Semantic Data Management

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Introduction and Motivation

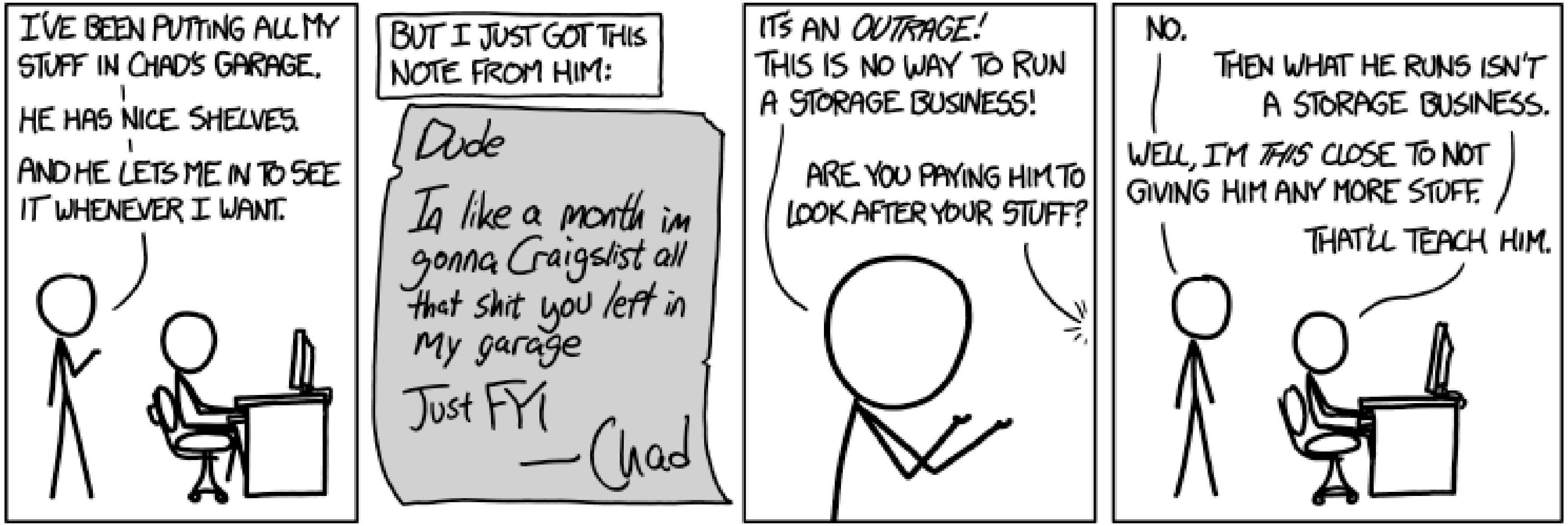
VARIETY IN COMPLEX DATA ECOSYSTEMS

“WITHOUT DATA, YOU’RE JUST ANOTHER PERSON WITH AN OPINION”

W. Edwards Deming, American Statistician

Data-driven paradigm

New Business Model: Instagram’s Fable


I'VE BEEN PUTTING ALL MY STUFF IN CHAD'S GARAGE.
HE HAS NICE SHELVES.
AND HE LETS ME IN TO SEE IT WHENEVER I WANT.
BUT I JUST GOT THIS NOTE FROM HIM:
Dude
In like a month im gonna Craigslist all that shit you left in my garage
Just FYI
— Chad
IT'S AN OUTRAGE! THIS IS NO WAY TO RUN A STORAGE BUSINESS!
ARE YOU PAYING HIM TO LOOK AFTER YOUR STUFF?
NO.
THEN WHAT HE RUNS ISN'T A STORAGE BUSINESS.
WELL, I'M THIS CLOSE TO NOT GIVING HIM ANY MORE STUFF.
THAT'LL TEACH HIM.

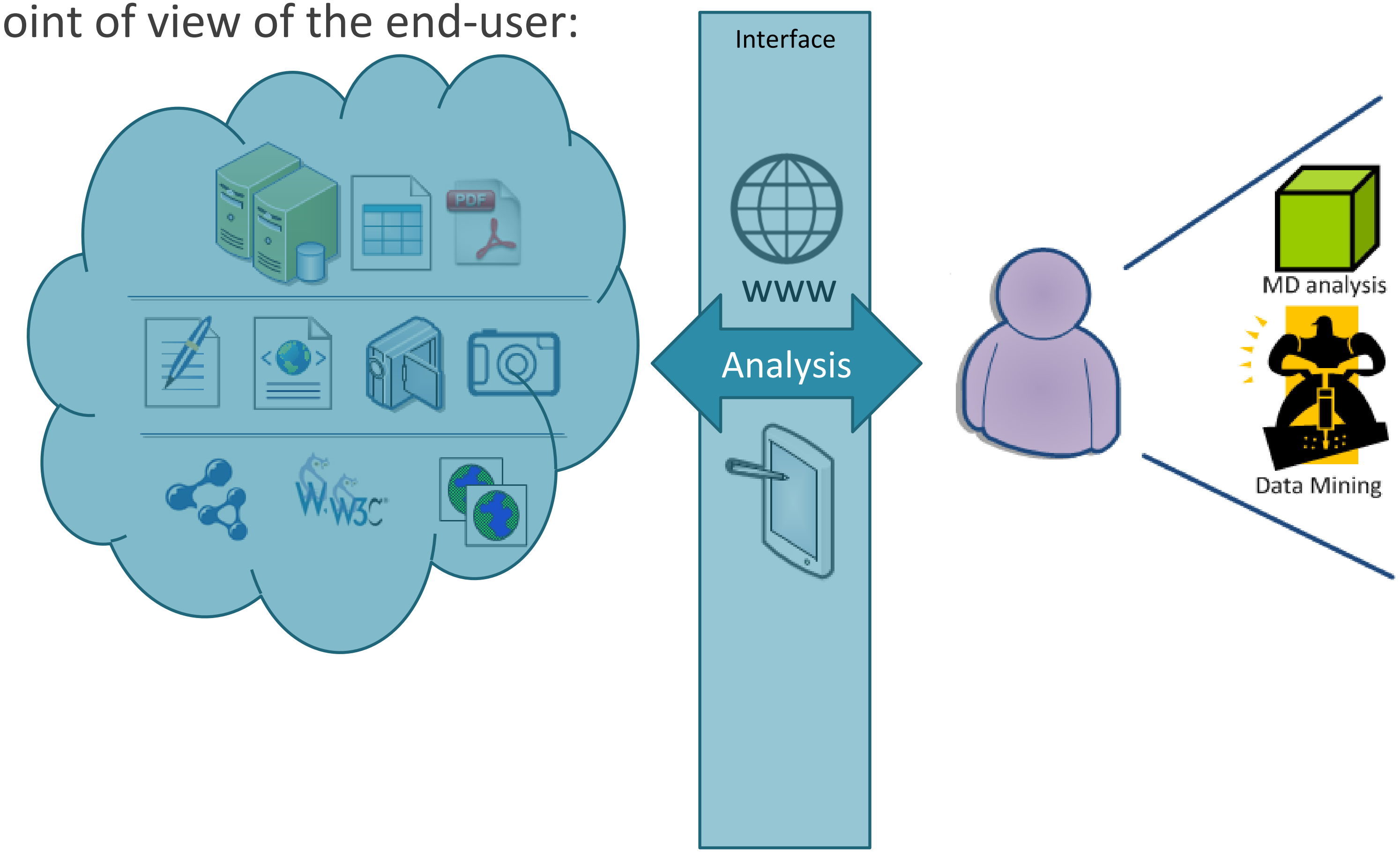
(xkcd.com)

Challenges of the Data-Driven Economy

FROM THE IT POINT OF VIEW

Data Analysis Democratisation

From the point of view of the end-user:



What is Big Data?

VOLUME

Veracity

Velocity

Value

vArIaBiLiTy

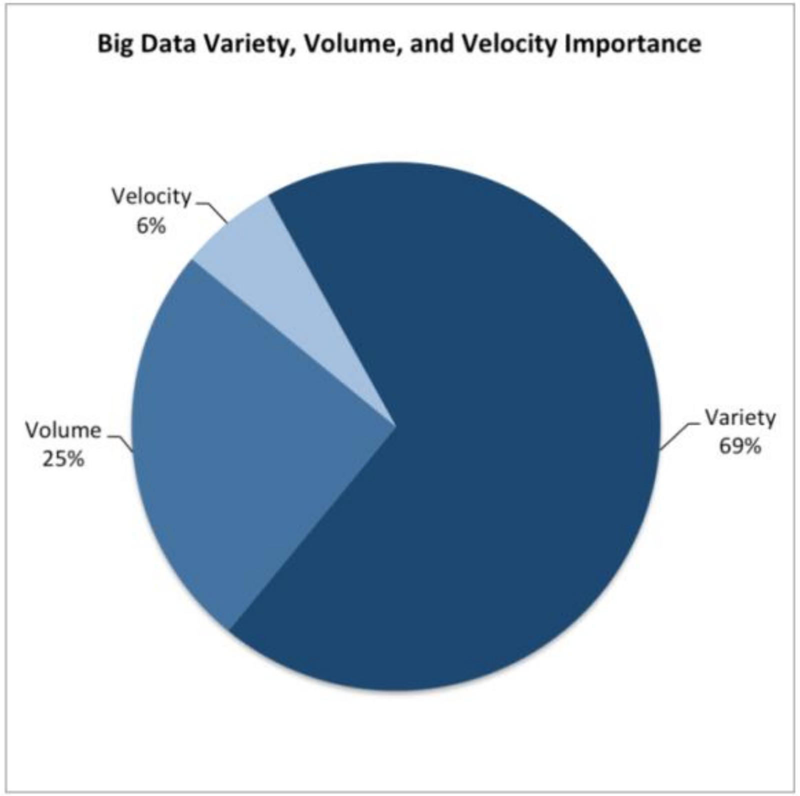
Variety

Today, the Focus is on Variety

That Big Data is synonymous with large volumes of data is a **myth**

*“Rather, it is the ability to **integrate** more sources of data than ever before — new data, old data, big data, small data, structured data, unstructured data, social media data, behavioral data, and legacy data”*

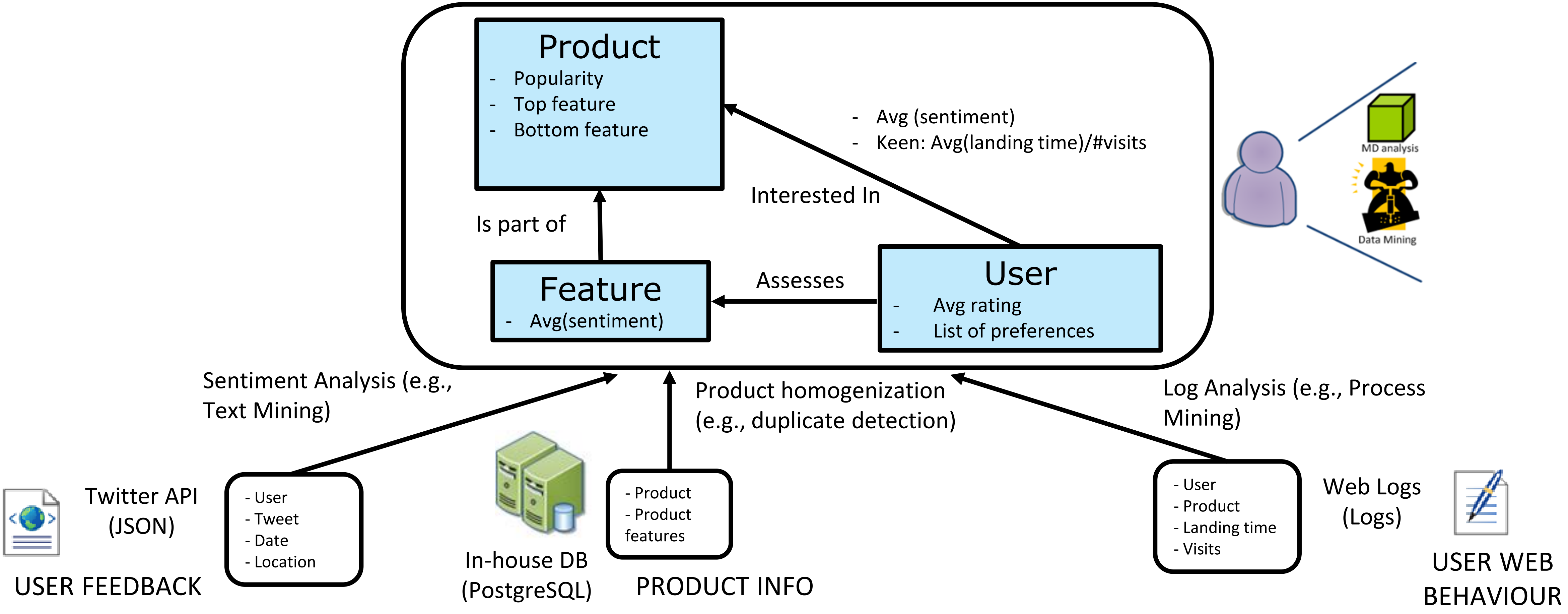
The Variety Challenge



MIT Sloan Management Review (2016): http://sloanreview.mit.edu/article/variety-not-volume-is-driving-big-data-initiatives/

Model-First (Load-Later)

Typical of Data Warehousing (ETL)



Product
- Popularity
- Top feature
- Bottom feature

Is part of

Interested In

- Avg (sentiment)
- Keen: Avg(landing time)/#visits

Feature
- Avg(sentiment)

Assesses

User
- Avg rating
- List of preferences

Sentiment Analysis (e.g., Text Mining)

Product homogenization (e.g., duplicate detection)

Log Analysis (e.g., Process Mining)

Twitter API (JSON)

- User
- Tweet
- Date
- Location

USER FEEDBACK

In-house DB (PostgreSQL)

- Product
- Product features

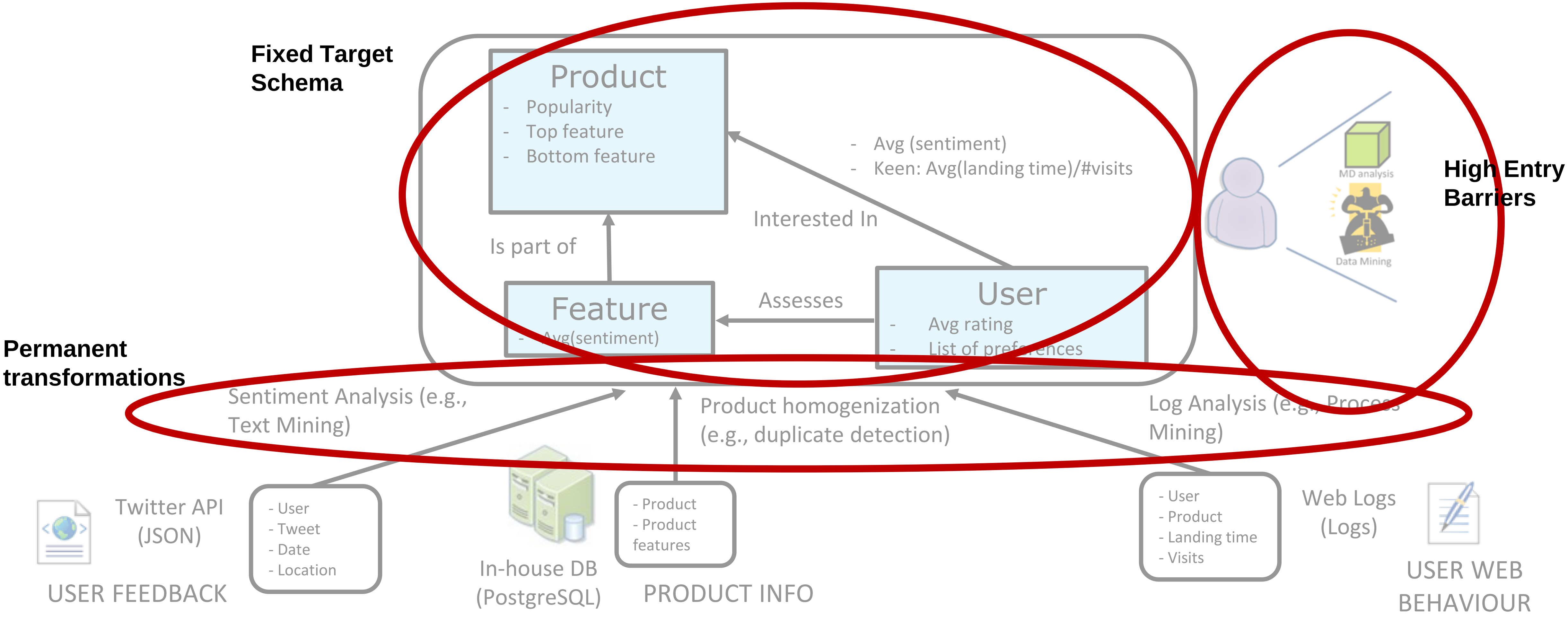
PRODUCT INFO

- User
- Product
- Landing time
- Visits

Web Logs (Logs)

USER WEB BEHAVIOUR

Drawbacks


Fixed Target Schema
Product
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MD analysis
Data Mining
High Entry Barriers
Permanent transformations
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The Data Lake

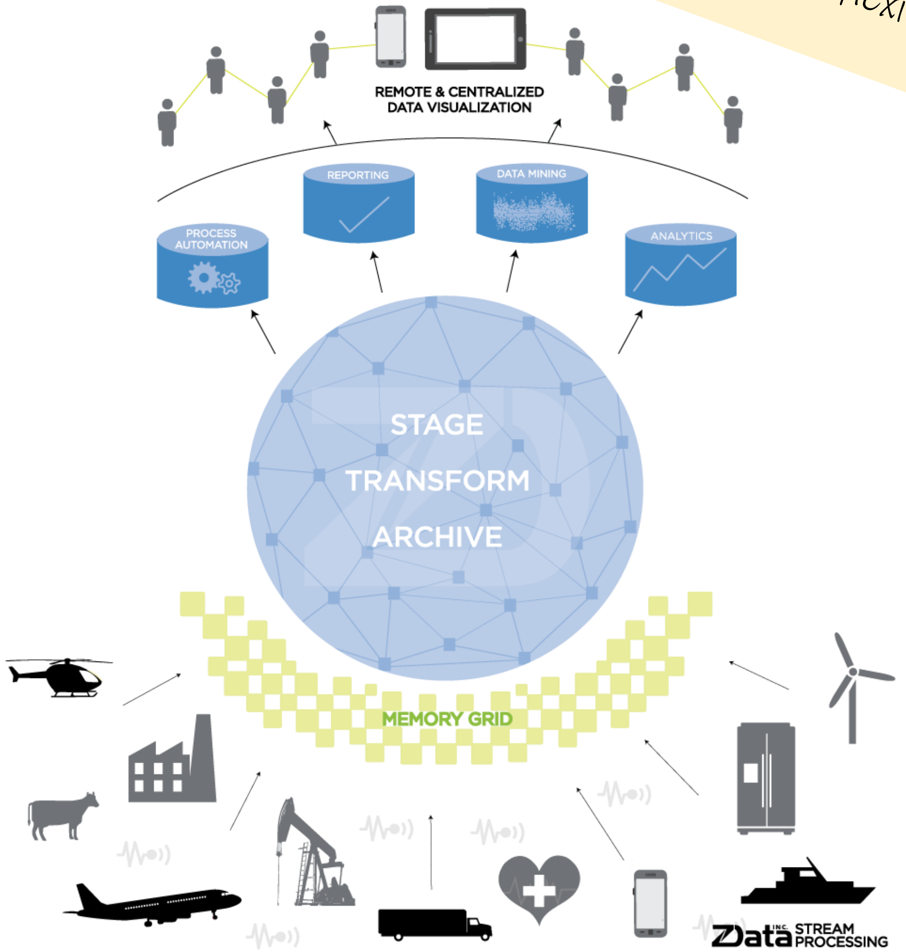
IDEA: Load-first, Model-Later

Modeling at load time restricts the potential analysis that can be done later (Big Analytics)

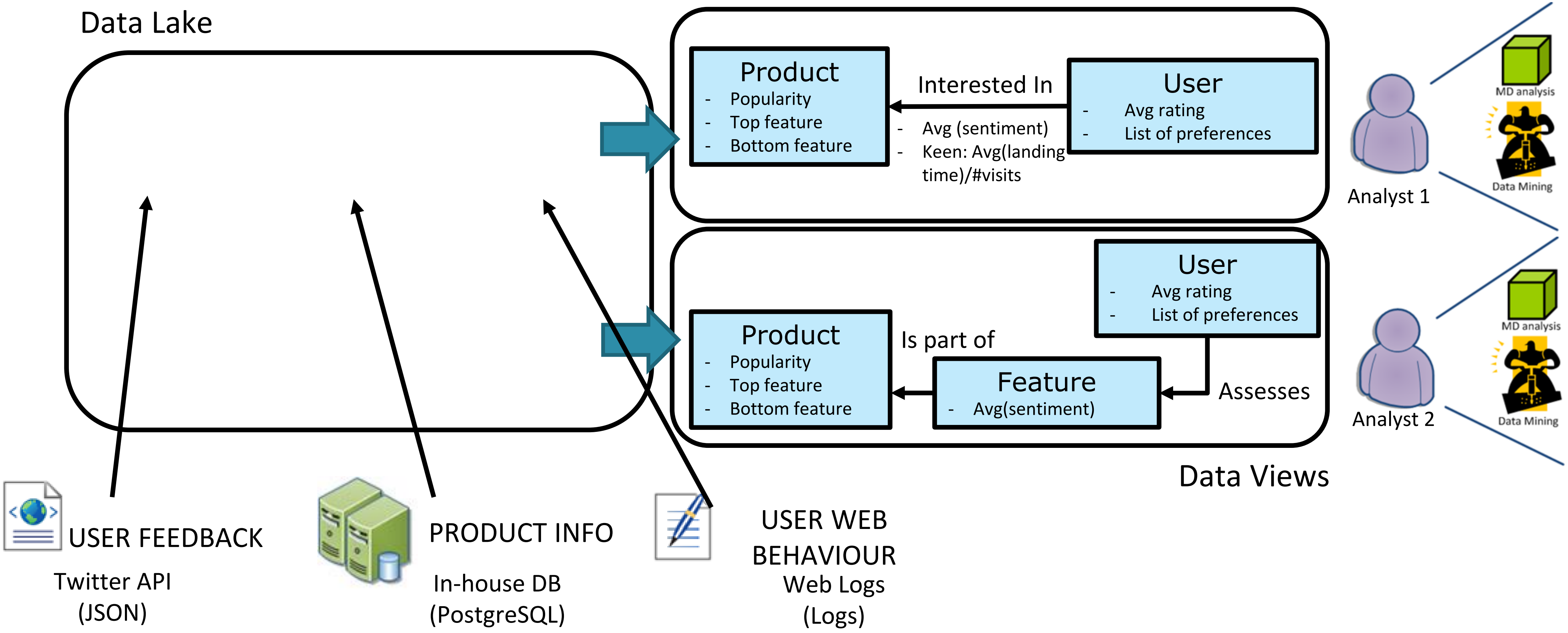
Store raw data and create on-demand views to handle with precise analysis needs

It is not a technology or architecture, it is a philosophy

The goal is flexibility



Load-First Model-Later



Data Lake

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Assesses

Data Views

Analyst 1

Analyst 2

USER FEEDBACK
Twitter API
(JSON)

PRODUCT INFO
In-house DB
(PostgreSQL)

USER WEB BEHAVIOUR
Web Logs
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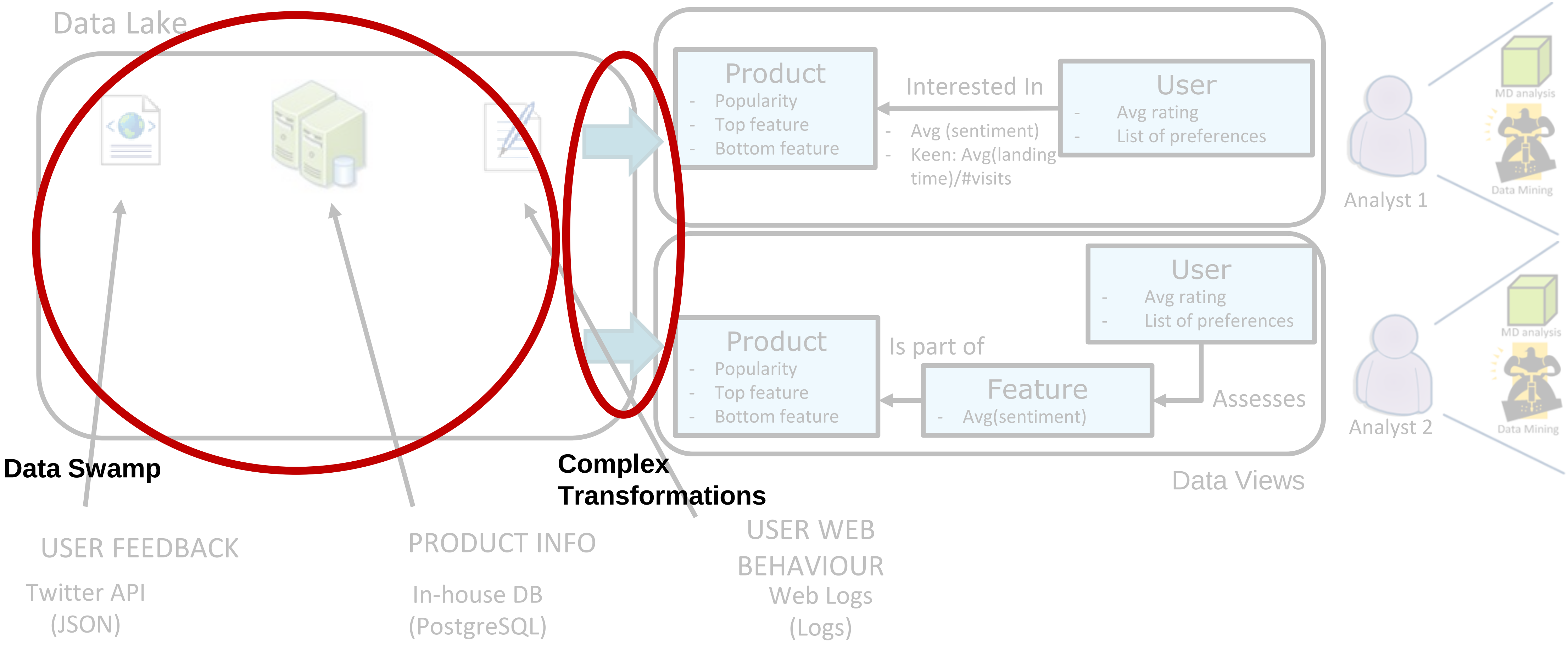
Drawbacks



Data Lake

Data Swamp

Complex Transformations

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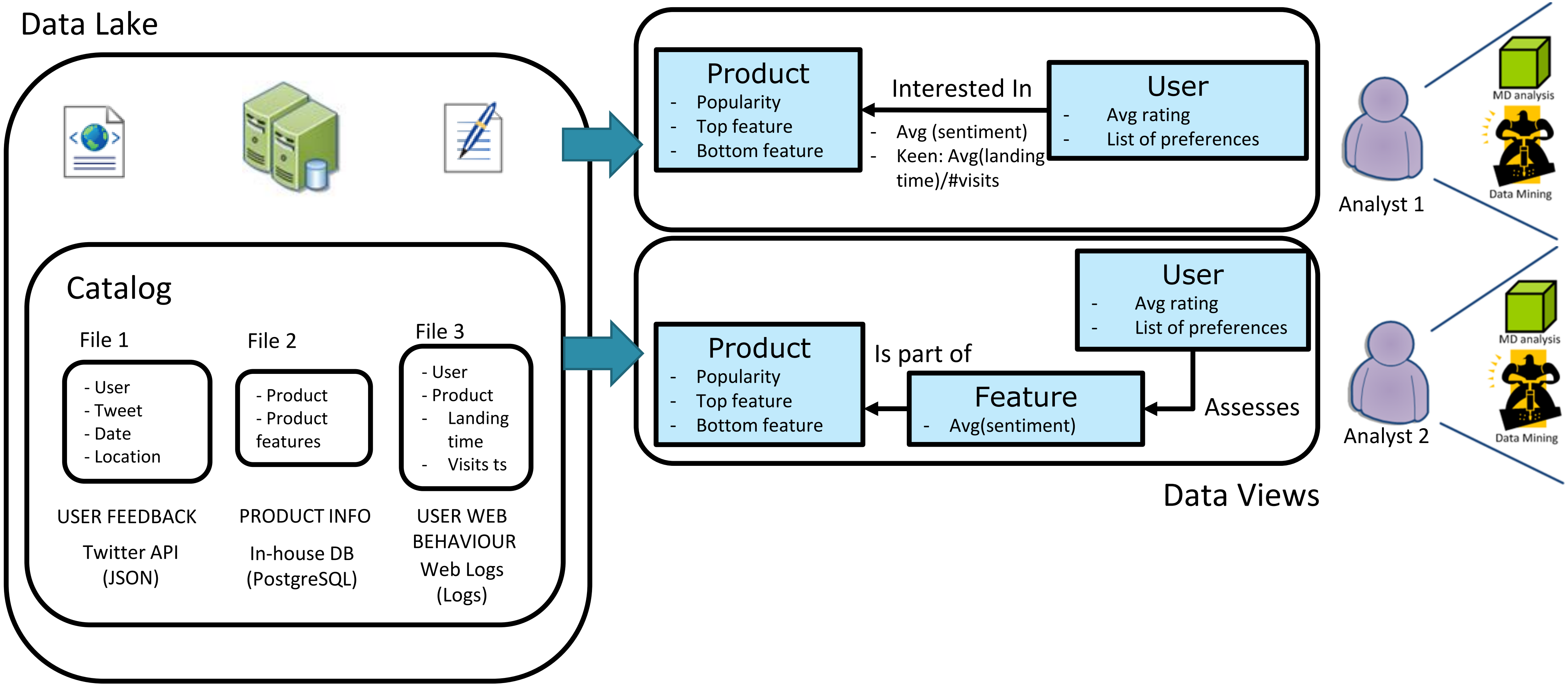
From Swamps to Semantic Data Lakes



Data Lake

Catalog

File 1

- User
- Tweet
- Date
- Location

USER FEEDBACK

Twitter API (JSON)

File 2

- Product
- Product features

PRODUCT INFO

In-house DB (PostgreSQL)

File 3

- User
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USER WEB BEHAVIOUR

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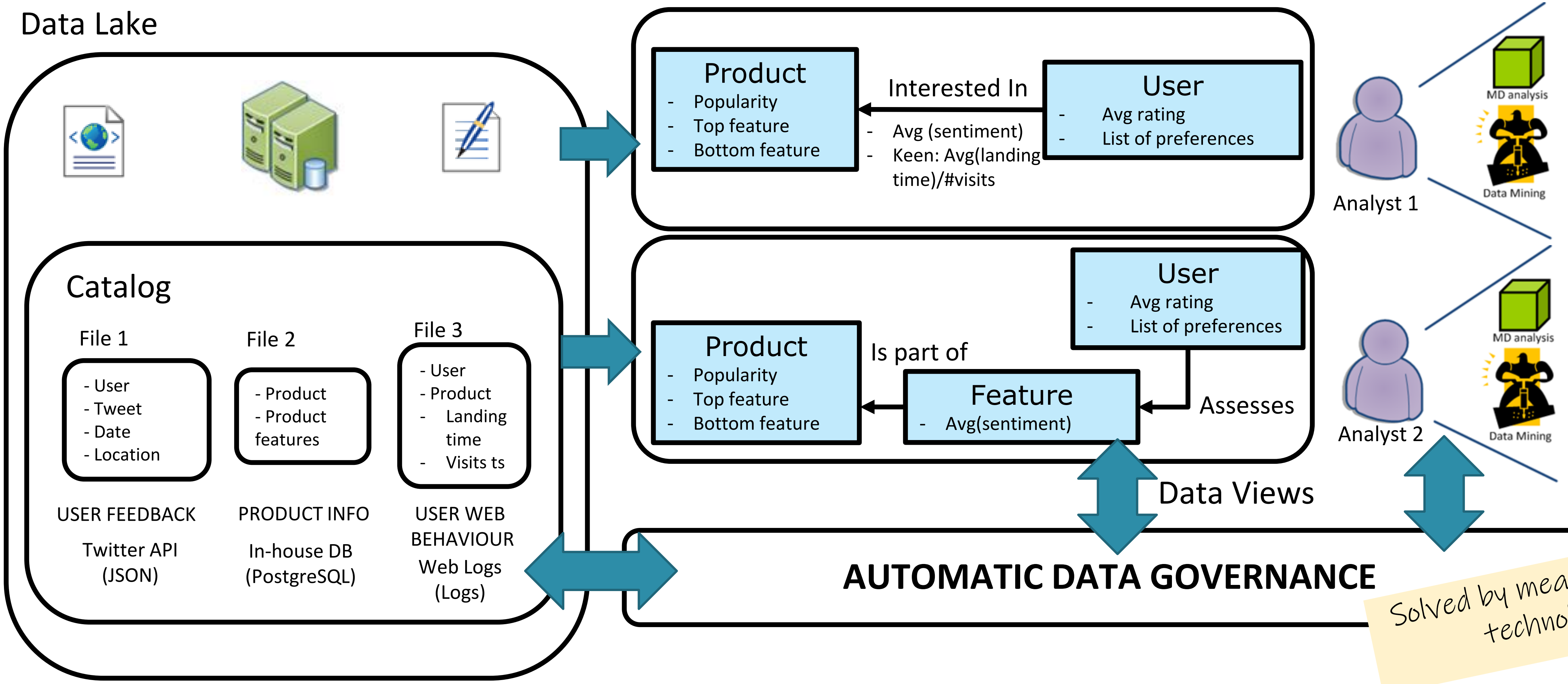
From IT-Centered to User-Centered



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Data Views

AUTOMATIC DATA GOVERNANCE

Solved by means of graph technologies

Data Variety: Graphs to the Rescue

Graph Data Model in a Nutshell

Occurrence-oriented

- It is a schemaless data model
  - There is no explicit schema
  - Data (and its relationships) may quickly vary
- Objects and relationships as first-class citizens
  - *An object o relates (through a relationship r) to another object o'*
    - *Such relationship is often known as a triple (o r o')*
  - Both objects and relationships may contain properties
- Built on top of the graph theory
  - Euler (18th century)
  - More natural and intuitive than the relational model to deal with relationships

Notation (I)

A **graph** *G* is a set of nodes and edges: *G (N, E)*

N - **Nodes** (or vertices): $n_1, n_2, \dots n_m$

E - **Edges** are represented as pairs of nodes: (n_1, n_2)

- An edge is said to be **incident** to n_1 and n_2 (also, n_1 and n_2 are said to be **adjacent)**
- An edge is drawn as a line between n_1 *and* n_2
- **Directed edges** entail direction: **from** n_1 **to** n_2
- An edge is said to be **multiple** if there is another edge exactly relating the same nodes
- An **hyperedge** is an edge inciding in more than 2 nodes

Types of graphs:

- **Multigraph**: If it contains at least one multiple edge
- **Simple graph**: If it does not contain multiple edges
- **Hypergraph**: A graph allowing hyperedges

Notation (II)

Size (of a graph): #edges

Degree (of a node): #(incident edges)

- The degree of a node denotes the node adjacency
- The neighbourhood of a node are all its adjacent nodes

Out-degree (of a node): #(edges leaving the node)

- Sink node: A node with 0 out-degree

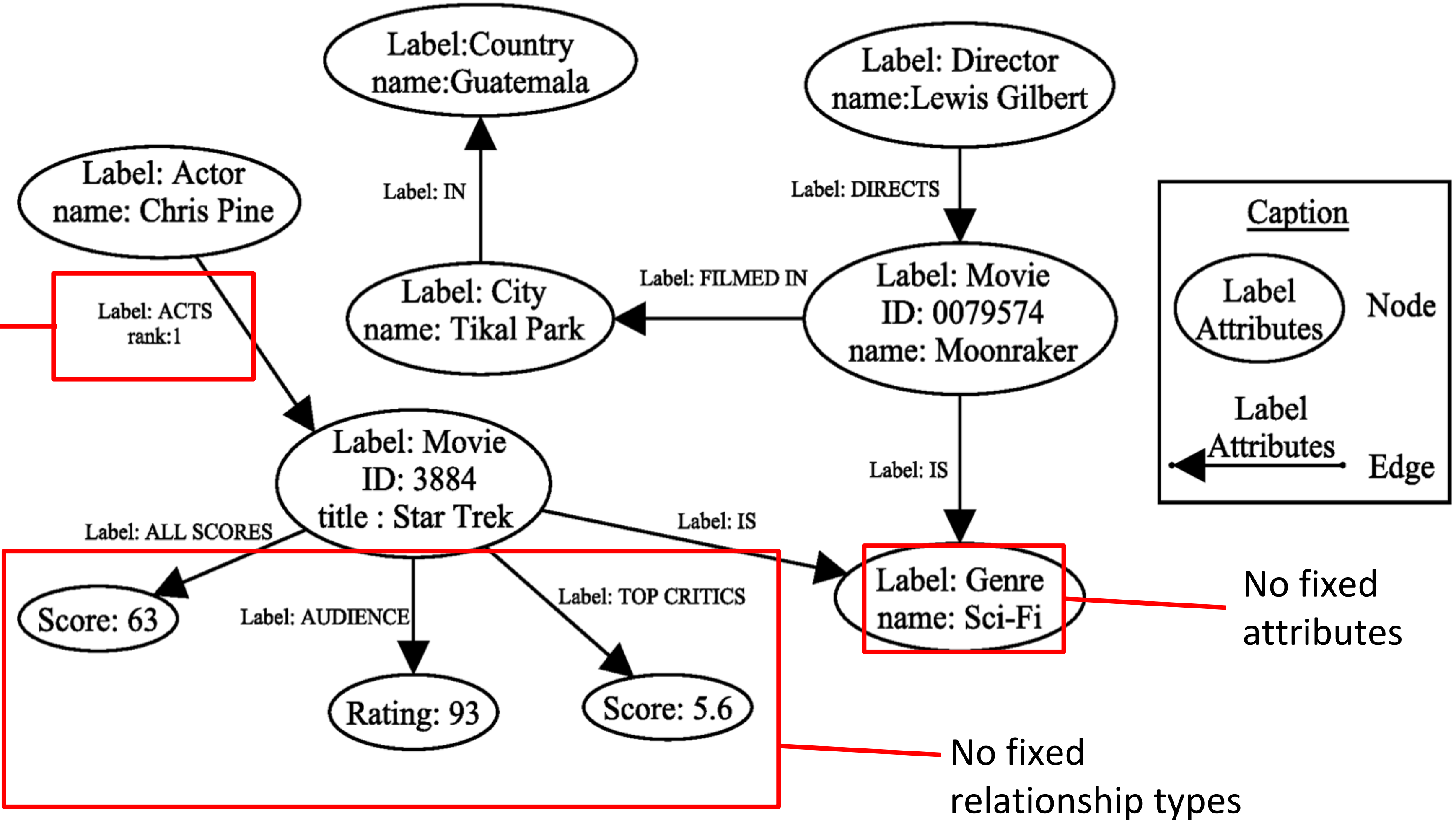
In-degree (of a node): #(incoming edges reaching the node)

- Source node: A node with 0 in-degree

Cliques and trees are specific kinds of graphs

- **Clique**: Every node is adjacent to every other node
- **Tree**: A connected acyclic simple graph

Example



Edge attributes

No fixed attributes

No fixed relationship types

Showcasing Graphs

Crossing data from social networks it is possible to identify a graph like the one that follows:

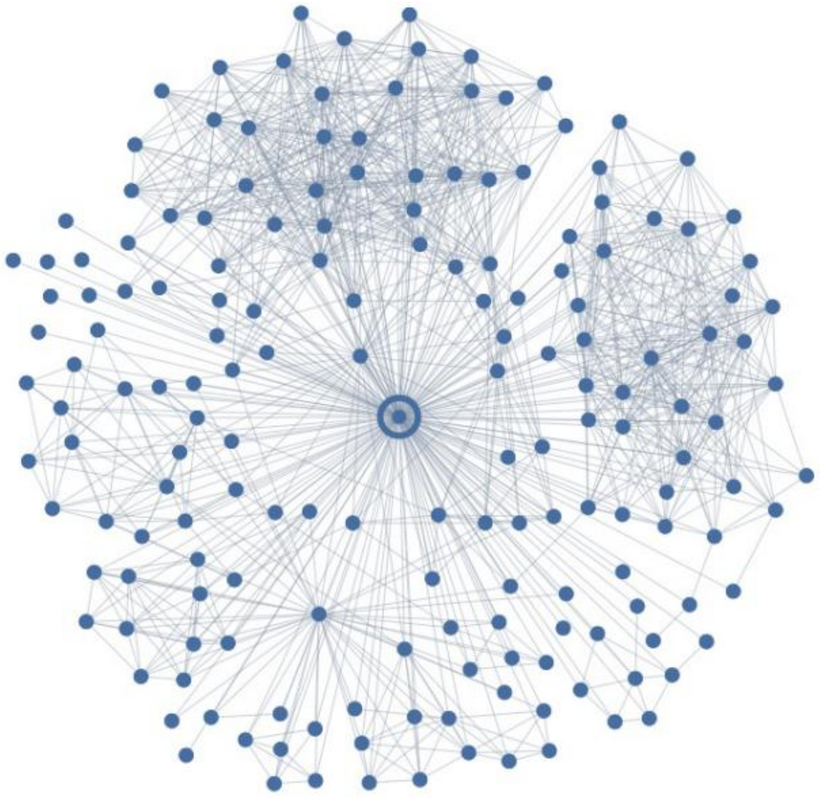
- In the centre there is a specific person *P*
- The rest are *P* connections and connections among them

Using sociology techniques…

- We can identify *P social foci*:
  - Dense clusters of connections, representing relationships
  - Typically, college friends, coworkers, relatives, etc.
- The *significant other* can be identified by a high *dispersion* rate
  - Highly connected with *P* connections,
  - But with a high dispersion degree wrt *P* social foci

Hypothesis: when the node with higher dispersion degree Identified is not the partner, this couple is likely to split up in a period of 60 days

L. Backstrom, J. Kleinberg. Romantic Partnerships and the Dispersion of Social Ties: A Network Analysis of Relationship Status on Facebook https://arxiv.org/pdf/1310.6753v1.pdf



Graph Data Models and Data Analytics

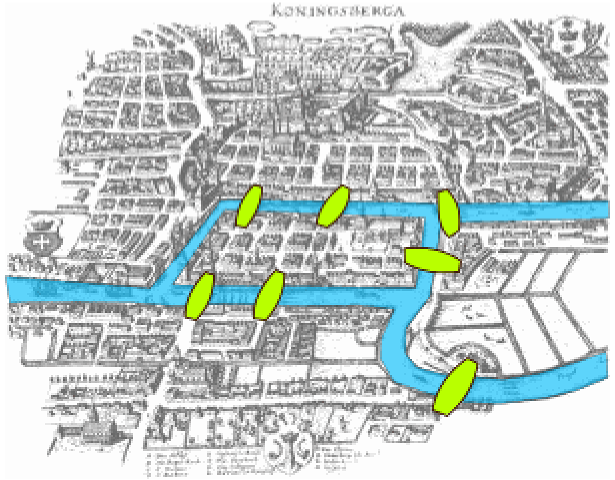
From a data management point of view:

- They are extremely flexible
- Schemaless by definition
- **Data and metadata are stored together** (i.e., data with annotations)
    - *Thus, we say that they store semantic (i.e., together with its meaning) data*
- Custom annotations facilitate data governance

Graphs are not only about data variety

From a data analytics point of view:

- Allow to exploit the data structure topology
    - Shortest path, centrality measures, community detection, etc.
- Graph data analytics is deterministic (i.e., by default non-probabilistic)
- Plenty of advances to enable probabilistic analysis on top of graphs
    - E.g. Graph embeddings and Graph Neural Networks (GNNs)



Seven Bridges of Koningsberg
(the birth of graph theory)

See additional material
"The Ubiquity of Large
Graphs"

Graph Data Models

What is a Graph Data Model?

Graph data models are composed of data structures, constraints and operators:

Data Structures

- Nodes
- Edges
- Properties

Constraints

- From a data structure point of view: nodes and edges are disjoint
- From a schema point of view: schemaless

Operators

- Graph operators (grounded in the graph theory): pattern matching, reachability, neighbourhood, etc.
  - For these operations: graphs are translated into mathematical structures (!)
- Algebraic operators (coming from databases): selection, projection, join, union, aggregation, etc.

Graph Data Models

Two main families:

- **Property Graphs**
  - Born in the Database field
  - Not predefined semantics
  - Assume a Closed-World semantics
  - Generate data silos
  - Algebraic operations on top of traditional graph operations

- **Knowledge Graphs**
  - Born in the Knowledge Representation field
  - May assume an Open-World semantics
  - Facilitate data sharing and linking
  - Two main families
    - RDF and RDF(S)
      - Born in the Semantic Web field
      - Vocabulary-based pre-defined semantics
      - Combine traditional graph operations, algebraic operations and simple reasoning operations
    - Description Logics (DL)-based languages (e.g., OWL)
      - Subsets of first-order logic
      - Pre-defined semantics based on logics
      - Reasoning operations grounded in logics

Summary

Graphs are the perfect data model to tackle data variety:

- Semantic expressiveness
- Semantic relatedness

As a result, data and metadata (semantic annotations on data) are stored together

- Data is stored with its meaning
- Machine-readable metadata opens the door to automatic data management

Main graph families

- Property graphs
- Knowledge graphs

Thanks! Any Question?