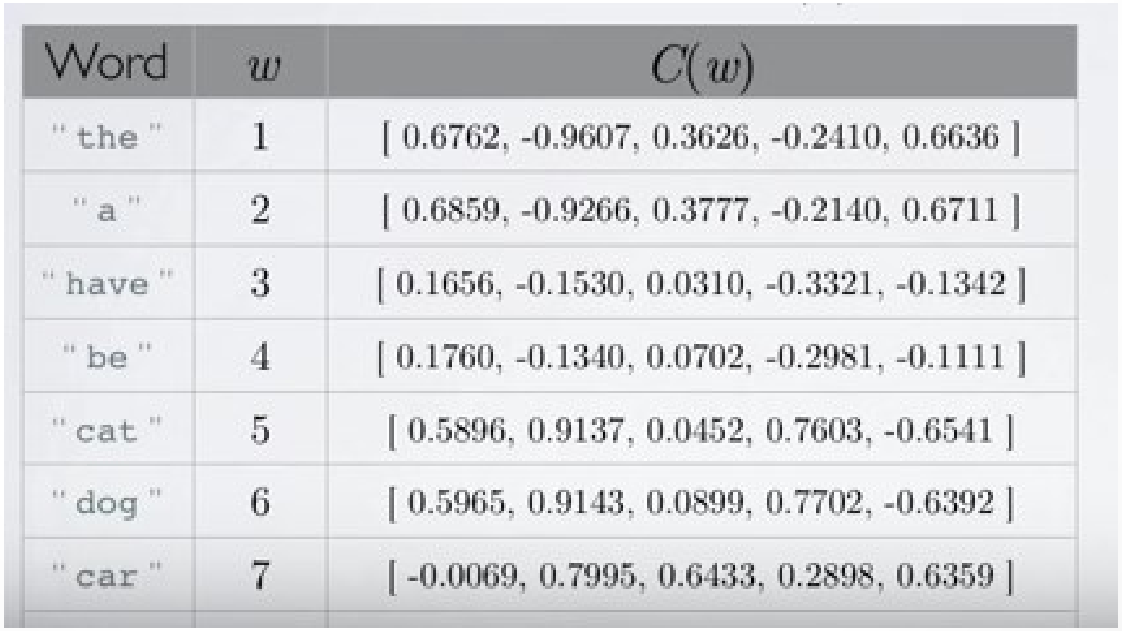
# Representation Discovery

(Slides by Piotr Mirowski, Hugo Larochelle, Omer Levy, Yoav Goldberg, Graham Neubig, and Tomas Mikolov)

# Distributed Representation

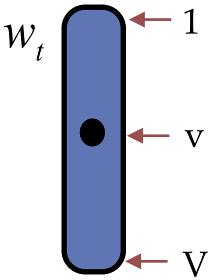
- Each word is associated with a continuous valued vector



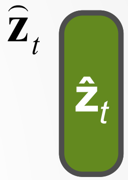
| Word | $w$ | $C(w)$ |
|---|---|---|
| `" the "` | 1 | [ 0.6762, -0.9607, 0.3626, -0.2410, 0.6636 ] |
| `" a "` | 2 | [ 0.6859, -0.9266, 0.3777, -0.2140, 0.6711 ] |
| `" have "` | 3 | [ 0.1656, -0.1530, 0.0310, -0.3321, -0.1342 ] |
| `" be "` | 4 | [ 0.1760, -0.1340, 0.0702, -0.2981, -0.1111 ] |
| `" cat "` | 5 | [ 0.5896, 0.9137, 0.0452, 0.7603, -0.6541 ] |
| `" dog "` | 6 | [ 0.5965, 0.9143, 0.0899, 0.7702, -0.6392 ] |
| `" car "` | 7 | [ -0.0069, 0.7995, 0.6433, 0.2898, 0.6359 ] |

# Vector-space representation of words

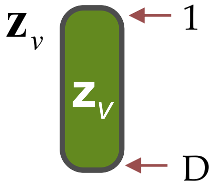
“**One-hot**” of “**one-of-V**”
representation
of a word token at position *t*
in the text corpus,
with **vocabulary of size *V***



**Vector-space representation**
of the prediction
of **target word $w_t$**
(we predict a vector of size *D*)

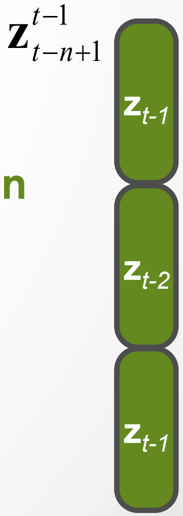


**Vector-space representation**
of any word *v*
in the vocabulary
using a vector of **dimension *D***



Also called
**distributed representation**

**Vector-space representation**
of the **$t^{th}$ word history**:
e.g., concatenation
of *n*-1 vectors of size *D*



# Predictive

- Input:
  - word history/context (**one-hot** or **distributed representation**)
- Output:
  - target word(s) (**one-hot** or **distributed representation**)
- **Function** that **approximates word likelihood**:
  - **Collobert & Weston**
  - **Continuous bag-of-words**
  - **Skip-gram**
  - …

# Learning continuous space models

- How do we **learn the word representations z** for each word in the vocabulary?
- How do we **learn the model** that predicts a word or its representation $\hat{z}_t$ given a word context?

- Simultaneous learning of **model** and **representation**

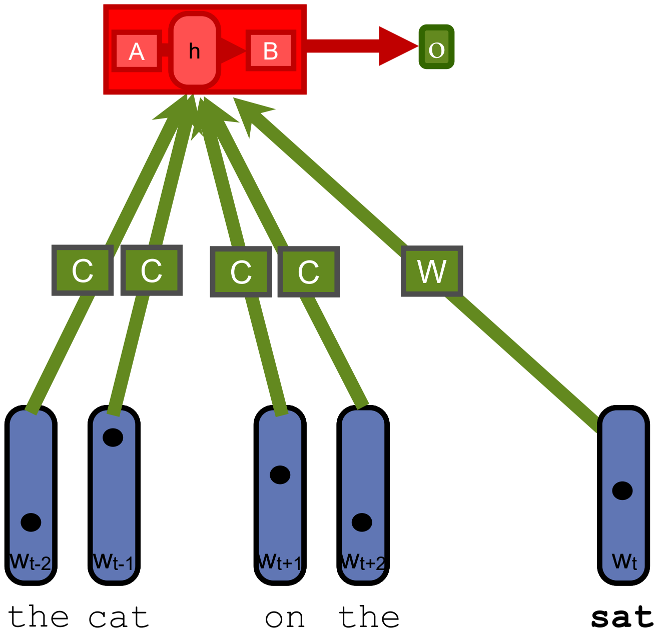
# Collobert & Weston

Prediction network: 2 layer network outputting a scalar

word embedding
space $\Re^D$
in dimension
*D*=100 to 300

**Word embedding matrices**

discrete word
space {1, ..., *V*}
*V*>100k words



$$P\left(w_t \mid \mathbf{w}_{t-c}^{t-1}, \mathbf{w}_{t+1}^{t+c}\right) = \frac{e^{o(w)}}{\sum_v e^{o(v)}}$$

Solution: negative sampling
Max margin Loss:

max{0, 1-(o(w)-o(w’))}

Parameters: (2?)DxV + (2c+1)DxH + Hx1
*Denominator: Iterate over V <not feasible>*

[Mikolov et al, 2013a; Mnih & Kavukcuoglu, 2013;
http://code.google.com/p/word2vec ]

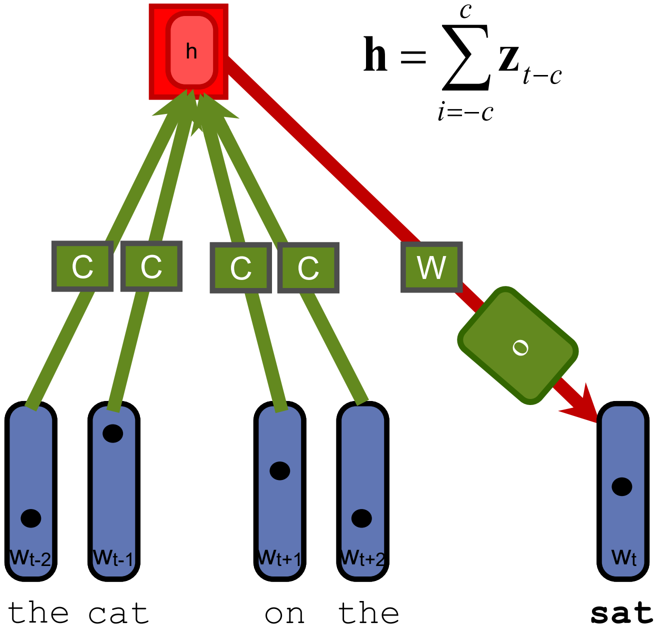
# Continuous Bag-of-Words

Simple sum

word embedding
space $\Re^D$
in dimension
$D$=100 to 300

**Word embedding matrices**

discrete word
space {1, ..., $V$}
$V$>100k words



$$\mathbf{h} = \sum_{i=-c}^{c} \mathbf{z}_{t-c}$$

$$\mathbf{o} = \mathbf{W}\mathbf{h}$$

$$P\left(w_t \mid \mathbf{w}_{t-c}^{t-1}, \mathbf{w}_{t+1}^{t+c}\right) = \frac{e^{o(w)}}{\sum_v e^{o(v)}}$$

Parameters: 2DxV + 2$c$×$D$ + $D$×$V$

Problem: large output space!

[Mikolov et al, 2013a; Mnih & Kavukcuoglu, 2013;
http://code.google.com/p/word2vec ]

# Aside

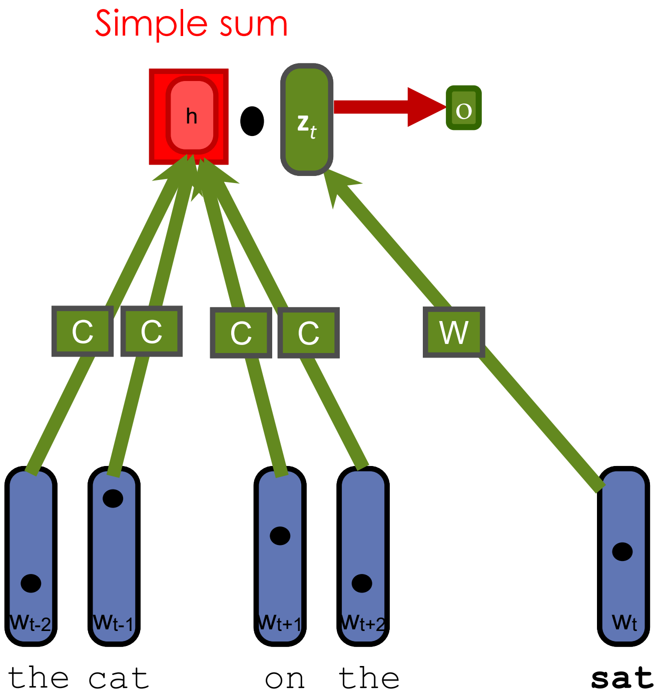
- Sum of vectors of words is a good baseline embedding for a short document
  - Short document = a bag of words since position information is lost
- See Section 11.6 (Goldberg) for the computation of document similarity

# Continuous Bag-of-Words

word embedding space $\Re^D$ in dimension $D$=100 to 300

**Word embedding matrices**

discrete word space {1, ..., $V$} $V$>100k words



$$\mathbf{h} = \sum_{i=-c}^{c} \mathbf{z}_{t-c}$$

$$\mathbf{o}=\mathbf{h}.\mathbf{z}_t$$

**Negative sampling for scalability (6B words)**

$$\Pr(D=1|c)=\sigma(h.w)$$
$$\Pr(D=0|c)=\sigma(-h.w')$$

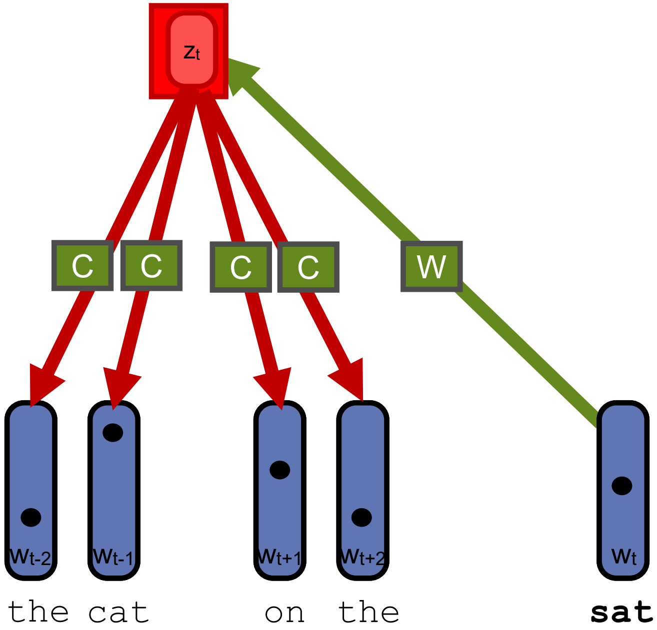
Parameters: 2DxV

good word+context pairs

bad word+context pairs

$$\mathcal{L}(\Theta; D, \bar{D}) = \sum_{(w,c)\in D} \log P(D=1|w,c) + \sum_{(w',c)\in \bar{D}} \log P(D=0|w',c)$$

# Skip-gram



word embedding space $\Re^D$ in dimension $D$=100 to 1000

**Word embedding matrices**

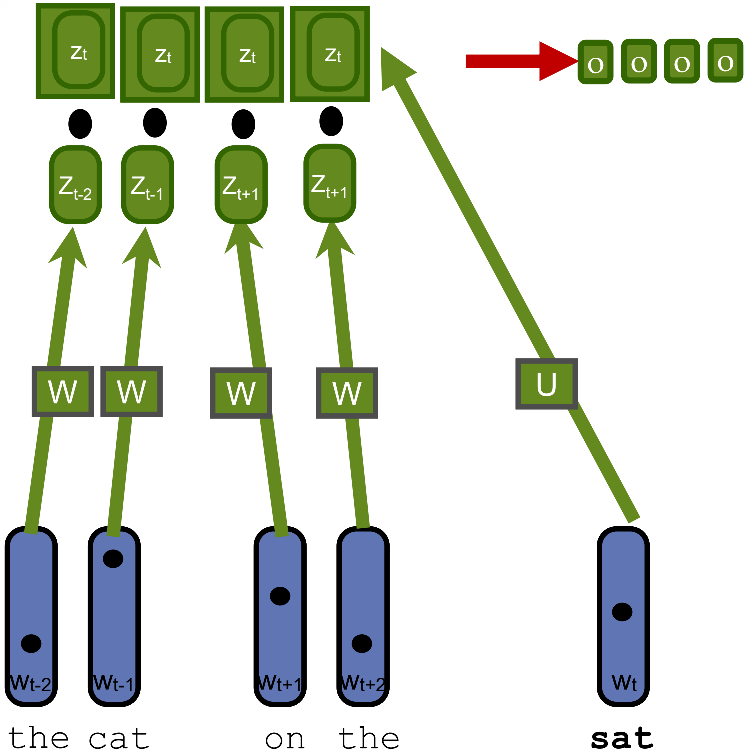
discrete word space {1, ..., $V$} $V$>100k words

$o = z_{t+i} \cdot z_t \quad i=-2,-1,1,2$

Parameters: 2DxV

[Mikolov et al, 2013a, 2013b; Mnih & Kavukcuoglu, 2013; http://code.google.com/p/word2vec ]

# Skip-gram



word embedding space $\Re^D$ in dimension $D$=100 to 1000

**Word embedding matrices**

discrete word space $\{1, ..., V\}$ $V$>100k words

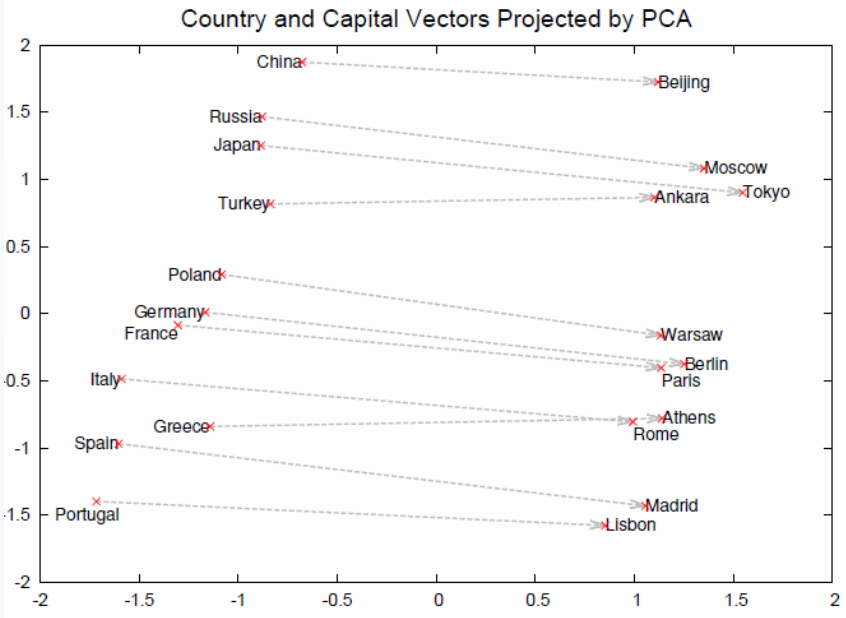
$o = z_{t+i} . z_t \quad i = -2, -1, 1, 2$

$Pr(D=1 | c) = \sigma(c_i . w)$
$Pr(D=0 | c) = \sigma(-c_i . w')$

Parameters: 2DxV
*(Scales to 33B words)*

[Mikolov et al, 2013a, 2013b; Mnih & Kavukcuoglu, 2013; http://code.google.com/p/word2vec ]

# Vector-space word representation without LM



[Image credits: Mikolov et al (2013) "Distributed Representations of Words and Phrases and their Compositionality", *NIPS*]

Word and phrase representation learned by skip-gram **exhibit linear structure** that enables **analogies with vector arithmetics**.

This is **due to training objective**, input and output (before softmax) are in **linear relationship**.

The sum of vectors in the loss function is the sum of log-probabilities (or log of product of probabilities), i.e., comparable to the AND function.

[Mikolov et al, 2013a, 2013b; http://code.google.com/p/word2vec]

# Examples of Word2Vec embeddings

Example of word embeddings obtained using Word2Vec on the 3.2B word Wikipedia:

- Vocabulary *V*=2M
- Continuous vector space *D*=200
- Trained using CBOW

| debt | aa | decrease | met | slow | france | jesus | xbox |
|---|---|---|---|---|---|---|---|
| debts | aaarm | increase | meeting | slower | marseille | christ | playstation |
| repayments | samavat | increases | meet | fast | french | resurrection | wii |
| repayment | obukhovskii | decreased | meets | slowing | nantes | savior | xbla |
| monetary | emerlec | greatly | had | slows | vichy | miscl | wiiware |
| payments | gunss | decreasing | welcomed | slowed | paris | crucified | gamecube |
| repay | dekhen | increased | insisted | faster | bordeaux | god | nintendo |
| mortgage | minizini | decreases | acquainted | sluggish | aubagne | apostles | kinect |
| repaid | bf | reduces | satisfied | quicker | vend | apostle | dsiware |
| refinancing | mortardepth | reduce | first | pace | vienne | bickertonite | eshop |
| bailouts | ee | increasing | persuaded | slowly | toulouse | pretribulational | dreamcast |

[Mikolov et al, 2013a, 2013b; http://code.google.com/p/word2vec]

# Semantic-syntactic word evaluation task

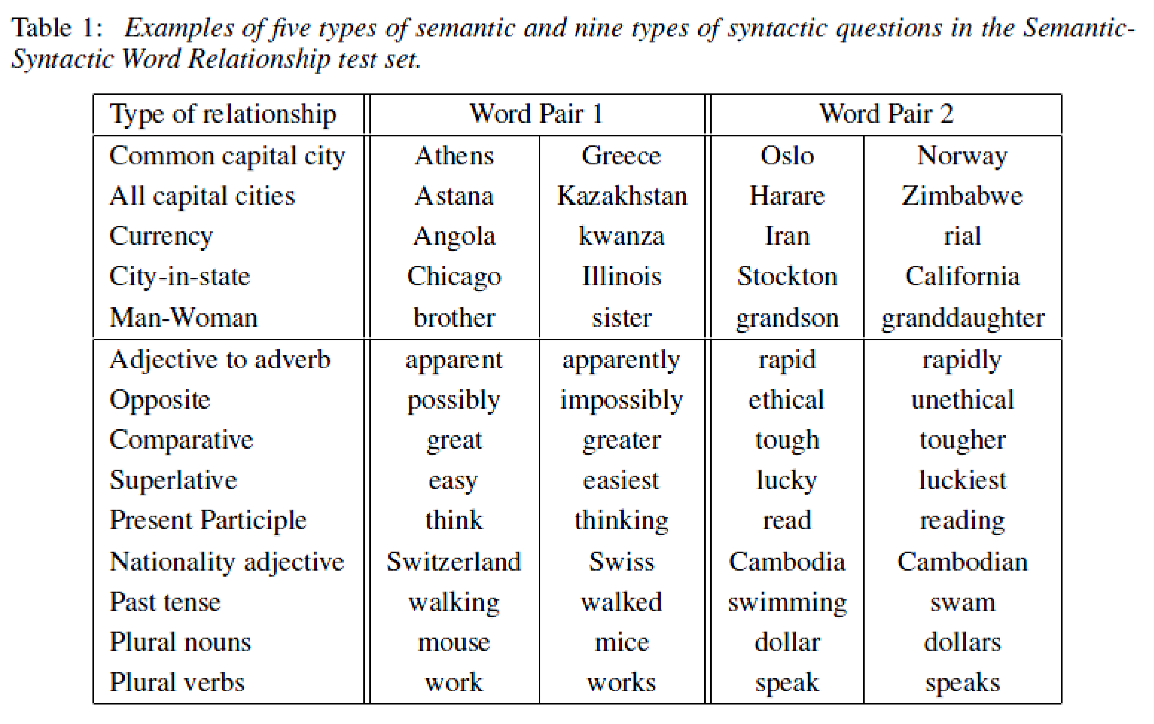


Table 1: *Examples of five types of semantic and nine types of syntactic questions in the Semantic-Syntactic Word Relationship test set.*

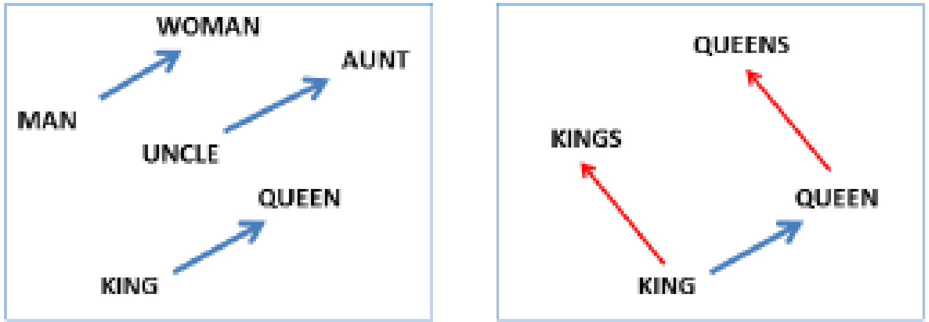
| Type of relationship | Word Pair 1 | | Word Pair 2 | |
|---|---|---|---|---|
| Common capital city | Athens | Greece | Oslo | Norway |
| All capital cities | Astana | Kazakhstan | Harare | Zimbabwe |
| Currency | Angola | kwanza | Iran | rial |
| City-in-state | Chicago | Illinois | Stockton | California |
| Man-Woman | brother | sister | grandson | granddaughter |
| Adjective to adverb | apparent | apparently | rapid | rapidly |
| Opposite | possibly | impossibly | ethical | unethical |
| Comparative | great | greater | tough | tougher |
| Superlative | easy | easiest | lucky | luckiest |
| Present Participle | think | thinking | read | reading |
| Nationality adjective | Switzerland | Swiss | Cambodia | Cambodian |
| Past tense | walking | walked | swimming | swam |
| Plural nouns | mouse | mice | dollar | dollars |
| Plural verbs | work | works | speak | speaks |

[Image credits: Mikolov et al (2013) "Efficient Estimation of Word Representation in Vector Space", *arXiv*]

[Mikolov et al, 2013a, 2013b; http://code.google.com/p/word2vec]

# Syntactic and Semantic tests

Observed that word embeddings obtained by RNN-LDA have linguistic regularities “a” is to “b” as “c” is to _
**Syntactic:** king is to kings as queen is to **queens**
**Semantic:** clothing is to shirt as dish is to **bowl**



**Vector offset method**

$z_1$ - $z_2$ + $z_3$ = $\hat{z}$ $z_V$

**cosine similarity**

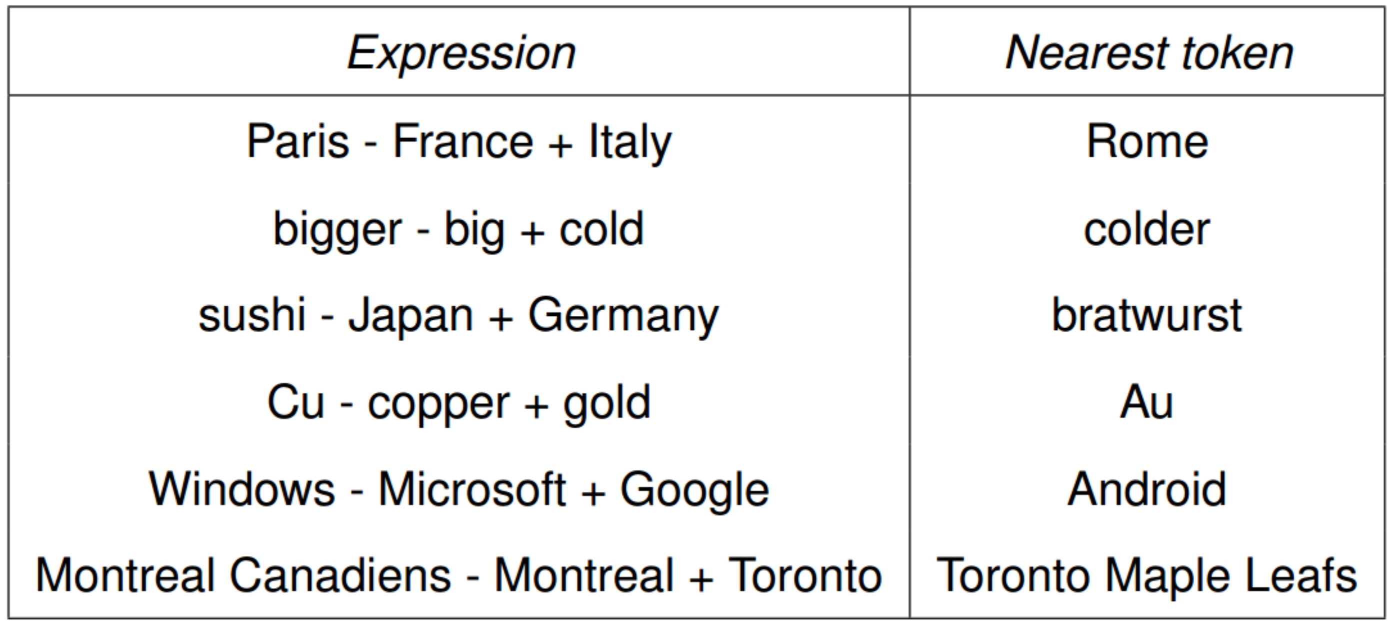
$$\arg\max_{b^*\in V}\left(\cos\left(b^*, b - a + a^*\right)\right)$$

$$\arg\max_{b^*\in V}\frac{\cos\left(b^*, b\right)\cos\left(b^*, a^*\right)}{\cos\left(b^*, a\right)+\varepsilon}$$

$$\arg\max_{b^*\in V}\left(\cos\left(b^*, b\right) - \cos\left(b^*, a\right) + \cos\left(b^*, a^*\right)\right)$$

3]

# Linguistic Regularities - Examples

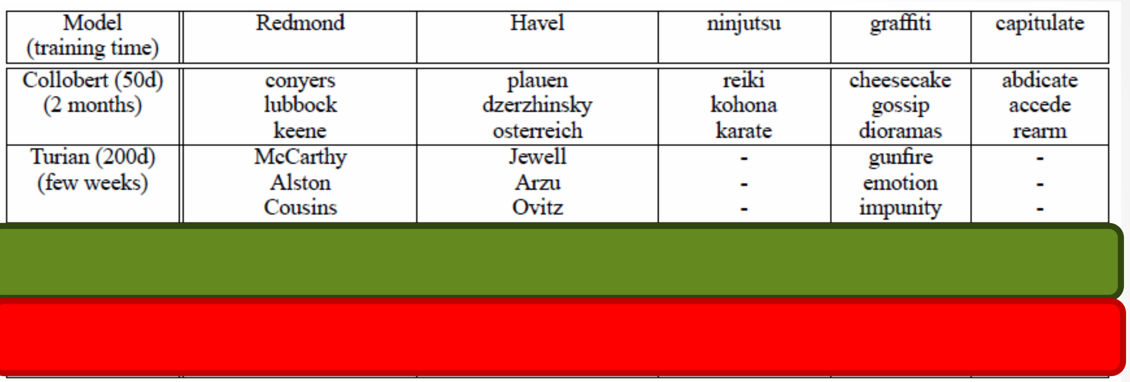


| *Expression* | *Nearest token* |
|---|---|
| Paris - France + Italy | Rome |
| bigger - big + cold | colder |
| sushi - Japan + Germany | bratwurst |
| Cu - copper + gold | Au |
| Windows - Microsoft + Google | Android |
| Montreal Canadiens - Montreal + Toronto | Toronto Maple Leafs |

# Speed-up over full softmax

LBL with **full softmax**, trained on APNews data, **14M words**, **V=17k** **7days**

**Skip-gram** (context 5) with phrases, trained using **negative sampling**, on Google data, **33G** words, **V=692k + phrases** **1 day**



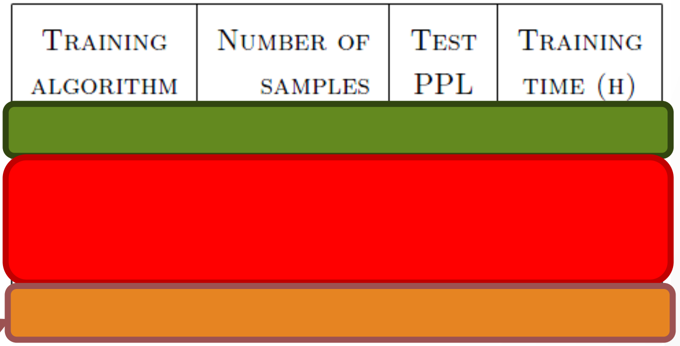
| Model (training time) | Redmond | Havel | ninjutsu | graffiti | capitulate |
|---|---|---|---|---|---|
| Collobert (50d) (2 months) | conyers<br>lubbock<br>keene | plauen<br>dzerzhinsky<br>osterreich | reiki<br>kohona<br>karate | cheesecake<br>gossip<br>dioramas | abdicate<br>accede<br>rearm |
| Turian (200d) (few weeks) | McCarthy<br>Alston<br>Cousins | Jewell<br>Arzu<br>Ovitz | -<br>-<br>- | gunfire<br>emotion<br>impunity | -<br>-<br>- |

[Image credits: Mikolov et al (2013) "Distributed Representations of Words and Phrases and their Compositionality", *NIPS*]

LBL (2-gram, 100d) with **full softmax**, **1 day**

LBL (2-gram, 100d) with **noise contrastive estimation** **1.5 hours**

RNN (100d) with **50-class hierarchical softmax** **0.5 hours** (own experience)



| TRAINING ALGORITHM | NUMBER OF SAMPLES | TEST PPL | TRAINING TIME (H) |
|---|---|---|---|

Penn TreeBank data (900k words, V=10k)

[Image credits: Mnih & Teh (2012) "A fast and simple algorithm for training neura probabilistic language models", *ICML*]

[Mnih & Teh, 2012; Mikolov et al, 2010-2012, 2013b]

# What is `word2vec`?

- `word2vec` is **not** a single algorithm
- It is a **software package** for representing words as vectors, containing:
  - Two distinct models
    - CBoW
    - **Skip-Gram** **(SG)**
  - Various training methods
    - **Negative Sampling** **(NS)**
    - Hierarchical Softmax
  - A rich preprocessing pipeline
    - Dynamic Context Windows
    - Subsampling
    - Deleting Rare Words

# What is SGNS learning?

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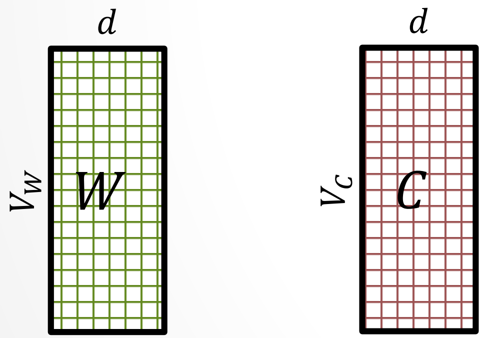
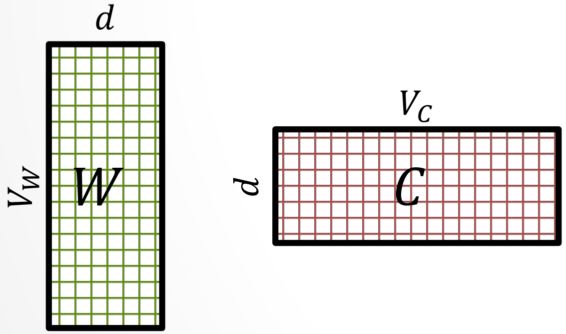
- Take SGNS's embedding matrices ($W$ and $C$)



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

# What is SGNS learning?

- Take SGNS's embedding matrices ($W$ and $C$)
- Multiply them
- What do you get?



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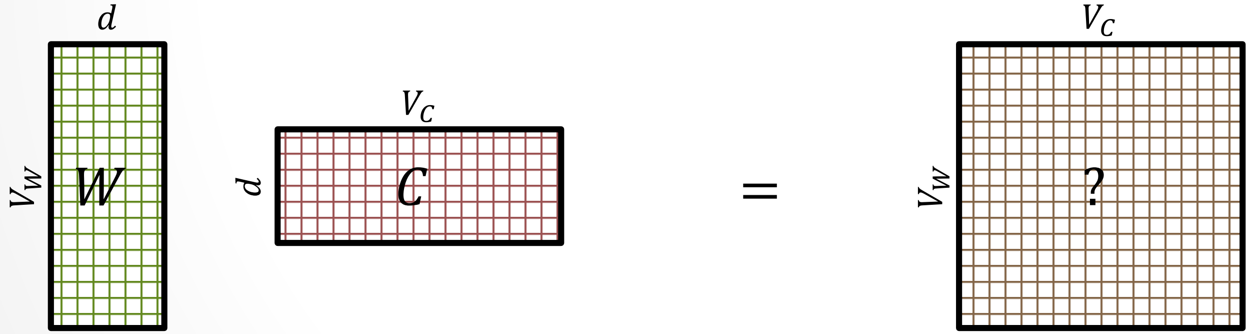
# What is SGNS learning?

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

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



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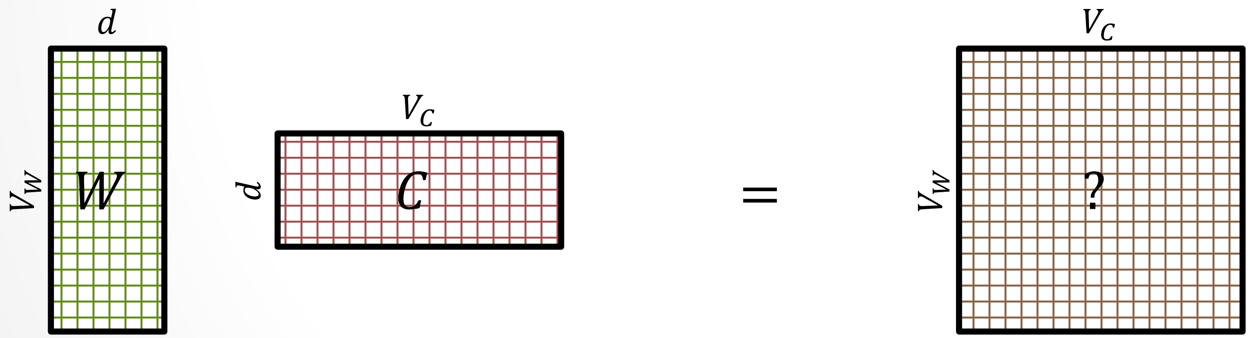
# What is SGNS learning?

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



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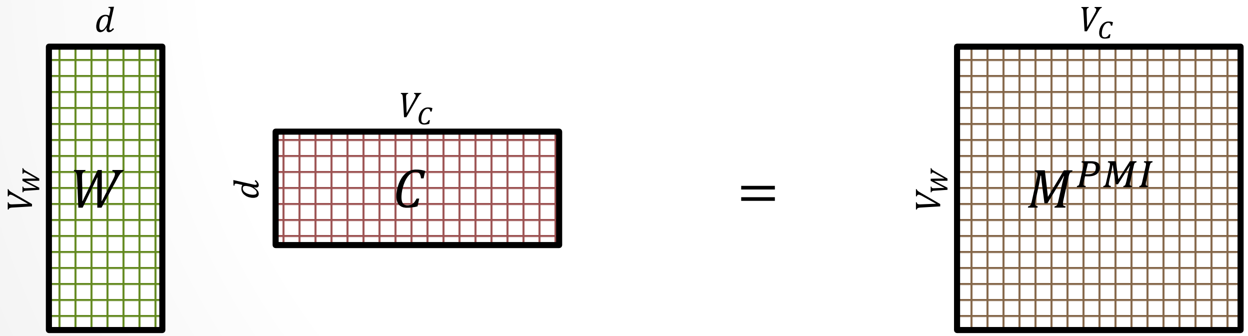

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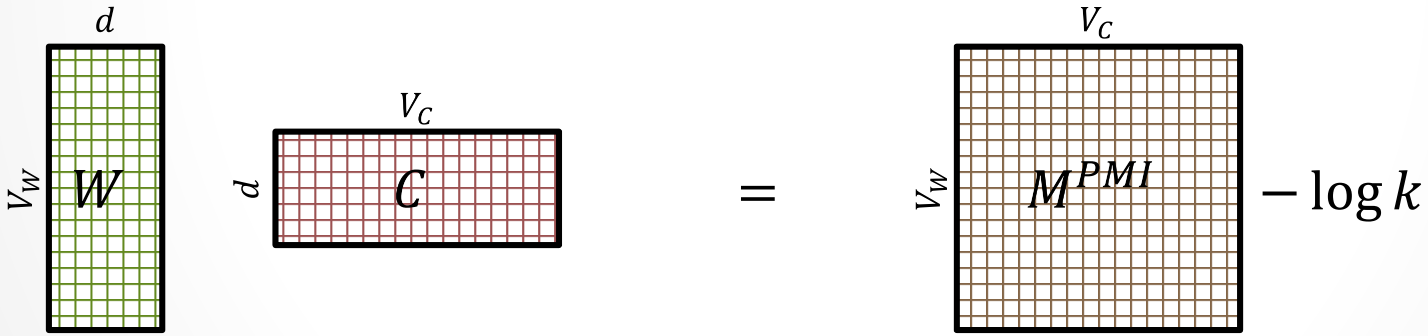
# What is SGNS learning?

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

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



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# GLOVE

- SGNS

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

- GLOVE

$$\vec{w} \cdot \vec{c} + b_w + b_c = \log\left(\#(w, c)\right) \quad \forall (w, c) \in D$$

# Follow up work

Baroni, Dinu, Kruszewski (2014): Don't count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors

- Turns out neural based approaches are very close to traditional distributional semantics models
- Luckily, word2vec significantly outperformed the best previous models across many tasks ☺

- How to reconcile good results ???

# The Big Impact of “Small” Hyperparameters

- `word2vec` & GloVe are more than just algorithms…
- Introduce **new hyperparameters**
- May seem minor, but **make a big difference** in practice

# New Hyperparameters

- **Preprocessing** **(word2vec)**
  - Dynamic Context Windows
  - Subsampling
  - Deleting Rare Words

- **Postprocessing** **(GloVe)**
  - Adding Context Vectors

- **Association Metric** **(SGNS)**
  - Shifted PMI
  - Context Distribution Smoothing

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# Dynamic Context Windows

Marco saw a furry little wampimuk hiding in the tree.

# Dynamic Context Windows

Marc saw a furry little wampimuk hiding in the tree.

# Dynamic Context Windows

saw a furry little wampimuk hiding in the tree.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| word2vec: | $\frac{1}{4}$ | $\frac{2}{4}$ | $\frac{3}{4}$ | $\frac{4}{4}$ | | $\frac{4}{4}$ | $\frac{3}{4}$ | $\frac{2}{4}$ | $\frac{1}{4}$ |
| GloVe: | $\frac{1}{4}$ | $\frac{1}{3}$ | $\frac{1}{2}$ | $\frac{1}{1}$ | | $\frac{1}{1}$ | $\frac{1}{2}$ | $\frac{1}{3}$ | $\frac{1}{4}$ |
| Aggressive: | $\frac{1}{8}$ | $\frac{1}{4}$ | $\frac{1}{2}$ | $\frac{1}{1}$ | | $\frac{1}{1}$ | $\frac{1}{2}$ | $\frac{1}{4}$ | $\frac{1}{8}$ |

**The Word-Space Model** *(Sahlgren, 2006)*

# Adding Context Vectors

- SGNS creates word vectors $\vec{w}$
- SGNS creates auxiliary context vectors $\vec{c}$
  - So do GloVe and SVD

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- SGNS creates word vectors $\vec{w}$
- SGNS creates auxiliary context vectors $\vec{c}$
  - So do GloVe and SVD

- Instead of just $\vec{w}$
- Represent a word as: $\vec{w} + \vec{c}$

- Introduced by Pennington et al. (2014)
- Only applied to GloVe

# **Adapting** Hyperparameters across Algorithms

# Context Distribution Smoothing

- SGNS samples $c' \sim P$ to form **negative** $(w, c')$ examples

- Our analysis assumes $P$ is the unigram distribution

$$P(c) = \frac{\#c}{\sum_{c' \in V_C} \#c'}$$

# Context Distribution Smoothing

- SGNS samples $c' \sim P$ to form **negative** $(w, c')$ examples
- Our analysis assumes $P$ is the unigram distribution
- In practice, it's a **smoothed** unigram distribution

$$P^{0.75}(c) = \frac{(\#c)^{0.75}}{\sum_{c' \in V_C} (\#c')^{0.75}}$$

- This little change makes a big difference

# Context Distribution Smoothing

- We can **adapt** context distribution smoothing to PMI!
- Replace $P(c)$ with $P^{0.75}(c)$:

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

- Consistently improves **PMI** on **every task**
- **Always use Context Distribution Smoothing!**

# Comparing Algorithms

# Controlled Experiments

- Prior art was unaware of these hyperparameters
- Essentially, comparing “apples to oranges”
- We allow **every algorithm** to use **every hyperparameter**

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* If transferable

# Systematic Experiments

- 9 Hyperparameters
  - 6 New
- 4 Word Representation Algorithms
  - PPMI (Sparse & Explicit)
  - SVD(PPMI)
  - SGNS
  - GloVe
- 8 Benchmarks
  - 6 Word Similarity Tasks
  - 2 Analogy Tasks
- **5,632 experiments**

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# Hyperparameter Settings

## Classic Vanilla Setting

*(commonly used for distributional baselines)*

- Preprocessing
    - <None>

- Postprocessing
    - <None>

- Association Metric
    - Vanilla PMI/PPMI

# Hyperparameter Settings

## Classic Vanilla Setting

*(commonly used for distributional baselines)*

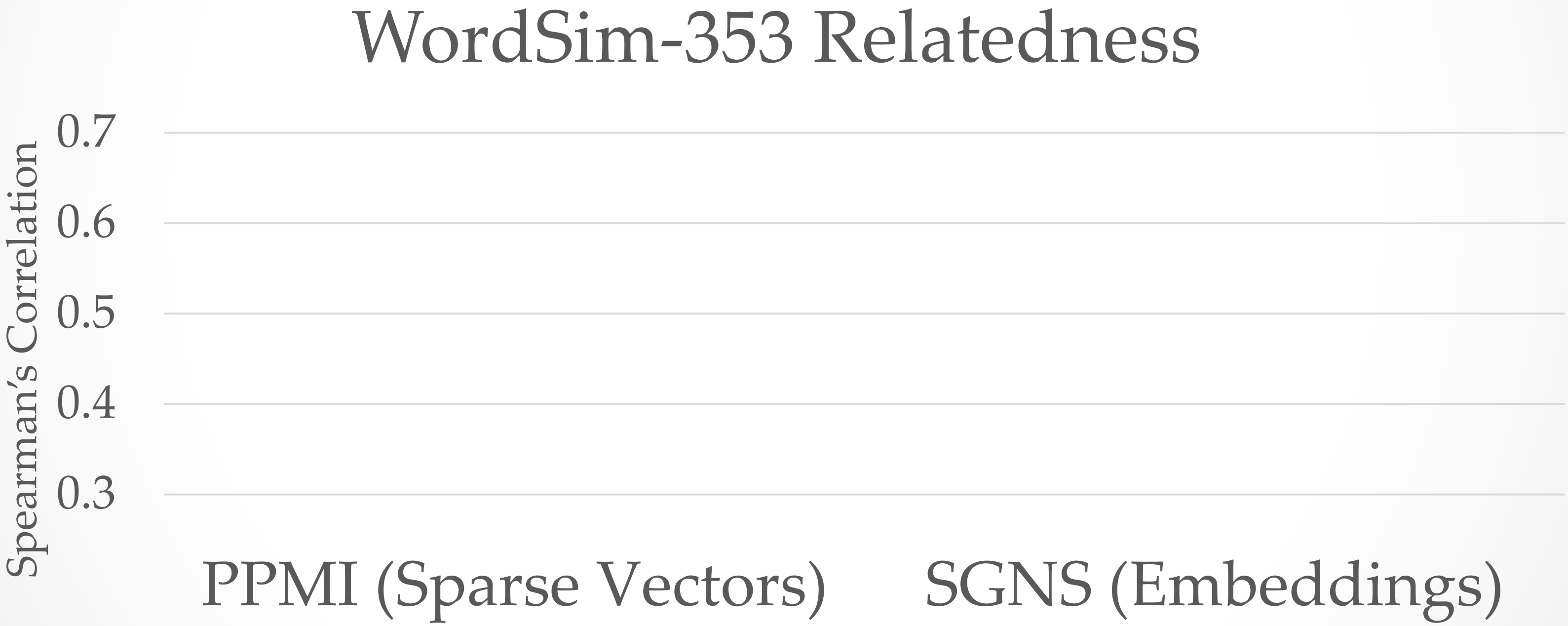
- Preprocessing
    - <None>
- Postprocessing
    - <None>
- Association Metric
    - Vanilla PMI/PPMI

## Recommended word2vec Setting

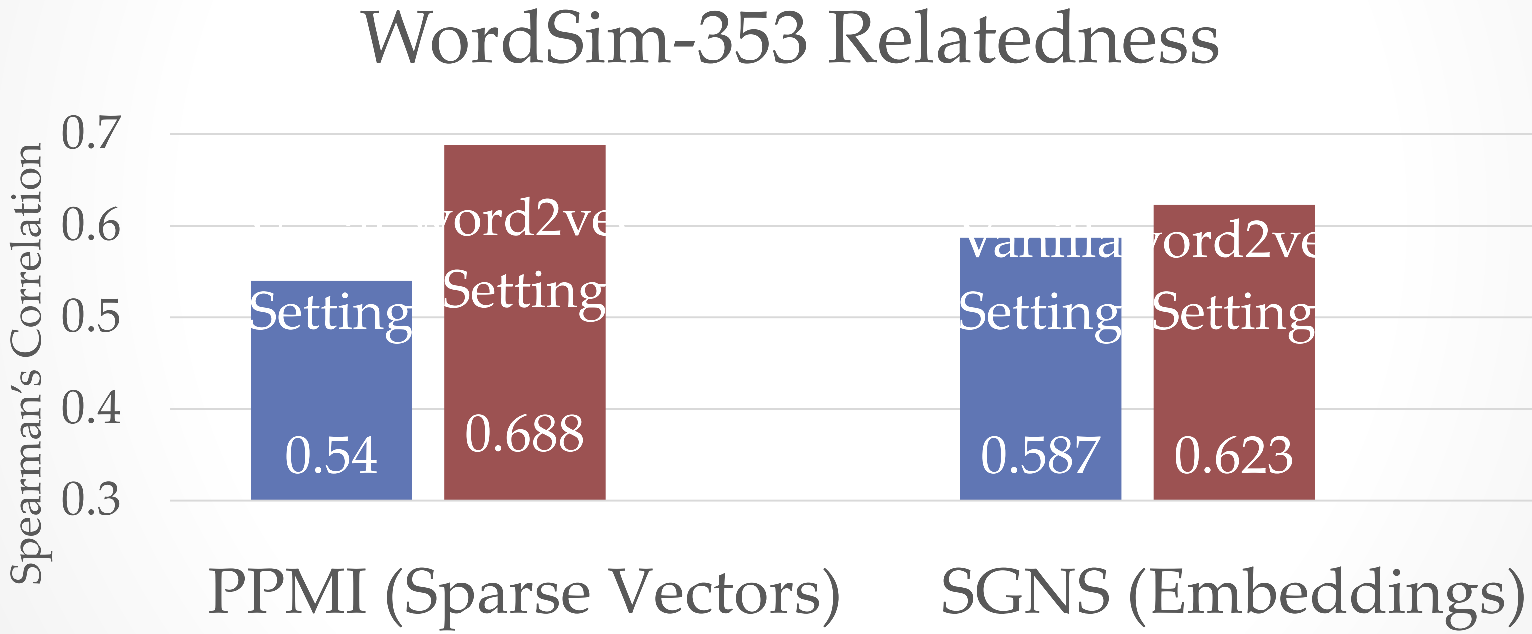
*(tuned for SGNS)*

- Preprocessing
    - Dynamic Context Window
    - Subsampling
- Postprocessing
    - <None>
- Association Metric
    - Shifted PMI/PPMI
    - Context Distribution Smoothing

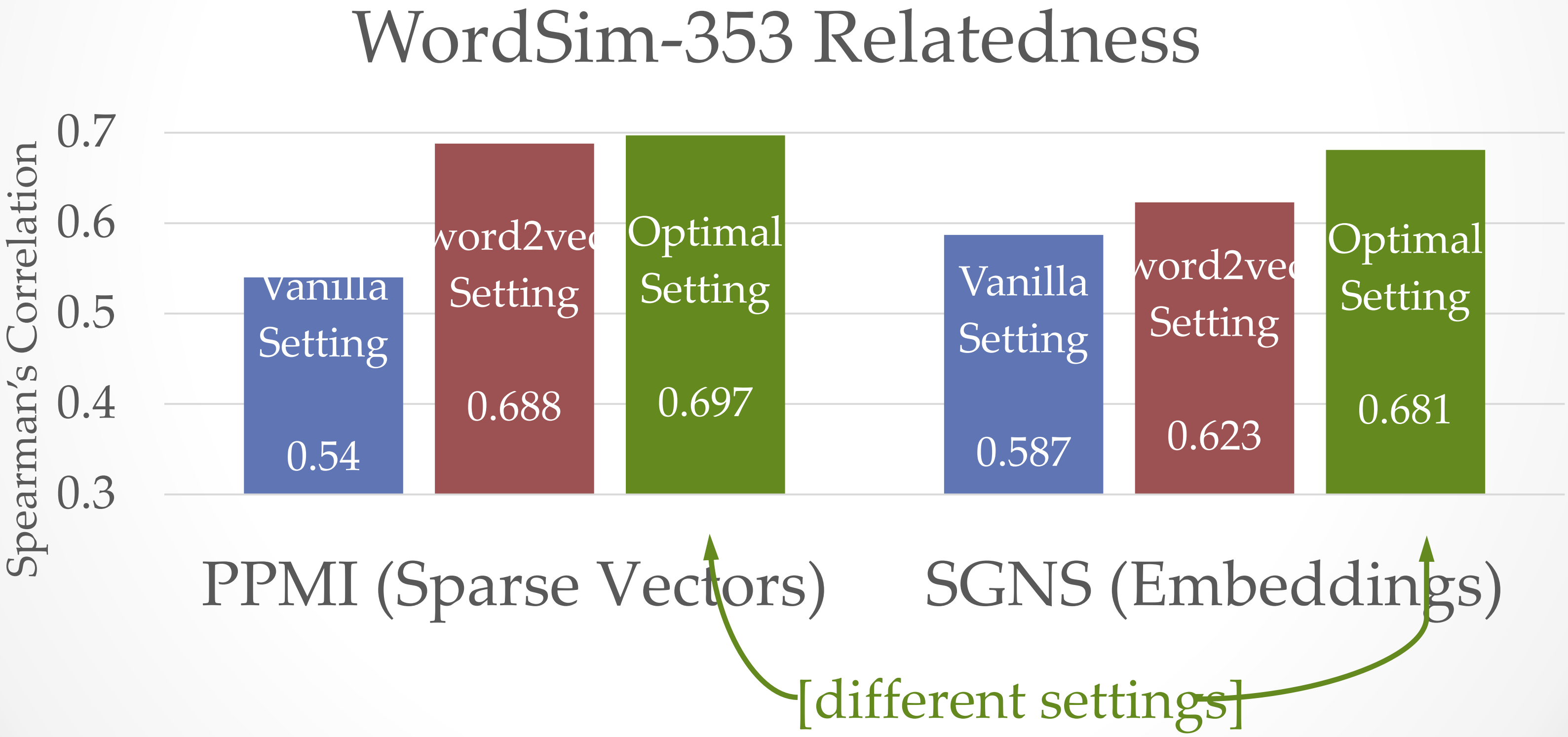
# Experiments



# Experiments: “Oranges to Oranges”



# Experiments: Hyperparameter Tuning



# Overall Results

- **Hyperparameters** often have stronger effects than **algorithms**
- **Hyperparameters** often have stronger effects than **more data**
- **Prior superiority claims** were not exactly accurate

# Note on Dot Product

- We have been using $c^T w$ as the similarity score

- In case c and w come from different spaces
  one can use $c^T U w$ as the score
  where parameters of U matrix are also learnt

- Equivalent to projecting c in w space.

# Domain Adaptation of Embeddings

- Pretrained embeddings W
  - And small new corpus

- Method 1
  - Fine tune all embeddings of W in a task-specific manner
  - Problem: only words in small dataset get changed

- Method 2
  - Learn a projection T. W' = WT
  - Problem: can't separate close-by words

- Method 3
  - Learn a full new vector U. W' = WT+U
  - Problem: need more data

# Other Details

- Padding
    - Zero
    - Padding embedding
- Unknown Words
    - Unk embedding
- Word Dropout
    - randomly replace words with Unk
    - Use a/(a+#w) as dropout rate
- Word Dropout as regularization
    - Dropout rate not dependent on #w

# Limitations of Distributional Similarity

- What kind of similarity is hard to ~control?
  - Small context: more syntax-based embedding
  - Large context: more topical embeddings
  - Context based on parses: more functional embeddings

- Sensitive to superficial differences
  - Dog/dogs
- Black sheep
  - People don't say the obvious
- Antonyms
- Corpus bias
  - "encode every kind of psychological bias we can look for"
  - Females<->family and not career;

- Lack of context
  - See Elmo [2018]
- Not interpretable

# Retrofitting Embeddings

- Additional evidence – e.g., Wordnet

- Graph: nodes – words, edges – related

- New objective: find matrix $\hat{W}$ such that
    - $\hat{w}$ is close to W for each word
    - $\hat{w}$ of words related in the graph is close

$$\Psi(Q) = \sum_{i=1}^{n} \left[ \alpha_i \| w_i - \hat{w}_i \|^2 + \sum_{(i,j)\in E} \beta_{ij} \| \hat{w}_i - \hat{w}_j \|^2 \right]$$

# Sparse Embeddings

- Each dimension of word embedding is not interpretable

- Add a sparsity constraint to
  - Increase the information content of non-zero dimensions in each word

# De-biasing Embeddings

## (Bolukbasi etal 16)

| **Extreme *she*** | **Extreme *he*** |
|---|---|
| 1. homemaker | 1. maestro |
| 2. nurse | 2. skipper |
| 3. receptionist | 3. protege |
| 4. librarian | 4. philosopher |
| 5. socialite | 5. captain |
| 6. hairdresser | 6. architect |
| 7. nanny | 7. financier |
| 8. bookkeeper | 8. warrior |
| 9. stylist | 9. broadcaster |
| 10. housekeeper | 10. magician |

**Gender stereotype *she*-*he* analogies**

| | | |
|---|---|---|
| sewing-carpentry | registered nurse-physician | housewife-shopkeeper |
| nurse-surgeon | interior designer-architect | softball-baseball |
| blond-burly | feminism-conservatism | cosmetics-pharmaceuticals |
| giggle-chuckle | vocalist-guitarist | petite-lanky |
| sassy-snappy | diva-superstar | charming-affable |
| volleyball-football | cupcakes-pizzas | lovely-brilliant |

**Gender appropriate *she*-*he* analogies**

| | | |
|---|---|---|
| queen-king | sister-brother | mother-father |
| waitress-waiter | ovarian cancer-prostate cancer | convent-monastery |

Identify pairs to “neutralize”, find the direction of the trait to neutralize, and ensure that they are neutral in that direction