Database Systems
10 NoSQL Systems

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SCIENCE
PASSION
TECHNOLOGY

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Announcements/Org

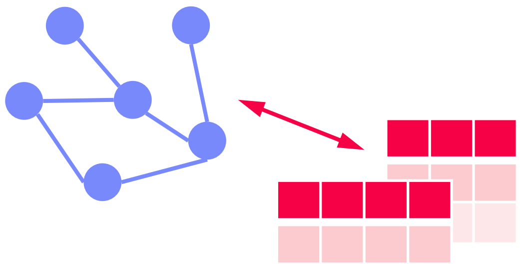
- **#1 Video Recording**
  - Since lecture 03, video/audio recording
  - Link in **TeachCenter** & **TUbe**
- **#2 Exercises**
  - **Exercise 1 graded**, feedback in TC, office hours
  - **Exercise 2 in progress of being graded**
  - Exercise 3 published, due Jun 04, 11.59pm
- **#3 Exam Dates**
  - **Jun 24, 4pm, HS i13**
  - **Jun 27, 4pm, HS i13**
  - **Jun 27, 7.30pm, HS i13**
  - Additional dates for repetition (beginning of WS19)

Exam starts +10min, working time: 90min
(no lecture materials)

77.4%
60.4%

SQL vs NoSQL Motivation

- **#1 Data Models/Schema**
  - **Non-relational:** key-value, graph, doc, time series (logs, social media, documents/media, sensors)
  - Impedance mismatch / complexity
  - **Pay-as-you-go/schema-free** (flexible/implicit)



- **#2 Scalability**
  - Scale-up vs simple scale-out
  - Horizontal partitioning (sharding) and scaling
  - **Commodity hardware, network, disks** ($)

- **NoSQL Evolution**
  - Late 2000s: Non-relational, distributed, open source DBMSs
  - Early 2010s: NewSQL: modern, distributed, relational DBMSs
  - Not Only SQL: combination with relational techniques

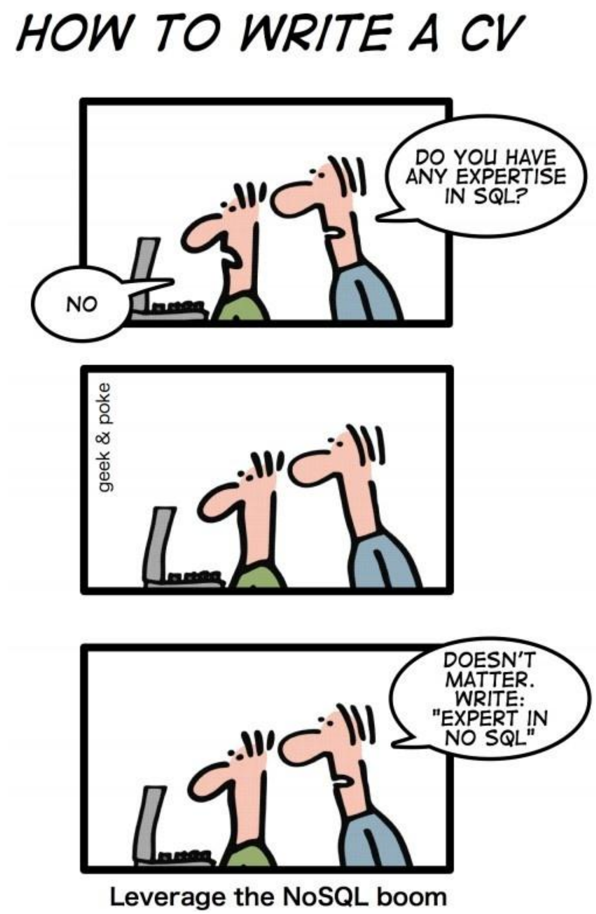
  ➔ **RDBMS and specialized systems** (consistency/data models)

[**Credit:** http://nosql-database.org/]

Agenda

- **Consistency and Data Models**
- **Key-Value Stores**
- **Document Stores**
- **Graph Processing**
- **Time Series Databases**

Lack of standards and **imprecise classification**



[Wolfram Wingerath, Felix Gessert, Norbert Ritter: NoSQL & Real-Time Data Management in Research & Practice. **BTW 2019**]

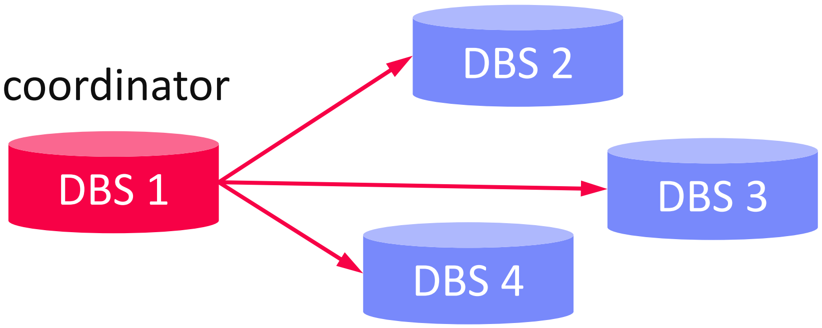
Consistency and Data Models

Recap: ACID Properties

- **Atomicity**
  - A transaction is executed atomically (**completely or not at all**)
  - If the transaction fails/aborts no changes are made to the database (**UNDO**)
- **Consistency**
  - A successful transaction ensures that all **consistency constraints are met** (referential integrity, semantic/domain constraints)
- **Isolation**
  - Concurrent transactions are executed in isolation of each other
  - **Appearance of serial transaction execution**
- **Durability**
  - **Guaranteed persistence** of all changes made by a successful transaction
  - In case of system failures, the database is recoverable (**REDO**)

Two-Phase Commit (2PC) Protocol

- **Distributed TX Processing**
  - N nodes with logically related but physically distributed data (e.g., vertical data partitioning)
  - **Distributed TX processing to ensure consistent view** (atomicity/durability)
- **Two-Phase Commit** (via 2N msgs)
  - **Phase 1 PREPARE:** check for successful completion, logging
  - **Phase 2 COMMIT:** release locks, and other cleanups
  - **Problem: Blocking protocol**



- **Excursus: Wedding Analogy**
  - Coordinator: marriage registrar
  - **Phase 1:** Ask for willingness
  - **Phase 2:** If all willing, declare marriage

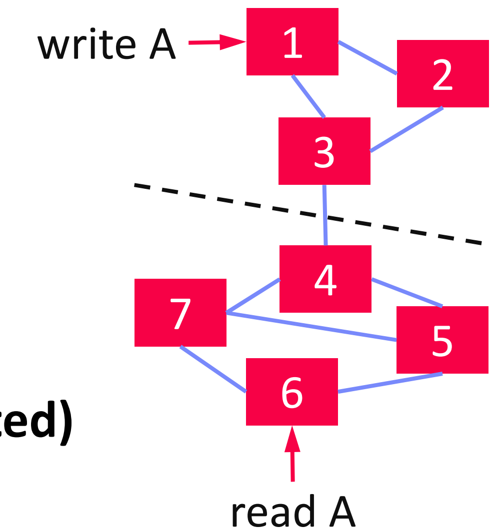
CAP Theorem

- **Consistency**
  - **Visibility of updates** to distributed data (atomic or linearizable consistency)
  - Different from ACIDs consistency in terms of integrity constraints
- **Availability**
  - **Responsiveness** of a services (clients reach available service, **read/write**)
- **Partition Tolerance**
  - Tolerance of temporarily **unreachable network partitions**
  - System characteristics (e.g., latency) maintained
- **CAP Theorem** ***"You can have AT MOST TWO of these properties for a networked shared-data systems."***
- **Proof**

[Eric A. Brewer: Towards robust distributed systems (abstract). **PODC 2000**]

[Seth Gilbert, Nancy A. Lynch: Brewer's conjecture and the feasibility of consistent, available, partition-tolerant web services. **SIGACT News 2002**]

CAP Theorem, cont.



- **CA: Consistency & Availability (ACID single node)**
  - Network partitions cannot be tolerated
  - Visibility of updates (**consistency**) in conflict with **availability** ➔ **no distributed systems**

- **CP: Consistency & Partition Tolerance (ACID distributed)**
  - Availability cannot be guaranteed
  - **On connection failure, unavailable** (wait for overall system to become consistent)

- **AP: Availability & Partition Tolerance (BASE)**
  - Consistency cannot be guaranteed, use of optimistic strategies
  - Simple to implement, main concern: availability to ensure revenue ($$$)

  ➔ **BASE consistency model**

BASE Properties

- **Basically Available**
  - **Major focus on availability**, potentially with outdated data
  - No guarantee on global data consistency across entire system
- **Soft State**
  - Even without explicit state updates, the **data might change** due to asynchronous propagation of updates and nodes that become available
- **Eventual Consistency**
  - Updates eventually propagated, system would reach consistent state if no further updates, and network partitions fixed
  - No temporal guarantees on changes are propagated

Eventual Consistency

[Peter Bailis, Ali Ghodsi: Eventual consistency today: limitations, extensions, and beyond. **Commun. ACM 2013**]

- **Basic Concept**
  - Changes made to a copy eventually migrate to all
  - If update activity stops, replicas will **converge to a logically equivalent state**
  - **Metric:** time to reach consistency (probabilistic bounded staleness)

Amazon SimpleDB	500ms
Cassandra	200ms
Amazon S3	12s

- **#1 Monotonic Read Consistency**
  - After reading data object A, the client never reads an older version
- **#2 Monotonic Write Consistency**
  - After writing data object A, it will never be replaced with an other version
- **#3 Read Your Own Writes / Session Consistency**
  - After writing data object A, a client never reads an older version
- **#4 Causal Consistency**
  - If client 1 communicated to client 2 that data object A has been updated, subsequent reads on client 2 return the new value

Key-Value Stores

Motivation and Terminology

- **Motivation**
  - **Basic key-value mapping via simple API** (more complex data models can be mapped to key-value representations)
  - **Reliability at massive scale on commodity HW** (cloud computing)

- **System Architecture**
  - **Key**-value maps, where values can be of a variety of data types
  - APIs for CRUD operations (create, read, update, delete)
  - Scalability via sharding (horizontal partitioning)

users:1:a	“Inffeldgasse 13, Graz”
users:1:b	“[12, 34, 45, 67, 89]”
users:2:a	“Mandellstraße 12, Graz”
users:2:b	“[12, 212, 3212, 43212]”

- **Example Systems**
  - **Dynamo** (2007, AP) → **Amazon DynamoDB** (2012)
  - **Redis** (2009, CP/AP)

[Giuseppe DeCandia et al: Dynamo: amazon's highly available **key-value store**. **SOSP 2007**]

Example Systems

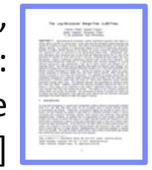
- **Redis Data Types**
  - Redis is not a plain KV-store, but “data structure server” with persistent log (**appendfsync no/everysec/always**)
  - **Key:** ASCII string (max 512MB, common key schemes: comment:1234:reply.to)
  - **Values:** strings, lists, sets, sorted sets, hashes (map of string-string), etc

- **Redis APIs**
  - **SET/GET/DEL:** insert a key-value pair, lookup value by key, or delete by key
  - **MSET/MGET:** insert or lookup multiple keys at once
  - **INCRBY/DECBY:** increment/decrement counters
  - Others: EXISTS, LPUSH, LPOP, LRANGE, LTRIM, LLEN, etc

- **Other systems**
  - Classic KV stores (AP): **Riak**, **Aerospike**, **Voldemort**, **LevelDB**, **RocksDB**, **FoundationDB**, **Memcached**
  - Wide-column stores: **Google BigTable** (CP), **Apache HBase** (CP), **Apache Cassandra** (AP)

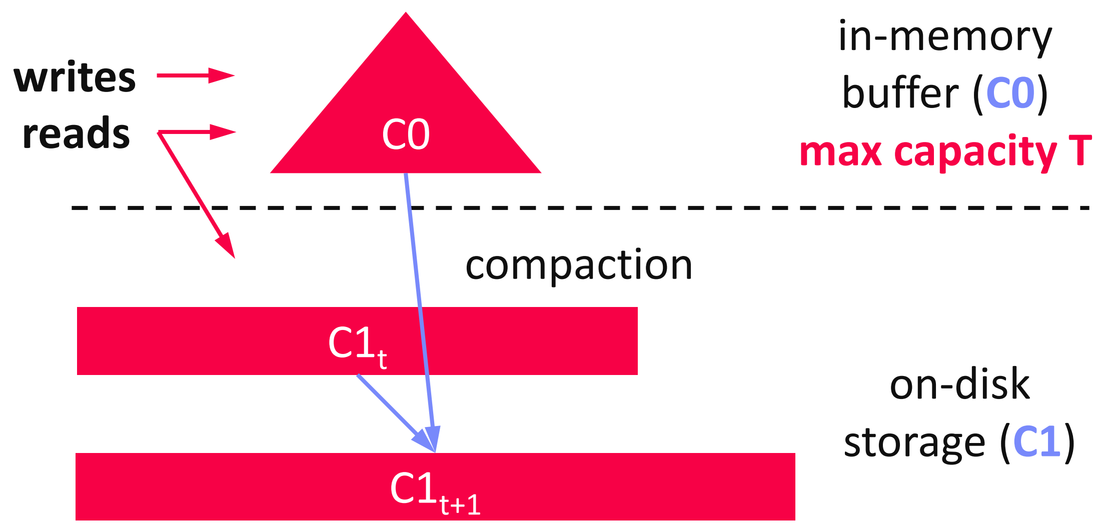
Log-structured Merge Trees

[Patrick E. O'Neil, Edward Cheng, Dieter Gawlick, Elizabeth J. O'Neil: The Log-Structured Merge-Tree (LSM-Tree). **Acta Inf. 1996**]



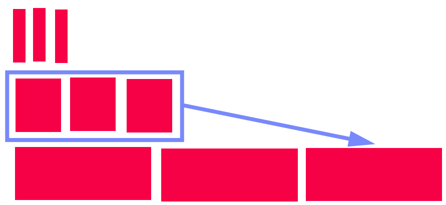
- **LSM Overview**
  - Many KV-stores rely on LSM-trees as their storage engine (e.g., **BigTable**, **DynamoDB**, **LevelDB**, **Riak**, **RocksDB**, **Cassandra**, **HBase**)
  - **Approach:** Buffers writes in memory, flushes data as sorted runs to storage, merges runs into larger runs of next level (compaction)

- **System Architecture**
  - Writes in C0
  - Reads against C0 and C1
  - Compaction (rolling merge): sort, merge, including **deduplication**

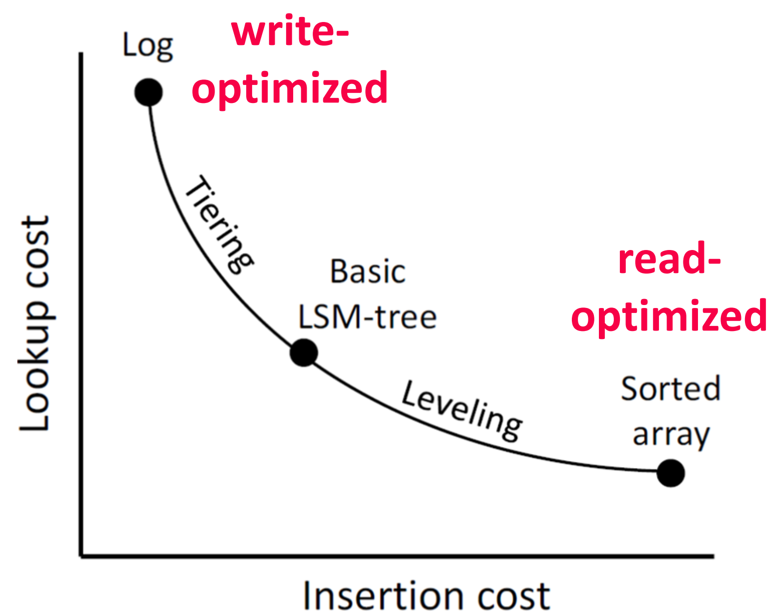


Log-structured Merge Trees, cont.

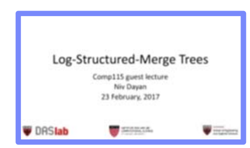
- **LSM Tiering**
  - Keep up to T-1 runs per level L
  - Merge all runs of L_i into 1 run of L_{i+1}
    - L1
    - L2
    - L3



- **LSM Leveling**
  - Keep 1 run per level L
  - Merge run of Li with Li+1
    - L1
    - L2
    - L3



[Niv Dayan: Log-Structured-Merge Trees, **Comp115 guest lecture, 2017**]



Document Stores

Recap: JSON (JavaScript Object Notation)

- **JSON Data Model**
  - Data exchange format for **semi-structured data**
  - **Not as verbose as XML** (especially for arrays)
  - Popular format (e.g., Twitter)

```
{“students:”[
  {“id”: 1, “courses”:[
    {“id“:“INF.01014UF”, “name“:“Databases”},
    {“id“:“706.550”, “name“:“AMLS”}]},
 {“id”: 5, “courses”:[
    {“id“:“706.004”, “name“:“Databases 1”}]},
]}
```

- **Query Languages**
  - **Most common: libraries** for tree traversal and data extraction
  - **JSONig:** XQuery-like query language
  - **JSONPath:** XPath-like query language

JSONiq Example:

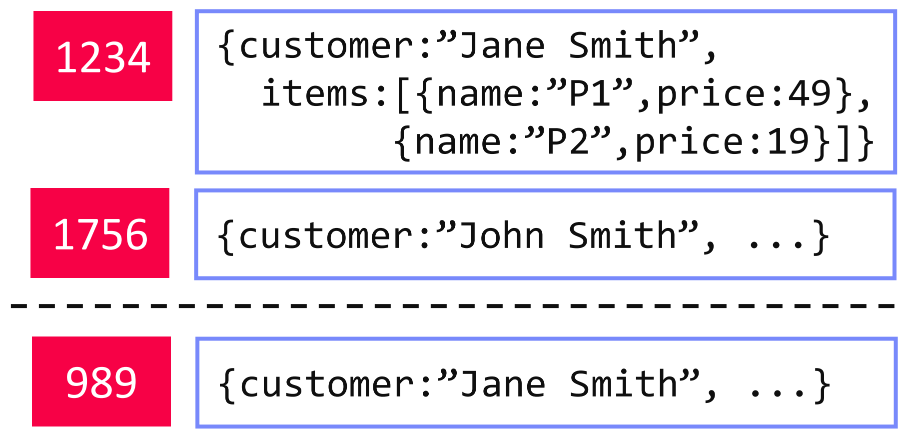
```
declare option jsoniq-version “…”;
for $x in collection(“students”)
  where $x.id lt 10
  let $c := count($x.courses)
  return {“sid”:$x.id, “count”:$c}
```

[http://www.jsoniq.org/docs/JSONiq/html-single/index.html]

Motivation and Terminology

- **Motivation**
  - Application-oriented management of **structured, semi-structured, and unstructured information** (pay-as-you-go, schema evolution)
  - Scalability via parallelization on commodity HW (cloud computing)

- **System Architecture**
  - Collections of (**key**, **document**)
  - Scalability via sharding (horizontal partitioning)
  - Custom SQL-like or functional query languages



- **Example Systems**
  - **MongoDB** (C++, 2007, **CP**) → **RethinkDB**, **Espresso**, **Amazon DocumentDB** (Jan 2019)
  - **CouchDB** (Erlang, 2005, **AP**) → **CouchBase**

Example MongoDB

[**Credit:** https://api.mongodb.com/python/current]

- **Creating a Collection**

```
import pymongo as m
conn = m.MongoClient(“mongodb://localhost:123/”)
db = conn[“dbs19”]      # database dbs19
cust = db[“customers”]  # collection customers
```

- **Inserting into a Collection**

```
mdict = {
  “name“: “Jane Smith”,
  “address”: “Inffeldgasse 13, Graz”
}
id = cust.insert_one(mdict).inserted_id
# ids = cust.insert_many(mlist).inserted_ids
```

- **Querying a Collection**

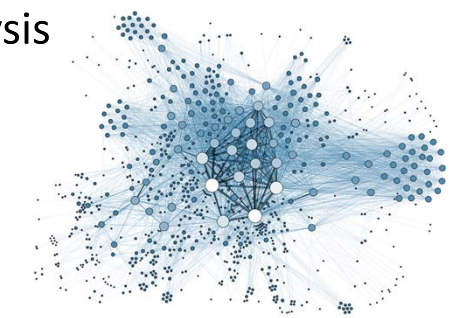
```
print(cust.find_one({"_id": id}))

ret = cust.find({"name": "Jane Smith"})
for x in ret:
  print(x)
```

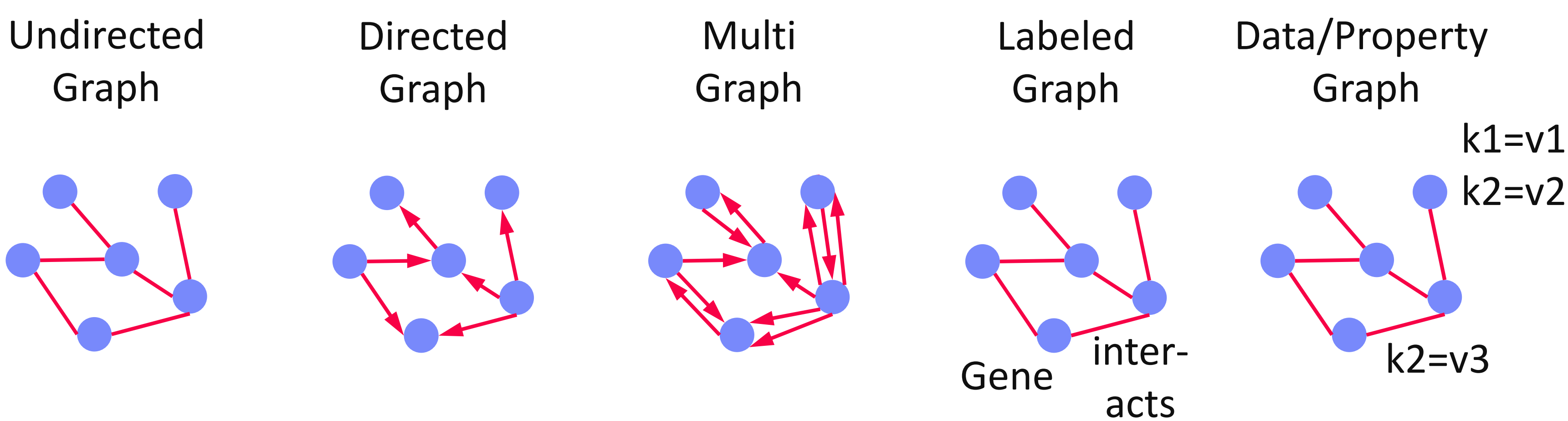
Graph Processing

Motivation and Terminology

- **Ubiquitous Graphs**
  - **Domains:** social networks, open/linked data, knowledge bases, bioinformatics
  - **Applications:** influencer analysis, ranking, topology analysis



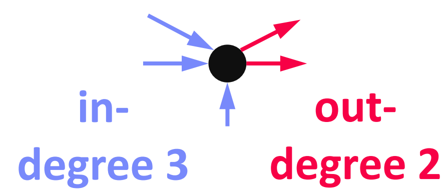
- **Terminology**
  - Graph G = (V, E) of vertices V (set of nodes) and edges E (set of links between nodes)
  - **Different types of graphs**



Terminology and Graph Characteristics

- **Terminology, cont.**
  - **Path:** Sequence of edges and vertices (**walk:** allows repeated edges/vertices)
  - **Cycle:** Closed walk, i.e., a walk that starts and ends at the same vertex
  - **Clique:** Subgraph of vertices where every two distinct vertices are adjacent

- **Metrics**
  - **Degree** (in/out-degree): number of incoming/outgoing edges of that vertex
  - **Diameter:** Maximum distance of pairs of vertices (longest shortest-path)

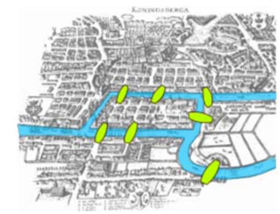


- **Power Law Distribution**
  - Degree of most real graphs follows a power law distribution

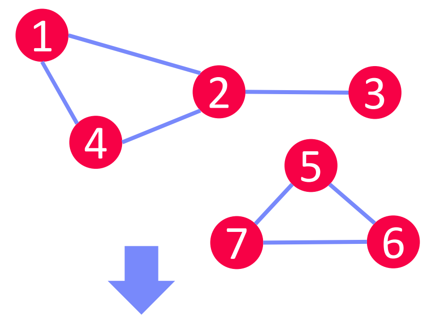
Vertex-Centric Processing

[Grzegorz Malewicz et al: Pregel: a system for large-scale graph processing. **SIGMOD 2010**]

- **Google Pregel**
  - Name: Seven Bridges of Koenigsberg (Euler 1736)
  - "Think-like-a-vertex" computation model
  - Iterative processing in super steps, comm.: message passing



- **Programming Model**
  - Represent graph as collection of vertices w/ edge (adjacency) lists
  - Implement algorithms via Vertex API
  - Terminate if all vertices halted / no more msgs




```
public abstract class Vertex {
  public String getID();
  public long superstep();
  public VertexValue getValue();

  public compute(Iterator<Message> msgs);
  public sendMsgTo(String v, Message msg);
  public void voteToHalt();
}
```

2 [1, 3, 4]
7 [5, 6]
4 [1, 2]
1 [1, 2, 4]

Worker 1

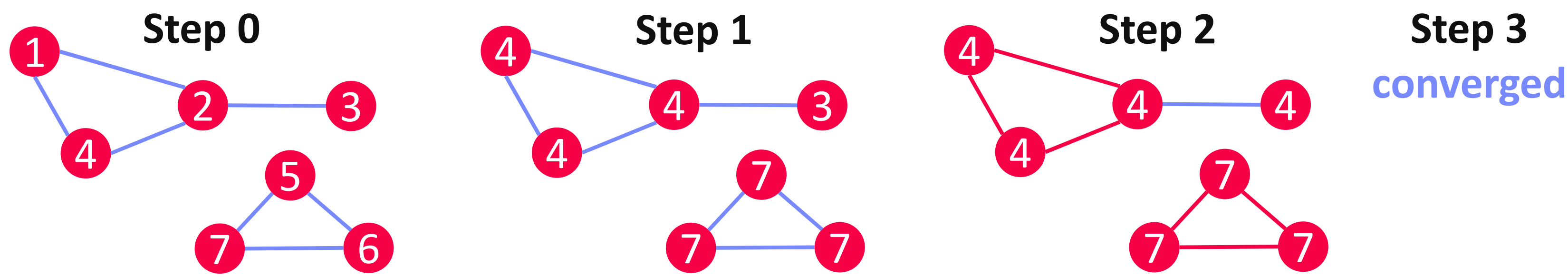
---

5 [6, 7]
3 [2]
6 [5, 7]

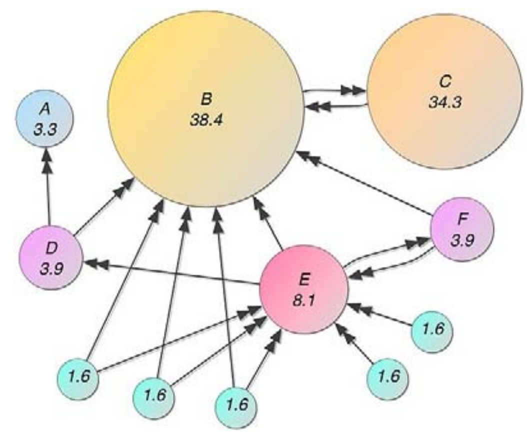
Worker 2

Vertex-Centric Processing, cont.

- **Example1: Connected Components**
  - Determine connected components of a graph (subgraphs of connected nodes)
  - Propagate max(current, msgs) if != current to neighbors, terminate if no msgs



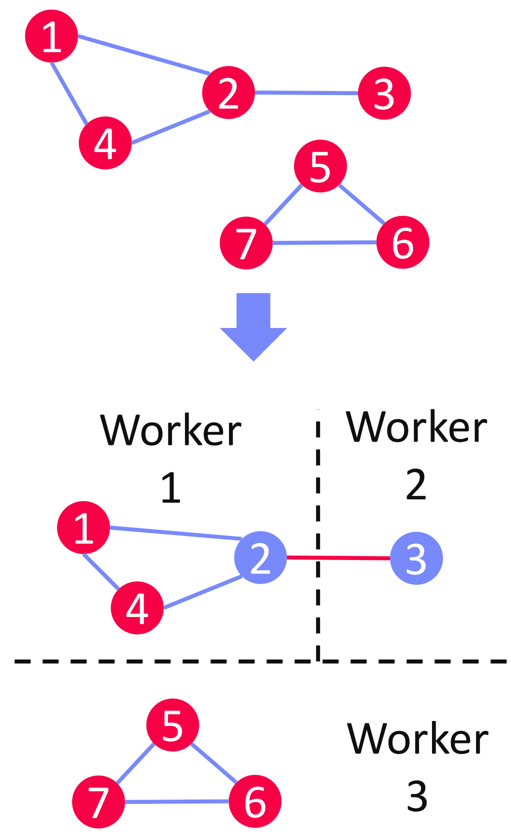
- **Example 2: Page Rank**
  - Ranking of webpages by importance / impact
  - **#1:** Initialize vertices to 1/numVertices()
  - **#2:** In each super step
    - Compute current vertex value:
      `value = 0.15/numVertices()+0.85*sum(msg)`
    - Send to all neighbors:
      `value/numOutgoingEdges()`



[**Credit:** https://en.wikipedia.org/wiki/PageRank]

Graph-Centric Processing

- **Motivation**
  - Exploit graph structure for algorithm-specific optimizations (number of network messages, scheduling overhead for super steps)
  - **Large diameter / average vertex degree**
- **Programming Model**
  - **Partition graph into subgraphs** (block/graph)
  - Implement algorithm directly against subgraphs (internal and boundary nodes)
  - Exchange messages in super steps only between boundary nodes → **faster convergence**

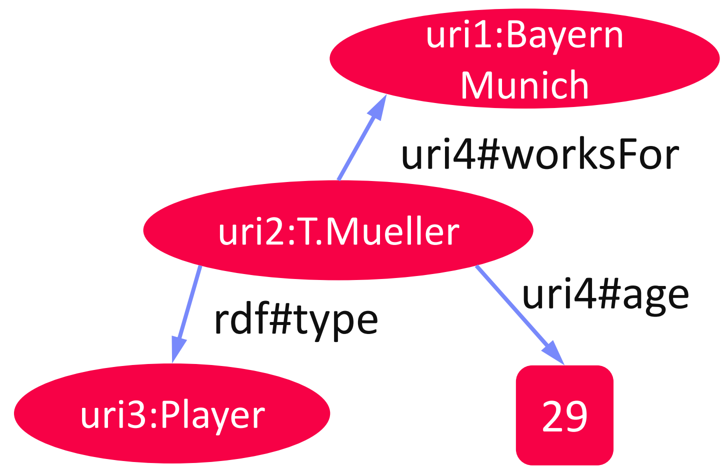


[Yuanyuan Tian, Andrey Balmin, Severin Andreas Corsten, Shirish Tatikonda, John McPherson: From "Think Like a Vertex" to "Think Like a Graph". **PVLDB 2013**]

[Da Yan, James Cheng, Yi Lu, Wilfred Ng: Blogel: A Block-Centric Framework for Distributed Computation on Real-World Graphs. **PVLDB 2014**]

Resource Description Framework (RDF)

- **RDF Data**
  - Data and meta data description via triples
  - **Triple: (subject, predicate, object)**
  - Triple components can be URIs or literals
  - Formats: e.g., RDF/XML, RDF/JSON, Turtle
  - RDF graph is a directed, labeled multigraph



- **Querying RDF Data**
  - SPARQL (SPARQL Protocol And RDF Query Language)
  - Subgraph matching

```
SELECT ?person
WHERE {
  ?person rdf:type uri3:Player ;
          uri4:worksFor uri1:"Bayern Munich" .
}
```

- **Selected Example Systems**

aws Amazon Neptune, AllegroGraph, *Sparksee, Apache Marmotta, Jena

Example Systems

- **Understanding Use in Practice**
  - Types of graphs user have
  - Graph computations run
  - Types of graph systems used

[Siddhartha Sahu, Amine Mhedhbi, Semih Salihoglu, Jimmy Lin, M. Tamer Özsu: The Ubiquity of Large Graphs and Surprising Challenges of Graph Processing. **PVLDB 2017**]

Technology	Software	# Users	
Graph Database System	ArangoDB [3]	40	233
	Caley [8]	14	
	DGraph [14]	33	
	JanusGraph [35]	32	
	Neo4j [48]	69	
	OrientDB [53]	45	
RDF Engine	Apache Jena [38]	87	115
	Sparksee [64]	5	
	Virtuoso [67]	23	
Distributed Graph Processing Engine	Apache Flink (Gelly) [17]	24	39
	Apache Giraph [21]	8	
	Apache Spark (GraphX) [27]	7	
Query Language	Gremlin [28]	82	82
Graph Library	Graph for Scala [22]	4	97
	GraphStream [24]	8	
	Graphtool [25]	28	
	NetworKit [50]	10	
	NetworkX [51]	27	
	SNAP [62]	20	
Graph Visualization	Cytoscape [13]	93	116
	Elasticsearch (X-Pack Graph) [16]	23	
Graph Representation	Conceptual Graphs [11]	6	6

Graph X

- **Summary of State of the Art Runtime Techniques**

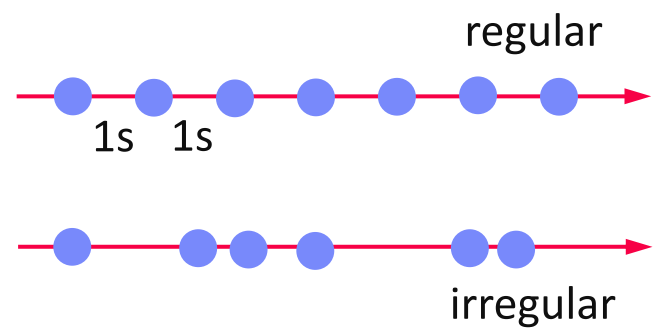
[Da Yan, Yingyi Bu, Yuanyuan Tian, Amol Deshpande, James Cheng: Big Graph Analytics Systems. **SIGMOD 2016**]

Time Series Databases

Motivation and Terminology

- **Ubiquitous Time Series**
  - **Domains:** Internet-of-Things (IoT), sensor networks, smart production/planet, telemetry, stock trading, server/application metrics, event/log streams
  - **Applications:** monitoring, anomaly detection, time series forecasting
  - Dedicated storage and analysis techniques ➔ Specialized systems

- **Terminology**
  - Time series X is a sequence of data points x_i for a specific measurement identity (e.g., sensor) and time granularity
  - **Regular** (equidistant) time series (x_i) vs **irregular** time series (t_i, x_i)








Example InfluxDB

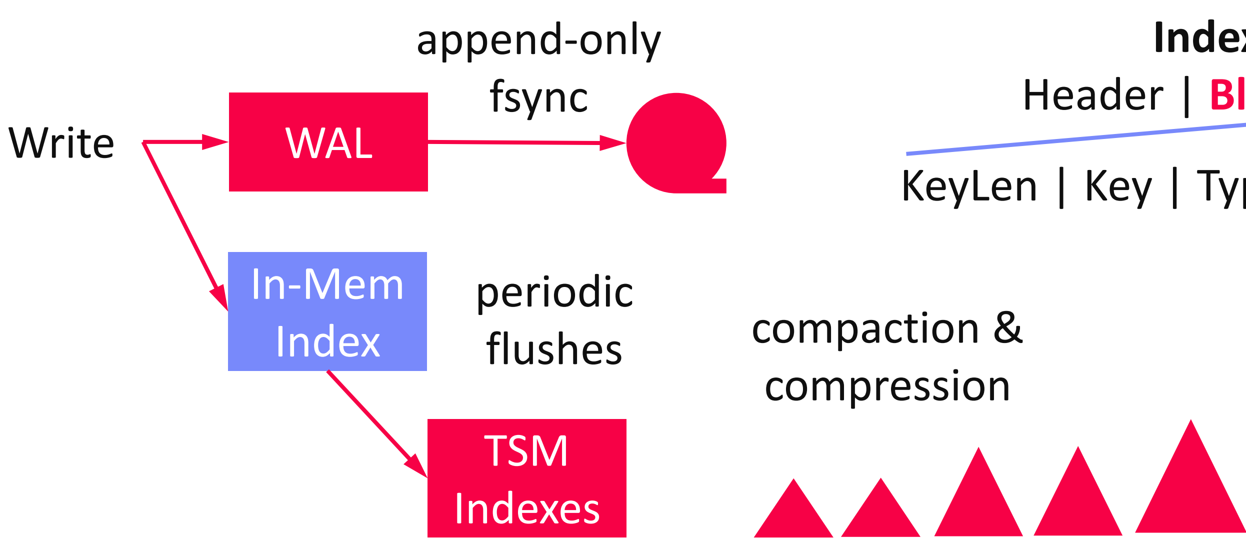
[Paul Dix: InfluxDB Storage Engine Internals, CMU Seminar, 09/2017]

- **Input Data**

```
cpu,region=west,host=A
  user=85,sys=2,idle=10 1443782126
```

Measurement: cpu; Tags: region=west,host=A; Attributes (values): user=85,sys=2,idle=10; Time: 1443782126

- **System Architecture**
  - Written Go, originally **key-value store**, now **dedicated storage engine**
  - **Time Structured Merge Tree (TSM)**, similar to LSM
  - Organized in shards, TSM indexes and inverted index for reads



Index per TSM file:
Header | **Blocks** | Index | Footer

KeyLen | Key | Type | Min T | Max T| Off | …

periodic drop of shards (files) according to retention policy

Example InfluxDB, cont.

- **Compression (of blocks)**
  - Compress up to 1000 values per block (Type | Len | Timestamps | Values)
  - **Timestamps:** Run-length encoding for regular time series; Simple8B or uncompressed for irregular
  - **Values:** double delta for FP64, bits for Bool, double delta + zig zag for INT64, Snappy for strings

- **Query Processing**
  - SQL-like and functional APIs for filtering (e.g., range) and aggregation
  - Inverted indexes

```
SELECT percentile(90, user)
  FROM cpu WHERE time>now()-12h
  AND "region"='west'
  GROUP BY time(10m), host
```

Measurement to fields:
cpu → [user,sys,idle]
host → [A, B]
Region → [west, east]

Posting lists:
cpu → [1,2,3,4,5,6]
host=A → [1,2,3]
host=B → [4,5,6]
region=west → [1,2,3]

Other Systems

- **Prometheus**
  - Metrics, high-dim data model, sharding and federation custom storage and query engine, implemented in Go
- **OpenTSDB**
  - TSDB on top of HBase or Google BigTable, Hadoop
- **TimescaleDB**
  - TSDB on top of PostgreSQL, standard SQL and reliability
- **Druid**
  - Column-oriented storage for time series, OLAP, and search
- **IBM Event Store**
  - HTAP system for high data ingest rates, and data-parallel analytics via Spark
  - Shard-local logs → groomed data

[Ronald Barber et al: Evolving Databases for New-Gen Big Data Applications. **CIDR 2017**]

Conclusions and Q&A

- **Summary 10 NoSQL Systems**
  - Consistency and Data Models
  - Key-Value and Document Stores
  - Graph and Time Series Databases

- **Next Lectures (Part B: Modern Data Management)**
  - **11 Distributed file systems and object storage** [May 27]
  - **12 Data-parallel computation (MapReduce, Spark)** [**May 27**]
  - **13 Data stream processing systems** [**Jun 03**]
  - **Jun 17: Q&A and exam preparation**