

YAHOO!

Graphical Models for the Internet

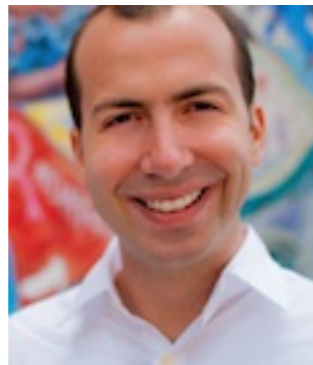
Amr Ahmed & Alexander Smola

Yahoo! Research & Australian National University, Santa Clara, CA
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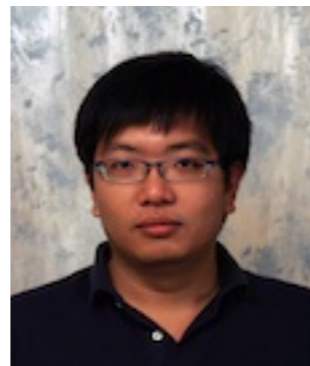
Thanks



Mohamed
Aly



Joey
Gonzalez



Yucheng
Low



Qirong
Ho



Shravan
Narayanamurthy



Vanja
Josifovski



Choon Hui
Teo



Eric
Xing



James
Petterson



Sergiy
Matyusevich



Jake
Eisenstein



Shuang Hong
Yang



Vishy
Vishwanathan



Markus
Weimer



Alexandros
Karatzoglou

1. Data on the Internet



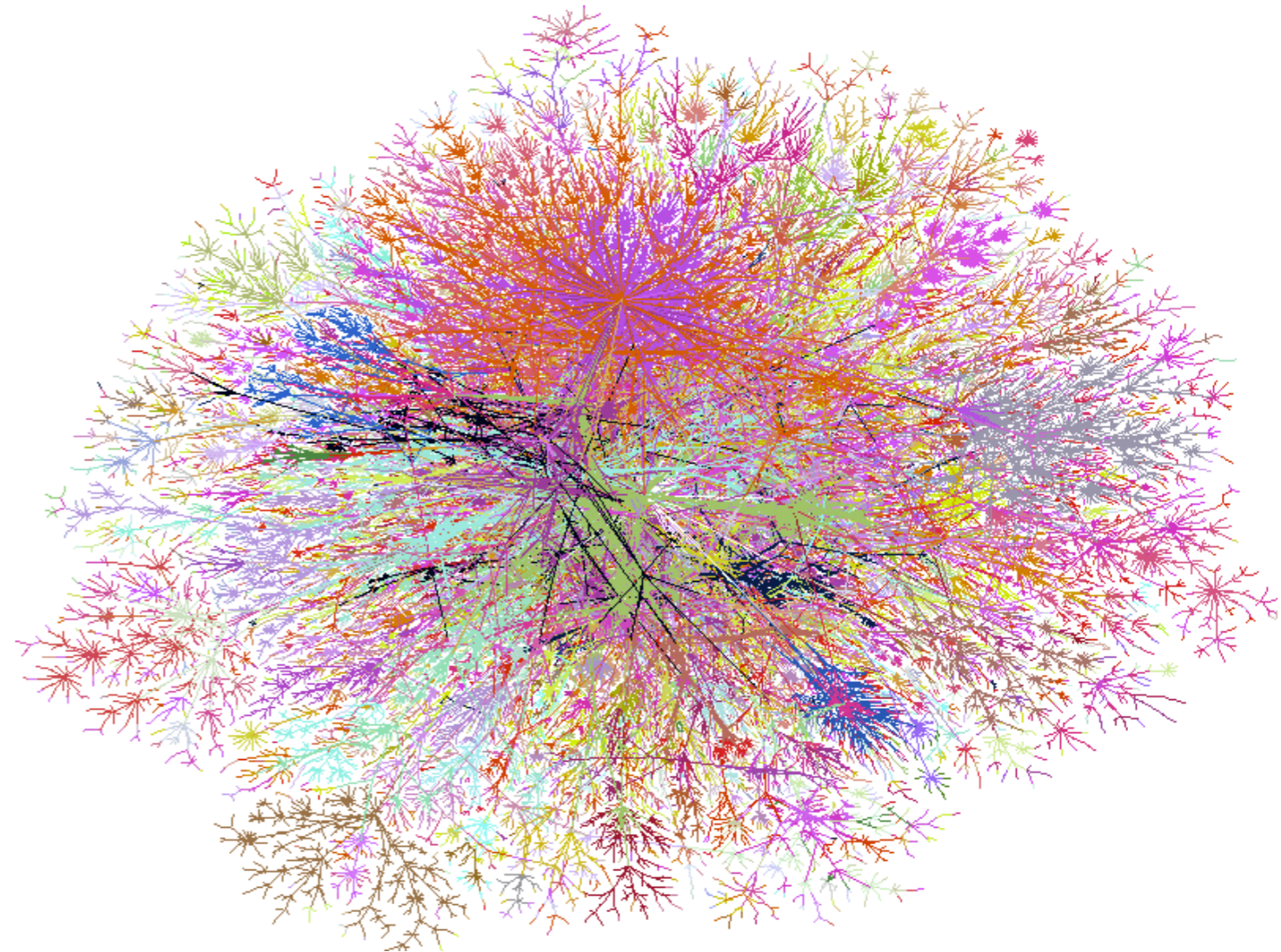
Size calibration

- **Tiny** (2 cores)
(512MB, 50MFlops, 1000 samples)
- **Small** (4 cores)
(4GB, 10GFlops, 100k samples)
- **Medium** (16 cores)
(32GB, 100GFlops, 1M samples)
- **Large** (256 cores)
(512GB, 1TFlops, 100M samples)
- **Massive**
... need to work hard get it to work



Data

- Webpages (content, graph)
- Clicks (ad, page, social)
- Users (OpenID, FB Connect)
- e-mails (Hotmail, Y!Mail, Gmail)
- Photos, Movies (Flickr, YouTube, Vimeo ...)
- Cookies / tracking info (see Ghostery)
- Installed apps (Android market etc.)
- Location (Latitude, Loopt, Foursquared)
- User generated content (Wikipedia & co)
- Ads (display, text, DoubleClick, Yahoo)
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- Reviews (Yelp, Y!Local)
- Third party features (e.g. Experian)
- Social connections (LinkedIn, Facebook)
- Purchase decisions (Netflix, Amazon)
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- Search terms (Google, Bing)
- Timestamp (everything)
- News articles (BBC, NYTimes, Y!News)
- Blog posts (Tumblr, Wordpress)
- Microblogs (Twitter, Jaiku, Meme)



>10B useful webpages

The Web for \$100k/month

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- **10 billion pages**
(this is a small subset, maybe 10%)
10k/page = 100TB
(\$10k for disks or EBS 1 month)
- **1000 machines**
10ms/page = 1 day
afford 1-10 MIP/page
(\$20k on EC2 for 0.68\$/h)
- **10 Gbit link**
(\$10k/month via ISP or EC2)
 - 1 day for raw data
 - 300ms/page roundtrip
 - **1000 servers for 1 month**
(\$70k on EC2 for 0.085\$/h)

Data - Identity & Graph

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100M-1 B vertices

Data - User generated content

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flickr™



You Tube

DISQUS

yelp. 

> 1 B images, 40h video/minute

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crawl it

flickr™



DISQUS



You Tube

yelp. 

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Data - Messages

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> 1 B texts

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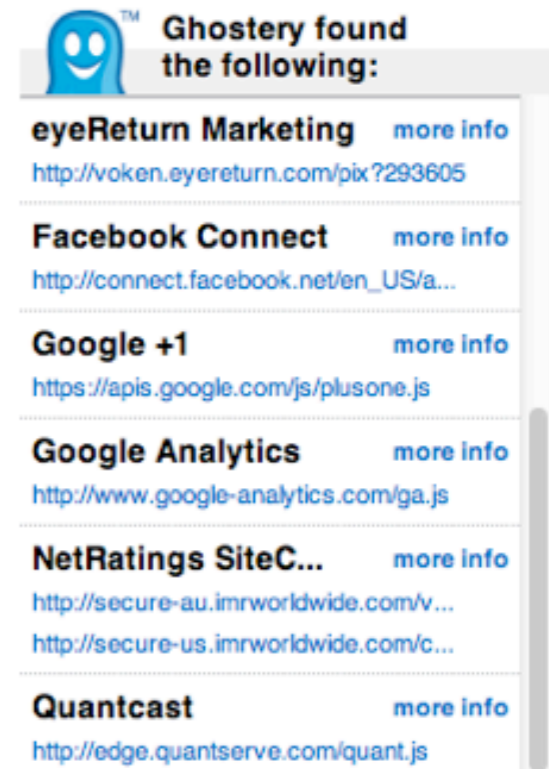


> 1 B texts

impossible without NDA

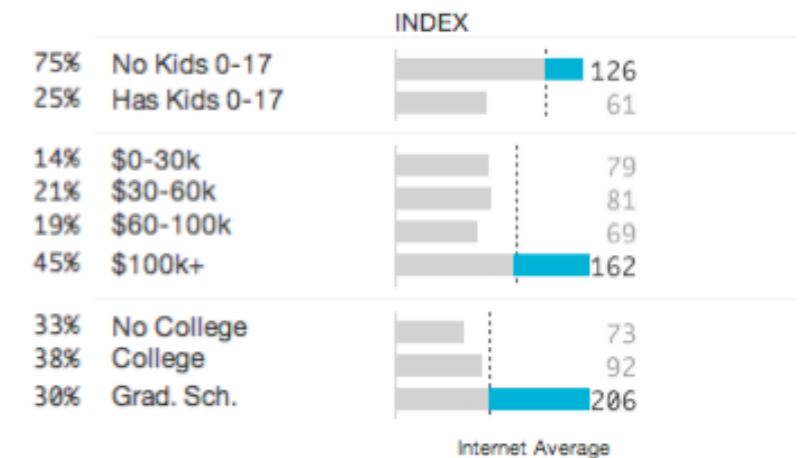
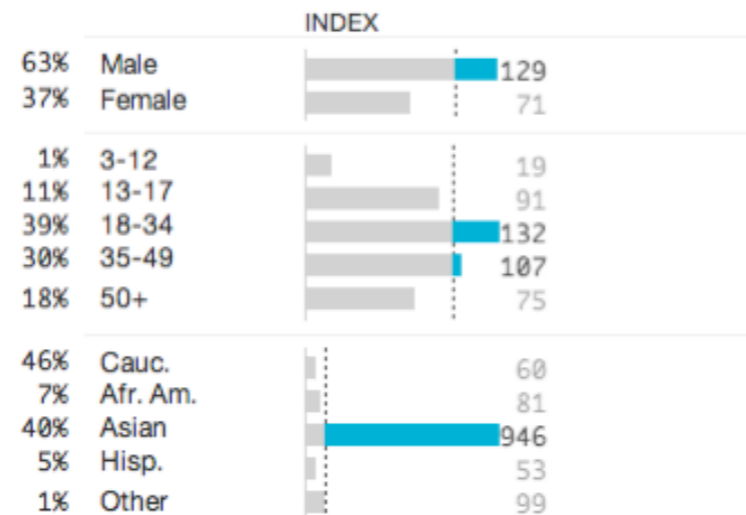
Data - User Tracking

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Updated Sep 10, 2011 • Next: Sep 21, 2011 by 9AM PDT

US Demographics



alex.smola.org

> 1 B 'identities'

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Privacy Information

Privacy Policy:

<http://www.facebook.com/policy.php>

Data Collected:

Anonymous (browser type, location, page views), Pseudonymous (IP address, "actions taken")

Data Sharing:

Data is shared with third parties. 

Data Retention:

Data is deleted from backup storage after 90 days. 

Privacy Information

Privacy Policy:

<http://www.google.com/intl/en/priv...>

Data Collected:

Anonymous (ad serving domains, browser type, demographics, language settings, page views, time/date), Pseudonymous (IP address)

Data Sharing:

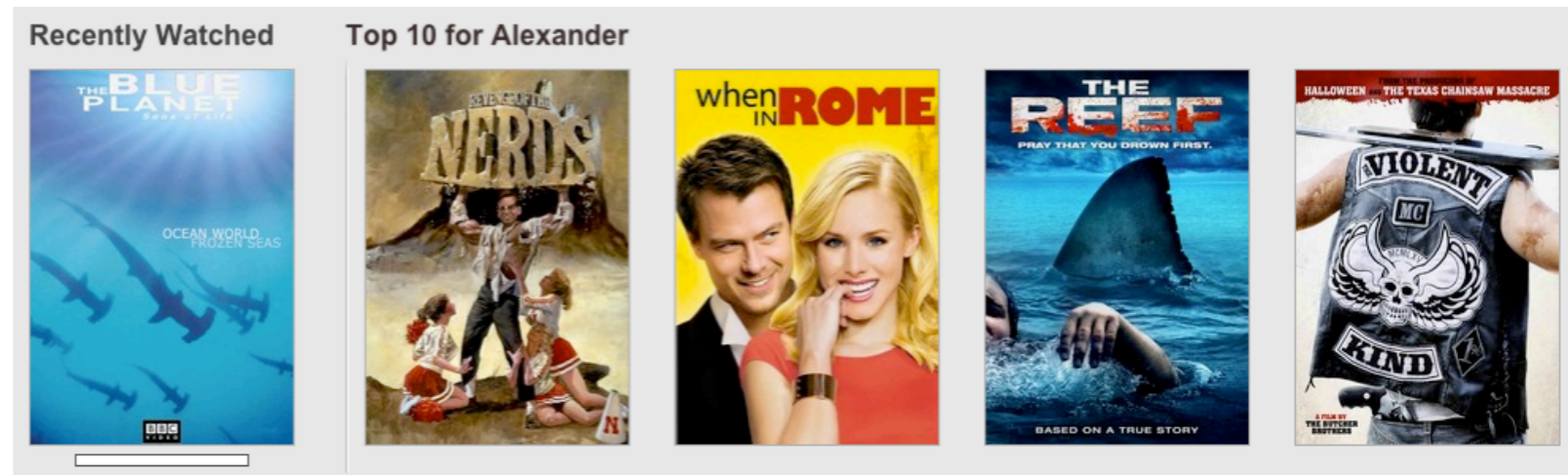
Anonymous data is shared with third parties. 

Data Retention:

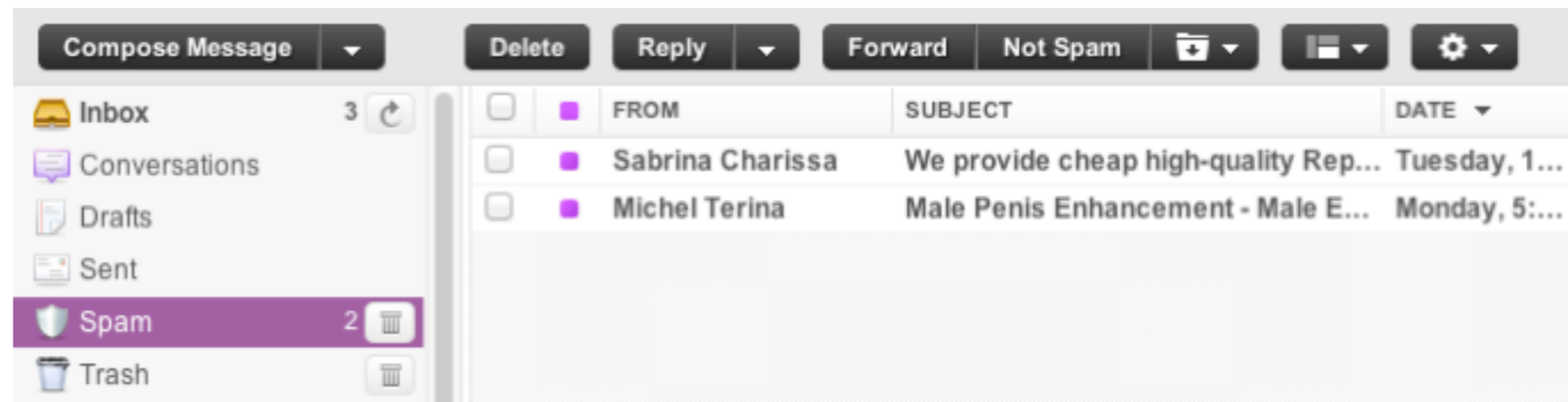
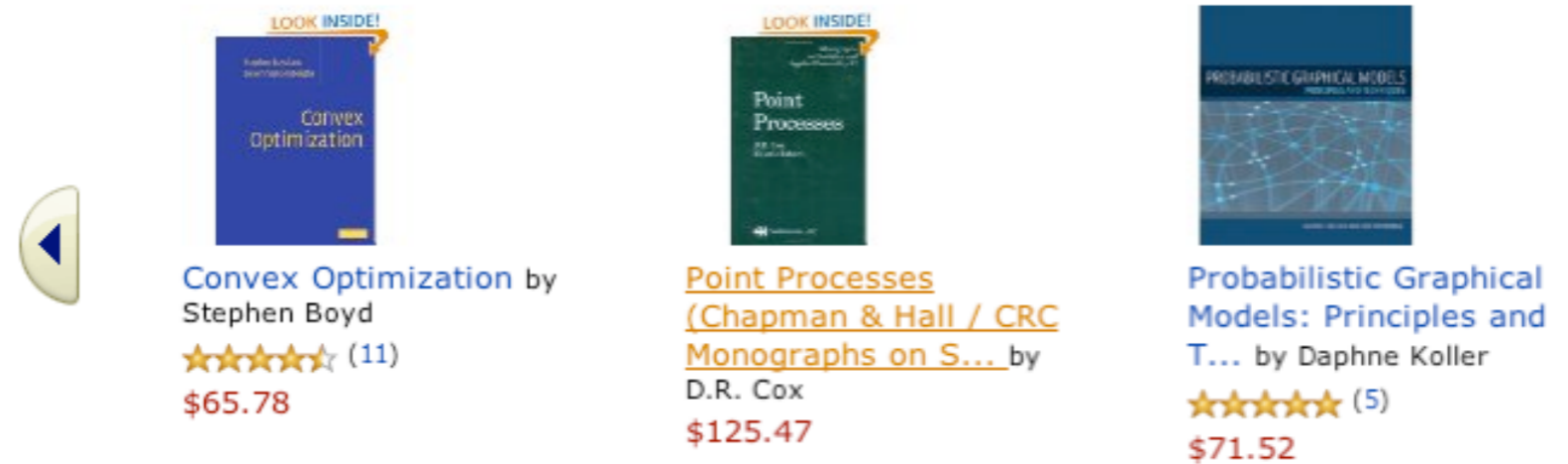
Undisclosed 

Personalization

- 100-1000M users
 - Spam filtering
 - Personalized targeting & collaborative filtering
 - News recommendation
 - Advertising



Customers Who Bought This Item Also Bought



- Large parameter space (25 parameters = 100GB)
- Distributed storage (need it on every server)
- Distributed optimization
- Model synchronization
- Time dependence
- Graph structure

(implicit) Labels

no labels
(typical case)

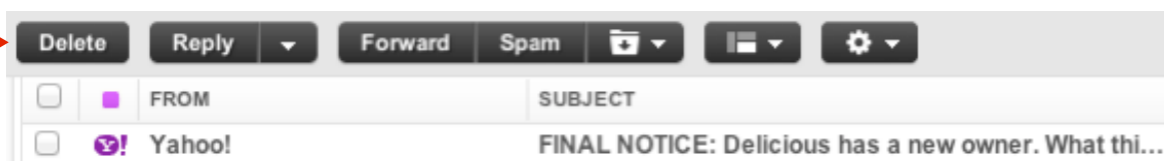
- Ads



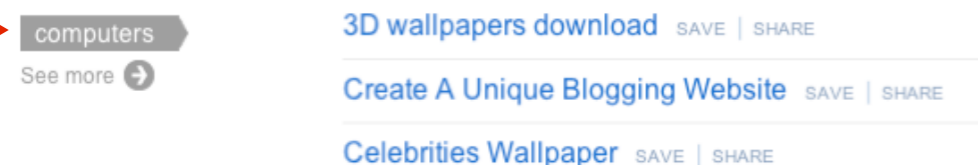
- Click feedback



- Emails

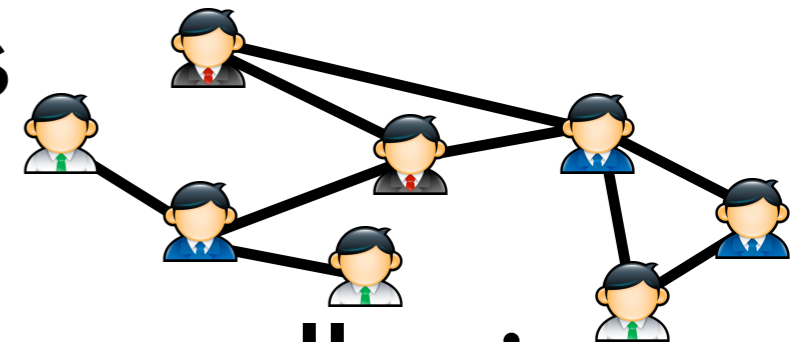


- Tags



- Editorial data is very expensive! Do not use!

- Graphs



- Document collections



- Email/IM/Discussions



- Query stream



Challenges

- **Scale**
 - Billions of instances (documents, clicks, users, ads)
 - Rich data structure (ontology, categories, tags)
 - Model **does not fit into single machine**
- **Modeling**
 - Plenty of unlabeled data, temporal structure, side information
 - User-understandable structure
 - **Solve problem. Don't simply apply clustering/LDA/PCA/ICA**
 - **We only cover building blocks**
- **Inference**
 - 10k-100k clusters/discrete objects, 1M-100M unique tokens
 - **Communication**

Roadmap

- **Tools**
 - Load distribution, balancing and synchronization
 - Clustering, Topic Models
- **Models**
 - Dynamic non-parametric models
 - Sequential latent variable models
- **Inference Algorithms**
 - Distributed batch
 - Sequential Monte Carlo
- **Applications**
 - User profiling
 - News content analysis & recommendation

2. Basic Tools





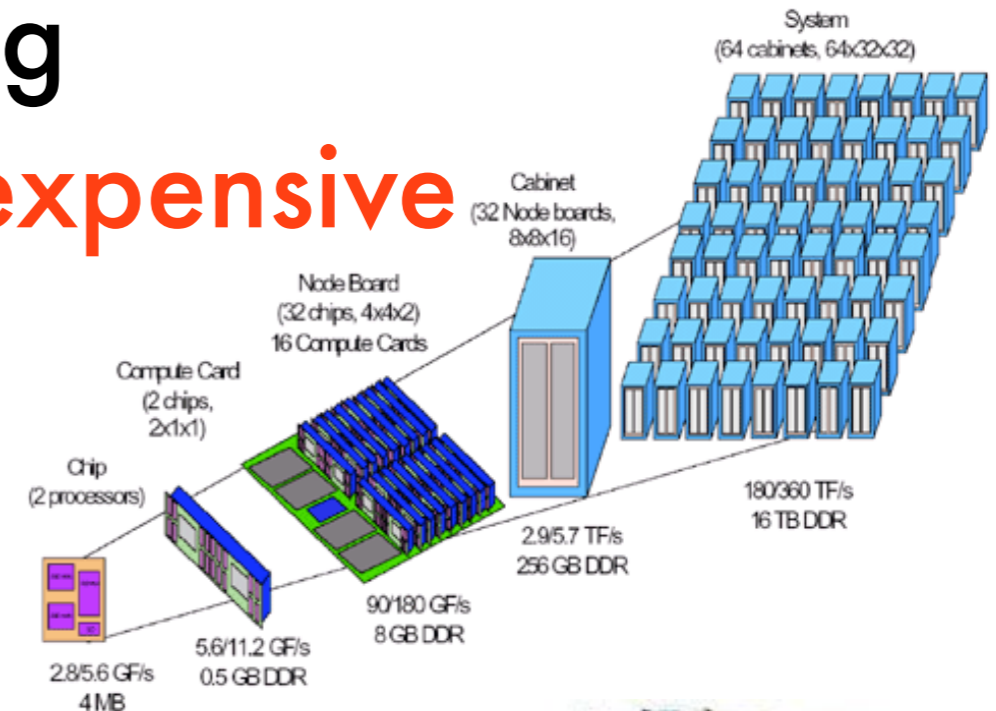
Systems

Algorithms run on **MANY REAL** and **FAULTY** boxes not Turing machines. So we need to deal with it.

Commodity Hardware

- High Performance Computing

Very reliable, custom built, **expensive**



- Consumer hardware

Cheap, efficient, easy to replicate,

Not very reliable, deal with it!



The Joys of Real 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**

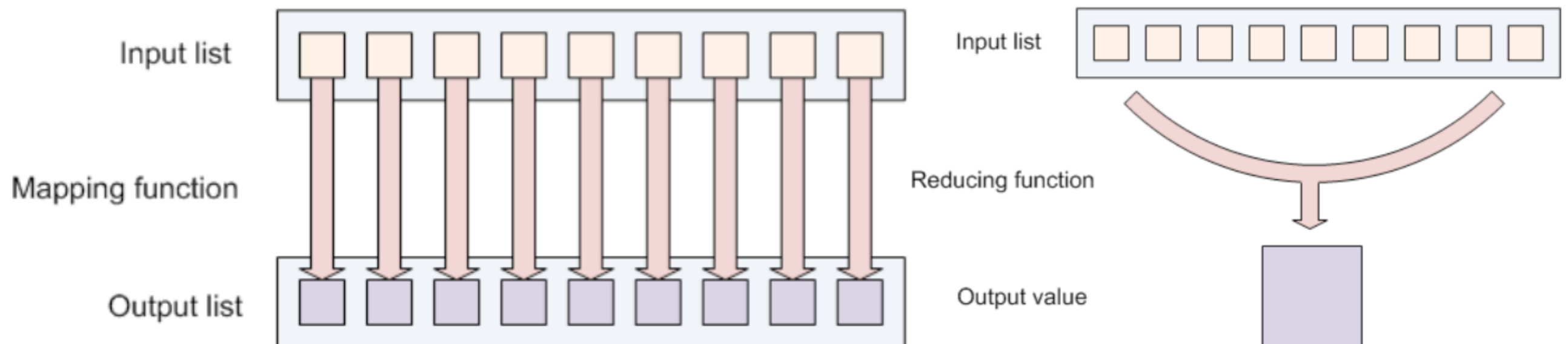
slow disks, bad memory, misconfigured machines, flaky machines, etc.

Slide from talk of Jeff Dean



Map Reduce

- 1000s of (faulty) machines
- Lots of jobs are mostly embarrassingly parallel (except for a sorting/transpose phase)
- Functional programming origins
 - `Map(key,value)`
processes each (key,value) pair and outputs a new (key,value) pair
 - `Reduce(key,value)`
reduces all instances with same key to aggregate



from Ramakrishnan, Sakrejda, Canon, DoE 2011

Map Reduce

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

Map Reduce

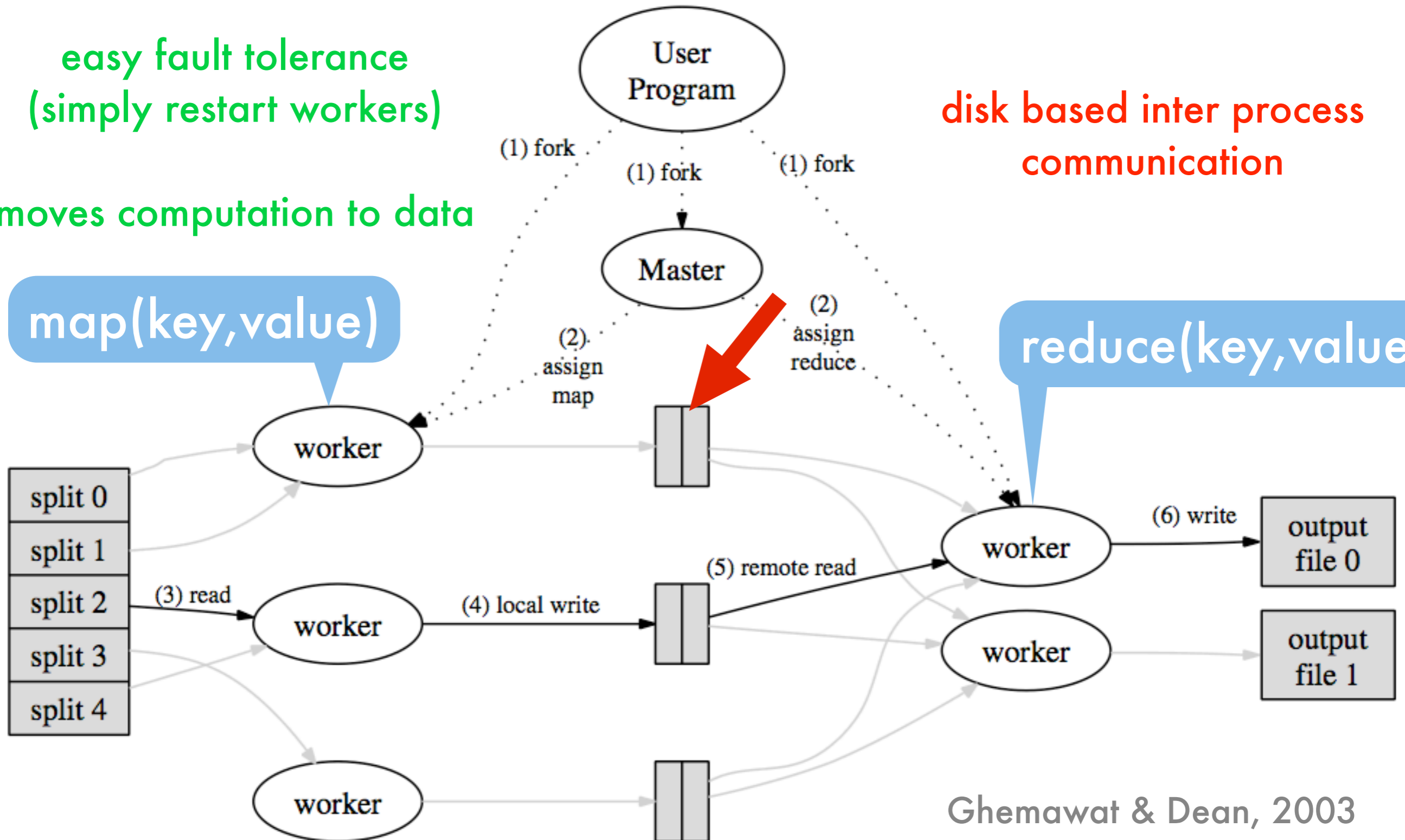
easy fault tolerance
(simply restart workers)

moves computation to data

disk based inter process
communication

map(key,value)

reduce(key,value)



Map Reduce

- Map must be stateless in blocks
- Reduce must be commutative in data
- Fault tolerance
 - Start jobs where the data is (nodes run the filesystem, too)
 - 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
- Need to wait for last reducer

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unsuitable for
algorithms with
many iterations

Many alternatives

- **Dryad/LINQ**
Microsoft - directed acyclic graphs
- **S4**
Yahoo - streaming directed acyclic graphs
- **Pregel**
Google - bulk synchronous processing
- **YARN**
Use Hadoop scheduler directly
- **Mesos, Hadoop workalikes & patches**



Clustering



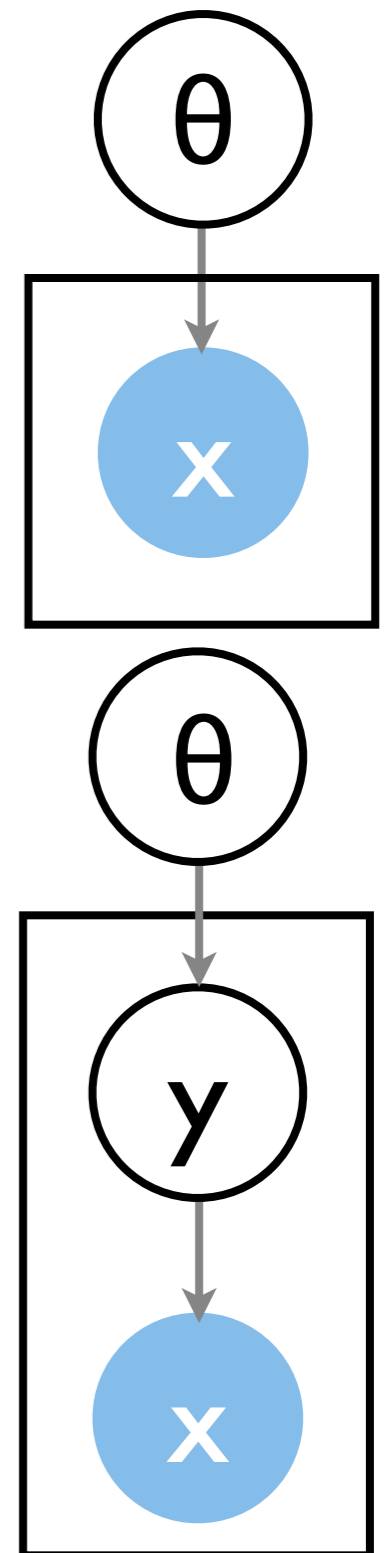
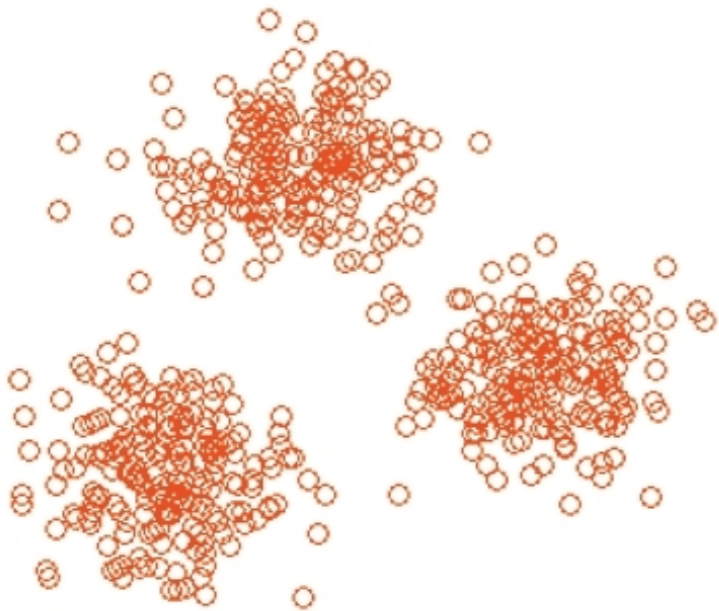
Clustering

Density Estimation

$$p(x, \theta) = p(\theta) \prod_{i=1}^n p(x_i | \theta)$$

Clustering

$$p(x, y, \theta) = p(\pi) \prod_{k=1}^K p(\theta_k) \prod_{i=1}^n p(y_i | \pi) p(x_i | \theta, y_i)$$



Clustering

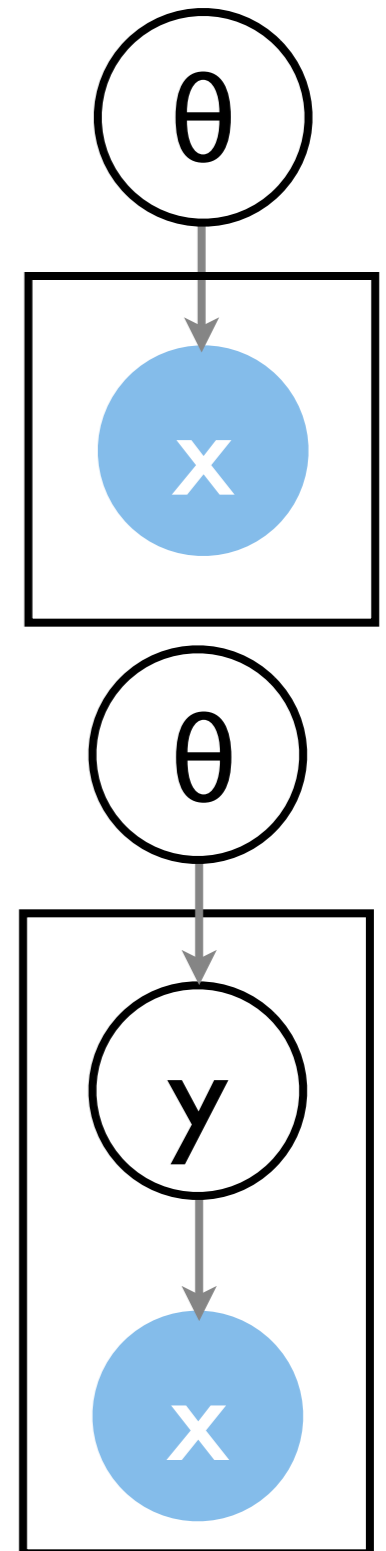
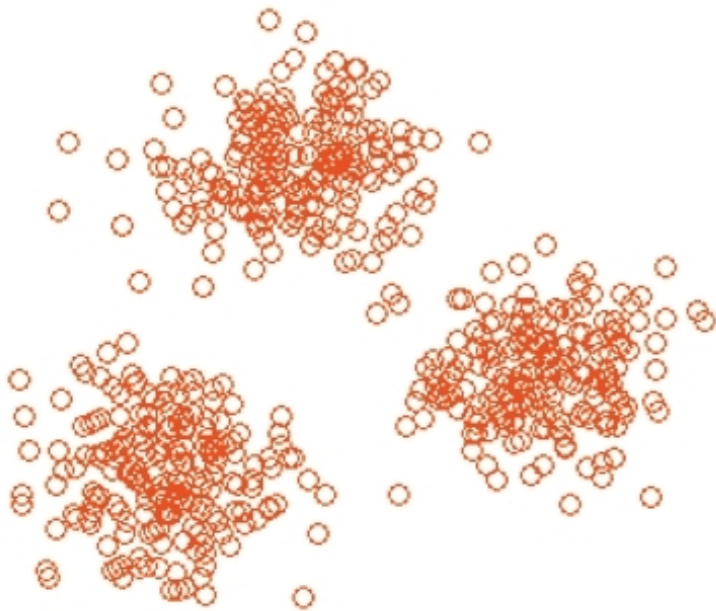
Density Estimation

$$p(x, \theta) = p(\theta) \prod_{i=1}^n p(x_i | \theta)$$

find θ

Clustering

$$p(x, y, \theta) = p(\pi) \prod_{k=1}^K p(\theta_k) \prod_{i=1}^n p(y_i | \pi) p(x_i | \theta, y_i)$$



Clustering

Density Estimation

log-concave

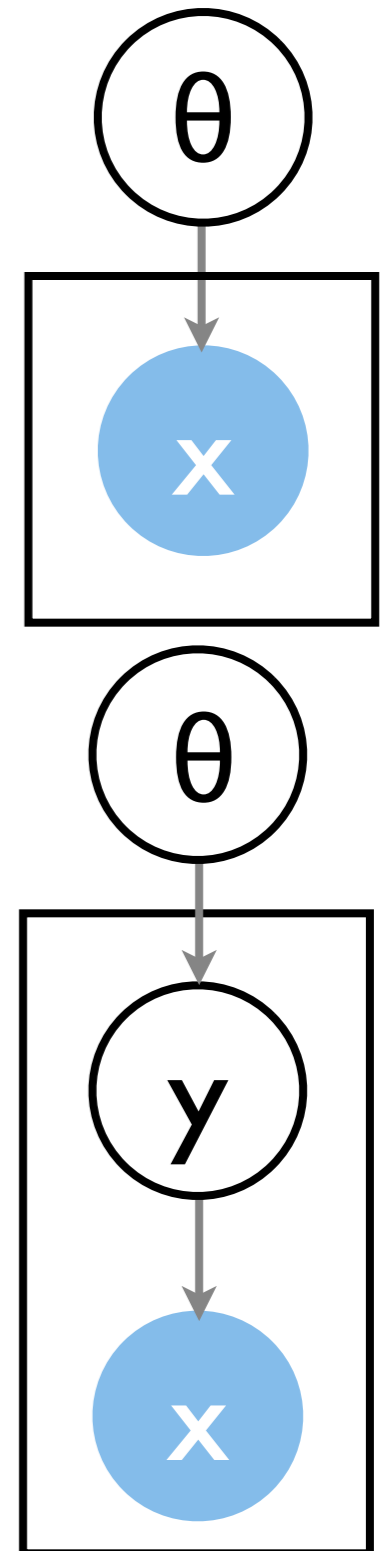
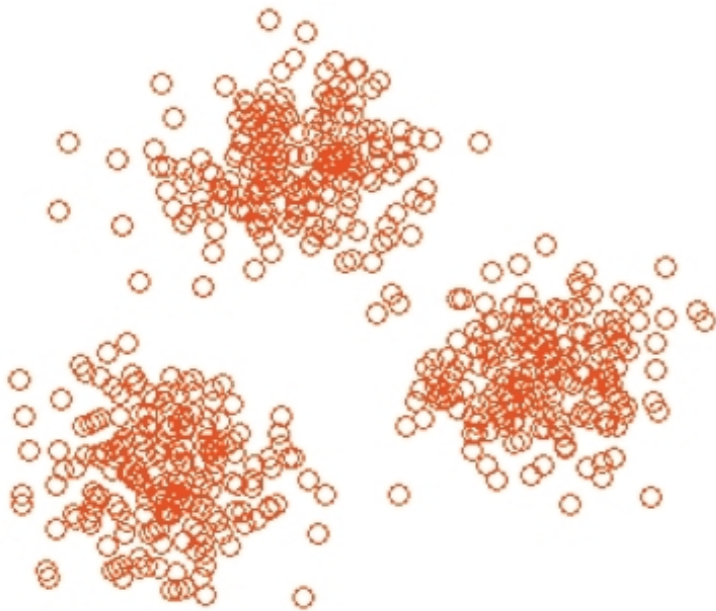
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general nonlinear



Clustering

- Optimization problem

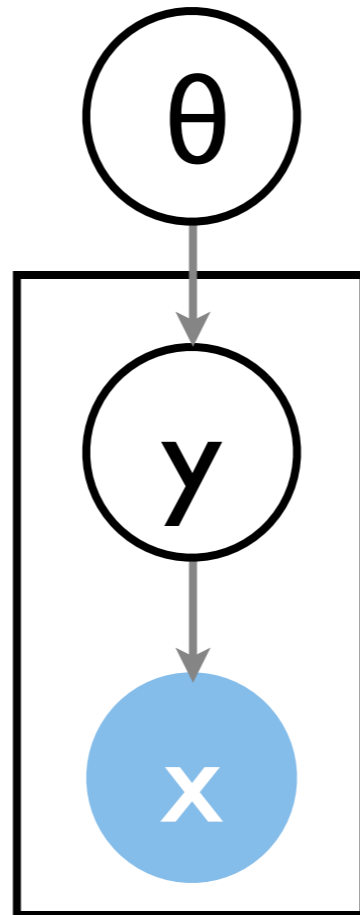
$$\text{maximize}_{\theta} \sum_y p(x, y, \theta)$$

$$\text{maximize}_{\theta} \log p(\pi) + \sum_{k=1}^K \log p(\theta_k) + \sum_{i=1}^n \log \sum_{y_i \in \mathcal{Y}} [p(y_i | \pi) p(x_i | \theta, y_i)]$$

- Options

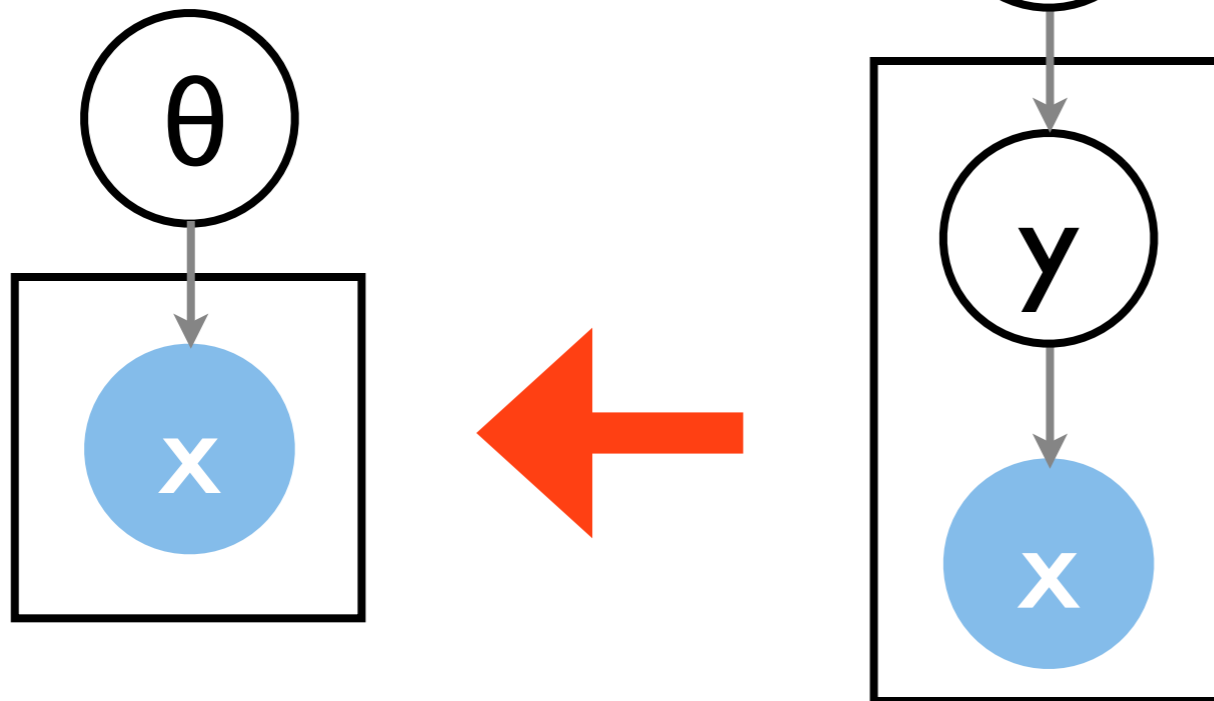
- Direct nonconvex optimization (e.g. BFGS)
- Sampling (draw from the joint distribution) for memory efficiency
- Variational approximation (concave lower bounds aka EM algorithm)

Clustering



Clustering

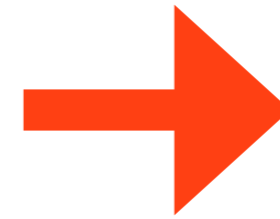
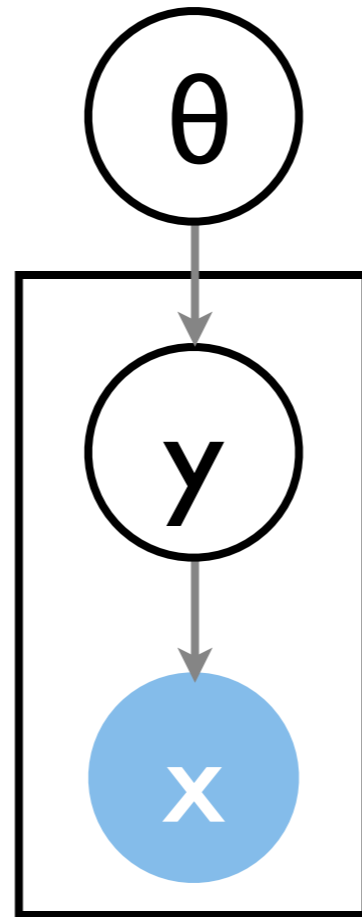
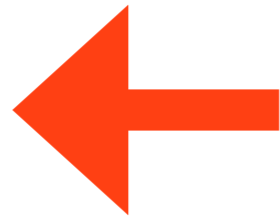
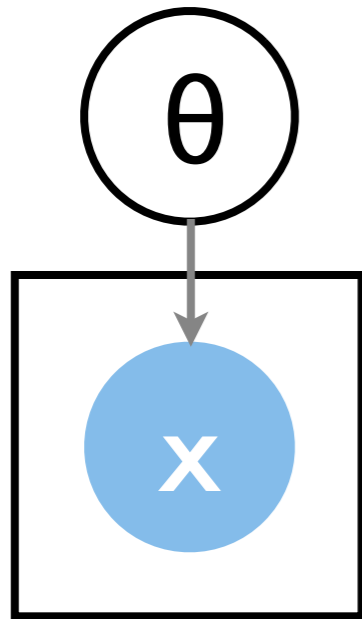
- Integrate out y



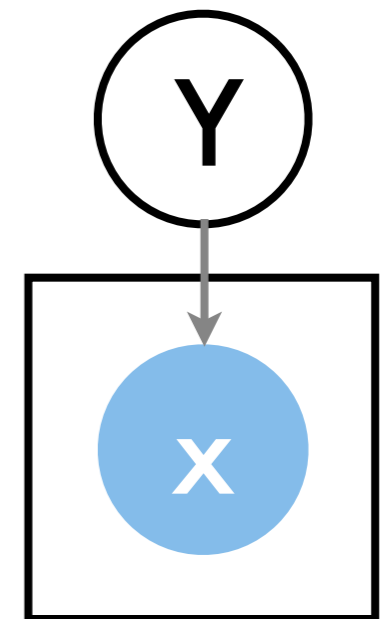
- Nonconvex optimization problem
- EM algorithm

Clustering

- Integrate out y



- Integrate out θ








- Nonconvex optimization problem
- EM algorithm

- Y is coupled
- Sampling
- Collapsed p

$$p(y|x) \propto p(\{x\} | \{x_i : y_i = y\} \cup X_{\text{fake}})p(y|Y \cup Y_{\text{fake}})$$






Gibbs sampling

- **Sampling:**
Draw an instance x from distribution $p(x)$
- **Gibbs sampling:**
 - In most cases direct sampling not possible
 - Draw one set of variables at a time

		
	0.45	0.05
	0.05	0.45

Gibbs sampling






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(b,g) - draw $p(.,g)$

Gibbs sampling






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 (g, g) - draw $p(g, .)$

Gibbs sampling






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 (g, g) - draw $p(g, .)$
 (g, g) - draw $p(., g)$

Gibbs sampling






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Draw an instance x from distribution $p(x)$
- Gibbs sampling:
 - In most cases direct sampling not possible
 - Draw one set of variables at a time

		
	0.45	0.05
	0.05	0.45

(b, g) - draw $p(., g)$
 (g, g) - draw $p(g, .)$
 (g, g) - draw $p(., g)$
 (b, g) - draw $p(b, .)$

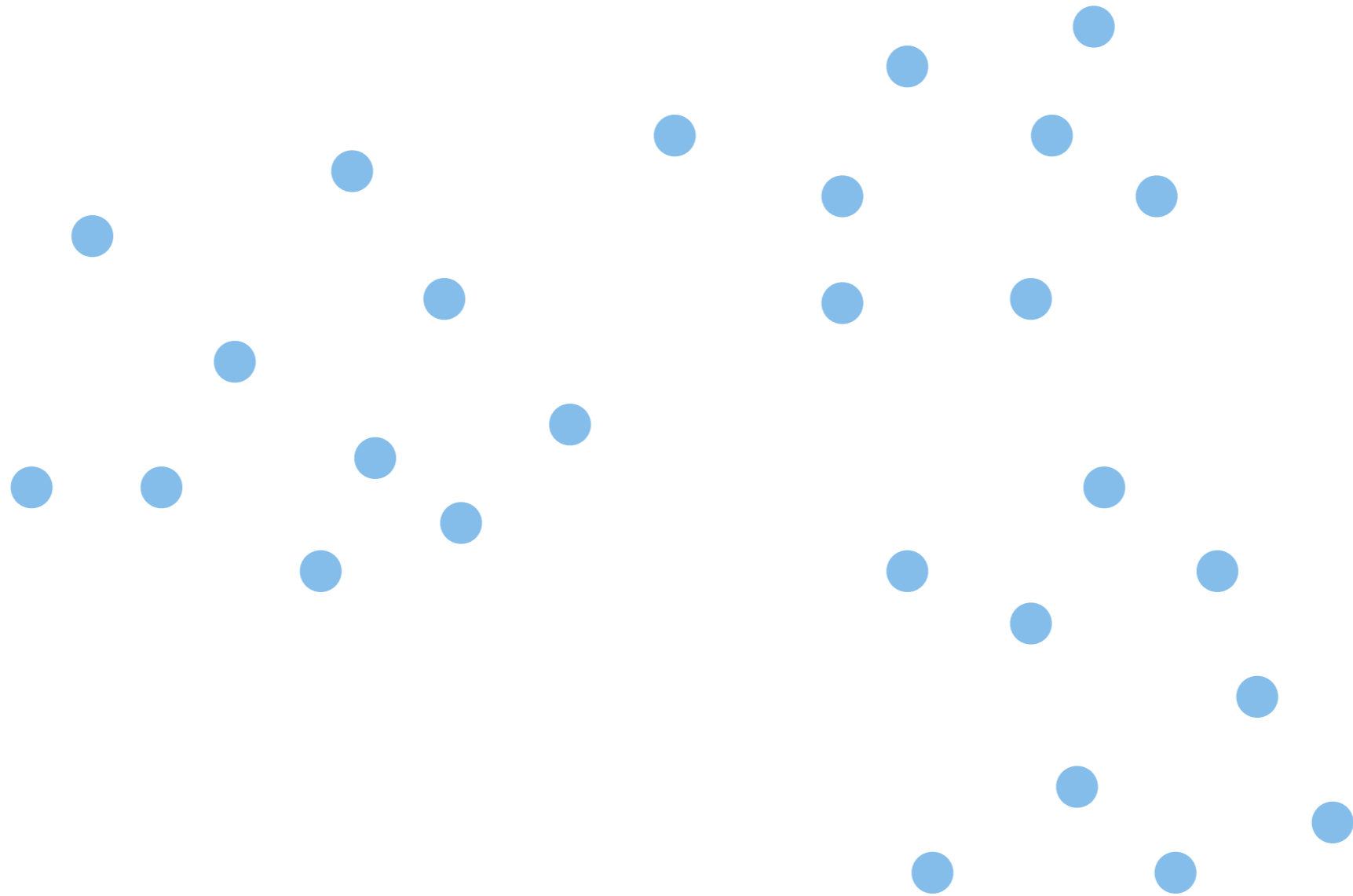
Gibbs sampling

- Sampling:
Draw an instance x from distribution $p(x)$
- Gibbs sampling:
 - In most cases direct sampling not possible
 - Draw one set of variables at a time

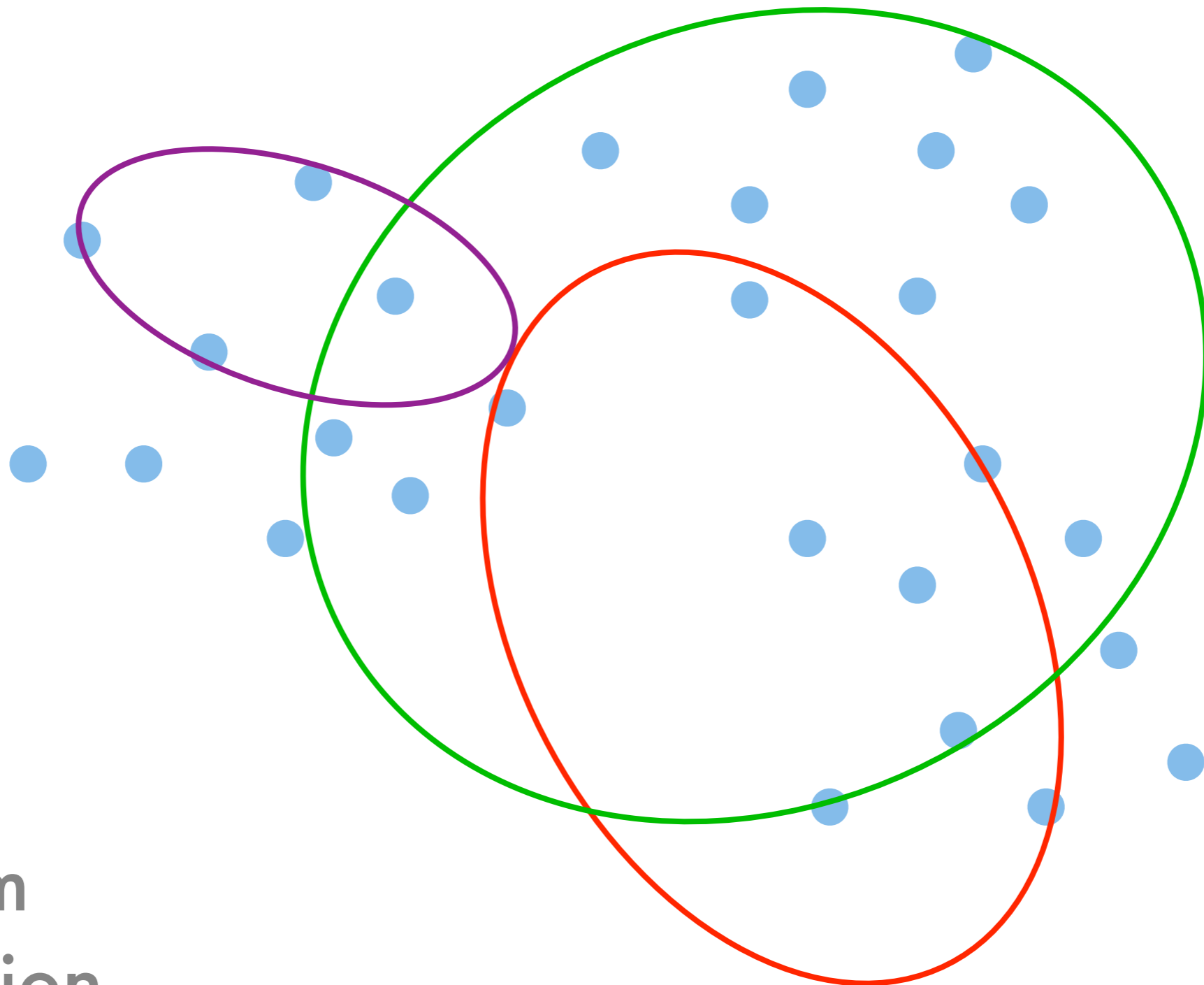
		
	0.45	0.05
	0.05	0.45

(b, g) - draw $p(., g)$
 (g, g) - draw $p(g, .)$
 (g, g) - draw $p(., g)$
 (b, g) - draw $p(b, .)$
 (b, b) ...

Gibbs sampling for clustering

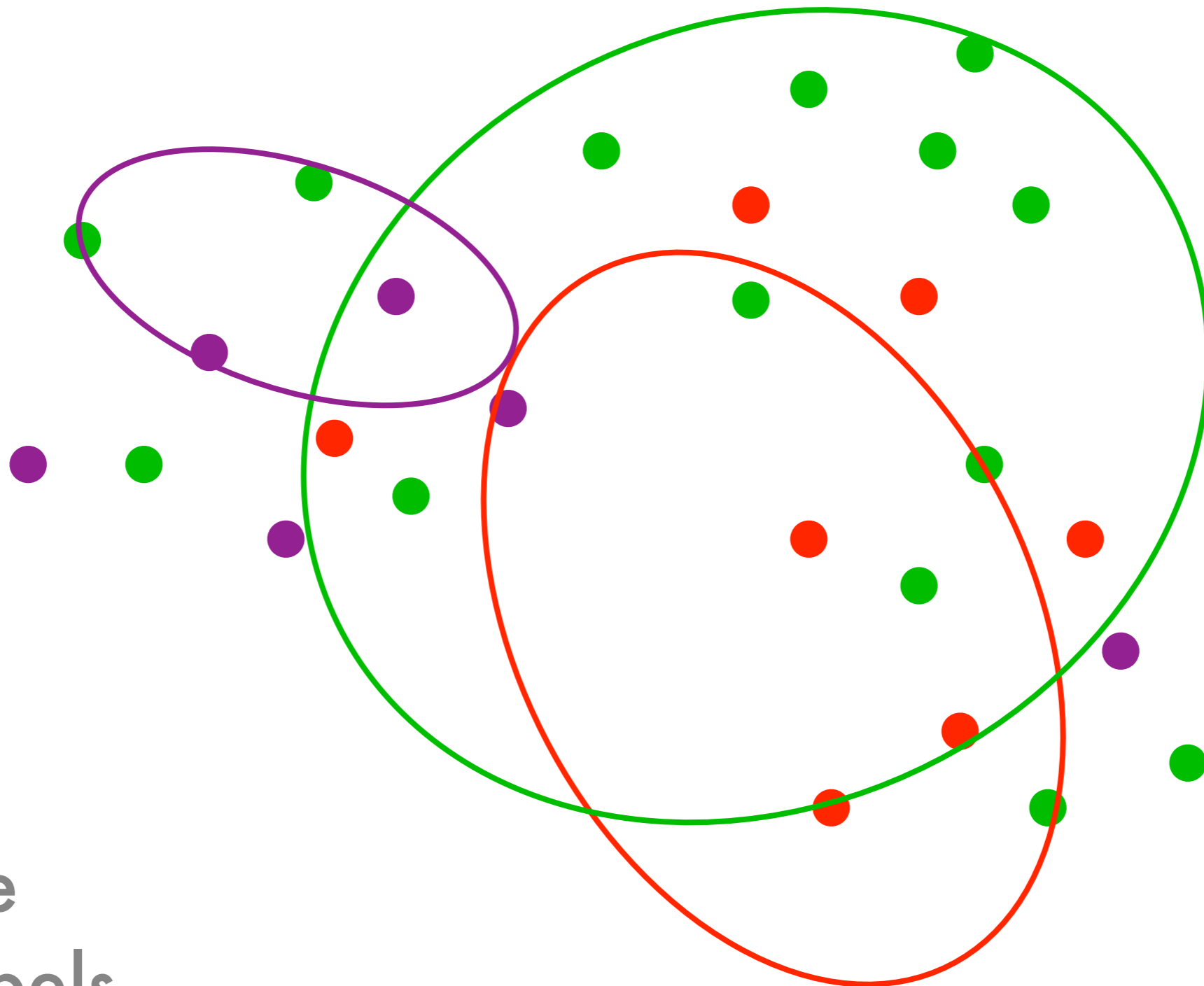


Gibbs sampling for clustering



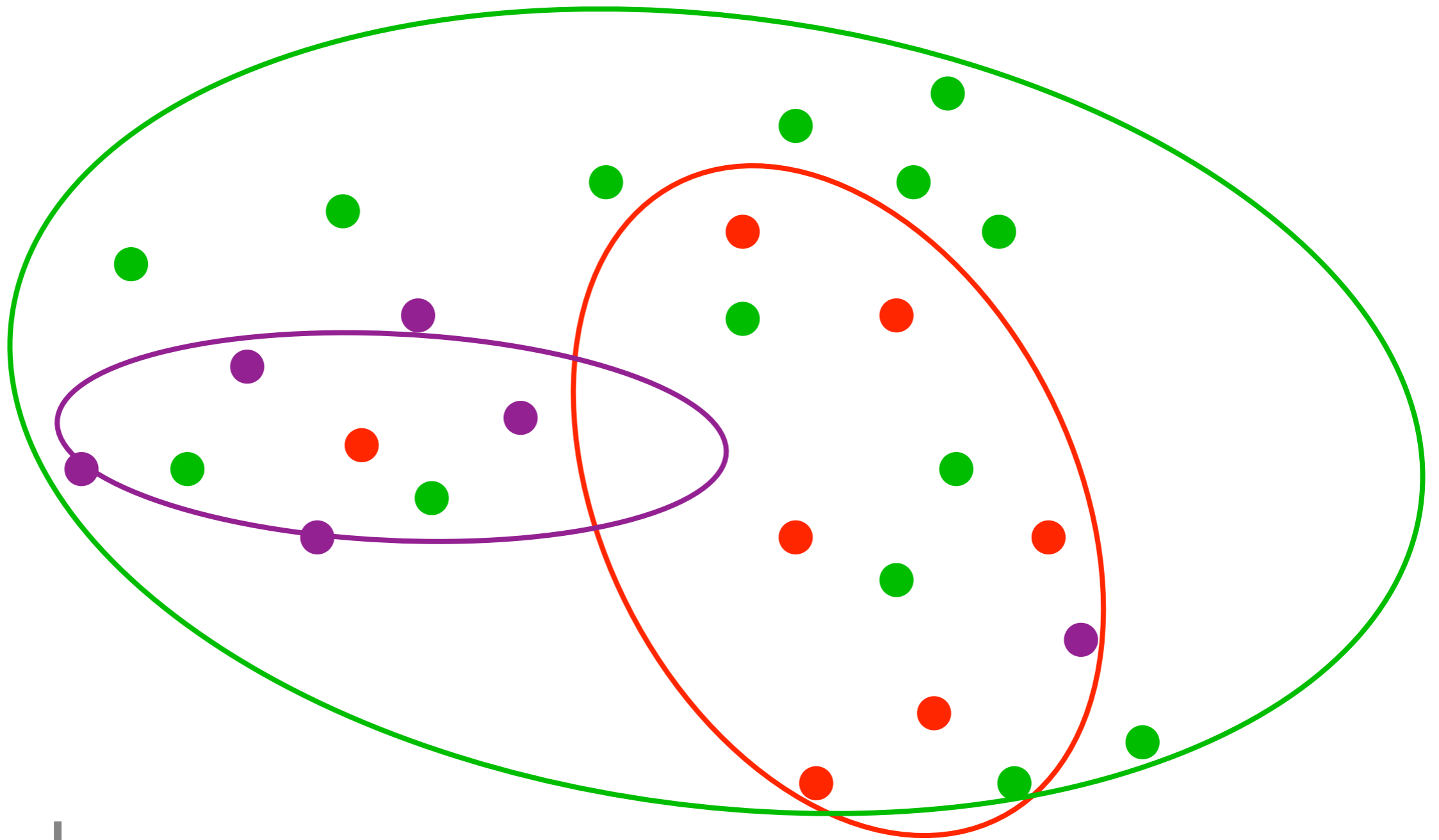
random
initialization

Gibbs sampling for clustering



sample
cluster labels

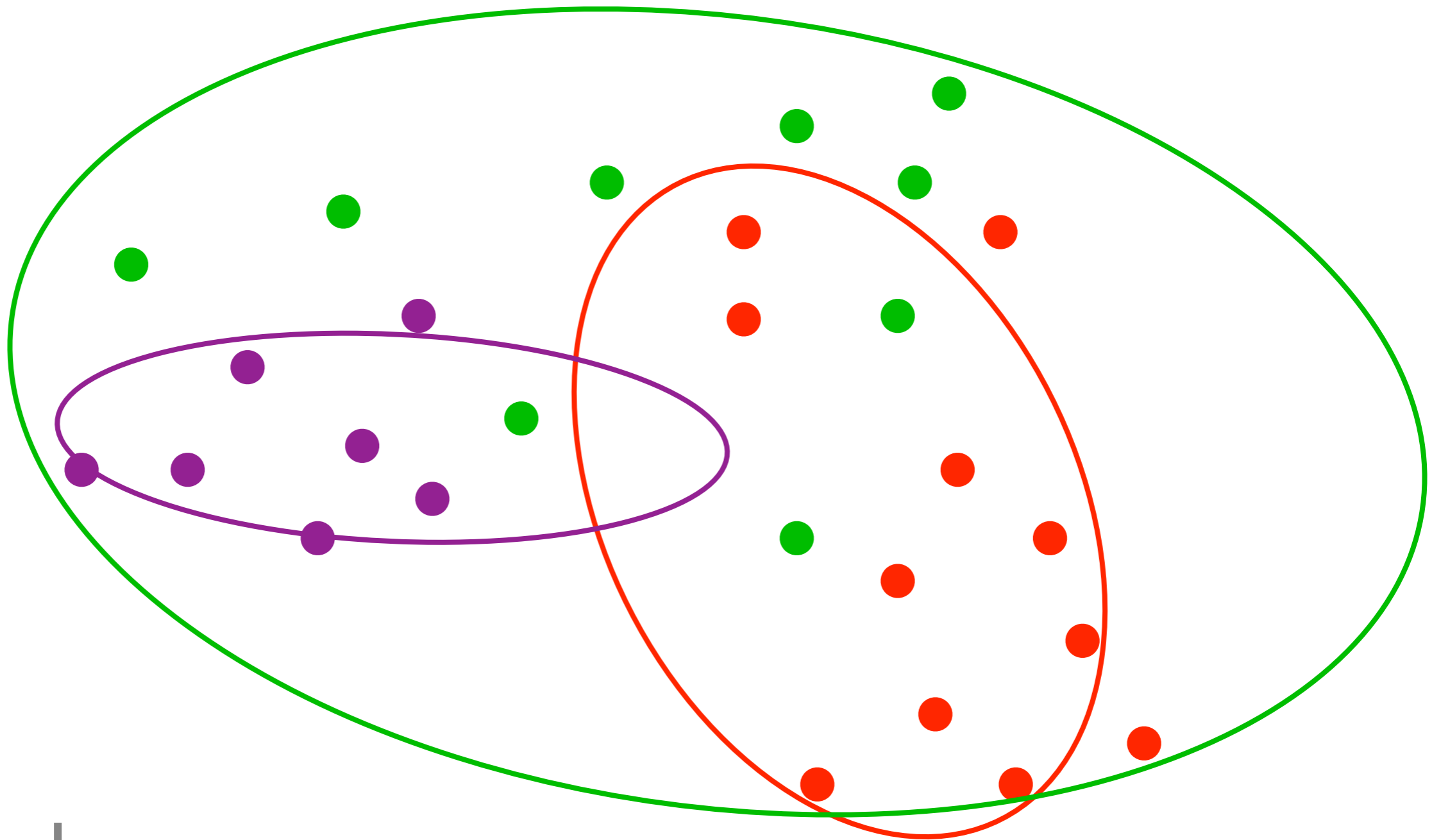
Gibbs sampling for clustering



resample

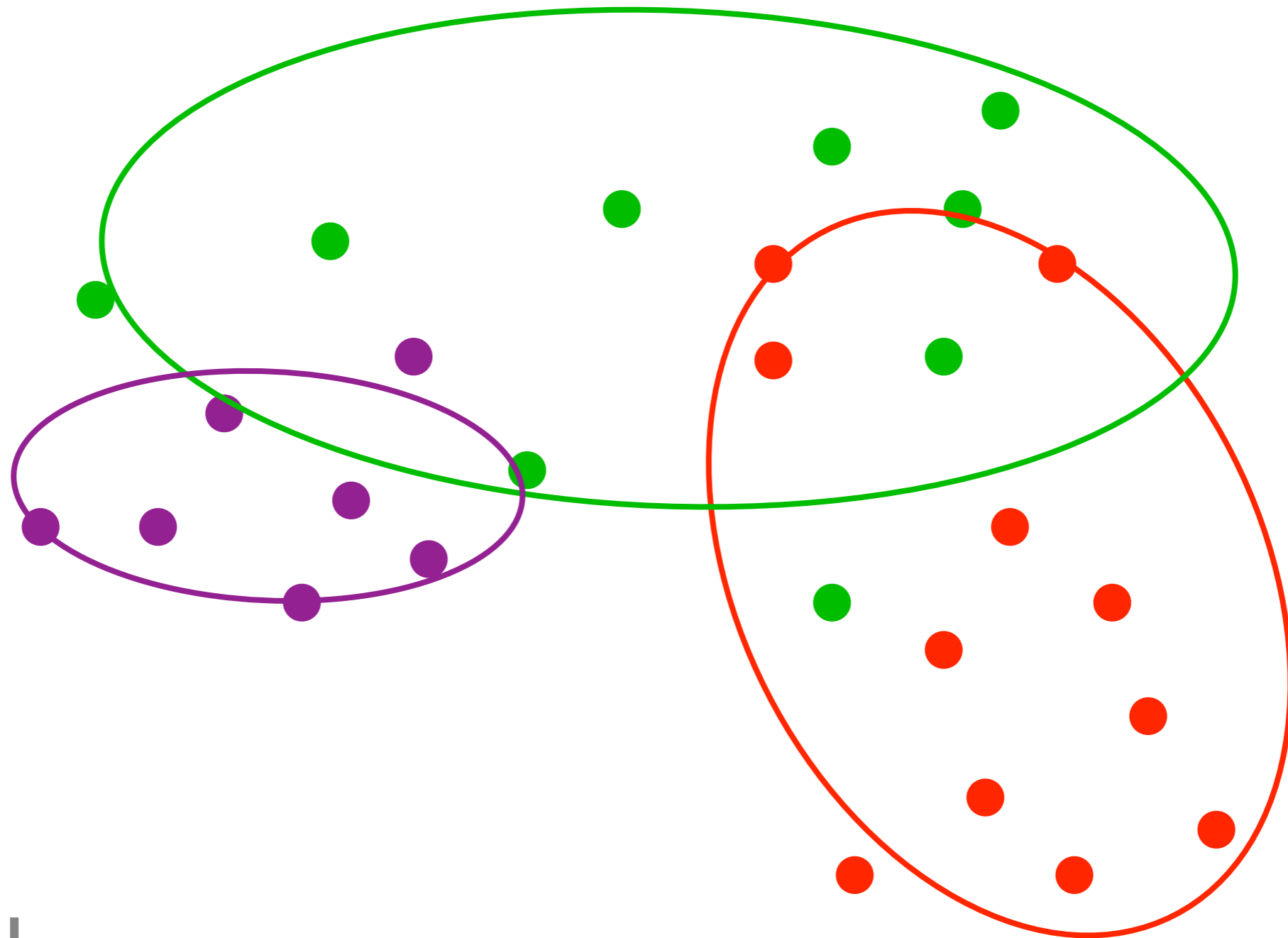
cluster model

Gibbs sampling for clustering



resample
cluster labels

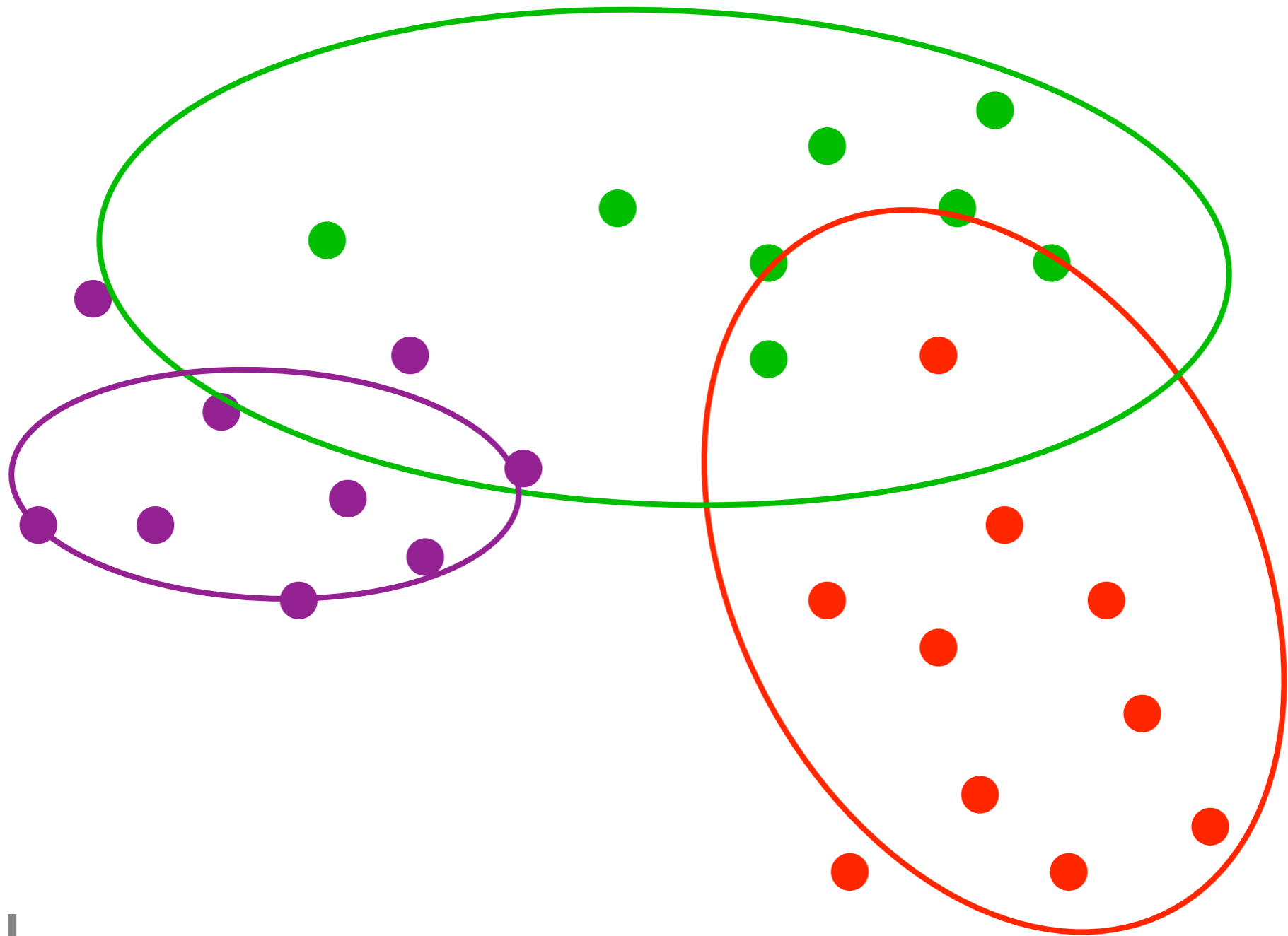
Gibbs sampling for clustering



resample

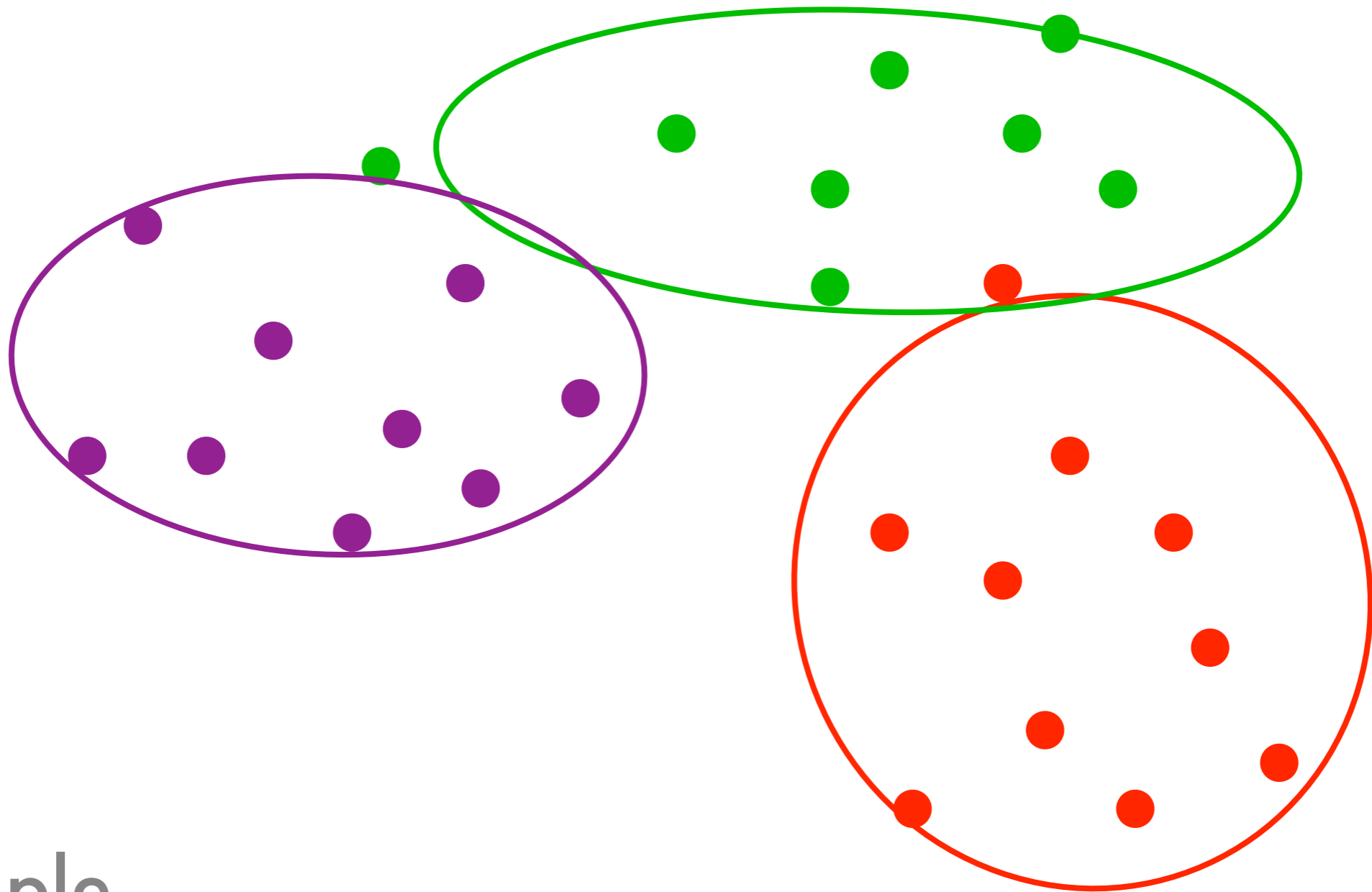
cluster model

Gibbs sampling for clustering



resample
cluster labels

Gibbs sampling for clustering



resample

cluster model

e.g. Mahout Dirichlet Process Clustering

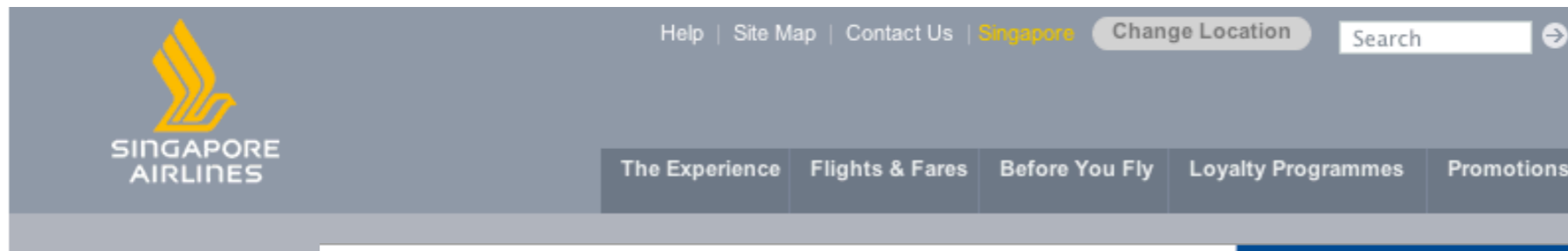


Topic models



Grouping objects

Grouping objects



SINGAPORE AIRLINES

Help | Site Map | Contact Us | Singapore | Change Location | Search

The Experience | Flights & Fares | Before You Fly | Loyalty Programmes | Promotions

Book a Flight | Check In

Round Trip One Way

From:



myEMAIL | IVLE | LIBRARY | MAPS | CALENDAR | SITEMAP | CONTACT | e-CARDS

Search in GO

ABOUT NUS | GLOBAL | ADMISSIONS | ENTERPRISE | CAMPUS LIFE | GIVING | CAREERS@NUS

Home | About Us | Services | Events & Promotions | Shopping, Wining & Dining | Contact | Sitemap

Singapore

CHIJMES
restaurants • bars • shops

Discover a century of resplendent living history behind the cloistered walls.

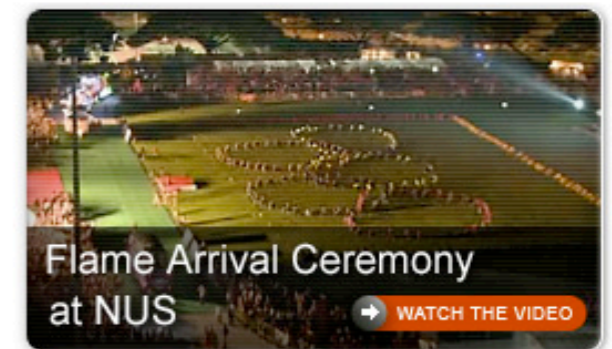
Chijmes, a premier lifestyle destination in Singapore

Owned by: Managed by: Property Manager:



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Feedback | Terms & Conditions



Flame Arrival Ceremony at NUS

WATCH THE VIDEO



Joint Evacuation Exercises

- 7 & 14 Sept 2010
- 10am - 12pm
- Heng Mui Keng Terrace & vicinity

MORE DETAILS

STAFF

ALUMNI

VISITORS

YAHOO!

Grouping objects

The screenshot shows the United Airlines website interface. At the top, there's the United logo and navigation links for 'My profile', 'Worldwide sites', and 'Customer service'. Below this is a menu with categories like 'Planning & booking', 'Reservations & check-in', 'Mileage Plus', and 'Services & information'. A search bar is also present. The main content area features a large promotional banner for 'Use 30% fewer miles on your next United flight.' with an illustration of a person holding a large orange balloon shaped like a percentage sign. To the right of the banner is a 'Log in' section with fields for 'Mileage Plus # or email address' and 'Password', along with a 'Remember me' checkbox and 'Log in' button. Below the login section are links for 'Start with My Mileage Plus' and 'My reservations'. Further down, there's a 'Travel information' section with links to 'Updates to baggage & standby policies' and 'View travel requirements and regulations'. At the bottom of the main content area, there's a 'United news and deals' section with several links, including 'Travel waiver issued due to Hurricane Earl', 'E-Fares: Save on weekend getaways', and 'United-Continental merger'. A 'Search' button is located at the bottom right of the main content area.

The screenshot shows the Australian National University (ANU) website. At the top, there's a navigation menu with links for 'Calendar', 'Sitemap', 'Contact', and 'e-CARDS'. Below this is a search bar with the text 'Search ANU...' and a 'GO' button. The main content area features a large banner with the text 'The Australian National University' and a background image of a building. Below the banner is another navigation menu with links for 'Current Students', 'Research & Education', 'About ANU', and 'Staff'. At the bottom of the main content area, there's a section with the text 'Forests renew after Black Saturday fires' and 'School of Music at Floriade'. A 'Search' button is located at the bottom right of the main content area.

The footer section of the United Airlines website shows ownership and management information. It includes the text 'Owned by:', 'Managed by:', and 'Property Manager:'. Below this are logos for 'SUNTEC Real Estate Investment Trust', 'ARA', and 'APC AFAC Investment Management Pte Ltd'. A copyright notice is also present: 'Copyright © 2006 Chijmes. All rights reserved.'

The footer section of the Australian National University website shows navigation and content. It includes a 'Search' button and a 'GO' button. Below this is a navigation menu with links for 'Current Students', 'Research & Education', 'About ANU', and 'Staff'. At the bottom of the main content area, there's a section with the text 'Forests renew after Black Saturday fires' and 'School of Music at Floriade'. A 'Search' button is located at the bottom right of the main content area.

Grouping objects

The screenshot shows the United Airlines website interface. At the top, there are navigation links for "My profile", "Worldwide sites", and "Customer service". Below this is a search bar and a menu with categories like "Planning & booking", "Reservations & check-in", "Mileage Plus", and "Services & information". The main content area is divided into several sections: "Flights" with a "BOOK FLIGHT" and "REDEEM MILES" section, a "Log in" section with fields for "Mileage Plus # or email address" and "Password", and a "Travel information" section. There are also promotional banners, such as "Use 30% fewer miles on your next United flight" and "Earn up to 30,000 Bonus Miles".

The screenshot shows the Australian National University (ANU) website. The header includes the ANU logo and the text "The Australian National University". Below the header is a navigation menu with links for "HOME", "FUTURE STUDENTS", "CURRENT STUDENTS", "RESEARCH & EDUCATION", "ABOUT ANU", and "STAFF". The main content area features a news article titled "Ash forests rise and rise again" with a sub-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." Below the article are several navigation buttons: "PROSPECTIVE STUDENTS", "CURRENT STUDENTS", "STAFF", "ALUMNI", and "VISITORS". There is also a video player for "Joint Evacuation Exercises" and a "WATCH THE VIDEO" button.

The screenshot shows the Chez Panisse website. The header features the "Chez Panisse" logo. Below the logo is a navigation menu with links for "RESERVATIONS", "MENUS", "ABOUT", "SPECIAL EVENTS", "STORE", and "CONTACT". The "ABOUT" link is highlighted. Below the navigation menu is a list of links: "CHEZ PANISSE", "ALICE WATERS", "OUR CHEFS", "FRIENDS", "PRESS", "FOUNDATION & MISSION".



ng, Wining & Dining | Contact | Sitemap | About Suntec REIT



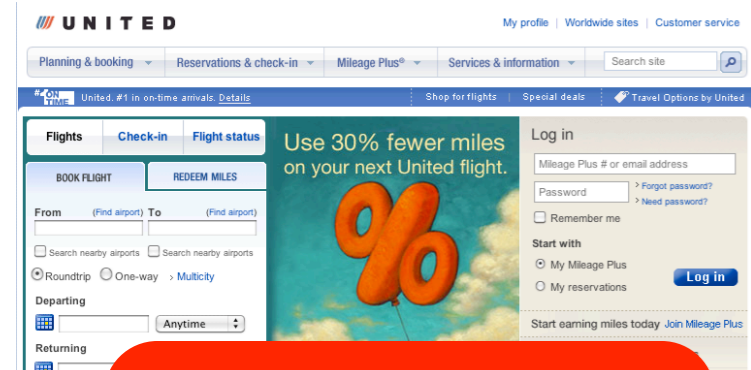
Grouping objects

The image shows a screenshot of the United Airlines website. The page features a navigation menu at the top with options like 'Planning & booking', 'Reservations & check-in', and 'Mileage Plus'. A large red speech bubble with the word 'airline' is overlaid on the page. Below the navigation, there are sections for flight booking, including 'BOOK FLIGHT' and 'REDEEM MILES', and a 'Log in' section. A promotional banner for 'Use 30% fewer miles on your next United flight' is visible. The bottom of the page includes a footer with 'Need Help?' and 'Book A Flight Guide'.

The image shows a screenshot of the Australian National University (ANU) website. The page features a navigation menu at the top with options like 'EXPLORE ANU', 'A-Z INDEX', and 'Search ANU...'. A large red speech bubble with the word 'university' is overlaid on the page. Below the navigation, there are sections for 'HOME', 'FUTURE STUDENTS', 'CURRENT STUDENTS', 'RESEARCH & EDUCATION', 'ABOUT ANU', and 'STAFF'. A prominent article titled 'Ash forests rise and rise again' is featured, along with a 'Higher Degree Research' section. The bottom of the page includes a footer with 'PROSPECTIVE STUDENTS', 'CURRENT STUDENTS', 'STAFF', 'ALUMNI', and 'VISITORS'.

The image shows a screenshot of the Chez Panisse restaurant website. The page features a navigation menu at the top with options like 'Home', 'Wining & Dining', 'Contact', 'Sitemap', and 'About Suntec REIT'. A large red speech bubble with the word 'restaurant' is overlaid on the page. Below the navigation, there are sections for 'RESERVATIONS', 'MENUS', 'ABOUT', 'SPECIAL EVENTS', 'STORE', and 'CONTACT'. The background of the page shows a photograph of the restaurant's interior, which is a rustic, industrial-style space with a sign that reads 'BAR DE LA'. The bottom of the page includes a footer with '© 1999-2010 Chez Panisse Restaurant & Café. All Rights Reserved.' and 'Directions Reservations Contact'.

Grouping objects



UNITED My profile | Worldwide sites | Customer service

Planning & booking | Reservations & check-in | Mileage Plus® | Services & information | Search site

Use 30% fewer miles on your next United flight.

Log in

Mileage Plus # or email address

Password

Remember me

Start with

My Mileage Plus

My reservations

Log in

Start earning miles today Join Mileage Plus

USA



RESERVATIONS RESTAURANT & CAFÉ

MENUS RESTAURANT • CAFÉ MONDAY NIGHTS • WINE LIST

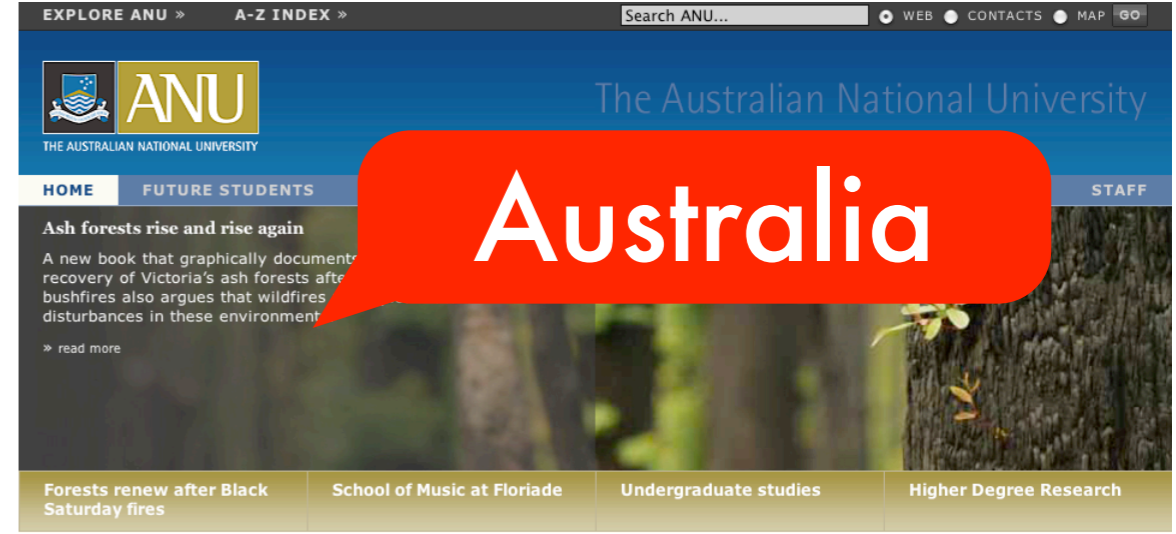
ABOUT CHEZ PANISSE • ALICE WATERS OUR CHEFS • FRIENDS • PRESS FOUNDATION & MISSION

SPECIAL EVENTS CALENDAR

STORE BOOKS • POSTERS • GIFTS

CONTACT INFORMATION DIRECTIONS • MAILING LIST

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EXPLORE ANU > A-Z INDEX > Search ANU... WEB CONTACTS MAP GO

ANU THE AUSTRALIAN NATIONAL UNIVERSITY

The Australian National University

HOME FUTURE STUDENTS STAFF

Ash forests rise and rise again

A new book that graphically documents recovery of Victoria's ash forests after bushfires also argues that wildfires disturbances in these environment

read more

Forests renew after Black Saturday fires | School of Music at Floriade | Undergraduate studies | Higher Degree Research

Australia



SINGAPORE AIRLINES

Book a Flight | Check in | Flight Status | My Bookings

Round Trip | One Way | Stopover/Multi-city

Departure City

Destination City

Adults: 1 | Children (2-11): 0 | Infants: 0

Need Help? View Book A Flight G

SIA Holidays | Hotel Bookings

NUS National University of Singapore

myEMAIL IVLE LIBRARY MAPS CALENDAR SITEMAP CONTACT e-CARDS

Search search for... in NUS Websites GO

ABOUT NUS GLOBAL ADMISSIONS EDUCATION RESEARCH ENTERPRISE CAMPUS LIFE GIVING CAREERS@NUS

A Leading Global University Centred in Asia

Home | About Us | Services | Events & Promotions | Shopping, Wining & Dining | Contact | Sitemap | About Suntec REIT

Flame Arrival Ceremony at NUS

WATCH THE VIDEO

Joint Evacuation Exercises

7 & 14 Sept 2010

10am - 12pm

Heng Mui Keng Terrace & vicinity

MORE DETAILS

ALUMNI VISITORS

Singapore



CHIJMES restaurant

Discover living in Singapore

Chijmes, a premier lifestyle destination in Singapore

Owned by: SUNTEC | Managed by: ARA | Property Manager: PC

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YAHOO!

Topic Models

UNITED My profile | Worldwide sites | Customer service

Planning & booking | Reservations & check-in | Mileage Plus | Services & information

Use 30% fewer miles on your next United flight.

BOOK FLIGHT REDEEM MILES

From (Find airport) To (Find airport)

Roundtrip One-way Multicity

Departing Anytime

Returning Anytime

Search by Schedule & price Price & Flex

Adult (child or senior?)

Cabin Economy Refundable

Promotion code or Electronic certificate

Log in to view all seating options

Advanced Search

Cars Hotels Vacations

Learn more

USA
airline

EXPLORE ANU | A-Z INDEX | Search ANU... | WEB | CONTACTS

ANU THE AUSTRALIAN NATIONAL UNIVERSITY

HOME | FUTURE STUDENTS | CURRICULUM | ABOUT ANU

Ash forests rise and rise again

A new book that graphically documents the recovery of Victoria's ash forests after the bushfires also argues that wildfires are typical disturbances in these environments.

Forests renew after Black Saturday fires | School of Music at Monash | Undergraduate studies | Higher Degree Research

Australia
university

SINGAPORE AIRLINES

The Experience | Flights & Fares | Before You Fly | Loyalty Programmes | Promotions

Book a Flight | Check In | Flight Status | My Bookings | Member Log-in

Round Trip One Way Stopover/Multi-city

From: Depart: Departure City

To: Return: Destination City

Must travel on these dates

Adults: Children (2-11): Infants:

Need Help? View Book A Flight

SIA Holidays | Hotel Bookings

Singapore - Bangkok SGD 395* | Singapore - Hong Kong SGD 546* | Singapore - Taipei SGD 768* | Singapore - Tokyo (Haneda) SGD 983* | Singapore - Sydney | Singapore - London

Singapore
airline

NUS National University of Singapore

myEMAIL | IVLE | LIBRARY | MAPS | CALENDAR | SITEMAP | CONTACT | CARDS

Search search for... in NUS Websites GO

ABOUT NUS | GLOBAL | ADMISSIONS | EDUCATION | RESEARCH | ENTERPRISE | CAMPUS LIFE | GIVING | CAREERS@NUS

A Leading Global University

Game Arrival Ceremony NUS

Joint Evacuation Exercises

7 & 14 Sept 2010

10am - 12pm

Heng Mui Keng Terrace & vicinity

PROSPECTIVE STUDENTS | CURRENT STUDENTS | STAFF | ALUMNI | VISITORS

Singapore
university

Chez Panisse

RESERVATIONS RESTAURANT & CAFÉ

MENUS RESTAURANT • CAFÉ MONDAY NIGHTS • WINE LIST

ABOUT CHEZ PANISSE • ALICE WATERS OUR CHEFS • FRIENDS • PRESS FOUNDATION & MISSION

SPECIAL EVENTS CALENDAR

STORE BOOKS • POSTERS • GIFTS

CONTACT INFORMATION DIRECTIONS • MAILING LIST

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USA
food

Services | Events & Promotions | Shopping, Wining & Dining | Contact | Sitemap | About Suntec REIT

Chijmes

restaurants • bars • shops

Discover a century of resplendent living history behind the cloisters

Chijmes, a premier lifestyle destination in Singapore

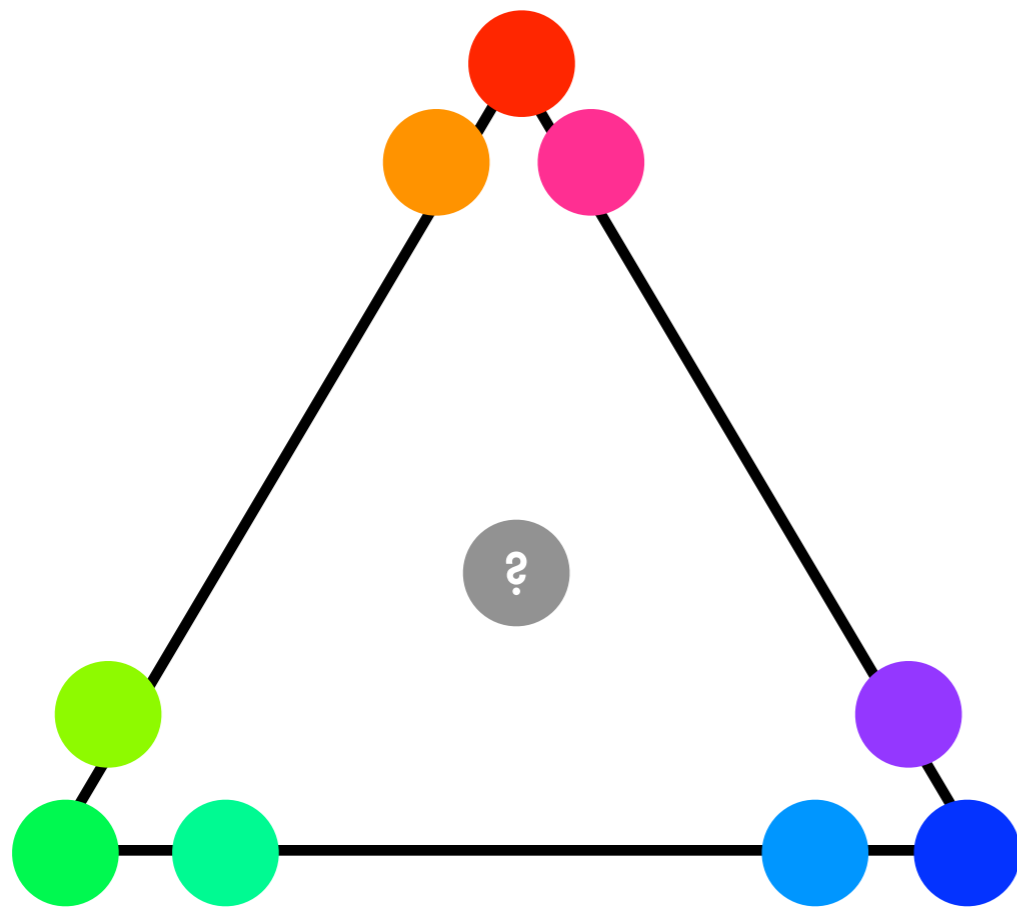
Owned by: SUNTEC | Managed by: ARA | Property Manager: APC

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Singapore
food

Clustering & Topic Models

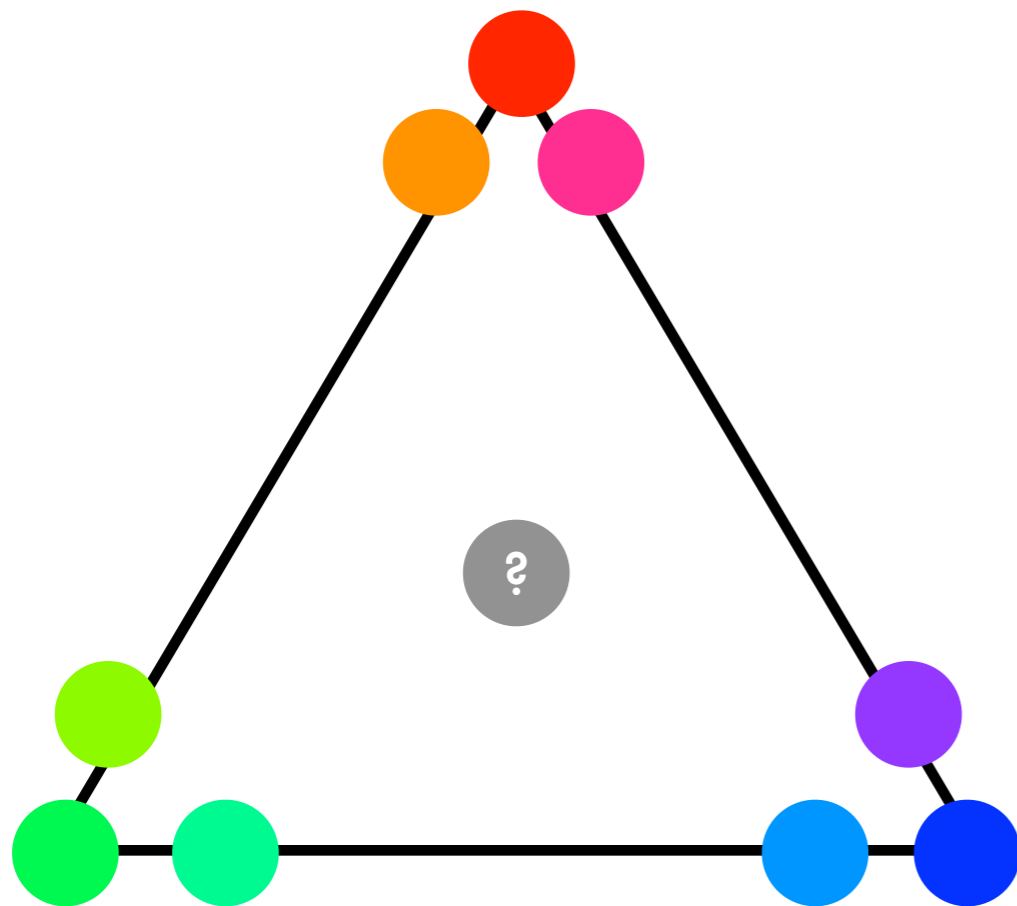
Clustering



group objects
by prototypes

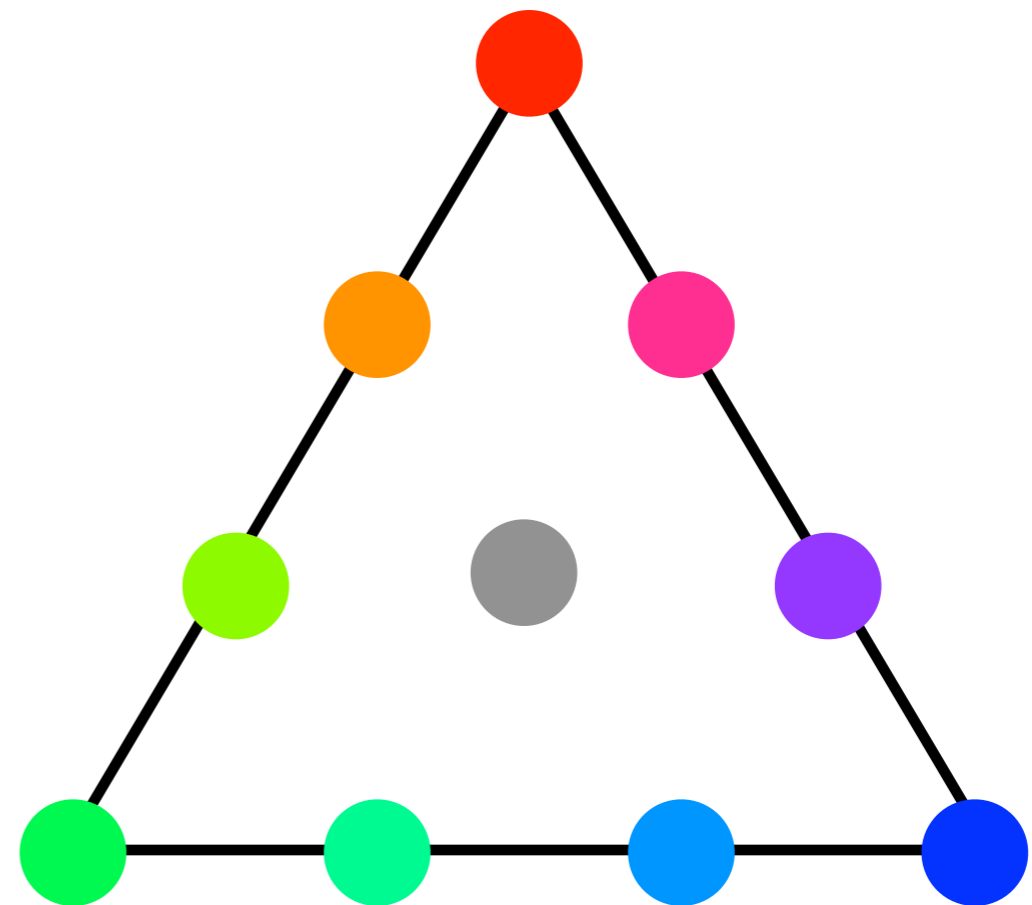
Clustering & Topic Models

Clustering



group objects
by prototypes

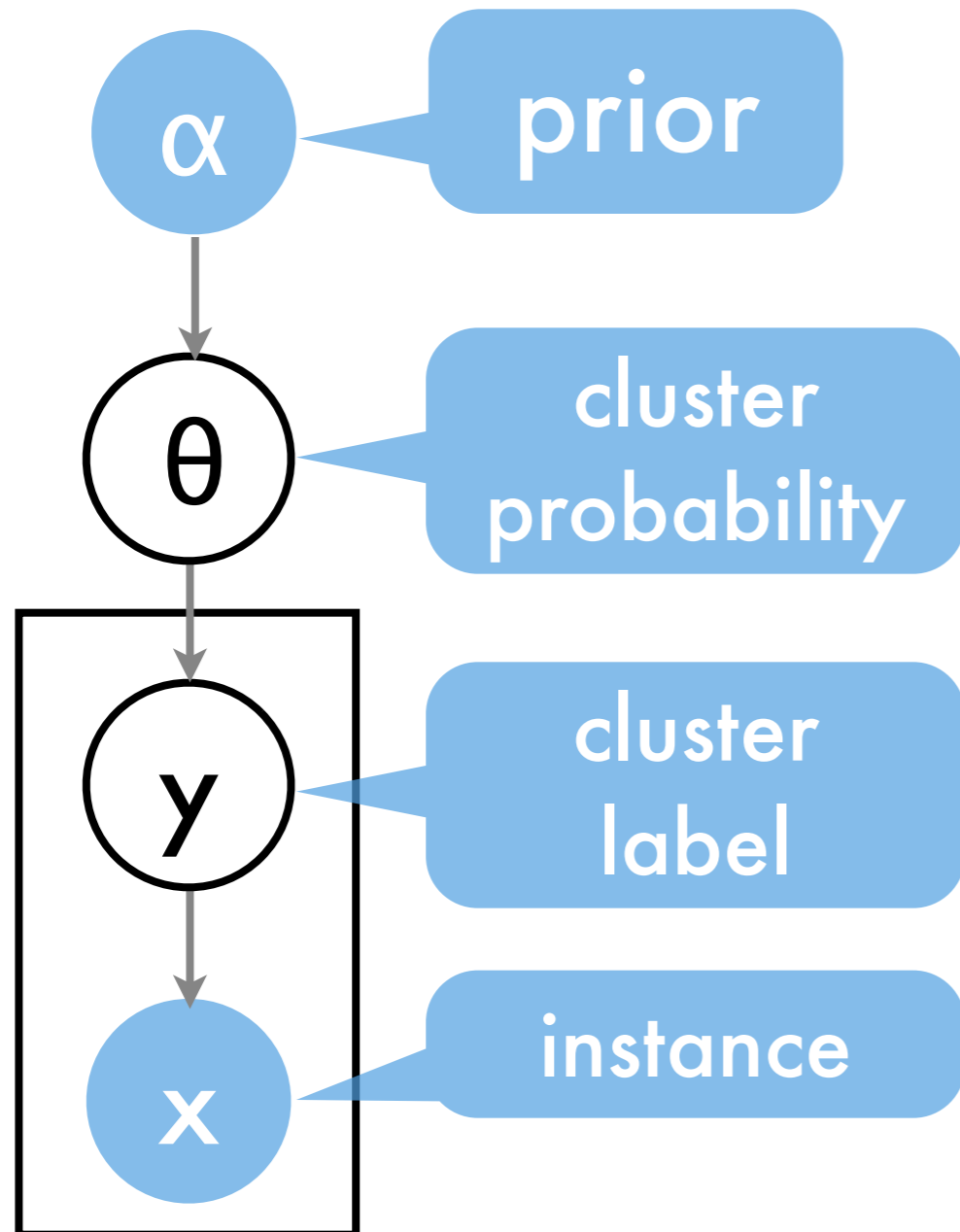
Topics



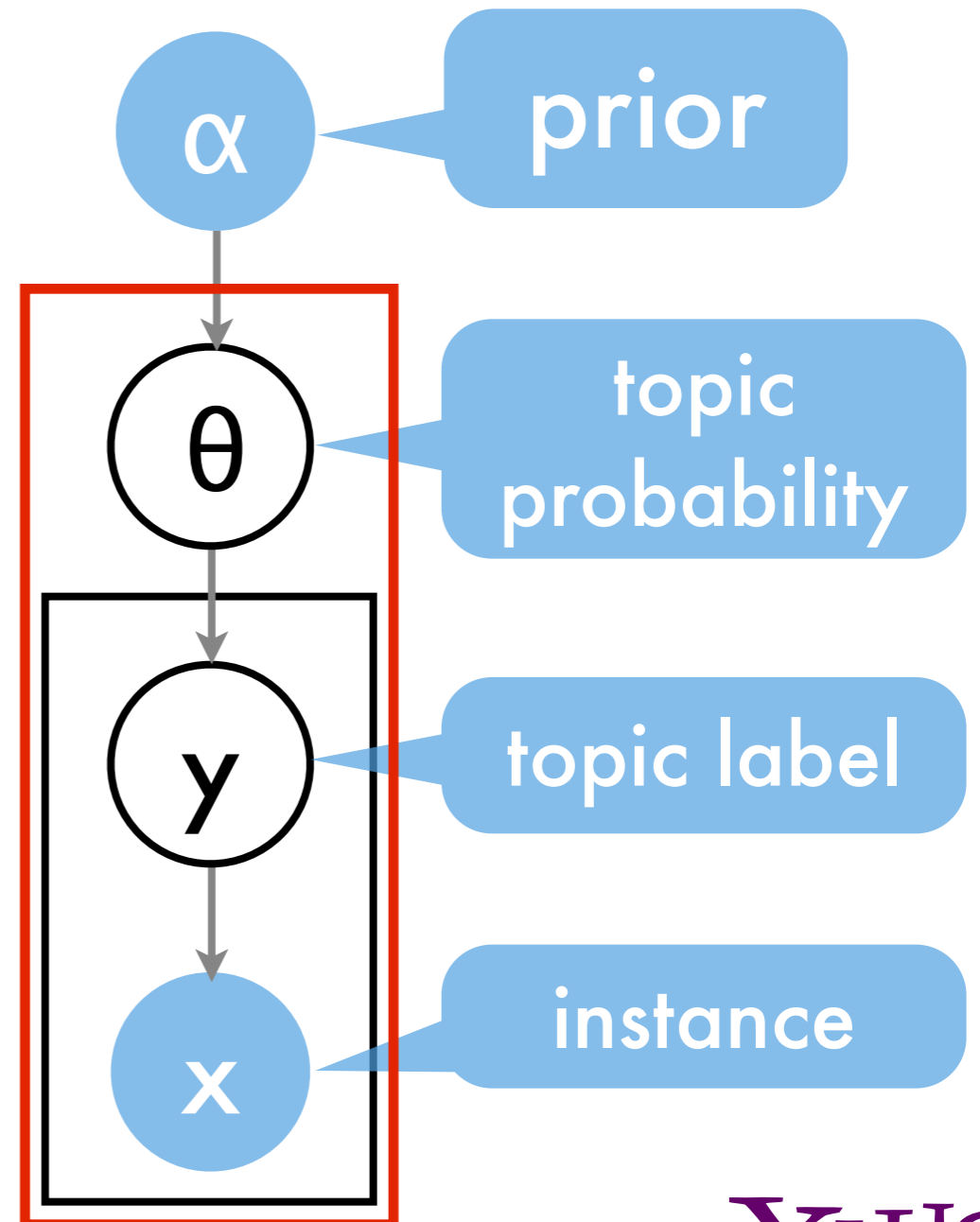
decompose objects
into prototypes

Clustering & Topic Models

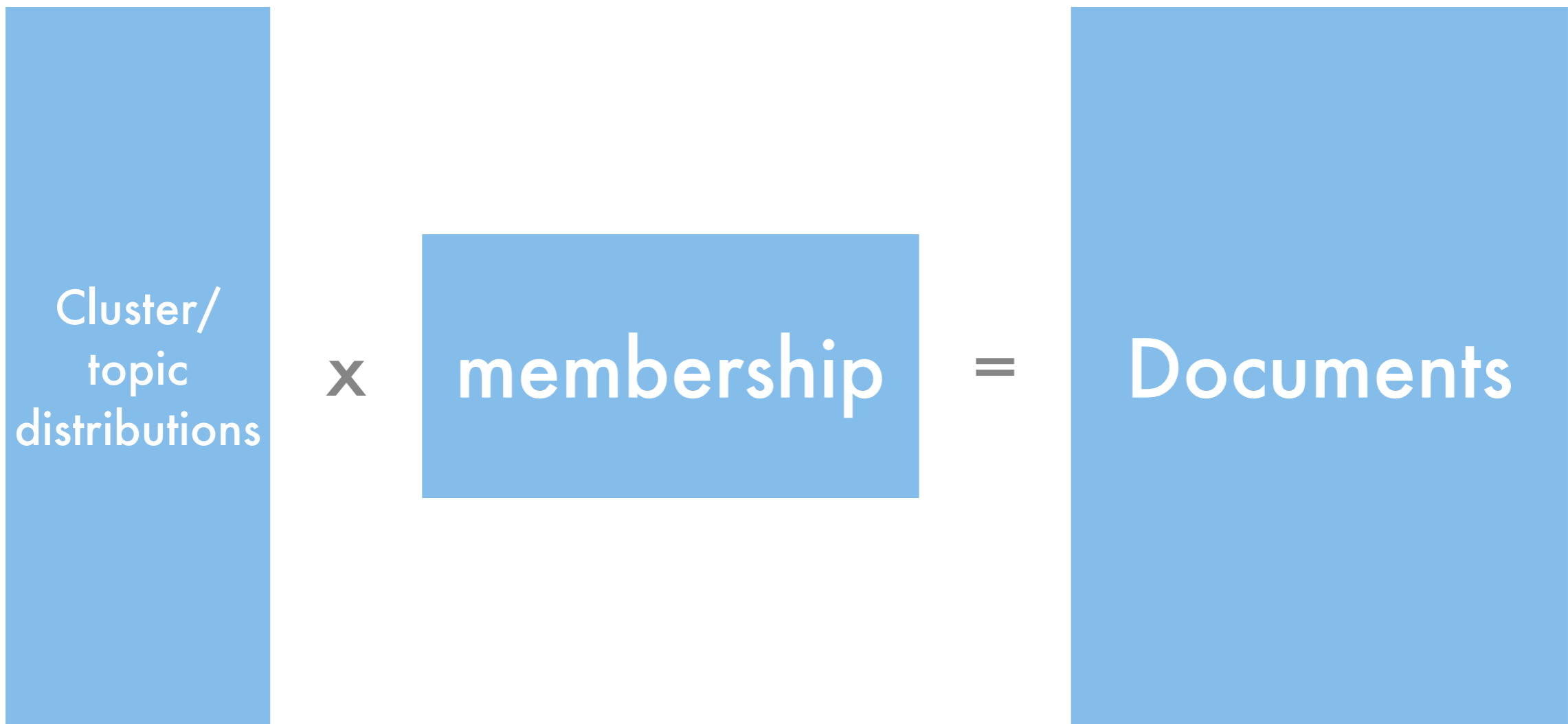
clustering



Latent Dirichlet Allocation



Clustering & Topic Models



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

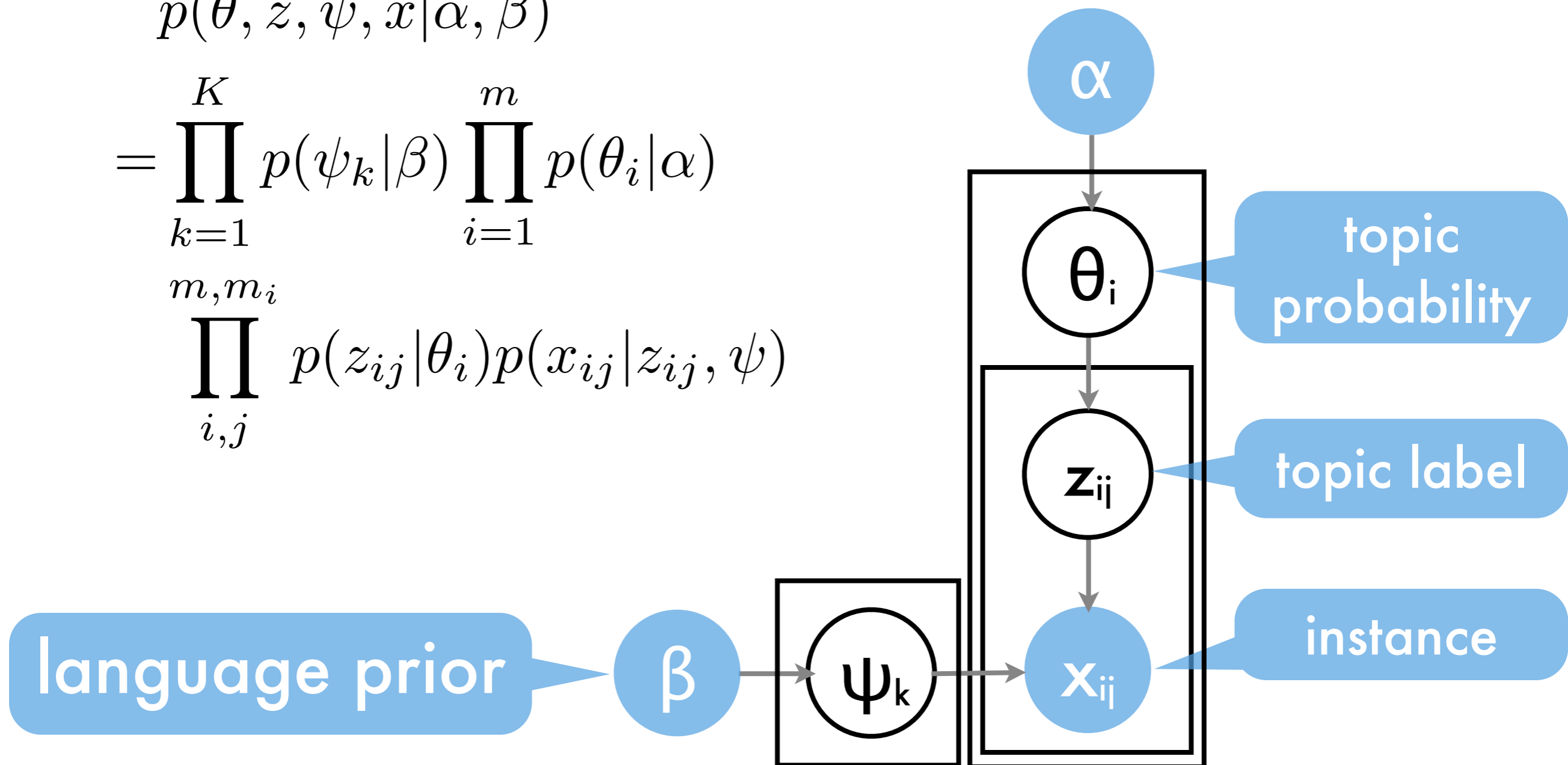
Topics in text

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

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

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

$$= \prod_{k=1}^K p(\psi_k | \beta) \prod_{i=1}^m p(\theta_i | \alpha)$$

sample θ
independently

$$\prod_{i,j} p(z_{ij} | \theta_i) p(x_{ij} | z_{ij}, \psi)$$

sample z
independently

language prior

β

Ψ_k

α

θ_i

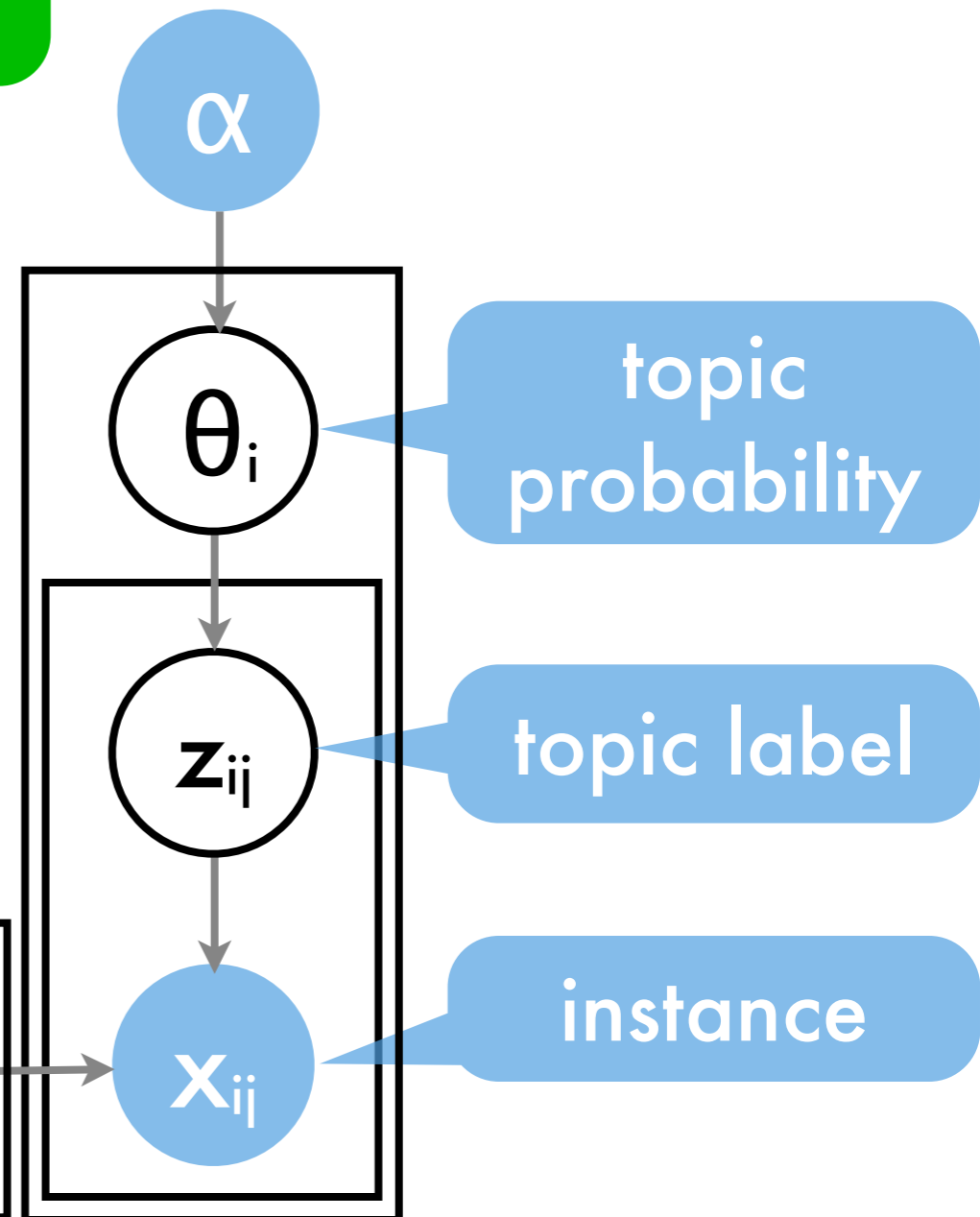
z_{ij}

x_{ij}

topic probability

topic label

instance



Joint Probability Distribution

sample Ψ
independently

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

$$= \prod_{k=1}^K p(\psi_k | \beta) \prod_{i=1}^m p(\theta_i | \alpha)$$

sample θ
independently

$$\prod_{i,j} p(z_{ij} | \theta_i) p(x_{ij} | z_{ij}, \psi)$$

sample z
independently

language prior

β

Ψ_k

α

θ_i

z_{ij}

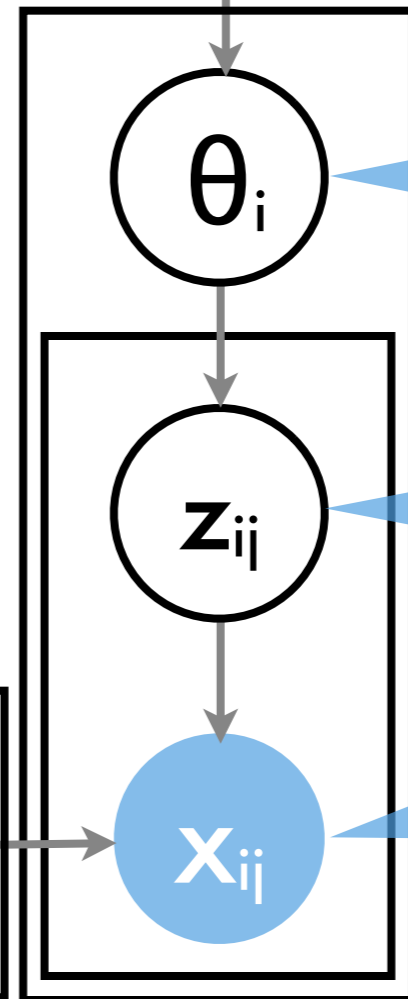
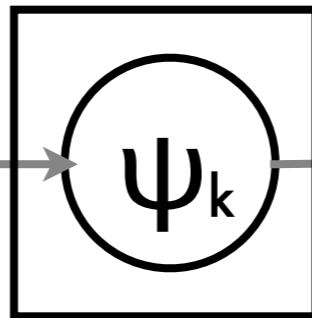
x_{ij}

slow

topic probability

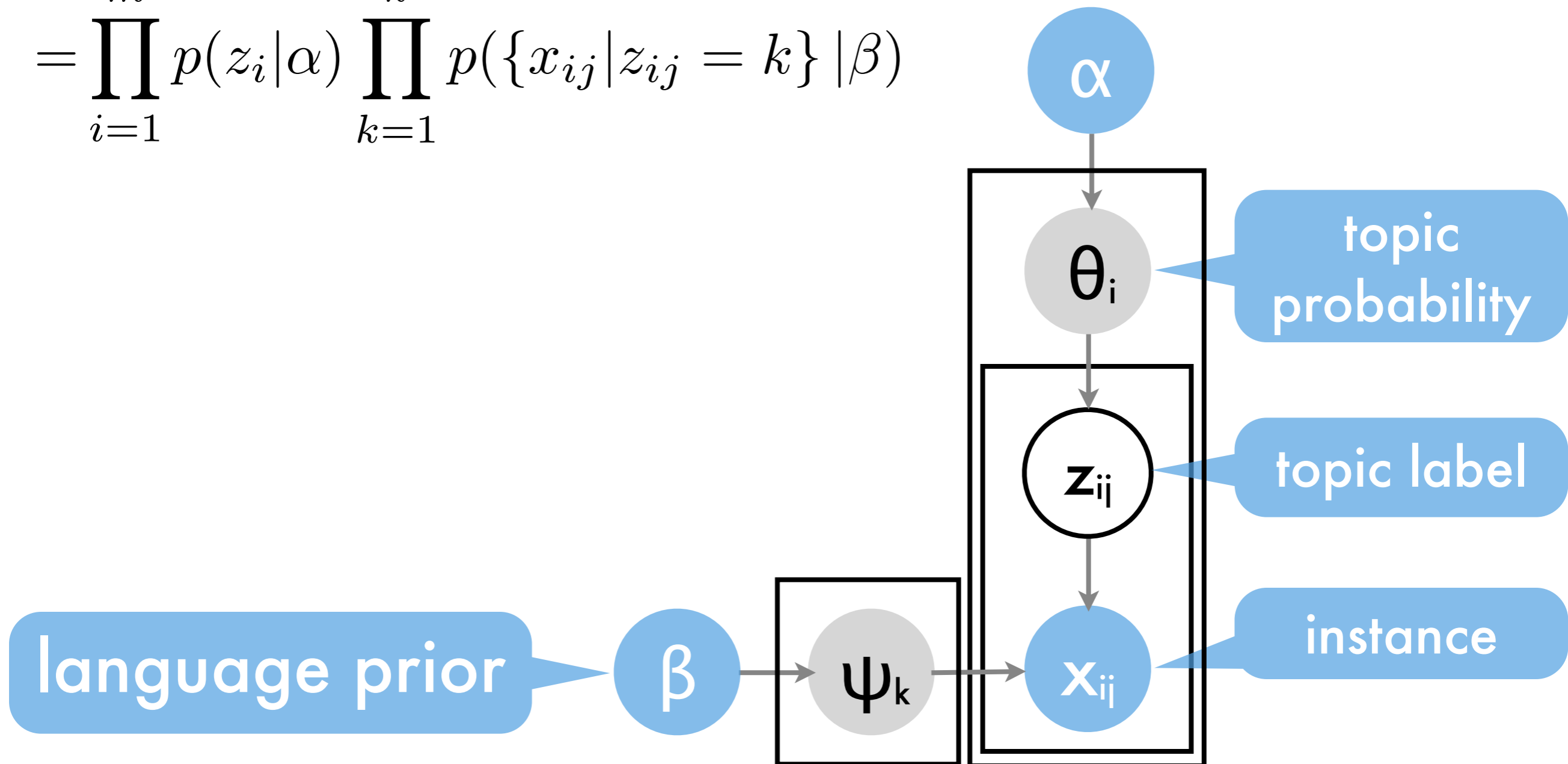
topic label

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

language prior

β

ψ_k

x_{ij}

α

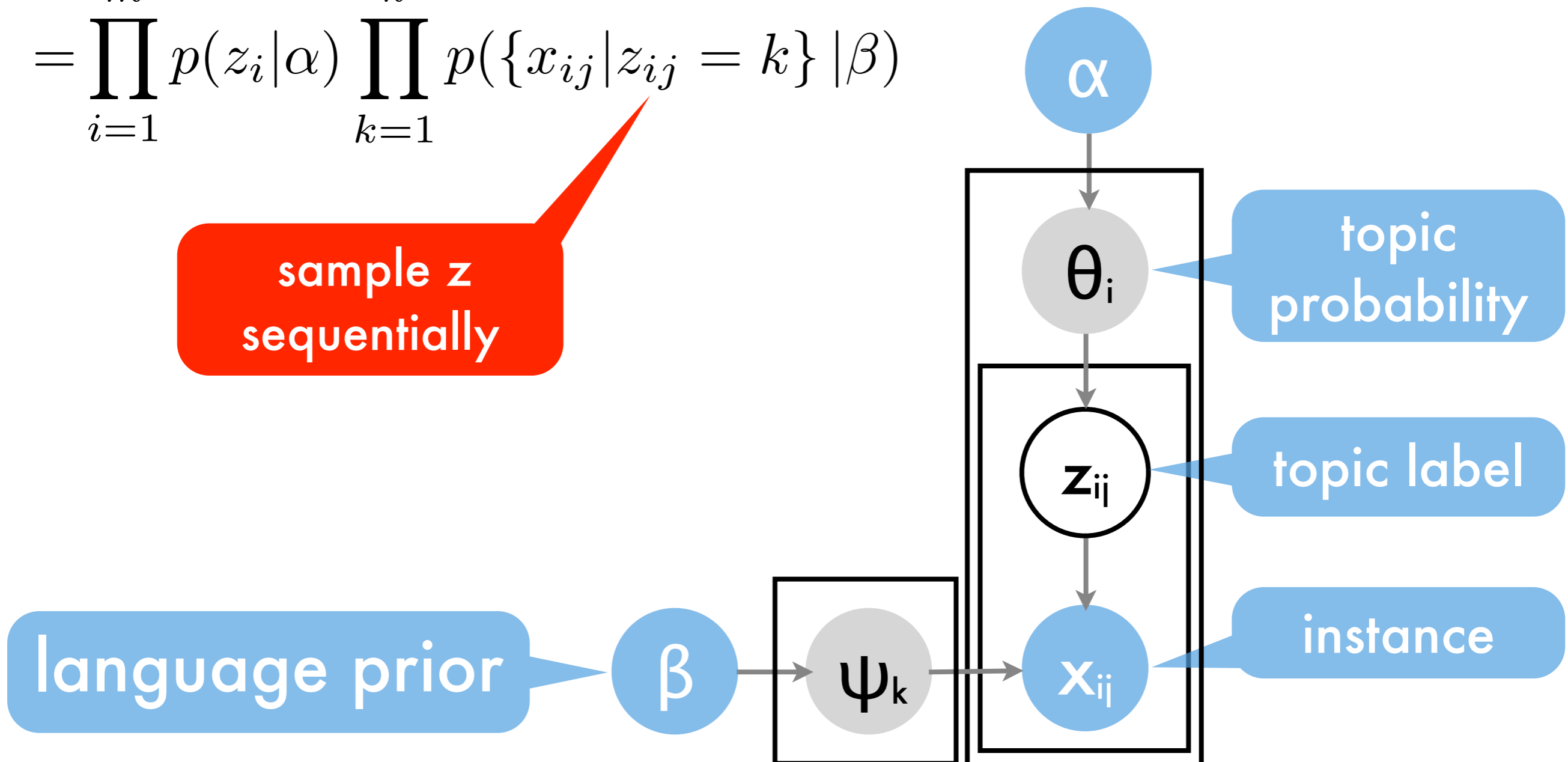
θ_i

z_{ij}

topic
probability

topic label

instance



Collapsed Sampler

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

sample z
sequentially

language prior

β

ψ_k

x_{ij}

z_{ij}

θ_i

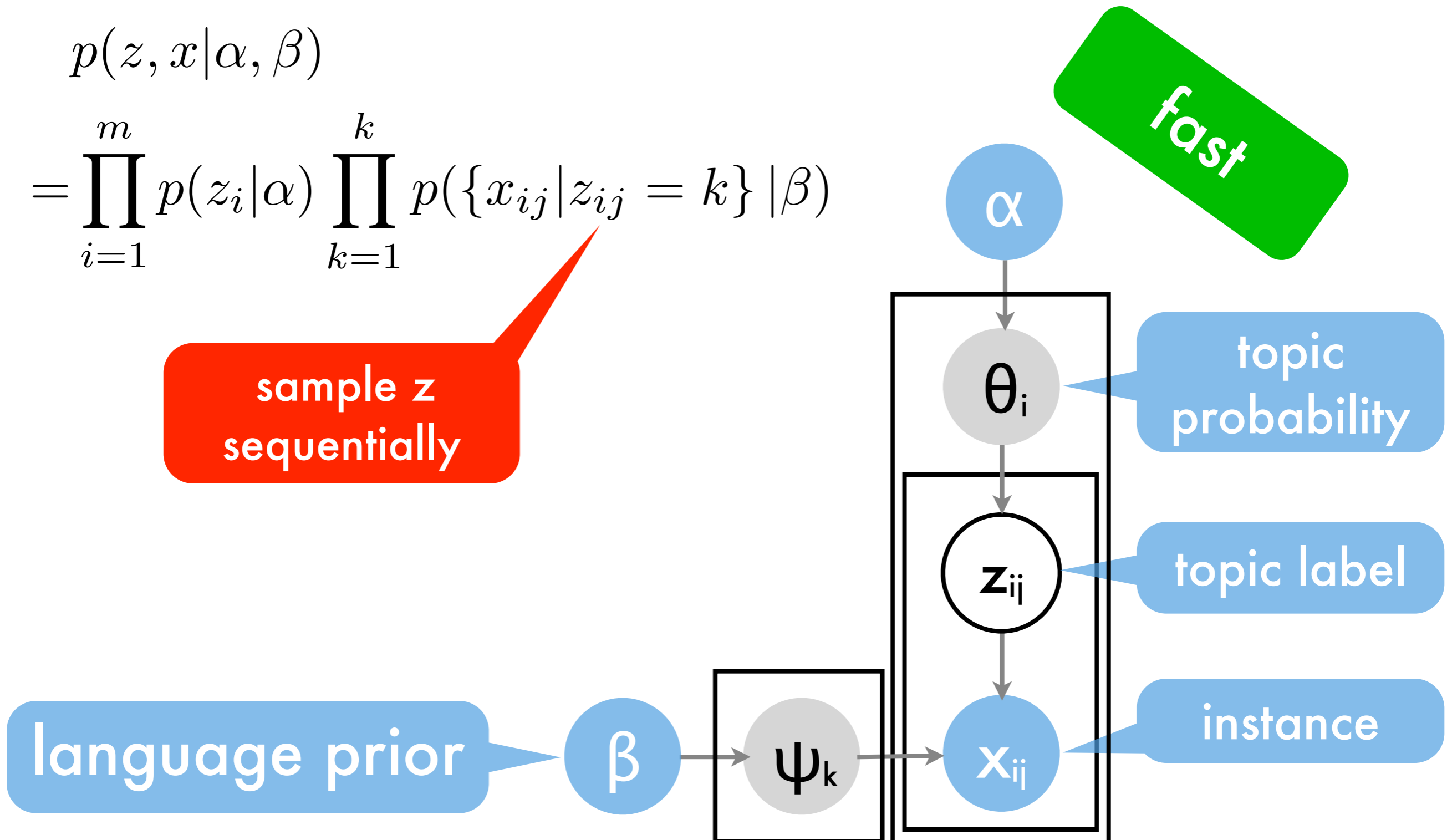
α

topic
probability

topic label

instance

fast



Collapsed Sampler

Griffiths & Steyvers, 2005

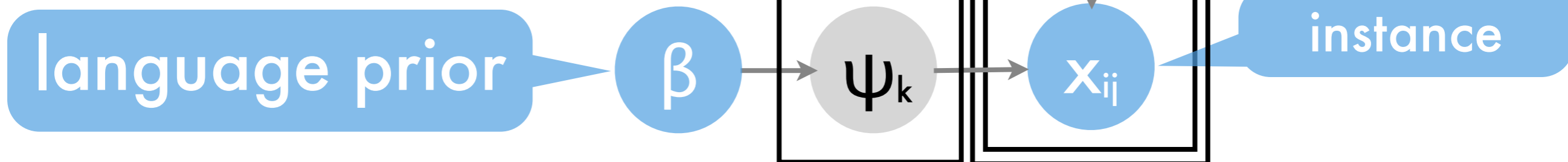
$$p(z, x | \alpha, \beta)$$

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

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

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

language prior



Collapsed Sampler

Griffiths & Steyvers, 2005

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

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

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

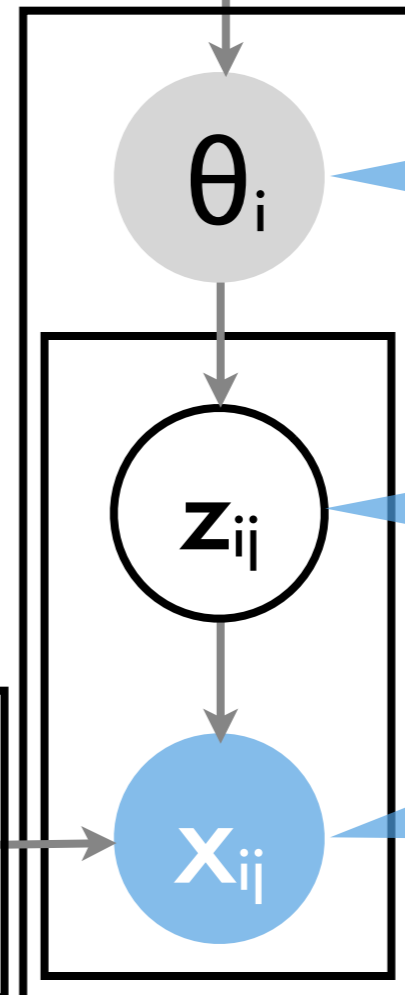
$$\frac{n^{-ij}(t, w) + \beta_t}{n^{-i}(t) + \sum_t \beta_t}$$

fast

language prior

β

ψ_k



topic probability

topic label

instance

Sequential Algorithm (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
 - Update CPU local (word, topic) table
 - Update global (word, topic) table

Sequential Algorithm (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
 - Update CPU local (word, topic) table
 - Update global (word, topic) table

this kills parallelism

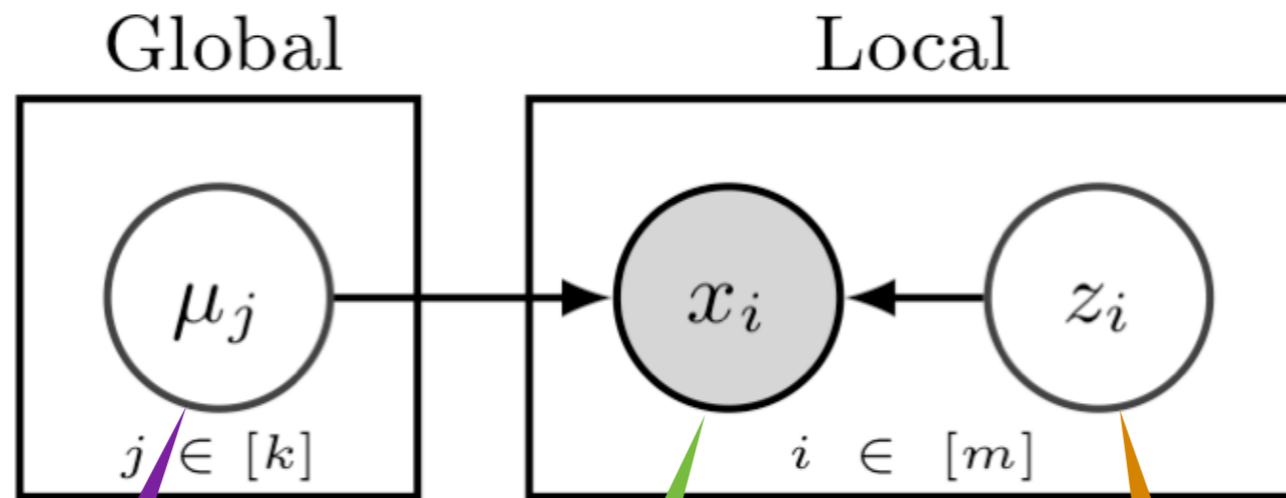
3. Design Principles



Scaling Problems



3 Problems

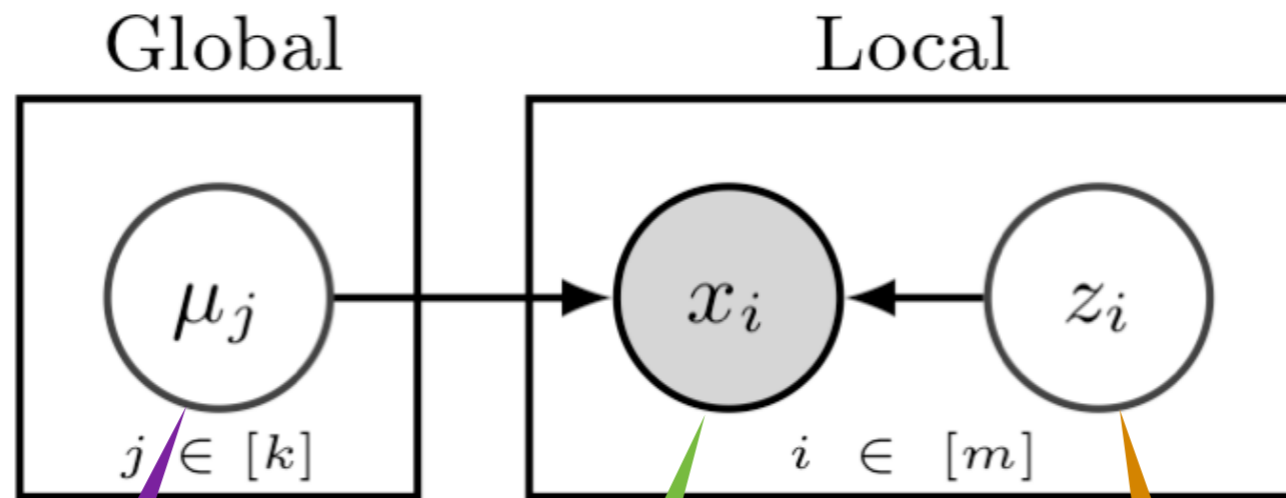


mean
variance
cluster weight

data

cluster ID

3 Problems

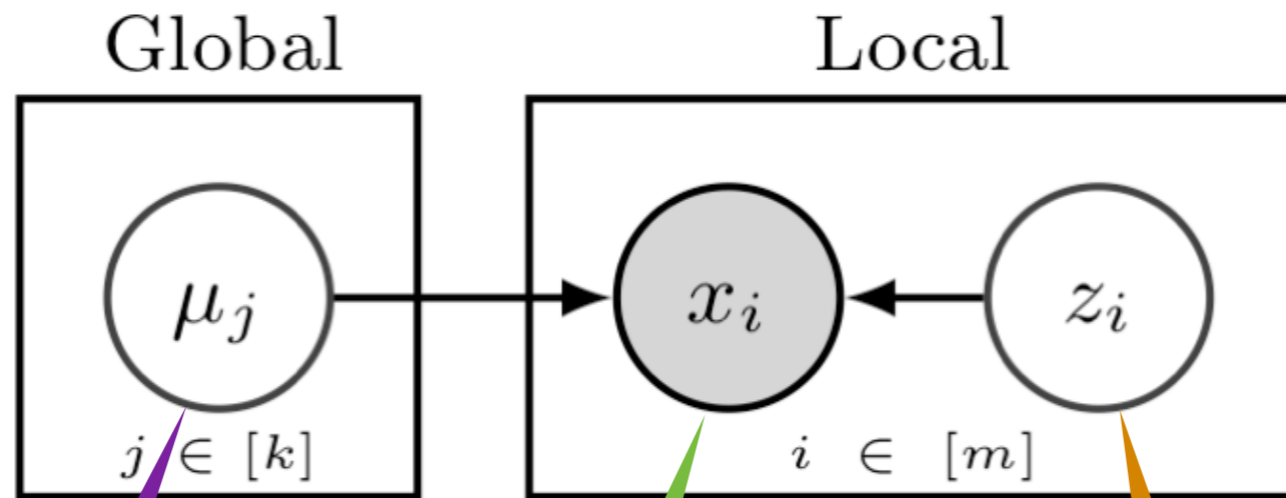


global state

data

local state

3 Problems



too big for
single machine

huge

only local

3 Problems

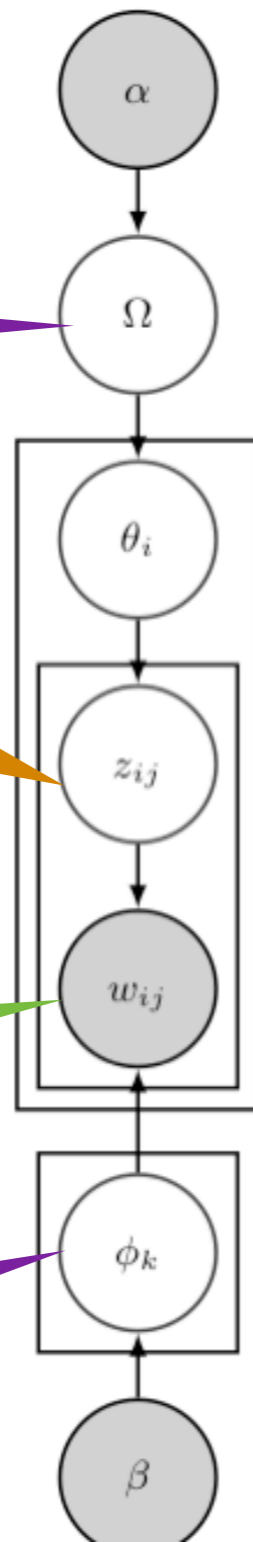
Vanilla LDA

global state

local state

data

global state



3 Problems

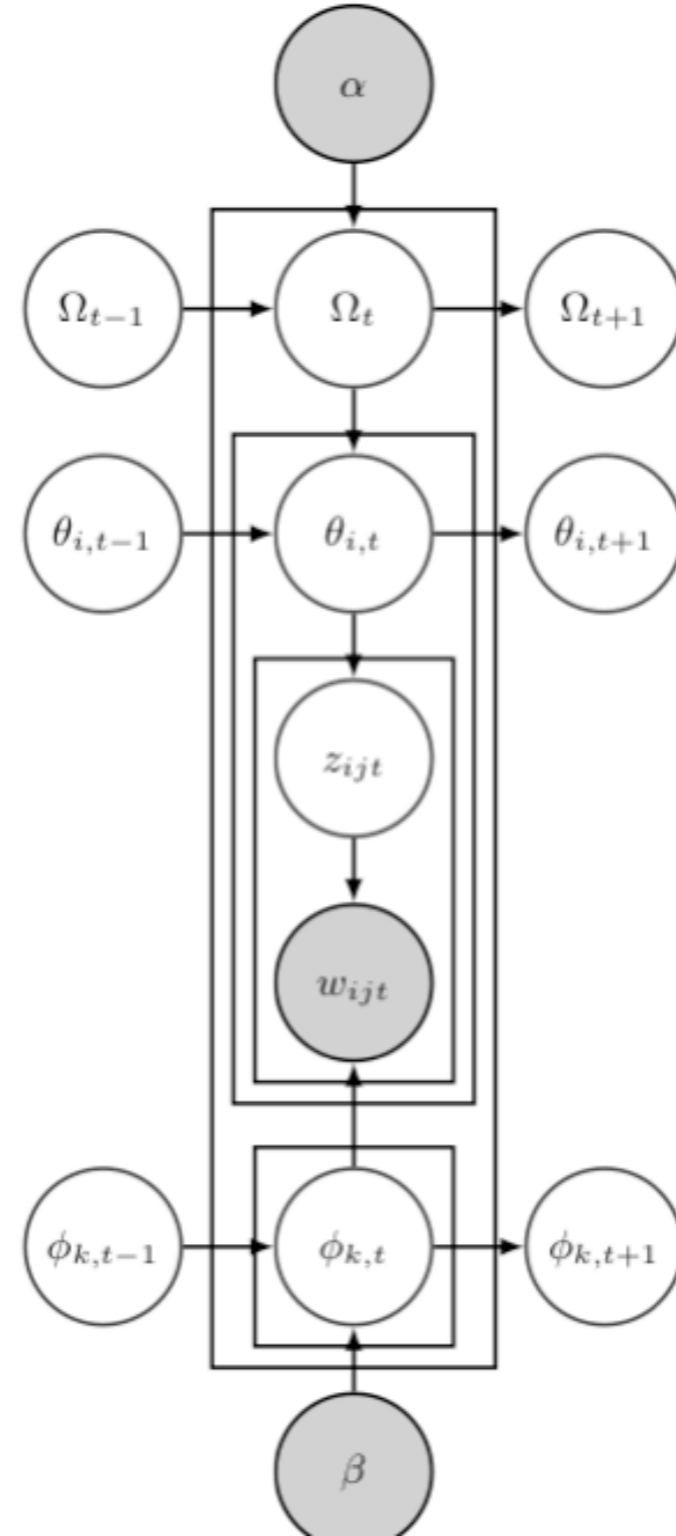
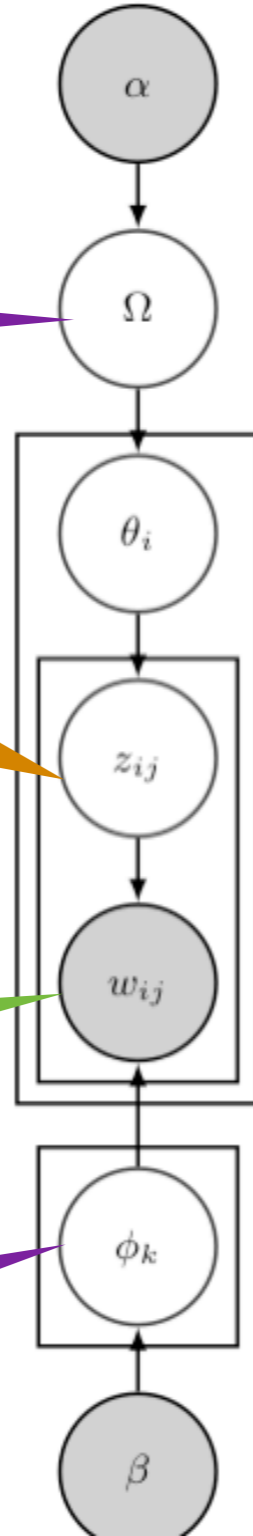
Vanilla LDA

global state

local state

data

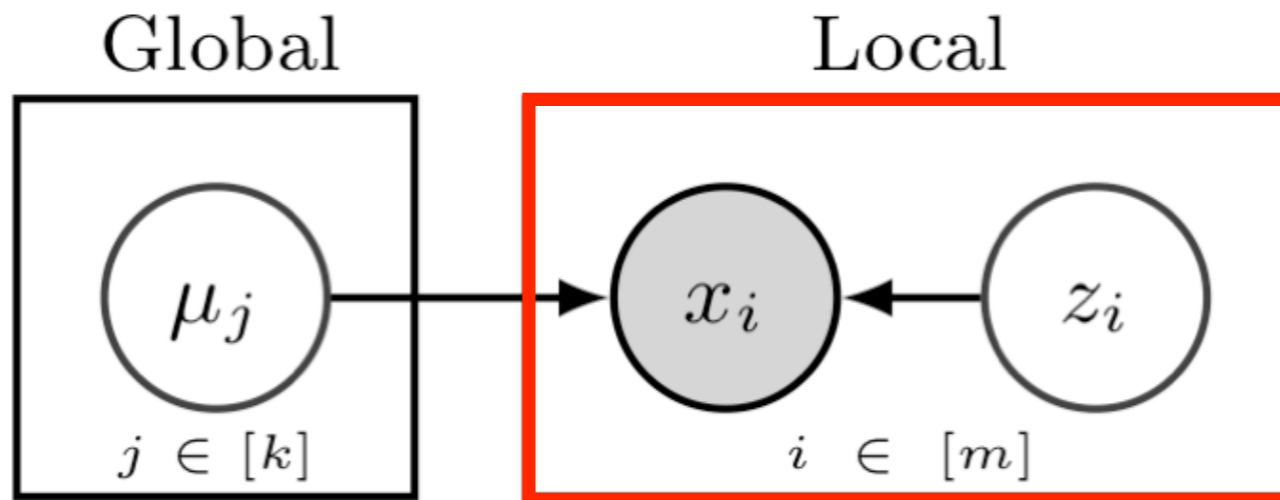
global state



User profiling

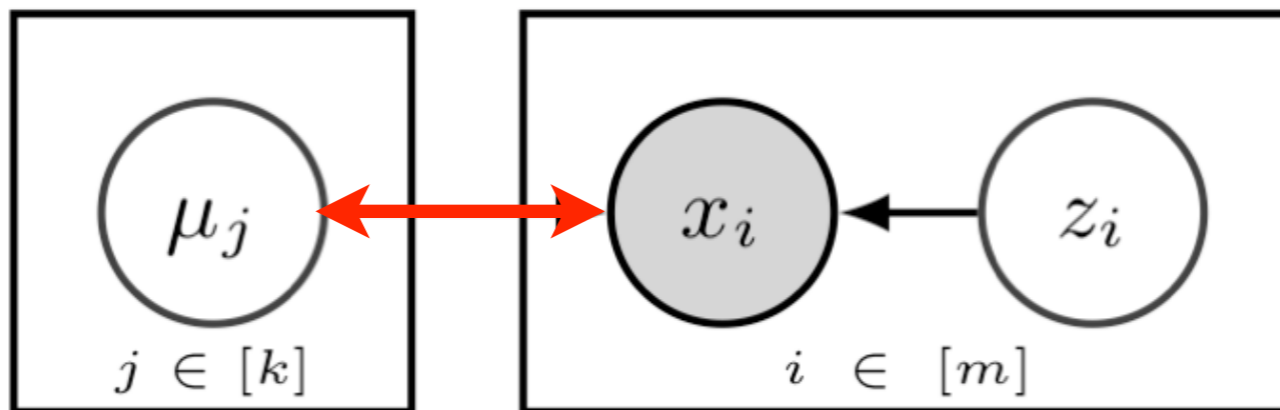
3 Problems

local state
is too large

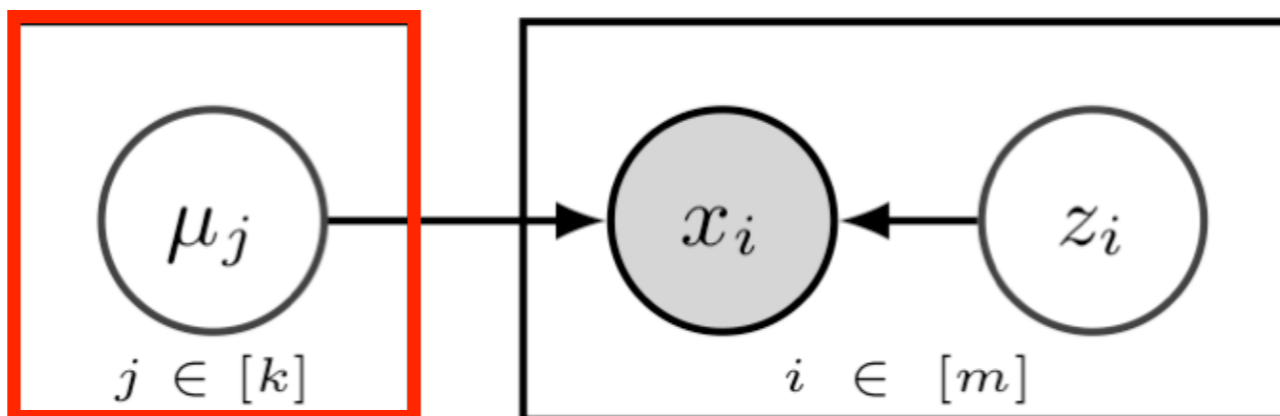


does not fit
into memory

global state
is too large



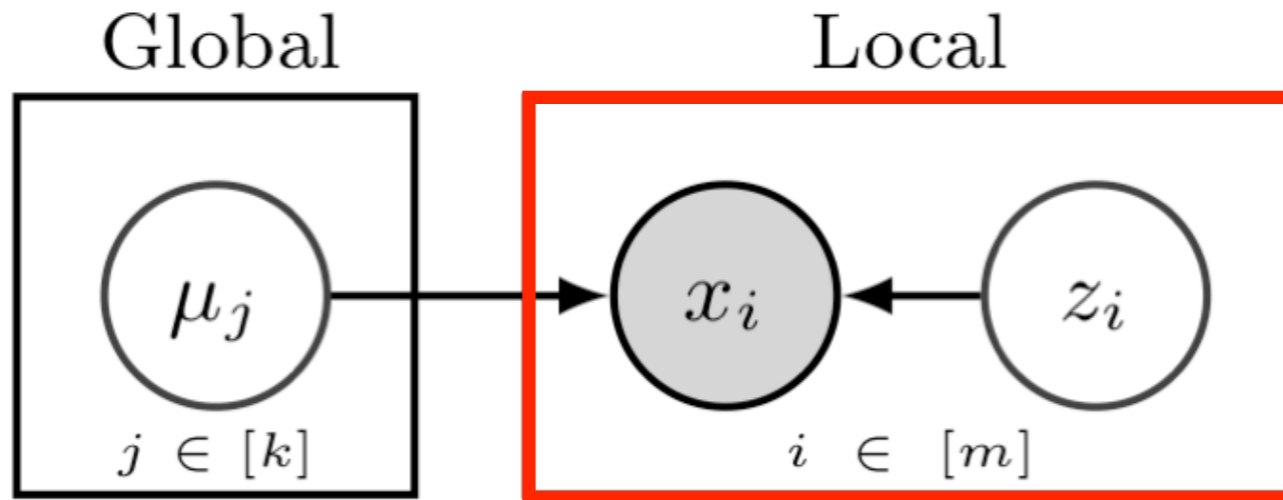
network load
& barriers



does not fit
into memory

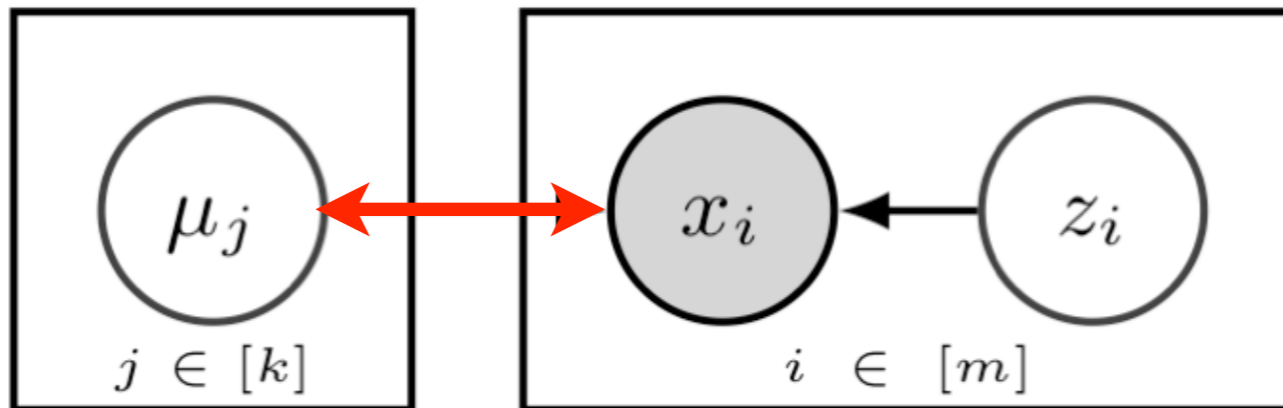
3 Problems

local state
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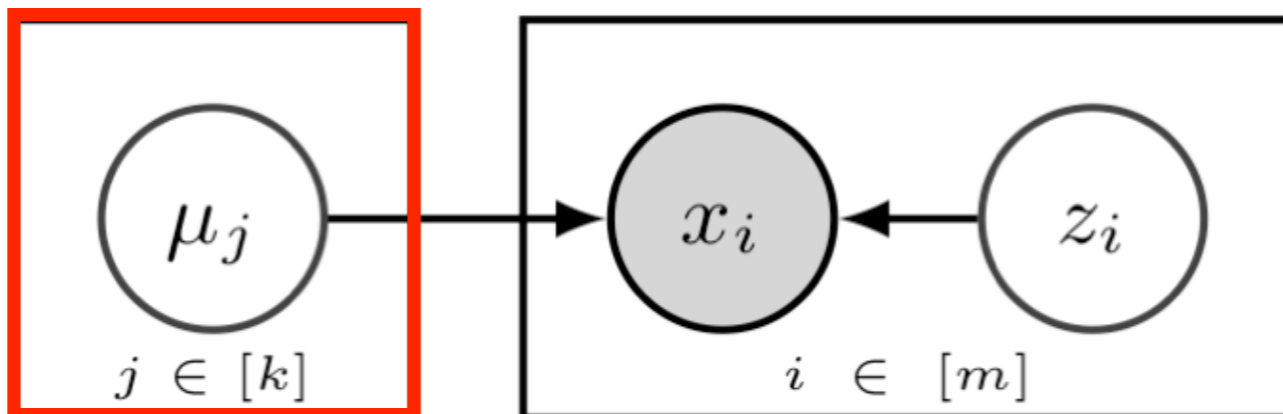


stream local
data from disk

global state
is too large



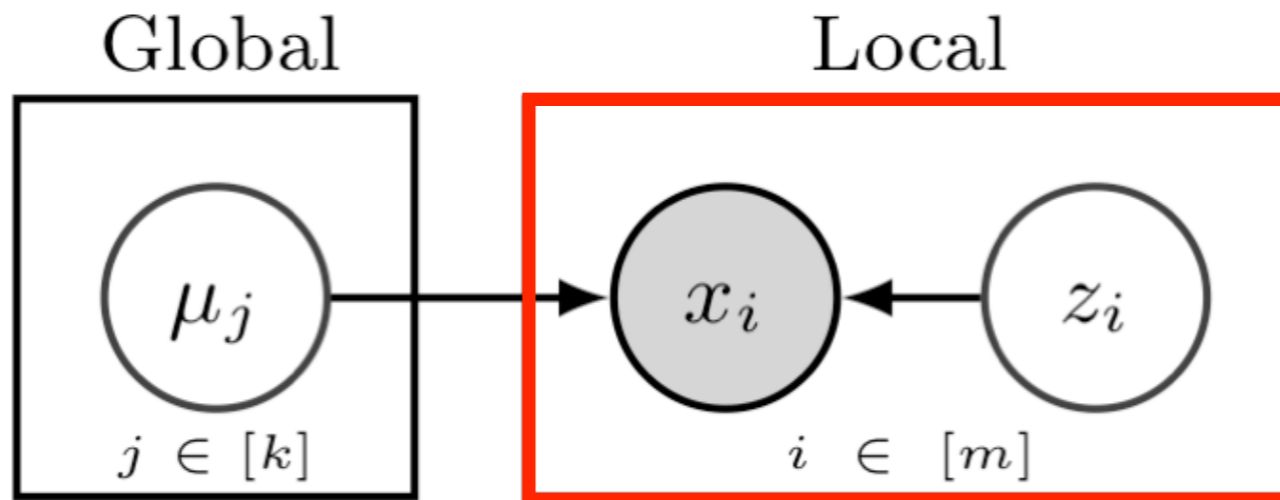
network load
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does not fit
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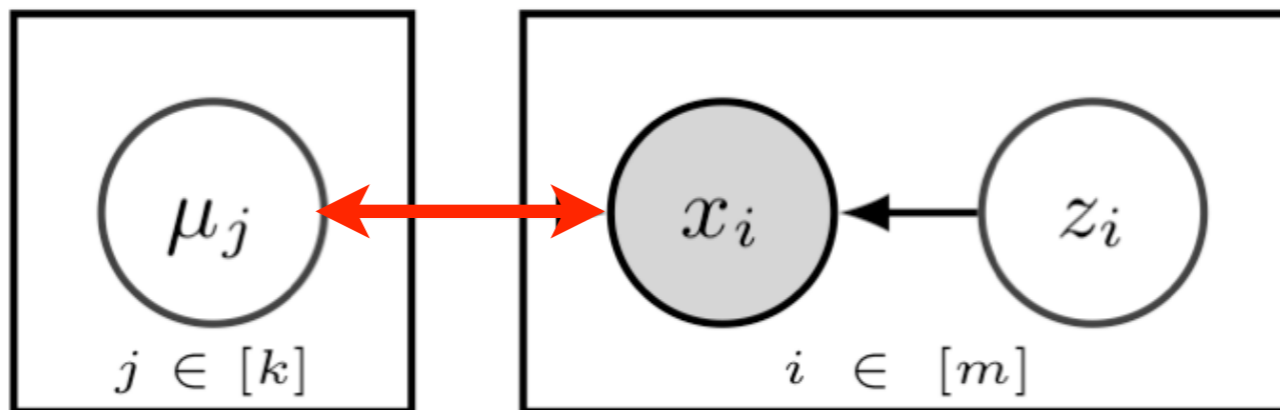
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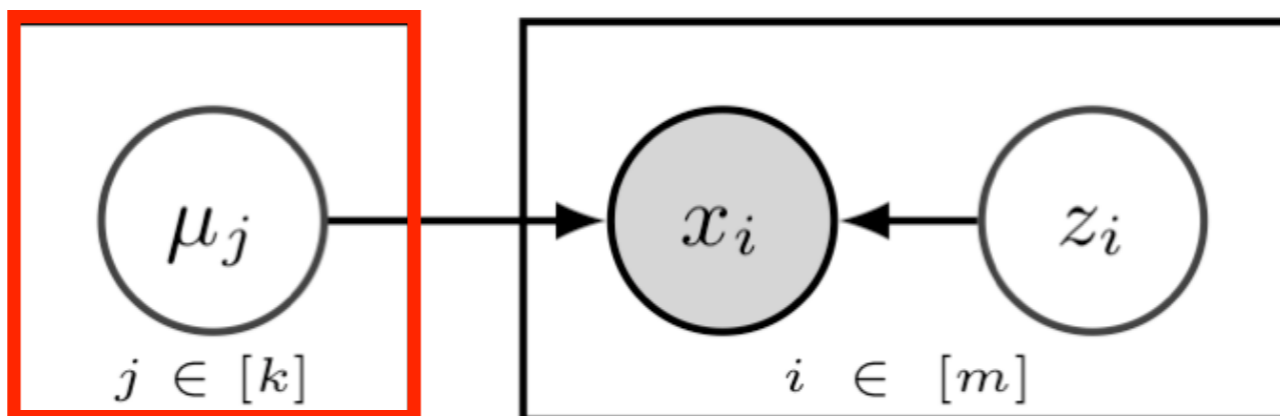


stream local
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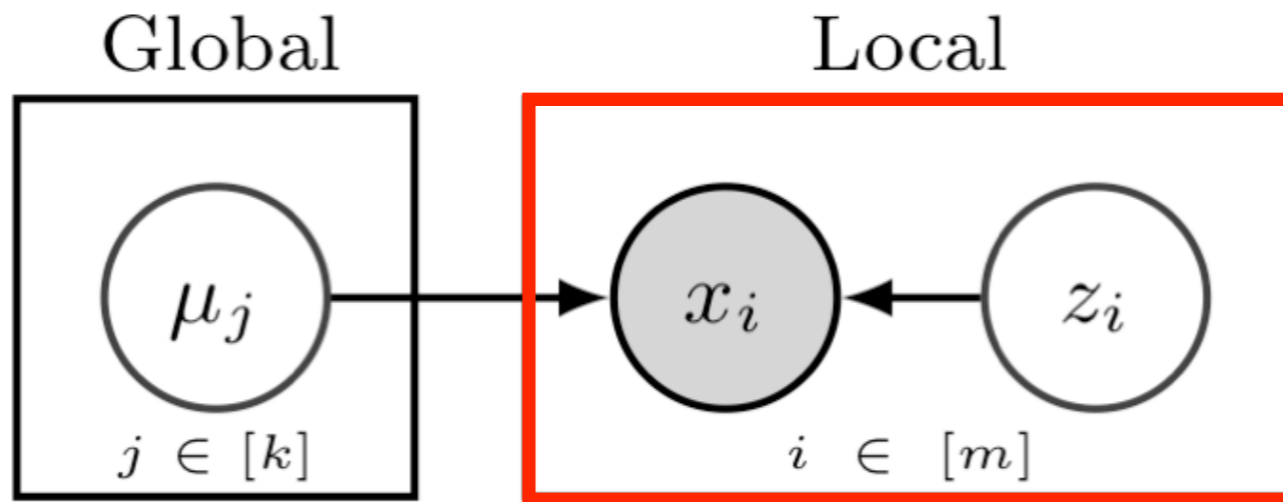
asynchronous
synchronization



does not fit
into memory

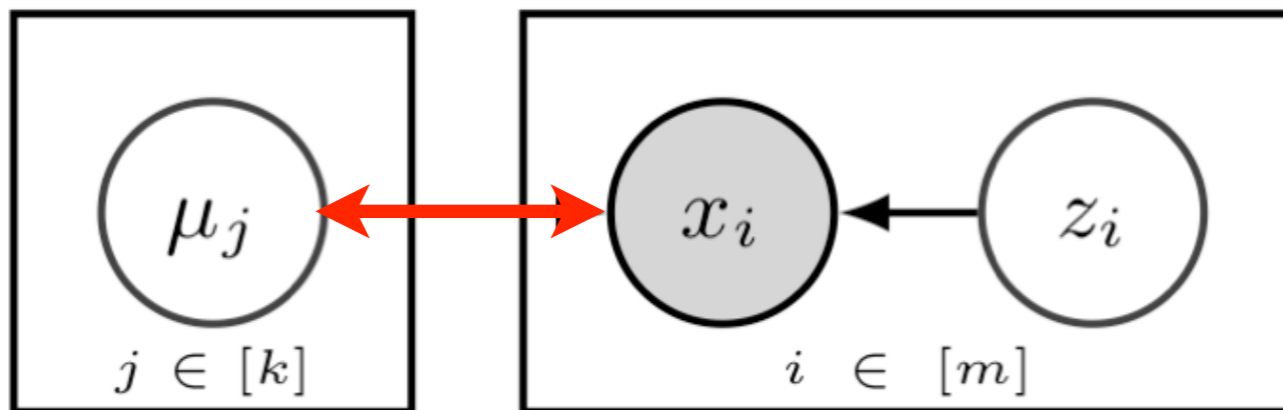
3 Problems

local state
is too large

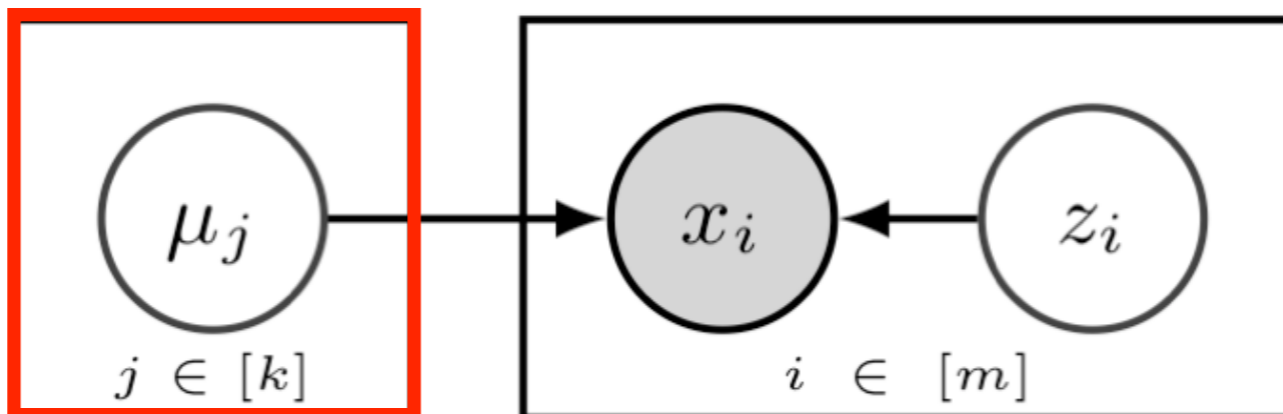


stream local
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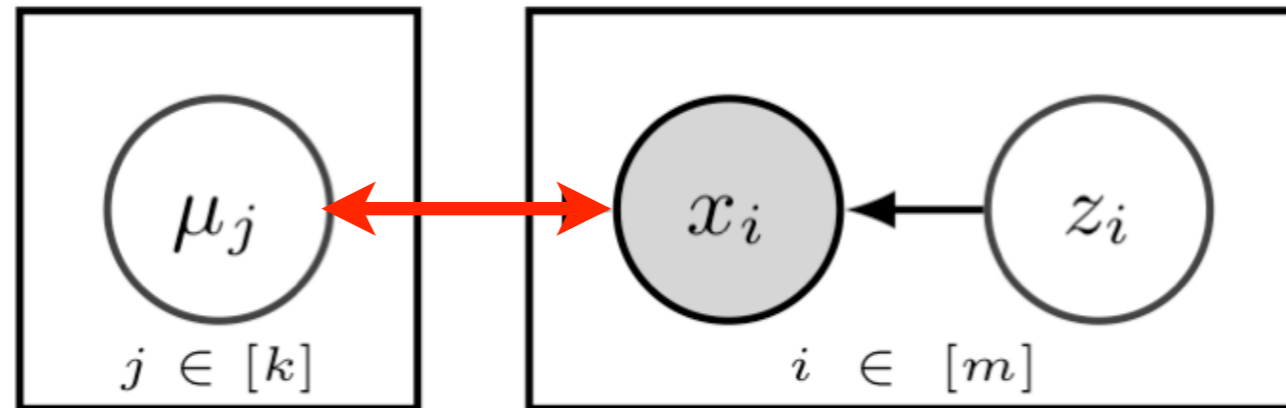


partial view

Global state synchronization

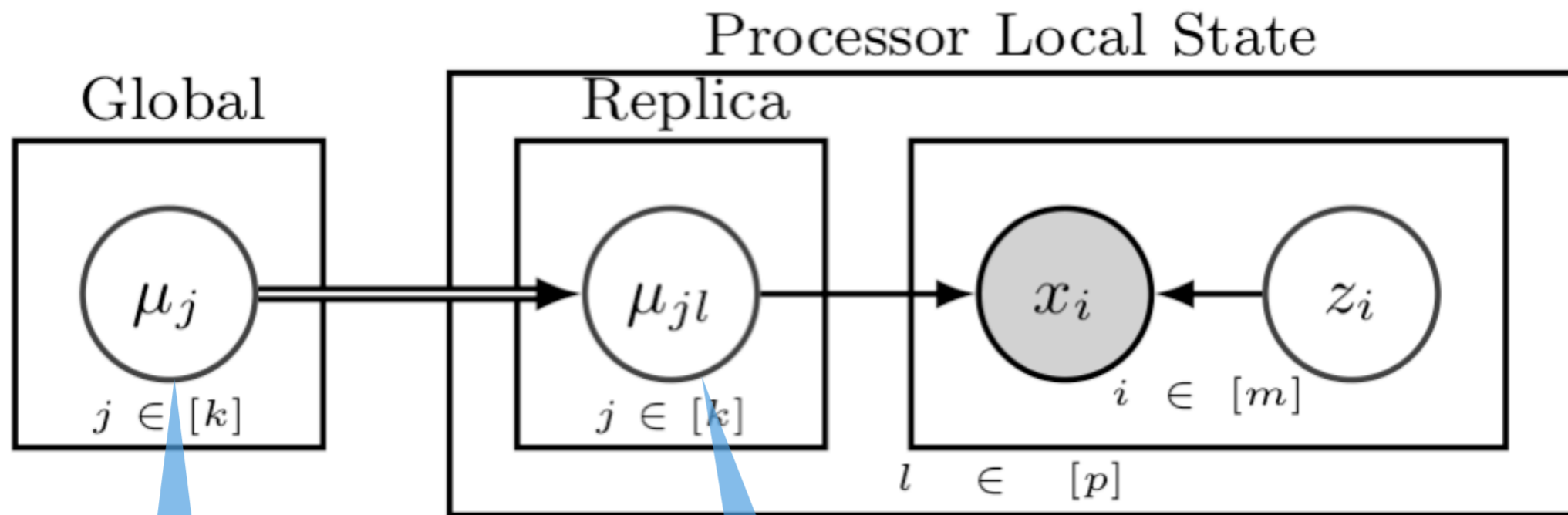


Lock and Barrier



- Changes in μ affect distribution in z
- Changes in z affect distribution in μ
(in particular for a collapsed sampler)
- Lock z , then recompute μ
- Lock all but single z_i (for collapsed sampler)

Variable replication

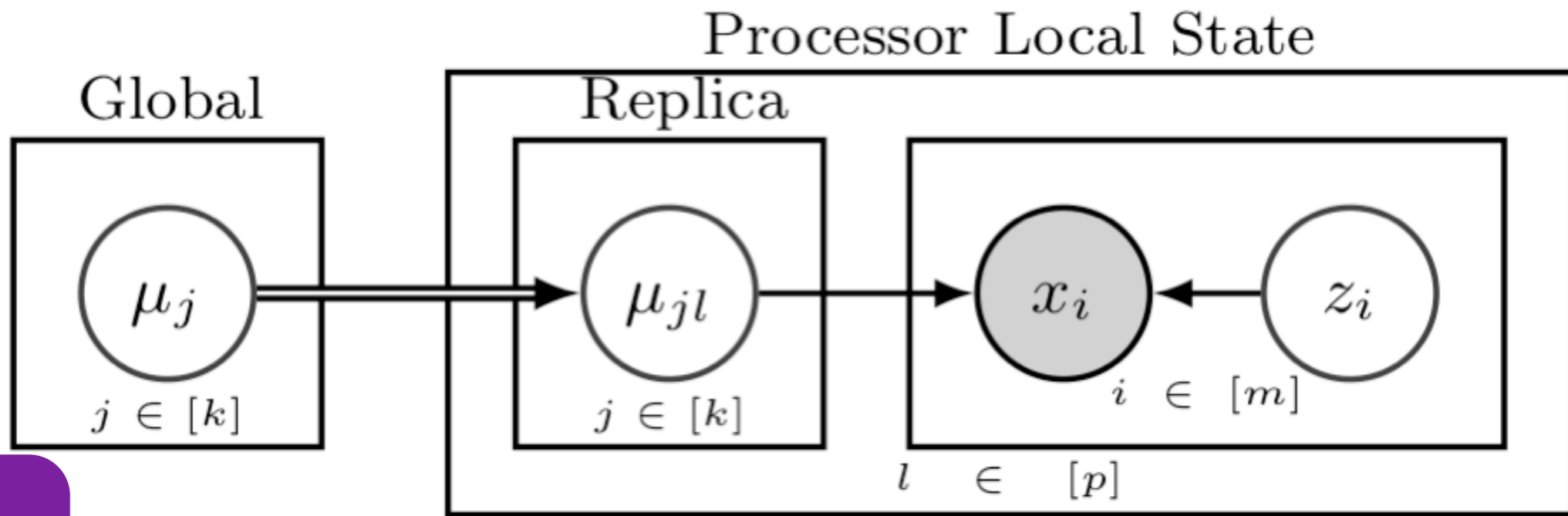


background sync

1 copy per machine

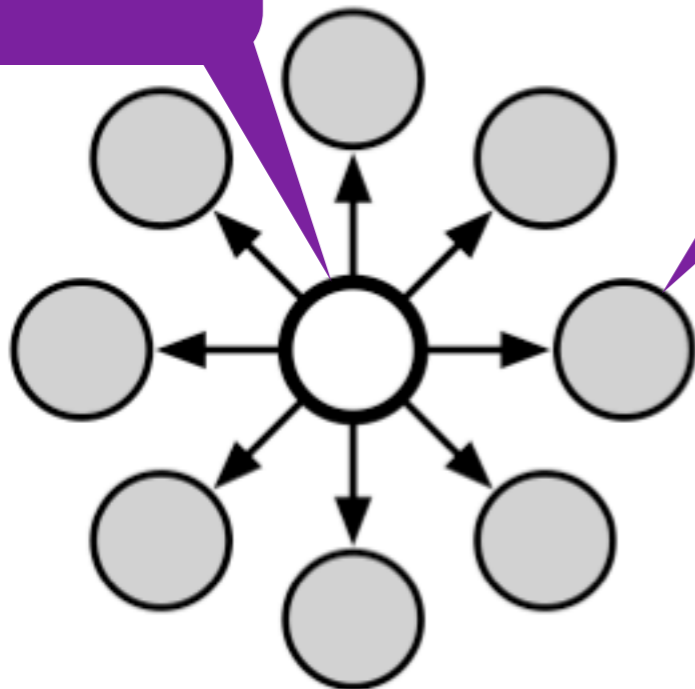
- No locks between machines to access z
- Synchronization mechanism for global μ needed
- In LDA this is the local copy of the (topic,word) counts

Distribution

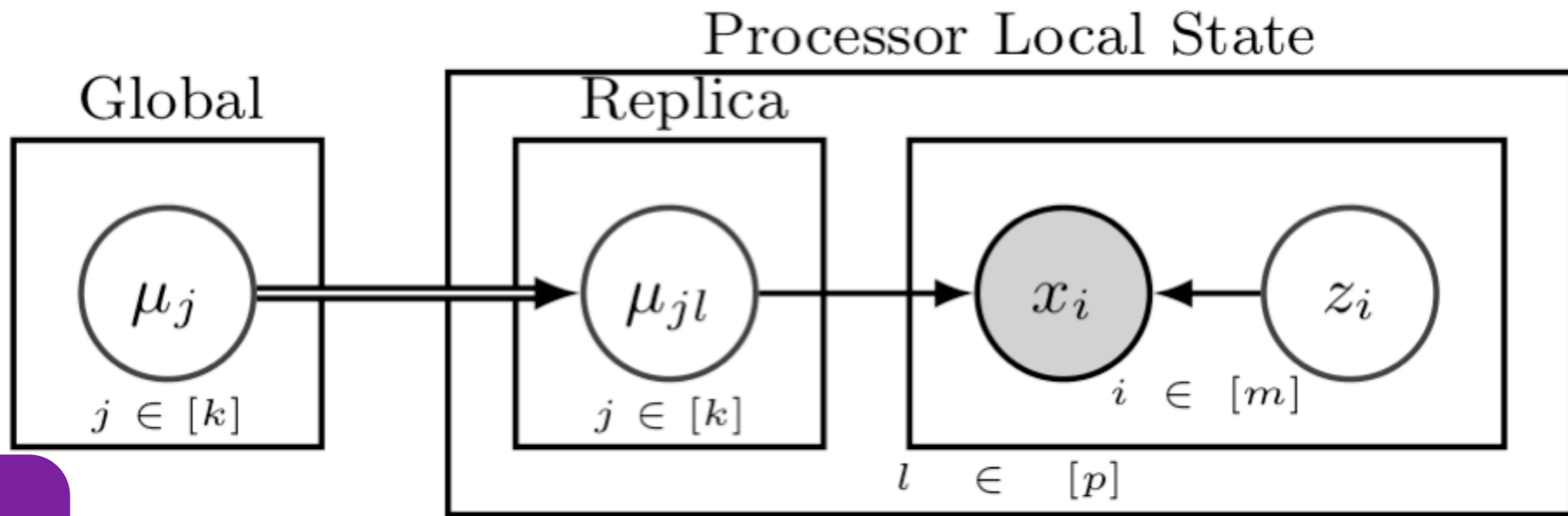


global

replica



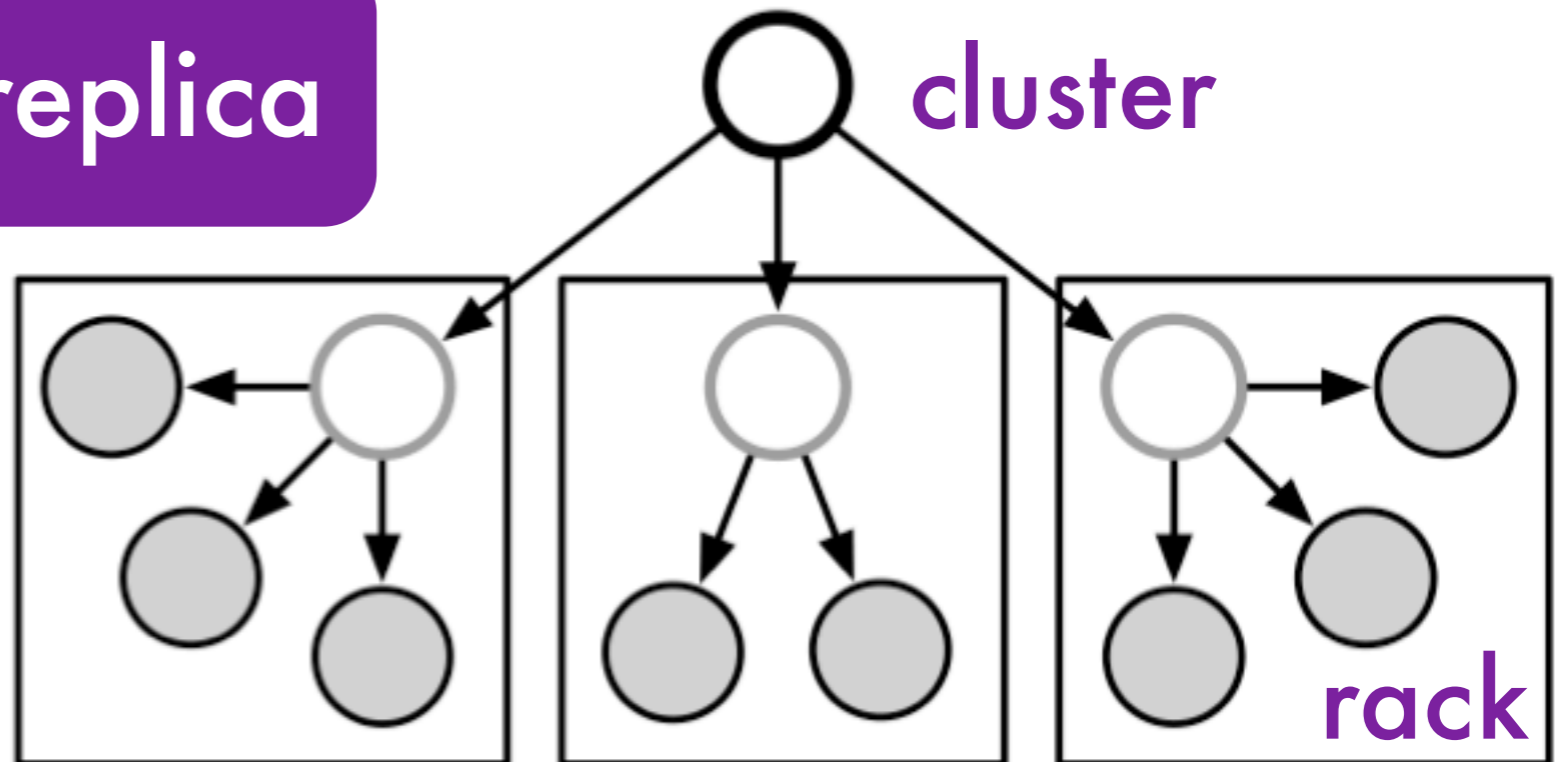
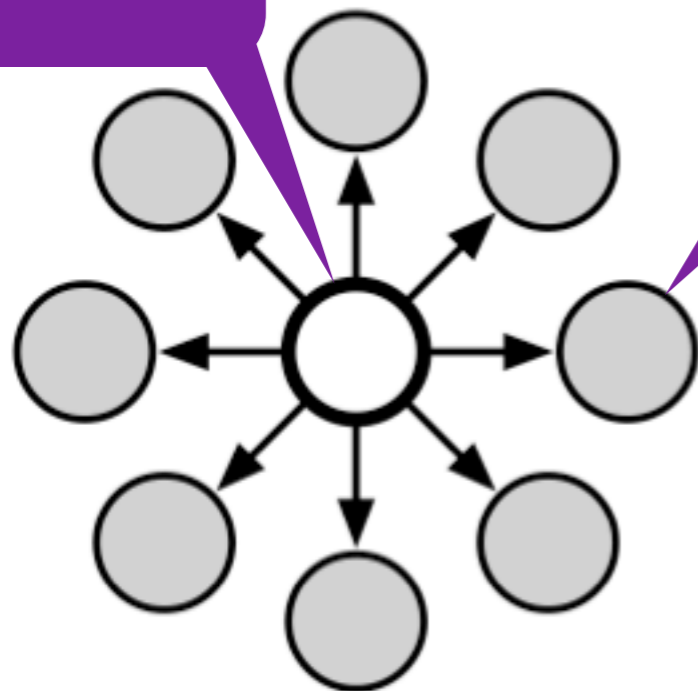
Distribution



global

replica

cluster



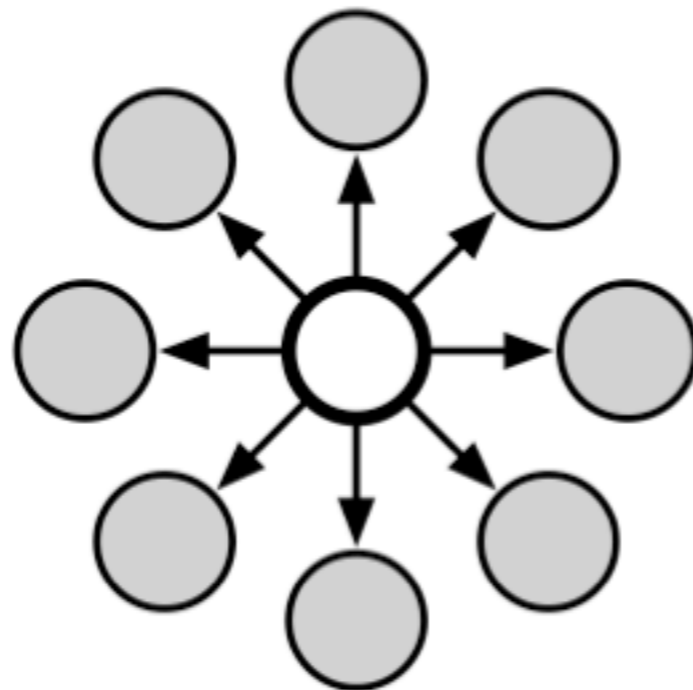
rack

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

$$\begin{aligned} \delta &\leftarrow x \ominus x^{\text{old}} \\ x^{\text{old}} &\leftarrow x \\ x^{\text{global}} &\leftarrow x^{\text{global}} \oplus \delta \end{aligned}$$



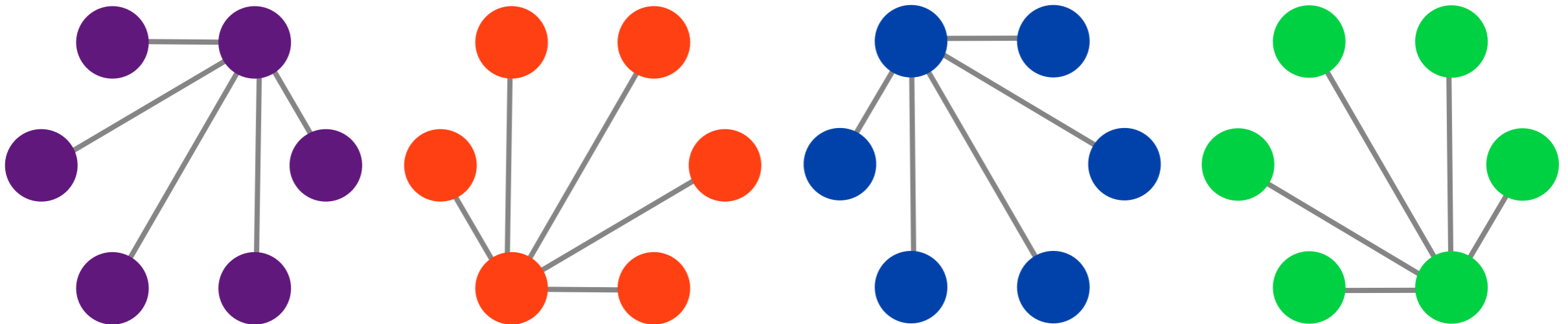
global to local

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

Distribution

- Dedicated server for variables
 - Insufficient bandwidth (hotspots)
 - Insufficient memory
- Select server via consistent hashing
(random trees a la Karger et al. 1999 if needed)

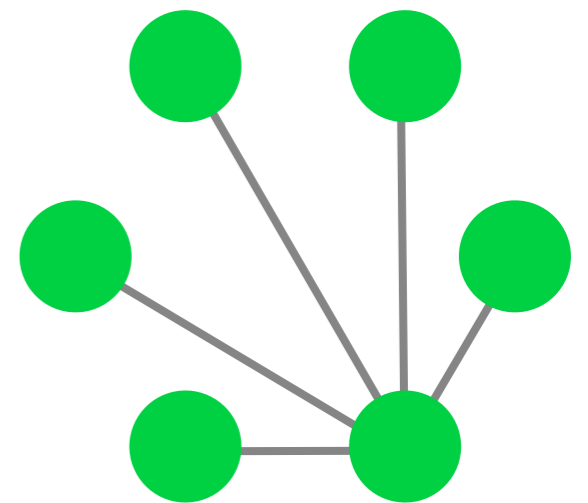
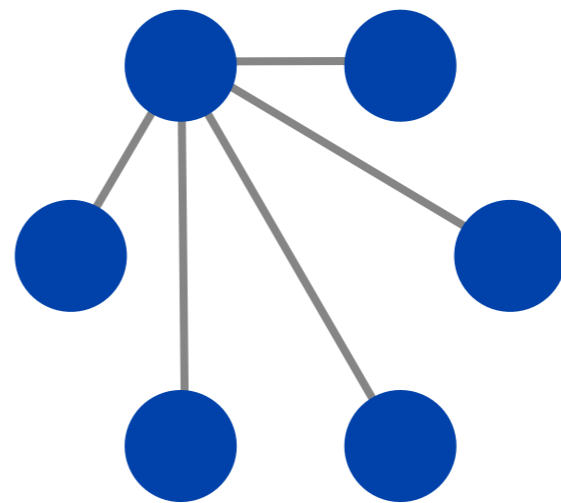
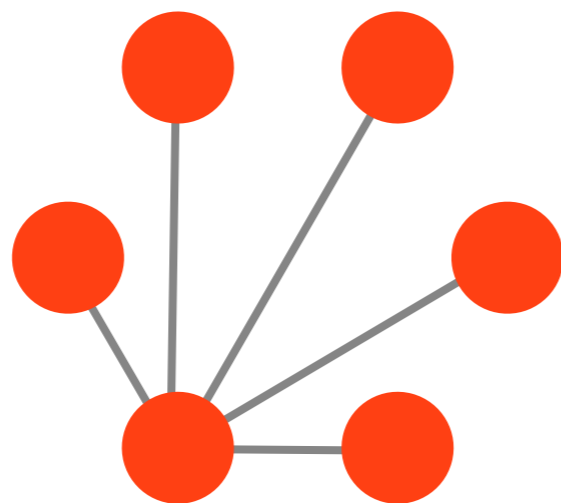
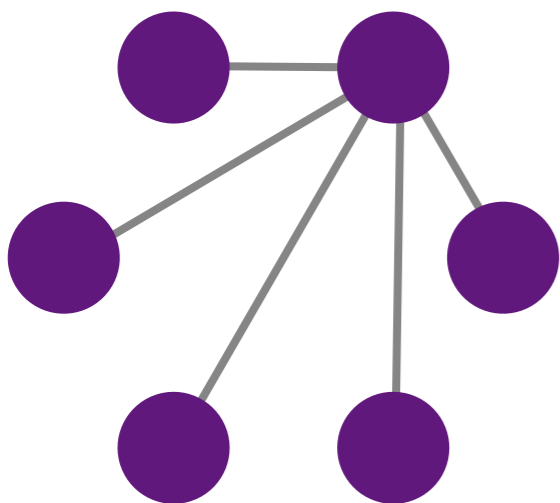
$$m(x) = \operatorname{argmin}_{m \in M} h(x, m)$$



Distribution & fault tolerance

- Storage is $O(1/k)$ per machine
- Communication is $O(1)$ per machine
- Fast snapshots $O(1/k)$ per machine (stop sync and dump state per vertex)

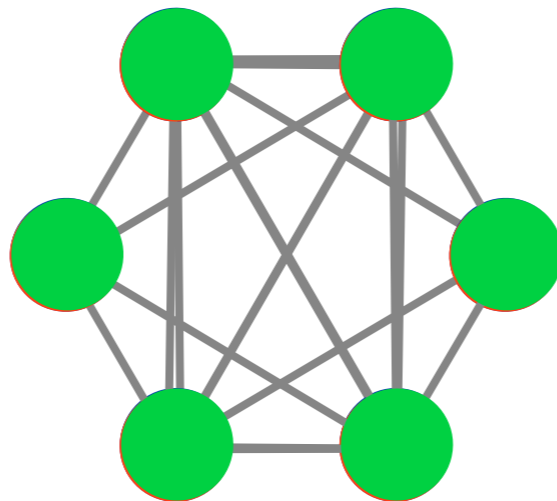
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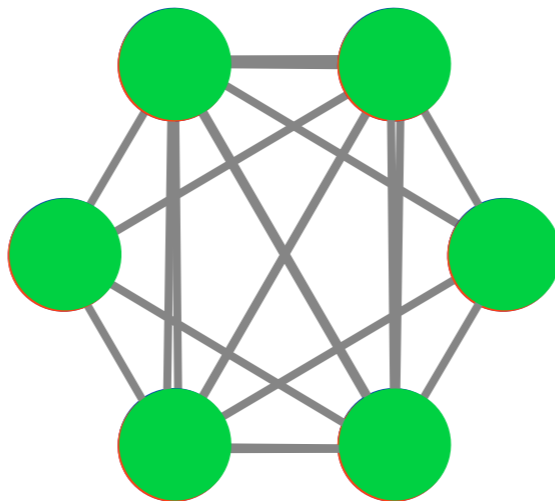
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Distribution & fault tolerance

- Storage is $O(1/k)$ per machine
- Communication is $O(1)$ per machine
- Fast snapshots $O(1/k)$ per machine (stop sync and dump state per vertex)
- $O(k)$ open connections per machine
- $O(1/k)$ throughput per machine

$$m(x) = \operatorname{argmin}_{m \in M} h(x, m)$$



Synchronization Protocol



Synchronization

- Data rate between machines is $O(1/k)$
- Machines operate asynchronously (barrier free)
- Solution
 - Schedule message pairs
 - Communicate with r random machines simultaneously

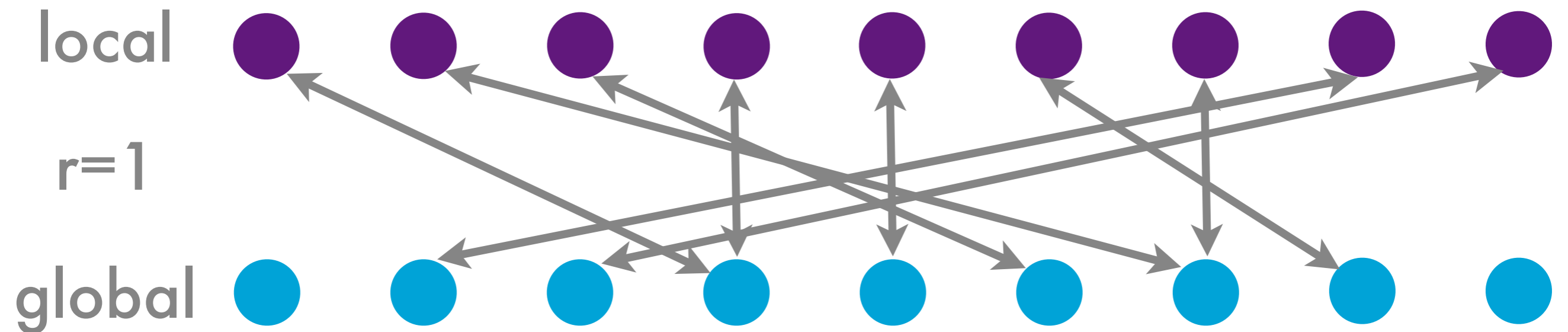


$r=1$



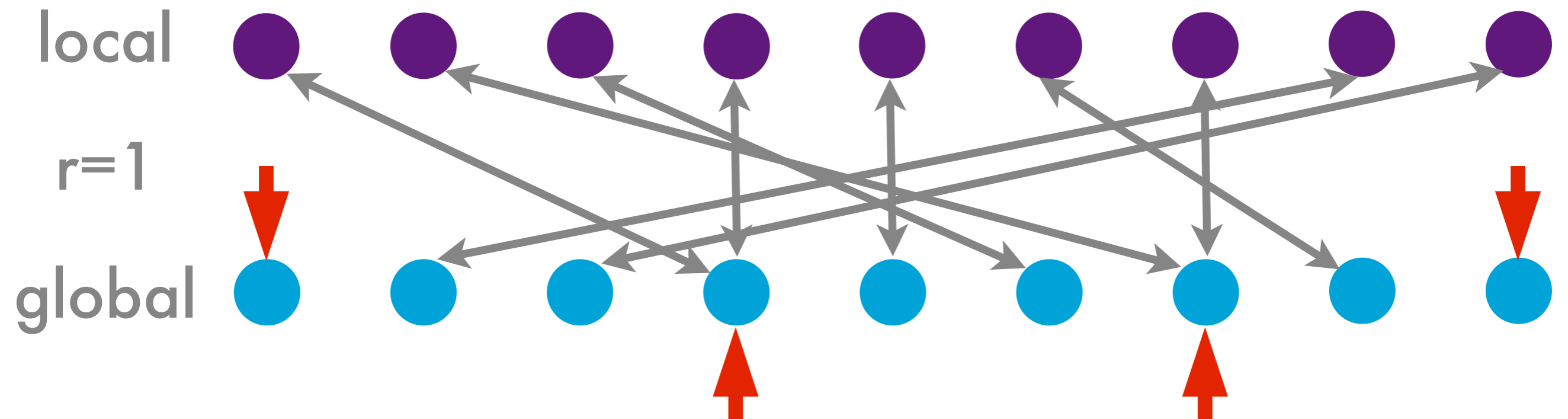
Synchronization

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Synchronization

- Data rate between machines is $O(1/k)$
- Machines operate asynchronously (barrier free)
- Solution
 - Schedule message pairs
 - Communicate with r random machines simultaneously
 - Use Luby-Rackoff PRPG for load balancing
- Efficiency guarantee

$$1 - e^{-r} \sum_{i=0}^r \left[1 - \frac{i}{r}\right] \frac{r^i}{i!} \leq \text{Eff} \leq 1 - e^{-r}$$

4 simultaneous connections are sufficient

Architecture



Sequential Algorithm (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
 - Update CPU local (word, topic) table
 - Update global (word, topic) table

Sequential Algorithm (Gibbs sampler)

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this kills parallelism

Distributed asynchronous sampler

- For 1000 iterations do (independently per computer)
 - For each thread/core do
 - For each document do
 - For each word in the document do
 - Resample topic for the word
 - Update local (document, topic) table
 - Generate computer local (word, topic) message
 - In parallel update local (word, topic) table
 - In parallel update global (word, topic) table

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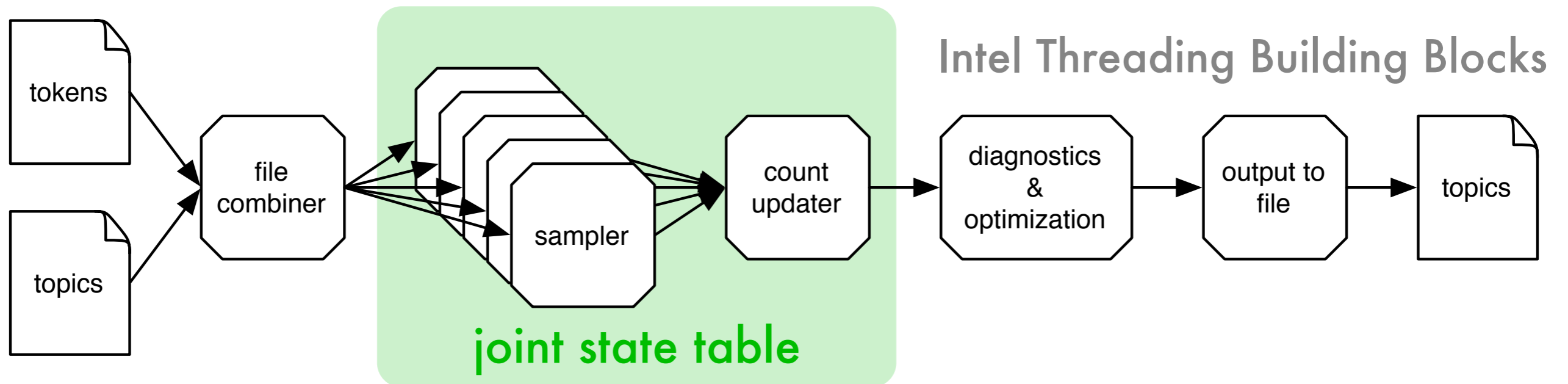
concurrent
cpu hdd net

minimal
view

continuous
sync

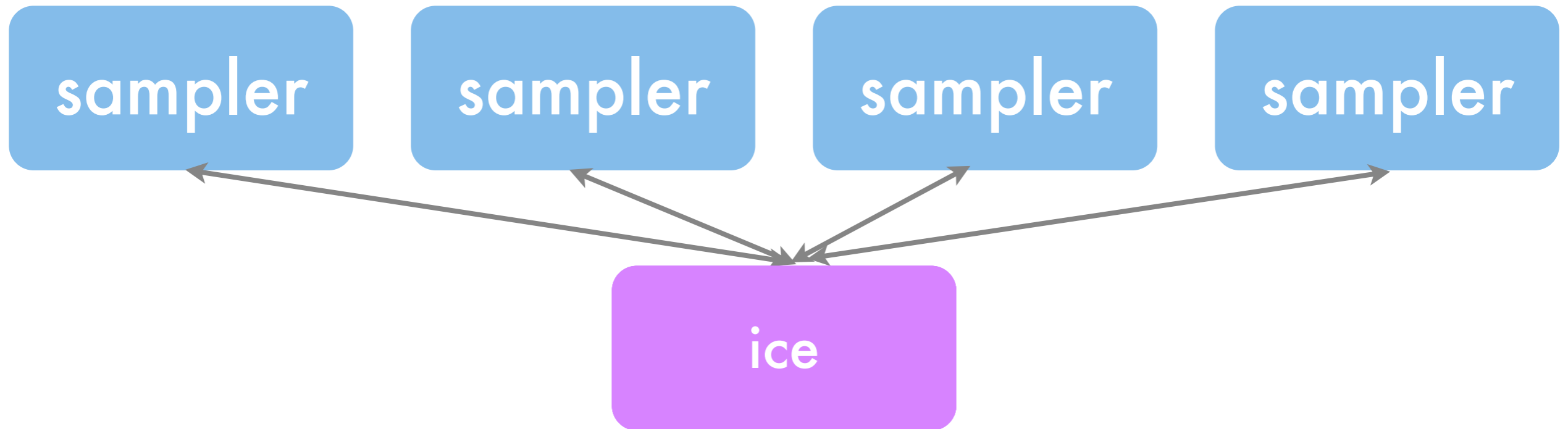
barrier
free

Multicore Architecture



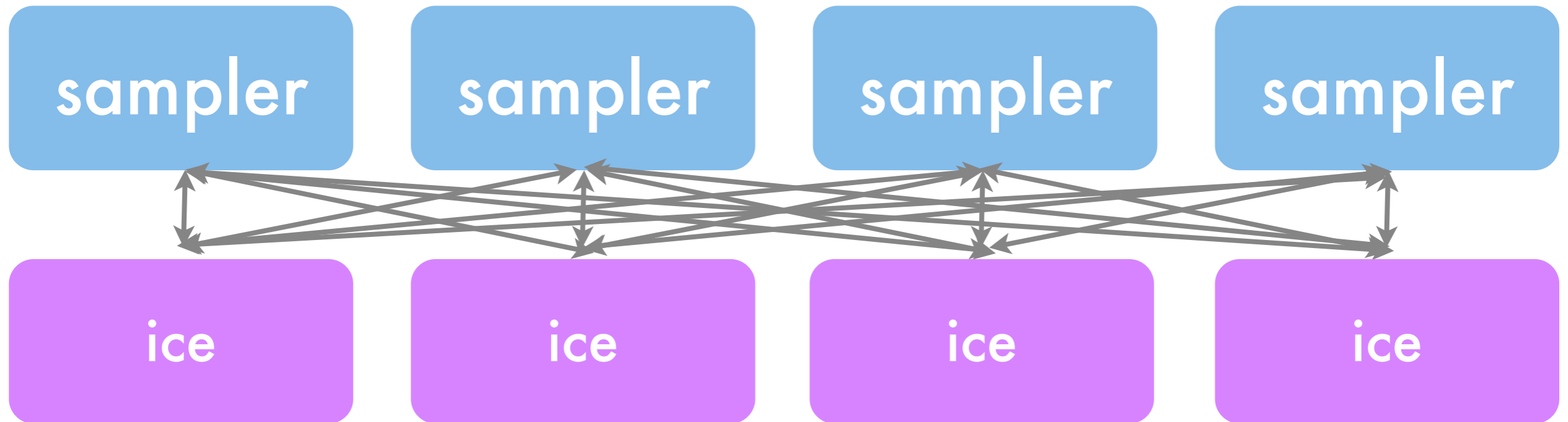
- Decouple multithreaded sampling and updating (almost) avoids stalling for locks in the sampler
- Joint state table
 - much less memory required
 - samplers synchronized (10 docs vs. millions delay)
- Hyperparameter update via stochastic gradient descent
- No need to keep documents in memory (streaming)

Cluster Architecture



- Distributed (key,value) storage via ICE
- Background asynchronous synchronization
 - single word at a time to avoid deadlocks
 - no need to have joint dictionary
 - uses disk, network, cpu simultaneously

Cluster Architecture



- Distributed (key,value) storage via ICE
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 - no need to have joint dictionary
 - uses disk, network, cpu simultaneously

Making it work

- **Startup**
 - Naive: randomly initialize topics on each node (read from disk if already assigned - hotstart)
 - Forward sampling for startup **much faster**
 - Aggregate changes on the fly
- **Failover**
 - State constantly being written to disk (worst case we lose 1 iteration out of 1000)
 - Restart via standard startup routine
- **Achilles heel: need to restart from checkpoint if even a single machine dies.**

Easily extensible

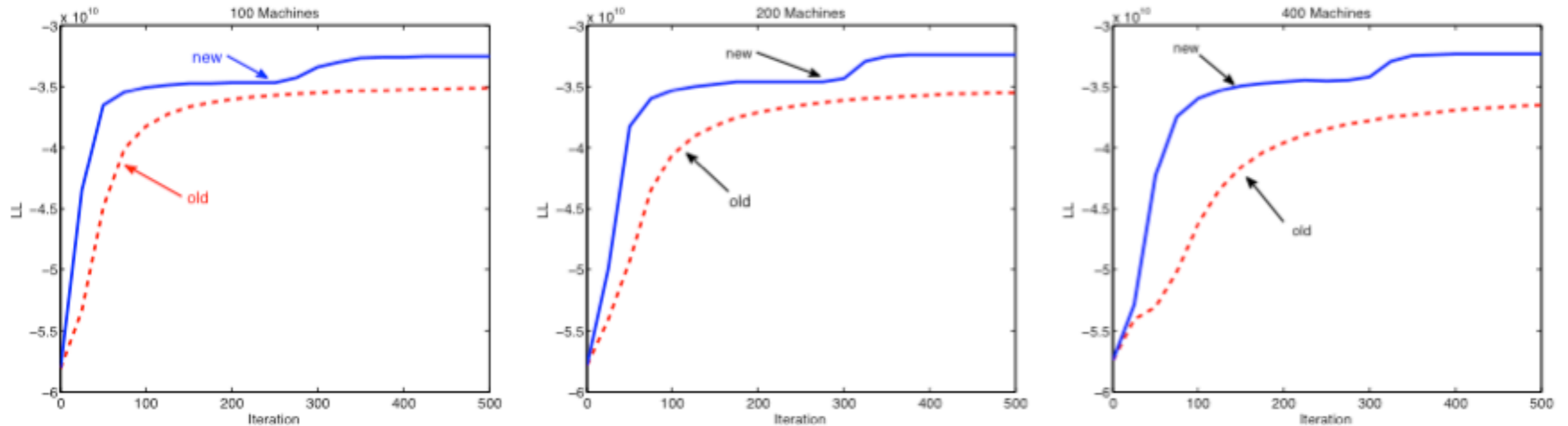
- **Better language model (topical n-grams)**
can process millions of users (vs 1000s)
- **Conditioning on side information (upstream)**
estimate topic based on authorship, source,
joint user model ...
- **Conditioning on dictionaries (downstream)**
integrate topics between different languages
- **Time dependent sampler for user model**
approximate inference per episode

	Google LDA	Mallet	Irvine'08	Irvine'09	Yahoo LDA
Multicore	no	yes	yes	yes	yes
Cluster	MPI	no	MPI	point 2 point	ICE
State table	dictionary split	separate sparse	separate	separate	joint sparse
Schedule	synchronous exact	synchronous exact	synchronous exact	asynchronous approximate messages	asynchronous exact

Speed (2010 numbers)

- **1M documents per day** on 1 computer
(1000 topics per doc, 1000 words per doc)
- **350k documents per day** per node
(context switches & memcached & stray reducers)
- **8 Million docs** (Pubmed)
(sampler does not burn in well - too short doc)
 - Irvine: **128 machines, 10 hours**
 - Yahoo: **1 machine, 11 days**
 - Yahoo: **20 machines, 9 hours**
- **20 Million docs** (Yahoo! News Articles)
 - Yahoo: **100 machines, 12 hours**

Fast sampler



- 8 Million documents, 1000 topics, {100,200,400} machines, LDA
- Red (symmetric latency bound message passing)
- Blue (asynchronous bandwidth bound message passing & message scheduling)
 - 10x faster synchronization time
 - 10x faster snapshots
 - Scheduling improves 10% already on 150 machines

Roadmap

- **Tools**
 - Load distribution, balancing and synchronization
 - Clustering, Topic Models
- **Models**
 - Dynamic non-parametric models
 - Sequential latent variable models
- **Inference Algorithms**
 - Distributed batch
 - Sequential Monte Carlo
- **Applications**
 - User profiling
 - News content analysis & recommendation