# 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.

# How to represent meaning in a computer?

Common answer: Use a taxonomy like WordNet that has hypernyms (is-a) relationships and synonym sets (good):

```
from nltk.corpus import wordnet as wn
panda = wn.synset('panda.n.01')
hyper = lambda s: s.hypernyms()
list(panda.closure(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')]
```

```
S: (adj) full, good
S: (adj) estimable, good, honorable, respectable
S: (adj) beneficial, good
S: (adj) good, just, upright
S: (adj) adept, expert, good, practiced,
proficient, skillful
S: (adj) dear, good, near
S: (adj) good, right, ripe
…
S: (adv) well, good
S: (adv) thoroughly, soundly, good
S: (n) good, goodness
S: (n) commodity, trade good, good
```

# Problems with this discrete representation

- Great as resource but missing nuances, e.g. **synonyms**:
  adept, expert, good, practiced, proficient, skillful?

- Missing new words (impossible to keep up to date):
  wicked, badass, nifty, crack, ace, wizard, genius, ninjia
- Subjective
- Requires human labor to create and adapt
- Hard to compute accurate word similarity →

# Problems with this discrete representation

The vast majority of rule-based **and** statistical NLP work regards words as atomic symbols: hotel, conference, walk

In vector space terms, this is a vector with one 1 and a lot of zeroes

[0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]

Dimensionality: 20K (speech) – 50K (PTB) – 500K (big vocab) – 13M (Google 1T)

We call this a "one-hot" representation. Its problem:

motel [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0] AND
hotel [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0] = 0

# Distributional similarity based representations

You can get a lot of value by representing a word by means of its neighbors

"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

government debt problems turning into **banking** crises as has happened in

saying that Europe needs unified **banking** regulation to replace the hodgepodge

↖ These words will represent *banking* ↗

# How to make neighbors represent words?

Answer: With a cooccurrence matrix X

- 2 options: full document vs windows
- Word - document cooccurrence matrix will give general topics (all sports terms will have similar entries) leading to "Latent Semantic Analysis"

- Window allows us to capture both syntactic (POS) and semantic information →

# Window based cooccurence 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.

# Window based cooccurence matrix

- 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 |

# Problems with simple cooccurrence vectors

Increase in size with vocabulary

Very high dimensional: require a lot of storage

Subsequent classification models have sparsity issues

→ Models are less robust

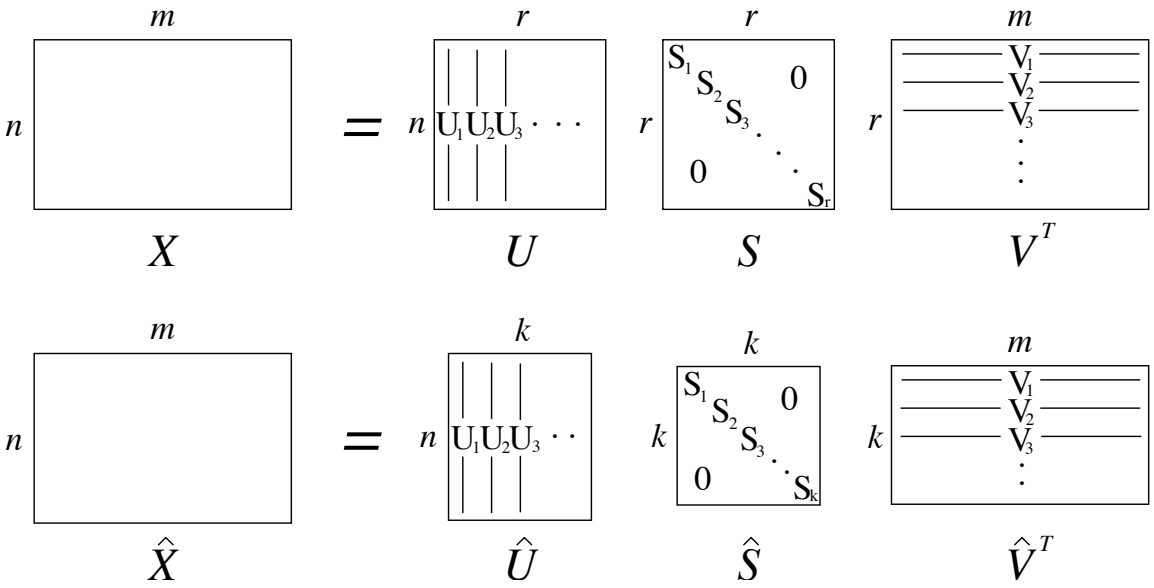
# Solution: Low dimensional vectors

- Idea: store "most" of the important information in a fixed, small number of dimensions: a dense vector
- Usually around 25 – 1000 dimensions

- How to reduce the dimensionality?

# Method 1: Dimensionality Reduction on X

Singular Value Decomposition of cooccurrence matrix *X*.




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

# Simple SVD word vectors in Python

Corpus:
I like deep learning. I like NLP. I enjoy flying.

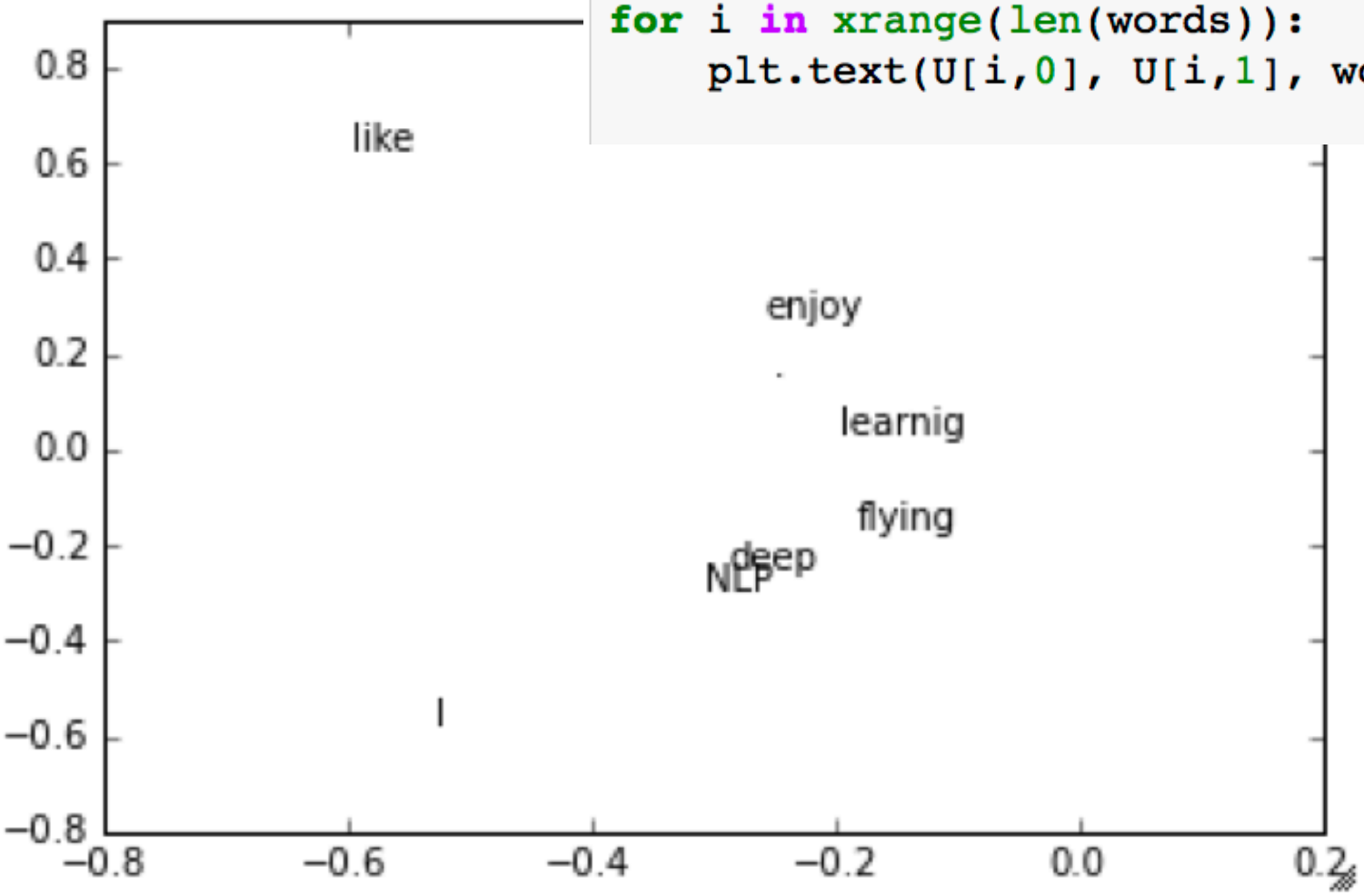
```
import numpy as np
la = np.linalg
words = ["I", "like", "enjoy",
         "deep","learnig","NLP","flying","."]
X = np.array([[0,2,1,0,0,0,0,0],
              [2,0,0,1,0,1,0,0],
              [1,0,0,0,0,0,1,0],
              [0,1,0,0,1,0,0,0],
              [0,0,0,1,0,0,0,1],
              [0,1,0,0,0,0,0,1],
              [0,0,1,0,0,0,0,1],
              [0,0,0,0,1,1,1,0]])

U, s, Vh = la.svd(X, full_matrices=False)
```

# Simple SVD word vectors in Python

Corpus: I like deep learning. I like NLP. I enjoy flying.
Printing first two columns of U corresponding to the 2 biggest singular values

```
for i in xrange(len(words)):
    plt.text(U[i,0], U[i,1], words[i])
```



# Word meaning is defined in terms of vectors

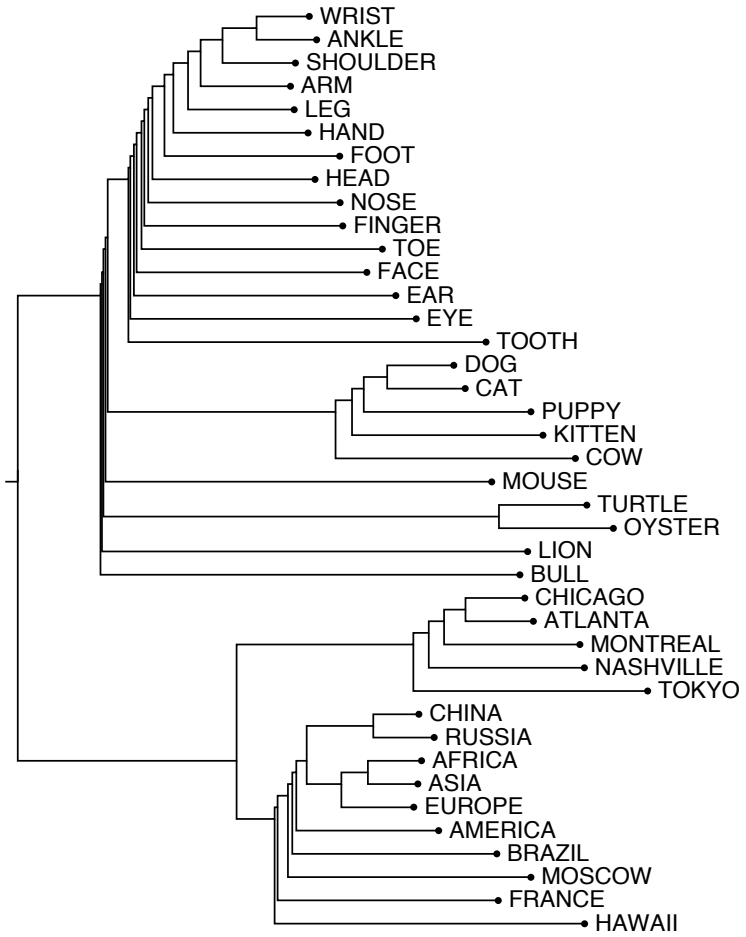
- In all subsequent models, including deep learning models, a word is represented as a dense vector

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

# Hacks to X

- Problem: function words (the, he, has) are too frequent → syntax has too much impact. Some fixes:
  - min(X,t), with t~100
  - Ignore them all
- Ramped windows that count closer words more
- Use Pearson correlations instead of counts, then set negative values to 0
- +++

# Interesting semantic patters emerge in the vectors




An Improved Model of Semantic Similarity Based on Lexical Co-Occurrence
Rohde et al. 2005

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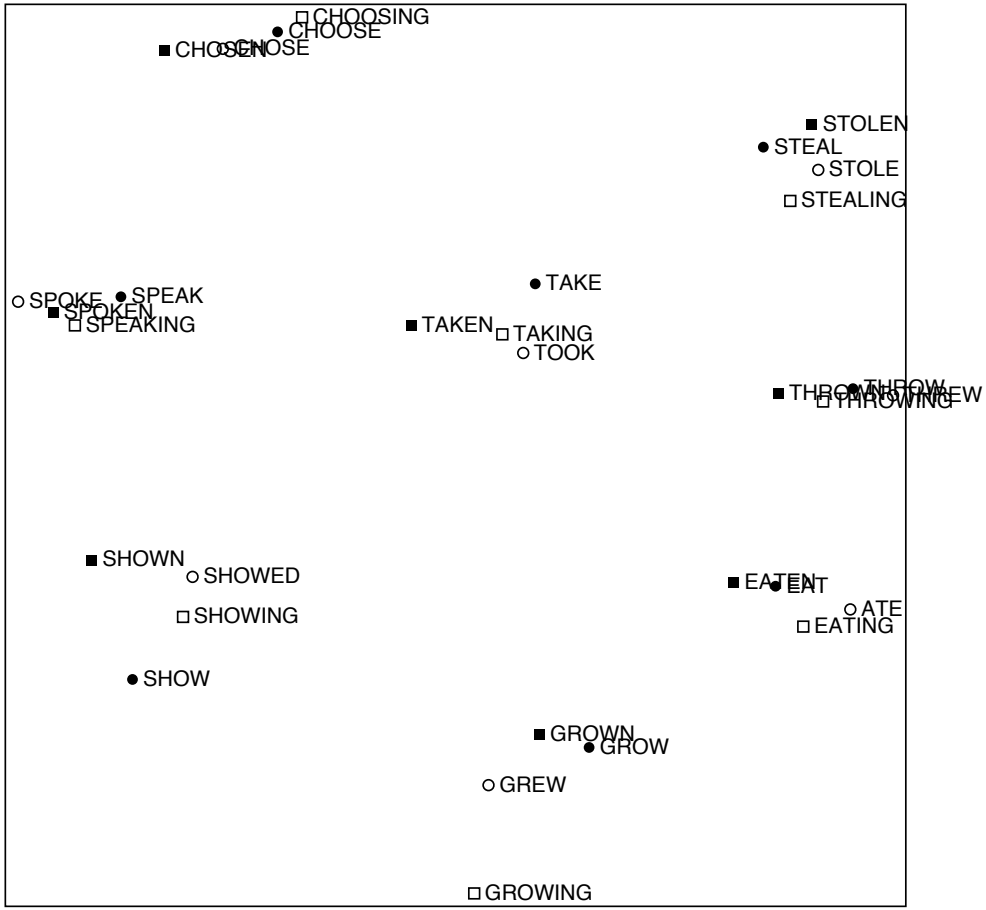


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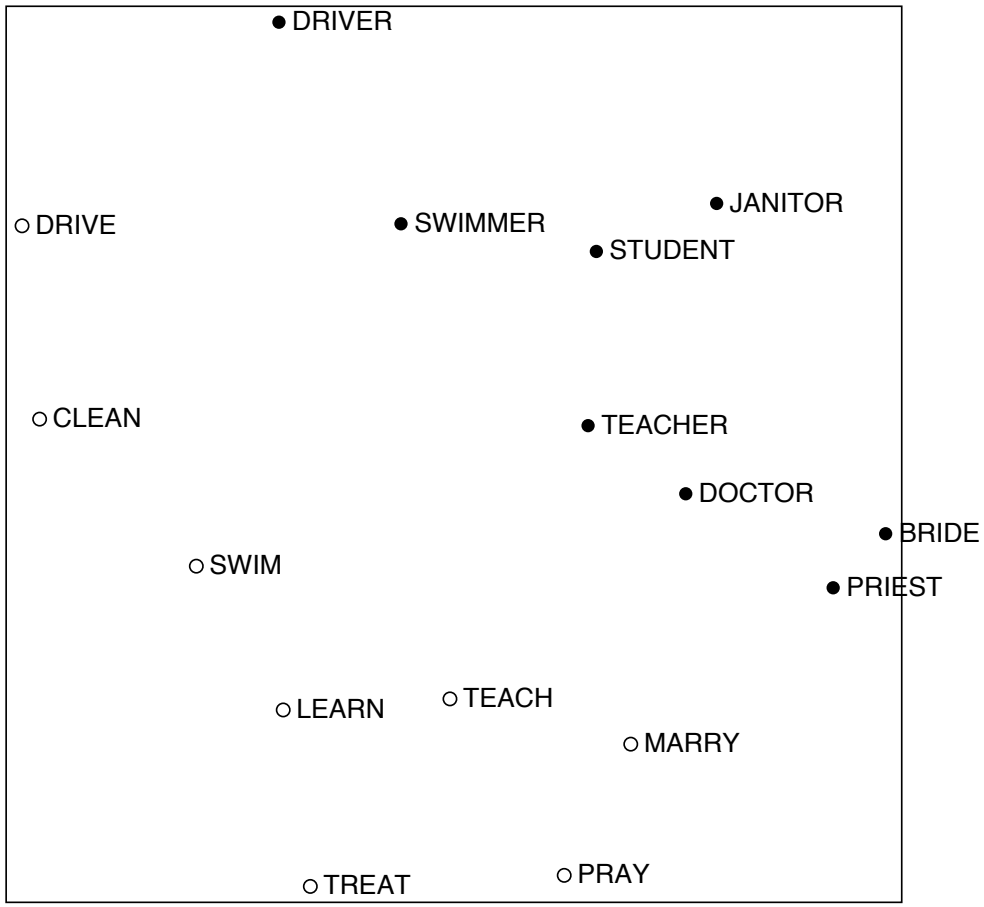


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# Problems with SVD

Computational cost scales quadratically for n x m matrix:

O($mn^2$) flops (when n<m)

→ Bad for millions of words or documents

Hard to incorporate new words or documents

Different learning regime than other DL models

# Idea: Directly learn low-dimensional word vectors

- Old idea. Relevant for this lecture & deep learning:
  - Learning representations by back-propagating errors. (Rumelhart et al., 1986)
  - A neural probabilistic language model (Bengio et al., 2003)
  - NLP from Scratch (Collobert & Weston, 2008)
  - A recent and even simpler model: word2vec (Mikolov et al. 2013) → intro now

# Main Idea of word2vec

- Instead of capturing cooccurrence counts directly,
- Predict surrounding words of every word
- Both are quite similar, see "*Glove: Global Vectors for Word Representation*" by Pennington et al. (2014)

- Faster and can easily incorporate a new sentence/ document or add a word to the vocabulary

# Details

- Predict surrounding words in a window of length c of every word.
- Objective function: Maximize the log probability of any context word given the current center word:
- $$J(\theta) = \frac{1}{T}\sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j}|w_t)$$

# Details

- Predict surrounding words in a window of length c of every word
- For $p(w_{t+j}|w_t)$ the simplest first formulation is

$$p(w_O|w_I) = \frac{\exp\left({v'_{w_O}}^\top v_{w_I}\right)}{\sum_{w=1}^{W} \exp\left({v'_w}^\top v_{w_I}\right)}$$

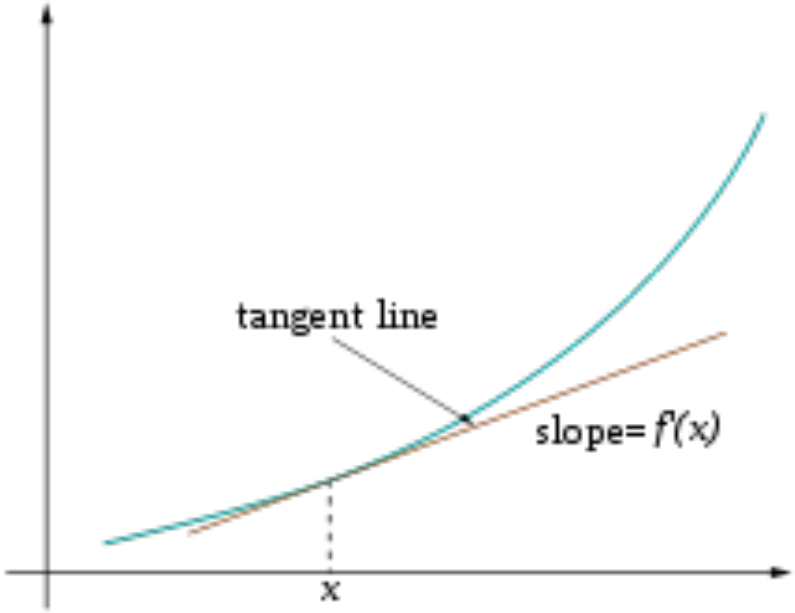
- where v and v′ are “input” and “output” vector representations of w (so every word has two vectors!)
- This is essentially “dynamic” logistic regression

# Cost/Objective functions

We will optimize (maximize or minimize) our objective/cost functions

For now: minimize → gradient descent

Refresher with trivial example: (from Wikipedia)
Find a local minimum of the function
$f(x)=x^4-3x^3+2$, with derivative $f'(x)=4x^3-9x^2$.




```
x_old = 0
x_new = 6 # The algorithm starts at x=6
eps = 0.01 # step size
precision = 0.00001

def f_derivative(x):
    return 4 * x**3 - 9 * x**2

while abs(x_new - x_old) > precision:
    x_old = x_new
    x_new = x_old - eps * f_derivative(x_old)

print("Local minimum occurs at", x_new)
```

# Derivations of gradient

- Whiteboard (see video if you're not in class ;)
- Most basic Lego piece, speed will depend on participation
- Useful basics: $\frac{\partial \mathbf{x}^T \mathbf{a}}{\partial \mathbf{x}} = \frac{\partial \mathbf{a}^T \mathbf{x}}{\partial \mathbf{x}} = \mathbf{a}$

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

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

# Whiteboard!

# Approximations: PSet 1

- With large vocabularies this objective function is not scalable and would train too slowly! → Why?

- Idea: approximate the normalization or
- Define negative prediction that only samples a few words that do not appear in the context
- Similar to focusing on mostly positive correlations
- You will derive and implement this in Pset 1!

# Linear Relationships in word2vec

These representations are *very good* at encoding dimensions of similarity!

- Analogies testing dimensions of similarity can be solved quite well just by doing vector subtraction in the embedding space

  Syntactically

  - $x_{apple} - x_{apples} \approx x_{car} - x_{cars} \approx x_{family} - x_{families}$

  - Similarly for verb and adjective morphological forms

  Semantically (Semeval 2012 task 2)

  - $x_{shirt} - x_{clothing} \approx x_{chair} - x_{furniture}$
  - $x_{king} - x_{man} \approx x_{queen} - x_{woman}$

# Count based vs direct prediction

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

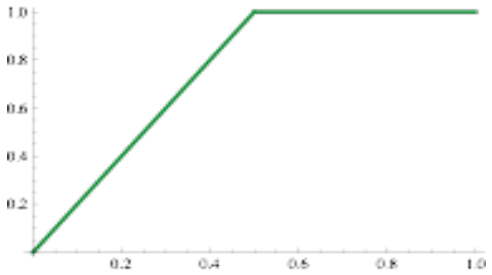
- Fast training
- Efficient usage of statistics
- Primarily used to capture word similarity
- Disproportionate importance given to small counts

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

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

# Combining the best of both worlds: GloVe

$$J = \frac{1}{2}\sum_{ij} f(P_{ij})\left(w_i \cdot \tilde{w}_j - \log P_{ij}\right)^2$$

$f \sim$ 


- 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


leptodactylidae

rana

eleutherodactylus

# Word Analogies

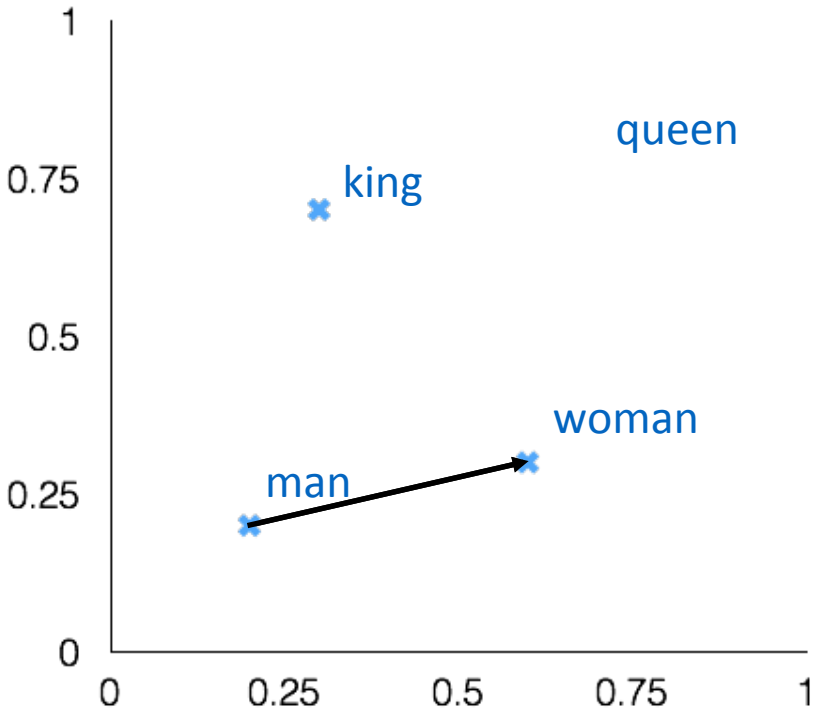
Test for linear relationships, examined by Mikolov et al. (2014)

a:b :: c:?

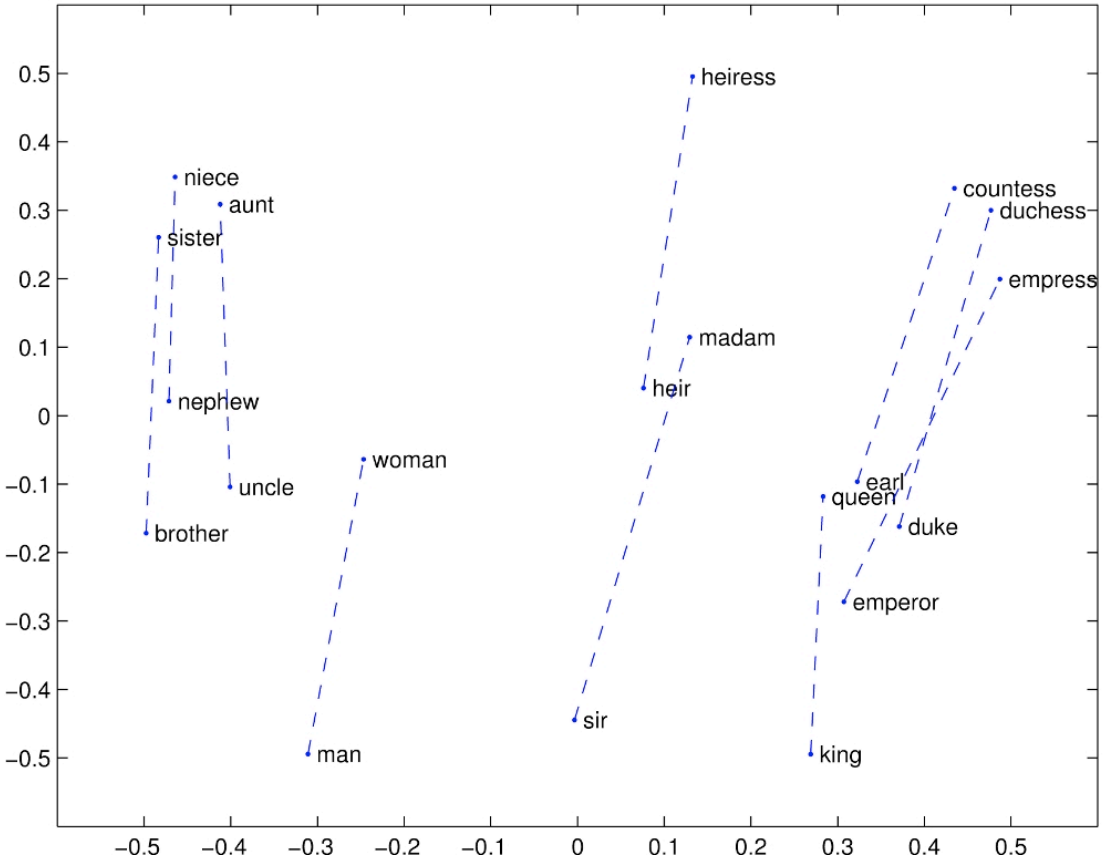
$$d = \arg\max_x \frac{(w_b - w_a + w_c)^T w_x}{||w_b - w_a + w_c||}$$

man:woman :: king:?

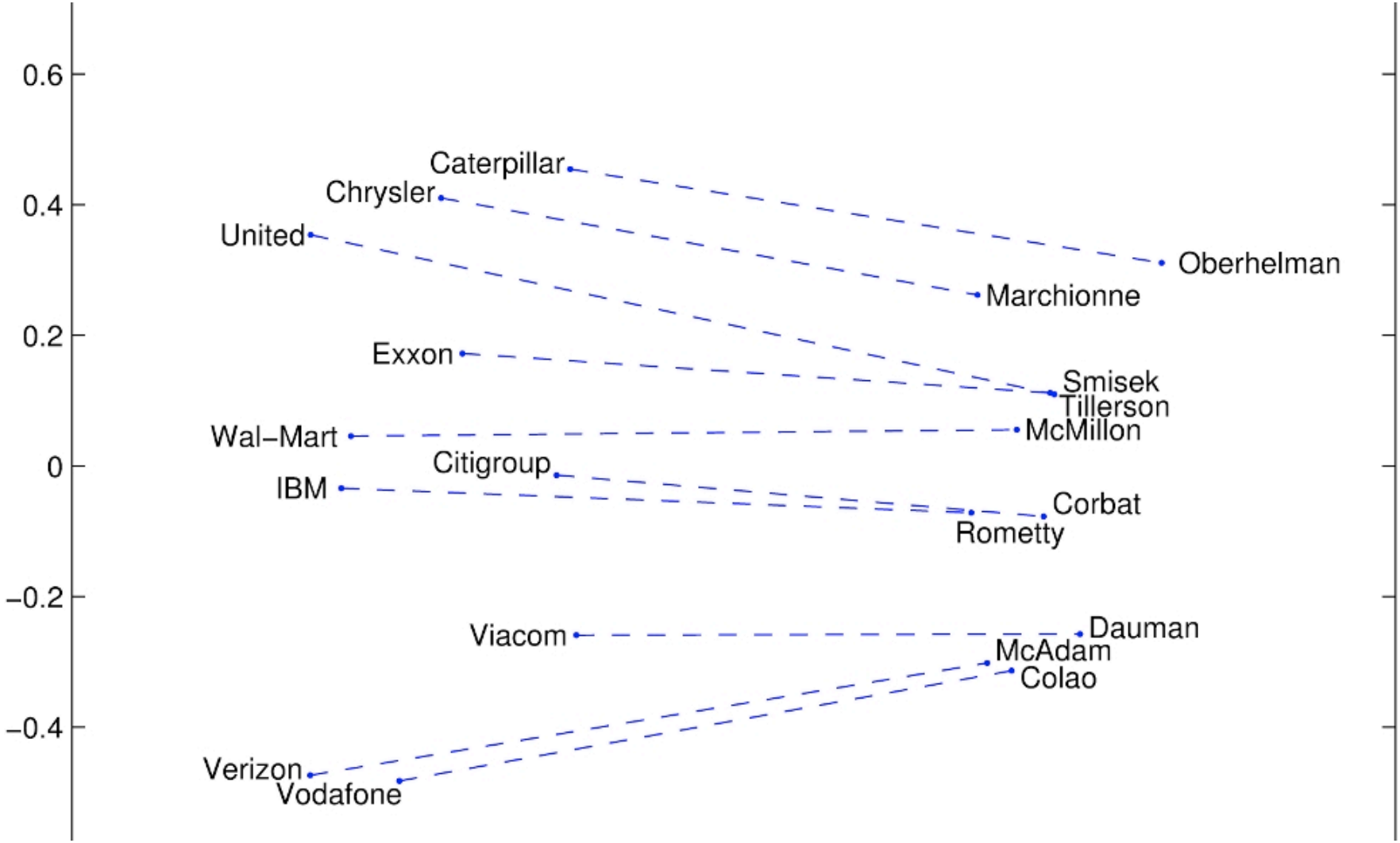
| | | |
|---|---|---|
| + | king | [ 0.30 0.70 ] |
| - | man | [ 0.20 0.20 ] |
| + | woman | [ 0.60 0.30 ] |
| | queen | [ 0.70 0.80 ] |



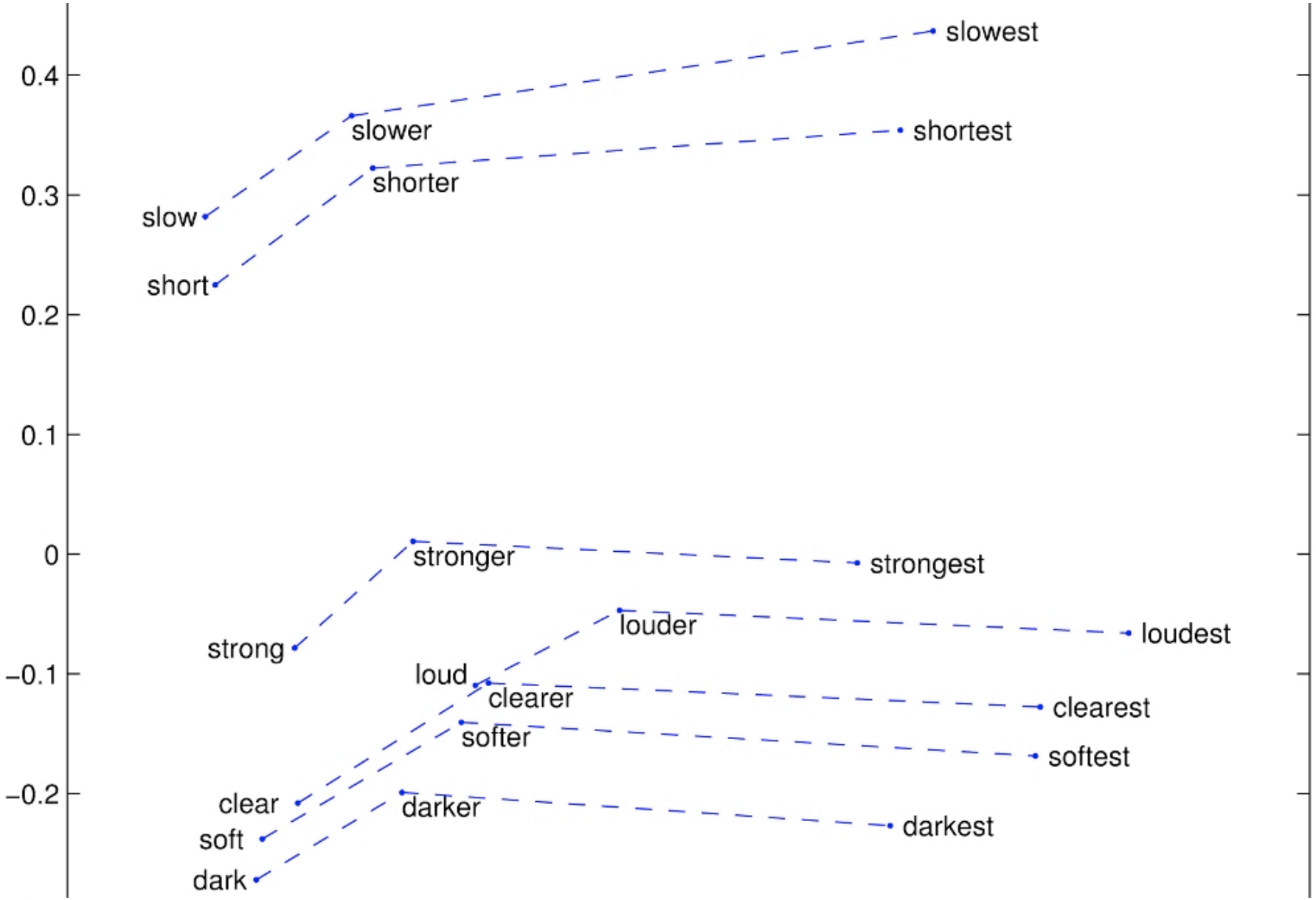
# Glove Visualizations



# Glove Visualizations: Company - CEO

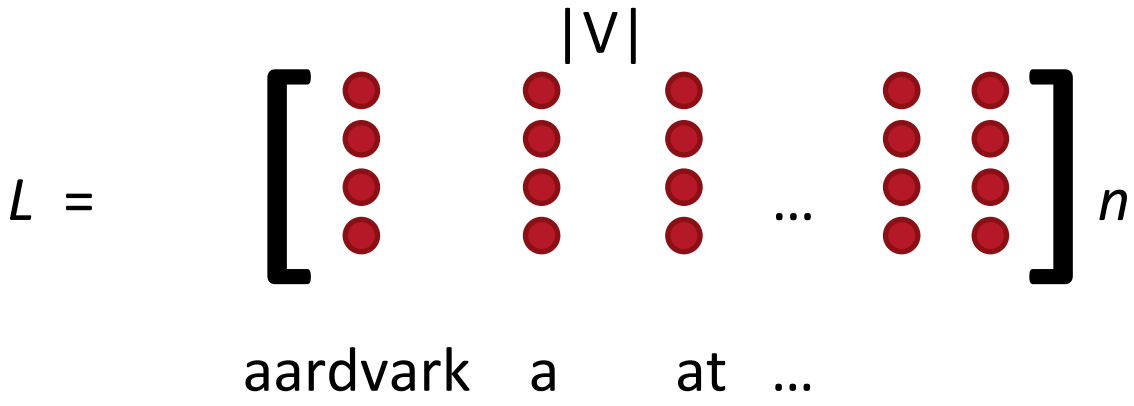


# Glove Visualizations: Superlatives



# Word embedding matrix

- Initialize most word vectors of future models with our "pre-trained" embedding matrix $L \in \mathbb{R}^{n \times |V|}$




- Also called a look-up table
  - Conceptually you get a word's vector by left multiplying a one-hot vector *e* (of length |V|) by *L*: $x = Le$

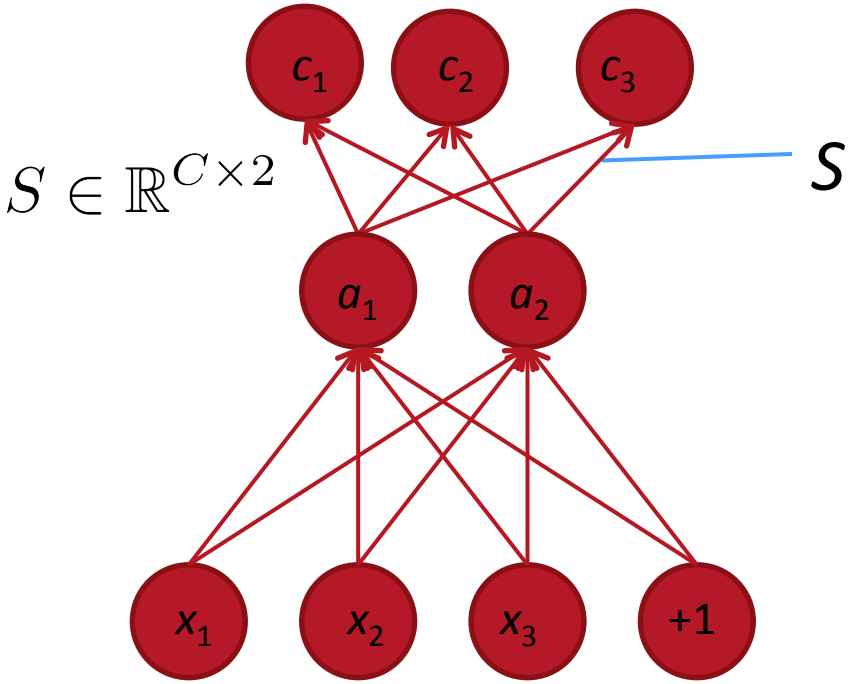
# Advantages of low dimensional word vectors

What is the major benefit of deep learned word vectors?

Ability to also propagate **any** information into them via neural networks (next lecture).

$$P(c \mid d, \lambda) = \frac{e^{\lambda^\top f(c,d)}}{\sum_{c'} e^{\lambda^\top f(c',d)}}$$

$$p(c|x) = \frac{\exp(S_c.a)}{\sum_{c'} \exp(S_{c'}.a)}$$



# Advantages of low dimensional word vectors

- Word vectors will form the basis for all subsequent lectures.
- All our semantic representations will be vectors!
- We can compute compositional representations for longer phrases or sentences with them and solve lots of different tasks. → Next lecture!