Advanced Data Management (CSCI 640/490)

Scalable Dataframes

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Recent History in Databases

• Early 2000s: Commercial DBs dominated, Open-source DBs missing features
• Mid 2000s: MySQL adopted by web companies
• Late 2000s: NoSQL dos scale horizontally out of the box
• Early 2010s: New DBMSs that can scale across multiple machines natively and provide ACID guarantees
NewSQL Definitions

• Stonebraker's Definition:
  - SQL as the primary interface
  - ACID support for transactions
  - Non-locking concurrency control
  - High per-node performance
  - Parallel, **shared-nothing** architecture (what about shared-disk?)

• Wikipedia (Pavlo): A class of modern relational DBMSs that provide the same scalable performance of NoSQL systems for OLTP workloads while still maintaining the ACID guarantees of a traditional DBMS.

[A. Pavlo]
NewSQL Positioning

[Diagram showing scaling and guarantees for NO SQL, NEW SQL, and TRADITIONAL in a 2D space]

[A. Pavlo]
Three Types of NewSQL Systems

• New Architectures
  - New codebase without architectural baggage of legacy systems
  - Examples: VoltDB, Spanner, Clustrix

• Transparent Sharding Middleware:
  - Transparent data sharding & query redirecting over cluster of single-node DBMSs
  - Examples: citusdata, ScaleArc (usually support MySQL/postgres wire)

• Database-as-a-Service:
  - Distributed architecture designed specifically for cloud-native deployment
  - Examples: xeround, GenieDB, FathomDB (usually based on MySQL)
What went wrong?

- Almost every NewSQL company from the last decade has closed, sold for scraps, or pivoted to other markets
- Why?
  - Selling an OLTP Database System is hard
  - Startup cost of a relational system is harder than NoSQL
  - Existing DBMS Systems (MySQL, postgresql) are Good
  - Cloud Disruption
    - Can't sell on-premises
    - Can't complete on cost with cloud vendors
  - Lack of Open Source
Conclusions

- NewSQL is dead
- Academic: the NewSQL movement was a success
- Business: a failure for those who embraced the NewSQL mantle
- Next?
  - You still need humans to design, configure, and optimize logical/physical aspects of a database
  - Humans are expensive
  - Automation is the future.

[A. Pavlo]
Spanner Overview

- Focus on scaling databases focused on OLTP (not OLAP)
- Since OLTP, focus is on sharding rows
- Tries to satisfy CAP (which is impossible per CAP Theorem) by not worrying about 100% availability
- External consistency using multi-version concurrency control through timestamps
- ACID is important
- Structured: universe with zones with zone masters and then spans with span masters
- SQL-like (updates allow SQL to be used with Spanner)
Spanner and the CAP Theorem

Which type of system is Spanner?
- C: consistency, which implies a single value for shared data
- A: 100% availability, for both reads and updates
- P: tolerance to network partitions

Which two?
- CA: close, but not totally available
- So actually CP
External Consistency

- Traditional DB solution: **two-phase locking**—no writes while client reads
- "The system behaves as if all transactions were executed sequentially, even though Spanner actually runs them across multiple servers (and possibly in multiple datacenters) for higher performance and availability" [Google]
- Semantically indistinguishable from a single-machine database
- Uses multi-version concurrency control (MVCC) using **timestamps**
- Spanner uses **TrueTime** to generate monotonically increasing timestamps across all nodes of the system
Google Cloud Spanner

- https://cloud.google.com/spanner/
- Features:
  - Global Scale: thousands of nodes across regions / data centers
  - Fully Managed: replication and maintenance are automatic
  - Transactional Consistency: global transaction consistency
  - Relational Support: Schemas, ACID Transactions, SQL Queries
  - Security
  - Highly Available
More Recent Tests: Spanner vs. MySQL

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</table>

[P. Bakkum and D. Cepeda, 2017]
Latency: Spanner vs. MySQL

Latency at 3,000 Queries per Second

[P. Bakkum and D. Cepeda, 2017]
Latency: Spanner vs. MySQL

Latency at 9,000 Queries per Second

- **Spanner**
- **MySQL**

[P. Bakkum and D. Cepeda, 2017]
Throughput: Spanner vs. MySQL

Median Latency as Throughput Increases

- MySQL (median)
- spanner 9 nodes (median)
- spanner 15 nodes (median)
- spanner 30 nodes (median)

[P. Bakkum and D. Cepeda, 2017]
Max Throughput vs. Nodes

[P. Bakkum and D. Cepeda, 2017]
Spanner: Latency vs. Nodes

Latency at 3000 QPS vs Nodes

[Graph showing latency decreasing as nodes increase]

[P. Bakkum and D. Cepeda, 2017]
Assignment 4

• Work on Data Integration and Data Fusion
• Integrate artist datasets from different institutions (Met, NGA, AIC, CMA)
  - Integrate information based on ids and matching
• Record Matching:
  - Which artists are the same?
• Data Fusion:
  - Names
  - Dates
  - Nationalities
Scalable Dataframes
History of Dataframes

• Originally in *Statistical Models in S*, [J. M. Chambers & T. J. Hastie, 1992]
• R, open-source alternative to S, developed in 2000 (with dataframes)
• Pandas, 2009
• Spark, 2010 (resilient distributed dataset [RDD], Dataset API)

[D. Petersohn, 2022]
Formalizing Dataframes

- Combines parts of matrices, databases, and spreadsheets
- Ordered rows (unlike databases)
- Types can be inferred at runtime, not the same across all columns
- Lots of "intuitive" functions (600+)
Differences between Databases & Dataframes

**Convenience**

Entire query at once

**Flexible**

Strict schema

**Versatility**

SFW or bust

**Incremental + inspection**

Mixed types, R/C and data/metadata equiv.

**600+ functions**

[D. Petersohn, 2022]
Scaling Dataframes

• Solutions:
  - Spark
  - Dask
  - Polars
  - Vaex
  - Modin
Scaling up your pandas workflows with Modin

D. Petersohn
Ibis Overview
Blazing fast dataframes in Python with Polars

J. L. C. Rodríguez