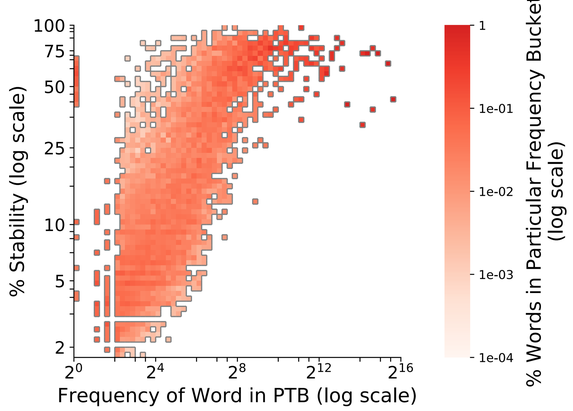
Factors Influencing the Surprising Instability of Word Embeddings

Laura Wendlandt, Jonathan K. Kummerfeld, Rada Mihalcea

University of Michigan *{wenlaura,jkummerf,mihalcea}@umich.edu*

The Problem

Many common embedding algorithms have large amounts of instability.



- Why do medium-frequency words have a huge variance in stability?
- What factors affect stability?

What is Stability?

Stability = *percent overlap between ten nearest neighbors in an embedding space*

$$\text{stability} = \frac{100}{|\text{words}|} \sum_{\text{words}} \frac{\text{neighbors}_0 \cap \text{neighbors}_1}{10}$$

- **neighbors$_0$** = ten words most similar to the word in embedding space 0
- **neighbors$_1$** = ten words most similar to the word in embedding space 1

Example: ***international*** *in 2 embedding spaces*

Stability = 40%

Model 1	*Model 2*
metropolitan	ballet
national	**metropolitan**
egyptian	bard
rhode	chicago
society	**national**
debut	state
folk	exhibitions
reinstallation	**society**
chairwoman	whitney
philadelphia	**rhode**

The Model

We build a ridge regression model that aims to predict the stability of a word given: (1) word properties; (2) data properties; and (3) algorithm properties.

Data Used
- New York Times (NYT)— six domains: US, NY, Business, Arts, Sports, All NYT
- Europarl

Algorithms Used
- *word2vec* skip-gram model
- GloVe
- PPMI

Feature	*Weight*
Lower training data position of word W	-1.52
Higher training data position of W	-1.49
Primary POS = Numeral	1.12
Primary POS = Other	-1.08
Primary POS = Punctuation mark	-1.02
Overlap between corpora vocabulary	1.01
Primary POS = Adjective	-0.92
Primary POS = Adposition	-0.92

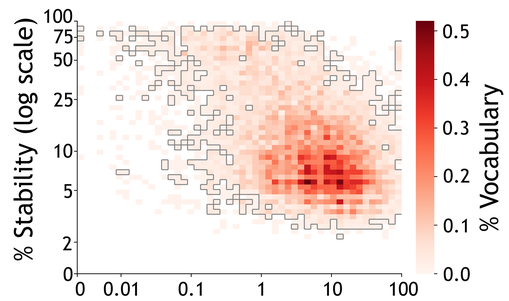
Feature	*Weight*
Do the two domains match?	0.91
Primary POS = Verb	-0.88
Primary POS = Conjunction	-0.84
Primary POS = Noun	-0.81
Primary POS = Adverb	-0.79
Do the two algorithms match?	0.78
Secondary POS = Pronoun	0.62
Primary POS = Determiner	-0.48

Lessons Learned: What Contributes to the Stability of an Embedding

1 *Curriculum learning is important.*

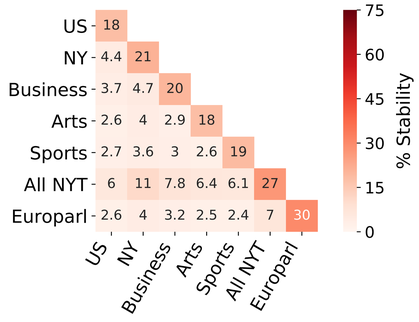
Curriculum learning = *order of training data given to an algorithm*

The top two features (by magnitude) of the regression model capture where the word first appears in the training data.



Stability of word2vec as a property of the starting word position in the training data of the PTB.

2 *Stability within domains is greater than across domains.*

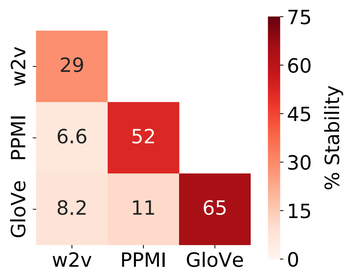


Percent stability broken down by domain.

3 *POS is one of the biggest factors in stability.*

Primary POS	*Avg. Stability*
Numeral	47%
Verb	31%
Determiner	31%
Adjective	31%
Noun	30%
Adverb	29%
Pronoun	29%
Conjunction	28%
Particle	26%
Adposition	25%

4 *Overall, GloVe is the most stable embedding algorithm.*



Percent stability broken down between algorithm (in-domain data only).

5 *Frequency is not a major factor in stability.*

Frequency does correlate with stability. However, in the presence of all of these other features, frequency becomes a minor factor.

Model with frequency:
R^2 score of 0.301

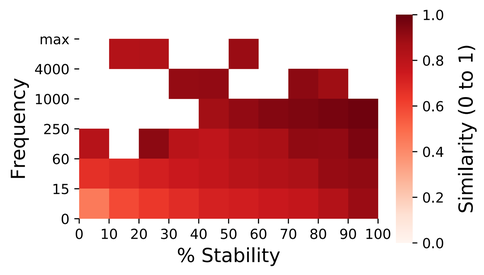
Model without frequency:
R^2 score of 0.301

Model with **only** frequency:
R^2 score of 0.008

6 *Stability affects some downstream tasks.*

Word stability correlates slightly with performance on word similarity tasks.

For POS tagging using an LSTM-based model, the LSTM compensates for instability by shifting unstable word vectors.



Word vector shift, measured as cosine similarity between initial and final vectors.

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