facebook

Real-time Analytics at Facebook

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Agenda

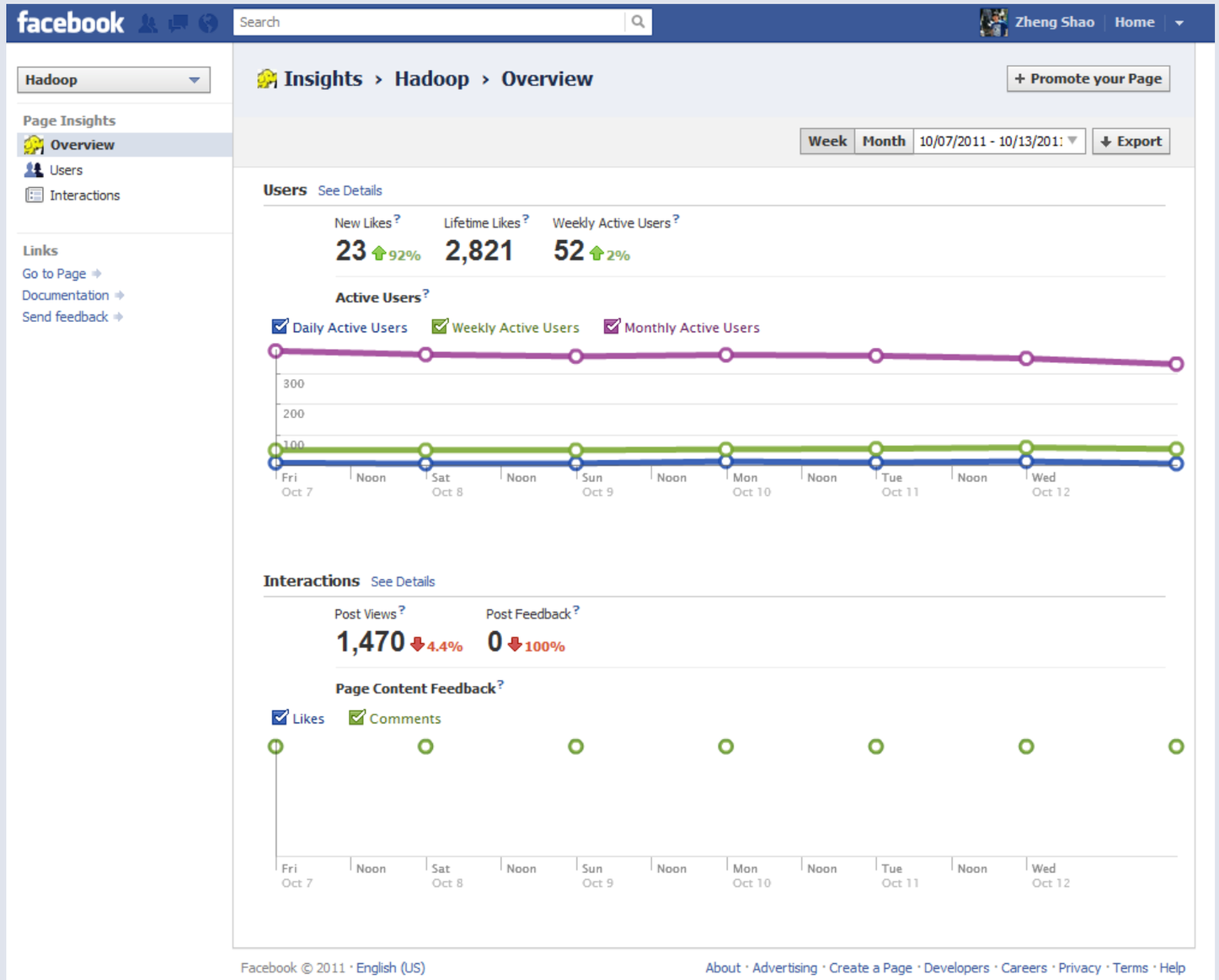
1. Analytics and Real-time
2. Data Freeway
3. Puma
4. Future Works

Analytics and Real-time

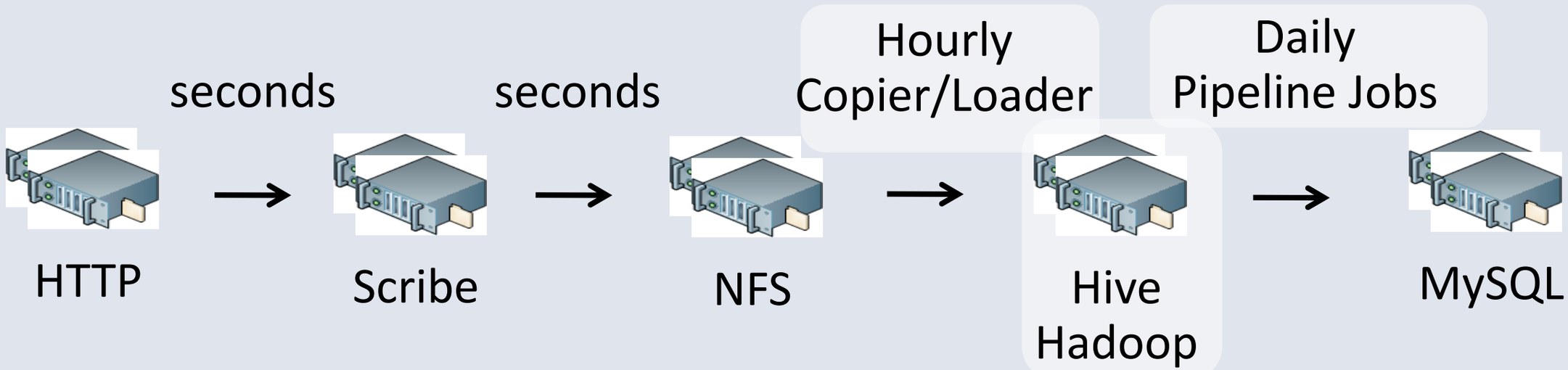
what and why

Facebook Insights

- Use cases
  - Websites/Ads/Apps/Pages
  - Time series
  - Demographic break-downs
  - Unique counts/heavy hitters
- Major challenges
  - Scalability
  - Latency

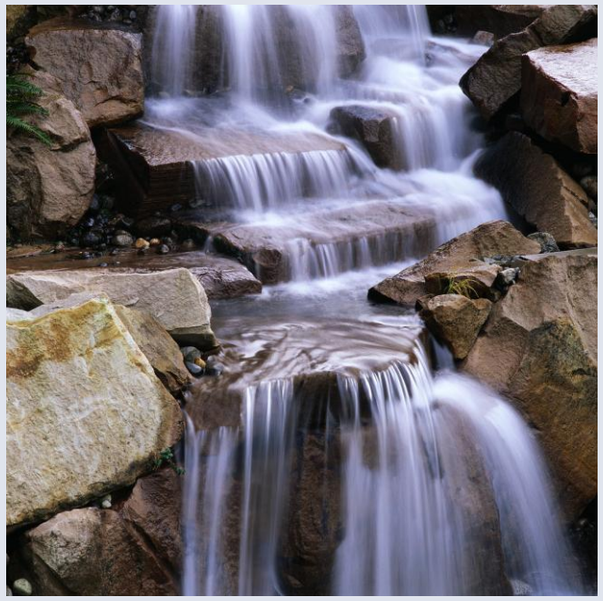


Analytics based on Hadoop/Hive



- 3000-node Hadoop cluster
- Copier/Loader: Map-Reduce hides machine failures
- Pipeline Jobs: Hive allows SQL-like syntax
- Good scalability, but poor latency! 24 – 48 hours.

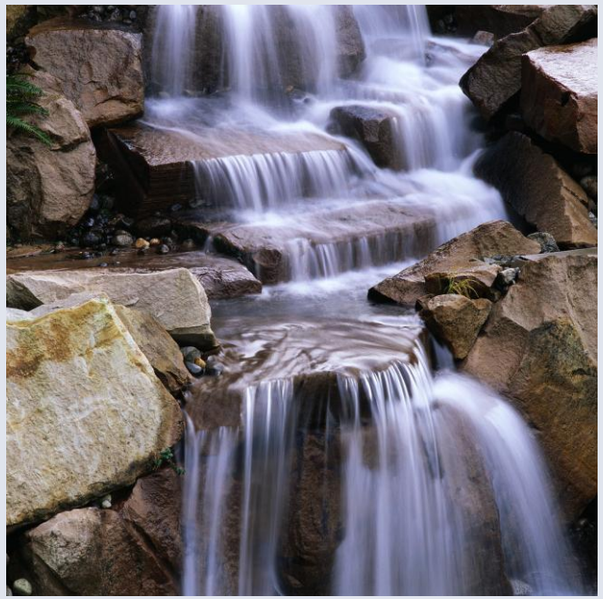
How to Get Lower Latency?



- Small-batch Processing
  - Run Map-reduce/Hive every hour, every 15 min, every 5 min, …
  - How do we reduce per-batch overhead?
- Stream Processing
  - Aggregate the data as soon as it arrives
  - How to solve the reliability problem?

Decisions

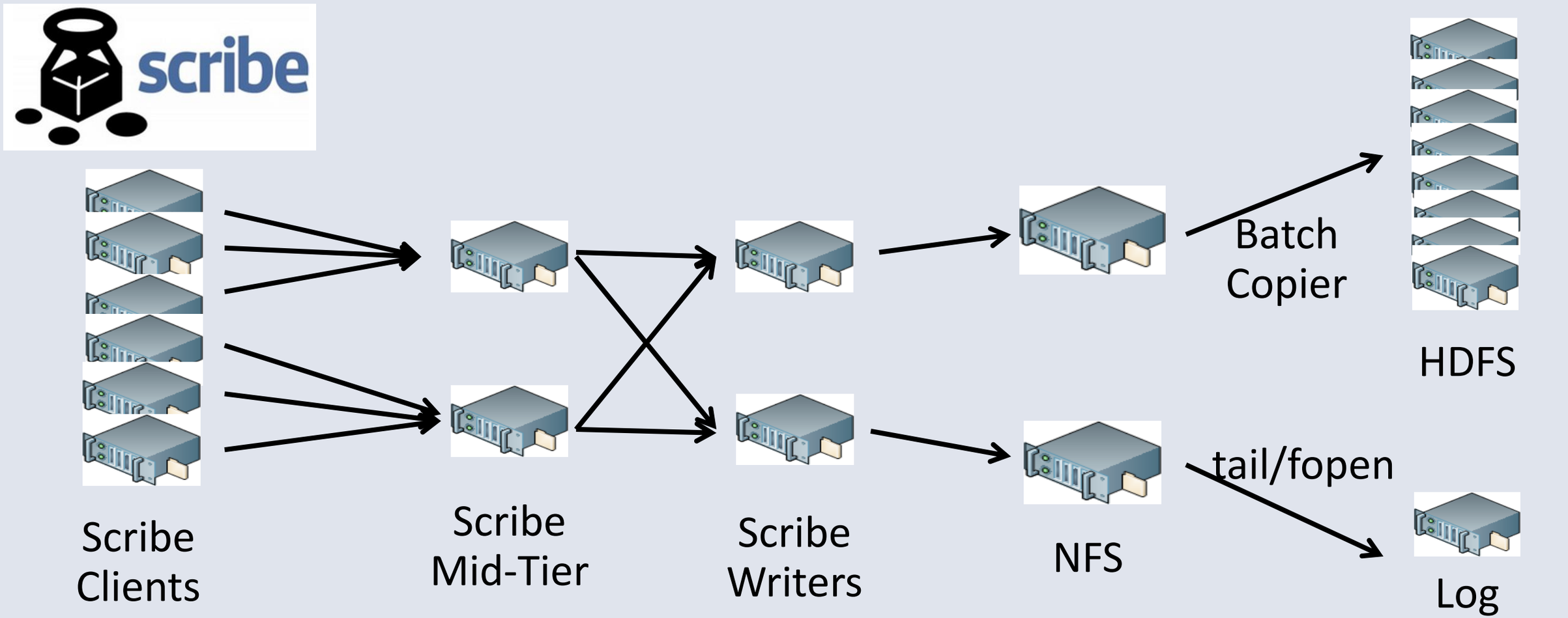
- Stream Processing wins!



- Data Freeway
  - Scalable Data Stream Framework
- Puma
  - Reliable Stream Aggregation Engine

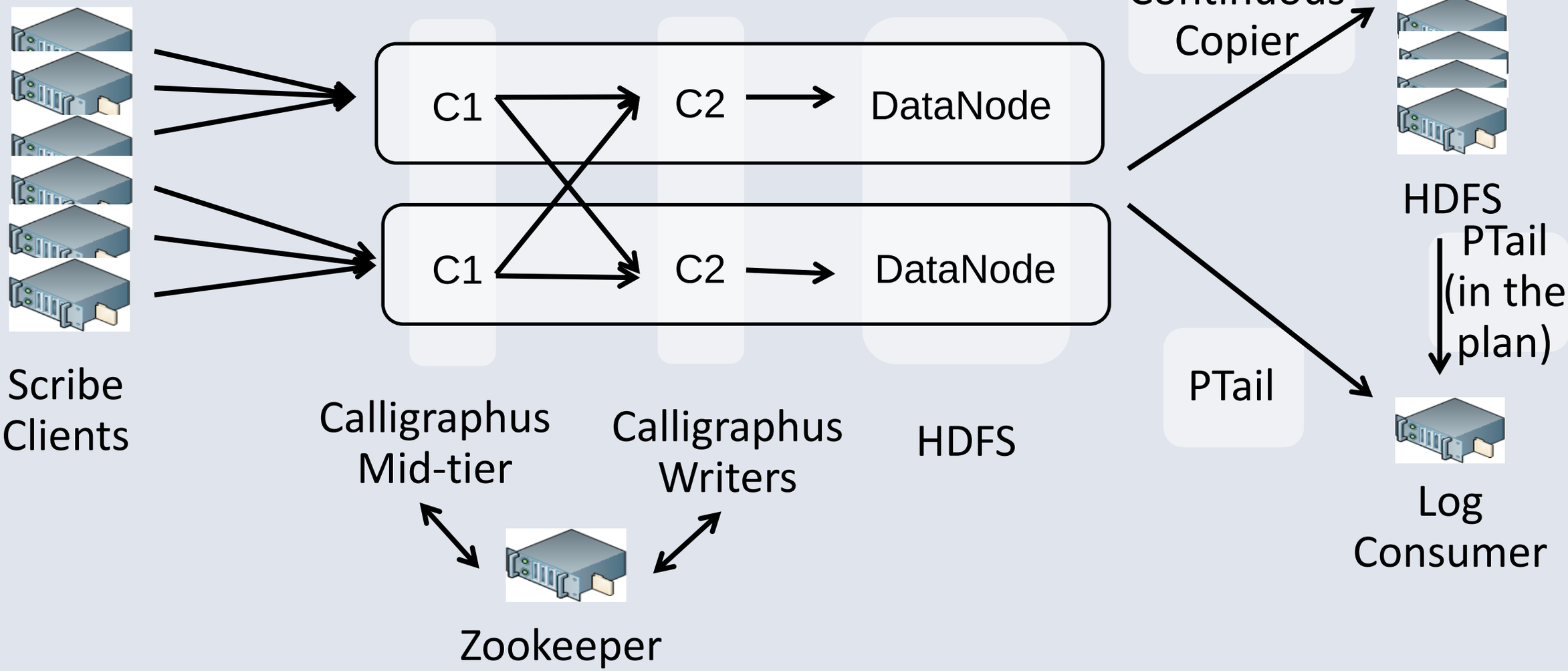
Data Freeway

scalable data stream



- Simple push/RPC-based logging system
- Open-sourced in 2008. 100 log categories at that time.
- Routing driven by static configuration.

Data Freeway



- 9GB/sec at peak, 10 sec latency, 2500 log categories

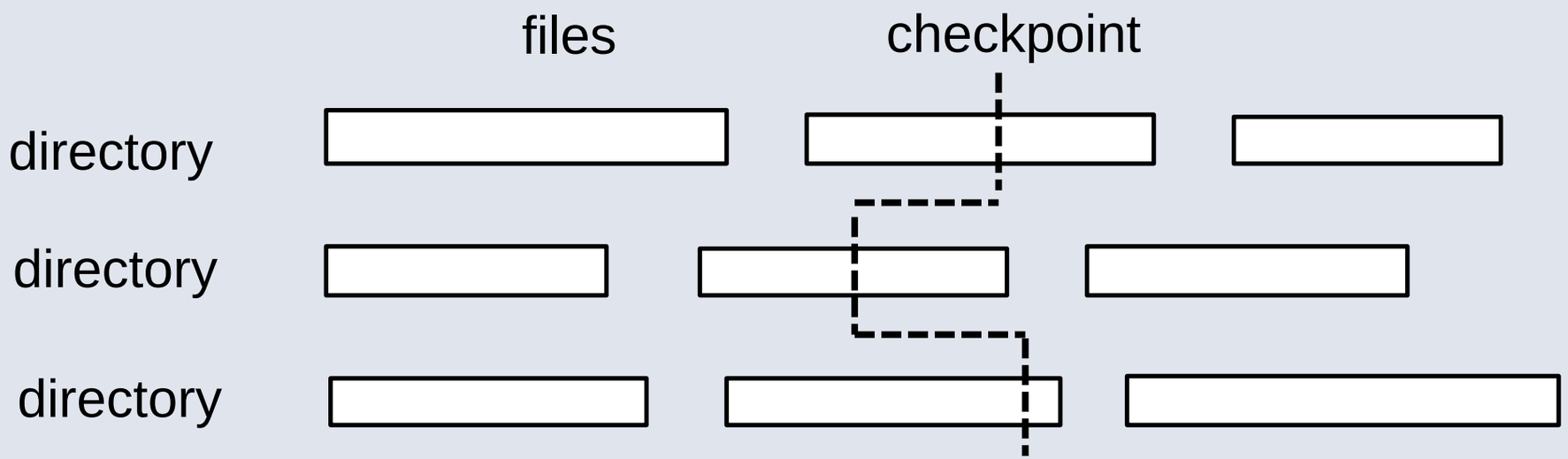
Calligraphus

- RPC → File System
  - Each log category is represented by 1 or more FS directories
  - Each directory is an ordered list of files
- Bucketing support
  - Application buckets are application-defined shards.
  - Infrastructure buckets allows log streams from x B/s to x GB/s
- Performance
  - Latency: Call sync every 7 seconds
  - Throughput: Easily saturate 1Gbit NIC

Continuous Copier

- File System → File System
- Low latency and smooth network usage
- Deployment
  - Implemented as long-running map-only job
  - Can move to any simple job scheduler
- Coordination
  - Use lock files on HDFS for now
  - Plan to move to Zookeeper

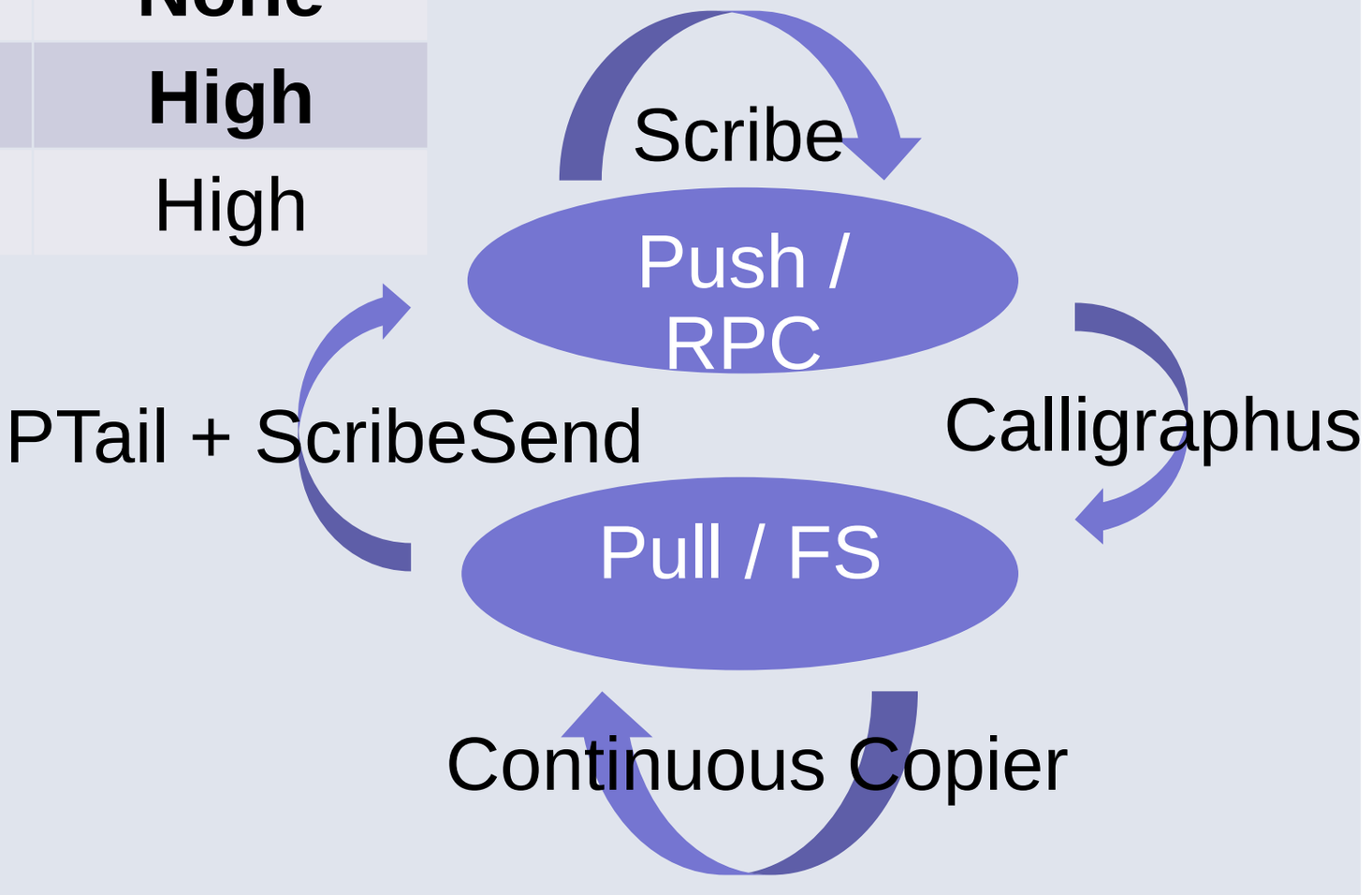
PTail



- File System → Stream (→ RPC)
- Reliability
  - Checkpoints inserted into the data stream
  - Can roll back to tail from any data checkpoints
  - No data loss/duplicates

Channel Comparison

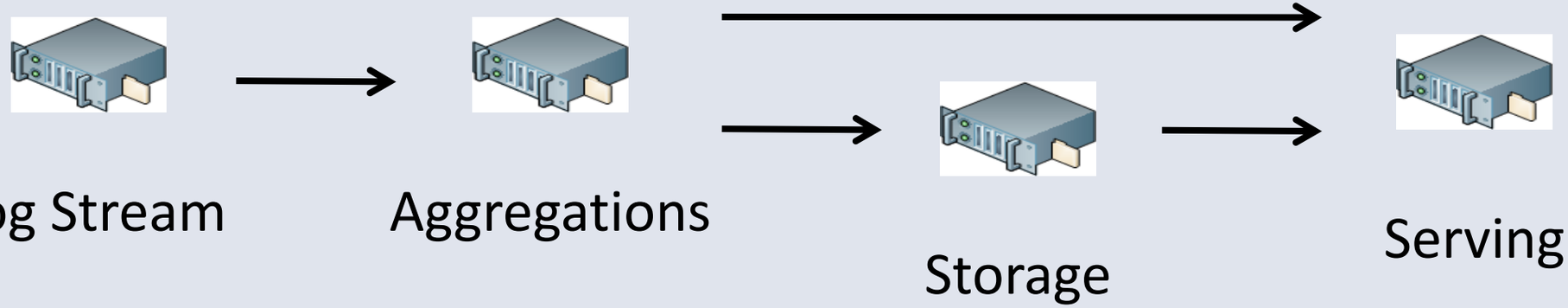
	Push / RPC	Pull / FS
Latency	**1-2 sec**	10 sec
Loss/Dups	Few	**None**
Robustness	Low	**High**
Complexity	**Low**	High



Puma

real-time aggregation/storage

Overview

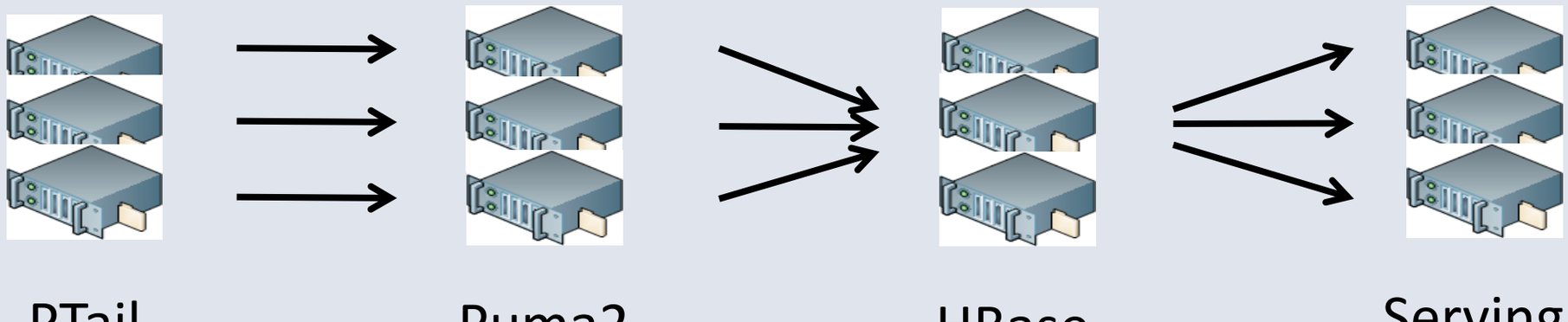


- ~ 1M log lines per second, but light read
- Multiple Group-By operations per log line
- The first key in Group By is always time/date-related
- Complex aggregations: Unique user count, most frequent elements

MySQL and HBase: one page

	MySQL	HBase
Parallel	Manual sharding	Automatic load balancing
Fail-over	Manual master/slave switch	Automatic
Read efficiency	High	Low
Write efficiency	Medium	High
Columnar support	No	Yes

Puma2 Architecture



- PTail provide parallel data streams
- For each log line, Puma2 issue “increment” operations to HBase. Puma2 is symmetric (no sharding).
- HBase: single increment on multiple columns

Puma2: Pros and Cons

- Pros

- Puma2 code is very simple.
- Puma2 service is very easy to maintain.

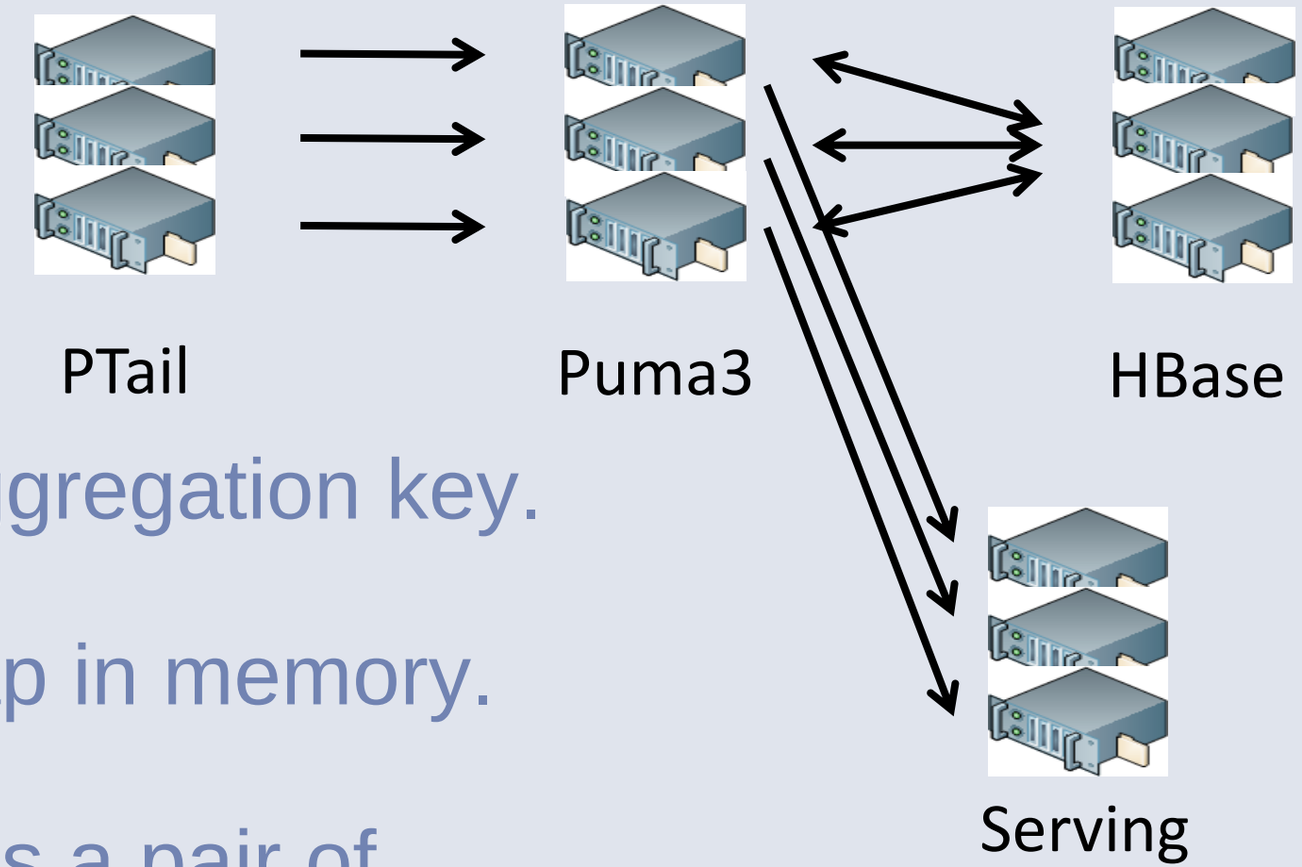
- Cons

- “Increment” operation is expensive.
- Do not support complex aggregations.
- Hacky implementation of “most frequent elements”.
- Can cause small data duplicates.

Improvements in Puma2

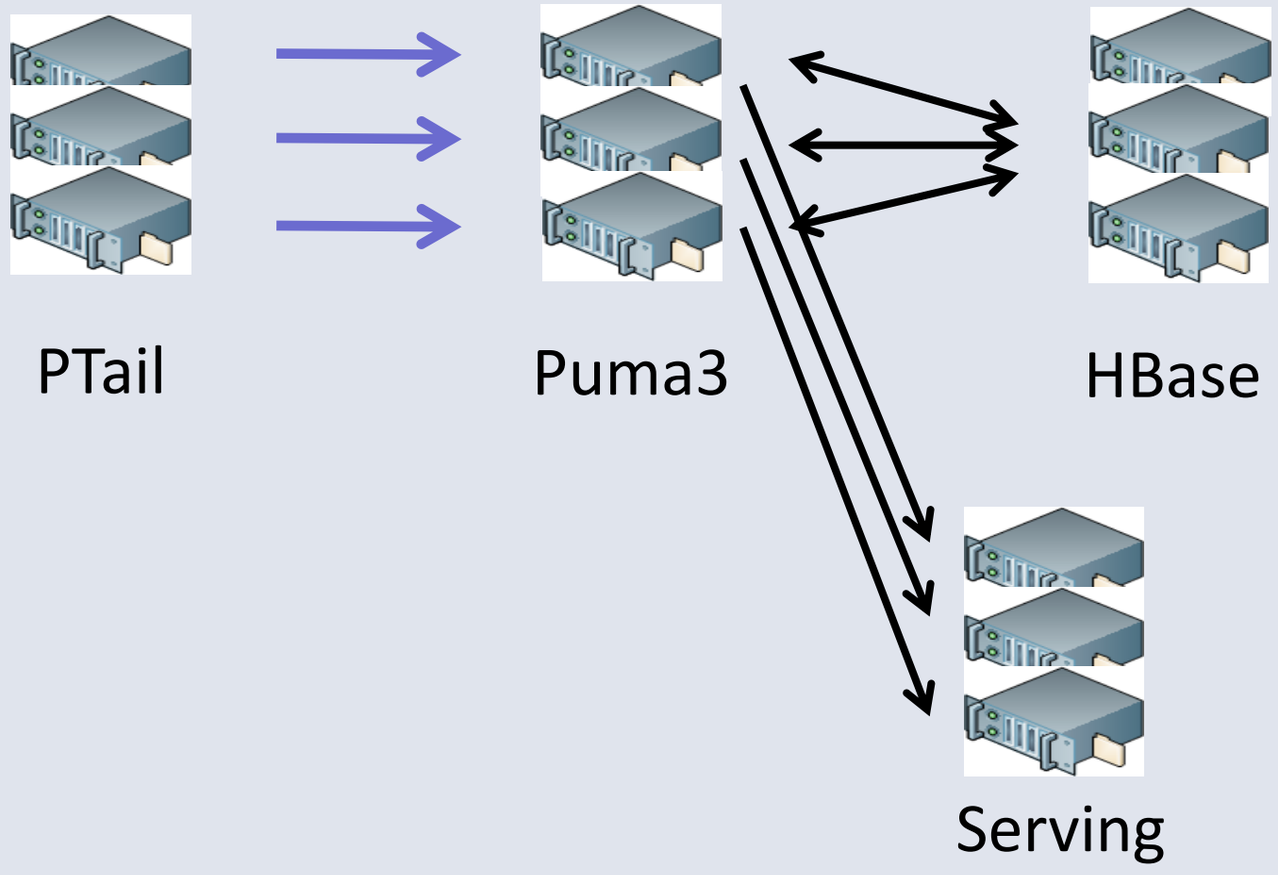
- Puma2
  - Batching of requests. Didn’t work well because of long-tail distribution.
- HBase
  - “Increment” operation optimized by reducing locks.
  - HBase region/HDFS file locality; short-circuited read.
  - Reliability improvements under high load.
- Still not good enough!

Puma3 Architecture



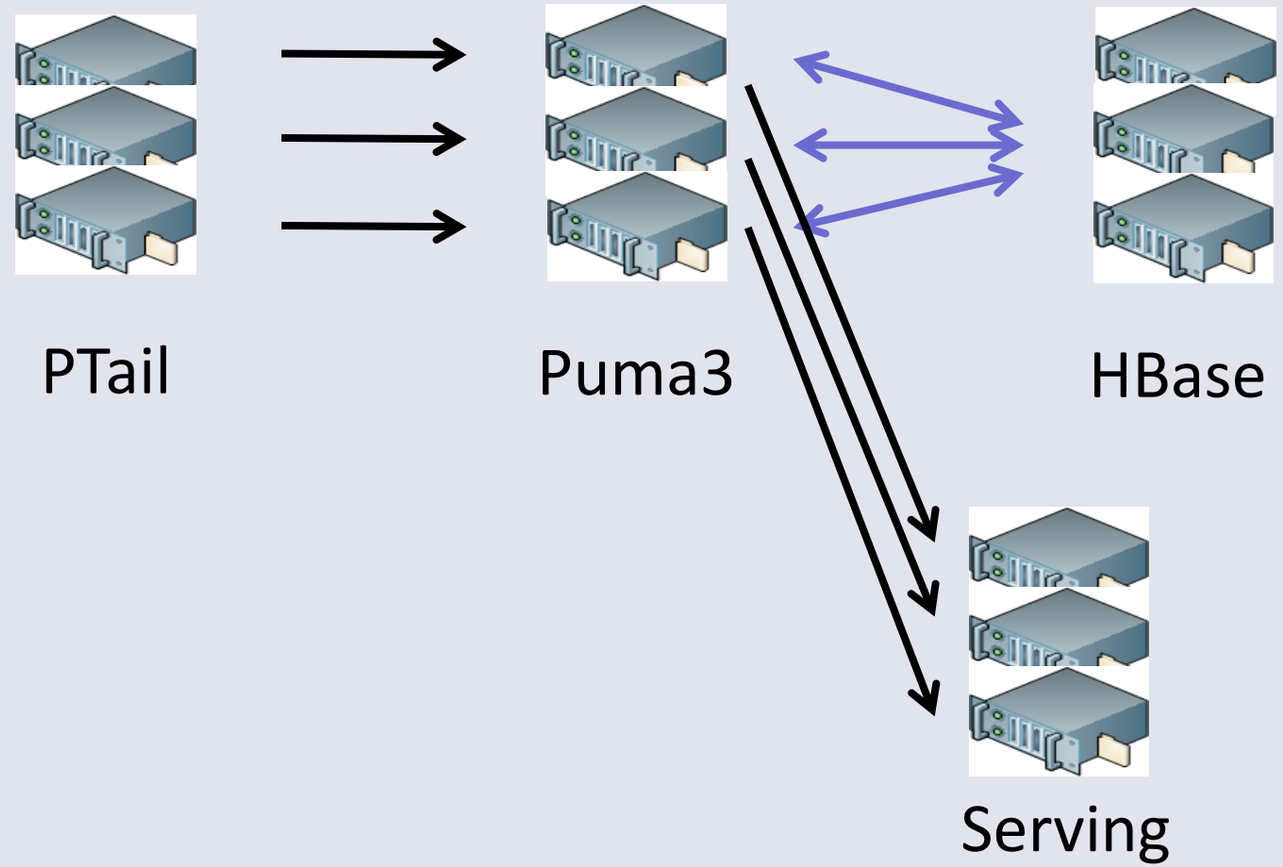
- Puma3 is sharded by aggregation key.
- Each shard is a hashmap in memory.
- Each entry in hashmap is a pair of
  an aggregation key and a user-defined aggregation.
- HBase as persistent key-value storage.

Puma3 Architecture



- Write workflow
  - For each log line, extract the columns for key and value.
  - Look up in the hashmap and call user-defined aggregation

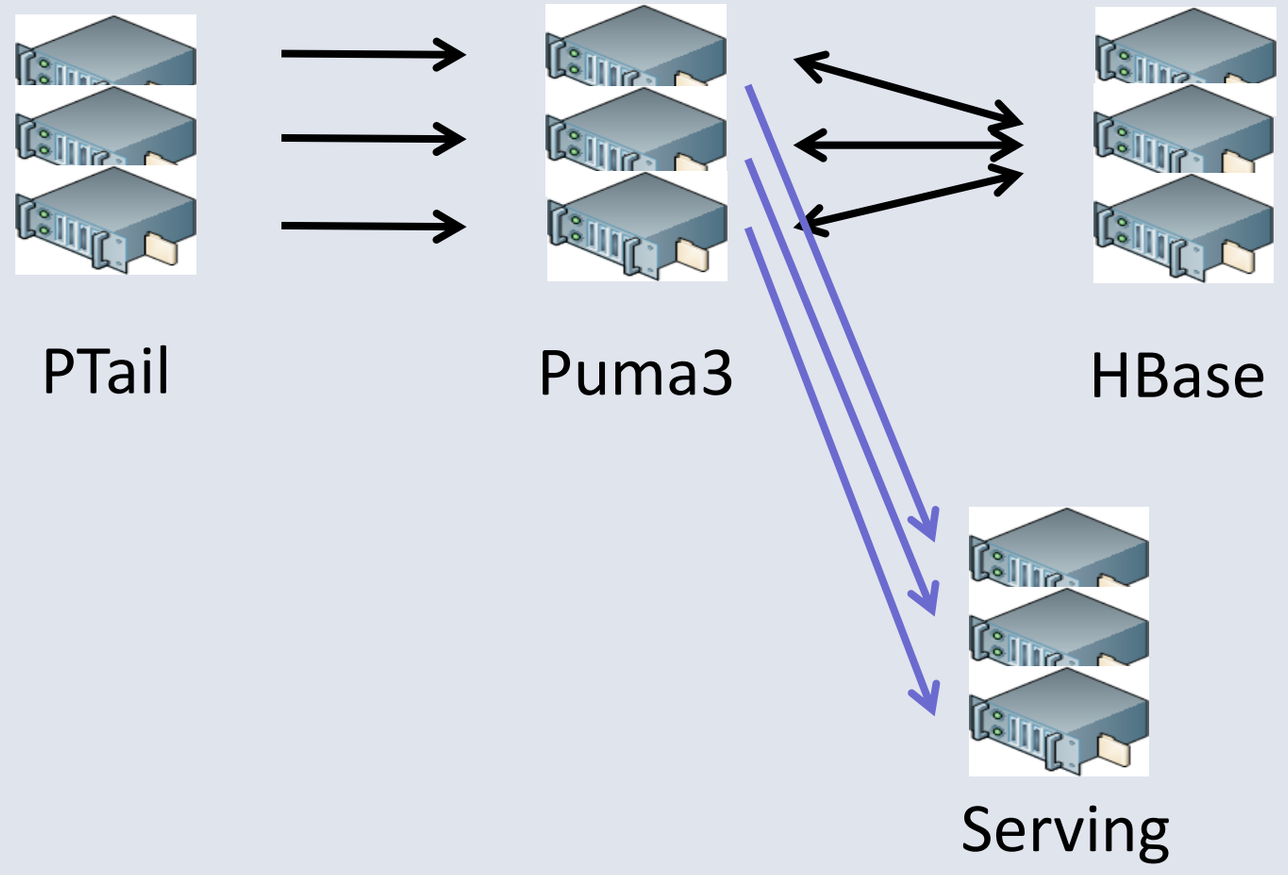
Puma3 Architecture



- Checkpoint workflow

- Every 5 min, save modified hashmap entries, PTail checkpoint to HBase
- On startup (after node failure), load from HBase
- Get rid of items in memory once the time window has passed

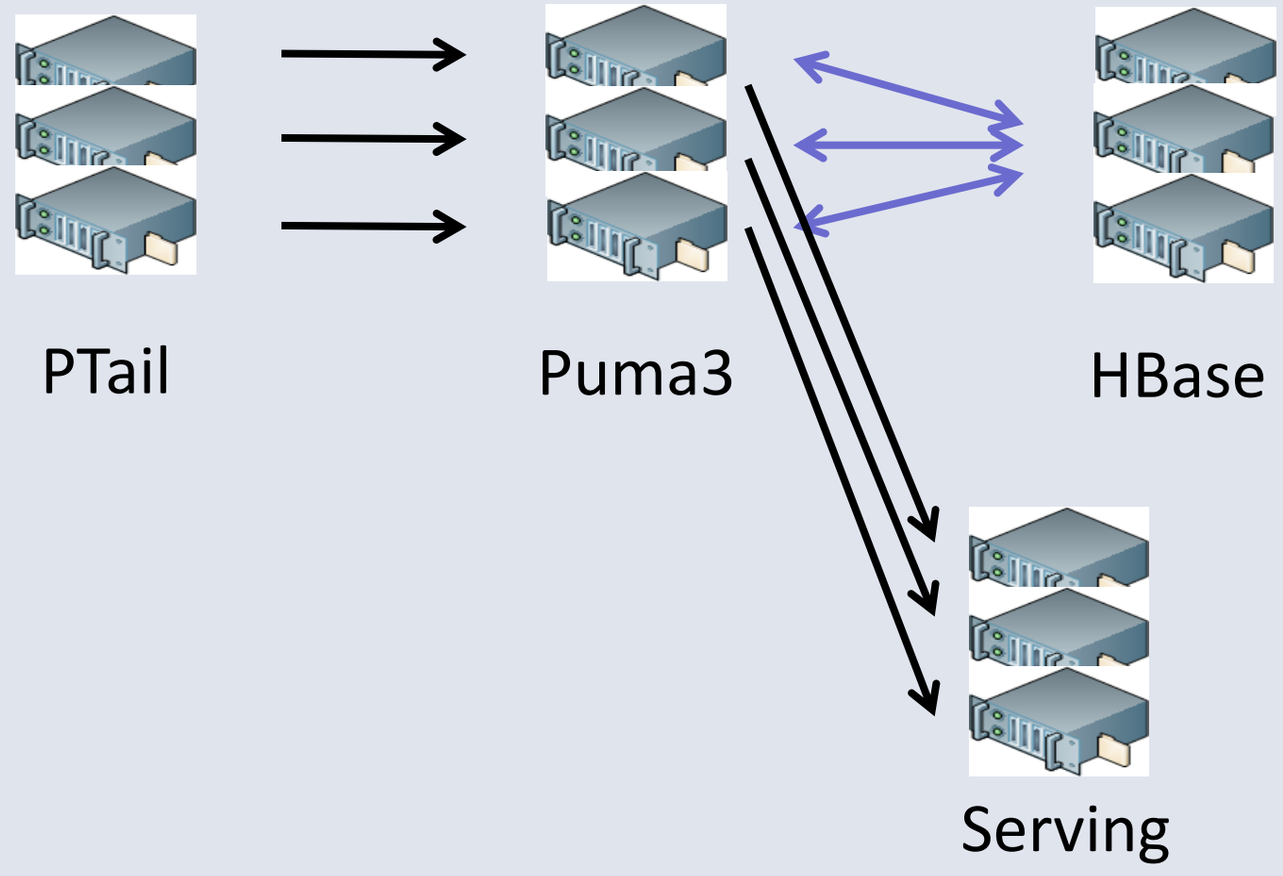
Puma3 Architecture



- Read workflow

- Read uncommitted: directly serve from the in-memory hashmap; load from Hbase on miss.
- Read committed: read from HBase and serve.

Puma3 Architecture



- Join
  - Static join table in HBase.
  - Distributed hash lookup in user-defined function (udf).
  - Local cache improves the throughput of the udf a lot.

Puma2 / Puma3 comparison

- Puma3 is much better in write throughput
  - Use 25% of the boxes to handle the same load.
  - HBase is really good at write throughput.
- Puma3 needs a lot of memory
  - Use 60GB of memory per box for the hashmap
  - SSD can scale to 10x per box.

Puma3 Special Aggregations

- Unique Counts Calculation
  - Adaptive sampling
  - Bloom filter (in the plan)
- Most frequent item (in the plan)
  - Lossy counting
  - Probabilistic lossy counting

PQL – Puma Query Language

- CREATE INPUT TABLE t (‘time', ‘adid’, ‘userid’);

- CREATE VIEW v AS
  SELECT *, udf.age(userid)
  FROM t
  WHERE udf.age(userid) > 21

- CREATE HBASE TABLE h …

- CREATE LOGICAL TABLE l …

- CREATE AGGREGATION ‘abc’
  INSERT INTO l (a, b, c)
  SELECT
      udf.hour(time),
      adid,
      age,
      count(1),
      udf.count_distinc(userid)
  FROM v
  GROUP BY
      udf.hour(time),
      adid,
      age;

Future Works

challenges and opportunities

Future Works

- Scheduler Support
  - Just need simple scheduling because the work load is continuous
- Mass adoption
  - Migrate most daily reporting queries from Hive
- Open Source
  - Biggest bottleneck: Java Thrift dependency
  - Will come one by one

Similar Systems

- STREAM from Stanford
- Flume from Cloudera
- S4 from Yahoo
- Rainbird/Storm from Twitter
- Kafka from Linkedin

Key differences

- Scalable Data Streams

- 9 GB/sec with < 10 sec of latency
- Both Push/RPC-based and Pull/File System-based
- Components to support arbitrary combination of channels

- Reliable Stream Aggregations

- Good support for Time-based Group By, Table-Stream Lookup Join
- Query Language: Puma : Realtime-MR = Hive : MR
- No support for sliding window, stream joins

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