CS447: Natural Language Processing

http://courses.engr.illinois.edu/cs447

Lecture 8: Vector Semantics and Word Embeddings

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Today's lecture

The Distributional Hypothesis

From words to sparse vectors
that capture distributional similarities

From words to dense vectors
via word embeddings

How do we represent words?

As atomic symbols?

[e.g. as in a traditional n-gram language model, or when we use them as explicit features in a classifier]

As very high-dimensional one-hot vectors?

[e.g. as in a naive neural language model]

As very high-dimensional sparse vectors?

[to capture so-called distributional similarities]

As lower-dimensional dense vectors?

["word embeddings" — important prerequisite for neural NLP]

What should word representations capture?

Vector representations of words were originally motivated by attempts to capture lexical semantics (the meaning of words) so that words that have similar meanings have similar representations

These representations may also capture some morphological or syntactic properties of words (parts of speech, inflections, stems etc.).

Why do we care about word similarity?

Question answering:

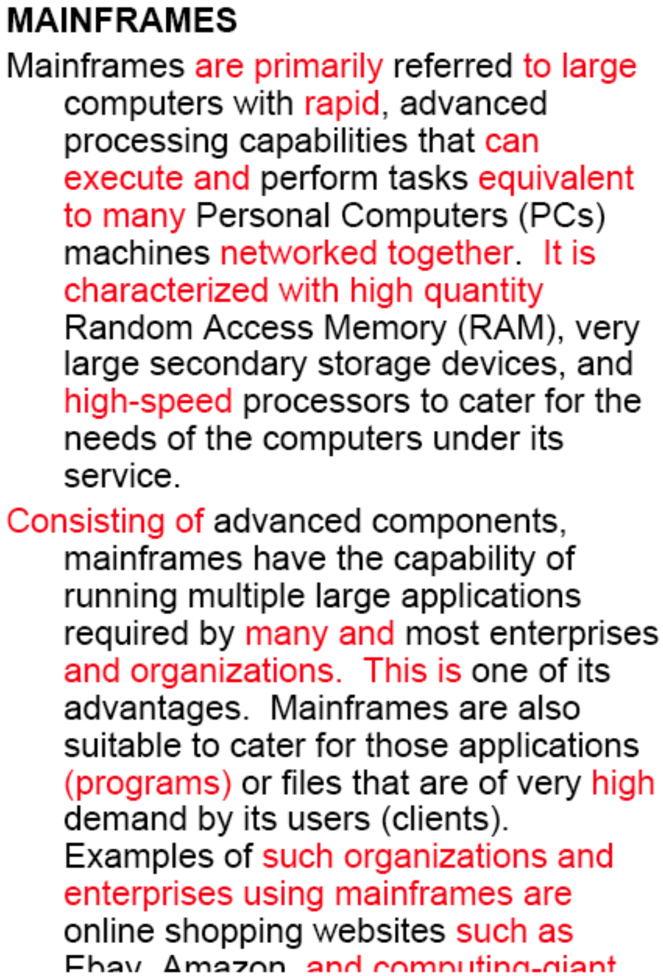
Q: “How *tall* is Mt. Everest?”

Candidate A: “The official *height* of Mount Everest is 29029 feet”

“*tall*” is similar to “*height*”

Why do we care about word similarity?

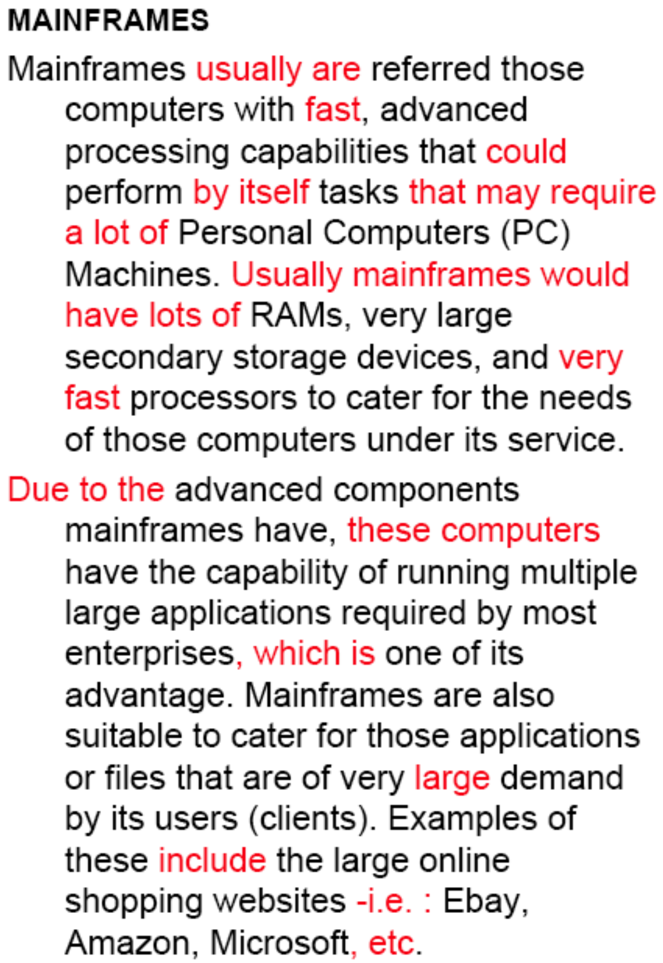
Plagiarism detection



MAINFRAMES

Mainframes are primarily referred to large computers with rapid, advanced processing capabilities that can execute and perform tasks equivalent to many Personal Computers (PCs) machines networked together. It is characterized with high quantity Random Access Memory (RAM), very large secondary storage devices, and high-speed processors to cater for the needs of the computers under its service.

Consisting of advanced components, mainframes have the capability of running multiple large applications required by many and most enterprises and organizations. This is one of its advantages. Mainframes are also suitable to cater for those applications (programs) or files that are of very high demand by its users (clients). Examples of such organizations and enterprises using mainframes are online shopping websites such as Ebay, Amazon, and computing-giant



MAINFRAMES

Mainframes usually are referred those computers with fast, advanced processing capabilities that could perform by itself tasks that may require a lot of Personal Computers (PC) Machines. Usually mainframes would have lots of RAMs, very large secondary storage devices, and very fast processors to cater for the needs of those computers under its service.

Due to the advanced components mainframes have, these computers have the capability of running multiple large applications required by most enterprises, which is one of its advantage. Mainframes are also suitable to cater for those applications or files that are of very large demand by its users (clients). Examples of these include the large online shopping websites -i.e. : Ebay, Amazon, Microsoft, etc.

Different approaches to lexical semantics

Lexicographic tradition:

- Use lexicons, thesauri, ontologies
- Assume words have discrete word senses:

bank1 = financial institution; bank2 = river bank, etc.

- May capture explicit relations between word (senses): “dog” is a “mammal”, etc.

Distributional tradition:

- Map words to (sparse) vectors that capture corpus statistics
- Contemporary variant: use neural nets to learn dense vector “embeddings” from very large corpora

(this is a prerequisite for most neural approaches to NLP)

- If each word type is mapped to a single vector, this ignores the fact that words have multiple senses or parts-of-speech

The distributional hypothesis

The Distributional Hypothesis

Zellig Harris (1954):

“oculist and eye-doctor … occur in almost the same environments”

“If A and B have almost identical environments we say that they are synonyms.”

John R. Firth 1957:

You shall know a word by the company it keeps.

The contexts in which a word appears
tells us a lot about what it means.

Words that appear in similar contexts have similar meanings

Why do we care about word contexts?

What is tezgüino?

A bottle of tezgüino is on the table.

Everybody likes tezgüino.

Tezgüino makes you drunk.

We make tezgüino out of corn.

(Lin, 1998; Nida, 1975)

The contexts in which a word appears tells us a lot about what it means.

Two ways NLP uses context for semantics

Distributional similarities (vector-space semantics):

Use the set of contexts in which words (= word types) appear to measure their similarity

Assumption: Words that appear in similar contexts (*tea, coffee*) have similar meanings.

Word sense disambiguation (future lecture)

Use the context of a particular occurrence of a word (token) to identify which sense it has.

Assumption: If a word has multiple distinct senses (e.g. *plant*: *factory* or *green plant*), each sense will appear in different contexts.

Word similarities as vector distances

Distributional Similarities

Measure the semantic similarity of words
in terms of the similarity of the contexts
in which the words appear

Represent words as vectors such that
— each vector element (dimension)
corresponds to a different context
— the vector for any particular word captures
how strongly it is associated with each context

Compute the semantic similarity of words
as the similarity of their vectors.

Distributional similarities

Distributional similarities use the set of contexts in which words appear to measure their similarity.

They represent each word *w* as a vector $\mathbf{w}$

$$\mathbf{w} = (w_1, \ldots, w_N) \in \mathbf{R}^N$$

in an N-dimensional vector space.

- Each dimension corresponds to a particular context c_n
- Each element w_n of $\mathbf{w}$ captures the degree to which the word *w* is associated with the context c_n.
- w_n depends on the co-occurrence counts of *w* and c_n

The similarity of words *w* and *u* is given by the similarity of their vectors $\mathbf{w}$ and $\mathbf{u}$

Documents as contexts

Let’s assume our corpus consists of a (large) number of documents (articles, plays, novels, etc.)

In that case, we can define the contexts of a word as the sets of documents in which it appears.

Conversely, we can represent each document as the (multi)set of words which appear in it.

- Intuition: Documents are similar to each other if they contain the same words.
- This is useful for information retrieval, e.g. to compute the similarity between a query (also a document) and any document in the collection to be searched.

Term-Document Matrix

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	6	117	0	0

A Term-Document Matrix is a 2D table:

- Each cell contains the frequency (count) of the term (word) *t* in document *d*: $\mathrm{tf}_{t,d}$
- Each column is a vector of counts over words, representing a document
- Each row is a vector of counts over documents, representing a word

Term-Document Matrix

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battle	1	1	8	15
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clown	6	117	0	0

Two documents are similar if their vectors are similar
Two words are similar if their vectors are similar

What is a ‘context’?

There are many different definitions of context that yield different kinds of similarities:

Contexts defined by nearby words:

How often does *w* appear near the word *drink*?
Near = “*drink* appears within a window of ±k words of *w*”,
or “*drink* appears in the same document/sentence as *w*”
This yields fairly broad thematic similarities.

Contexts defined by grammatical relations:

How often is (the noun) *w* used as the subject (object) of the verb *drink*? (Requires a parser).
This gives more fine-grained similarities.

Using nearby words as contexts

- Decide on a fixed vocabulary of N context words $c_1..c_N$

  Context words should occur frequently enough in your corpus that you get reliable co-occurrence counts, but you should ignore words that are too common ('stop words': *a*, *the, on, in, and, or, is, have,* etc.)

- Define what 'nearby' means

  For example: *w* appears near *c if* c appears within ±5 words of *w*

- Get co-occurrence counts of words *w* and contexts *c*

- Define how to transform co-occurrence counts of words *w* and contexts *c* into vector elements w_n

  For example: compute (positive) PMI of words and contexts

- Define how to compute the similarity of word vectors

  For example: use the cosine of their angles.

Defining and counting co-occurrence

Defining co-occurrences:

- **Within a fixed window**: v_i occurs within ±n words of *w*
- **Within the same sentence:** requires sentence boundaries
- **By grammatical relations**:
  v_i occurs as a subject/object/modifier/… of verb *w*
  (requires parsing - and separate features for each relation)

Counting co-occurrences:

- f_i as **binary features** (1,0): *w* does/does not occur with v_i
- f_i as **frequencies**: w occurs *n* times with v_i
- f_i as **probabilities**:
  e.g. f_i is the probability that v_i is the subject of *w*.

Getting co-occurrence counts

Co-occurrence as a binary feature:

Does word w ever appear in the context c? (1 = yes/0 = no)

	arts	boil	data	function	large	sugar	water
apricot	0	1	0	0	1	1	1
pineapple	0	1	0	0	1	1	1
digital	0	0	1	1	1	0	0
information	0	0	1	1	1	0	0

Co-occurrence as a frequency count:

How often does word w appear in the context c? (0…n times)

	arts	boil	data	function	large	sugar	water
apricot	0	1	0	0	5	2	7
pineapple	0	2	0	0	10	8	5
digital	0	0	31	8	20	0	0
information	0	0	35	23	5	0	0

Typically: 10K-100K dimensions (contexts), very sparse vectors

Counts vs PMI

Sometimes, low co-occurrences counts are very informative, and high co-occurrence counts are not:

- Any word is going to have relatively high co-occurrence counts with very common contexts (e.g. “it”, “anything”, “is”, etc.), but this won’t tell us much about what that word means.
- We need to identify when co-occurrence counts are more likely than we would expect by chance.

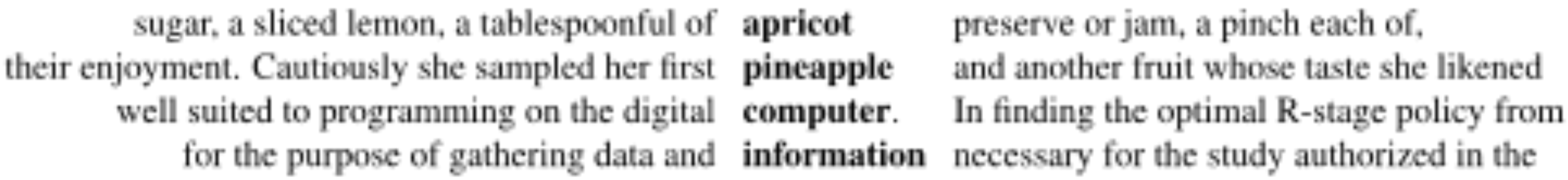
We can use pointwise mutual information (PMI) values instead of raw frequency counts:

$$PMI(w,c) = \log \frac{p(w,c)}{p(w)p(c)}$$

But this requires us to define $p(\mathrm{w}, \mathrm{c})$, $p(\mathrm{w})$ and $p(\mathrm{c})$

Word-Word Matrix

Context: ± 7 words



sugar, a sliced lemon, a tablespoonful of	**apricot**	preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first	**pineapple**	and another fruit whose taste she likened
well suited to programming on the digital	**computer**.	In finding the optimal R-stage policy from
for the purpose of gathering data and	**information**	necessary for the study authorized in the

Resulting word-word matrix:

f(w, c) = how often does word w appear in context c:
“information” appeared six times in the context of “data”

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	

$$p_{ij} = \frac{f_{ij}}{\sum_{i=1}^{W}\sum_{j=1}^{C} f_{ij}}$$

$$p(w_i) = \frac{\sum_{j=1}^{C} f_{ij}}{N}$$

$$p(c_j) = \frac{\sum_{i=1}^{W} f_{ij}}{N}$$

Count(w,context)

	computer	data	pinch	result	sugar
apricot	0	0	1	0	1
pineapple	0	0	1	0	1
digital	2	1	0	1	0
information	1	6	0	4	0

p(w=information, c=data) = 6/19 = .32

p(w=information) = 11/19 = .58

p(c=data) = 7/19 = .37

	p(w,context)					**p(w)**
	computer	data	pinch	result	sugar	
apricot	0.00	0.00	0.05	0.00	0.05	0.11
pineapple	0.00	0.00	0.05	0.00	0.05	0.11
digital	0.11	0.05	0.00	0.05	0.00	0.21
information	0.05	0.32	0.00	0.21	0.00	0.58
p(context)	0.16	0.37	0.11	0.26	0.11	

Computing PMI of *w* and *c*: Using a fixed window of ± k words

$$PMI(w,c) = \log \frac{p(w,c)}{p(w)p(c)}$$

N: How many tokens does the corpus contain?

$f(w) \leq N$: How often does w occur?

$f(w, c) \leq f(w,)$: How often does w occur with c in its window?

$f(\mathrm{c}) = \sum_w f(w, c) \leq N$: How many tokens have c in their window?

$p(w) = f(w)/N$

$p(\mathrm{c}) = f(c)/N$

$p(w, c) = f(w, c)/N$

Computing PMI of *w* and *c*: *w* and *c* in the same sentence

$$PMI(w,c) = \log \frac{p(w,c)}{p(w)p(c)}$$

N:	How many sentences does the corpus contain?
$f(w) \leq N$:	How many sentences contain w?
$f(w, c) \leq f(w)$:	How many sentences contain w and c?
$f(\mathrm{c}) \leq N$:	How many sentences contain c?

$p(w) = f(w)/N$

$p(\mathrm{c}) = f(c)/N$

$p(w, c) = f(w, c)/N$

Positive Pointwise Mutual Information

PMI is negative when words co-occur less than expected by chance.

This is unreliable without huge corpora:

With $P(w_1) \approx P(w_2) \approx 10^{-6}$, we can’t estimate whether $P(w_1,w_2)$ is significantly different from 10^{-12}

We often just use positive PMI values, and replace all PMI values < 0 with 0:

Positive Pointwise Mutual Information (PPMI):

$$\begin{aligned} \text{PPMI}(w,c) &= \text{PMI}(w,c) \quad \text{if } \text{PMI}(w,c) > 0 \\ &= 0 \qquad\qquad\quad\;\; \text{if } \text{PMI}(w,c) \leq 0 \end{aligned}$$

PMI and smoothing

PMI is biased towards infrequent events:

If $P(\mathrm{w, c}) = P(\mathrm{w}) = P(\mathrm{c})$, then $\mathrm{PMI(w,c)} = \log(1/P(\mathrm{w}))$
So $\mathrm{PMI(w, c)}$ is larger for rare words w with low $P(\mathrm{w})$.

Simple remedy: Add-k smoothing of $P(\mathrm{w, c}), P(\mathrm{w}), P(\mathrm{c})$ pushes all PMI values towards zero.
Add-k smoothing affects low-probability events more, and will therefore reduce the bias of PMI towards infrequent events.

(Pantel & Turney 2010)

Vector similarity as vector distances

In distributional models, every word is a point in *n*-dimensional space.
How do we measure the similarity between two points/vectors?

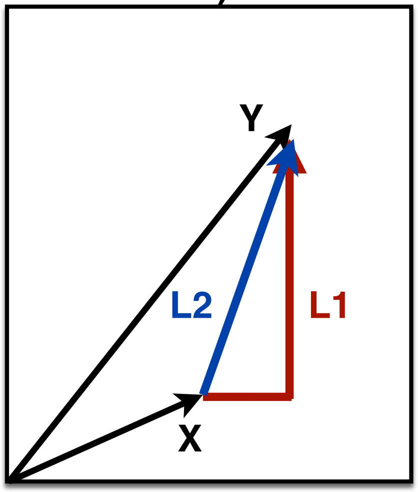
In general:

- **Manhattan distance** (Levenshtein distance, L1 norm)

$$dist_{L1}(\vec{x}, \vec{y}) = \sum_{i=1}^{N} |x_i - y_i|$$

- **Euclidian distance** (L2 norm)

$$dist_{L2}(\vec{x}, \vec{y}) = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2}$$



Dot product as similarity

If the vectors consist of simple binary features (0,1), we can use the **dot product** as **similarity metric**:

$$sim_{dot-prod}(\vec{x}, \vec{y}) = \sum_{i=1}^{N} x_i \times y_i$$

The dot product is a bad metric if the vector elements are arbitrary features: it prefers **long** vectors

- If one x_i is very large (and y_i nonzero), *sim(**x,y**)* gets very large
  If the number of nonzero x_i and y_is is very large, *sim(**x,y**)* gets very large.
- Both can happen with frequent words.

$$\text{length of } \vec{x} : |\vec{x}| = \sqrt{\sum_{i=1}^{N} x_i^2}$$

Vector similarity: Cosine

One way to define the similarity of two vectors is to use the cosine of their angle.

The cosine of two vectors is their dot product, divided by the product of their lengths:

$$\mathrm{sim}_{cos}(\vec{x}, \vec{y}) = \frac{\sum_{i=1}^{N} x_i \times y_i}{\sqrt{\sum_{i=1}^{N} x_i^2}\sqrt{\sum_{i=1}^{N} y_i^2}} = \frac{\vec{x} \cdot \vec{y}}{|\vec{x}||\vec{y}|}$$

sim(**w**, **u**) = 1: **w** and **u** point in the same direction
sim(**w**, **u**) = 0: **w** and **u** are orthogonal
sim(**w**, **u**) = –1: **w** and **u** point in the opposite direction

Word Embeddings

Words as input to neural models

We typically think of words as atomic symbols,
but neural nets require input in vector form.

Naive solution: one-hot encoding (dim(**x**) = |V|)

- “a” = (1,0,0,…0), “aardvark” = (0,1,0,…,0), ….
- Very high-dimensional, very sparse vectors (most elements 0)
- No ability to generalize across similar words
- Still requires a lot of parameters.

How do we obtain low-dimensional, dense vectors?

- Low-dimensional => our models need far fewer parameters
- Dense => lots of elements are non-zero
- We also want words that are similar to have similar vectors

Vector representations of words

"Traditional" distributional similarity approaches represent words as sparse vectors

- Each dimension represents one specific context
- Vector entries are based on word-context co-occurrence statistics (counts or PMI values)

Alternative, dense vector representations:

- We can use Singular Value Decomposition to turn these sparse vectors into dense vectors (Latent Semantic Analysis)
- We can also use neural models to explicitly learn a dense vector representation (embedding) (word2vec, Glove, etc.)

Sparse vectors = most entries are zero

Dense vectors = most entries are non-zero

(Static) Word Embeddings

A (static) word embedding is a function that maps each word type to a single vector

— these vectors are typically dense and have much lower dimensionality than the size of the vocabulary

— this mapping function typically ignores that the same string of letters may have different senses (dining table vs. a table of contents) or parts of speech (to table a motion vs. a table)

— this mapping function typically assumes a fixed size vocabulary (so an UNK token is still required)

Word2Vec Embeddings

Main idea:
Use a binary classifier to predict which words appear in the context of (i.e. near) a target word.
The parameters of that classifier provide a dense vector representation of the target word (embedding)

Words that appear in similar contexts (that have high distributional similarity) will have very similar vector representations.

These models can be trained on large amounts of raw text (and pre-trained embeddings can be downloaded)

Word2Vec (Mikolov et al. 2013)

The first really influential dense word embeddings

Two ways to think about Word2Vec:

— a simplification of neural language models

— a binary logistic regression classifier

Variants of Word2Vec

— Two different context representations: CBOW or Skip-Gram

— Two different optimization objectives:
Negative sampling (NS) or hierarchical softmax

Skip-Gram with negative sampling

Train a binary classifier that decides whether a target word *t* appears in the context of other words $c_{1..k}$

— **Context**: the set of k words near (surrounding) *t*

— Treat the target word *t* and any word that *actually* appears in its context in a real corpus as **positive** examples

— Treat the target word *t* and *randomly sampled* words that don't appear in its context as **negative** examples

— Train a **binary logistic regression** classifier to distinguish these cases

— The **weights** of this classifier depend on the **similarity** of t and the words in $c_{1..k}$

Use the weights of this classifier as embeddings for *t*

Skip-Gram Goal

Given a tuple (t,c) = target, context

(*apricot*, *jam*)

(*apricot*, *aardvark*)

Return the probability that c is a real context word:

$P(\ D = +\ \mid t, c)$

$P(\ D = -\ \mid t, c) \ = \ 1 - P(D = + \mid t, c)$

Skip-Gram Training data

Training sentence:

... lemon, a tablespoon of **apricot** jam a pinch ...

c1 c2 t c3 c4

Training data: input/output pairs centering on *apricot*

Assume a +/- 2 word window

Positive examples:
(apricot, tablespoon), (apricot, of), (apricot, jam), (apricot, a)

For each positive example, create k **negative examples**, using noise words:

(apricot, aardvark), (apricot, puddle)…

Word2Vec: Negative Sampling

Training data: D+ ∪ D-

D+ = actual examples from training data

Where do we get D- from?

Lots of options.

Word2Vec: for each good pair (w,c), sample k words and add each w_i as a negative example (w_i,c) to D'

(D' is k times as large as D)

Words can be sampled according to corpus frequency or according to smoothed variant where freq'(w) = $\text{freq(w)}^{0.75}$

(This gives more weight to rare words)

Word2Vec: Negative Sampling

Training objective:
Maximize log-likelihood of training data D+ ∪ D-:

$$\mathscr{L}(\Theta, D, D') = \sum_{(w,c)\in D} \log P(D = 1|w, c) + \sum_{(w,c)\in D'} \log P(D = 0|w, c)$$

The Skip-Gram classifier

Use logistic regression to predict whether the pair (*t*, *c*) (target word *t* and a context word c), is a positive or negative example:

$$P(+|t,c) = \frac{1}{1+e^{-t\cdot c}}$$

$$\begin{aligned} P(-|t,c) &= 1-P(+|t,c) \\ &= \frac{e^{-t\cdot c}}{1+e^{-t\cdot c}} \end{aligned}$$

Assume that t and c are represented as vectors, so that their dot product *tc* captures their similarity

To capture the entire context window $c_{1..k}$, assume the words in $c_{1:k}$ are independent (multiply) and take the log:

$$\begin{aligned} P(+|t,c_{1:k}) &= \prod_{i=1}^{k} \frac{1}{1+e^{-t\cdot c_i}} \\ \log P(+|t,c_{1:k}) &= \sum_{i=1}^{k} \log \frac{1}{1+e^{-t\cdot c_i}} \end{aligned}$$

Where do we get vectors t, c from?

Iterative approach:
Assume an initial set of vectors, and then adjust them during training to maximize the probability of the training examples.

How to compute p(+ | t, c)?

Intuition:

Words are likely to appear near similar words

Model similarity with dot-product!

Similarity(t,c) $\propto t \cdot c$

Problem:

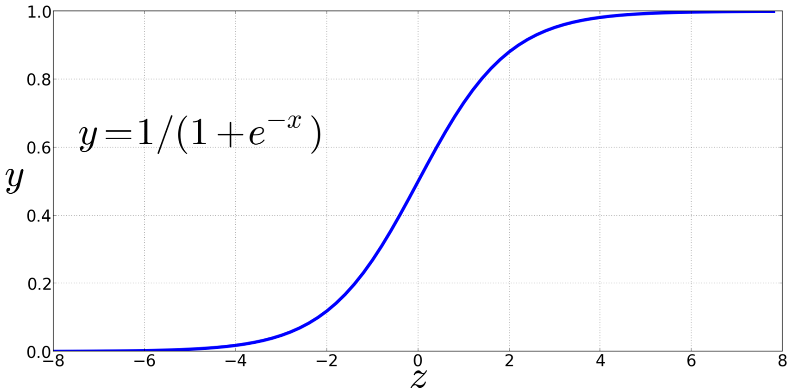
Dot product is not a probability!

(Neither is cosine)

Turning the dot product into a probability

The sigmoid lies between 0 and 1:

$$\sigma(x) = \frac{1}{1+\exp(-x)}$$



$$P(+\,|\,t,c) = \frac{1}{1+exp(-t\cdot c)}$$

$$P(-\,|\,t,c) = 1 - \frac{1}{1+exp(-t\cdot c)} = \frac{exp(-t\cdot c)}{1+exp(-t\cdot c)}$$

Word2Vec: Negative Sampling

Distinguish “good” (correct) word-context pairs (D=1), from “bad” ones (D=0)

Probabilistic objective:

$P(\, D = 1 \mid \text{t}, \text{c}\,)$ defined by sigmoid:

$$P(D = 1|w,c) = \frac{1}{1 + exp(-s(w,c))}$$

$P(\, D = 0 \mid \text{t}, \text{c}\,) = 1 - P(\, D = 0 \mid \text{t}, \text{c}\,)$

$P(\, D = 1 \mid \text{t}, \text{c}\,)$ should be high when $(\text{t}, \text{c}) \in \text{D+}$, and low when $(\text{t,c}) \in \text{D-}$

Summary: How to learn word2vec (skip-gram) embeddings

For a vocabulary of size V: Start with V random 300-dimensional vectors as initial embeddings

Train a logistic regression classifier to distinguish words that co-occur in corpus from those that don’t

Pairs of words that co-occur are positive examples

Pairs of words that don't co-occur are negative examples

Train the classifier to distinguish these by slowly adjusting all the embeddings to improve the classifier performance

Throw away the classifier code and keep the embeddings.

Evaluating embeddings

Compare to human scores on word similarity-type tasks:

WordSim-353 (Finkelstein et al., 2002)
SimLex-999 (Hill et al., 2015)
Stanford Contextual Word Similarity (SCWS) dataset (Huang et al., 2012)
TOEFL dataset: *Levied is closest in meaning to: imposed, believed, requested, correlated*

Properties of embeddings

Similarity depends on window size C

C = ±2 The nearest words to *Hogwarts:*

Sunnydale

Evernight

C = ±5 The nearest words to *Hogwarts:*

Dumbledore

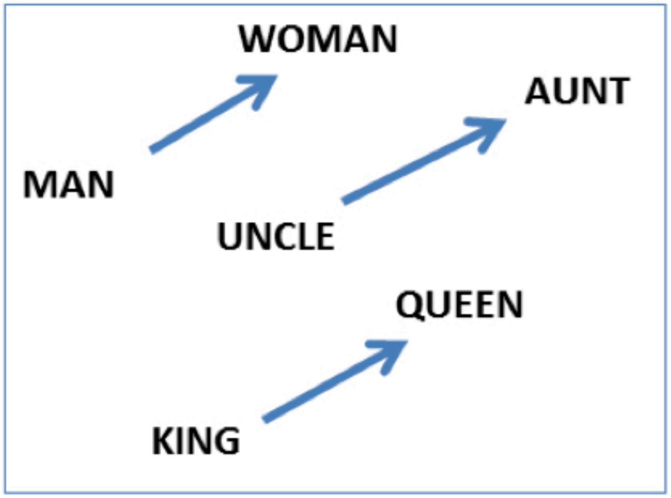
Malfoy

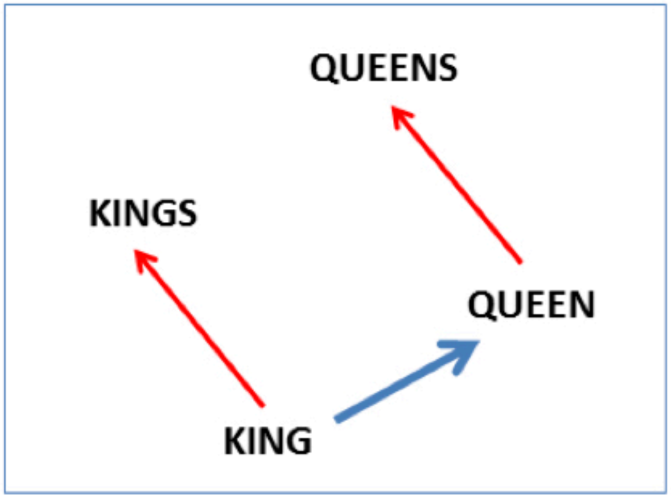
halfblood

Analogy: Embeddings capture relational meaning!

vector(‘*king*’) - vector(‘*man*’) + vector(‘*woman*’) = vector(‘queen’)

vector(‘*Paris*’) - vector(‘*France*’) + vector(‘*Italy*’) = vector(‘*Rome*’)





Using Word Embeddings

Using pre-trained embeddings

Assume you have pre-trained embeddings E.
How do you use them in your model?

- Option 1: Adapt E during training

Disadvantage: only words in training data will be affected.

- Option 2: Keep E fixed, but add another hidden layer that is learned for your task
- Option 3: Learn matrix $T \in \dim(\text{emb})\times\dim(\text{emb})$ and use rows of $E' = ET$ (adapts all embeddings, not specific words)
- Option 4: Keep E fixed, but learn matrix $\Delta \in R^{|V|\times\dim(\text{emb})}$ and use $E' = E + \Delta$ or $E' = ET + \Delta$ (this learns to adapt specific words)

More on embeddings

Embeddings aren’t just for words!

- You can take any discrete input feature (with a fixed number of K outcomes, e.g. POS tags, etc.) and learn an embedding matrix for that feature.

Where do we get the input embeddings from?

- We can learn the embedding matrix during training.
- Initialization matters: use random weights, but in special range (e.g. [-1/(2d), +(1/2d)] for d-dimensional embeddings), or use Xavier initialization
- We can also use pre-trained embeddings
- LM-based embeddings are useful for many NLP task

Dense embeddings you can download!

Word2vec (Mikolov et al.)
https://code.google.com/archive/p/word2vec/
Fasttext http://www.fasttext.cc/

Glove (Pennington, Socher, Manning)
http://nlp.stanford.edu/projects/glove/