



# GloVe: Global Vectors for Word Representation

Presented at the  
2014 Conference on Empirical Methods in Natural Language Processing.  
Authored by  
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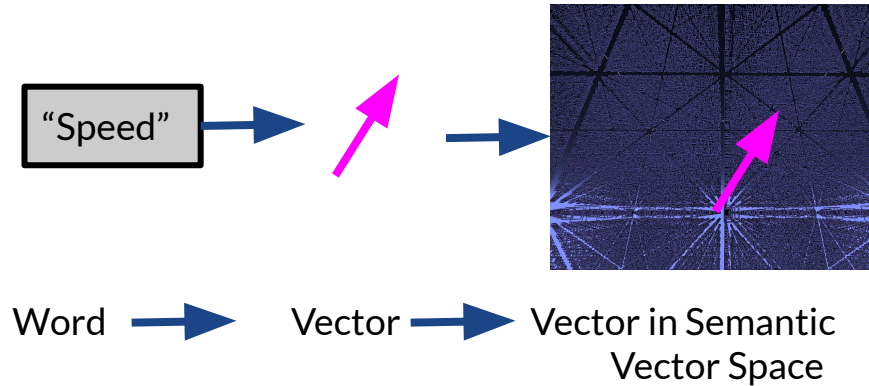
Presented by Chang Ju Kim, Tommy Sanford, Ben Mo, Erik Svetlichny, Tim Budding

# Getting Up to Speed:



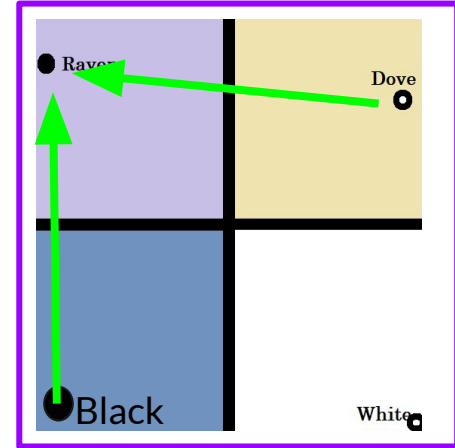
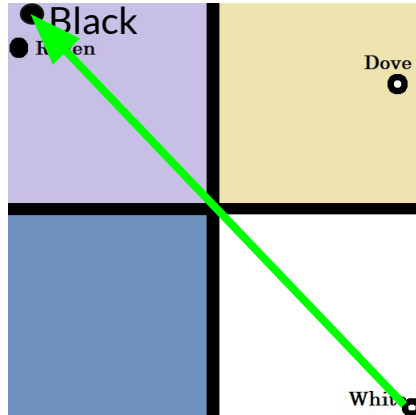
To be able to define words in vector space so that computers can perform complex language tasks using a mathematical framework e.g. solving analogies.

Jargonspeak: want a word vector space with a meaningful substructure.



# Motivating Question

How can we construct a meaningful vector space using a collection of text documents?





# How to evaluate Word Embeddings

Benchmarks tested in the paper

- Word analogy
  - “A is to B as C is to \_\_”
- Word similarity
  - Find how similar two different words are
  - Distance between word vectors should correlate to how similar in meaning the words are
  - Commonly uses cosine similarity
- Named entity recognition
  - Tag entities in text with its type
  - e.g. ConLL-03 - 4 Types: person, location, organization, miscellaneous



# How to evaluate Word Embeddings

## Other evaluators

- Outlier Detection
  - Find words that do not belong
- Concept Categorization
  - Split a group of words into categories
- Part of Speech Tagging
  - Assign part of speech to different words
- Chunking
  - Group words from a sentence into phrases
- Sentiment Analysis
  - Classify text between positive or negative



# Related Work

Two main model categories:

1. Global matrix factorization methods (LSA)
  - a. (+) Uses matrices (so statistical information is easily used)
  - b. (-) Bad at word analogies (what words occur frequent with others)
2. Local shallow window-based methods (skip-gram)
  - a. (+) Great at word analogies (what words occurs frequently with others)
  - b. (-) Needs to scan through the documents (doesn't directly use statistical data)



# Matrix Factorization: Generating the Matrix

Main objective: decompose large matrices containing statistics about text.

Two methods to get the large matrix:

1. Latent Semantic Analysis (LSA):  $n \times d$  matrix
  - Rows: words
  - Columns: # of documents in the corpus
  - Entries: # of times word appears in each document
2. Hyperspace Analogue to Language (HAL):  $n \times n$  matrix
  - Rows: words
  - Columns: words
  - Entries: # of times and how close word<sub>1</sub> appears near word<sub>2</sub>

Getting the matrix allows you to perform computations on it

# Problem with the Matrix

Frequent words are disproportionately large in the matrix.

- E.g. *the* and *and* appear frequently with other words.

Thus, to an article about bananas, it will seem like *the* and *and* are closely associated with bananas despite having little to do with their meaning.

Main workarounds include COALS, PPMI, and HPCA

Article 3 of the US constitution. Has only 378 words, but 27 *the*s and 17 *ands*

## Article III

### Section 1

*The* judicial Power of *the* United States, shall be vested in one Supreme Court, *and* in such inferior Courts as *the* Congress may from time to time ordain *and* establish. *The* Judges, both of *the* supreme *and* inferior Courts, shall hold their Offices during good Behavior; *and* shall, at stated Times, receive for their Services, a Compensation, which shall not be diminished during their Continuance in Office.

### Section 2

*The* Judicial Power shall extend to all Cases, in Law *and* Equity, arising under this Constitution, the Laws of *the* United States; *and* Treaties made, or which shall be made, under their Authority;---to all Cases affecting Ambassadors, other public Ministers *and* Consuls;---to all Cases of admiralty *and* maritime Jurisdiction;---to Controversies to which *the* United States shall be a Party;---to Controversies between two or more States;---between a State *and* Citizens of another State;---between Citizens of different States;---between Citizens of *the* same State claiming Lands under Grants of different States; *and* between a State, or *the* Citizens thereof, *and* foreign States, Citizens or Subjects.

In all Cases affecting Ambassadors, other public Ministers *and* Consuls, *and* those in which a State shall be a Party, *the* Supreme Court shall have original Jurisdiction. In all *the* other Cases before mentioned, *the* Supreme Court shall have appellate Jurisdiction, both as to Law *and* Fact, with such Exceptions, *and* under such Regulations as *the* Congress shall make.

*The* Trial of all Crimes, except in Cases of Impeachment, shall be by Jury; *and* such Trial shall be held in *the* State where *the* said Crimes shall have been committed; but when not committed within any State, *the* Trial shall be at such Place or Places as *the* Congress may by Law have directed.

### Section 3

Treason against *the* United States, shall consist only in levying War against them, or in adhering to their Enemies, giving them Aid *and* Comfort. No Person shall be convicted of Treason unless on *the* testimony of two Witnesses to *the* same overt Act, or on Confession in open court.

*The* Congress shall have Power to declare *the* Punishment of Treason, but no Attainder of Treason shall work Corruption of Blood, or Forfeiture except during *the* Life of *the* Person attainted.



# Window-Based Methods

A different approach that focuses on local context windows.

Current approaches either **predict a word's context given the word**, or **predict a word given the context**.

- **Skip-gram**, **Continuous bag-of-words (CBOW)** (Aka word2vec)
  - Trains a neural network using local windows
  - Uses the probability vector from that neural network
- **vLBL**, **ivLBL** (log bilinear models)
  - Predicts next word by linearly combining the representations of previous/context words
- These schemes end up being fairly good at the analogies task

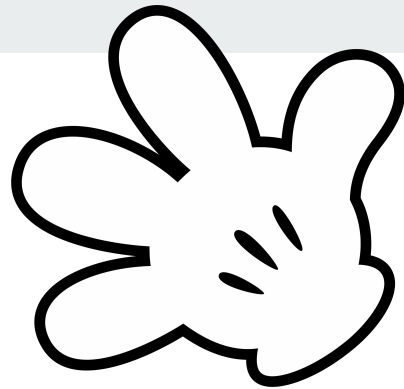
"I [do not like green eggs and ham.] I do not like them, Sam-I-Am."

A window size of 3 centered around 'green'





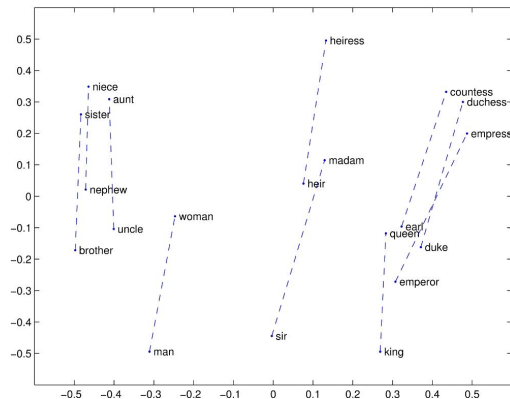
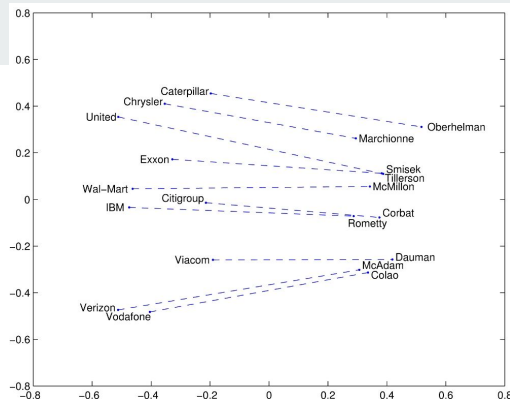
# Introduction to GloVe



- Authors - Jeffrey Pennington, Richard Socher, Christopher D. Manning. 2014
- Developed by the Computer Science Department, Stanford University
- Problem: current models are great at capturing “fine grained semantic and syntactic regularities” but the causes are “opaque.”

# GloVe Model Explained

- Unsupervised ML algorithm for obtaining vector representations for words
- Algorithm incorporates context - other words in close proximity
- Builds a term-term matrix
  - Ex.  $X(i, j)$  gets larger and larger the more the word  $i$  appears in the context of word  $j$





# Correspondence Matrix

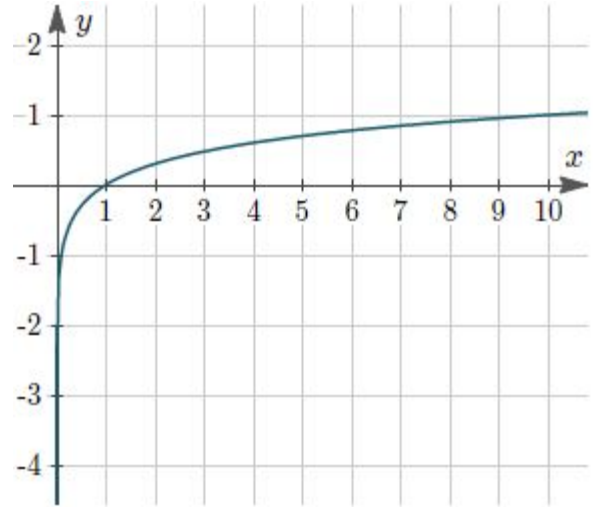
- $s = \text{"machine learning is fun"}$
- $X(\text{machine}, \text{learning}) += 1$
- $X(\text{machine}, \text{is}) += \frac{1}{2}$
- $X(\text{machine}, \text{fun}) += \frac{1}{3}$
- $X(\text{learning}, \text{fun}) += \frac{1}{2}$
- $X$  is usually a sparse matrix
- This pattern continues up to a tolerance levels

$X(i, j) += 1/(\text{dist}(i, j))$  where  $\text{dist}(i, j)$  is the number of positions away  $j$  is from  $i$ .

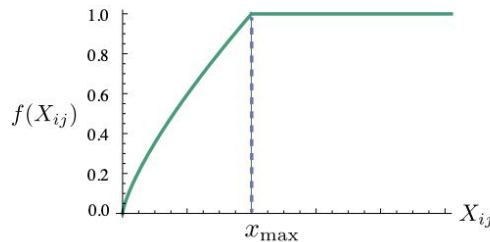
$s$	$s[0]$	$s[1]$	$s[2]$	$s[3]$
$s[0]$	0	1	$\frac{1}{2}$	$\frac{1}{3}$
$s[1]$	1	0	1	$\frac{1}{2}$
$s[2]$	$\frac{1}{2}$	1	0	1
$s[3]$	$\frac{1}{3}$	$\frac{1}{2}$	1	0

# Matrix Scaling

- Values that are non-zero tend to be very large
- To scale down,  $\log(1 + X(i,j))$  becomes the target.



# GloVe Weighting and Equation



- Assign a weight to all  $X(i, j)$  entries

$$f(x) = \begin{cases} (x/x_{\max})^\alpha & \text{if } x < x_{\max} \\ 1 & \text{otherwise} \end{cases}$$

$\alpha = 0.75, X_{\max} = 100$

$$w_i^T \tilde{w}_k + b_i + \tilde{b}_k = \log(X_{ik})$$

- Final loss function:

$$\hat{J} = \sum_{i,j} f(X_{ij}) (w_i^T \tilde{w}_j - \log X_{ij})^2$$



## Model Complexity

$$J = \sum_{i,j=1}^V f(X_{ij})(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij})^2 \quad (8)$$

- Complexity of evaluating the cost function (8) scales with the number of non-zero entries in  $X$  denoted  $|X|$ .
- Worst Case:  $|X| = |V|^2$
- To achieve better bounds we need to make some assumptions!



# Assumptions

Assume that the co-occurrence of word  $i$  with word  $j$  can be modeled using a power-law function of the frequency rank of that word pair, i.e.

$$X_{ij} = \frac{k}{(r_{ij})^\alpha} \quad (17)$$

Where  $r_{ij}$  is the frequency ranking of the word pair  $i$  and  $j$ .

The most frequently occurring pair of words has  $r = 1$ , the second most frequent has  $r = 2$ . etc.





# Implications

Under the assumption on the previous slide we have two cases for  $|X|$  summarized below.

$$|X| = \begin{cases} O(|C|) & \text{if } \alpha < 1, \\ O(|C|^{1/\alpha}) & \text{if } \alpha > 1. \end{cases} \quad (22)$$

The authors say that their corpora are well modeled by  $\alpha = 1.25$  in which case we have

$$|X| = O(|C|^{0.8}).$$



## Experiments - What Can We Test

- Analogies are a common measure of word embeddings, written as

**a:b::c:d**

or, equivalently, “a is to b as c is to d.” Goal is to predict d given a, b, and c.

- Model prediction is given by

$$d = \operatorname{argmax}_{d \in V} \operatorname{sim}(d, b - a + c)$$

Where  $\operatorname{sim}(x, y)$  is a function which measures similarity of vectors, e.g. cosine similarity



# Experiments - Original Paper

- Reported over 70% accuracy on an analogy test set published by Mikolov et al. (2013a)
  - This dataset is heavily biased towards analogies of the form “capital is to country as capital is to country”<sup>(1)</sup> e.g. Paris is to France as Rome is to Italy”
- Our experiments are performed on the “[Bigger Analogy Test Set \(BATS\)](#)” published by Gladkova et al. (2016) using the pretrained GloVe vectors available at ([GloVe: Global Vectors for Word Representation](#))

1. Gladkova et al. (2016)



# Experimental Difficulties

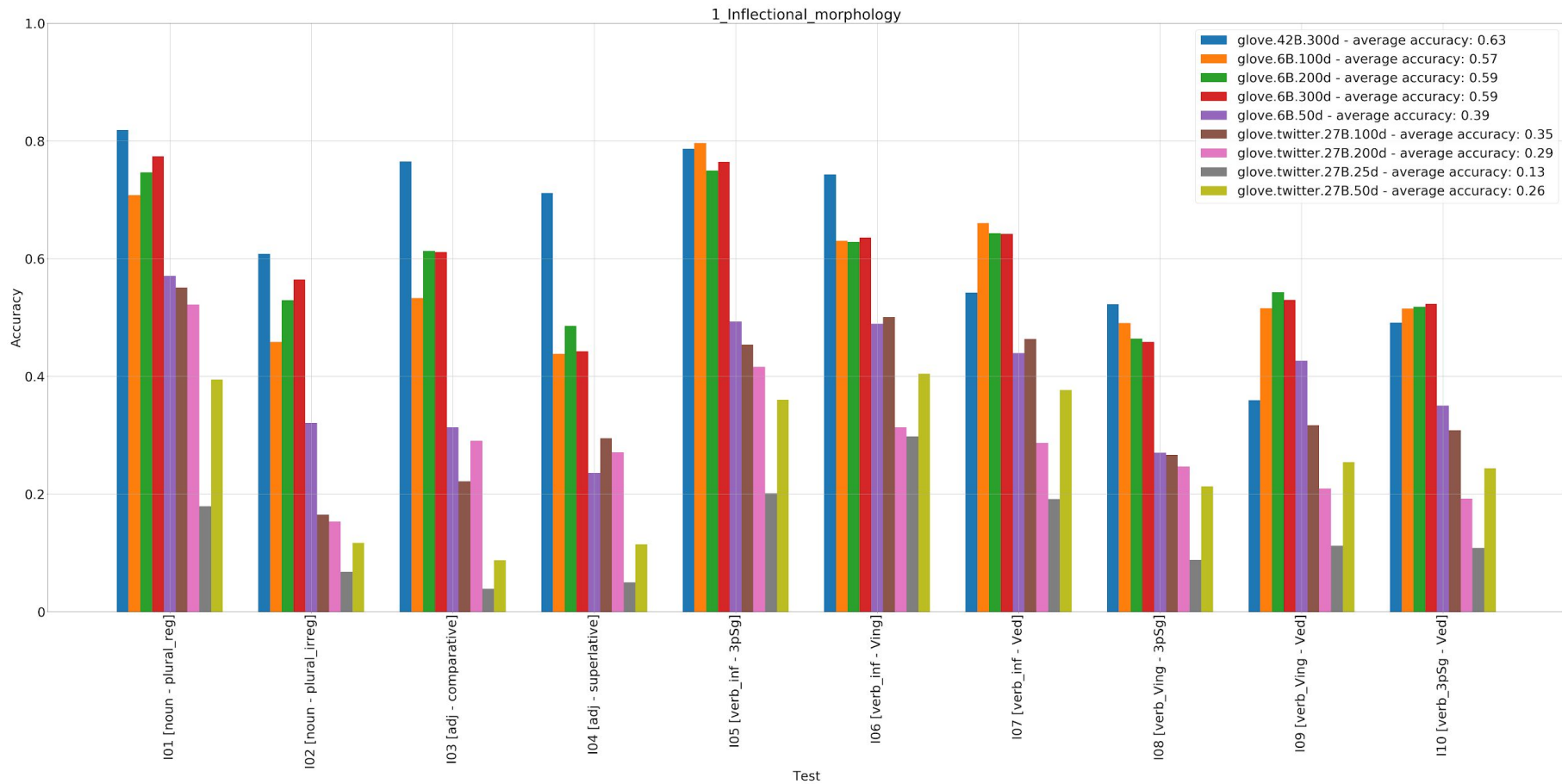
- Tried (and failed) to use open source library “vecto”
- Some of the pretrained vocabularies are LARGE i.e. 2.2. million words each stored as a 300 dimensional vector.
- Analogies can have multiple correct answers which increases difficulty of parsing input files and makes it difficult to use a fixed batch size for computation.



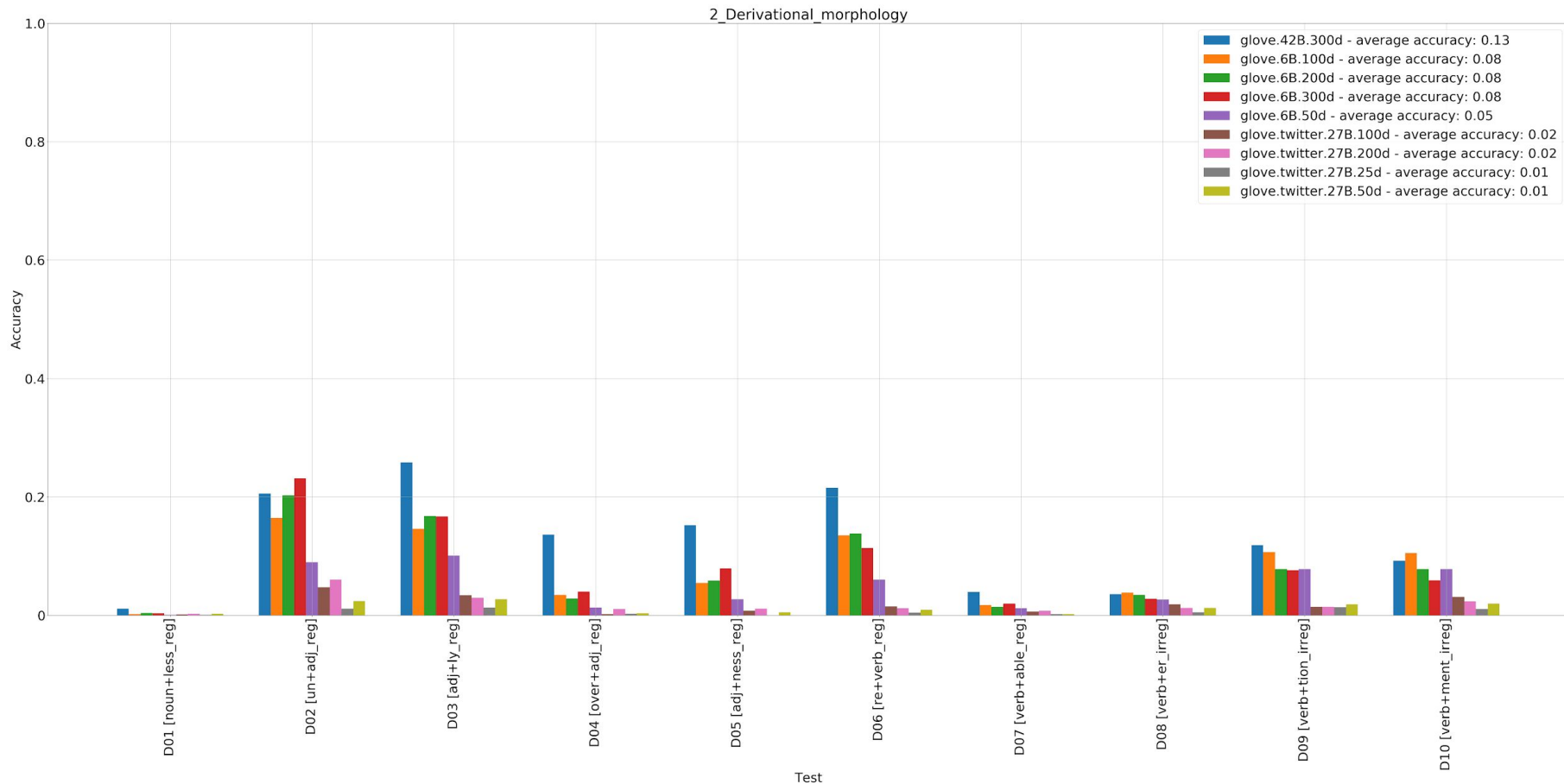
# What We Were Able to Do

- Tested 9 out of 10 of the pretrained GloVe models from (<https://nlp.stanford.edu/projects/glove/>) on most of the analogy test sets in BATS.
- We were unable to test every model against every analogy test set due to limited compute power.
  - For the smaller models we were able to test against >90% of the total analogies
  - For the larger models only tested against ~50% of the total analogies.

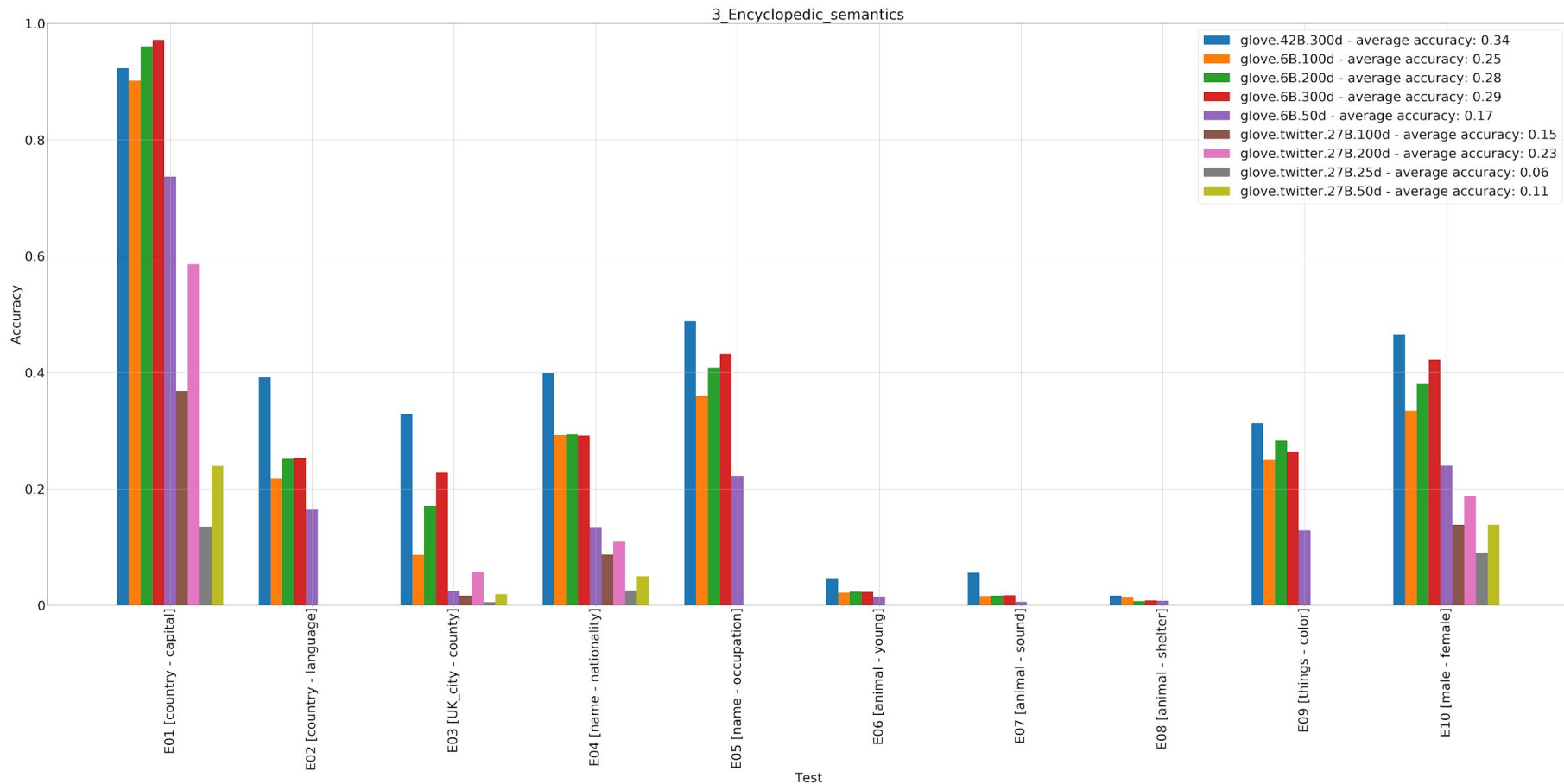
# Experimental Results



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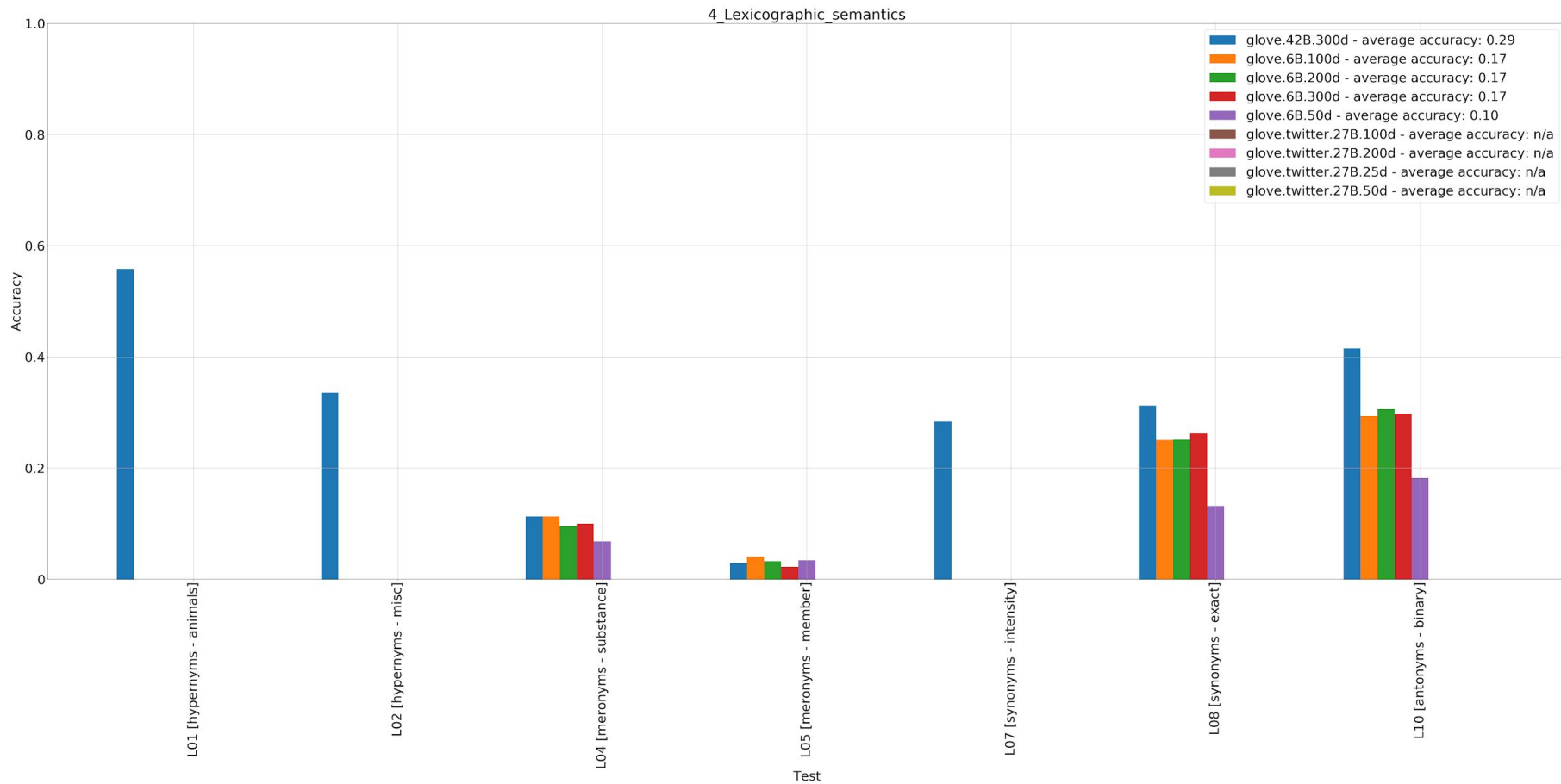


# Experimental Results





# Experimental Results





# Experiment - Conclusion

Glove works very well on:

- Modifications that don't change the meaning by a lot (e.g. book to books, angry to angrier)
- Countries to capitals

Glove performs poorly on:

- Modifications that change the meaning (e.g. bone to boneless, authorized to unauthorized)
- Words that are related but don't mean the same thing / don't have the same form (e.g. cat to kitten, flag to fabric)



# Citations

1. Pennington, Jeffrey, et al. “GloVe: Global Vectors for Word Representation.” *Empirical Methods in Natural Language Processing (EMNLP)*, 2014, pp. 1532–1543, [www.aclweb.org/anthology/D14-1162](http://www.aclweb.org/anthology/D14-1162).
2. Gladkova, Anna, et al. “Analogy-Based Detection of Morphological and Semantic Relations with Word Embeddings: What Works and What Doesn't.” *Proceedings of the NAACL-HLT SRW*, 2016, pp. 8–15., doi:10.18653/v1/N16-2002.



**Thank You**