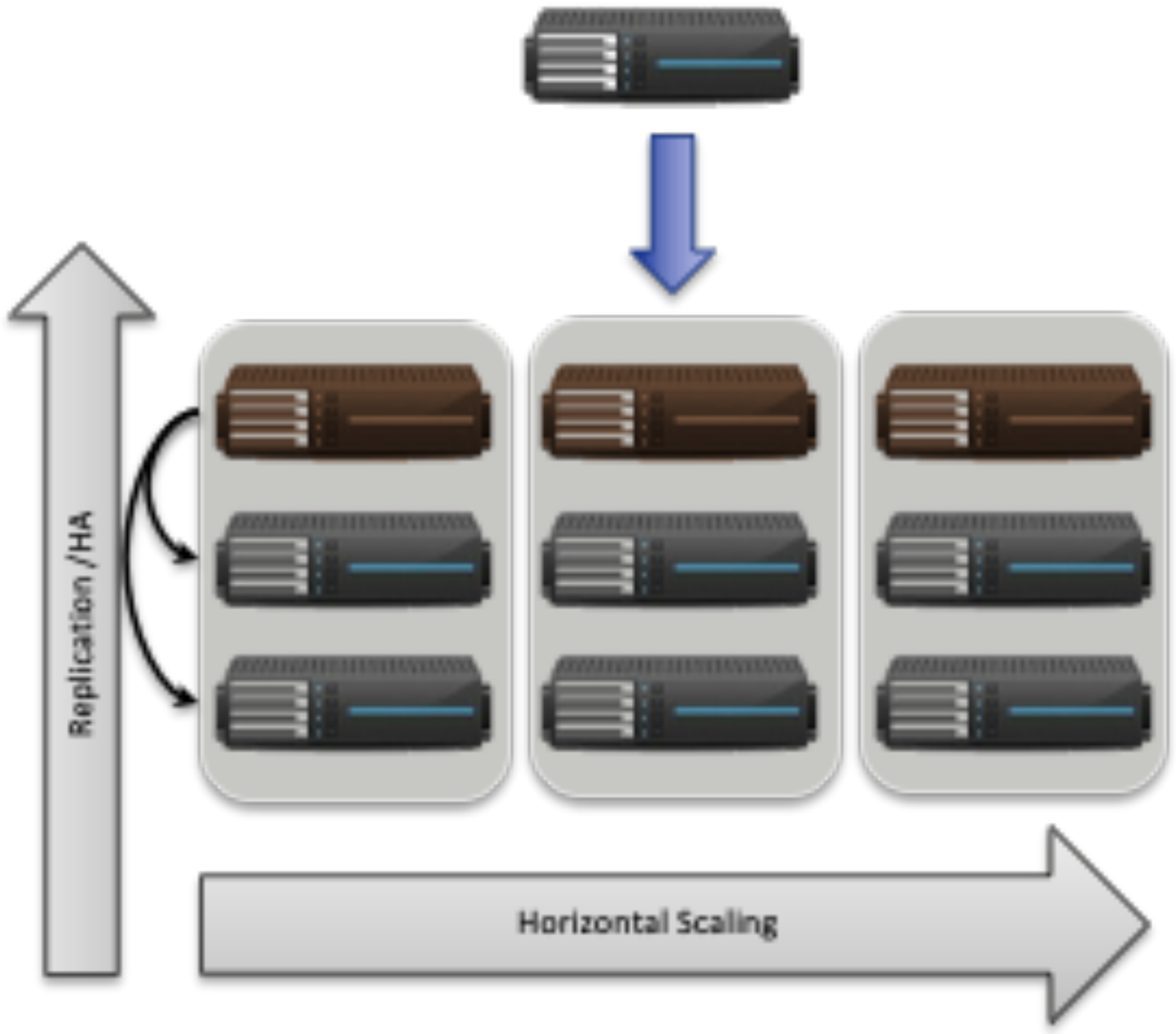
Better data locality



In-Memory
Caching



Distributed Architecture



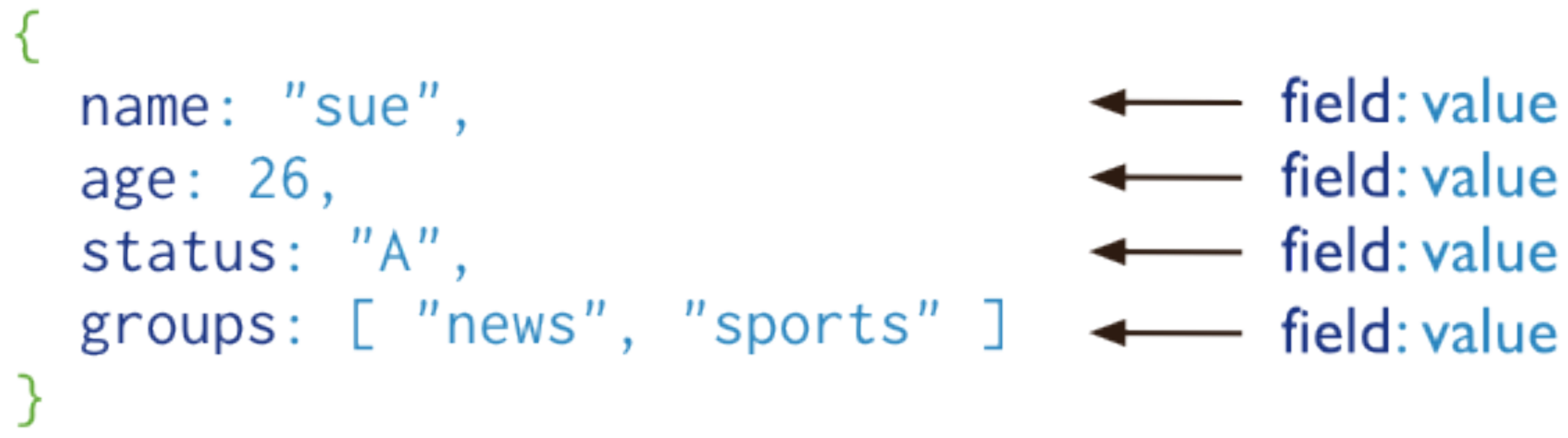
Terminology: SQL vs MongoDB

SQL Terms/Concepts	MongoDB Terms/Concepts
database	database
table	collection
row	document
column	field
index	index
table joins (e.g. select queries)	embedded documents and linking
Primary keys	_id field is always the primary key
Aggregation (e.g. group by)	aggregation pipeline

Data Model: Structure of a JSON-document:

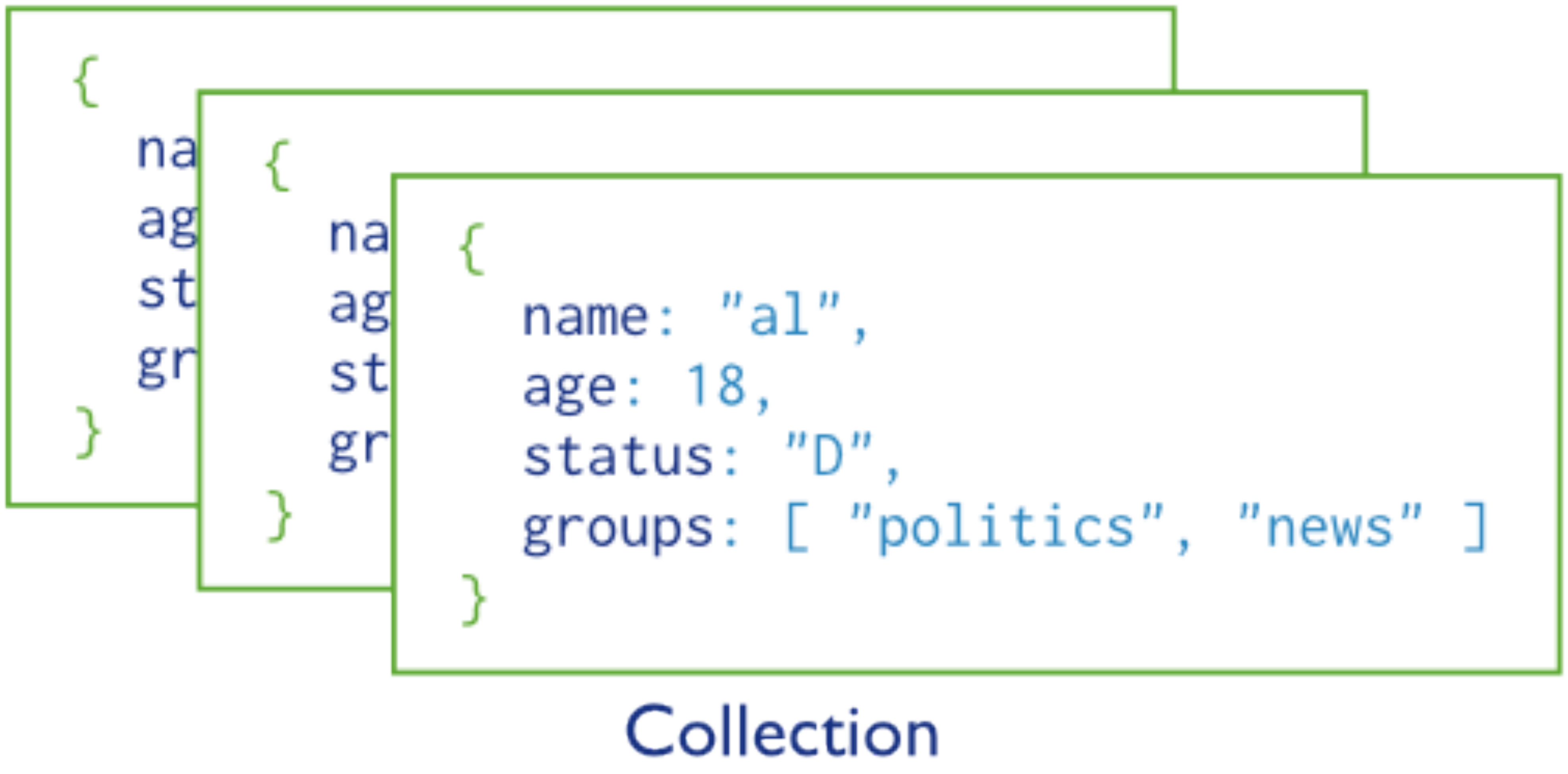
The value of field:

- Native data types
- Arrays
- Other documents



```
{
  name: "sue",
  age: 26,
  status: "A",
  groups: [ "news", "sports" ]
}
```

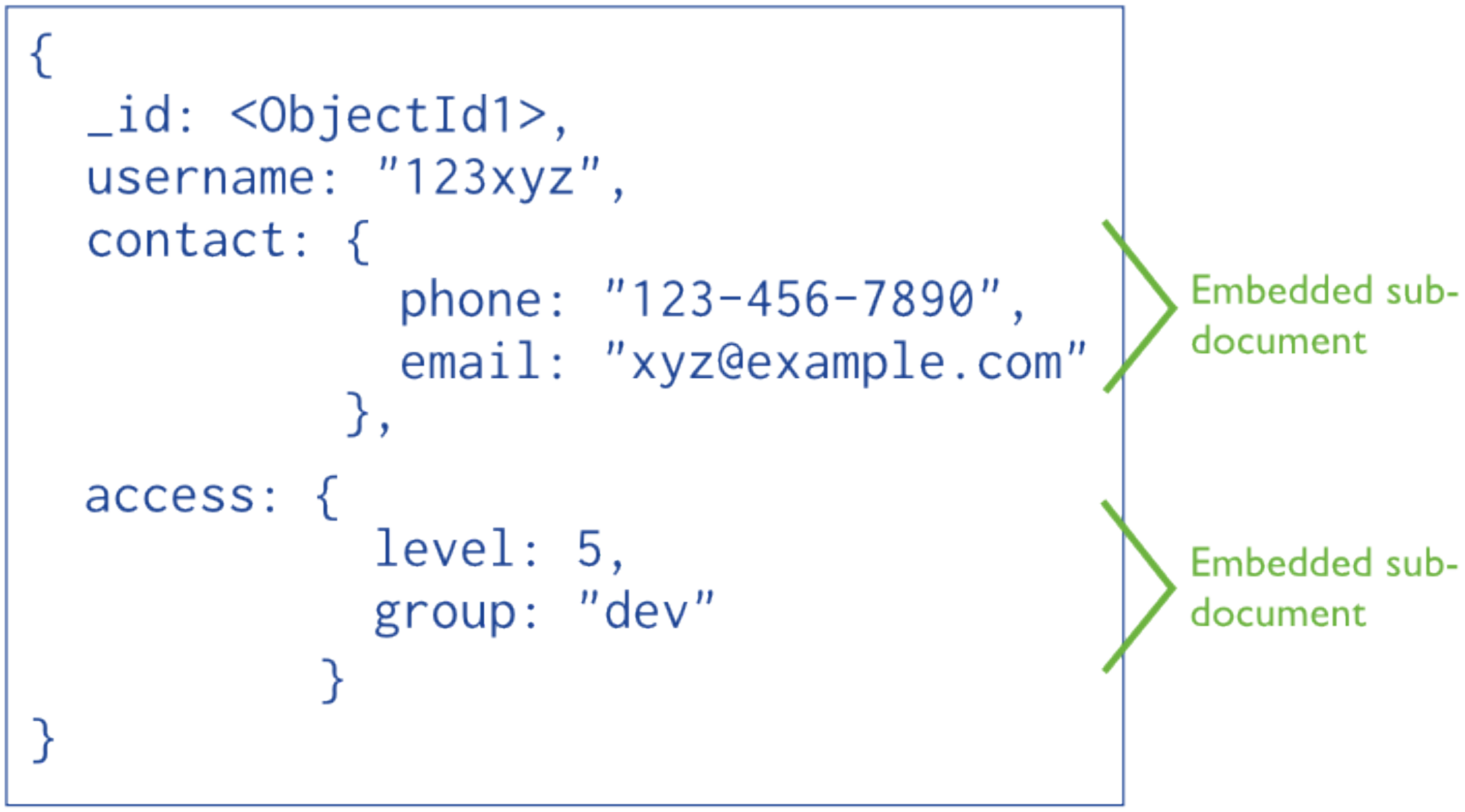
Data Model: Collections of Documents



```
{
  name: "al",
  age: 18,
  status: "D",
  groups: [ "politics", "news" ]
}
```

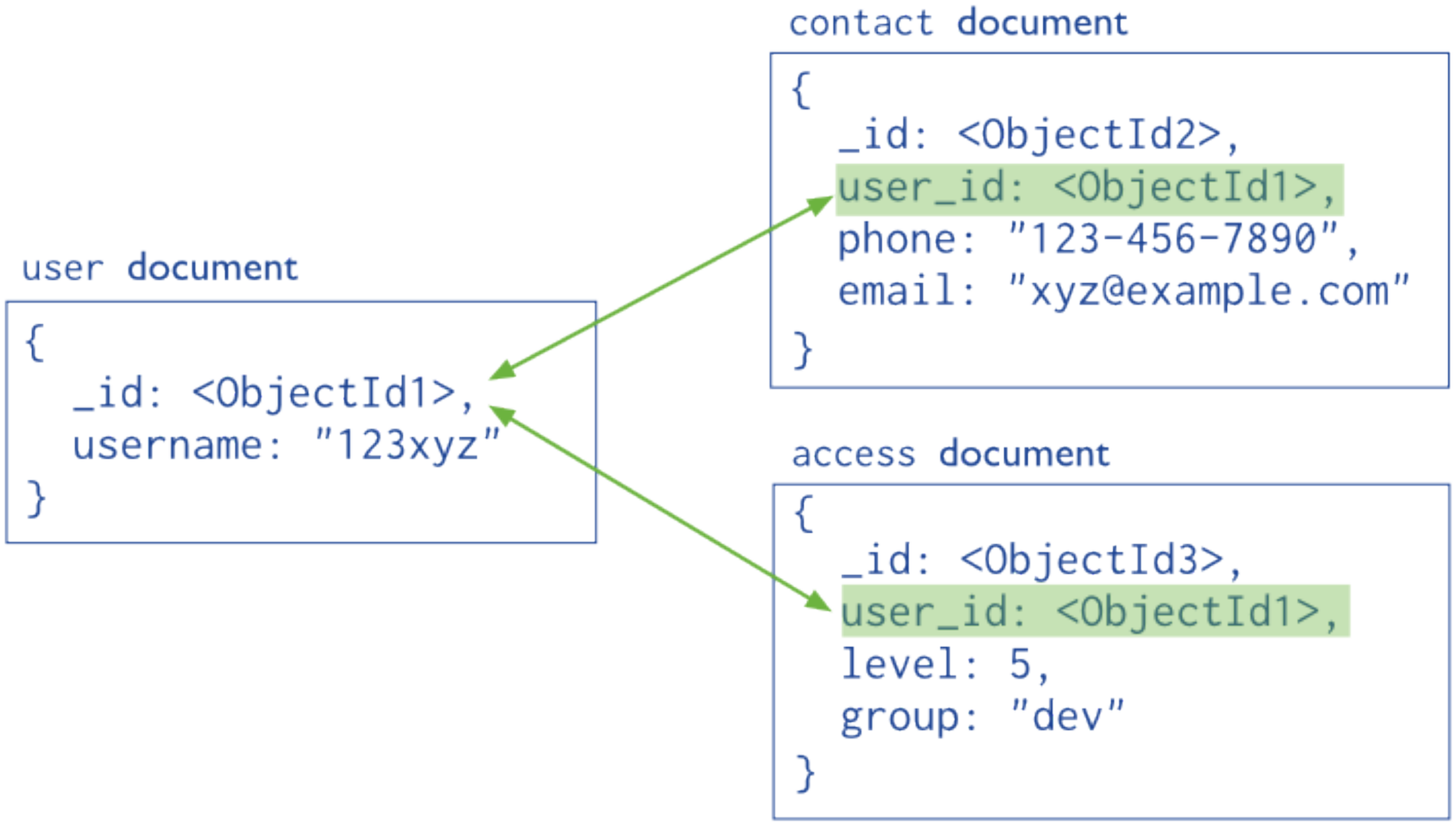
Rule: Every document must have an _id.

Data Model: Embedded documents:



```
{
  _id: <ObjectId1>,
  username: "123xyz",
  contact: {
              phone: "123-456-7890",
              email: "xyz@example.com"
            },
  access: {
             level: 5,
             group: "dev"
           }
}
```

Reference documents



contact document

```
{
  _id: <ObjectId2>,
  user_id: <ObjectId1>,
  phone: "123-456-7890",
  email: "xyz@example.com"
}
```

user document

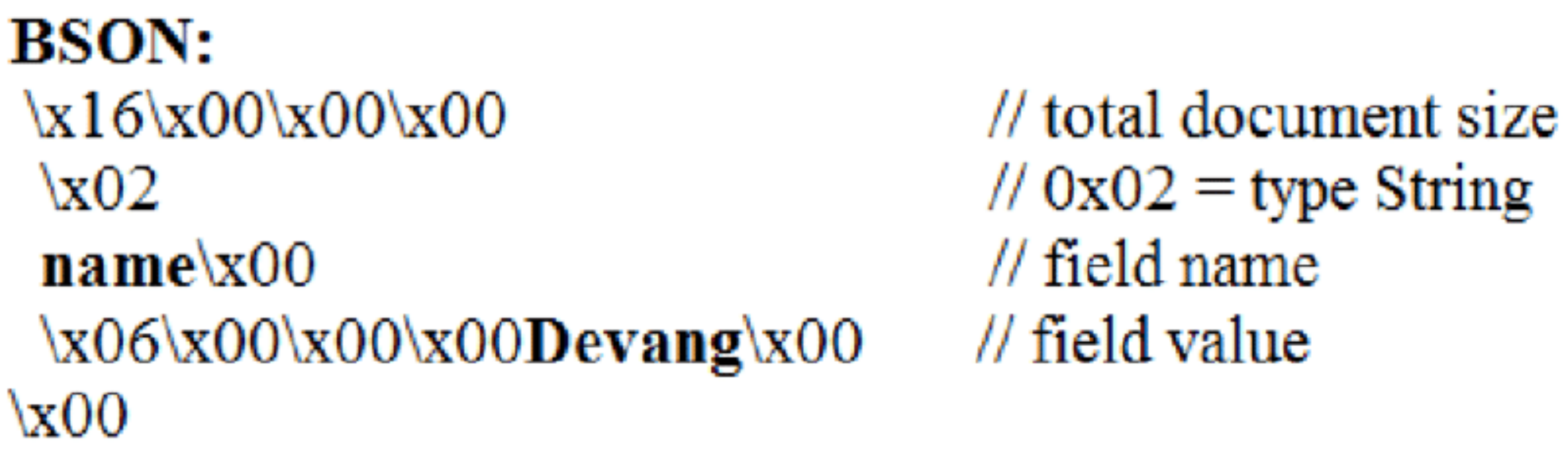
```
{
  _id: <ObjectId1>,
  username: "123xyz"
}
```

access document

```
{
  _id: <ObjectId3>,
  user_id: <ObjectId1>,
  level: 5,
  group: "dev"
}
```

Storage: BSON Format

- Binary-encoded serialization of JSON-like documents optimized for space and speed
- BSON types are a superset of JSON types[94]
- Zero or more key/value pairs are stored as a single entity[93]
- Large entities are prefixed with a length field to facilitate scanning



```
BSON:
 \x16\x00\x00\x00                    // total document size
  \x02                               // 0x02 = type String
  name\x00                           // field name
  \x06\x00\x00\x00Devang\x00         // field value
\x00
```

[94] JSON does not have a date or a byte array type, for example

[93] Each entry consists of a field name, a data type, and a value

+ −

Operations

÷ ×

Create

Create a database

```
use database_name
```

Create a collection

```
db.createCollection(name, options)
```

Insert

```
db.<collection_name>.insert({"name": "nguyen". "age": 24, "gender": "male"})
```

```
db.employee.insert({
    name: "sally",
    salary: 15000,
    designation: "MTS",
    teams: [ "cluster-management" ]
})`
```

Read

```
  db.<collection_name>.find().pretty()
```

```
db.employee                 #collection
    .find( {
    salary: {$gt:18000}, #condition
        {name:1}            #projection
    })
.sort({salary:1})           #modifier
```

Update

```
db.employee #collection
.update(
 {salary:{$gt:18000}}, #Update Criteria
 {$set: {designation: "Manager"}}, #Update Action
 {multi: true} #Update Option
)
```

Multi-option allows multiple document update

Delete

```
db.employee.remove(
     {salary:{$lt:10000}}, #Remove Criteria
)
```

Aggregates

SQL-like aggregation functionality

Pipeline documents from a collection pass through an aggregation pipeline

Expressions produce output documents based on calculations performed on input documents

Example:

```
db.parts.aggregate(
    {$group : {_id: type, totalquantity :
    { $sum: quantity}
}})
```

Save

```
db.employee.save(
    {  _id:ObjectId('string_id'),
       "name": "ben",
       "age": 23,
       "gender":
       "male"
})
```

Drop

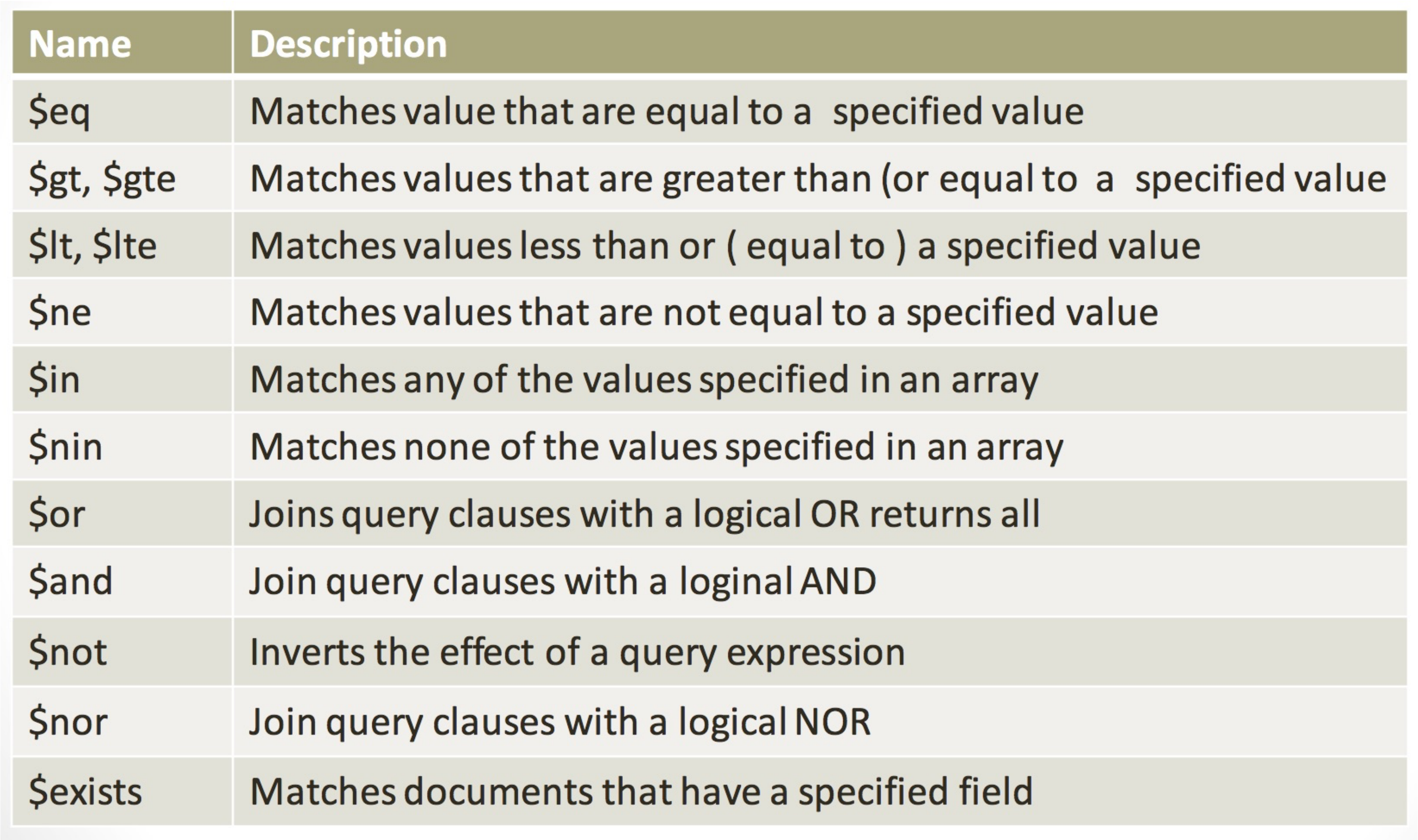
- Drop a database
- Drop it: `db.dropDatabase()`
- Drop a collection:

```
db.<collection_name>.drop()
```

Mapping to SQL

SQL Statement	MongoDB commands
SELECT * FROM table	db.collection.find()
SELECT * FROM table WHERE artist = ‘Nirvana’	db.collection.find({Artist:”Nirvana”})
SELECT* FROM table ORDER BY Title	db.collection.find().sort(Title:1)
DISTINCT	.distinct()
GROUP BY	.group()
>=, <	$gte, $lt

Comparison Operators



Name	Description
$eq	Matches value that are equal to a specified value
$gt, $gte	Matches values that are greater than (or equal to a specified value
$lt, $lte	Matches values less than or (equal to) a specified value
$ne	Matches values that are not equal to a specified value
$in	Matches any of the values specified in an array
$nin	Matches none of the values specified in an array
$or	Joins query clauses with a logical OR returns all
$and	Join query clauses with a loginal AND
$not	Inverts the effect of a query expression
$nor	Join query clauses with a logical NOR
$exists	Matches documents that have a specified field

source

Indexes

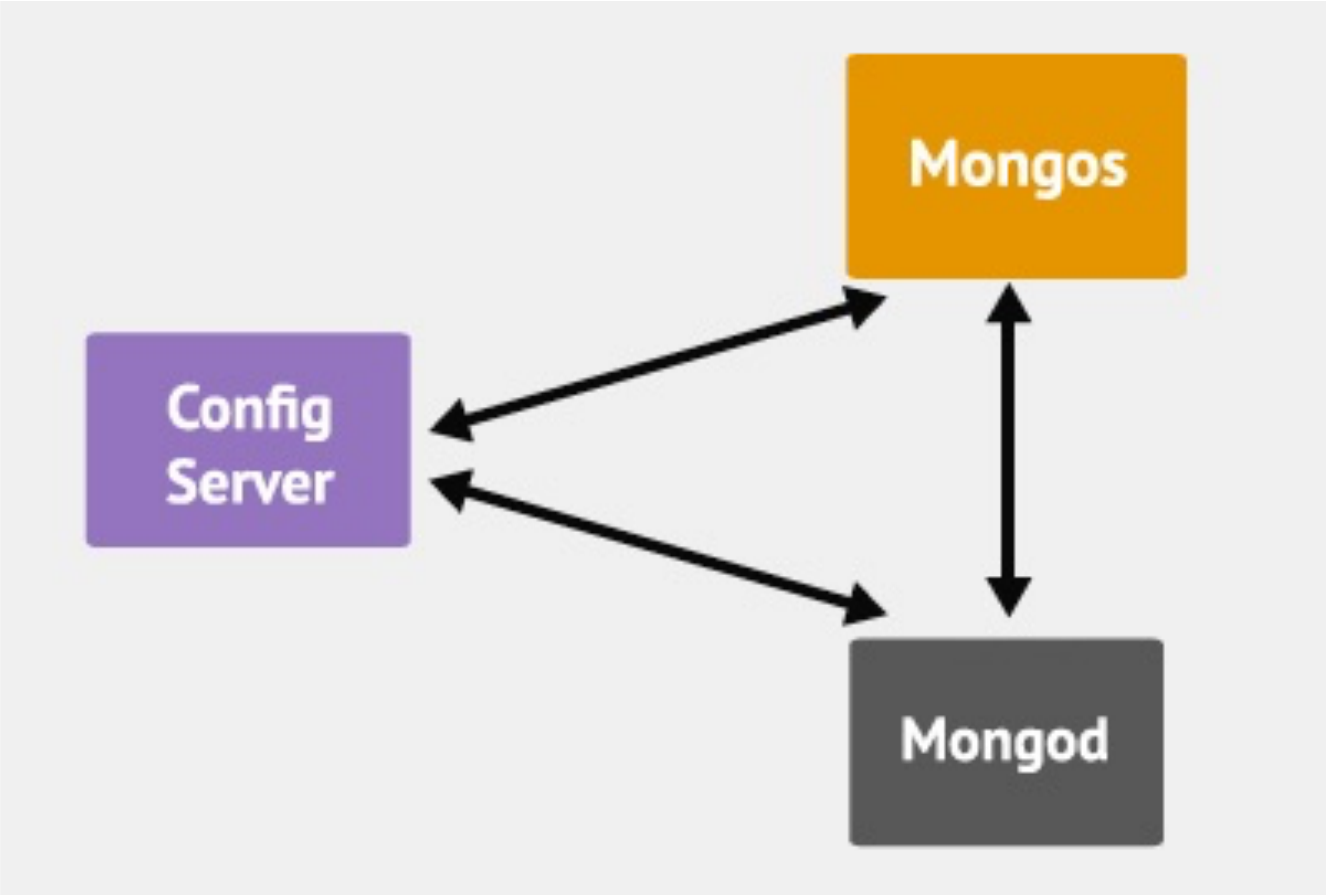
- B+ tree indexes
- An index is automatically created on the _id field (the primary key)
- Users can create other indexes to improve query performance or to enforce Unique values for a particular field
- Supports single field index as well as Compound index
- Like SQL order of the fields in a compound index matters
- If you index a field that holds an array value, MongoDB creates separate index entries for every element of the array

Sparse Indexes

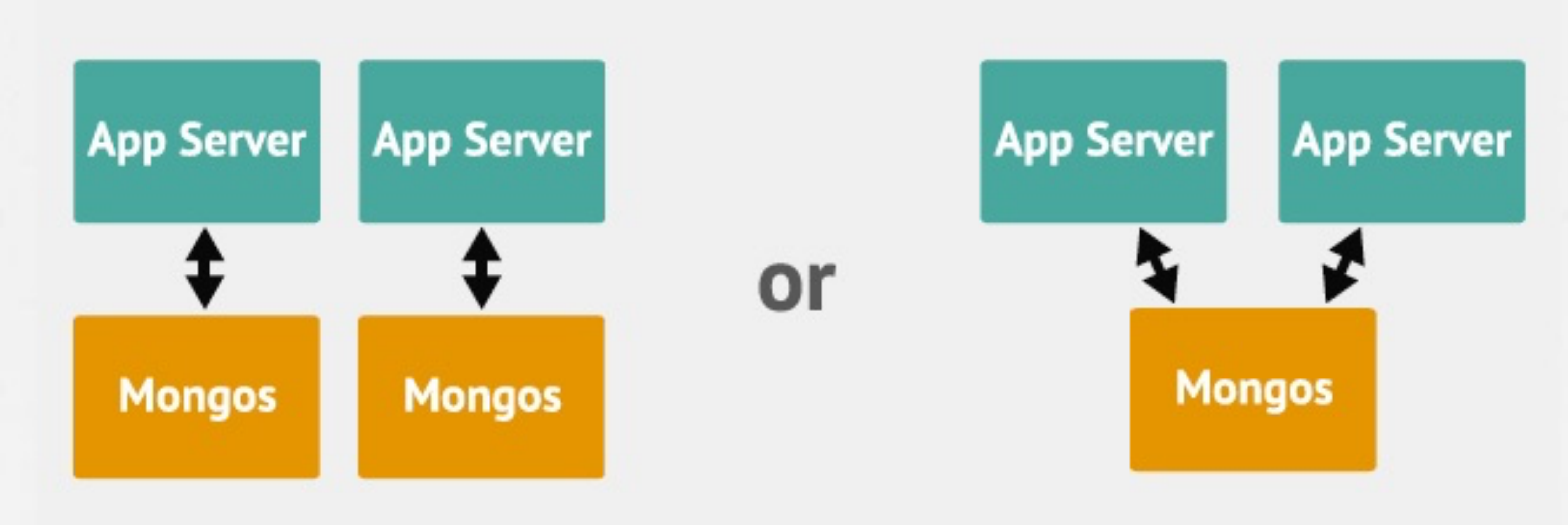
- Sparse_- property of an index ensures that the index only contain entries for documents that have the indexed field. (so ignore records that do not have the field defined)
- If an index is both unique and sparse – then the system will reject records that have a duplicate key value but allow records that do not have the indexed field defined

Architecture

- Mongod – Database instance
- Mongos - Sharding processes:
  - Like a database router processes all requests
  - Decides how many and which *mongod* should receive the query
  - No local data
  - Collects the results, and sends it back to the client.
- Config Server
  – Stores cluster chunk ranges and locations
  – Can have only 1 or 3 (production must have 3)



Mongod and Mongos



Client

- Mongo – an interactive shell (a client)
- Fully functional JavaScript environment for use with a MongoDB
- You can have one mongos for the whole system no matter how many mongods you have
- OR you can have one local mongos for every client if you wanted to minimize network latency.

Replication

For redundancy MongoDB provides asynchronous replication.

Only one database node is in charge of write operations at any given time (called primary server/node).

Read operations may go to this same server for strong consistency semantics or to any of its replica peers if eventual consistency is sufficient.

Master Slave Replication

Consists of two servers out of one which takes the role of a master handling write requests and replicating those operations to the second server, the slave.

Replica Sets

Consists of groups of MongoDB nodes that work together to provide automated failover.

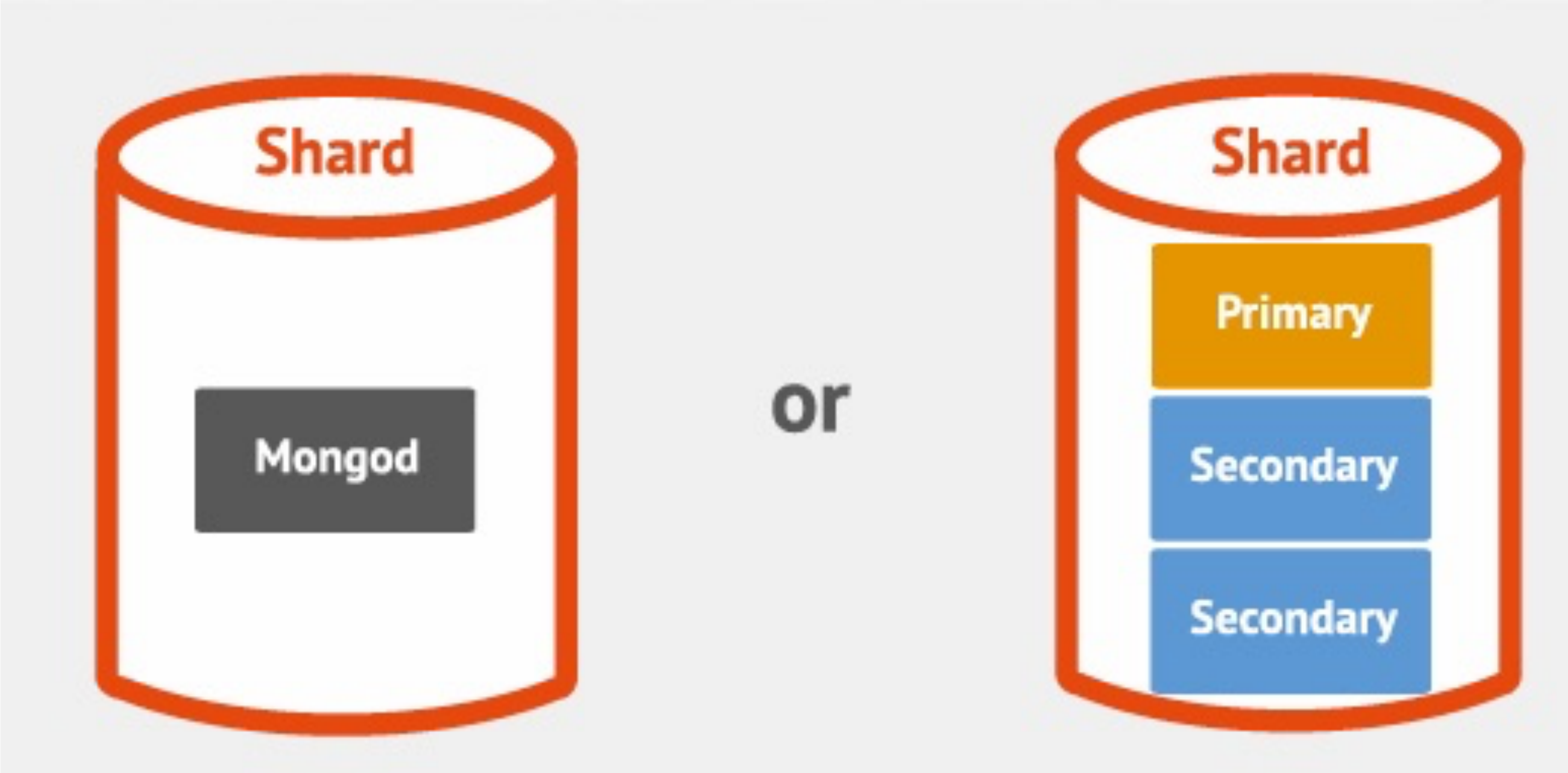
Replica Sets are described as an "an elaboration on the existing master/slave replication, adding **automatic failover** and automatic recovery of member nodes"

Partitioning

- called Sharding in MongoDB
- User defines shard key for partitioning
- Shard key defines range of data
- Key space is like points on a line
- Range is a segment of that line

What is a Shard?

- Shard is a node of the cluster
- Shard can be a single mongod or a replica set
- Default max chunk size: 64mb
- MongoDB automatically splits & migrates chunks when max reached



Auto-sharding

- Minimal effort required
  - Enable Sharding for a database
  - Shard collection within database
  - Decide Sharding Strategy

MongoDB Sharding Strategies

- Ranged
- Hashed
- Tag-aware

Range Sharding

- Splits shards based on sub-range of a key (or also multiple keys combined)
  - Simple Shard Key: {deviceId}
  - Composite Shard Key: {deviceId, timestamp}

Hash Sharding

- MongoDB applies a MD5 hash on the key when a hash shard key is used:
  - Hash Shard Key(deviceId) = MD5(deviceId)
  - Ensures data is distributed randomly within the range of MD5 values

Tag Sharding

Tag-aware sharding allows subset of shards to be tagged, and assigned to a sub-range of the shard-key.

Example: Sharding User Data belong to users from 100 “regions”

Collection: Users, Shard Key: {uId, regionCode}

Tag based on macro regions

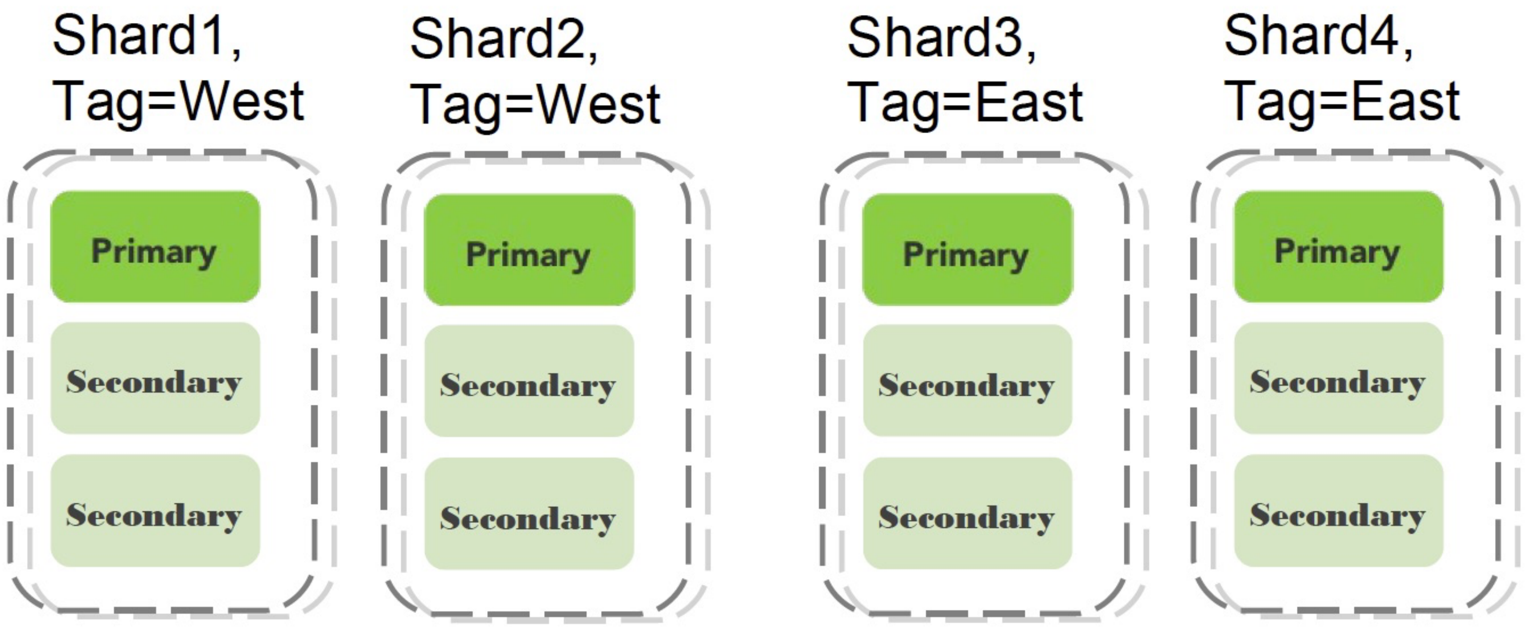
Tag Sharding Example

Collection: Users, **Shard Key:** {uId, regionCode}

Tag	Start	End
West	MinKey, MinKey	MaxKey,50
East	MinKey, 50	MaxKey, MaxKey

Assign Regions 1-50 to the West

Assign Regions 51-100 to the East



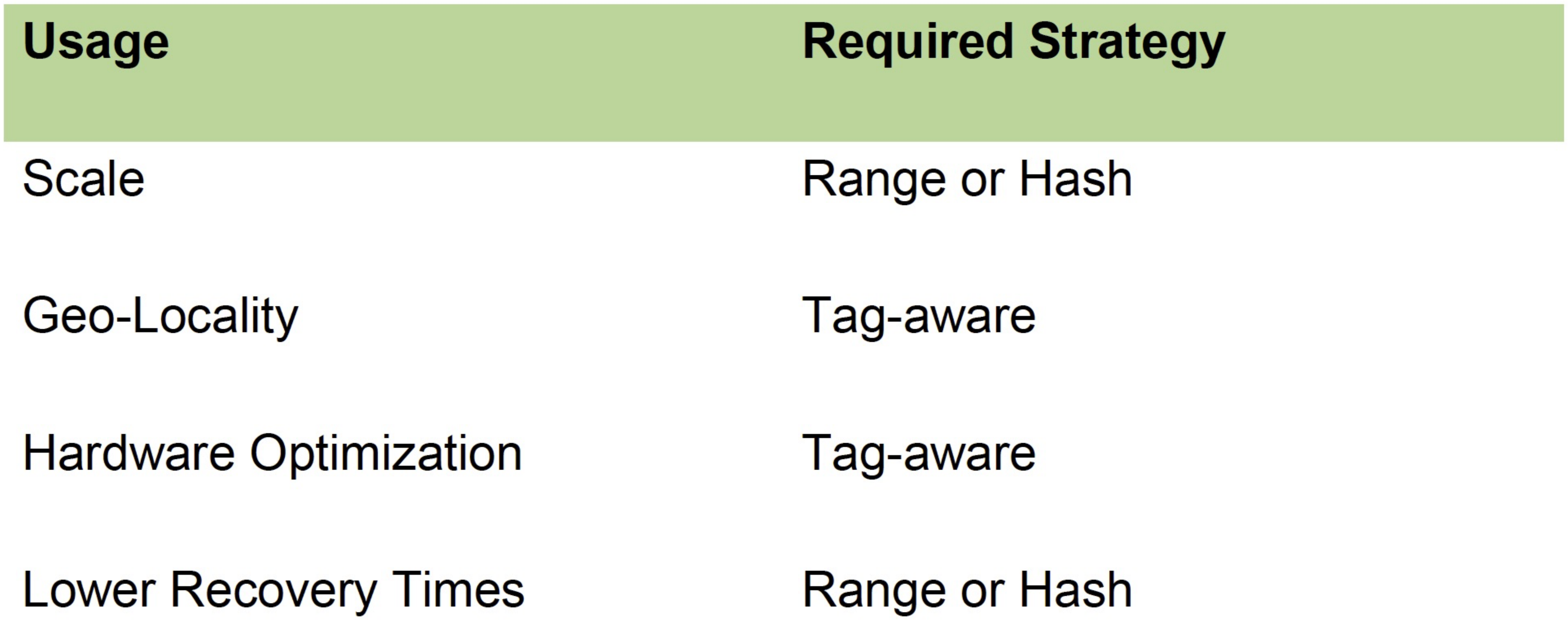
Shard1, Tag=West

Shard2, Tag=West

Shard3, Tag=East

Shard4, Tag=East

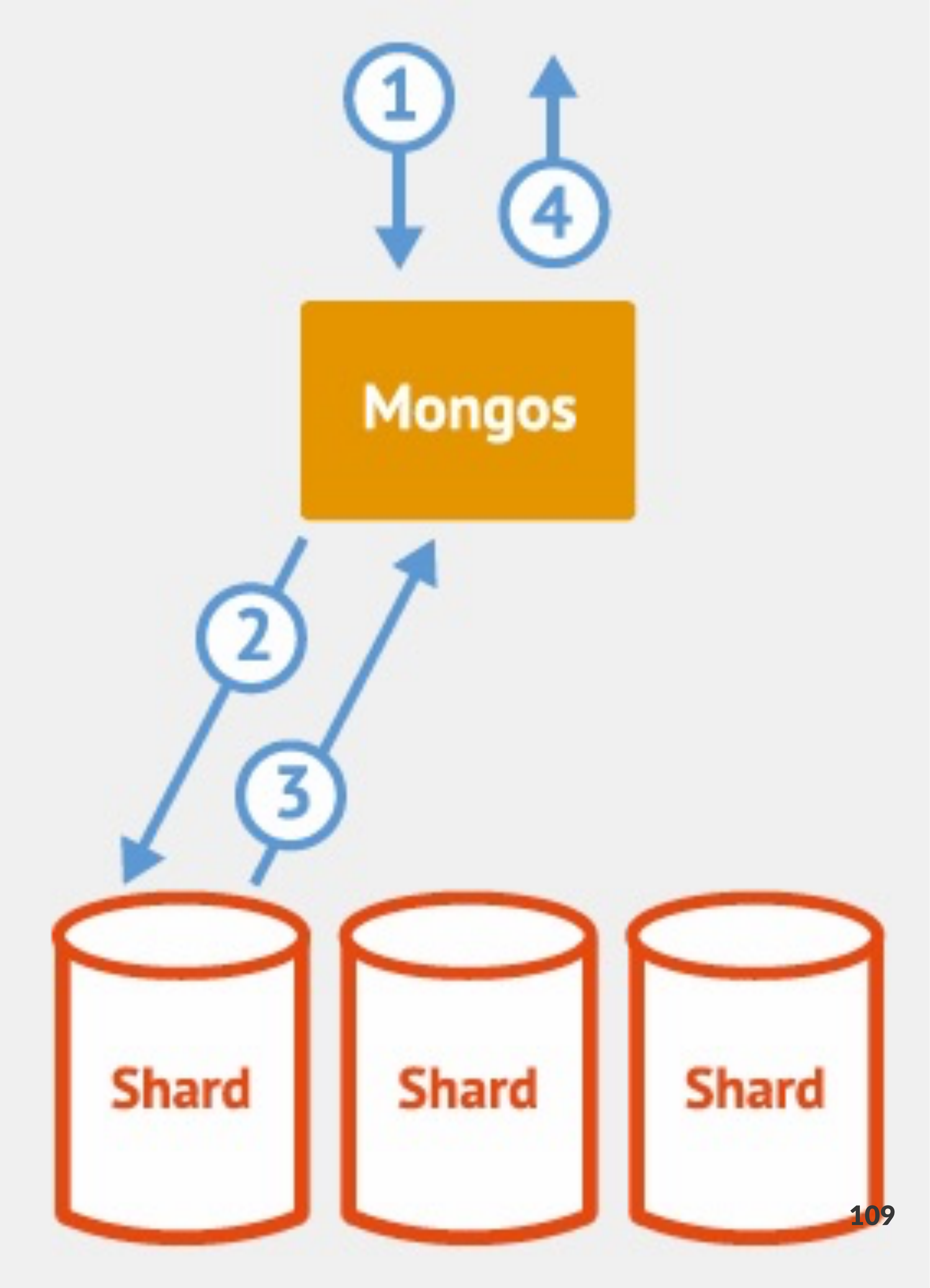
Which Sharding to use?



Usage	Required Strategy
Scale	Range or Hash
Geo-Locality	Tag-aware
Hardware Optimization	Tag-aware
Lower Recovery Times	Range or Hash

Routing and Balancing

- Queries routed to specific shards
- MongoDB balances cluster
- MongoDB migrates data to new nodes

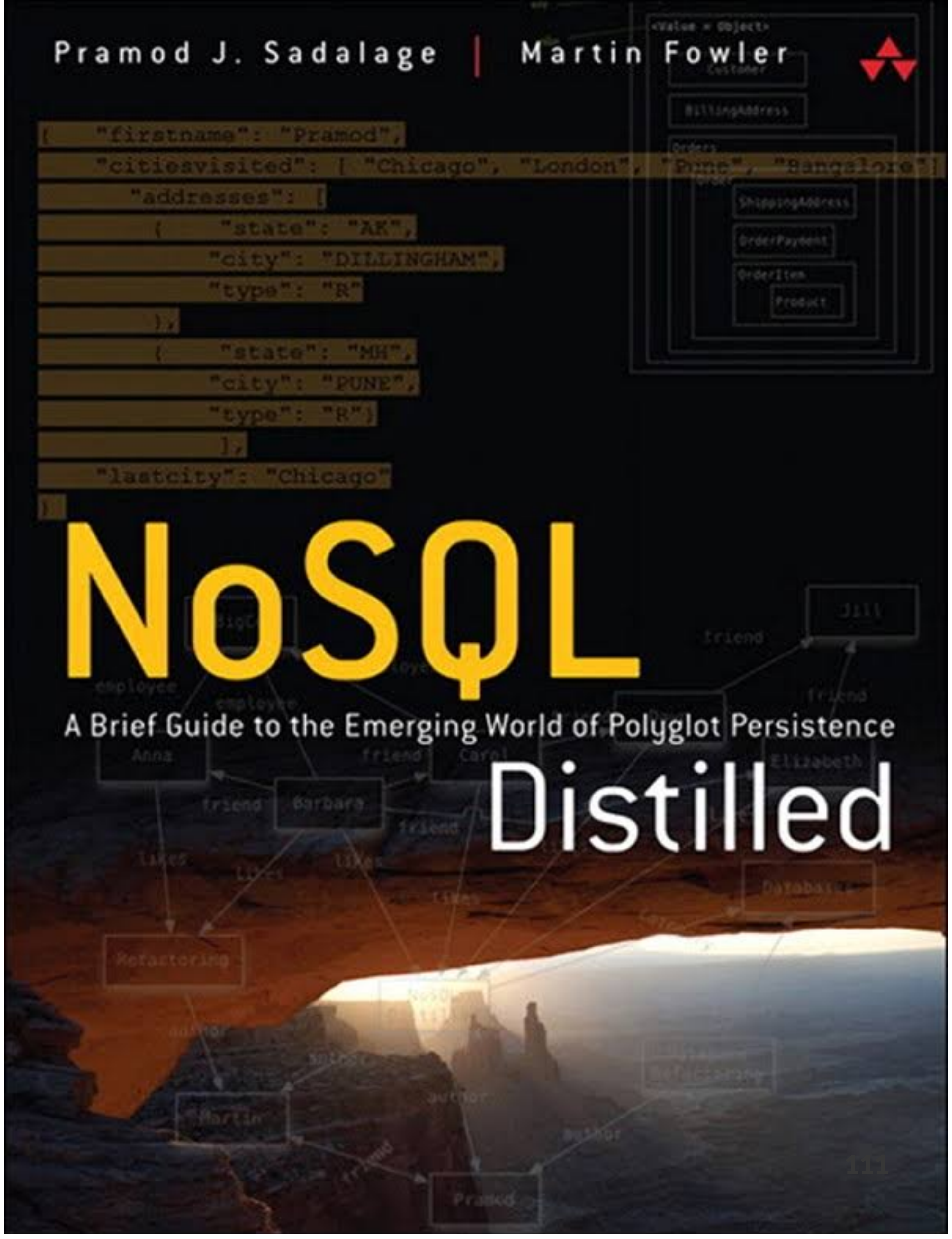


MongoDB Security

- SSL
  - between client and server
  - Intra-cluster communication
- Authorization at the database level
  - Read Only/Read+Write/Administrator

References

- Mongodb.com
- No SQL Distilled by P. Sadalage and M. Fowler
- MongoDB Applied Design Patters by R. Copeland
- The Definitive Guide to MongoDB by Plugge, Membry and Hawkins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