Quantitative text analysis: Topic Models

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MY 459: Quantitative Text Analysis

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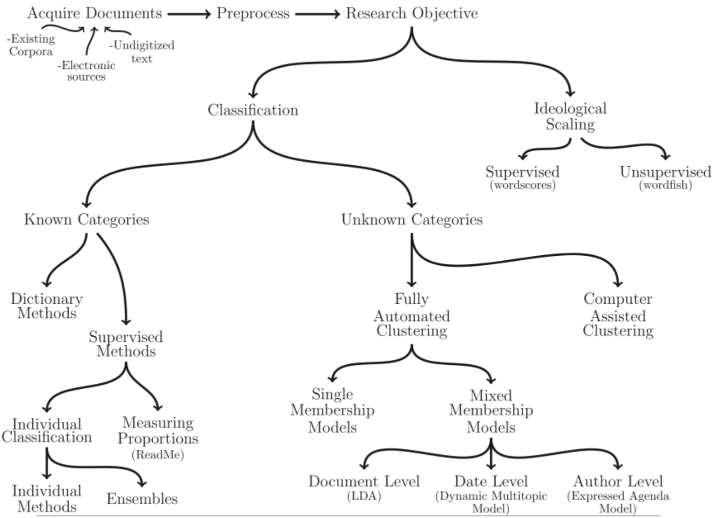
Course website: lse-my459.github.io

1. Overview and Fundamentals
2. Descriptive Statistical Methods for Text Analysis
3. Automated Dictionary Methods
4. Machine Learning for Texts
5. Supervised Scaling Models for Texts
6. *Reading Week*
7. Unsupervised Models for Scaling Texts
8. Similarity and Clustering Methods
9. Topic models
10. Word embeddings
11. Working with Social Media

Overview of text as data methods



Outline

- Overview of topic models
- Latent Dirichlet Allocation (LDA)
- Validating the output of topic models
- Examples
- Choosing the number of topics
- Extensions of LDA

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Topic Models

- Topic models are algorithms for discovering the main "themes" in an unstructured corpus
- 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.

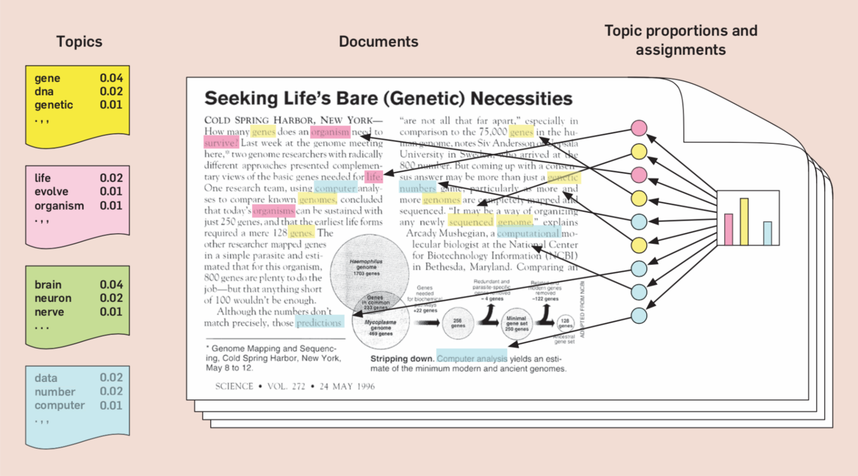

Illustration of the LDA generative process

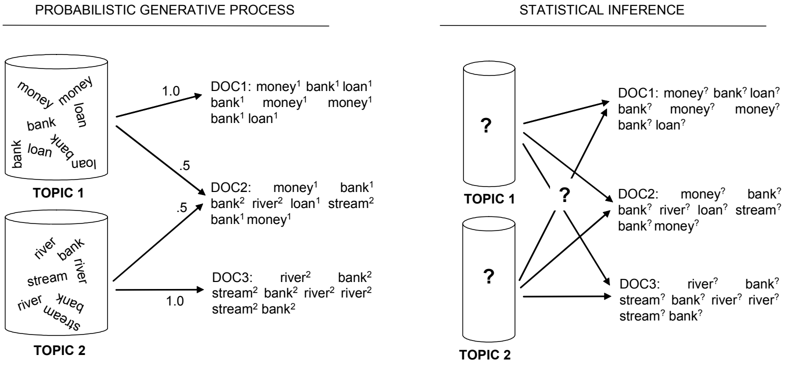

Figure 2. Illustration of the generative process and the problem of statistical inference underlying topic models

(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!

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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:

α=parameter of Dirichlet prior on distribution of topics over docs.

θ_i=topic distribution for document i

δ=parameter of Dirichlet prior on distribution of words over topics

β_k=word distribution for topic k

Latent Dirichlet Allocation

Key parameters:

1. $\theta =$ matrix of dimensions N documents by K topics where θ_{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

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2. $\beta =$ matrix of dimensions K topics by M words where β_{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

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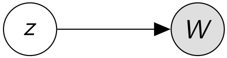

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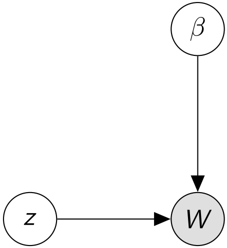

$\beta = M \times K$ matrix where β_{im} indicates prob(topic$=k$) for word m

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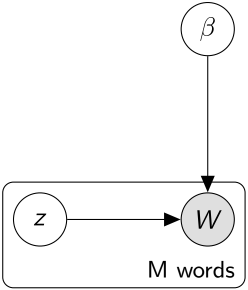

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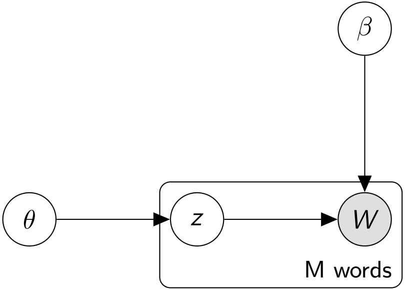

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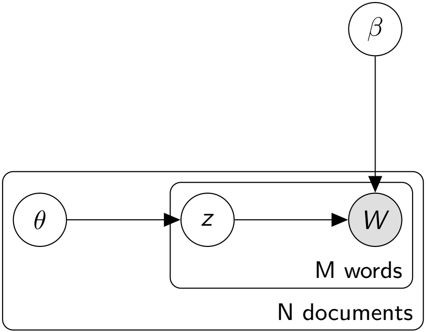

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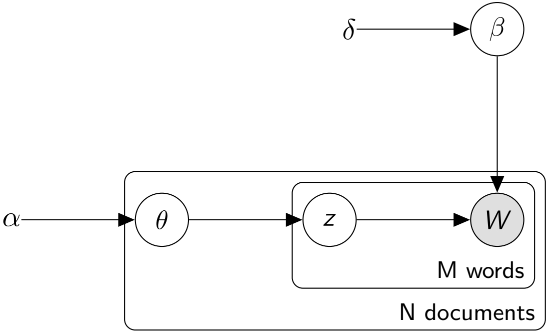

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Validation

From Quinn et al, AJPS, 2010:

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   - Does variation in topic usage correspond with expected events?
4. Hypothesis validity
   - Can topic variation be used effectively to test substantive hypotheses?

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

Right topic 1: **Ideologies** (proportion = .27, average lr-scale value = 5.00) konservativ, nationalsozialismus, rechtsradikal, radikal, ordnung, politik, nazi, recht, menschen, konservative *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) npd, rechts, cdu, csu, rechten, parteien, leute, aber, verbinde, rechtsradikalen *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) ausländerfeindlichkeit, gewalt, ausländer, demokratie, nationalismus, rechtsradikalismus, diktatur, national, intoleranz, faschismus *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) nazis, neonazis, rechtsradikale, rechte, radikale, radikalismus, partei, ausländerfeindlich, reich, nationale *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)

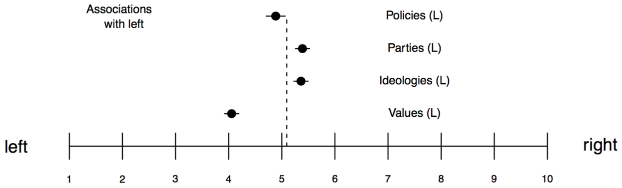
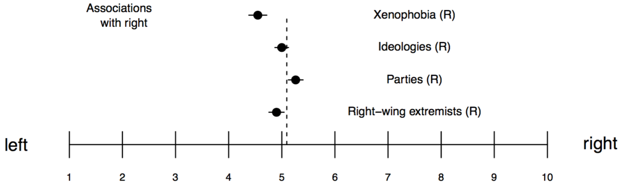


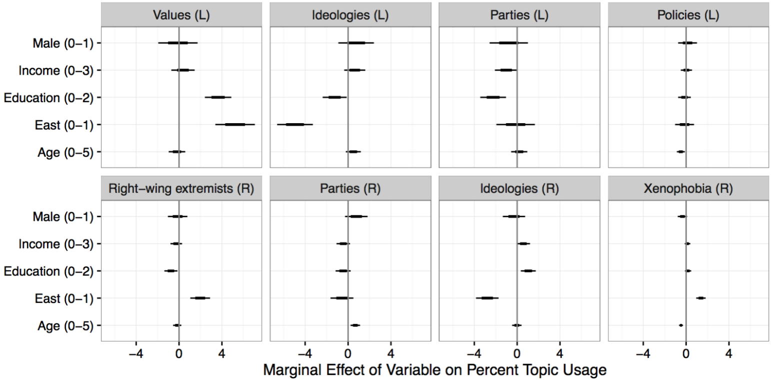
Fig. 7: Left-right scale means for different subsamples of associations with **right** (dashed = sample mean, bars = 95% Cis)



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.

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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

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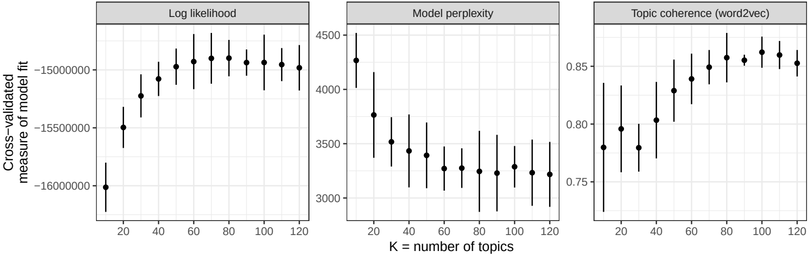
- One approach is to decide based on cross-validated model fit



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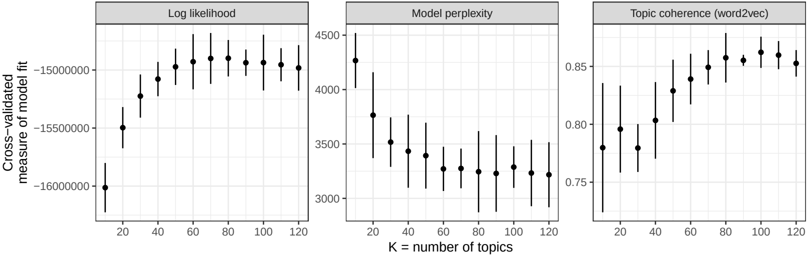

- **BUT**: "there is often a negative relationship between the best-fitting model and the substantive information provided".

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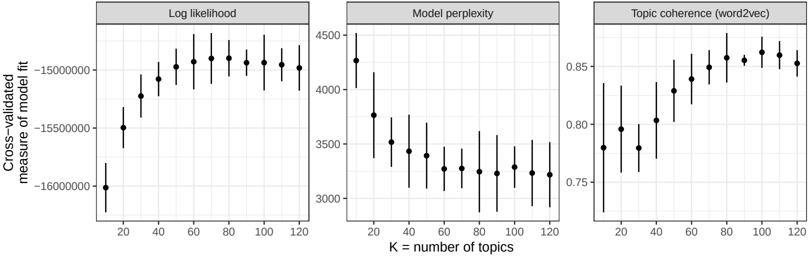


- **BUT**: "there is often a negative relationship between the best-fitting model and the substantive information provided".
- GS propose to choose K based on "substantive fit."

Model evaluation using "perplexity"

- can compute a likelihood for "held-out" data
- perplexity: can be computed as (using VEM):

$$\text{perplexity}(w) = \exp\left\{ -\frac{\sum_{d=1}^{M} \log p(w_d)}{\sum_{d=1}^{M} N_d} \right\}$$

- lower perplexity score indicates better performance

Evaluating model performance: human judgment

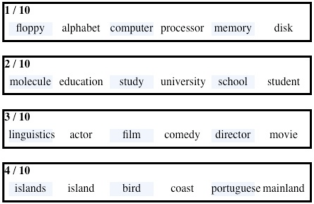
(Chang, Jonathan et al. 2009. "Reading Tea Leaves: How Humans Interpret Topic Models." *Advances in neural information processing systems*.)

Uses human evaluation of:

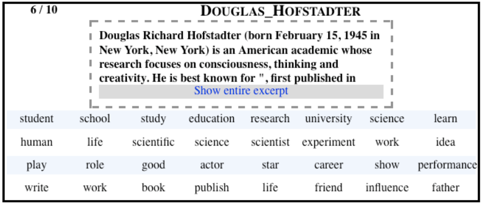
- whether a topic has (human-identifiable) semantic coherence: word intrusion, asking subjects to identify a spurious word inserted into a topic
- whether the association between a document and a topic makes sense: topic intrusion, asking subjects to identify a topic that was not associated with the document by the model

Example

Word Intrusion



Topic Intrusion



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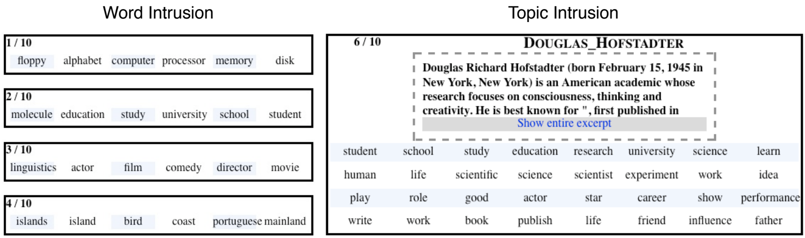

- conclusions: the quality measures from human benchmarking were negatively correlated with traditional quantitative diagnostic measures!

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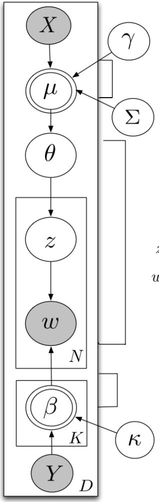
Extensions of LDA

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:

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

Language Model:

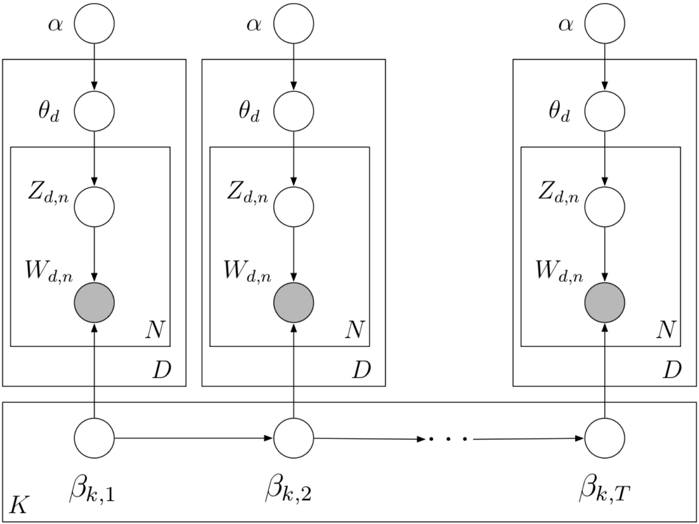
$$\theta_d \sim \text{LogisticNormal}(\mu_d, \Sigma)$$
$$z_{d,n} \sim \text{Mult}(\theta_d)$$
$$w_{d,n} \sim \text{Mult}(\beta_d^{k=z_{d,n}})$$

Topical Content:

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

- **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

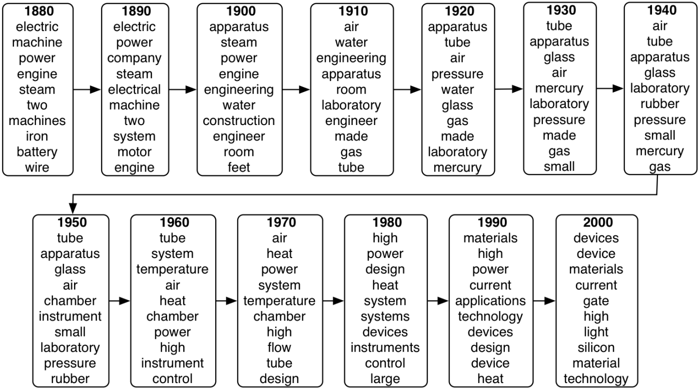


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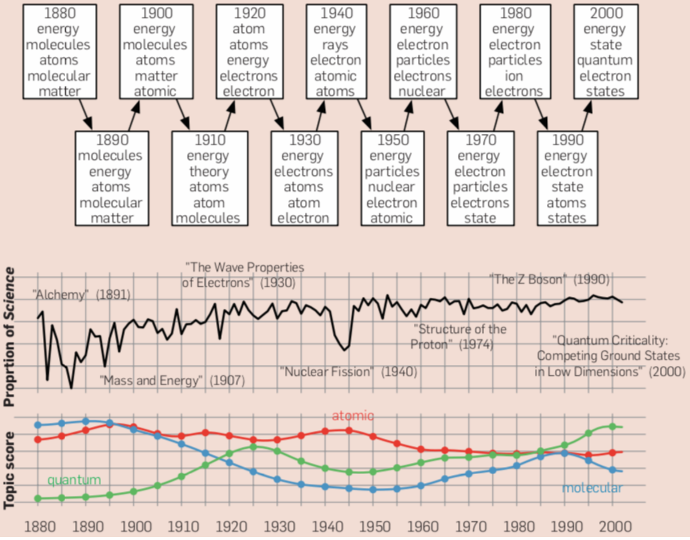
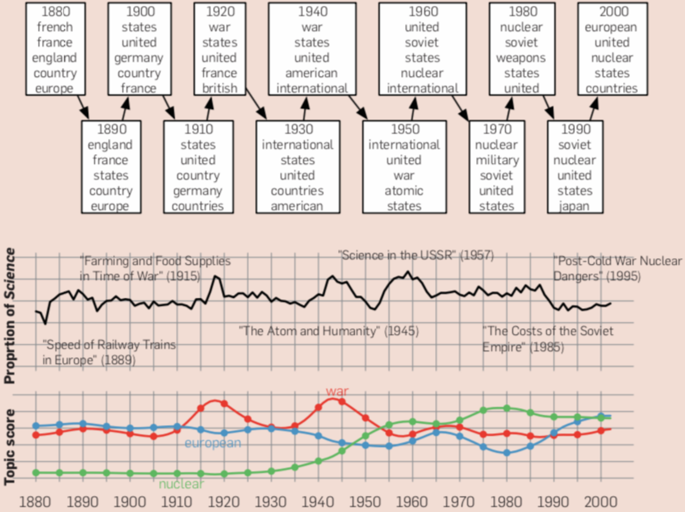
Figure 5. Two topics from a dynamic topic model. This model was fit to *Science* from 1880 to 2002. We have illustrated the top words at each decade.




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