

CS 425 / ECE 428  
Distributed Systems  
Fall 2020

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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](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

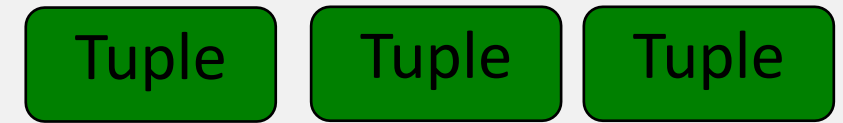
- An ordered list of elements
- E.g., < tweeter, tweet >
  - E.g., < “Miley Cyrus”, “Hey! Here’s my new song!” >
  - E.g., < “Justin Bieber”, “Hey! Here’s MY new song!” >
- E.g., < URL, clicker-IP, date, time >
  - E.g., < coursera.org, 101.102.103.104, 4/4/2014, 10:35:40 >
  - E.g., < coursera.org, 101.102.103.105, 4/4/2014, 10:35:42 >

Tuple



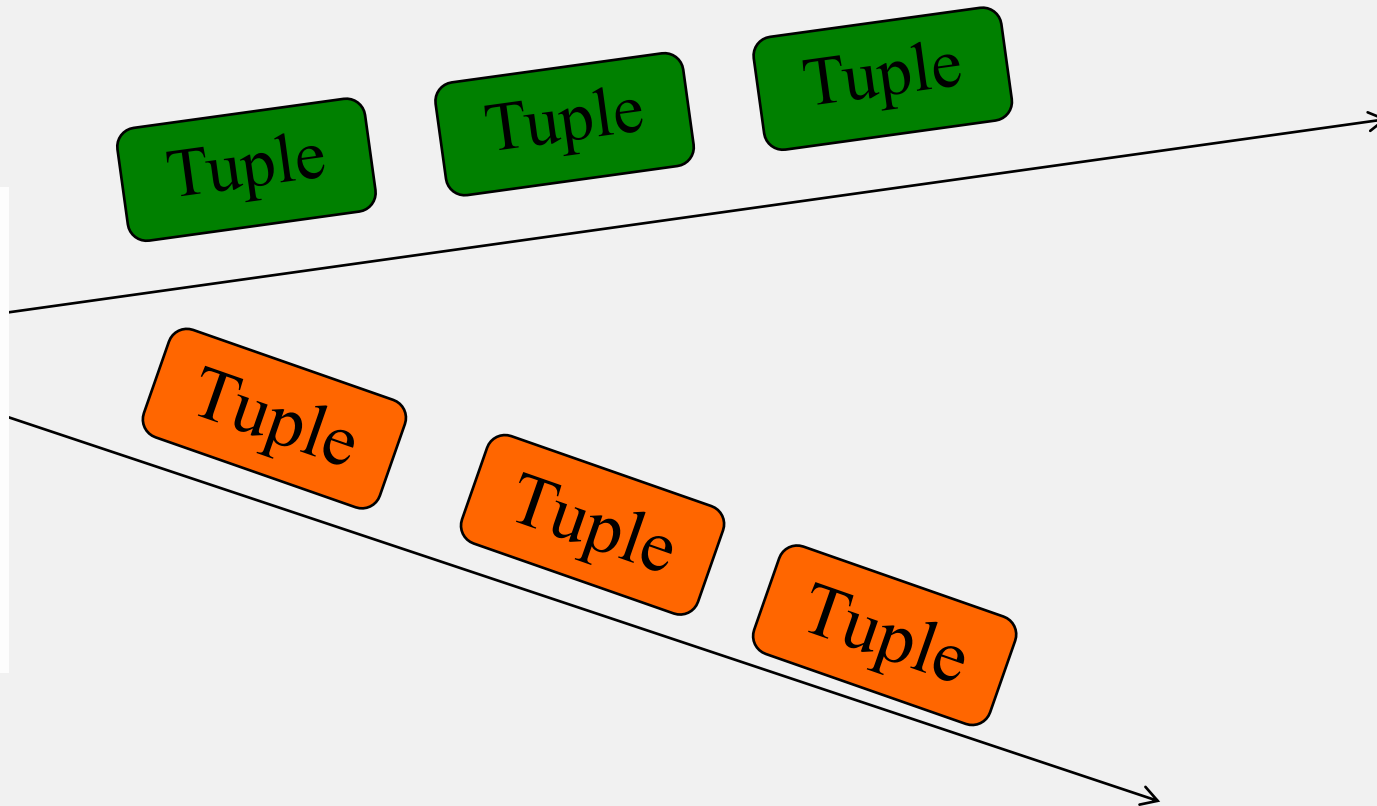
# Stream

- 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>, ...

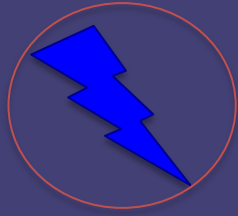


# Spout

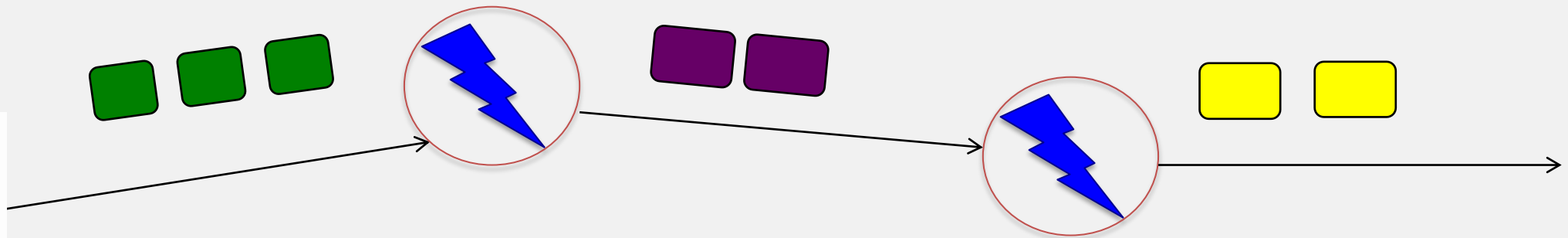
- A Storm entity (process) that is a source of streams
- Often reads from a crawler or DB



# Bolt

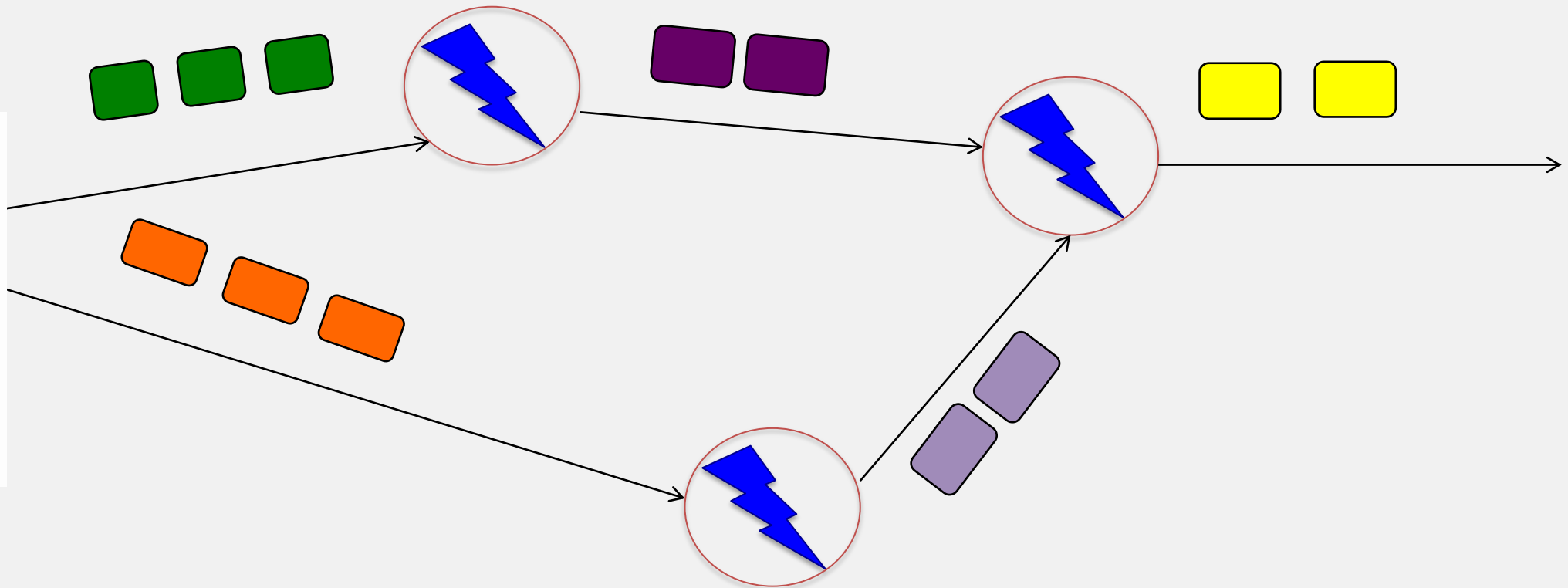


- A Storm entity (process) that
  - Processes input streams
  - Outputs more streams for other bolts



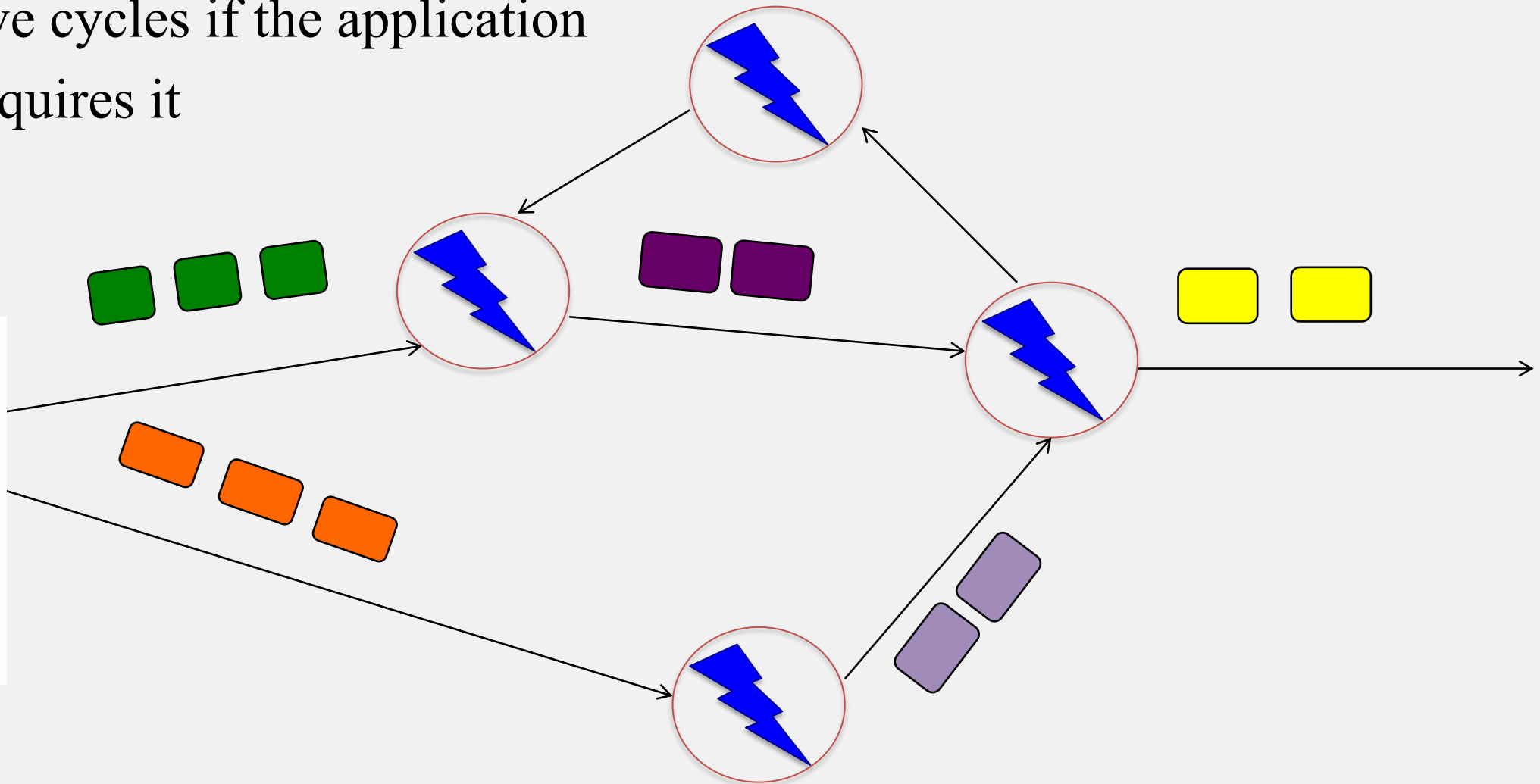
# Topology

- 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

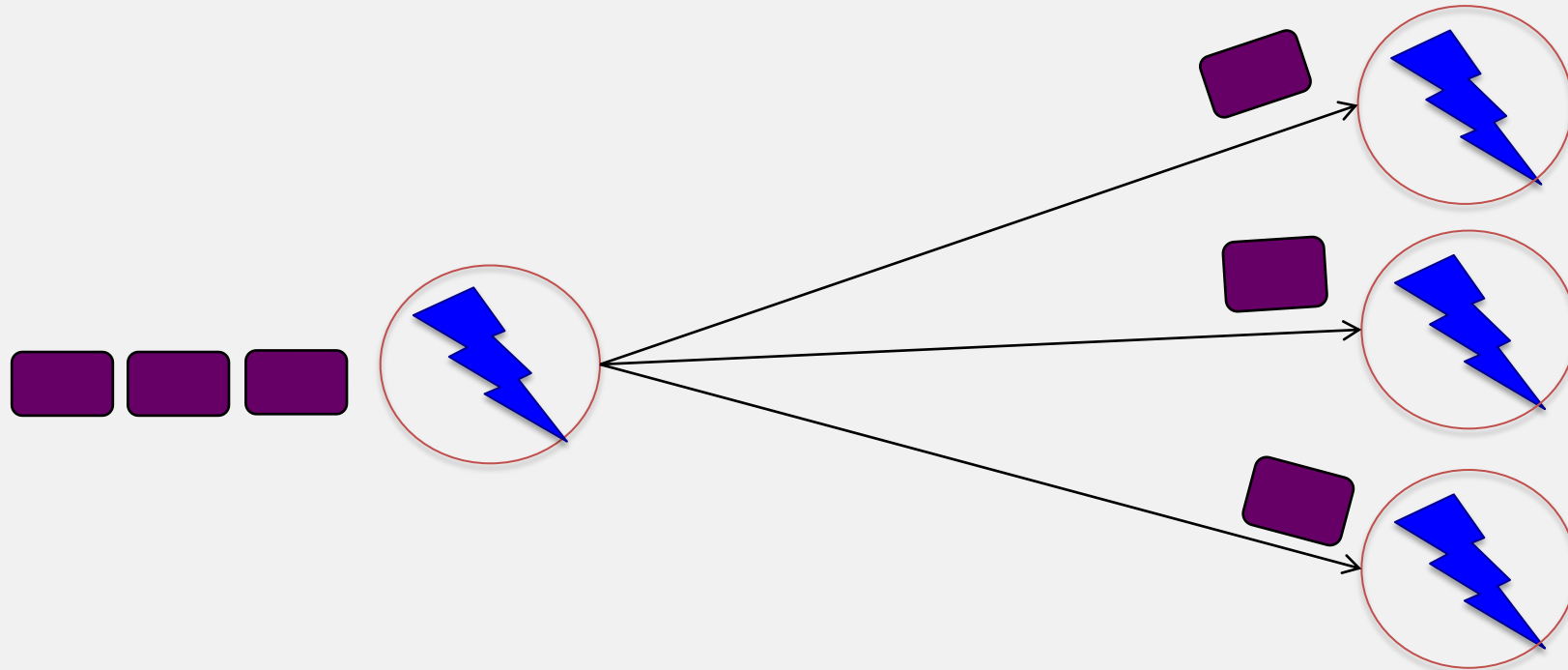
- Have multiple processes (“tasks”) constitute a bolt
- Incoming streams split among the tasks
- Typically each incoming tuple goes to one task in the bolt
  - Decided by “**Grouping strategy**”
- Three types of grouping are popular



# Grouping

- **Shuffle Grouping**

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

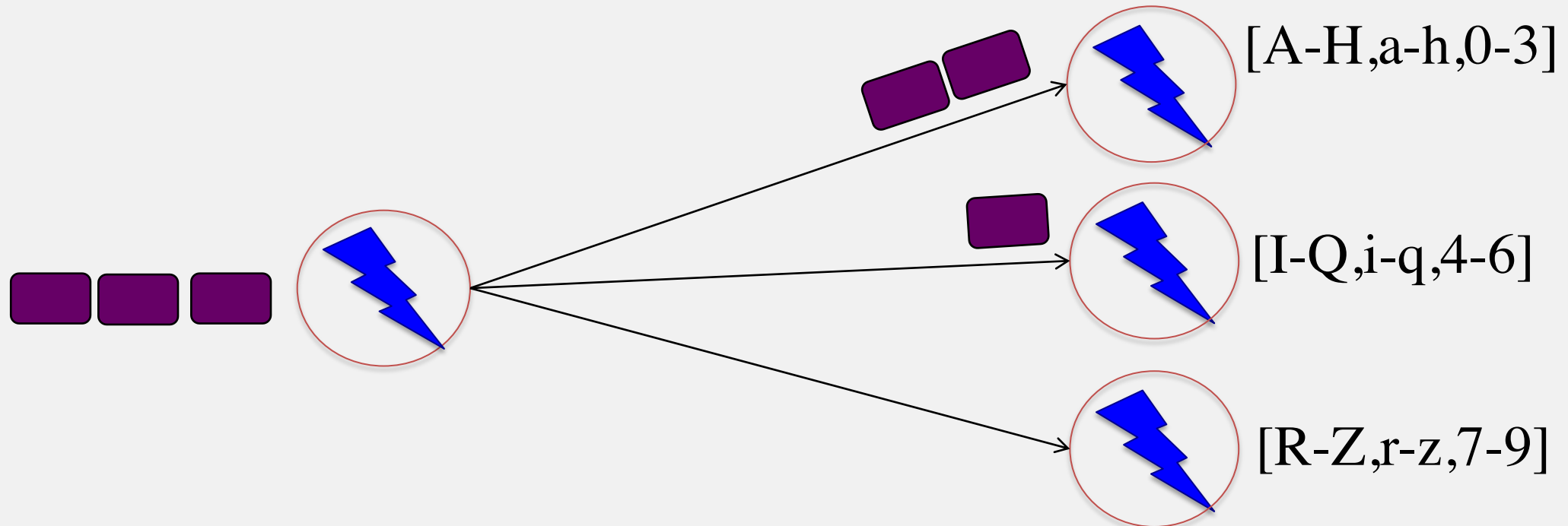




# Grouping

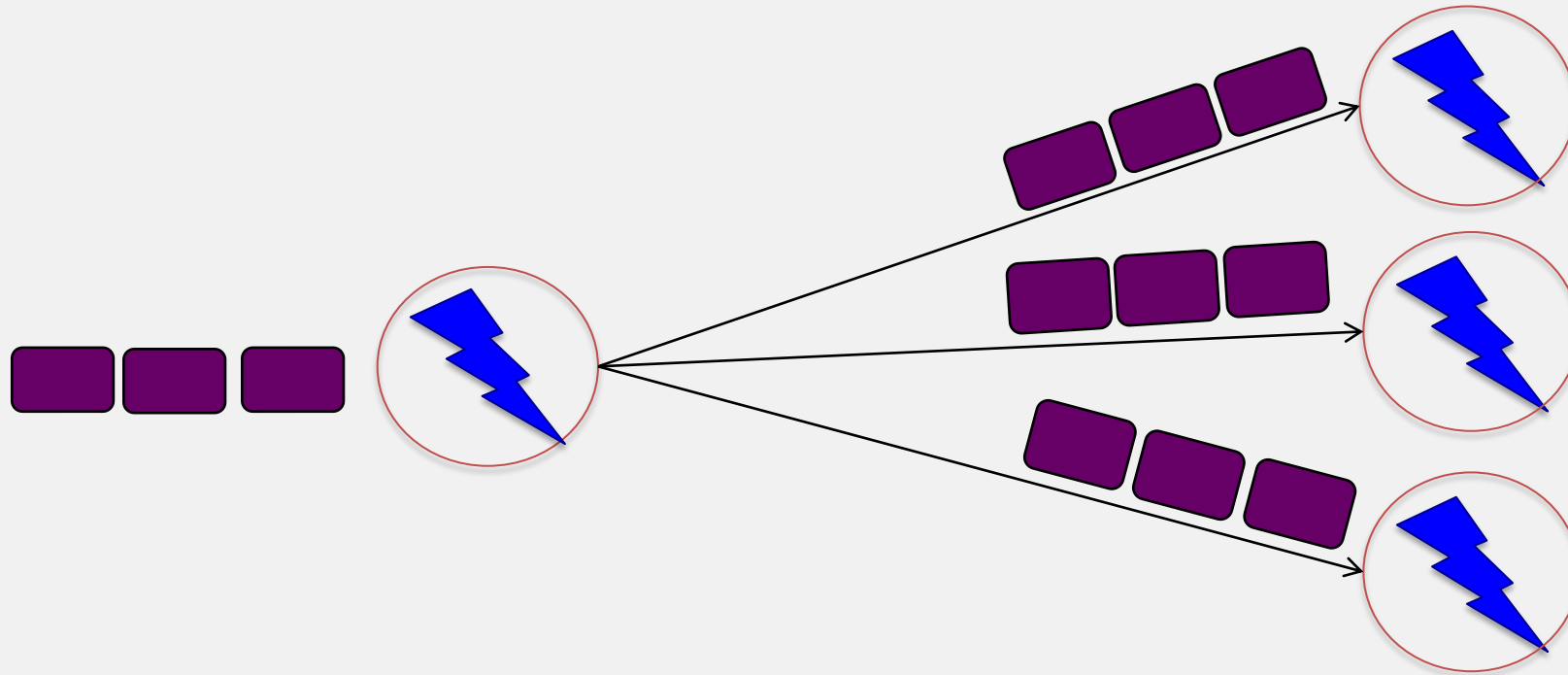
- **Fields Grouping**

- 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

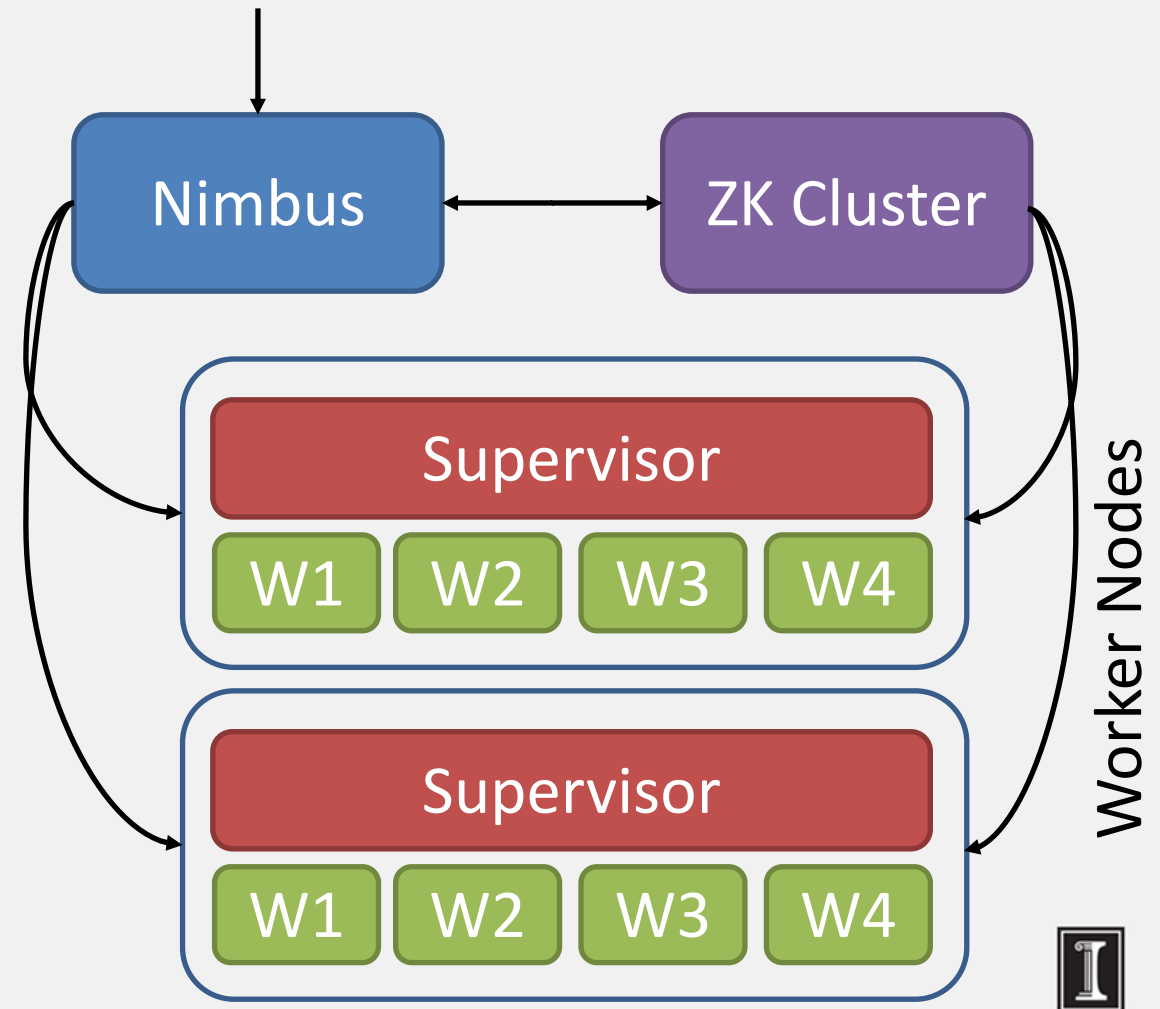
- **All Grouping**
  - All tasks of bolt receive all input tuples



# 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

## Job Submission



# 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 be 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

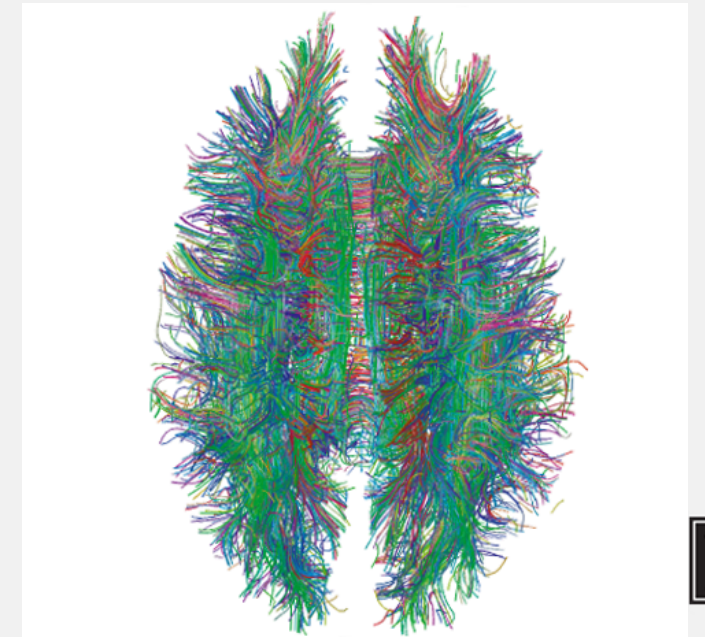
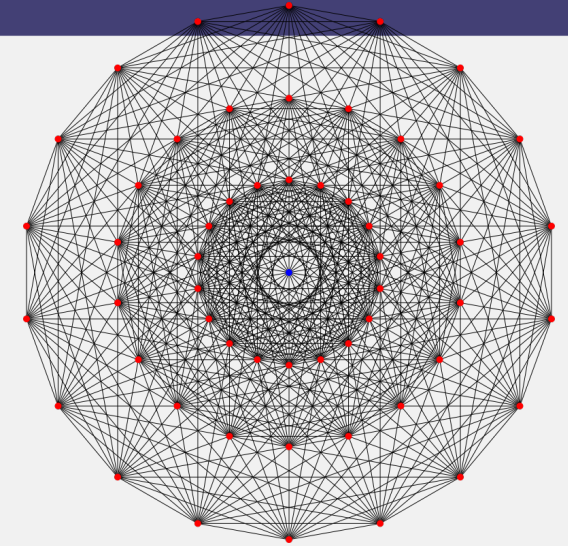
- Distributed Graph Processing
- Google's Pregel system
  - Inspiration for many newer graph processing systems: Piccolo, Giraph, GraphLab, PowerGraph, LFGGraph, X-Stream, etc.





# 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!



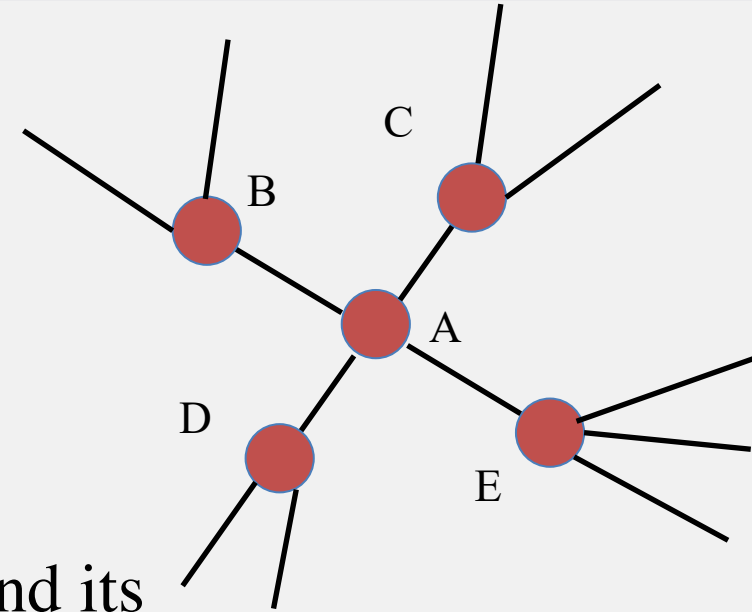
# Why Hard?

- 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:  $B \rightarrow A, C \rightarrow A, D \rightarrow A, \dots$
  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.,  $A \rightarrow B, C, D, E$
- Graph processing terminates after: i) fixed iterations, or ii) vertices stop changing values

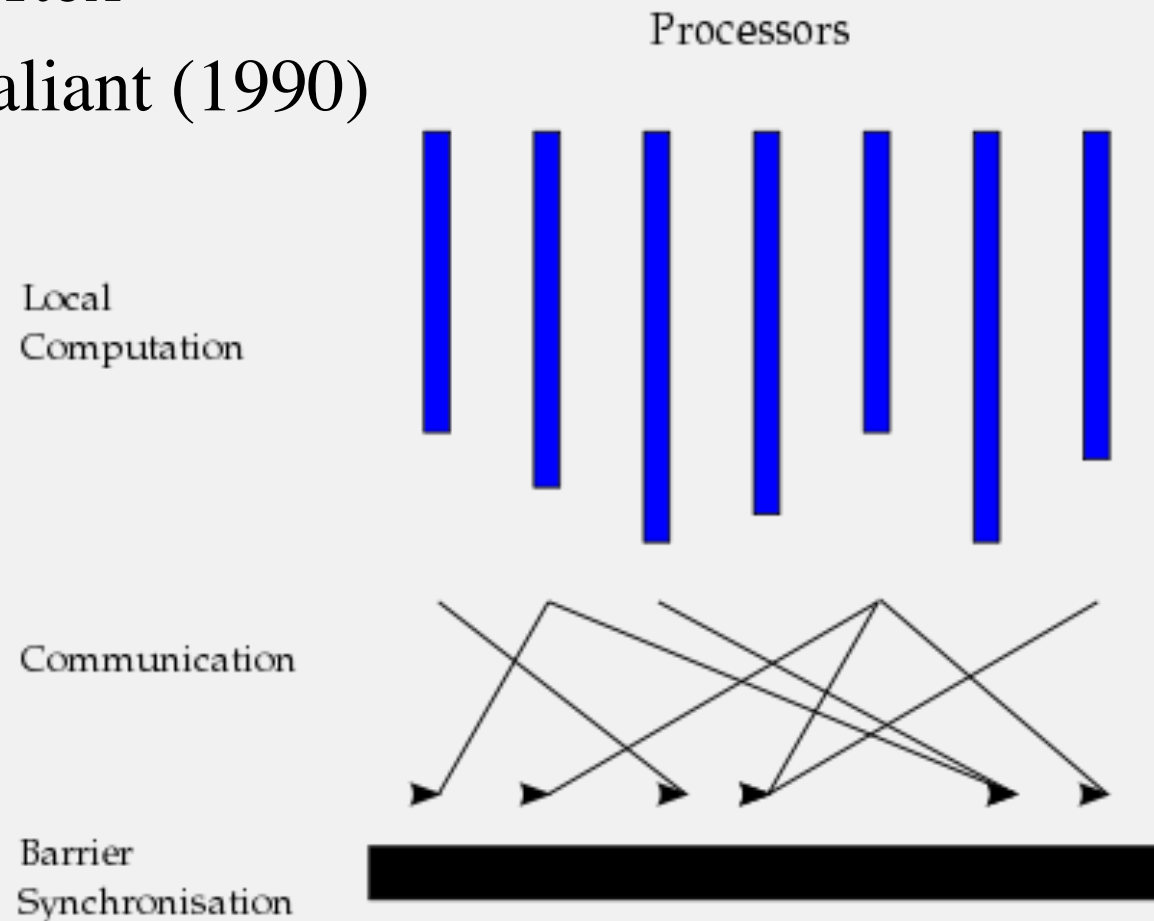


# Hadoop/MapReduce to the Rescue?

- 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

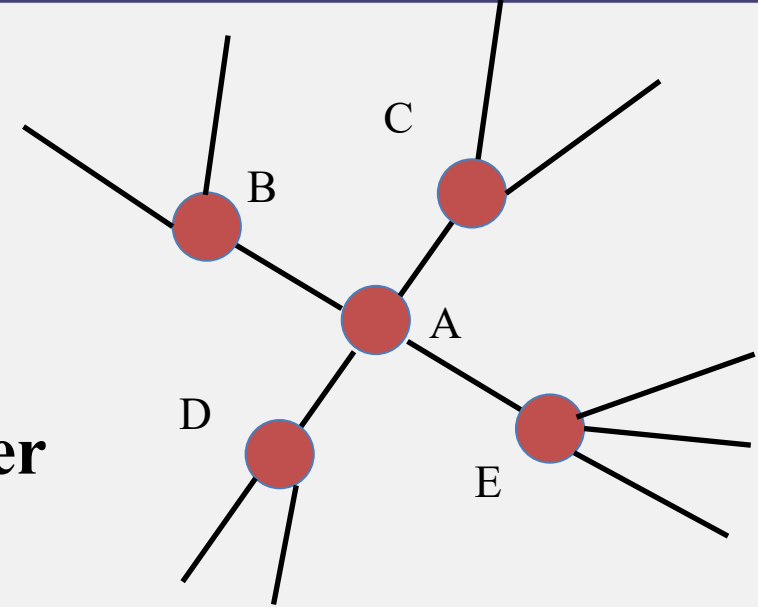
- “Think like a vertex”
- Originally by Valiant (1990)



Source: [http://en.wikipedia.org/wiki/Bulk\\_synchronous\\_parallel](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, LFGGraph, X-Stream: more advanced

