Scaling Stream Processing Out and Up

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International Workshop on Web Data Processing & Reasoning
(WDPAR 2018)

Big Fast Data

- Data is growing and can be evaluated
  - Tweets, social networks (statuses, check-ins, shared content), blogs, click streams, various logs, …
  - *Facebook: > 845M active users, > 8B messages/day*
  - *Twitter: > 140M active users, > 340M tweets/day*
- Everyone is interested!

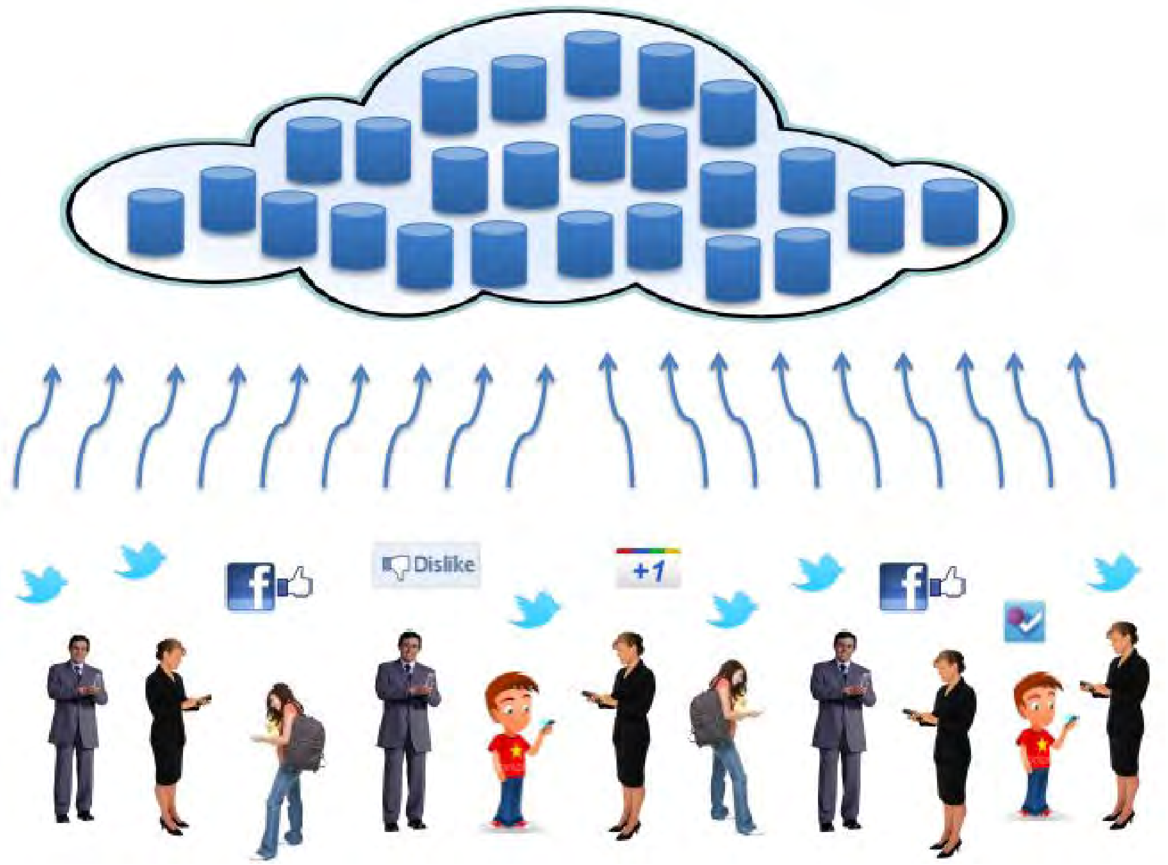


Image: Michael Carey

But there is so much more…

- Autonomous Driving
  - Requires rich navigation info
  - Rich data sensor readings
  - 1GB data per minute per car (all sensors)[1]

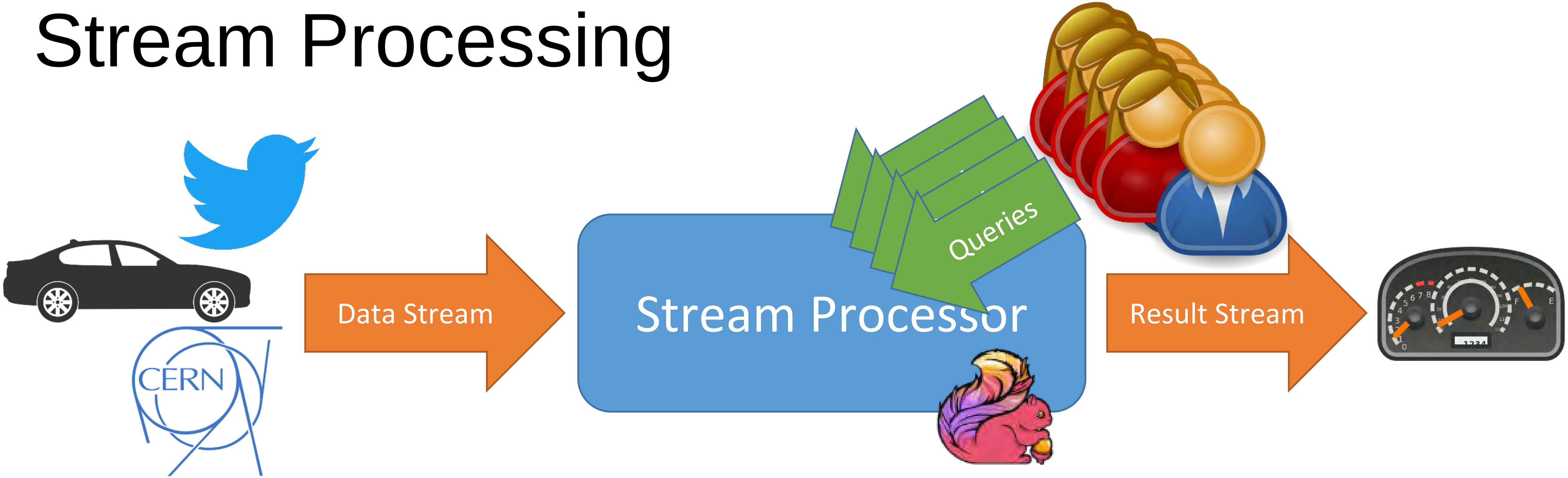
- Traffic Monitoring
  - High event rates: millions events / sec
  - High query rates: thousands queries / sec
  - Queries: filtering, notifications, analytical

Source: http://theroadtochangeindia.wordpress.com/2011/01/13/better-roads/

- Pre-processing of sensor data
  - CERN experiments generate ~1PB of measurements per second.
  - Unfeasible to store or process directly, fast preprocessing is a must.

[1]Cobb: http://www.hybridcars.com/tech-experts-put-the-brakes-on-autonomous-cars/

Stream Processing



Interesting streams
- Many different queries
- Continuous results

Why is this hard?

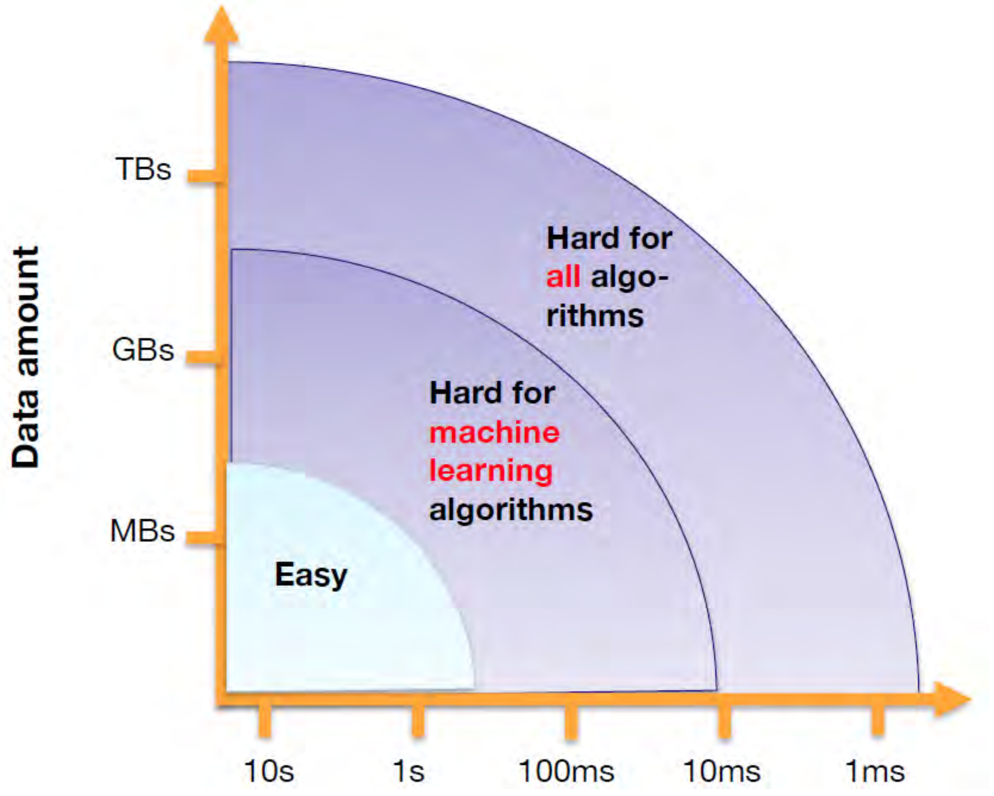


Image: Peter Pietzuch

Tension between *performance* and *algorithmic expressiveness*

Agenda

Introduction to Streams

- Stream processing 101
- Efficient aggregation

Scale-Out Stream Processing Systems

- Ingredients of a stream processing system
- More details on Flink

Scale-Up Stream Processing

- New hardware

With slides from Data Artisans, Volker Markl, and Sebastian Bress

Stream Processing 101

Based on the Data Flow Model

What is a Stream?

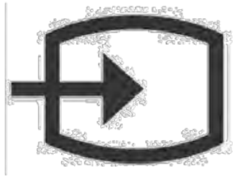
- Unbounded data
  - Conceptually infinite, ever growing set of ***data items / events***
  - Practically continuous stream of data, which needs to be processed / analyzed
- Push model
  - Data production and procession is controlled by the source
  - Publish / subscribe model
- Concept of time
  - Often need to reason about ***when*** data is produced and when processed data should be output
  - Time agnostic, processing time, ingestion time, event time

This part is largely based on Tyler Akidau‘s great blog on streaming - https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101

Event Time

Event Time

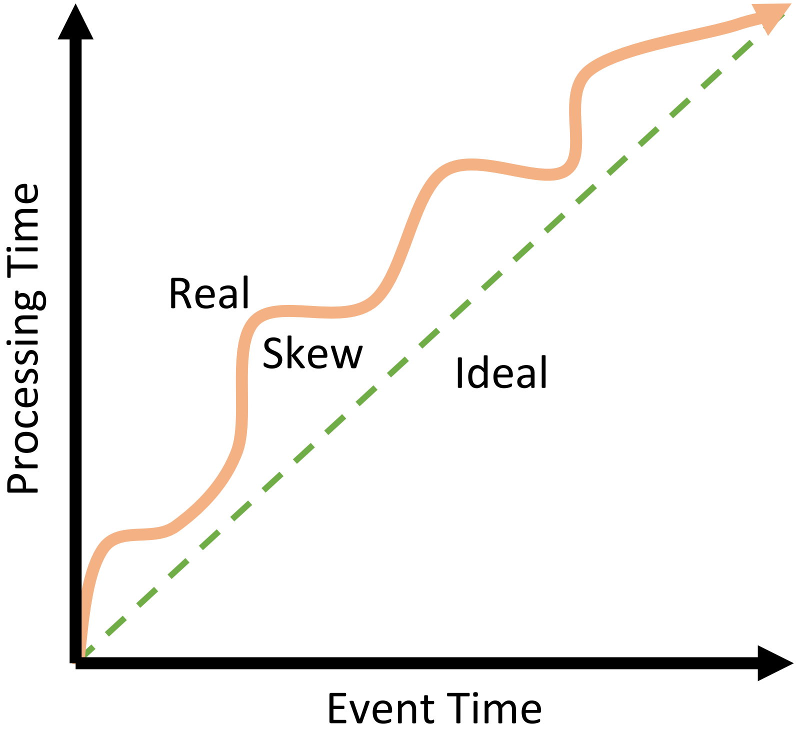
Ingestion Time



Processing Time

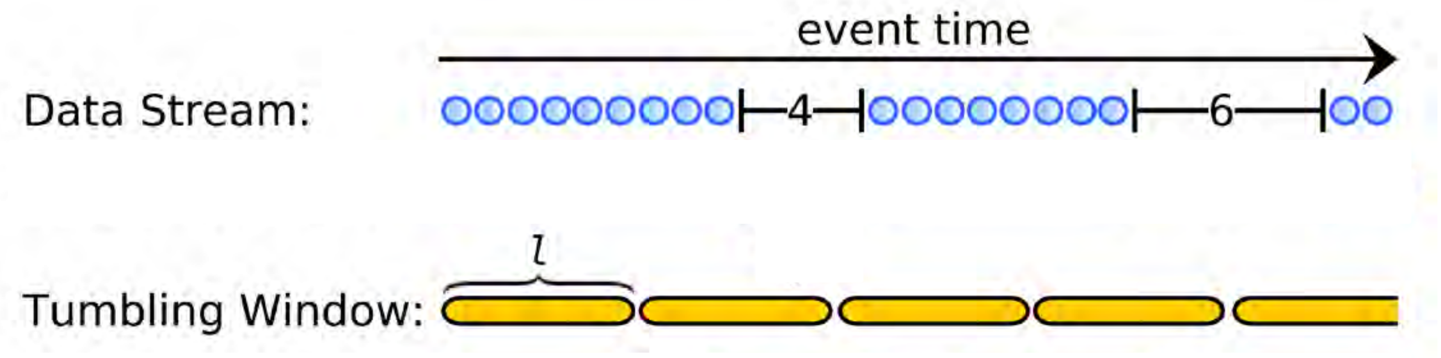
- Event time
  - Data item production time
- Ingestion time
  - System time when data item is received
- Processing time
  - System time when data item is processed

- Typically, these do not match!
- In practice, streams are unordered!



Windows

- Fixed
  - Also tumbling
- Sliding
  - Also hopping
- Session
  - Based on activity



- Triggered by
  - Event time, processing time, count, *watermark*
- Eviction policy
  - Window width / size

Processing Time Windows

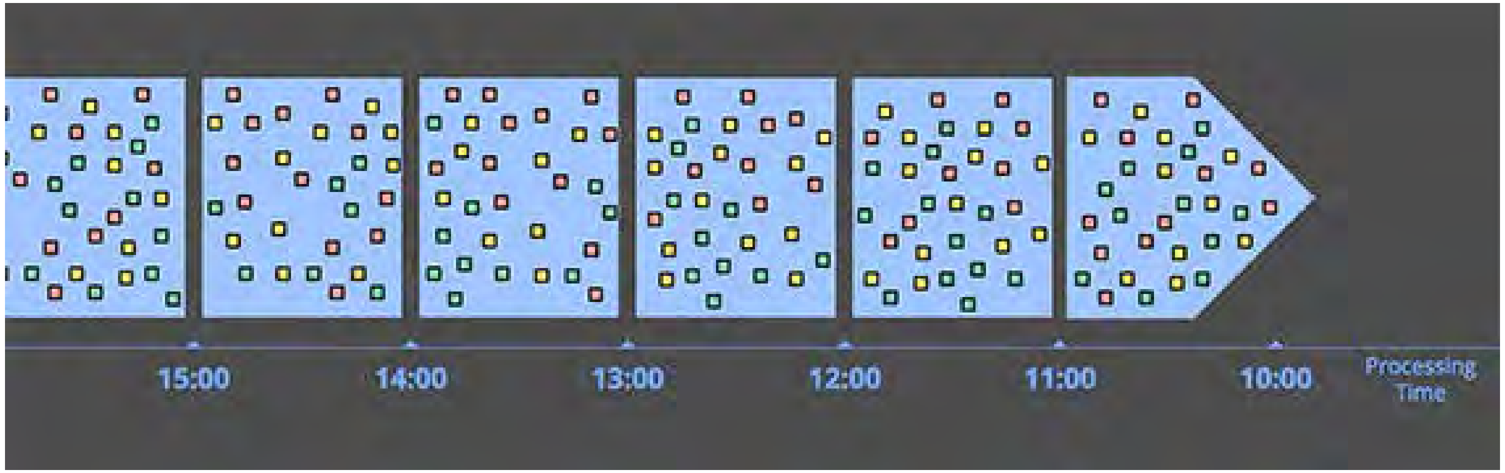
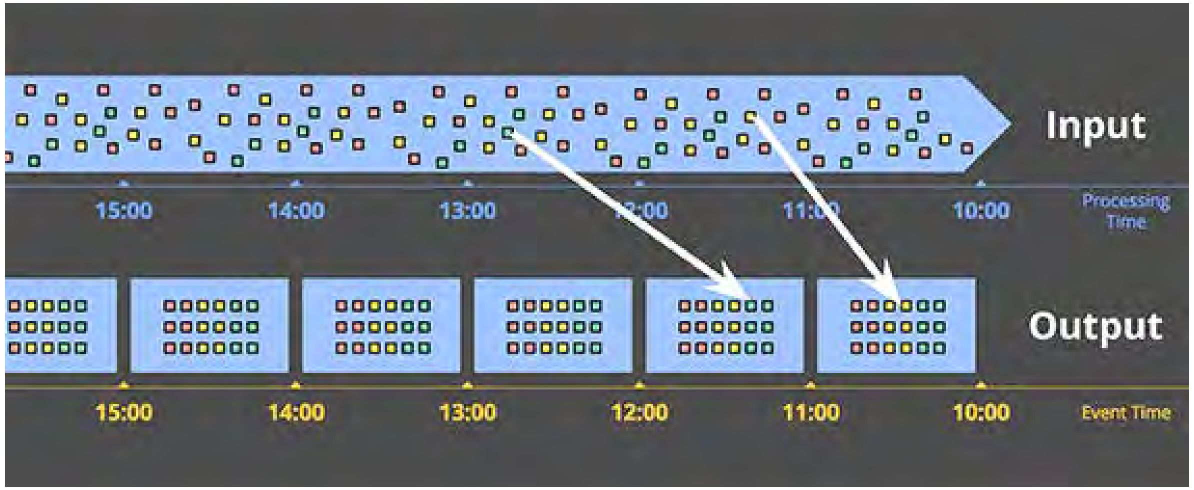
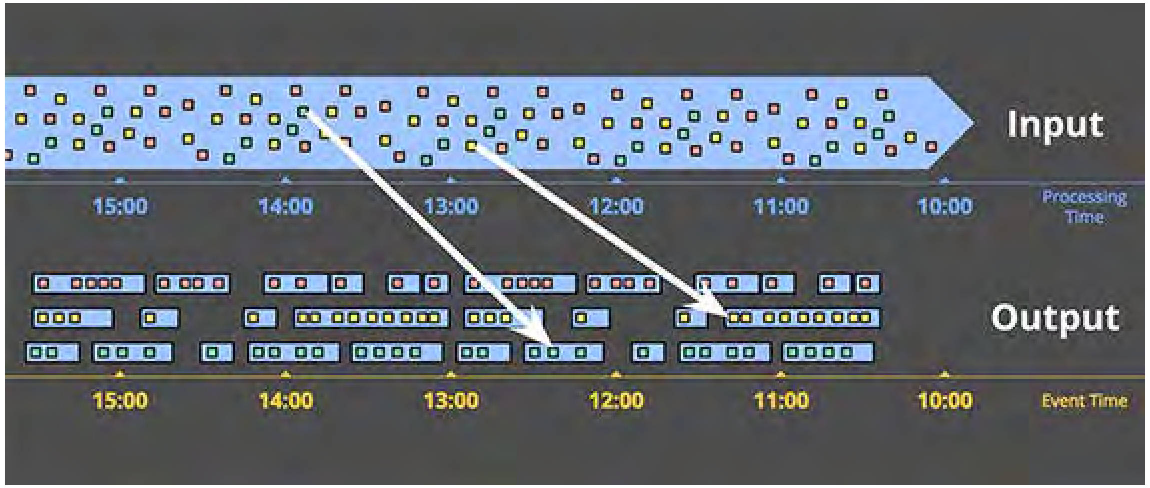


Image: Tyler Akidau

- System waits for x time units
  - System decides on stream partitioning
  - Simple, easy to implement
  - Ignores any time information in the stream -> any aggregation can be arbitrary
- Similar: Counting Windows

Event Time Windows



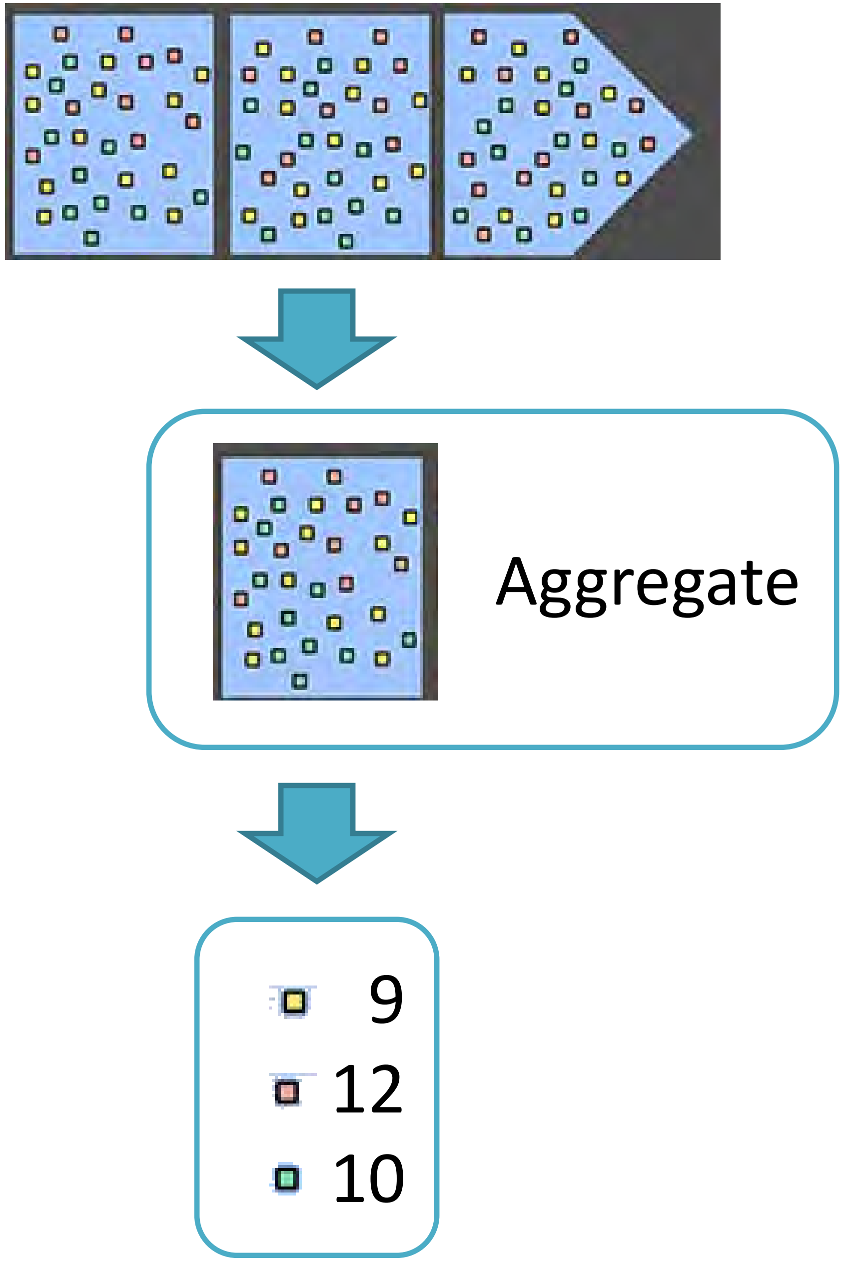


Images: Tyler Akidau

- Windows based on the time information in stream
  - Adheres to stream semantic
  - Correct calculations
  - Buffering required, potentially unordered (more on this later)

Basic Stream Operators

- Windowed Aggregation
  - E.g., average speed
  - Sum of URL accesses
  - Daily highscore
- Windowed Join
  - Correlated observations in timeframe
  - E.g., temperature in time



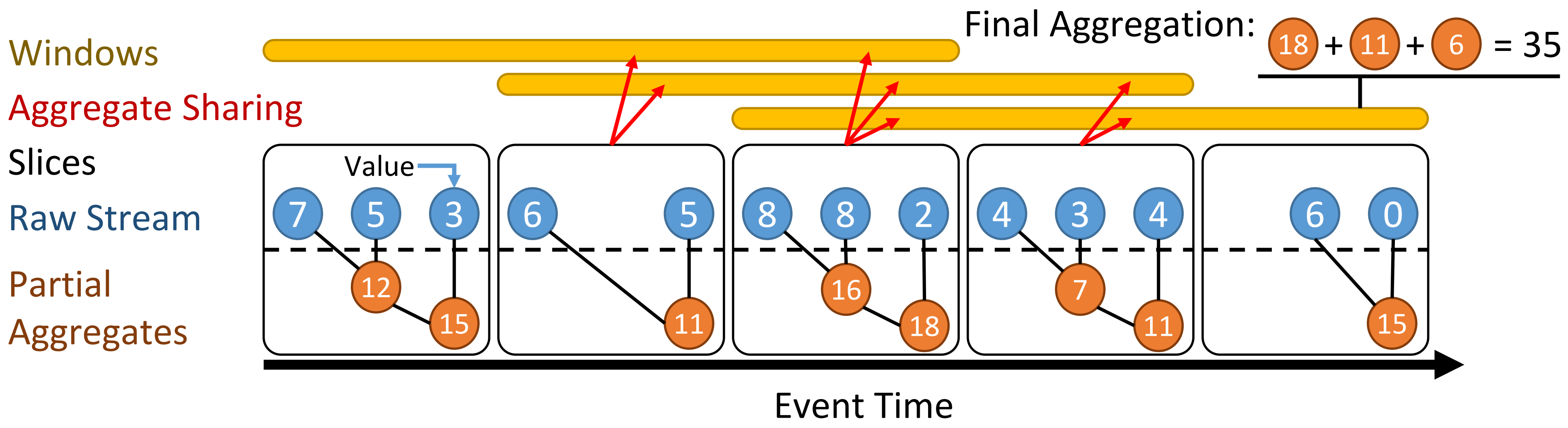
Efficient Window Aggregation

Stream processing on overlapping windows

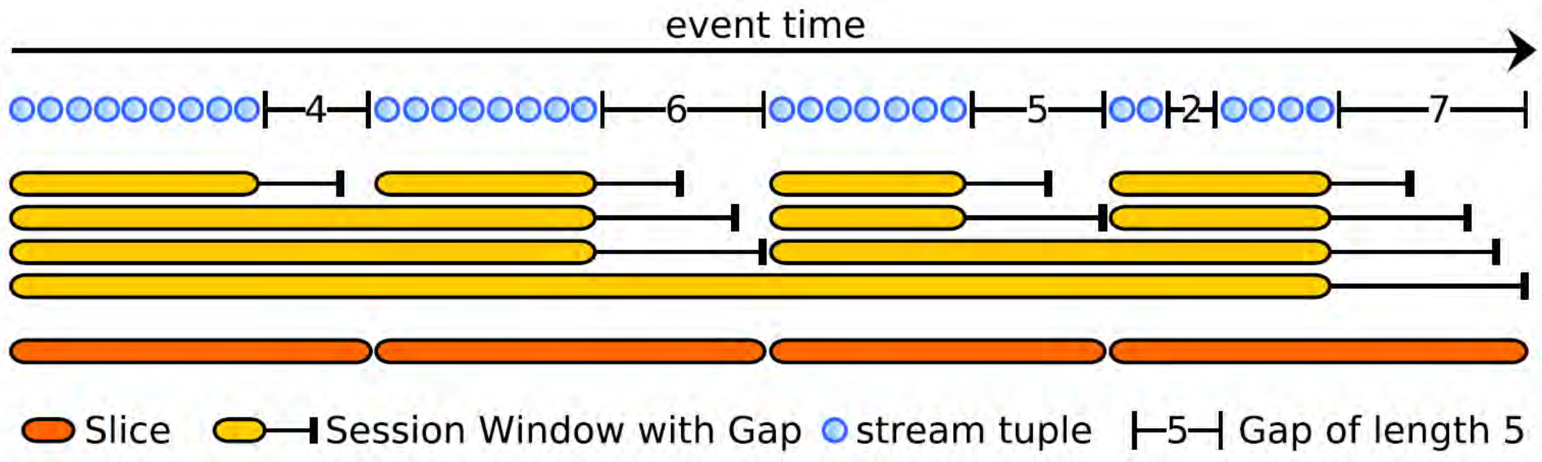
Aggregate computation is redundant

Partial aggregates can be shared

Challenge: session windows, user defined windows, out of order tuples



Session Window Observations



Stream Slicing Example:
Concurrent Session Windows with gaps 3,5,6, and 7

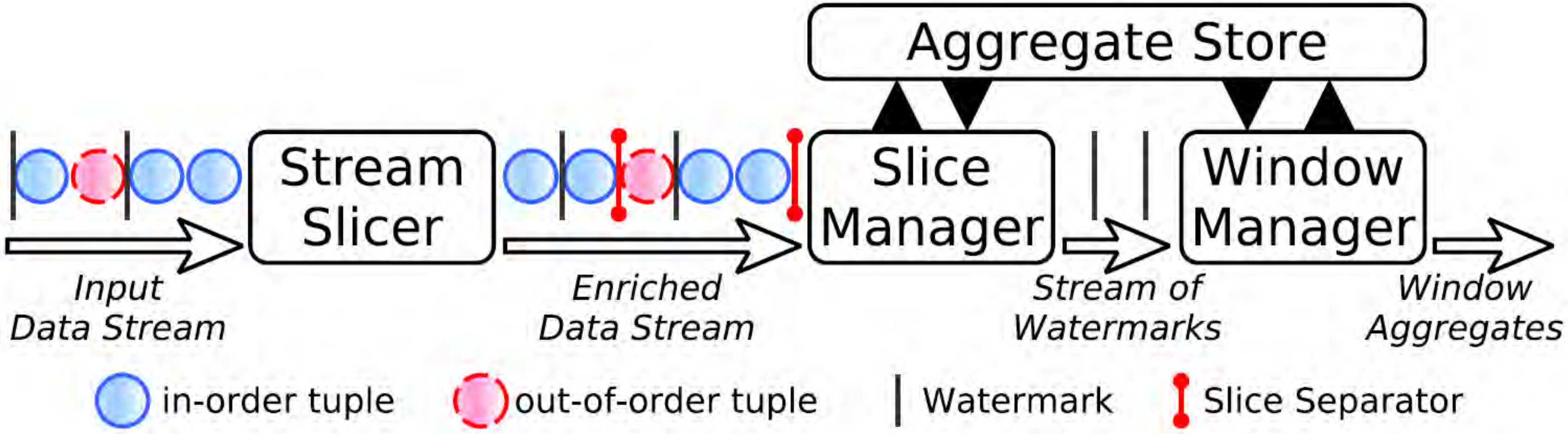
Windows with different gaps share partial aggregates

Session windows can share aggregates with sliding and tumbling windows

Slice on session and gap is equivalent to session slice

Slicing depends on session window with smallest gap

Generalized Stream Slicing*



Stream Slicer for non overlapping slices

Slice Manager for slice updates (out of order tuples) and window borders

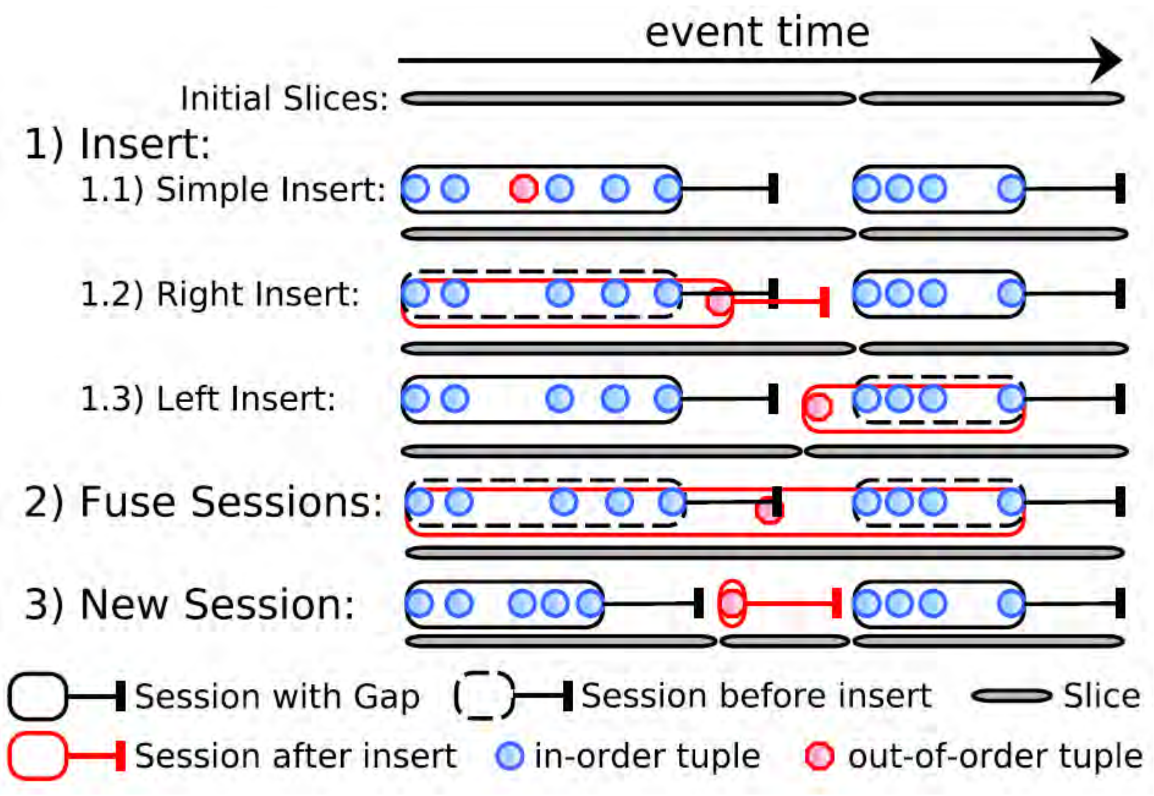
Aggregate Store computes and stores partial aggregates (eager and lazy)

Window Manager combines aggregates and outputs windows

* **Scotty: Efficient Window Aggregation for out-of-order Stream Processing.** Jonas Traub, Philipp M. Grulich, Alejandro Rodríguez Cuellar, Sebastian Breß, Asterios Katsifodimos, Tilmann Rabl, Volker Markl. ICDE 2018.

Out-of-Order Tuple Processing

- Slice Manager keeps minimum number of slices for out-of-order tuples
- Out-of-order tuple lead to updates
- Sufficient to store one partial aggregate per slice
- Reduced memory footprint



Stream Processing Systems

What makes a system a stream processing system?

8 Requirements of Big Streaming

- Keep the data moving
  - Streaming architecture
- Declarative access
  - E.g. StreamSQL, CQL
- Handle imperfections
  - Late, missing, unordered items
- Predictable outcomes
  - Consistency, event time
- Integrate stored and streaming data
  - Hybrid stream and batch
- Data safety and availability
  - Fault tolerance, durable state
- Automatic partitioning and scaling
  - Distributed processing
- Instantaneous processing and response

The 8 Requirements of Real-Time Stream Processing – Stonebraker et al. 2005

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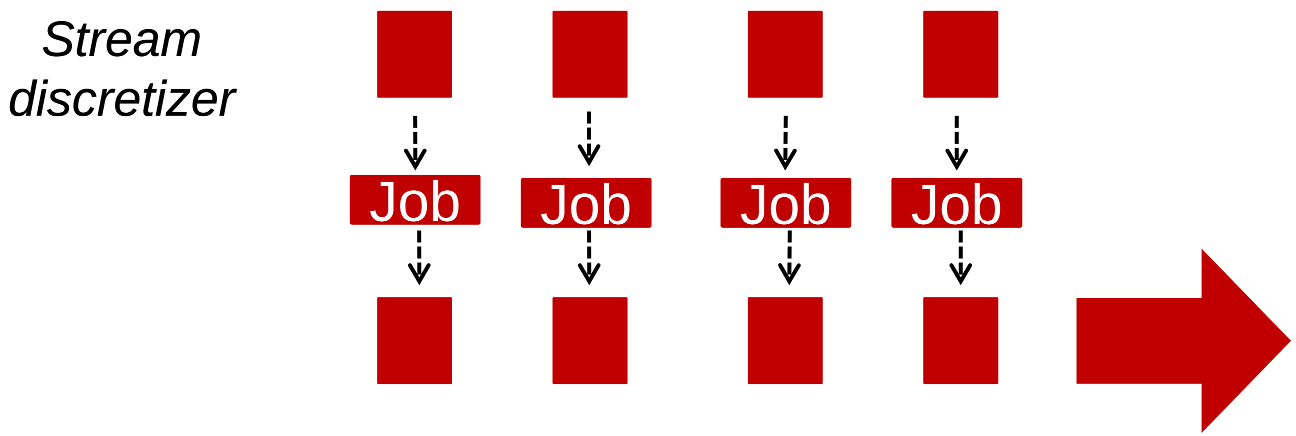
Big Data Processing

- Databases can process very large data since forever (see VLDB)
  - Why not use those?
- Big data is not (fully) structured
  - No good for database ☹
- We want to learn more from data than just
  - Select, project, join
- First solution: MapReduce

How to keep data moving?

Discretized Streams (mini-batch)




```
while (true) {
  // get next few records
  // issue batch computation
}
```

Native streaming


```
while (true) {
   // process next record
}
```

Discussion of Mini-Batch

- Easy to implement
- Easy consistency and fault-tolerance
- Hard to do event time and sessions

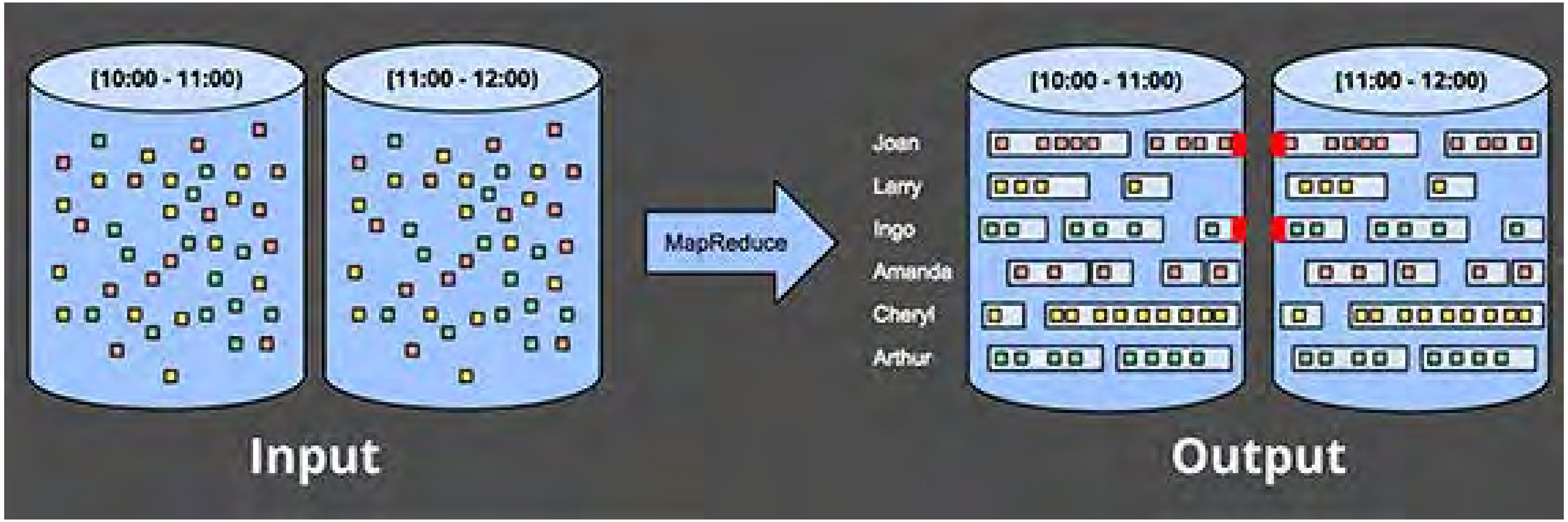
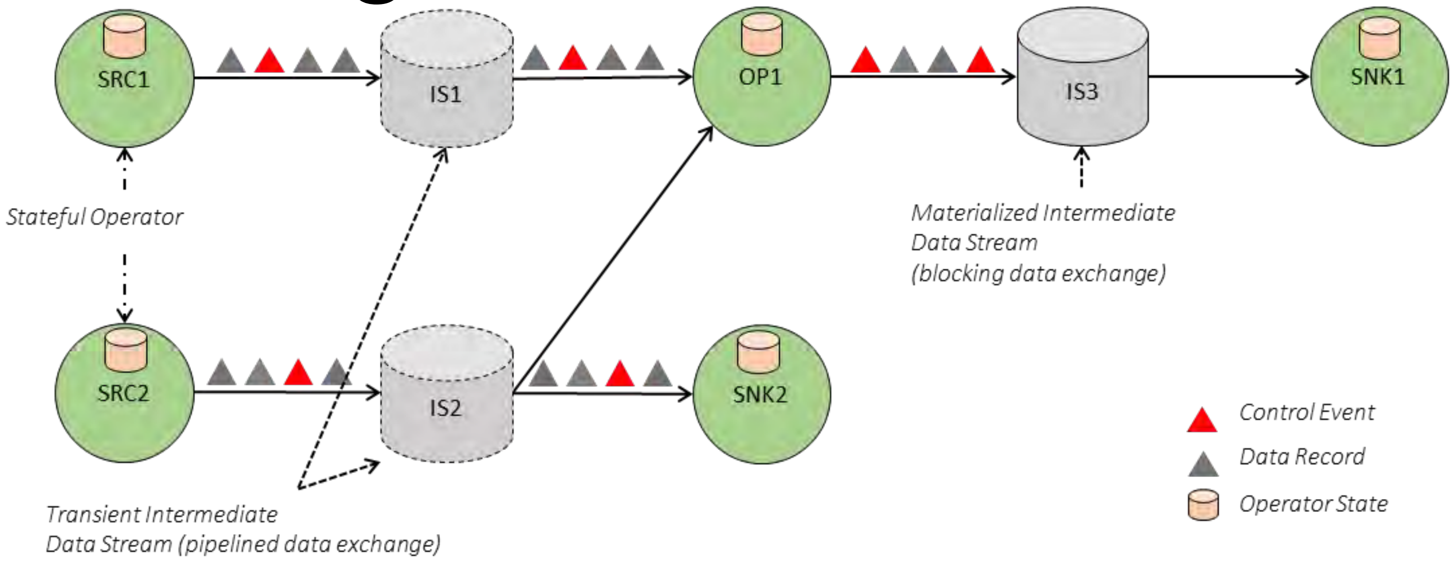


Image: Tyler Akidau

True Streaming Architecture



- Program = DAG* of operators and intermediate streams
- Operator = computation + state
- Intermediate streams = logical stream of records

- Stream transformations
  - Basic transformations: *Map, Reduce, Filter, Aggregations*…
  - Binary stream transformations: *CoMap, CoReduce*…
  - Windowing semantics: *Policy based flexible windowing (Time, Count, Delta…)*
  - Temporal binary stream operators: *Joins, Crosses*…
  - Native support for iterations

Handle Imperfections – Watermarks

- Data items arrive early, on-time, or late
- Solution: Watermarks
  - Perfect or heuristic measure on when window is complete

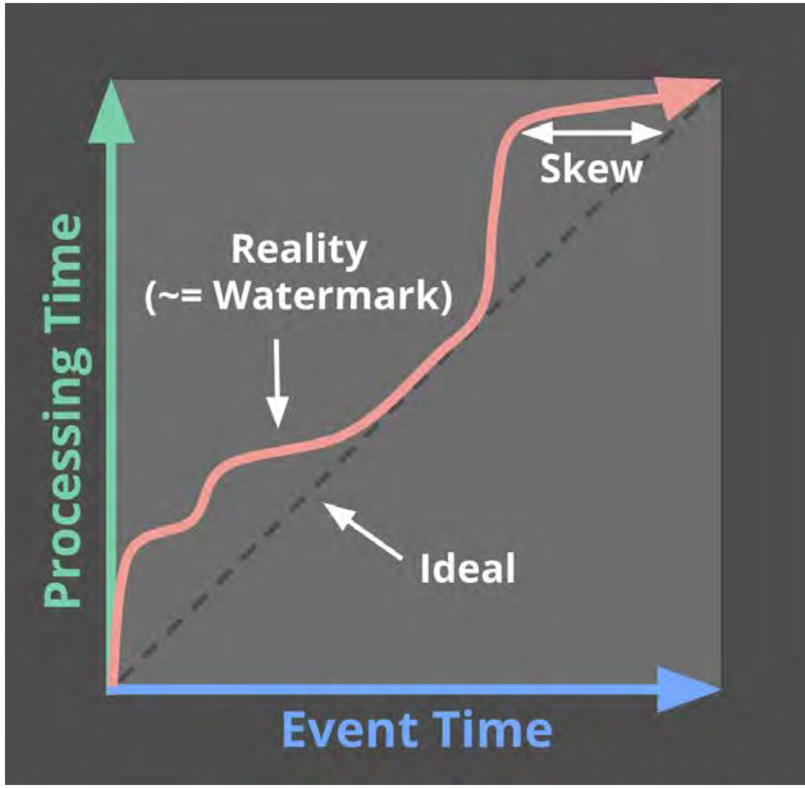


Image: Tyler Akidau

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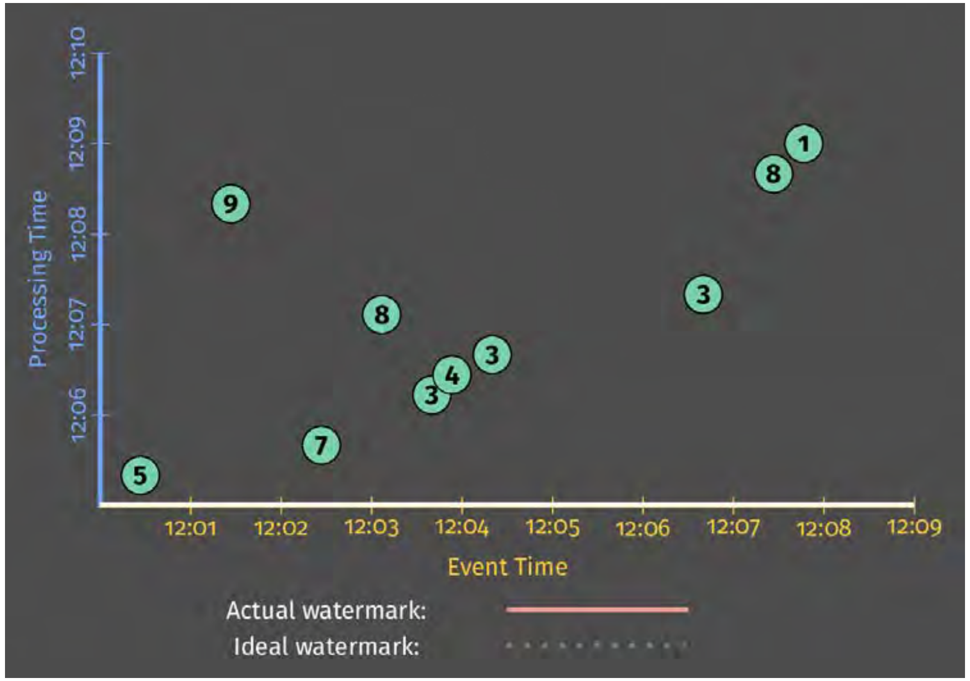


Image: Tyler Akidau

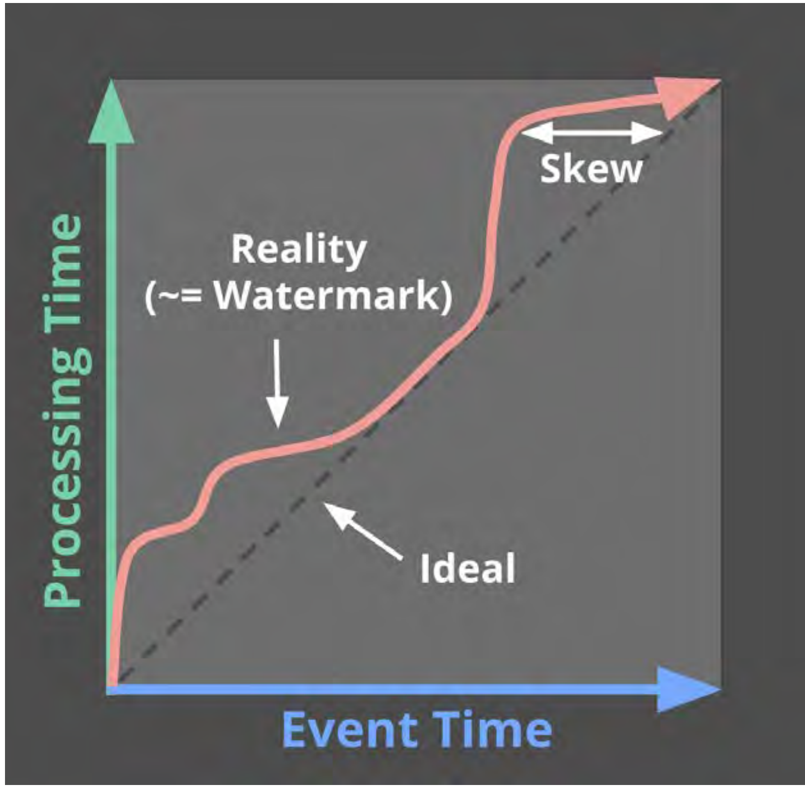
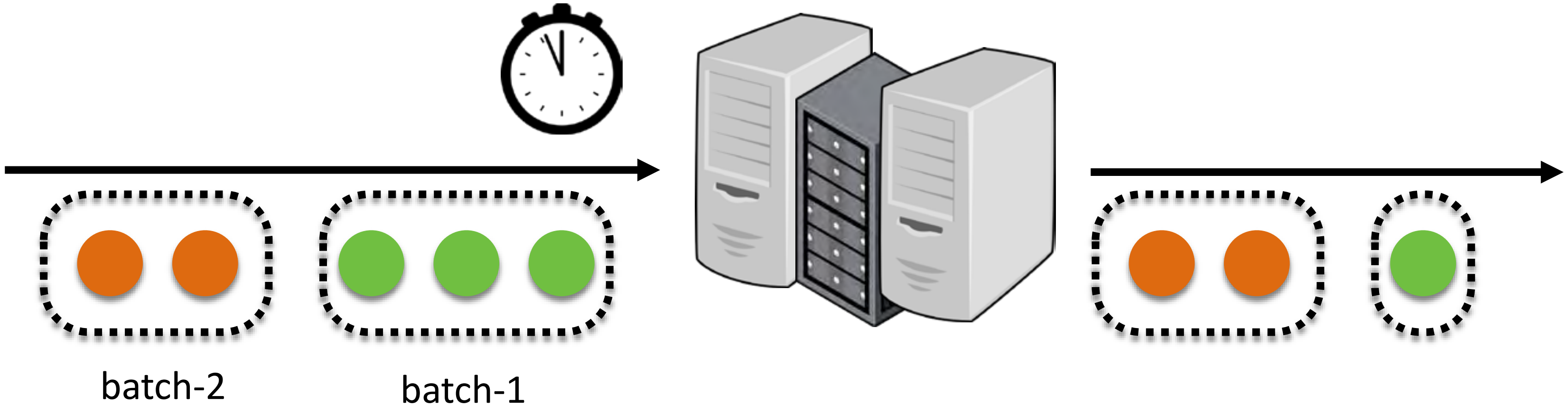


Image: Tyler Akidau

Data Safety and Availability

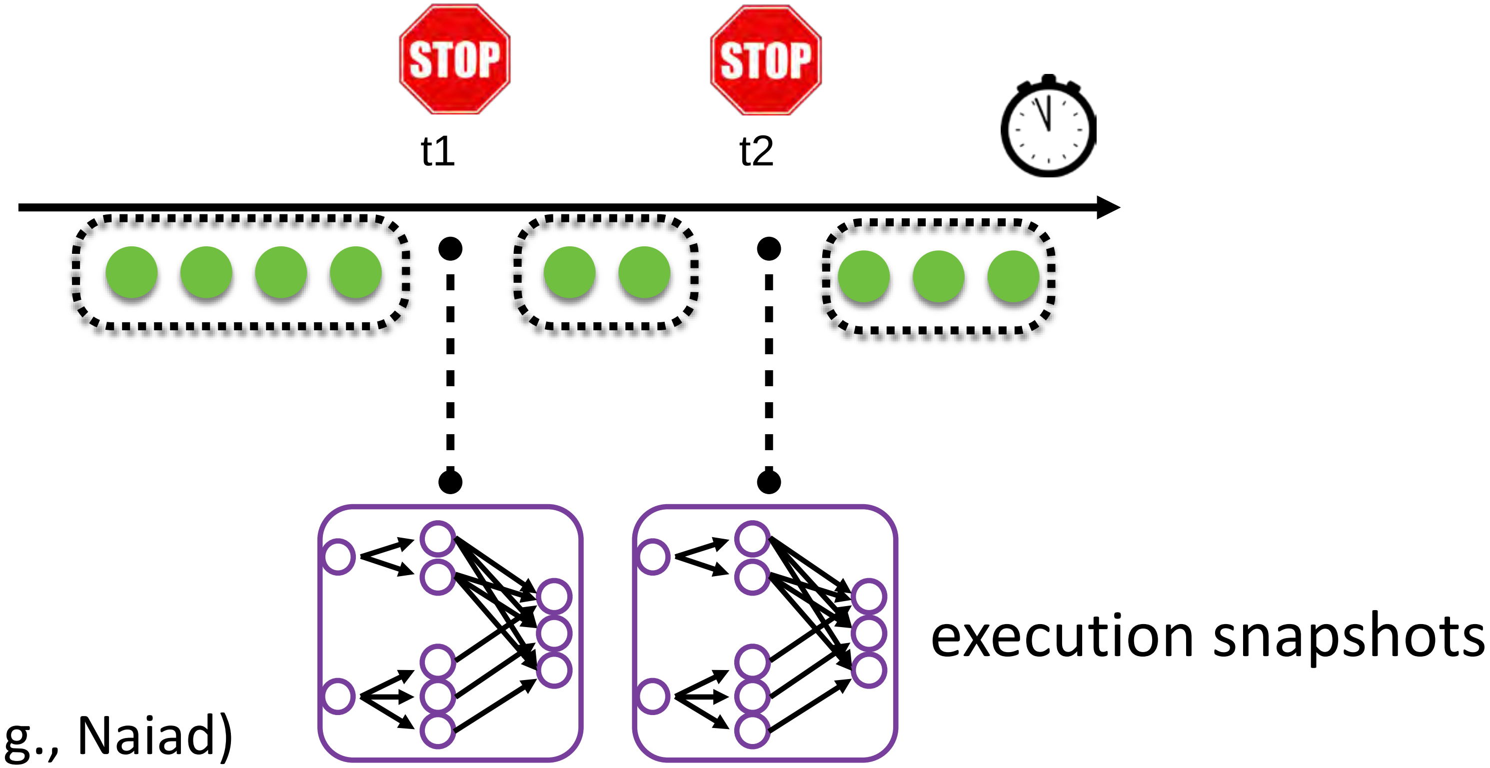
- Ensure that operators see all events
  - "At least once"
  - Solved by replaying a stream from a checkpoint
  - No good for correct results
- Ensure that operators do not perform duplicate updates to their state
  - "Exactly once"
  - Several solutions
- Ensure the job can survive failure

Lessons Learned from Batch



- If a batch computation fails, simply repeat computation as a transaction
- Transaction rate is **constant**
- Can we apply these principles to a true streaming execution?

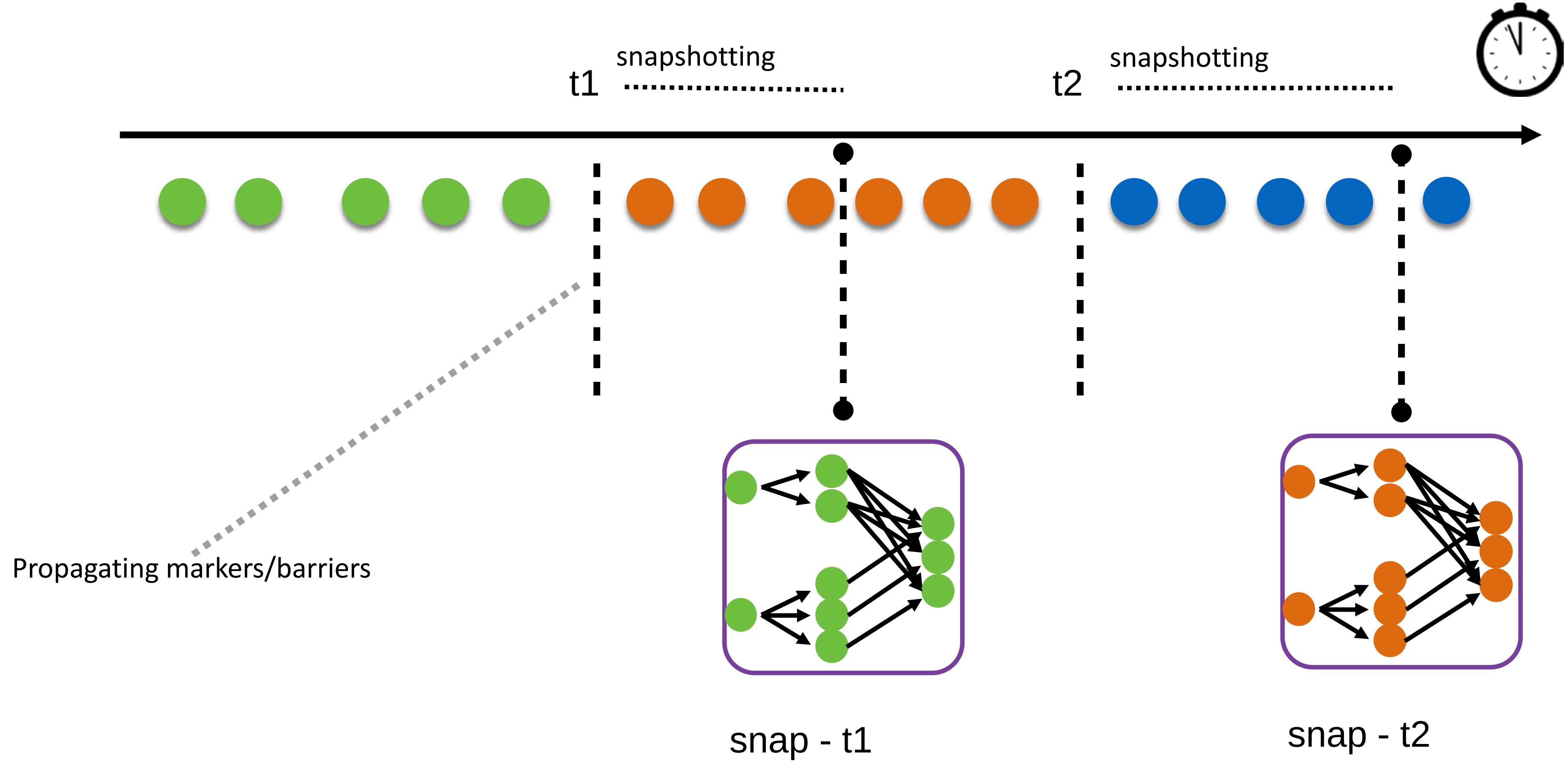
Taking Snapshots – the naïve way



Initial approach (e.g., Naiad)

- Pause execution on t1,t2,..
- Collect state
- Restore execution

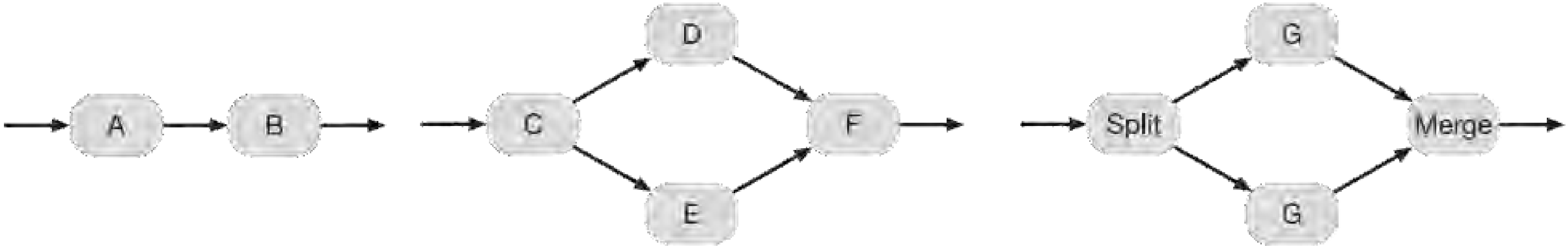
Asynchronous Snapshots in Flink



[Carbone et. al. 2015] "Lightweight Asynchronous Snapshots for Distributed Dataflows", Tech. Report. http://arxiv.org/abs/1506.08603

Automatic partitioning and scaling

- 3 Types of Parallelization



(a) Pipeline-parallel A || B. (b) Task-parallel D || E. (c) Data-parallel G || G.

- Big streaming systems should support all three

Apache Flink–
A Success Story
created in Berlin

Stratosphere: General Purpose Programming + Database Execution

Draws on
Database Technology

- Relational Algebra
- Declarativity
- Query Optimization
- Robust Out-of-core

Adds

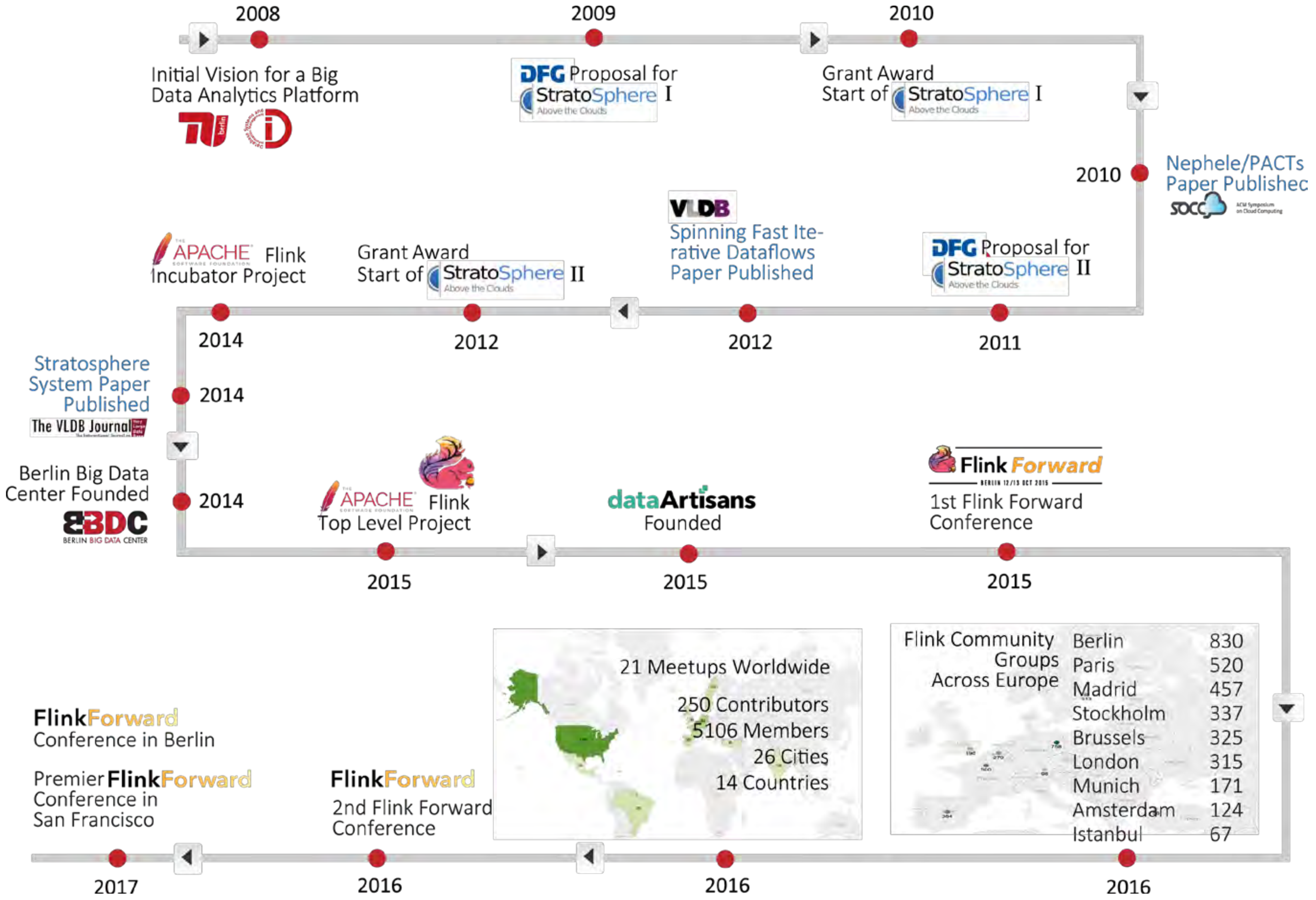
- Iterations
- Advanced Dataflows
- General APIs
- Native Streaming

Draws on
MapReduce Technology

- Scalability
- User-defined Functions
- Complex Data Types
- Schema on Read

33

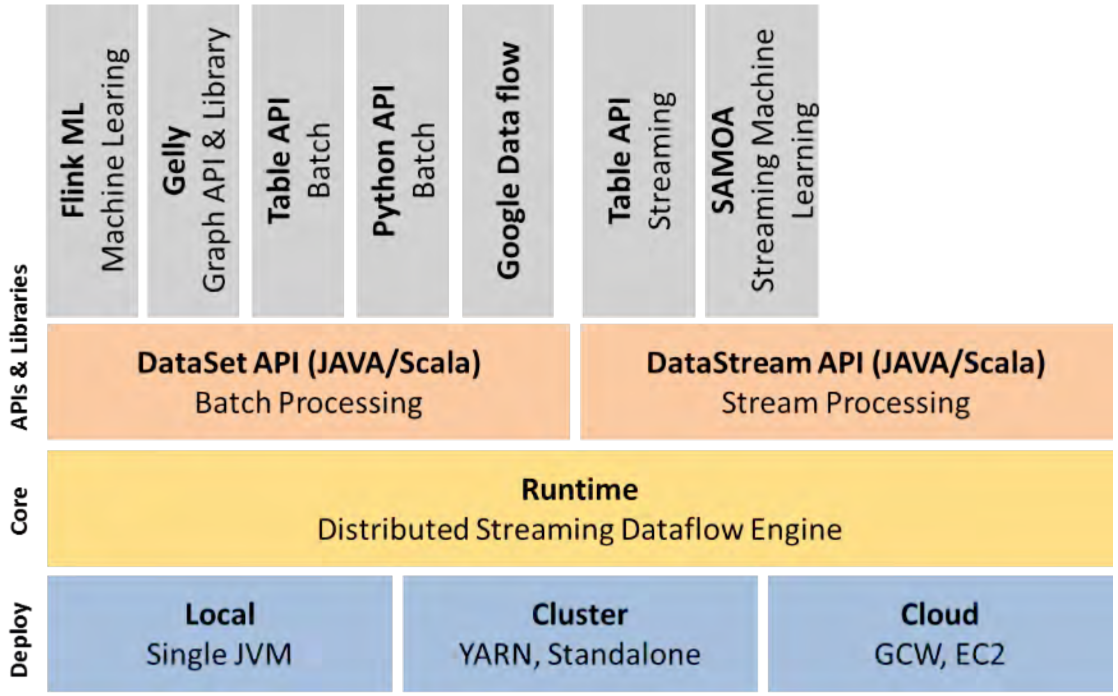
Timeline


2008
Initial Vision for a Big Data Analytics Platform
2009
DFG Proposal for StratoSphere I
Above the Clouds
2010
Grant Award Start of StratoSphere I
2010
Nephele/PACTs Paper Published
SOCC
2011
DFG Proposal for StratoSphere II
2012
VLDB
Spinning Fast Iterative Dataflows Paper Published
2012
Grant Award Start of StratoSphere II
2014
APACHE Flink Incubator Project
2014
Stratosphere System Paper Published
The VLDB Journal
2014
Berlin Big Data Center Founded
BBDC
BERLIN BIG DATA CENTER
2015
APACHE Flink Top Level Project
2015
dataArtisans Founded
2015
Flink Forward
1st Flink Forward Conference
2016
Flink Community Groups Across Europe
Berlin 830
Paris 520
Madrid 457
Stockholm 337
Brussels 325
London 315
Munich 171
Amsterdam 124
Istanbul 67
2016
21 Meetups Worldwide
250 Contributors
5106 Members
26 Cities
14 Countries
2016
FlinkForward
2nd Flink Forward Conference
2017
FlinkForward
Conference in Berlin
Premier FlinkForward
Conference in San Francisco

What is Apache Flink?

Apache Flink is an open source platform for scalable batch and stream data processing.

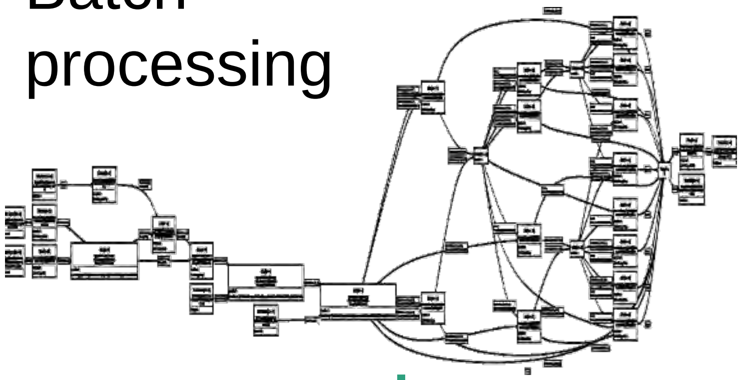
- The core of Flink is a distributed streaming dataflow engine.
  - Executing dataflows in parallel on clusters
  - Providing a reliable foundation for various workloads
- **DataSet** and **DataStream** programming abstractions are the foundation for user programs and higher layers



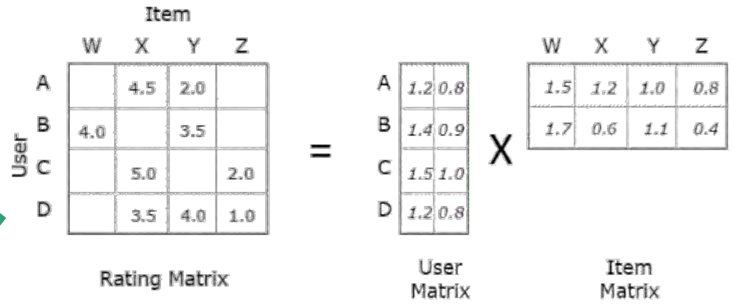
http://flink.apache.org

What can I do with it?

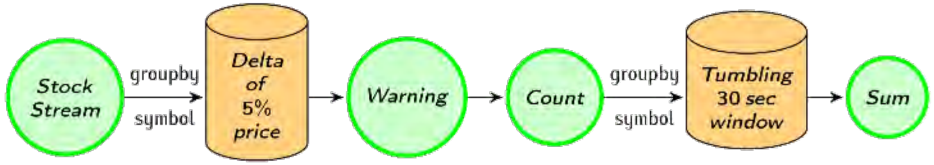
Batch processing



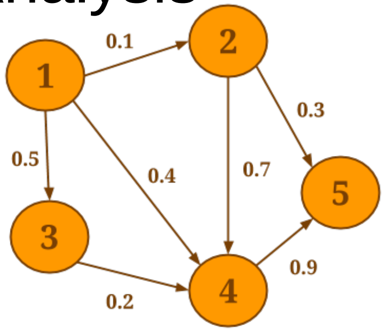
Machine Learning at scale



Stream processing



Graph Analysis



Flink

A big data processing system that can **natively** support all these workloads.

Big Data Analytics Ecosystem

Applications & Languages

Hive | Cascading | Giraph

Mahout | Pig | Crunch

Data processing engines

MapReduce | Flink

Spark | Storm | Tez

App and resource management

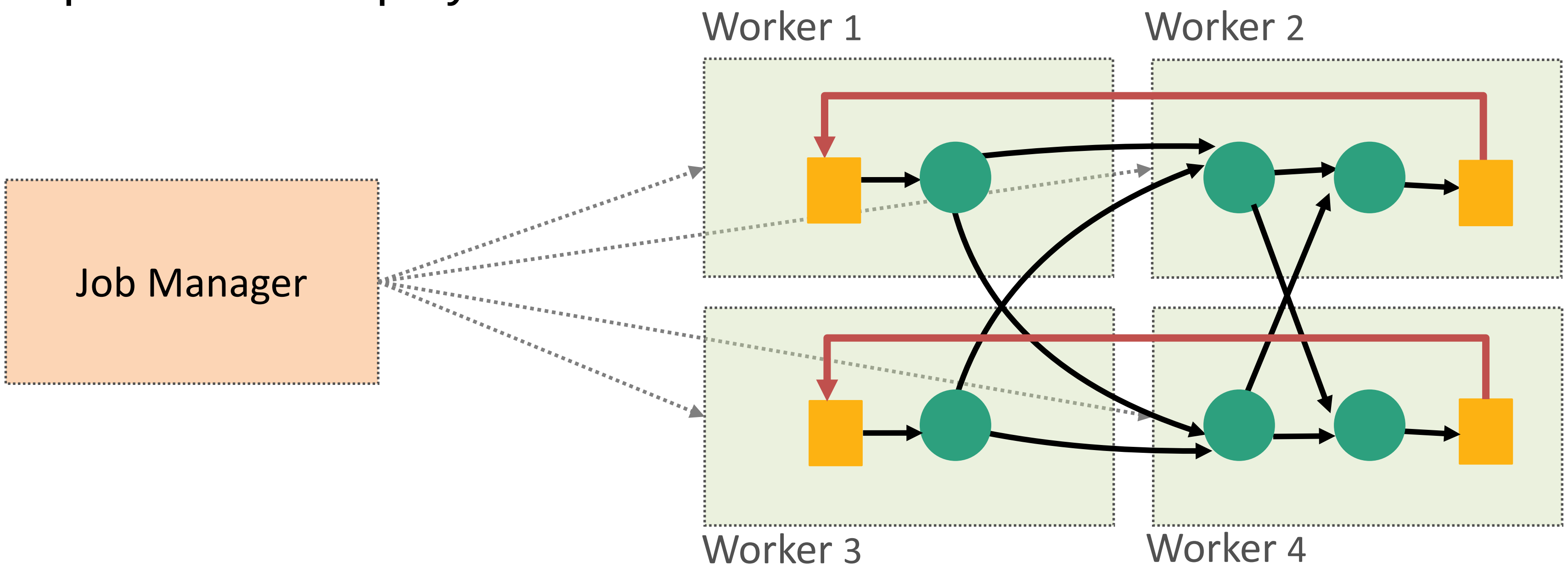
Yarn | Mesos

Storage, streams

HDFS | HBase | Kafka | …

Architecture

- Hybrid MapReduce and MPP database runtime
- Pipelined/Streaming engine
  - Complete DAG deployed



Sneak peak: Two of Flink’s APIs

```
case class Word (word: String, frequency: Int)
```

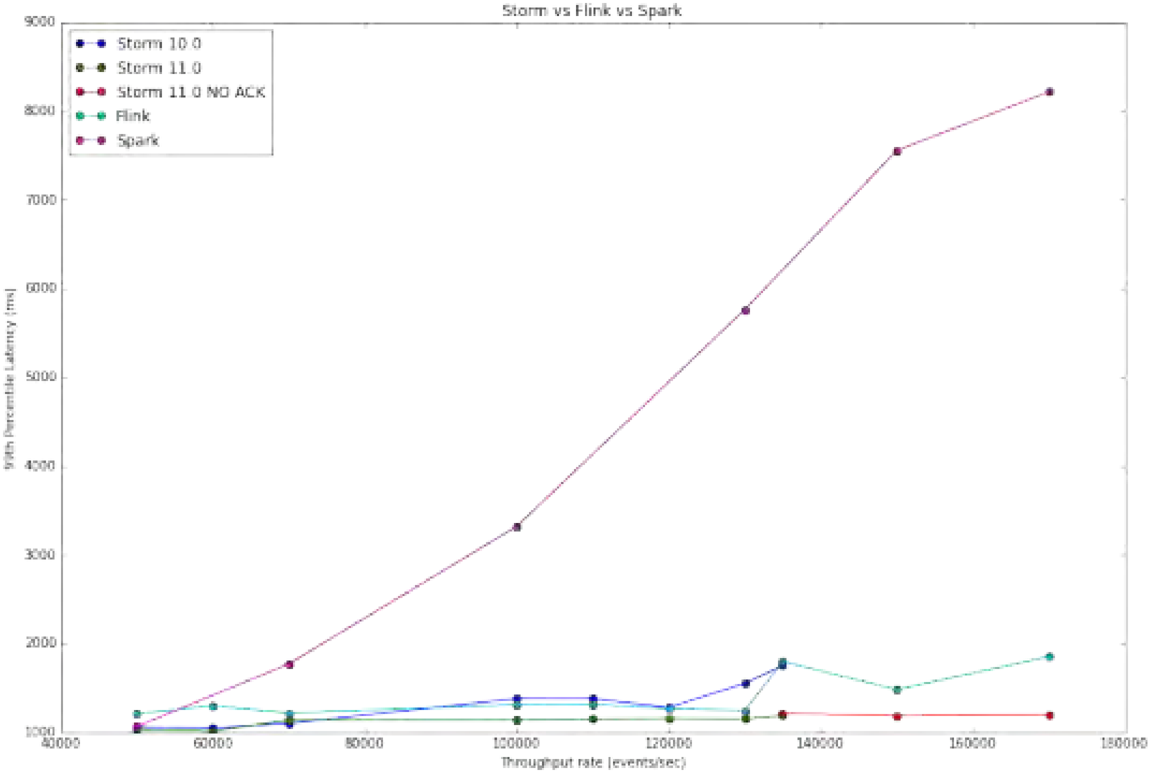
DataSet API (batch):

```
val lines: DataSet[String] = env.readTextFile(...)
lines.flatMap {line => line.split(" ")
                                .map(word => Word(word,1))}
      .groupBy("word").sum("frequency")
      .print()
```

DataStream API (streaming):

```
val lines: DataStream[String] = env.fromSocketStream(...)
lines.flatMap {line => line.split(" ")
                                .map(word => Word(word,1))}
     .keyBy("word")
     .window(Time.of(5,SECONDS)).every(Time.of(1,SECONDS))
     .sum("frequency”)
     .print()
```

Yahoo! Benchmark Results

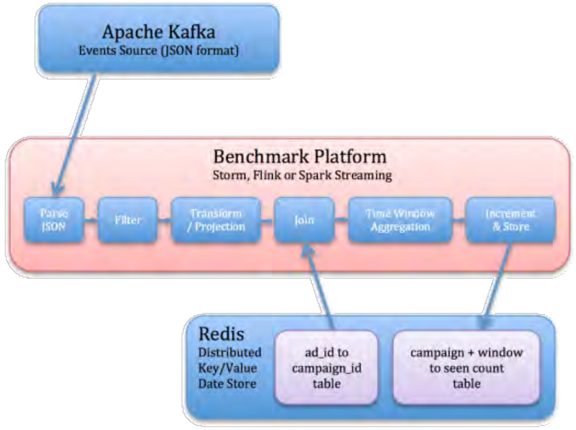


Source: http://yahooeng.tumblr.com/post/135321837876/benchmarking-streaming-computation-engines-at

Performed by Yahoo! Engineering, Dec 16, 2015

[..]Storm 0.10.0, 0.11.0-SNAPSHOT and Flink 0.10.1 show sub- second latencies at relatively high throughputs[..]. Spark streaming 1.5.1 supports high throughputs, but at a relatively higher latency.

Flink achieves highest throughput with competitive low latency!



Our benchmarks*

Streaming

	2 Node	4 Node	8 Node
Storm	408K	696K	992K
Spark	379K	642K	912K
Flink	1230K	1260K	1260K

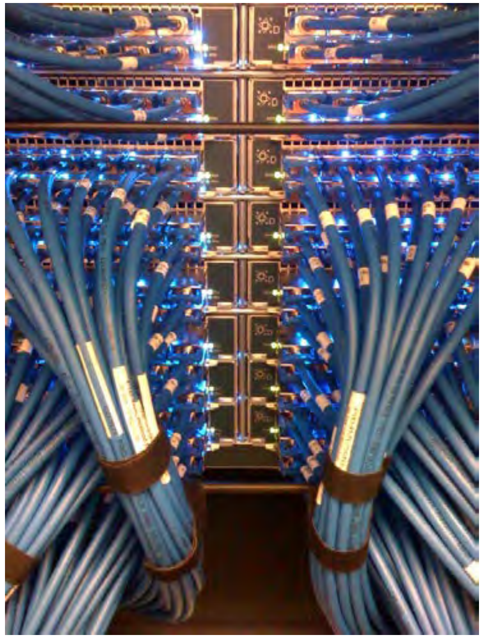
Windowed Aggregations

* **Benchmarking Distributed Stream Data Processing Systems.** Jeyhun Karimov, Tilmann Rabl, Asterios Katsifodimos, Roman Samarev, Henri Heiskanen, and Volker Markl. ICDE 2018

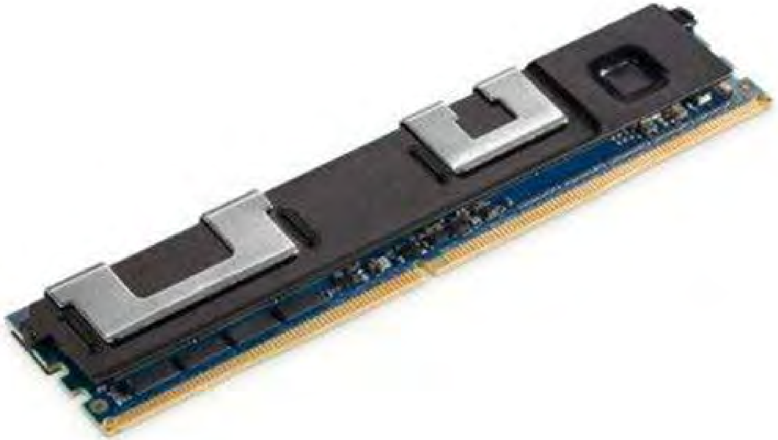
Stream Processing on Modern Hardware

Modern Hardware

Multi-Core CPUs

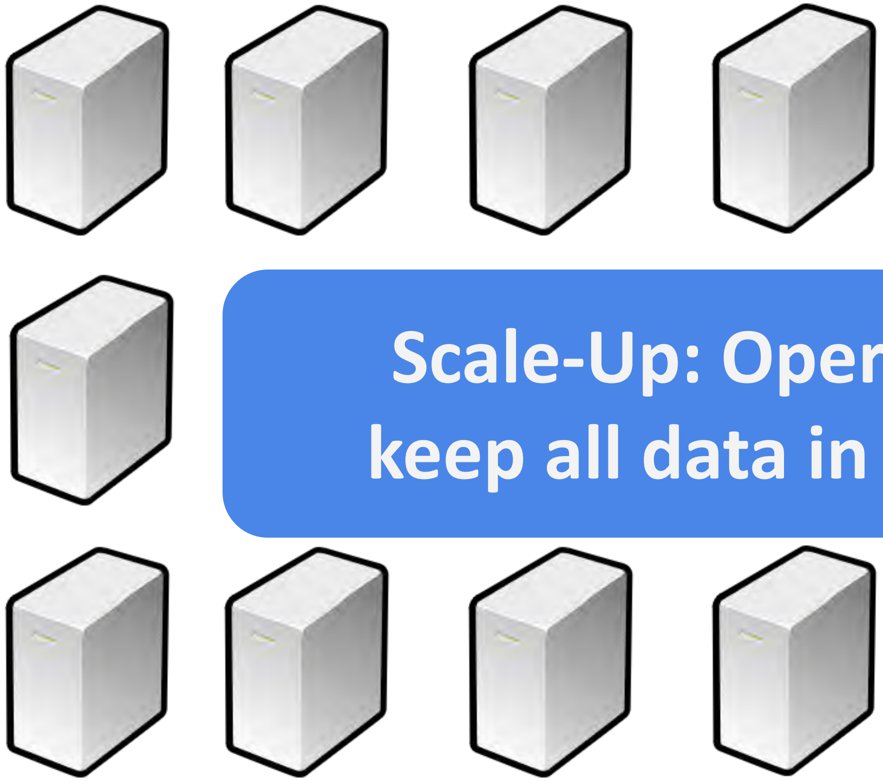


Fast Networks

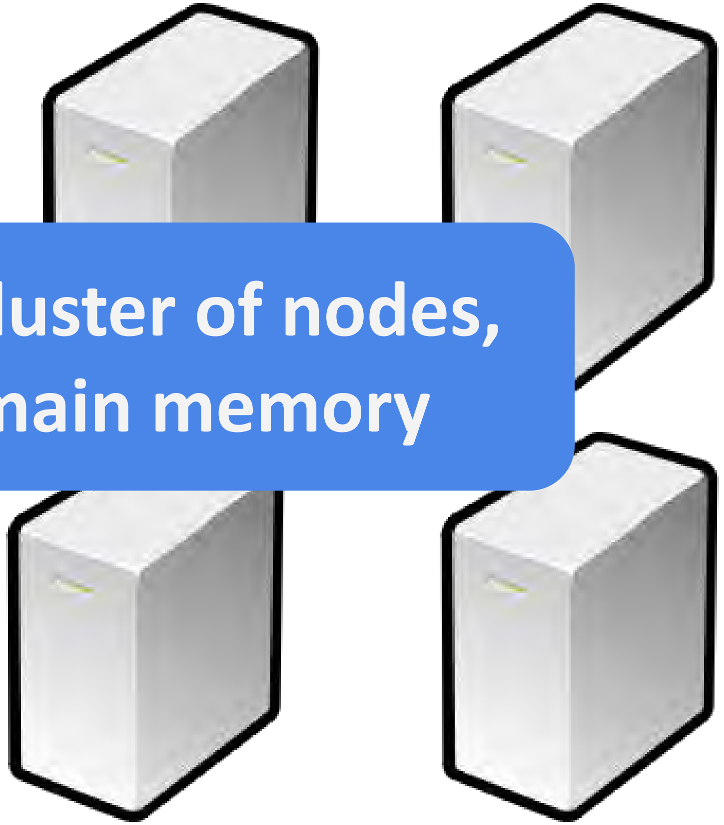


Non-Volatile Memory

Scale Out vs. Scale Up Stream Processing



Scale-Up: Operate a small cluster of nodes, keep all data in distributed main memory



Scale Out Systems

Scale Up Systems

Modern Multi-Core CPUs

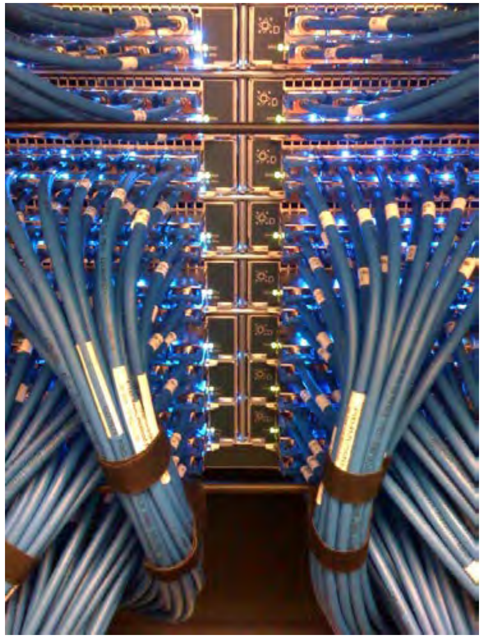
- High Parallelism:
  - Multiple cores (task parallelism): Multiple threads can perform different tasks at the same time
  - Vector units (data parallelism): The same instruction is performed on multiple data items at once
- High Memory Bandwidth:
  - Aggregated memory bandwidth of 51.2GB/s per CPU (DDR3-1600 memory with four channels, 12.8GB/s per channel)
  - Multiple processors are organized in NUMA (Non-Uniform Memory Access) architecture
  - Cache coherent memory across all CPUs

Modern Multi-Core CPUs

Two principle resource limitations:

- Computation Bound:
  - Executing many instructions per input tuple
  - Performing many function calls
  - Encountering many branch mispredictions
- Memory Bound:
  - Bound by Memory Latency:
    - Random Memory Accesses (e.g., hash table operations)
  - Bound by Memory Bandwidth:
    - Executing few instructions per input tuple
    - Reading input tuples sequentially with maximal memory speed

Fast Networks



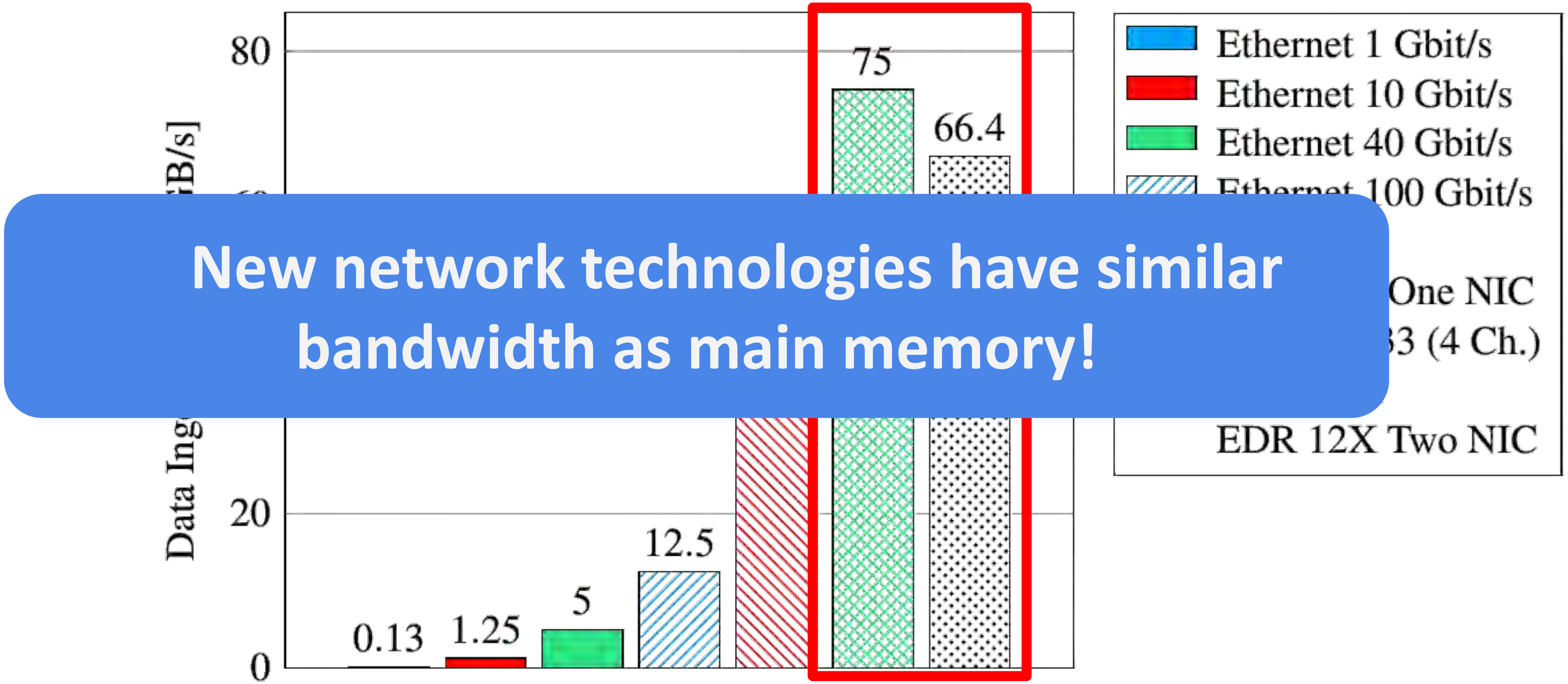
- **Infiniband:**
  - A new generation network protocol, native support for RDMA
  - Very high bandwidth (currently ~100Gbit per port)
  - Very small access latency to memory of remote machine (~1 microsecond for InfiniBand FDR 4x)

- **RDMA (R**emote **D**irect **M**emory **A**ccess):
  - Network adapter can directly read or write to application memory of remote machine

  → Avoids the overhead of copying data into OS buffers

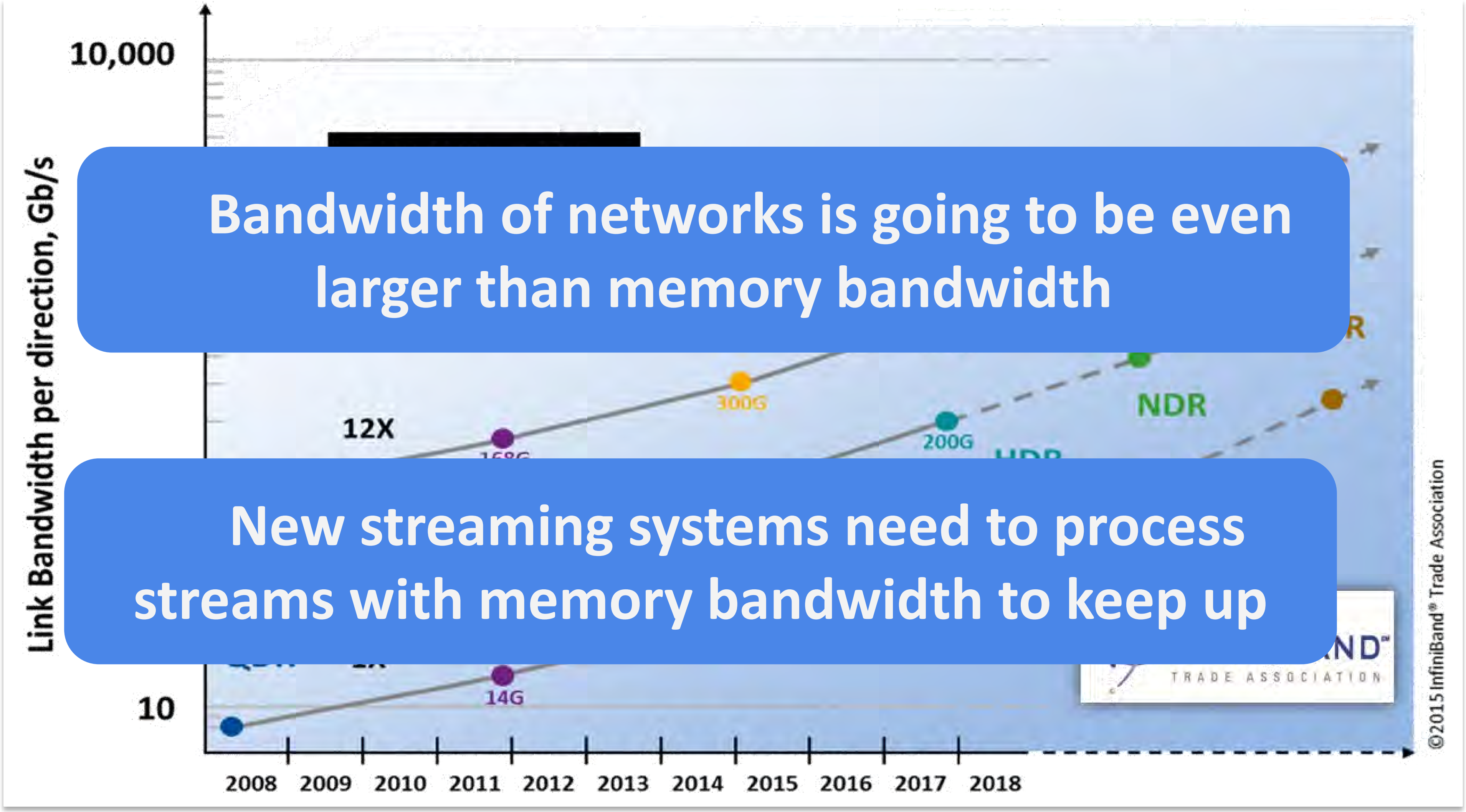
  →Can access remote memory without consuming any CPU time in the remote machine

Bandwidth of Different Network Technologies



Source: Following Binning et al. The End of Slow Networks: It's Time for a Redesign. VLDB 2016.

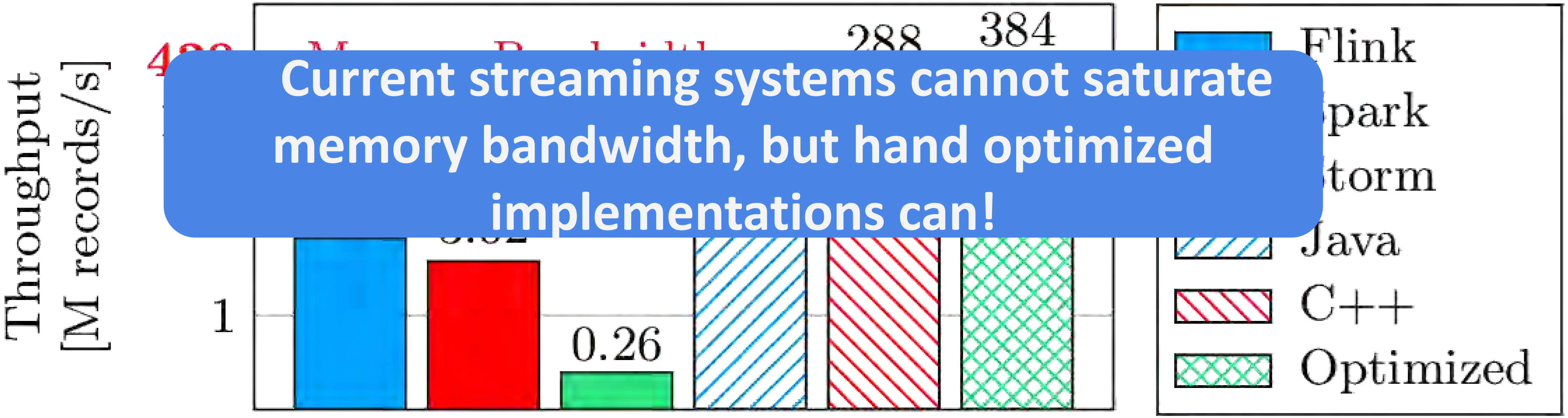
Infiniband Future



Bandwidth of networks is going to be even larger than memory bandwidth

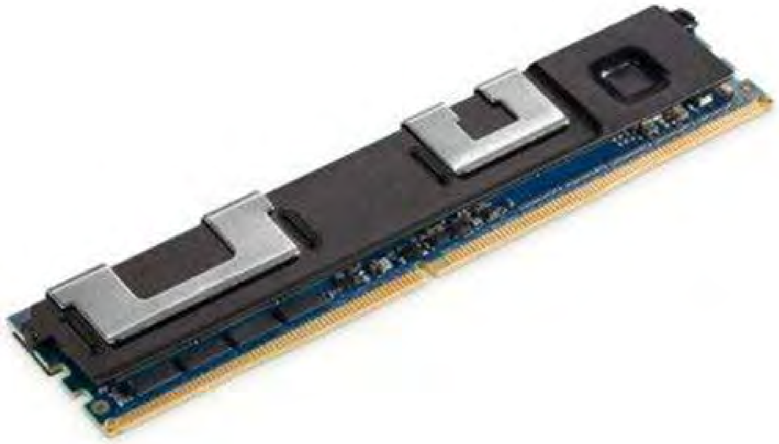
New streaming systems need to process streams with memory bandwidth to keep up

Scale Up vs. Scale Out Stream Processing



Current streaming systems cannot saturate memory bandwidth, but hand optimized implementations can!

Non-Volatile Memory



- Also called Storage Class Memory (SCM)
- Blurs the distinction between
  - Memory (= fast, expensive, volatile)
  - Storage (= slow, cheap, non-volatile)
- Byte-addressable; accessing NVRAM is similar to accessing DRAM
- Latencies are within the same order of magnitude as DRAM
- 10x higher density than DRAM, allows to keep more data (state) in-memory

Non-Volatile Memory: Use Cases

- Accelerate Checkpointing
  - Use NVRAM to store checkpoints
  - Reduces checkpointing overhead during run-time
  - Accelerates starting time when a node comes up again

- New system architectures:
  - Keep all data in NVRAM, no redo recovery needed!
  - Very fast startup times compared to checkpointing-based systems
  - Cache frequently accessed data in RAM for fast access

Non-Volatile Memory: Challenges

- **Any point crash recovery:** byte-addressable persistency makes any write to memory persistent
  → System may crash at any time and writes (log file) may be incomplete
  → Classic recovery techniques assume block-wise atomic writes for blocks on disk

- **Hole detection:** when a transaction just allocates chunks in NVRAM but has not written anything yet, there can be empty log records (holes) in the NVRAM log space

- **Partial write detection:** detect during recovery that transaction has not fully finished writing log data to NVRAM

Towards Scale Up Streaming Systems

Modern hardware allows us to built even faster streaming systems:

- **Scale-Up architecture:** operate a small cluster of nodes, which can keep all data and state in main memory

- **Fast Networks:** offer low latency and high bandwidth communication between nodes

- **Reduced Logging Overhead:** checkpoint application data in NVRAM

Conclusion

Introduction to Streams

- How to do real streaming

Stream Processing Systems

- Ingredients of a stream processing system
- Flink

Streaming on Modern Hardware

- How to optimize

Future Work

- Edge and fog
- Geodistribution

Thank You

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We are hiring!