Big Data Systems

Big Data Parallelism

- Huge data set
  - crawled documents, web request logs, etc.
- Natural parallelism:
  - can work on different parts of data independently
  - image processing, grep, indexing, many more

Challenges

- Parallelize application
  - Where to place input and output data?
  - Where to place computation?
  - How to communicate data? How to manage threads? How to avoid network bottlenecks?
- Balance computations
- Handle failures of nodes during computation
- Scheduling several applications who want to share infrastructure

Goal of MapReduce

- To solve these distribution/fault-tolerance issues once in a reusable library
  - To shield the programmer from having to re-solve them for each program
- To obtain adequate throughput and scalability
- To provide the programmer with a conceptual framework for designing their parallel program

Map Reduce

- Overview:
  - Partition large data set into M splits
  - Run map on each partition, which produces R local partitions; using a partition function R
    - Hidden intermediate shuffle phase
  - Run reduce on each intermediate partition, which produces R output files

Details

- Input values: set of key-value pairs
    - Job will read chunks of key-value pairs
    - “key-value” pairs a good enough abstraction
- Map(key, value):
    - System will execute this function on each key-value pair
    - Generate a set of intermediate key-value pairs
- Reduce(key, values):
    - Intermediate key-value pairs are sorted
    - Reduce function is executed on these intermediate key-values

Count words in web-pages

```
Map(key, value) {
   // key is url
   // value is the content of the url
   For each word W in the content
      Generate(W, 1);
}


Reduce(key, values) {
   // key is word (W)
   // values are basically all 1s
   Sum = Sum all 1s in values

   // generate word-count pairs
   Generate (key, sum);
}
```

Reverse web-link graph

Go to google advanced search:
"find pages that link to the page:" cnn.com

```
Map(key, value) {
   // key = url
   // value = content
   For each url, linking to target
      Generate(output target, url);
}

Reduce(key, values) {
   // key = target url
   // values = all urls that point to the target url
   Generate(key, list of values);
}
```

- Question: how do we implement “join” in MapReduce?
  - Imagine you have a log table L and some other table R that contains say user information
  - Perform Join (L.uid == R.uid)
    - Say size of L >> size of R
    - Bonus: consider real world zipf distributions

Comparisons

- Worth comparing it to other programming models:
  - distributed shared memory systems
  - bulk synchronous parallel programs
  - key-value storage accessed by general programs
- More constrained programming model for MapReduce
- Other models are latency sensitive, have poor throughput efficiency
- MapReduce provides for easy fault recovery

Implementation

- Depends on the underlying hardware: shared memory, message passing, NUMA shared memory, etc.
- Inside Google:
  - commodity workstations
  - commodity networking hardware (1Gbps - 10Gbps now - at node level and much smaller bisection bandwidth)
  - cluster = 100s or 1000s of machines
  - storage is through GFS

MapReduce Input

- Where does input come from?
  - Input is striped+replicated over GFS in 64 MB chunks
  - But in fact Map always reads from a local disk
  - They run the Maps on the GFS server that holds the data
- Tradeoff:
  - Good: Map reads at disk speed (local access)
  - Bad: only two or three choices of where a given Map can run
    - potential problem for load balance, stragglers

Intermediate Data

- Where does MapReduce store intermediate data?
  - On the local disk of the Map server (not in GFS)
- Tradeoff:
  - Good: local disk write is faster than writing over network to GFS server
  - Bad: only one copy, potential problem for fault-tolerance and load-balance

Output Storage

- Where does MapReduce store output?
    - In GFS, replicated, separate file per Reduce task
    - So output requires network communication -- slow
    - It can then be used as input for subsequent MapReduce

Question

- What are the scalability bottlenecks for MapReduce?

Scaling

- Map calls probably scale
  - but input might not be infinitely partitionable, and small input/intermediate files incur high overheads
- Reduce calls probably scale
  - but can't have more workers than keys, and some keys could have more values than others
- Network may limit scaling
- Stragglers could be a problem

Fault Tolerance

- The main idea: Map and Reduce are deterministic, functional, and independent
  - so MapReduce can deal with failures by re-executing
- What if a worker fails while running Map?
  - Can we restart just that Map on another machine?
  - Yes: GFS keeps copy of each input split on 3 machines
  - Master knows, tells Reduce workers where to find intermediate files

Fault Tolerance

- If a Map finishes, then that worker fails, do we need to re-run that Map?
  - Intermediate output now inaccessible on worker's local disk.
  - Thus need to re-run Map elsewhere *unless* all Reduce workers have already fetched that Map's output.
- What if Map had started to produce output, then crashed?
  - Need to ensure that Reduce does not consume the output twice
- What if a worker fails while running Reduce?

Role of the Master

- Keeps state regarding the state of each worker machine (pings each machine)
- Reschedules work corresponding to failed machines
- Orchestrates the passing of locations to reduce functions

Load Balance

- What if some Map machines are faster than others?
  - Or some input splits take longer to process?
  - Solution: many more input splits than machines
  - Master hands out more Map tasks as machines finish
  - Thus faster machines do bigger share of work
- But there's a constraint:
  - Want to run Map task on machine that stores input data
  - GFS keeps 3 replicas of each input data split
  - only three efficient choices of where to run each Map task

Stragglers

- Often one machine is slow at finishing very last task
  - bad hardware, overloaded with some other work
- Load balance only balances newly assigned tasks
- Solution: always schedule multiple copies of very last tasks!

How many MR tasks?

- Paper uses M = 10x number of workers, R = 2x.
  - More =>
    - finer grained load balance.
    - less redundant work for straggler reduction.
    - spread tasks of failed worker over more machines
    - overlap Map and shuffle, shuffle and Reduce.
  - Less => big intermediate files w/ less overhead.
  - M and R also maybe constrained by how data is striped in GFS (e.g., 64MB chunks)

Discussion

- what are the constraints imposed on map and reduce functions?
- how would you like to expand the capability of map reduce?

Map Reduce Criticism

- “Giant step backwards” in programming model
- Sub-optimal implementation
- “Not novel at all”
- Missing most of the DB features
- Incompatible with all of the DB tools

Comparison to Databases

- Huge source of controversy; claims:
  - parallel databases have much more advanced data processing support that leads to much more efficiency
    - support an index; selection is accelerated
    - provides query optimization
  - parallel databases support a much richer semantic model
    - support a schema; sharing across apps
    - support SQL, efficient joins, etc.

Where does MR win?

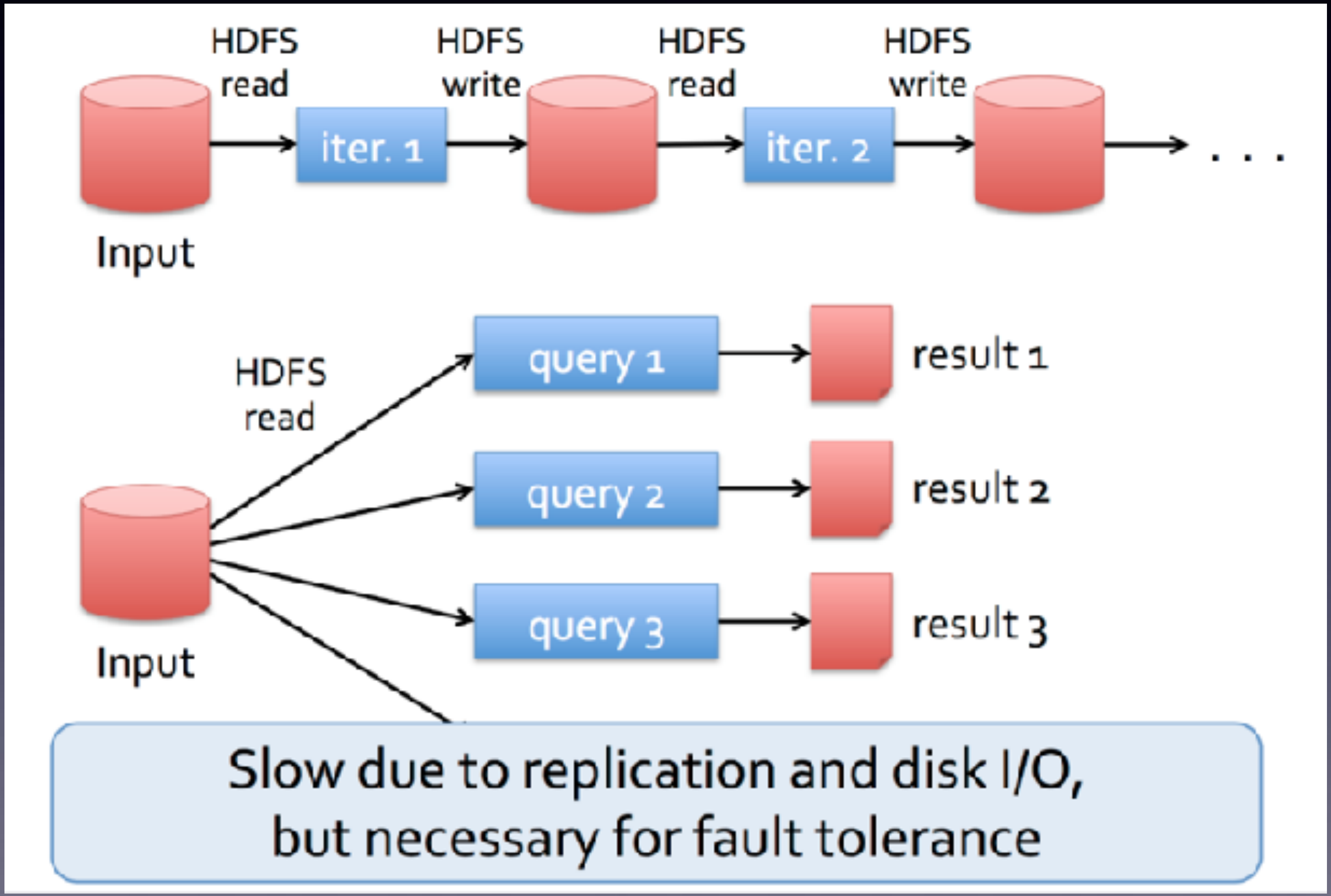
- Scaling
- Loading data into system
- Fault tolerance (partial restarts)
- Approachability

Spark Motivation

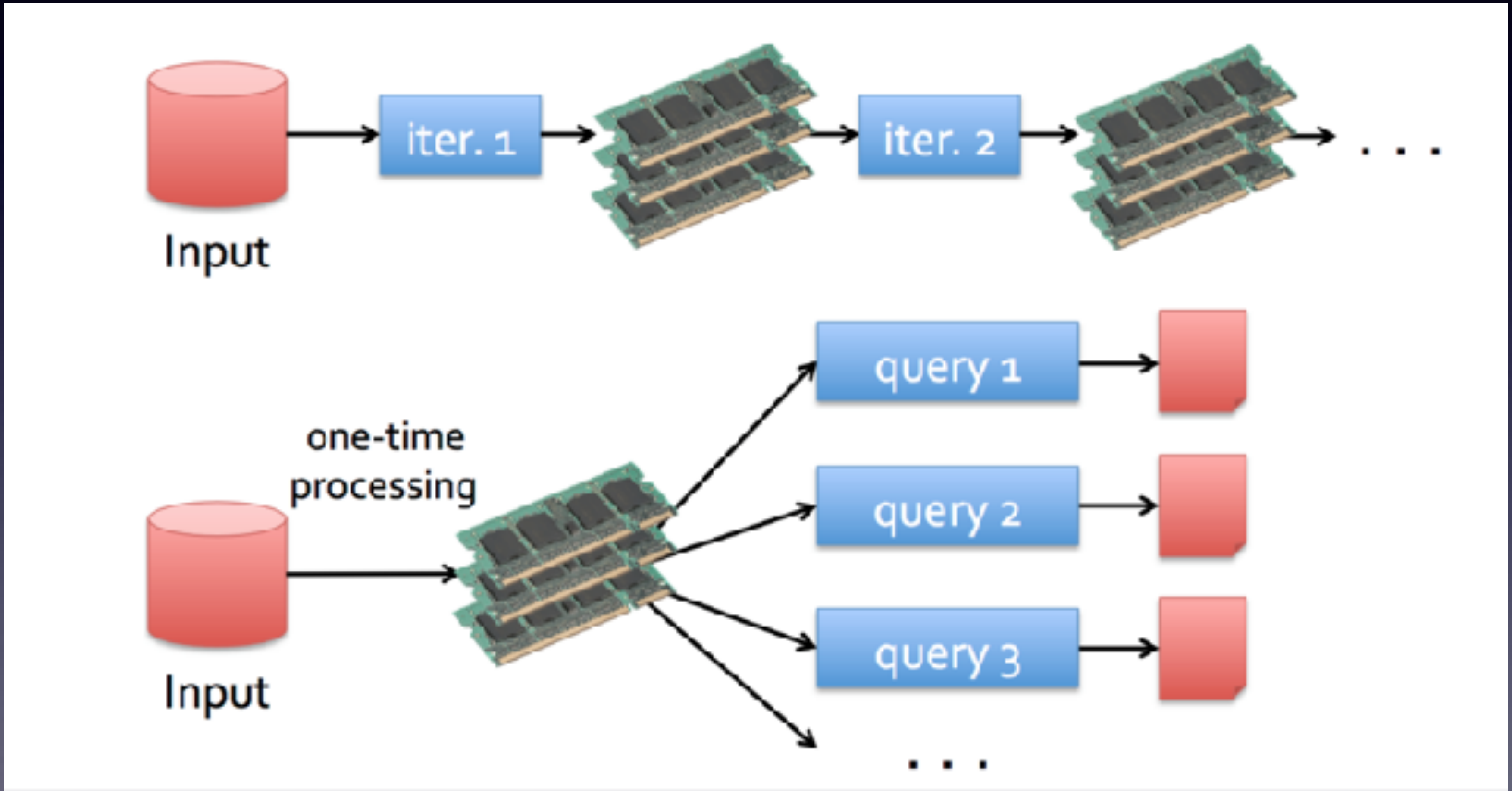
- MR Problems
  - cannot support complex applications **efficiently**
  - cannot support interactive applications **efficiently**
- Root cause
  - Inefficient data sharing

In MapReduce, the only way to share data across jobs is stable storage -> **slow**!

Motivation


HDFS read
HDFS write
HDFS read
HDFS write
iter. 1
iter. 2
. . .
Input
HDFS read
query 1
query 2
query 3
result 1
result 2
result 3
Input
Slow due to replication and disk I/O,
but necessary for fault tolerance

Goal: In-Memory Data Sharing



Challenge

- How to design a distributed memory abstraction that is both fault tolerant and efficient?

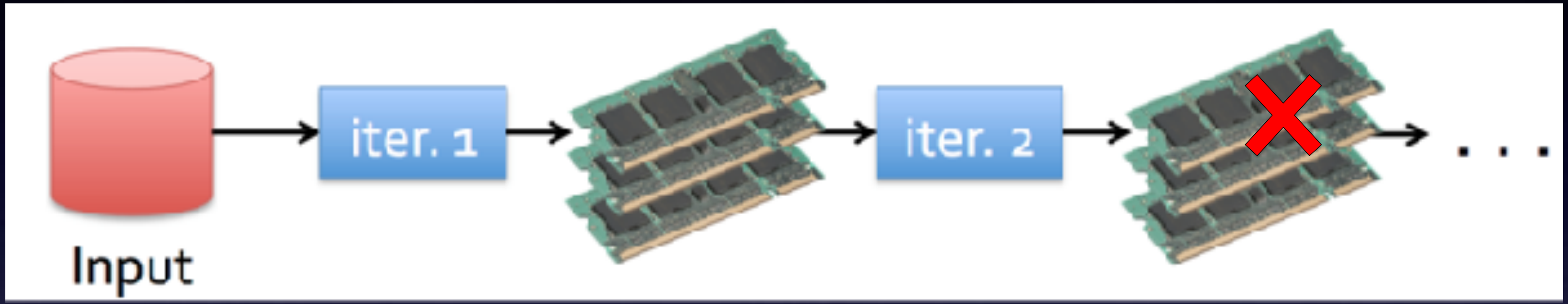
Other options

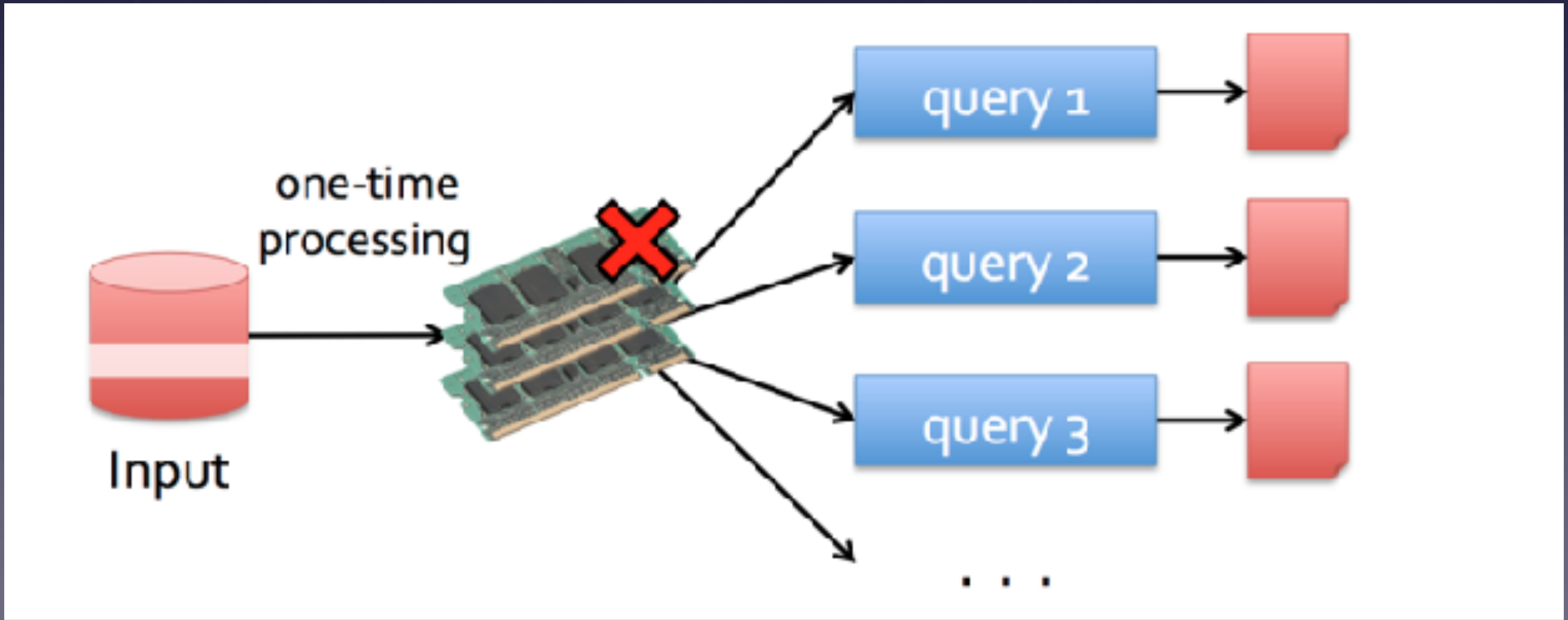
- Existing storage abstractions have interfaces based on fine-grained updates to mutable state
  - E.g., RAMCloud, databases, distributed mem, Piccolo
- Requires replicating data or logs across nodes for fault tolerance
  - Costly for data-intensive apps
  - 10-100x slower than memory write

RDD Abstraction

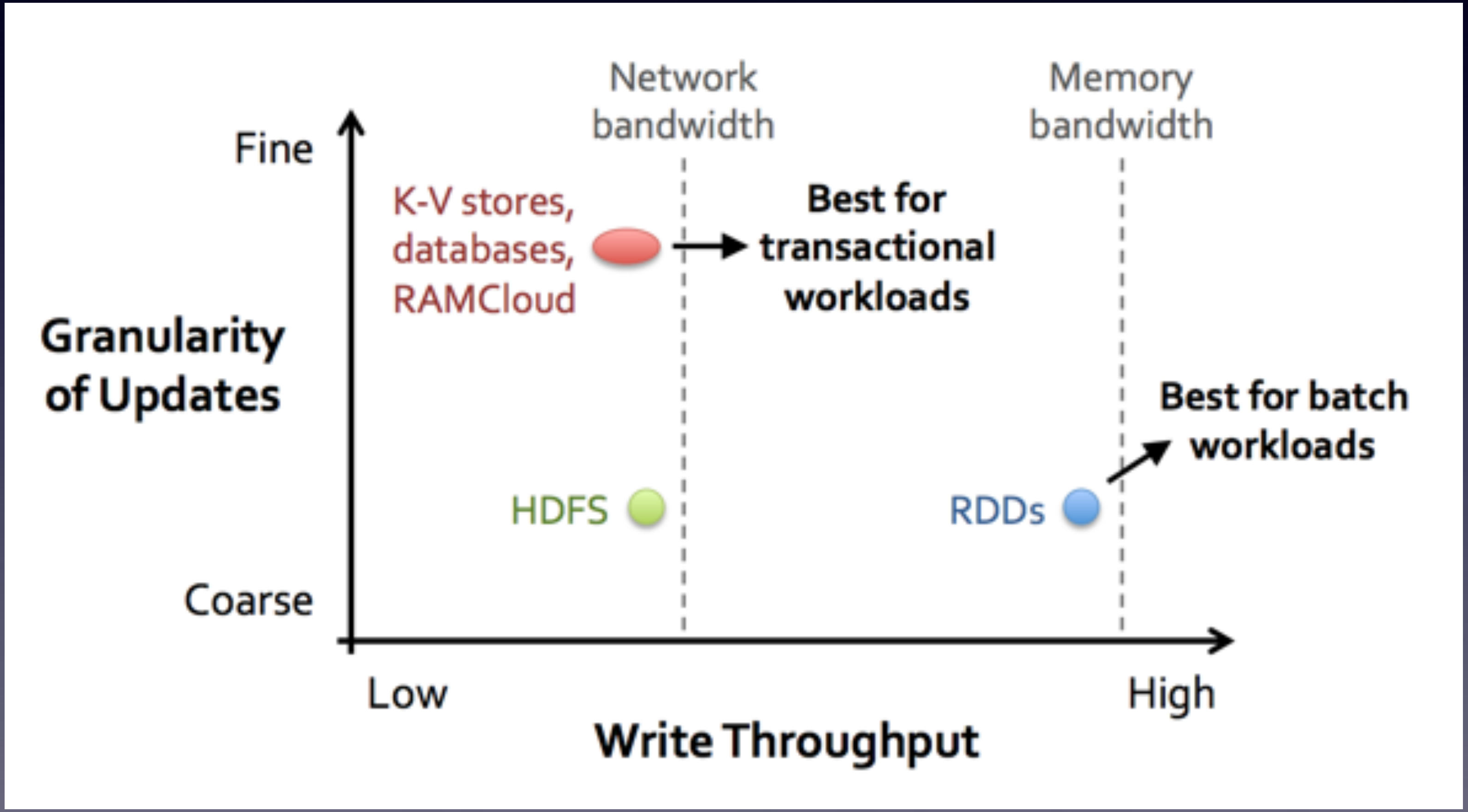
- Restricted form of distributed shared memory
  - immutable, partitioned collection of records
  - can only be built through coarse-grained deterministic transformations (map, filter, join…)
- Efficient fault-tolerance using lineage
  - Log coarse-grained operations instead of fine-grained data updates
  - An RDD has enough information about how it's derived from other dataset
  - Recompute lost partitions on failure

Fault-tolerance





Design Space



Operations

- Transformations (e.g. map, filter, groupBy, join)
  - Lazy operations to build RDDs from other RDDs
- Actions (e.g. count, collect, save)
  - Return a result or write it to storage

Example: Mining Console Logs

Load error messages from a log into memory, then interactively search

Base RDD

Transformed RDD

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split('\t')[2])
messages.persist()
```

Action

```
messages.filter(lambda s: "foo" in s).count()
messages.filter(lambda s: "bar" in s).count()
. . .
```

Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)

Result: scaled to 1 TB data in 5-7 sec (vs 170 sec for on-disk data)

RDD Fault Tolerance

RDDs track the transformations used to build them (their *lineage*) to recompute lost data

E.g:

```
messages = textFile(...).filter(lambda s: s.contains(“ERROR”))
                        .map(lambda s: s.split(‘\t’)[2])
```

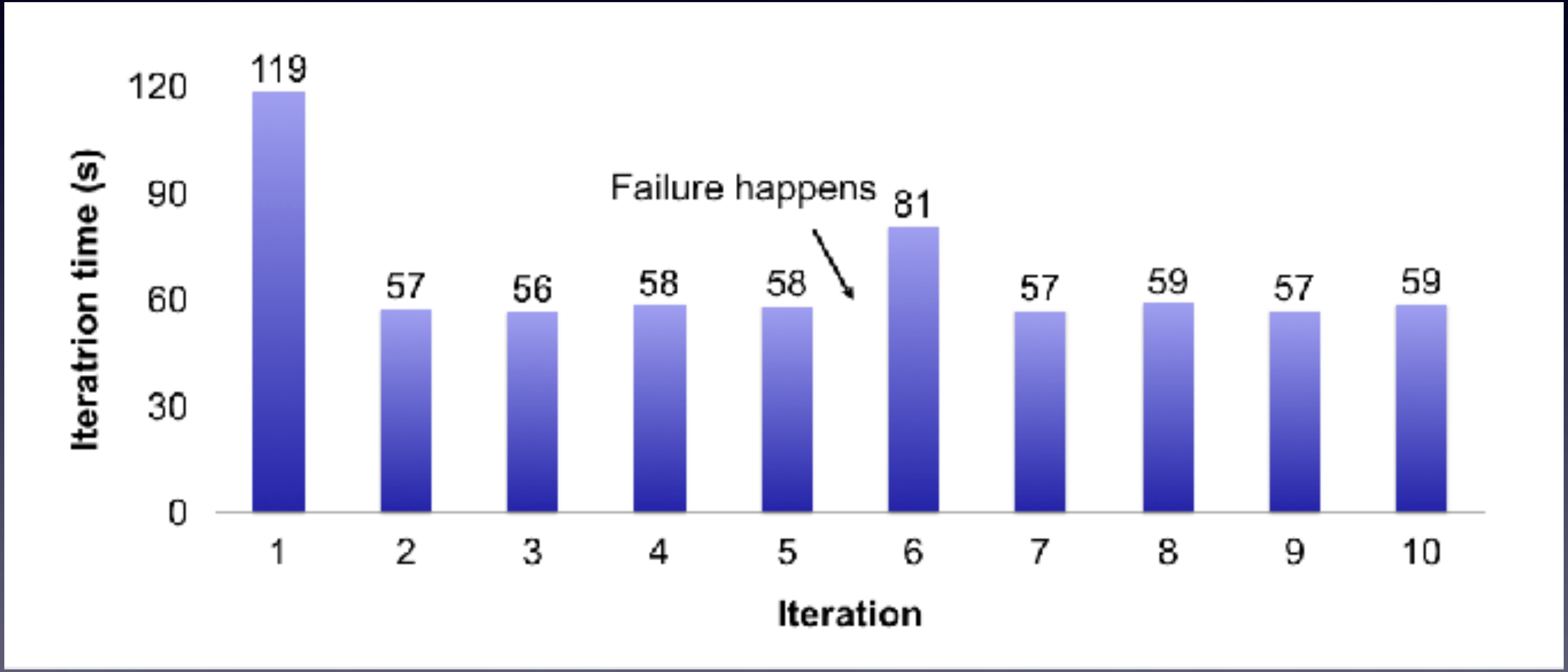
Lineage

- Spark uses the lineage to schedule jobs
  - Transformation on the same partition form a stage
    - Joins, for example, are a stage boundary
    - Need to reshuffle data
- A job runs a single stage
  - pipeline transformation within a stage
- Schedule job where the RDD partition is

Lineage & Fault Tolerance

- Great opportunity for ***efficient*** fault tolerance
  - Let's say one machine fails
  - Want to recompute only its state
  - The lineage tells us what to recompute
    - Follow the lineage to identify all partitions needed
    - Recompute them
- For last example, identify partitions of lines missing
  - All dependencies are “narrow”; each partition is dependent on one parent partition
  - Need to read the missing partition of lines; recompute the transformations

Fault Recovery



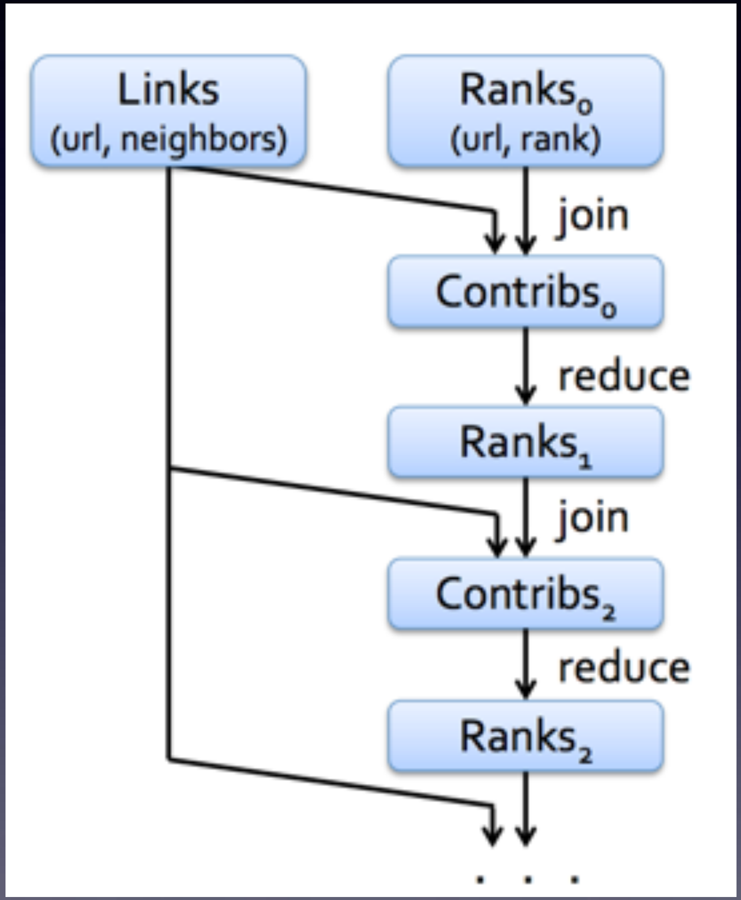
Example: PageRank

1. Start each page with a rank of 1
2. On each iteration, update each page's rank to

$$\Sigma_{i \in \text{neighbors}} \text{rank}_i \,/\, |\text{neighbors}_i|$$

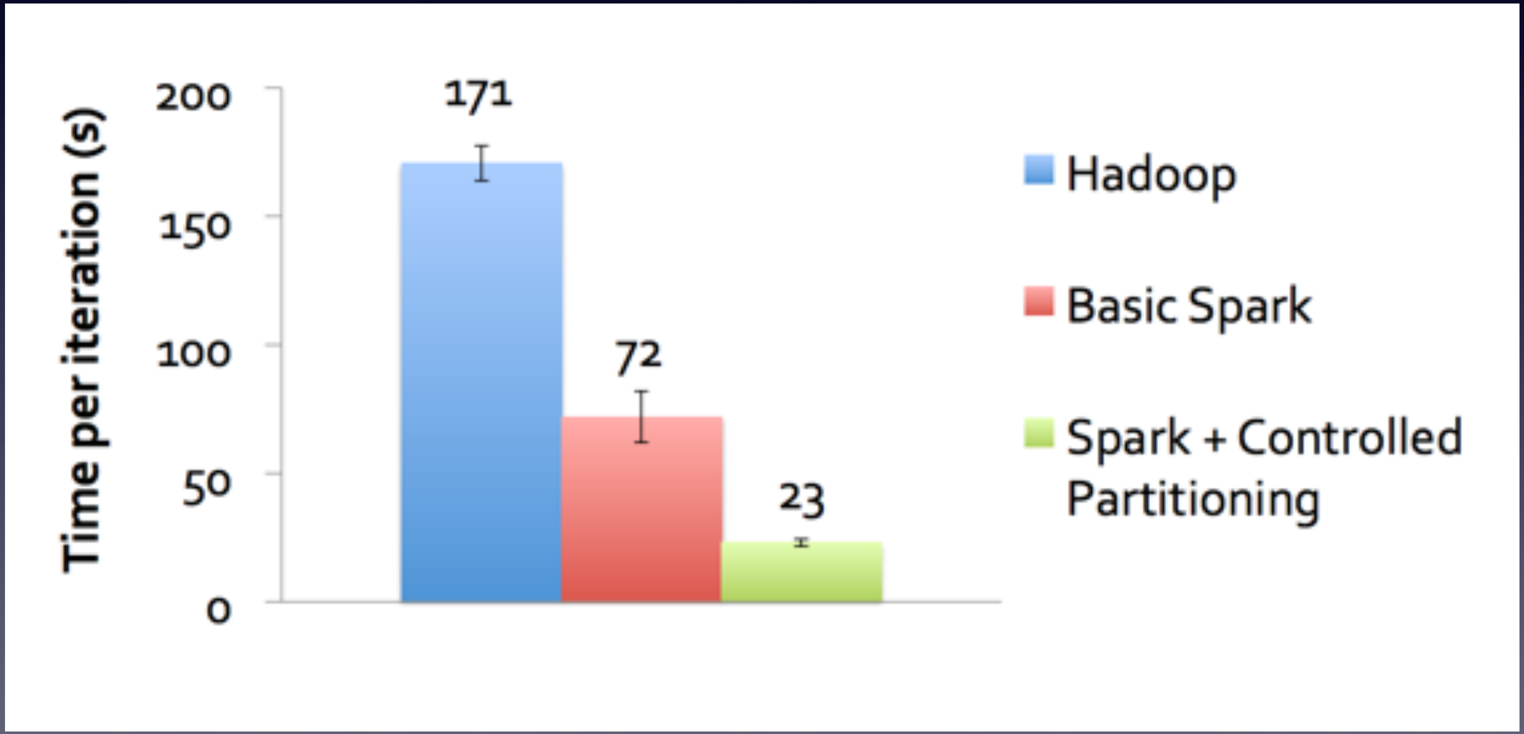
```
links = // RDD of (url, neighbors) pairs
ranks = // RDD of (url, rank) pairs

for (i <- 1 to ITERATIONS) {
  ranks = links.join(ranks).flatMap {
    (url, (links, rank)) =>
      links.map(dest => (dest, rank/links.size))
  }.reduceByKey(_ + _)
}
```

Optimizing Placement



- links & ranks repeatedly joined
- Can co-partition them (e.g., hash both on URL)
- Can also use app knowledge, e.g., hash on DNS name

PageRank Performance



TensorFlow: System for ML

- Open Source, lots of developers, external contributors
- Used in: RankBrain (rank results), Photos (image recognition), SmartReply (automatic email responses)

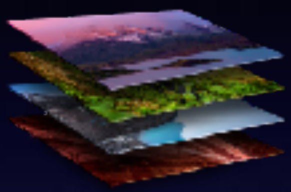
Three types of ML

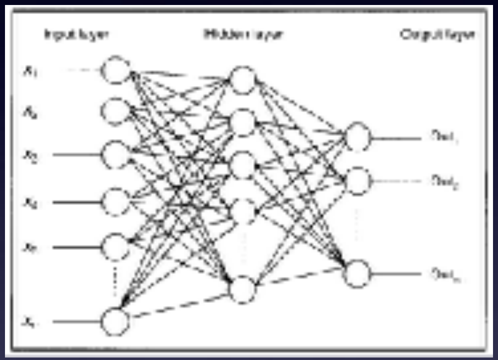
- Large scale training: huge datasets, generate models
  - Google's previous DistBelief for 100s of machines
- Low latency inference: running models in datacenters, phones, etc.
  - Custom engines
- Testing new ideas
  - Single node flexible systems (Torch, Theano)

TensorFlow

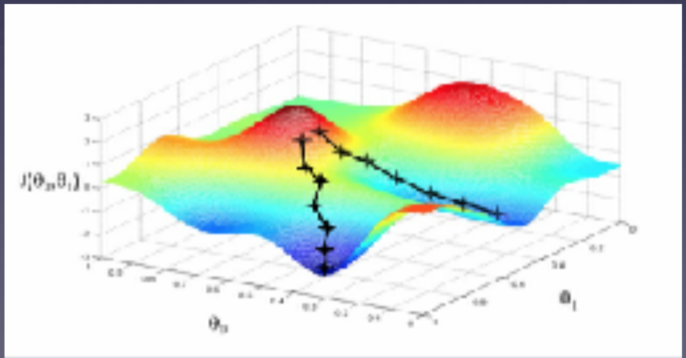
- Common way to write programs
- Dataflow + Tensors
- Mutable state
- Simple mathematical operations
- Automatic differentiation

Background: NN Training

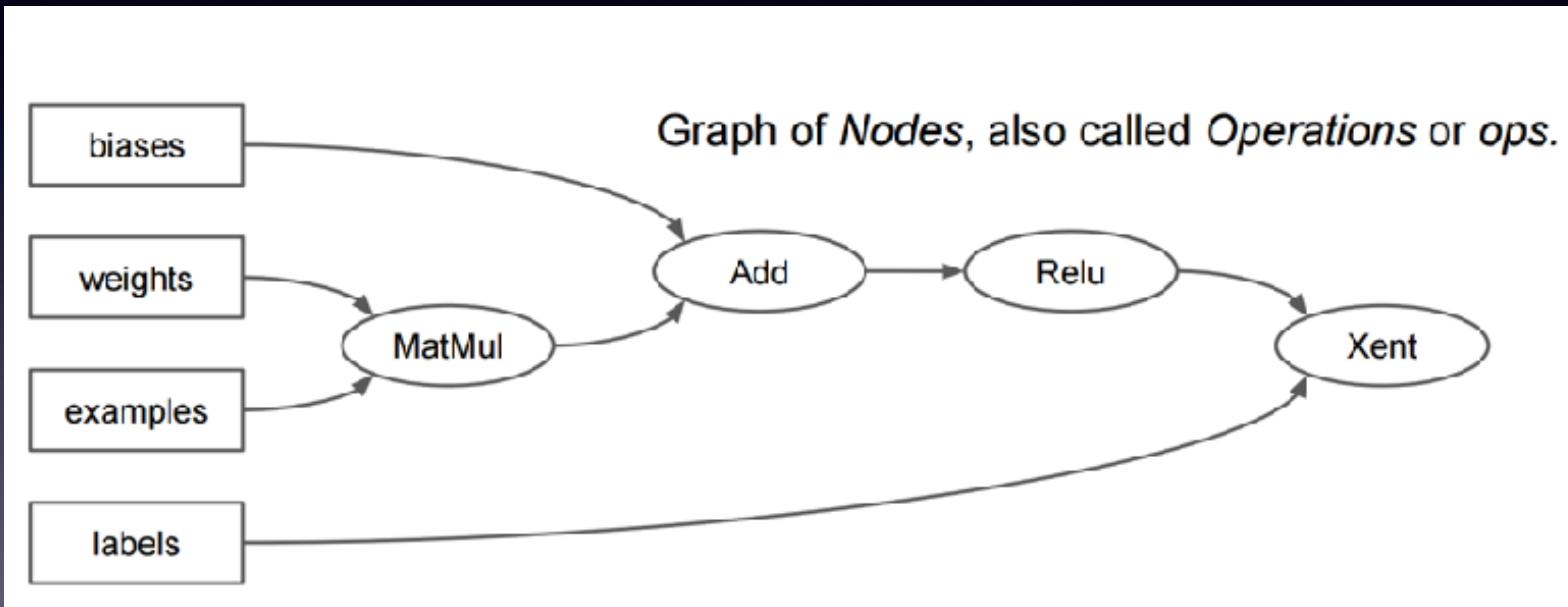




- Take input image
- Compute loss function (forward pass)
- Compute error gradients (backward pass)
- Update weights
- Repeat

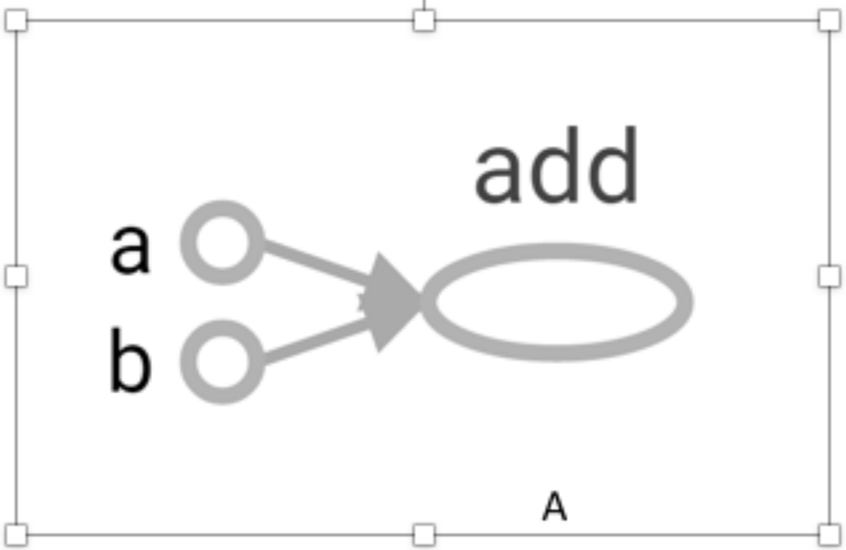


Computation is a DFG



Example Code

```
import tensorflow as tf
a = tf.constant(2, name='a')
b = tf.constant(3, name='b')
A = tf.add(a, b, name = 'add')
```

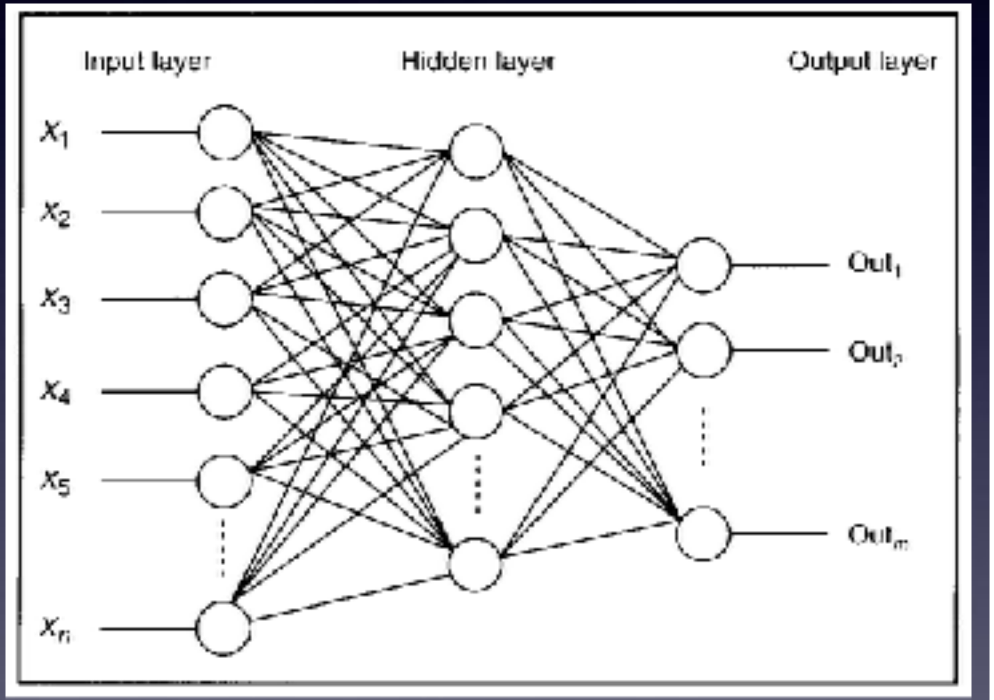


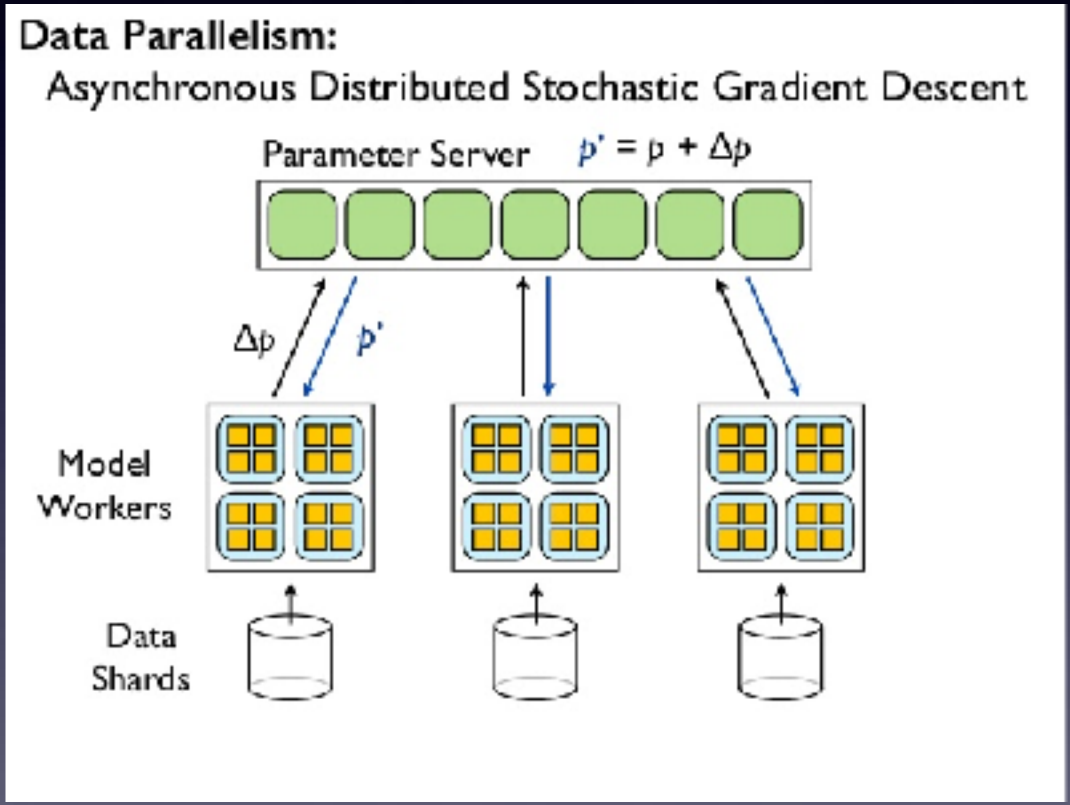

```
with tf.Session() as sess:
    print sess.run(A)
```

Example Code

```
# 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.
```

Parameter Server Architecture





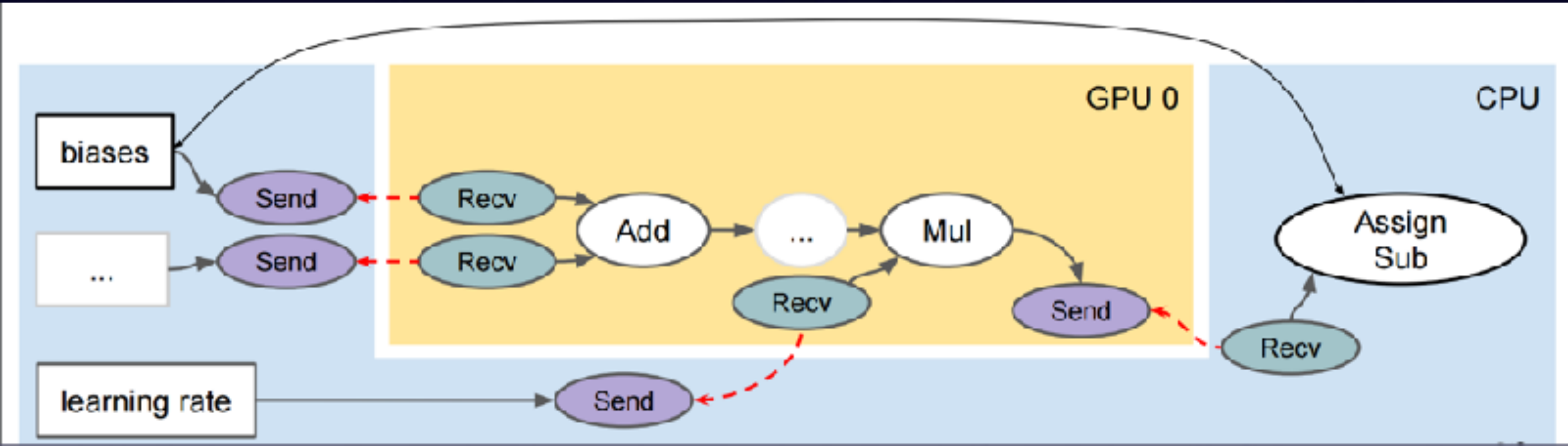
Stateless workers, stateful parameter servers (DHT)

Commutative updates to parameter server

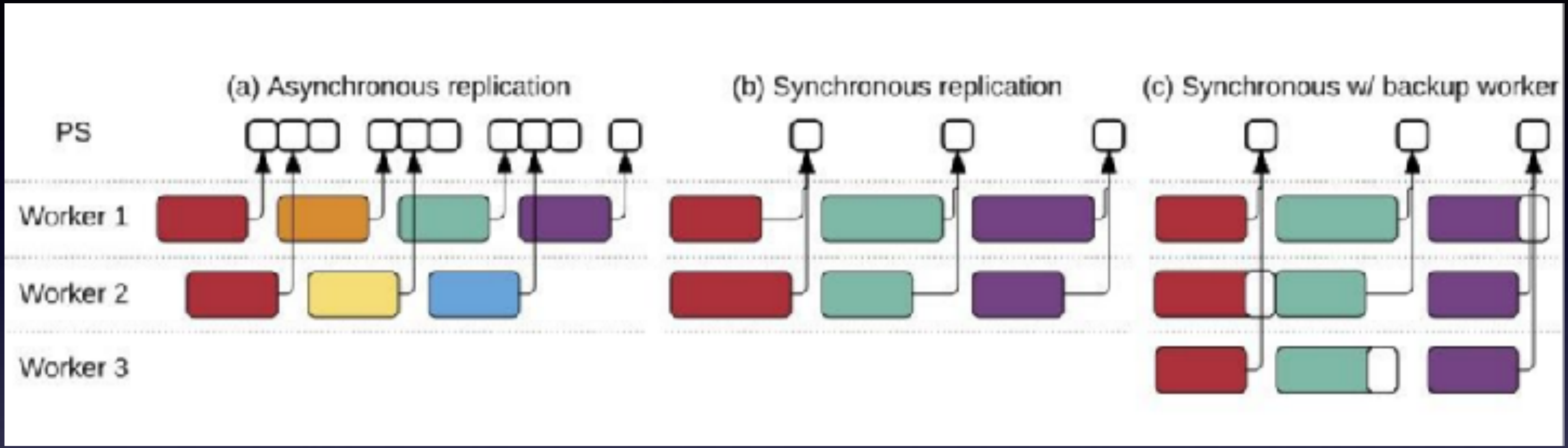
TensorFlow

- Flexible architecture for mapping operators and parameter servers to different devices
- Supports multiple concurrent executions on overlapping subgraphs of the overall graph
- Individual vertices may have mutable state that can be shared between different executions of the graph

TensorFlow handles the glue



Synchrony?



- Asynchronous execution is sometimes helpful, addresses stragglers
- Asynchrony causes consistency problems
- TensorFlow: pursues synchronous training
  - But adds k backup machines to reduce the straggler problem
  - Uses domain specific knowledge to enable this optimization

Open Research Problems

- Automatic placement: data flow - great mechanism, but not clear how to use it appropriately
  - mutable state - split round-robin across parameter server nodes, stateless tasks replicated on GPUs as much as it fits, rest on CPUs
- How to take data flow representation to generate more efficient code?