Guidelines for Designing New Data Architectures

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CONSULTANCY

Rick F. van der Lans

Rick F. van der Lans is a highly-respected independent analyst, consultant, author, and internationally acclaimed lecturer specializing in data warehousing, business intelligence, big data, and database technology. He is managing director of R20/Consultancy BV.

He has presented countless seminars, webinars, and keynotes at industry-leading conferences. Rick helps clients worldwide to design their data warehouse, big data, and business intelligence architectures and solutions and assists them with selecting the right products. He has been influential in introducing the new logical data warehouse architecture worldwide which helps organizations to develop more agile business intelligence systems.

He is the author of several books on computing, including his *Data Virtualization: Selected Writings* and *Data Virtualization for Business Intelligence Systems*. Some of these books are available in different languages. Books such as the popular *Introduction to SQL* is available in English, Dutch, Italian, Chinese, and German and is sold world wide. He also authored numerous whitepapers for vendors.

In 2018 he was selected the sixth most influential BI analyst worldwide by onalytica.com.

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Agenda and Subjects

1. Introduction: Why a New Data Architecture?
2. Terminology and Concepts
3. Introduction to Data Architectures
4. New Technologies for Data Storage, Processing, and Analytics
5. Steps 1-3: Setting the Stage
6. Step 4: Architectural Design Principles
7. Step 5: Reference Data Architectures
8. Step 6-7: Designing New Data Architectures
9. Steps 8-9: Final Steps
10. Closing Remarks

Part 1:
Introduction: Why a New Data Architecture?

Unlocking success in digital transformations

October 2018 | Survey

Digital transformations are even more difficult than traditional change efforts to pull off. But the results from the most effective transformations point to five factors for success.

Most Popular   Media Monitoring   Social Media   Agencies   Trends   Digital Marketing

4 Steps to Help You Become a Data Driven Company in 2019

CLEMENT RENÉ

Data is a business asset beyond imagination – here is why (and where)

It has almost become embarrasing to say that data is a business asset and should be treated as one *(the same goes for information)*.

The 'data is an asset' or a 'data is a business asset' message is not new. It goes back over two decades. However, despite the fact that so many people have said it so often before, we still see that there is a difference between preach and practice.

It's not that organizations fail to understand t

data, information and actionable intelligence (

Inc.

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TECHNOLOGY

3 Ways Your Company Should Be Like Google, and 1 Way it Definitely Shouldn't

You don't have to be the world's most popular search engine in order to innovate. Here are four things you can learn from

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Projects › Data Economy

Principles for a Data Economy (with the ALI)

With the rise of an economy in which data is a tradeable asset globally, more certainty is needed with regard to the legal rules that are applicable to the transactions in which data is an asset. Critical questions arise such as who has which right with regard to the data generated by connected devices? They need to be answered urgently, as lack of clarity in this field potentially hinders innovation and growth and, more importantly, troubles consumers, data-driven industries, and start-ups.

For an overview of past and upcoming meetings of this project, please click here.

ELI Members, who are interested in actively contributing to the development of this project are invited to

QUALITANCE   CONTACT US   BLOG

Data Disruption is Here

in Future horizons   posted on January 11, 2018   by Mike Parsons   3 minutes   0 Comments

If software is eating the world, then data is swallowing it. The four highest valued companies in the US are tech heavyweights Apple, Google, Microsoft, and Amazon. Facebook is close behind in 8th position.

Popular Posts

Future Horizons in Review - 5 Tech Conversations That Ruled in 2018

What to Expect from Immersive Technologies in 2019

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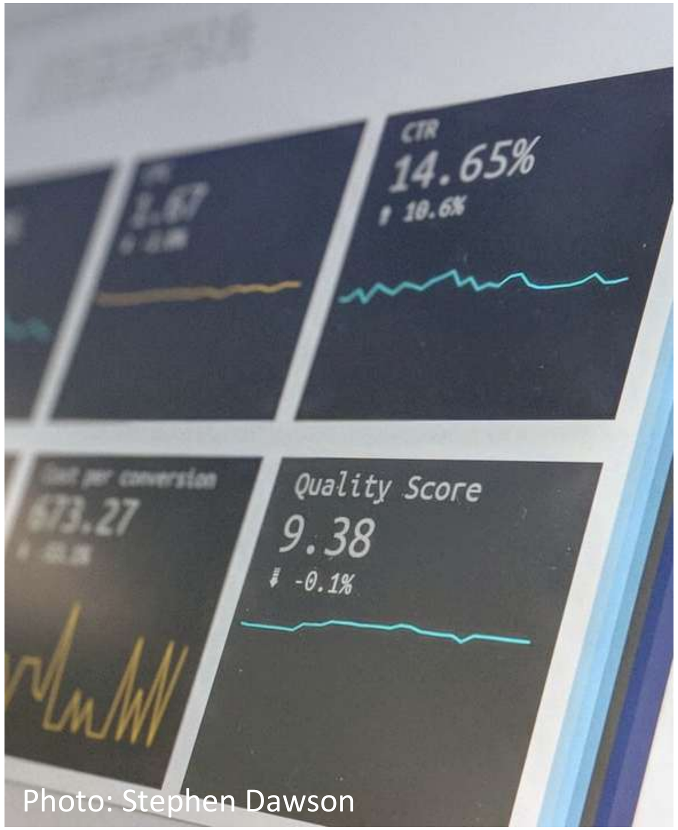
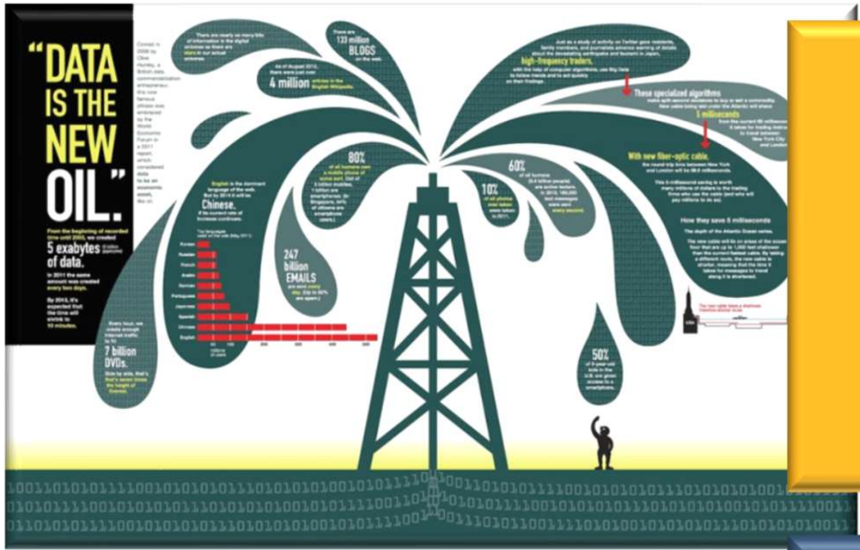
Examples of ‘Doing More’ with Data



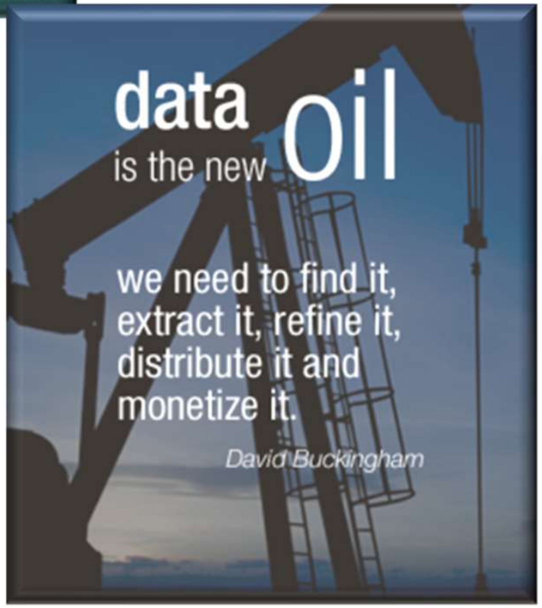
- Enabling self-service reporting, dashboards, and for analytics to work with (near) real-time data
- Combining internal with external data to enrich analytical capabilities
- Accelerating AI/machine learning initiatives to discover new patterns or trends in the data
- Simplifying deployment of IoT technology to generate more data on the machines and business processes
- Offering edge analytics in which real-time data is analyzed continuously and near the place where the data is produced by the sensor or business process


"DATA IS THE NEW OIL."
5 exabytes of data.
7 billion DVDs.


Data is the new oil!


OIL
DATA


Data is the new oil
DATA
DATA
DATA
this is good news, right?


data is the new oil
we need to find it, extract it, refine it, distribute it and monetize it.
David Buckingham


DATA
is the new oil


BIG DATA

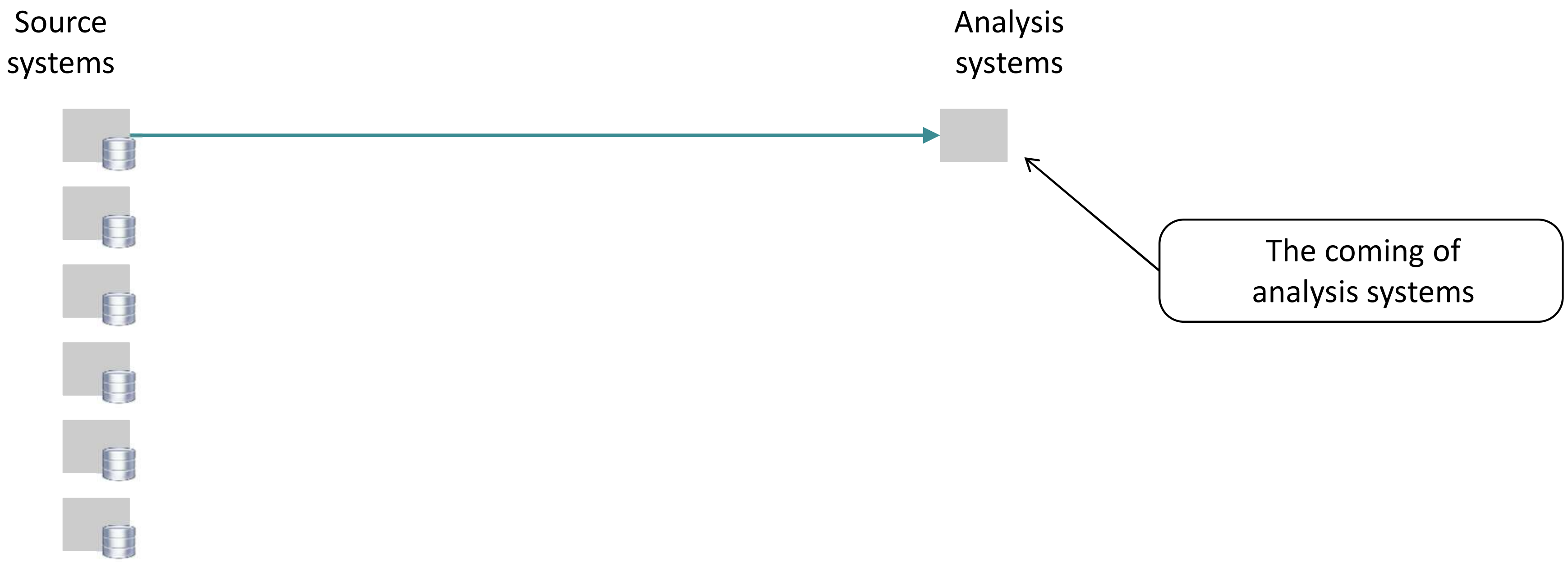
Data hasn't changed,
it's just more of the same

Data *consumption* has changed

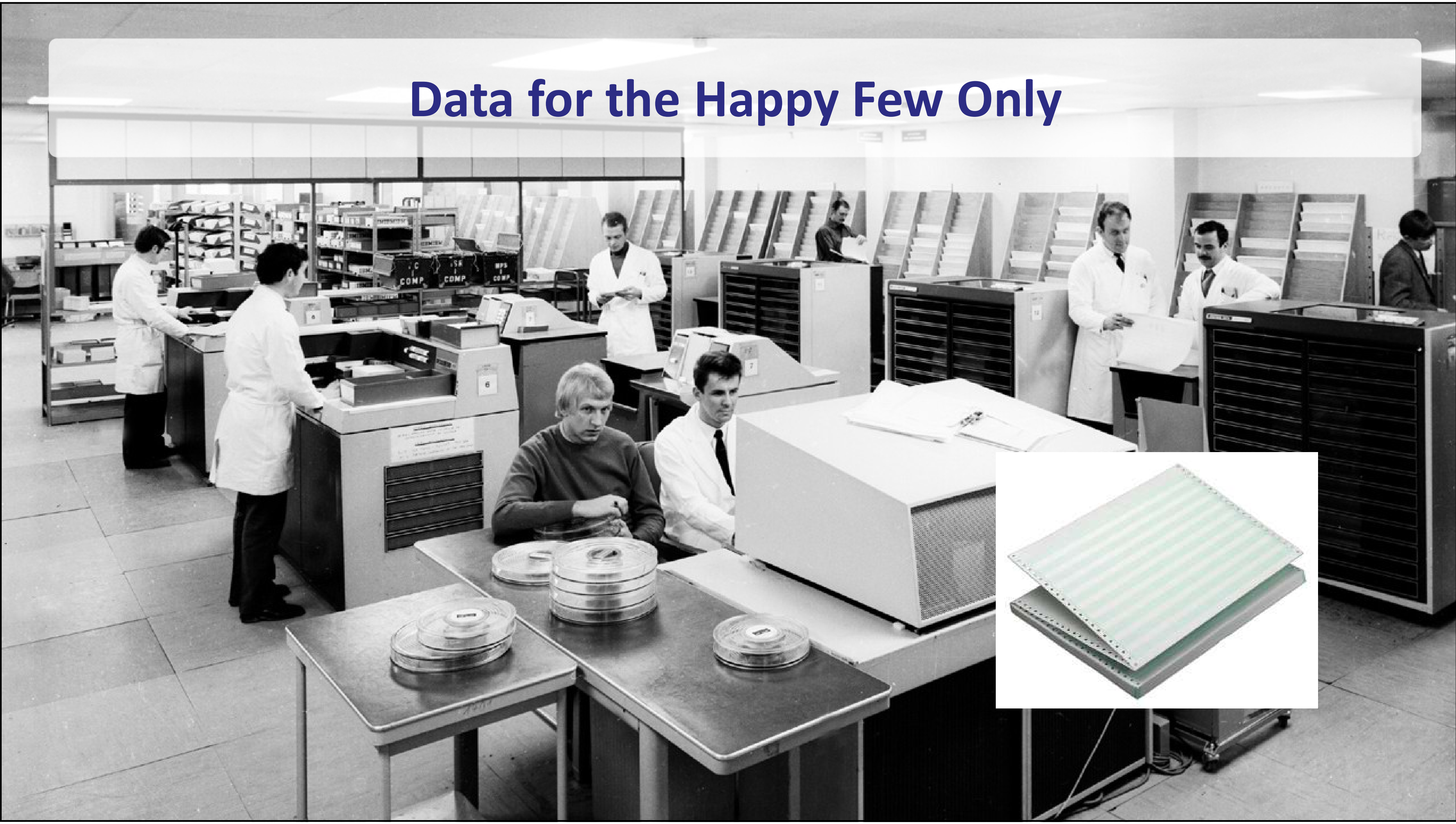
Self-service BI
Embedded BI
Supplier- and Customer-driven BI
Applied AI in Text, Image, Video Analysis
Edge Analytics
Data Marketplace
Data Science
Automated decisions
…

Evolution of the Data Processing Landscape (1)

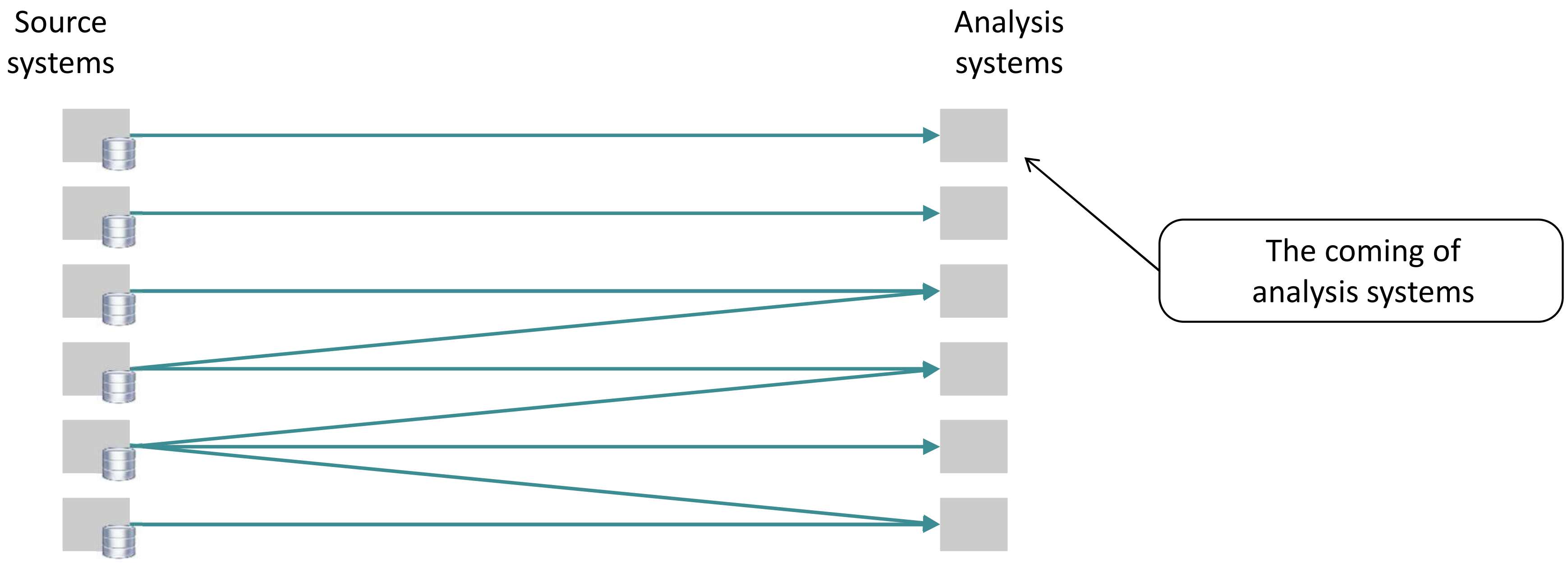
Evolution of the Data Processing Landscape (2)



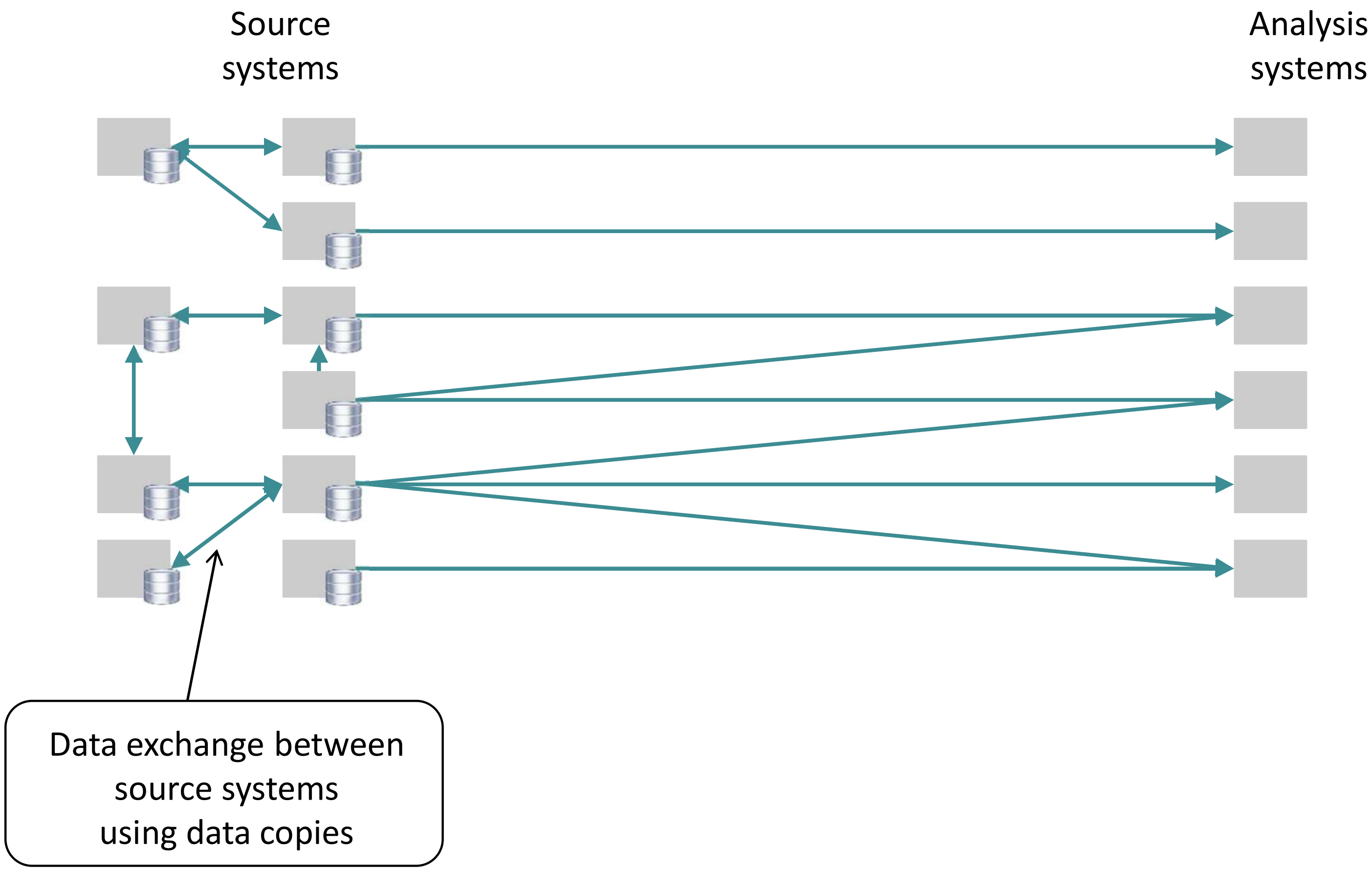
Data for the Happy Few Only



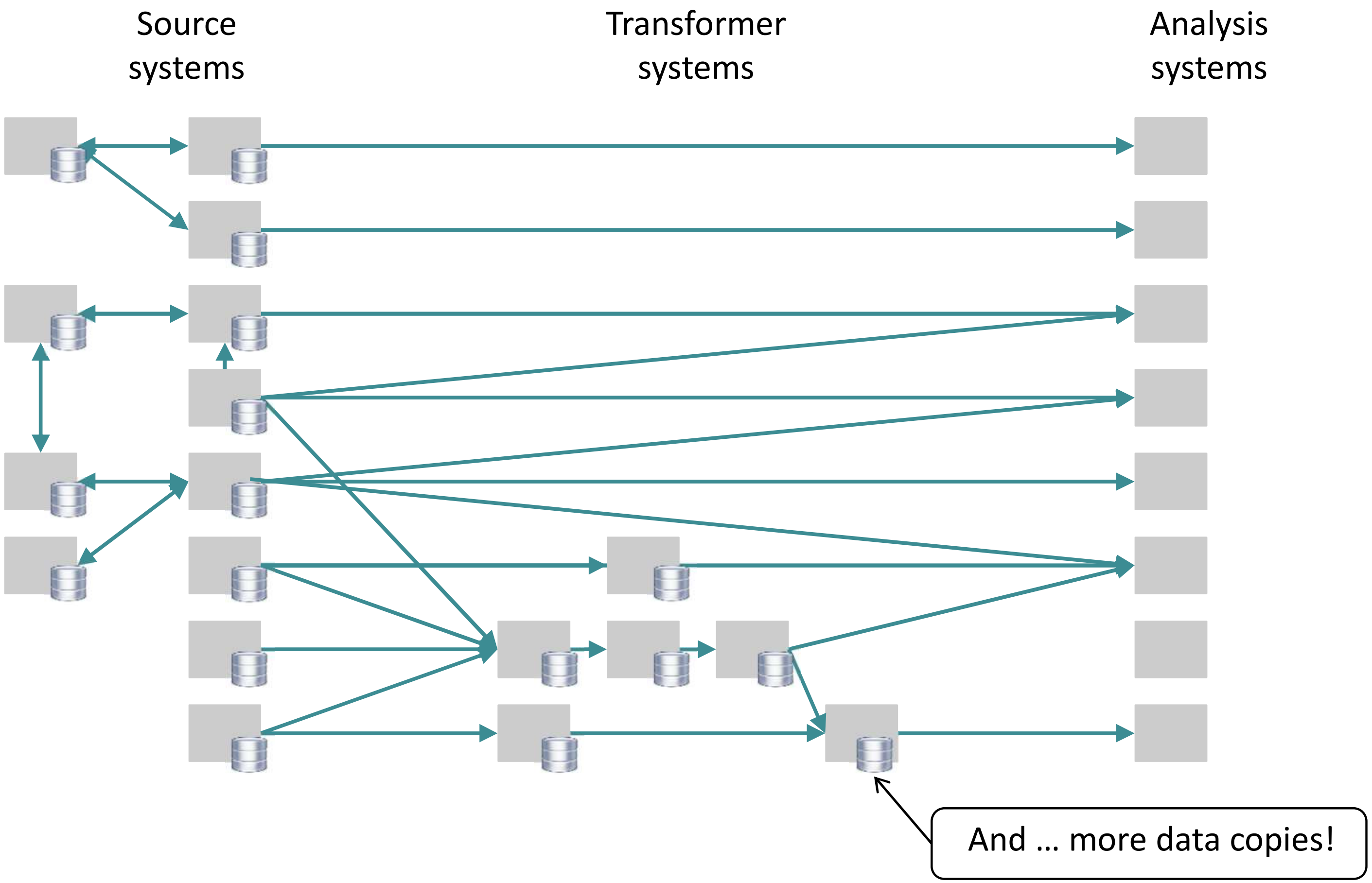
Evolution of the Data Processing Landscape (2)



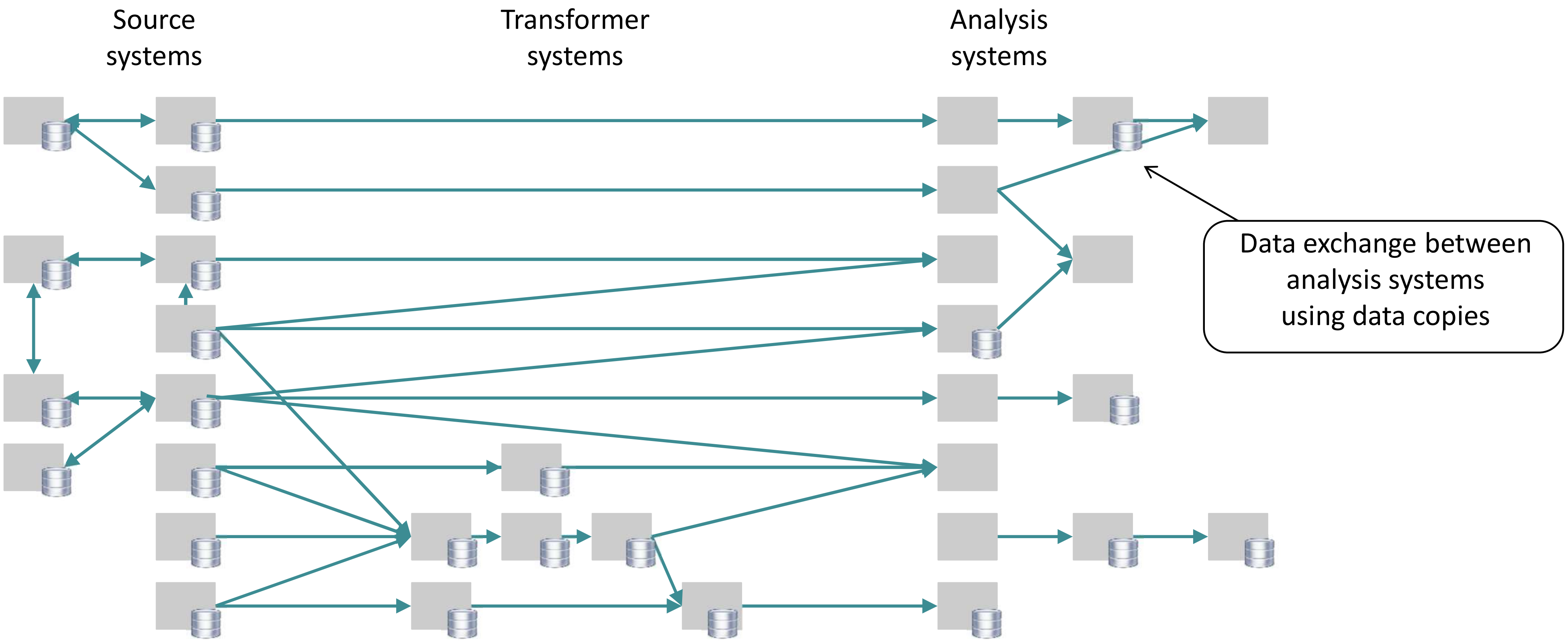
Evolution of the Data Processing Landscape (3)



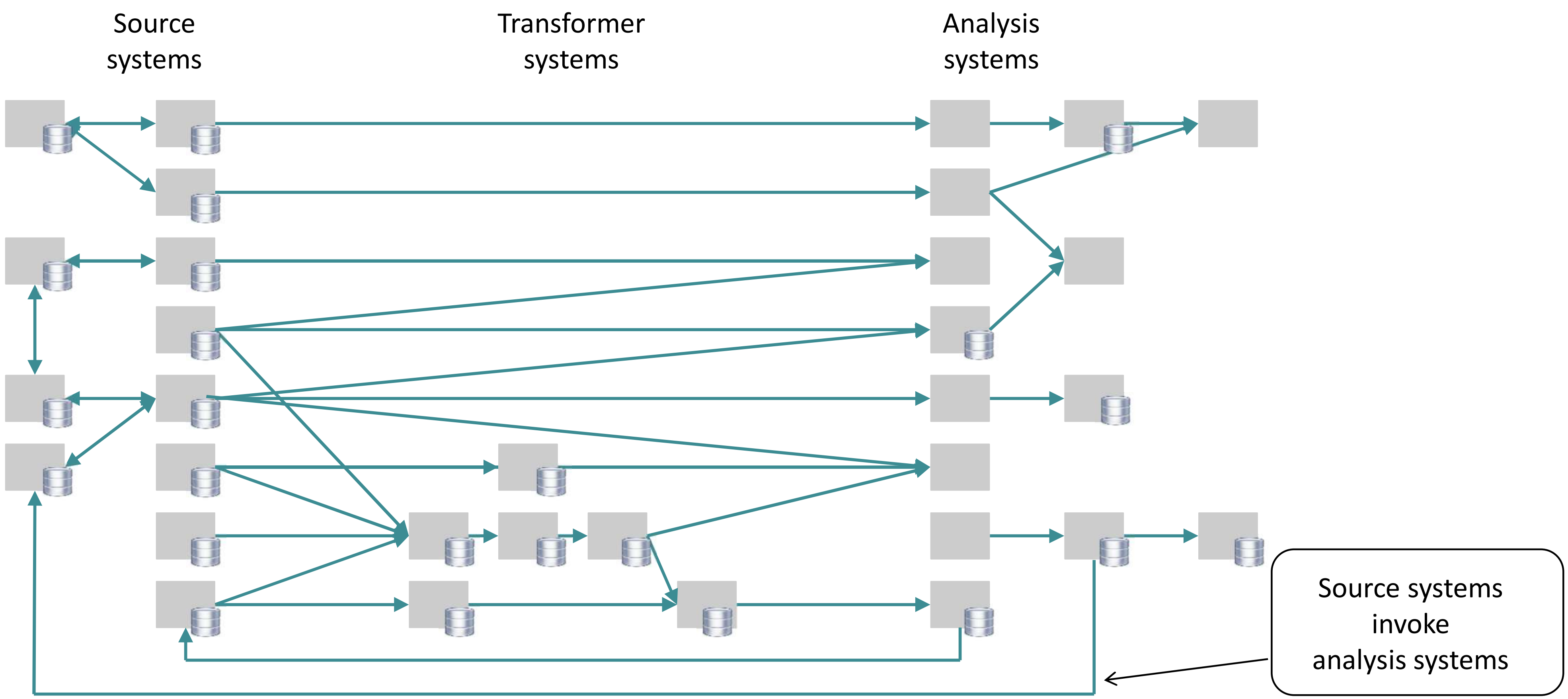
Evolution of the Data Processing Landscape (4)



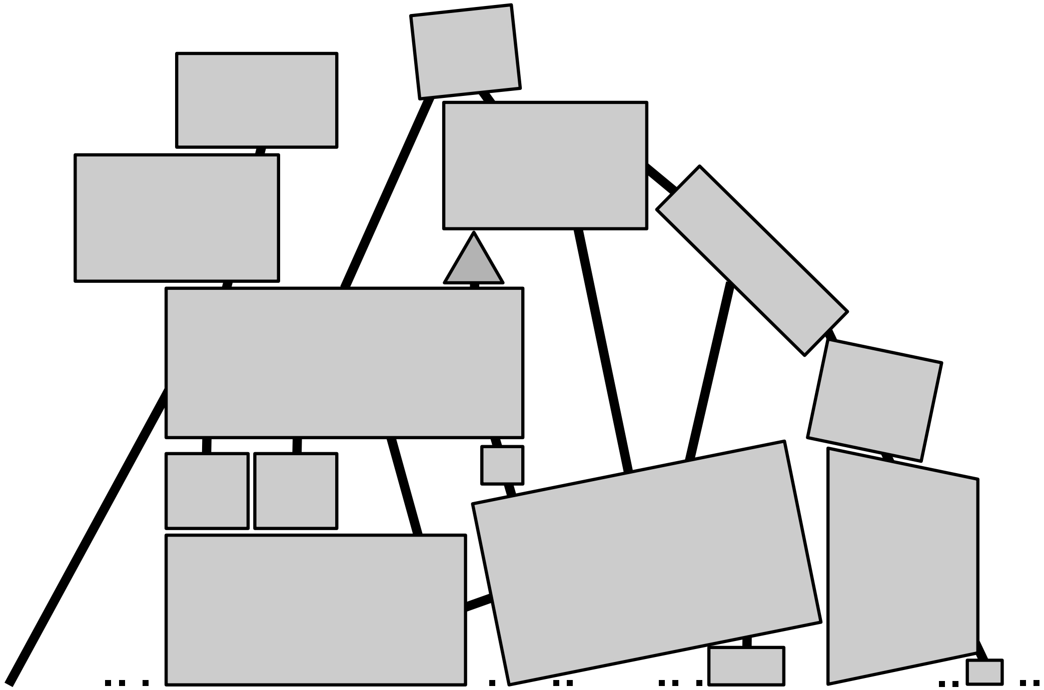
Evolution of the Data Processing Landscape (5)



Evolution of the Data Processing Landscape (6)



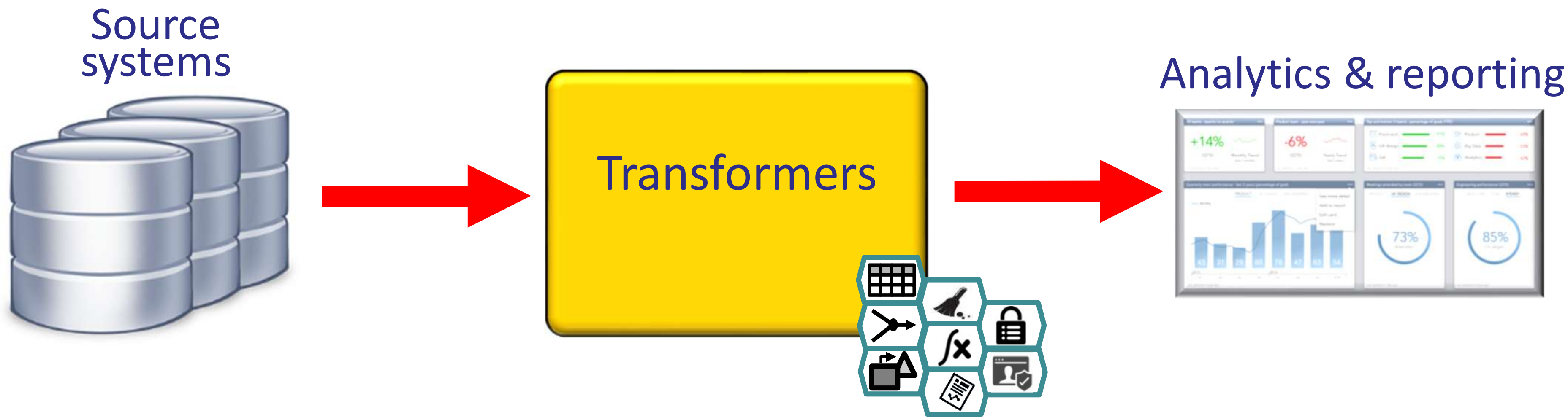
“Wobbly” Foundation of the Data Processing Landscape



Raising the Bar for ICT systems

Part 2:
Terminology and Concepts

The Transformers



Data structure
Integration
Transformation
Data security

Data cleansing
Analytical
Visualization
Data privacy

Examples of Transformers

- Data value transformations
- Data structure transformations
- Aggregations
- Filters
- Groupings
- Calculations
- Integrations
- Technical corrections
- Functional corrections
- Anonymizations
- Historizations
- …

- Summarize
- Keywords extraction
- Translate
- Named Entity Recognition (NER)
- Optical Character Recognition (OCR)
- Text-to-speech
- Speech-to-text
- Data tagging
- Sentiment analysis
- Pattern recognition
- …

- Clustering
- Normalization
- Interpolation
- Extrapolation
- Binning
- Sampling
- Regression
- …

- Vector-to-Raster Conversion
- Containment
- Clipping
- Spatial intersection
- Buffering
- …

Transformer for Correcting Data

Custid	Lastname	Gender	City	Zipcode
12345	Jansen	Man	Rotterdam, ZH	2651 BJ
23324	Visser	V	Delft, ZH	2289 BG
57657	Dekker	Vrouw	Zwolle, OV	4011 AE
65461	Brouwer	M	Breda, NB	4811 AD

Correct

Custid	Lastname	Gender	City	Zipcode
12345	Jansen	M	Rotterdam, ZH	2651 BJ
23324	Visser	V	Delft, ZH	2289 BG
57657	Dekker	V	Zwolle, OV	
65461	Brouwer	M	Breda, NB	4811 AD

Transformer for Grouping Data

Custid	Transactionid	Datetime	Productid	Quantity	Price
12345	13463	202603121145	P34	3	3,50
12345	13463	202603121145	P66	2	2,75
12345	13463	202603121145	P87	1	1,95
12345	29365	202603130927	P66	2	2,75
57657	37721	202603131650	P12	1	4,00
57657	37721	202603131650	P66	2	2,75
65461	43846	202603141012	P73	4	0,75
65461	57290	202603151430	P19	5	2,40
65461	57290	202603151430	P66	3	2,75

Group, calculate

Transactionid	Datetime	Total amount
13463	202603121145	17,95
29365	202603130927	5,50
37721	202603131650	9,50
43846	202603141012	3,00
57290	202603151430	20,25

Transformer for Integrating and Grouping Data

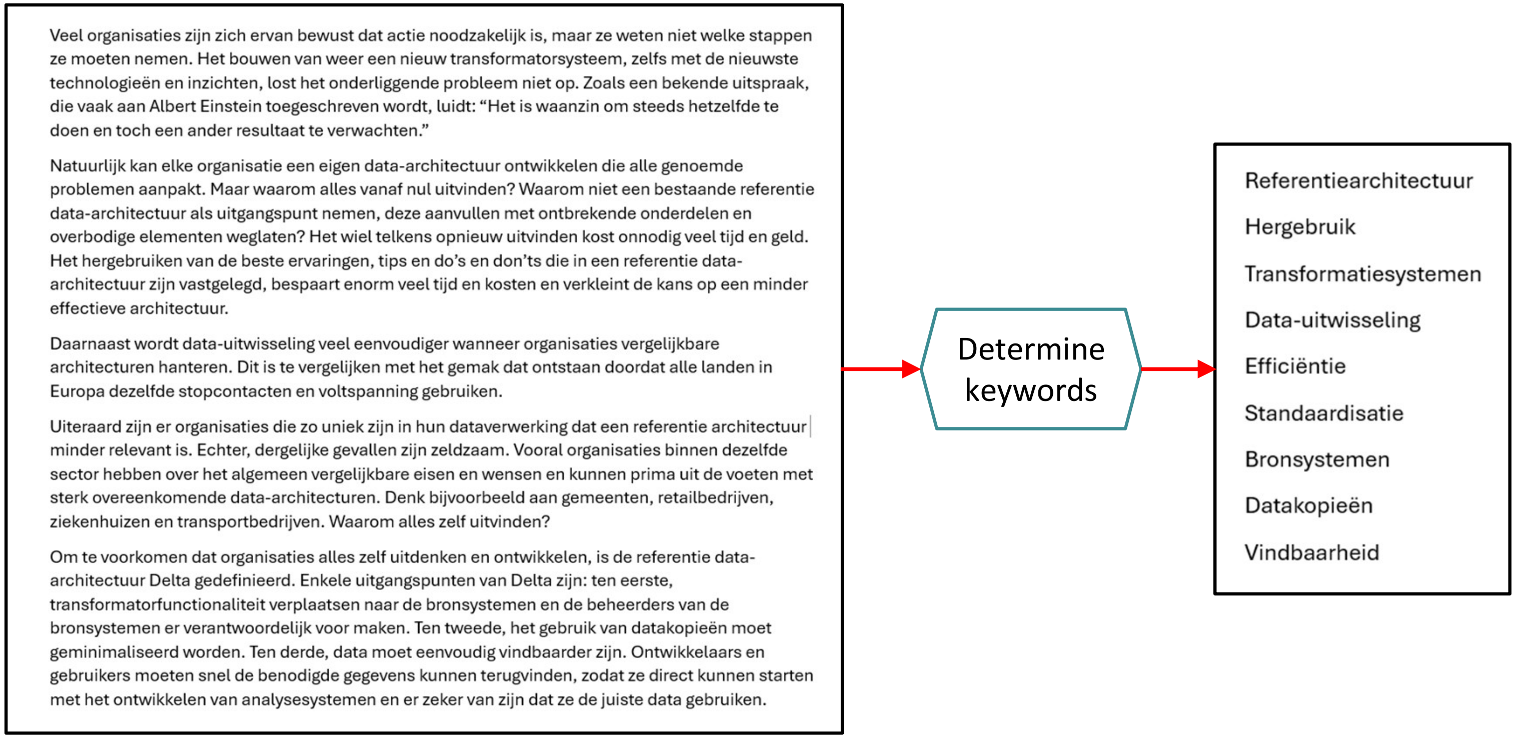
Custid	Lastname	Gender	City	Zipcode
12345	Jansen	Man	Rotterdam, ZH	2651 BJ
23324	Visser	V	Delft, ZH	2289 BG
57657	Dekker	Vrouw	Zwolle, OV	4011 AE
65461	Brouwer	M	Breda, NB	4811 AD

Custid	Transactionid	Datetime	Productid	Quantity	Price
12345	13463	202603121145	P34	3	3,50
12345	13463	202603121145	P66	2	2,75
12345	13463	202603121145	P87	1	1,95
12345	29365	202603130927	P66	2	2,75
57657	37721	202603131650	P12	1	4,00
57657	37721	202603131650	P66	2	2,75
65461	43846	202603141012	P73	4	0,75
65461	57290	202603151430	P19	5	2,40
65461	57290	202603151430	P66	3	2,75

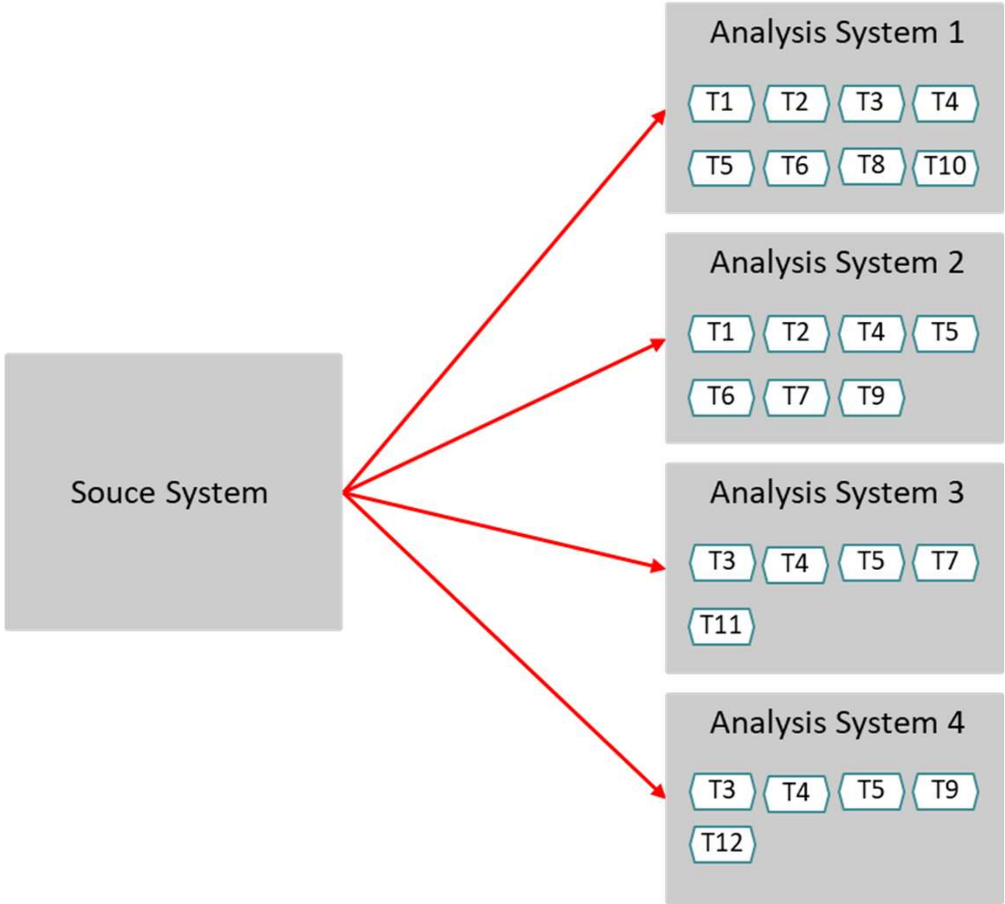
Integrate,
correct,
transform,
group,
calculate

Custid	Lastname	Gender	City	Province	Zipcode	Number of trans	Total
12345	Jansen	M	Rotterdam	Zuid-Holland	2651 BJ	2	23,45
23324	Visser	V	Delft	Zuid-Holland	2289 BG	0	0,00
57657	Dekker	V	Zwolle	Overijssel	4011 AE	1	9,50
65461	Brouwer	M	Breda	Noord-Brabant	4811 AD	2	23,25

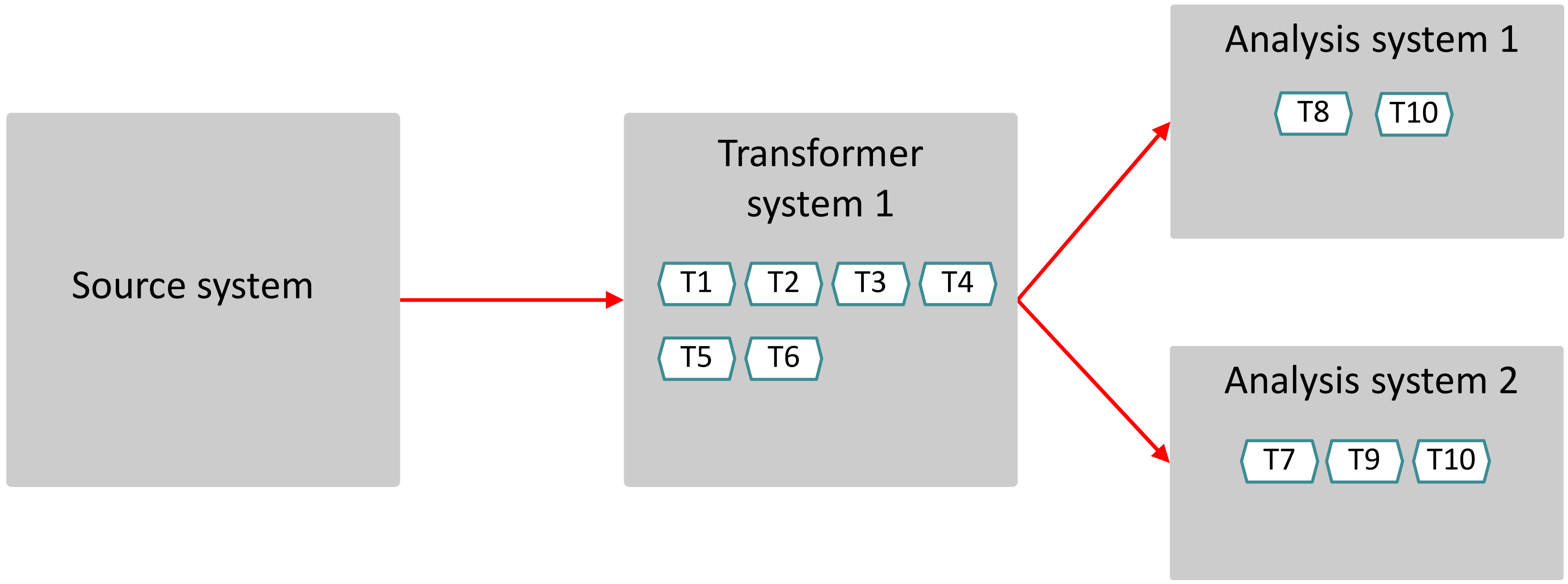
Transformer for Determining Keywords



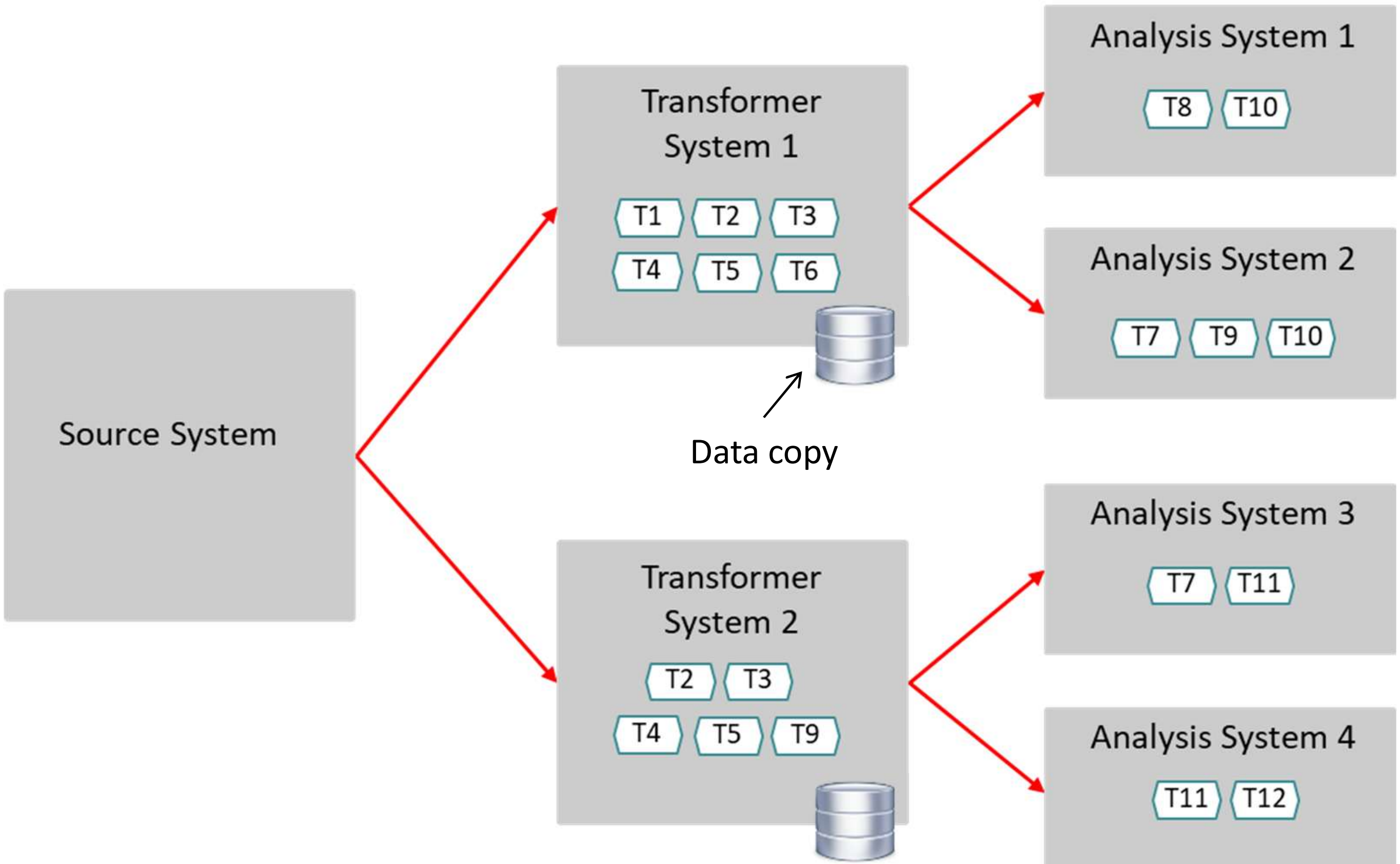
Duplicate Transformers in Analysis Systems



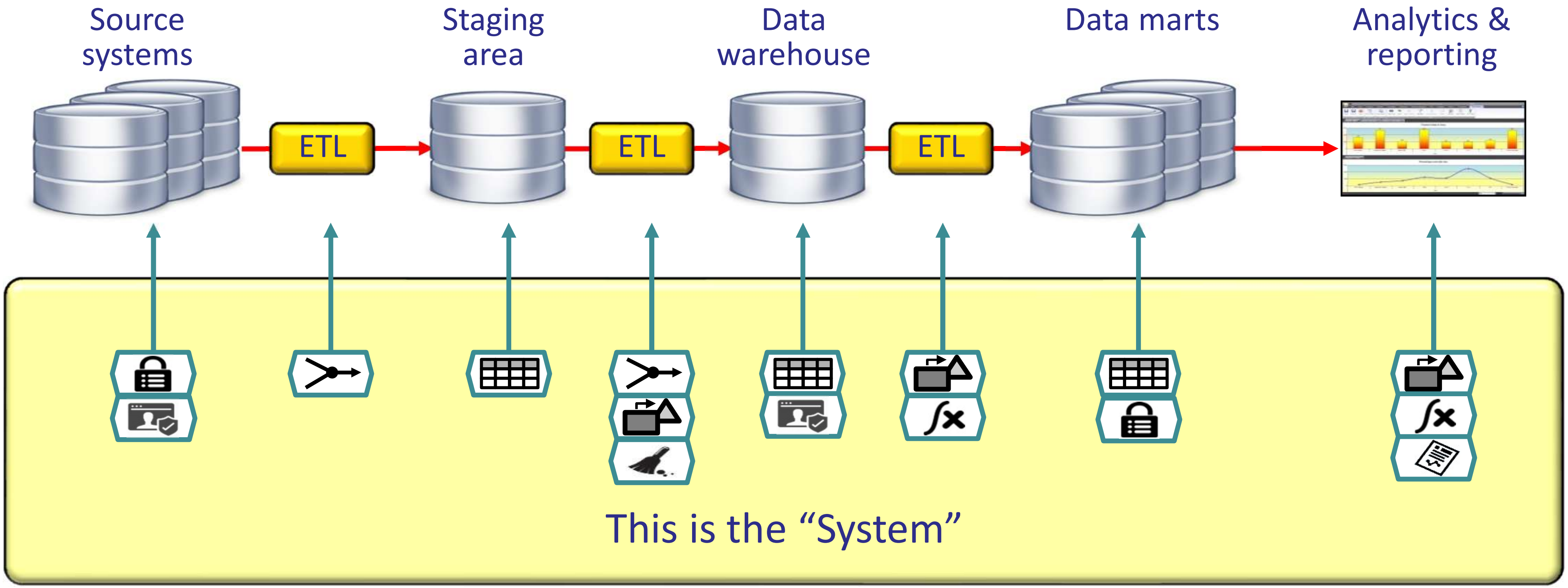
Centralizing Transformers



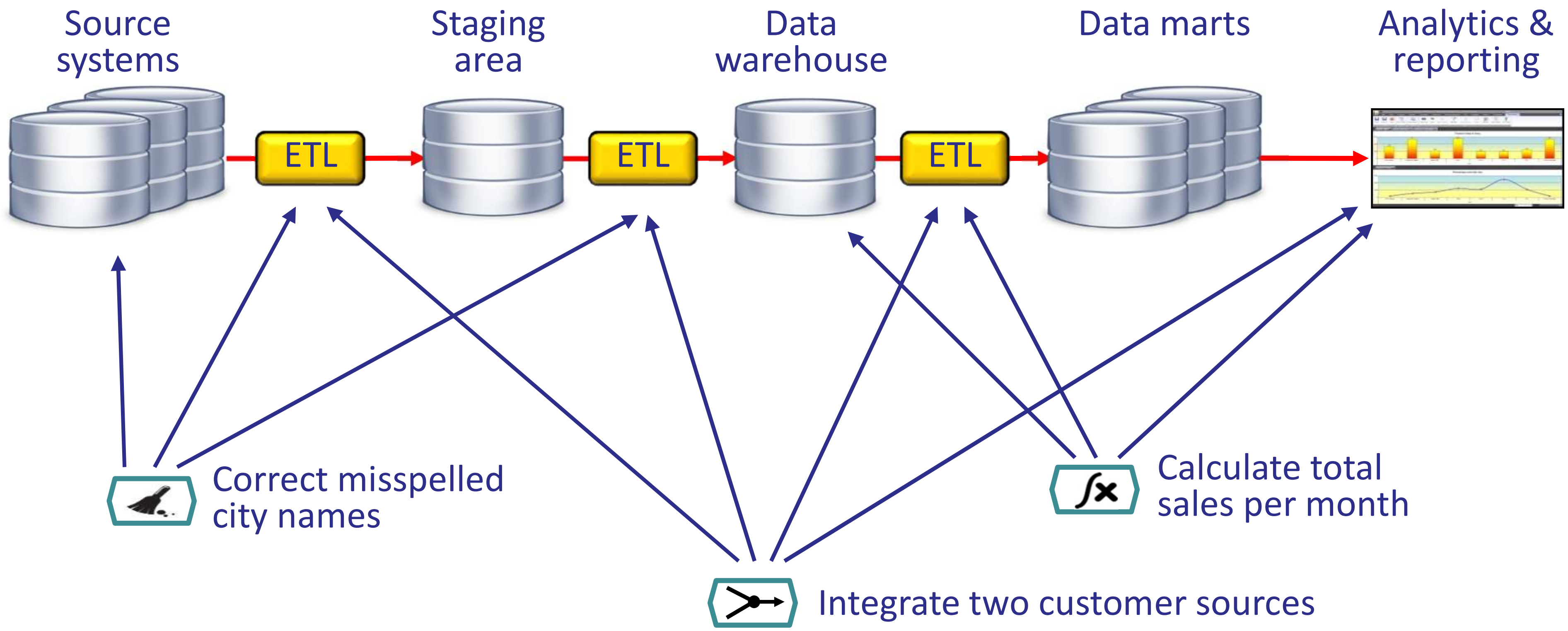
Dupulicate Transformers in Transformer Systems



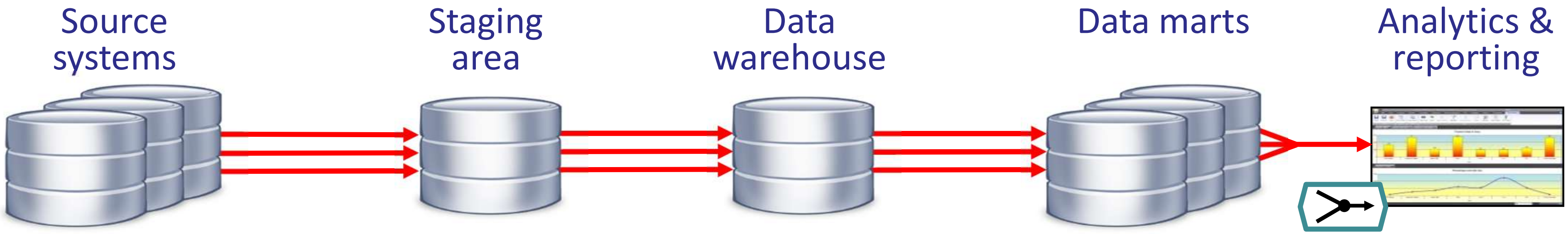
Transformers in Data Warehouse Environments



Where to Implement Transformers?

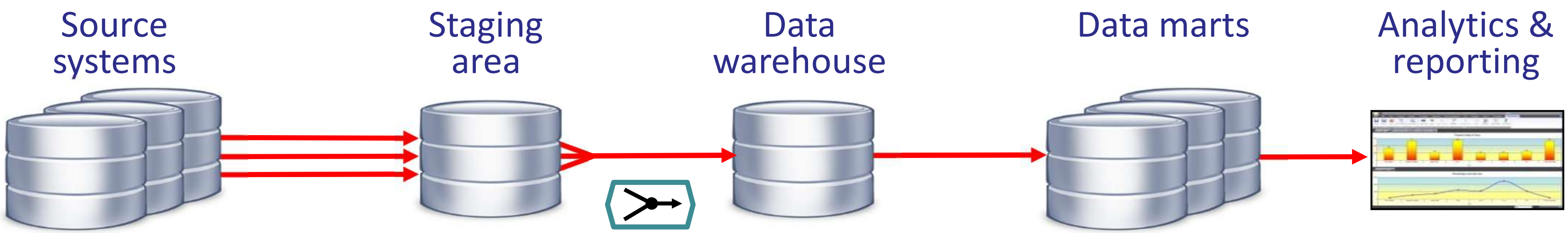


Example: Integration and Aggregation (1)



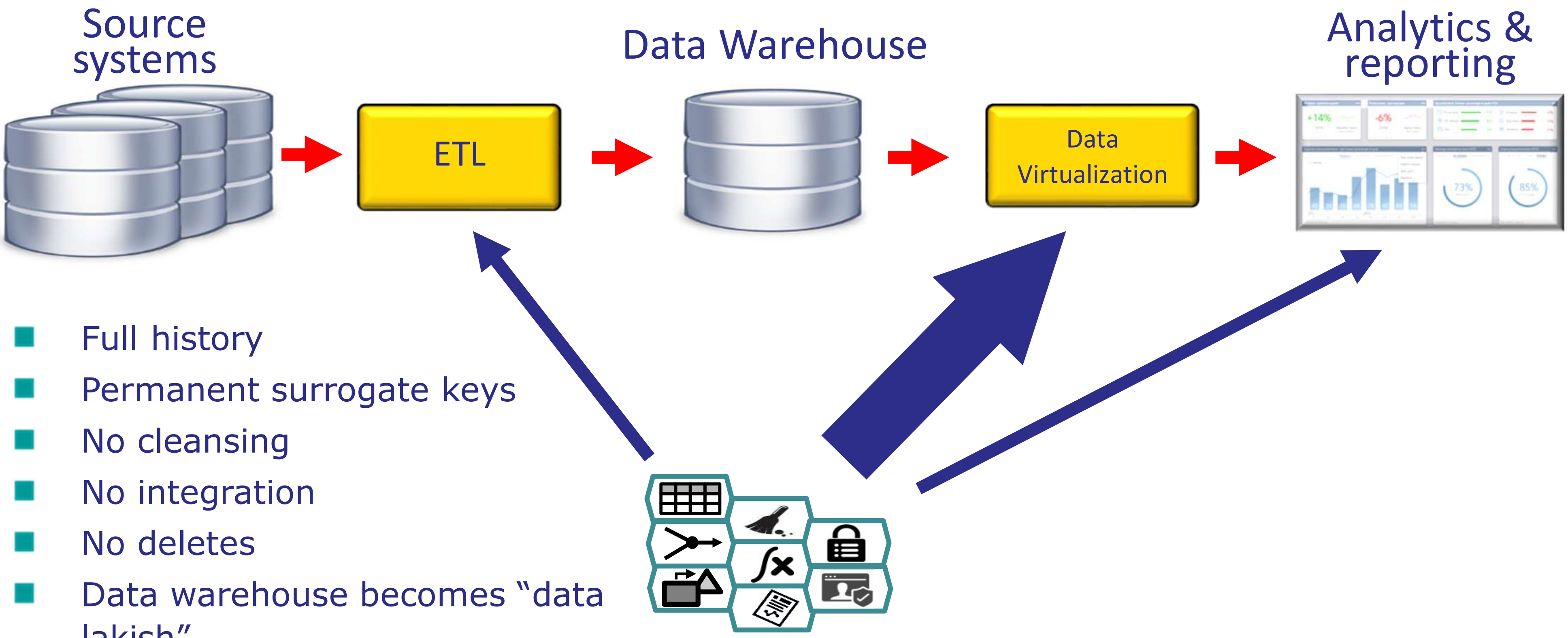
- Slow processing of integration logic in reports
- Complex queries in reports
- No sharing of integration logic across reports and tools
- Potential errors and inconsistencies in reports
- Fast copying and lower data latency
- Data structure of source database determines all data structures
- Use of original raw data possible
- What about integration errors?

Example: Integration and Aggregation (2)



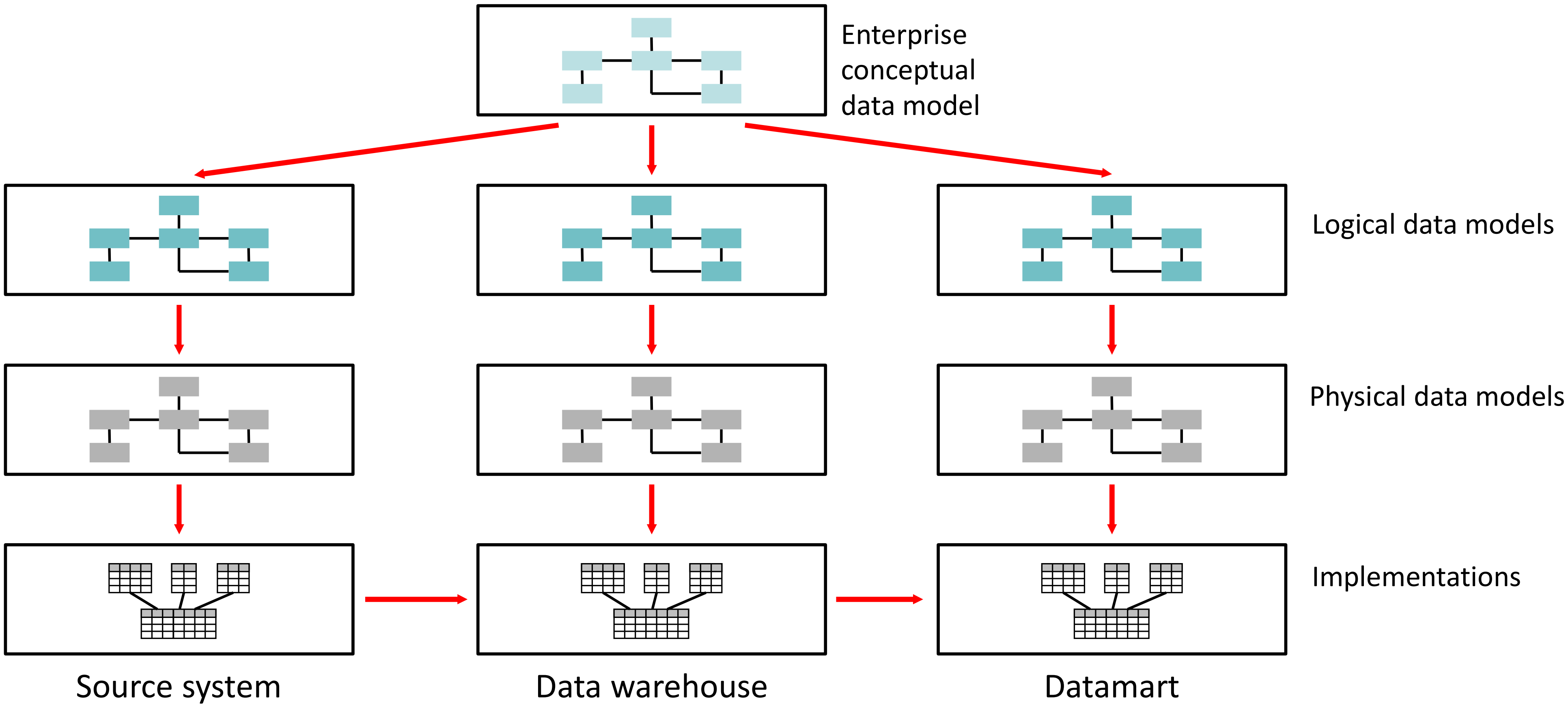
- Fast processing of integration logic in reports
- Simpler queries in reports
- Sharing of integration logic across reports and tools
- Potential errors and inconsistencies in ETL
- Slower copying and higher data latency
- Data structure of source database does not determine all data structures
- Use of original raw data possible
- Integration errors easier to fix

Implementing the Transformers

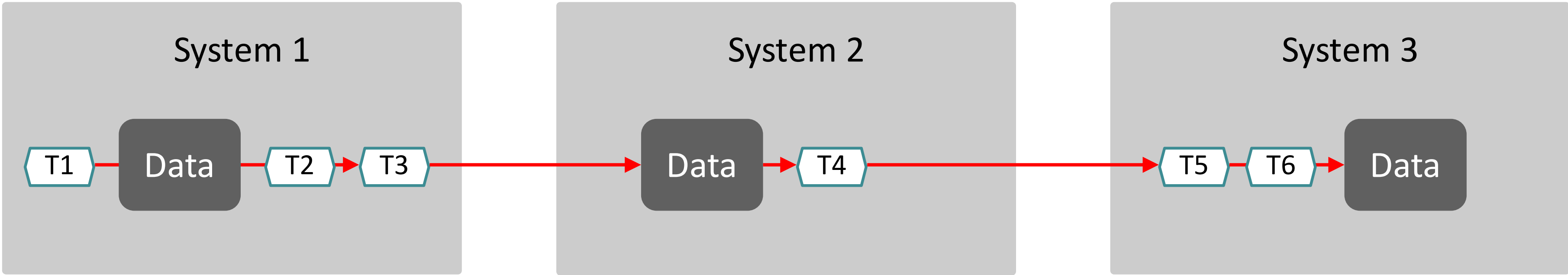


- Full history
- Permanent surrogate keys
- No cleansing
- No integration
- No deletes
- Data warehouse becomes “data lakish”

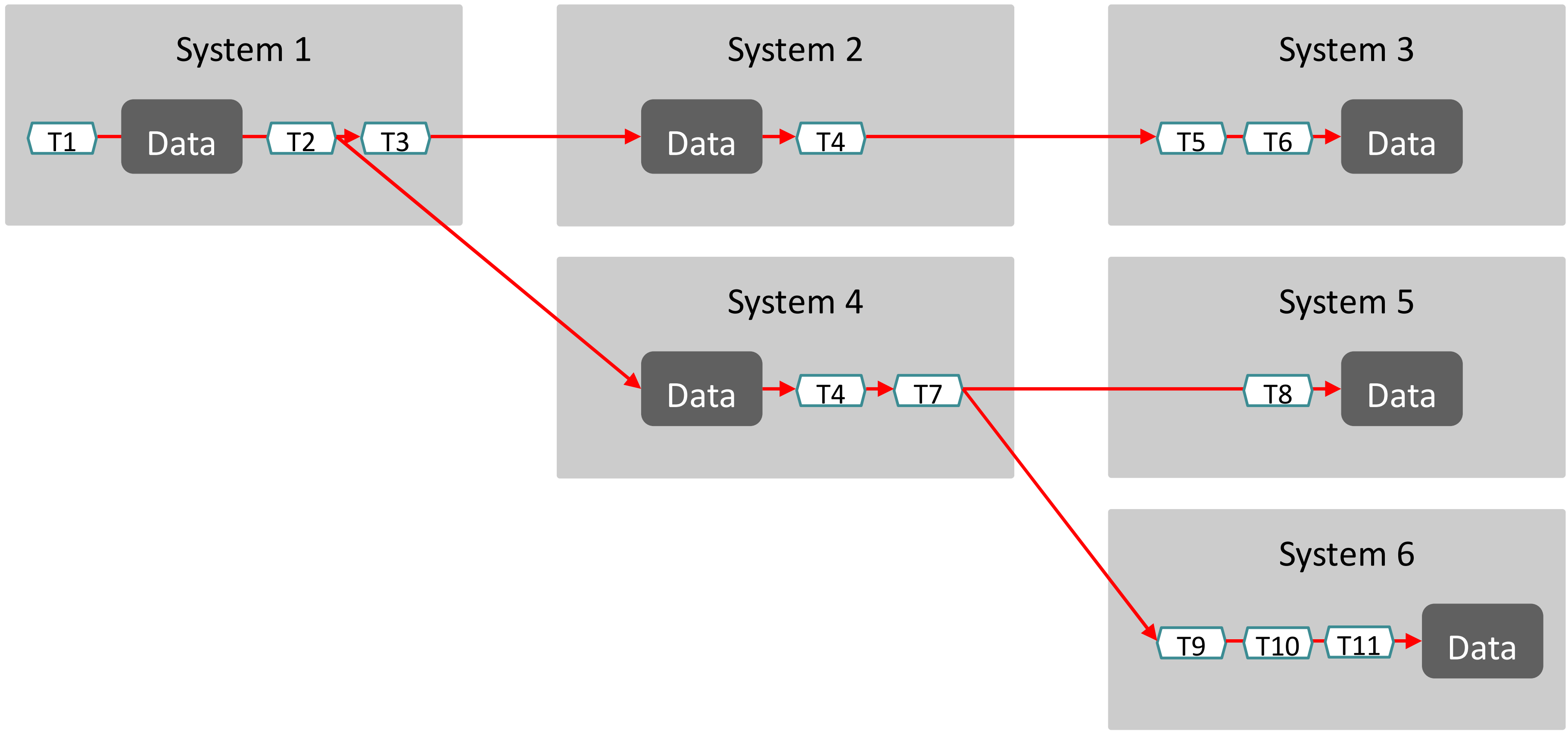
Vertical and Horizontal Lineage



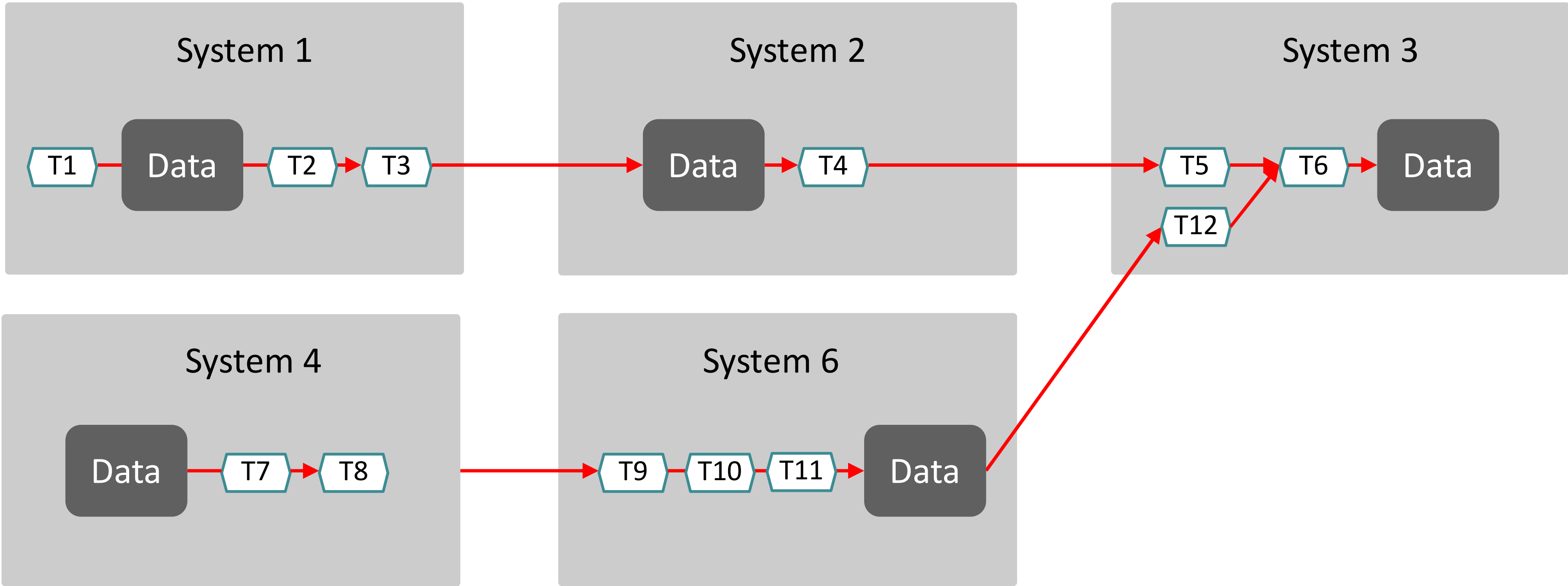
Example of a Data Path with Transformers



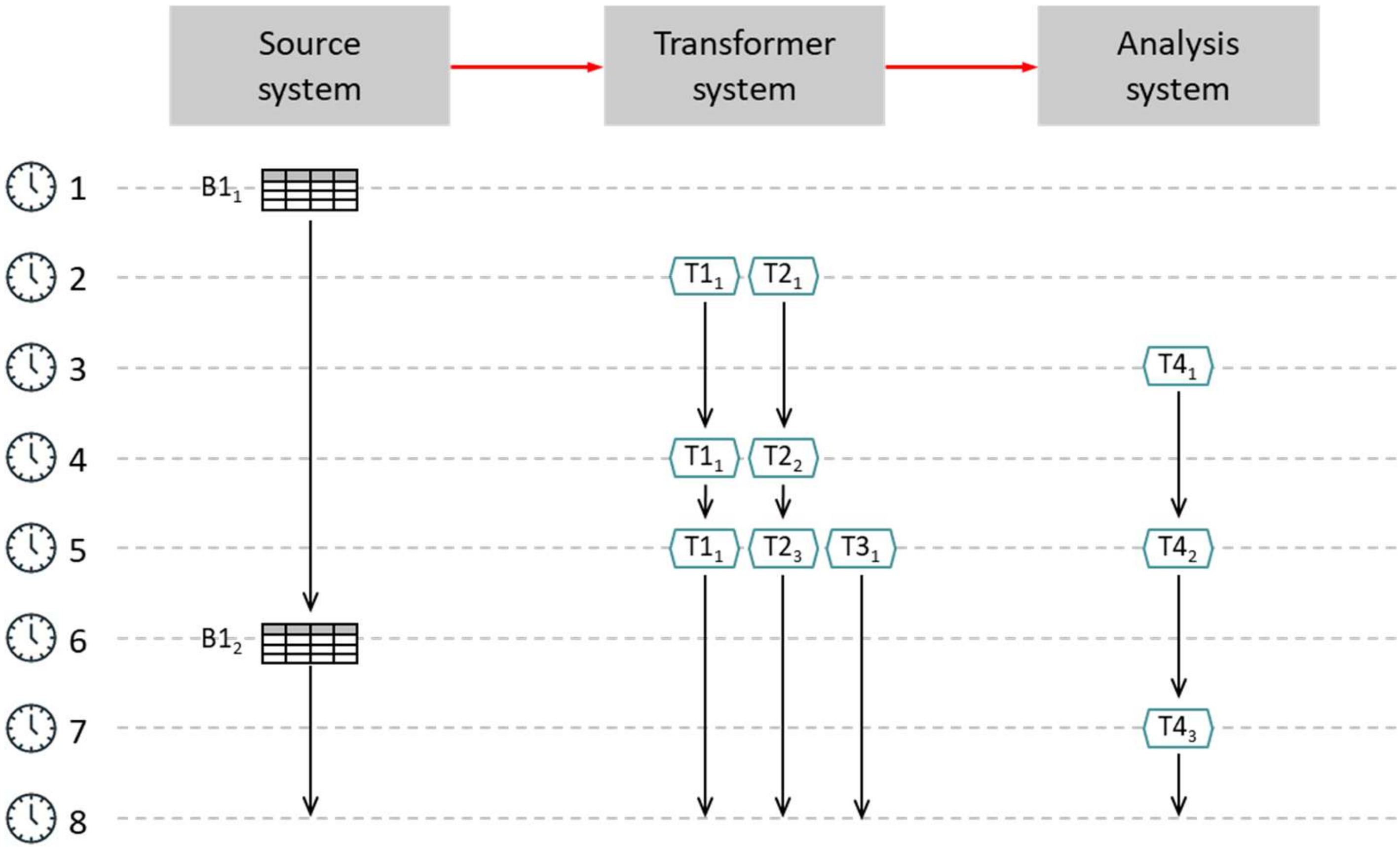
Data Path with Splits



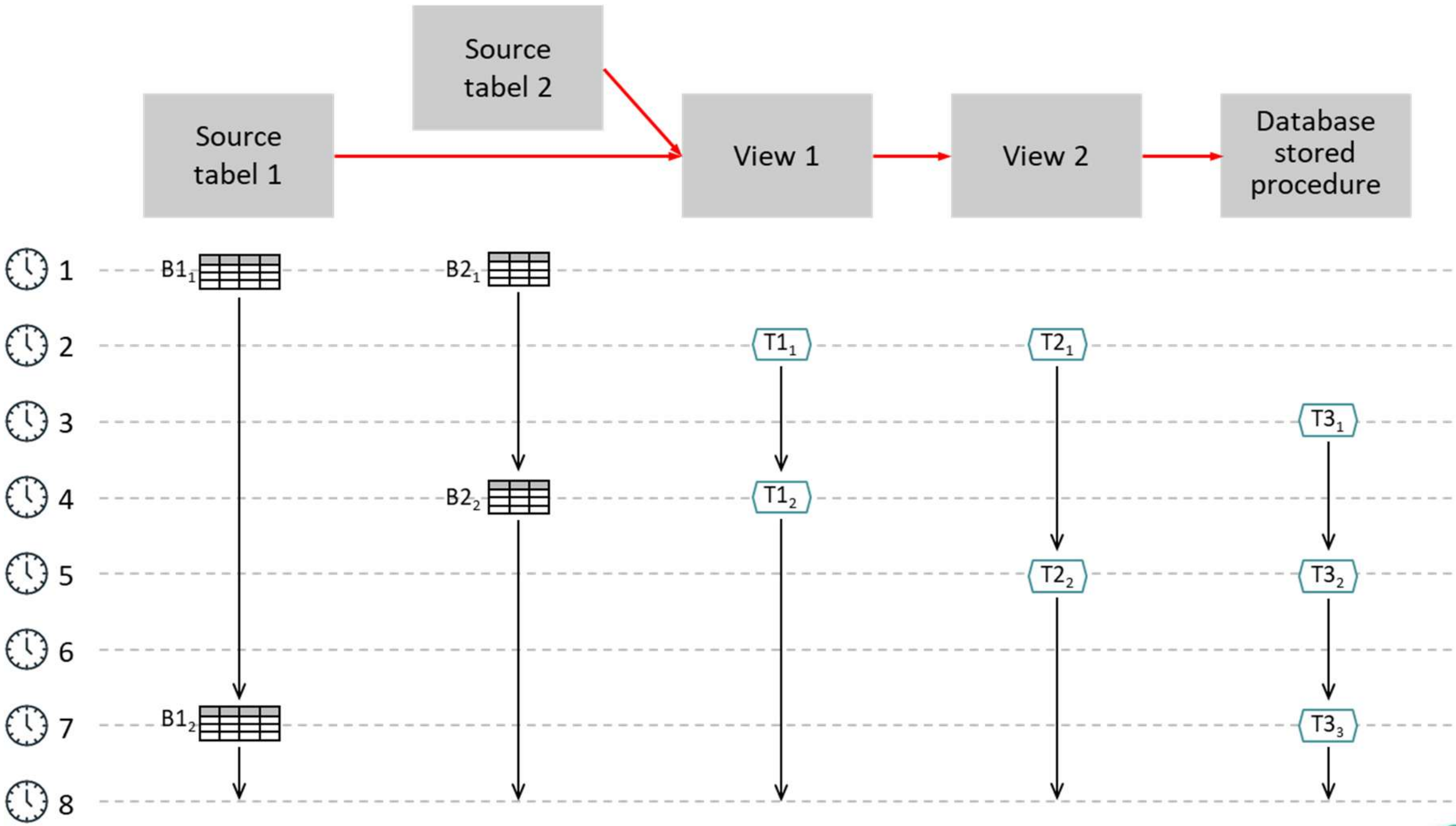
Data Path with Joins



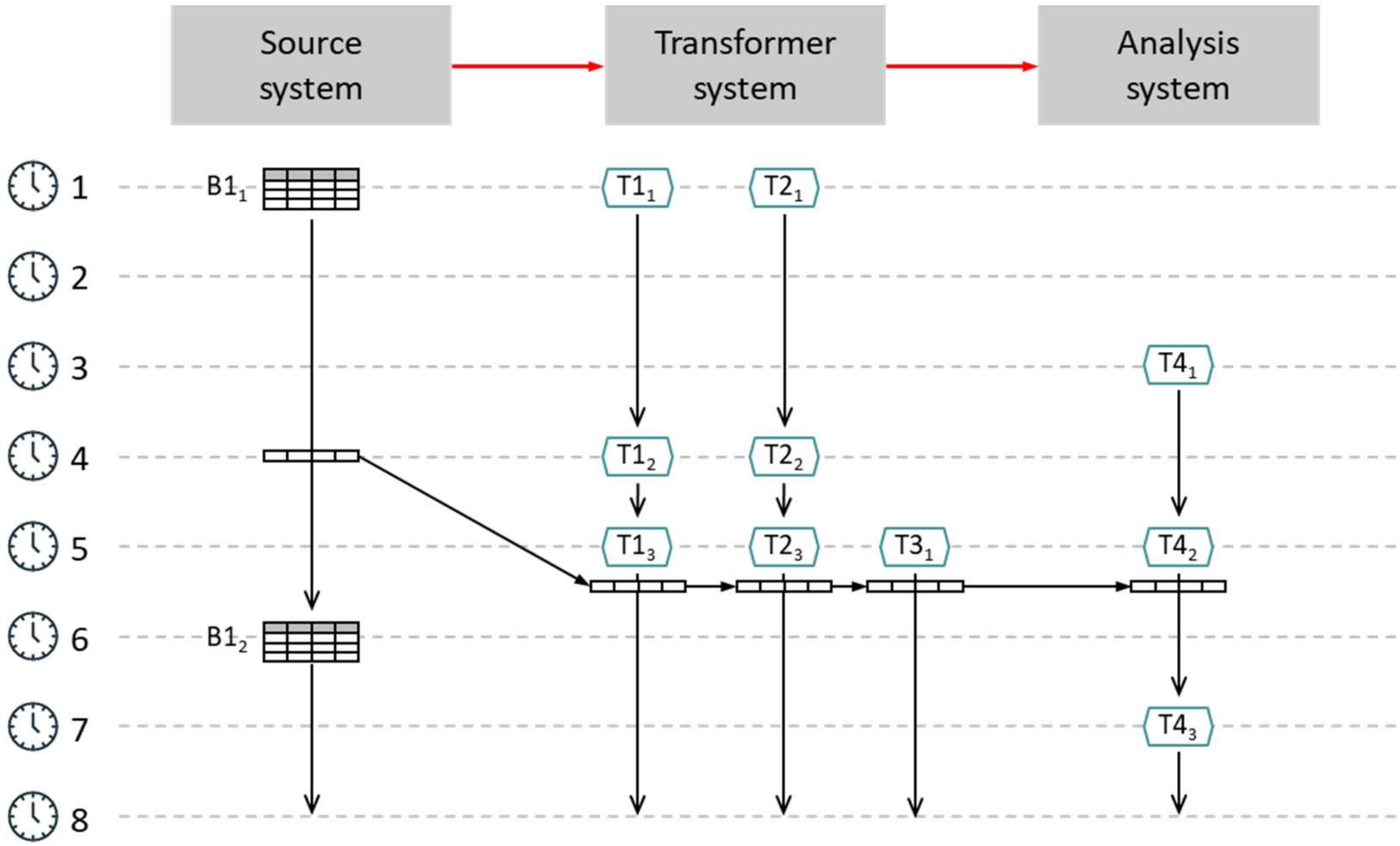
Example Horizontal Lineage (1)



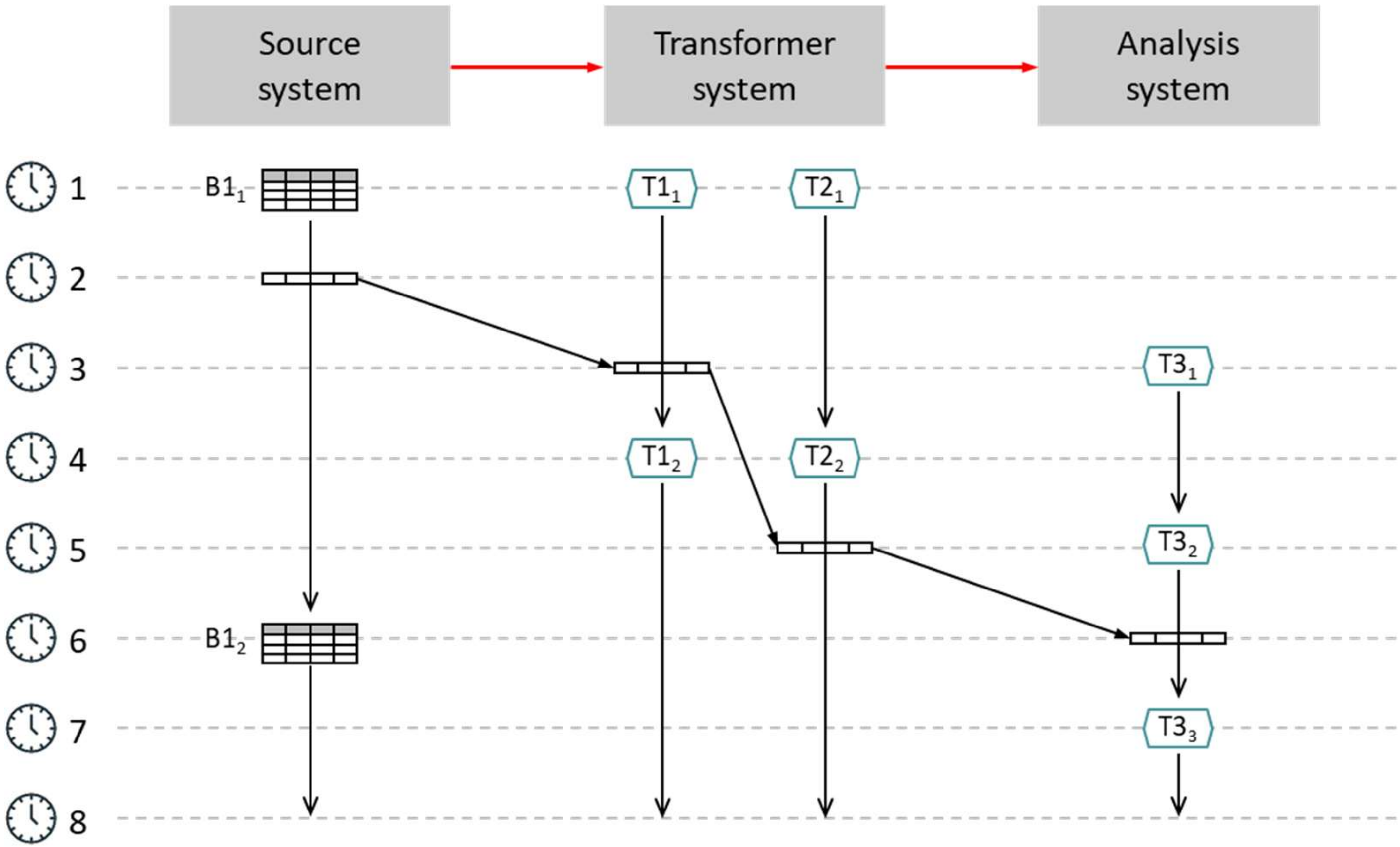
Example Horizontal Lineage (2) Within a Database



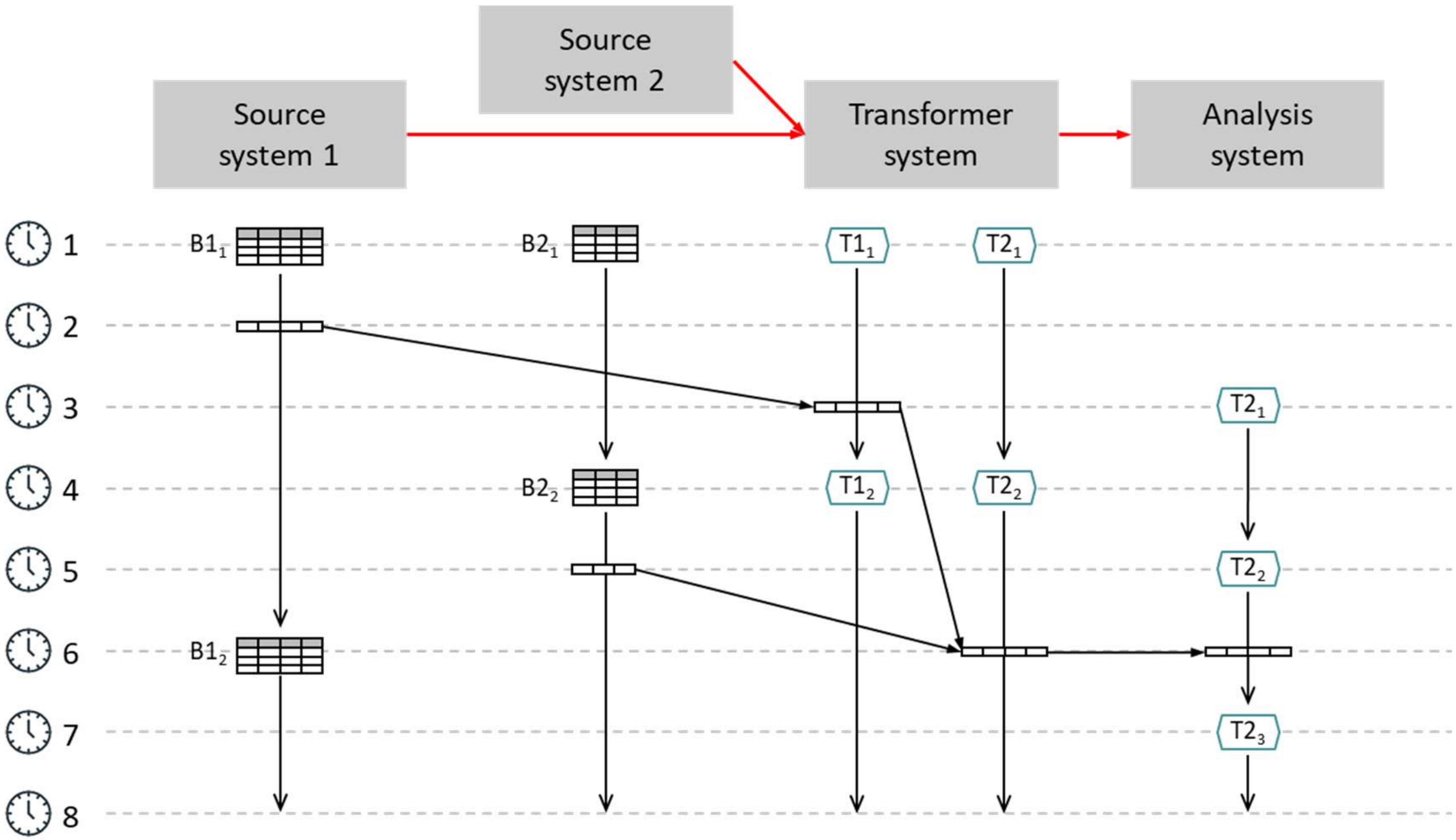
Operational Lineage (1) Simple Realtime Query



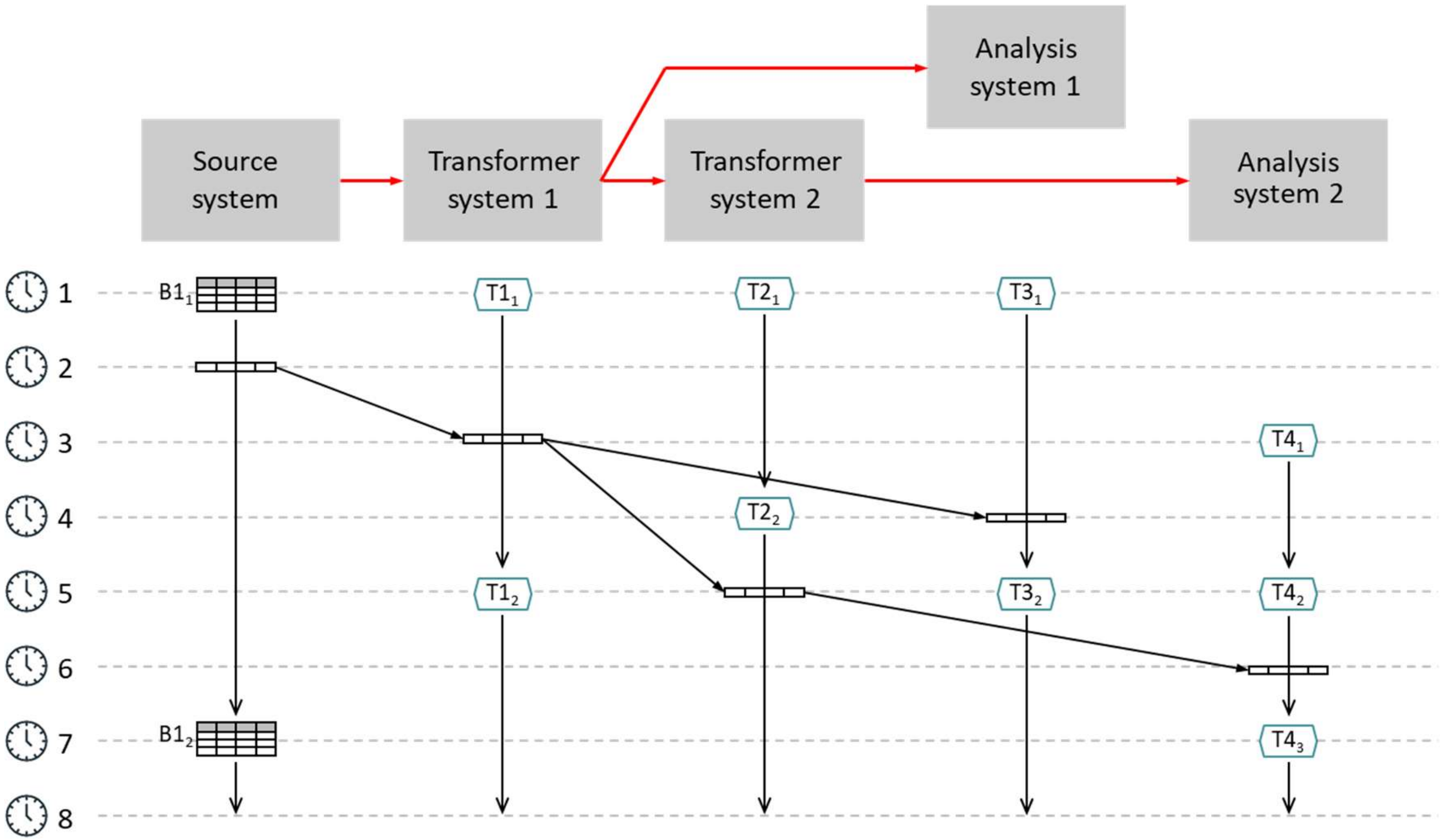
Operational Lineage (2) With Data Copies



Operational Lineage (3) Integration



Operational Lineage (4) Split



Master Data: Two Customer Tables

Customer table in **Sales** System

ID	Name	Initials	Date Entered	City	State
12345	Young	N	Aug 4, 2008	San Francisco	CA
23324	Stills	S	Sep 10, 2009	New Orleans	LA
57657	Furay	R	Oct 16, 2010	Yellow Springs	OH
65461	Palmer	B	Nov 22, 2011	Boston	MA
…	…	…	…	…	…

Customer table in **Finance** System

ID	Name	Initials	Date Entered	City	State
C5729	Young	N	Sep 16, 2007	San Francisco	CA
LA781	Stils	S	Dec 8, 2010	New Orleans	LA
J7301	Furay	R	Jan 10, 2008	Yellow Springs	OH
K8839	Palmer	B	Feb 11, 2009	New York	NY
…	…	…	…	…	…

The Master Customer Table

Master Customer table

ID	Version	Sales ID	Finance ID	Date Entered	Name	Initials	City	State
MD12	1	12345	C5729	Sep 16, 2007	Young	N	San Francisco	CA
MD13	1	23324	LA781	Sep 10, 2009	Stills	S	New Orleans	LA
MD14	1	57657	J7301	Jan 10, 2008	Furay	R	Yellow Springs	OH
MD15	1	65461	K8839	Feb 11, 2009	Palmer	B	New York	NY
MD15	2	65461	K8839	Nov 22, 2011	Palmer	B	Boston	MA
…	…	…	…	…	…	…	…	…

Joining Needs Master Data

Integrate

ID	Name	Initials	Date Entered	City	State
12345	Young	N	Aug 4, 2008	San Francisco	CA
23324	Stills	S	Sep 10, 2009	New Orleans	LA
57657	Furay	R	Oct 16, 2010	Yellow Springs	OH
65461	Palmer	B	Nov 22, 2011	Boston	MA
…	…	…	…	…	…

ID	Name	Initials	Date Entered	City	State
C5729	Young	N	Sep 16, 2007	San Francisco	CA
LA781	Stils	S	Dec 8, 2010	New Orleans	LA
J7301	Furay	R	Jan 10, 2008	Yellow Springs	OH
K8839	Palmer	B	Feb 11, 2009	New York	NY
…	…	…	…	…	…

ID	Version	Sales ID	Finance ID	Date Entered	Name	Initials	City	State
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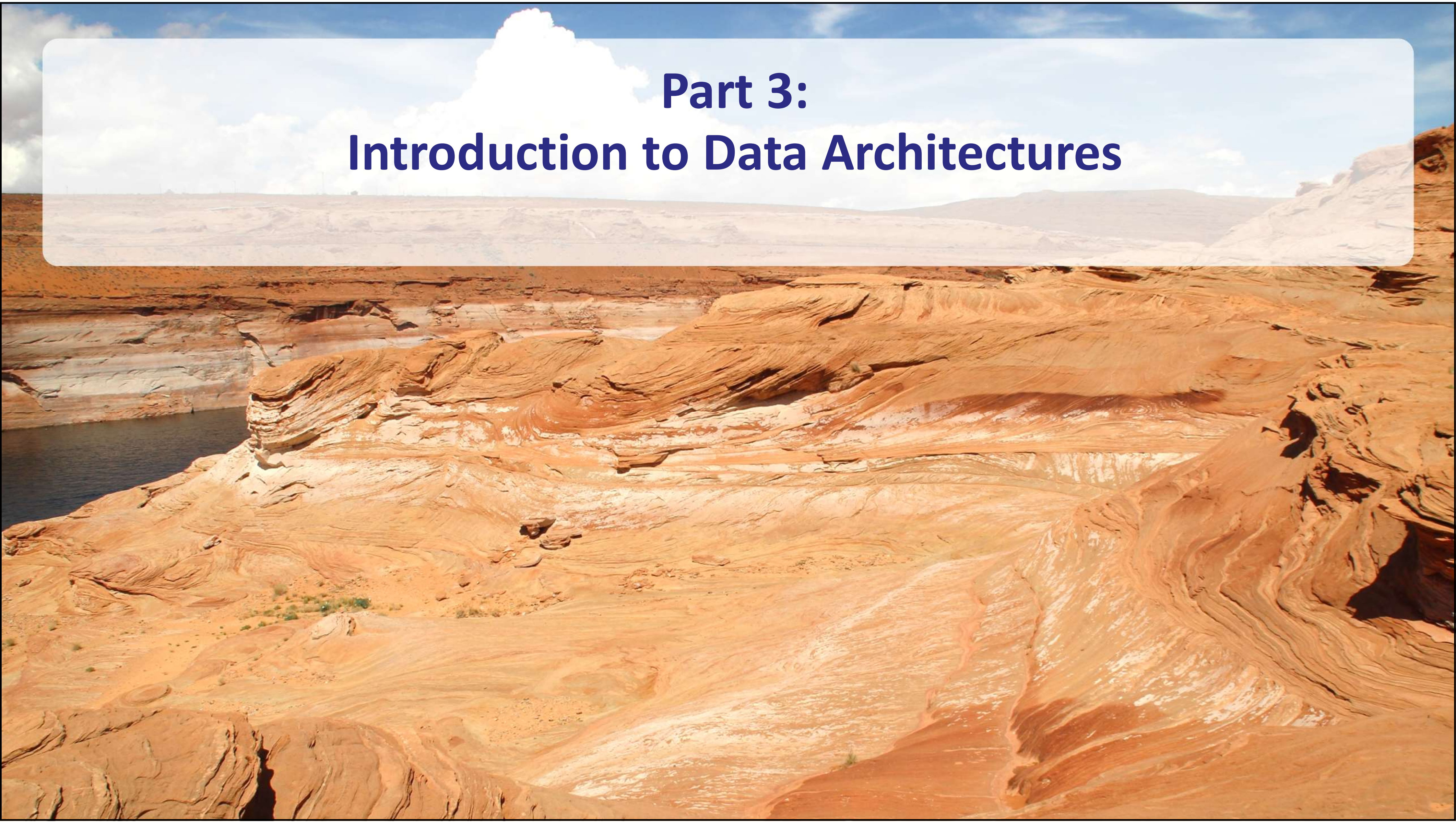
MD15	2	65461	K8839	Nov 22, 2011	Palmer	B	Boston	MA
…	…	…	…	…	…	…	…	…

Example: Cohelion (Master Data-driven BI)

Accounts Payable	30,809	35,972	37,370	37,668	37,346	33,360	34,141	42,505
Profit - Loss Accounts								
Gross profit	79,150	56,450	61,467	77,134				60,400
EBIT	11,327	-732	-1,247	11,101				-374
Sales Income	201,736	167,789	170,810	222,655	199,000	185,254	7,600	131,000
Rental Income	0	0	0	0	0	0	0	0
Other income	0	0	0	0	0	0	0	0
Expense Accounts								
Office Expense	812	681	790	532	960	372	1,010	455

Actual	**185,254.00**
Manual	20,248.00
SalesForce - Feed	30,855.00
SAP - Feed	134,151.00

Part 3:
Introduction to Data Architectures



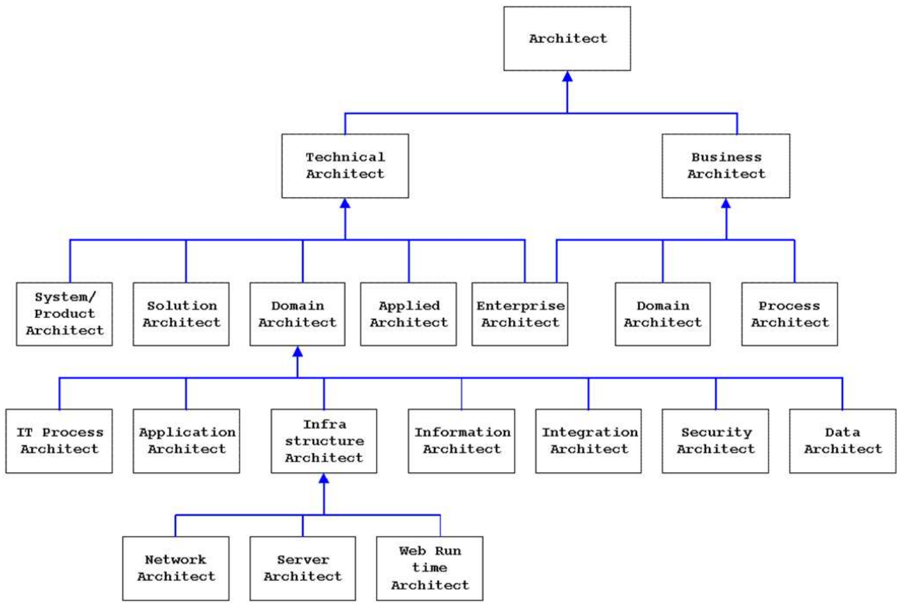
What is a Data Architecture?

- Wikipedia: A *data architecture* is composed of models, policies, rules or standards that govern which data is collected, and how it is stored, arranged, integrated, and put to use in data systems and in organizations.
- Examples of data architectures:
  - Data warehouse architecture
  - Data streaming architecture
  - Transactional system

Data Architects versus Solutions Architects

Data Architects	Solutions Architects
… focus on how information moves across the system from one application to another	… look at the overall technological environment of the company
… collaborate with clients to determine the specifications of the project, as well as the business goals that will align with the collected data	… meet with their clients and establish their specific technology needs based on their business objectives
… design the data model for the organization; where to store the customer data, how to retrieve the data; who can read the data	… has a more technical point of view. Do we select a cloud solution, or on premise? What will the network look like? How will everything be connected without failures?

So Many Different Types of Architects



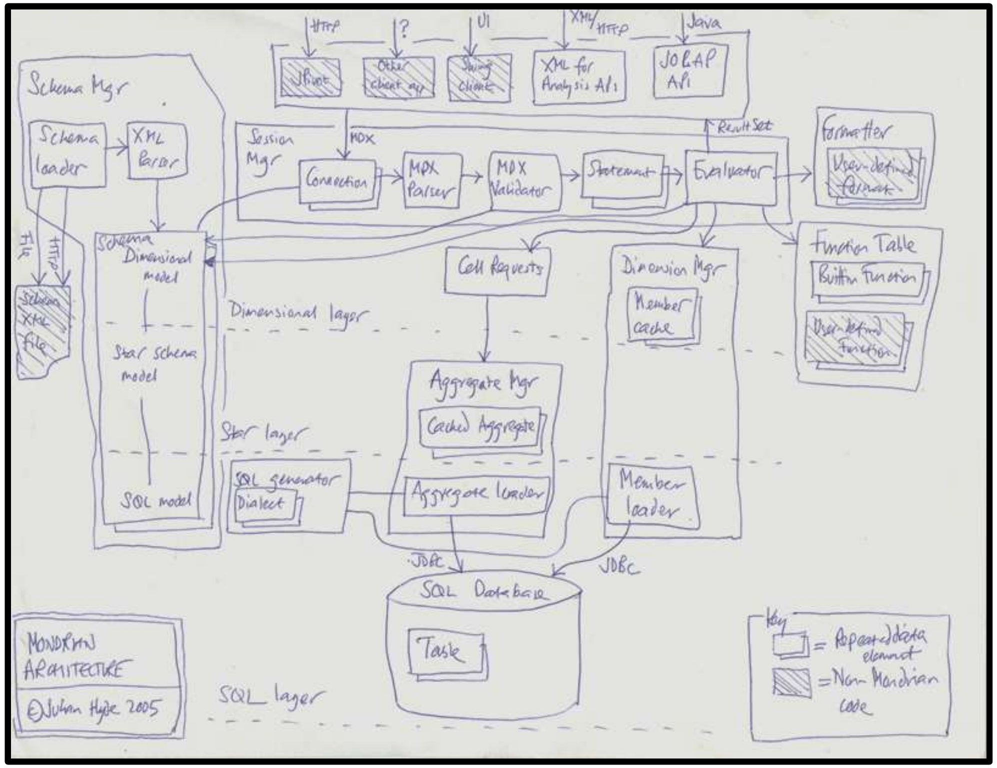
Paul Catalin Tomoiu : In [the] IT world, an architect is a person with enough knowledge to find a high level solution to a challenge in an IT environment.

The challenge type, defines the nature of the architecture role.

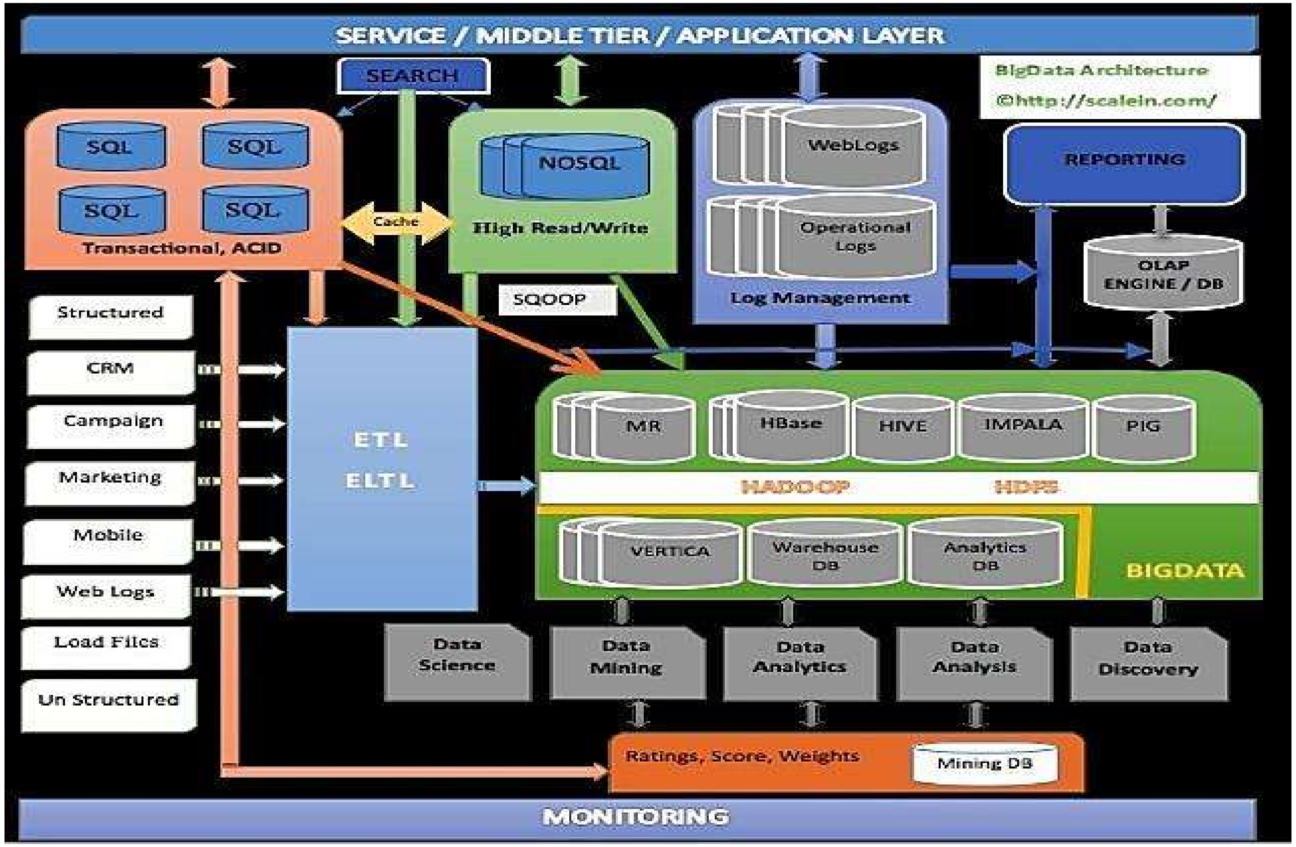
We can speak about an Enterprise Architecture, a Business Architecture, Data Architecture, Solution Architecture, IT Technical Architecture, Application Architecture, Software Architecture, Security Architecture, etc.

Source: https://blog.prabasiva.com/2008/08/21/different-types-of-architects/

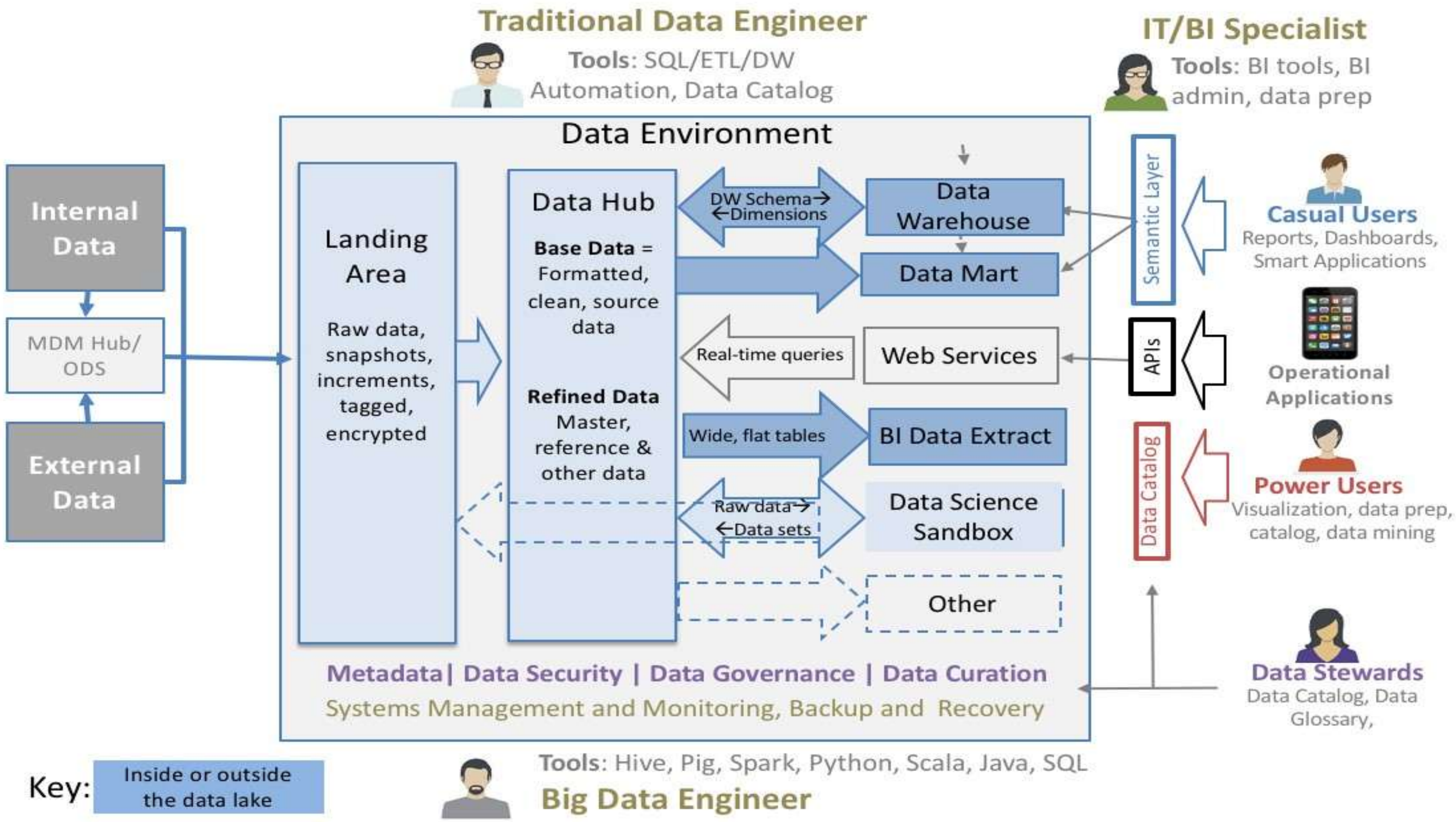
The Birth of a Data Architecture



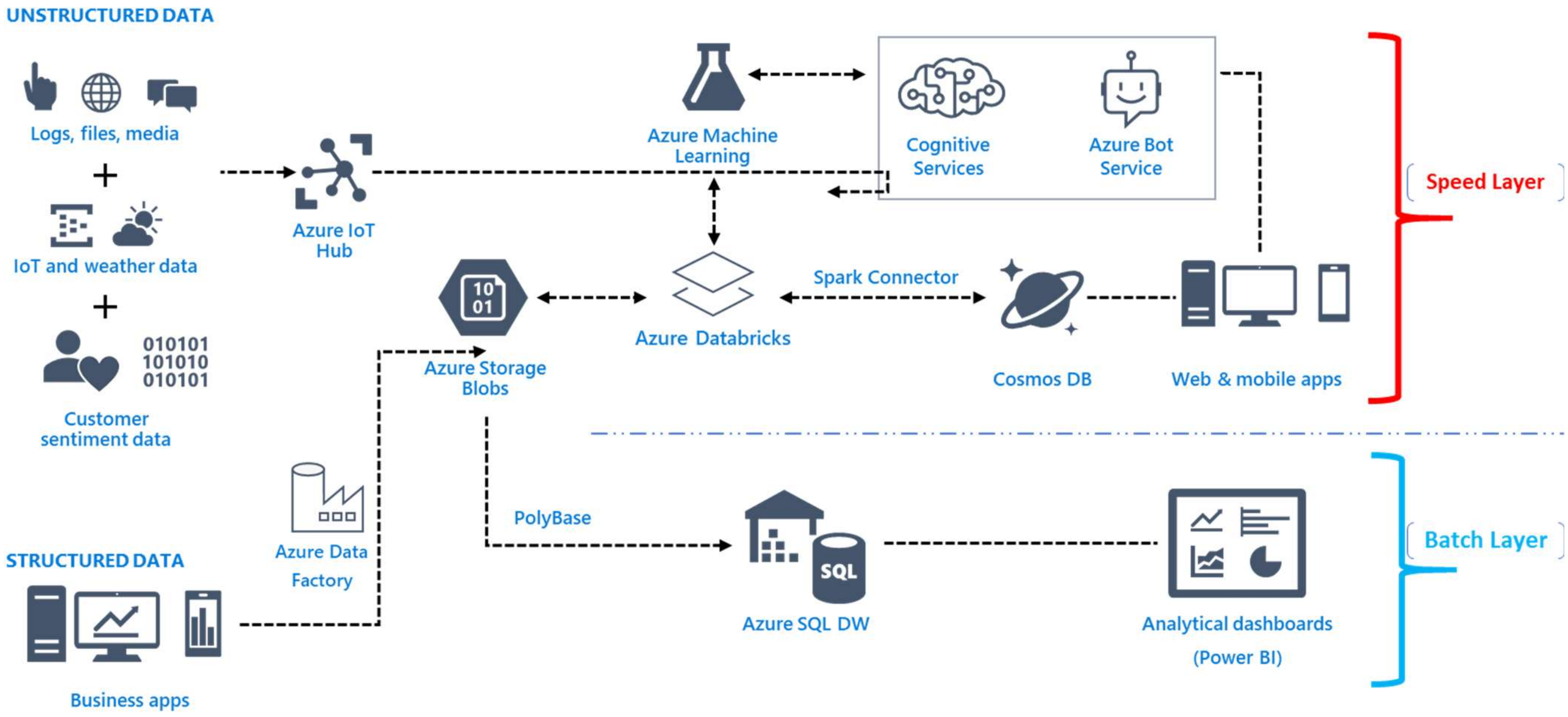
Example Data Architecture (1)



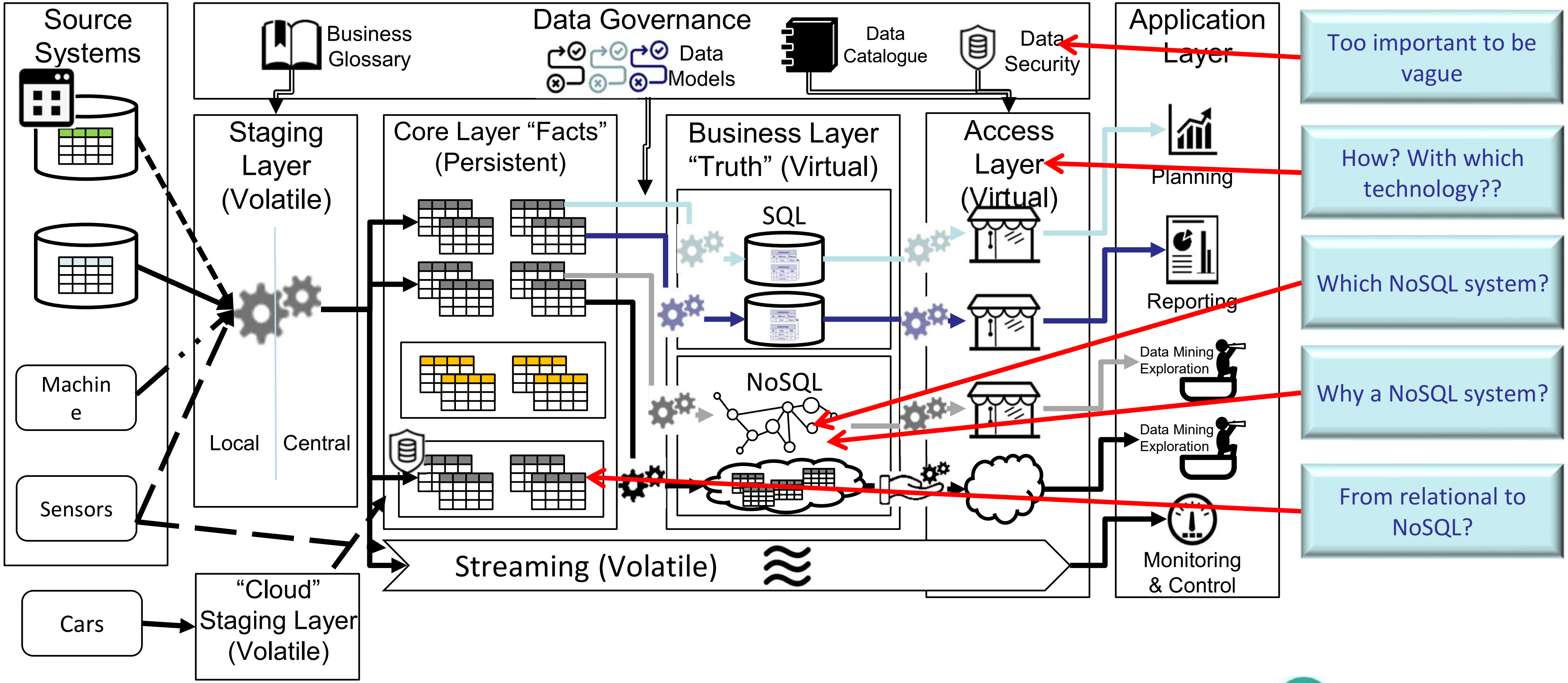
Example Data Architecture (2)



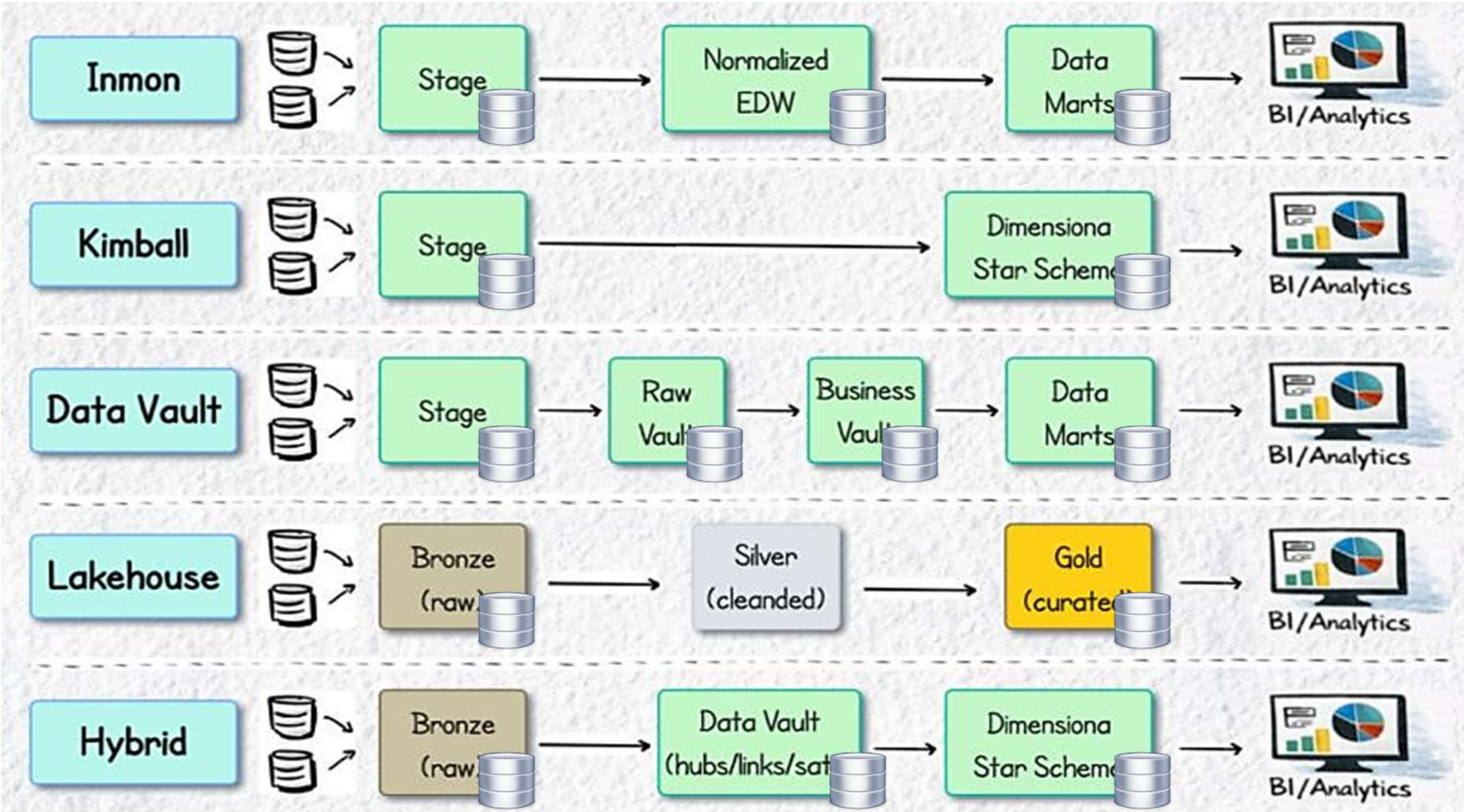
Example Data Architecture (3)



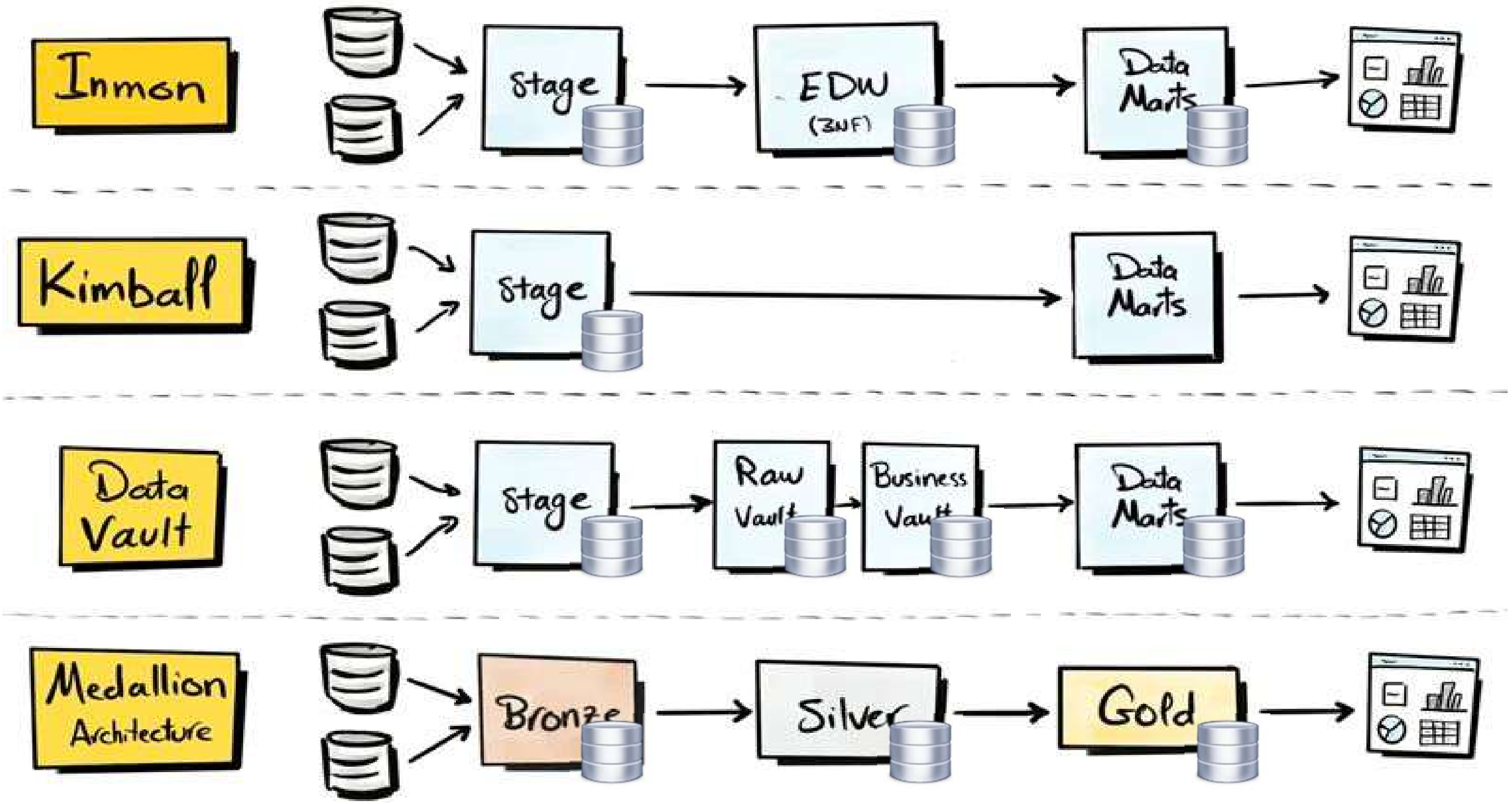
Example Data Architecture (4)



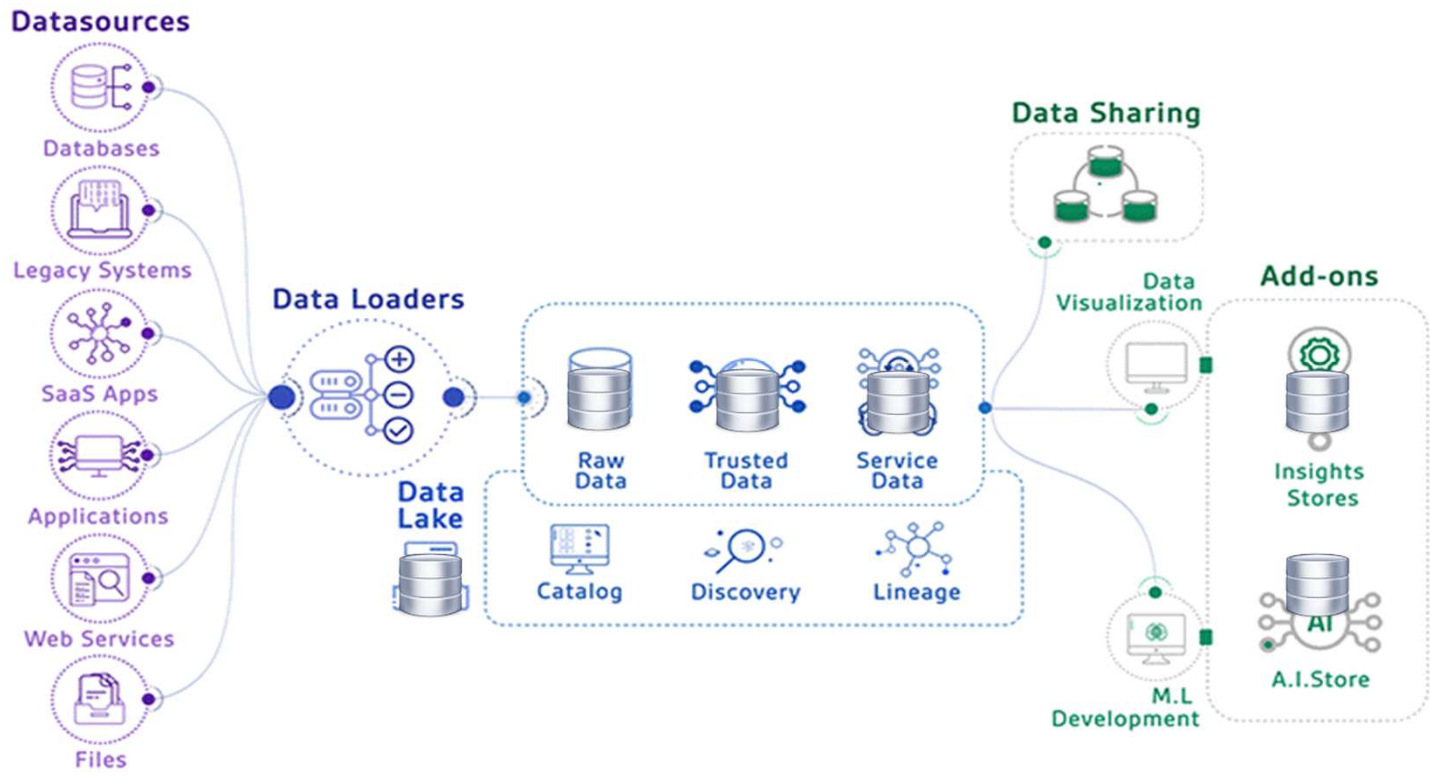
Data-copy Rich, Partial Data Architectures (1)



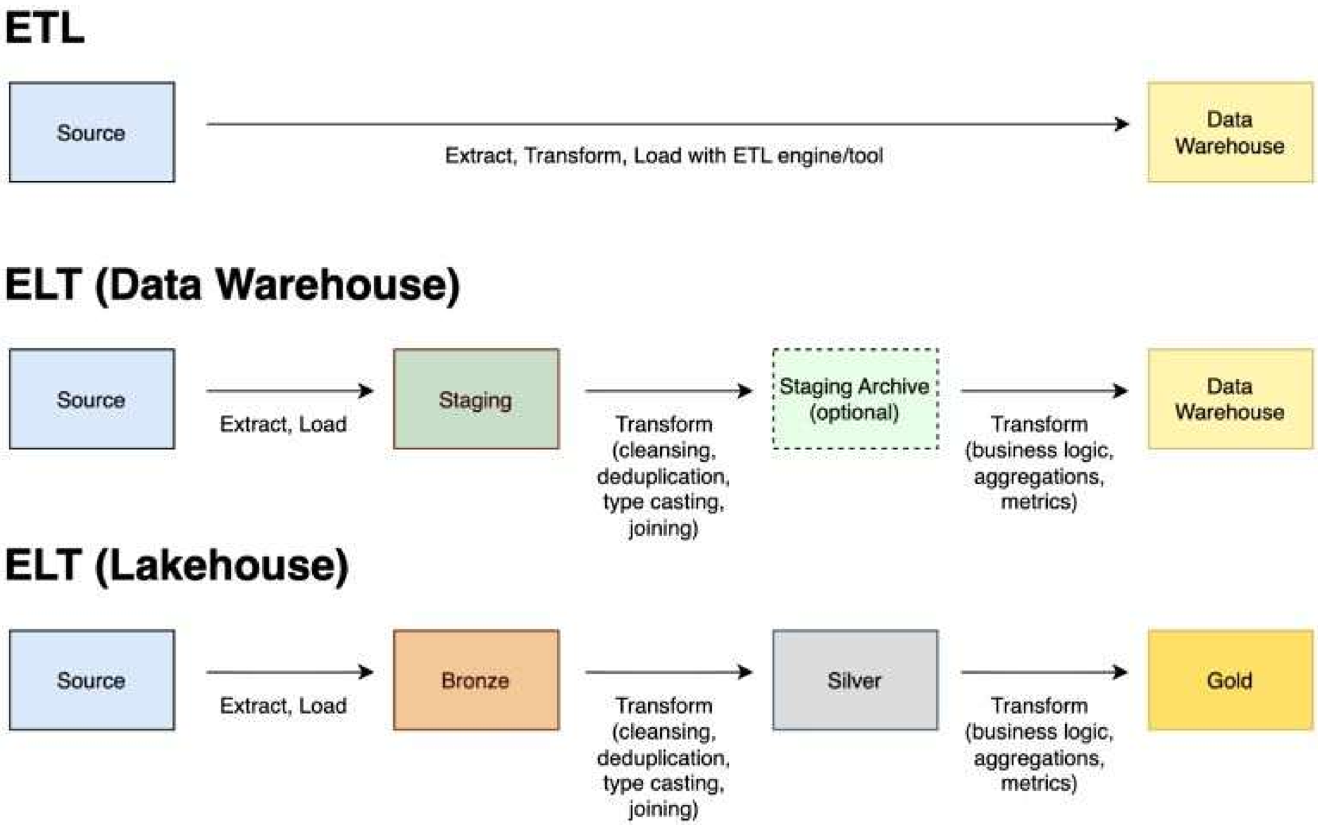
Data-copy Rich, Partial Data Architectures (2)



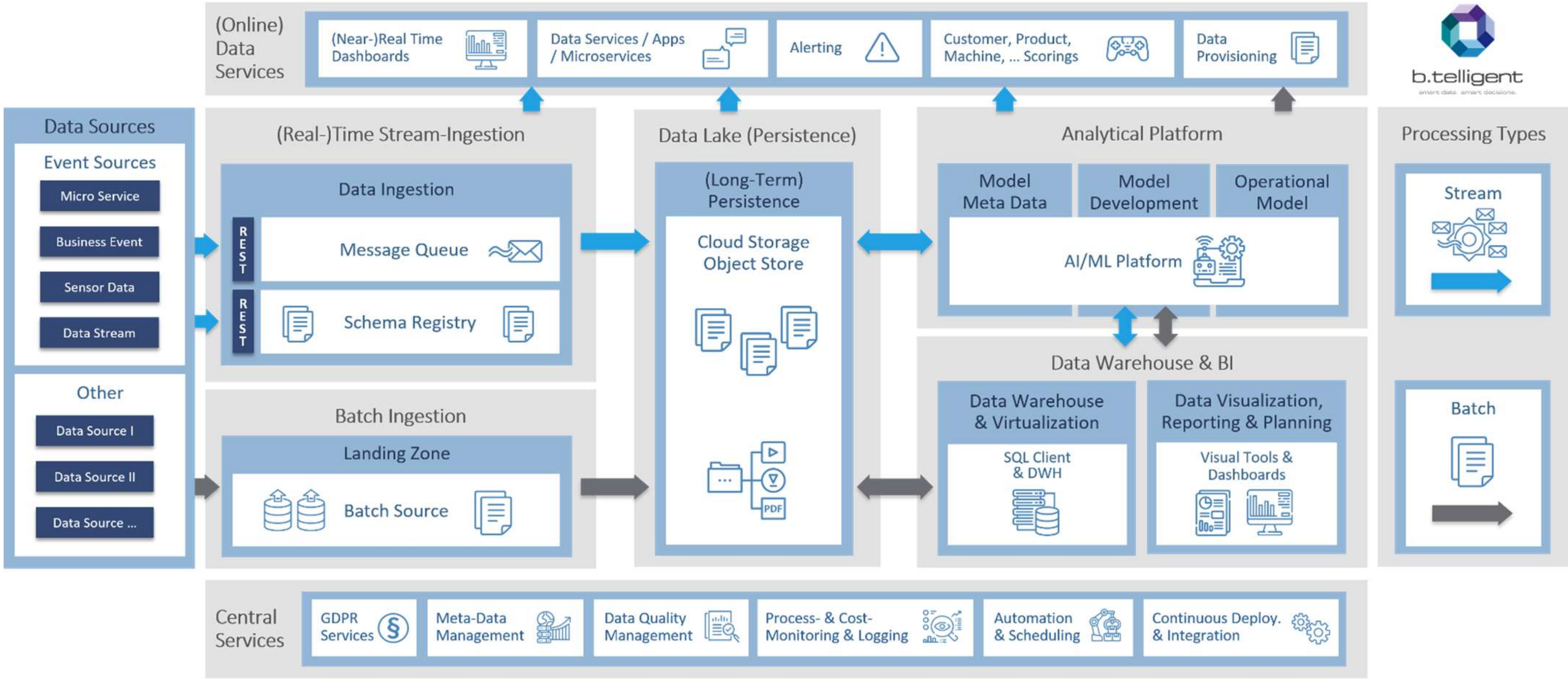
Data-copy Rich, Partial Data Architectures (3)



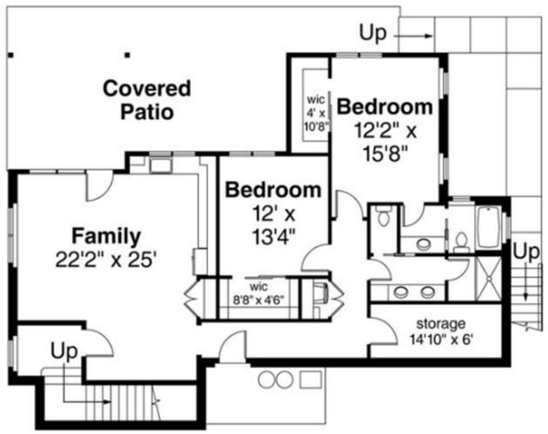
Data-copy Rich, Partial Data Architectures (4)

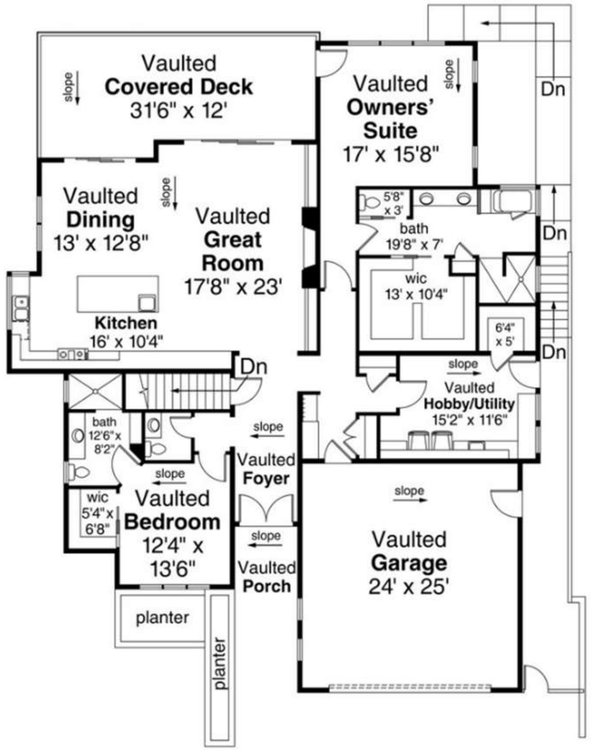


Data-copy Rich Data Architectures



Architecture of a House





Architecture of a House (IT Style)

Electricity | Internet | Water drainage | Water supply

Community rooms
- Living room
- Dining room

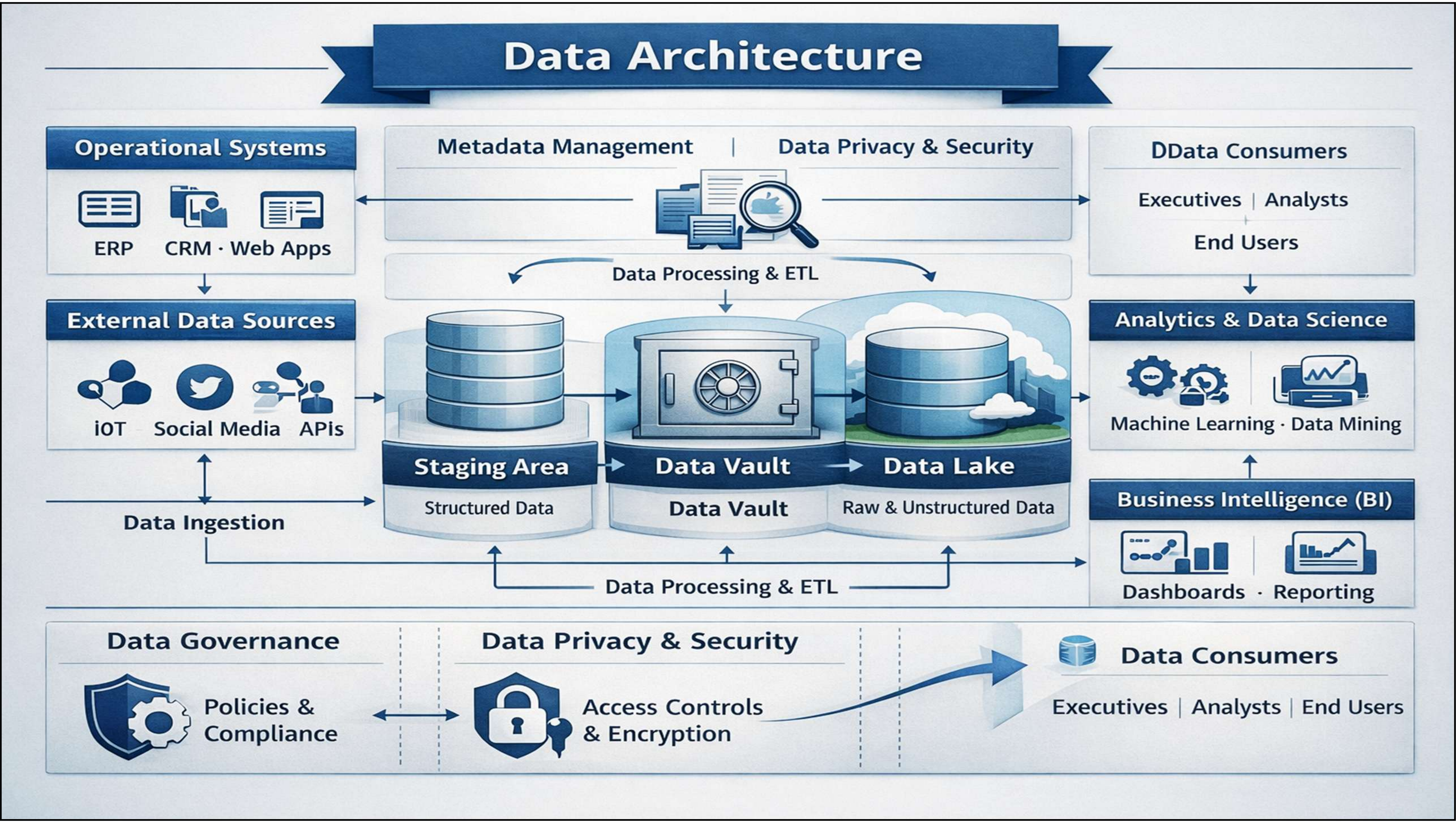
Sleeping rooms
- Parents room
- Children's rooms

Wet rooms
- Restrooms
- Bathroom
- Kitchen

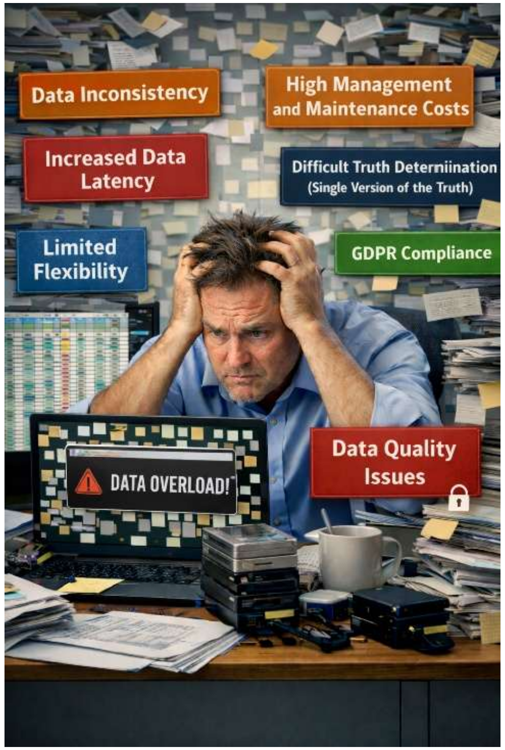
Storage rooms
- Garage
- Walk-in closet
- Basement

Relaxation rooms
- Private film theater
- Front garden
- Back garden

Connector rooms
- Stairs
- Hallway
- Corridors


Data Architecture
Operational Systems
ERP
CRM · Web Apps
Metadata Management
Data Privacy & Security
DData Consumers
Executives
Analysts
End Users
Data Processing & ETL
External Data Sources
iOT
Social Media
APIs
Staging Area
Structured Data
Data Vault
Data Vault
Data Lake
Raw & Unstructured Data
Analytics & Data Science
Machine Learning · Data Mining
Business Intelligence (BI)
Dashboards · Reporting
Data Ingestion
Data Processing & ETL
Data Governance
Policies & Compliance
Data Privacy & Security
Access Controls & Encryption
Data Consumers
Executives
Analysts
End Users

Disadvantages of Data Copying



- Data inconsistency
- Difficult determination of the truth ("single version of the truth")
- Limited flexibility and agility
- High management, development, and maintenance costs
- More complex compliance with General Data Protection Regulation (GDPR)
- Complex data synchronization issues
- Data quality challenges
- More complex data security
- Outdated data (increased data latency)
- …

Patients Suffering From:

Acute Copying Urge Disorder

Pathological Data Accumulation Disorder

Excessive Digital Reproduction Condition

Type II Redundancy Syndrome

Post-Storage Compulsive Replication

Duplicitis Chronica

What Comes First?

Data Architecture

Products / Technology

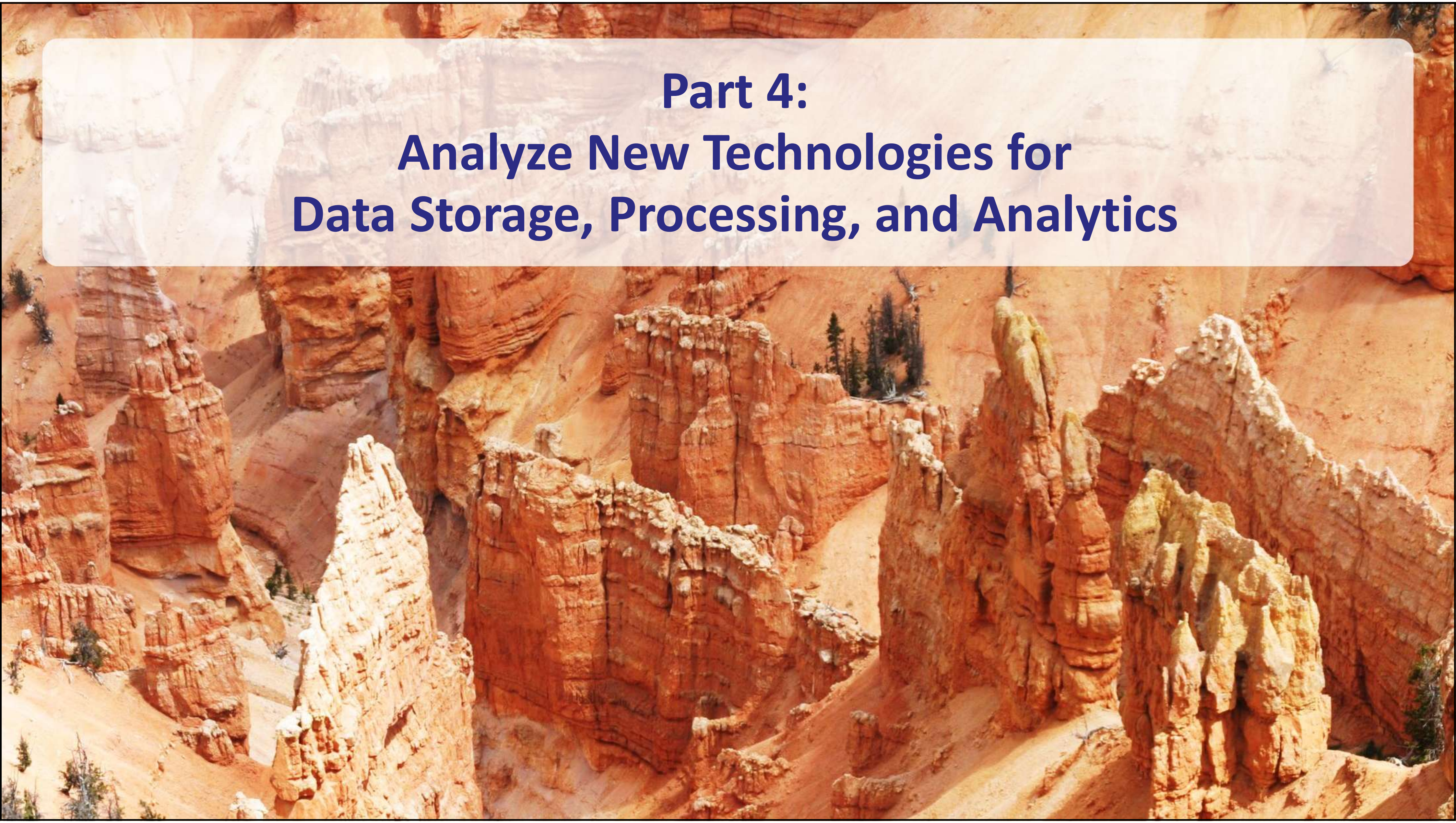
Products / Technology

Data Architecture

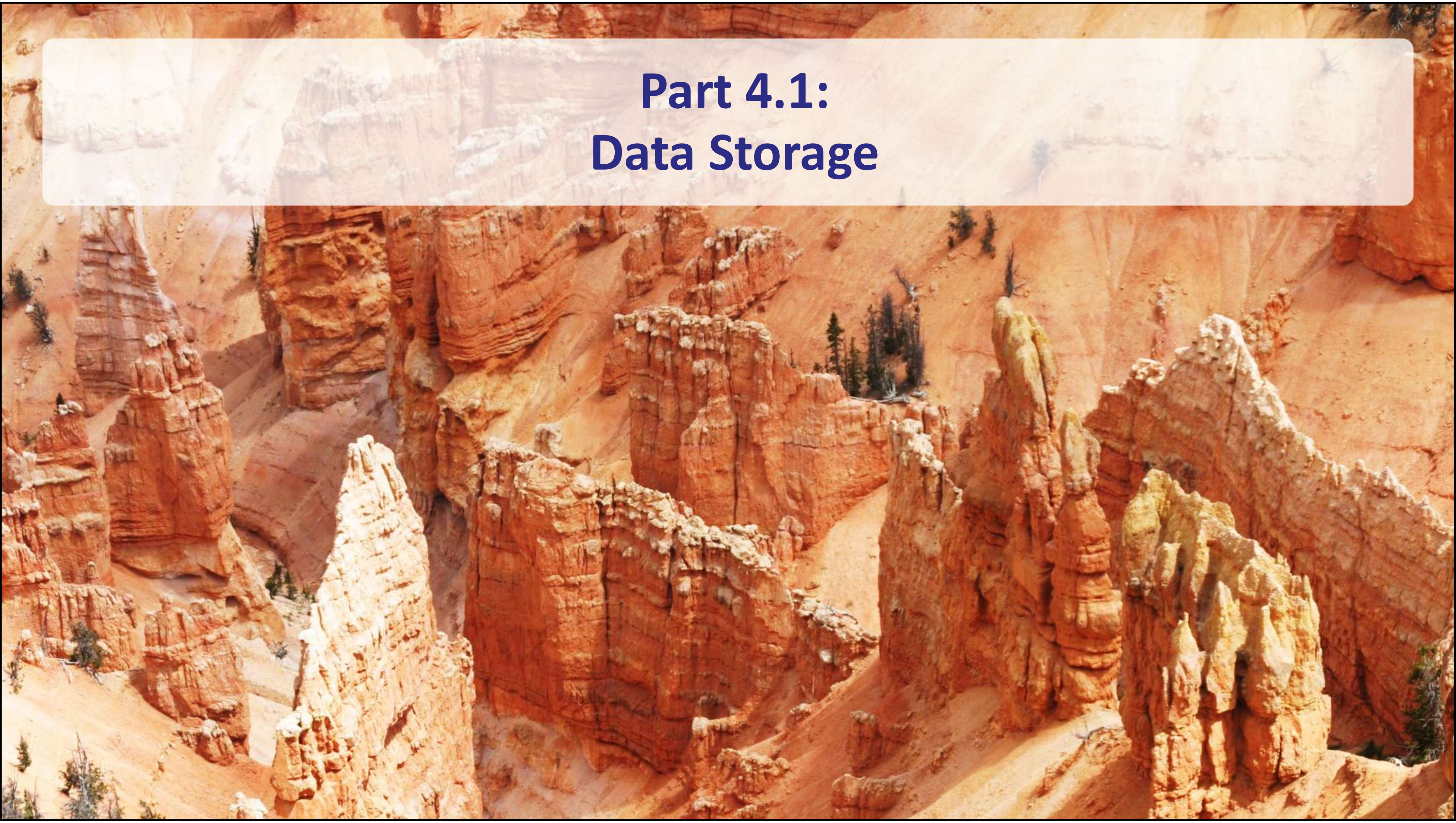
Roadmap for Designing Data Architectures

1. Determine business motivations
2. Determine new requirements
3. Analyze the existing environment
4. Define architectureal design principles
5. Selecta reference data architecture
6. Desogn the new data architecture
7. Determine the implementation approach
8. Select new products and technologies
9. Introduce the data architecture within the organization

Part 4:
Analyze New Technologies for Data Storage, Processing, and Analytics

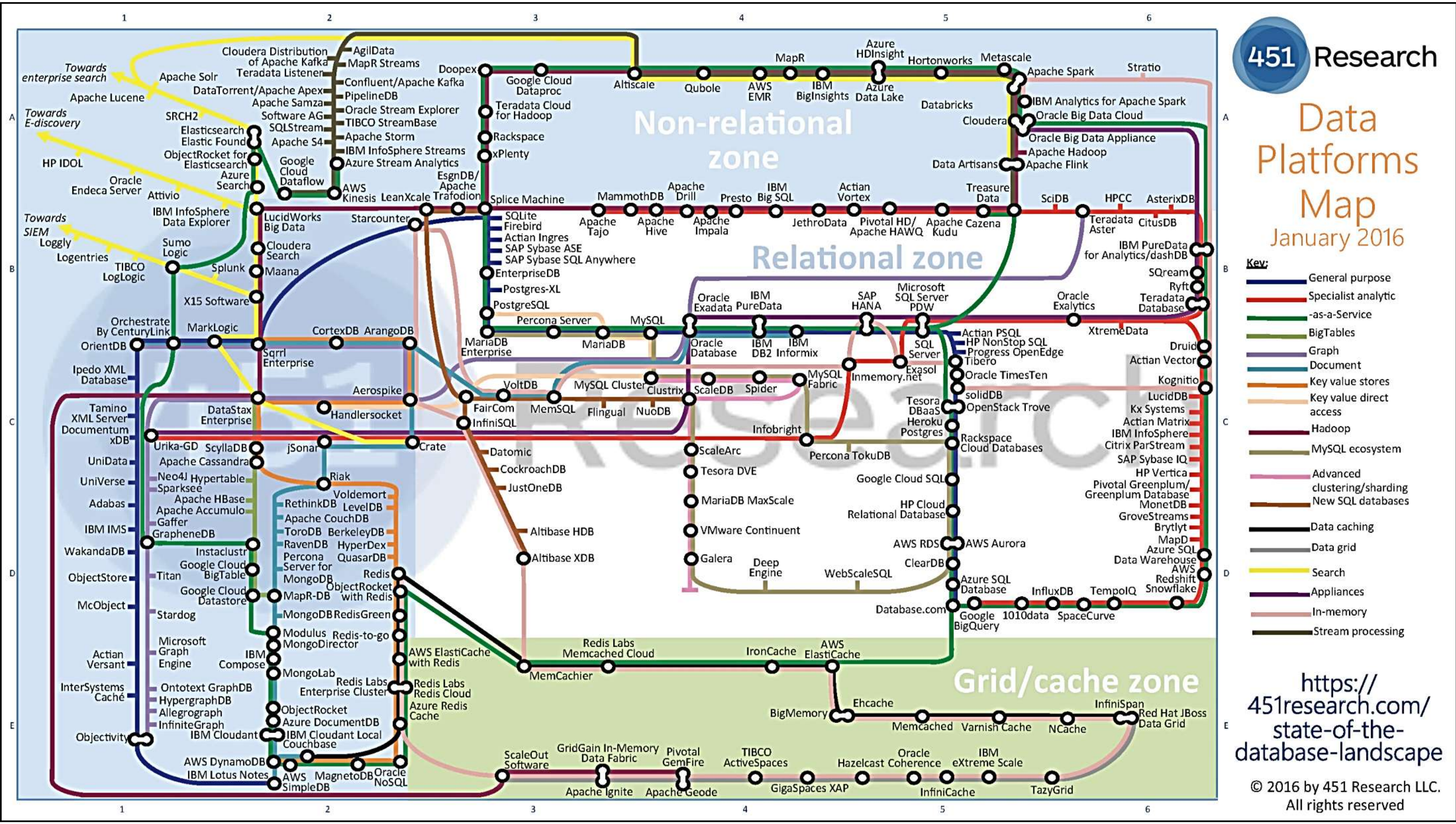


Part 4.1:
Data Storage



Trends in Database Market

- More data, more queries, more transactions, more concurrent users, more complex queries, …
- Coming and going of products
- Less standards
  - Less portability
- No interchangeable products
- Specialization of products
  - Limited use cases


451 Research
Data Platforms Map
January 2016
Non-relational zone
Relational zone
Grid/cache zone
Towards enterprise search
Towards E-discovery
Towards SIEM
Apache Solr
Apache Lucene
SRCH2
HP IDOL
Oracle Endeca Server
Attivio
Elasticsearch
Elastic Found
ObjectRocket for Elasticsearch
Azure Search
Google Cloud Dataflow
AWS Kinesis
LeanXcale
EsgnDB/ Apache Trafodion
Splice Machine
Cloudera Distribution of Apache Kafka
Teradata Listener
DataTorrent/Apache Apex
Apache Samza
Software AG
SQLStream
Apache S4
AgilData
MapR Streams
Confluent/Apache Kafka
PipelineDB
Oracle Stream Explorer
TIBCO StreamBase
Apache Storm
IBM InfoSphere Streams
Azure Stream Analytics
Doopex
Google Cloud Dataproc
Teradata Cloud for Hadoop
Rackspace
xPlenty
Altiscale
Qubole
AWS EMR
MapR
IBM BigInsights
Azure HDInsight
Azure Data Lake
Hortonworks
Metascale
Databricks
Cloudera
Apache Spark
Stratio
IBM Analytics for Apache Spark
Oracle Big Data Cloud
Oracle Big Data Appliance
Apache Hadoop
Apache Flink
Data Artisans
Treasure Data
MammothDB
Apache Drill
Presto
IBM Big SQL
Actian Vortex
Apache Tajo
Apache Hive
Apache Impala
JethroData
Pivotal HD/ Apache HAWQ
Apache Kudu
Cazena
SciDB
HPCC
AsterixDB
Teradata Aster
CitusDB
IBM PureData for Analytics/dashDB
SQream
Ryft
Teradata Database
Oracle Exalytics
XtremeData
IBM InfoSphere Data Explorer
Loggly
Logentries
Sumo Logic
TIBCO LogLogic
Splunk
X15 Software
LucidWorks Big Data
Cloudera Search
Maana
Starcounter
SQLite
Firebird
Actian Ingres
SAP Sybase ASE
SAP Sybase SQL Anywhere
EnterpriseDB
Postgres-XL
PostgreSQL
Percona Server
MySQL
MariaDB Enterprise
MariaDB
Oracle Exadata
IBM PureData
SAP HANA
Microsoft SQL Server PDW
Oracle Database
IBM DB2
IBM Informix
SQL Server
Actian PSQL
HP NonStop SQL
Progress OpenEdge
Tibero
Oracle TimesTen
Exasol
Inmemory.net
Orchestrate By CenturyLink
MarkLogic
OrientDB
CortexDB
ArangoDB
Sqrrl Enterprise
Ipedo XML Database
Aerospike
Tamino XML Server
Documentum xDB
DataStax Enterprise
Handlersocket
FairCom
InfiniSQL
VoltDB
MemSQL
MySQL Cluster
Clustrix
Flingual
NuoDB
ScaleDB
Spider
MySQL Fabric
Infobright
Percona TokuDB
ScaleArc
Tesora DVE
MariaDB MaxScale
VMware Continuent
Galera
Deep Engine
WebScaleSQL
Crate
jSonar
Urika-GD
ScyllaDB
Apache Cassandra
UniData
UniVerse
Adabas
IBM IMS
WakandaDB
ObjectStore
McObject
Actian Versant
InterSystems Caché
Objectivity
Neo4J
Hypertable
Sparksee
Apache HBase
Apache Accumulo
Gaffer
GrapheneDB
Instaclustr
Titan
Google Cloud BigTable
Google Cloud Datastore
Stardog
Microsoft Graph Engine
IBM Compose
Ontotext GraphDB
HypergraphDB
Allegrograph
InfiniteGraph
IBM Cloudant
AWS DynamoDB
IBM Lotus Notes
AWS SimpleDB
MagnetoDB
Oracle NoSQL
Riak
Voldemort
RethinkDB
LevelDB
Apache CouchDB
ToroDB
BerkeleyDB
RavenDB
HyperDex
Percona Server for MongoDB
QuasarDB
Redis
ObjectRocket with Redis
MapR-DB
MongoDB
RedisGreen
Modulus
Redis-to-go
MongoDirector
MongoLab
Redis Labs Enterprise Cluster
ObjectRocket
Azure DocumentDB
IBM Cloudant Local
Couchbase
Datomic
CockroachDB
JustOneDB
Altibase HDB
Altibase XDB
solidDB
Tesora DBaaS
OpenStack Trove
Heroku Postgres
Rackspace Cloud Databases
Google Cloud SQL
HP Cloud Relational Database
AWS RDS
AWS Aurora
ClearDB
Azure SQL Database
Database.com
Google BigQuery
1010data
InfluxDB
SpaceCurve
TempoIQ
Snowflake
AWS Redshift
Azure SQL Data Warehouse
MapD
Brytlyt
GroveStreams
MonetDB
Pivotal Greenplum/ Greenplum Database
HP Vertica
SAP Sybase IQ
Citrix ParStream
IBM InfoSphere
Actian Matrix
Kx Systems
LucidDB
Kognitio
Actian Vector
Druid
AWS ElastiCache with Redis
Redis Labs Redis Cloud
Azure Redis Cache
MemCachier
Redis Labs Memcached Cloud
IronCache
AWS ElastiCache
BigMemory
Ehcache
Memcached
Varnish Cache
NCache
InfiniSpan
Red Hat JBoss Data Grid
ScaleOut Software
GridGain In-Memory Data Fabric
Apache Ignite
Pivotal GemFire
Apache Geode
TIBCO ActiveSpaces
GigaSpaces XAP
Hazelcast
Oracle Coherence
InfiniCache
IBM eXtreme Scale
TazyGrid
Key:
General purpose
Specialist analytic
-as-a-Service
BigTables
Graph
Document
Key value stores
Key value direct access
Hadoop
MySQL ecosystem
Advanced clustering/sharding
New SQL databases
Data caching
Data grid
Search
Appliances
In-memory
Stream processing
https://451research.com/state-of-the-database-landscape
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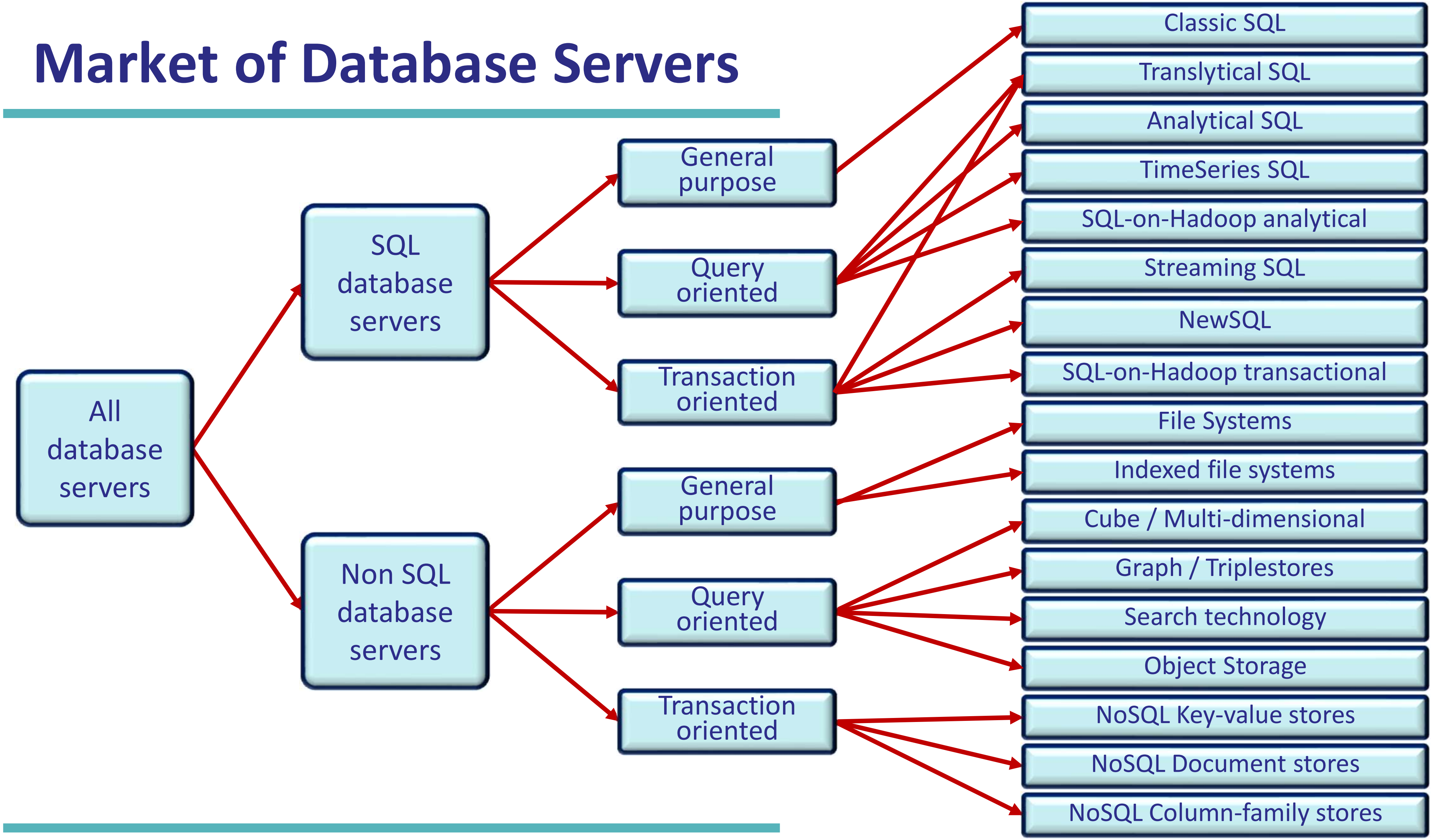
Market of Database Servers



Specialization of Cars

Database Technology has Changed

Generic Database Solutions

↓

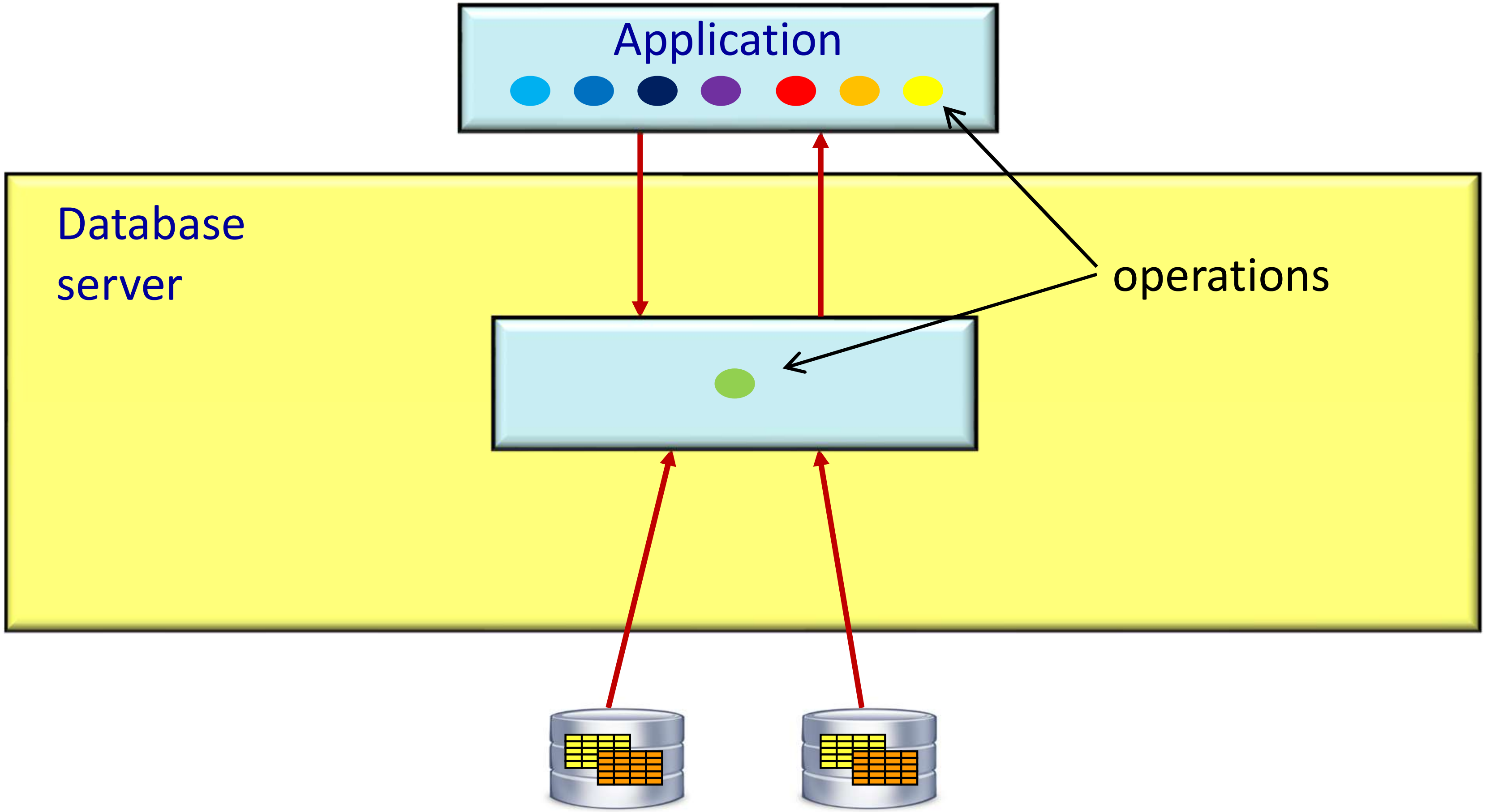
Specialized Database Solutions

Use Case Agnostic

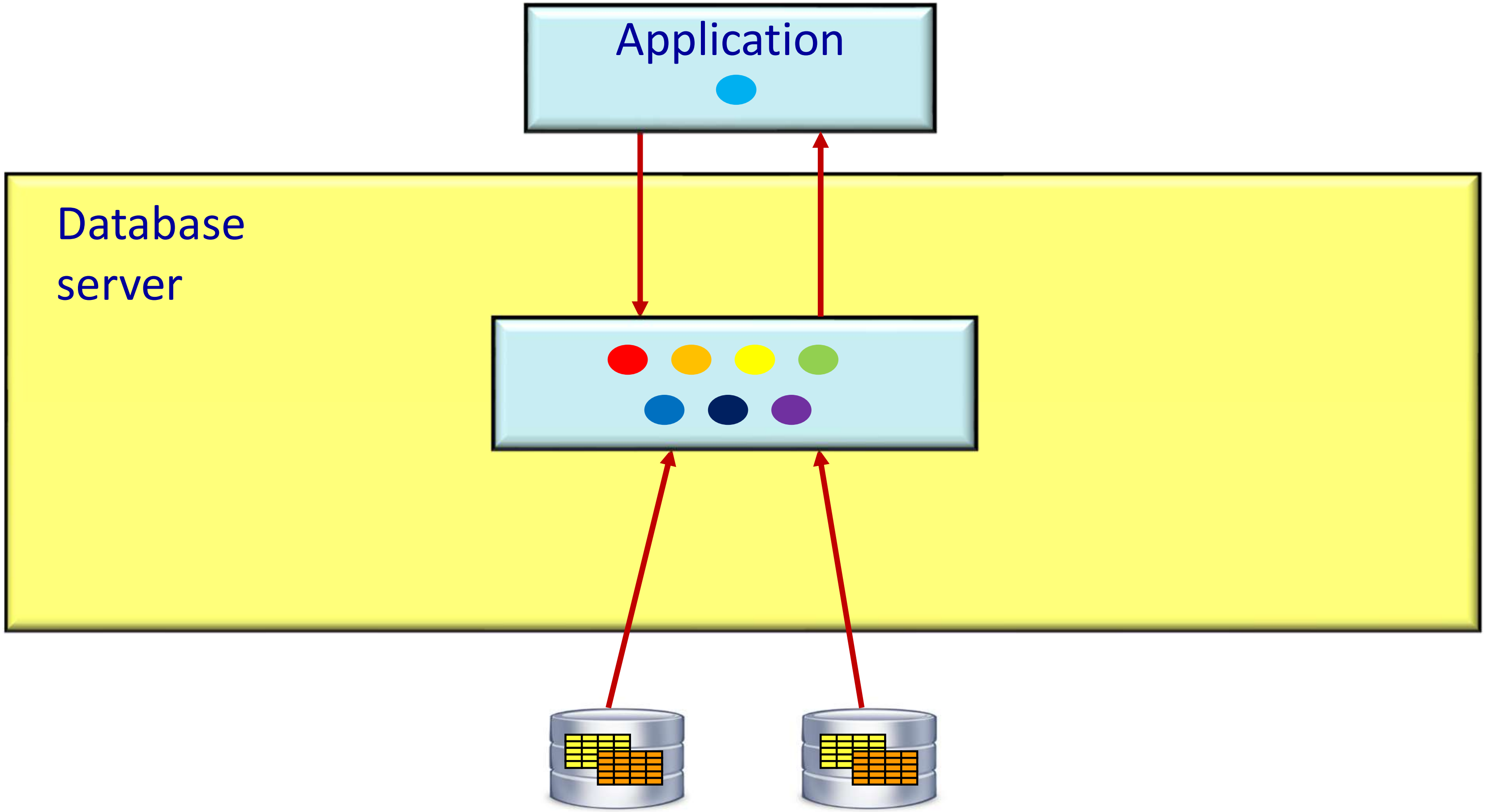
↓

Use Case Specific

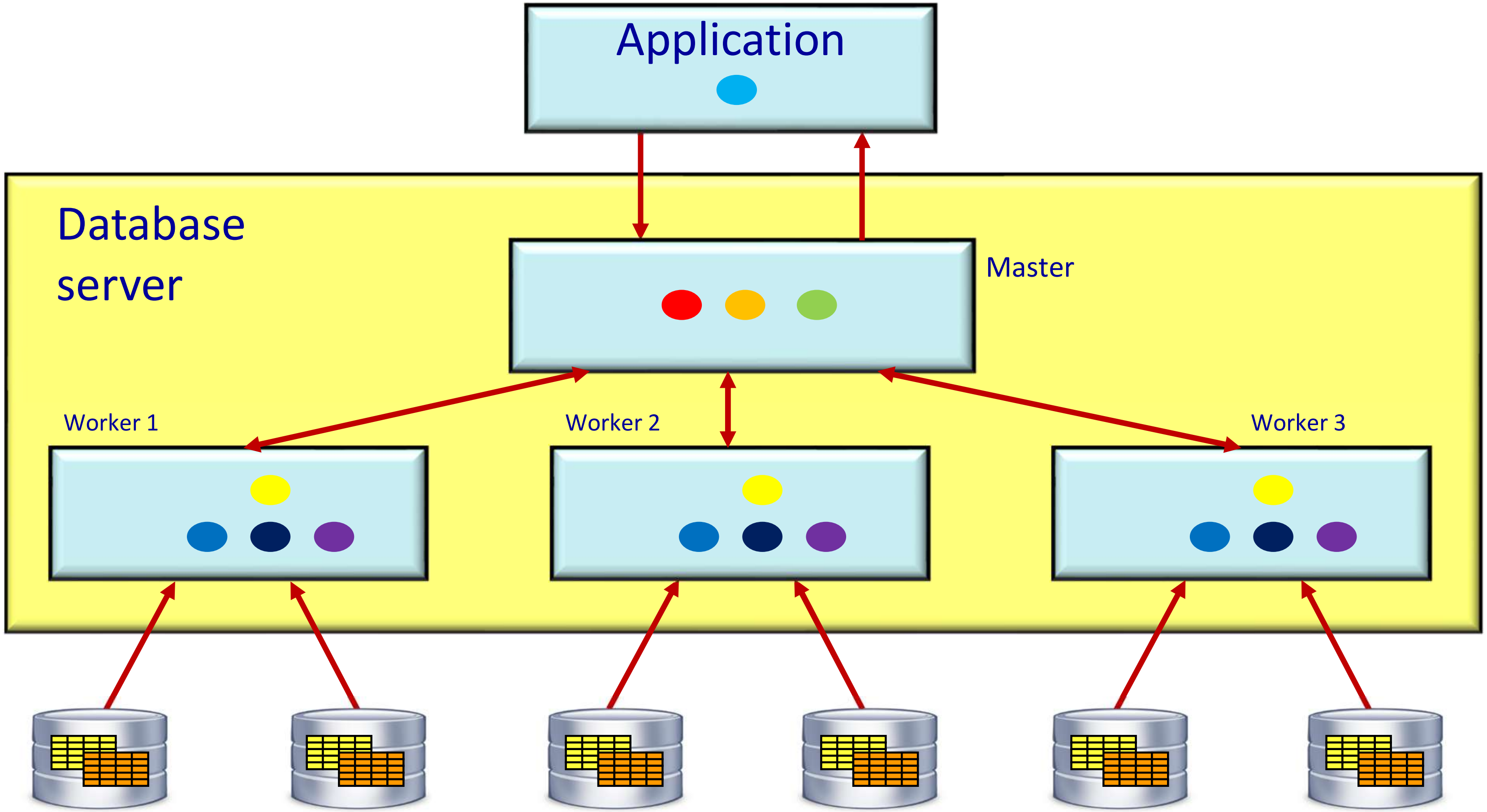
Application-based Analytics



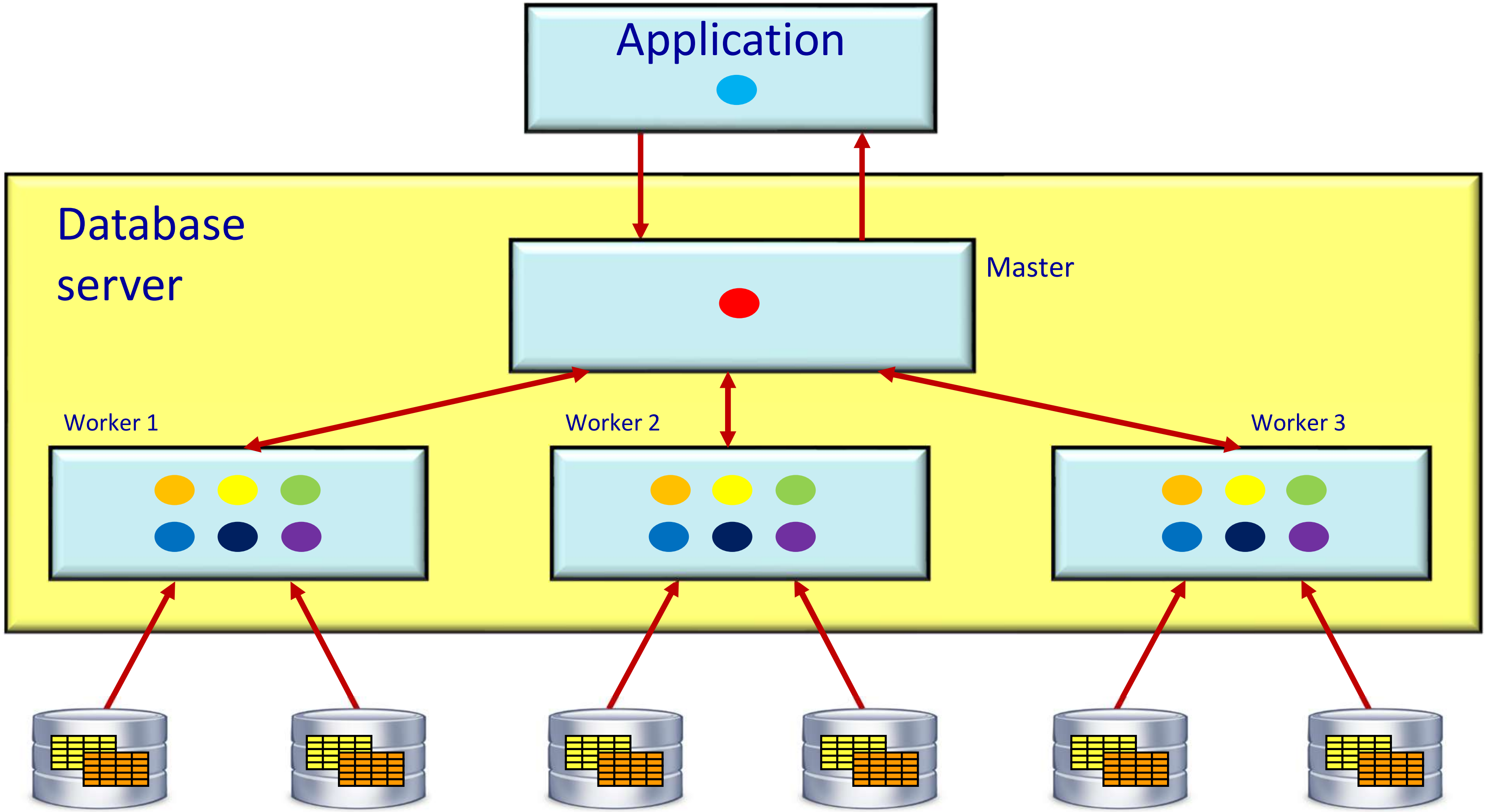
In-Database Analytics



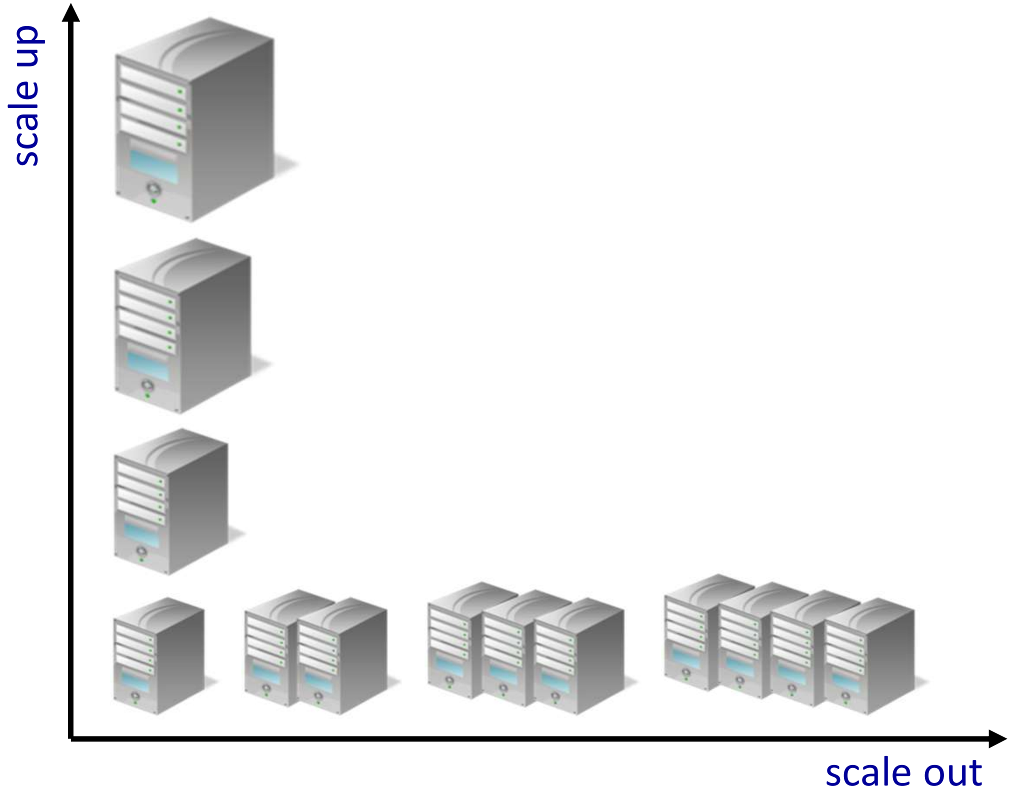
Partial Parallel Analytics



Full Parallel Analytics

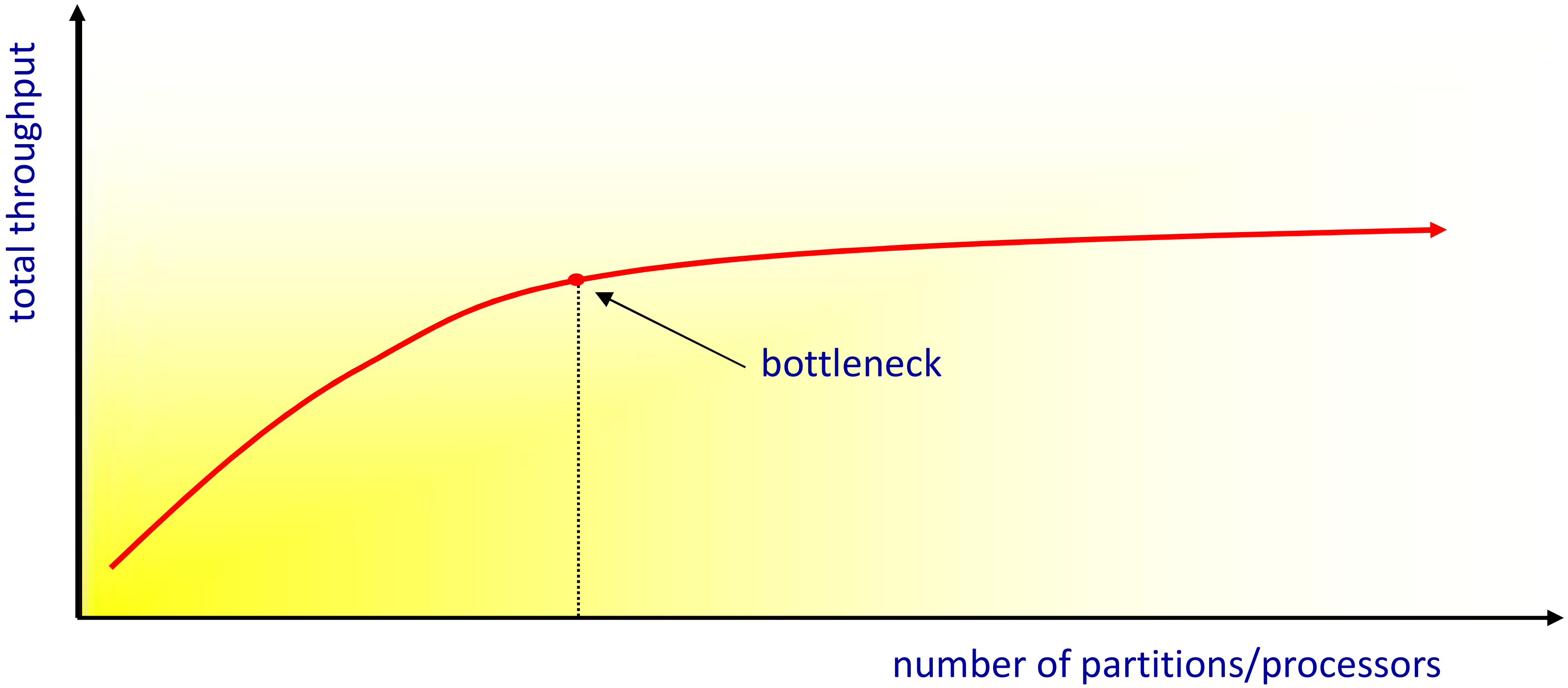


Scale Up versus Scale Out



- Scale up (vertical scaling) means adding more resources to one node in a system
- Scale out (horizontal scaling) means adding more nodes to a system
  - Continuous availability/redundancy
  - Cost/performance flexibility
  - Contiguous upgrades
  - Geographical distribution

Effect of Partitions on Query Response



NoSQL Database Servers

APACHE HBASE

mongoDB

redis

Cassandra

Google BigTable

Azure Cosmos DB

CouchDB relax

LevelDB

RAVENDB

riak

UpscaleDB

Couchbase

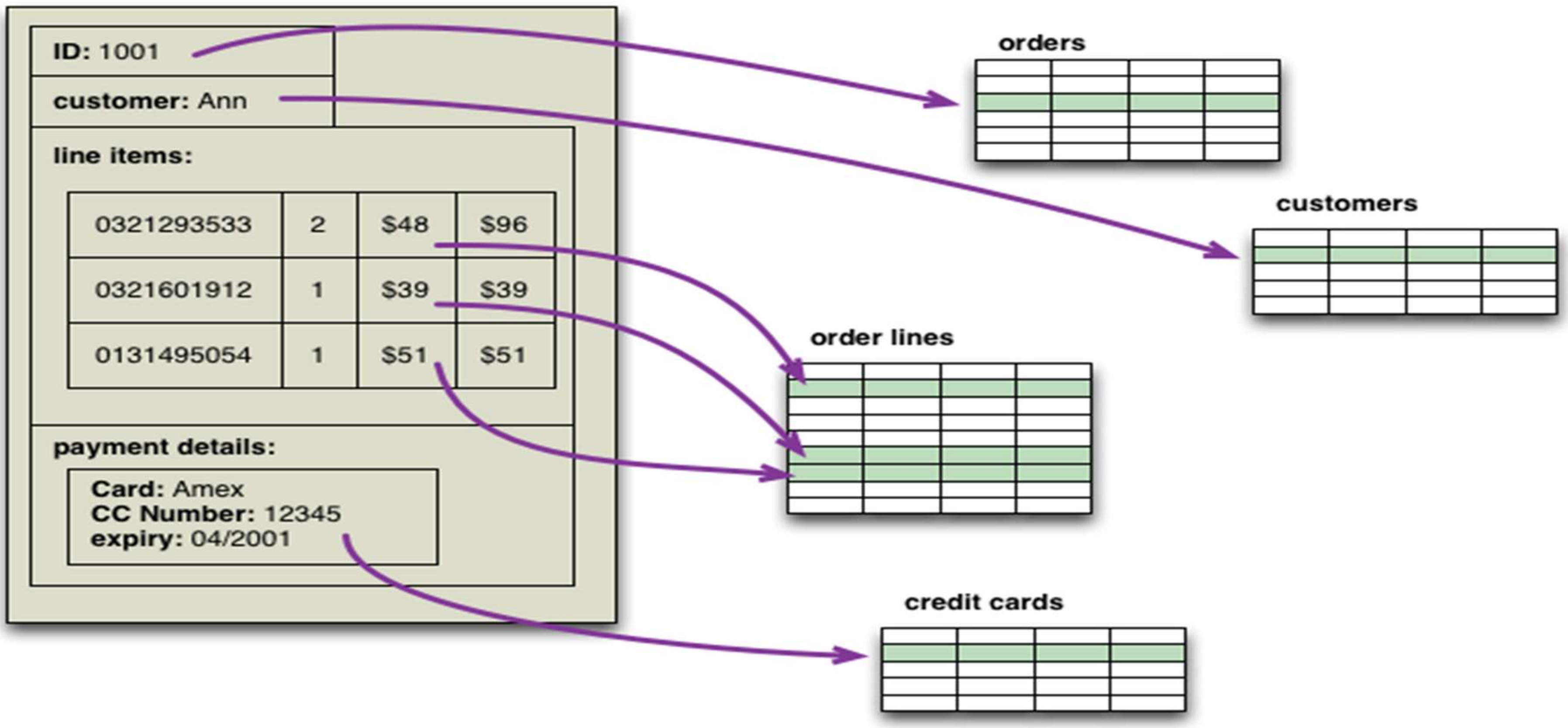
HYPERTABLE

memCached

Tricks to Improve Performance

- Aggregate data model
  - To remove the impedance mismatch
- Design architecture to scale-out
  - Sharding
- Reduce functionality (security, query power, data integrity, …)
- Lower consistency
- Give developers full control over internal processing
- “Push down” complex operations

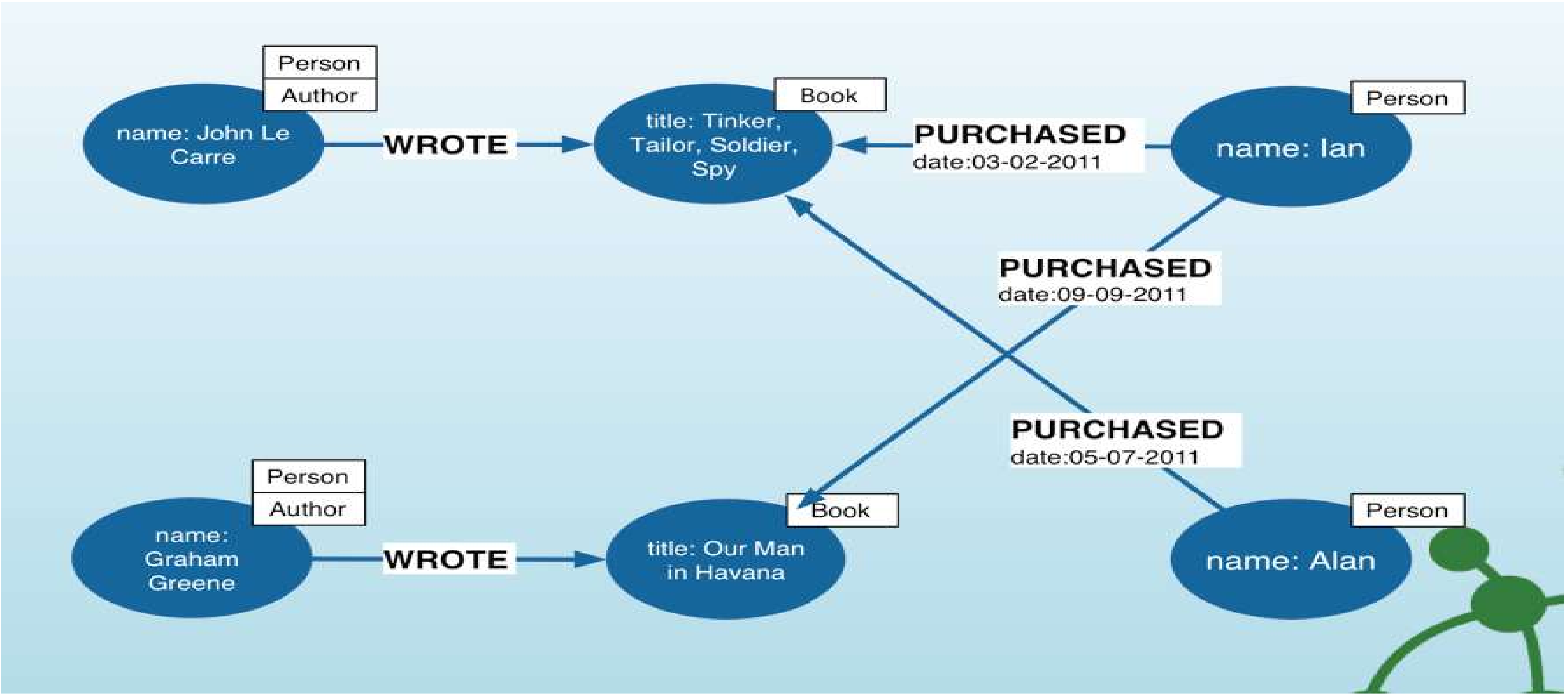
NoSQL: Aggregate Data Model



Typical NoSQL Use Cases

- Transactional
- Big transactional workload
- Single record/document transactions
- Massive data ingestion
- Simple reporting – point queries
- Dynamic data structures
- Complex data structures
- "Narrow" data model

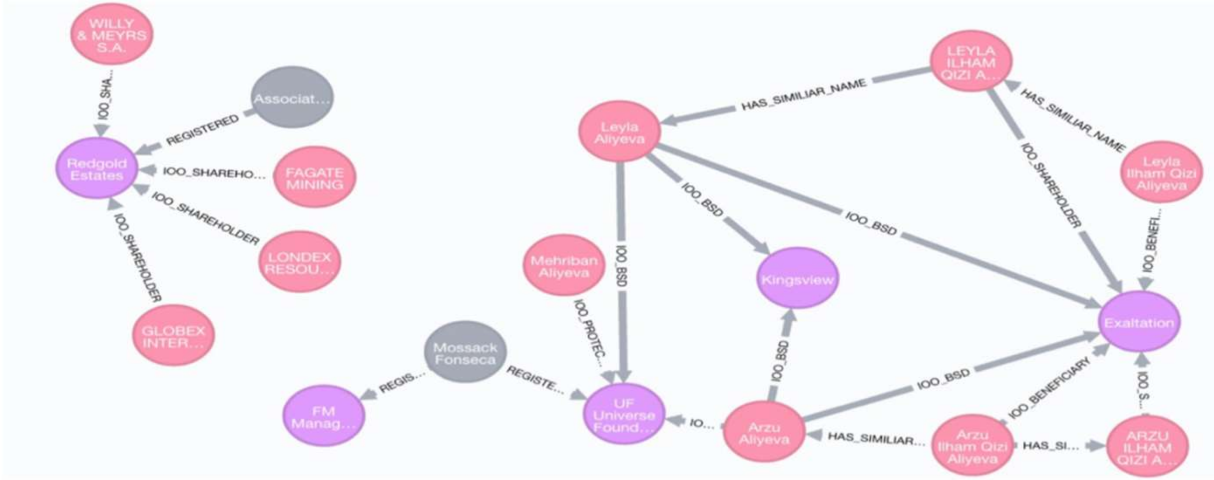
Graph Database Servers



Source: M. Hunger, Neo Technology, Data Modeling with Neo4j, Aug 2013

Application Areas Graph Databases

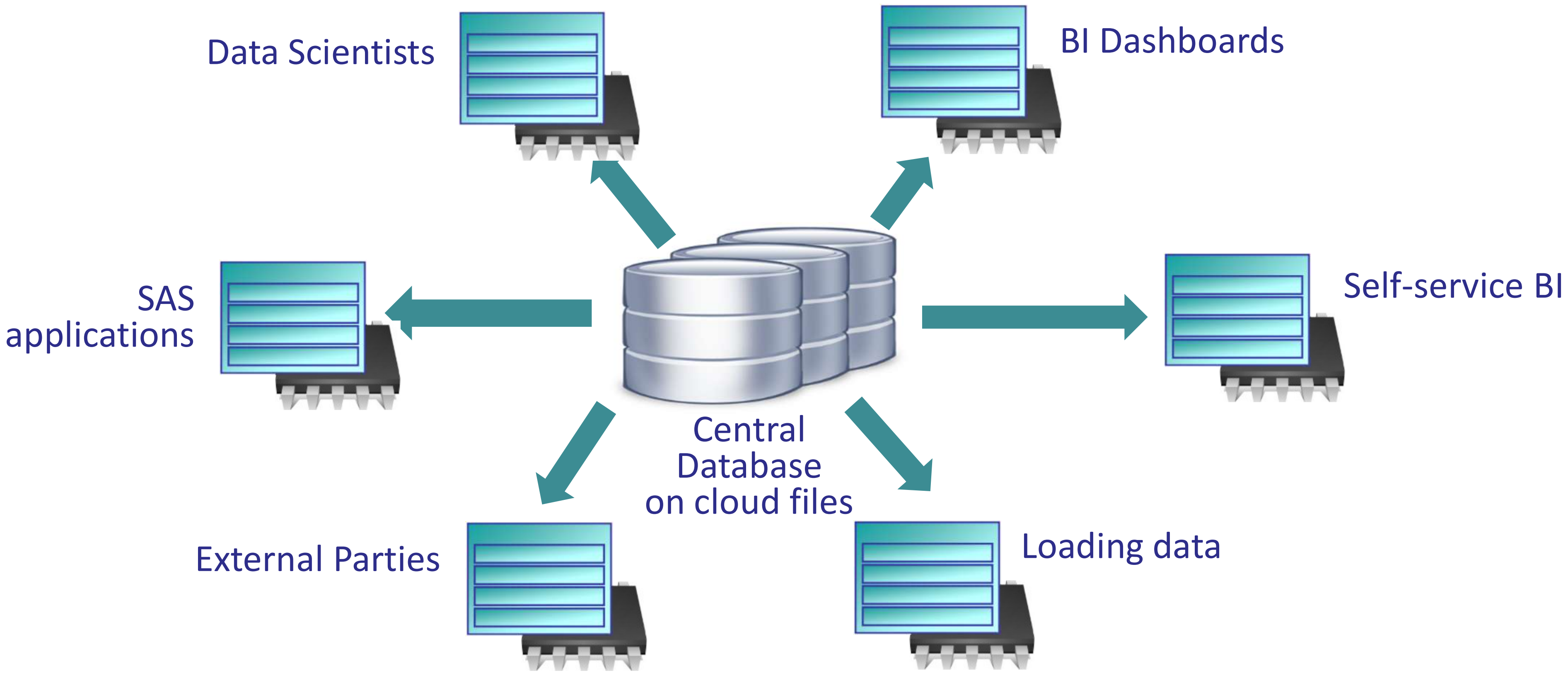
- Social network analysis
- Network impact analysis
- Optimal route determination
- Internet retail recommendations
- Logistics
- Fraud analysis
- Securities and debts
- “Panama papers”
- And many more



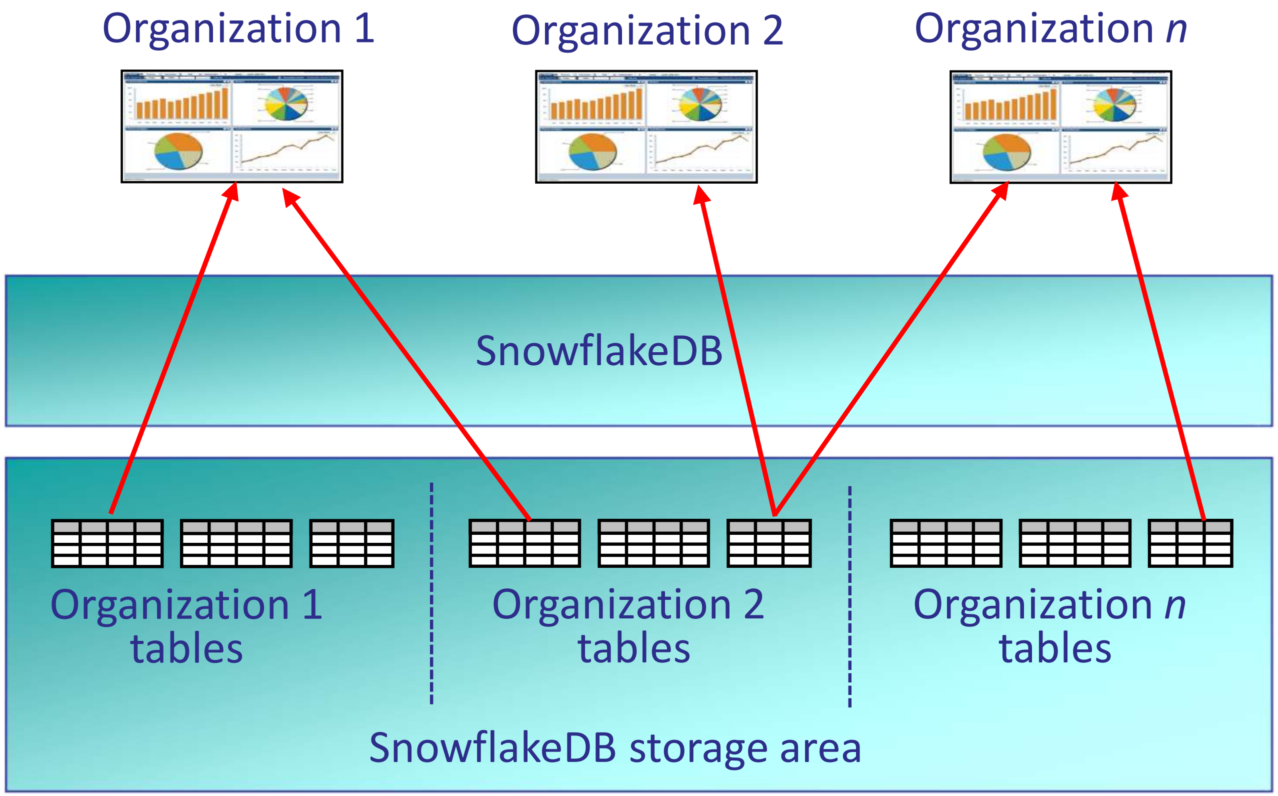
Analytical SQL Database Servers

Examples	
1010Data	Microsoft Azure Synapse
Amazon Redshift and Athena	OmniSci (MapD)
Apache HAWQ	Oracle Database In-Memory
BlazingSQL	SAP HANA
CitusDB (PostgreSQL)	SAP Sybase IQ
ClickHouse SQL	SnowflakeDB
Databricks Delta Lake	Splice Machine
Edge Intelligence	SQream
Exasol	Starburst (Trino formerly Presto)
Google BigQuery	Teradata Vantage
Greenplum	XTremeData dbX
IBM DB2 Warehouse on Cloud	Several SQL-on-Hadoop engines
Ignite InfoBright DB	Vertica
Kinetica	And many others …
Kognitio WX2	

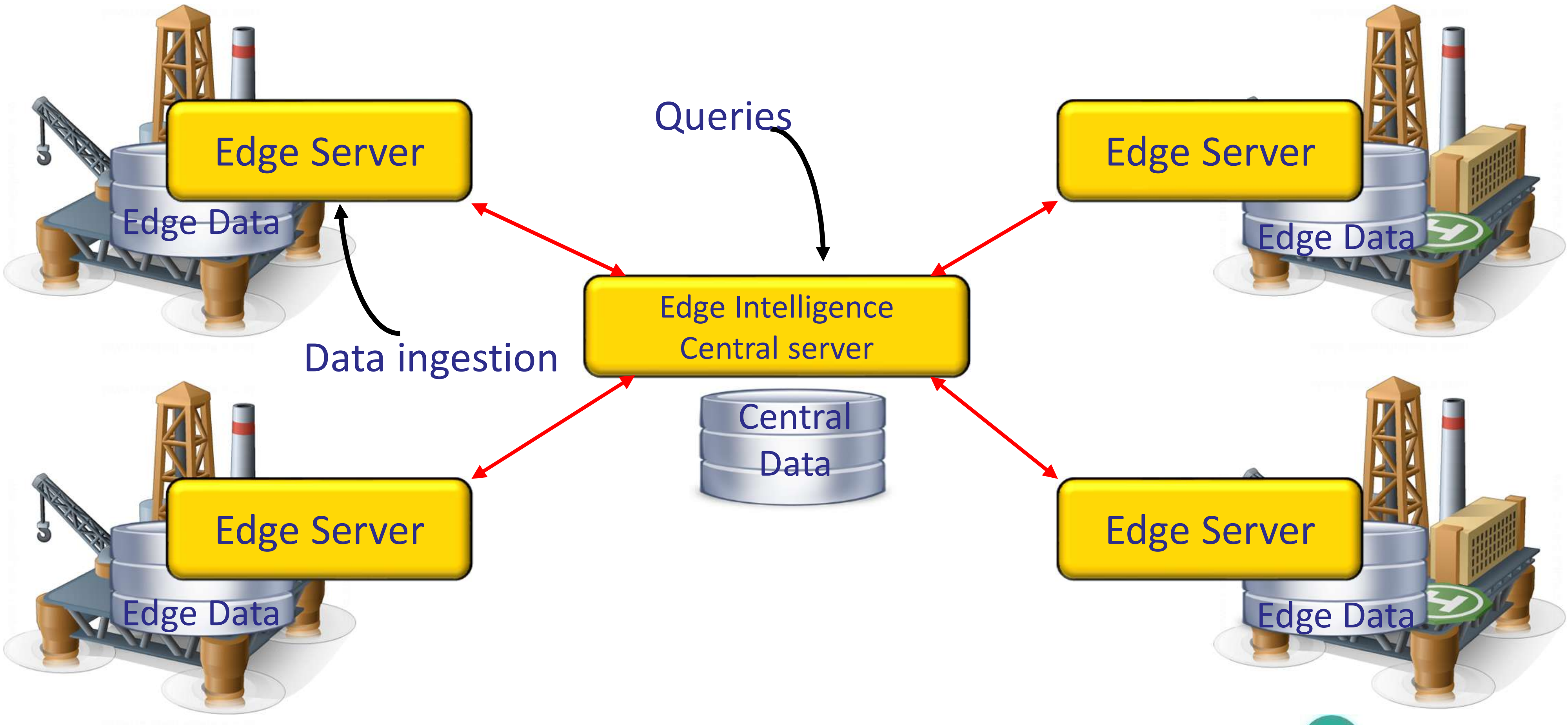
Example 1: Snowflake



Example 1: Snowflake



Example 2: Edge Intelligence



Example 2: Edge Intelligence

Non-replicated Data at Edge 1

Store_id	Customer	Datetime	...
1	Metheny	2017-11-01 12:00:08	...
1	Johnson	2017-11-01 12:10:18	...
1	Young	2017-11-01 12:12:33	...
1	Morrison	2017-11-01 12:50:09	...
1	Harris	2017-11-01 12:55:45	...

Replicated Data at Edge 1

Customer	...
Metheny	...
Johnson	...
Young	...
Morrison	...
Harris	...
Mitchell	...
Stills	...
Dylan	...
Brown	...

Non-replicated Data at Edge 2

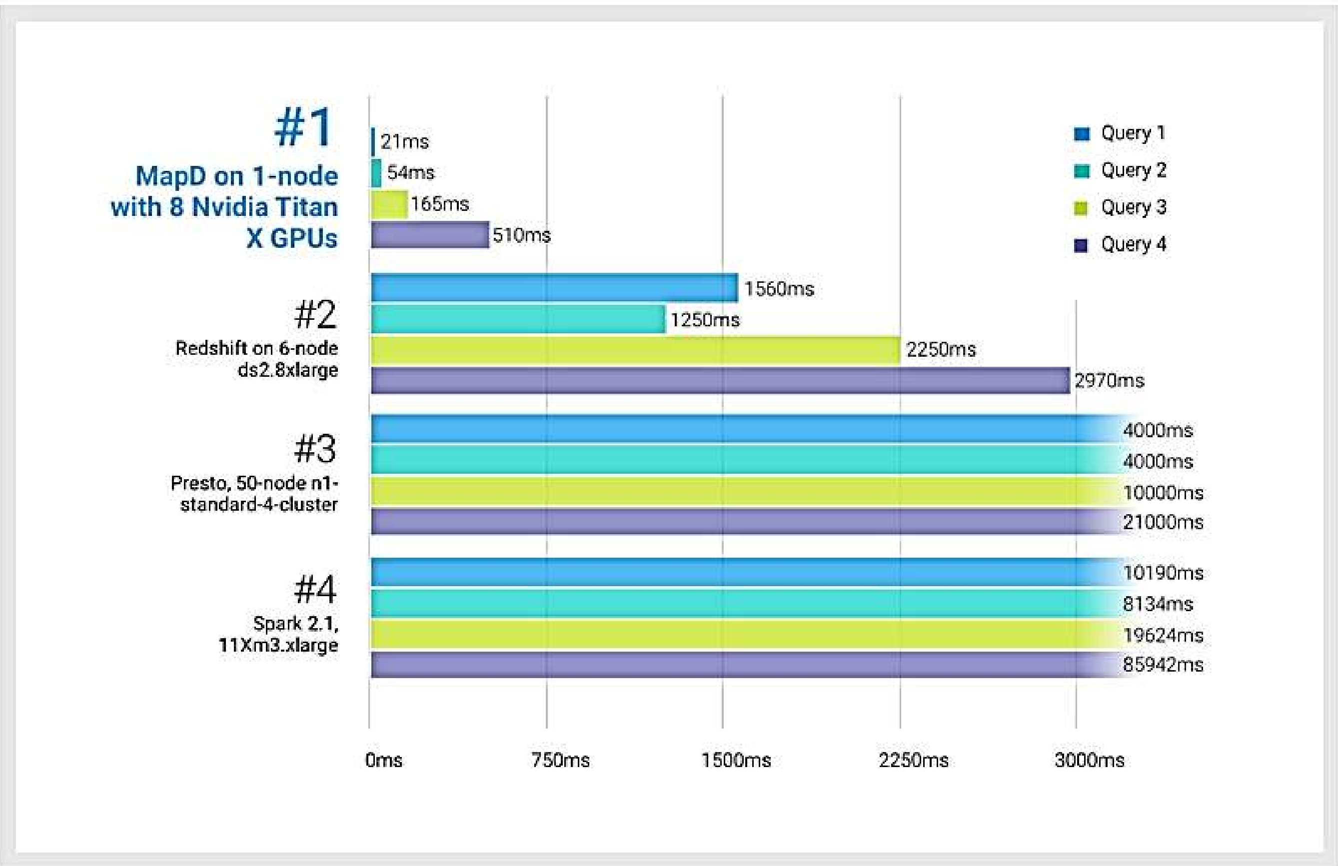
Store_id	Customer	Datetime	...
2	Metheny	2017-11-01 12:01:32	...
2	Mitchell	2017-11-01 12:05:42	...
2	Stills	2017-11-01 12:11:39	...
2	Dylan	2017-11-01 12:12:30	...
2	Brown	2017-11-01 12:40:19	...

Replicated Data at Edge 2

Customer	...
Metheny	...
Johnson	...
Young	...
Morrison	...
Harris	...
Mitchell	...
Stills	...
Dylan	...
Brown	...

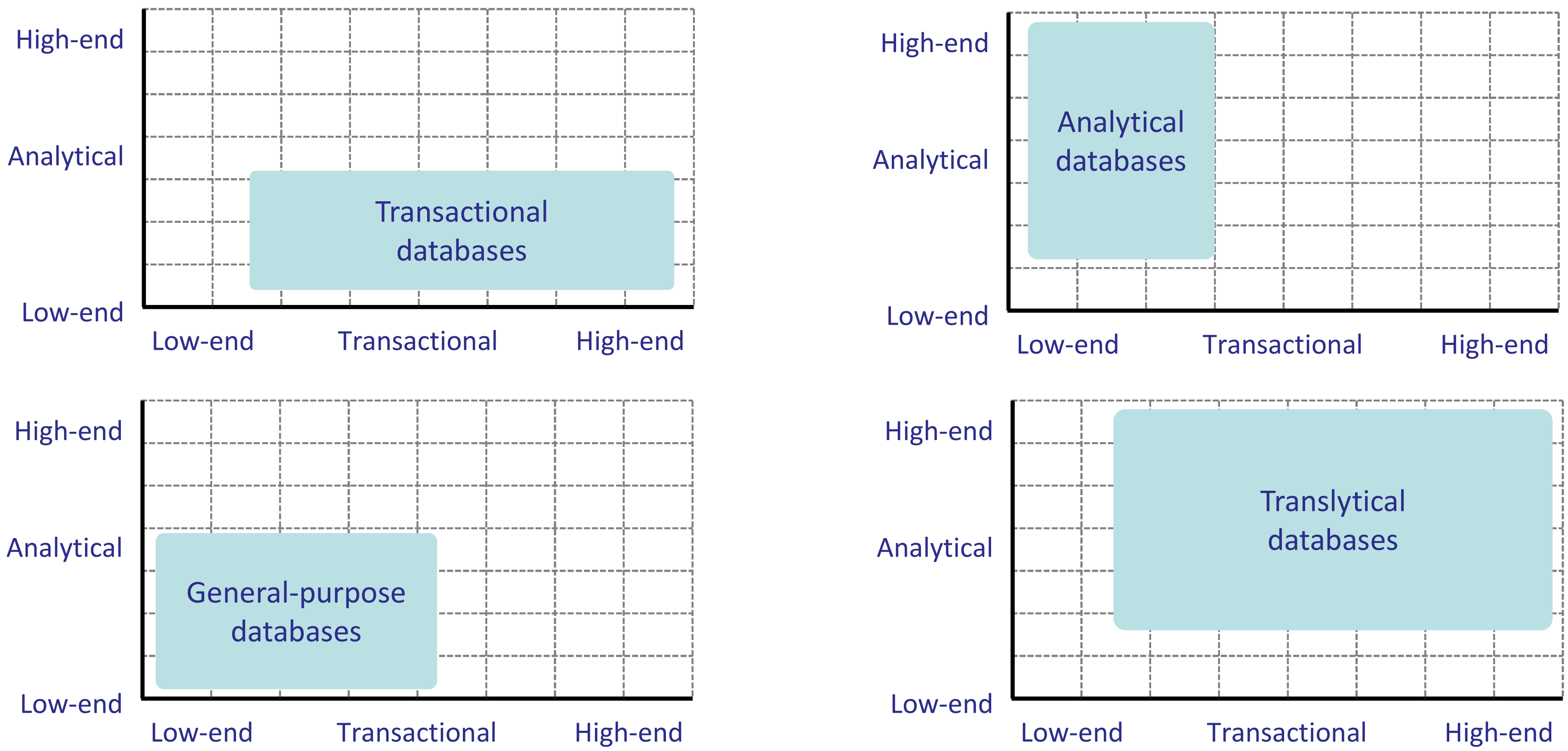
NVIDIA TITAN V: GPU With More Than 5,000 Cores

Comparison of GPU-based Analytical SQL Databases



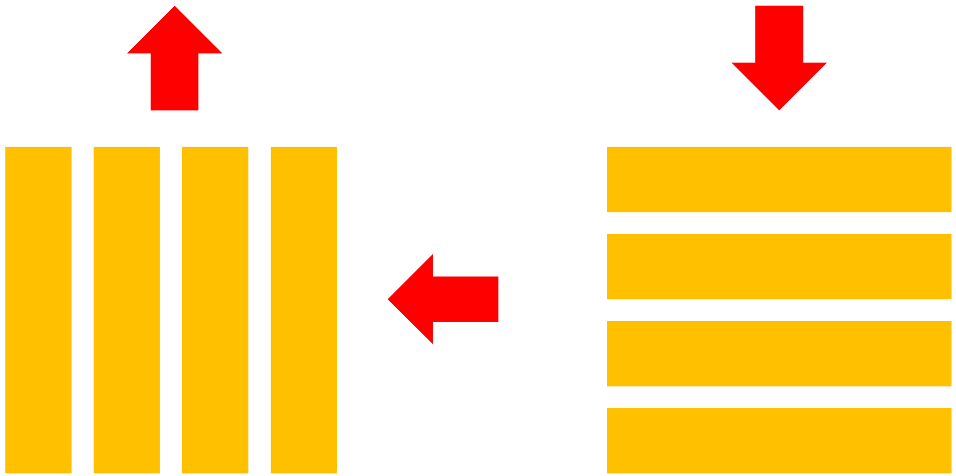
- Products: BlazingSQL, Kinetica, HeavyDB (OmniSciDB, MapD), SQream
- They make use of the parallel power of GPU's
- Long-term data persistency is not their core business

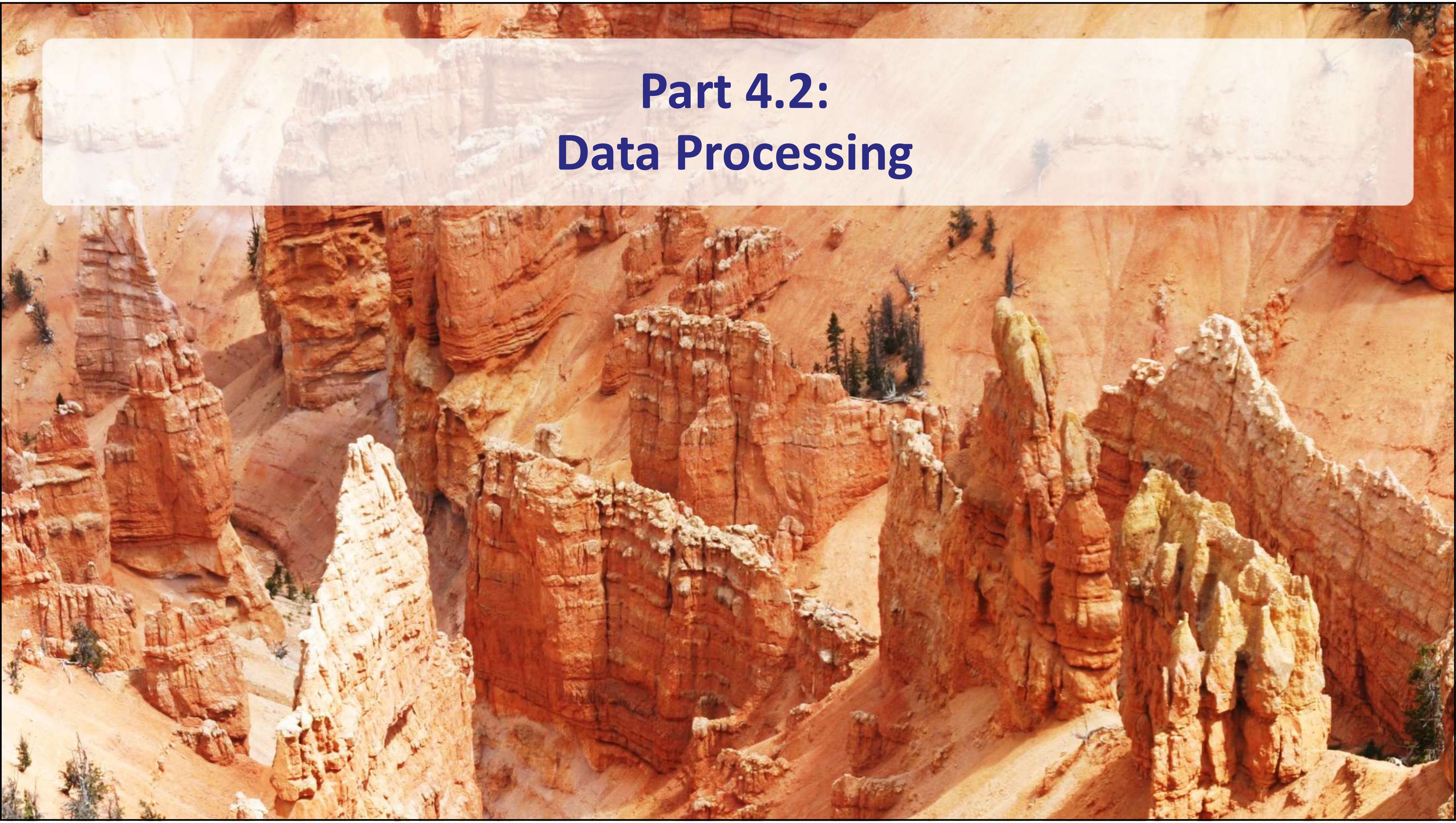
Four Categories of SQL Databases



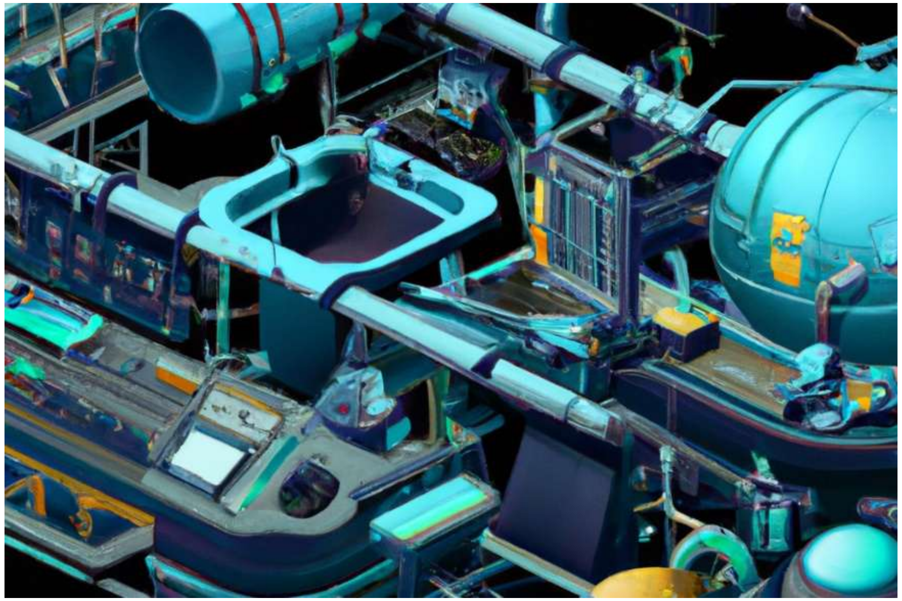
Example: SingleStore (translytical)

ID	Name	Initials	Date Entered	City	State
12345	Young	N	Aug 4, 2008	San Francisco	CA
23324	Stills	S	Sep 10, 2009	New Orleans	LA
57657	Furay	R	Oct 16, 2010	Yellow Springs	OH
65461	Palmer	B	Nov 22, 2011	Boston	MA
…	…	…	…	…	…




Part 4.2:
Data Processing

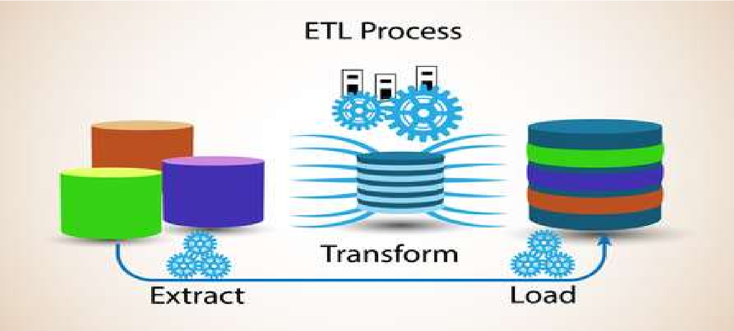
Categories for Data Processing



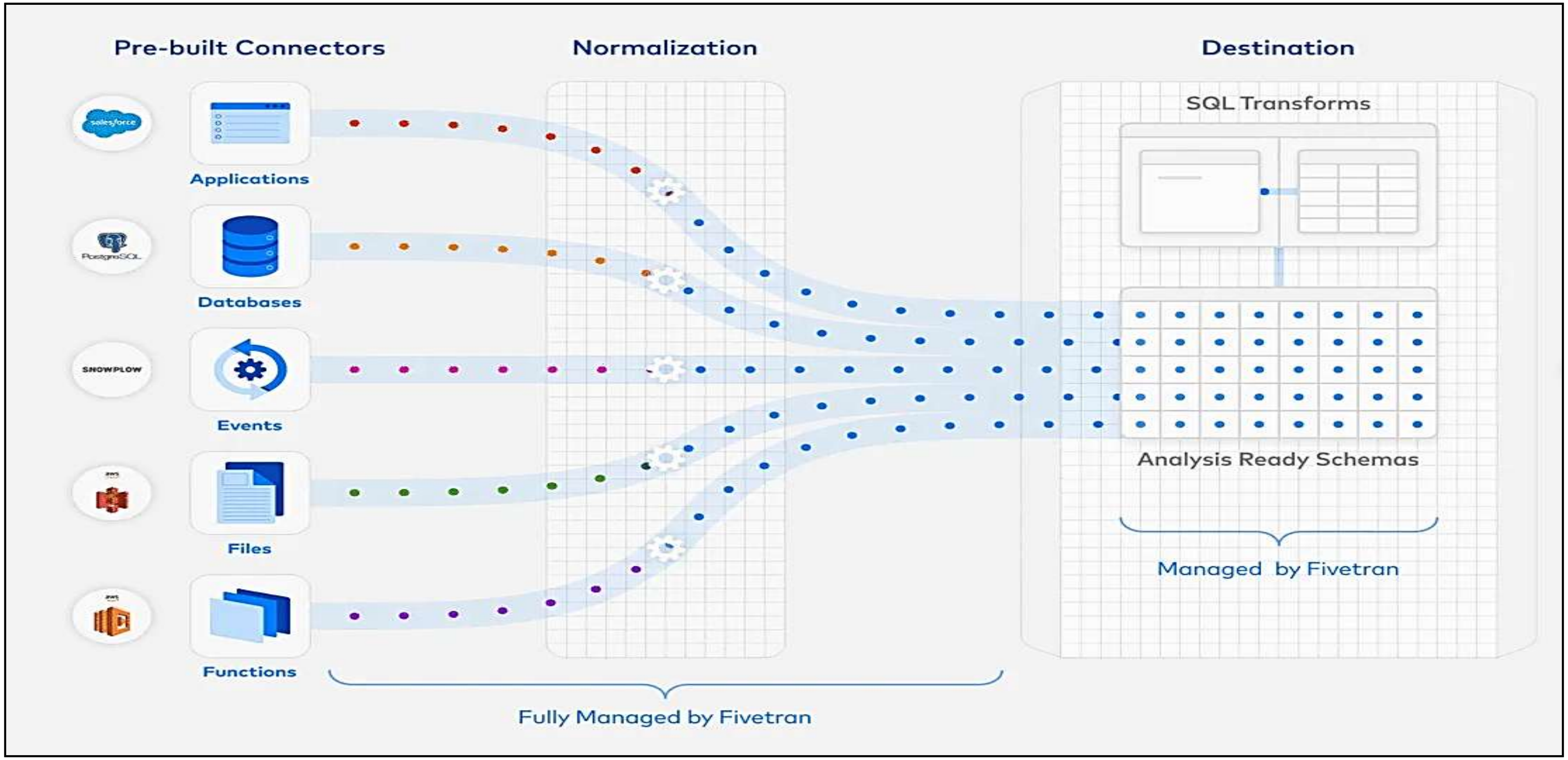
- ETL (Extract Transform Load)
- Data Replication (Change Data Capture)
- ESB (Enterprise Service Bus)
- Data Virtualization

ETL = Extract Transform Load

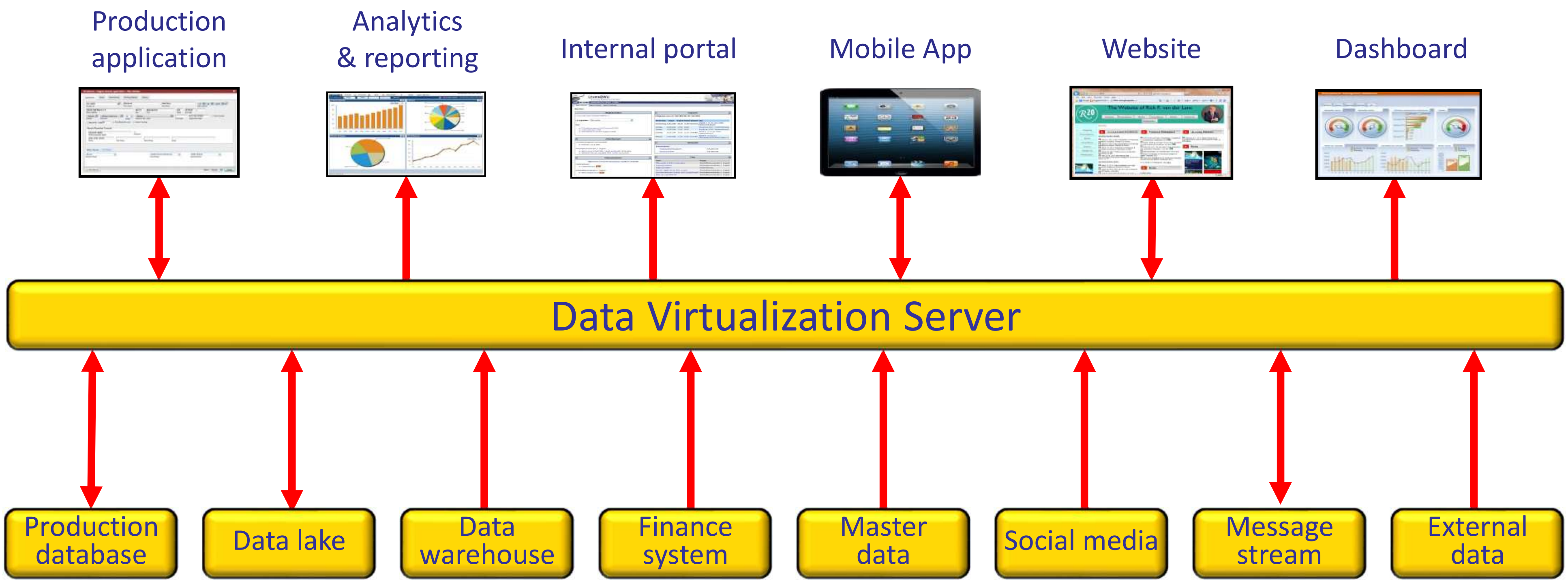
- Transforming of data structures
  - To a data structure suitable for reporting and analysis
- Cleansing of data
- Integration of data from production systems
- Transforming data
  - Filtering, aggregating, projecting, joining, splitting, …
- Scheduling the ETL process
  - Batch-oriented
- Managing the ETL process



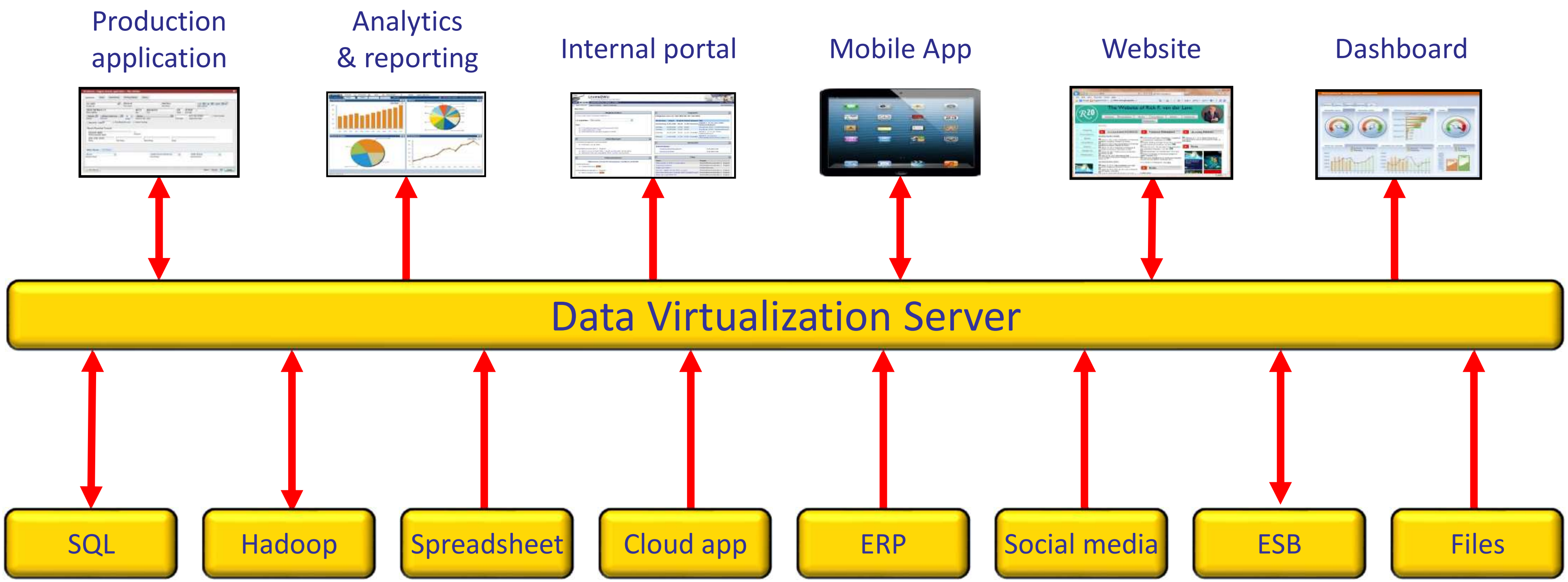
Example: Fivetran



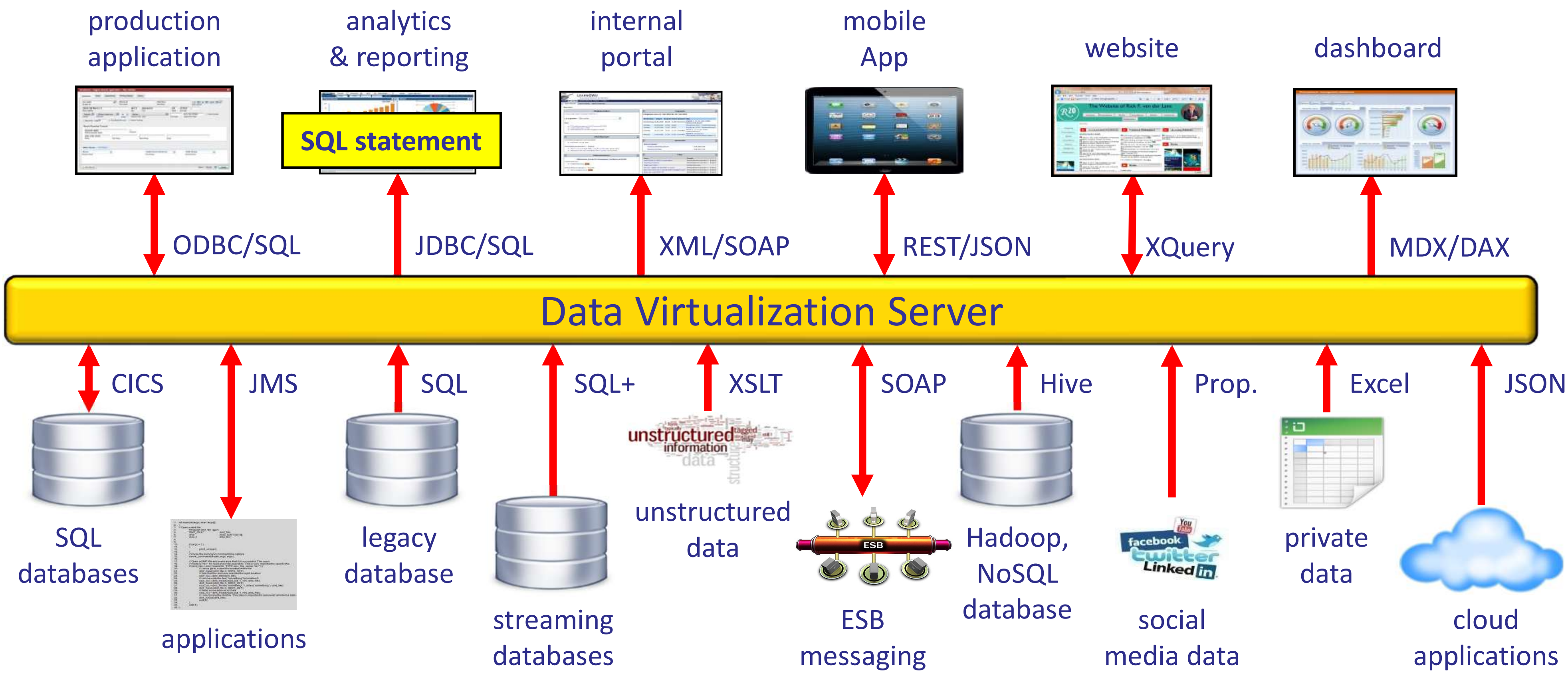
Data Virtualization Overview (1)



Data Virtualization Overview (2)



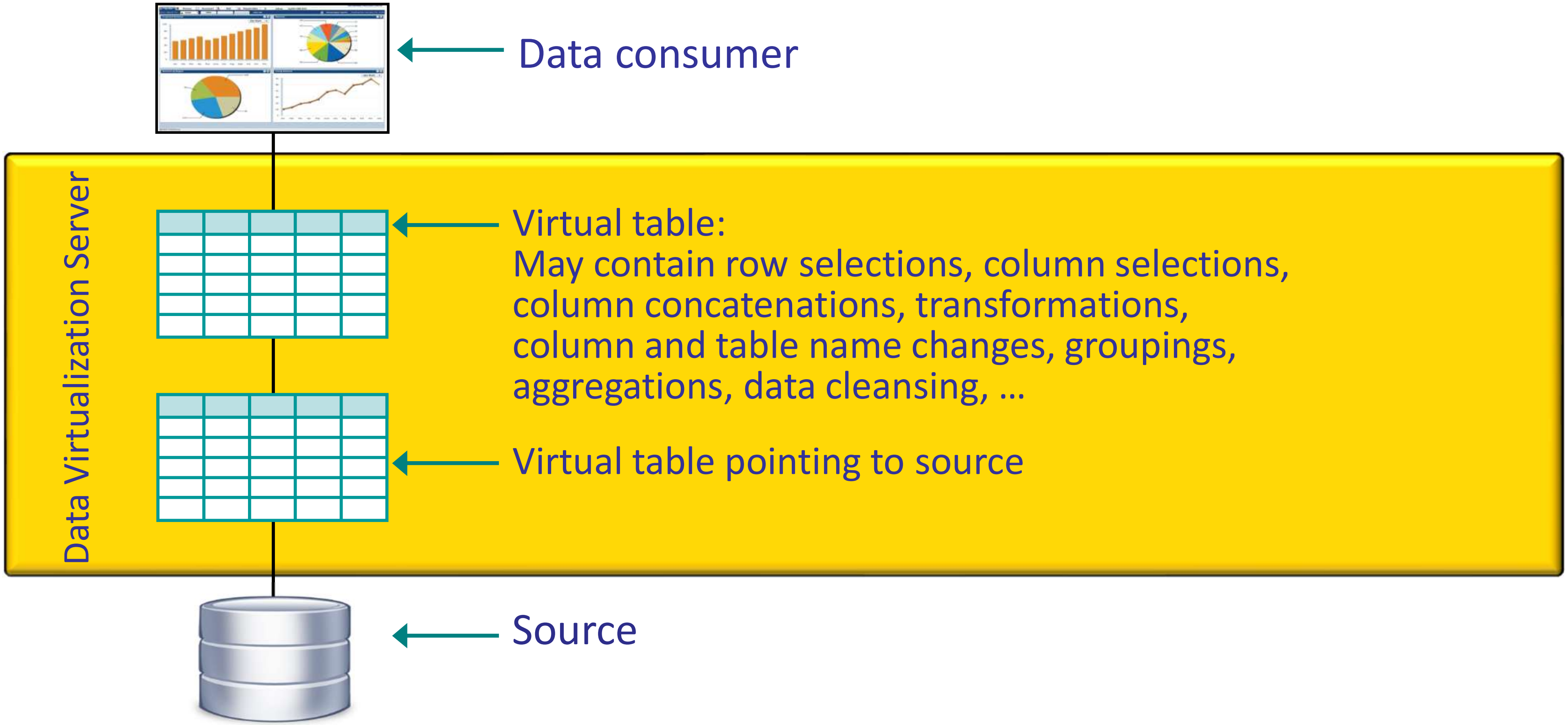
Data Virtualization Overview (3)



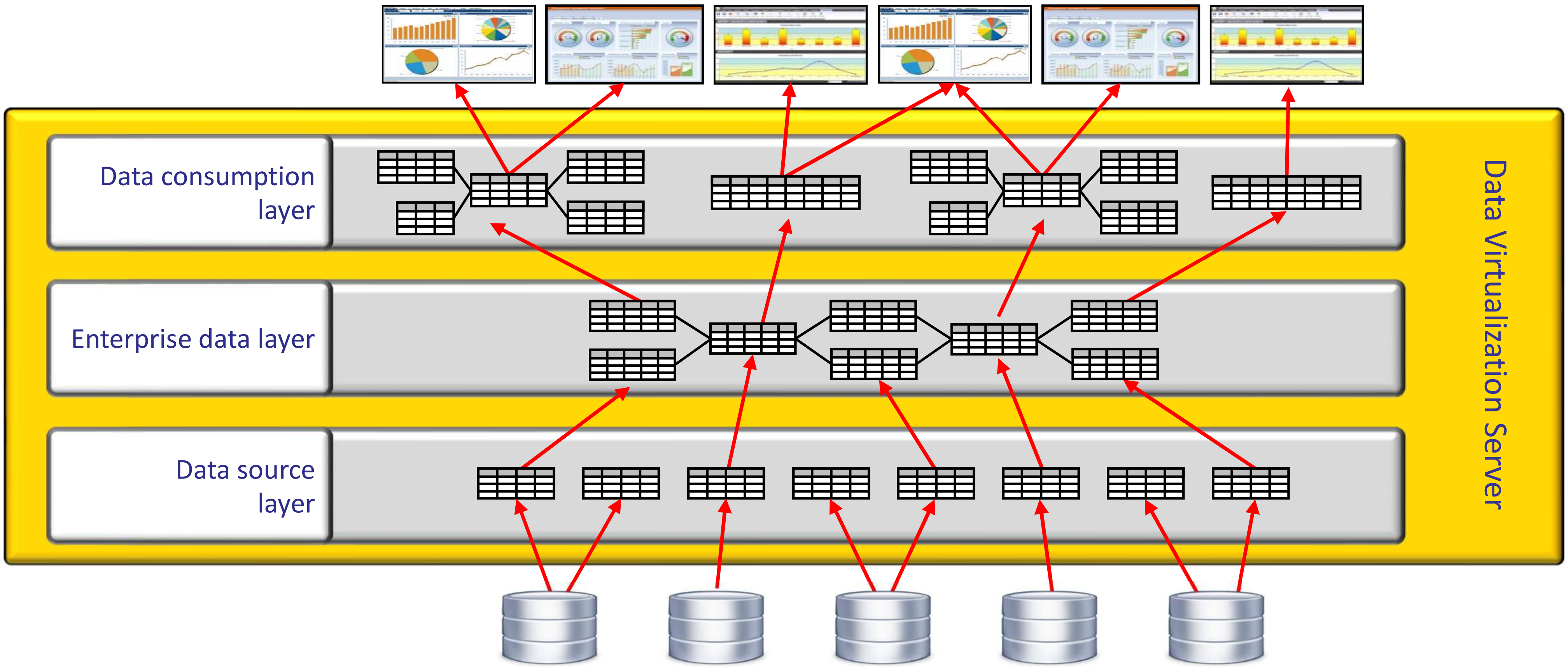
The Market of Data Virtualization Servers

- AtScale
- DataVirtuality (Pipes, Pipes Prof, LDW)
- Denodo Platform
- Dremio
- Fraxses
- IBM InfoSphere Federation Server & IBM Data Virtualization Manager for z/OS (formerly Rocket Data Virtualization)
- Red Hat JBoss Data Virtualization (Teiid) ??
- Stone Bond Enterprise Enabler Virtuoso
- TIBCOData Virtualization (formerly Cisco & Composite)
- Zetaris
- And many more …

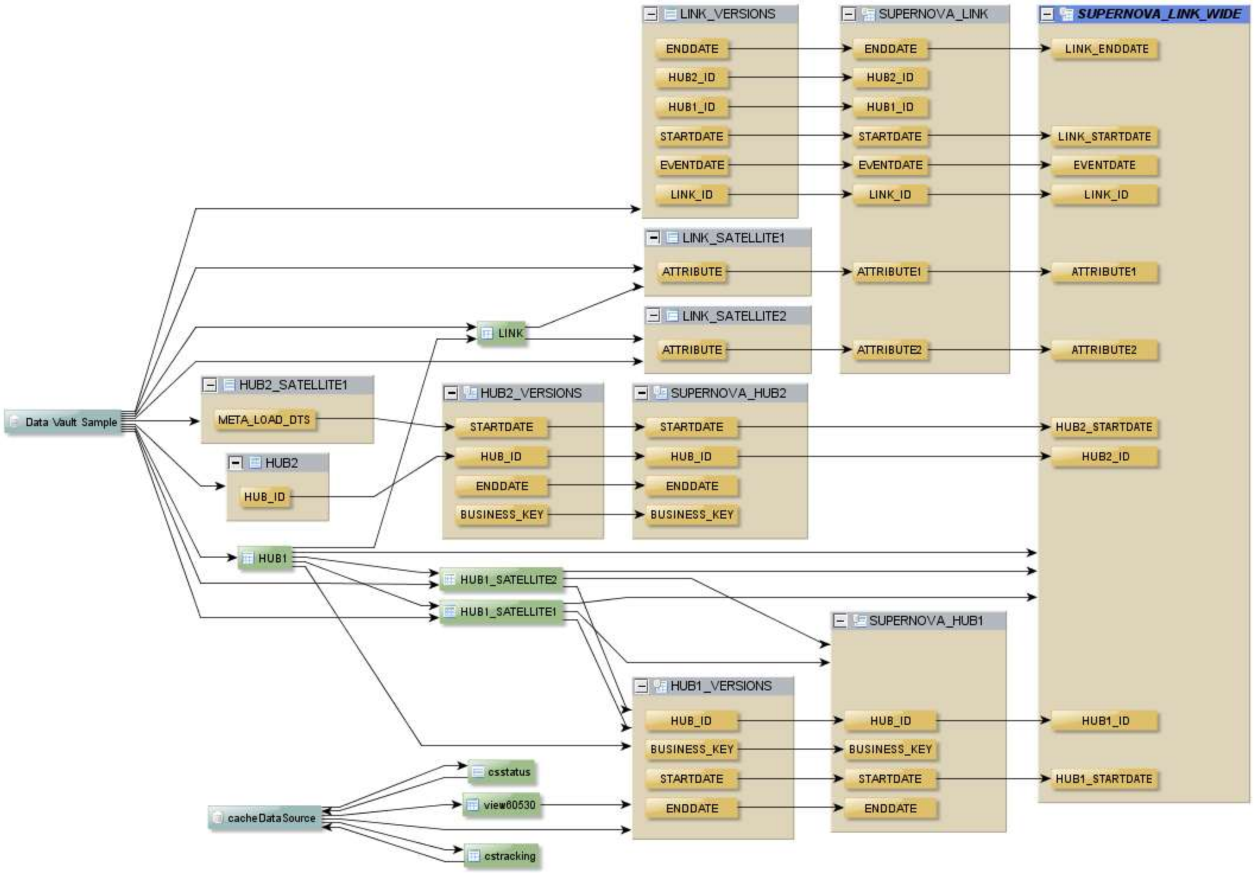
Developing Virtual Tables



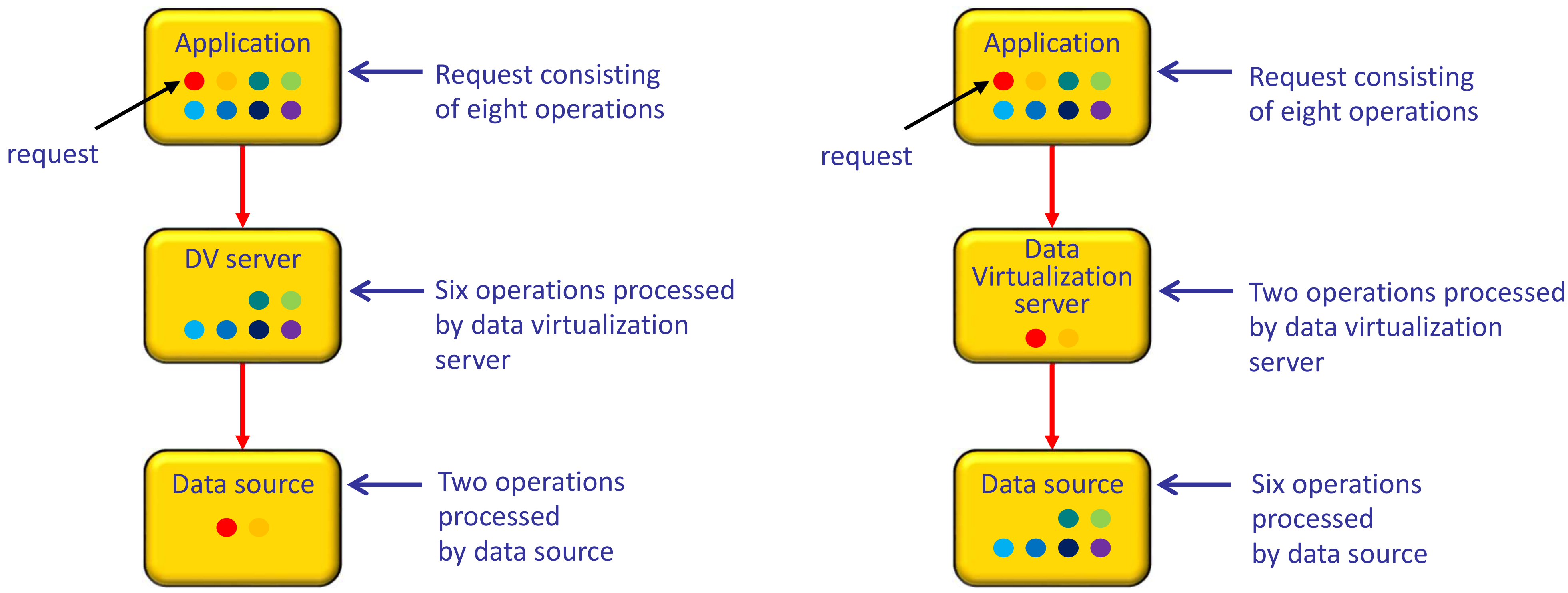
Layers of Virtual Tables



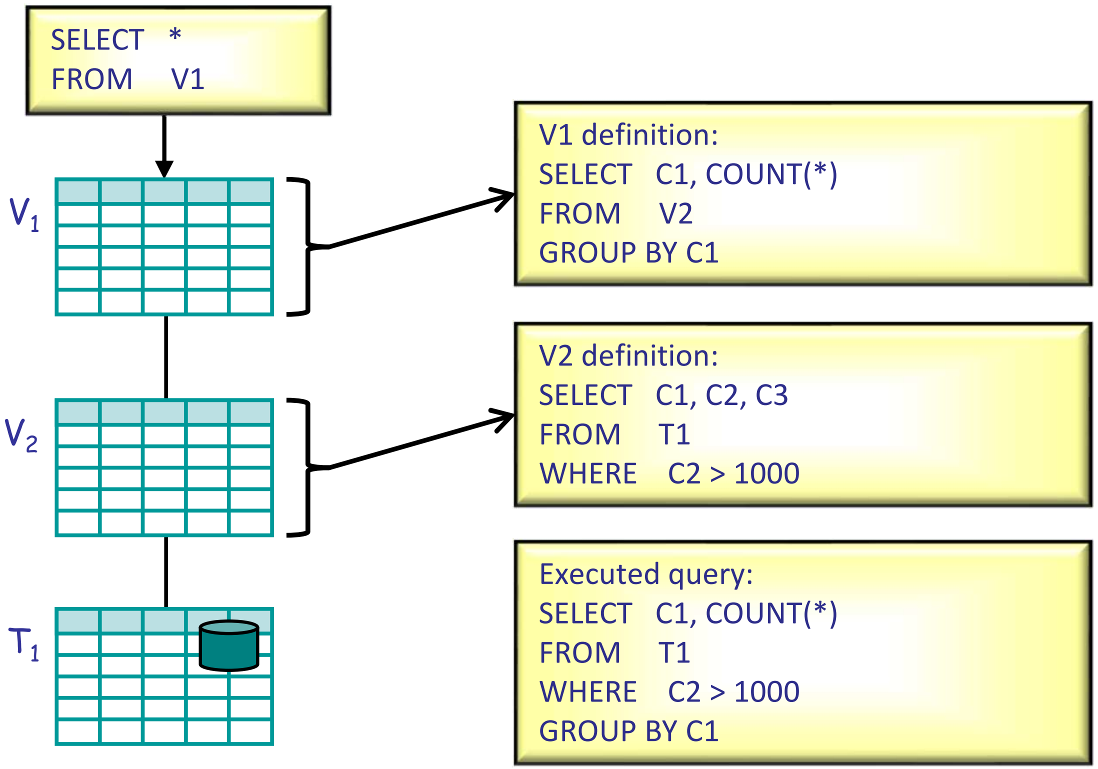
Lineage and Impact Analysis



Improved Performance Through Query Pushdown



Many Levels and One Query



Push Down Query Processing

Data Virtualization Server

(1) Incoming Query:

```
SELECT C2, CONCAT(C5, C6)
FROM   Virtual table
WHERE  C1 = > 1000
AND    C4 BETWEEN 10 AND 20
```

(3) Executed Query:

```
SELECT C2, CONCAT(C5, C6)
FROM   Result
```

Data Source

(2) Executed Query:

```
SELECT C2, C5, C6
FROM   Table
WHERE  C1 = > 1000
AND    C4 BETWEEN 10 AND 20
```

Accessing Files

Data Virtualization Server

(1) Incoming Query:

```
SELECT C2, CONCAT(C5, C6)
FROM   Virtual table
WHERE  C1 = > 1000
AND    C4 BETWEEN 10 AND 20
```

(3) Executed Query:

```
SELECT C2, CONCAT(C5, C6)
FROM   Result
WHERE  C1 = > 1000
AND    C4 BETWEEN 10 AND 20
```

Data Source

(2) Executed Query:

```
SELECT C1, C2, C4, C5, C6
FROM   File
```

Inferred Filters

Data Virtualization Server

(1) Incoming Query:

```
SELECT T1.C1, T1.C2, T2.C2
FROM   T1, T2
WHERE  T1.C1 = T2.C1
AND    T1.C1 => 1000
AND    T2.C2 BETWEEN 10 AND 20
```

(3) Executed Query:

```
SELECT T1.C1, T1.C2, T2.C2 FROM
T1, T2
WHERE  T1.C1 = T2.C1
```

Data Source

(2a) Executed Query:

```
SELECT C1, C2
FROM   T1
WHERE  C1 => 1000
```

Data Source

(2b) Executed Query:

```
SELECT C1, C2
FROM   T2
WHERE  T2.C1 => 1000
AND    T2.C2 BETWEEN 10
       AND 20
```

Join of Data Sources with Query Injection

Data Virtualization Server

(1) Incoming Query:

```
SELECT Tbig.C1, Tbig.C2
FROM   Tsmall, Tbig
WHERE  Tsmall.C1 = Tbig.C1
```

(4) Executed Query:

```
SELECT *
FROM   Result
```

Data Source

(2) Executed Query:

```
SELECT C1
FROM   Tsmall
```

Data Source

(3) Executed Query:

```
SELECT C1, C2
FROM   Tbig
WHERE  C1 in
       (v1, v2, v3, …)
```

Join of Data Sources with Ship Join

Data Virtualization Server

(1) Incoming Query:

```
SELECT T1.C1, T1.C2, T2. C2
FROM   Tbig1, Tbig2
WHERE  Tbig1.C1 = Tbig2.C1
```

(4) Executed Query:

```
SELECT *
FROM   Result
```

Data Source

(2) Executed Query:

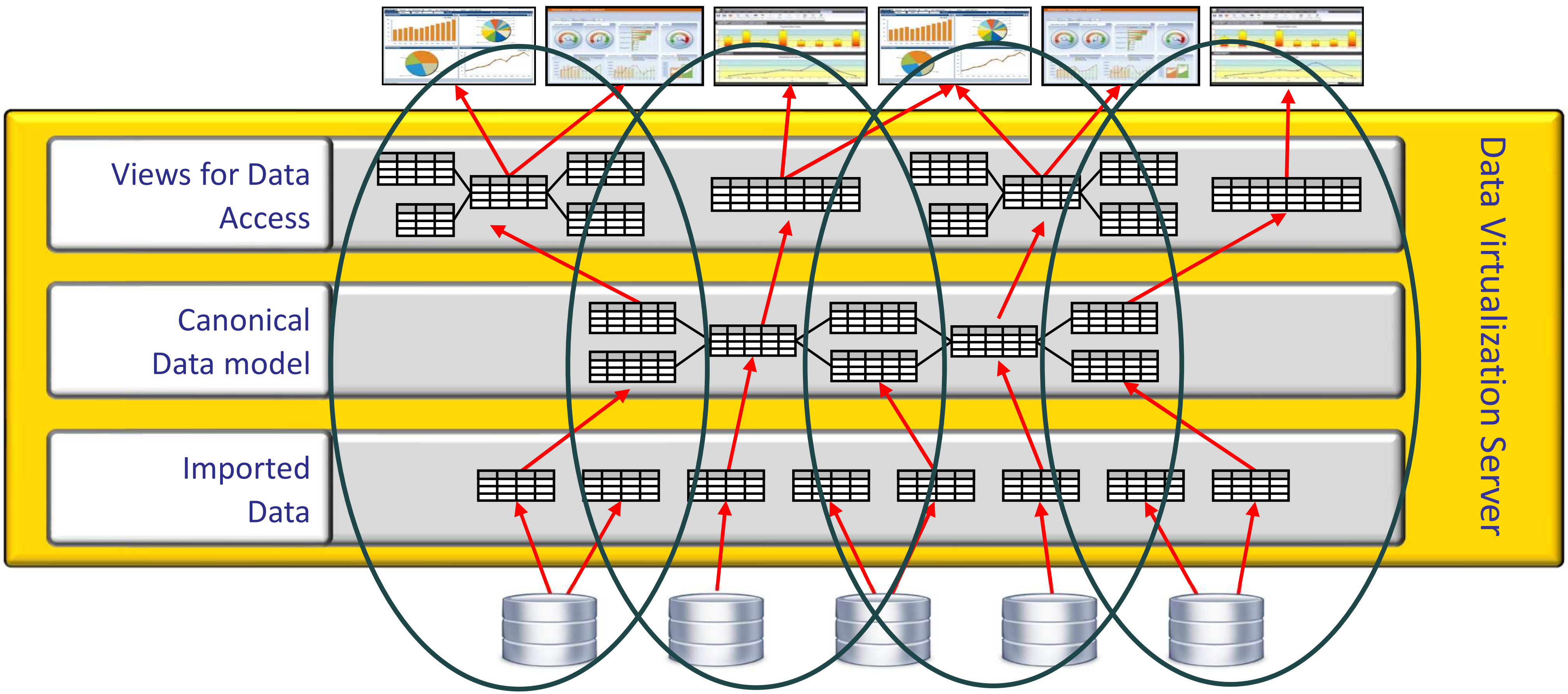
```
SELECT C1, C2
FROM   Tbig1
```

Data Source

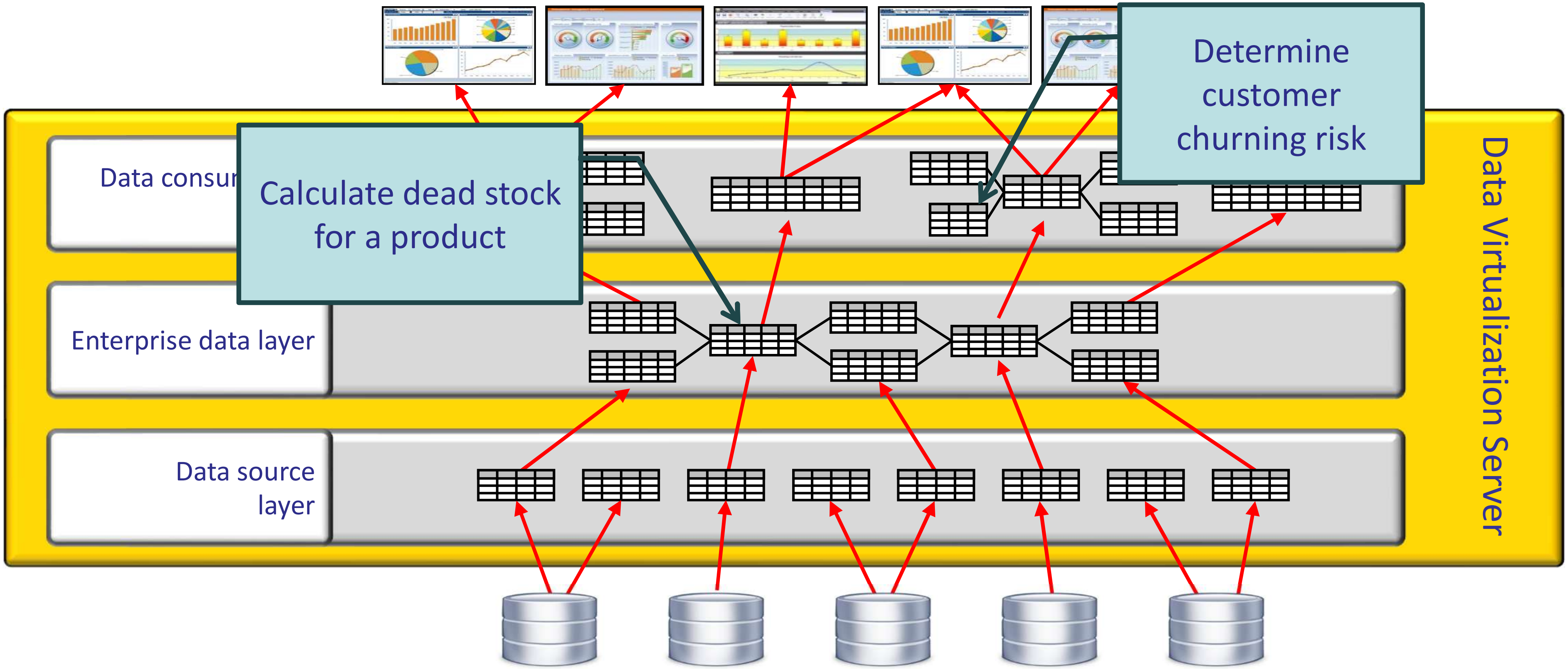
(3) Executed Query:

```
CREATE TEMP TABLE TEMP;
INSERT INTO TEMP
SELECT *
FROM   Tbig1;
SELECT TEMP.C1, TEMP.C2,
       Tbig2.C2
FROM   TEMP, Tbig2
WHERE  TEMP.C1 = Tbig2.C1;
DROP TEMPORARY TABLE TEMP;
```

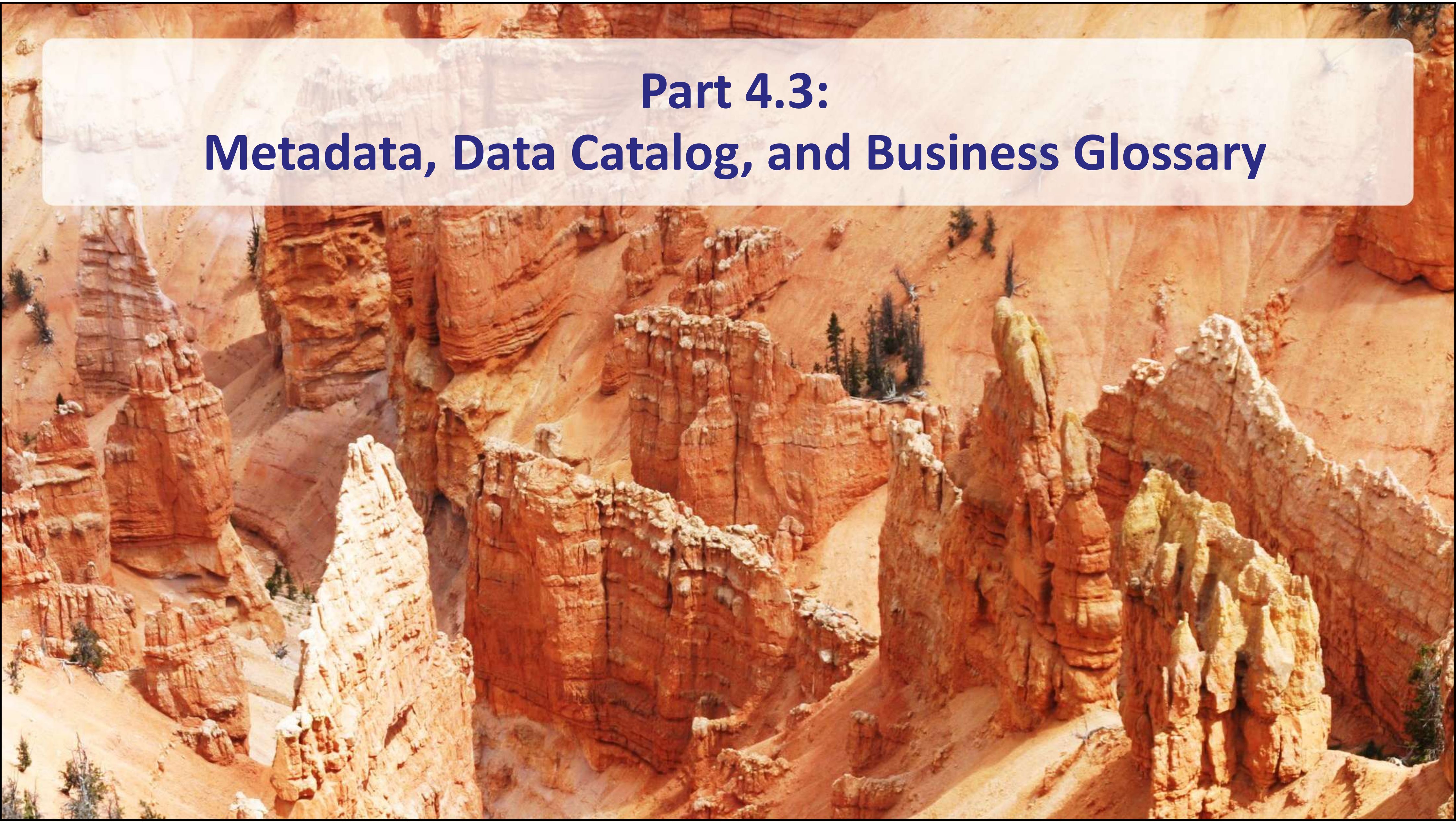
Evolutionary Development Approach



Improved Productity Through Sharing



Part 4.3:
Metadata, Data Catalog, and Business Glossary



Types of Metadata

Metadata on Data

- Textual definition
- Description
- Annotations by users and IT specialists
- Data lineage including transformations
- Retention information
- Qualifications: trustworthiness, completeness, data quality, …
- Value descriptions
- Original or masked/anonymized
- Ontology
- Owner and support
- …

Metadata on Metadata

- Retention information on metadata
- History of metadata
- Qualifications: trustworthiness, completeness, data quality, …
- Metadata value descriptions
- Original or masked/anonymized metadata
- Owner and support
- …

Metadata in 1976

DE DATA DICTIONARY/DIRECTORY (DD/D)

door L. Delport

1.1 Wat is een DD/D? (Data Dictionary/Directory) (gegevenskataloog)

Zeer algemeen kunnen we een DD/D als volgt bepalen:
Een DD/D is een katalogus die de omschrijving bevat van alle informatie-elementen die in een bedrijf bestaan.' Deze bepaling laat natuurlijk de weg open

1.2 Waarom hebben we een DD/D nodig?

Centralisatie, het vermijden van dubbele gegevens en het opzoeken en vinden van informatie langs allerlei wegen en door middel van allerlei sleutels zijn technieken eigen aan M.I.S. (7) en systemen van gegevensbanken.

Informatie jaargang 18 nr. 7/8 pag. 430 t/m 491 Amsterdam juli/augustus 1976

A Target Audience Shift of Metadata

IT Specialists

- Developers
- DBAs
- Designers
- Testers
- …

→

Business Users

- Self-service BI users
- Power users
- Dashboard users
- Data scientists
- Auditors
- …

Numerous Solutions that Manage Metadata

- Home made metadata systems
- Professional data catalogs and business glossaries: Alation, Apache Atlas, Collibra, Informatica, TIBCO EBX, …
- Scraping and linking: ASG, Manta, SQLdep (Collibra), …
- Data warehouse automation: Astera, Attunity Compose, BiGenius, TimeXtender, WhereScape, …
- BI tools: semantic layers
- ETL tools
- Data profiling tools
- Data quality tools
- Data virtualization servers: Data Virtuality, Denodo, Fraxses, Tibco DV, …
- And many more …

Instant Metadata

Stock overview

Note: This is an aggregated report. Most data is first calculated at the native resolution (per group and pool), and the results are summed or averaged for an aggregated report.

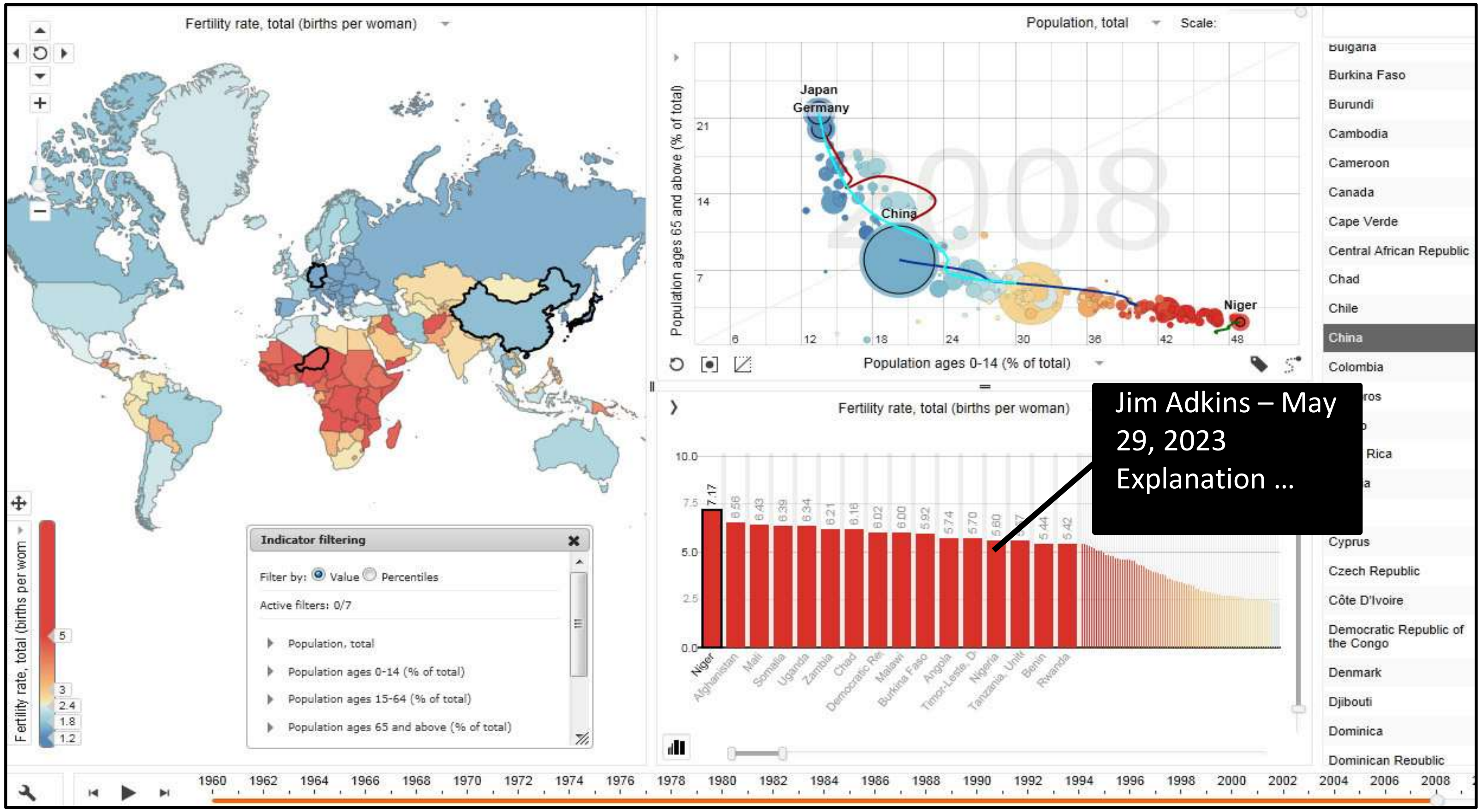
	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Trend vs last year	Overall
Total demand	128,213	127,098	117,923	116,033	115,431	108,253	114,681	117,610	115,882	115,554	115,122	116,106	116,849		117,289
Total inventory	145,401	144,654	144,753	143,668	142,977	142,224	141,258	139,011	138,414	137,690	137,108	136,660	136,191		140,770
Total available inventory	111,562	111,719	113,504	114,175	114,342	112,682	113,106	112,081	110,908	109,726	108,631	107,575	106,545		111,274
Available Bycicles	100,653	101,344	102,974	103,659	103,766	101,010	101,180	100,155	98,982	97,800	96,705	95,649	94,619		99,884
Rented Bycicles	10,909	10,375	10,530	10,516	10,576	11,672	11,926	11,926	[illegible]	[illegible]	[illegible]	[illegible]	11,926		11,389
Unservicable Bycicles	6,490	6,528	7,793	6,931	7,094	7,716	7,990	7,040	[illegible]	[illegible]	[illegible]	[illegible]	7,158		7,142
In repair Bycicles	2,445	2,508	2,635	2,809	2,607	2,749	2,499	2,744	[illegible]	[illegible]	[illegible]	[illegible]	2,667		2,652
Storage Bycicles	1,223	1,652	1,526	3,836	4,205	4,568	4,934	2,515	[illegible]	[illegible]	[illegible]	[illegible]	3,072		2,981
Lost / Stolen Bycicles	23,681	22,247	19,295	15,917	14,729	14,509	12,729	14,631	[illegible]	[illegible]	[illegible]	[illegible]	16,749		16,721
Rebrand In	0	0	0	0	0	0	0	-	[illegible]	[illegible]	[illegible]	-	-		0
Rebrand Out	0	0	0	0	0	0	0	-	[illegible]	[illegible]	[illegible]	-	-		0
Lease In	0	0	9	20	0	35	116	-	-	-	-	-	-		26

Available Bycicles
Jan

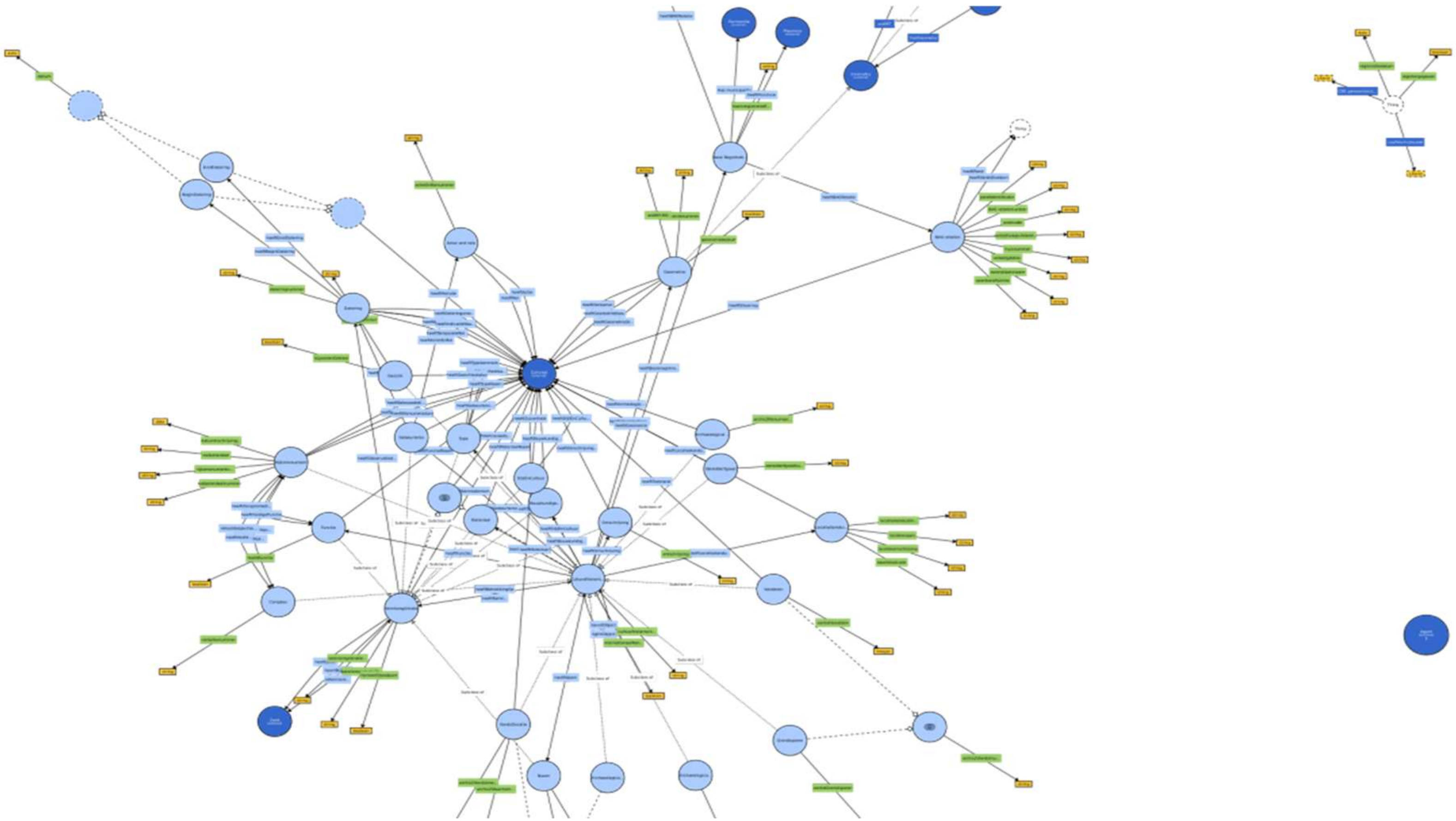
Forecast: 98,982

Actual is entered manually. Forecast is the last month repeated, but adjusted for all inventory increase and decrease of that month. Formula: Available Bycicles + Rebrand - Scrap - Loss - Sales Capex Volume. All values are taken from the previous month.

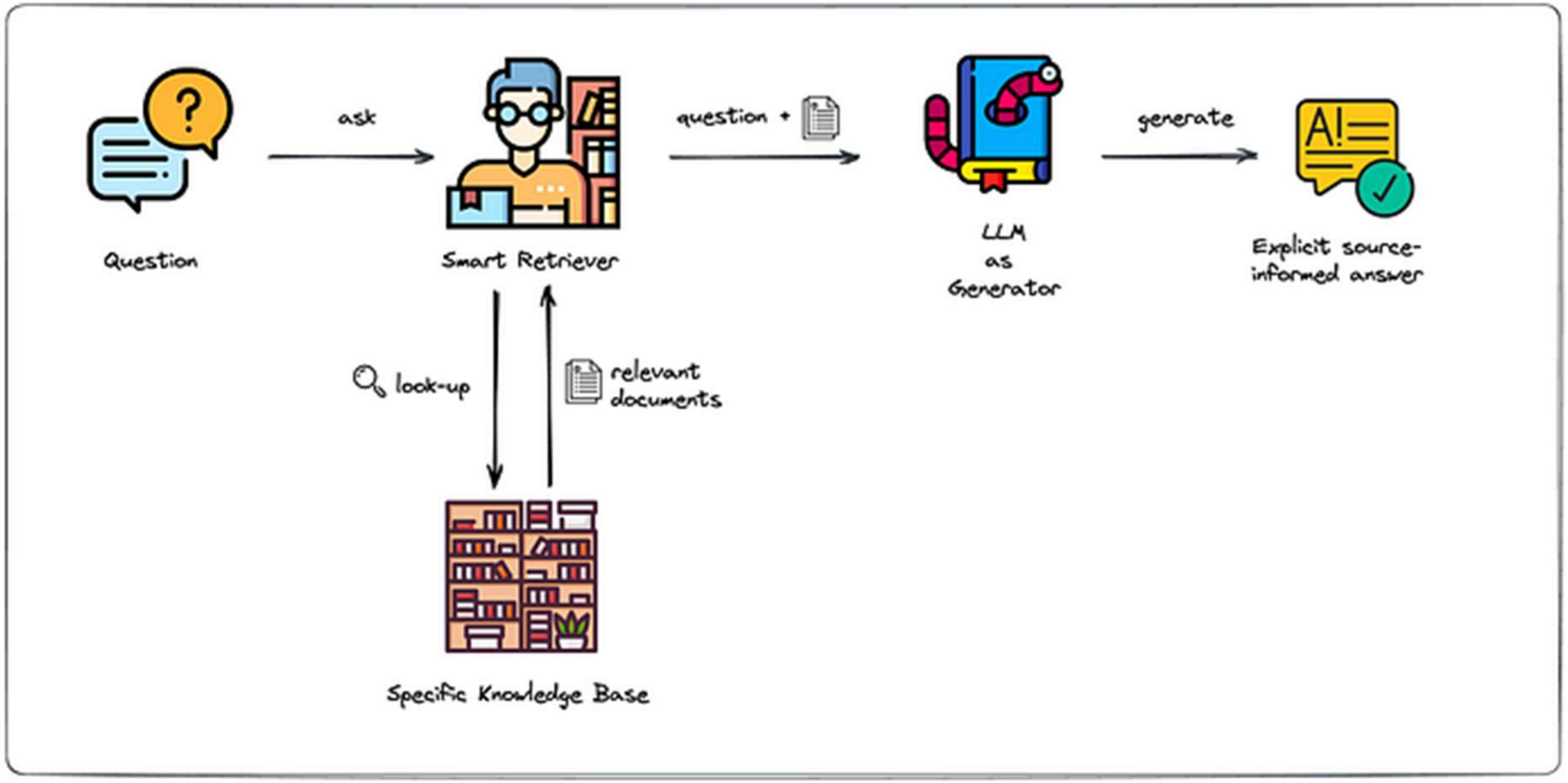
Adding Annotations on Data Points



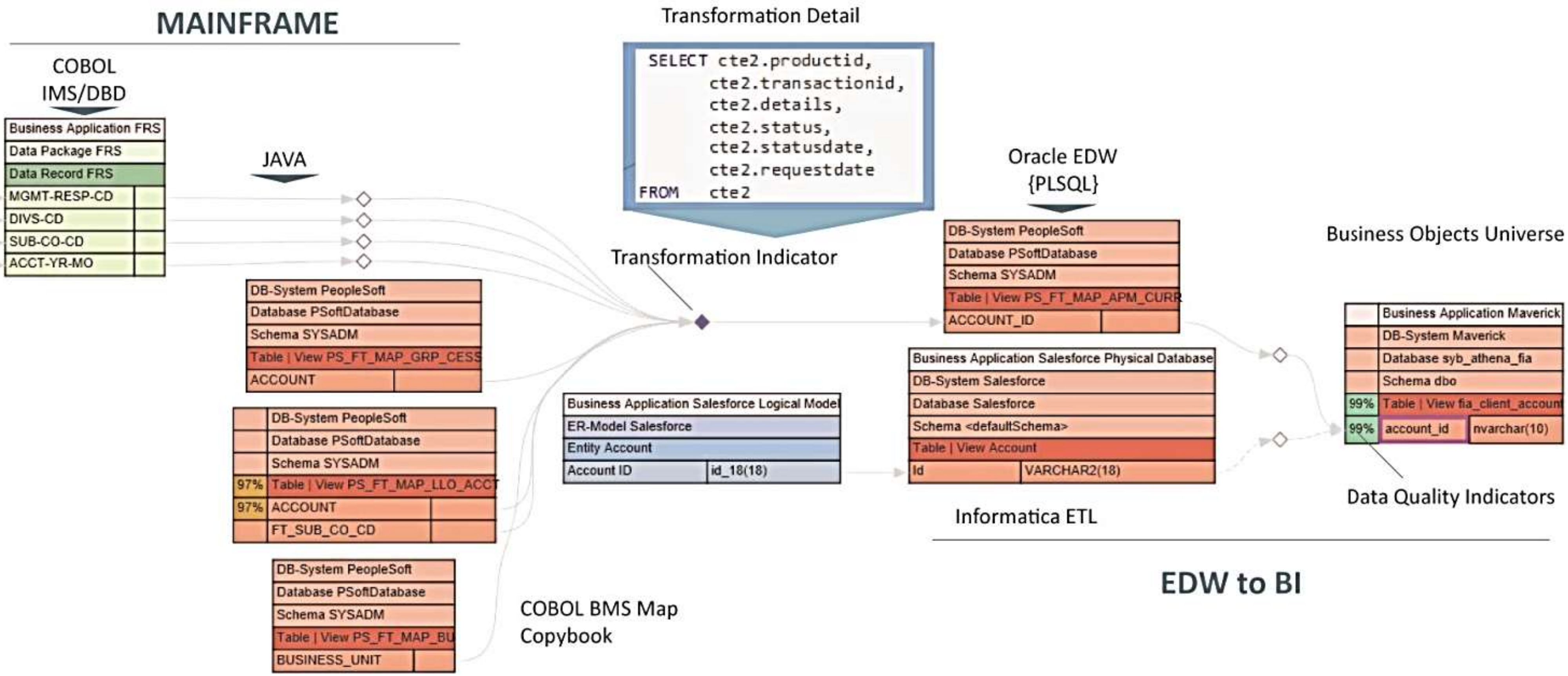
Generating an Onthology (for AI?)



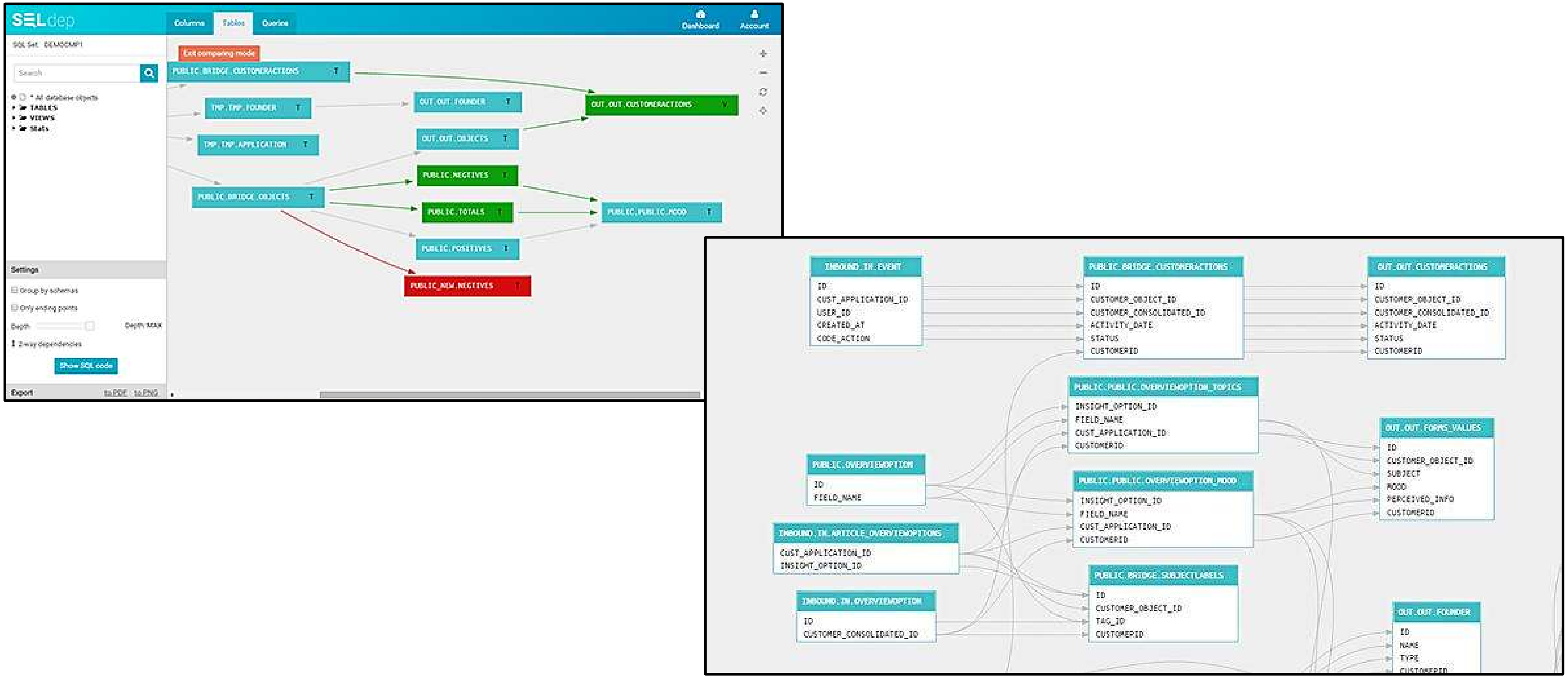
Retrieval Augmented Generation



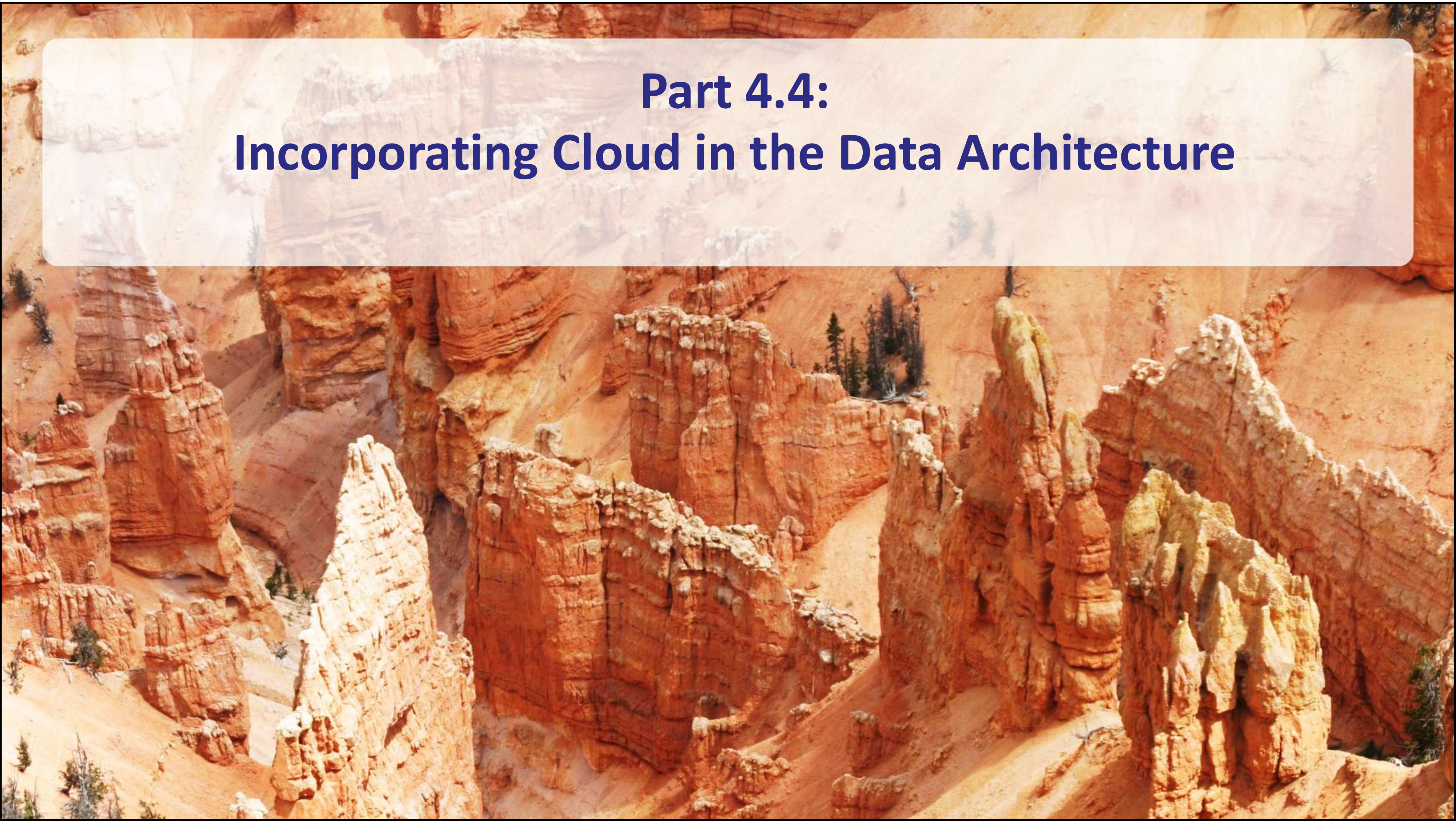
Example: Lineage Through Scraping by ASG



Example: Lineage Through Scraping by SQLdep (Collibra)



Part 4.4:
Incorporating Cloud in the Data Architecture



Cloud Platforms are Becoming the New Mainframes

Mainframe = Lock In

- Proprietary operating systems
- Proprietary system management software
- Proprietary database servers
- Proprietary security systems
- Proprietary development environments
- Proprietary JCLs
- Proprietary …

Cloud Platform = Lock In?

- Proprietary operating systems
- Proprietary management software
- Proprietary database servers
  - E.g. Amazon: RDS, RedShift (SQL), S3, …
- Proprietary security systems
- Proprietary development environments
  - E.g. Microsoft Azure: Reporting Services, Analytics services, Data Management Services, …
- Proprietary …

Data Storage Technologies Available on Cloud Platforms

Cloud Platform	Data Storage Technology
Amazon AWS	Aurora DocumentDB DynamoDB Elasticache for Redis RDS Redshift S3 Timestream
Google	BigQuery Cloud Bigtable Cloud Firestore Cloud Spanner Cloud SQL
Microsoft Azure	Cache for Redis Cosmos DB Data Lake SQL Database Synapse Analytics

Stay Cloud Platform Independent

(IT sovereignty)

=

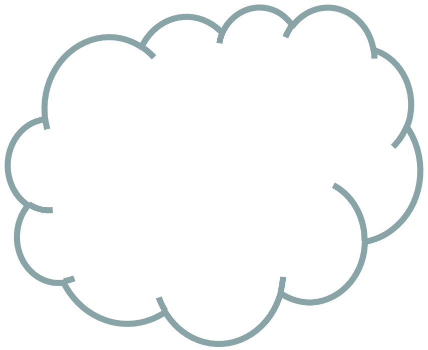
Design to Migrate

Watch Out For Egress Costs!

Public Cloud	Typical Data Egress Charge (per GB)	Cost to move 10 TB, *per month*	Discounted Data Egress Charge (per GB) for 100 TB	Cost to move 100 TB, *per month*
Azure	$0.08	$800	$0.07	$7,000
AWS	$0.02	$200	$0.02	$2,000
Google Cloud Platform	$0.11	$1100	$0.08	$8,000
Oracle	Free up to 10TB	free	$0.0085-$0.050 depending on geography	$850 to $5,000

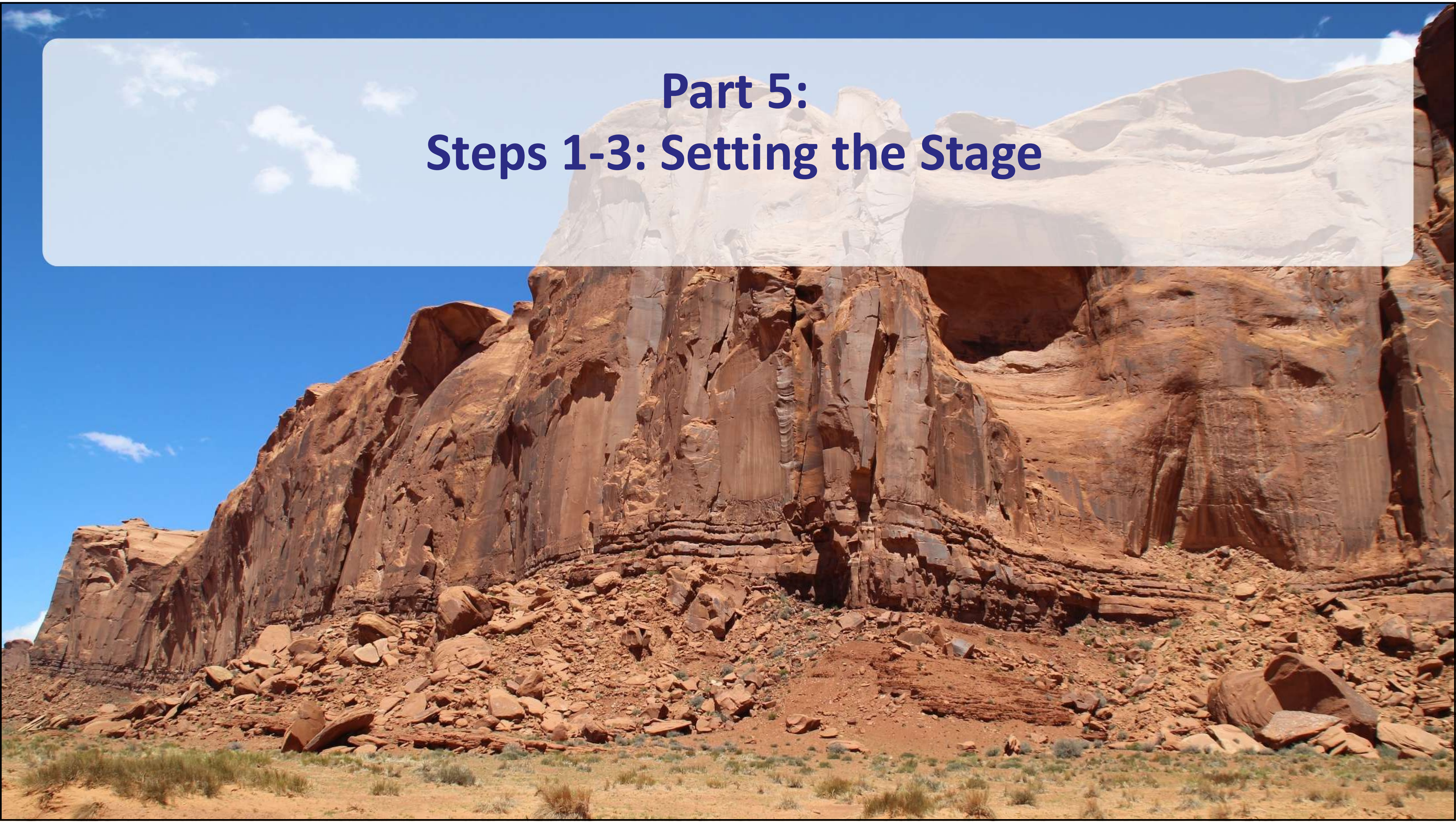
Source: https://www.factioninc.com/blog/it-challenges/egress-charges-how-to-prevent-costs/

Cloud Platform Fees

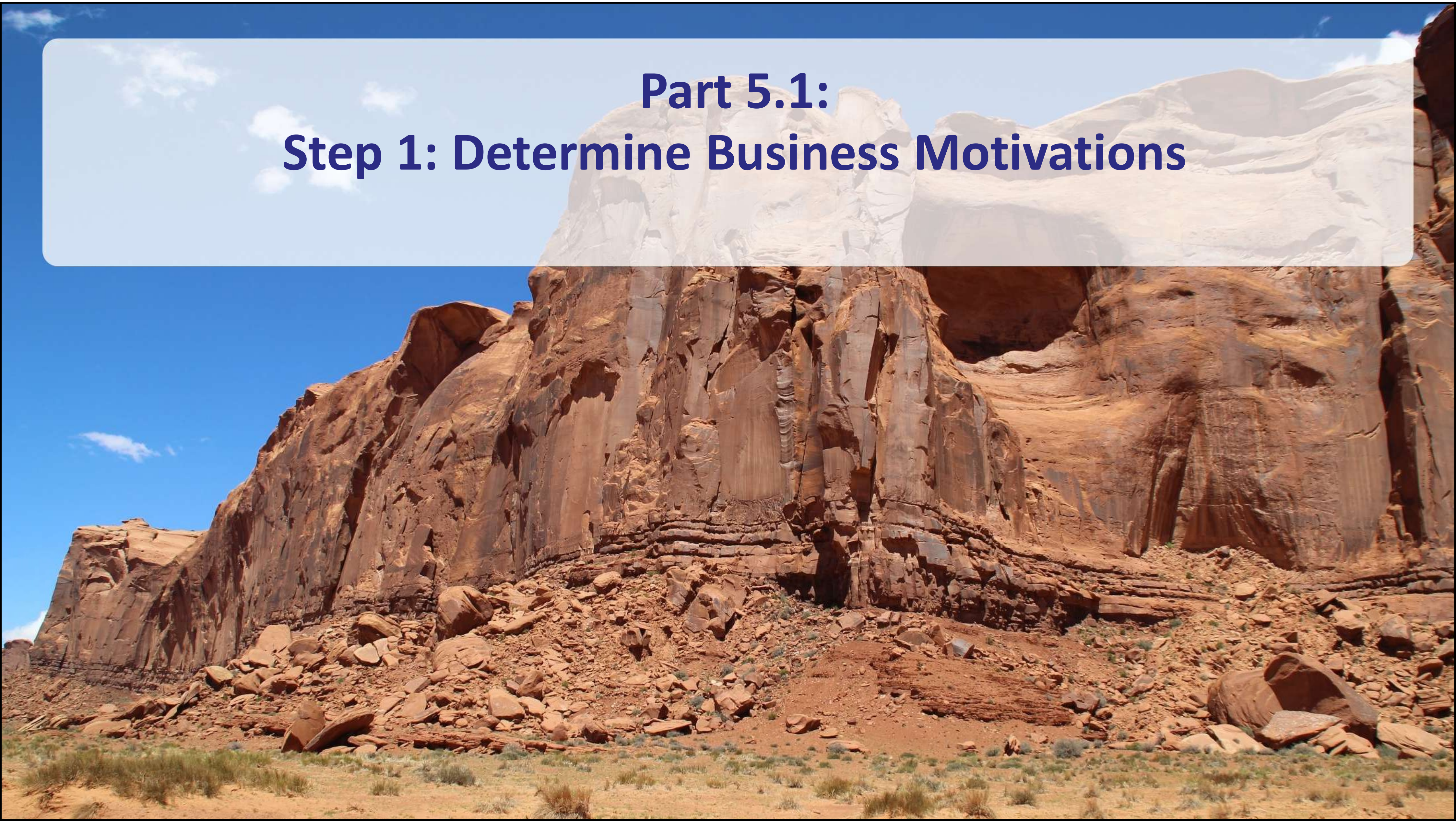


- Fees can have influence on data architecture
- Example:
  - SnowflakeDB: pay for data usage (queries)
    - Store more derived data
  - Exasol: pay for environment size (queries for free)
    - Work with views in stead of physical data marts
- How well can the technology exploit the cloud platform?
  - E.g. cloud is endless MPP, what about the database server?
- Pushing processing into the cloud, close to where data is produced

Part 5:
Steps 1-3: Setting the Stage



Part 5.1:
Step 1: Determine Business Motivations



Poor Examples of Business Motivations

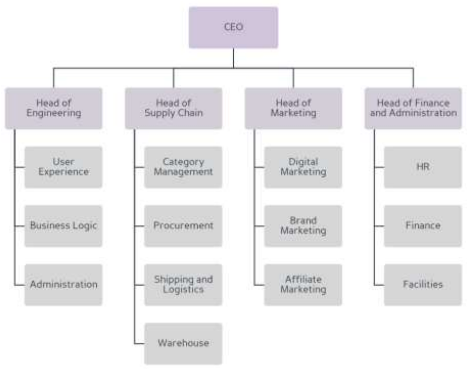

Photo: Jimmy Chang

- Change insights and requirements
- Deployment of self-service BI
- Optimization of existing data architecture
- The platform on which the current BI system is hosted externally is old and needs to be replaced
- Move to the cloud
- Data science is not very well supported by current data warehouse environment
- We want to do more with the data we have, but it's hard to get to it

Proper Business Motivations

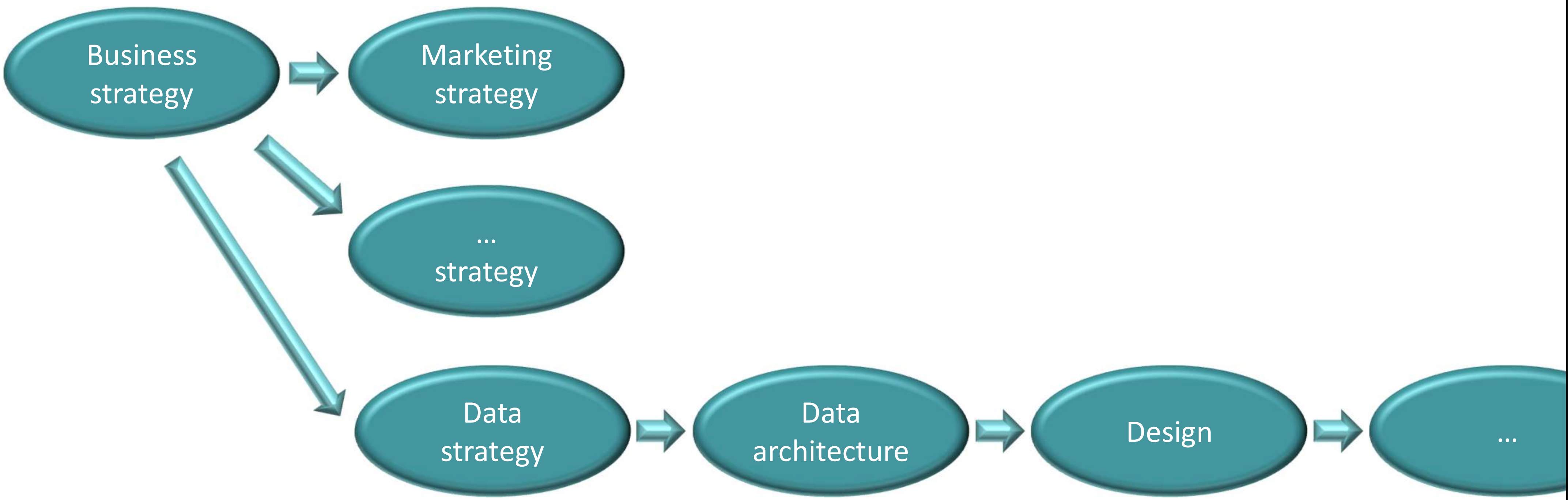
- Competitive improvement
  - Improving reaction speed to customer requests
- Support for customer journey and valuestream
- New business model
  - Allow customers real-time access to data
- Lower costs of specific business processes to improve margin
- Organization under threat
  - New competitor
- Comply with new laws and regulations
  - E.g. GDPR, CCPA, PSD2

Business Strategy and Data Strategy

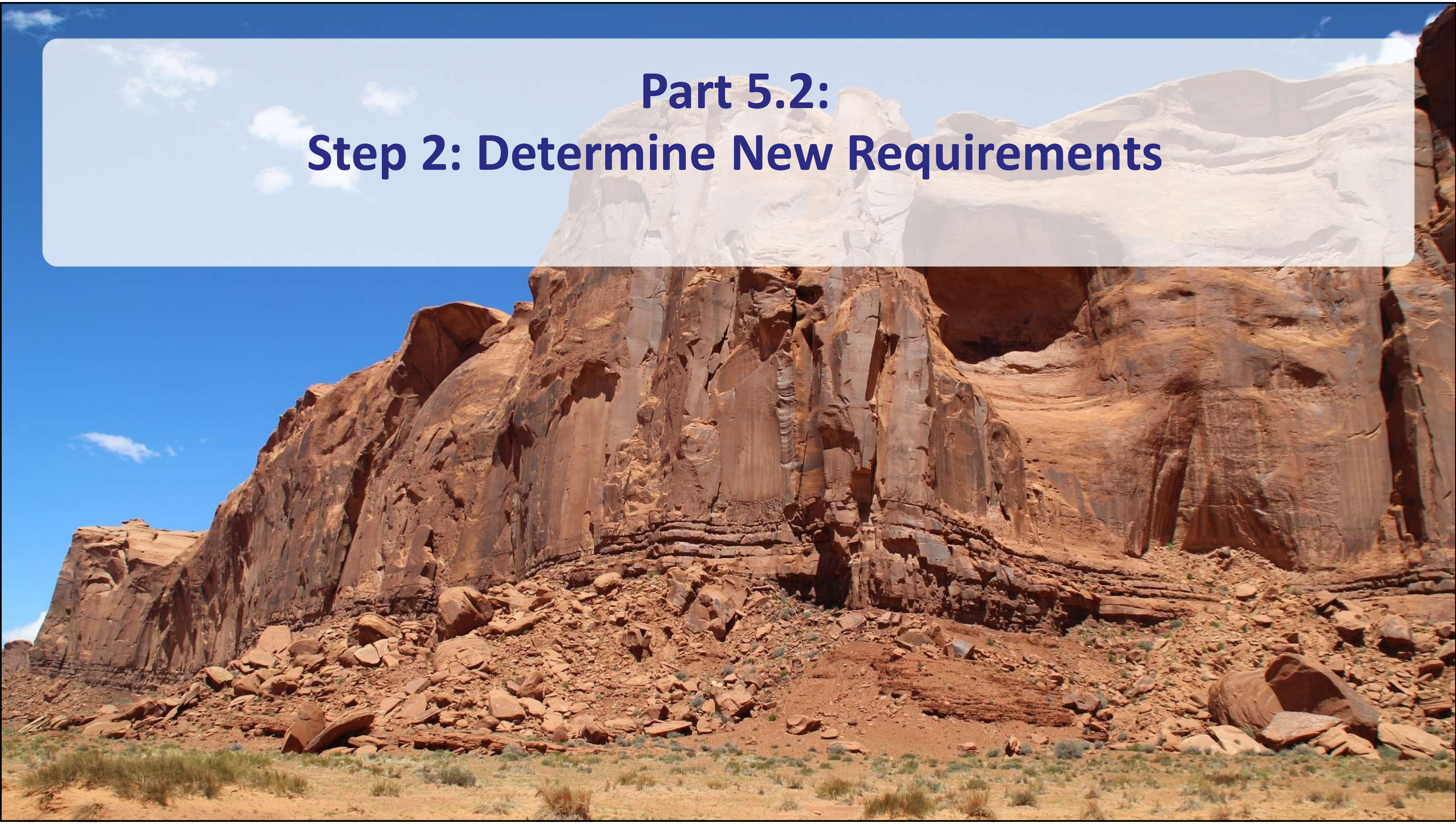


- Business Strategy
  - The challenges of top executives
    - New regulations, competitors, …
  - The main concerns for current business processes
  - Future business developments
    - New business domains
- Data Strategy
  - New data architecture has to “fit” the data strategy
  - New demands for data delivery

From Strategy to Data Architecture and Onwards



Part 5.2:
Step 2: Determine New Requirements



Determine New Requirements (1)

Photo: Markus Spiske

- New analytical functionality
- Lower latency for reports
- More users
- More access to metadata
- Migration to cloud platform
- More data
- More transparency of architecture
- Better security
- Deployment of data science
- …

Determine New Whishes and Requirements (2)

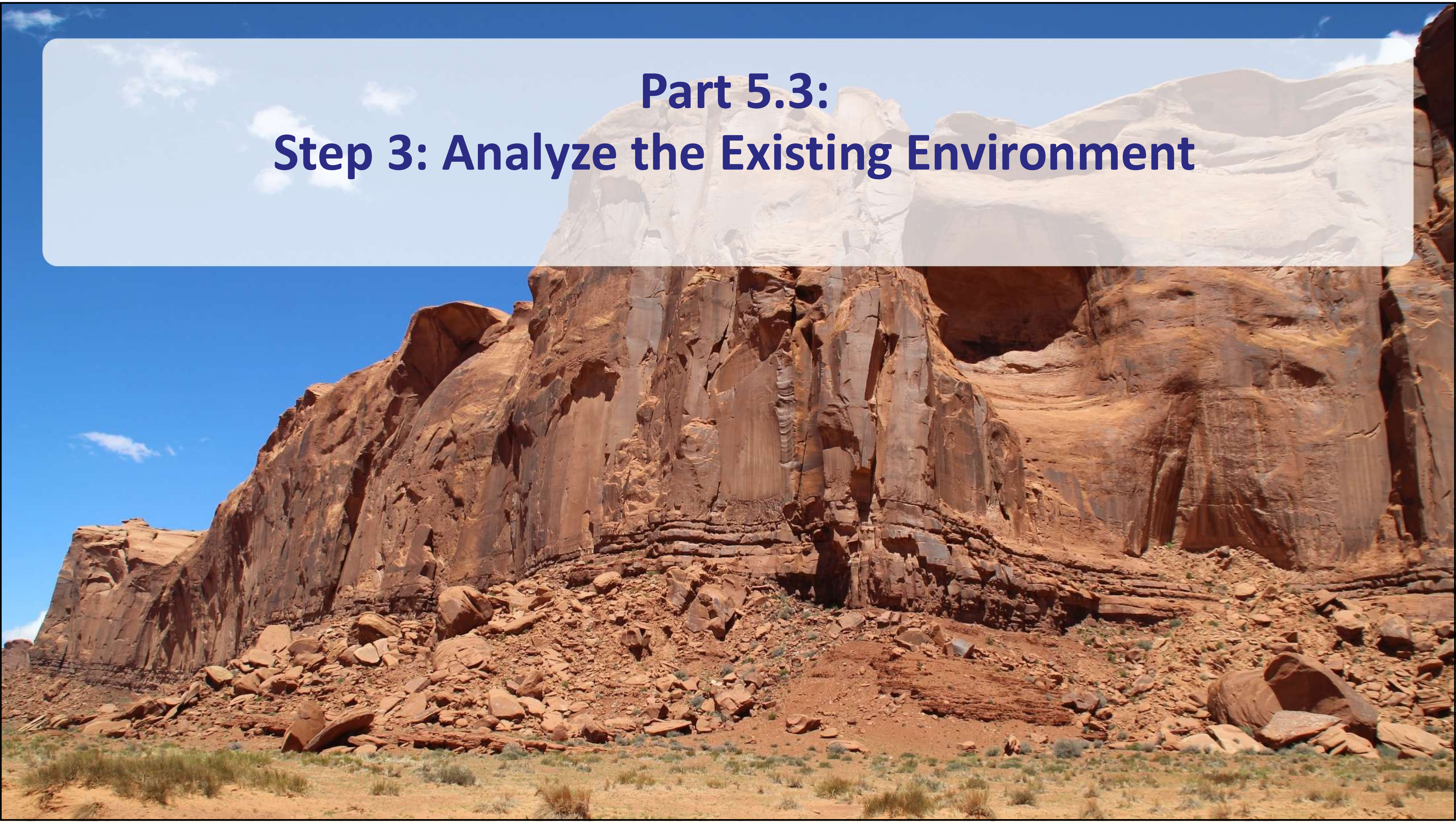

Photo: Markus Spiske

- Reconstruction of processes and decisions
- Data-shop to discover and describe data
- Migrate/redevelop source systems
- Synchronization of source systems
- Minimize data copies
- Sharing data with other organizations
  - Cross-organization analysis systems
- Making data AI-ready
- Strengthening data security and privacy
- Handling unstructured data: video, sound, text, and images
- Simplifying the data processing landscape
- Smarter uses of new technology
- …

Determine Constraints

- Laws and regulations
  - GDPR, CCPA, PSD2, …
- Budget restrictions
- Software limitations
  - One-stop shopping, open source preferred, company preferences, …
- Hardware limitations
  - No easy processing, memory or storage scalability, …
- Current legacy systems
  - Mainframe-based, proprietary applications, plain old, out-of-date/obsolete development environments
- Internal ICT skills

Part 5.3:
Step 3: Analyze the Existing Environment



Determine Current ICT Bottlenecks

- Performance
- Report latency
- Productivity - backlog
- Functionality
- Costs too high
- Business – ICT cooperation
- Non-professional IT organization
- Not IT savvy
- …

Analyze Existing Applications

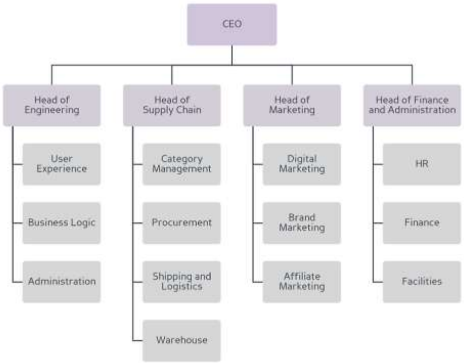
- Data producers
  - Can we access the database directly or through an API?
  - Current workload?
  - Homemade or application?
- Data transformers and transporters
  - Home-made or professional (e.g. ETL, bus, data virtualization)?
  - Implementation style?
- Data Consumers
  - Homemade?
  - Internal or external?

Analyze Technology and Products in Use

Photo: Maxine Rossignol

- Selected products and versions
- Selected (cloud) platforms
- License costs
- Infrastructure
- Potential migration challenges

Determine the Culture of the IT Organization



- Traditional?
- Risk evasive?
- No experience with modern technologies?
- Cynical towards new developments?

Determine IT Maturity Level of Organization (1)

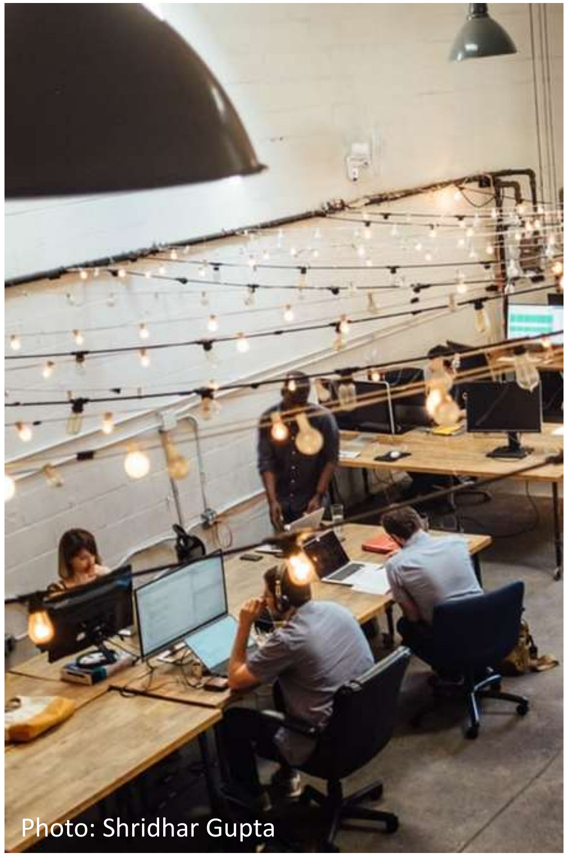


Photo: Shridhar Gupta

- Data processing checks
  - Is data primarily stored to support business processes and to conform to reporting regulations?
  - Can DBAs see the data?
  - Are ETL processes started manually?
  - Is ETL crash automatically fixed?
  - Are transformers scattered across all modules?
  - Is metadata available and kept up to date?
  - Are “old” reports reproducible?

Determine IT Maturity Level of Organization (2)

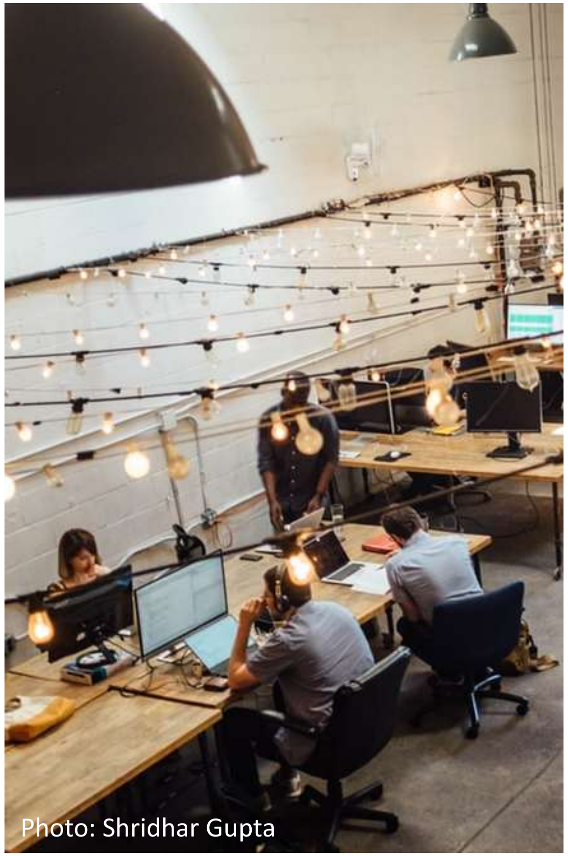


Photo: Shridhar Gupta

- Data consumption
  - Do reports primarily show what has happened within business processes?
  - High data latency?
  - Do they use predictive analytics to optimize business processes and decision-making processes?
- Data management
  - Ownership of data assigned?
  - Is there focus on data quality?
  - Are there procedures in place to fix incorrect data?

Determine IT Maturity Level of Organization (3)

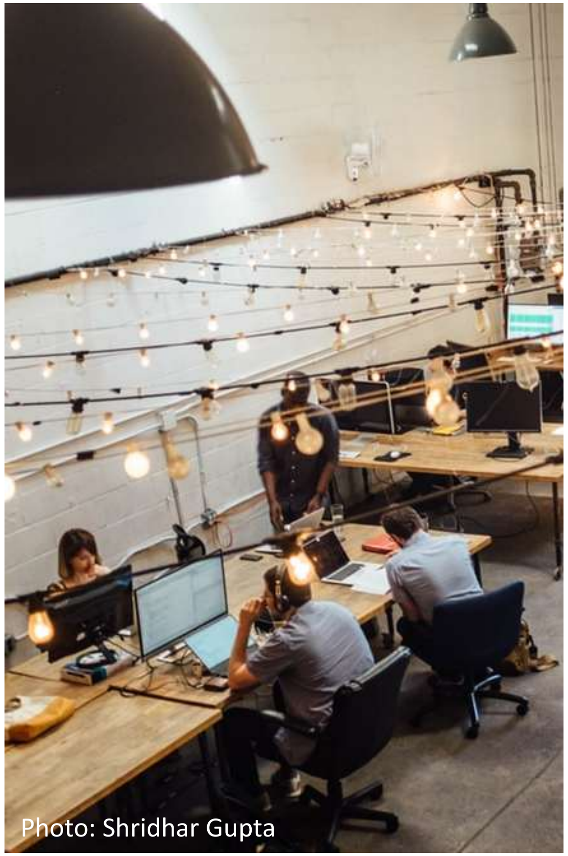
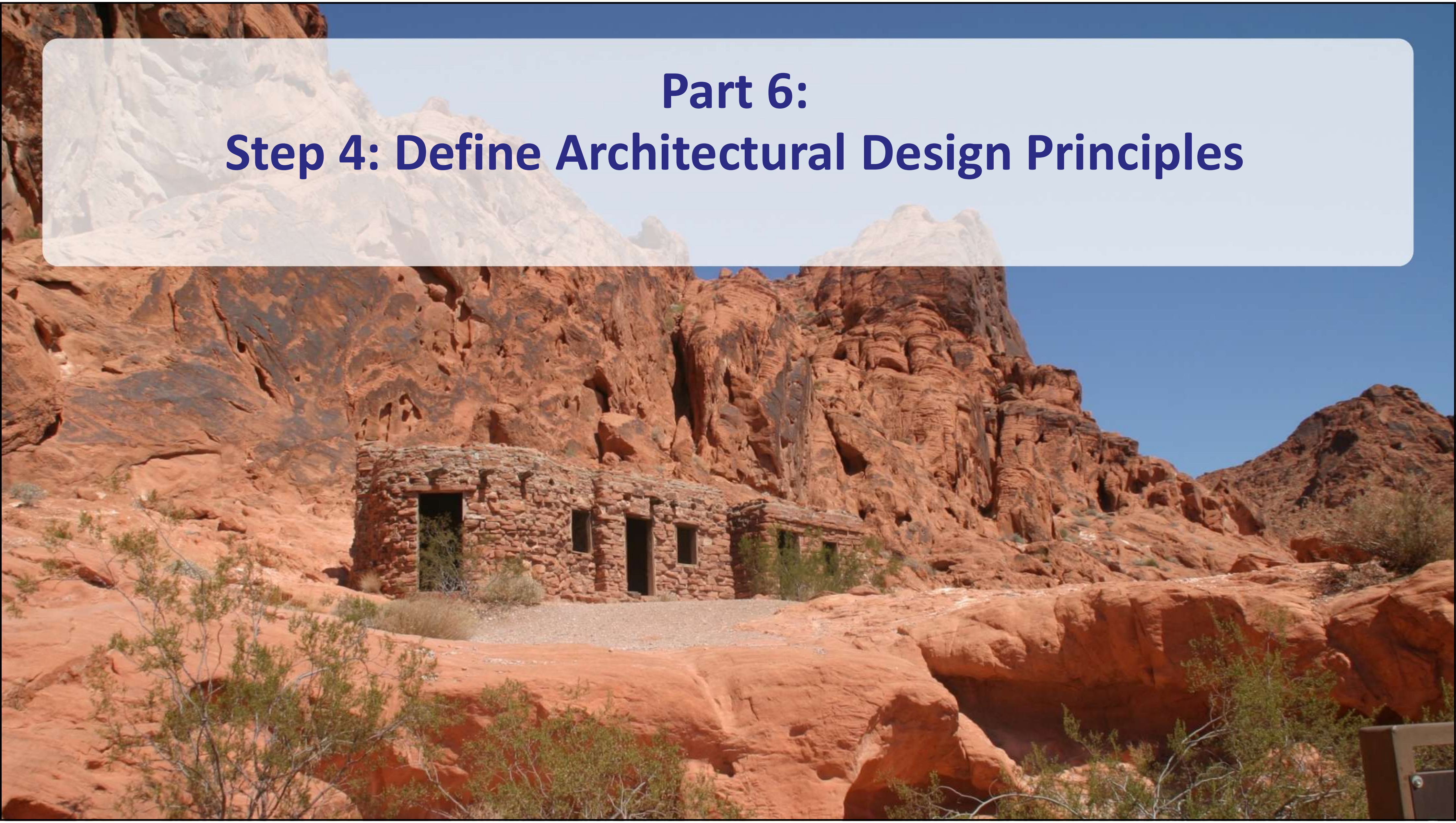


Photo: Shridhar Gupta

- ICT skills
  - All development outsourced?
  - Many tool-jockeys?
  - Performance anxiety?
  - Minimal knowledge of new technologies?

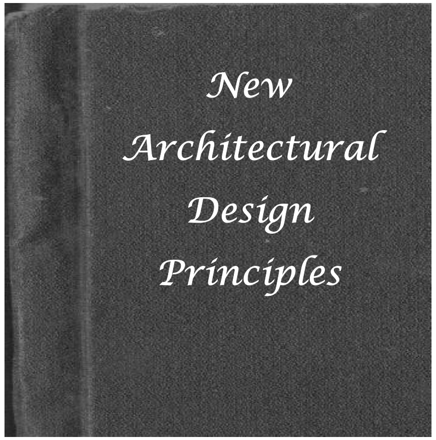
Part 6:
Step 4: Define Architectural Design Principles



Forget Old Architectural Design Principles

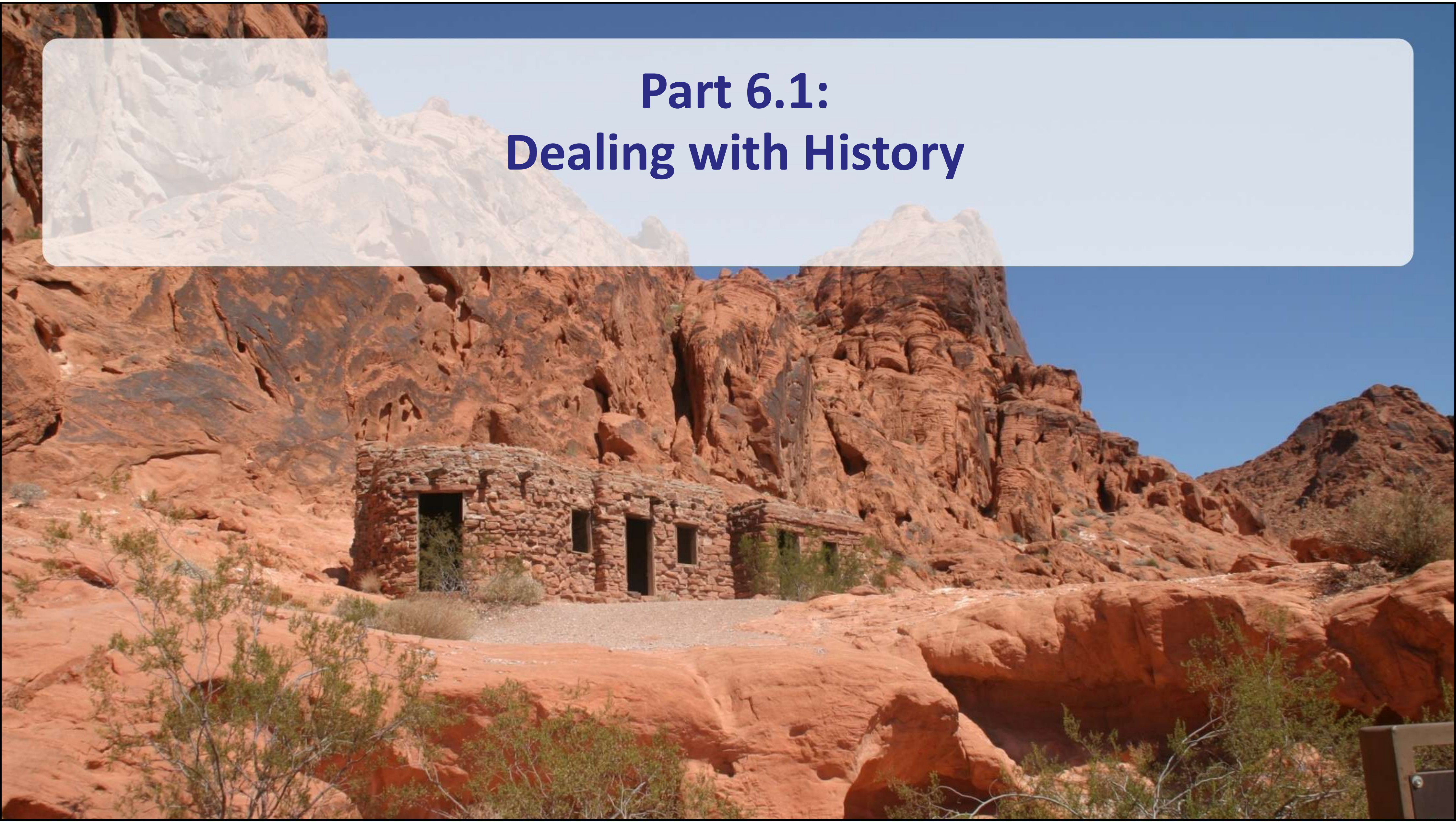
- No reporting on the production database
  - Reporting and transaction workloads clash
- *Physical* data marts are needed to improve reporting performance
- Data marts need a star schema design to speed up analytical queries
- ETL is used to transform data
  - Batch oriented
- When SQL databases are used
  - Indexes are required to improve query performance
  - Use locking for concurrency management
  - Not ideal for MPP
  - Need constant tuning by DBA
- ...

Examples of Architectural Design Principles



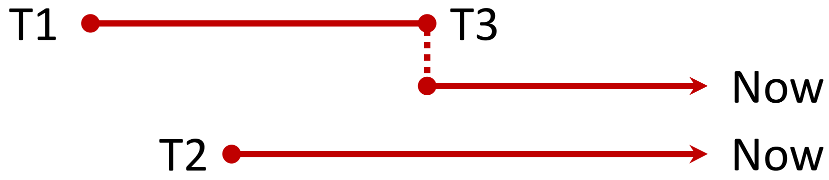
- Centralized and active transformers
  - Searchable definitions and descriptions for technical and business users
  - Lineage and impact analysis
- One universal architecture for all forms of data consumption
  - Standard reporting, self-service BI, apps, data science, …
- Data storage and access technology agnostic
  - Hadoop, SQL, cubes, …
  - Abstraction
- Push the processing to the data, not the data to the processing
  - Decentralized data production
  - Edge analytics
  - Hyper-decentralized data production and storage
- Generator-driven
- …

Part 6.1:
Dealing with History



Modeling History: Simple History for Updates

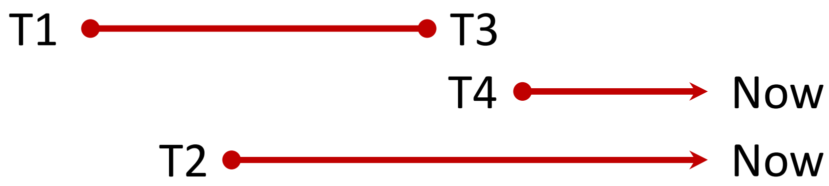
Cid	City	Start	End
C1	London	T1	T3
C1	Leicester	T3	Now
C2	Paris	T2	Now



- No gaps in history
- Only one value for an object on a specific datetime
- Supports following queries:
  - What is the current value – Where End = Now
  - What was the value on a specific datetime - Where date between Start and End

Modeling History: Simple History for Updates with Gaps

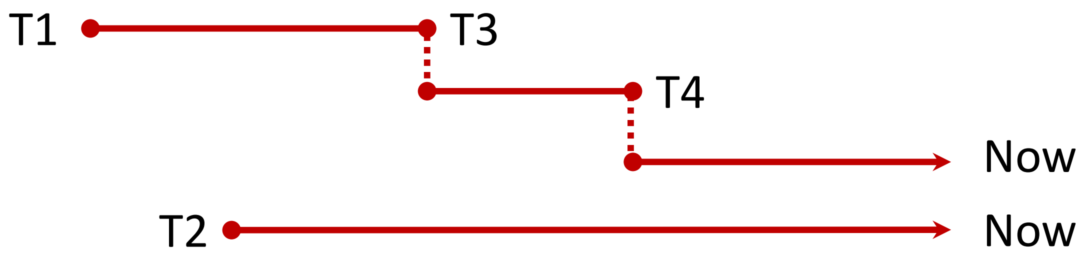
Cid	City	Start	End
C1	London	T1	T3
C1	Leicester	T4	Now
C2	Paris	T2	Now



- No gaps in history
- Only one value for an object on a specific datetime
- Supports following queries:
  - What is the current value – Where End = Now
  - What was the value on a specific datetime - Where date between Start and End - may return no values

Modeling History: Simple History for Updates Without Gaps

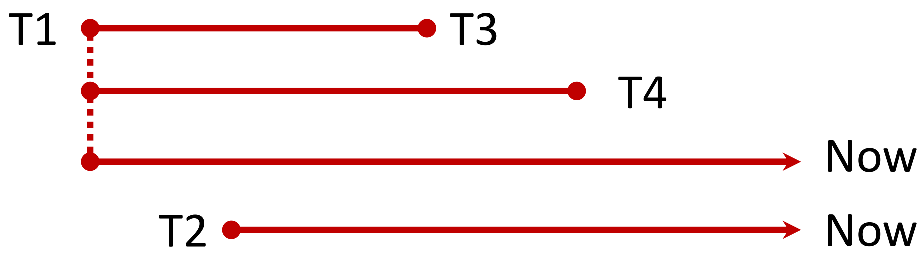
Cid	City	Start	End
C1	London	T1	T3
C1	Gap	T3	T4
C1	Leicester	T4	Now
C2	Paris	T2	Now



- No gaps in history
- Only one value for an object on a specific datetime
- Supports following queries:
  - What is the current value – Where End = Now
  - What was the value on a specific datetime - Where date between Start and End – always returns a value; sometimes nothing

Modeling History: Corrections

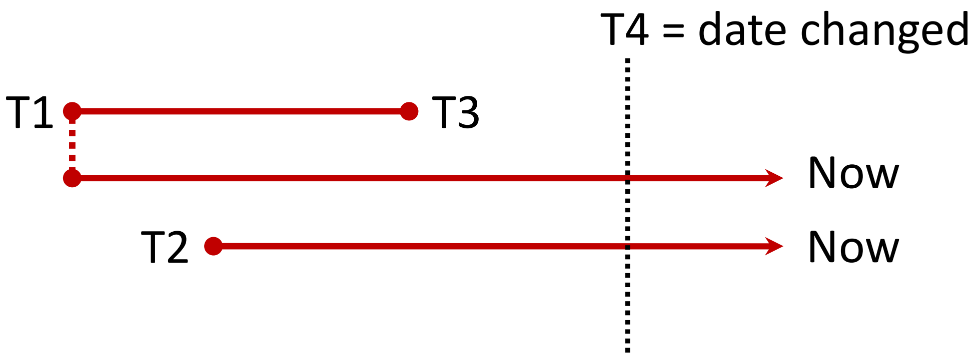
Cid	City	Start	End
C1	Londdon	T1	T3
C1	Londn	T1	T4
C1	London	T1	Now
C2	Paris	T2	Now



- No gaps in history
- Multiple values for an object on a specific datetime
- Supports following queries:
  - What is the current value – Where End = Now
  - What was the value on a specific datetime – Get the oldest where date between Start and End

Modeling History: Delayed Corrections

Cid	City	Start	End	Changed
C1	Londdon	T1	T3	T4
C1	London	T1	Now	
C2	Paris	T2	Now	



- Extra column required
- No gaps in history
- Multiple values for an object on a specific datetime
- Supports following queries:
  - What is the current value – Where End = Now
  - What was the value on a specific datetime – Get the oldest where date between Start and End

Modeling History: Logging Updates and Corrections

Cid	City	Start	End	Changed	Insert id	Change id
C1	London	T1	T2		Insert1	Update1
C1	Leicester	T2	Now		Insert2	
C2	Paris	T3	T4		Insert3	Update2
C2	Lyon	T4	T5		Insert4	Delete1

Change id	Who	When	Where	…
Insert1	User1	T1	…	…
Insert2	User2	T2	…	…
Insert3	User1	T3	…	…
Insert4	User3	T4	…	…
Update1	User2	T2	…	…
Update2	User4	T4	…	…
Delete1	User5	T5	…	…

- Log table for auditing purposes
- Batch inserts, updates, and deletes

Modeling Streaming Data: Single Values

Incoming Stream
T1, S1, Temp=50
T2, S1, Temp=52
T3, S2, Temp=51
T4, S3, Temp=49
T5, S1, Temp=52;
T5, S2, Temp=53

Key	Start	End	Sensor	Temp	Avg Temp
1		T1	S1	50	50
2	T1	T2	S1	52	51
5	T2	T5	S1	52	51,3
3		T3	S2	51	51
6	T3	T5	S2	53	52
4		T4	S3	49	49

- Key is unique artificial value
- Measurement is considered as temperature since previous measurement
- Sensor data is arriving in the right order

Modeling Streaming Data: Multiple Values

Incoming Stream
T1, S1, Temp=50
T2, S1, Temp=52
T3, S2, Temp=51
T4, S3, Temp=49
T5, S1, Temp=52; S2, Temp=53

Key	Start	End	Sensor	Temp	Avg Temp
1		T1	S1	50	50
2	T1	T2	S1	52	51
5	T2	T5	S1	52	51,3
3		T3	S2	51	51
6	T3	T5	S2	53	52
4		T4	S3	49	49

- Key is unique artificial value
- Stream records are flattened
- Measurement is considered as temperature since previous measurement
- Sensor data is arriving in the right order

Modeling Streaming Data: Delta Values

Incoming Stream
T1, S1, Temp=50
T2, S1, Temp=+2
T3, S2, Temp=51
T4, S3, Temp=49
T5, S1, Temp=+0
T5, S2, Temp=+2

Key	Start	End	Sensor	Temp	Avg Temp
1		T1	S1	50	50
2	T1	T2	S1	52	51
5	T2	T5	S1	52	51,3
3		T3	S2	51	51
6	T3	T5	S2	53	52
4		T4	S3	49	49

- Key is unique artificial value
- Measurement is considered as change in temperature
- Sensor data is arriving in the right order

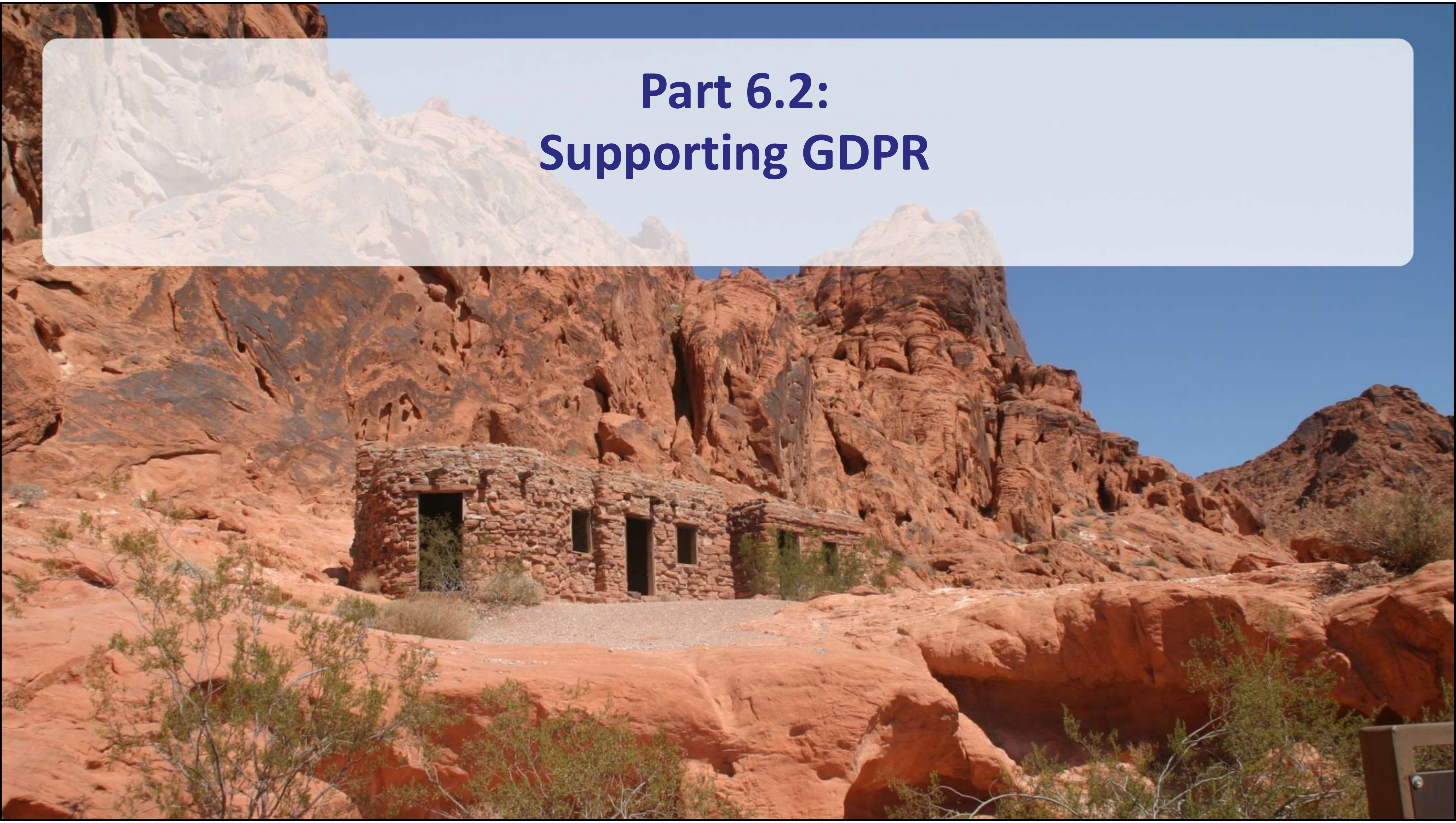
Modeling Streaming Data: Log Data

Incoming Stream
T1, Insert, C1, London
T2, Update, C1, Leicester
T3, Insert, C2, Paris
T4, Insert, C3, Berlin
T5, Update, C1, Manchester
T5, Update, C3, Munich

Cid	City	Start	End
C1	London	T1	T2
C1	Leicester	T2	T5
C1	Machester	T5	Now
C2	Paris	T3	Now
C3	Berlin	T4	T5
C3	Munich	T5	Now

- Business key used
- Stream is seen as data entry
- Careful with parallel inserts; order not unimportant
  - Loading with hashed keys?

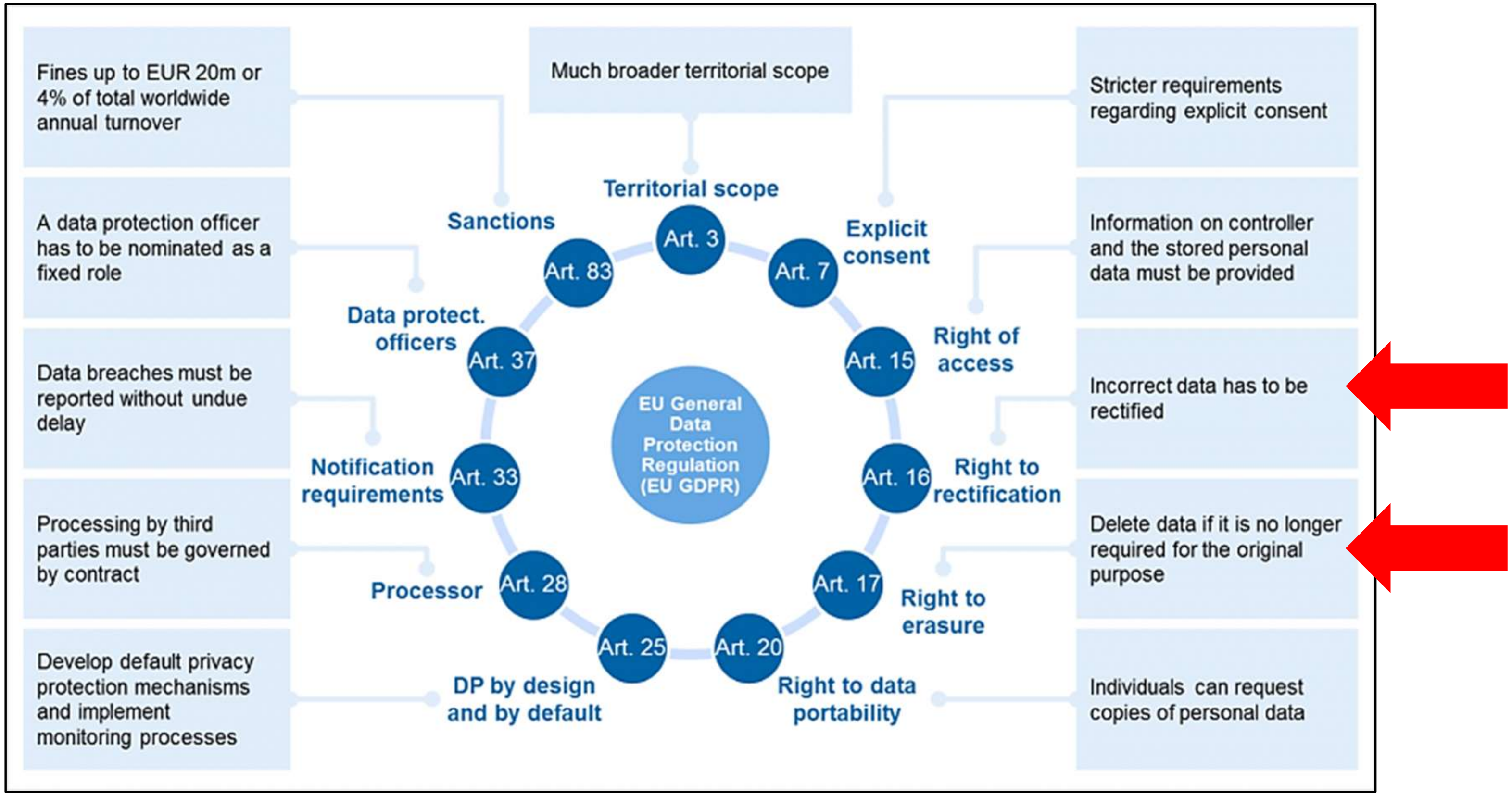
Part 6.2:
Supporting GDPR



GDPR – The Right to be Forgotten

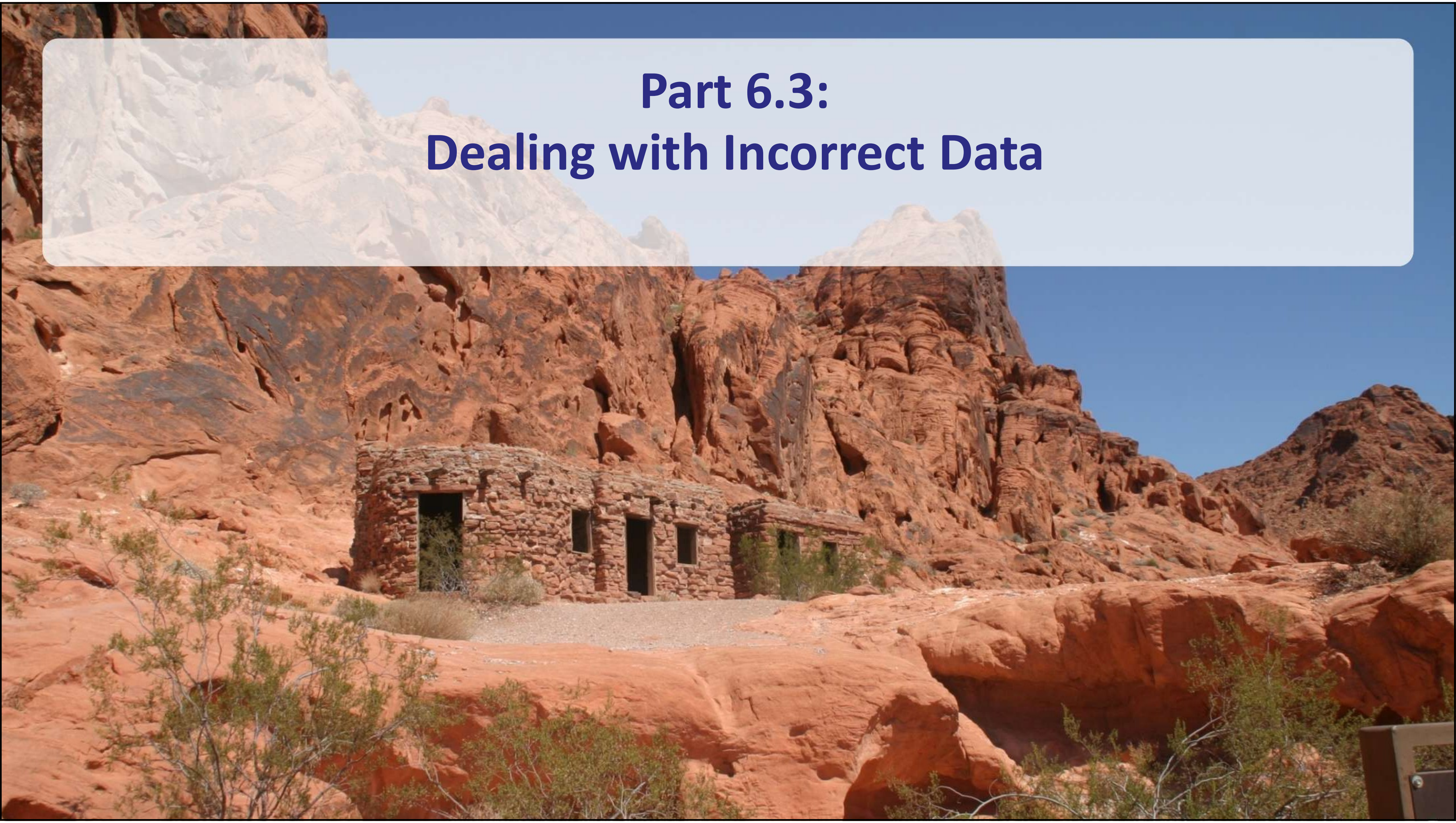
- Art. 17 GDPR Right to erasure (right to be forgotten)
  - The rule primarily regulates erasure obligations
- According to this, personal data must be erased immediately where the data are no longer needed for their original processing purpose, or the data subject has withdrawn his consent and there is no other legal ground for processing, the data subject has objected and there are no overriding legitimate grounds for the processing, or erasure is required to fulfill a statutory obligation under the EU law or the right of the Member States.
- In addition, data must naturally be erased if the processing itself was against the law in the first place
- A data subject should have the right to have personal data concerning him or her rectified

Requirements of GDPR

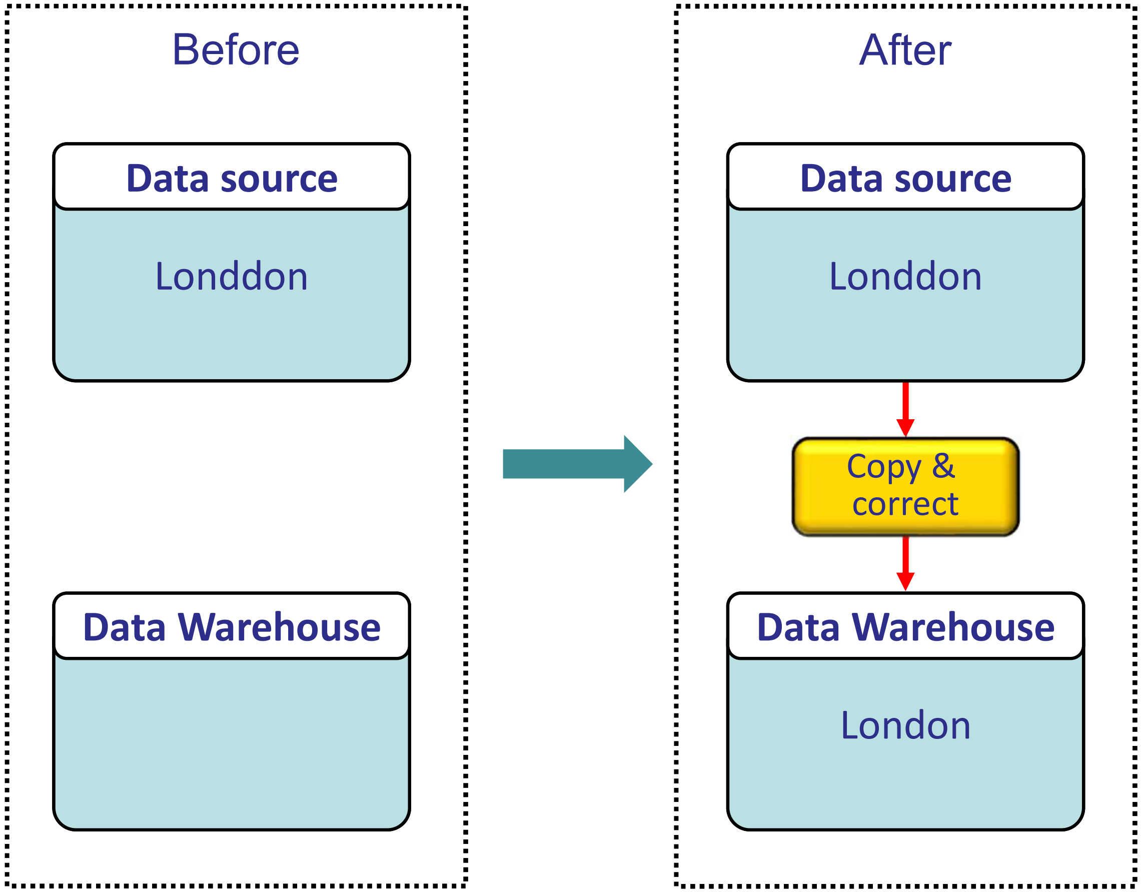


Source: Banking Hub, November 2017;
see https://www.bankinghub.eu/banking/finance-risk/gdpr-deep-dive-implement-right-forgotten

Part 6.3:
Dealing with Incorrect Data

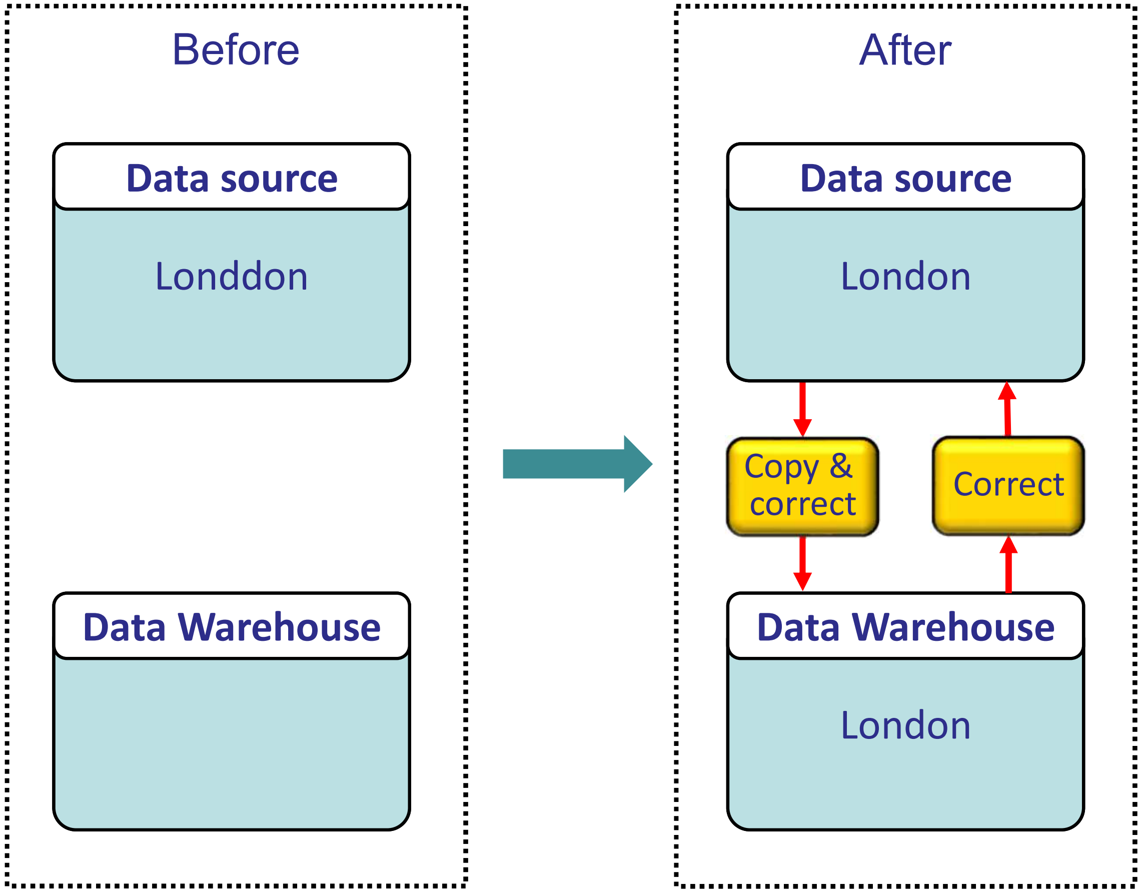


Data Correction Strategies: Simple



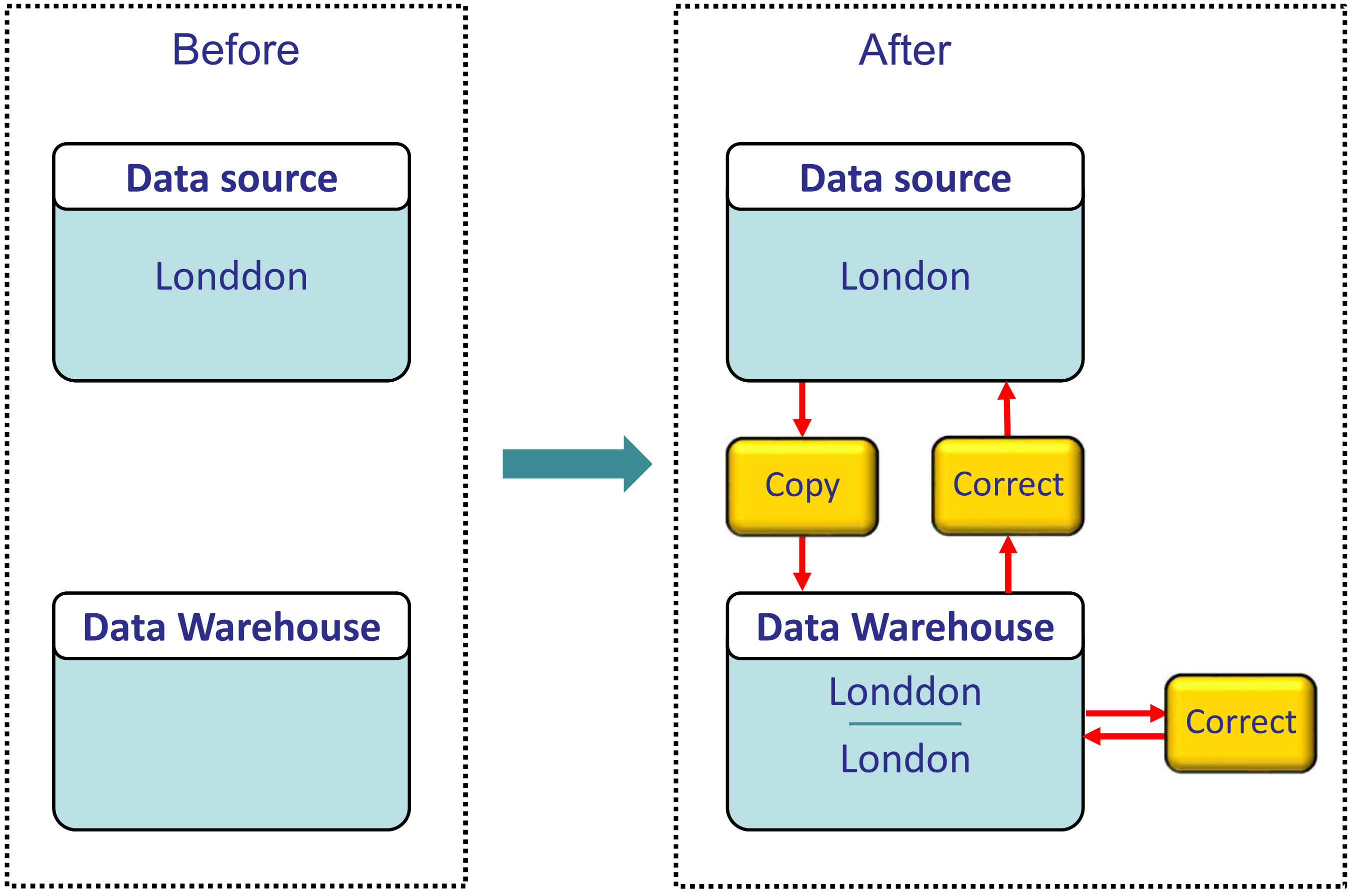
- Restricted to programmable cleansing operations
- Easy to implement
- Source doesn't benefit from cleansing
- Source and data warehouse inconsistent
- No impact on organization
- No time travel supported

Data Correction Strategies: Synchronize



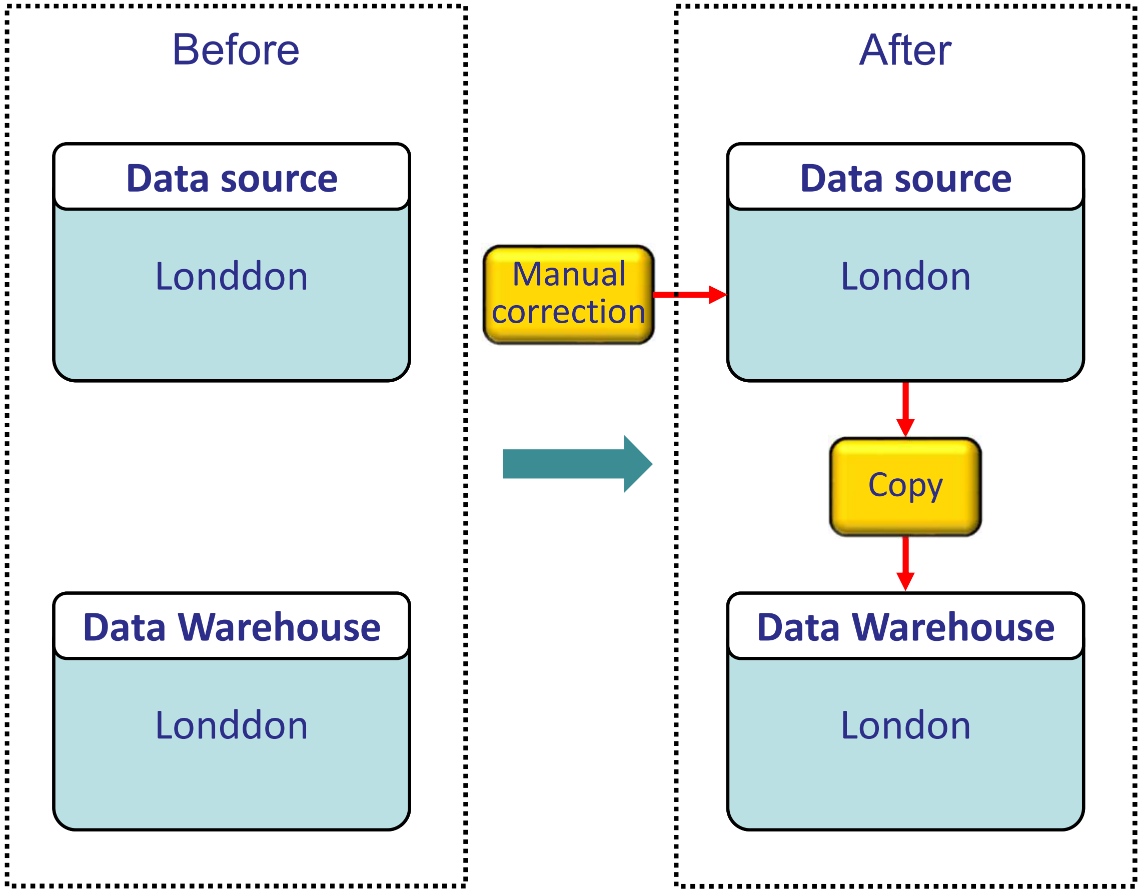
- Manual or automated process?
- Source benefits from cleansing
- Source and data warehouse consistent
- Impact on organization
- No time travel supported

Data Correction Strategies: Time Travel



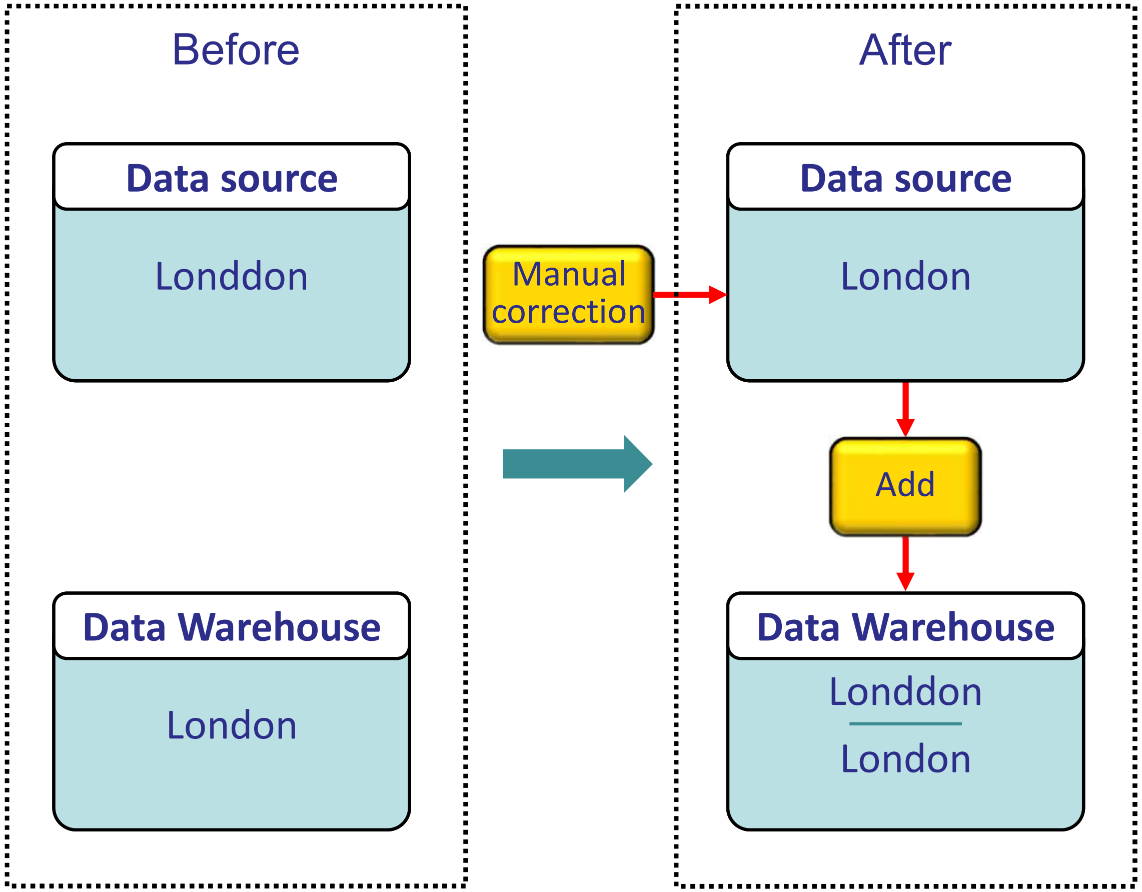
- Restricted to programmable cleansing operations
- Source benefits from cleansing
- Source and data warehouse consistent
- Time travel supported

Data Correction Strategies: Manual Corrections



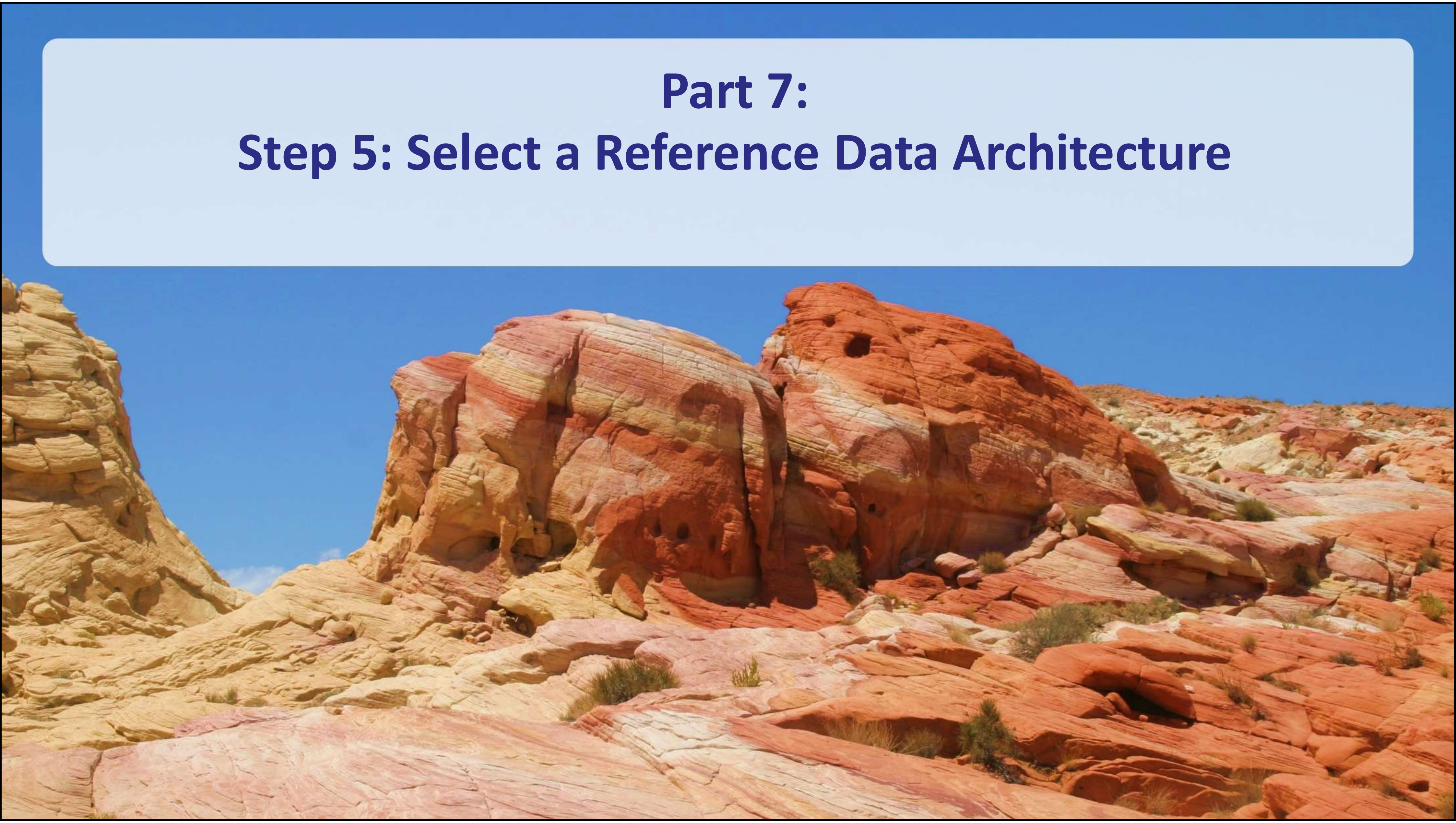
- User corrections
- Source benefits from cleansing
- Source and data warehouse consistent
- Impact on organization
- No time travel supported

Data Correction Strategies: Manual Corrections + Time Travel



- User corrections
- Source benefits from cleansing
- Source and data warehouse consistent
- Impact on organization
- Time travel supported

Part 7:
Step 5: Select a Reference Data Architecture



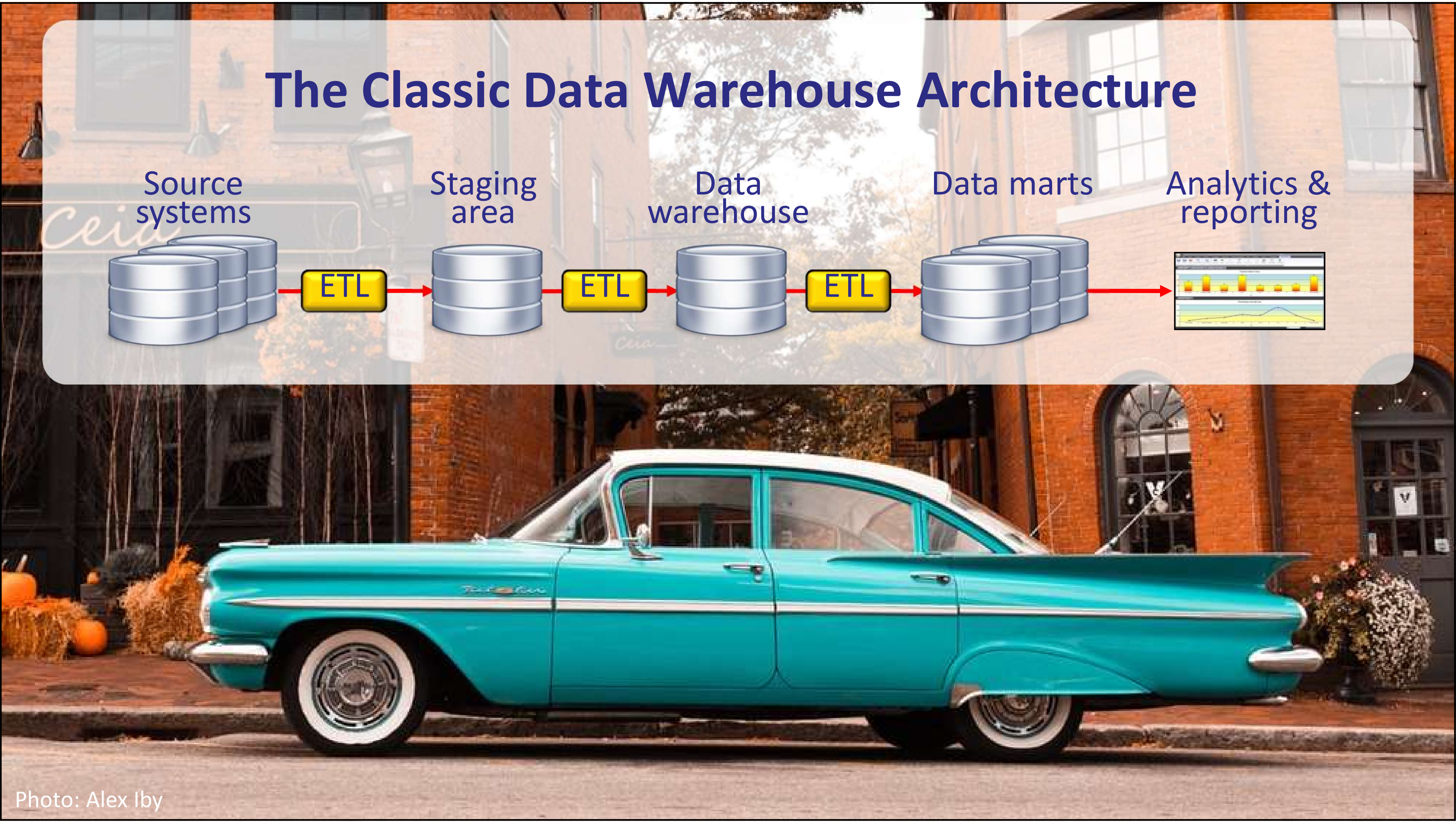
Roadmap for Designing Data Architectures

1. Determine business motivations
2. Determine new requirements
3. Analyze the existing environment
4. Define architectureal design principles
5. Selecta reference data architecture
6. Desogn the new data architecture
7. Determine the implementation approach
8. Select new products and technologies
9. Introduce the data architecture within the organization

Common Challenges

- Source data must be queryable
- Developers and data consumers can’t find data easily
- Every insert, update, delete and query should be logged for reconstruction purposes and transparency
- Horizontal and operational lineage
- CRUD interface for real-time synchronization
- Centralized, reusable, versioned business logic
- Proper authorization when integrating data

Part 7.1:
The Classic Data Warehouse Architecture


The Classic Data Warehouse Architecture
Source systems
ETL
Staging area
ETL
Data warehouse
ETL
Data marts
Analytics & reporting
Photo: Alex Iby

Yesterday: Data Warehouse and Data Consumption

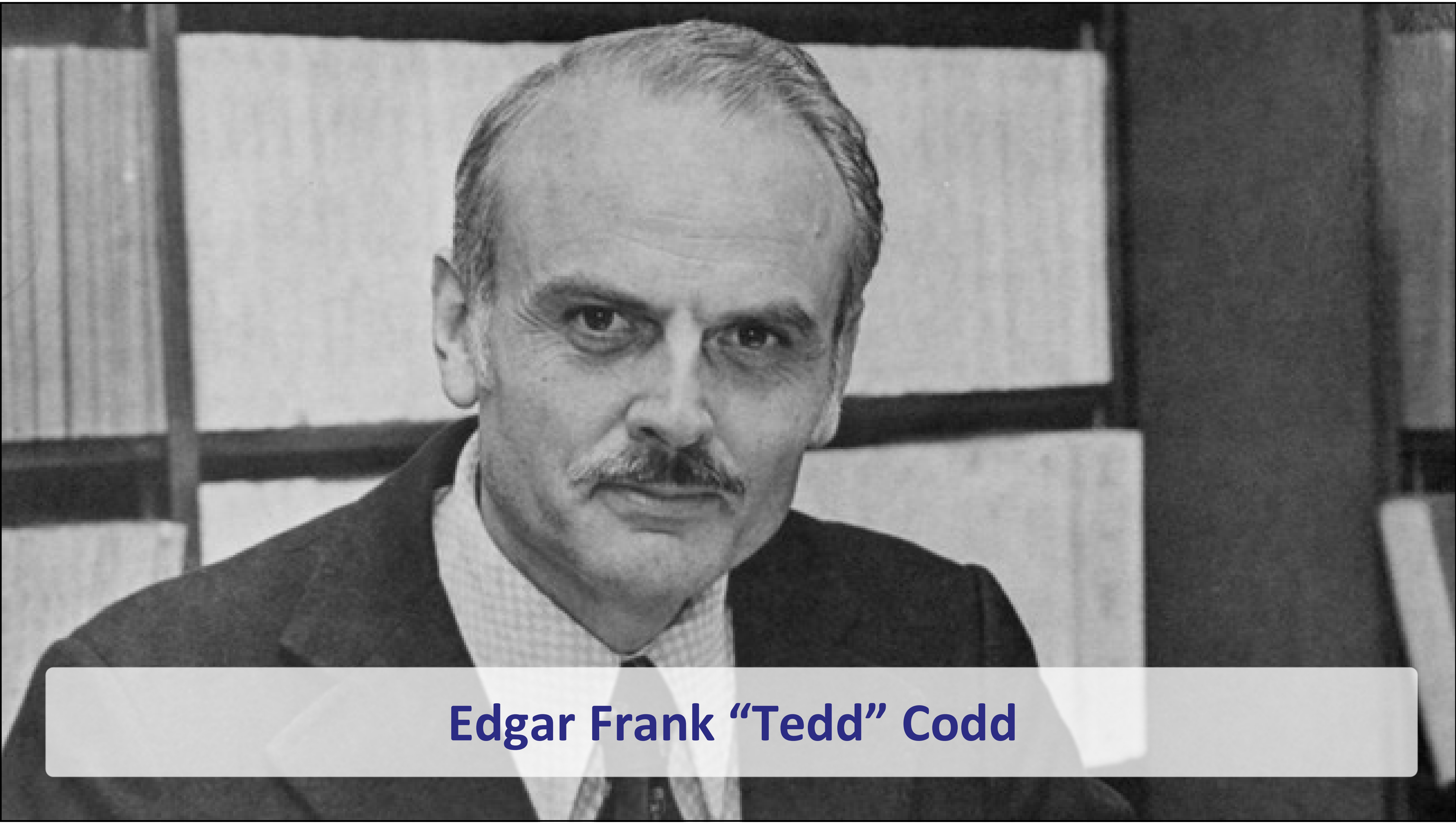
Developers	Development Styles	Report Types	Consumers
IT specialists	Pre-programmed, auditable, governable, formally tested	Batch and online business reports	Business users
			Legislators

Today & Tomorrow: Data Warehouse and Data Comsumption

Developers	Development Styles	Report Types	Consumers
IT specialists	Pre-programmed, auditable, governable, formally tested	Batch and online business reports	Business users
			Legislators
			External parties
		Customer-facing apps	Consumers
		Streaming analytics	Business users, machines
	Self-service, investigative	Ad-hoc reports	Business users
Business Users	Pre-programmed	Simple data retrieval	Business users
	Self-service, investigative	Ad-hoc reports	Business users
		Data mining, statistics	Data scientists
		Dark data analysis	Business users and IT

The Classic Data Warehouse Architecture is Like a Rigid Assembly Line

Part 7.2:
The Logical Data Warehouse Architecture



Edgar Frank “Tedd” Codd

Ted Codd – June 1970

> Future users of large data banks must be protected from having to know how the data is organized (…) application programs should remain unaffected when the internal representation of data is changed …

Source: https://cs.uwaterloo.ca/~david/cs848s14/codd-relational.pdf

Ted Codd on Data Independence

The 1981 ACM Turing Award Lecture

Delivered at ACM '81, Los Angeles, California, November 9, 1981

The 1981 ACM Turing Award was presented to Edgar F. Codd, an IBM Fellow of the San Jose Research Laboratory, by President Peter Denning on November 9, 1981 at the ACM Annual Conference in Los Angeles, California. It is the Association's foremost award for technical contributions to the computing community.

Codd was selected by the ACM General Technical Achievement Award Committee for his "fundamental and continuing contributions to the theory and practice of database management systems." The originator of the relational model for databases, Codd has made further important contributions in the development of relational algebra, relational calculus, and normalization of relations.

Edgar F. Codd joined IBM in 1949 to prepare programs for the Selective Sequence Electronic Calculator. Since then, his work in computing has encompassed logical design of computers (IBM 701 and Stretch), managing a computer center in Canada, heading the development of one of the first operating systems with a general multiprogramming capability, contributing to the logic of self-reproducing automata, developing high level techniques for software specification, creating and extending the relational approach to database management, and developing an English analyzing and synthesizing subsystem for casual users of relational databases. He is also the author of *Cellular Automata*, an early volume in the ACM Monograph Series.

Codd received his B.A. and M.A. in Mathematics from Oxford University in England, and his M.Sc. and Ph.D. in Computer and Communication Sciences from the University of Michigan. He is a Member of the National Academy of Engineering (USA) and a Fellow of the British Computer Society.

The ACM Turing Award is presented each year in commemoration of A. M. Turing, the English mathematician

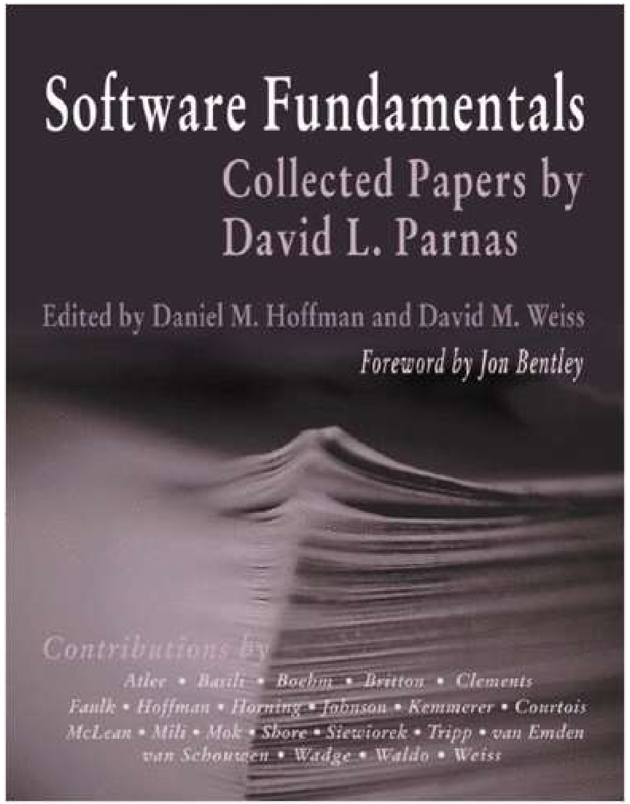
2. Motivation

The most important motivation for the research work that resulted in the relational model was the objective of providing a sharp and clear boundary between the logical and physical aspects of database management (including database design, data retrieval, and data manipulation). We call this the *data independence objective.*

A second objective was to make the model structurally simple, so that all kinds of users and programmers could have a common understanding of the data, and could therefore communicate with one another about the database. We call this the *communicability objective.*

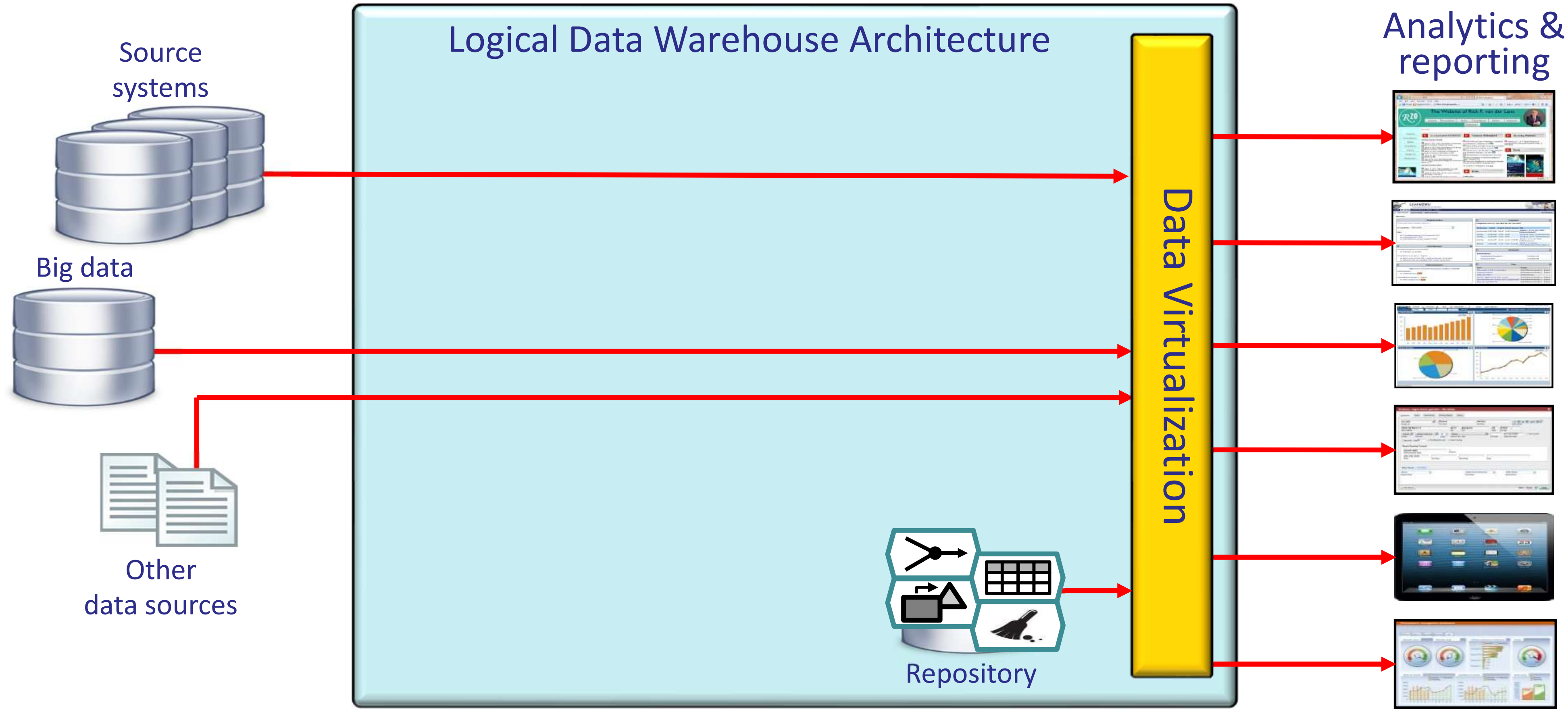
A third objective was to introduce high level language concepts (but not specific syntax) to enable users to express operations upon large chunks of information at a time. This entailed providing a foundation for set-oriented processing (i.e., the ability to express in a single statement the processing of multiple sets of records at a time). We call this the *set-processing objective.*

David Parnas - Information Hiding - 1972

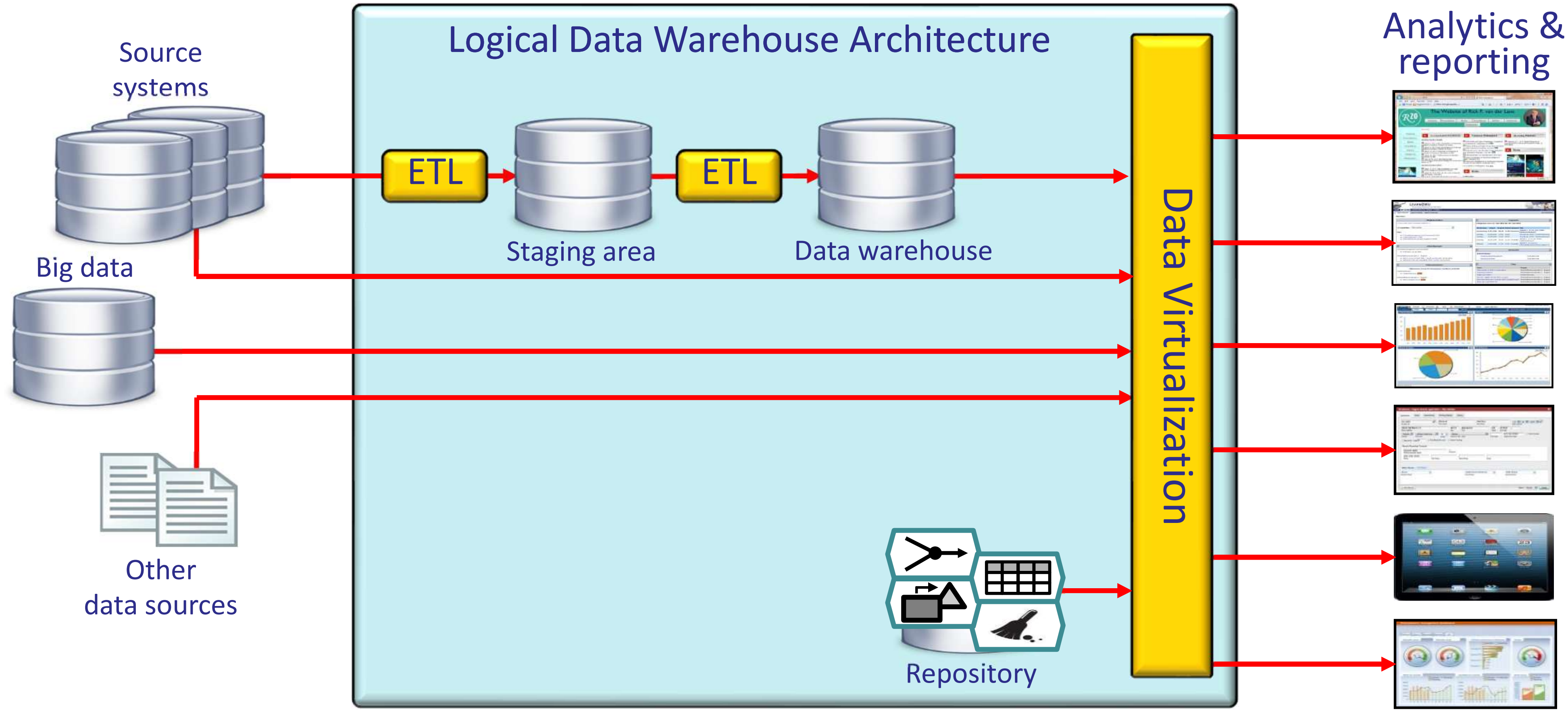


http://www.cs.umd.edu/class/spring2003/cmsc838p/Design/criteria.pdf

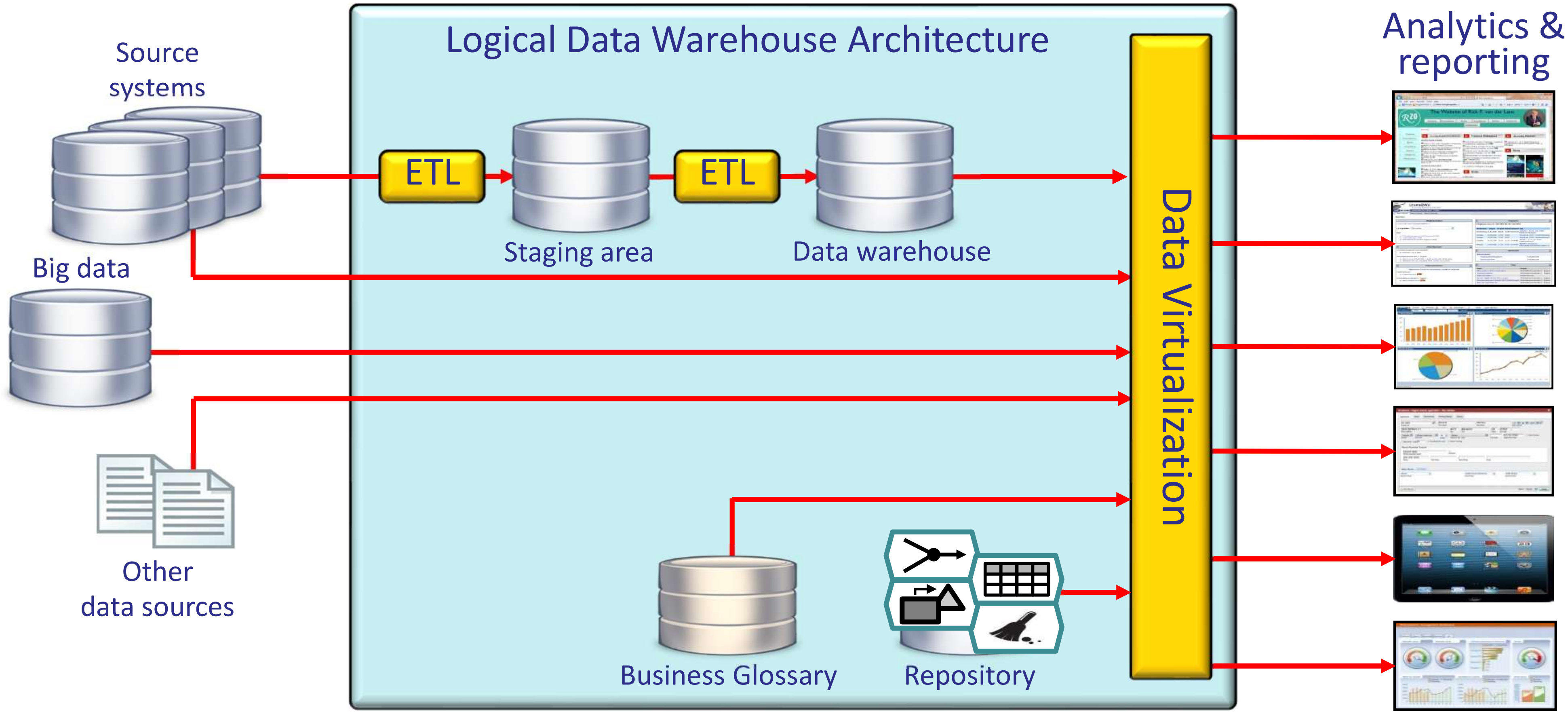
The Logical Data Warehouse Architecture (1)



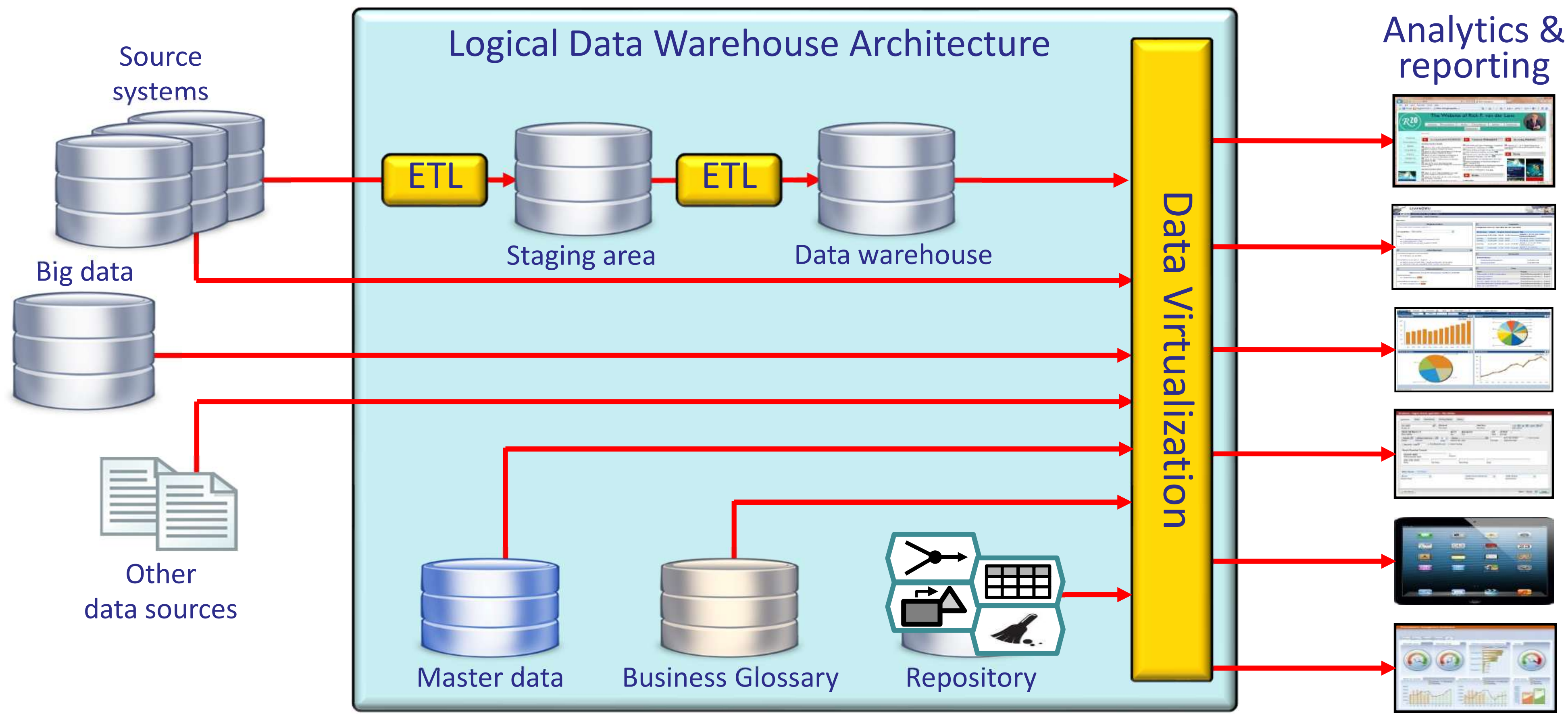
The Logical Data Warehouse Architecture (2)



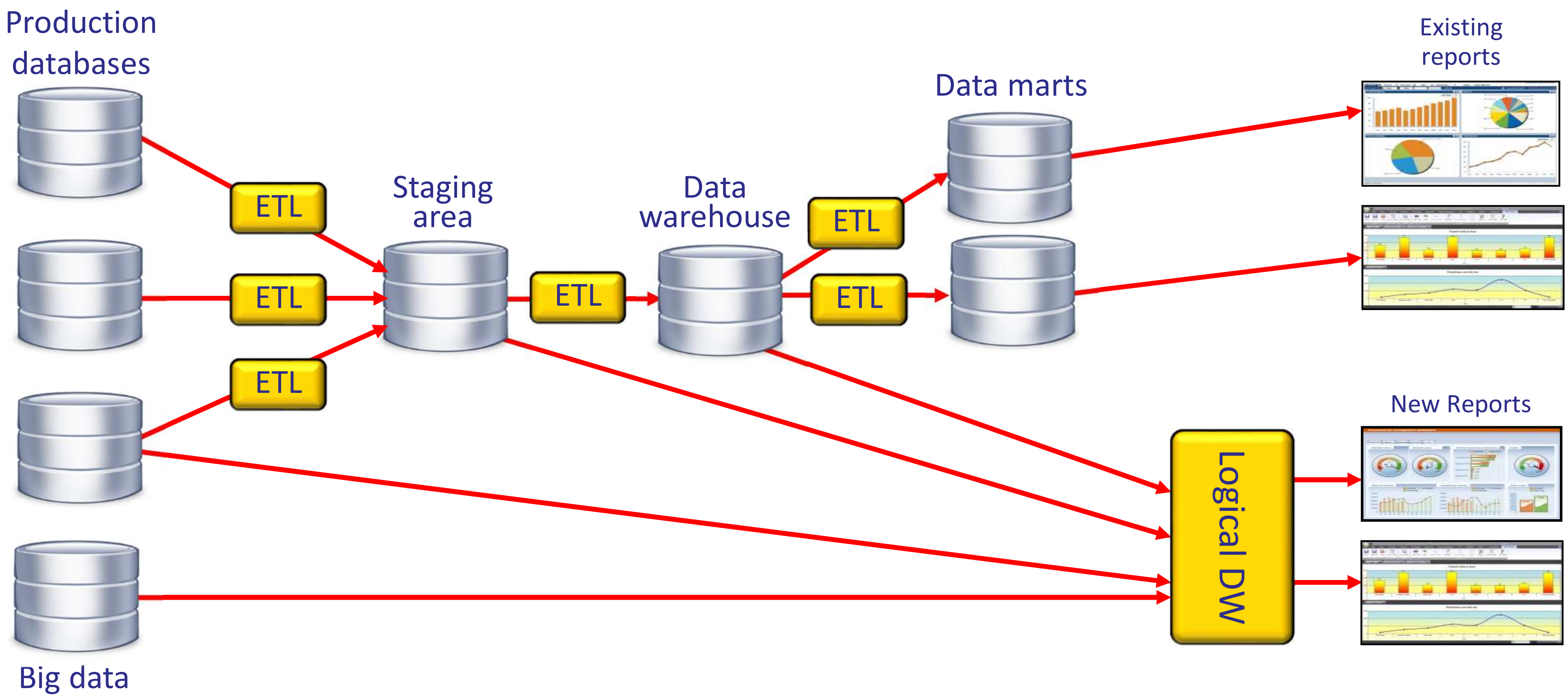
The Logical Data Warehouse Architecture (3)



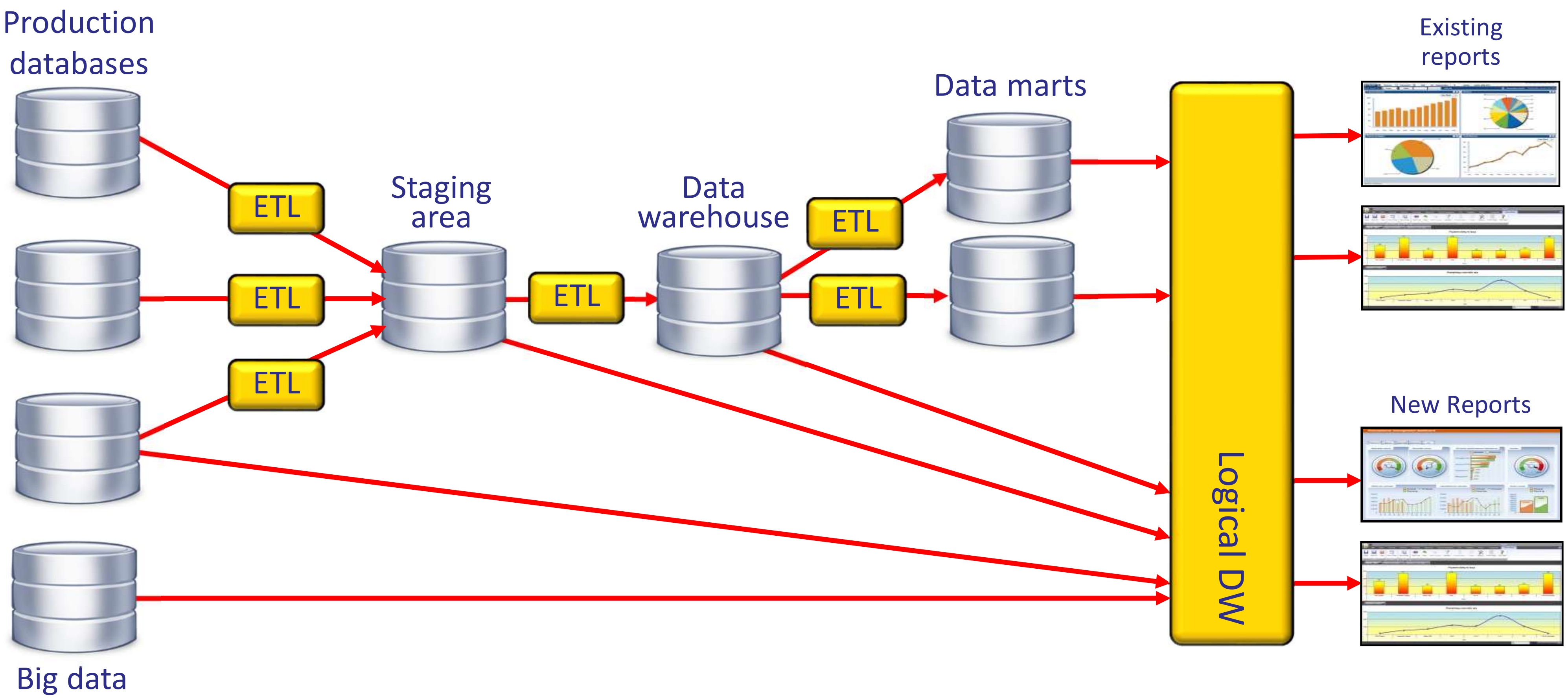
The Logical Data Warehouse Architecture (4)



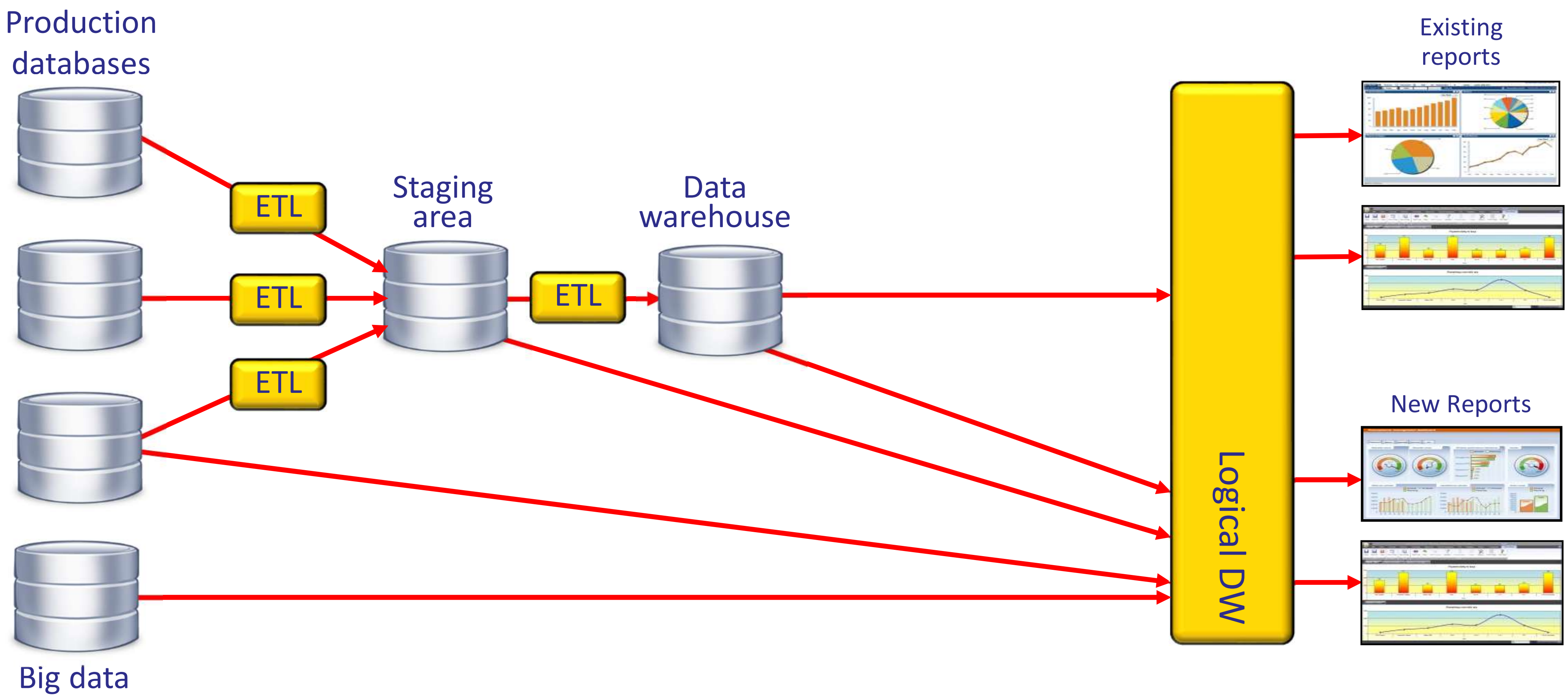
Wrap the Old Data Warehouse (1)

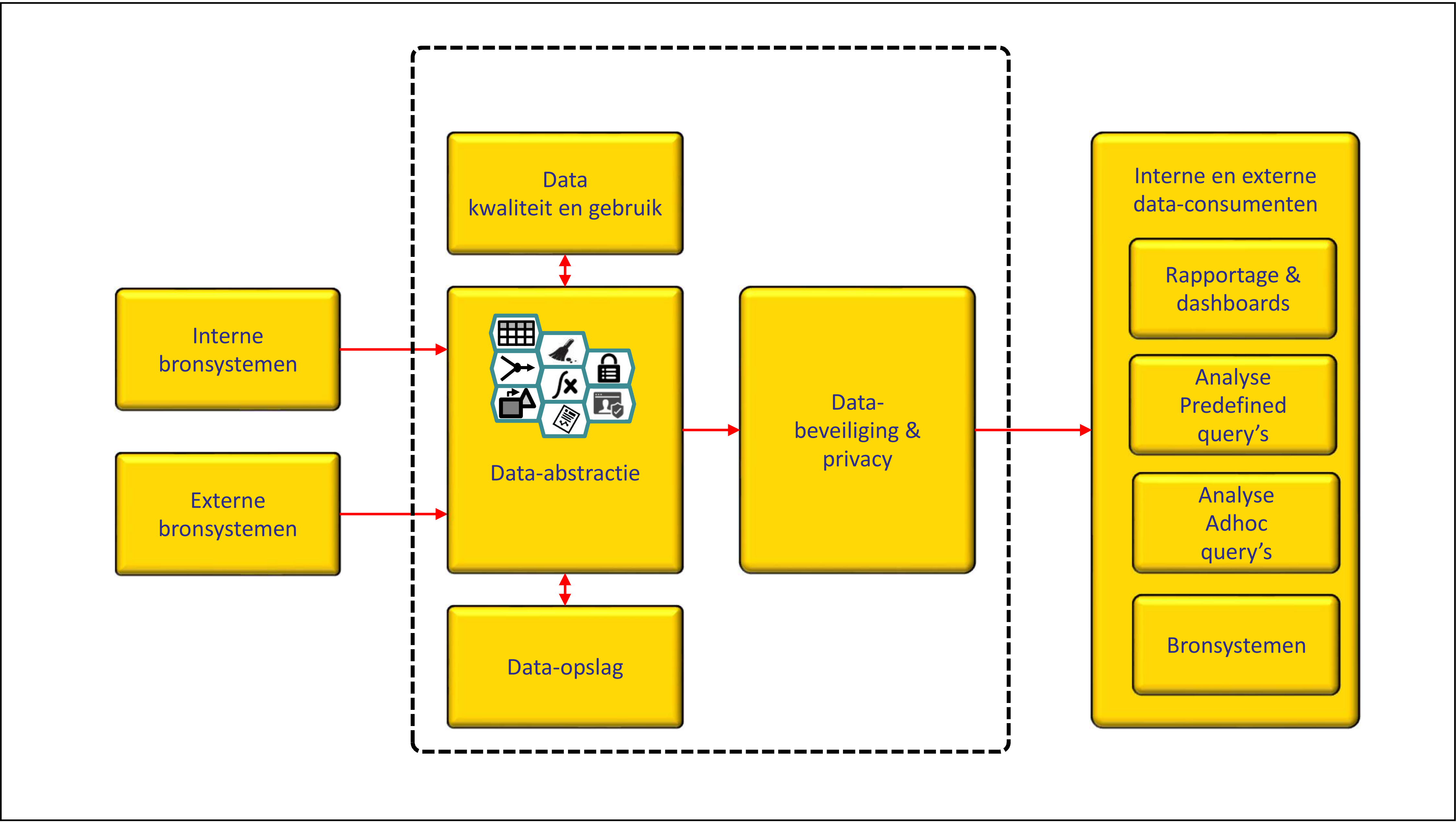


Wrap the Old Data Warehouse (2)

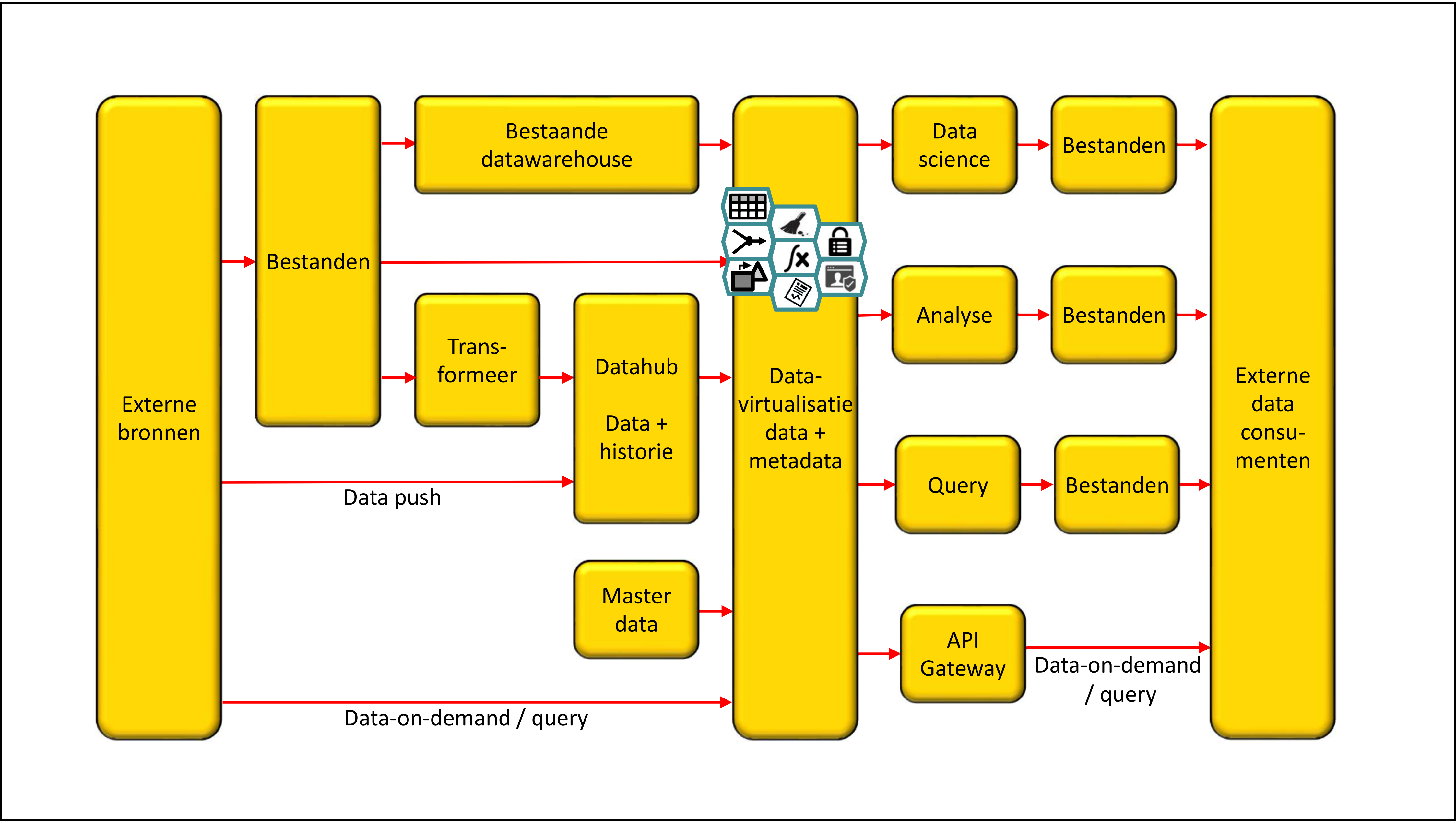


Wrap the Old Data Warehouse (3)

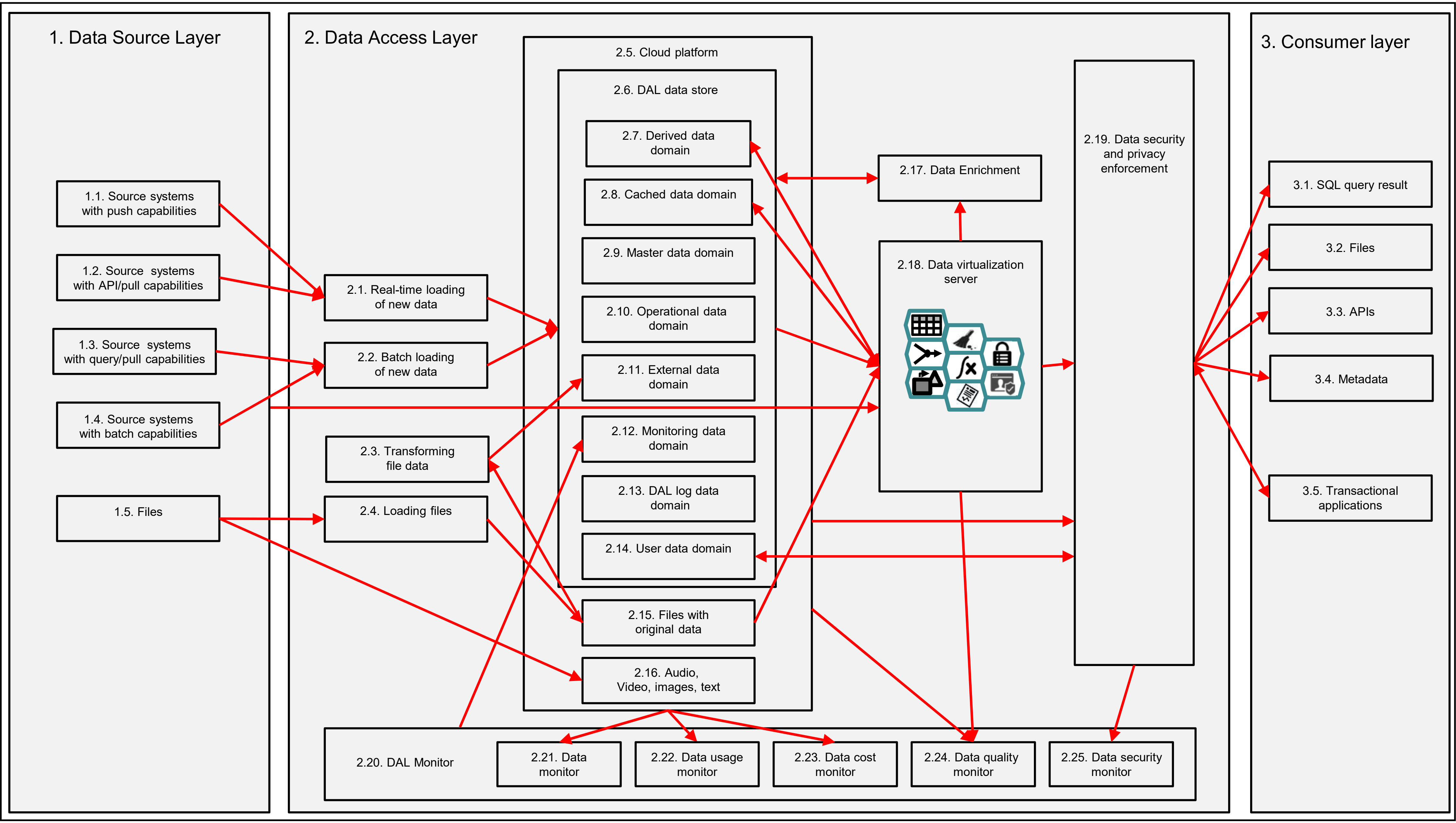




Interne bronsystemen
Externe bronsystemen
Data kwaliteit en gebruik
Data-abstractie
Data-opslag
Data-beveiliging & privacy
Interne en externe data-consumenten
Rapportage & dashboards
Analyse Predefined query's
Analyse Adhoc query's
Bronsystemen



Externe bronnen
Bestanden
Bestaande datawarehouse
Trans- formeer
Datahub
Data + historie
Data push
Master data
Data-on-demand / query
Data- virtualisatie data + metadata
Data science
Analyse
Query
API Gateway
Bestanden
Bestanden
Bestanden
Data-on-demand / query
Externe data consu- menten


1. Data Source Layer
1.1. Source systems with push capabilities
1.2. Source systems with API/pull capabilities
1.3. Source systems with query/pull capabilities
1.4. Source systems with batch capabilities
1.5. Files
2. Data Access Layer
2.1. Real-time loading of new data
2.2. Batch loading of new data
2.3. Transforming file data
2.4. Loading files
2.5. Cloud platform
2.6. DAL data store
2.7. Derived data domain
2.8. Cached data domain
2.9. Master data domain
2.10. Operational data domain
2.11. External data domain
2.12. Monitoring data domain
2.13. DAL log data domain
2.14. User data domain
2.15. Files with original data
2.16. Audio, Video, images, text
2.17. Data Enrichment
2.18. Data virtualization server
2.19. Data security and privacy enforcement
2.20. DAL Monitor
2.21. Data monitor
2.22. Data usage monitor
2.23. Data cost monitor
2.24. Data quality monitor
2.25. Data security monitor
3. Consumer layer
3.1. SQL query result
3.2. Files
3.3. APIs
3.4. Metadata
3.5. Transactional applications

Part 7.3:
The Data Lake

Data Science Steps

Defining goals

Data selection

Data understanding

Data enrichment

Data cleansing

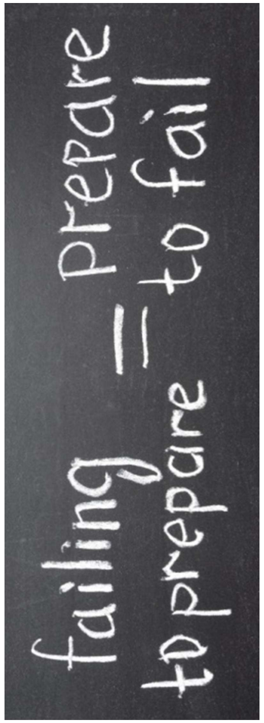
Data coding

Creating analytical model

Analytics

Understanding results

Data Coding



- Computation
  - examples: divide all monthly salaries by 1000; round all prices
- Grouping continuous values
  - example: all transaction between 08:00 and 10:30 will belong to group 1, all transactions between 10:31 and 12:00 will belong to group 2
  - do groups need equal sizes (with respect to ranges)?
  - do groups need equal numbers of values?
- Scaling
  - most neural networks accept numeric data only in the range 0.0 to 1.0 or -1.0 to 1.0; used for continuous values, such as salary and weight
- Normalizing
  - sum all elements, and divide each element by the sum
  - value represents the percentage of contribution
- Symbolic to numeric transformations
  - example: the string "yes" becomes 1, and "no" becomes 0
- Coding discrete values
  - transform a column with fixed set of values (F) into F columns with yes/no values

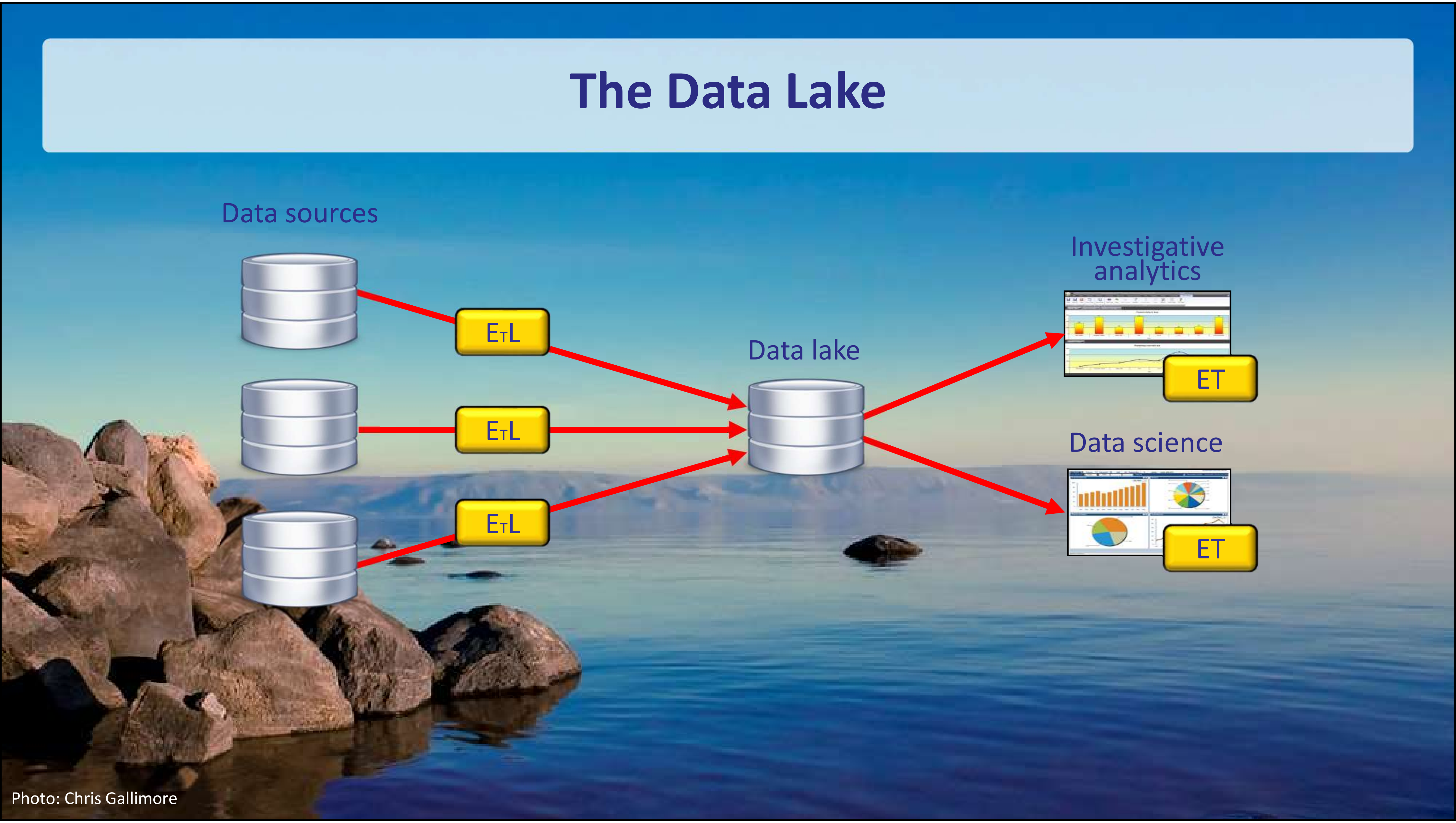
Common Definition of Data Lake

James Serra:

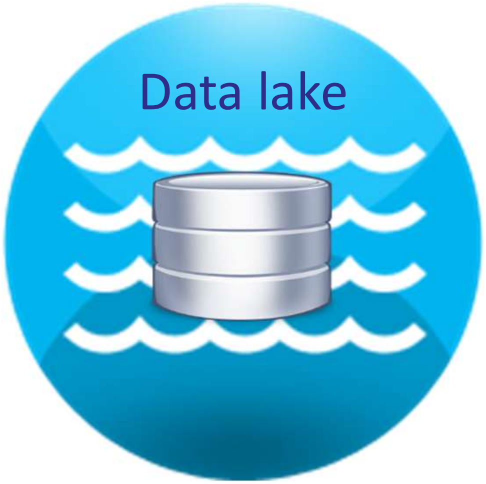
A “data lake” is a storage repository, usually in Hadoop, that holds a vast amount of raw data in its native format until it is needed. It’s a great place for investigating, exploring, experimenting, and refining data, in addition to archiving data.

Photo: Chris Gallimore

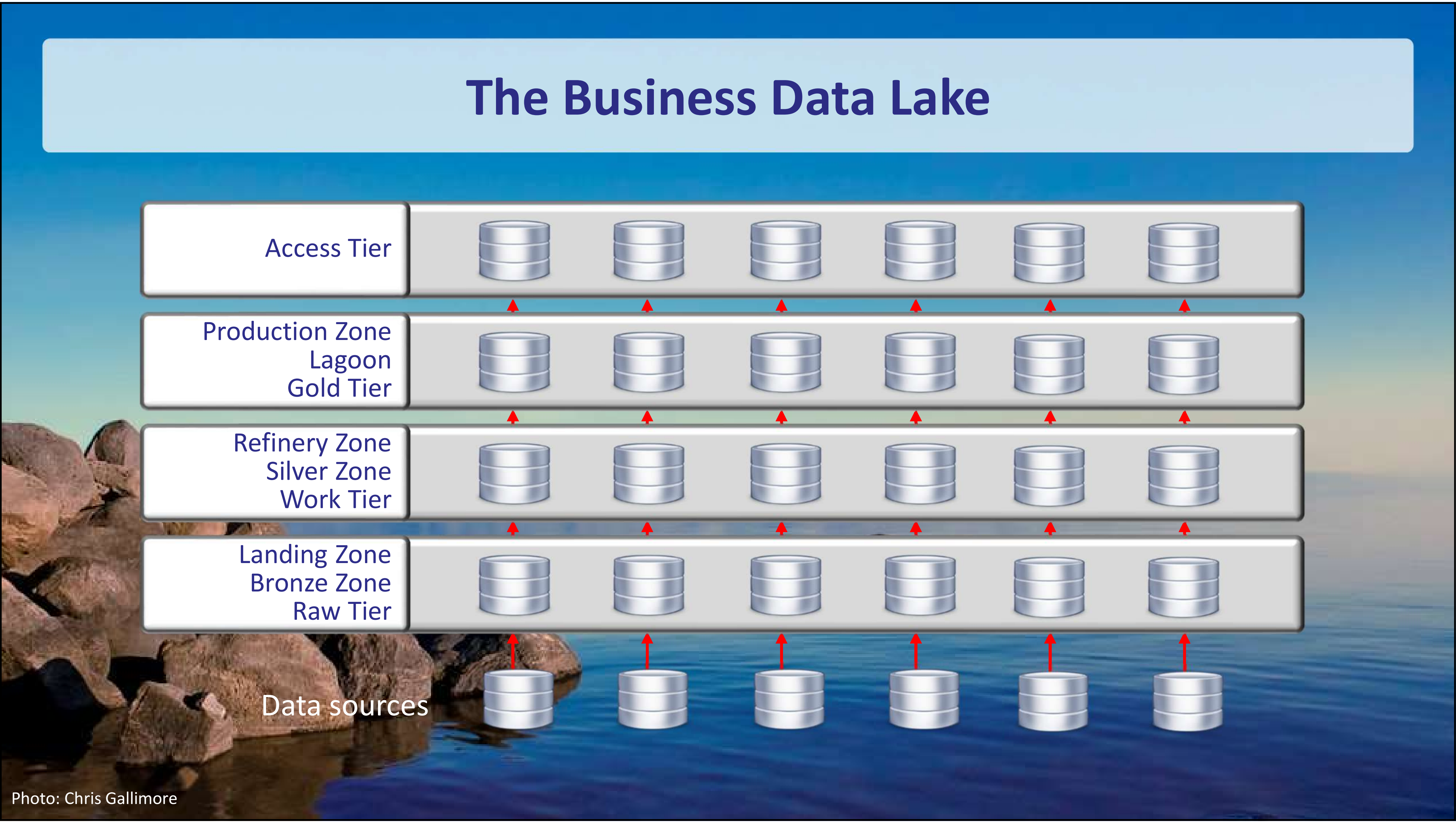
Source: http://www.jamesserra.com/archive/2015/04/what-is-a-data-lake/


The Data Lake
Data sources
ETL
ETL
ETL
Data lake
Investigative analytics
ET
Data science
ET
Photo: Chris Gallimore

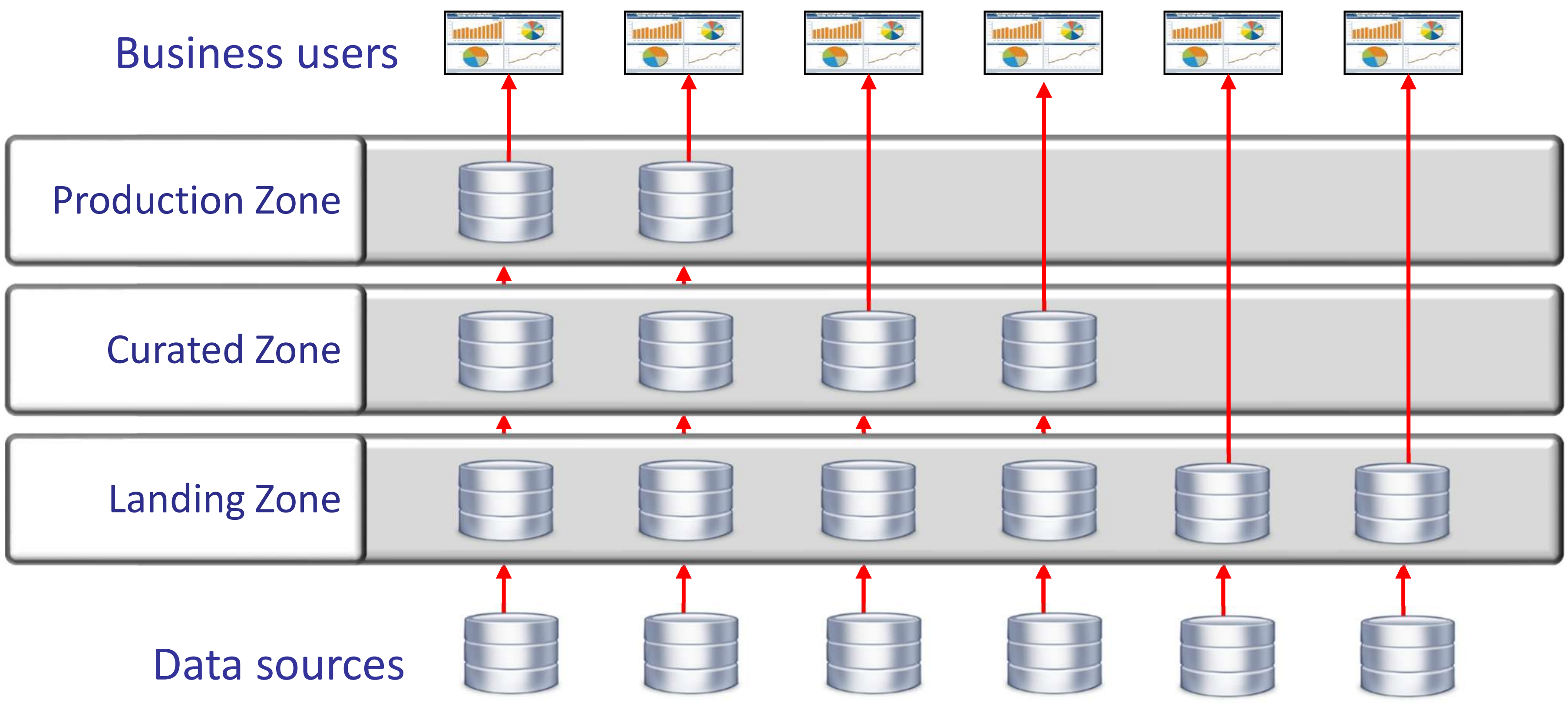
Challenges of a Physical Data Lake



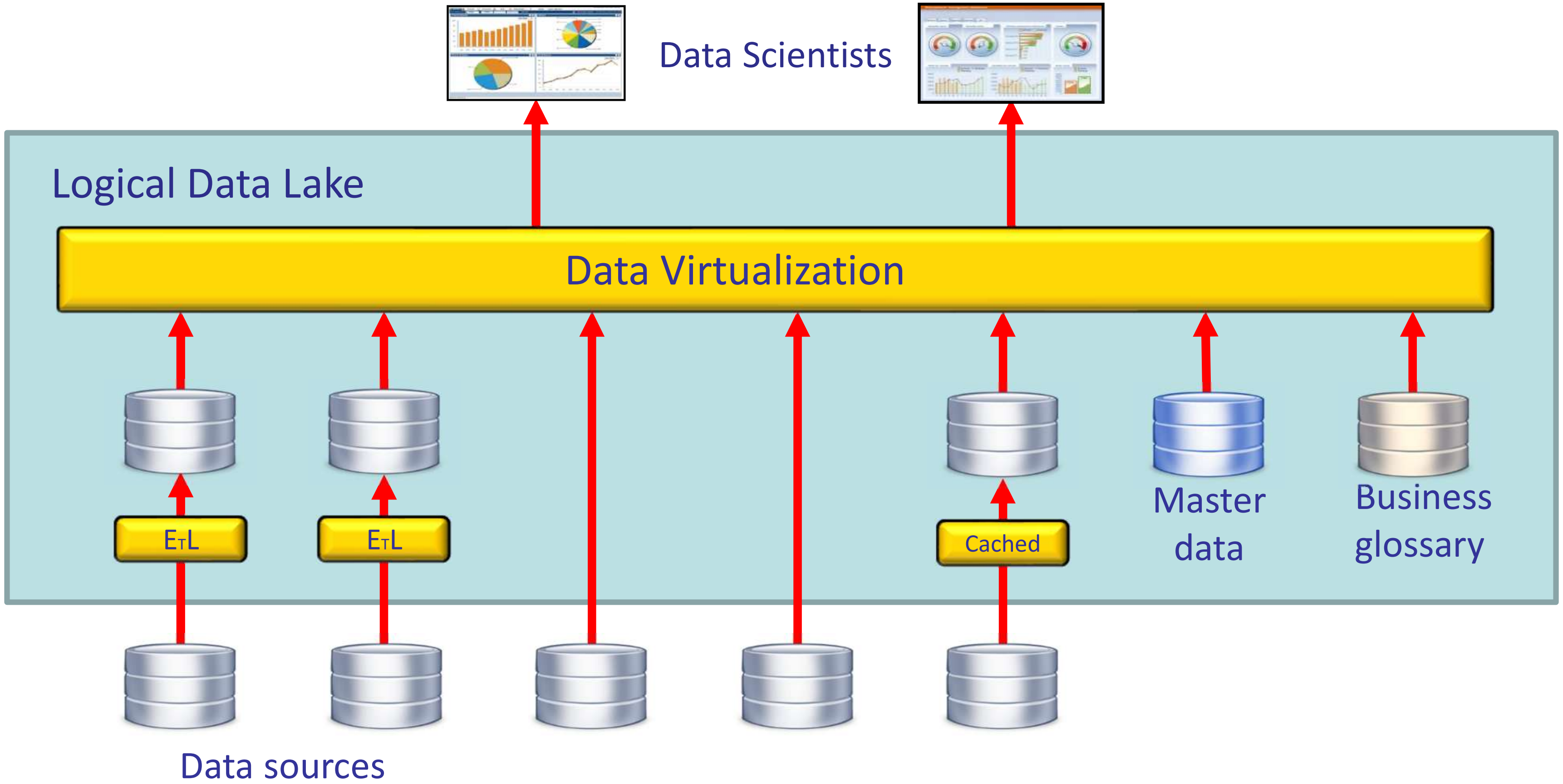
- Big data too big to move
  - Too slow to copy and bandwidth issues
- Complex "T" moved to data consumption
- Company politics
- Data privacy and protection regulations
- Data in data lake is stored outside original security realm
- Metadata to describe data
- Some sources are hard to copy
  - For example, mainframe data
- Refreshing of data lake
- Management of data lake required
- …


The Business Data Lake
Access Tier
Production Zone
Lagoon
Gold Tier
Refinery Zone
Silver Zone
Work Tier
Landing Zone
Bronze Zone
Raw Tier
Data sources
Photo: Chris Gallimore

A Data Lake With Multiple Zones

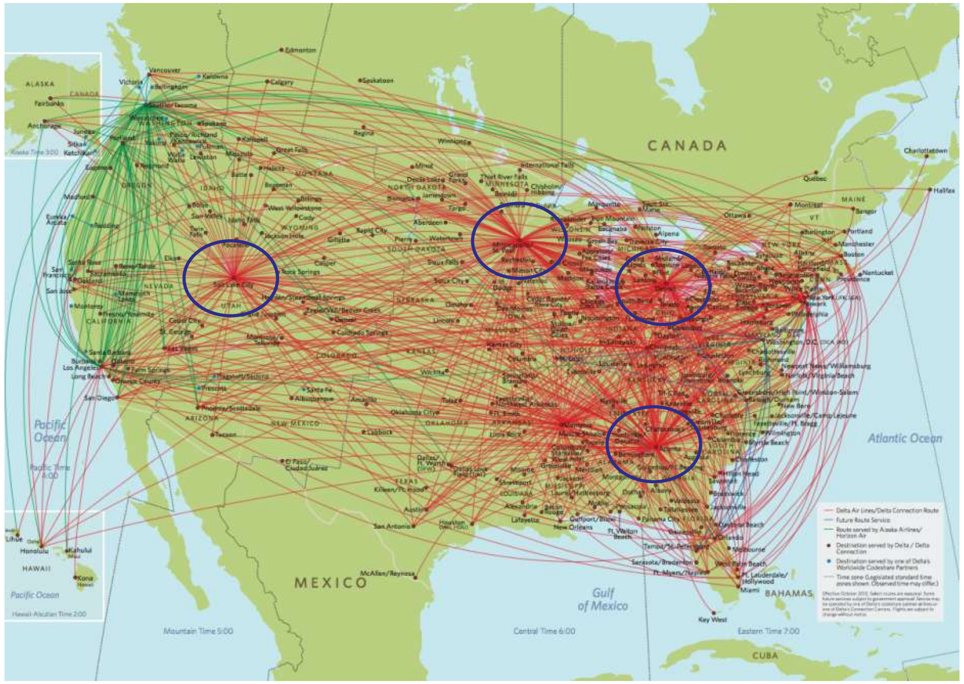


The Logical (Virtual) Data Lake



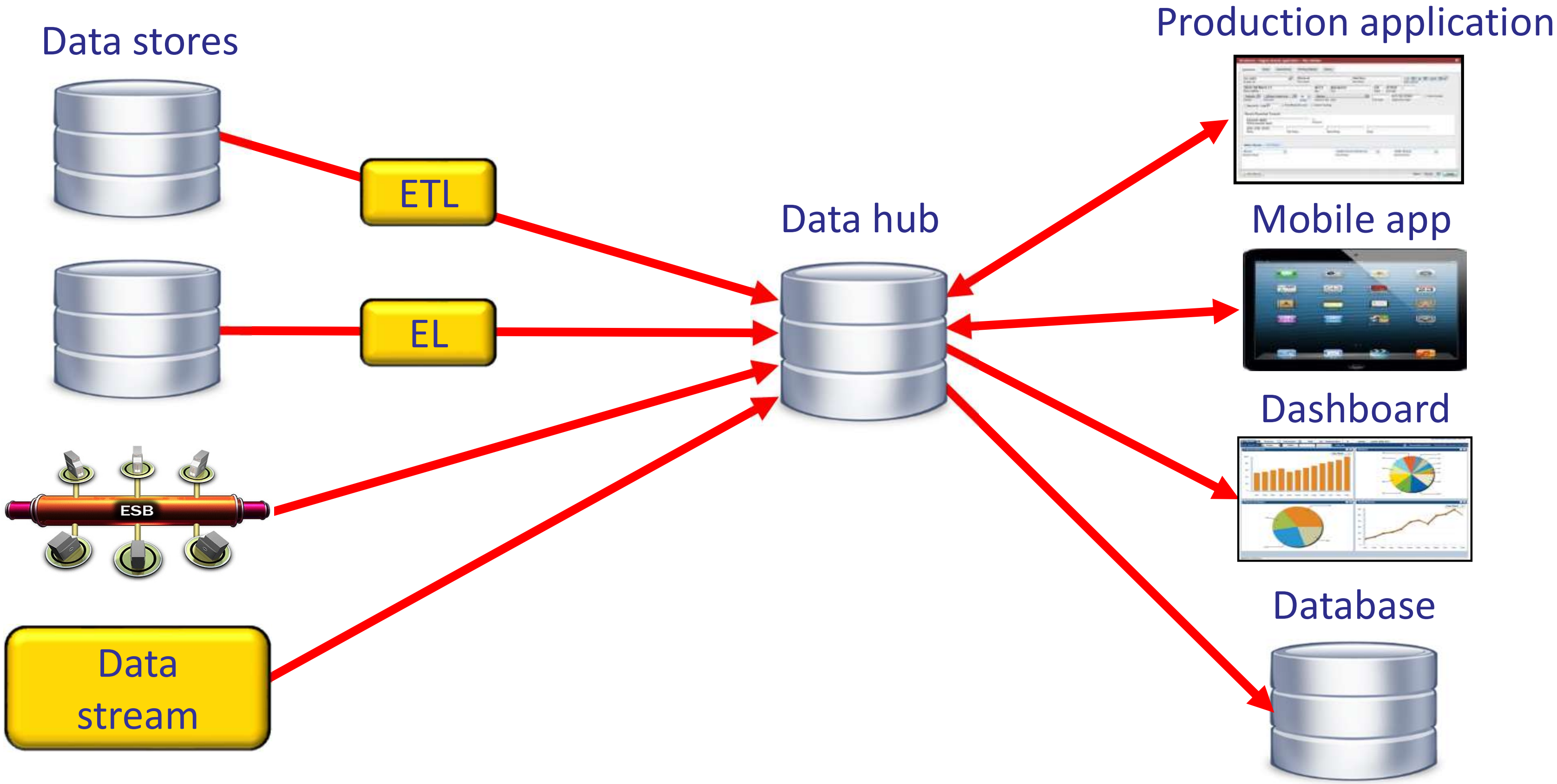
Part 7.4:
The Data Hub

What is a Data Hub?

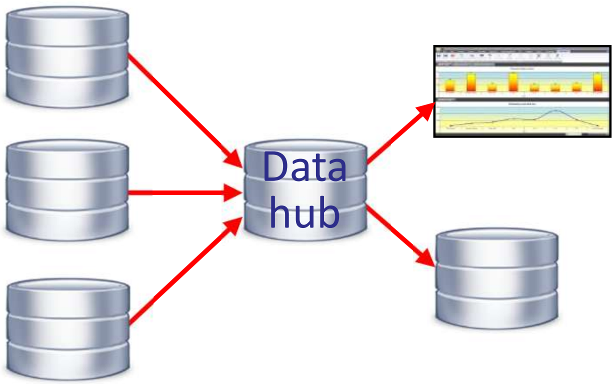


- Wikepedia: A data hub is a collection of data from multiple sources organized for distribution, sharing, and often subsetting and sharing. Generally this data distribution is in the form of a hub and spoke architecture

The Data Hub (Sharing of Data)

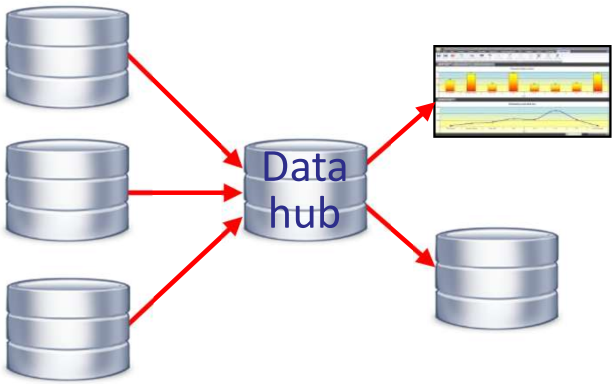


Characteristics of the Data Hub



- The main goal of a data hub is to organize data efficiently, storing it in a cost-efficient manner and expose it towards key business functions
- It excels in easy integration, and enables de-duplication, security, quality and data standardization
- The data hub can be leveraged to enable data processing activities with the end use-case in mind, and typically has governance capabilities
- Although operationally focused, it can be trusted as an analytical data source

Data Hub Versus the Rest Of the World



- Data hub versus *data warehouse*: a data hub is generally non-integrated and often at different grains
- Data hub versus *operational data store*: a data hub does not need to be limited to operational data
- Data hub versus *data lake*: a data lake tends to store data in one place for availability, and allow/require the consumer to process or add value to the data
- Data warehouses and data lakes may be endpoints, data hubs are not endpoints, they serve as points of intermediation and data exchange

Comparison of Three Data Storage Environments

DATA WAREHOUSE	DATA LAKE	DATA HUB
• STRUCTURED FOR ANALYTICS • CONSUMED BY PEOPLE AS A SELF-SERVICE • FOCUSED ON DECISION MAKING	• (UN)STRUCTURED FOR DISCOVERY • CONSUMED BY DATA PROFESSIONALS AND ALGORITHMS • FOCUSED ON DEEP LEARNING, AI	• STRUCTURED FOR DATA PORTABILITY • CONSUMED BY PEOPLE AND APPS • FOCUSED ON DATA INTEGRITY AND SPEED FOR SHARING

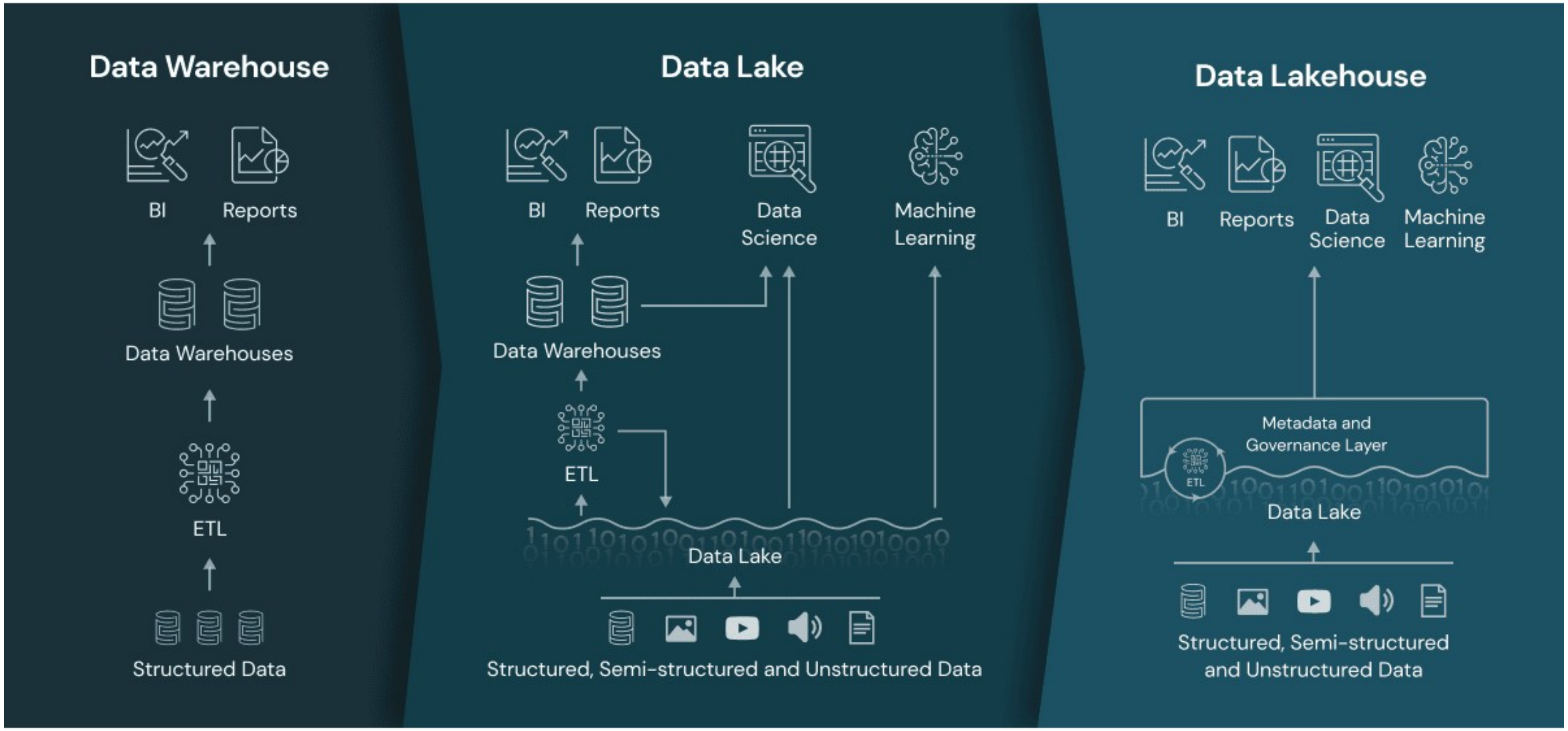
Source: Talend; see https://www.talend.com/resources/customer-360-data-hub/

Part 7.5:
The Data Lakehouse

Definitions of Data Lakehouse

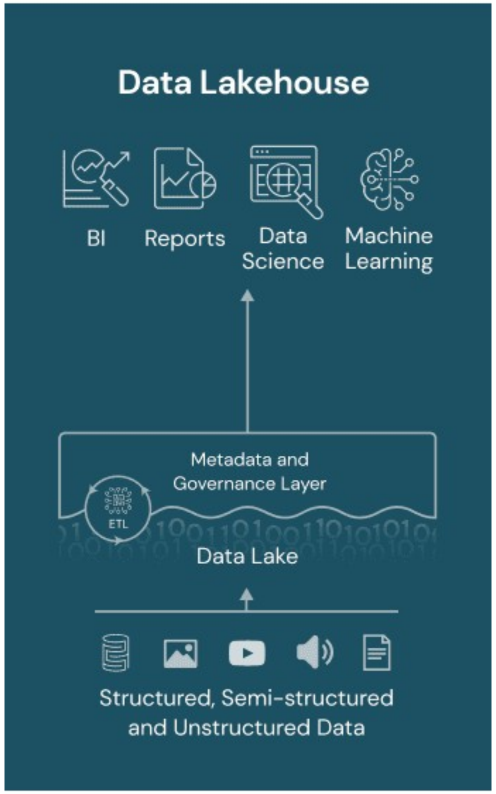
- DataBricks: "A data lakehouse is a […] open data management architecture that combines the flexibility, cost-efficiency, and scale of data lakes with the data management and ACID transactions of data warehouses, enabling business intelligence (BI) and machine learning (ML) on all data."
- Striim, John Kutay: "A data lakehouse is a new, big-data storage architecture that combines the best features of both data warehouses and data lakes. A data lakehouse enables a single repository for all your data (structured, semi-structured, and unstructured) while enabling best-in-class machine learning, business intelligence, and streaming capabilities."
- Dremio, Deepa Sankar: "A [data] lakehouse has the performance and optimization of a data warehouse combined with the flexibility of a data lake."
- Wikipedia: "Databricks develops and sells a cloud data platform using the marketing term lakehouse, a portmanteau based on the terms data warehouse and data lake."

A Comparison of Three Data Architectures



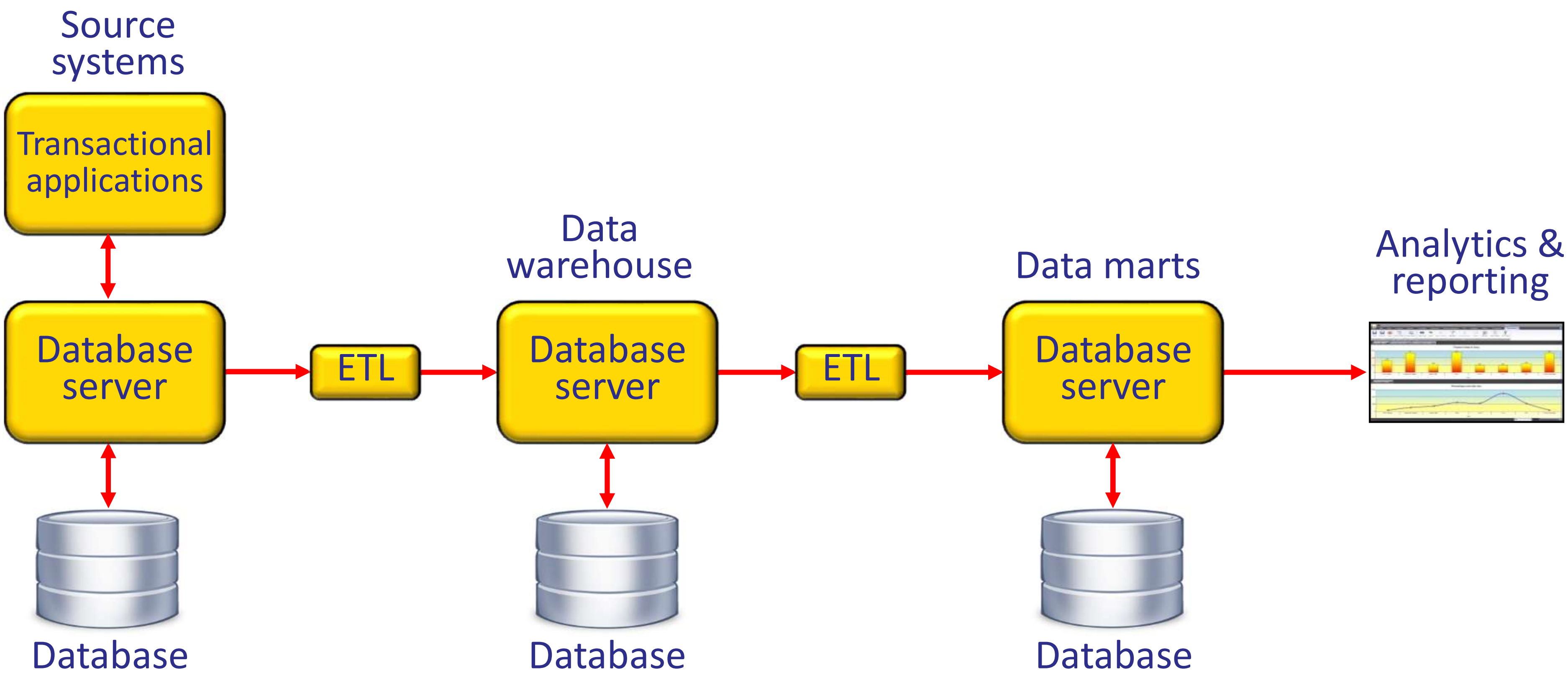
Source: Databricks.com

Key Characteristics of a Data Lakehouse

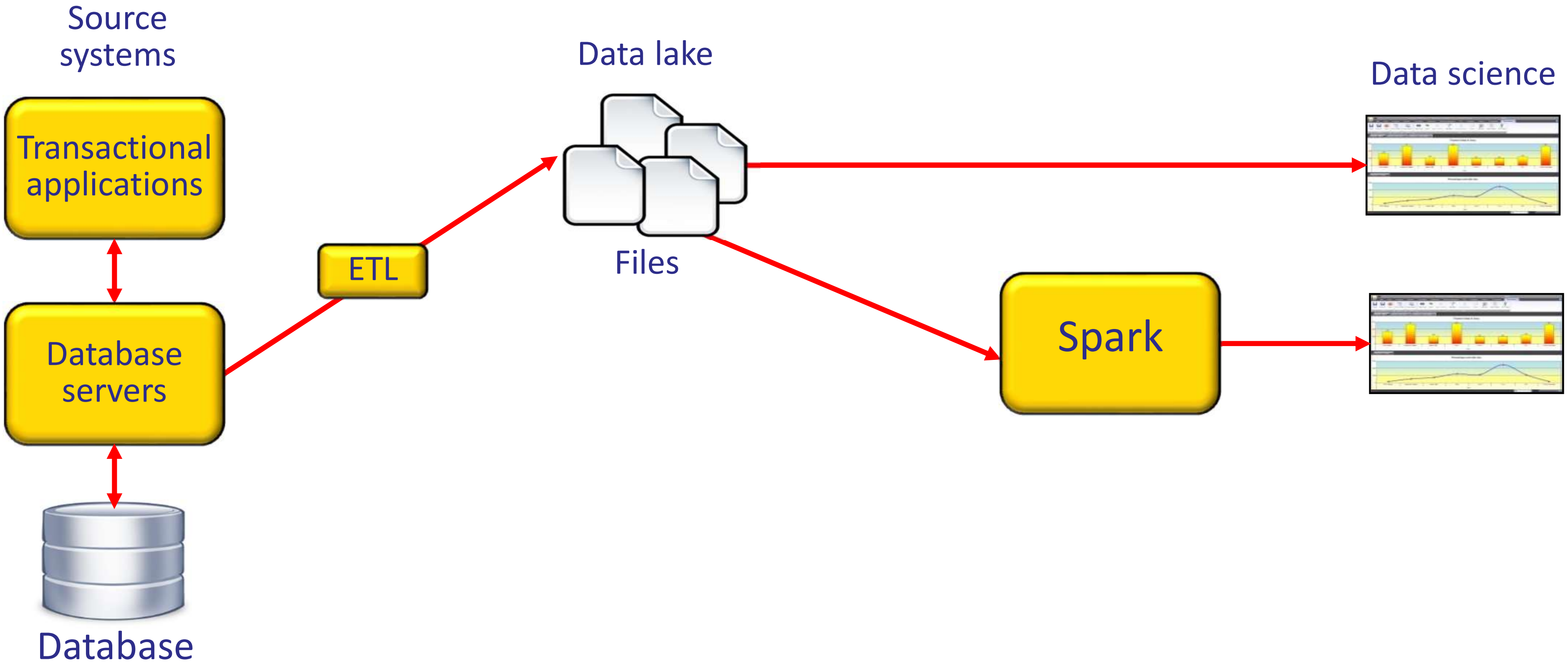


- Two use cases: BI and data science
- Data is stored once
- Supports structured and unstructured data
- Schema enforcement
- Open file formats
- Low-cost data storage
- ACID compliant

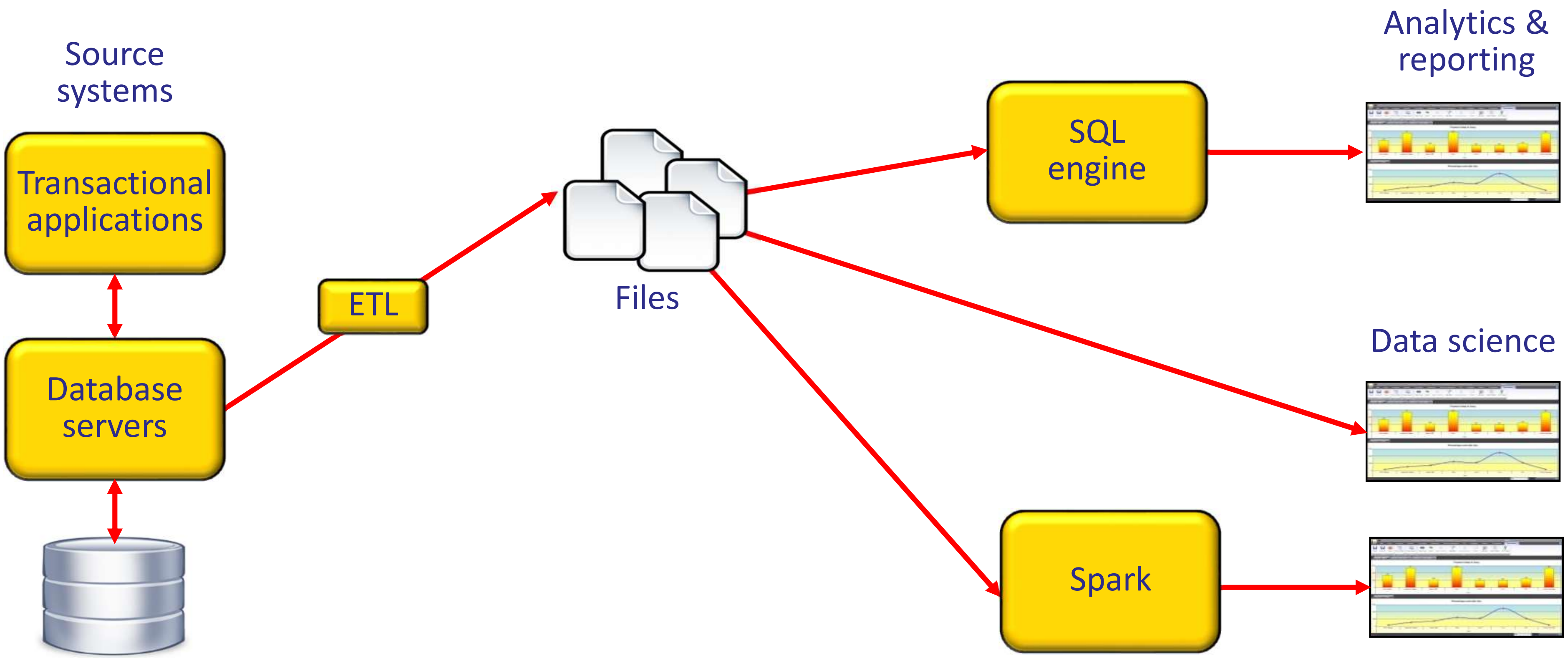
The Data Warehouse Architecture in More Detail



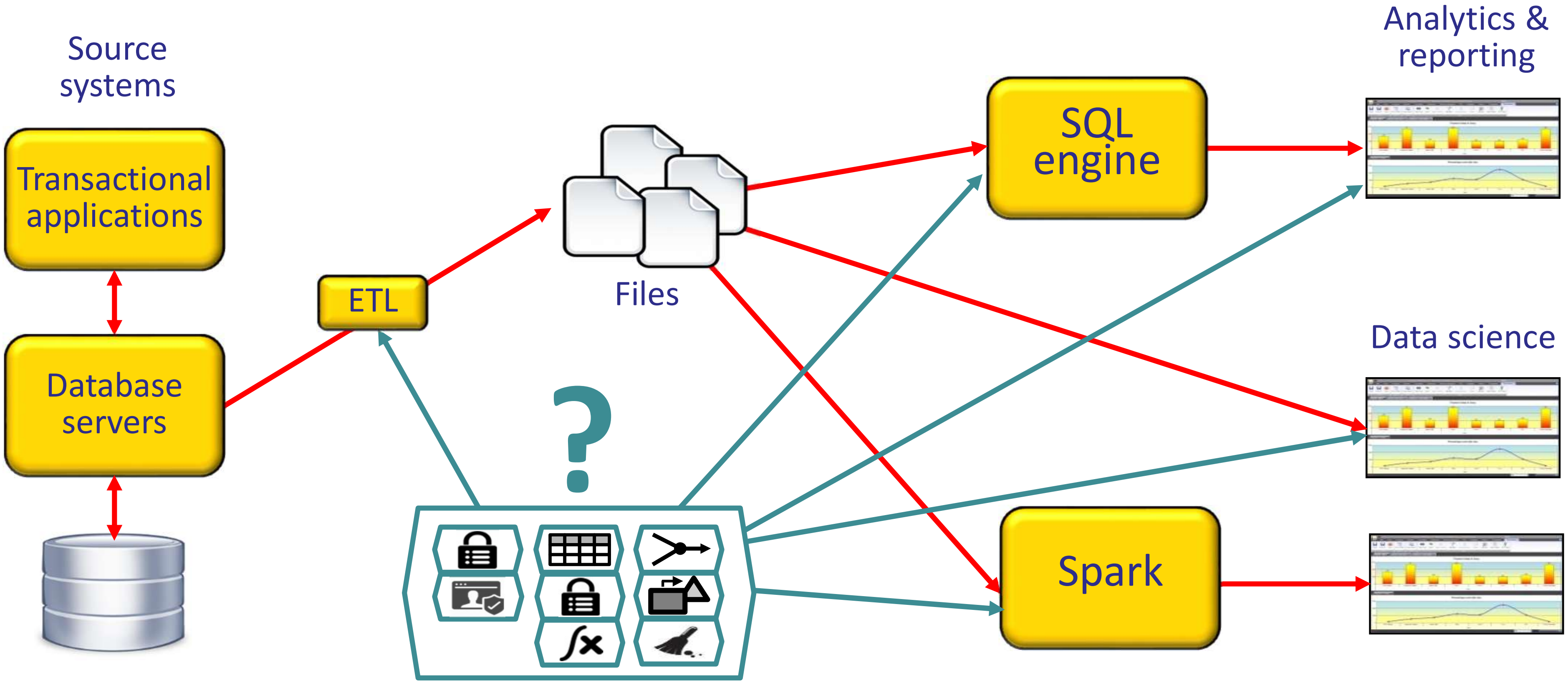
The Data Lake Architecture in More Detail



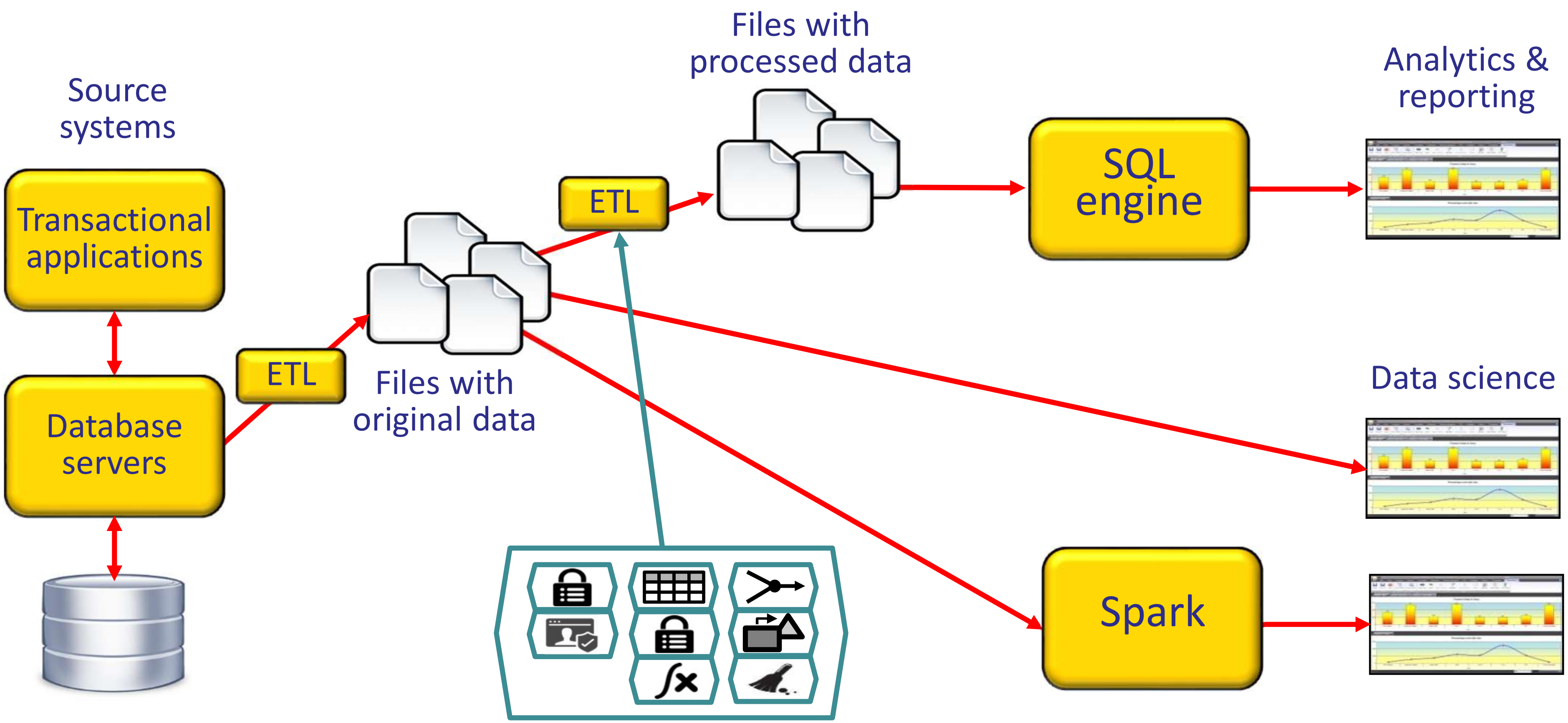
The Data Lakehouse Architecture in More Detail



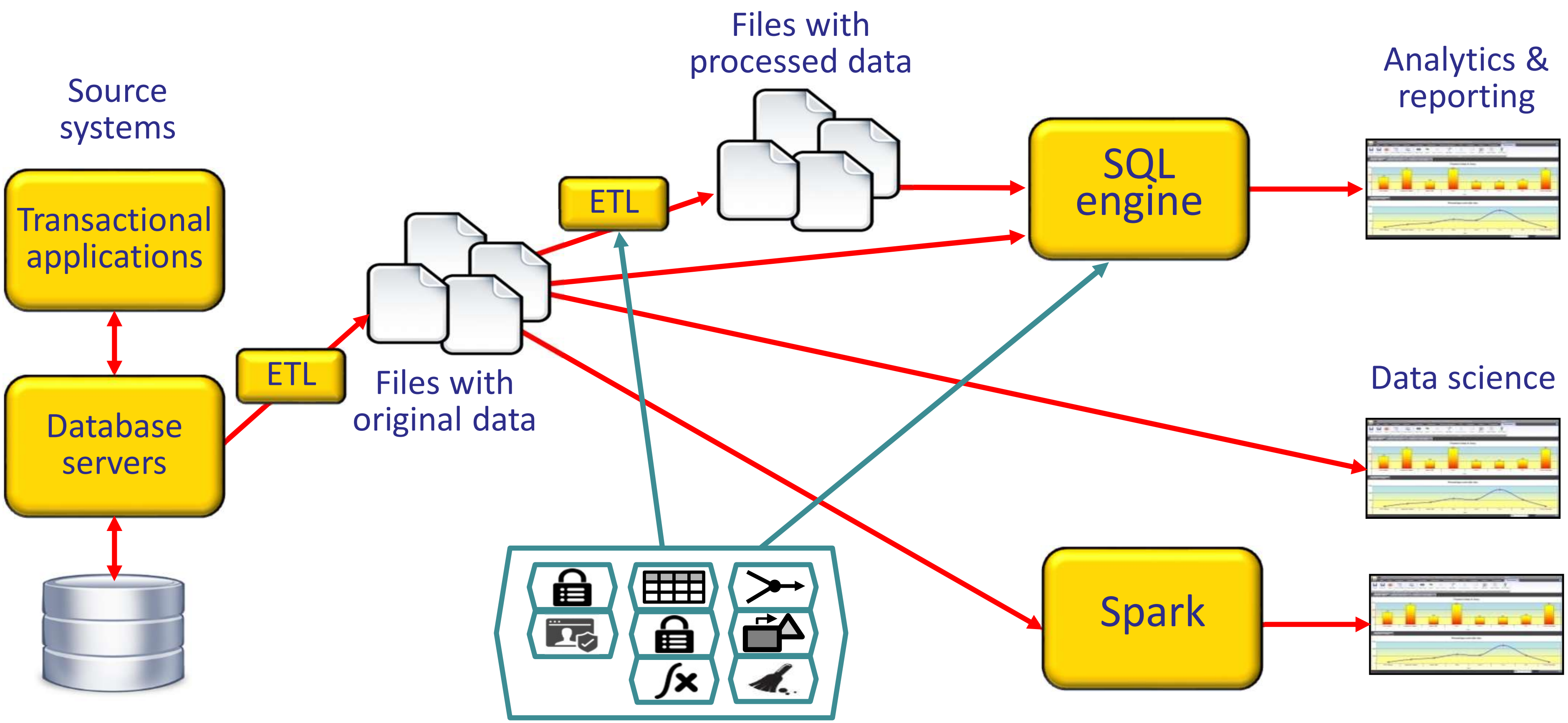
Where to Implement Transformers?



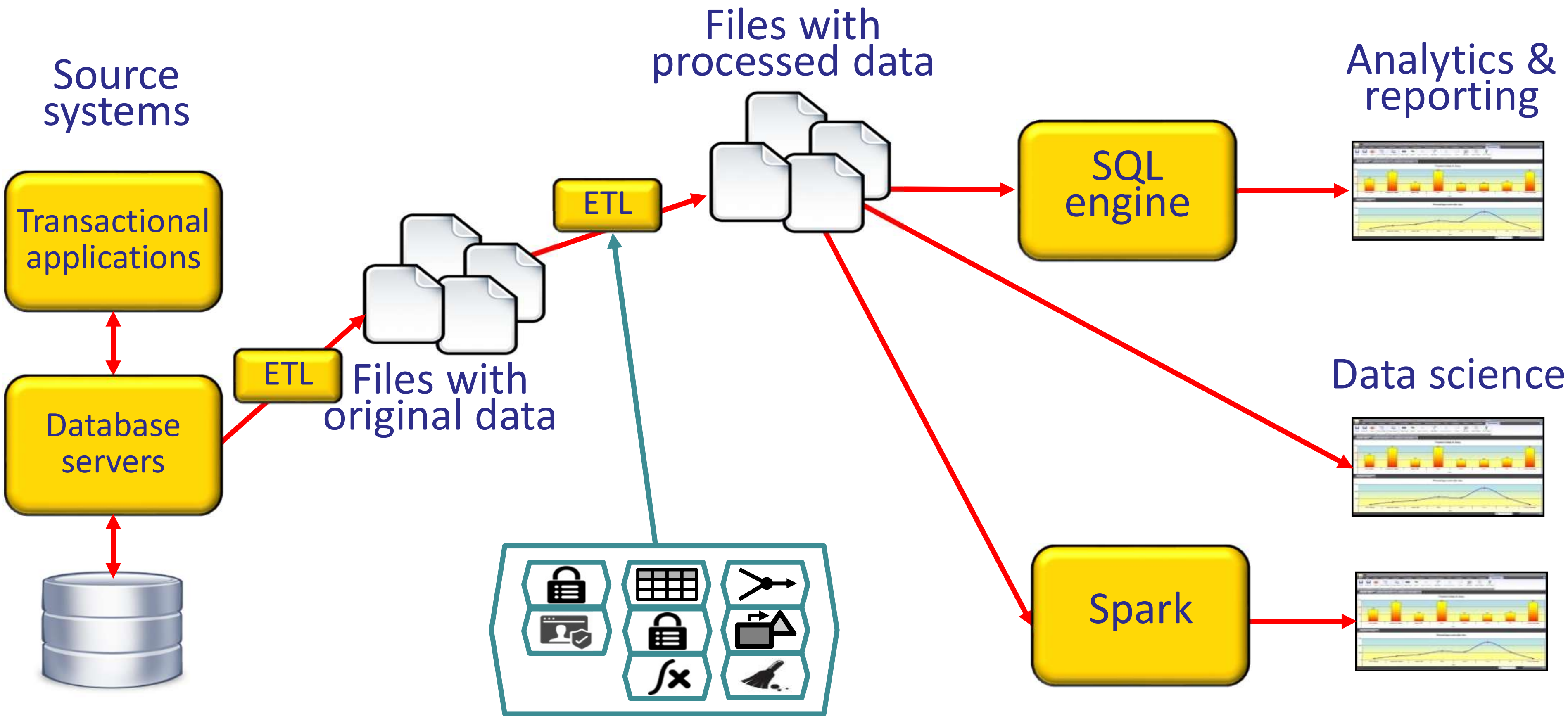
Solution 1: *All* BI via Processed Data



Solution 2: *Some* BI via Processed Data



Solution 3: Both Use Cases via Processed Data



High-Level Comparison of Three Architectures

Characteristic	Data Warehouse	Data lake	Data Lakehouse
Type of data	Structured	Structured and unstructured	Structured and unstructured
Use cases	BI, reporting, dashboarding	Experimental, investigative	Both
Schema enforcement	Yes	Optional	Optional
Open file format	No	Yes	Yes
Low-cost data storage	No	Yes	Yes
ACID-compliant	Yes	No	Yes
Near real-time data	No	Yes	Yes
Non-siloed	No	No	Yes
Data copies minimal	No	No	Yes
Anonymization	Yes	Depends	Depends
Auditable	Yes	Depends	Depends
Performance optimized for BI	Yes	No	?
Performance optimized for data science	No	Yes	Yes

Based on assumptions

Source: Various articles in the Internet

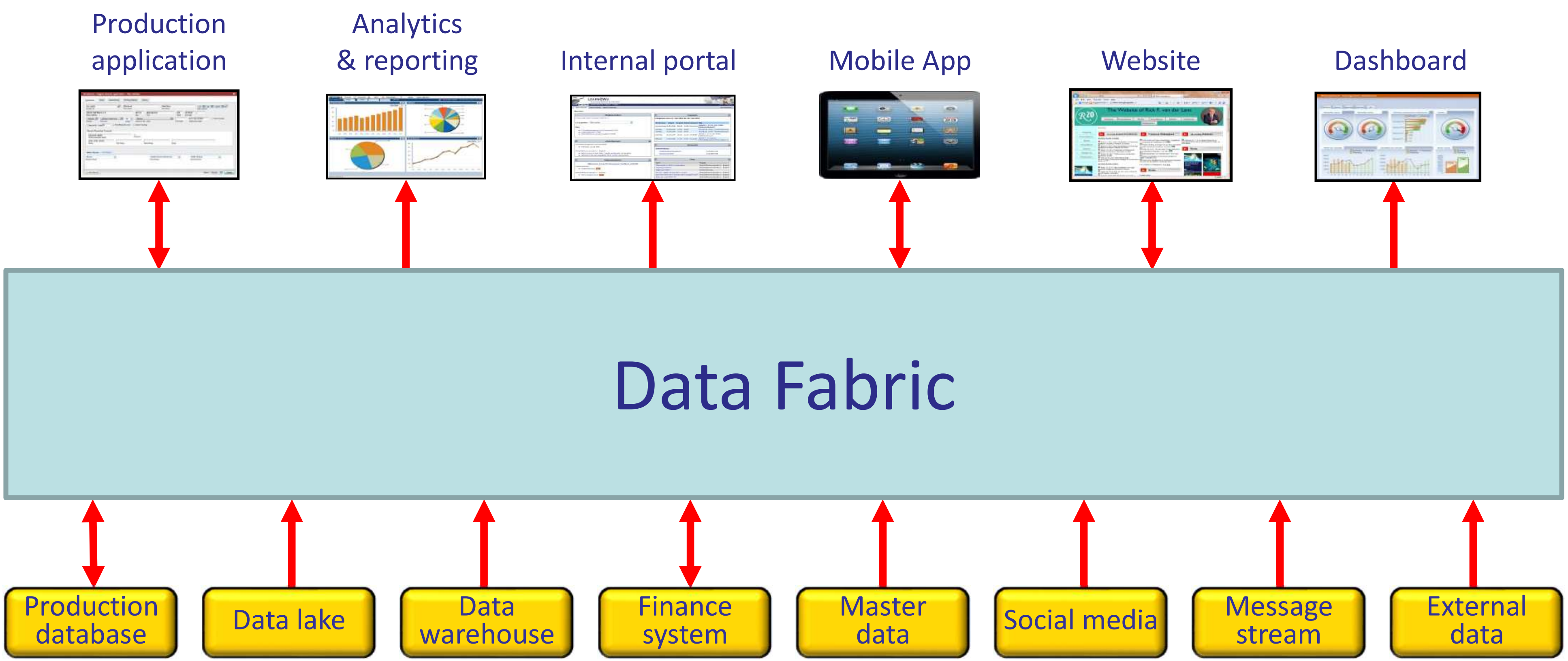
Part 7.6:
The Data Fabric

What is the Data Fabric?

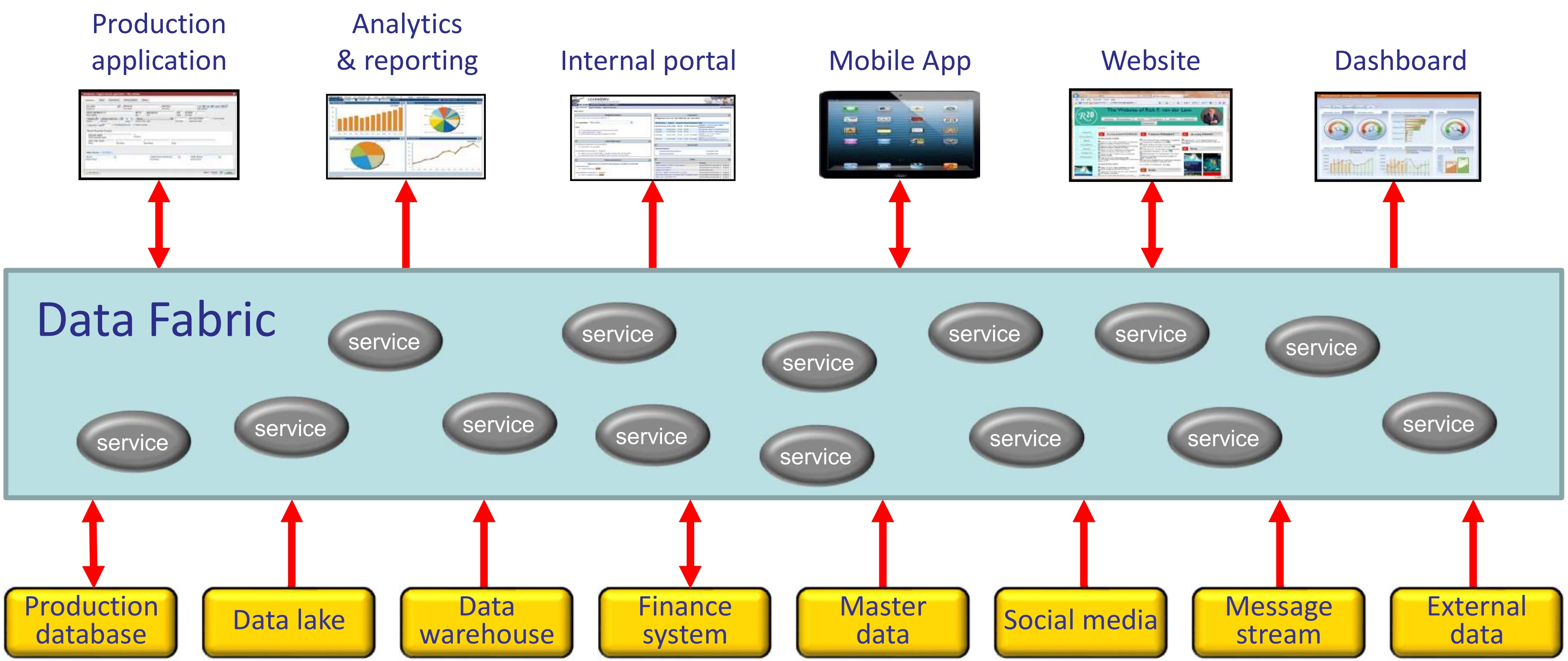

Photo: Clint Adair

- Gartner: A data fabric is generally a custom-made design that provides reusable data services, pipelines, semantic tiers or APIs via combination of data integration approaches in an orchestrated fashion.
- Gartner: Data fabric enables *frictionless access* and sharing of data in a distributed data environment. It enables a *single* and *consistent* data management framework, which allows seamless data access and processing by design across otherwise siloed storage.

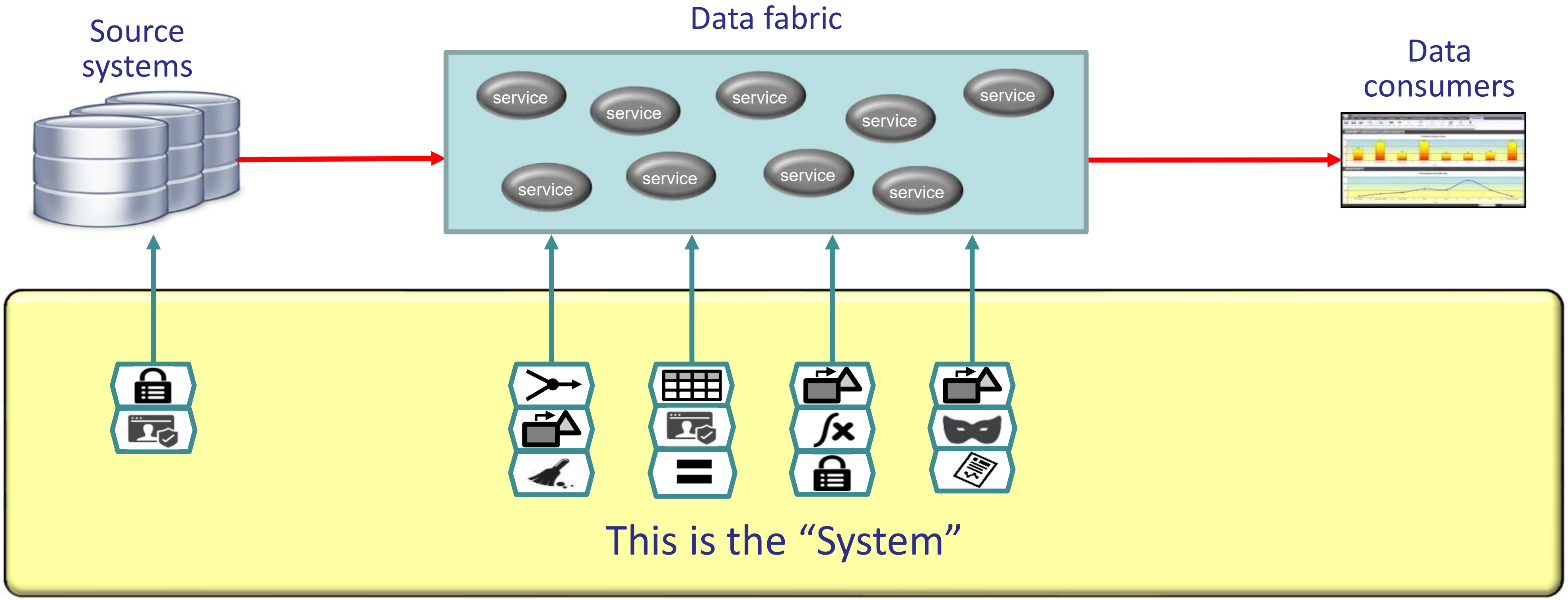
The Data Fabric



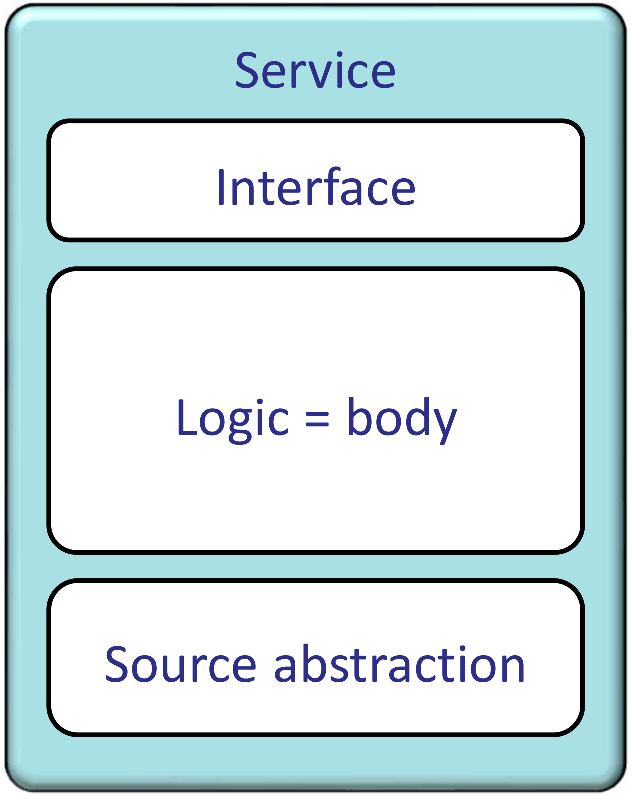
The Services of a Data Fabric



Data Fabrics and Transformers

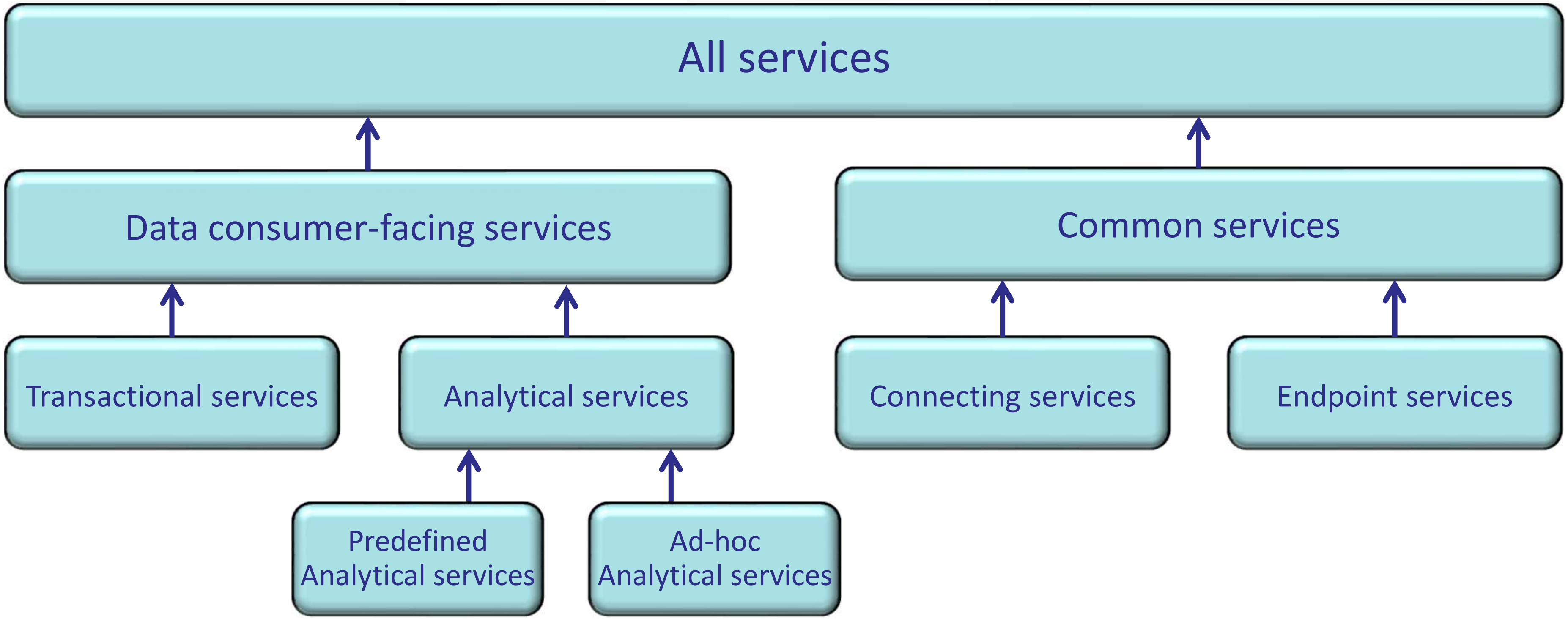


The Components of Services

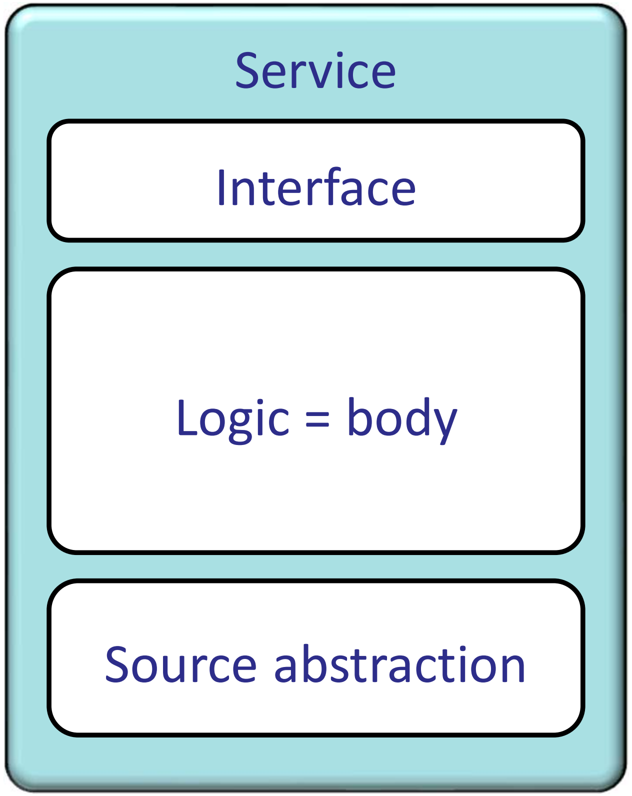


- The interface component is responsible for handling incoming parameters and outgoing results
- The logic of the service form the body
- The body deals with transformers
- Abstraction layer to make it independent of changes to the IT systems

A Data Fabric Consists of Different Types of Services

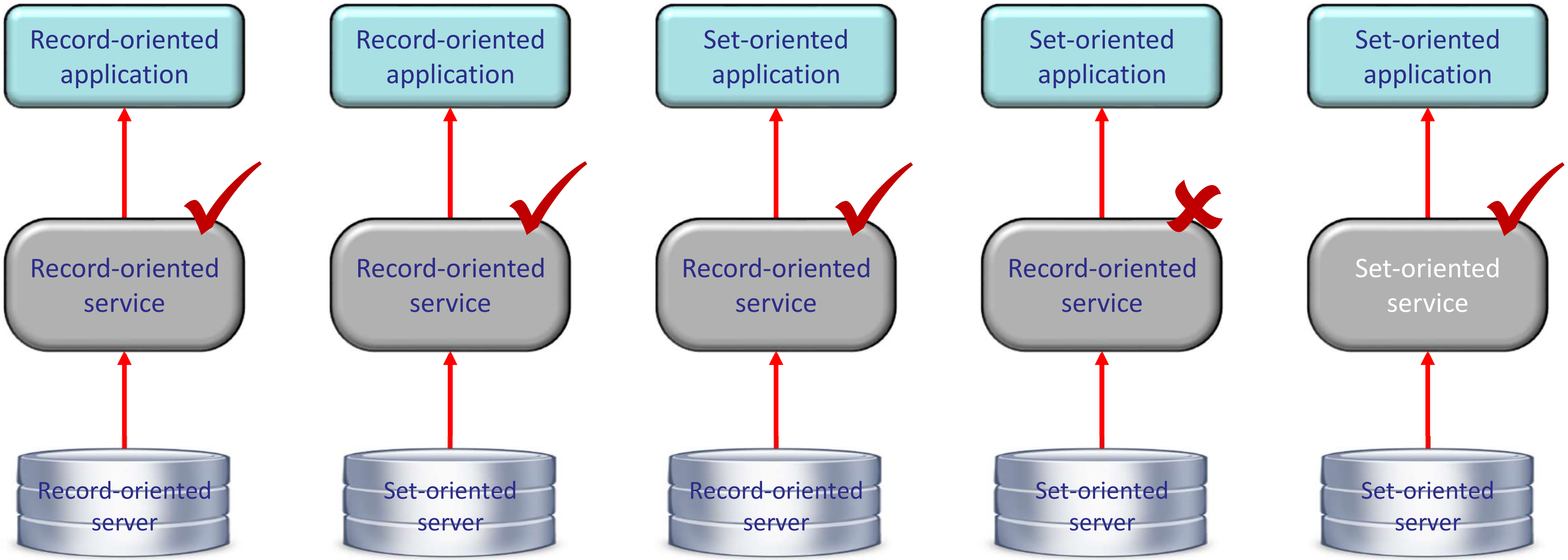


12 Capabilities for Frictionless Data Access

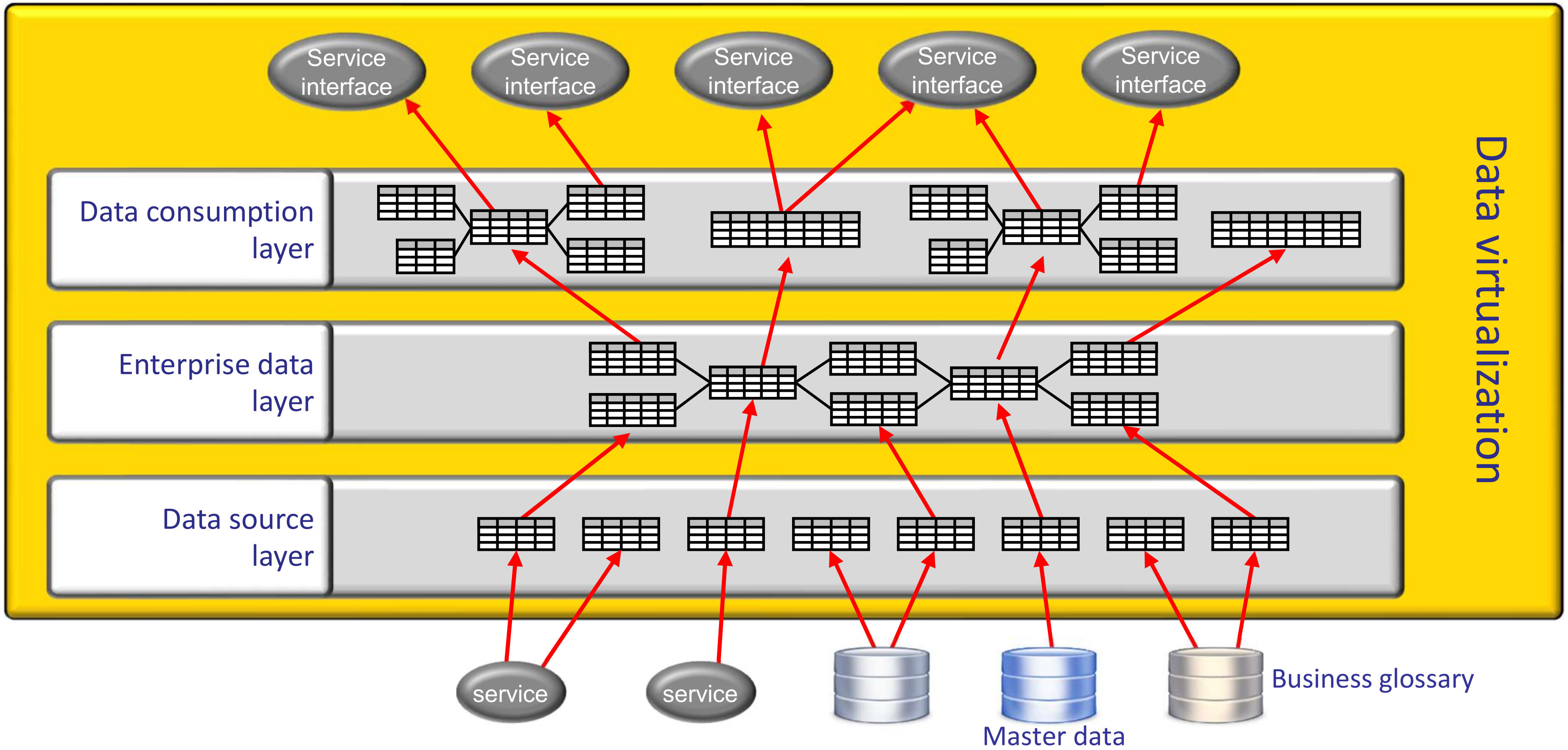


- Data preparation, such as transformations, calculations, aggregations, filters, joins, …
- Adaptable logic
- High performance
- Data access by many data consumption forms
- Access to all the data sources
- Processing of all types of data
- Data security and privacy
- Real-time data access
- Read and write data access
- Data minimization
- Event processing
- Technical and business metadata management
- Master and reference data management

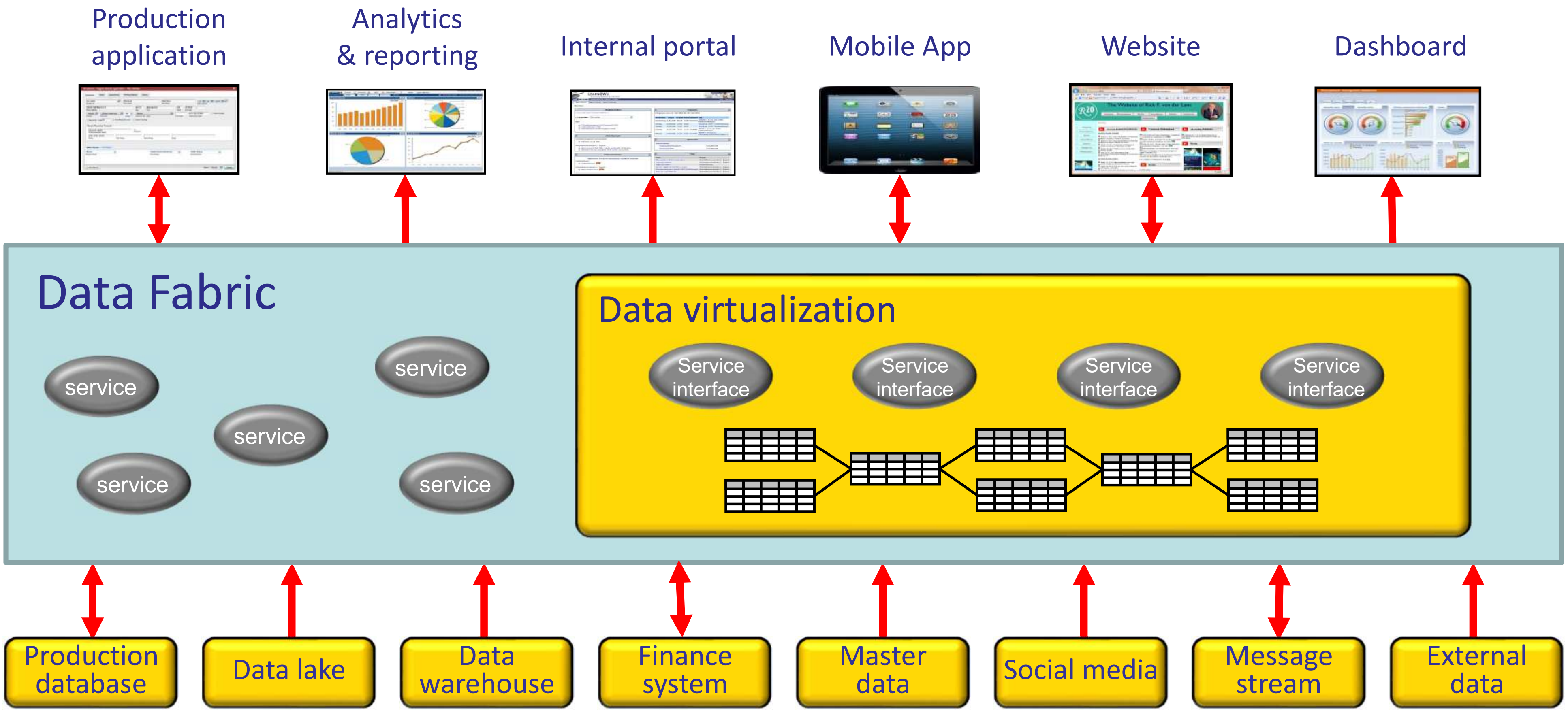
Record-Oriented or Set-Oriented Interface?



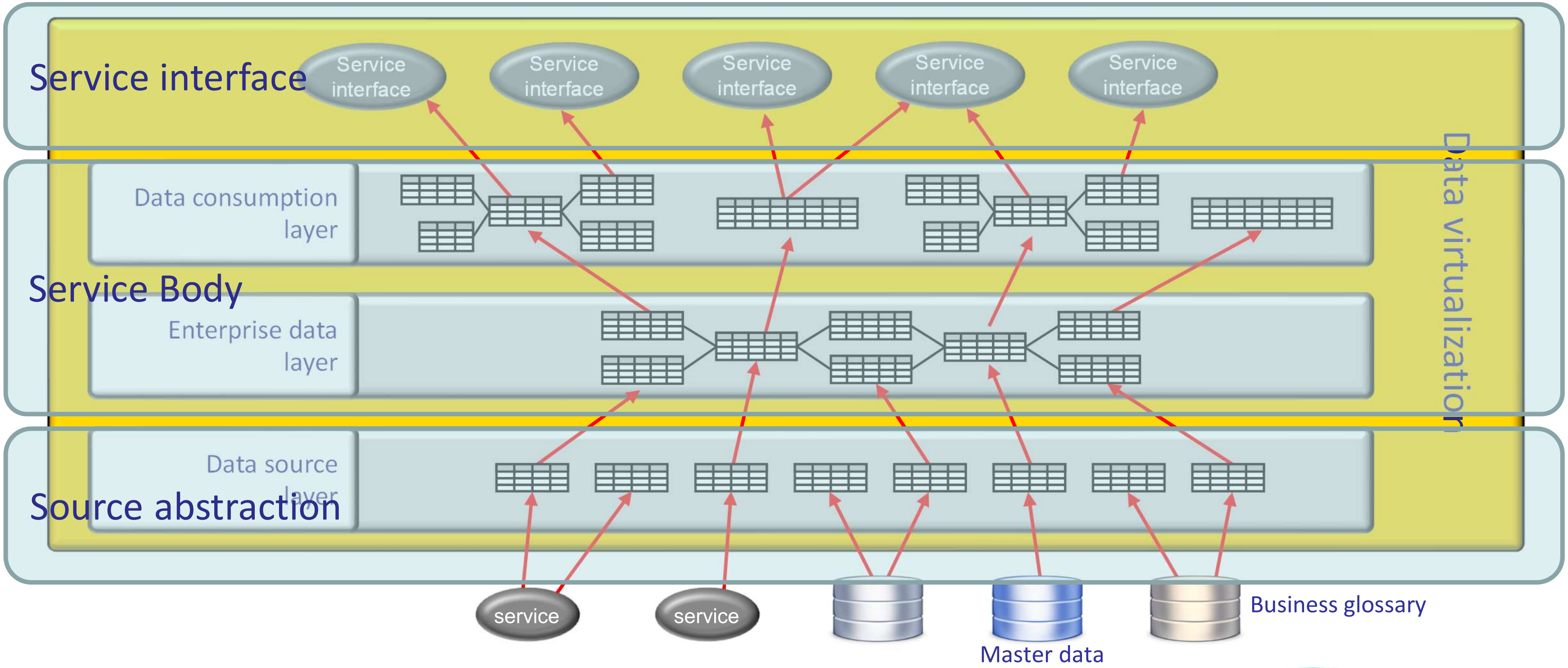
Developing Data Fabric Services with Data Virtualization



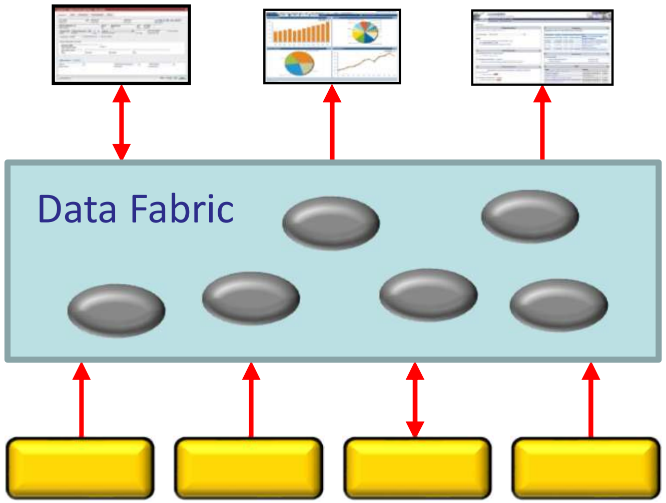
The Data Fabric



Developing Data Fabric Services with Data Virtualization

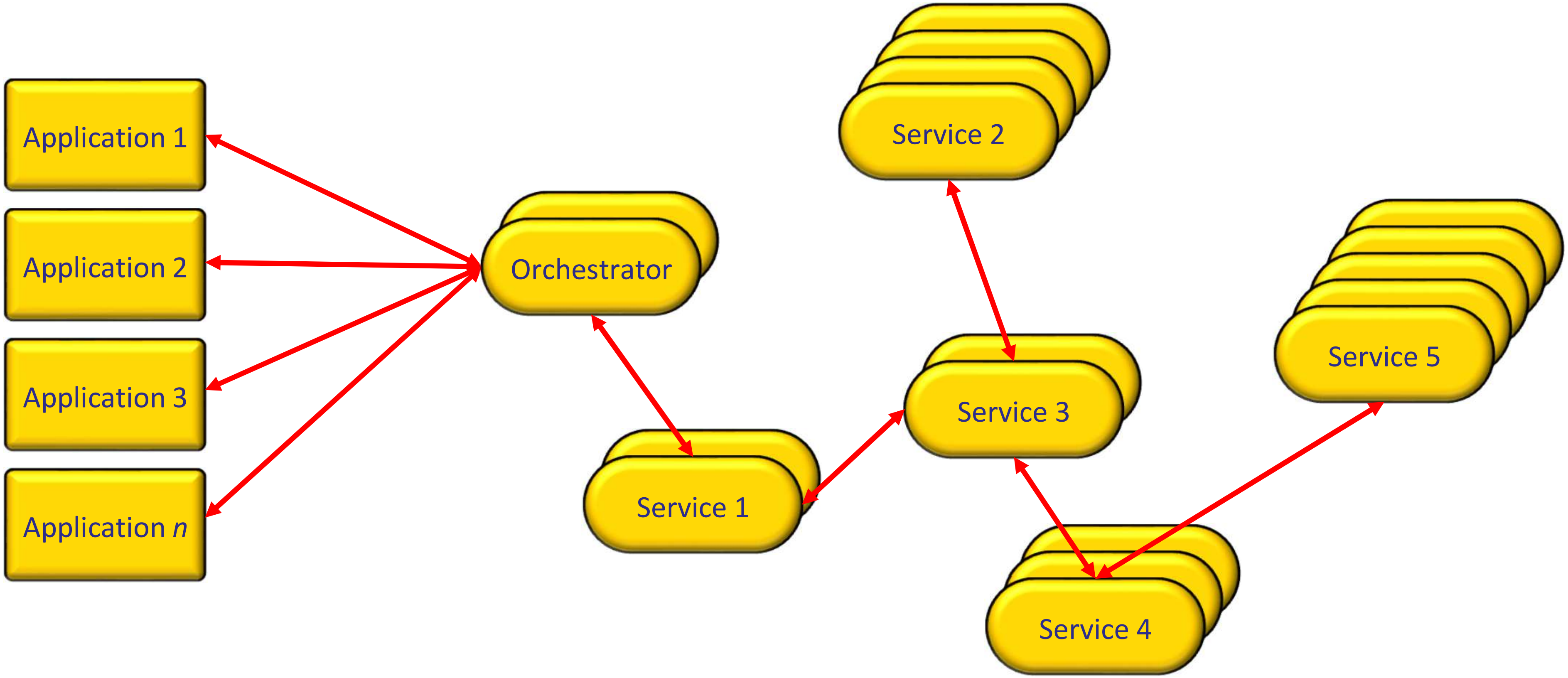


Remarks on Data Fabric



- Poorly defined concept
- Metadata is required
- Master data needed to integrate data correctly
- A data fabric may contain a data warehouse, data lake, or data hub
- Dedicated tool market is small, e.g. Cinchy
- Data fabric must support transactional and analytical workloads

Data Fabric ≠ Micro-Services Architecture

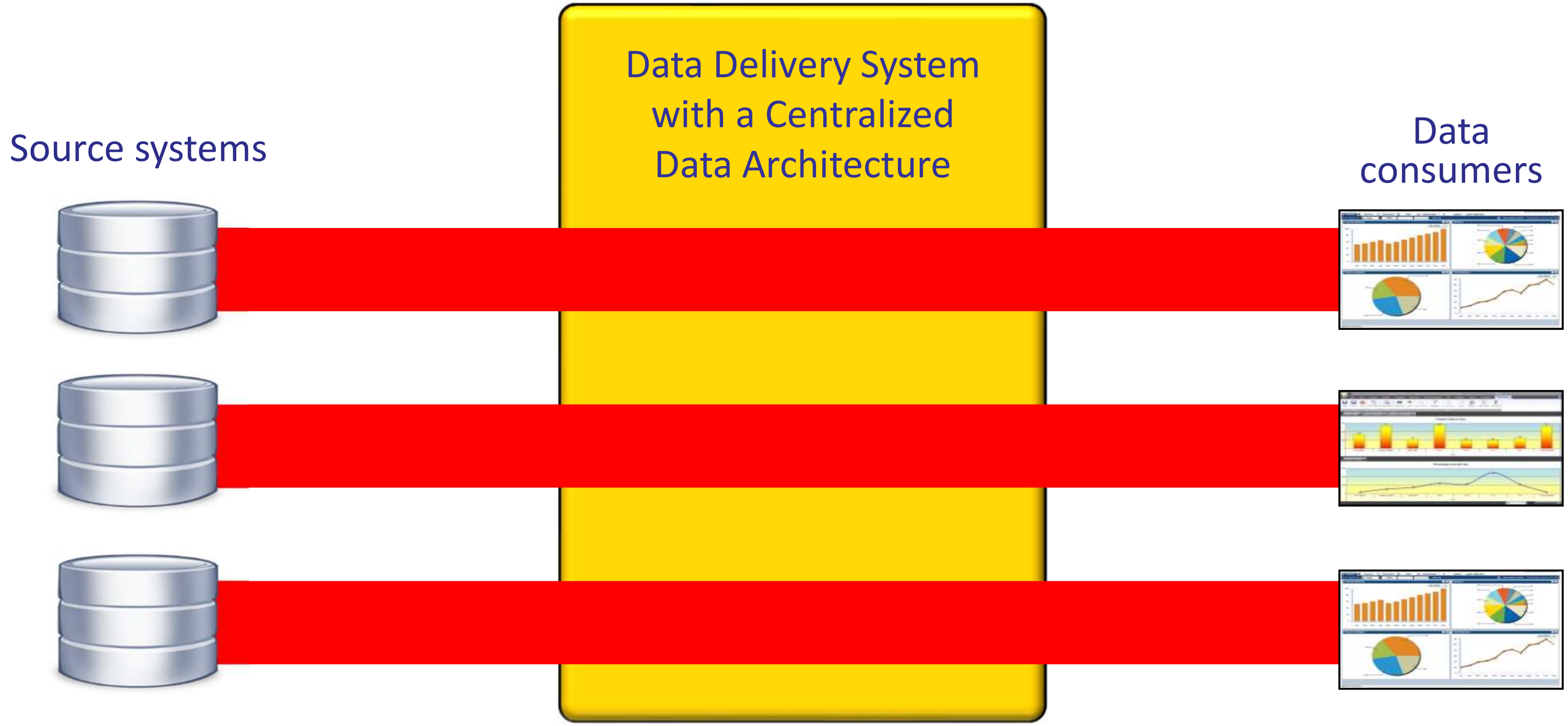


Part 7.7:
The Data Mesh

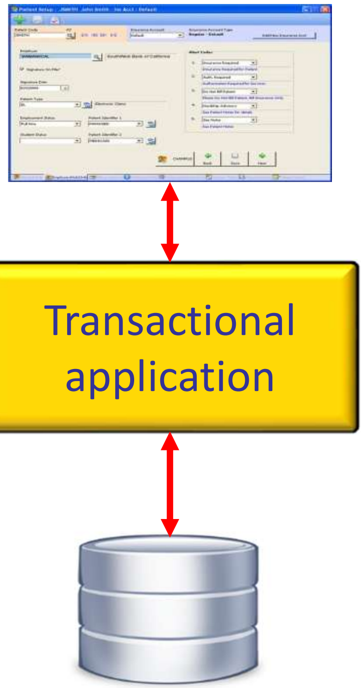
What is a Data Mesh?

- Introduced by Zhamak Dehghani:
- "Data platforms based on the data lake architecture have common failure modes that lead to *unfulfilled promises* at scale.
- To address these failure modes we need to shift from the *centralized paradigm* of a lake, or its predecessor data warehouse.
- We need to shift to a paradigm that draws from *modern distributed architecture*: considering *domains* as the first class concern, applying platform thinking to create self-serve data infrastructure, and *treating data as a product*."

Single-Domain Data Consumers

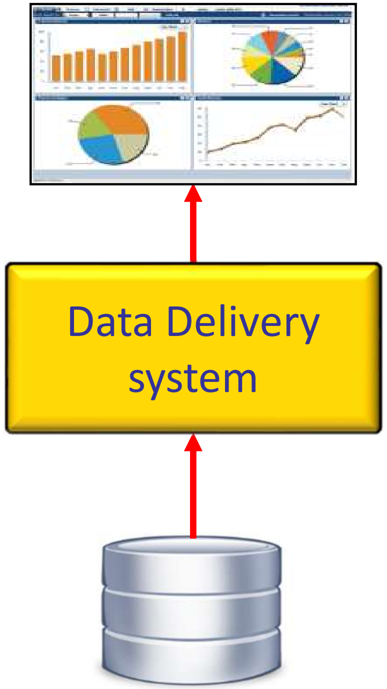


Data Engineers for Transactional Applications



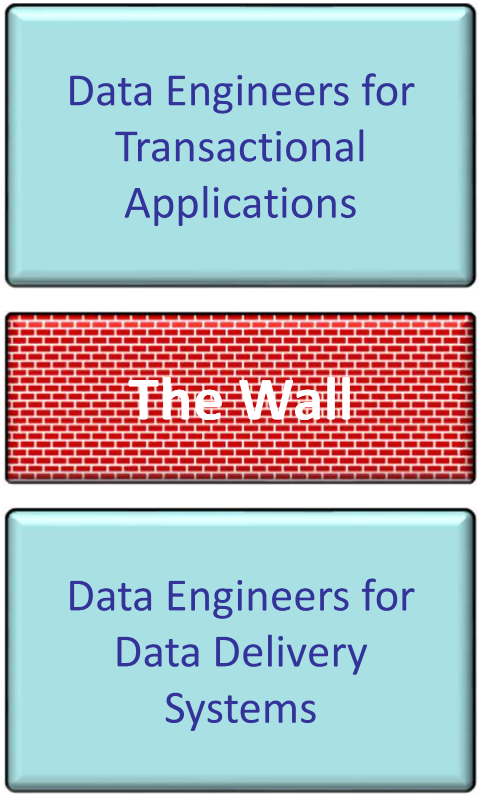
- They are single-domain experts
- They focus only on data requirements of transactional applications
  - Not on other forms of data consumption, such as BI
- They do not make the data easily consumable
- They implement all the business rules
- They know about all the exceptions
- They know when changes are implemented

Data Engineers for Data Delivery Systems



- They need to understand the data of all the domains
  - Hyper-domain experts
- They need to transform the data into consumable data
- They need to work with data not designed to be integrated
- They need to understand all the business rules that need to be applied
  - Complex ETL processes
- They need to understand the data requirements of the data consumers
- They need to deal with SLAs of the data consumers

The Wall between Two Groups of Data Engineers

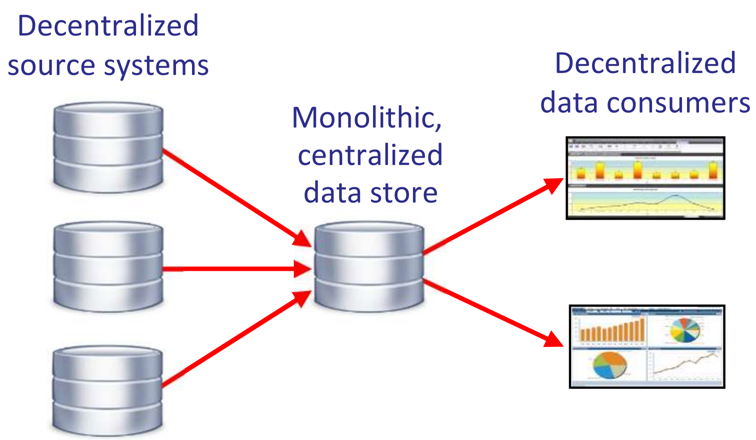


- Different groups of data engineers
- Different tool sets
- Different responsibilities
- Changes of data or data structures not always communicated
- Who owns the data and who is responsible for data quality?
- How to implement “the right to be forgotten/corrected”?

Interfaces of Transactional Applications

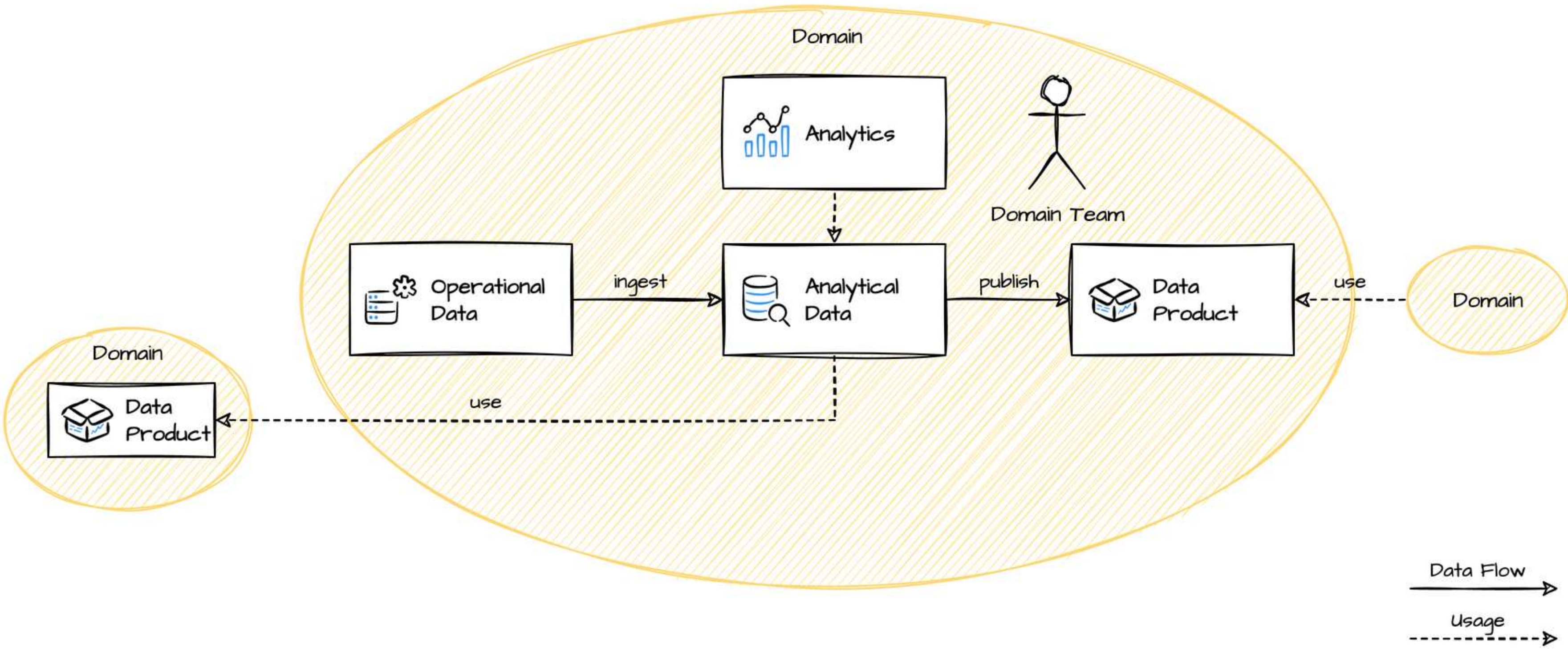
- Most are not developed to offer an interface
- Interfaces that do exist, are commonly developed for record-oriented access
- Direct database access complex or not always allowed
- Rarely support for historic data
- Risky to bypass multi-tenant systems

Traditional Centralized, Monolithic Architectures



- Large and complex monolithic solutions
- Single-domain versus multi-domain experts
  - Application developers = single-domain experts
  - Data engineers = multi-domain experts
  - Data consumers = single-domain experts
- Data engineers need to understand all the business logic
- Who owns the data in the central database?
- Storage of redundant data

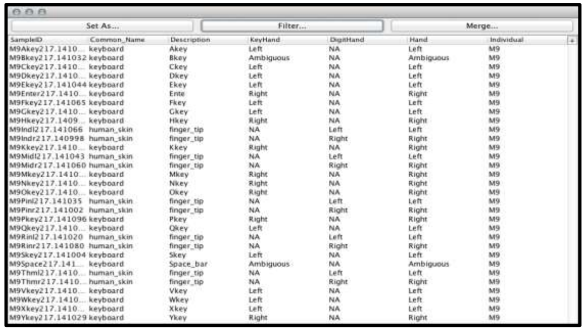
A Domain-Oriented Architecture



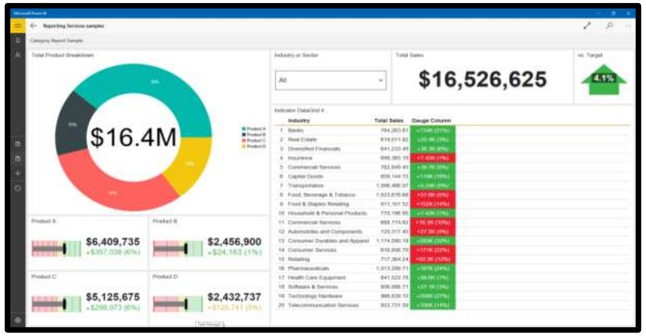
datamesh-architecture.com

Potential Data Products

Data as file



Report



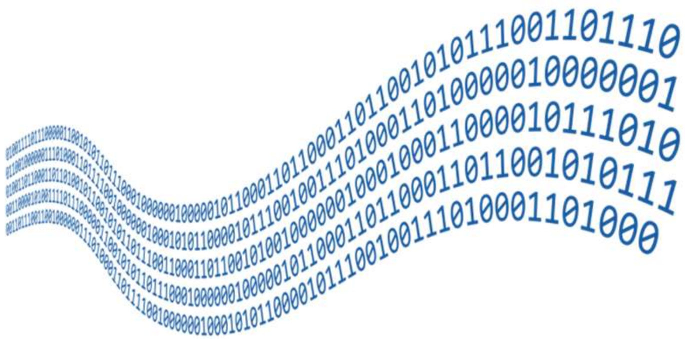
Service

Data via SQL

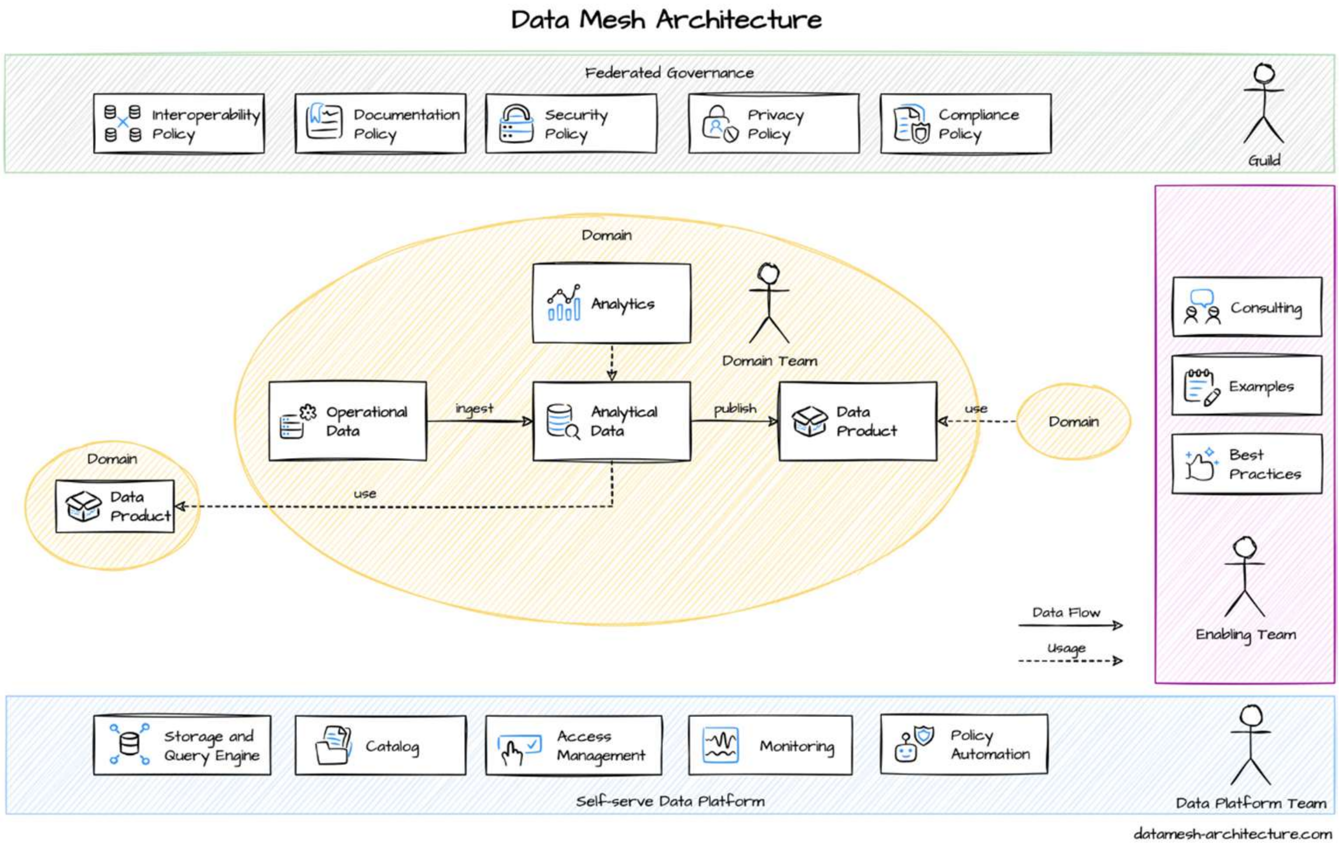
Apps

Embeddable KPI

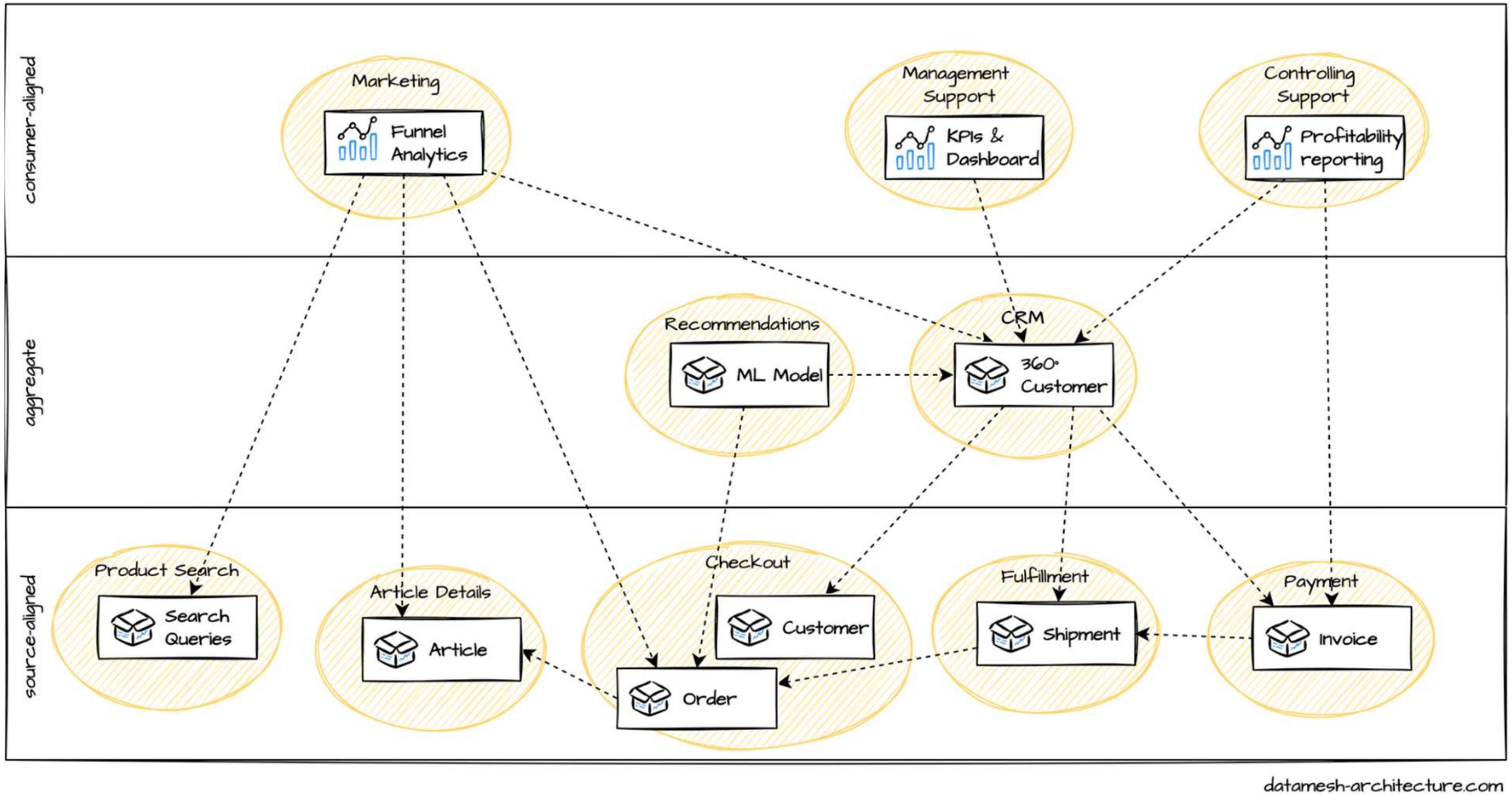
Stream of Data



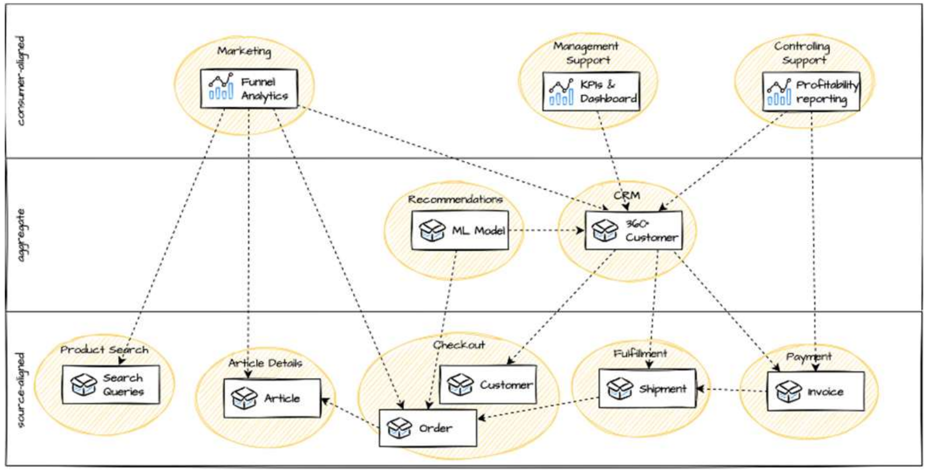
The Periphery of a Domain

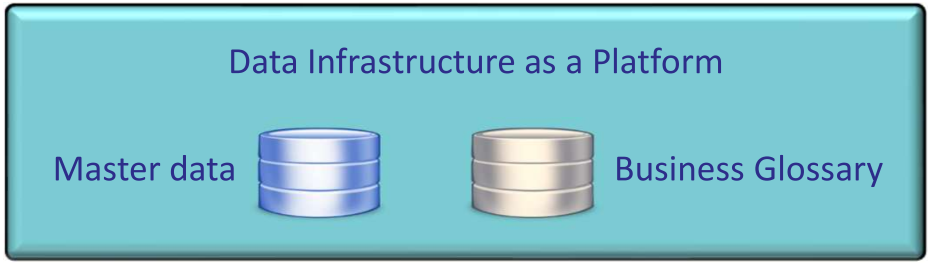


The Mesh Itself



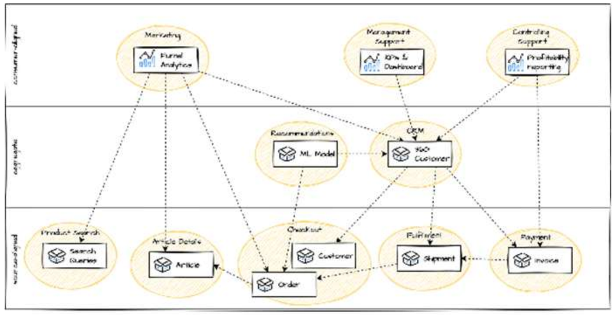
The Foundation: Data Infrastructure as a Platform





- Scalable polyglot big data storage
- Encryption for data at rest and in motion
- Data product versioning
- Data product schema
- Data product de-identification
- Unified data access control and logging
- Data pipeline implementation and orchestration
- Data product discovery, catalog registration and publishing
- Data governance and standardization
- Data product lineage
- Data product monitoring/alerting/log
- Data product quality metrics (collection and sharing)
- In memory data caching
- Federated identity management
- Compute and data locality
- …

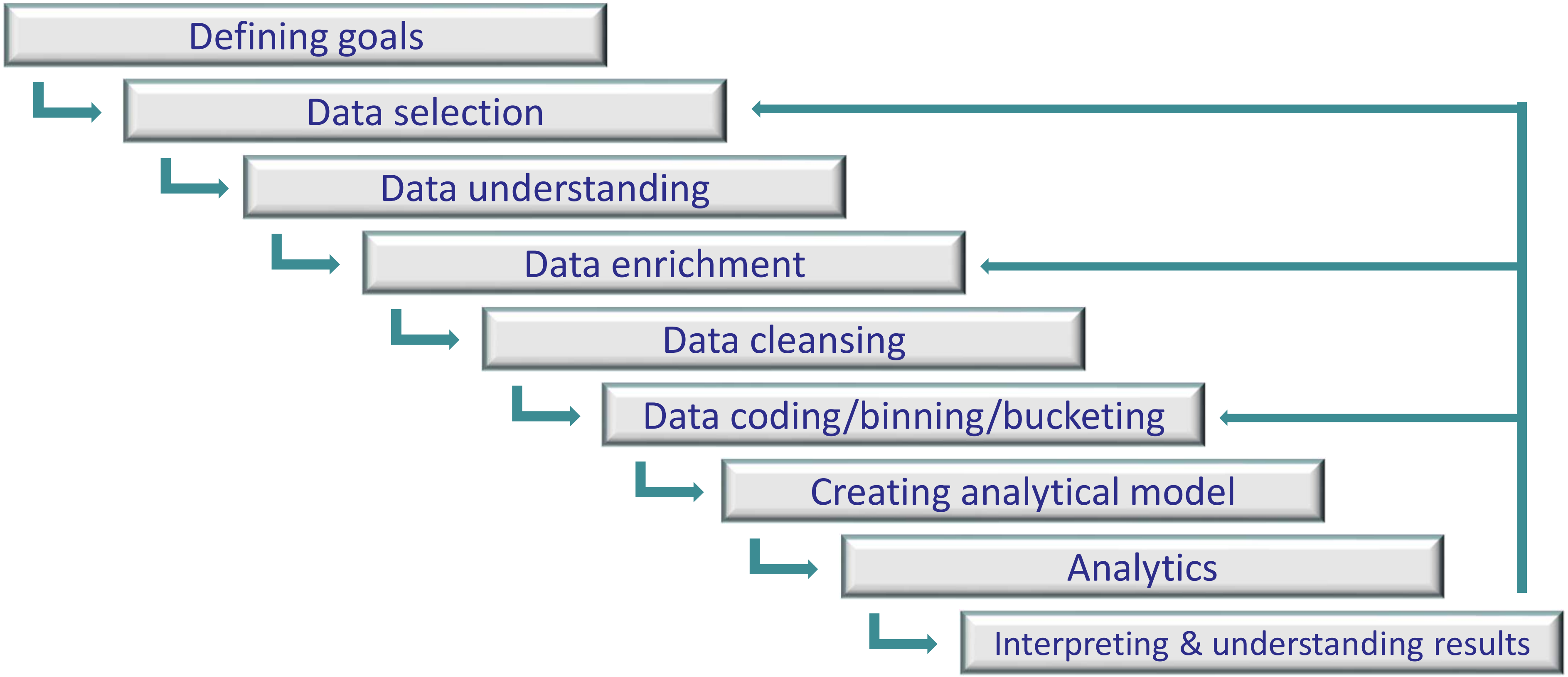
Data Mesh Challenges



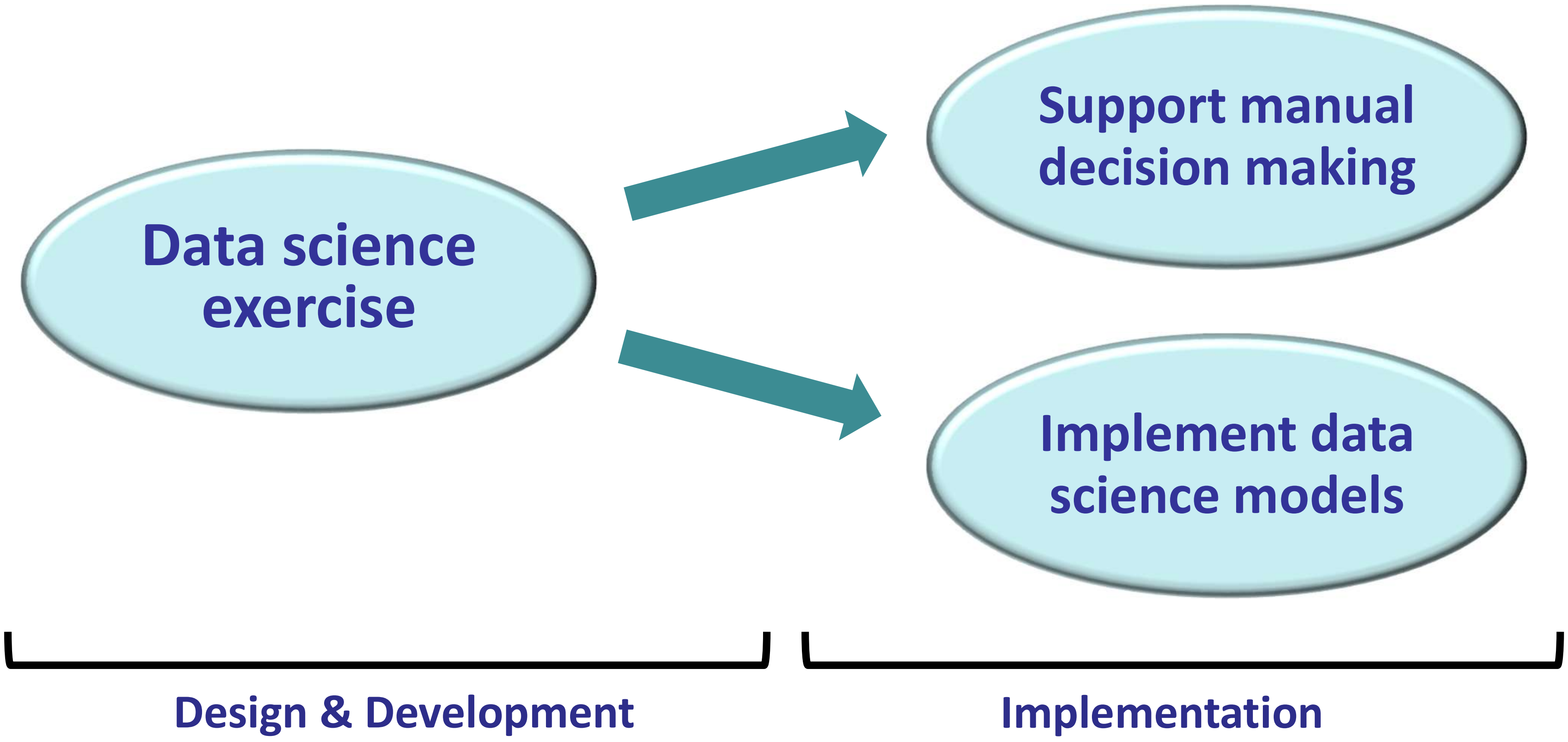
- Massive organizational change for IT
- Standardization of interfaces required
- How clear are BI requirements when new transactional applications are developed?
- Development of transactional applications more complex
- What about transactional applications that are bought?
  - Do they need to be wrapped?
- What about multi-domain transactional applications?
- Distribution of knowledge of data delivery technologies

Part 7.8:
Embedding Data Science Models in Data Architectures

Development Steps for Data Science



Operationalization of Data Science Models



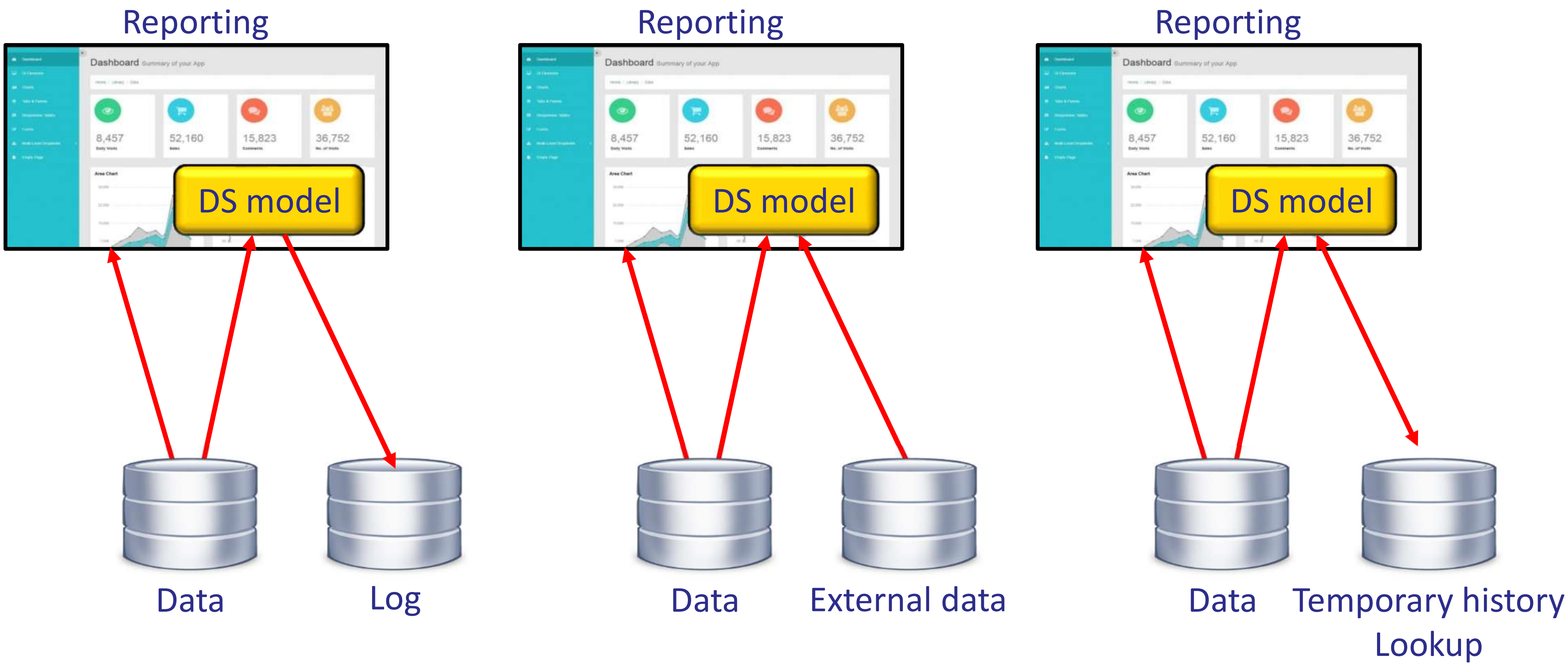
Operationalization of Data Science Models

Type of Decision	Example
Singular manual decision	What will be the impact on total sales of acquiring company X?
Repeatable manual decision	Does a specific location have the right characteristics for opening a new shop?
Partial automated decision	In a call center: What is the churn risk for a customer? What should we offer?
Full automated decision without automated reaction	When credit card payment is dubious, send message to operator
Full automated decision with automated reaction	When sensor indicates the component is heating up too fast, switch off machine
…	…

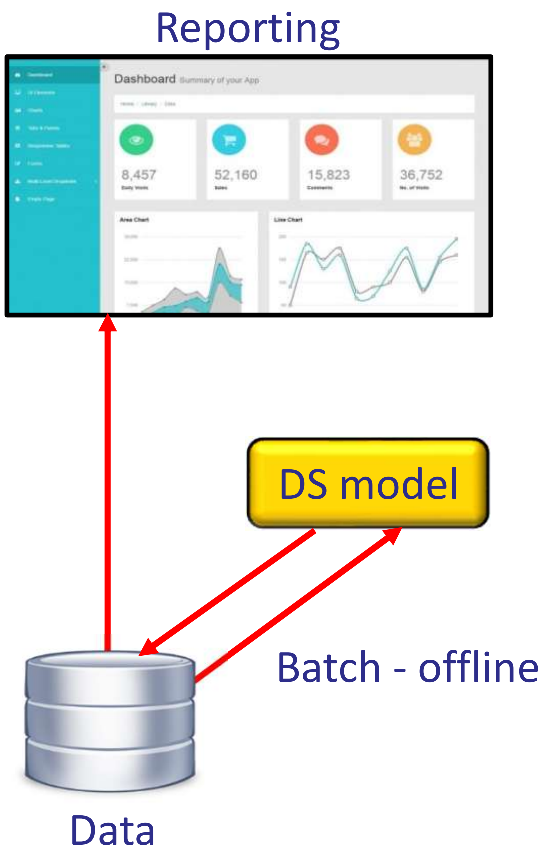
Requirements for a Supporting Data Architecture

- Versioning of data science models
  - Immutable models
- Auditable data science models
  - Reproducible data for reproducible models
  - Transparency of models
- Different codings must be easy and quick to apply
- Self-learning models or not?
- Delivering metadata
  - Descriptions, definitions, tags, relationships, searchable
- Fast evaluation of models
  - Max time to execute model, SLAs
- And many more …

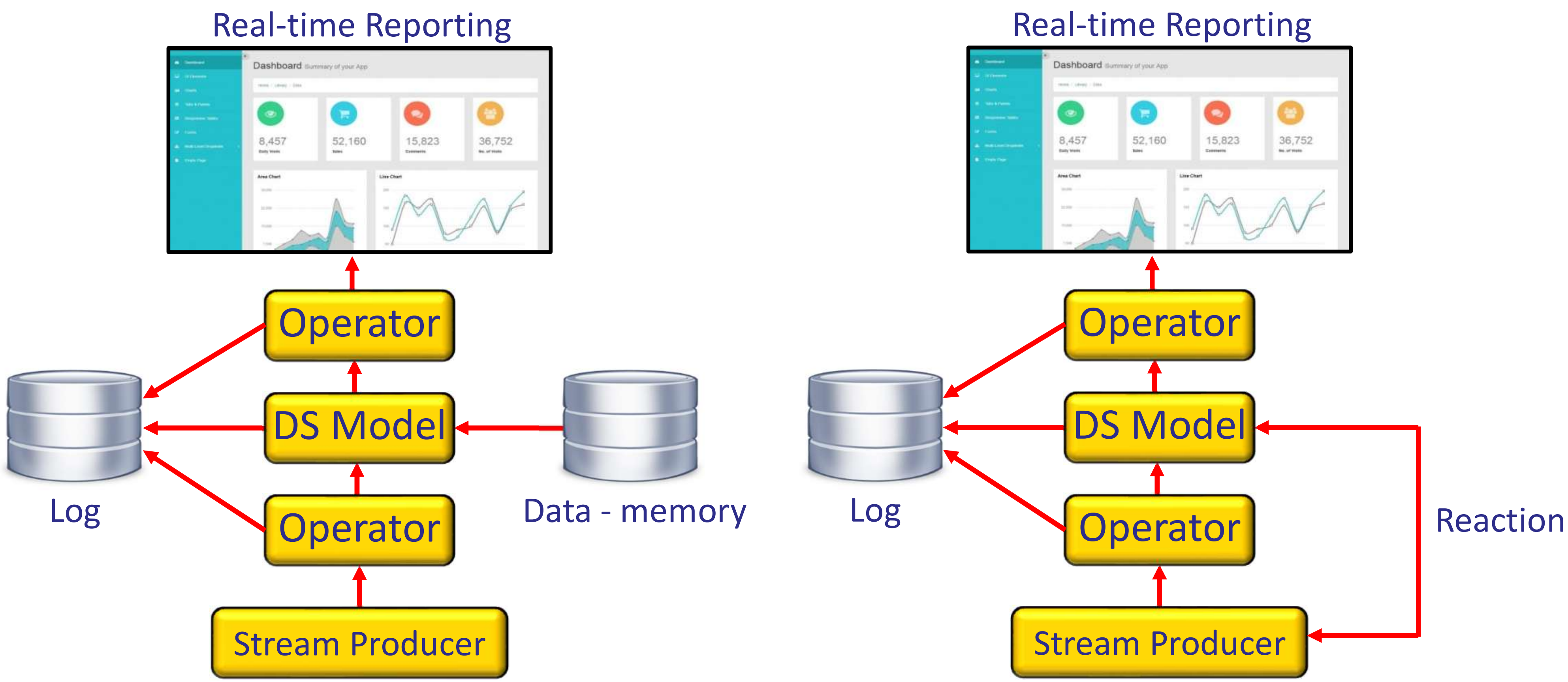
Architectural Aspects (1)



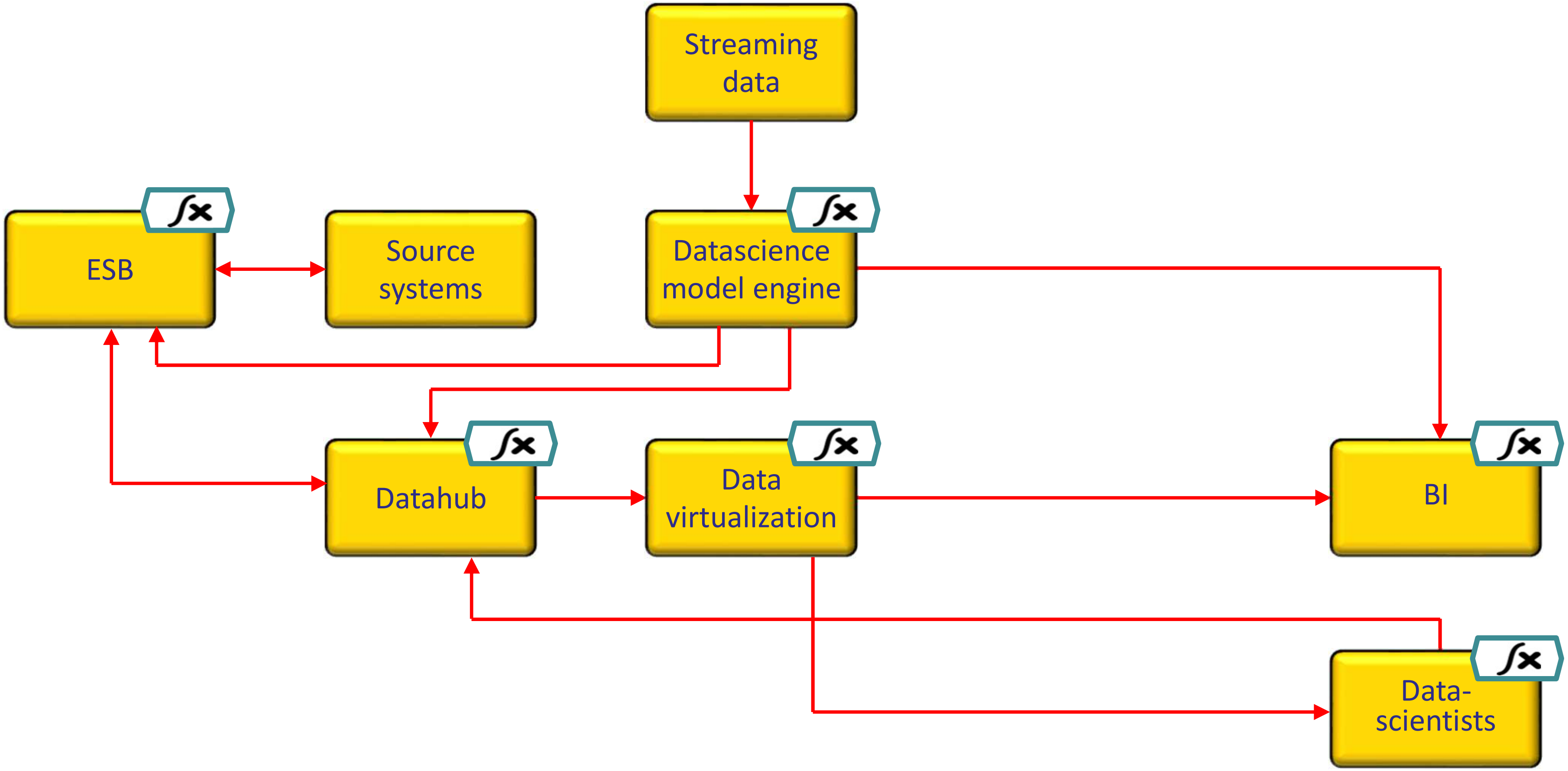
Architectural Aspects (2)



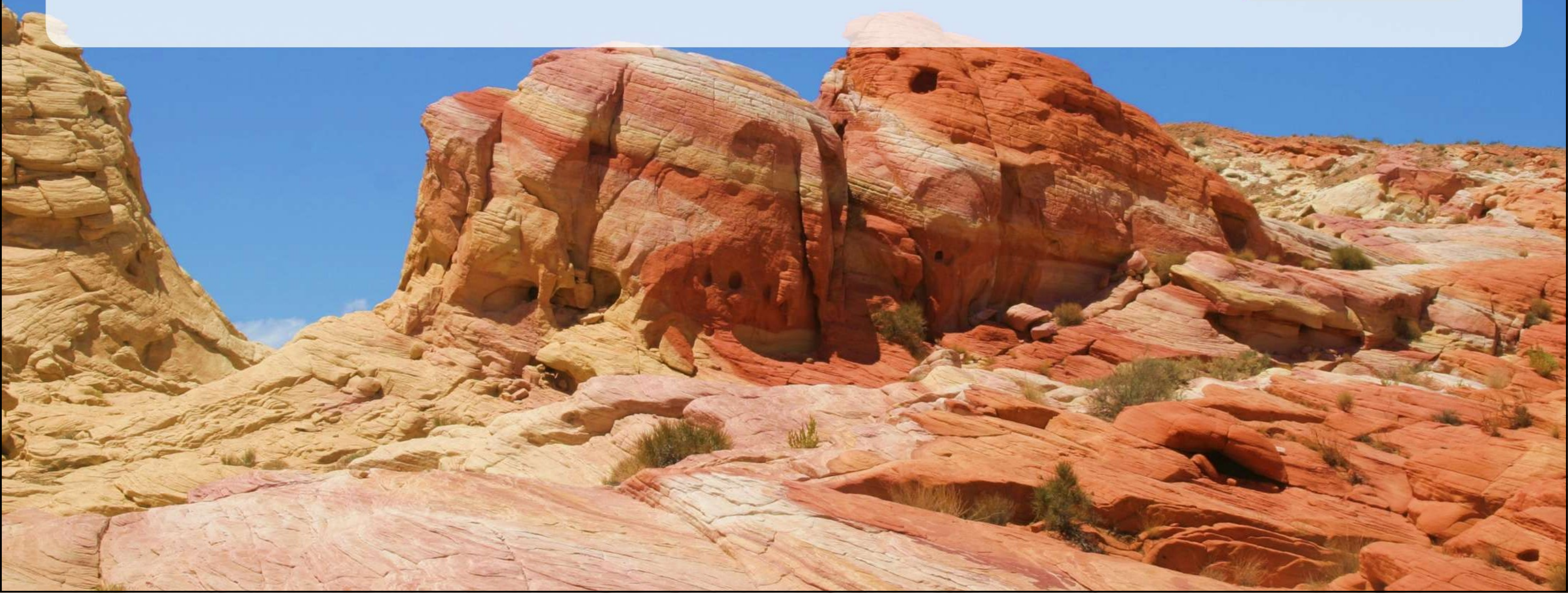
Architectural Aspects (3)



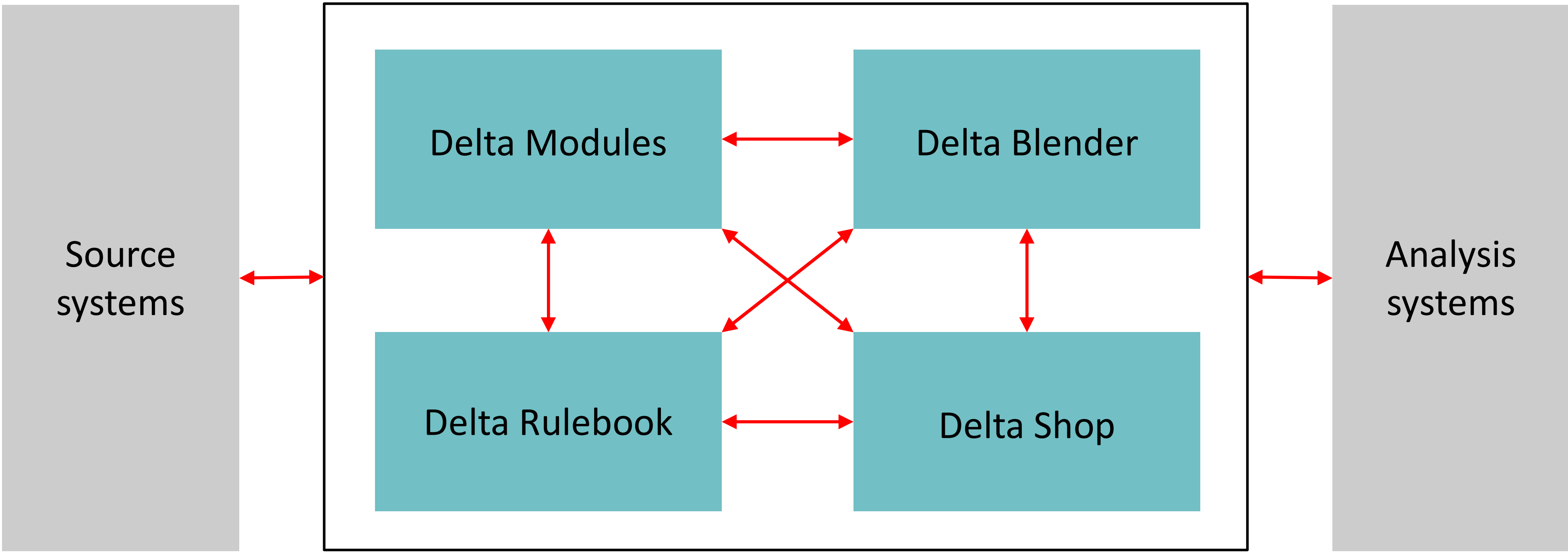
Example of a Data Architecture



Part 7.9:
The Delta Data Architecture
Under Development



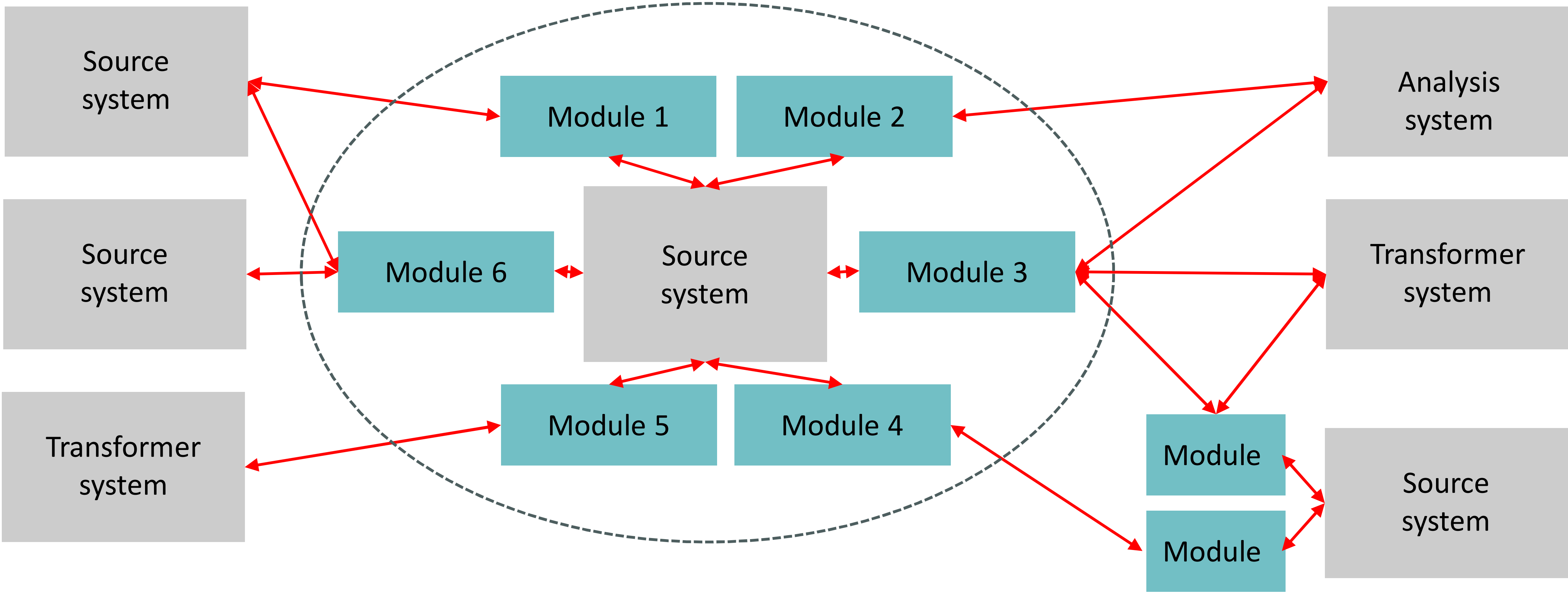
Delta: A Modern, Enterprise Data Architecture



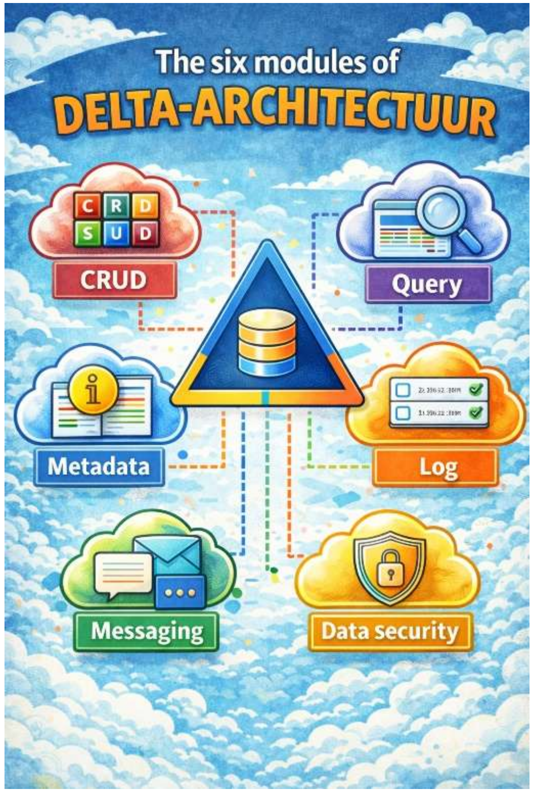
Functions of Source Systems

- Entering, modifying, and deleting data
  - For many business objects
- Retrieving data
- Securing data
- Data quality
- Backup and recovery tasks
- Calculating results
- Handling workflow and processes
- Triggering events
- *Connections with other systems*
- …

Wrapping the Source Systems - Abstraction

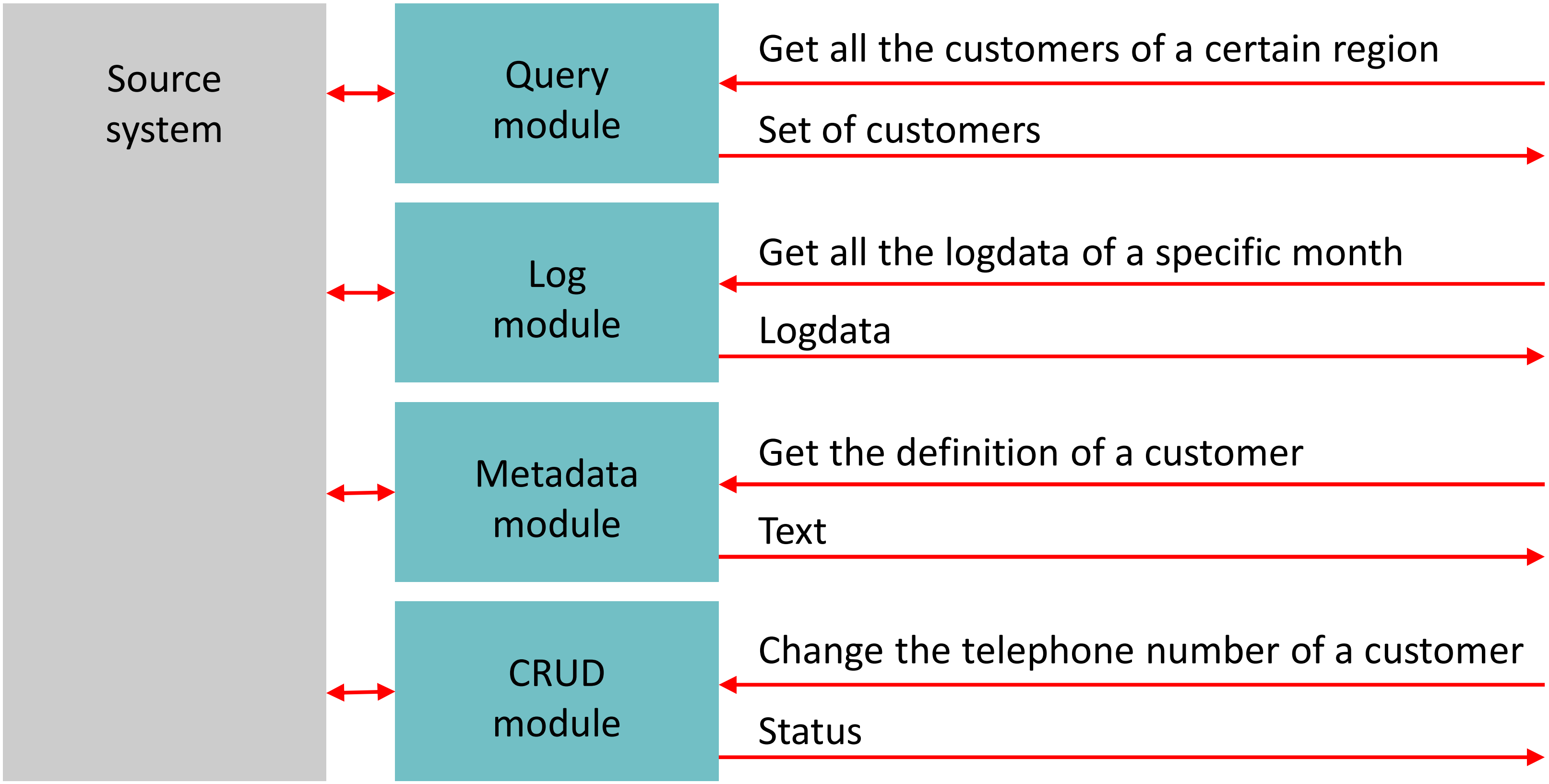


Six Delta Modules to Wrap Source Systems



- CRUD
- Query
- Metadata
- Log
- Messaging
- Data security

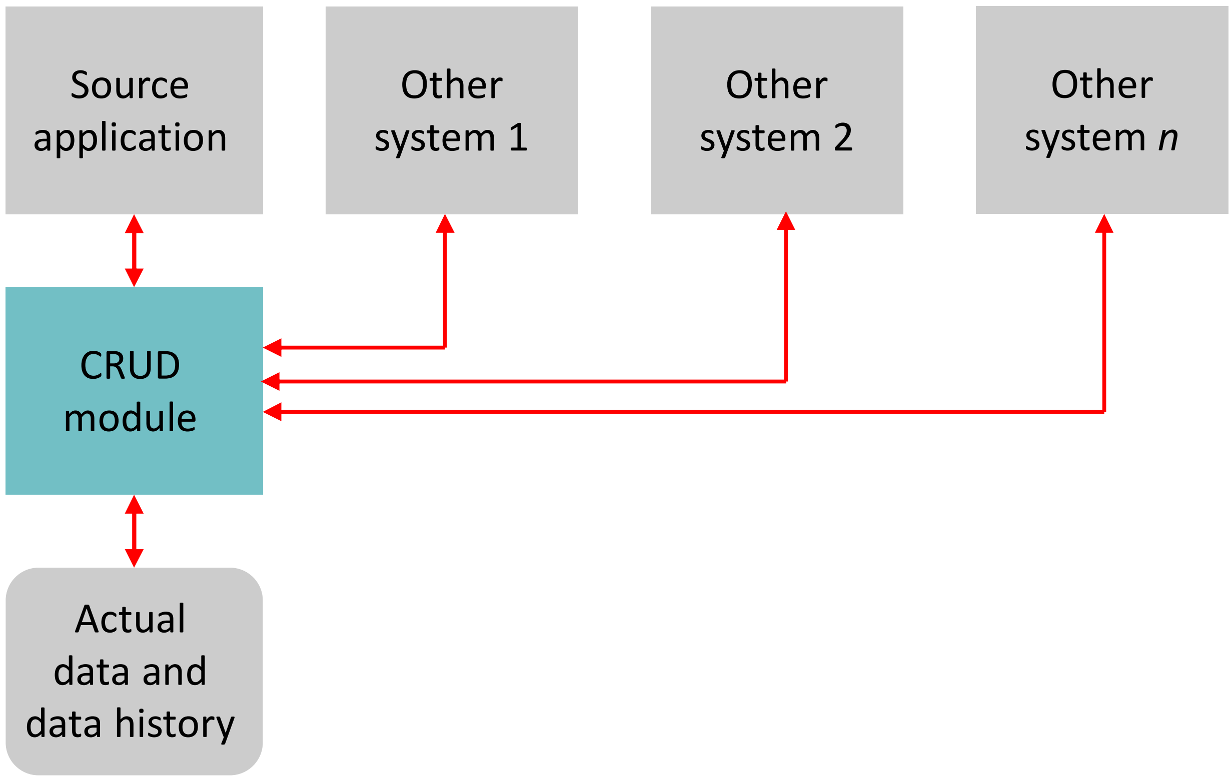
Modules and Functions



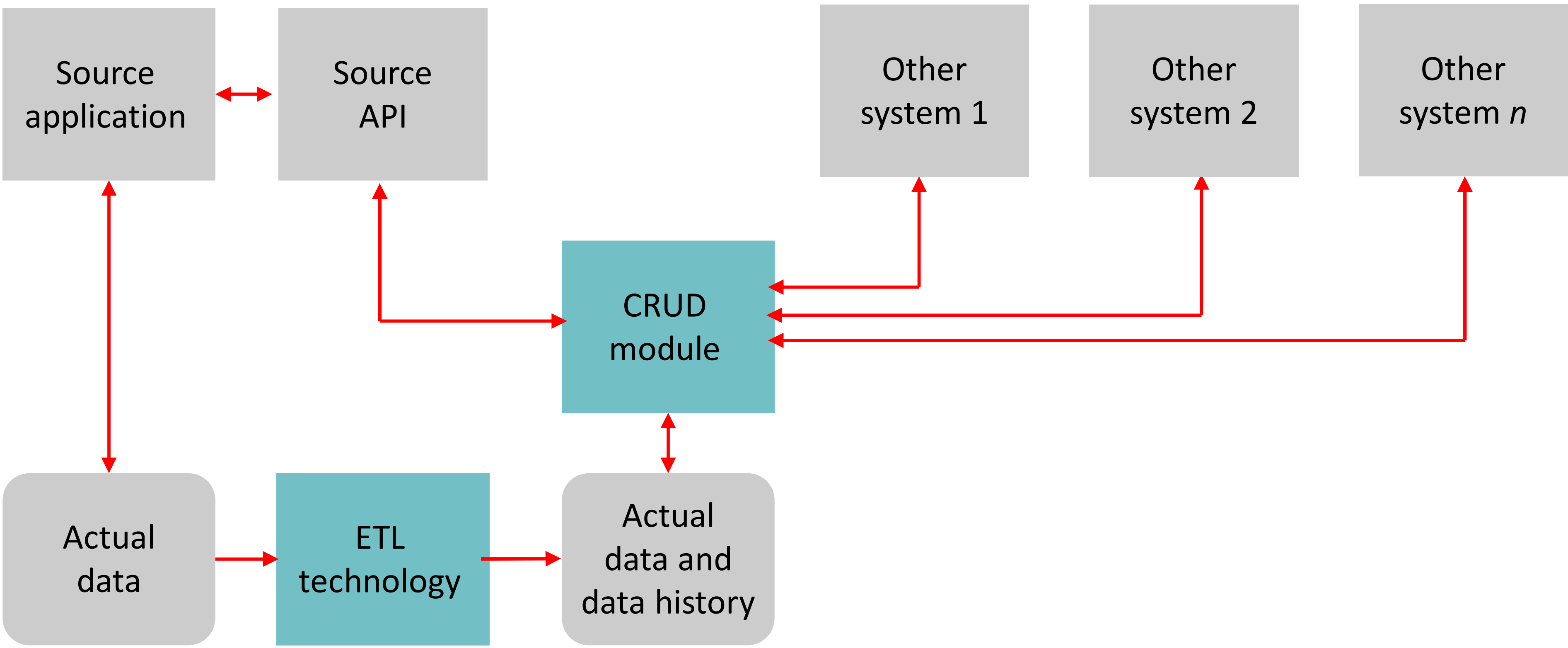
Functions of CRUD modules

- Offer functions to enter, view, modify, and delete data
- Hide internal and external source systems and files
- Data complies with the Enterprise Data Model
- Support time travel
  - Maintains data history if the source system does not
  - Two time dimensions: transaction time and real time
- Work with individual business objects
- Enforce data quality rules
- Involved in source system synchronization
- Replaces data exchange with data sharing
- …

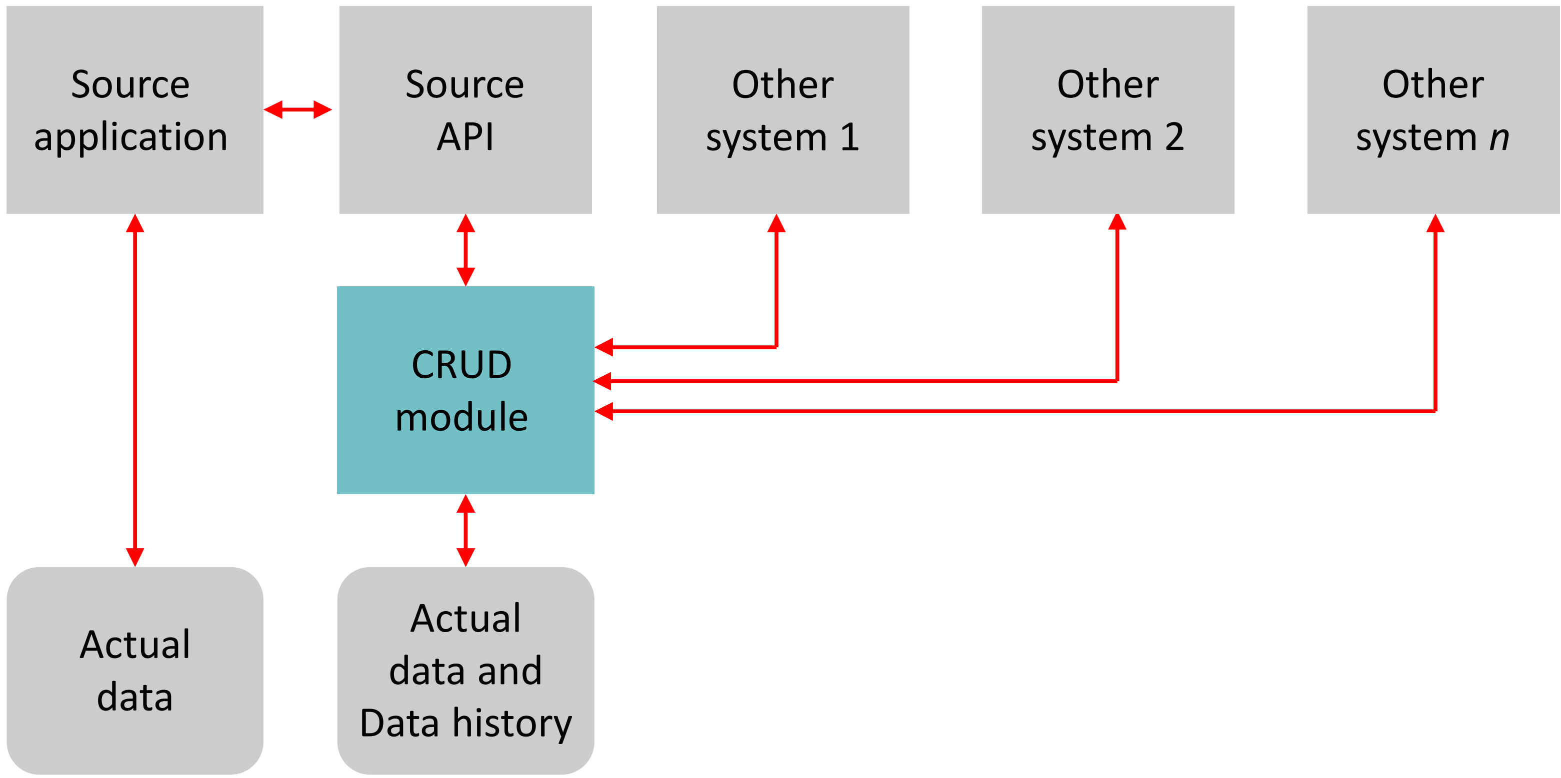
CRUD Module (1) The Dream



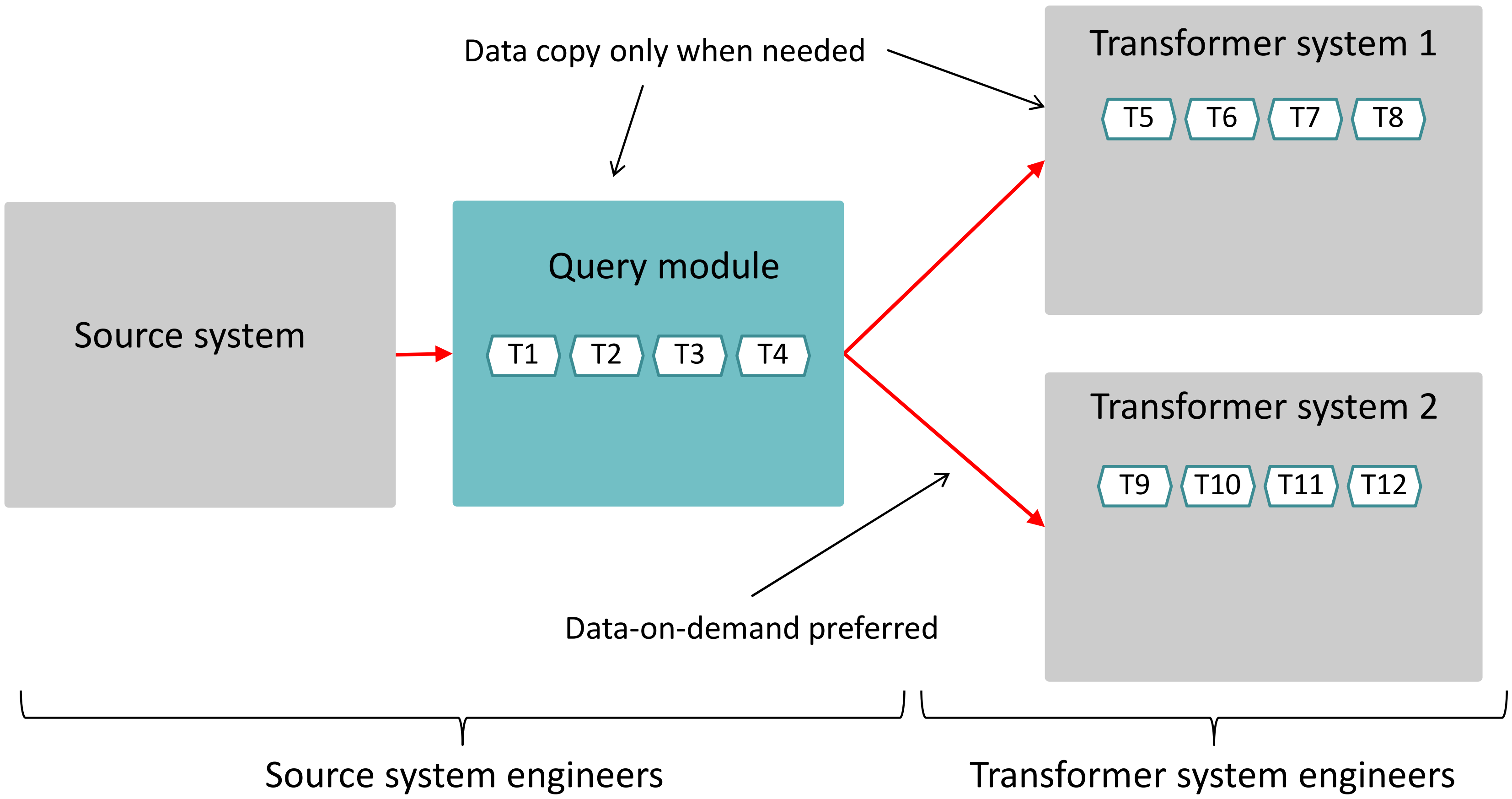
CRUD Module (2) Via API of Source System and ETL



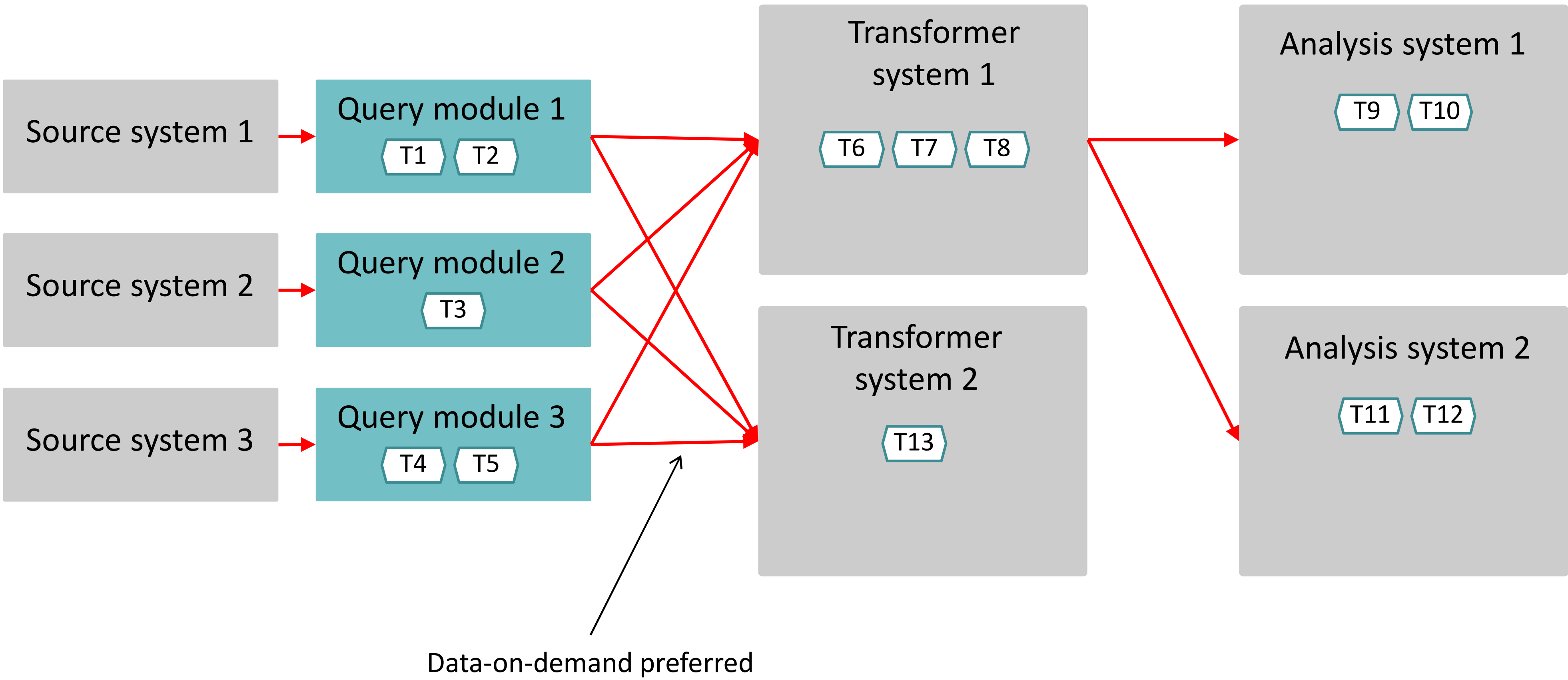
CRUD Module (3) Via API of Source System



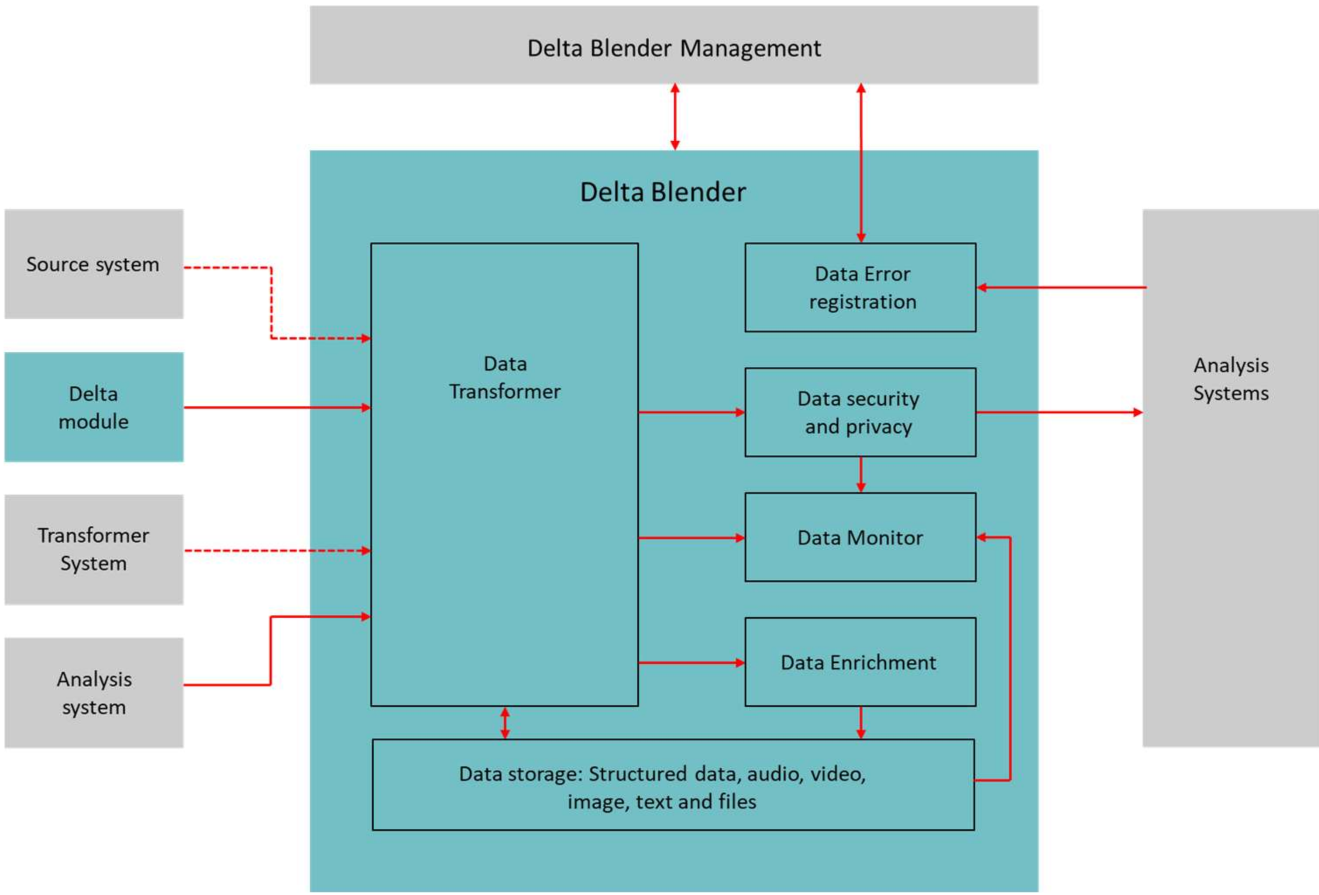
Transformers Closer to the Source Systems



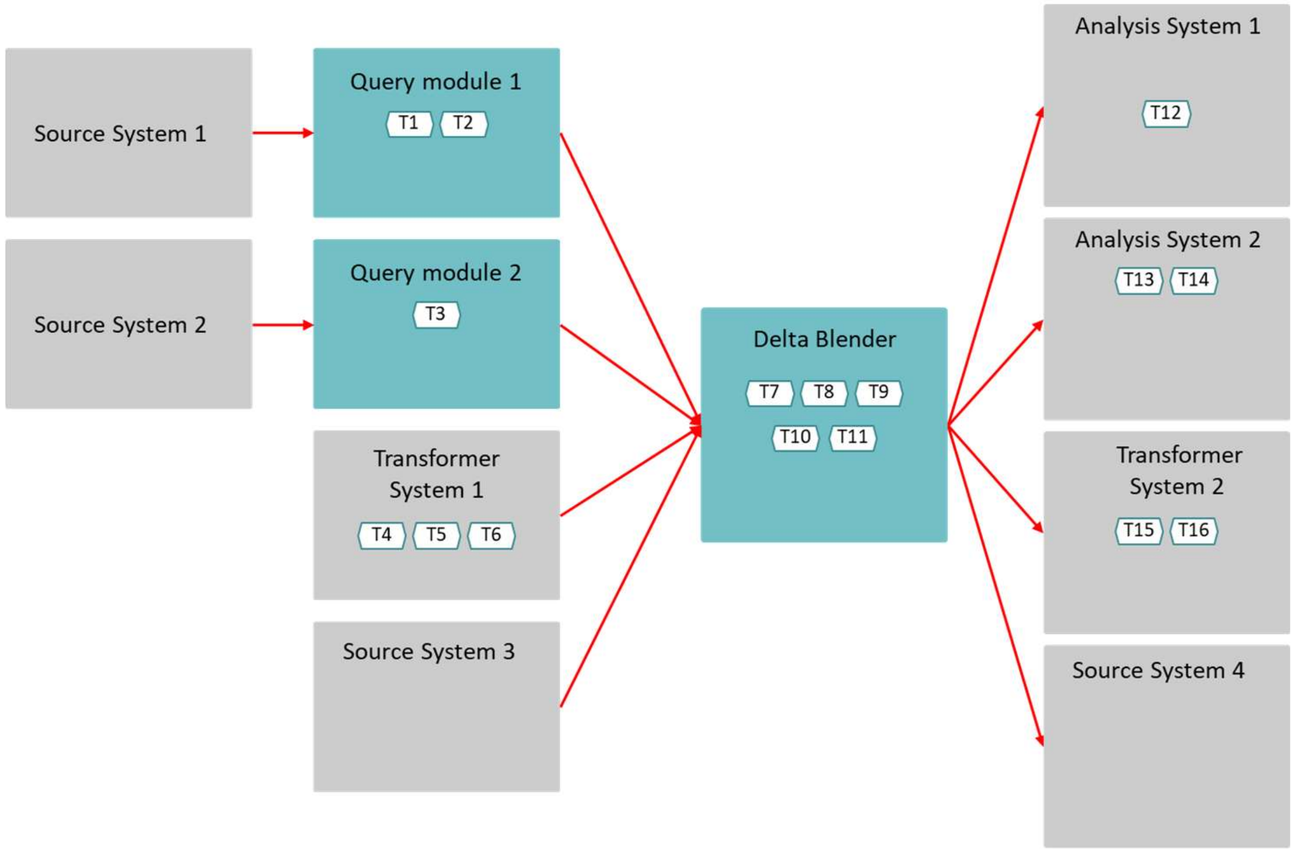
Transforming Data in Query Modules



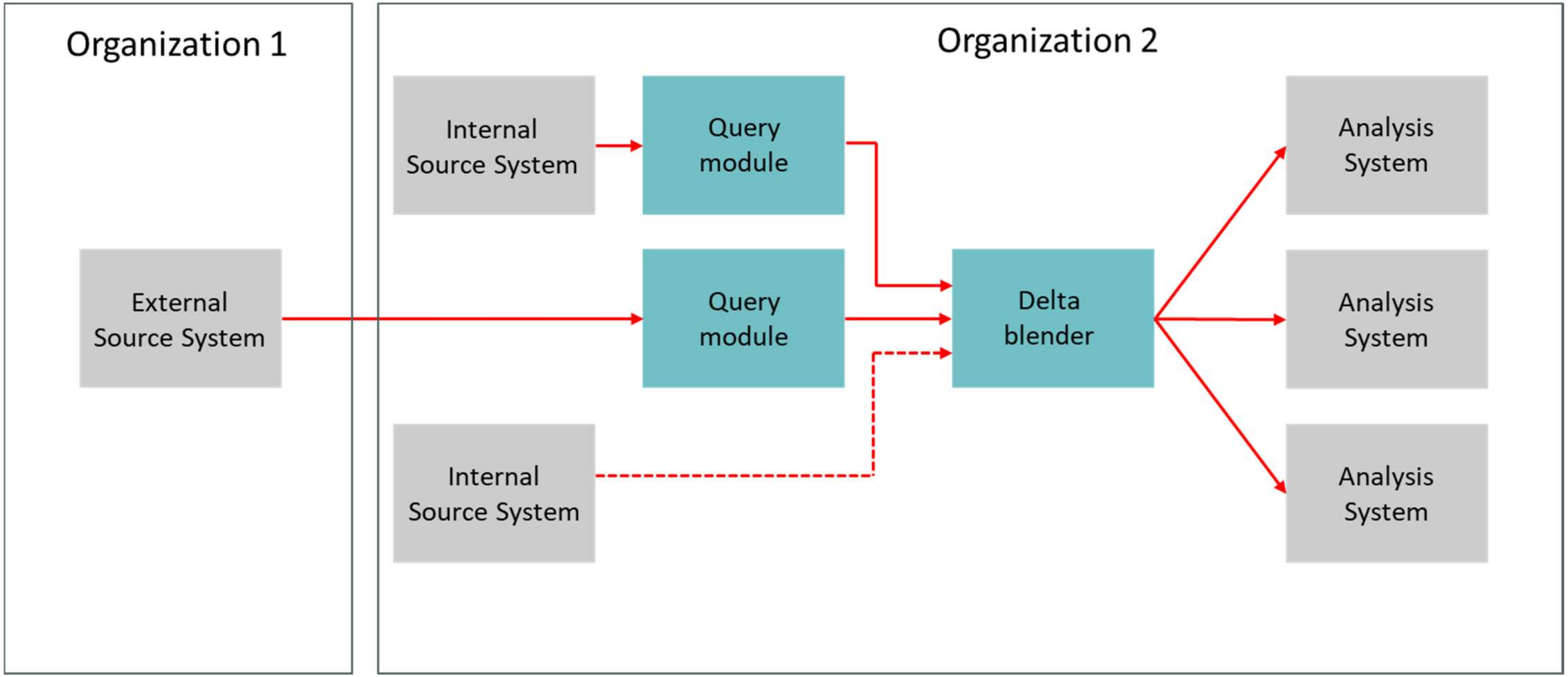
Delta Blender: Produces Ready-to-use Data



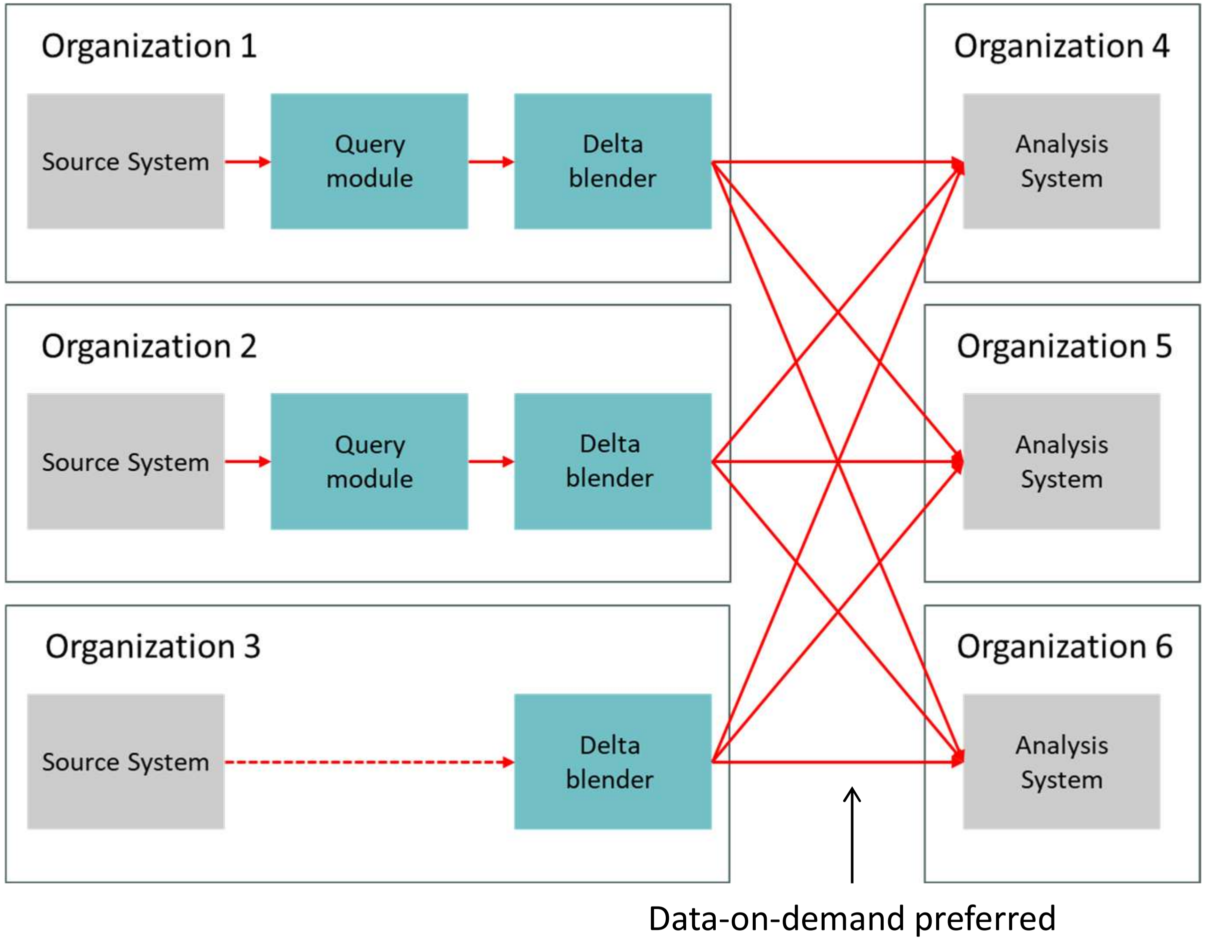
Delta Blender: Transformers



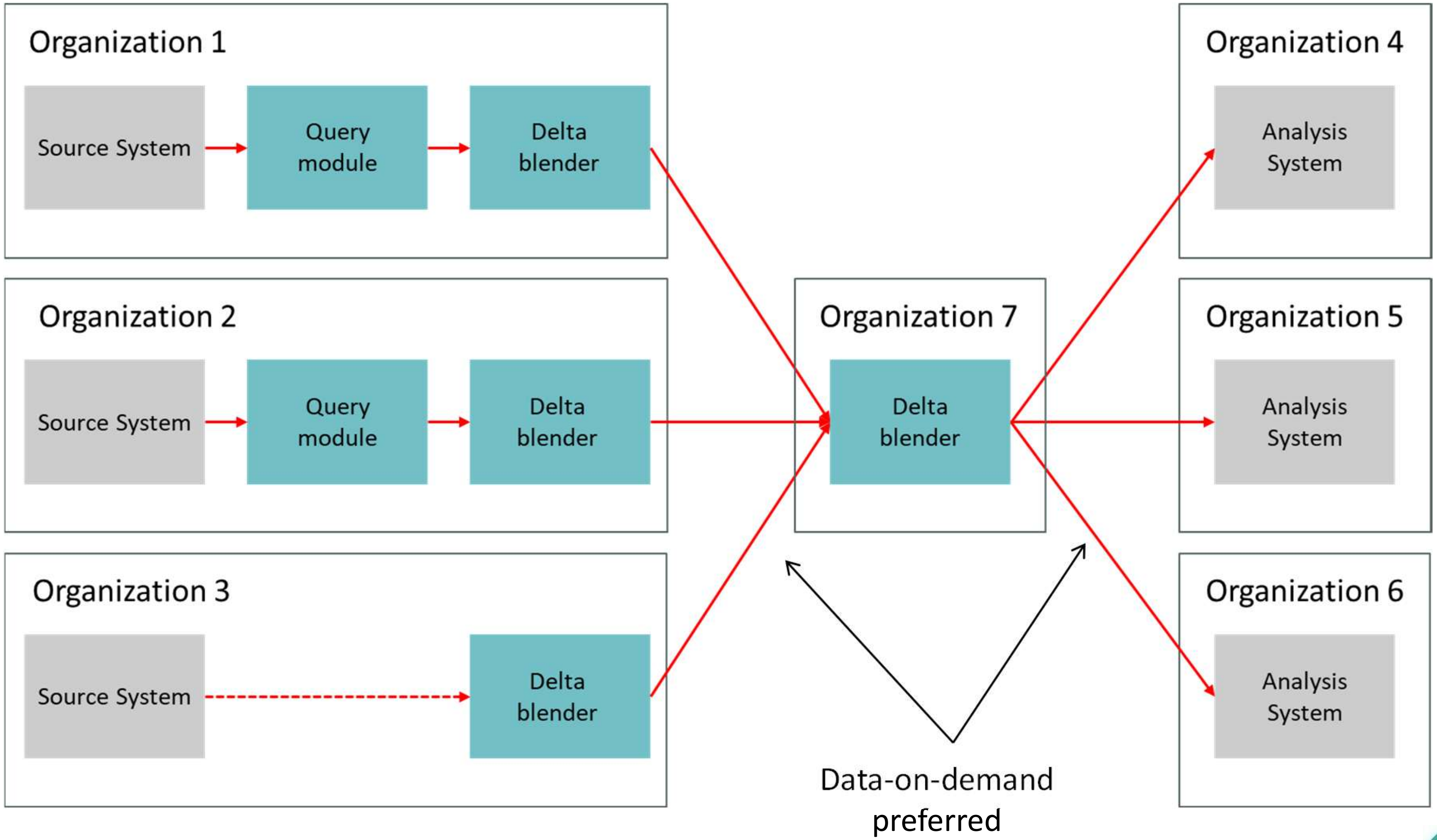
Local Federated Data Architecture



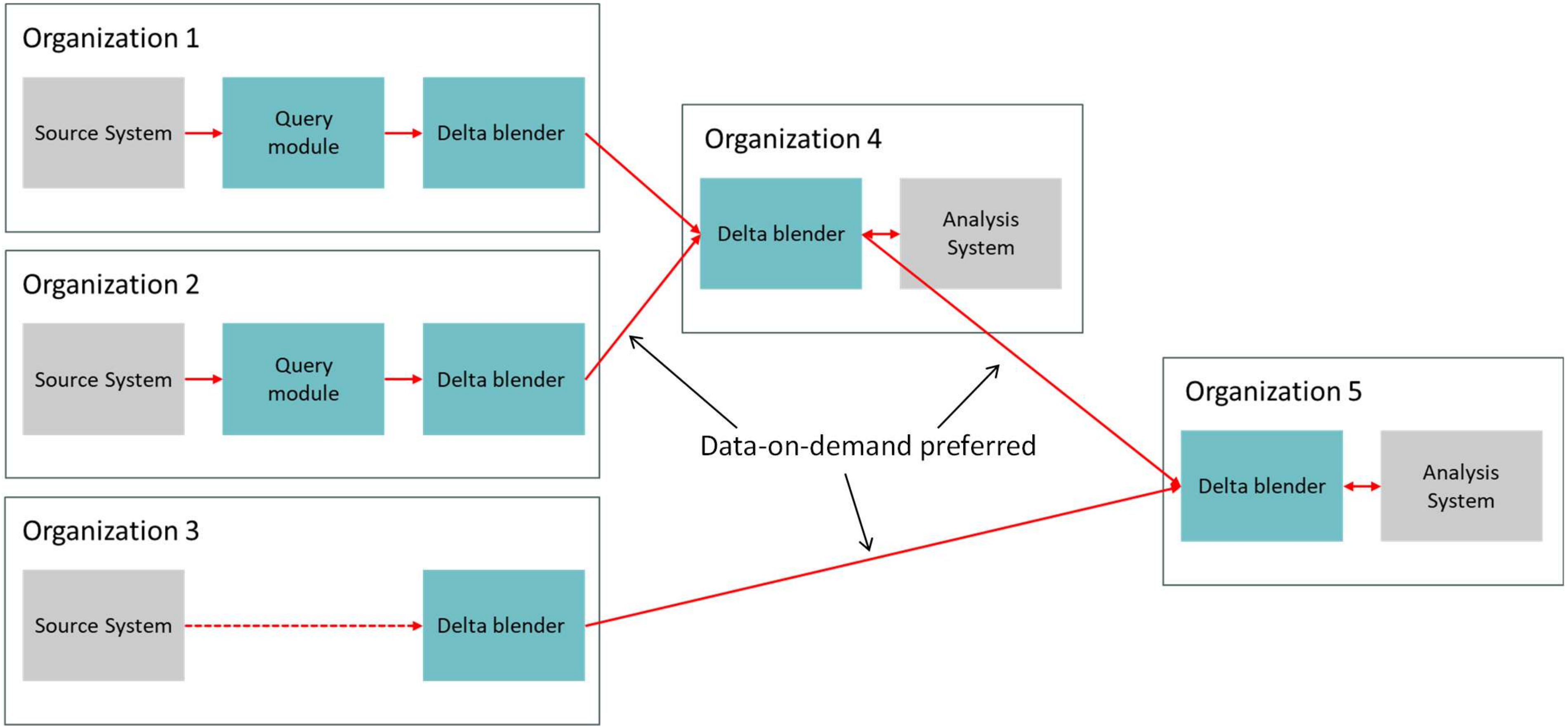
No Federated Data Architecture



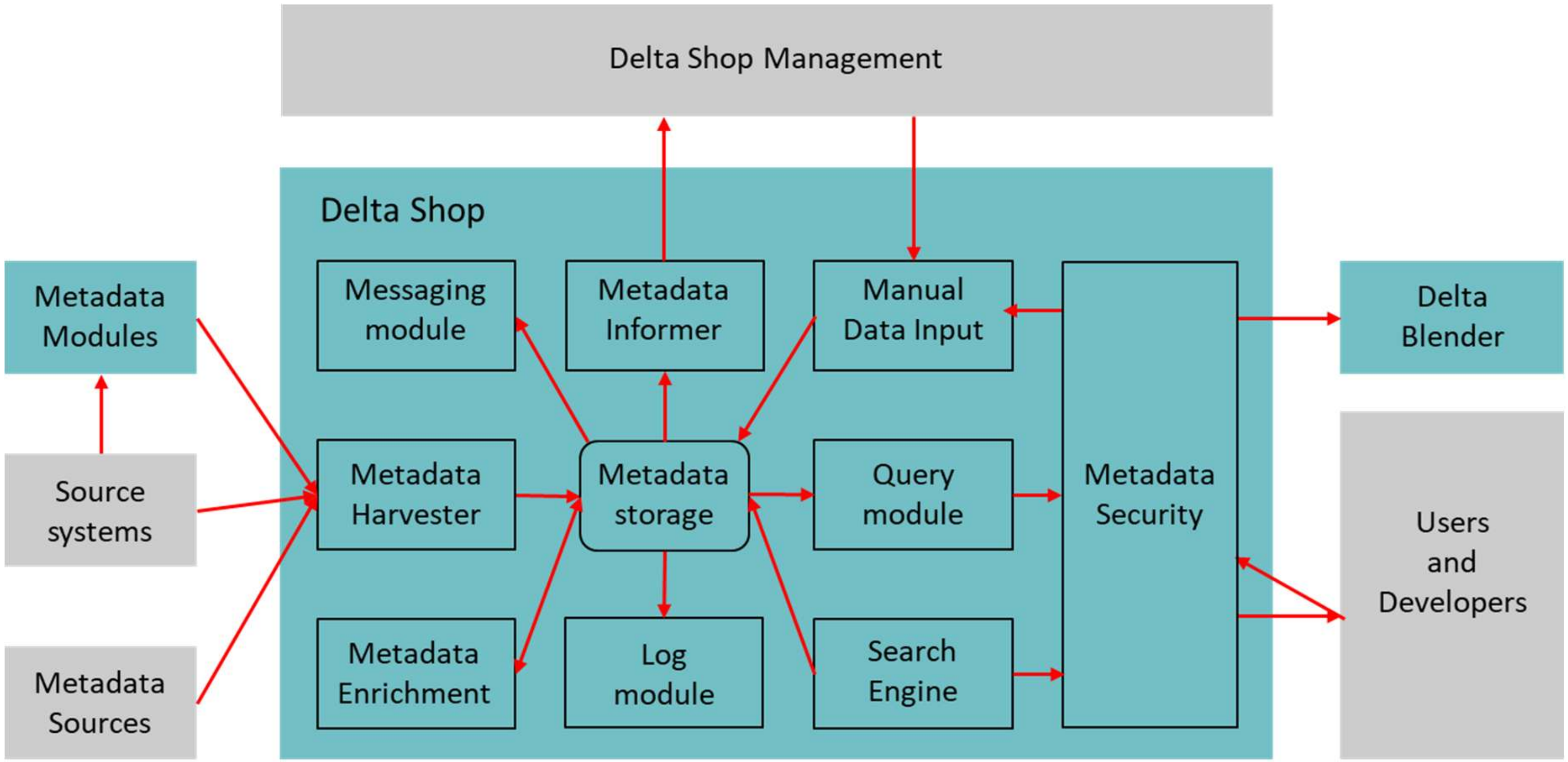
Global Federated Data Architecture



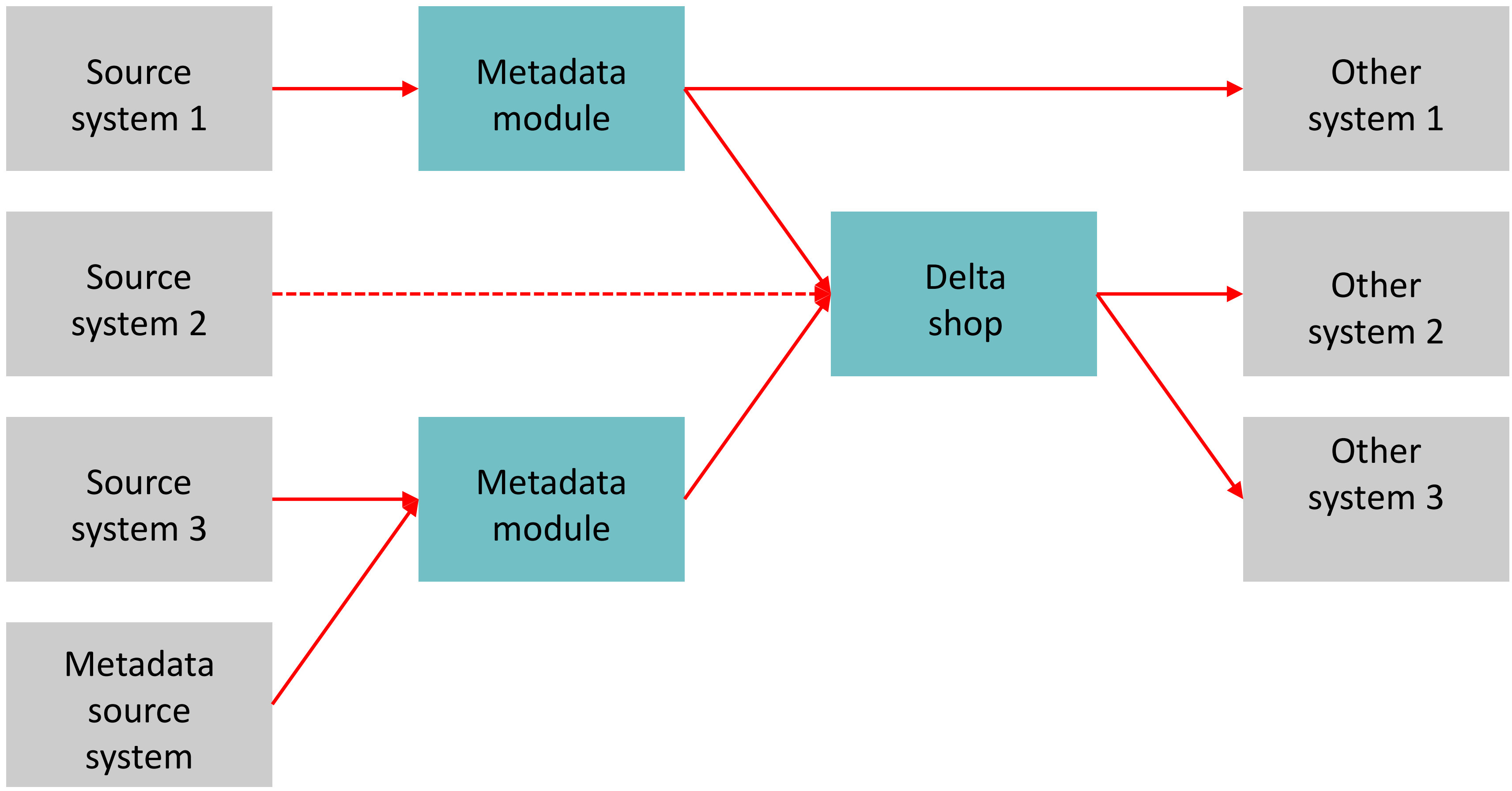
Layered Globale Federated Data Architecture



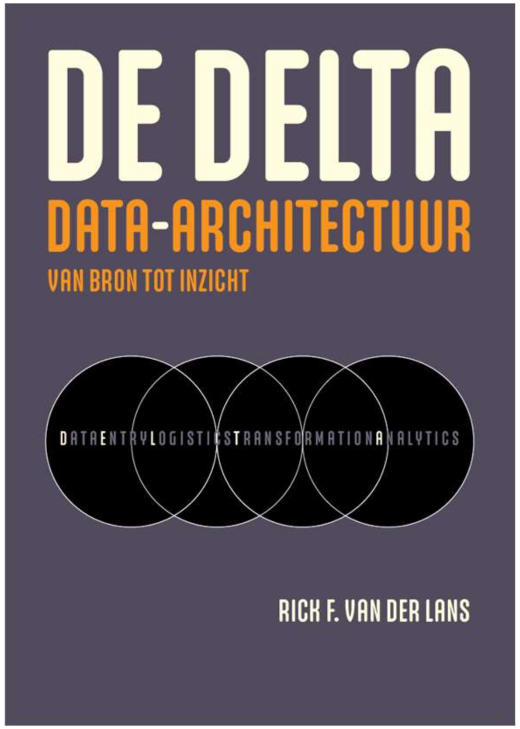
Delta Shop Components - Metadata



Metadata Modules and the Delta Shop



Summary of the Delta Data Architecture

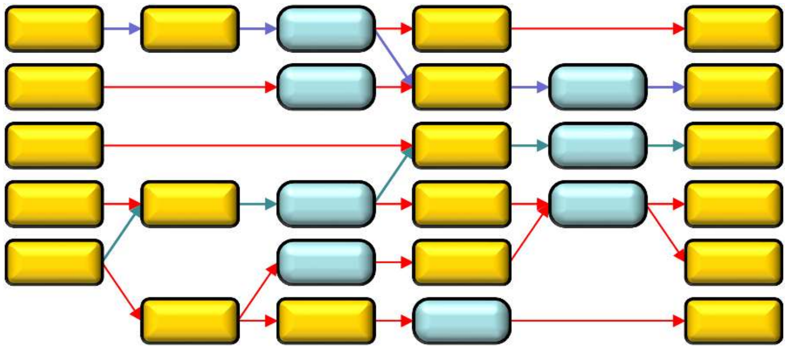


- Enterprise data architecture
  - From source to insight
  - Data must be ready-to-use, discoverable, and insightful
  - It’s about the transformers, not the databases
  - Metadata for everyone
- Federated data architecture
  - Unbridled creation of data copies must stop
  - Data-on-demand, not data-by-copy
  - Avoid duplicate transformers
- Transparent data architecture
  - Operational lineage for reconstruction, transparency, and auditability
- Modular data architecture
  - Co-exist with existing solutions

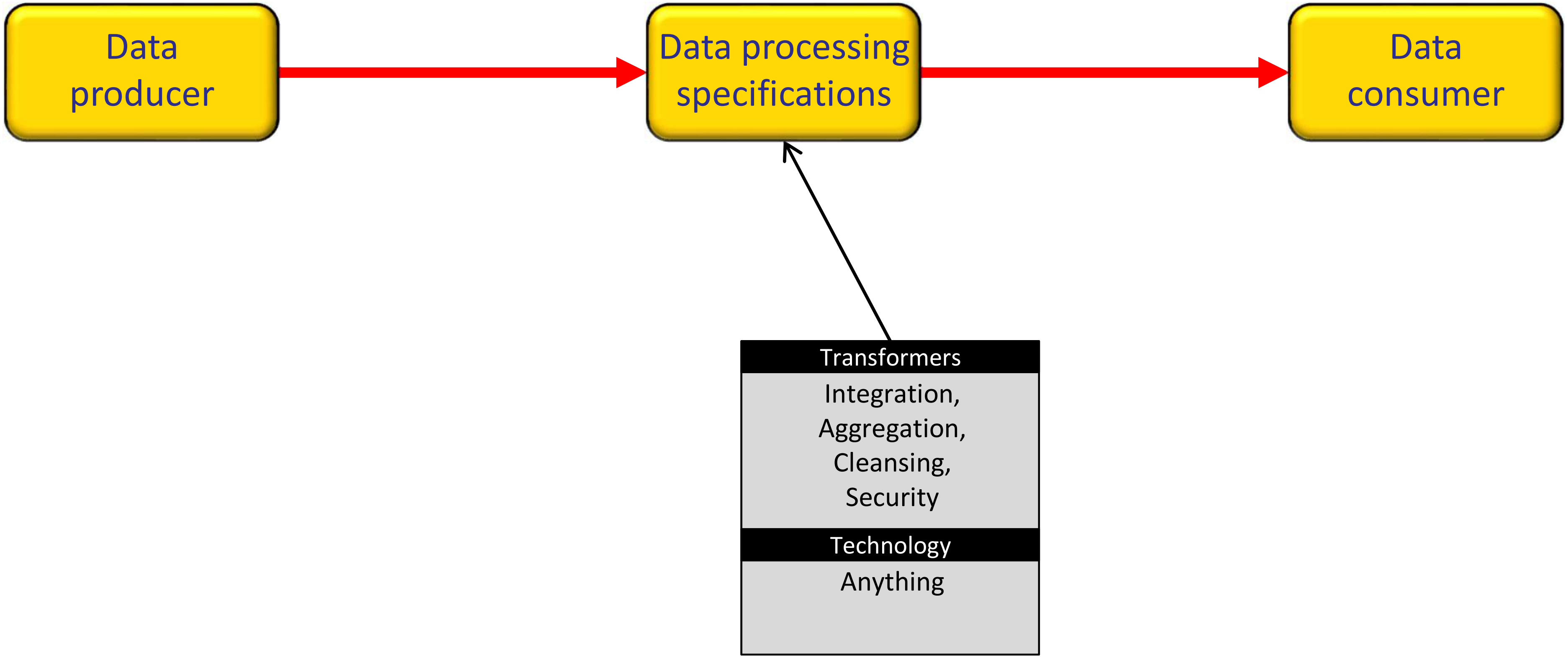

Part 8:
Steps 7-8: Design the New Data Architecture,
Determine the Implementation Approach

What is a Data Track?

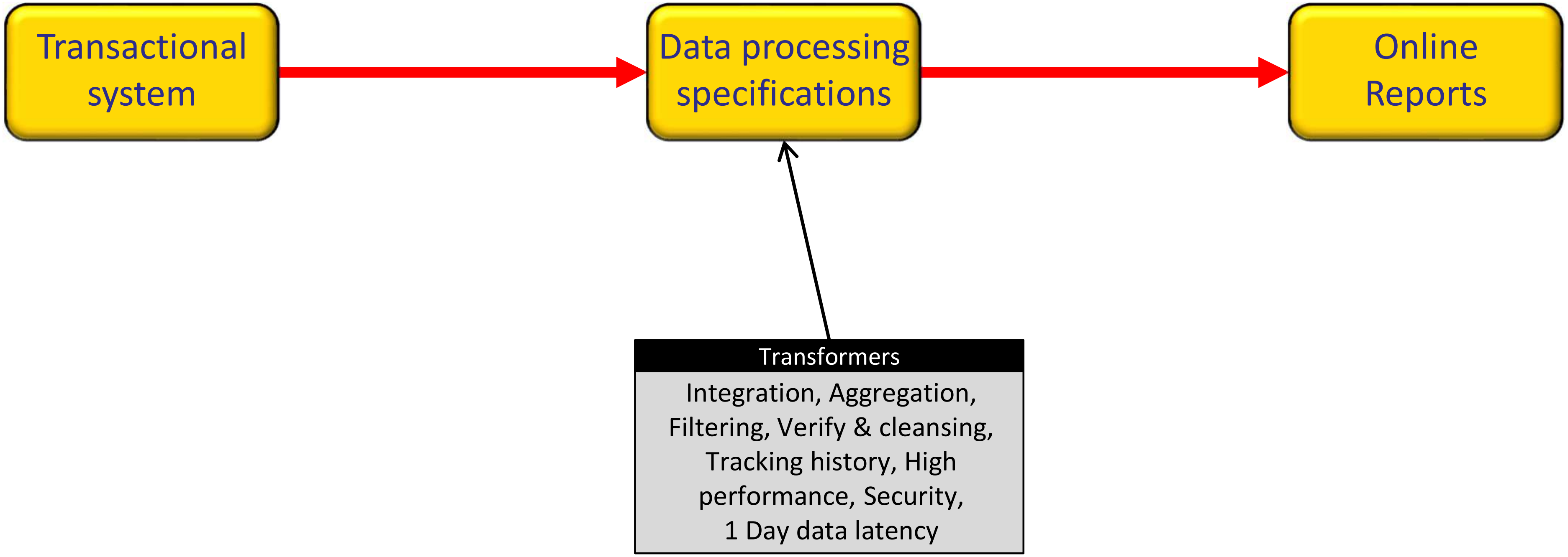
- A *data track* indicates how data “flows” from data producers to data consumers, and specifies the transformers to be applied and by which module.
- Multiple data consumers can share one data track.
- Data tracks may merge and split.



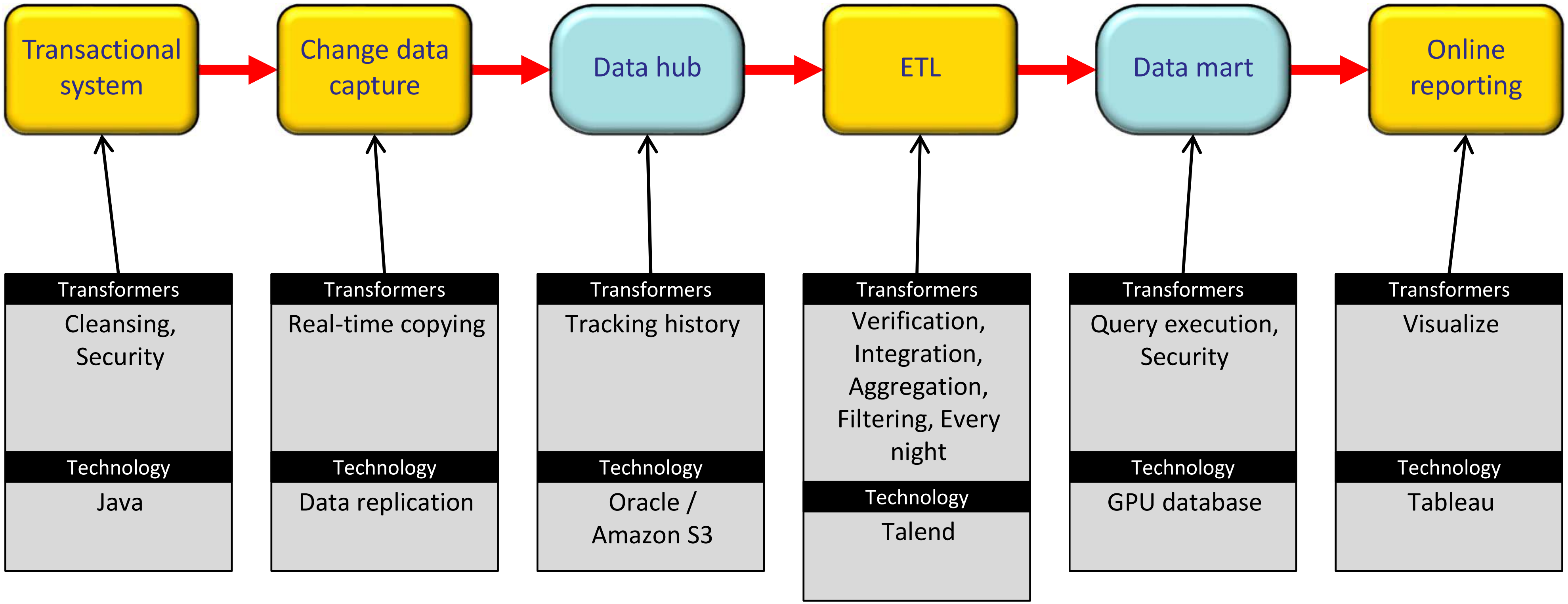
A Data Track Diagram



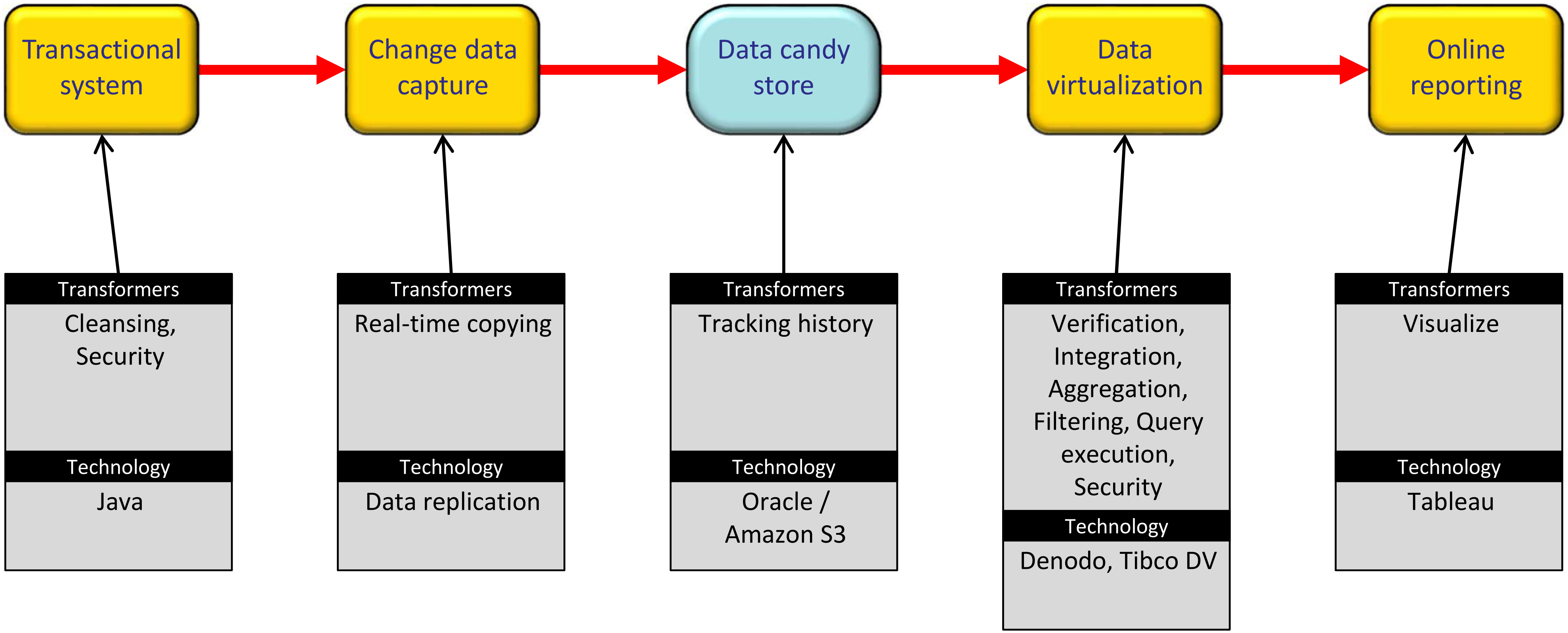
Data Track Example: Standard Online Reporting (1)



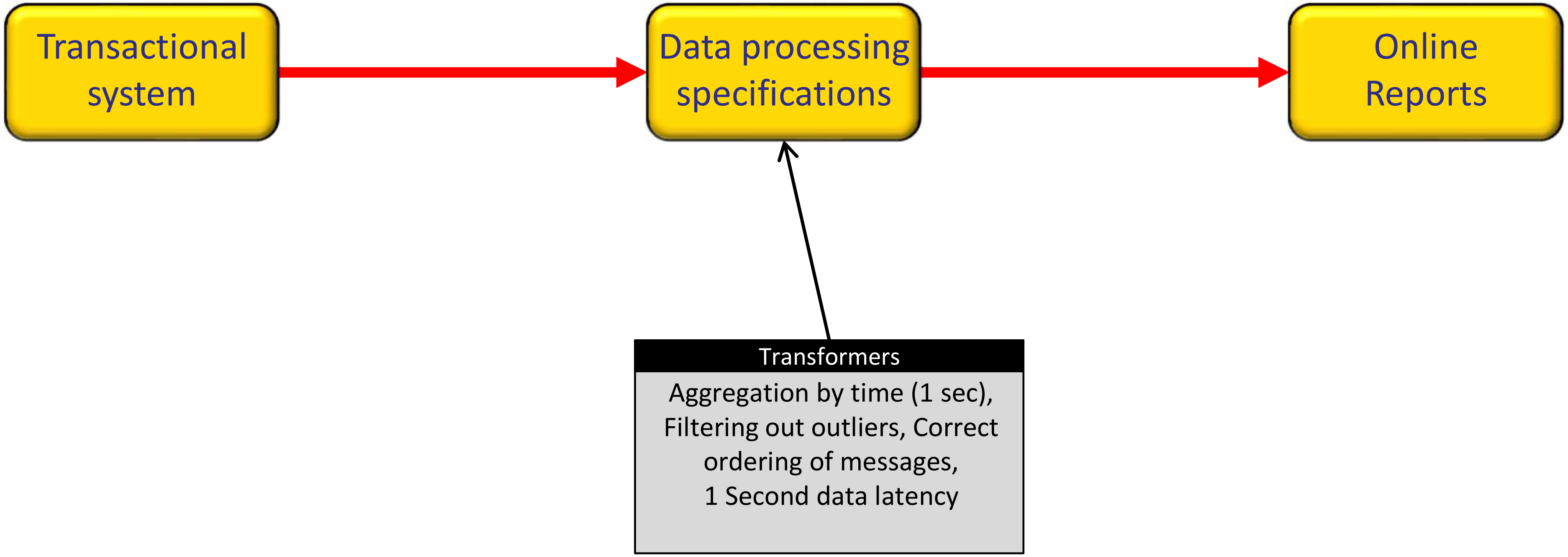
Data Track Example: Standard Online Reporting (2)



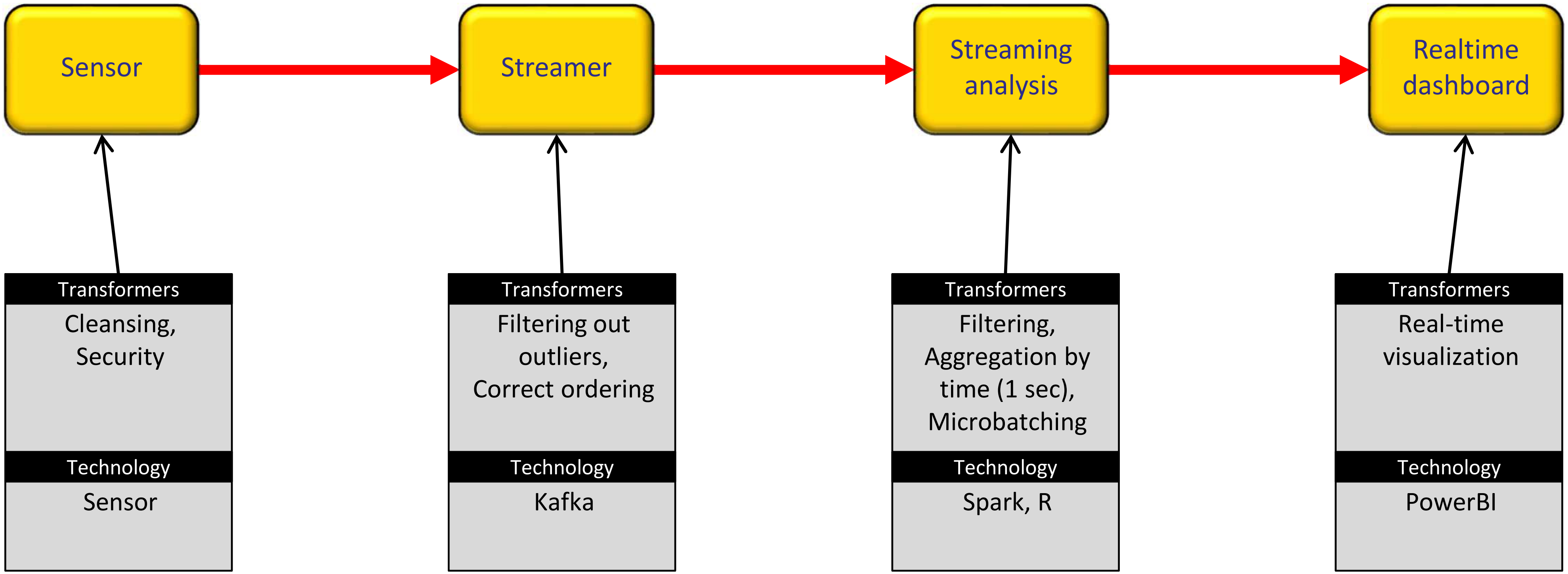
Data Track Example: Standard Online Reporting (3)



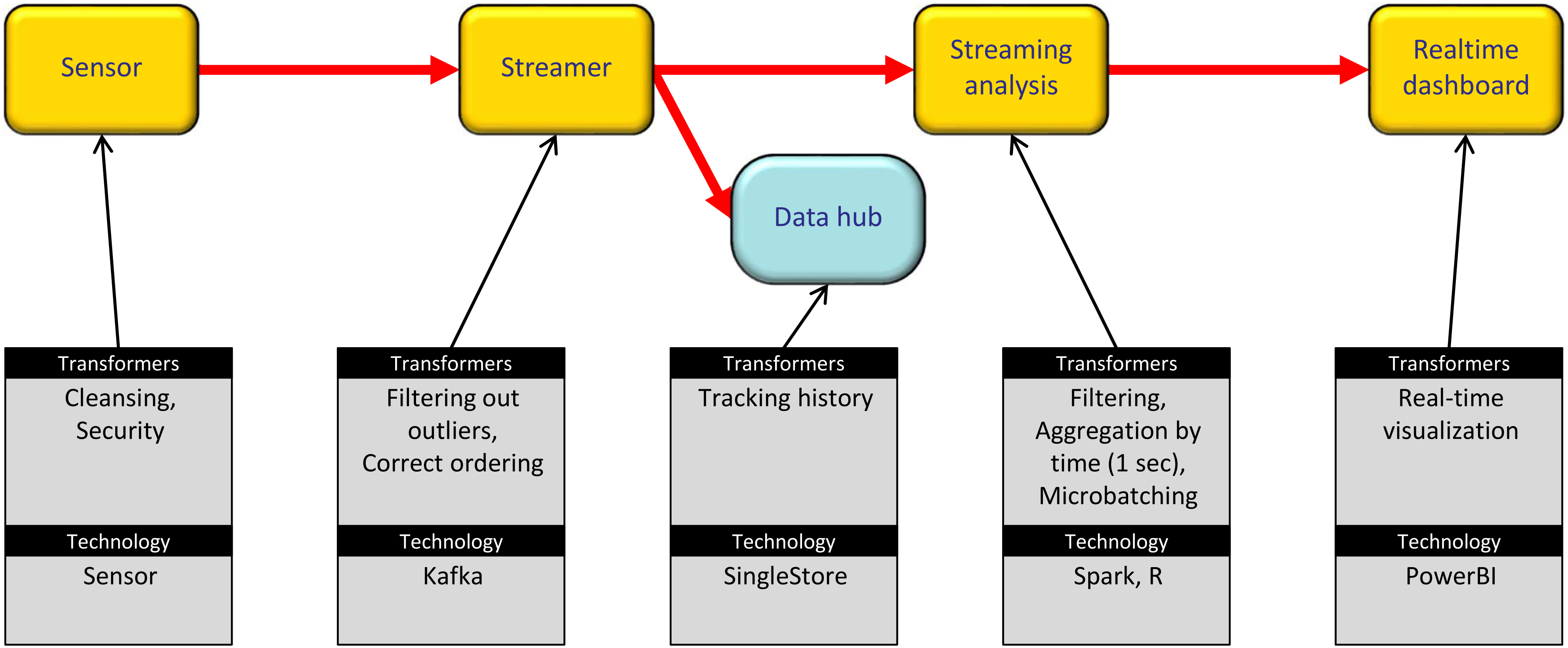
Data Track Example: Streaming Real-time Dashboard (1)



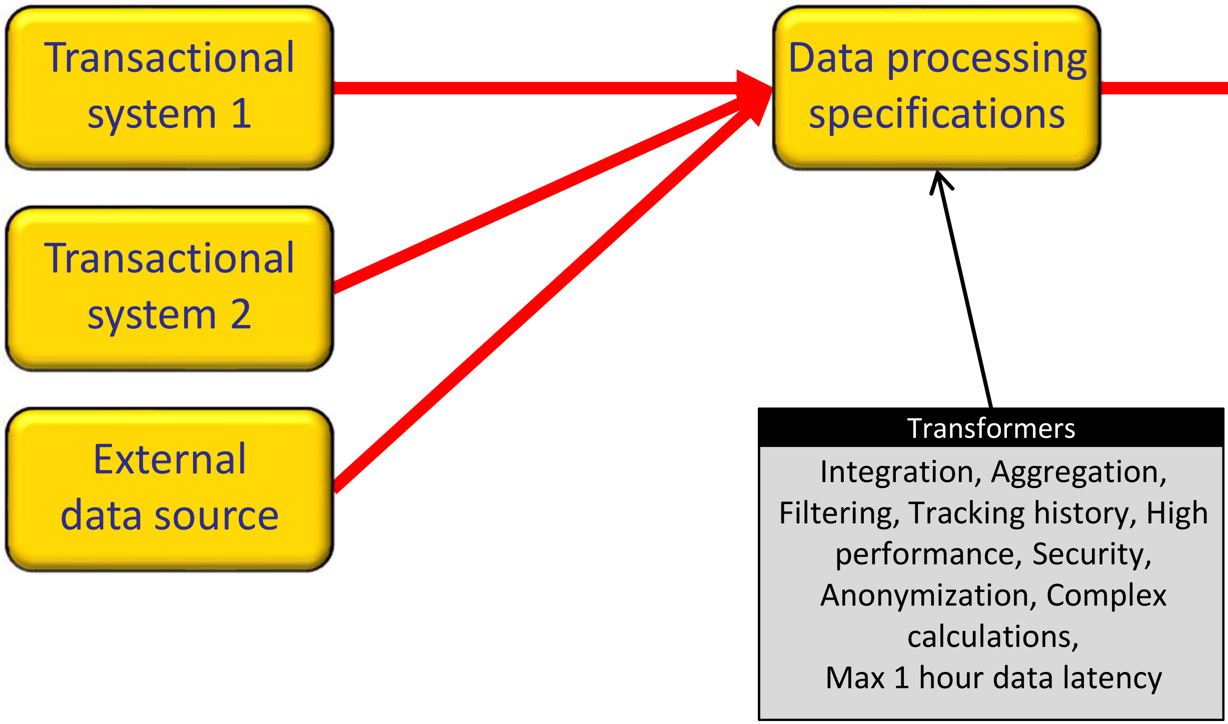
Data Track Example: Streaming Real-time Dashboard (2)



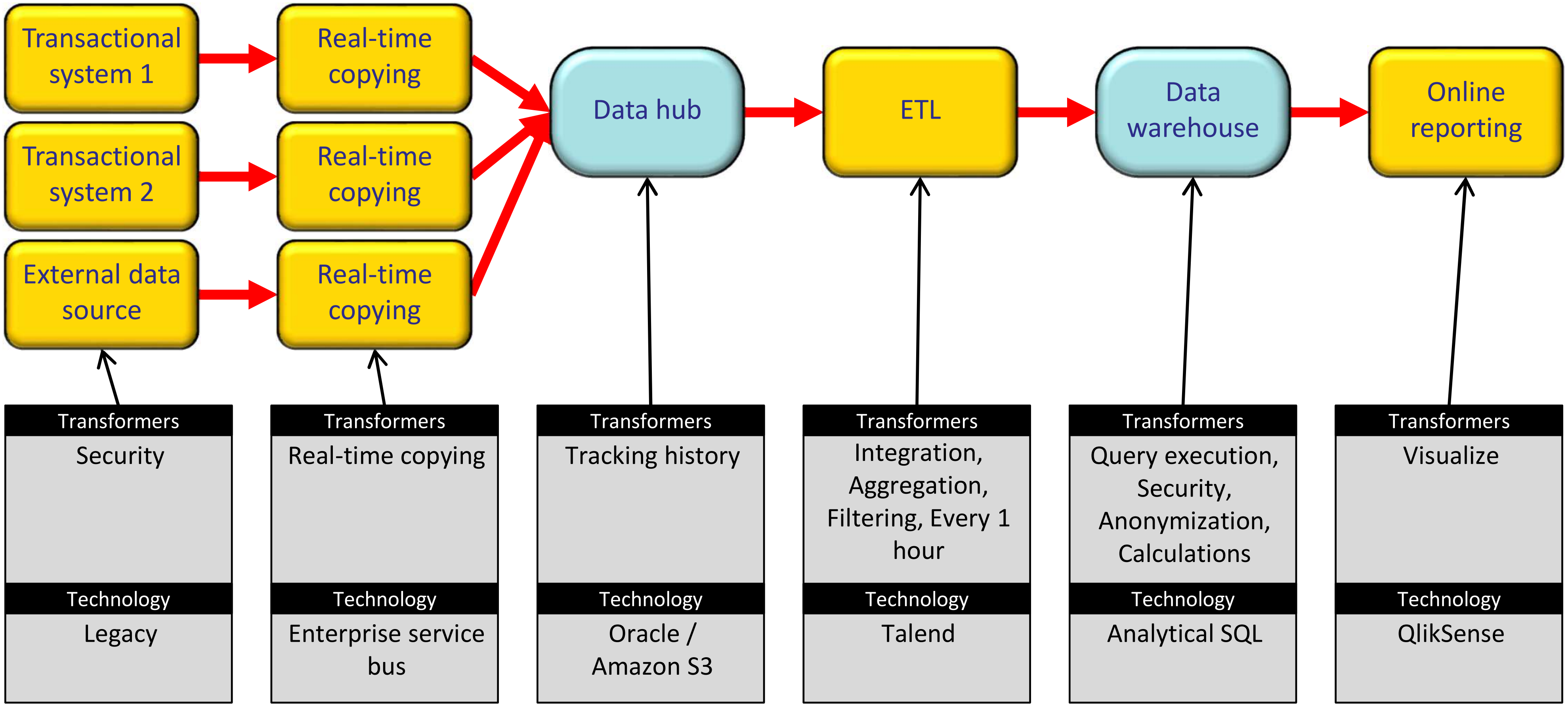
Data Track Example: Streaming Real-time Dashboard (3)



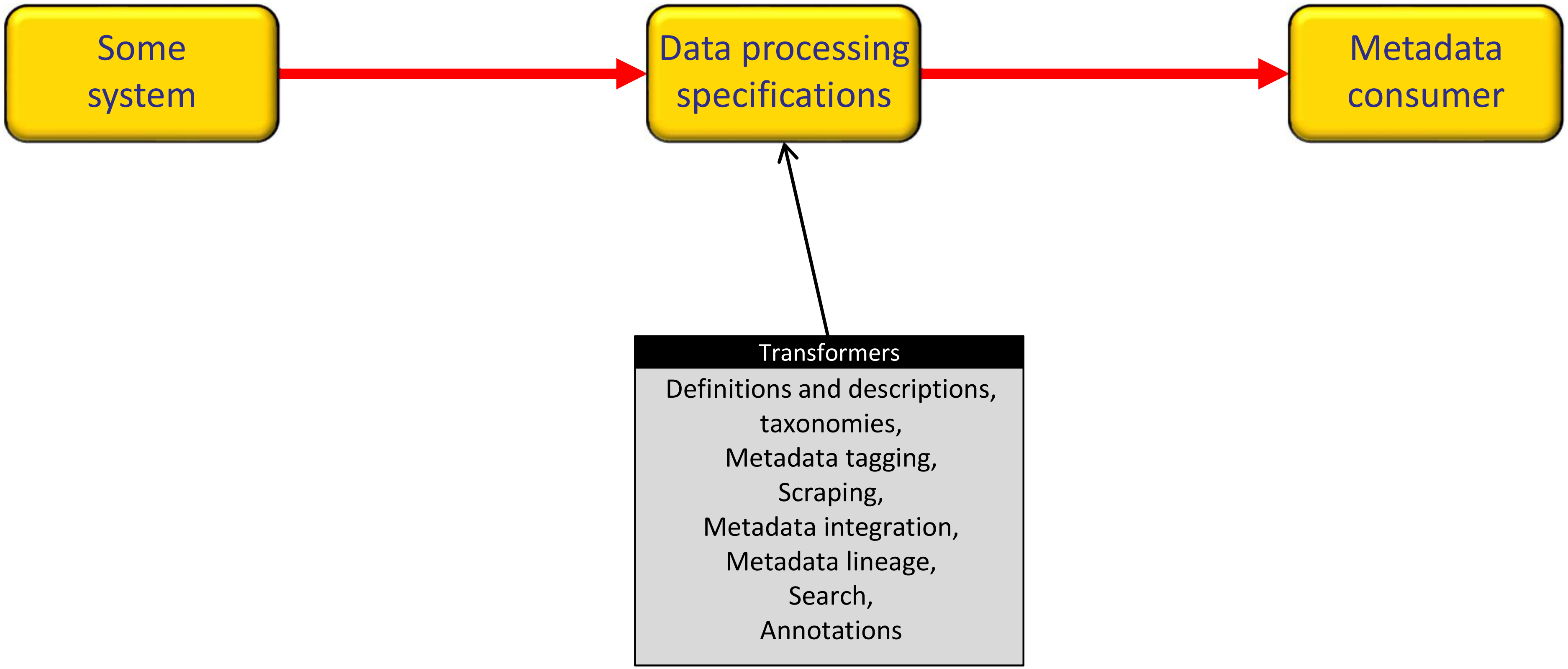
Data Track Example: Integrated Online Reporting (1)



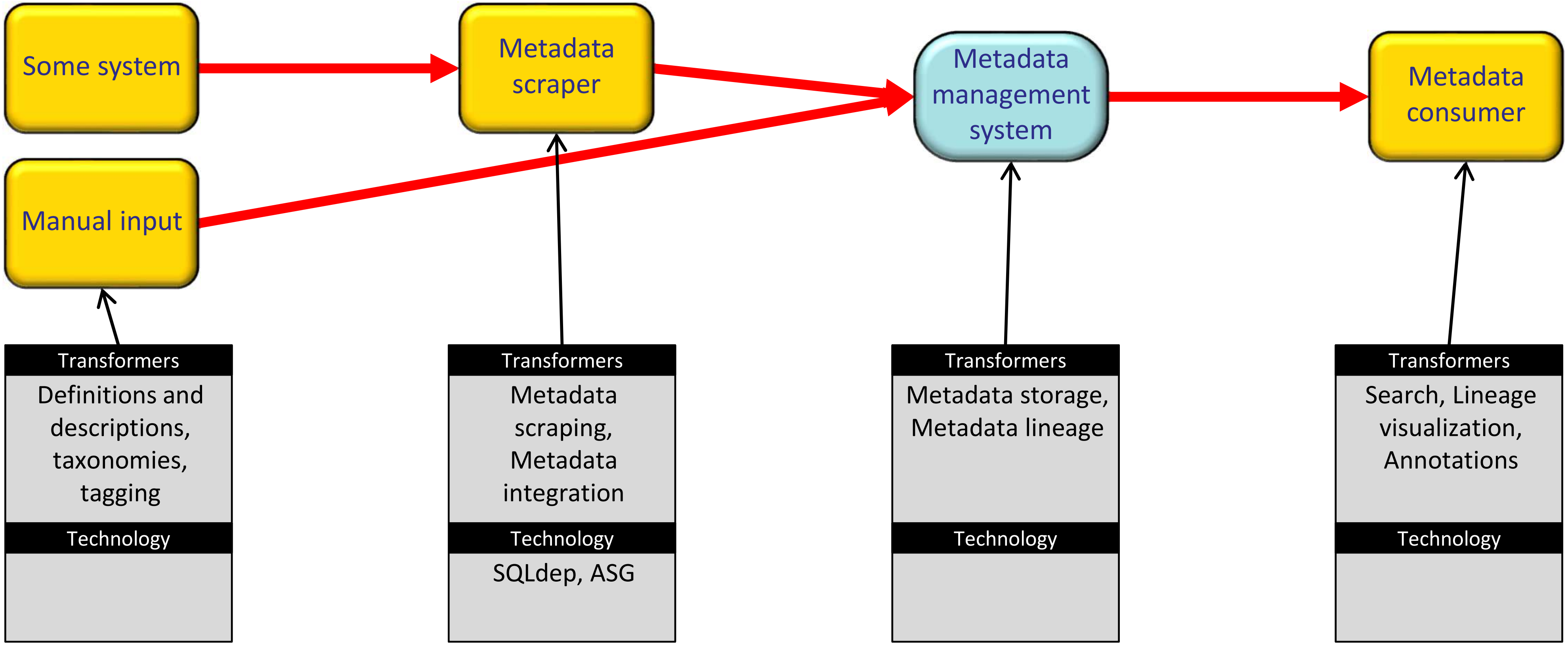
Data Track Example: Integrated Online Reporting (2)



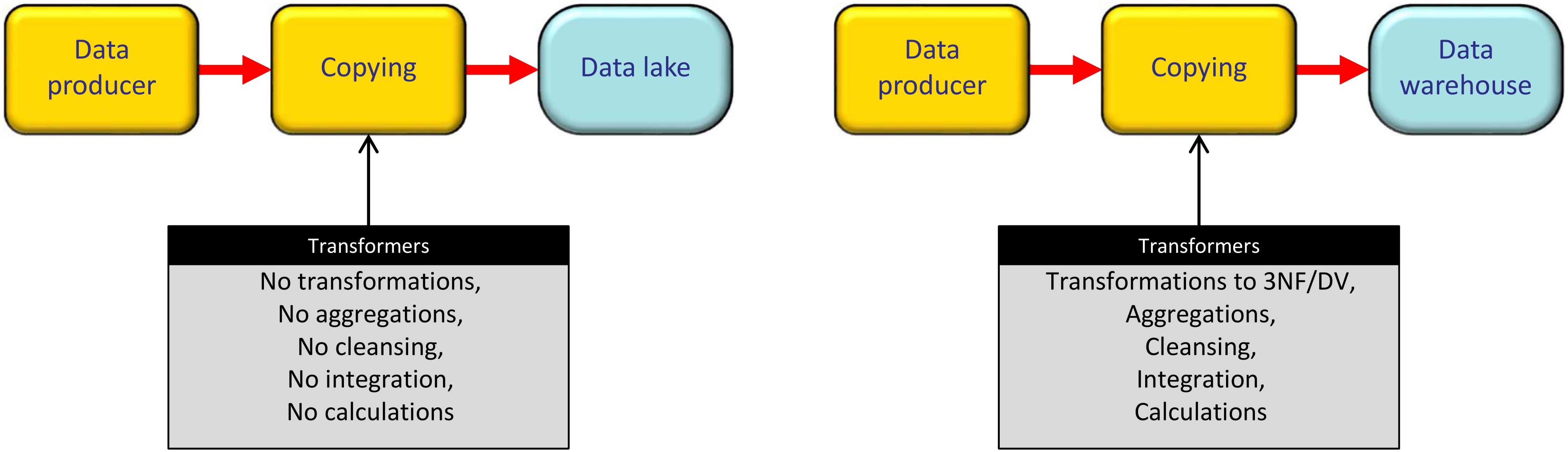
Data Track Example: Metadata Delivery (1)



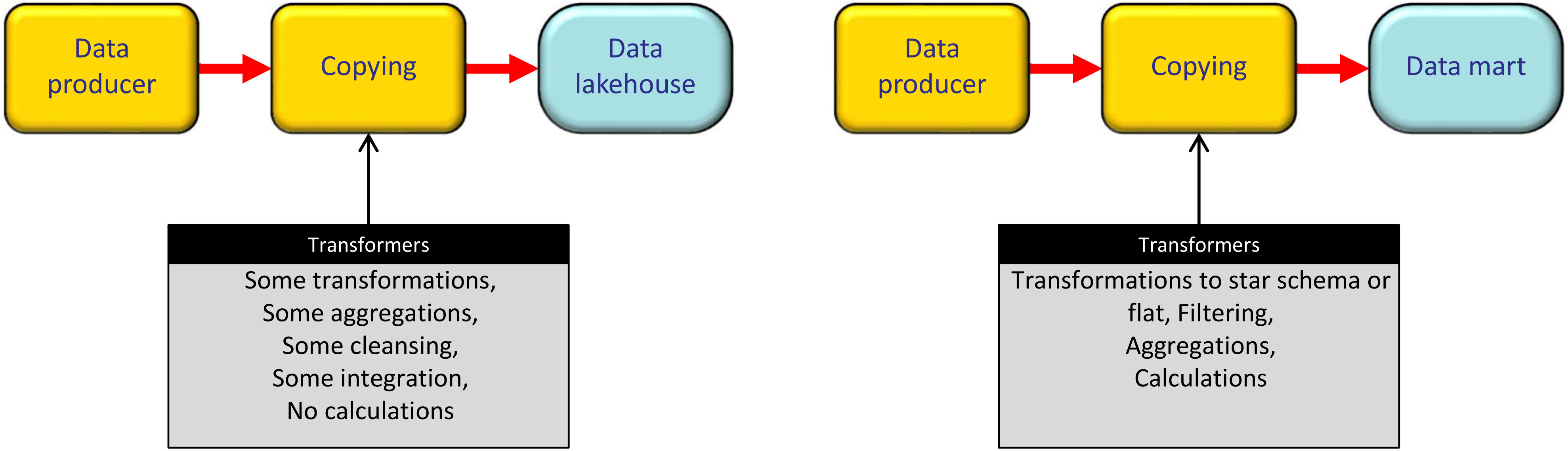
Data Track Example: Metadata Delivery (2)



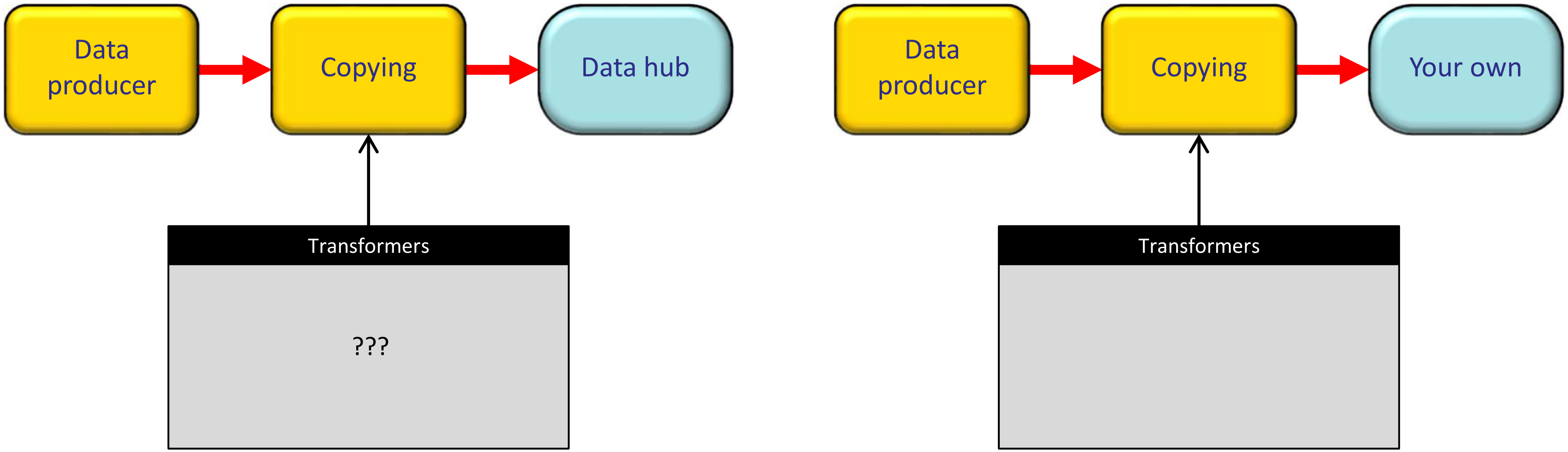
What's in a Name? (1)



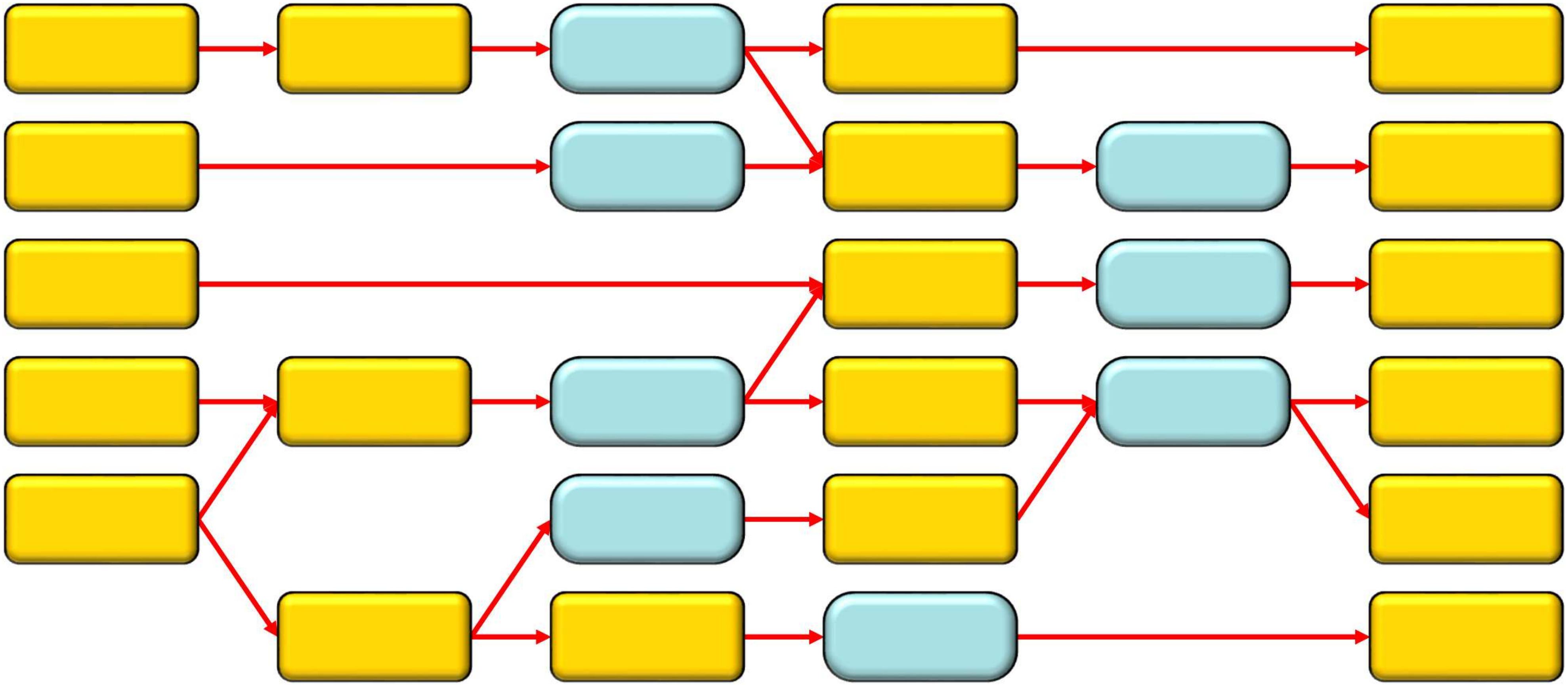
What's in a Name? (2)



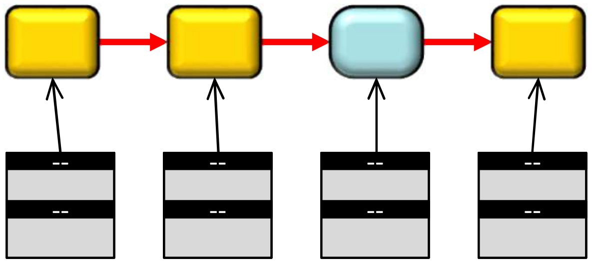
What's in a Name? (3)



High-Level View of the Tracks

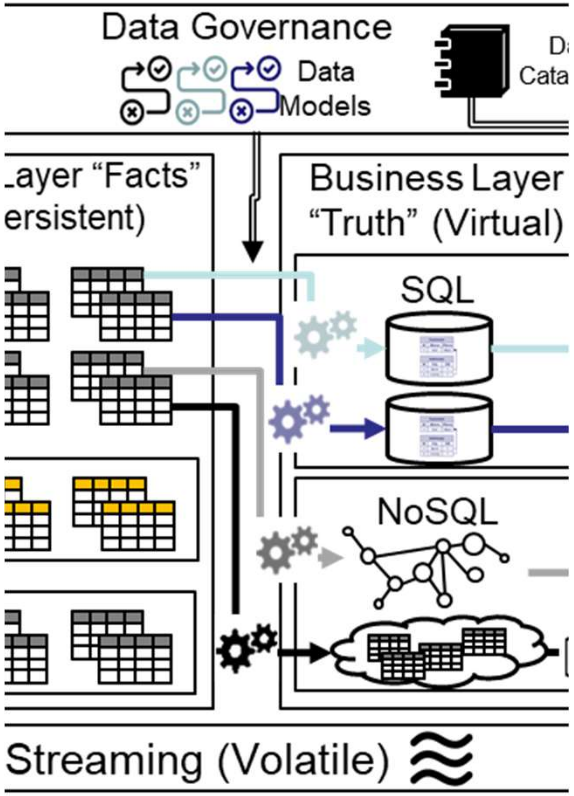


Recommendations for Designing Data Tracks



- Design them "backwards" (from consumer to producer)
- Identify transformers first, before assigning of the specs to modules
- One data track can support many comparable data consumers
- Define data track patterns!
  - Architectural design principle?
- Don't solve specific problems

Determine the Intermediate Diagrams



- The current data architecture diagram
- The new data architecture diagram
  - The dream
  - Will never be reached
- The intermediate data architectures
  - The path from current to new
  - Make the steps as small as possible
  - Preferred: Each step leads to business value
- Think big, act small

Part 9:
Steps 8-9: Final Steps

Roadmap for Designing Data Architectures

1. Determine business motivations
2. Determine new requirements
3. Analyze the existing environment
4. Define architectureal design principles
5. Selecta reference data architecture
6. Desogn the new data architecture
7. Determine the implementation approach
8. Select new products and technologies
9. Introduce the data architecture within the organization

Part 9.1:
Step 8: Select New Products and Technologies

Developing the Request for Information

Photo: Brett Jordan

- Get access to in-depth technological know-how
  - To ask the right questions
- Use distinguishing questions
- Weighs of requirements – explain why
- Closed questions – easier for comparisons
- Deliver sufficient info to let vendor provide details for pricing and products
- Are extra modules/versions required?
- Remember the new requirements!

Product and Vendor Evaluation (1)


Photo: Clay Banks

- Evaluation of products
  - Features, performance, costs, market share
- Local support and partners
  - Experience?
- Extra software required
  - Master data management for complex integration
  - Data cleansing
  - Database server for reference tables and caches
  - Data security
  - Special connectors/drivers

Product and Vendor Evaluation (2)

Photo: Clay Banks

- Products need to “fit” the architecture
- The intended use cases of the products must match use cases of organization
- Do you need the best tool?
  - Remember Betamax and quadrophonic records
- One-stop shopping or best-of-breed?
  - Minimize number of vendors
  - Never independent of zero vendors

Product and Vendor Evaluation (3)

- Standardize for back-end tools
  - If use cases allow
  - Not one BI tool for all forms of data consumption
- Open Source software
  - Open source ≠ Non-proprietary software
  - Standards = Non-proprietary software
  - Study how active the development group is
  - What if open source vendor goes commercial?
    - MySQL, Revolutionary Analytics (R), …

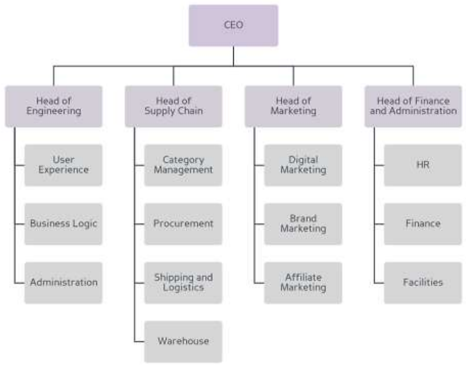
The Proof of Concept/Pilot

Photo: Haupes, Co

- The PoC must be representative of the new system
  - Data: size, characteristics (value distribution, uniqueness), anonymized data?
  - Applications and reports must have a representative complexity
- Performance
  - Multi-user tests
  - Experts required
- Tough SLAs must be tested!
  - Can be expensive
- Invite vendors to install and optimize software themselves
- Select ICT personnel for PoC
  - Developers who enjoy working with new technology and are willing to stay over the weekend

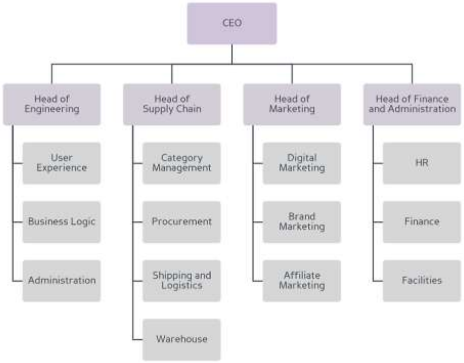
Part 9.2:
Step 9: Introduce the Data Architecture Within the Organization

Introduction Within the Organization (1)



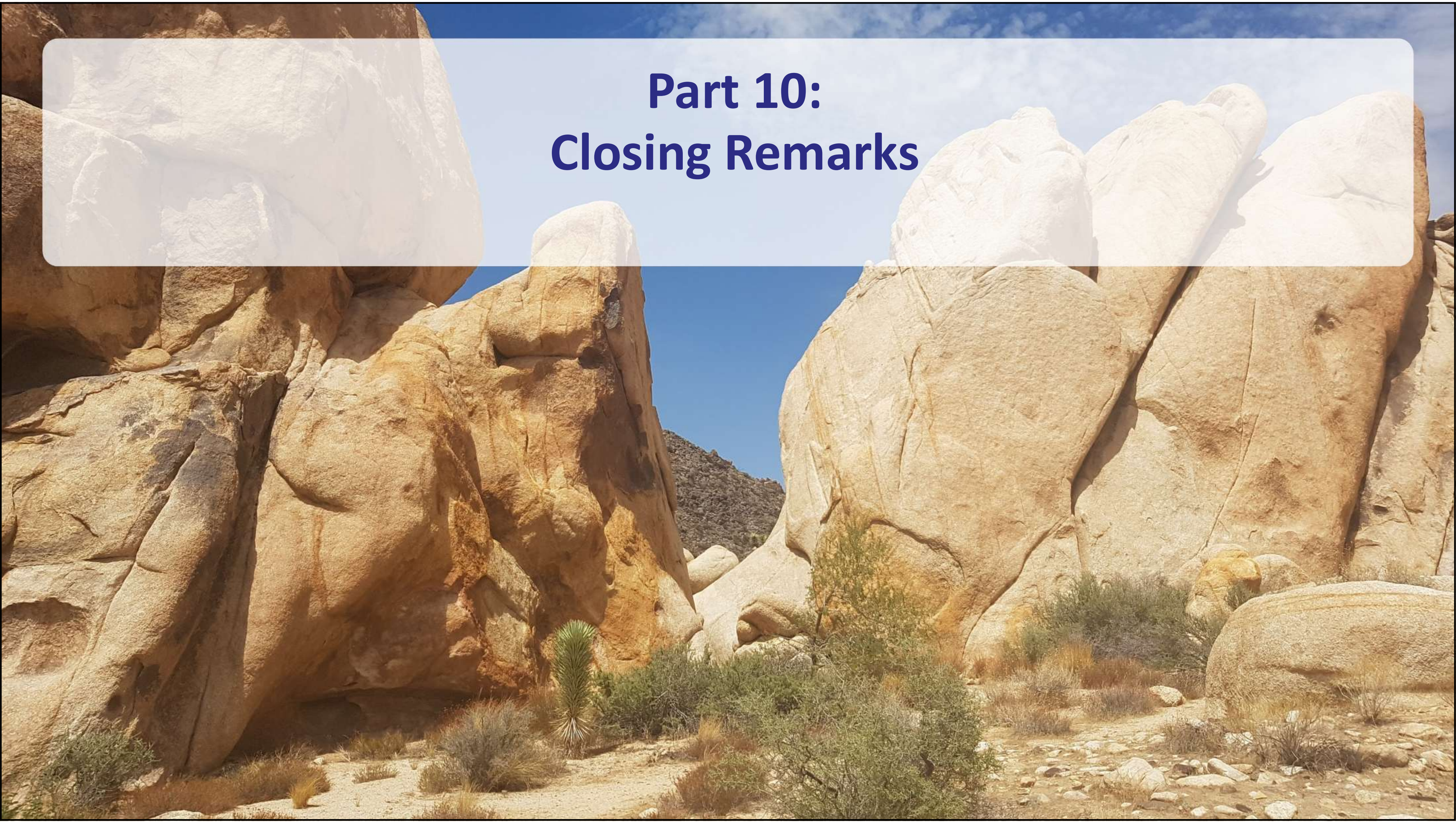
- Three approaches for introduction
  - Via business
  - Via IT bottom up (Trojan horse)
  - Via IT top down
- Identify resistance
  - DBA, source owners, …
- Educational/missionary program for everyone
  - From programmers to C-level management
  - De-mystify
  - Refute the mythical performance problem
  - Sell the new data architecture
  - Find a champion

Introduction Within the Organization (2)



- Impact of new data architecture on organization
  - New roles and new responsibilities, examples
    - New roles related to data stewardship
    - Ownership of data
    - Data science models to support business users cooperating
    - New BI tools
  - Training

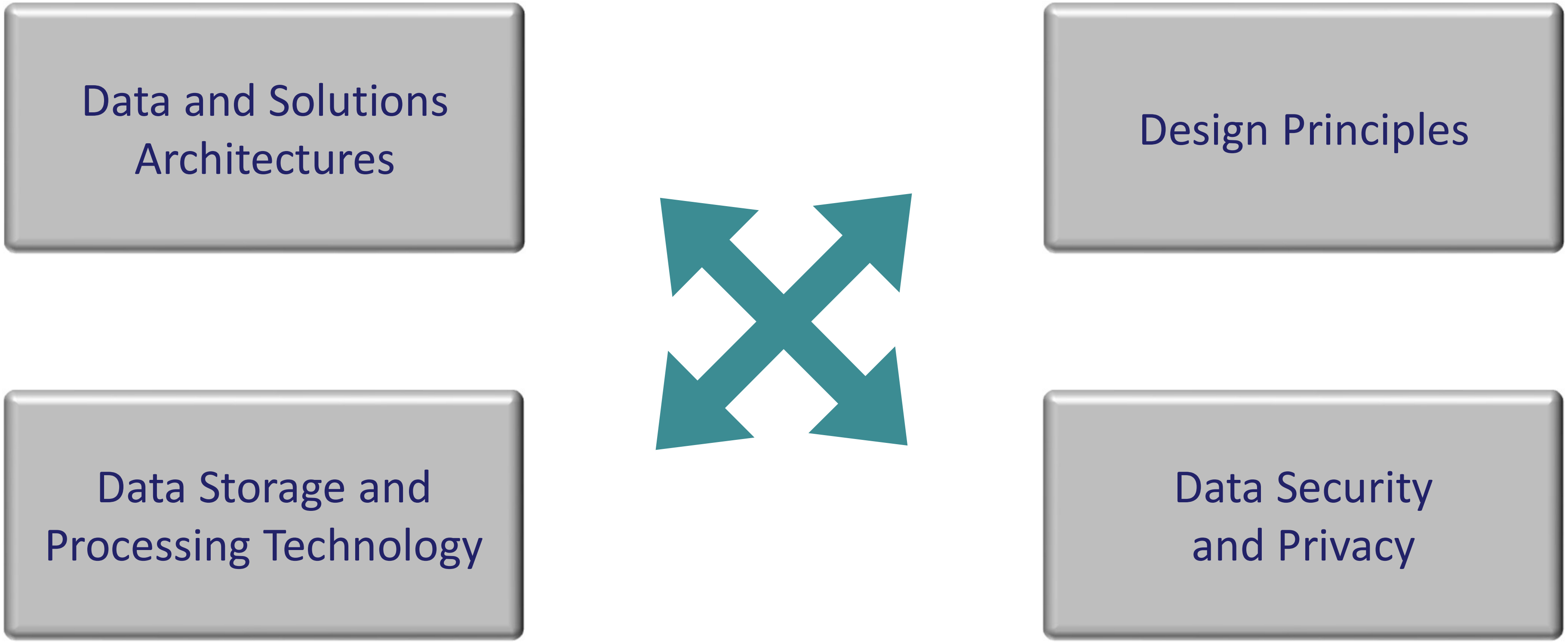
Part 10:
Closing Remarks



Time to Start!

- New data architectures are required
- Focus on transformers, before drawing the storage "boxes"
- Architects must be familiar with the strengths, weaknesses, and use cases of data storage and processing technologies
  - Without this knowledge:
    - Unnecessarily complex architecture
    - Incorrect use of technology
    - Not able to use the full power of a technology
- Design guidelines impact architecture
- Design a data architecture from source to insight

From a Linear to a Holistic Approach




That's all Folks!