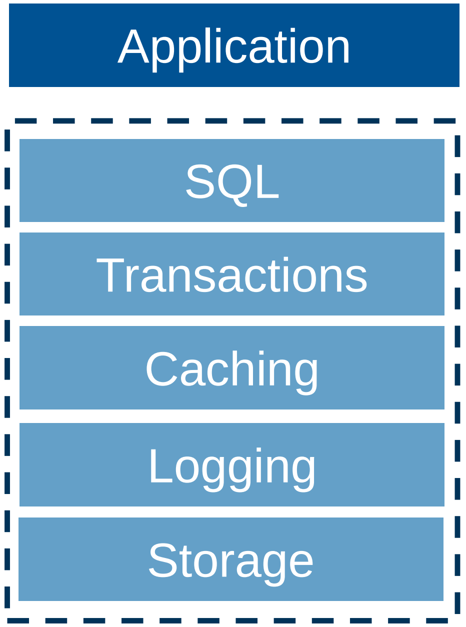
Cloud-Based Data Processing

OLTP in the cloud (DBaaS)

Jana Giceva

Traditional OLTP database design

- Monolithic relational database stack did not change much in the last 30-40 years



- SQL layer: compiler, optimizer, query processing, access methods
- Transaction layer: transaction manager, locking, undo management
- Caching: buffer cache
- Logging: redo logging, crash recovery, back-up/restore
- Storage: durable storage

Traditional OLTP database design

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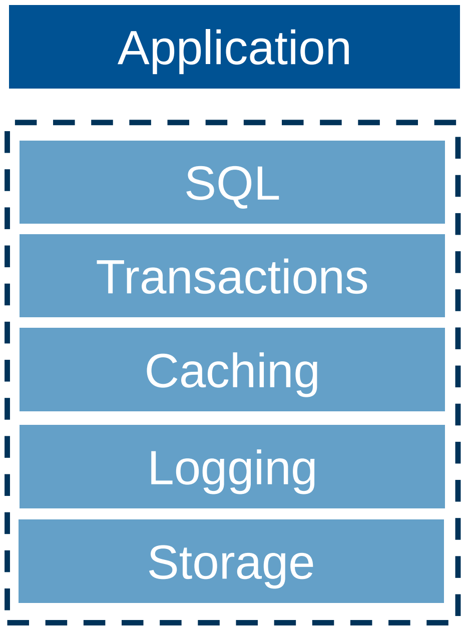
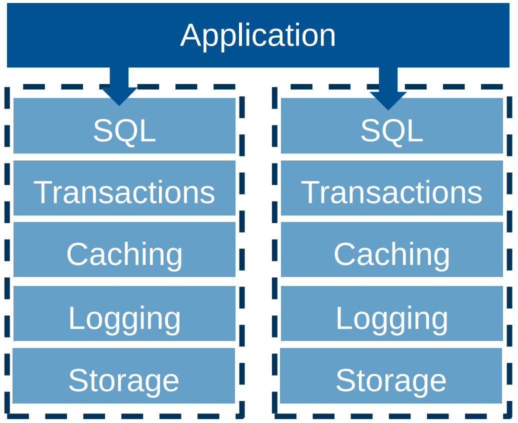


- Works for on premise deployments:
  - In-memory databases (scale-up servers)
  - Fast storage solutions (SSDs, SAN)
  - Expensive reliable hardware
  - Managed by a DB administrator
    - Control software update cycles and plan downtimes

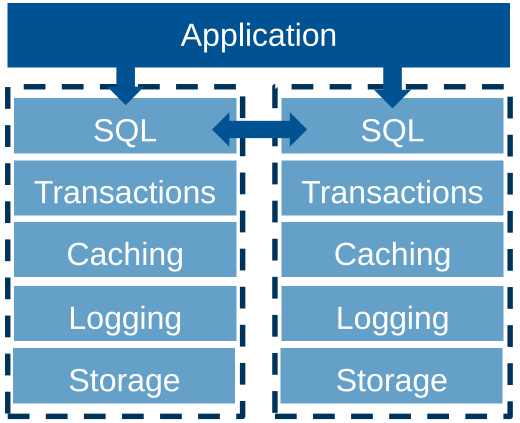
Conventional OLTP database scale-out

Different conventional approaches for scaling out databases:

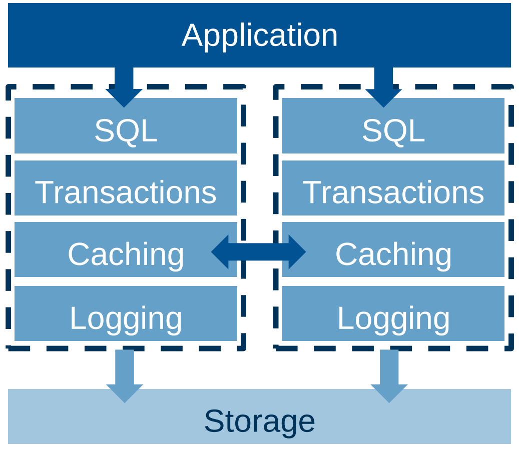
Sharding
coupled at the application layer



Shared Nothing
coupled at the SQL layer



Shared Disk
coupled at the caching and storage layer



But the tightly coupled monolithic stack remains

Cloud environment

- Failures happen all the time
  - Permanent vs transient failures
  - Slow or overloaded components (nodes)
- Geo-distributed datacenters
- Different requirements and expectations
  - Cost, elasticity, availability, tail latency at scale (see next slide)
- Fast and expensive vs. slow and cheap storage
  - Trade-off high-performance vs. durability and scalability
- Different guarantees of ephemeral and persistent storage media

OLTP in the cloud (DBaaS)

Expectations:

- Durability guarantees
- Support large databases (e.g., 100TB)
- Scalability (e.g., workload, dataset size, etc.)
- Fault tolerance
- High availability (e.g., 99.999% availability)
- High performance (low tail latency, high throughput)
- Elastic with workload demand (pay-as-you-go)
- Small blast radius (the impact of a failure)
- Economic (good performance/cost ratio)
- Data locality guarantees (e.g., GDPR compliance)

OLTP in the cloud

- **Conflicting goals:**
  - Support both **large databases** (e.g., 100TB data) AND provide **high availability** (i.e., small mean-time-to-recovery) is **contradictory.**
  - Small mean-time-to-recovery requires small data.

- Many challenging questions:
  - How do we make the system elastic (with load and data, respectively)?
  - How do we ensure fast recovery?
  - How do we provide high availability?
  - How do we achieve good performance?
  - How do we keep replicas consistent?
  - How do we optimize for the new bottlenecks (e.g., reduce write amplification)?
  - How do we efficiently execute distributed transactions in a geo-distributed environment?

- **Not possible with traditional monolithic database architectures.**

State-of-the-art DBaaS architectures

There are four prominent DBaaS systems offered today on the major cloud providers:

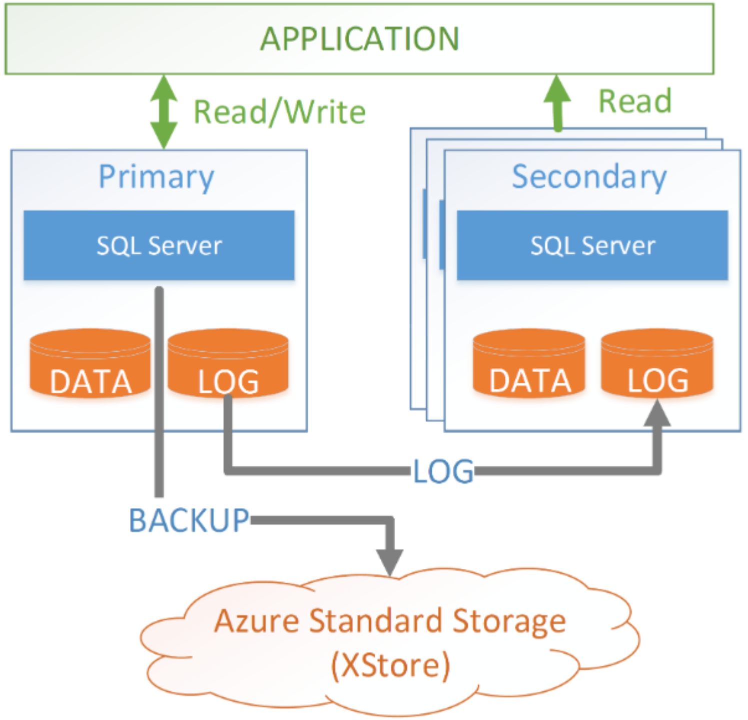
1. Non-partitioned shared-nothing log replicated state machine (Microsoft’s HADR for SQL Server)
2. Non-partitioned shared-data (Aurora, Socrates, Taurus, POLARDB)
3. Partitioned shared-nothing log replicated state machine (Spanner, CockroachDB, POLARDB-X)
   – Requires distributed transactions
4. Tightly coupled nodes over fast interconnect (Oracle’s RAC and Exadata)

Non-partitioned shared-nothing log replicated state machine

Non-partitioned, shared-nothing LRST

Today’s solution for SQL Server offered in Microsoft Azure

- Primary node processes all update transactions
- Ships update logs to all follower replicas
- Primary replica periodically backs-up data to Azure’s storage service (XStore)
  - A log is backed up every 5 min
  - A full back-up is done once per week
- Follower replicas process read-only queries
- Needs four nodes (1 primary, 3 secondary) to guarantee high availability and durability.



img src: Socrates (SIGMOD’19)

Advantages

- The service is stable and mature
  - The HADR architecture has been used successfully for million of databases in Azure

- Has high performance
  - Every compute node has a full, local copy of the database

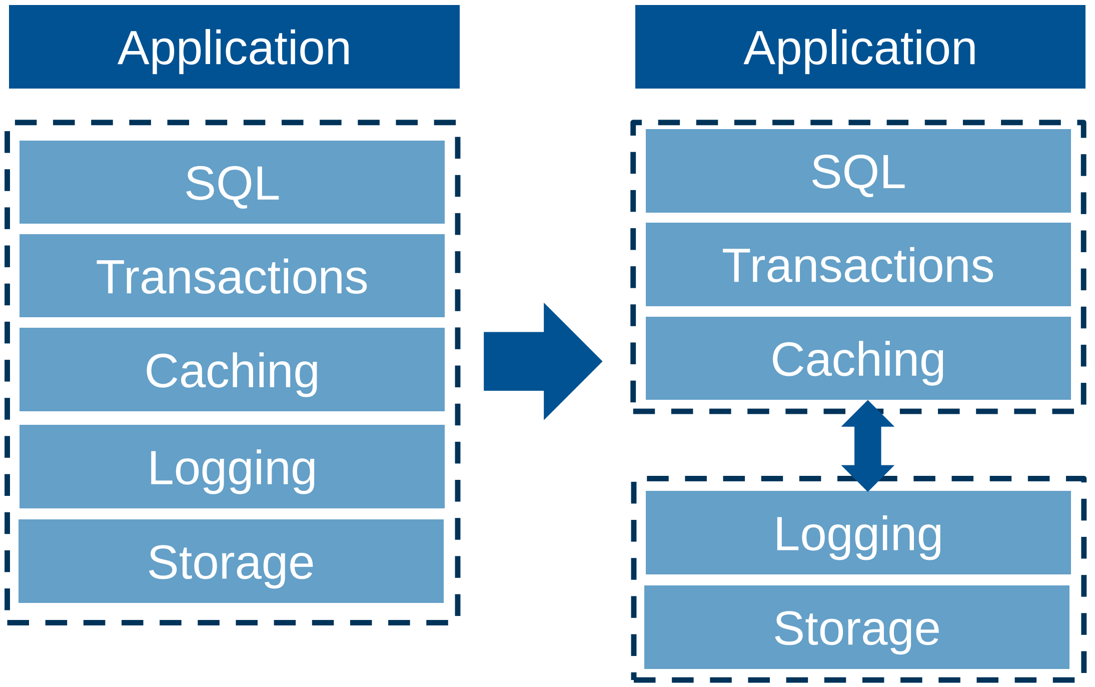
Limitations

- The size of a database cannot grow beyond the storage capacity of a single node (machine).
- Replicas required for resilience and load are coupled.
- O(size-of-data) operations create issues.
  - The cost of seeding a new node (replica) is linear with the size of the database
  - Back-up / restore
  - Scale-up and down
  - Are all examples of operations whose cost grows linearly with the size of the database.
- A special case occurs with long-running transactions when the log grows beyond the storage capacity of the machine and cannot be truncated until the long-running transaction commits.
- Hence, today SQL DB limits the size of the database to 4 TB.

Non-partitioned shared-data log replicated state machine

Key insight: decompose RDBMS functionality

- Decompose monolithic database stack into its fundamental building blocks.



Compute service layer executed by nodes optimized for query processing.
Uses the **storage service** over the network.

Purpose-built, scale-out, self-healing, multi-tenant database-optimized **storage service.**

Decoupling compute and storage

- Advantages:
  - Easy to scale up/down with the load demand
    - Simply add/remove compute nodes
  - Easy to scale up/down the size of the database
  - Easy to replace misbehaving or unreachable compute nodes
  - Easy to fail over from a writer to a replica
    - The expensive part of the operation is handled by the storage layer.
  - Replicating the storage across multiple nodes not coupled with workload demand

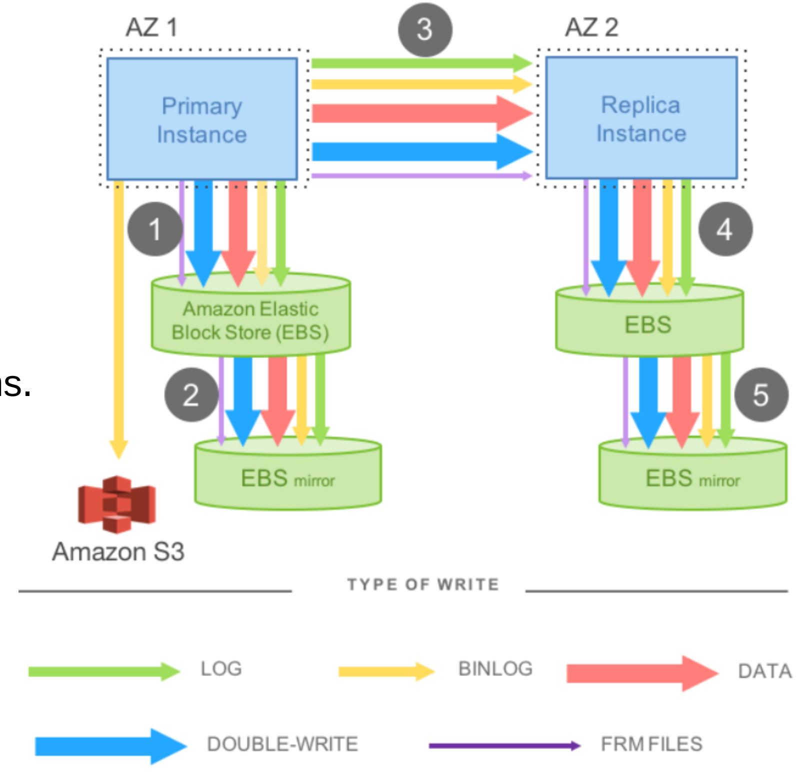
But do the layers remain the same?

Traditionally the interaction between the compute and storage layers has **many inefficiencies**

- RDBMSs organize data in pages.
  - Page modifications are periodically flushed to disk.
- Page modifications are also recorded in a redo log.
  - The log is written to disk in a continuous stream.

- Lot of redundant writes to disk, especially with replicas.
  - E.g., a single logical DB write can lead into multiple (up to five) physical disk writes → performance problems.
  - A lot of data needs to be sent over the network → the I/O bottleneck moves to the network.

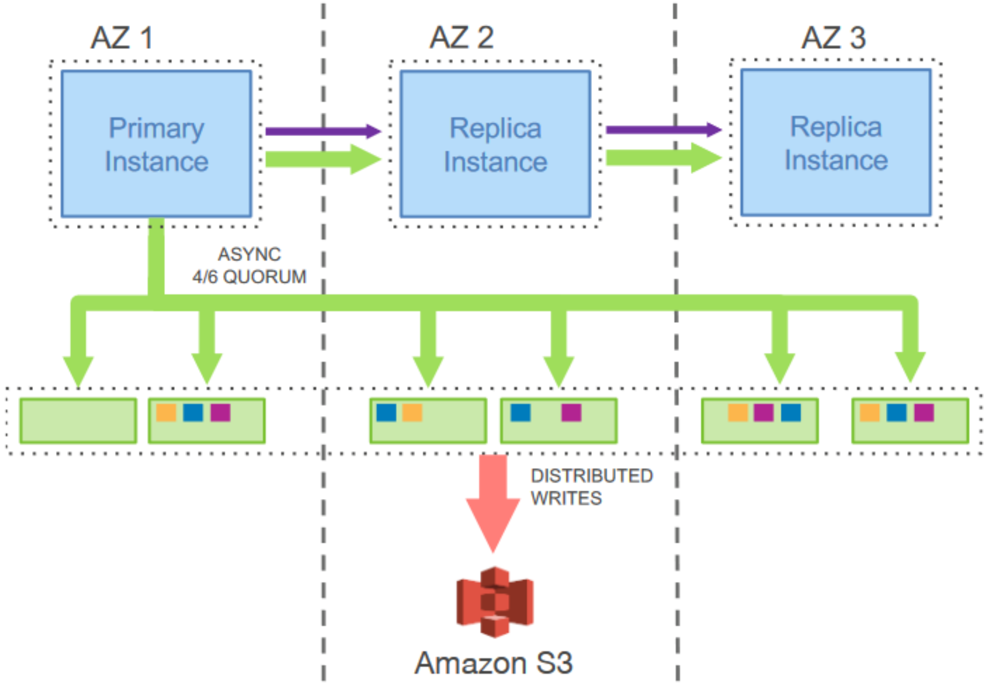
- DB admins combat write amplification by reducing the frequency of page flushes.
  - At the cost of slower crash recovery.



img src: Aurora (SIGMOD'17)

Solution: **The Log is the Database**

- Example system **Amazon Aurora**
- Compute nods **only write redo log records** to the distributed storage layer.
  - For correctness purposes the Log is the database!
- The **storage layer re-constructs the page** images **from log records** on demand
  - Any pages that the storage layer materializes (in the background) are a cache of log applications.

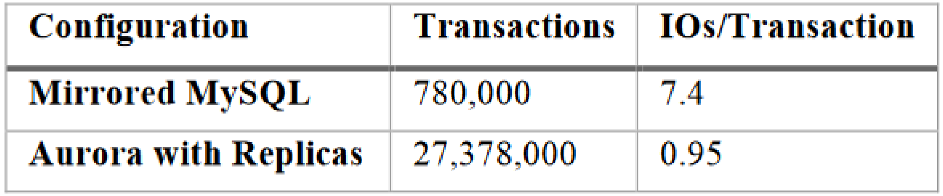


img src: Aurora (SIGMOD'17)

Advantages

- Reduces network I/O, as the primary only ships the log records + metadata updates to the replicas

Table 1: Network IOs for Aurora vs MySQL



Configuration	Transactions	IOs/Transaction
Mirrored MySQL	780,000	7.4
Aurora with Replicas	27,378,000	0.95

- Less pressure on the network allows more aggressive data replication
  – better durability, availability, and minimizing the impact of jitter (more parallel reads).

- Moving processing (check-pointing, backup/recovery, etc.) to storage:
  – Improves availability as we have lower crash recovery time
  – Minimizes jitter caused by background processes.

Durability at scale

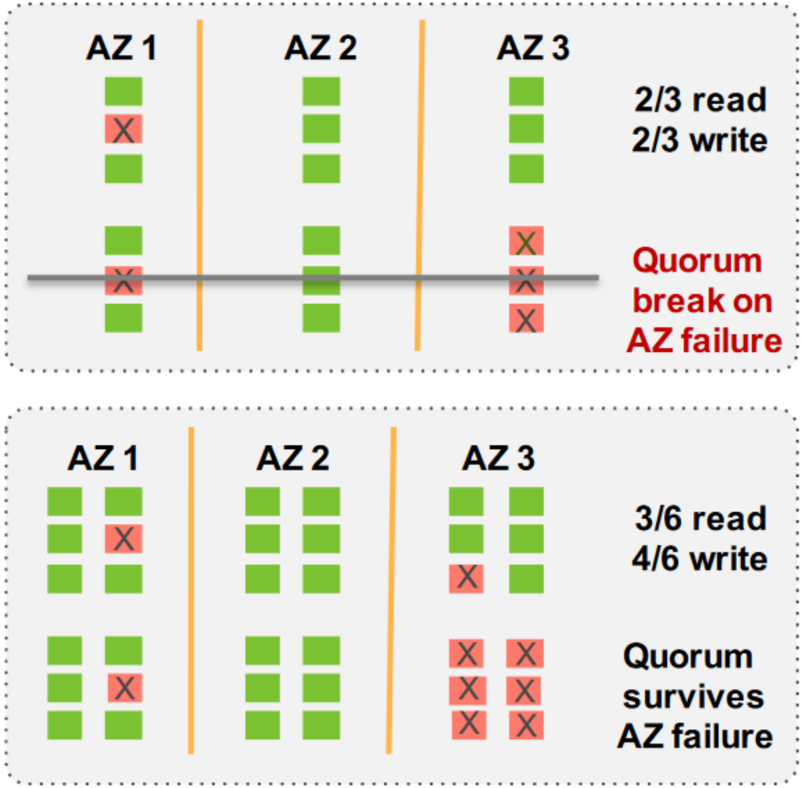
- Another benefit of decoupling storage and compute
  - The lifetime of a database instance is not linked/coupled with storing the data.
    - instances fail, are shut-down, become unavailable, are resized up/down based on workload, etc.

- The storage layer ensures the data is stored durably and resiliently to failure.
  - Goal is to be fault tolerant not only to transient failures but also to entire data centers / availability zone.

- Additionally, both data and log should be partitioned for scalability.

Aurora’s quorum and cell based architecture

- Why are 3 replicas and 2/3 read/write quorum insufficient at cloud-scale?
  - Assume an AZ fails and another transient fault occurs.
- Aurora replicates all writes six times to three AZs with 4/6 write quorum and 3/6 read quorum.
  - can tolerate the loss of an entire AZ without losing data availability.
  - can recover rapidly from larger failures.



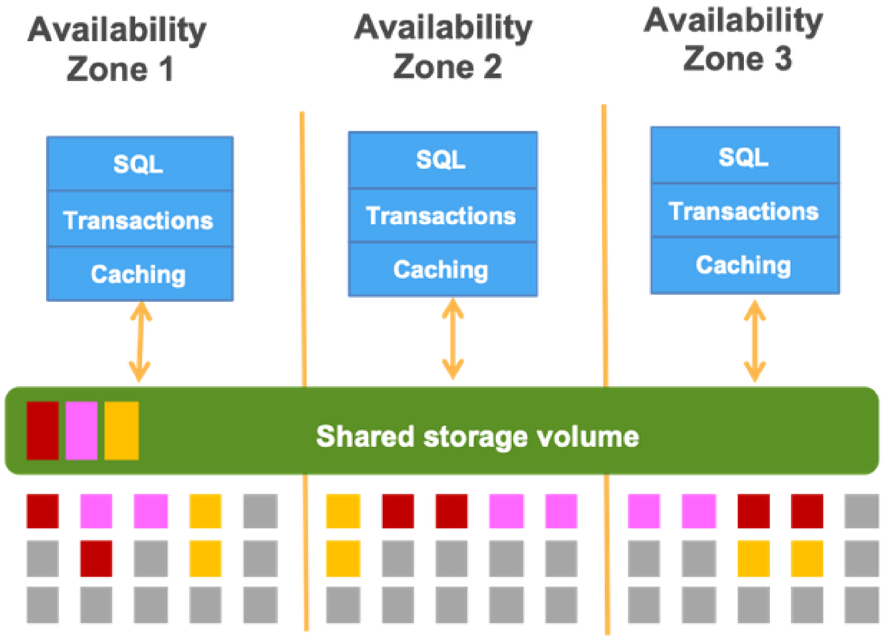
img src: Aurora (SIGMOD’18)

Data sharding: fast repairs and catch-up

- Amazon Aurora's replication is based on sharding and scale-out.

- When a fault occurs, need a fast recovery
  - Low mean-time-to-recover (MTTR) to increase availability.
  - Need to partition the database in small enough chunks (fixed size segments) that are fast to copy and repair.

- In Aurora:
  - A database is sharded into 10GB logical units.
  - Each unit is replicated six ways, spread across a large distributed storage fleet.

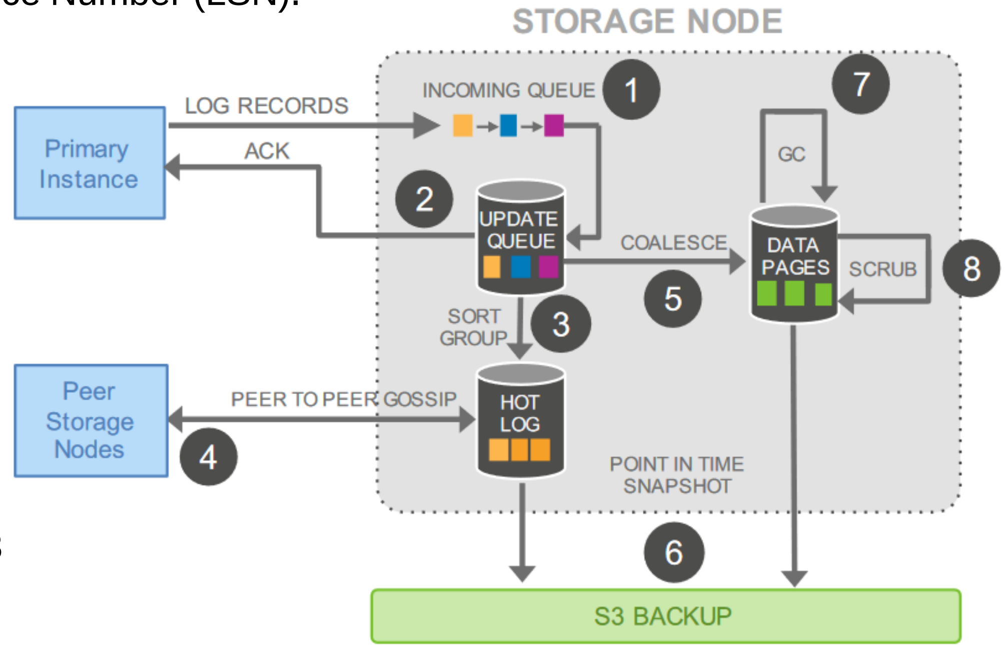


img src: All Things Distributed Blog by Werner Vogel

How does the storage layer work?

- Each log record has an associated Log Sequence Number (LSN).

- Storage node steps:
  1. Receive a log record and add it to an in-memory queue
  2. Persist record on disk and acknowledge
  3. Organize records and identify gaps in the log since some batches may be lost
  4. Gossip with peers to fill the gaps
  5. Coalesce log records into new data pages
  6. Periodically stage log and new pages to S3
  7. Periodically garbage collect old versions
  8. Periodically validate CRC codes on pages



img src: Aurora (SIGMOD'17)

What about reads?

- As with most databases, a read often hits the buffer cache
- What happens in case of a buffer cache miss?
  - A quorum read is expensive and is best avoided.
  - Aurora’s client-side storage driver tracks which writes were successful for which segments.
    - No need for a quorum read on routine page reads
  - The only time a read quorum is needed is during recovery on a database instance restart.
    - The initial set of LSN markers must be reconstructed by asking storage nodes.

Separate durability from availability

- Microsoft's Socrates extends the shared-data architecture.

- **Key ideas:**

1. **Separate Log from Storage** and make the Log first class citizen.

2. Differentiate **when to use fast vs slow storage**.

- **Advantages:**
  - Separates **durability** (implemented by the log)
    - fundamental property to avoid data loss
  - from **availability** (implemented by the storage tier)
    - needed to provide good quality of service

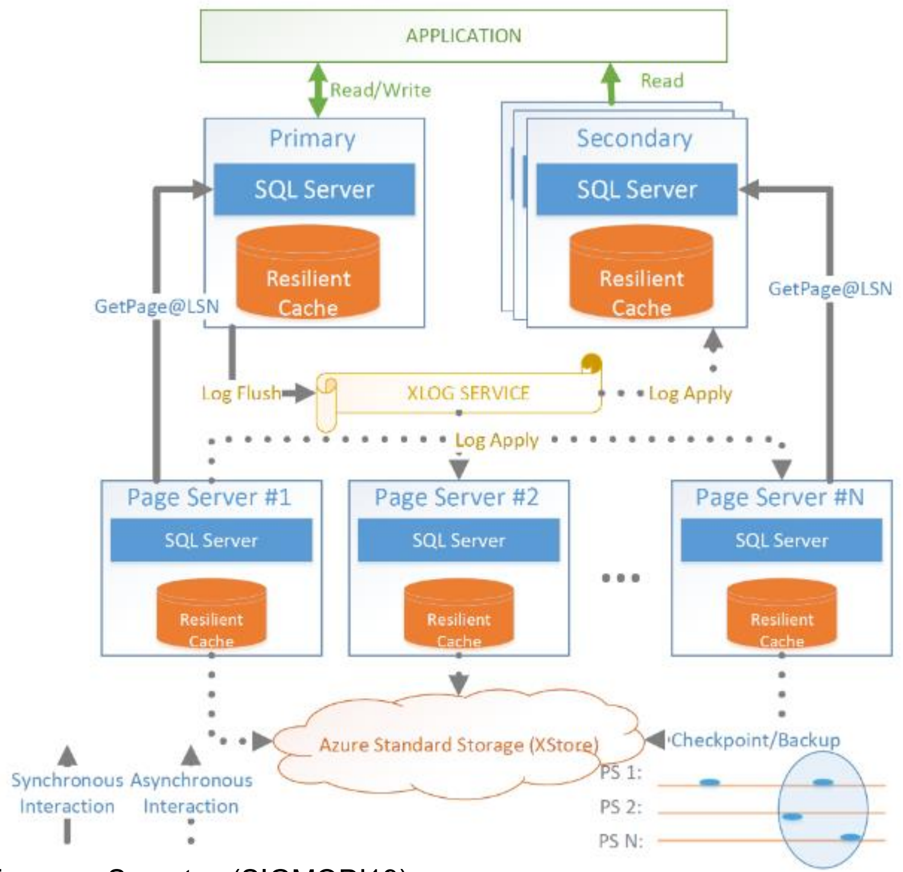
  - In contrast to availability, durability does not require copies in fast storage
  - In contrast to durability, availability does not need a fixed number of replicas.

Why should the log be treated separately?

- The log is a **potential bottleneck** of any OLTP system
  - Every update must be logged before a transaction is committed
  - The log is shipped to all replicas to keep them consistent
  - Storing it on slow storage media can hurt performance.

- **How to provide a highly performant logging solution at cloud scale?**
  - Make the log durable in fast storage and fault-tolerant by replicating it
  - Reading and shipping log records is more scalable if the log is decoupled from other storage

Further decomposition of DB functionality



img src: Socrates (SIGMOD'19)

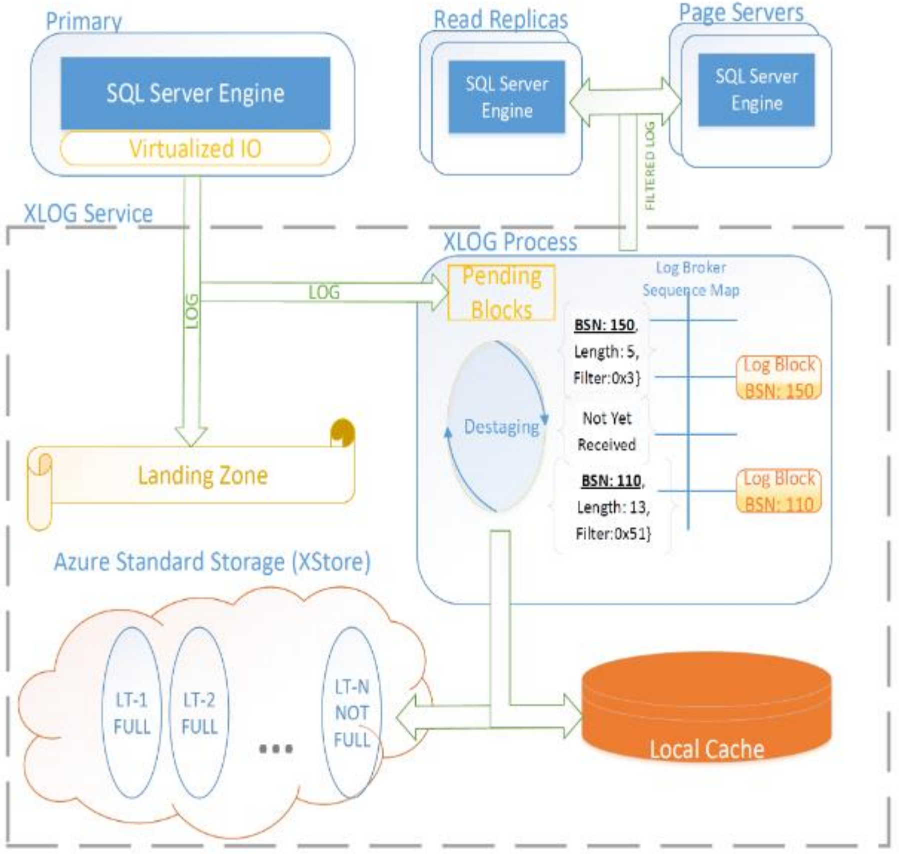
Compute tier.
Compute nodes. The primary instance handles all read/write transactions. Multiple followers handle read-only queries. Cache hot pages in memory.

Log tier. Separate log service to ensure low commit latencies and good scalability.

Storage tier.
Each page server keeps a copy of a partition of the database in-memory or fast local SSDs.

Azure Storage Service tier.
The page servers checkpoint data pages and create back-ups in the slow but cheap XStore tier.

Logging as a cloud-native service

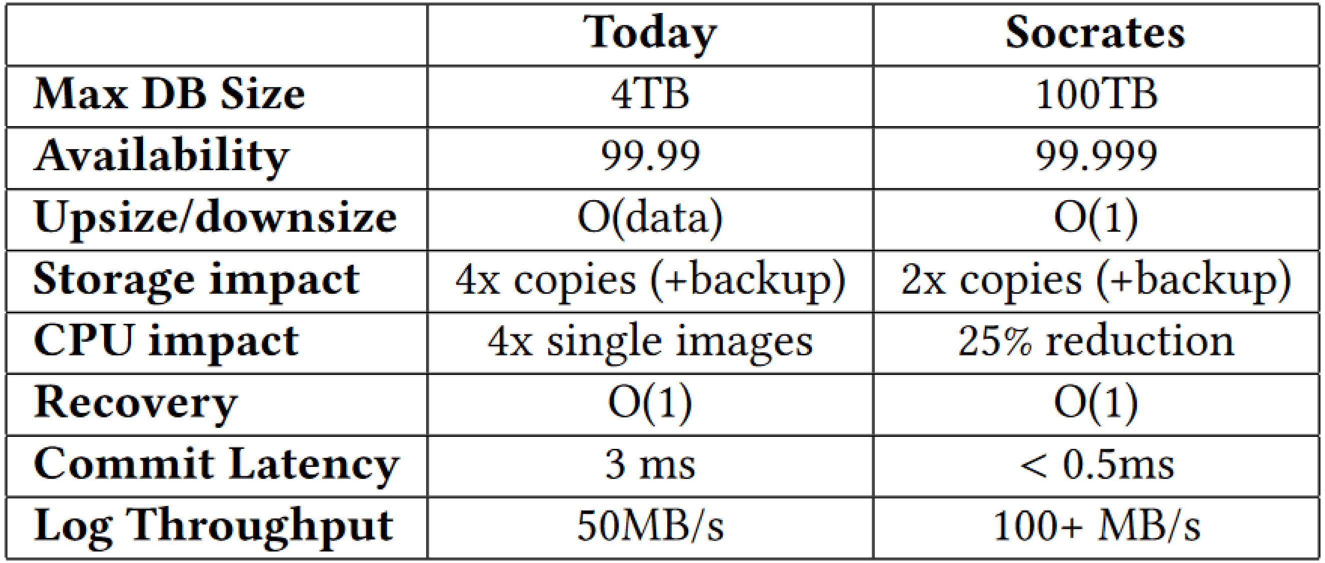


img src: Socrates (SIGMOD'19)

- 1. The Primary Compute node writes log blocks directly to a Landing Zone (fast durable storage)
  - Synchronous operation that needs low latency
  - For durability, keep 3 replicas of all data.
- 2. The Primary also writes all log blocks to the XLOG Process that disseminates the blocks to Page Servers and the follower replicas.
  - Asynchronous writes and possibly lossy.
  - LZ for durability, XLOG for availability.
- 3. The XLOG Process waits for blocks to be made durable, orders the OoO blocks (after filling in the gaps), and de-stages the archived blocks to fast local and slow remote storage.
- 4. Consumers (Followers, Page Servers) pull log blocks from the XLOG service.

Socrates

- Uses less expensive copies of data in the fast local storage
- Fewer copies of data overall and less networking bandwidth
- Less compute resources to keep copies up-to-date



	Today	Socrates
Max DB Size	4TB	100TB
Availability	99.99	99.999
Upsize/downsize	O(data)	O(1)
Storage impact	4x copies (+backup)	2x copies (+backup)
CPU impact	4x single images	25% reduction
Recovery	O(1)	O(1)
Commit Latency	3 ms	< 0.5ms
Log Throughput	50MB/s	100+ MB/s

img src: Socrates (SIGMOD'19)

Distributed Transactions
(quick re-cap)

Distributed Transactions

- Recall **atomicity** in the context of ACID transactions
  - A transaction either **commits** or **aborts**
  - If it commits, its updates are durable
  - If it aborts, it has no visible side-effects
  - ACID consistency (preserving invariants) relies on atomicity

- If the transaction updates data on multiple nodes, this implies
  - Either all nodes must commit, or all must abort
  - If any node crashes, all must abort

- Ensuring this is the **atomic commitment** problem.

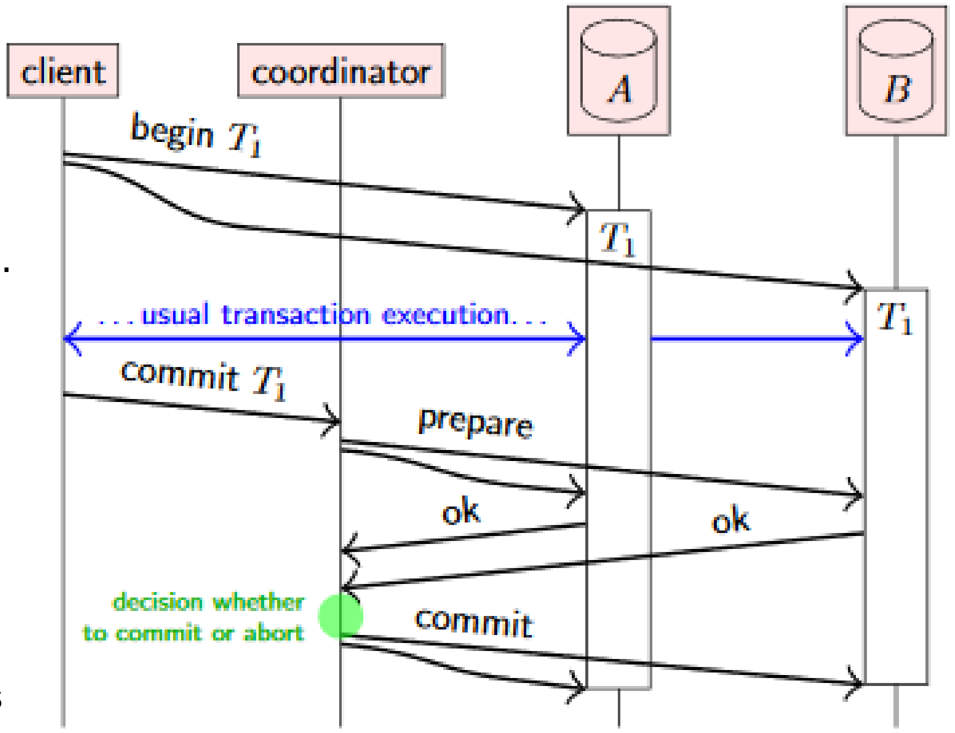
Two-phase commit (2PC)

- **Two-phase commit protocol**
  most common algorithm to ensure atomic commitment across multiple nodes.
  [Gray, 1978]

- Not to be confused with two-phase locking (2PL).

- **What if the coordinator crashes?**
  – Coordinator writes the decision to disk
  – When it recovers, it reads decision from disk and sends it to replicas
  – Problem if coordinator crashes after prepare, but before broadcasting decision
  – Algorithm is blocked until coordinator recovers

- **Solution: consensus (total order broadcast).**


client
coordinator
A
B
begin T_1
T_1
T_1
. . . usual transaction execution. . .
commit T_1
prepare
ok
ok
decision whether to commit or abort
commit

img src: Martin Kleppmann (Cambridge)

Fault-tolerant 2PC (1/2)

- **Fault tolerant 2PC** based on **Paxos Commit** [Gray and Lamport, 2006]

- Every node that participates in the transaction uses total order broadcast to disseminate its vote (commit or abort).

- If node A suspects that node B has failed, then A may try to vote to abort on behalf of B.

```
on initialisation for transaction $T$ do
    $commitVotes[T] := \{\}$; $replicas[T] := \{\}$; $decided[T] :=$ false
end on

on request to commit transaction $T$ with participating nodes $R$ do
    for each $r \in R$ do send (Prepare, $T, R$) to $r$
end on

on receiving (Prepare, $T, R$) at node $replicaId$ do
    $replicas[T] := R$
    $ok =$ "is transaction $T$ able to commit on this replica?"
    total order broadcast (Vote, $T, replicaId, ok$) to $replicas[T]$
end on

on a node suspects node $replicaId$ to have crashed do
    for each transaction $T$ in which $replicaId$ participated do
        total order broadcast (Vote, $T, replicaId$, false) to $replicas[T]$
    end for
end on
```

Fault-tolerant 2PC (2/2)

- **Fault tolerant 2PC** based on **Paxos Commit** [Gray and Lamport, 2006]
- Potential race condition if two (conflicting) votes received from the same node (e.g., by node A voting on B’s behalf).
- Resolved due to total order broadcast + counting only the first vote to arrive.

```
on delivering (Vote, $T$, $replicaId$, $ok$) by total order broadcast do
    if $replicaId \notin commitVotes[T] \wedge replicaId \in replicas[T] \wedge$
            $\neg decided[T]$ then
        if $ok$ = true then
            $commitVotes[T] := commitVotes[T] \cup \{replicaId\}$
            if $commitVotes[T] = replicas[T]$ then
                $decided[T]$ := true
                commit transaction $T$ at this node
            end if
        else
            $decided[T]$ := true
            abort transaction $T$ at this node
        end if
    end if
end on
```

Partitioned log-replicated state machine

Google's Spanner

- A database system with million's of nodes, petabytes of data, distributed across datacenters worldwide.

- Consistency properties:
  - **Serializable** transaction isolation
  - **Linearizable** reads and writes
  - Many **shards,** each holding a subset of the data; atomic commit of transactions across shards

- Many standard techniques:
  - State machine replication (Paxos) within a shard
  - Two-phase locking (2PL) for serializability
  - Two-phase commit (2PC) for cross-shard atomicity

- The interesting bit: read-only transactions require **no locks!**

Spanner – Partitioned (Log-replicated SM)

- To address the O(size of data) issues
  - Spanner shards the data logically into partitions called splits
- Multiple copies of a split are kept consistent using Paxos
  - Only one of the partition replicas can modify data – the leader.
  - Other replicas can only read.
- The main challenge in geo-replication is keeping the replicas consistent
  - Key innovation with the True Time facility.

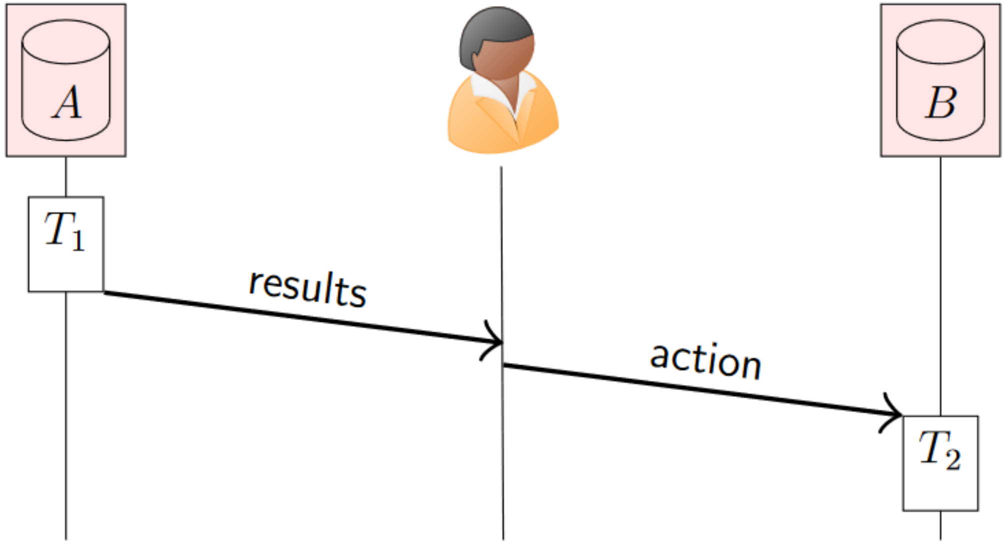
Consistent snapshots

- A read-only transaction observes a **consistent snapshot:**

- Approach: **multi-version concurrency control** (MVCC)
  - Each read-write transaction T_w has commit timestamp t_w
  - Every value is tagged with timestamp t_w of transaction that wrote it (not overwriting previous value)
  - Read-only transaction T_r has snapshot t_r
  - T_r ignores values with $t_w > t_r$; observes most recent value with $t_w \leq t_r$

Obtaining commit timestamps

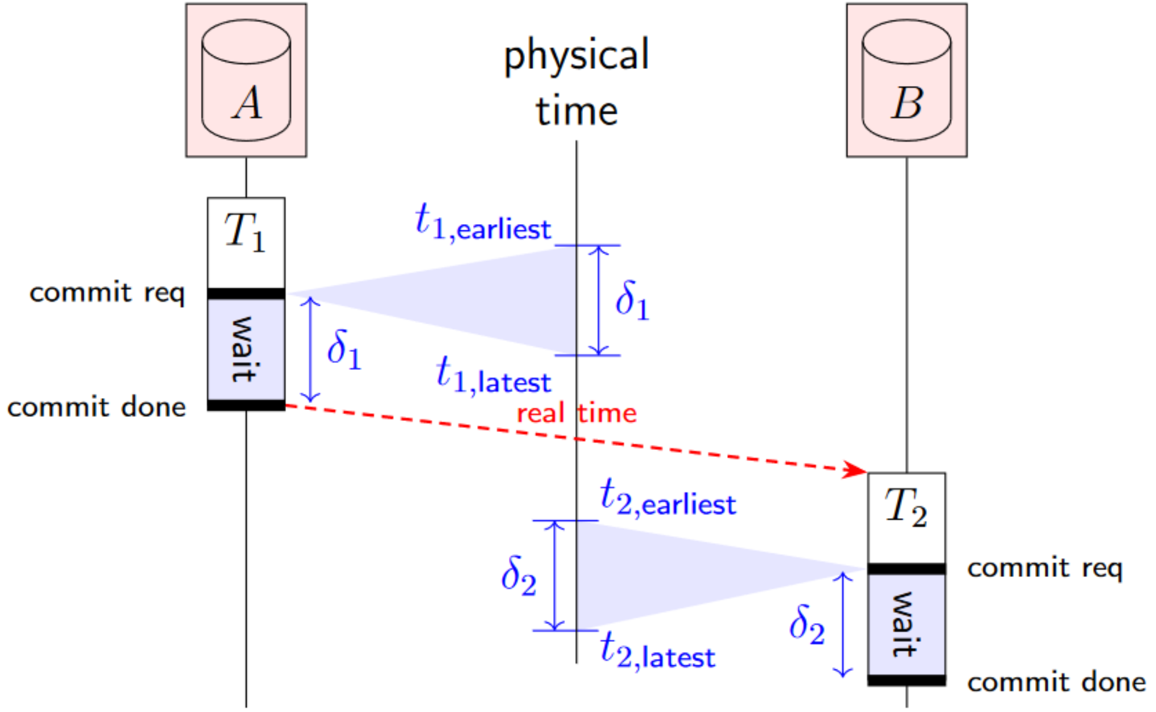
- Must ensure that whenever $T_1 \rightarrow T_2$, we have $t_1 < t_2$
  - Physical clocks may be **inconsistent with causality**
  - Can we use Lamport clocks instead?
  - Problem: linearizability depends on **read-time order,** and logical clocks may not reflect on this!



img src: Martin Kleppmann (Cambridge)

True Time: explicit physical clock uncertainty

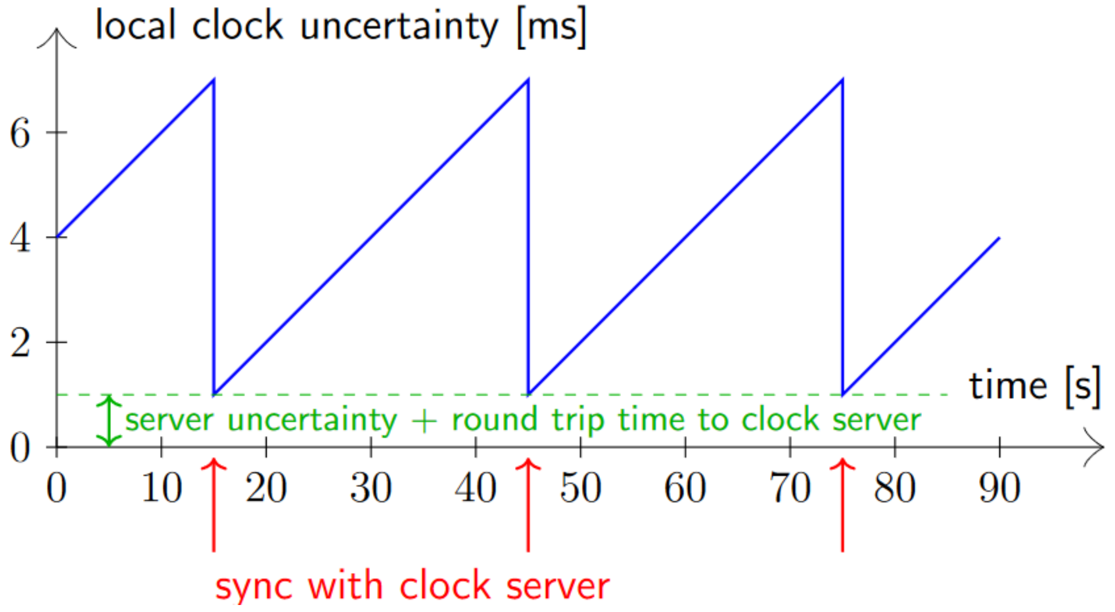
- Spanner's TrueTime clock returns $[t_{earliest}, t_{latest}]$.
- True physical timestamp must lie within that range.
- On commit, wait for uncertainty $\delta_i = t_{i,latest} - t_{i,earliest}$, and assign t_{latest} as timestamp for transaction T_i



img src: Martin Kleppmann (Cambridge)

Determining clock uncertainty in TrueTime

- Clock servers with **atomic clock** or **GPS receiver** in each datacenter, servers report their clock uncertainty.
- Each node syncs its quartz clock with a server every 30 sec. Between syncs, assume worst case drift of 200ppm.



img src: Martin Kleppmann (Cambridge)

Other systems for geo-distributed transactions

- Strong consistency and serializability for geo-distributed transactions.
  - CockroachDB: The resilient Geo-Distributed SQL Database (Parallel Commits)
  - Calvin: Fast Distributed Transactions for Partitioned Database Systems
  - Ocean Vista: Gossip-Based Visibility Control for Speedy Geo-Distributed Transactions
  - Building Consistent Transactions with Inconsistent Replication
  - SLOG: Serializable, Low-latency, Geo-replicated Transactions

Rack-scale solutions using fast interconnects

Distributed transactions can scale

- With low-latency high-bandwidth network interconnects using RDMA:
  - The End of a Myth: Distributed Transactions can Scale (NAM-DB, SI)
  - Strong consistency is not hard to get: 2PL and 2PC on Thousands of Cores
  - No compromises: distributed transactions with consistency, availability, and performance (FaRM, serializability)
  - FaSST: Fast, Scalable, and Simple Distributed Transactions with Two-sided (RDMA) datagram RPCs

- Oracle’s RAC and Exadata
  - All nodes of a cluster are tightly coupled on a fast InfiniBand interconnect
  - Shared cache fusion layer over a distributed storage tier with storage cells
    - Optimized network writes/transfers (zero-copy, OS-bypassing, parallel writing, prioritizing critical OLTP I/O writes/transfers, etc.)

References

The material covered in this class is mainly based on:

- All Things Distributed Blog by Werner Vogel (Amazon's CTO) (link)
- Slides from "*Distributed Systems*" course from University of Cambridge (link)

Papers:

- Amazon Aurora: Design Considerations for High Throughput Cloud-Native Relational Databases (SIGMOD 2017)
- Amazon Aurora: On Avoiding Distributed Consensus for I/Os, Commits and Membership Changes (SIGMOD 2018)
- Socrates: The New SQL Sever in the Cloud (SIGMOD 2019)
- Spanner: Google's Globally-Distributed Database (OSDI 2012)
- https://docplayer.net/62056362-The-limits-of-open-source-in-extreme-scale-storage-systems-design.html

Other relevant (industry) systems:

- Taurus Database: How to be Fast, Available, and Frugal in the Cloud (SIGMOD 2020)
- Cloud-Native Database Systems at Alibaba: Opportunities and Challenges (VLDB 2019)
- CockroachDB: The Resilient Geo-Distributed SQL Database (SIGMOD 2020)