SCIENCE
PASSION
TECHNOLOGY

Architecture of DB Systems
10 Cloud DBMSs

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Last update: Jan 13, 2021

Announcements/Org

- **#1 Video Recording**
  - Link in TeachCenter & TUbe (lectures will be public)
  - Optional attendance (independent of COVID)
- **#2 COVID-19 Restrictions** (HS i5)
  - Corona Traffic Light: **RED**
  - Temporarily webex lectures until end of semester
- **#3 Projects**
  - Deadline **Jan 21, 11.59pm**
    (**soft deadline**, submissions accepted until Feb 28)
  - Performance target: ~ `T(SUT) < 4 * T(ref_impl)`
- **#4 Course Evaluation and Exam**
  - Evaluation period: **Dec 15 – Jan 31**
  - Exam date: **Feb 19** (virtual webex oral exams, 45min each)

Agenda

- **Cloud Computing Background**
- **PaaS: SQL on Hadoop**
- **SaaS: Cloud DBs and Cloud DWHs**
- **FaaS: Serverless Database Systems**

Cloud Computing Background

Motivation Cloud Computing

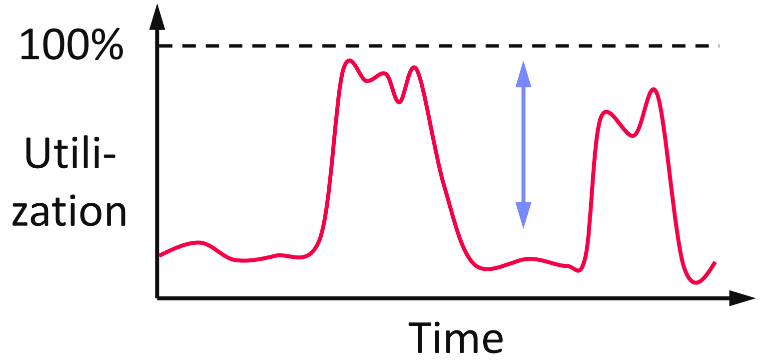
- **Definition Cloud Computing**
  - **On-demand, remote storage and compute resources, or services**
  - **User:** computing as a utility (similar to energy, water, internet services)
  - **Cloud provider:** computation in data centers / multi-tenancy
- **Service Models**
  - **IaaS: Infrastructure as a service** (e.g., storage/compute nodes)
  - **PaaS: Platform as a service** (e.g., distributed systems/frameworks)
  - **SaaS: Software as a Service** (e.g., email, databases, office, github)

→ **Transforming IT Industry/Landscape**

- Since ~2010 increasing move from on-prem to cloud resources
- System software licenses become increasingly irrelevant
- Few cloud providers dominate IaaS/PaaS/SaaS markets (w/ 2018 revenue): **Microsoft Azure Cloud** ($ 32.2B), **Amazon AWS** ($ 25.7B), **Google Cloud** (N/A), **IBM Cloud** ($ 19.2B), **Oracle Cloud** ($ 5.3B), **Alibaba Cloud** ($ 2.1B)

Motivation Cloud Computing, cont.

- **Argument #1: Pay as you go**
  - No upfront cost for infrastructure
  - Variable utilization ➔ over-provisioning
  - **Pay per use or acquired resources**



- **Argument #2: Economies of Scale**
  - Purchasing and managing IT infrastructure at scale ➔ **lower cost** (applies to both HW resources and IT infrastructure/system experts)
  - Focus on **scale-out on commodity HW** over scale-up ➔ **lower cost**

- **Argument #3: Elasticity**
  - Assuming perfect scalability, work done in **constant time * resources**
  - Given virtually unlimited resources allows to reduce time as necessary

100 days @ 1 node

≈

1 day @ 100 nodes

(but beware Amdahl's law: max speedup **sp = 1/s**)

Anatomy of a Data Center

Commodity CPU:
Xeon E5-2440: 6/12 cores
Xeon Gold 6148: 20/40 cores

Server:
Multiple sockets,
RAM, disks

Rack:
16-64 servers +
top-of-rack switch

Cluster:
Multiple racks + cluster switch

Data Center:
>100,000 servers

[Google
Data Center,
Eemshaven,
Netherlands]

Infrastructure as a Service (IaaS)

- **Overview**
  - Resources for **compute**, **storage**, **networking** as a service
    ➔ Virtualization as key enabler (simplicity and auto-scaling)
  - **Target user:** sys admin / developer

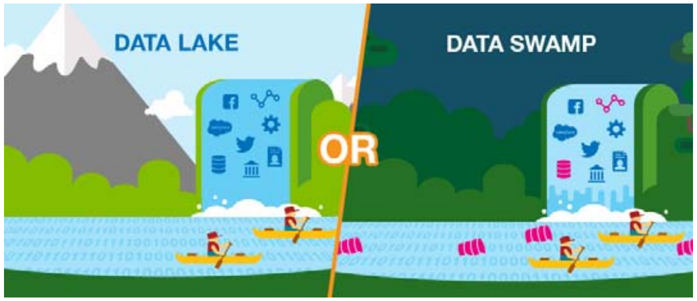
Computing as a utility

- **Storage**
  - Amazon AWS Simple Storage Service (S3)
  - OpenStack Object Storage (Swift)
  - IBM Cloud Object Storage
  - Microsoft Azure Blob Storage
- **Compute**
  - Amazon AWS Elastic Compute Cloud (EC2)
  - Microsoft Azure Virtual Machines (VM)
  - IBM Cloud Compute

PaaS: SQL on Hadoop

Data-parallel Computation

- **Concept "Data Lake"**
  - **Store massive amounts of structured and un/semi-structured data** (append only, no update in place)
  - **No need for architected schema** or upfront costs (unknown analysis)
  - Typically: file storage in open, raw formats (inputs and intermediates)



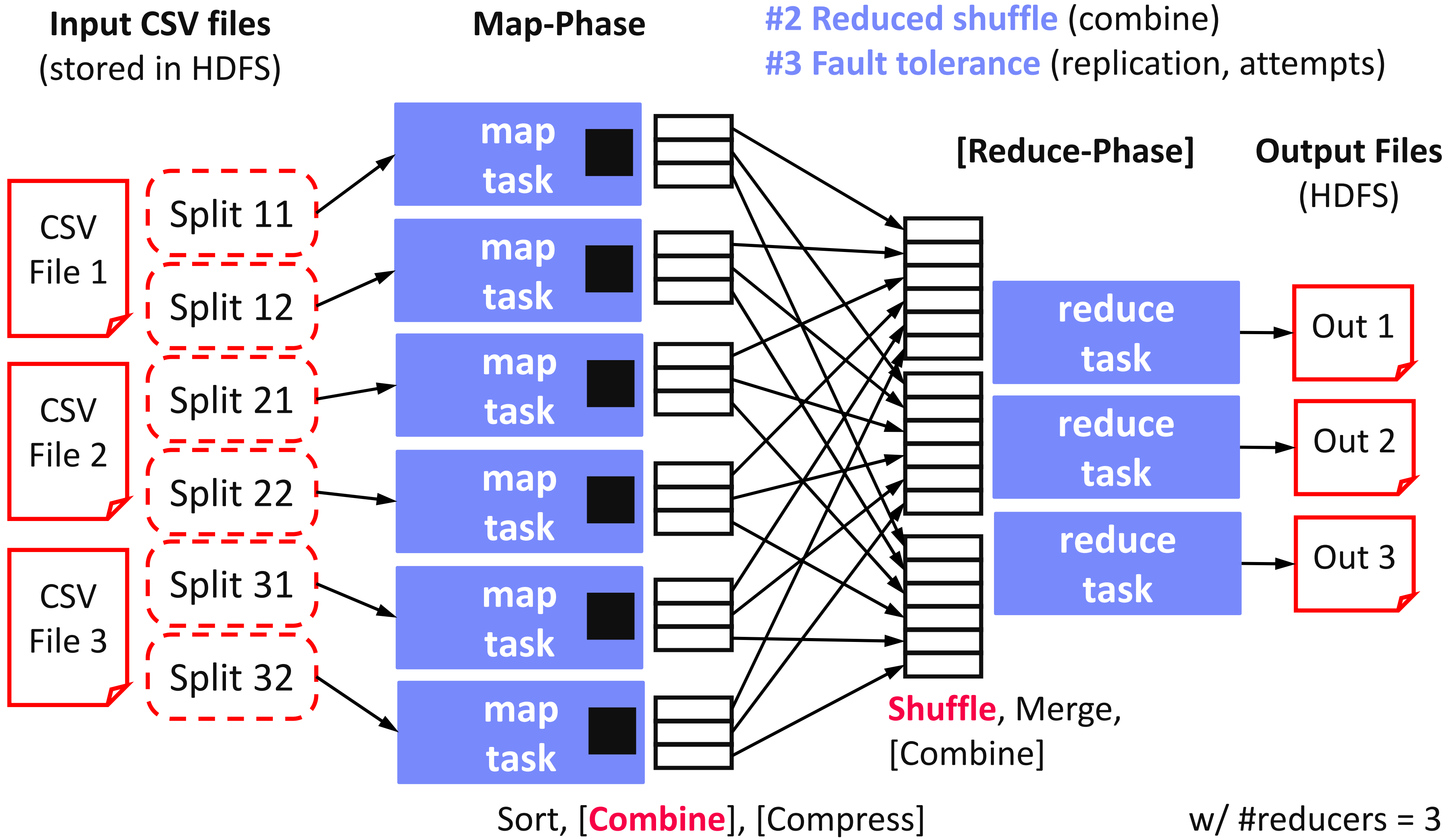
[**Credit:** www.collibra.com]

- **Distributed Storage and Analysis**
  - Central abstraction: **distributed collection** Different physical representations
  - **Easy distribution** of pairs via horizontal partitioning (aka shards, partitions)
  - Frameworks: Hadoop MR, Spark, Flink
  - Deployment: on-prem and/or **cloud**

Key	Value
4	Delta
2	Bravo
1	Alfa
3	Charlie
5	Echo
6	Foxtrot
7	Golf
1	Alfa

Recap: MapReduce – Execution Model

#1 Data Locality (delay sched., write affinity)
#2 Reduced shuffle (combine)
#3 Fault tolerance (replication, attempts)



A History on "SQL on Hadoop"

[Daniel Abadi, Shivnath Babu, Fatma Ozcan, Ippokratis Pandis: Tutorial: SQL-on-Hadoop Systems. **PVLDB 8(12) 2015**]

(see DM Exercise 4)

- **Criticism MapReduce for Data Analytics**
  - Litter control of data flow, simplicity leads to inefficiencies
  - Fault tolerance not always necessary
  - Lack of integration into existing eco system of data analysis

[Andrew Pavlo et al.: A comparison of approaches to large-scale data analysis. **SIGMOD 2009**]

[Spyros Blanas et al.: A comparison of join algorithms for log processing in MapReduce. **SIGMOD 2010**]

- **SQL on Hadoop**
  - Query engines on distributed file systems and open storage formats (e.g., CSV, Sequence files, Avro, **Parquet**, **OCR**, **Arrow**)
  - Challenges w.r.t. metadata (schema/stats), and resource management
  - Non-relational data (e.g., JSON), and unclean, irregular, unreliable data

  ➔ **Specialized "SQL on Hadoop"** systems (with open / native storage formats)

A History on "SQL on Hadoop" – Systems

- **Hadoop Eco-system**
  - **HBase:** logical tables, CRUD, key-value storage on HDFS
  - **Hive:** SQL queries executed as MapReduce jobs (OLAP)
  - **Hive on Tez/Spark:** SQL queries executed as DAGs of operations

- **Proprietary Systems**
  - **MS SCOPE**
  - **HadoopDB**/Hadapt → Teradata (2014)
  - **Facebook Presto**
  - **Cloudera Impala**
  - **IBM BigSQL**

[Ronnie Chaiken et al.: SCOPE: easy and efficient parallel processing of massive data sets. **PVLDB 1(2) 2008**]

[Azza Abouzeid et al.: HadoopDB: An Architectural Hybrid of MapReduce and DBMS Technologies for Analytical Workloads. **PVLDB 2(1) 2009**]

[Marcel Kornacker et al.: Impala: A Modern, Open-Source SQL Engine for Hadoop. **CIDR 2015**]

[Scott C. Gray, Fatma Ozcan, Hebert Pereyra, Bert van der Linden and Adriana Zubiri: SQL-on-Hadoop without compromise, **IBM Whitepaper 2014**]

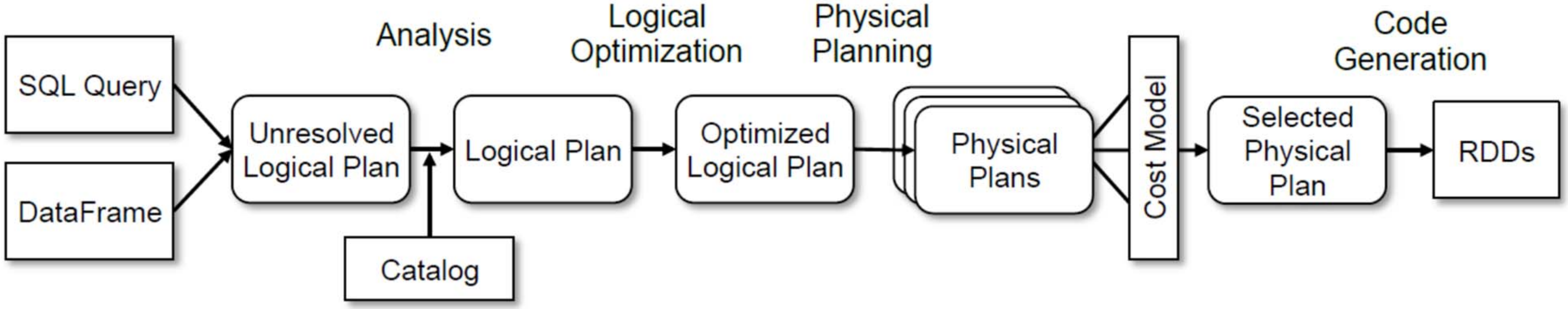
A History on “SQL on Hadoop” – SparkSQL

- **Overview** SparkSQL
  - New dataframe / dataset abstractions with various data source (+ pushdown)
  - SQL and programmatic APIs
  - Rewrite ruleset for query optimization
  - Off-heap data storage (`sun.misc.Unsafe`)
  - Whole-stage code generation

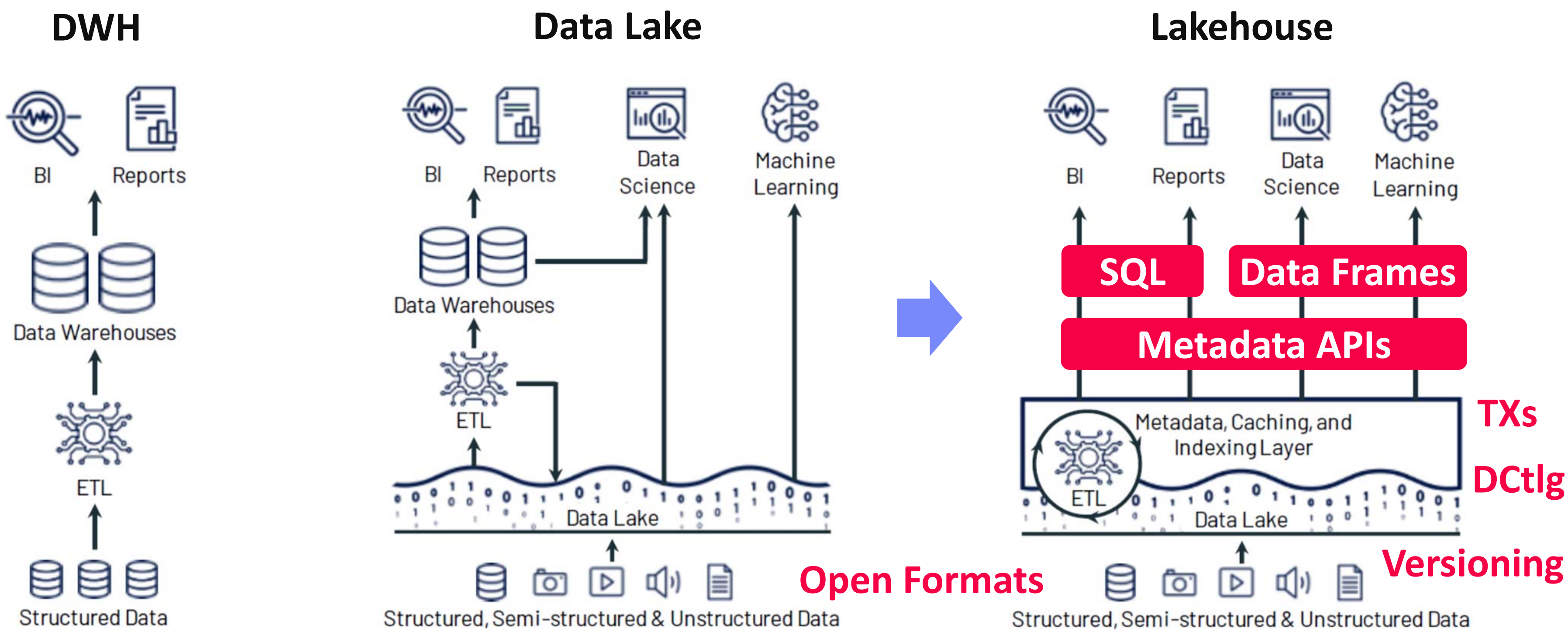
[Reynold S. Xin, Josh Rosen, Matei Zaharia, Michael J. Franklin, Scott Shenker, Ion Stoica: Shark: SQL and rich analytics at scale. **SIGMOD 2013**]

[Michael Armbrust et al.: Spark SQL: Relational Data Processing in Spark. **SIGMOD 2015**]

- **Query Planning**



Example Delta Lake (and Lakehouse Architecture)



[Michael Armbrust et al: **Delta Lake:** High-Performance ACID Table Storage over Cloud Object Stores. **PVLDB 13(12) 2020**]

[Michael Armbrust, Ali Ghodsi, Reynold Xin, Matei Zaharia: **Lakehouse:** A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics, **CIDR 2021**]

SaaS: Cloud DBs and Cloud DWHs

Cloud Databases (DBaaS)

- **Motivation DBaaS**
  - Simplified setup, maintenance, tuning and auto scaling
  - Multi-tenant systems (scalability, learning opportunities)
  - Different types based on workload (OLTP vs OLAP, NoSQL)

Microsoft

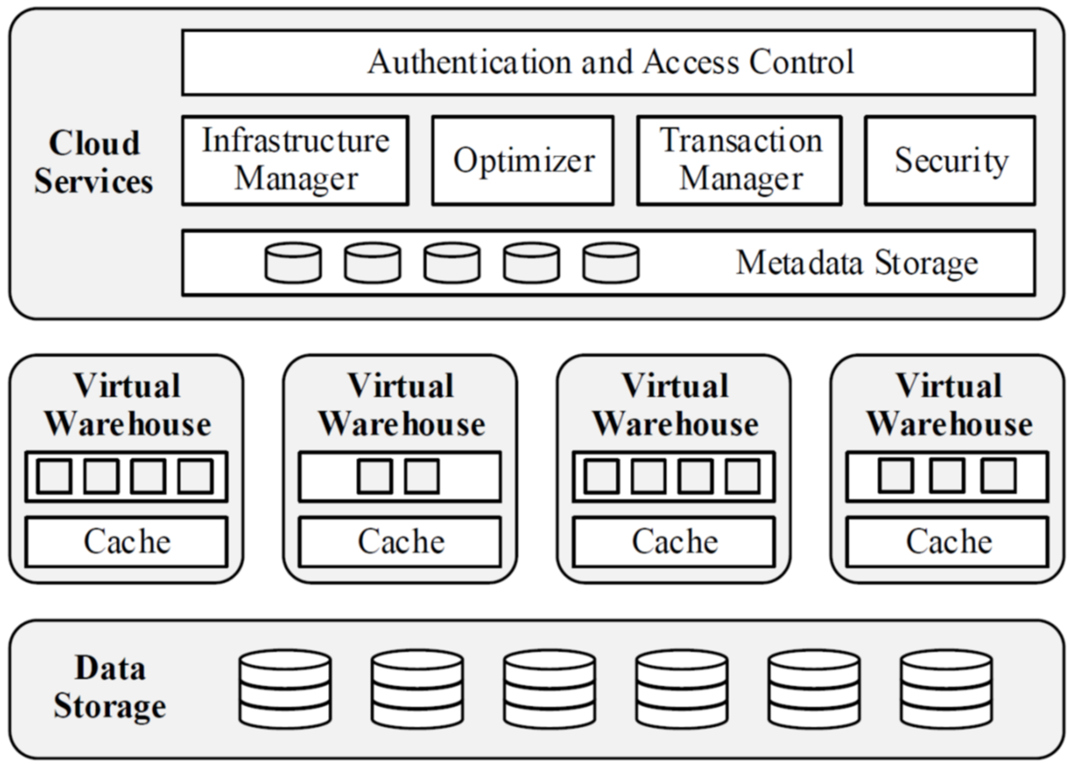
- **Elastic Data Warehouses**
  - Motivation: Intersection of data warehousing, cloud computing, distributed storage
  - Example Systems
    - **#1** Snowflake
    - **#2** Google BigQuery (Dremel)
    - **#3** Amazon Redshift
    - Azure SQL Data Warehouse / **#4** Azure SQL Database Hyperscale (Socrates)

Commonalities:
SQL, **column stores**,
data on **object store / DFS**,
elastic cloud scaling

Example Snowflake

[Benoît Dageville et al.: The Snowflake Elastic Data Warehouse. **SIGMOD 2016**]

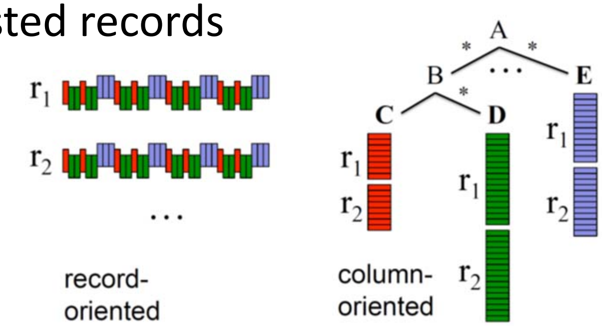
- **Motivation** (impl started late 2012)
  - **Enterprise-ready DWH solution for the cloud** (elasticity, semi-structured)
  - Pure SaaS experience, high availability, cost efficient
- **Cloud Services**
  - Manage virtual DHWs, TXs, and queries
  - Meta data and catalogs
- **Virtual Warehouses**
  - Query execution in EC2
  - Caching/intermediates
- **Data Storage**
  - **Storage in AWS S3**
  - PAX / hybrid **columnar**
  - **Min-max pruning**



Example Google BigQuery

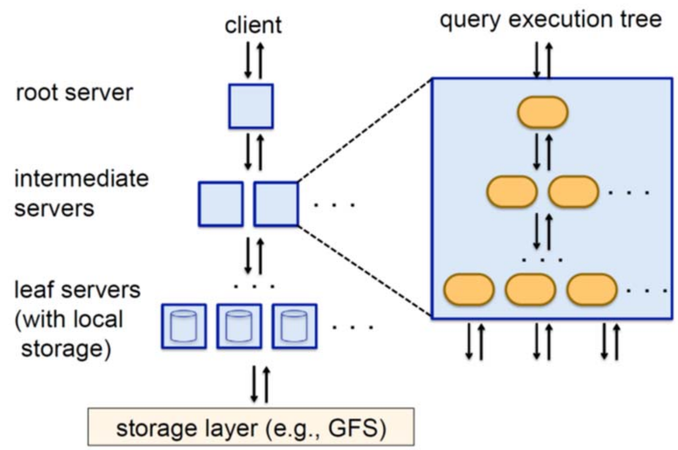
[Sergey Melnik et al.: Dremel: Interactive Analysis of Web-Scale Datasets. **PVLDB 3(1) 2010**]

- **Background Dremel**
  - Scalable and fast in-situ analysis of read-only nested data (DFS, BigTable)
  - **Data model:** protocol buffers - strongly-typed nested records
  - **Storage model:** columnar storage of nested data (efficient splitting and assembly records)
  - Query execution via multi-level serving tree



- **BigQuery System Architecture**
  - Public impl of internal Dremel system (2012)
  - SQL over structured, nested data (OLAP, BI)
  - **Extensions:** web Uis, REST APIs and ML
  - **Data storage:** Colossus (NextGen GFS)

[Kazunori Sato: An Inside Look at Google BigQuery, Google BigQuery White Paper 2012.]

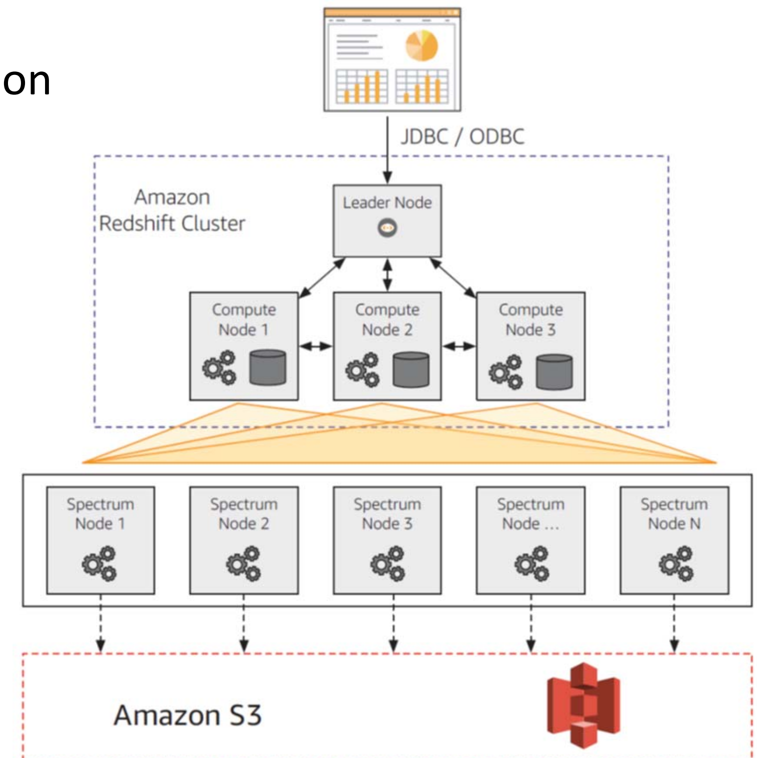


Example Amazon Redshift

[Anurag Gupta et al.: Amazon Redshift and the Case for Simpler Data Warehouses. **SIGMOD 2015**]

[Mengchu Cai et al.: Integrated Querying of SQL database data and S3 data in Amazon Redshift. **IEEE Data Eng. Bull. 41(2) 2018**]

- **Motivation** (release 02/2013)
  - **Simplicity and cost-effectiveness** (fully-managed DWH at petabyte scale)
- **System Architecture**
  - **Data plane:** data storage and SQL execution
  - **Control plane:** workflows for monitoring, and managing databases, AWS services
- **Data Plane**
  - Initial engine licensed from ParAccel
  - Leader node + sliced compute nodes in **EC2** (with **local storage**)
  - Replication across nodes + **S3 backup**
  - **Query compilation** in C++ code
  - Support for **flat and nested files**

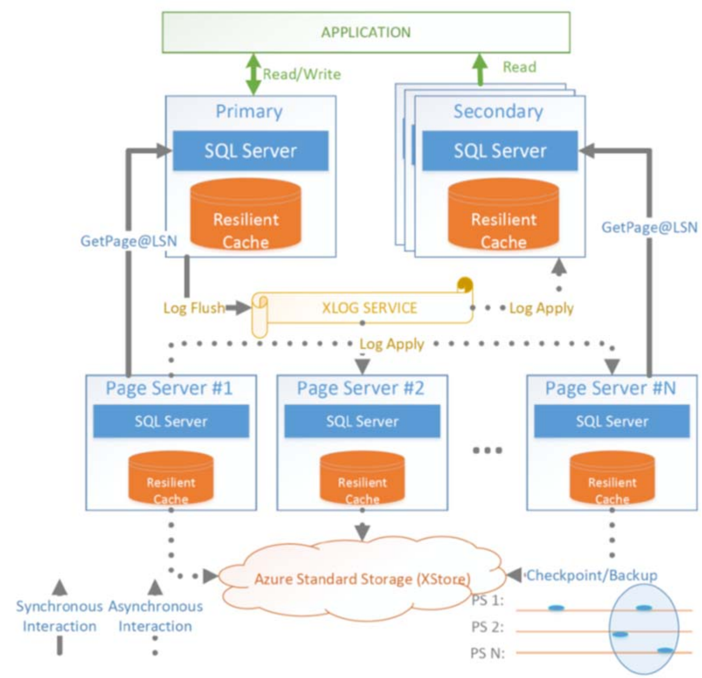


Example Microsoft Hyperscale (OLTP)

[Panagiotis Antonopoulos et al.: Socrates: The New SQL Server in the Cloud. **SIGMOD 2019**]

- **Overview**
  - Challenges of monolithic DBMSs in the cloud (cost-elasticity → scale-out/in data movement, availability/SW updates)
  - Socrates: new OLTP cloud database system **Azure DB Hyperscale**

- **Key Features**
  - **Separated Compute, Storage, Log**
  - **SQL Server** compute node w/ secondary and SSD-based caching
  - 128GB Page Servers → up to 100TB DB
  - Log server (landing zone, long-term log storage)
  - Azure storage layer
  - Period checkpointing



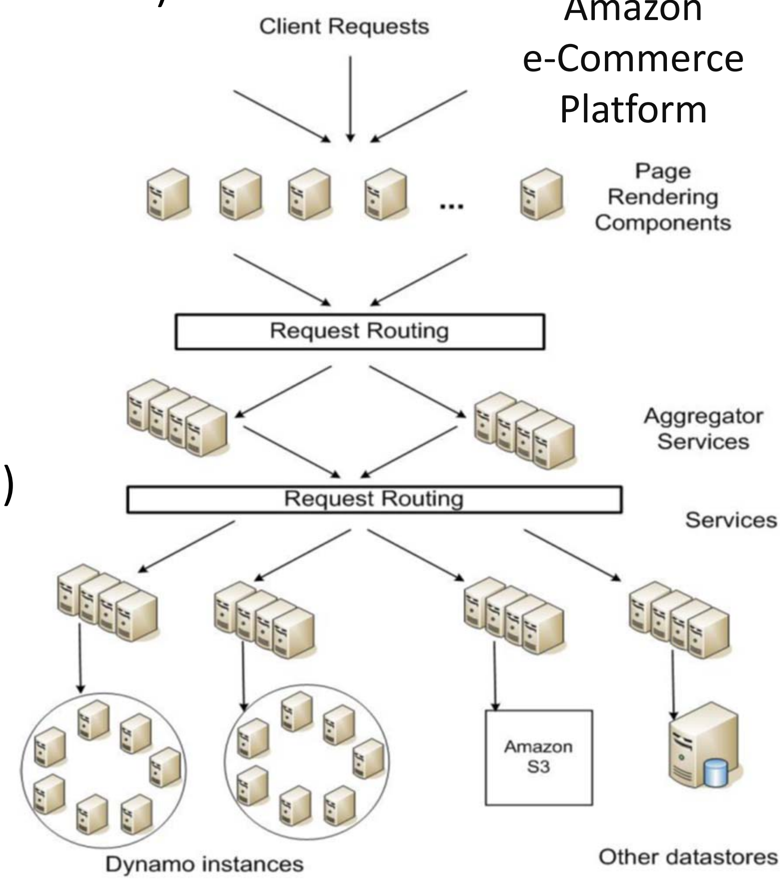
[Microsoft Mechanics: What is Azure Database Hyperscale?, https://www.youtube.com/watch?v=Z9AFnKI7sfI]

Example Dynamo (KV Store)

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

- **Motivation**
  - **Simple**, **highly-available** data storage for small objects in ~1MB range
  - Aim for **good load balance** (99.9th percentile SLAs)
- **#1 System Interface**
  - Simple get(k, ctx) and put(k, ctx) ops
- **#2 Partitioning**
  - **Consistent hashing** of nodes and keys on circular ring for **incremental scaling**
  - Nodes hold **multiple virtual nodes** for **load balance** (add/rm, heterogeneous)
- **#3 Replication**
  - Each data item **replicated N times** (at coord node and N-1 successors)
  - Eventual consistency with async update propagation based on **vector clocks**
  - Replica synchronization via **Merkle trees**

Amazon e-Commerce Platform

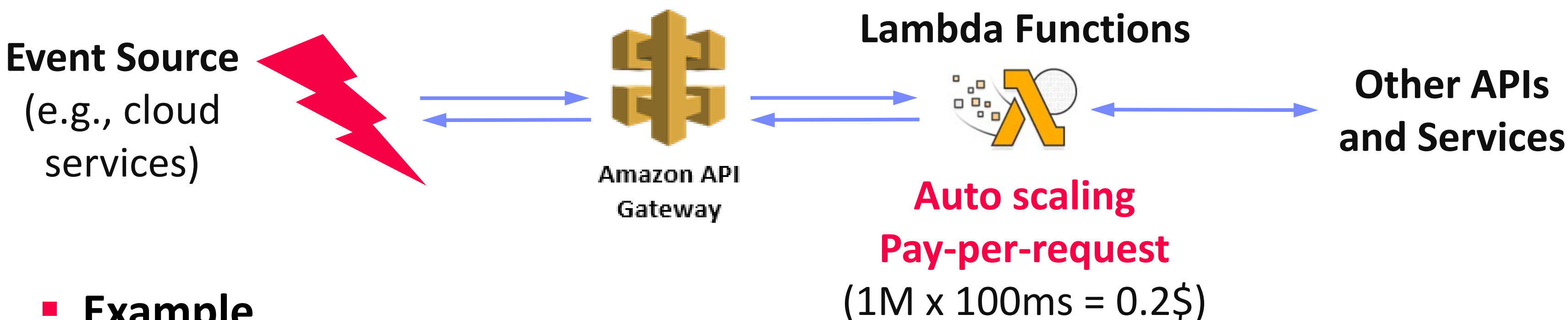


FaaS: Serverless Database Systems

Serverless Computing

[Joseph M. Hellerstein et al: Serverless Computing: One Step Forward, Two Steps Back. **CIDR 2019**]

- **Definition Serverless**
  - **FaaS:** functions-as-a-service (event-driven, stateless input-output mapping)
  - Infrastructure for deployment and auto-scaling of APIs/functions
  - Examples: **Amazon Lambda**, **Microsoft Azure Functions**, etc



- **Example**

```
import com.amazonaws.services.lambda.runtime.Context;
import com.amazonaws.services.lambda.runtime.RequestHandler;

public class MyHandler implements RequestHandler<Tuple, MyResponse> {
    @Override
    public MyResponse handleRequest(Tuple input, Context context) {
       return expensiveStatelessComputation(input);
    }
}
```

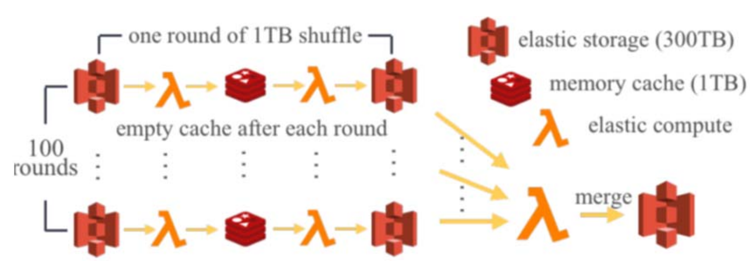
Applications

- **Embarrassingly-Parallel Use Cases**
  - Stateless image/video processing (thumbnails, encoding, rendering)
  - ML inference/scoring (e.g., object classification and detection)
  - Distributed compilation, unit testing

- **Data Analytics – CloudSort** (http://sortbenchmark.org/)

[Qifan Pu, Shivaram Venkataraman, Ion Stoica: Shuffling, Fast and Slow: Scalable Analytics on Serverless Infrastructure. **NSDI 2019**] (Locus)

  - Minimum cost for sorting 100TB
  - 500x slower on serverless compared to VMs → reason: **slow data shuffling**
  - Multi-round, hybrid shuffle (w/ same range partitioner)
    - Small, fast storage (e.g., Redis) for intermediates per round
    - Large, slow storage (S3) output
  - Final merge of runs into S3

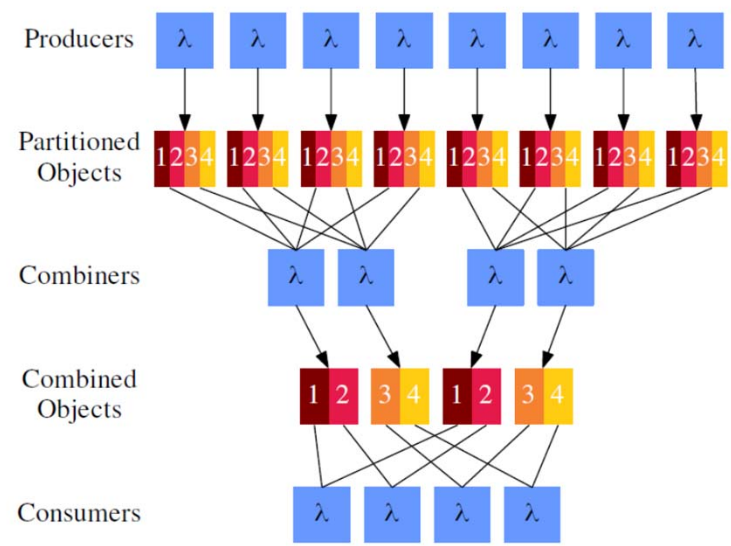


FaaS Query Processing – Starling (MIT)

- **Motivation**
  - Avoid pre-provisioning, and data loading
  - Pay per query w/ competitive performance
  - Tunable cost-performance per query

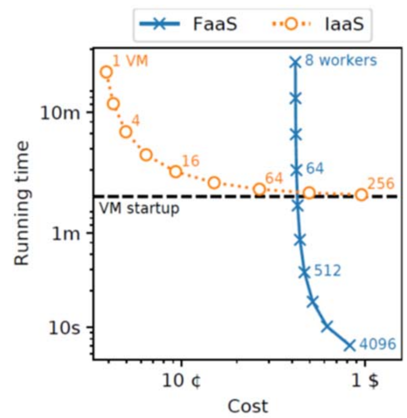
[Matthew Perron, Raul Castro Fernandez, David J. DeWitt, Samuel Madden: Starling: A Scalable Query Engine on Cloud Functions. **SIGMOD 2020**]

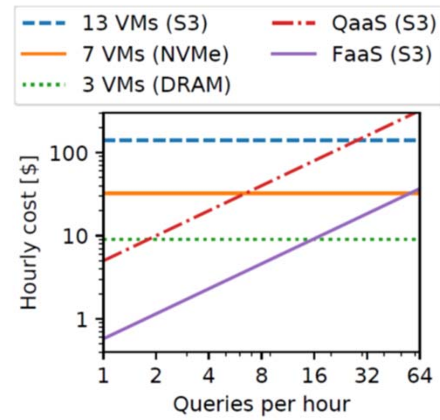
- **Starling Query Processing**
  - Coordinator compiles queries, and schedules tasks
  - Open input formats (CSV, ORC, Parquet)
  - Intermediates stored in S3
  - Shuffling: Mitigate many file problem by writing single file per task, read portions
  - Data centric query compilation
  - Task pipelining and straggler mitigation



FaaS Query Processing – Lambada (ETH)

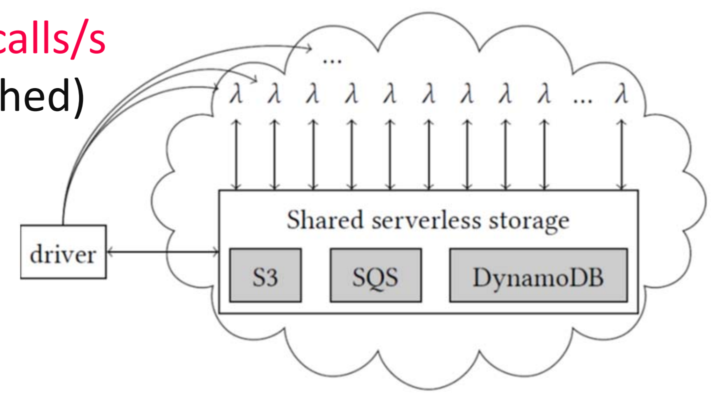
- **Potential Analysis**
  - Simulation of scan 1TB from S3 (**2min VM startup**, 4s fun startup)
  - Short startup + demand scaling
  - **Interactive analytics on cold data** (e.g., Hydrology, HE Physics)





- **Lambada Query Processing**
  - Driver on client machine w/ **batched, two-level invocation**
  - Data-parallel execution solely with serverless workers (lambda funs)
  - **Parquet scan operator** (sel/proj pushdown)
  - **Exchange operators** for join/sort/group-by (communication through shared storage)

~220 calls/s (batched)

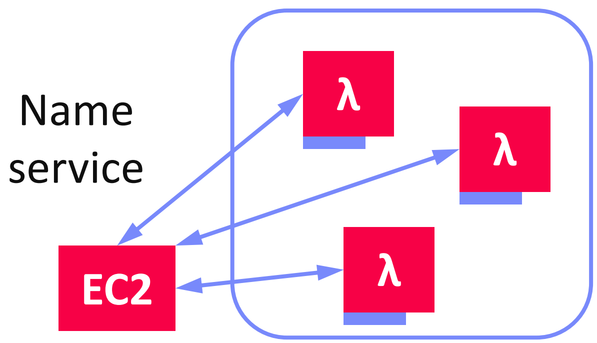


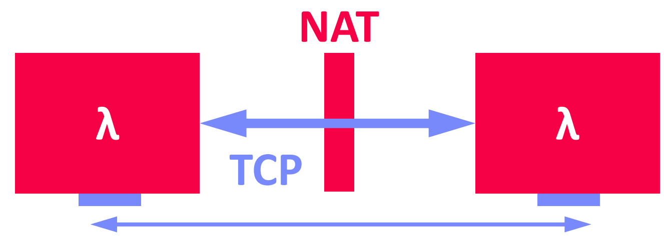
[Ingo Müller et al: Lambada: Interactive Data Analytics on Cold Data Using Serverless Cloud Infrastructure. **SIGMOD 2020**]

FaaS Query Processing – Lambada (ETH), cont.

[Michal Wawrzoniak et al: Boxer: Data Analytics on Network-enabled Serverless Platforms, **CIDR 2021**]

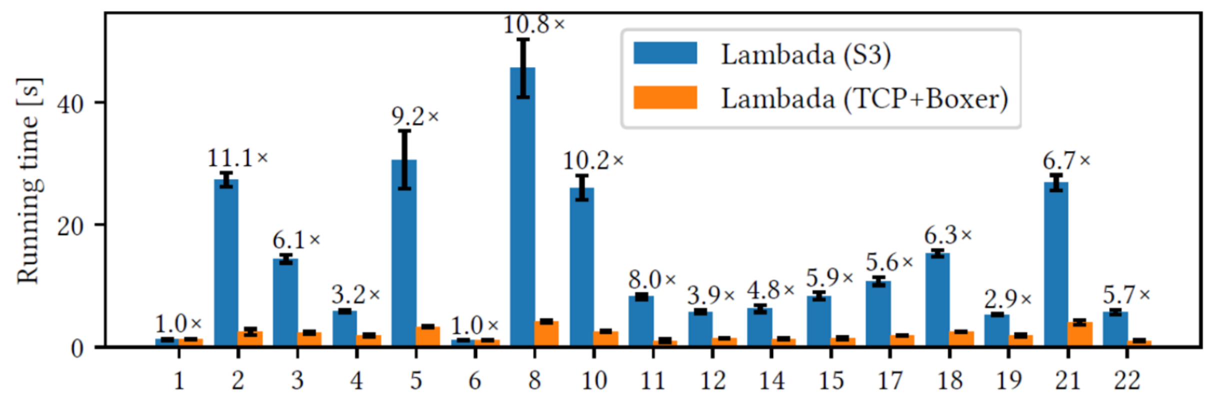
- **Function-to-function TCP Networking**
  - Problem: FaaS functions behind NAT
  - NAT Hole Punching (e.g., P2P research, exchange network addresses)
  - Setup and communication processes





Boxer lib intercepts connect(), exchanges IP info, and established normal TCP connection

- **TPC-H Performance**

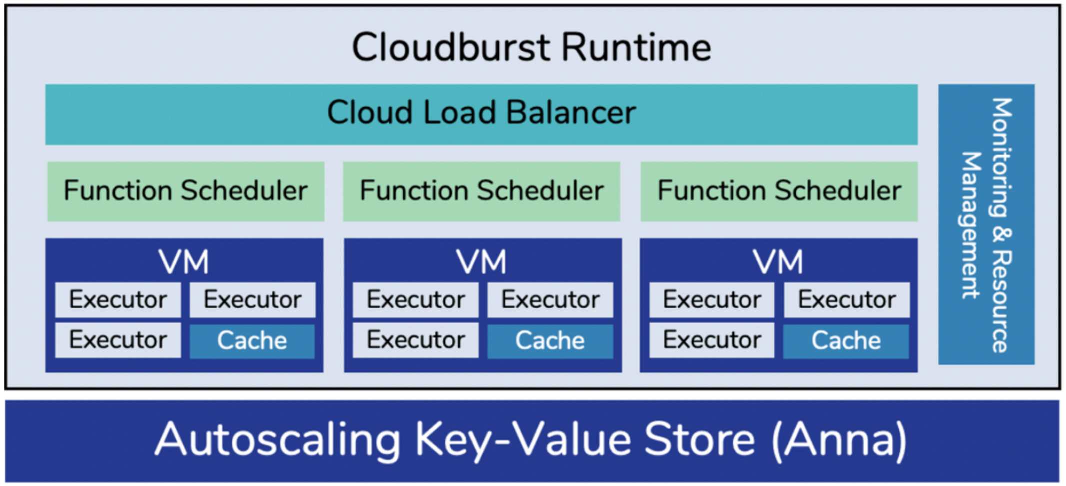


FaaS Query Processing – Cloudburst (UC Berkeley)

[Vikram Sreekanti et al: Cloudburst: Stateful Functions-as-a-Service. **PVLDB 13(11) 2020**]

- **Motivation**
  - Autoscaling serverless computing, with low-latency mutable state ➔ broader class of apps
  - State sharing and mutable caches co-located w/ functions (data locality)

- **Architecture**
  - VM orchestration via Kubernetes
  - Logical disaggregation with physical co-location
  - Functions interact w/ the cache not KV-Store
  - Anna periodically propagates key updates
  - Coordination-free consistency (via lattice data types: MapLattice)



Prototype not compatible w/ Public Cloud Lambda Functions

Summary and Q&A

- **Cloud Computing Background**
- **PaaS: SQL on Hadoop**
- **SaaS: Cloud DBs and Cloud DWHs**
- **FaaS: Serverless Database Systems**

Is FaaS/serverless the right underlying abstraction for query processing?
(general-purpose, startup time, price model, elasticity)

- **Next Lectures** (Part C)
  - **11** **Modern Concurrency Control** [Jan 20]
  - **12** **Modern Storage and HW Accelerators** [Jan 27]