CS 425 / ECE 428
Distributed Systems
Fall 2018

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Lecture 22: Stream Processing, Graph Processing

Stream Processing: What We’ll Cover

- Why Stream Processing
- Storm

Stream Processing Challenge

- Large amounts of data => Need for real-time views of data
  - Social network trends, e.g., Twitter real-time search
  - Website statistics, e.g., Google Analytics
  - Intrusion detection systems, e.g., in most datacenters
- Process large amounts of data
  - With latencies of few seconds
  - With high throughput

MapReduce?

- Batch Processing => Need to wait for entire computation on large dataset to complete
- Not intended for long-running stream-processing

Which one of these is NOT a stream processing job?

A) Uber

Calculating surge prices [https://www.youtube.com/watch?v=YUBPimFvcN4]

B) LinkedIn

Aggregating updates into one email [http://www.vldb.org/pvldb/vol10/p1634-noghabi.pdf]

C) Netflix

Understanding user behavior to improve personalization [https://www.youtube.com/watch?v=p8qSWE_nAAE]

D) TripAdvisor

Calculating earnings per day & fraud detection [https://www.youtube.com/watch?v=KQ5OnL2hMBY]

E) All of them

F) None of them → all of them are stream processing jobs!

Enter Storm

- Apache Project
- http://storm.apache.org/
- Highly active JVM project
- Multiple languages supported via API
  - Python, Ruby, etc.

- Used by over 30 companies including
  - Twitter: For personalization, search
  - Flipboard: For generating custom feeds
  - Weather Channel, WebMD, etc.

Storm Components

- Tuples
- Streams
- Spouts
- Bolts
- Topologies

Tuple

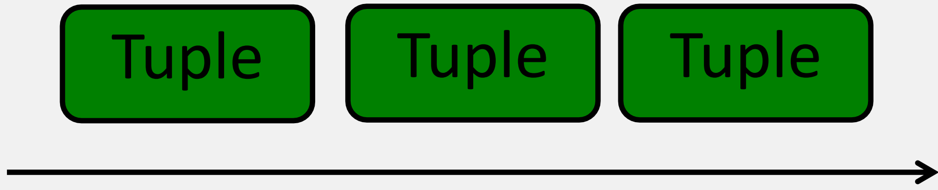
- An ordered list of elements
- E.g., <tweeter, tweet>
  - E.g., <“Miley Cyrus”, “Hey! Here’s my new song!”>
  - E.g., <“Justin Bieber”, “Hey! Here’s MY new song!”>

- E.g., <URL, clicker-IP, date, time>
  - E.g., <coursera.org, 101.102.103.104, 4/4/2014, 10:35:40>
  - E.g., <coursera.org, 101.102.103.105, 4/4/2014, 10:35:42>

Tuple

Stream

- Sequence of tuples
  - Potentially unbounded in number of tuples

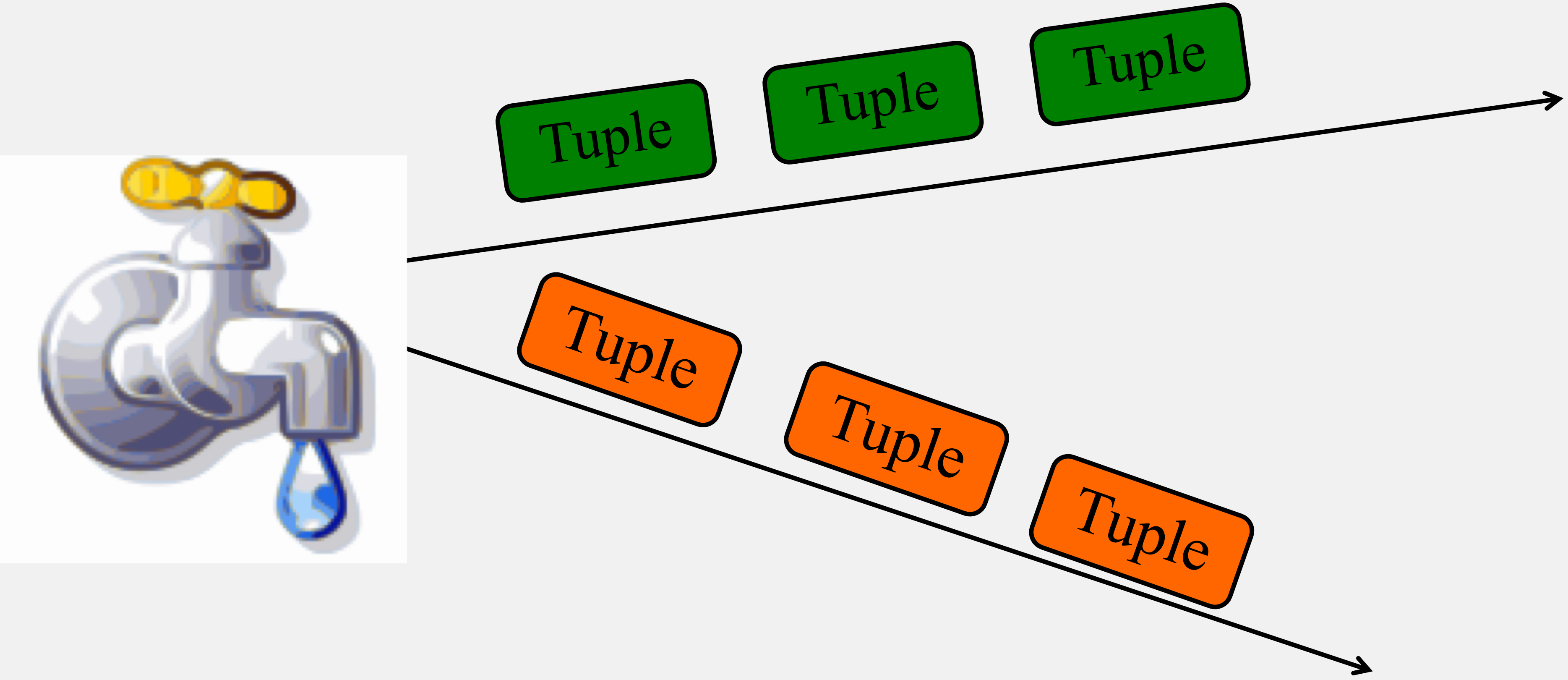


- Social network example:
  - <“Miley Cyrus”, “Hey! Here’s my new song!”>,
    <“Justin Bieber”, “Hey! Here’s MY new song!”>,
    <“Rolling Stones”, “Hey! Here’s my old song that’s still a super-hit!”>, …

- Website example:
  - <coursera.org, 101.102.103.104, 4/4/2014, 10:35:40>, <coursera.org, 101.102.103.105, 4/4/2014, 10:35:42>, …

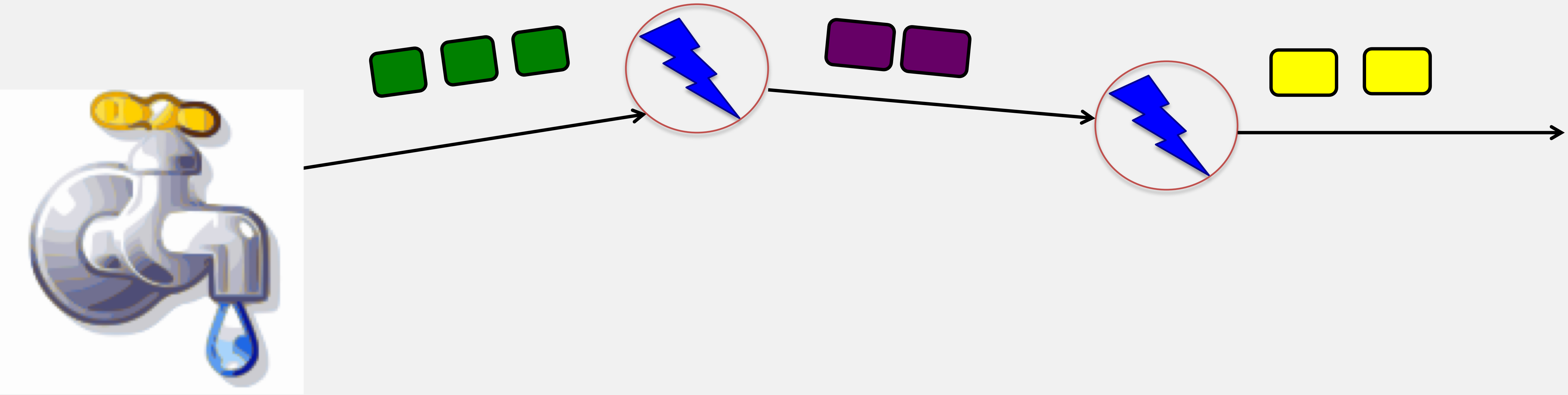
Spout

- A Storm entity (process) that is a source of streams
- Often reads from a crawler or DB



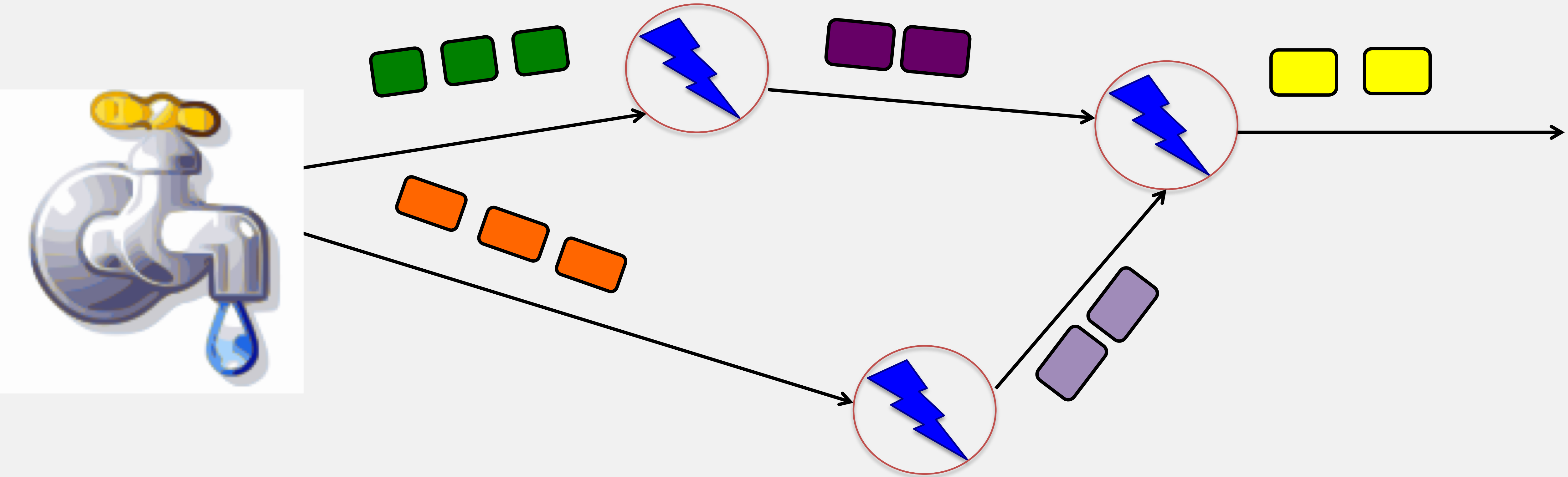
Bolt

- A Storm entity (process) that
  - Processes input streams
  - Outputs more streams for other bolts



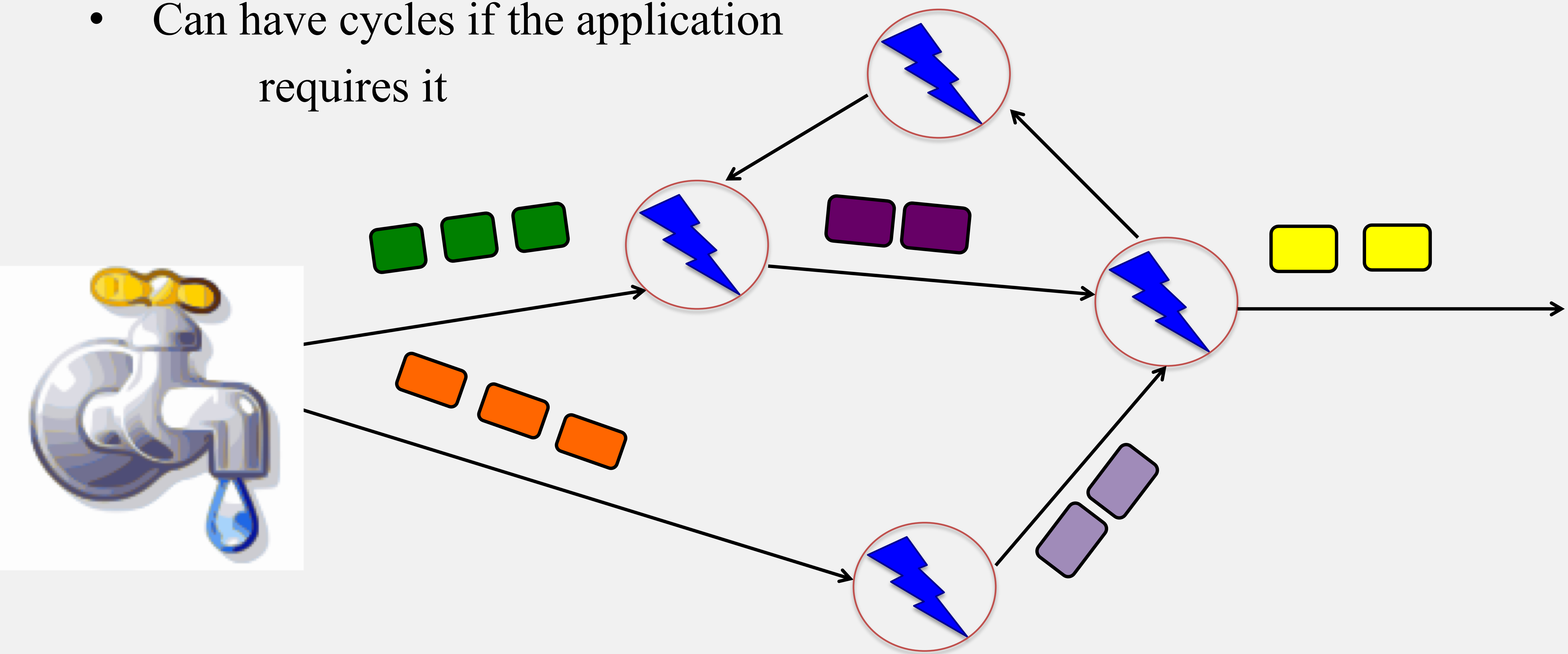
Topology

- A directed graph of spouts and bolts (and output bolts)
- Corresponds to a Storm "application"



Topology

- Can have cycles if the application requires it



Bolts come in many Flavors

- Operations that can be performed
  - **Filter**: forward only tuples which satisfy a condition
  - **Joins**: When receiving two streams A and B, output all pairs (A,B) which satisfy a condition
  - **Apply/transform**: Modify each tuple according to a function
  - And many others

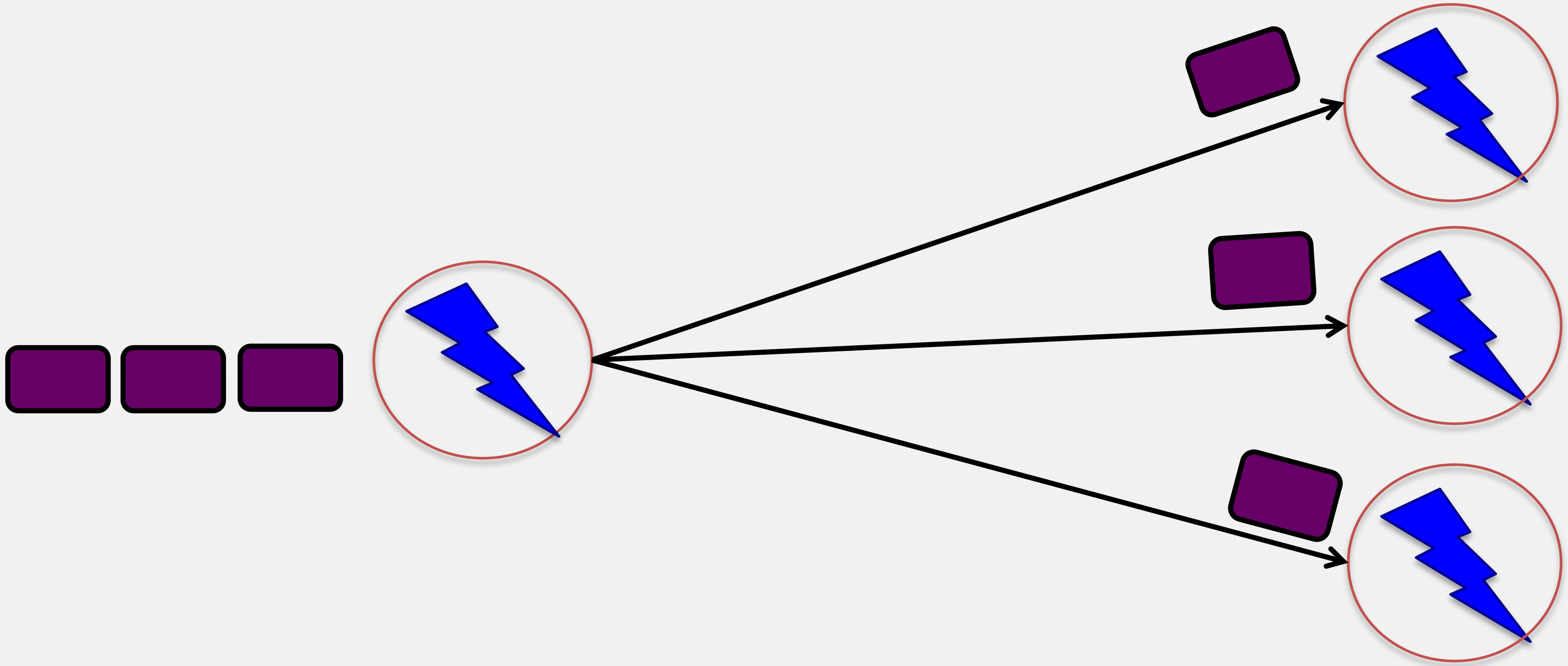
- But bolts need to process a lot of data
  - Need to make them fast

Parallelizing Bolts

- Have multiple processes ("tasks") constitute a bolt
- Incoming streams split among the tasks
- Typically each incoming tuple goes to one task in the bolt
  - Decided by "Grouping strategy"
- Three types of grouping are popular

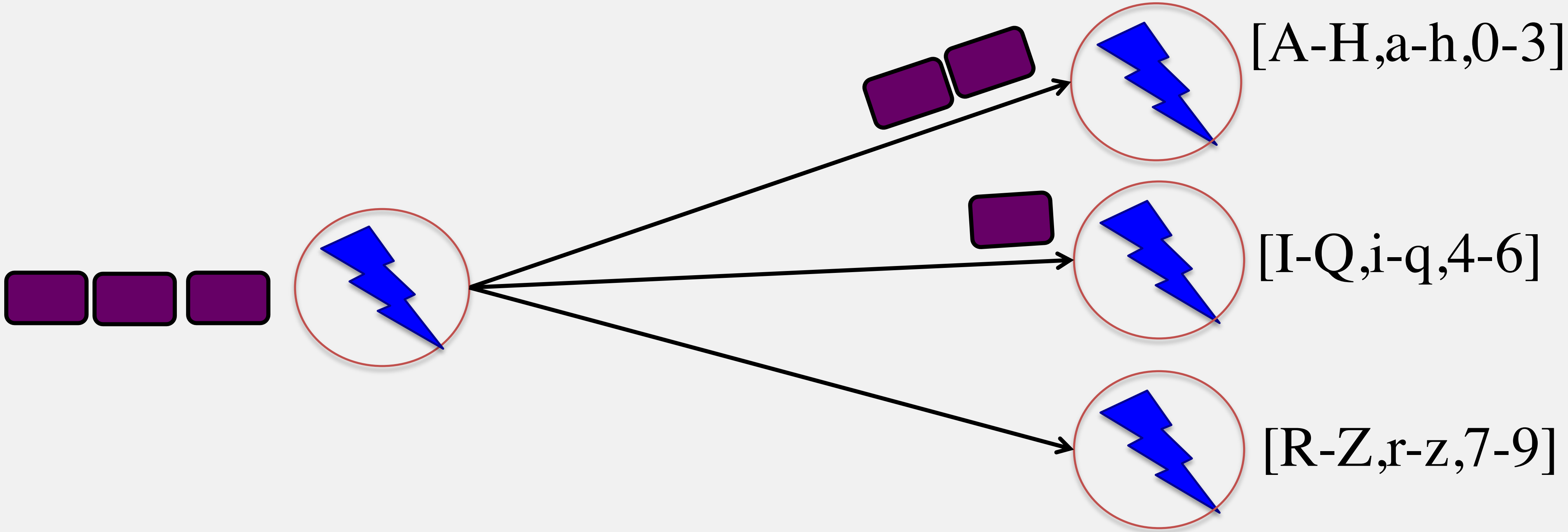
Grouping

- **Shuffle Grouping**
  - Streams are distributed evenly among the bolt's tasks
  - Round-robin fashion



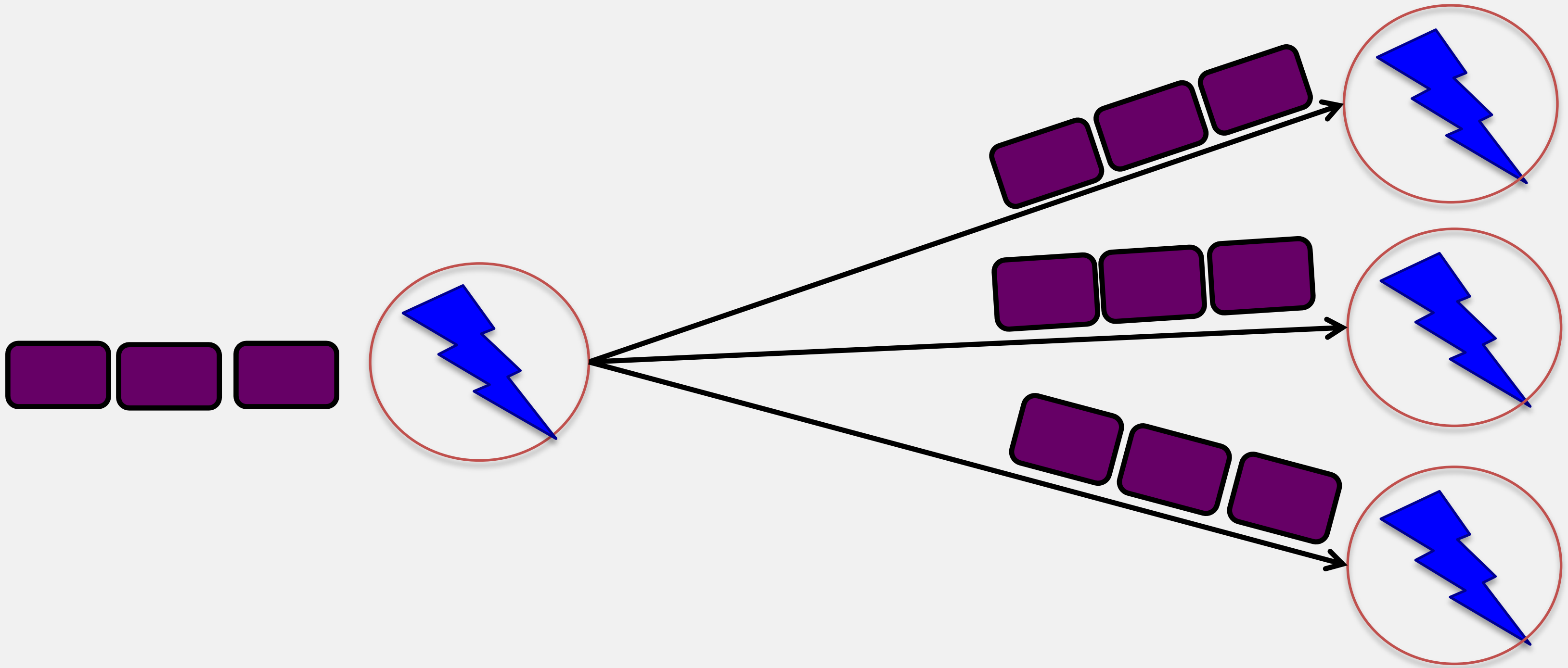
Grouping

- **Fields Grouping**
  - Group a stream by a subset of its fields
  - E.g., All tweets where twitter username starts with [A-H,a-h,0-3] go to task 1, tweets starting with [I-Q,i-q,4-6]go to task 2, tweets starting with [R-Z,r-z,7-9] go to task 3



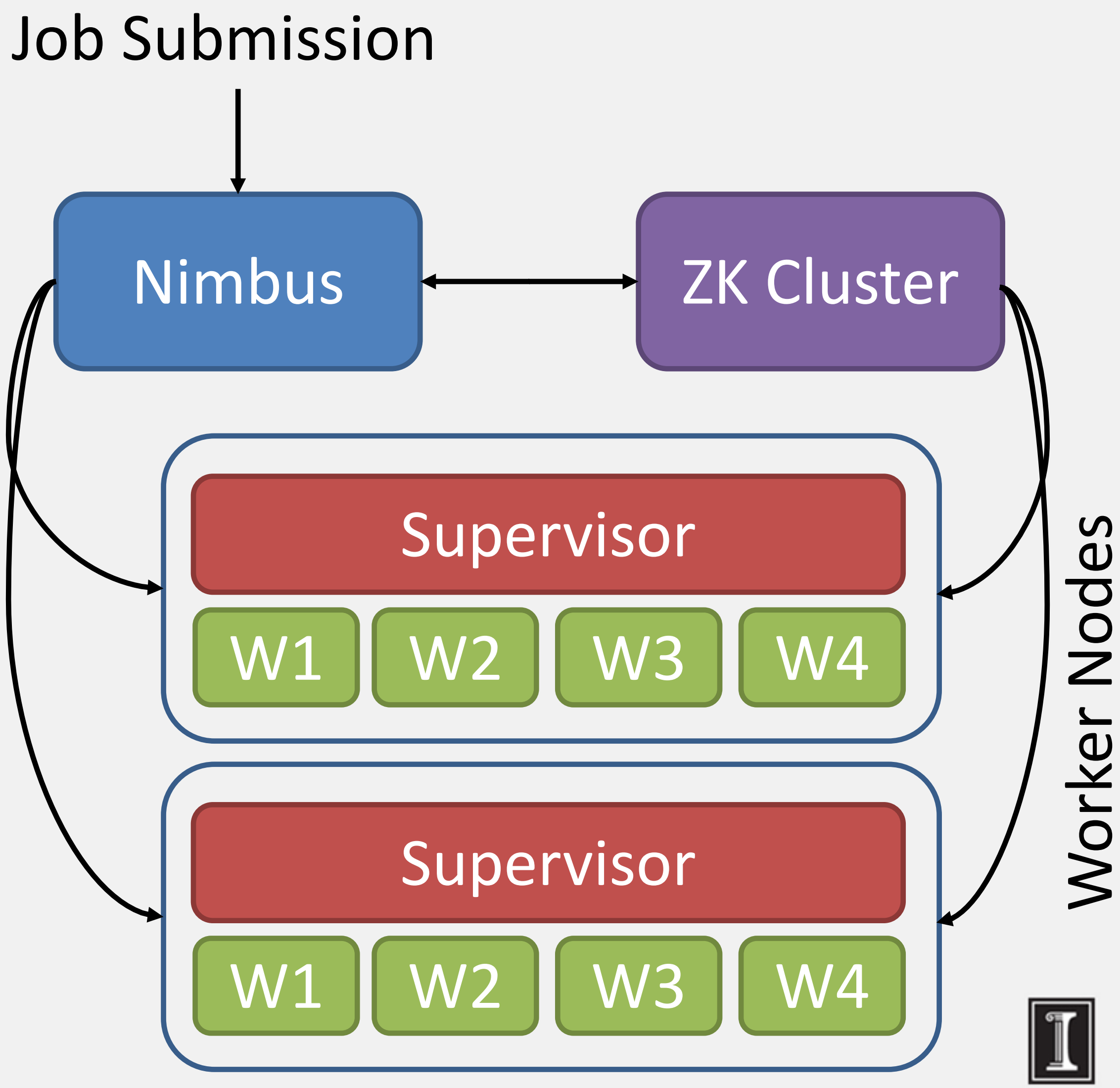
Grouping

- **All Grouping**
  - All tasks of bolt receive all input tuples



Storm Cluster

- Master node
  - Runs a daemon called *Nimbus*
  - Responsible for
    - Distributing code around cluster
    - Assigning tasks to machines
    - Monitoring for failures of machines
- Worker node
  - Runs on a machine (server)
  - Runs a daemon called *Supervisor*
  - Listens for work assigned to its machines
  - Runs “Executors”(which contain groups of tasks)
- Zookeeper
  - Coordinates Nimbus and Supervisors communication
  - All state of Supervisor and Nimbus is kept here



Failures

- A tuple is considered failed when its topology (graph) of resulting tuples fails to be fully processed within a specified timeout

- **Anchoring**: Anchor an output to one or more input tuples
  - Failure of one tuple causes one or more tuples to replayed

API For Fault-Tolerance (OutputCollector)

- **Emit**(tuple, output)
  - Emits an output tuple, perhaps anchored on an input tuple (first argument)
- **Ack**(tuple)
  - Acknowledge that you (bolt) finished processing a tuple
- **Fail**(tuple)
  - Immediately fail the spout tuple at the root of tuple topology if there is an exception from the database, etc.
- Must remember to ack/fail each tuple
  - Each tuple consumes memory. Failure to do so results in memory leaks.

Twitter’s Heron System

- Fixes the inefficiencies of Storm’s acking mechanism (among other things)
- Uses **backpressure**: a congested downstream tuple will ask upstream tuples to slow or stop sending tuples

1. TCP Backpressure: uses TCP windowing mechanism to propagate backpressure
2. Spout Backpressure: node stops reading from its upstream spouts
3. Stage by Stage Backpressure: think of the topology as stage-based, and propagate back via stages

- Use:
  - Spout+TCP, or
  - Stage by Stage + TCP
- Beats Storm throughput handily (see Heron paper)

Summary: Stream Processing

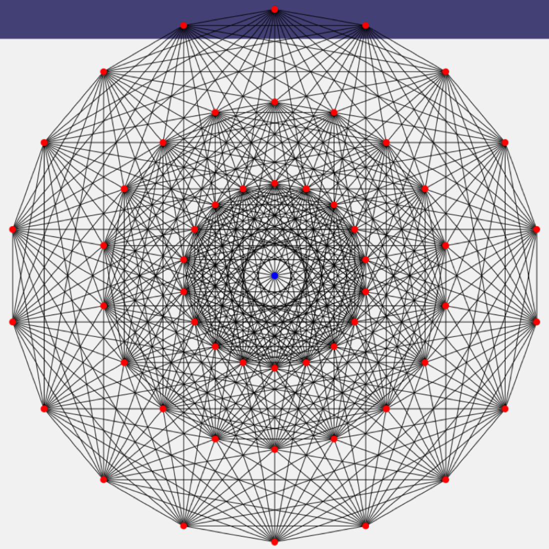
- Processing data in real-time a big requirement today
- Storm
  - And other sister systems, e.g., Spark Streaming, Heron
- Parallelism
- Application topologies
- Fault-tolerance

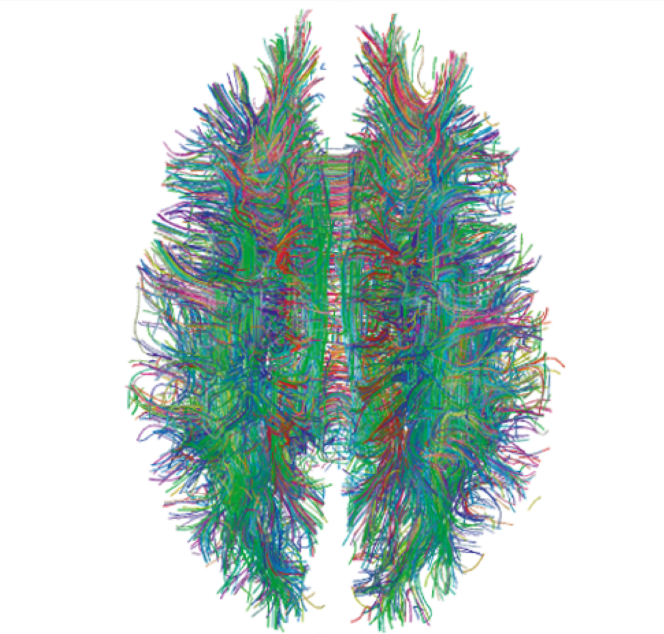
Graph Processing: What We'll Cover

- Distributed Graph Processing
- Google's Pregel system
    - Inspiration for many newer graph processing systems: Piccolo, Giraph, GraphLab, PowerGraph, LFGraph, X-Stream, etc.

Lots of Graphs

- Large graphs are all around us
  - Internet Graph: vertices are routers/switches and edges are links
  - World Wide Web: vertices are webpages, and edges are URL links on a webpage pointing to another webpage
    - Called "Directed" graph as edges are uni-directional
  - Social graphs: Facebook, Twitter, LinkedIn
  - Biological graphs: Brain neurons, DNA interaction graphs, ecosystem graphs, etc.





Source: Wikimedia Commons, Wikipedia

Graph Processing Operations

- Need to derive properties from these graphs
- Need to summarize these graphs into statistics
- E.g., find shortest paths between pairs of vertices
  - Internet (for routing)
  - LinkedIn (degrees of separation)
- E.g., do matching
  - Dating graphs in match.com (for better dates)
- PageRank
  - Web Graphs
  - Google search, Bing search, Yahoo search: all rely on this

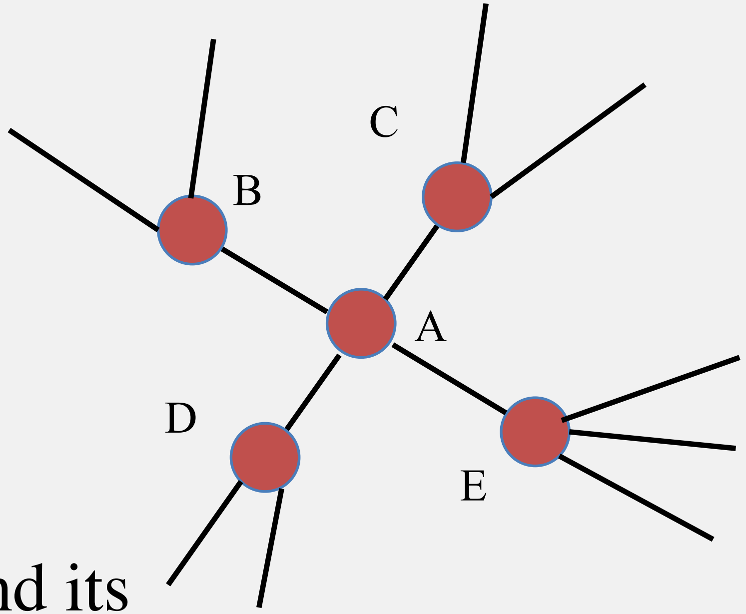
- And many (many) other examples!

Why Hard?

- Because these graphs are large!
  - Human social network has 100s Millions of vertices and Billions of edges
  - WWW has Millions of vertices and edges
- Hard to store the entire graph on one server and process it
  - On one beefy server: may be slow, or may be very expensive (performance to cost ratio very low)
- Use distributed cluster/cloud!

Typical Graph Processing Application

- Works in *iterations*
- Each vertex assigned a *value*
- In each iteration, each vertex:
  1. Gather: Gathers values from its immediate neighbors (vertices who join it directly with an edge). E.g., @A: B→A, C→A, D→A,…
  2. Apply: Does some computation using its own value and its neighbors values.
  3. Scatter: Updates its new value and sends it out to its neighboring vertices. E.g., A→B, C, D, E
- Graph processing terminates after: i) fixed iterations, or ii) vertices stop changing values



Hadoop/MapReduce to the Rescue?

- Multi-stage Hadoop
- Each stage == 1 graph iteration
- Assign vertex ids as keys in the reduce phase

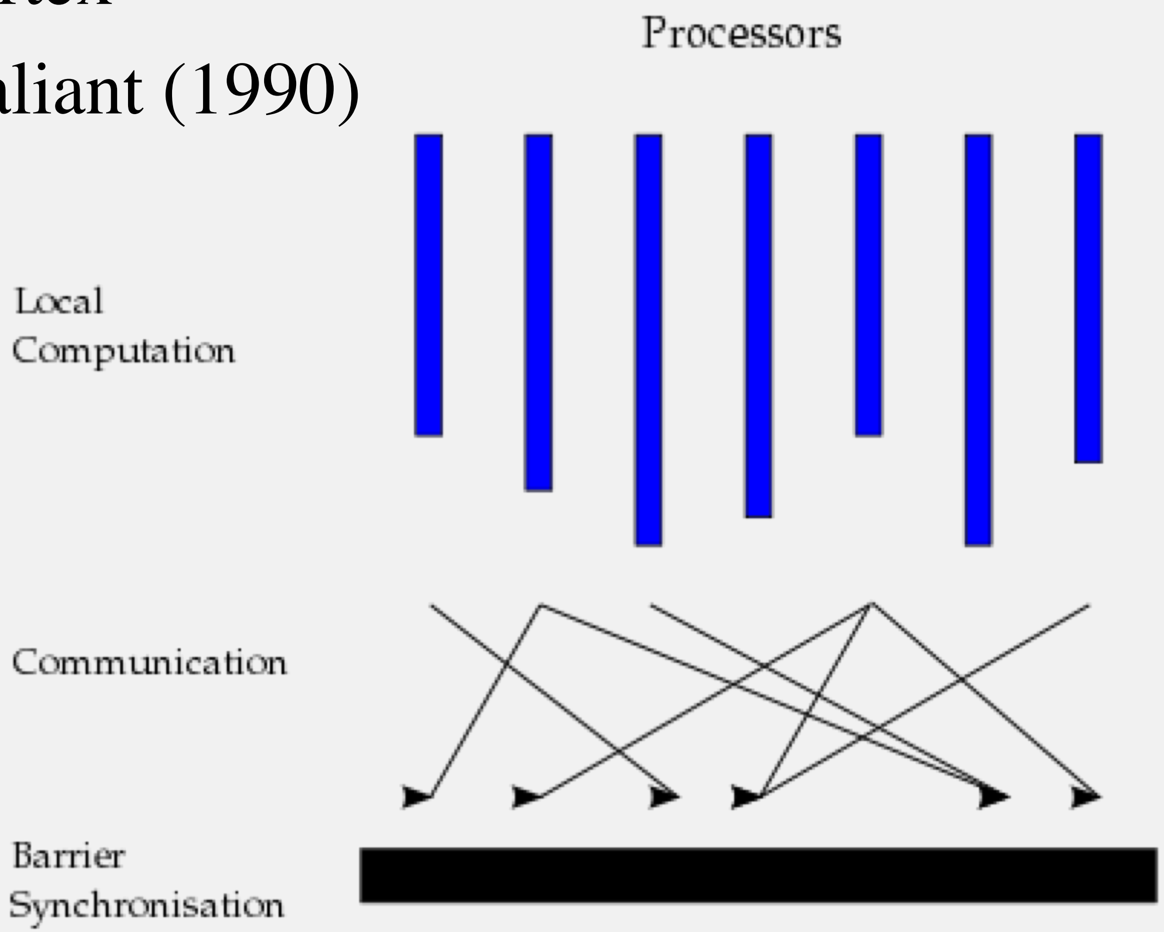
☺ Well-known

☹ At the end of every stage, transfer all vertices over network (to neighbor vertices)

  - ☹ All vertex values written to HDFS (file system)
  - ☹ Very slow!

Bulk Synchronous Parallel Model

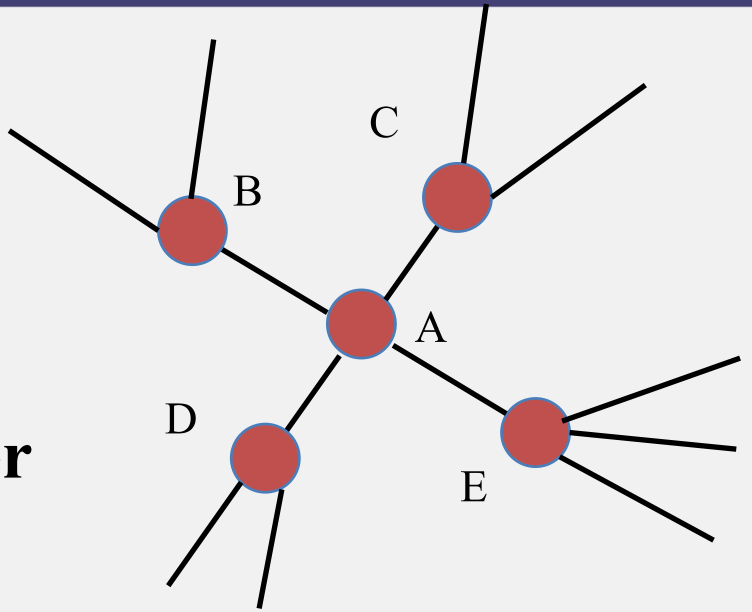
- "Think like a vertex"
- Originally by Valiant (1990)



Source: http://en.wikipedia.org/wiki/Bulk_synchronous_parallel

Basic Distributed Graph Processing

- "Think like a vertex"
- Assign each vertex to one server
- Each server thus gets a subset of vertices
- In each iteration, each server performs **Gather-Apply-Scatter** for all its assigned vertices
  - Gather: get all neighboring vertices' values
  - Apply: compute own new value from own old value and gathered neighbors' values
  - Scatter: send own new value to neighboring vertices



Assigning Vertices

- How to decide which server a given vertex is assigned to?
- Different options
  - Hash-based: Hash(vertex id) modulo number of servers
    - Remember consistent hashing from P2P systems?!
  - Locality-based: Assign vertices with more neighbors to the same server as its neighbors
    - Reduces server to server communication volume after each iteration
    - Need to be careful: some "intelligent" locality-based schemes may take up a lot of upfront time and may not give sufficient benefits!

Pregel System By Google

- Pregel uses the master/worker model
  - Master (one server)
    - Maintains list of worker servers
    - Monitors workers; restarts them on failure
    - Provides Web-UI monitoring tool of job progress
  - Worker (rest of the servers)
    - Processes its vertices
    - Communicates with the other workers
- Persistent data is stored as files on a distributed storage system (such as GFS or BigTable)
- Temporary data is stored on local disk

Pregel Execution

1. Many copies of the program begin executing on a cluster
2. The master assigns a partition of input (vertices) to each worker
    - Each worker loads the vertices and marks them as *active*
3. The master instructs each worker to perform a iteration
    - Each worker loops through its active vertices & computes for each vertex
    - Messages can be sent whenever, but need to be delivered before the end of the iteration (i.e., the barrier)
    - When all workers reach iteration barrier, master starts next iteration
4. Computation halts when, in some iteration: no vertices are active and when no messages are in transit
5. Master instructs each worker to save its portion of the graph

Fault-Tolerance in Pregel

- **Checkpointing**
  - Periodically, master instructs the workers to save state of their partitions to persistent storage
    - e.g., Vertex values, edge values, incoming messages
- **Failure detection**
  - Using periodic “ping” messages from master → worker
- **Recovery**
  - The master reassigns graph partitions to the currently available workers
  - The workers all reload their partition state from most recent available checkpoint

How Fast Is It?

- Shortest paths from one vertex to all vertices
  - SSSP: “Single Source Shortest Path”
- On 1 Billion vertex graph (tree)
  - 50 workers: 180 seconds
  - 800 workers: 20 seconds
- 50 B vertices on 800 workers: 700 seconds (~12 minutes)
- Pretty Fast!

Summary: Graph Processing

- Lots of (large) graphs around us
- Need to process these
- MapReduce not a good match
- Distributed Graph Processing systems: Pregel by Google
- Many follow-up systems
  - Piccolo, Giraph: Pregel-like
  - GraphLab, PowerGraph, LFGraph, X-Stream: more advanced