Statistical Topic Models for Science and Innovation Policy

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Science and Innovation

“Whether it's improving our health or harnessing clean energy, protecting our security or succeeding in the global economy, our future depends on reaffirming America's role as the world's engine of scientific discovery and technological innovation.”

— President Barack Obama

… Behind the Scenes

“The public has generally treated this progress as something that just happened, without recognizing that it is, in fact, largely the result of a sustained federal commitment to support science through science policies.”

— http://science-policy.net

Science and Innovation Policy

- Goal: identify administrative, financial, political actions
- Actions chosen to have impact on, e.g.,
  - Stimulating breakthrough research
  - Increasing economic prosperity
  - Broadening participation
- Government, private sector, education
- This talk: statistical models for facilitating efficient, data-driven science policy decisions

Examples of Policy Actions

- Funding actions:
  - Using federal funds for research on human stem cells
  - “People not projects” vs. pre-defined deliverables
- Patenting actions:
  - Granting software patents
- Educational actions:
  - Running high school outreach activities
  - Providing mentoring programs

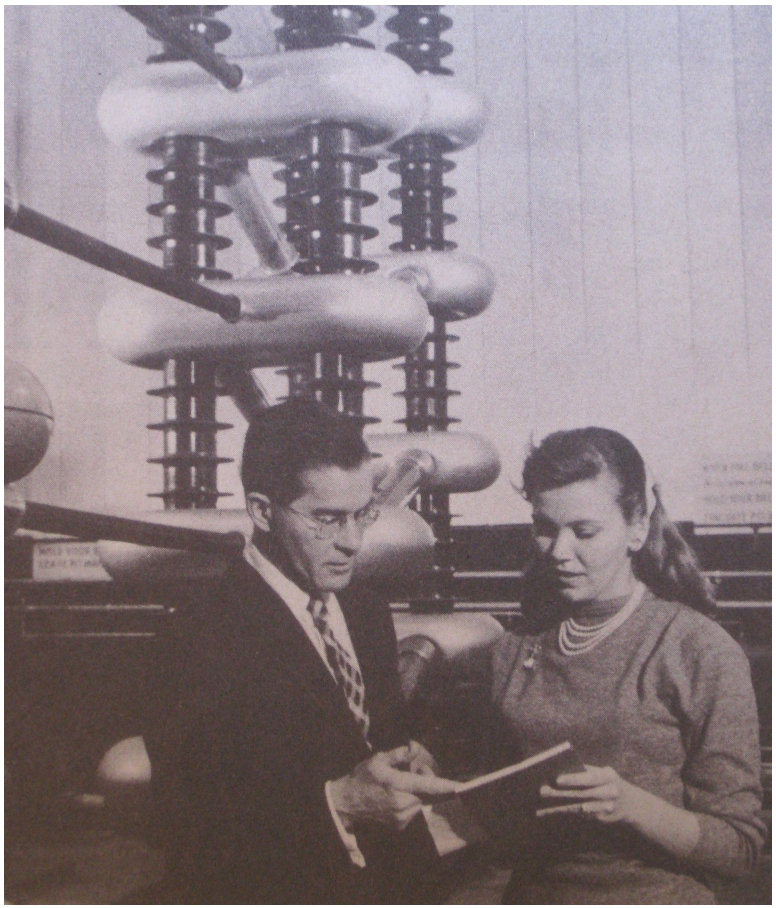
Data-Driven Policy Decisions

Candida Hofer

- Discovery: identifying possible policy actions
- Prediction: estimating expected impact
- Evaluation: assessing observed outcomes

⇒ Automated data analysis

Data: 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

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

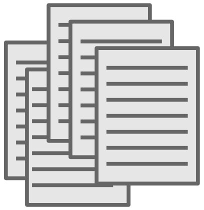
My Research Goal

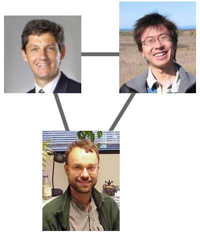
```
    $line .= <CASEBOOKS>;
    redo unless eof(CASEBOOKS);
}

$line =~ s/\\\t/xyzdrptmpxyz/g;
@columns = split("\t", $line);
$columns[3] = uc $columns[3];
$line = join("\t", @columns);
$line =~ s/xyzdrptmpxyz/\\\t/g;
```

$$\prod_t \frac{\Gamma(W\beta)}{\Gamma(\beta)^W} \frac{\prod_w \Gamma(N_{w|t}+\beta)}{\Gamma(N_{.|t}+W\beta)}$$

$+$

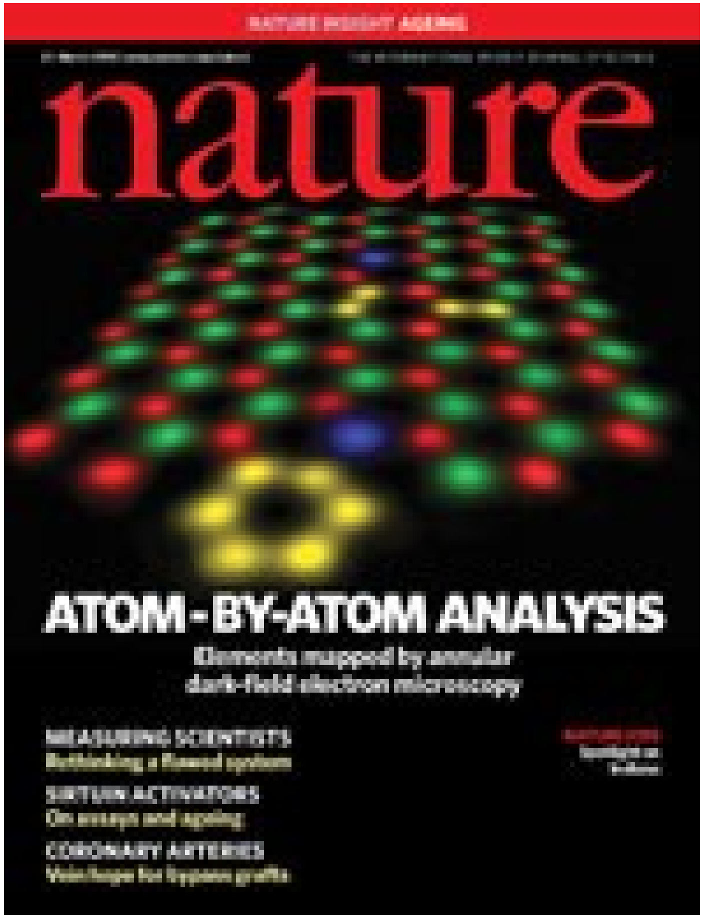




$\rightarrow$

To develop new statistical models and computational tools for representing and analyzing large quantities of complex data in order to better enable scientific policy-makers to identify and evaluate high-impact policy actions and advance the study of science and innovation policy.

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

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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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?

kriging
covariance
mean
estimate
weight
random
mse
matrix
conditional
point

vs.

gaussian
regression
covariance
prediction
function
bayesian
process
prior
distribution
matrix

Topics and Words

probability

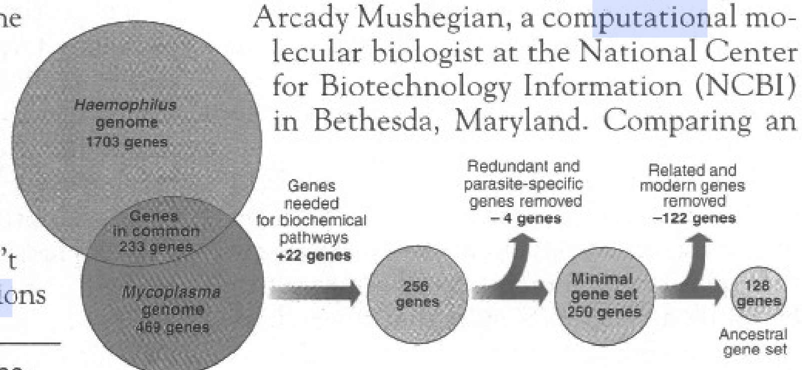
human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living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

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 "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.

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

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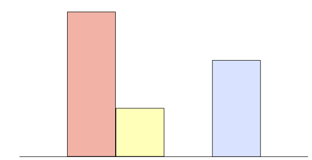
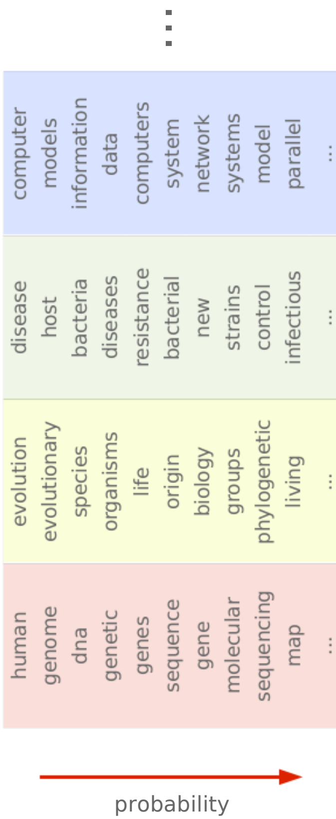


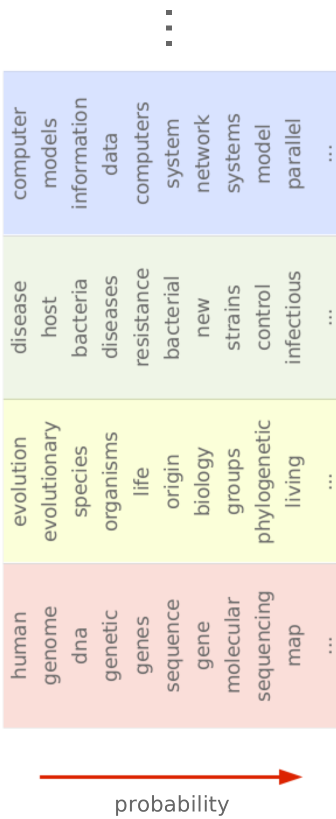
Generative Statistical Modeling

- 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

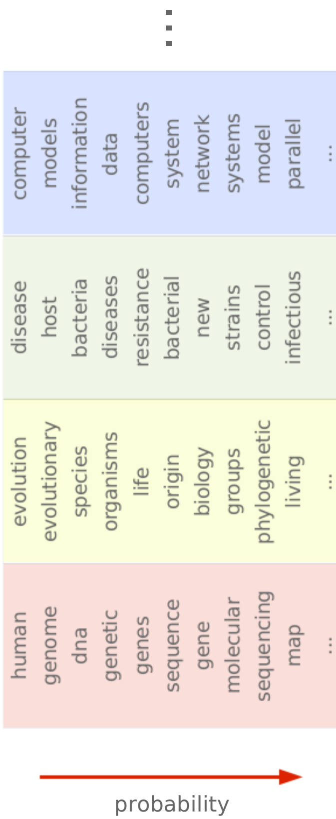
Generative Process

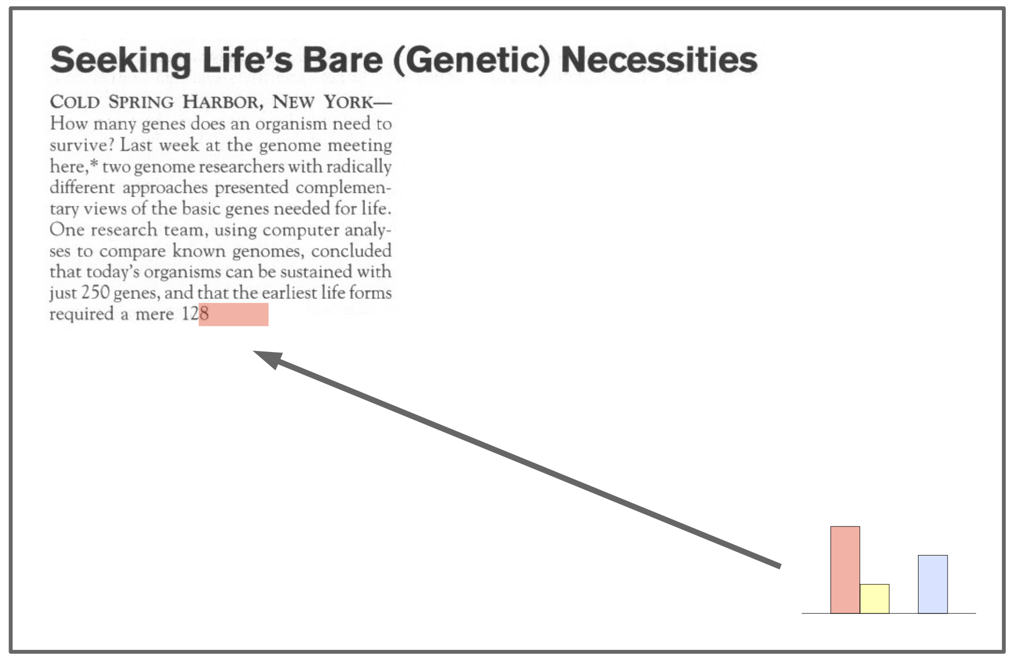


Choose a Distribution Over Topics



Choose a Topic





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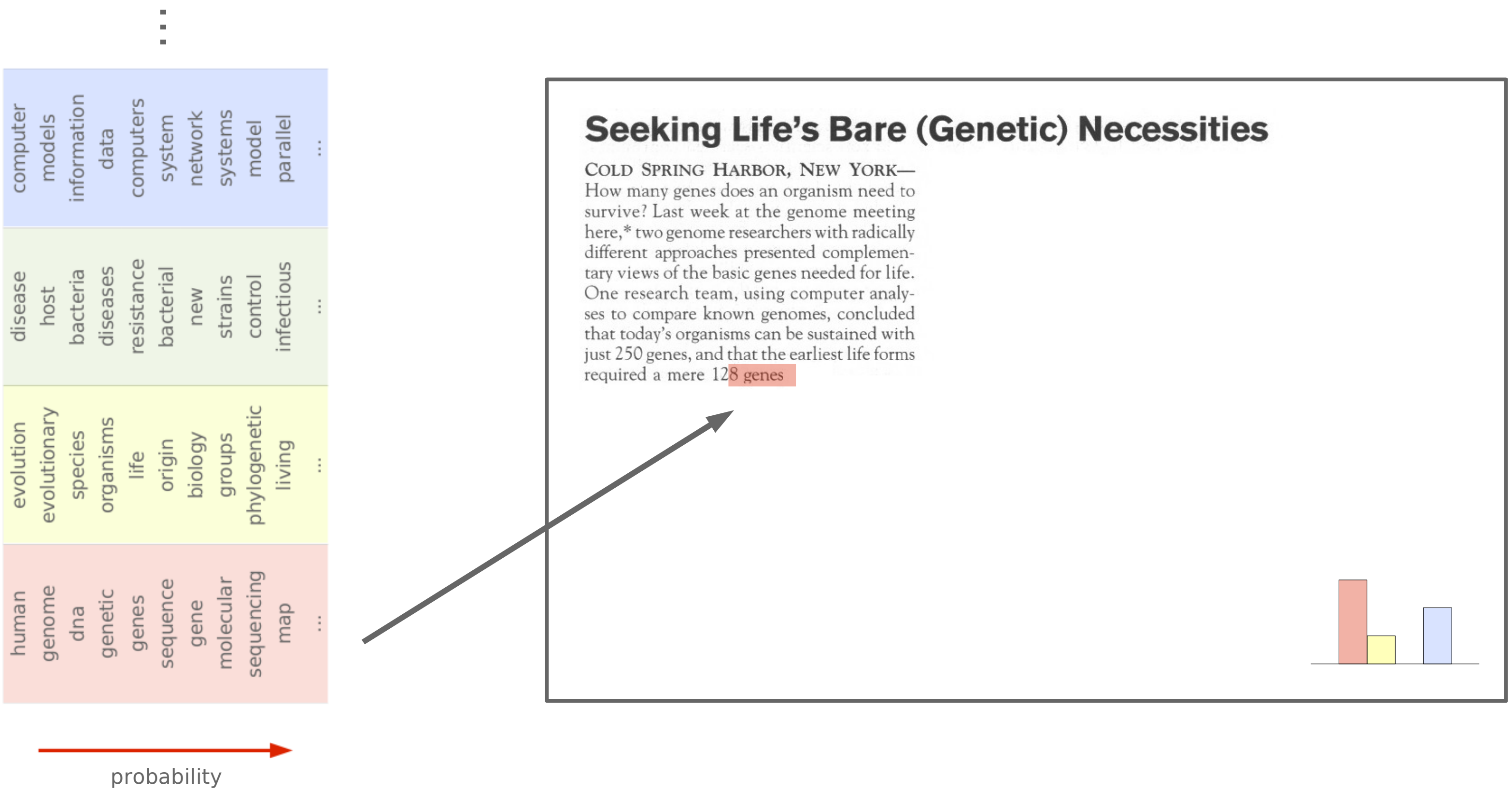
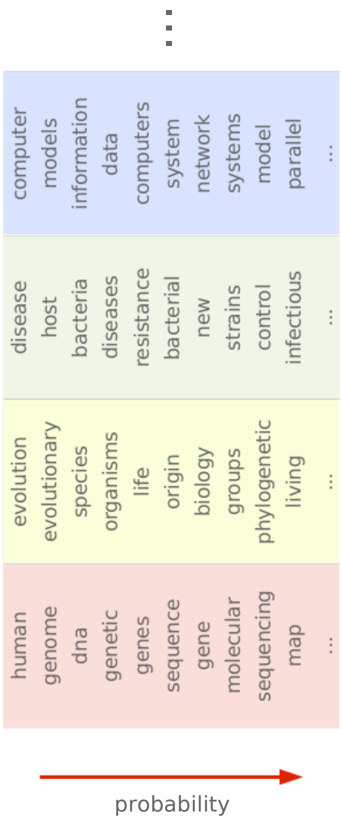
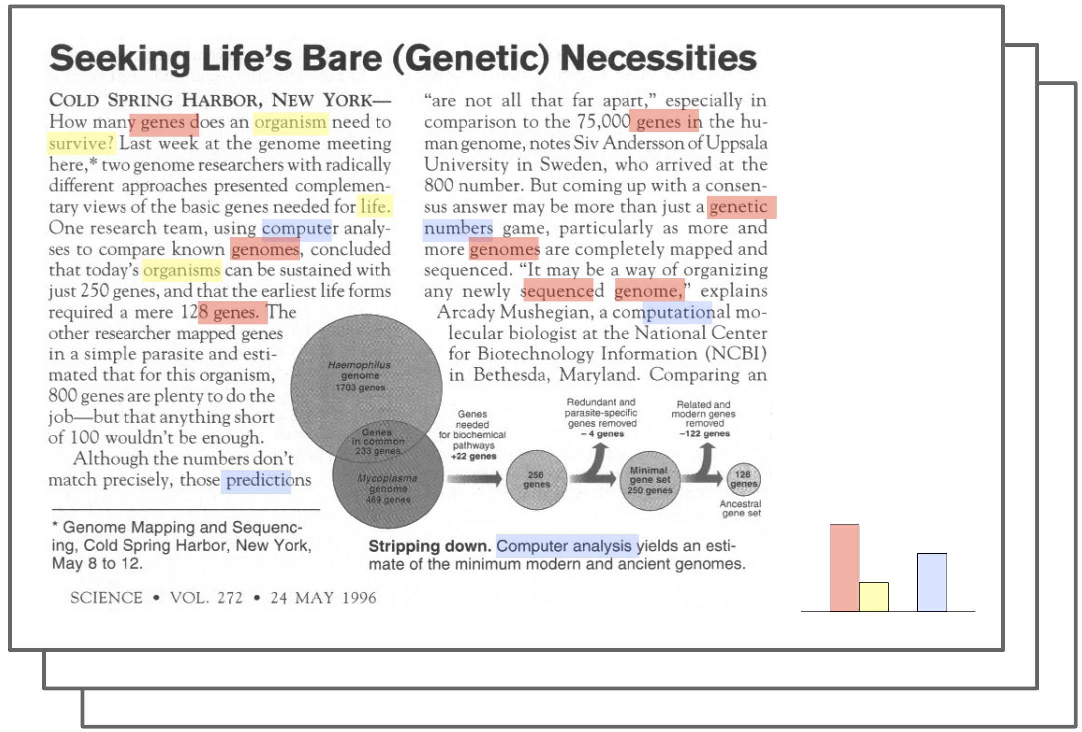
Choose a Word



… And So On





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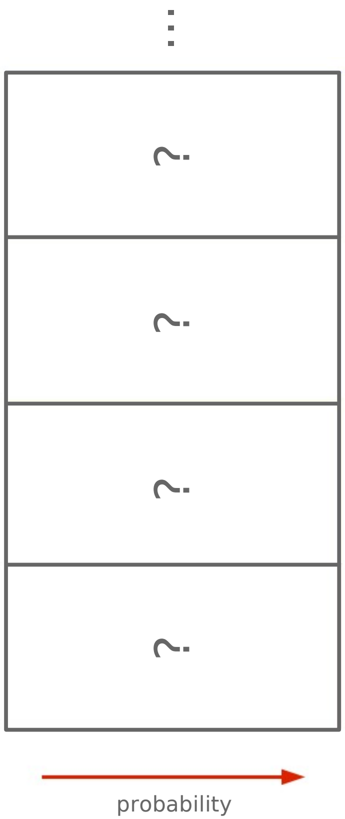
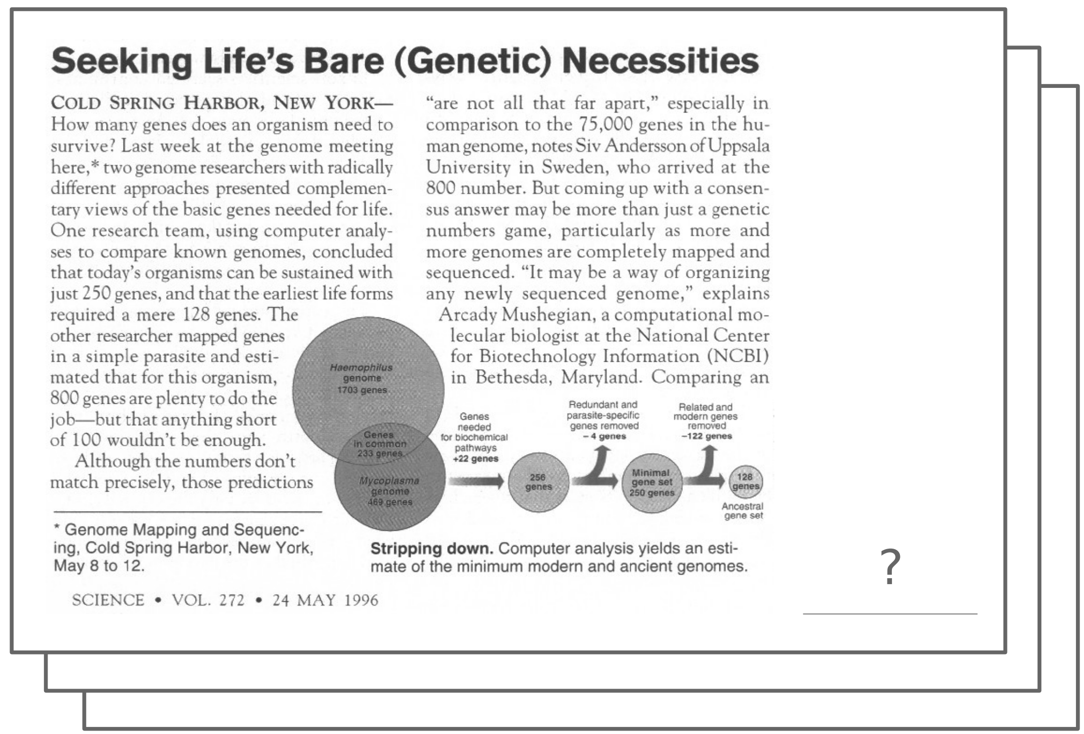
Real Data: Statistical Inference





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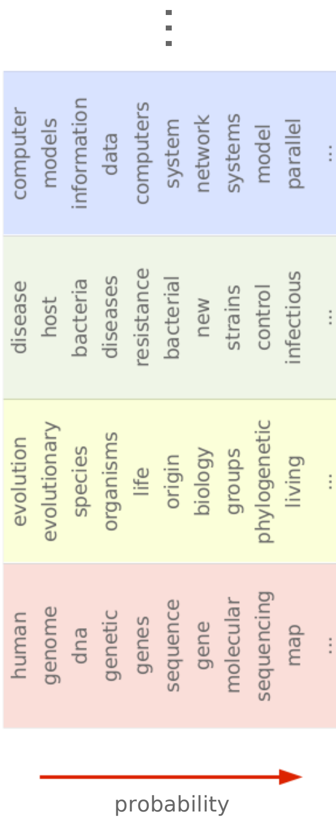
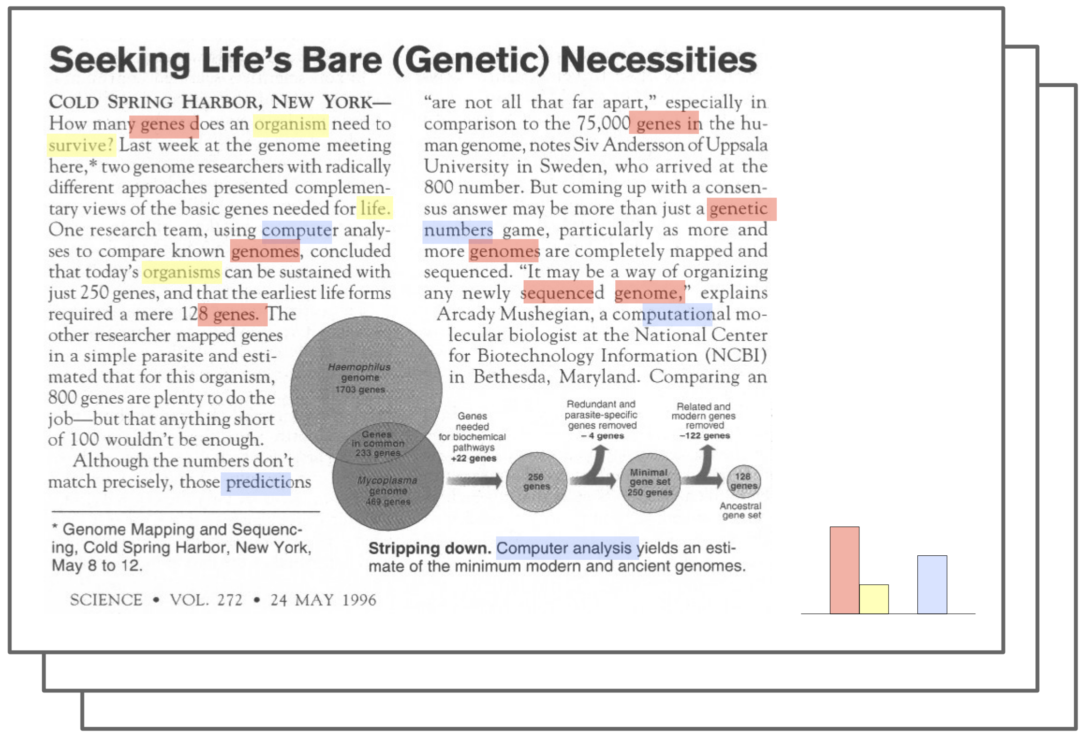
Statistical Inference

- 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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- 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 ...”

Preprocess your data to remove stop words...

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

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

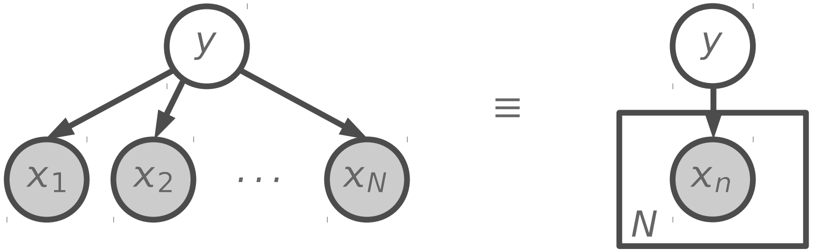
Wait, but how do I choose the right number of topics?

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

Directed Graphical Models

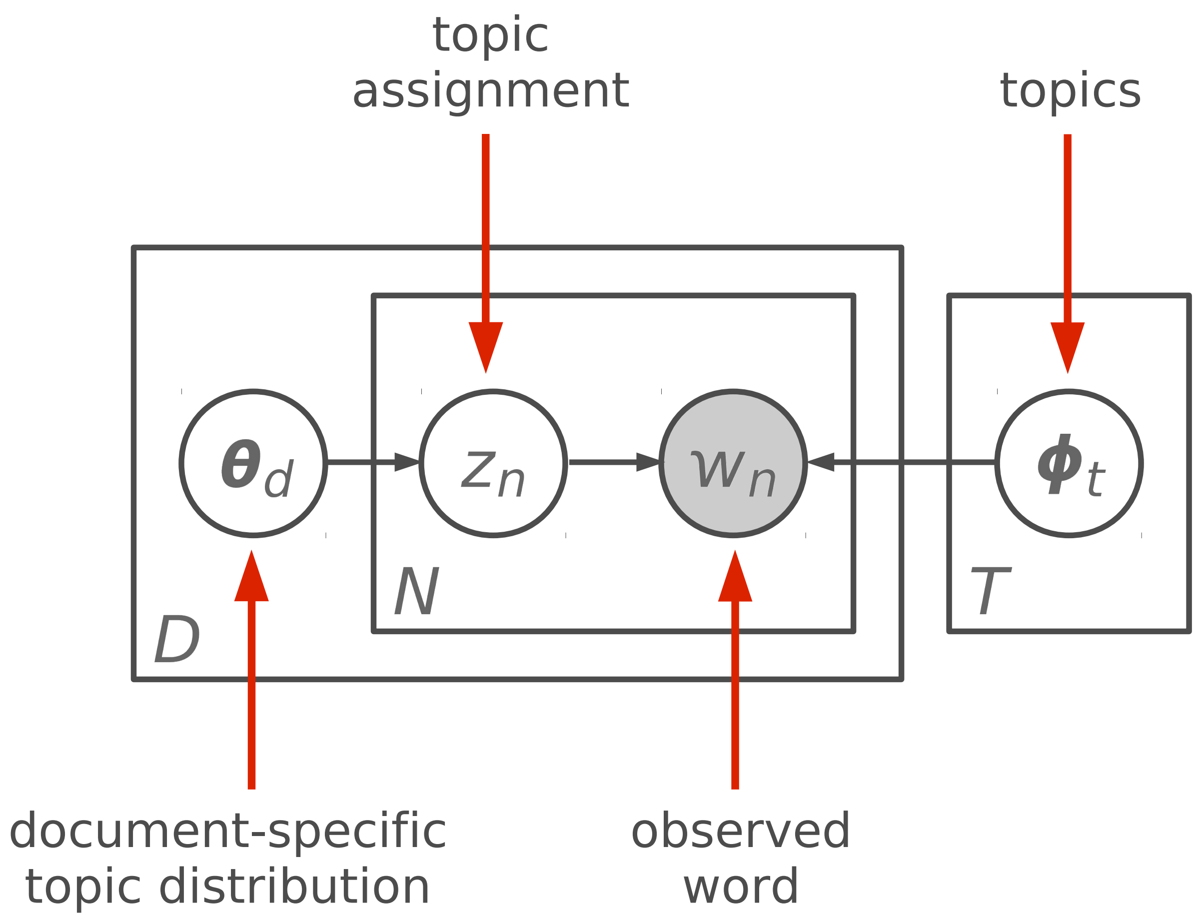
$$P(y, x_1, \ldots, x_N) = P(y) \prod_{n=1}^{N} P(x_n \,|\, y)$$

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



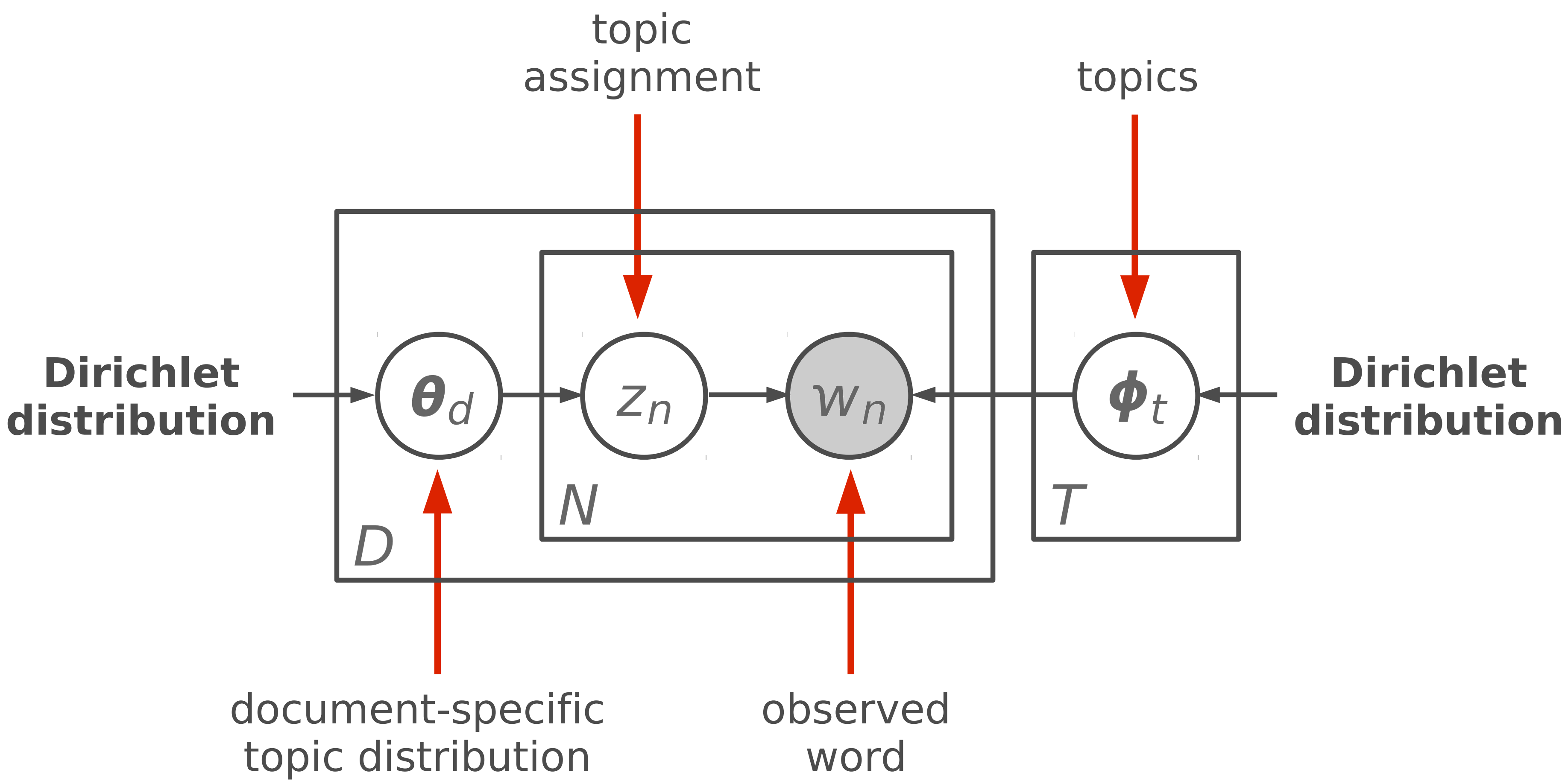
Statistical Topic Modeling

[Hofmann, '99]



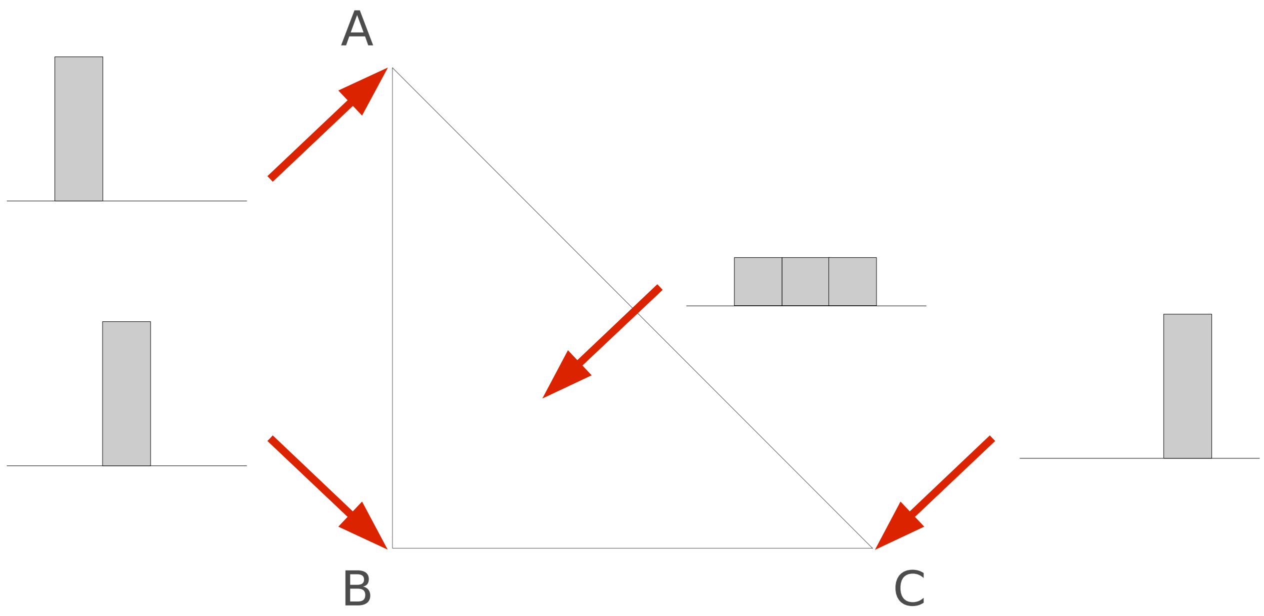
Latent Dirichlet Allocation (LDA)

[Blei, Ng & Jordan, '03]



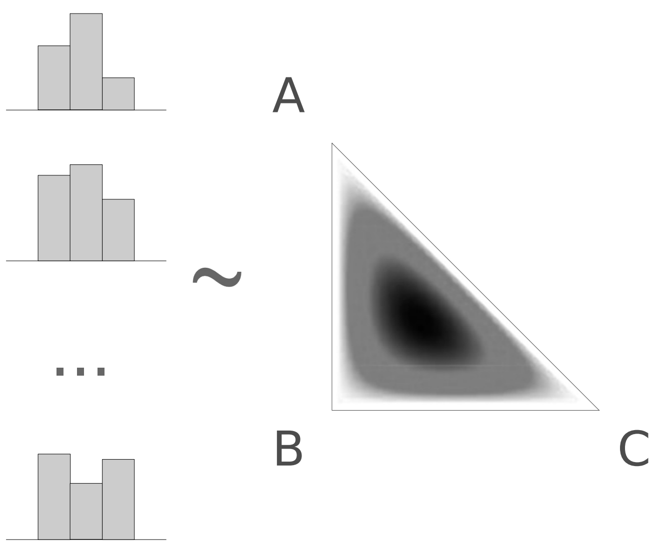
Discrete Probability Distributions

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



Dirichlet Distribution

- Distribution over discrete probability distributions:

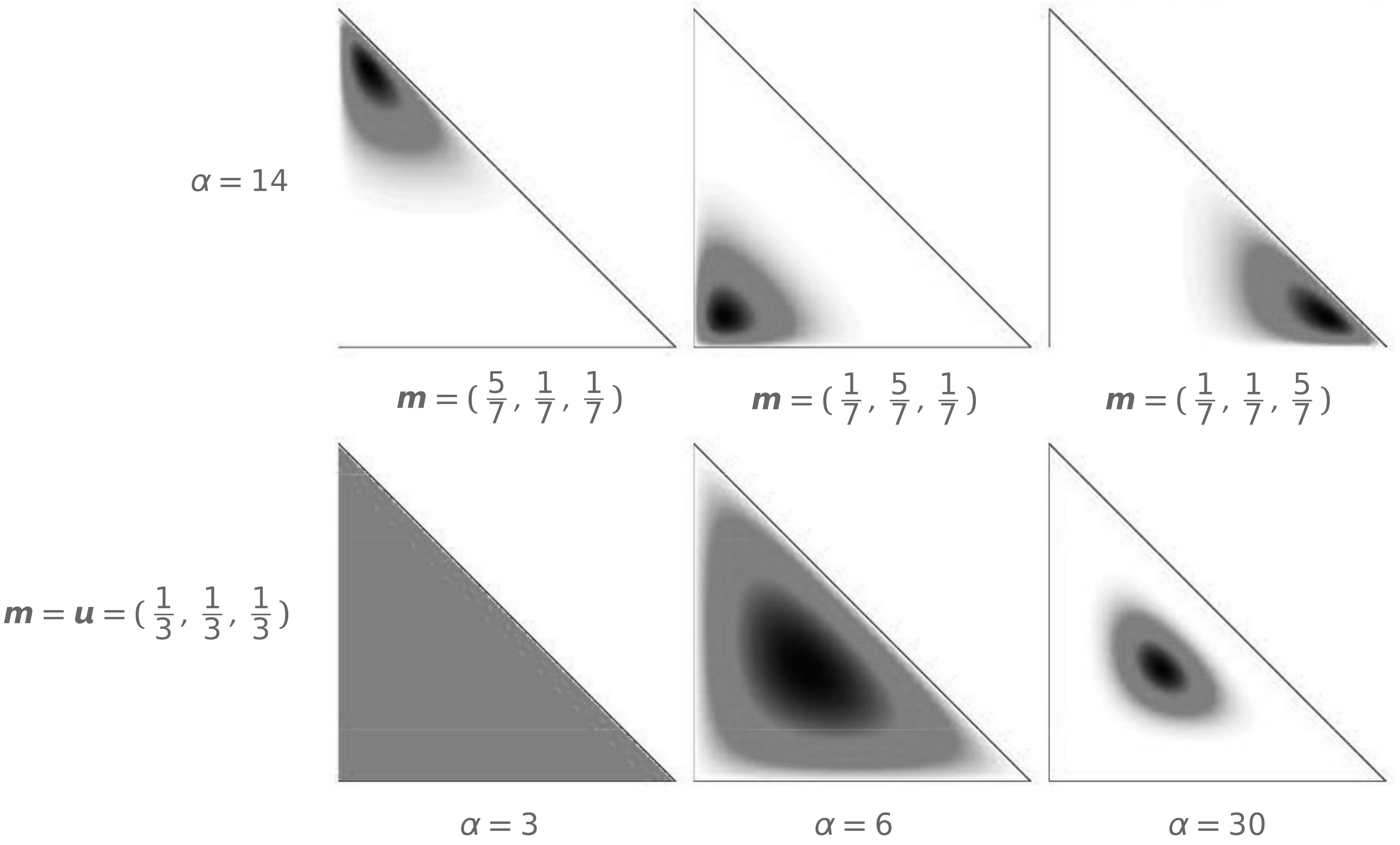


$$\equiv \quad \boldsymbol{p} \sim \mathrm{Dir}(\alpha \boldsymbol{m})$$

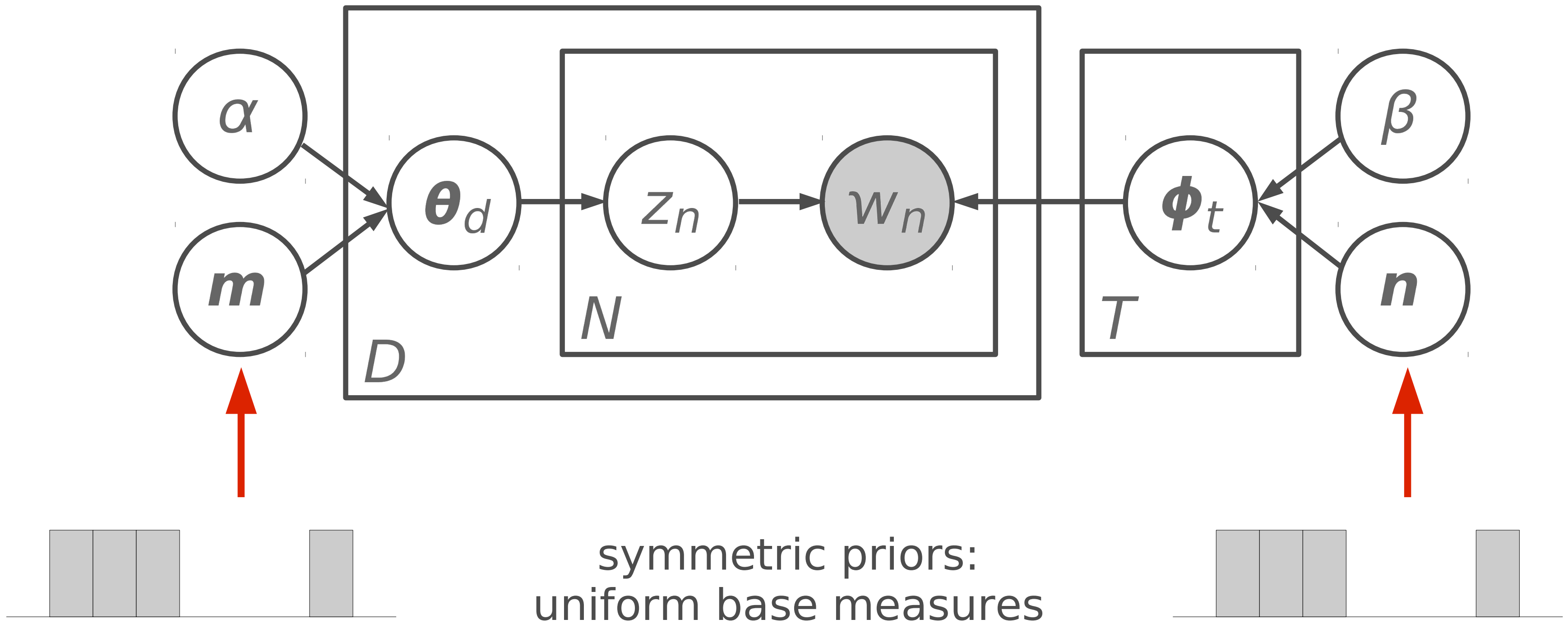
base measure (mean)

concentration parameter

Dirichlet Parameters



Dirichlet Priors for LDA



symmetric priors:
uniform base measures

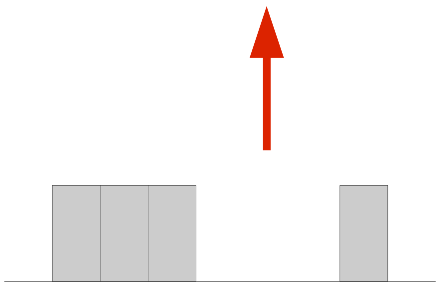
Dirichlet Priors for LDA

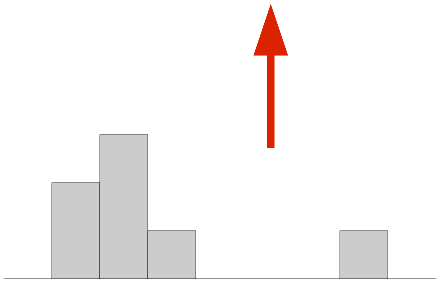
- Two scalar concentration parameters: α and β
- Concentration parameters are usually set heuristically
  - e.g., $\alpha = 50$ and $\beta = 0.01W$
- Some recent work on learning optimal values for the concentration parameters from data
- No rigorous study of the Dirichlet priors:
  - e.g., asymmetric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

Symmetric → Asymmetric

- Use prior over $\Theta = \{\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_D\}$ as a running example
- Uniform base measure → nonuniform base measure

$\Theta \sim \mathrm{Dir}(\alpha \boldsymbol{m})$ $\Theta \sim \mathrm{Dir}(\alpha \boldsymbol{m})$



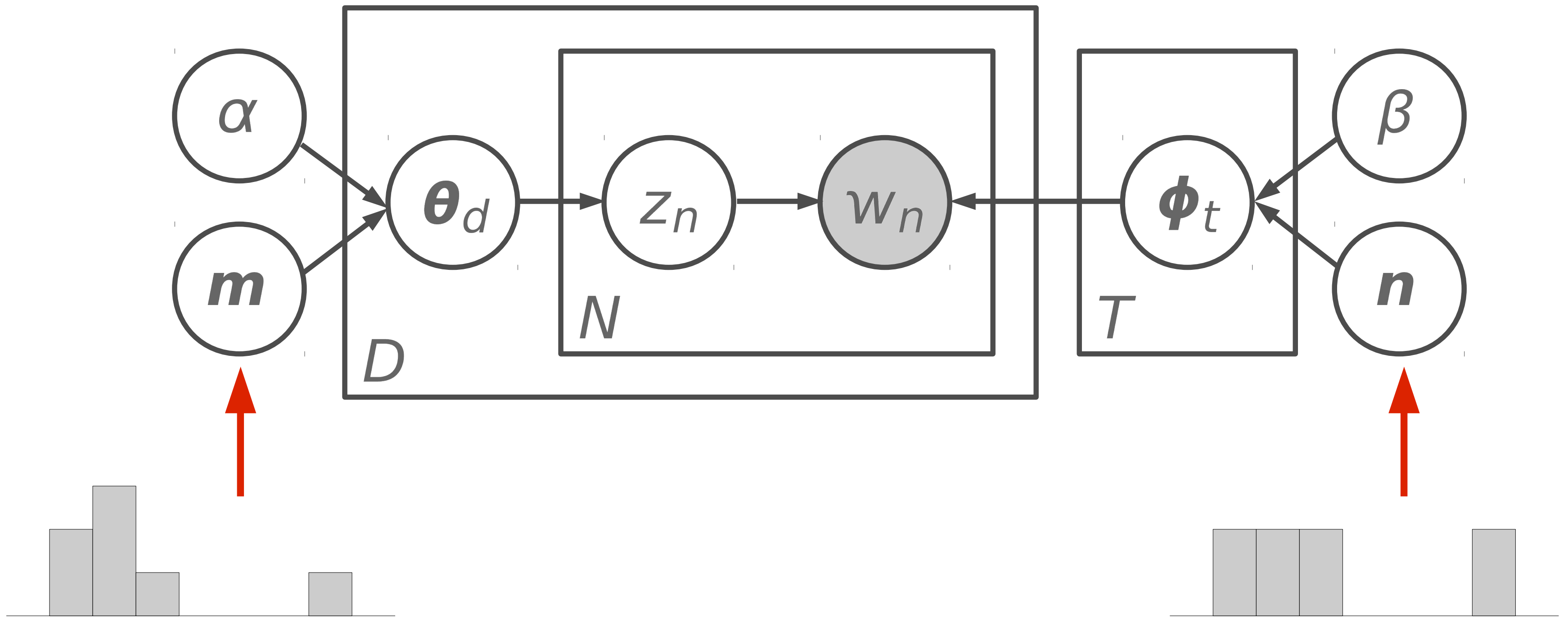


- Asymmetric prior: some topics more likely a priori

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

after

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

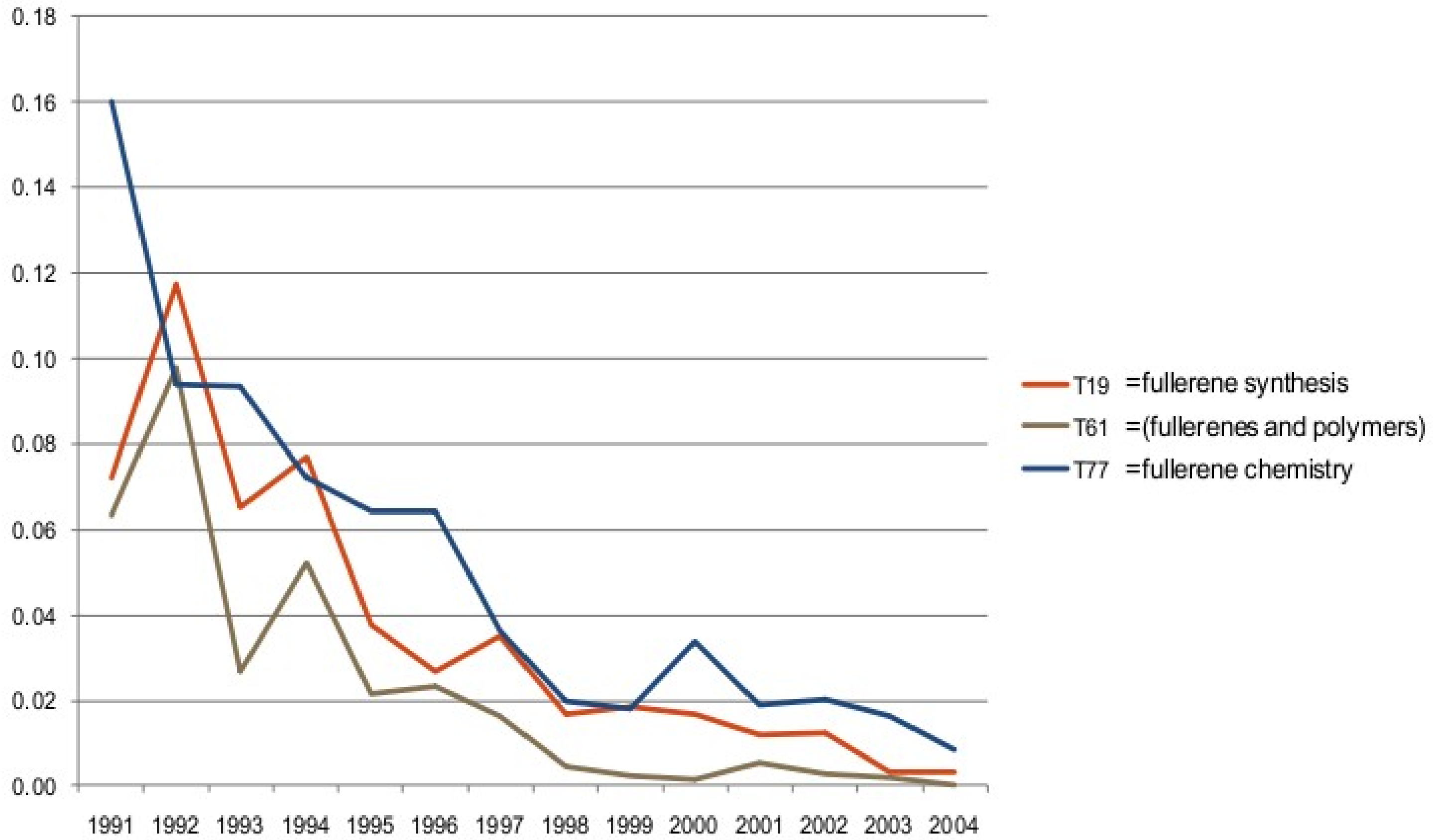
“Off-the-Shelf” Topic Modeling

I can model technology emergence by analyzing patent abstracts!

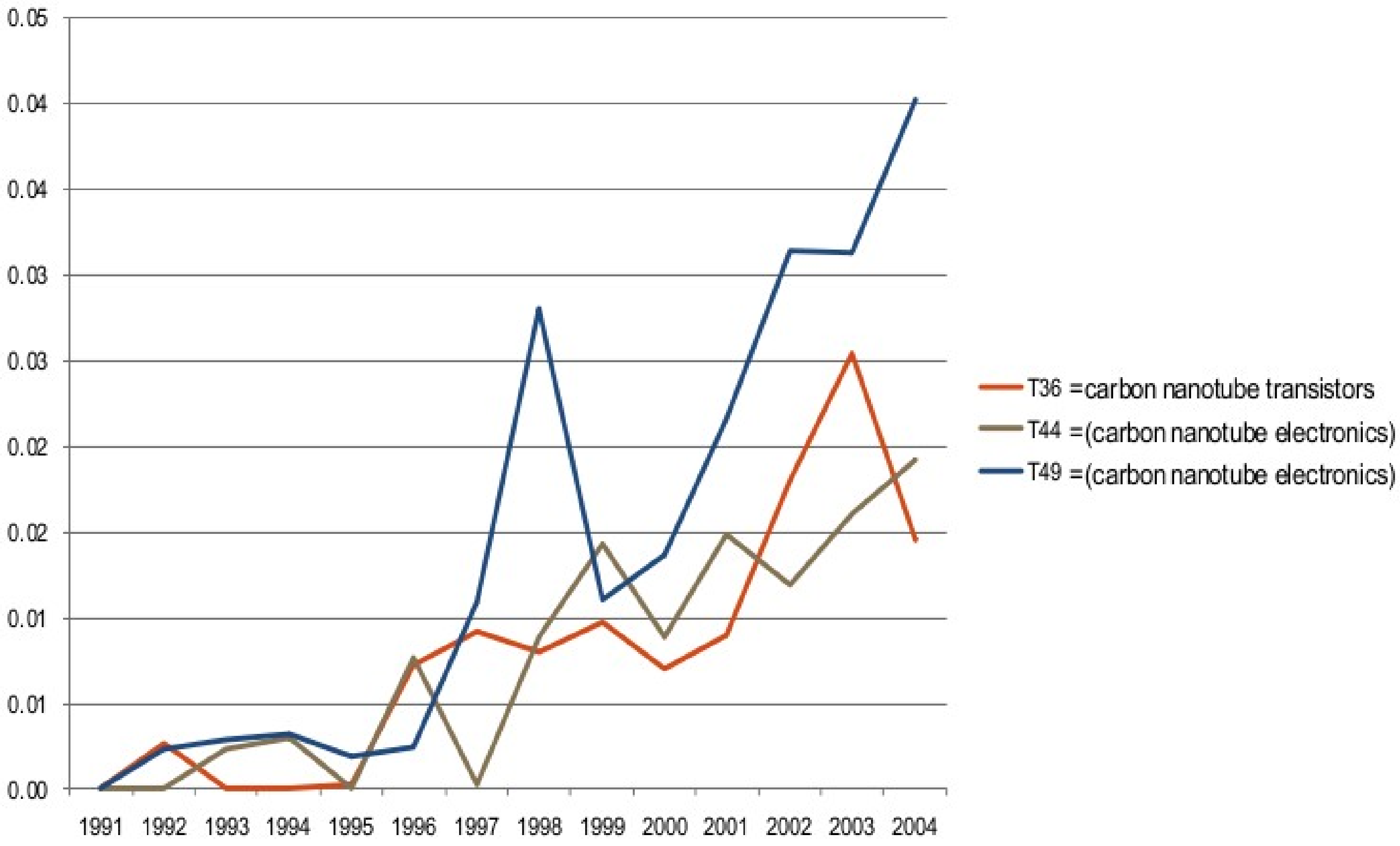
Great! Let me know if you need any more help!

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

Declining Topics



Rising Topics



Building Other Tools

- Polylingual topic modeling [Mimno et al., EMNLP '09]
  - Track scientific progress in other countries
  - Simultaneously model text in many languages
  - Need robustness to word usage in many languages
- Topic-based language modeling [Wallach, ICML '06]
  - Predict the next word given previous words
  - Have to model stop words; cannot strip them

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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

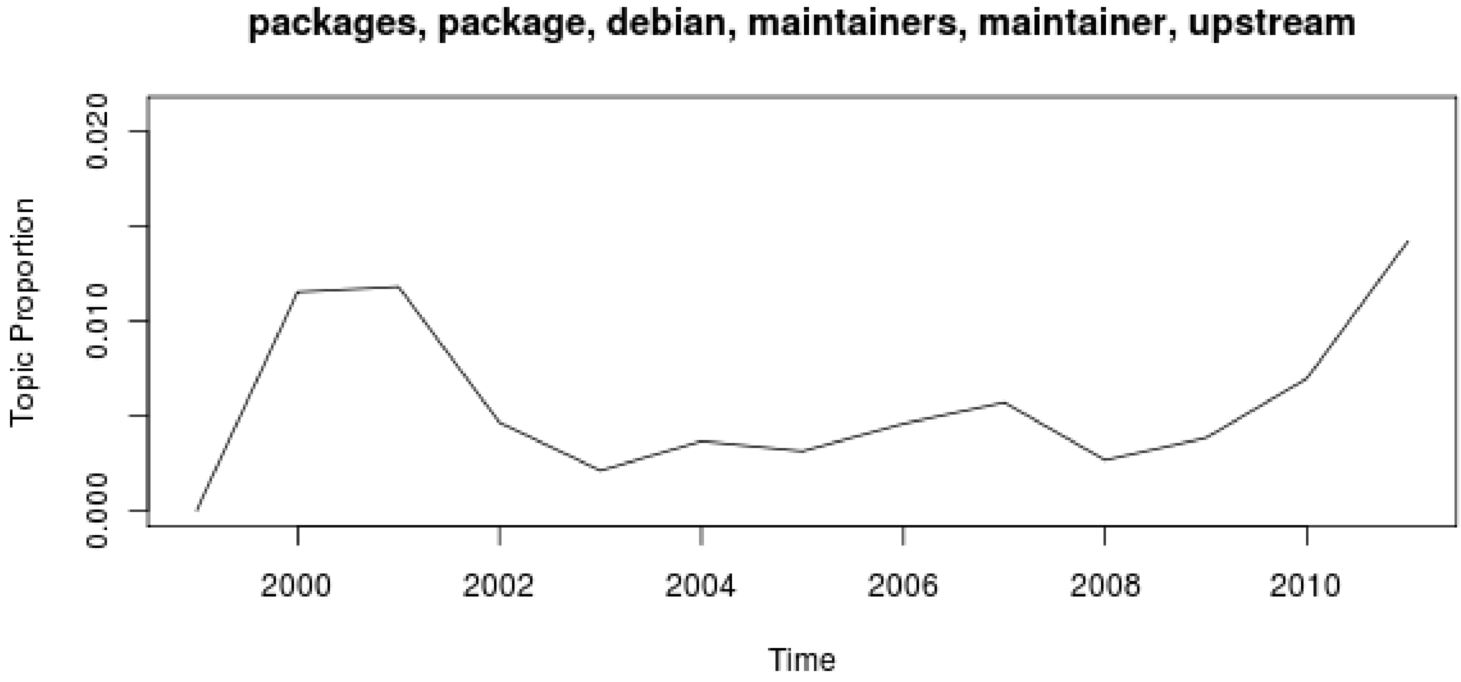
Analyzing Debian Mailing Lists

- 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)

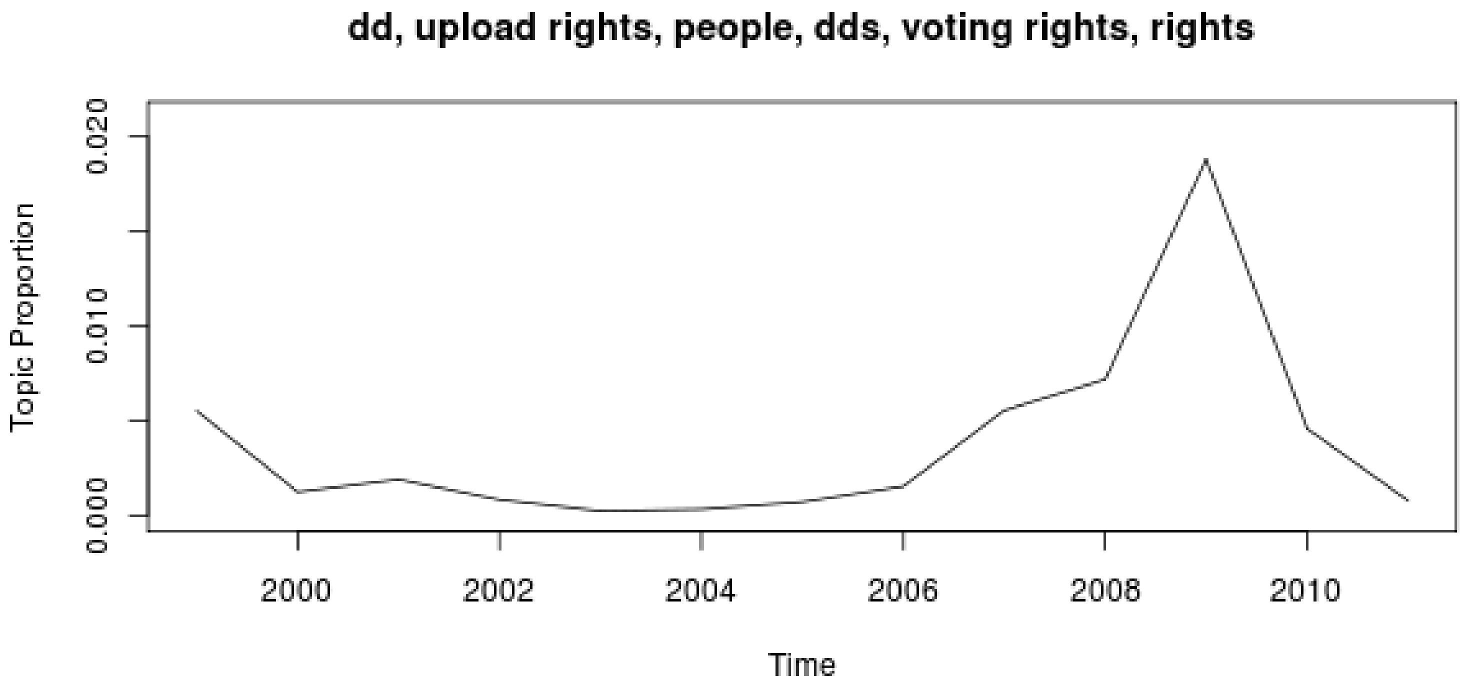
100 Topics

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 ...

Topic Usage Over Time



Topic Usage Over Time



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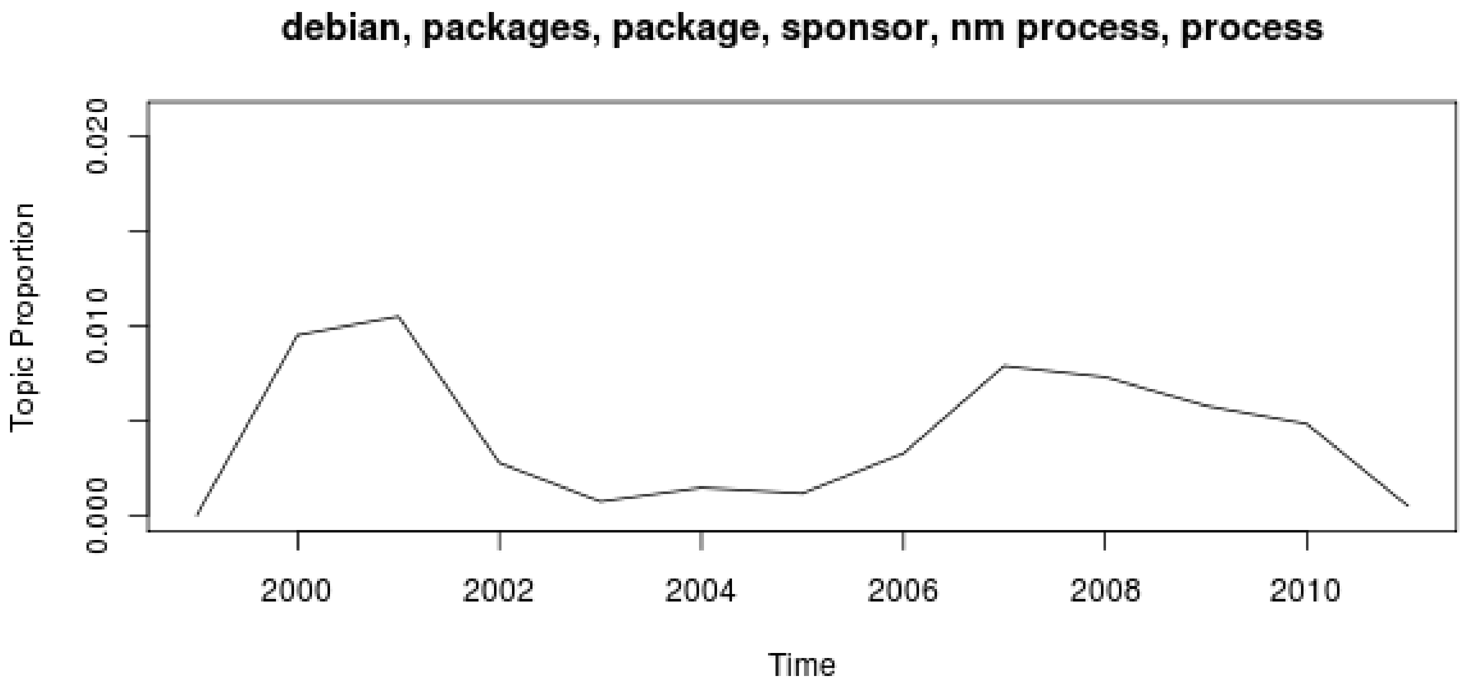
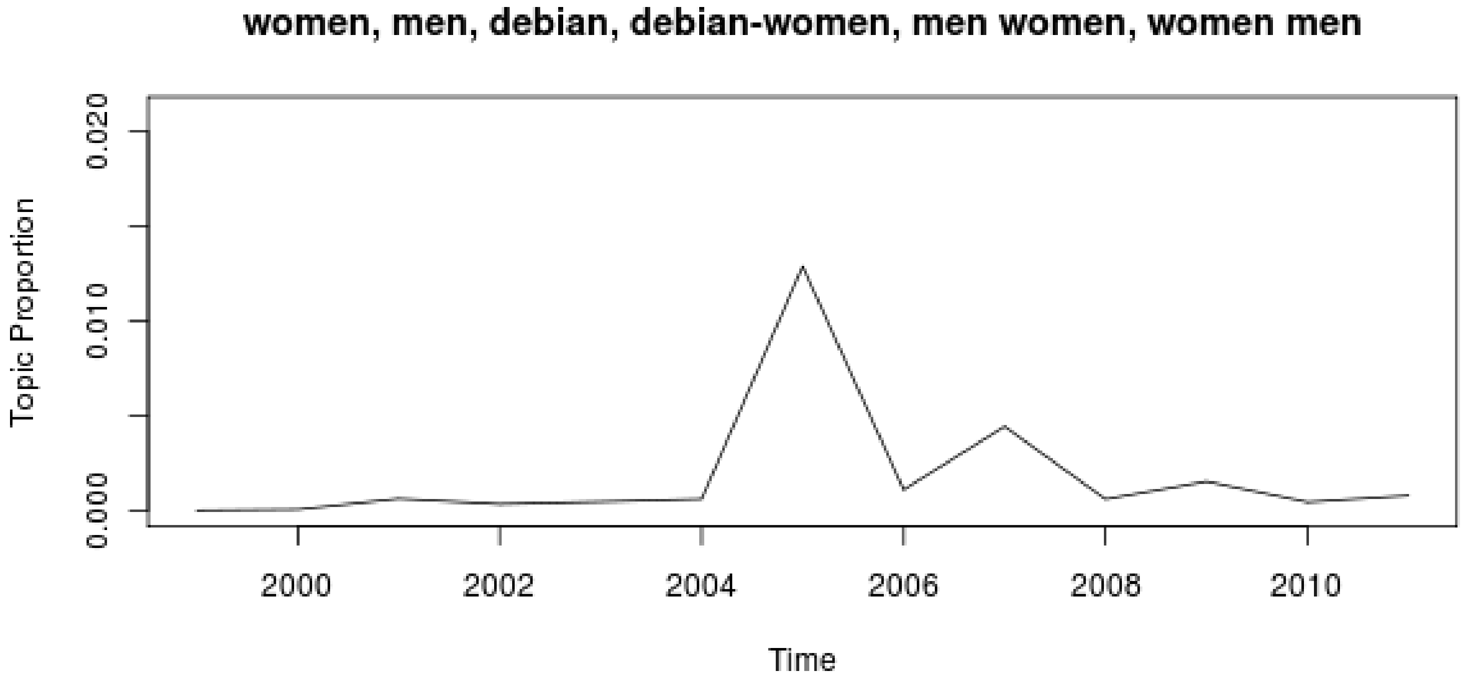


Topic Usage Over Time



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

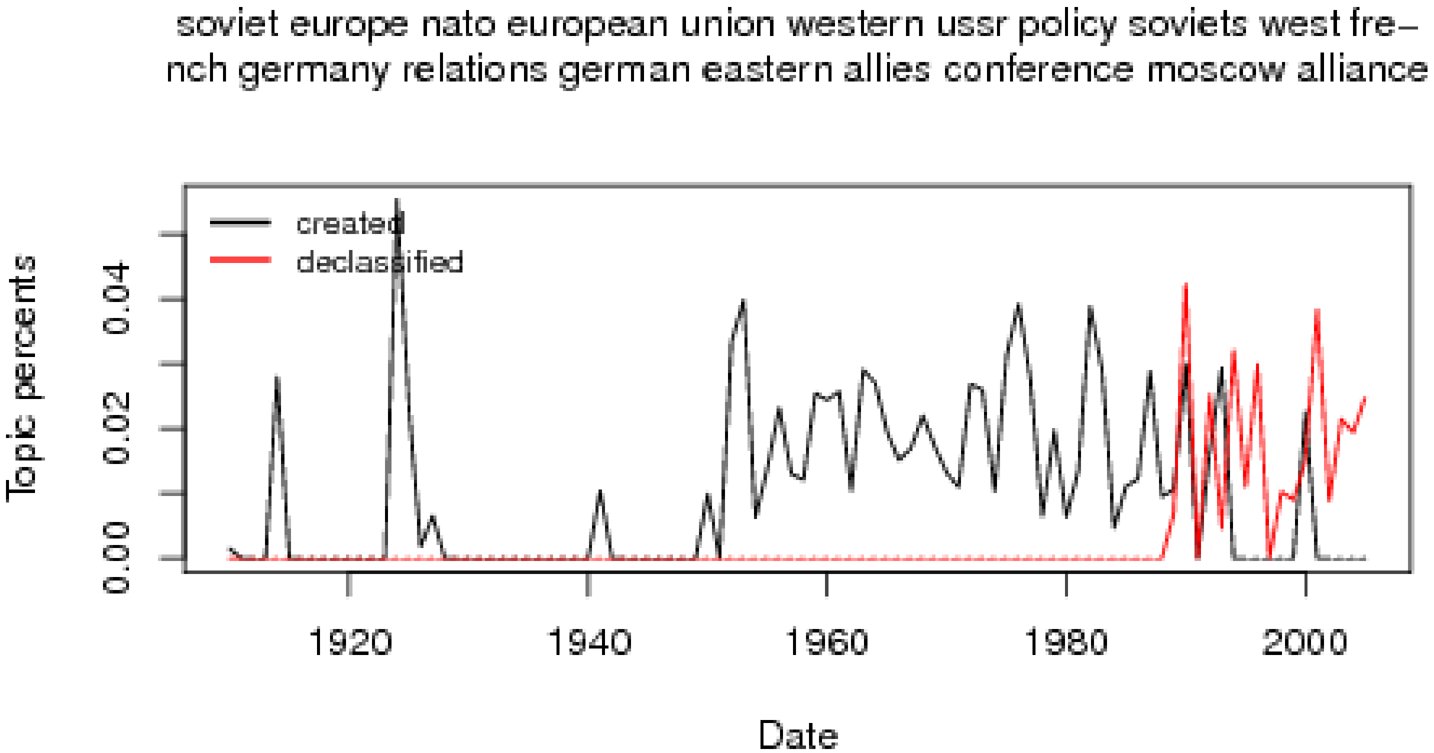
Document Declassification

- 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

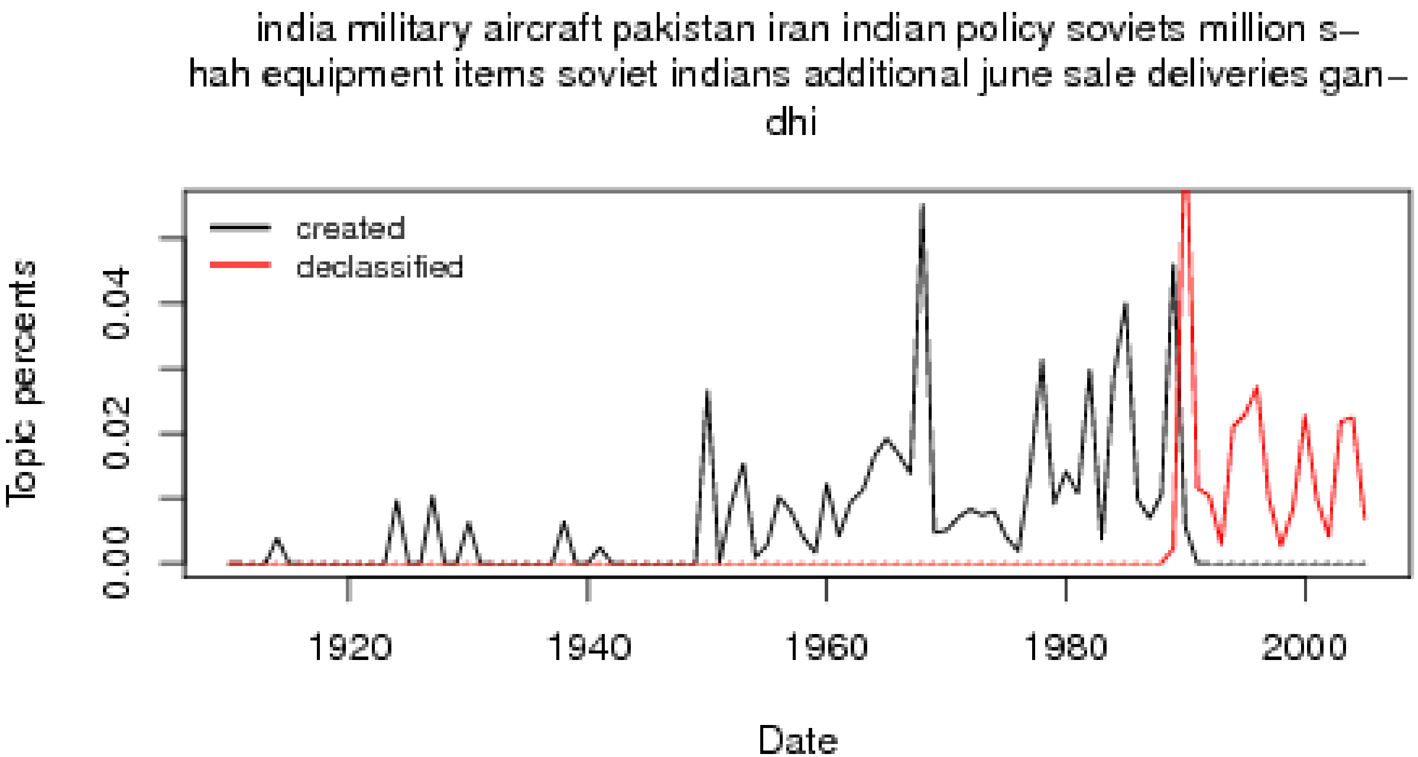
Declassified Documents

- 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)

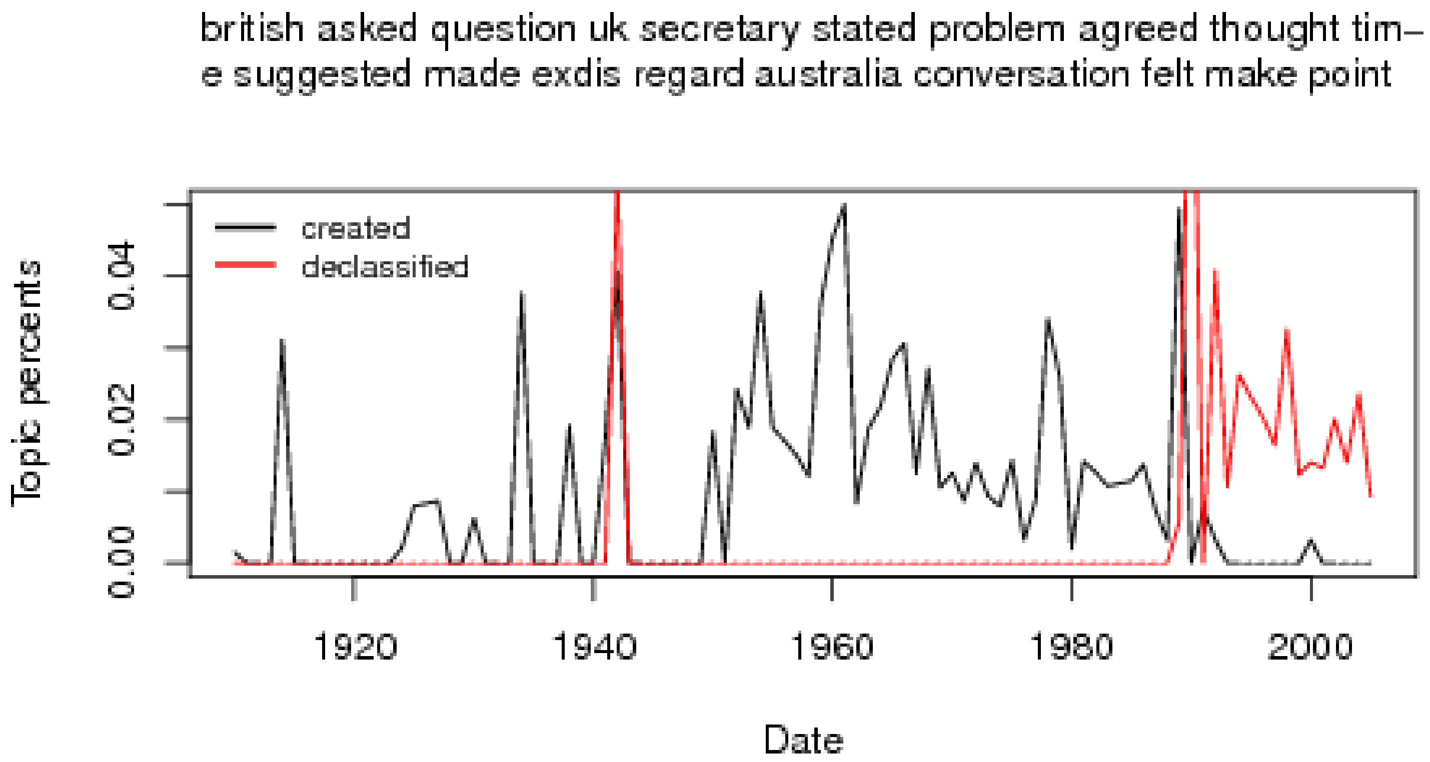
Declassification by Topic



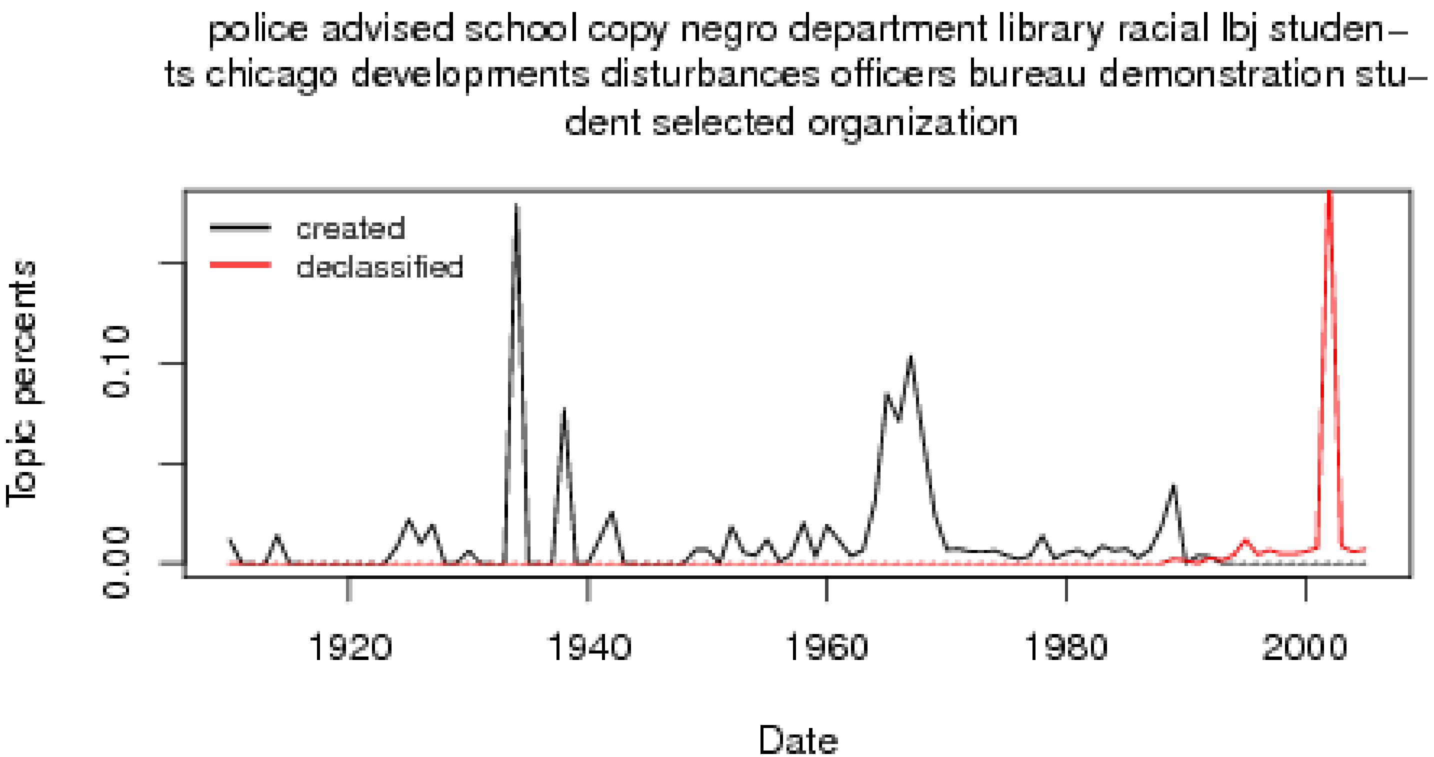
Topic Declassification



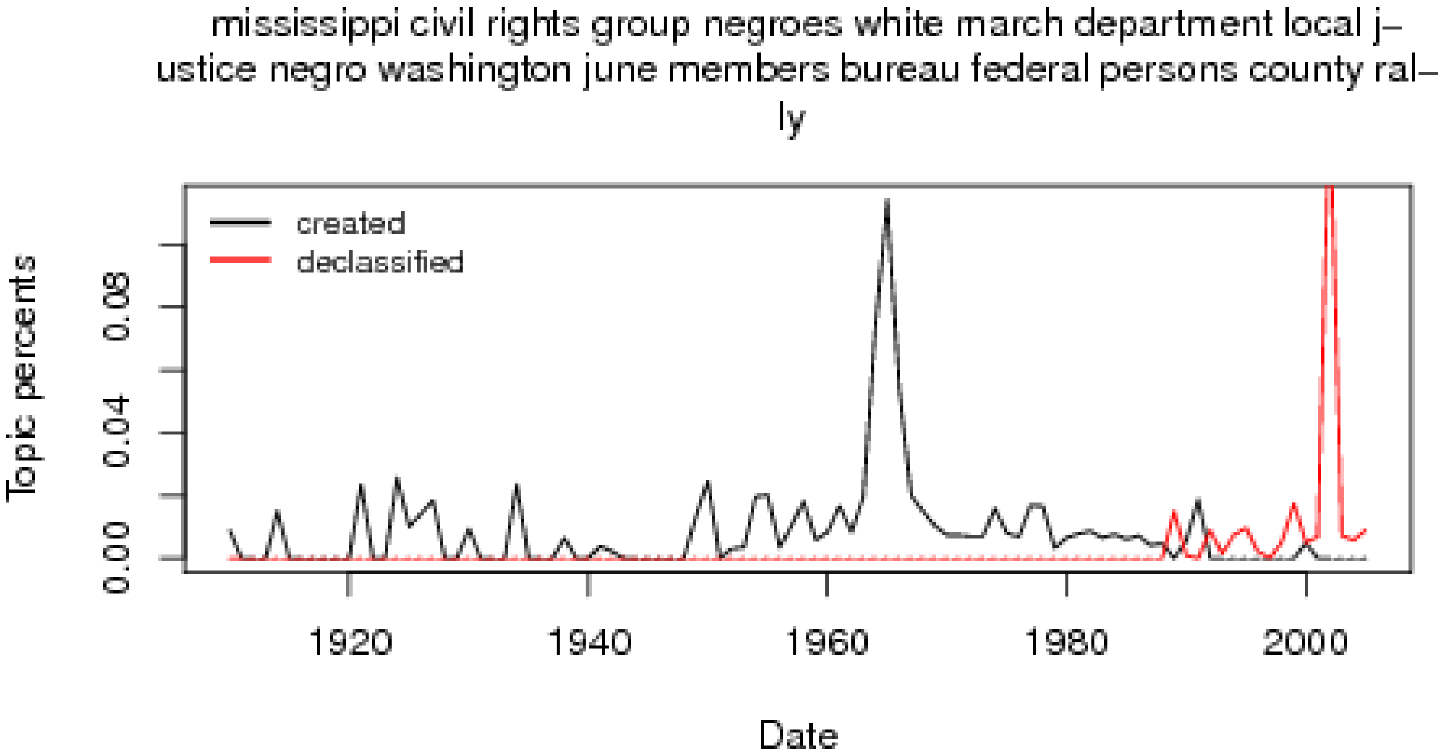
Topic Declassification



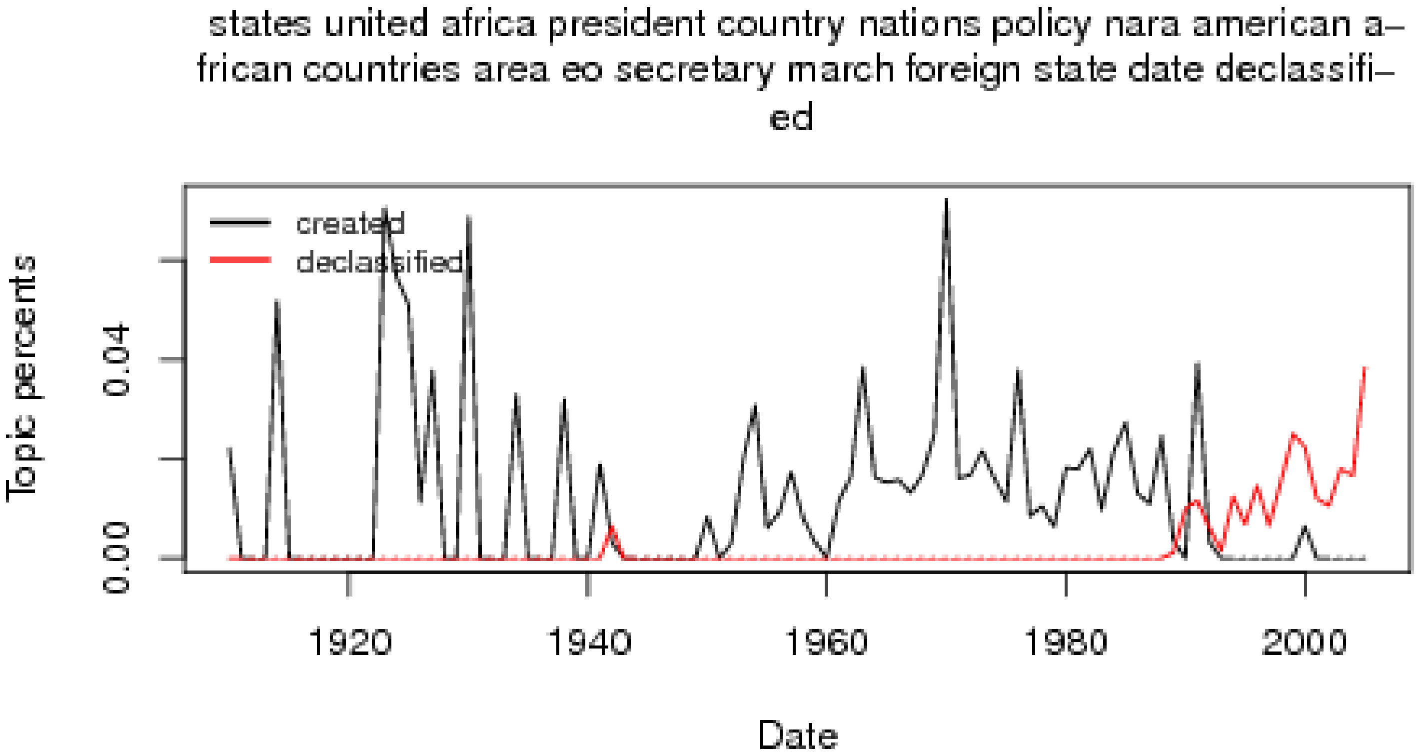
Topic Declassification



Topic Declassification



Topic Declassification



Thanks!

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