Training Session: Topic models

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materials: github.com/NetDem-USC/training

Overview of text as data methods

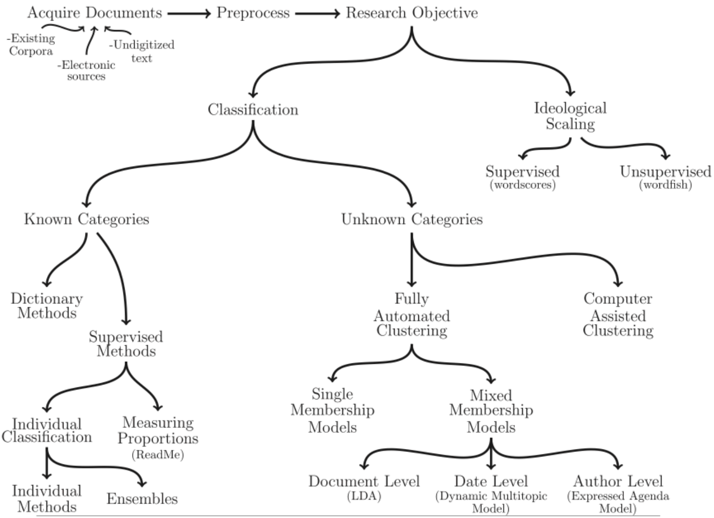

Fig. 1 in Grimmer and Stewart (2013)

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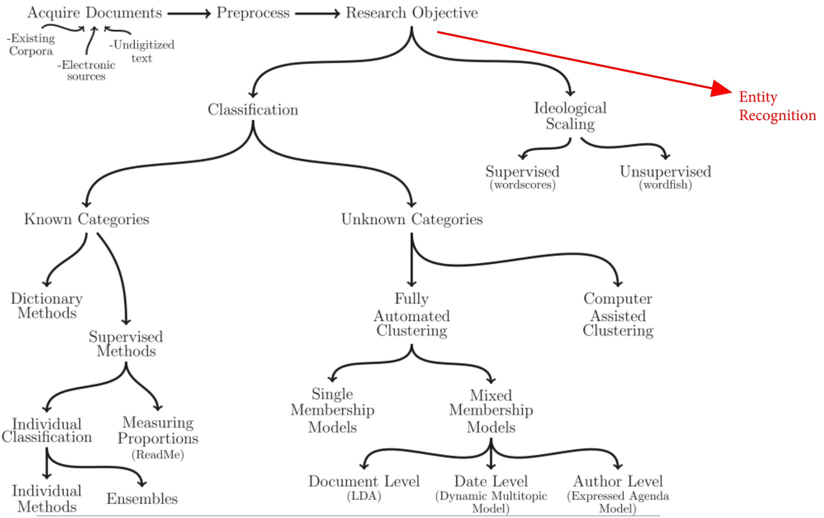

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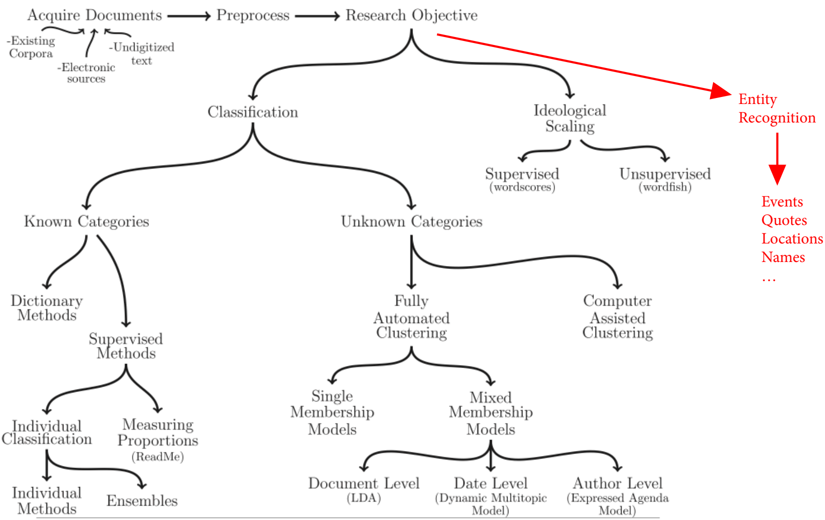

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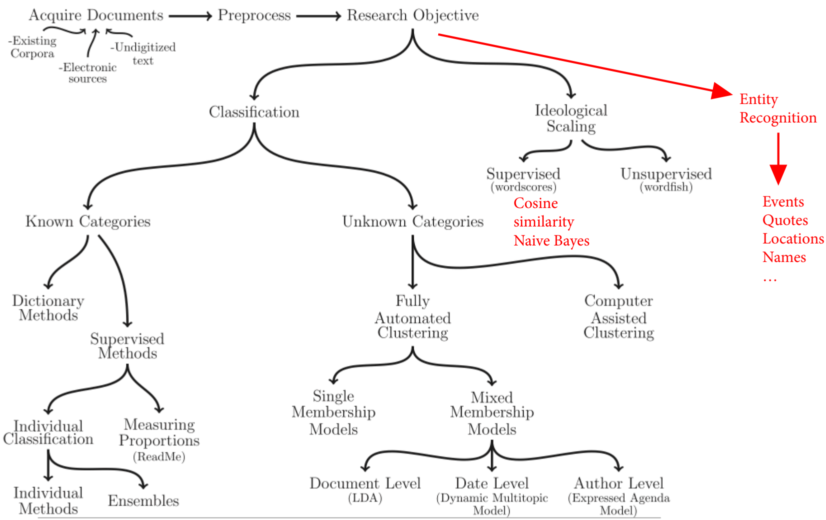

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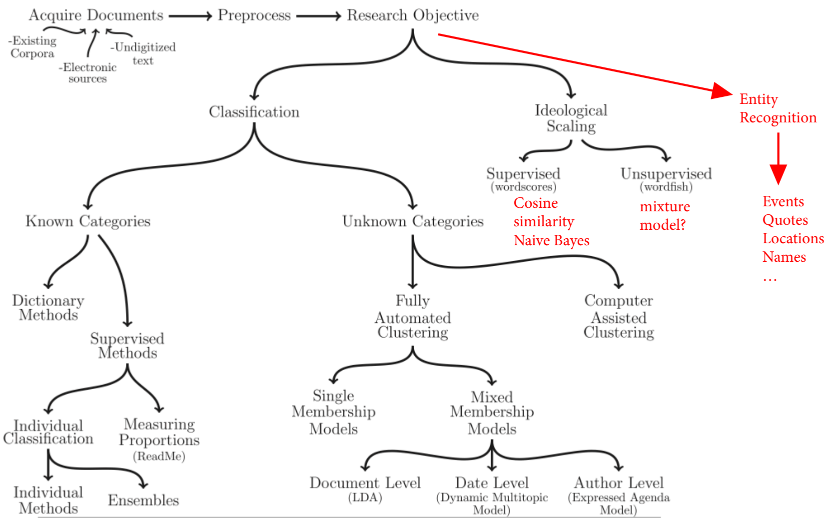

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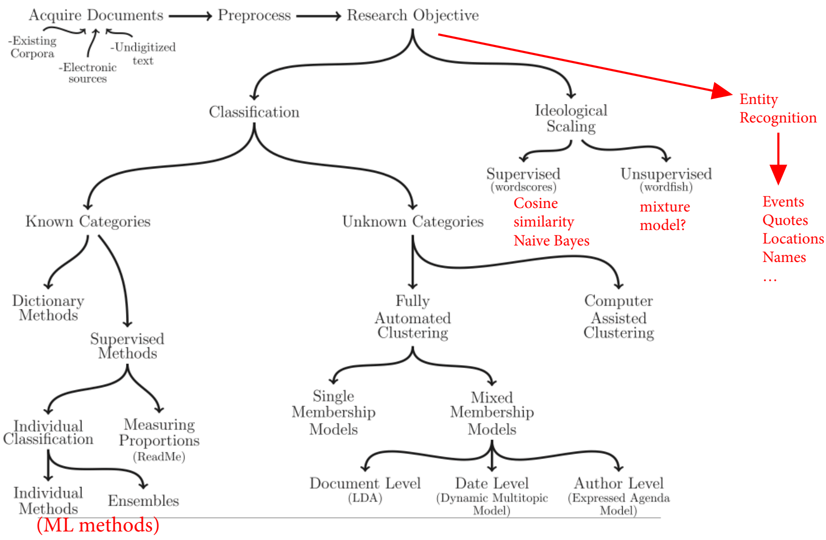

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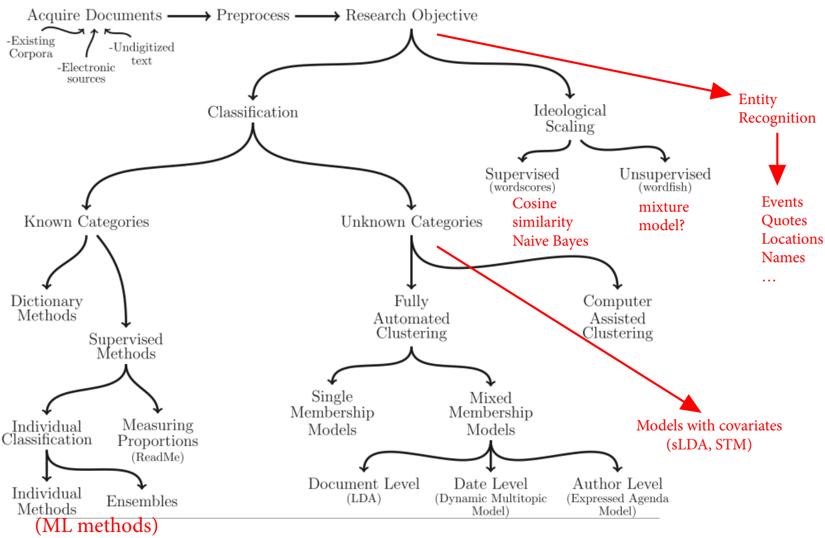

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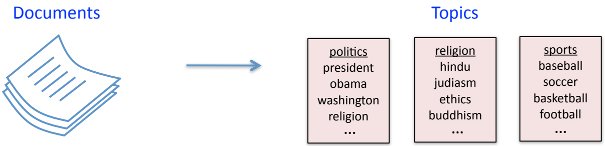
Latent Dirichlet allocation (LDA)

- **Topic models** are powerful tools for exploring large data sets and for making inferences about the content of documents



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Documents

Topics

politics	religion	sports
president	hindu	baseball
obama	judiasm	soccer
washington	ethics	basketball
religion	buddhism	football
...	...	...

- Many applications in information retrieval, document summarization, and classification

New document

Words $w_1, \ldots, w_N$

What is this document about?

weather	.50
finance	.49
sports	.01

Distribution of topics θ

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Distribution of topics θ

- LDA is one of the simplest and most widely used topic models

Latent Dirichlet Allocation

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

Probabilistic model with 3 steps:

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

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

Plate notation

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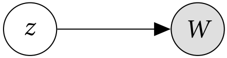

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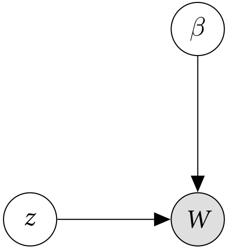

$\beta = M \times K$ matrix where β_{im} indicates prob(topic=k) for word m

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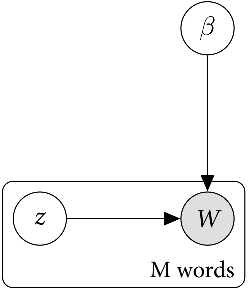

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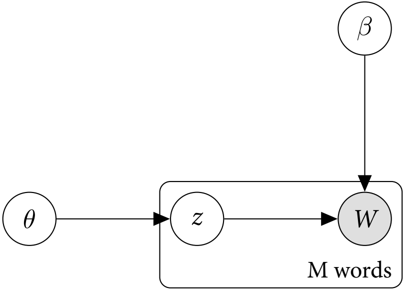

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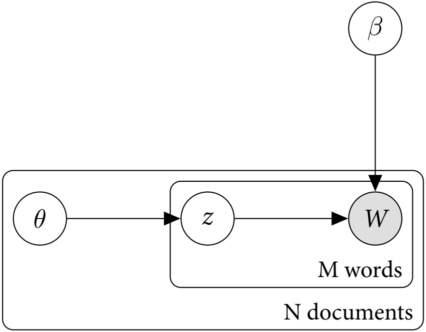

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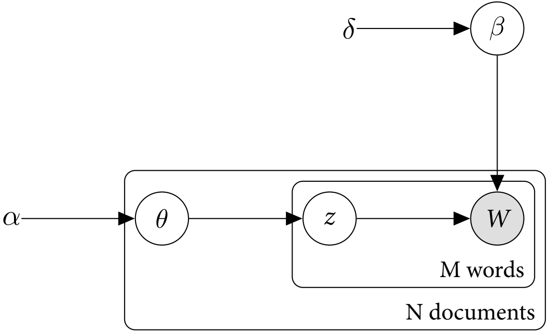

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   - Does variation in topic usage correspond with expected events?
4. Hypothesis validity
   - Can topic variation be used effectively to test substantive hypotheses?

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) 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)

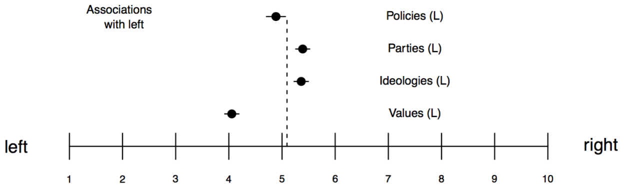
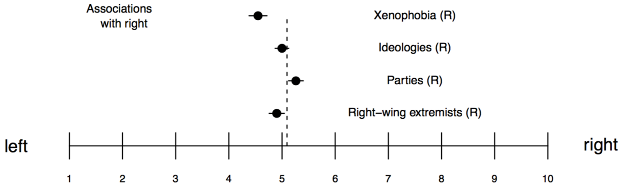


Fig. 7: Left-right scale means for different subsamples of associations with **right** (dashed = sample mean, bars = 95% Cis)



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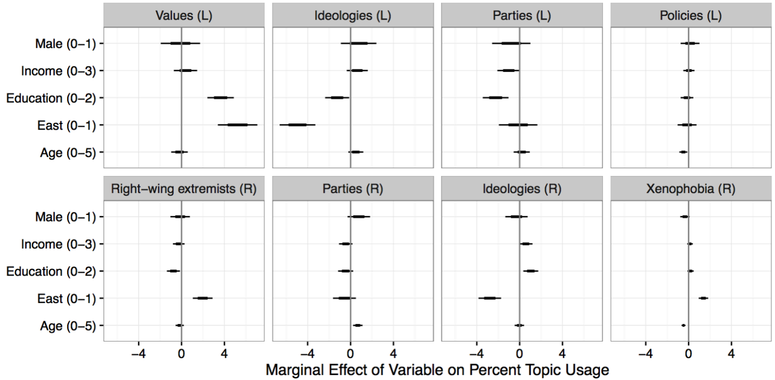
Example: open-ended survey responses

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

Choosing the number of topics

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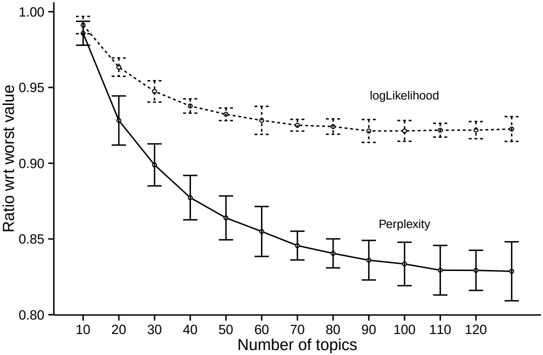

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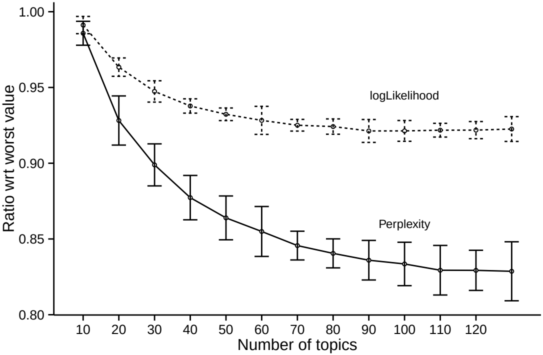

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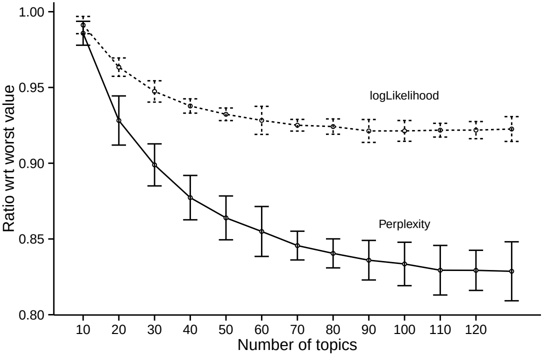


- **BUT**: "there is often a negative relationship between the best-fitting model and the substantive information provided".
- GS propose to choose K based on "substantive fit."

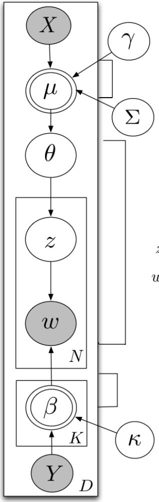
Extensions of LDA

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:

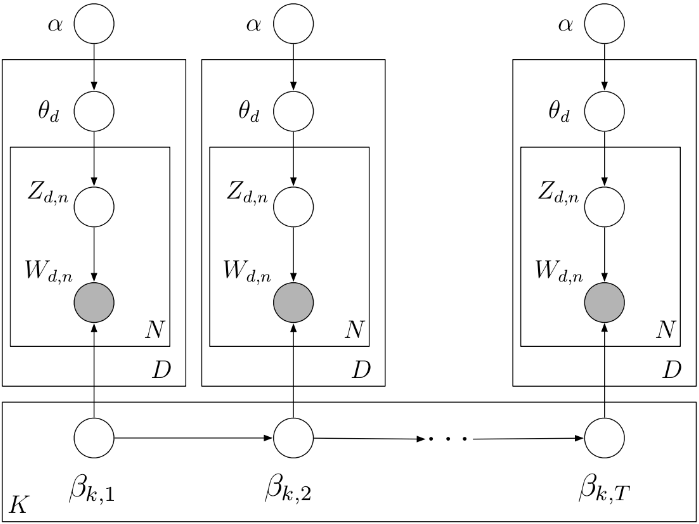
$$\theta_d \sim \text{LogisticNormal}(\mu_d, \Sigma)$$
$$z_{d,n} \sim \text{Mult}(\theta_d)$$
$$w_{d,n} \sim \text{Mult}(\beta_d^{k=z_{d,n}})$$

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"

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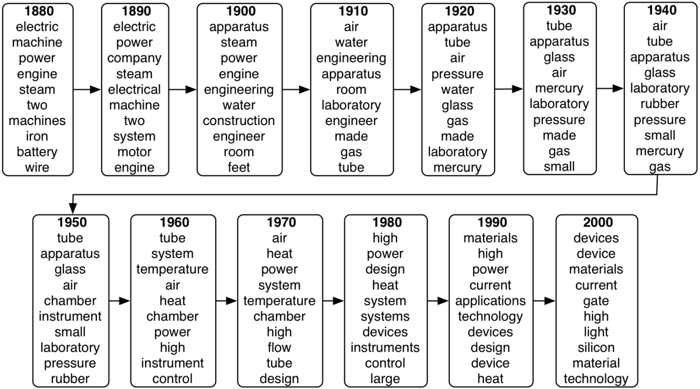

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- Word usage is drawn from a Poisson-IRT model:

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\begin{aligned}
W_{im} &\sim \text{Poisson}(\lambda_{im}) \\
\lambda_{im} &= exp(\alpha_i + \psi_m + \beta_m \times \theta_i)
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- Estimation using EM algorithm.
- Identification:
  - Unit variance restriction for θ_i
  - Choose a and b such that $\theta_a > \theta_b$