Vector Semantics

15 February 2022
Assignment 3

Due 10 p.m. on Wednesday.

Worksheet 4

First part due now
Fill in the rest during class today, due tonight
Shared reading
What do words mean?
There are many approaches to word meaning.
Dictionaries define words for people (using other words):

1. The animal.
   a. A domesticated carnivorous mammal, *Canis familiaris* (or *C. lupus familiaris*), which typically has a long snout, an acute sense of smell, non-retractile claws, and a barking, howling, or whining voice, widely kept as a pet or for hunting, herding livestock, guarding, or other utilitarian purposes.

   Dogs are believed to have been domesticated from the wolf, *C. lupus*, in the Mesolithic period, and there are now numerous breeds that vary greatly in size, shape, and colour. Some now live in a wild or feral state. Cf. sense 3b.

   Frequently in figurative contexts (in quot. OE. with contemptuous reference to the torturers of St Vincent). Cf. also figurative use at sense 1b, extended uses at sense 5, and *black dog* n. 2.

   OE—2006

   b. figurative. In phrases with *of*-complement (now frequently after *the dogs of war* at *Phrases 11*), denoting a person or personified thing likened to a dog, esp. in being vicious, watchful, subservient, or ravening.

   ?c1225—1995

   c. With distinguishing word denoting variety or use.

   *bull, cattie, cour, fielh, guide, gun, parlour, sheep, toy dog*, etc.: see the first element.

   ?c1225—2006
We can try to encode definitional meaning using logical rules like:

\[ \forall x . \text{Dog}(x) \Rightarrow \text{Mammal}(x) \]
Or we can arrange word senses into hierarchies of sets of synonyms (synsets), as WordNet does:
Context as meaning
He filled the wampimuk, passed it around, and we all drank some.
We found a hairy little wampimuk sleeping behind a tree.

Example by Marco Baroni
The idea of *distributional modeling* is to represent the meaning of a word through the contexts in which it is observed.

Similar words appear in similar contexts.
“The meaning of a word is its use in language”

“If [words] A and B have almost identical environments we say that they are synonyms.”
Zellig Harris, 1954

“You shall know a word by the company it keeps.”
John Firth, 1957
What words can appear in these contexts?

Word 1
drown, bathroom, shower, fill, fall, lie, electrocute, toilet, whirlpool, iron, gin

Word 2
eat, fall, pick, slice, peel, lie, tree, throw, fruit, pie, bite, crab, grate

Word 3
advocate, overthrow, establish, citizen, ideal, representative, dictatorship, campaign, bastion, freedom

Word 4
spend, enjoy, remember, last, pass, end, die, happen, brighten, relive
What words can appear in these contexts?

**Word 1**
- bathtub
  - drown, bathroom, shower, fill, fall, lie, electrocute, toilet, whirlpool, iron, gin

**Word 2**
- eat, fall, pick, slice, peel, lie, tree, throw, fruit, pie, bite, crab, grate

**Word 3**
- advocate, overthrow, establish, citizen, ideal, representative, dictatorship, campaign, bastion, freedom

**Word 4**
- spend, enjoy, remember, last, pass, end, die, happen, brighten, relive
What words can appear in these contexts?

**bathtub**
drown, bathroom, shower, fill, fall, lie, electrocute, toilet, whirlpool, iron, gin

**apple**
eat, fall, pick, slice, peel, lie, tree, throw, fruit, pie, bite, crab, grate

**Word 3**
advocate, overthrow, establish, citizen, ideal, representative, dictatorship, campaign, bastion, freedom

**Word 4**
spend, enjoy, remember, last, pass, end, die, happen, brighten, relive
What words can appear in these contexts?

**bathtub**
- drown, bathroom, shower, fill, fall, lie, electrocute, toilet, whirlpool, iron, gin

**apple**
- eat, fall, pick, slice, peel, lie, tree, throw, fruit, pie, bite, crab, grate

**democracy**
- advocate, overthrow, establish, citizen, ideal, representative, dictatorship, campaign, bastion, freedom

**Word 4**
- spend, enjoy, remember, last, pass, end, die, happen, brighten, relive
What words can appear in these contexts?

- **Bathtub**
  - drown, bathroom, shower, fill, fall, lie, electrocute, toilet, whirlpool, iron, gin

- **Apple**
  - eat, fall, pick, slice, peel, lie, tree, throw, fruit, pie, bite, crab, grate

- **Democracy**
  - advocate, overthrow, establish, citizen, ideal, representative, dictatorship, campaign, bastion, freedom

- **Day**
  - spend, enjoy, remember, last, pass, end, die, happen, brighten, relive
Similar words appear in similar contexts.

We can measure similarity in meaning as similarity in contexts.
One more:

Word 5

eat, paint, peel, last,
apple, fruit, juice,
lemon, blue, grow
One more:

orange
eat, paint, peel, last,
apple, fruit, juice,
lemon, blue, grow
Similar words appear in similar contexts.

We can measure similarity in meaning as similarity in contexts.

But if a word has multiple meanings like orange, it will appear in a mixture of contexts.
We can describe the contexts of a word by counting other words nearby.
They picked up red apples that had fallen to the ground.
Eating apples is healthy.
She ate a red apple.
Pick an apple.
They picked up red apples that had fallen to the ground.

Eating apples is healthy.

She ate a red apple.

Pick an apple.
They *picked up red apples that had fallen* to the ground.

*Eating apples is healthy.*

*She ate a red apple.*

*Pick an apple.*

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If we count context words in a larger corpus, we get counts like these:

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<td>244</td>
<td>47</td>
<td>221</td>
<td>208</td>
<td>160</td>
<td>145</td>
<td>156</td>
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Every context word becomes a dimension.
If we count context words in a larger corpus, we get counts like these:

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<td>orange</td>
<td>265</td>
<td>22</td>
<td>25</td>
<td>62</td>
<td>220</td>
<td>64</td>
<td>74</td>
<td>111</td>
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**Similarity between two words as proximity in space**

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Visualizing a modern word embedding model using the Tensorflow projector:

projector.tensorflow.org
Train embeddings on different decades of historical text to see meanings shift:

Embeddings reflect cultural bias!

Ask “Paris : France :: Tokyo : x”

\[ x = Japan \]

Algorithms that use embeddings as part of e.g., hiring searches for programmers, might lead to bias in hiring
Embeddings reflect cultural bias!

Ask “Paris : France :: Tokyo : x”

\[ x = \text{Japan} \]

Ask “father : doctor :: mother : x”

Algorithms that use embeddings as part of e.g., hiring searches for programmers, might lead to bias in hiring
Embeddings reflect cultural bias!

Ask “Paris : France :: Tokyo : x”

x = Japan

Ask “father : doctor :: mother : x”

x = nurse

Algorithms that use embeddings as part of e.g.,
hiring searches for
programmers, might lead to
bias in hiring
Embeddings reflect cultural bias!

Ask “Paris : France :: Tokyo : x”
\[ x = \text{Japan} \]

Ask “father : doctor :: mother : x”
\[ x = \text{nurse} \]

Ask “man : computer programmer :: woman : x”

Algorithms that use embeddings as part of e.g., hiring searches for programmers, might lead to bias in hiring.
Embeddings reflect cultural bias!

Ask “Paris : France :: Tokyo : x”

x = Japan

Ask “father : doctor :: mother : x”

x = nurse

Ask “man : computer programmer :: woman : x”

x = homemaker

Algorithms that use embeddings as part of e.g., hiring searches for programmers, might lead to bias in hiring
Embeddings reflect cultural bias!

Ask \("Paris : France :: Tokyo : x\)"

\(x = Japan\)

Ask \("father : doctor :: mother : x\)"

\(x = nurse\)

Ask \("man : computer programmer :: woman : x\)"

\(x = homemaker\)

Algorithms that use embeddings as part of e.g., hiring searches for programmers, might lead to bias in hiring

Bolukbasi, Tolga, Kai-Wei Chang, James Y. Zou, Venkatesh Saligrama, and Adam T. Kalai. “Man is to computer programmer as woman is to homemaker? debiasing word embeddings”. In NeurIPS, pp. 4349–4357. 2016.
Further reading
Groups
Acknowledgments

This class incorporates material from:

Katrin Erk

Jurafsky & Martin, *Speech and Language Processing*, 3rd ed. draft