DD2418 Language Engineering
7a: Lexical semantics

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Levels of linguistic analysis

Words	Morphology, Phonology
Sentences	Syntax
Meaning	Semantics
Language use	Pragmatics

Lexical semantics

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

transporting yourself   transporting something

- *move* to the next room, *move furniture*
- a *good* man, a *good* painter

moral quality   technical skills

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

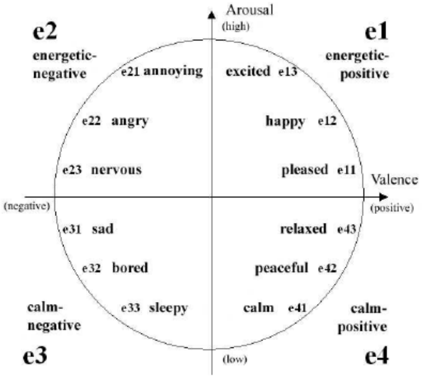
Words that are not synonyms, but still related because they are used in the same domain.

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



Lexical semantics

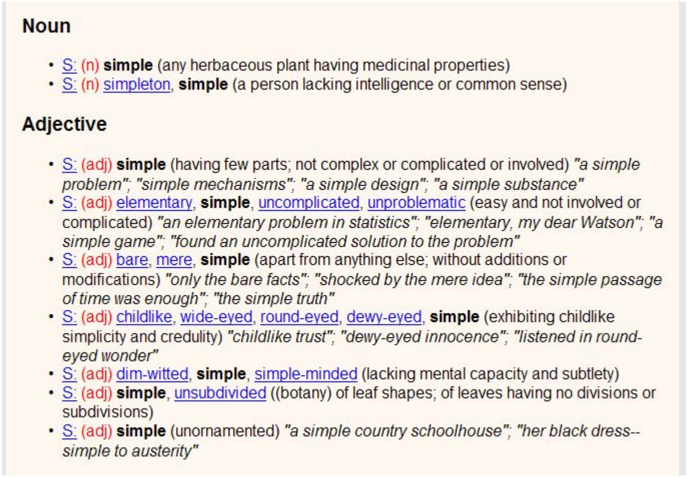
We are looking for a way to represent meaning of words in a way usable for a computer program.

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.

WordNet



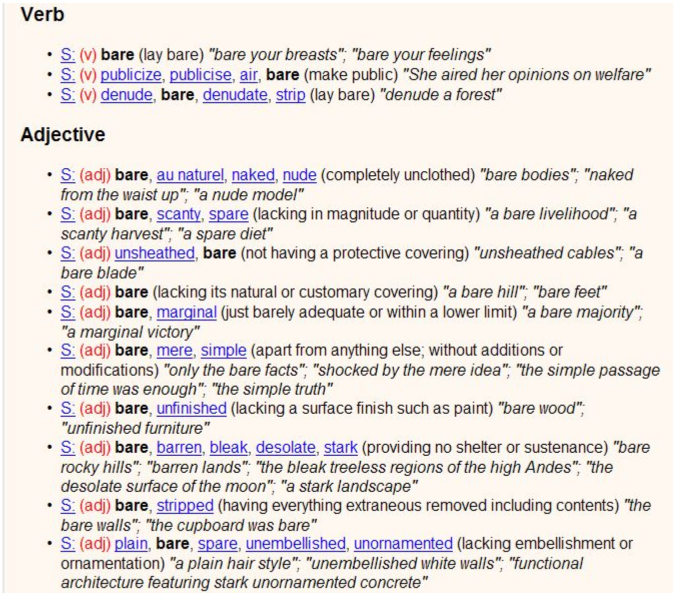
Noun

- 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"*

WordNet



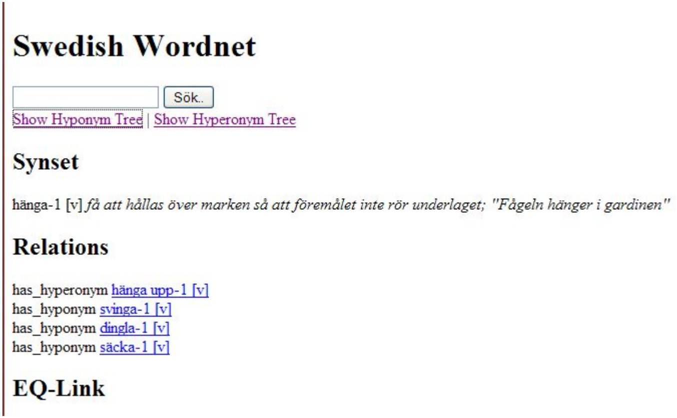
Verb

- 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



Swedish Wordnet

Synset

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

Relations

has_hyperonym hänga 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?

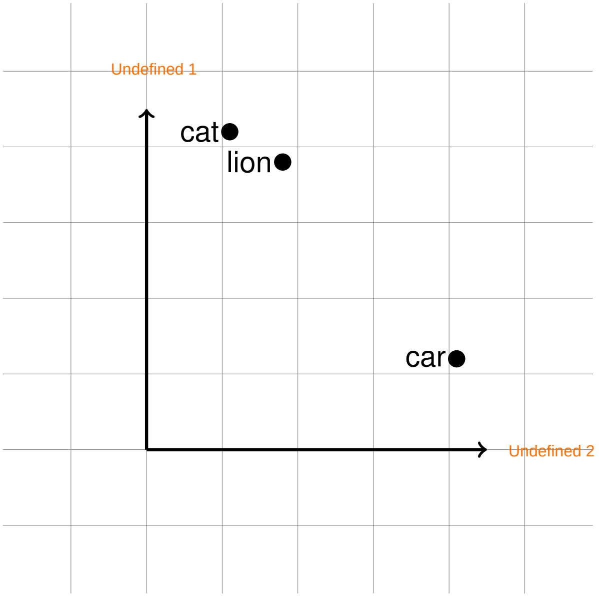
We want words of similar meaning have similar representations.

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

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

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*.

		Documents						
		1	2	3	4	5	...	*n*
	aalborg	1						
	aback		1		1			
	abandon		1					
Words	...							
	zombie					1		
	zone							
	zurich			1				

Word-document matrix

The word vector for *aback* is highlighted below.

		Documents					
	1	2	3	4	5	...	*n*
aalborg	1						
aback	**0**	**1**	**0**	**1**	**0**	**...**	**0**
abandon		1					
Words ...			...				
zombie					1		
zone							
zurich			1				

Word windows

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

… I would like $\underbrace{\textbf{to}}_{\text{focus word}}$ know the plans for …

look 2 steps to left and right

Word-word matrix

$$\begin{array}{lr|cccc}
 & & \multicolumn{4}{c}{\text{Context words}} \\
 & & \text{know} & \text{the} & \text{plans} & \ldots \\
\hline
 & \text{know} & 0 & 98 & 2 & \ldots \\
\text{Focus words} & \text{the} & 98 & 12 & 11 & \ldots \\
 & \text{plans} & 2 & 11 & 0 & \ldots \\
 & \ldots & & & & \ddots
\end{array}$$

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*

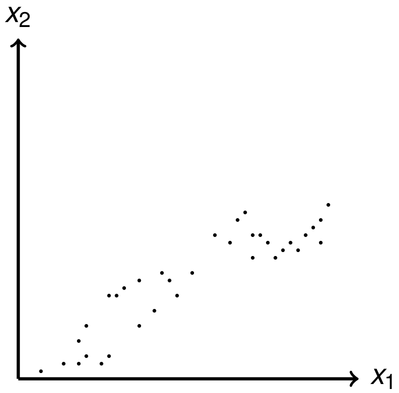
Vectors obtained from *word-word* matrices:

- 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

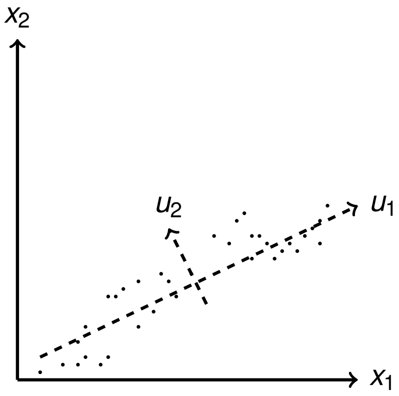


Suppose we want to reduce the dimension from 2 to 1

Keep the dimension which has the highest variance.

datapoints are more spread out in x1 than in x2 -> variance larger in the x1 dimesion

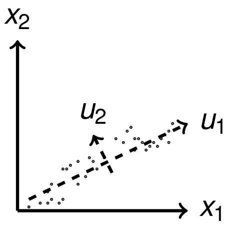
Dimensionality reduction



-u1 has higher variance here.
-u1 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



x1 and x2 has an interpretation...they are number of occurrences in this word in doc x1 and x2

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 $\boldsymbol{X}$ of words and contexts, we can factor it into

$$\boldsymbol{X} = \boldsymbol{W}\boldsymbol{S}\boldsymbol{U}^\top$$

$$\boxed{\quad X \quad} = \boxed{\quad W \quad}\ \boxed{\ S\ }\ \boxed{\quad U^T \quad}$$

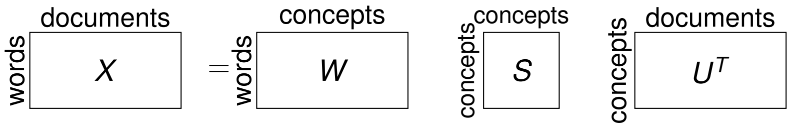
such that

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

Singular Value Decomposition (SVD)

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

$$\boldsymbol{X} = \boldsymbol{W}\boldsymbol{S}\boldsymbol{U}^\top$$



Latent Semantic Analysis (LSA)

We now remove the last columns of $\boldsymbol{W}$ (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.

		Documents					
		*c*1	*c*2	*c*3	*g*1	*g*2	*g*3
Words	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:

$$
\begin{array}{r|rrrrrr}
\text{human} & -0.07 & 0.13 & 0.44 & 0.60 & 0.30 & 0.06 \\
\text{computer} & -0.19 & 0.26 & -0.23 & -0.22 & 0.53 & 0.52 \\
\text{user} & -0.36 & 0.57 & 0.41 & 0.16 & -0.13 & -0.04 \\
\text{response} & -0.29 & 0.44 & -0.03 & -0.43 & -0.42 & -0.10 \\
\text{survey} & -0.40 & 0.16 & -0.58 & 0.21 & 0.33 & -0.25 \\
\text{graph} & -0.54 & -0.42 & 0.08 & -0.01 & 0.06 & -0.51 \\
\text{trees} & -0.33 & -0.32 & 0.44 & -0.45 & 0.27 & 0.25 \\
\text{theory} & -0.40 & -0.29 & -0.19 & 0.35 & -0.51 & 0.58
\end{array}
$$

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:

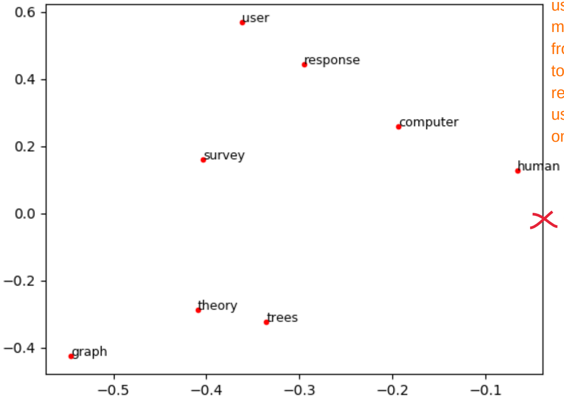
human	−0.07	0.13
computer	−0.19	0.26
user	−0.36	0.57
response	−0.29	0.44
survey	−0.40	0.16
graph	−0.54	−0.42
trees	−0.33	−0.32
theory	−0.40	−0.29

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

from maybe 100,000 dimensions

Example, cont.

Visualization of the word vectors.



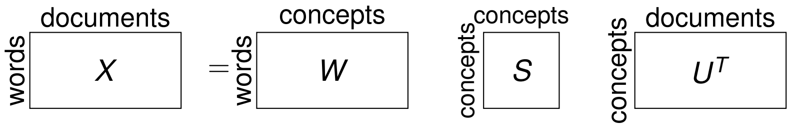
using cosine similarity matrix, can see similarity from origin to human, origin to computer origin to response, origin to user...so can put them in one cluster

origin

Singular Value Decomposition (SVD)

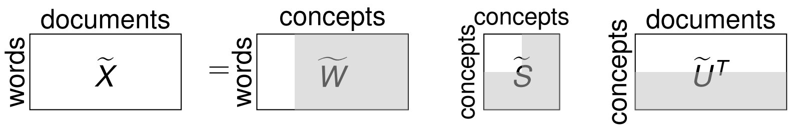
Given a matrix $\boldsymbol{X}$ of words and contexts, we can factor it into

$$\boldsymbol{X} = \boldsymbol{W}\boldsymbol{S}\boldsymbol{U}^\top$$



Dimensionality reduction

$$\widetilde{\boldsymbol{X}} = \widetilde{\boldsymbol{W}}\widetilde{\boldsymbol{S}}\widetilde{\boldsymbol{U}}^{\top}$$



keep white part

Dimensionality reduction

	Original X					
	Documents					
	$c1$	$c2$	$c3$	$g1$	$g2$	$g3$
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

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

Visualizations from a bigger corpus

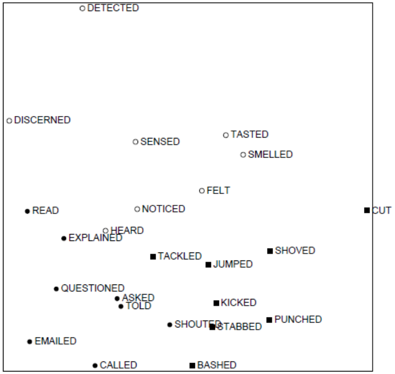


Figure 10: Multidimensional scaling of three verb semantic classes.

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 a incremental method

Random indexing is a simpler and more flexible approach to contructing 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:

$$\ldots \text{ I } \text{would like } \underbrace{\textbf{to}}_{\text{focus word}} \text{ know the } \text{plans for } \ldots$$

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 $\underbrace{\textbf{to}}_{\text{focus word}}$ know the plans for . . .

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:

$$\ldots \text{ I } \text{would like } \underbrace{\textbf{to}}_{\text{focus word}} \text{ know the } \text{plans for } \ldots$$

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

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

$$v(France) - v(Paris) + v(Rome) = v(Italy)$$
$$v(king) - v(man) + v(woman) = v(queen)$$

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

word2vec

follows distributional hypothesis.

Imagine (again) a context window sliding over text:

… I would like $\underbrace{\textbf{to}}_{\text{focus word}}$ know the plans for …

green highlight: focus word, blue highlight: context words

Then: Train a classifier that either

- 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.)

word2vec

Each word has two vectors:

- w (the focus word vector),
- $\widetilde{w}$ (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

$$\ldots \text{ I } \boxed{\text{would like}} \; \underbrace{\boxed{\textbf{to}}}_{\text{focus word}} \; \boxed{\text{know the}} \text{ plans for } \ldots$$

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

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

sigmoid function

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

That is, we want to learn the vectors $\widetilde{\textbf{would}}$ and **to**, so that $(\widetilde{\textbf{would}}^T \cdot \textbf{to})$ 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 $\underbrace{\textbf{to}}_{\text{focus word}}$ know the plans for . . .

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

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

$$\ldots \text{ I would like } \underbrace{\textbf{to}}_{\text{focus word}} \text{ know the plans for } \ldots$$

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

according to MIkolov

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

in assignment 3, we will sample 10

After that update the weight before moving the window

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:

$$- \sum_{(v,\widetilde{u}) \in \text{pos}} \log \sigma(\widetilde{u}^T v) - \sum_{(v,\widetilde{u}) \in \text{neg}} \log \sigma(-\widetilde{u}^T v) =$$

$$\sum_{(v,\widetilde{u}) \in \text{pos}} \log(1 + e^{-\widetilde{u}^T v}) + \sum_{(v,\widetilde{u}) \in \text{neg}} \log(1 + e^{\widetilde{u}^T v})$$

Note that both $\widetilde{u}$ 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 u tilde or v

Gradient of the loss function (1)

focus word v

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

$$\frac{\partial}{\partial v}\Big[\sum_{(v,\widetilde{u})\in \text{pos}} \log(1+e^{-\widetilde{u}^T v}) + \sum_{(v,\widetilde{u})\in \text{neg}} \log(1+e^{\widetilde{u}^T v})\Big] =$$

$$-\sum_{(v,\widetilde{u})\in \text{pos}} \frac{\widetilde{u}e^{-\widetilde{u}^T v}}{1+e^{-\widetilde{u}^T v}} + \sum_{(v,\widetilde{u})\in \text{neg}} \frac{\widetilde{u}e^{\widetilde{u}^T v}}{1+e^{\widetilde{u}^T v}} =$$

$$-\sum_{(v,\widetilde{u})\in \text{pos}} \widetilde{u}(1-\sigma(\widetilde{u}^T v)) + \sum_{(v,\widetilde{u})\in \text{neg}} \widetilde{u}(1-\sigma(-\widetilde{u}^T v)) =$$

$$\sum_{(v,\widetilde{u})\in \text{pos}} \widetilde{u}(\sigma(\widetilde{u}^T v)-1) + \sum_{(v,\widetilde{u})\in \text{neg}} \widetilde{u}\sigma(\widetilde{u}^T v)$$

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

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

Gradient of the loss function (2)

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

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

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

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

$$-\frac{ve^{-\tilde{u}_i^T v}}{1 + e^{-\tilde{u}_i^T v}} = -v(1 - \sigma(\tilde{u}_i^T v)) = v(\sigma(\tilde{u}_i^T v) - 1)$$

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.

$$\ldots \text{ I } \text{would like } \underbrace{\textbf{to}}_{\text{focus word}} \text{ know the } \text{plans for } \ldots$$

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.

word2vec summary

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

Glove

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 ($u \cdot v$)

Glove

Each word has two vectors:

- w (the focus word vector),
- $\widetilde{w}$ (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:

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

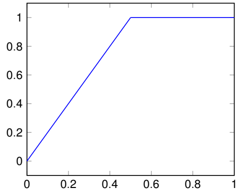
"Context" typically is a window ± 2 positions in the text.

Glove

We then minimize the following loss function:

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

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



Glove

The loss function

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

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

Glove

This is a non-convex optimtization 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 $\widetilde{w}$. What should we do with those?

Answer: return the sum! $w + \widetilde{w}$ 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.

Sum-up

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)