# RECSM Summer School: Social Media and Big Data Research

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# Discovery in Large-Scale Social Media Data

# Overview of text as data methods

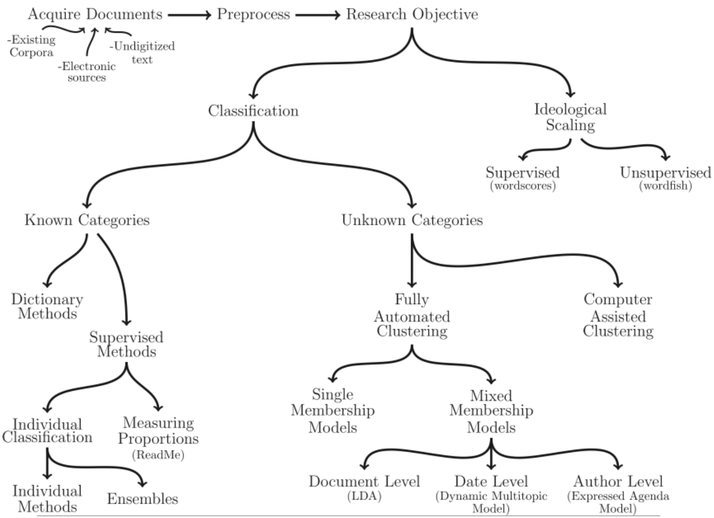



Fig. 1 in Grimmer and Stewart (2013)

# Overview of techniques

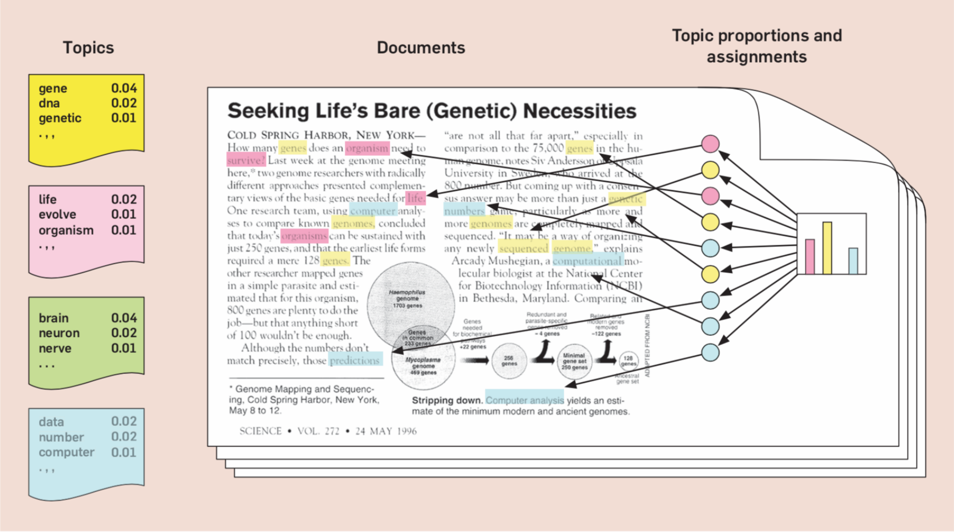
- Descriptive analysis:
  - What are the characteristics of this corpus? How do some documents compare to others?
  - Keyness, collocation analysis, readability scores, Cosine/Jaccard similarity...
- Clustering and scaling:
  - What groups of documents are there in this corpus? Can documents be placed on a latent dimension?
  - Cluster analysis, principal component analysis, wordfish..
- Topic modeling:
  - What are the main themes in this corpus? How do different documents relate to words differently?
  - LDA, STM

# Topic Models

- Topic models are algorithms for discovering the main "themes" in an unstructured corpus   Modelos estadísticos
- Can be used to organize the collection according to the discovered themes
- Requires no prior information, training set, or human annotation – only a decision on $K$ (number of topics)
- Most common: Latent Dirichlet Allocation (LDA) – Bayesian mixture model for discrete data where topics are assumed to be uncorrelated
- LDA provides a generative model that describes how the documents in a dataset were created
    - Each of the $K$ *topics* is a distribution over a fixed vocabulary
    - Each document is a collection of words, generated according to a multinomial distribution, one for each of $K$ topics

# Latent Dirichlet Allocation

**Figure 1. The intuitions behind latent Dirichlet allocation. We assume that some number of "topics," which are distributions over words, exist for the whole collection (far left). Each document is assumed to be generated as follows. First choose a distribution over the topics (the histogram at right); then, for each word, choose a topic assignment (the colored coins) and choose the word from the corresponding topic. The topics and topic assignments in this figure are illustrative—they are not fit from real data. See Figure 2 for topics fit from data.**



# Illustration of the LDA generative process

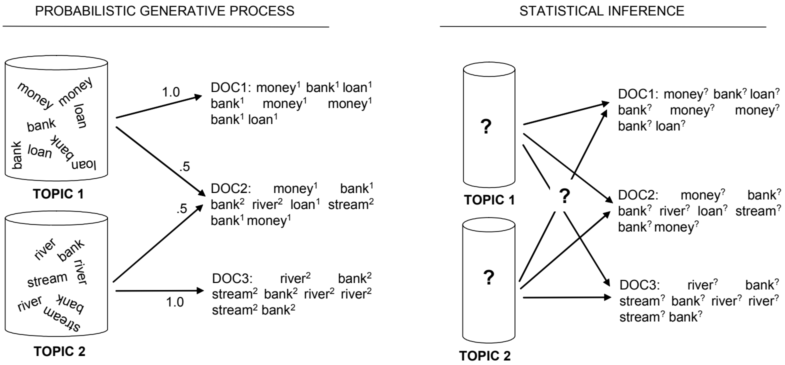



**Figure 2.** Illustration of the generative process and the problem of statistical inference underlying topic models

(from Steyvers and Griffiths 2007)

# Topics example

Topic 247

| word | prob. |
|---|---|
| DRUGS | .069 |
| DRUG | .060 |
| MEDICINE | .027 |
| EFFECTS | .026 |
| BODY | .023 |
| MEDICINES | .019 |
| PAIN | .016 |
| PERSON | .016 |
| MARIJUANA | .014 |
| LABEL | .012 |
| ALCOHOL | .012 |
| DANGEROUS | .011 |
| ABUSE | .009 |
| EFFECT | .009 |
| KNOWN | .008 |
| PILLS | .008 |

Topic 5

| word | prob. |
|---|---|
| RED | .202 |
| BLUE | .099 |
| GREEN | .096 |
| YELLOW | .073 |
| WHITE | .048 |
| COLOR | .048 |
| BRIGHT | .030 |
| COLORS | .029 |
| ORANGE | .027 |
| BROWN | .027 |
| PINK | .017 |
| LOOK | .017 |
| BLACK | .016 |
| PURPLE | .015 |
| CROSS | .011 |
| COLORED | .009 |

Topic 43

| word | prob. |
|---|---|
| MIND | .081 |
| THOUGHT | .066 |
| REMEMBER | .064 |
| MEMORY | .037 |
| THINKING | .030 |
| PROFESSOR | .028 |
| FELT | .025 |
| REMEMBERED | .022 |
| THOUGHTS | .020 |
| FORGOTTEN | .020 |
| MOMENT | .020 |
| THINK | .019 |
| THING | .016 |
| WONDER | .014 |
| FORGET | .012 |
| RECALL | .012 |

Topic 56

| word | prob. |
|---|---|
| DOCTOR | .074 |
| DR. | .063 |
| PATIENT | .061 |
| HOSPITAL | .049 |
| CARE | .046 |
| MEDICAL | .042 |
| NURSE | .031 |
| PATIENTS | .029 |
| DOCTORS | .028 |
| HEALTH | .025 |
| MEDICINE | .017 |
| NURSING | .017 |
| DENTAL | .015 |
| NURSES | .013 |
| PHYSICIAN | .012 |
| HOSPITALS | .011 |

**Figure 1.** An illustration of four (out of 300) topics extracted from the TASA corpus.

(from Steyvers and Griffiths 2007)

Often $K$ is quite large!

# Latent Dirichlet Allocation

- Document = random mixture over latent topics
- Topic = distribution over n-grams

Probabilistic model with 3 steps:

1. Choose $\theta_i \sim \mathrm{Dirichlet}(\alpha)$
2. Choose $\beta_k \sim \mathrm{Dirichlet}(\delta)$
3. For each word in document *i*:
    - Choose a topic $z_m \sim \mathrm{Multinomial}(\theta_i)$
    - Choose a word $w_{im} \sim \mathrm{Multinomial}(\beta_{i,k=z_m})$

where:
$\alpha$=parameter of Dirichlet prior on distribution of topics over docs.
$\theta_i$=topic distribution for document *i*
$\delta$=parameter of Dirichlet prior on distribution of words over topics
$\beta_k$=word distribution for topic *k*

# Latent Dirichlet Allocation

Key parameters:

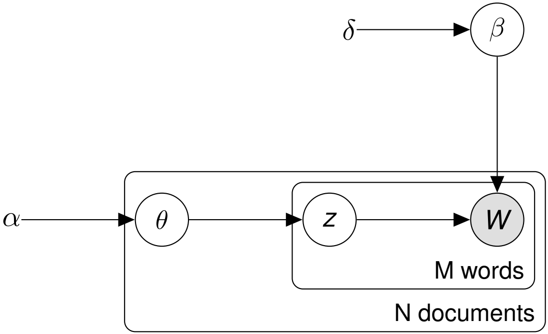
1. $\theta$ = matrix of dimensions N documents by K topics where $\theta_{ik}$ corresponds to the probability that document $i$ belongs to topic $k$; i.e. assuming $K = 5$:

| | T1 | T2 | T3 | T4 | T5 |
|---|---|---|---|---|---|
| Document 1 | 0.15 | 0.15 | 0.05 | 0.10 | 0.55 |
| Document 2 | 0.80 | 0.02 | 0.02 | 0.10 | 0.06 |
| ... | | | | | |
| Document $N$ | 0.01 | 0.01 | 0.96 | 0.01 | 0.01 |

2. $\beta$ = matrix of dimensions K topics by M words where $\beta_{km}$ corresponds to the probability that word $m$ belongs to topic $k$; i.e. assuming $M = 6$:

| | W1 | W2 | W3 | W4 | W5 | W6 |
|---|---|---|---|---|---|---|
| Topic 1 | 0.40 | 0.05 | 0.05 | 0.10 | 0.10 | 0.30 |
| Topic 2 | 0.10 | 0.10 | 0.10 | 0.50 | 0.10 | 0.10 |
| ... | | | | | | |
| Topic $k$ | 0.05 | 0.60 | 0.10 | 0.05 | 0.10 | 0.10 |

# Plate notation




$\beta = M \times K$ matrix where $\beta_{im}$ indicates prob(topic=$k$) for word $m$
$\theta = N \times K$ matrix where $\theta_{ik}$ indicates prob(topic=$k$) for document $i$

# Validation

From Quinn et al, AJPS, 2010:

1. Semantic validity
   - Do the topics identify coherent groups of tweets that are internally homogenous, and are related to each other in a meaningful way?
2. Convergent/discriminant construct validity
   - Do the topics match existing measures where they should match?
   - Do they depart from existing measures where they should depart?
3. Predictive validity
   - Does variation in topic usage correspond with expected events?
4. Hypothesis validity
   - Can topic variation be used effectively to test substantive hypotheses?

# Example: open-ended survey responses

Bauer, Barberá *et al*, *Political Behavior*, 2016.

- Data: General Social Survey (2008) in Germany
- Responses to questions: *Would you please tell me what you associate with the term "left"? and would you please tell me what you associate with the term "right"?*
- Open-ended questions minimize priming and potential interviewer effects
- Sparse Additive Generative model instead of LDA (more coherent topics for short text)
- $K = 4$ topics for each question

# Example: open-ended survey responses

Table 1: Top scoring words associated with each topic, and English translations)

| |
|---|
| Left topic 1: **Parties** (proportion = .26, average lr-scale value = 5.38)<br>linke, spd, partei, linken, pds, politik, kommunisten, parteien, grünen, punks<br>*the left, spd, party, the left, pds, politics, communists, parties, greens, punks* |
| Left topic 2: **Ideologies** (proportion = .26, average lr-scale value = 5.36)<br>kommunismus, links, sozialismus, lafontaine, rechts, aber, gysi, linkspartei, richtung, gleichmacherei<br>*communism, left, socialism, lafontaine, right, but, gysi, left party, direction, levelling* |
| Left topic 3: **Values** (proportion = .24, average lr-scale value = 4.06)<br>soziale, gerechtigkeit, demokratie, soziales, bürger, gleichheit, gleiche, freiheit, rechte, gleichberechtigung<br>*social, justice, democracy, social, citizen, equality, equal, freedom, rights, equal rights* |
| Left topic 4: **Policies** (proportion = .24, average lr-scale value =4.89)<br>sozial, menschen, leute, ddr, verbinde, kleinen, einstellung, umverteilung, sozialen, vertreten<br>*social, humans, people, ddr, associate, the little, attitude, redistribution, social, represent* |

| |
|---|
| Right topic 1: **Ideologies** (proportion = .27, average lr-scale value = 5.00)<br>konservativ, nationalsozialismus, rechtsradikal, radikal, ordnung, politik, nazi, recht, menschen, konservative<br>*conservative, national socialism, right-wing radicalism, radical, order, politics, nazi, right, people, conservatives* |
| Right topic 2: **Parties** (proportion = .25, average lr-scale value = 5.26)<br>npd, rechts, cdu, csu, rechten, parteien, leute, aber, verbinde, rechtsradikalen<br>*npd, right, cdu, csu, the right, parties, people, but, associate, right-wing radicalists* |
| Right topic 3: **Xenophobia** (proportion = .25, average lr-scale value = 4.55)<br>ausländerfeindlichkeit, gewalt, ausländer, demokratie, nationalismus, rechtsradikalismus, diktatur, national, intoleranz, faschismus<br>*xenophobia, violence, foreigners, democracy, nationalism, right-wing radicalism, dictatorship, national, intolerance, fascism* |
| Right topic 4: **Right-wing extremists** (proportion = .23, average lr-scale value = 4.90)<br>nazis, neonazis, rechtsradikale, rechte, radikale, radikalismus, partei, ausländerfeindlich, reich, nationale<br>*nazis, neonazis, right-wing radicalists, rightists, radicals, radicalism, party, xenophobia, rich, national* |

**Note:** "proportion" indicates the average estimated probability that any given response is assigned to a topic. "average lr-scale value" is the mean position on the left-right scale (from 0 to 10) of individuals whose highest probability belongs to that particular topic.

Bauer, Barberá *et al*, *Political Behavior*, 2016.

# Example: open-ended survey responses

Fig. 6: Left-right scale means for different subsamples of associations with **left** (dashed = sample mean, bars = 95% Cis)

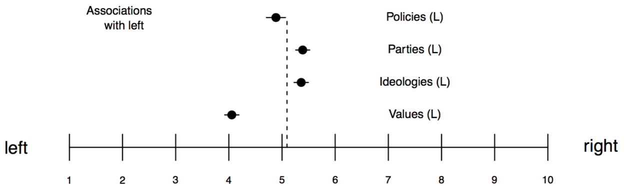
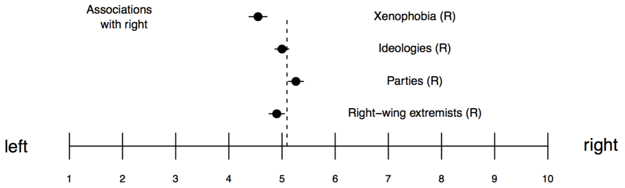


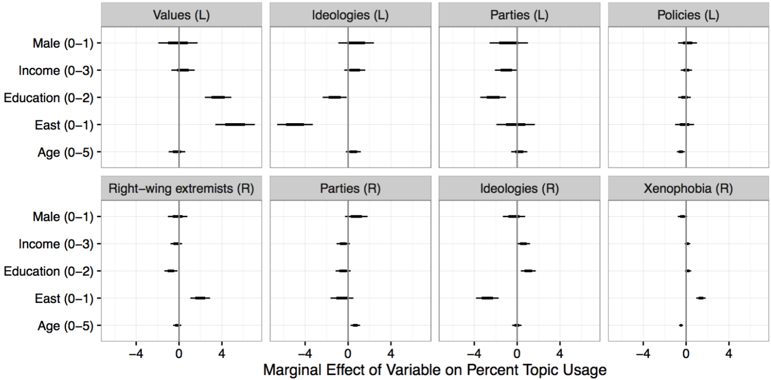

Fig. 7: Left-right scale means for different subsamples of associations with **right** (dashed = sample mean, bars = 95% Cis)




Bauer, Barberá *et al*, *Political Behavior*, 2016.

# Example: open-ended survey responses

Fig. 9: Systematic relationship between associations with “left” and “right” and characteristics of respondents




**Note:** Each line indicates a 95% confidence interval (and 66% confidence interval in darker color) for the coefficient of eight different regressions of topic usage (in a scale from 0 to 100) at the respondent level on seven individual-level characteristics. The line on the bottom right corner (second row, second plot), for example, shows that individual a one-category change in age is associated with around one percentage point increase in the probability that the individual associated “right” with political parties.

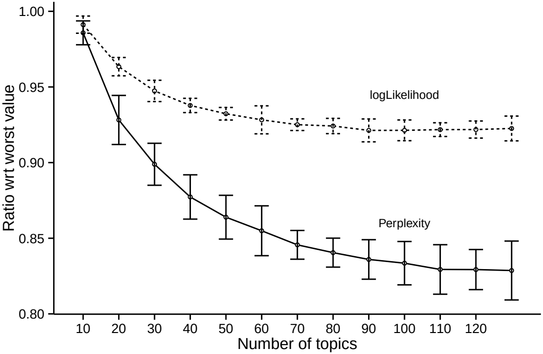
Bauer, Barberá *et al*, *Political Behavior*, 2016.

# Example: topics in US legislators' tweets

- Data: 651,116 tweets sent by US legislators from January 2013 to December 2014.
- 2,920 documents = 730 days $\times$ 2 chambers $\times$ 2 parties
- Why aggregating? Applications that aggregate by author or day outperform tweet-level analyses (Hong and Davidson, 2010)
- $K = 100$ topics (more on this later)
- Validation: http://j.mp/lda-congress-demo

# Choosing the number of topics

- Choosing $K$ is "one of the most difficult questions in unsupervised learning" (Grimmer and Stewart, 2013, p.19)
- We chose $K = 100$ based on cross-validated model fit.




- **BUT**: "there is often a negative relationship between the best-fitting model and the substantive information provided".
- GS propose to choose $K$ based on "substantive fit."

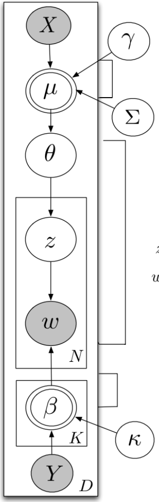
# Extensions of LDA

1. Structural topic model (Roberts et al, 2014, AJPS)
2. Dynamic topic model (Blei and Lafferty, 2006, ICML; Quinn et al, 2010, AJPS)
3. Hierarchical topic model (Griffiths and Tenembaun, 2004, NIPS; Grimmer, 2010, PA)

Why?

- Substantive reasons: incorporate specific elements of DGP into estimation
- Statistical reasons: structure can lead to better topics.

# Structural topic model




**Topic Prevalence:**

$$\begin{aligned} \mu_{d,k} &= X_d \gamma_k \\ \gamma_k &\sim \mathcal{N}(0, \sigma_k^2) \\ \sigma_k^2 &\sim \text{Gamma}(s^\gamma, r^\gamma) \end{aligned}$$

**Language Model:**

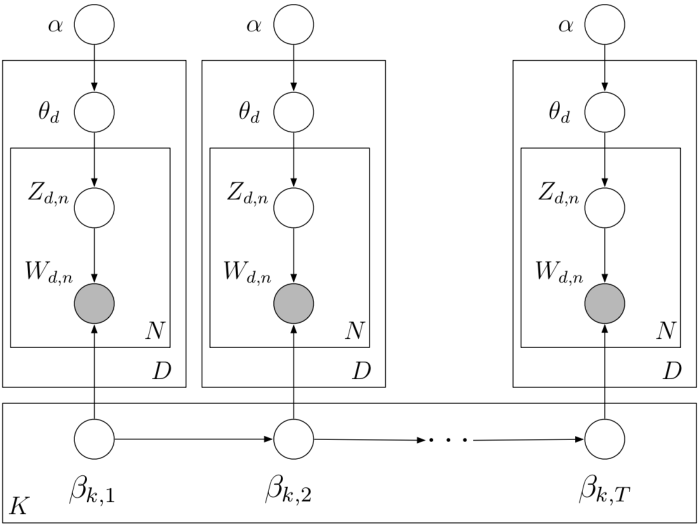
$$\begin{aligned} \theta_d &\sim \text{LogisticNormal}(\mu_d, \Sigma) \\ z_{d,n} &\sim \text{Mult}(\theta_d) \\ w_{d,n} &\sim \text{Mult}(\beta_d^{k=z_{d,n}}) \end{aligned}$$

**Topical Content:**

$$\begin{aligned} \beta_{d,v}^k &\propto \exp(m_v + \kappa_v^{\cdot,k} + \kappa_v^{y,\cdot} + \kappa_v^{y,k}) \\ \kappa_v^{y,k} &\sim \text{Laplace}(0, \tau_v^{y,k}) \\ \tau_v^{y,k} &\sim \text{Gamma}(s^\kappa, r^\kappa) \end{aligned}$$

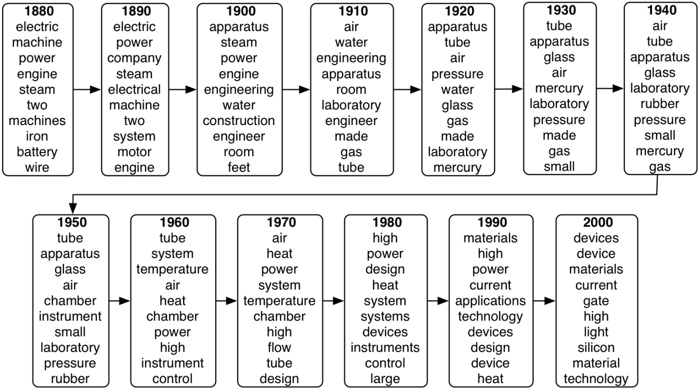
- **Prevalence**: Prior on the mixture over topics is now document-specific, and can be a function of covariates (documents with similar covariates will tend to be about the same topics)
- **Content**: distribution over words is now document-specific and can be a function of covariates (documents with similar covariates will tend to use similar words to refer to the same topic)

# Dynamic topic model



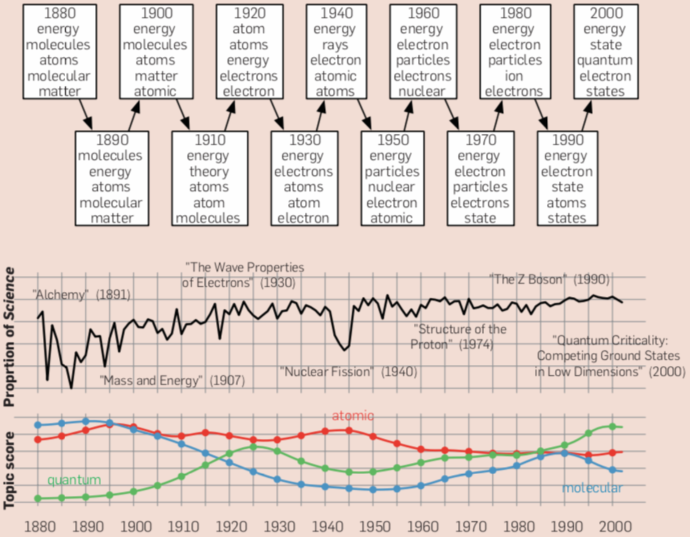

**Source**: Blei, “Modeling Science”

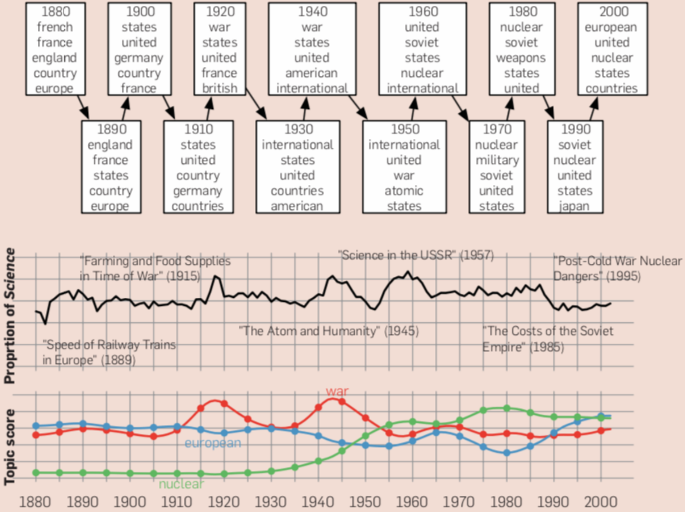
# Dynamic topic model




**Source**: Blei, “Modeling Science”

**Figure 5. Two topics from a dynamic topic model. This model was fit to *Science* from 1880 to 2002. We have illustrated the top words at each decade.**





1880 french france england country europe
1890 england france states country europe
1900 states united germany country france
1910 states united country germany countries
1920 war states united france british
1930 international states united countries american
1940 war states united american international
1950 international united war atomic states
1960 united soviet states nuclear international
1970 nuclear military soviet united states
1980 nuclear soviet weapons states united
1990 soviet nuclear united states japan
2000 european united nuclear states countries
Proprtion of Science
"Farming and Food Supplies in Time of War" (1915)
"Science in the USSR" (1957)
"Post-Cold War Nuclear Dangers" (1995)
"Speed of Railway Trains in Europe" (1889)
"The Atom and Humanity" (1945)
"The Costs of the Soviet Empire" (1985)
Topic score
war
european
nuclear
1880
1890
1900
1910
1920
1930
1940
1950
1960
1970
1980
1990
2000