POIR 613: Computational Social Science

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Today

1. Project
   - One-page proposal due October 14 **(Friday)**
2. Topic models
3. Guided coding session
4. Presentation
5. Solutions to challenge 6

Topic models

Overview of QTA (Grimmer and Stewart, 2013)

1. Acquire textual data:
   - Existing corpora; scraped data; digitized text
2. Preprocess the data:
   - Bag-of-words vs word embeddings
3. Apply method appropriate to research goal:
   - Describe and compare documents
     - Readability; similarity; keyness metrics
   - Classify documents into known categories
     - Dictionary methods
     - Supervised machine learning
   - Classify documents into unknown categories
     - Document clustering
     - Topic models
   - Scale documents on latent dimension
     - Known dimension: wordscores
     - Unknown dimensions: wordfish

Outline

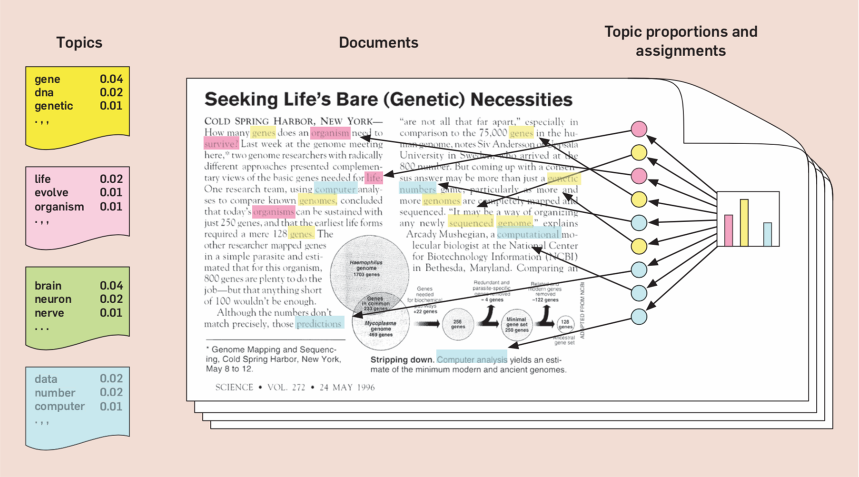
- Overview of topic models
- Latent Dirichlet Allocation (LDA)
- Validating the output of topic models
- Examples
- Choosing the number of topics
- Extensions of LDA

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.



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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:

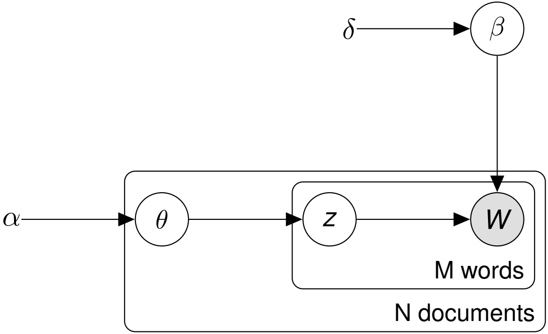
1. θ = matrix of dimensions N documents by K topics where θ_{ik} corresponds to the probability that document i belongs to topic k; i.e. assuming $K = 5$:

	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

2. β = 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



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

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Validation

From Quinn et al, AJPS, 2010:

1. Semantic validity
   - Do the topics identify coherent groups of documents 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?

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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)

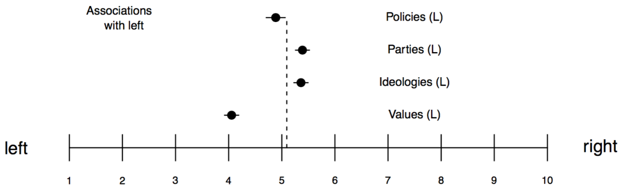
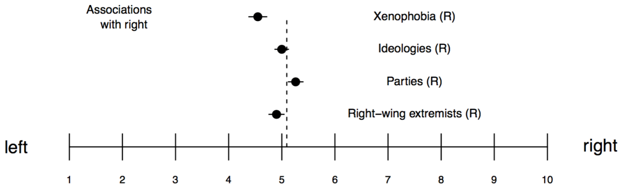


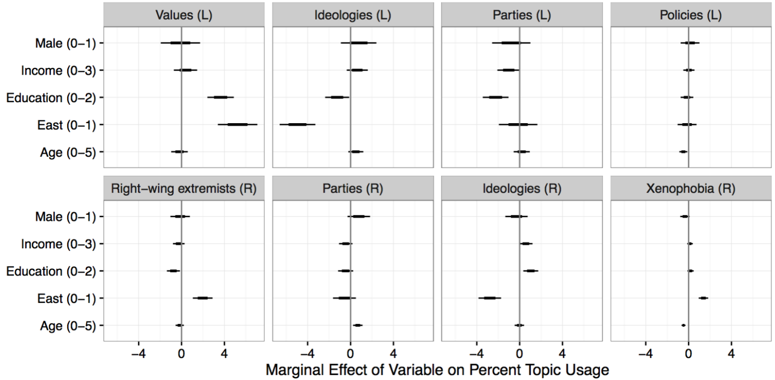
Fig. 7: Left-right scale means for different subsamples of associations with **right** (dashed = sample mean, bars = 95% Cis)



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.

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

Example: topics in US legislators' tweets

Barberá *et al*, *American Political Science Review*, 2020.

- Data: tweets sent by US legislators, samples of the public, and media outlets.
- LDA with $K = 100$ topics
- Topic predictions are used to understand agenda-setting dynamics (who leads? who follows?)
- Validation: http://j.mp/lda-congress-demo

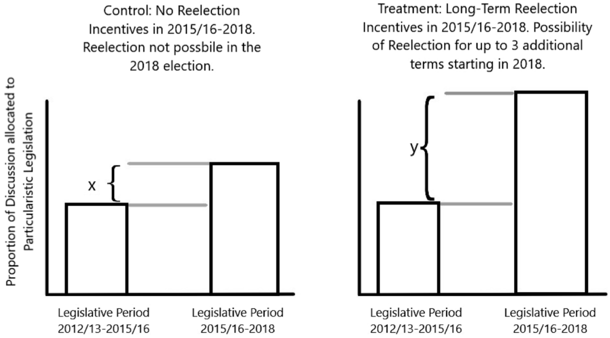
Example: particularistic legislation in Mexico

Motolinia, *American Political Science Review*, 2021.

- Data: transcripts of legislative sessions in Mexican states
- Topic model to identify “particularistic” legislation; i.e. laws with clear benefits to voters
- Each topic is then classified into particularistic or not
- Validation: correlation with spending
- Use exogenous electoral reform that allowed legislators to be re-elected

Example: particularistic legislation in Mexico

FIGURE 4. Visual Representation of the Difference-in-Differences Design



Motolinia, *American Political Science Review*, 2021

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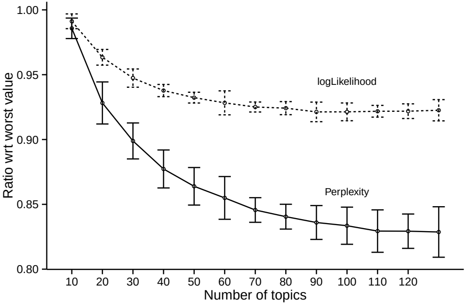
Choosing the number of topics

- Choosing K is "one of the most difficult questions in unsupervised learning" (Grimmer and Stewart, 2013, p.19)
- Common approach: decide based on cross-validated model fit, using "elbow method"



- **BUT**: "there is often a negative relationship between the best-fitting model and the substantive information provided". Many choose K based on "substantive fit," via a manual inspection of topics and documents

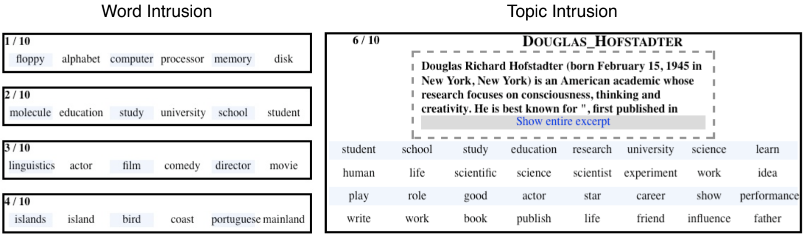
Evaluating model performance: human judgment

Chang, Jonathan et al. 2009. "Reading Tea Leaves: How Humans Interpret Topic Models." *Advances in neural information processing systems*. (See also Ying et al, 2021, Political Analysis.)

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



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

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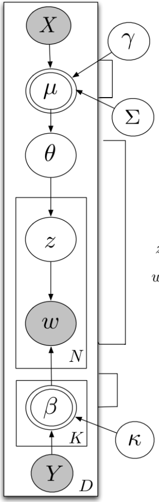
Extensions of LDA

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)
4. Anchored topic model and other semi-supervised approaches

Why?

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

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:

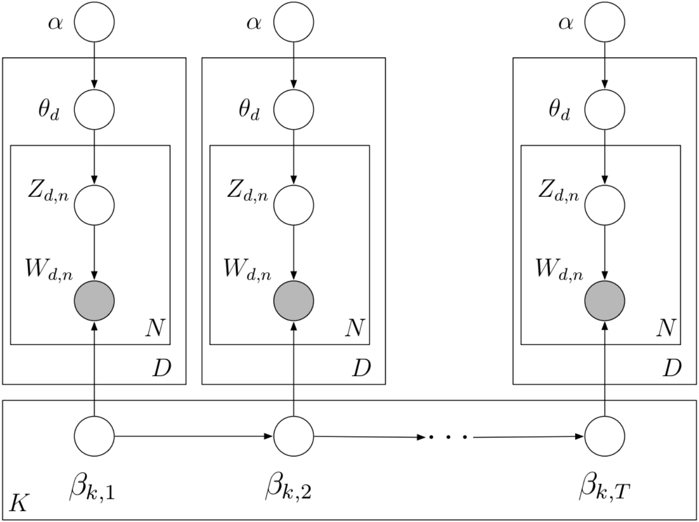
$$\theta_d \sim \text{LogisticNormal}(\mu_d, \Sigma)$$
$$z_{d,n} \sim \text{Mult}(\theta_d)$$
$$w_{d,n} \sim \text{Mult}(\beta_d^{k=z_{d,n}})$$

Topical Content:

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

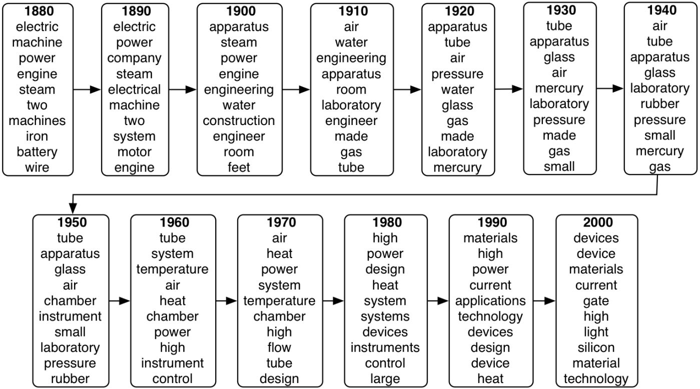
- **Prevalence**: Prior on the mixture over topics is now document-specific, and can be a function of covariates (documents with similar covariates will tend to be about the same topics)
- **Content**: distribution over words is now document-specific and can be a function of covariates (documents with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

Dynamic topic model



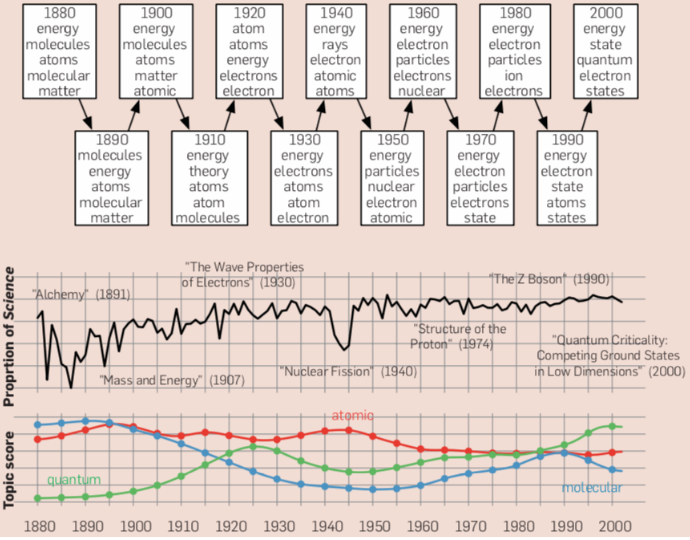
Source: Blei, “Modeling Science”

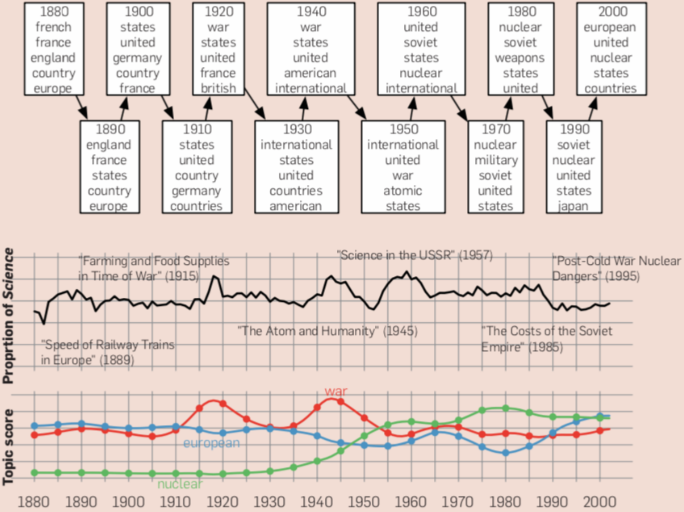
Dynamic topic model



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
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1930
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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