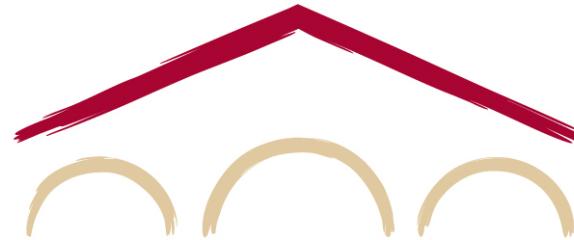


Natural Language Processing with Deep Learning

CS224N/Ling284



Christopher Manning
Lecture 1: Introduction and Word Vectors

Lecture Plan

Lecture 1: Introduction and Word Vectors

1. The course (10 mins)
2. Human language and word meaning (15 mins)
3. Word2vec introduction (15 mins)
4. Word2vec objective function gradients (25 mins)
5. Optimization basics (5 mins)
6. Looking at word vectors (10 mins or less)

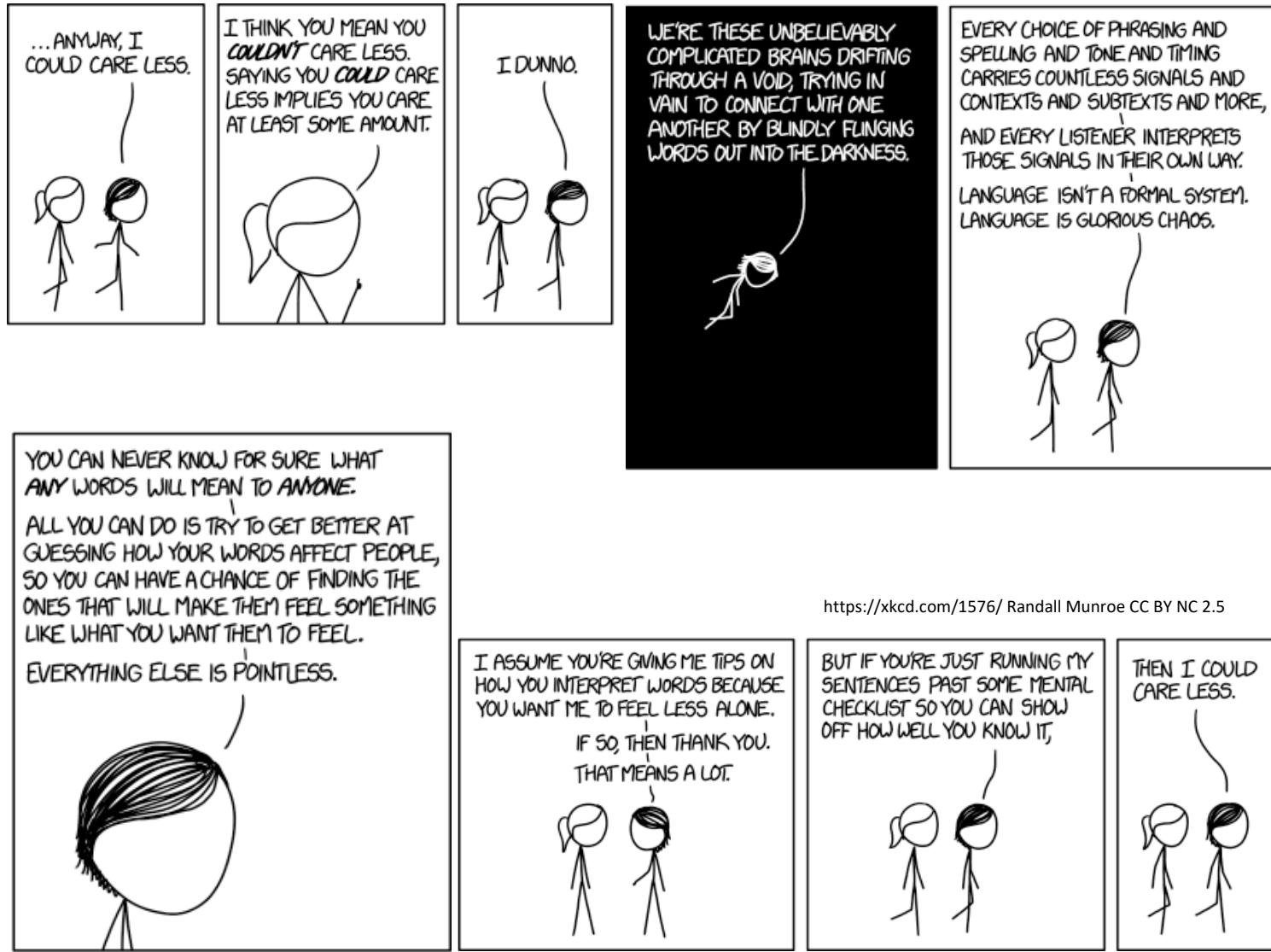
Key learning today: The (really surprising!) result that word meaning can be represented rather well by a large vector of real numbers

What do we hope to teach?

1. The foundations of the effective modern methods for deep learning applied to NLP
 - Basics first, then key methods used in NLP: Recurrent networks, attention, transformers, etc.
2. A big picture understanding of human languages and the difficulties in understanding and producing them
3. An understanding of and ability to build systems (in PyTorch) for some of the major problems in NLP:
 - Word meaning, dependency parsing, machine translation, question answering

Lecture Plan

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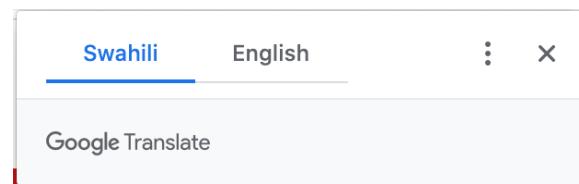
Trained on text data, neural machine translation is quite good!



<https://kiswahili.tuko.co.ke/>

Malawi yawapoteza mawaziri 2 kutokana na maafa ya COVID-19

TUKO.co.ke imefahamishwa kuwa waziri wa serikali ya mitaa Lingson Belekanyama na mwenzake wa uchukuzi Sidik Mia walifariki dunia ndani ya saa mbili tofauti.



Malawi loses 2 ministers due to COVID-19 disaster

TUKO.co.ke has been informed that local government minister Lingson Belekanyama and his transport counterpart Sidik Mia died within two separate hours.

GPT-3: A first step on the path to universal models



The SEC said, “Musk, your tweets are a blight.

*They really could cost you your job,
if you don't stop all this tweeting at night.”*

*Then Musk cried, “Why?
The tweets I wrote are not mean,
I don't use all-caps
and I'm sure that my tweets are clean.”*

*“But your tweets can move markets
and that's why we're sore.*

*You may be a genius and a billionaire,
but it doesn't give you the right to
be a bore!”*

S: I broke the window.

Q: What did I break?

S: I gracefully saved the day.

Q: What did I gracefully save?

S: I gave John flowers.

Q: Who did I give flowers to?

S: I gave her a rose and a guitar.

Q: Who did I give a rose and a guitar to?

How many users have signed up since the start of 2020?

`SELECT count(id) FROM users`

`WHERE created_at > '2020-01-01'`

What is the average number of influencers each user is subscribed to?

`SELECT avg(count) FROM (SELECT user_id, count(*)
FROM subscribers GROUP BY user_id)
AS avg_subscriptions_per_user`

How do we represent the meaning of a word?

Definition: **meaning** (Webster dictionary)

- the idea that is represented by a word, phrase, etc.
- the idea that a person wants to express by using words, signs, etc.
- the idea that is expressed in a work of writing, art, etc.

Commonest linguistic way of thinking of meaning:

signifier (symbol) \Leftrightarrow signified (idea or thing)

= denotational semantics

How do we have usable meaning in a computer?

Common NLP solution: Use, e.g., [WordNet](#), a thesaurus containing lists of **synonym sets** and **hyponyms** (“is a” relationships).

e.g., synonym sets containing “good”:

```
from nltk.corpus import wordnet as wn
poses = { 'n':'noun', 'v':'verb', 's':'adj (s)', 'a':'adj', 'r':'adv'}
for synset in wn.synsets("good"):
    print("{}: {}".format(poses[synset.pos()],
                          ", ".join([l.name() for l in synset.lemmas()])))
```

```
noun: good
noun: good, goodness
noun: good, goodness
noun: commodity, trade_good, good
adj: good
adj (sat): full, good
adj: good
adj (sat): estimable, good, honorable, respectable
adj (sat): beneficial, good
adj (sat): good
adj (sat): good, just, upright
...
adverb: well, good
adverb: thoroughly, soundly, good
```

e.g., hyponyms of “panda”:

```
from nltk.corpus import wordnet as wn
panda = wn.synset("panda.n.01")
hyper = lambda s: s.hyponyms()
list(pandaclosure(hyper))
```

```
[Synset('procyonid.n.01'),
Synset('carnivore.n.01'),
Synset('placental.n.01'),
Synset('mammal.n.01'),
Synset('vertebrate.n.01'),
Synset('chordate.n.01'),
Synset('animal.n.01'),
Synset('organism.n.01'),
Synset('living_thing.n.01'),
Synset('whole.n.02'),
Synset('object.n.01'),
Synset('physical_entity.n.01'),
Synset('entity.n.01')]
```

Problems with resources like WordNet

- Great as a resource but missing nuance
 - e.g., “proficient” is listed as a synonym for “good”
This is only correct in some contexts
- Missing new meanings of words
 - e.g., wicked, badass, nifty, wizard, genius, ninja, bombest
 - Impossible to keep up-to-date!
- Subjective
- Requires human labor to create and adapt
- Can’t compute accurate word similarity →

Representing words as discrete symbols

In traditional NLP, we regard words as discrete symbols:
`hotel, conference, motel` – a **localist** representation

Means one 1, the rest 0s

Such symbols for words can be represented by **one-hot** vectors:

`motel = [0 0 0 0 0 0 0 0 0 1 0 0 0 0]`

`hotel = [0 0 0 0 0 0 1 0 0 0 0 0 0]`

Vector dimension = number of words in vocabulary (e.g., 500,000)

Problem with words as discrete symbols

Example: in web search, if user searches for “Seattle motel”, we would like to match documents containing “Seattle hotel”

But:

$$\begin{aligned}\text{motel} &= [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0] \\ \text{hotel} &= [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]\end{aligned}$$

These two vectors are **orthogonal**

There is no natural notion of **similarity** for one-hot vectors!

Solution:

- Could try to rely on WordNet’s list of synonyms to get similarity?
 - But it is well-known to fail badly: incompleteness, etc.
- **Instead: learn to encode similarity in the vectors themselves**

Representing words by their context

- **Distributional semantics:** A word's meaning is given by the words that frequently appear close-by
 - “*You shall know a word by the company it keeps*” (J. R. Firth 1957: 11)
 - One of the most successful ideas of modern statistical NLP!
- When a word w appears in a text, its **context** is the set of words that appear nearby (within a fixed-size window).
- Use the many contexts of w to build up a representation of w

...government debt problems turning into **banking** crises as happened in 2009...
...saying that Europe needs unified **banking** regulation to replace the hodgepodge...
...India has just given its **banking** system a shot in the arm...

These **context words** will represent **banking**

Word vectors

We will build a dense vector for each word, chosen so that it is similar to vectors of words that appear in similar contexts

$$\text{banking} = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{pmatrix}$$

Note: **word vectors** are also called **word embeddings** or **(neural) word representations**
They are a **distributed** representation

Word meaning as a neural word vector – visualization

expect =
$$\begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \\ 0.487 \end{pmatrix}$$



3. Word2vec: Overview

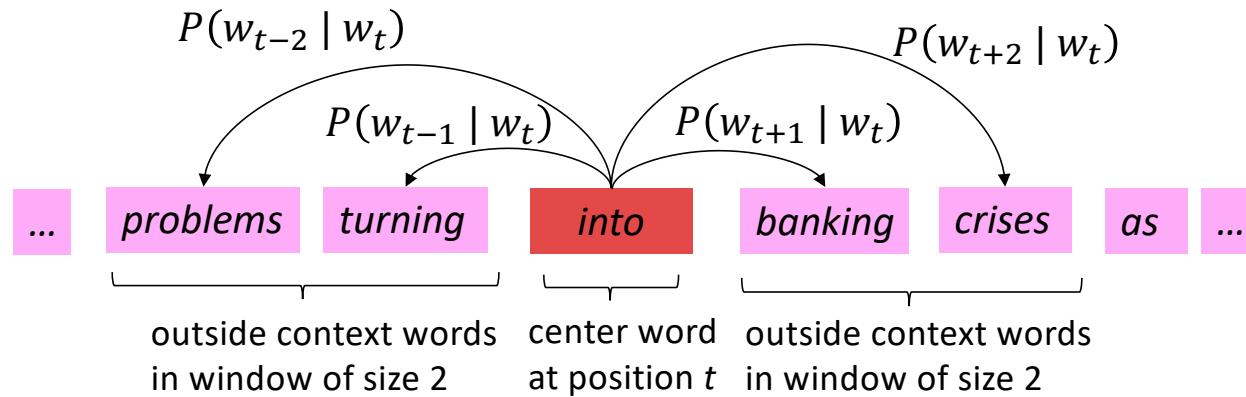
Word2vec (Mikolov et al. 2013) is a framework for learning word vectors

Idea:

- We have a large corpus (“body”) of text
- Every word in a fixed vocabulary is represented by a **vector**
- Go through each position t in the text, which has a center word c and context (“outside”) words o
- Use the **similarity of the word vectors** for c and o to **calculate the probability** of o given c (or vice versa)
- **Keep adjusting the word vectors** to maximize this probability

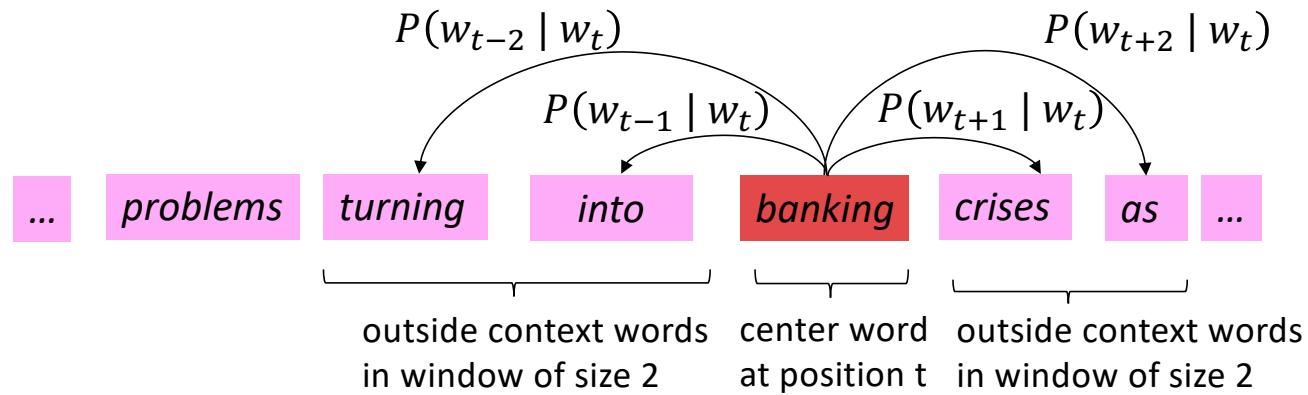
Word2Vec Overview

Example windows and process for computing $P(w_{t+j} | w_t)$



Word2Vec Overview

Example windows and process for computing $P(w_{t+j} | w_t)$



Word2vec: objective function

For each position $t = 1, \dots, T$, predict context words within a window of fixed size m , given center word w_j . Data likelihood:

$$\text{Likelihood} = L(\theta) = \prod_{t=1}^T \prod_{\substack{-m \leq j \leq m \\ j \neq 0}} P(w_{t+j} | w_t; \theta)$$

θ is all variables
to be optimized

sometimes called a *cost* or *loss* function

The **objective function** $J(\theta)$ is the (average) negative log likelihood:

$$J(\theta) = -\frac{1}{T} \log L(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \log P(w_{t+j} | w_t; \theta)$$

Minimizing objective function \Leftrightarrow Maximizing predictive accuracy

Word2vec: objective function

- We want to minimize the objective function:

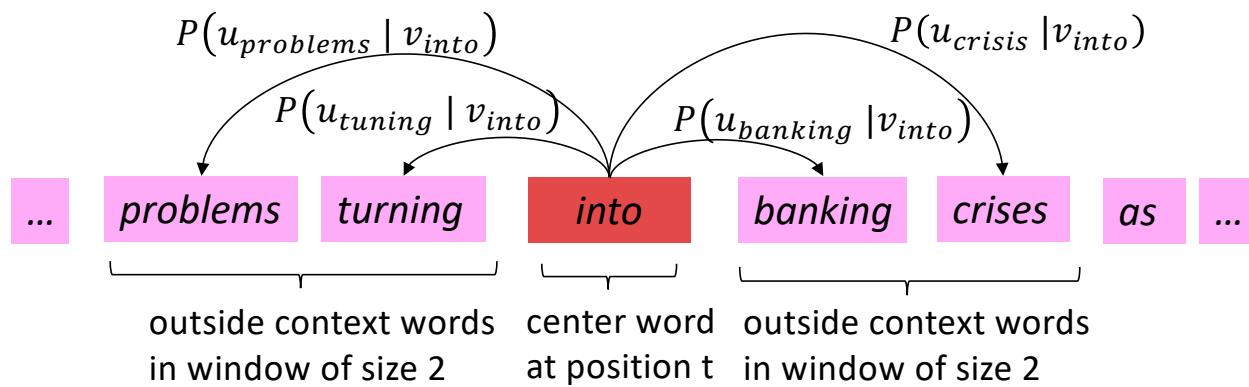
$$J(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \log P(w_{t+j} | w_t; \theta)$$

- **Question:** How to calculate $P(w_{t+j} | w_t; \theta)$?
- **Answer:** We will use two vectors per word w :
 - v_w when w is a center word
 - u_w when w is a context word
- Then for a center word c and a context word o :

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

Word2Vec Overview with Vectors

- Example windows and process for computing $P(w_{t+j} | w_t)$
- $P(u_{problems} | v_{into})$ short for $P(problems | into ; u_{problems}, v_{into}, \theta)$



Word2vec: prediction function

- ② Exponentiation makes anything positive

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

① Dot product compares similarity of o and c .
 $u^T v = u \cdot v = \sum_{i=1}^n u_i v_i$
Larger dot product = larger probability

③ Normalize over entire vocabulary
to give probability distribution

- This is an example of the **softmax function** $\mathbb{R}^n \rightarrow (0,1)^n$

$$\text{softmax}(x_i) = \frac{\exp(x_i)}{\sum_{j=1}^n \exp(x_j)} = p_i$$

- The softmax function maps arbitrary values x_i to a probability distribution p_i

- “max” because amplifies probability of largest x_i
- “soft” because still assigns some probability to smaller x_i
- Frequently used in Deep Learning

Open region

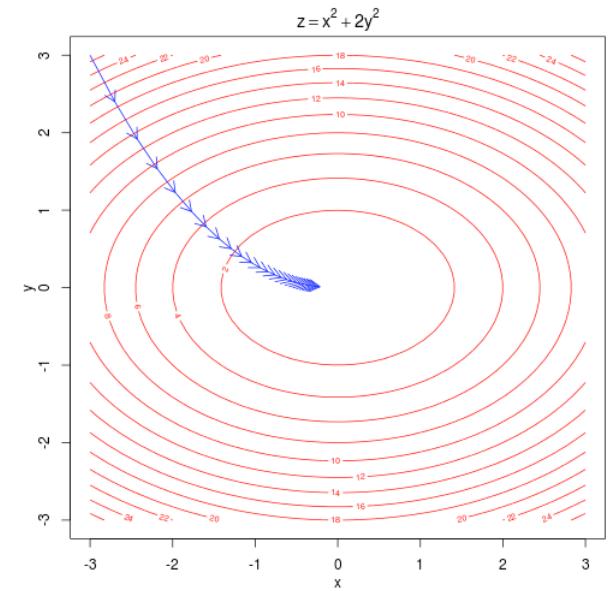
But sort of a weird name
because it returns a distribution!

To train the model: Optimize value of parameters to minimize loss

To train a model, we gradually adjust parameters to minimize a loss

- Recall: θ represents **all** the model parameters, in one long vector
- In our case, with d -dimensional vectors and V -many words, we have:
- Remember: every word has two vectors

$$\theta = \begin{bmatrix} v_{aardvark} \\ v_a \\ \vdots \\ v_{zebra} \\ u_{aardvark} \\ u_a \\ \vdots \\ u_{zebra} \end{bmatrix} \in \mathbb{R}^{2dV}$$



- We optimize these parameters by walking down the gradient (see right figure)
- We compute **all** vector gradients!

4. Word2vec derivations of gradient

- Zoom U. Whiteboard – see video or revised slides
- The basic Lego piece: The chain rule
- Useful basic fact: $\frac{\partial \mathbf{x}^T \mathbf{a}}{\partial \mathbf{x}} = \frac{\partial \mathbf{a}^T \mathbf{x}}{\partial \mathbf{x}} = \mathbf{a}$
- If in doubt: write it out with indices

Chain Rule

- Chain rule! If $y = f(u)$ and $u = g(x)$, i.e., $y = f(g(x))$, then:

$$\frac{dy}{dx} = \frac{dy}{du} \frac{du}{dx} = \frac{df(u)}{du} \frac{dg(x)}{dx}$$

- Simple example: $\frac{dy}{dx} = \frac{d}{dx} 5(x^3 + 7)^4$

$$y = f(u) = 5u^4$$

$$u = g(x) = x^3 + 7$$

$$\frac{dy}{du} = 20u^3$$

$$\frac{du}{dx} = 3x^2$$

$$\frac{dy}{dx} = 20(x^3 + 7)^3 \cdot 3x^2$$

Interactive Whiteboard Session!

$$J(\theta) = \frac{1}{T} \sum_{t=1}^T \sum_{-m \leq j \leq m, j \neq 0} \log p(w_{t+j} | w_t)$$

Let's derive gradient for center word together

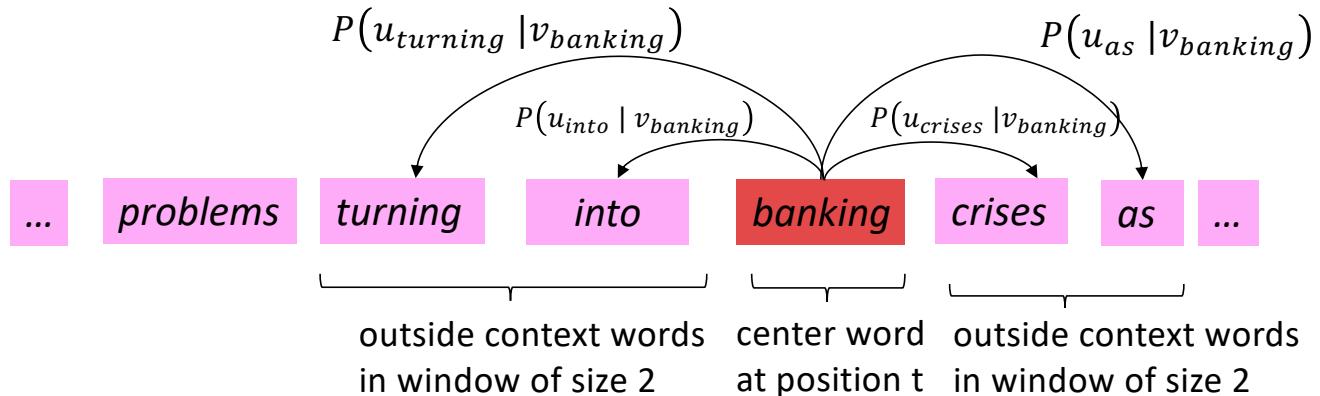
For one example window and one example outside word:

$$\log p(o|c) = \log \frac{\exp(u_o^T v_c)}{\sum_{w=1}^V \exp(u_w^T v_c)}$$

You then also need the gradient for context words (it's similar; left for homework). That's all of the parameters θ here.

Calculating all gradients!

- We went through the gradient for each center vector v in a window
- We also need gradients for outside vectors u
 - Derive at home!
- Generally in each window we will compute updates for all parameters that are being used in that window. For example:



Word2vec: More details

Why two vectors? → Easier optimization. Average both at the end.

Two model variants:

1. Skip-grams (SG)

Predict context (“outside”) words (position independent) given center word

2. Continuous Bag of Words (CBOW)

Predict center word from (bag of) context words

This lecture so far: **Skip-gram model**

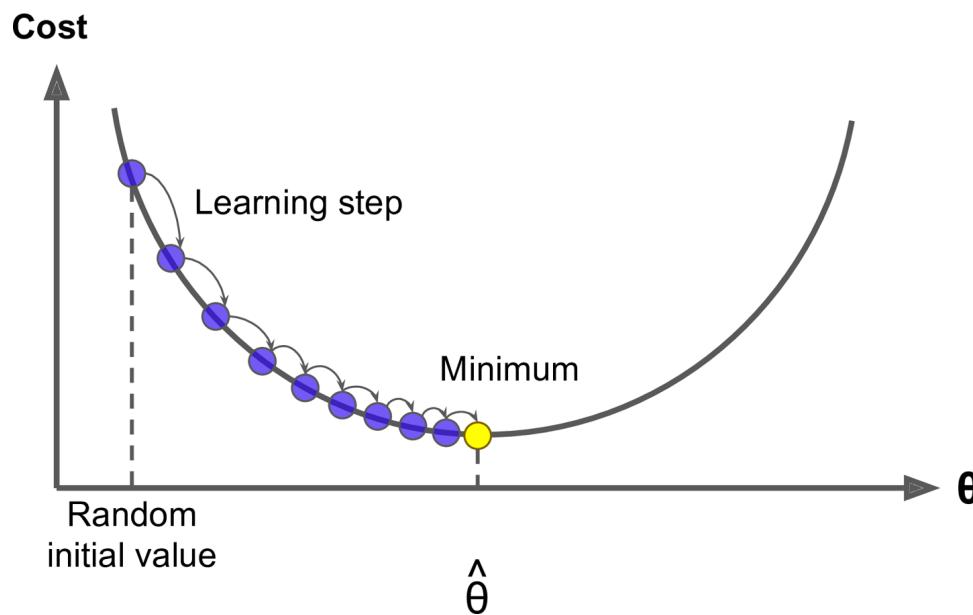
Additional efficiency in training:

1. Negative sampling

So far: Focus on **naïve softmax** (simpler but more expensive training method)

5. Optimization: Gradient Descent

- We have a cost function $J(\theta)$ we want to minimize
- **Gradient Descent** is an algorithm to minimize $J(\theta)$
- **Idea:** for current value of θ , calculate gradient of $J(\theta)$, then take **small step in direction of negative gradient**. Repeat.



Note: Our objectives may not be convex like this ☹

But life turns out to be okay ☺

Gradient Descent

- Update equation (in matrix notation):

$$\theta^{new} = \theta^{old} - \alpha \nabla_{\theta} J(\theta)$$

α = *step size* or *learning rate*

- Update equation (for single parameter):

$$\theta_j^{new} = \theta_j^{old} - \alpha \frac{\partial}{\partial \theta_j^{old}} J(\theta)$$

- Algorithm:

```
while True:  
    theta_grad = evaluate_gradient(J,corpus,theta)  
    theta = theta - alpha * theta_grad
```

Stochastic Gradient Descent

- **Problem:** $J(\theta)$ is a function of **all** windows in the corpus (potentially billions!)
 - So $\nabla_{\theta} J(\theta)$ is **very expensive to compute**
- You would wait a very long time before making a single update!
- **Very** bad idea for pretty much all neural nets!
- **Solution: Stochastic gradient descent (SGD)**
 - Repeatedly sample windows, and update after each one
- Algorithm:

```
while True:  
    window = sample_window(corpus)  
    theta_grad = evaluate_gradient(J,window,theta)  
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```

Lecture Plan

1. The course (10 mins)
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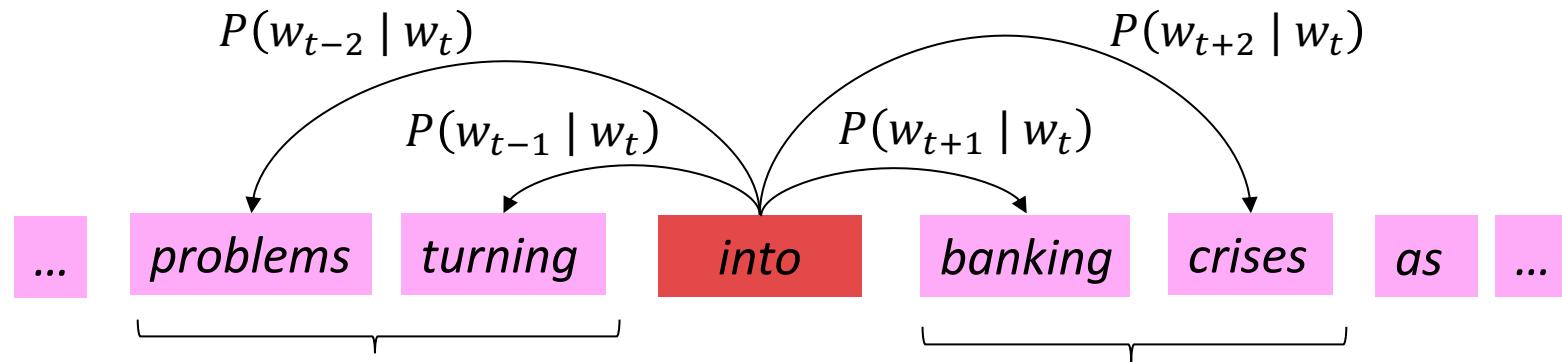
Lecture 2: Word Vectors, Word Senses, and Neural Network Classifiers

1. Course organization (2 mins)
2. Finish looking at word vectors and word2vec (10 mins)
3. Optimization basics (8 mins)
4. Can we capture the essence of word meaning more effectively by counting? (8m)
5. The GloVe model of word vectors (8 min)
6. Evaluating word vectors (12 mins)
7. Word senses (6 mins)
8. Review of classification and how neural nets differ (8 mins)
9. Introducing neural networks (14 mins)

Key Goal: To be able to read word embeddings papers by the end of class

2. Review: Main idea of word2vec

- Start with random word vectors
- Iterate through each word in the whole corpus
- Try to predict surrounding words using word vectors: $P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$



- **Learning:** Update vectors so they can predict actual surrounding words better
- Doing no more than this, this algorithm learns word vectors that capture well word similarity and meaningful directions in a wordspace!

Word2vec parameters and computations

$$\begin{bmatrix} \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \end{bmatrix}$$

U

outside

$$\begin{bmatrix} \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \end{bmatrix}$$

V

center

$$\begin{bmatrix} \bullet \\ \bullet \\ \bullet \\ \bullet \\ \bullet \end{bmatrix}$$

$U \cdot v_4^T$

dot product

$$\begin{bmatrix} \bullet \\ \bullet \\ \bullet \\ \bullet \end{bmatrix}$$

$\text{softmax}(U \cdot v_4^T)$

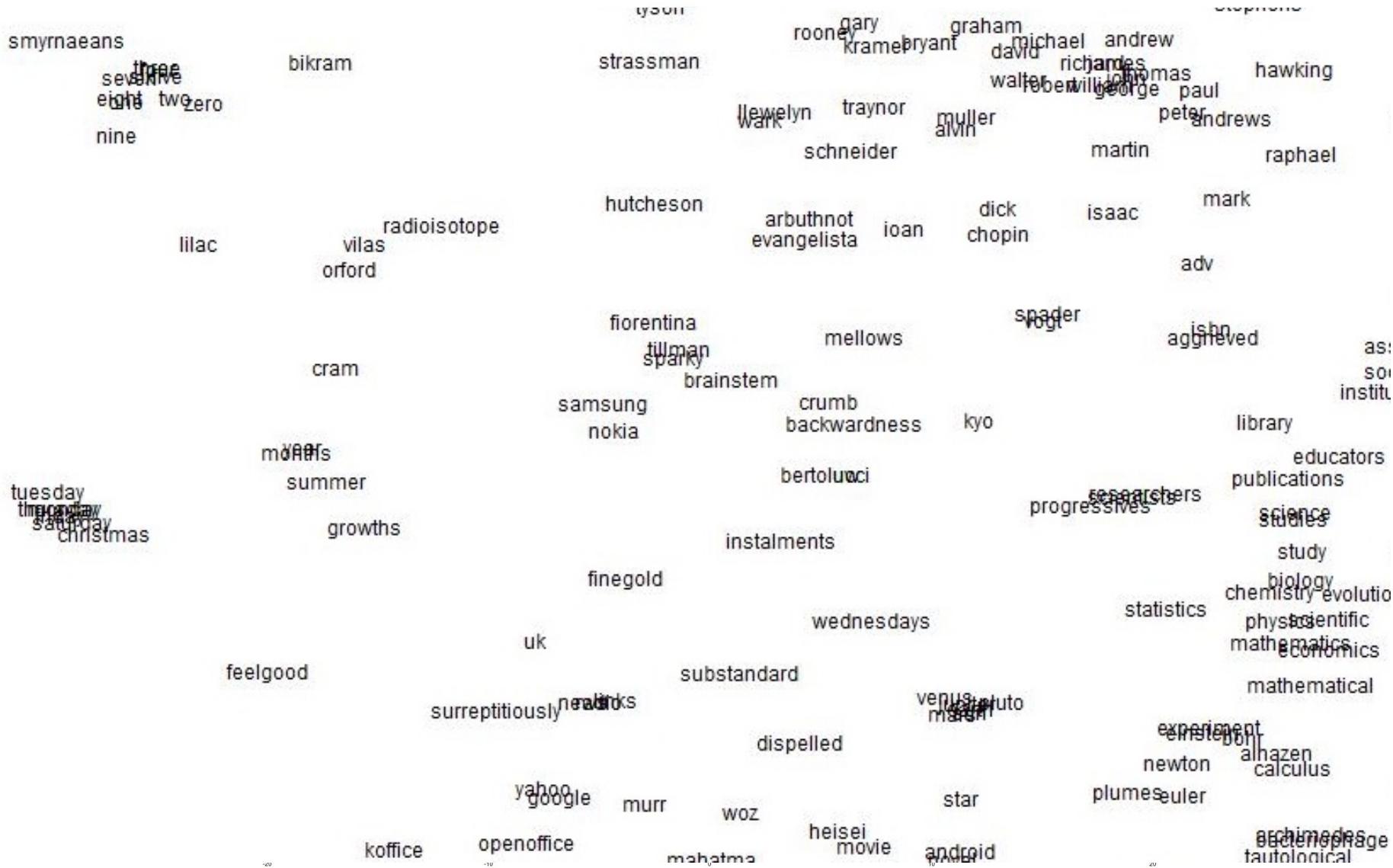
probabilities

“Bag of words” model!

The model makes the same predictions at each position

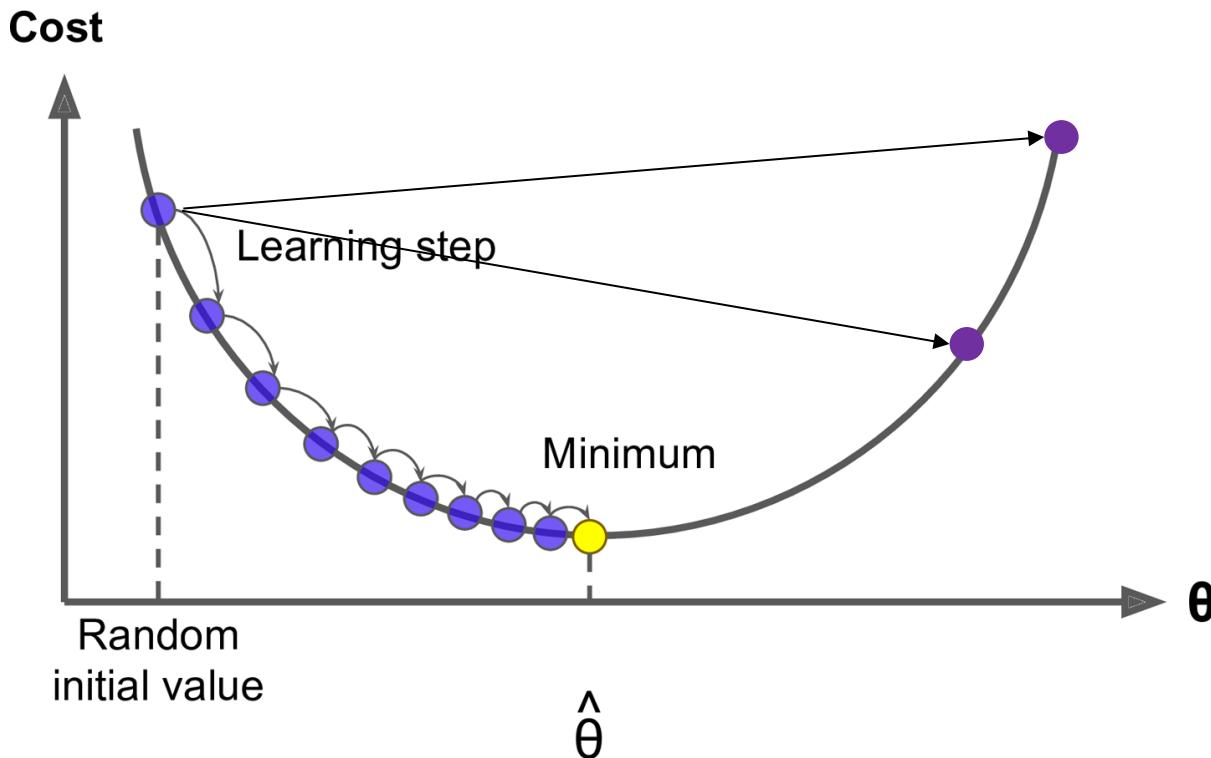
We want a model that gives a reasonably high probability estimate to *all* words that occur in the context (at all often)

Word2vec maximizes objective function by putting similar words nearby in space



3. Optimization: Gradient Descent

- To learn good word vectors: We have a cost function $J(\theta)$ we want to minimize
- **Gradient Descent** is an algorithm to minimize $J(\theta)$ by changing θ
- **Idea:** from current value of θ , calculate gradient of $J(\theta)$, then take **small step in the direction of negative gradient**. Repeat.



Note: Our objectives may not be convex like this ☹

But life turns out to be okay 😊

Gradient Descent

- Update equation (in matrix notation):

$$\theta^{new} = \theta^{old} - \alpha \nabla_{\theta} J(\theta)$$

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Stochastic Gradient Descent

- **Problem:** $J(\theta)$ is a function of **all** windows in the corpus (often, billions!)
 - So $\nabla_{\theta} J(\theta)$ is **very expensive** to compute
- You would wait a very long time before making a single update!
- **Very** bad idea for pretty much all neural nets!
- **Solution: Stochastic gradient descent (SGD)**
 - Repeatedly sample windows, and update after each one, or each small batch
- Algorithm:

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while True:  
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    theta = theta - alpha * theta_grad
```

Stochastic gradients with word vectors! [Aside]

- Iteratively take gradients at each such window for SGD
- But in each window, we only have at most $2m + 1$ words, so $\nabla_{\theta} J_t(\theta)$ is very sparse!

$$\nabla_{\theta} J_t(\theta) = \begin{bmatrix} 0 \\ \vdots \\ \nabla_{v_{like}} \\ \vdots \\ 0 \\ \nabla_{u_I} \\ \vdots \\ \nabla_{u_{learning}} \\ \vdots \end{bmatrix} \in \mathbb{R}^{2dV}$$

Stochastic gradients with word vectors!

- We might only update the word vectors that actually appear!
- Solution: either you need sparse matrix update operations to only update certain **rows** of full embedding matrices U and V , or you need to keep around a hash for word vectors

Rows not columns
in actual DL
packages!

$$|V| \begin{bmatrix} \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}^d$$

- If you have millions of word vectors and do distributed computing, it is important to not have to send gigantic updates around!

2b. Word2vec algorithm family: More details

Why two vectors? → Easier optimization. Average both at the end

- But can implement the algorithm with just one vector per word ... and it helps

Two model variants:

1. Skip-grams (SG)

Predict context (“outside”) words (position independent) given center word

2. Continuous Bag of Words (CBOW)

Predict center word from (bag of) context words

We presented: **Skip-gram model**

Additional efficiency in training:

1. Negative sampling

So far: Focus on **naïve softmax** (simpler, but expensive, training method)

The skip-gram model with negative sampling (HW2)

- The normalization term is computationally expensive
- $$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$
- Hence, in standard word2vec and HW2 you implement the skip-gram model with **negative sampling**
- Main idea: train binary logistic regressions for a true pair (center word and a word in its context window) versus several noise pairs (the center word paired with a random word)

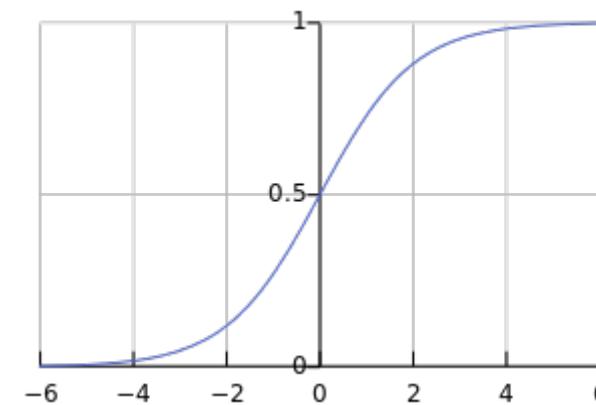
The skip-gram model with negative sampling (HW2)

- From paper: “Distributed Representations of Words and Phrases and their Compositionality” (Mikolov et al. 2013)
- Overall objective function (they maximize):

$$J(\theta) = \frac{1}{T} \sum_{t=1}^T J_t(\theta)$$

$$J_t(\theta) = \log \sigma(u_o^T v_c) + \sum_{j=1}^k \mathbb{E}_{j \sim P(w)} [\log \sigma(-u_j^T v_c)]$$

- The logistic/sigmoid function: $\sigma(x) = \frac{1}{1+e^{-x}}$
(we'll become good friends soon)
- We maximize the probability
of two words co-occurring in first log
and minimize probability of noise words



The skip-gram model with negative sampling (HW2)

- Notation more similar to class and HW2:

$$J_{\text{neg-sample}}(\mathbf{u}_o, \mathbf{v}_c, U) = -\log \sigma(\mathbf{u}_o^T \mathbf{v}_c) - \sum_{k \in \{K \text{ sampled indices}\}} \log \sigma(-\mathbf{u}_k^T \mathbf{v}_c)$$

- We take k negative samples (using word probabilities)
- Maximize probability that real outside word appears, minimize probability that random words appear around center word
- Sample with $P(w)=U(w)^{3/4}/Z$, the unigram distribution $U(w)$ raised to the $3/4$ power (We provide this function in the starter code).
- The power makes less frequent words be sampled more often

4. Why not capture co-occurrence counts directly?

Building a co-occurrence matrix X

- 2 options: windows vs. full document
- Window: Similar to word2vec, use window around each word → captures some syntactic and semantic information
- Word-document co-occurrence matrix will give general topics (all sports terms will have similar entries) leading to “Latent Semantic Analysis”

Example: Window based co-occurrence matrix

- Window length 1 (more common: 5–10)
- Symmetric (irrelevant whether left or right context)
- Example corpus:
 - I like deep learning
 - I like NLP
 - I enjoy flying

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

Co-occurrence vectors

- Simple count co-occurrence vectors
 - Vectors increase in size with vocabulary
 - Very high dimensional: require a lot of storage (though sparse)
 - Subsequent classification models have sparsity issues → Models are less robust
- Low-dimensional vectors
 - Idea: store “most” of the important information in a fixed, small number of dimensions: a dense vector
 - Usually 25–1000 dimensions, similar to word2vec
 - How to reduce the dimensionality?

Classic Method: Dimensionality Reduction on X (HW1)

Singular Value Decomposition of co-occurrence matrix X

Factorizes X into $U\Sigma V^T$, where U and V are orthonormal

$$\underbrace{\begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}}_{X^k} = \underbrace{\begin{bmatrix} * & * \\ * & * \\ * & * \end{bmatrix}}_U \underbrace{\begin{bmatrix} \bullet & & \\ & \bullet & \\ & & \bullet \end{bmatrix}}_{\Sigma} \underbrace{\begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}}_{V^T}$$

Retain only k singular values, in order to generalize.

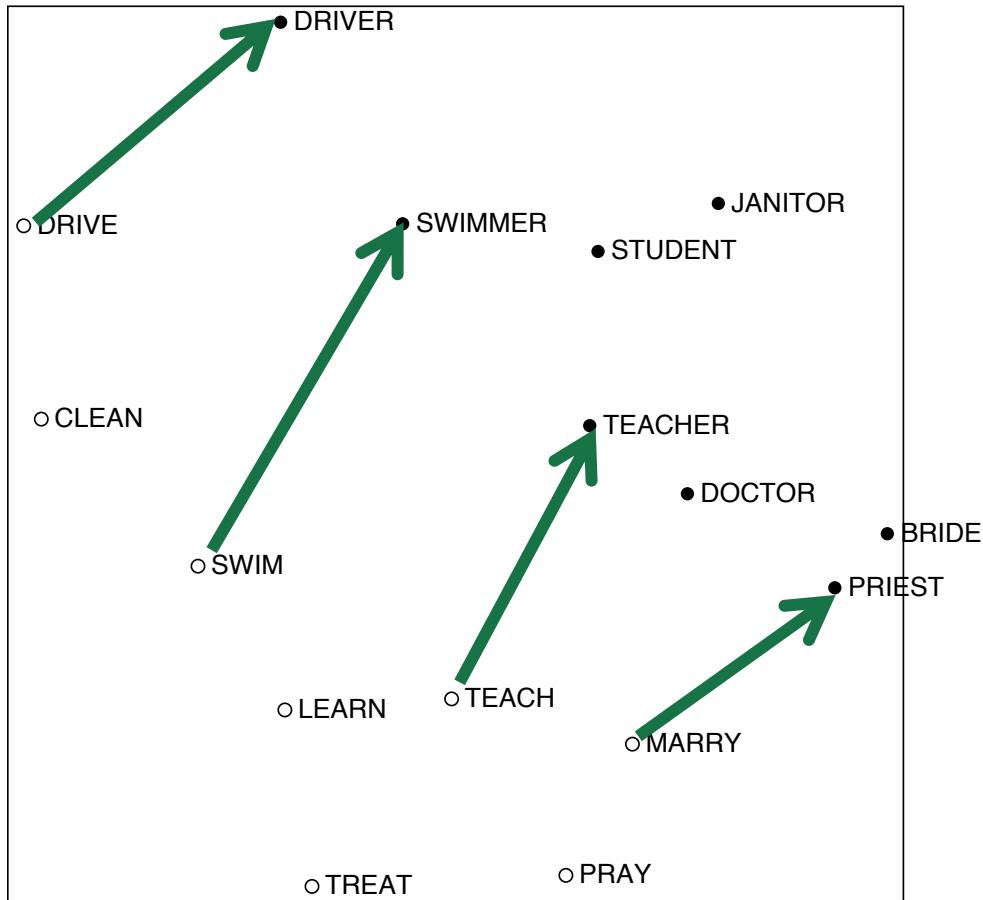
\hat{X} is the best rank k approximation to X , in terms of least squares.

Classic linear algebra result. Expensive to compute for large matrices.

Hacks to X (several used in Rohde et al. 2005 in COALS)

- Running an SVD on raw counts doesn't work well
- Scaling the counts in the cells can help *a lot*
 - Problem: function words (*the, he, has*) are too frequent → syntax has too much impact. Some fixes:
 - log the frequencies
 - $\min(X,t)$, with $t \approx 100$
 - Ignore the function words
- Ramped windows that count closer words more than further away words
- Use Pearson correlations instead of counts, then set negative values to 0
- Etc.

Interesting semantic patterns emerge in the scaled vectors



COALS model from
Rohde et al. ms., 2005. An Improved Model of Semantic Similarity Based on Lexical Co-Occurrence

5. Towards GloVe: Count based vs. direct prediction

- LSA, HAL (Lund & Burgess),
- COALS, Hellinger-PCA (Rohde et al, Lebret & Collobert)

- Fast training
- Efficient usage of statistics
- Primarily used to capture word similarity
- Disproportionate importance given to large counts

- Skip-gram/CBOW (Mikolov et al)
- NNLM, HLBL, RNN (Bengio et al; Collobert & Weston; Huang et al; Mnih & Hinton)

- Scales with corpus size
- Inefficient usage of statistics
- Generate improved performance on other tasks
- Can capture complex patterns beyond word similarity

Encoding meaning components in vector differences

[Pennington, Socher, and Manning, EMNLP 2014]

Crucial insight: Ratios of co-occurrence probabilities can encode meaning components

	$x = \text{solid}$	$x = \text{gas}$	$x = \text{water}$	$x = \text{random}$
$P(x \text{ice})$	large	small	large	small
$P(x \text{steam})$	small	large	large	small
$\frac{P(x \text{ice})}{P(x \text{steam})}$	large	small	~1	~1

Encoding meaning in vector differences

[Pennington, Socher, and Manning, EMNLP 2014]

Crucial insight: Ratios of co-occurrence probabilities can encode meaning components

	$x = \text{solid}$	$x = \text{gas}$	$x = \text{water}$	$x = \text{fashion}$
$P(x \text{ice})$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(x \text{steam})$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$\frac{P(x \text{ice})}{P(x \text{steam})}$	8.9	8.5×10^{-2}	1.36	0.96

Encoding meaning in vector differences

Q: How can we capture ratios of co-occurrence probabilities as linear meaning components in a word vector space?

A: Log-bilinear model: $w_i \cdot w_j = \log P(i|j)$

with vector differences

$$w_x \cdot (w_a - w_b) = \log \frac{P(x|a)}{P(x|b)}$$

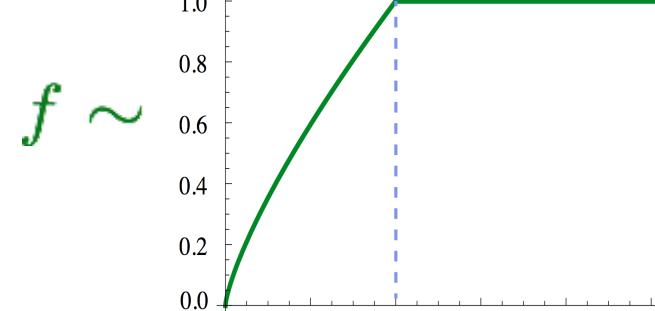
Combining the best of both worlds

GloVe [Pennington, Socher, and Manning, EMNLP 2014]

$$w_i \cdot w_j = \log P(i|j)$$

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

- Fast training
- Scalable to huge corpora
- Good performance even with small corpus and small vectors



GloVe results

Nearest words to
[frog](#):

1. frogs
2. toad
3. litoria
4. leptodactylidae
5. rana
6. lizard
7. eleutherodactylus



[litoria](#)



[rana](#)



[leptodactylidae](#)



[eleutherodactylus](#)

6. How to evaluate word vectors?

- Related to general evaluation in NLP: Intrinsic vs. extrinsic
- Intrinsic:
 - Evaluation on a specific/intermediate subtask
 - Fast to compute
 - Helps to understand that system
 - Not clear if really helpful unless correlation to real task is established
- Extrinsic:
 - Evaluation on a real task
 - Can take a long time to compute accuracy
 - Unclear if the subsystem is the problem or its interaction or other subsystems
 - If replacing exactly one subsystem with another improves accuracy → Winning!

Intrinsic word vector evaluation

- Word Vector Analogies

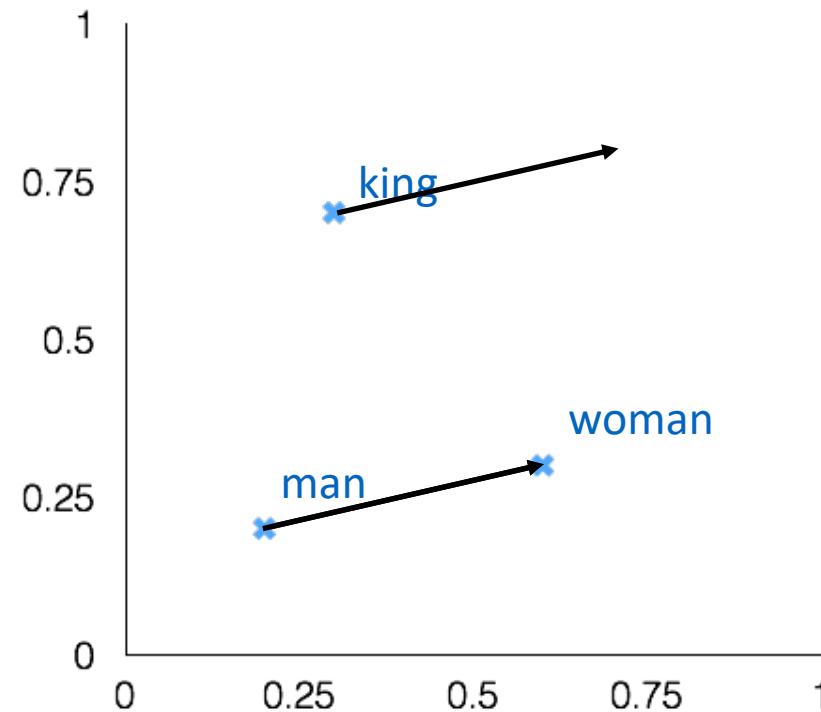
$$a:b :: c:?$$



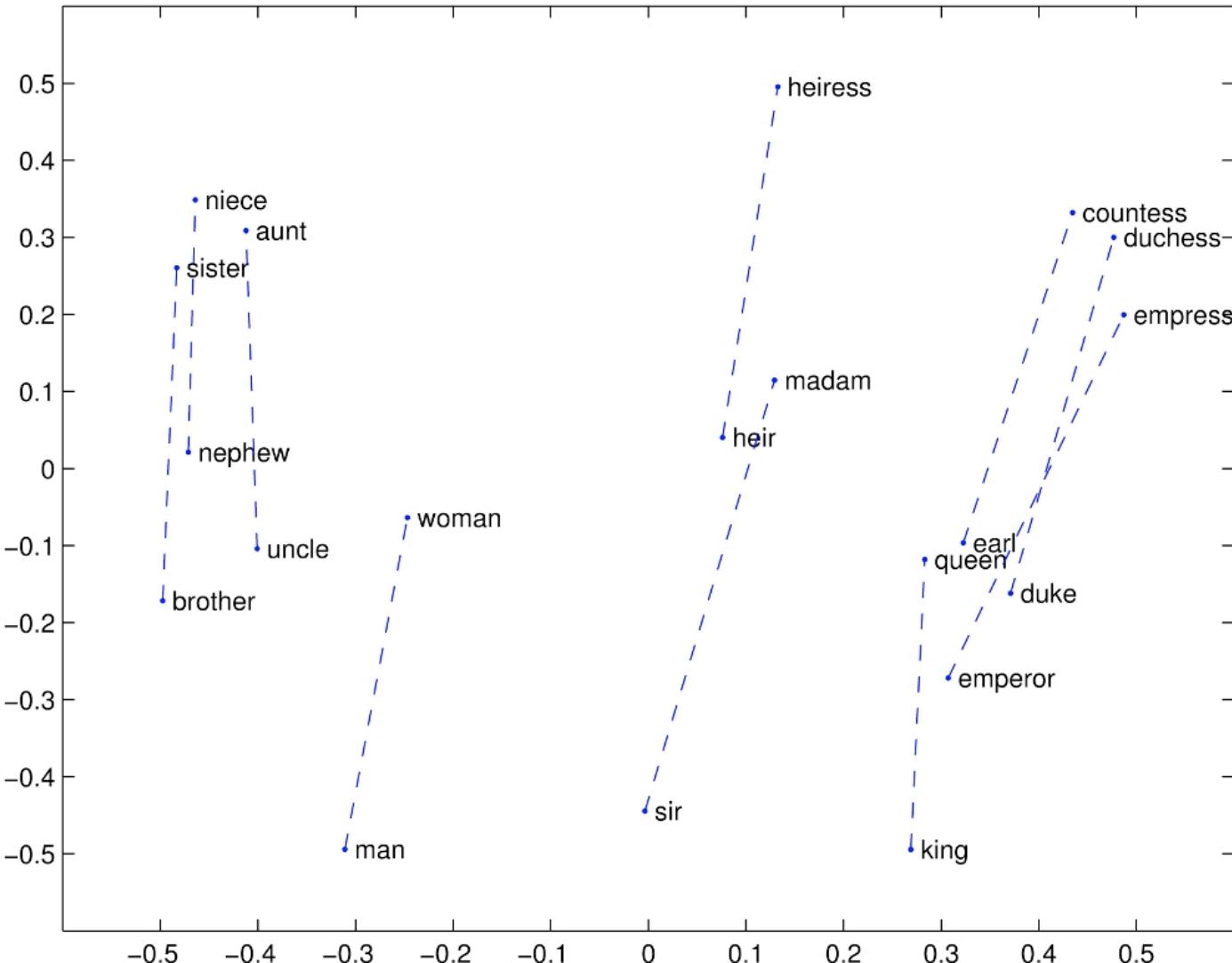
man:woman :: king:?

$$d = \arg \max_i \frac{(x_b - x_a + x_c)^T x_i}{\|x_b - x_a + x_c\|}$$

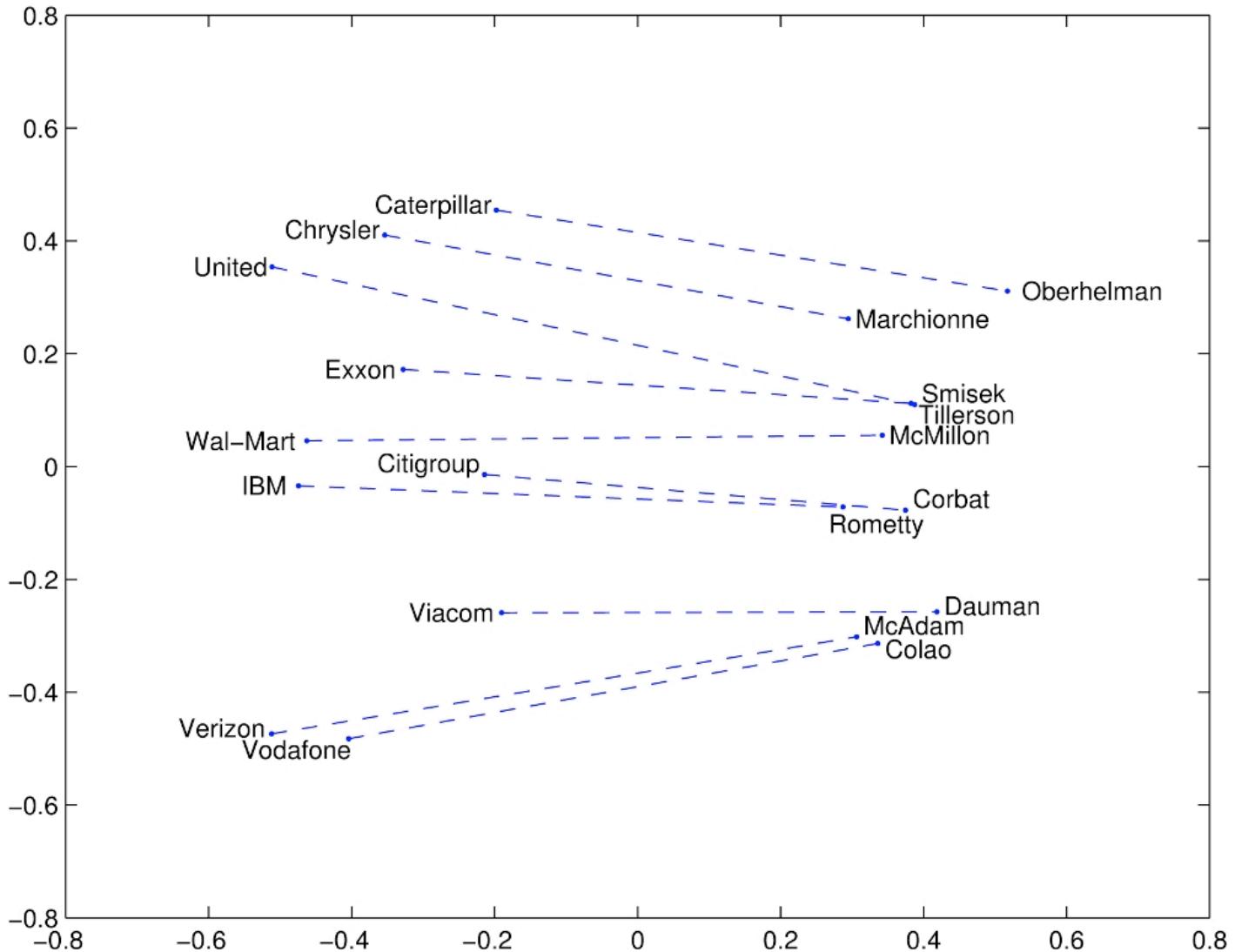
- Evaluate word vectors by how well their cosine distance after addition captures intuitive semantic and syntactic analogy questions
- Discarding the input words from the search!
- Problem: What if the information is there but not linear?



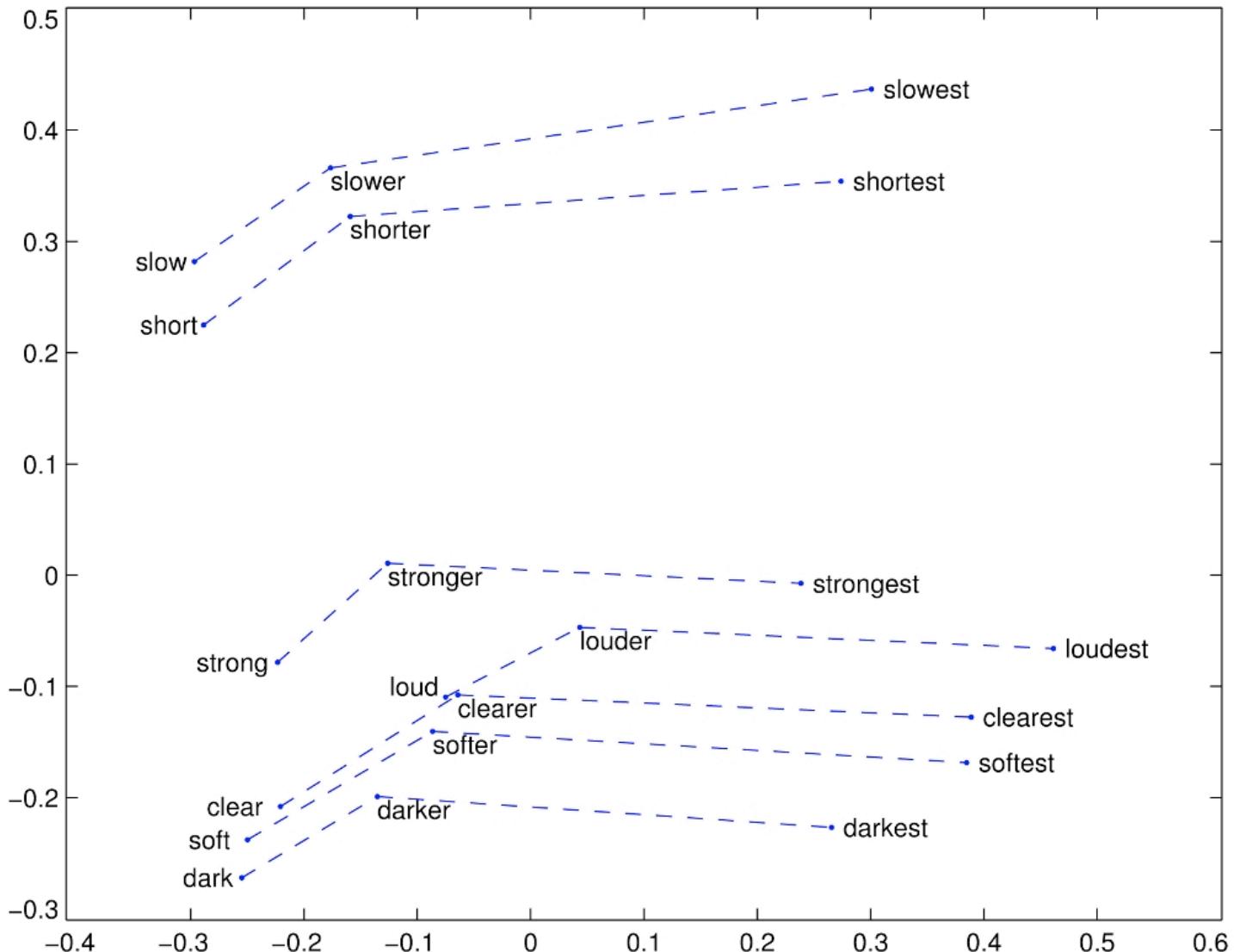
Glove Visualizations



Glove Visualizations: Company - CEO



Glove Visualizations: Comparatives and Superlatives



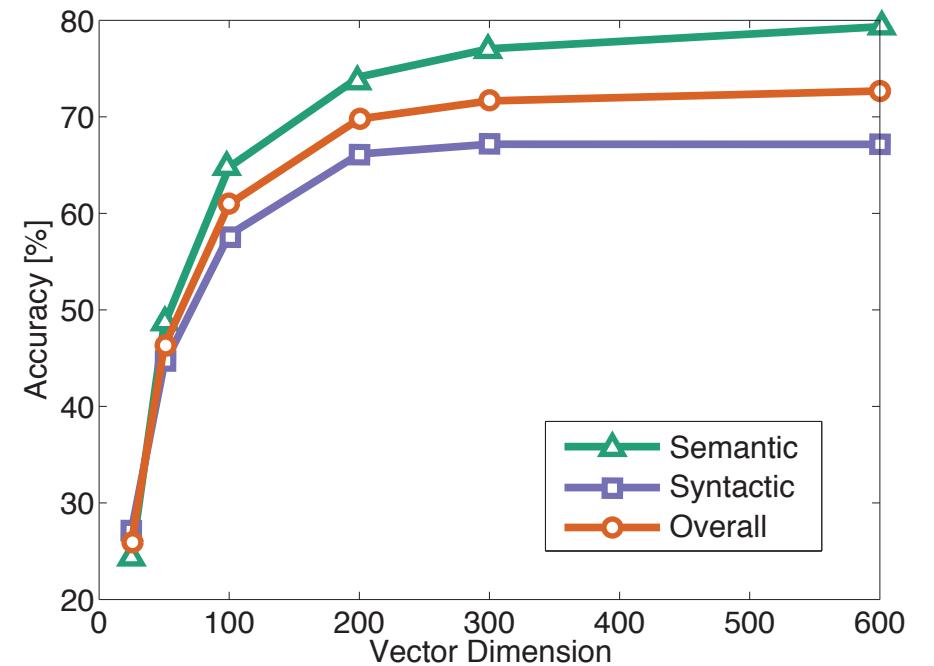
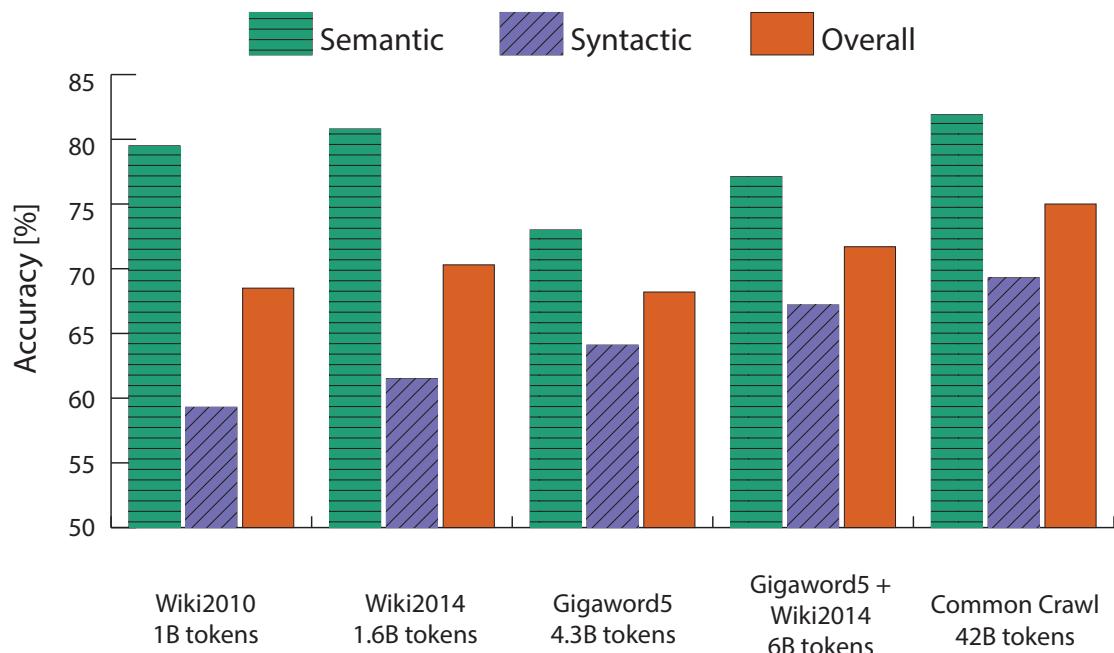
Analogy evaluation and hyperparameters

Glove word vectors evaluation

Model	Dim.	Size	Sem.	Syn.	Tot.
SVD	300	6B	6.3	8.1	7.3
SVD-S	300	6B	36.7	46.6	42.1
SVD-L	300	6B	56.6	63.0	60.1
CBOW [†]	300	6B	63.6	<u>67.4</u>	65.7
SG [†]	300	6B	73.0	66.0	69.1
GloVe	300	6B	<u>77.4</u>	67.0	<u>71.7</u>

Analogy evaluation and hyperparameters

- More data helps
- Wikipedia is better than news text!
- Dimensionality
- Good dimension is ~ 300



Another intrinsic word vector evaluation

- Word vector distances and their correlation with human judgments
- Example dataset: WordSim353 <http://www.cs.technion.ac.il/~gabr/resources/data/wordsim353/>

Word 1	Word 2	Human (mean)
tiger	cat	7.35
tiger	tiger	10
book	paper	7.46
computer	internet	7.58
plane	car	5.77
professor	doctor	6.62
stock	phone	1.62
stock	CD	1.31
stock	jaguar	0.92

Correlation evaluation

- Word vector distances and their correlation with human judgments

Model	Size	WS353	MC	RG	SCWS	RW
SVD	6B	35.3	35.1	42.5	38.3	25.6
SVD-S	6B	56.5	71.5	71.0	53.6	34.7
SVD-L	6B	65.7	<u>72.7</u>	75.1	56.5	37.0
CBOW [†]	6B	57.2	<u>65.6</u>	68.2	57.0	32.5
SG [†]	6B	62.8	65.2	69.7	<u>58.1</u>	37.2
GloVe	6B	<u>65.8</u>	<u>72.7</u>	<u>77.8</u>	53.9	<u>38.1</u>
SVD-L	42B	74.0	76.4	74.1	58.3	39.9
GloVe	42B	75.9	83.6	82.9	59.6	47.8
CBOW*	100B	68.4	79.6	75.4	59.4	45.5

- Some ideas from Glove paper have been shown to improve skip-gram (SG) model also (e.g., average both vectors)

Extrinsic word vector evaluation

- Extrinsic evaluation of word vectors: All subsequent NLP tasks in this class. More examples soon.
- One example where good word vectors should help directly: **named entity recognition**: identifying references to a person, organization or location

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

7. Word senses and word sense ambiguity

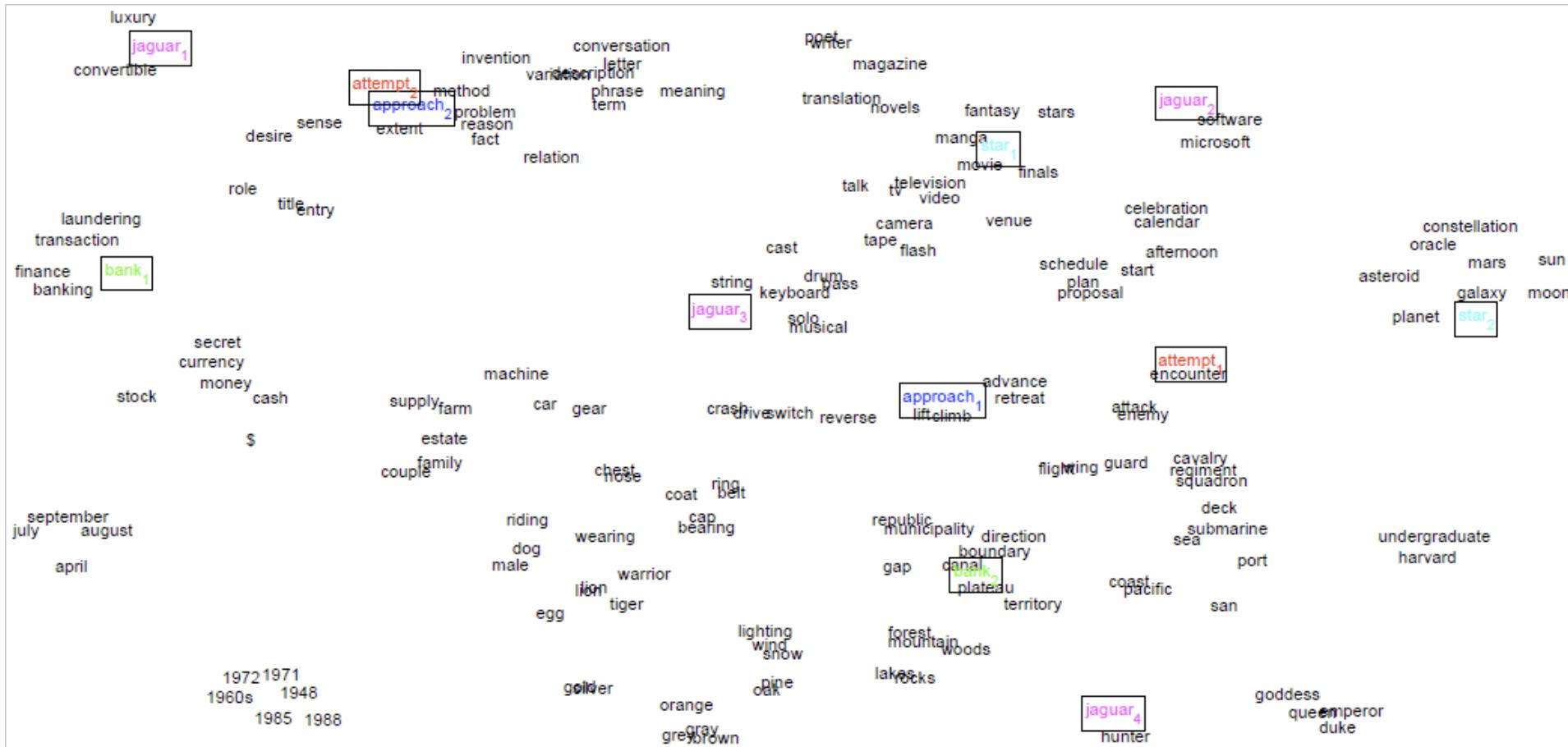
- Most words have lots of meanings!
 - Especially common words
 - Especially words that have existed for a long time
- Example: **pike**
- Does one vector capture all these meanings or do we have a mess?

pike

- A sharp point or staff
- A type of elongated fish
- A railroad line or system
- A type of road
- The future (coming down the pike)
- A type of body position (as in diving)
- To kill or pierce with a pike
- To make one's way (pike along)
- In Australian English, pike means to pull out from doing something: *I reckon he could have climbed that cliff, but he piked!*

Improving Word Representations Via Global Context And Multiple Word Prototypes (Huang et al. 2012)

- Idea: Cluster word windows around words, retrain with each word assigned to multiple different clusters bank_1 , bank_2 , etc.



Linear Algebraic Structure of Word Senses, with Applications to Polysemy

(Arora, ..., Ma, ..., TACL 2018)

- Different senses of a word reside in a linear superposition (weighted sum) in standard word embeddings like word2vec
- $v_{\text{pike}} = \alpha_1 v_{\text{pike}_1} + \alpha_2 v_{\text{pike}_2} + \alpha_3 v_{\text{pike}_3}$
- Where $\alpha_1 = \frac{f_1}{f_1+f_2+f_3}$, etc., for frequency f
- Surprising result:
 - Because of ideas from *sparse coding* you can actually separate out the senses (providing they are relatively common)!

tie				
trousers	season	scoreline	wires	operatic
blouse	teams	goalless	cables	soprano
waistcoat	winning	equaliser	wiring	mezzo
skirt	league	clinching	electrical	contralto
sleeved	finished	scoreless	wire	baritone
pants	championship	replay	cable	coloratura