Advanced Data Management (CSCI 640/490)

Graph Databases

Dr. David Koop

Time Series Data

- A row of data that consists of a timestamp, a value, optional tags

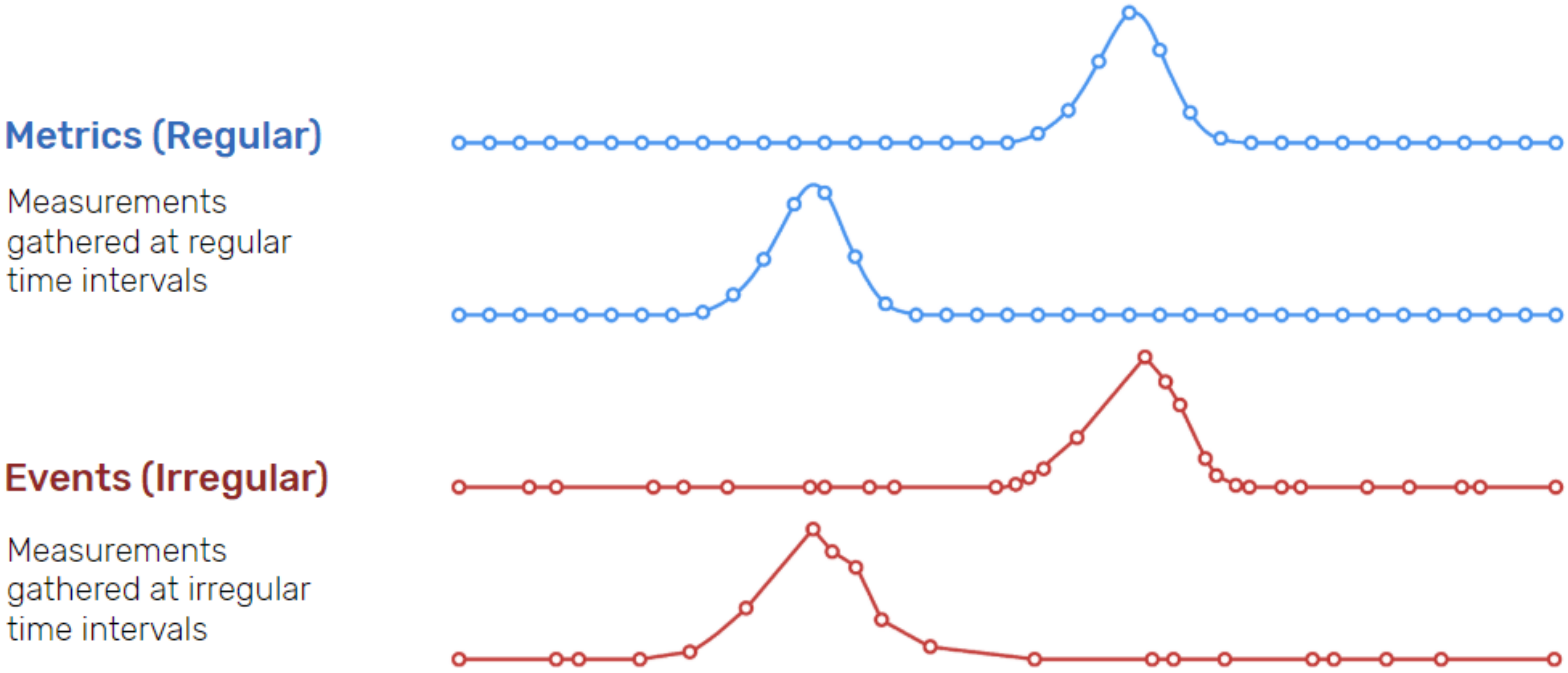
ul1

timestamp	tags					value
time	generated	message_subtype	scaler	short_id	tenant	value
2016-07-12T11:51:45Z	"true"	"34"	"4"	"3"	"saarlouis"	465110000
2016-07-12T11:51:45Z	"true"	"34"	"-6"	"2"	"saarlouis"	0.06196699999999994
2016-07-12T12:10:00Z	"true"	"34"	"7"	"5"	"saarlouis"	49370000000
2016-07-12T12:10:00Z	"true"	"34"	"6"	"2"	"saarlouis"	18573000000
2016-07-12T12:10:00Z	"true"	"34"	"5"	"7"	"saarlouis"	5902300000

[A. Bader, 2017]

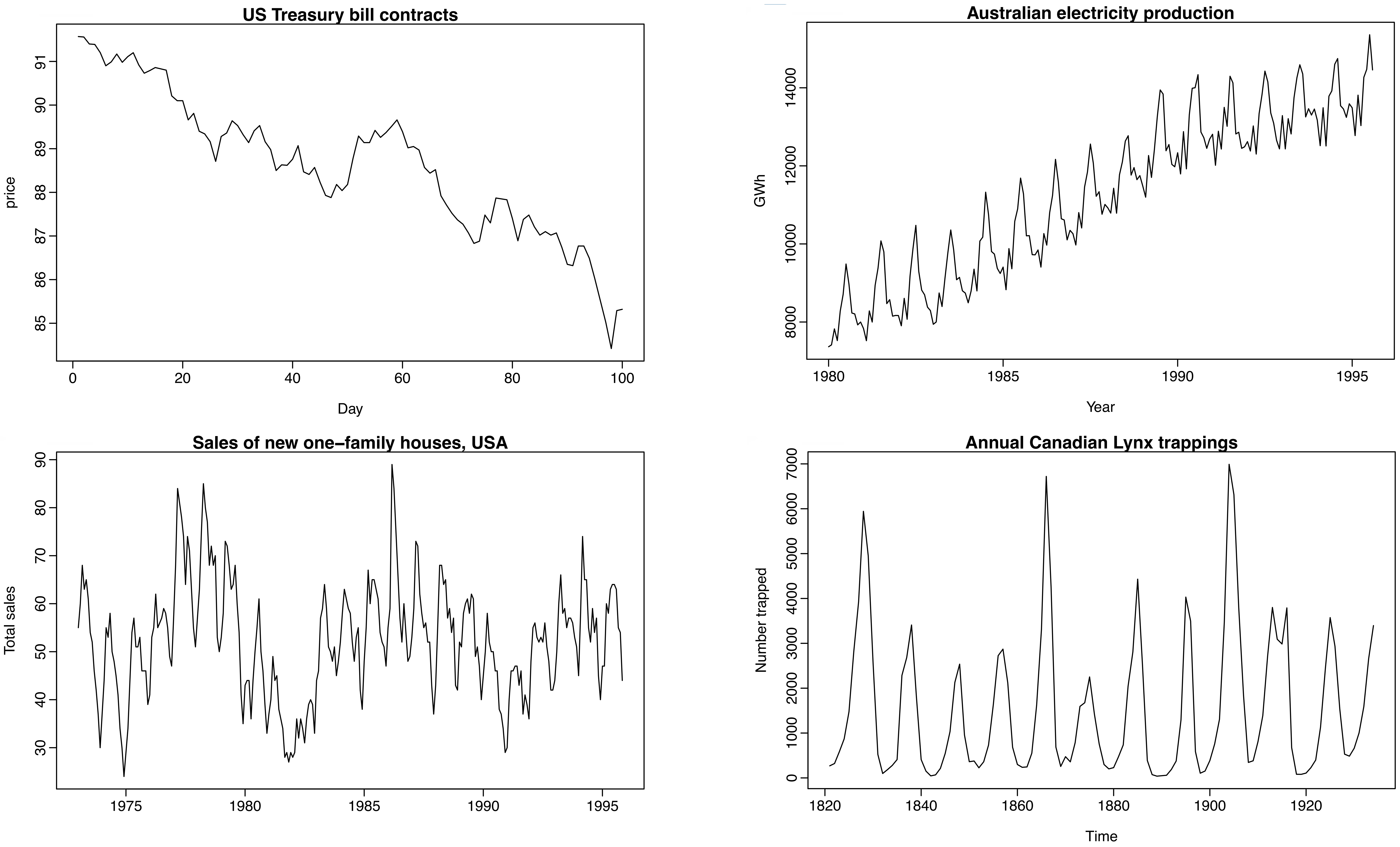
Time Series Data

- Metrics: measurements at regular intervals
- Events: measurements that are not gathered at regular intervals



[InfluxDB]

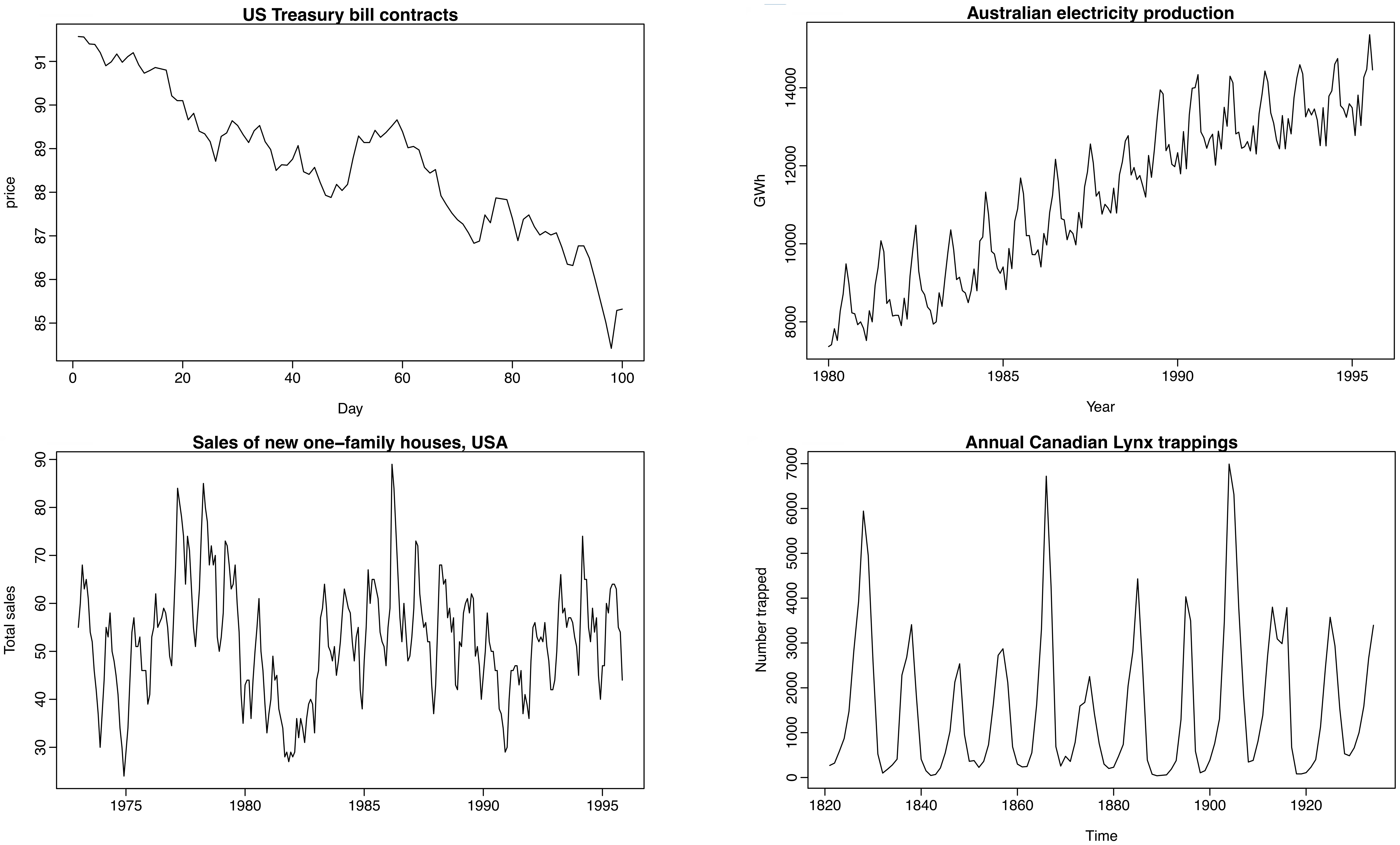
Examples



[R. J. Hyndman]

Examples

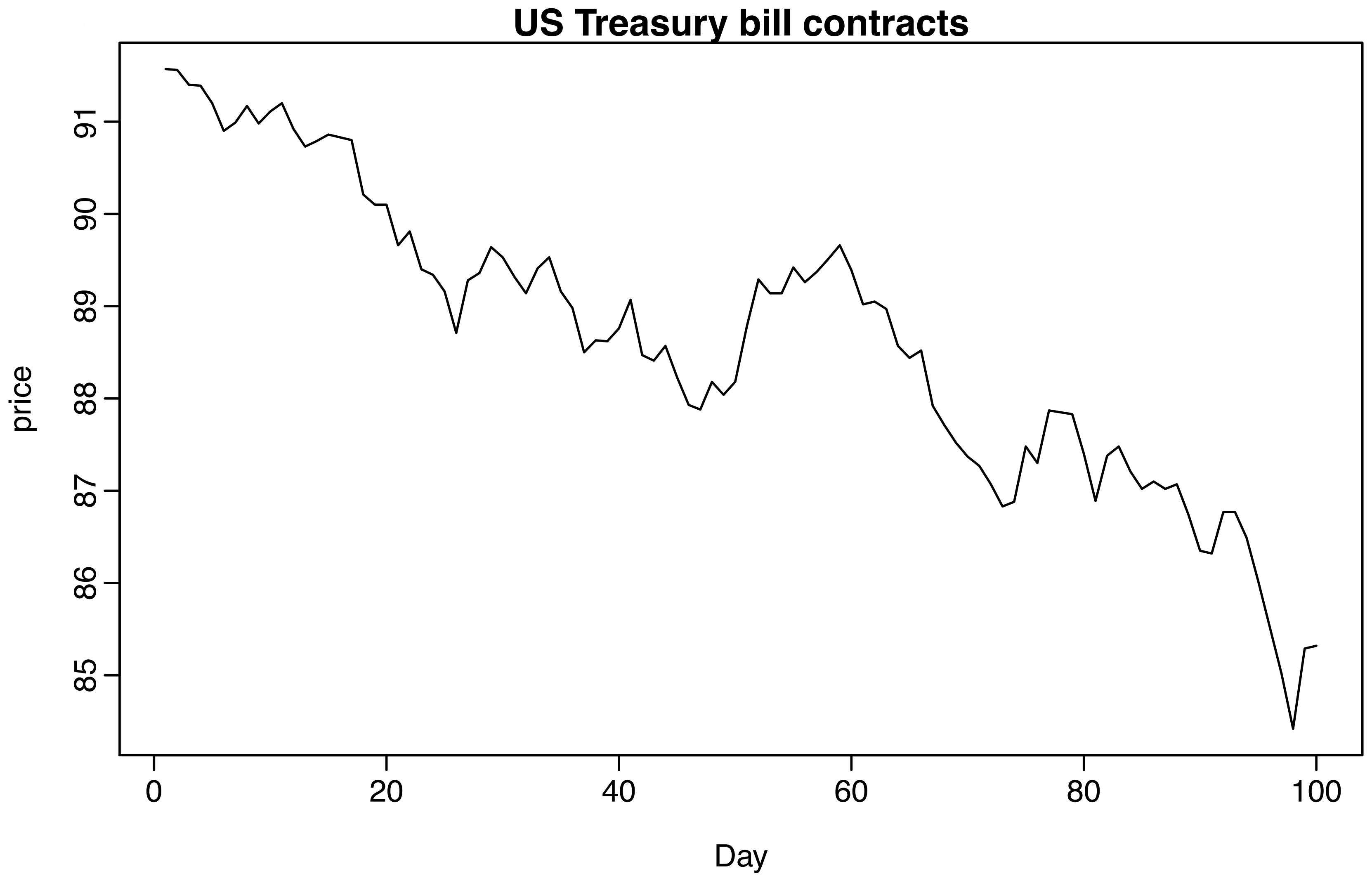
Trend

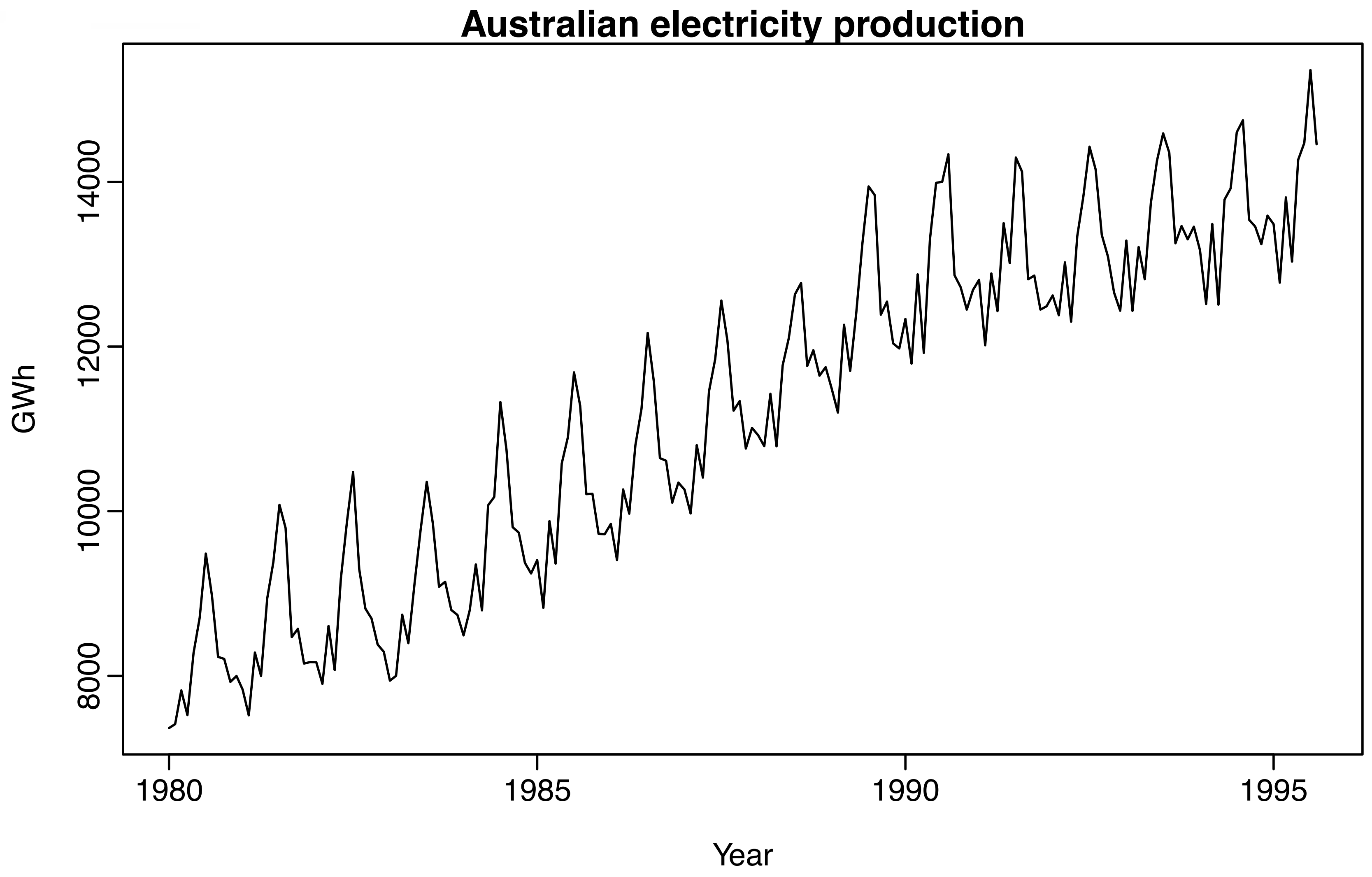


[R. J. Hyndman]

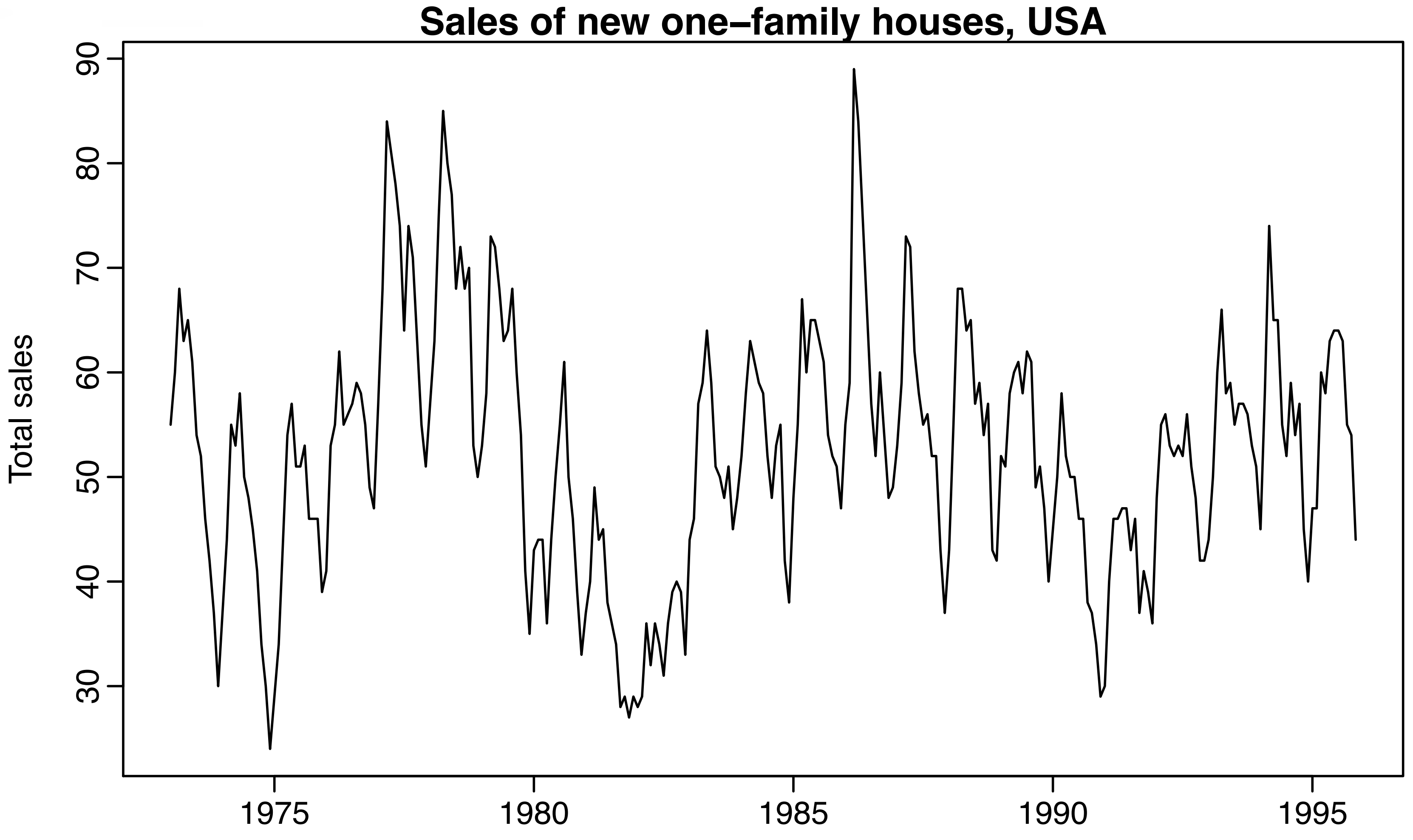
Examples

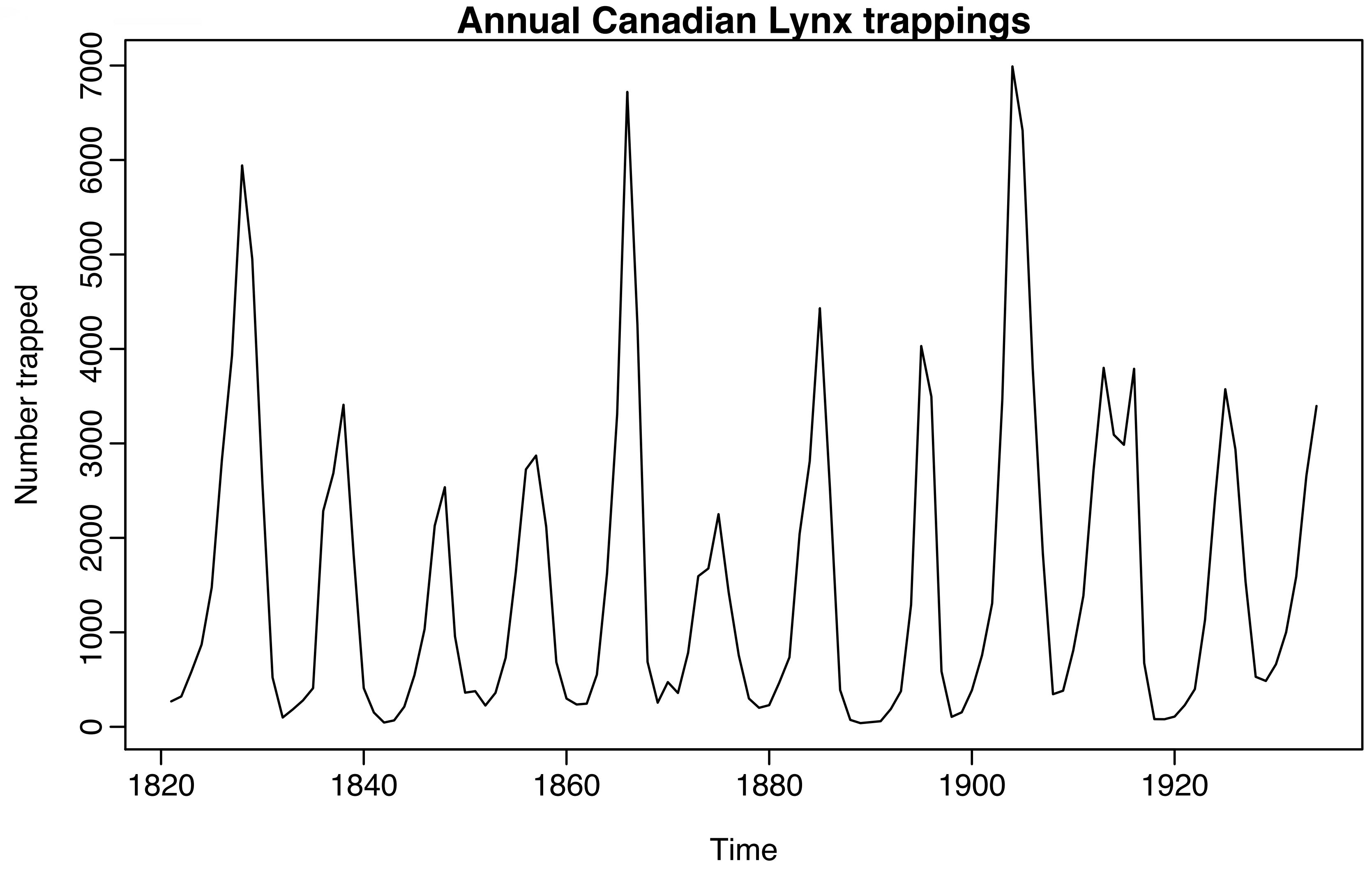
Trend





Trend + Seasonality

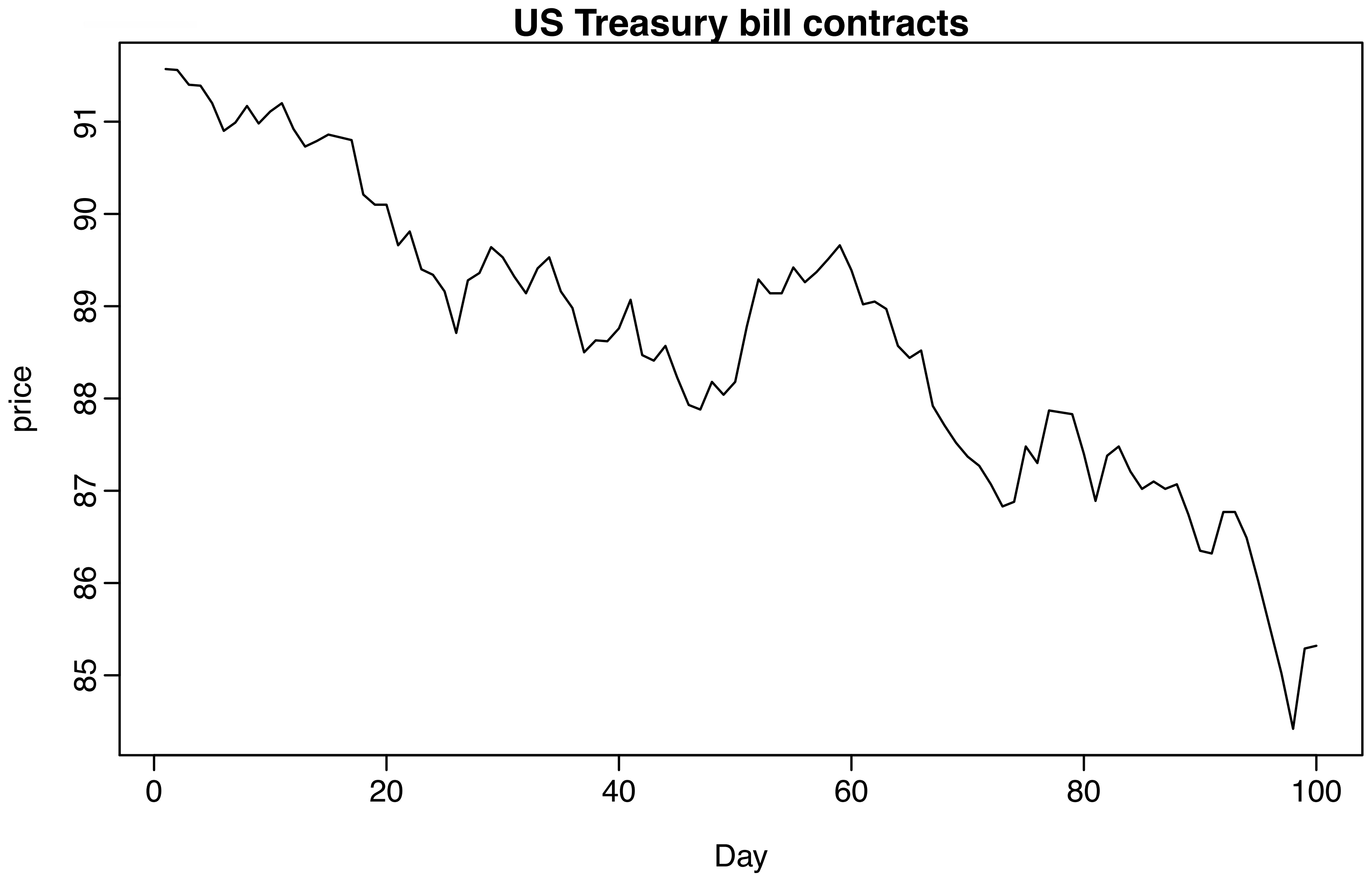


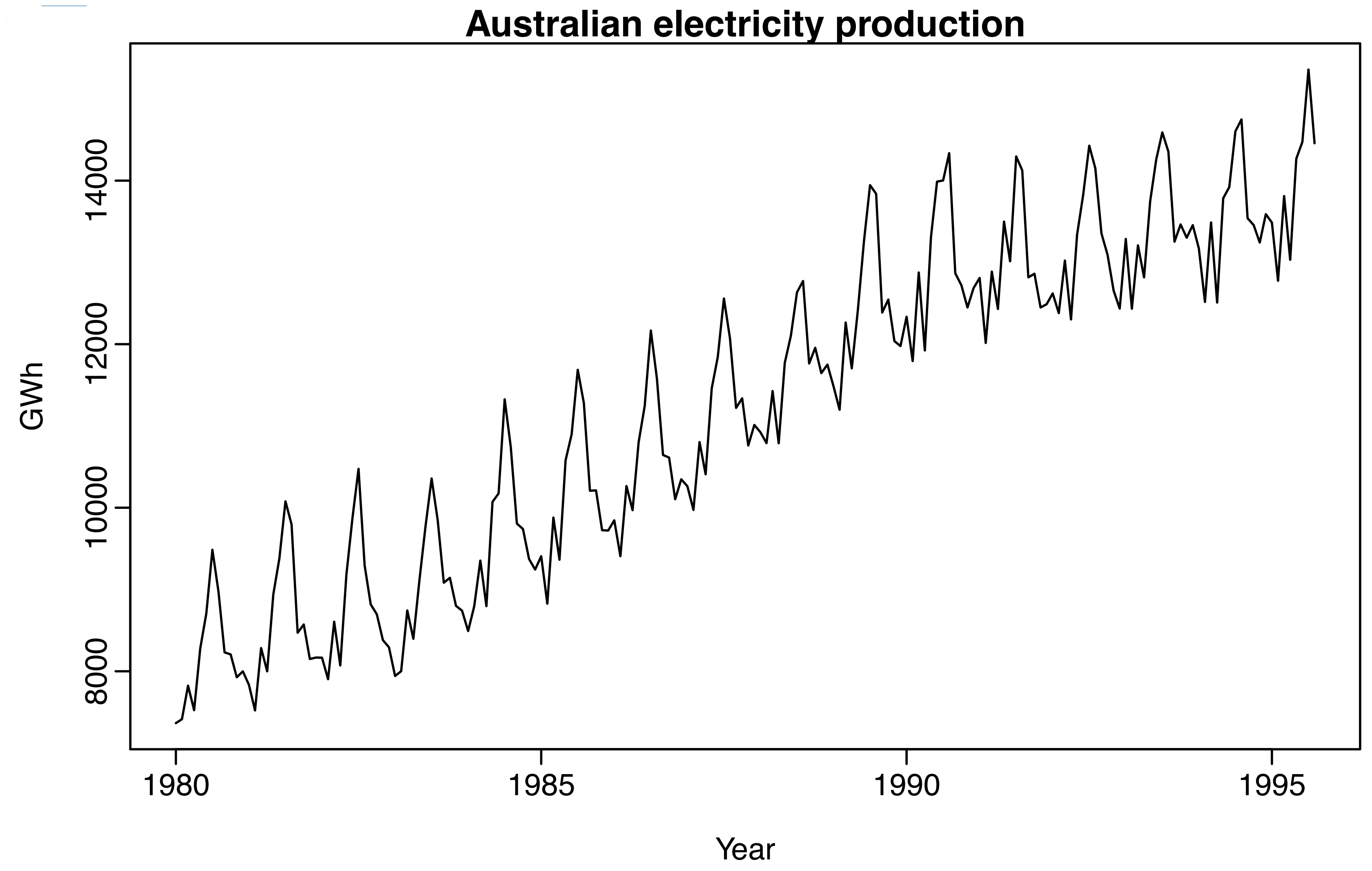


[R. J. Hyndman]

Examples

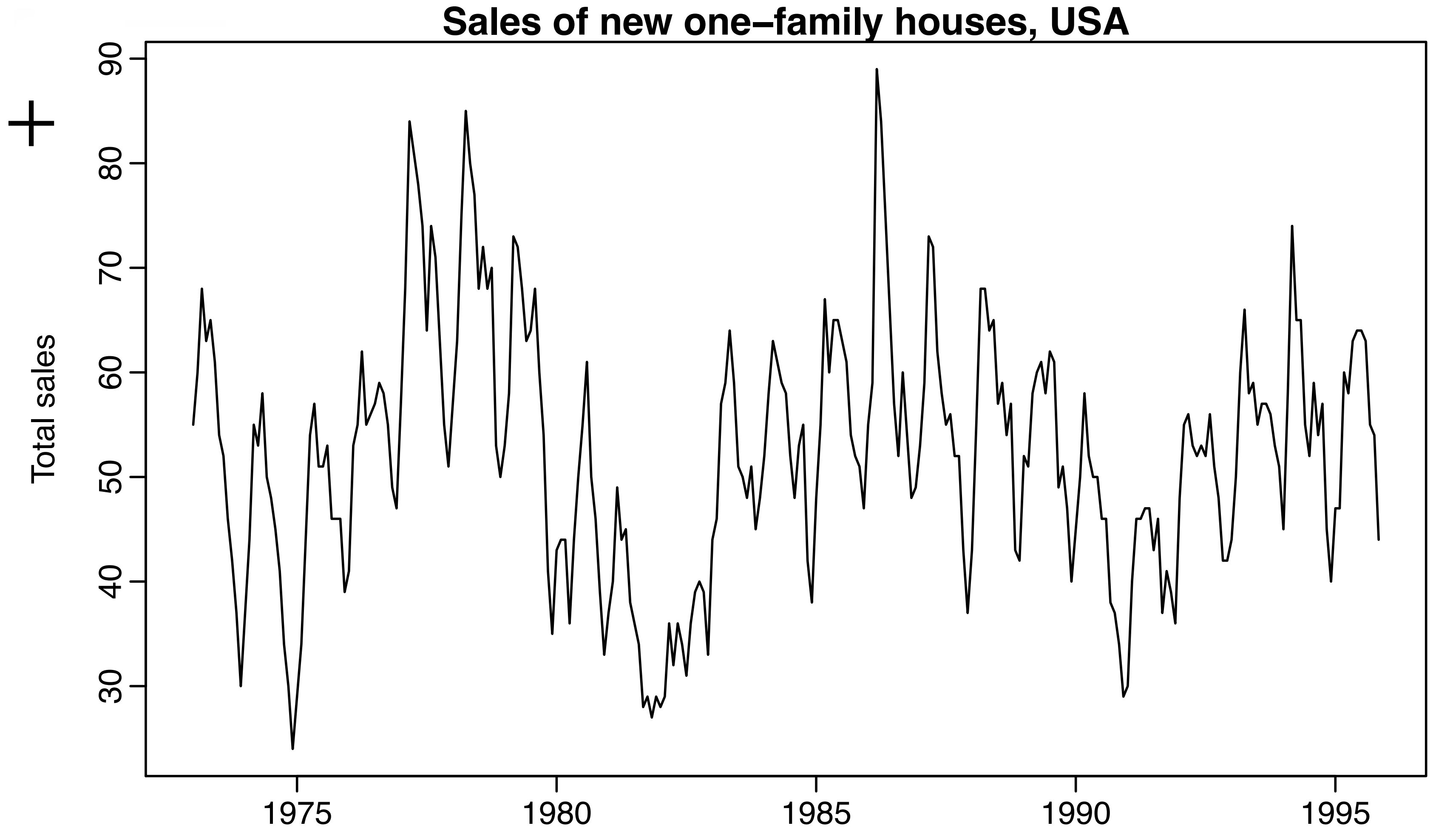
Trend

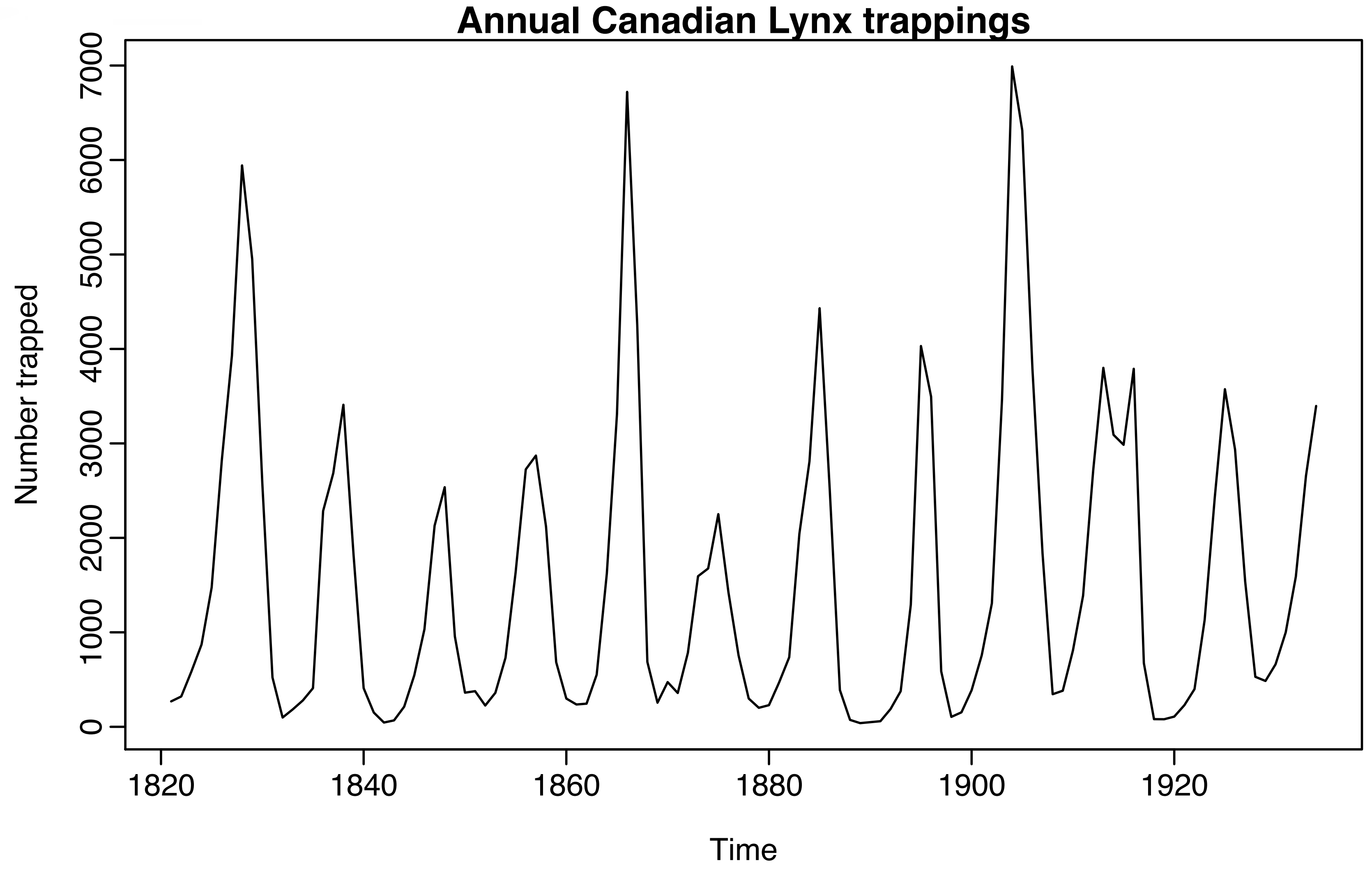




Trend + Seasonality

Seasonality + Cyclic

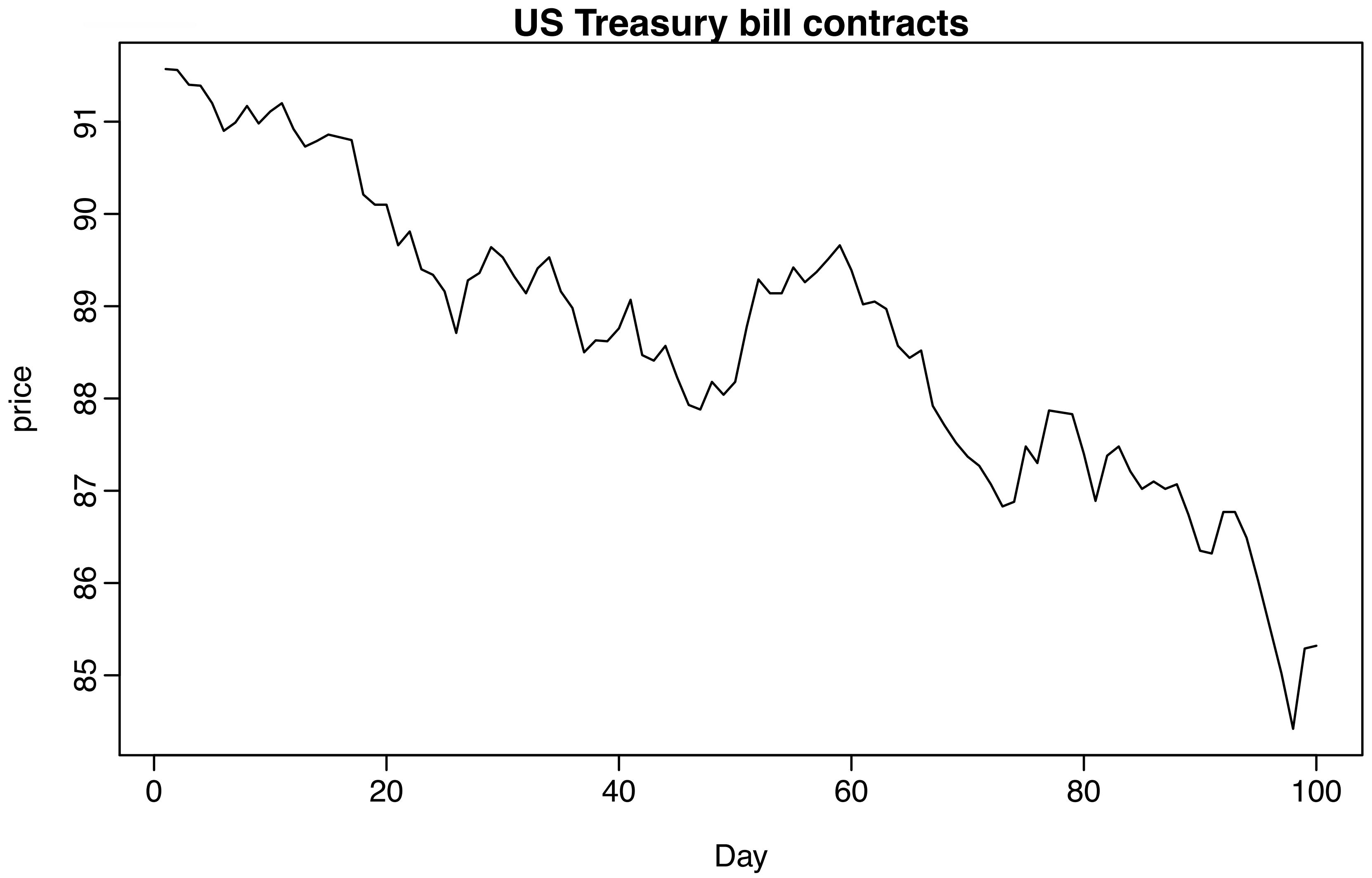


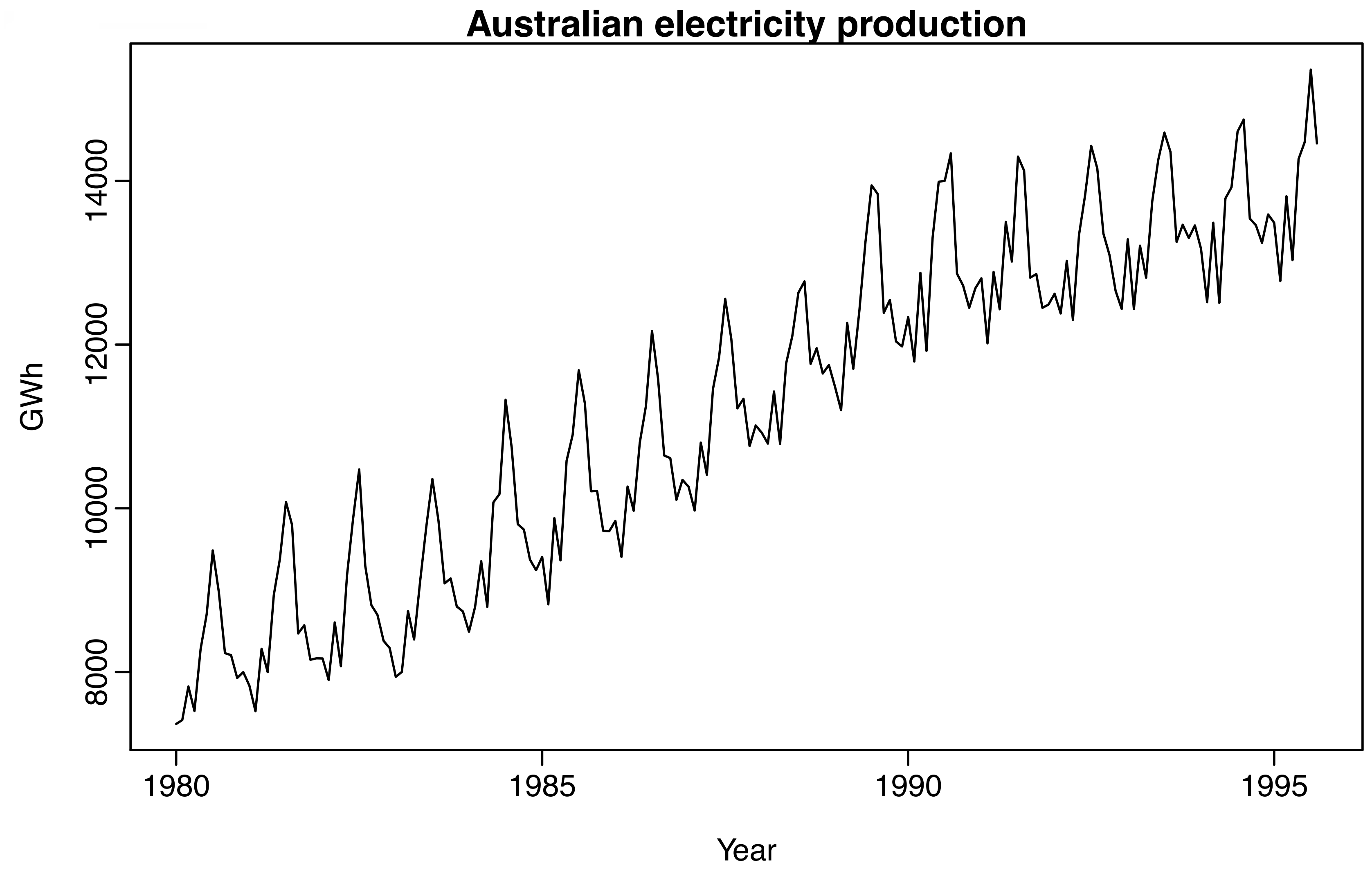


[R. J. Hyndman]

Examples

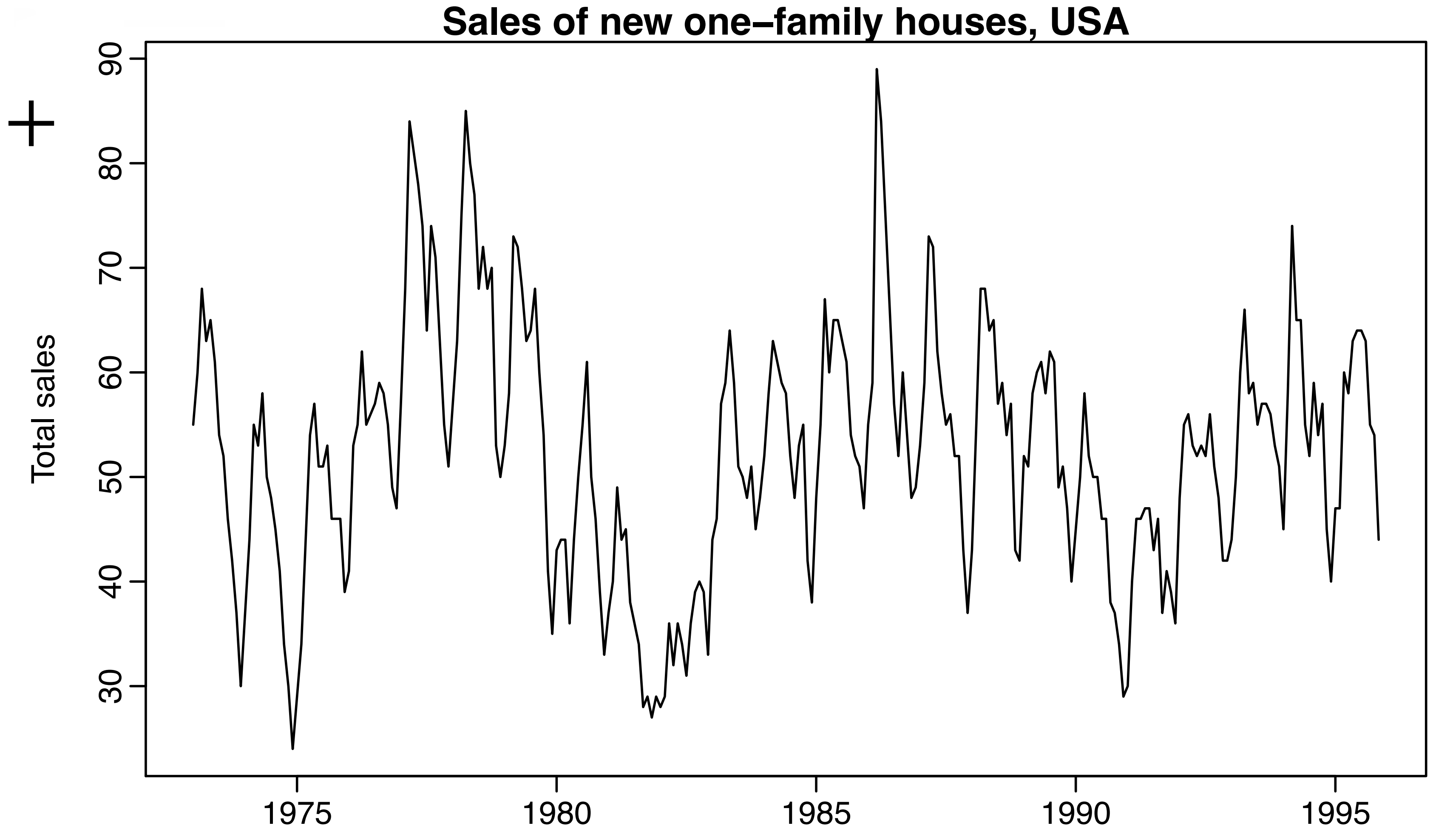
Trend

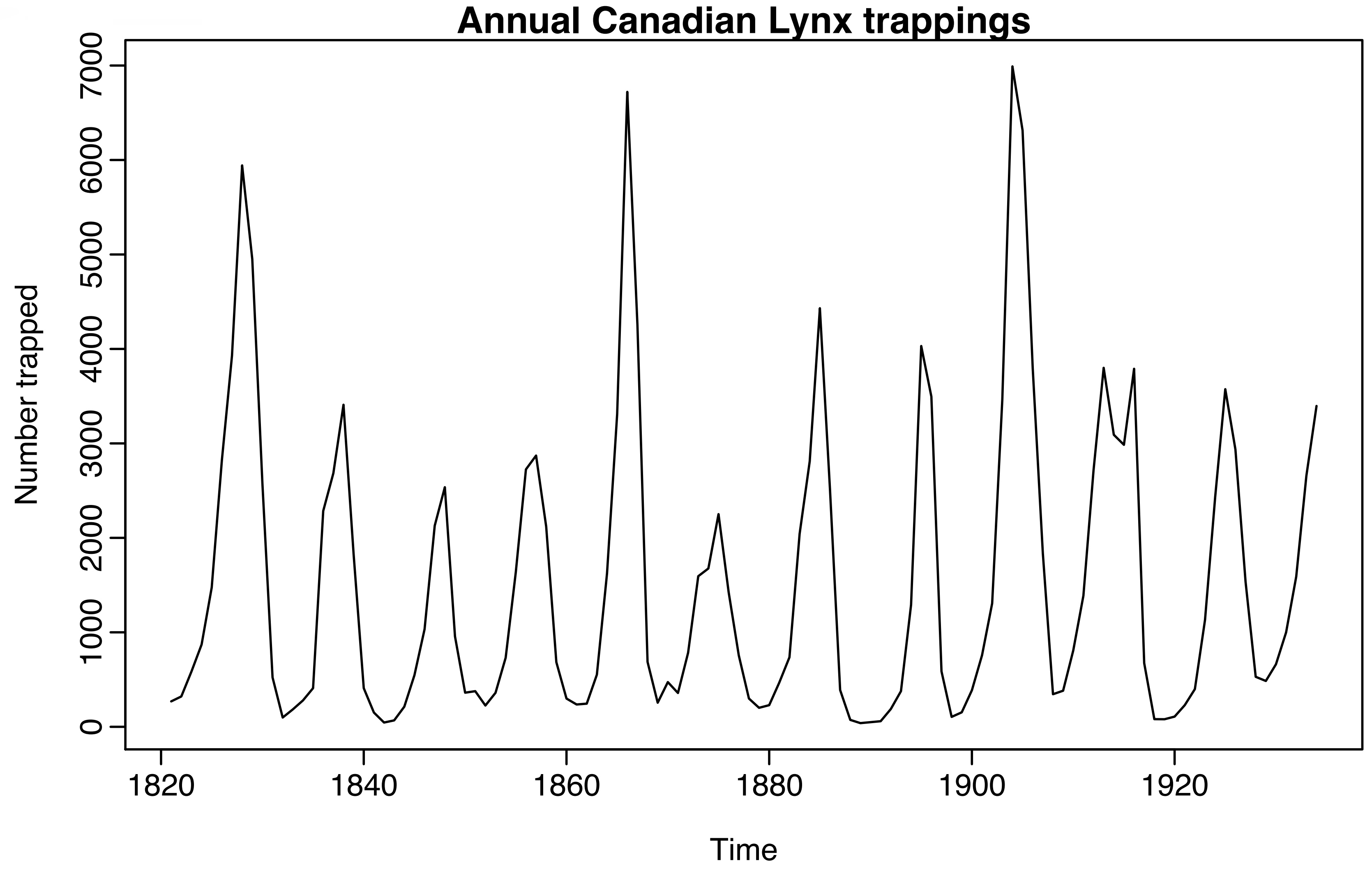




Trend + Seasonality

Seasonality + Cyclic





Stationary

[R. J. Hyndman]

Polars Support for Datetime

- Has separate types for date (`pl.Date`), time (`pl.Time`), and datetime (`pl.Datetime`)
- `pl.date, pl.time, pl.datetime`: convenience method to create objects
- Can convert from a string to a datetime using `.str.to_datetime()`
  - If no format is specified, **infers** the format from the data
  - Can specify the format, but uses **rust** specification (docs)
- Stores as a 64-bit integer representing the number of time units since the UNIX epoch (1970-01-01 00:00:00)
  - Time units can be milliseconds (`ms`), microseconds (`us`), or nanoseconds (`ns`)
  - Defaults to microseconds (`us`)

Resampling

- Two directions:
  - Downsample: higher frequency to lower frequency
  - Upsample: lower frequency to higher frequency
  - The index or time_column column must be in **sorted** order!
- Downsample is a special case of `group_by` in polars (`group_by_dyanmic`)
  - ```
    (df.group_by_dynamic("date", every="1y")
         .agg(pl.col("close").mean()))
    ```
- Polars has a dedicated `upsample` method:
  - ```
    (df.upsample(time_column="time", every="15m")
         .fill_null(strategy="forward"))
    ```
- String language for the `every` argument

Time Series Databases

- Most time series data is heavy **inserts**, few updates
- Also analysis tends to be on ordered data with trends, prediction, etc.
- Can also consider **stream** processing
- Focus on time series allows databases to specialize
- Examples:
  - InfluxDB (noSQL)
  - TimescaleDB (SQL-based)

What is a Time Series Database?

- A DBMS is called TSDB if it can
  - store a row of data that consists of timestamp, value, and optional tags
  - store multiple rows of time series data grouped together
  - can query for rows of data
  - can contain a timestamp or a time range in a query

ul1

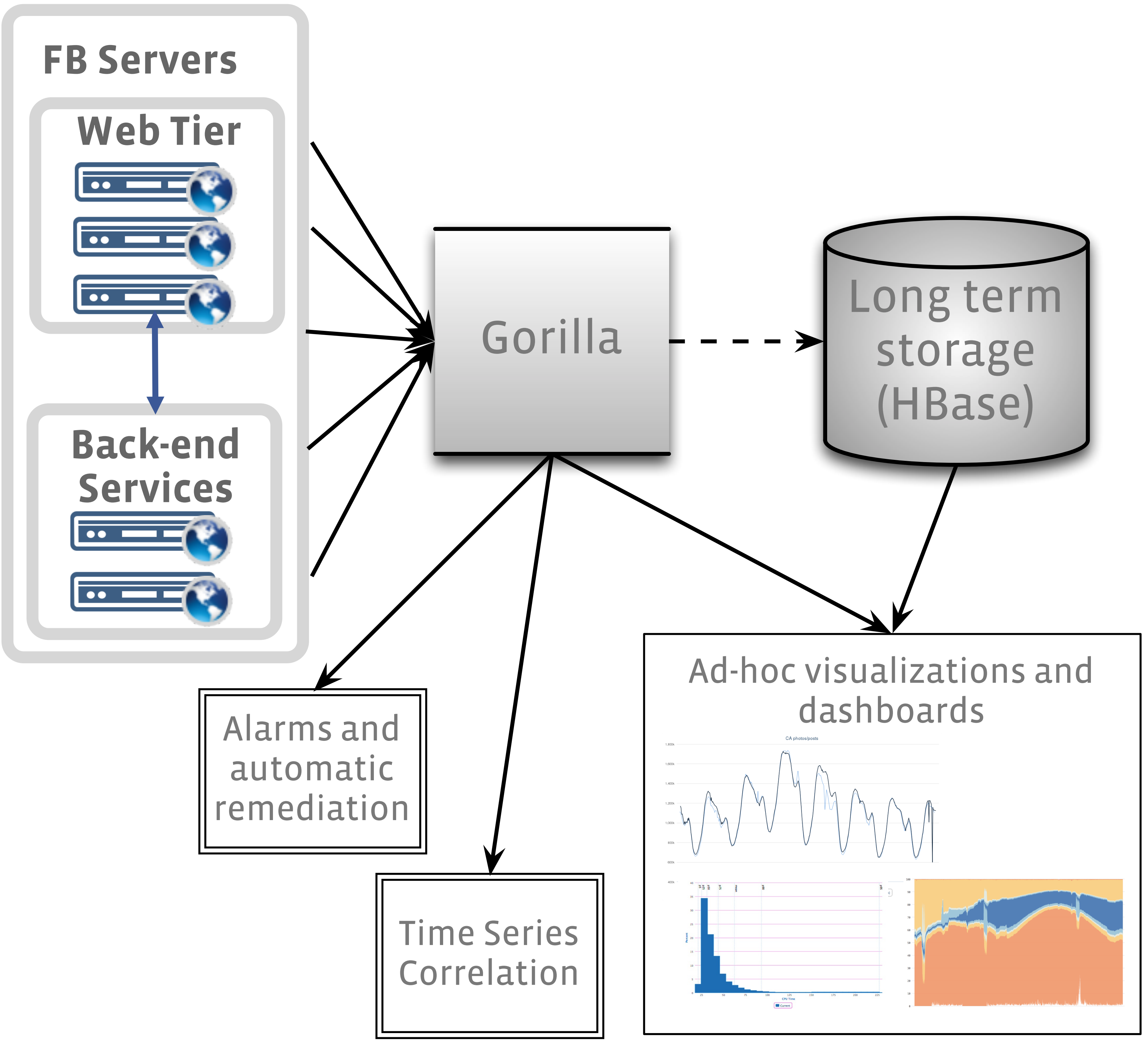
"SELECT * FROM ul1 WHERE time >= '2016-07-12T12:10:00Z'"

time	generated	message_subtype	scaler	short_id	tenant	value
2016-07-12T11:51:45Z	"true"	"34"	"4"	"3"	"saarlouis"	465110000
2016-07-12T11:51:45Z	"true"	"34"	"-6"	"2"	"saarlouis"	0.061966999999999994
2016-07-12T12:10:00Z	"true"	"34"	"7"	"5"	"saarlouis"	49370000000
2016-07-12T12:10:00Z	"true"	"34"	"6"	"2"	"saarlouis"	18573000000
2016-07-12T12:10:00Z	"true"	"34"	"5"	"7"	"saarlouis"	5902300000

[A. Bader, 2017]

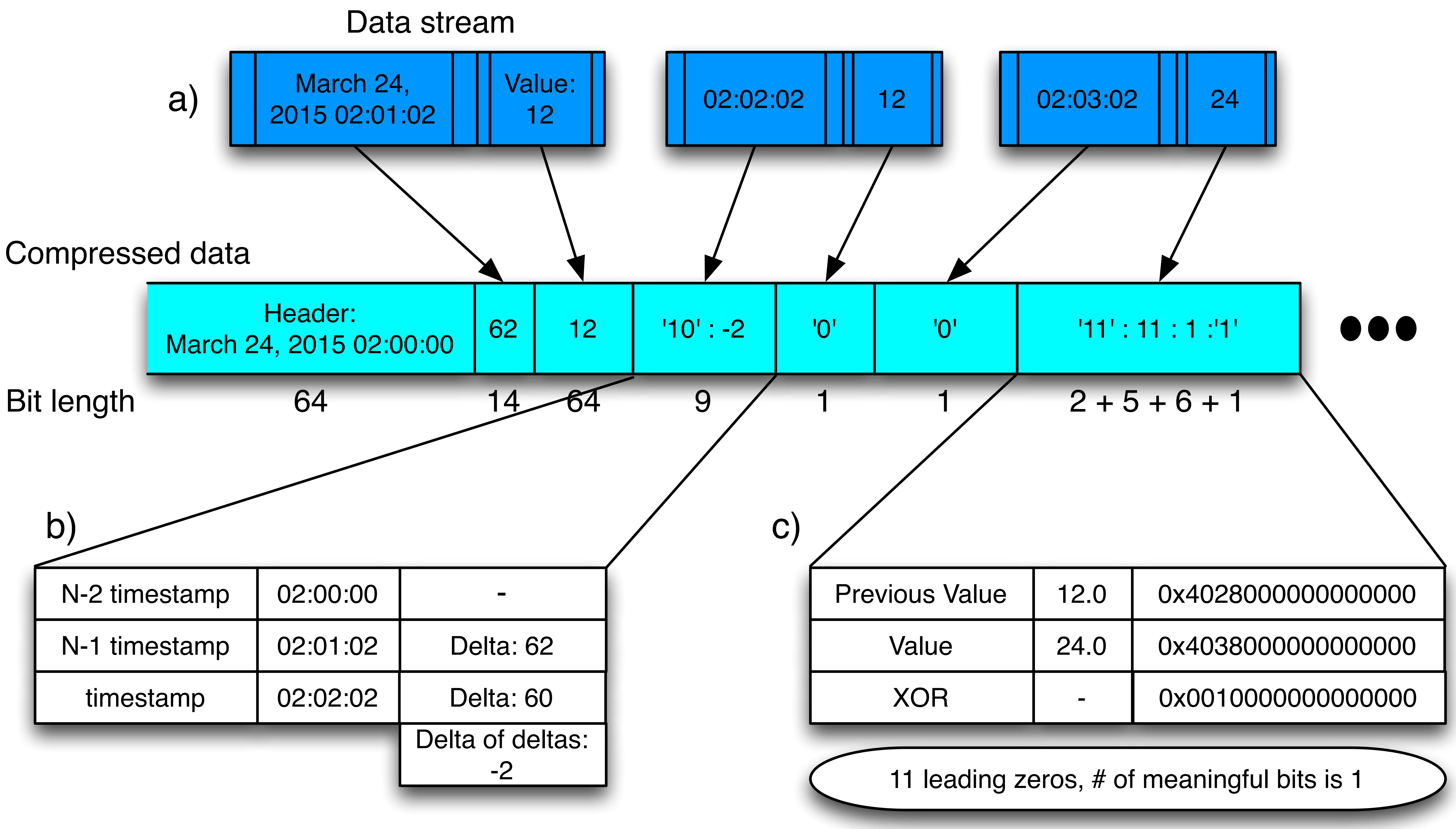
Gorilla Motivation

- Large-scale internet services rely on lots of services and machines
- Want to monitor the health of the systems
- Writes dominate
- Want to detect state transitions
- Must be highly available and fault tolerant



[Pelkonen et al., 2015]

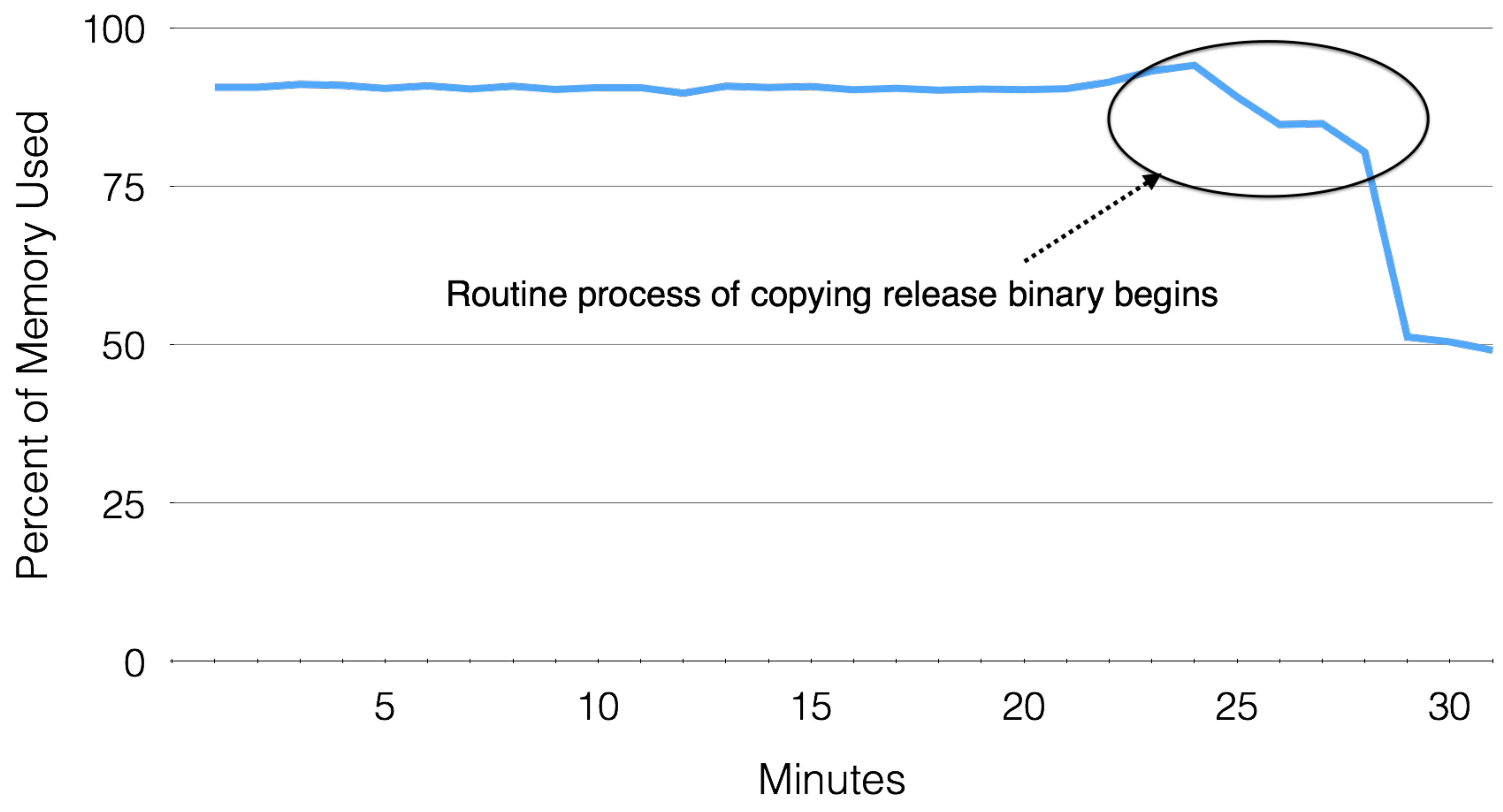
Gorilla Compression



[Pelkonen et al., 2015]

Enabling Gorilla Features

- Correlation Engine: "What happened around the time my service broke?"
- Charting: Horizon charts to see outliers and anomalies
- Aggregations: Rollups locally in Gorilla every couple of hours



[Pelkonen et al., 2015]

Gorilla Lessons Learned

- Prioritize recent data over historical data
- Read latency matters
- High availability trumps resource efficiency
  - Withstand single-node failures and "disaster events" that affect region
  - "[B]uilding a reliable, fault tolerant system was the most time consuming part of the project"
  - "[K]eep two redundant copies of data in memory"

[Pelkonen et al., 2015]

Assignment 4

- Work on Data Integration and Data Fusion
- Integrate university ranking datasets from different institutions
- Integrate information based on names and matching
- Record Matching:
  - Which universities are the same?
- Data Fusion:
  - Names
  - Enrollments
  - Rankings
- Courselet is posted

Courselets

- All should now be available
- You should have received an email with a link to surveys

Test 2

- Next Monday, Nov. 10
- Similar format, but more emphasis on topics we have covered including the research papers

Graphs: Social Networks

[P. Butler, 2010]

What is a Graph?

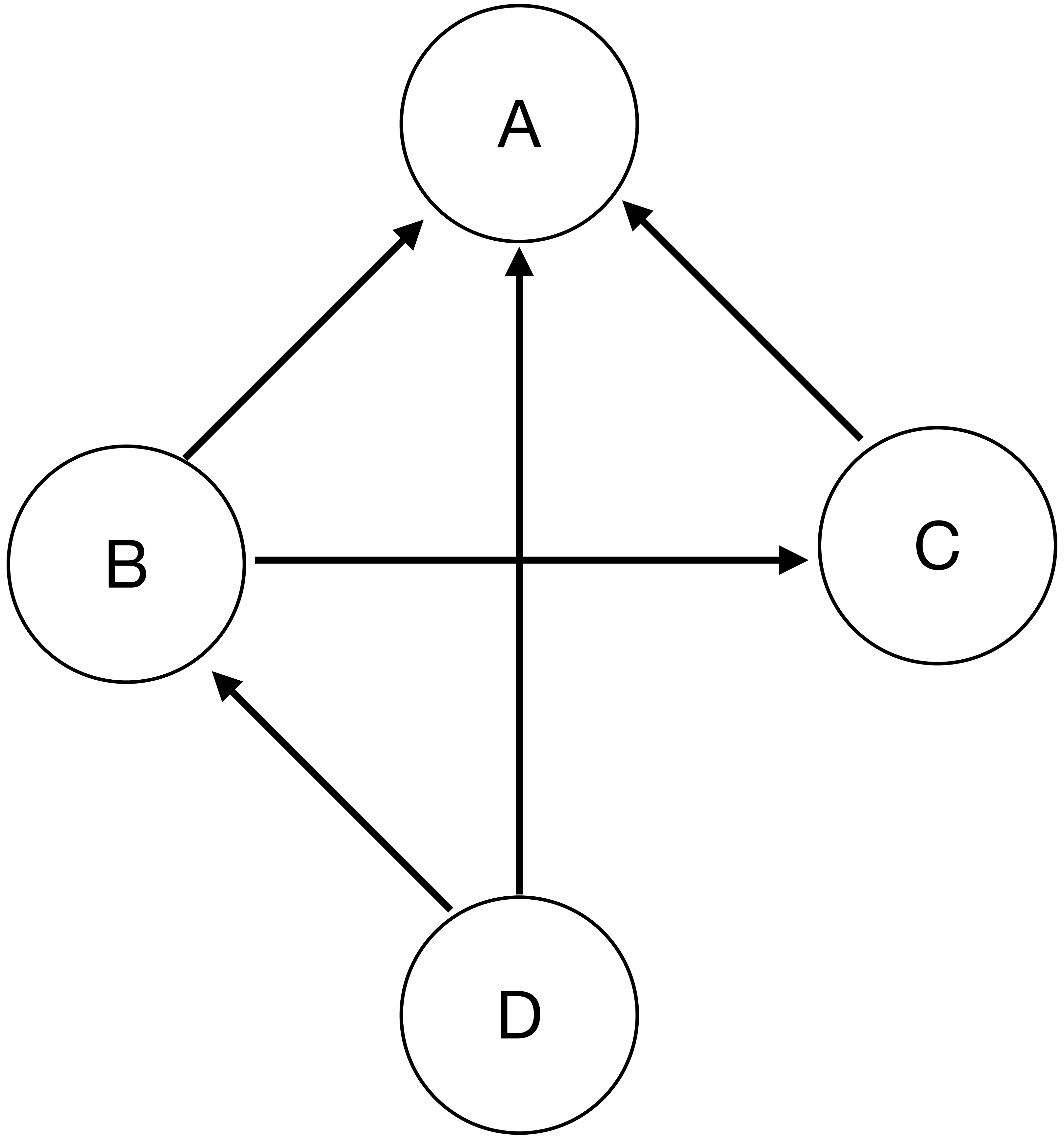
- An abstract representation of a set of objects where some pairs are connected by links.

Object (Vertex, Node)

Link (Edge, Arc, Relationship)

[M. De Marzi, 2012]

What is a Graph?

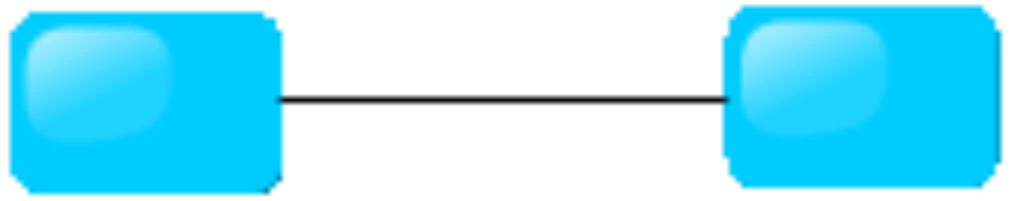


- In computing, a **graph** is an abstract **data structure** that represents set objects and their relationships as **vertices** and **edges/links**, and supports a number of graph-related **operations**
- Objects (nodes): `{A,B,C,D}`
- Relationships (edges): `{(D,B),(D,A),(B,C),(B,A),(C,A)}`
- Operation: shortest path from `D` to `A`

[K. Salama, 2016]

Different Kinds of Graphs

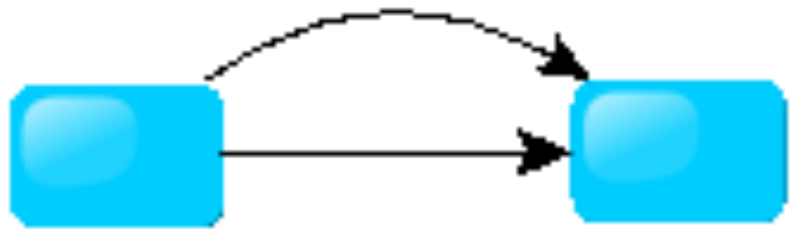
- Undirected Graph



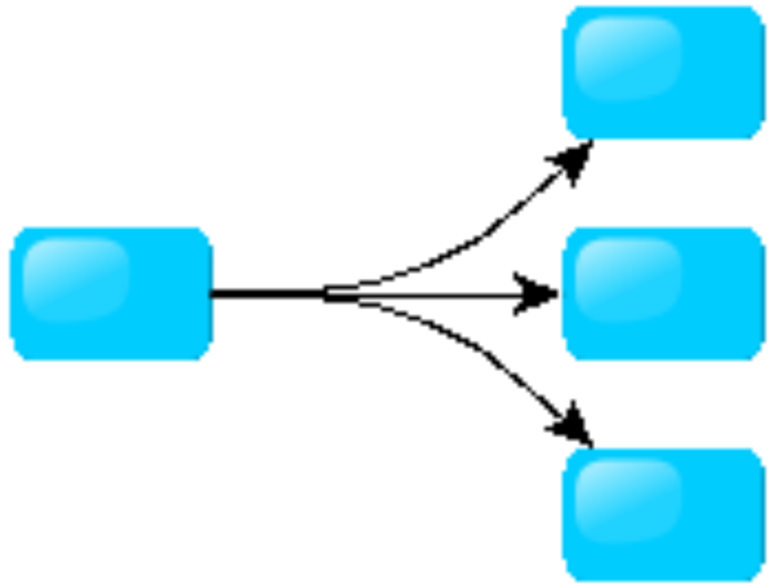
- Directed Graph

- Pseudo Graph

- Multi Graph



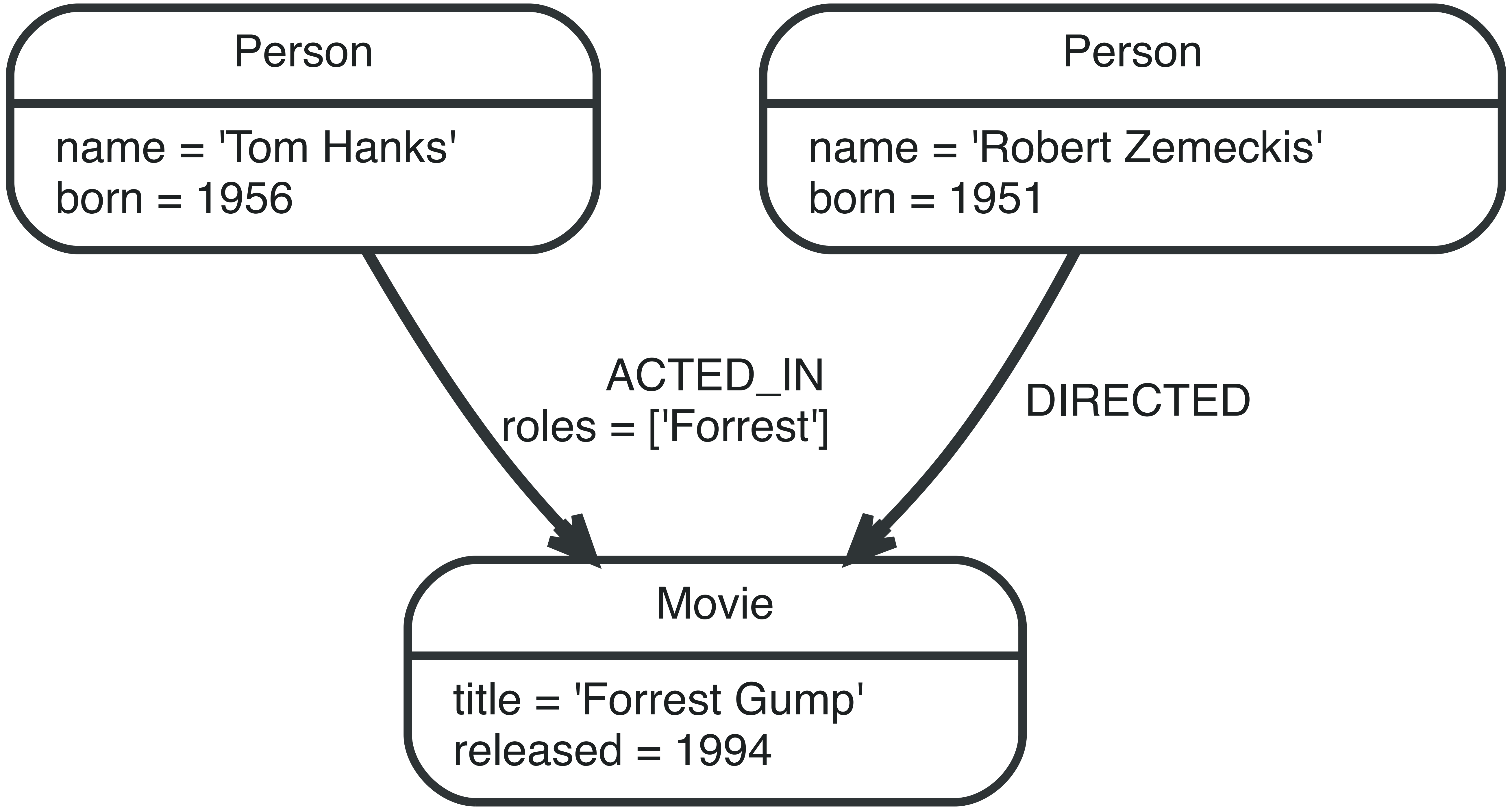
- Hyper Graph



[M. De Marzi, 2012]

Graphs with Properties

- Each vertex or edge may have properties associated with it
- May include identifiers or classes



[neo4j]

Types of Graph Operations

- Connectivity Operations:
  - number of vertices/edges, in- and out-degrees of vertices
  - histogram of degrees can be useful in comparing graphs
- Path Operations: cycles, reachability, shortest path, minimum spanning tree
- Community Operations: clusters (cohesion and separation)
- Centrality Operations: degree, vulnerability, PageRank
- Pattern Matching: subgraph isomorphism
  - can use properties
  - useful in fraud/threat detection, social network suggestions

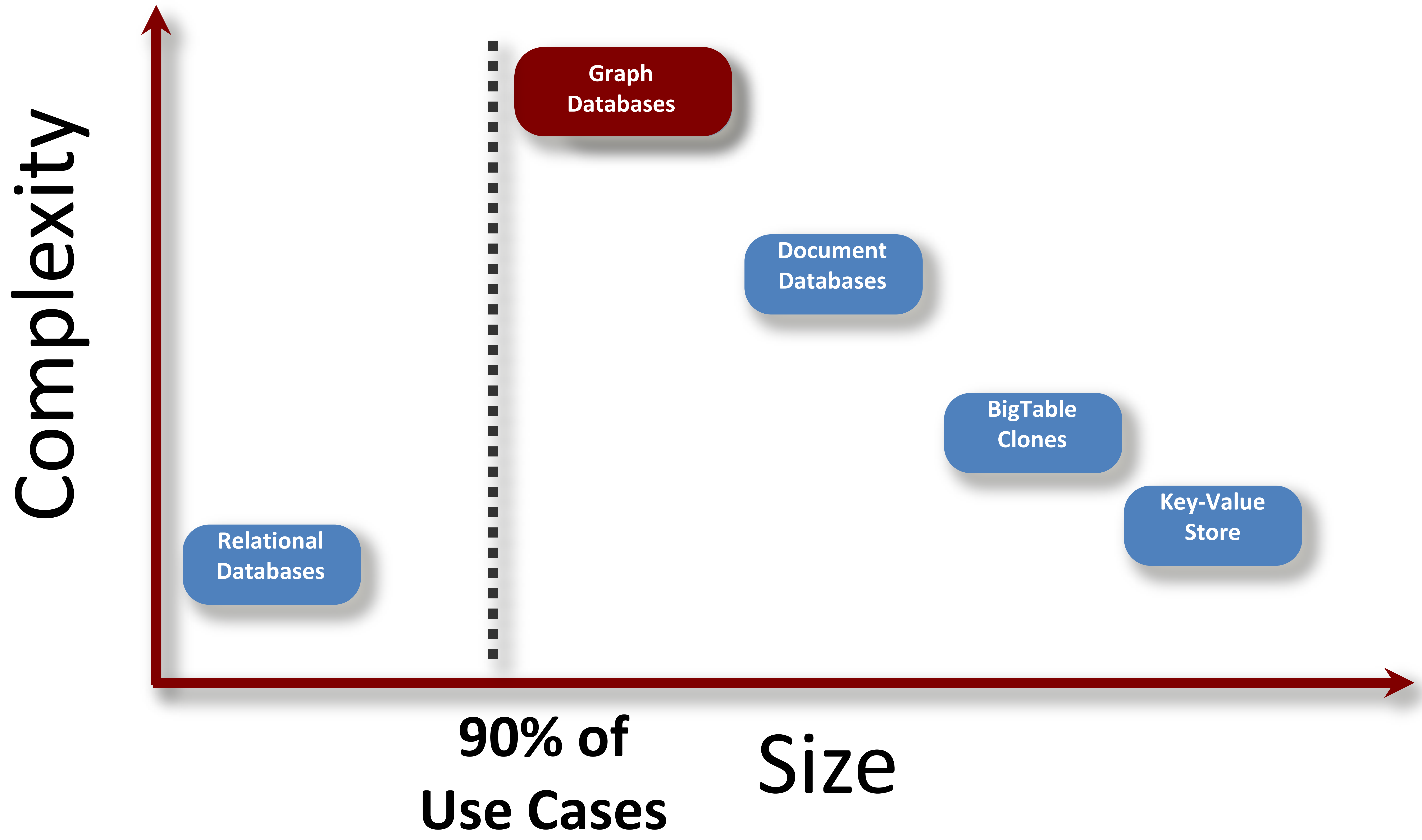
[K. Salama, 2016]

What is a Graph Database?

- A database with an explicit graph structure
- Each node knows its adjacent nodes
- As the number of nodes increases, the cost of a local step (or hop) remains the same
- Plus an Index for lookups

[M. De Marzi, 2012]

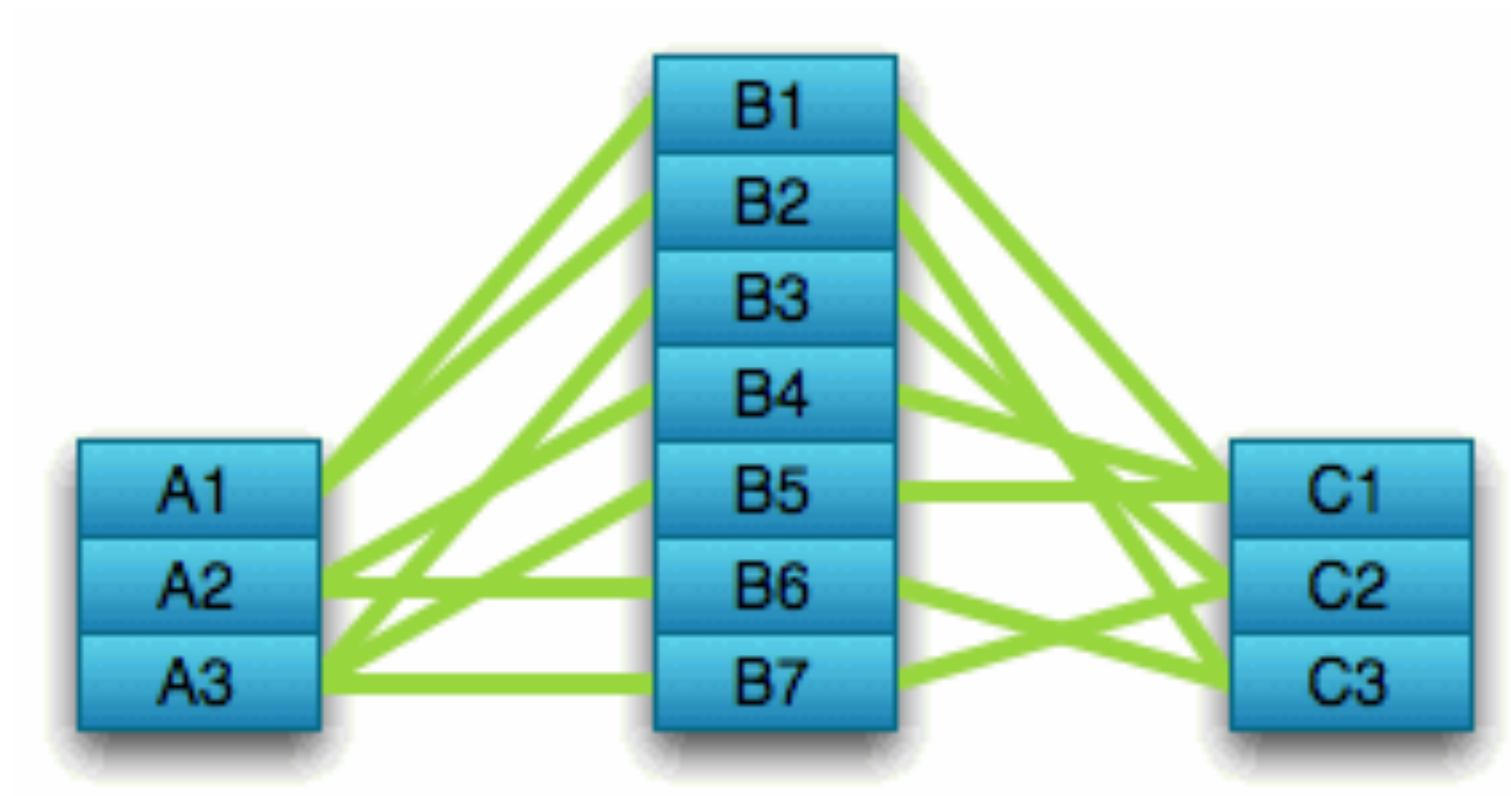
How do Graph Databases Compare?



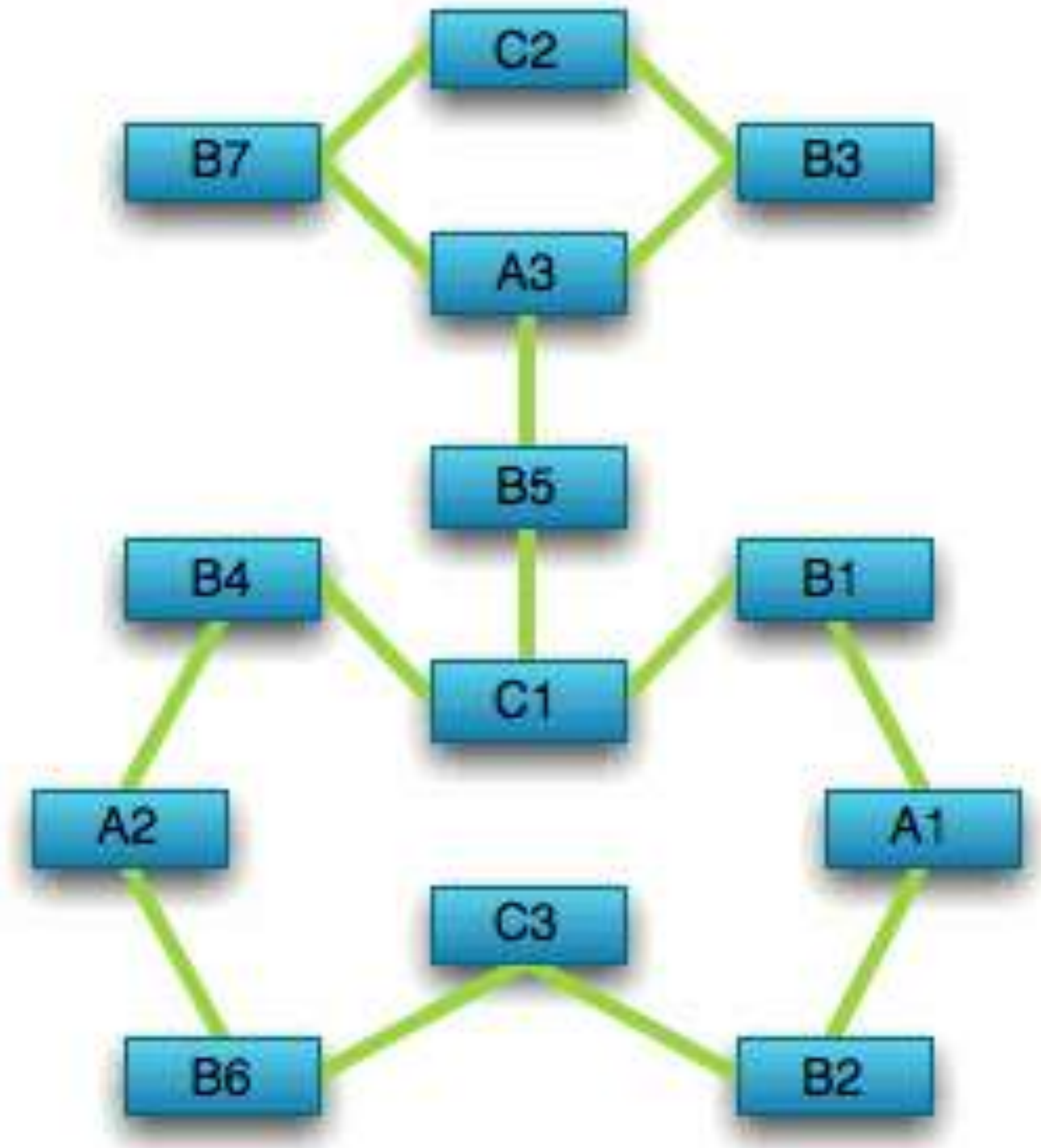
[M. De Marzi, 2012]

Graph Databases Compared to Relational Databases

Optimized for aggregation



Optimized for connections

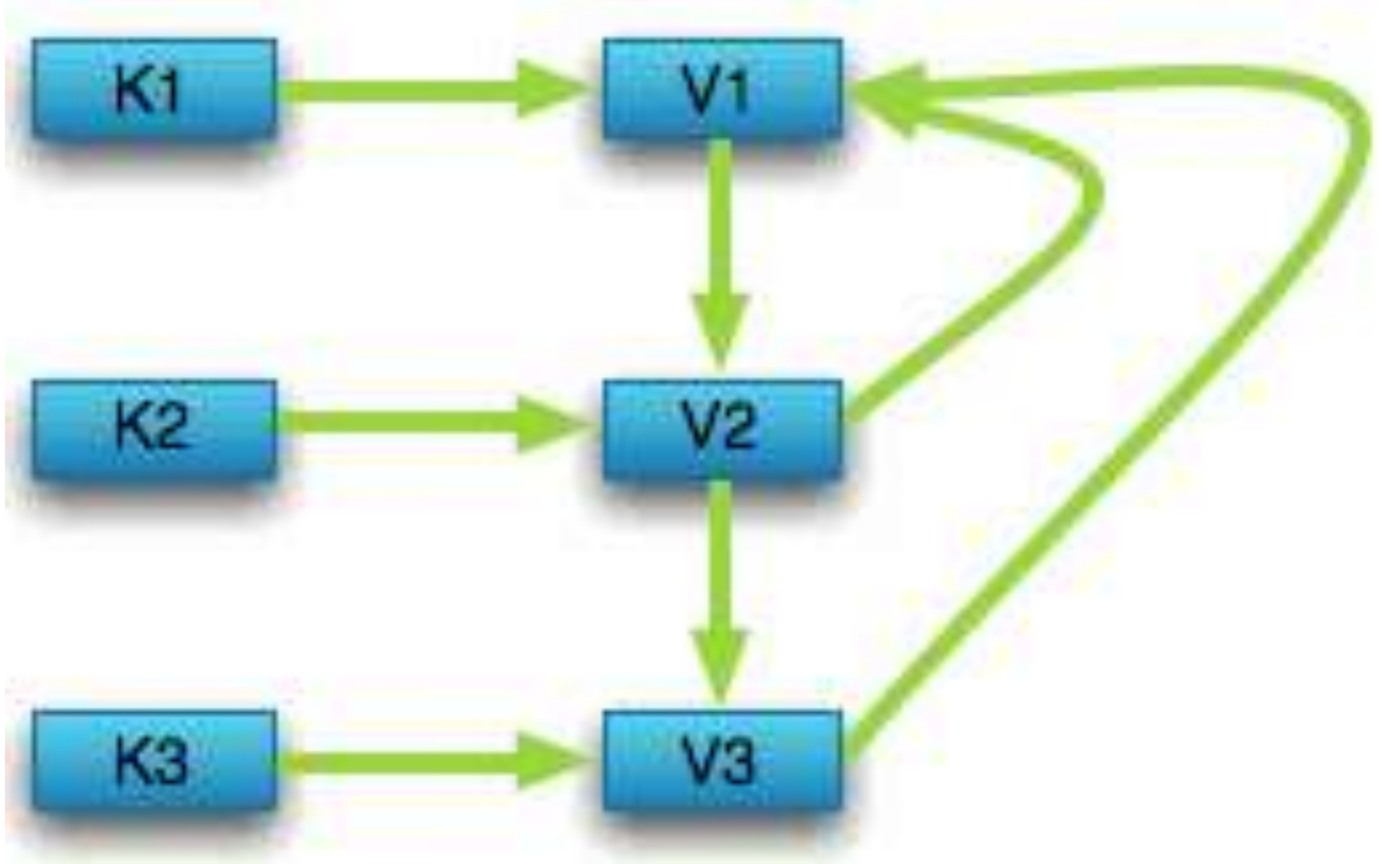


[M. De Marzi, 2012]

Graph Databases Compared to Key-Value Stores

Optimized for simple look-ups

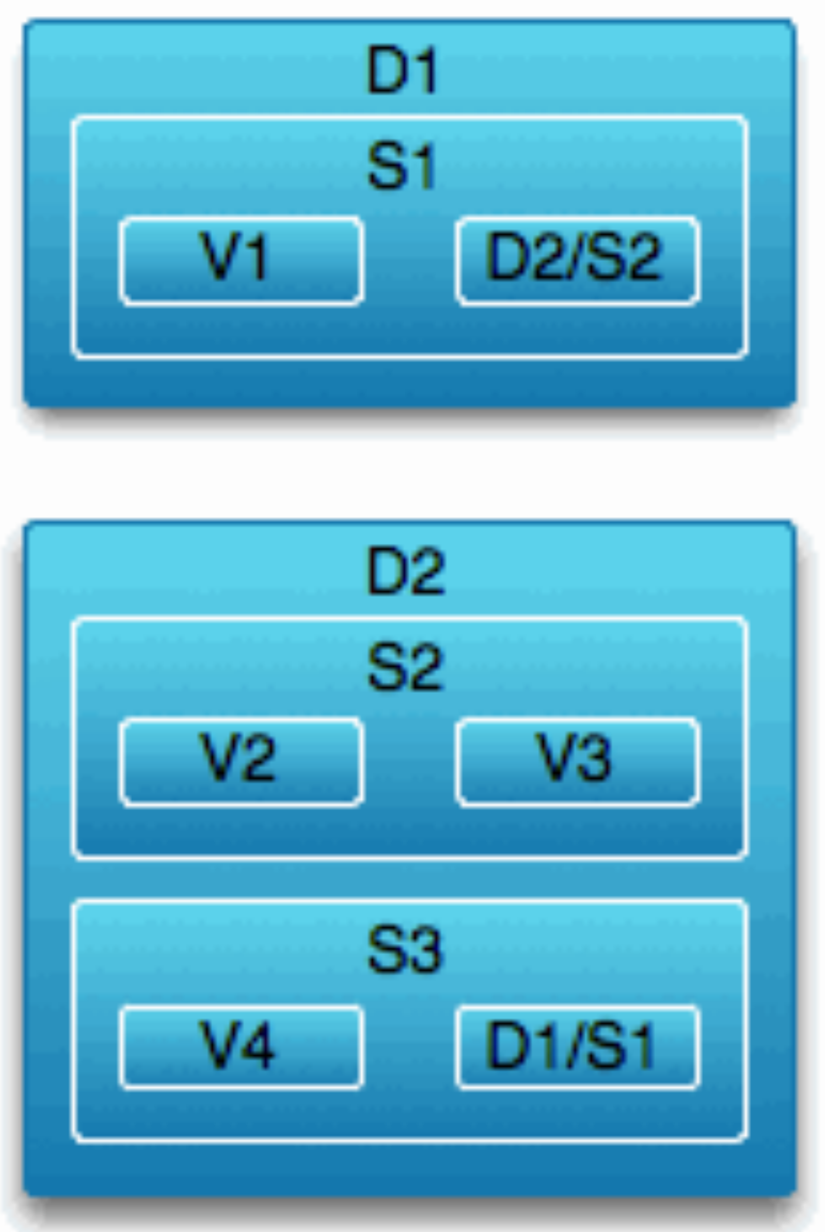
Optimized for traversing connected data



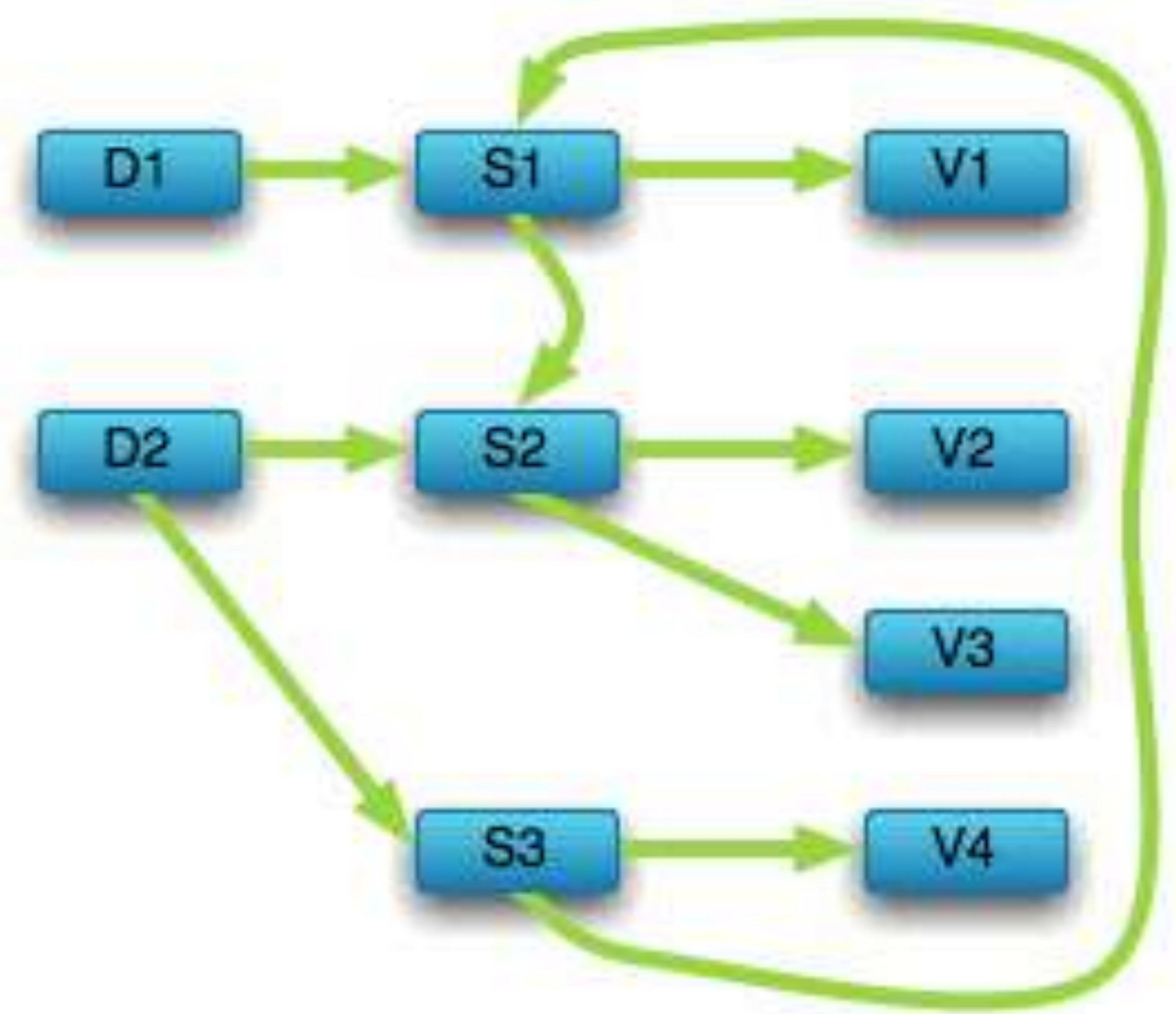
[M. De Marzi, 2012]

Graph Databases Compared to Document Stores

Optimized for "trees" of data



Optimized for seeing the forest and the trees, and the branches, and the trunks



[M. De Marzi, 2012]

The Ubiquity of Large Graphs and Surprising Challenges of Graph Processing

S. Sahu, A. Mhedhbi, S. Salihoglu, J. Lin, and M. T. Özsu

The Future is Big Graphs

S. Sakr et al

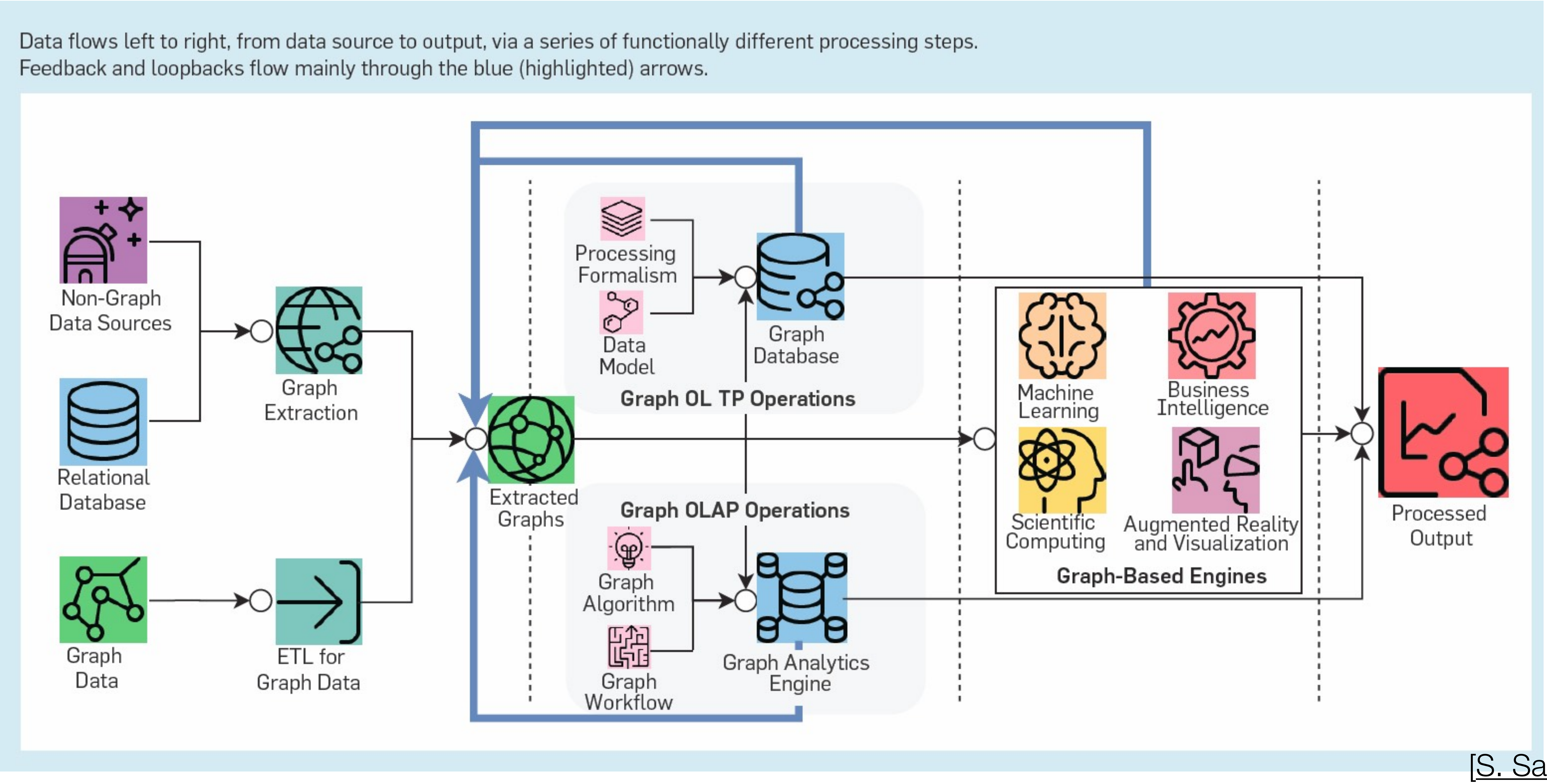
CACM

Insights for the Future of Graph Processing

- Graphs are ubiquitous abstractions enabling reusable computing tools for graph processing with applications in every domain.
- Diverse workloads, standard models and languages, algebraic frameworks, and suitable and reproducible performance metrics will be at the core of graph processing ecosystems in the next decade.

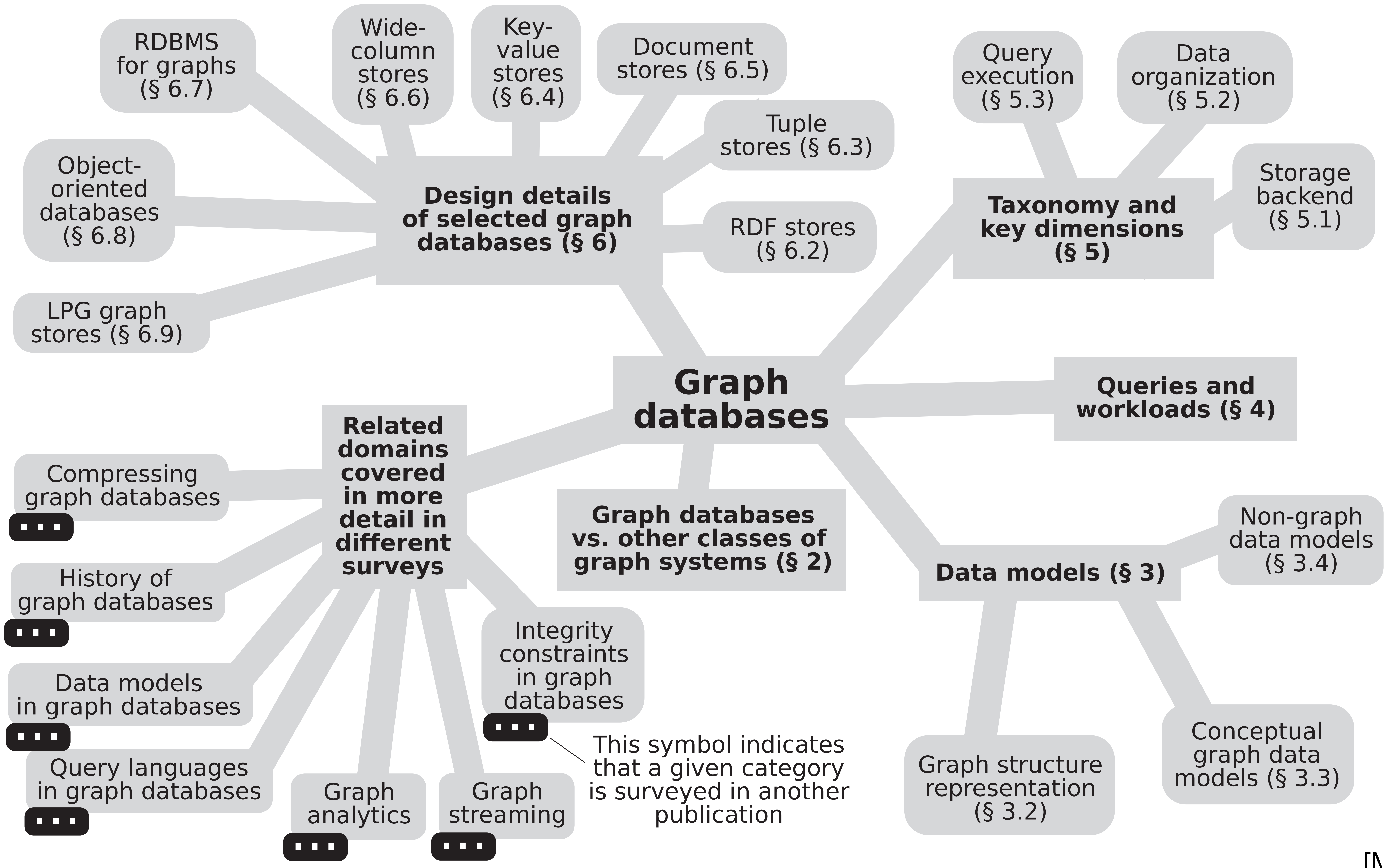
[S. Sakr et al.]

Pipeline for Graph Processing



[S. Sakr et al.]

Graph Databases Landscape



[M. Besta et al., 2024]

Why Graph Database Models?

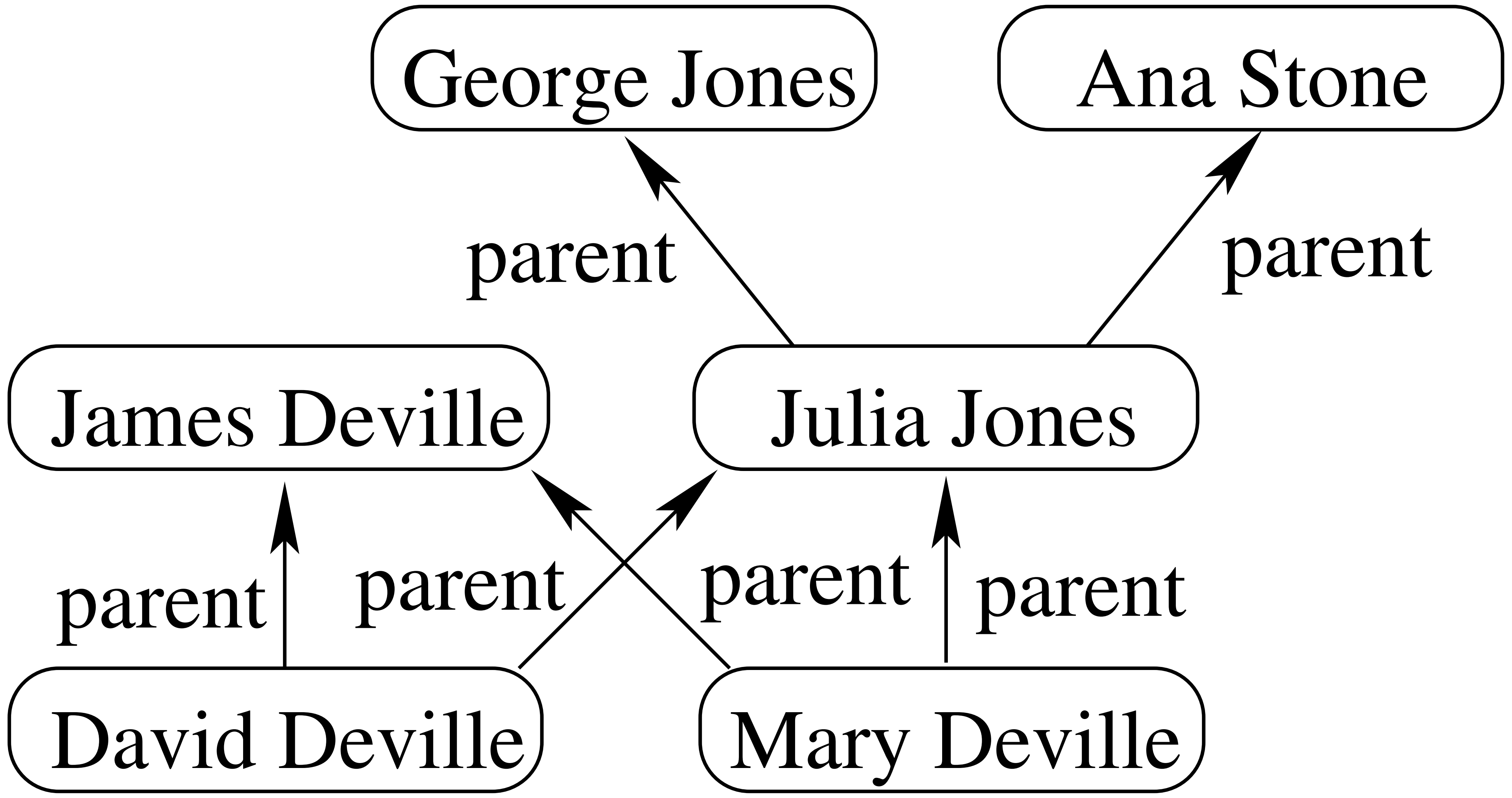
- Graphs has been long ago recognized as one of the most simple, natural and intuitive knowledge representation systems
- Graph data structures allow for a natural modeling when data has graph structure
- Queries can address direct and explicitly this graph structure
- Implementation-wise, graph databases may provide special graph storage structures, and take advantage of efficient graph algorithms available for implementing specific graph operations over the data

[R. Angles and C. Gutierrez, 2017]

Relational Model

NAME	LASTNAME
George	Jones
Ana	Stone
Julia	Jones
James	Deville
David	Deville
Mary	Deville

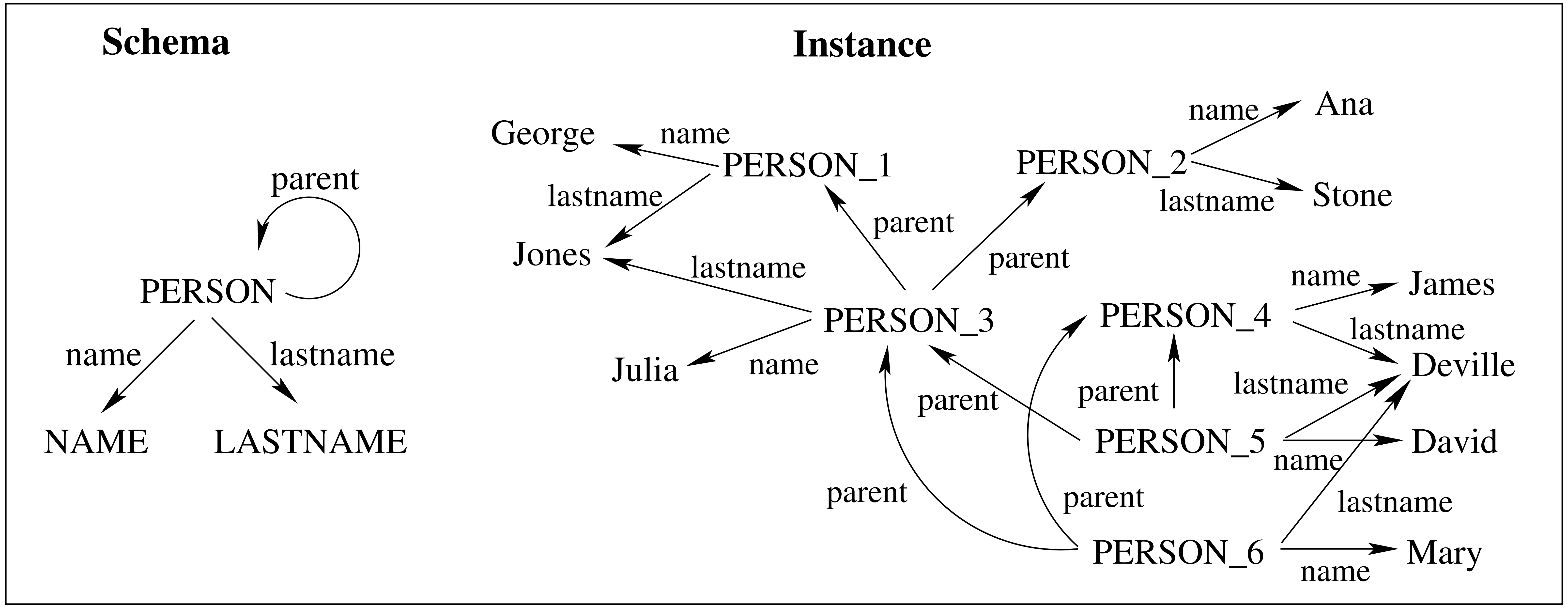
PERSON	PARENT
Julia	George
Julia	Ana
David	James
David	Julia
Mary	James
Mary	Julia



[R. Angles and C. Gutierrez, 2017]

Basic Labeled Model (Gram)

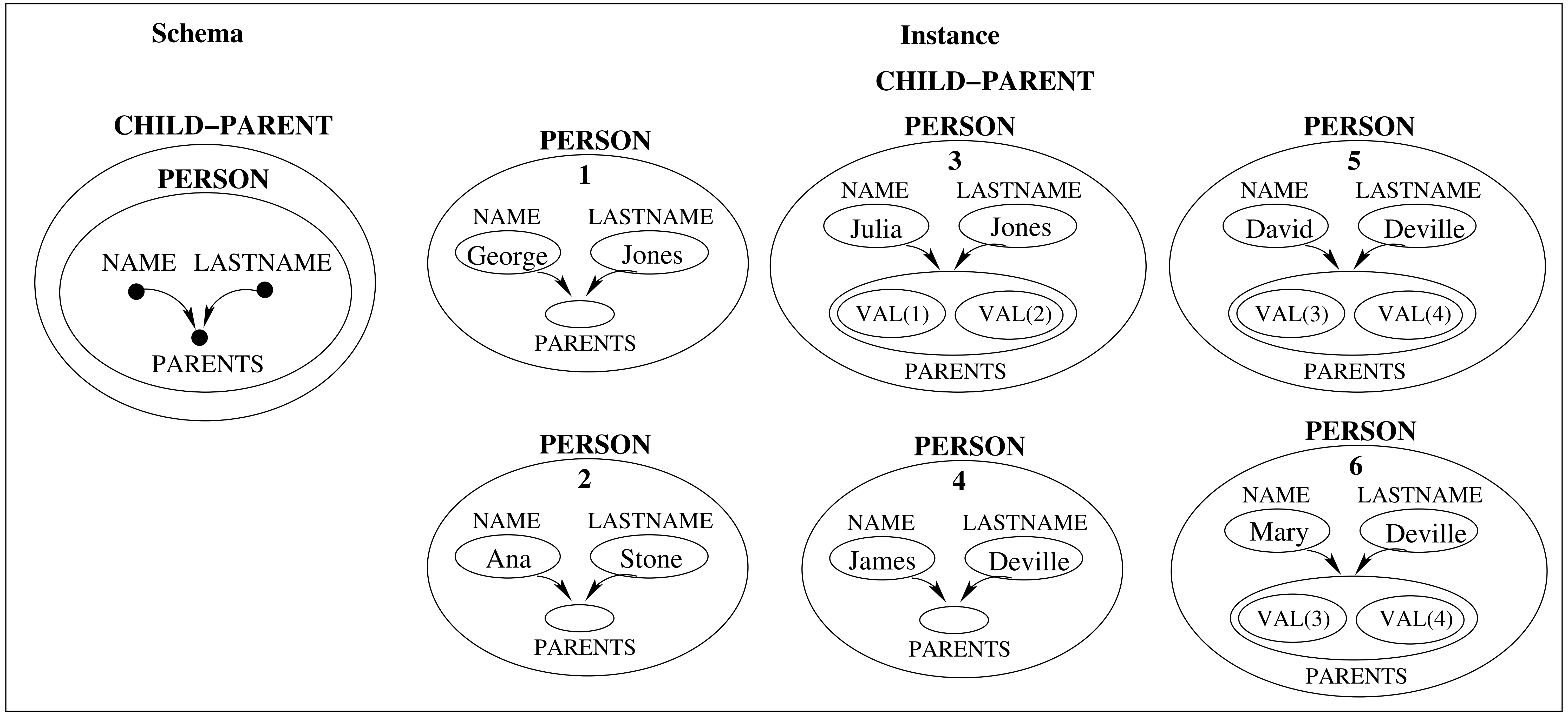
- Directed graph with nodes and edges labeled by some vocabulary
- Gram is a directed labeled multigraph
  - Each node is labeled with a symbol called a **type**
  - Each edge has assigned a label representing a **relation** between types



[R. Angles and C. Gutierrez, 2017]

Hypergraph Model (Groovy)

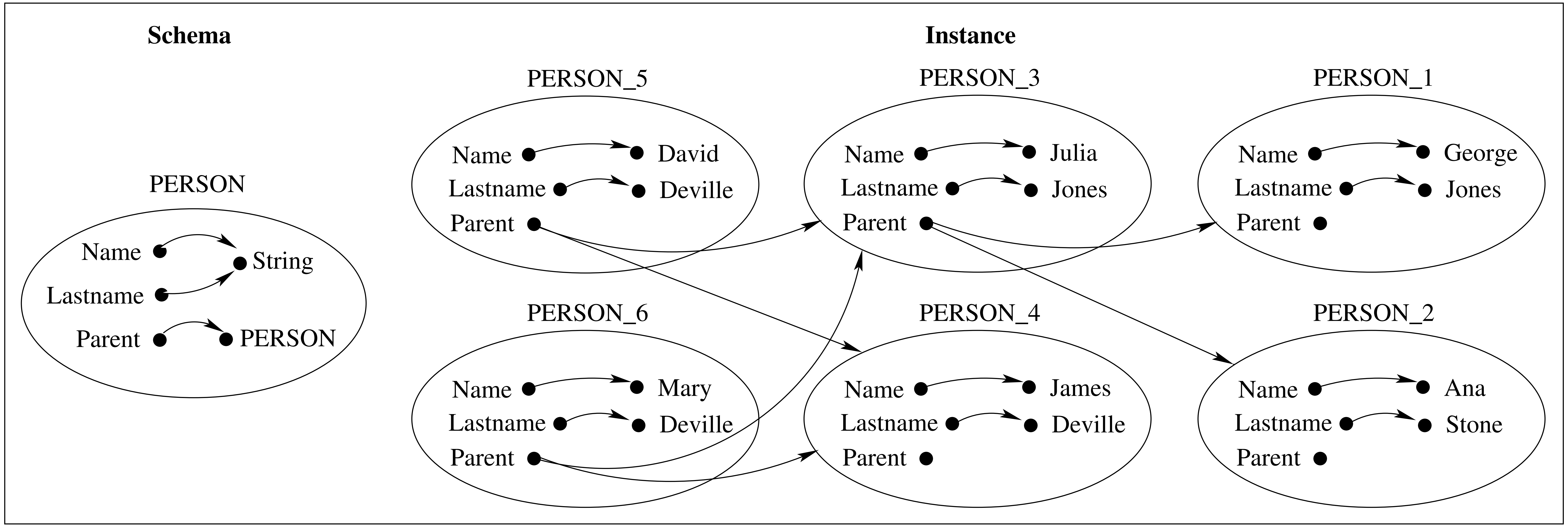
- Notion of edge is extended to **hyperedge**, which relates an arbitrary set of nodes
- Hypergraphs allow the definition of complex objects (undirected), functional dependencies (directed), object-ID and (multiple) structural inheritance



[R. Angles and C. Gutierrez, 2017]

Hypernode Model

- Hypernode is a directed graph whose nodes can themselves be graphs (or hypernodes), allowing **nesting** of graphs
- **Encapsulates** information



[R. Angles and C. Gutierrez, 2017]

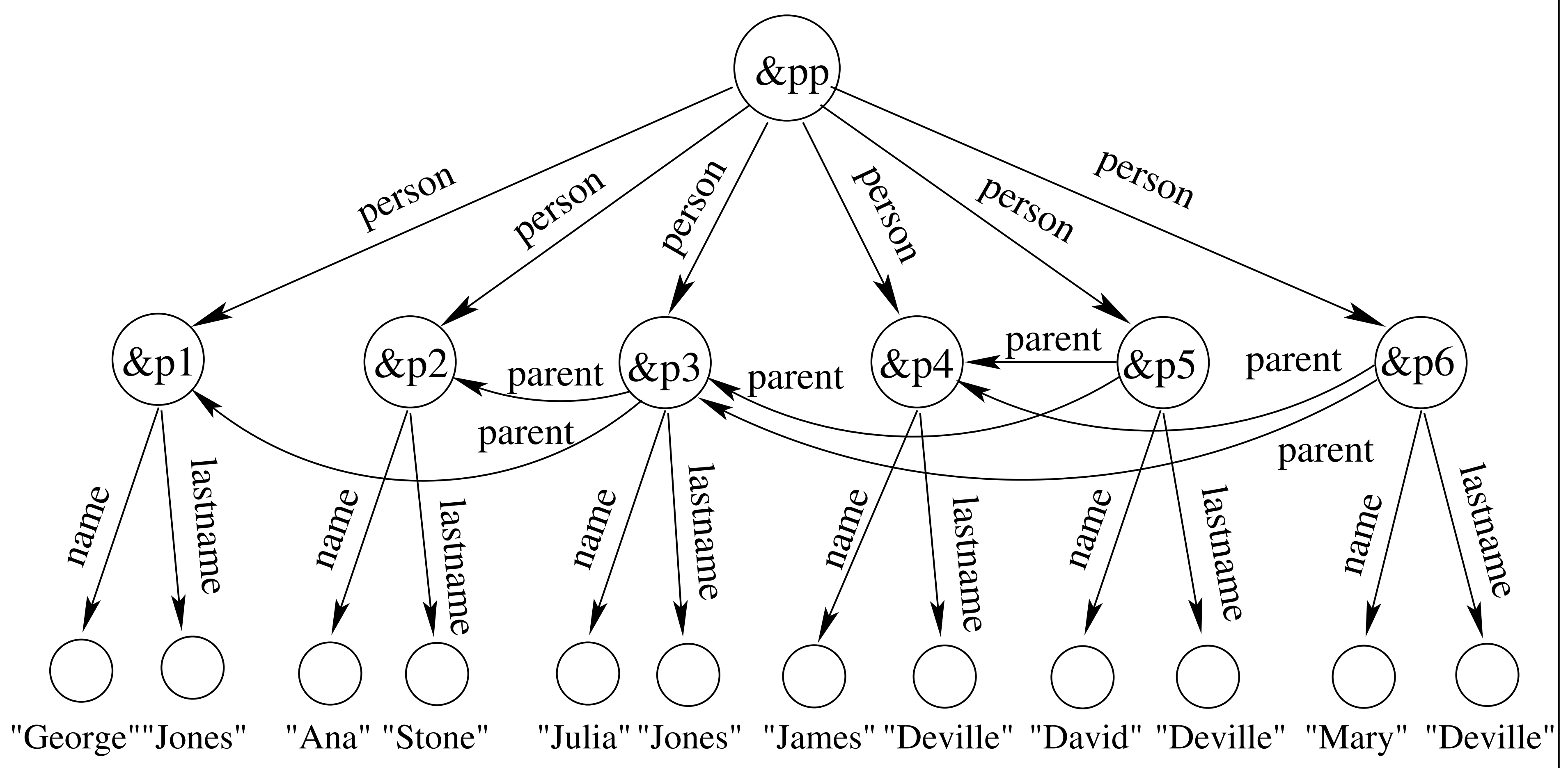
Semistructured (Tree) Model: (OEM Graph)

- "Self-describing" data like JSON and XML
- OEM uses pointers to data in the tree

OEM Syntax

```
{ person : &p1 { name : "George" ,
                 lastname : "Jones" }
  person : &p2 { name : "Ana" ,
                 lastname : "Stone" }
  person : &p3 { name : "Julia" ,
                 lastname : "Jones" ,
                 parent : &p1 ,
                 parent : &p2 }
  person : &p4 { name : "James" ,
                 lastname : "Deville" }
  person : &p5 { name = "David",
                 lastname : "Deville" ,
                 parent : &p3 ,
                 parent : &p4 }
  person : &p6 { name = "Mary" ,
                 lastname : "Deville" ,
                 parent : &p3 ,
                 parent : &p4 }  }
```

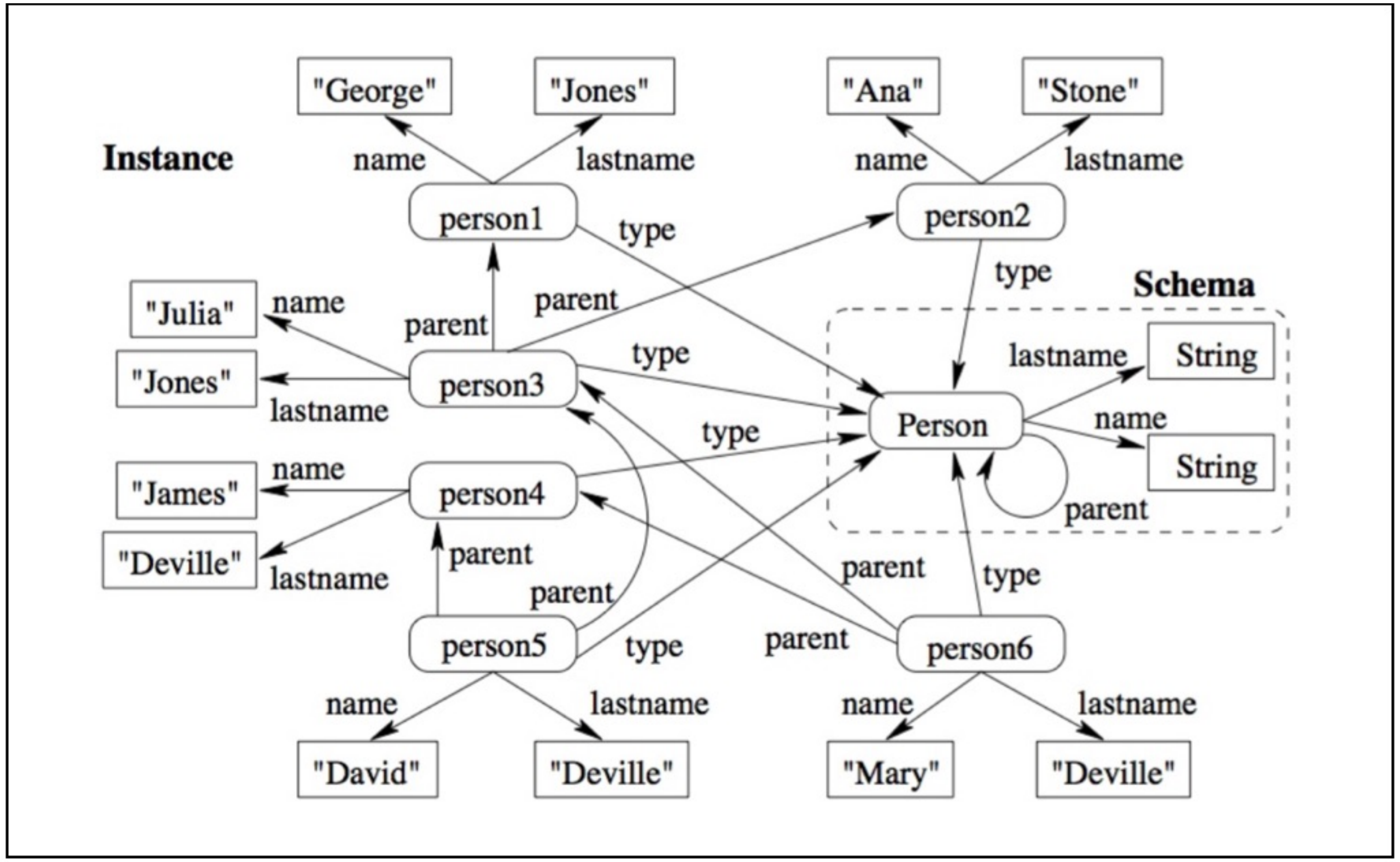
OEM Graph



[R. Angles and C. Gutierrez, 2017]

RDF (Triple) Model

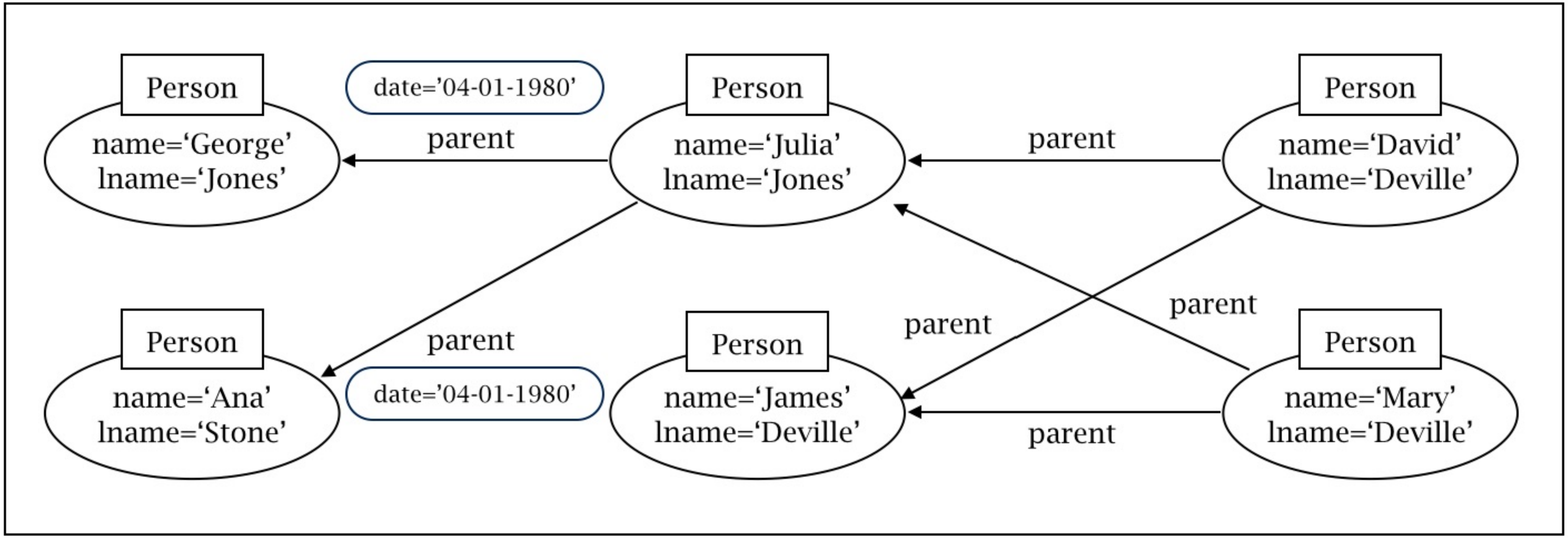
- Interconnect resources in an extensible way using graph-like structure for data
- Schema and instance are **mixed** together
- SPARQL to query
- Semantic web



[R. Angles and C. Gutierrez, 2017]

Property Graph Model (Cypher in neo4j)

- Directed, labelled, attributed multigraph
- Properties are **key/value pairs** that represent metadata for nodes and edges



[R. Angles and C. Gutierrez, 2017]

Types of Graph Queries

- Adjacency queries (neighbors or neighborhoods)
- Pattern matching queries (related to graph mining)
  - Graph patterns with structural extension or restrictions
  - Complex graph patterns
  - Semantic matching
  - Inexact matching
  - Approximate matching
- Reachability queries (connectivity)

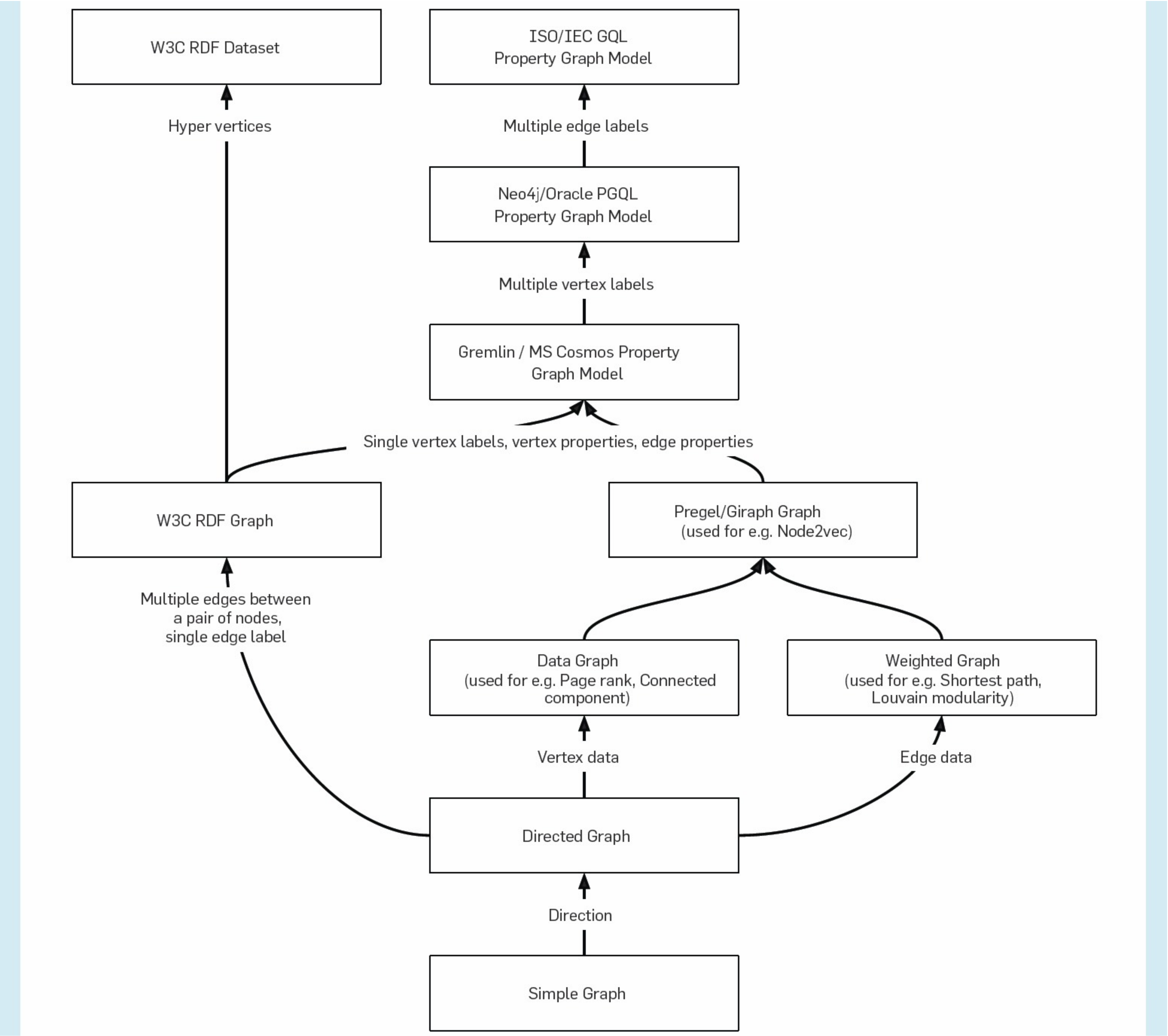
[R. Angles and C. Gutierrez, 2017]

Types of Graph Queries (continued)

- Analytical queries
  - Summarization queries
  - Complex analytical queries (PageRank, characteristic path length, connected components, community detection, clustering coefficient)

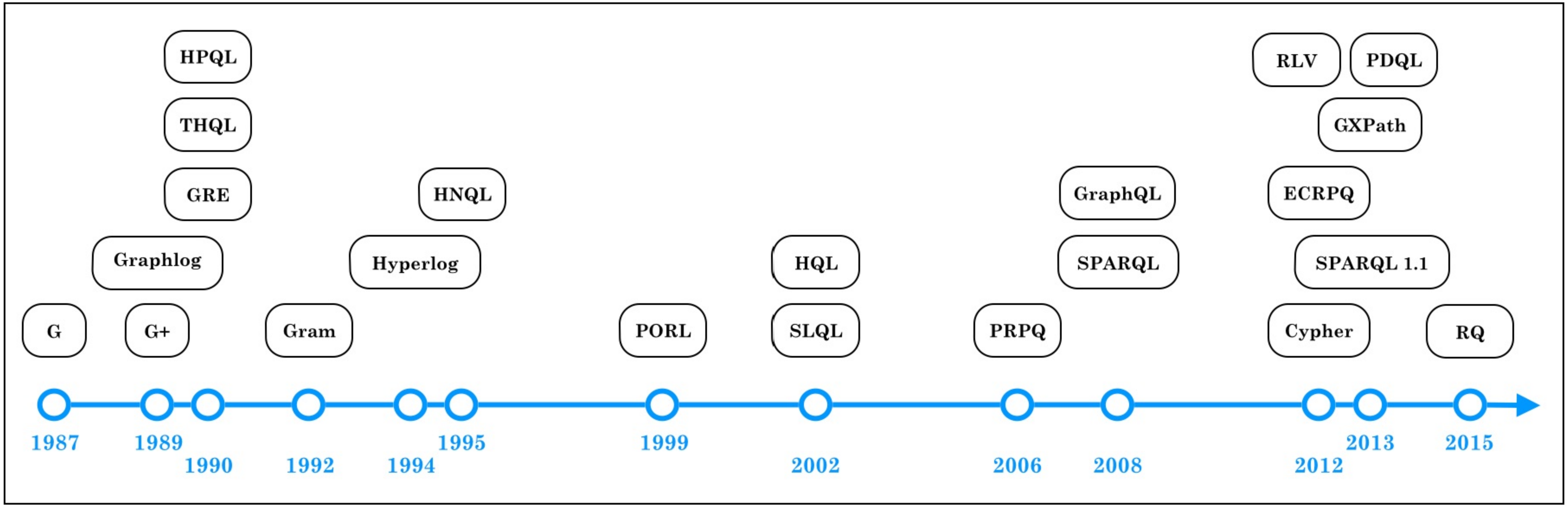
[R. Angles and C. Gutierrez, 2017]

Graph Structures



[S. Sakr et al.]

Graph Query Languages



[R. Angles and C. Gutierrez, 2017]

Cypher

- Implemented by neo4j system
- Expresses reachability queries via path expressions
  - `p = (a)-[:knows*]->(b)`: nodes from `a` to `b` following `knows` edges
- ```
  START x=node:person(name="John")
  MATCH (x)-[:friend]->(y)
  RETURN y.name
  ```

[R. Angles and C. Gutierrez, 2017]
  ```

SPARQL (RDF)

- Uses SELECT-FROM-WHERE pattern like SQL
- ```
  SELECT ?N
  FROM <http://example.org/data.rdf>
  WHERE { ?X rdf:type voc:Person . ?X voc:name ?N }
  ```

[R. Angles and C. Gutierrez, 2017]
  ```

Comparing Graph Database Systems: Features

Data Storage

Graph Database	Main memory	External memory	Backend Storage	Indexes
AllegroGraph	•	•		•
DEX	•	•		•
Filament	•		•	
G-Store		•		
HyperGraphDB	•	•	•	•
InfiniteGraph		•		•
Neo4j	•	•		•
Sones	•			•
vertexDB		•	•	

Operations/Manipulation

Graph Database	Data Definition Language	Data Manipulat. Language	Query Language	API	GUI
AllegroGraph	•	•	•	•	•
DEX				•	
Filament				•	
G-Store	•		•	•	
HyperGraphDB				•	
InfiniteGraph				•	
Neo4j				•	
Sones	•	•	•	•	•
vertexDB				•	

[R. Angles, 2012]

Comparing Graph Database Systems: Representation

Graph Data Structures

	Graphs				Nodes		Edges		
Graph Database	Simple graphs	Hypergraphs	Nested graphs	Attributed graphs	Node labeled	Node attribution	Directed	Edge labeled	Edge attribution
AllegroGraph	•				•		•	•	
DEX				•	•	•	•	•	•
Filament	•				•		•	•	
G-Store	•				•		•	•	
HyperGraphDB		•			•		•	•	
InfiniteGraph				•	•	•	•	•	•
Neo4j				•	•	•	•	•	•
Sones		•		•	•	•	•	•	•
vertexDB	•				•		•	•	

Entites & Relations

	Schema			Instance					
Graph Database	Node types	Property types	Relation types	Object nodes	Value nodes	Complex nodes	Object relations	Simple relations	Complex relations
AllegroGraph					•			•	
DEX	•		•	•	•		•	•	
Filament					•			•	
G-Store					•			•	
HyperGraphDB	•		•		•			•	•
InfiniteGraph	•		•	•	•		•	•	
Neo4j				•	•		•	•	
Sones					•			•	•
vertexDB					•			•	

[R. Angles, 2012]

Comparing Graph Database Systems: Queries

Query Support

	Type			Use		
Graph Database	Query Lang.	API	Graphical Q. L.	Retrieval	Reasoning	Analysis
AllegroGraph	○	●	●	●	●	●
DEX		●		●		●
Filament		●		●		
G-Store	●			●		
HyperGraphDB		●		●		
InfiniteGraph		●		●		
Neo4j	○	●		●		
Sones	●		●	●		●
vertexDB		●		●		

Types of Queries

	Adjacency		Reachability				
Graph Database	Node/edge adjacency	k-neighborhood	Fixed-length paths	Regular simple paths	Shortest path	Pattern matching	Summarization
Allegro	●		●			●	
DEX	●		●	●	●	●	
Filament	●		●			●	
G-Store	●		●	●	●	●	
HyperGraph	●					●	
Infinite	●		●	●	●	●	
Neo4j	●		●	●	●	●	
Sones	●					●	
vertexDB	●		●	●		●	

[R. Angles, 2012]

The (sorry) State of Graph Database Systems

Peter Boncz

Keynote, EDBT-ICDT 2022

The Future of Graph Data Processing

- Q1: Is there a demand for more expressive languages and libraries for analyzing relationships in a graph?
- Q2: Do we need OLAP/OLTP architectures or their hybrid version (HTAP for graphs) in order to execute graph analytical workloads? Is on cloud better than on premise?
- Q3: What are the requirements in terms of scalability, performance and benchmarking?
- Q4: Are graph-only stores sufficient or are polystores needed for the future of graph analytics?
- Q5: What is needed in terms of DSL and APIs for enabling graph analytics for data science and ML (and LLM) tasks?
- Q6: Since graphs are continuously evolving data structures, what is desirable in terms of analytical operators for dynamic, incremental and streaming graphs?

[A. Bonafati et al., 2025]

Expressiveness of Graph Languages

- Should support path queries and subgraph matching
- Difference between holistic analytics (entire graph) or online queries where only a portion of the graph is required?
- Levels:
  - Node: centrality, node similiarity
  - Path: graph traversal methods
  - Subgraph: community detection
  - Learning-oriented: node embedding, dynamic graph inference

[A. Bonafati et al., 2025]

Scalability

- Scale-up (vertical) and scale-out (horizontal) requirements: going to need scale-out for some datasets
- Graph databases can be huge in memory (much more than disk storage)
- Useful to have graph-specific benchmarks
- No one-size-fits-all solution

[A. Bonafati et al., 2025]