Word Embeddings

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Images by Dong Nguyen

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What is a *wampos*?

some believe that	**wampos**	scales have medicinal qualities
approach to fighting	**wampos**	(and general wildlife) trafficking
Even though	**wampos**	scales are made of exactly the

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Figure: Photo by Piekfrosch; CC-BY-SA-3.0

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wampos = *pangolin*

You shall know a word by the company it keeps (Firth, J. R. 1957:11)

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Figure: Photo by Piekfrosch;

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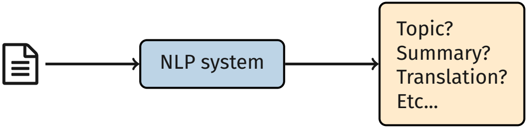
You shall know a word by the company it keeps (Firth, J. R. 1957:11)

The distributional hypothesis: Words that occur in similar contexts tend to have similar meanings

Recap: NLP



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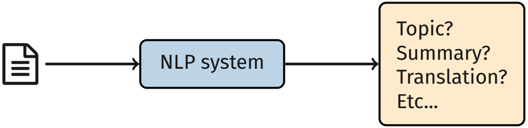

- Rule-based
- Machine Learning-based

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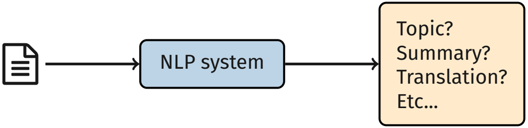
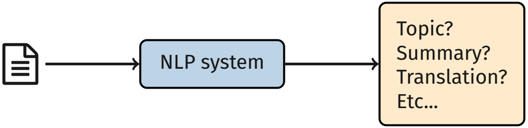


- Rule-based
- Machine Learning-based

How can we convert texts into numbers?

Recap: NLP



- Rule-based
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Bag-of-words, TF-IDF, ...

Recap: One hot encoding

Map each word to a unique identifier
e.g. *cat (3)* and *dog (5)*.
$\rightarrow$ Vector representation: all zeros, except 1 at the ID

cat	0	0	1	0	0	0	0
dog	0	0	0	0	1	0	0
car	0	0	0	0	0	0	1

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What are limitations of one hot encodings?

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Even related words have distinct vectors!

High number of dimensions

😔

Recap: Topic Modeling

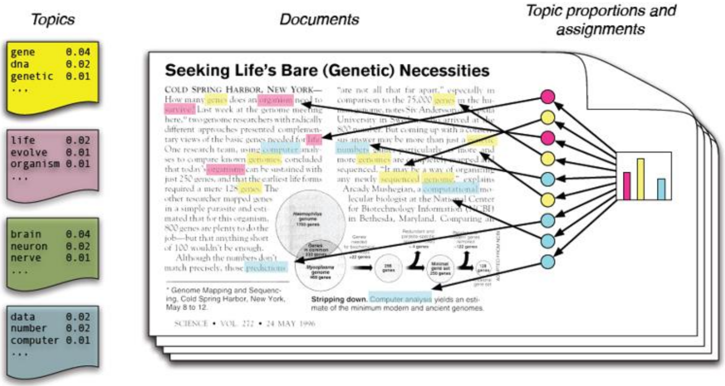

Figure: Text Clustering handout (Ayoub Bagheri)

Why do we need word embeddings?

Word representations

How can we represent the *meaning* of words?

Word representations

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So we can ask:

- How similar is *cat* to *dog*, or *Paris* to *London*?
- How similar is *document A* to *document B*?

Word representations

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So we can ask:

- How similar is *cat* to *dog*, or *Paris* to *London*?
- How similar is *document A* to *document B*?

And use such representations for:

- various NLP tasks: translation, classification, etc.
- studying linguistic questions

Words as vectors

The vector representations should:

- capture semantics
  - similar words should be close to each other in the vector space
  - relation between vectors should reflect the relationship between words
- be efficient (vectors with fewer dimensions are easier to work with)
- be interpretable

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How similar are *smart* and *intelligent?* (not similar 0–10 very similar):
How similar are *easy* and *big* (not similar 0–10 very similar):

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- capture semantics
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- be interpretable

How similar are *smart* and *intelligent?* (not similar 0–10 very similar): 9.2
How similar are *easy* and *big* (not similar 0–10 very similar): 1.12
(*SimLex-999 dataset*)

How are they used?

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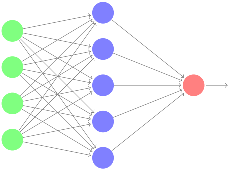

In neural networks (text classification, sequence tagging, etc..)

cat	0.52	0.48	-0.01	···	0.28
dog	0.32	0.42	-0.09	···	0.78

As research objects

Word embeddings (*vs* One-hot encoding)

Word embeddings:

- Vectors are short; typically 50-1024 dimensions ☺
- Very effective for many NLP tasks ☺
- Vectors are dense (mostly non-zero values)
- Individual dimensions are less interpretable ☹

cat	0.52	0.48	-0.01	...	0.28
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Learning word embeddings

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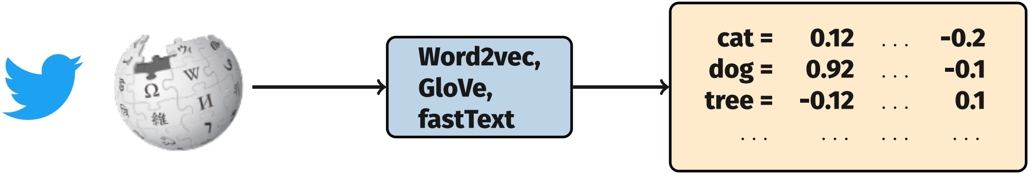

Training data

How can we train a model to learn the meaning of words?
Which data can we use for supervised learning?

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Key idea:

Use text itself as training data for the model!

A form of *self-supervision*.

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A form of *self-supervision*.

Example: Train a neural network to predict the next word given previous words.

A neural probabilistic language model. Bengio et al. (2003), JMLR [url]

Natural language processing (almost) from scratch, Collobert et al. (2011), JMLR, [url]

Exercise: Word prediction task

`yesterday I went to the` **?**

`A new study has highlighted the positive` **?**

Which word comes next?

Common Models

- Word2Vec
- fastText
- GloVe
- Bert

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- Bert

Word2Vec

The domestic **cat** is a small, typically furry carnivorous mammal

w_{-2} w_{-1} w_0 w_1 w_2 w_3 w_4 w_5

We have **target** words (*cat*) and **context** words (here: window=5).

Remember: distributional hypothesis

Word2Vec

Two different tasks (context):

- Continuous Bag-Of-Words (CBOW)
- Skipgram

Two training regimes

- Hierachical softmax
- Negative sampling

https://code.google.com/archive/p/word2vec/

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient Estimation of Word Representations in Vector Space. In Proceedings of Workshop at ICLR, 2013 [url]

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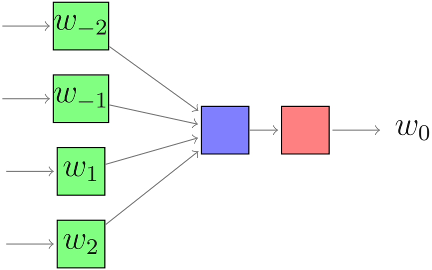

`one snowy ? she went`

Word2Vec

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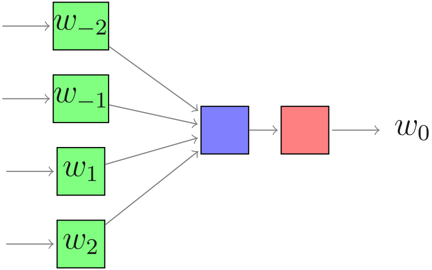

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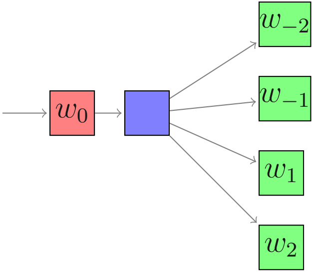
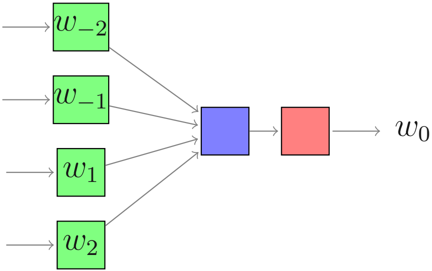
skipgram



`? ? day ? ?`

Word2Vec

Continuous Bag-Of-Words (CBOW)



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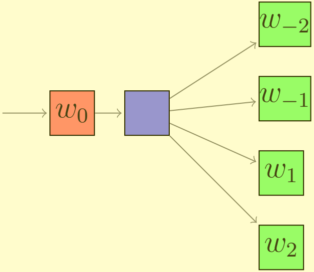

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Word2Vec: skipgram overview

The domestic **cat** is a small, typically furry carnivorous mammal

word (w)	**context (c)**	**label**
cat	small	1
cat	furry	1
cat	car	0
...	...	...

Word2Vec: skipgram overview

The domestic **cat** is a small, typically furry carnivorous mammal

word (w)	**context (c)**	**label**
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1. **Create examples**
   - Positive examples: Target word and neighboring context
   - Negative examples: Target word and randomly sampled words from the lexicon (*negative sampling*)
2. Train a **logistic regression** model to distinguish between the positive and negative examples
3. The resulting **weights** are the embeddings!

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Embedding vectors are essentially a byproduct!

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Word2Vec: skipgram

The domestic **cat** is a small, typically furry carnivorous mammal

$c1 \quad c2 \quad w \quad c3 \; c4 \; c5 \quad c6 \quad c7$

We have **target** words (*cat*) and **context** words (here: window=5).

The probability that *c* is a real context word:

$$P(+|w,c)$$

The probability that *c* is not a real context word:

$$P(-|w,c)$$

Word2Vec: skipgram

Intuition: A word *c* is likely to occur near the target if its embedding is similar to the target embedding.

$$\approx \mathbf{w} \cdot \mathbf{c}$$

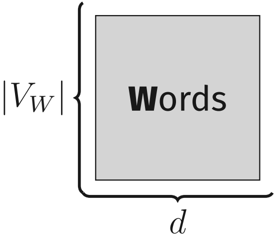
Turn this into a probability using the sigmoid function

$$P(+|w, c) = \frac{1}{1 + e^{-\mathbf{w} \cdot \mathbf{c}}}$$

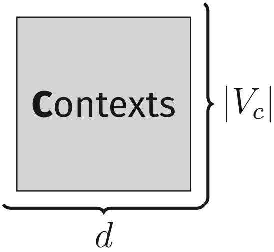
See also: 6.8 of Speech and Language Processing (3rd ed. draft), Dan Jurafsky and James H. Martin
https://web.stanford.edu/~jurafsky/slp3/

Word2Vec

Words:
Each word w is represented as a d-dimensional vector.



Contexts:
Each word c is represented as a d-dimensional vector.



All vectors are initialized with random weights.

Word2vec: skipgram (learning)

We **start** with random embedding vectors.

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During training:

- *Maximize* the similarity between the embeddings of the target word and context words from the positive examples
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After training:

- frequent word-context pairs in data: $\mathbf{w} \cdot \mathbf{c}$ high
- not word-context pairs in data: $\mathbf{w} \cdot \mathbf{c}$ low

Exercise (5 min)

- Go to `https://projector.tensorflow.org/`. The site should load 'Word2Vec 10K' vectors by default (see left panel).
- What are the 5 nearest words to '*cat*'?
- What are the 5 nearest words to '*computer*'?

fastText

Limitation of word2vec: Can't handle unknown words :(

fastText is very similar to word2vec, but each word is **represented as a bag of character n-grams** (+ the word itself). $\leq$ and $\geq$ mark word boundaries.

Example: *where* with $n = 3$: <wh, whe, her, ere, re> and <where>

Representation of a word: The sum of the vector representations of its n-grams.

Enriching Word Vectors with Subword Information, Bojanowski et al., TACL 2017, [url], software: https://fasttext.cc/

GloVe

- First create a *global word-word co-occurrence matrix* (how frequent pairs of words occur with each other). Requires a pass through the entire corpus at the start!
- Training objective: learn word embeddings so that their dot products equals the log of the words' co-occurrence probability.

GloVe: Global Vectors for Word Representation, Pennington et al., EMNLP 2015 [url], software
https://nlp.stanford.edu/projects/glove/

Pre-trained embeddings

- I want to build a system to solve a task (e.g. sentiment analysis)
  - Use pre-trained embedddings. Should I fine-tune?
    - Lots of data: yes
    - Just a small dataset: no
- Analysis (e.g. bias, semantic change)
  - Train embeddings from scratch

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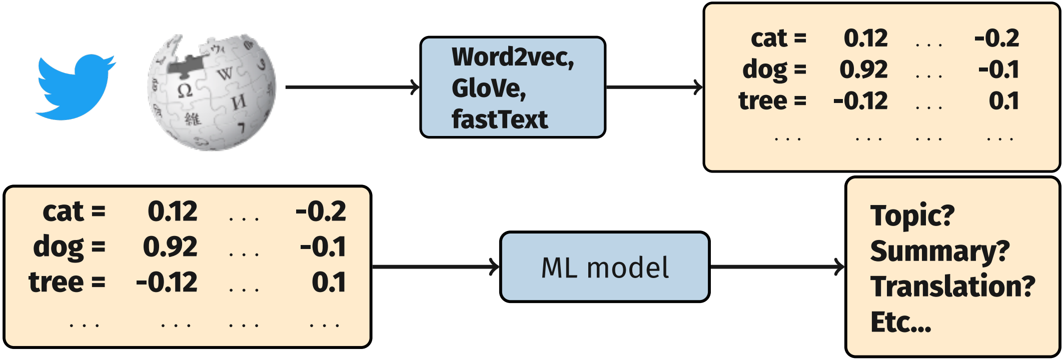
Using word embeddings

Downstream Tasks



Downstream Task Performance

Model	Dev	Test	ACE	MUC7
Discrete	91.0	85.4	77.4	73.4
SVD	90.8	85.7	77.3	73.7
SVD-S	91.0	85.5	77.6	74.3
SVD-L	90.5	84.8	73.6	71.5
HPCA	92.6	**88.7**	81.7	80.7
HSMN	90.5	85.7	78.7	74.7
CW	92.2	87.4	81.7	80.2
CBOW	93.1	88.2	82.2	81.1
GloVe	**93.2**	88.3	**82.9**	**82.2**

Figure: *GloVe: Global Vectors for Word Representation*, J. Pennington, R. Socher and C.D. Manning (2014)

Properties of word embeddings

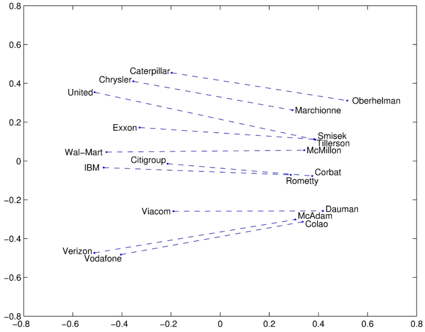


Figure: company - ceo

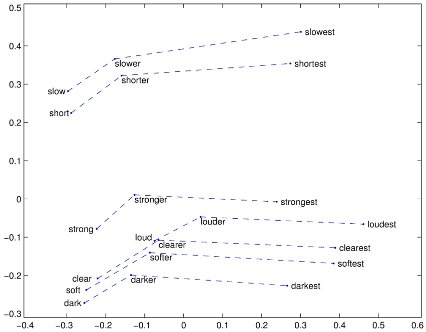


Figure: comparative - superlative

Source: https://nlp.stanford.edu/projects/glove/

Applications: Semantic change

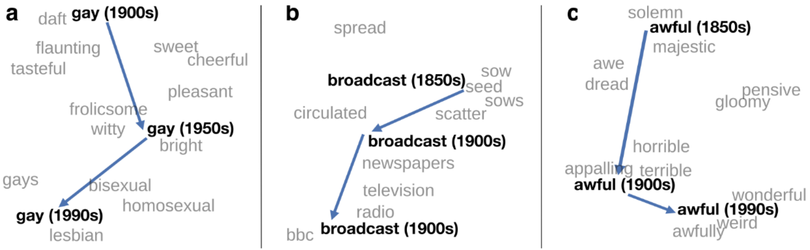
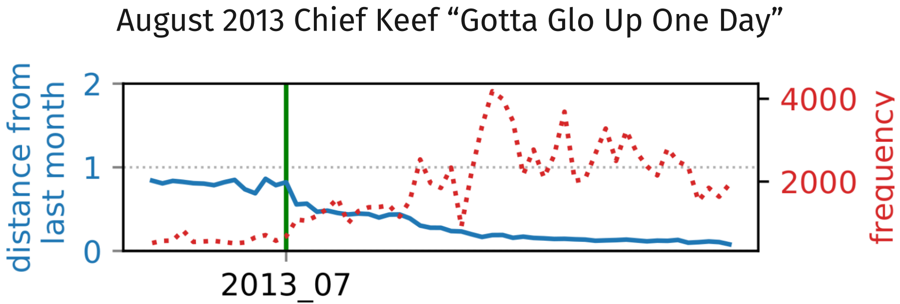


Figure 1. from Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change, Hamilton et al., ACL 2016 [url]

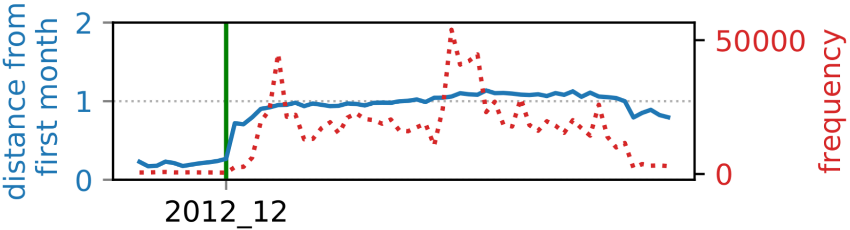
Semantic change: *glo*



P. Shoemark*, F. F. Liza*, D. Nguyen, S. A. Hale, B. McGillivray. Room to glo: A systematic comparison of semantic change detection approaches with word embeddings, EMNLP 2019 [url]

Semantic change: *vine*

Launched January 2013



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Evaluation

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Types of evaluation

1. Extrinstic evaluation
2. Intrinsic evaluation

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0.12	...	-0.2

Intrinsic evaluation

- Similarity
- Analogies
- Clustering
- Coherence
- Probing classifiers

Similarity

- Similarity
- Analogies
- Clustering
- Coherence
- Probing classifiers

Input: Dataset with relatedness or similarity scores for pairs of words.

Goal: High (pearson or spearman) correlation between scores and the cosine similarity of the embeddings for the two words.

Example from *WordSim353*:
wood and *forest*: 7.73
money and *cash*: 9.15
month and *hotel*: 1.81

Analogies

- Similarity
- Analogies
- Clustering
- Coherence
- Probing classifiers

```
Base/3rd Person Singular Present
see:sees return: ?

Singular/Plural
year:years law: ?

Meronyms
player:team fish: ?

UK city county
york:yorkshire Exeter: ?
```

(Mikolov et al. 2013 [url]; Gladkova et al. 2016 [url])

Analogies: 3COSADD

- Similarity
- Analogies
- Clustering
- Coherence
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This method is referred to by Levy and Goldberg (2014) as **3COSADD**
$\mathbf{a} - \mathbf{a}^* \approx \mathbf{b} - \mathbf{b}^*$. We can find $\mathbf{b}^*$ as follows:

$$\operatorname*{argmax}_{\mathbf{b}^* \in V} cos(\mathbf{b}^*, \mathbf{b} - \mathbf{a} + \mathbf{a}^*)$$

Clustering

- Similarity
- Analogies
- Clustering
- Coherence
- Probing classifiers

Cluster the words based on their embeddings and compare them against a known categorization.

Evaluation methods for unsupervised word embeddings, Schnabel et al. EMNLP 2015 [url]

Coherence

- Similarity
- Analogies
- Clustering
- Coherence
- Probing classifiers

Are words in the neighborhood of the *query* word mutually related? Present four words (query word + two close neighbors + intruder). Task: identify the intruder (e.g. Turkers).

Example: (a) *finally*; (b) *eventually*; (c) *immediately*; (d) *put*

Which word is the intruder?

Evaluation methods for unsupervised word embeddings, Schnabel et al. EMNLP 2015 [url]

Coherence: Intruder

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Probing classifiers

- Similarity
- Analogies
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Also called *diagnostic classifiers*

Mostly used to evaluate sentence embeddings, but sometimes also used for analyzing word embeddings.

But, be careful! Performance might seem high, but classifier might learn other signals (e.g. word frequency, part of speech classes) than what you focus on.

What you can cram into a single $&!# vector: Probing sentence embeddings for linguistic properties, Conneau et al., ACL 2018 [url]

Resources

Resources

Readings:

- *Contextual Word Representations: Putting Words into Computers*, Noah A. Smith, 2020 https://cacm.acm.org/magazines/2020/6/245162-contextual-word-representations/fulltext
- *Vector Semantics and Embeddings (Chapter 6)*, Speech and Language Processing (3rd ed. draft), Dan Jurafsky and James H. Martin, 2020 https://web.stanford.edu/~jurafsky/slp3/
- *SimLex-999: Evaluating Semantic Models with (Genuine) Similarity Estimation*, Felix Hill, Roi Reichart, and Anna Korhonen, 2014 https://arxiv.org/abs/1408.3456v1

Videos:

- *Stanford CS224N: NLP with Deep Learning | Winter 2019 | Lecture 1 – Introduction and Word Vectors* (and lecture 2): https://www.youtube.com/watch?v=8rXD5-xhemo
- video's by Jordan Boyd-Graber, e.g. *Understanding Word2Vec* https://www.youtube.com/watch?v=QyrUentbkvw and others

Resources: blogposts

- *The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning)* by Jay Alammar http://jalammar.github.io/illustrated-bert/ (2018)
- *The Illustrated Word2vec* by Jay Alammar http://jalammar.github.io/illustrated-word2vec/ (2019)
- *Generalized Language Models* by Lilian Weng https://lilianweng.github.io/lil-log/2019/01/31/generalized-language-models.html

Software

- **word2vec**: gensim (https://radimrehurek.com/gensim/) and official implementation (https://code.google.com/archive/p/word2vec/).
- **fasttext**: official implementation (https://fasttext.cc/)
- **GloVe**: official implementation (https://nlp.stanford.edu/projects/glove/)
- **Hugging Face**: for BERT and other transformer models (https://huggingface.co/)

The end

Addendums

Contextual word embeddings

Tokens versus types

The hut is located near the bank of the river

Tokens	Types
The	the
hut	hut
is	is
located	located
near	near
the	bank
bank	of
of	river
the	
river	

Contextualized word representations

So far: an embedding for **each word (type)**.

*Today, I went to the **bank** to deposit a check.*

bank	0.52	0.48	-0.01	⋯	0.28

*The hut is located near the **bank** of the river.*

bank	-0.27	0.28	-0.07	⋯	0.82

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*Today, I went to the **bank** to deposit a check.*

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*The hut is located near the **bank** of the river.*

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Key idea in NLP:

Can we have an embedding for each **word token?**

Contextualized word representations

Key idea: Have embeddings for each **word token**

Previously:

- One embedding for each word **type**
- A table where each word is mapped to a vector.

Now:

- One embedding for each work **token**
- Embeddings for a token are created based on the context
- There is *no single* embedding for a word anymore.

BERT

Two tasks:

- Masked LM
- Next sentence prediction

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, Devlin et al. NAACL 2019 [url]

BERT

Two tasks:

- Masked LM
- Next sentence prediction

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`my dog is hairy`

- mask word:
  `my dog is [MASK]`

(some details are omitted.)

BERT

Two tasks:

- Masked LM
- Next sentence prediction

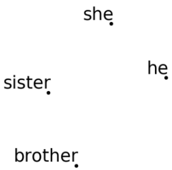
Input = [CLS] the man went to [MASK] store [SEP] he bought a gallon [MASK] milk [SEP]
Label = IsNext

Input = [CLS] the man [MASK] to the store [SEP] penguin [MASK] are flight ## less birds [SEP]
Label=NotNext

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, Devlin et al. NAACL 2019 [url]

Biases in word embeddings

Biases in word embeddings



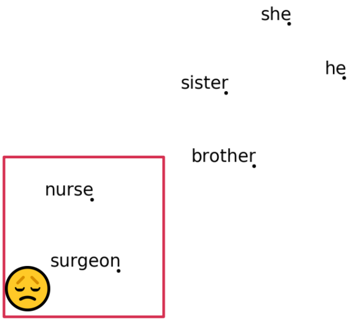
Measuring gender bias:

- To assess NLP models and investigate the impact of ‘bias mitigation’ techniques
- To study societal trends

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings, Bolukbasi, et al. NIPS 2016 [url]

Semantics derived automatically from language corpora contain human-like biases, Caliskan, Bryson, Narayanan, Science 2017 [url]

Biases in word embeddings



Pre-trained GloVe model on Twitter

Measuring gender bias:

- To assess NLP models and investigate the impact of ‘bias mitigation’ techniques
- To study societal trends

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings, Bolukbasi, et al. NIPS 2016 [url]

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Biases reflected in analogy tasks

Biases reflected in analogy tasks:

man is to *computer programmer* as *woman* is to ? : x = homemaker
father is to *doctor* as *mother* is to ? : x = nurse

Note: Input words are excluded as possible answers! (see also Nissim et al. 2020 [url])

Compare: gender-specific words (e.g., *brother, businesswoman*) vs. *gender-neutral* words (e.g. *nurse*, *teacher*).

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings, Bolukbasi, et al. NIPS 2016 [url]

Biases in word embeddings

$$S_{(a,b)}(\mathrm{x,y}) = cos(\underbrace{\mathrm{a}}_{\text{embedding}_{she}} - \underbrace{\mathrm{b}}_{\text{embedding}_{he}}, x-y) \quad if \quad \underbrace{\|x-y\|_2}_{L_2 \text{ distance}} \leq \delta$$

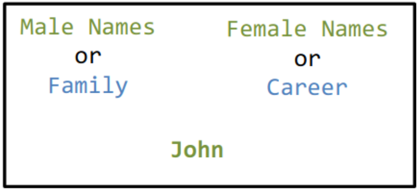
Gender appropriate she-he analogies
queen–king sister–brother ovarian cancer–prostate cancer mother–father convent–monastery

Gender stereotype she-he analogies
nurse–surgeon sassy–snappy cupcakes–pizzas lovely–brilliant vocalist–guitarist

Bolukbasi et al. look at 300-dimensional embeddings from w2vec Google news corpus.

Word-Embedding Association Test

- The Implicit Association Test (IAT) is based on response times and has been widely used.



Semantics derived automatically from language corpora contain human-like biases, Caliskan, Bryson, Narayanan, Science 2017 [url]

Word-Embedding Association Test

- The Implicit Association Test (IAT) is based on response times and has been widely used.
- Word-Embedding Association Test (WEAT) by Caliskan et al: use the cosine similarity between pairs of vectors as analogous to reaction time in the IAT

Were able to replicate well-known IAT findings!

Semantics derived automatically from language corpora contain human-like biases, Caliskan, Bryson, Narayanan, Science 2017 [url]

Word-Embedding Association Test

Let X and Y be two sets of **target words** of equal size;
Let A, B be the two sets of **attribute words**.
For a given target word w we get a score:

$$s(w, A, B) = mean_{a \in A} cos(\vec{w}, \vec{a}) - mean_{b \in B} cos(\vec{w}, \vec{b})$$

Target words X—flowers: aster, clover, hyacinth, crocus, rose, ...
Target words Y—insects: ant, caterpillar, flea, spider, bedbug, ...
Attribute words A—pleasant: freedom, love, peace, cheer, ...
Attribute words B—unpleasant: abuse, crash, filth, murder, divorce,...

Semantics derived automatically from language corpora contain human-like biases, Caliskan, Bryson, Narayanan, Science 2017 [url]

Word-Embedding Association Test

Let X and Y be two sets of **target words** of equal size;
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For a given target word w we get a score:

$$s(w, A, B) = mean_{a \in A} cos(\vec{w}, \vec{a}) - mean_{b \in B} cos(\vec{w}, \vec{b})$$

Target words X—math: math, algebra, numbers, calculus, ...
Target words Y—arts: poetry, art, dance, literature, ...
Attribute words A—male: male, man, boy, brother, he, him, ...
Attribute words B—female: female, woman, girl, sister, she, her,..

Semantics derived automatically from language corpora contain human-like biases, Caliskan, Bryson, Narayanan, Science 2017 [url]

Word-Embedding Association Test

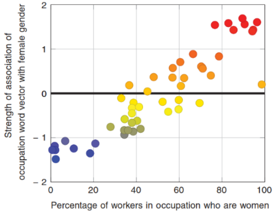


Fig. 1. Occupation-gender association. Pearson's correlation coefficient $\rho = 0.90$ with $P < 10^{-18}$.

Figure from: Semantics derived automatically from language corpora contain human-like biases, Caliskan, Bryson, Narayanan, Science 2017 [url]

Perpetuation of bias in sentiment analysis

> *"I had tried building an algorithm for sentiment analysis based on word embeddings [..]. When I applied it to restaurant reviews, I found it was ranking Mexican restaurants lower. The reason was not reflected in the star ratings or actual text of the reviews. It's not that people don't like Mexican food.* ***The reason was that the system had learned the word "Mexican" from reading the Web****."*

(emphasis mine)

http://blog.conceptnet.io/posts/2017/conceptnet-numberbatch-17-04-better-less-stereotyped-word-vectors/

Back-up

Backup

- Vector Representations
- Cosine Similarity
- Word Vectors
- Context
- Stability of Embeddings
- Word2Vec
- Word Analogies
- Semantic Change: Emojis
- Evaluation by Analogies: Misleading

recap!

Vector representations

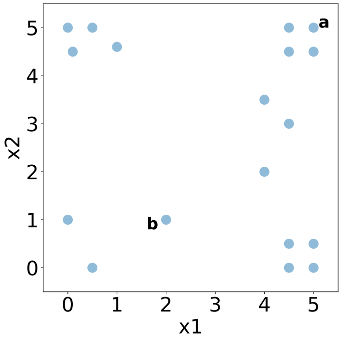


Figure: Points in a two dimensional vector space

```
a = [5, 5]
b = [2, 1]
```

a is a *two-dimensional* vector

recap!

Vector representations

```
a = [5, 5, 2]
b = [2, 1, 0]
```

a is a *three-dimensional* vector

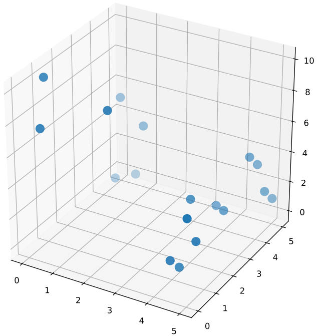


Figure: Points in a three dimensional vector space

recap!

Vector representations

```
a = [5, 5, 2]
b = [2, 1, 0]
```

a is a *three-dimensional* vector

Key idea in NLP:

Can we **represent words as vectors** (i.e. points in a vector space?)

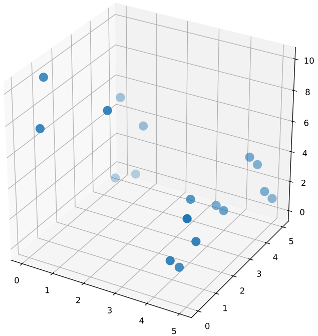


Figure: Points in a three dimensional vector space

Cosine Similarity

We can use cosine similarity to find similar words in the vector space.

- **dog**: *dogs, cat, man, cow, horse*
- **car**: *driver, cars, automobile, vehicle, race*
- **amsterdam**: *netherlands, rotterdam, dutch, centraal, paris*
- **chocolate**: *candy, beans, caramel, butter, liquor*

$$\text{cosine}(\mathbf{v}, \mathbf{w}) = \frac{\mathbf{v} \cdot \mathbf{w}}{|\mathbf{v}||\mathbf{w}|} \tag{1}$$

Cosine Similarity: Why

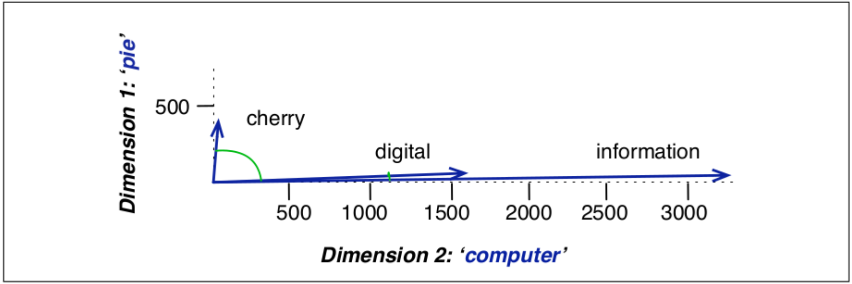


Figure: *Vector Semantics and Embeddings (Chapter 6)*, Speech and Language Processing (3rd ed. draft), Dan Jurafsky and James H. Martin, 2020

$$\mathbf{v} \cdot \mathbf{w} = |\mathbf{v}||\mathbf{w}| \, \text{cosine}(\mathbf{v}, \mathbf{w}) \tag{2}$$

Cosine Similarity: Vector Length

$$P(+|\mathbf{w}, \mathbf{c}) = \frac{1}{1 + e^{-\mathbf{w} \cdot \mathbf{c}}} \tag{3}$$

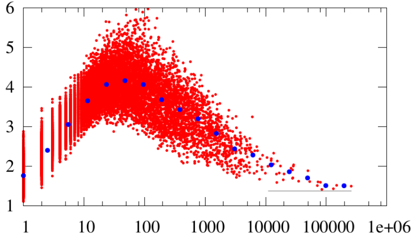


Figure: *Measuring Word Significance using Distributed Representations of Words*, Adriaan M. J. Schakel and Benjamin J. Wilson (2015)

Word vectors based on co-occurrences

documents as context
word-document matrix

	doc_1	doc_2	doc_3	doc_4	doc_5	doc_6	doc_7
cat	5	2	0	1	4	0	0
dog	7	3	1	0	2	0	0
car	0	0	1	3	2	1	1

Word vectors based on co-occurrences

documents as context
word-document matrix

	doc_1	doc_2	doc_3	doc_4	doc_5	doc_6	doc_7
cat	5	2	0	1	4	0	0
dog	7	3	1	0	2	0	0
car	0	0	1	3	2	1	1

neighboring words as context
word-word matrix

	cat	dog	car	bike	book	house	tree
cat	0	3	1	1	1	2	3
dog	3	0	2	1	1	3	1
car	0	0	1	3	2	1	1

Word vectors based on co-occurrences

There are many variants:

- Context (words, documents, which window size, etc.)
- Weighting (raw frequency, etc.)

Vectors are sparse: Many zero entries.
Therefore: Dimensionality reduction is often used (e.g., SVD)

These methods are sometimes called **count-based** methods as they work directly on **co-occurrence** counts.

recap!

Design decision: context

The distributional hypothesis: Words that occur in similar contexts tend to have similar meanings.

recap!

Design decision: context

The distributional hypothesis: Words that occur in similar contexts tend to have similar meanings.

How do we define our **context**?

Context

`Australian scientist` **`discovers`** `star with telescope`

context window = 1

Context

`Australian scientist` **`discovers`** `star with telescope`

context window = 2

Context

`Australian scientist` **`discovers`** `star with telescope`

context window = sentence

Context

`Australian scientist` **`discovers`** `star with telescope`

context window = sentence

Smaller contexts $\rightarrow$ syntactic properties
Large contexts $\rightarrow$ semantic/topical properties

Example Levy and Golbert, ACL 2014 for *hogwarts*:
window=2: *evernight* and *sunnydale* vs. window=5: *dumbledore*, *hallows*

(Levy and Golbert, ACL 2014; Melamud, NAACL 2016; and others)

Stability of embeddings

Many factors can have an effect on the training (corpus size, presence/absence of documents, etc...). How *stable* are embeddings?

Measures of stability: One simple method is looking at the overlap between nearest neighbors in an embedding space

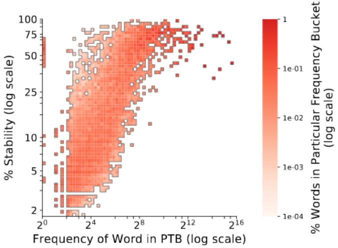


Figure: *word2vec* embeddings: lower frequency words have lower stability and higher frequency words have higher stability (Figure 1 from Wendlandt et al. 2018)

Factors Influencing the Surprising Instability of Word Embeddings, Wendlandt et al., NAACL 2018 [url]

Stability of embeddings

Antoniak and Mimno et al. 2018:

- The training corpus is only a sample!
- But: they were sensitive to the presence of specific documents
- *“with smaller corpora comes greater variability, and we recommend that practitioners use bootstrap sampling to generate an ensemble of word embeddings for each sub-corpus and present both the mean and variability of any summary statistics”*

Evaluating the Stability of Embedding-based Word Similarities, Antoniak and Mimno, TACL 2018 [url]

Word2vec: skipgram (learning)

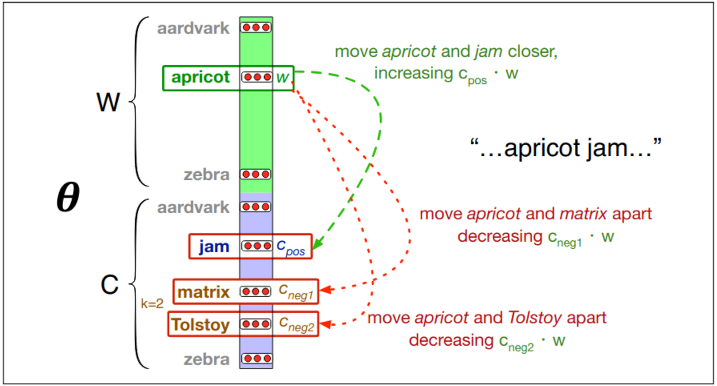


Figure: Figure 6.14 from Speech and Language Processing (3rd ed. draft), Dan Jurafsky and James H. Martin
https://web.stanford.edu/~jurafsky/slp3/

Word analogies

We can look at analogies in the vector space, for example:
king - man + woman $\approx$ *queen*

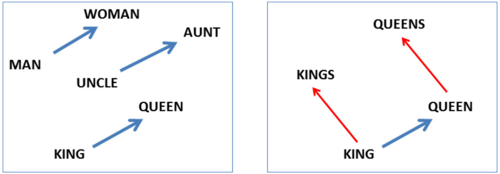
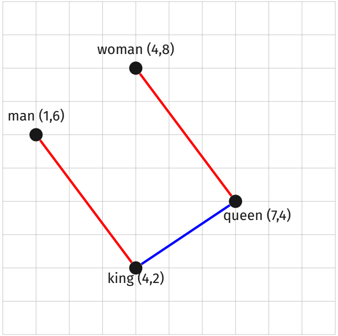


Figure: Figure 2 from Linguistic Regularities in Continuous Space Word Representations, Mikolov et al. NAACL 2013 [url]

Word analogies: math

We can look at analogies in the vector space, for example:
king - man + woman $\approx$ *queen*

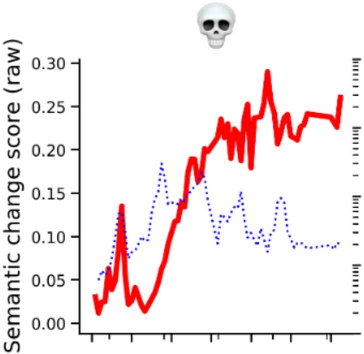



```
king-man = [4,2] - [1,6] = [3,-4]
king-man + woman = [3,-4] + [4,8] = [7,4]
```

Word analogies: warning

https://blog.esciencecenter.nl/king-man-woman-king-9a7fd2935a85
These analogies only work with cheating!

Semantic change: emojis



2012: *zombie, corpse, bury, undead, murder*
2013–: *lmao* and similar terms.

A. Robertson, F. Ferdousi Liza, D. Nguyen, B. McGillivray, S. A. Hale. Semantic Journeys: Quantifying Change in Emoji Meaning from 2012–2018, 4th International Workshop on Emoji Understanding and Applications in Social Media 2021 [url]

Evaluation by Analogies: Misleading

- Similarity
- Analogies
- Clustering
- Coherence
- Probing classifiers

This method is referred to by Levy and Goldberg (2014) as **3COSADD**
$\mathbf{a} - \mathbf{a}^* \approx \mathbf{b} - \mathbf{b}^*$. We can find $\mathbf{b}^*$ as follows:

$$\operatorname*{argmax}_{\mathbf{b}^* \in V} cos(\mathbf{b}^*, \mathbf{b} - \mathbf{a} + \mathbf{a}^*)$$

Linzen 2016 notes that results can be misleading: The offsets are often very small, so that often just the nearest neighbor to **b** is returned.
Control setting: Just return the nearest neighbor of **b**

Utrecht University

Issues in evaluating semantic spaces using word analogies, Tal Linzen. 2016 [url]