Extreme computing
Data streams and low latency processing

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Outline

Data streams and low latency processing
- Overview
- Data stream management
- Data stream mining
- Low latency processing

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 what you see on youtube
  - Data streams have structure and semantics, they're not audio or video data

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 data streams?

- 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 100 most frequent source-destination pairings overall and 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% from one transaction to the next
    - Notify when some stock price only increases for longer than 10 minutes.
    - Notify me 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 field in data
  - Implicit: timestamp given when items arrive
- Representation of time
  - Physical: date/time
  - Logical: integer sequence number

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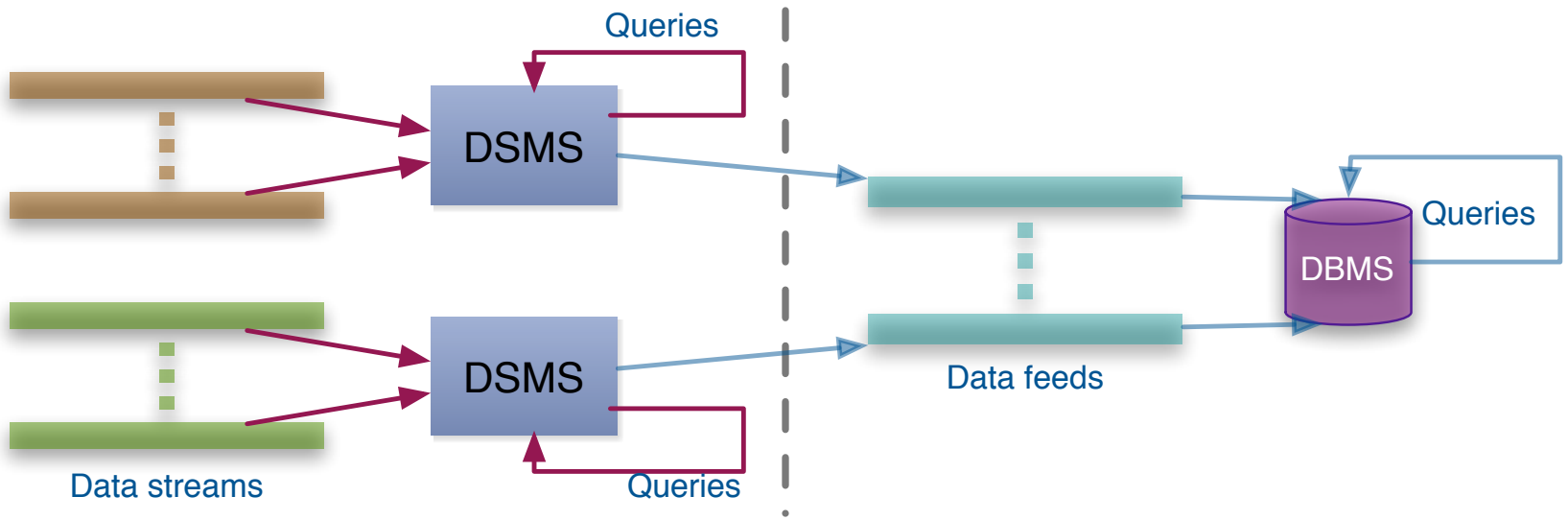
Database management *vs.* data stream management



- 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

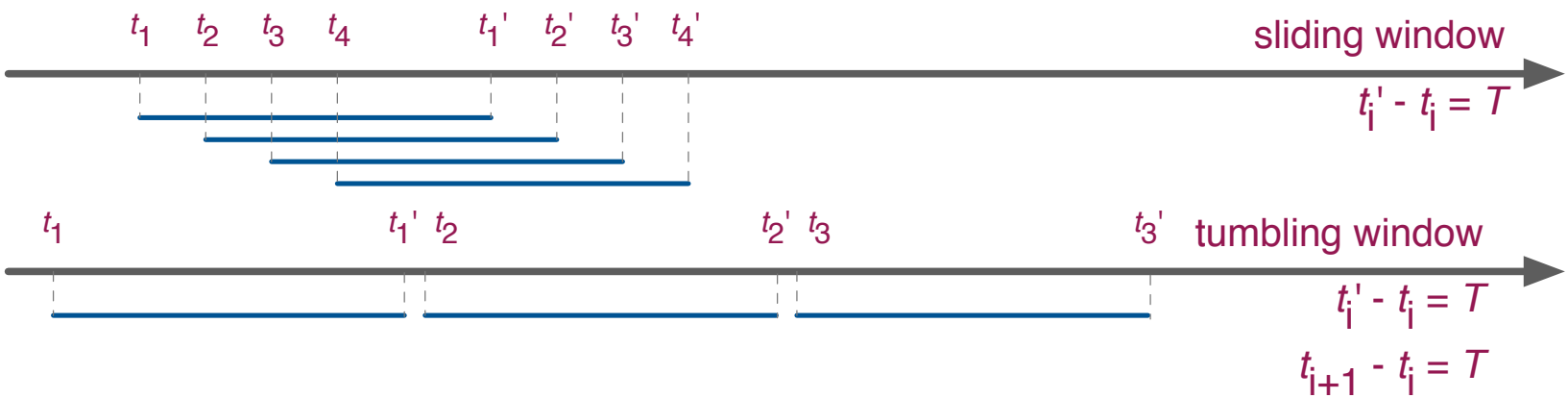
- Model: transient relations
- Relation: tuple sequence
- Data update: appends
- Query: persistent
- Query answer: approximate
- Query evaluation: one pass
- Query plan: adaptive

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)

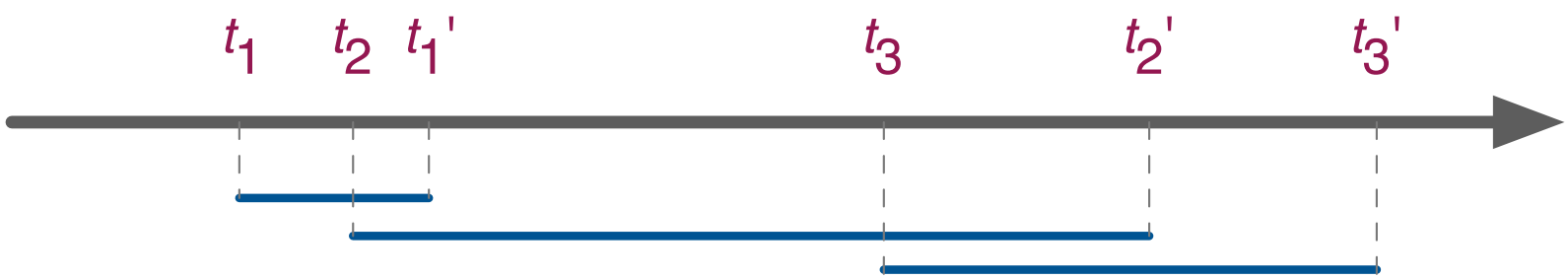
Ordering attribute based windows

- 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

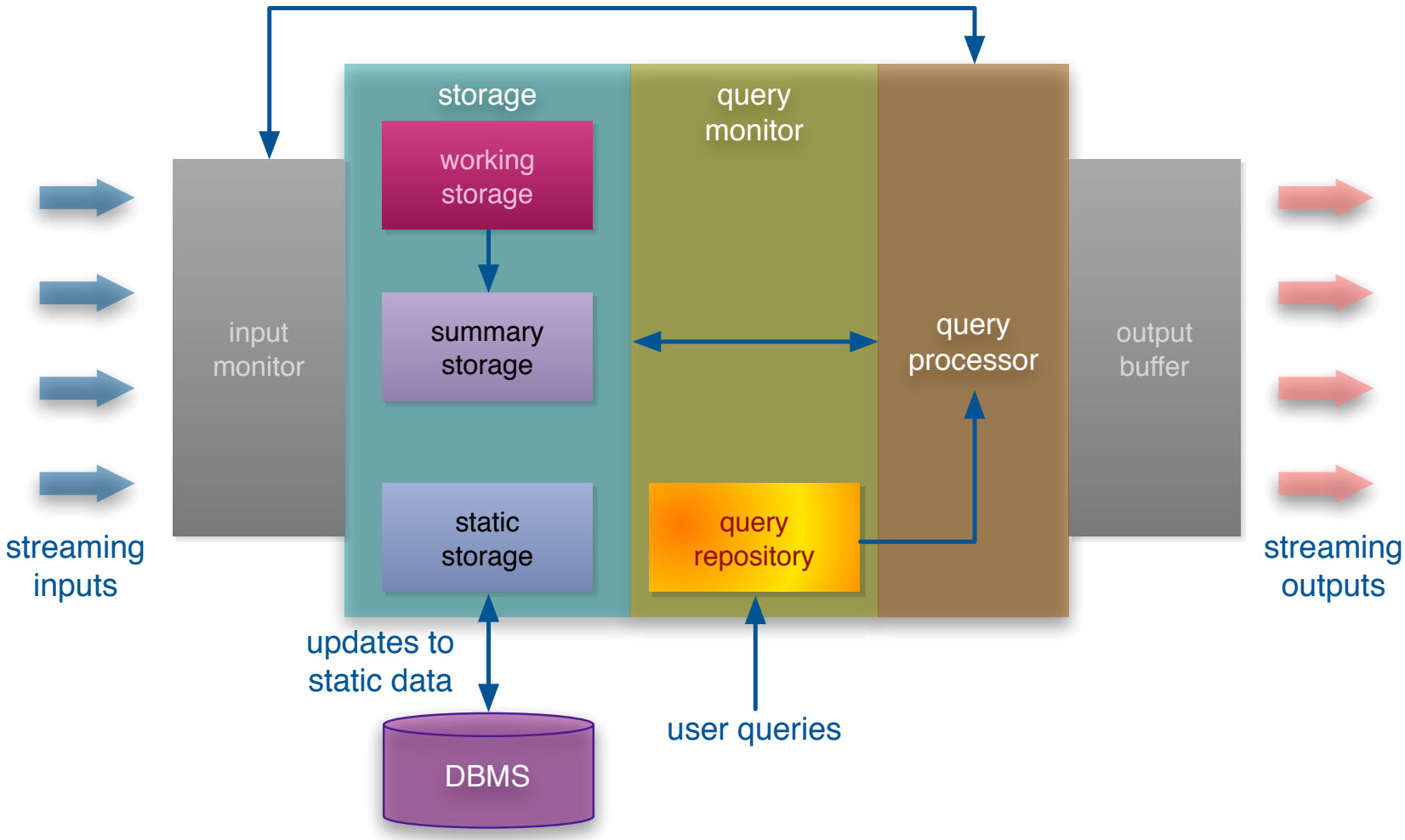
- Window of size N elements (sliding, tumbling) over the stream
- Problematic with non-unique timestamps associated with stream elements
- Ties broken arbitrarily may lead to non-deterministic output
- Potentially unpredictable with respect to fluctuating input rates
  - But dual of time based windows 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" markers
  - 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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Why is it important?

- 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
  - Suppose we believe that certain groups of evil-doers are meeting occasionally in hotels to plot doing evil
  - We want to find people who at least twice have stayed at the same hotel on the same day
  - Generalised to a number of questions
    - 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

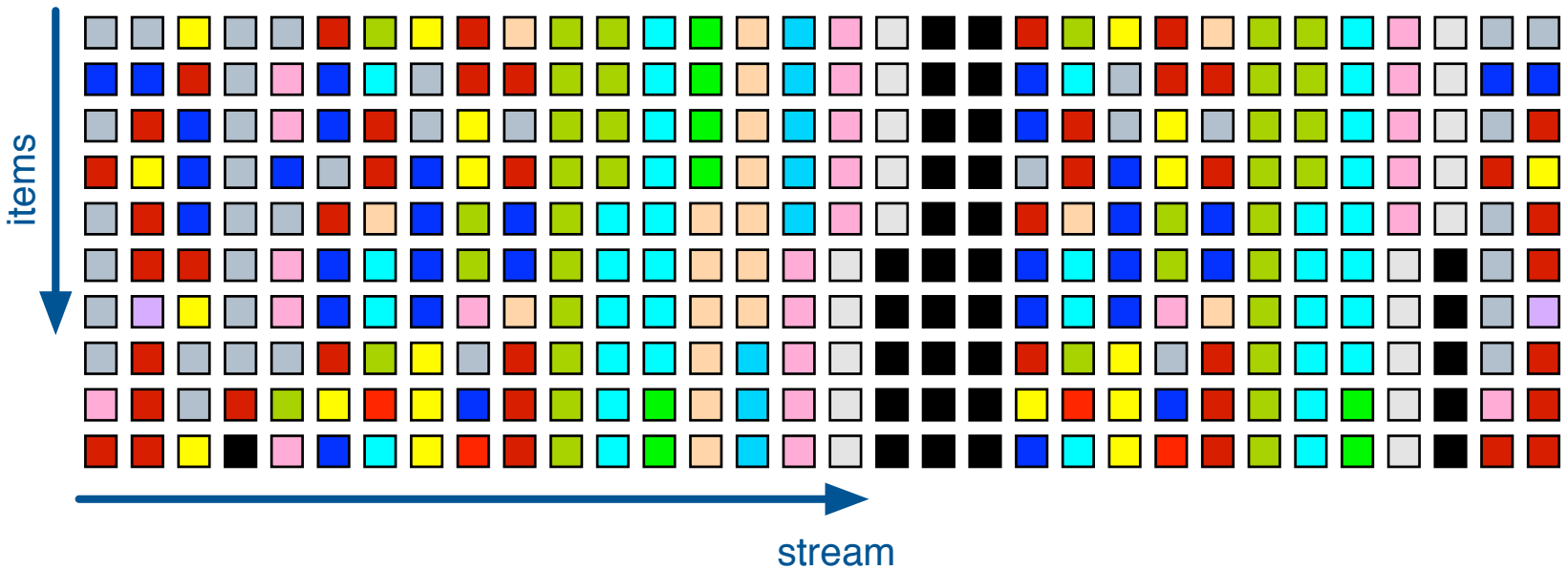
Frequent pattern mining

- Frequent pattern mining refers to finding patterns that occur more frequently than a prespecified 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 the discovery of 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
    - Tradeoff 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

The problem in more detail

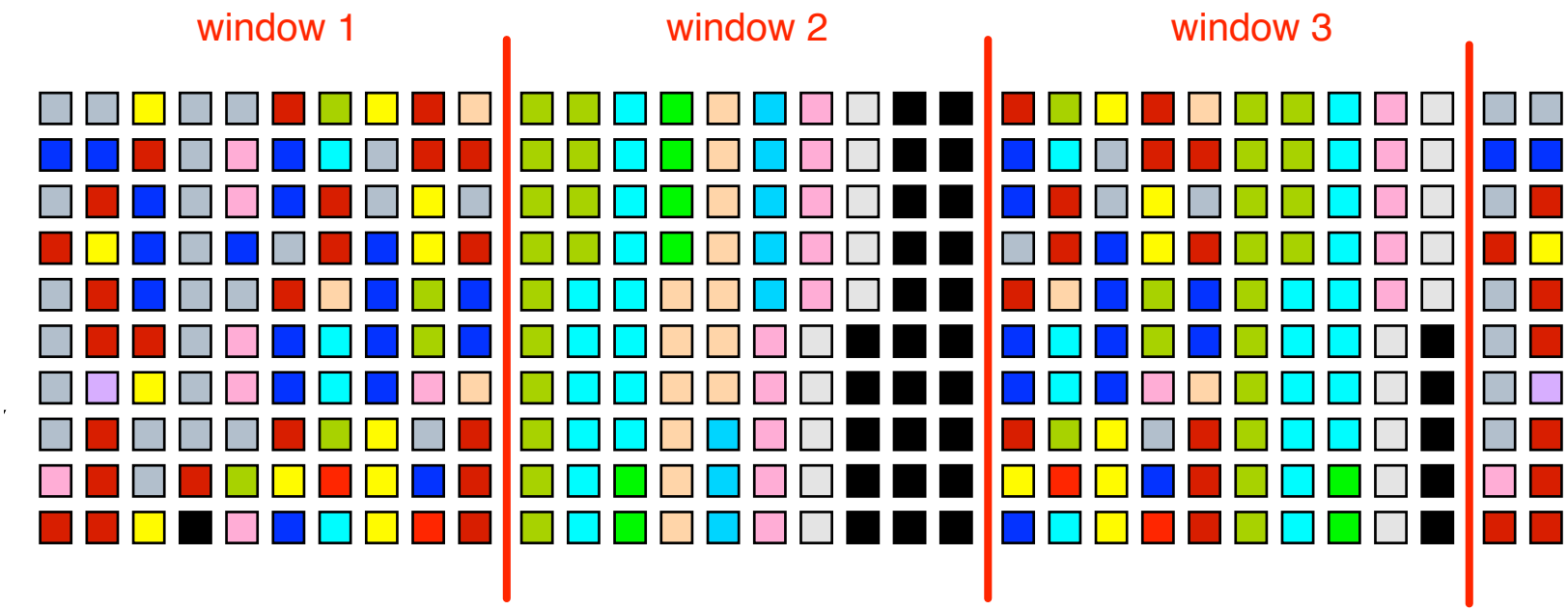


Problem statement

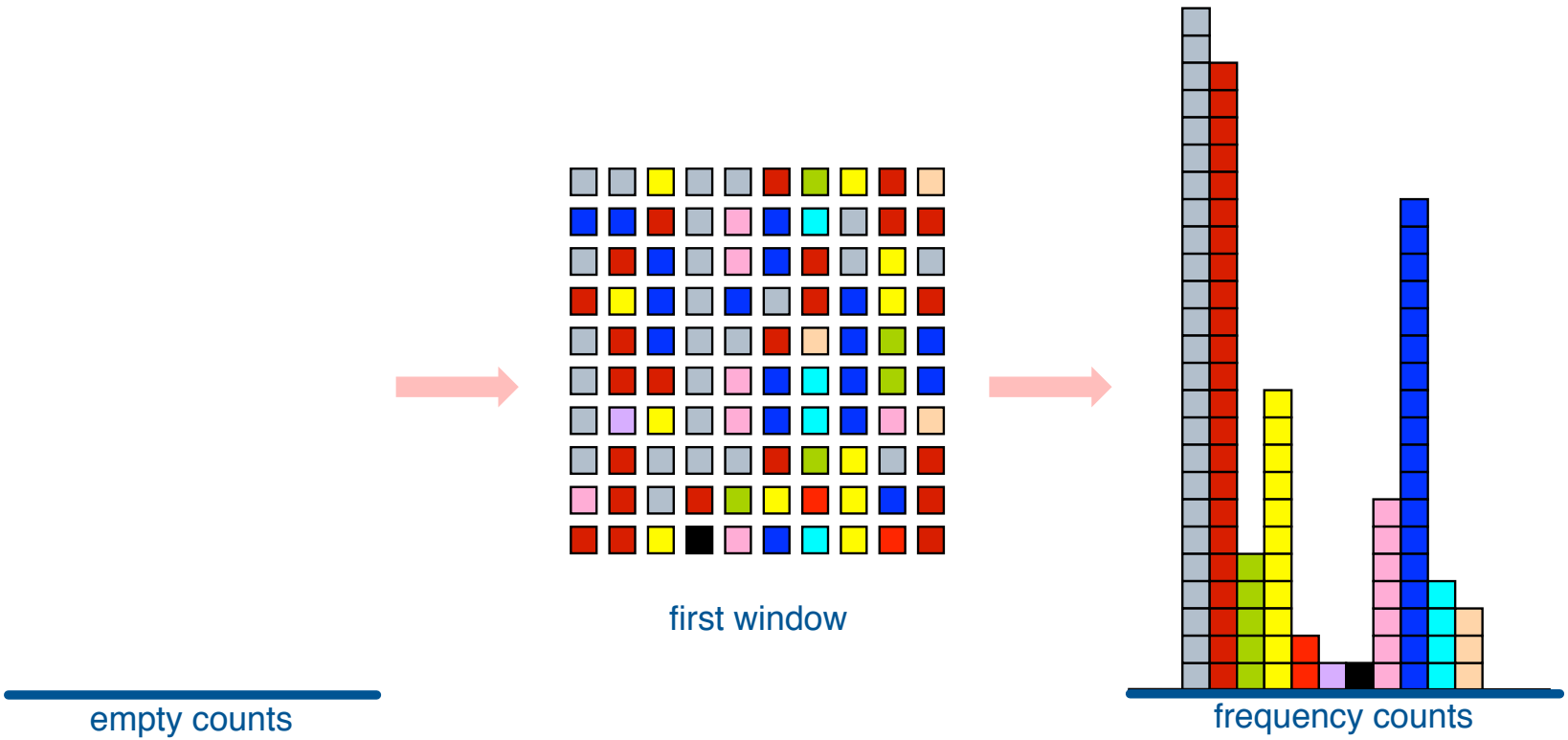
Identify all items whose current frequency exceeds some support threshold s (*e.g.*, 0.1%)

Lossy counting in action

- Divide the incoming stream into windows

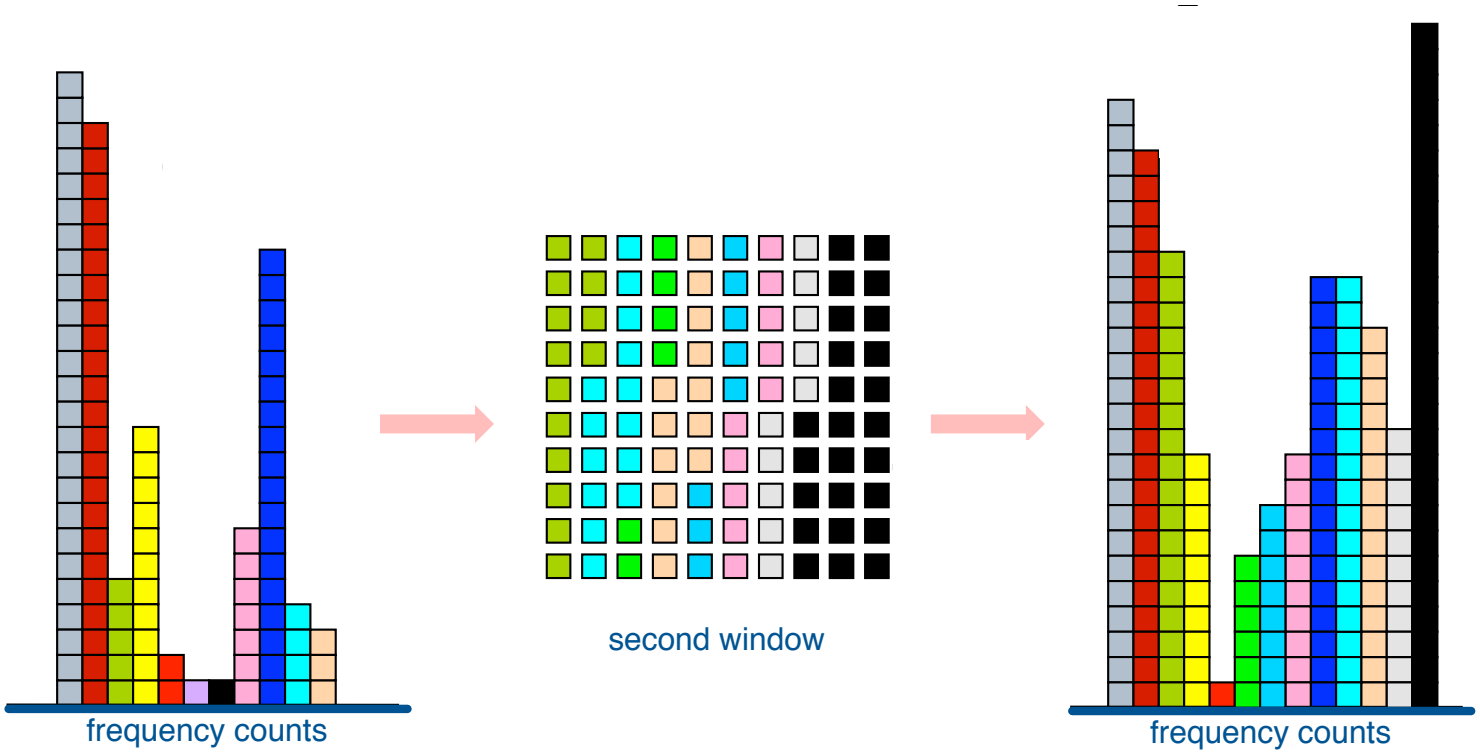


First window comes in



- At window boundary, adjust counters

Next window comes in



- At window boundary, adjust counters

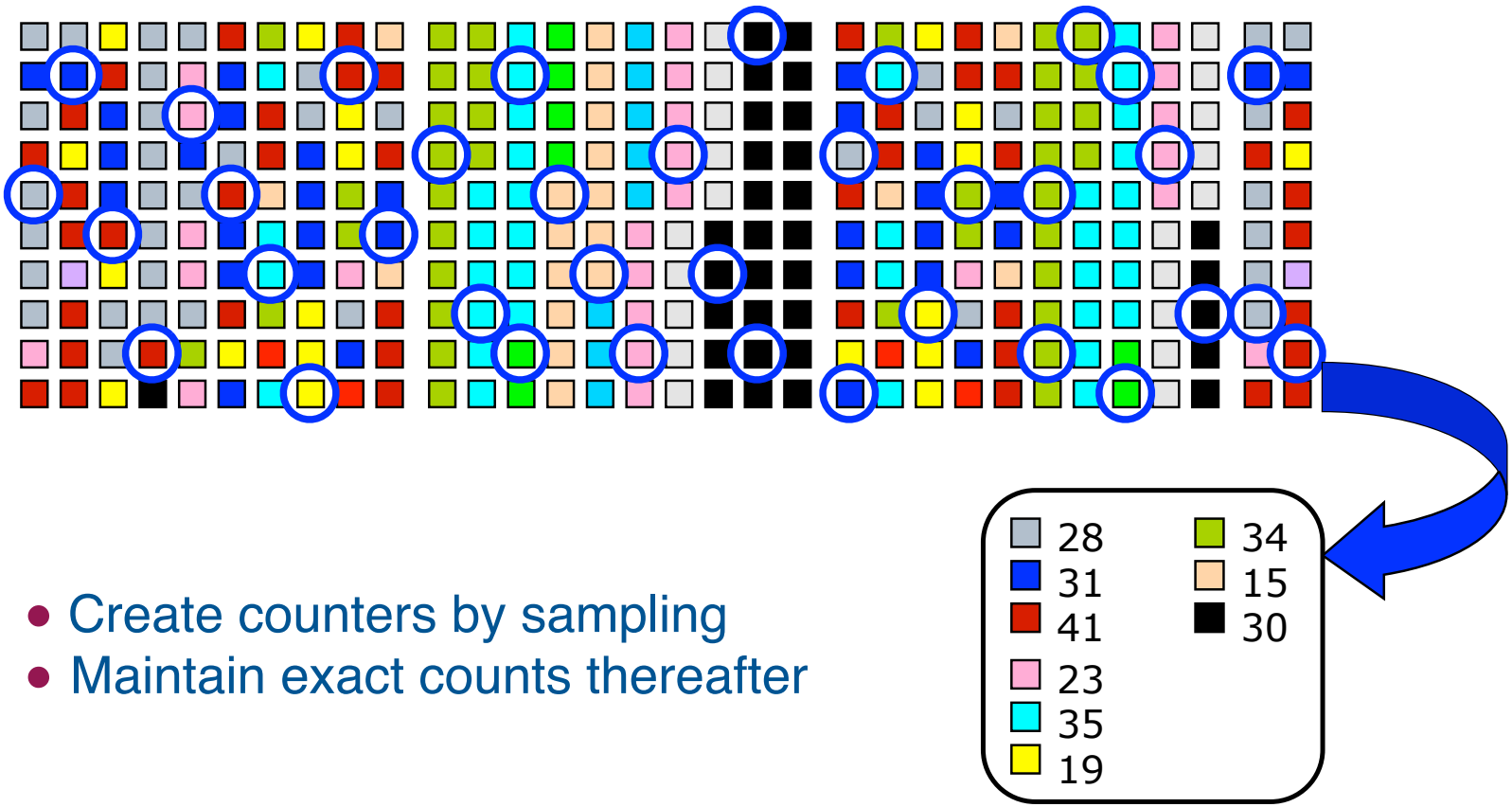
Lossy counting algorithm

- 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 $w = \frac{1}{\epsilon}$
  - Each bucket labelled by a value $\frac{N}{w}$ 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 $\Delta = b_{\text{current}} - 1$ where b_{current} is the current bucket label
- When switching to a new bucket, all entries with $f + \Delta < b_{\text{current}}$ are released

Lossy counting observations

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

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 unsuccesfull coin toss
  - If frequency goes down to zero, release the entry

Sticky sampling observations

- For a finite stream of length N
  - Sampling rate $= \frac{2}{N\epsilon} \log\left(\frac{1}{s\delta}\right)$
  - 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 $\frac{2}{\epsilon} \log\left(\frac{1}{s\delta}\right)$
  - 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

From items to itemsets

- Lossy counting has been extended to itemsets
- Straightforward generalisation
  - Fixed memory budget
  - All subsets of the stored batch are checked and pruned
  - If the frequency of a new entry is greater than the number of buckets in memory, a new entry is added

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What is it and why do we need it?

- 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

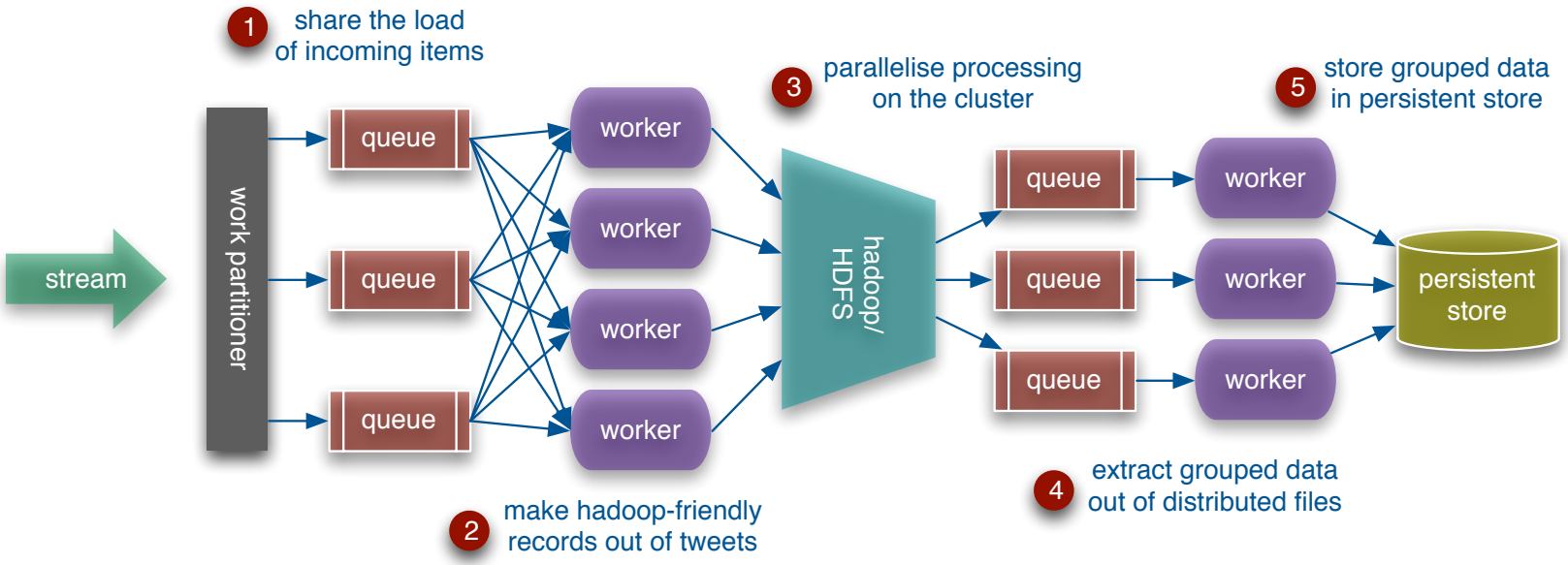
- Consider the following use-case
- A stream of incoming information needs to be summarised by some identifying information
  - For instance, group tweets by hash-tag; or, group clicks by URL;
  - And maintain accurate counts
- But do that at a massive scale and in real time
- **Not** so much about handling the incoming load, but using it
  - That's when 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/s, that's 20MB/s
  - But this 20MB/s needs to filter PBs of data in less than 0.1s; that's an EB/s[1] throughput

[1] Likely even ZB/s

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![2])
- 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

[2] `http://storm-project.net/`

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

Storm streams, spouts, and bolts

Streams

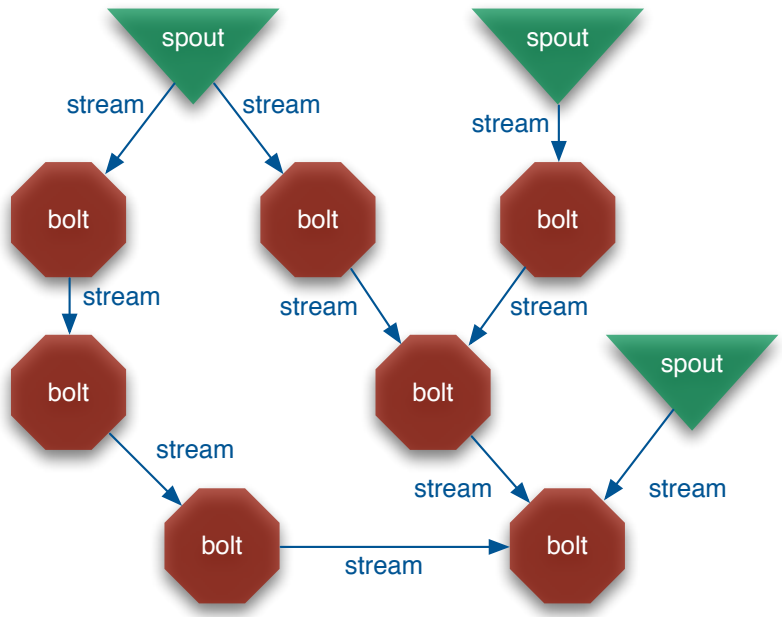
- The basic collection abstraction: an unbounded sequence of tuples
- Streams are transformed by the processing elements of a topology

Spouts

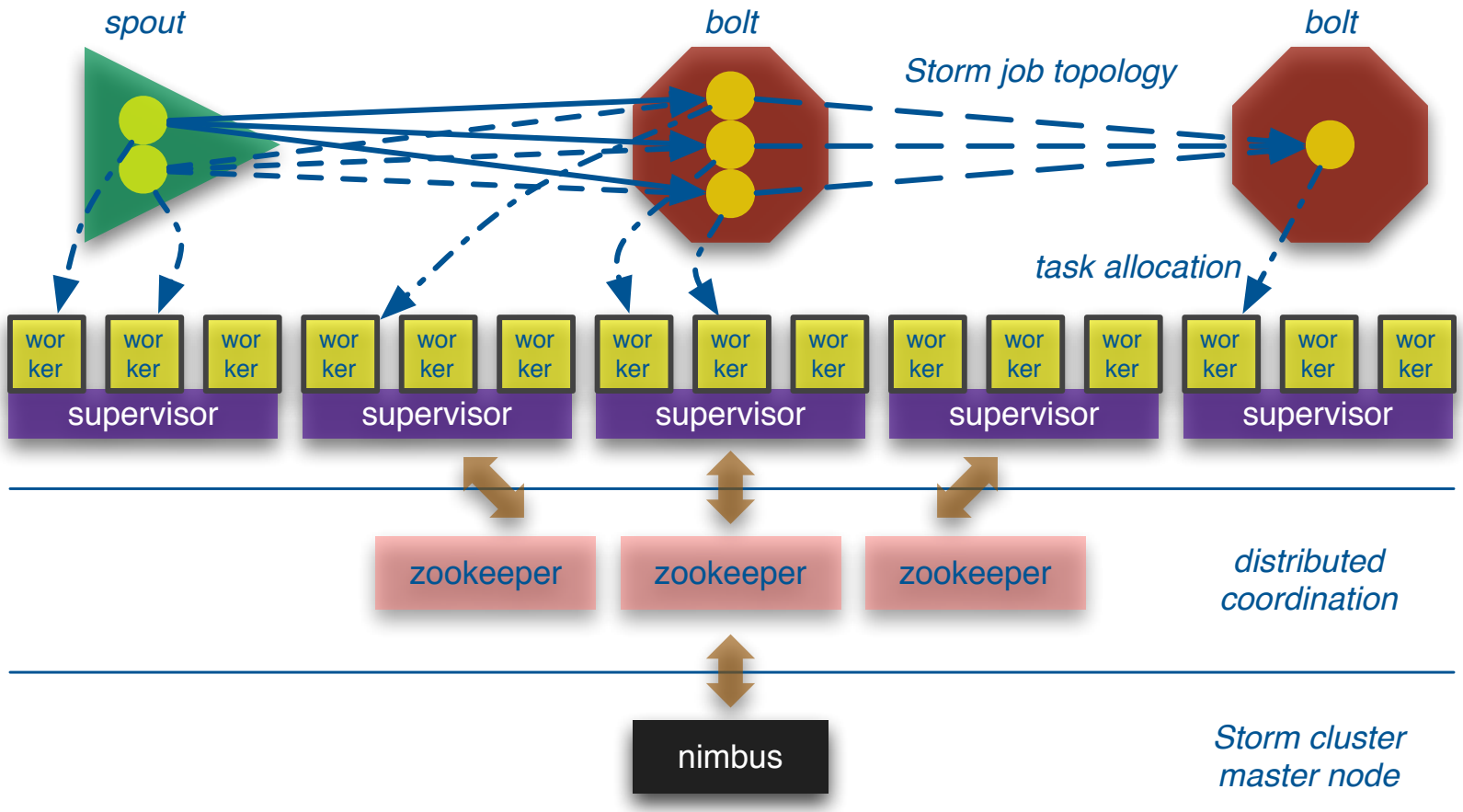
- Stream generators
- May propagate a single stream to multiple consumers

Bolts

- Subscribe to streams
- Stream transformers
- Process incoming streams and produce new ones



Storm architecture

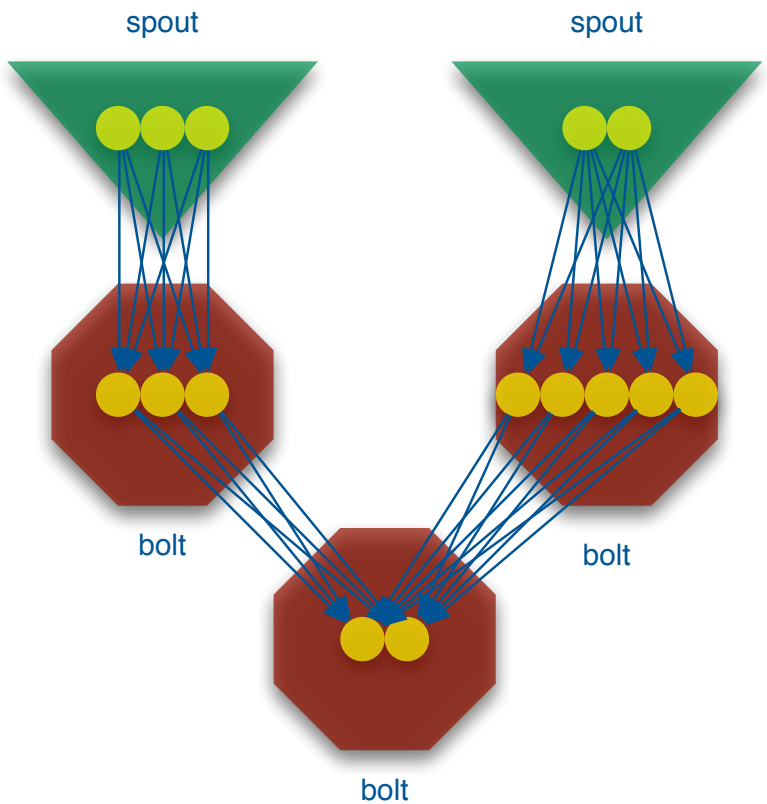


A few more details

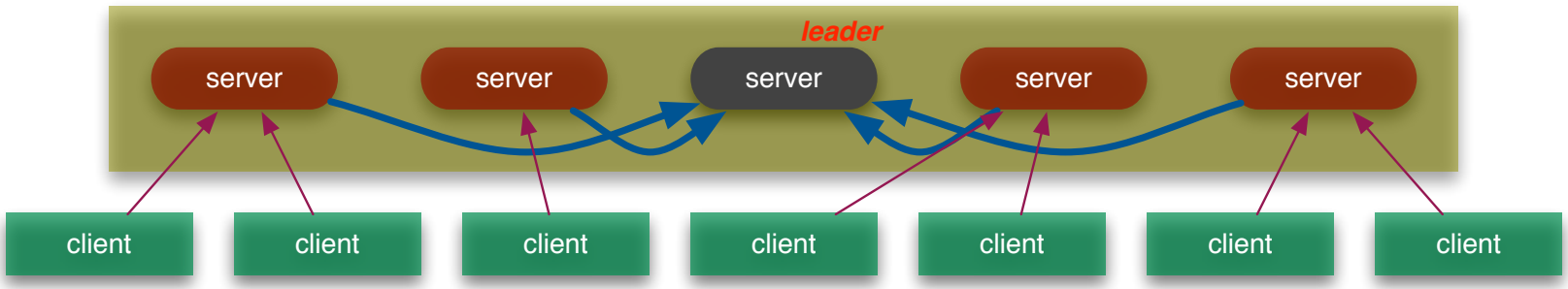
- One supervisor per processing node
- Supervisors start workers as instructed by the topology
  - Each worker is a different process
- Each spout/bolt in the topology has a number of tasks
  - The degree of parallelism of the given spout/bolt
- Workers execute tasks by using a thread per task
- Tasks are allocated to workers in a round-robin fashion
- Example scenario
  - Cluster with 50 quad-core physical nodes; 50 supervisors
  - Each node can start 4 workers; thus, at most 200 workers in a topology
    - No sense using more: hardware supports only 200 simultaneous workers
  - Each spout/bolt in the topology will have its own degree of parallelism; let's assume there are 800 tasks across all spouts/bolts
  - Using all workers: $800/200 = 4$ tasks/worker (4 threads/process)
  - Using 100 workers: $800/100 = 8$ tasks/worker (8 threads/process)
- By tuning the number of tasks and workers we can tune the performance of a topology and the utilisation of the cluster

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)



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: good-old word count

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