Text Mining, pt. II

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MACS 40500: Computational Methods for American Politics

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Lecture Outline

1. Text Mining Revisited
2. Mixed Membership Models
3. Latent Dirichlet Allocation
4. Structural Topic Modeling
5. Some Code for Text Mining

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- Our goal today? Uncover structure in text data, which is usually considered some mixture of topics in a single document $\rightsquigarrow$ topic models
- We will briefly touch on *structural* topic models at the end

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The Basics of Topic Models

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- Topic modeling is distinct from clustering given the assumed nature of the **membership** of topics in a document: *mixed* membership vs. *single* membership

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  Policy formation requires input from multiple stakeholders.

  Congressional committees should be required to subpoena stakeholders in related hearings.

  Republicans and Democrats don't seem to want to work together to find a solution to the policy gridlock crisis in Congress.

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    - "who pays more attention to education, conservatives or liberals?"

Clustering or Topics?

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Document $\rightsquigarrow$ One Cluster

Doc 1

Doc 2

Doc 3

$\vdots$

Doc N

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$\vdots$

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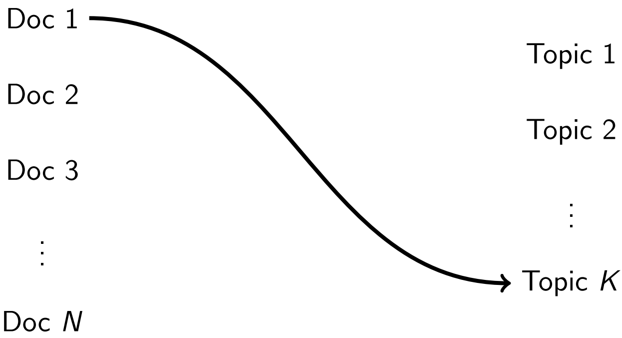

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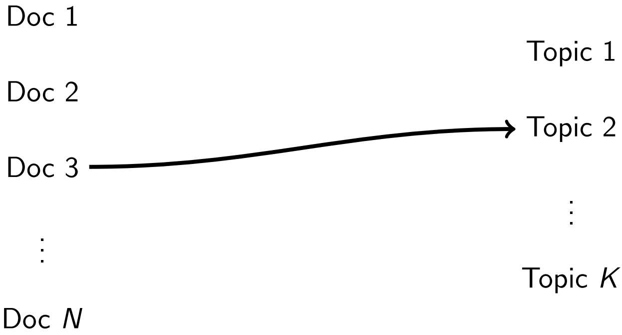

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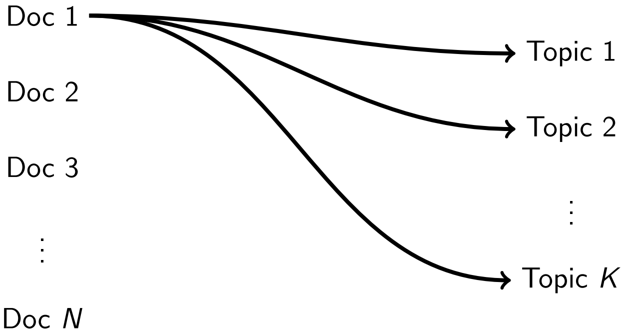

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- Core assumption $\rightsquigarrow$ documents exhibit different topics, and in different proportions
  - e.g., A speech by Trump might be 50% drawn from the topic `IMMIGRATION`, 40% from the topic `AMERICA`, 9.9% from the topic `GREAT`, 0.1% from the topic `SECURITY`

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- So... where do the *words* in the documents come from?

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- Aggregating across these steps for all words and all topics $\rightsquigarrow$ in the documents, which are the only things we actually observe

Generating Words: Step 1

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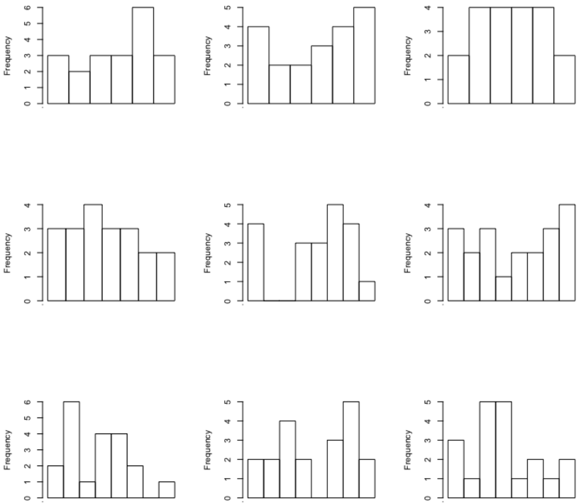

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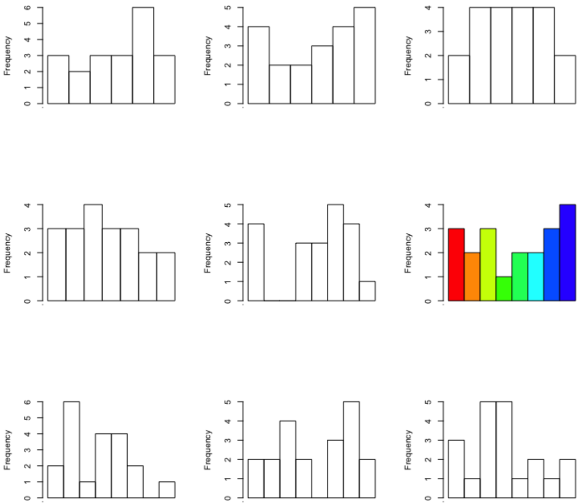

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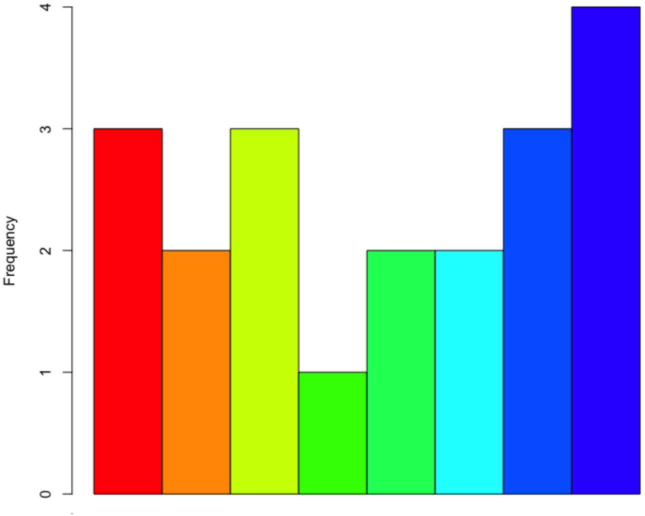

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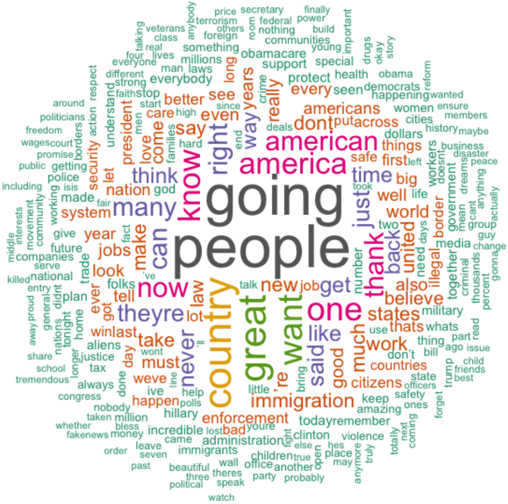

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- **latent Dirichlet allocation** $\rightsquigarrow$ specific type of probabilistic topic model controlling the assignment of words to topics
- In sum, we want to model the most likely-to-exist combined membership of words across all topics, in a probabilistic way

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    - In most social science applications, the number of topics, k, is not picked automatically; a general approach to fit multiple models at multiple values of k and compare
    - As with all unsupervised learning, interpretation is non-trivial, and requires a lot of **thinking** and **validation**

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- The sum of the topic proportions across all topics for each document is one, and the sum of the word probabilities for each topic is one

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   - e.g., a certain topic like `IMMIGRATION` consistently (or at least *suddenly*) appears, so stop there
2. Its best practice, at a minimum, to check that findings are robust in some neighborhood
   - e.g., if best model likely has $k = 15$, check whether $k = 10 - 20$ yield similar patterns, and thus inferences

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3. Record parameter values on a document for a specific topic distribution (θ), and the word distributions for the topics (β)
4. Find the highest log-likelihood across many specifications of a similar distribution of words over topics, and topics over documents,

$$\mathcal{L}(\mathbf{w}) = \log pr(\mathbf{w}|\beta, \theta) = \sum_{d} \log pr(w_d|\beta, \theta),$$

where **w** are the words in the test set

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- The intuition is to calculate the likelihood of seeing the test words, given what we know produced the training set

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- (*hint*: `topicmodels` includes a function `perplexity()` which calculates this value for a model

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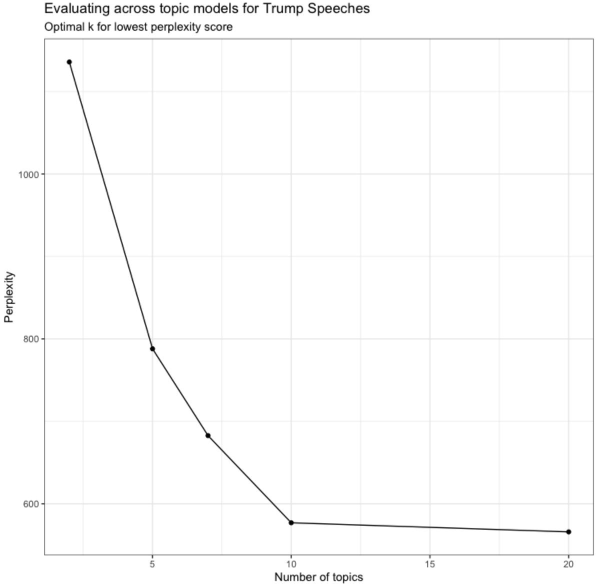

Evaluating across topic models for Trump Speeches
Optimal k for lowest perplexity score
Perplexity
1000
800
600
5
10
15
20
Number of topics

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- But this may be non-trivial to include: STM $=$ LDA $+$ contextual information
- STM, then, allows more precise estimation and usually more interpretable results (and essentially allows for a NHST framework)
- In brief, STMs model the topic distribution as a function of the document metadata

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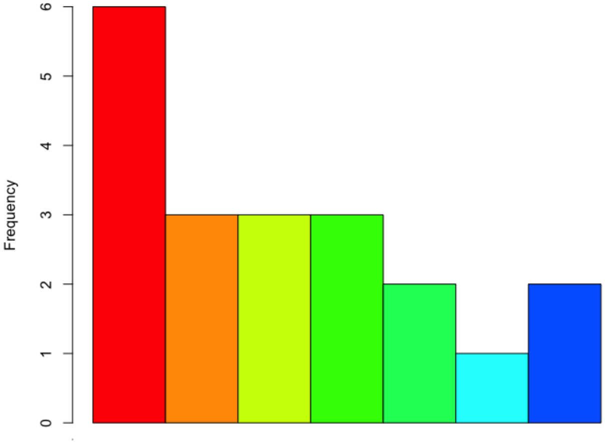
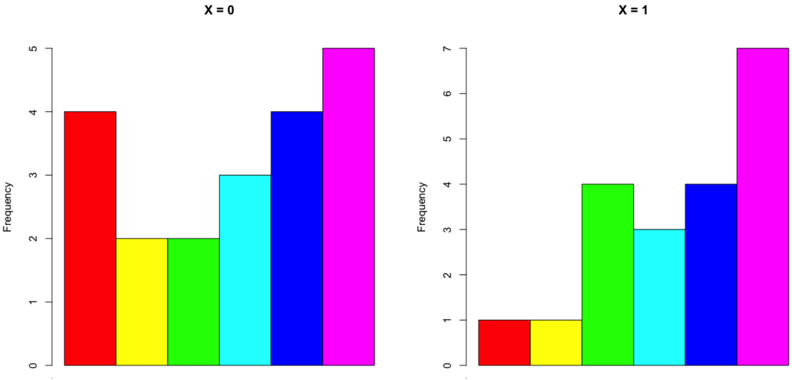
- But in the STM world, the documents have metadata associated with them (usually denoted as X_d, where d indexes the documents)
- Then, just like LDA, a topic is defined as a *mixture* over words where each word has a probability of belonging to a topic
- And a document is a mixture over topics, where a single document can be composed of multiple topics

Topic Distribution over Documents (θ): LDA



Topic Distribution over Documents (θ): STM



Word Distribution per Topic (β): LDA

Word Distribution per Topic (β): STM

Figure: $X = 0$

Figure: $X = 1$

Lecture Outline