Word Embeddings

Overview

- Representing meaning

- Word embeddings: Early work

- Word embeddings via language models

- Word2vec and Glove

- Evaluating embeddings

- Design choices and open questions

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- **Representing meaning**

- Word embeddings: Early work

- Word embeddings via language models

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Representing meaning

What do words mean?

How do they get their meaning?

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tiger   cat   dog   table

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Representing meaning

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Perhaps more pertinent for modeling language:
How can we represent the meaning of words in a form that is computationally flexible?

Words are atomic symbols

The strings `cat`, `tiger`, `dog` and `table` are different from each other

If we systematically replace all words with unique identifiers, does their meaning change?

Think about substituting `cat` with `uniq-id-1`, `table` with `uniq-id-53`, ...

As long as we are consistent in our substitution, sentence meaning would not be harmed

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Various perspectives exist

An ontology: Eg. WordNet

Synonyms/Hypernyms (Ordered by Estimated Frequency) of noun cat

8 senses of cat

Sense 1
cat, true cat
=> feline, felid

Sense 2
guy, cat, hombre, bozo
=> man, adult male

Sense 3
Cat
=> gossip, gossiper, gossipmonger, rumormonger, rumourmonger, newsmonger

Sense 4
kat, khat, qat, quat, cat, Arabian tea, African tea
=> stimulant, stimulant drug, excitant

Sense 5
cat-o'-nine-tails, cat
=> whip

Sense 6
Caterpillar, cat
=> tracked vehicle

Sense 7
big cat, cat
=> feline, felid

Sense 8
computerized tomography, computed tomography, CT, computerized axial tomography, computed axial tomography, CAT
=> X-raying, X-radiation

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Such a taxonomy shows hypernymy relationships between words

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Such a taxonomy shows hypernymy relationships between words

- A high precision resource

- Typically manually built
    - Hard to keep it up-to-date
    - New words enter our lexicon, words change meaning over time

- Does not necessarily reflect how words are used in real life
    - Perhaps related to the previous concern

- Various methods for computing similarities between words using such an ontology.
    - Eg: using distances in the hypernym hierarchy such as the Wu & Palmer similarity measure

computerized tomography, computed tomography, CT, computerized axial tomography, computed axial tomography, CAT
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The distributional hypothesis

Words that occur in the same context have similar meanings
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- – Firth (1957) : "You shall know a word by the company it keeps"

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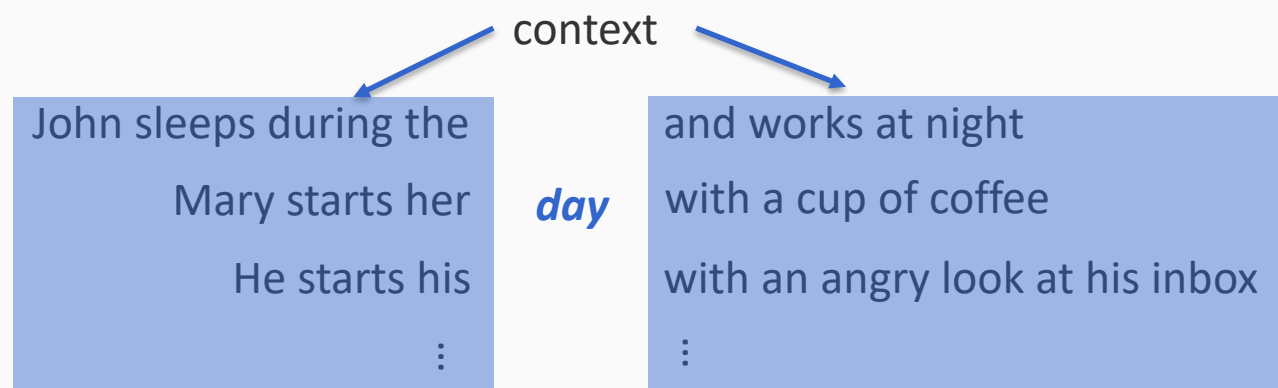- The key idea: To characterize the meaning of a word, we need to we characterize the distribution of its context

John sleeps during the   and works at night

Mary starts her   *day*   with a cup of coffee

He starts his   with an angry look at his inbox

⋮   ⋮

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- What context?

  Commonly interpreted as neighboring words in text, but could be syntactic/semantic/discourse/pragmatic/… context.

  We will see more about context soon
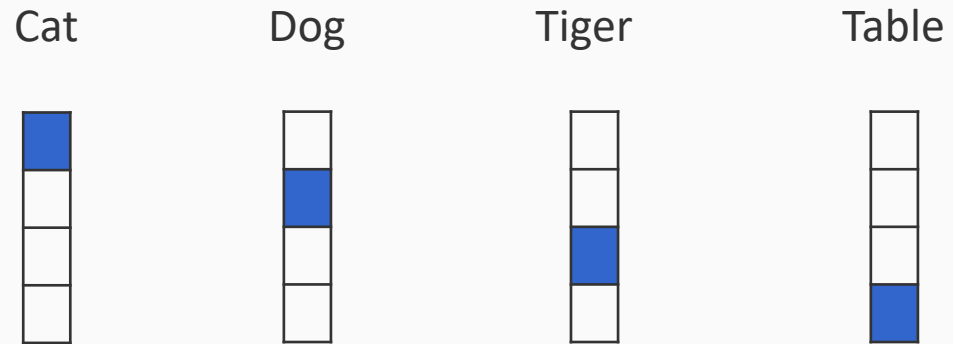
Symbolic vs. Distributed representations

- The words `cat`, `tiger`, `dog` and `table` are symbols

- Just knowing the symbols does not tell us anything about what they mean. For example:

  1. Cats and tigers are conceptually closer to each other than to dogs or tables
  2. Cats, tigers and dogs are closer to each other than tables

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- What we need: A representation scheme that inherently captures similarities between similar objects

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Symbolic vs. Distributed representations

For example: Think about feature representations

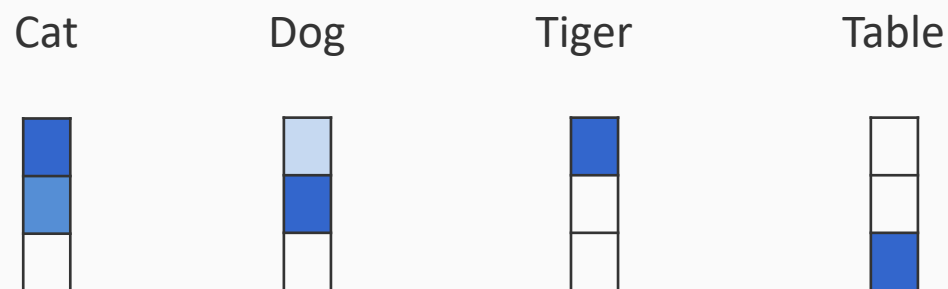| Cat	Dog	Tiger	Table

These **one-hot vectors** do not capture inherent similarities

Distances or dot products are all equal

Symbolic vs. Distributed representations

Distributed representations capture similarities better

– Think of them as vector valued representations can coalesce superficially distinct objects

Dense vector (often lower dimensional) representations can capture similarities better

Word embeddings (or word vectors)

A mapping from words to a vector space
- – Could be a fixed mapping that is context independent (word2vec, Glove, etc)
    - We will see these very soon

- – Could be a parameterized mapping that is context dependent (ELMo, BERT, etc)
    - We will see these later in the semester

A first step in any neural network model for textual inputs
- – First, convert words to vectors, then attend to the task you want to solve

Perspectives on word embeddings

1. **They capture distributional semantics**: Embeddings are low dimensional vectors that are constructed by appealing to the distributional hypothesis

2. **They are distributed representations of words**: The embedding dimensions represent underlying aspects of meaning and words are characterized by membership to these latent dimensions

3. **They provide features**: Word embeddings are a widely-used, convenient *learned* feature representations.