10. Topic Models II: Beyond LDA (flipped)

DS-GA 1015, Text as Data
Arthur Spirling

April 20, 2021

Housekeeping

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But topic prevalence and topic content are $f(X)$ [STM]

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CTM "CTM is able to model that a session discussing teachers is more likely to also discuss education than energy" Generally, CTM outperforms LDA (in holdout likelihood sense), and supports more topics.

Results

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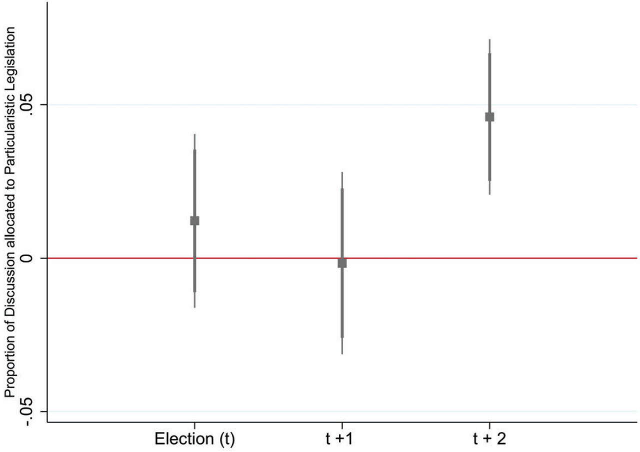

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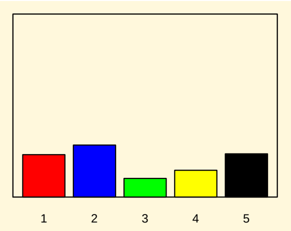

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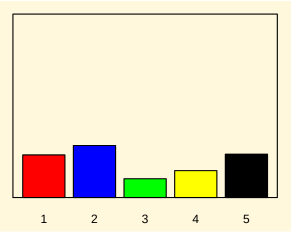

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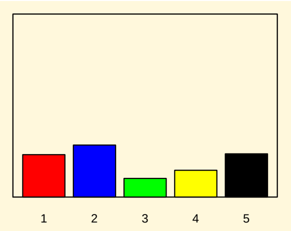

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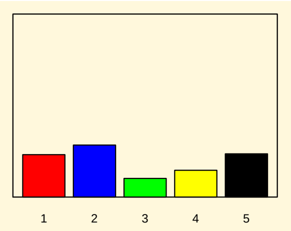

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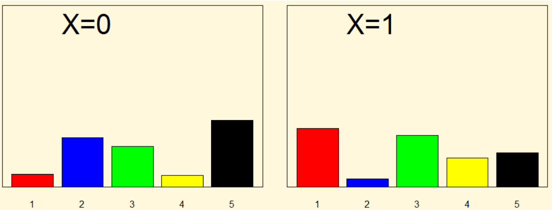

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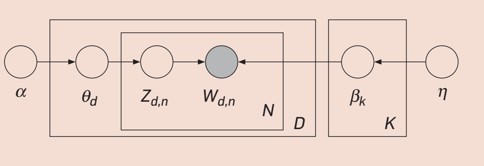

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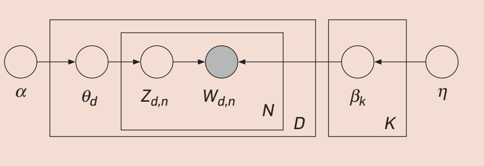
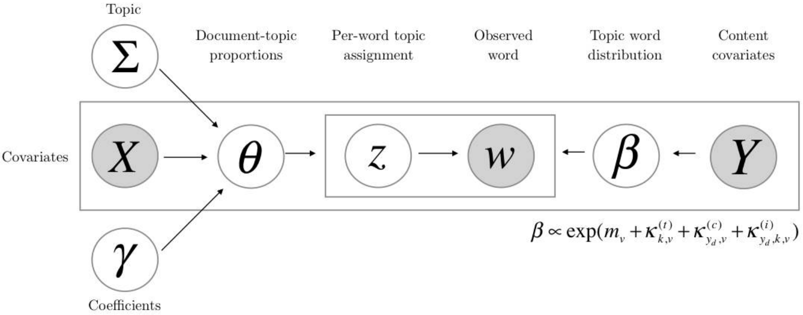


α
θ_d
$Z_{d,n}$
$W_{d,n}$
N
D
β_k
K
η



Topic
Document-topic proportions
Per-word topic assignment
Observed word
Topic word distribution
Content covariates
Covariates
Coefficients
$\beta \propto \exp(m_v + \kappa^{(t)}_{k,v} + \kappa^{(c)}_{y_d,v} + \kappa^{(i)}_{y_d,k,v})$

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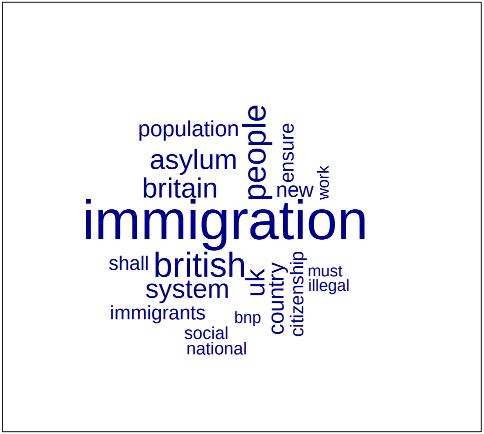

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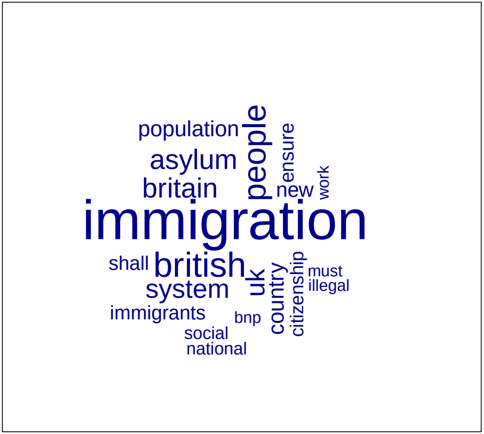

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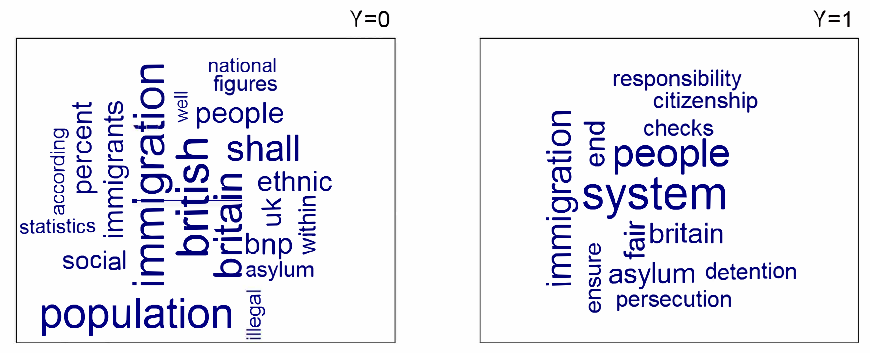

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$\rightarrow$ generally seems the case that people are more interested in prevalence than content effects.

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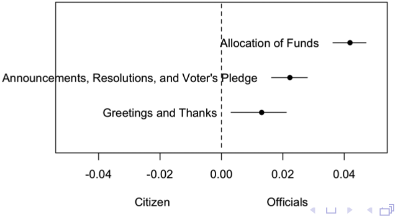

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3. Are the ‘effects’ in the STM causal? If not, why not, and can you give a scenario where they would be?

Embeddings

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What is a ‘one hot encoding’?

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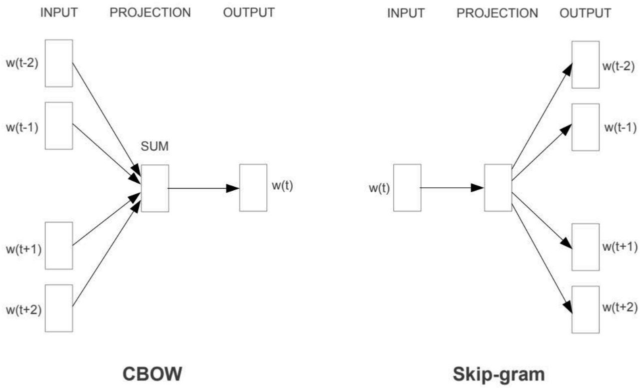

CBOW Schematic

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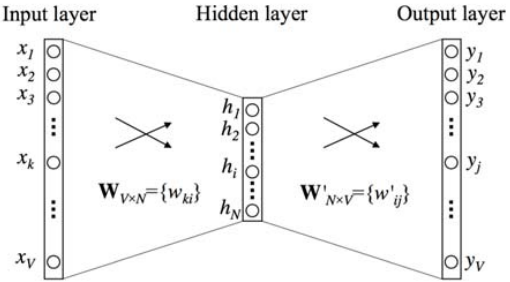

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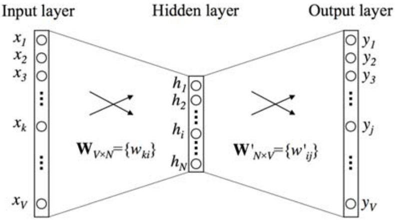

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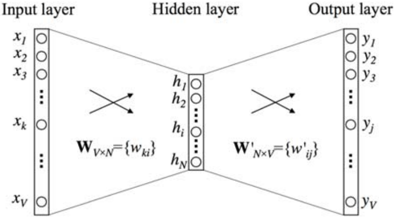

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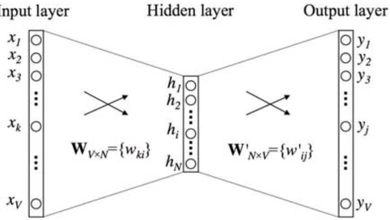

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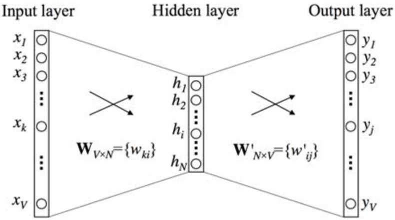

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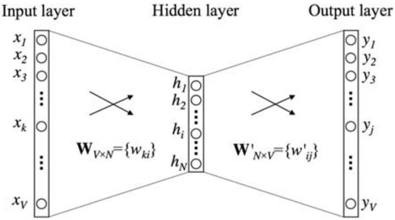

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Imagine creating a large matrix of the words $\times$ contexts in which they are found (other words), and then factorizing that matrix.

Some evidence GloVe is more stable and does better on some tasks.

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Various other pre-trained versions out there, and you can fit your own (locally).

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2 The downloadable embeddings for both W2V and GloVe were trained in 2013/4. Does this matter?

Can you give an example of a word that had a specific meaning then but a different one before or after that time?

Analogies

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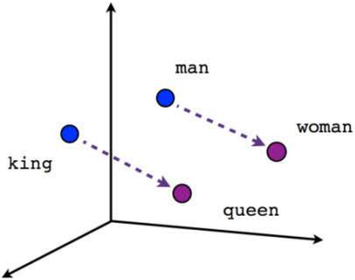
$$v_{\text{queen}} - v_{\text{woman}} + v_{\text{men}} \approx v_{\text{king}}$$



Male-Female

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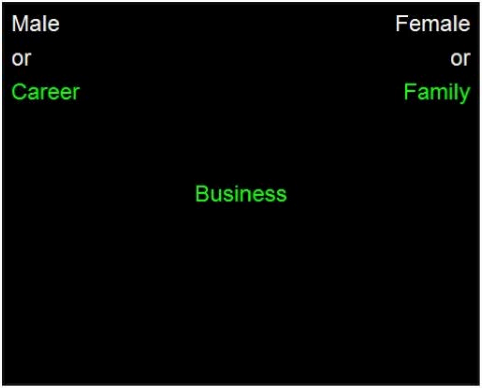

Matching to Real World Data

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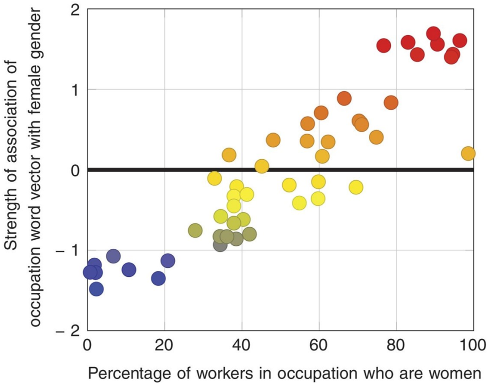
Can use word embeddings distances to predict real-world participation in various occupations.



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1. How do we know whether a word embedding vector is a good representation or not? How could we test the merits of one particular model versus another?

2. Embeddings reflect cultural biases. What does this mean for our work? What should we do about this?

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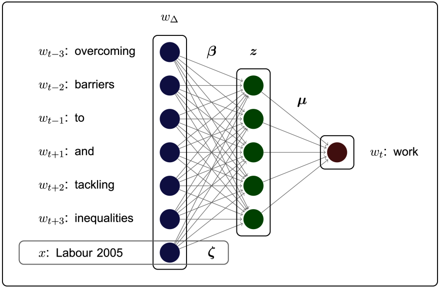
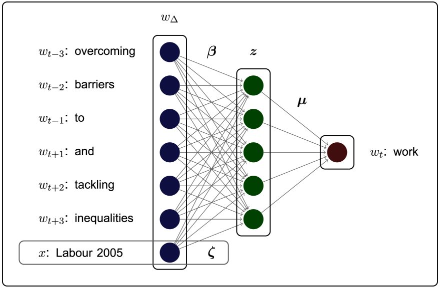
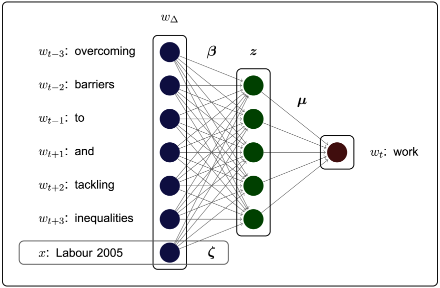


Using metadata: Rheault and Cochrane, 2020



We can add covariates into our embeddings.

Using metadata: Rheault and Cochrane, 2020



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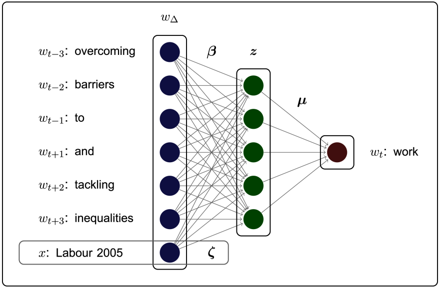
Here, ζ is an indicator for party-year. And is of the same dimensions as the embeddings themselves.

Using metadata: Rheault and Cochrane, 2020



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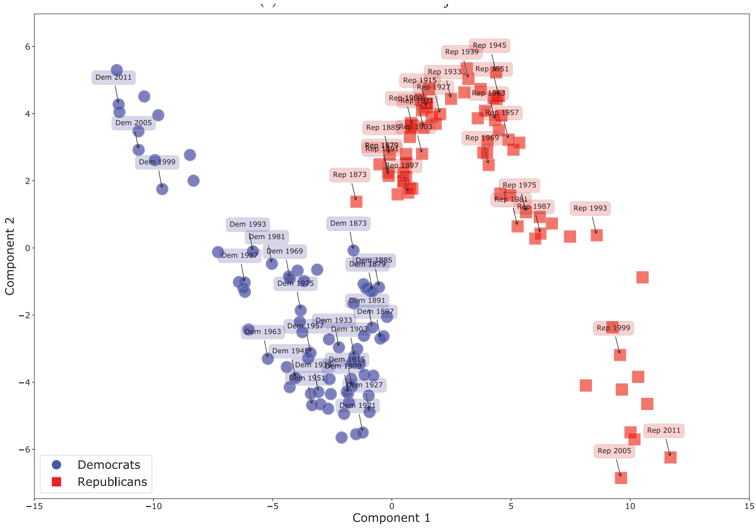
Here, ζ is an indicator for party-year. And is of the same dimensions as the embeddings themselves.

We can do a data reduction (e.g. PCA) on that matrix of ζs and then e.g. plot its dimensions. . .

Results for US



Results for UK