13. Topics in Embeddings (flipped)

DS-GA 1015, Text as Data
Arthur Spirling

May 4, 2021

Housekeeping

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1 Homework coming in today May 4, 2021, at 11pm.

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4 Evaluations

Self-Promotion

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Big Picture(s)

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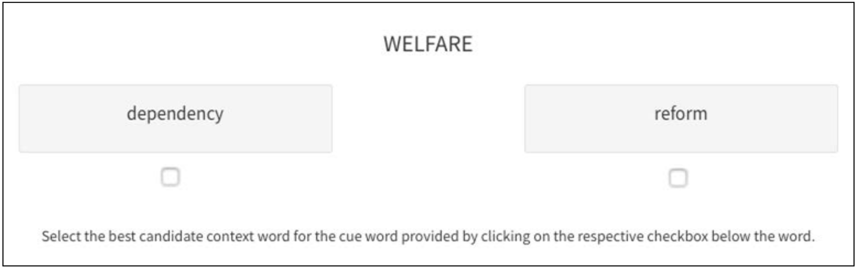
Which one of these portraits is more realistic?


WELFARE
dependency
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Select the best candidate context word for the cue word provided by clicking on the respective checkbox below the word.

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As with all such representational strategies (topic models, TF-IDF), there are (literally thousands) of modeling options available...

How should political scientists choose among them?

Why do we ask?

$\boxed{\textbf{How should political scientists choose among them?}}$

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So, embeddings are **only** useful to the extent they capture semantically meaningful information about politics: focus on 'intrinsic' evaluation criteria.

But how can we evaluate this?

The Solution

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We get remarkable, human-like performance from embeddings models in terms of meaning. ✓

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Avoid small windows, few dimensions but otherwise results are robust to these parameter choices. ✓

Pretrained embeddings work about as well as anything else. ✓

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GloVe appears to be more robust than Word2vec, but both are equally liked by humans. ✓

Implementing Choices

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For each pair we estimate 10 sets of embeddings (250 in all).

Also compare to `GloVe` and `Word2Vec` (skip-gram) pretrained.

Evaluation Criteria

technical criteria: model loss and computation time.

model variance (stability): within-model Pearson correlation of nearest neighbor rankings across multiple initializations.

query search ranking correlation: Pearson and rank correlations of cosine similarities.

human preference: a “Turing test” assessment and rank deviations from human generated lists.

Corpora

Corpus	Period	Docs.	Tokens	Tok/Doc.	Vocab
Congressional Record	1991-2011	1.4M	3.4×10^8	238	92k
Hansard	1935-2013	4.3M	7.2×10^8	162	79k
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Here we will focus on: Congressional Record and `GloVe`.

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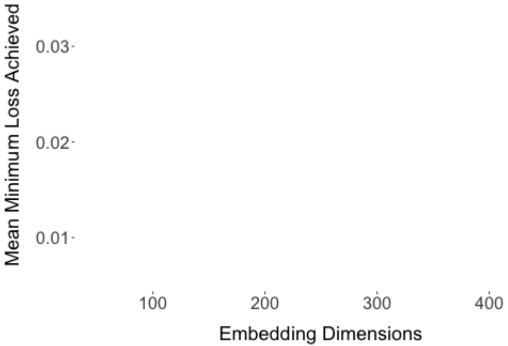

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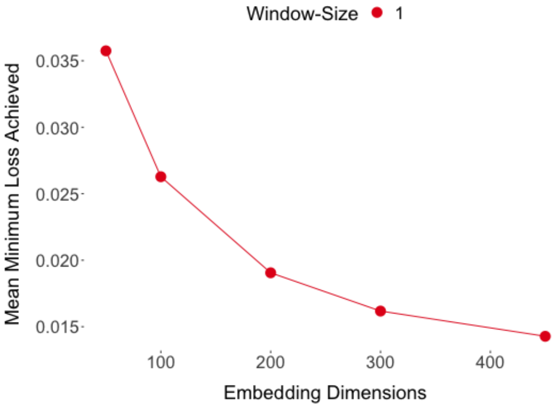

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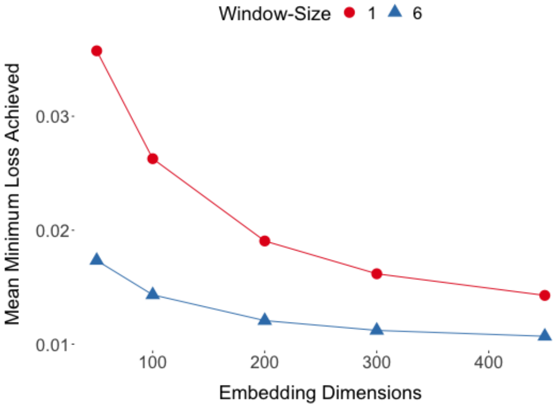

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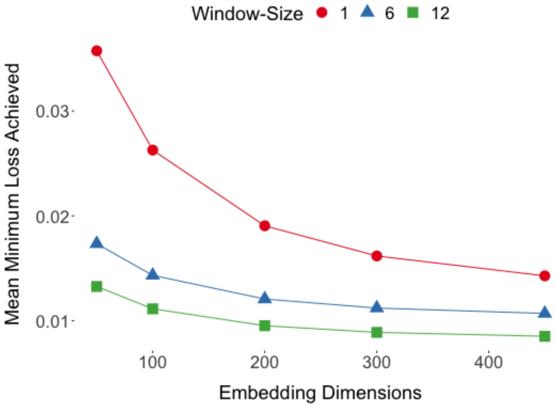

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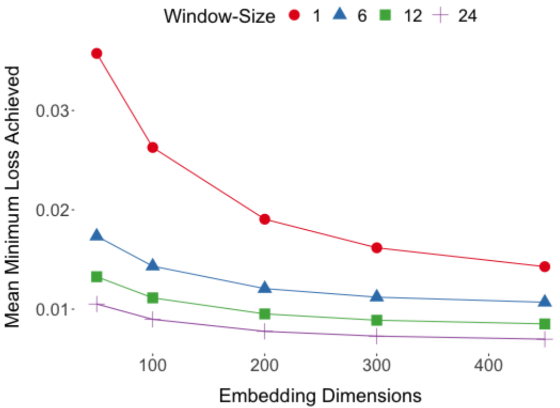

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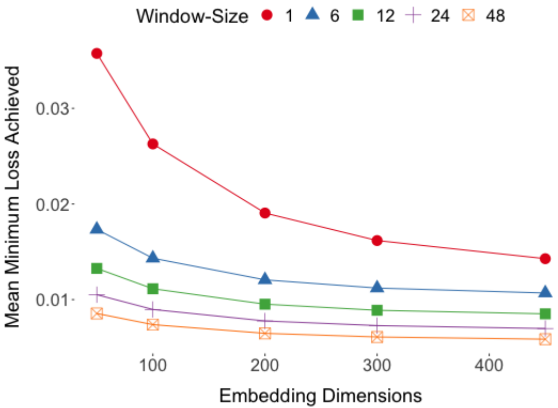

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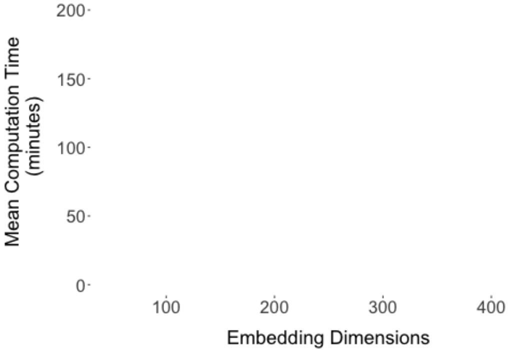

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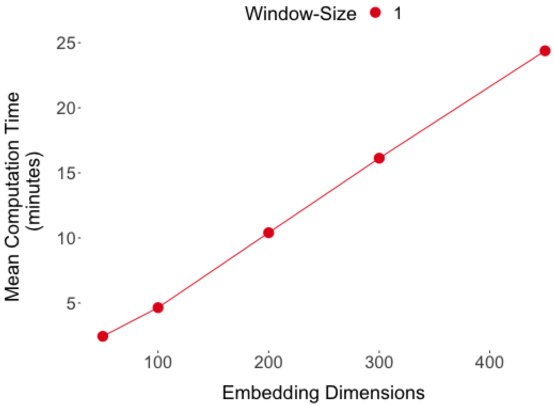

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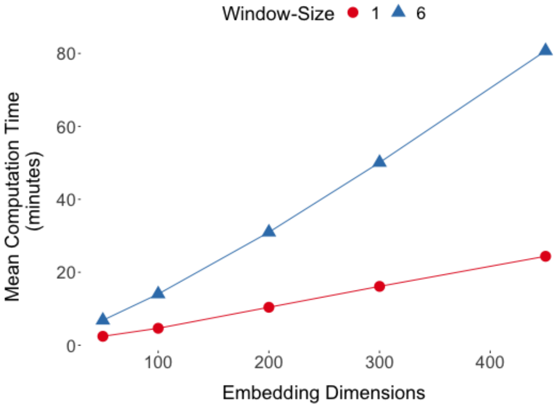

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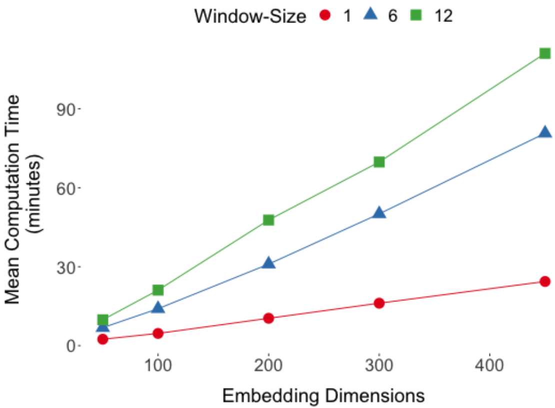

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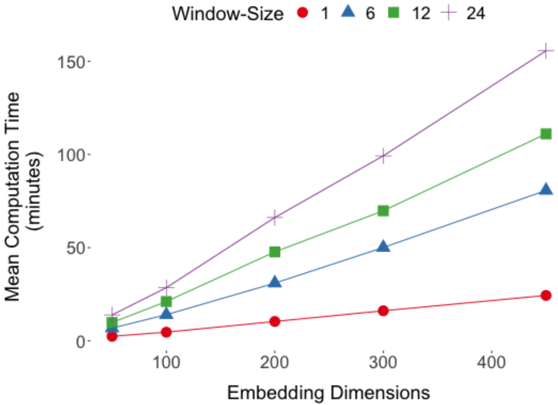

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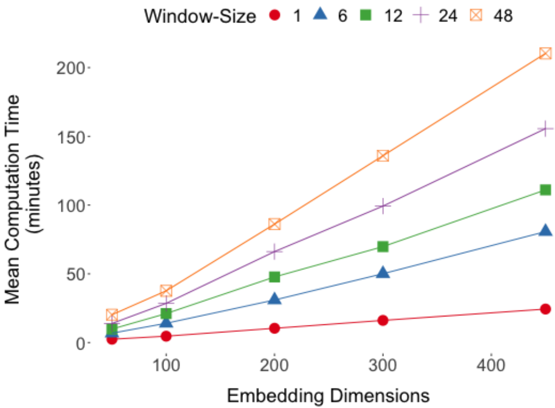

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We cannot compare the two directly.

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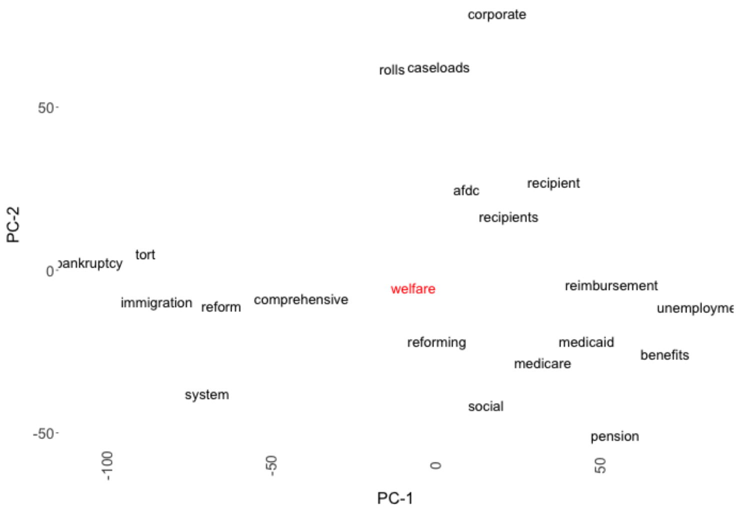
```

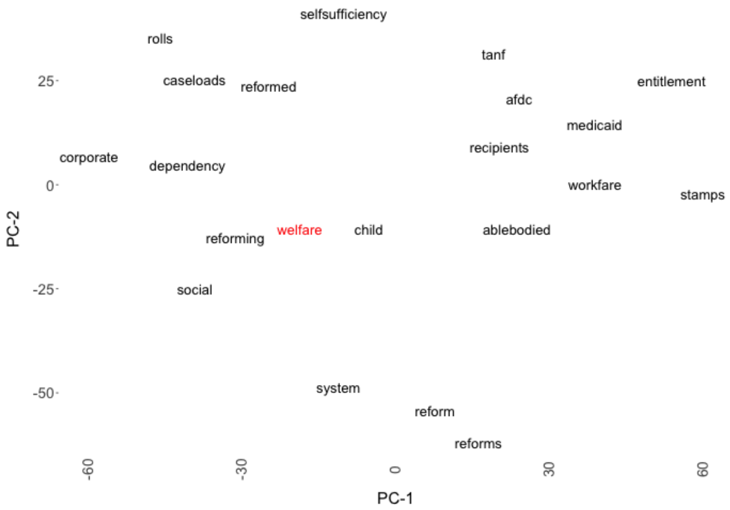
As queries we use:

- 100 randomly chosen terms from vocabulary.
- 10 curated politics terms: `democracy`, `freedom`, `equality`, `justice`, `immigration`, `abortion`, `welfare`, `taxes`, `republican`, `democrat`.

Visually (1-50)



Visually (6-300).



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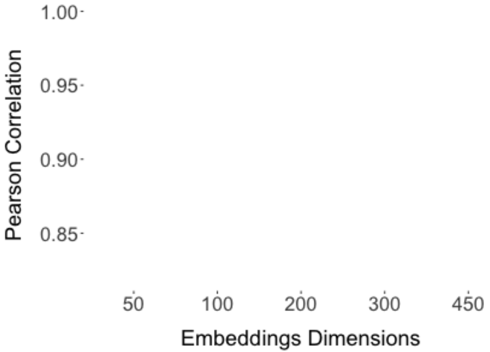
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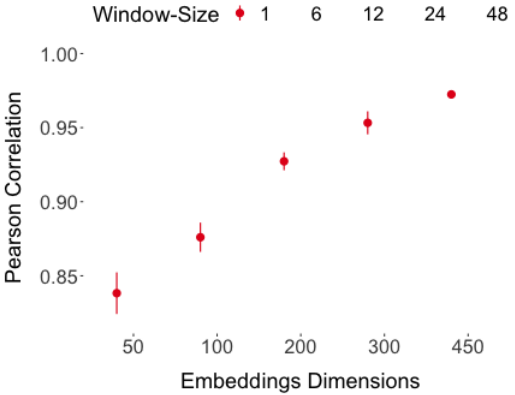
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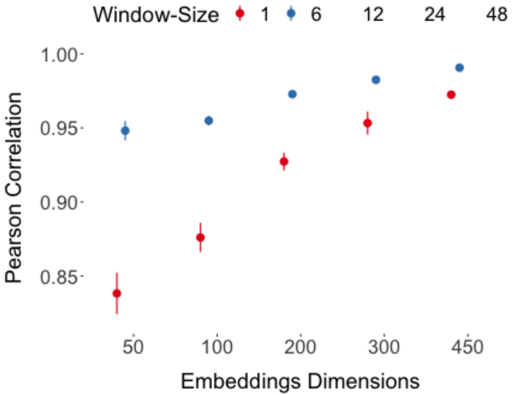
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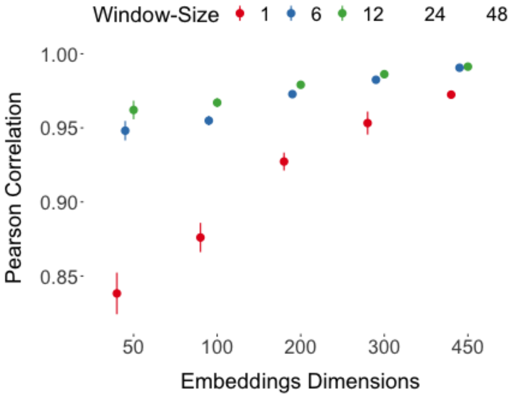
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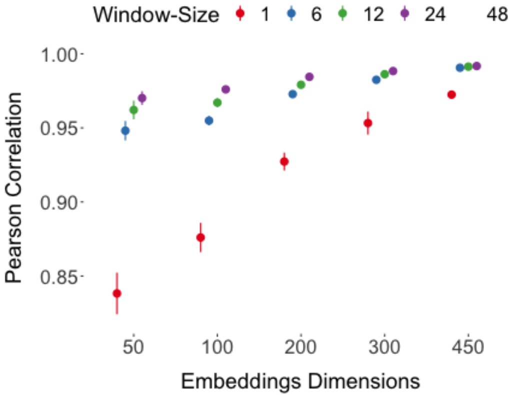

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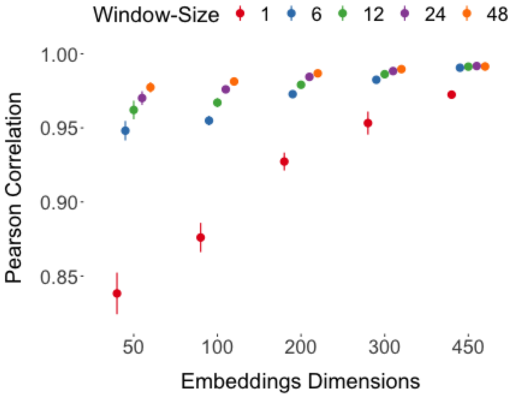

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Query Search Correlations (curated queries)

	1_50	1_300	1_450	6_50	6_300	6_450	48_50	48_300	48_450	pretrained
pretrained										1
48_450									1	0.7
48_300								1	1	0.7
48_50							1	0.94	0.94	0.7
6_450						1	0.88	0.92	0.93	0.68
6_300					1	0.99	0.88	0.92	0.92	0.68
6_50				1	0.88	0.87	0.91	0.83	0.83	0.65
1_450			1	0.71	0.77	0.78	0.74	0.77	0.77	0.6
1_300		1	0.98	0.71	0.77	0.77	0.74	0.76	0.76	0.59
1_50	1	0.82	0.81	0.7	0.66	0.66	0.65	0.64	0.64	0.52

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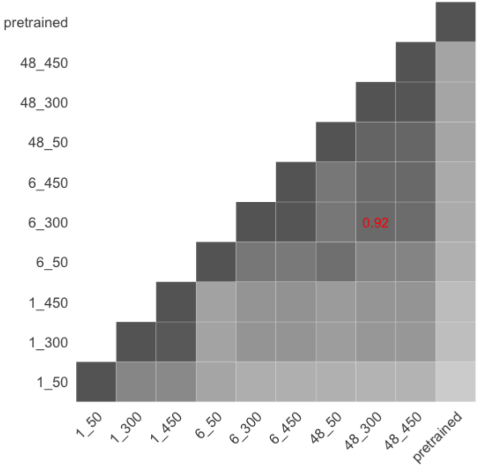

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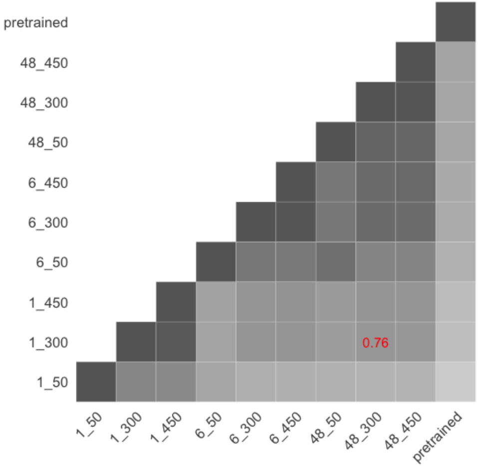

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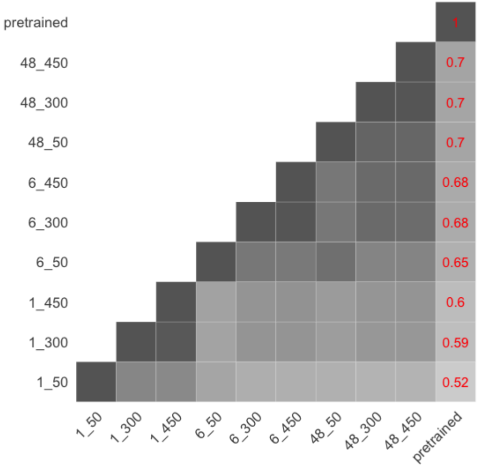

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RShiny App: Definitions

Context Words

A famous maxim in the study of linguistics states that:

You shall know a word by the company it keeps. (Firth, 1957)

This task is designed to help us understand the nature of the ''company'' that words ''keep'': that is, their CONTEXT.

Specifically, for a CUE WORD, its CONTEXT WORDS include words that:

- Tend to occur in the vicinity of the CUE WORD. That is, they are words that appear close to the CUE WORD in written or spoken language.

AND/OR

- Tend to occur in similar situations to the CUE WORD in spoken and written language. That is, they are words that regularly appear with other words that are closely related to the CUE WORD.

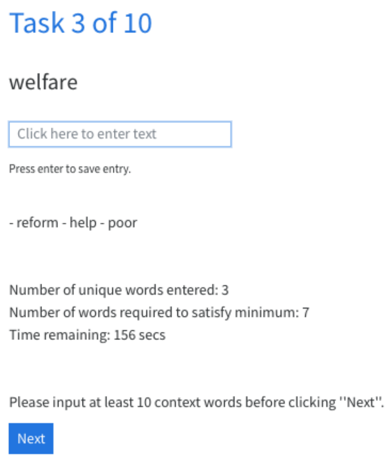
For example, CONTEXT WORDS for the cue word COFFEE include:

1. *cup* (tends to occur in the vicinity of COFFEE).
2. *tea* (tends to occur in similar situations to COFFEE, for example when discussing drinks).

Click ''Next'' to continue

Next

RShiny App-1: Context Word Generation



RShiny App-2: "Turing" Context Word Evaluation

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WELFARE

dependency

reform

Select the best candidate context word for the cue word provided by clicking on the respective checkbox below the word.

Click "Next" to continue

Next

RShiny App-2: “Turing” Context Word Evaluation

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Machine: 1 - Human: 0

Candidate: Local 6-300
Baseline: Human

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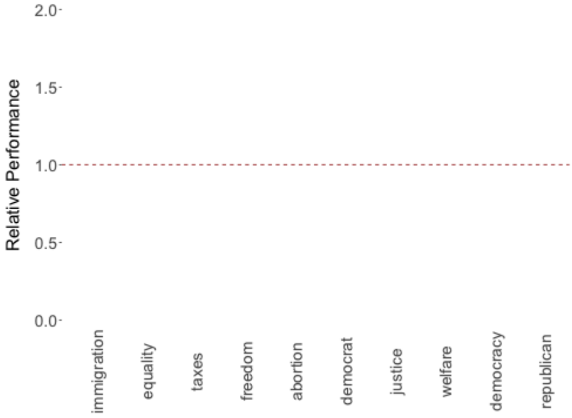

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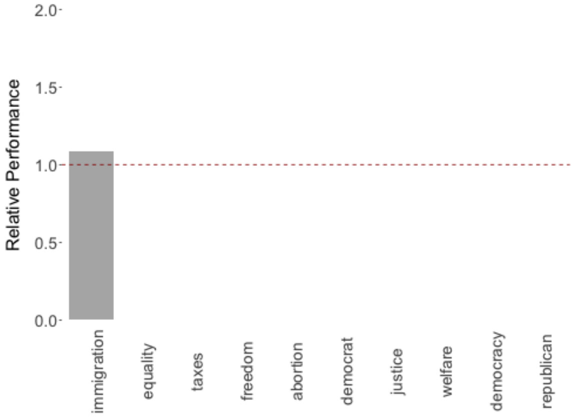
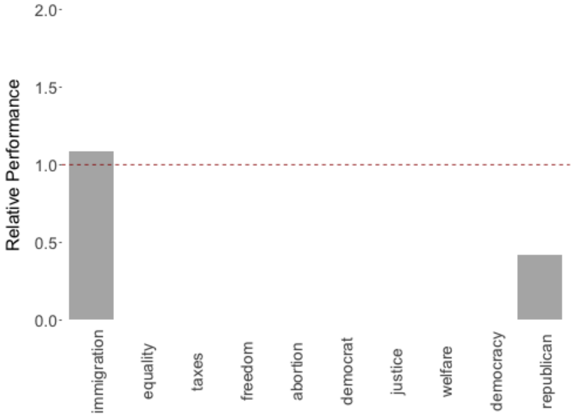


Candidate: Local 6-300
Baseline: Human



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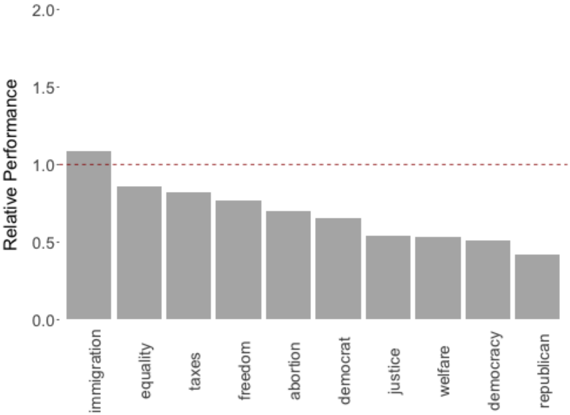

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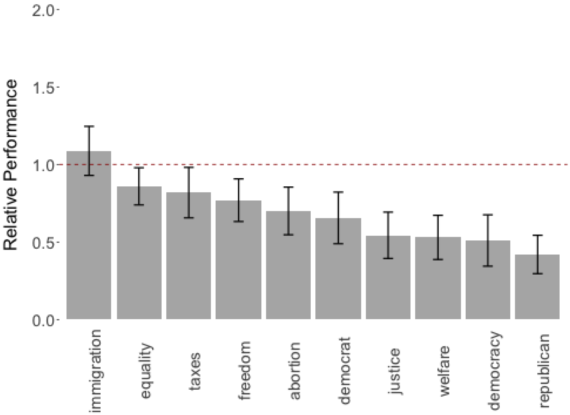

Candidate: GloVe pretrained
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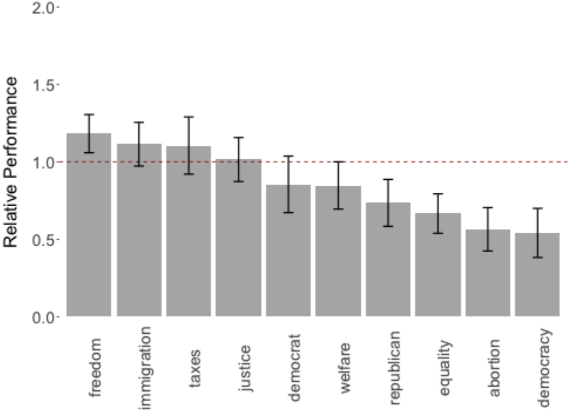
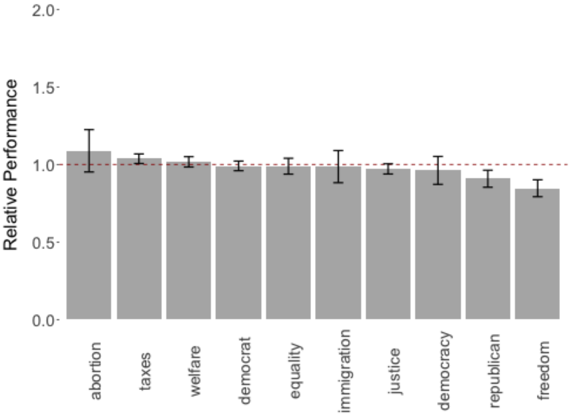


Candidate: Local 48-300
Baseline: Local 6-300



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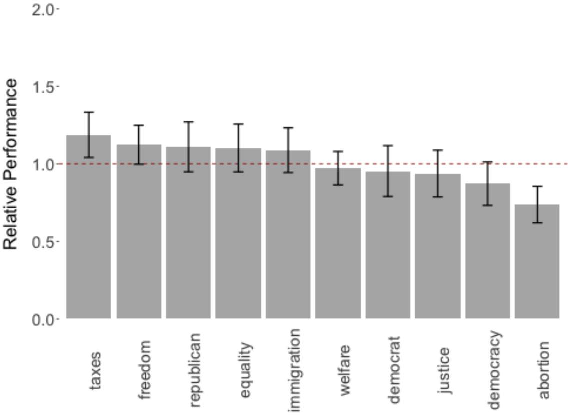
We find this **not** to be the case but humans seem to not care.

Candidate: `GloVe` pretrained
Baseline: `W2V` pretrained



Embedding Regression

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where X_1 and X_2 are group memberships (or something more continuous)

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where D is the dimension of the vector, and we have n such incidences of that word in our corpus (and each one is embedded).

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$$y_i = \left[-0.62, \quad -1.46, \quad 0.58, \quad \cdots \quad -1.82, \quad 0.31, \quad -0.27\right]$$

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taking the mean of the embeddings for `voted`, `on`, `the`, `and`, `it`, `passed` will yield an embedding for `bill`.

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Can be learned quite easily from a large corpus, and only needs to be estimated once. Then each new embedding ($\mathbf{v}_w$) is obtained **a la carte**, assuming you have the context.

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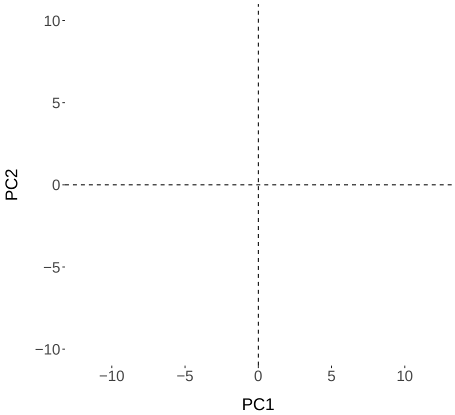

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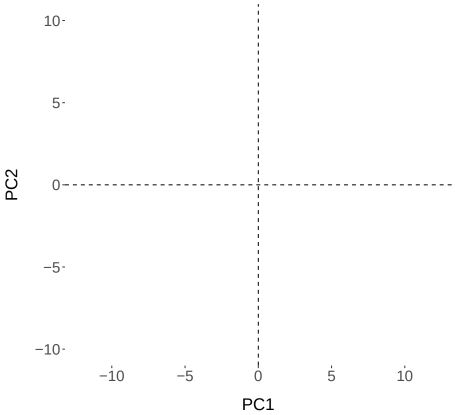

"...that painted *a* deeply unflattering picture *of* president Trump but stopped short *of* accusing him *of* criminal..."

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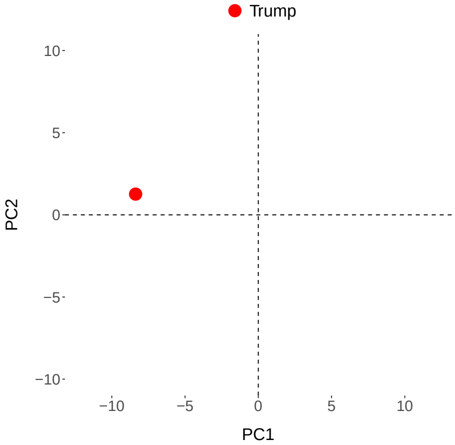

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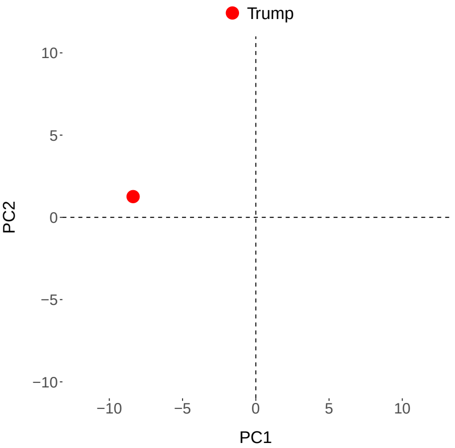

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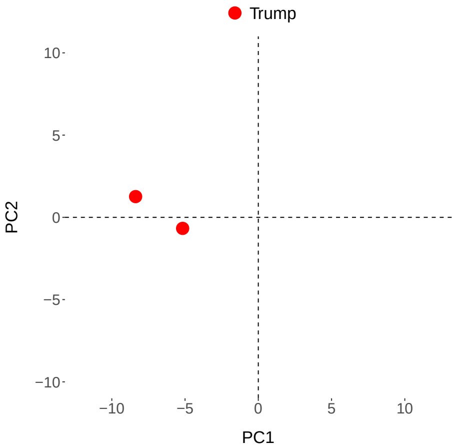

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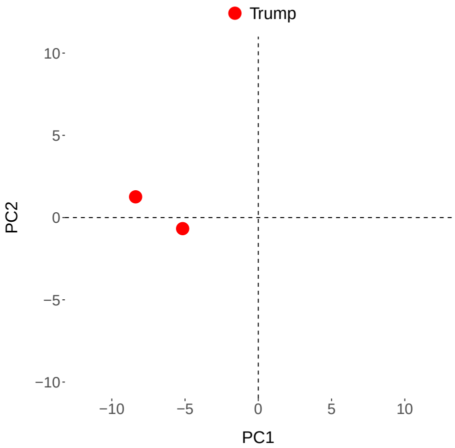

"...raise two spades superior rebid `trump` one since north has three strong spades..."

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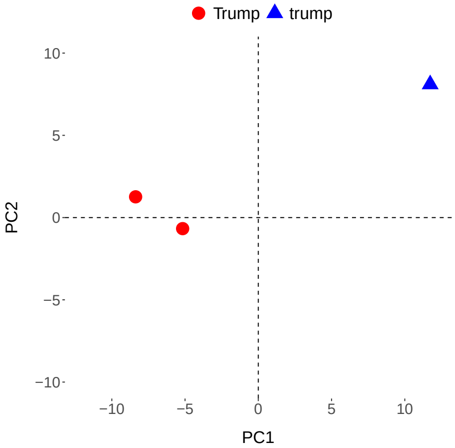

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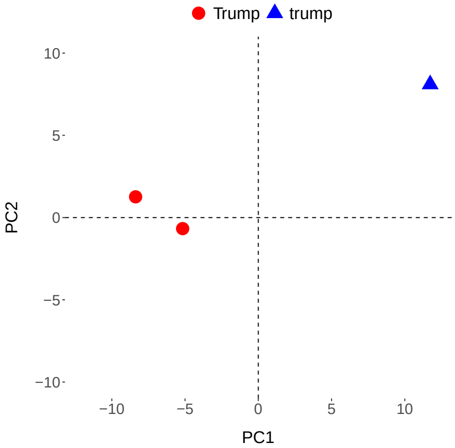

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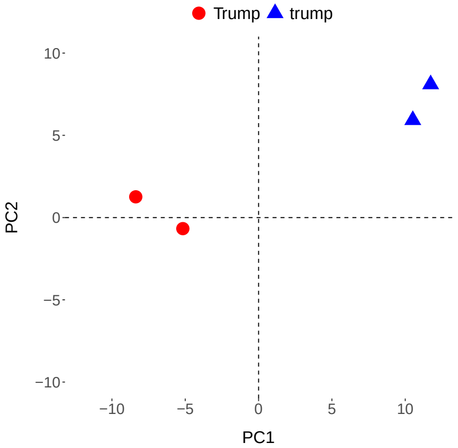

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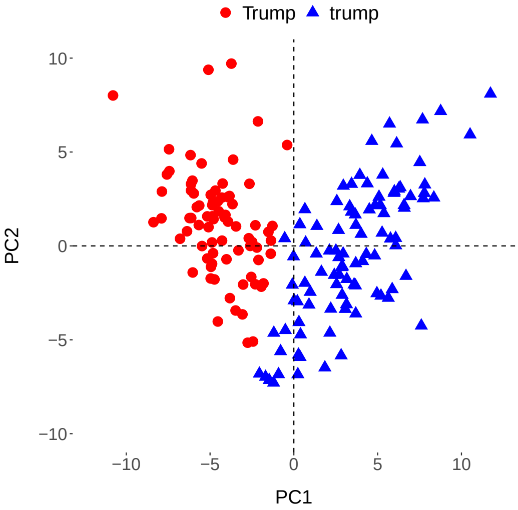

And they make sense.

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Trump		trump	
untransformed	**transformed**	**untransformed**	**transformed**
but	biden	but	declarer
that	upbraided	only	spades
even	barack	that	trumps
because	obama	one	rebid
the	presidential	they	overcall
not	rhetoric	not	bidder
would	bellicose	well	bids
what	inauguration	same	bidding
when	elect	this	anthropocentrism
this	impeachment	both	obeyed

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...and Group R is an indicator variable capturing group membership, equal to 1 if i is a member of group R, 0 otherwise.

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Can quantify uncertainty with permutation test.

Application: Partisan Differences

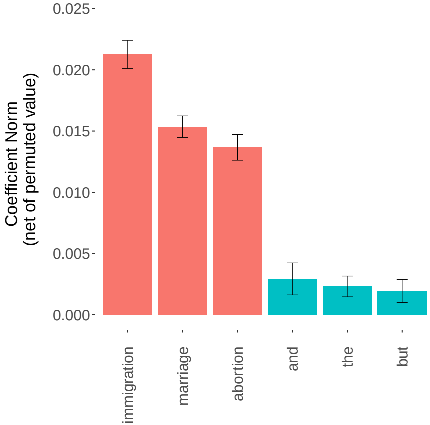


Figure: Partisan semantic differences using a corpus of the Congressional Record (Sessions 111 - 114).

Case Study 2: The Meaning of Empire

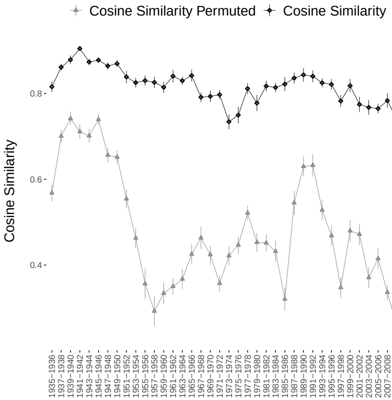


Figure: Distance between British and American understanding of `Empire`, 1935–2010. As corpora we use Congressional Record and Parliamentary Speeches (Hansard).

Application: The Meaning of Empire

US	UK
colonial	british
germany	colonial
france	australia
german	britain
italy	kingdom
british	territories
australia	overseas
french	colonies
colonies	countries
territory	whole

(a) 1945–46

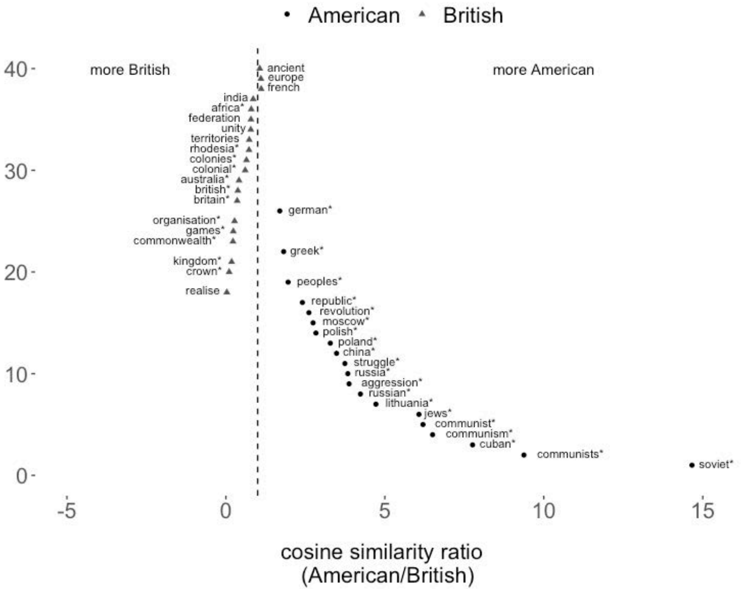
US	UK
communist	british
russian	colonial
soviet	commonwealth
lithuania	colonies
communism	territories
russia	britain
moscow	australia
republic	india
revolution	rhodesia
communists	countries

(b) 1957–58

Table: Meaning of `Empire`: post-war and 1950s

‘Most’ UK vs US NNs (1950s)

'Most' UK vs US NNs (1950s)



Software: `ConText`

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So, something like. . .

```
model1 <- conText(target ~ party + gender, corpus = cr_corpus,
     bootstrap = TRUE, num_bootstraps = 20, groupby = c("party
    ", "gender"), permute = TRUE, num_permutations = 100,
    window = 6, valuetype = "fixed", case_insensitive = TRUE,
    hard_cut = FALSE, verbose = FALSE)
```

Thank You!