Text Mining, pt. II

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MACS 40800: Unsupervised Machine Learning

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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

Lecture Outline

Text Mining

- Today we return to an unsupervised framework for mining text

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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 given several projects interested in these

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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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  The problem of polarization flows from a refusal of Republicans and Democrats to work together.

  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

Topic 1

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$\vdots$

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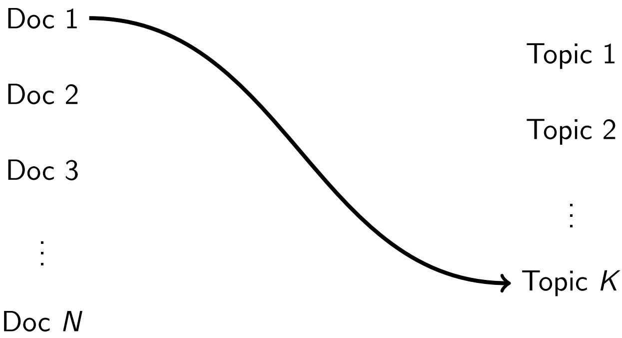

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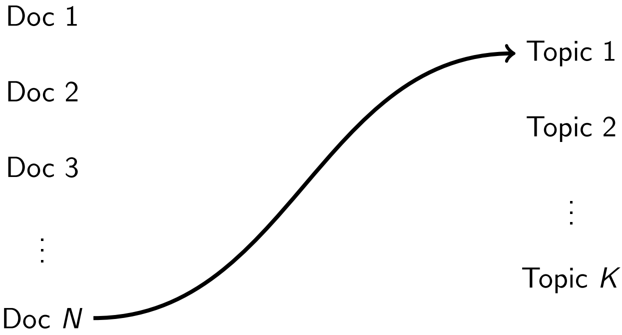

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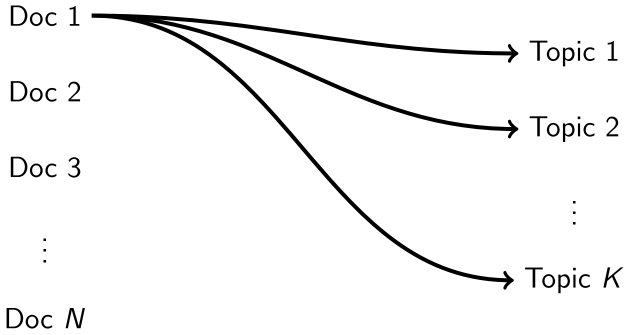

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  - e.g., A speech by Trump might be 50% drawn from the topic `IMMIGRATION`, 40% from the topic `AMERICA`, 9.9% from the topic `GREAT`, 0.1% from the topic `SECURITY`

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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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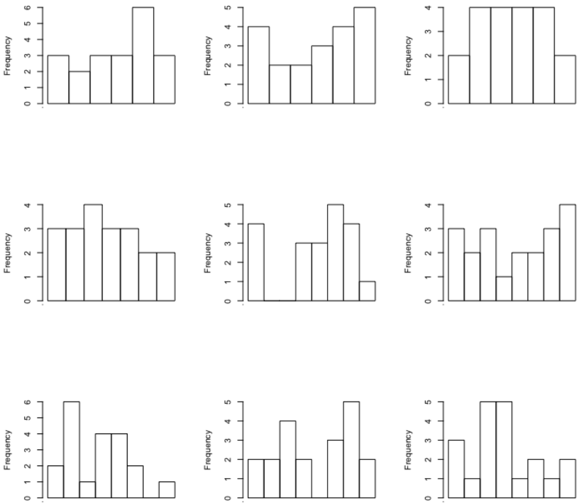

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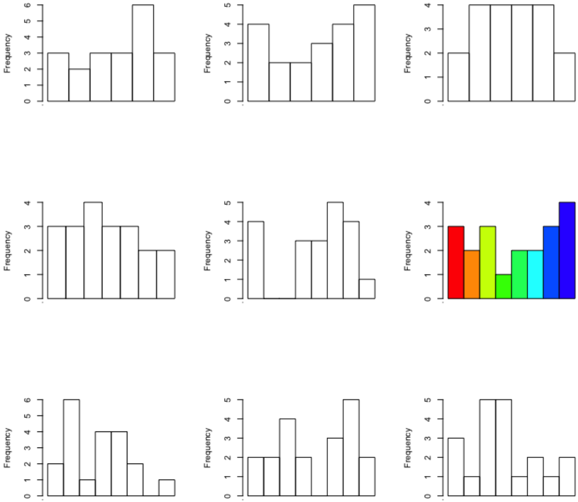

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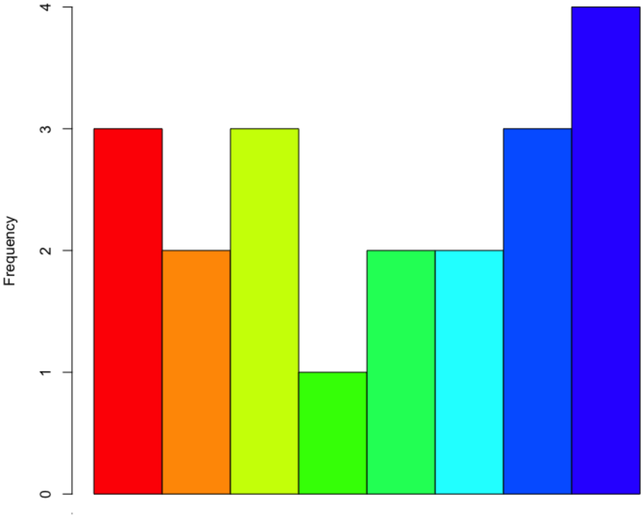

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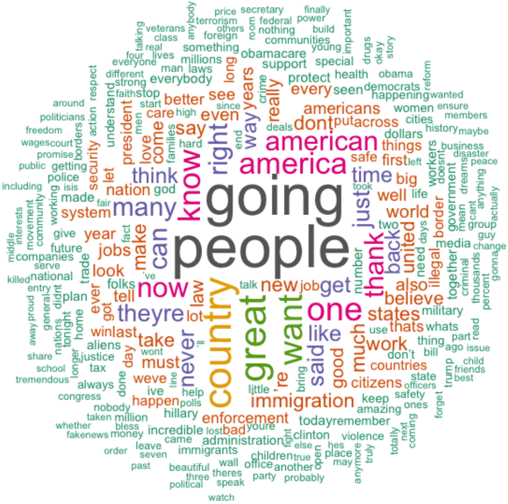

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- **latent Dirichlet allocation** $\rightsquigarrow$ specific type of probabilistic topic model controlling the assignment of words to topics
- In sum, we want to model the most likely-to-exist combined membership of words across all topics, in a probabilistic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

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where $\mathbf{w}$ are the words in the test set

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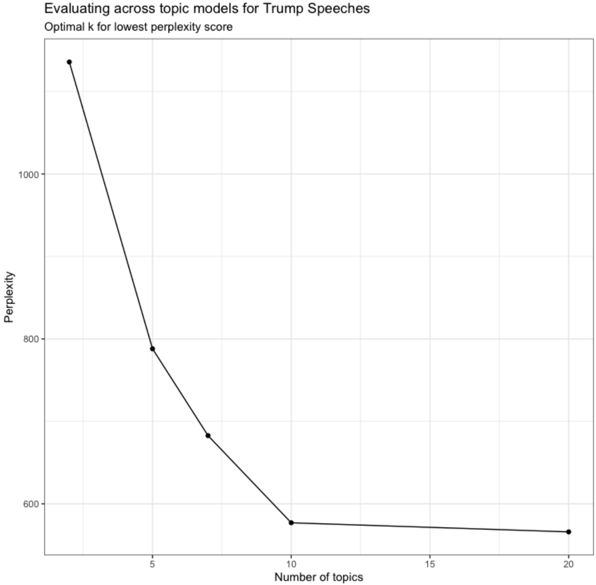
Evaluating across topic models for Trump Speeches
Optimal k for lowest perplexity score
Perplexity
1000
800
600
5
10
15
20
Number of topics

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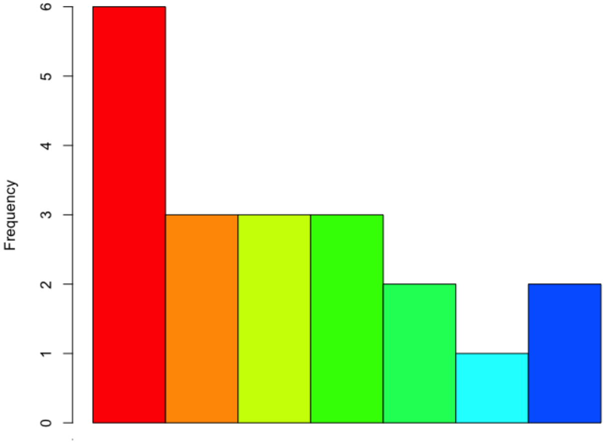
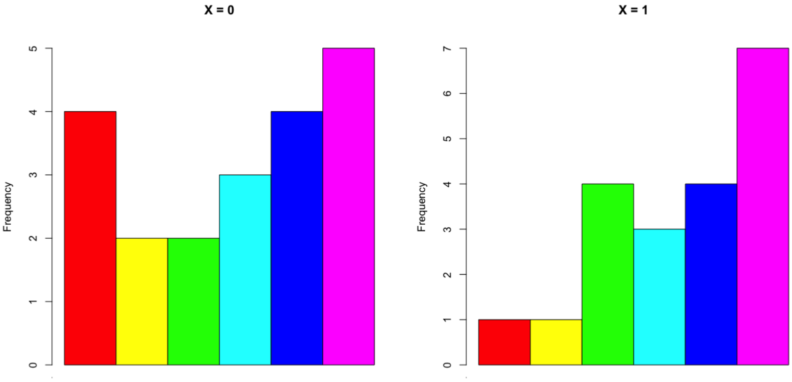
- But in the STM world, the documents have metadata associated with them (usually denoted as X_d, where d indexes the documents)
- Then, just like LDA, a topic is defined as a *mixture* over words where each word has a probability of belonging to a topic
- And a document is a mixture over topics, where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