

SCIENCE PASSION TECHNOLOGY

Data Management 10 NoSQL Systems

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Last update: Dec 13, 2021

#1 Video Recording Link in TUbe & TeachCenter (lectures will be public)

Announcements/Org

- Optional attendance (independent of COVID)
- Virtual lectures (recorded) until end of the year <u>https://tugraz.webex.com/meet/m.boehm</u>

#2 Exercise Submissions

- Exercise 2: in process of begin graded (→ before Xmas)
- Exercise 3: due Dec 21, 11.59pm, provided data
- Exercise 4: extra credit, published Dec 11

#3 Course Evaluation and Exam

- Evaluation period: Jan 01 Feb 15
- Exam dates: Feb 04, 12.30pm and Feb 04, 5.30pm (90+min written exam, start 10 late)



cisco Webex



[https://mboehm7.github.io/ teaching/ws2122_dbs/T3_data.zip]



2



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)

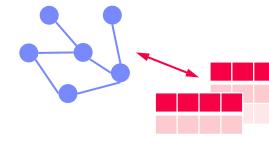
#2 Scalability

3

- 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)





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NXSQL	Your Ultimate Guide to the hion Relational Universe!
NOSCI. DEFINITION/Next Generation Database relational, distributed, open-source and horizo	
the original intention has been modern web-sc	
growing rapidly. Often more characteristics app simple AFL exertisadly consistent / BACK (not A mislanding term "noop" (the community now to as an also to score-thing list the definition about as and i stallog comment. Speci / Singent" (ii) we set by 2005)	anslates it mostly with "not only sof") shou to iteaci on Tarwors, 15 constructive feedback to

[Credit: <u>http://nosql-</u> database.org/]



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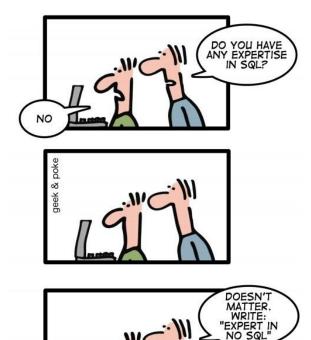


Agenda

- Consistency and Data Models
- Key-Value Stores
- Document Stores
- Graph Processing
- Time Series Databases
- Exercise 4: Large-Scale Data Analysis

Lack of standards and imprecise classification

HOW TO WRITE A CV





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

Leverage the NoSQL boom





Consistency and Data Models





Recap: ACID Properties

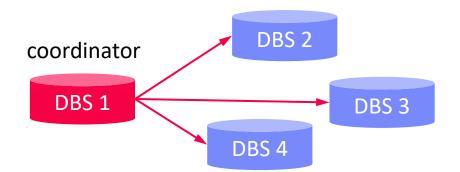
- Atomicity
 - A transaction is executed atomically (completely or not at all)
 - If the transaction fails/aborts no changes are made to the database (UNDO)
- Consistency
 - A successful transaction ensures that all consistency constraints are met (referential integrity, semantic/domain constraints)
- 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







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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."

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

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Proof

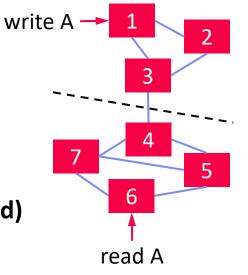
[Seth Gilbert, Nancy A. Lynch: Brewer's conjecture and the feasibility of consistent, available, partitiontolerant web services. **SIGACT News 2002**]





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**]

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- 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)

500ms
200ms
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 older 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	users:1:a	"Inffeldgasse 13, Graz"
 Key-value maps, where values can be of a variety of data types 	users:1:b	"[12, 34, 45, 67, 89]"
 APIs for CRUD operations (create, read, update, delete) 	users:2:a	"Mandellstraße 12, Graz"
 Scalability via sharding (horizontal partitioning) 	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)





Key-Value Stores



Log-structured Merge Trees

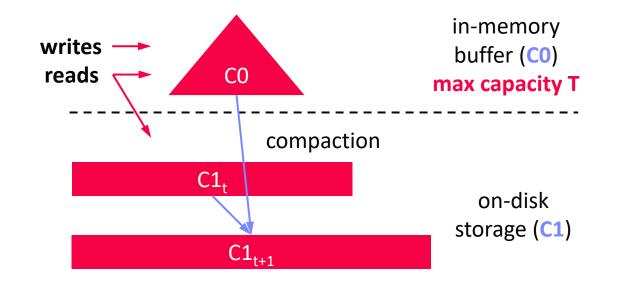
[Patrick E. O'Neil, Edward Cheng, Dieter Gawlick, Elizabeth J. O'Neil: The Log-Structured Merge-Tree (LSM-Tree). Acta Inf. 1996]



- 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 (w/ buffer for C1)
- Compaction (rolling merge): sort, merge, including deduplication

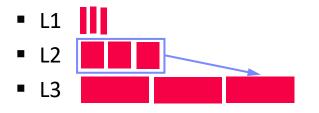






Log-structured Merge Trees, cont.

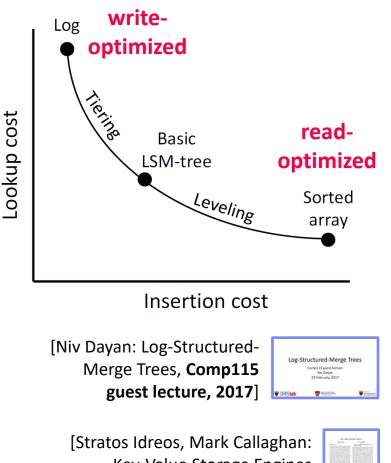
- LSM Tiering
 - Keep up to T-1 runs per level L
 - Merge all runs of L_i into 1 run of L_{i+1}



LSM Leveling

- Keep 1 run per level L
- Merge run of Li with Li+1





Key-Value Storage Engines (Tutorial), **SIGMOD 2020**]







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)

Query Languages

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

```
{"students:"[
    {"id": 1, "courses":[
        {"id":"INF.01017UF", "name":"DM"},
        {"id":"706.550", "name":"AMLS"}]},
    {"id": 5, "courses":[
        {"id":"706.520", "name":"DIA"}]},
]}
```

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]



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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

	1234	<pre>{customer:"Jane Smith", items:[{name:"P1",price:49}, {name:"P2",price:19}]}</pre>
	1756	<pre>{customer:"John Smith",}</pre>
-		
	989	<pre>{customer:"Jane Smith",}</pre>

Example Systems

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



Document Stores



[Credit: <u>https://api.mongodb.com/</u> python/current]

Example MongoDB

 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)
```



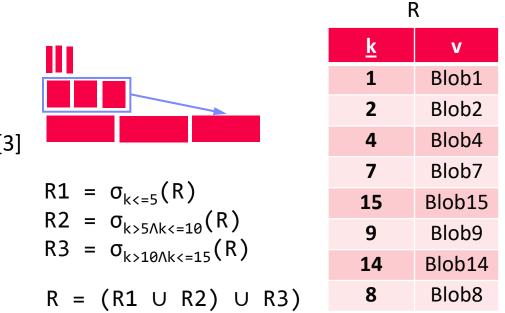


BREAK (and Test Yourself)

- NoSQL Systems (10/100 points)
 - Describe the concept and system architecture of a key-value store, including techniques for achieving high write throughput, and scale-out in distributed environments. [...]

Solution

- Key-value store system architecture [4]
- Write-throughput via LSM (log-structured merge tree) [3]
- Horizontal partitioning [3] (see 07 Physical Design)







Graph Processing



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ISDS

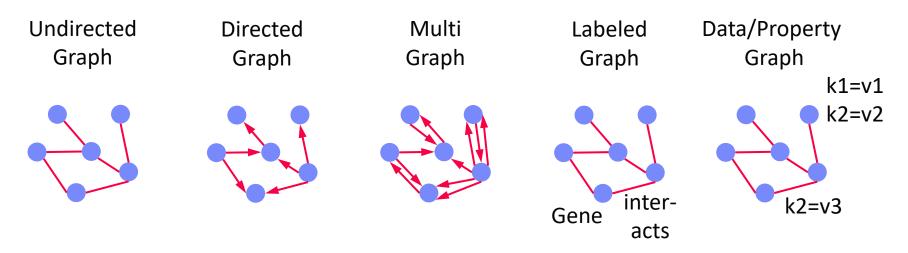
Motivation and Terminology

- 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

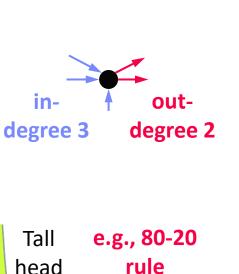
- Degree (in/out-degree): number of incoming/outgoing edges of that vertex
- Diameter: Maximum distance of pairs of vertices (longest shortest-path)

Power Law Distribution

 Degree of most real graphs follows a power law distribution



Long tail







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

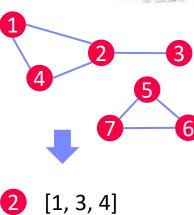
Programming Model

- 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();
}
```

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





[Grzegorz Malewicz et al: Pregel:

SIGMOD 2020 Test of Time Award

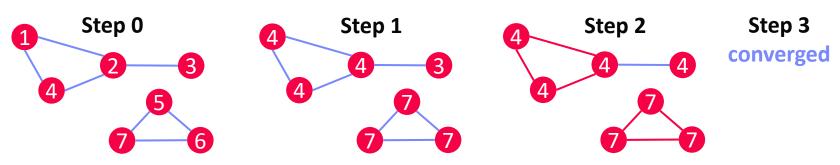
a system for large-scale graph processing. SIGMOD 2010



Vertex-Centric Processing, cont.

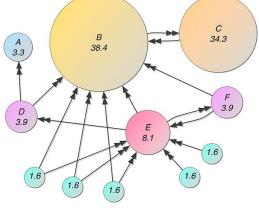
Example1: Connected Components

- 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: <u>https://en.</u> 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

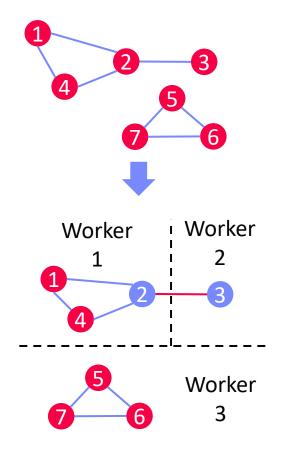
- Partition graph into subgraphs (block/graph)
- Implement algorithm directly against subgraphs (internal and boundary nodes)
- Exchange messages in super steps only between boundary nodes
 faster convergence

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- 5983			SALS:
10.024			
270		1533	
- 55053			1000
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[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)

SELECT ?person

?person rdf:type uri3:Player ;

WHERE {

- 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

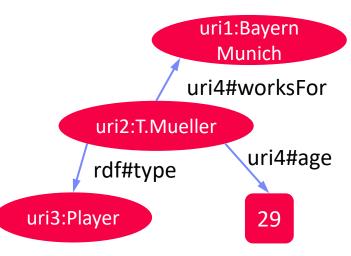
- SPARQL (SPARQL Protocol And RDF Query Language)
- Subgraph matching
- Selected
 Example Systems



}



uri4:worksFor uri1:"Bayern Munich" .







Excursus: Example Systems





Understanding Use in Practice

- Types of graphs user have
- Graph computations run
- Types of graph systems used

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[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	# U	Jsers
	ArrangoDB [3]	40	
	Caley [8]	14	
Graph Database	DGraph [14]	33	233
System	JanusGraph [35]	32	233
	Neo4j [48]	69	
	OrientDB [53]	45	
	Apache Jena [38]	87	
RDF Engine	Sparksee [64]	5	115
	Virtuoso [67]	23	
Distributed Creat	Apache Flink (Gelly) [17]	24	
Distributed Graph	Apache Giraph [21]	8	39
Processing Engine	Apache Spark (GraphX) [27]	7	
Query Language	Gremlin [28]	82	82
	Graph for Scala [22]	4	
	GraphStream [24]	8	
Crowb Librory	Graphtool [25]	28	97
Graph Library	NetworKit [50]	10	97
	NetworkX [51]	27	
	SNAP [62]	20	
Crearly Visualization	Cytoscape [13]	93	116
Graph Visualization	Elasticsearch	22	110
	(X-Pack Graph) [16]	23	
Graph Representation	Conceptual Graphs [11]	6	6



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Summary of State of the Art Runtime Techniques

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





Excursus: Future Graph Processing Systems

- Community Perspective
 - 2019 Dagstuhl Seminar on Big Graph Processing Systems
 - Opportunities and challenges:
 - Abstractions, Ecosystems, and Performance



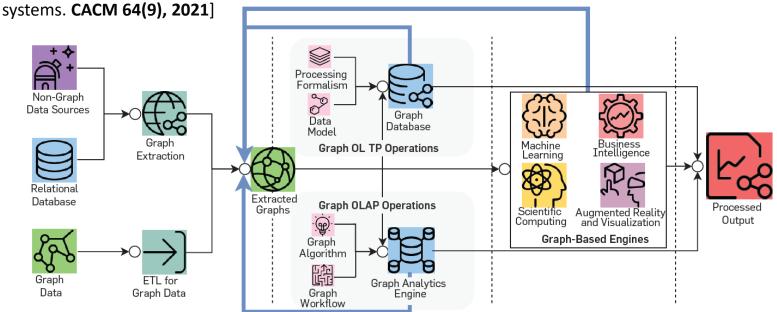
wiki/File:Dagstuhl DSC02285.jpg]

[Credit: https://commons.wikimedia.org/

contributed articles The Future Is Big Graphs: A Community View on Graph Processing Systems

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[Sherif Sakr et al: The future is big graphs: a community view on graph processing systems. **CACM 64(9)**, **2021**]



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Time Series Databases





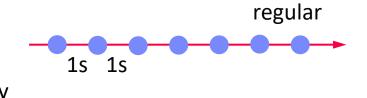
Motivation and Terminology

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)





irregular



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Example InfluxDB

- Input Data cpu, region=west, host=A Tags
 user=85, sys=2, idle=10 1443782126
- System Architecture

Measurement

Time

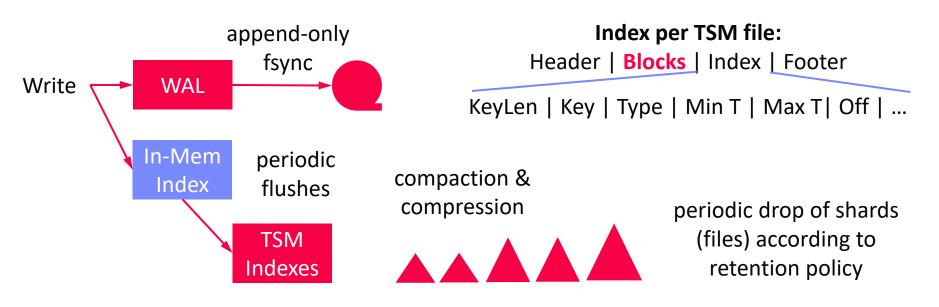


[Paul Dix: InfluxDB Storage Engine Internals, CMU Seminar, 09/2017]

Written in Go, originally key-value store, now dedicated storage engine

Fields (values)

- Time Structured Merge Tree (TSM), similar to LSM
- Organized in shards, TSM indexes and inverted index for reads



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Example InfluxDB, cont.

- Compression (of blocks)
 - Compress up to 1000 values per block (Type | Len | Timestamps | Values)
 - Timestamps: Delta + 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





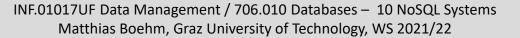




[Ronald Barber et al: Evolving Databases for New-Gen Big Data Applications. **CIDR 2017**]

[Christian Garcia-Arellano et al: **Db2 Event Store:** A Purpose-Built IoT Database Engine. **PVLDB 13(12) 2020**]











Exercise 4: Large-Scale Data Analysis

Published: Dec 11 Deadline: Jan 18

Entire Exercise is Extra Credit



- (#3 Win Environment) Download https://github.com/steveloughran/winutils/tree/master/hadoop-
 - 2.7.1/bin/winutils.exe (or https://github.com/cdarlint/winutils)
 - Create environment variable HADOOP_HOME="<some-path>/hadoop"



ISD

#1 Pick your Spark Language Binding

Task 4.1 Apache Spark Setup

Java, Scala, Python

#2 Install Dependencies

- Java: Maven spark-core, spark-sql
- Python: pip install pyspark

<groupId>org.apache.spark</groupId> <artifactId>spark-core_2.11</artifactId> <version>2.4.7</version> </dependency> <dependency> <groupId>org.apache.spark</groupId> <artifactId>spark-sql_2.11</artifactId> <version>2.4.7</version> </dependency>

<dependency>

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Task 4.2 Query Processing via Spark RDDs

- #1 Spark Context Creation
 - Create a spark context sc w/ local master (local[*])
- #2 Implement Q09 via RDD Operations
 - Implement Q09 in self-contained executeQ09RDD()
 - All reads should use sc.textFile(fname)
 - RDD operations only → stdout
- Note: Query will be shared by Dec 28

https://spark.apache.org/ docs/latest/rddprogramming-guide.html



11/25 points

Task 4.3 Query Processing via Spark SQL

- #1 Spark Session Creation
 - Create a spark session via a spark session builder and w/ local master (local[*])
- SQL processing of high importance in modern data management

- #2 Implement Q09 via Dataset Operations
 - Implement Q09 self-contained in executeQ09Dataset()
 - All reads should use sc.read().format("csv")
 - SQL or Dataset operations only → out07.json
- WebUI INFO Utils: Successfully started service 'SparkUI' on port 4040. INFO SparkUI: Bound SparkUI to [...] http://192.168.108.220:4040





5/25

points



6/25

points

Task 4.4 Graph Processing

Input Co-author graph

 AuthPapersCOO.csv (coordinate format)
 AuthPapersCSR.csv (compressed sparse row)

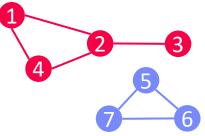
1	author,co-author
2	1001634,70215
3	1001634,519925

1	author, co-authors
2	1001634,70215:519925:1444319:2383440
3	1243968,76416:323847:407298:688292:918500:1198961:1231227:1256611:1377989

#1 Compute Connected Components

- Leverage Spark to compute assignment of vertices to components
- Write output to text file, print #components to stdout
- APIs up to you (e.g., Spark RDDs, Spark SQL, Spark GraphX)

```
Example
                       # initialize state with vertex ids
                   37
38 c = seq(1, nrow(G));
  Apache
                   39
                       diff = Inf;
  SystemDS
                   40
                       iter = 1;
                   41
                       # iterative computation of connected components
                   42
                       while( diff > 0 & (maxi==0 | iter<=maxi) ) {</pre>
                   43
                         u = max(rowMaxs(G * t(c)), c);
                   44
                         diff = sum(u != c)
                   45
                         c = u; # update assignment
                   46
```





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 Storage and Data Analysis [Jan 10]
 - 12 Data stream processing systems, Q&A [Jan 17]

