PARAMETER SERVER

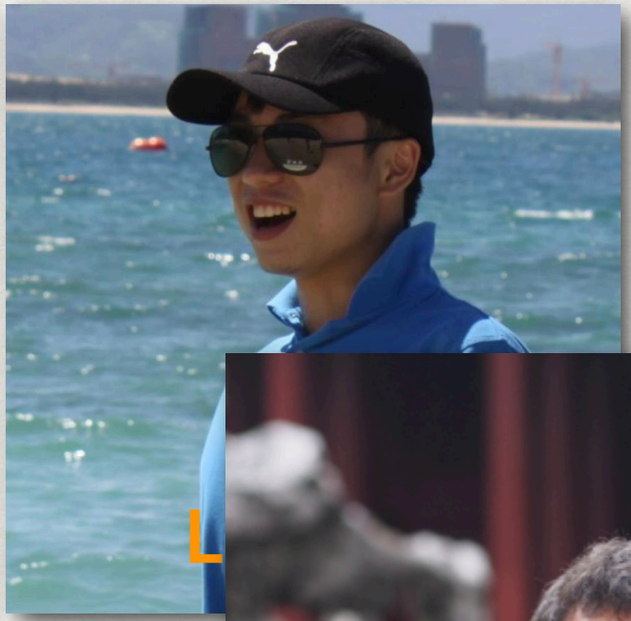
09-22-2018 YIQING MA

OUTLINE

- # First : Basic Knowledge PS (Story, Principle and Detail)
- # Second: Tutorial of PS (how to code Parameter Sever)

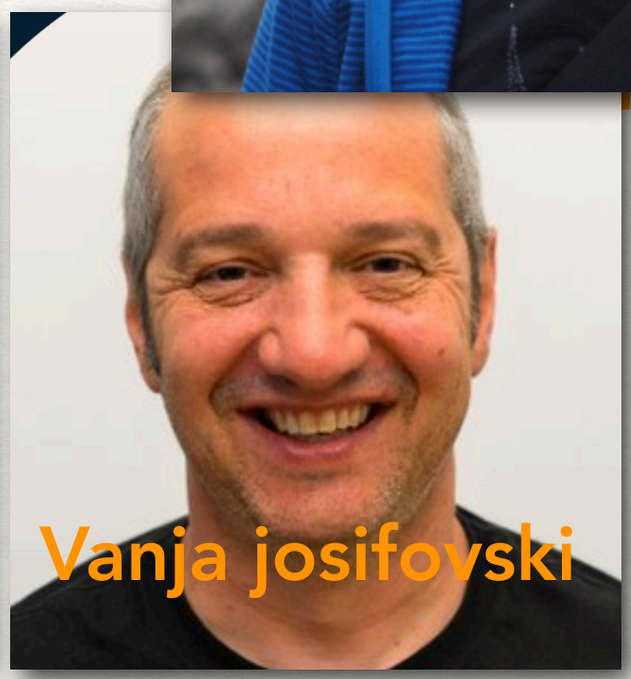
#	Third: State-Of-The-Art of Parameter Server
1	• Scaling Distributed Machine Learning with the Parameter Server
2	• Parameter Hub: High Performance Parameter Servers for Efficient Distributed Deep Neural Network Training
3	• Blink: A fast NVLink-based collective communication library
4	• HiPS: Hierarchical Parameter Synchronization in Large-Scale Distributed Machine Learning

LEVEL 1 PART



FAST … EEP

SCAL… …RVER



Bor-Yiing Su

Machine Intelligence

Eugene J. Shekita

Google

在 google.com 的电子邮件经过验证

Databases Machine Learning

OUTLINE

1. BackGround
   Models , hardware

2. Bipartite design
   Communication, Key layout, Recovery

3. Efficiency
   Consistency models

4. Improving the layout
   submodular load balancing

BACKGROUND

DATA FLOW

Df loss(x)

LOSS GRADIENT

f(x)

DATA

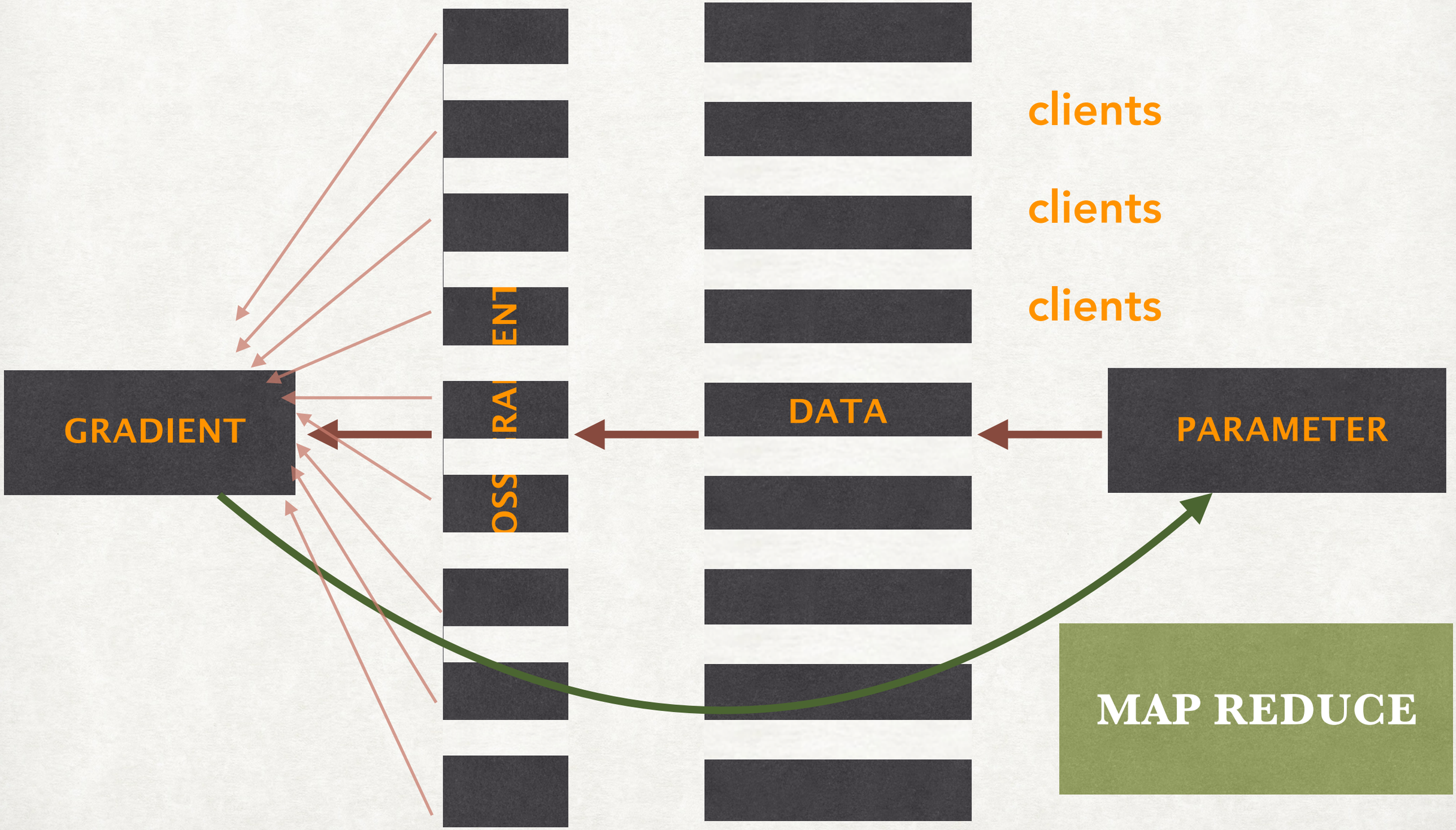
$$x \cdot w$$

$$x^t \cdot g$$

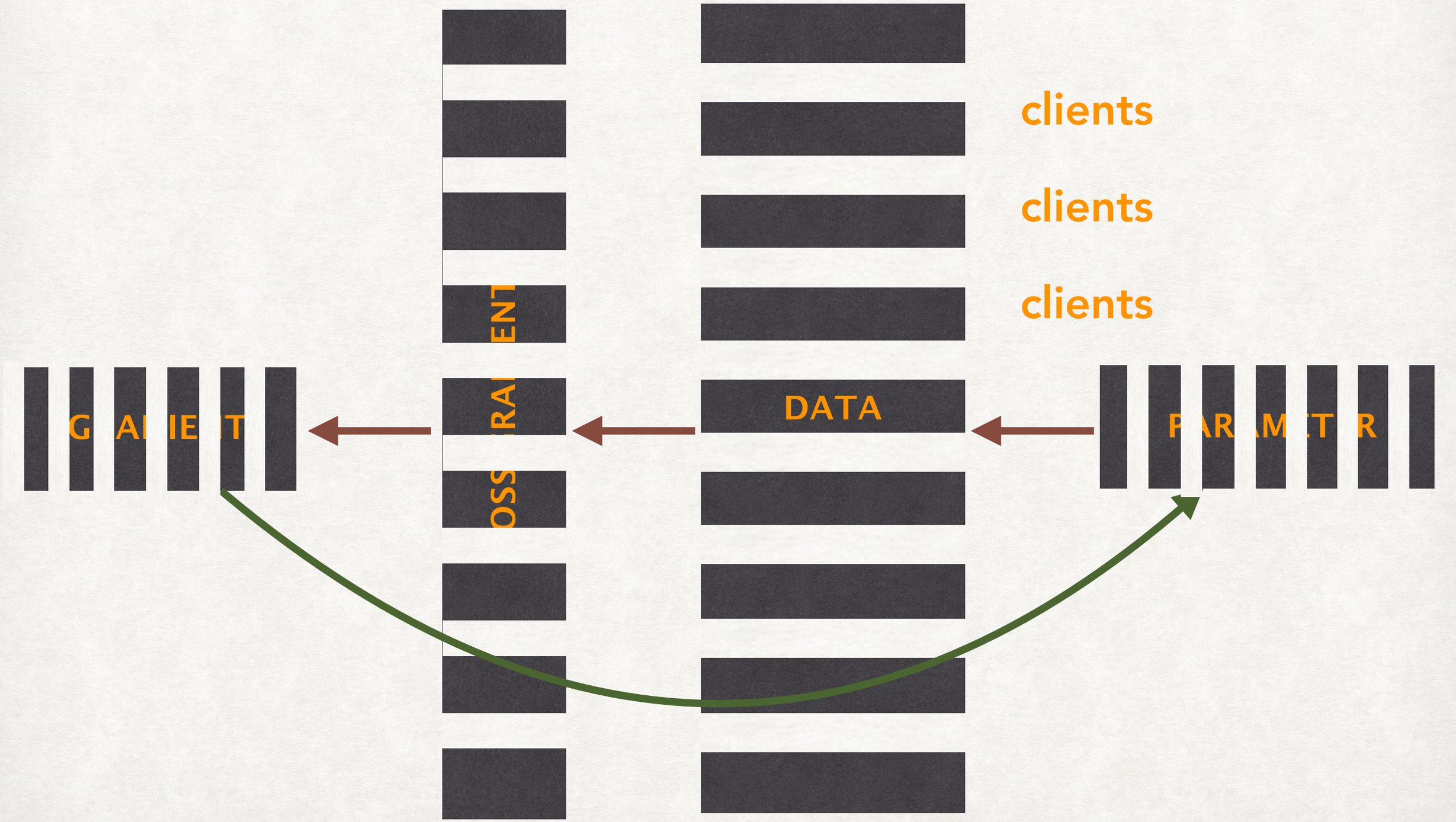
GRADIENT

PARAMETER

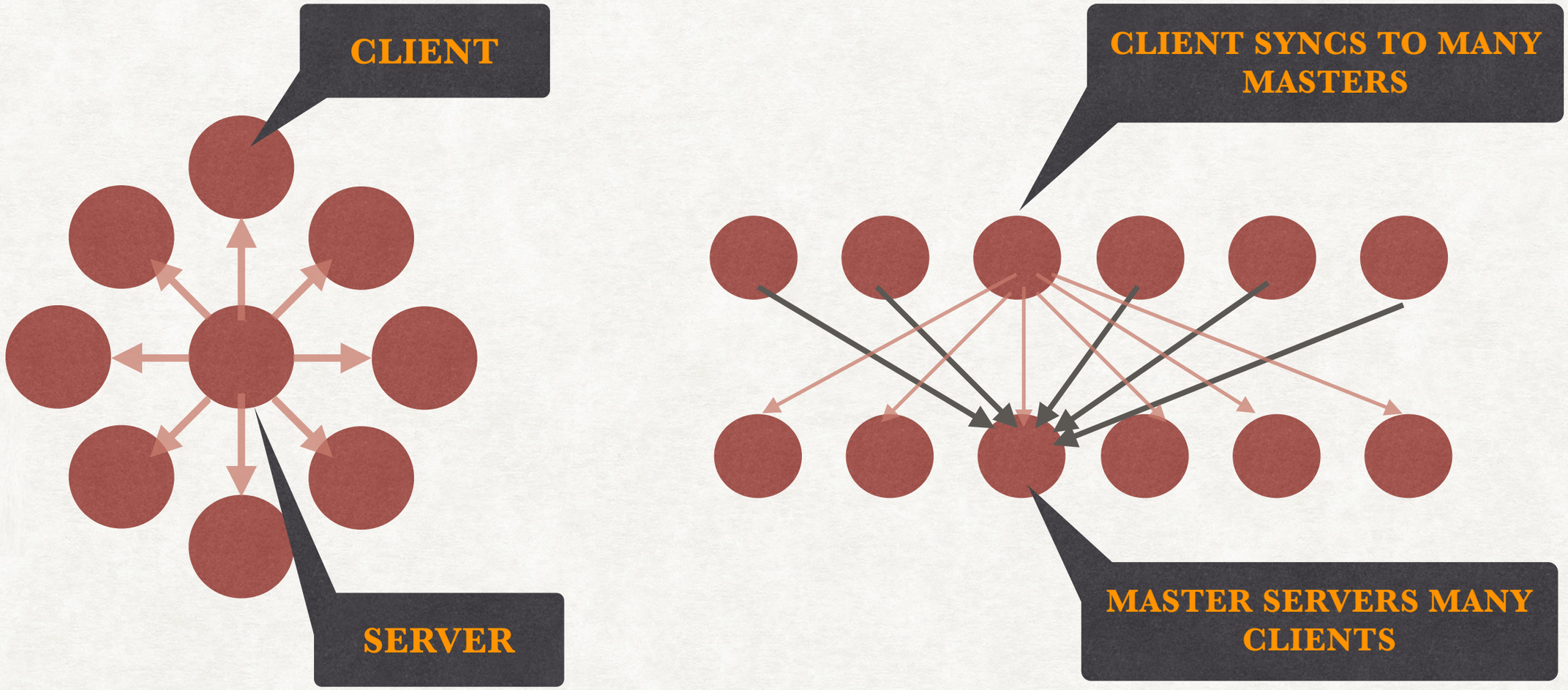
DATA FLOW


clients
clients
clients
GRADIENT
DATA
PARAMETER
MAP REDUCE

DATA FLOW

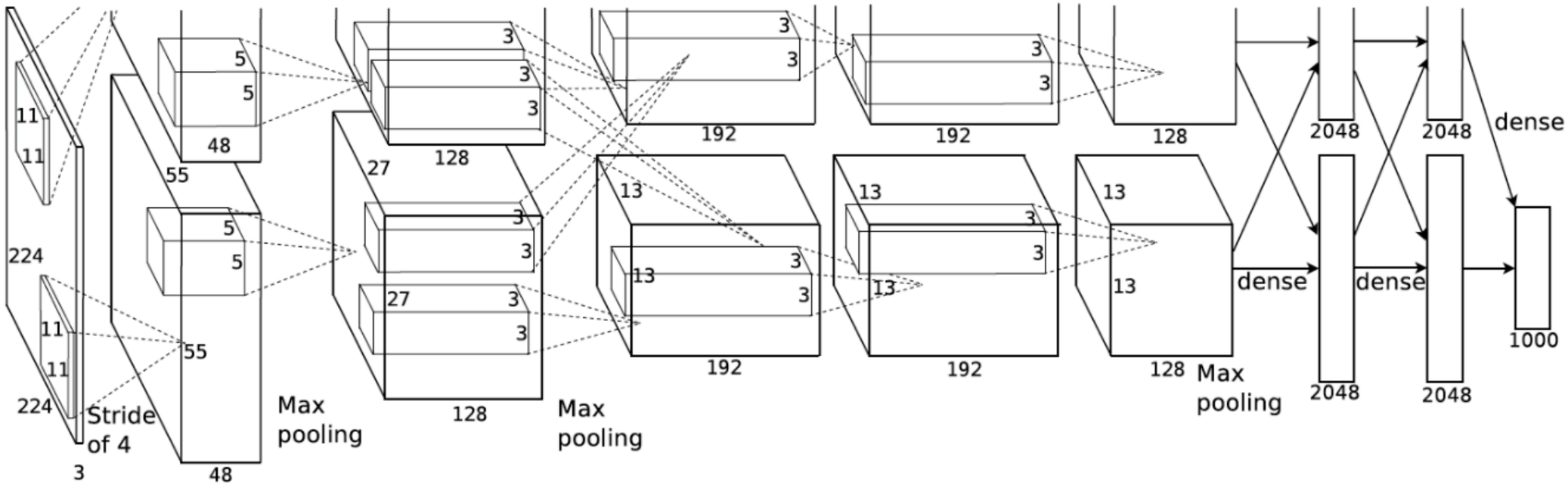


COMMUNICATION PATTERN



Put(keys,values,clock) ,get (keys,valuse,clock)

DEEP NETWORK

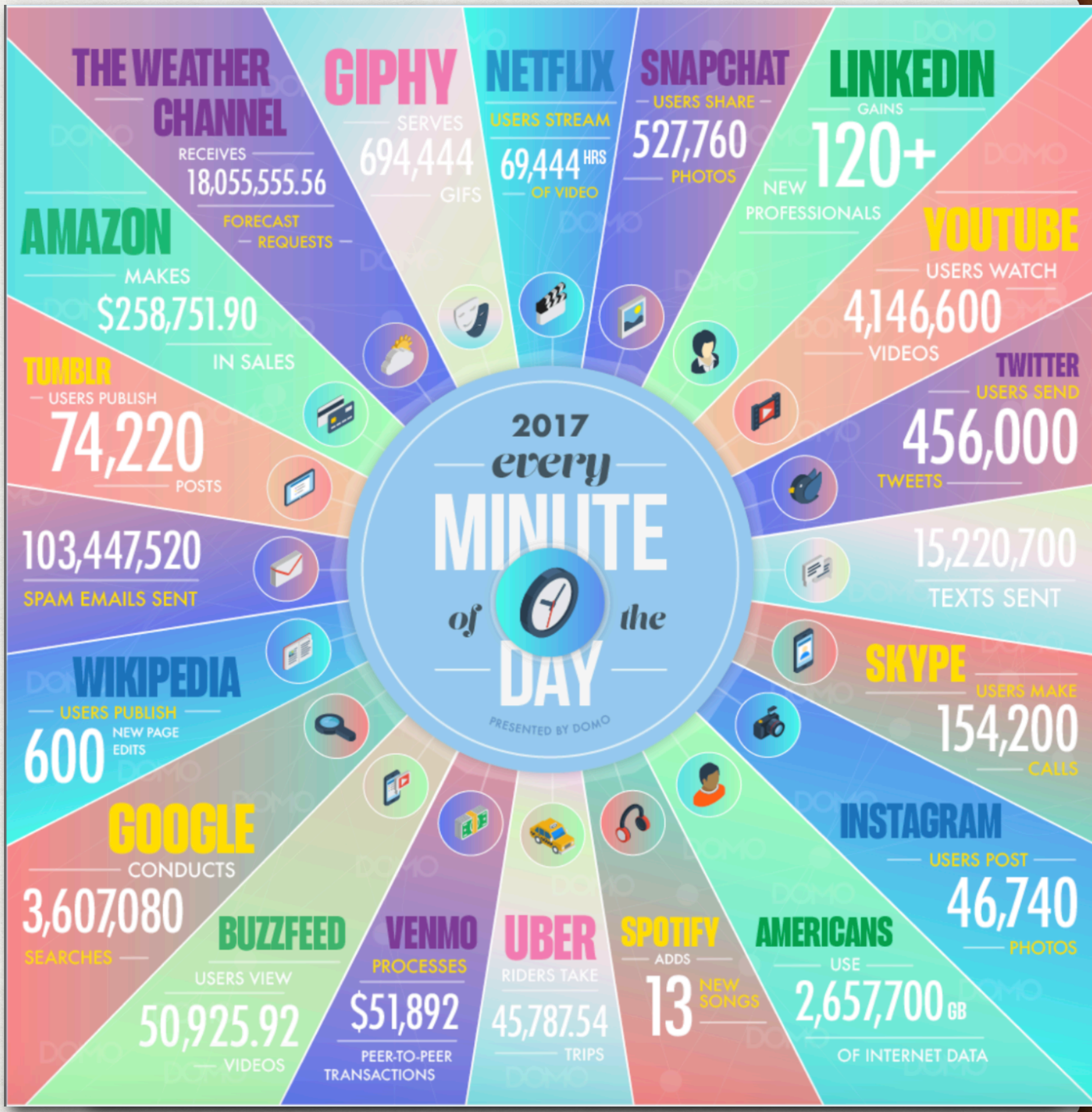


Architecture for the paper

- Gradients are more structured (groups per layer)
- Hierarchical structure (multi GPU to host to server)

DATA PER MIN 2018

We scale:
100TB data
1000 machine
100B parameters
1B inserts/s
4B documents
2M topics/s



STUFF FAILS A LOT . DEAL WITH IT

Typical first year for a new cluster:

- 0.5 overheating (power down most machines in < 5mins,~1-2 days to recover)
- 1 PDU failure (~500-1000 machines suddenly disappear, ~6 hours to come back)
- 1 rack-move (plenty of warning,~500-1000 machines powered down, ~6 hours)
- 1 network rewiring (rolling ~5% of machines down over 2-day span)
- 20 rack failures (40-80 machines instantly disappear, 1-6 hours to get back)
- 5 racks go wonky (40-80 machines see 50% packet loss)
- 8 network maintenances(4 might cause ~30-minute random connectivity losses)
- 12 router reloads (takes out DNS and external vips for a couple minutes)
- 3 router failures (have to immediately pull traffic for an hour)
- dozens of minor 30-second blips for dns
- 1000 individual machine failures
- Thousands of hard drive failures

(Slide courtesy Jeff Dean)

Slow disks, bad memory, misconfigured machines, flaky machines, etc.

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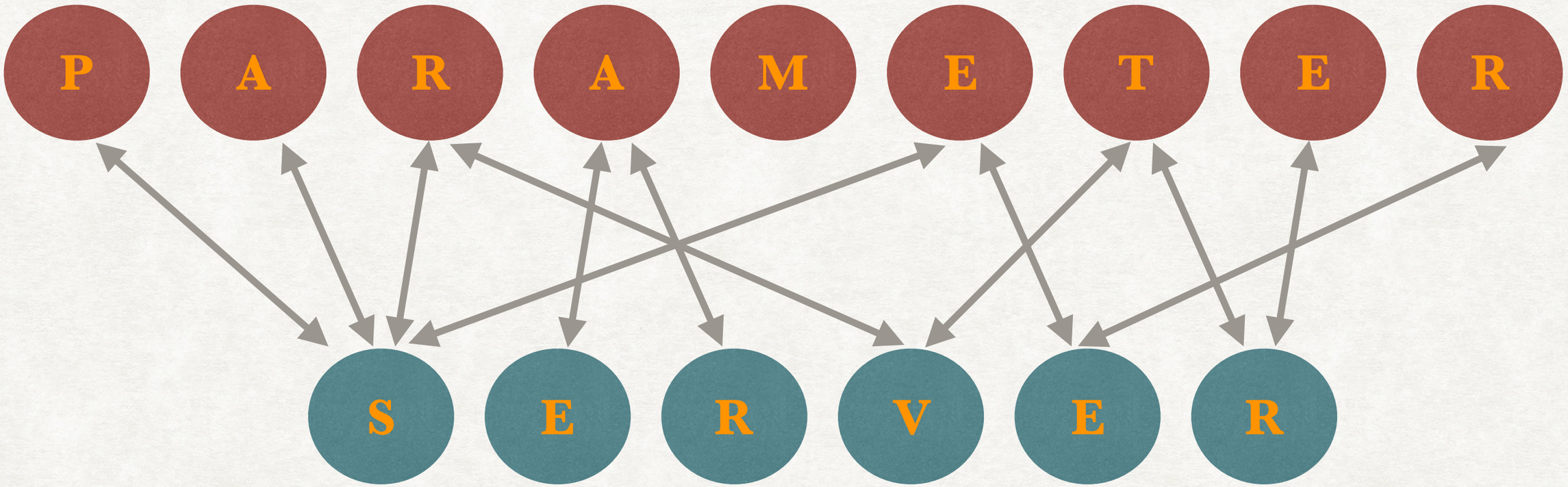
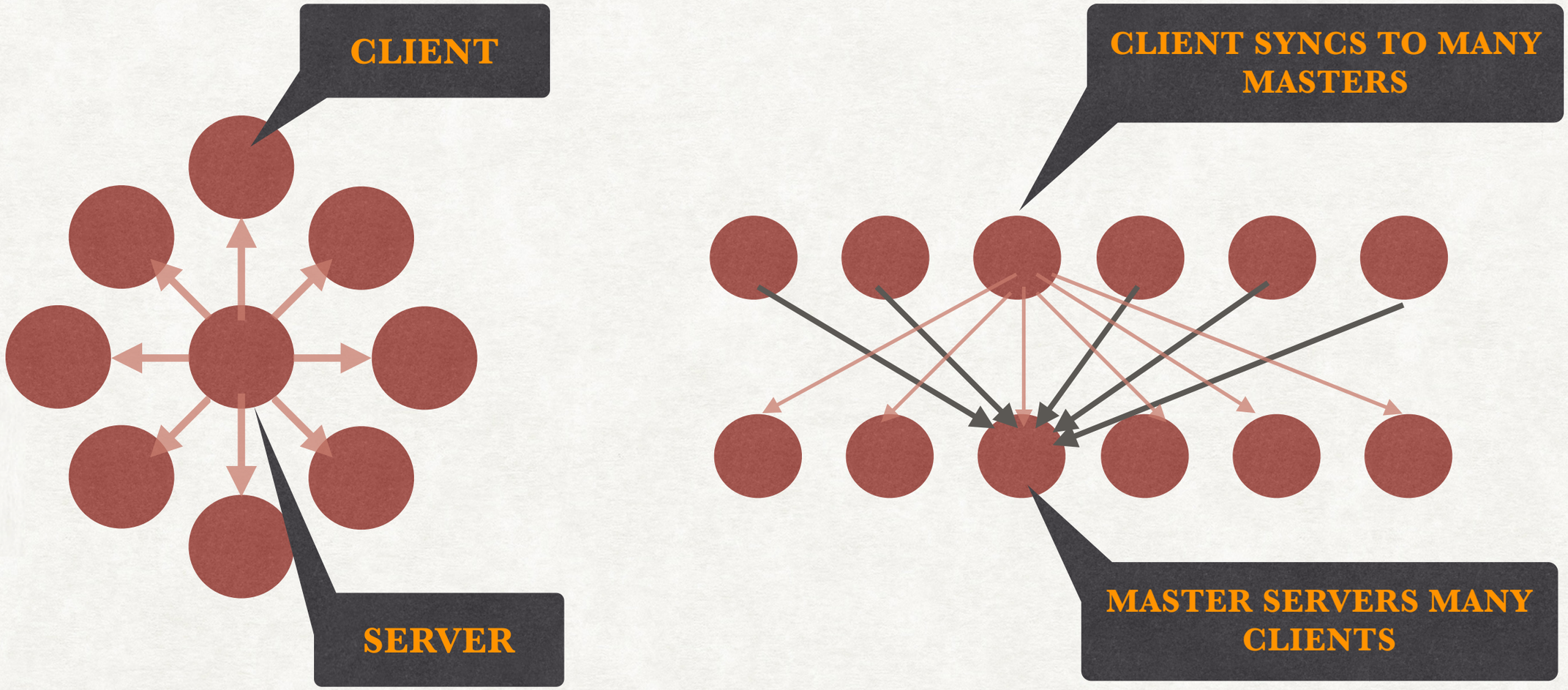
4. Improving the layout
   submodular load balancing


P A R A M E T E R
S E R V E R

COMMUNICATION PATTERN



Put(keys,values,clock) ,get (keys,valuse,clock)

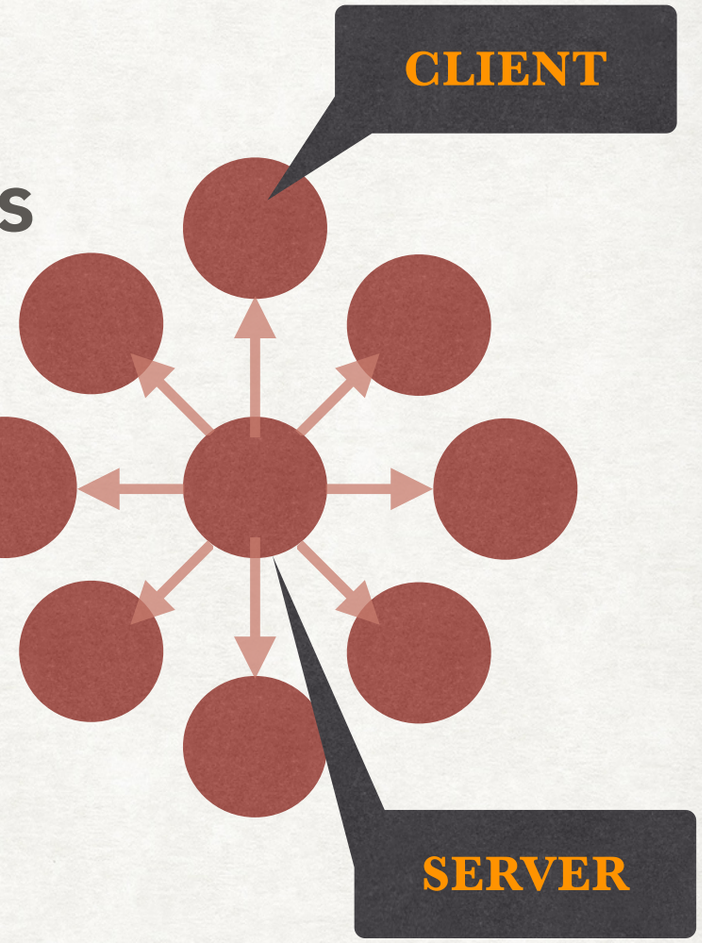
GENERAL PARALLEL ALGORITHM TEMPLATE

Clients have local view of parameters.

P2P is infeasible since $O(n^2)$ connections

Synchronize with parameter server

- Reconciliation protocol
  average parameters, lock variables
- Synchronization schedule
  asynchronous, synchronous, episodic
- Load distribution algorithm
  uniform distribution, fault tolerance, recovery.

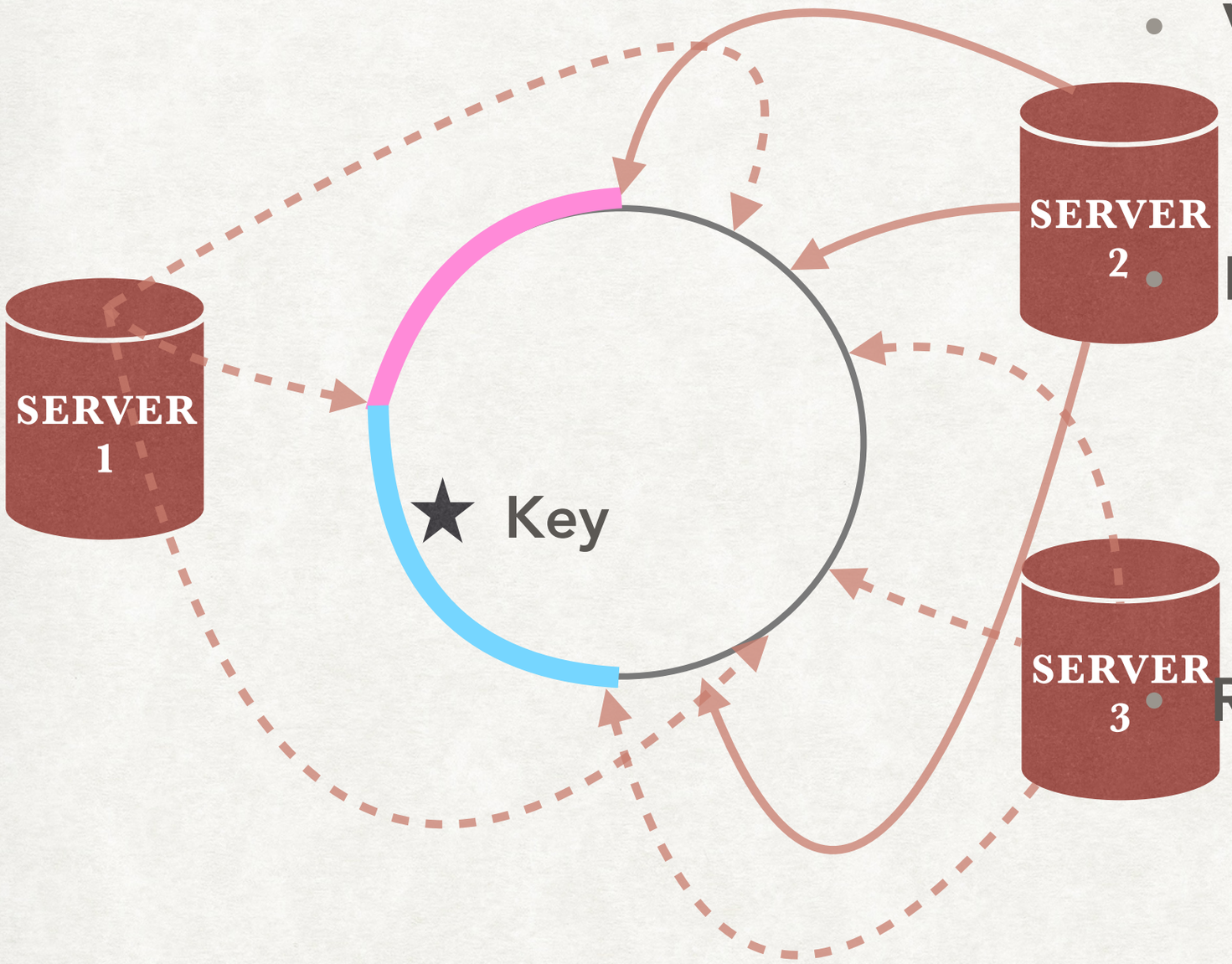


Smola & Narayanamurthy, 2010, VLDB
Gonzalez et al., 2012, WSDM
Shervashidze et al., 2013 , WWW

Also at Google, Baidu,
Facebook, Amazon,
Yahoo, Microsoft…

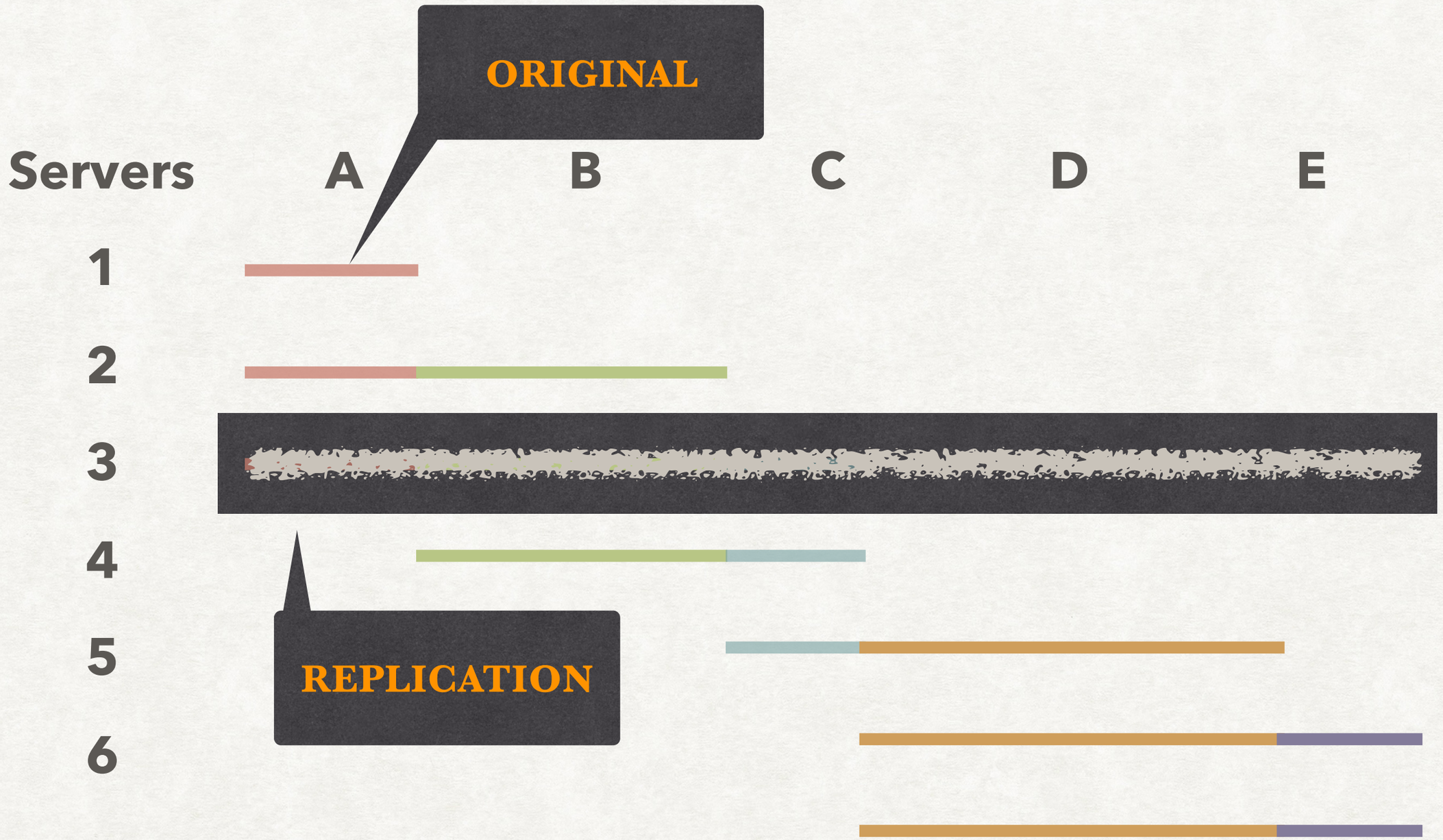
KEY LAYOUT AND RECOVERY

KEYS ARRANGED IN A DHT

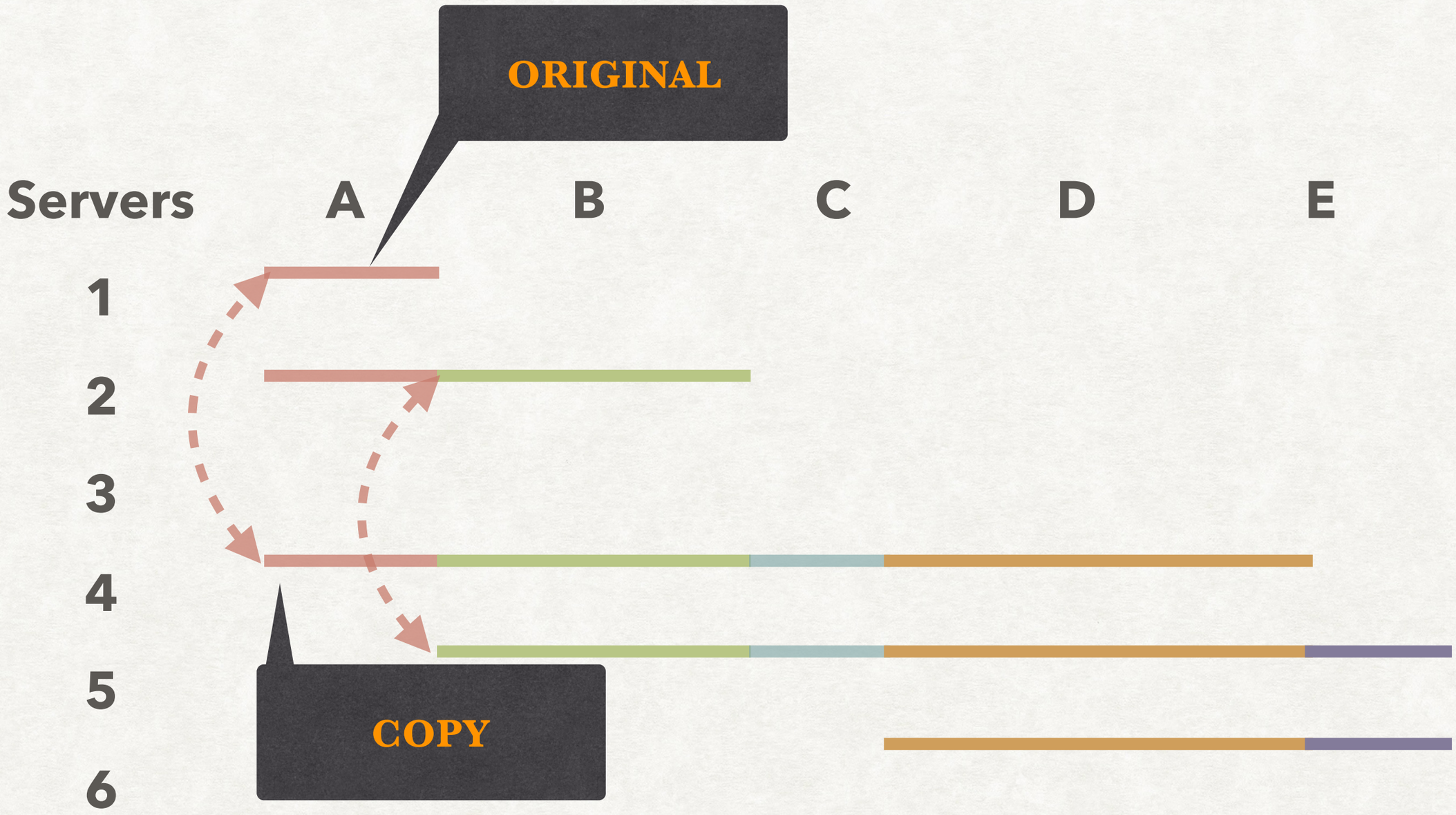


- Virtual Servers
  - Load balancing
  - multithreading
- DHT
  - Contiguous key range for clients
  - Easy bulk sync
  - Easy insertion of servers
- Replication
  - Machines hold replicas
  - Easy fallback
  - Easy insertion /repair

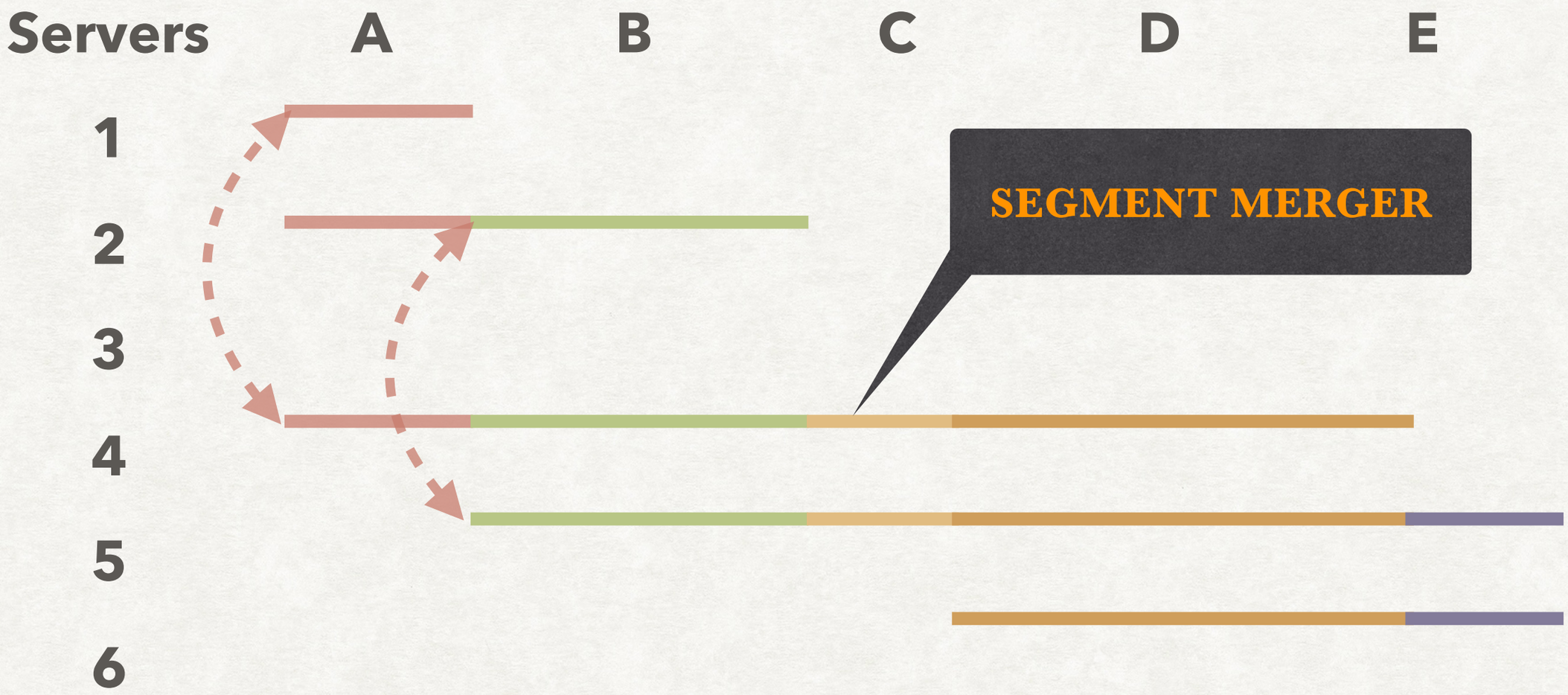
KEY LAYOUT



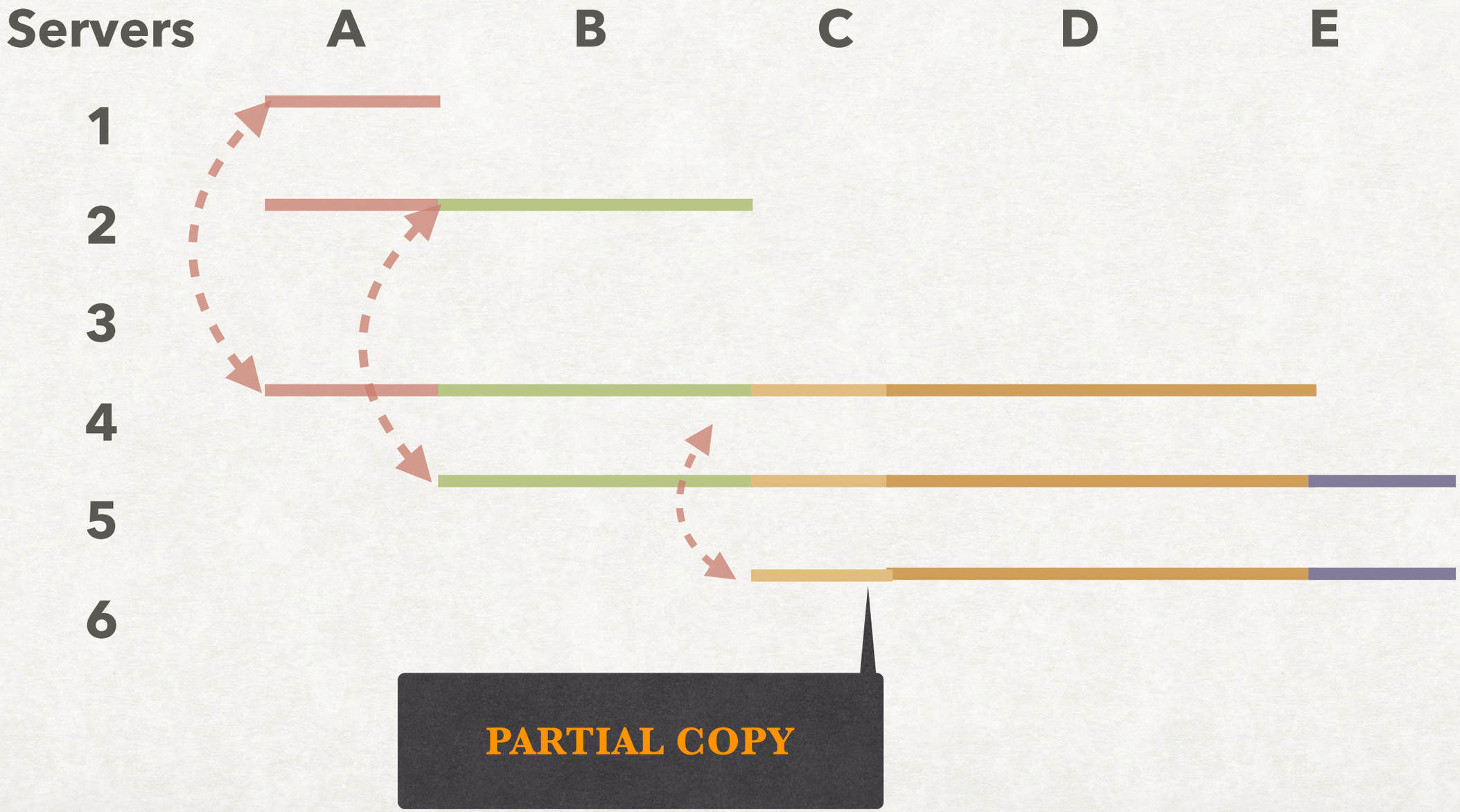
KEY LAYOUT



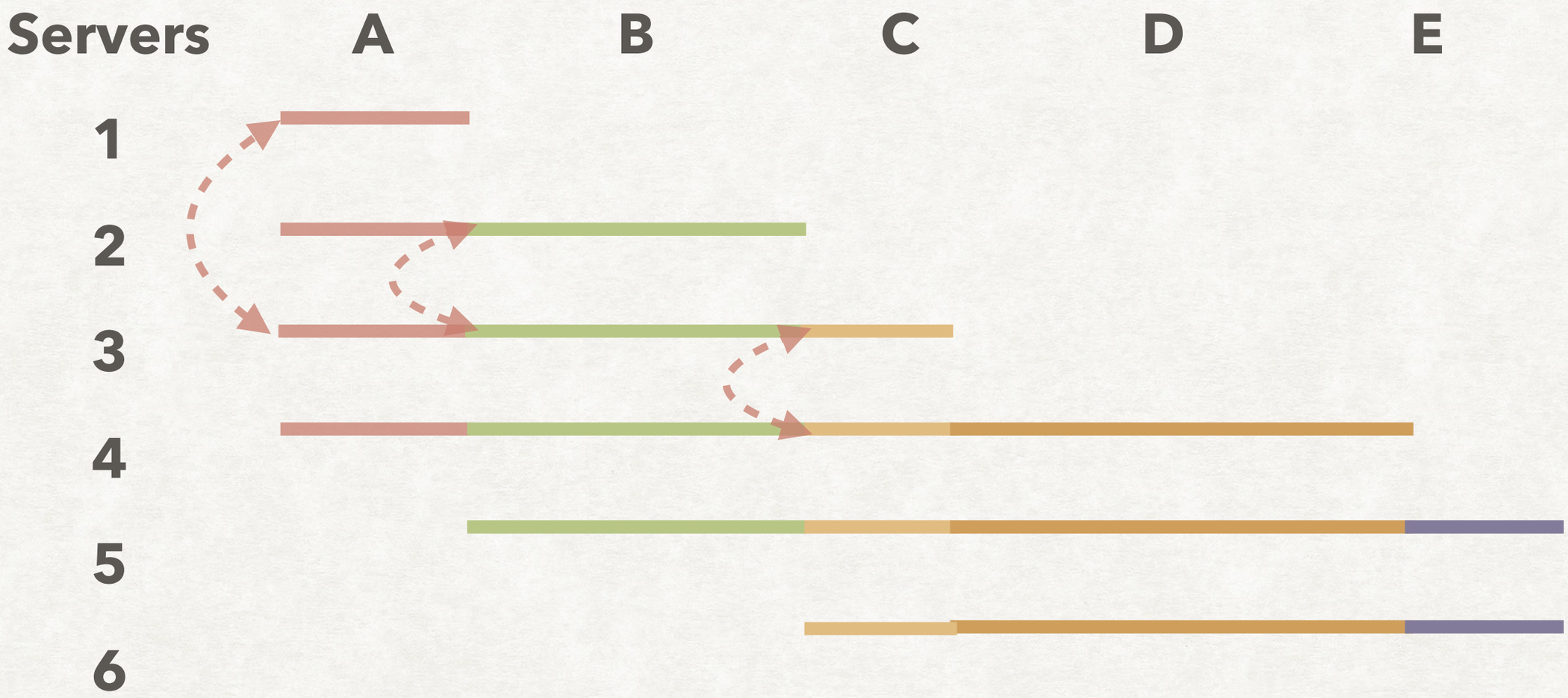
KEY LAYOUT



KEY LAYOUT



KEY LAYOUT ★



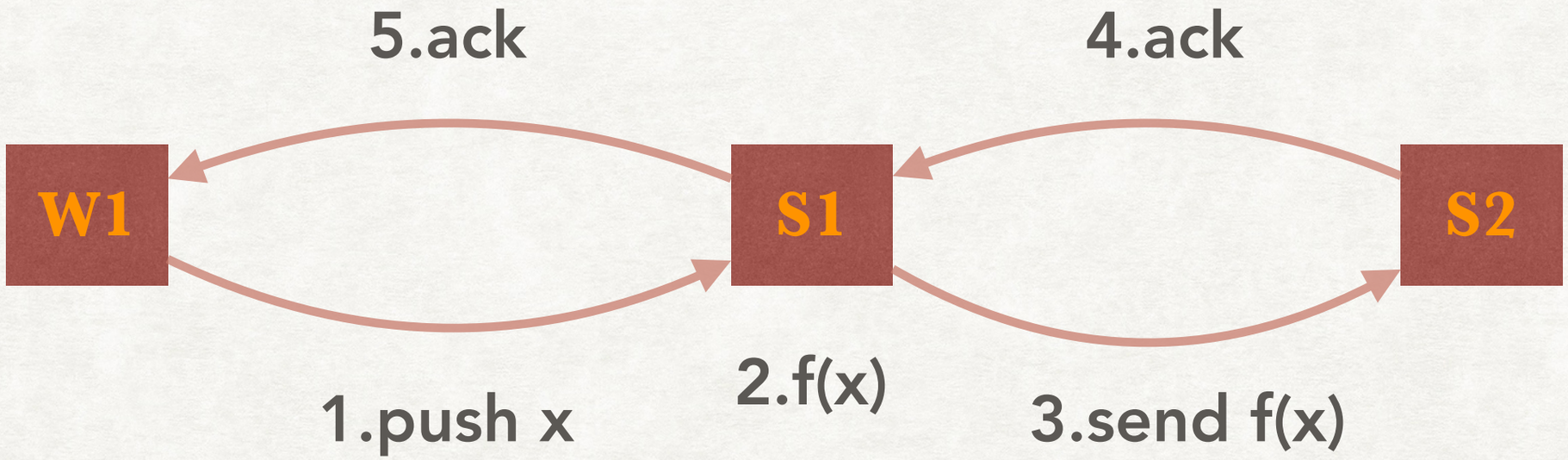
- Precopy server content to new candidate(3)
- After precopy ended, send log
- For k virtual servers this cause O(k^{-2}) delay
- Consistency using vector clocks

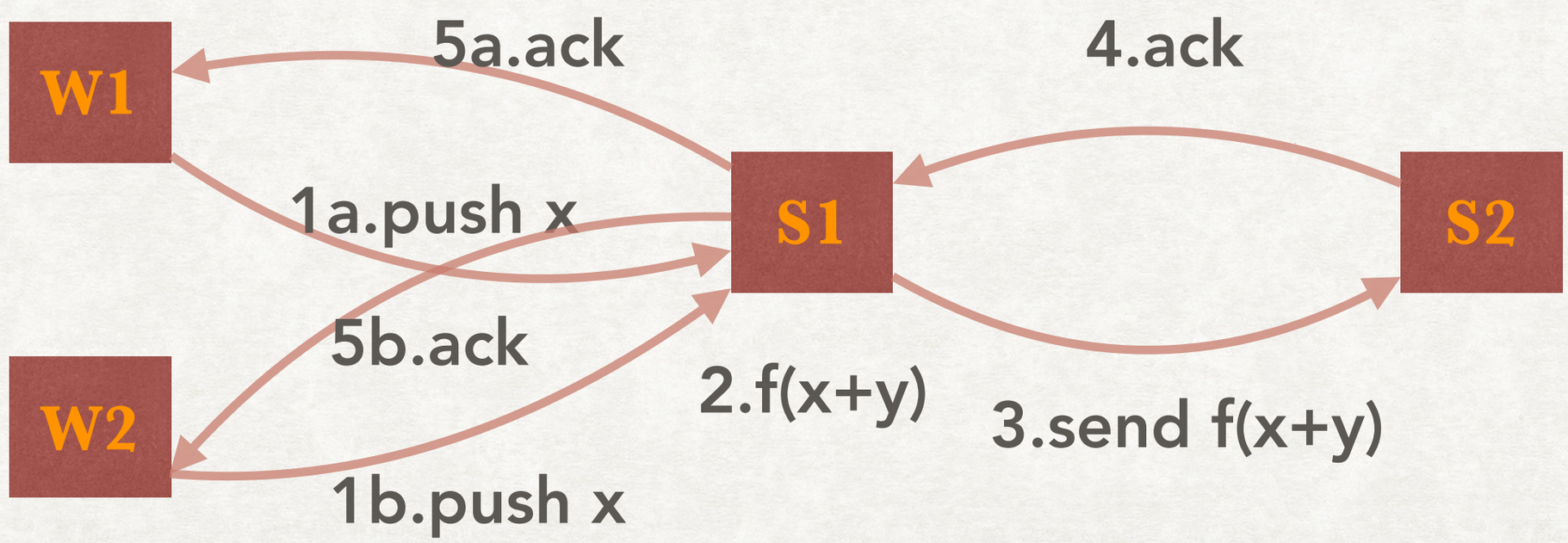
COMMUNICATION

SIMPLE API

- Clients and Servers share much code
- Send data to server
  - Asynchronously in an interval
    push(key_list, value_list, flag)
  - Receive data from server in an interval
    pull(key_list, value_list, flag)
- Avoid sending single items
  - Serialization overhead - protobuf message
  - Consistency overhead - O(c) vector clocks

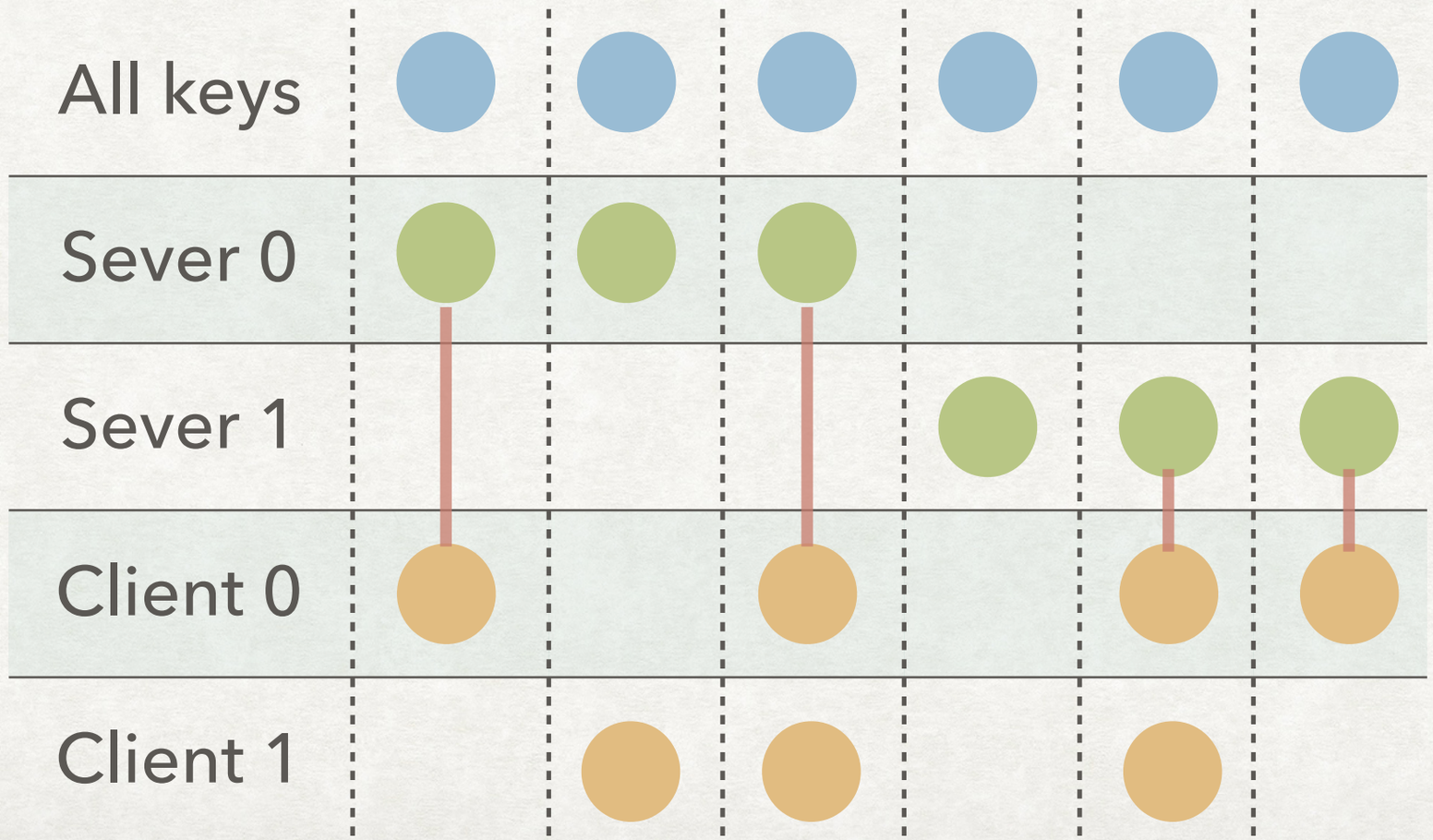
MESSAGE AGGREGATION ON SERVER





SEND AS LITTLE AS POSSIBLE

- Only send data the receiver needs
  - A server node maintain segments of keys
  - Client nodes may have different working sets



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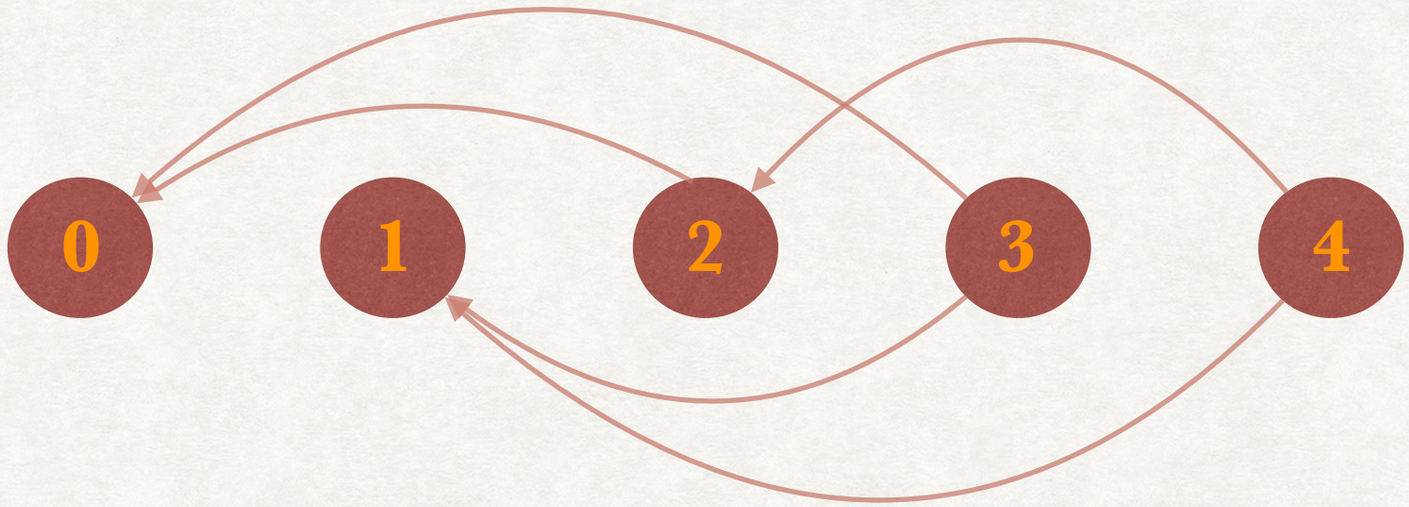
CLOCKS AND CONSISTENCY

CONSISTENCY MODEL

Sequential

Eventual

Bounded delay



Via task processing engine on client/controller

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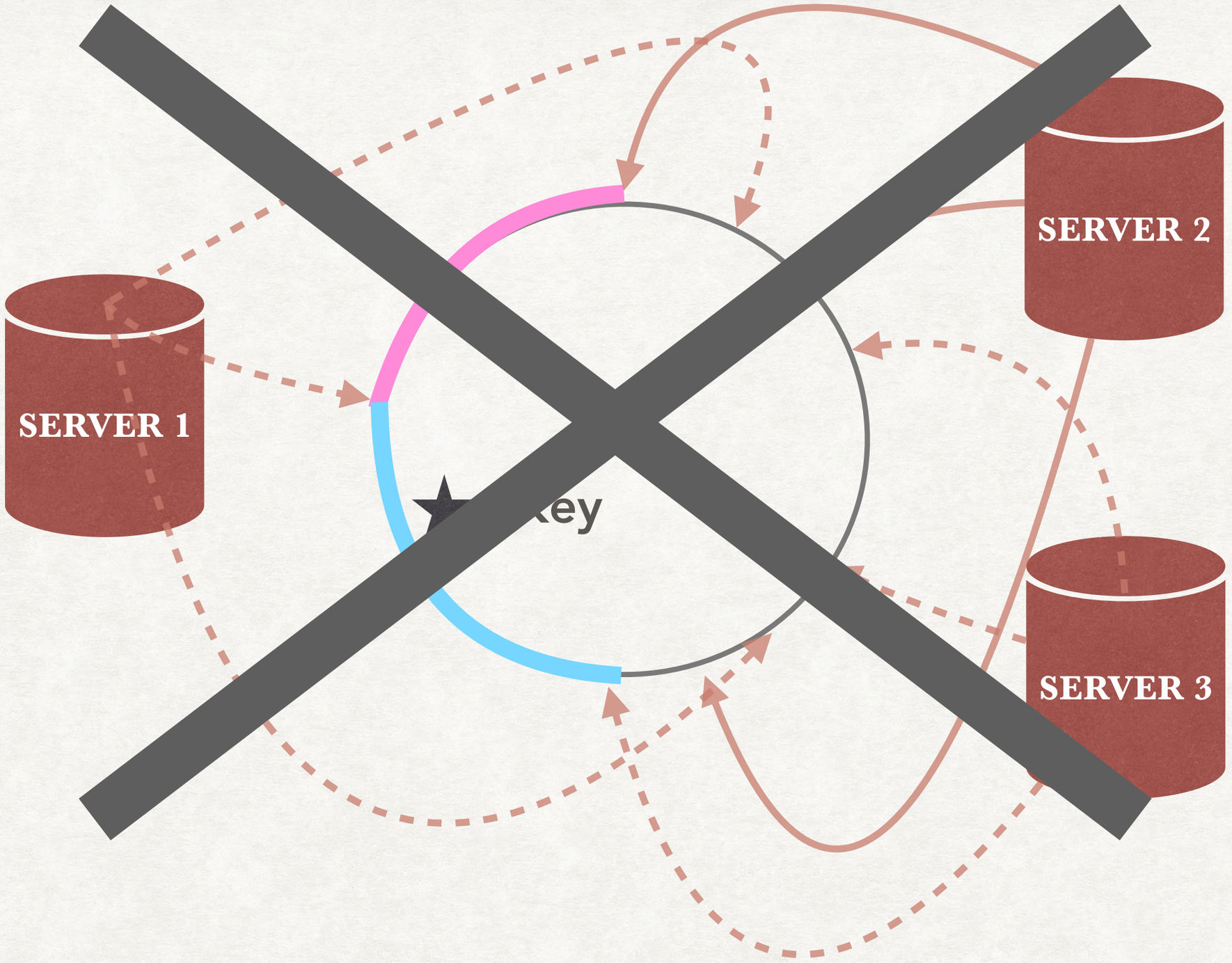
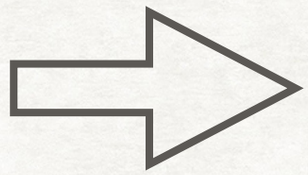
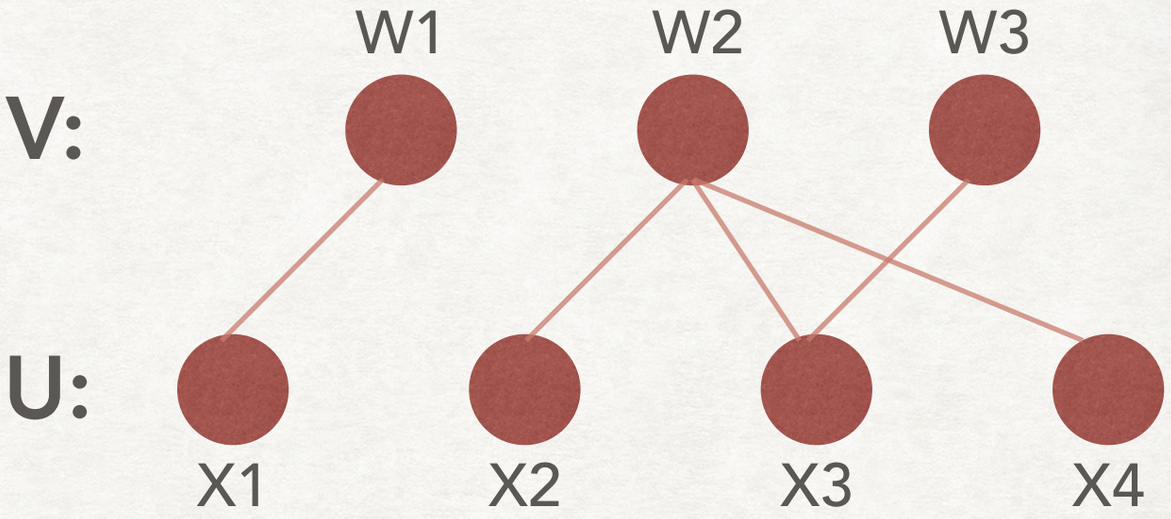


Improved key layout

LOCAL KEY DISTRIBUTION

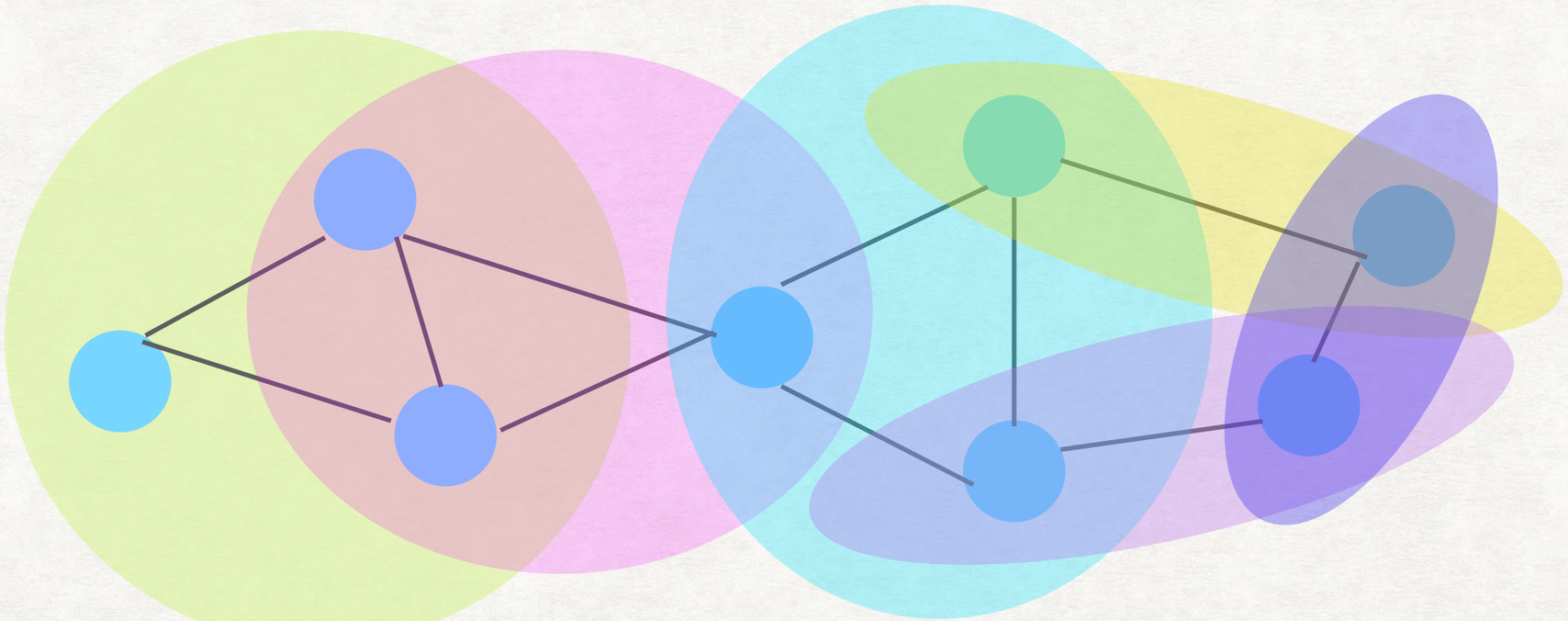
X1 = (.1, __, __)
X2 = (__, .3, __)
X3 = (__, .4, .3)
X4 = (__, .9, __)





- Randomly partitioning data leads to lots of network traffic between clients & servers
- Clients:documents ,user activity
  (needs to cache all relevant parameters)
- Servers :parameters

LOCAL KEY DISTRIBUTION



- Randomly partitioning data leads to lots of network traffic between clients & servers
- Clients:documents ,user activity
  (needs to cache all relevant parameters)
- Servers :parameters

GOALS

- Memory

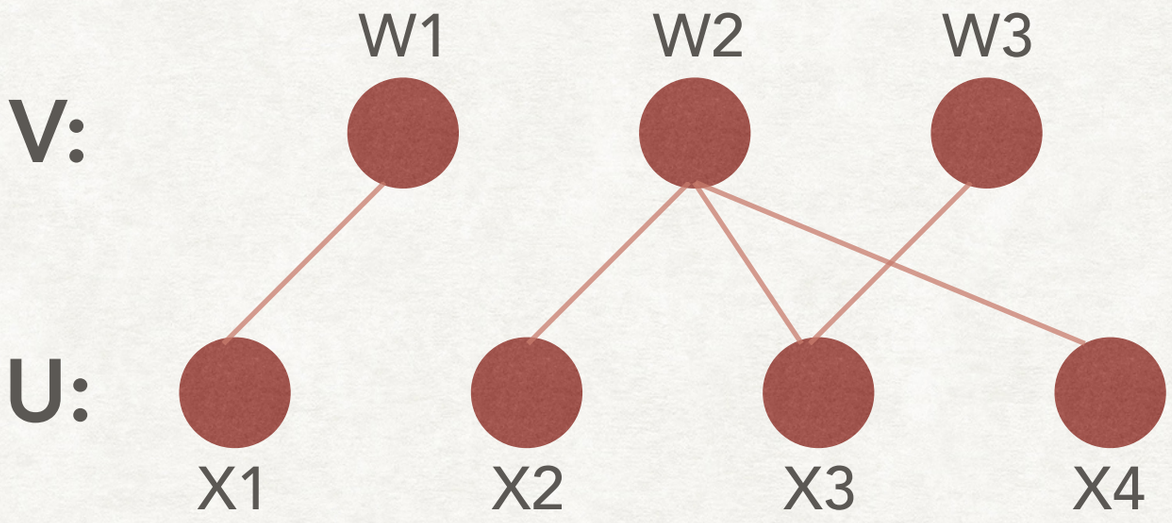
  Must not exceed client memory allowance (cache all relevant variables)
- Work

  Should balance workload over clients
- Network

  Should minimize communication cost
- Without loss of generality assume bipartite graph to be partitioned

MEMORY

- Graph G(U, V, E)
- Select vertices in U with few neighbors
- Minimizing memory



$$\min imize\_\_\max_{i}\left|N(U_i)\right|\_\_ whereN(U_i) := \bigcup_{u \in U_i} N(u)$$

WORST CLIENT

MEMORY LOAD

NEIGHBORS IN V

MEMORY

- # Neighbors of U_i is a submodular function (if v already a neighbor, adding u is free)
- Submodular load balancing problem (Svitkina and Fleischer, 2011)

Submodular Approximation: Sampling-Based Algorithms and Lower Bounds*

Zoya Svitkina Lisa Fleischer

$$\text{min}imize \_\_ \max_i \left| N(U_i) \right| \_\_ where N(U_i) := \bigcup_{u \in U_i} N(u)$$

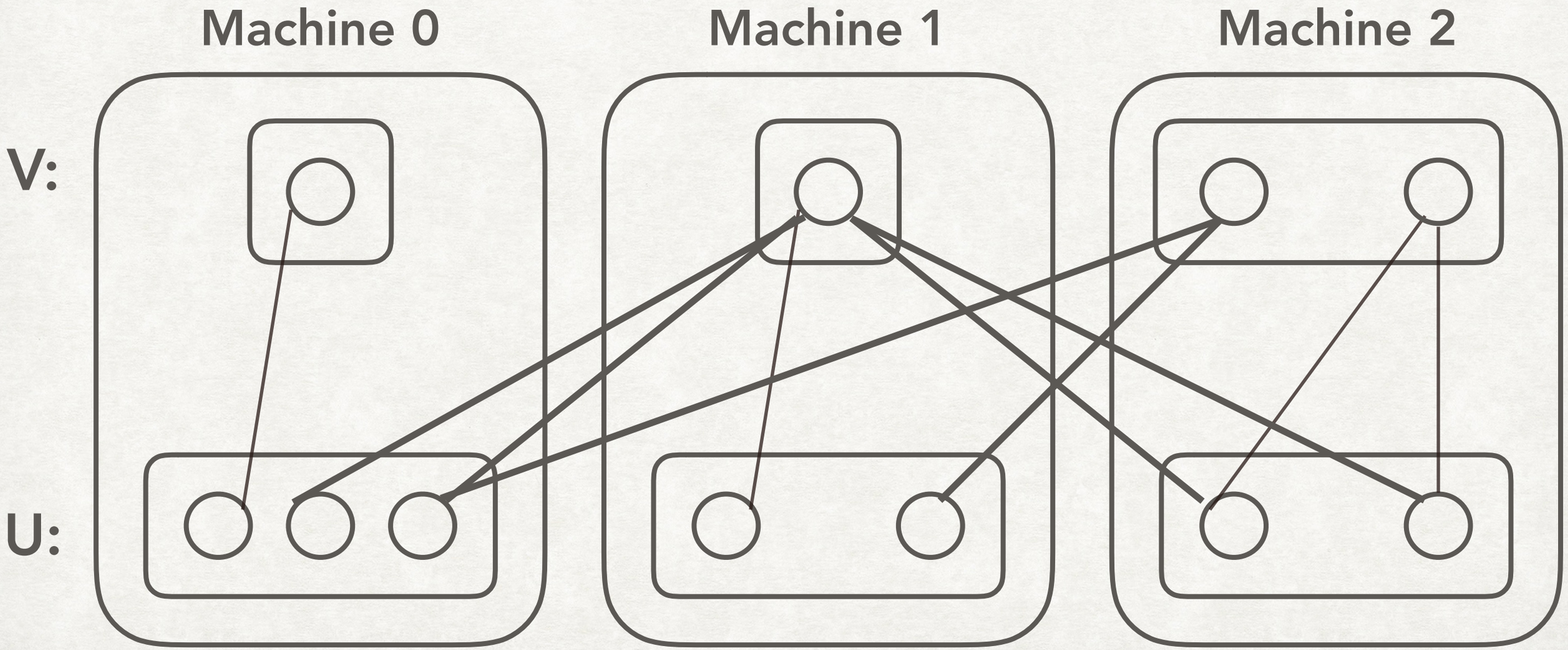
WORST CLIENT

MEMORY LOAD

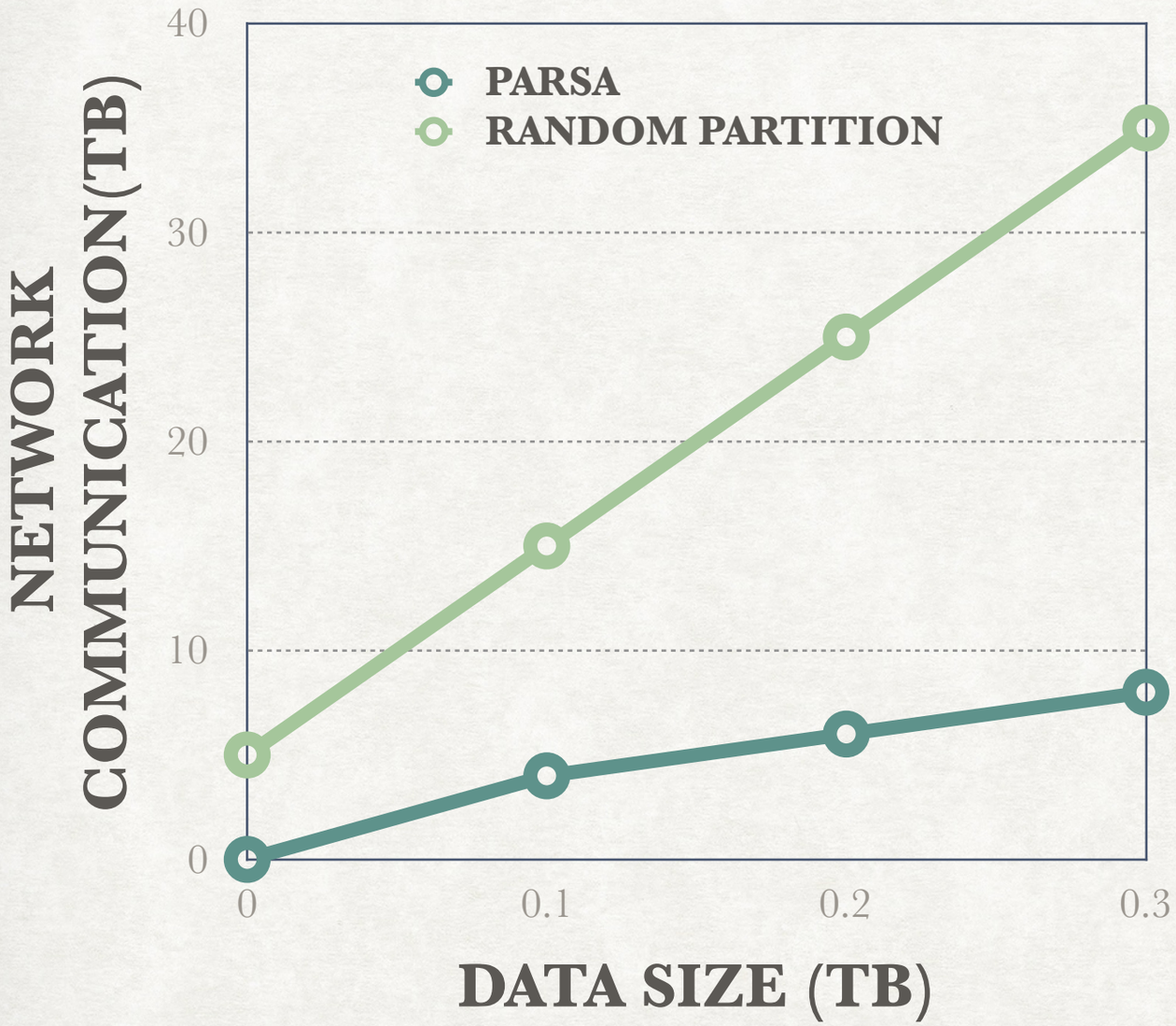
NEIGHBORS IN V

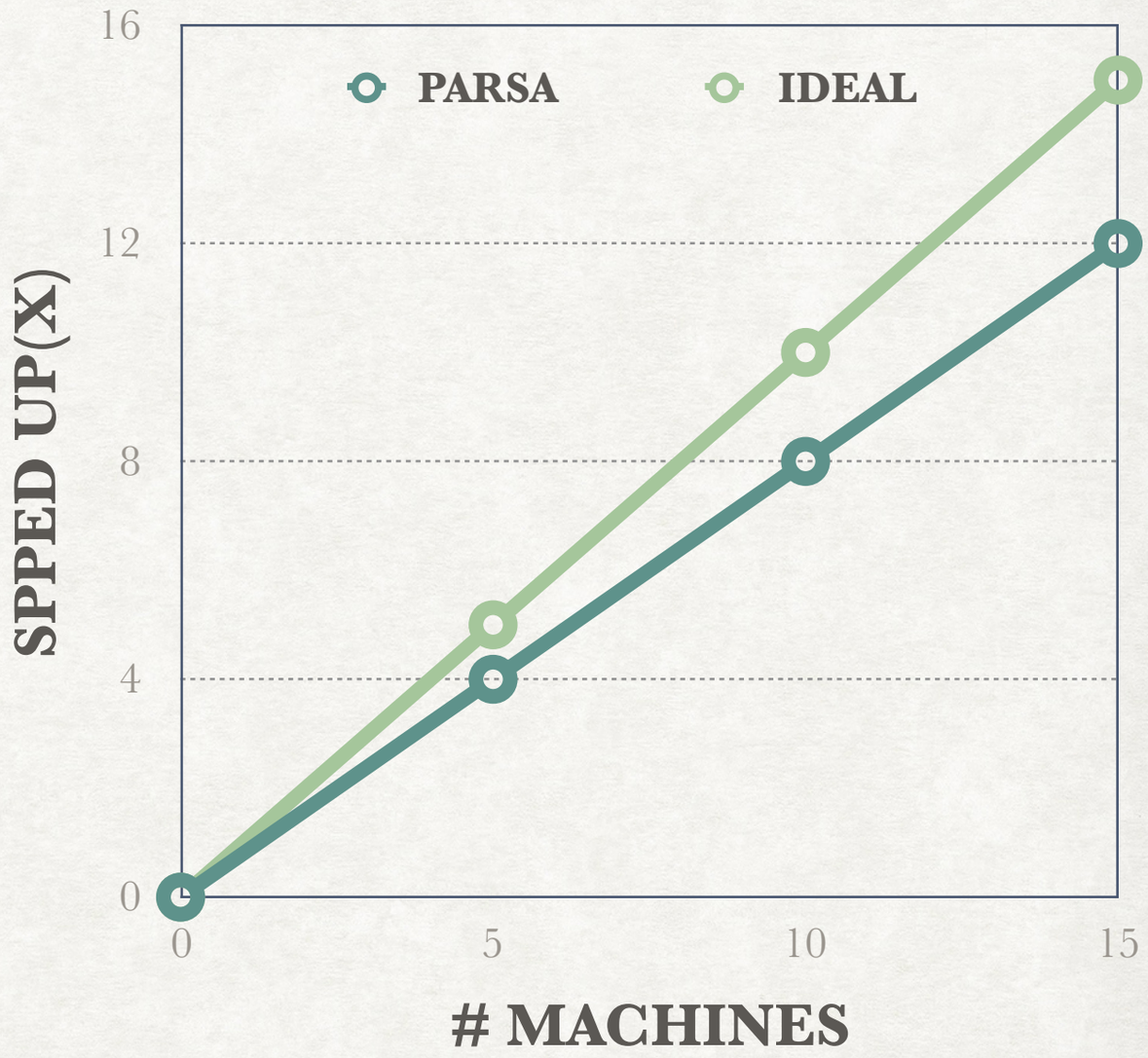
NETWORK

- Put a server on each client.
- Communication cost per machine



BANDWIDTH SAVING





CONCLUDE

- 0.Communication —— PS Parellel Pattern
- 1.Clock —— Version Number
- 2.Key layout and RecoveryDHT
- 3.Consistency model —— Bounded Delay
- 4.Partition Data —— Submodular Load Balancing & Local key distribution

LEVEL 2 PART

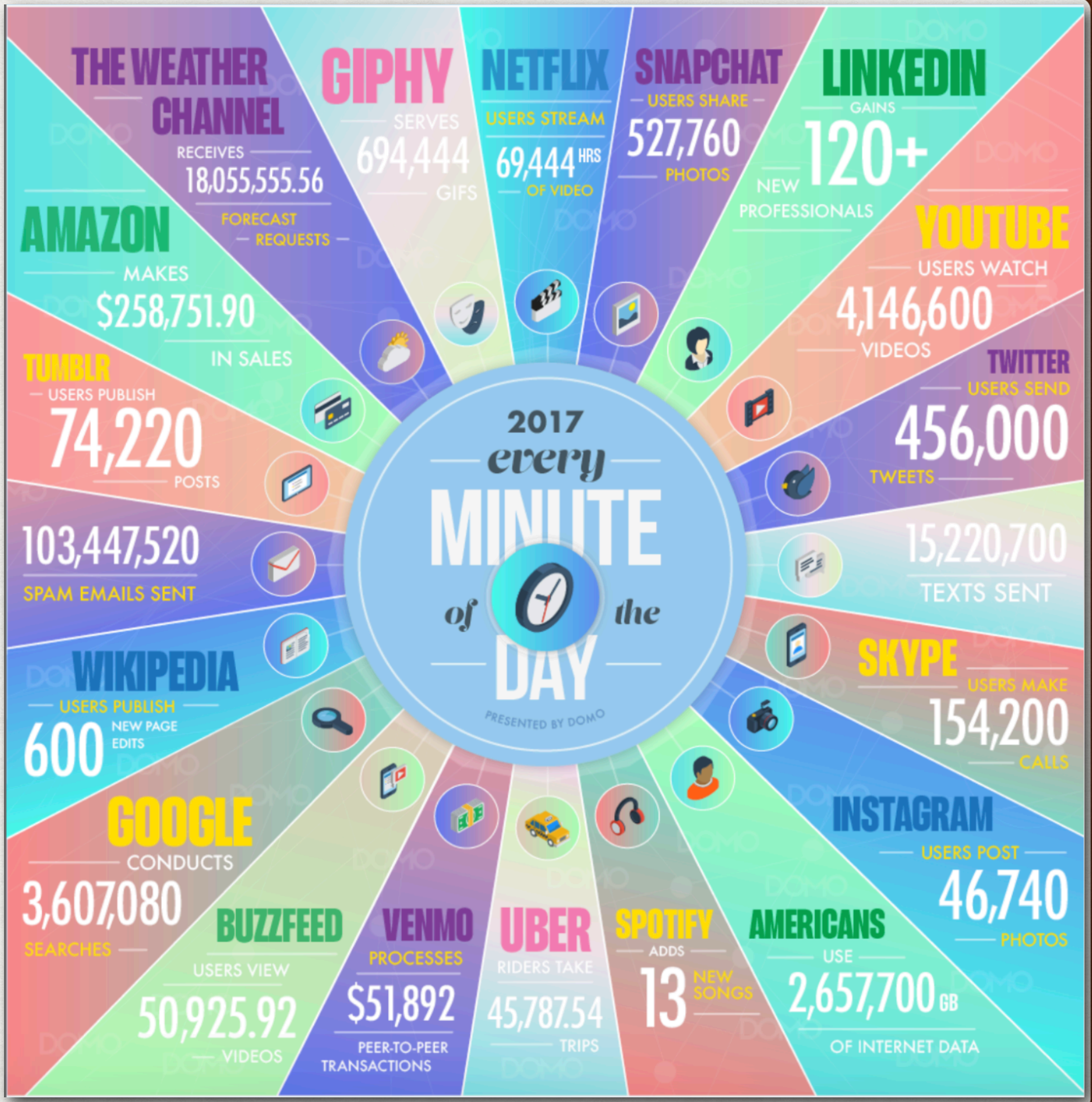
TUTORIAL

- Focus on the design and implementation of large scale machine learning systems
- Parallel and distributed algorithms.
- Several coding examples
- Provide real datasets and machines

APPLICATION & DATA

DATA PER MIN 2018

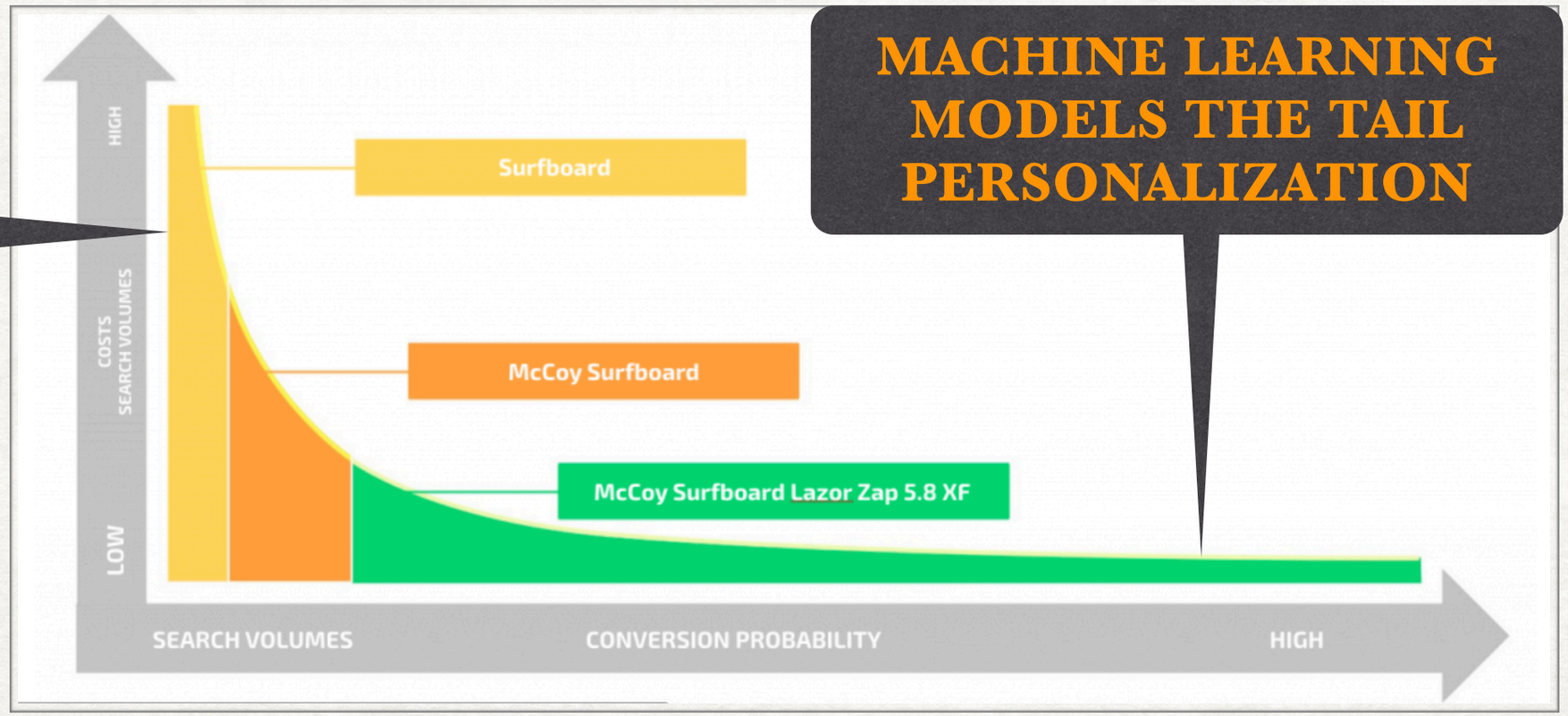
We scale:
100TB data
1000 machine
100B parameters
1B inserts/s
4B documents
2M topics/s



DATA ARE SPARSE

- Most categories have only few data
- A little of category has most of the data

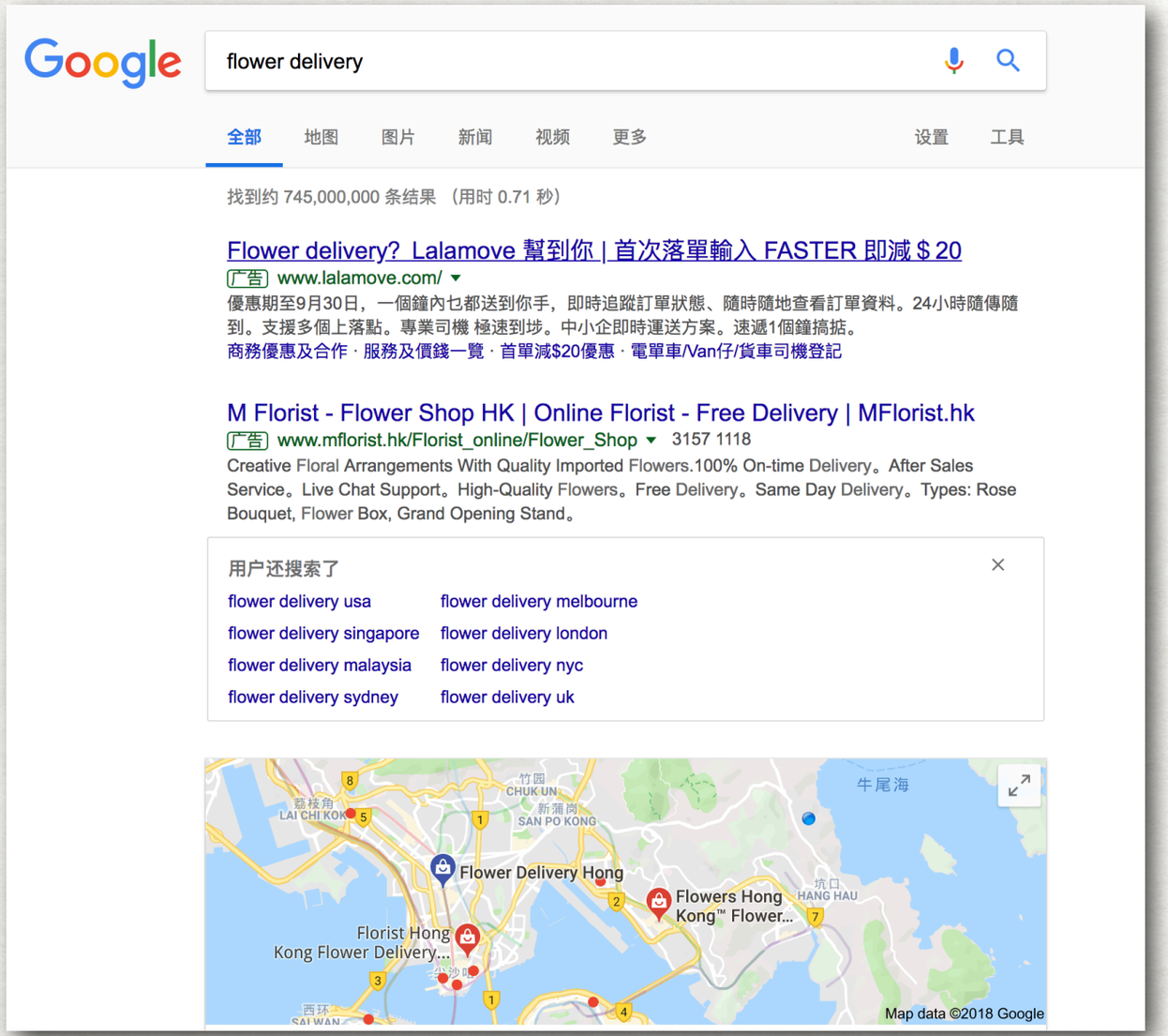
SIMPLE STATISTIC TOOLS MODEL THE HEAD WELL



MACHINE LEARNING MODELS THE TAIL PERSONALIZATION

ONLINE ADVERTISING

- The major revenue source of internet search companies

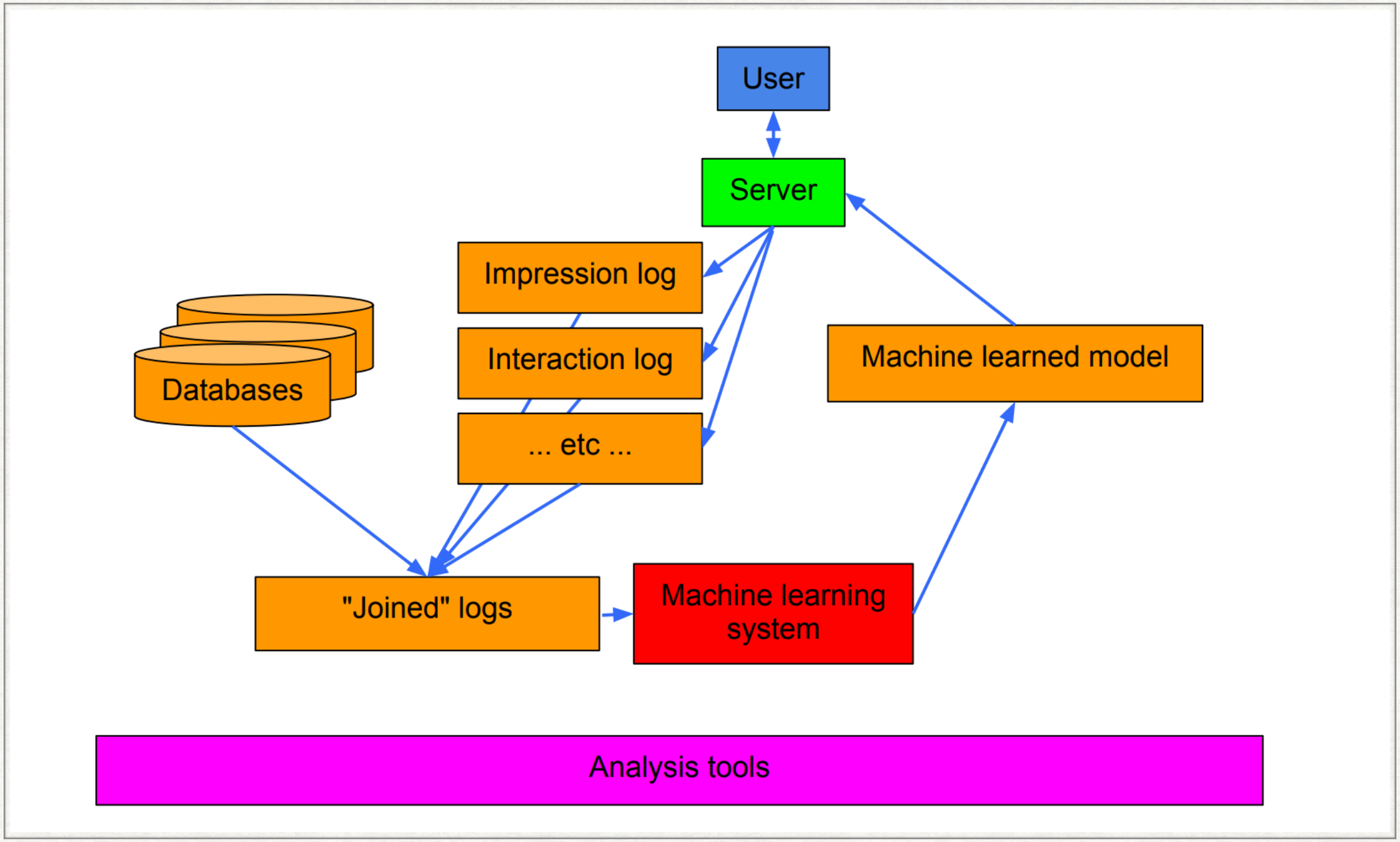


- Ads are ranked by:

$$p(click \mid Ad, user, scene) \times bid\_price(Ad)$$

- Our goal is here to : predict the click-through-rate of this Ads.

SYSTEM ARCHITECTURE



- Google Sibyl

MACHINE LEARNING APPROACH

- Represent {Ad,user,scene} as a feature vector x, let y (clicked or not clicked) be the label, then model p (y | x)
- A common way

$$p(y \mid x, w) = \frac{1}{1 + \exp(y \langle x, w \rangle)}$$

- Then learn w by **FACTORIZATION MACHINE**
- Also increasing interests on Deep learning

FEATURE ENGINEERING

- Feature Engineering is the most effective way to improve the model performance
- Often contain multiple feature groups
- Three major sources : ads, users, advertisers

N-GRAM

- Uni-gram:international, flower, delivery…
- Bi-gram : international flower,flower delivery
- For short text, even desirable generate all possible n-grams, then filter out unimportant ones

IMPORTANT THINGS

- * Style - bold style really catches eyes.
- * Personalization - User profile,Ad profile…
- * Feature combination
  - Produce a combination group of feature

DATA SCALE OF AD CTR

- Only 1 year search log produces 2 trillions examples.
- Sub-sampling? Not works because of personalization.
- The feature for this task is mainly **16 hundred billions of features.**

INDUSTRY DATA SCALE

- * 100 billions of samples
- * 10 billions of features
- * 1T - 1P training data

```
1102654752 Jun 30 17:18 part-13075.gz
1099726070 Jun 30 17:18 part-13076.gz
1101590533 Jun 30 17:18 part-13077.gz
1100016199 Jun 30 17:19 part-13078.gz
1100637016 Jun 30 17:19 part-13079.gz
1102254166 Jun 30 17:20 part-13080.gz
1103309165 Jun 30 17:21 part-13081.gz
```

WHERE TO STORE THE DATA

- * Lots of disks
- * Fail at any time
- [hardware]

ACCESS PATTERN

- Files are large10GB
- * sequential read and append.

GOOGLE FILE SYSTEM

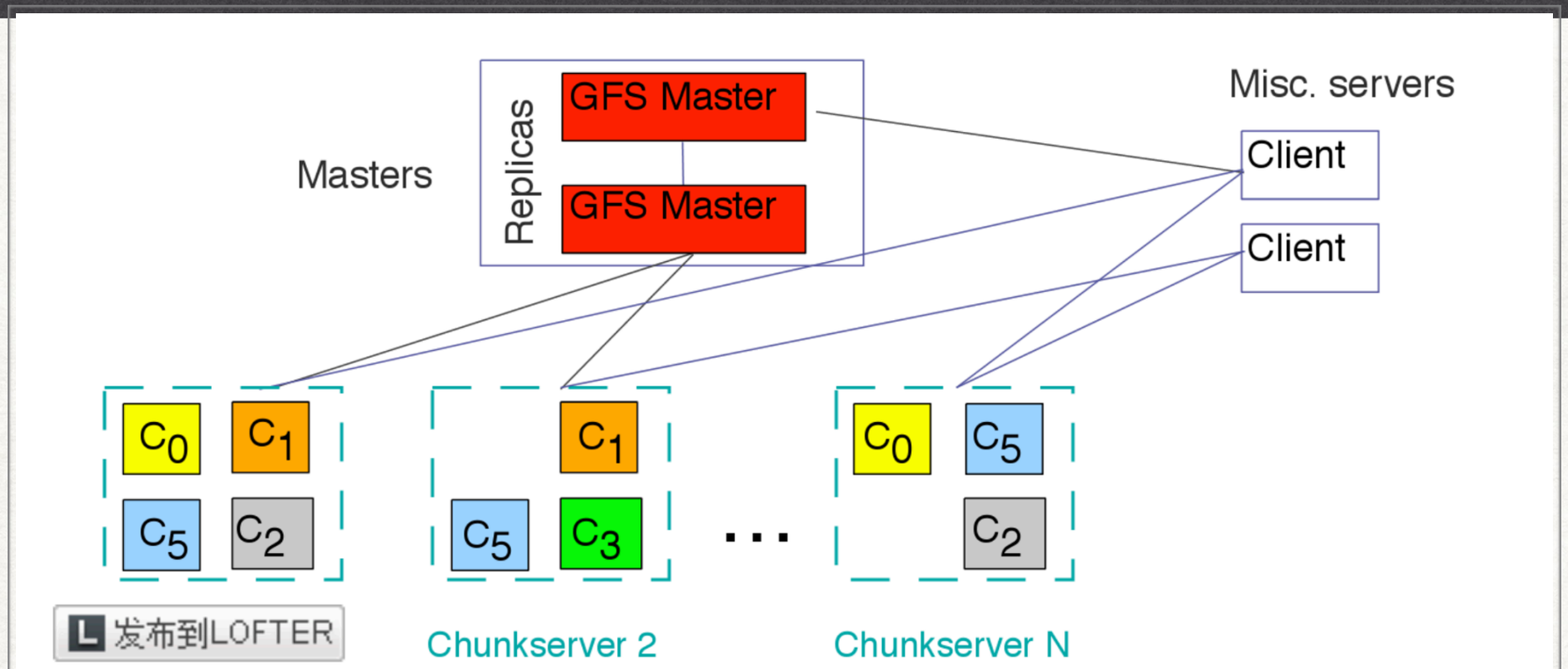


图1. GFS的架构图

- ✦ Data are replicated
  - ★ write success only if all replicas are done
- ✦ Request data:
  - ★ ask master for the location
  - ★ ask chunk server for the data
- ✦ New generations: Colossus

HDFS

- ✦ Open source implementation of GFS
- ✦ operations:
  - ★ hadoop fs -ls, -get, -put, -head, -cat, ...
  - ★ libhdfs: C API
  - ★ mount to local filesystem
- ✦ A little bit slower than GFS (personal experience)
- ✦ Large delay
  - ★ hadoop fs -ls /xxx (8000 files)
- ✦ Sometimes reading the training data uses more times than training

CONCLUDE 1

- ✦ 数据长尾分布
- ✦ 广告预测任务需要用机器学习模型去二分预测CTR
- ✦ CTR可以用特征工程，特征组合去做优化
- ✦ 数据量巨大的时候，怎么存，DISK，datacenter, google file system,HDFS

SPARSE TRAINING DATA

HIGH-DIMENSIONAL DATA ARE SPARSE

- ✦ Why high dimension?
  - ★ make the classifier's job easier
  - ★ linear method is often good enough
- ✦ Why sparse?
  - ★ easy to storage (only store non-zero entries)
  - ★ affordable computation cost
- ✦ Key difference to dense data when using
  - ★ require a lot of random read/write

STORE AND COMPUTING

COMPRESS STORAGE

	0	1	2
0		10	20
1	3		
2		87	
3	57		

- ✦ Sparse row-major:

  offset = [0, 2, 3, 4, 5]

  index = [1, 2, 0, 1, 0]

  value = 10 | 20 | 3 | 87 | 57

- ✦ Sparse column-major:

  offset = [0, 2, 4, 5]

  index = [1, 3, 0, 2, 0]

  value = 3 | 57 | 10 | 87 | 20

✦Access a(i,j) under row-major:

```
k = binary_search(index[offset[i]], index[offset[i+1]], j)
return valid(k) ? value(offset[i]+k) : 0
```

Y=AX

✦ Sample C++ codes.

ALL OFFSET, INDEX, VALUE ARE READ SEQUENTIALLY

```
// matrix-vector multiplication: y = A * x
void SparseMatrix<V>::times(const V* x const, V* y) const {
                                    ; ++i) {  // i-th row
                                    j < offset[i+1]; ++j)
      y_i += x[index[j]] * value[j];
    y[i] = y_i;
  }
} else {
  memset(y, 0, sizeof(V)*rows());
  for (size_t i = 0; i < cols(); ++i) {  // i-th column
    V x_i = x[i];
    for (size_t j = offset[i]; j < offset[i+1]; ++j)
                                    ue[j];
}
```

WRITE Y SEQUENTIALLY
BUT READ X IN RANDOM

WRITE X SEQUENTIALLY
BUT WRITE Y IN RANDOM

Numbers Everyone Should Know

L1 cache reference	0.5 ns
Branch mispredict	5 ns
L2 cache reference	7 ns
Mutex lock/unlock	100 ns
Main memory reference	100 ns
Compress 1K bytes with Zippy	10,000 ns
Send 2K bytes over 1 Gbps network	20,000 ns
Read 1 MB sequentially from memory	250,000 ns
Round trip within same datacenter	500,000 ns
Disk seek	10,000,000 ns
Read 1 MB sequentially from network	10,000,000 ns
Read 1 MB sequentially from disk	30,000,000 ns
Send packet CA->Netherlands->CA	150,000,000 ns

10 times { 0.5 ns, 5 ns

10 times { 7 ns, 100 ns

slides by Jeff Dean

Google

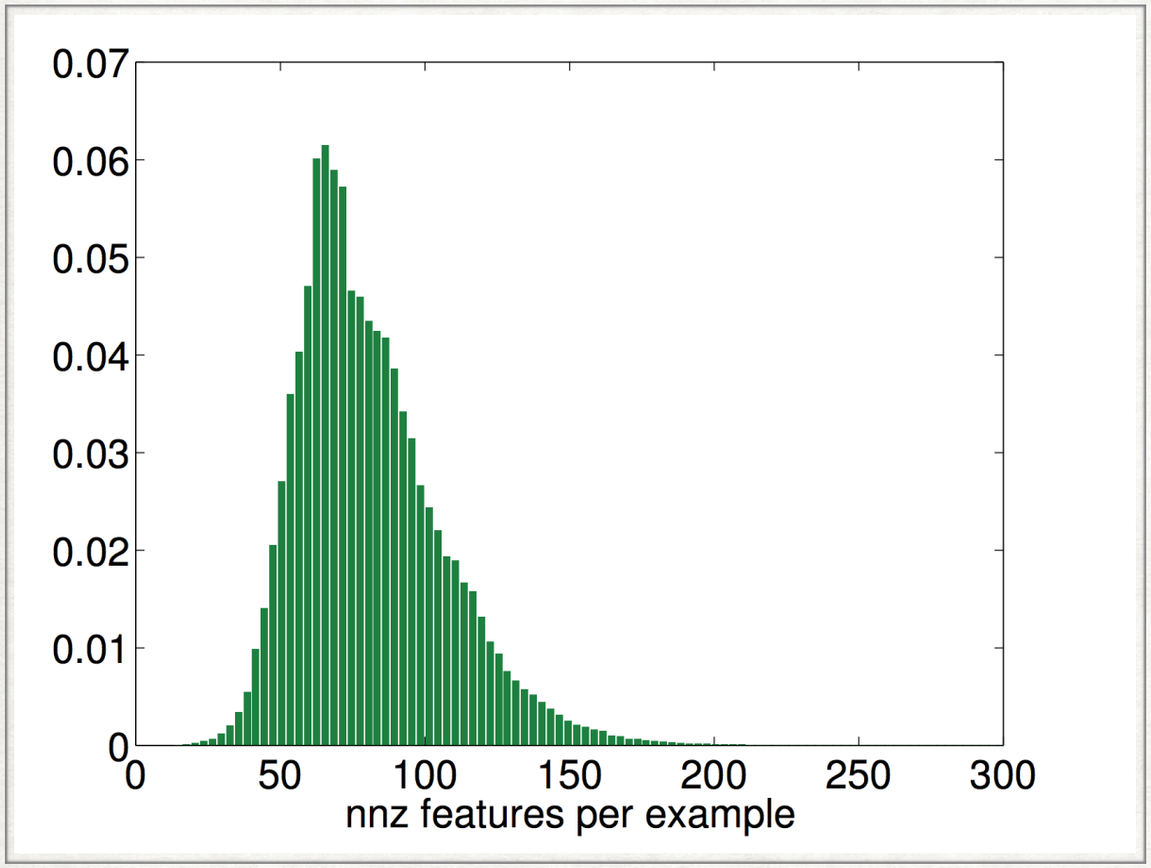
COST OF Y=AX

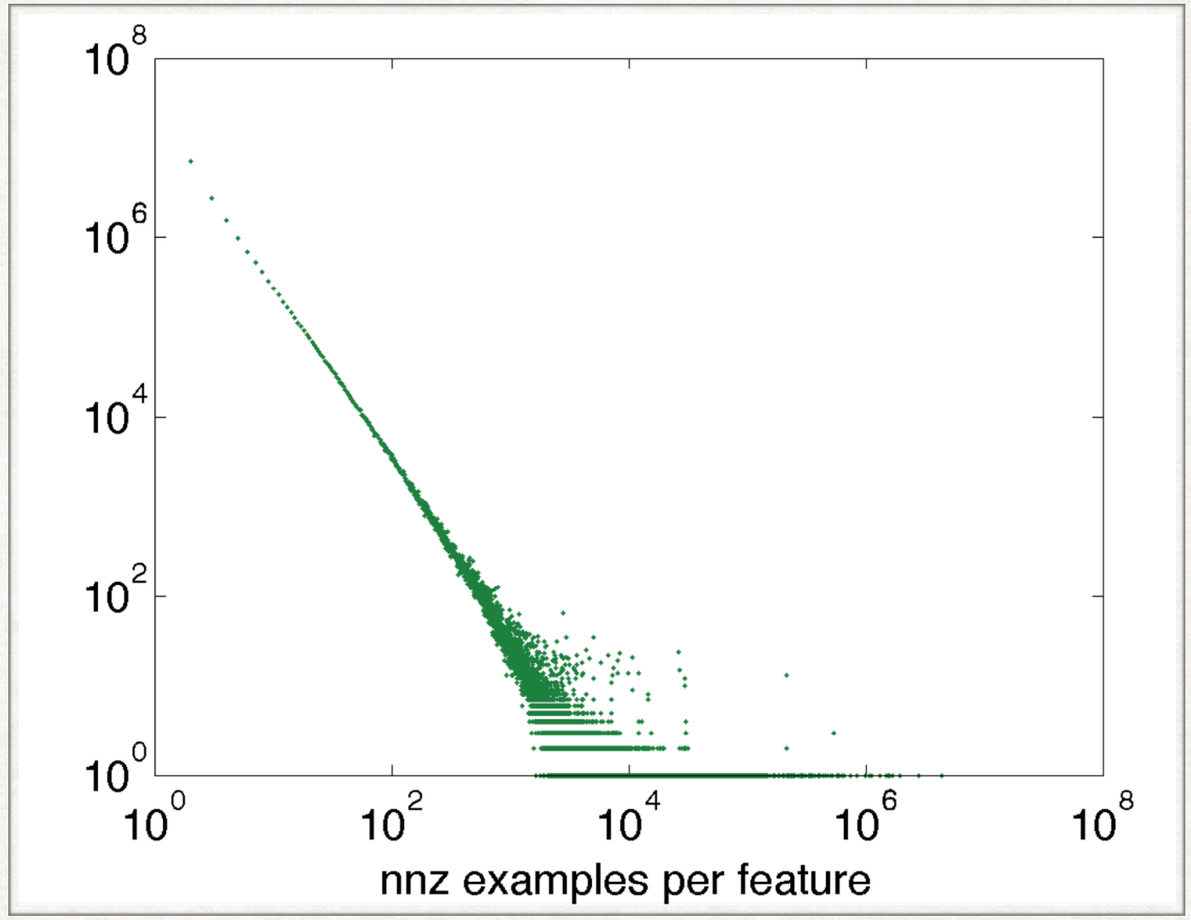
- ✦ The computation cost is O(nnz(A))
- ✦ The random access dominates the cost:

$$\approx L2-cache-reference(nnz(A))$$

- ✦ In theory: process 1.4e8 nnz entries per second
- ✦ In reality: 8.4e7 nnz entries per second
  - ★ 4.3M x 17.4M sparse matrix
  - ★ mac mbp, Intel i7 2.3GHz cpu
  - ★ single thread

PATTERNS OF SPARSITY





✦ Non-zero entries are distributed irregularly on features

★ imbalanced workload partition

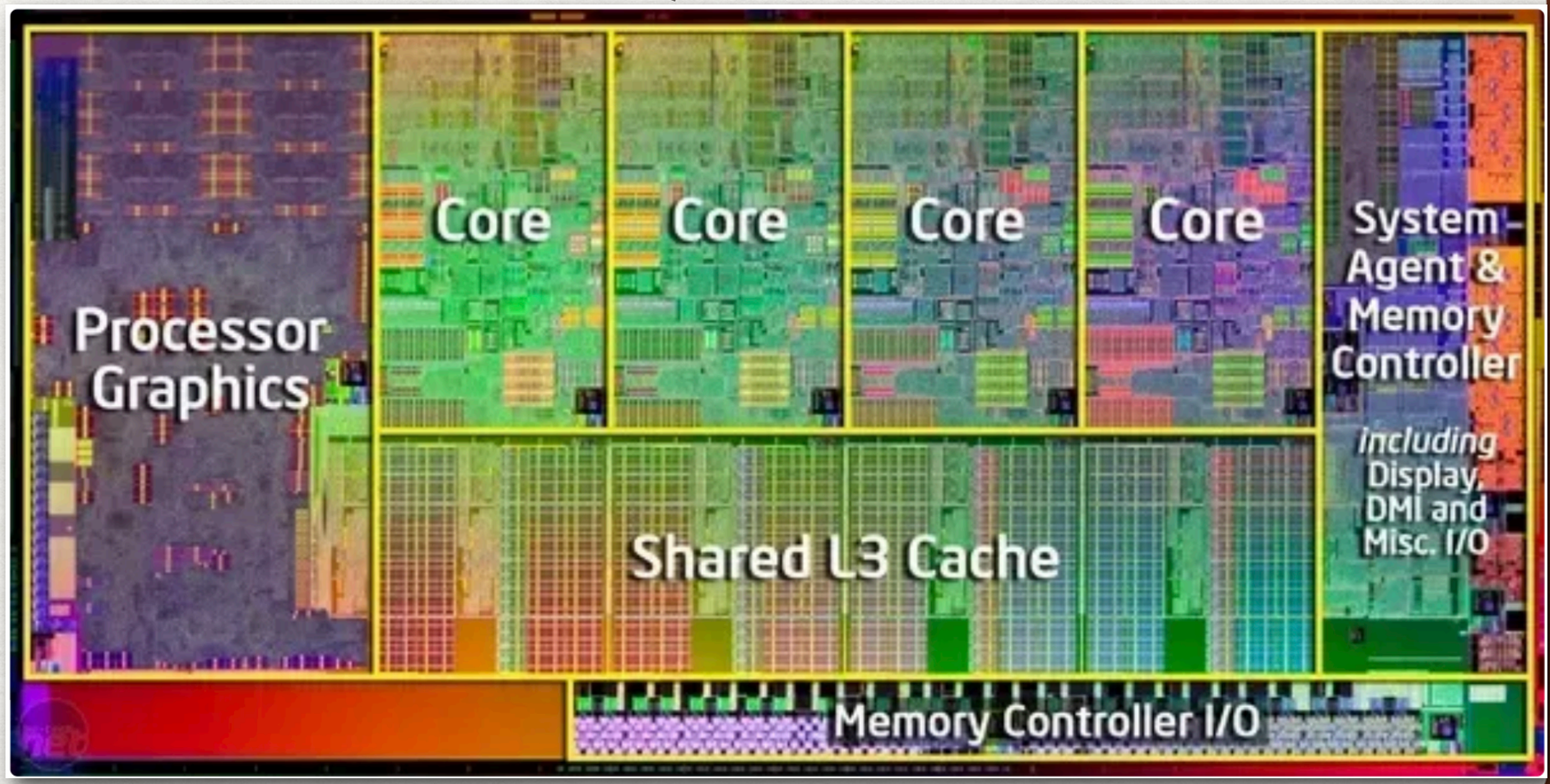
★ ill conditional number

MULTI-THREAD IMPLEMENTATION

CPU

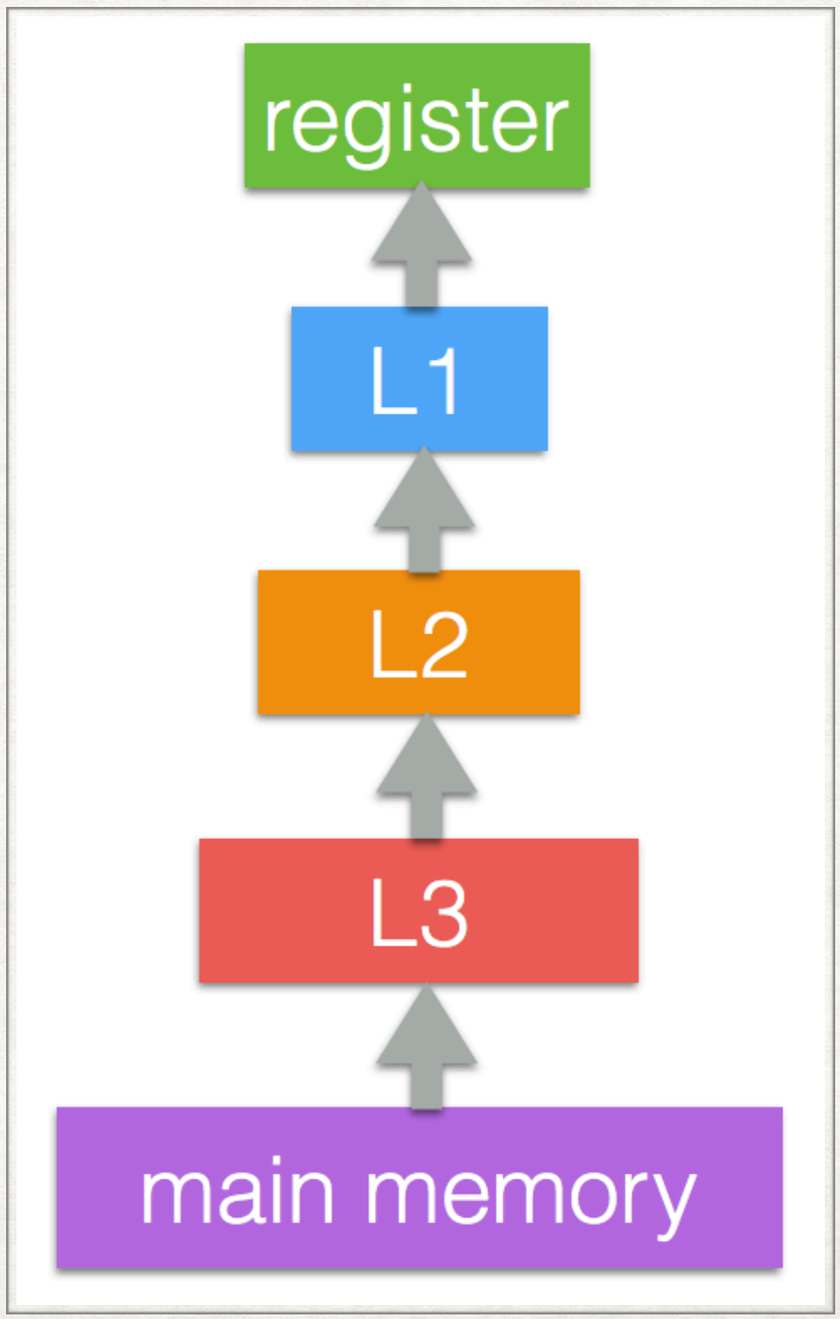
- Multiple cores (4-8)
- Multiple sockets (1-4)
- 2-4 GHz clock
- Memory interface 20-40 GB/s
- Internal bandwidth > 100GB/s

core i7



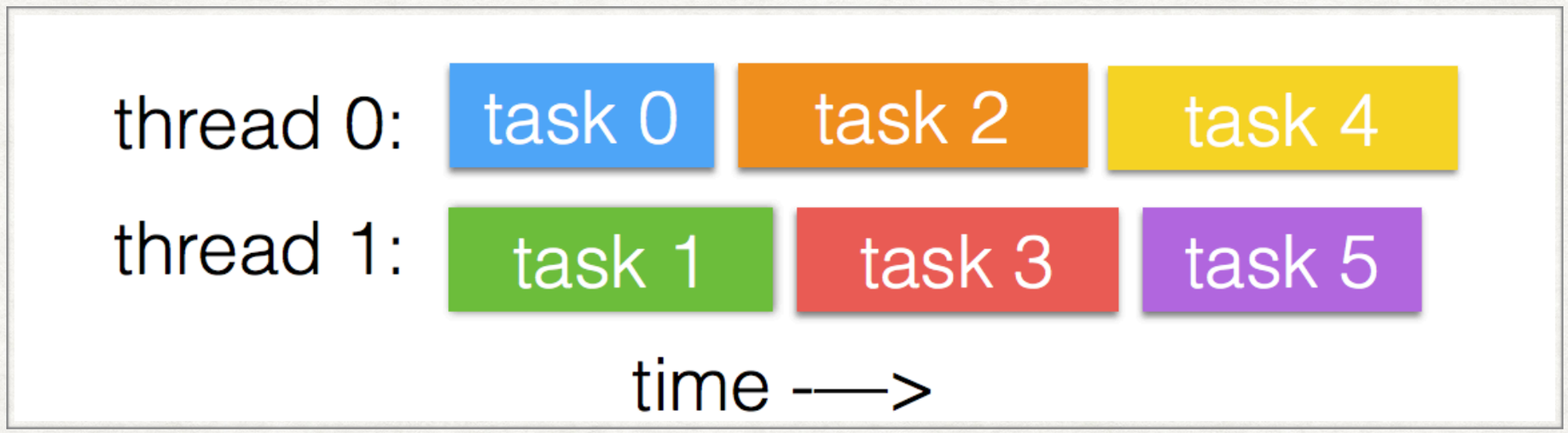
BENEFITS OF MULTI-THREAD

- Use more computation units
  - Float point units
- Hide memory latency
  - Run something else when the data are not ready
    - Fetch data from memory ~100 cycles



USING THREAD POOL

- ✦ A pool of threads, each one keeps fetching and executing unfinished tasks
- ✦ Create a pool with n threads: ThreadPool pool(n)
- ✦ Add a task into the pool: pool.add(task)
- ✦ Start executing: pool.startWorkers()



MULTI-THREAD Y= AX

- ✦ Assume row major
- ✦ Compute a segment of y

```
void rangeTimes(SizeR row_range, const V* const x, V* y) const;
```

- ✦ Divide y into several segments, each one is assigned to a thread

```
ThreadPool pool(num_threads);
int num_tasks = rowMajor() ? num_threads * 10 : num_threads;
for (int i = 0; i < num_tasks; ++i) {
  pool.add([this, x, y, row_range, num_tasks, i](){
      rangeTimes(row_range.evenDivide(num_tasks, i), x, y);
    });
}
pool.startWorkers();
```

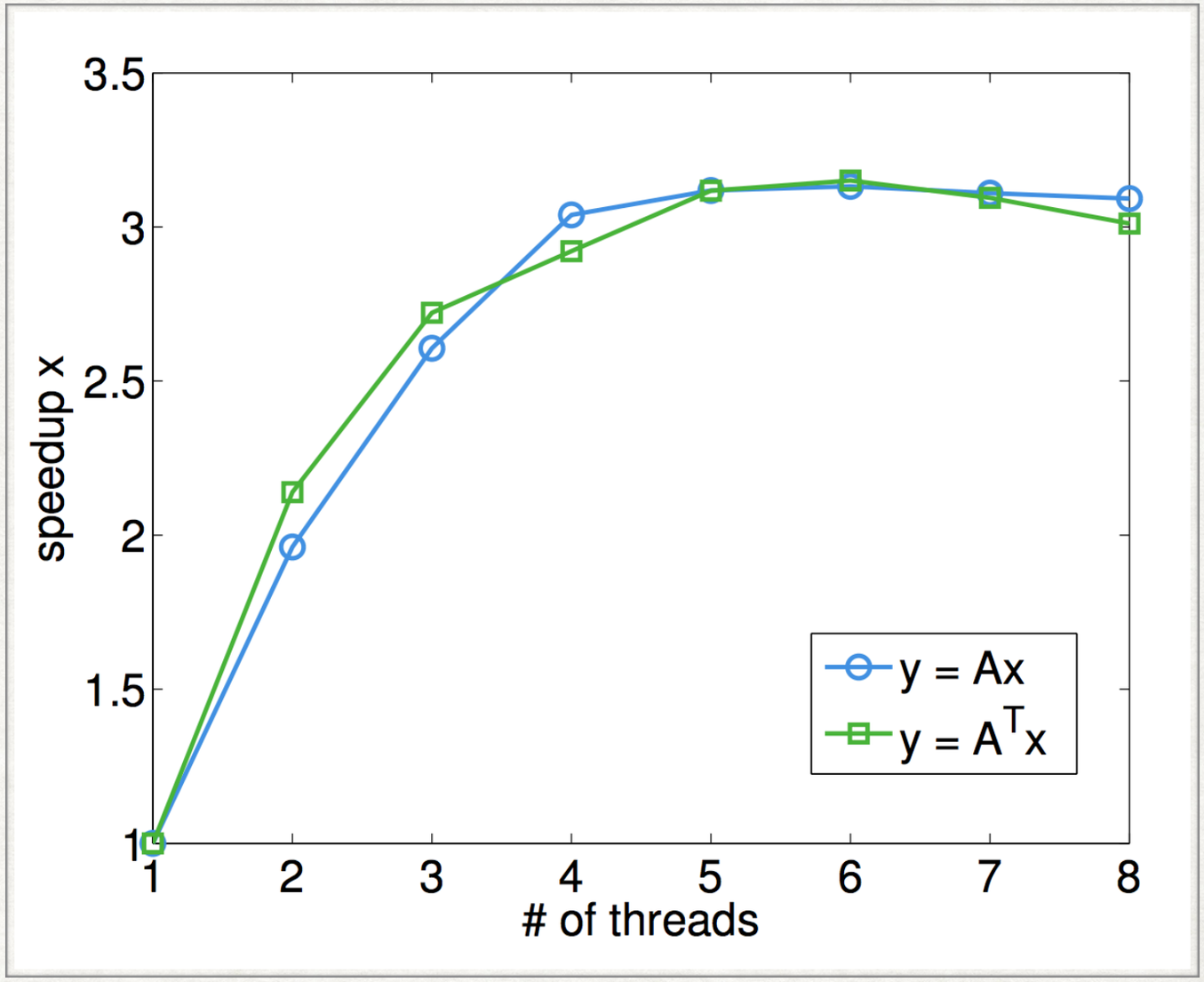
C++11 LAMBDA FUNCTIONS

HOW ABOUT COLUMN-MAJOR?

- ✦ Equivalence to $x = A^T y$ for row-major A
- ✦ multi-threads concurrently write the same y
- ✦ Several possible solutions:
  - ★ convert into a row-major matrix first
  - ★ lock y[i] (or a segment) before write it
  - ★ each thread writes only a segment of y

EXPERIMENTS

- ✦ data: CTRa
- ✦ row major,
  4.3M rows,
  17.4M columns,
  354M nnz entries
- ✦ MBP Pro,
  Intel i7 2.3GHz,
  4 cores,
  8 hyper-threads



ROW MAJOR OR COLUMN MAJOR

✦No big difference for individual and whole access

★Choose the one how data are stored

✦ Use row major when need read individual rows

★ SGD, minibatch SGD, online learning

✦ Use column major when need read columns

★ (block) Coordinate descent

✦ Converting cost 2*nnz(A) random access

MORE

- Other Operations? BLAS,LAPACK
  - ★ Timothy A. Davis, Direct Methods for Sparse Linear Systems, SIAM, 2006
- Existing packages:
  - ★ SuiteSparse, Eigen3…
  - ★ Jeff Dean is using it…

Bug 613 - Bug in internal::psqrt SSE implementation

Status: RESOLVED FIXED	**Reported**: 2013-06-13 17:54 UTC by Jeff Dean
Product: Eigen	**Modified**: 2013-06-14 09:52 UTC (History)
Component: Core - general	

add subtract	`mat3 = mat1 + mat2;` `mat3 = mat1 - mat2;`	`mat3 += mat1;` `mat3 -= mat1;`
scalar product	`mat3 = mat1 * s1;` `mat3 = mat1 / s1;`	`mat3 *= s1;` `mat3 /= s1;`

matrix/vector products *	`col2 = mat1 * col1;`
	`row2 = row1 * mat1;`
	`mat3 = mat1 * mat2;`
		`row1 *= mat1;`
		`mat3 *= mat1;`

transposition adjoint *	`mat1 = mat2.transpose();` `mat1 = mat2.adjoint();`	`mat1.transposeInP` `mat1.adjointInPla`

dot product
inner product *
	`scalar = vec1.dot(vec2);`
	`scalar = col1.adjoint() * col2;`
	`scalar = (col1.adjoint() * col2).value();`	

outer product *	`mat = col1 * col2.transpose();`	

CONCLUDE

- ✦ 高维稀疏数据，怎么优化存储——压缩存储法
- ✦ 高维稀疏数据，怎么优化计算——
- Y=AX
- 两种方法：一个是按行分开，一个是按列分开
- ✦ 多线程模型——Thread pool
- ✦ 按行分 or 按列分 去并行计算 Y=AX

到现在我们都只是多线程的并行。没有多machine.
拆分的都是对A而言，数据拆分，没有对模型也就是x做拆分。

DISTRIBUTED OPTIMIZATION

MOTIVATION

✦For big data, machines are scarce resources

✦ We must find the solution as economic as possible

★ saving several iterations may mean hundreds of machine hours

(hundreds of $ on ec2)

BATCH AND ONLINE

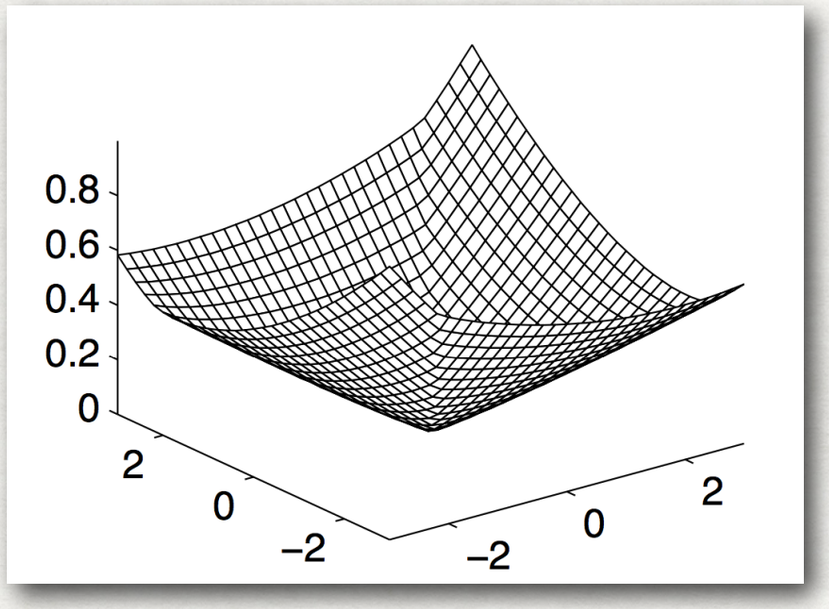
✦BATCH ——Very large dataset available

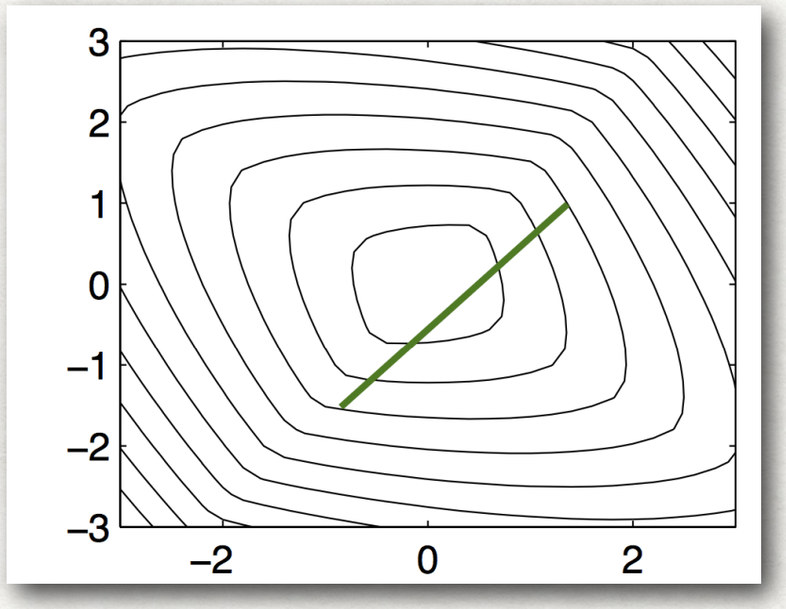
✦Online —— Data -> Compute -> Loop

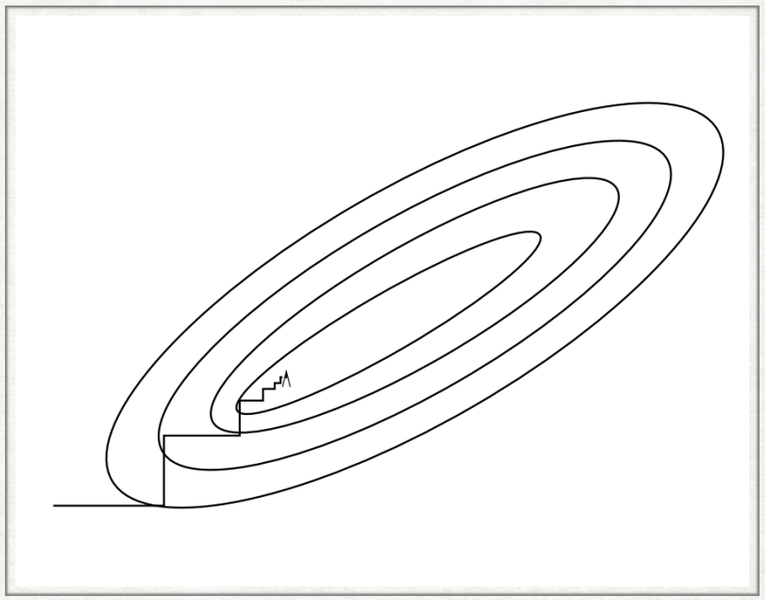
ISSUE FOR SPARSE DATA

- ML is all about Gradient Descent

May sensitive to the learning rate







- $w^{t+1} = w^t - \eta \left[\sum_{k \leq t} \mathrm{diag}(\nabla f(w^k))^2 \right]^{-\frac{1}{2}} \nabla f(w^t)$

MULTI-THREAD

LOGISTIC REGRESSION

- The most expensive part: compute gradients
- For logistic loss:

$$f(w) = \text{sum}(\log(1 + \exp(y. * (Xw))$$
$$\nabla f(w) = X^T(y./(1 + \exp(y. * (Xw))))$$

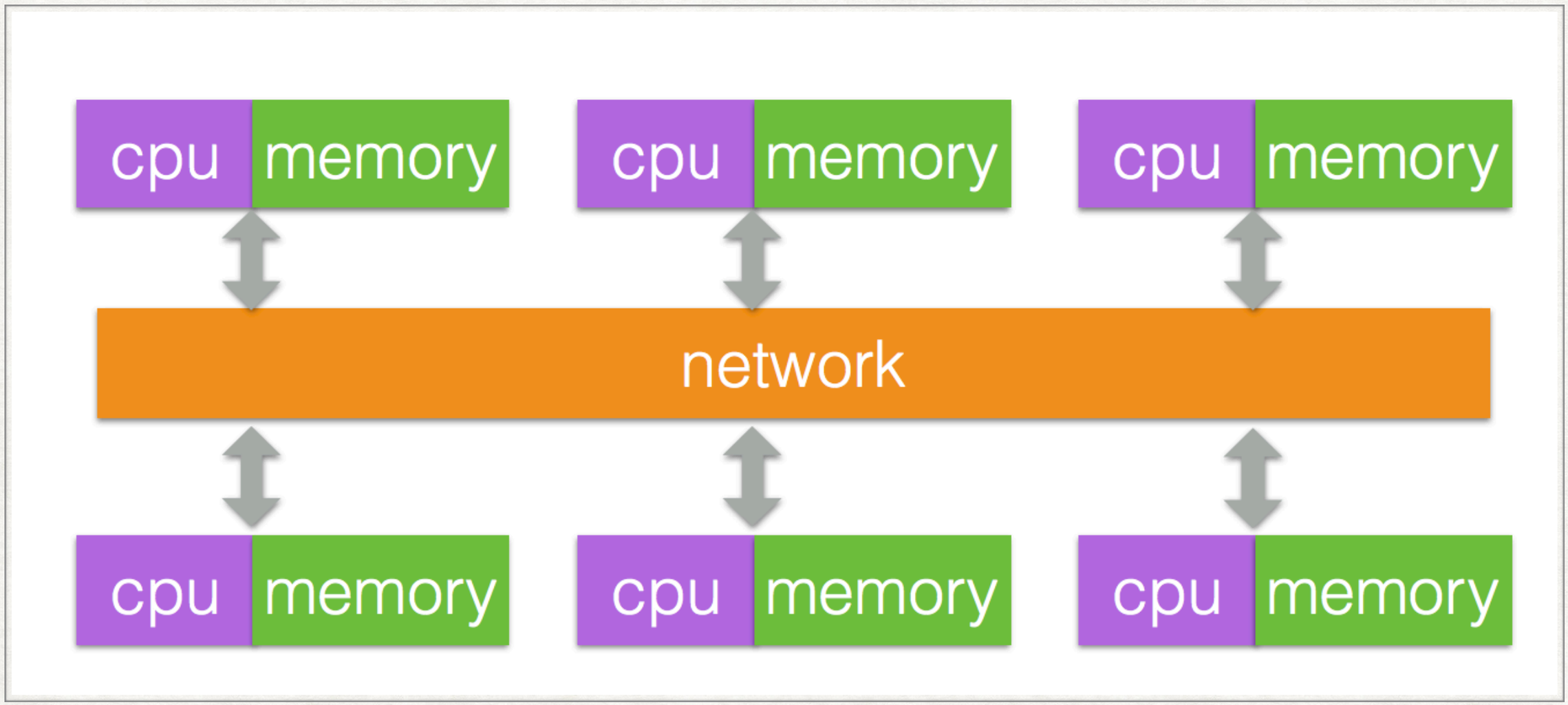
- Two key steps

- Multi-threaded by previous technologies

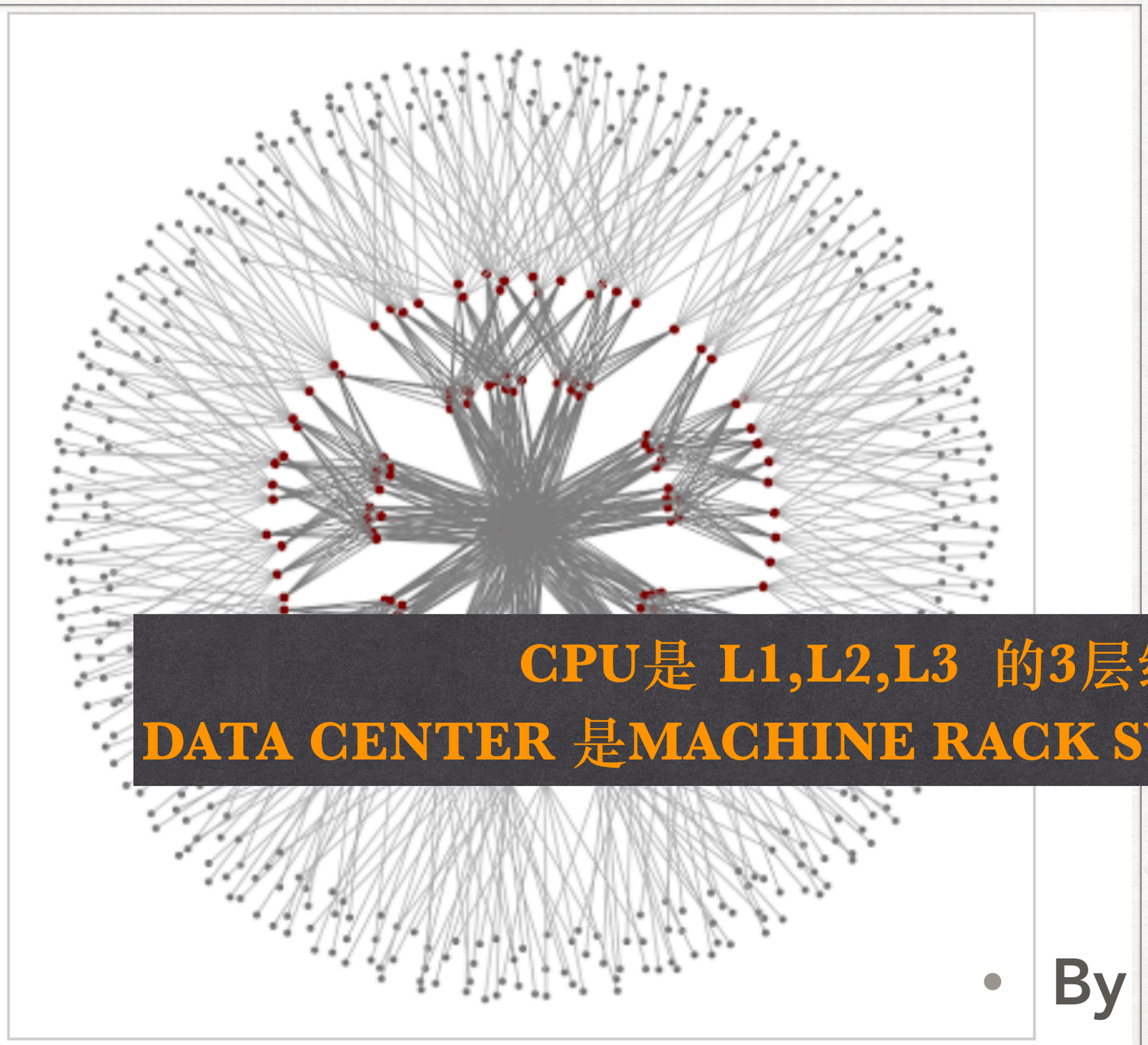
DISTRIBUTED IMPLEMENTATION

DISTRIBUTED ARCHITECTURE

- Data are exchange via network



DATA CENTER



- 3-level fat-tree
- 432 servers
- (grey)
- 180 switches
- (red)

CPU是 L1,L2,L3 的3层级
DATA CENTER 是MACHINE RACK SWITCH 的3层级

- By Brighten Godfrey

Numbers Everyone Should Know

L1 cache reference	0.5 ns
Branch mispredict	5 ns
L2 cache reference	7 ns
Mutex lock/unlock	100 ns
Main memory reference	100 ns
Compress 1K bytes with Zippy	10,000 ns
Send 2K bytes over 1 Gbps network	20,000 ns
Read 1 MB sequentially from memory	250,000 ns
Round trip within same datacenter	500,000 ns
Disk seek	10,000,000 ns
Read 1 MB sequentially from network	10,000,000 ns
Read 1 MB sequentially from disk	30,000,000 ns
Send packet CA->Netherlands->CA	150,000,000 ns

500 times

slides by Jeff Dean

Google

DATA PARTITION

- Assume Data is not so large

W

X

Y = AX

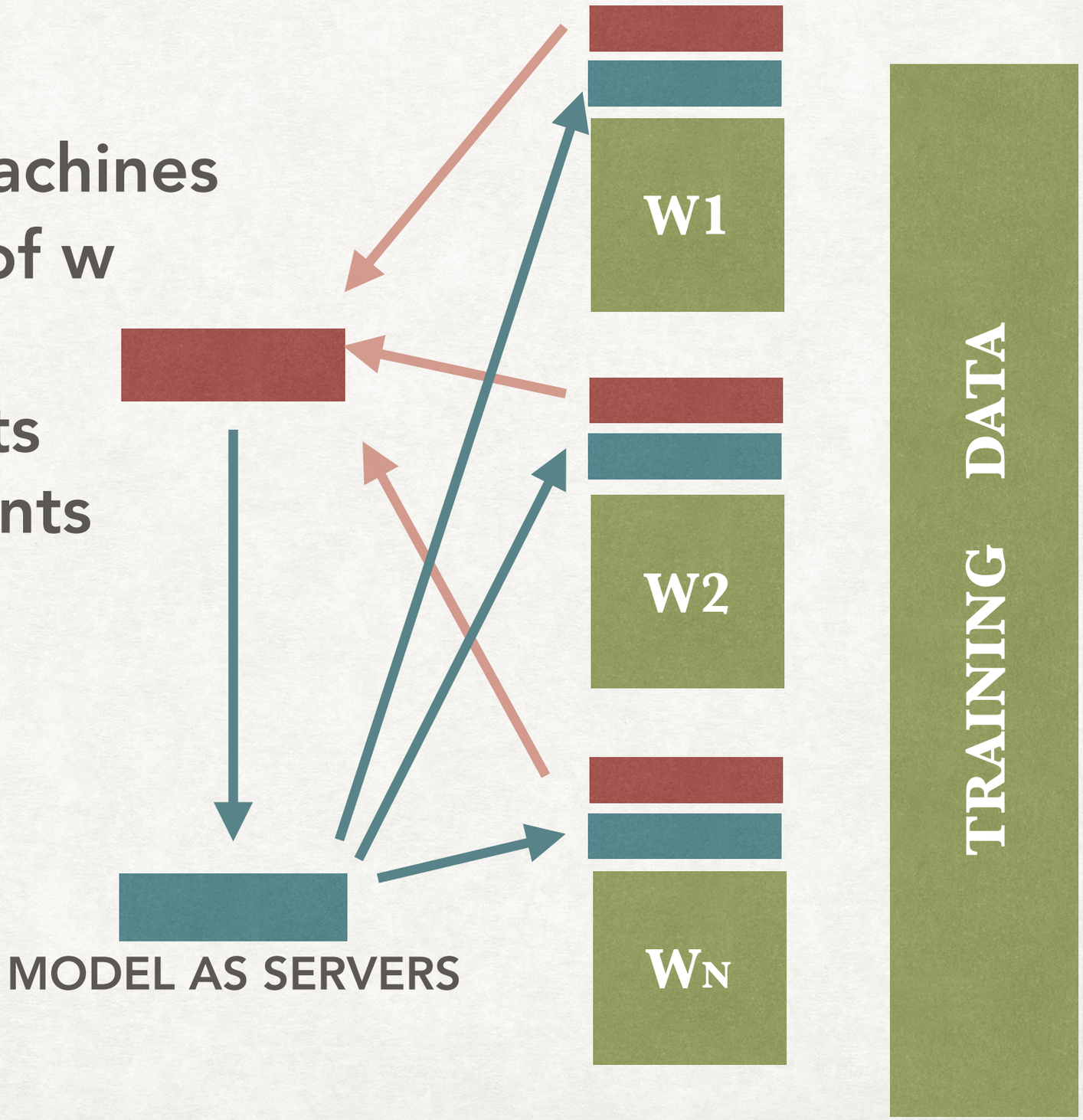
A 代指这里的 X

X 代指这里的 W

我们这里只是分割的X，（数据），没有分割到模型

DISTRIBUTED IMPLEMENTAION

Partition data into machines
Get the working set of w
Iterate t = 1, 2, ...
    Compute gradients
    Aggregate gradients
    Update w
Get updated w



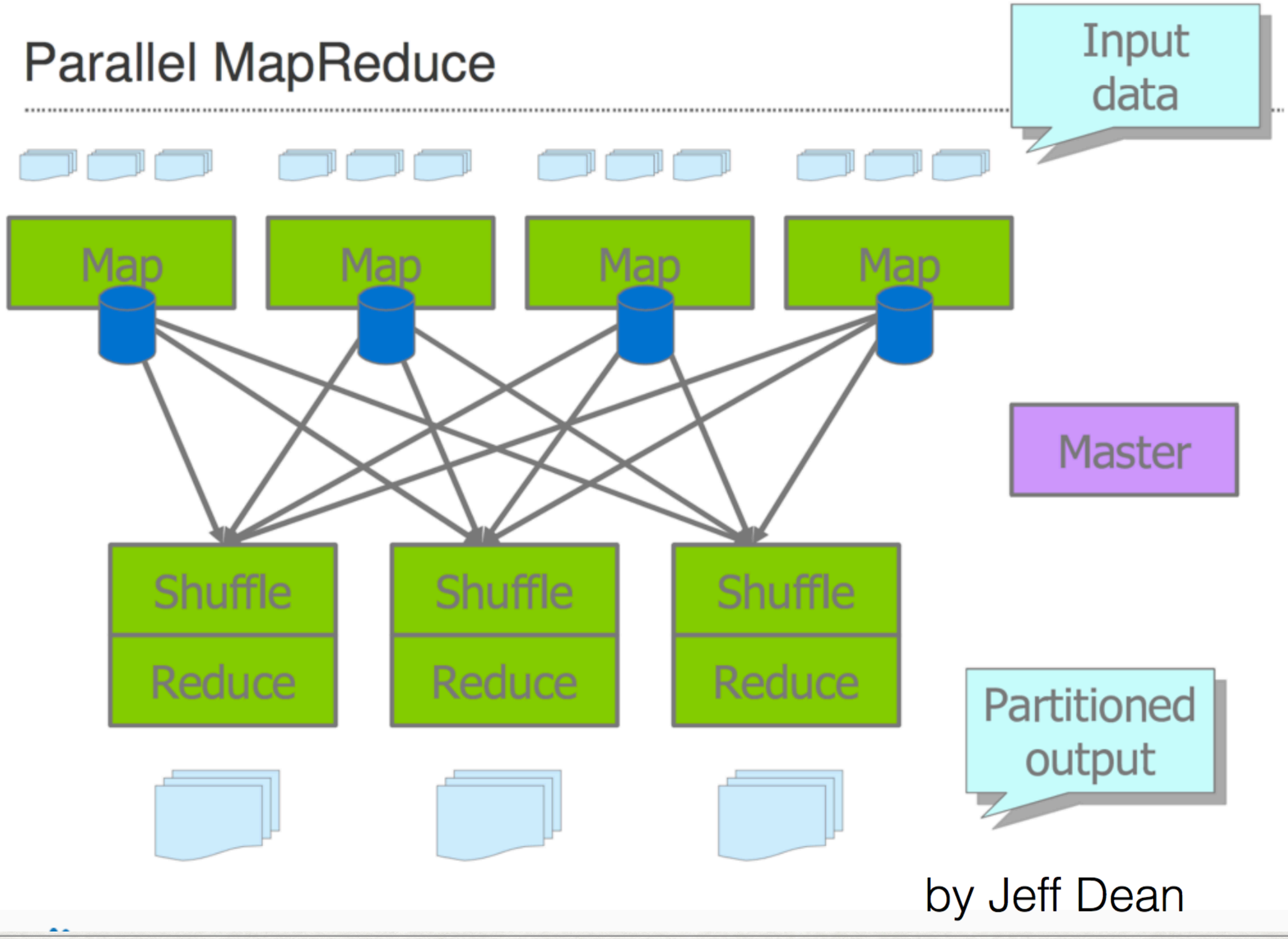
MAP REDUCE

- ✦ Proposed by Google, open source Hadoop, Spark
- ✦ Need to specify two primary methods
  - ★ map (k, v) —> [k’, v’]*
  - ★ reduce (k, [v]*) —> [k,v’]

IMPLEMENT GD

- ✦ Each iteration is a map/reduce
  - ★ map: each worker computes gradients, emits (feature_id, gradient_value)
  - ★ reduce: sum gradient with the same featured id

Parallel MapReduce



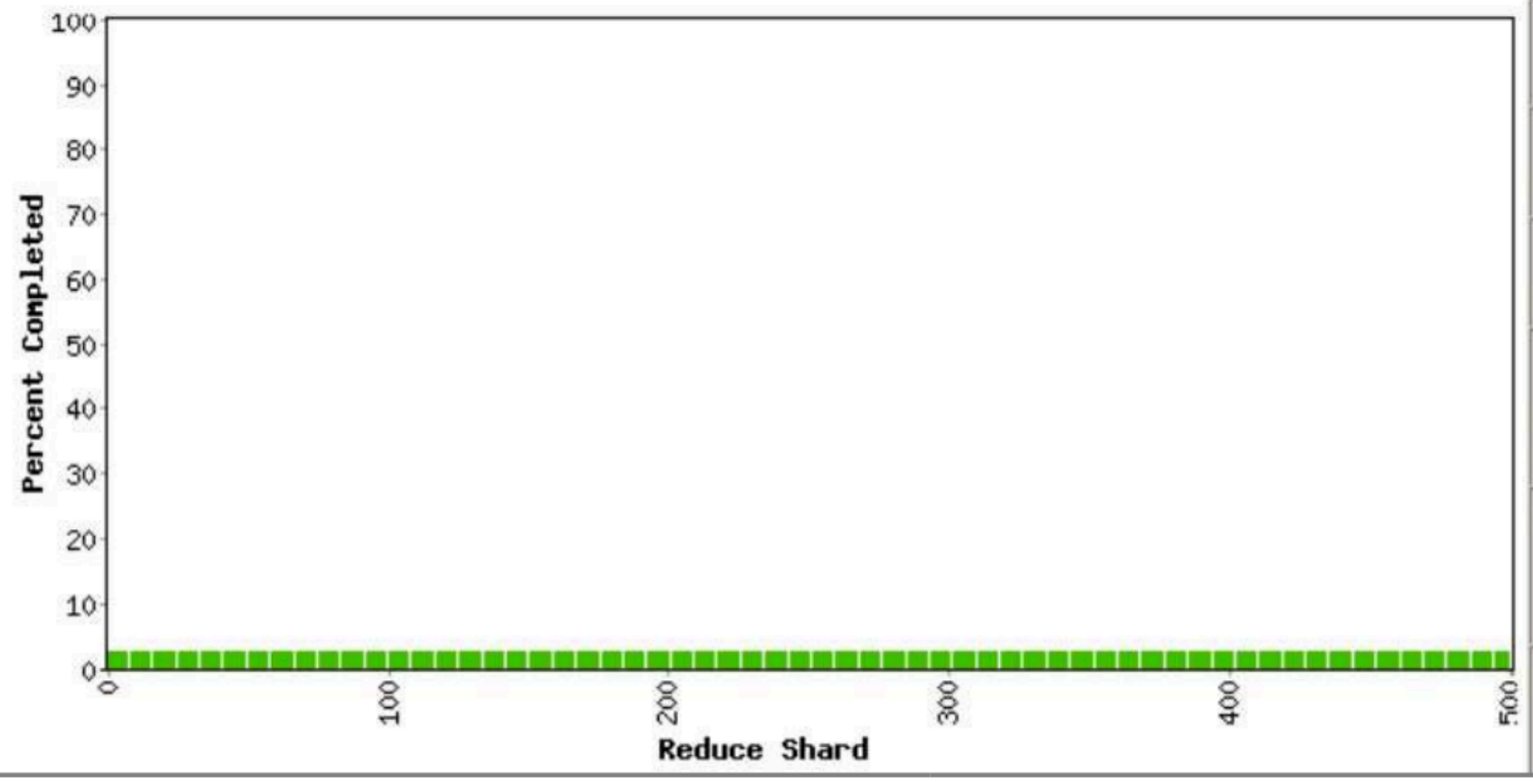
by Jeff Dean

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 00 min 18 sec

323 workers; 0 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	0	323	878934.6	1314.4	717.0
Shuffle	500	0	323	717.0	0.0	0.0
Reduce	500	0	0	0.0	0.0	0.0



Counters

Variable	Minute
Mapped (MB/s)	72.5
Shuffle (MB/s)	0.0
Output (MB/s)	0.0
doc-index-hits	145825686
docs-indexed	506631
dups-in-index-merge	0
mr-operator-calls	508192
mr-operator-	506631

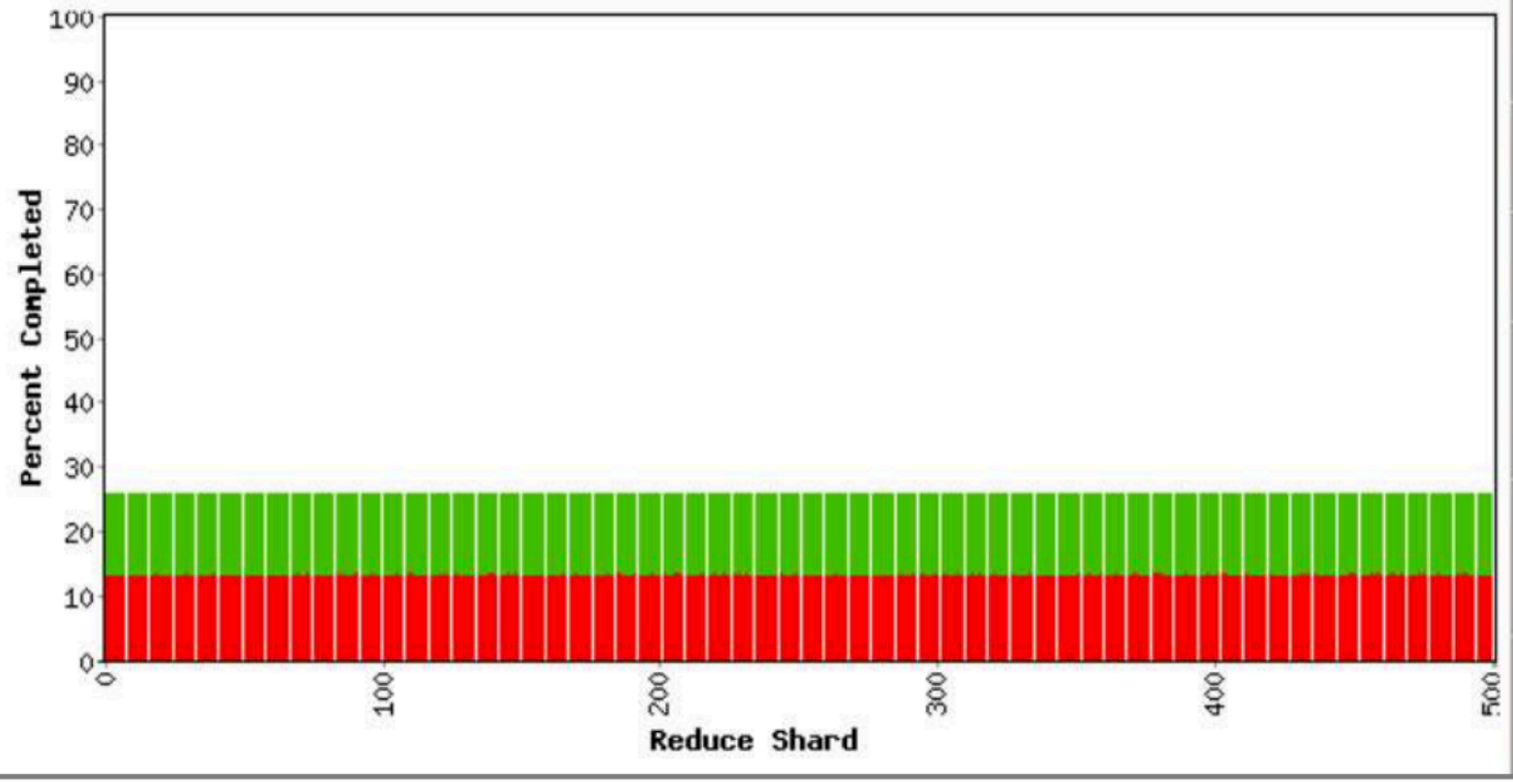
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 05 min 07 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	1857	1707	878934.6	191995.8	113936.6
Shuffle	500	0	500	113936.6	57113.7	57113.7
Reduce	500	0	0	57113.7	0.0	0.0



Counters

Variable	Minute
Mapped (MB/s)	699.1
Shuffle (MB/s)	349.5
Output (MB/s)	0.0
doc-index-hits	5004411944
docs-indexed	17290135
dups-in-index-merge	0
mr-operator-calls	17331371
mr-operator-outputs	17290135

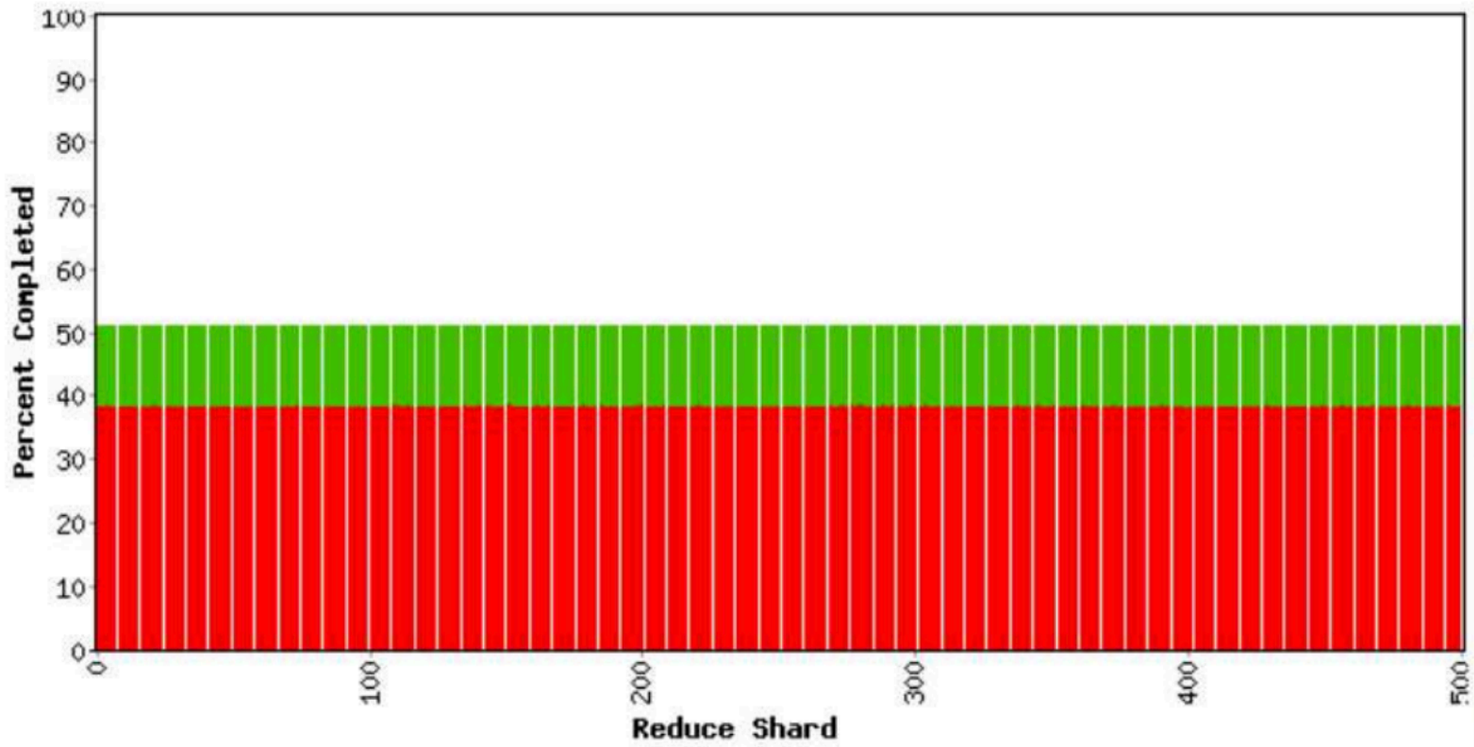
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 10 min 18 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	5354	1707	878934.6	406020.1	241058.2
Shuffle	500	0	500	241058.2	196362.5	196362.5
Reduce	500	0	0	196362.5	0.0	0.0



Counters

Variable	Minute
Mapped (MB/s)	704.4
Shuffle (MB/s)	371.9
Output (MB/s)	0.0
doc-index-hits	5000364228
docs-indexed	17300709
dups-in-index-merge	0
mr-operator-calls	17342493
mr-operator-outputs	17300709

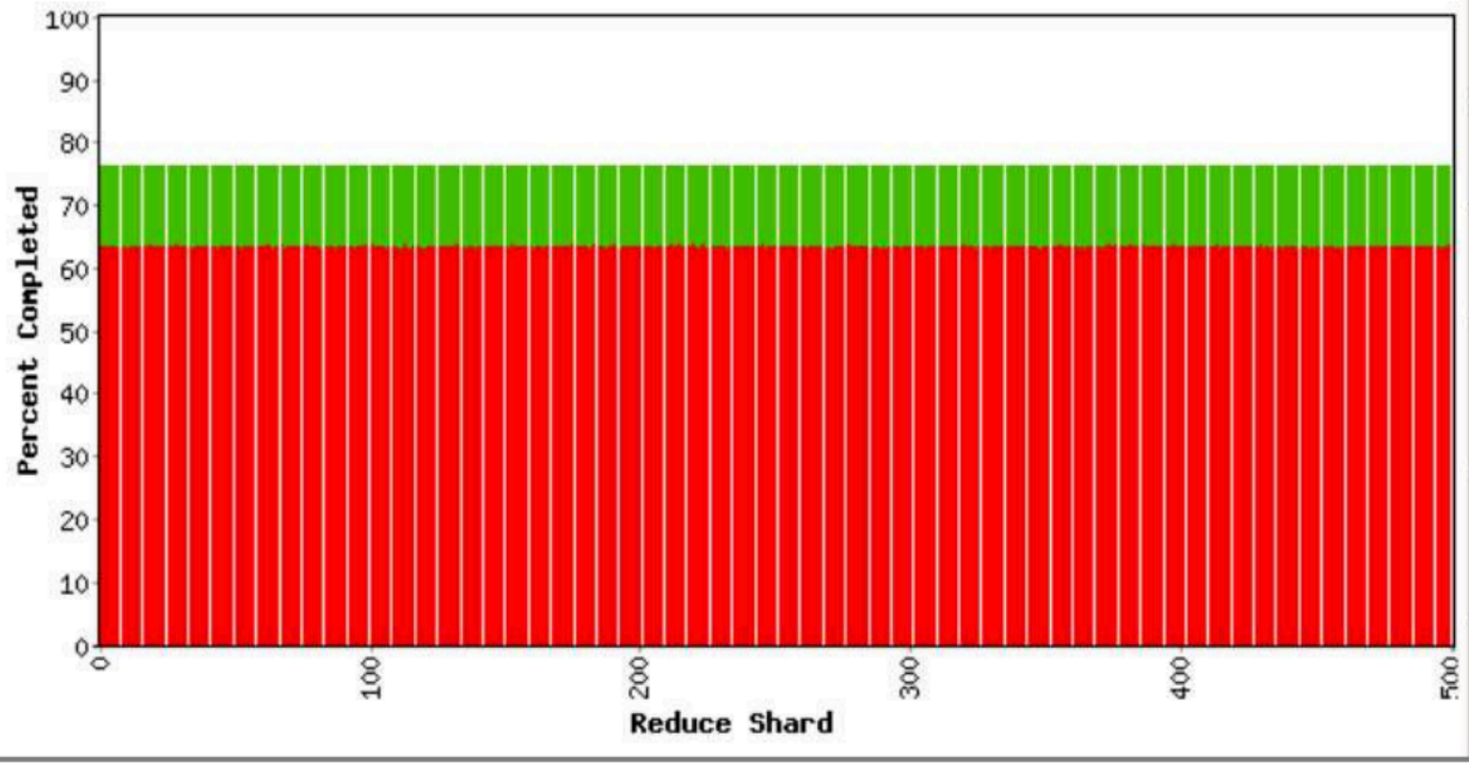
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 15 min 31 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	8841	1707	878934.6	621608.5	369459.8
Shuffle	500	0	500	369459.8	326986.8	326986.8
Reduce	500	0	0	326986.8	0.0	0.0



Counters

Variable	Minute
Mapped (MB/s)	706.5
Shuffle (MB/s)	419.2
Output (MB/s)	0.0
doc-index-hits	4982870667
docs-indexed	17229926
dups-in-index-merge	0
mr-operator-calls	17272056
mr-operator-outputs	17229926

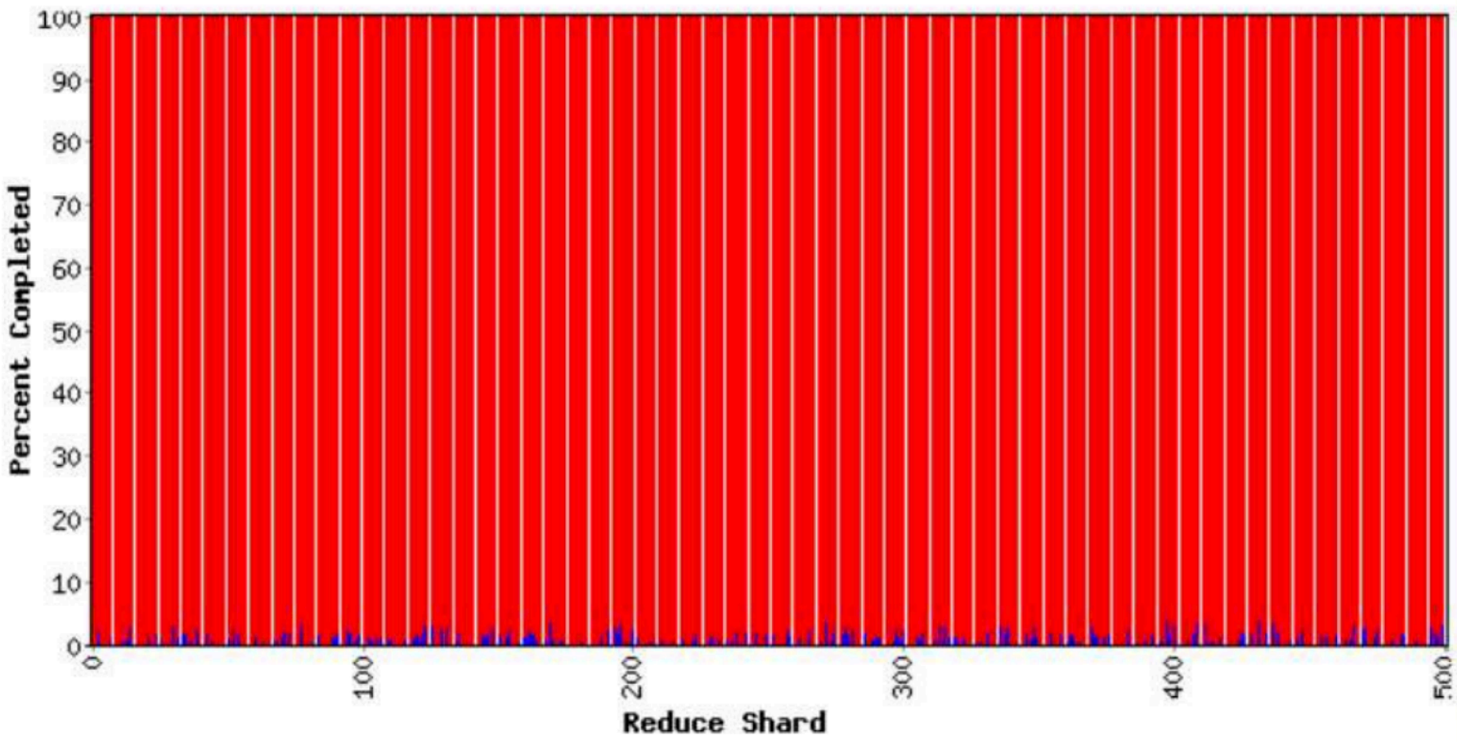
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 29 min 45 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	195	305	523499.2	523389.6	523389.6
Reduce	500	0	195	523389.6	2685.2	2742.6



Counters

Variable	Minute	
Mapped (MB/s)	0.3	
Shuffle (MB/s)	0.5	
Output (MB/s)	45.7	
doc-index-hits	2313178	105
docs-indexed	7936	
dups-in-index-merge	0	
mr-merge-calls	1954105	
mr-merge-outputs	1954105	

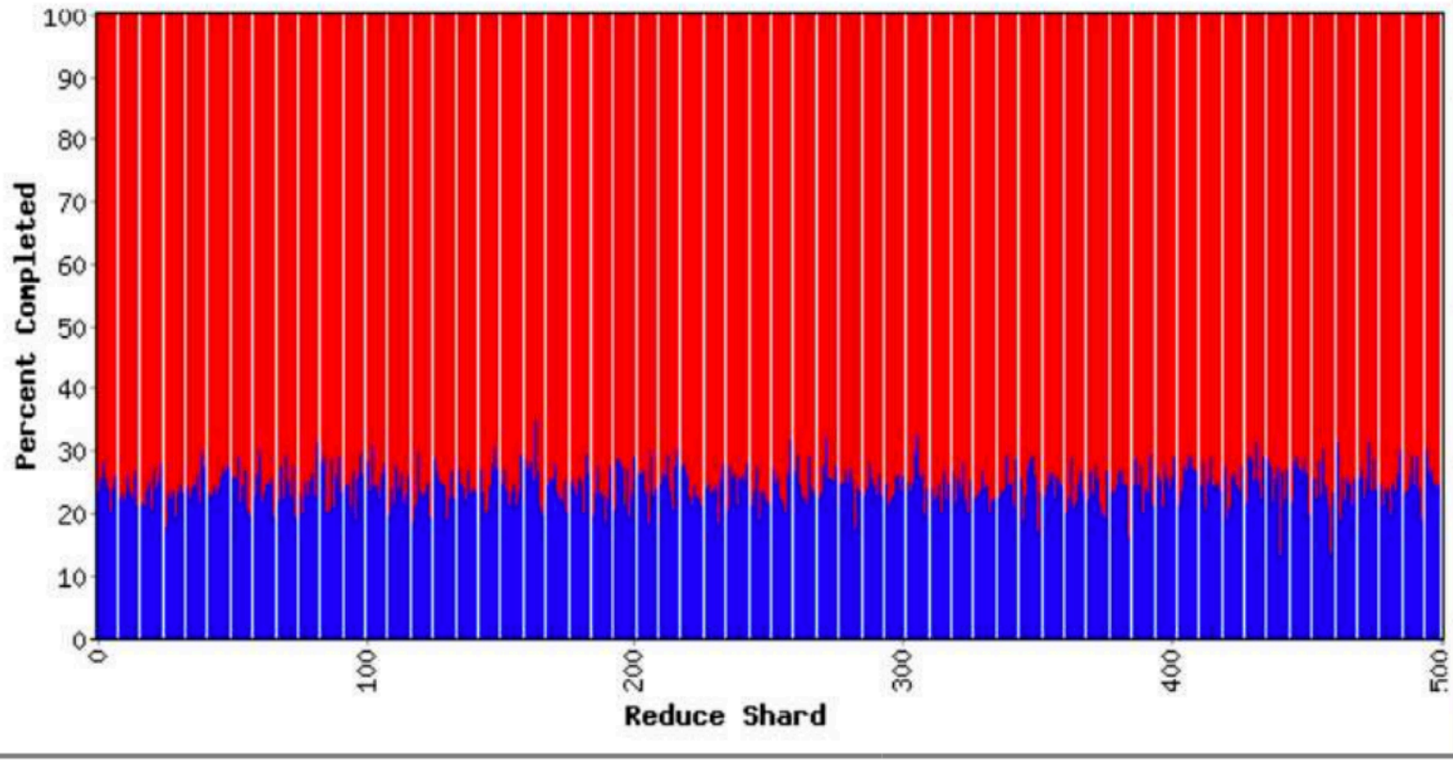
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 31 min 34 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	133837.8	136929.6



Counters

Variable	Minute
Mapped (MB/s)	0.0
Shuffle (MB/s)	0.1
Output (MB/s)	1238.8
doc-index-hits	0
docs-indexed	0
dups-in-index-merge	0
mr-merge-calls	51738599
mr-merge-outputs	51738599

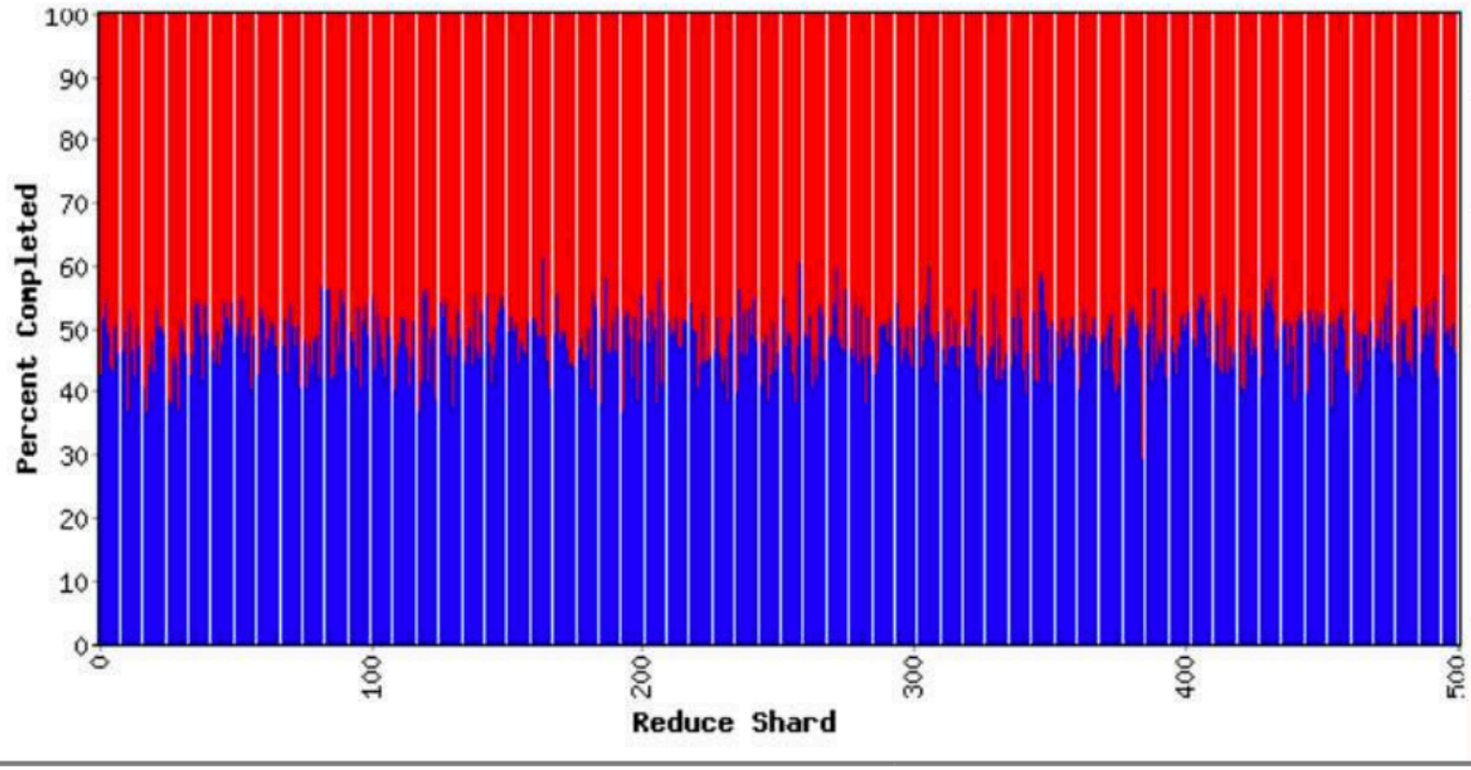
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 33 min 22 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	263283.3	269351.2



Counters

Variable	Minute	
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	1225.1	
doc-index-hits	0	1(
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	51842100	
mr-merge-outputs	51842100	

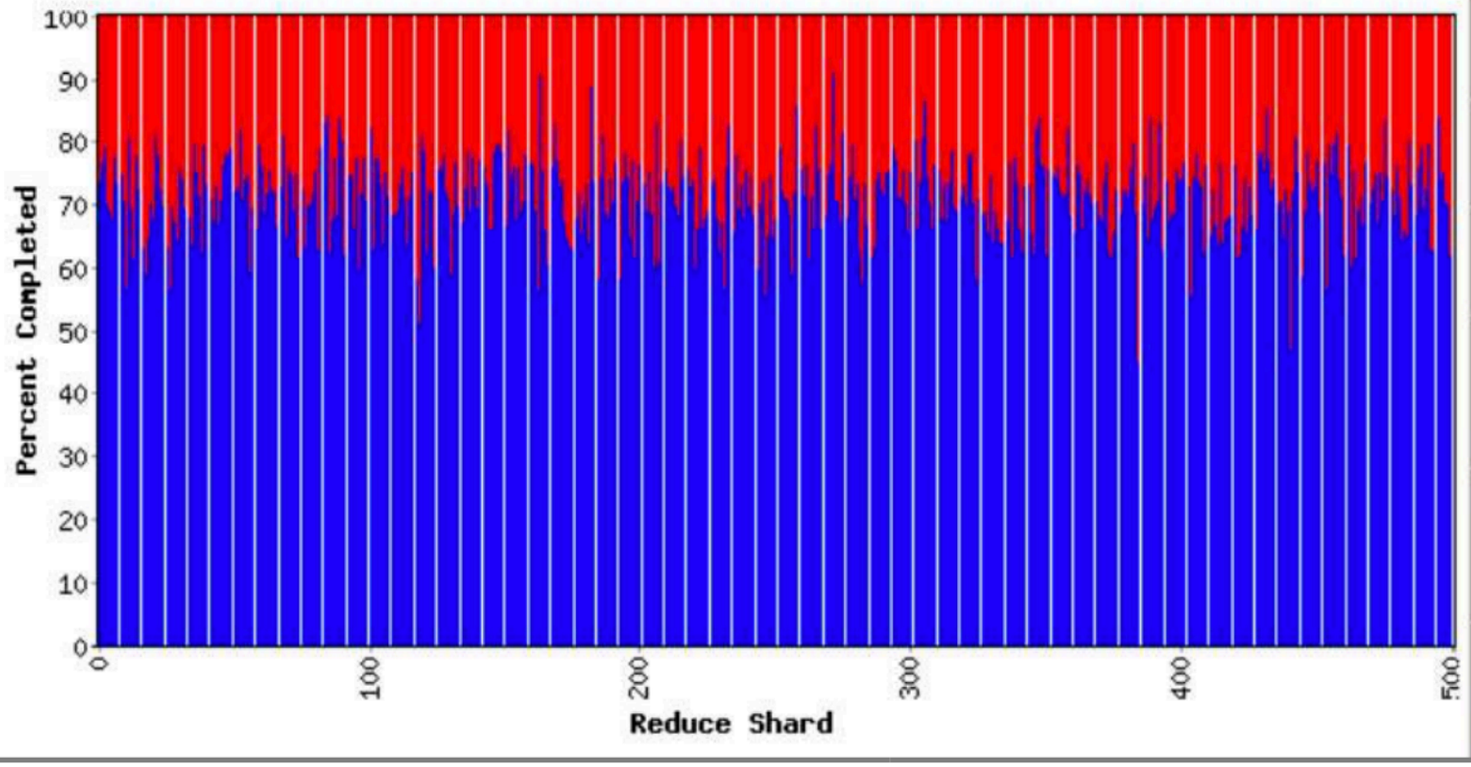
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 35 min 08 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	390447.6	399457.2



Counters

Variable	Minute
Mapped (MB/s)	0.0
Shuffle (MB/s)	0.0
Output (MB/s)	1222.0
doc-index-hits	0
docs-indexed	0
dups-in-index-merge	0
mr-merge-calls	51640600
mr-merge-outputs	51640600

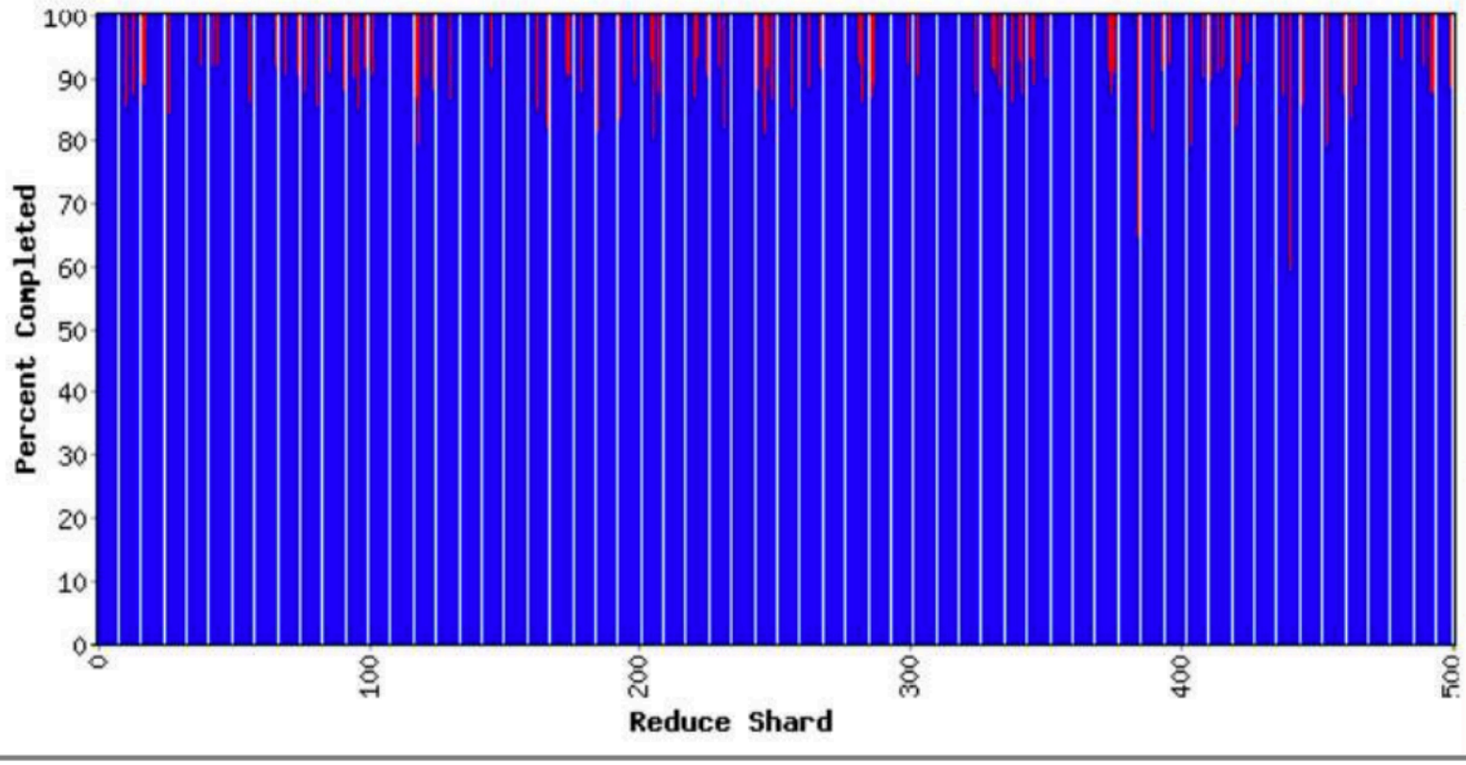
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 37 min 01 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	520468.6	520468.6
Reduce	500	406	94	520468.6	512265.2	514373.3



Counters

Variable	Minute
Mapped (MB/s)	0.0
Shuffle (MB/s)	0.0
Output (MB/s)	849.5
doc-index-hits	0
docs-indexed	0
dups-in-index-merge	0
mr-merge-calls	35083350
mr-merge-outputs	35083350

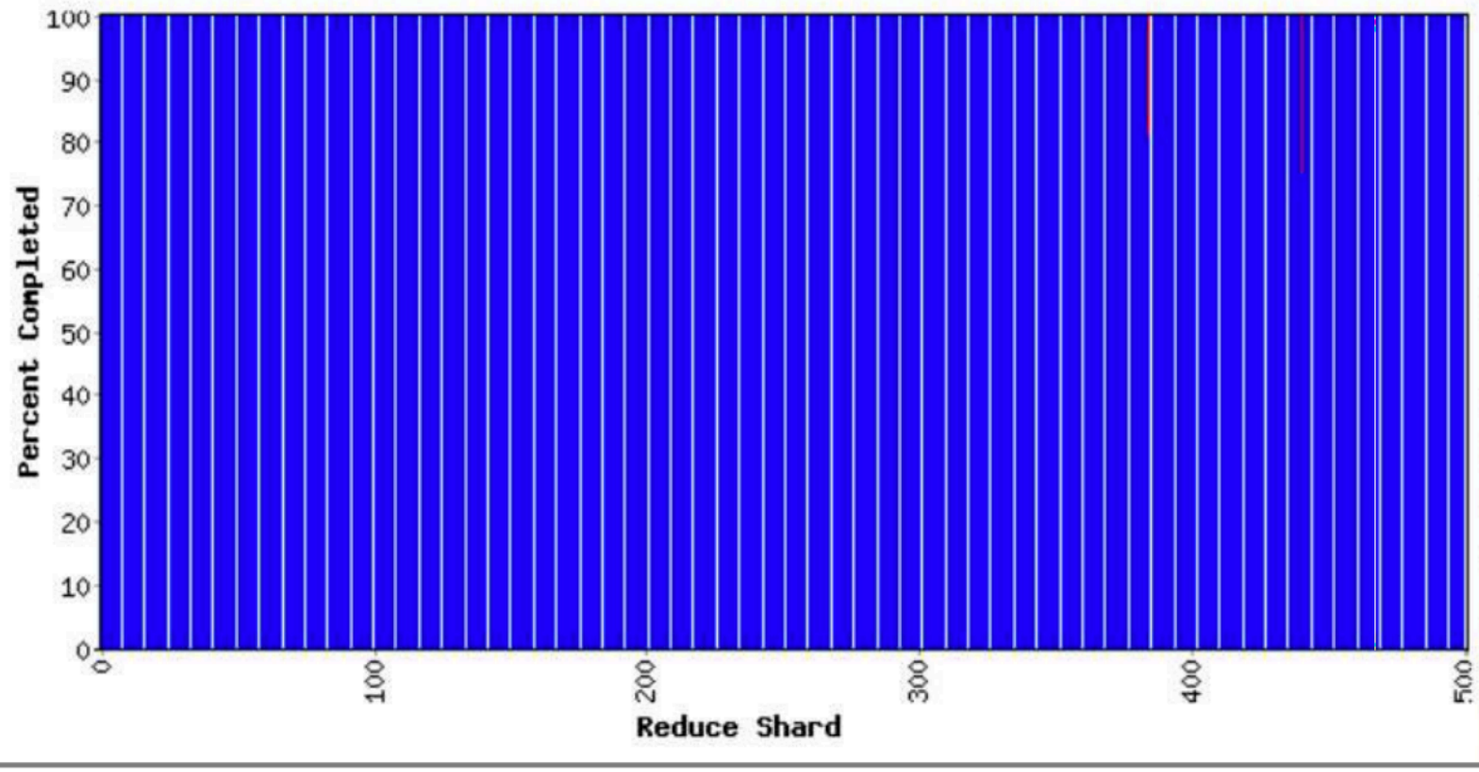
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 38 min 56 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	519781.8	519781.8
Reduce	500	498	2	519781.8	519394.7	519440.7



Counters

Variable	Minute	
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	9.4	
doc-index-hits	0	105
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	394792	
mr-merge-outputs	394792	

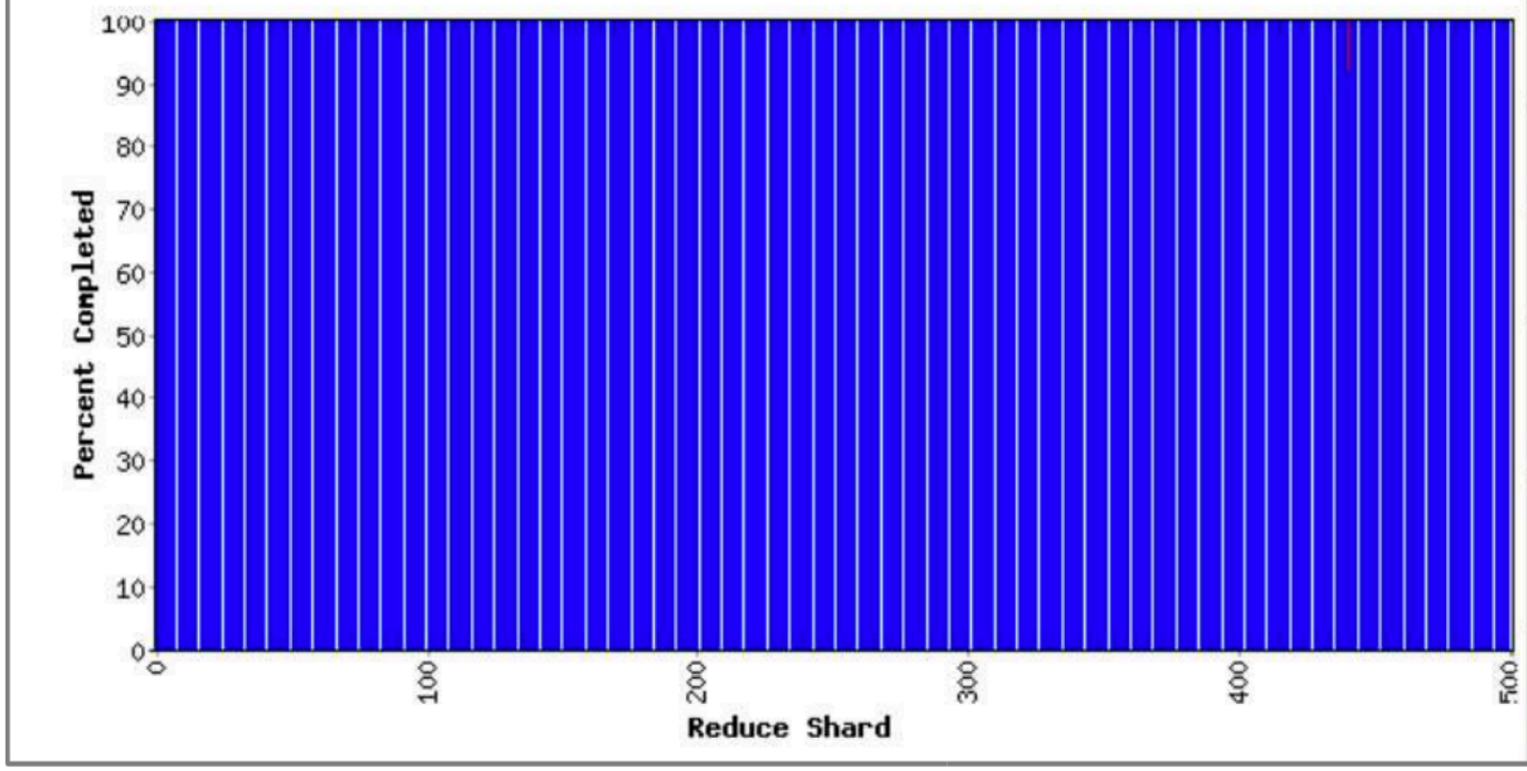
Google

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 40 min 43 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	519774.3	519774.3
Reduce	500	499	1	519774.3	519735.2	519764.0



Counters

Variable	Minute	
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	1.9	
doc-index-hits	0	105
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	73442	
mr-merge-outputs	73442	

Google

PRACTICE GUIDE

- ✦ Use #map >> #reduce > #machines
  - ★ fine granularity tasks
  - ★ better load balance
- ✦ Do not use it if you have a lot of iterations, 10 is fine, 100 is terrible
  - ★ good for feature extraction
  - ★ often not good for optimization

MPI

A message passing interface

- ✦ Proposed and implemented by HPC community
- ✦ OpenMPI: http://www.open-mpi.org/
- ✦ mpich: http://www.mpich.org/

BASIC MODEL

- ✦ Group
  - ★ ordered set of processes
  - ★ rank from 0 to N-1 (for N processes)
- ✦ Communicator
  - ★ group of processes that can communicate with each other
  - ★ default communicator: MPI_COMM_WORLD

A MPI PROGRAM STRUCTURE

- #include “mpi.h”
- initialize MPI environment: MPI_Init
- MPI_xxx()
- MPI_Finalize()

```c
int main(int argc, char *argv[]) {
  MPI_Init(&argc, &argv);
  int my_rank, rank_size;
  MPI_Comm_rank(MPI_COMM_WORLD, &my_rank);
  MPI_Comm_size(MPI_COMM_WORLD, &rank_size);
  printf("# of processses %d, my rank %d\n", rank_size, my_rank);
  MPI_Finalize();
}
```

COLLECTIVE ROUTINES

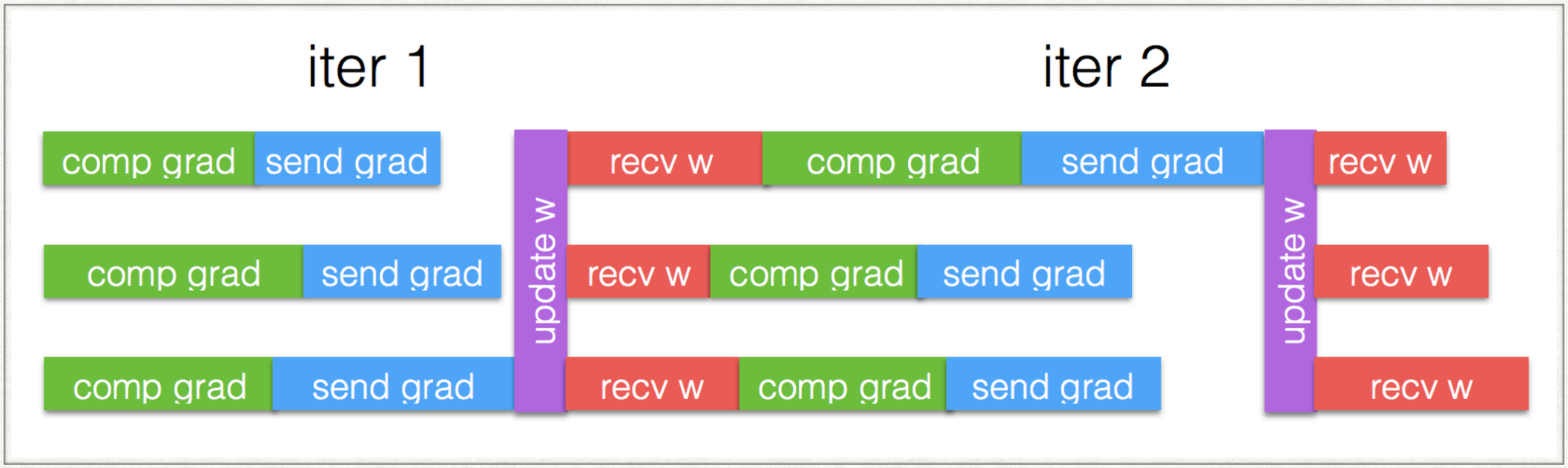
✦Reduce the gradients:

```
MPI_Reduce(local_grad.data( ),
global_grad->data( ),
feature_size,
MPI_DOUBLE,
MPI_SUM
0,
MPI_COMM_WORLD)
```

✦Broadcast the weight

```
MPI_Bcast(weight.data(),
feature_size,
MPI_DOUBLE,
0,
MPI_COMM_WORLD);
```

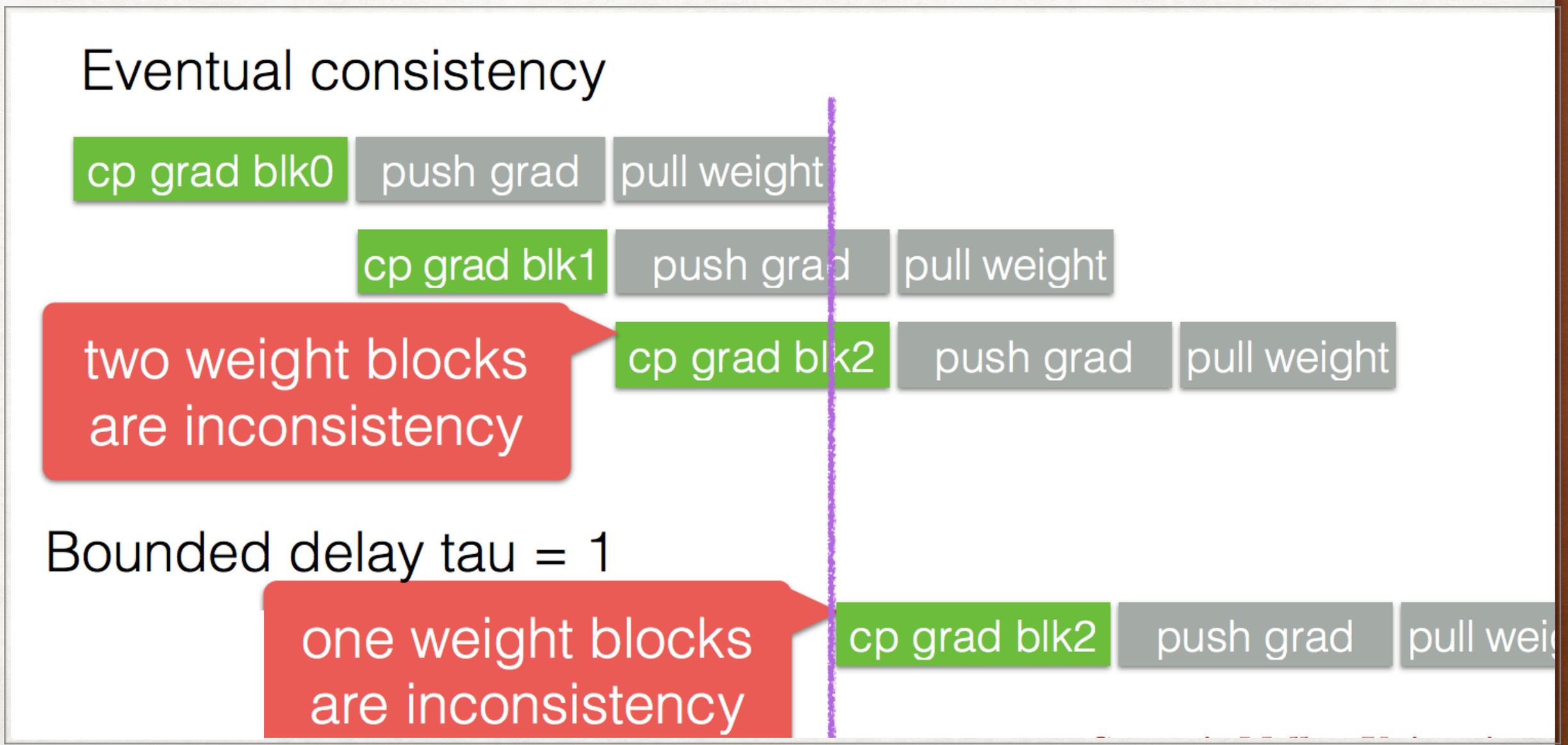
PERFORMANCE ANALYSIS



- ✦ CPU is idle when
  - ★ send gradient and receive weight
  - ★ waiting all machines are done
- ✦ We should parallel CPU and I/O

ASYNCHRONOUS UPDATING

- Parallel CPU and I/O, hide synchronization cost
- A worker:



ANALYSIS

✦ Lvar: correlation of features in a block

✦ Lcov: correlation of features between too neighbor blocks

✦ -bounded delay

✦ fixed learning rate guarantee convergence (even for non-convex problems)

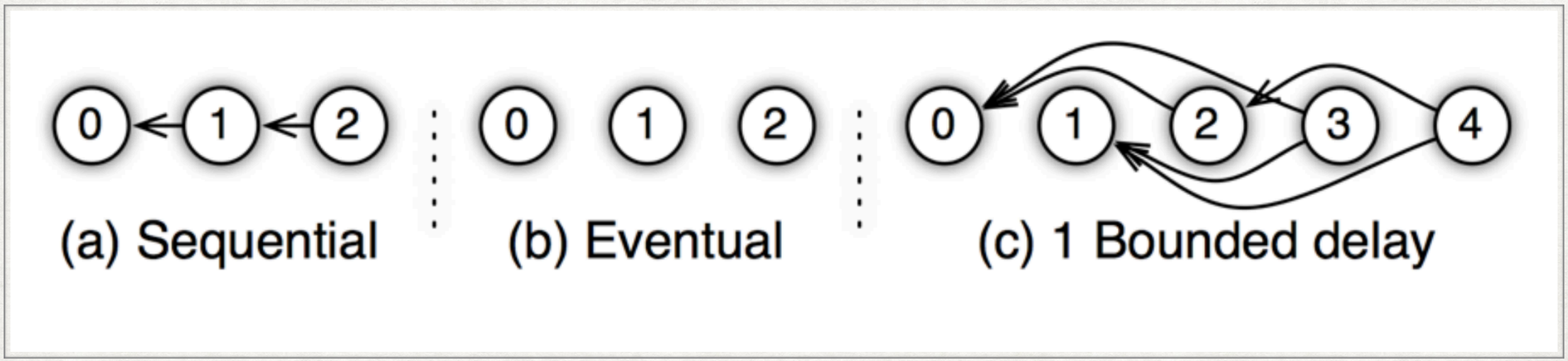
$$\eta_t = O\left(\frac{1}{L_{var} + \tau L_{cov}}\right)$$

make features in a block less correlated

make blocks less correlated

IMPLEMENT VIA PARAMETER SERVER

- Communication API:
- Range push and pull
- ✦ TASK: a pull or push or user-defined function
- One iteration (can contain push and pull)
- ✦ Task dependency graph:



IMPLEMENT BOUNDED-DELAY

- ✦ LinearBlockIterator::run()
- ★ executed at the scheduler

```
for (int iter = 0; iter < cf.max_pass_of_data(); ++iter) {
  std::random_shuffle(block_order.begin(), block_order.end());
  for (int b : block_order)  {
    Task update;
    update.set_wait_time(time - tau);
    auto cmd = RiskMinimization::setCall(&update);
    cmd->set_cmd(RiskMinCall::UPDATE_MODEL);
    // set the feature key range will be updated in this block
    blocks[b].second.to(cmd->mutable_key());
    time = pool->submit(update);
  }
```

EXPERIMENTS

SPARSE LOGISTIC REGRESSION

$$\min_{w \in \mathbb{R}^p} \sum_{i=1}^{n} \log(1 + \exp(-y_i \langle x_i, w \rangle)) + \lambda \|w\|_1$$

Training

examples	170 B
features	65 B
raw text data	636 T
machines	1,000
cores	16,000

Comparison

	Algorithm	Model	LOC
System-A	L-BFGS	Sequential	10K
System-B	Block CD	Sequential	30K
Parameter Server	Block CD	Bounded Delay + KKT	300

CONVERGE SPEED

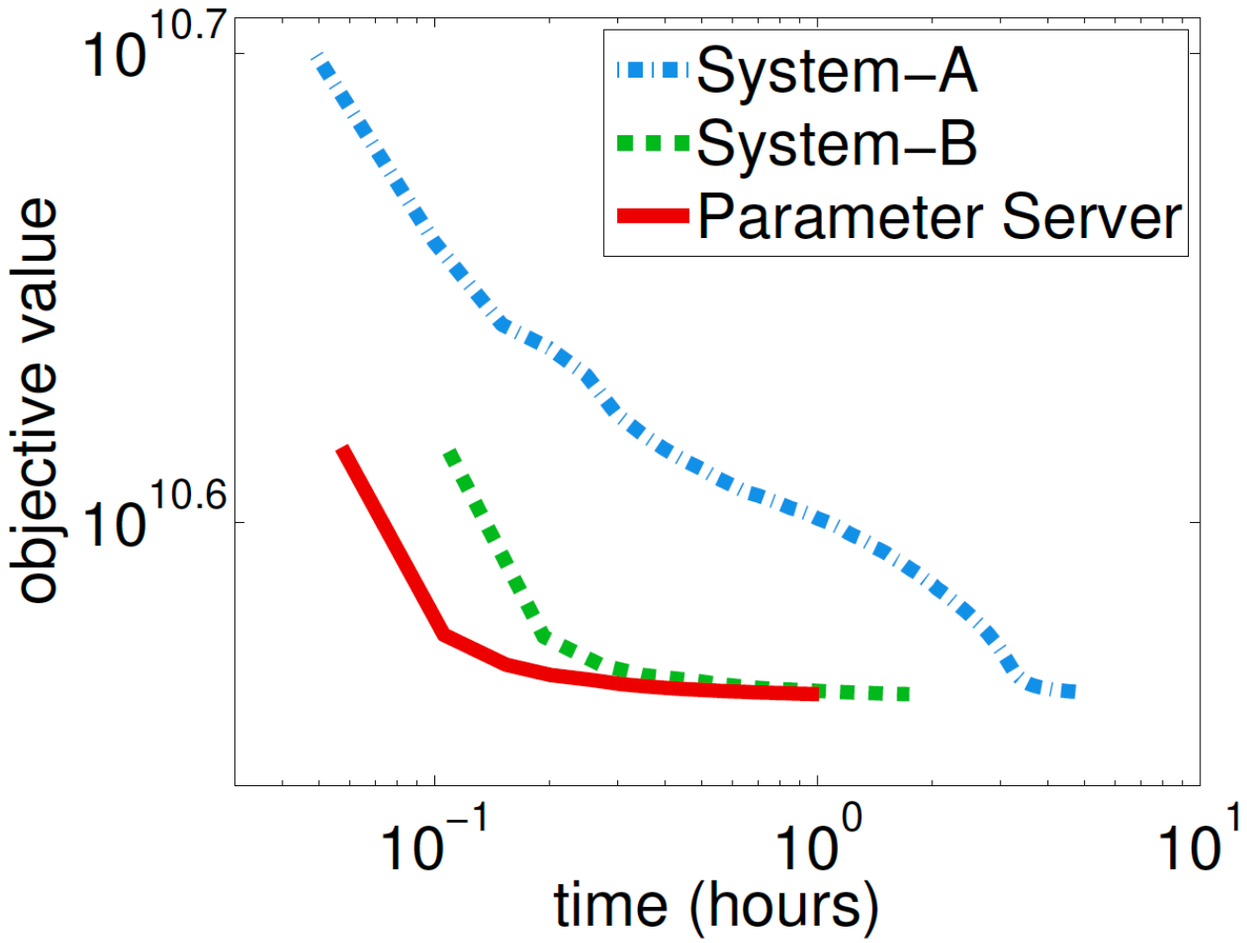
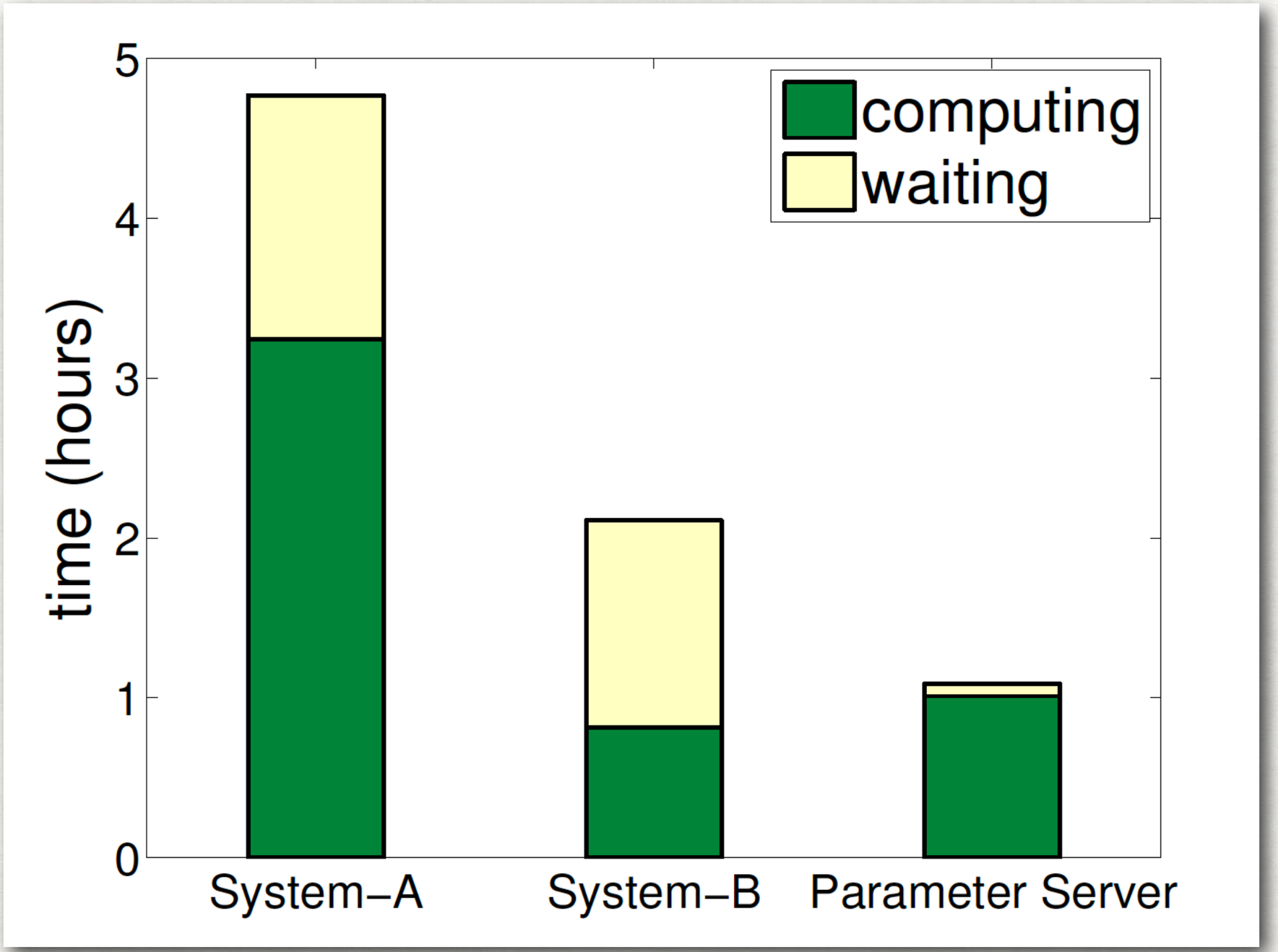


Figure 9: Convergence of sparse logistic regression. The goal is to minimize the objective rapidly.

- 5000TB CTR data
- 100B Variables
- 1000 Machines

- System A, B are on very large internet company

SCHEDULING EFFICIENCY



DEMO

https://github.com/mli/parameter_server

```
mkdir your_working_dir
cd your_working_dir
git clone git@github.com:mli/parameter_server.git .
git clone git@github.com:mli/parameter_server_third_party.git third_party
git clone git@github.com:mli/parameter_server_data.git data
third_party/install.sh
cd src && make -j8
mpirun -np 4 ./ps_mpi -num_servers 1 -num_workers 2 -app ../config/rcv1_l1lr.config
```

BOUNDED-DELAY

Sequential model

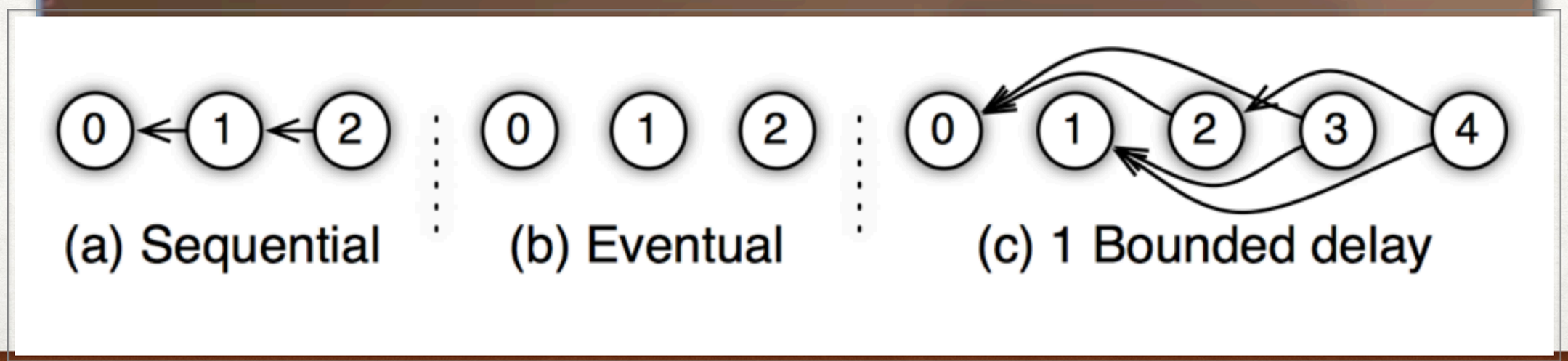
```
block_iterator {
# turn it off for debug use
random_feature_block_order : true

# block-coordinate updating. We divide a feature group into feature_block_ra
# x nnz_feature_per_instance blocks. If = 0, then use all features
feature_block_ratio : 4

max_pass_of_data : 20

# bounded-delay consistency
max_block_delay : 0

# convergance critiria. stop if the relative objective <= epsilon
epsilon : 1e-3
}
```



BOUNDED-DELAY

Bounded-delay = 1

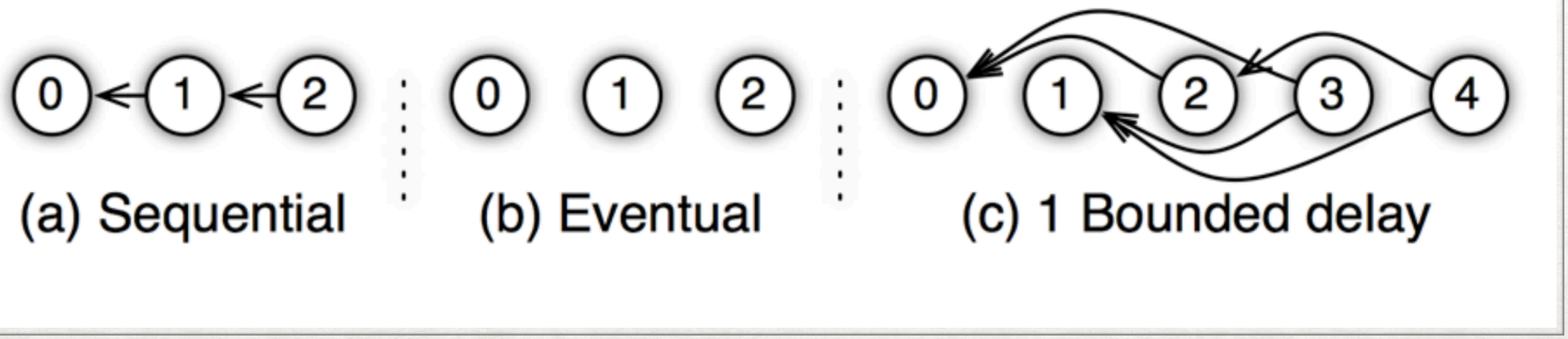
```
block_iterator {
# turn it off for debug use
random_feature_block_order : true

# block-coordinate updating. We divide a feature group into feature_block_ratio
# x nnz_feature_per_instance blocks. If = 0, then use all features
feature_block_ratio : 4

max_pass_of_data : 20

# bounded-delay consistency
max_block_delay : 1

# convergance critiria. stop if the relative objective <= epsilon
epsilon : 1e-3
}
```



BOUNDED-DELAY

Bounded-delay = 10

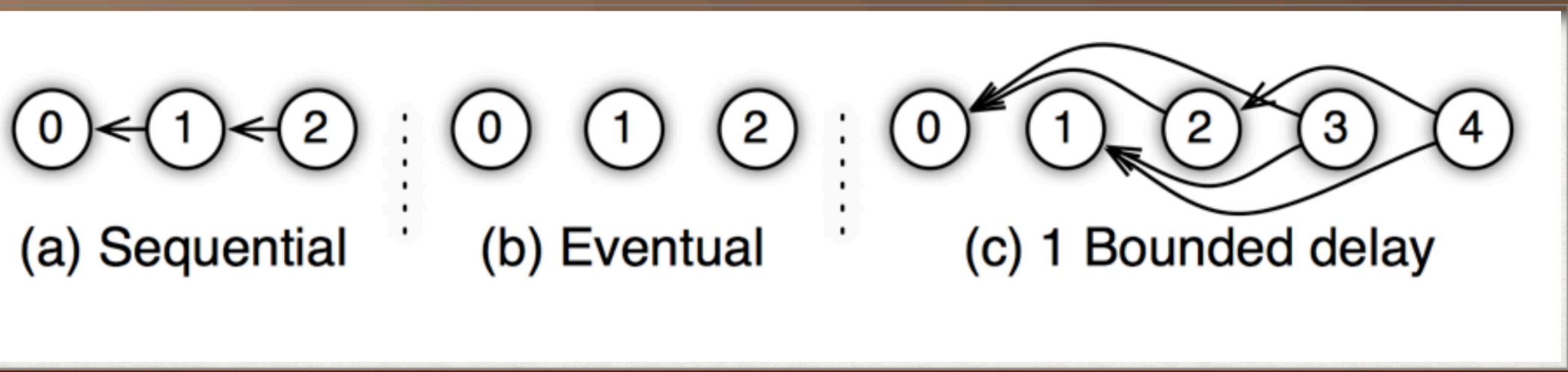
```
block_iterator {
# turn it off for debug use
random_feature_block_order : true

# block-coordinate updating. We divide a feature group into feature_block_ratio
# x nnz_feature_per_instance blocks. If = 0, then use all features
feature_block_ratio : 4

max_pass_of_data : 20

# bounded-delay consistency
max_block_delay : 10

# convergance critiria. stop if the relative objective <= epsilon
epsilon : 1e-3
}
```



BOUNDED-DELAY

Time difference

```
iter |  objective    relative |     |w|_0 | threshold  #activet |(app:min max) total
 ----+-------------------------+----------+---------------------+----------------
   0 | 6.20489e+05  1.000e+00 |   4595903 | 1.0e+20     6236013 |  10.7  12.9  20.1
   1 | 5.44760e+05  1.390e-01 |   3639910 | 1.4e-01     6236013 |   3.1   8.1  12.8
   2 | 5.12328e+05  6.330e-02 |   3270141 | 5.7e-06     3855248 |   2.2   8.5  12.1
   3 | 4.94491e+05  3.607e-02 |   2842948 | 2.2e-06     3354501 |  -0.0  10.8  12.2
[mpiexec@limucn11] Sending Ctrl-C to processes as requested
[mpiexec@limucn11] Press Ctrl-C again to force abort
/home/parameter_server/bin # mpirun -np 20 -hostfile /home/hosts ./ps_mpi -num_servers 2\
 -num_workers 8 -num_threads 8 -app ../config/ctr_l1lr.config -interface venet0:0
training data info: 4102531 examples with feature range [0,6236013)
system started...loaded data... in 4.631 sec
features are partitioned into 328 blocks
     |        training         |  sparsity |      KKT filter     |    time (sec.)
iter |  objective    relative |     |w|_0 | threshold  #activet |(app:min max) total
 ----+-------------------------+----------+---------------------+----------------
   0 | 6.23131e+05  1.000e+00 |   4581403 | 1.0e+20     6236013 |   9.5  10.3  14.2
   1 | 5.46933e+05  1.393e-01 |   3645061 | 1.7e-01     6236013 |   4.2   6.0   8.4
   2 | 5.13948e+05  6.418e-02 |   3279605 | 2.5e-06     3866977 |   4.0   6.8   9.1
   3 | 4.95783e+05  3.664e-02 |   2851889 | 4.6e-06     3368239 |   3.4   6.8   8.5
   4 | 4.84539e+05  2.320e-02 |   2575522 | 2.8e-06     2919564 |   3.5   7.1   8.5
```

BOUNDED-DELAY

Time difference

```
iter |  objective    relative |      |w|_0 | threshold  #activet |(app:min max) total
 ----+------------------------+----------+---------------------+----------------
   0 | 6.23131e+05  1.000e+00 |   4581403 | 1.0e+20     6236013 |   9.5  10.3  14.2
   1 | 5.46933e+05  1.393e-01 |   3645061 | 1.7e-01     6236013 |   4.2   6.0   8.4
   2 | 5.13948e+05  6.418e-02 |   3279605 | 2.5e-06     3866977 |   4.0   6.8   9.1
   3 | 4.95783e+05  3.664e-02 |   2851889 | 4.6e-06     3368239 |   3.4   6.8   8.5
   4 | 4.84539e+05  2.320e-02 |   2575522 | 2.8e-06     2919564 |   3.5   7.1   8.5
   5 | 4.76894e+05  1.603e-02 |   2369592 | 1.3e-06     2625512 |   2.0   7.3   7.7
[mpiexec@limucn11] Sending Ctrl-C to processes as requested
[mpiexec@limucn11] Press Ctrl-C again to force abort
/home/parameter_server/bin # mpirun -np 20 -hostfile /home/hosts ./ps_mpi -num_servers 2\
 -num_workers 8 -num_threads 8 -app ../config/ctr_l1lr.config -interface venet0:0
training data info: 4102531 examples with feature range [0,6236013)
system started...loaded data... in 4.746 sec
features are partitioned into 328 blocks
     |        training          |  sparsity |      KKT filter      |    time (sec.)
iter |  objective    relative |      |w|_0 | threshold  #activet |(app:min max) total
 ----+------------------------+----------+---------------------+----------------
   0 | 6.78717e+05  1.000e+00 |   4445893 | 1.0e+20     6236013 |   8.7  11.4  10.0
   1 | 5.88903e+05  1.525e-01 |   3751689 | 3.8e-01     6236013 |   3.9   8.2   5.2
   2 | 5.48595e+05  7.347e-02 |   3449582 | 1.4e-05     4008882 |   2.6   9.4   5.1
   3 | 5.40386e+05  1.519e-02 |   3132958 | 4.8e-06     3628338 |   0.9   9.3   5.0
```

BOUNDED-DELAY

同样 bound delay =1

features are partitioned into 328 blocks

iter	training objective	training relative	sparsity |w|_0	KKT filter threshold	KKT filter #activet	time (sec.) (app:min	time (sec.) max	time (sec.) total
0	6.23131e+05	1.000e+00	4581403	1.0e+20	6236013	9.5	10.3	14.2
1	5.46933e+05	1.393e-01	3645061	1.7e-01	6236013	4.2	6.0	8.4
2	5.13948e+05	6.418e-02	3279605	2.5e-06	3866977	4.0	6.8	9.1
3	4.95783e+05	3.664e-02	2851889	4.6e-06	3368239	3.4	6.8	8.5
4	4.84539e+05	2.320e-02	2575522	2.8e-06	2919564	3.5	7.1	8.5

features are partitioned into 117 blocks

iter	training objective	training relative	sparsity |w|_0	KKT filter threshold	KKT filter #activet	time (sec.) (app:min	time (sec.) max	time (sec.) total
0	6.44041e+05	1.000e+00	4530211	1.0e+20	6236013	9.2	10.2	12.9
1	5.67173e+05	1.355e-01	3661299	1.7e-01	6236013	4.4	5.5	7.0
2	5.29233e+05	7.169e-02	3359908	1.5e-05	3921960	3.9	6.8	7.2
3	5.09476e+05	3.878e-02	2956505	7.7e-06	3474482	2.5	5.8	7.1
4	4.96425e+05	2.629e-02	2686934	8.3e-06	3057918	1.9	6.8	7.4
5	4.87602e+05	1.809e-02	2478667	5.9e-06	2760234	1.8	9.2	6.4

SGD

Stochastic Gradient Descent OR mini-batch SGD

✦ The cost of an iteration is small

✦ Often converges faster than batch algorithm such as gradient descent

✦ A sequential algorithm

✦ Stochastic gradient descent is used more widely than coordinate descent

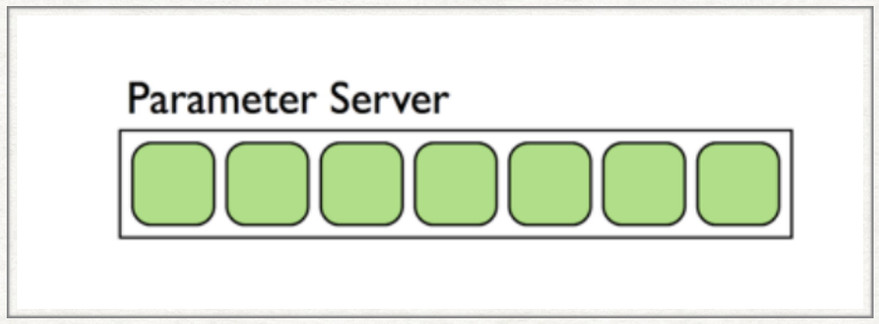
✦ Distributing SGD is more difficulty than CD

★ Samples are often more correlated comparing to features

PARALLEL MODELS

✦ Google brain

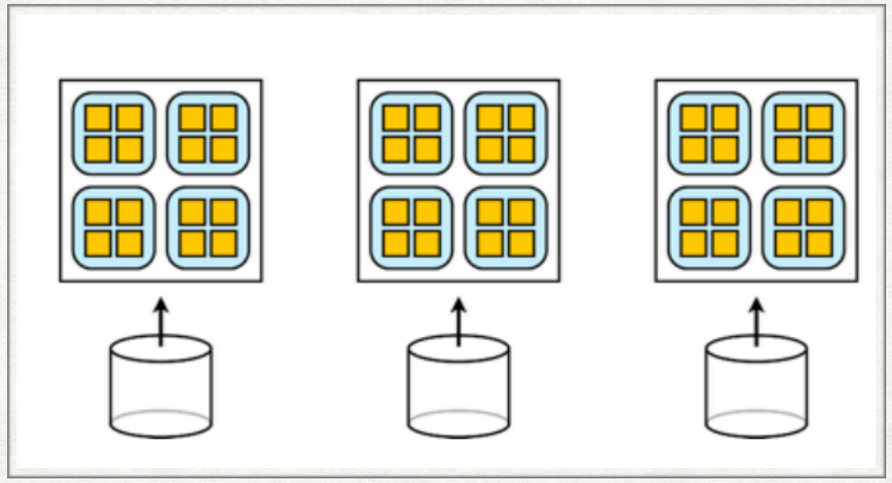
✦ Several worker groups update the parameter at the same time



✦ Good system performance

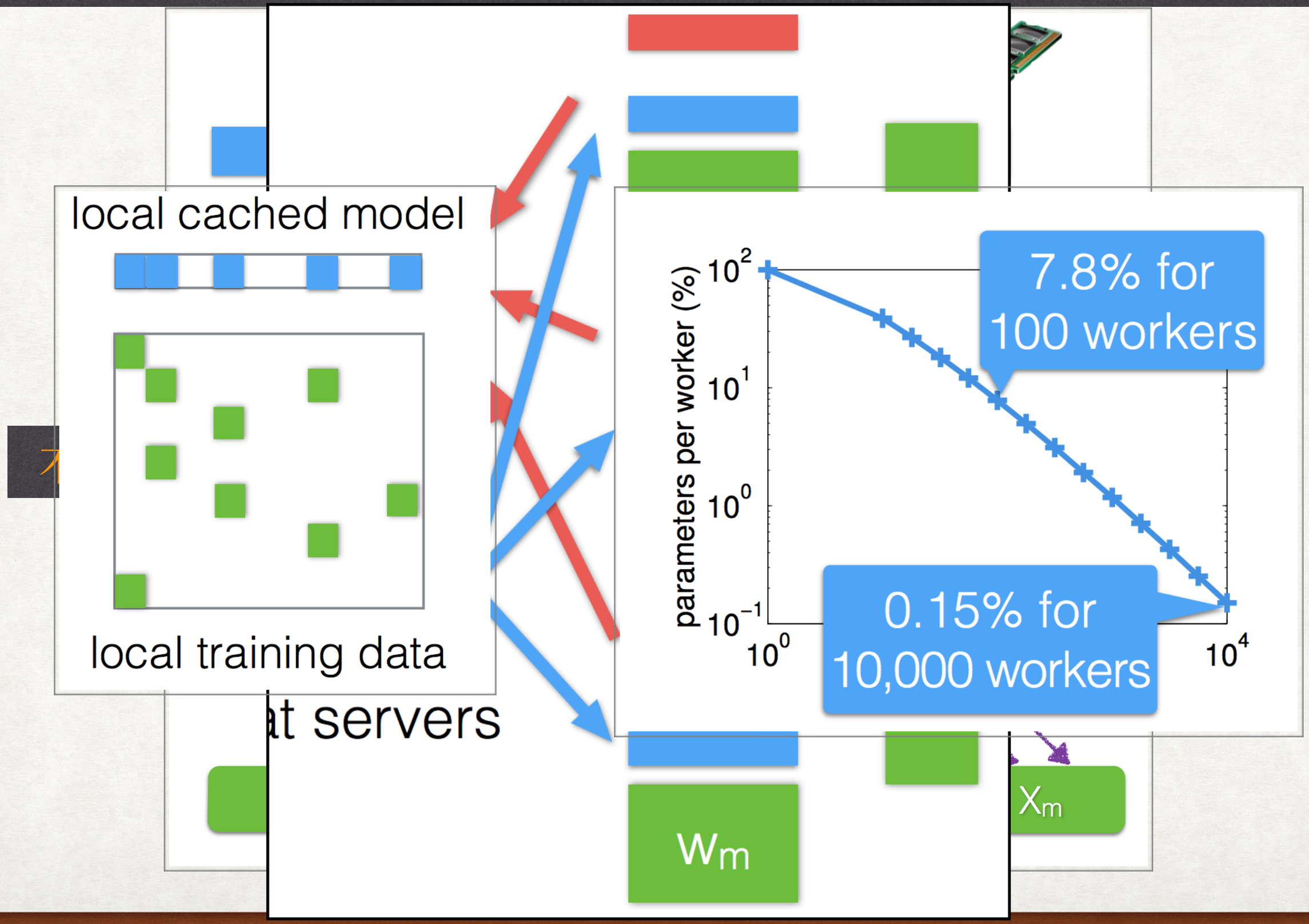
✦ May affect the convergence rate

★ 10x machine may only have 2x speedup



IMPLEMENTATION

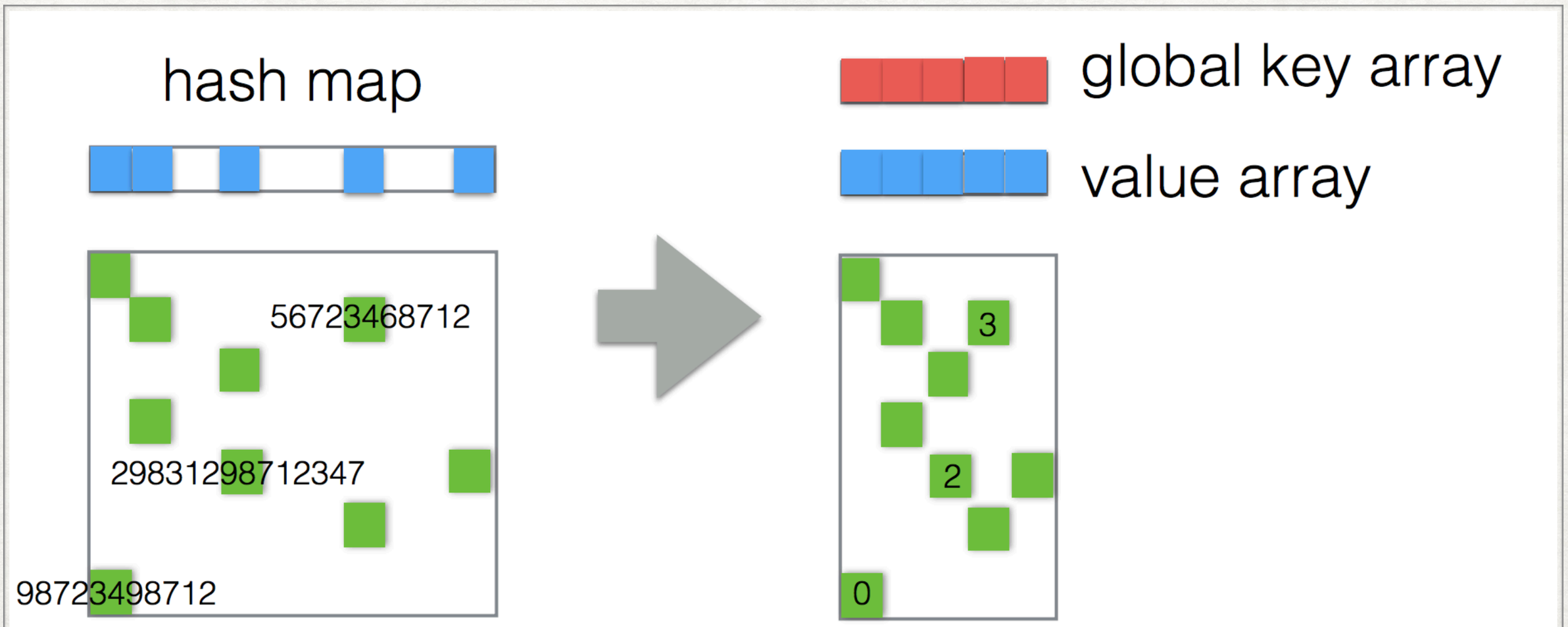
MODEL/DATA PARTITION



COMPACT REPRESENTATION

hash map->Localize Keys

Each worker machine maps global features id into local features id 0, 1, 2,



TERMINOLOGY

✦ Message: data for communication

✦ Van: send/receive message

✦ Customer: an application or a shared parameters

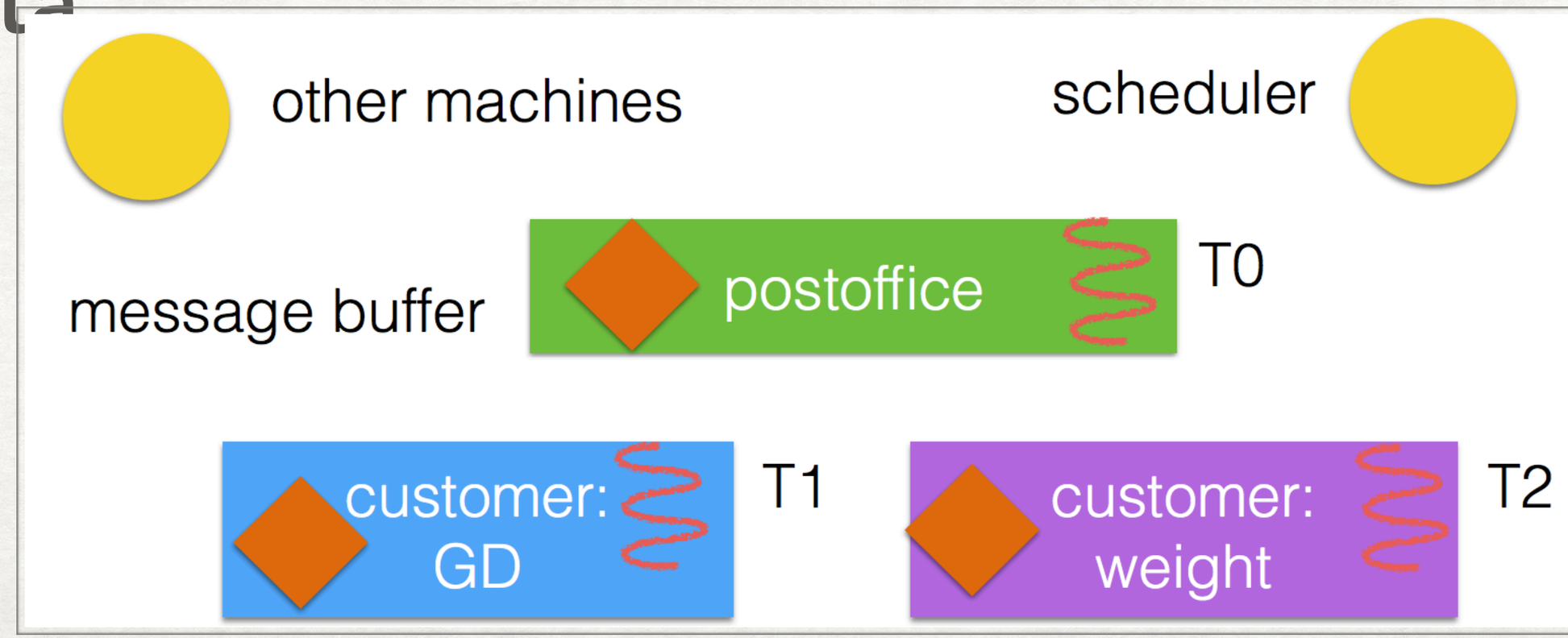
✦ Postoffice: allow customers to deliver messages and notify customers incoming messages

✦ Yellowpages:
all customers and live machines

TERMINOLOGY

```
> mpirun -hostfile ../../hosts -np 20 ./ps_mpi -int
erface eth0 -num_servers 4 -num_workers 12 -num_thre
ads 8 -app ../config/ctr_l1lr.config
```

data



CONCLUSTION

✦Support extremely large model

✦ Asynchronous

Flexible consistency model

✦ Use like writing single-thread matlab/numpy/Rlike codes

✦ A little bit complex to under the system

★ necessary to reach the best performance

LEVEL 3 PART