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Extreme Computing

Data streams and low latency processing

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DATA STREAM BASICS

What is a data stream?

- Large data volume, likely structured, arriving at a very high rate
  - Potentially high enough that the machine cannot keep up with it
- Not (only) what you see on youtube
  - Data streams can have structure and semantics, they're not only audio or video

- Definition (Golab and Ozsu, 2003)
  - A data stream is a real-time, continuous, ordered (implicitly by arrival time of explicitly by timestamp) sequence of items. It is impossible to control the order in which items arrive, nor it is feasible to locally store a stream in its entirety.

Why do we need a data stream?

- Online, real-time processing
- Potential objectives
  - Event detection and reaction
  - Fast and potentially approximate online aggregation and analytics at different granularities
- Various applications
  - Network management, telecommunications
    Sensor networks, real-time facilities monitoring
  - Load balancing in distributed systems
  - Stock monitoring, finance, fraud detection
  - Online data mining (click stream analysis)

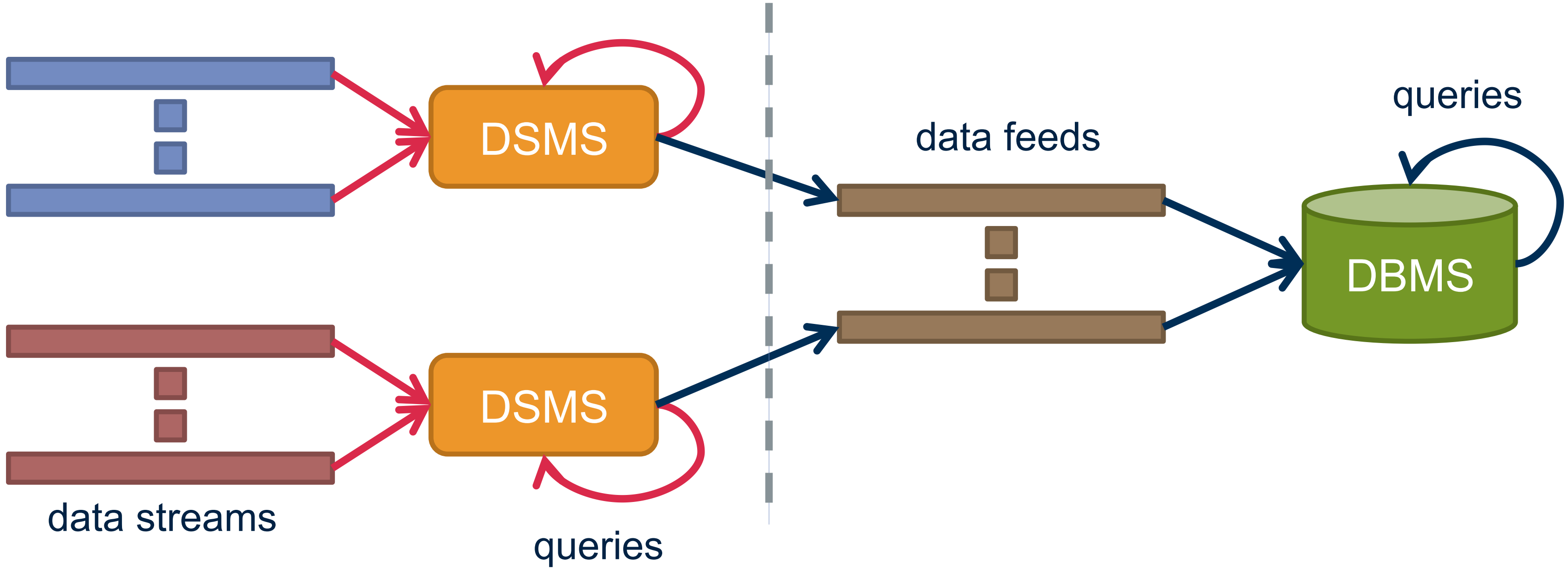
Example uses

- Network management and configuration
  - Typical setup: IP sessions going through a router
  - Large amounts of data (300GB/day, 75k records/second sampled every 100 measurements)
  - Typical queries
    - What are the most frequent source-destination pairings per router?
    - How many different source-destination pairings were seen by router 1 but not by router 2 during the last hour (day, week, month)?
- Stock monitoring
  - Typical setup: stream of price and sales volume
  - Monitoring events to support trading decisions
  - Typical queries
    - Notify when some stock goes up by at least 5%
    - Notify when the price of XYZ is above some threshold and the price of its competitors is below than its 10 day moving average

Structure of a data stream

- Infinite sequence of items (elements)
- One item: structured information, i.e., tuple or object
- Same structure for all items in a stream
- Timestamping
  - Explicit: date/time field in data
  - Implicit: timestamp given when items arrive
- Representation of time
  - Physical: date/time
  - Logical: integer sequence number

Database management vs. data stream management



- Data stream management system (DSMS) at multiple observation points
  - Voluminous streams-in, reduced streams-out
- Database management system (DBMS)
  - Outputs of data stream management system can be treated as data feeds to database

DBMS vs. DSMS

- DBMS
  - Model: persistent relations
  - Relation: tuple set/bag
  - Data update: modifications
  - Query: transient
  - Query answer: exact
  - Query evaluation: arbitrary
  - Query plan: fixed

- DSMS
  - Model: transient relations
  - Relation: tuple sequence
  - Data update: appends
  - Query: persistent
  - Query answer: approximate
  - Query evaluation: one pass
  - Query plan: adaptive

Windows

- Mechanism for extracting a finite relation from an infinite stream
- Various window proposals for restricting processing scope
  - Windows based on ordering attributes (e.g., time)
  - Windows based on item (record) counts
  - Windows based on explicit markers (e.g., punctuations) signifying beginning and end
  - Variants (e.g., some semantic partitioning constraint)

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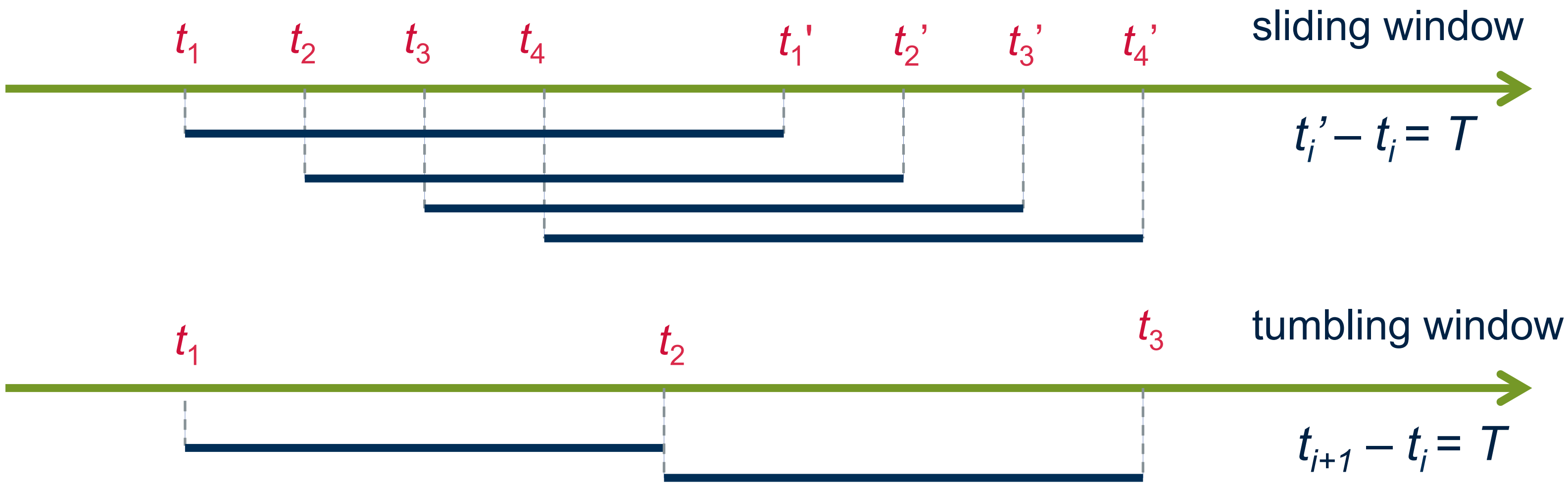
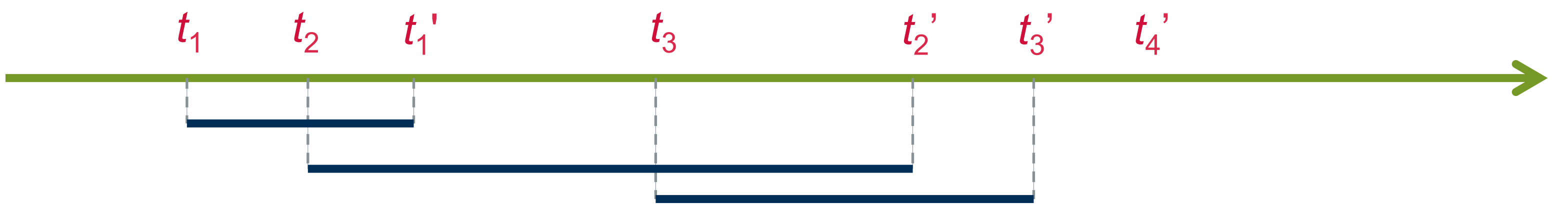
Ordering attribute based windows

- Assumes the existence of an attribute that defines the order of stream elements/records (e.g., time)
- Let *T* be the window length (size) expressed in units of the ordering attribute (e.g., *T* may be a time window)



Count-based windows

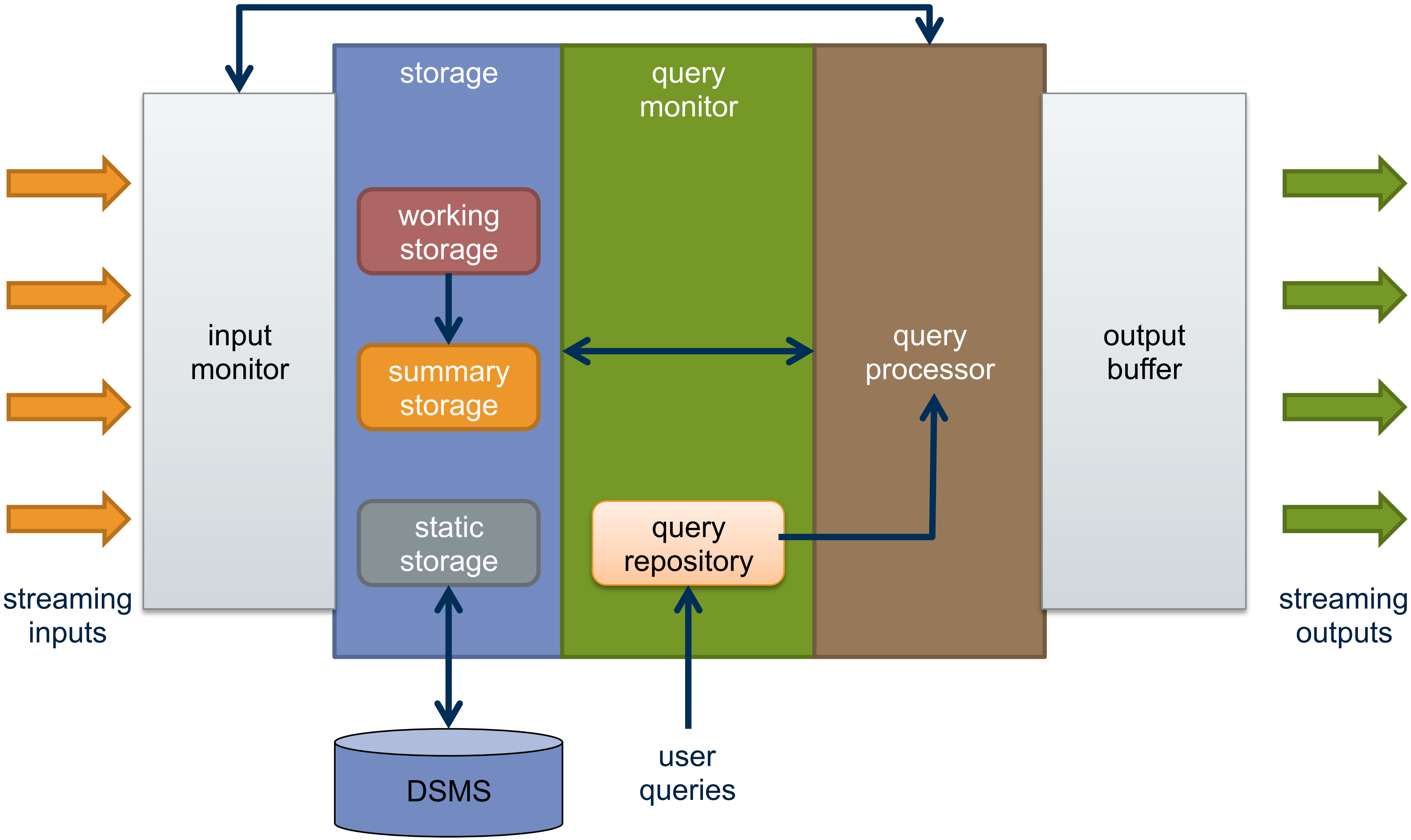
- Window of size *N* elements (sliding, tumbling) over the stream
- Problematic with non-unique timestamps associated with stream elements
- Ties broken arbitrarily may lead to non-deterministic output
- Potentially unpredictable with respect to fluctuating input rates
  - But dual of time based windows for constant arrival rates
  - Arrival rate λ elements/time-unit, time-based window of length T, count-based window of size N; $N = \lambda T$



Punctuation-based windows

- Application-inserted “end-of-processing”
  - Each next data item identifies “beginning-of-processing”
- Enables data item-dependent variable length windows
  - Examples: a stream of auctions, an interval of monitored activity
- Utility in data processing: limit the scope of operations relative to the stream
- Potentially problematic if windows grow too large
  - Or even too small: too many punctuations

Putting it all together: architecting a DSMS



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STREAM MINING

Data stream mining

- Numerous applications
  - Identify events and take responsive action in real time
  - Identify correlations in a stream and reconfigure system
- Mining query streams: Google wants to know what queries are more frequent today than yesterday
- Mining click streams: Yahoo wants to know which of its pages are getting an unusual number of hits in the past hour
- Big brother
  - Who calls whom?
  - Who accesses which web pages?
  - Who buys what where?
  - All those questions answered in real time
- We will focus on frequent pattern mining

Frequent pattern mining

- Frequent pattern mining refers to finding patterns that occur more frequently than a pre-specified threshold value
  - Patterns refer to items, itemsets, or sequences
  - Threshold refers to the percentage of the pattern occurrences to the total number of transactions
    - Termed as support
- Finding frequent patterns is the first step for association rules
  - $A \rightarrow B$: A implies B
- Many metrics have been proposed for measuring how strong an association rule is
  - Most commonly used metric: confidence
  - Confidence refers to the probability that set B exists given that A already exists in a transaction
    - confidence($A \rightarrow B$) = support($A \wedge B$) / support(A)

Frequent pattern mining in data streams

- Frequent pattern mining over data streams differs from conventional one
  - Cannot afford multiple passes
    - Minimised requirements in terms of memory
    - Trade off between storage, complexity, and accuracy
    - You only get one look
- Frequent items (also known as heavy hitters) and itemsets are usually the final output
- Effectively a counting problem
  - We will focus on two algorithms: lossy counting and sticky sampling

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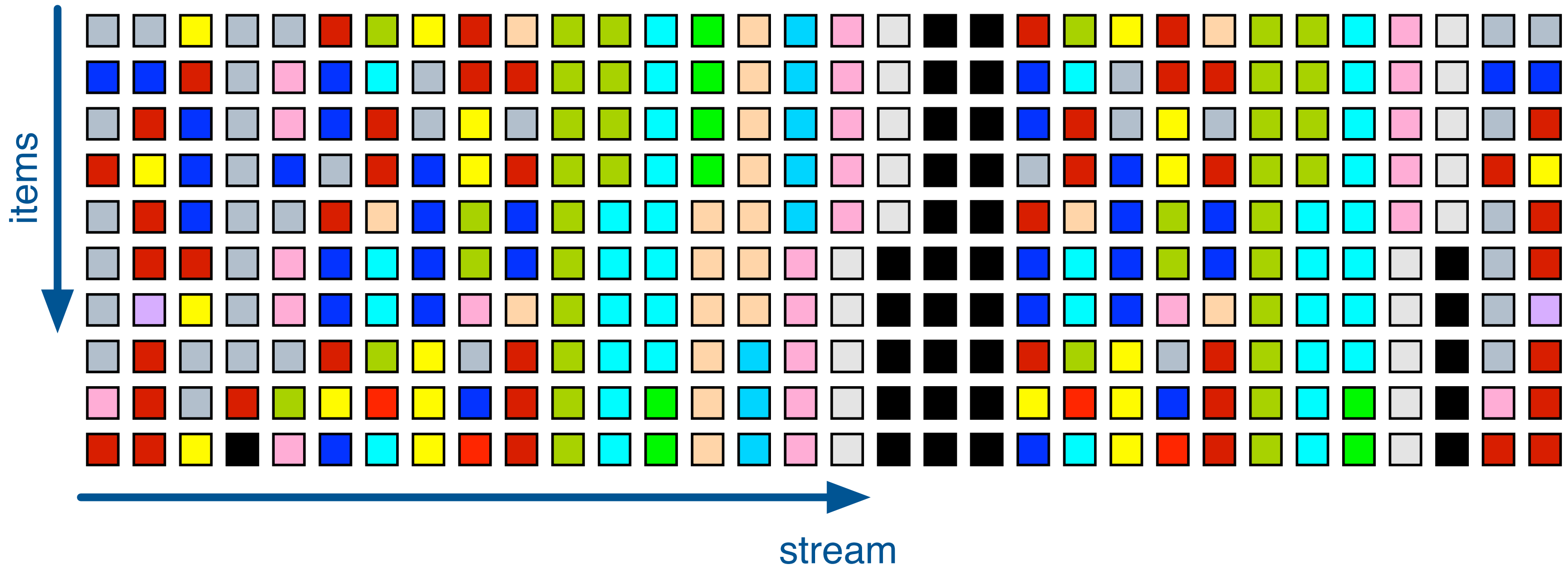
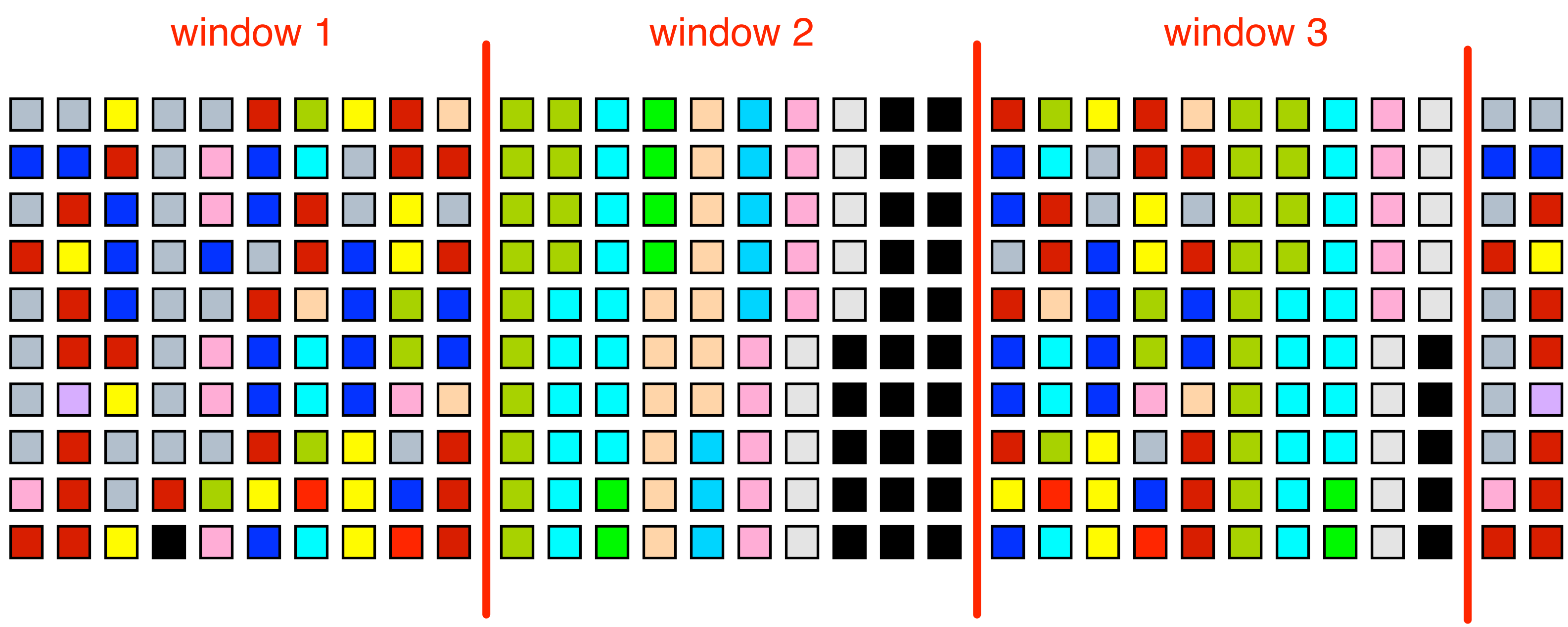
The problem in more detail



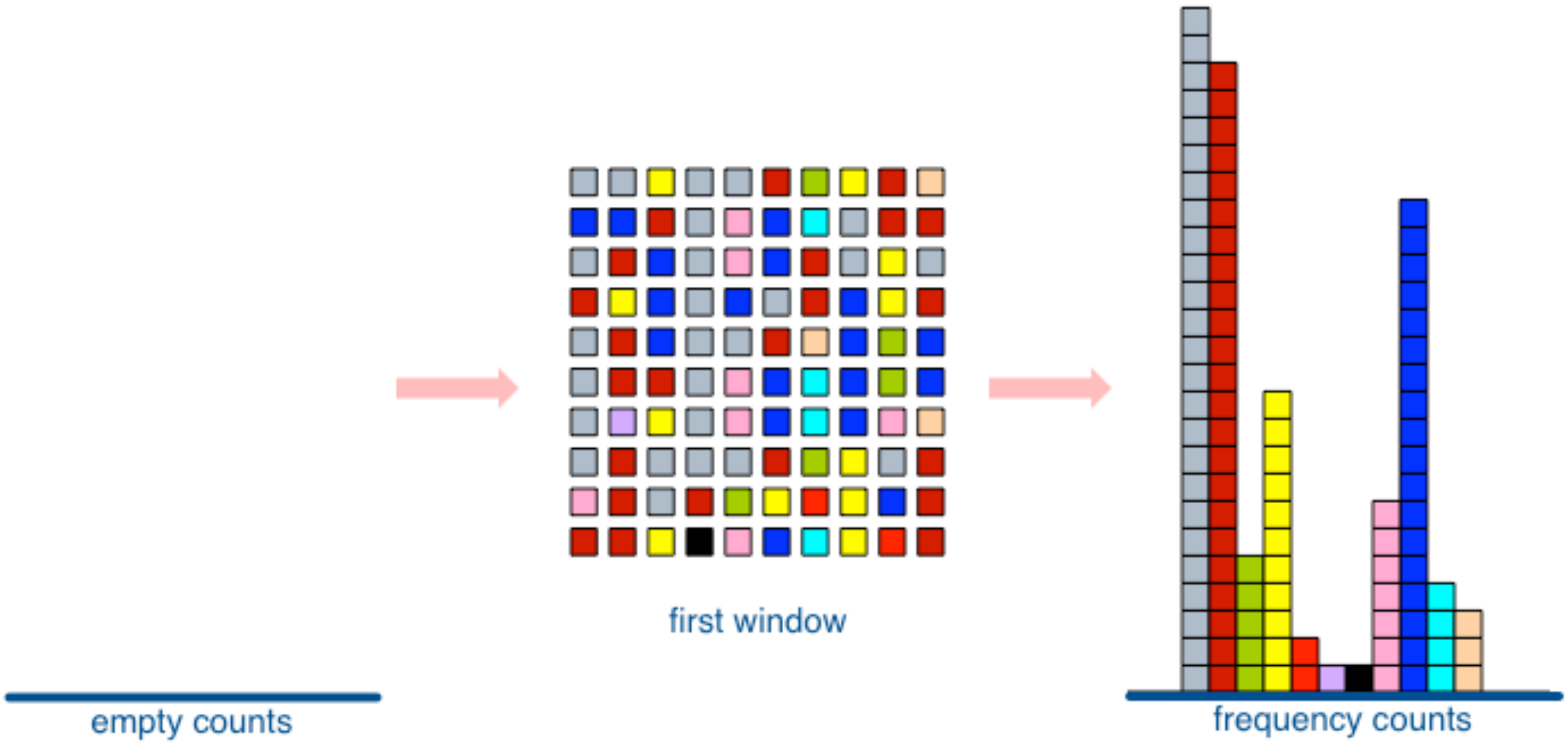
- Problem statement
  - Identify all items whose current frequency exceeds some support threshold *s* (*e.g.*, 0.1%)

Lossy counting in action

- Divide the incoming stream into windows

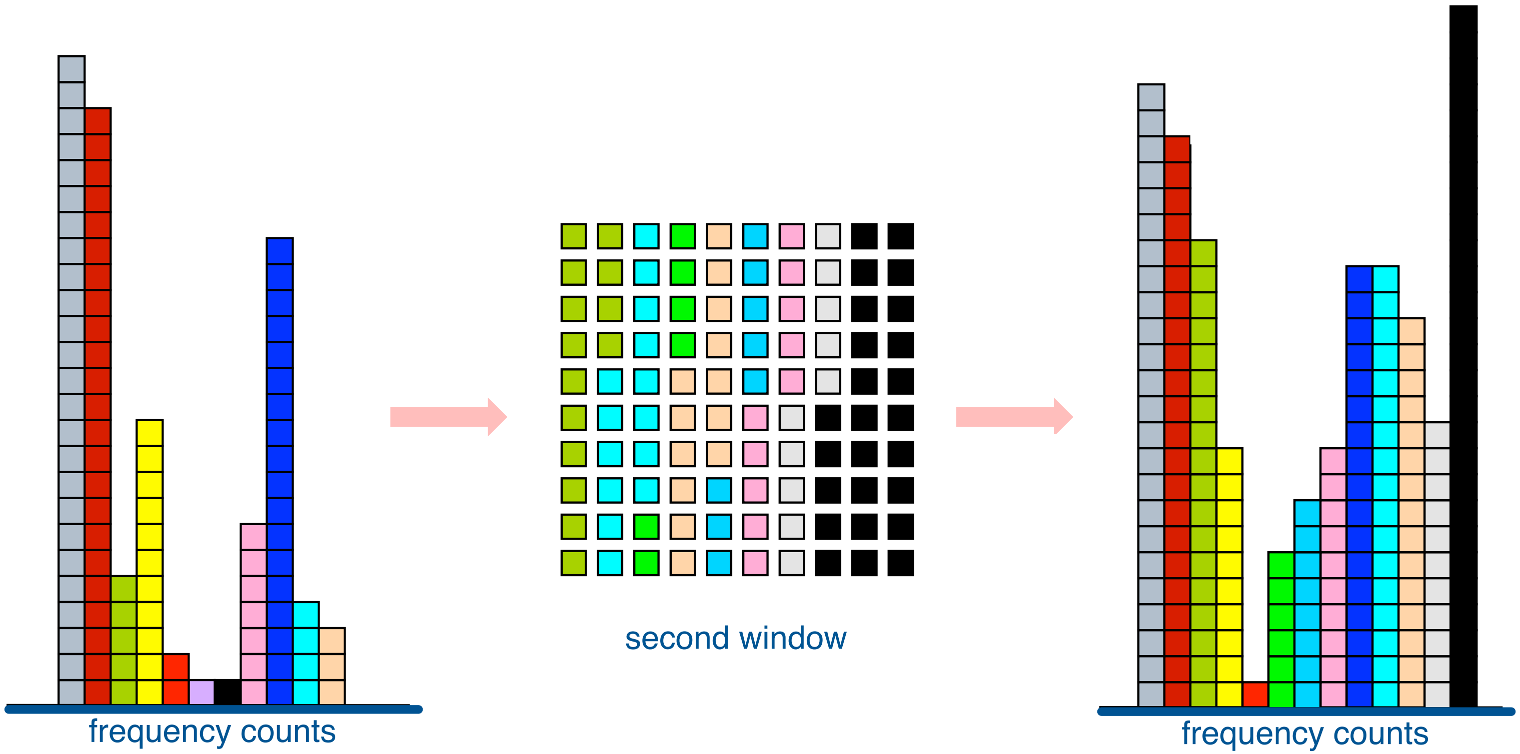


First window comes in



- At window boundary, adjust counters

Next window comes in



- At window boundary, adjust counters

Lossy counting algorithm

- Deterministic technique; user supplies two parameters
  - Support s; error ε
- Simple data structure, maintaining triplets of data items e, their associated frequencies f, and the maximum possible error Δ in f : (e, f, Δ)
- The stream is conceptually divided into buckets of width $w = 1/\varepsilon$
  - Each bucket labelled by a value N/w where N starts from 1 and increases by 1
- For each incoming item, the data structure is checked
  - If an entry exists, increment frequency
  - Otherwise, add new entry with $\Delta = b_{current} - 1$ where $b_{current}$ is the current bucket label
- When switching to a new bucket, all entries with $f + \Delta < b_{current}$ are released

Lossy counting observations

- How much do we undercount?
  - If current size of stream is N
  - ...and window size is $1/\varepsilon$
  - ...then frequency error ≤ number of windows, *i.e.*, εN
- Empirical rule of thumb: set ε = 10% of support s
  - Example: given a support frequency s = 1%,
  - …then set error frequency ε = 0.1%
- Output is elements with counter values exceeding $sN - \varepsilon N$
- Guarantees
  - Frequencies are underestimated by at most εN
  - No false negatives
  - False positives have true frequency at least $sN-\varepsilon N$
- In the worst case, it has been proven that we need $1/\varepsilon \times \log(\varepsilon N)$ counters

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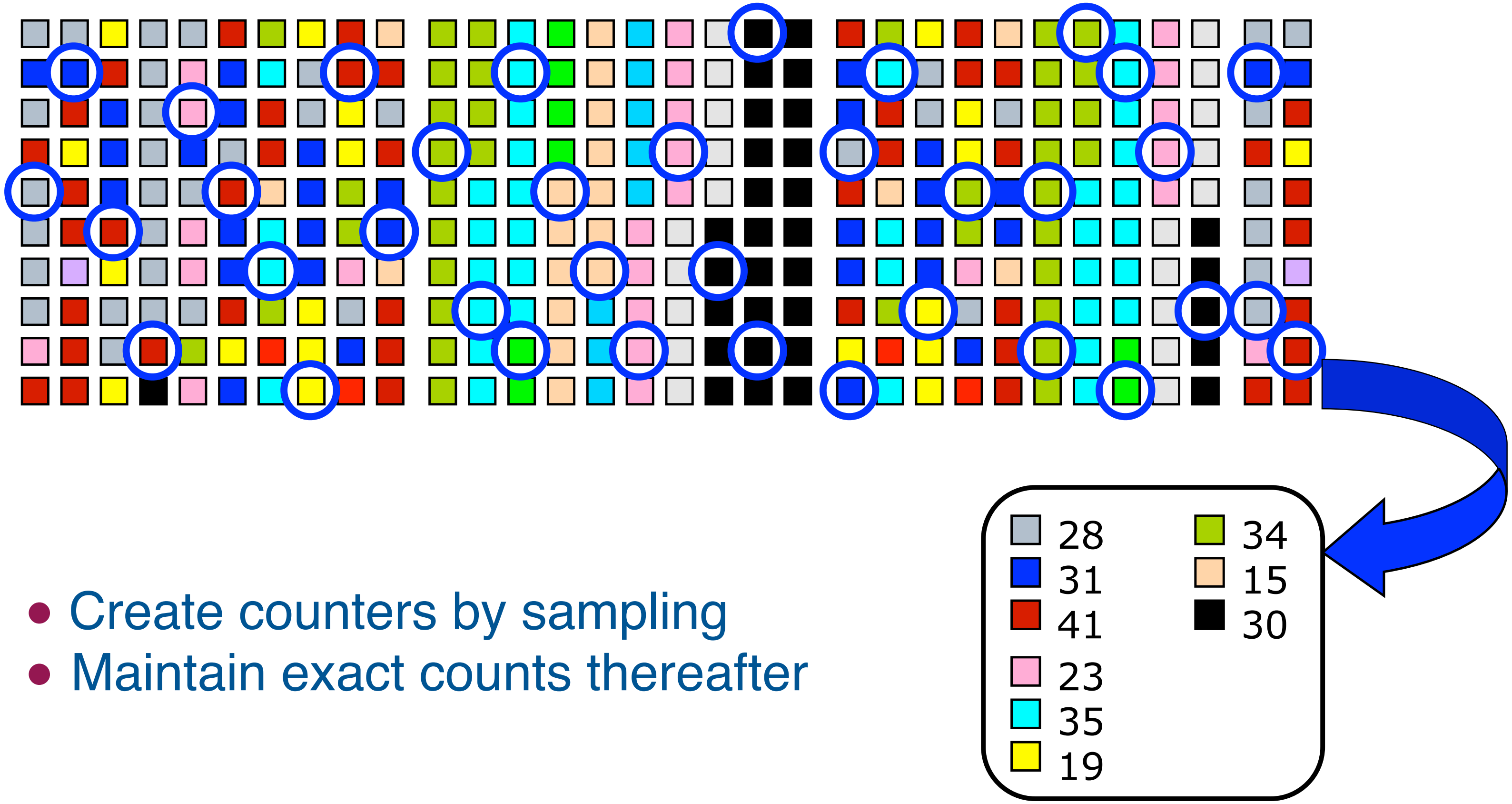
Sticky sampling



- Create counters by sampling
- Maintain exact counts thereafter

Sticky sampling algorithm

- Probabilistic technique; user supplies three parameters
  - Support s; error ε; probability of failure δ
- Simple data structure, maintaining pairs of data items e and their associated frequencies f : (e, f)
- The sampling rate decreases gradually with the increase in the number of processed data elements
- For each incoming item, the data structure is checked
  - If an entry exists, increment frequency
  - Otherwise sample the item with the current sampling rate
  - If selected, add new entry; else ignore the item
- With every change in the sampling rate, toss a coin for each entry
  - Decreasing the frequency of the entry for each unsuccessful coin toss
  - If frequency goes down to zero, release the entry

Sticky sampling observations

- For a finite stream of length N
- Sampling rate = $2/N\varepsilon \times \log(1/s\delta)$
  - δ is the probability of failure—user configurable
- Same guarantees with lossy counting, but probabilistic
- Same rule of thumb as lossy counting, but with a probabilistic and user configurable failure probability δ
- Generalisation to infinite streams of unknown N
  - (probabilistically) expected number of counters is = $2/\varepsilon \times \log(1/s\delta)$
  - Independent of N

- Comparison
  - Lossy counting is deterministic; sticky sampling is probabilistic
  - In practice, lossy counting is more accurate
  - Sticky sampling extends to infinite streams with same error guarantees as lossy counting

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STORM AND LOW-LATENCY PROCESSING

Low latency processing

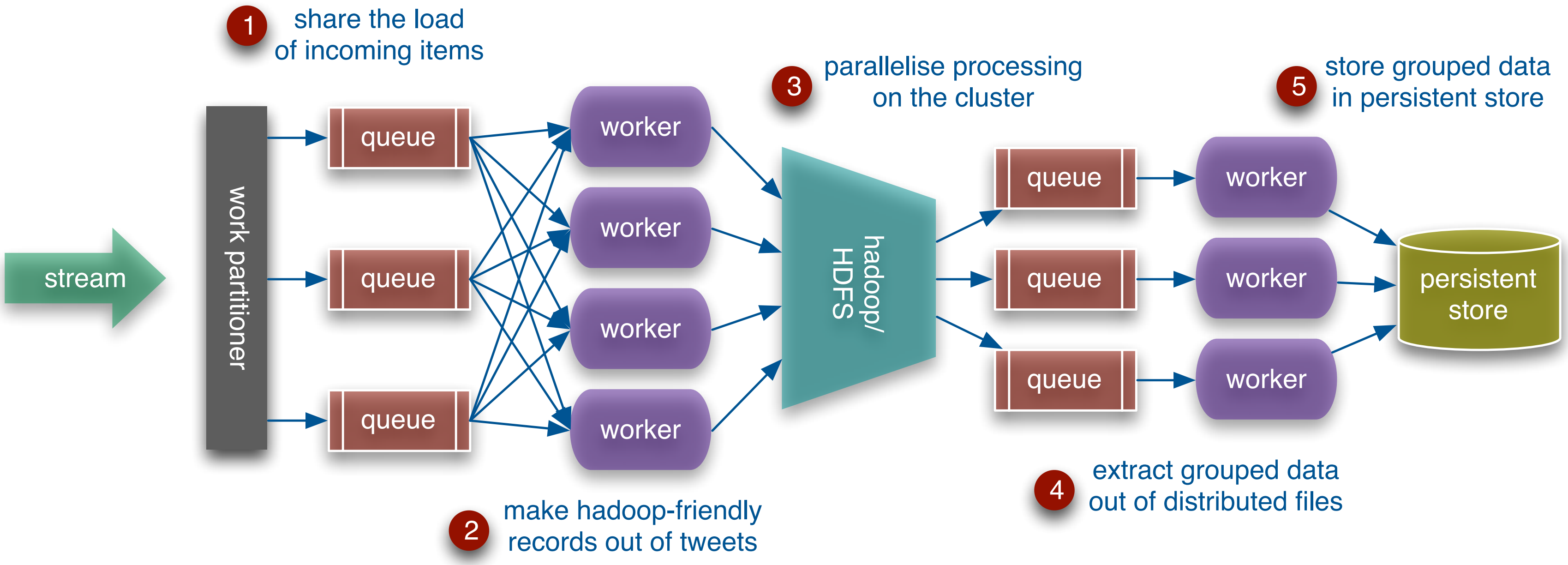
- Similar to data stream processing, but with a twist
  - Data is streaming into the system (from a database, or a network stream, or an HDFS file, or …)
  - We want to process the stream in a distributed fashion
  - And we want results as quickly as possible
- Numerous applications
  - Algorithmic trading: identify financial opportunities (e.g., respond as quickly as possible to stock price rising/falling
  - Event detection: identify changes in behaviour rapidly
- Not (necessarily) the same as what we have seen so far
  - The focus is not on summarising the input
  - Rather, it is on “parsing” the input and/or manipulating it on the fly

The problem

- Consider the following use-case
- A stream of incoming information needs to be summarised by some identifying token
  - For instance, group tweets by hash-tag; or, group clicks by URL;
  - And maintain accurate counts
- But do that at a massive scale and in real time
- Not so much about handling the incoming load, but using it
  - That's where latency comes into play
- Putting things in perspective
  - Twitter's load is not that high: at 15k tweets/s and at 150 bytes/tweet we're talking about 2.25MB/s
  - Google served 34k searches/s in 2010: let's say 100k searches/s now and an average of 200 bytes/search that's 20MB/s
  - But this 20MB/s needs to filter PBs of data in less than 0.1s; that's an EB/s throughput

A rough approach

- Latency
  - Each point 1 – 5 in the figure introduces a high processing latency
  - Need a way to transparently use the cluster to process the stream



- Bottlenecks
  - No notion of locality
    - Either a queue per worker per node, or data is moved around
  - What about reconfiguration?
    - If there are bursts in traffic we need to shutdown, reconfigure and redeploy

Storm

- Started up as backtype; widely used in Twitter
- Open-sourced (you can download it and play with it!
  - http://storm-project.net/
- On the surface, Hadoop for data streams
  - Executes on top of a (likely dedicated) cluster of commodity hardware
  - Similar setup to a Hadoop cluster
    - Master node, distributed coordination, worker nodes
    - We will examine each in detail
- But whereas a MapReduce job will finish, a Storm job—termed a topology —runs continuously
  - Or rather, until you kill it

Storm topologies

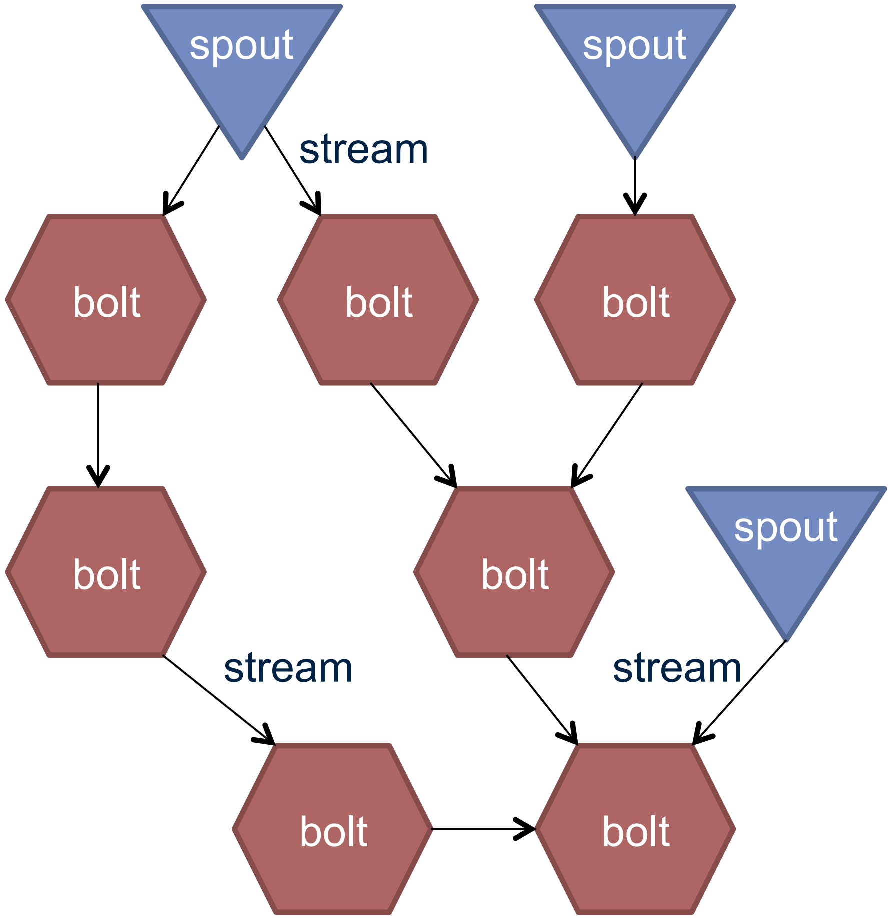
- A Storm topology is a graph of computation
  - Graph contains nodes and edges
  - Nodes model processing logic (i.e., transformation over its input)
  - Directed edges indicate communication between nodes
  - No limitations on the topology; for instance one node may have more than one incoming edges and more than one outgoing edges
- Storm processes topologies in a distributed and reliable fashion

Streams, spouts, and bolts

- Streams
  - The basic collection abstraction: an unbounded sequence of tuples
  - Streams are transformed by the processing elements of a topology

- Spouts
  - Stream generators
  - May propagate a single stream to multiple consumers

- Bolts
  - Subscribe to streams
  - Streams transformers
  - Process incoming streams and produce new ones



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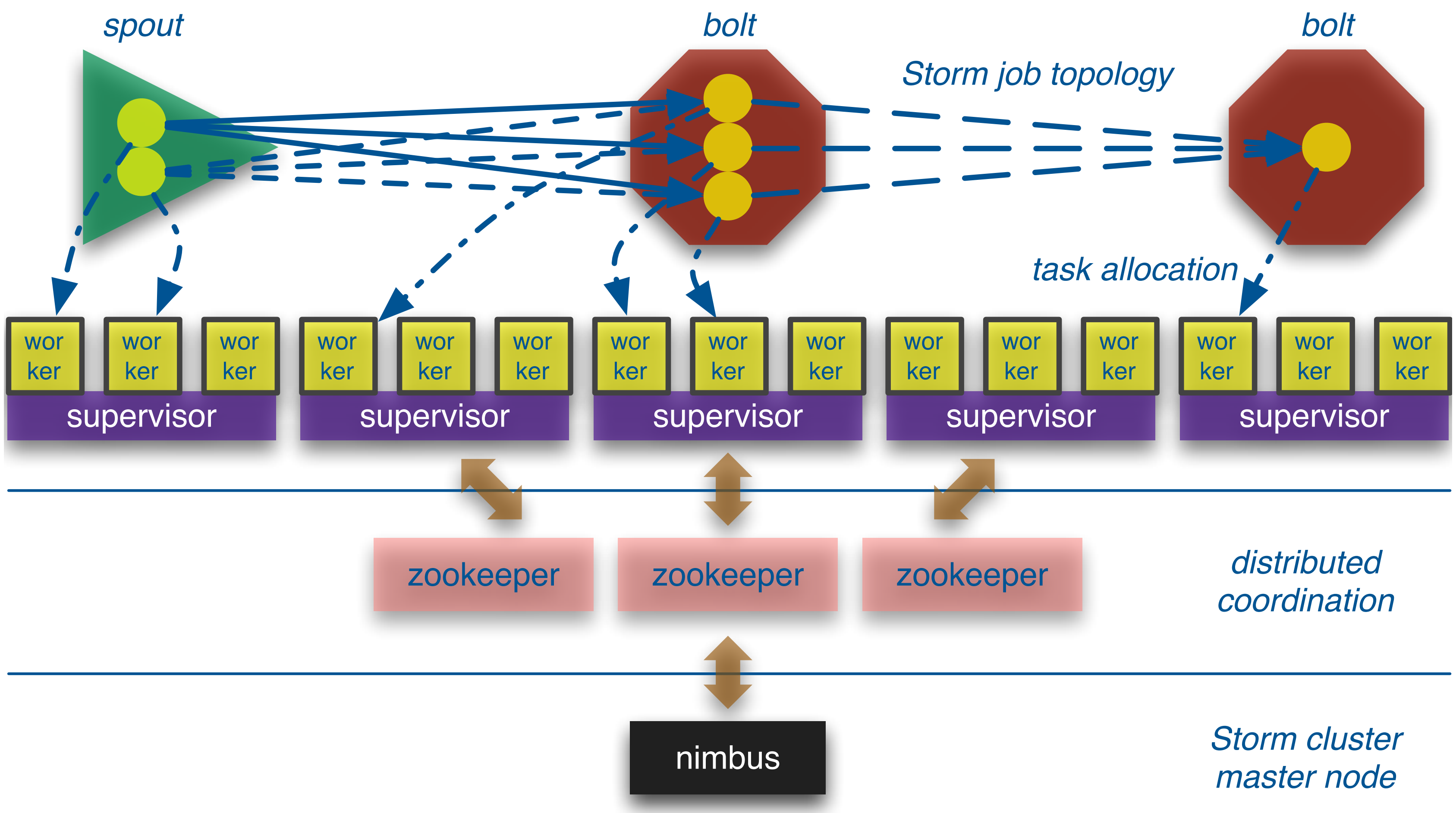
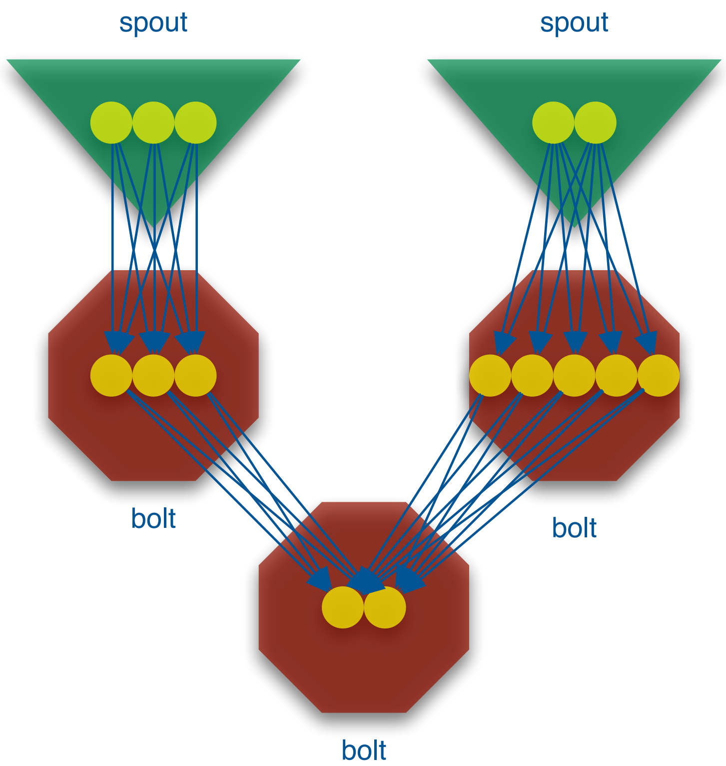
Storm architecture



From topology to processing: stream groupings

- Spouts and bolts are replicated in taks, each task executed in parallel by a worker
  - User-defined degree of replication
  - All pairwise combinations are possible between tasks
- When a task emits a tuple, which task should it send to?
- Stream groupings dictate how to propagate tuples
  - Shuffle grouping: round-robin
  - Field grouping: based on the data value (e.g., range partitioning)



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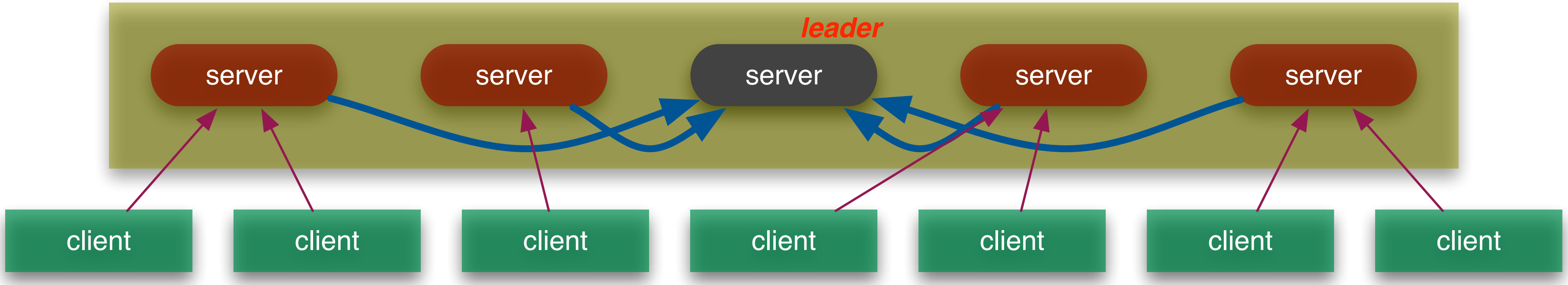
Zookeeper: distributed reliable storage and coordination



- Design goals
  - Distributed coordination service
  - Hierarchical name space
  - All state kept in main memory, replicated across servers
  - Read requests are served by local replicas
  - Client writes are propagated to the leader
  - Changes are logged on disk before applied to in-memory state
  - Leader applies the write and forwards to replicas

- Guarantees
  - Sequential consistency: updates from a client will be applied in the order that they were sent
  - Atomicity: updates either succeed or fail; no partial results
  - Single system image: clients see the same view of the service regardless of the server
  - Reliability: once an update has been applied, it will persist from that time forward
  - Timeliness: the clients' view of the system is guaranteed to be up-to-date within a certain time bound

Putting it all together: word count

```
// instantiate a new topology
TopologyBuilder builder = new TopologyBuilder();
// set up a new spout with five tasks
builder.setSpout("spout", new RandomSentenceSpout(), 5);
// the sentence splitter bolt with eight tasks
builder.setBolt("split", new SplitSentence(), 8)
    .shuffleGrouping("spout"); // shuffle grouping for the ouput
// word counter with twelve tasks
builder.setBolt("count", new WordCount(), 12)
    .fieldsGrouping("split", new Fields("word")); // field grouping
// new configuration
Config conf = new Config();
// set the number of workers for the topology; the 5x8x12=480 tasks
// will be allocated round-robin to the three workers, each task
// running as a separate thread
conf.setNumWorkers(3);
// submit the topology to the cluster
StormSubmitter.submitTopology("word-count", conf, builder.createTopology());
```

Summary

- Introduced the notion of data streams and data stream processing
- Discussed the architecture of a data stream management system
  - Differences to a DBMS
  - Architectural choices
- Described use-cases and algorithms for stream mining
  - Lossy counting and sticky sampling
- Introduced frameworks for low-latency stream processing
  - Storm