Demystifying Neural Word Embeddings

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September 2015

Language

Language

People use language to communicate

Language

People use language to communicate

Language is Everywhere

Language

People use language to communicate

Language is Everywhere

- Newspapers

Language

People use language to communicate

Language is Everywhere

- Newspapers
- Scientific articles

Language

People use language to communicate

Language is Everywhere

- Newspapers
- Scientific articles
- Medicine (patient records)

Language

People use language to communicate

Language is Everywhere

- Newspapers
- Scientific articles
- Medicine (patient records)
- Patents

Language

People use language to communicate

Language is Everywhere

- Newspapers
- Scientific articles
- Medicine (patient records)
- Patents
- Law

Language

People use language to communicate

Language is Everywhere

- Newspapers
- Scientific articles
- Medicine (patient records)
- Patents
- Law
- Product reviews

Language

People use language to communicate

Language is Everywhere

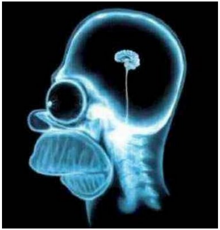
- Newspapers
- Scientific articles
- Medicine (patient records)
- Patents
- Law
- Product reviews
- Blogs
- Facebook, Twitter
- ...

A lot of text.

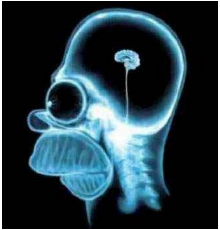
Need to understand what's being said.

this is where we come in.

NLP

text →  → meaning

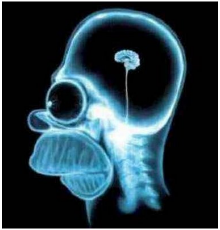
NLP

text →  → meaning

What does it mean to **understand**?

NLP

text



meaning

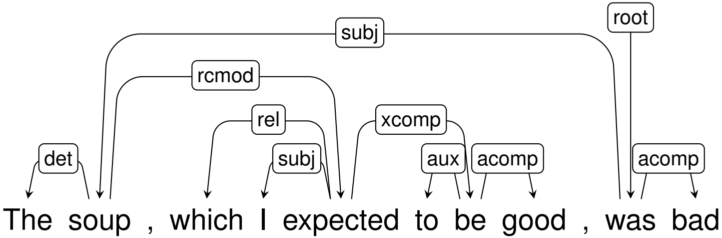
What does it mean to **understand**?

I focus on the building blocks

Understanding the Structure

The soup , which I expected to be good , was bad

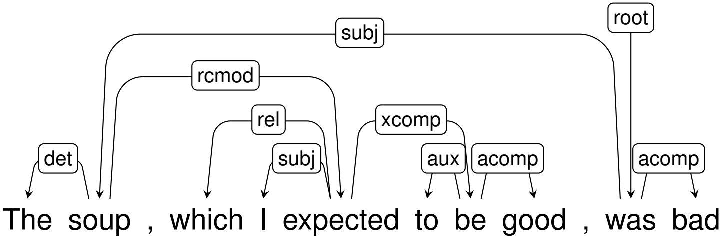
Understanding the Structure



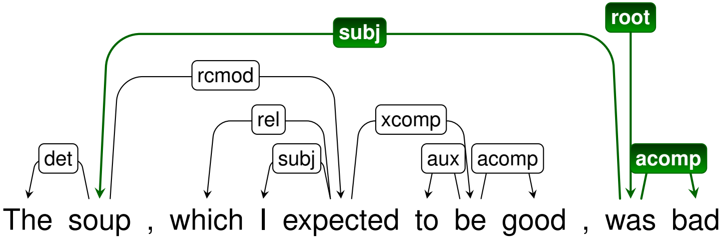
Understanding the Structure

This is called **Syntactic Parsing**.

Understanding the Structure



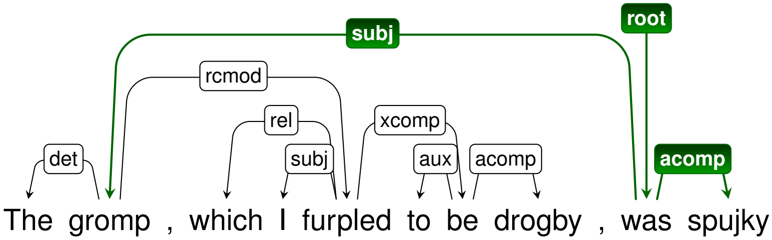
Understanding the Structure

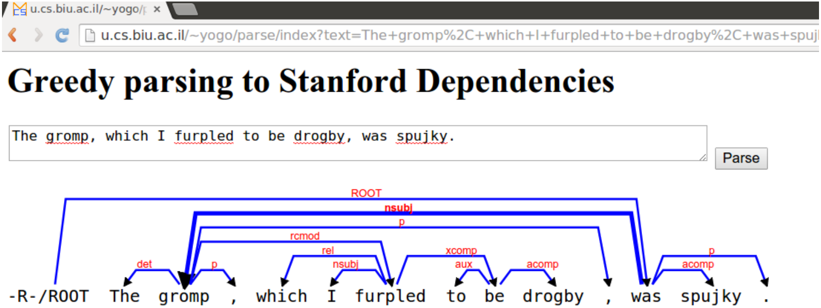


Understanding the Structure

The gromp , which I furpled to be drogby , was spujky

Understanding the Structure




u.cs.biu.ac.il/~yogo/
u.cs.biu.ac.il/~yogo/parse/index?text=The+gromp%2C+which+I+furpled+to+be+drogby%2C+was+spuj
Greedy parsing to Stanford Dependencies
The gromp, which I furpled to be drogby, was spujky.
Parse
ROOT
nsubj
p
rcmod
rel
nsubj
det
p
xcomp
aux
acomp
p
acomp
-R-/ROOT The gromp , which I furpled to be drogby , was spujky .

Understanding the Structure

Can understand **structure** without understanding **words**.

But the words are also important.

I almost gave you a talk about parsing.

Today we will focus on the words.

Understanding the Words

soup was bad

Understanding the Words

soup was bad
soup was awful

Understanding the Words

soup was bad
soup was awful
soup was lousy

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

chowder was nasty

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

chowder was nasty
pudding was terrible

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

chowder was nasty
pudding was terrible
cake was bad

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

chowder was nasty
pudding was terrible
cake was bad
hamburger was lousy

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

chowder was nasty
pudding was terrible
cake was bad
hamburger was lousy

service was poor

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

chowder was nasty
pudding was terrible
cake was bad
hamburger was lousy

service was poor
atmosphere was shoddy

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

chowder was nasty
pudding was terrible
cake was bad
hamburger was lousy

service was poor
atmosphere was shoddy
hammer was heavy

Understanding the Words

soup was bad
soup was awful
soup was lousy
soup was abysmal
soup was icky

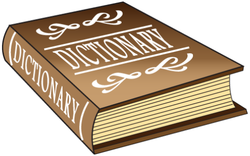
chowder was nasty
pudding was terrible
cake was bad
hamburger was lousy

service was poor
atmosphere was shoddy
hammer was heavy

- To the computer, each word is just a symbol, so these are all the same.
- But to us, some are more similar than others.
- We'd like a word representation that can capture that.

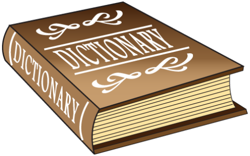
Representing Words

Use a dictionary?



Representing Words

Use a dictionary?



Doesn't scale.

Representing Words

The distributional Hypothesis

Dr. Baroni saw a hairy little wampinuck sleeping behind a tree

Dr. Baroni saw a hairy little wampinuck sleeping behind a tree

The Distributional Hypothesis – Haris, 1954

Words in similar contexts tend to have similar meanings

Firth, 1957

"*you should know a word by the company it keeps*"

Co-occurrence

```
he curtains open and the moon shining in on the barely
ars and the cold , close moon " . And neither of the w
rough the night with the moon shining so brightly , it
made in the light of the moon . It all boils down , wr
 surely under a crescent moon , thrilled by ice-white
sun , the seasons of the moon ? Home , alone , Jay pla
m is dazzling snow , the moon has risen full and cold
un and the temple of the moon , driving out of the hug
 in the dark and now the moon rises , full and amber a
bird on the shape of the moon over the trees in front
 But I could n't see the moon or the stars , only the
rning , with a sliver of moon hanging among the stars
 they love the sun , the moon and the stars . None of
the light of an enormous moon . The plash of flowing w
man 's first step on the moon ; various exhibits , aer
 the inevitable piece of moon rock . Housing The Airsh
oud obscured part of the moon . The Allied guns behind
```

Words as Vectors

- Represent each word as a sparse, high dimensional vector of the words that co-occur with it.

  `moon = (the:324, shining:4, cold:1, brightly:2, stars:12, elephant:0, ...)`

- Words are similar if their vectors are similar.
- We measure similarity using geometric measures, for example *cosine distance*.
- But more intuitively, **words are similar if they share many similar contexts.**

Weighting

Re-weight the counts using corpus-level statistics to reflect co-occurrence *significance*

Positive Pointwise Mutual Information (PPMI)

$$\mathrm{PPMI}(\mathrm{target}, \mathrm{ctxt}) = \max(0, \log \frac{\mathrm{P}(\mathrm{target}, \mathrm{ctxt})}{\mathrm{P}(\mathrm{target})\mathrm{P}(\mathrm{ctxt})})$$

Weighting

Adjusting raw co-occurrence counts:

	bright	in		
stars	385	10788	...	$\leftarrow$ Counts
stars	43.6	5.3	...	$\leftarrow$ PPMI

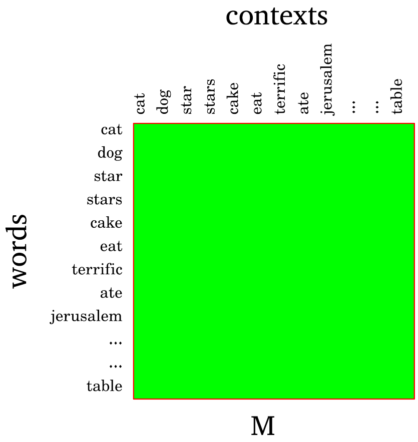
Other weighting schemes:

- TF-IDF
- Local Mutual Information
- Dice

See Ch4 of J.R. Curran's thesis (2004) and S. Evert's thesis (2007) for surveys of weighting methods

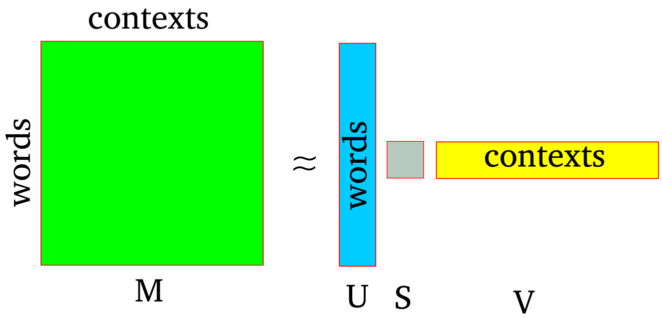
Words as Vectors

We can arrange the words in a huge, sparse matrix, where each row is a word, and each column is a context.



Words as Vectors

We often apply SVD or similar technique of dimensionality reduction.



Words as Vectors – It works

Nearest neighbours to dog

- cat
- horse
- fox
- pet
- rabbit
- pig
- animal
- mongrel
- sheep
- pigeon

Words as Vectors – It works

Nearest neighbours to dog

2-word window

- cat
- horse
- fox
- pet
- rabbit
- pig
- animal
- mongrel
- sheep
- pigeon

Words as Vectors – It works

Nearest neighbours to dog

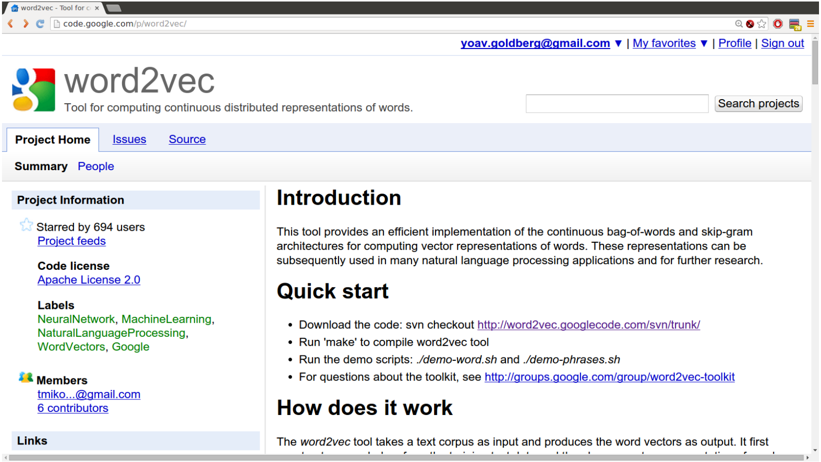
2-word window

- cat
- horse
- fox
- pet
- rabbit
- pig
- animal
- mongrel
- sheep
- pigeon

30-word window

- kennel
- puppy
- pet
- bitch
- terrier
- rottweiler
- canine
- cat
- to bark
- Alastian

word2vec



word2vec - Tool for c
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word2vec
Tool for computing continuous distributed representations of words.
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Project feeds
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Members
tmiko...@gmail.com
6 contributors
Links
Introduction
This tool provides an efficient implementation of the continuous bag-of-words and skip-gram architectures for computing vector representations of words. These representations can be subsequently used in many natural language processing applications and for further research.
Quick start
• Download the code: svn checkout http://word2vec.googlecode.com/svn/trunk/
• Run 'make' to compile word2vec tool
• Run the demo scripts: ./demo-word.sh and ./demo-phrases.sh
• For questions about the toolkit, see http://groups.google.com/group/word2vec-toolkit
How does it work
The word2vec tool takes a text corpus as input and produces the word vectors as output. It first

Google word2vec

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MLMU.cz - Radim Řehůřek - Word2vec & friends (7.1.2015 ...

www.youtube.com/watch?v=wTp3P2UnTfQ
Jan 14, 2015 - Uploaded by Marek Modrý
I'll go over a particular model published by Google, called **word2vec**, its optimizations, applications and ...

Word2Vec convergence on Vimeo

https://vimeo.com/112168934
Nov 18, 2014
This is "**Word2Vec** convergence" by MaciejLyst on Vimeo, the home for high quality videos and the people who ...

Statistical Semantic入門~分布仮説からword2vecまで #1 ...

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Feb 5, 2014
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word2vecによる自然言語処理

西尾泰和
2014年05月 発行
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フォーマット ePub mobi

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内容 | 目次

Tomas Mikolovらによって提案されたニューラルネットワーク（CBOW, Skip-gram）のオープンソース実装word2vecについて、基本的な使い方を体験し、さらにその仕組みを学ぶ書籍です。
基本的な使い方から、自分の好きなコーパスの作り方、登場の背景、仕組み、さらには応用例や弱点についてもコンパクトなボリュームで概観できます。付録にはword2vecの出力結果を主成分分析を使って可視化する方法について解説しています。
なお本書はEbook版のみの販売となります。

著者の西尾さんによる本書の解題[リンク]

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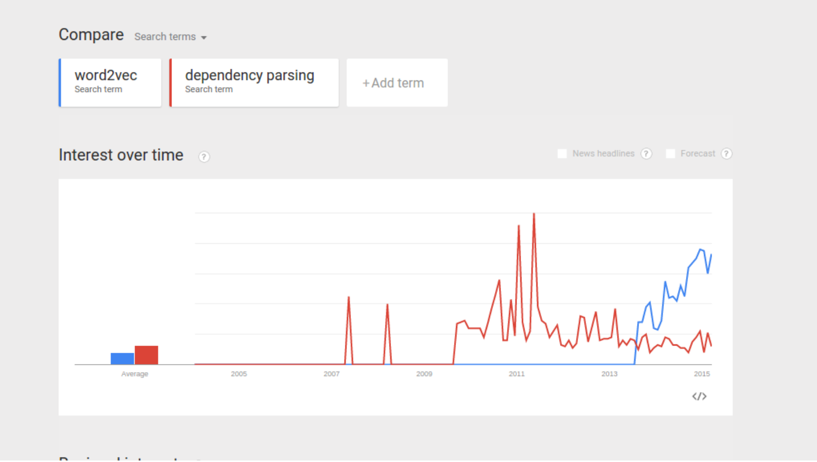
[feedbackページへ]


Compare
Search terms
word2vec
Search term
dependency parsing
Search term
+Add term
Interest over time
News headlines
Forecast
Average
2005
2007
2009
2011
2013
2015
Regional interest

From Distributional to Distributed Semantics

The new kid on the block

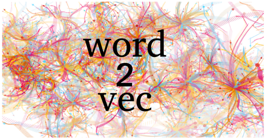
- Deep learning / neural networks.
- "Distributed" word representations.
  - Feed text into neural-net. Get back "word embeddings".
  - Each word is represented as a low-dimensional vector.
  - Vectors capture "semantics".
- `word2vec` (Mikolov et al)

word2vec

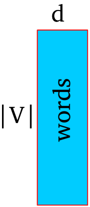
Text

WIKIPEDIA

feed in text



wait a few hours



dog = (0.12,-0.32,0.92,0.43,-0.3 ...)
cat = (0.15,-0.29,0.90,0.39,-0.32 ...)

chair = (0.8,0.9,-0.76,0.29,0.52 ...)

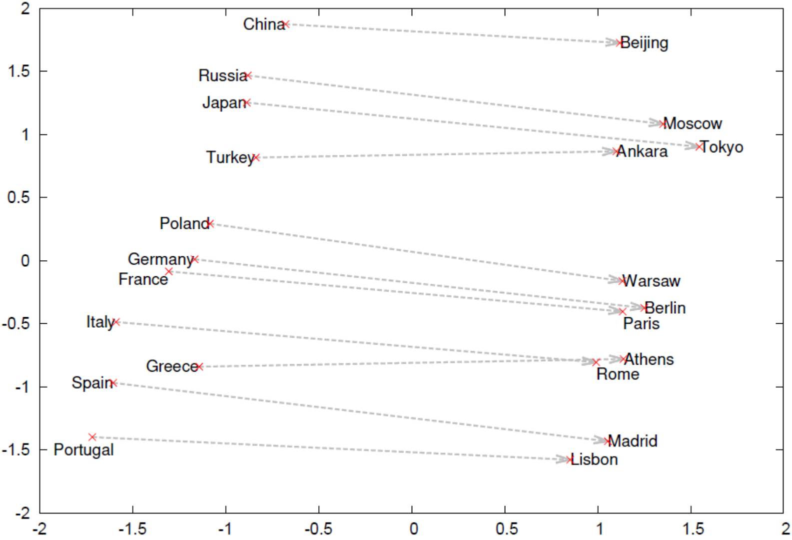
get a |V|xd matrix W where each row is a vector for a word

word2vec

- dog
  - cat, dogs, dachshund, rabbit, puppy, poodle, rottweiler, mixed-breed, doberman, pig
- sheep
  - cattle, goats, cows, chickens, sheeps, hogs, donkeys, herds, shorthorn, livestock
- november
  - october, december, april, june, february, july, september, january, august, march
- jerusalem
  - tiberias, jaffa, haifa, israel, palestine, nablus, damascus katamon, ramla, safed
- teva
  - pfizer, schering-plough, novartis, astrazeneca, glaxosmithkline, sanofi-aventis, mylan, sanofi, genzyme, pharmacia

word2vec

Other appealing properties



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Tokyo
Turkey
Ankara
Poland
Germany
France
Warsaw
Berlin
Paris
Italy
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Spain
Athens
Rome
Madrid
Portugal
Lisbon
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2

Mikolov et al. (2013a,b,c)

$$\underset{\text{king}}{b} \qquad \underset{\text{man}}{a} \qquad \underset{\text{woman}}{a^*} \qquad \underset{\text{queen}}{b^*}$$

$$\text{king} - \text{man} + \text{woman} = \text{queen}$$

Mikolov et al. (2013a,b,c)

$$\overset{b}{\text{Tokyo}} - \overset{a}{\text{Japan}} + \overset{a^*}{\text{France}} = \overset{b^*}{\text{Paris}}$$

Mikolov et al. (2013a,b,c)

$$\underset{\text{best}}{b} - \underset{\text{good}}{a} + \underset{\text{strong}}{a^*} = \underset{\text{strongest}}{b^*}$$

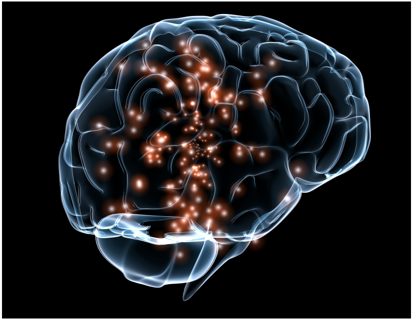
Mikolov et al. (2013a,b,c)

$$\overset{b}{\text{best}} - \overset{a}{\text{good}} + \overset{a^*}{\text{strong}} = \overset{b^*}{\text{strongest}}$$

vectors in $\mathbb{R}^n$

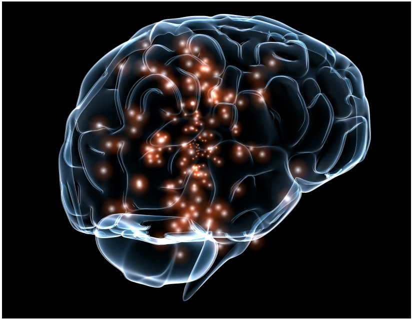
Seems magical.

Seems magical.



"Neural computation, just like in the brain!"

Seems magical.



“Neural computation, just like in the brain!”

How does this actually work?

How does word2vec work?

word2vec implements several different algorithms:

Two training methods

- Negative Sampling
- Hierarchical Softmax

Two context representations

- Continuous Bag of Words (CBOW)
- Skip-grams

How does word2vec work?

word2vec implements several different algorithms:

Two training methods

- **Negative Sampling**
- Hierarchical Softmax

Two context representations

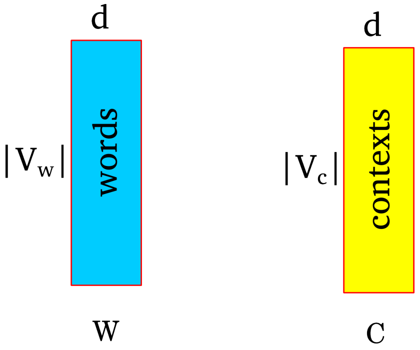
- Continuous Bag of Words (CBOW)
- **Skip-grams**

We'll focus on skip-grams with negative sampling.

intuitions apply for other models as well.

How does word2vec work?

- Represent each word as a *d* dimensional vector.
- Represent each context as a *d* dimensional vector.
- Initalize all vectors to random weights.
- Arrange vectors in two matrices, *W* and *C*.



How does word2vec work?

While more text:

- Extract a word window:

A springer is [	a	cow	or	**heifer**	close	to	calving	].
	c_1	c_2	c_3	w	c_4	c_5	c_6	

- w is the focus word vector (row in W).
- c_i are the context word vectors (rows in C).

How does word2vec work?

While more text:

- Extract a word window:

`A springer is [`	`a`	`cow`	`or`	**`heifer`**	`close`	`to`	`calving`	`].`
	c_1	c_2	c_3	w	c_4	c_5	c_6	

- Try setting the vector values such that:

$$\sigma(w \cdot c_1) + \sigma(w \cdot c_2) + \sigma(w \cdot c_3) + \sigma(w \cdot c_4) + \sigma(w \cdot c_5) + \sigma(w \cdot c_6)$$

is **high**

How does word2vec work?

While more text:

- Extract a word window:

`A springer is [`	`a`	`cow`	`or`	**`heifer`**	`close`	`to`	`calving`	`].`
	c_1	c_2	c_3	w	c_4	c_5	c_6	

- Try setting the vector values such that:

$$\sigma(w \cdot c_1) + \sigma(w \cdot c_2) + \sigma(w \cdot c_3) + \sigma(w \cdot c_4) + \sigma(w \cdot c_5) + \sigma(w \cdot c_6)$$

  is **high**

- Create a corrupt example by choosing a random word w'

`[`	`a`	`cow`	`or`	**`comet`**	`close`	`to`	`calving`	`]`
	c_1	c_2	c_3	w'	c_4	c_5	c_6	

- Try setting the vector values such that:

$$\sigma(w' \cdot c_1) + \sigma(w' \cdot c_2) + \sigma(w' \cdot c_3) + \sigma(w' \cdot c_4) + \sigma(w' \cdot c_5) + \sigma(w' \cdot c_6)$$

  is **low**

How does word2vec work?

The training procedure results in:

- $w \cdot c$ for **good** word-context pairs is **high.**
- $w \cdot c$ for **bad** word-context pairs is **low.**
- $w \cdot c$ for **ok-ish** word-context pairs is **neither high nor low.**

As a result:

- Words that share many contexts get close to each other.
- Contexts that share many words get close to each other.

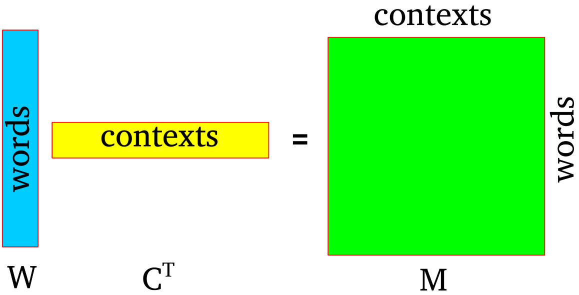
At the end, word2vec throws away C and returns W.

Reinterpretation

Imagine we didn't throw away C. Consider the product $WC^\top$

Reinterpretation

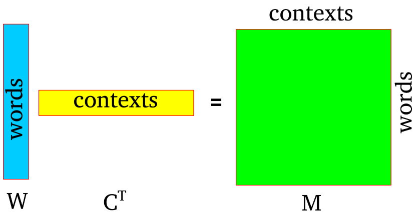
Imagine we didn't throw away C. Consider the product $WC^\top$



The result is a matrix M in which:

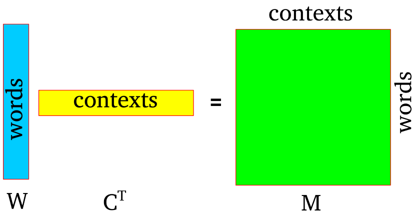
- Each row corresponds to a word.
- Each column corresponds to a context.
- Each cell correspond to $w \cdot c$, an association measure between a word and a context.

Reinterpretation



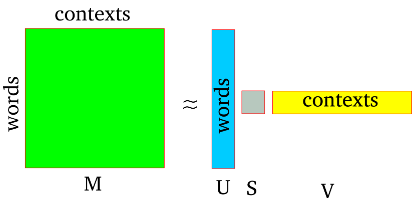
Does this remind you of something?

Reinterpretation



Does this remind you of something?

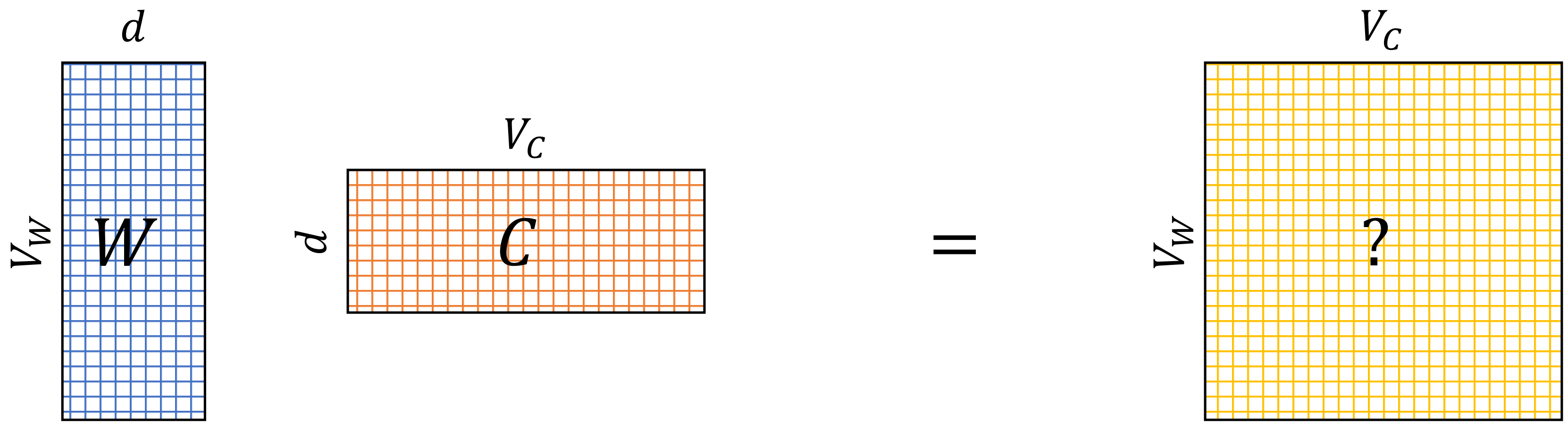
Very similar to SVD over distributional representation:



What is SGNS learning?

- A $V_W \times V_C$ matrix
- Each cell describes the relation between a specific word-context pair

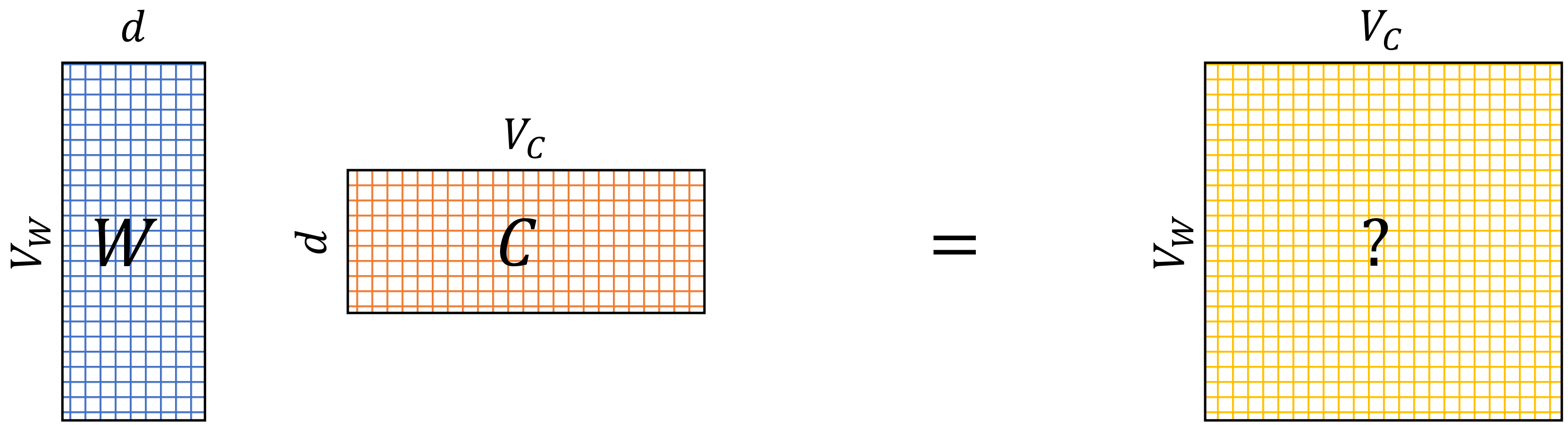
$$\vec{w} \cdot \vec{c} = ?$$



"Neural Word Embeddings as Implicit Matrix Factorization"
Levy & Goldberg, NIPS 2014

What is SGNS learning?

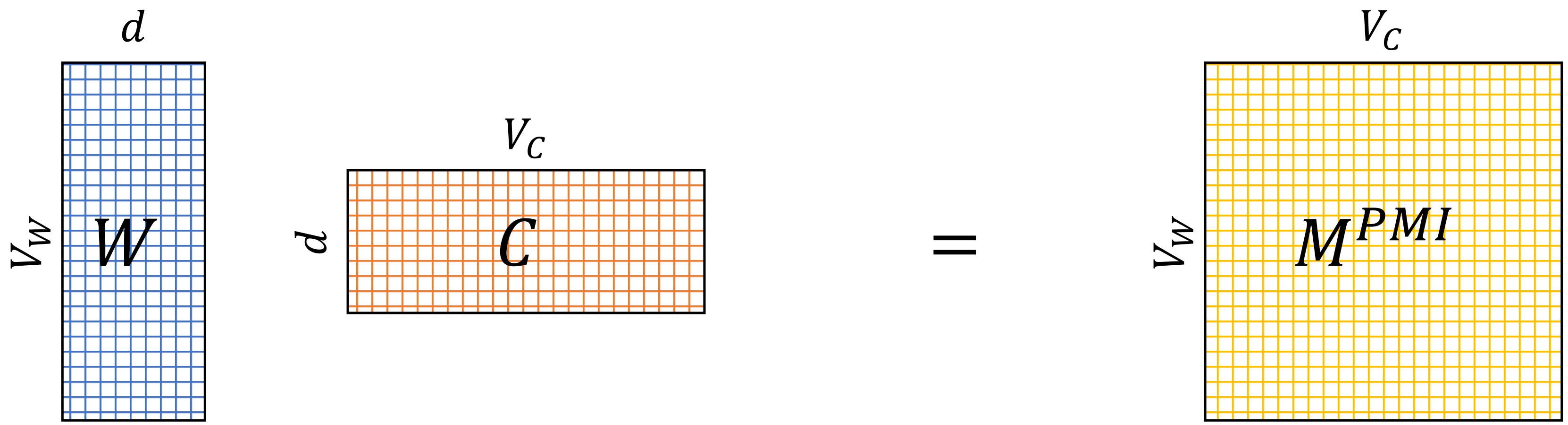
- We **prove** that for large enough d and enough iterations



"Neural Word Embeddings as Implicit Matrix Factorization"
Levy & Goldberg, NIPS 2014

What is SGNS learning?

- We **prove** that for large enough d and enough iterations
- We get the word-context PMI matrix

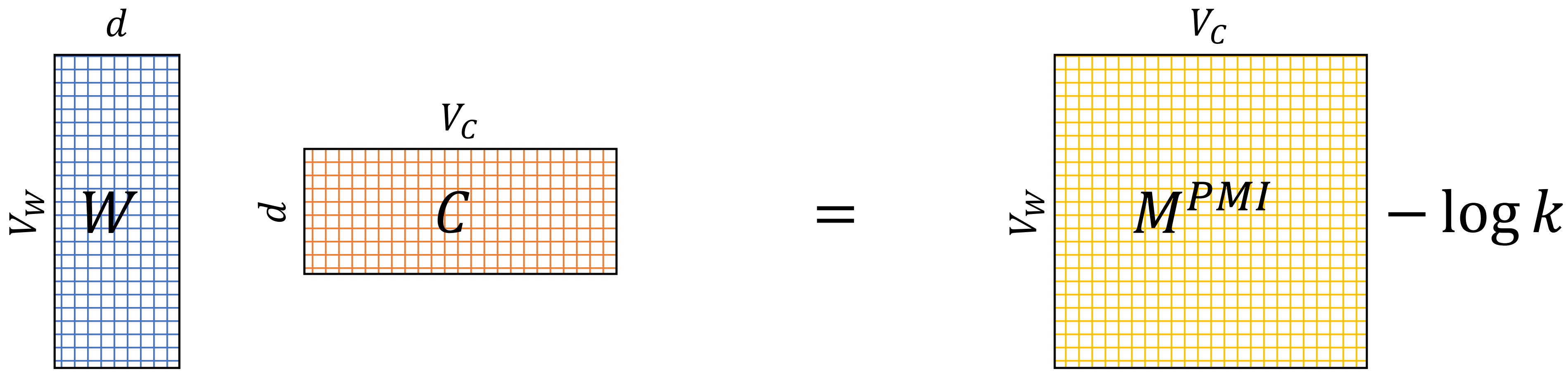


"Neural Word Embeddings as Implicit Matrix Factorization"
Levy & Goldberg, NIPS 2014

What is SGNS learning?

- We **prove** that for large enough d and enough iterations
- We get the word-context PMI matrix, shifted by a global constant

$$Opt(\vec{w} \cdot \vec{c}) = PMI(w, c) - \log k$$



"Neural Word Embeddings as Implicit Matrix Factorization"
Levy & Goldberg, NIPS 2014

What is SGNS learning?

- SGNS is doing something very similar to the older approaches
- SGNS is factorizing the traditional word-context PMI matrix
- So does SVD!
- Do they capture the same similarity function?

SGNS vs SVD

Target Word	SGNS	SVD
cat	dog rabbit cats poodle pig	dog rabbit pet monkey pig

SGNS vs SVD

Target Word	SGNS	SVD
wine	wines grape grapes winemaking tasting	wines grape grapes varietal vintages

SGNS vs SVD

Target Word	SGNS	SVD
November	October December April January July	October December April June March

But `word2vec` is still better, isn't it?

- Plenty of evidence that `word2vec` outperforms traditional methods
  - In particular: "Don't count, predict!" (Baroni et al., 2014)

- How does this fit with our story?

The Big Impact of “Small” Hyperparameters

Hyperparameters

- `word2vec` is more than just an algorithm…
- Introduces many **engineering tweaks** and **hyperpararameter settings**
  - May seem minor, but **make a big difference** in practice
  - Their impact is often more significant than the embedding algorithm's
- These modifications can be ported to distributional methods!

Levy, Goldberg, Dagan (In submission)

Hyperparameters

- Preprocessing
- Association Metric
- Postprocessing

Levy, Goldberg, Dagan (In submission)

Hyperparameters

- Preprocessing
- **Association Metric**
- Postprocessing

Levy, Goldberg, Dagan (In submission)

Association Metric Hyperparameters

- Since SGNS and PMI are strongly related,
  we can import 2 of SGNS's hyperparameters to traditional PMI:

1. Shifted PMI
2. **Negative Sampling Smoothing**

- Both stem from the negative sampling procedure

Levy, Goldberg, Dagan (In submission)

Negative Sampling Smoothing

- Recall that SGNS picks $w' \sim P$ to form negative (w', c) examples

- Our analysis assumes P is the unigram distribution

$$P\,(w) = \frac{\#w}{\sum_{w' \in V_W} \#w'}$$

Levy, Goldberg, Dagan (In submission)

Negative Sampling Smoothing

- Recall that SGNS picks $w' \sim P$ to form negative (w', c) examples

- Our analysis assumes P is the unigram distribution

- In practice, it's a **smoothed** unigram distribution

$$P^{0.75}(w) = \frac{(\#w)^{0.75}}{\sum_{w' \in V_W} (\#w')^{0.75}}$$

- This little change makes a big difference

Levy, Goldberg, Dagan (In submission)

Negative Sampling Smoothing

- This smoothing has an analogue in PMI

- Replace $P(w)$ with $P^{0.75}(w)$:

$$PMI^{0.75}(w,c) = \log \frac{P(w,c)}{P^{0.75}(w)P(c)}$$

- Yields a **dramatic** improvement with **every method** on **every task**

Levy, Goldberg, Dagan (In submission)

Experiments & Results

- We compared several methods, while controlling for hyperparameters
    - PPMI, SVD(PPMI), SGNS, GloVe

- Methods perform on-par in most tasks
    - Slight advantage to SVD in word similarity
    - SGNS is better at syntactic analogies
    - SGNS is robust in general

- **Negative sampling smoothing** accounts for much of the differences observed in "Don't count, predict!"

Levy, Goldberg, Dagan (In submission)

Other Hyperparameters

- There are many other hyperparameters that can be investigated
- Perhaps the most interesting one is **the type of context**

What’s in a Context?

What's in a Context?

- Importing ideas from embeddings improves distributional methods

- Can distributional ideas also improve embeddings?

- **Idea:** change SGNS's default **BoW contexts** into **dependency contexts**

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Example

Australian scientist discovers star with telescope

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Target Word

Australian scientist <u>discovers</u> star with telescope

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Bag of Words (BoW) Context

Australian scientist discovers star with telescope

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

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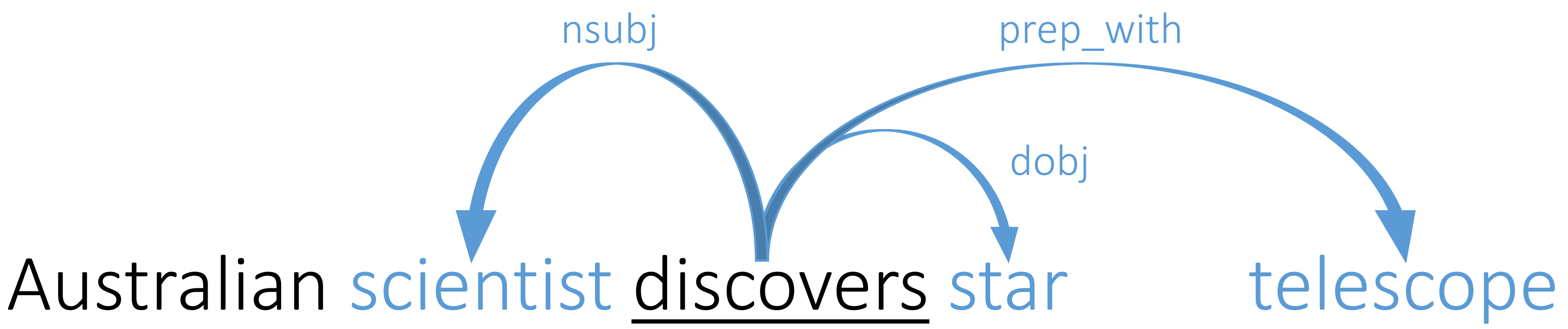
Levy & Goldberg, ACL 2014

Syntactic Dependency Context

Australian scientist <u>discovers</u> star with telescope

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Syntactic Dependency Context



“Dependency-Based Word Embeddings”
Levy & Goldberg, ACL 2014

Syntactic Dependency Context

“Dependency-Based Word Embeddings”
Levy & Goldberg, ACL 2014

Embedding Similarity with Different Contexts

Target Word	Bag of Words (k=5)	Dependencies
Hogwarts (Harry Potter's school)	Dumbledore hallows half-blood Malfoy Snape	Sunnydale Collinwood Calarts Greendale Millfield
	Related to Harry Potter	**Schools**

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Embedding Similarity with Different Contexts

Target Word	Bag of Words (k=5)	Dependencies
Turing (computer scientist)	nondeterministic non-deterministic computability deterministic finite-state	Pauling Hotelling Heting Lessing Hamming
	Related to computability	**Scientists**

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Embedding Similarity with Different Contexts

Target Word	Bag of Words (k=5)	Dependencies
dancing (dance gerund)	singing dance dances dancers tap-dancing	singing rapping breakdancing miming busking
	Related to dance	**Gerunds**

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

What is the effect of different context types?

- Thoroughly studied in distributional methods
  - Lin (1998), Padó and Lapata (2007), and many others…

General Conclusion:

- Bag-of-words contexts induce ***topical*** similarities
- Dependency contexts induce ***functional*** similarities
  - Share the same semantic type
  - Cohyponyms

- Holds for **embeddings** as well

“Dependency-Based Word Embeddings”
Levy & Goldberg, ACL 2014

Peeking into Skip-Gram's Black Box

- In explicit representations, we can **look** at the features and analyze

- But embeddings are a black box!
- Dimensions are latent and don't necessarily have any meaning

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Peeking into Skip-Gram's Black Box

- Skip-Gram allows a peek…

- Contexts are embedded in the same space!

- Given a word w, find the contexts c it "activates" most:

$$\arg\max_{c}(\vec{w} \cdot \vec{c})$$

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Associated Contexts

Target Word	Dependencies
Hogwarts	students/prep_at^{-1} educated/prep_at^{-1} student/prep_at^{-1} stay/prep_at^{-1} learned/prep_at^{-1}

“Dependency-Based Word Embeddings”
Levy & Goldberg, ACL 2014

Associated Contexts

Target Word	Dependencies
Turing	machine/nn^{-1} test/nn^{-1} theorem/poss^{-1} machines/nn^{-1} tests/nn^{-1}

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Associated Contexts

Target Word	Dependencies
dancing	dancing/conj
	dancing/conj^{-1}
	singing/conj^{-1}
	singing/conj
	ballroom/nn

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

Analyzing Embeddings

- We show a way to ***linguistically*** analyze embeddings
- Together with the ability to engineer contexts…
- …we now have the tools to create **task-tailored** embeddings!

"Dependency-Based Word Embeddings"
Levy & Goldberg, ACL 2014

But there's still one question left...

- How do you explain this?

$$\text{king} - \text{man} + \text{woman} = \text{queen}$$

But there's still one question left…

- How do you explain this?

Tokyo – Japan + France = Paris

But there’s still one question left…

- How do you explain this?

$$\text{best} - \text{good} + \text{strong} = \text{strongest}$$

Kings, Queens, and Vector Arithmetic

Analogies

man is to $woman$ as $king$ is to $?$

- Mikolov et al.: analogies can be recovered by simple vector arithmetic

$$king - man + woman = queen$$

- Why does this work?

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Why does vector arithmetic reveal analogies?

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Why does vector arithmetic reveal analogies?

- We wish to find the closest x to $king - man + woman$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Why does vector arithmetic reveal analogies?

- We wish to find the closest x to $king - man + woman$
- This is done with cosine similarity:

$$\arg\max_{x}(\cos(x, king - man + woman))$$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Why does vector arithmetic reveal analogies?

- We wish to find the closest x to $king - man + woman$
- This is done with cosine similarity:

$$\arg\max_{x}(\cos(x, king - man + woman)) =$$

$$\arg\max_{x}(\cos(x, king) - \cos(x, man) + \cos(x, woman))$$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

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vector arithmetic $=$ similarity arithmetic

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

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vector arithmetic = similarity arithmetic

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Why does vector arithmetic reveal analogies?

- We wish to find the closest x to $king - man + woman$
- This is done with cosine similarity:

$$\arg\max_x(\cos(x, king - man + woman)) =$$

$$\arg\max_x(\underbrace{\boxed{\cos(x, king)}}_{\text{royal?}} - \cos(x, man) + \underbrace{\boxed{\cos(x, woman)}}_{\text{female?}})$$

vector arithmetic $=$ **similarity arithmetic**

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

What does each similarity term mean?

- Observe the joint features with explicit representations!

$queen \cap king$	$queen \cap woman$
uncrowned	Elizabeth
majesty	Katherine
second	impregnate
…	…

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Can we do better?

“Linguistic Regularities…”
Levy & Goldberg, CoNLL 2014

Let’s look at some mistakes…

“Linguistic Regularities…”
Levy & Goldberg, CoNLL 2014

Let’s look at some mistakes…

England – London + Baghdad = ?

“Linguistic Regularities…”
Levy & Goldberg, CoNLL 2014

Let’s look at some mistakes…

England – London + Baghdad = Iraq

“Linguistic Regularities…”
Levy & Goldberg, CoNLL 2014

Let's look at some mistakes…

England – London + Baghdad = Mosul?

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

The Additive Objective

$$\cos(Iraq, England) - \cos(Iraq, London) + \cos(Iraq, Baghdad)$$

$$\cos(Mosul, England) - \cos(Mosul, London) + \cos(Mosul, Baghdad)$$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

The Additive Objective

$$\cos(Iraq, England) - \cos(Iraq, London) + \cos(Iraq, Baghdad)$$

0.15

0.13

$$\cos(Mosul, England) - \cos(Mosul, London) + \cos(Mosul, Baghdad)$$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

The Additive Objective

$$\cos(Iraq, England) - \cos(Iraq, London) + \cos(Iraq, Baghdad)$$

0.15 0.13

0.13 0.14

$$\cos(Mosul, England) - \cos(Mosul, London) + \cos(Mosul, Baghdad)$$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

The Additive Objective

$$\cos(Iraq, England) - \cos(Iraq, London) + \cos(Iraq, Baghdad)$$

0.15 0.13 0.63

0.13 0.14 0.75

$$\cos(Mosul, England) - \cos(Mosul, London) + \cos(Mosul, Baghdad)$$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

The Additive Objective

$$\cos(Iraq, England) - \cos(Iraq, London) + \cos(Iraq, Baghdad)$$

$$0.15 \qquad 0.13 \qquad 0.63 \qquad = 0.65$$

$$0.13 \qquad 0.14 \qquad 0.75 \qquad = 0.74$$

$$\cos(Mosul, England) - \cos(Mosul, London) + \cos(Mosul, Baghdad)$$

“Linguistic Regularities…”
Levy & Goldberg, CoNLL 2014

The Additive Objective

$$\cos(Iraq, England) - \cos(Iraq, London) + \cos(Iraq, Baghdad)$$

$$0.15 \qquad 0.13 \qquad 0.63 \qquad = 0.65$$

$$0.13 \qquad 0.14 \qquad 0.75 \qquad = 0.74$$

$$\cos(Mosul, England) - \cos(Mosul, London) + \cos(Mosul, Baghdad)$$

- **Problem:** one similarity might dominate the rest

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

How can we do better?

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

How can we do better?

- Instead of **adding** similarities, **multiply** them!

“Linguistic Regularities…”
Levy & Goldberg, CoNLL 2014

How can we do better?

- Instead of **adding** similarities, **multiply** them!

$$\arg\max_{x}\left(\frac{\cos(x, king)\cos(x, woman)}{\cos(x, man)}\right)$$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

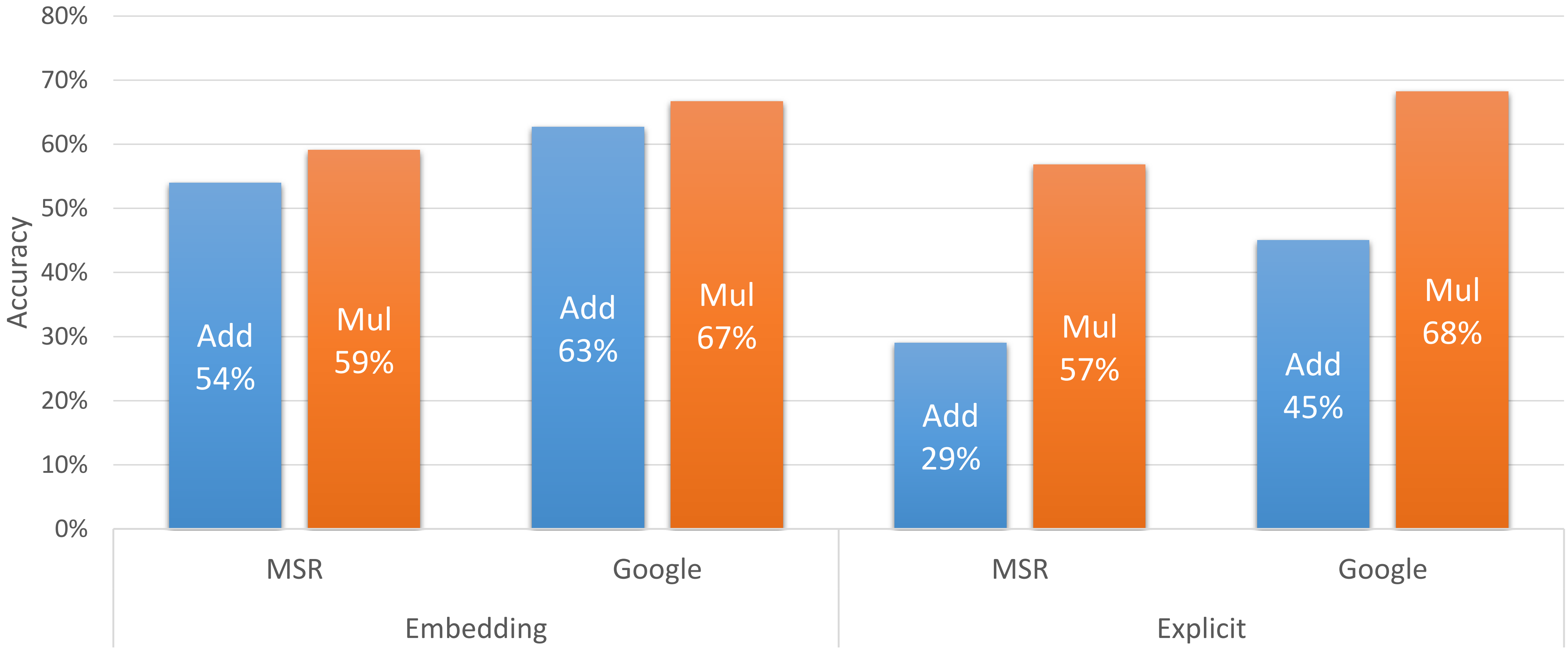
How can we do better?

- Instead of **adding** similarities, **multiply** them!

$$\arg\max_{x}\left(\frac{\cos(x, king)\cos(x, woman)}{\cos(x, man)}\right)$$

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Multiplication > Addition



"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Kings, Queens, and Vector Arithmetic

- Why does vector arithmetic reveal analogies?

Because **vector arithmetic** is equivalent to **similarity arithmetic**.

- We can improve analogy recovery with the **multiplicative objective**

"Linguistic Regularities…"
Levy & Goldberg, CoNLL 2014

Conclusion

To Summarize

- In order to communicate...
- ...we need to understand language.
- The building blocks:
  - Understanding structure.
  - Understanding words.
- Representing words as vectors can go a long way
- ...but shouldn't be treated as magical.
- By understanding what's going on behind the scenes, one can **improve** and **control** the behavior of the models.
  - better analogical reasoning.
  - syntactic contexts $\rightarrow$ more functional similarities.
- Understanding language is hard. Still a long way to go.

Thanks – for + listening =)