American's (and Comparative's) Next Top(ic) Models

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- Explosion in popularity $\rightarrow$ the potential for uninformed applications
- Done well and interpreted correctly, can be a valuable tool

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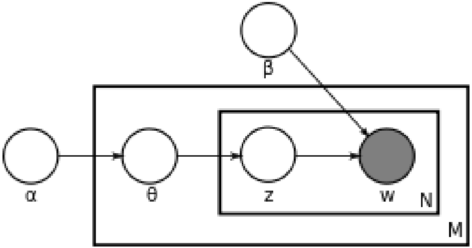
  - In fact, "topics" is sometimes begging the question
  - Also means you want a LOT of data

The Godfather–Latent Dirchlet Allocation

- Developed by David Blei, Andrew Ng and *the* Michael I. Jordan (Blei, Ng, and Jordan, 2003)
- Given only a number of topics, concentration parameter α and a collection of documents, produces a distribution of "topics" over those documents
- Does not incorporate covariates about the documents



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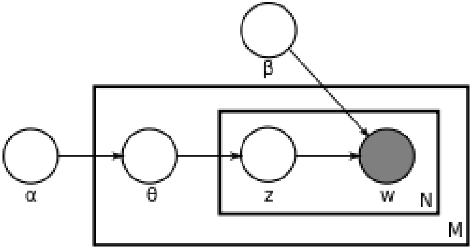

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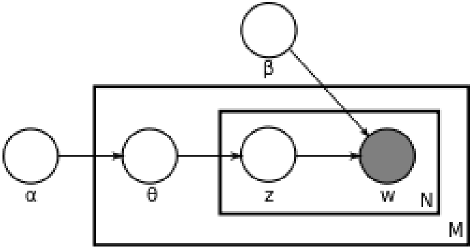

- LDA is a generative topic model–the fundamental assumption is that each document is created via draws from some distribution
- With the caveat that word order doesn't matter–"bag of words"

The summary of how LDA works

From Barberà et al (2013)

1. The topic distribution for document w is determined by: $\theta \sim \text{Dirichlet}(\alpha)$
2. The word distribution for topic k is determined by: $\beta \sim \text{Dirichlet}(\delta)$
3. For each of the words in document w
   (a) Choose a topic $z_n \sim \text{Multinomial}(\theta)$
   (b) Choose a word w_n from $p(w_n|z_n, \beta)$, a multinomial probability conditioned on z_n.

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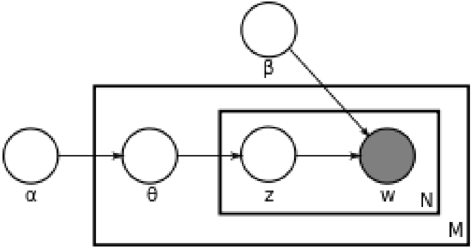

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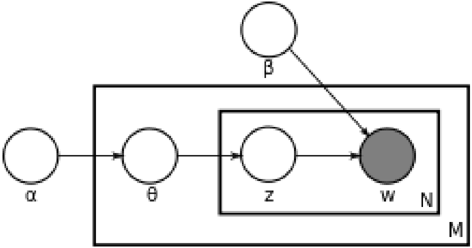

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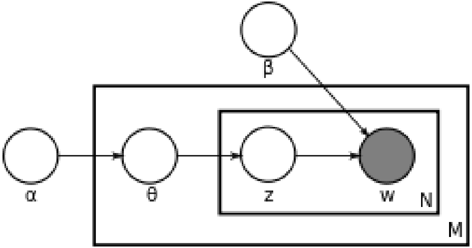

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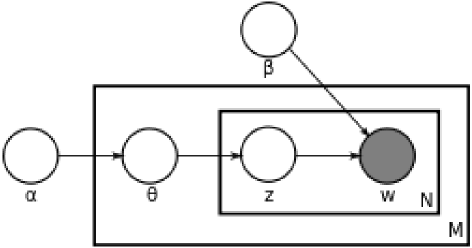

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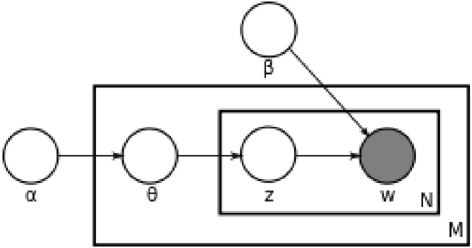

  - The prior distribution of words over topics (β) and topics over documents (α) is a symmetric Dirichlet
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- As Grimmer and Stewart (2013) put it: "all quantitative models of language are wrong–but some are useful"

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- The intuition behind each of these methods is to optimize one variable while holding the others constant, iterating across all of the variables many times

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    - $\alpha = \frac{50}{K}$

Let's give it a try

- Go to https://github.com/kmunger/Topic_Modelsand find the R file LDA.R
- We're going to walk through an example

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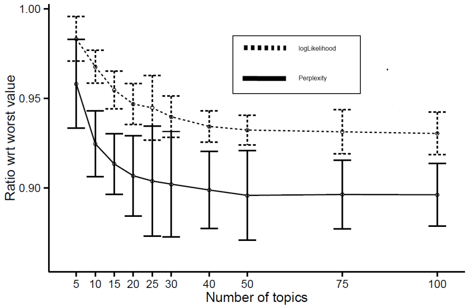
  - An example from my work



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- So you've run LDA and named your topics
- You can use a non-parametric method like loess to establish "significant" changes
- However, your results might not be robust to changing K, or even to re-running LDA with a different random seed!

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  - Exclusivity: if a high probability word is specific to a single topic

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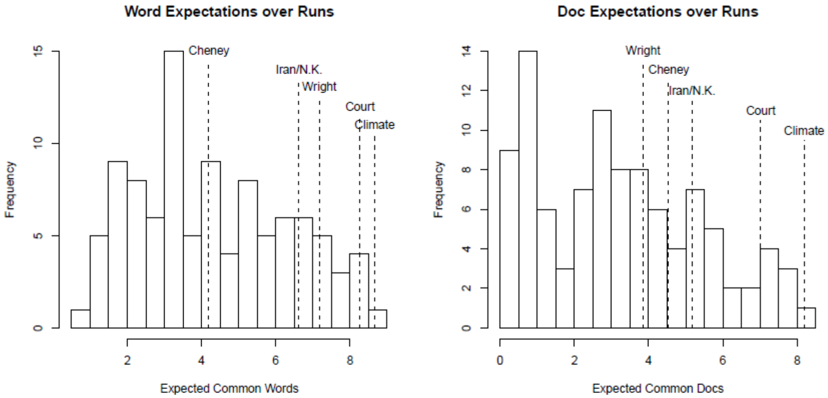
- These are open problems in the field, just to be aware of–but don't use LDA and focus on a single topic without being careful!

Topic Stability: Figure 4 from Roberts, Stewart, and Tingley (2014)

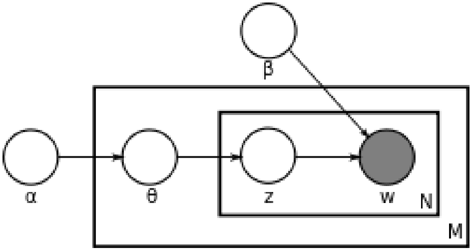


Let's give it a try–AGAIN

- Go to `https://github.com/kmunger/Topic_Models` and find the R file STM.R
- This model takes a while to run, so let's get it started before we talk about it

LDA–changing assumptions

- Assumptions of LDA:



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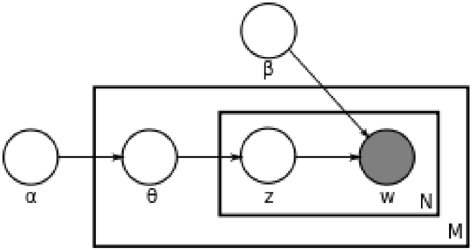

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- They have a package on CRAN, and it's been integrated into later topic models

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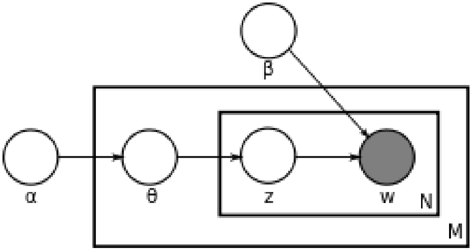

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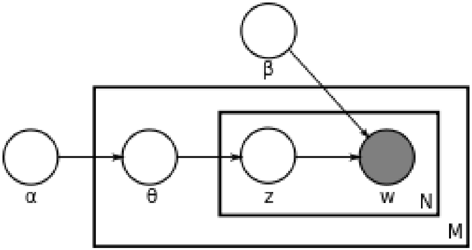

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  - Thus, too many topics is better than too few

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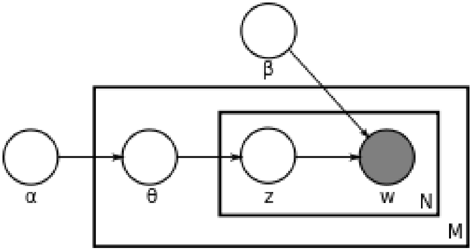

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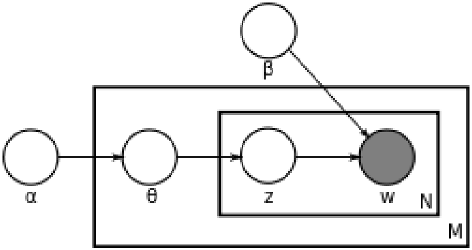

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- This is akin to sentiment models that don't incorporate negation
- The problem is that NLP software is difficult to install and use, and often doesn't work well without hand-processing

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- It *also* has a strong addition to the problem of multimodality–spectral initialization

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  - Works best on large document sets
  - Eats up memory–can't be used for vocabularies over 10,000 words

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- Obviously, this is harder than downloading an R package
- There are specific applications for which people have designed excellent topic models; don't reinvent the wheel

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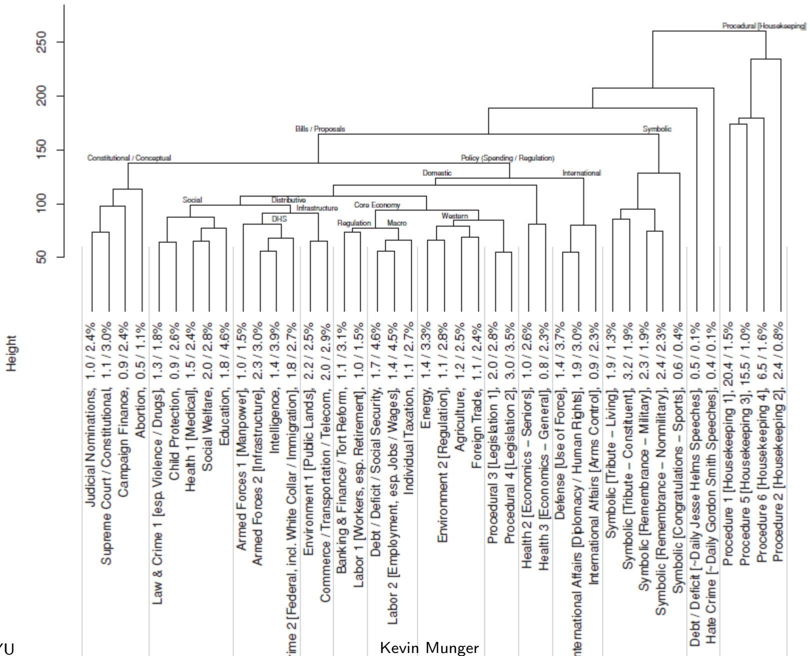
- They take the process of topic validation very seriously
- They also find that topics are clustered hierarchically

FIGURE 1 Agglomerative Clustering of 42-Topic Model



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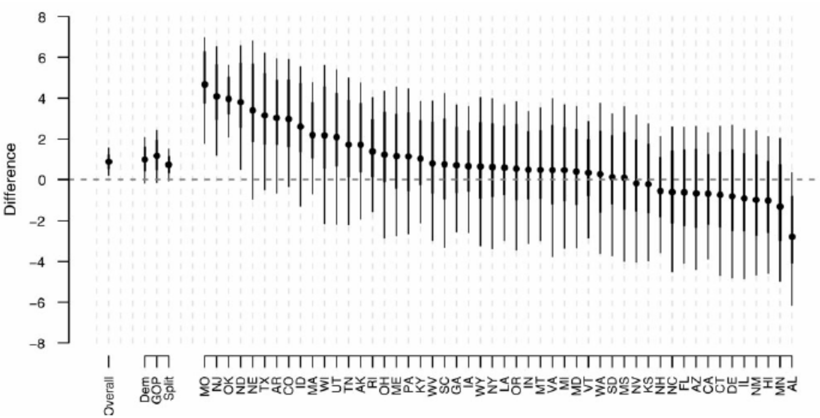
- The crucial difference in the model is that documents are clustered at the author level
- Also excellent work in the paper validating the results


Difference
8
6
4
2
0
−2
−4
−6
−8
Overall
Dem
GOP
Split
MO NJ OK ND NE TX AR CO ID MA WI UT TN AK RI OH ME PA KY WV SC GA IA WY NY LA OR IN MT VA MI MD VT WA SD MS NV KS NH NC FL AZ CA CT DE IL NM HI MN AL

Thanks!

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