

# 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)



# Course logistics in brief

- Instructor: Christopher Manning
- Head TA and co-instructor: Abigail See
- TAs: Many wonderful people! See website
- Time: TuTh 4:30–5:50, Nvidia Aud (→ video)
- Other information: see the class webpage:
  - <http://cs224n.stanford.edu/>  
a.k.a., <http://www.stanford.edu/class/cs224n/>
  - Syllabus, **office hours**, “handouts”, TAs, Piazza
    - Office hours start **this Thursday**
  - Slides uploaded before each lecture



# What do we hope to teach?

1. An understanding of the effective modern methods for deep learning
  - Basics first, then key methods used in NLP: Recurrent networks, attention, 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



# What's different this year?

- Lectures (including guest lectures) covering new material: character models, transformers, safety/fairness, multitask learn.
- 5x one-week assignments instead of 3x two-week assignments
- Assignments covering new material (NMT with attention, ConvNets, subword modeling)
- Using PyTorch rather than TensorFlow
- Assignments due *before class* (4:30pm) not at midnight!
- Gentler but earlier ramp-up
  - First assignment is easy, but due *one week from today!*
- No midterm

# Course work and grading policy

- 5 x 1-week Assignments: 6% + 4 x 12%: 54%
  - HW1 is released today! Due next Tuesday! At 4:30 p.m.
  - Please use @stanford.edu email for your Gradescope account
- Final Default or Custom Course Project (1–3 people): 43%
  - Project proposal: 5%, milestone: 5%, poster: 3%, report: 30%
  - Final poster session attendance expected! (See website.)
  - **Wed Mar 20, 5pm-10pm** (put it in your calendar!)
- Participation: 3%
  - (Guest) lecture attendance, Piazza, eval, karma – see website!
- Late day policy
  - 6 free late days; afterwards, 10% off per day late
  - Assignments not accepted after 3 late days per assignment
- Collaboration policy: Read the website and the Honor Code!  
Understand allowed ‘collaboration’ and how to document it

# High-Level Plan for Problem Sets

- HW1 is hopefully an easy on ramp – an IPython Notebook
- HW2 is pure Python (numpy) but expects you to do (multivariate) calculus so you really understand the basics
- HW3 introduces PyTorch
- HW4 and HW5 use PyTorch on a GPU (Microsoft Azure)
  - Libraries like PyTorch, Tensorflow (and Chainer, MXNet, CNTK, Keras, etc.) are becoming the standard tools of DL
- For FP, you either
  - Do the default project, which is SQuAD question answering
    - Open-ended but an easier start; a good choice for most
  - Propose a custom final project, which we approve
    - You will receive feedback from a **mentor** (TA/prof/postdoc/PhD)
  - Can work in teams of 1–3; can use any language

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Here is another view of Language



가

(writing)  
(knowledge)

가

Human Network Computer Network

~ .  
( . )

compression system 가 . ( .  
가 )

short message

# 1. How do we represent the meaning of a word?

word has rich meaning

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)

meaning what things represent .

, chair . denotation of the  
word chair , , ,

? => the word chair is sort of  
representing all the things that are chairs.

= denotational semantics

one - hot encoding .

meaning . It is very hard to  
formulate in computation.

# How do we have usable meaning in a computer?

kind of taxonomy

Common solution: Use e.g. WordNet, a thesaurus containing lists of **synonym sets** and **hypercnyms** ("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()])))
```

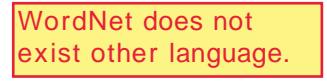
```
noun: good
noun: good, goodness
noun: good, goodness
noun: commodity, trade_good, good
adj: good
adj (sat): full, good
adj: good
adj (sat): estimable, good, honorable, respectable
adj (sat): beneficial, good
adj (sat): good
adj (sat): good, just, upright
...
adverb: well, good
adverb: thoroughly,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



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

WordNet	fixed discrete synonym set	가	.
Synonym	same meaning	.	.
Synonym	similar meaning	.	=> good <-> marvelous

# Representing words as discrete symbols

NLP: until 2012

2013 Neural net representation .

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

Means one 1, the rest 0s

Words can be represented by **one-hot** vectors:

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

atomic symbols

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:

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

These two vectors are **orthogonal**.

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

word similarity table	?
2005	.
table (=matrix)	가 . (2.5 trillion?)

**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**



가

# 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 sometimes called word embeddings or word representations. They are a distributed representation.

# Word meaning as a neural word vector – visualization

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



### 3. Word2vec: Overview

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

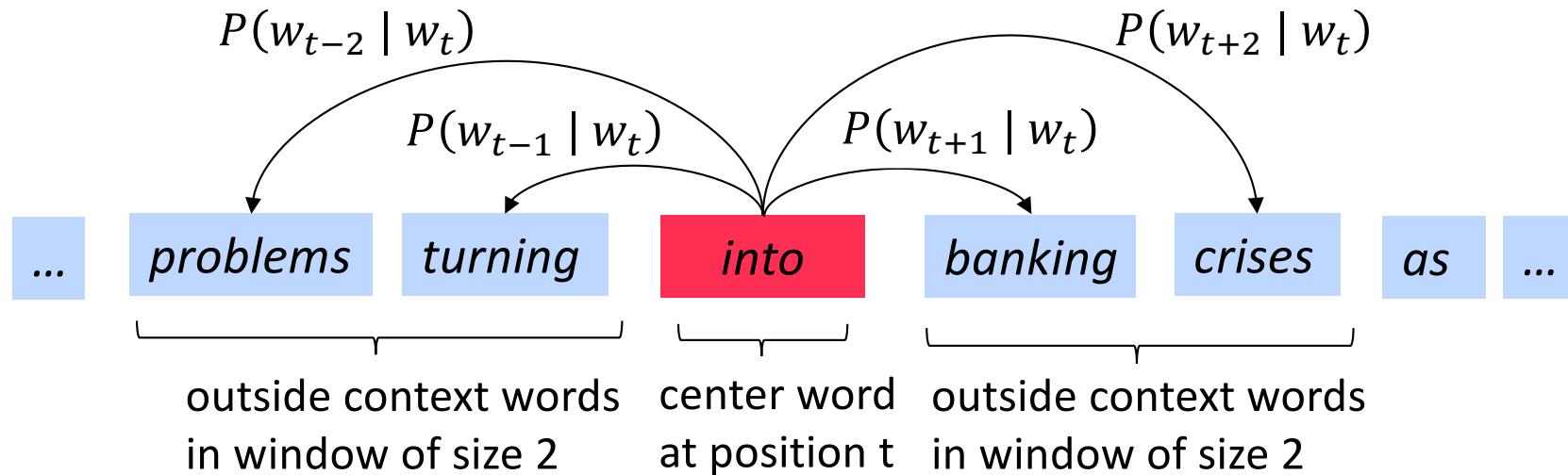
Bengio 가 word vector  
Mikolov very scalable way of  
learning .

Idea:

- We have a large corpus of text courpus corpora . random vector
- 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

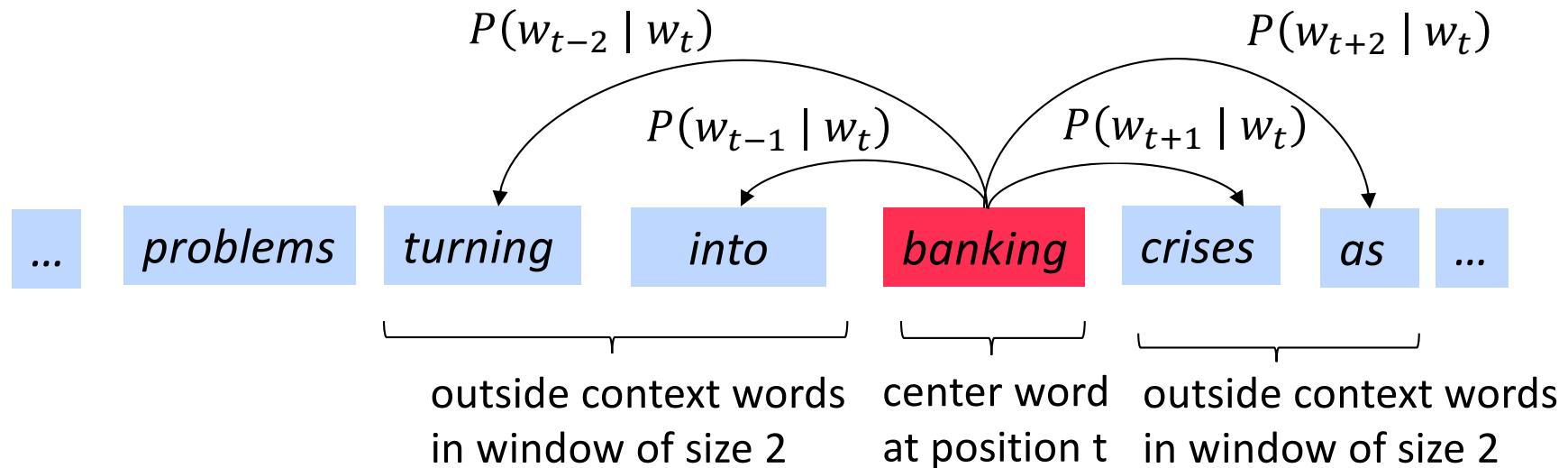
# Word2Vec Overview

- 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  $w_t$ .

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

$\theta$  is all variables to be optimized

sometimes called *cost* or *loss* function

model likelihood  
negative  
function  
).  
(  
, logarithm, average,  
objective

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

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

parameter가  
word vector가 .

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  $P(w_{t+j} | w_t; \theta)$  ?

가?

- 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  $o$ :

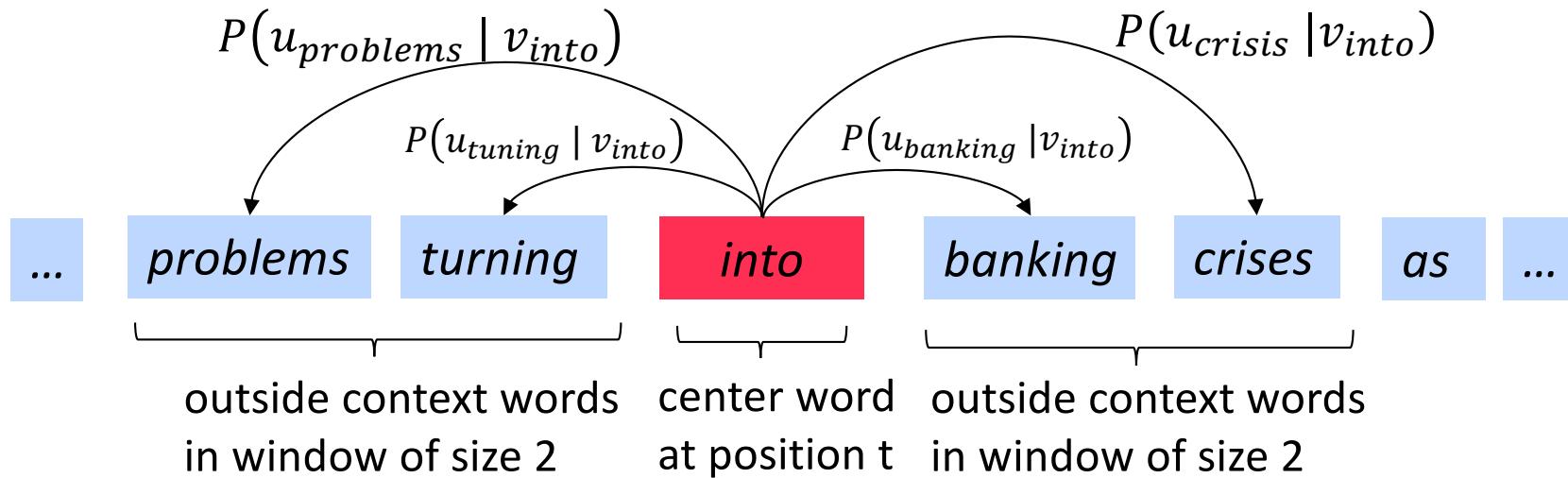
, vector quadratic  
expression .  
vector 가 optimization

This is not very beautiful, but in the end in order to capture as much as you can all of statistics, you are just going to average or concatenate these two vectors to represent each word. So, at the very end of the optimization after learning two vectors, for each word, we're just going to average two.

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

# 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

Exponentiation makes anything positive

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

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

Normalize over entire vocabulary  
to give probability distribution

- This is an example of the **softmax function**  $\mathbb{R}^n \rightarrow \mathbb{R}^n$

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

- 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

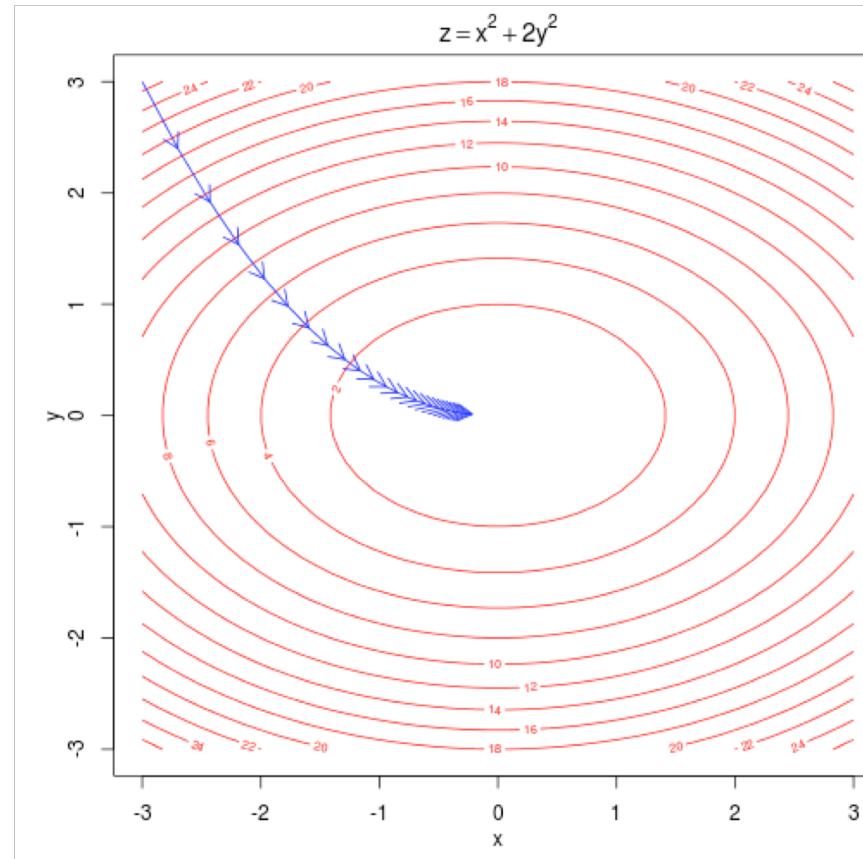
$\exp$	↑	positive
	,	big number
bigger	small	much smaller
	- - >	.
		.

# Training a model by optimizing parameters

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

E.g., below, for a simple convex function over two parameters

Contour lines show levels of objective function



# To train the model: Compute all vector gradients!

- Recall:  $\theta$  represents **all** model parameters, in one long vector
- In our case with  $d$ -dimensional vectors and  $V$ -many words:

(2 ) .

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

- Remember: every word has **two** vectors
- We optimize these parameters by walking down the gradient

## 4. Word2vec derivations of gradient

- Whiteboard – see video if you're not in class ;)
- The basic Lego piece
- Useful basics:  $\frac{\partial \mathbf{x}^T \mathbf{a}}{\partial \mathbf{x}} = \frac{\partial \mathbf{a}^T \mathbf{x}}{\partial \mathbf{x}} = \mathbf{a}$
- If in doubt: write out with indices
- Chain rule! If  $y = f(u)$  and  $u = g(x)$ , i.e.  $y = f(g(x))$ , then:

$$\frac{dy}{dx} = \frac{dy}{du} \frac{du}{dx}$$

# 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:

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

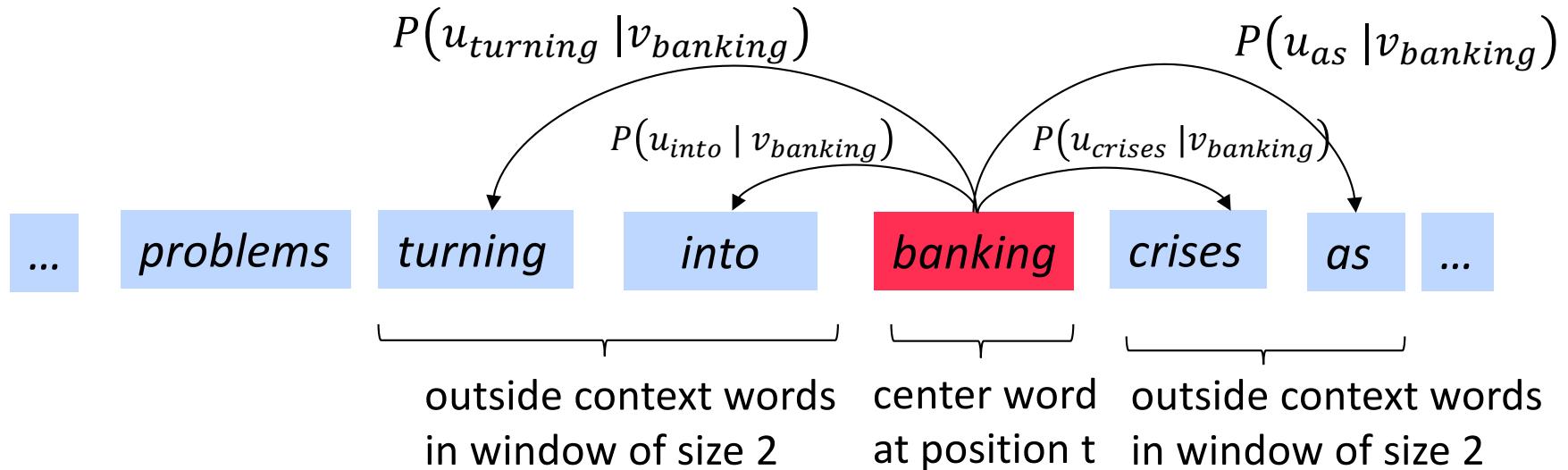
This is essentially "dynamic" logistic regression

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

# Calculating all gradients!

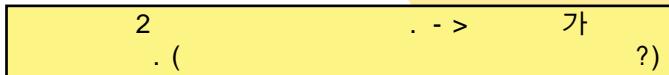
model very loose  
 $u, v$   
one probability distribution  
different context with different words가

- We went through 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.



2 . ?

Two model variants:

## 1. Skip-grams (SG)

Skip - grams

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:

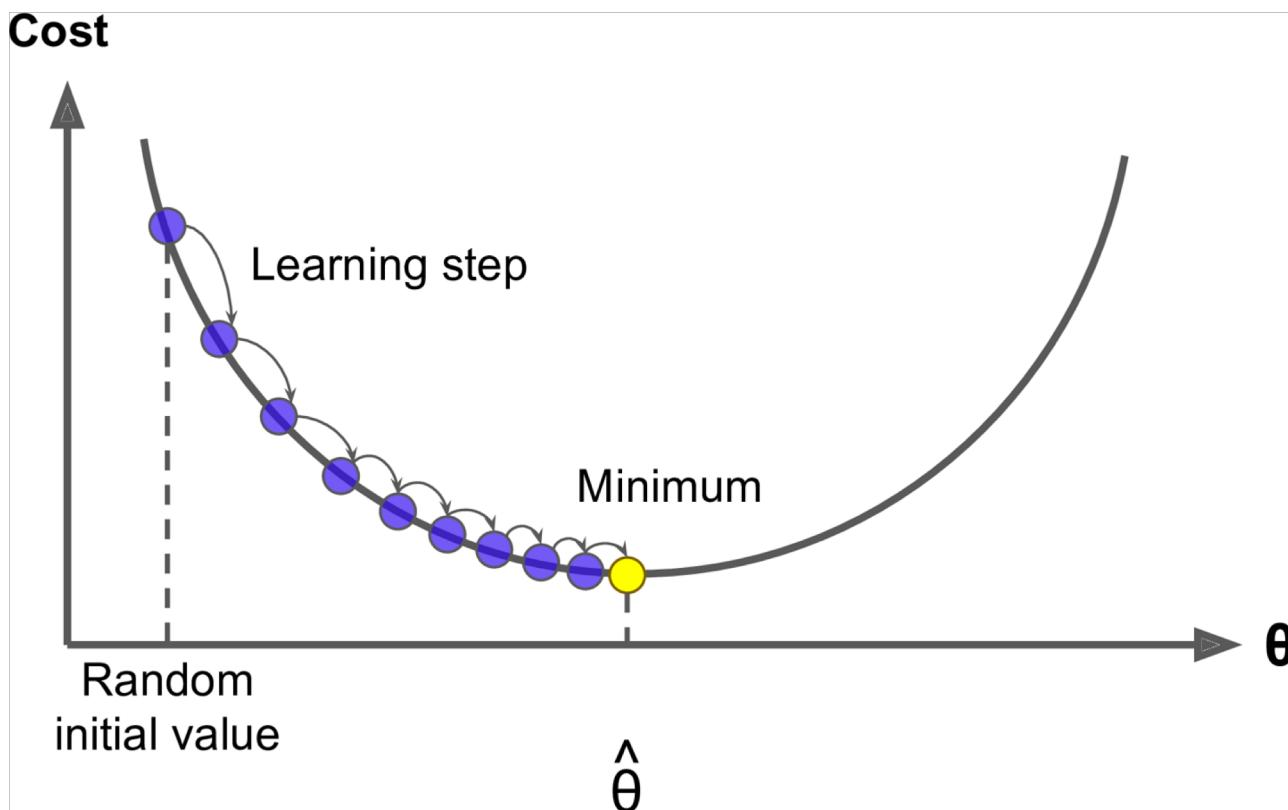
## 1. Negative sampling

Naive Softmax

So far: Focus on **naïve softmax** (simpler 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  $\theta$ , calculate gradient of  $J(\theta)$ , then take small step in direction of negative gradient. Repeat.



# Gradient Descent

- Update equation (in matrix notation):

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

$\alpha$  = 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

SGD gradient  
batch GD gradient approximation  
approximation suffling . . .

- 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)  
    theta = theta - alpha * theta_grad
```

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