

# DD2418 Language Engineering

## 7a: Lexical semantics

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# Levels of linguistic analysis

|              |                       |
|--------------|-----------------------|
| Words        | Morphology, Phonology |
| Sentences    | Syntax                |
| Meaning      | Semantics             |
| Language use | Pragmatics            |

What is the *meaning* of a word?

- ... i.e. what kind of object/entity is the meaning of a word?

Can we represent the meaning of a word in a computer program?

- ... and if so, how?

# What is the meaning of a word?

Linguistics answer:

- Words (*signifiers*) denote *concepts* (the *signified*)
  - e.g. “dog” denotes the concept of a dog
- A concept has an **extension** and an **intention**
  - e.g. extension = all dogs in the world
  - intention = the abstract idea of a dog

# Words and senses

A word can have several meanings, or *senses*. This can be due to one of a number of linguistic processes:

**Homonymy.** unrelated senses

- *bear* (the animal), and the verb *to bear*.

**Polysemy:** related senses

- *move* <sup>transporting yourself</sup> to the next room, *move* <sup>transporting something</sup> *furniture*
- a *good* <sup>moral quality</sup> man, a *good* <sup>technical skills</sup> painter

**Metaphors**

- *He got the idea.*
- *He bought the argument.*

# Semantic relations

Words (or rather word senses) can have various semantic relationships to one another.

- synonyms, e.g. *good-nice*
- antonyms, e.g. *good-bad*
- hypernyms and hyponyms (is-a relations), e.g. *animal-dog*
- meronyms (part-of relations), e.g. *tree-branch*
- metonyms, e.g. “*Agatha Christie is very exciting*”

# Semantic fields

Words that are not synonyms, but still related because they are used in the same domain.

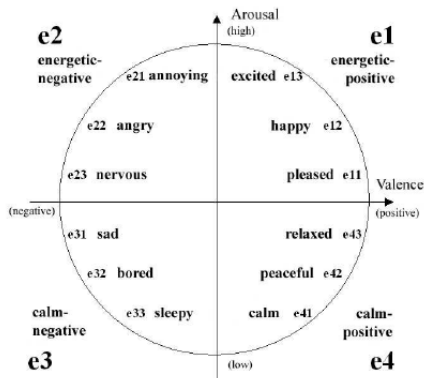
For instance:

*school, teacher, pupil, classroom, course, schedule, etc.*

# Sentiment

Words (not only adjectives) often comes with different connotations, which can be individually and culturally dependent.

emotional charges





We are looking for a way to represent meaning of words in a way usable for a computer program.

One possibility is to use an on-line *taxonomy* like **WordNet**, developed at Princeton.

WordNet specifies *hyponym* (is-a) relations, and *synonym sets*.

It has a web interface, and is also integrated into **NLTK**.

## Noun

- S: (n) **simple** (any herbaceous plant having medicinal properties)
- S: (n) simpleton, **simple** (a person lacking intelligence or common sense)

## Adjective

- S: (adj) **simple** (having few parts; not complex or complicated or involved) "*a simple problem*"; "*simple mechanisms*"; "*a simple design*"; "*a simple substance*"
- S: (adj) elementary, **simple**, uncomplicated, unproblematic (easy and not involved or complicated) "*an elementary problem in statistics*"; "*elementary, my dear Watson*"; "*a simple game*"; "*found an uncomplicated solution to the problem*"
- S: (adj) bare, mere, **simple** (apart from anything else; without additions or modifications) "*only the bare facts*"; "*shocked by the mere idea*"; "*the simple passage of time was enough*"; "*the simple truth*"
- S: (adj) childlike, wide-eyed, round-eyed, dewy-eyed, **simple** (exhibiting childlike simplicity and credulity) "*childlike trust*"; "*dewy-eyed innocence*"; "*listened in round-eyed wonder*"
- S: (adj) dim-witted, **simple**, simple-minded (lacking mental capacity and subtlety)
- S: (adj) **simple**, unsubdivided ((botany) of leaf shapes; of leaves having no divisions or subdivisions)
- S: (adj) **simple** (unornamented) "*a simple country schoolhouse*"; "*her black dress--simple to austerity*"

## Verb

- [S:](#) (v) **bare** (lay bare) *"bare your breasts"; "bare your feelings"*
- [S:](#) (v) [publicize](#), [publicise](#), [air](#), **bare** (make public) *"She aired her opinions on welfare"*
- [S:](#) (v) [denude](#), **bare**, [denudate](#), [strip](#) (lay bare) *"denude a forest"*

## Adjective

- [S:](#) (adj) **bare**, [au naturel](#), [naked](#), [nude](#) (completely unclothed) *"bare bodies"; "naked from the waist up"; "a nude model"*
- [S:](#) (adj) **bare**, [scanty](#), [spare](#) (lacking in magnitude or quantity) *"a bare livelihood"; "a scanty harvest"; "a spare diet"*
- [S:](#) (adj) [unsheathed](#), **bare** (not having a protective covering) *"unsheathed cables"; "a bare blade"*
- [S:](#) (adj) **bare** (lacking its natural or customary covering) *"a bare hill"; "bare feet"*
- [S:](#) (adj) **bare**, [marginal](#) (just barely adequate or within a lower limit) *"a bare majority"; "a marginal victory"*
- [S:](#) (adj) **bare**, [mere](#), [simple](#) (apart from anything else; without additions or modifications) *"only the bare facts"; "shocked by the mere idea"; "the simple passage of time was enough"; "the simple truth"*
- [S:](#) (adj) **bare**, [unfinished](#) (lacking a surface finish such as paint) *"bare wood"; "unfinished furniture"*
- [S:](#) (adj) **bare**, [barren](#), [bleak](#), [desolate](#), [stark](#) (providing no shelter or sustenance) *"bare rocky hills"; "barren lands"; "the bleak treeless regions of the high Andes"; "the desolate surface of the moon"; "a stark landscape"*
- [S:](#) (adj) **bare**, [stripped](#) (having everything extraneous removed including contents) *"the bare walls"; "the cupboard was bare"*
- [S:](#) (adj) [plain](#), **bare**, [spare](#), [unembellished](#), [unornamented](#) (lacking embellishment or ornamentation) *"a plain hair style"; "unembellished white walls"; "functional architecture featuring stark unornamented concrete"*

## Swedish Wordnet

 [Show Hyponym Tree](#) | [Show Hyperonym Tree](#)

### Synset

hånga-1 [v] *få att hållas över marken så att föremålet inte rör underlaget; "Fågeln hänger i gardinen"*

### Relations

has\_hyperonym [hånga upp-1 \[v\]](#)

has\_hyponym [svinga-1 \[v\]](#)

has\_hyponym [dingla-1 \[v\]](#)

has\_hyponym [säcka-1 \[v\]](#)

### EQ-Link

# Problems with WordNet

Has to be built and maintained by someone.

Subjective, ad-hoc, no (explicit) empirical basis.

Missing many nuances.

Binary distinction: Either a synonym, or not.

Hard to compute word similarity.

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## 7b: Word embeddings

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# Word embeddings

How can we represent the meaning of words?

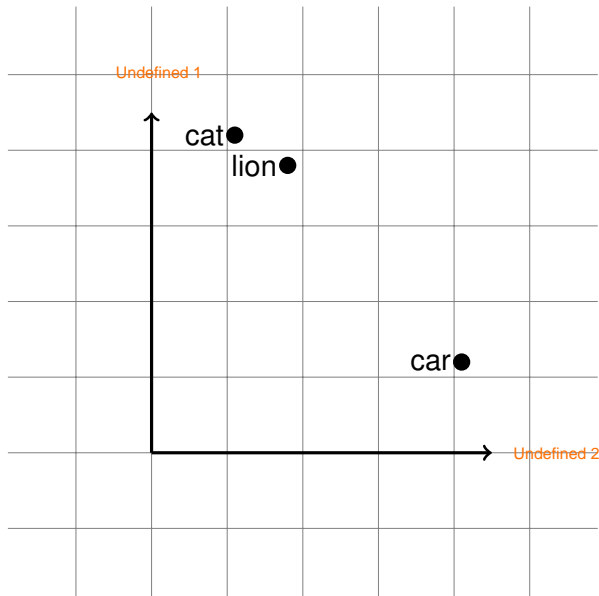
We want words of similar meaning have similar representations.

**Idea:** View words as points or vectors in a high-dimensional vector space (a “distributed” representation), e.g.:

$$(.003, .25, 1.2, -3.4, \dots, -.775)$$

Such vectors are often called *word embeddings* (because they are “embedded” in a vector space).

# Language as a vector space





# Distributional hypothesis

The *distributional hypothesis* says that if two words  $w_1$  and  $w_2$  tend to **co-occur with the same words**, then  $w_1$  and  $w_2$  **have a similar meaning**.

Wittgenstein: *The meaning of a word is its use in the language.*

Firth: *You shall know a word by the company it keeps.*

# Word-document matrix

One way of creating word vectors is through a *word-document matrix*.

|              |         | <i>Documents</i> |   |   |   |   |     |     |
|--------------|---------|------------------|---|---|---|---|-----|-----|
|              |         | 1                | 2 | 3 | 4 | 5 | ... | $n$ |
| <i>Words</i> | aalborg | 1                |   |   |   |   |     |     |
|              | aback   |                  | 1 |   | 1 |   |     |     |
|              | abandon |                  | 1 |   |   |   |     |     |
|              | ...     |                  |   |   |   |   |     |     |
|              | zombie  |                  |   |   |   | 1 |     |     |
|              | zone    |                  |   |   |   |   |     |     |
|              | zurich  |                  |   | 1 |   |   |     |     |

# Word-document matrix

The word vector for *aback* is highlighted below.

|              |              | <i>Documents</i> |          |          |          |          |            |          |
|--------------|--------------|------------------|----------|----------|----------|----------|------------|----------|
|              |              | 1                | 2        | 3        | 4        | 5        | ...        | $n$      |
| <i>Words</i> | aalborg      | 1                |          |          |          |          |            |          |
|              | <b>aback</b> | <b>0</b>         | <b>1</b> | <b>0</b> | <b>1</b> | <b>0</b> | <b>...</b> | <b>0</b> |
|              | abandon      |                  | 1        |          |          |          |            |          |
|              | ...          |                  |          | ...      |          |          |            |          |
|              | zombie       |                  |          |          |          | 1        |            |          |
|              | zone         |                  |          |          |          |          |            |          |
|              | zurich       |                  |          | 1        |          |          |            |          |

# Word windows

Another possibility would be to look in the immediate context of a word:

... I would like **to** know the plans for ...

  
focus  
word

look 2 steps to left and right

# Word-word matrix

|             |       | Context words |     |       |     |
|-------------|-------|---------------|-----|-------|-----|
|             |       | know          | the | plans | ... |
| Focus words | know  | 0             | 98  | 2     | ... |
|             | the   | 98            | 12  | 11    | ... |
|             | plans | 2             | 11  | 0     | ... |
|             | ...   |               |     |       | ... |

symmetrical matrix

# Meaning captured by word vectors

What 'meaning' do such word vectors capture?

Vectors obtained from *word-document* matrices:

- words with similar vectors tend to belong to the same semantic field
- e.g. *hospital* and *nurse*

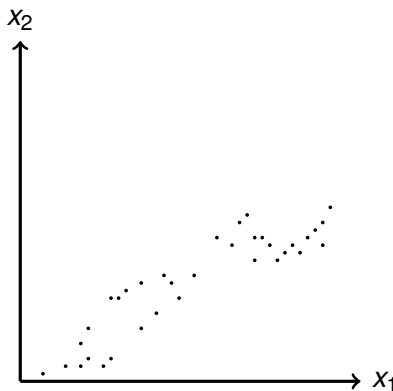
Vectors obtained from *word-word* matrices:

- words with similar vectors tend to have the same part-of-speech
- both syntactic and semantic relationships captured

The problem with such word vectors is that they are very *high-dimensional* and *sparse*.

Can we reduce the dimensionality?

# Dimensionality reduction

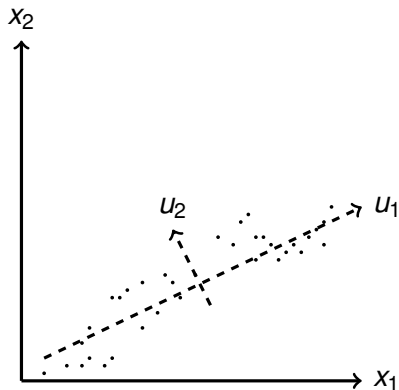


Suppose we want to reduce the dimension from 2 to 1

Keep the dimension which has the highest variance.

datapoints are more spread out in  $x_1$  than in  $x_2$  -> variance larger in the  $x_1$  dimension

# Dimensionality reduction

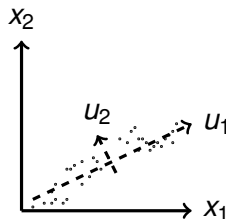


- $u_1$  has higher variance here.  
- $u_1$  will be the principal dimension and the first coordinate of each vector will be the principal component of each vector

Even better: Change bases into  $u_1$  and  $u_2$ . Keep the dimension with the highest variance.



# Dimensionality reduction



$x_1$  and  $x_2$  has an interpretation...they are number of occurrences in this word in doc  $x_1$  and  $x_2$

**On the other hand:**  $u_1$  and  $u_2$  do not correspond to contexts like  $x_1$  and  $x_2$ , but rather abstract concepts whose exact nature is unknown.

# Singular Value Decomposition (SVD)

Given a matrix  $\mathbf{X}$  of words and contexts, we can factor it into

$$\mathbf{X} = \mathbf{W}\mathbf{S}\mathbf{U}^T$$

|              |   |              |  |              |  |                |
|--------------|---|--------------|--|--------------|--|----------------|
| $\mathbf{X}$ | = | $\mathbf{W}$ |  | $\mathbf{S}$ |  | $\mathbf{U}^T$ |
|--------------|---|--------------|--|--------------|--|----------------|

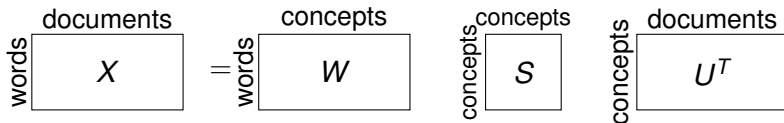
such that

- the columns of  $\mathbf{U}$  are the coordinate axes of the new coordinate system (the **principal directions**)
- the columns of  $\mathbf{W}$  are the coordinates along those axes (the **principal components**)
- $\mathbf{S}$  is a diagonal matrix of **scaling factors**, whose values reflect the relative importance of the columns of  $\mathbf{W}$ .

# Singular Value Decomposition (SVD)

Given a matrix  $\mathbf{X}$  of words and contexts, we can factor it into

$$\mathbf{X} = \mathbf{W}\mathbf{S}\mathbf{U}^T$$



# Latent Semantic Analysis (LSA)

We now remove the last columns of  $\mathbf{W}$  (they contain little information). they are columns along a dimension that has the least variance

The word vectors that remain are called *latent semantic vectors* (because latent semantic concepts have been uncovered).

The latent semantic vectors are crude representations of the meaning of the words.

# Example

We have 3 Computer Science articles and 3 Graph Theory articles.

The table shows words occurring in the titles of those articles.

|              |          | <i>Documents</i> |           |           |           |           |           |
|--------------|----------|------------------|-----------|-----------|-----------|-----------|-----------|
|              |          | <i>c1</i>        | <i>c2</i> | <i>c3</i> | <i>g1</i> | <i>g2</i> | <i>g3</i> |
| <i>Words</i> | human    | 1                | 0         | 0         | 0         | 0         | 0         |
|              | computer | 0                | 1         | 0         | 0         | 0         | 0         |
|              | user     | 1                | 1         | 1         | 0         | 0         | 0         |
|              | response | 0                | 1         | 1         | 0         | 0         | 0         |
|              | survey   | 0                | 1         | 0         | 0         | 1         | 0         |
|              | graph    | 0                | 0         | 0         | 1         | 1         | 1         |
|              | trees    | 0                | 0         | 0         | 1         | 0         | 1         |
|              | theory   | 0                | 0         | 0         | 1         | 1         | 0         |

# Example, cont.

The  $W$  matrix after SVD:

|          |       |       |       |       |       |       |
|----------|-------|-------|-------|-------|-------|-------|
| human    | −0.07 | 0.13  | 0.44  | 0.60  | 0.30  | 0.06  |
| computer | −0.19 | 0.26  | −0.23 | −0.22 | 0.53  | 0.52  |
| user     | −0.36 | 0.57  | 0.41  | 0.16  | −0.13 | −0.04 |
| response | −0.29 | 0.44  | −0.03 | −0.43 | −0.42 | −0.10 |
| survey   | −0.40 | 0.16  | −0.58 | 0.21  | 0.33  | −0.25 |
| graph    | −0.54 | −0.42 | 0.08  | −0.01 | 0.06  | −0.51 |
| trees    | −0.33 | −0.32 | 0.44  | −0.45 | 0.27  | 0.25  |
| theory   | −0.40 | −0.29 | −0.19 | 0.35  | −0.51 | 0.58  |

The  $S$  matrix:

$$\begin{pmatrix} 2.54 & & & & & \\ & 2.35 & & & & \\ & & 1.39 & & & \\ & & & 1.13 & & \\ & & & & 0.76 & \\ & & & & & 0.49 \end{pmatrix}$$

The first 2 column are the most important

## Example, cont.

From the  $S$  matrix, we can tell that the two first dimensions contain much more information than the remaining ones.

Hence, keep only the 2 first dimensions of  $W$ :

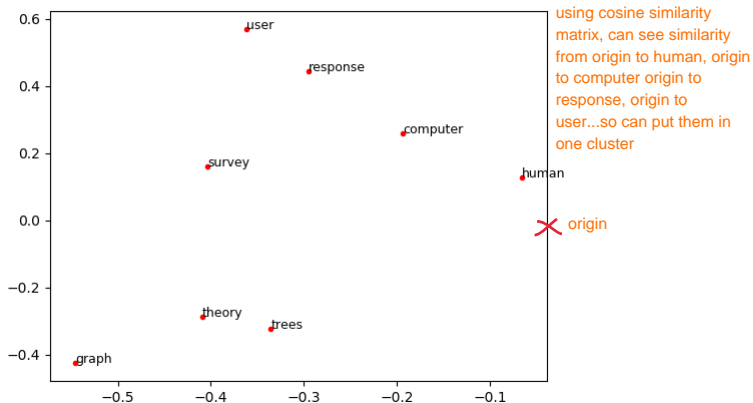
|          |       |       |
|----------|-------|-------|
| human    | -0.07 | 0.13  |
| computer | -0.19 | 0.26  |
| user     | -0.36 | 0.57  |
| response | -0.29 | 0.44  |
| survey   | -0.40 | 0.16  |
| graph    | -0.54 | -0.42 |
| trees    | -0.33 | -0.32 |
| theory   | -0.40 | -0.29 |

These are the word vectors! (In realistic applications, keep 50-1000 dimensions).

from maybe 100,000 dimensions

# Example, cont.

Visualization of the word vectors.

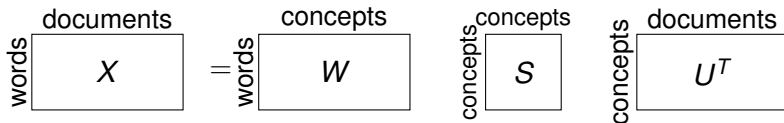




# Singular Value Decomposition (SVD)

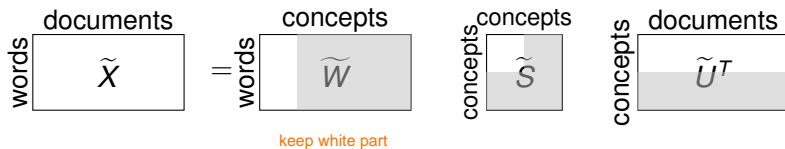
Given a matrix  $\mathbf{X}$  of words and contexts, we can factor it into

$$\mathbf{X} = \mathbf{W}\mathbf{S}\mathbf{U}^T$$



# Dimensionality reduction

$$\tilde{X} = \tilde{W}\tilde{S}\tilde{U}^T$$



# Dimensionality reduction

|          | Original $X$     |           |           |           |           |           | "Reconstructed" $\tilde{X}$ |           |           |           |           |           |
|----------|------------------|-----------|-----------|-----------|-----------|-----------|-----------------------------|-----------|-----------|-----------|-----------|-----------|
|          | <i>Documents</i> |           |           |           |           |           | <i>Documents</i>            |           |           |           |           |           |
|          | <i>c1</i>        | <i>c2</i> | <i>c3</i> | <i>g1</i> | <i>g2</i> | <i>g3</i> | <i>c1</i>                   | <i>c2</i> | <i>c3</i> | <i>g1</i> | <i>g2</i> | <i>g3</i> |
| human    | 1                | 0         | 0         | 0         | 0         | 0         | 0.12                        | 0.26      | 0.17      | -0.05     | 0.02      | -0.04     |
| computer | 0                | 1         | 0         | 0         | 0         | 0         | 0.26                        | 0.61      | 0.39      | -0.02     | 0.12      | -0.02     |
| user     | 1                | 1         | 1         | 0         | 0         | 0         | 0.55                        | 1.27      | 0.81      | -0.13     | 0.17      | -0.11     |
| response | 0                | 1         | 1         | 0         | 0         | 0         | 0.43                        | 1.00      | 0.64      | -0.08     | 0.15      | -0.07     |
| survey   | 0                | 1         | 0         | 0         | 1         | 0         | 0.28                        | 0.73      | 0.43      | 0.36      | 0.46      | 0.24      |
| graph    | 0                | 0         | 0         | 1         | 1         | 1         | -0.06                       | 0.08      | -0.070    | 1.15      | 0.98      | 0.80      |
| trees    | 0                | 0         | 0         | 1         | 0         | 1         | -0.08                       | -0.04     | -0.11     | 0.77      | 0.63      | 0.54      |
| theory   | 0                | 0         | 0         | 1         | 1         | 0         | -0.03                       | 0.10      | -0.02     | 0.83      | 0.72      | 0.58      |

# Visualizations from a bigger corpus



Figure 10: Multidimensional scaling of three verb semantic classes.

Rohde et al. (2005) An improved model of semantic similarity based on lexical co-occurrence. *Communications of the ACM*, 8(627-633), 116.

# Evaluation of word vectors

Evaluation can be both intrinsic and extrinsic.

Intrinsic evaluation consists of

- similarity tests
- synonymy tests (e.g. from the SAT / “högskoleprovet”)
- word analogy tests (“Athens is to Greece what Berlin is to \_\_\_\_\_”)

In addition, word vectors combine very well with neural network methods.

# Some variations

Some words are very common.

- *the* and *a* tend to co-occur with all nouns
- LSA tends to give too much importance to these common words
- either remove them, or
- count max  $n$  occurrences (e.g.  $n=100$ )
- give them a lower weight

Assymetric windows

- context words closest to the focus word are given more weight
- right context window larger than the left (or vice versa)

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## 7c: Random indexing

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# Problems with Latent Semantic Analysis

Computationally costly to factor the large matrix (which might be  $10^6 \times 10^6$ ).

The method is *not incremental*. Every time you get more data, you again need to factor a large matrix.



# Random indexing

random indexing is an incremental method

*Random indexing* is a simpler and more flexible approach to constructing word vectors.

Assign 2 vectors to every word  $w$ :

- a *random vector* (or *index vector*)  $r(w)$  of length  $d$  (typically  $d = 2000$ ).
- a *context vector*  $c(w)$  of length  $d$  as well.

$r(w)$  is initially filled with  $n$  non-zero values

- $n$  is typically 100    100 / 2000 of them
- a non-zero value is either 1 or -1, randomly selected

$c(w)$  is initially filled with 0.

# Random indexing

Use the sliding context window idea again:

... I would like **to** know the plans for ...  
focus word

In each step, compute:

$$c(w_i) += (r(w_{i-2}) + r(w_{i-1}) + r(w_{i+1}) + r(w_{i+2}))$$

e.g cosine similarity


Do this for a *lot* of text. In the end, a small distance between  $c(w_i)$  and  $c(w_k)$  indicates that  $w_i$  and  $w_k$  are semantically similar.

# Random indexing, example

| Word    | would             | like                | to                | know               | the               |
|---------|-------------------|---------------------|-------------------|--------------------|-------------------|
| Random  | (1 0 -1 0 0 1 0)  | (0 1 0 0 -1 -1 1)   | (0 0 0 1 0 1 1)   | (0 -1 0 1 1 0 0)   | (1 0 1 -1 0 0 -1) |
| Context | (0 -1 -5 -2 1 -3) | (-5 3 2 1 -3 -5 -5) | (-4 2 0 -3 1 2 2) | (-3 5 3 -1 -4 1 4) | (0 4 0 1 1 -1 0)  |

Compute one step of random indexing, using the vectors above and the situation below:

... I would like **to** know the plans for ...

  
focus  
word

# Random indexing, example

| Word    | would             | like                | to                | know               | the               |
|---------|-------------------|---------------------|-------------------|--------------------|-------------------|
| Random  | (1 1 -1 0 0 1 0)  | (0 1 0 0 -1 -1 1)   | (0 0 0 1 0 1 1)   | (0 -1 0 1 1 0 0)   | (1 0 1 -1 0 0 -1) |
| Diff    |                   |                     | (2 1 0 0 0 0 0)   |                    |                   |
| Context | (0 -1 -5 -2 1 -3) | (-5 3 2 1 -3 -5 -5) | (-4 2 0 -3 1 2 2) | (-3 5 3 -1 -4 1 4) | (0 4 0 1 1 -1 0)  |

Compute one step of random indexing, using the vectors above and the situation below:

... I would like **to** know the plans for ...

focus word

| Word    | would             | like                | to                | know               | the               |
|---------|-------------------|---------------------|-------------------|--------------------|-------------------|
| Random  | (1 1 -1 0 0 1 0)  | (0 1 -1 0 -1 -1 1)  | (0 0 0 1 0 1 1)   | (0 -1 0 -1 1 1 0)  | (1 0 1 -1 0 1 -1) |
| Context | (0 -1 -5 -2 1 -3) | (-5 3 2 1 -3 -5 -5) | (-2 3 0 -3 1 2 2) | (-3 5 3 -1 -4 1 4) | (0 4 0 1 1 -1 0)  |

updated context value after addition

# Random indexing

Random indexing was devised in 2000 by [Pentti Kanerva](#).

Empirically, it has shown to work very well. But there is no (known) theoretical justification for it.

vectors are going to be learn-able parameters

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## 7d: word2vec

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**word2vec** is a software package, released in 2013 by **Tomas Mikolov**.

word2vec could build word vectors for any language:

- quick, efficient
- word vectors trained with Word2Vec have many amazing features:

France is to Paris is like Italy is to Rome

$$v(\textit{France}) - v(\textit{Paris}) + v(\textit{Rome}) = v(\textit{Italy})$$

$$v(\textit{king}) - v(\textit{man}) + v(\textit{woman}) = v(\textit{queen})$$

Starting point of the neural network “revolution” in language engineering.

follows distributional hypothesis.

Imagine (again) a context window sliding over text:

... I would like **to** know the plans for ...

focus word

Then: Train a classifier that either

green highlight: focus word, blue highlight:  
context words

- can predict the focus word from the context words  
(continuous bag-of-words model),
- or vice versa (skipgram model)

(Actually, we don't care about this classifier. But the trainable parameters of the model will form our word vectors.)



Each word has two vectors:

- $w$  (the focus word vector),
- $\tilde{w}$  (the context word vector).

The dimensionality of the vectors is a hyperparameter of the method (typically 50-300).

The trainable parameters of the prediction model we are going to train are the vectors themselves.

The more dimension we have, the more fine-grained semantics distinction we can do between the words.  
But we will also need more training materials to get good quality vectors.

Content of the vectors will be the train-able parameters, so if we have 50-dimensional vectors and each word has 2 vectors, then each words have 100 train-able parameters. If we have 10,000 words in our vocabulary, then we will have 1,000,000 train-able parameters.

# The Skipgram prediction task

Skipgram = predict the context words from the focus word.

Predict: Given the focus word 'to', we want to find the probability of each other word in the vocabulary

... I would like **to** know the plans for ...  
focus word

We write  $P(u|v)$  to mean “the probability that  $u$  appears in the context of  $v$ ”.

For instance, we want  $P(\text{would}|\text{to})$  to be close to 1. because 'would' actually appear in the context of 'to'

We set  $P(u|v) = \sigma(\tilde{u}^T v)$ , where  $\sigma$  is the logistic function. binary logistic regression

That is, we want to learn the vectors **would** and **to**, so that

$(\text{would} \cdot \text{to})$  is as big as possible.  
dot product

so that when we put it into the sigmoid function, it will be as close as 1

'would' is a positive example for 'to' so as big as possible.

we will also need negative example, i.e. all words in the vocabulary that doesn't appear (blue) in the context of to, but cannot take all these words, since it will be a lot of computation, so we are going to do samplings

# Negative sampling

... I would like **to** know the plans for ...  
focus  
word

We also need **negative** samples, i.e. examples of words **not** appearing in the context of the focus word ( $k$  negative samples for every positive).

doesn't appear in the blue highlight

For instance, we can select “text” as a negative sample for “to”.

Then we want  $P(\mathbf{text}|\mathbf{to}) = \sigma(\widetilde{\mathbf{text}}^T \cdot \mathbf{to})$  to be close to 0.

That is,  $1 - P(\mathbf{text}|\mathbf{to}) = \sigma(-\widetilde{\mathbf{text}}^T \cdot \mathbf{to})$  should be close to 1.

# Choosing negative samples

Mikolov et al: Randomly choose negative samples according to the unigram distribution  $P_u$ , raised to 0.75.

$$P_s(w) = \frac{P_u(w)^{0.75}}{\sum_{w'} P_u(w')^{0.75}}$$

The “0.75” upsamples rare words a bit, e.g.:

$$0.01^{0.75} = 0.03$$

$$0.99^{0.75} = 0.992$$

# Training procedure (1)

First:

- obtain a **lot** of running text
- decide how long vectors we want (e.g. 50)
- for each word in the vocabulary create one **focus vector** and one **context vector**, randomly initialized
- decide on the size of the **context window** (e.g. 2)  
so we will look 2 words to the left and right of the focus words

## Training procedure (2)

We will now obtain positive and negative samples by moving through the text.

... I would like **to** know the plans for ...

focus word

Positive examples: (to,would), (to,like), (to,know), (to,the)

according to Mikolov

For each positive example, sample 5-20 negative examples.

After that update the weight before moving the window

in assignment 3, we will sample 10

Then move word window one step, and collect more positive and negative examples.

Semi-supervised learning: You get the labels of data points for free!

# Loss function

to update the parameters during training

reuse the same loss function in binary logistic regression, i.e negative log probability of the data

We want to maximize the probability of the positive examples pos, and minimize the probability of the negative examples neg.

Equivalently, we want to minimize the loss defined as:

$$\begin{aligned} & - \sum_{(v, \tilde{u}) \in \text{pos}} \log \sigma(\tilde{u}^T v) - \sum_{(v, \tilde{u}) \in \text{neg}} \log \sigma(-\tilde{u}^T v) = \\ & \sum_{(v, \tilde{u}) \in \text{pos}} \log(1 + e^{-\tilde{u}^T v}) + \sum_{(v, \tilde{u}) \in \text{neg}} \log(1 + e^{\tilde{u}^T v}) \end{aligned}$$

Note that both  $\tilde{u}$  and  $v$  are trainable parameters.

unlike binary logistic regression where we only train theta, now u and v are trainable parameters

In order to minimize this function, we need to compute the gradient both w.r.t  $\tilde{u}$  or  $v$

# Gradient of the loss function (1)

focus word  $v$

Gradient of the loss function w.r.t. a particular  $v$ :

$$\begin{aligned} \frac{\partial}{\partial v} [ & \sum_{(v, \tilde{u}) \in \text{pos}} \log(1 + e^{-\tilde{u}^T v}) + \sum_{(v, \tilde{u}) \in \text{neg}} \log(1 + e^{\tilde{u}^T v}) ] = \\ & - \sum_{(v, \tilde{u}) \in \text{pos}} \frac{\tilde{u} e^{-\tilde{u}^T v}}{1 + e^{-\tilde{u}^T v}} + \sum_{(v, \tilde{u}) \in \text{neg}} \frac{\tilde{u} e^{\tilde{u}^T v}}{1 + e^{\tilde{u}^T v}} = \\ & - \sum_{(v, \tilde{u}) \in \text{pos}} \tilde{u} (1 - \sigma(\tilde{u}^T v)) + \sum_{(v, \tilde{u}) \in \text{neg}} \tilde{u} (1 - \sigma(-\tilde{u}^T v)) = \\ & \sum_{(v, \tilde{u}) \in \text{pos}} \tilde{u} (\sigma(\tilde{u}^T v) - 1) + \sum_{(v, \tilde{u}) \in \text{neg}} \tilde{u} \sigma(\tilde{u}^T v) \end{aligned}$$

This is not enough. This is only enough to update  $v$ , but we also need to update  $\tilde{u}$

Note that all vectors are parameters, so we also need to compute the gradient w.r.t. a particular  $\tilde{u}$ . (see next slide)



# Gradient of the loss function (2)

Gradient of the loss function w.r.t. a particular  $\tilde{u}_i$ .

If  $\tilde{u}_i$  is in the context of  $v$ , i.e.  $(v, \tilde{u}_i)$  is a **positive** example:

for positive example,  
everything on this side will  
just be constant and will  
disappear when we take the  
gradient

$$\frac{\partial}{\partial \tilde{u}_i} \left[ \sum_{(v, \tilde{u}) \in \text{pos}} \log(1 + e^{-\tilde{u}^T v}) + \sum_{(v, \tilde{u}) \in \text{neg}} \log(1 + e^{\tilde{u}^T v}) \right] =$$
$$-\frac{v e^{-\tilde{u}_i^T v}}{1 + e^{-\tilde{u}_i^T v}} = -v(1 - \sigma(\tilde{u}_i^T v)) = v(\sigma(\tilde{u}_i^T v) - 1)$$

If  $\tilde{u}_i$  is **not** in the context of  $v$ , i.e.  $(v, \tilde{u}_i)$  is a **negative** example:

(left as an exercise) have to do because required for gradient descent in assignment 3

## Training procedure (3)

We obtain positive and negative samples by moving through the text.

... I would like **to** know the plans for ...

focus word

Positive examples: (to,would), (to,like), (to,know), (to,the)

Negative examples could be: (to, text), (to, giraffe), ...

Use gradient descent to update the vectors **to**,  
would, like, know, ... (all context vectors above) for both positive and negative

Then move word window one step, and collect more positive and negative examples.

Some nice ideas used in word2vec:

- Word vectors are obtained as a **by-product** when learning an artificial task (that we don't care about).
- **Semi-supervised learning**: Obtaining positive and negative examples for the learning task just by stepping through the text.
- **Dot product as similarity** between word vectors.
- Learning focus vectors and context vectors simultaneously using gradient descent.
- **Negative sampling** to speed up the learning process.

# DD2418 Language Engineering

## 7e: Glove

Johan Boye, KTH

In 2014, Pennington, Socher and Manning proposed *Glove* (GLObal word Vectors).

Glove directly *specifies* how similar different word vectors should be, by means of a loss function that should be minimized

- words that often appear in one another's contexts should have similar vectors
- words that appear very rarely in one another's contexts should have dissimilar vectors
- similarity = dot product ( $u \cdot v$ )

Each word has two vectors:

- $w$  (the focus word vector),
- $\tilde{w}$  (the context word vector).

The dimensionality of the vectors is a hyperparameter of the method (typically 50-300).

We now compute for every pair of words  $i, j$ :

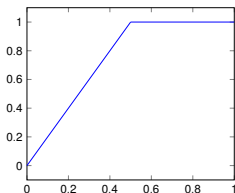
$X_{ij}$  = number of times word  $j$  appears in the context of word  $i$

“Context” typically is a window  $\pm 2$  positions in the text.

We then minimize the following loss function:

$$\frac{1}{2} \sum_{i,j=1}^V f(X_{ij})(w_i^T \tilde{w}_j - \log X_{ij})^2$$

where  $f(x)$  is a function that penalizes very common word combinations, e.g.:  $f(x) = \begin{cases} (x/x_{max})^{0.75} & \text{if } x < x_{max} \\ 1 & \text{otherwise} \end{cases}$



The loss function

$$L = \frac{1}{2} \sum_{i,j=1}^V f(X_{ij})(w_i^T \tilde{w}_j - \log X_{ij})^2$$

need to compute gradient wrt to context and focus vector

can be mimimized e.g. using gradient descent.

With, say, 100,000 words, and a vector dimension of 300, we have  $2 \cdot 100,000 \cdot 300 = 60$  million parameters.

...since every word  $i$  has *two* vectors.

Given all those vectors  $w_i = (w_{i,1}, \dots, w_{i,n})$ , we need to compute the gradient of  $L$  w.r.t. each  $w_{i,k}$  (and likewise for all  $\tilde{w}$ ).



This is a non-convex optimization problem, so we are *not* guaranteed a best solution...

... but empirically, the solution one finds tends to be good.

Remember, each word has two vectors:  $w$  and  $\tilde{w}$ . What should we do with those?

Answer: return the sum!  $w + \tilde{w}$  is the final word vector for the word.

# Pretrained Glove vectors

Pre-trained Glove vectors for English, trained on Wikipedia, (with dimensionalities 50, 100, 200, 300) can be downloaded from `nlp.stanford.edu/data/glove.6B.zip`

There are also bigger collections, trained on Common Crawl, for download.

## Computational lexical semantics: Representing the meaning of words

- Distributional hypothesis
- Distributed word representation (as a vector of numbers)
- Latent Semantic Analysis (1988)
- Random Indexing (2000)
- word2vec (2013)
- Glove (2014)