

Scaling Machine Learning

Models, Architectures and Algorithms

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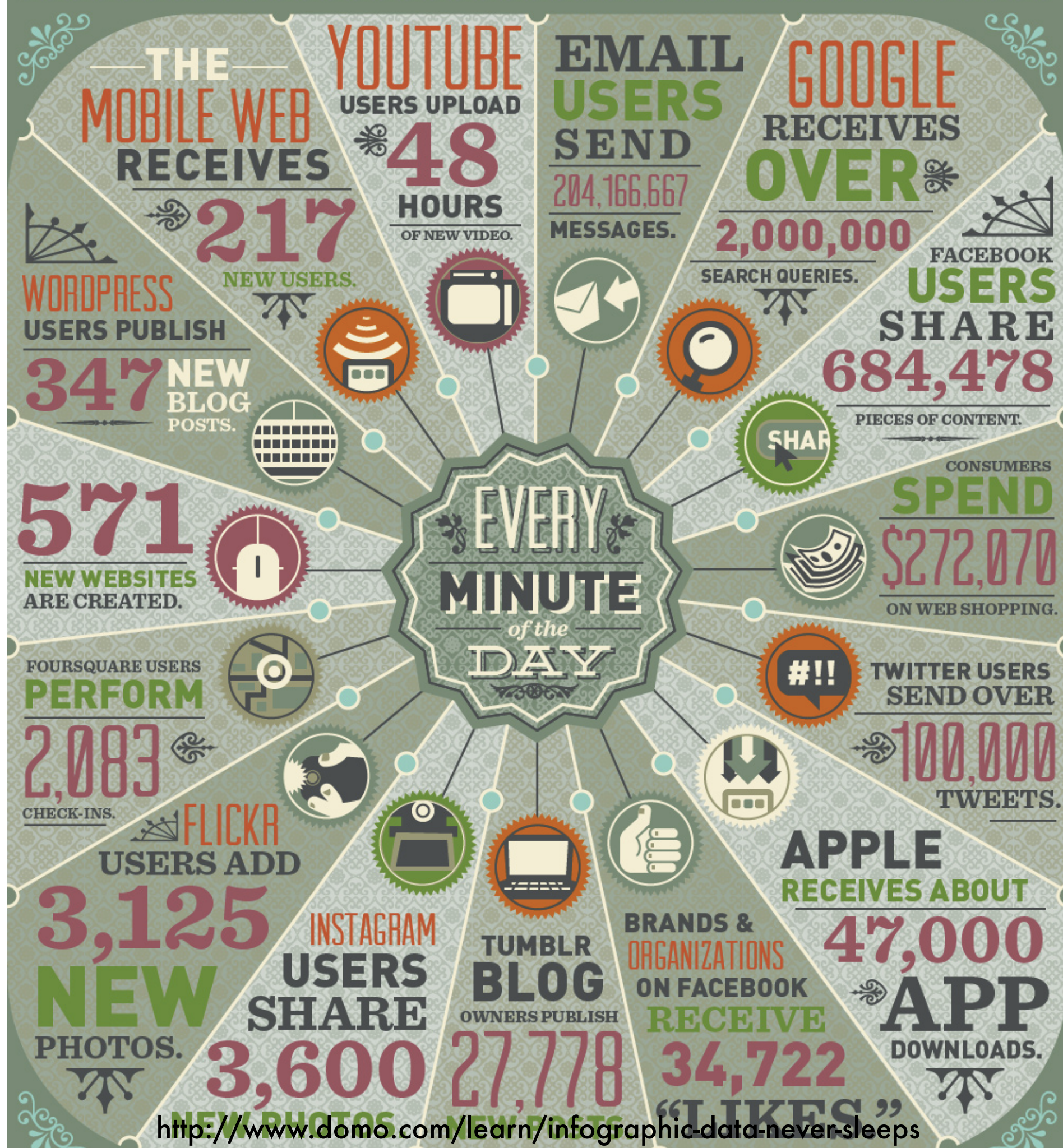
Outline

- **Data**
Actions, Interactions, User generated content
- **Architectures**
MapReduce, Graphs, Streams, Parameterserver
- **Models and Algorithms**
 - Logistic regression (advertising, search)
Distributed proximal gradient
 - Scaling Topic models (personalization, profiling)
 - Modeling (user generated) data and behavior

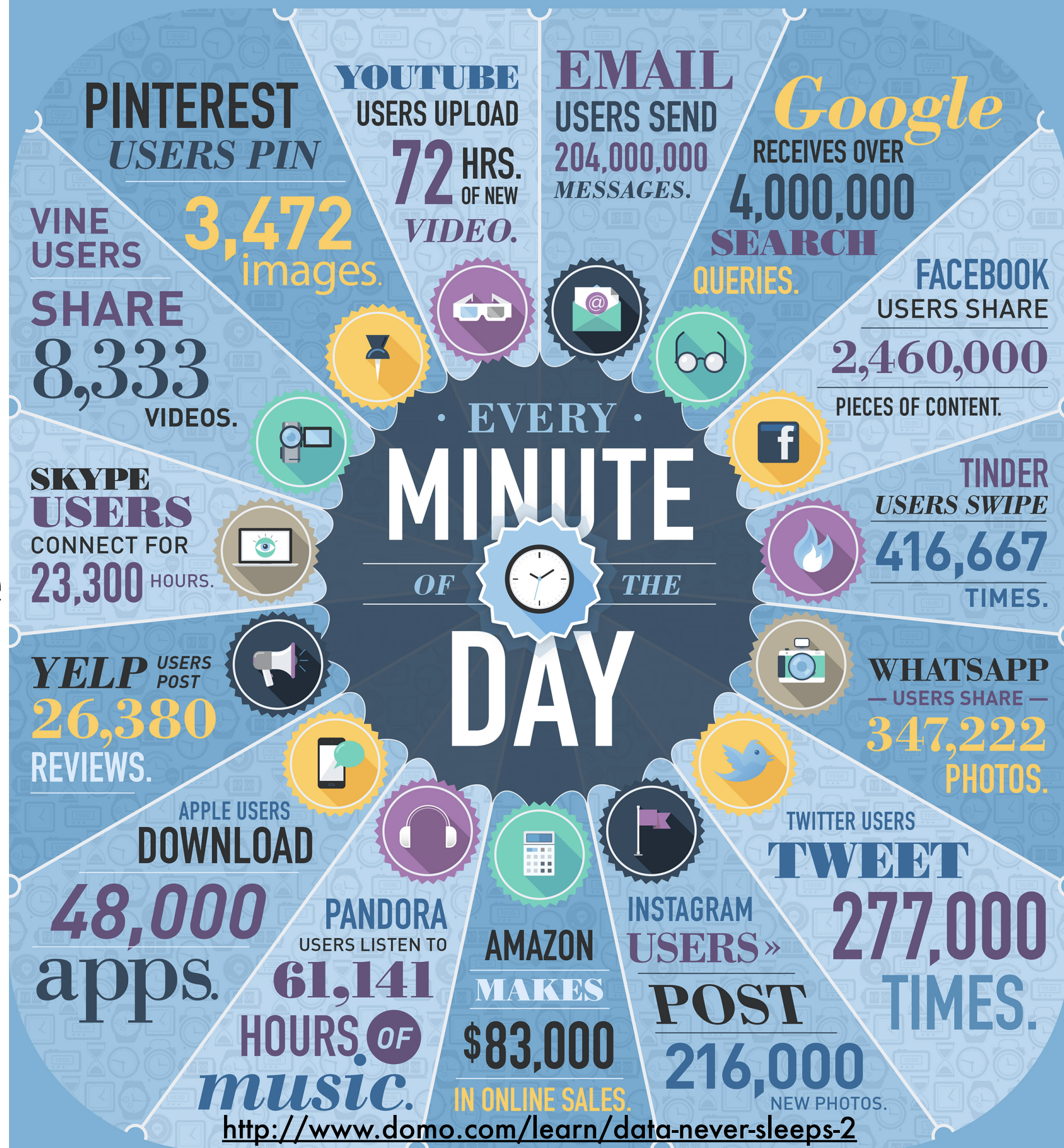


Data

Data per minute 2012



Data per minute 2014



Computational Advertising

mesothelioma

Web Videos News Images Books More Search tools

About 2,970,000 results (0.21 seconds)

Mesothelioma Compensation
Ad www.nationalmesotheliomaclaims.com/
The Money's Already There. \$30 Billion Asbestos Trust Fund
What Is Mesothelioma? - National Claims Center - Mesothelioma Claims

Mesothelioma Symptoms - Mesothelioma-Answers.org
Ad www.mesothelioma-answers.org/
By Anna Kaplan, M.D. 101 Facts about Mesothelioma.
Asbestos - Treatments - Top Doctors - Free Mesothelioma Book

CA Mesothelioma Resource - californiamesothelioma.com
Ad www.californiamesothelioma.com/ (800) 259-9249
Learn about mesothelioma & receive a free book of helpful answers.
What is Mesothelioma? - Asbestos Exposure in CA - California Legal Rights

Mesothelioma Cancer - Mesothelioma.com
www.mesothelioma.com/mesothelioma/
by Dr. Howard Jack West - Apr 2, 2014 - Mesothelioma is an aggressive cancer affecting the membrane lining ... Between 50 and 70% of all mesotheliomas are of the epithelial variety.
Mesothelioma Symptoms - Mesothelioma Prognosis - Mesothelioma Survival Rate

Mesothelioma - Wikipedia, the free encyclopedia
en.wikipedia.org/wiki/Mesothelioma Wikipedia
Mesothelioma (or, more precisely, malignant mesothelioma) is a rare form of cancer that develops from cells of the mesothelium, the protective lining that covers ...
Asbestos - Mesothelium - Paul Kraus - Category:Mesothelioma

Ads

Mesothelioma
www.mesothelioma-attorney-locators.com/
Easily Find Mesothelioma Attorneys.
Locations Across The United States

CA Mesothelioma
www.mesotheliomatreatmentcenters.org/
Mesothelioma? Get the Money you Deserve Fast-Help Filing your Claim

Mesothelioma Compensation
www.mesotheliomaclaimscenter.info/
(877) 456-3935
Mesothelioma? Get Money You Deserve Fast! Get Help with Filing a Claim.

California Mesothelioma
www.mesotheliomaattorney-usa.com/Legal
(888) 707-4525
100% Free Mesothelioma Legal Help!
\$30 Billion Trust Fund Available.

Mesothelioma
meso.lawyers.local.alotresults.com/
Seasoned Lawyers in your Area.
In your Local Lawyer Listings!

sponsored
search picks
position of
ad using

$$p(\text{click}|\text{ad}) \cdot \text{bid}(\text{ad})$$

estimate it

4 million/minute

Carnegie Mellon University

Spam filtering

200 million/minute

imbalanced
dataset

Upcoming MLSS Volunteer tasks

Mallory Deptola Hi Volunteers! Again, thanks for volunteering to help out during MLSS 2014. W... 8:04 am (2 days ago)

Mallory Deptola via smola.org to Alex, Zico 8:51 am (2 days ago)

Hi Guys,

I was wondering if you could add the audio/visual tasks to the volunteer spreadsheet. I am not sure how you would like to go about handling them – would it be based on the speaker schedule that they would need to man the camera? How many people per recording?

If you just wanted to those tasks to the list, that'd be great! <https://docs.google.com/spreadsheets/d/1fawSYWppJARcvmk-PpOfvoLi9XvVq6fcY6fAF4-2Qno/edit#gid=0>

Delete all spam messages now (messages that have been in Spam more than 30 days will be automatically deleted)

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	EM Office	Donation To You: - Hello Dear, This is a personal email directed to you by Chris and Colin Weir. Chris and Colin Weir	11:48 am
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	钟	{Spam?} hwitek; 请审批 - Hi hwitek; 研发人员的考核与激励是企业高层领导、研发经理、人力资源经理最为头疼的问题之一，	8:49 am
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	GMEE2014	【Conference Notification】 (July 3, 2014 G--M--E--E--2014 EI & ISTP) - GMEE2014 September 21-22 2014 Internationa	8:10 am
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Esther	TTP_EI Compendex and ISTP index GMEE (Green Materials and Environmental Engineering) - GMEE2014 September	8:03 am
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	EachBuyer	EachBuyer Deals For Jun.2014.Vol.19 - If you are unable to see the message below, click here to view. If you do not wish to	Jun 27
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	CUEE2014	-Civil, Urban and Environment→ EI&ISTP ---C-U-E-E-2014- ✱ →submission due: July 12- - 2014 International Conference	Jun 27
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	EachBuyer	Up to 90% off! End This Week. - To unsubscribe please click here. EachBuyer Email not displaying correctly? Click here to	Jun 27
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Call For Papers	IEEE Big Data 2014 paper submission deadline is extended to July 13, 2014 - We have received many reuquests to extenc	Jun 27
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Tara Alngindabu	Up up and away - Make sure you always get all of our most sensational deals. Add JS Design to your address book today.	Jun 27
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Dan Roy	page for Alex - http://xn--12cu8ak3e3dxde4cn.com/akl/	Jun 27
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	krisman@emirates.ae	Please I want to propose something important to you. - Dear Friend, I am Barrister Krishnan Al-Qassimi, an attorney at law	Jun 26
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Delta Air Lines	Flights Reminder: Your June Medallion STATEMENT - An Insider look at travel, deals and your account. JUNE 2014 Helli	Jun 26
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	ACSIJ Journal	ACSIJ Journal Call for Papers July 2014 - Call for Papers Advances in Computer Science : an International Journal (ACSIJ)	Jun 26

Recommendation & Ranking

maximize interaction probability for whole page

Foreign Movies > **Classic Foreign Movies** Subgenres ▼

Sort by Suggestions for You ▼

really?

The image displays a screenshot of a movie recommendation interface. At the top, there's a blue header with the title 'Recommendation & Ranking'. Below it, a text prompt says 'maximize interaction probability for whole page'. The main content area shows a 'Classic Foreign Movies' section with a 'Sort by' dropdown set to 'Suggestions for You'. A red speech bubble with the text 'really?' points to the 'Suggestions for You' dropdown. Below the header, there's a grid of 12 movie posters arranged in two rows of six. The posters include: 'The Good, the Bad and the Ugly', 'Chariots of the Gods', 'For a Few Dollars More', 'Das Boot', 'Once Upon a Time in the West', 'Godzilla vs Mothra', 'Godzilla vs Monster Zero', 'Nosferatu', 'Barbarella', 'Godzilla Raids Again', 'Big Boss', and 'Ghidorah the Three-Headed Monster'.

Time series & trends

Topics

Subscribe



machine learning

Search term

data mining

Search term

big data

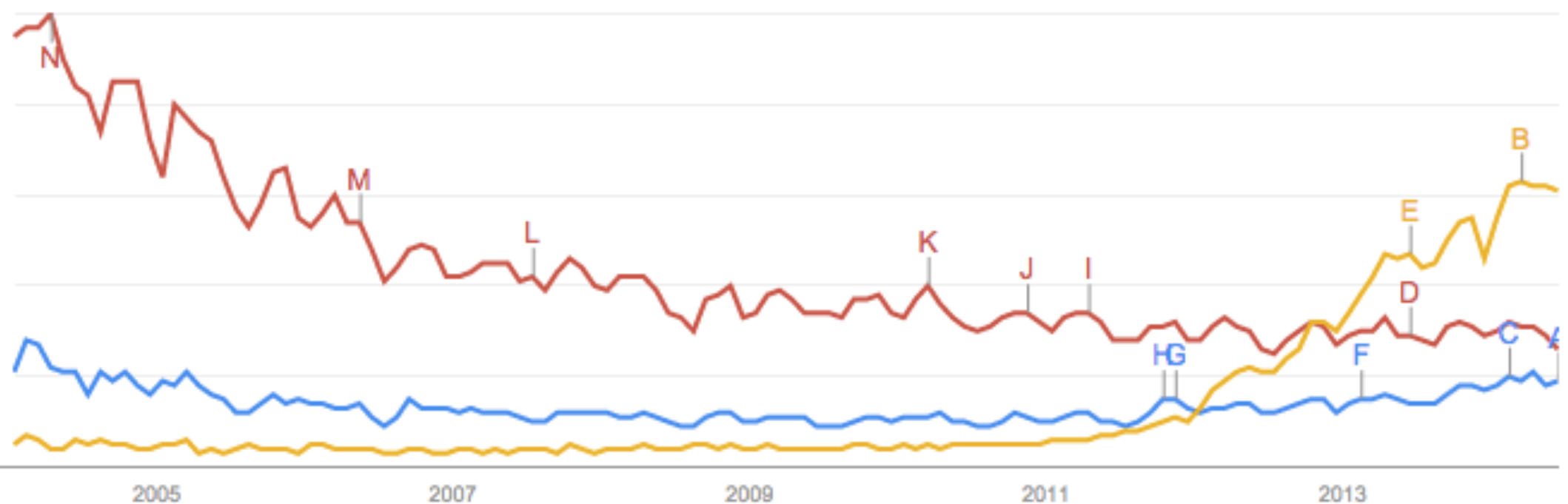
Search term

+ Add term

Interest over time ?

☒ News headlines

☐ Forecast ?



More data

- News articles & events (NY Times, GNews)
- Blogs / microblogs (Tumblr, Twitter, Weibo)
- Reviews (IMDB, Yelp, Amazon)
- Comments (YouTube, Reddit)
- Messages (Facebook, Hangouts, SMS)
- Graphs (Friends, Followers, Webpages)
- Information diffusion (Meme tracking)
- Spatiotemporal (GMaps, Foursquare, Twitter)

Lots more data

- **Bioinformatics**
DNA Microarrays, High throughput sequencing
- **Astronomy**
Square Kilometer Array, Radio telescopes
- **Medicine**
MRI / MEG scans, Connectome, Health records
- **Finance** (e.g. high frequency trading)
- **Geophysics** (e.g. oil discovery)
- **Industrial process monitoring**

Summary

- **Expensive data \neq big data**
(1000 brain scans are expensive)
- **Big data** requires **big models**
(1000 parameter model on TB of data)
- Big data needs systems built for it
(don't ship data to computation)
- **Vast range of problem domains**
- **Vast range of statistical models**



Architecture



Real Hardware

Machines

Bulk transfer is at least 10x faster

- CPU

- 8-64 cores (Intel/AMD servers)
- 2-3 GHz (close to 1 IPC per core peak) - over 100 GFlops/socket
- 8-32 MB Cache (essentially accessible at clock speed)
- Vectorized multimedia instructions (AVX 256bit wide, e.g. add, multiply, logical)

- RAM

- 16-256 GB depending on use
- 3-8 memory banks (each 32bit wide - atomic writes!)
- DDR3 (up to 100GB/s per board, random access 10x slower)

- Harddisk

- 4 TB/disk
- 100 MB/s sequential read from SATA2
- 5ms latency for 10,000 RPM drive, i.e. random access is slow

- Solid State Drives

- 500 MB/s sequential read
- Random writes are really expensive (read-erase-write cycle for a block)



The real joy of hardware

Typical first year for a new cluster:

- ~0.5 **overheating** (power down most machines in <5 mins, ~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% packetloss)
- ~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**

Jeff Dean's Stanford slides

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

Why a single machine is not enough

- Data (lower bounds)
 - 10-100 Billion documents (webpages, e-mails, ads, tweets)
 - 100-1000 Million users on Google, Facebook, Twitter, Hotmail
 - 1 Million days of video on YouTube
 - 100 Billion images on Facebook
- Processing capability for single machine 1TB/hour
But we have much more data
- Parameter space for models is too big for a single machine
Personalize content for many millions of users
- Process on **many cores** and **many machines simultaneously**

Cloud pricing

- Google Compute Engine and Amazon EC2

Instance type	Virtual Cores	Memory	Price (US\$)/Hour (US hosted)
n1-standard-1	1	3.75GB	\$0.070
n1-standard-2	2	7.5GB	\$0.140
n1-standard-4	4	15GB	\$0.280
n1-standard-8	8	30GB	\$0.560
n1-standard-16	16	60GB	\$1.120

\$10,000/year

- Storage

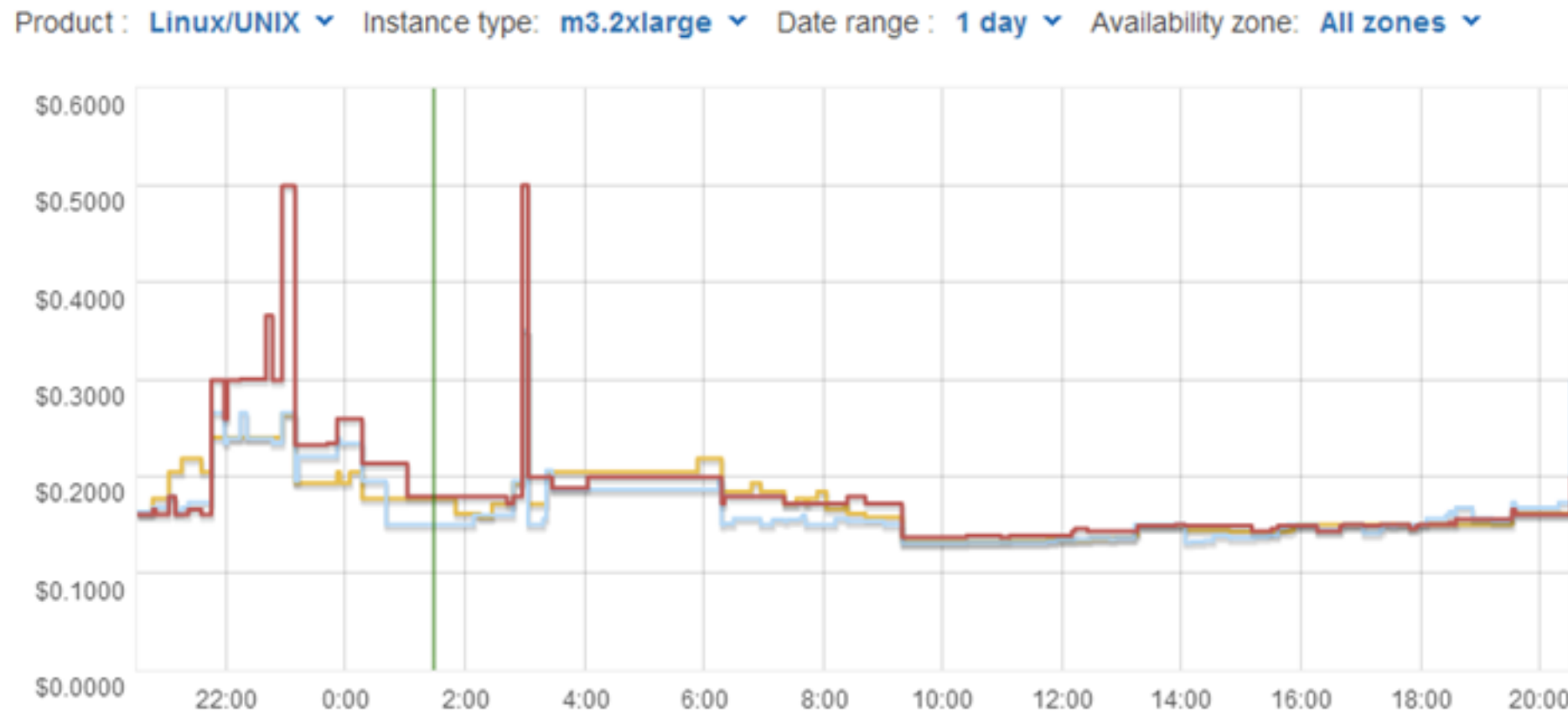
Standard Provisioned Space	\$0.04 GB / month
SSD Provisioned Space	\$0.325 GB / month
Snapshot storage	\$0.125 GB / month
IO operations	No additional charge

**Spot instances
much cheaper**

- Amazon EBS General Purpose (SSD) volumes
- \$0.10 per GB-month of provisioned storage
- Amazon EBS Provisioned IOPS (SSD) volumes
- \$0.125 per GB-month of provisioned storage
 - \$0.10 per provisioned IOPS-month
- Amazon EBS Magnetic volumes
- \$0.05 per GB-month of provisioned storage
 - \$0.05 per 1 million I/O requests
- Amazon EBS Snapshots to Amazon S3
- \$0.095 per GB-month of data stored

Real Hardware

- can and will fail
- Spot instances much cheaper (but can lead to preemption). Design algorithms for it!





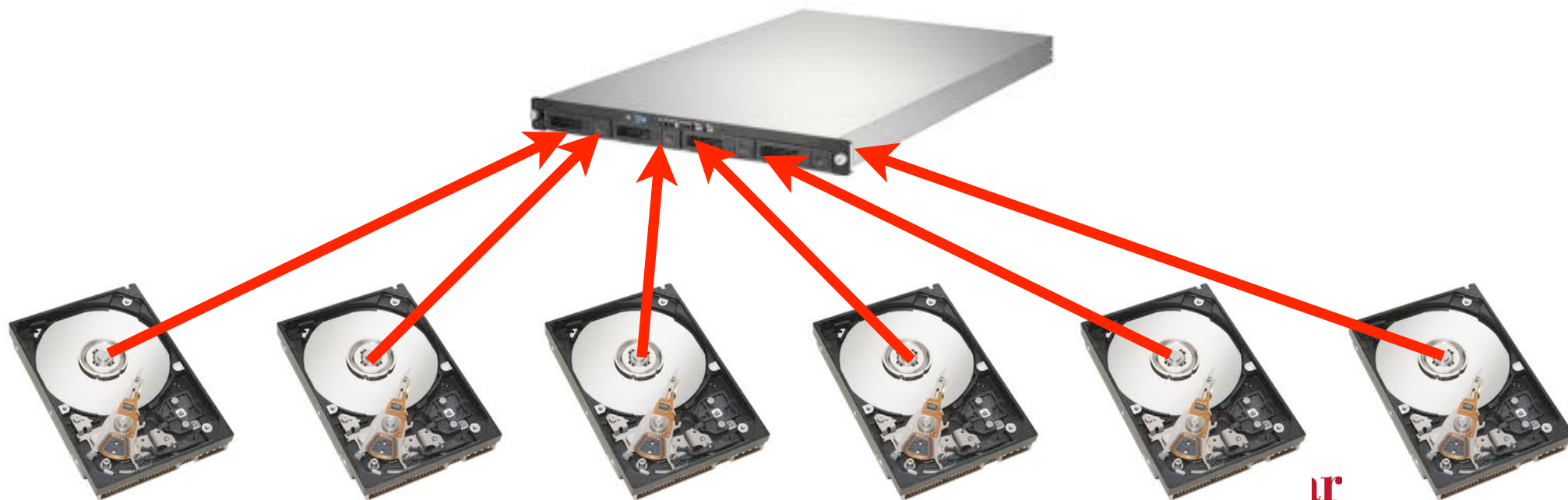
Work & storage



File systems

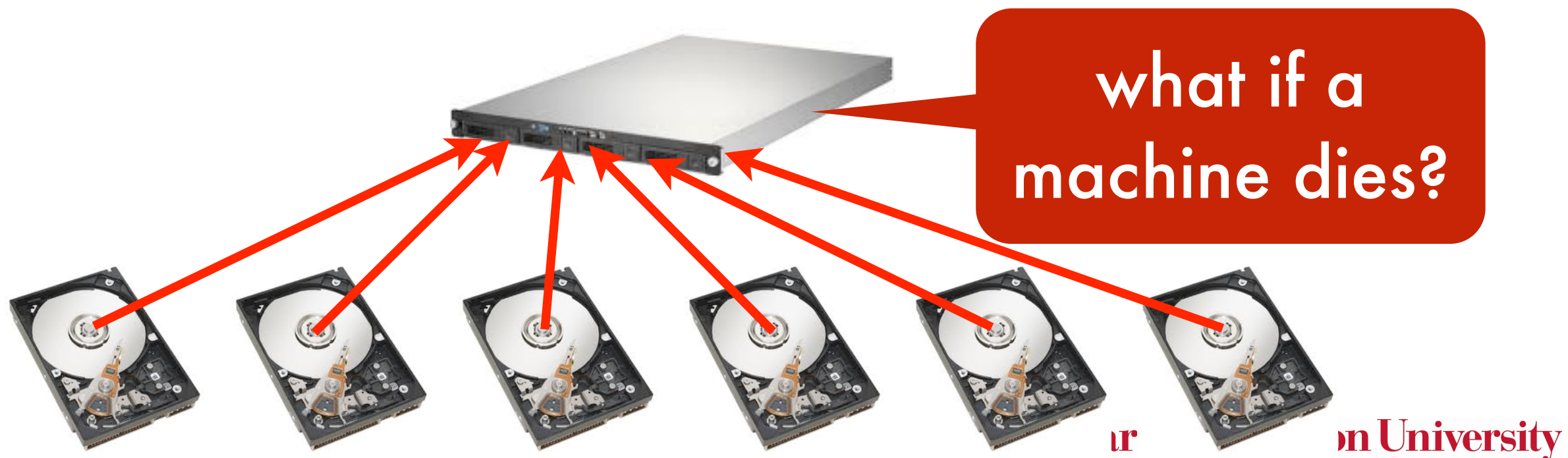
RAID

- Redundant array of inexpensive disks (optional fault tolerance)
 - Aggregate storage of many disks
 - Aggregate bandwidth of many disks
- RAID 0 - stripe data over disks (good bandwidth, faulty)
- RAID 1 - mirror disks (mediocre bandwidth, fault tolerance)
- RAID 5 - stripe data with 1 disk for parity (good bandwidth, fault tolerance)
- Even better - use error correcting code for fault tolerance, e.g. (4,2) code, i.e. two disks out of 6 may fail



RAID

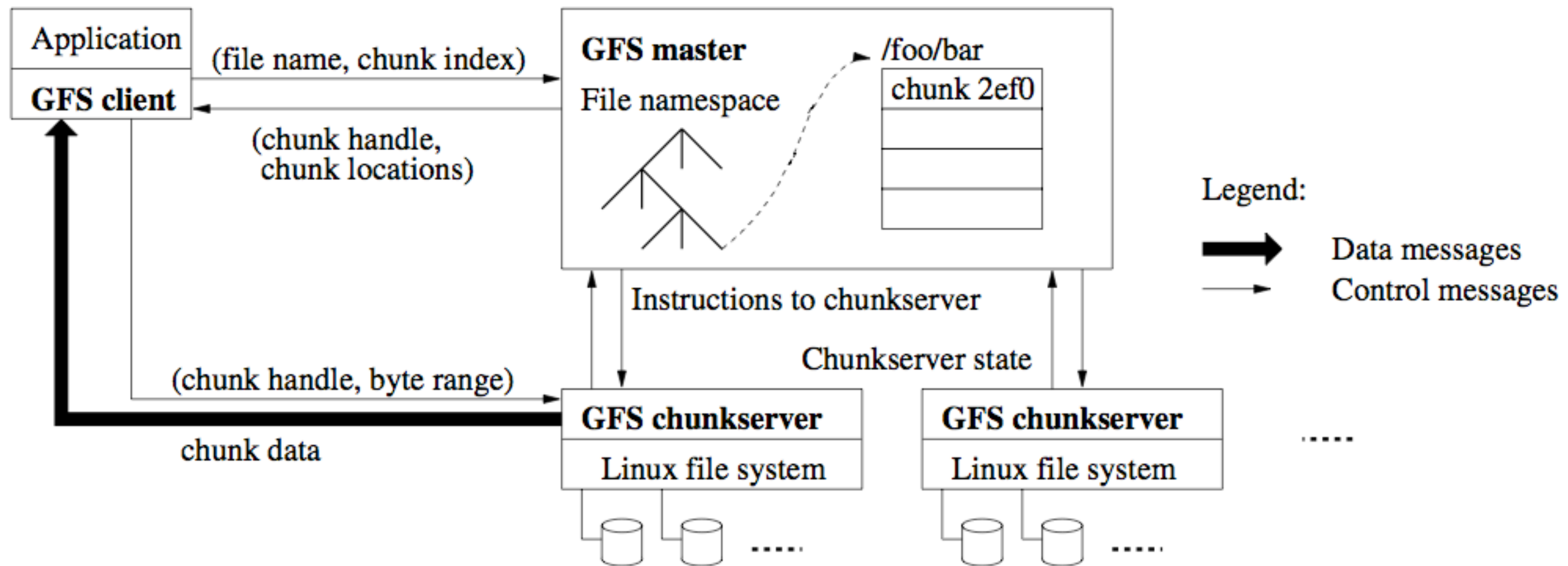
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Distributed replicated file systems

- Internet workload
 - Bulk sequential writes
 - Bulk sequential reads
 - **No random writes (possibly random reads)**
 - High bandwidth requirements per file
 - High availability / replication
- Non starters
 - Lustre (high bandwidth, but no replication outside racks)
 - Gluster (POSIX, more classical mirroring, see Lustre)
 - NFS/AFS/whatever - doesn't actually parallelize

Google File System / HadoopFS

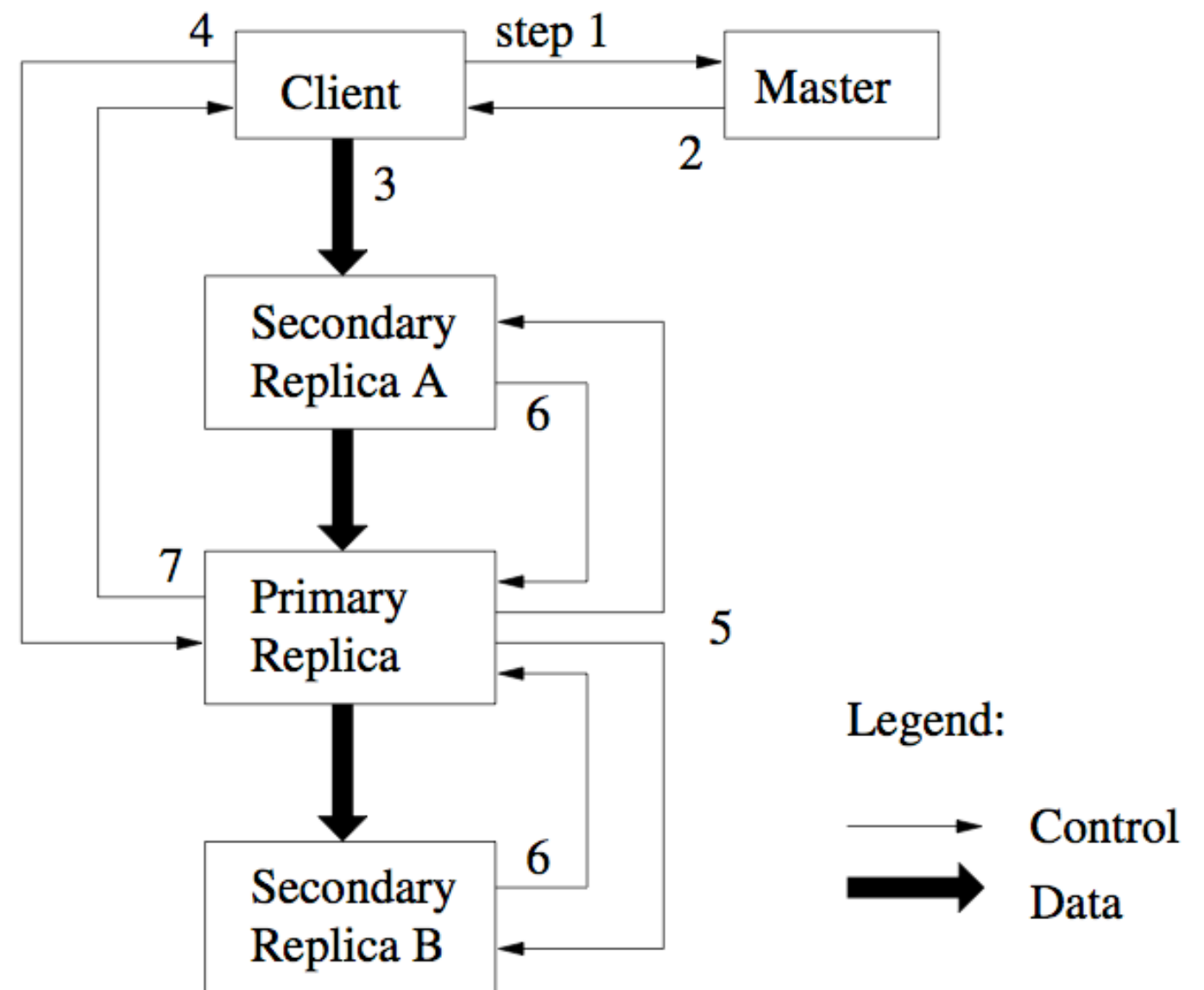


Ghemawat, Gobioff, Leung, 2003

- Chunk servers hold blocks of the file (64MB per chunk)
- Replicate chunks (chunk servers do this autonomously). **More bandwidth and fault tolerance**
- **Master distributes, checks faults, rebalances (Achilles heel)**
- Client can do bulk read / write / random reads

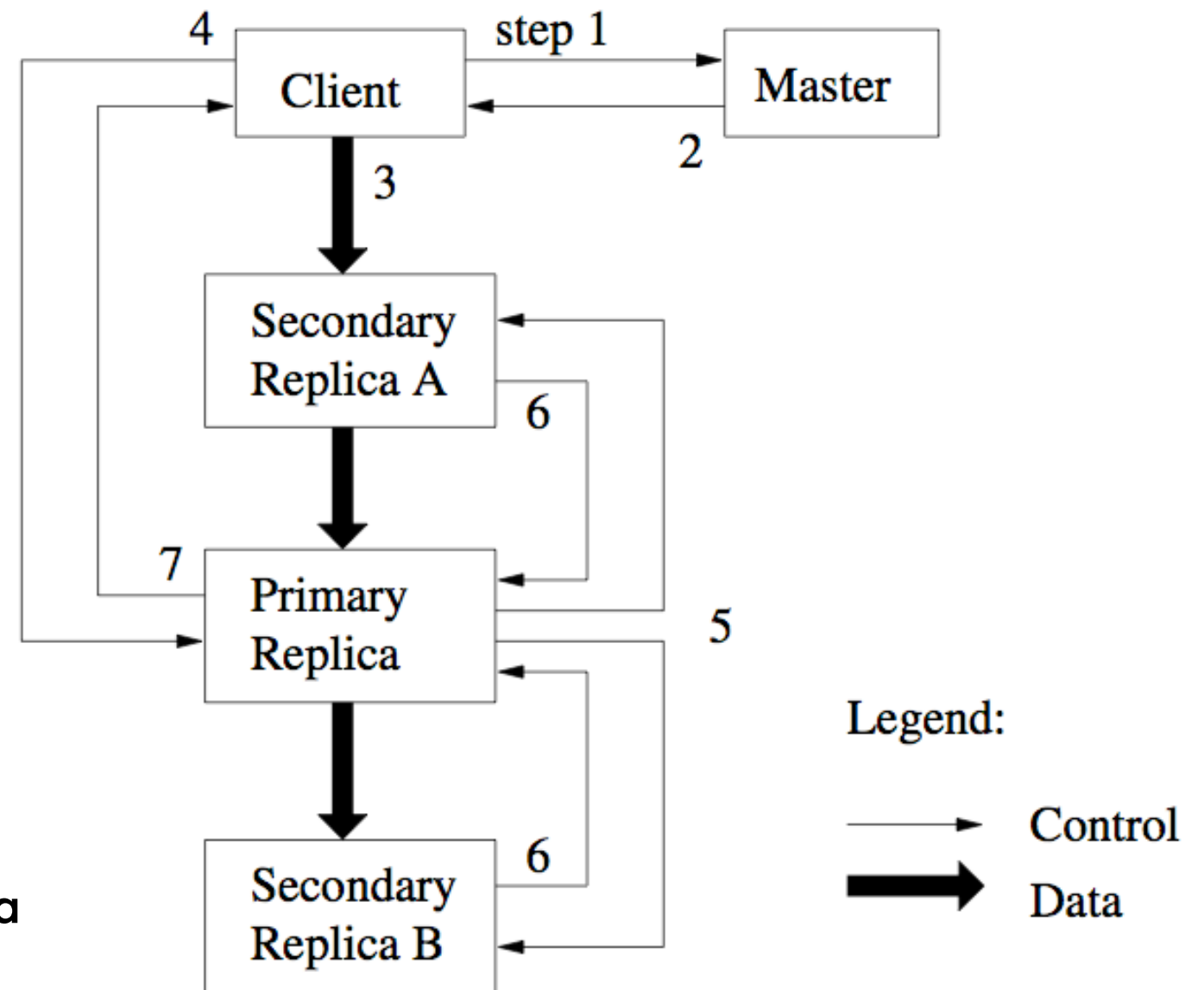
Google File System / HDFS

- Client requests chunk from master
- Master responds with replica location
- Client writes to replica A
- Client notifies primary replica
- Primary replica requests data from replica A
- Replica A sends data to Primary replica
- Primary replica confirms write to client



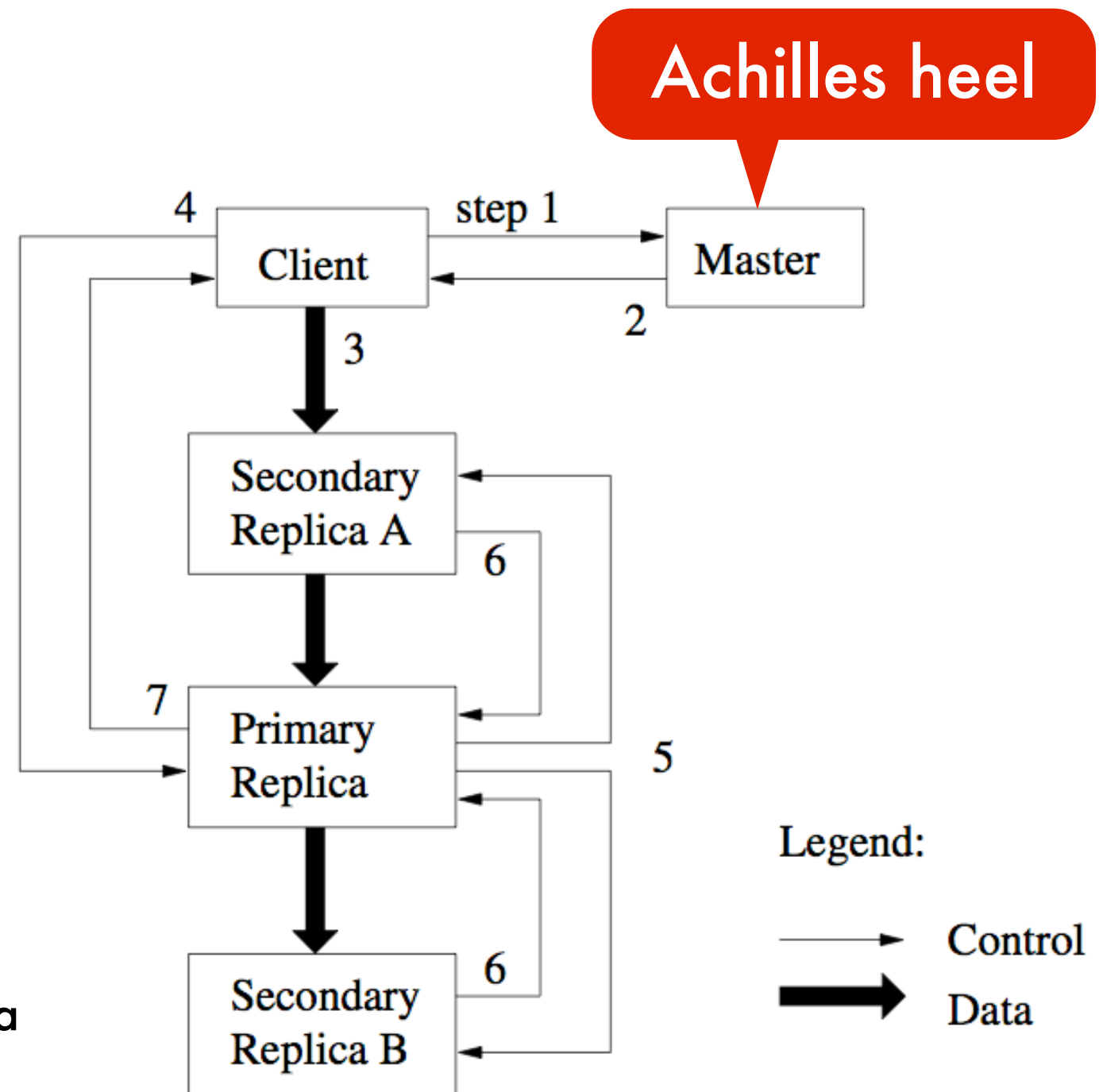
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- Master ensures nodes are live
 - Chunks are checksummed
 - Can control replication factor for hotspots / load balancing
 - Deserialize master state by loading data structure as flat file from disk (fast)



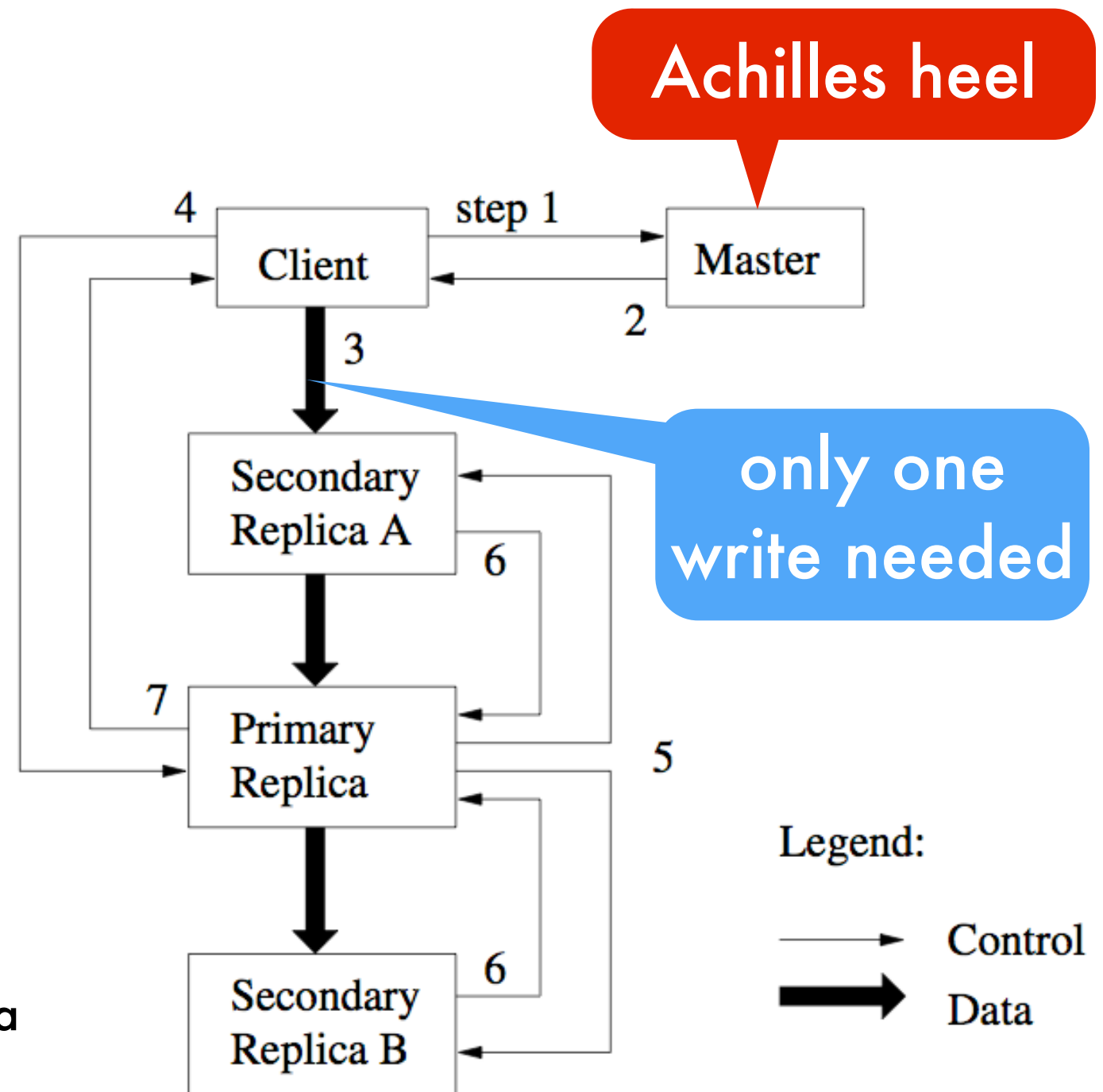
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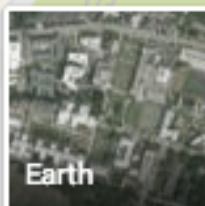
Carnegie Mellon University, Pittsburgh, PA

Carnegie Mellon University

[\(412\) 268-2000](tel:(412)268-2000)

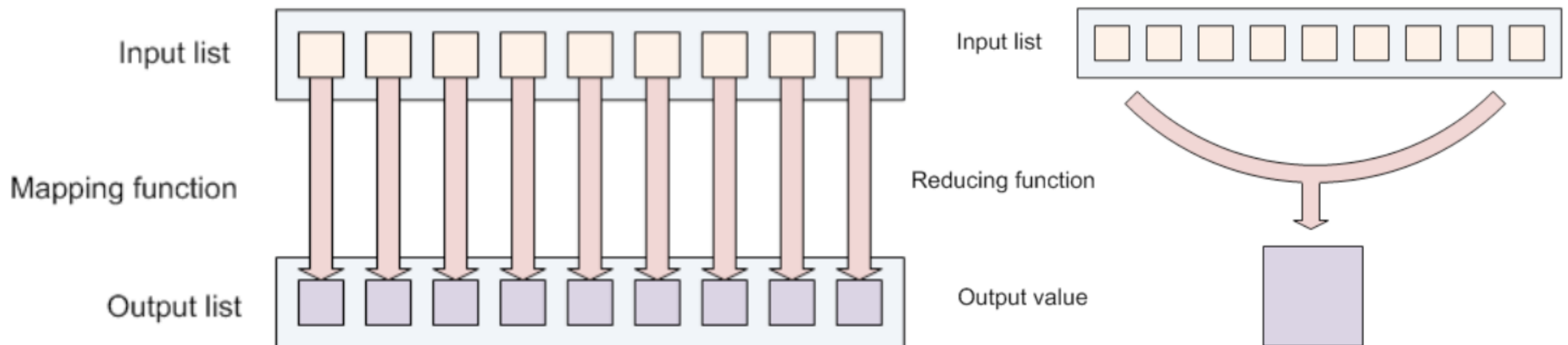
4.7 ★★★★★ 117 reviews

Map Reduce & Processing



Map Reduce

- 1000s of (faulty) machines
- Lots of jobs are embarrassingly parallel (except for a sorting/transpose phase)
- Functional programming origins
 - **Map(key,value)** processes (key,value) pairs and outputs new (key,value) pair
 - **Reduce(key,value)** reduces all instances with same key to aggregate
- Example - (naive) wordcount
 - **Map(docID, document)** for each document emits many (wordID, count) pairs
 - **Reduce(wordID, count)** sums over all wordID, emits (wordID, aggregate)



from Ramakrishnan, Sakrejda, Canon, DoE 2011

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Map Reduce

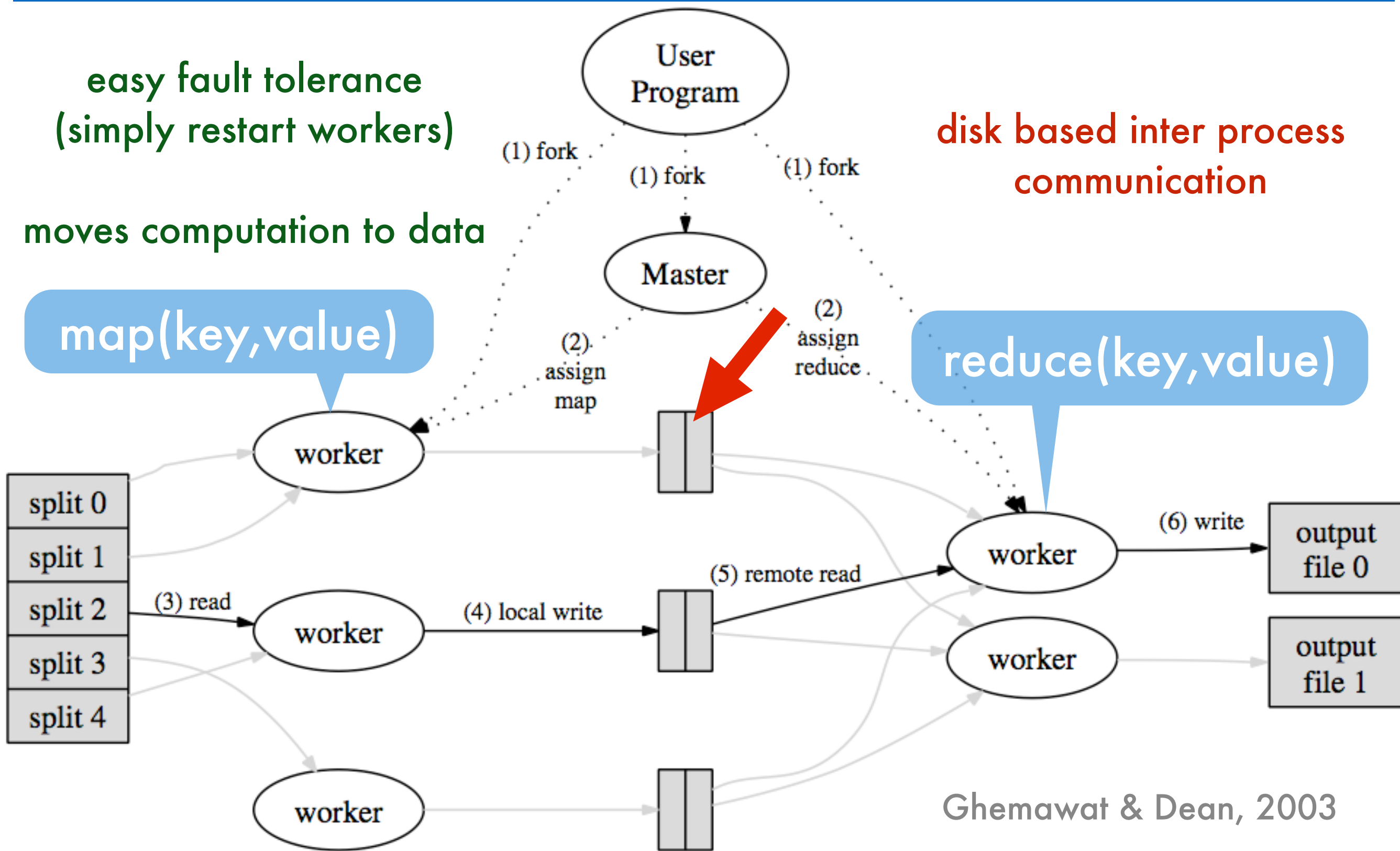
easy fault tolerance
(simply restart workers)

moves computation to data

map(key,value)

disk based inter process
communication

reduce(key,value)



Map Combine Reduce

- Combine aggregates keys within machine before sending to reducer
- Map must be stateless in blocks
- Reduce must be commutative in data
- Fault tolerance
 - Start jobs where the data is (move code not data)
 - Restart machines if maps fail (have replicas)
 - Restart reducers based on intermediate data
- Good fit for many algorithms
- Good if only a small number of MapReduce iterations needed
- Need to request machines at each iteration (time consuming)
- State lost in between maps
- Communication only via file I/O

Example - Gradient Descent

- Objective

$$\underset{w}{\text{minimize}} \sum_{i=1}^m l(x_i, y_i, w) + \frac{\lambda}{2} \|w\|^2$$

- Algorithm

- compute gradient

$$g := \sum_{i=1}^m \partial_w l(x_i, y_i, w)$$

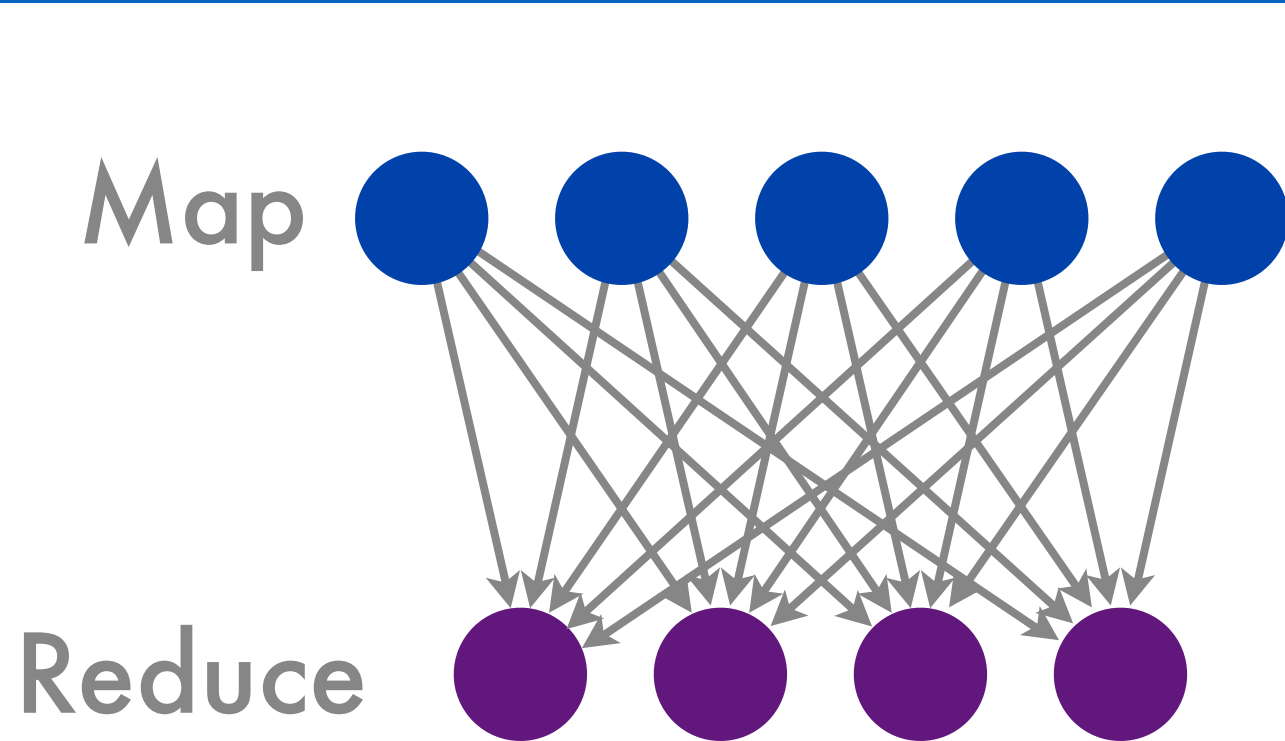
- On each data point via Map(i,data)

- Sum gradient via Reduce(coordinate)

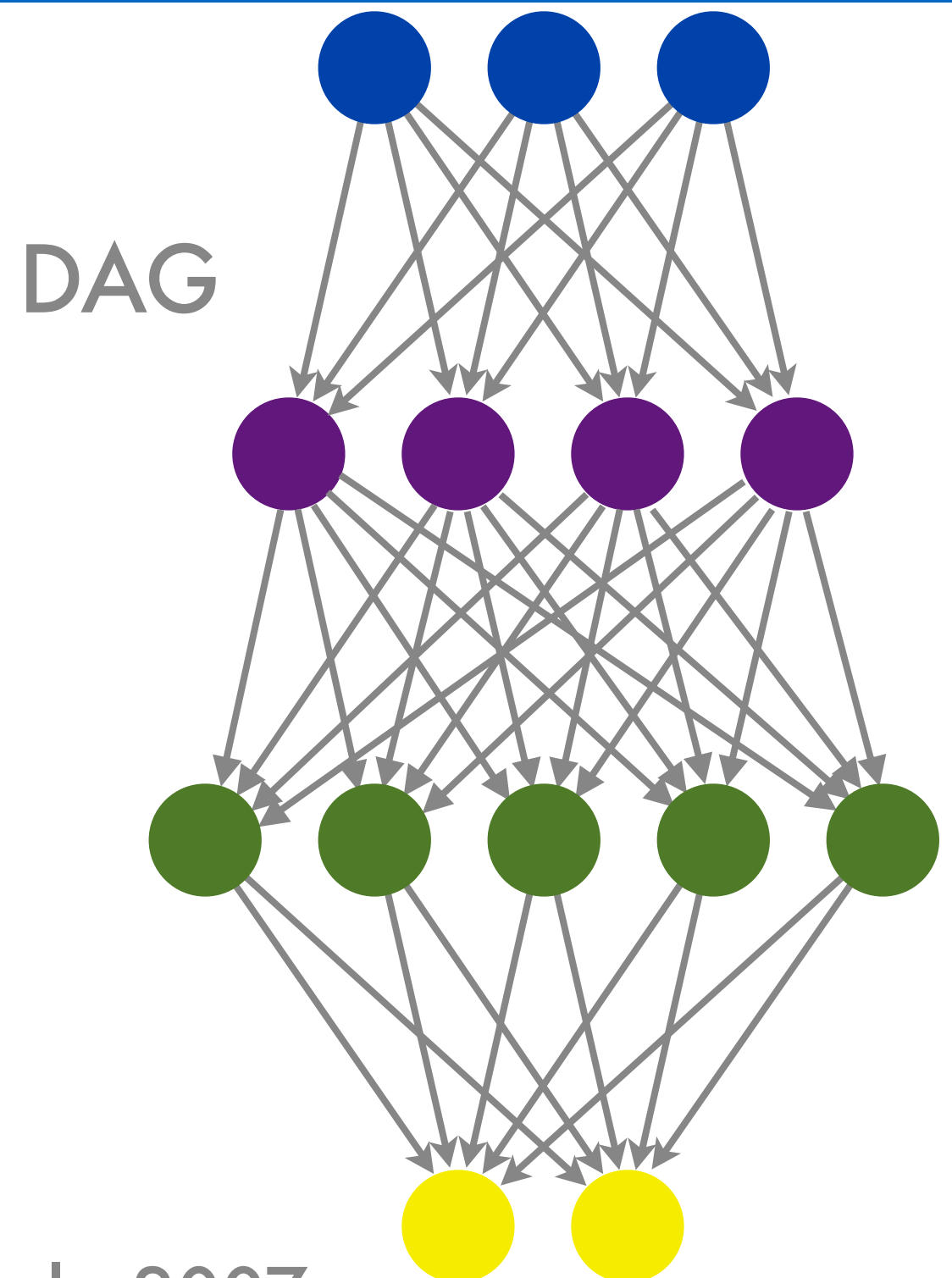
- perform update step $w \leftarrow w - \eta(g + \lambda w)$
(much better with line search)

- repeat

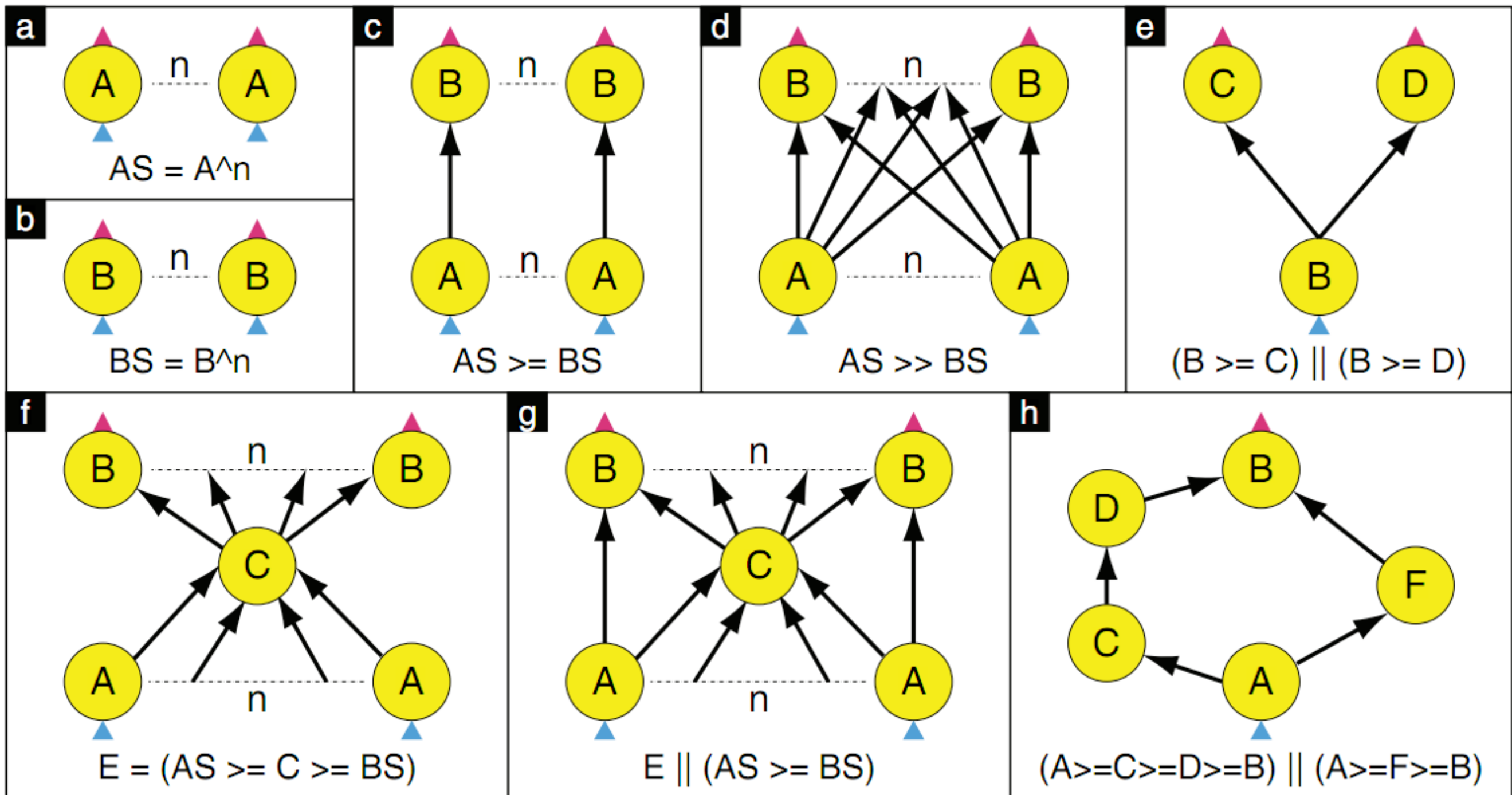
Dryad



- Directed acyclic graph
- System optimizes parallelism
- Different types of IPC (memory FIFO/network/file)
- Tight integration with .NET (allows easy prototyping)

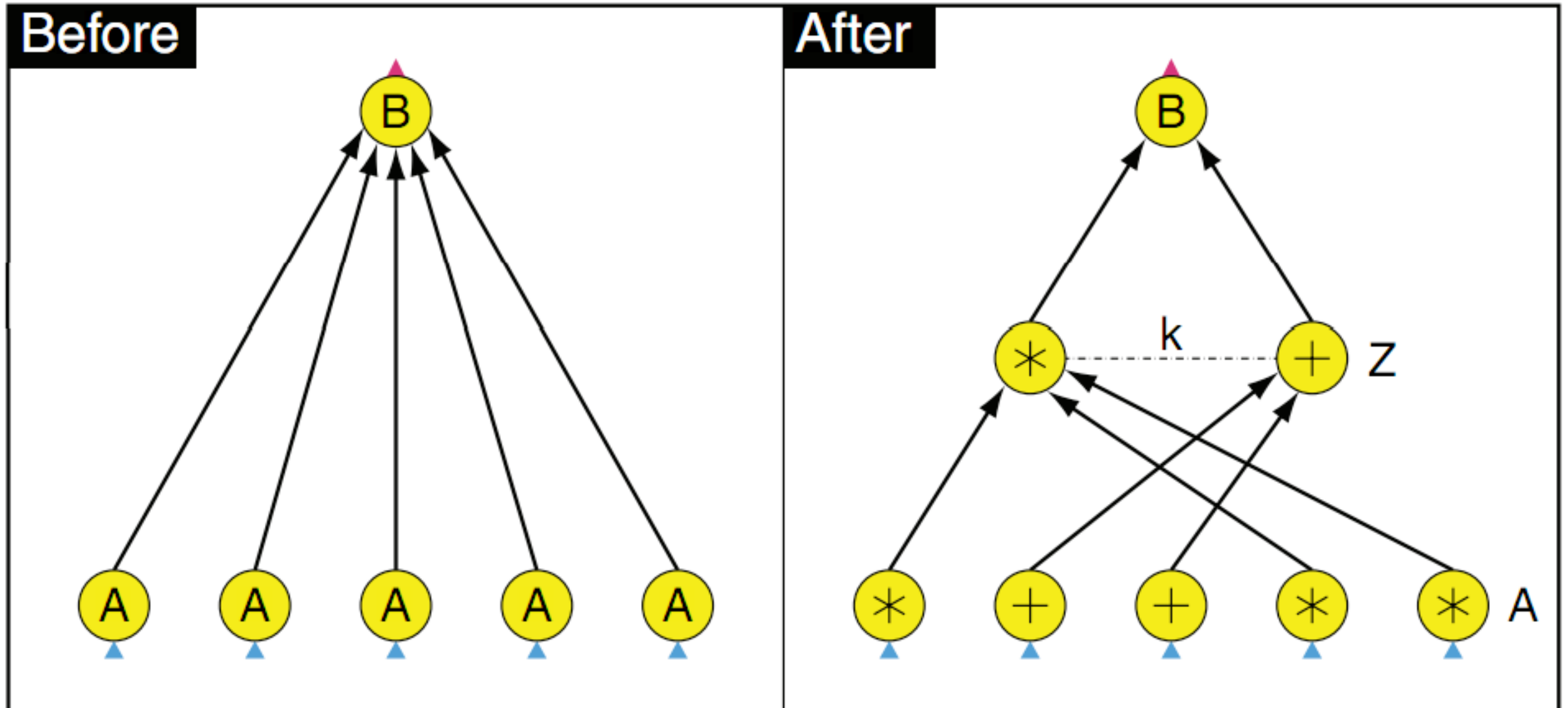


DRYAD



graph description language

DRYAD



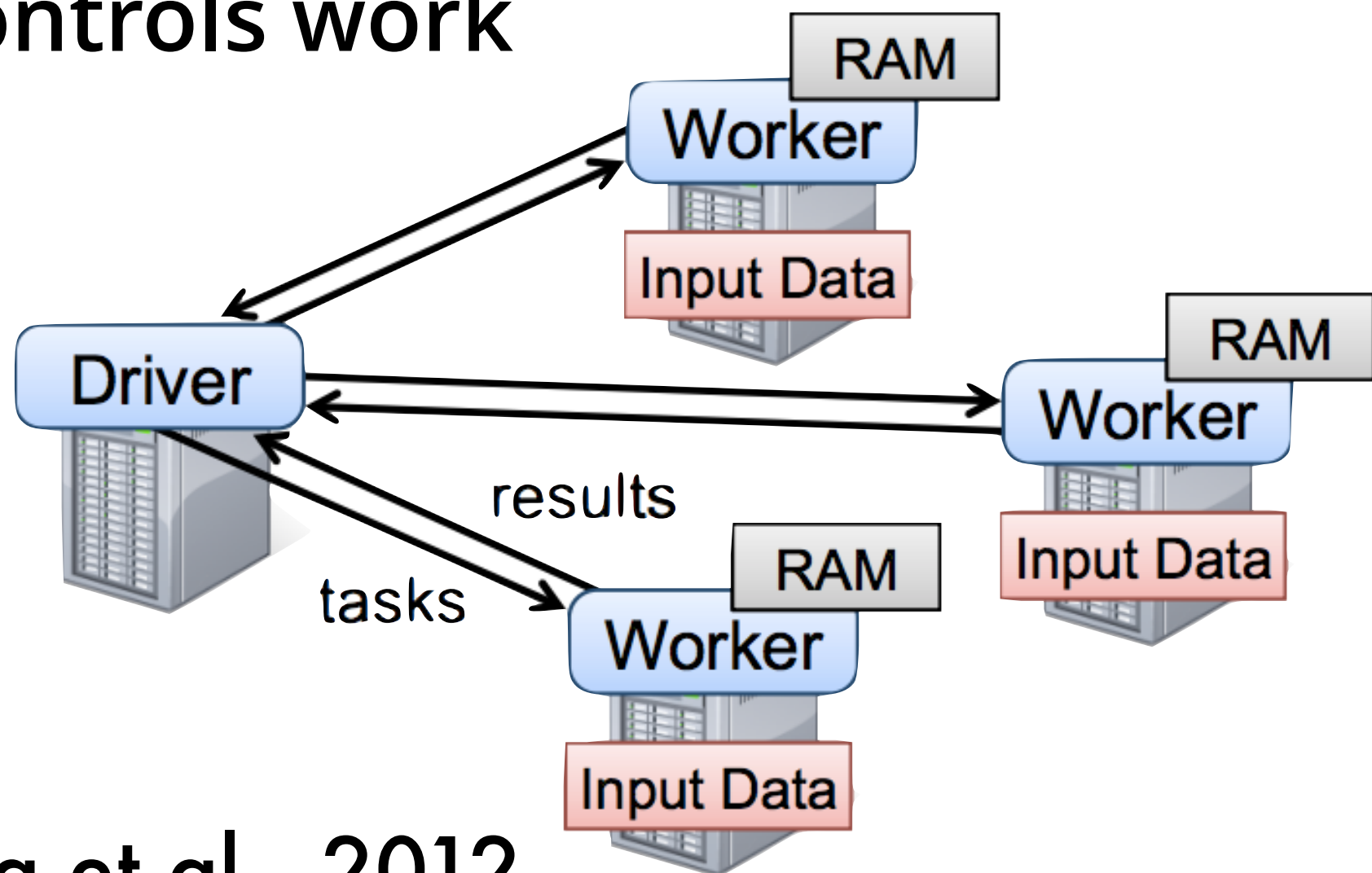
automatic graph refinement

A rear three-quarter view of a blue Chevrolet Spark hatchback. The car is parked on a paved surface in front of a building with large glass windows. The windows reflect the warm, golden light of a sunset or sunrise, showing silhouettes of trees and buildings. The car features a silver roof rack, a black rear wiper, and a black rear bumper with a single exhaust tip. The license plate is blue with white text, reading "MICHIGAN 028M179" and "FEB • MANUFACTURER • 12". The word "SPARK" is visible on the right side of the rear hatch. The word "Spark" is overlaid in large white font on the left side of the car.

Spark

Resilient Distributed Datasets

- Data is transformed by processing
- Store intermediate data using lineage
- Driver controls work

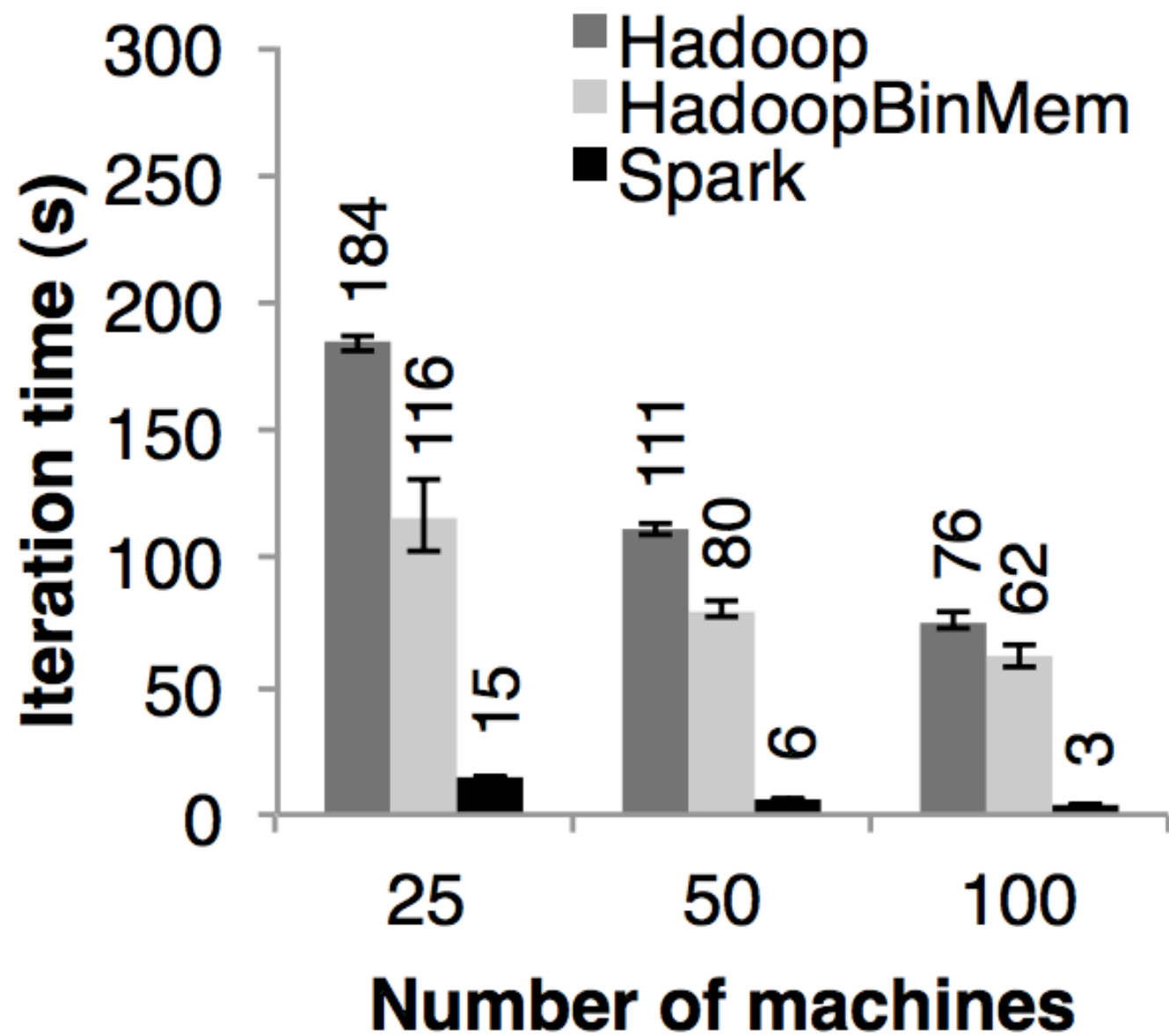


Beyond MapReduce

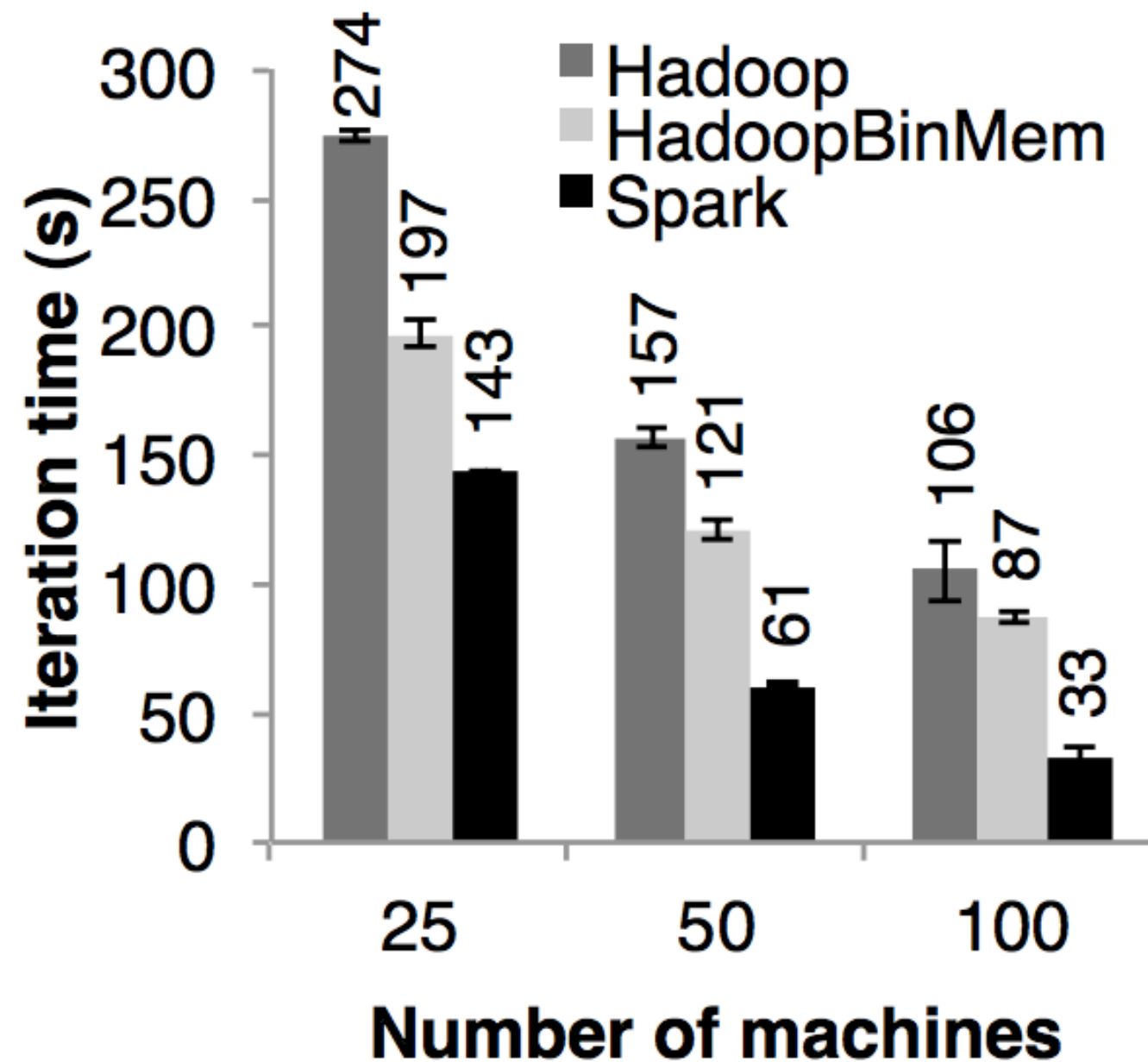
Transformations	$map(f : T \Rightarrow U) : RDD[T] \Rightarrow RDD[U]$ $filter(f : T \Rightarrow Bool) : RDD[T] \Rightarrow RDD[T]$ $flatMap(f : T \Rightarrow Seq[U]) : RDD[T] \Rightarrow RDD[U]$ $sample(fraction : Float) : RDD[T] \Rightarrow RDD[T]$ (Deterministic sampling) $groupByKey() : RDD[(K, V)] \Rightarrow RDD[(K, Seq[V])]$ $reduceByKey(f : (V, V) \Rightarrow V) : RDD[(K, V)] \Rightarrow RDD[(K, V)]$ $union() : (RDD[T], RDD[T]) \Rightarrow RDD[T]$ $join() : (RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (V, W))]$ $cogroup() : (RDD[(K, V)], RDD[(K, W)]) \Rightarrow RDD[(K, (Seq[V], Seq[W]))]$ $crossProduct() : (RDD[T], RDD[U]) \Rightarrow RDD[(T, U)]$ $mapValues(f : V \Rightarrow W) : RDD[(K, V)] \Rightarrow RDD[(K, W)]$ (Preserves partitioning) $sort(c : Comparator[K]) : RDD[(K, V)] \Rightarrow RDD[(K, V)]$ $partitionBy(p : Partitioner[K]) : RDD[(K, V)] \Rightarrow RDD[(K, V)]$
Actions	$count() : RDD[T] \Rightarrow Long$ $collect() : RDD[T] \Rightarrow Seq[T]$ $reduce(f : (T, T) \Rightarrow T) : RDD[T] \Rightarrow T$ $lookup(k : K) : RDD[(K, V)] \Rightarrow Seq[V]$ (On hash/range partitioned RDDs) $save(path : String) : \text{Outputs RDD to a storage system, e.g., HDFS}$

rich language & preprocessor

Improvement over MapReduce



(a) Logistic Regression



(b) K-Means



Mu Li



Li Zhou



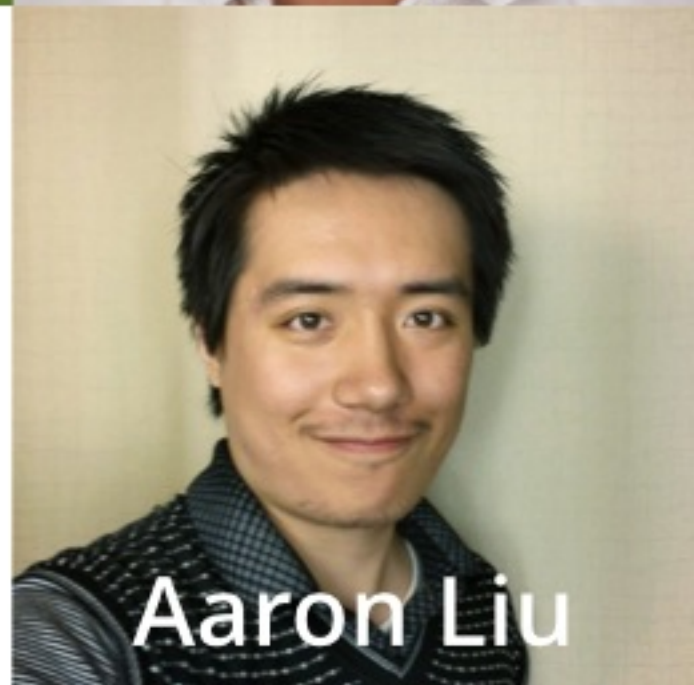
Dave Andersen



Junwoo Park

parameterserver.org

blog.smola.org @smolix



Aaron Liu



Amr Ahmed



Vanja Josifovski



Bor-Yiing Su



Eugene Shekita

A vibrant green rolling hill under a blue sky with white clouds. The hill is covered in lush green grass, and the sky is a deep blue with scattered white clouds. The word "Background" is written in large white letters across the center of the image.

Background

The Challenge

- Scale
 - 100s Terabytes of data
 - 1000s of computers
 - 100 Billions of parameters
- Reality
 - **Faulty machines**
 - Shared cluster
- Performance
 - Front end serving machines
 - Real time response

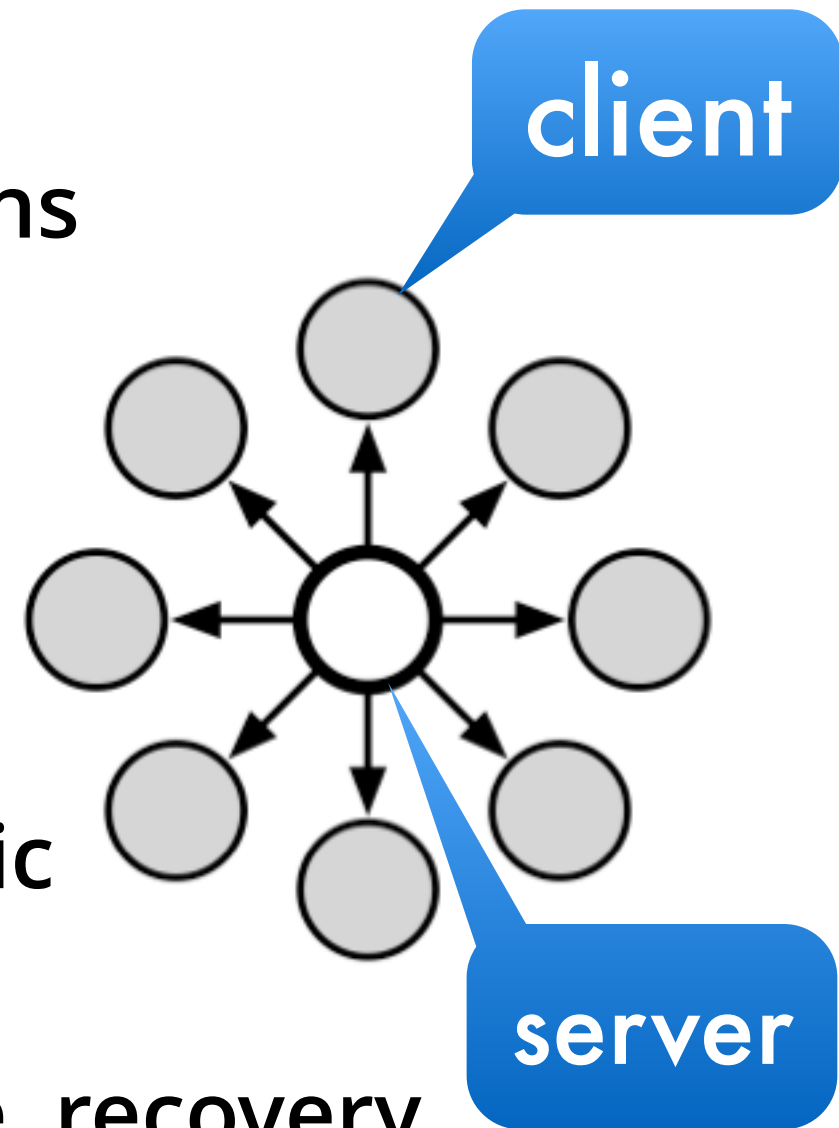


Machine Learning Problems

- Many models have $O(1)$ blocks of $O(n)$ terms (LDA, logistic regression, recommender systems)
- More terms than what fits into RAM (personalized CTR, large inventory, action space)
- Local model typically fits into RAM
- Data needs many disks for distribution
- Decouple data processing from aggregation
- Optimize for the 80% of all ML problems

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

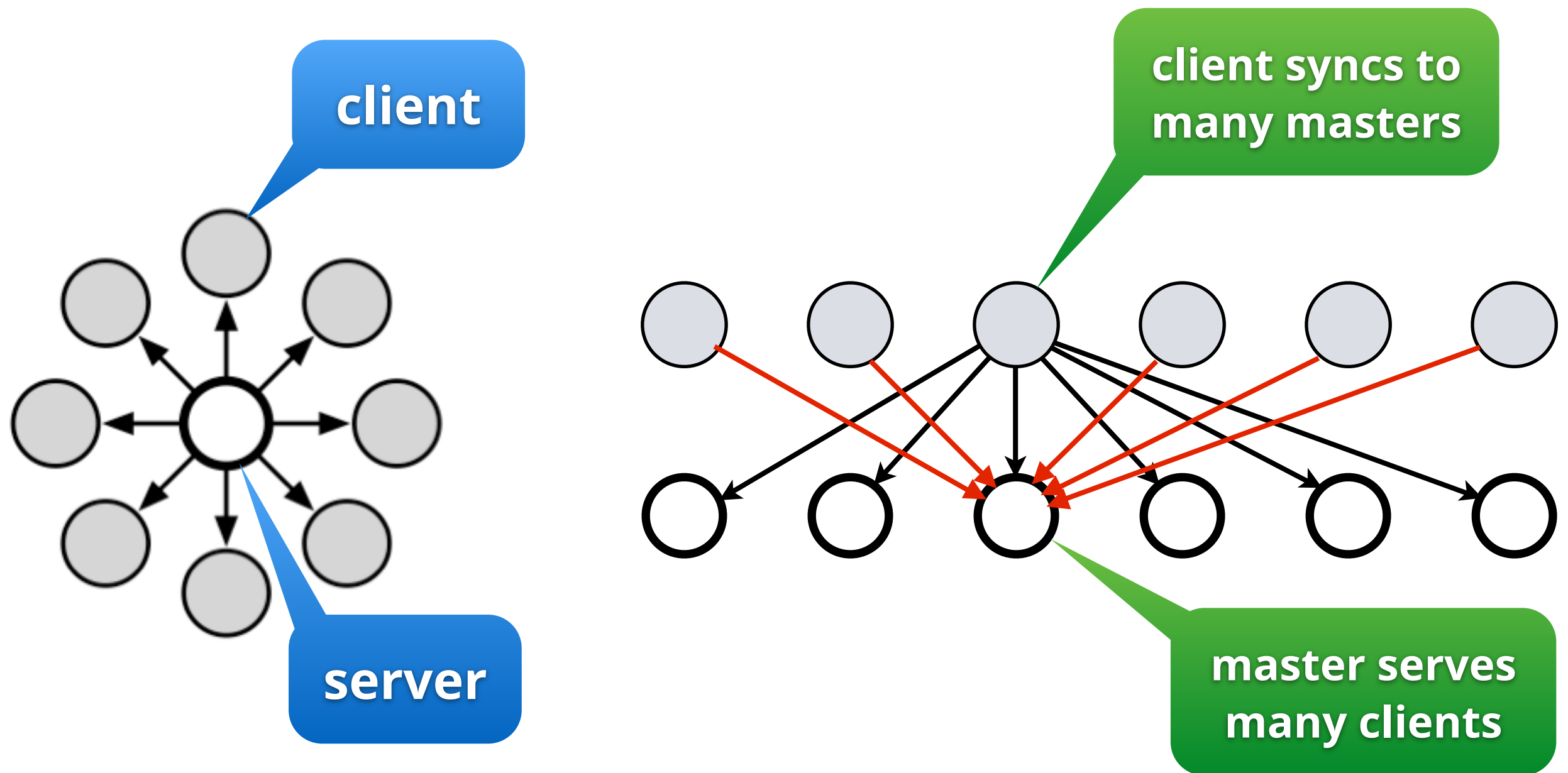


Smola & Narayanamurthy, 2010, VLDB

Gonzalez et al., 2012, WSDM

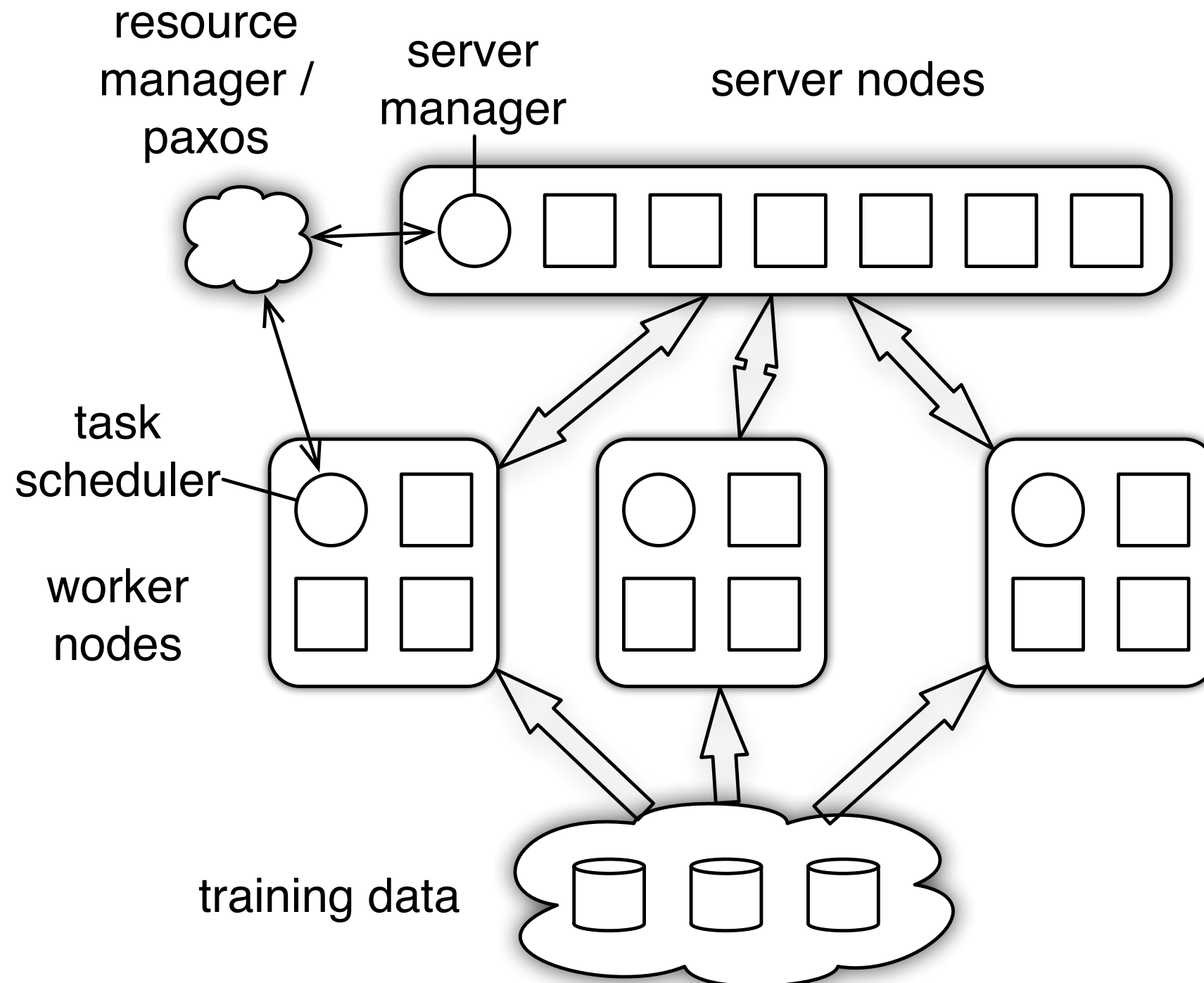
Shervashidze et al., 2013, WWW

Communication pattern



`put(keys,values,clock), get(keys,values,clock)`

Architecture

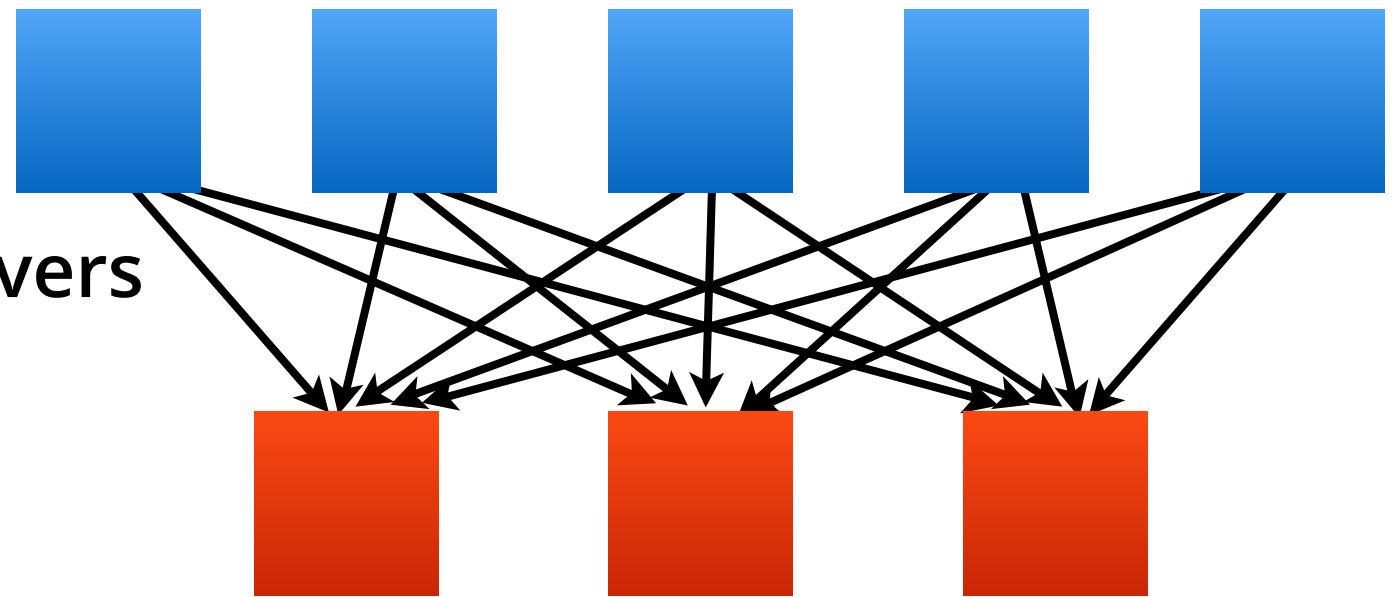




Key layout & recovery

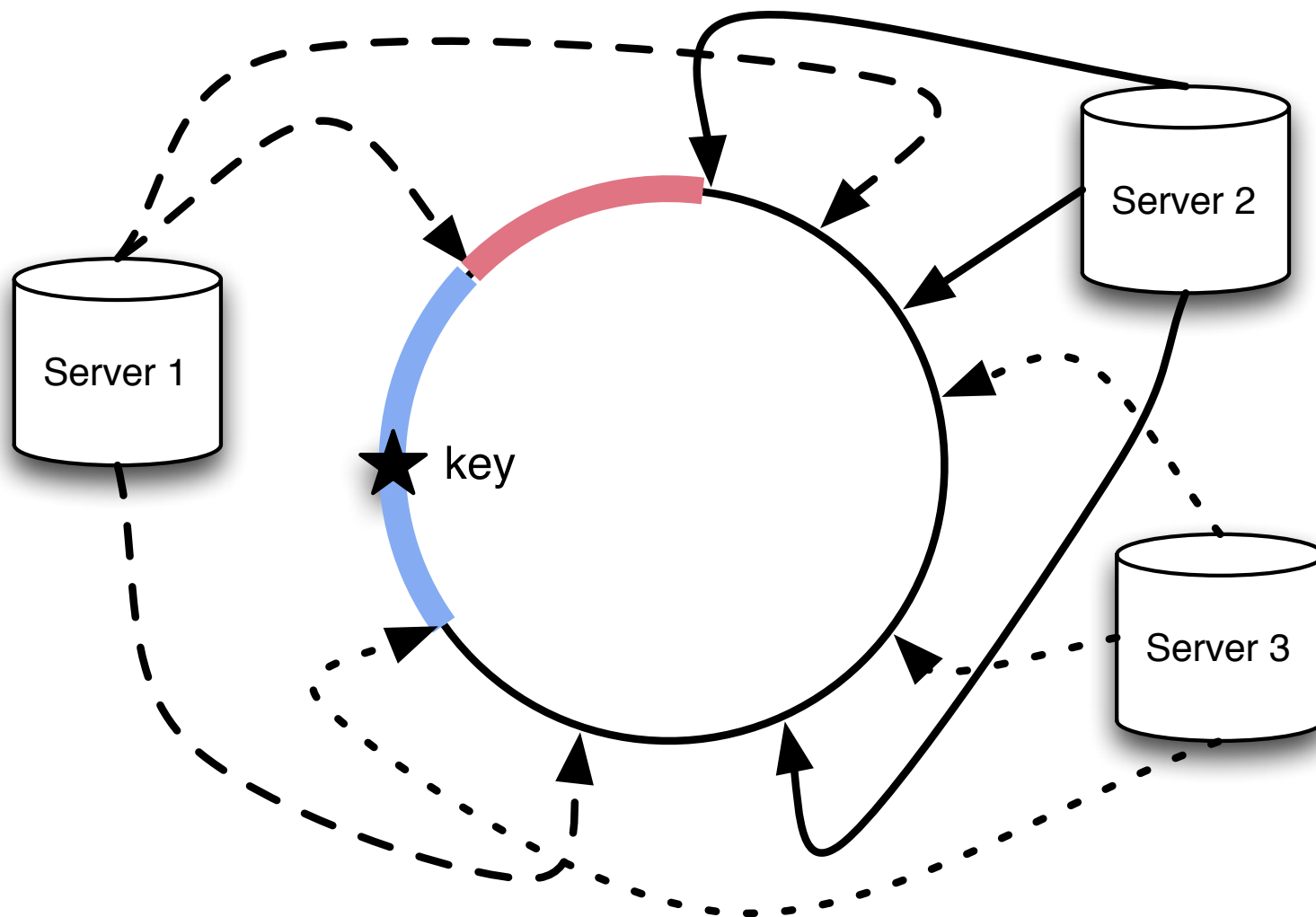
Consistent Hashing

- Caching
 - Store many (key,value) pairs
 - Linear scaling in clients & servers
 - Automatic key distribution
- memcached
 - (key,value) servers
 - client access library distributes access patterns
 - randomized $O(n)$ bandwidth
 - aggregate $O(n)$ bandwidth
 - load balancing via hashing
 - no versioned writes / vector clocks
 - very expensive to iterate over all keys for a given server



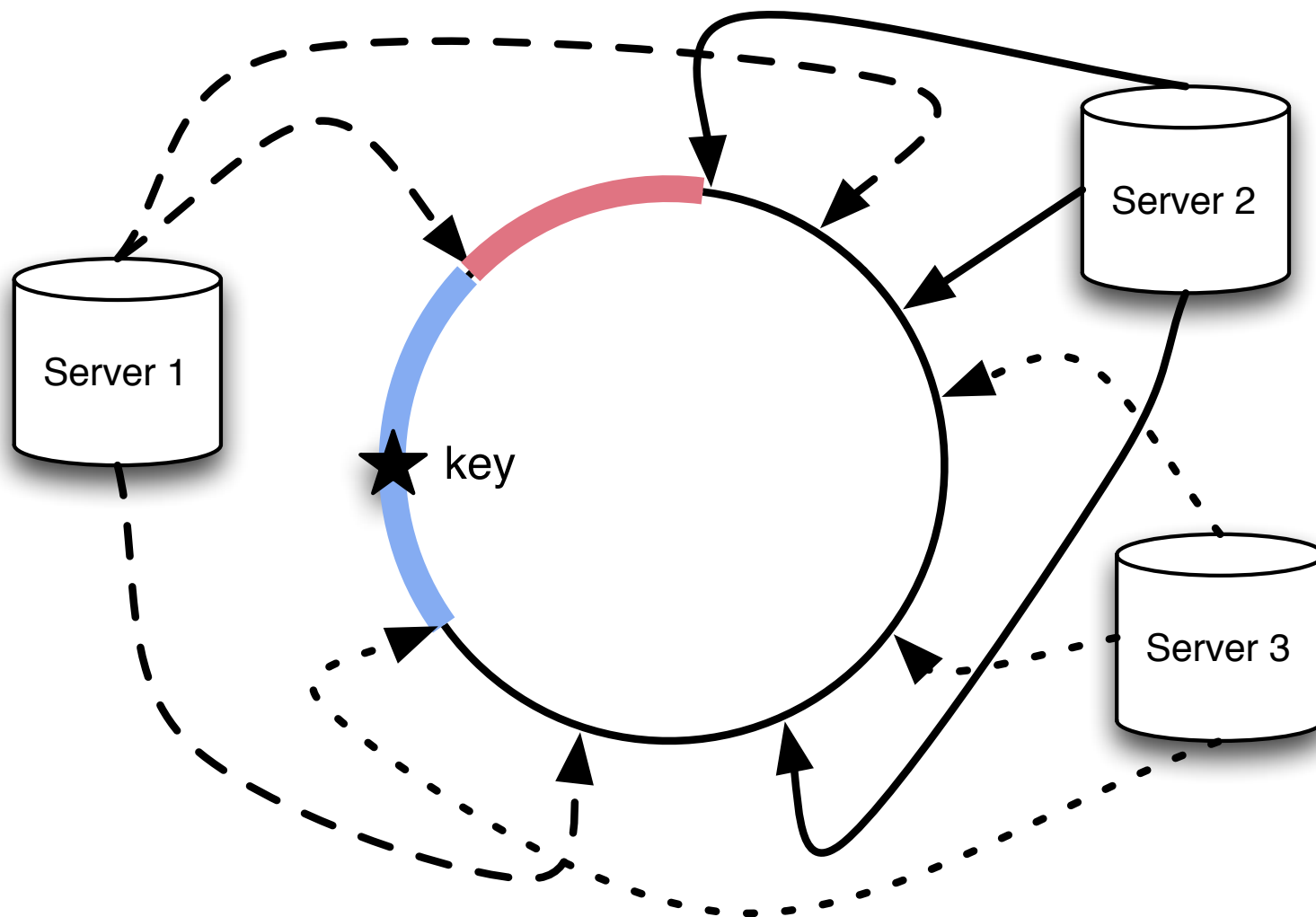
$$m(\text{key}, \mathcal{M}) = \operatorname{argmin}_{m' \in \mathcal{M}} h(\text{key}, m')$$

Keys arranged in a DHT



- Virtual servers
 - loadbalancing
 - multithreading
- DHT
 - contiguous key range for clients
 - easy bulk sync
 - easy insertion of servers
- Replication
 - Machines hold replicas
 - Easy fallback
 - Easy insertion / repair

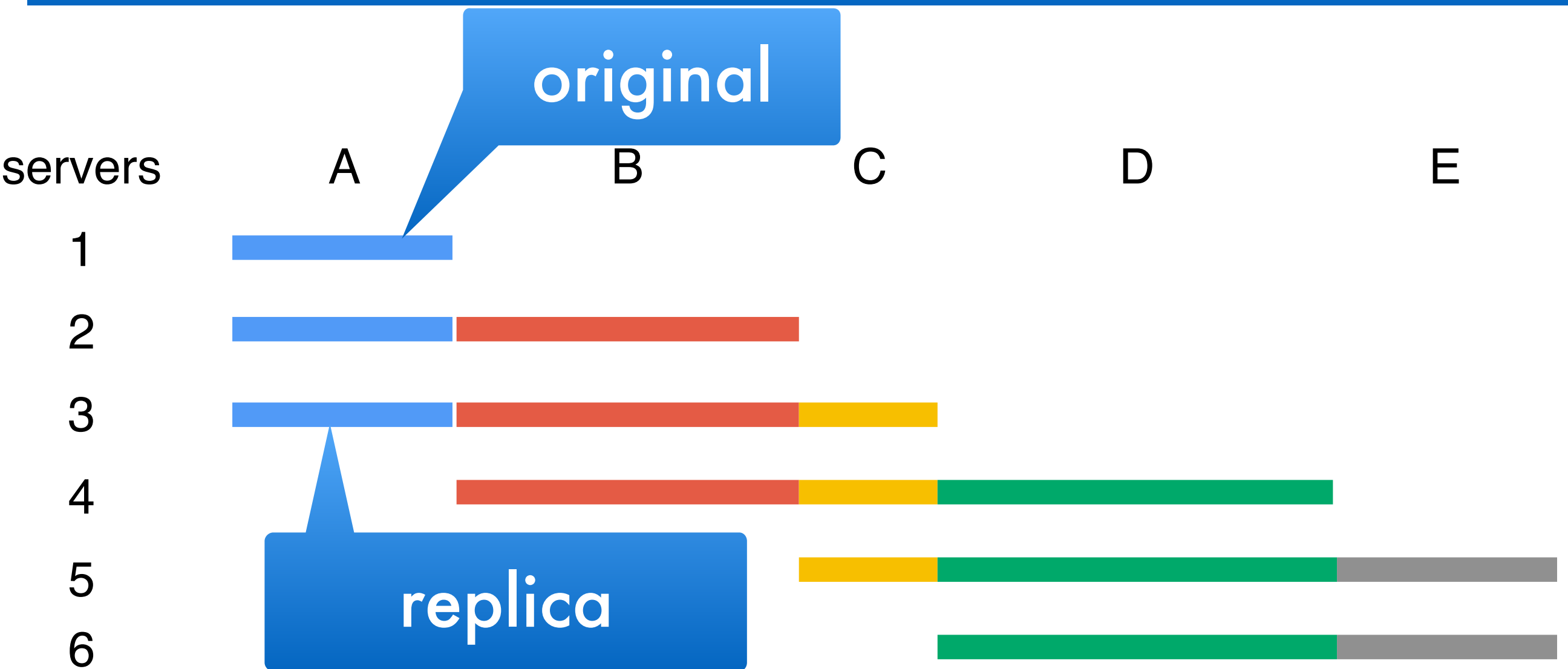
Keys arranged in a DHT



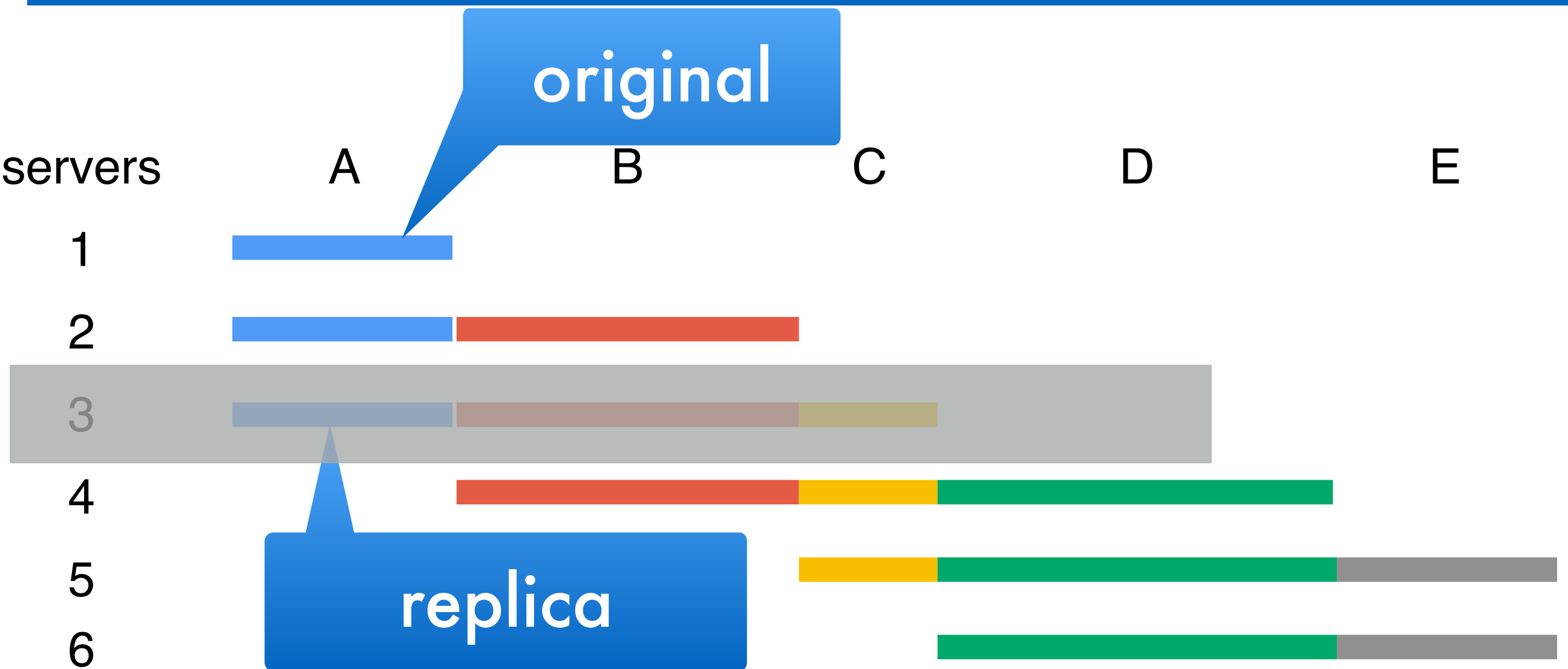
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 - loadbalancing
 - multithreading
- DHT
 - contiguous key range for clients
 - easy bulk sync
 - easy insertion of servers
- Replication
 - Machines hold replicas
 - Easy fallback
 - Easy insertion / repair

Yes, we screwed up before!
And everyone copied us!

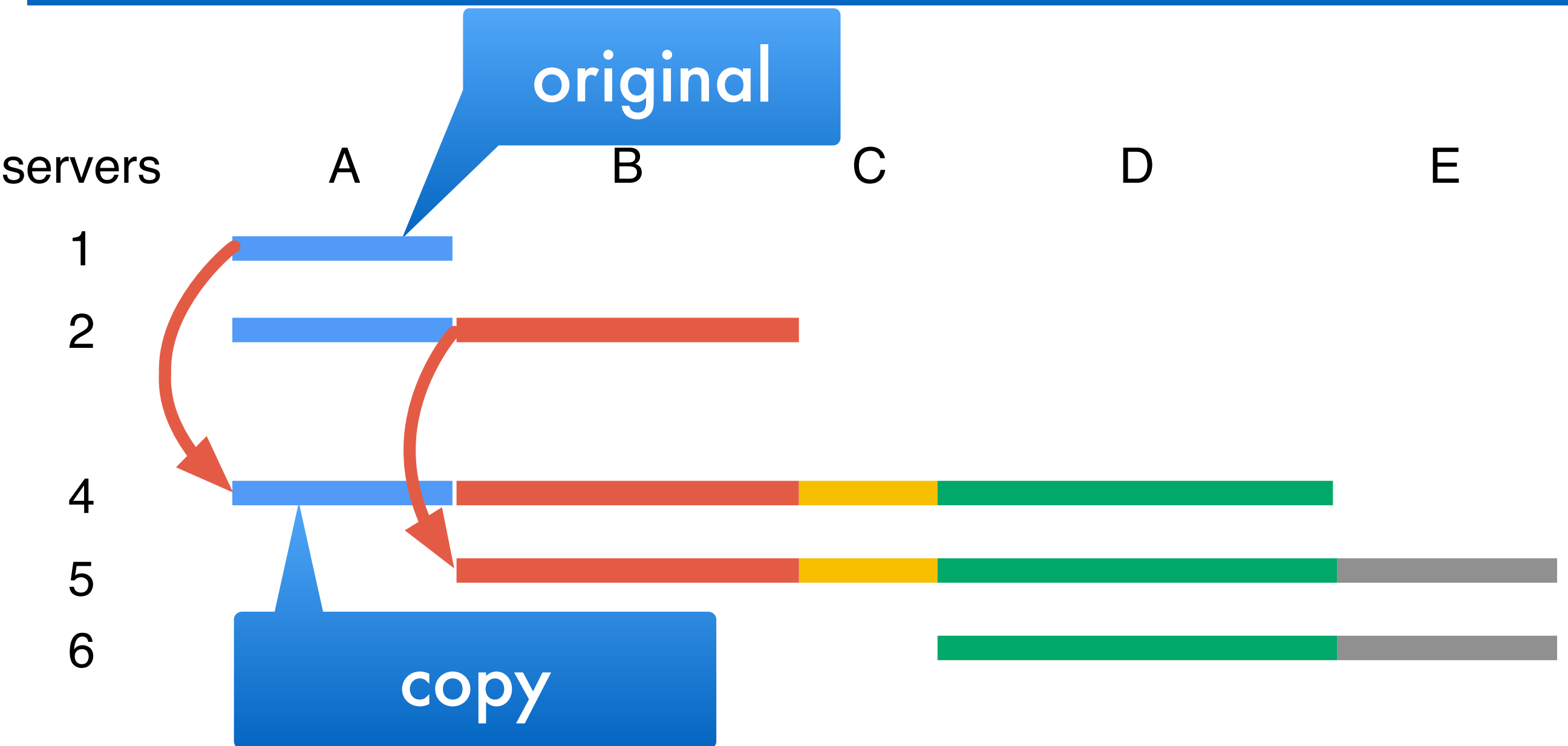
Key layout



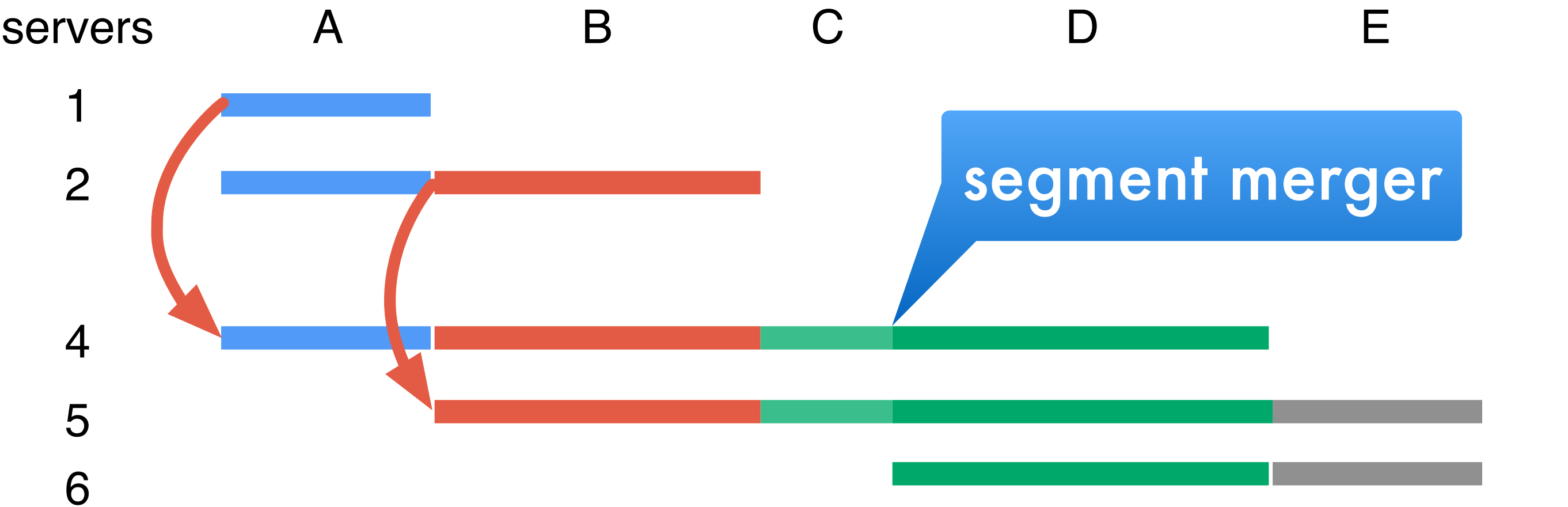
Key layout



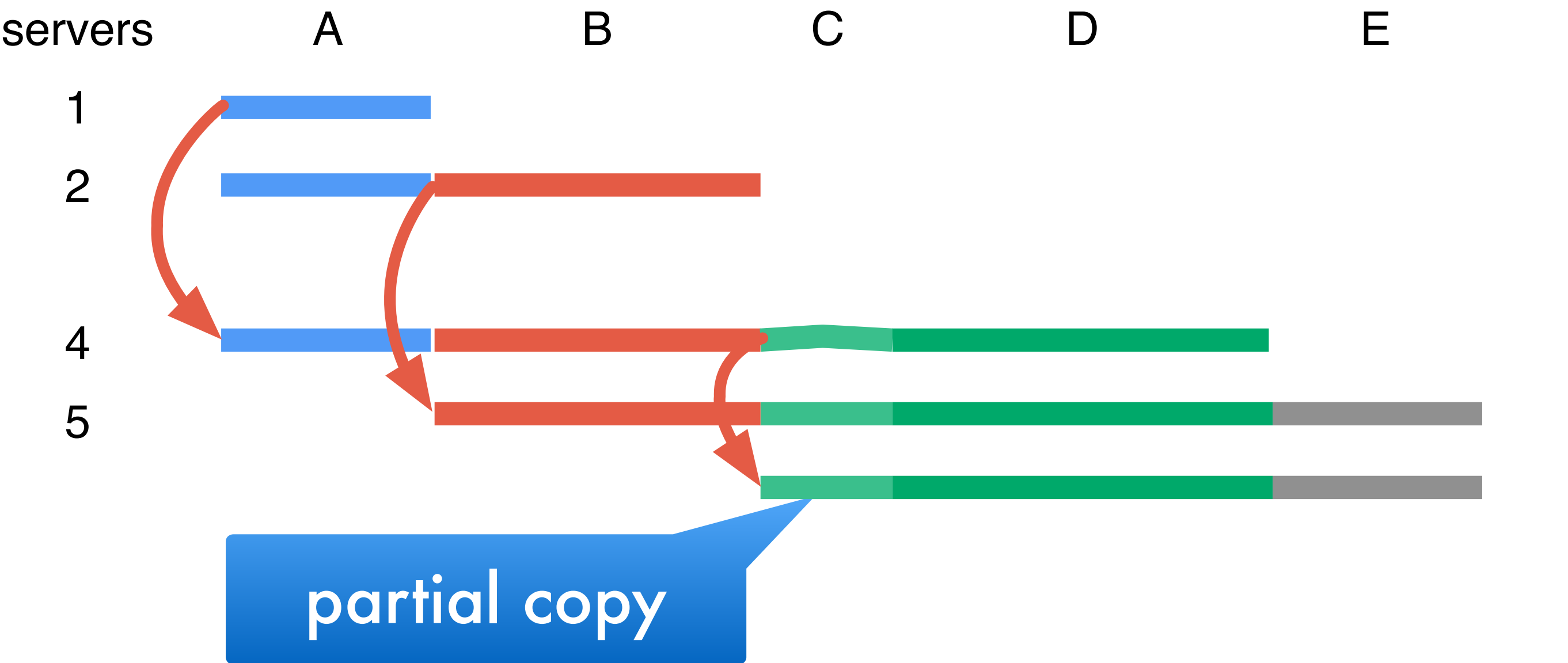
Key layout



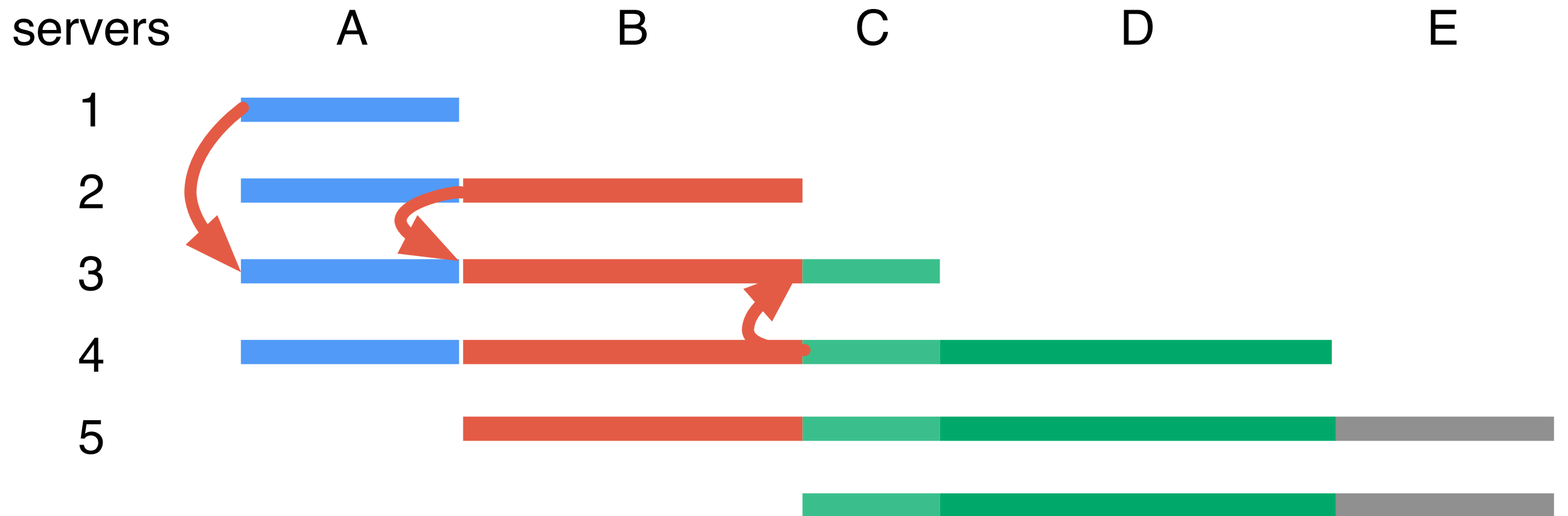
Key layout



Key layout



Recovery / server insertion



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

Communication



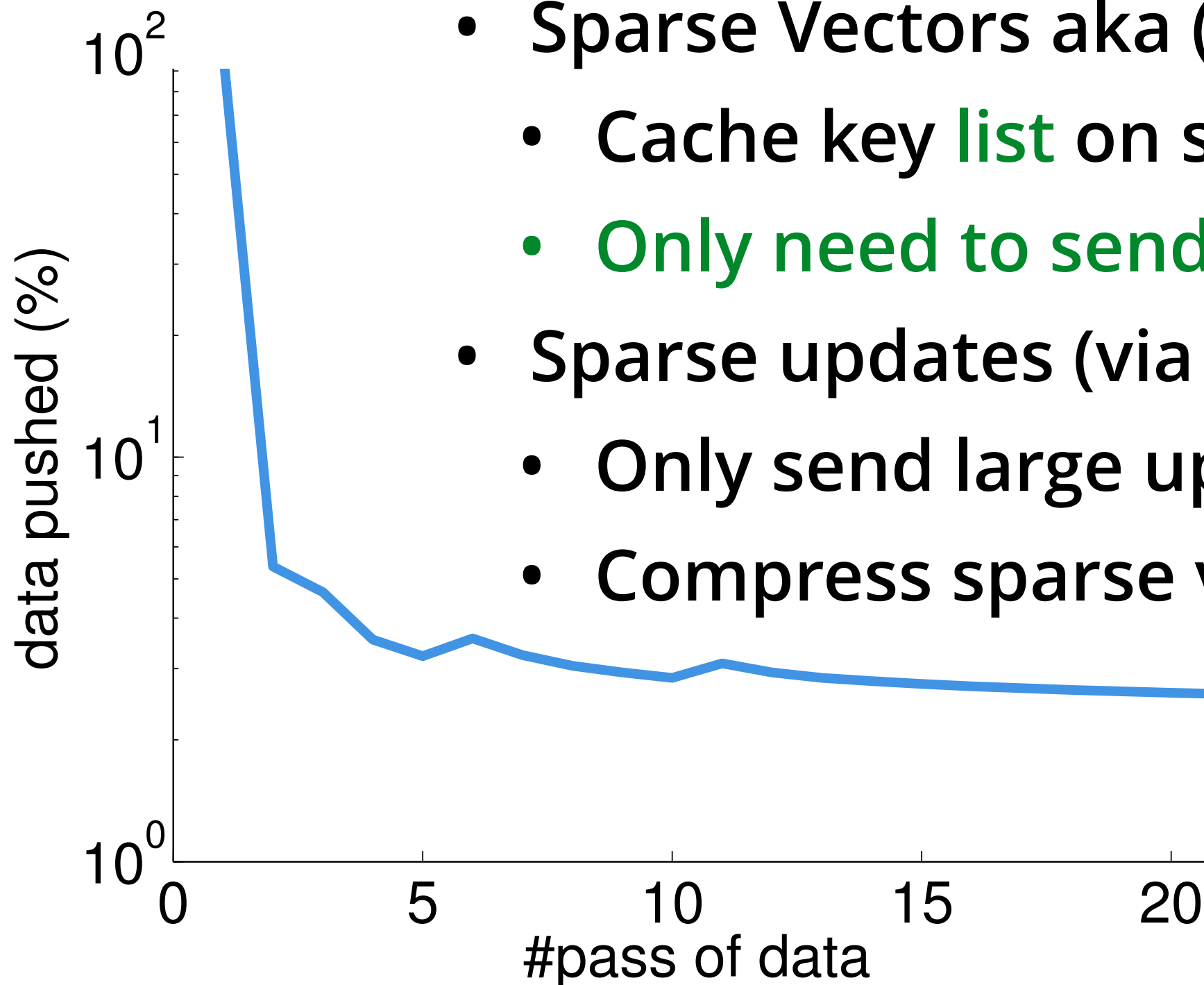
Message Compression

- Convergence speed depends on communication efficiency
 - Sending (key,value) pairs is inefficient
Send only values (cache key list) instead
 - Sending small gradients is inefficient
Send only sufficiently large ones instead
 - Updating near-optimal values is inefficient
Send only large violators of KKT conditions
- Filter data before sending

Filters

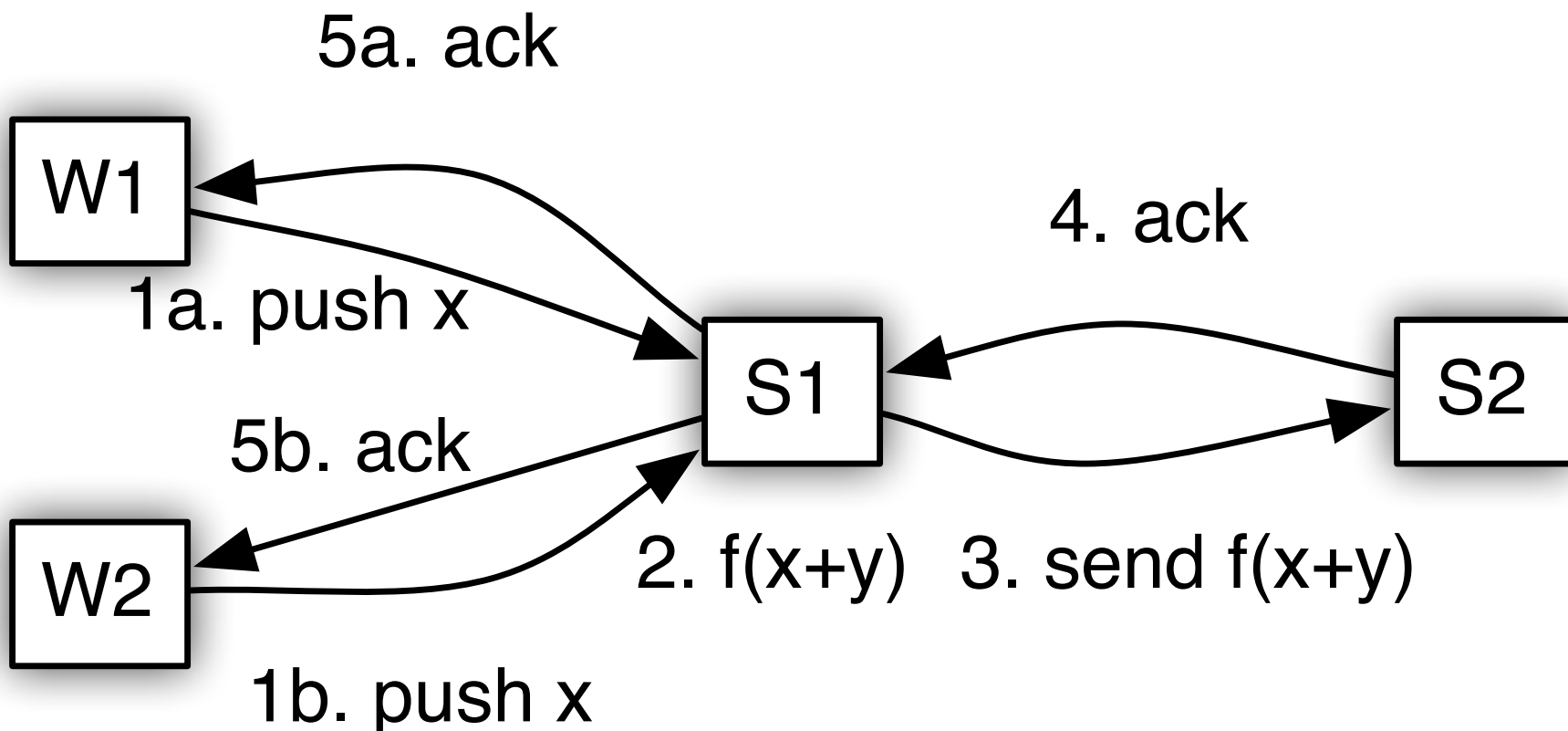
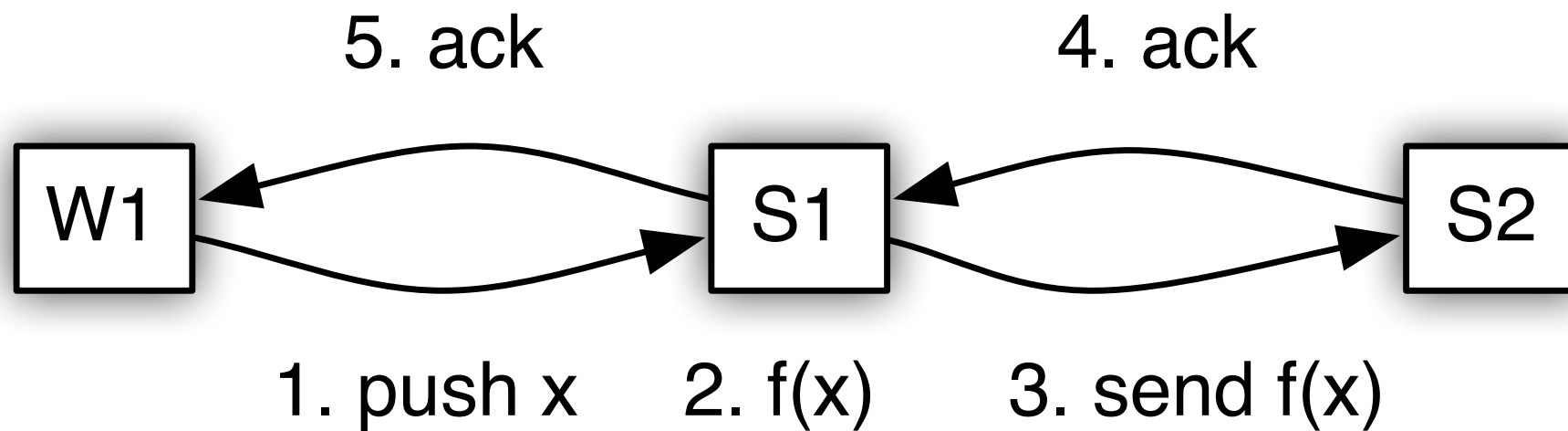
- **Scheduling**
have controller decide when to send
(this requires very smart controller)
- **Filtering**
have algorithm decide when to shut up
 - Gradient (only send large gradients)
 - KKT (only send variables violating KKT)
 - Randomized (sparse random vectors)
 - Quantization (reduce accuracy)

Message Compression



- Sparse Vectors aka (key,value) pairs
 - Cache key **list** on server
 - **Only need to send values**
- Sparse updates (via user defined filter)
 - Only send large updates
 - Compress sparse value list

Message Aggregation on Server



Messaging

- Datatypes are `eigen3` native
 - Dense vectors
 - Sparse vectors
- `Push(Header flag)`
- `Pull(Header flag)`
Flag may specify
 - Value or delta update
 - key range
 - recipient (all server, all clients, particular node)

Shared pointer. No copy on queue (by default)!

Consistency models

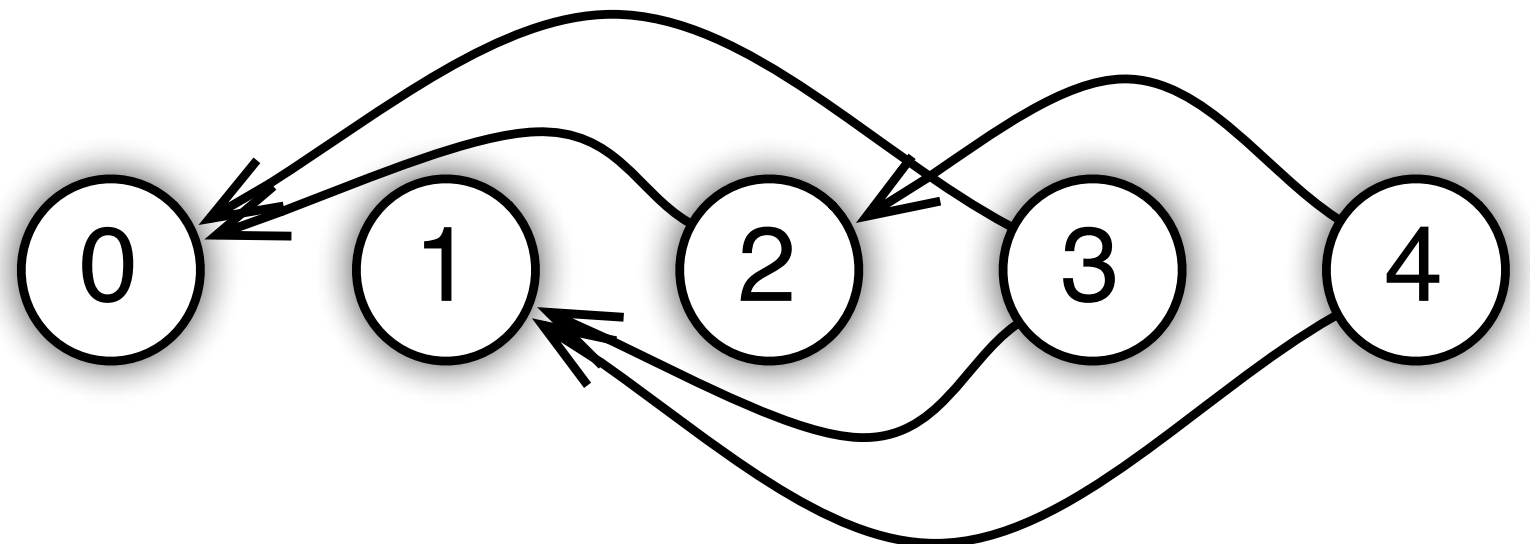
(a) Sequential



(b) Eventual



(c) Bounded delay



via task processing engine on client/controller

Vector Clocks for Ranges

- Keep track of when we received an update from a client / server.
- For c clients this means $O(c)$ metadata
This is impossible to store per key (Dynamo)
- Very cheap and feasible for ranges
- When inconsistent ranges, split segments
[A,D] splits into [A,B], [B,C] and [C,D] when receiving message for [B,C]
- This is infrequent + defragmentation



Models



Logistic Regression

Recall - Computational Advertising

mesothelioma

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Ad www.mesothelioma-answers.org/
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Asbestos - Treatments - Top Doctors - Free Mesothelioma Book

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What is Mesothelioma? - Asbestos Exposure in CA - California Legal Rights

Mesothelioma Cancer - Mesothelioma.com
www.mesothelioma.com/mesothelioma/
by Dr. Howard Jack West - Apr 2, 2014 - Mesothelioma is an aggressive cancer affecting the membrane lining ... Between 50 and 70% of all mesotheliomas are of the epithelial variety.
Mesothelioma Symptoms - Mesothelioma Prognosis - Mesothelioma Survival Rate

Mesothelioma - Wikipedia, the free encyclopedia
en.wikipedia.org/wiki/Mesothelioma Wikipedia
Mesothelioma (or, more precisely, malignant mesothelioma) is a rare form of cancer that develops from cells of the mesothelium, the protective lining that covers ...
Asbestos - Mesothelium - Paul Kraus - Category:Mesothelioma

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estimate it

4 million/minute

Carnegie Mellon University

Estimating Probabilities

- Logistic model (exponential family)

$$p(y|t) \propto \exp\left(\frac{1}{2}yt\right) \text{ where } y \in \{\pm 1\}$$

y will tend to agree with the sign of t (find t)

- Normalizing terms

$$\begin{aligned} p(y|t) &= \frac{\exp\left(\frac{1}{2}yt\right)}{\exp\left(\frac{1}{2}t\right) + \exp\left(-\frac{1}{2}t\right)} = \frac{\exp\left(\frac{1}{2}yt\right)}{\exp\left(\frac{1}{2}yt\right) + \exp\left(-\frac{1}{2}yt\right)} \\ &= \frac{1}{1 + \exp(-yt)} \end{aligned}$$

(Penalized) Maximum Likelihood

- **Goal**
Find t that correlates with y
- **Strategy**
Use covariates x and function $f(x)$

$$p(y|x) = \frac{1}{1 + \exp(-yf(x))}$$

- **Penalty against overfitting / Bayes rule**

$$p(f|X, Y) \propto p(f) \prod_{i=1}^m \frac{1}{1 + \exp(-y_i f(x_i))}$$

Penalized Maximum Likelihood

- Picking a function class

$$f(x) = \langle w, x \rangle$$

- Picking a prior

$$\log p(f) = \lambda \|w\|_1 + \text{const.}$$

we want sparse models for advertising

- Picking an inference strategy

$$\begin{aligned} & \underset{w}{\text{minimize}} -\log p(f|X, Y) \\ & \underset{w}{\text{minimize}} \sum_{i=1}^m \log(1 + \exp(-y_i \langle w, x_i \rangle)) + \lambda \|w\|_1 \end{aligned}$$

- $\log p(w_i) = \frac{1}{2}w_i^2 + \text{const.}$
- $\log p(w_i) = |w_i| + \text{const.}$
- $\log p(w_i) = \log(0.1 + |w_i|) + \text{const.}$

Proximal Algorithm

- Problem - l_1 norm is non-smooth
- Proximal operator

$$\operatorname{argmin}_w \|w\|_1 + \frac{\gamma}{2} \|w - (w_t - \eta g_t)\|$$

(more generally use penalty on w)

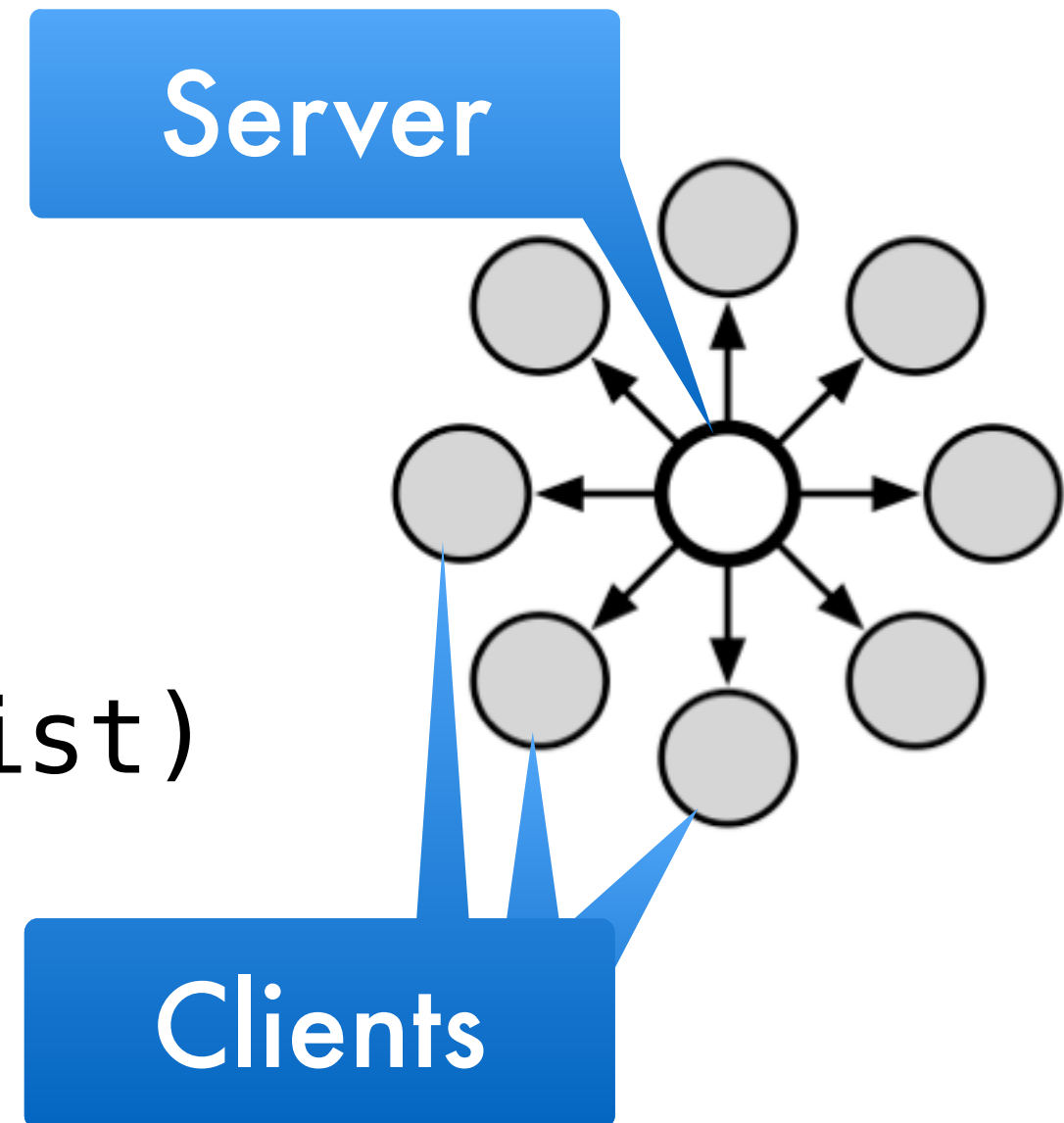
- Updates for l_1 are

$$w_i \leftarrow \operatorname{sgn}(w_i) \max(0, |w_i| - \epsilon)$$

(update and project back to polytope)

Generic Parallel Template

- Compute gradient on (subset of data) on each client
- Send gradient from client to server asynchronously
`push(key_list, value_list)`
- Proximal gradient update on server
- Server returns parameters
`pull(key_list, value_list)`



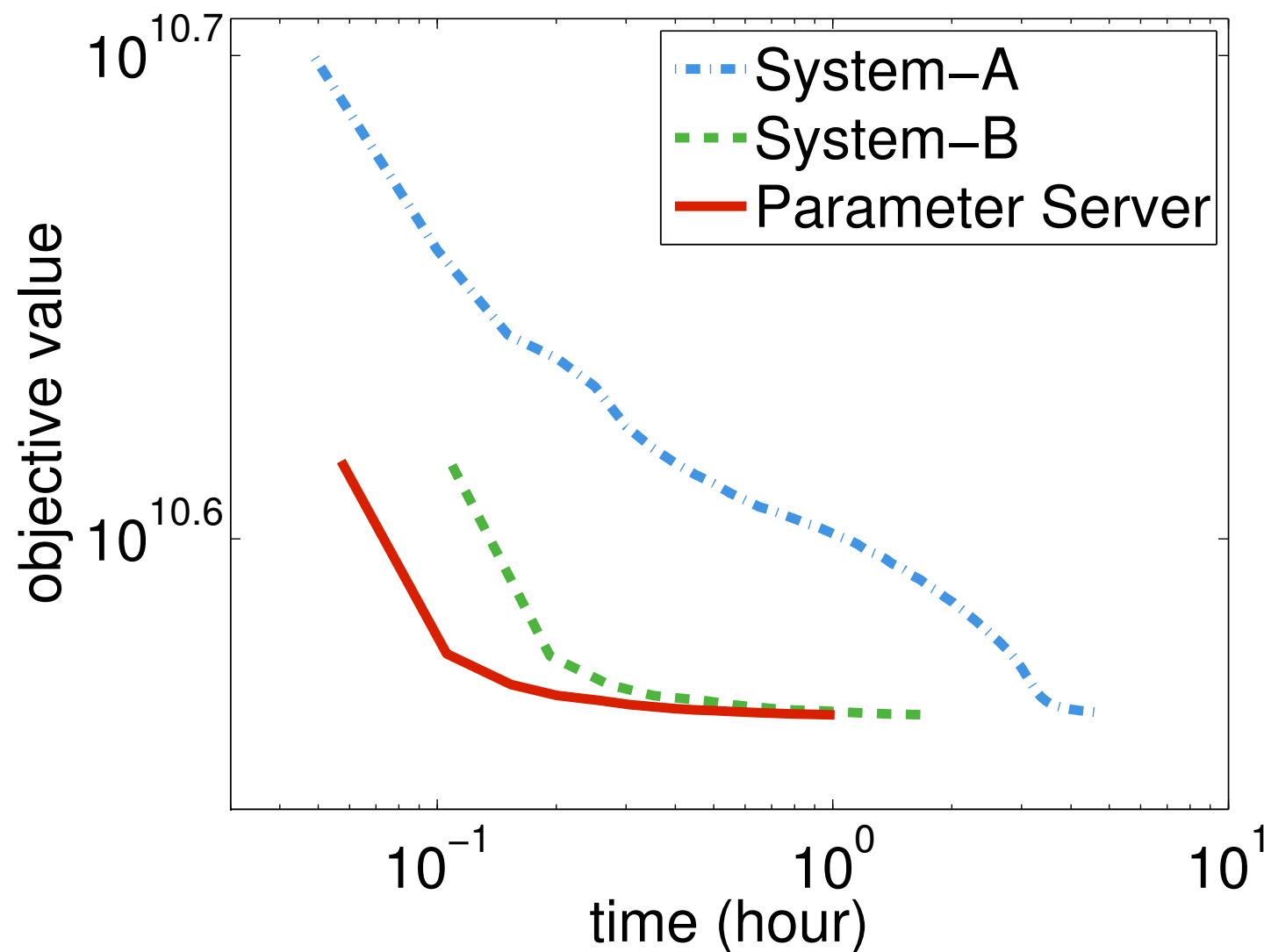
Guinea pig - logistic regression

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

- **Implementation on Parameter Server**

	Method	Consistency	LOC
System-A	L-BFGS	Sequential	10,000
System-B	Block PG	Sequential	30,000
Parameter Server	Block PG	Bounded Delay KKT Filter	300

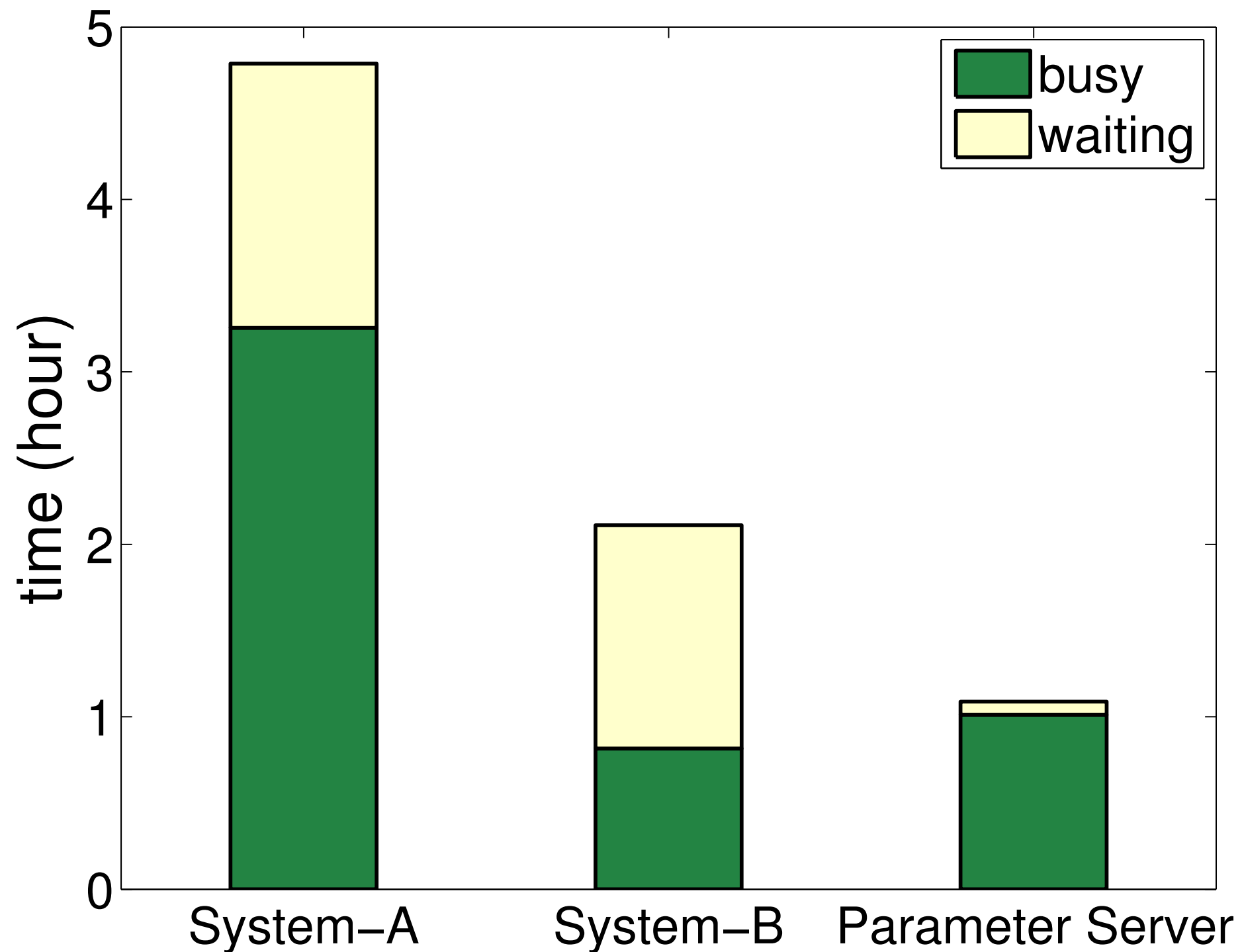
Convergence speed



**500TB CTR data
100B variables
1000 machines**

- **System A and B are production systems at a very large internet company ...**

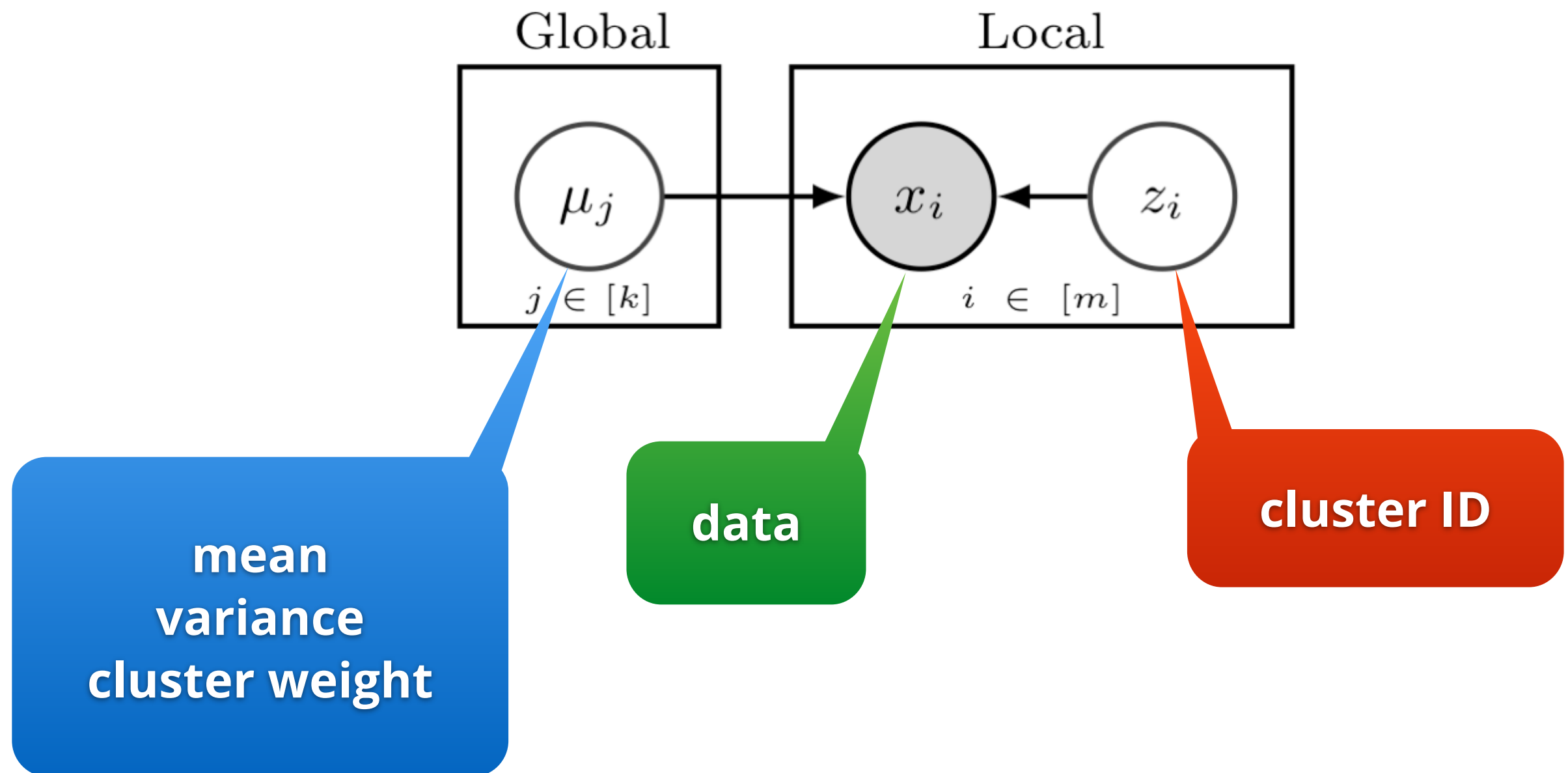
Scheduling Efficiency



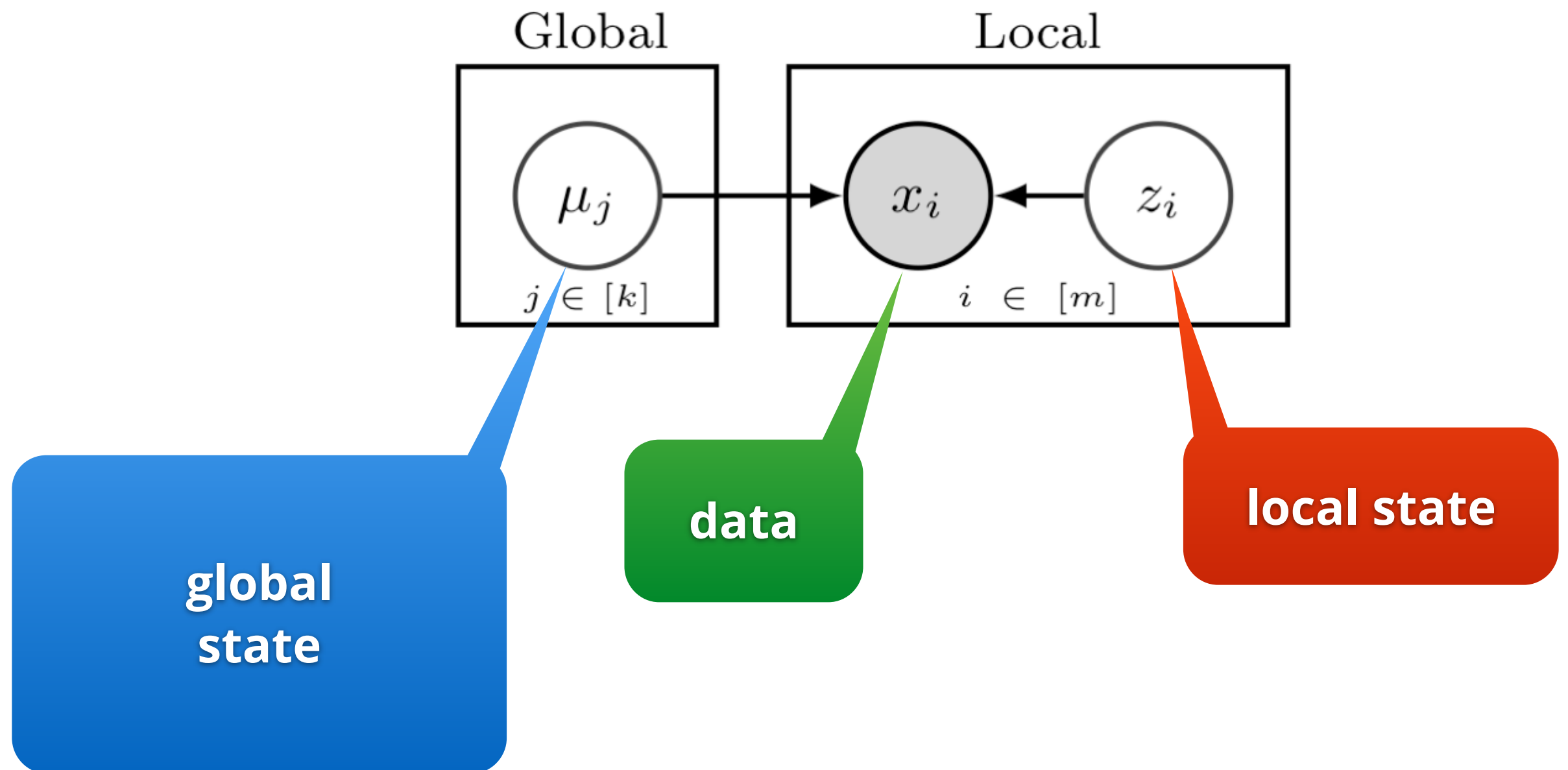


Scaling Latent Variable Models

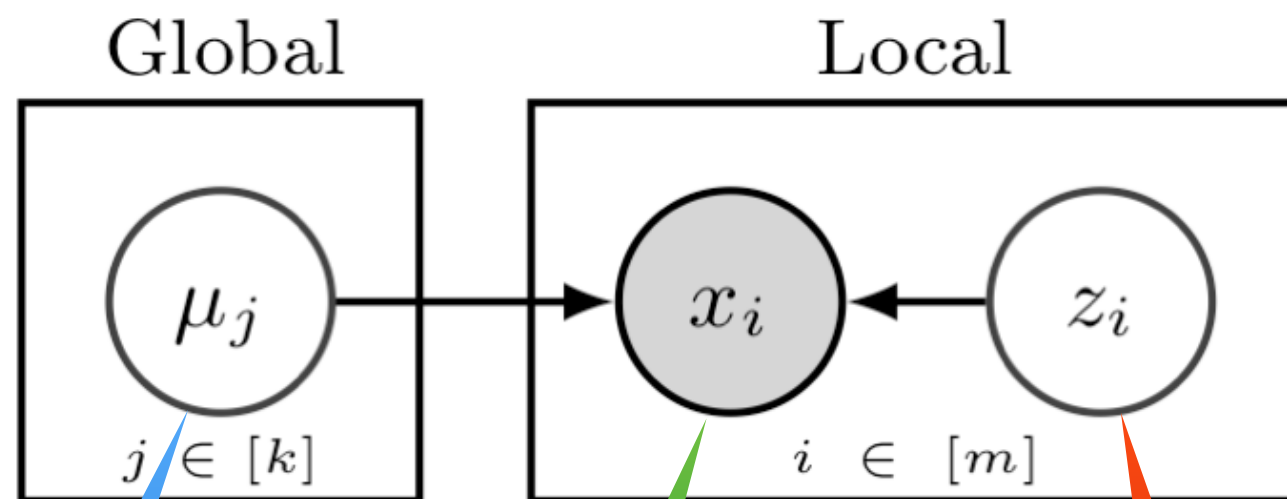
Clustering



Clustering



Clustering

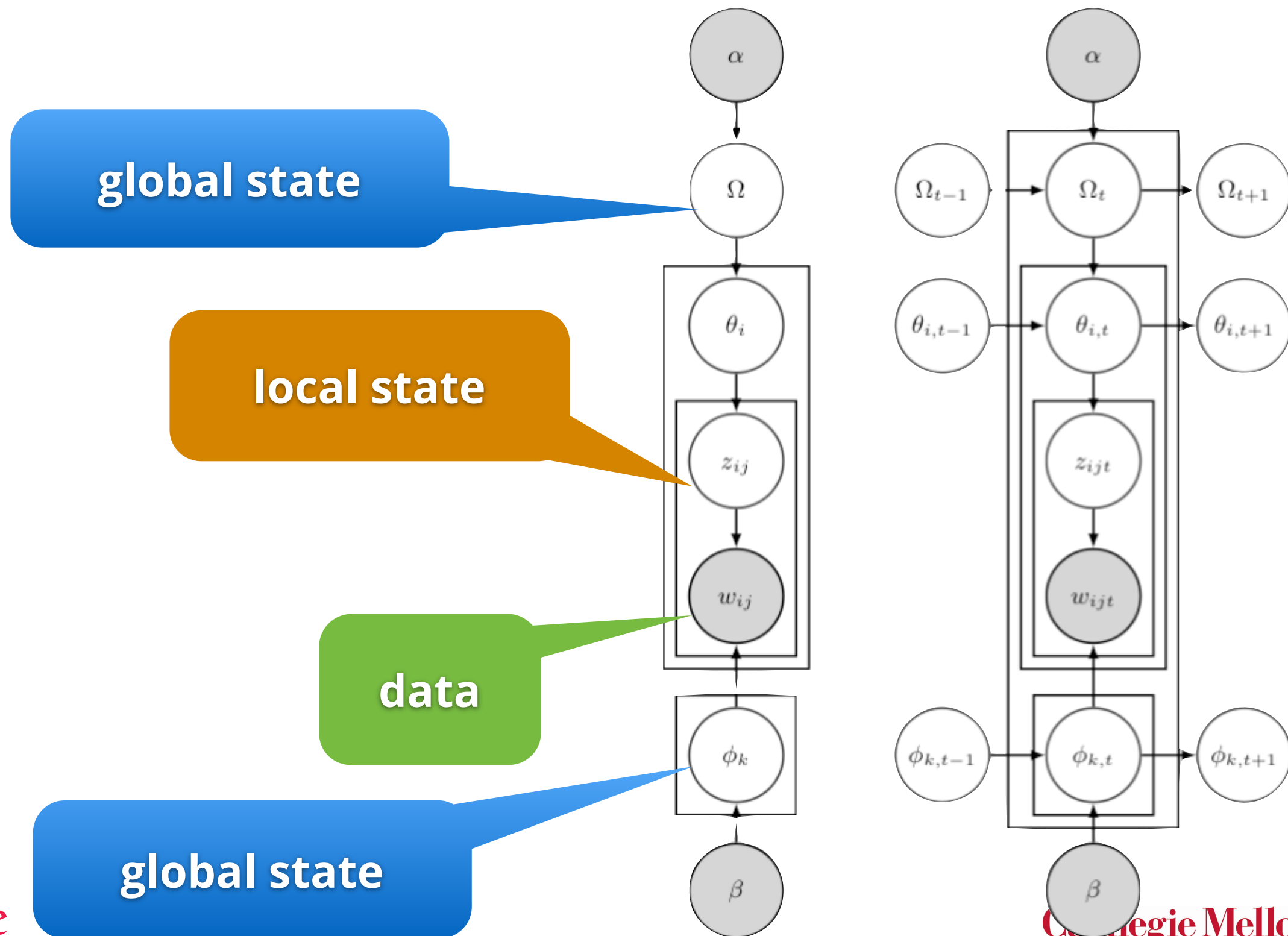


too big for
a single machine

huge

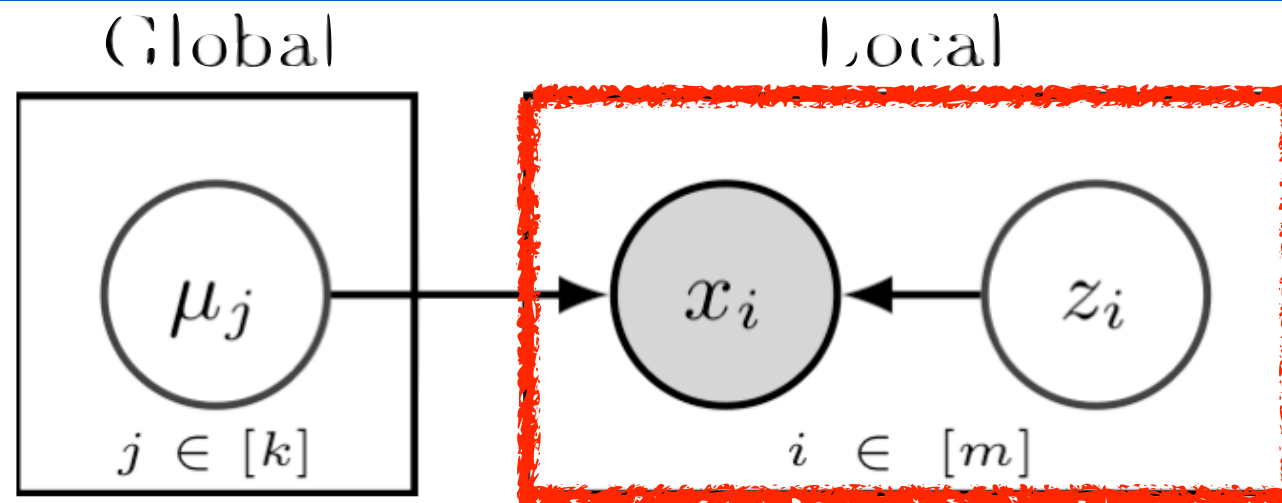
only local

Fancy models



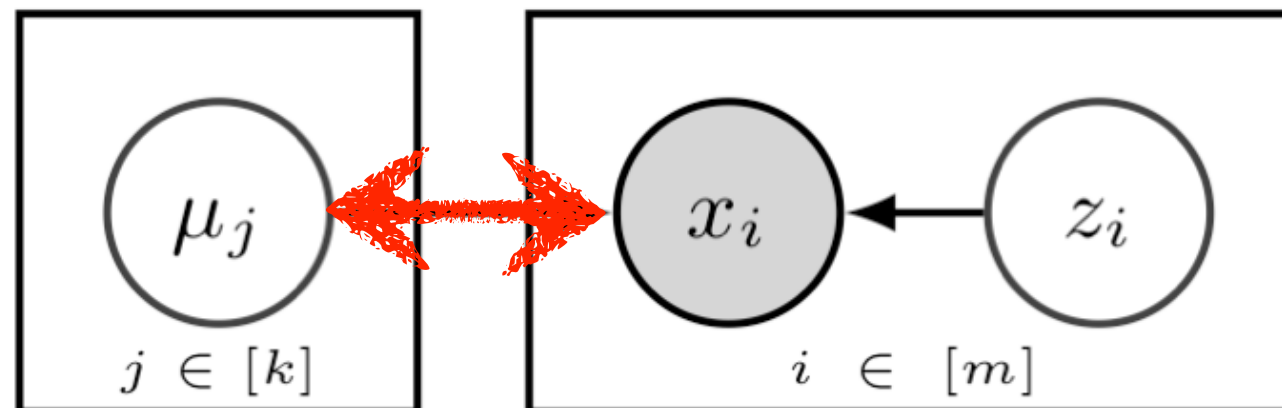
ParameterServer to the rescue

local state
is too large

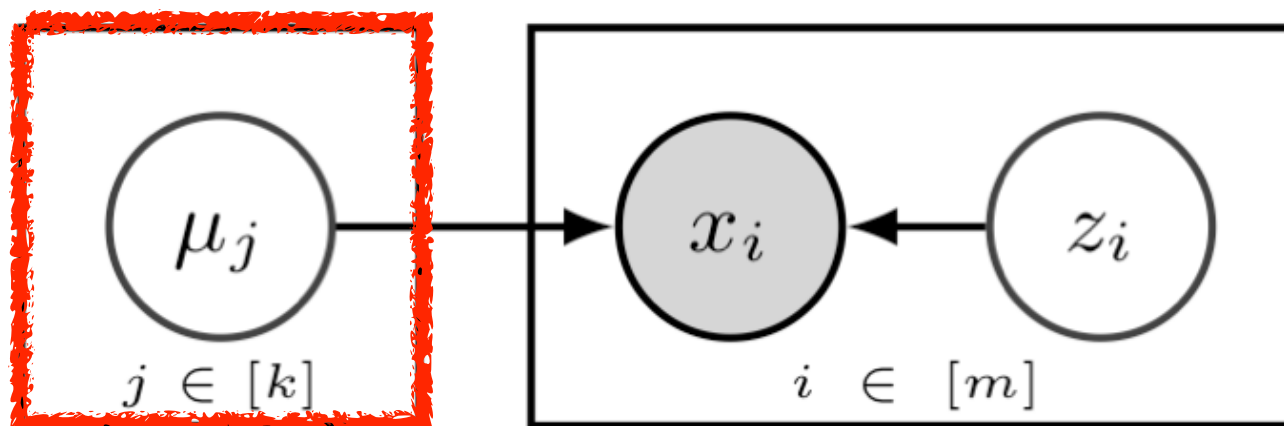


does not fit
into memory

global state
is too large



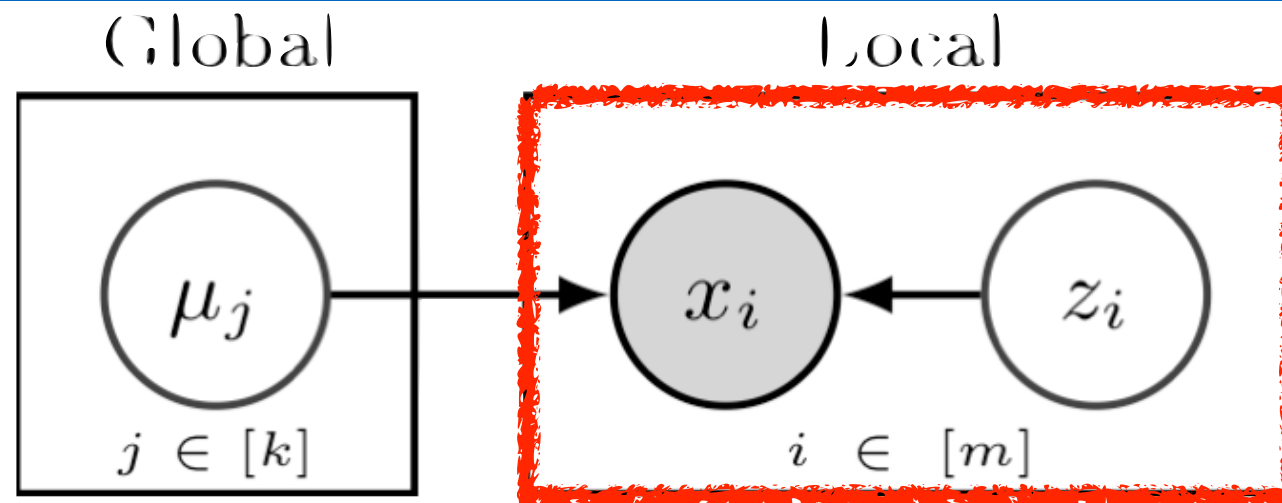
network load
& barriers



does not fit
into memory

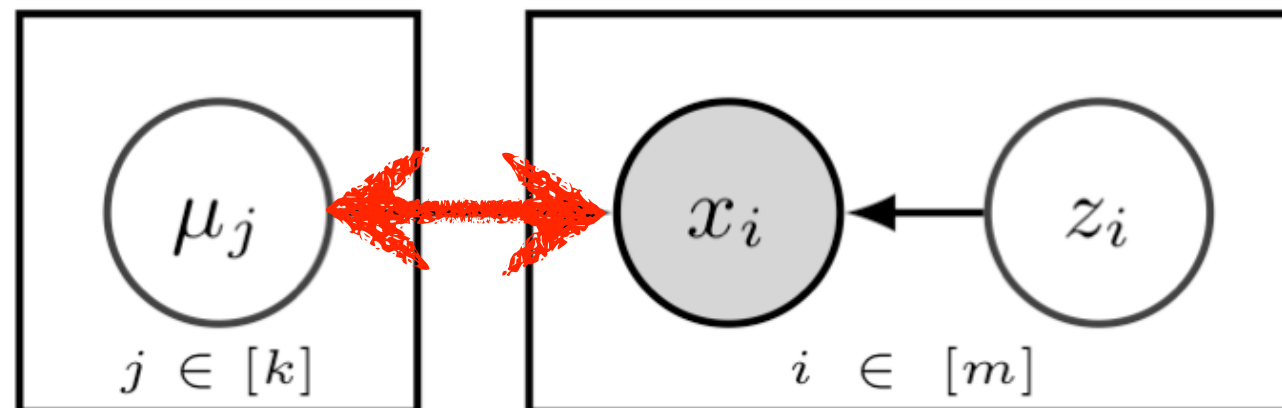
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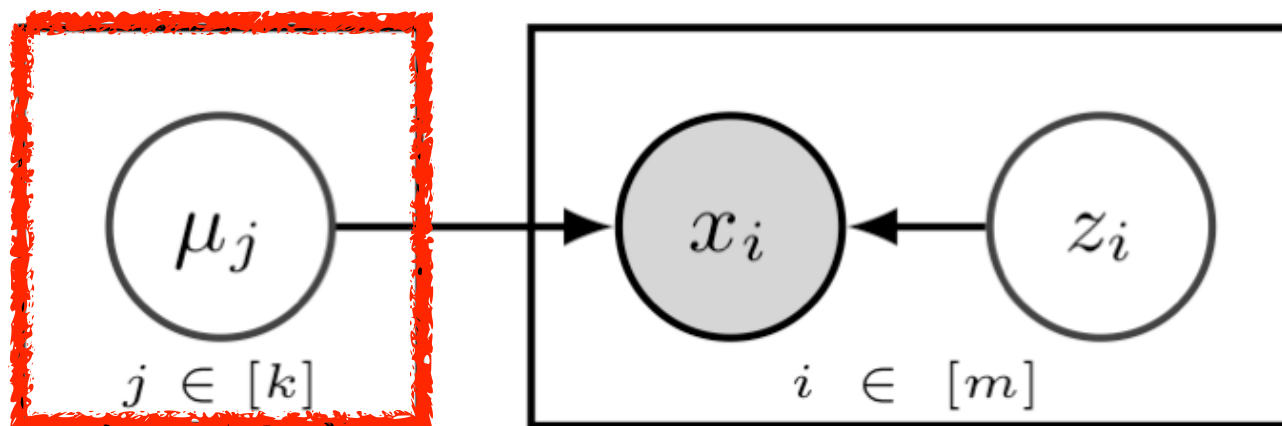


stream local
data from disk

global state
is too large



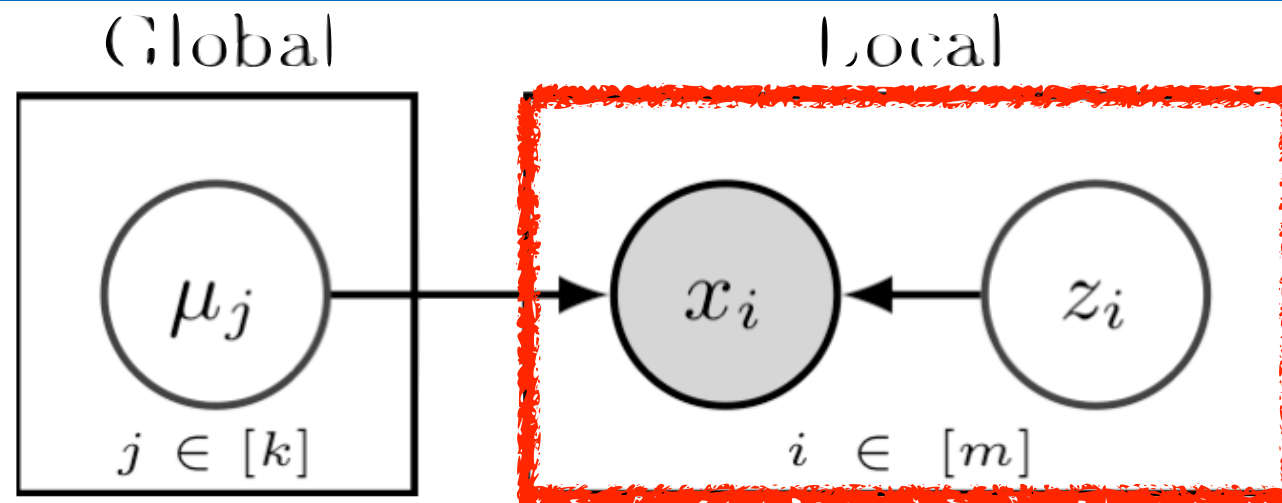
network load
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does not fit
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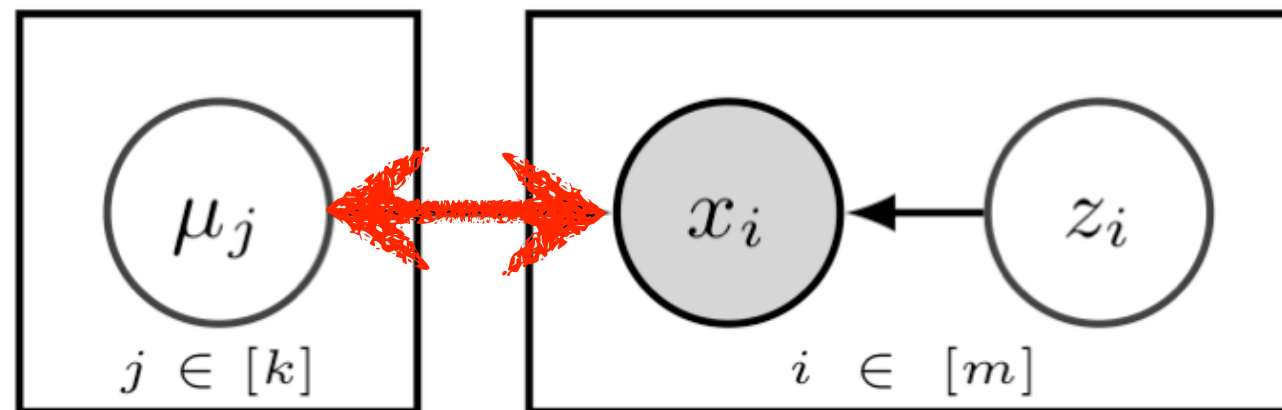
ParameterServer to the rescue

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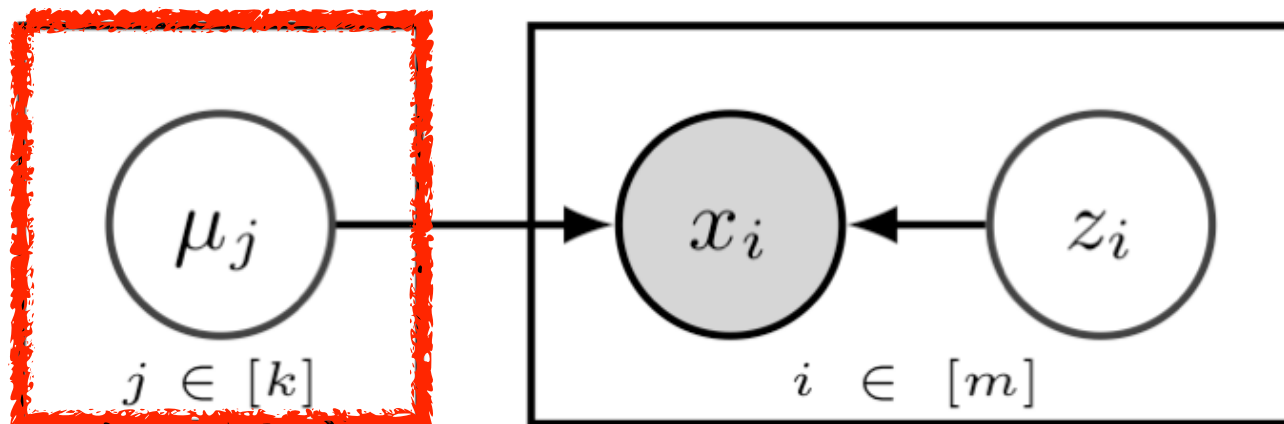


stream local
data from disk

global state
is too large



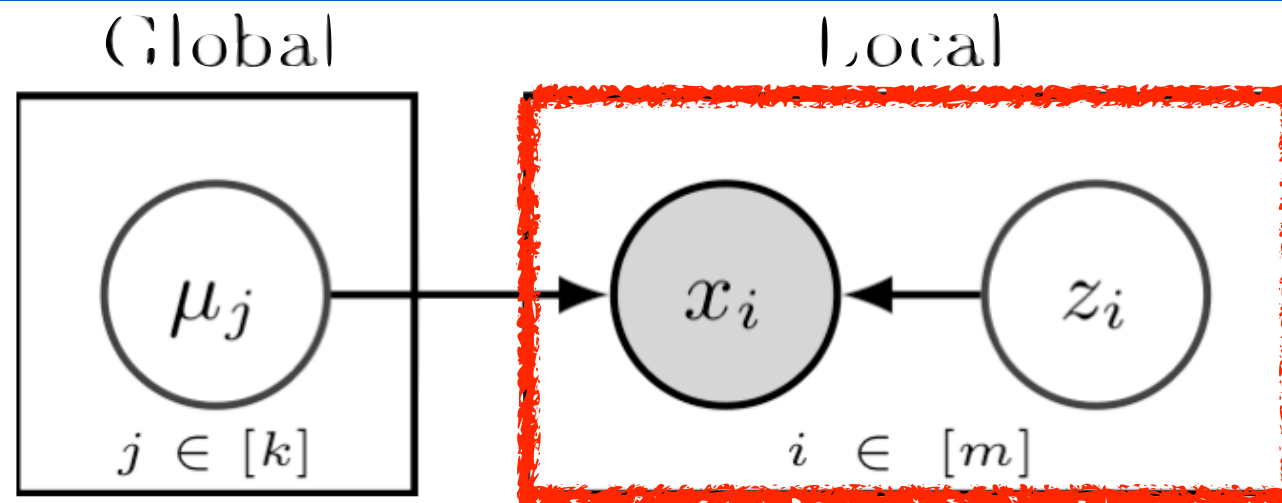
asynchronous
synchronization



does not fit
into memory

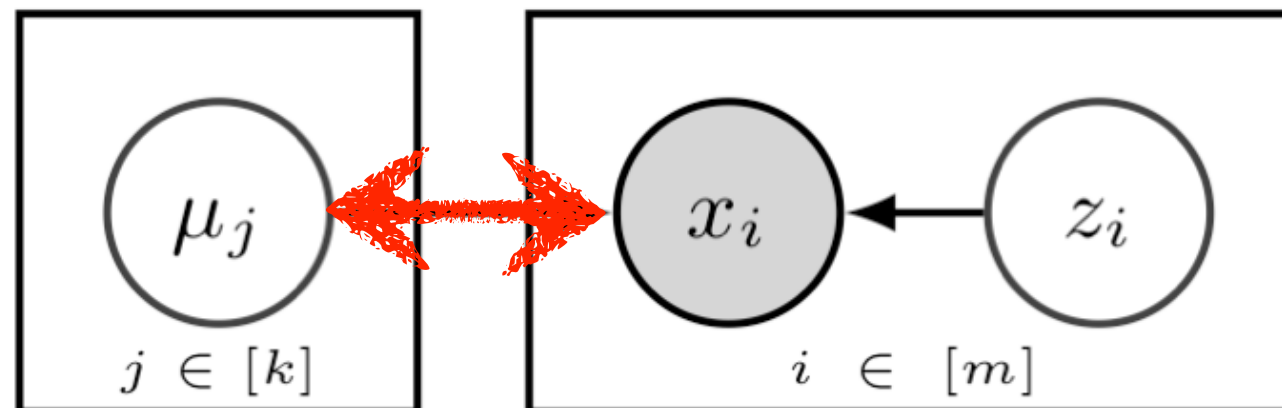
ParameterServer to the rescue

local state
is too large

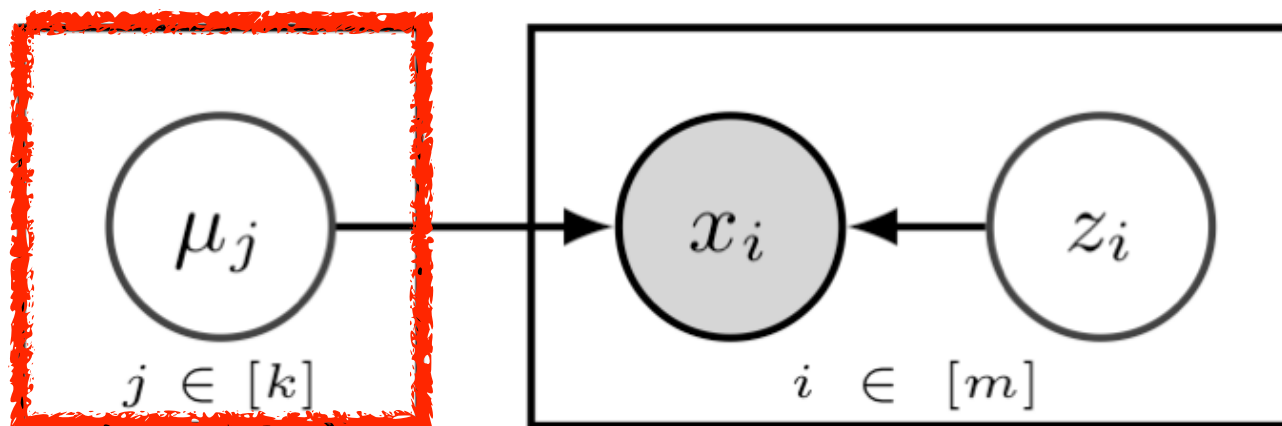


stream local
data from disk

global state
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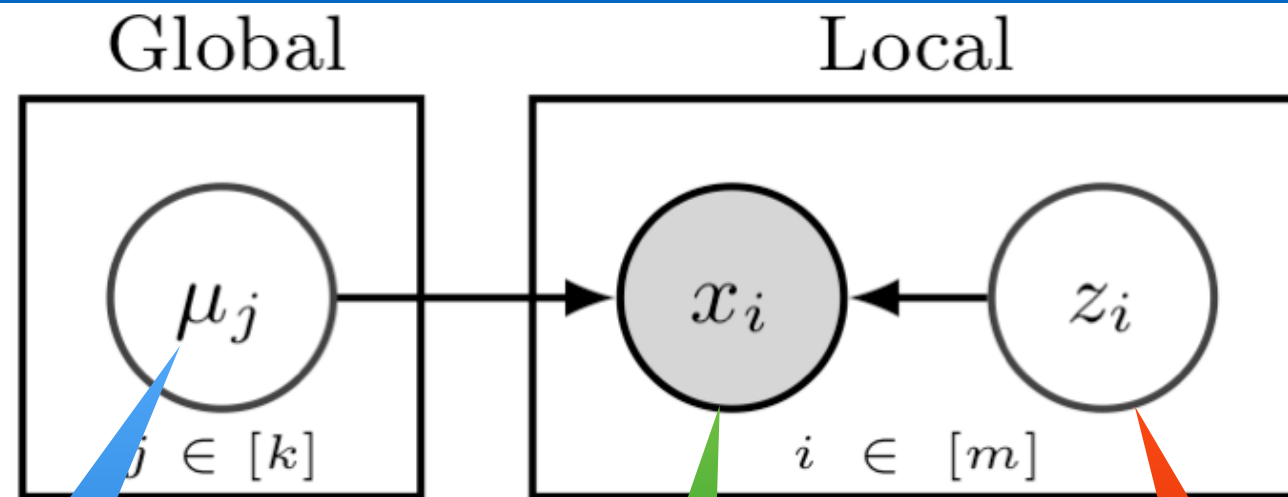


asynchronous
synchronization



partial view
shared between
threads

Synchronization Strategy



mean
variance
cluster weight

data

cluster ID

- Locally Gibbs Sample cluster ID

$$p(z_i | x_i, \text{rest}) \propto p(z_i | Z^{-i}) p(x_i | X^{-i}, Z^{-i}, z_i)$$

- Communicate changes in statistics of data to server (mean, variance, cluster size)

Mixture of Gaussians

- Multinomial with Dirichlet for cluster ID

$$p(Z|\theta) = \prod_{i=1}^m \theta_{z_i} \text{ and } p(\theta|\alpha) = \text{Dir}(\alpha)$$

- Integrating out multinomial yields collapsed

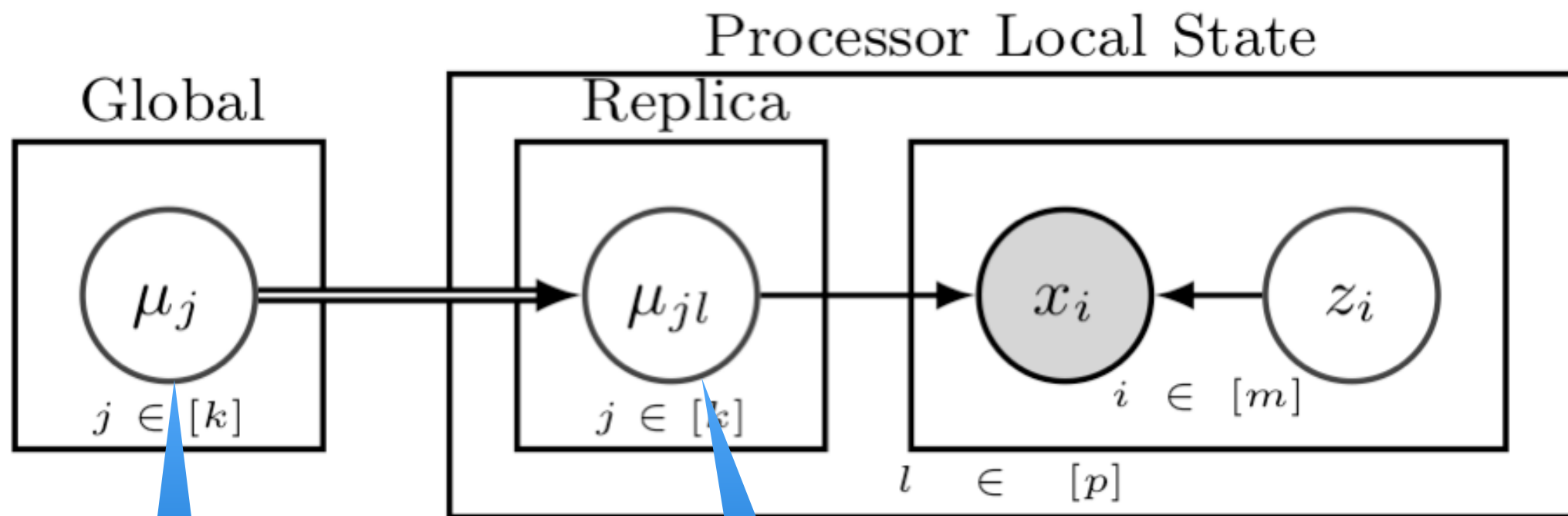
$$p(z_i = z | Z^{-i}) = \frac{n_z^{-i} + \alpha_z}{n - 1 + \sum_{z'} \alpha_{z'}}$$

- Gaussian with Gauss-Wishart for data

$$x_i | z_i \sim \mathcal{N}(\mu_{z_i}, \Sigma_{z_i}) \text{ and } (\mu_{z_i}, \Sigma_{z_i}) \sim \text{GaussWishart}(m_0, \mu_0, Q_0)$$

- Only need to sync $(n_z, l_z, Q_z) := \sum_{z_i=z} (1, x_i, x_i x_i^\top)$

Local and Global Variables

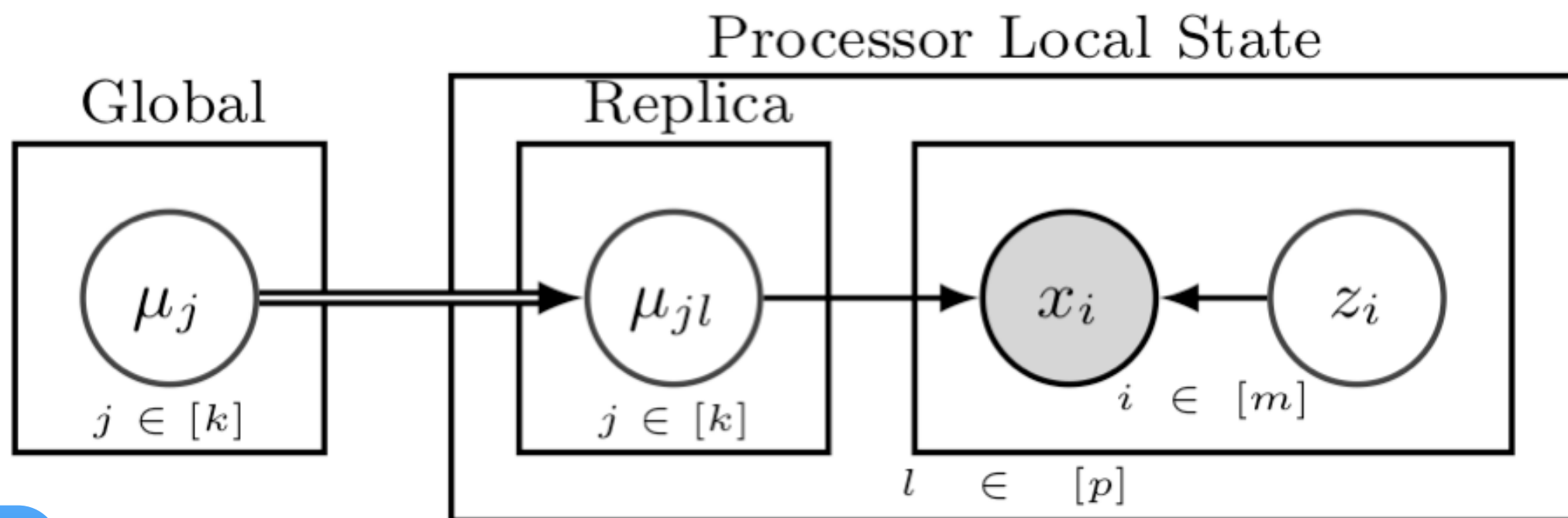


background sync

1 copy per machine

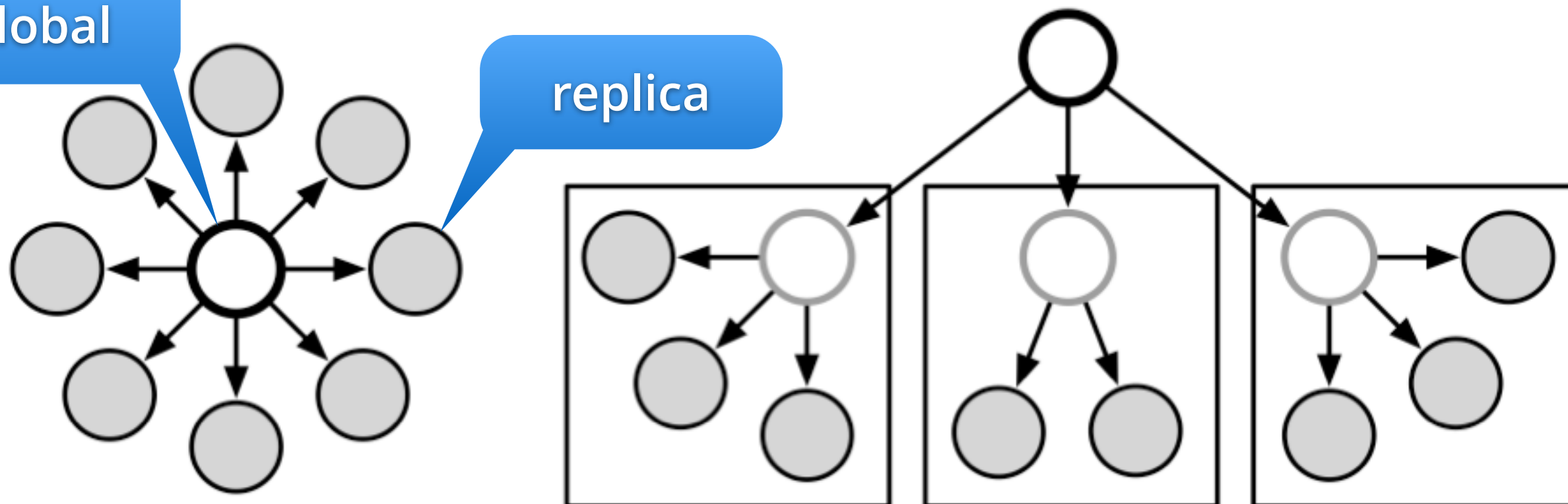
- No locks between machines to access z
- Synchronization mechanism for global μ needed
- In LDA this is the local copy of the (topic, word) counts

Local and Global Variables



global

replica

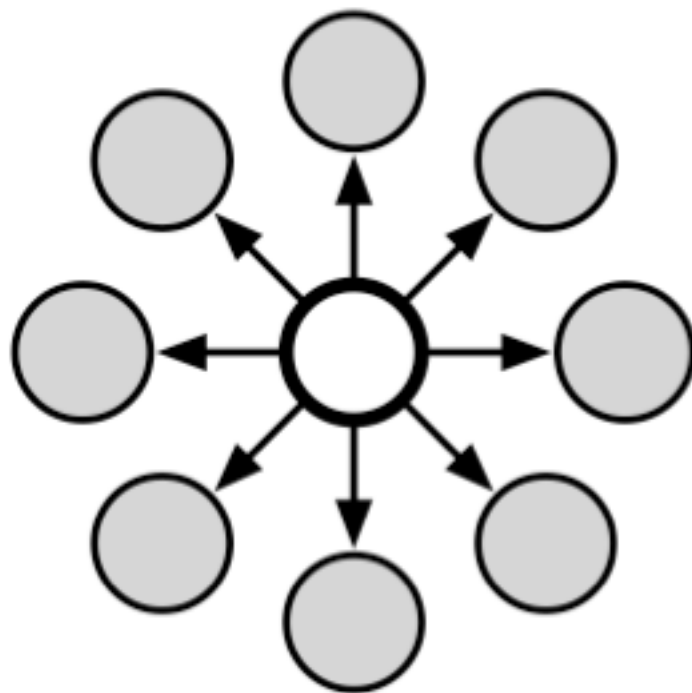


Message Passing

- Start with common state
- Child stores old and new state
- Parent keeps global state
- Transmit differences asynchronously
 - Inverse element for difference
 - Abelian group for commutativity
(sum, log-sum, cyclic group, exponential families)

local to global

$$\begin{aligned}\delta &\leftarrow x - x^{\text{old}} \\ x^{\text{old}} &\leftarrow x \\ x^{\text{global}} &\leftarrow x^{\text{global}} + \delta\end{aligned}$$



global to local

$$\begin{aligned}x &\leftarrow x + (x^{\text{global}} - x^{\text{old}}) \\ x^{\text{old}} &\leftarrow x^{\text{global}}\end{aligned}$$



Models

Grouping objects

Grouping objects

The collage features three distinct web interfaces:

- Singapore Airlines:** The top section shows the airline's header with the logo, navigation links (Help, Site Map, Contact Us, Singapore, Change Location), a search bar, and a menu (The Experience, Flights & Fares, Before You Fly, Loyalty Programmes, Promotions).
- National University of Singapore (NUS):** The middle section displays the NUS logo and a comprehensive navigation bar including myEMAIL, IVLE, LIBRARY, MAPS, CALENDAR, SITEMAP, CONTACT, and e-CARDS. Below this is a search bar and a secondary navigation menu (ABOUT NUS, GLOBAL, ADMISSIONS, EDUCATION, RESEARCH, ENTERPRISE, CAMPUS LIFE, GIVING, CAREERS@NUS).
- Chijmes:** The bottom section shows a website for Chijmes, featuring a large image of a historic building, the text "Discover a century of resplendent living history behind the cloistered walls.", and logos for Suntec, ARA, and APC.

A blue speech bubble with the word "Singapore" is positioned over the NUS website, indicating the common theme of the grouped objects.

Grouping objects

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Services & information

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Shop for flights

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Travel Options by United

Flights

Check-in

Flight status

BOOK FLIGHT

REDEEM MILES

From (Find airport)

To (Find airport)

☐ Search nearby airports

☐ Search nearby airports

☒ Roundtrip

☐ One-way

> Multicity

Departing

Anytime

Returning

Anytime

Search by

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> E-Fares: Save on weekend getaways

> Opt to send your bags ahead

> Wireless check-in, paperless boarding

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United-Continental merger

Learn more about the merger

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☒ My Mileage Plus

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> Updates to baggage & standby policies

> View travel requirements and regulations

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A STAR ALLIANCE MEMBER

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e-CARDS

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in NUS Websites

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GIVING

CAREERS@NUS

Search ANU...

WEB

CONTACTS

MAP

GO

The Australian National University

CURRENT STUDENTS

RESEARCH & EDUCATION

ABOUT ANU

STAFF

ts the spectacular natural

er the Black Saturday

re typical natural


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Owned by:

Managed by:

Property Manager:







Forests renew after Black Saturday fires

School of Music at Floriade

Undergraduate studies

Higher Degree Research

Grouping objects

The screenshot shows the United Airlines website interface. At the top, there's a navigation bar with 'UNITED' logo and links like 'My profile', 'Worldwide sites', and 'Customer service'. Below this is a search bar and a 'Search site' button. The main content area is divided into several sections: 'Flights' with 'Check-in' and 'Flight status' tabs; a 'BOOK FLIGHT' section with 'From' and 'To' fields and a 'Search' button; a 'REDEEM MILES' section; a 'Log in' section with 'Mileage Plus # or email address' and 'Password' fields; a 'Start with' section with radio buttons for 'My Mileage Plus' and 'My reservations'; a 'Travel information' section with links to 'Updates to baggage & standby policies' and 'View travel requirements and regulations'; a 'United news and deals' section with a large orange percentage sign graphic and a 'Learn more' link; a 'United-Continental merger' section with a 'Learn more about the merger' link; and a 'Need Help?' section with links to 'Book A Flight Guide', 'SIA Holidays', and 'Hotel Bookings'. The bottom of the page features a 'A STAR ALLIANCE MEMBER' logo and a 'Book Now' button.

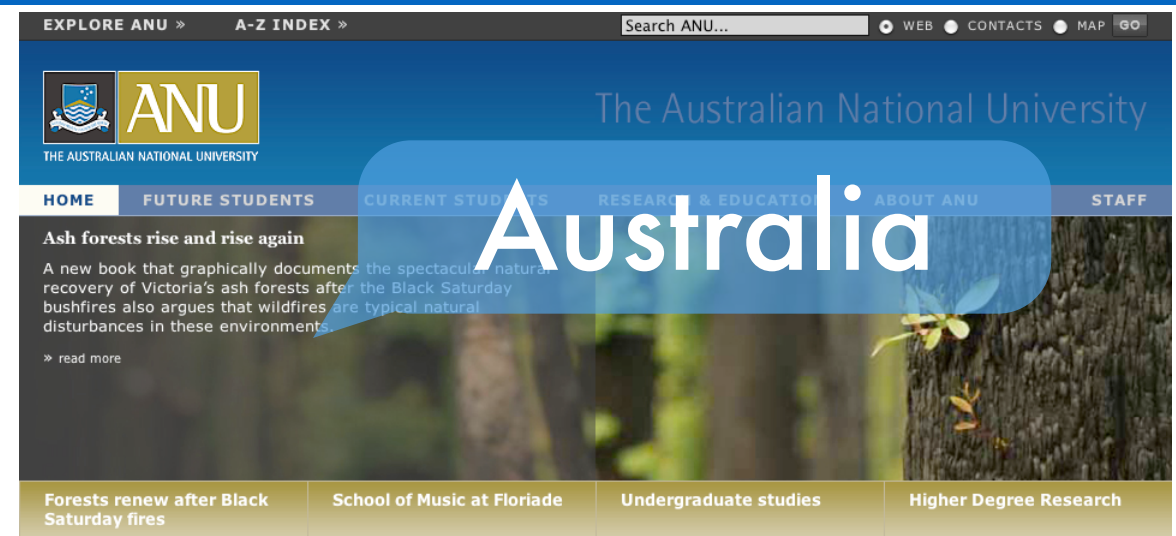
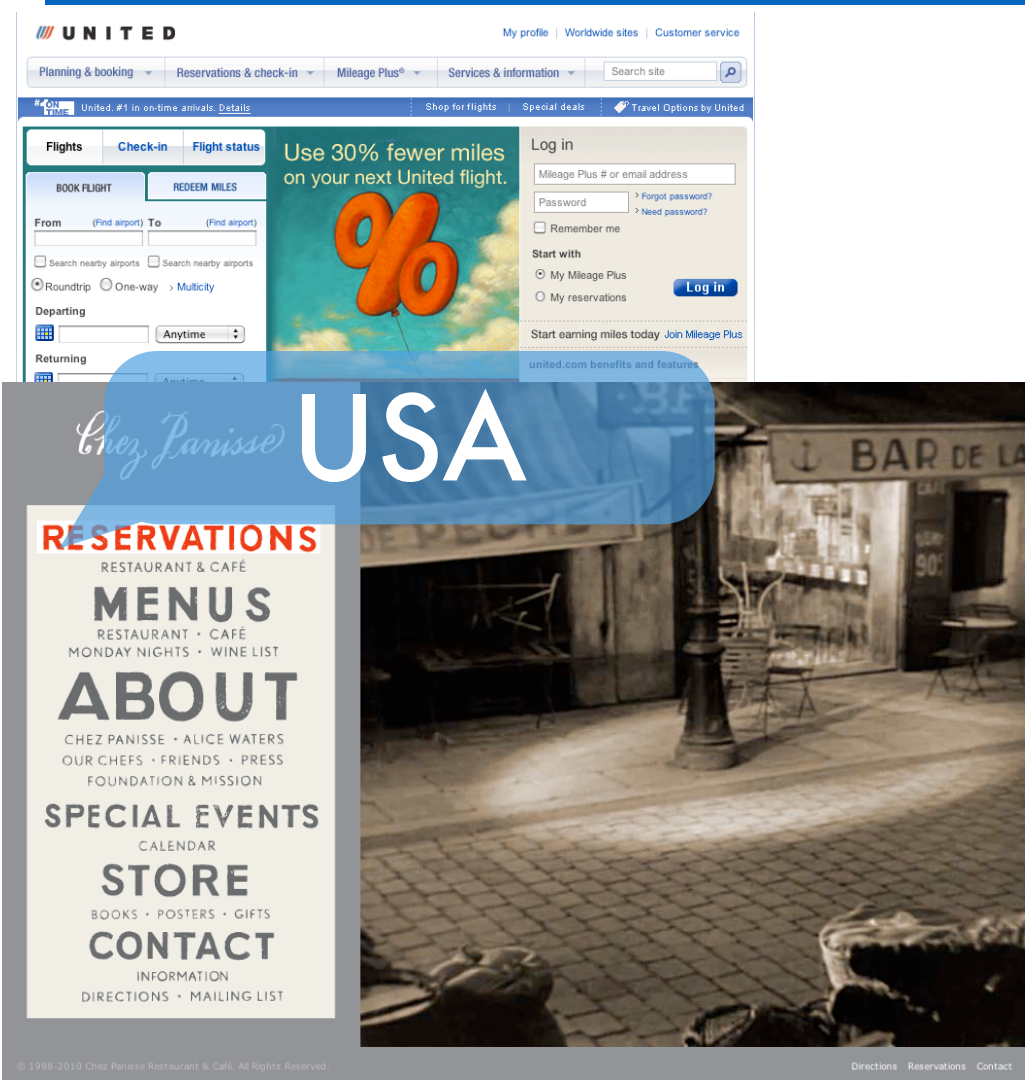
The screenshot shows the Australian National University (ANU) website. At the top, there's a navigation bar with 'EXPLORE ANU' and 'A-Z INDEX' links, a search bar, and links for 'WEB', 'CONTACTS', and 'MAP'. Below this is the ANU logo and the text 'The Australian National University'. The main content area is divided into several sections: a 'HOME' section with a large image of a forest and a headline 'Ash forests rise and rise again'; a 'FUTURE STUDENTS' section with a headline 'A new book that graphically documents the spectacular natural recovery of Victoria's ash forests after the Black Saturday bushfires also argues that wildfires are typical natural disturbances in these environments'; a 'CURRENT STUDENTS' section with a headline 'Forests renew after Black Saturday fires'; a 'RESEARCH & EDUCATION' section with a headline 'School of Music at Floriade'; an 'ABOUT ANU' section with a headline 'Undergraduate studies'; and a 'STAFF' section with a headline 'Higher Degree Research'. The bottom of the page features a navigation bar with links for 'PROSPECTIVE STUDENTS', 'CURRENT STUDENTS', 'STAFF', 'ALUMNI', and 'VISITORS'.

The screenshot shows the Chez Panisse Restaurant & Café website. At the top, there's a navigation bar with 'Reservations', 'Menus', 'About', 'Special Events', 'Store', and 'Contact' links. Below this is a large image of the restaurant's exterior at night. The main content area is divided into several sections: a 'RESERVATIONS' section with a 'Book Now' button; a 'MENUS' section with a 'Show Schedule' button; an 'ABOUT' section with a 'Learn more' link; a 'SPECIAL EVENTS' section with a 'Calendar' link; a 'STORE' section with a 'Buy Now' button; and a 'CONTACT' section with a 'Contact Us' button. The bottom of the page features a navigation bar with links for 'Directions', 'Reservations', and 'Contact'.

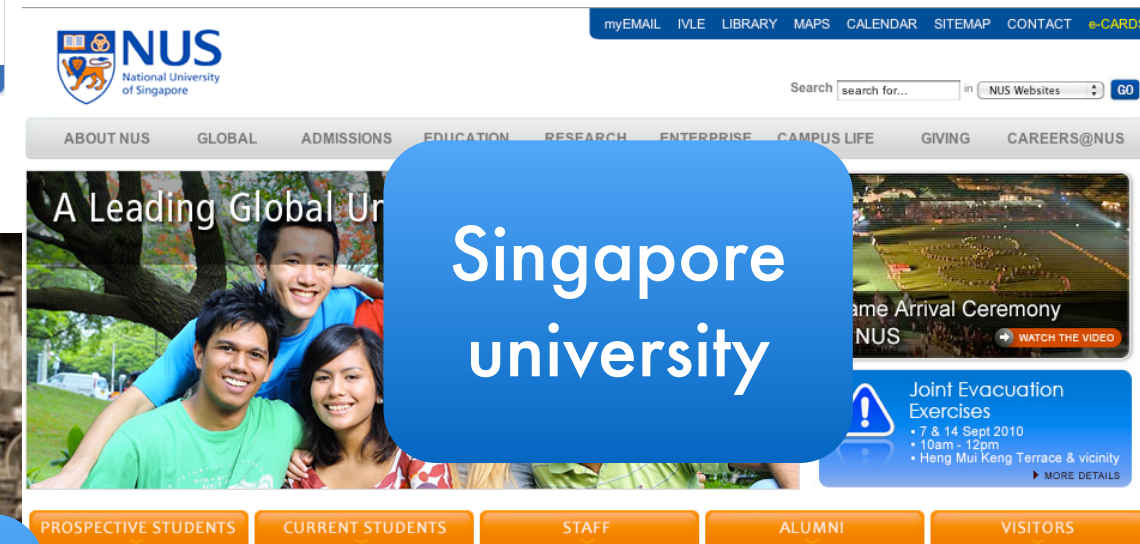
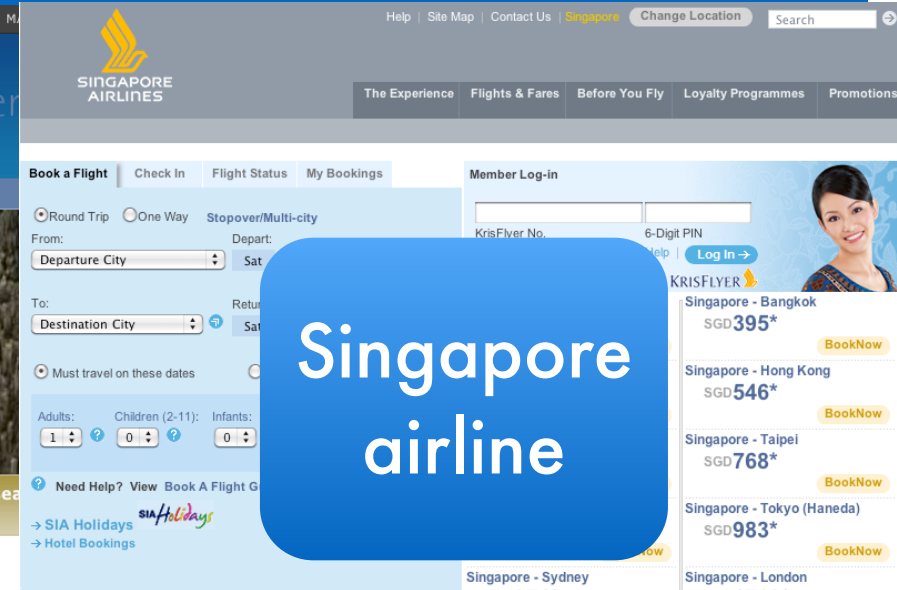
Grouping objects



Grouping objects

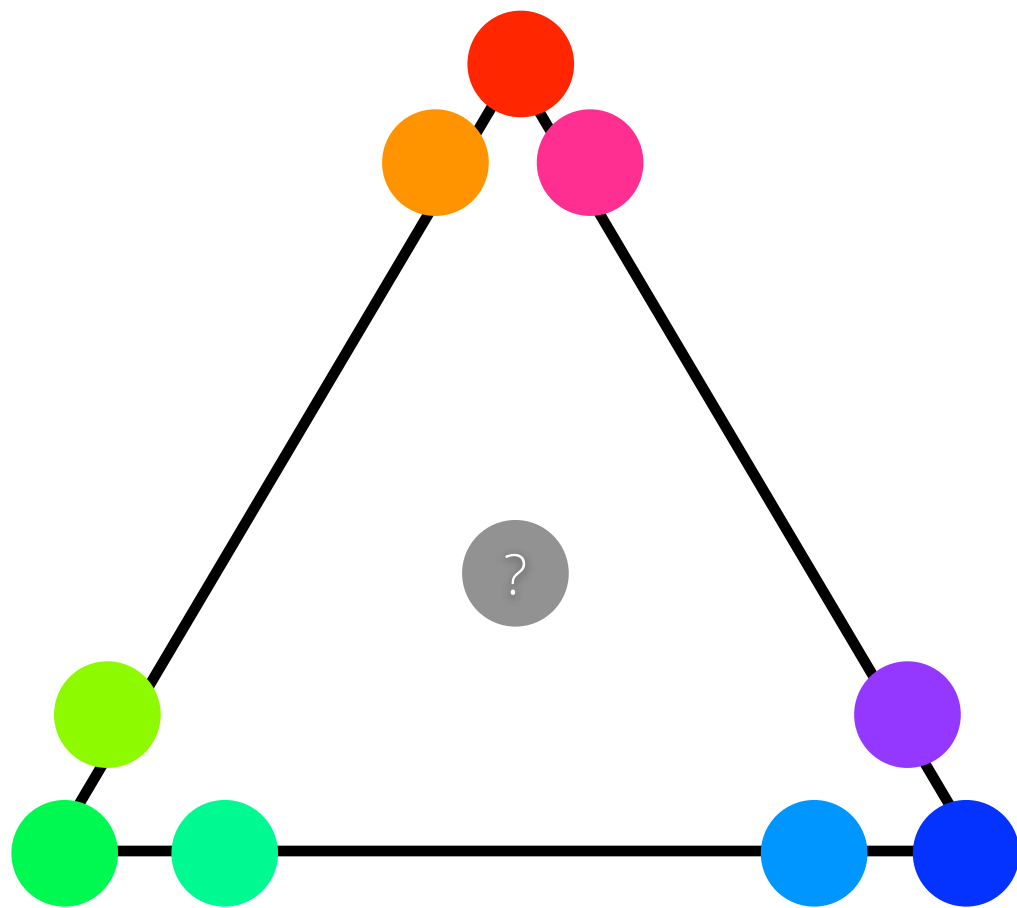


Topic Models



Clustering & Topic Models

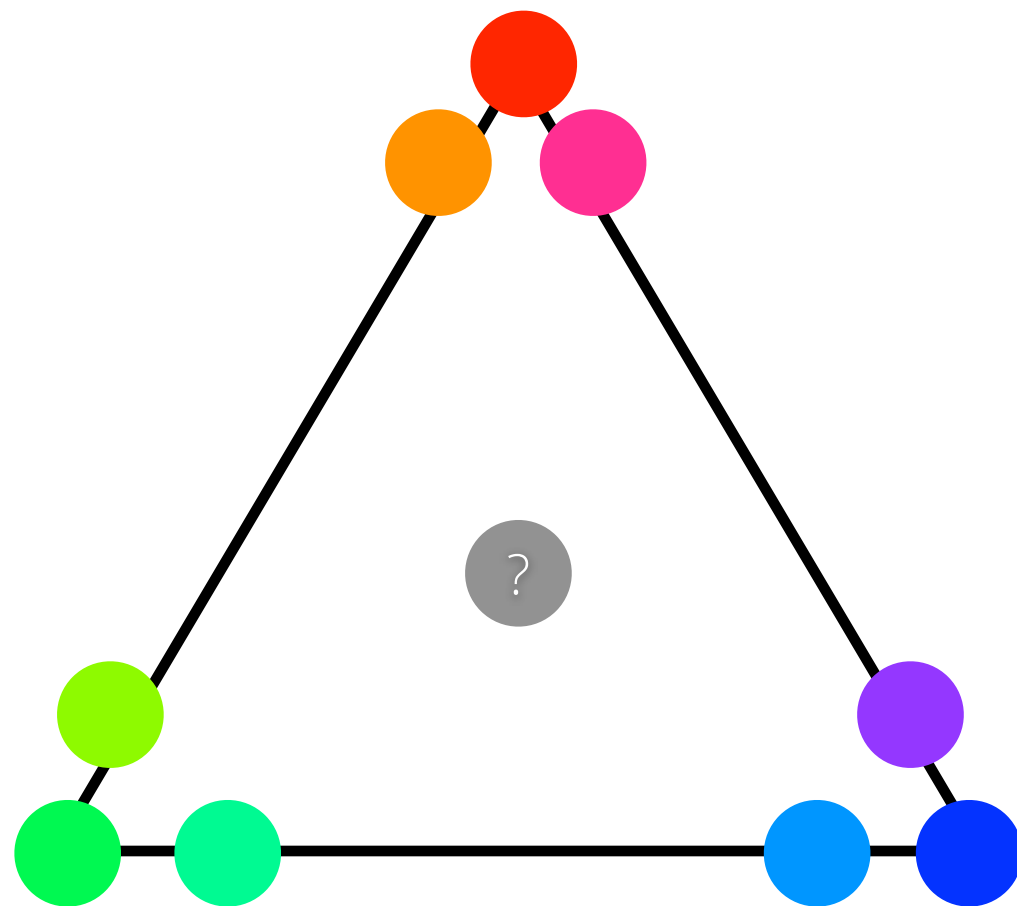
Clustering



group objects
by prototypes

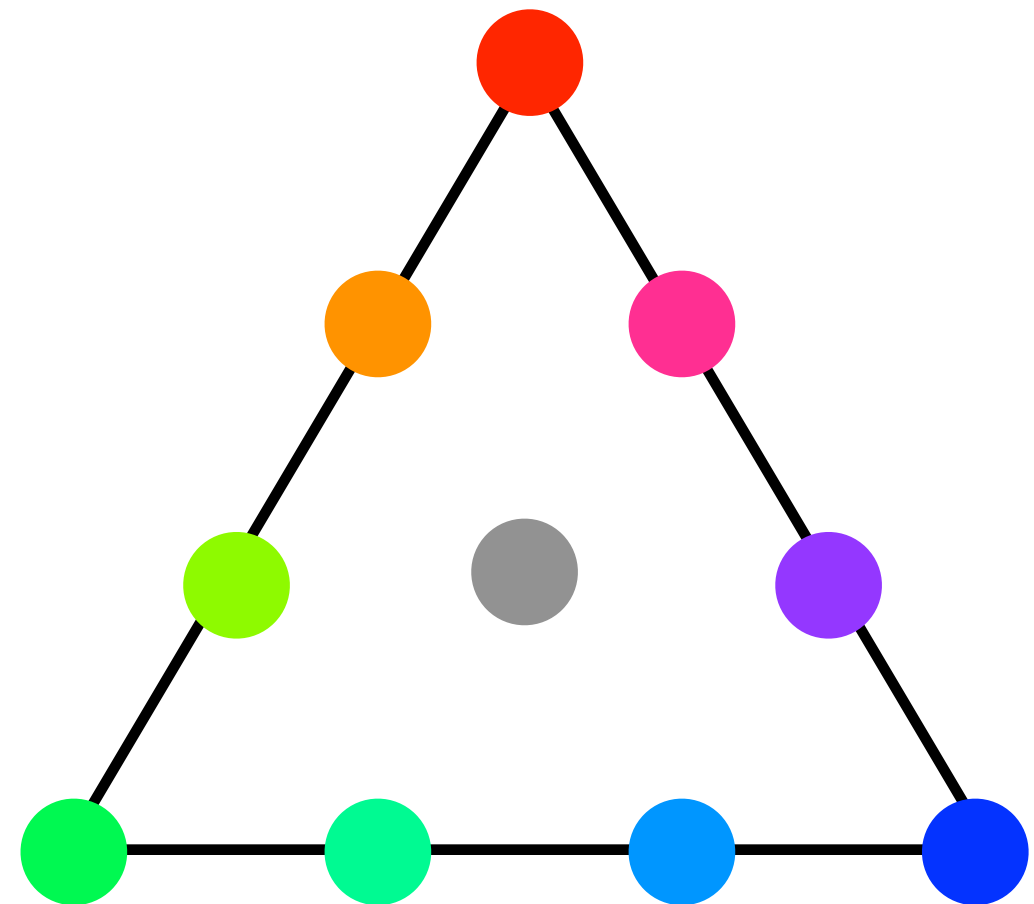
Clustering & Topic Models

Clustering



group objects
by prototypes

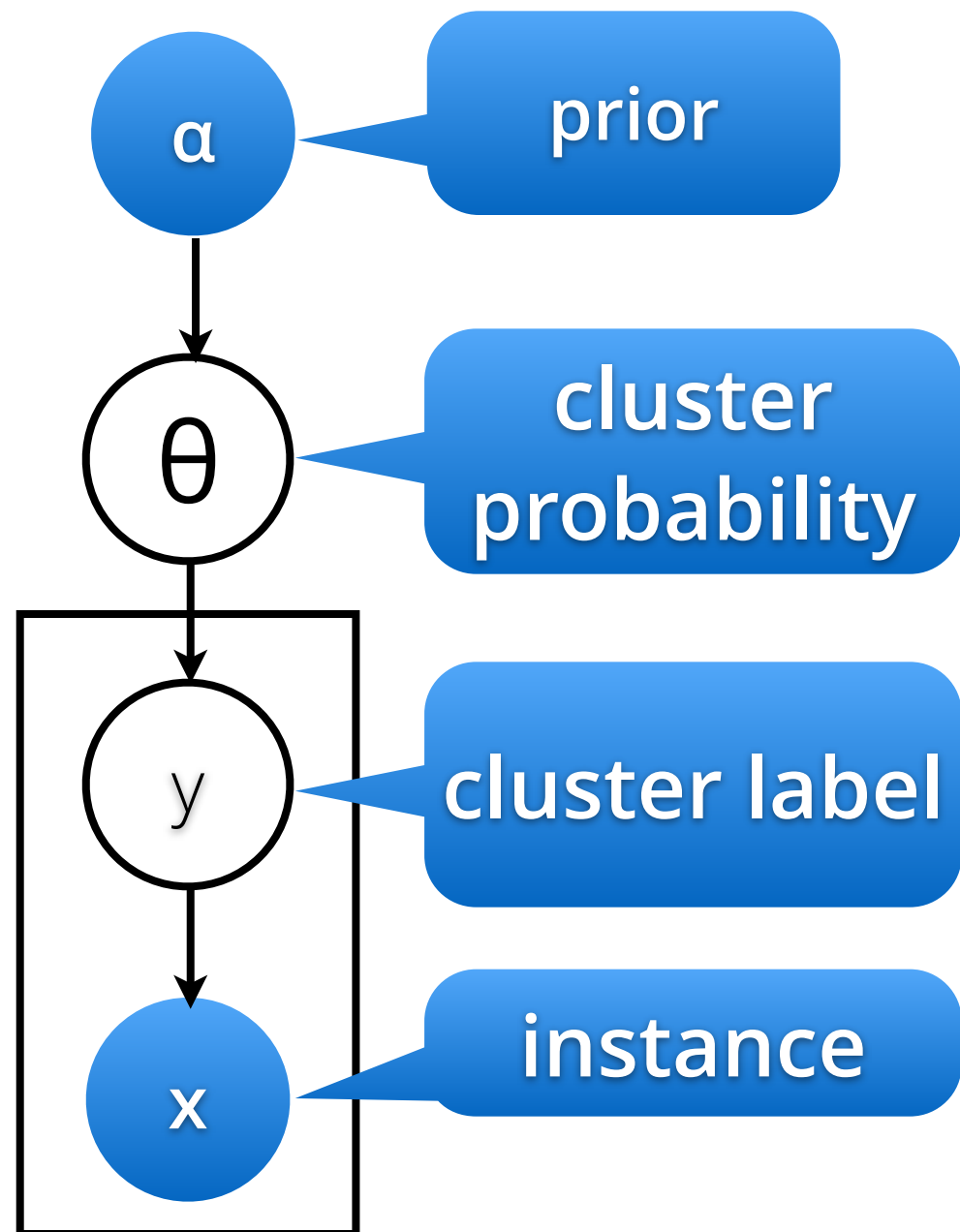
Topics



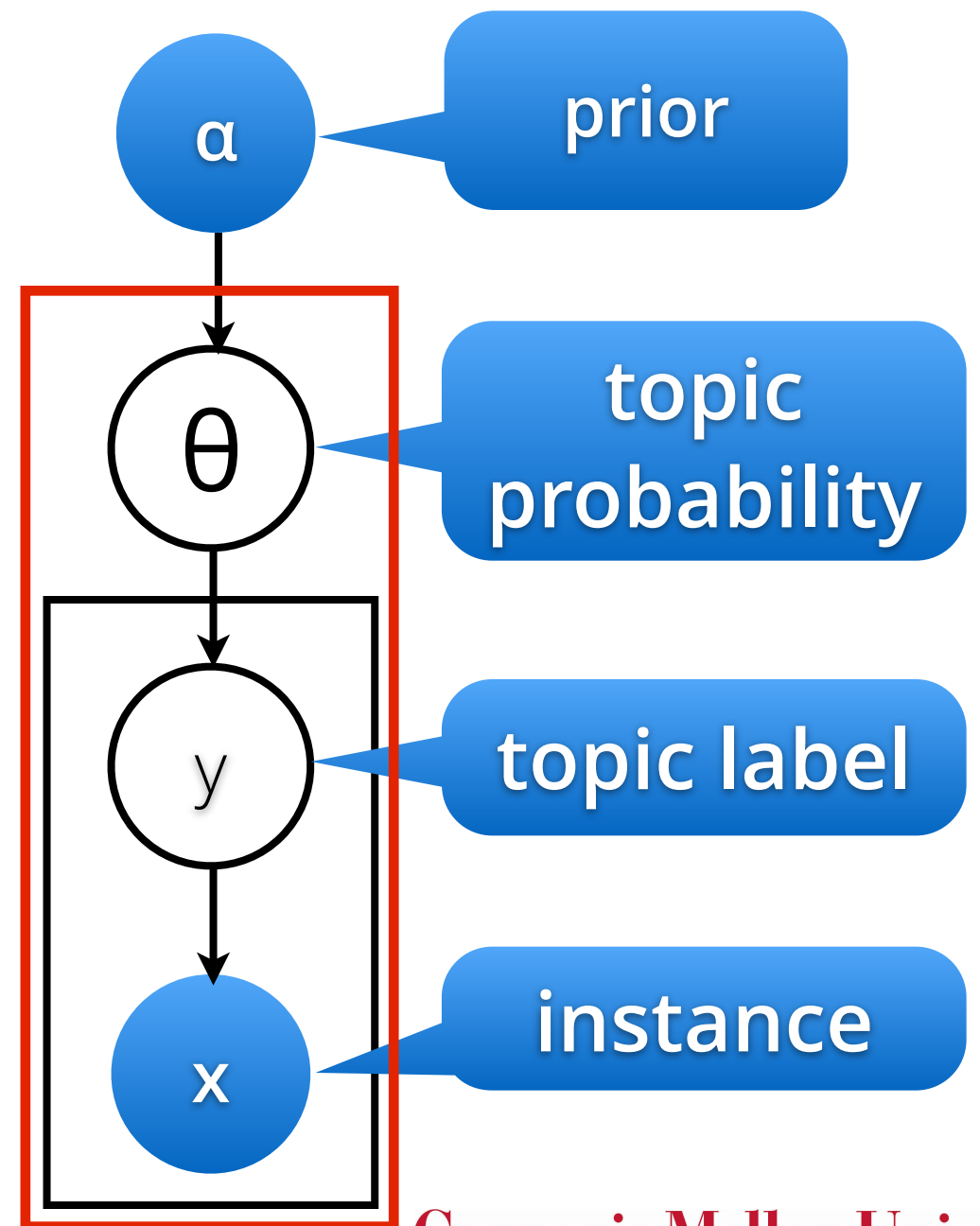
decompose objects
into prototypes

Clustering & Topic Models

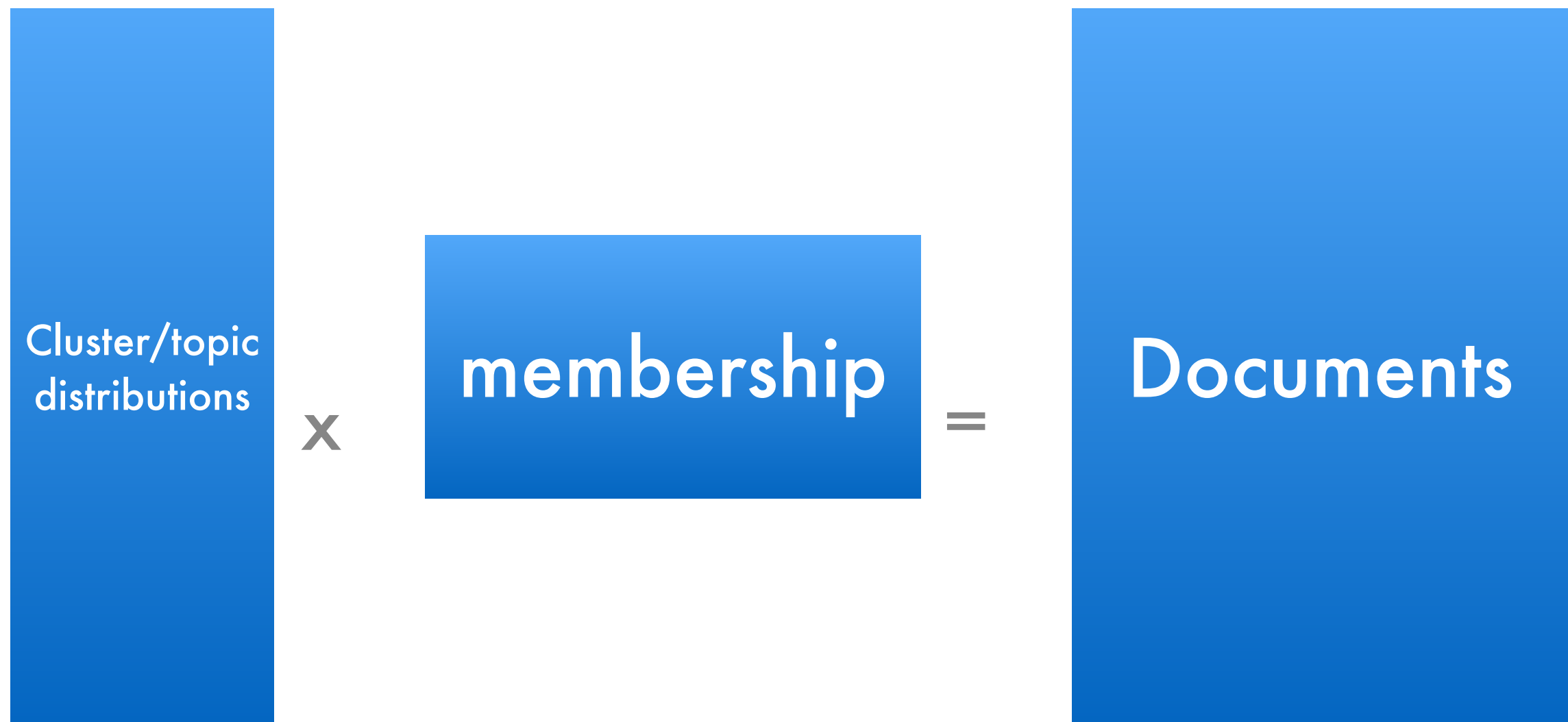
clustering



Latent Dirichlet Allocation



Clustering & Topic Models



clustering: (0, 1) matrix
topic model: stochastic matrix
LSI: arbitrary matrices

Topics in text

The William Randolph Hearst Foundation will give \$1.25 million to Lincoln Center, Metropolitan Opera Co., New York Philharmonic and Juilliard School. “Our board felt that we had a real opportunity to make a mark on the future of the performing arts with these grants an act every bit as important as our traditional areas of support in health, medical research, education and the social services,” Hearst Foundation President Randolph A. Hearst said Monday in announcing the grants. Lincoln Center’s share will be \$200,000 for its new building, which will house young artists and provide new public facilities. The Metropolitan Opera Co. and New York Philharmonic will receive \$400,000 each. The Juilliard School, where music and the performing arts are taught, will get \$250,000. The Hearst Foundation, a leading supporter of the Lincoln Center Consolidated Corporate Fund, will make its usual annual \$100,000 donation, too.

Latent Dirichlet Allocation; Blei, Ng, Jordan, JMLR 2003

Gibbs Sampling

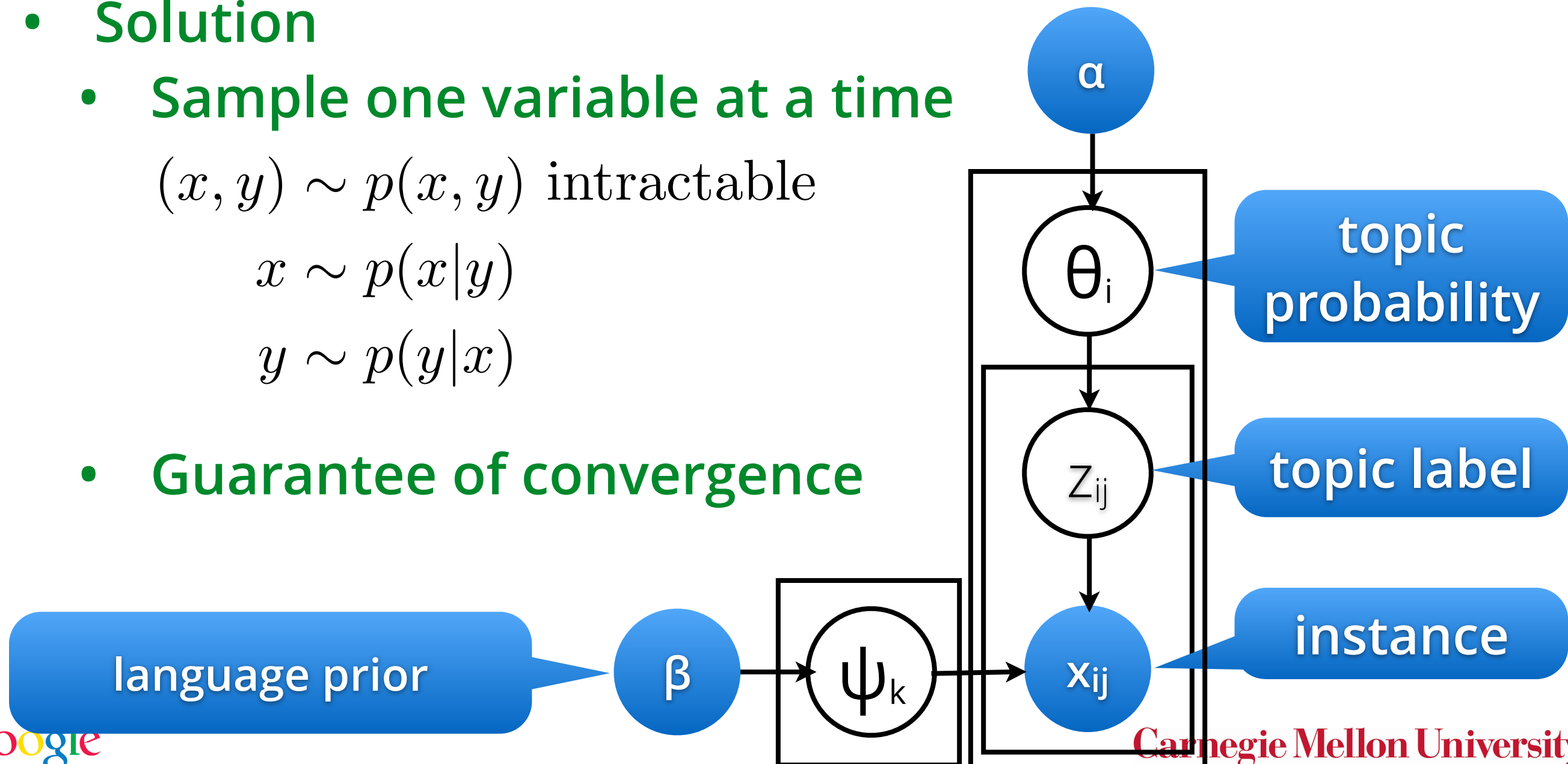
- Goal - sample topics and language model
- Problem - joint distribution intractable
- Solution
 - Sample one variable at a time

$(x, y) \sim p(x, y)$ intractable

$x \sim p(x|y)$

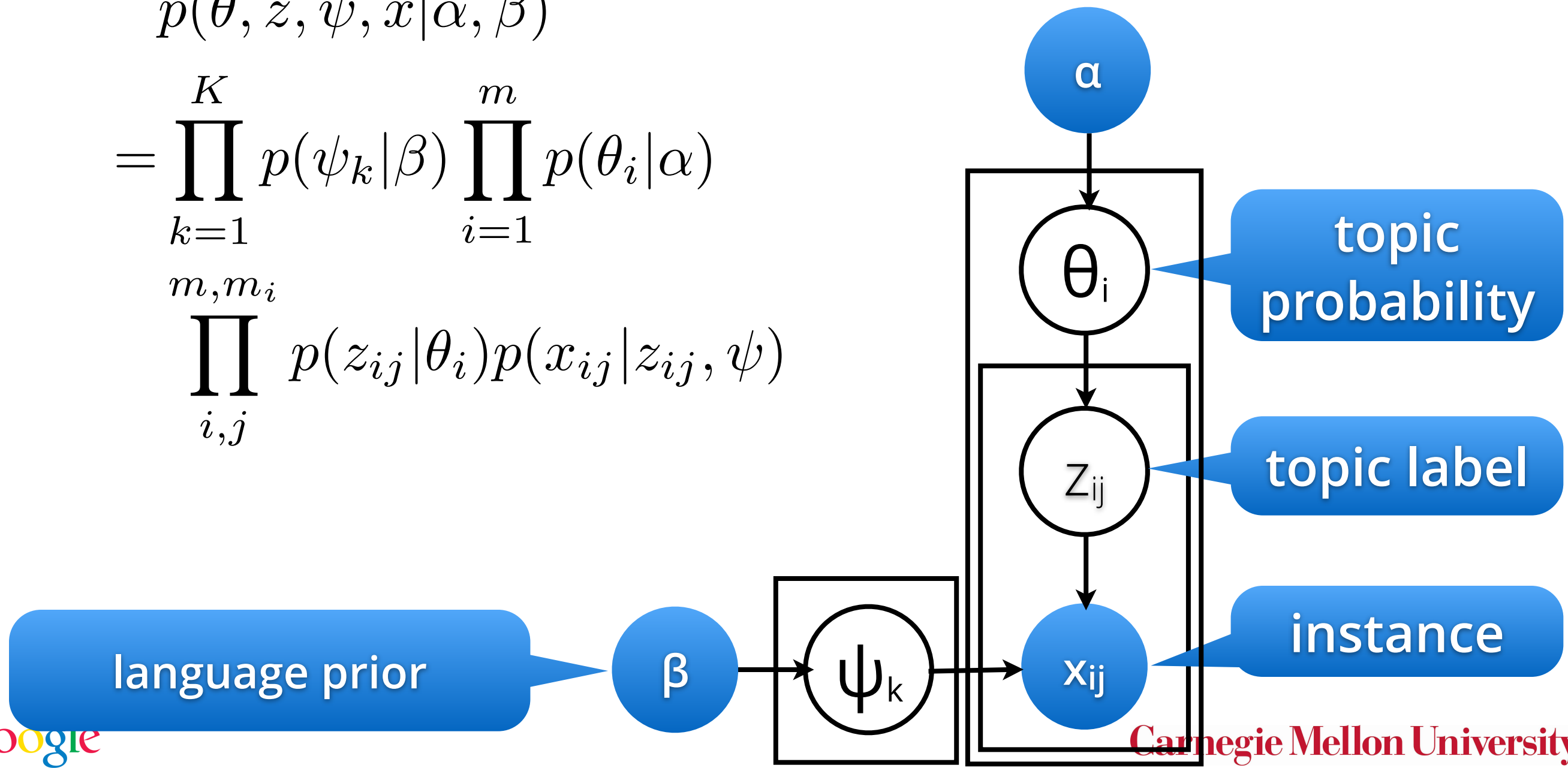
$y \sim p(y|x)$

- Guarantee of convergence



Joint Probability Distribution

$$\begin{aligned} & p(\theta, z, \psi, x | \alpha, \beta) \\ &= \prod_{k=1}^K p(\psi_k | \beta) \prod_{i=1}^m p(\theta_i | \alpha) \\ & \quad \prod_{i,j} p(z_{ij} | \theta_i) p(x_{ij} | z_{ij}, \psi) \end{aligned}$$



Joint Probability Distribution

sample ψ
independently

sample θ
independently

$$p(\theta, z, \psi, x | \alpha, \beta) = \prod_{k=1}^K p(\psi_k | \beta) \prod_{i=1}^m p(\theta_i | \alpha) \prod_{i,j} p(z_{ij} | \theta_i) p(x_{ij} | z_{ij}, \psi)$$

sample z
independently

language prior

β

ψ_k

α

θ_i

z_{ij}

x_{ij}

topic
probability

topic label

instance

Joint Probability Distribution

sample ψ
independently

sample θ
independently

slow

$$p(\theta, z, \psi, x | \alpha, \beta) = \prod_{k=1}^K p(\psi_k | \beta) \prod_{i=1}^m p(\theta_i | \alpha) \prod_{i,j} p(z_{ij} | \theta_i) p(x_{ij} | z_{ij}, \psi)$$

sample z
independently

language prior

β

ψ_k

α

θ_i

z_{ij}

x_{ij}

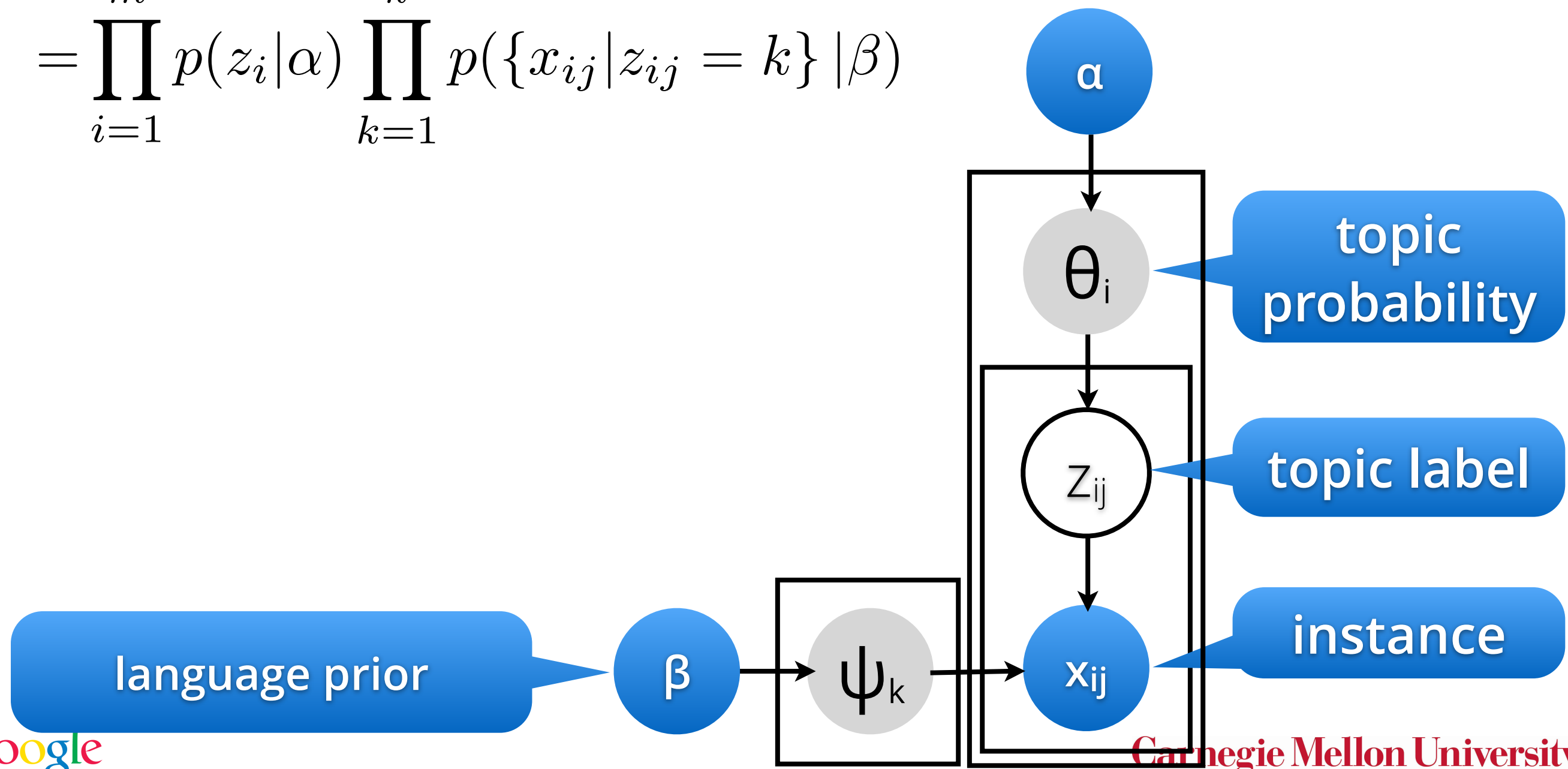
topic
probability

topic label

instance

Collapsed Sampler

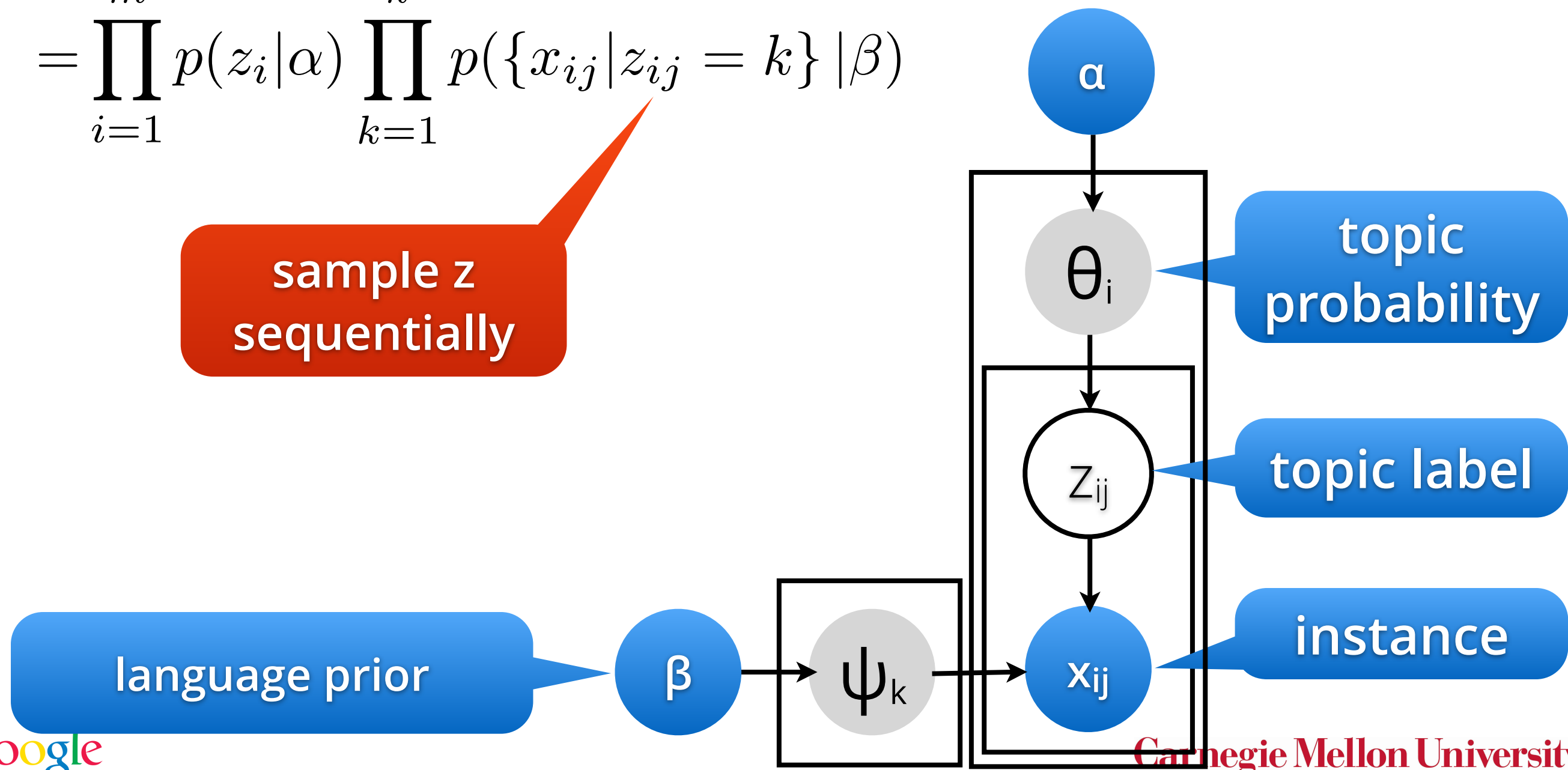
$$p(z, x | \alpha, \beta)$$
$$= \prod_{i=1}^m p(z_i | \alpha) \prod_{k=1}^K p(\{x_{ij} | z_{ij} = k\} | \beta)$$



Collapsed Sampler

$$p(z, x | \alpha, \beta) = \prod_{i=1}^m p(z_i | \alpha) \prod_{k=1}^K p(\{x_{ij} | z_{ij} = k\} | \beta)$$

sample z
sequentially

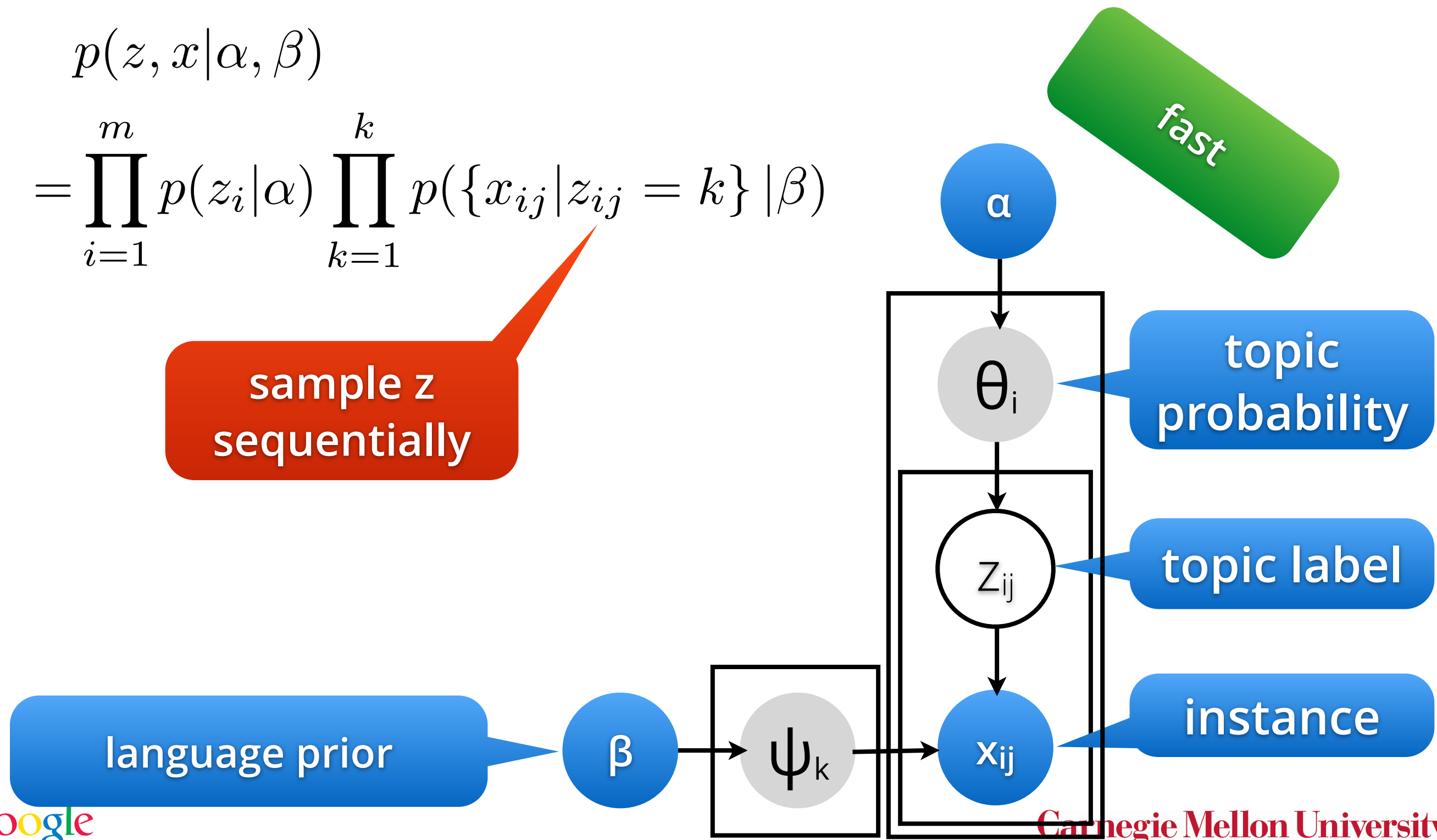


Collapsed Sampler

$$p(z, x | \alpha, \beta) = \prod_{i=1}^m p(z_i | \alpha) \prod_{k=1}^K p(\{x_{ij} | z_{ij} = k\} | \beta)$$

sample z
sequentially

fast



Collapsed Sampler

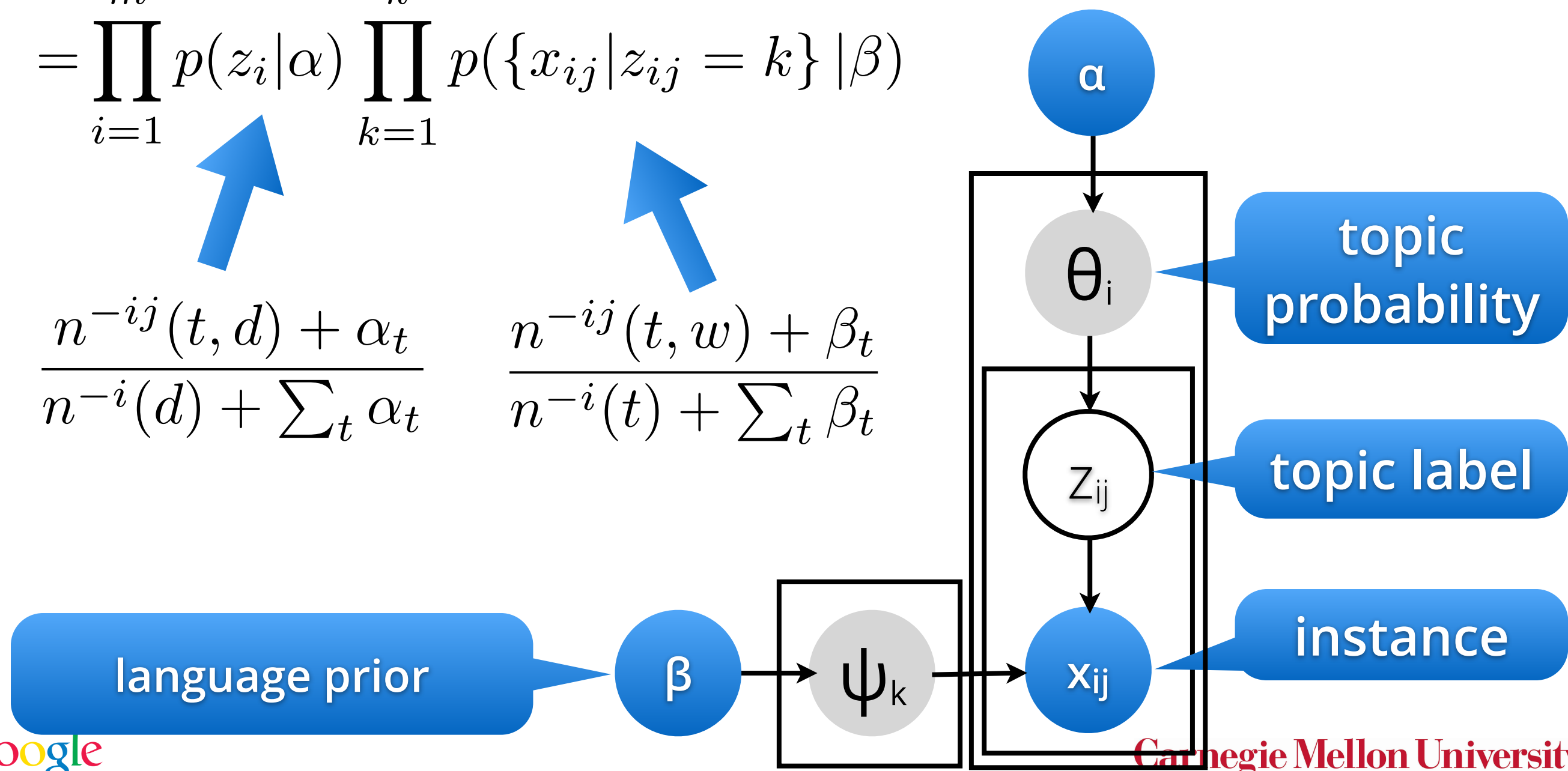
Griffiths & Steyvers, 2005

$$p(z, x | \alpha, \beta)$$

$$= \prod_{i=1}^m p(z_i | \alpha) \prod_{k=1}^K p(\{x_{ij} | z_{ij} = k\} | \beta)$$

$$\frac{n^{-ij}(t, d) + \alpha_t}{n^{-i}(d) + \sum_t \alpha_t}$$

$$\frac{n^{-ij}(t, w) + \beta_t}{n^{-i}(t) + \sum_t \beta_t}$$



Collapsed Sampler

Griffiths & Steyvers, 2005

$$p(z, x | \alpha, \beta) = \prod_{i=1}^m p(z_i | \alpha) \prod_{k=1}^K p(\{x_{ij} | z_{ij} = k\} | \beta)$$

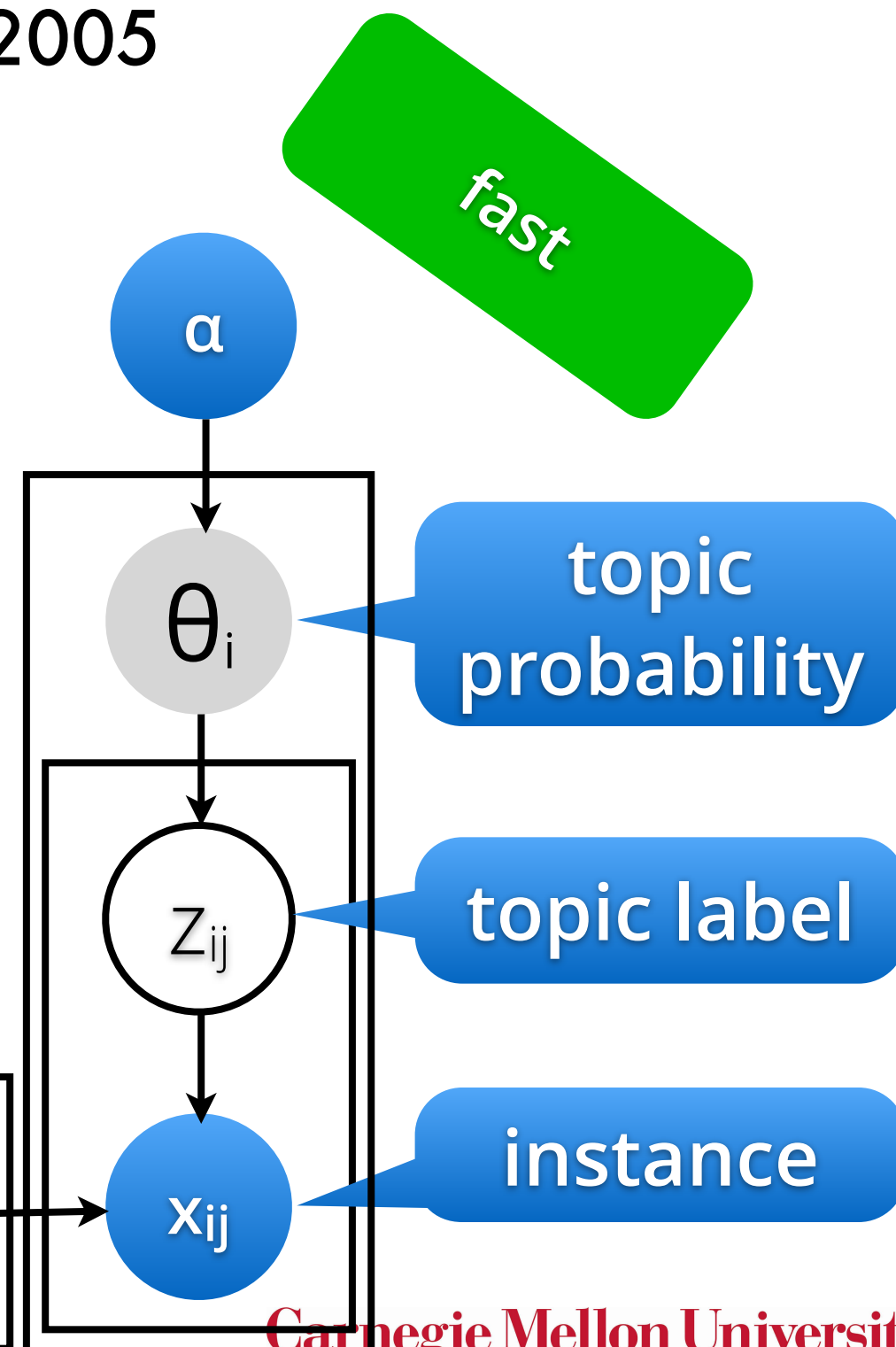
$$\frac{n^{-ij}(t, d) + \alpha_t}{n^{-i}(d) + \sum_t \alpha_t}$$

$$\frac{n^{-ij}(t, w) + \beta_t}{n^{-i}(t) + \sum_t \beta_t}$$

language prior

β

ψ_k



Gibbs Sampler

- For 1000 iterations do
 - For each document do
 - For each word in the document do
 - Resample topic for the word
 - Lock (word,topic) table
 - Update local (document, topic) table
 - Update (word,topic) table
 - Unlock (word,topic) table

this kills parallelism

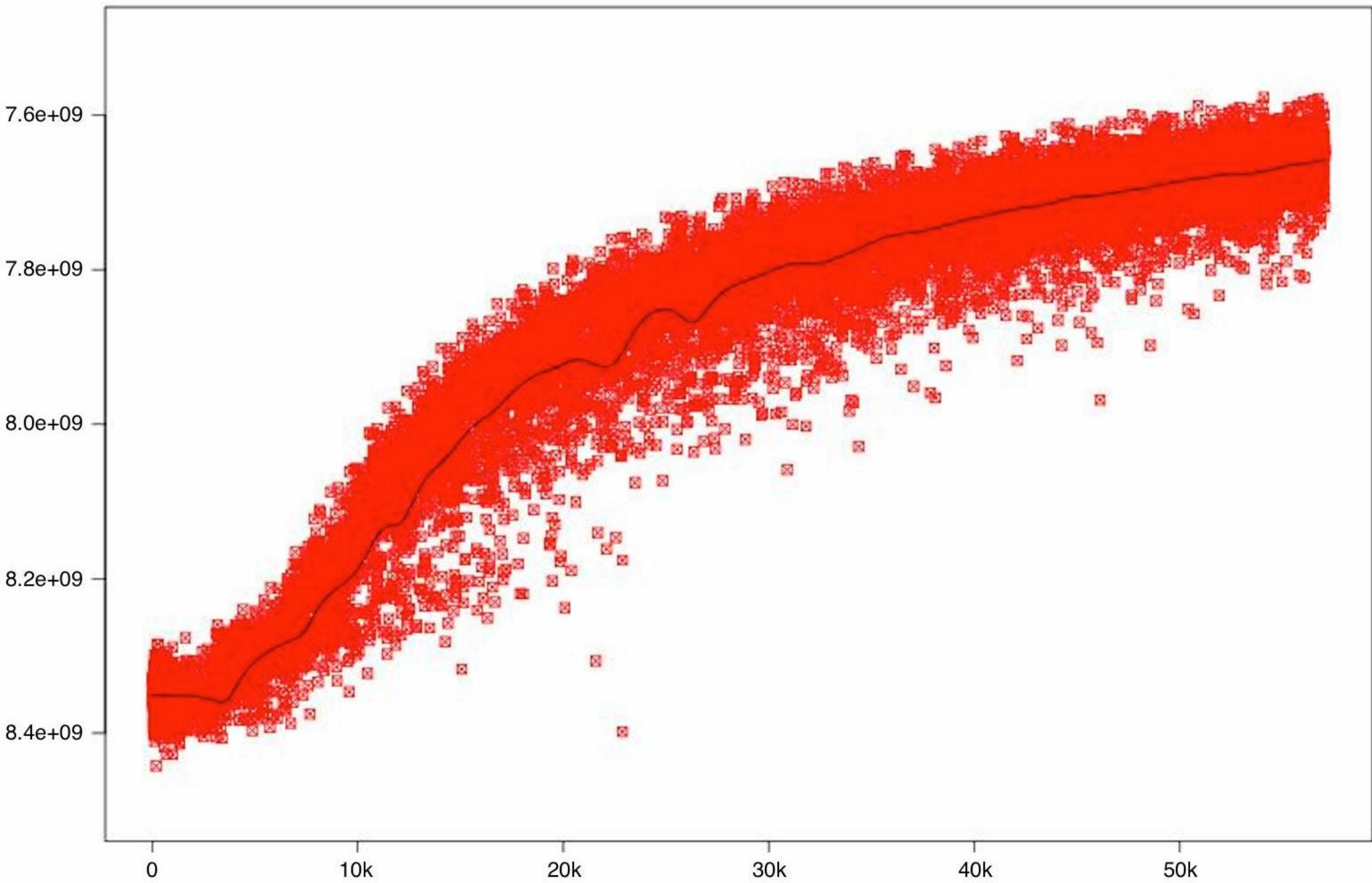
Gibbs Sampler

- For 1000 iterations do
 - For each document do
 - For each word in the document do
 - Resample topic for the word
 - Lock local (word,topic) table
 - Update local (document, topic) table
 - Update local (word,topic) table
 - Unlock local (word,topic) table
 - Synchronize local and global tables

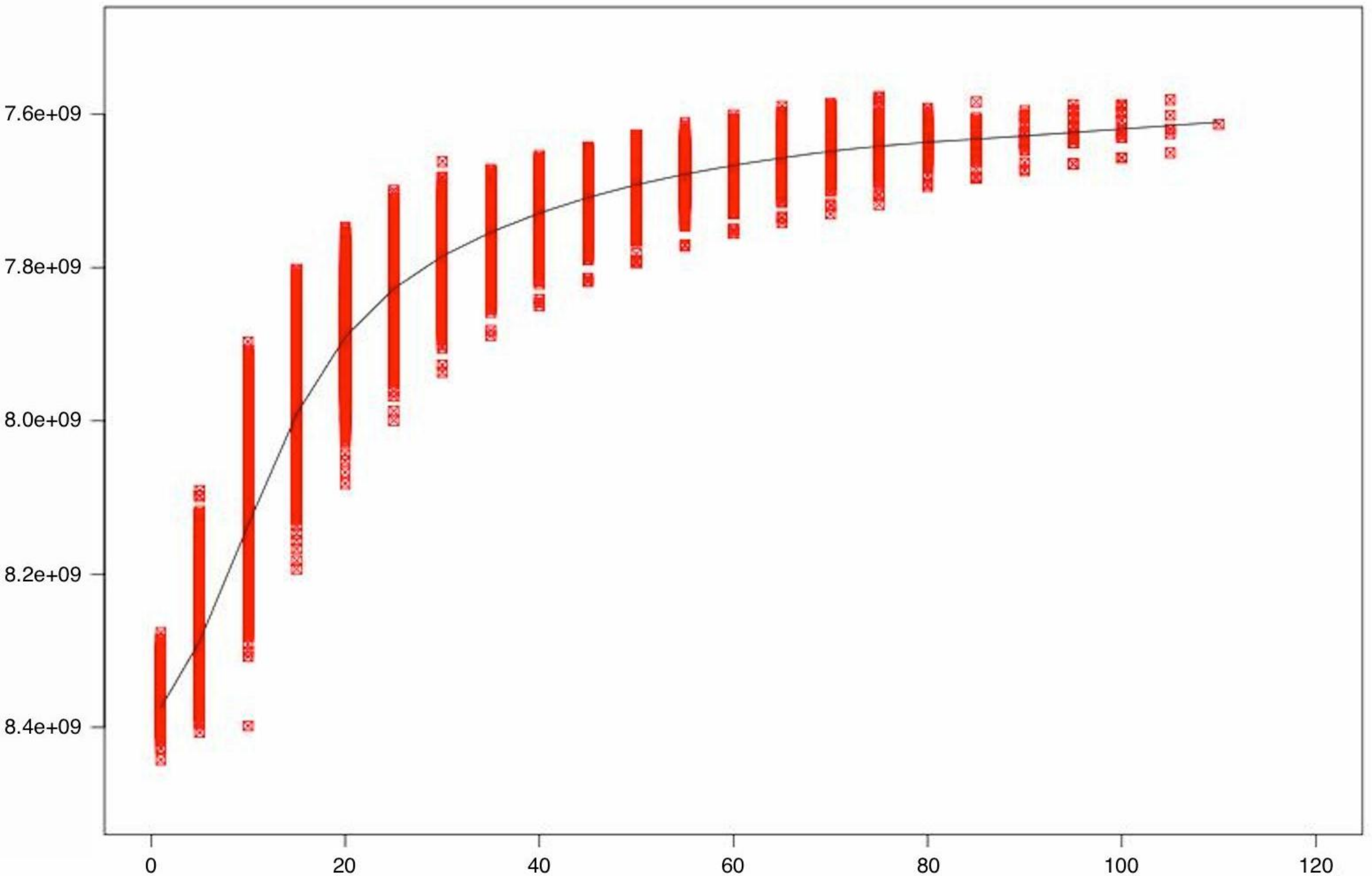
this kills multithreading

Gibbs Sampler

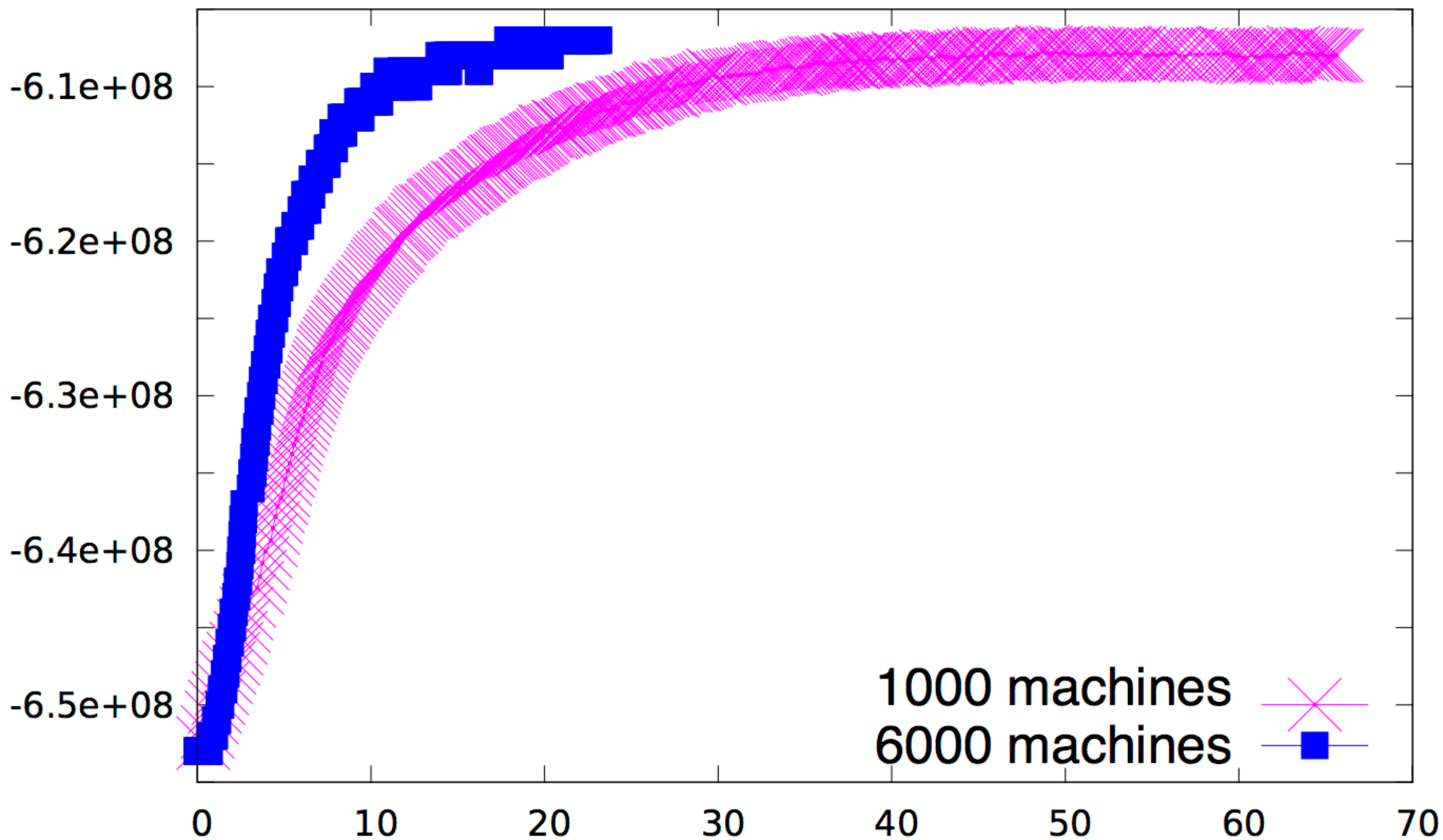
- For 1000 iterations do
 - For each document do
 - For each word in the document do
 - Resample topic for the word
 - Update local (document, topic) table
 - Generate local update message
 - Update local table
 - Lock local (word,topic) table
 - Update local (word,topic) table
 - Unlock local (word,topic) table
 - Synchronize local and global tables



Log-Likelihood distribution as a function of runtime (s) for workers



Log-Likelihood distribution as a function of iteration count for workers



Palo Verde, AZ
3 Gigawatt
Largest nuclear reactor in the USA



Palo Verde, AZ
3 Gigawatt
Largest nuclear reactor in the USA

1 machine = 10 cores
1 core = 50 watt
consumption of 3 Megawatt



Techie

Mike

25-34 single male
living with friends

Mike works as a graphic designer in a small agency and one day wants to run his own agency.

He's got an iPhone and a Vodafone 360 H1 by Samsung phone, one personal and one for work. He follows friends and key people in the design industry via Twitter, blogs, and RSS feeds. He uses his iPhone for work emails and his H1 for Facebook.

He uses Twitter to post updates about what he's up to with his project work as well as using it as a tool to find out what people are up to and to invite them to events. He uses Facebook to share personal photos and video and keeps a Tumblr blog to post interesting things he discovers and share them with his friends and followers.



Socialite

Zoë

18-33 single female
living with friends

Zoë is studying a Masters in International Development unsure of what the future lies ahead of her.

She is constantly using the Facebook app on her Vodafone 360 M1 by Samsung phone as well as on her PC to upload and tag photos and videos from places she's been to with her friends, as well as to find out and comment on who's been where at which club nights and parties.

She regularly texts and messages her friends to find out if they've heard about a new pop-up shop she heard about via a flyer, or one-off warehouse party started by friends of friends.



Cost-conscious

Geoff

35-49 married male
with young kids

Geoff works as an senior architect in a large practice, and has a wife and a young girl and 6-month baby boy. He thinks the time is right to start looking for a bigger home for his family.

Geoff uses his Vodafone 360 H1 to take photos and videos of prospective sites he visits. He purchased the H1 because of its ability to check email, surf the web, use apps, and take photos and video.

He loves the built-in camera and also uses this phone on holiday to take snaps of the family as it fits in his pocket and doesn't want to carry a large SLR around with him. He likes to upload his photos and video to Flickr and share them with his family and friends. He also creates photo books from his holidays snaps to give as gifts to his parents.

User Profiling



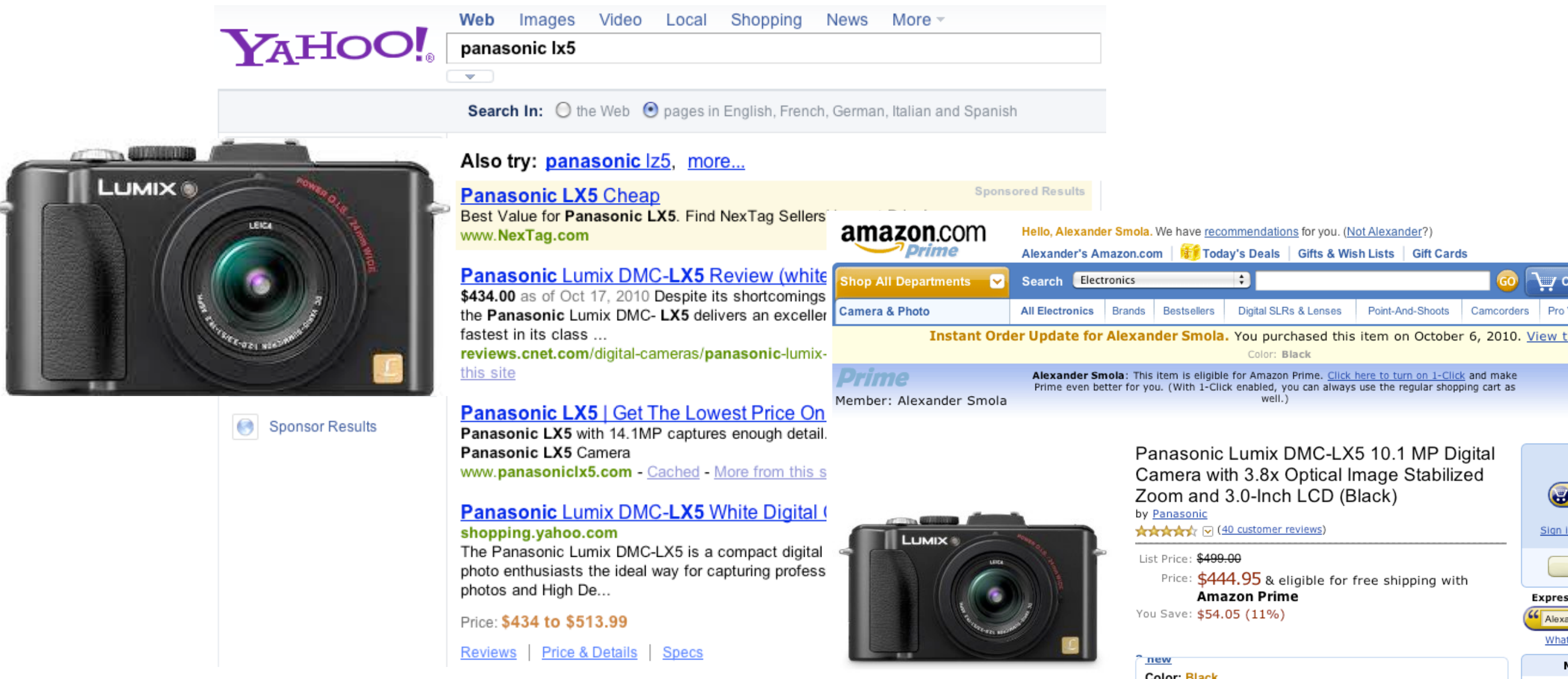
User Profiling

Buying a Camera



time

Buying a Camera



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by [Panasonic](#)
★★★★★ (40 customer reviews)

List Price: ~~\$499.00~~
Price: **\$444.95** & eligible for free shipping with **Amazon Prime**
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LUMIX
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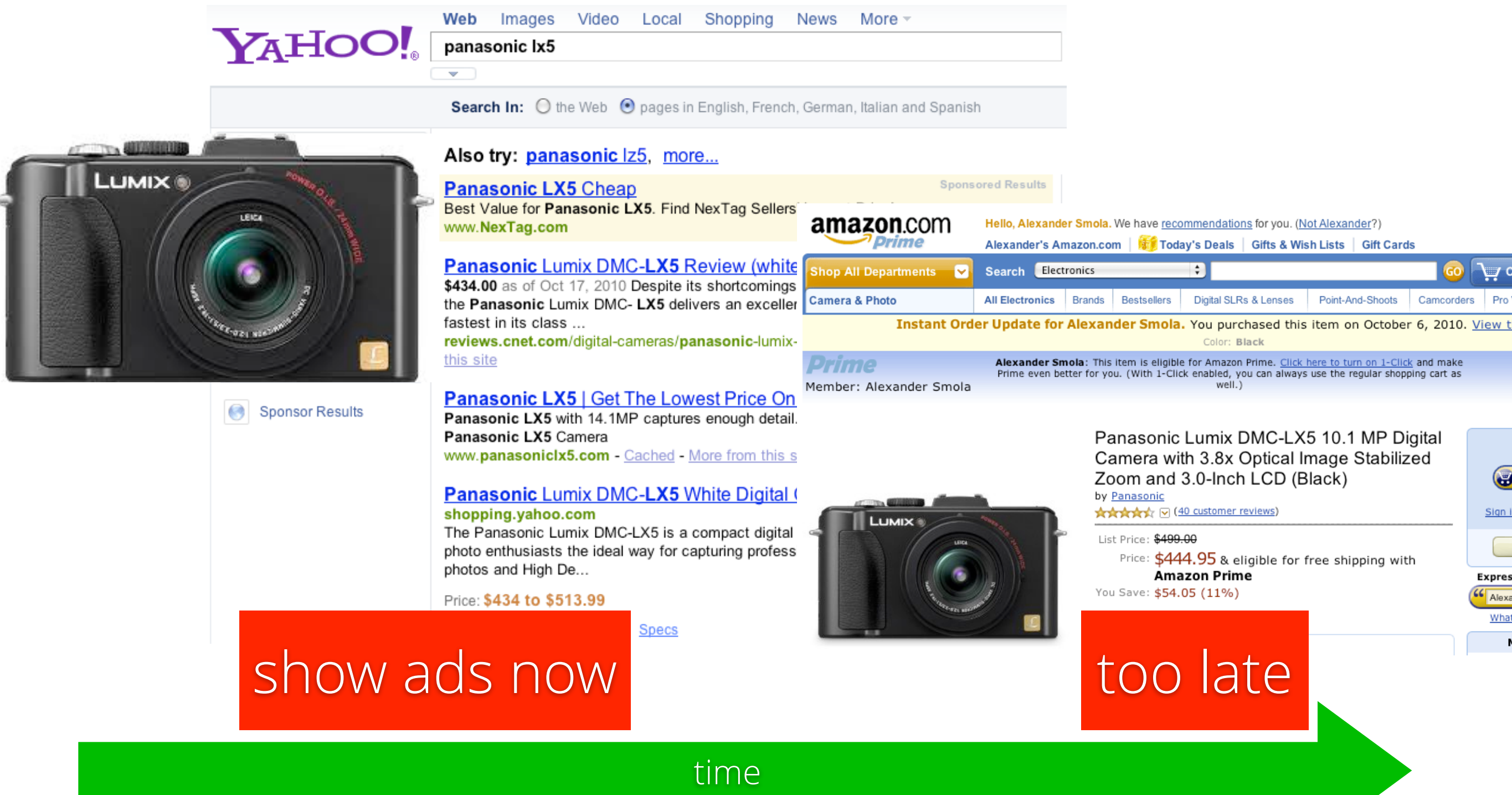
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You Save: **\$54.05 (11%)**

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Color: **Black**

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Buying a Camera



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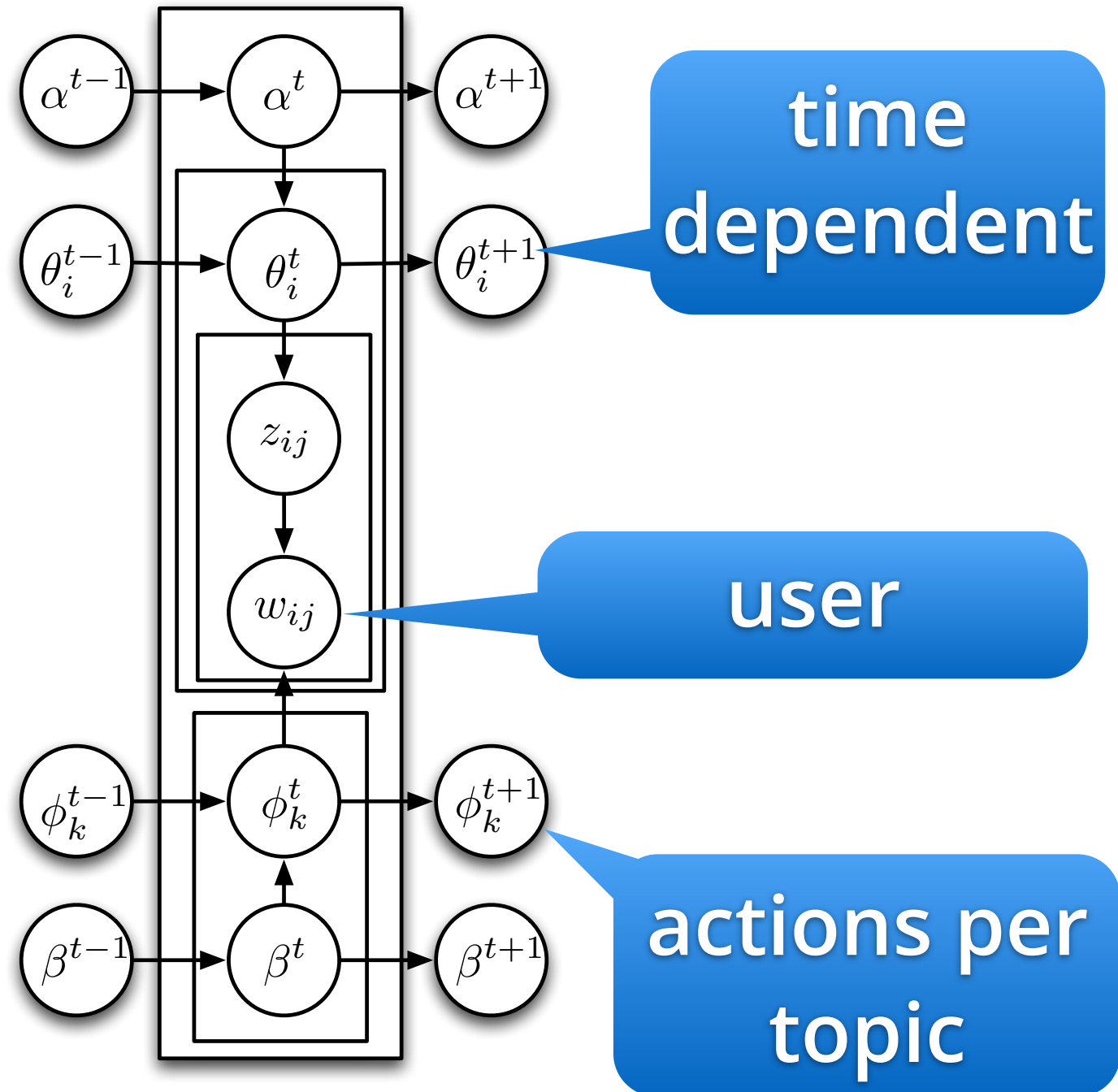
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too late

time

Statistical Model

plain
LDA



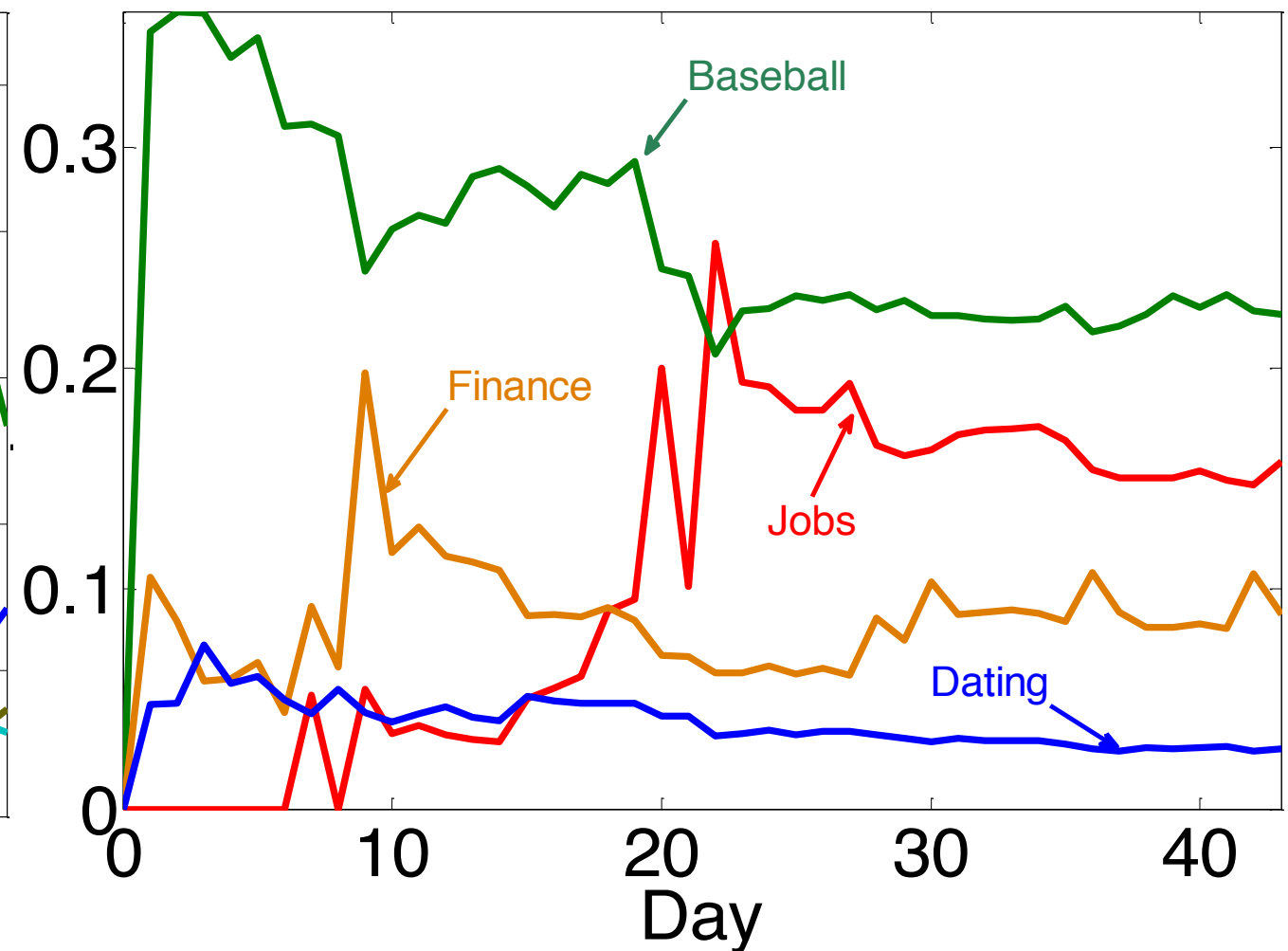
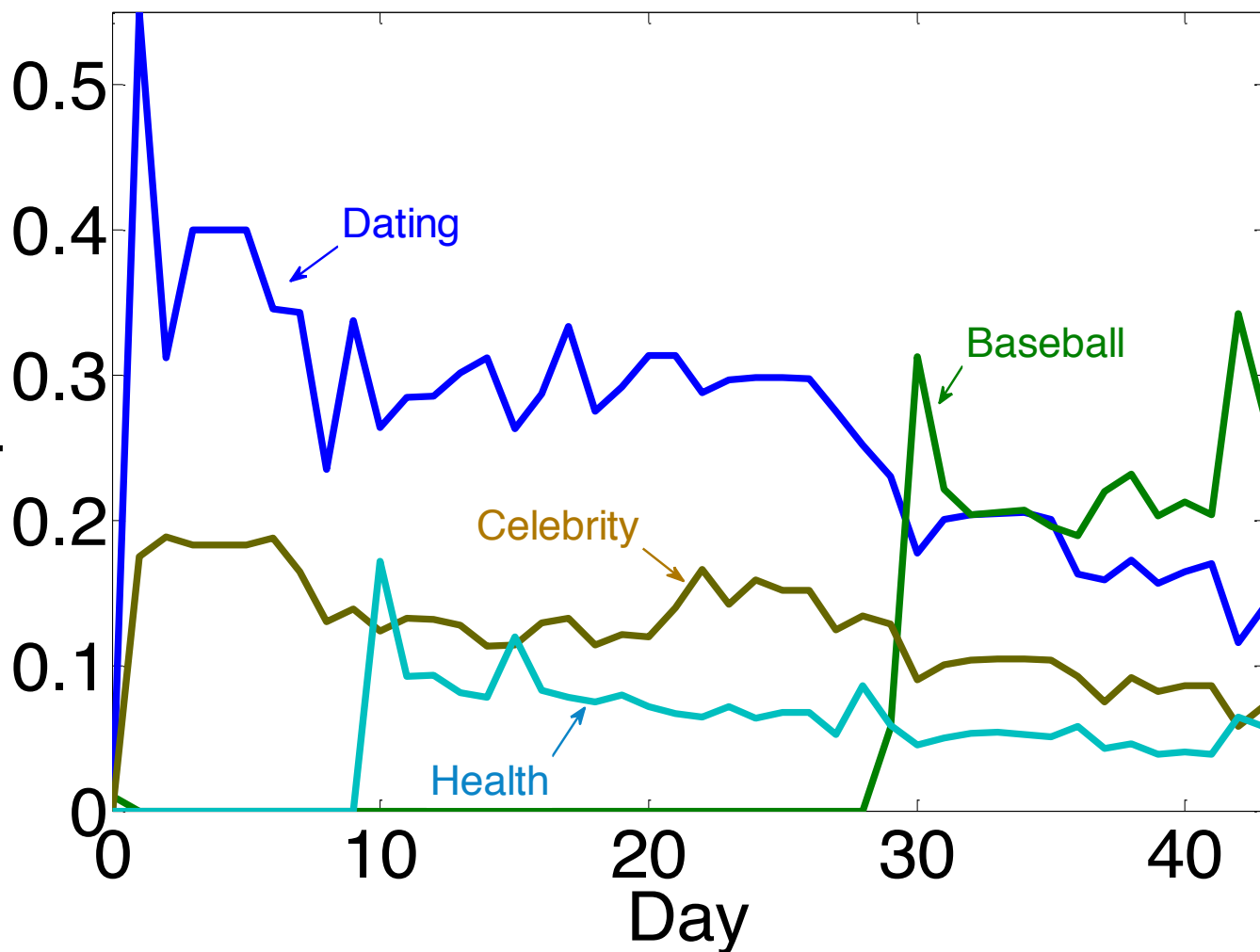
- Topic model

- Users - Documents
- Actions - Words
- Interests - Topics

- Πάντα ρει (everything flows)

- Users' interest preferences change over time
- Interests change over time
- Changing flavor of the day

Some Users



Dating

women
men
dating
singles
personals
seeking
match

Baseball

League
baseball
basketball,
doublehead
Bergesen
Griffey
bullpen
Greinke

Celebrity

Snooki
Tom
Cruise
Katie
Holmes
Pinkett
Kudrow
Hollywood

Health

skin
body
fingers
cells
toes
wrinkle
layers

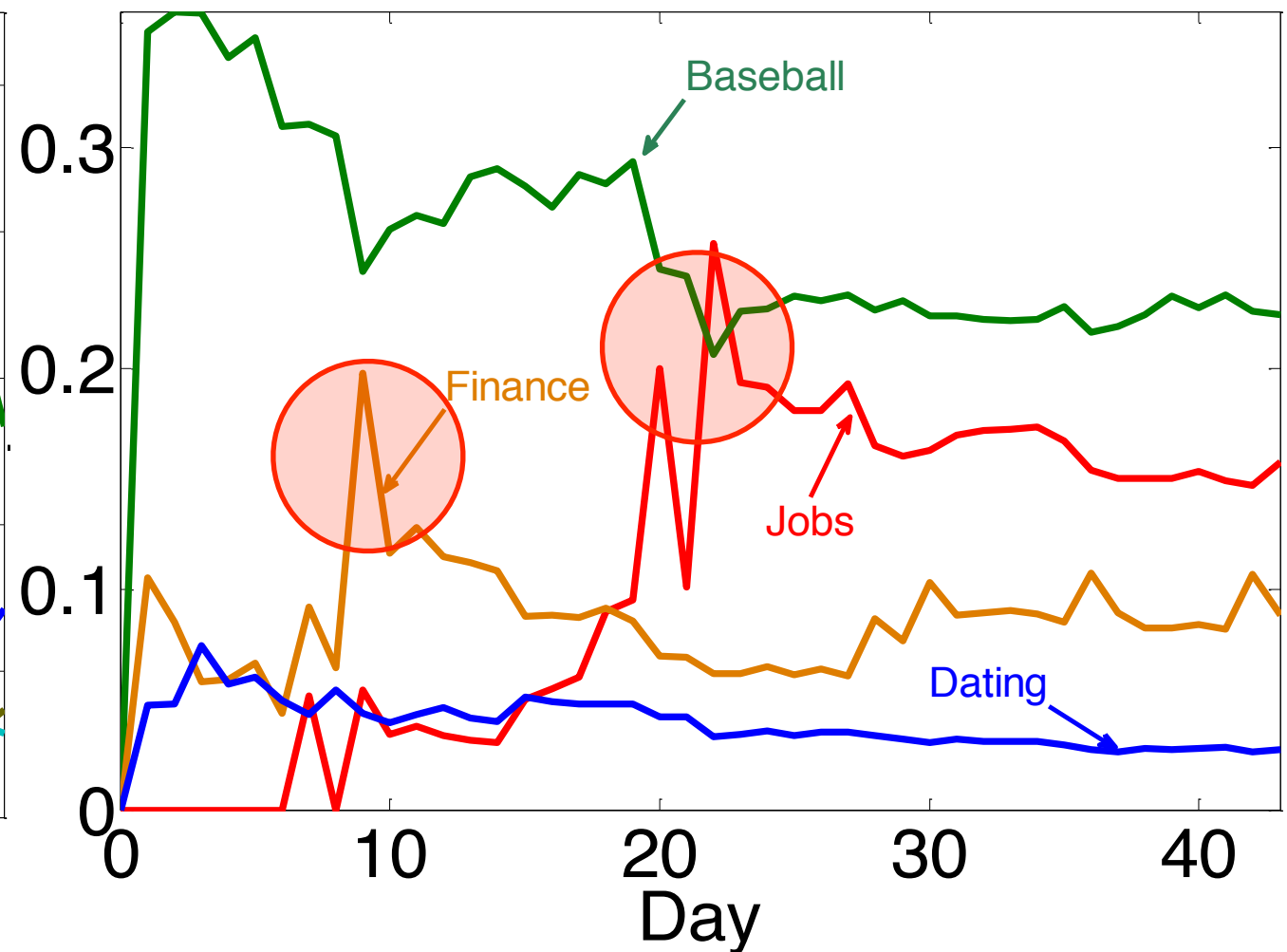
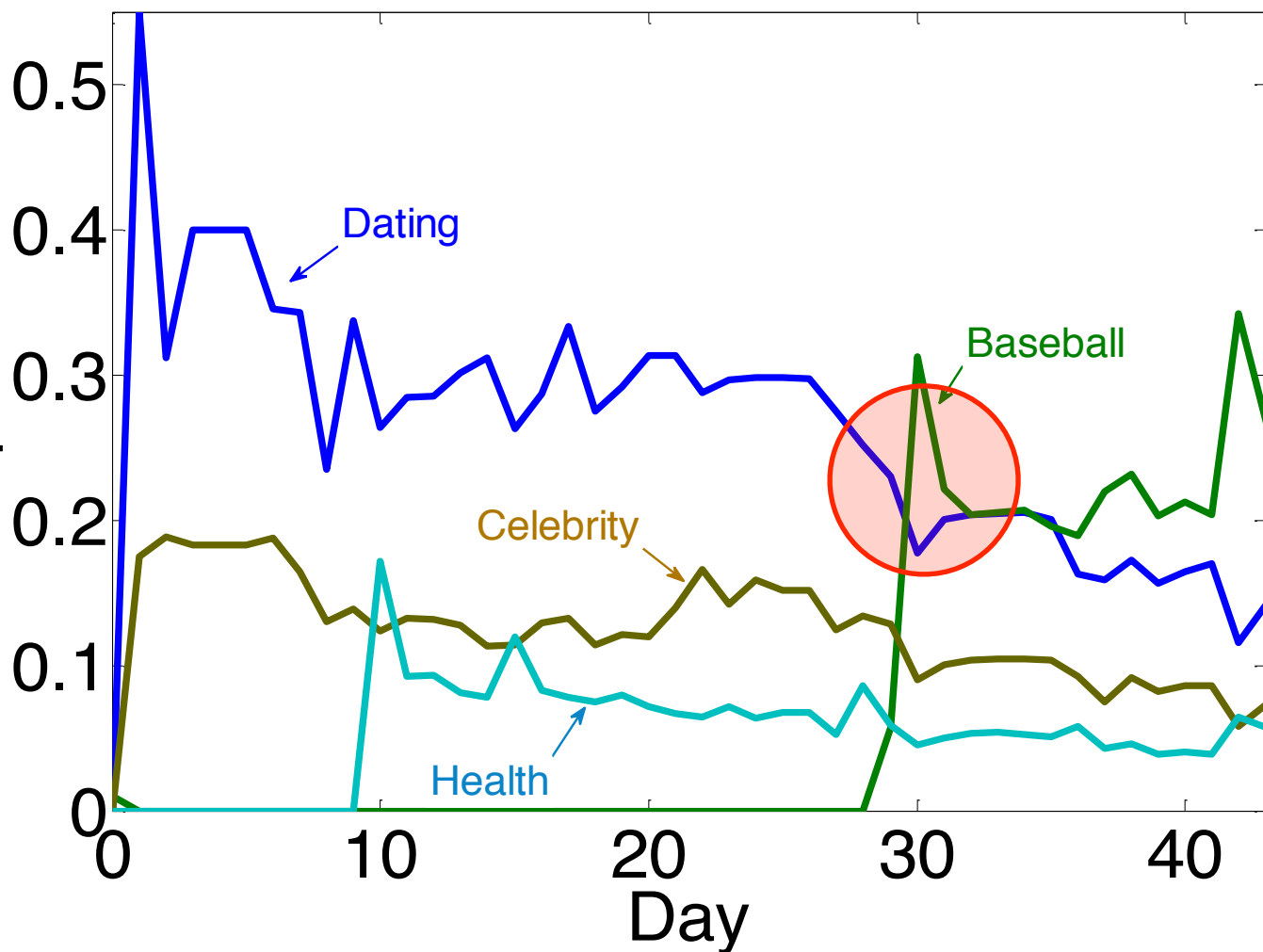
Jobs

job
career
business
assistant
hiring
part-time
receptionist

Finance

financial
Thomson
chart
real
Stock
Trading
currency

Some Users



Dating

women
men
dating
singles
personals
seeking
match

Baseball

League
baseball
basketball,
doublehead
Bergesen
Griffey
bullpen
Greinke

Celebrity

Snooki
Tom
Cruise
Katie
Holmes
Pinkett
Kudrow
Hollywood

Health

skin
body
fingers
cells
toes
wrinkle
layers

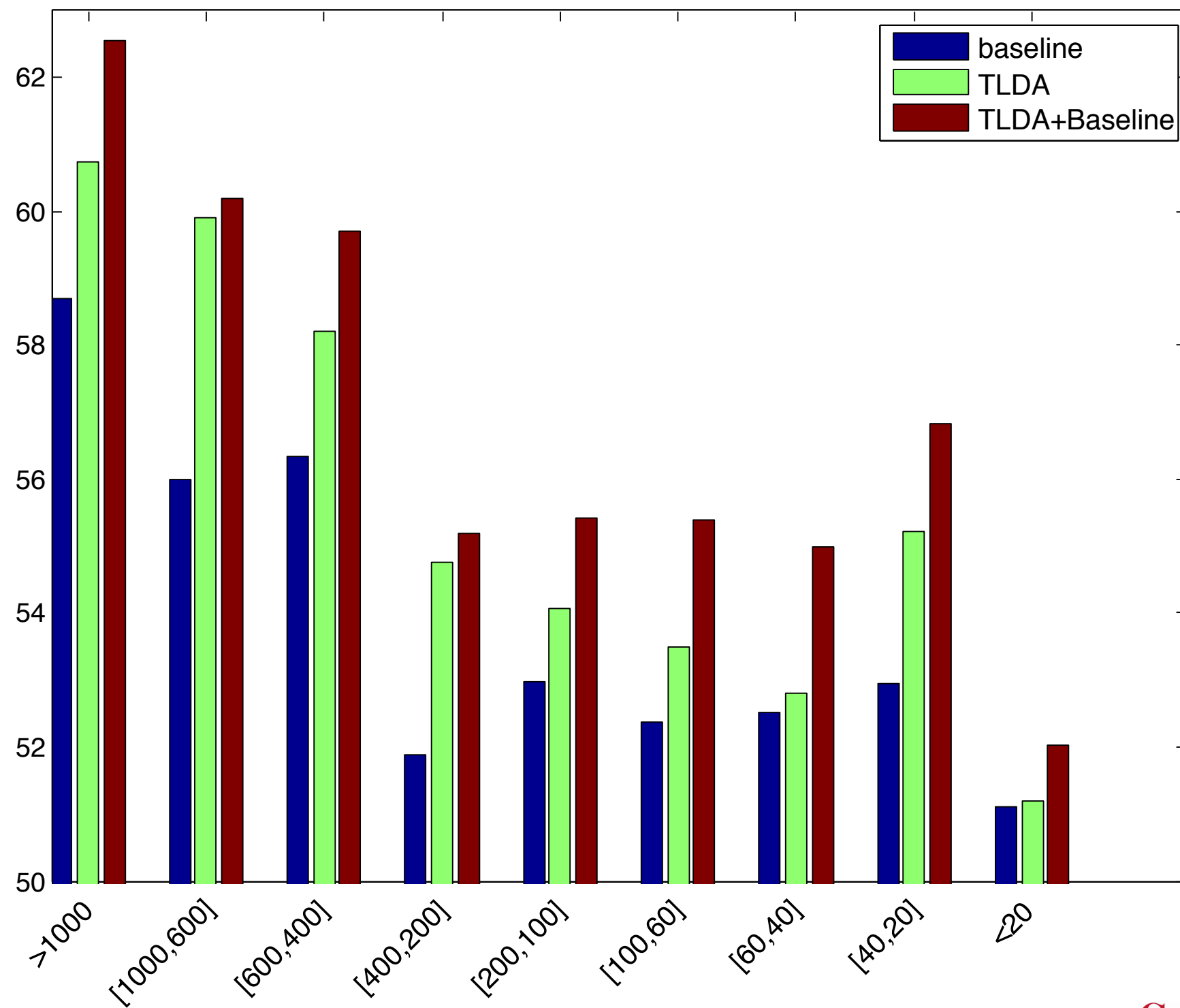
Jobs

job
career
business
assistant
hiring
part-time
receptionist

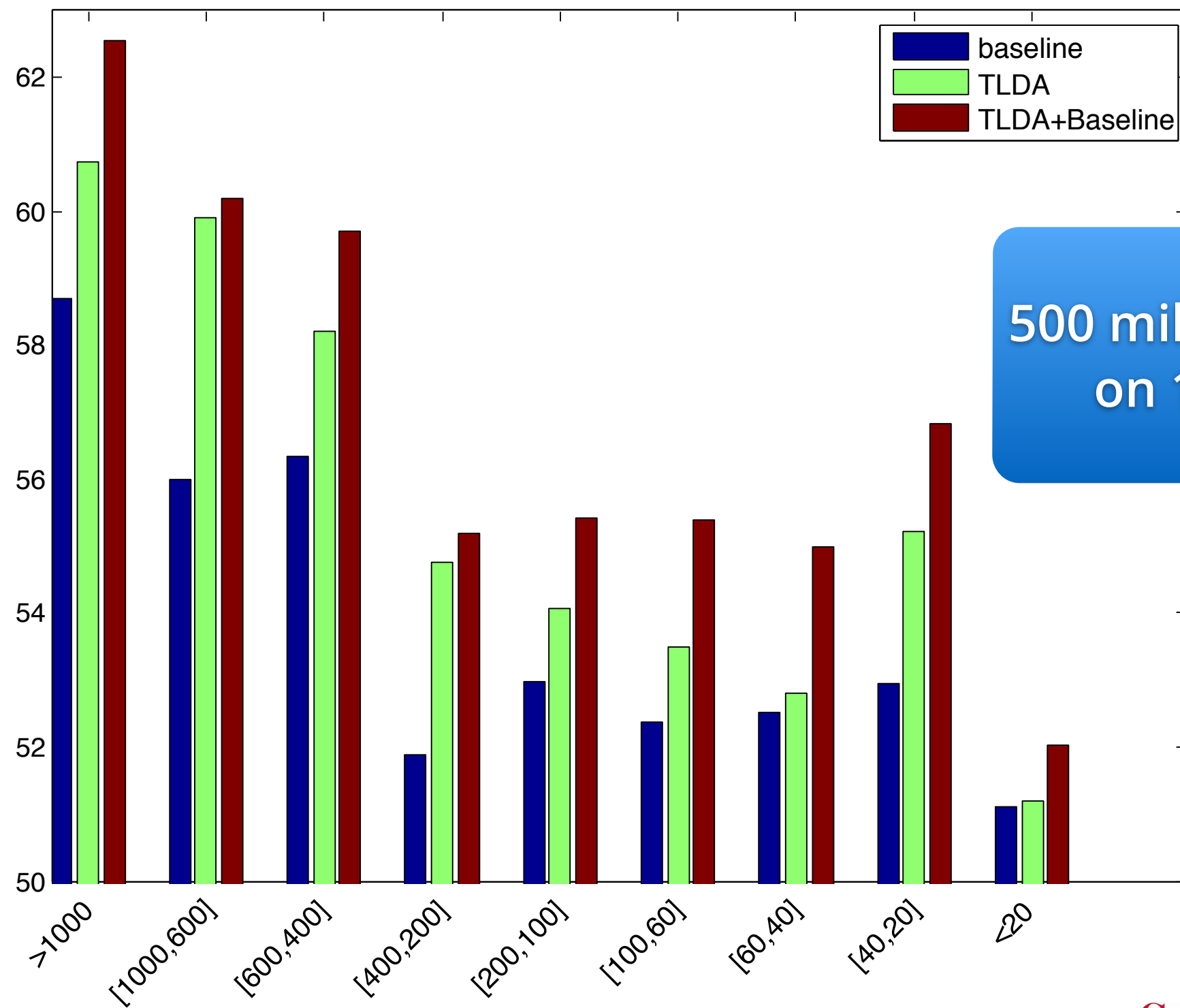
Finance

financial
Thomson
chart
real
Stock
Trading
currency

Improvement (\$\$\$)



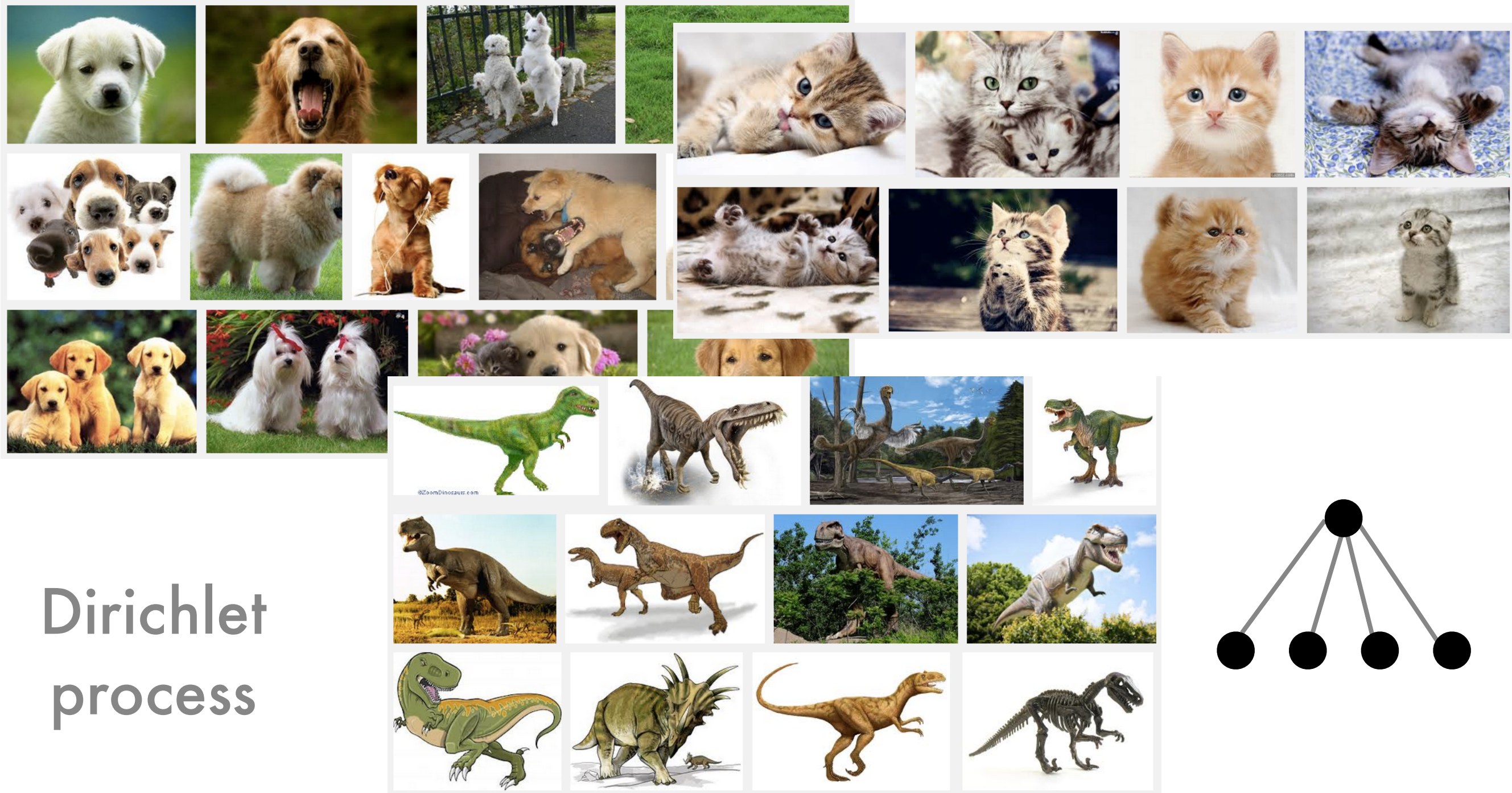
Improvement (\$\$\$\$)



500 million users per day
on 1000 machines



Modeling stuff - Clusters

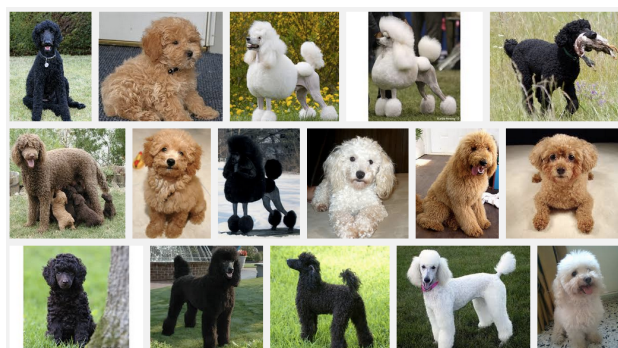
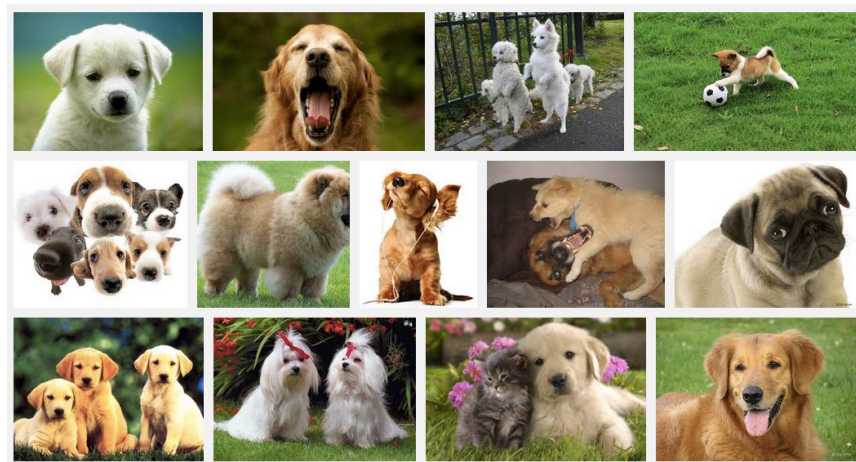


Dirichlet
process

Modeling stuff

Hierarchy of Clusters

Adams, Ghahramani, Jordan, 2008

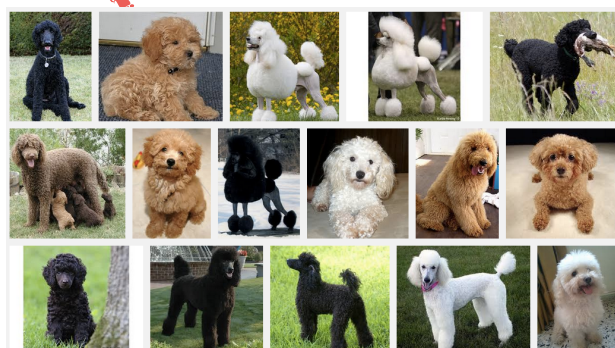
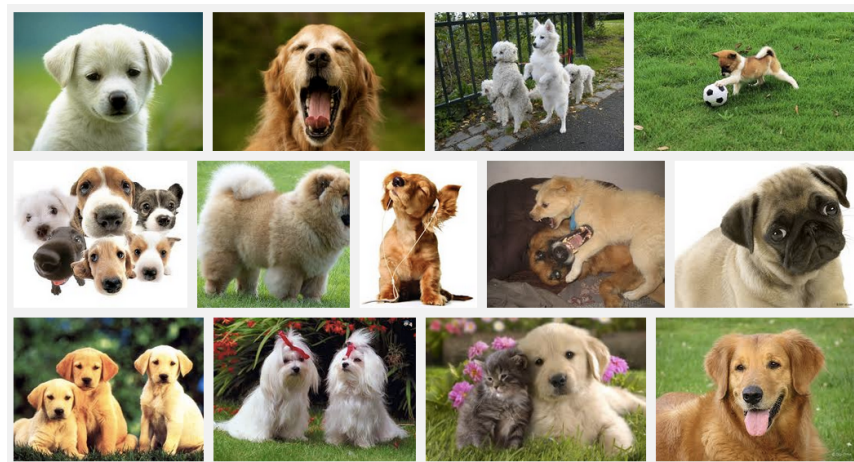
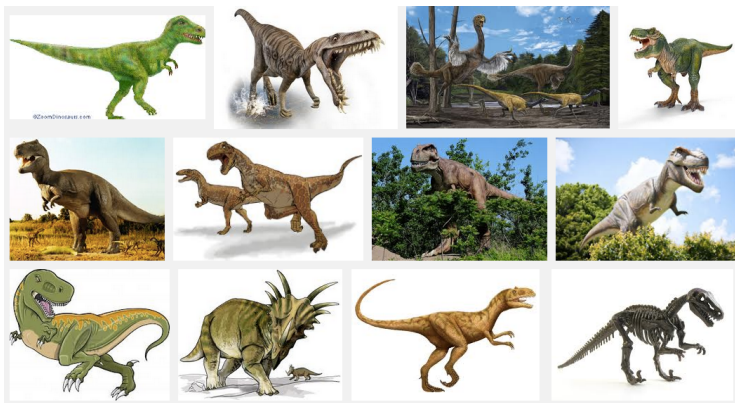


e.g. hierarchical
stick breaking

Modeling stuff

Hierarchy of Clusters

Adams, Ghahramani, Jordan, 2008

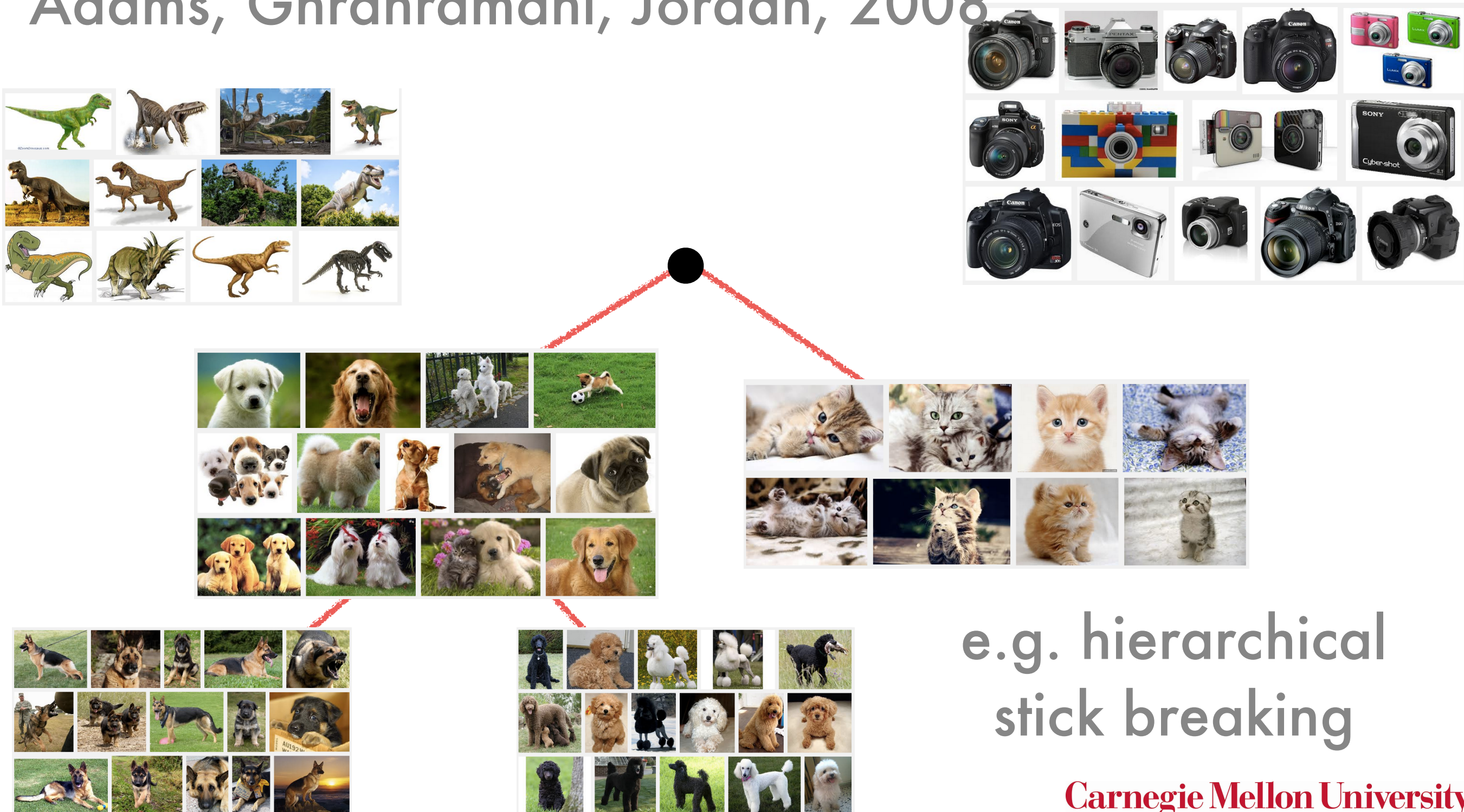


e.g. hierarchical
stick breaking

Modeling stuff

Hierarchy of Clusters

Adams, Ghahramani, Jordan, 2008

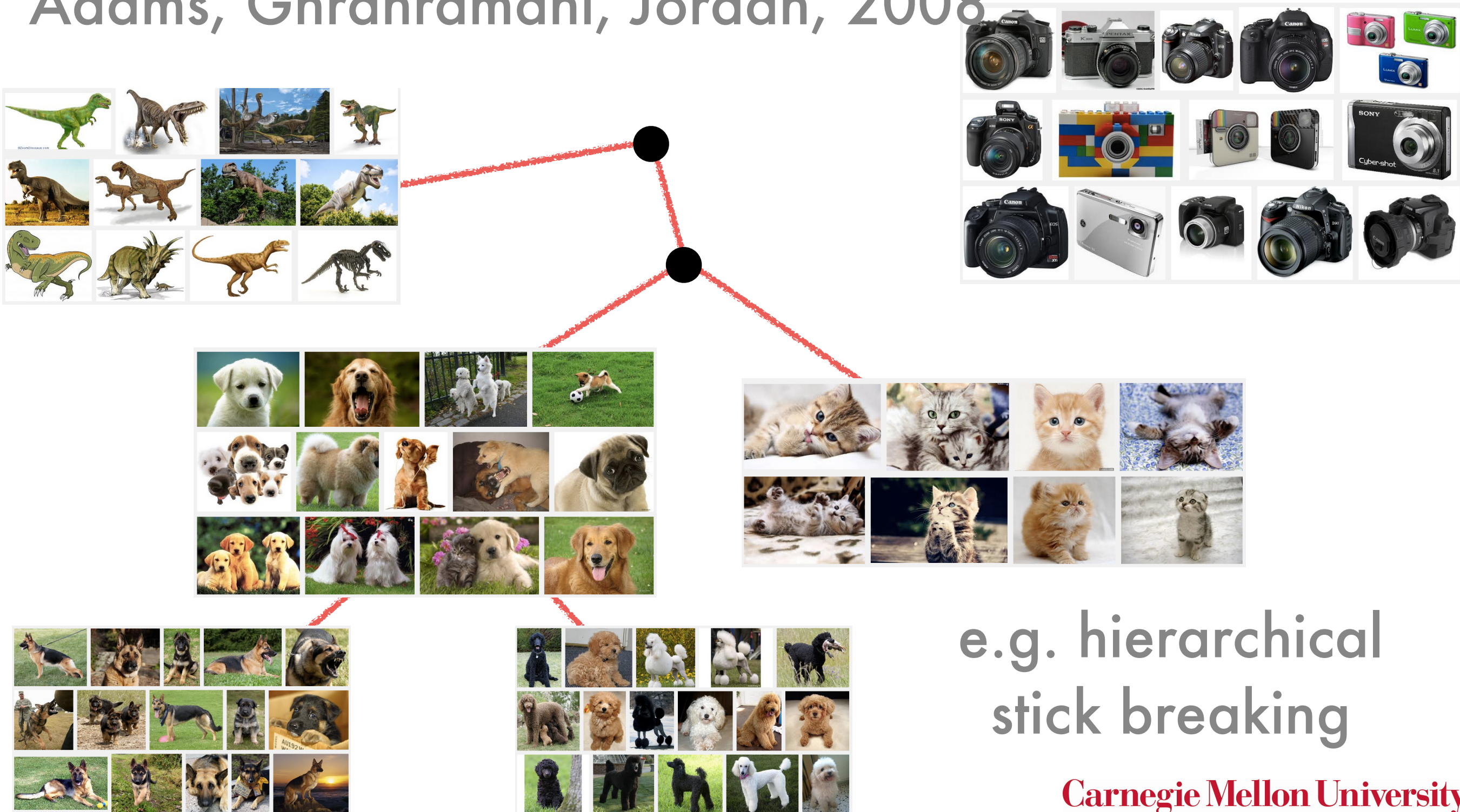


e.g. hierarchical
stick breaking

Modeling stuff

Hierarchy of Clusters

Adams, Ghahramani, Jordan, 2008

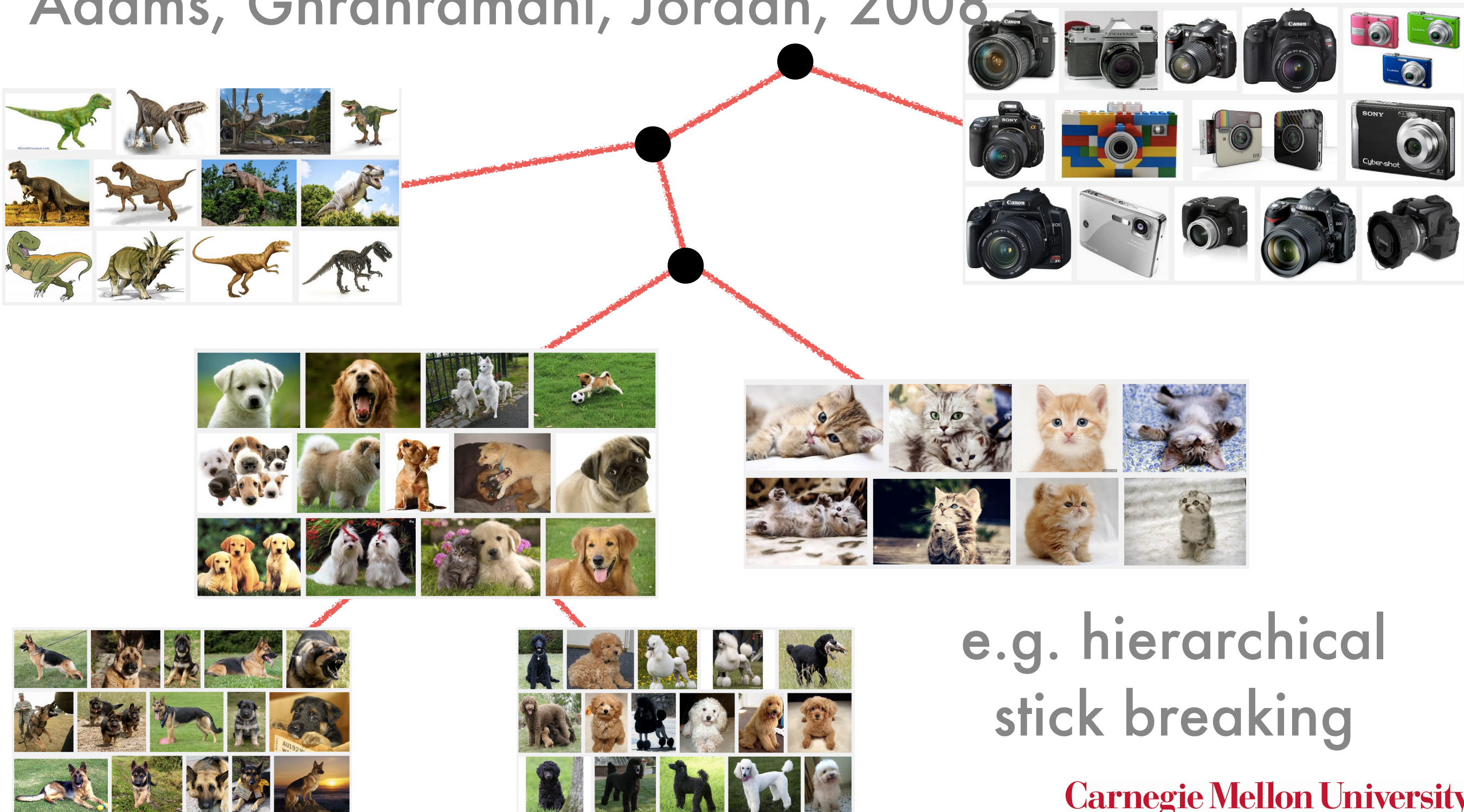


e.g. hierarchical
stick breaking

Modeling stuff

Hierarchy of Clusters

Adams, Ghahramani, Jordan, 2008



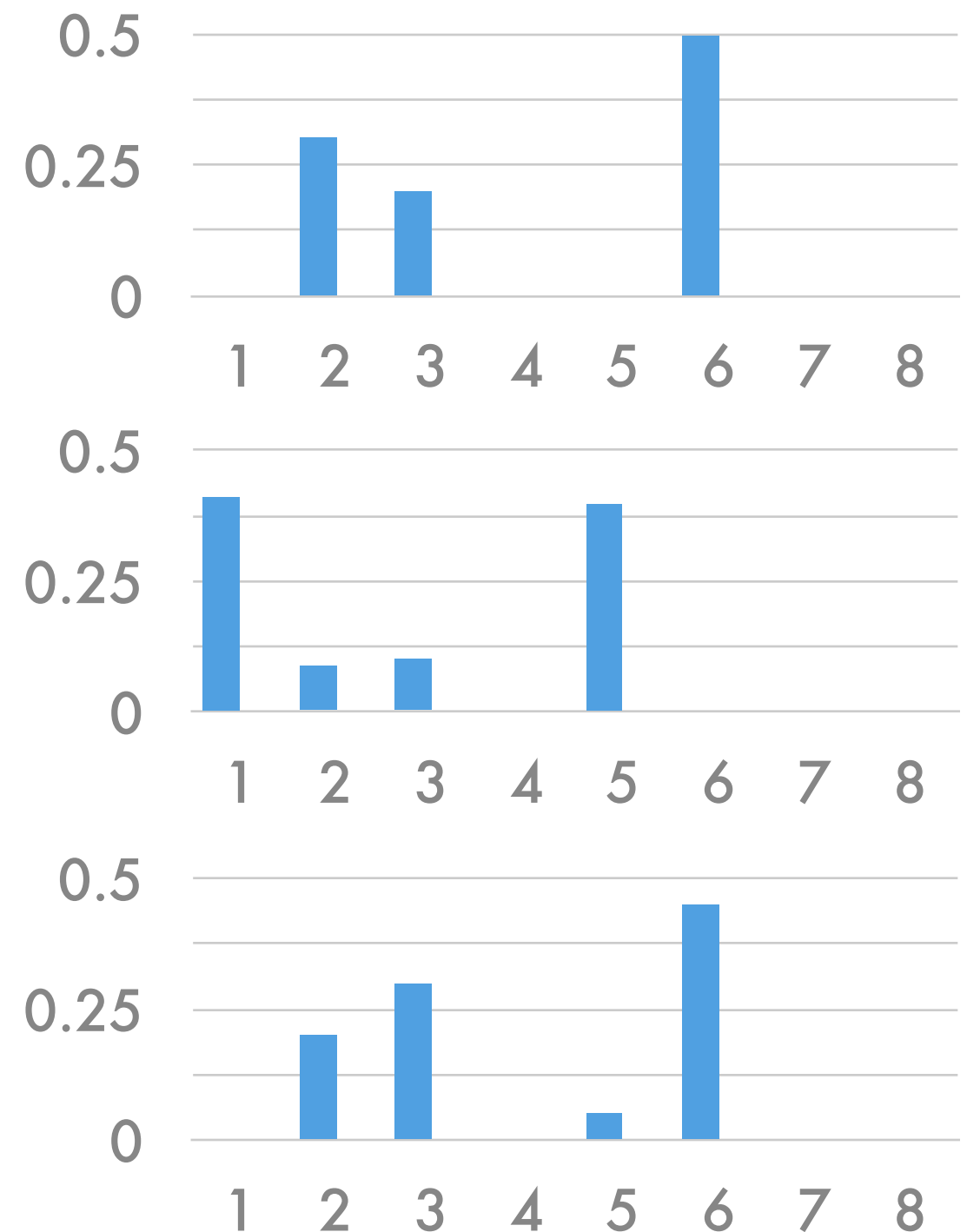
e.g. hierarchical
stick breaking

Recall - Factorial representations

Blei, Ng, Jordan 2003

"Arts"	"Budgets"	"Children"	"Education"
NEW	MILLION	CHILDREN	SCHOOL
FILM	TAX	WOMEN	STUDENTS
SHOW	PROGRAM	PEOPLE	SCHOOLS
MUSIC	BUDGET	CHILD	EDUCATION
MOVIE	BILLION	YEARS	TEACHERS
PLAY	FEDERAL	FAMILIES	HIGH
MUSICAL	YEAR	WORK	PUBLIC
BEST	SPENDING	PARENTS	TEACHER
ACTOR	NEW	SAYS	BENNETT
FIRST	STATE	FAMILY	MANIGAT
YORK	PLAN	WELFARE	NAMPHY
OPERA	MONEY	MEN	STATE
THEATER	PROGRAMS	PERCENT	PRESIDENT
ACTRESS	GOVERNMENT	CARE	ELEMENTARY
LOVE	CONGRESS	LIFE	HAITI

The William Randolph Hearst Foundation will give \$1.25 million to Lincoln Center, Metropolitan Opera Co., New York Philharmonic and Juilliard School. "Our board felt that we had a real opportunity to make a mark on the future of the performing arts with these grants an act every bit as important as our traditional areas of support in health, medical research, education and the social services," Hearst Foundation President Randolph A. Hearst said Monday in announcing the grants. Lincoln Center's share will be \$200,000 for its new building, which will house young artists and provide new public facilities. The Metropolitan Opera Co. and New York Philharmonic will receive \$400,000 each. The Juilliard School, where music and the performing arts are taught, will get \$250,000. The Hearst Foundation, a leading supporter of the Lincoln Center Consolidated Corporate Fund, will make its usual annual \$100,000 donation, too.

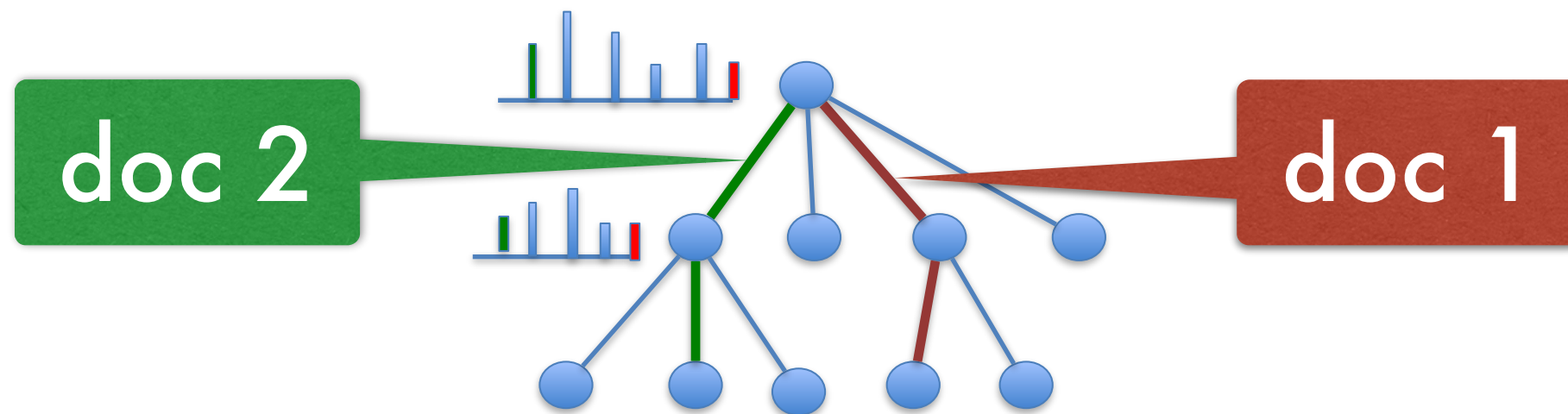


Hierarchical factorial representations

- Hierarchical Dirichlet Process (Teh et al. 2006)
 - Given hierarchy of objects
 - DP on children inherits from parent

$$G_i \sim DP(G_0, \gamma') \text{ and } G_0 \sim DP(H, \gamma)$$

- Nested Chinese Restaurant Process (Blei et al. 2010)



- Pachinko allocation (McCallum et al., 2010)
(use directed acyclic graph, often predefined)

Hierarchical factorial representations

- Hierarchical Dirichlet Process (Teh et al. 2006)
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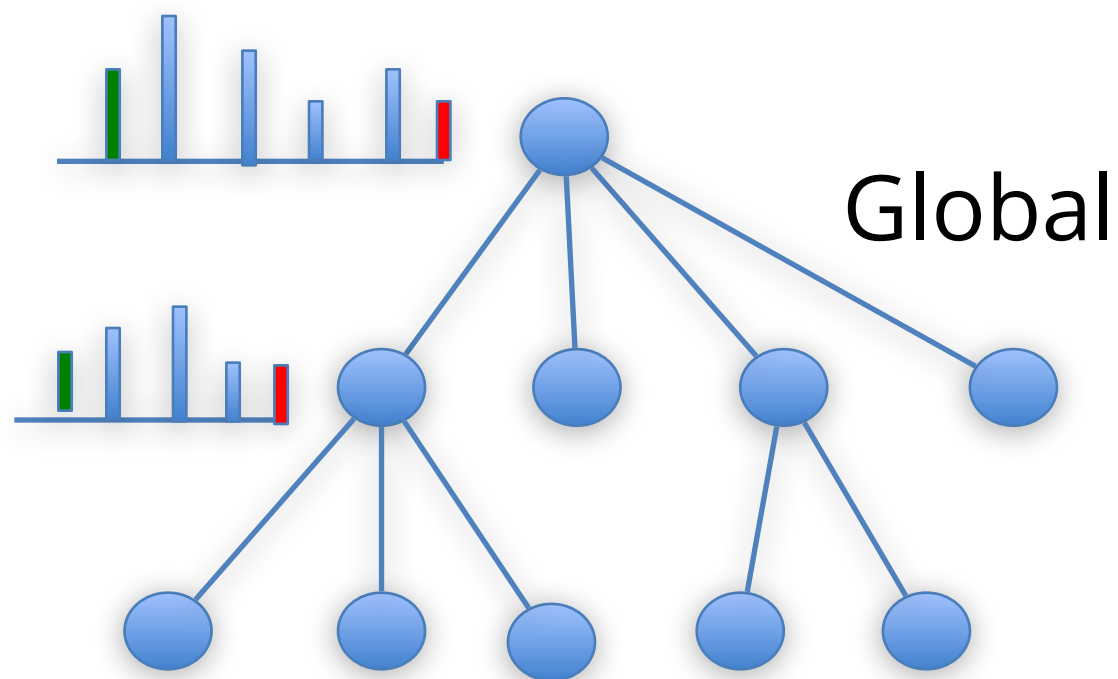
$$G_i \sim DP(G_0, \gamma') \text{ and } G_0 \sim DP(H, \gamma)$$

- Nested Chinese Restaurant Process (Blei et al. 2010)
 - (1) For each node t in the infinite tree draw a topic β_t independently.
 - (2) For each document d draw
 - (a) Draw a path c_d over the tree using the nCRP.
 - (b) Draw a distribution θ_d over levels in the tree using GEM(α_1, α_2).
 - (c) For all words in d draw a level t from θ_d and a corresponding word from β_t .
- Pachinko allocation (McCallum et al., 2010)
(use directed acyclic graph, often predefined)

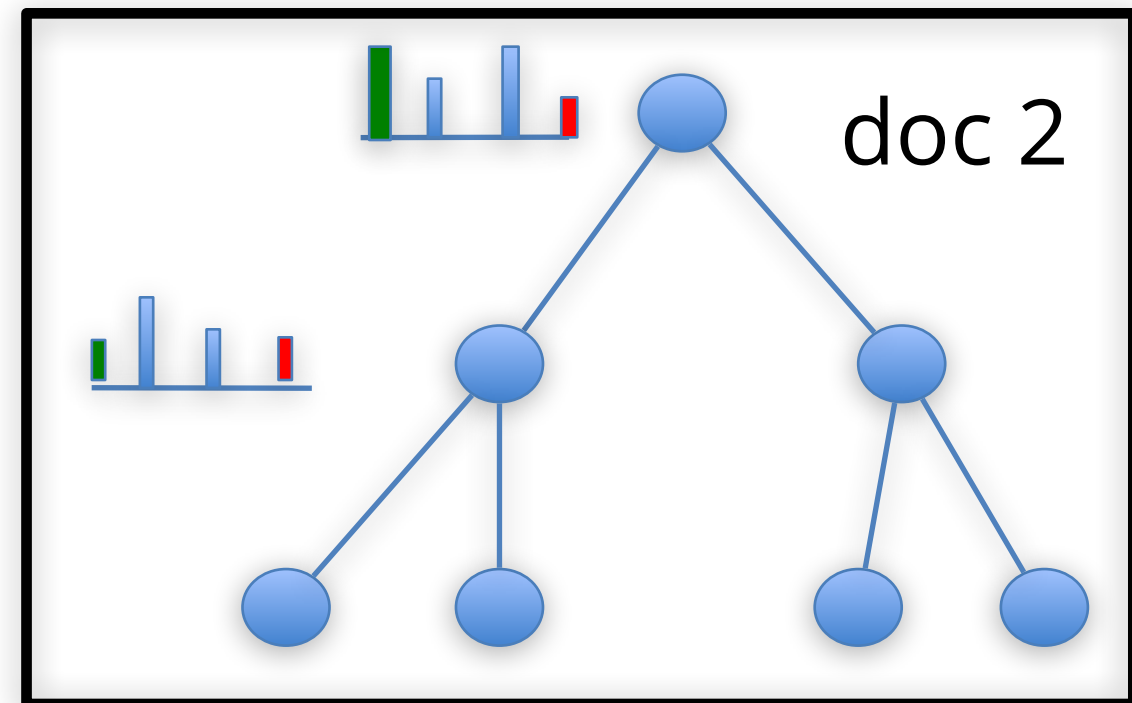
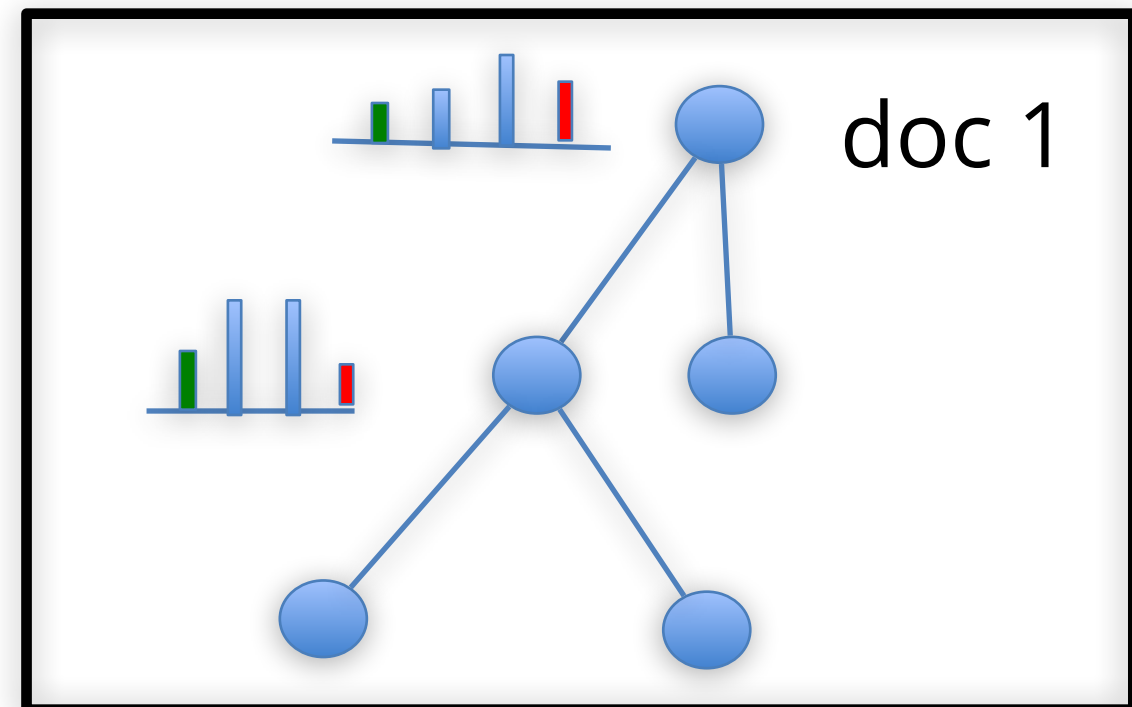
Variable resolution models

- Users have different levels of detail for preferences
(photography, Shostakovich, Bauhaus, -)
(Panasonic m43, classical music, -, NFL)
- Documents have different topics & levels of detail
(49ers, sports, and the Bay Area)
(Dirichlet process, machine learning, Twitter)
- Want tree distribution per object. Sharing of strength between different trees
- Nested Hierarchical Dirichlet Process (Paisley, Wang, Blei, Jordan, 2012)
- Nested Chinese Restaurant Franchise (Ahmed, Hong, Smola, 2013)

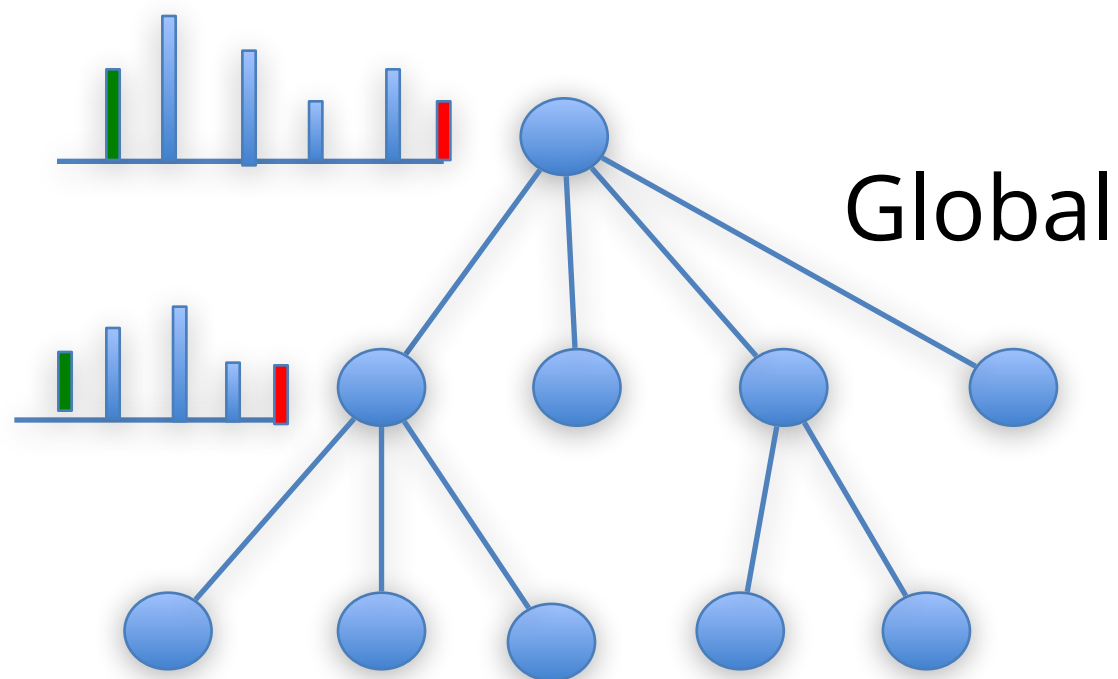
Generative Process



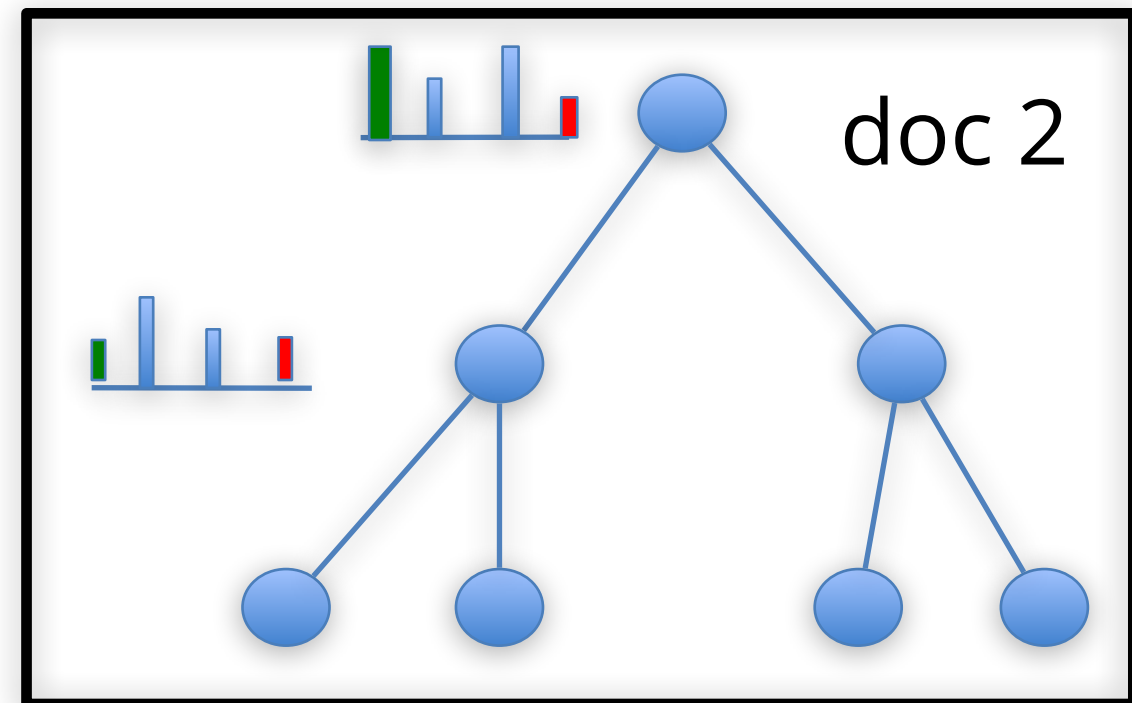
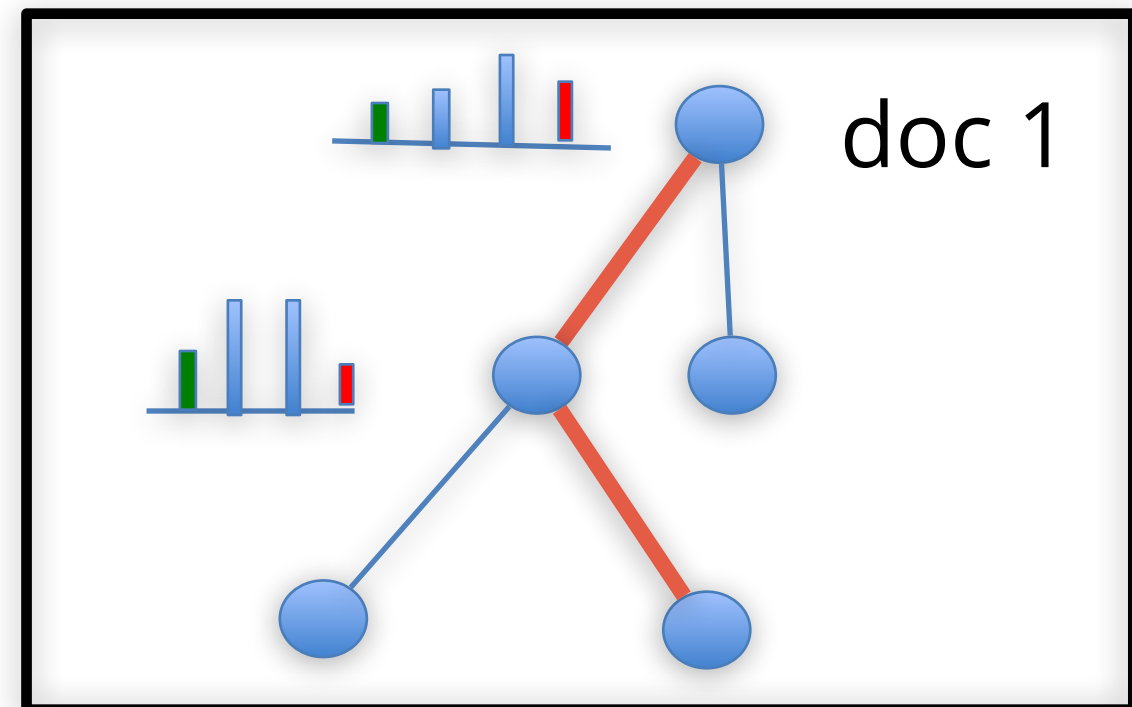
- for each document
 - for each word
 - select path in doc
 - if new in document then select from global
 - if new in global then add new path



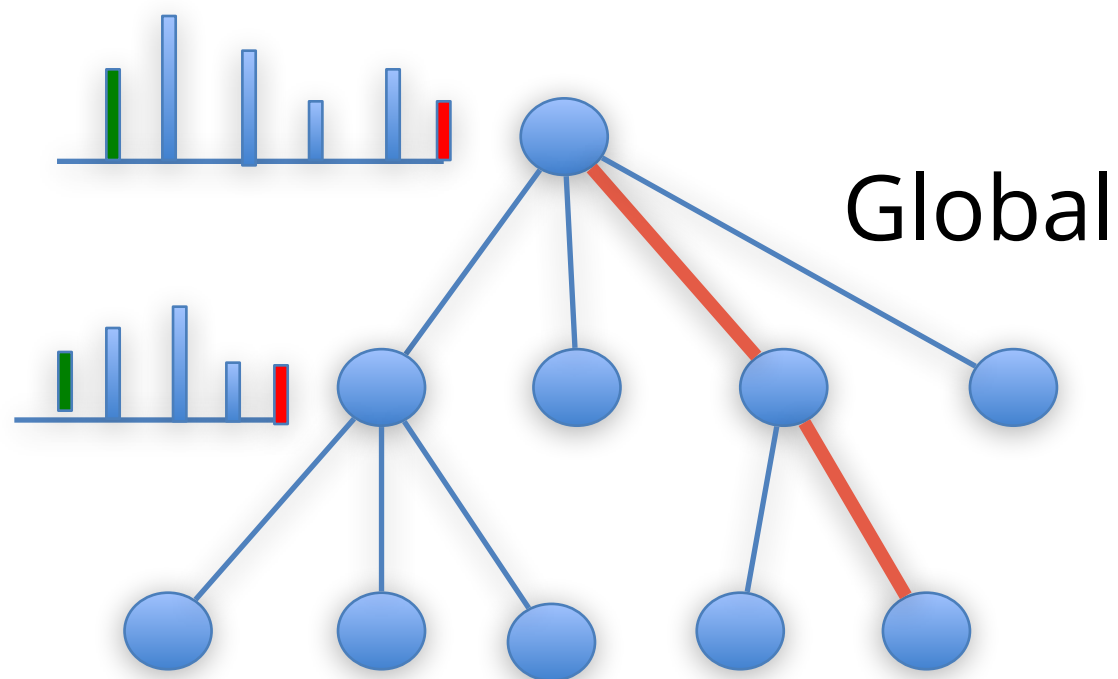
Generative Process



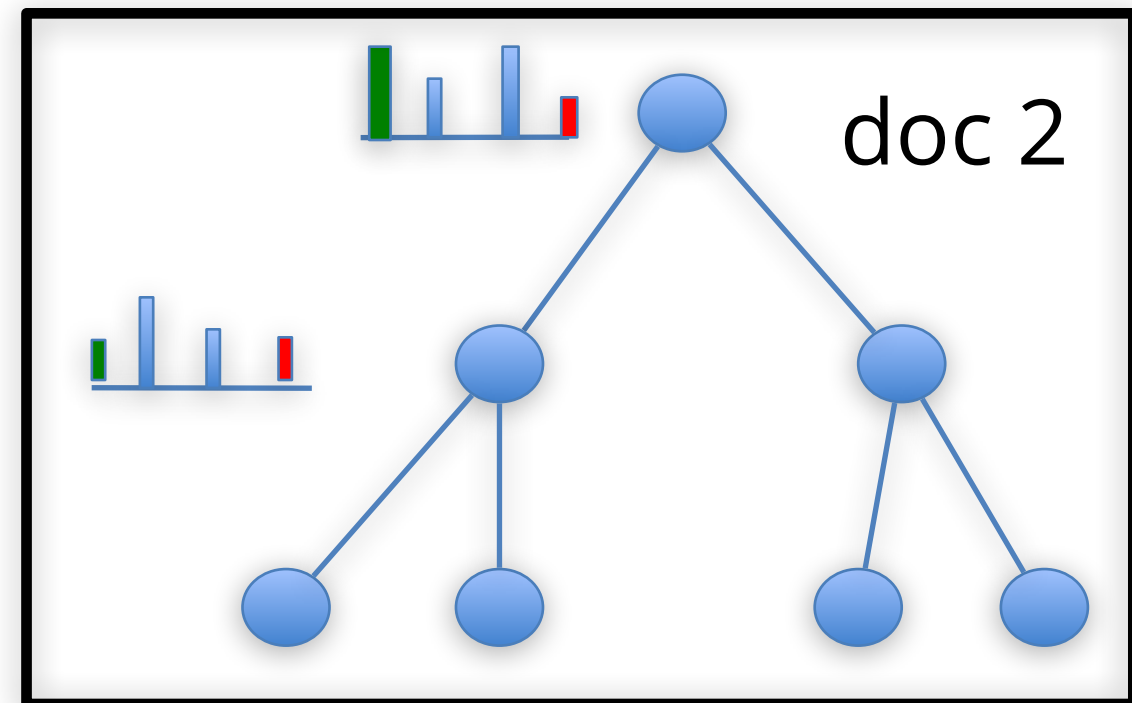
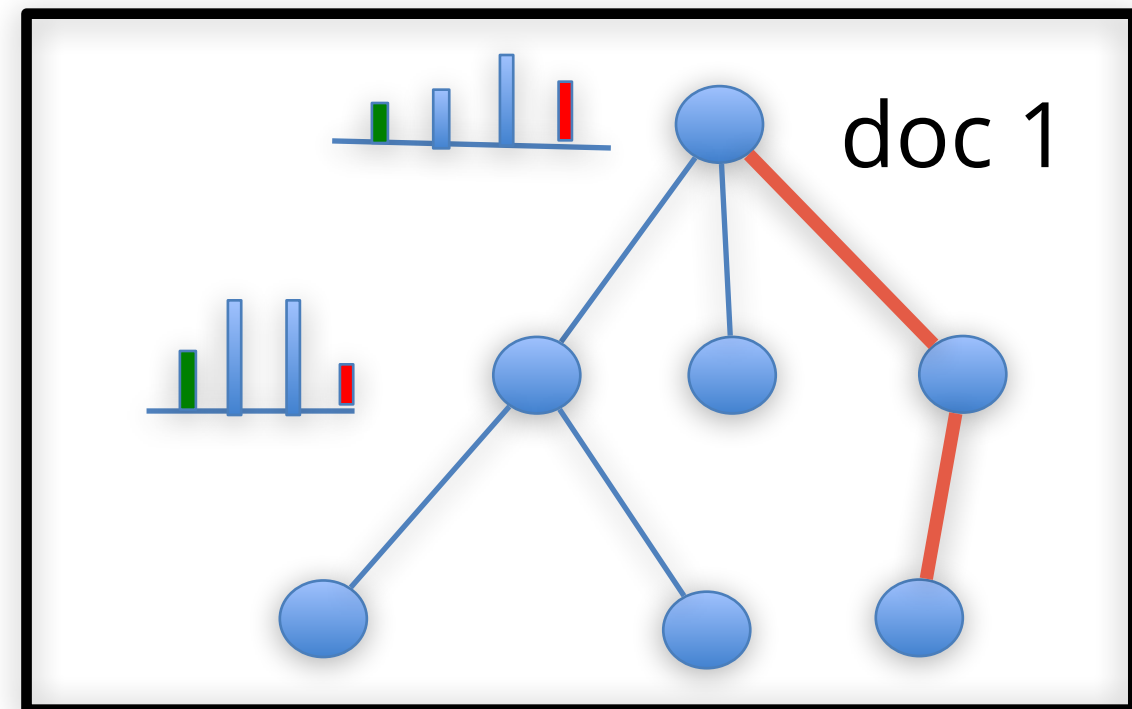
- for each document
 - for each word
 - select path in doc
 - if new in document then select from global
 - if new in global then add new path



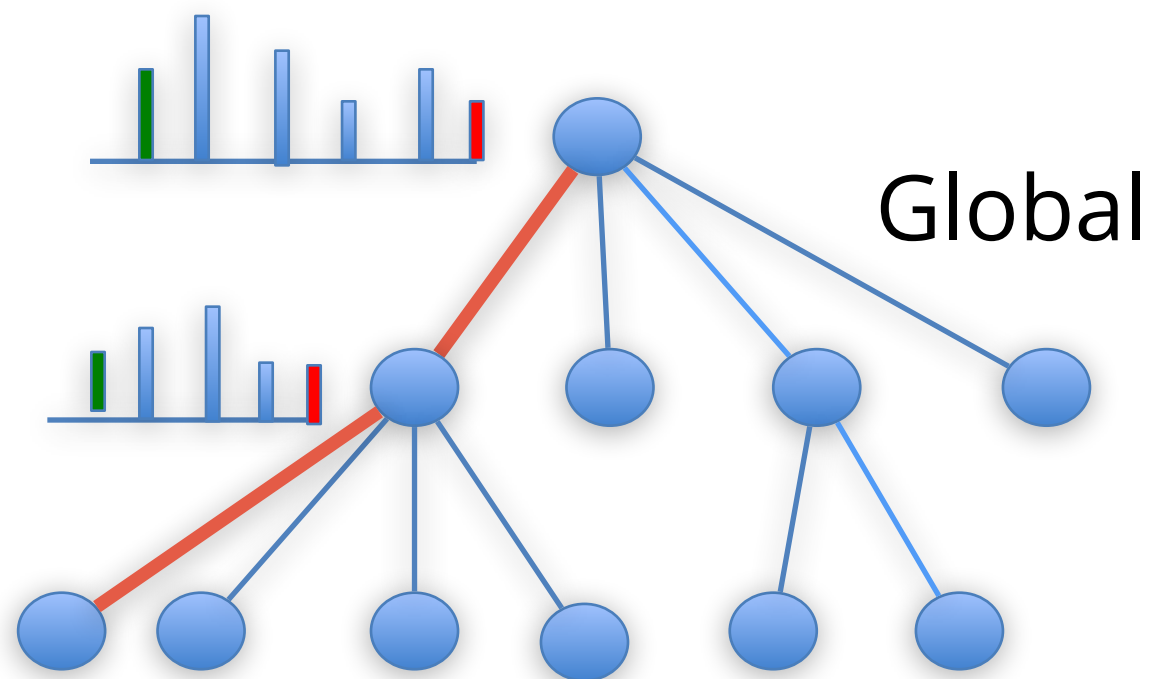
Generative Process



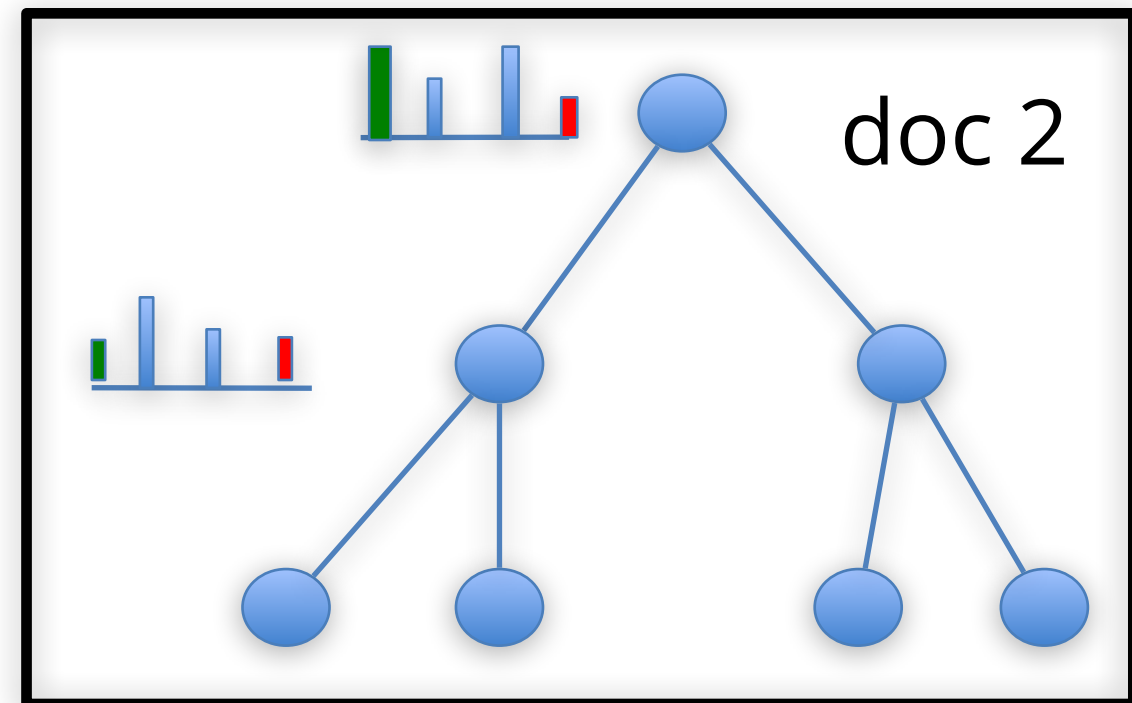
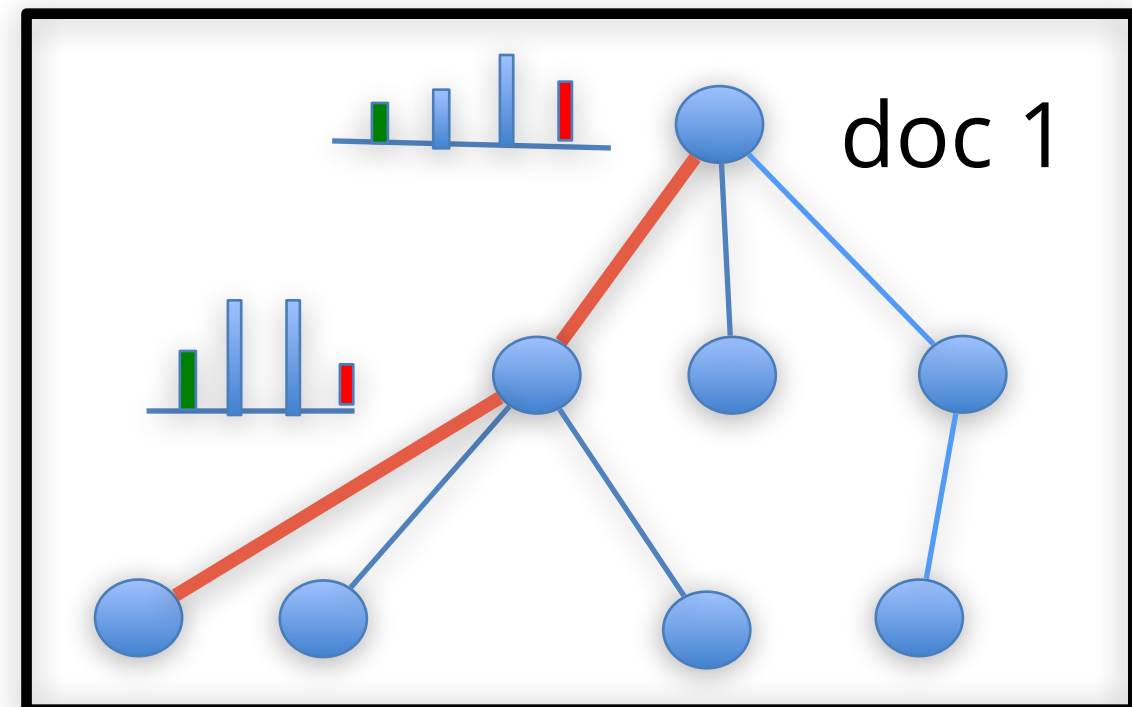
- for each document
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Generative Process



- for each document
 - for each word
 - select path in doc
 - if new in document then select from global
 - if new in global then add new path





Document Modeling

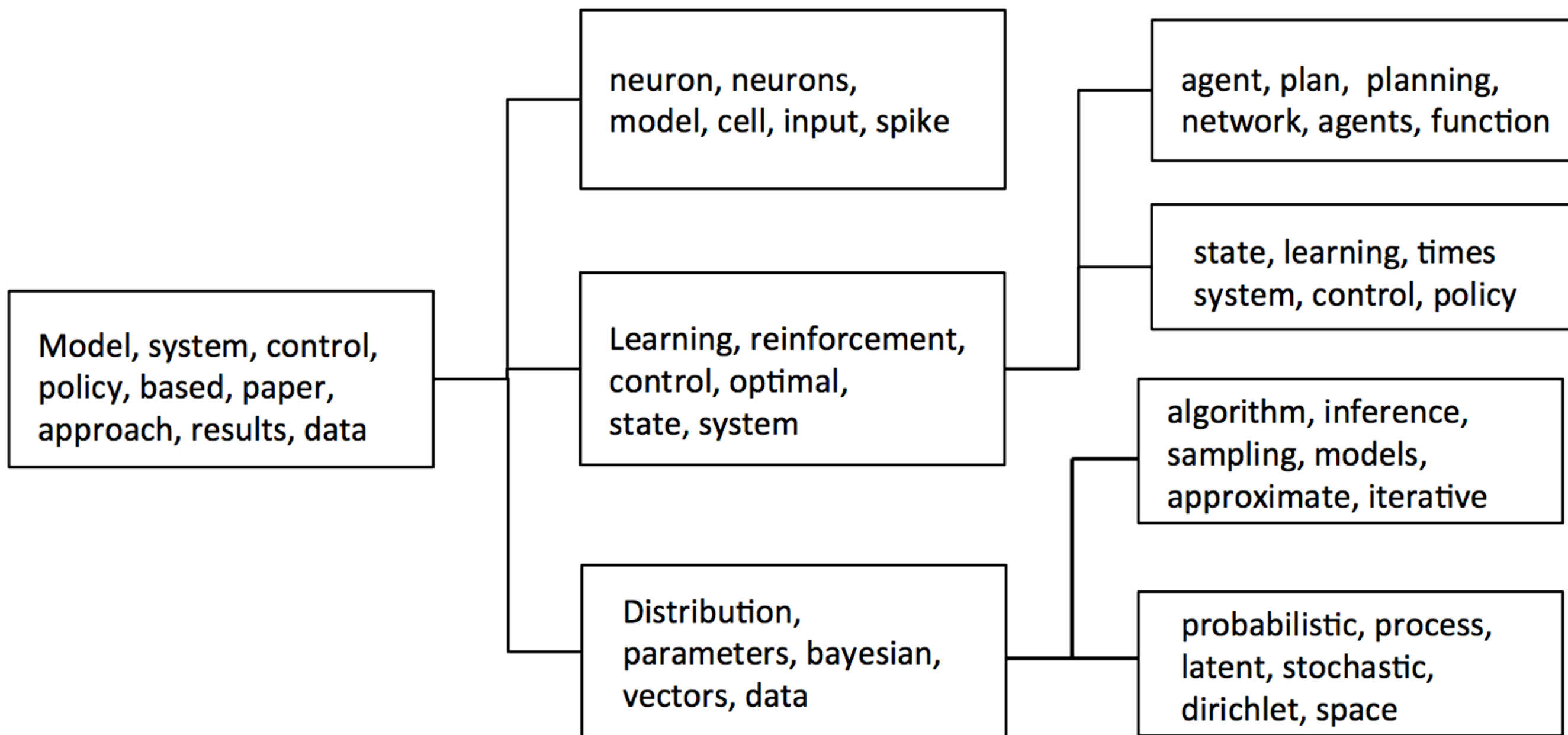
(Ahmed, Hong, Smola, 2012)

Generative Process

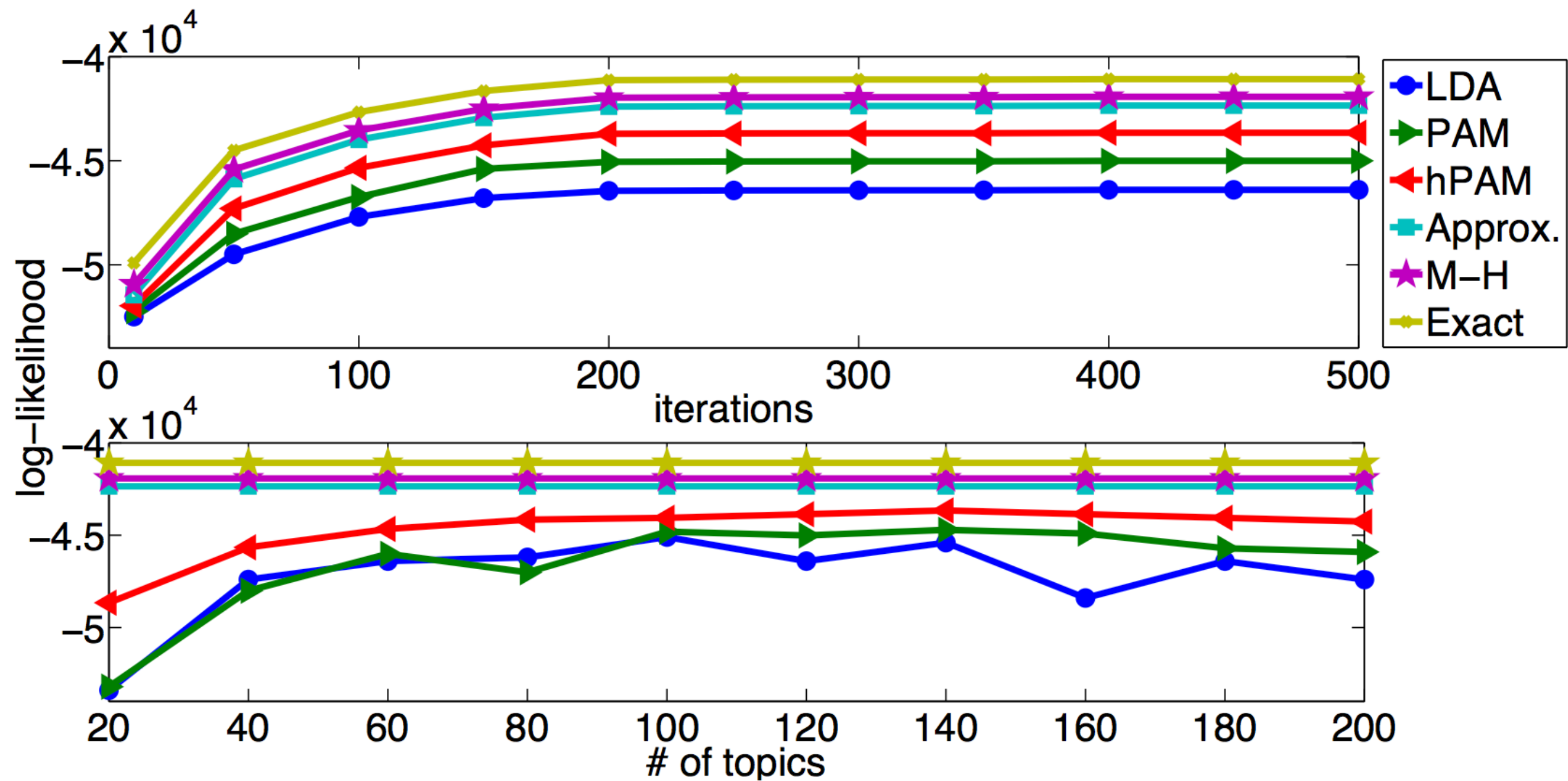
For each word i in document d :

- (a) Sample a node $v_{di} \sim \text{nCRF}(\gamma, \alpha, d)$.
- (b) If node $v_{d,i}$ is a *globally* new node then
 - i. $\phi_{v_{d,i}} \sim \text{Dir}(\omega \phi_{\pi(v_{d,i})})$
- (c) Sample word $w_{d,i} \sim \text{Multi}(\phi_{v_{d,i}})$.

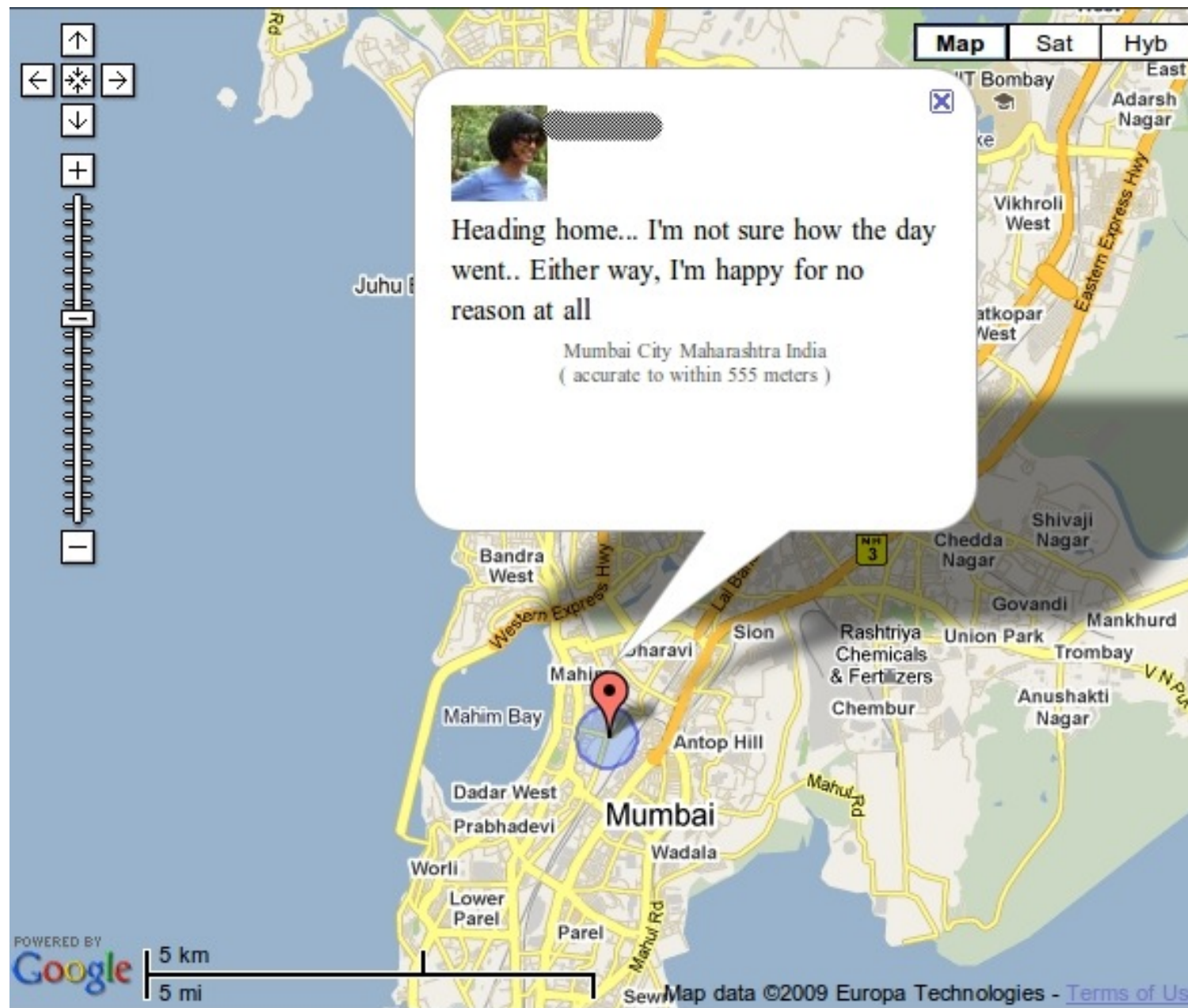
NIPS Corpus



NIPS Corpus



- Issue is sampling from hierarchy
Exact is very slow, Metropolis-Hastings somewhat faster, Approximation a la Wallach et al.



Location Modeling

(Ahmed, Hong, Tsioutsoulis, Smola 2013)

Data

- **Tweets**
 - 140 character string
 - User ID
 - Time
 - Location (on small subset of data)
- **Location estimation**
Geographical targeting, content filtering
- **User profiling**
Locations, interests

Modeling assumptions

User locations at variable resolution



Modeling assumptions

access advantage algorithm app assign
attributes bandwidth basis billion bound build case check
coefficients common compute converges data design different discuss disk
distributed efficient example expansion facebook faster
functions gaussian general give given graphs
hash idea inserted instance isomorphism iteration keeping
kernel keys kitchen learning linear load machine
mail map matrix means memory method models network
note number open optimization owns paper
parameters permalink possible problem process projection
provides quite random rather really releasing reproducibility require
research segment server several similar simply sinks store strategy
synchronize things times tweet uniformly unique updates used user value
variables vertex vertices whenever work

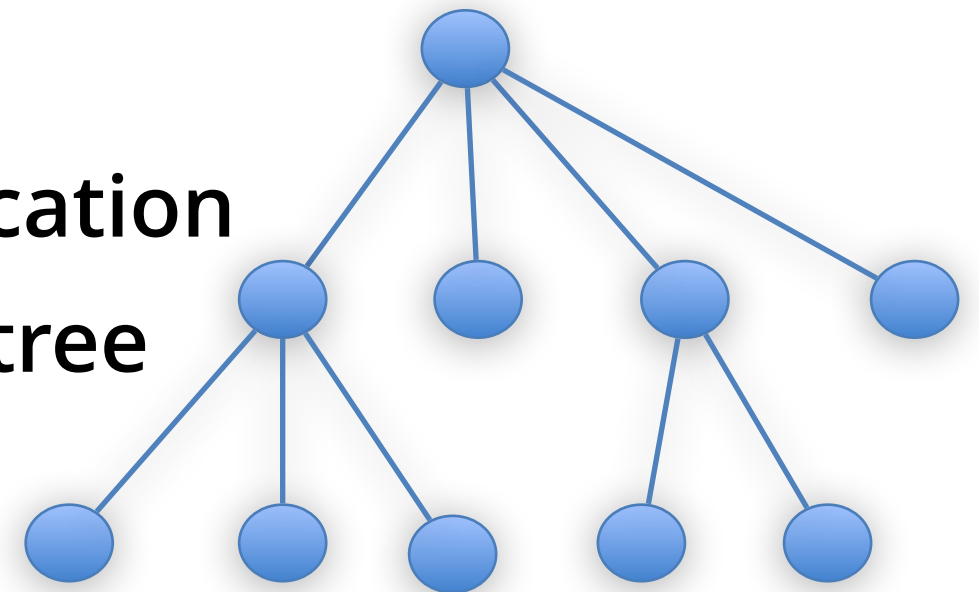
tagcloud on
blog.smola.org

Modeling assumptions

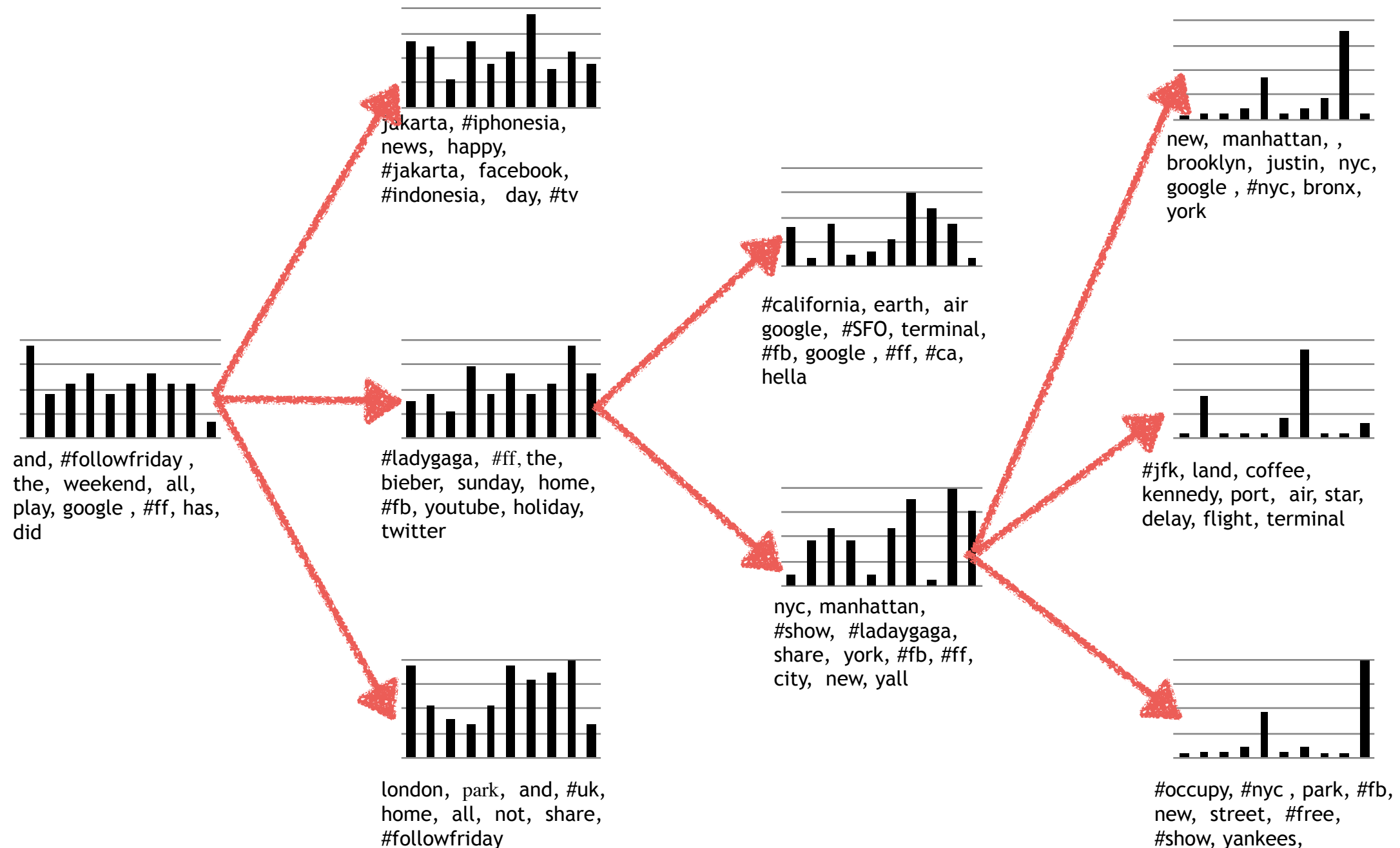
- User location has variable resolution (places, neighborhoods, cities)
- User content has variable detail (entities, stories, topics)
- Geographical affinity of location and topic (*I landed in SFO* probably means airport)
- Hierarchical model for text and location

Hierarchical modeling

- Arrange regions in a tree
 - Each node is a region
 - Each node models both text and location
- Cascade these distributions over the tree
 - Tree Gaussian MRF for locations
 - HDP for text
- Each user as a distribution over this region-tree



Topic hierarchy



Hierarchical modeling

- Arrange regions in a tree
 - Each node is a region
 - Each node models both text and location
- Cascade these distributions over the tree
 - Tree Gaussian MRF for locations

$$\mu_r \sim \mathcal{N}(\mu_{\pi(r)}, \Sigma_{\pi(r)})$$

$$\Sigma_r = \frac{1}{\text{level}(r)} \Sigma_0.$$

- Topic preference

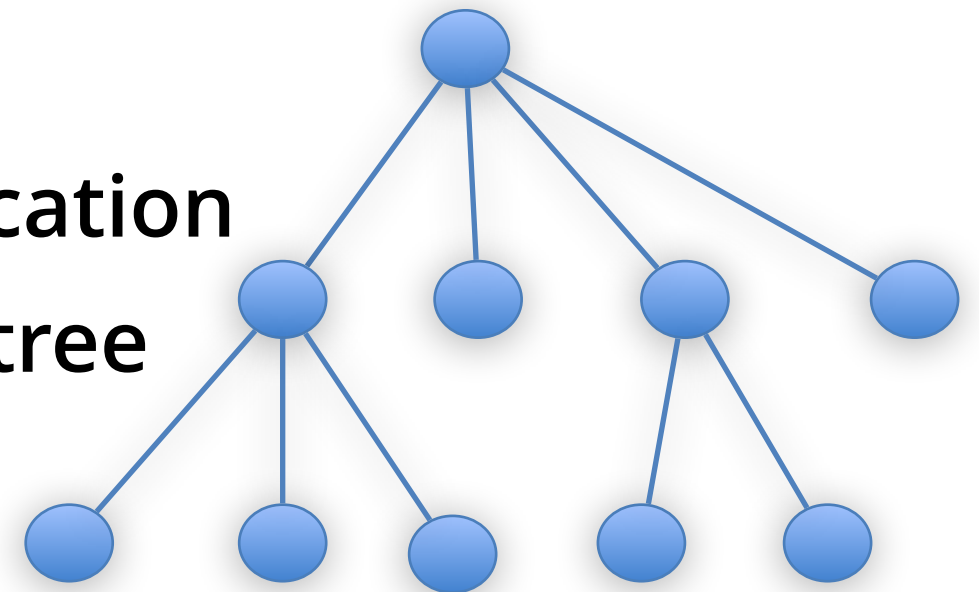
$$\theta_0 \sim \text{Dir}(\beta)$$

$$\theta_r \sim \text{Dir}(\lambda \theta_{\pi(r)})$$

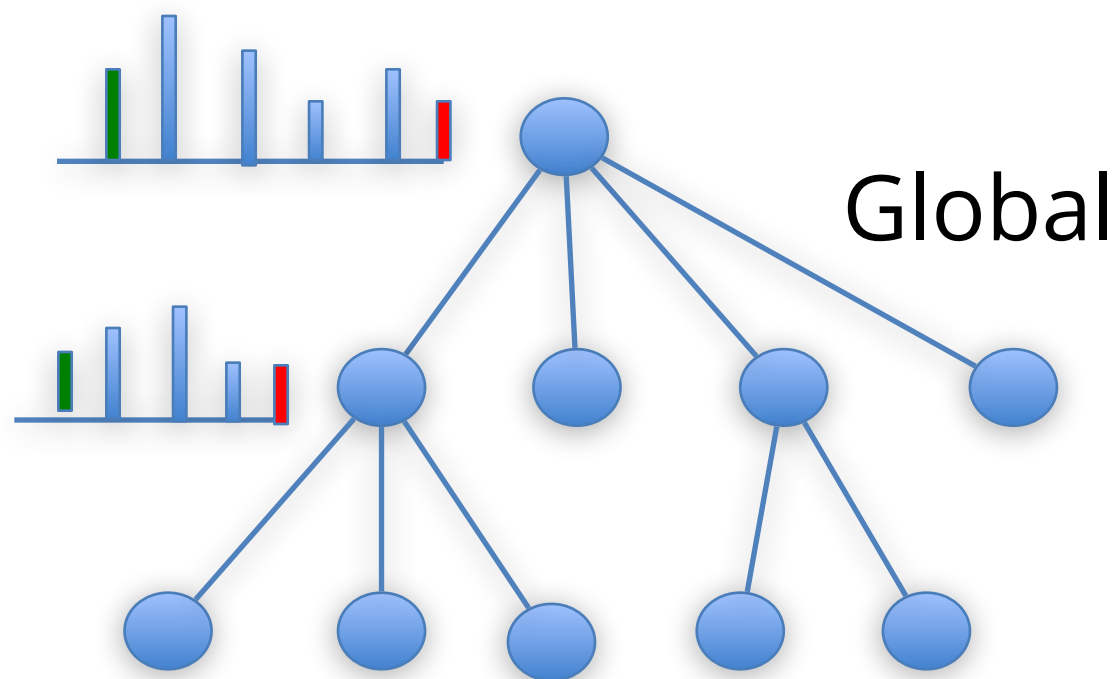
- Language model

$$\phi_0 \sim \text{Dir}(\eta).$$

$$\phi_r \sim \text{Dir}(\omega \phi_{\pi(r)})$$

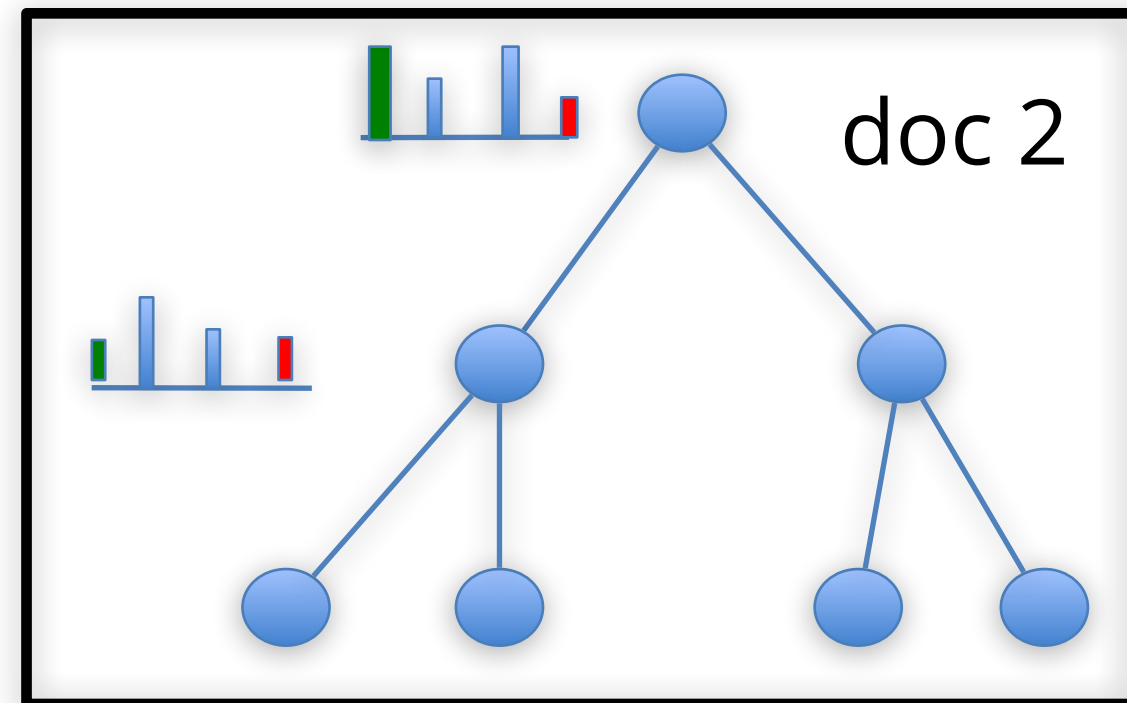
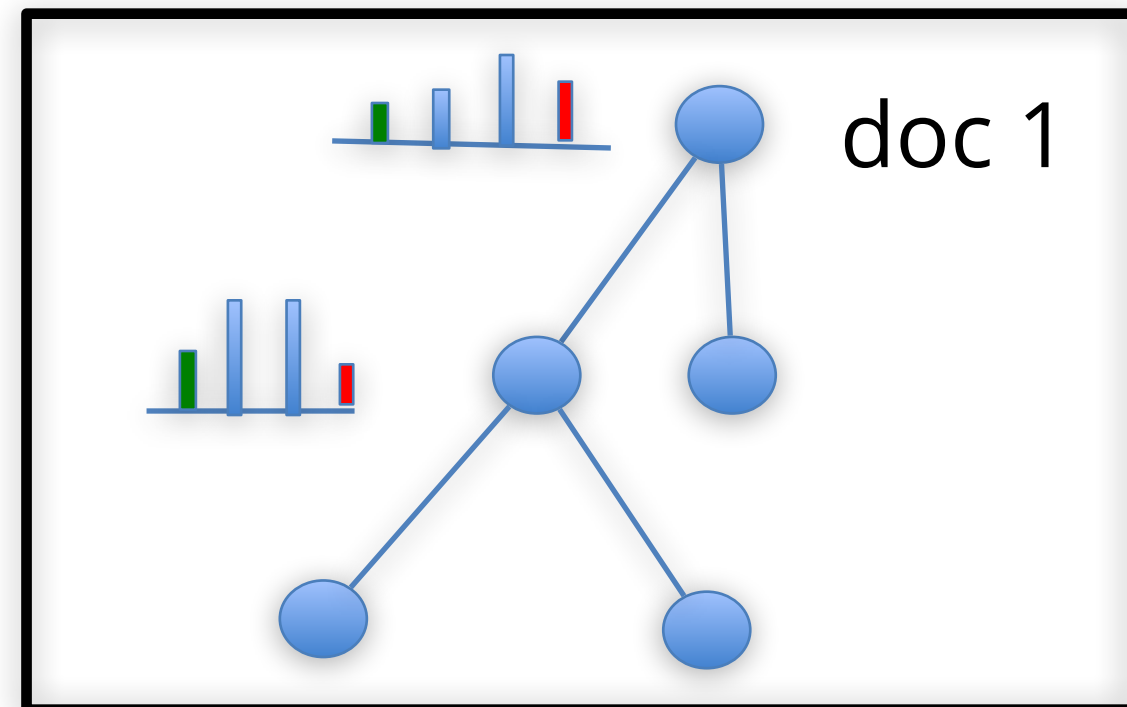


Generative Process



For each tweet d written by each user u :

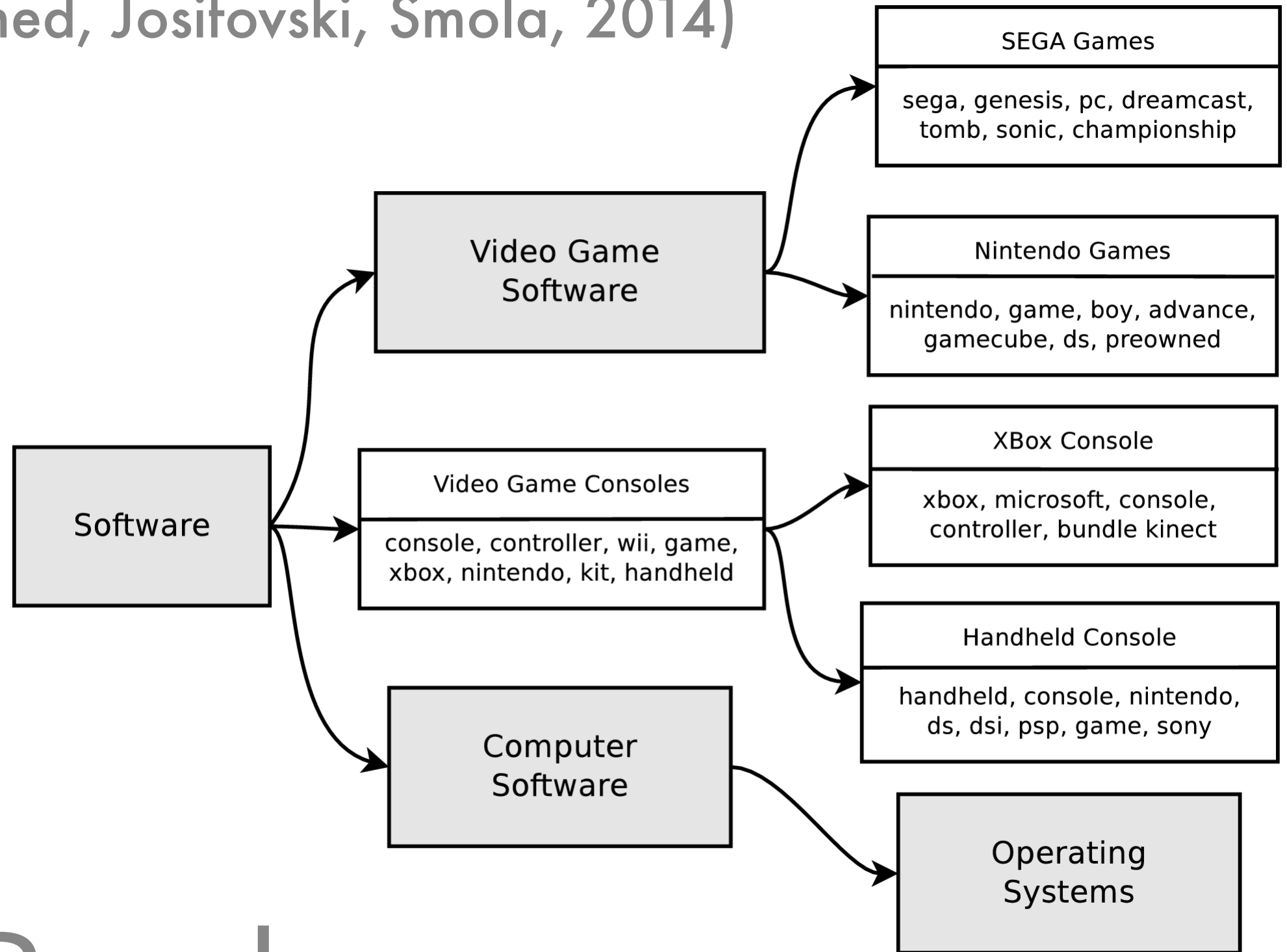
- (a) Sample a node $r_d \sim \text{nCRF}(\gamma, \alpha, u)$.
- (b) If node r_d is a *globally* new node then
 - i. $\mu_{r_d} \sim \mathcal{N}(\mu_{\pi(r_d)}, \Sigma_{\pi(r_d)})$
 - ii. $\phi_{r_d} \sim \text{Dir}(\omega \phi_{\pi(r_d)})$
 - iii. $\theta_{r_d} \sim \text{Dir}(\lambda \theta_{\pi(r_d)})$
- (c) Sample a location $l_d \sim \mathcal{N}(\mu_{r_d}, \Sigma_{r_d})$.
- (d) For each word $w_{(d,i)}$:
 - i. Sample a topic index $z_{(d,i)} \sim \text{Multi}(\theta_{r_d})$.
 - ii. Sample word $w_{(d,i)} \sim \text{Multi}(\bar{\Pi}_{z_{(d,i)}})$.



Results

Results on DS1	Avg. Error	Regions
(Yin et al., 2011)	150.06	400
(Hong et al., 2012)	118.96	1000
Approx.	91.47	2254
MH	90.83	2196
Exact	83.72	2051
Results on DS2	Avg. Error	Regions
(Eisenstein et al., 2010)	494	
(Wing & Baldridge, 2011)	479	
(Eisenstein et al., 2011)	501	
(Hong et al., 2012)	373	100
Approx.	298	836
MH	299	814
Exact	275	823

(Zhang, Ahmed, Josifovski, Smola, 2014)

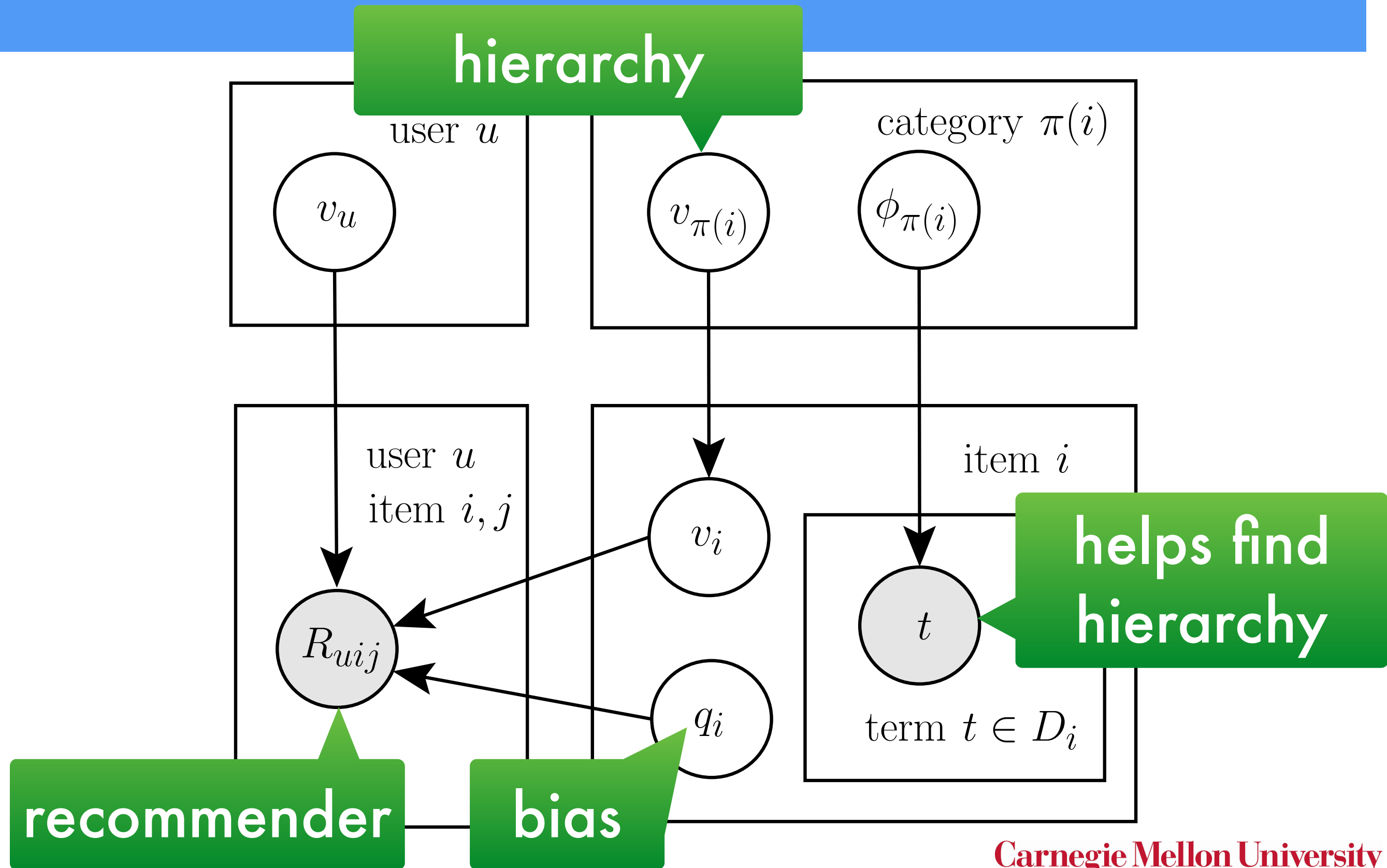


Purchase Recommendation

The Challenge

- Lots of (Co)purchase information per user
- Item metadata (brand, price, text)
- Recommend items
- Human generated taxonomy (modest cover)
 - Expensive to add items
 - Not always accurate for purchase
(hardware->(ps3, xbox, wii),
software->(ps3 games, xbox games, wii games))
- Want to recycle it if we have it

The model

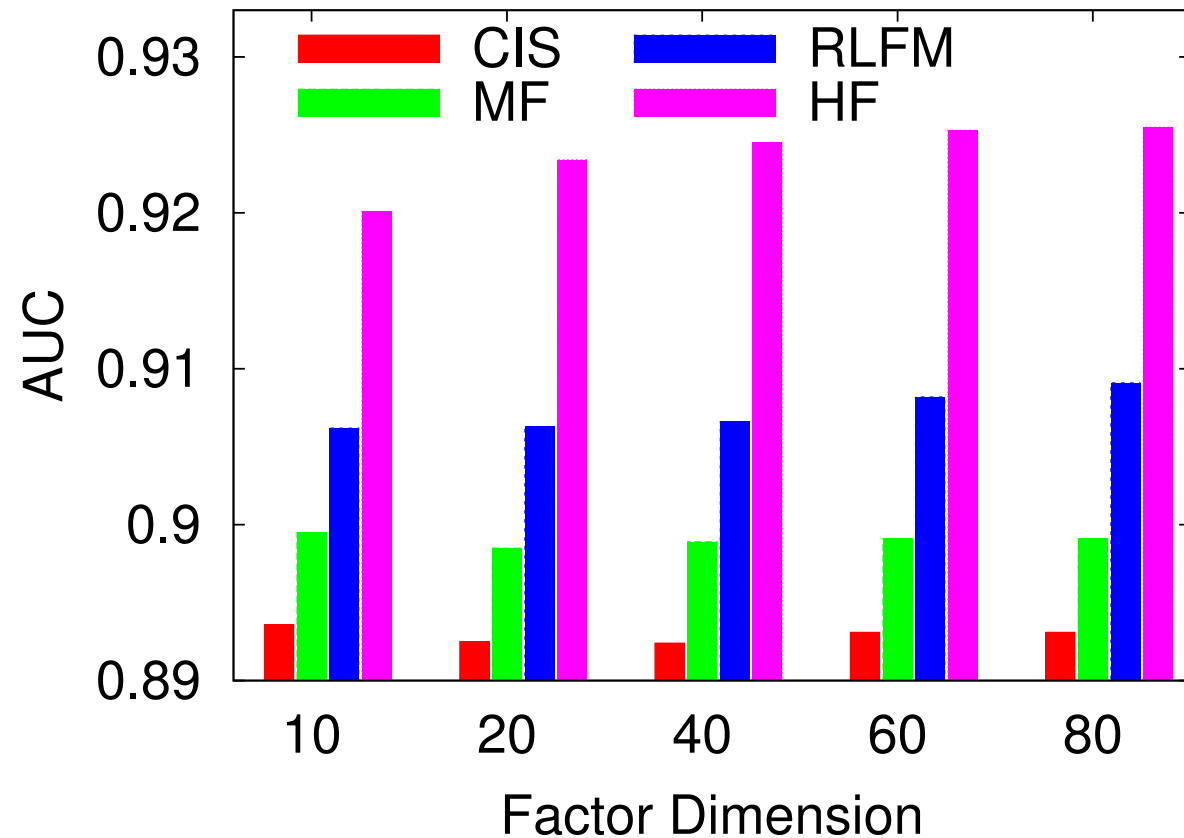


Inference

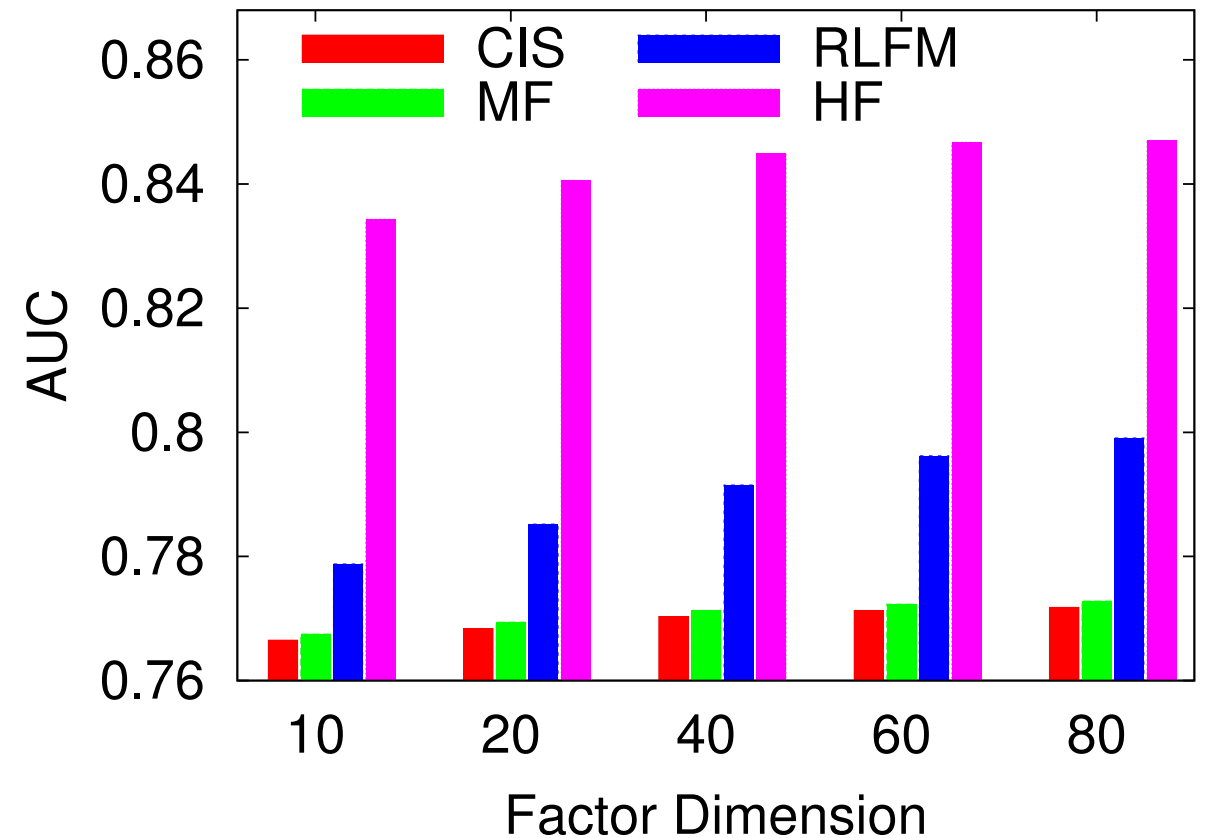
- Collapsed Gibbs sampling for hierarchy
- Stochastic gradient ascent to maximize recommendation likelihood
 - BPR style recommendation
 - Hierarchical parameter inheritance
- Incorporate existing human-generated ontology as prior on hierarchy

Results

dense data

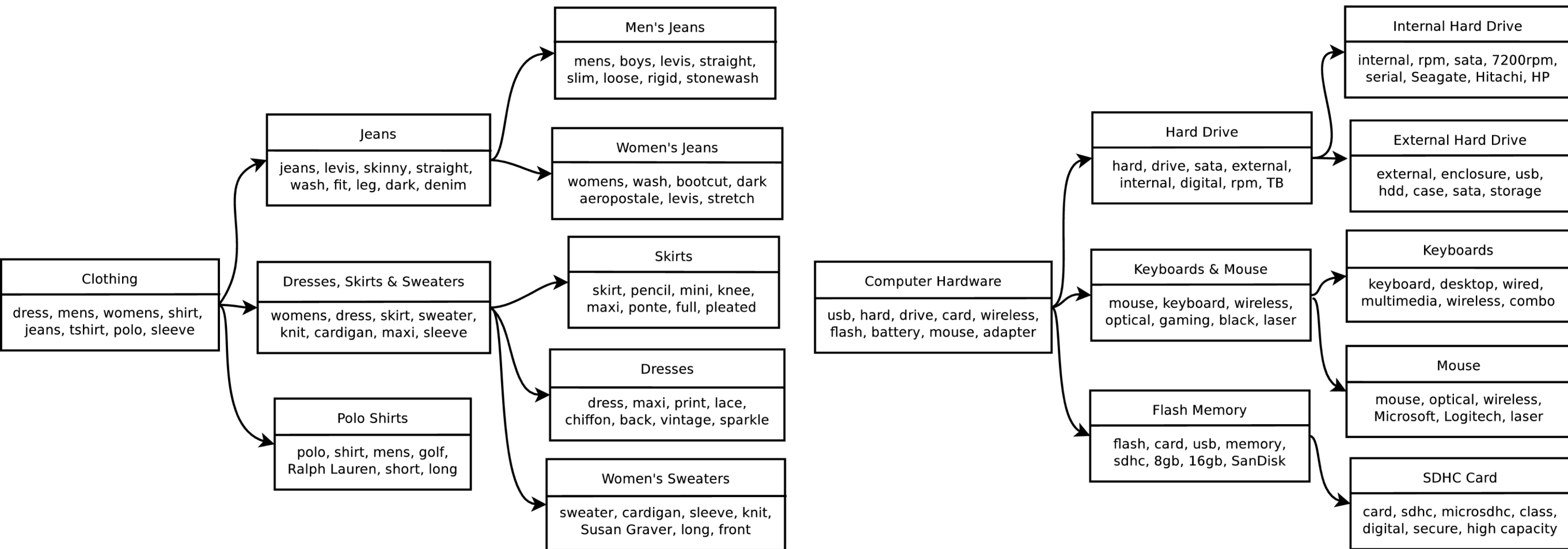


sparse data (singletons)



Item Frequency	1 - 10	11 - 30	31 - 100	101 - 300	301 - 1000	> 1000	Overall
MF	0.453	0.878	0.961	0.987	0.996	0.9996	0.899
CIS	0.444	0.860	0.948	0.982	0.995	0.9996	0.893
RLFM	0.529	0.863	0.957	0.987	0.996	0.9995	0.908
HF	0.617*	0.891*	0.965*	0.989	0.997	0.9996	0.925*

Inferred taxonomy



Migrant controls are just big con
SEE PAGE FIVE

WIN A NIKON DIGITAL CAMERA
WORTH £500 EACH SET
PLUS A DIGITAL PHOTO FRAME
FIVE SETS TO BE WON
SEE PAGE 22

INVEST 48 hours - Sport Page 17

ONLAHOR VICES BACK
from England snub - Page 17

BIRMINGHAM POST
REGIONAL NEWSPAPER OF THE YEAR
MONDAY, AUGUST 18, 2008 70p
Five die as aircraft collide
...ing to land at Coventry

THE Sun
30p
STILL TIME TO JOIN IN
EURO HOLDS FROM £9.50
TUESDAY PAGE 22

E: Baby-faced father of little Maisie

DAD AT

The Guardian
Alliance woe
helps Labour
poll surge
Dogenhouse Euro-threat

the guardian
Simon Schama: America will never be the same again
Backlash over Blair's school revolution
City academy plans condemned by ex-education secretary Morris
Betrayal: Second night of rioting
Column five: The shape of things to come

STAR
Friday June 26 2008
47.40 (inc. VAT)
ESSENTIAL GUIDE TO GOING OUT: AC/

FINANCIAL TIMES
MONDAY
celebrate the
SPECIAL REPORT INCLUDING THE FT RANKING OF THE WORLD'S

DAILY Mirror
WEDNESDAY 10 SEP 2008 24p
REBECCA'S TV BOMBSHELLS

METRO
Tuesday, Oct 28, 2008
'Online hoodies' talking

Beckham has got ** on his ******
What he wrote
After sex he fed me strawberries
Posh pictures are

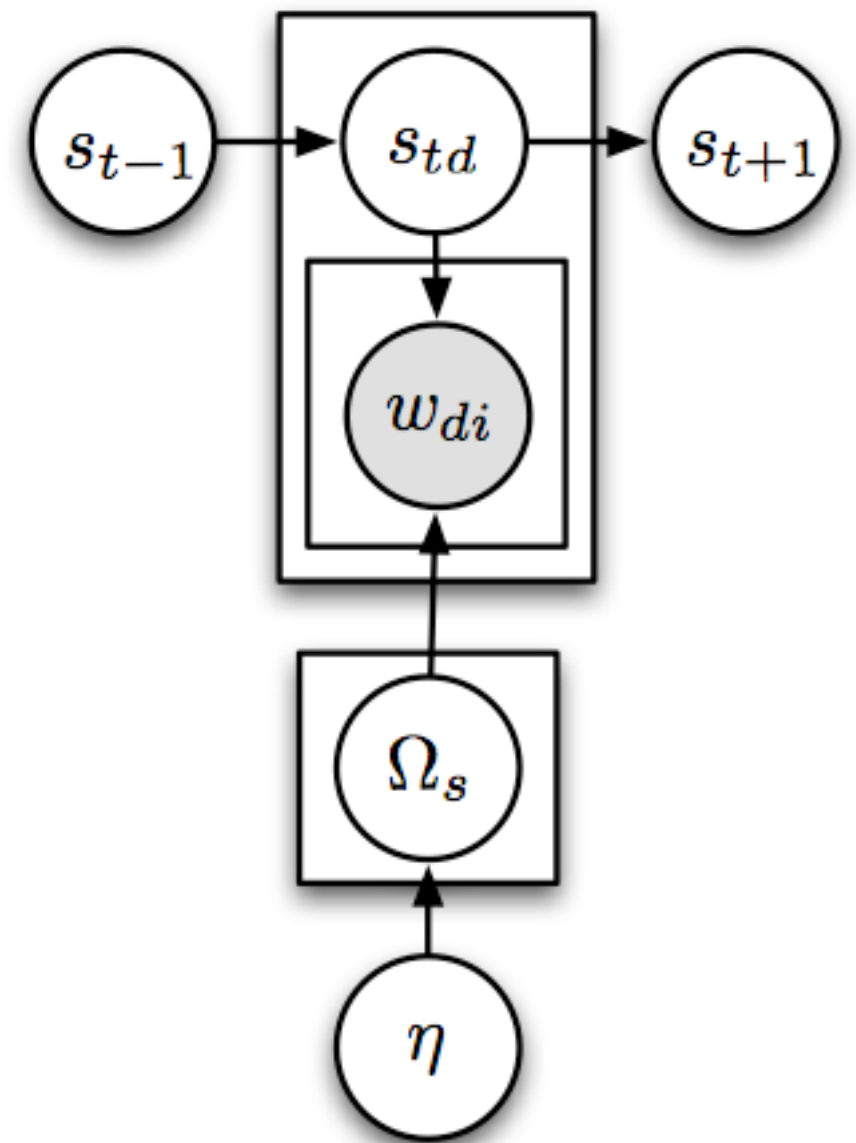
THE TIMES
No 68700 • MONDAY MAY 15 2006 • NEWSPAPER OF THE YEAR
How to survive a nightmare boss

News Stream

- Over 1 high quality news article per second (many orders of magnitude more for UGC)
- Multiple sources (Reuters, AP, CNN, ...)
- Same story from multiple sources
- Stories are related
- Goals
 - Aggregate articles into a storyline
 - Analyze the storyline (topics, entities)

Clustering / RCRP

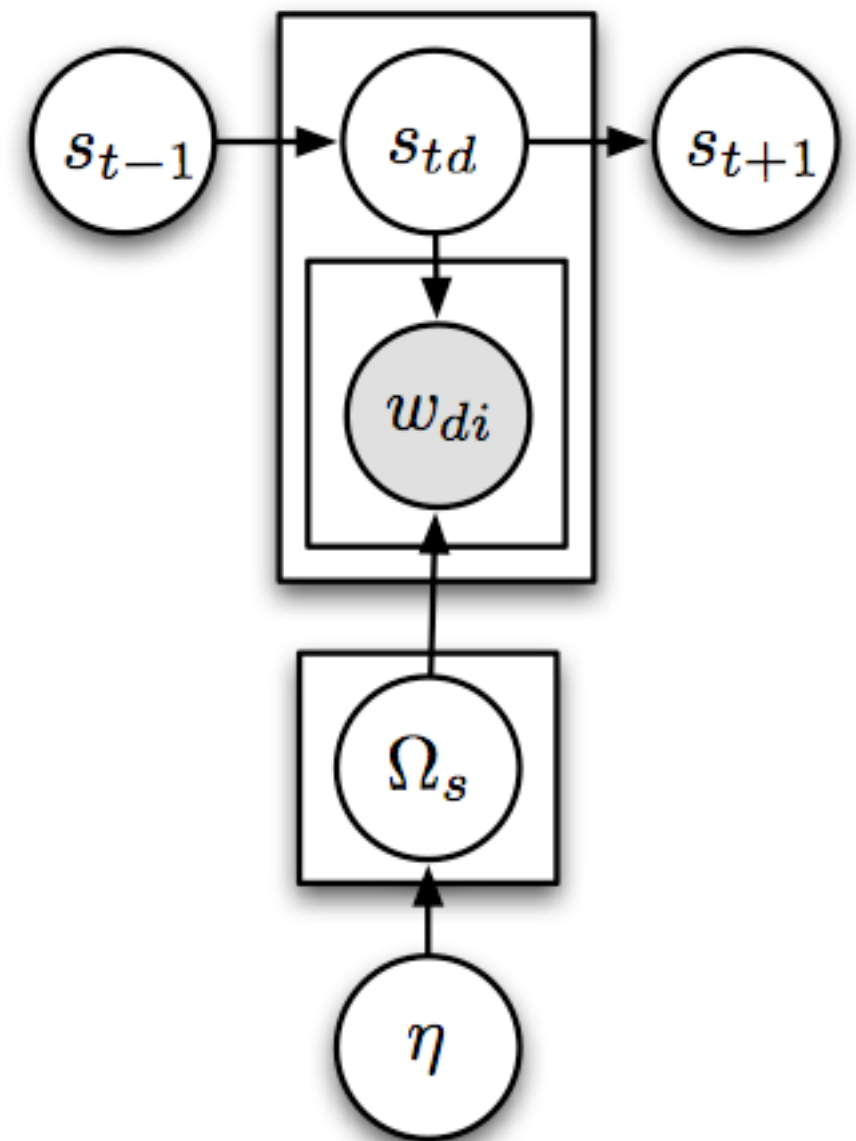
- Assume active story distribution at time t
 - Draw story indicator
 - Draw words from story distribution
 - Down-weight story counts for next day
- Ahmed & Xing, 2008



Clustering / RCRP

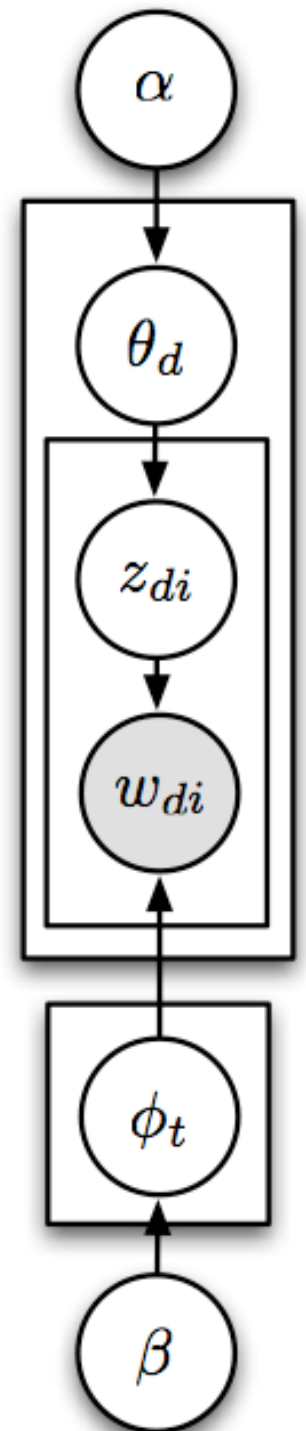
- Assume active story distribution at time t
- Draw story indicator
- Draw words from story distribution
- Down-weight story counts for next day
Ahmed & Xing, 2008

- Pro
 - Nonparametric model of story generation
 - No fixed number of stories
 - Efficient inference via collapsed sampler
- Con
 - We learn nothing!
 - No content analysis



Latent Dirichlet Allocation

- Generate topic distribution per article
 - Draw topics per word from topic distribution
 - Draw words from topic specific word distribution
- Blei, Ng, Jordan, 2003



Latent Dirichlet Allocation

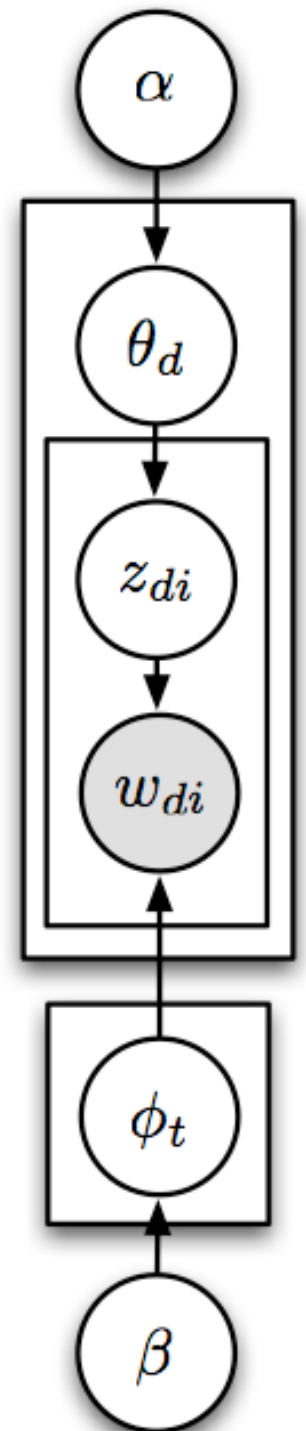
- Generate topic distribution per article
- Draw topics per word from topic distribution
- Draw words from topic specific word distribution
Blei, Ng, Jordan, 2003

- Pro

- Topical analysis of stories
- Topical analysis of words (meaning, saliency)
- More documents improve estimates

- Con

- No clustering





?

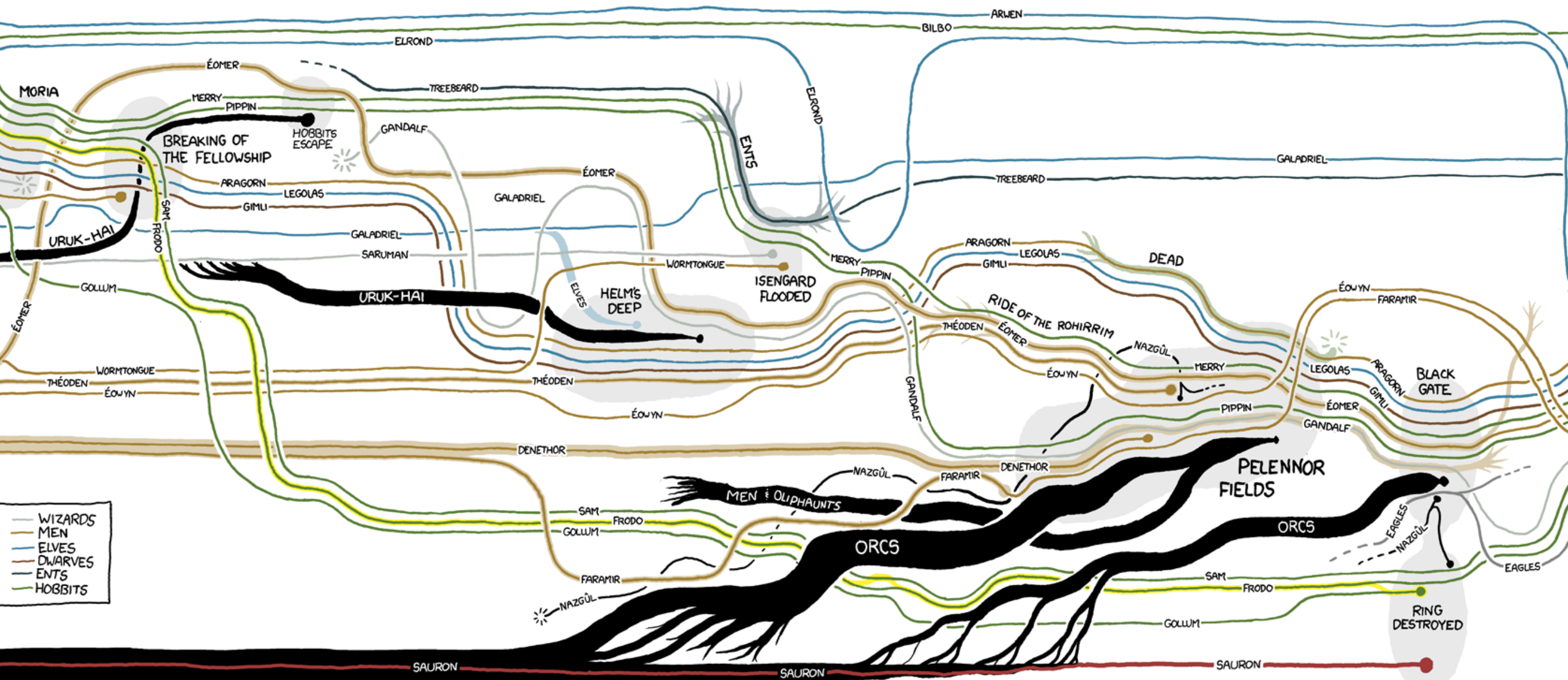


More Issues

- **Named entities are special, topics less**
(e.g. Tiger Woods and his mistresses)
- **Some stories are strange**
(topical mixture is not enough - dirty models)
- **Articles deviate from general story**
(Hierarchical DP)

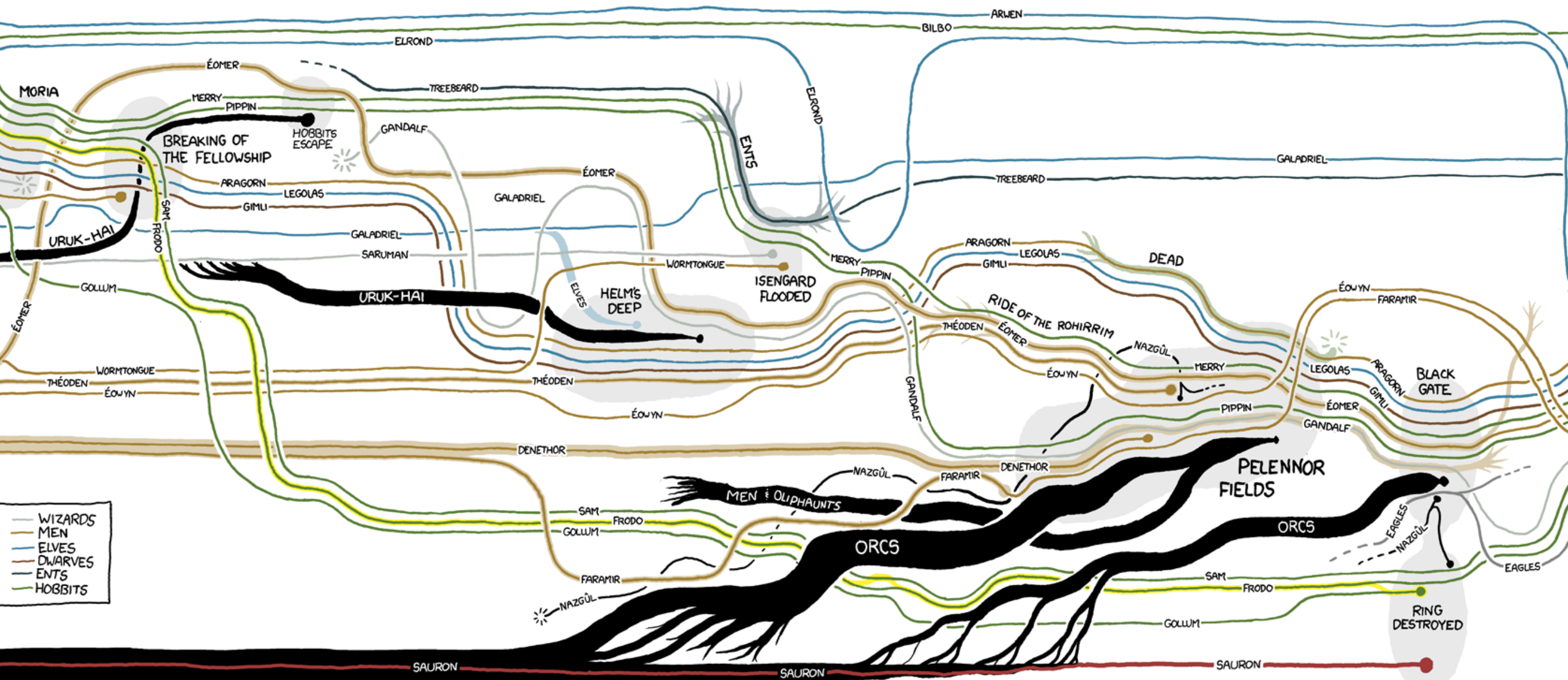
THESE CHARTS SHOW MOVIE CHARACTER INTERACTIONS.
THE HORIZONTAL AXIS IS TIME. THE VERTICAL GROUPING OF THE
LINES INDICATES WHICH CHARACTERS ARE TOGETHER AT A GIVEN TIME

LORD OF THE RINGS

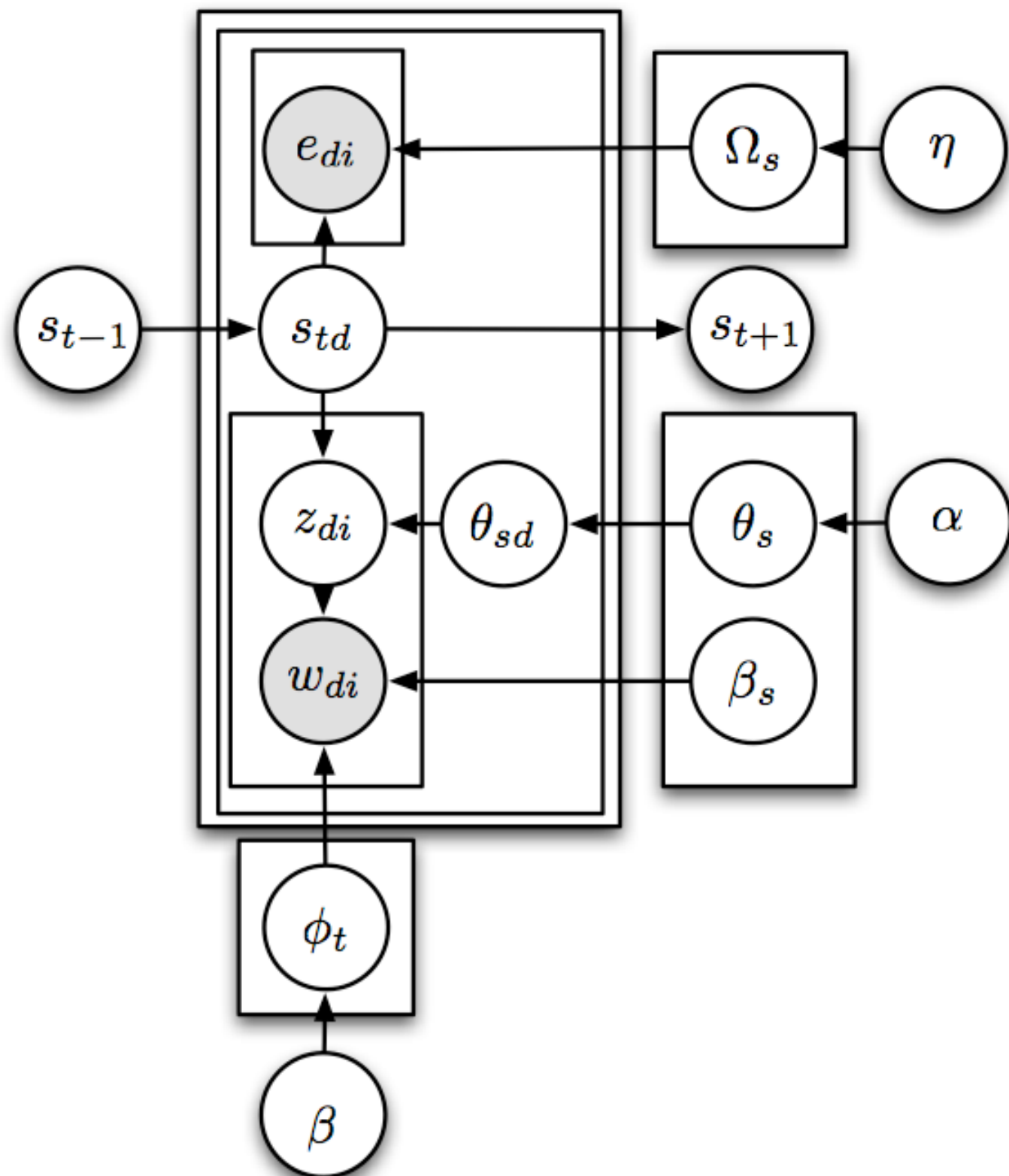


THESE CHARTS SHOW MOVIE CHARACTER INTERACTIONS.
THE HORIZONTAL AXIS IS TIME. THE VERTICAL GROUPING OF THE
LINES INDICATES WHICH CHARACTERS ARE TOGETHER AT A GIVEN TIME

Storylines

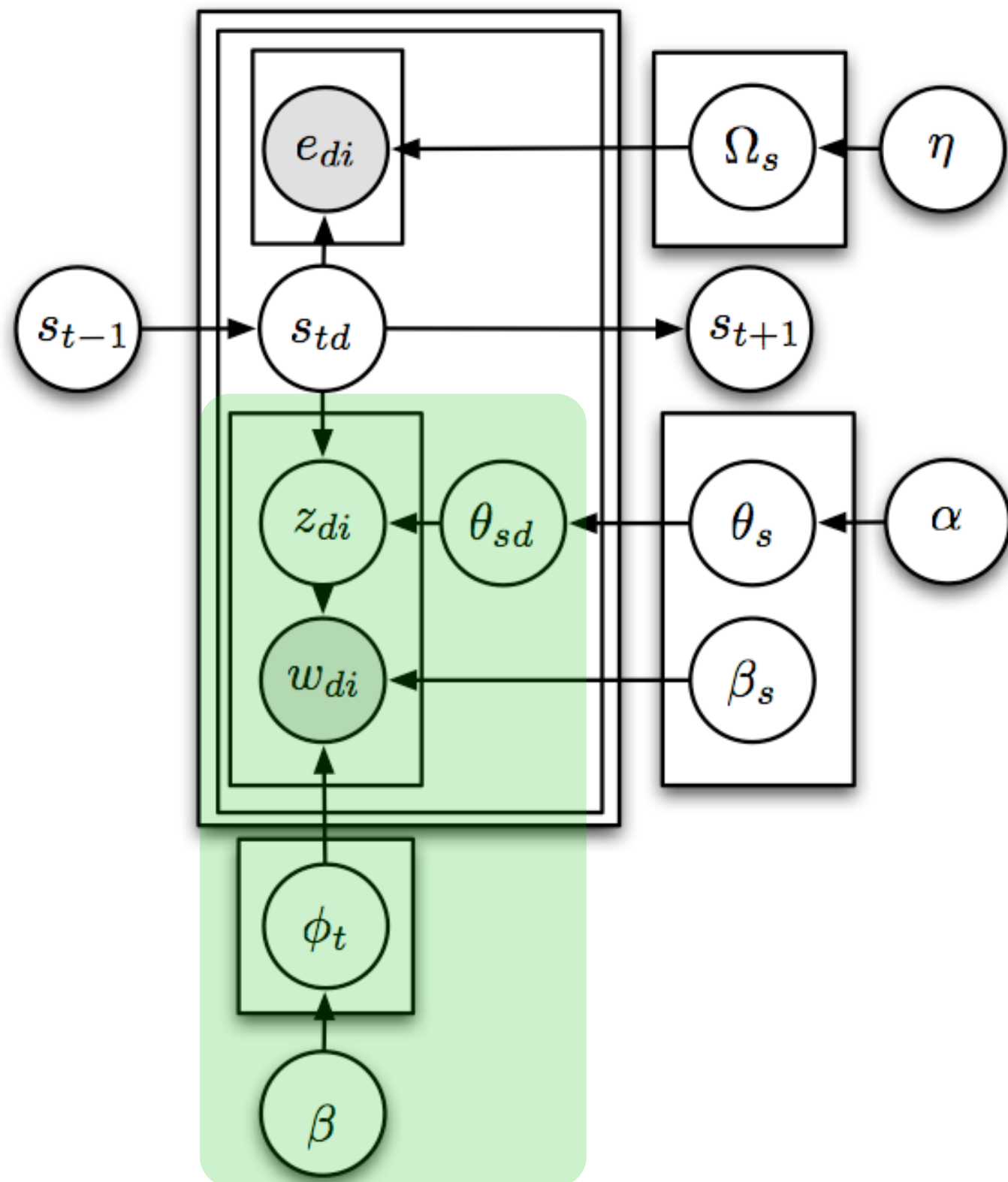


Storylines Model



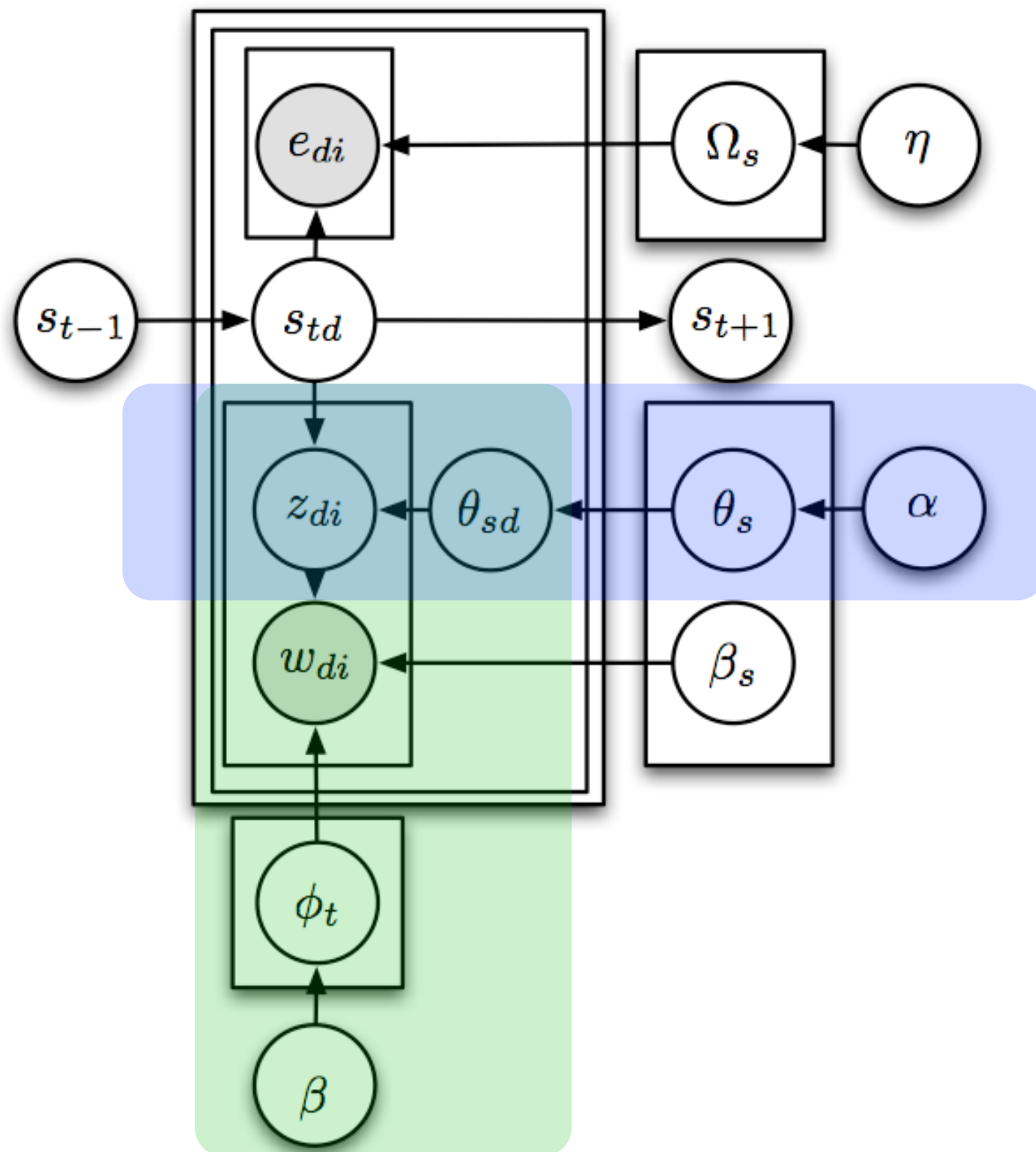
- Topic model
- Topics per cluster
- RCRP for cluster
- Hierarchical DP for article
- Separate model for named entities
- Story specific correction

Storylines Model



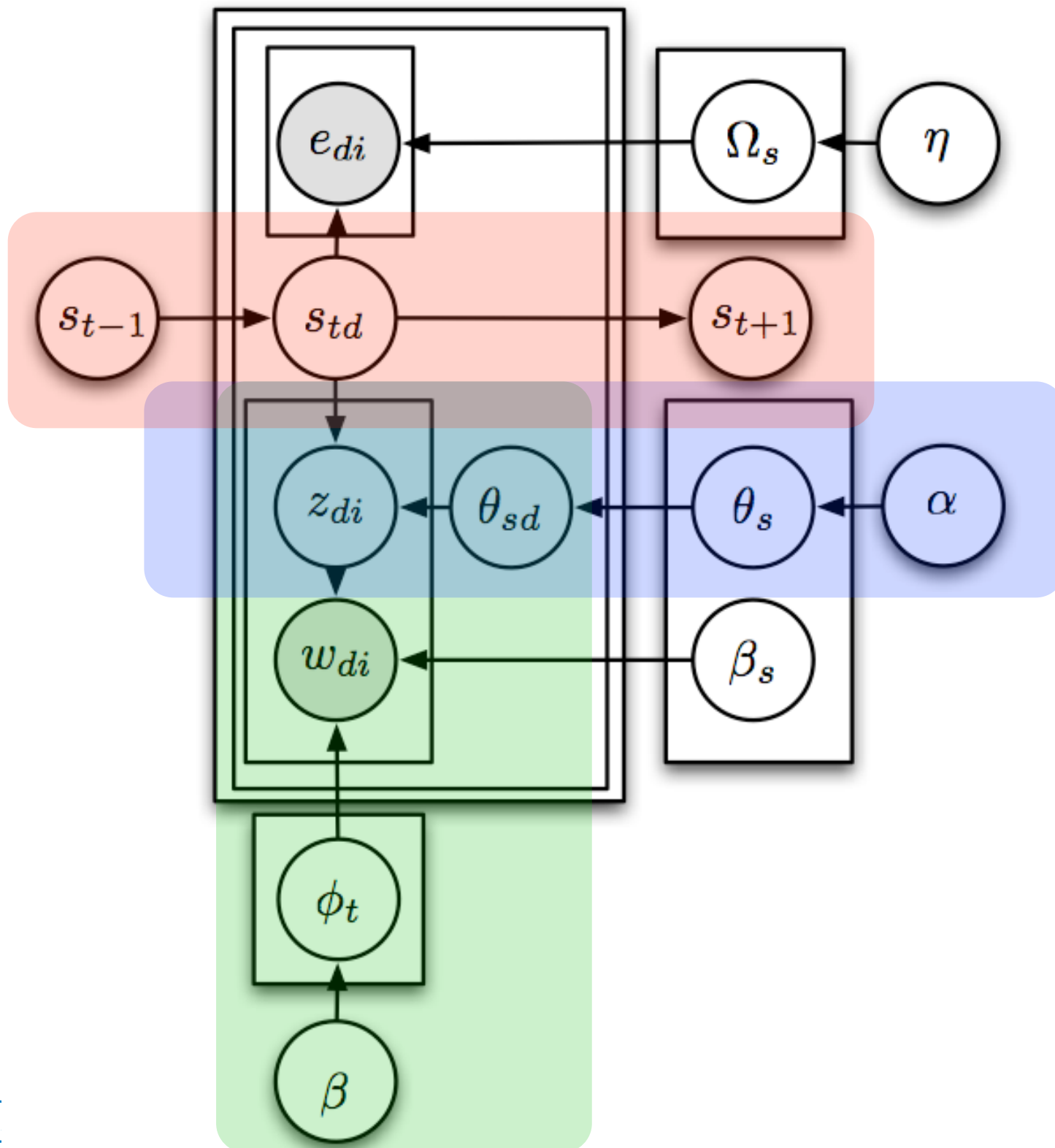
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- Hierarchical DP for article
- Separate model for named entities
- Story specific correction

Storylines Model



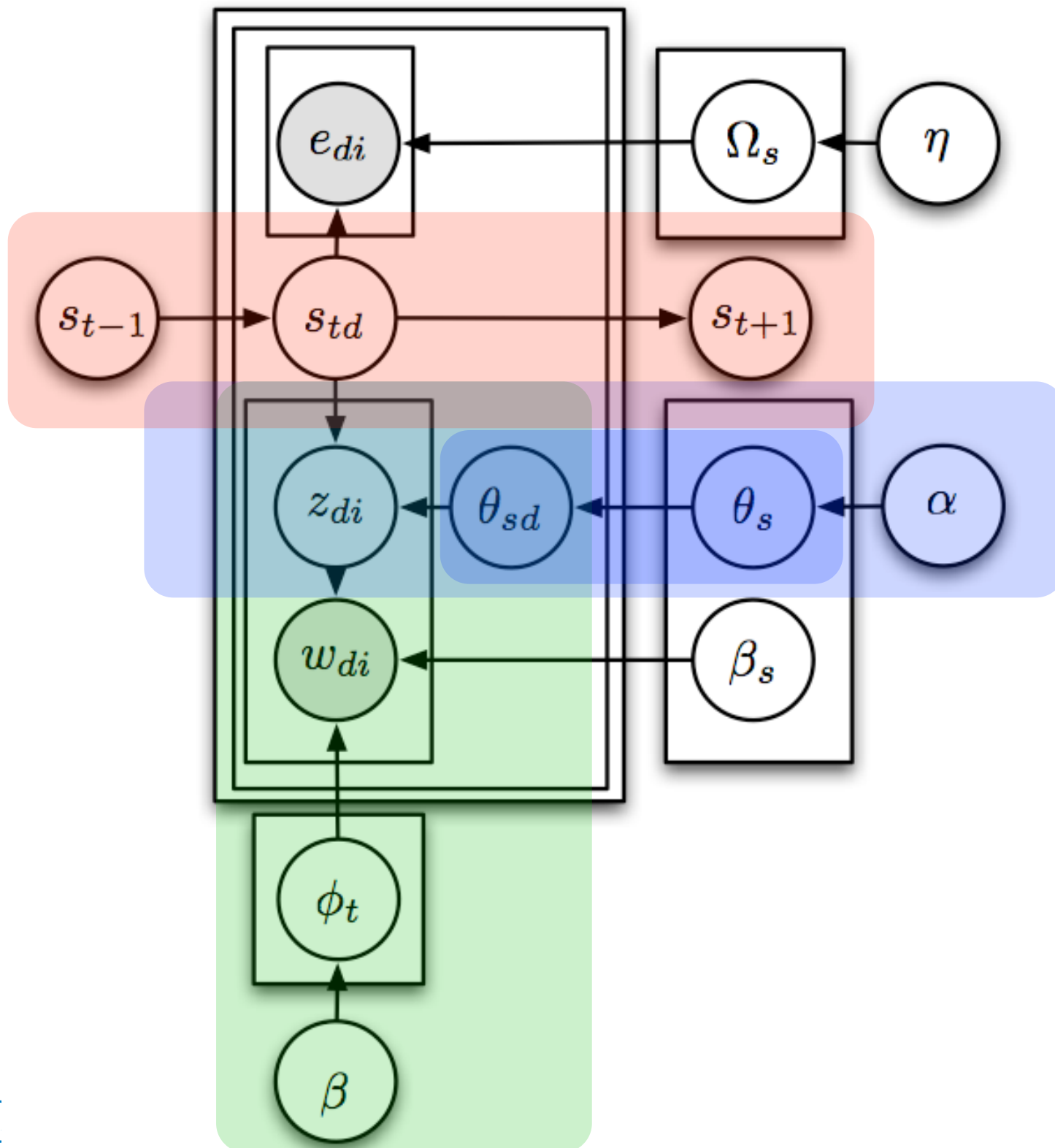
- Topic model
- Topics per cluster
- RCRP for cluster
- Hierarchical DP for article
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- Story specific correction

Storylines Model



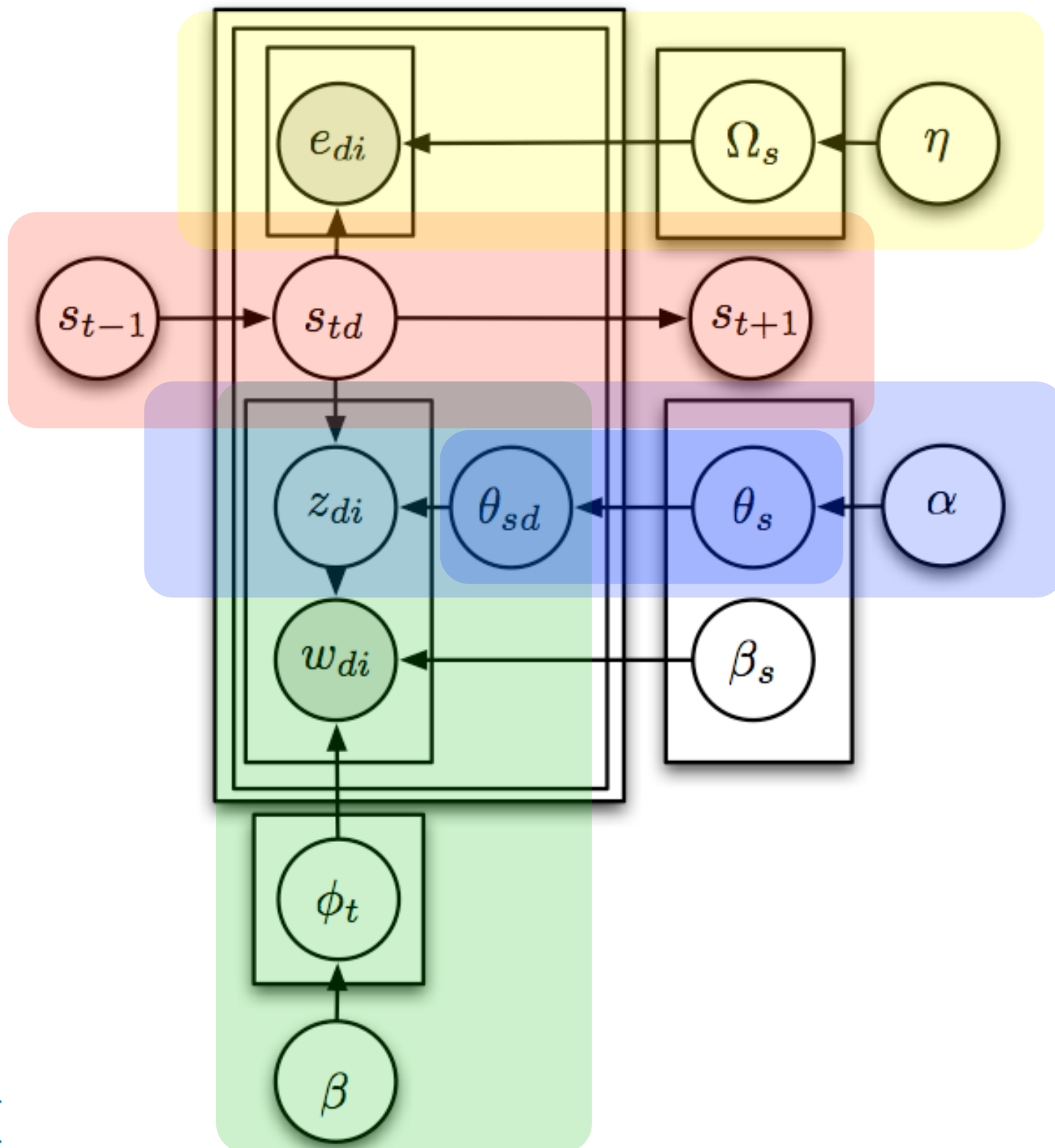
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Storylines Model



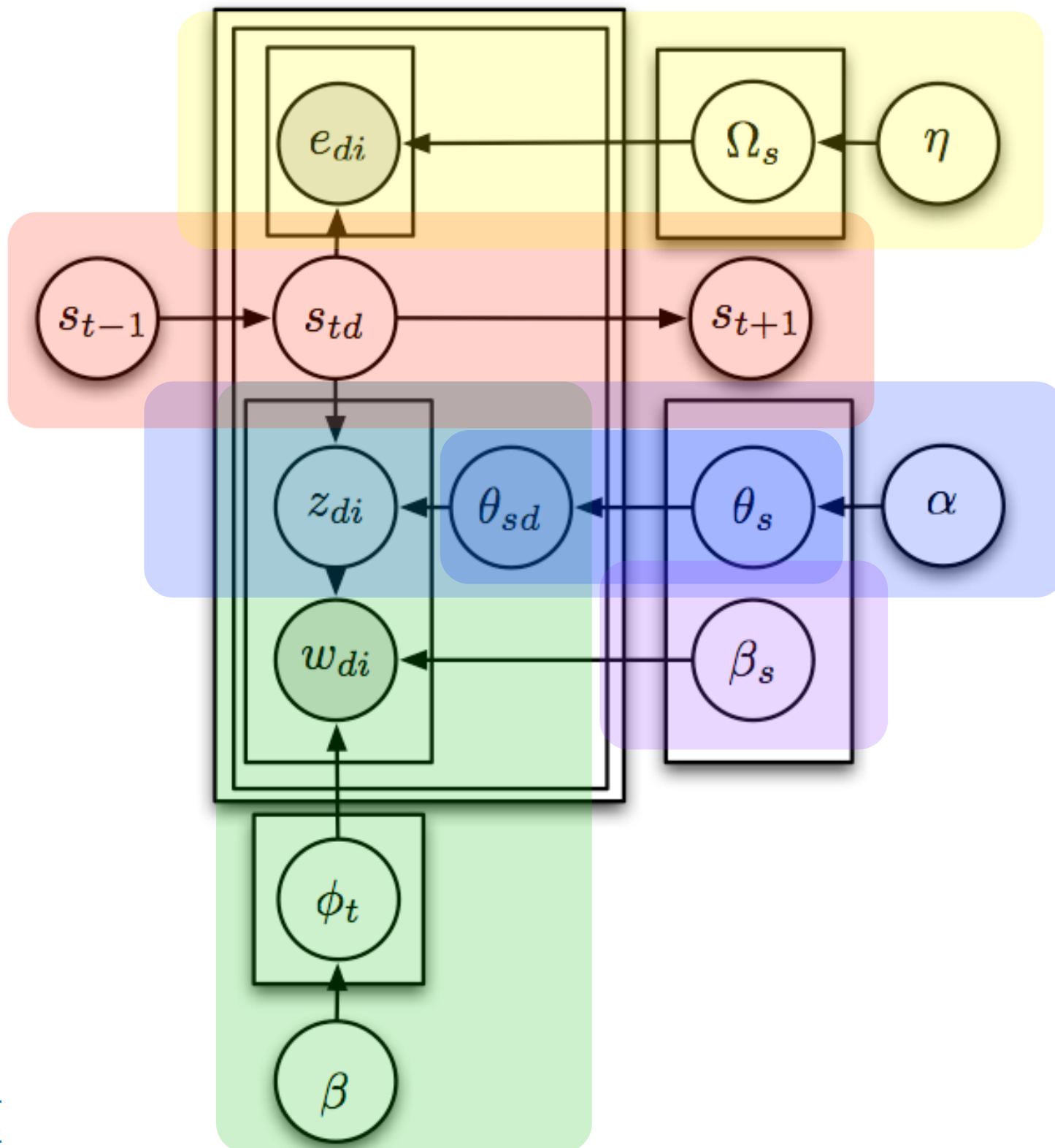
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Storylines Model



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Storylines Model



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Dynamic Cluster-Topic Hybrid

Sports
games
Won
Team
Final
Season
League
held

Politics
Government
Minister
Authorities
Opposition
Officials
Leaders
group

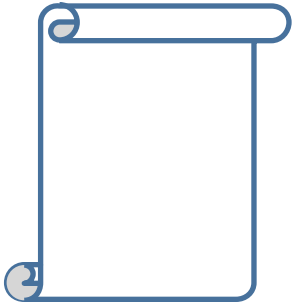
Accidents
Police
Attack
run
man
group
arrested
move

UEFA-soccer

Champions	Juventus
Goal	AC Milan
Coach	Lazio
Striker	Ronaldo
Midfield	Lyon
penalty	

Tax-Bill

Tax	Bush
Billion	Senate
Cut	Fleischer
Plan	White House
Budget	Republican
Economy	



Dynamic Cluster-Topic Hybrid

Sports
games
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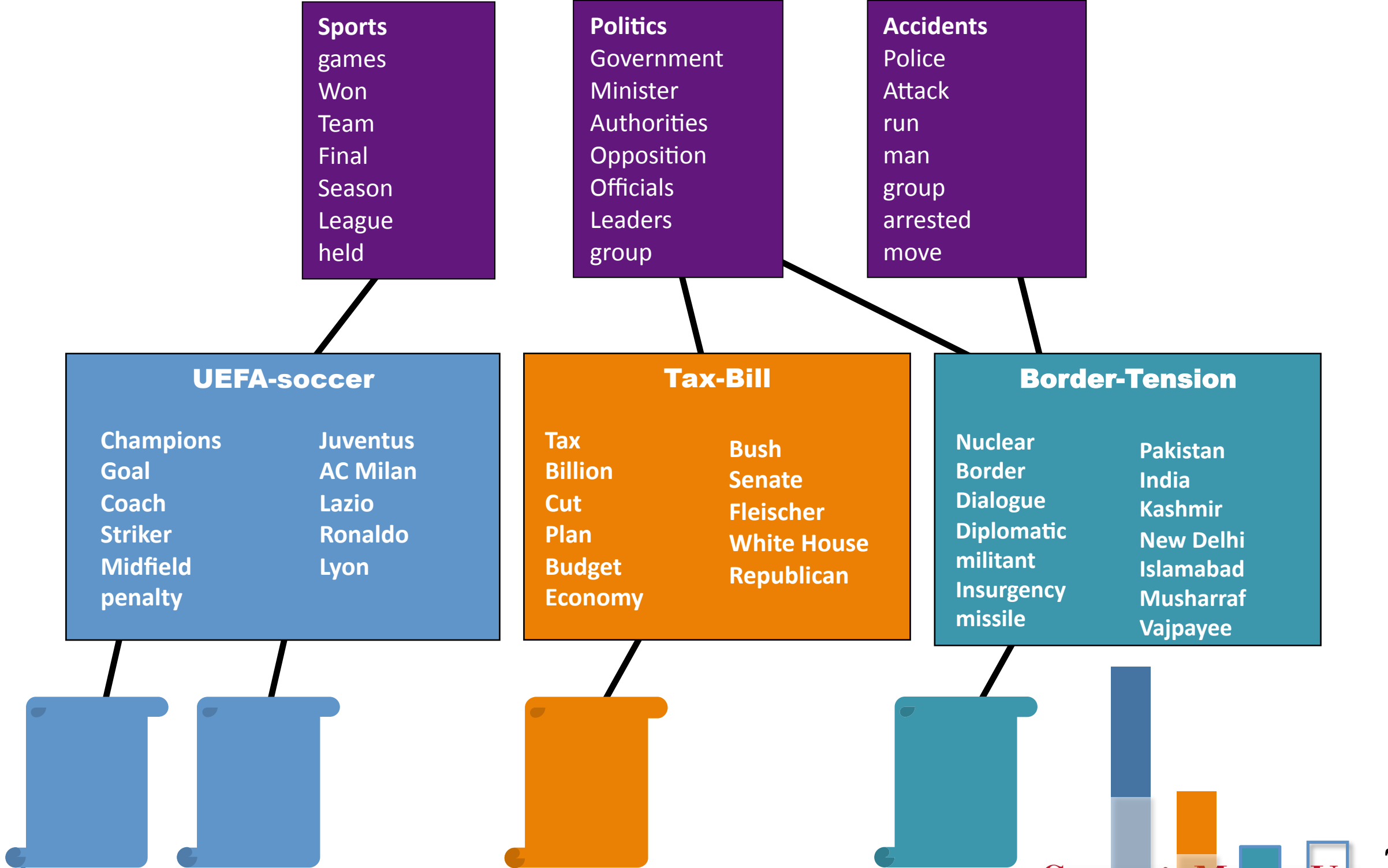
UEFA-soccer

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Tax-Bill

Tax	Bush
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Economy	

Dynamic Cluster-Topic Hybrid



Inference

- We receive articles as a stream
Want topics & stories now
- Variational inference infeasible
(RCRP, sparse to dense, vocabulary size)
- We have a 'tracking problem'
 - Sequential Monte Carlo
 - Use sampled variables of surviving particle
 - Use ideas from Cannini et al. 2009

Particle Filter

- Proposal distribution - draw stories s , topics z

$$p(s_{t+1}, z_{t+1} | x_{1...t+1}, s_{1...t}, z_{1...t})$$

using Gibbs Sampling for each particle

- Reweight particle via

$$p(x_{t+1} | x_{1...t}, s_{1...t}, z_{1...t})$$

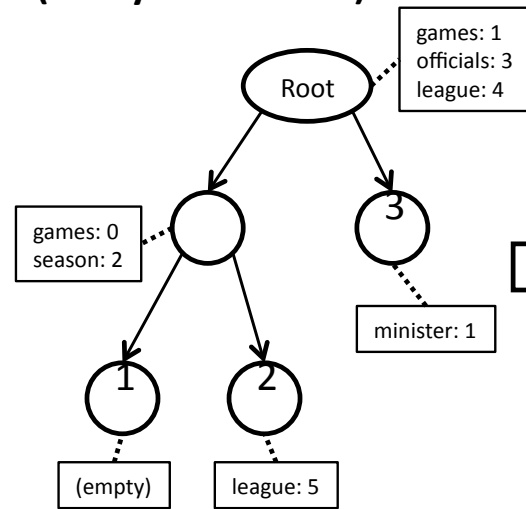
new data

past state

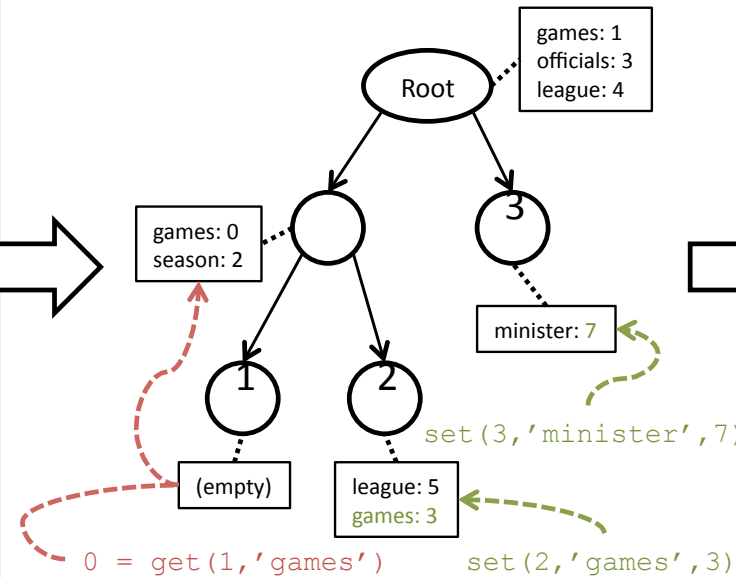
- Resample particles if l_2 norm too large
(resample some assignments for diversity, too)
- Compare to multiplicative updates algorithm
In our case predictive likelihood yields weights

Inheritance Tree

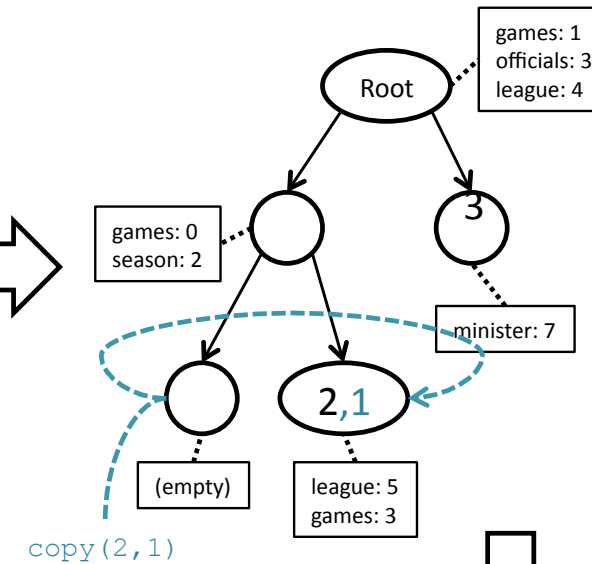
Initial tree
(ready for threads)



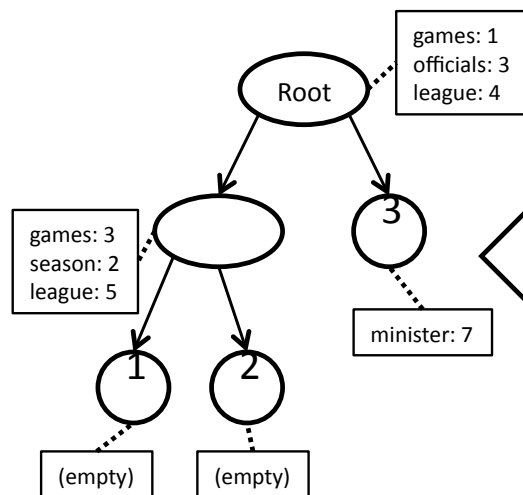
Filter threads *update* particles



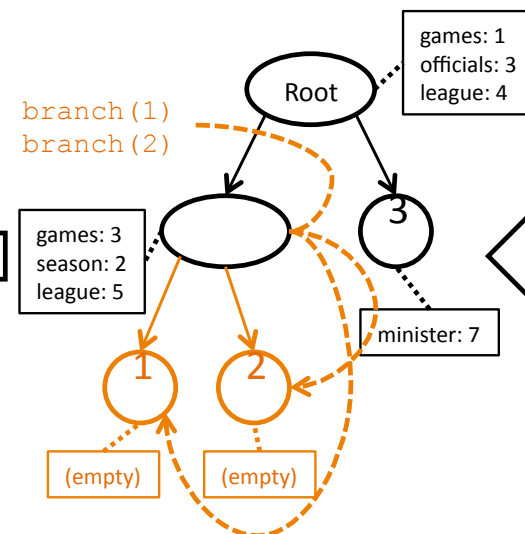
Resampling *copies* particles



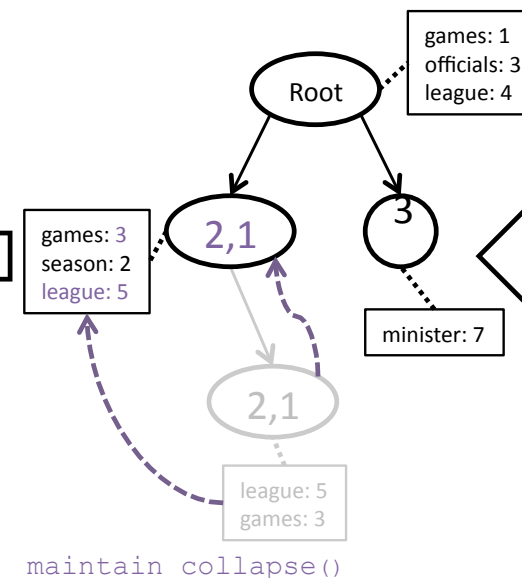
New initial tree
(ready for threads)



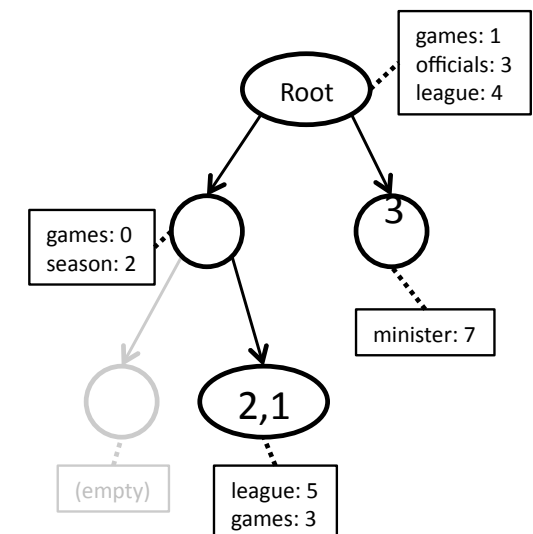
Create *new* leaves



Collapse long branches

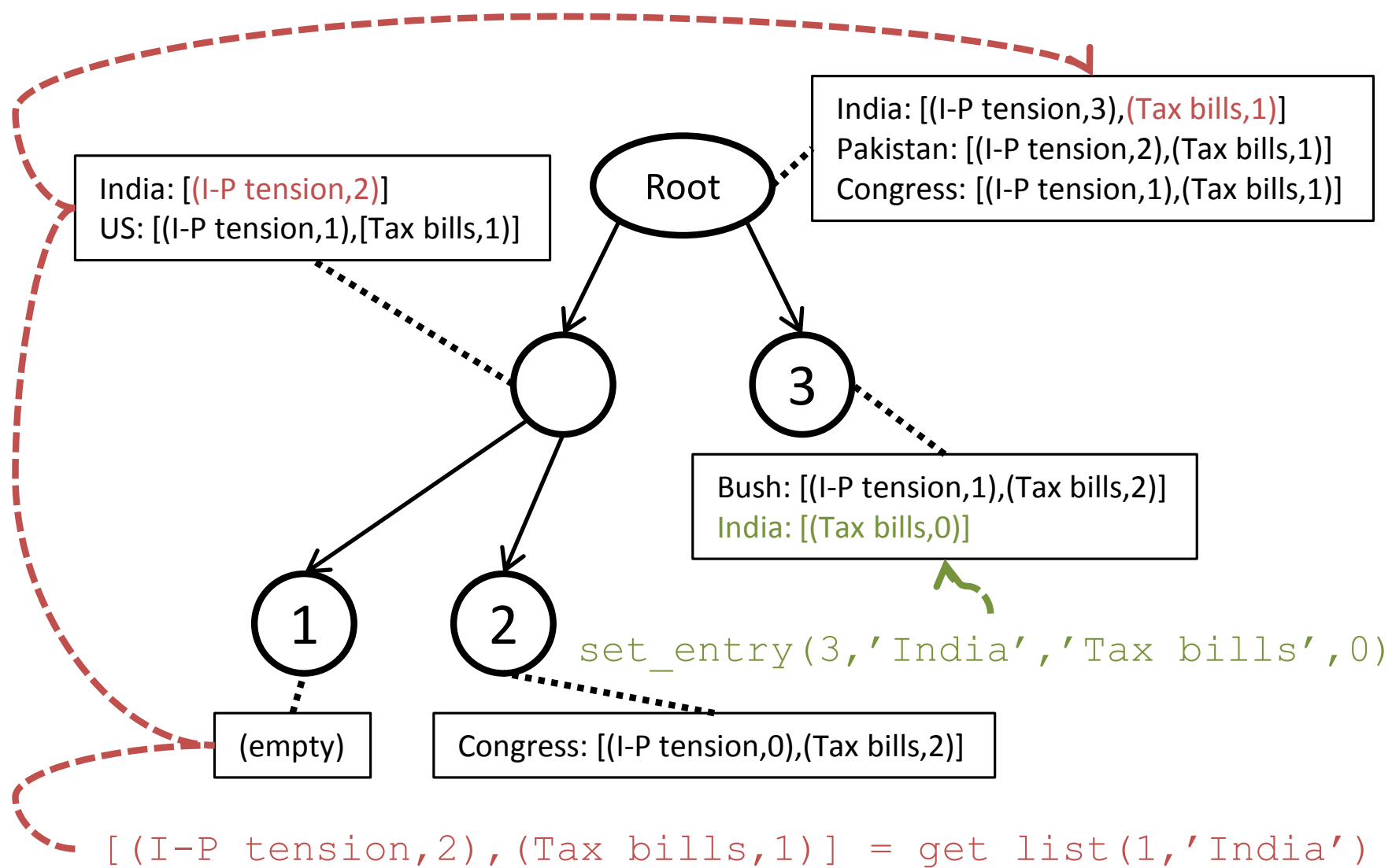


Prune unused branches



Extended Inheritance Tree

Extended Inheritance Tree



write only in the leaves
(per thread)

Note: "I-P tension" is short for "India-Pakistan tension"

Stories & Topics

TOPICS

Sports

games
won
team
final
season
league
held

Politics

government
minister
authorities
opposition
officials
leaders
group

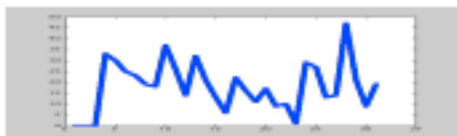
Unrest

police
attack
run
man
group
arrested
move

STORYLINES

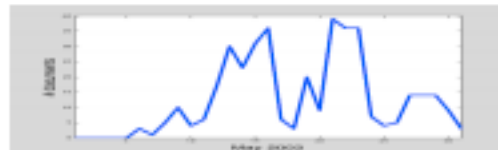
UEFA-soccer

champions	<i>Juventus</i>
goal	<i>AC Milan</i>
leg	<i>Real Madrid</i>
coach	<i>Milan</i>
striker	<i>Lazio</i>
midfield	<i>Ronaldo</i>
penalty	<i>Lyon</i>



Tax bills

tax	<i>Bush</i>
billion	<i>Senate</i>
cut	<i>US</i>
plan	<i>Congress</i>
budget	<i>Fleischer</i>
economy	<i>White House</i>
lawmakers	<i>Republican</i>



India-Pakistan tension

nuclear	<i>Pakistan</i>
border	<i>India</i>
dialogue	<i>Kashmir</i>
diplomatic	<i>New Delhi</i>
militant	<i>Islamabad</i>
insurgency	<i>Musharraf</i>
missile	<i>Vajpayee</i>

