Foundations of Natural Language Processing
Lecture 15
Distributional Semantics

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(slides from Alex Lascarides and Sharon Goldwater)

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Question Answering

- Question

  What is a good way to remove wine stains?

- Text available to the machine

  Salt is a great way to eliminate wine stains

- What is hard?

  – words may be related in other ways, including **similarity** and **gradation**
  – how to know if words have similar meanings?

Can we just use a thesaurus?

Problems:

- May not have a thesaurus in every language
- Even if we do, many words and phrases will be missing

So, let's try to compute similarity automatically.

Meaning from context(s)

- Consider the example from J&M (quoted from earlier sources):

  a bottle of *tezgüino* is on the table
  everybody likes *tezgüino*
  tezgüino makes you drunk
  we make *tezgüino* out of corn

Distributional hypothesis

- perhaps we can infer meaning just by looking at the contexts a word occurs in
- perhaps meaning IS the contexts a word occurs in (Wittgenstein!)
- either way, similar contexts imply similar meanings:
  - this idea is known as the **distributional hypothesis**

“Distribution”: a polysemous word

- Probability distribution: a function from outcomes to real numbers
- Linguistic distribution: the set of contexts that a particular item (here, word) occurs in

Distributional semantics: basic idea

- Represent each word w_i as a vector of its contexts
  - distributional semantic models also called **vector-space models**.

- Ex: each dimension is a context word; $= 1$ if it co-occurs with w_i, otherwise 0.

	`pet`	`bone`	`fur`	`run`	`brown`	`screen`	`mouse`	`fetch`
$w_1 =$	1	1	1	1	1	0	0	1
$w_2 =$	1	0	1	0	1	0	1	0
$w_3 =$	0	0	0	1	0	1	1	0

- Note: real vectors would be far more sparse

Questions to consider

- What defines "context"? (What are the dimensions, what counts as co-occurrence?)
- How to weight the context words (Boolean? counts? other?)
- How to measure similarity between vectors?

Two kinds of co-occurrence between two words:

First-order co-occurrence: (syntagmatic association)

- Typically nearby each other
  wrote is a first-order associate of *book*

Second-order co-occurrence: (paradigmatic association)

- Have similar neighbours
  wrote is a second-order associate of *said* and *remarked*

Defining the context

- Usually ignore **stopwords** (function words and other very frequent/uninformative words)

- Usually use a large window around the target word (e.g., 100 words, maybe even whole document)

- But smaller windows allow for relations other than cooccurrence: e.g., dependency relation from parser.

- Note: all of these for *semantic* similarity; for *syntactic* similarity, use a small window (1-3 words) and track *only* frequent words.

How to weight the context words

- binary indicators not very informative
- presumably more frequent co-occurrences matter more
- but, is frequency good enough?
  - frequent words are expected to have high counts in the context vector
  - regardless of whether they occur more often with this word than with others

Collocations

- We want to know which words occur *unusually* often in the context of w: more than we'd expect by chance?

- Put another way, what **collocations** include w?

Mutual information

- One way: use **pointwise mutual information**:

$$\mathrm{PMI}(x, y) = \log_2 \frac{P(x, y)}{P(x)P(y)}$$

$\Leftarrow$ Actual prob of seeing words x and y together

$\Leftarrow$ Predicted prob of same, if x and y are indep.

- PMI tells us how much more/less likely the cooccurrence is than if the words were independent

A problem with PMI

- In practice, PMI is computed with counts (using MLE).
- Result: it is over-sensitive to the chance co-occurrence of infrequent words
- See next slide: ex. PMIs from bigrams with 1 count in 1st 1000 documents of NY Times corpus

Example PMIs (Manning & Schütze, 1999, p181)

I_{1000}	w^1	w^2	w^1w^2	Bigram
16.95	5	1	1	Schwartz eschews
15.02	1	19	1	fewest visits
13.78	5	9	1	FIND GARDEN
12.00	5	31	1	Indonesian pieces
9.82	26	27	1	Reds survived
9.21	13	82	1	marijuana growing
7.37	24	159	1	doubt whether
6.68	687	9	1	new converts
6.00	661	15	1	like offensive
3.81	159	283	1	must think

Alternatives to PMI for finding collocations

- There are a **lot**, all ways of measuring statistical (in)dependence.
  - Student t-test
  - Pearson's χ^2 statistic
  - Dice coefficient
  - likelihood ratio test (Dunning, 1993)
  - Lin association measure (Lin, 1998)
  - and many more...

- Of those listed here, Dunning LR test probably most reliable for low counts.

- However, which works best may depend on particular application/evaluation.

Improving PMI

Rather than using a different method, can modify PMI itself to better handle low frequencies.

- Use **positive PMI** (PPMI): change all negative PMI values to 0.
  - Because for infrequent words, not enough data to accurately determine negative PMI values.

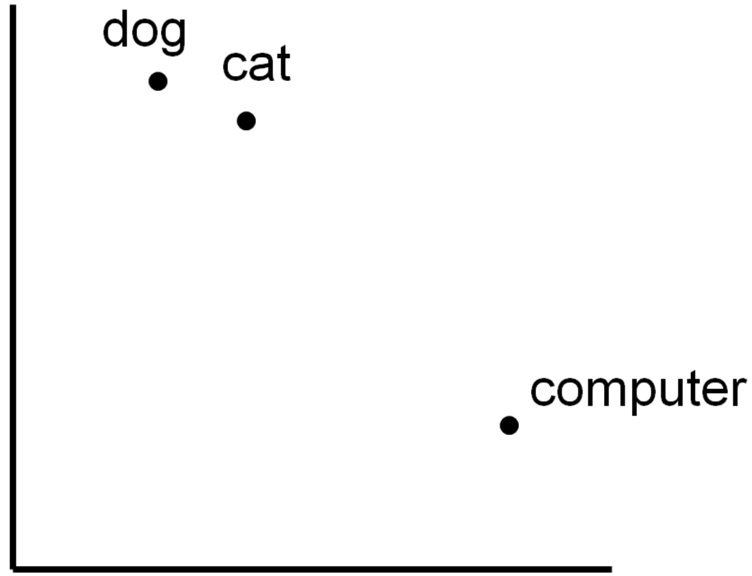
- Introduce smoothing in PMI computation.
  - See J&M or Levy et al. (2015) for a particularly effective method.

How to measure similarity

- So, let's assume we have context vectors for two words $\vec{v}$ and $\vec{w}$
- Each contains PMI (or PPMI) values for all context words
- One way to think of these vectors: as points in high-dimensional space

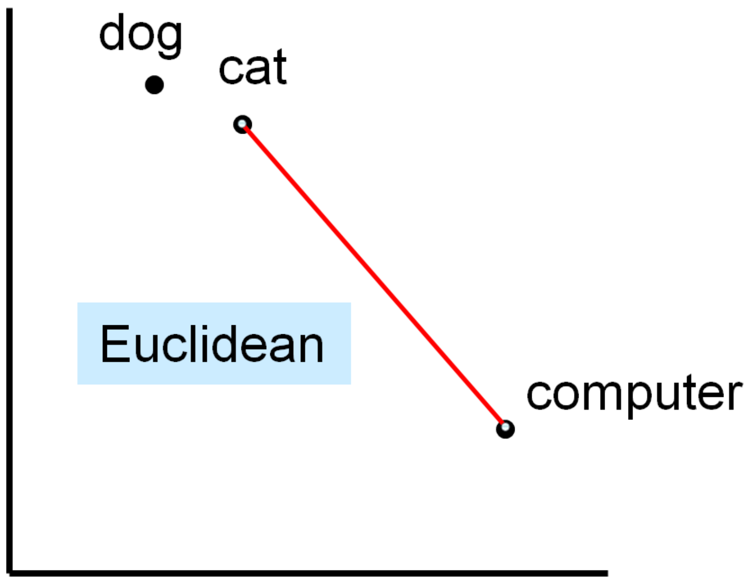
Vector space representation

- Ex. in 2-dim space: `cat` $= (v_1, v_2)$, `computer` $= (w_1, w_2)$



Euclidean distance

- We could measure (dis)similarity using Euclidean distance: $\left(\sum_i (v_i - w_i)^2\right)^{1/2}$



- But doesn't work well if even one dimension has an extreme value

Dot product

- Another possibility: take the dot product of $\vec{v}$ and $\vec{w}$:

$$\begin{aligned} \mathsf{sim}_{\mathsf{DP}}(\vec{v}, \vec{w}) &= \vec{v} \cdot \vec{w} \\ &= \sum_i v_i w_i \end{aligned}$$

  - Vectors are longer if they have higher values in each dimension.
  - So more frequent words have higher dot products.
  - But we don't want a similarity metric that's sensitive to word frequency.

Normalized dot product

- Some vectors are longer than others (have higher values):

$$[5,\ 2.3,\ 0,\ 0.2,\ 2.1] \quad \text{vs.} \quad [0.1,\ 0.3,\ 1,\ 0.4,\ 0.1]$$

  - If vector is context word counts, these will be *frequent* words
  - If vector is PMI values, these are likely to be *infrequent* words

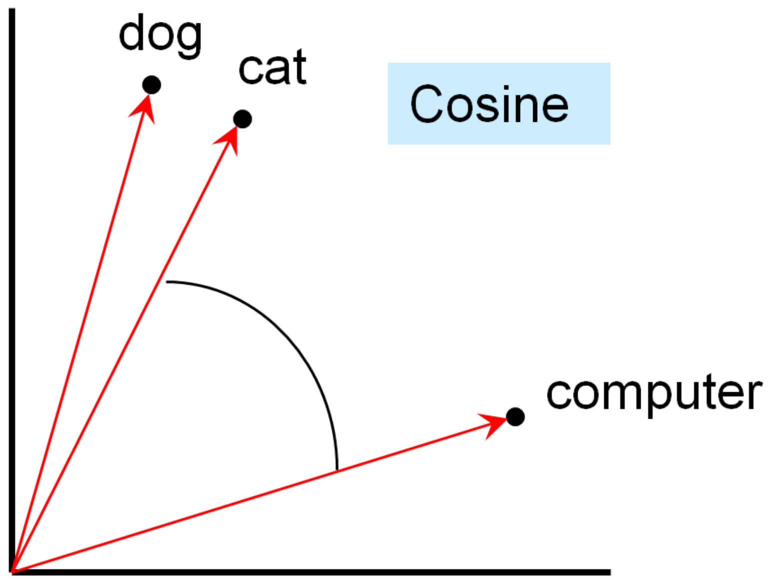
- Dot product is generally larger for longer vectors, regardless of similarity

- To correct for this, we **normalize**: divide by the length of each vector:

$$\mathsf{sim}_{\mathsf{NDP}}(\vec{v}, \vec{w}) = (\vec{v} \cdot \vec{w})/(|\vec{v}||\vec{w}|)$$

Normalized dot product = cosine

- The normalized dot product is just the cosine of the angle between vectors.



- Ranges from -1 (vectors pointing opposite directions) to 1 (same direction

Other similarity measures

- Again, many alternatives
  - Jaccard measure
  - Dice measure
  - Jenson-Shannon divergence
  - etc.

- Again, may depend on particular application/evaluation

Evaluation

- Extrinsic may involve IR, QA, automatic essay marking, ...
- Intrinsic is often a comparison to psycholinguistic data
  - Relatedness judgments
  - Word association

Relatedness judgments

- Participants are asked, e.g.: on a scale of 1-10, how related are the following concepts?

LEMON FLOWER

- Usually given some examples initially to set the scale , e.g.
  - LEMON-TRUTH = 1
  - LEMON-ORANGE = 10

- But still a funny task, and answers depend a lot on how the question is asked ('related' vs. 'similar' vs. other terms)

Word association

- Participants see/hear a word, say the first word that comes to mind
- Data collected from lots of people provides probabilities of each answer:

		ORANGE	0.16
		SOUR	0.11
		TREE	0.09
LEMON	$\Rightarrow$	YELLOW	0.08
		TEA	0.07
		JUICE	0.05
		...	

Example data from the Edinburgh Associative Thesaurus: `http://www.eat.rl.ac.uk/`

Comparing to human data

- Human judgments provide a ranked list of related words/associations for each word w
- Computer system provides a ranked list of most similar words to w
- Compute the Spearman rank correlation between the lists (how well do the rankings match?)
- Often report on several data sets, as their details differ

Learning a more compact space

- So far, our vectors have length V, the size of the vocabulary
- Do we really need this many dimensions?
- Can we represent words in a smaller dimensional space that preserves the similarity relationships of the larger space?

Latent Semantic Analysis (LSA)

- One of the earliest methods for reducing dimensions while preserving similarity.
- Uses Singular Value Decomposition, a linear-algebra-based method.
- Converts from sparse vectors with 1000s of dimensions to dense vectors with 10s-100s of dimensions.
- LSA representations actually work better than originals for many tasks.
- More details in optional reading: J&M (3rd ed.) Ch 19.5

Neural network methods

- Recent (and very hyped) new methods for learning reduced-dimensional representations (now often called **embeddings**).
- Ex: train a NN to predict context words based on input word. Use hidden layer(s) as the input word's vector representation.
- Deep mathematical similarities to LSA (Levy and Goldberg, 2014), but can be faster to train.
- Appeared to work better than LSA, but likely due to unfair comparisons (Levy et al., 2015).
- More details in optional reading: J&M (3rd ed.) Ch 19.6-19.7

Vector representations in practice

- Very hot topic in NLP
- Embeddings seem to capture both syntactic and semantic information.
- So, used for language modelling and to replace words as 'observations' in parsing and other models.
- As noted in Smoothing lecture: this can provide a kind of similarity-based smoothing (models learn to make similar predictions for similar words).

Current work: compositionality

- One definition of collocations: **non-compositional** phrases
  - White House: not just a house that is white
  - barn raising: involves more than the parts imply
- But a lot of language *is* compositional
  - red barn: just a barn that is red
  - wooden plank: nothing special here
- Can we capture compositionality in a vector space model?

Compositionality in a vector space

- More formally, compositionality implies some operator $\oplus$ such that

$$\text{meaning}(w_1 w_2) = \text{meaning}(w_1) \oplus \text{meaning}(w_2)$$

- Current work investigates possible operators
  - vector addition (doesn't work very well)
  - tensor product
  - nonlinear operations learned by neural networks

- One problem: words like not—themselves more like operators than points in space.

Summary

- Distributional semantics: represents word meanings as vectors computed from their contexts.
  - Long sparse vectors of counts, PMI values, or others
  - Short dense vectors using LSA, NNets, or others
- Similarity typically measured using cosine distance
- Can work well as input to other systems, but harder to evaluate intrinsically