CS 425 / ECE 428
Distributed Systems
Fall 2023

Aishwarya Ganesan

W/ Indranil Gupta (Indy)

Lecture 26 A: Stream Processing, Graph Processing

(and Optional Machine Learning)

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) None of them are stream processing

F) → 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.

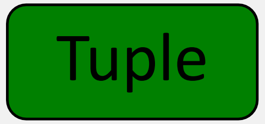
Storm Components

- Tuples
- Streams
- Spouts
- Bolts
- Topologies

Tuple

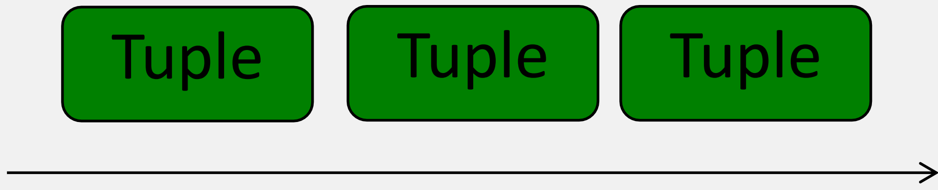
- An ordered list of elements
- E.g., <tweeter, tweet>
  - E.g., <“Miley Cyrus”, “Hey! Here’s my new song!”>
  - E.g., <“Justin Bieber”, “Hey! Here’s MY new song!”>

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



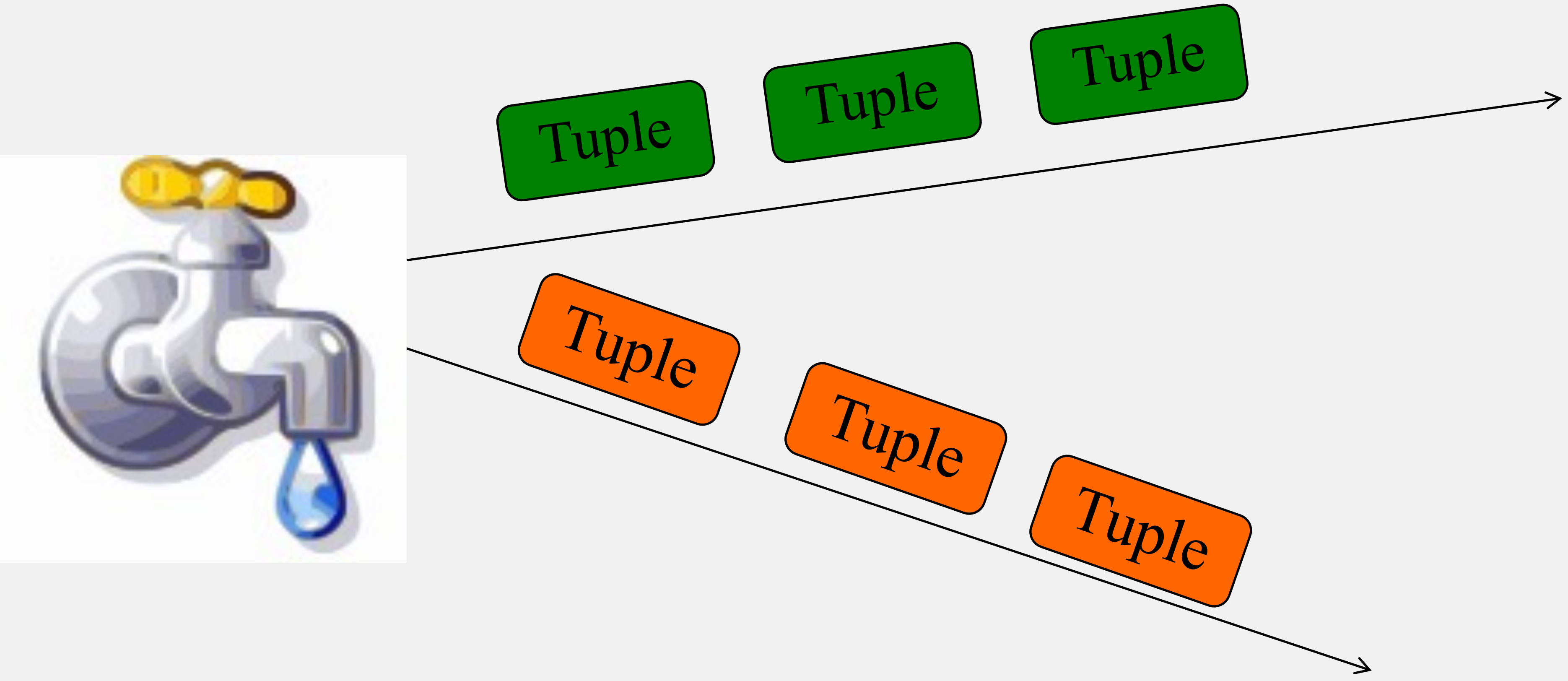
Stream

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

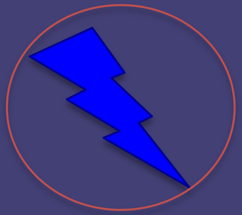


Spout

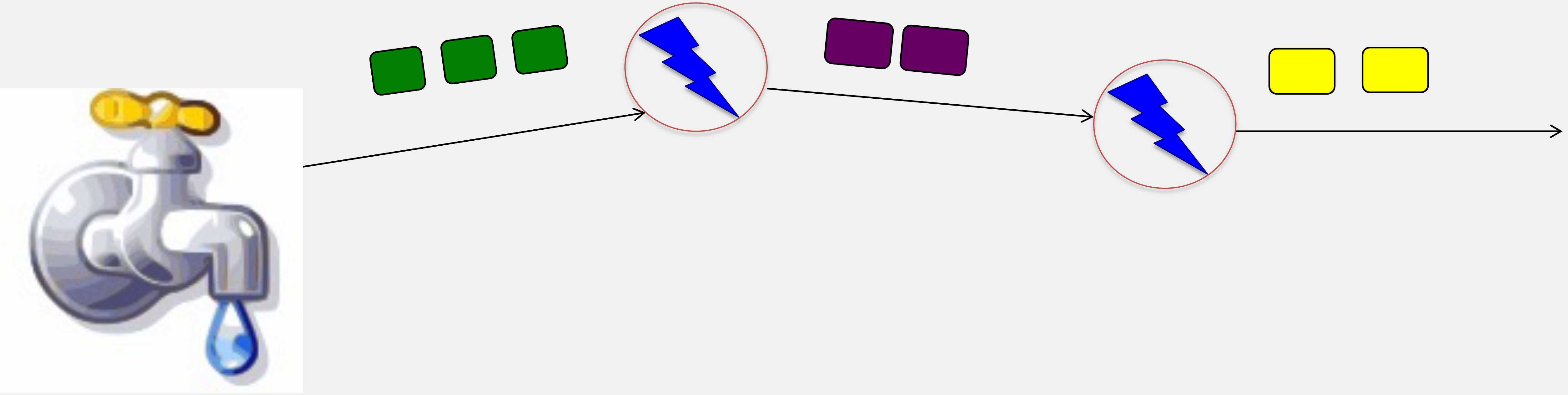
- A Storm entity (process) that is a source of streams
- Often reads from a crawler or DB



Bolt

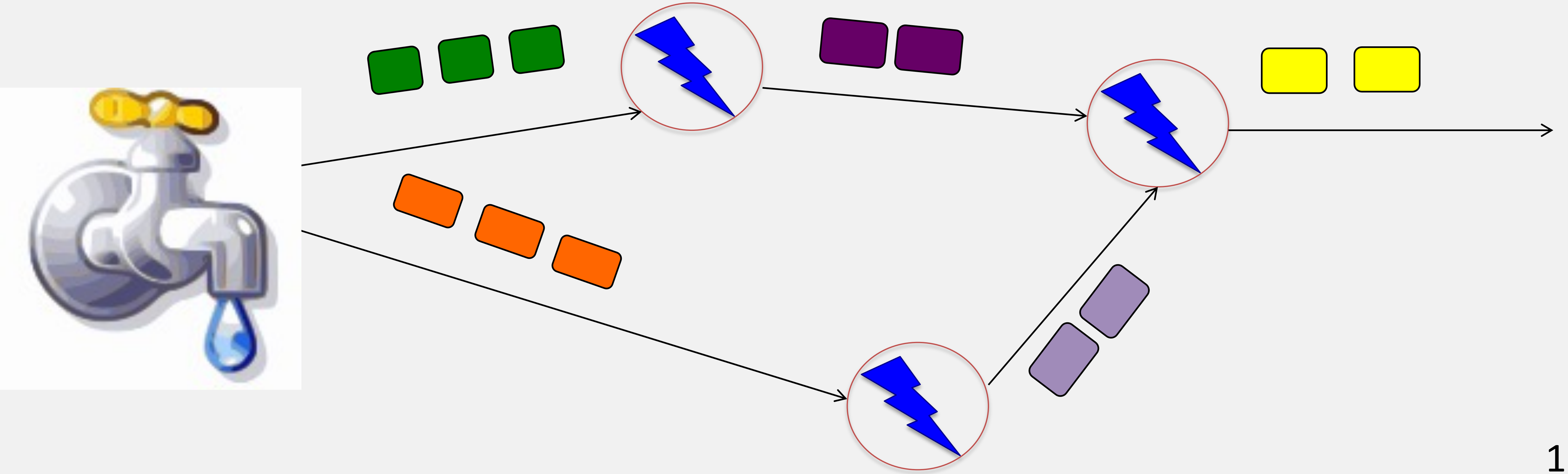


- A Storm entity (process) that
  - Processes input streams
  - Outputs more streams for other bolts



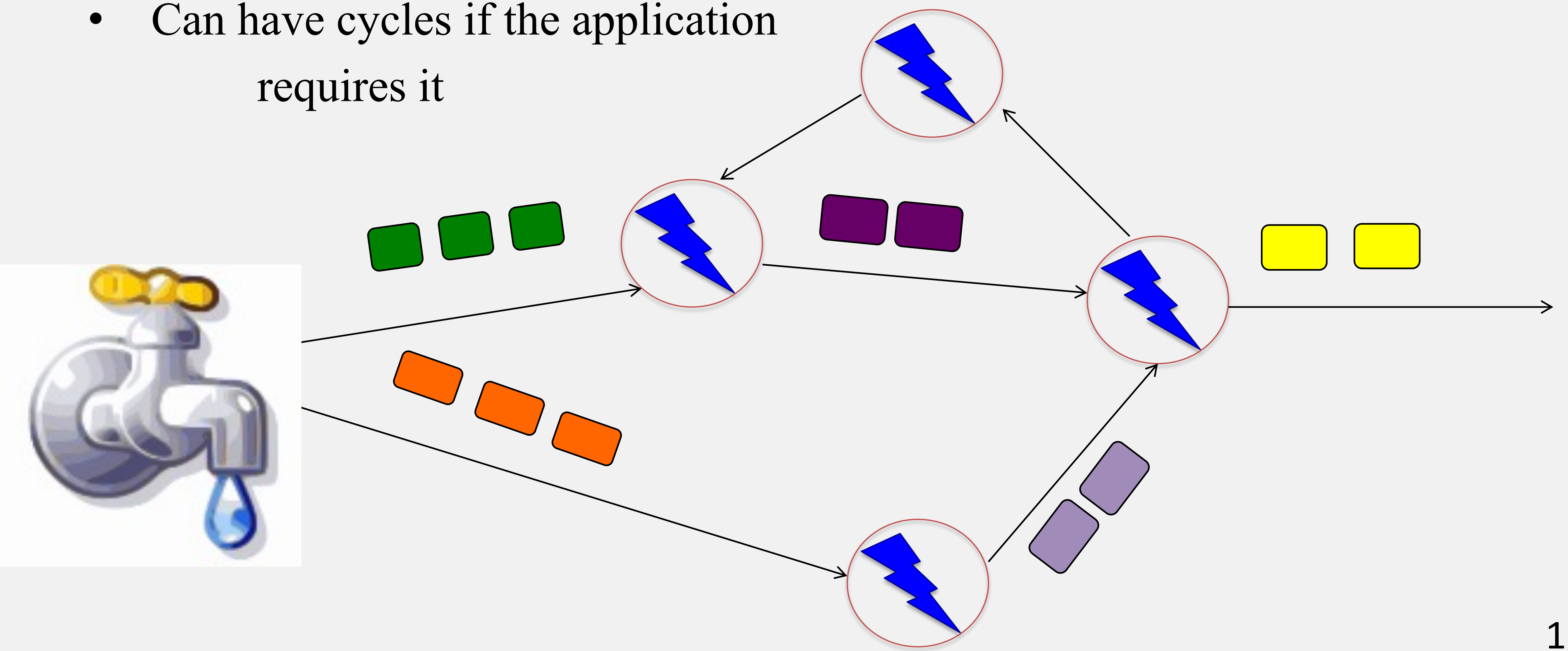
Topology

- 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

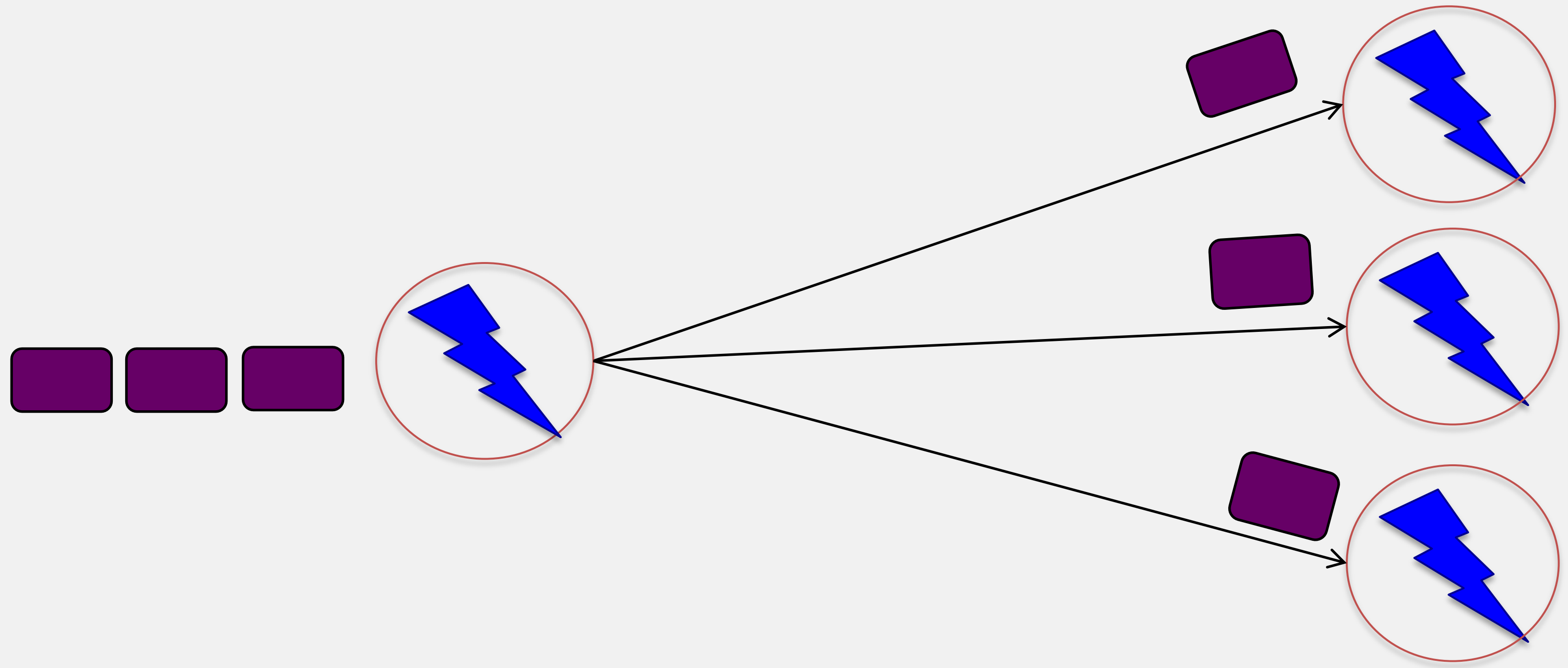
- But bolts need to process a lot of data
  - Need to make them fast

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

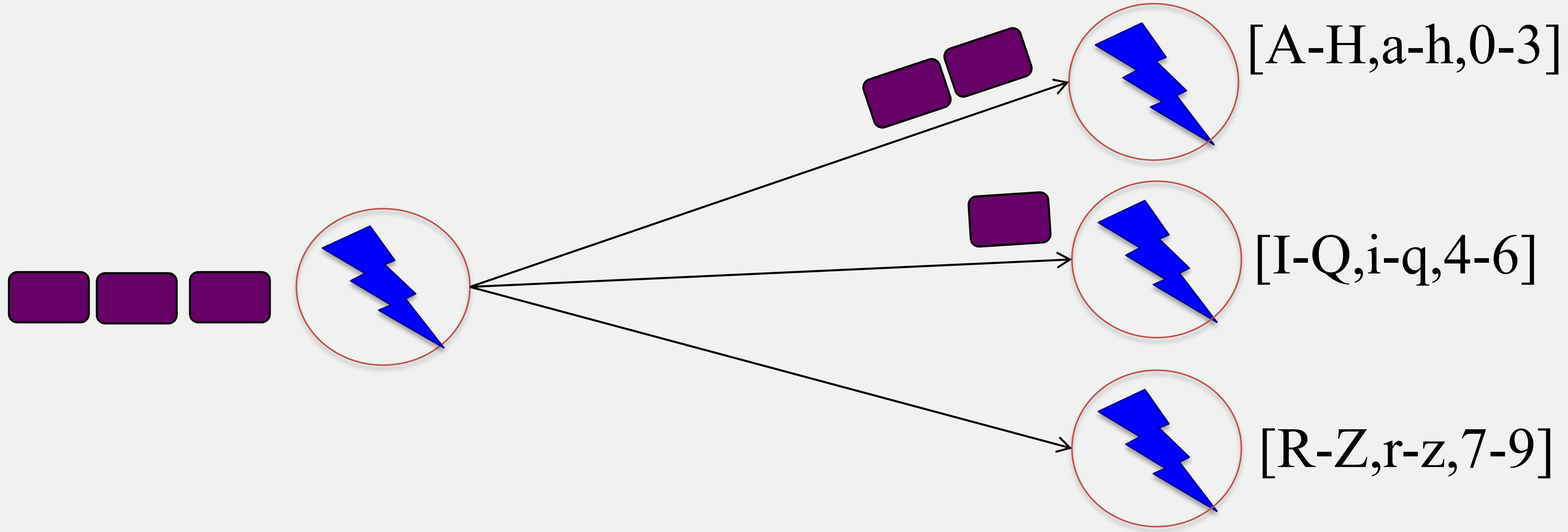
Grouping

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



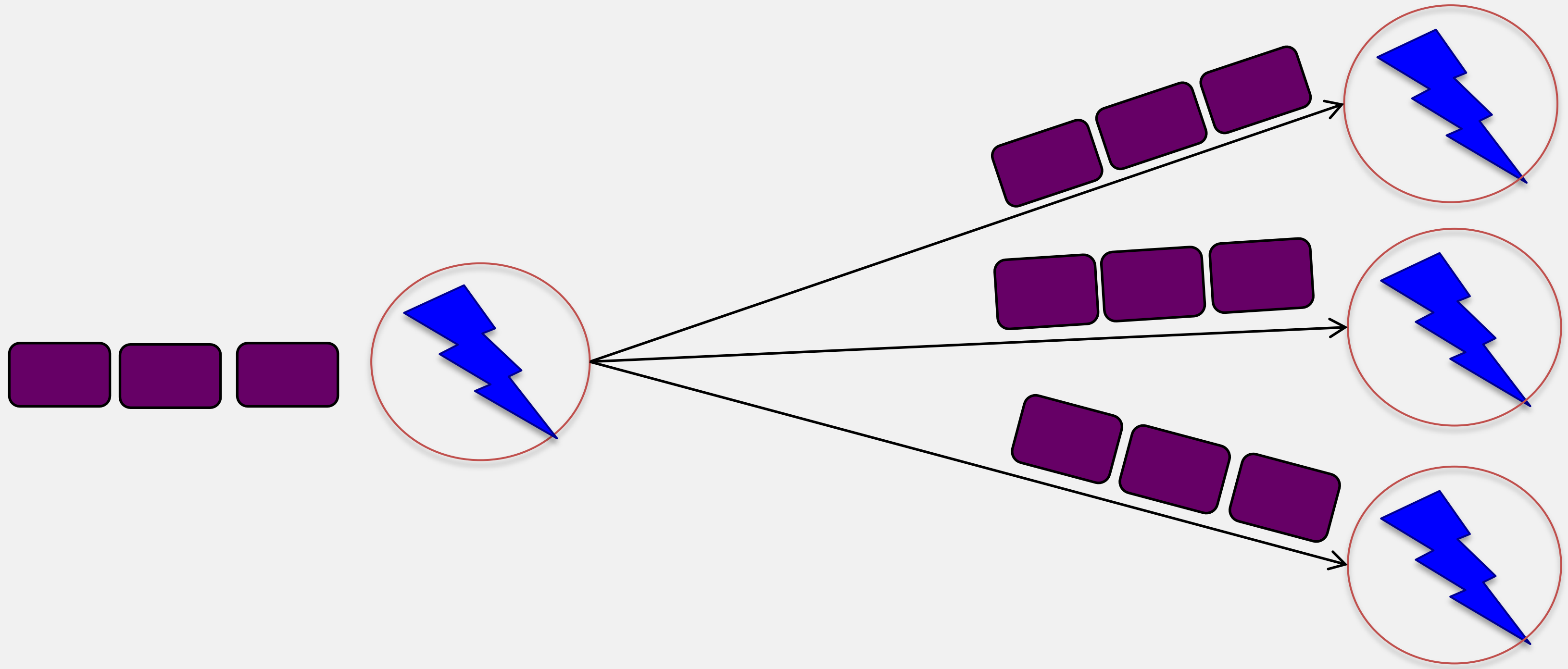
Grouping

- **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



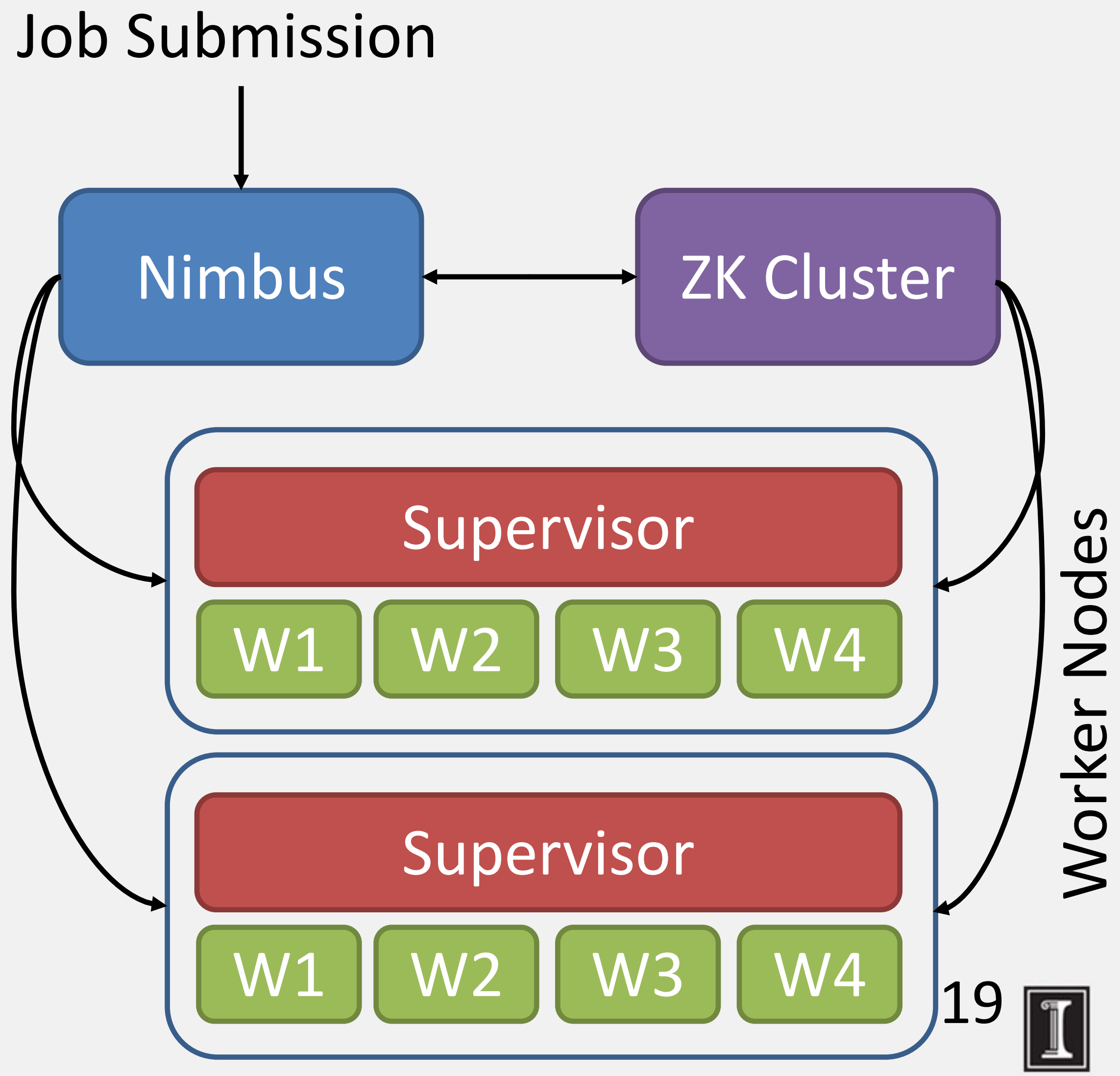
Grouping

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



Storm Cluster

- Master (Coordinator or Leader) 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 machine
  - 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 (Optional Additional Slide)

- 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

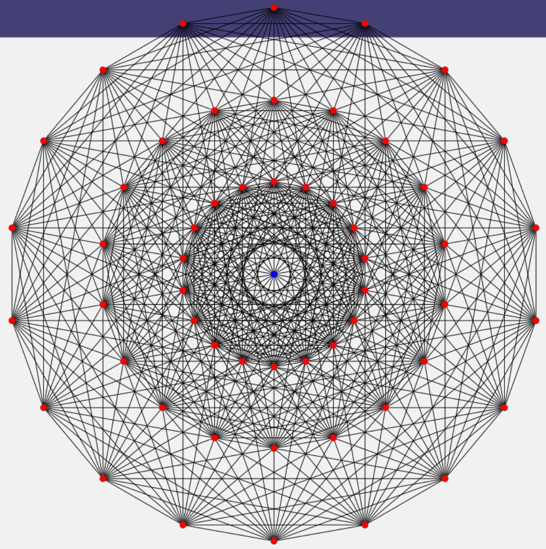
- Processing data in real-time a big requirement today
- Storm
  - And other sister systems, e.g., Spark Streaming, Heron, (LinkedIn's Samza, "Kafka", etc.)
- Parallelism
- Application topologies
- Fault-tolerance

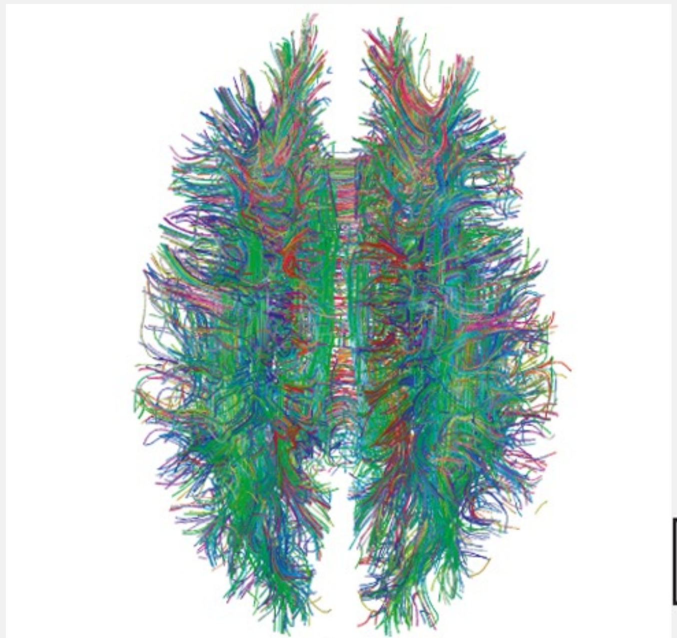
Graph Processing: What We'll Cover

- 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

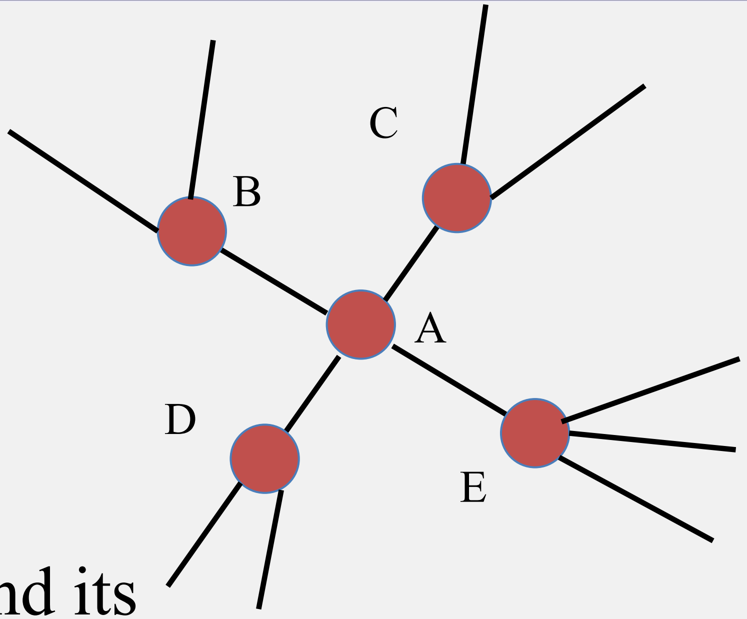
- And many (many) other examples!

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

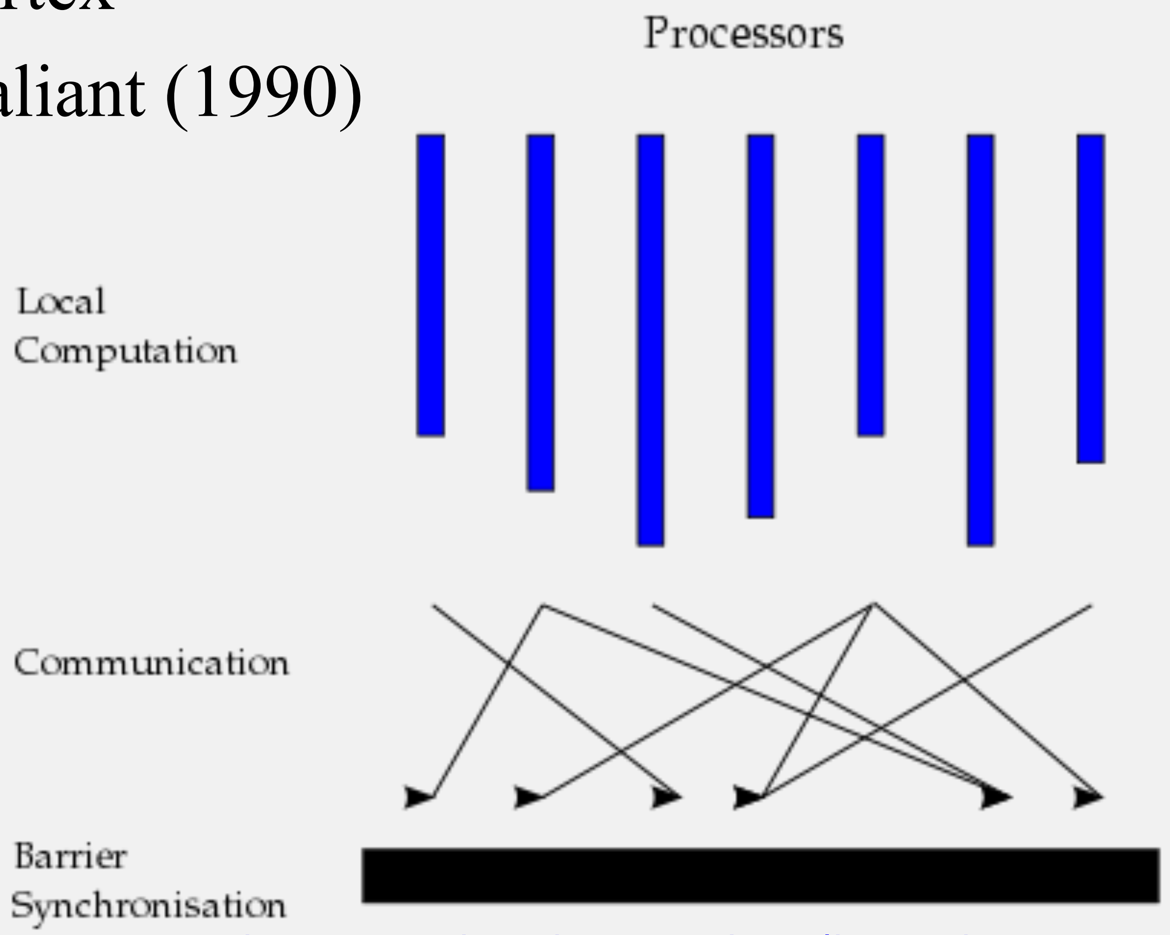
☹ At the end of every stage, transfer all vertices over network (to neighbor vertices)

  ☹ All vertex values written to HDFS (file system)

  ☹ Very slow!

Bulk Synchronous Parallel Model

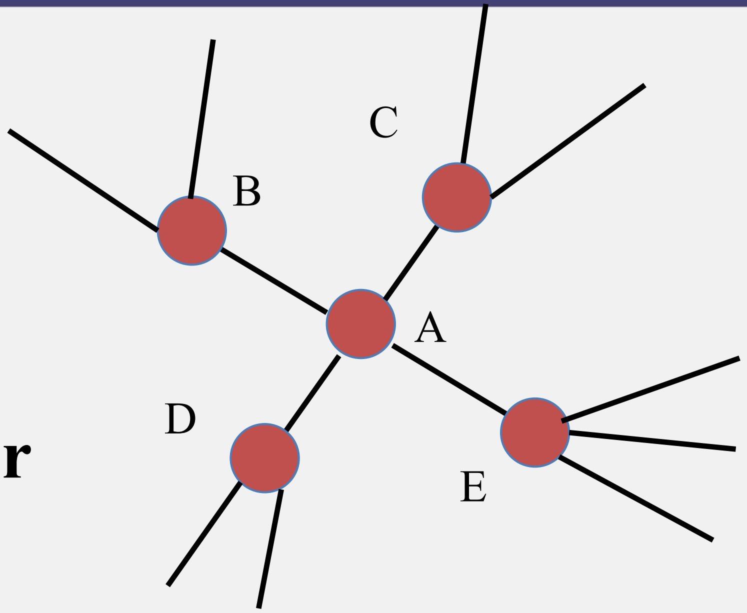
- “Think like a vertex”
- Originally by Valiant (1990)



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 leader/worker model
  - Leader (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 leader ("Master" originally) assigns a partition of input (vertices) to each worker
    - Each worker loads the vertices and marks them as *active*
3. The leader instructs each worker to perform an 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, leader starts next iteration
4. Computation halts when, in some iteration: no vertices are active and when no messages are in transit
5. Leader instructs each worker to save its portion of the graph

Fault-Tolerance in Pregel

- **Checkpointing**
  - Periodically, leader 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 leader → worker
- **Recovery**
  - The leader 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

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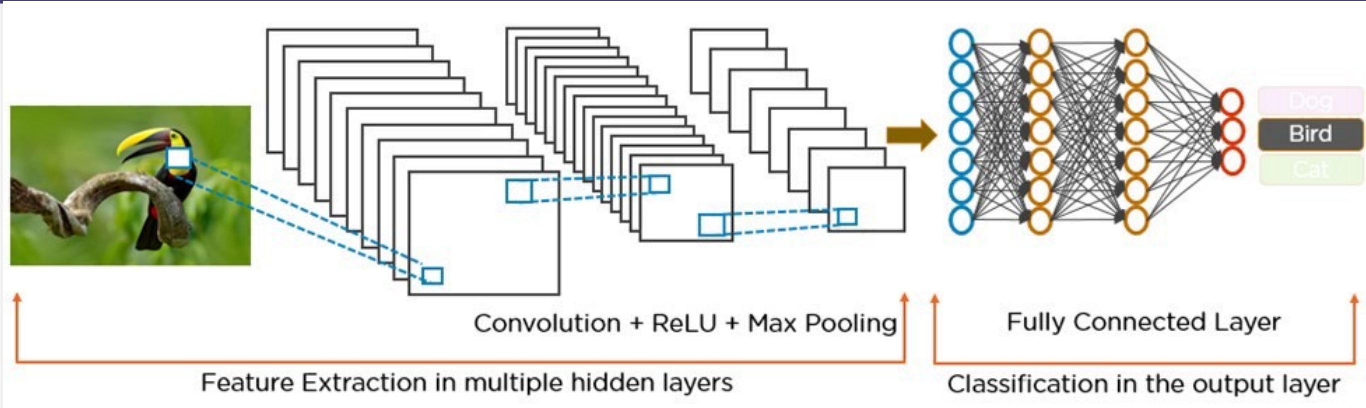
Lecture 26 A (contd.): Machine Learning (in syllabus)

Basic ML: SGD

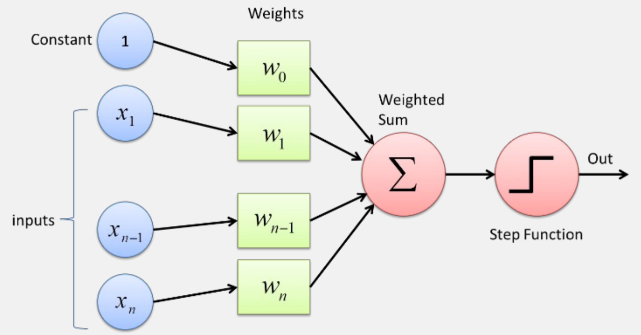
"Machine learning is nothing but damn statistics." – A lot of people

- Machine learning trains "models" (computer representations)
- Training vs. Inference (latter called Prediction, or Model Serving)
- Supervised vs. Unsupervised learning
- SGD = Stochastic Gradient Descent
  - Minimize an objective function that is smooth and differentiable
  - Popular variants: AdaGrad (adaptive gradient), Adam (adaptive moment), RMSProp
  - A common strawman application for many distributed ML papers!

Basic Neural Networks


Dog
Bird
Cat
Convolution + ReLU + Max Pooling
Fully Connected Layer
Feature Extraction in multiple hidden layers
Classification in the output layer

- ANN = Artificial Neural Network
  - Another kind of "model"
  - A common form of representation learning
  - Used widely in vision, NLP, …
- Graphs of operators
- Operators can be computationally heavy
- Graph can be in "stages" or "layers"



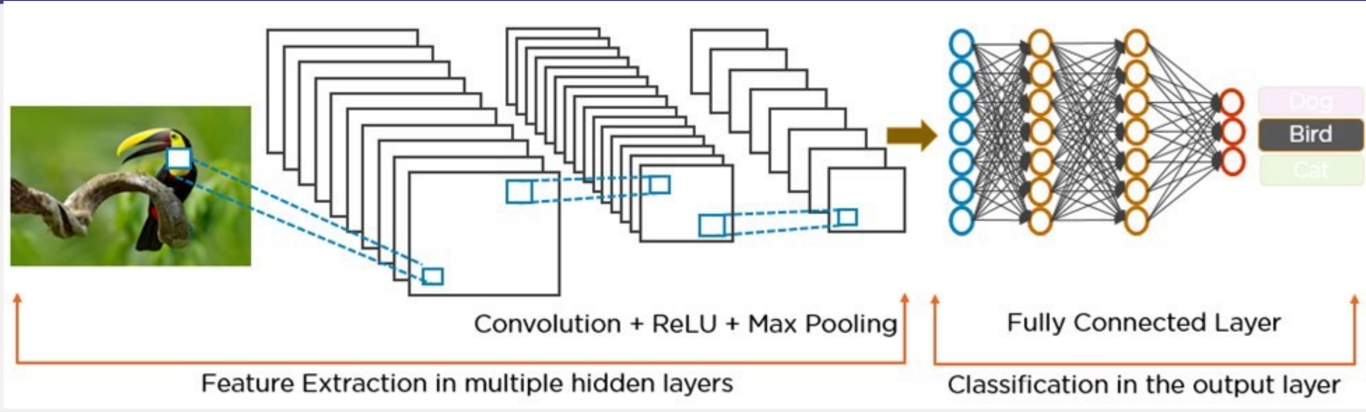
A Perceptron layer

- Common: All to all communication between operators in consecutive stages
- Most edges have a set of associated weights (parameters). (Exceptions: activation funcs (ReLU), dropout). The collection of these weights IS the model.

Basic Neural Networks (2)

- Data passed into train passes “forwards”, followed by calculating error against known result (supervised learning)
  - followed by “backward” pass that adjusts/updates the weights at operators (so that for an incorrect training pass, if the same input were to be passed through, the result would be correct)
- Data between operators: tensors (multi-dimensional vectors)
- Default: train on one item (forward + backward), followed by next item
  - Extension: train on a mini-batch of items
- After model is trained, Prediction/Inference needs only forward pass
- Emerging area: Online training : do both training and inference together (aka Continual training)
- Hyperparameter: configuration parameter for your model (not to be confused with a model “weight” == parameter), e.g., batch size

ANN Types: FFNN, CNNs, RNNs


Dog
Bird
Cat
Convolution + ReLU + Max Pooling
Fully Connected Layer
Feature Extraction in multiple hidden layers
Classification in the output layer

- FFNN: feed forward neural net (no loops)
- DNN: Deep NN
  - More than one stage
  - “Hidden” layers between input and output
- CNN: Convolutional NN
  - DNN + additional layers for convolutions
  - Transform data, e.g., sequence of filters that result in an activation/detection, e.g., image.
  - E.g., Facebook photo captioning
- RNN: Recurrent NN
  - DNN + loops within layer (e.g., time aspect (e.g., GIF), sequential aspects)
  - E.g., auto-correction on your phone
- Other types: GNN (graph neural net), Transformer, …
- A few neural nets used in evaluation of distributed machine learning
  - Inception(v3), (G)NMT, Resnet,…

Distributed Machine Learning

Training data – collection of input and output labels x_i, y_i of size N

Learn model weights w

Model size and N can be huge

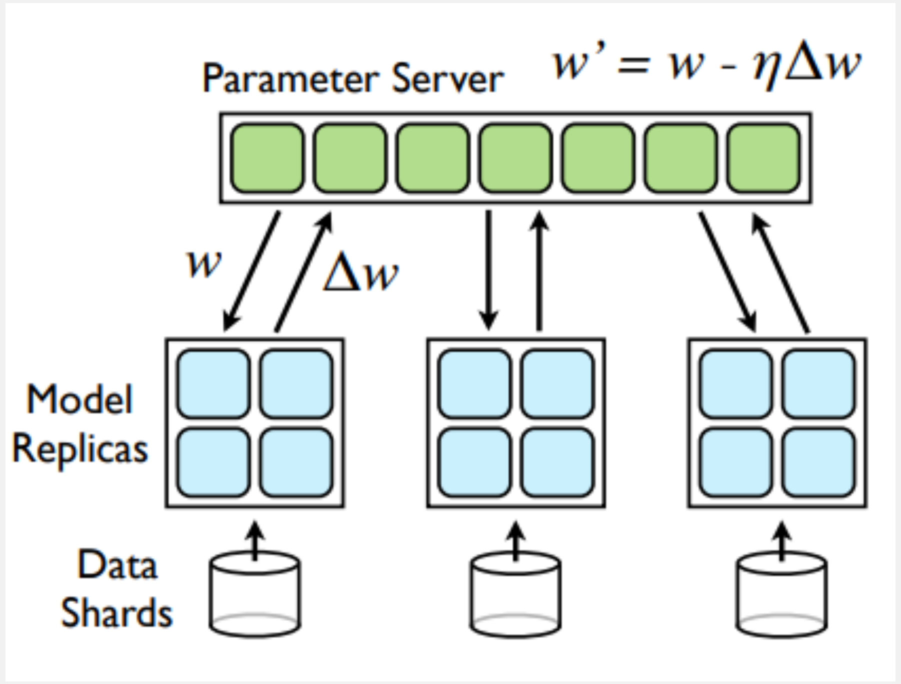
Centralized Machine Learning

Slow and often infeasible

Distributed Machine Learning

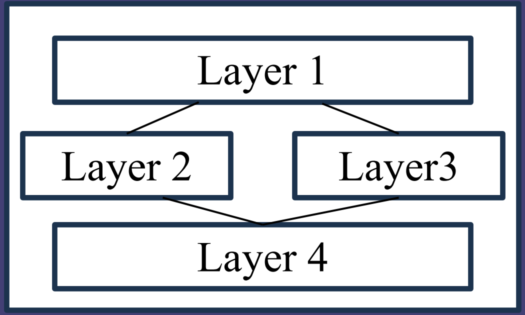
Parallelize via Multiple workers

"Parameter Server" to aggregate data from workers from current iteration and start next iteration at workers.



Dean, Jeffrey, et al. "Large scale distributed deep networks." Advances in Neural Information Processing Systems (NeurIPS) 25 (2012).

Kinds of Parallelism

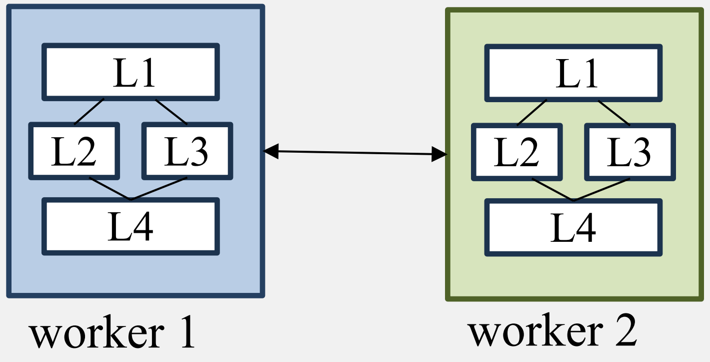


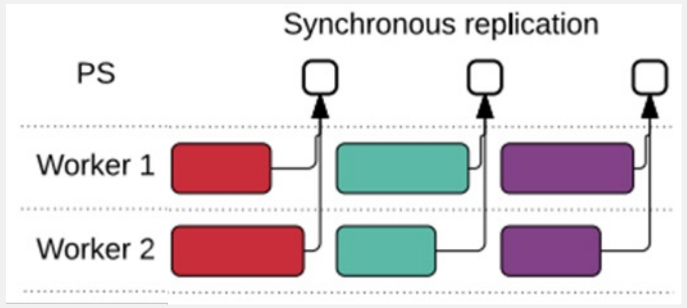
Data parallelism: multiple workers run same model, different data is sent to each device, data "batched" into mini-batches

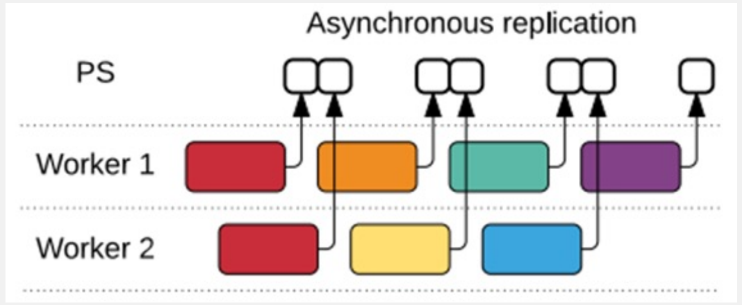
Workers synchronize after each mini-batch

1. Parameter Server approach
2. All-Reduce approach – workers multicast weights to all other workers

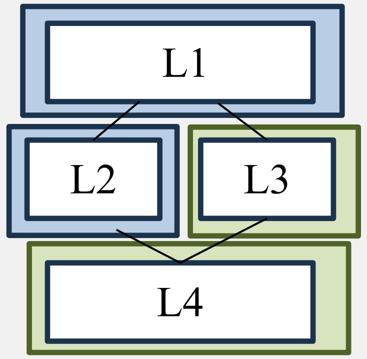
Variant: Asynchronous training







Model parallelism: same model (DNN graph) is split across multiple devices, one input passed through collection of devices at a time.



TensorFlow

Built by Google

Framework for large-scale training and inference

Hides details of distribution

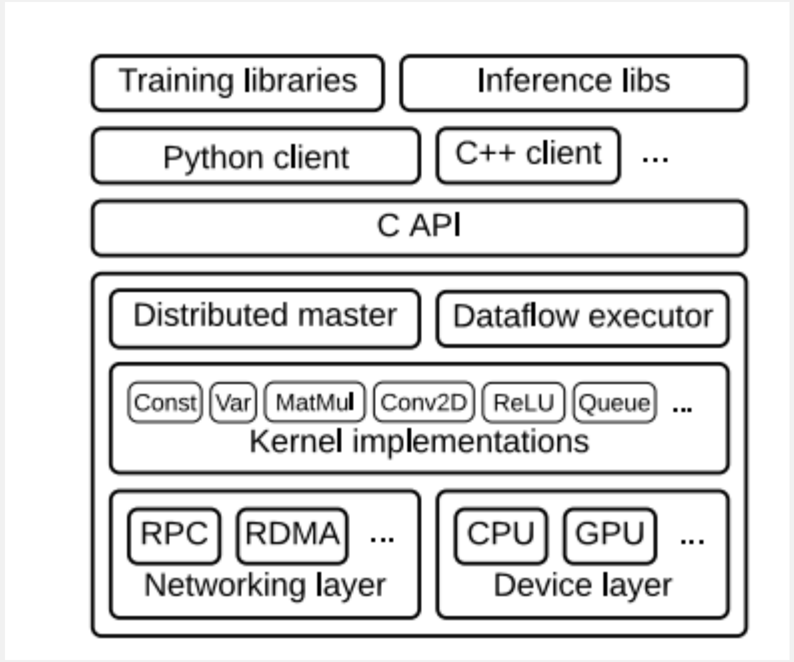
Uses dataflow graphs to represent computation, shared state, and operations that mutate state

Dataflow captures structure of computation in ML

Extensible, runtime contains over 200 standard operations

Support for CPUs, GPUs, and TPUs (Tensor Processing Units)

Different communication protocols



Abadi, Martín, et al. "TensorFlow: a system for Large-Scale machine learning." 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16). 2016.

Image classifier using TensorFlow API

```
# 1. Construct a graph representing the model.
x = tf.placeholder(tf.float32, [BATCH_SIZE, 784]) # Placeholder for input.
y = tf.placeholder(tf.float32, [BATCH_SIZE, 10]) # Placeholder for labels.

W_1 = tf.Variable(tf.random_uniform([784, 100])) # 784x100 weight matrix.
b_1 = tf.Variable(tf.zeros([100])) # 100-element bias vector.
layer_1 = tf.nn.relu(tf.matmul(x, W_1) + b_2) # Output of hidden layer.

W_2 = tf.Variable(tf.random_uniform([100, 10])) # 100x10 weight matrix.
b_2 = tf.Variable(tf.zeros([10])) # 10-element bias vector.
layer_2 = tf.matmul(layer_1, W_2) + b_2 # Output of linear layer.

# 2. Add nodes that represent the optimization algorithm.
loss = tf.nn.softmax_cross_entropy_with_logits(layer_2, y)
train_op = tf.train.AdagradOptimizer(0.01).minimize(loss)

# 3. Execute the graph on batches of input data.
with tf.Session() as sess: # Connect to the TF runtime.
     sess.run(tf.initialize_all_variables()) # Randomly initialize weights.
     for step in range(NUM_STEPS): # Train iteratively for NUM_STEPS.
            x_data, y_data = ... # Load one batch of input data.
            sess.run(train_op, {x: x_data, y: y_data}) # Perform one training step.
```

PyTorch

Another popular ML framework originally developed by Meta

Tesla Autopilot, Uber's Pyro, Hugging Face's Transformers

Dynamic computation graphs

Automatic computation of gradients

Implements many algorithms and components

Domain-specific – TorchText, TorchVision, and TorchAudio – include datasets

Tensors – n-dimensional arrays

Module – define what makes up the model and a forward member function.

E.g., Linear Module

- weight and bias as parameters
- forward function generates output as input * weight + bias

Example with DistributedDataParallel

```
dist.init_process_group("gloo", rank=rank, world_size=world_size) # create default process group

model = nn.Linear(10, 10).to(rank) # create local model
ddp_model = DDP(model, device_ids=[rank]) # construct DDP model

# define loss function and optimizer
loss_fn = nn.MSELoss()
optimizer = optim.SGD(ddp_model.parameters(), lr=0.001)

# forward pass
outputs = ddp_model(torch.randn(20, 10).to(rank))
labels = torch.randn(20, 10).to(rank)

# backward pass
loss_fn(outputs, labels).backward()

# update parameters
optimizer.step()
```

Jax

- ML framework from Google
- Provides a familiar NumPy-style API
- Multiple backends, including CPU, GPU, & TPU
- grad: automatic differentiation
- jit: compilation
- vmap: auto-vectorization
- pmap: automatic parallelization

Other ML

Distributed ML

assumes homogenous data across workers

Federated Machine Learning

allows heterogeneous data across workers

workers may be datacenters or mobile devices

failures, possibly privacy issues.

E.g., Google’s Federated learning to predict keystrokes from mobile devices

Summary of this Lecture, and one more video to watch!

Emerging topics in Distributed Computing

- Stream Processing (in syllabus)
- Graph Processing (in syllabus)
- Machine Learning (in syllabus)

- **Additional Video on Course website (In Syllabus, NOT optional): Spark**