

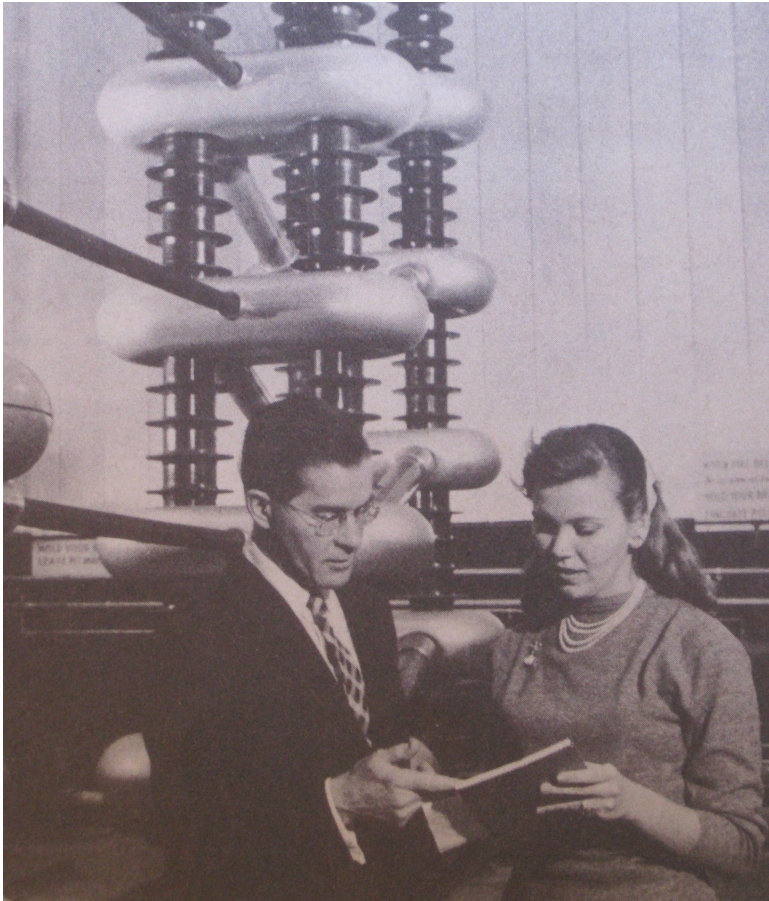
Statistical Topic Models for Studying Collaborative Processes

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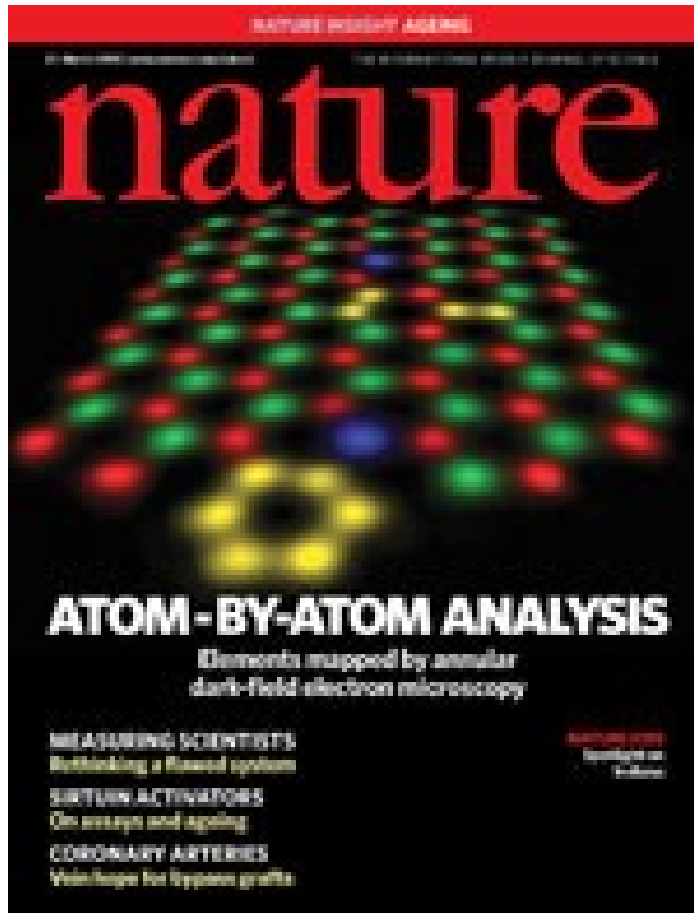
Products of Collaboration



“Scientific information is both the basic raw material for, and one of the principal products of, scientific research [...] Scientists find out what other scientists are accomplishing through [...] journals, books, abstracts and indexes, bibliographies, reviews.”

— NSF Brochure, 1962

Collaborate to Study Collaboration



“There needs to be a greater focus on what these [science interaction] data mean [...] This requires the input of social scientists, rather than just those more traditionally involved in data capture, such as computer scientists.”

— Julia Lane, NSF, 24 March 2010

Approach: Statistical Models

- Modeling challenges:
 - Aggregating and representing large data sets
 - Handling data from sources with disparate emphases
 - Reasoning under uncertain information
 - Performing efficient inference
- Bayesian latent (hidden) variable models:
 - Powerful and flexible [Wallach et al. & Adams et al., AISTATS '10]
 - This talk: statistical topic models

This Talk

- Background: statistical topic models
- Building “off-the-shelf” statistical topic models
- Some current and future projects:
 - Analyzing free software development communities
 - Predicting when to declassify documents

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- **Background: statistical topic models**
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Statistical Topic Modeling

- Three fundamental assumptions:
 - Documents have latent semantic structure (“topics”)
 - Can infer topics from word–document co-occurrences
 - Words are related to topics, topics to documents
- Given a data set, the goal is to
 - Learn the composition of the topics for that data set
 - Learn which topics are used in each document

Why Topic Models?

From (9) it can then be shown that (Exercise 1)

$$\lambda = \{ \mathbf{K}^{-1} - \mathbf{K}^{-1} \mathbf{M} (\mathbf{M}^T \mathbf{K}^{-1} \mathbf{M})^{-1} \mathbf{M}^T \mathbf{K}^{-1} \mathbf{z} + \mathbf{K}^{-1} \mathbf{M} (\mathbf{M}^T \mathbf{K}^{-1} \mathbf{M})^{-1} \mathbf{z} \}$$

so that the resulting prediction

$$\lambda^T \mathbf{Z} = \mathbf{k}^T \mathbf{z}$$

which is identical to what we would get from the generalized least squares estimate

$$k_0 - \mathbf{k}^T \mathbf{K}^{-1} \mathbf{z}$$

where $\gamma = \mathbf{m}(\mathbf{x}_0) - \mathbf{M}^T \mathbf{K}^{-1} \mathbf{z}$

Best linear unbiased prediction, named after the Soviet geostatistician G. Matheron (1951; Journel and Huijbregt 1978), is a Gaussian process is assumed to be an ordinary kriging prediction is called ordinary kriging. More general \mathbf{m} is known a priori, the prediction with the mean assumed 0 is called ordinary kriging. Pedder 1987 and Daley 1991

linear unbiased prediction for regression model did not explicitly consider the spatial setting. Cressie 1991 provides a further discussion on the history of various forms of kriging.

As noted in 1.3, A useful characterization c

kriging
covariance
mean
estimate
weight
random
mse
matrix
conditional
point

vs.

gaussian
regression
covariance
prediction
function
bayesian
process
prior
distribution
matrix

Definition 2.1 A Gaussian process is a collection of random variables indexed by a finite number of which have a joint Gaussian distribution.

A Gaussian process is completely specified by its mean function and covariance function.

We define mean function $m(\mathbf{x})$ and covariance function $C(\mathbf{x}, \mathbf{x}')$ as

$$m(\mathbf{x}) = \mathbb{E}[f(\mathbf{x})], \\ C(\mathbf{x}, \mathbf{x}') = \mathbb{E}[(f(\mathbf{x}) - m(\mathbf{x}))(f(\mathbf{x}') - m(\mathbf{x}'))]$$

A Gaussian process as

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), C(\mathbf{x}, \mathbf{x}'))$$

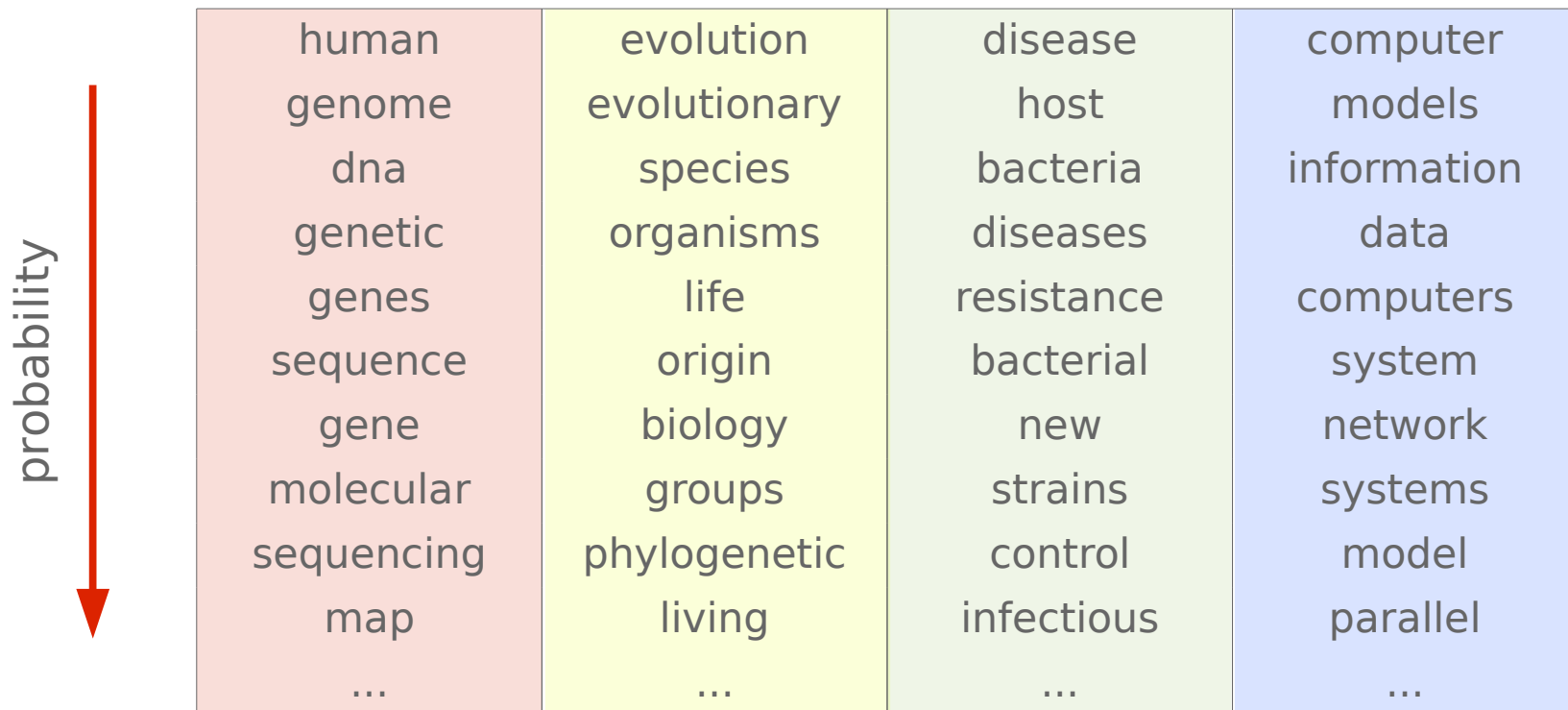
For notational simplicity we will treat f as a function, but it should not be done, see section 2.1.

The random variables represented by the Gaussian process at different locations or times. The random variables is time.

where the index set \mathcal{X} is the set of locations or times, e.g. \mathbb{R}^D . For notational convenience, we will use f_i to denote the random variable at location \mathbf{x}_i .

enumeration of the cases in the training set such that $f_i \triangleq f(\mathbf{x}_i)$ is the random variable at location \mathbf{x}_i as would be expected.

Topics and Words



Documents and Topics

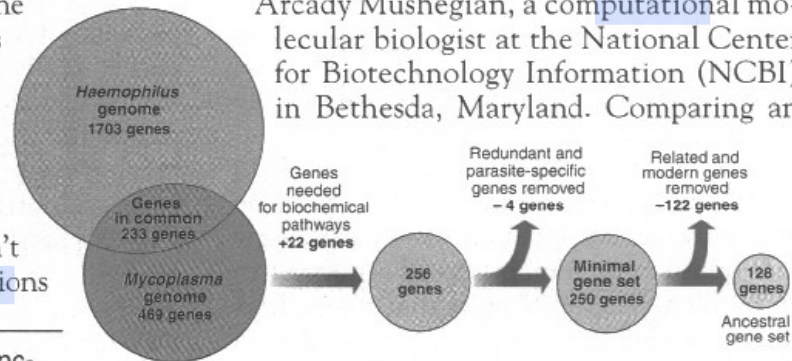
Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK— How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

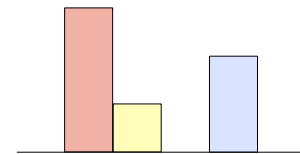
Although the numbers don't match precisely, those predictions

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

“are not all that far apart,” especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. “It may be a way of organizing any newly sequenced genome,” explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

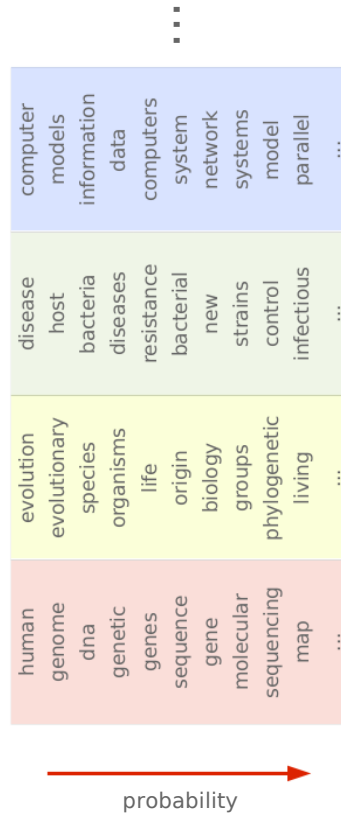


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Generative Statistical Modeling

- Assume data was generated by a probabilistic model:
 - Model may have hidden structure (latent variables)
 - Model defines a joint distribution over all variables
 - Model parameters are unknown
- Infer hidden structure and model parameters from data
- Situate new data in estimated model

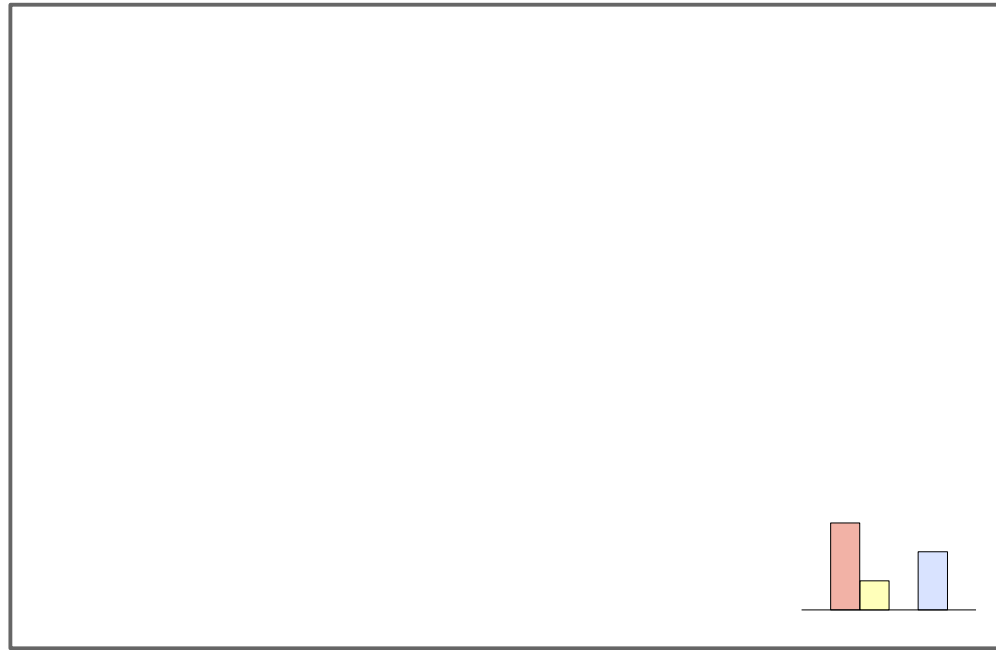
Generative Process



Choose a Distribution Over Topics



→
probability



Choose a Topic

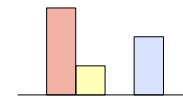
...

computer models information data computers system network systems model parallel ...
disease host bacteria diseases resistance bacterial new strains control infectious ...
evolution evolutionary species organisms life origin biology groups phylogenetic living ...
human genome dna genetic genes sequence gene molecular sequencing map ...

→ probability

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Choose a Word

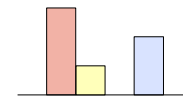
...

computer models information data computers system network systems model parallel ...	disease host bacteria diseases resistance bacterial new strains control infectious ...	evolution evolutionary species organisms life origin biology groups phylogenetic living ...	human genome dna genetic genes sequence gene molecular sequencing map ...
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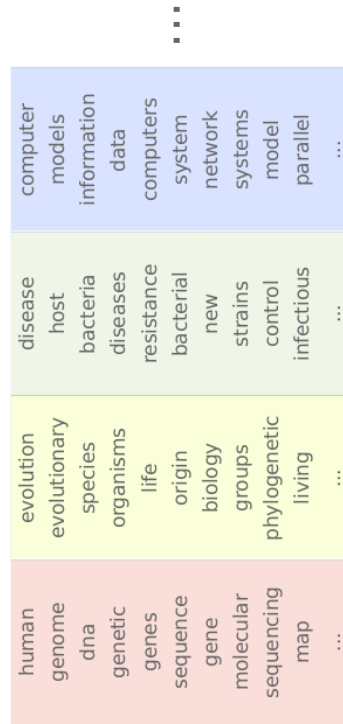
→
probability

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... And So On

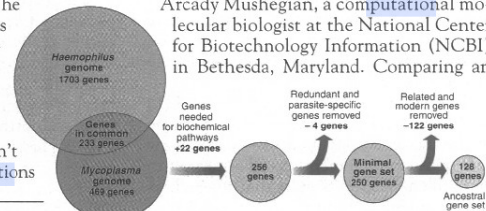


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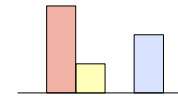
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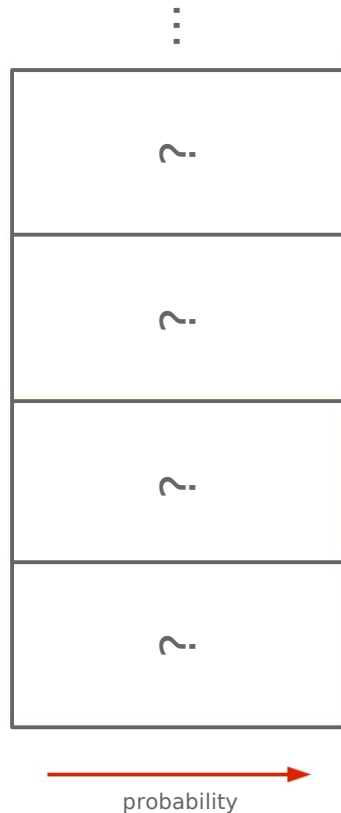
Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.



* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

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Real Data: Statistical Inference



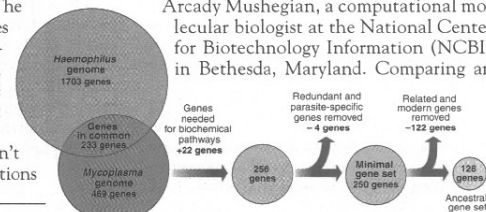
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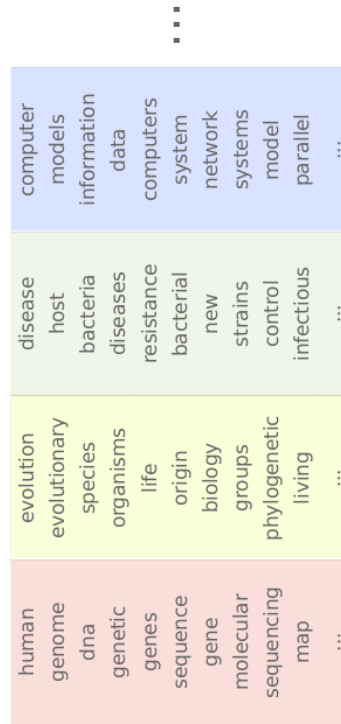
?

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Inference: Gibbs Sampling

- Randomly guess which topic “generated” each word:
- Given a set of guesses, can estimate probabilities
 - Initially the probabilities will be random
- Repeatedly refine the guess for each word:
 - Probability of guessing topic t for word w in document d is proportional to # of times topic t has been guessed for other words in document d and # of times topic t has been guessed for all other occurrences of word w

The End Result...

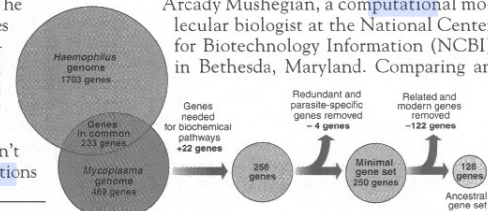


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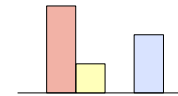
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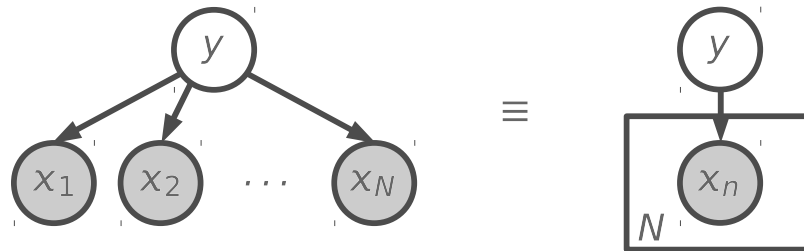
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Directed Graphical Models

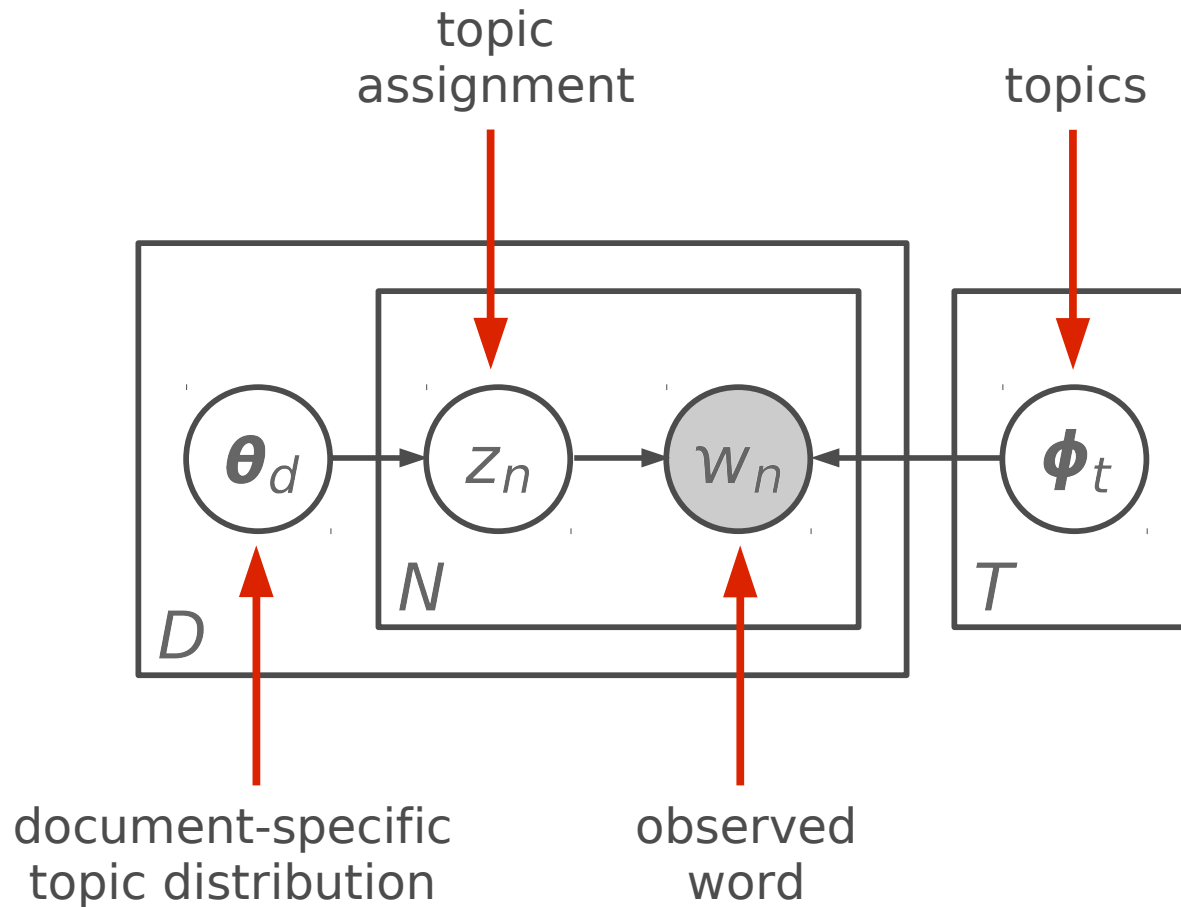
$$P(y, x_1, \dots, x_N) = P(y) \prod_{n=1}^N P(x_n | y)$$

- Nodes: random variables (latent or observed)
- Edges: probabilistic dependencies between variables
- Plates: “macros” that allow subgraphs to be replicated



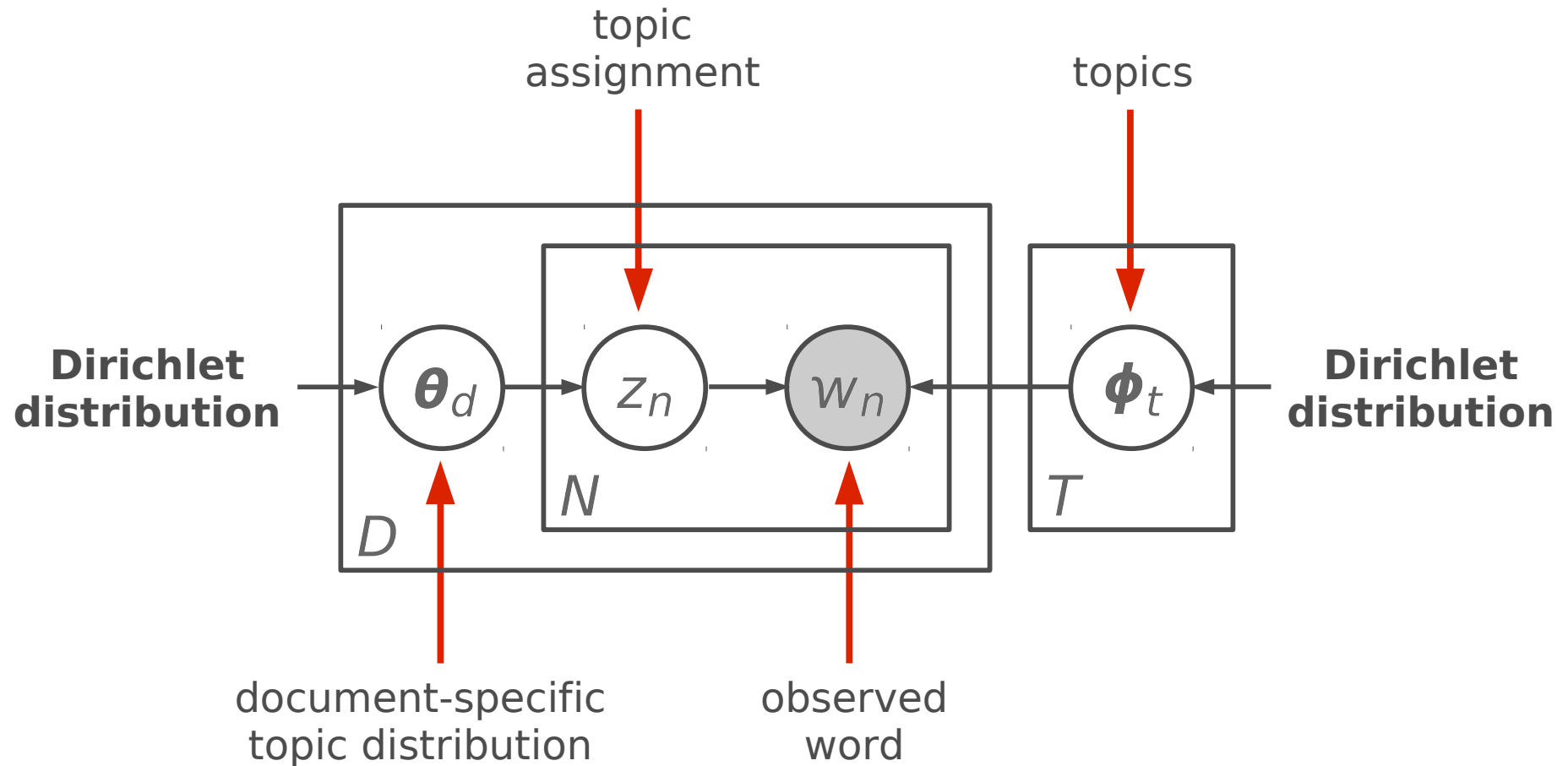
Statistical Topic Modeling

[Hofmann, '99]



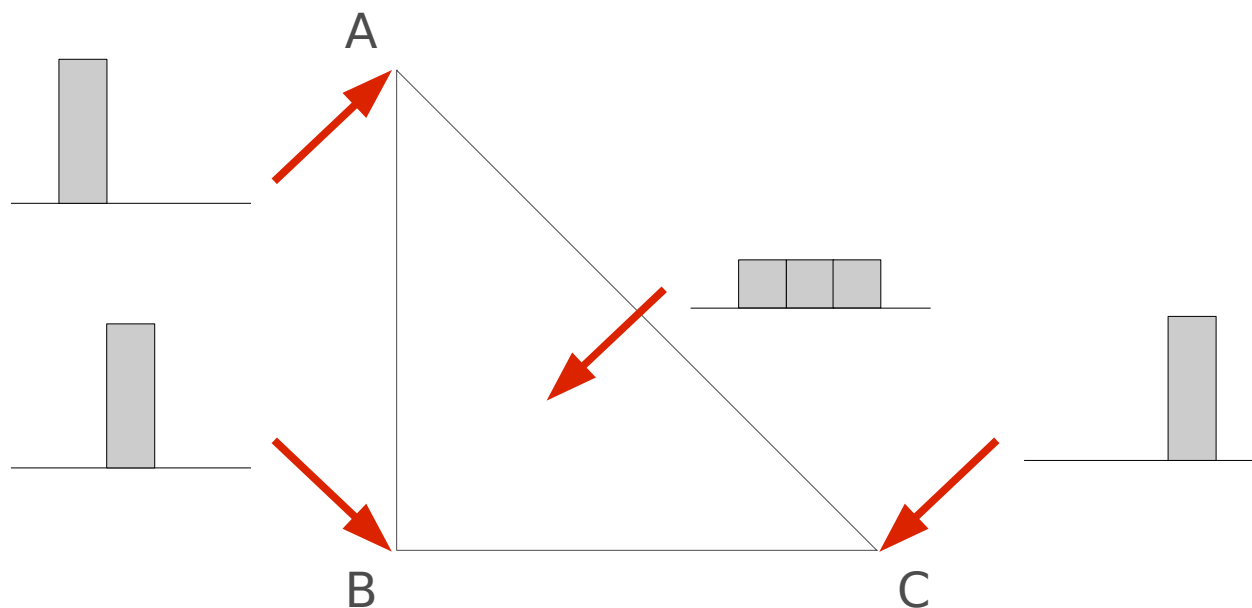
Latent Dirichlet Allocation (LDA)

[Blei, Ng & Jordan, '03]



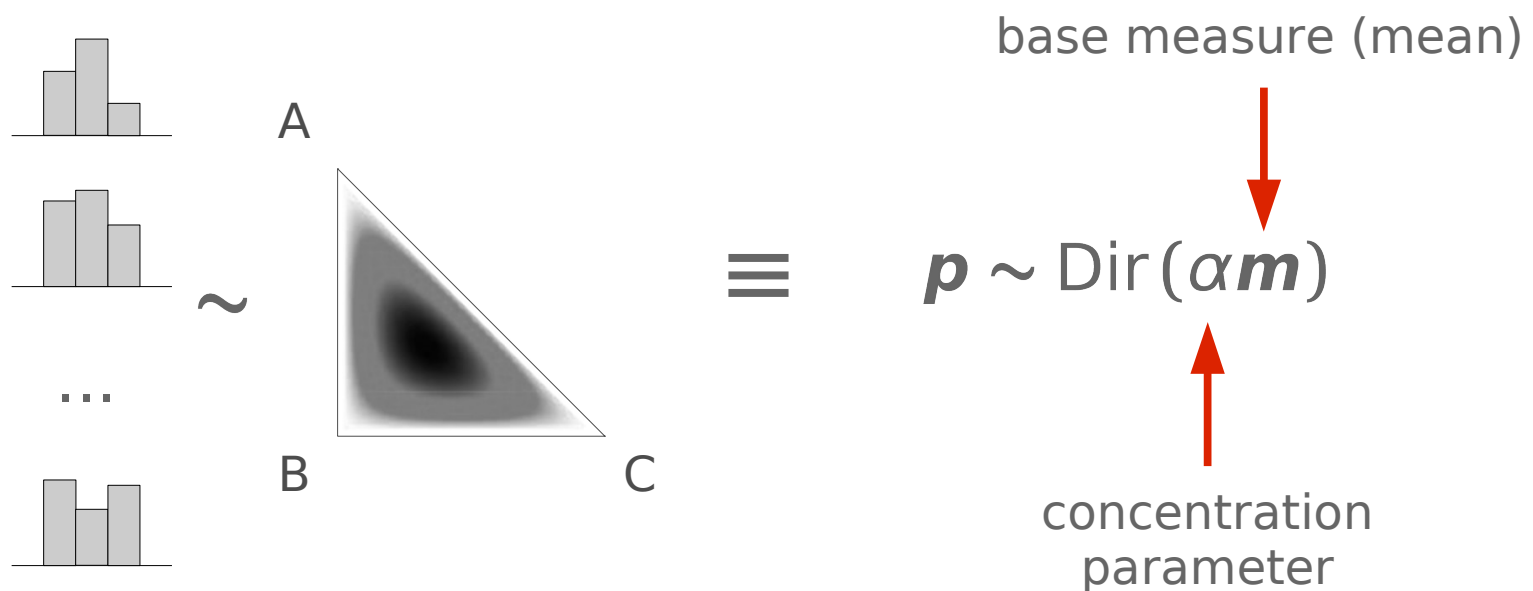
Discrete Probability Distributions

- 3-dimensional discrete probability distributions can be visually represented in 2-dimensional space:

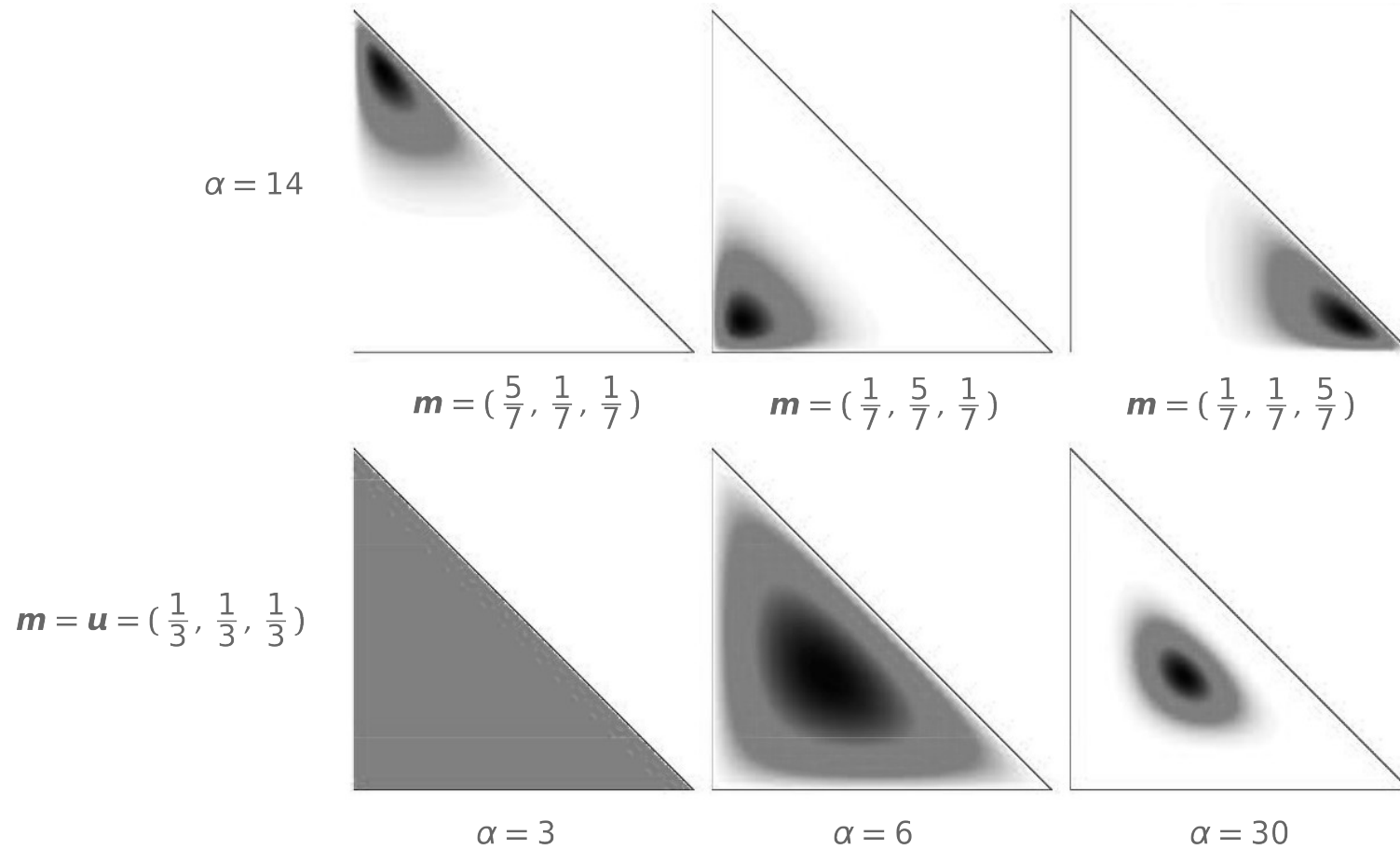


Dirichlet Distribution

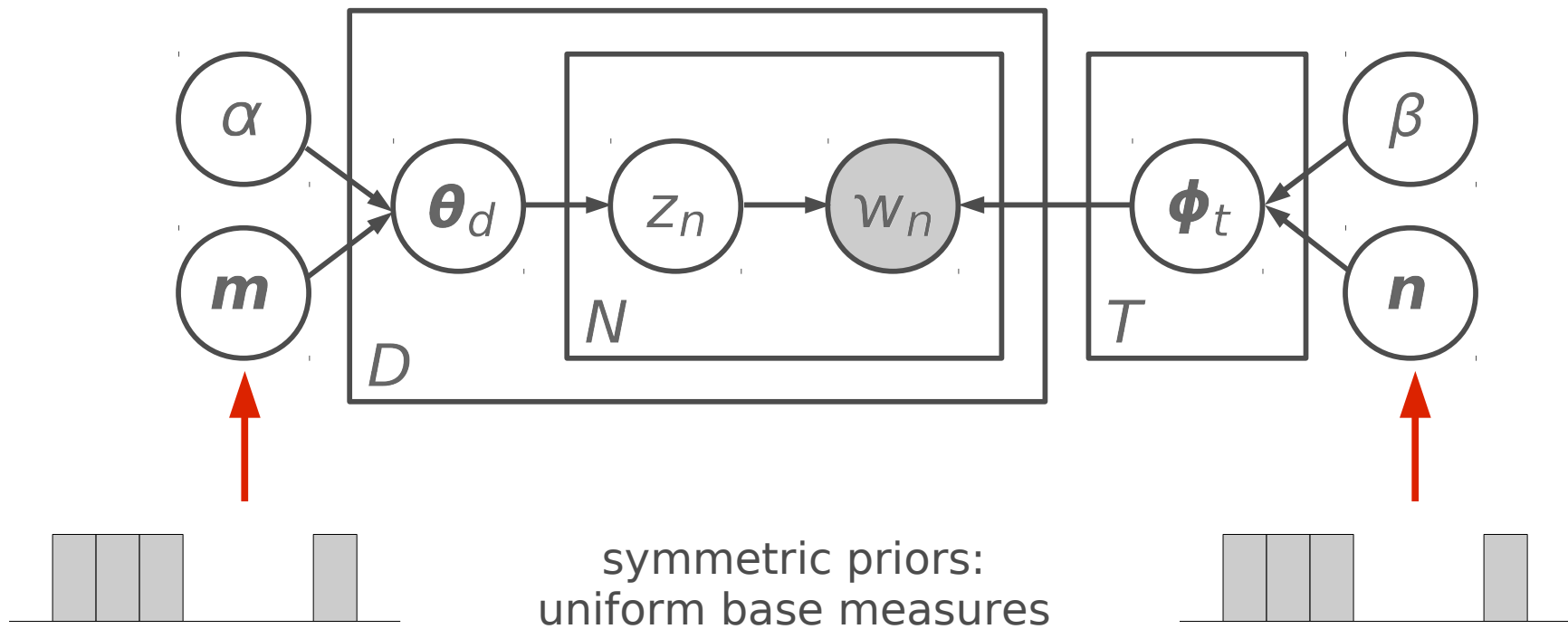
- Distribution over discrete probability distributions:



Dirichlet Parameters



Dirichlet Priors for LDA



This Talk

- Background: statistical topic models
- Building “off-the-shelf” statistical topic models
- Some current and future projects:
 - Analyzing free software development communities
 - Predicting when to declassify documents

The State of The Art

- Topic models are extremely popular
- ... but they're not always usable by non-experts
- Need to bridge this gap between producers and consumers of topic modeling technology:
 - Address problems/challenges faced by practitioners
 - Question unquestioned assumptions
 - Explore the interplay between theory and practice

“Off-the-Shelf” Topic Modeling



I want to model technology emergence by analyzing patent abstracts...

I have a statistical model that you can use...



“Off-the-Shelf” Topic Modeling



I want to model technology emergence by analyzing patent abstracts...

I have a statistical model that you can use...



a	a	the	the
field	the	of	invention
emission	carbon	a	of
an	and	to	to
electron	gas	and	present
...

“Off-the-Shelf” Topic Modeling?



Help! All my topics consist of “the, and of, to, a ...”



Now they all consist of “invention, present, thereof ...”



Wait, but how do I choose the right number of topics?

Preprocess your data to remove stop words...



Make a domain-specific list of stop words...



Evaluate the probability of unseen data for different numbers...



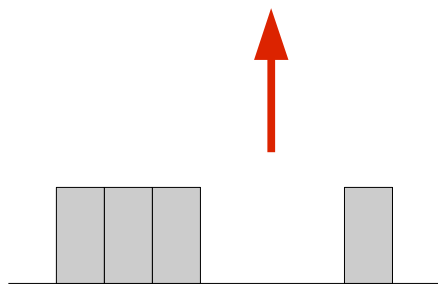
Dirichlet Priors for LDA

- Two scalar concentration parameters: α and β
- Concentration parameters are usually set heuristically
 - e.g., $\alpha = 50$ and $\beta = 0.01W$
- Some recent work on learning optimal values for the concentration parameters from data
- No rigorous study of the Dirichlet priors:
 - e.g., asymmetric vs. symmetric base measures
 - Effects of the base measures on the inferred topics

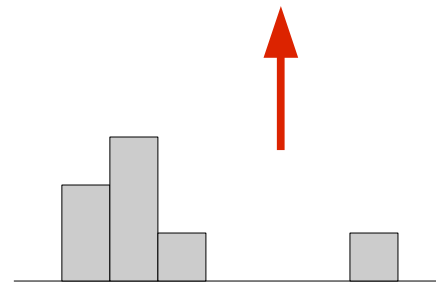
Symmetric \rightarrow Asymmetric

- Use prior over $\Theta = \{\theta_1, \dots, \theta_D\}$ as a running example
- Uniform base measure \rightarrow nonuniform base measure

$$\Theta \sim \text{Dir}(\alpha \mathbf{m})$$



$$\Theta \sim \text{Dir}(\alpha \mathbf{m})$$

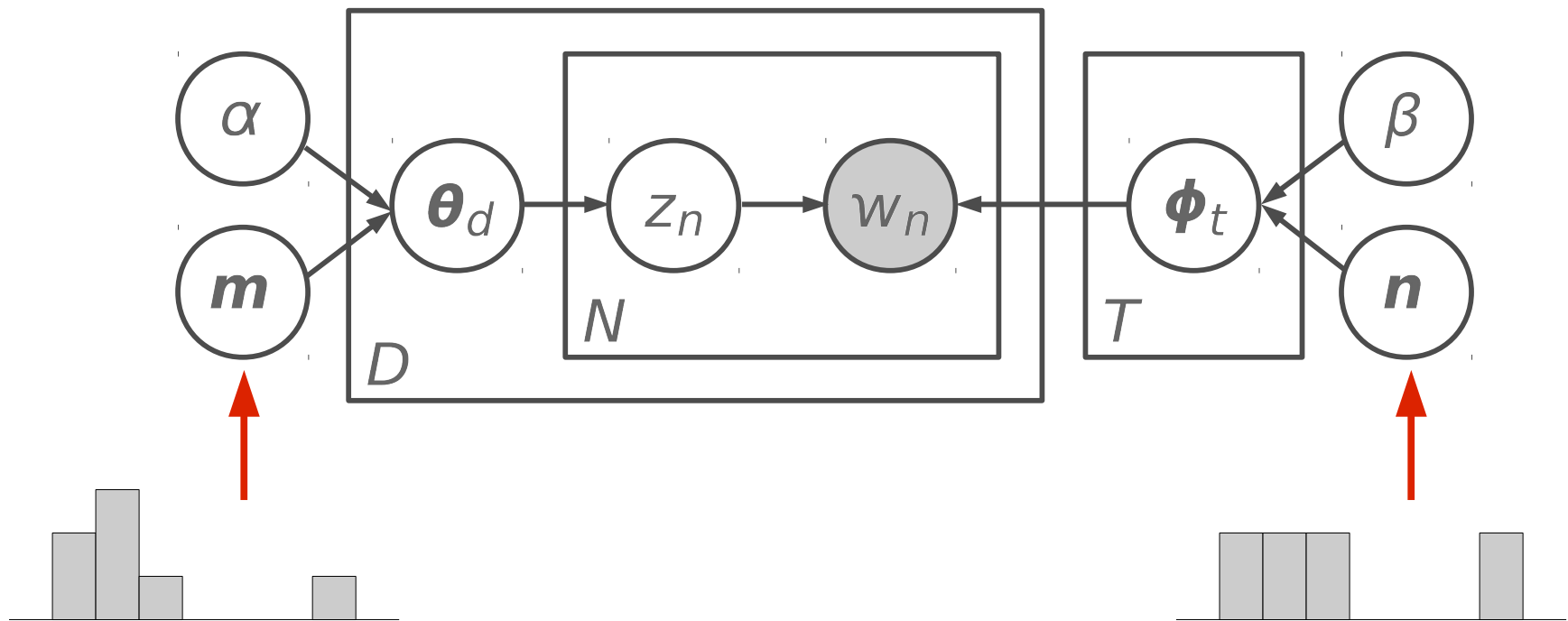


- Asymmetric prior: some topics more likely a priori

Data Sets

- Carbon nanotechnology patents:
 - Ultimate goal: track innovation and emergence
 - Fullerene and carbon nanotube patents
 - 1,016 abstracts (~100 words each)
 - 103,499 total words; 6,068 unique words
- 20 Newsgroups data (80,012 total words)
- New York Times articles (477,465 total words)

The Result



Inferred Topics

before →

a field emission an electron ...	a the carbon and gas ...	the of a to and ...	the invention of to present ...
--	---	------------------------------------	--

after →

the a of to and ...	carbon nanotubes nanotube catalyst substrate ...	metal catalytic transition catalyst from ...	composite polymer matrix weight fiber ...
------------------------------------	--	---	---

Intuition

- Topics should be distinct from each other:
 - Asymmetric prior over topics makes topics more similar to each other (and to corpus-wide word frequencies)
 - Want a symmetric prior to preserve topic “distinctness”
- Still have to account for power-law word usage:
 - Asymmetric prior over document-specific topic distributions means some topics (e.g., “the, a, of, to ...”) can be used more often than others in all documents

“Off-the-Shelf” Topic Modeling



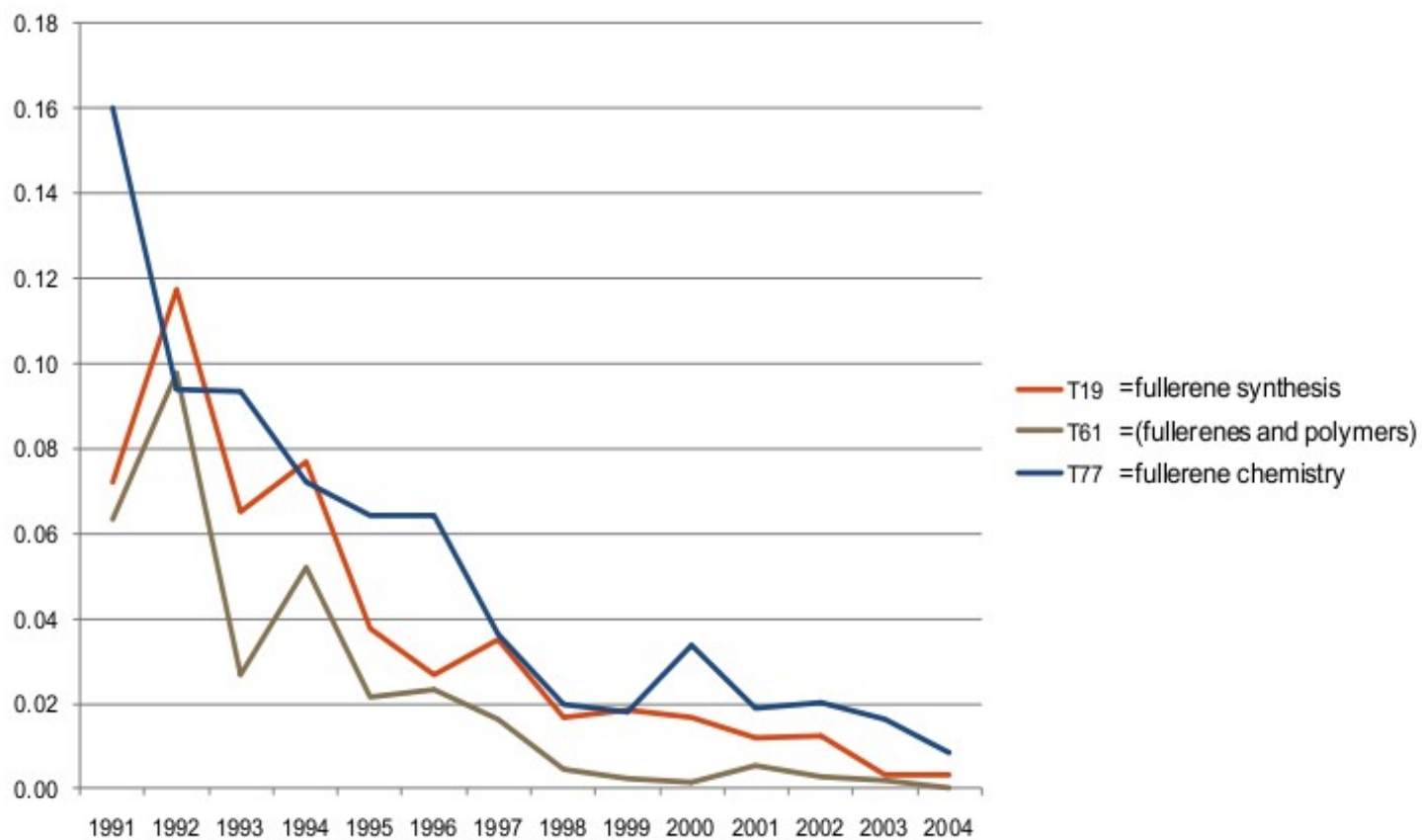
I can model technology emergence by analyzing patent abstracts!

Great! Let me know if you need any more help!

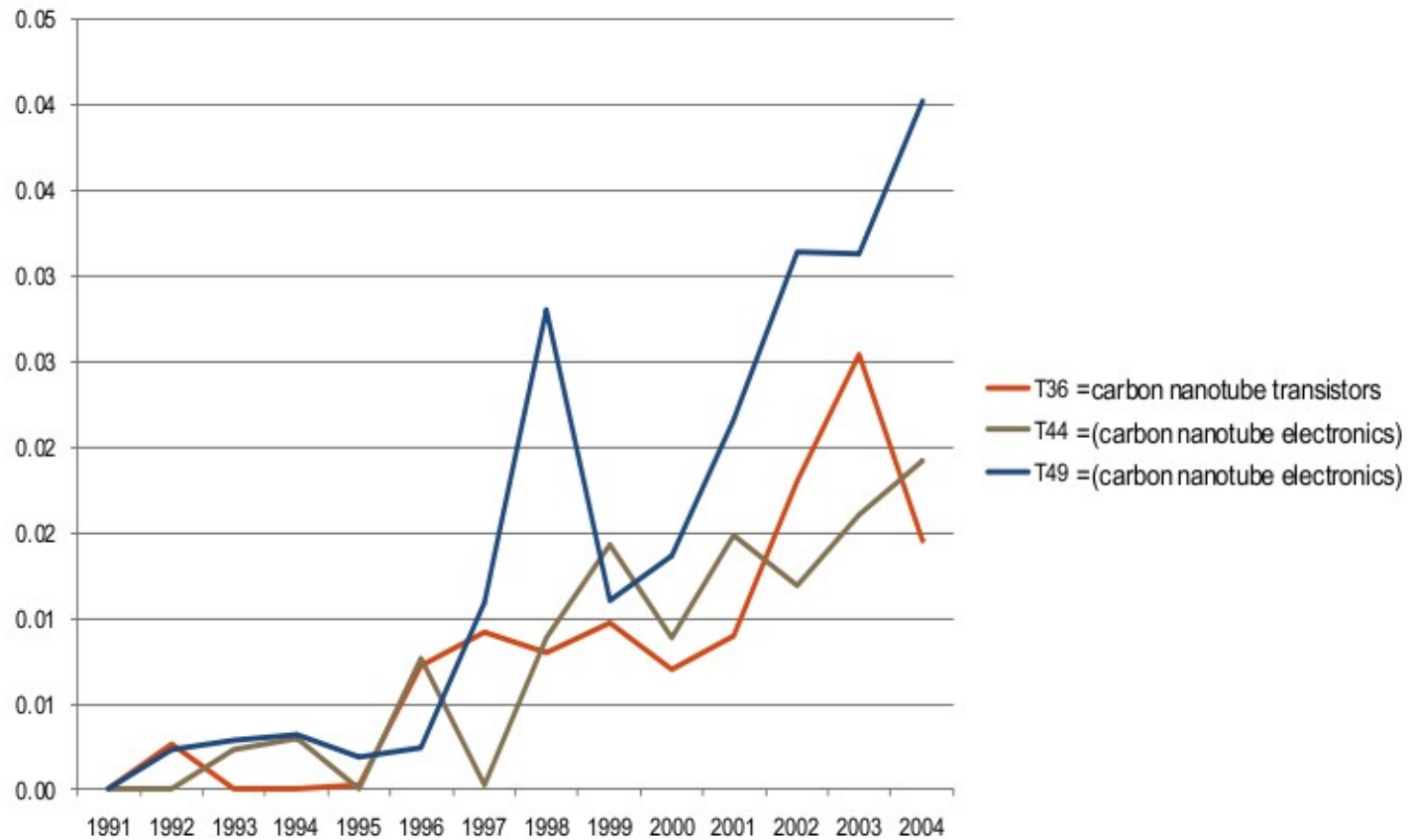


the	carbon	metal	composite
a	nanotubes	catalytic	polymer
of	nanotube	transition	matrix
to	catalyst	catalyst	weight
and	substrate	from	fiber
...

Declining Topics



Rising Topics



Topic Model Output in Practice

- Common to use a single random set of topic assignments (typically the last sample drawn)
- Not necessarily representative
- Other (better) approaches:
 - Average summary statistics over multiple samples
 - Use the posterior mode
 - Use hierarchical agglomerative clustering to construct a new aggregate set of topic assignments

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FOSS Development Communities

- Considerable commercial, noncommercial, academic interest in FOSS development communities:
 - Complex technological, legal, social structures
 - Geographically distributed collaboration
- Organizational and social processes underlying collaborative FOSS development are largely unknown:
 - Area of study for social and computer scientists

FOSS Collaboration Data

- Most FOSS collaboration data are publicly available:
 - Mailing lists, IRC channels
 - Commit messages, bug reports
 - Comments in source code, documentation
 - GPG keysigning records

⇒ Use these collaboration data to study organizational and social processes underlying FOSS development

Data Challenges

- Informal, messy, and often highly unstructured data:
 - Developers use different identifiers in different fora
 - IRC channels have multiple interleaved conversations
 - Mix of highly technical and “off-topic” discussion
 - Conversational style is often casual
- ⇒ Significant text analysis is required prior to developing models for answering social science questions

Analyzing Debian Mailing Lists

- Quoted text and signatures stripped
- Debian-project mailing list:
 - 19,347 messages
 - 1225797 words (max. 7,916 per message)
- Debian-women mailing list:
 - 4,124 messages
 - 228,076 words (max. 1,524 per message)

100 Topics

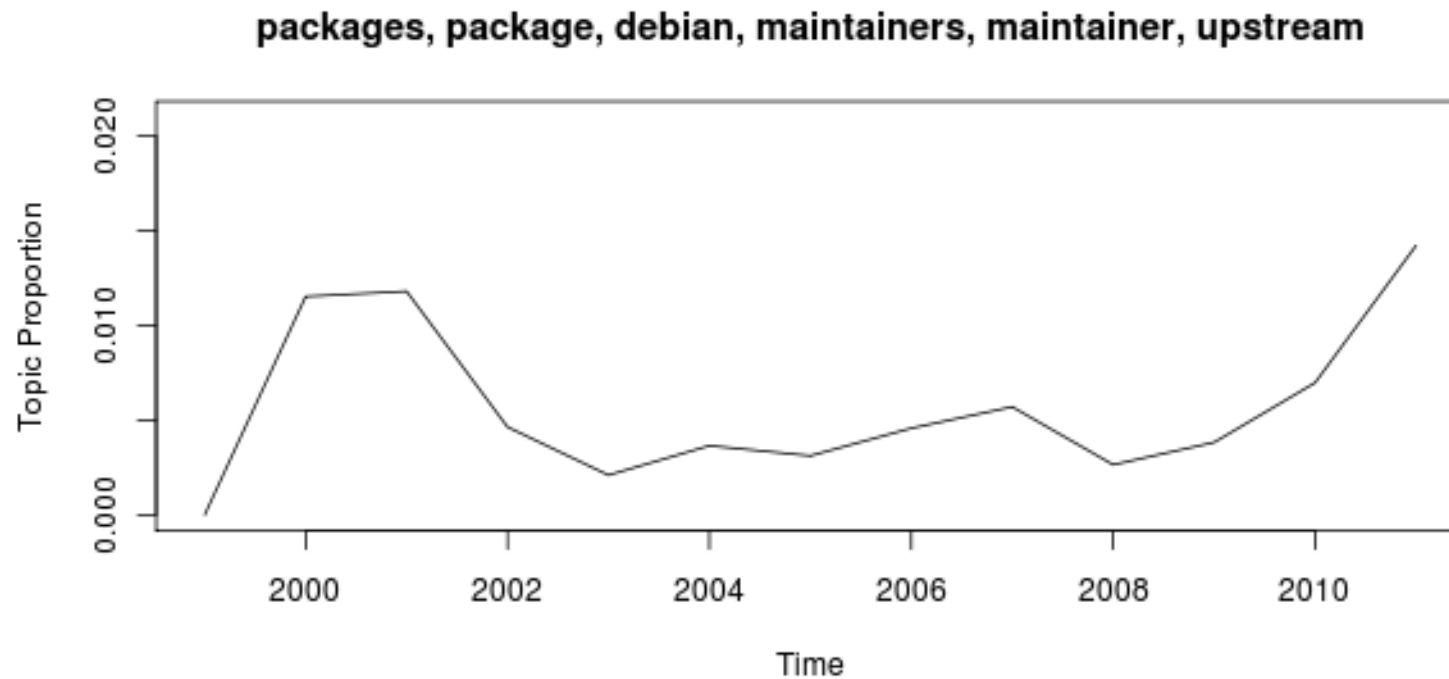
d-project →

package packages install apt-get apt ...	ubuntu debian patches derivatives lts ...	nm process applicant dam fd ...	ftp-master queue packages upload team ...
---	--	--	--

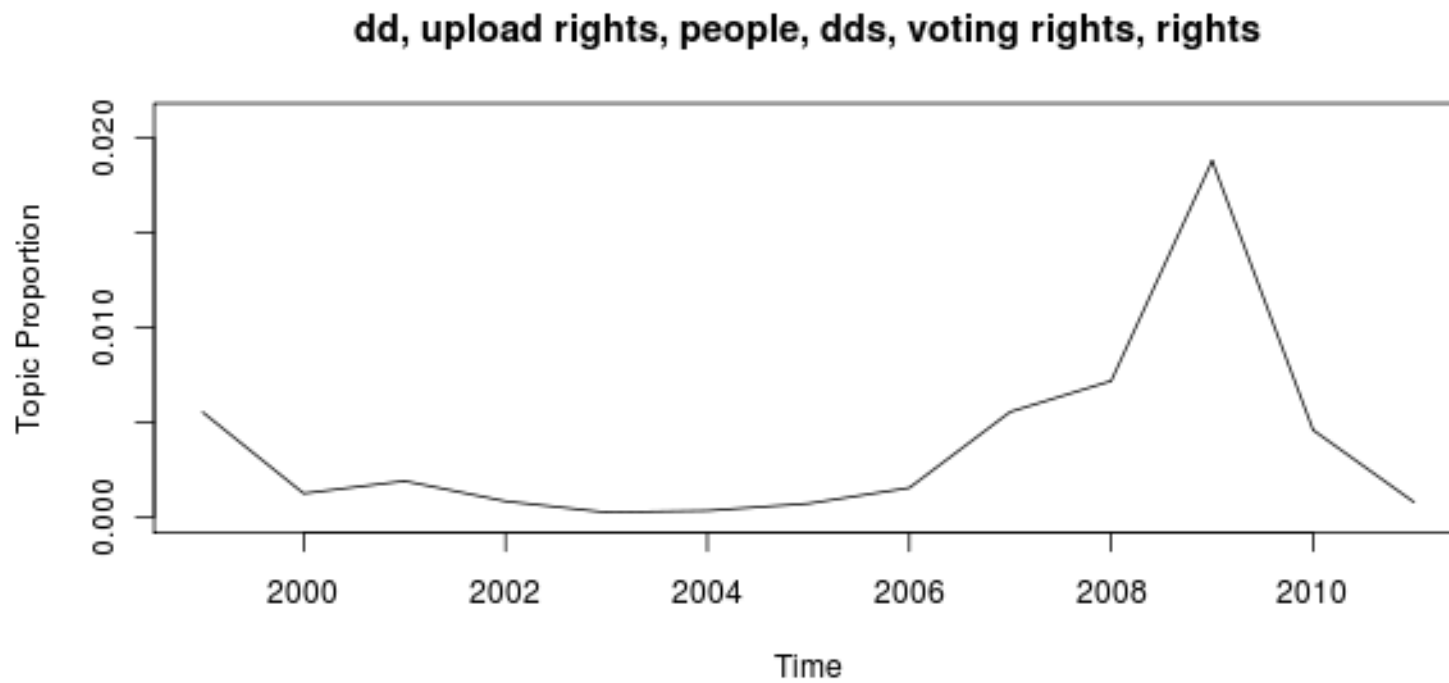
d-women →

women men female male man ...	website page site work d-w ...	post culture response posts behavior ...	nm debian process dd packages ...
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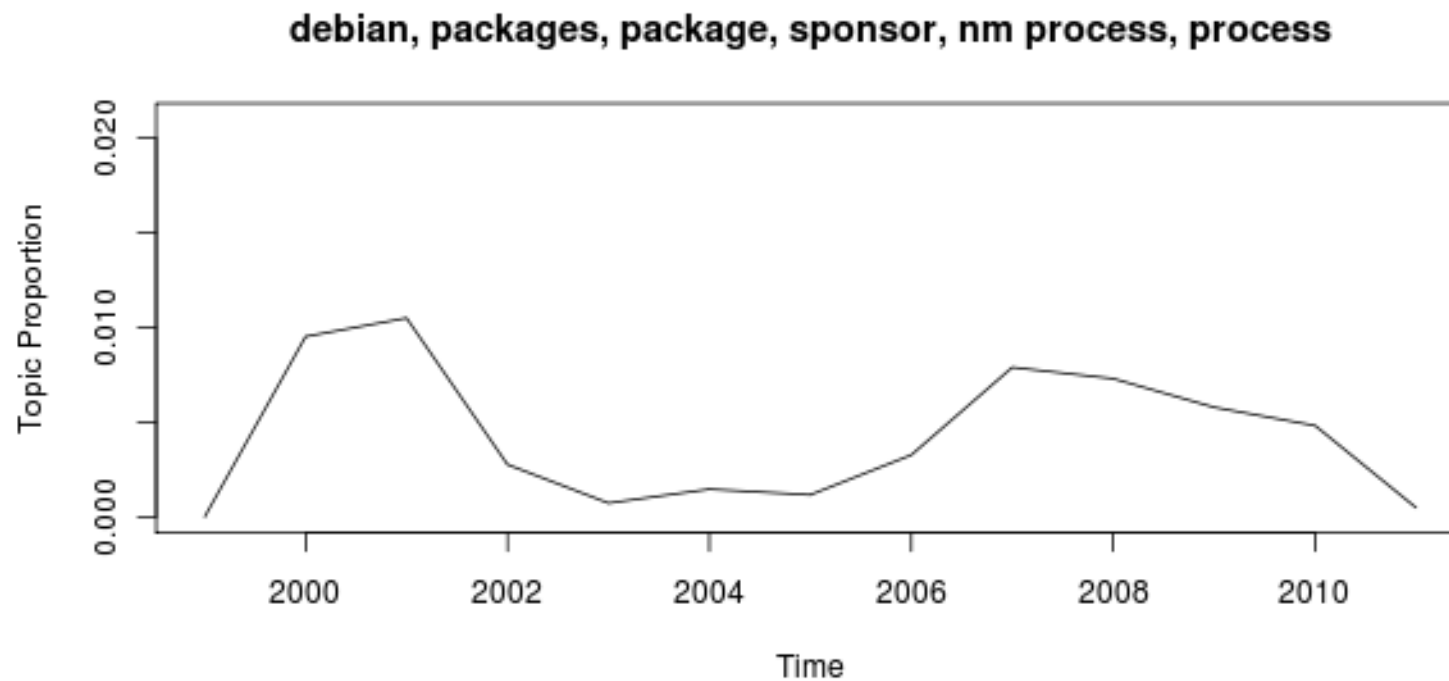
Topic Usage Over Time



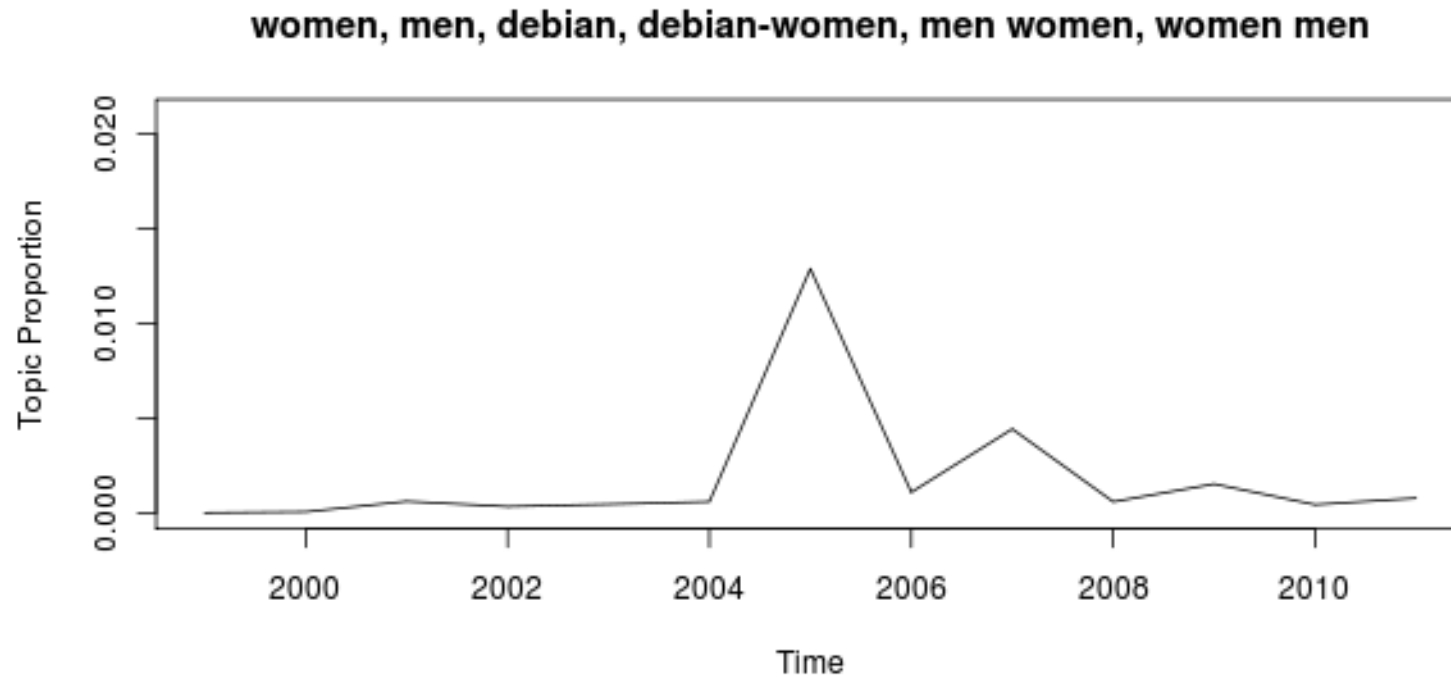
Topic Usage Over Time



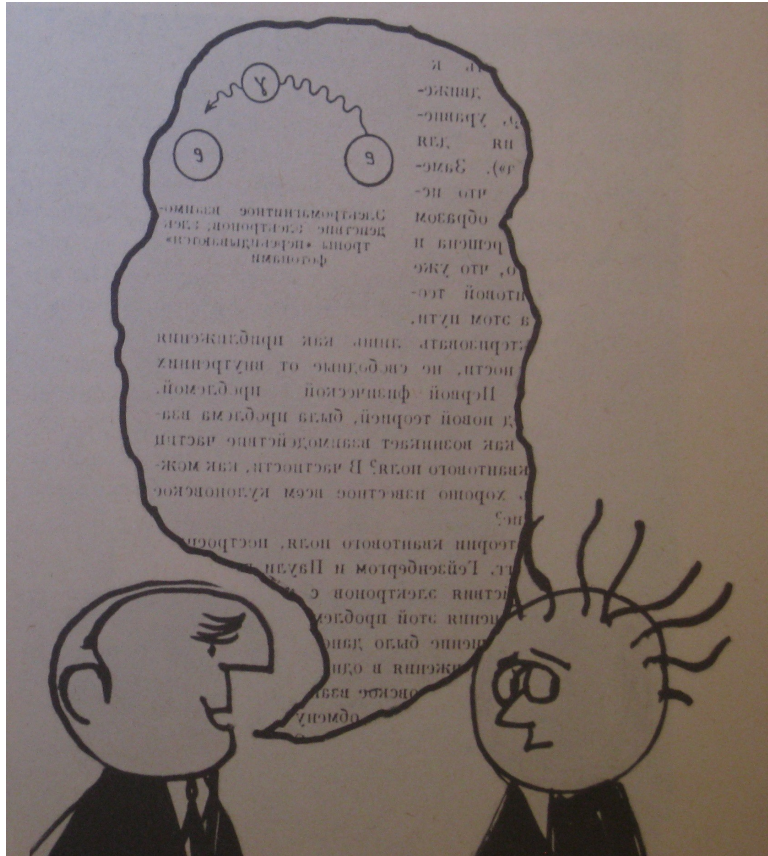
Topic Usage Over Time



Topic Usage Over Time



Cross-language Analysis



“He may know one language backwards and forward, but he can't communicate with a scientist who only knows another: a graphic illustration of the need for translation of foreign scientific documents.”

— NSF Brochure, 1962

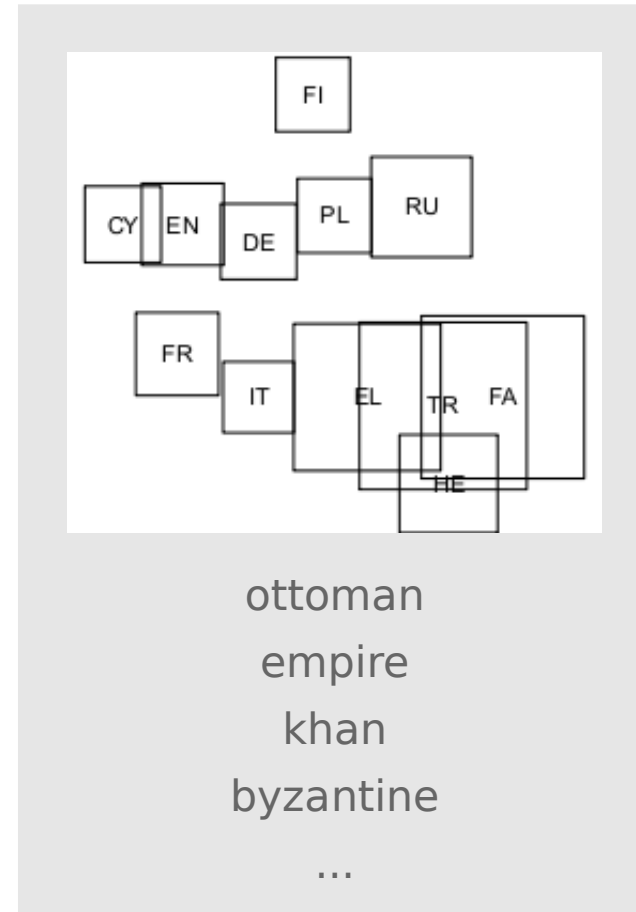
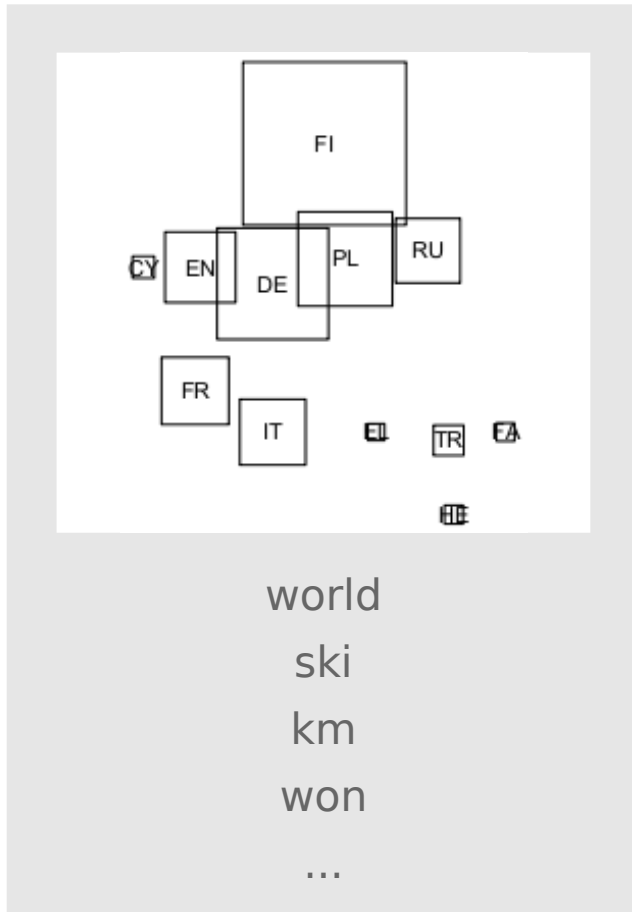
Polylingual Topics

CY sadwrn blaned gallair at lloeren mytholeg
DE space nasa sojus flug mission
EL διαστημικό sts nasa αγγλ small
EN **space mission launch satellite nasa spacecraft**
FA فضایی ماموریت ناسا مدار فضاانورد ماهواره
FI sojuz nasa apollo ensimmäinen space lento
FR spatiale mission orbite mars satellite spatial
HE החלל הארץ חלל כדור א תוכנית
IT spaziale missione programma space sojuz stazione
PL misja kosmicznej stacji misji space nasa
RU космический союз космического спутник станции
TR uzay soyuz ay uzaya salyut sovyetler

Polylingual Topics

CY	bardd gerddi iaith beirdd fardd gymraeg
DE	dichter schriftsteller literatur gedichte gedicht werk
EL	ποιητής ποίηση ποιητή έργο ποιητές ποιήματα
EN	poet poetry literature literary poems poem
FA	شاعر شعر ادبیات فارسی ادبی آثار
FI	runoilija kirjailija kirjallisuuden kirjoitti runo julkaisi
FR	poète écrivain littérature poésie littéraire ses
HE	משורר ספרות שירה סופר שירים המשורר
IT	poeta letteratura poesia opere versi poema
PL	poeta literatury poezji pisarz in jego
RU	поэт его писатель литературы поэзии драматург
TR	şair edebiyat şiir yazar edebiyatı adlı

Differences in Topic Emphasis



Aligned Corpora

- Fully parallel corpora: direct translations
 - Expensive to produce, relatively rare
- Partially parallel corpora: few parallel “glue” tuples
 - $< 25\%$ is sufficient to obtain aligned topics
- Comparable corpora: documents have similar content
 - e.g., Wikipedia in English, Portuguese, French, ...
 - e.g., documentation in multiple languages

Cross-cultural Study of FOSS

- Use Wikipedia pages, FOSS websites, documentation in different languages as aligned document tuples
- Use resultant topics to analyze mailing lists in order to study FOSS culture in different parts of the world
- Specifically interested in:
 - Brazil (governmental adoption of FOSS)
 - European countries (e.g., France)
 - United States

This Talk

- Background: statistical topic models
- Building “off-the-shelf” statistical topic models
- Some current and future projects:
 - Analyzing free software development communities
 - Predicting when to declassify documents

Document Declassification

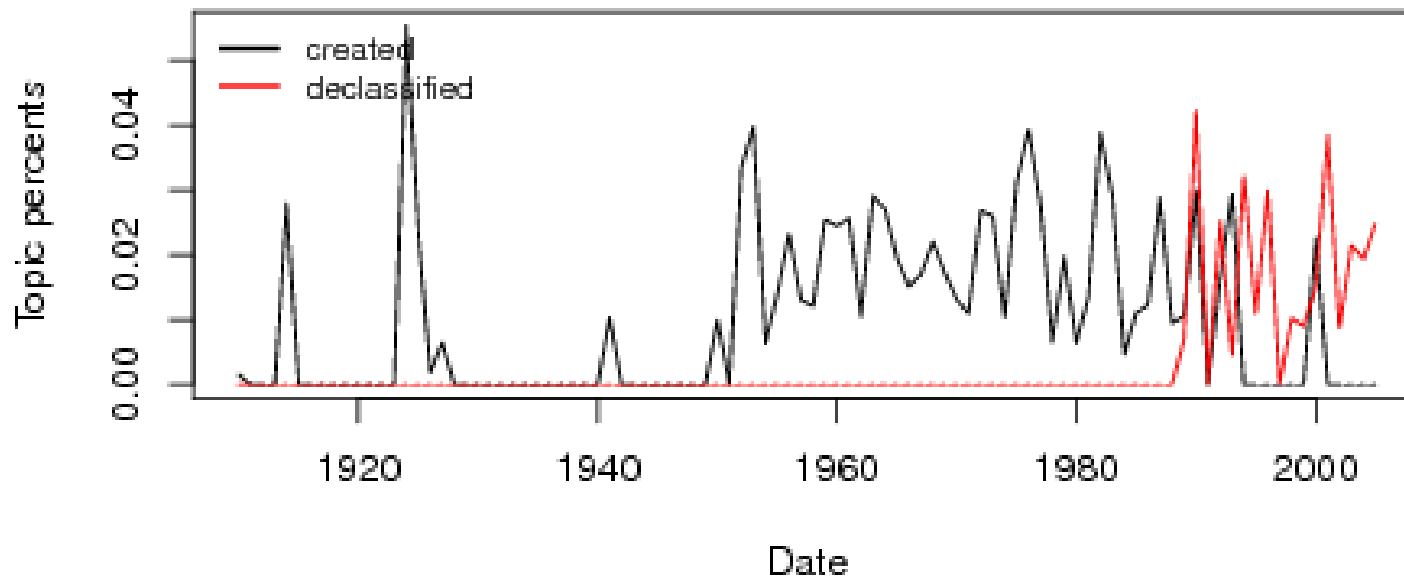
- Massive amount of secret data is protected as part of the United States Government Classification System
- Human readers manually declassified almost 29,000,000 pages of information in 2009
- Need automated tools:
 - Prioritize documents for human review
 - Academic study of (de)classification patterns

Declassified Documents

- Study classification patterns by looking at classification and declassification dates of declassified documents
- Model temporal patterns and document content
- Declassified Documents Reference System
 - 85,000 declassified documents
 - Classification, declassification dates
 - Issuer (e.g., White House)

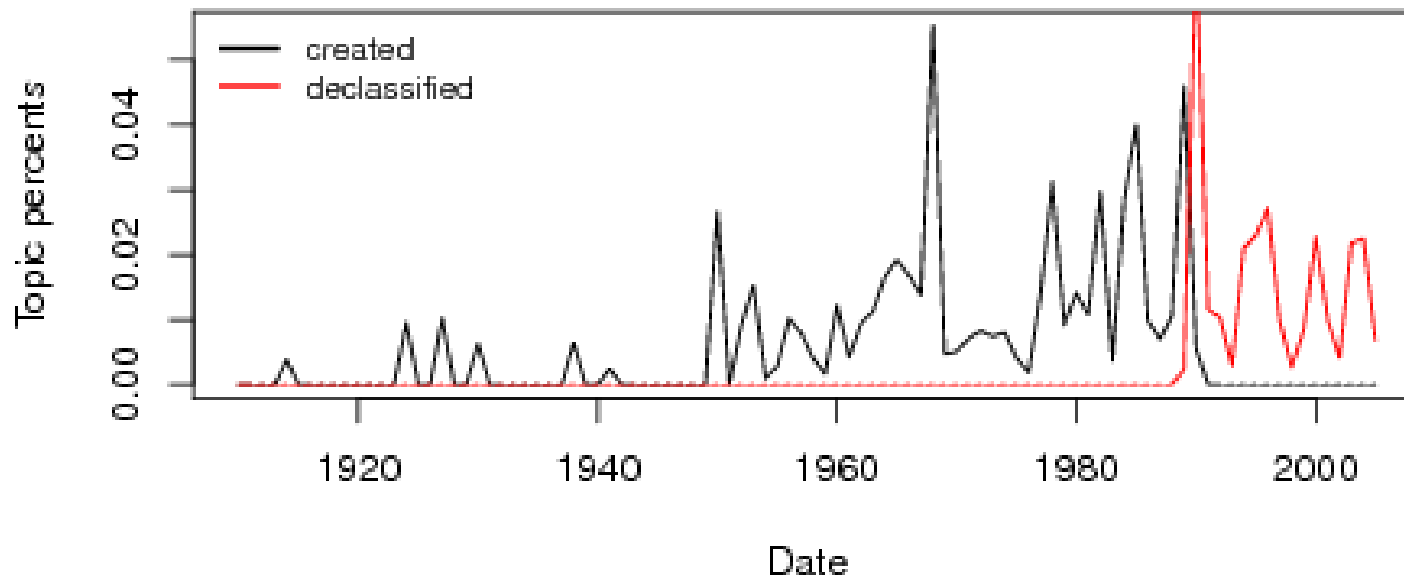
Declassification by Topic

soviet europe nato european union western ussr policy soviets west french germany relations german eastern allies conference moscow alliance



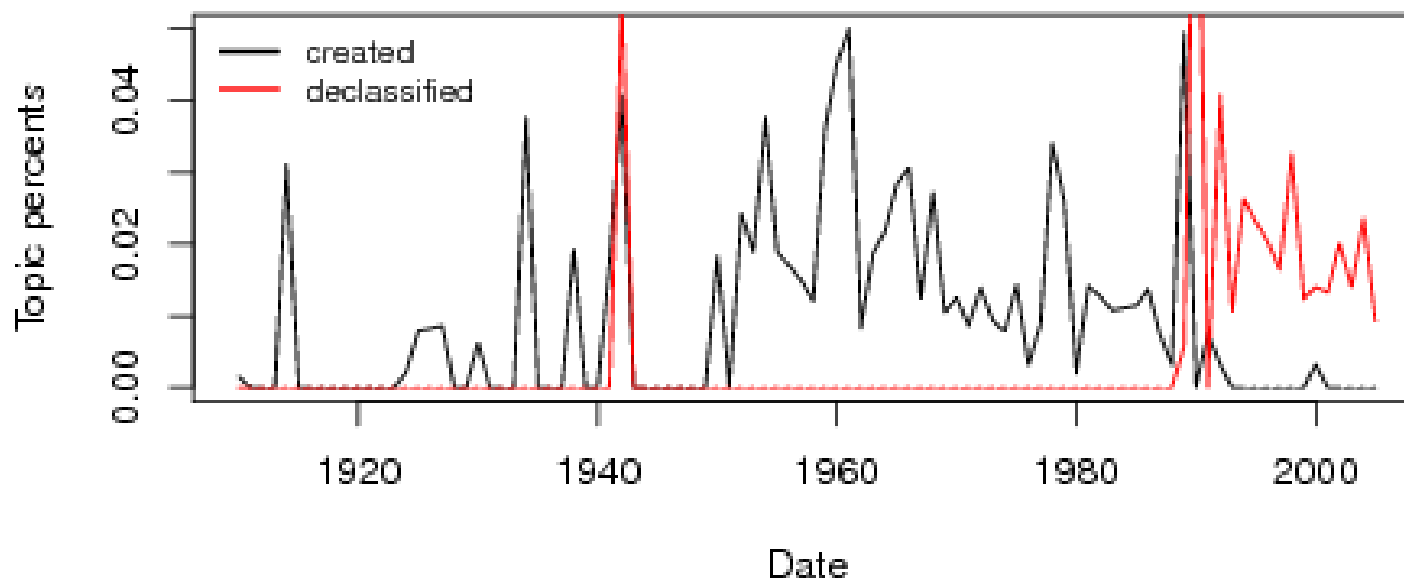
Topic Declassification

india military aircraft pakistan iran indian policy soviets million s-
hah equipment items soviet indians additional june sale deliveries gan-
dhi



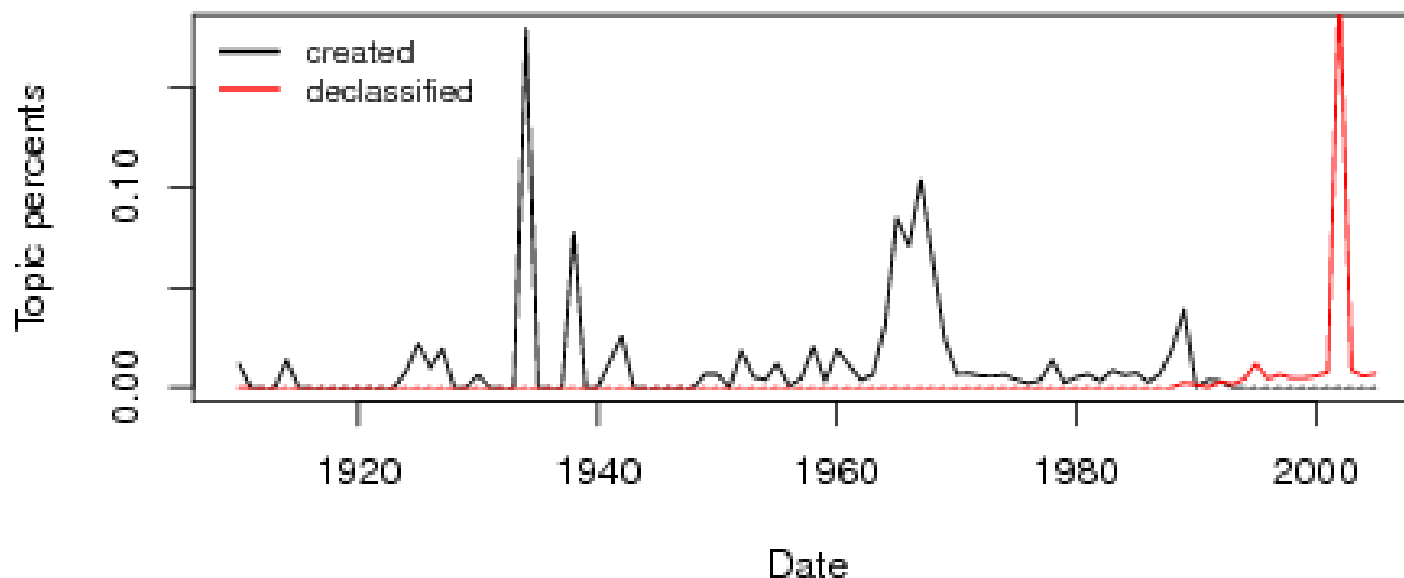
Topic Declassification

british asked question uk secretary stated problem agreed thought time-
e suggested made exdis regard australia conversation felt make point



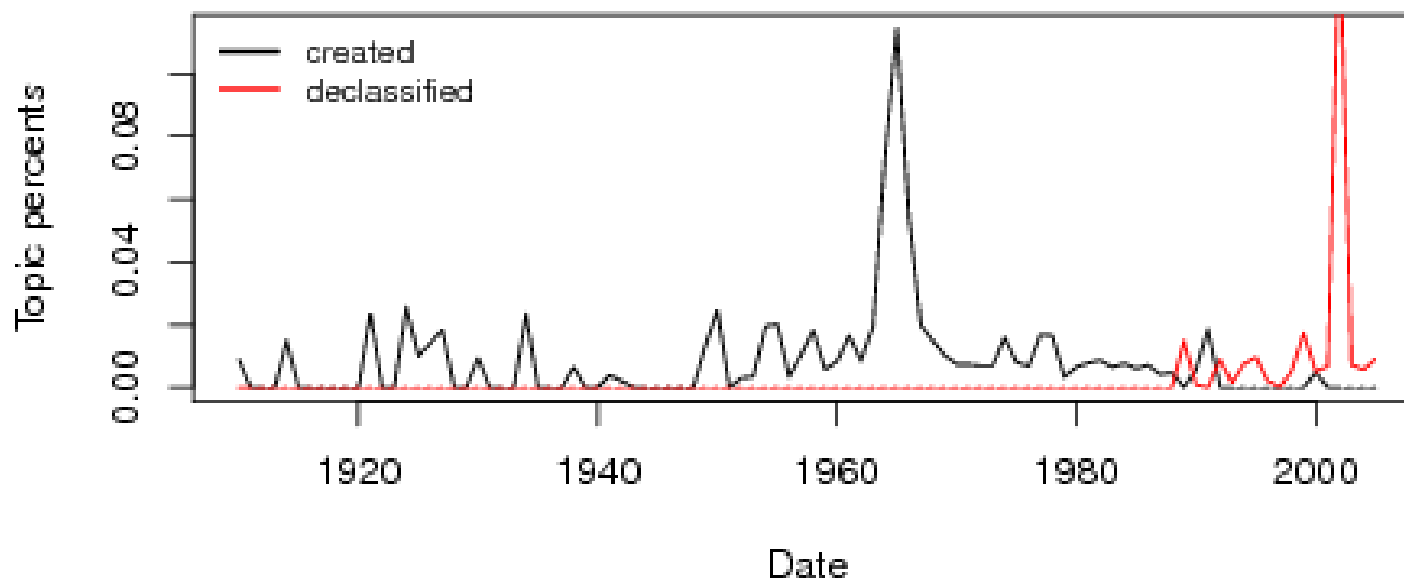
Topic Declassification

police advised school copy negro department library racial lbj studen-
ts chicago developments disturbances officers bureau demonstration stu-
dent selected organization



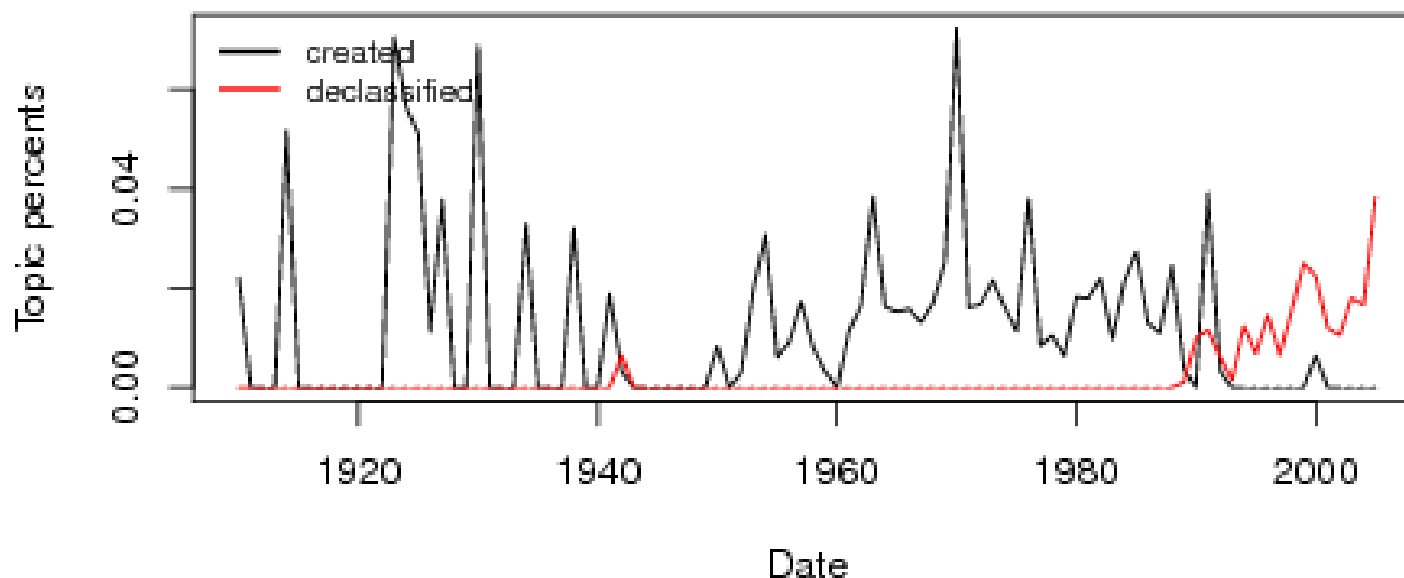
Topic Declassification

mississippi civil rights group negroes white march department local j-
ustice negro washington june members bureau federal persons county ral-
ly



Topic Declassification

states united africa president country nations policy nara american a-
frican countries area eo secretary march foreign state date declassifi-
ed



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