The Vector Space Model of Word Meaning
Informatics 1 CG: Lecture 13

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Reading:


Recap: Word Meaning

How do we represent the meaning of words? How is semantic knowledge organized?

- Semantic information is encoded in networks of linked nodes.
- Collins and Quillian network emphasizes hierarchical relations and cognitive economy; sentence verification times.
- Does not explain similarity and relatedness effects.
- Spreading activation model does but is difficult to falsify.
- Word meaning can be decomposed into semantic features.
- Feature-list theories account for sentence verification times by postulating that we compare lists of defining and characteristic features.
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Meanings of words are determined to a large extent by their distributional patterns. (Harris, 1968).

This leads to the distributional hypothesis about word meaning:

- the context surrounding a given word provides information about its meaning;
- words are similar if they share similar linguistic contexts;
- meaning captured quantitatively in terms of simple co-occurrence statistics.
Experimental evidence indicates that the cognitive system is sensitive to distributional information.

- Infants find word boundaries in artificial language only based on statistical regularities.
- They are also sensitive to transitional probabilities over tone sequences (Saffran et al., 1996).
- Frequency affects the sequence of acquisition for certain words. Adults tend to use basic-level nouns (e.g., dog) more frequently in interactions with children.
- Co-occurrence statistics influence lexical decision tasks.
Distribution is represented using a context vector.

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- Target words $w_1 \ldots w_n$: words represented with vectors.
- Context vector for $w$: all words that co-occur with $w$.
- Similar words should have similar vectors.
Distribution is represented using a context vector.

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Constructing Vector Spaces

Words occur in context:

- car engine hood tires truck trunk
- car emissions hood make model trunk
- Chomsky corpus noun parsing tagging wonderful

Contexts can be obtained from corpora (large collections of text).

Note that we have already removed stop words (frequent words such as *the*, *of*, *although*).
Constructing Vector Spaces

Select target words:

- Car
- Engine
- Hood
- Tires
- Truck
- Trunk

- Car emissions
- Hood
- Make
- Model
- Trunk

- Chomsky corpus noun parsing tagging wonderful
Define the context (here: symmetric, $-5$, $+5$):

- car, engine, hood, tires, truck, trunk
- car, emissions, hood, make, model, trunk
- Chomsky, corpus, noun, parsing, tagging, wonderful

Dimensions of context vectors: 14
Define the context (here: symmetric, −5, +5):

- Car
- Engine
- Hood
- Tires
- Truck
- Trunk

- Car emissions
- Hood
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- Chomsky
- Corpus
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- corpus
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Constructing Vector Spaces

Define the context (here: symmetric, $-5$, $+5$):

- **car**
- **engine**
- **hood**
- **tires**
- **truck**
- **trunk**

- **car**
- **emissions**
- **hood**
- **make**
- **model**
- **trunk**

- **Chomsky**
- **corpus**
- **noun**
- **parsing**
- **tagging**
- **wonderful**

- Dimensions of context vectors: 14
Create co-occurrence matrix:

<table>
<thead>
<tr>
<th></th>
<th>car</th>
<th>corpus</th>
<th>emissions</th>
<th>engine</th>
<th>hood</th>
<th>make</th>
<th>model</th>
<th>noun</th>
<th>parsing</th>
<th>tagging</th>
<th>tires</th>
<th>truck</th>
<th>trunk</th>
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<tbody>
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<td>car</td>
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<td>0</td>
<td>1</td>
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<tr>
<td>hood</td>
<td>1</td>
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<td>0</td>
</tr>
</tbody>
</table>
| Chomsky | 0 | 1     | 0         | 0      | 0    | 0    | 0     | 0    | 1       | 1       | 1     | 1     | 0     | 0         | 1
Informal algorithm for constructing vector spaces:

- pick the words you are interested in: target words;
- define number of words around target word: context window;
- count number of times the target word co-occurs with context words: co-occurrence matrix.

The context can also be defined in terms of documents, paragraphs, or sentences (rather than words around target word).
Measure the distance between vectors:

- **Euclidean**
- **Manhattan**
- **Cosine**
The cosine of the angle between two vectors $\mathbf{x}$ and $\mathbf{y}$ is:

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

The Euclidean distance of two vectors $\mathbf{x}$ and $\mathbf{y}$ is:

$$||\mathbf{x} - \mathbf{y}|| = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Many more similarity measures exist.
We represent document semantics also using vectors.

**Bag-of-words (BOW) model**: order of words is irrelevant.

**Nave version**: represent documents by word counts.

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<tr>
<td>$d_3$</td>
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<td>1</td>
<td>0</td>
<td>3</td>
<td>6</td>
<td>2</td>
</tr>
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Document-term co-occurrence matrix
Using the Vector Space Model

Can compute similarities between documents, or between documents and queries.

Query: “computer pointer”
**Problem:** the co-occurrence matrix can be very sparse (many zeros) and noisy (e.g., due to words with the same meaning).

```
auto engine bonnet tires lorry boot

car emissions hood make model trunk

make hidden Markov model emissions normalize
```
Problem: the co-occurrence matrix can be very sparse (many zeros) and noisy (e.g., due to words with the same meaning).

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- auto
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- car
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- trunk

make hidden Markov model emissions normalize
In order to address these problems, reduce the dimensionality of the co-occurrence matrix $M$:

- **project** the word vectors into a different subspace so that vector cosines more accurately represent semantic similarity;
- in lower dimensional space, synonym vectors may not be orthogonal;
- **singular value decomposition** is a widely used projection method; many others exist.
- **alternative**: restrict matrix dimensions to most reliable words.
Latent Semantic Analysis

- Best known vector space model (Landauer and Dumais, 1997).
- Natural language engineering:
  - lexicon acquisition (e.g., synonyms), unsupervised morphology;
  - essay grading, text coherence;
  - information retrieval;
  - language modeling, summarization, etc.
- Cognitive science:
  - semantic priming;
  - TOEFL 2nd language learning test.

http://lsa.colorado.edu/
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Till, Mross and Kintsch’s (1988) lexical decision experiment

The gardener pulled the hose around to the holes in the yard. Perhaps the water would solve his problem with the mole.
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ground
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ground  face
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ground  face  drown
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ground  face  drown  cancer
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The patient sensed that this was not a routine visit. The doctor hinted that there was reason to remove the mole.
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ground face drown cancer
Simulating Semantic Priming

Till, Mross and Kintsch’s (1988) results:

- words related to both senses of ambiguous word were primed immediately after presentation;
- after about 300 ms only the context appropriate associates remained significantly primed;

LSA model predicts:

- Larger cosines between ambiguous word and its related words than its control word;
- Vector average of context has a higher cosine with semantically congruent words.
The patient sensed that this was not a routine visit.
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The TOEFL Task

*Test of English as a Foreign Language* tests non-native speakers’ knowledge of English.

You will find the office at the main intersection.
(a) place
(b) crossroads
(c) roundabout
(d) building

This is a standard task in the cognitive modeling literature, and vectors space models are frequently used to solve it.
The TOEFL Task

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The TOEFL Task

- 80 items: 1 word/4 alternative words.
- Compute semantic representations for probe and answer words.
- Word with largest cosine to the probe is correct answer.
- LSA was trained on a 4.6 M corpus from encyclopedia.
- LSA answered 64.4% items correctly.
- Non-native speakers’ average is 64.5%.
- This average is adequate for admission in many US universities.
Discussion

**Strengths:**
- fully automatic construction;
- representationally simple: all we need is a corpus and some notion of what counts as a word;
- language-independent, cognitively plausible.

**Weaknesses:**
- many ad-hoc parameters when creating the model;
- ambiguous words: their meaning is the average of all senses;
- context words contribute indiscriminately to meaning.

The author received much acclaim for his new **book**.
For author acclaim his much received new **book**.