Twitter Messaging的架构演化之路

@sijieg | Twitter

Agenda

- Background
- Layered Architecture
- Design Details
- Performance
- Scale @Twitter
- Q & A

Publish-Subscribe

Online services - 10s of milliseconds

Transaction log, Queues, RPC

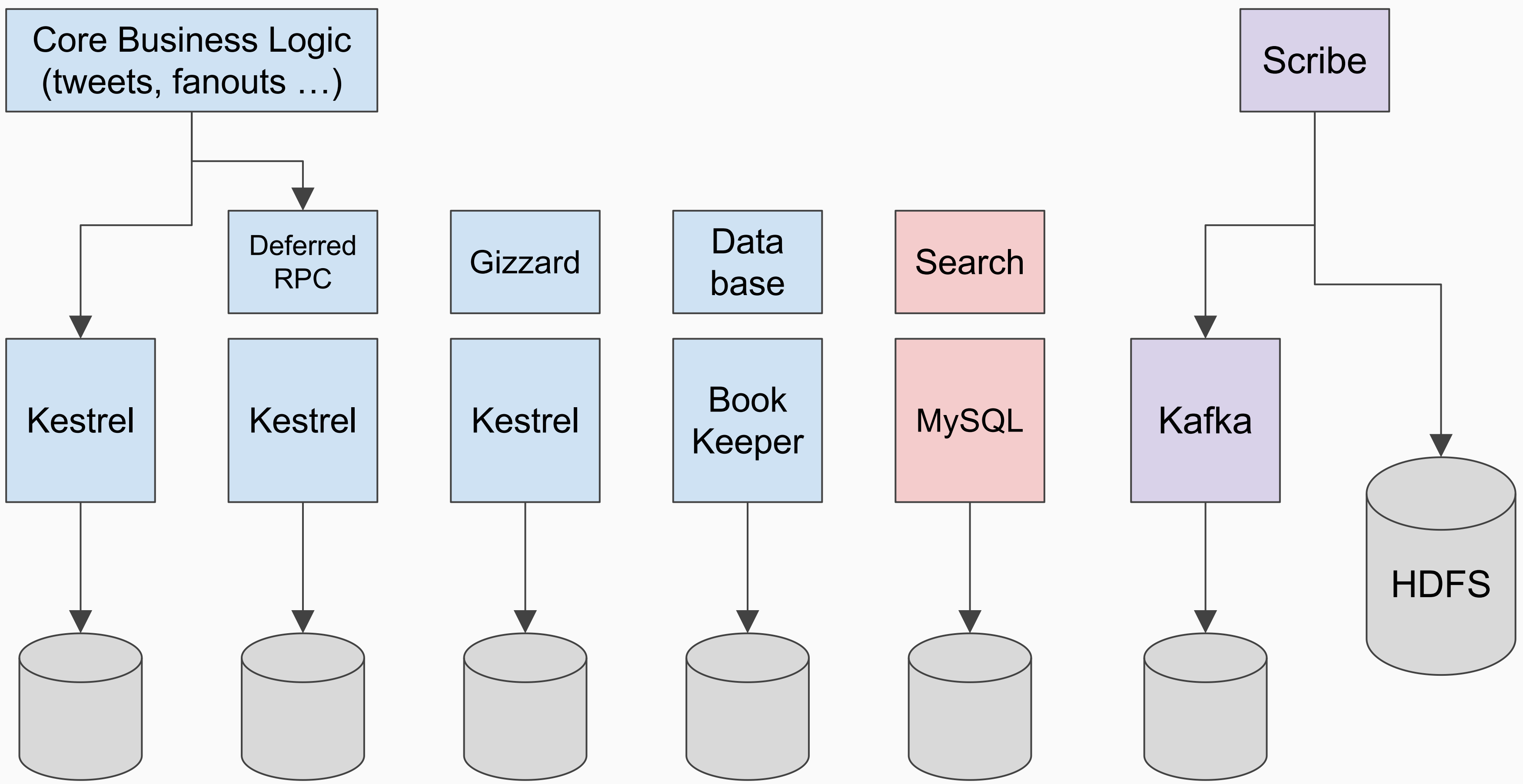
Near real-time processing - 100s of milliseconds

Change propagation, Stream Computing

Data delivery for analytics - seconds~minutes

Log collection, aggregation

Twitter Messaging at 2012



Online Services - Kestrel

Kestrel

- Simple
- Perform well (as long as queue fits in memory)
- Fan-out Queues: One per subscriber
- Reliable reads - per item transaction
- Cross DC replication

Kestrel Limitations

- Durability is hard to achieve - Each queue is a separate file
- Adding subscribers is expensive
  - Separate physical copy of the queue for each fanout
- Read-behind degrades performance - Too many random I/Os
- Scales poorly as #queues increase

Stream Computing - Kafka

Kafka

- Throughput/Latency through sequential I/O with small number of topics
- Avoid data copying - Direct Network I/O (sendfile)
- Batch Compression
- Cross DC replication (Mirroring)

Stream Computing - Kafka Limitation

Kafka Limitation

- Relies on filesystem page cache
- Limit #topics: Ideally one or handful topics per disk
- Performance degrades when subscriber falls behind - Too much random I/O
- No durability and replication (0.7)

Problems

Each of the systems came with their maintenance overhead

- **Software Components** - backend, clients and interop with the rest of Twitter stack
- **Manageability and Supportability** - deployment, upgrades, hardware maintenance and optimization
- **Technical know-how**

Rethink the messaging architecture

Unified Stack - tradeoffs for various workloads

Durable writes, intra-cluster and geo-replication

Multi tenancy

Scale resources independently - Cost efficiency

Ease of manageability

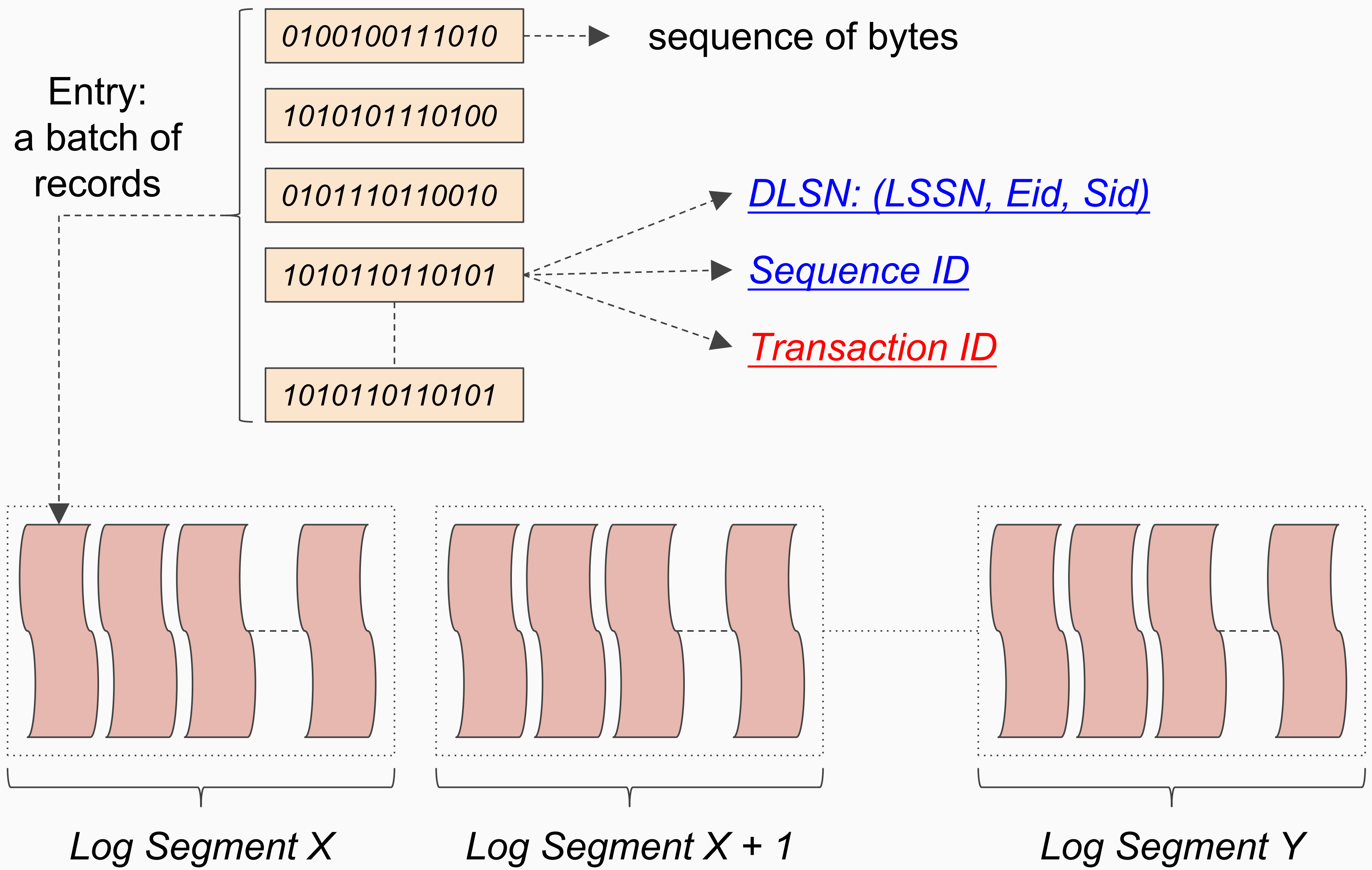
Layered Architecture

Data Model

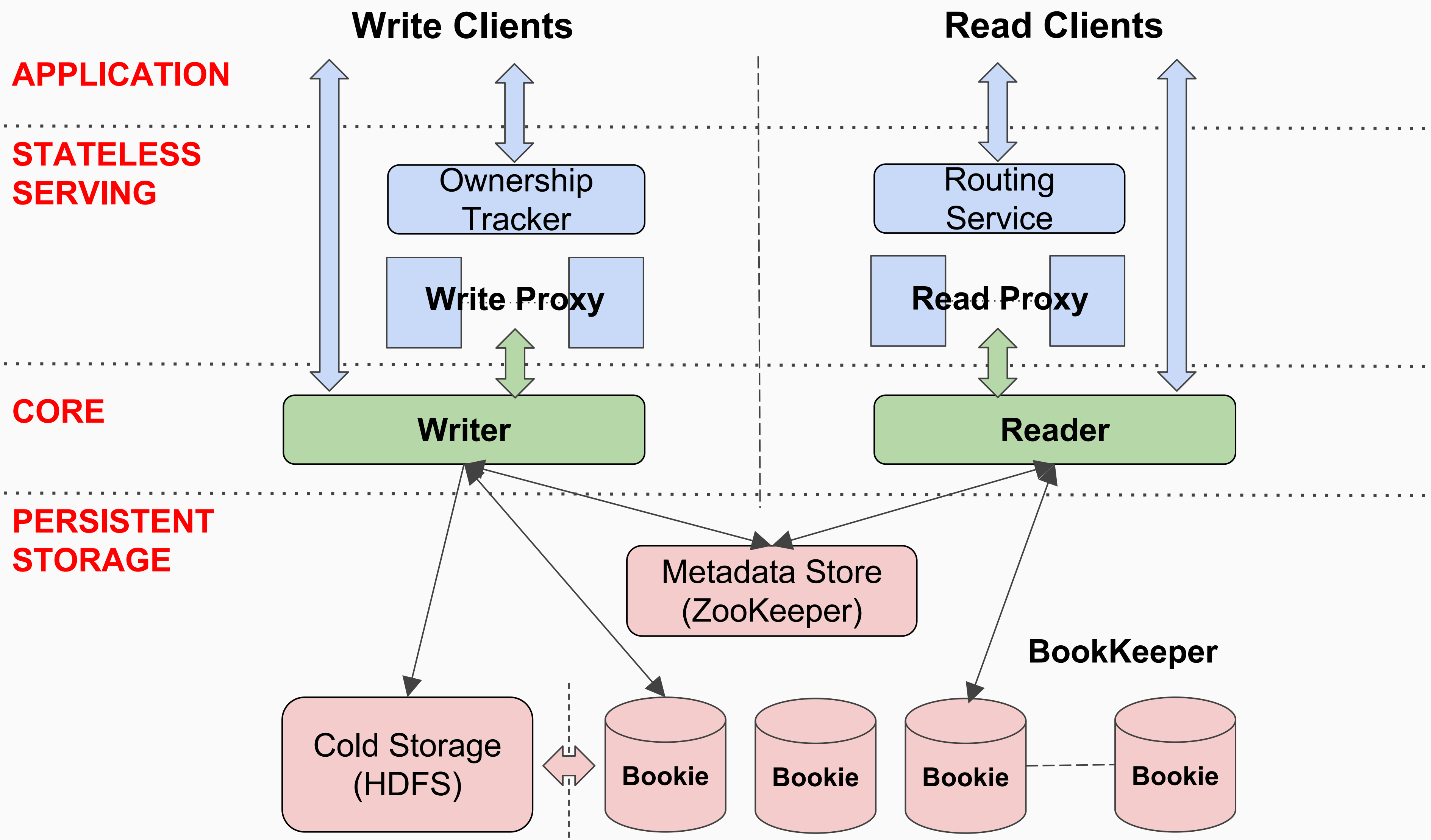
Software Stack

Data Flow

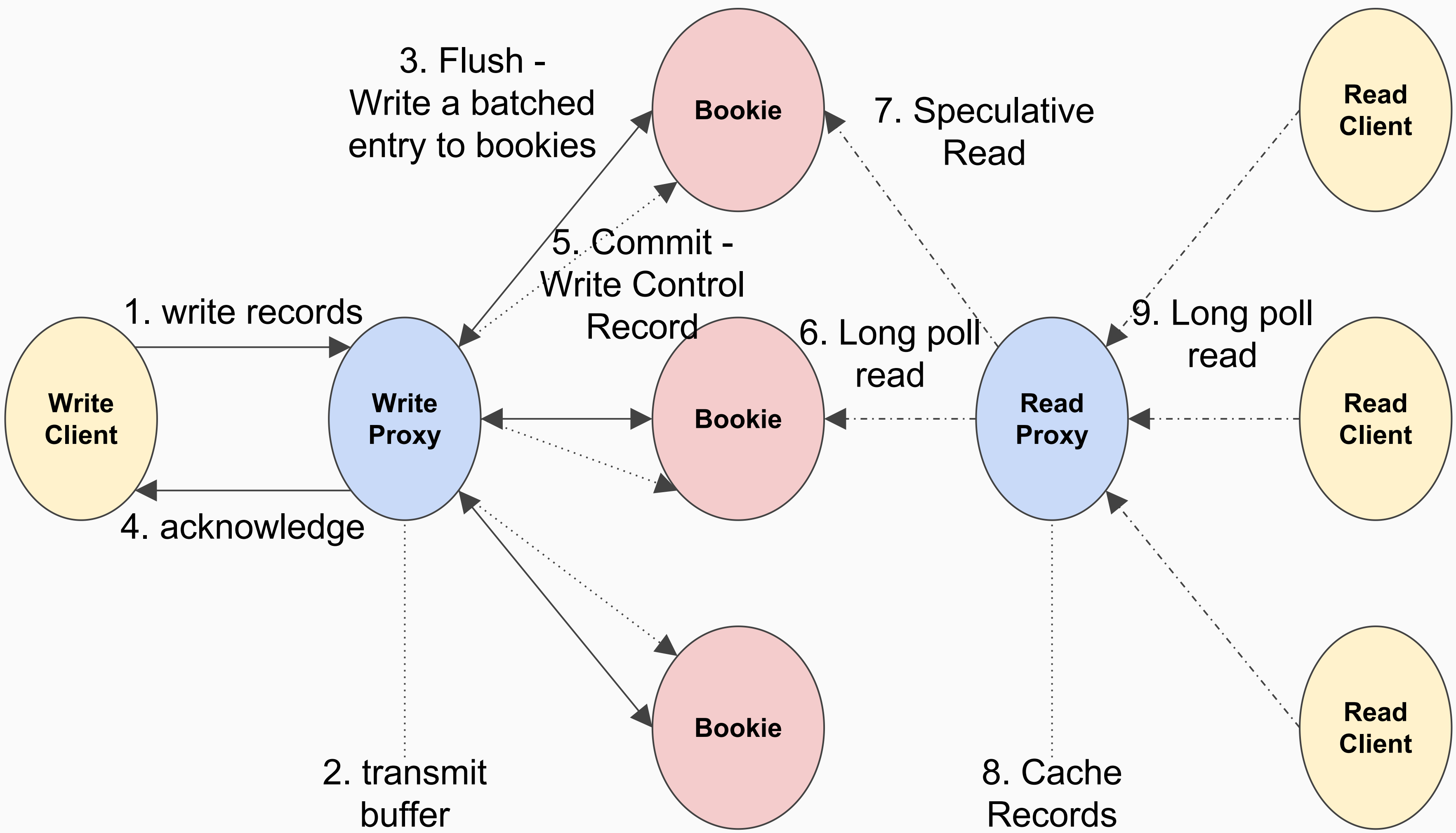
Log Stream


Entry:
a batch of
records
0100100111010
1010101110100
0101110110010
1010110110101
1010110110101
sequence of bytes
DLSN: (LSSN, Eid, Sid)
Sequence ID
Transaction ID
Log Segment X
Log Segment X + 1
Log Segment Y

Layered Architecture



Messaging Flow



Design Details

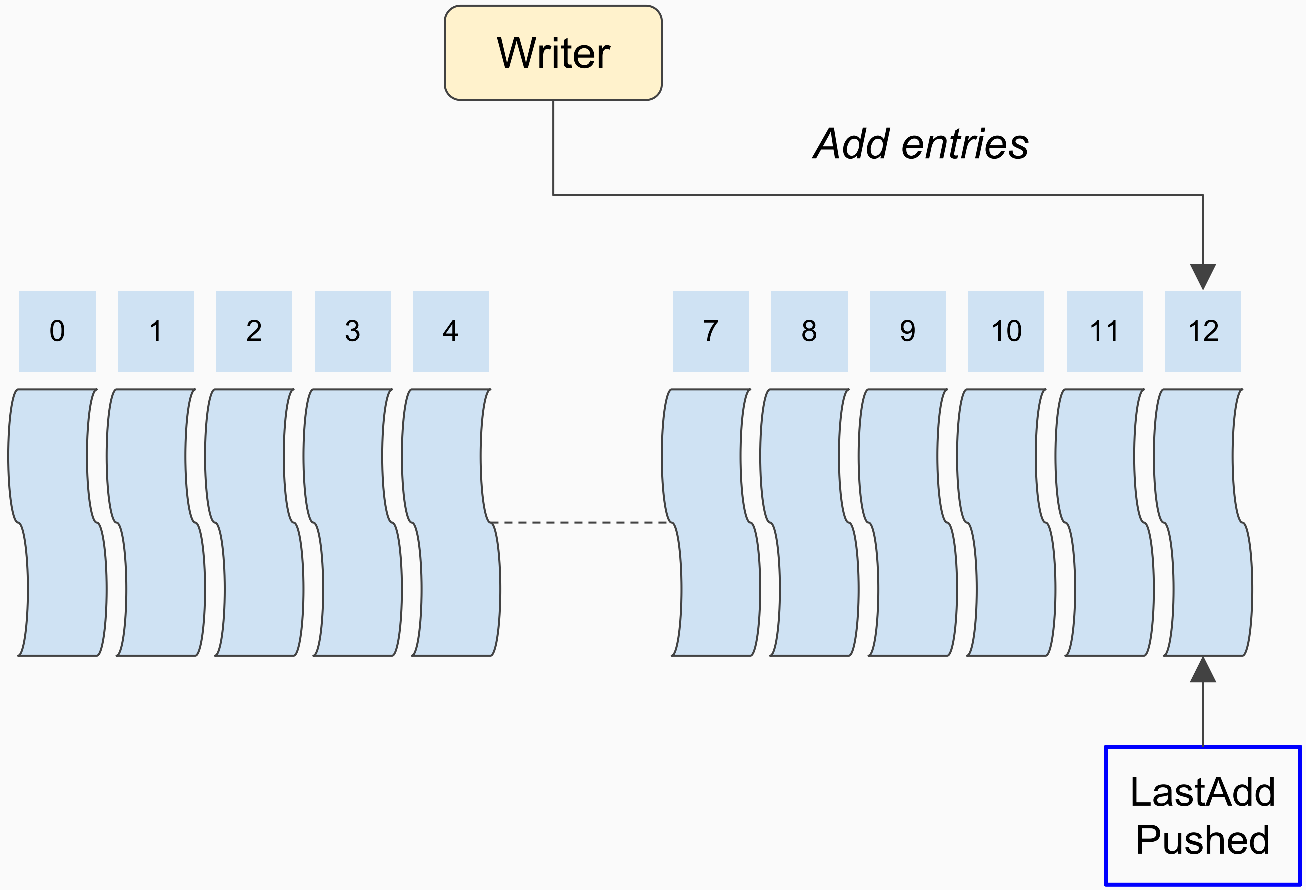
- Consistency
- Global Replicated Log

Consistency

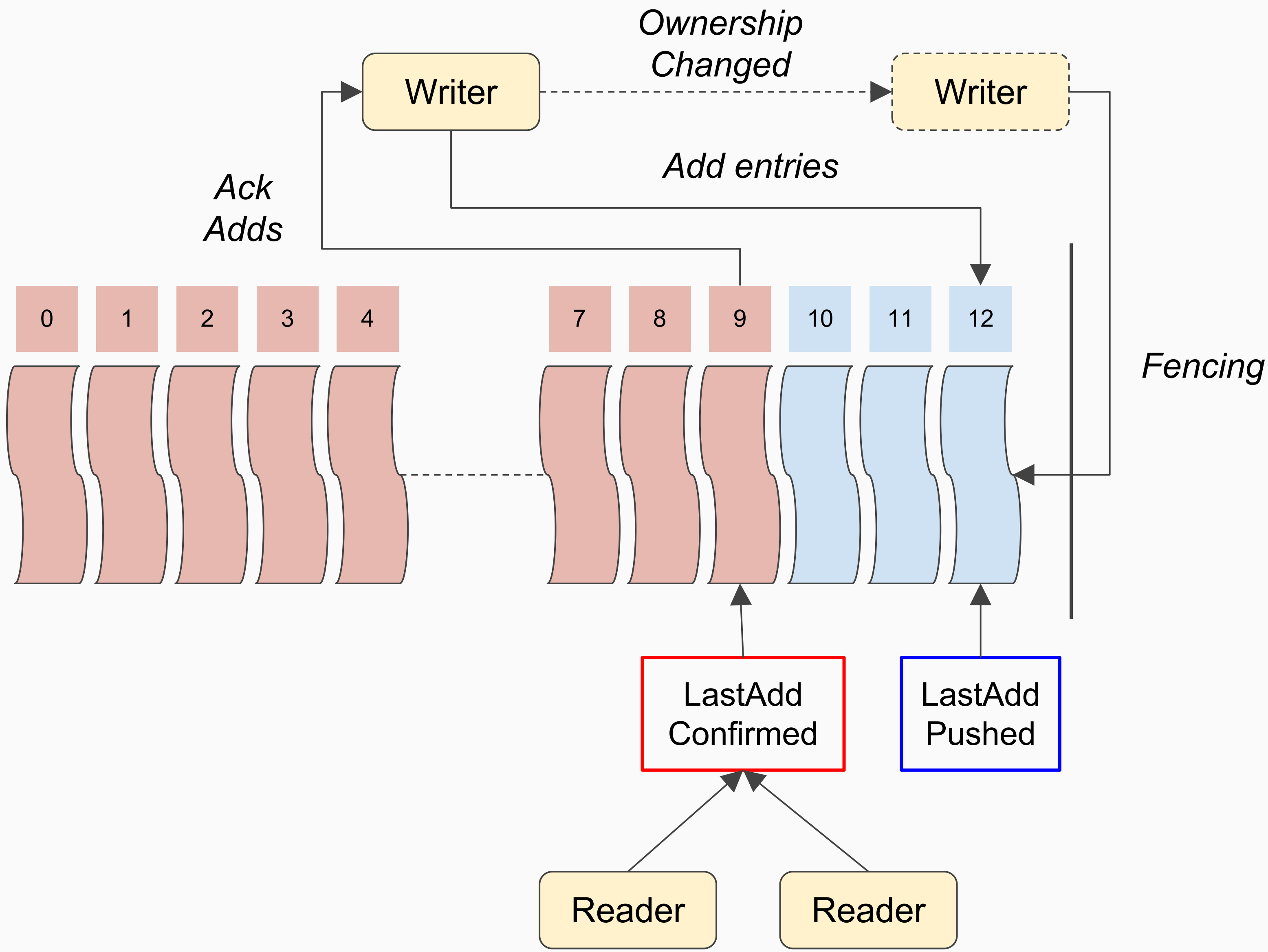
LastAddConfirmed => Consistent views among readers

Fencing => Consistent views among writers

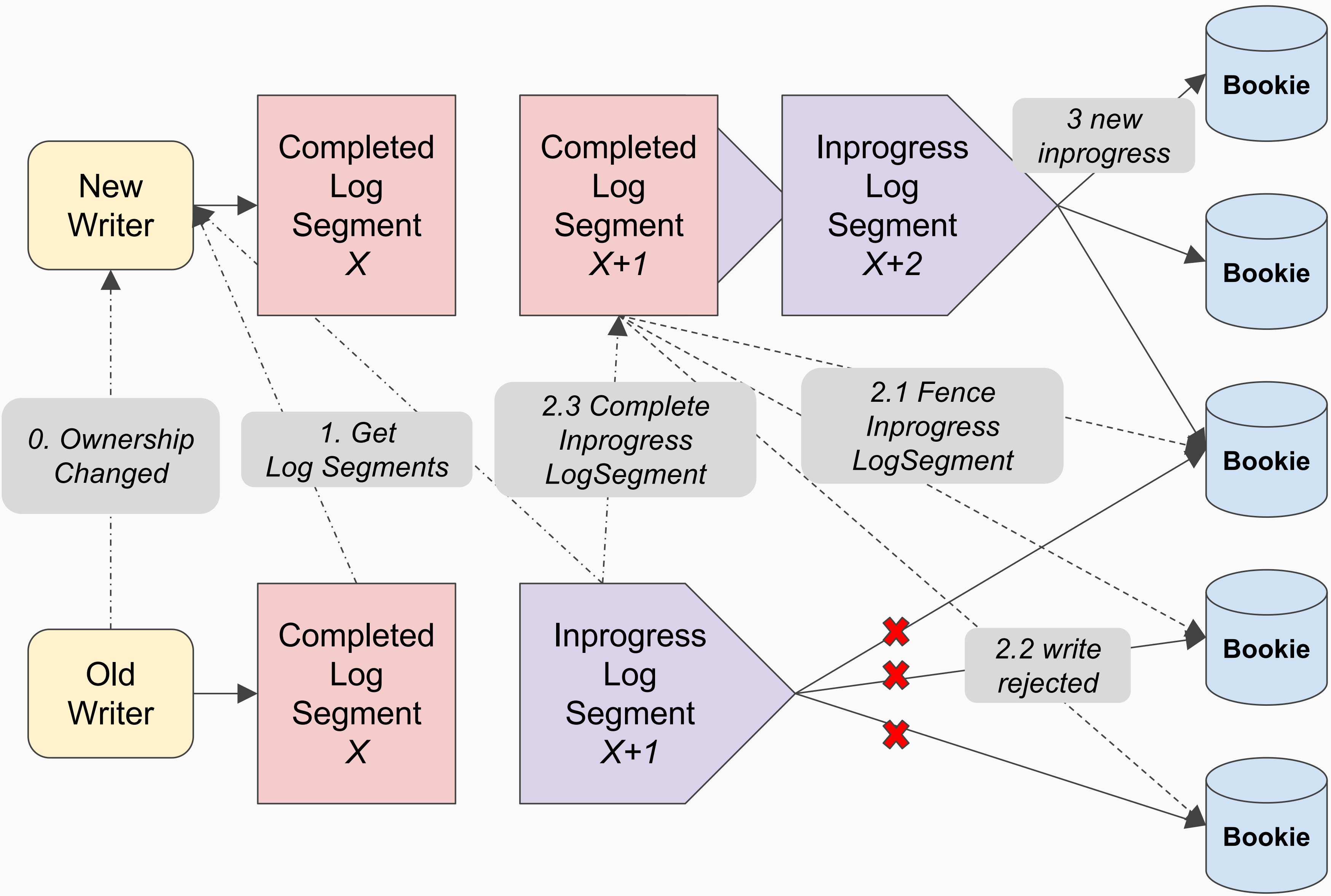
Consistency - LastAddPushed



Consistency - LastAddConfirmed



Consistency - Fencing



Consistency - Ownership Tracking

Ownership Tracking (~~*Leader Election*~~)

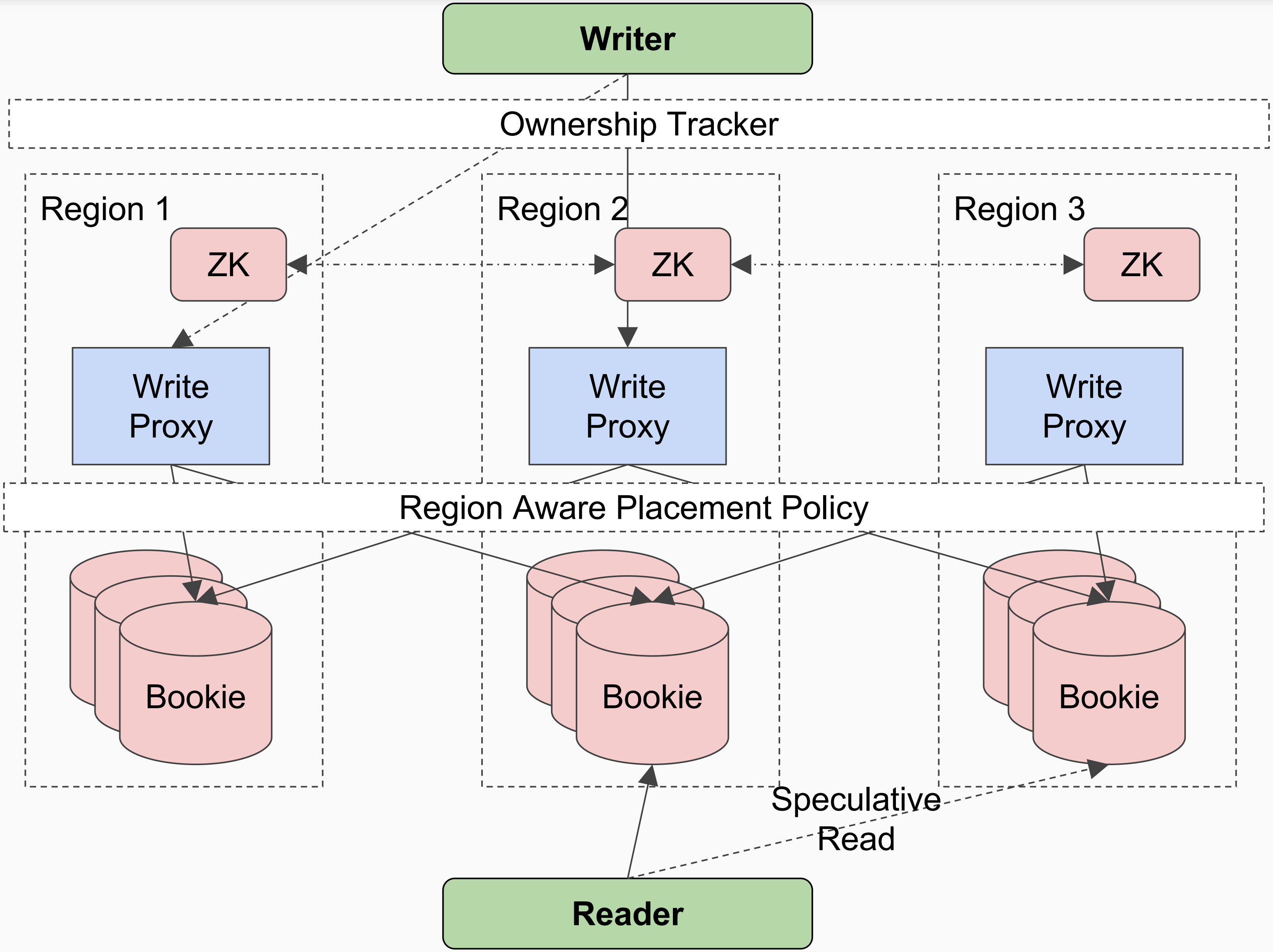
- ZooKeeper Ephemeral Znodes (leases)
- Aggressive Failure Detection (within a second)
  - TickTime = 500 (ms)
  - Session Timeout = 1000 (ms)

Global Replicated Log

Region Aware Data Placement

Cross Region Speculative Reads

Global Replicated Log



Region Aware Data Placement Policy

Hierarchical Data Placement

- Data is spread uniformly across available regions
- Each region uses rack aware placement policy
- Acknowledge only when the data is persisted in majority of regions

Cross Region Speculative Reads

Reader consults data placement policy for read order

- First : the bookie node that is closest to the client
- Second: the closest node that is in a different failure domain - different rack
- Third: the bookie node in a different closest region
- ...

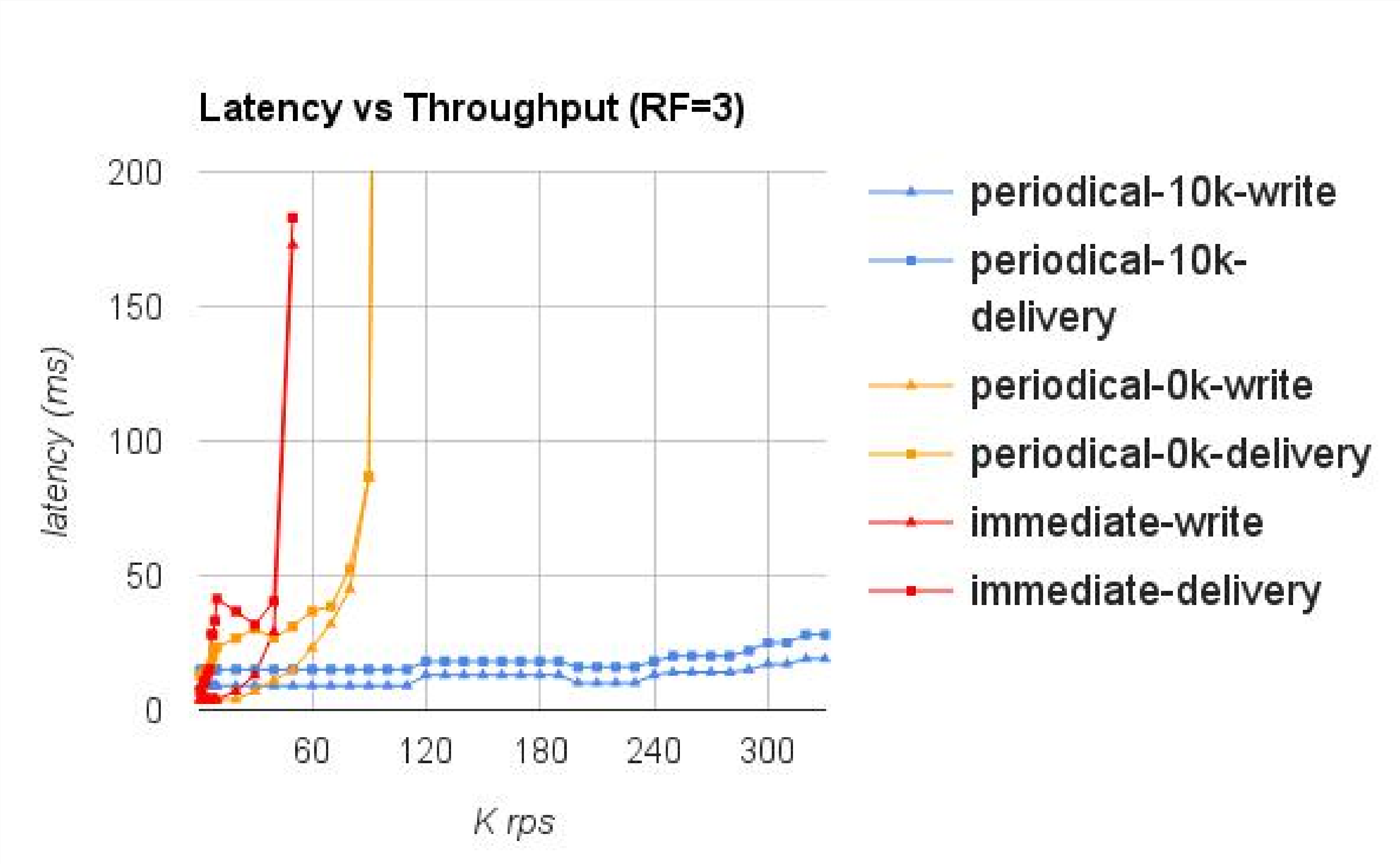
Performance

Latency vs Throughput

Scalability

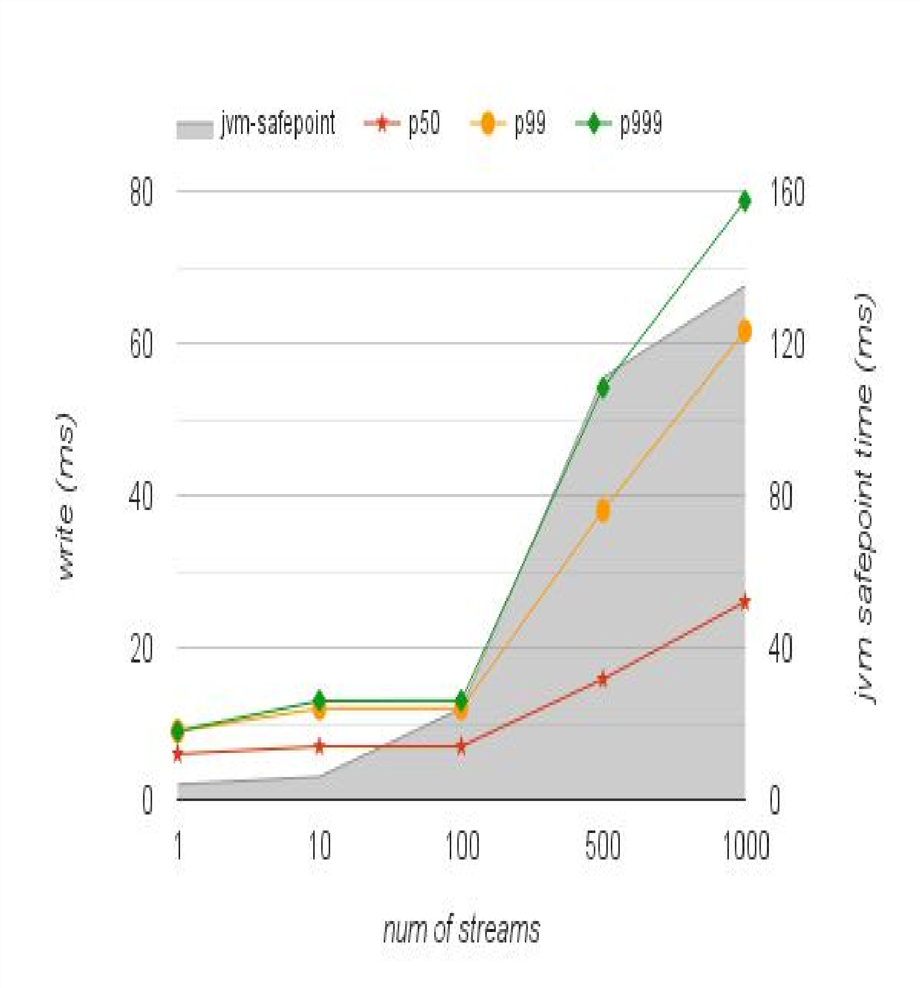
Efficiency

Support various workloads with latency/throughput tradeoffs

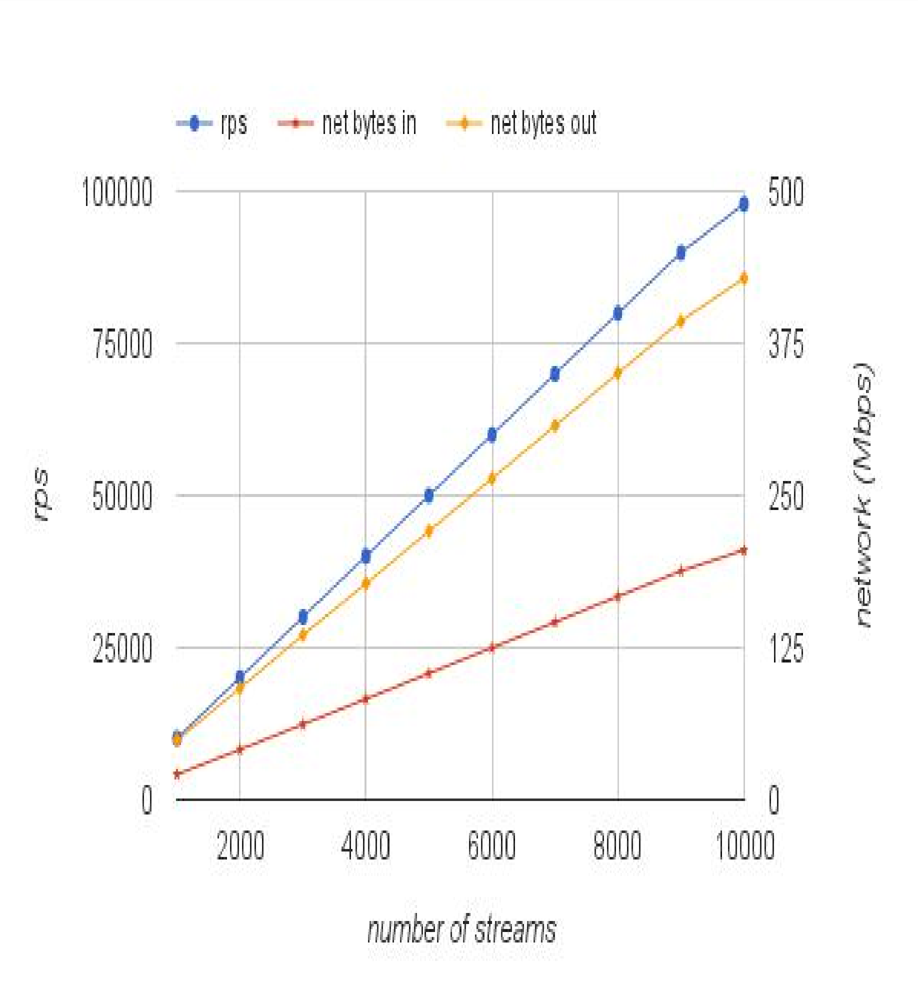


Latency and throughput under different flush policies

Scale with multiple streams (single node vs multiple nodes)

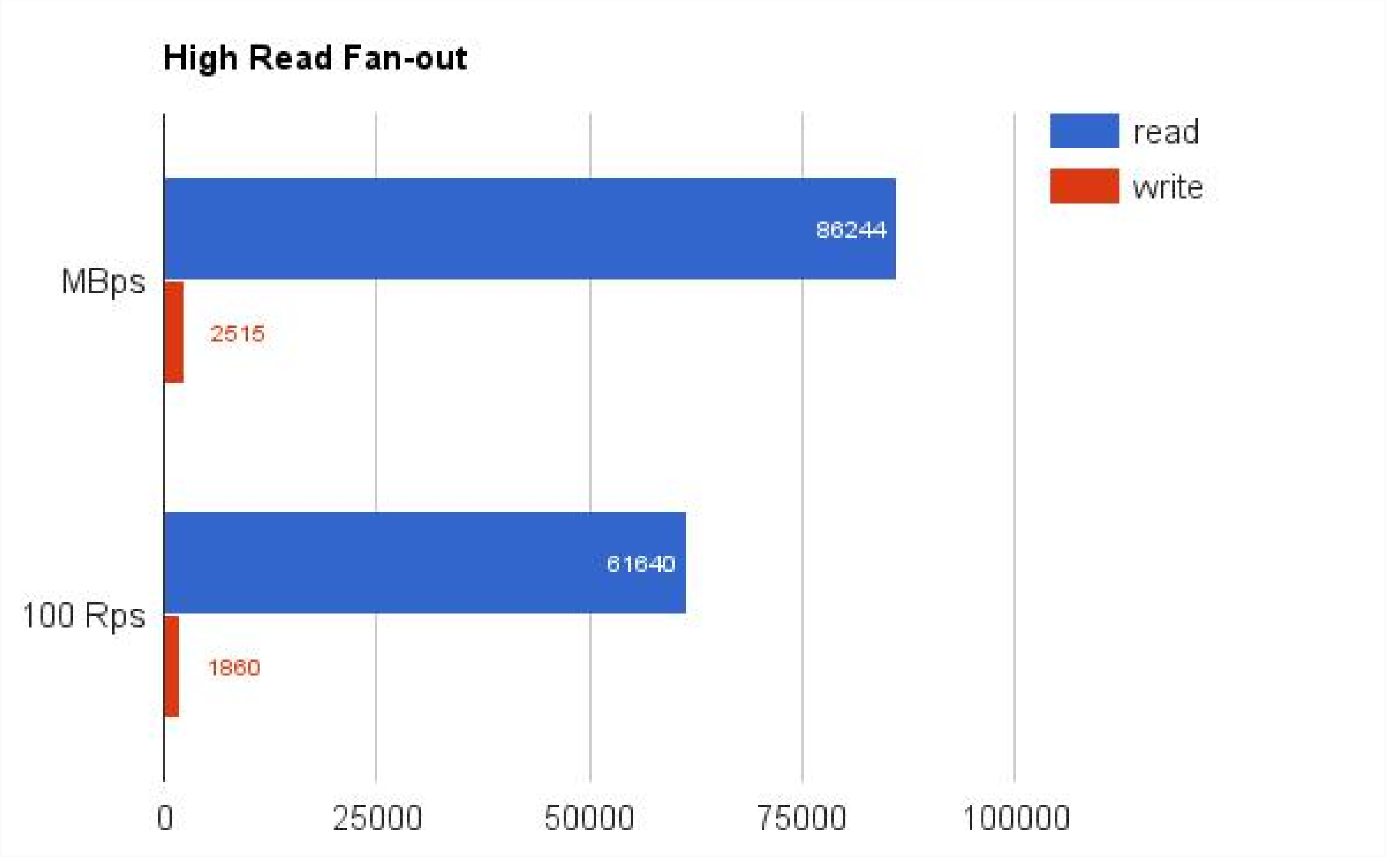


Under 100k rps, latency increased with number of streams increased on a single hybrid proxy



Each stream writes 100 rps. Throughput increased linearly with number of streams.

Scale with large number of fanout readers



Analytic application writes ***2.45GB*** per second, while the data has been fanout to ***40x*** to the readers.

Messaging

@ Twitter

Use Cases

Deployment

Scale

Applications at Twitter

Manhattan Key-Value Store

Durable Deferred RPC

Real-time search indexing

Self-Served Pub-Sub System / Stream Computing

Reliable cross datacenter replication

...

Scale at Twitter

One global cluster, and a few local clusters each dc

O(10^3) bookie nodes

O(10^3) global log streams and O(10^4) local log streams

O(10^6) live log segments

Pub-Sub: deliver ***O(1) trillion*** records per day, roughly accounting for ***O(10) PB*** per day

Lessons that we learned

Make foundation durable and consistent

Don’t trust filesystem

Think of workloads and I/O isolation

Keep persistent state as simple as possible

...

DistributedLog is the new messaging foundation

Layered Architecture

- Separated *Stateless Serving* from *Stateful Storage*
- Scale *CPU/Memory/Network* (shared mesos) independent of *Storage* (hybrid mesos)

Messaging Design

- Writes / Reads Isolation
- Scale *Writes* (Fan-in) independent of *Reads* (Fan-out)

Global Replicated Log

Future

Open source on Github (May)

https://github.com/twitter/distributedlog

Apache Incubating …

Q & A

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