Applied Natural Language Processing

Info 256

Lecture 4: Vector semantics and word embeddings (Sept. 6, 2023)

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Lexical semantics

"You shall know a word by the company it keeps"

[Firth 1957]

Zellig Harris, "Distributional Structure" (1954)

Ludwig Wittgenstein, Philosophical Investigations (1953)

everyone likes	______________	
a bottle of	______________	is on the table
	______________	makes you drunk
a cocktail with	______________	and seltzer

context

everyone likes	______	
a bottle of	______	is on the table
	______	makes you drunk
a cocktail with	______	and seltzer

Distributed representation

- Vector representation that encodes information about the distribution of contexts a word appears in
- Words that appear in similar contexts have similar representations (and similar meanings, by the distributional hypothesis).
- We have several different ways we can encode the notion of “context.”

Term-document matrix

	Hamlet	Macbeth	Romeo & Juliet	Richard III	Julius Caesar	Tempest	Othello	King Lear
knife	1	1	4	2		2		10
dog				6	12	2		
sword	2	2	7	5		5		17
love	64		135	63		12		48
like	75	38	34	36	34	41	27	44

Context = appearing in the same document.

Vectors

knife	1	1	4	2		2		10

sword	2	2	7	5		5		17

Vector representation of the term; vector size = number of documents

Cosine Similarity

$$cos(x, y) = \frac{\sum_{i=1}^{F} x_i y_i}{\sqrt{\sum_{i=1}^{F} x_i^2} \sqrt{\sum_{i=1}^{F} y_i^2}}$$

- We can calculate the cosine similarity of two vectors to judge the degree of their similarity [Salton 1971]

- Euclidean distance measures the magnitude of distance between two points
- Cosine similarity measures their orientation

	Hamlet	Macbeth	R&J	R3	JC	Tempest	Othello	KL
knife	1	1	4	2		2		10
dog				6	12	2		
sword	2	2	7	5		5		17
love	64		135	63		12		48
like	75	38	34	36	34	41	27	44

cos(knife, knife)	1
cos(knife, dog)	0.11
cos(knife, sword)	0.99
cos(knife, love)	0.65
cos(knife, like)	0.61

Term-context matrix

- Rows and columns are both words; cell counts = the number of times word w_i and w_j show up in the same context (e.g., a window of 2 tokens).

Dataset

- the big dog ate dinner
- the small cat ate dinner
- the white dog ran down the street
- the yellow cat ran inside

Dataset

- the big dog ate dinner
- the small cat ate dinner
- the white dog ran down the street
- the yellow cat ran inside

DOG terms (window = 2)

the big ate dinner the white ran down

Dataset

- the big dog ate dinner
- the small cat ate dinner
- the white dog ran down the street
- the yellow cat ran inside

DOG terms (window = 2)

the big ate dinner the white ran down

CAT terms (window = 2)

the small ate dinner the yellow ran inside

Term-context matrix

contexts

term

	the	big	ate	dinner	…
dog	2	1	1	1	…
cat	2	0	1	1	…

- Each cell enumerates the number of times a context word appeared in a window of 2 words around the term.
- How big is each representation for a word here?

We can also define “context” to be directional ngrams (i.e., ngrams of a defined order occurring to the left or right of the term)

Dataset

- the big dog ate dinner
- the small cat ate dinner
- the white dog ran down the street
- the yellow cat ran inside

DOG terms (window = 2)

L: the big, R: ate dinner, L: the white, R: ran down

CAT terms (window = 2)

L: the small, R: ate dinner, L: the yellow, R: ran inside

Term-context matrix

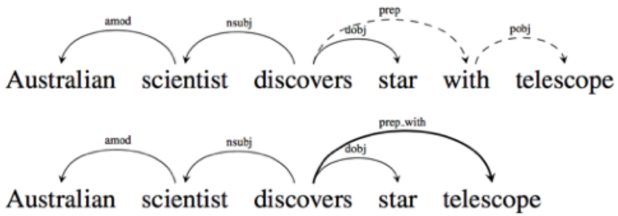
contexts

term

	L: the big	R: ate dinner	L: the small	L: the yellow	…
dog	1	1	0	0	…
cat	0	1	1	1	…

- Each cell enumerates the number of time a directional context phrase appeared in a specific position around the term.

Syntactic context



WORD	CONTEXTS
australian	scientist/amod^{-1}
scientist	australian/amod, discovers/nsubj^{-1}
discovers	scientist/nsubj, star/dobj, telescope/prep_with
star	discovers/dobj^{-1}
telescope	discovers/prep_with^{-1}

Lin 1998; Levy and Goldberg 2014

Target Word	BoW5	BoW2	DEPS
batman	nightwing aquaman catwoman superman manhunter	superman superboy aquaman catwoman batgirl	superman superboy supergirl catwoman aquaman
hogwarts	dumbledore hallows half-blood malfoy snape	evernight sunnydale garderobe blandings collinwood	sunnydale collinwood calarts greendale millfield
turing	nondeterministic non-deterministic computability deterministic finite-state	non-deterministic finite-state nondeterministic buchi primality	pauling hotelling heting lessing hamming
florida	gainesville fla jacksonville tampa lauderdale	fla alabama gainesville tallahassee texas	texas louisiana georgia california carolina
object-oriented	aspect-oriented smalltalk event-driven prolog domain-specific	aspect-oriented event-driven objective-c dataflow 4gl	event-driven domain-specific rule-based data-driven human-centered
dancing	singing dance dances dancers tap-dancing	singing dance dances breakdancing clowning	singing rapping breakdancing miming busking

contexts

term

	the	a	red	eats	stab	happy	in	cloud	for
knife	74	86	4		13		21		7
dog	65	58	1	6		7	17	1	3
sword	91	81	3		8		14		5
love	45	1		1		12	54	2	13
like	31	17				11	8	7	18

Weighting dimensions

- Not all dimensions are equally informative

TF-IDF

- Term frequency-inverse document frequency
- A scaling to represent a feature as function of how frequently it appears in a data point but accounting for its frequency in the overall collection
- IDF for a given term = the number of documents in collection / number of documents that contain term

TF-IDF

- Term frequency ($tf_{t,d}$) = the number of times term t occurs in document d; several variants (e.g., passing through log function).
- Inverse document frequency = inverse fraction of number of documents containing (D_t) among total number of documents N

$$tfidf(t,d) = tf_{t,d} \times \log \frac{N}{D_t}$$

IDF

contexts

term

	the	a	red	eats	stab	happy	in	cloud	for
knife	74	86	4		13		21		7
dog	65	58	1	6		7	17	1	3
sword	91	81	3		8		14		5
love	45	1		1		12	54	2	13
like	31	17				11	8	7	18

IDF	0	0	0.51	0.92	0.92	0.51	0	0.51	0

PMI

- Mutual information provides a measure of how independent two variables (X and Y) are.

- Pointwise mutual information measures the independence of two outcomes (x and y)

PMI

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

w = word, c = context

$$\log_2 \frac{P(w,c)}{P(w)P(c)}$$

What's this value for w and c that never occur together?

$$PPMI = \max\left(\log_2 \frac{P(w,c)}{P(w)P(c)}, 0\right)$$

	the	a	red	eats	stab	happ v	in	cloud	for	*total*
knife	74	86	4		13		21		7	205
dog	65	58	1	6		7	17	1	3	158
sword	91	81	3		8		14		5	202
love	45	1		1		12	54	2	13	128
like	31	17				11	8	7	18	92
total	306	243	8	7	21	30	114	10	46	*785*

$$\text{PMI}(w = \text{sword}, c = \text{stab}) = \log_2 \frac{P(w = \text{sword}, c = \text{stab})}{P(w = \text{sword})\ P(c = \text{stab})} = \log_2 \frac{\frac{8}{785}}{\frac{202}{785} \times \frac{21}{785}}$$

Evaluation

Intrinsic Evaluation

- Relatedness: correlation (Spearman/Pearson) between vector similarity of pair of words and human judgments

word 1	word 2	human score
midday	noon	9.29
journey	voyage	9.29
car	automobile	8.94
…	…	…
professor	cucumber	0.31
king	cabbage	0.23

WordSim-353 (Finkelstein et al. 2002)

Intrinsic Evaluation

- Analogical reasoning (Mikolov et al. 2013). For analogy Germany : Berlin :: France : ???, find closest vector to v("Berlin") - v("Germany") + v("France")

			target
possibly	impossibly	certain	uncertain
generating	generated	shrinking	shrank
think	thinking	look	looking
Baltimore	Maryland	Oakland	California
shrinking	shrank	slowing	slowed
Rabat	Morocco	Astana	Kazakhstan

Dense vectors from prediction

- Learning low-dimensional representations of words by framing a predicting task: using context to predict words in a surrounding window
- Transform this into a supervised prediction problem; similar to language modeling but we're ignoring order within the context window

Dense vectors from prediction

Skipgram model (Mikolov et al. 2013): given a single word in a sentence, predict the words in a context window around it.

a cocktail with gin
and seltzer

x	y
gin	a
gin	cocktail
gin	with
gin	and
gin	seltzer

Window size = 3

Dimensionality reduction

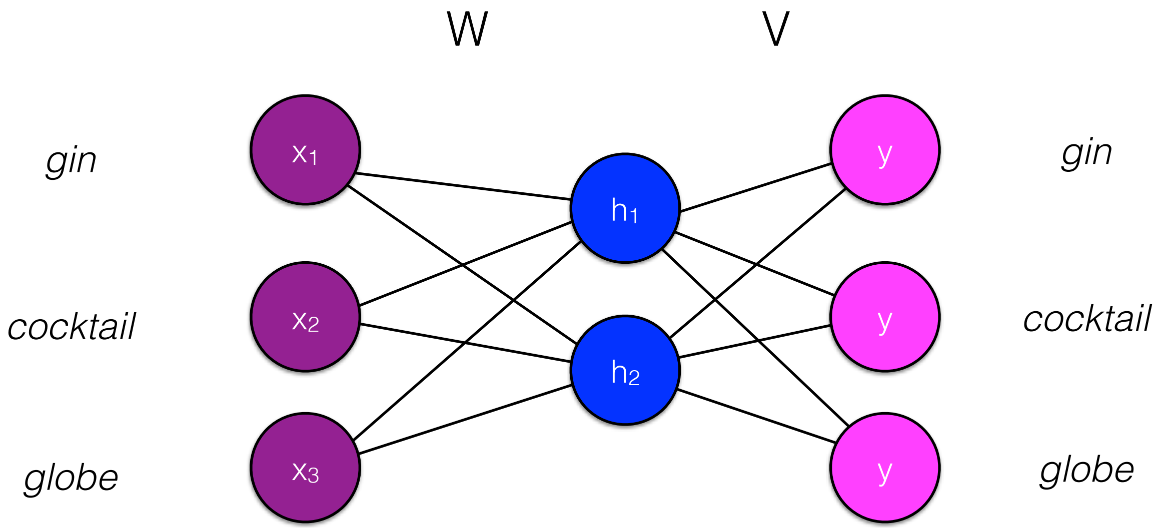
…	…
the	1
a	0
an	0
for	0
in	0
on	0
dog	0
cat	0
…	…

the is a point in V-dimensional space

the

4.1
-0.9

the is a point in 2-dimensional space

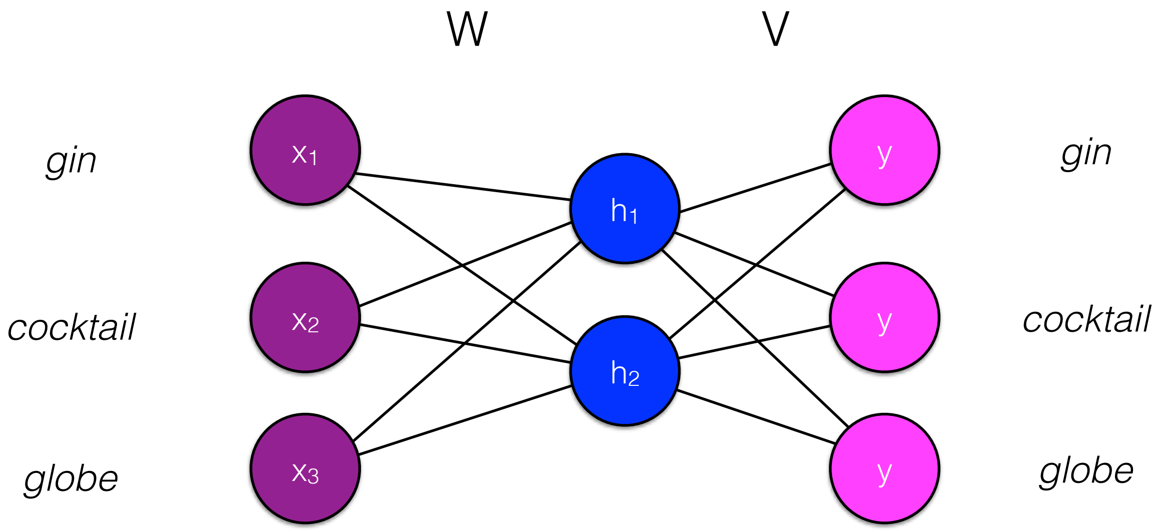


	x
gin	0
cocktail	1
globe	0

W	
-0.5	1.3
0.4	0.08
1.7	3.1

V		
4.1	0.7	0.1
-0.9	1.3	0.3

y
1
0
0



Only one of the inputs is nonzero.

= the inputs are really $W_{cocktail}$

W	
-0.5	1.3
0.4	0.08
1.7	3.1

V		
4.1	0.7	0.1
-0.9	1.3	0.3

x	W	
	0.13	0.56
	-1.75	0.07
	0.80	1.19
	-0.11	1.38
	-0.62	-1.46
	-1.16	-1.24
	0.99	-0.26
	-1.46	-0.85
	0.79	0.47
	0.06	-1.21
	-0.31	0.00
1	-1.01	-2.52
	-1.50	-0.14
	-0.14	0.01
	-0.13	-1.76
	-1.08	-0.56
	-0.17	-0.74
	0.31	1.03
	-0.24	-0.84
	-0.79	-0.18

$$x^\top W =$$

-1.01	-2.52

This is the embedding of the context

Word embeddings

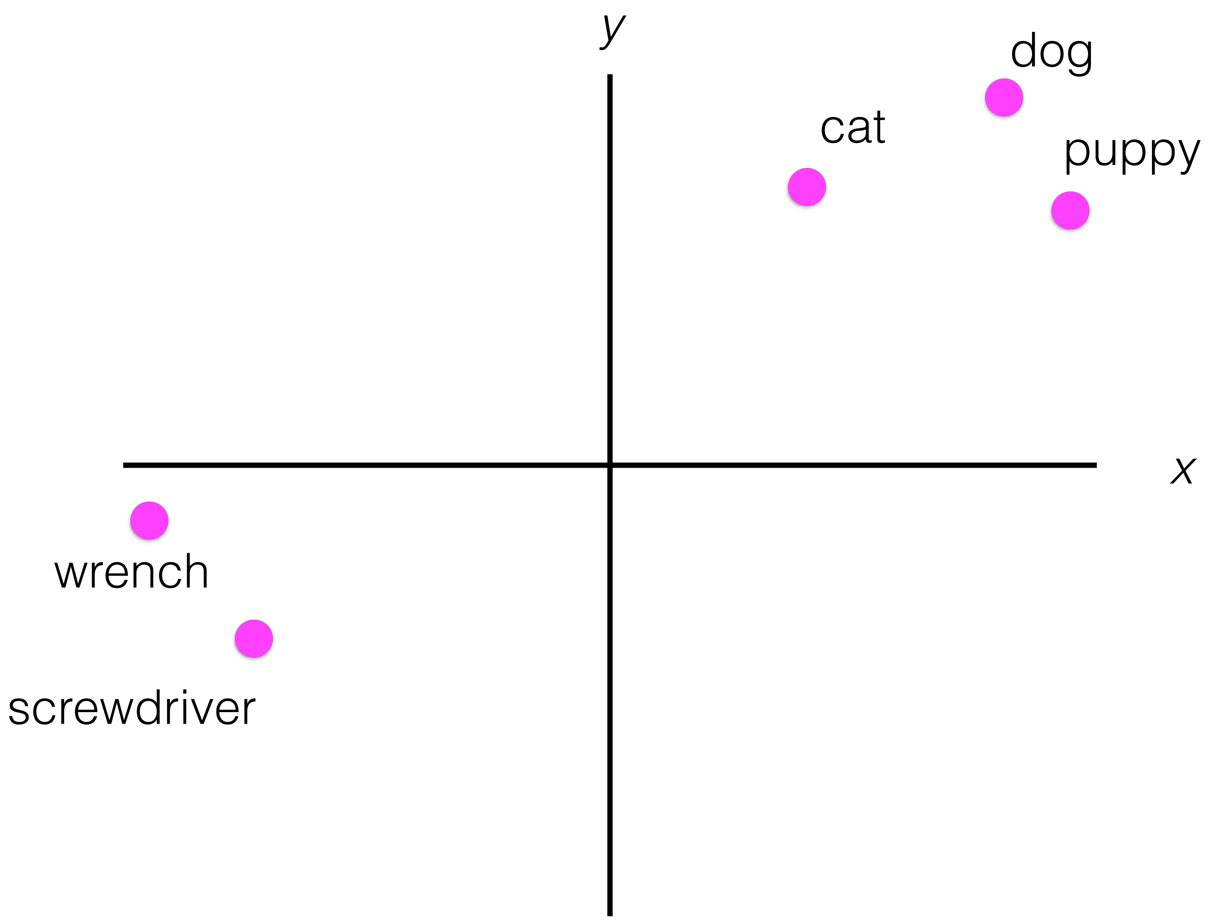
- Can you predict the output word from a vector representation of the input word?
- Rather than seeing the input as a one-hot encoded vector specifying the word in the vocabulary we're conditioning on, we can see it as indexing into the appropriate row in the weight matrix W

Word embeddings

- Similarly, V has one H-dimensional vector for each element in the vocabulary (for the words that are being predicted)

V			
gin	cocktail	cat	globe
4.1	0.7	0.1	1.3
-0.9	1.3	0.3	-3.4

This is the embedding of the word


y
dog
cat
puppy
x
wrench
screwdriver

- Why this behavior? *dog*, *cat* show up in similar positions

the	black	cat	jumped	on	the	table
the	black	dog	jumped	on	the	table
the	black	puppy	jumped	on	the	table
the	black	skunk	jumped	on	the	table
the	black	shoe	jumped	on	the	table

- Why this behavior? *dog*, *cat* show up in similar positions

the	black	[0.4, 0.08]	jumped	on	the	table
the	black	[0.4, 0.07]	jumped	on	the	table
the	black	puppy	jumped	on	the	table
the	black	skunk	jumped	on	the	table
the	black	shoe	jumped	on	the	table

To make the same predictions, these numbers need to be close to each other.

Activity

- `DistributionalSimilarity.ipynb`: Build high-dimensional, sparse word representations and find the context evidence that two words are similar.

- `WordEmbeddings.ipynb`: Train word2vec models using Gensim and explore the capacity for analogical reasoning.