Vector Space Models of Lexical Meaning
Seminar Word Embeddings for NLP and IR

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Outline

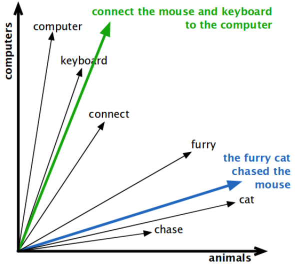
How do we represent word meanings formally?

Set theory based vs. Distributional

Set theory

All cats chase mice:
$\forall x \forall y((cat'(x) \wedge mouse'(y)) \rightarrow chase'(x, y))$
Each mouse is connected to a computer:
$\forall x(mouse'(x) \rightarrow \exists y(comp'(y) \wedge connect'(x, y))$

Vector models



Set theory based vs. Distributional

Set theory

Represent object, their properties and relations between them, meanings = constraints

Vector models

Capture distance and similarity, meanings = vectors in a semantic space, **more fine-grained representation**

The basic idea of vector space models

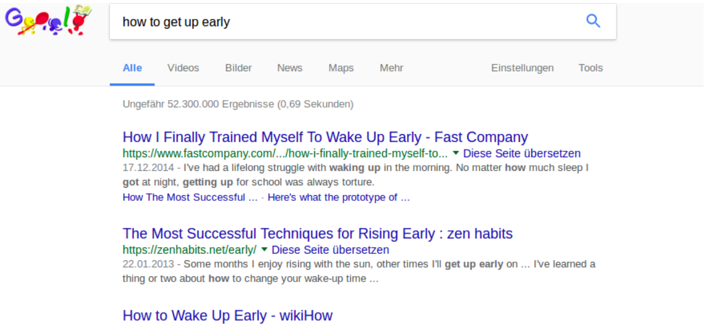
"You shall know a word by the company it keeps!"

— J. R. Firth (1957)

Distributional hypothesis

- Words that occur in similar contexts tend to have similar meanings
- Set of contexts for a word = distribution
- Distribution of the contexts represents the meaning

Document retrieval



- Input: a query
- Output: a set of documents ranked according to their relevance

Ignores the word order and the syntactic dependencies, but works well

Document retrieval

Task = find an overlap between the query and the documents

Vector space approach

- Words = basis vectors
- Queries and documents = vectors in the space

How to measure the similiraty between document and query?

$$Sim(\vec{q}, \vec{d}) = \sum_i q_i * d_i$$

Document retrieval: example

Term vocabulary: ⟨*England, Australia, Pietersen, Hoggard, run, wicket, catch, century, collapse*⟩

Document $d1$: *Australia collapsed as Hoggard took 6 wickets . Flintoff praised Hoggard for his excellent line and length .*

Document $d2$: *Flintoff took the wicket of Australia 's Ponting , to give him 2 wickets for the innings and 5 wickets for the match .*

Query q: { *Hoggard, Australia, wickets* }

$$\overrightarrow{q1} \,.\, \overrightarrow{d1} = \langle 0,1,0,1,0,1,0,0,0\rangle \,.\, \langle 0,1,0,2,0,1,0,0,1\rangle = 4$$

$$\overrightarrow{q1} \,.\, \overrightarrow{d2} = \langle 0,1,0,1,0,1,0,0,0\rangle \,.\, \langle 0,1,0,0,0,3,0,0,0\rangle = 4$$

vector coefficients = term-frequencies

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Document retrieval: more sophisticated approach (TF IDF)

Some words have more discriminating power!

The basic idea:

- If a word occurs only in few documents, it provides a stronger evidence for a particular meaning
- $\rightarrow$ should have a higher weight

Document retrieval: more sophisticated approach (TF IDF)

How to weight the words?

- count in how many documents a word occurs (document-frequency)
- coefficients in $=$ term-frequency/document-frequency
- or: coefficients in $=$ term-frequency **inverse document-frequency*

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$$\overrightarrow{q1} \,.\, \overrightarrow{d2} = \langle 0,1,0,1,0,1,0,0,0 \rangle \,.\, \langle 0,1/10,0,0/5,0,3/100,0,0,0/3 \rangle = 0.13$$

Document retrieval: more sophisticated approach (TF IDF)

Normalization by length

$$Sim(\vec{q}, \vec{d}) = \cos(\vec{q}, \vec{d})$$

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Normalization by length

$$Sim(\vec{q}, \vec{d}) = \cos(\vec{q}, \vec{d})$$

Why normalization?

To avoid the bias towards longer documents

Document retrieval: term-document matrix

$$
\begin{array}{l}
 \\
England \\
Australia \\
Pietersen \\
Hoggard \\
run \\
wicket \\
catch \\
century \\
collapse
\end{array}
\begin{array}{c}
\begin{array}{cc} d1 & d2 \end{array} \\
\begin{pmatrix}
0 & 0 \\
1/10 & 1/10 \\
0 & 0 \\
2/5 & 0/5 \\
0 & 0 \\
1/100 & 3/100 \\
0 & 0 \\
0 & 0 \\
1/3 & 0/3
\end{pmatrix}
\end{array}
$$

Why do we need this?

Better understand co-occurrence of the data to define word vectors

Document retrieval: what else is important?

How to reduce the size of a matrix?

Singular Value Decomposition(SVD)

SVD in a nutshell

- factors the original matrix into 3 matrices
- uses the 3 matrices to create a low-rank approximation

Document retrieval: what else is important?

SVD: getting more concrete

- clusters words along a few hundred semantic dimensions
- obtains semantic dimensions from the co-occurrence data
- filters out the noise
- higher-order co-occurrence: similar words appear in similar context

Quick wrap-up

What did we learn so far?

- How to represent a document/a query/a sentence as a vector
- How to measure the similarity between vectors
- How to weight different contextual terms
- How to capture the co-occurrence
- How to reduce large matrices

Context

A narrow definition of similarity

Words are similar if they occur in the same context

~~Context = a set of documents~~

Context = one document, one (partial) sentence

Context

A narrow definition of similarity

Words are similar if they occur in the same context

~~Context = a set of documents~~

Context = one document, one (partial) sentence

A narrow definition of context

Problem: similar words usually do not appear together within one context

$\rightarrow$ shorten context to one word

Context: window method

Topical similarity

$$
\begin{array}{l}
 \\
automobile \\
car \\
soccer \\
football
\end{array}
\begin{array}{c}
\begin{array}{ccccccc} wheel & transport & passenger & tournament & London & goal & match \end{array} \\
\begin{pmatrix}
1 & 1 & 1 & 0 & 0 & 0 & 0 \\
1 & 2 & 1 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 1 \\
0 & 0 & 1 & 1 & 1 & 2 & 1
\end{pmatrix}
\end{array}
$$

Context: window method

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\end{array}
$$

$automobile\ .\ car = 4$

$automobile\ .\ soccer = 0$

$automobile\ .\ football = 1$

$car\ .\ soccer = 1$

$car\ .\ football = 2$

$soccer\ .\ football = 5$

Context: window method

What about synonyms?

- use only few words from both sides of the target as context
- use context words as basis vector
- vector coefficients = weighted co-occurrence frequencies of each context word within the window
- also consider the direction (on which side from the target word?)

Context: pre-processing

Part-of-Speech Tagging

Tag the context, consider syntactic relations $\rightarrow$ vectors contain separate counts for each relation

Lemmatization

lemmatize context words

Context: a fine-grained representation

target word - *goal*

PoS Tagging

Giggs|NNP *scored*|VBD *the*|DT *first*|JJ *goal*|NN *of*|IN *the*|DT *football*|NN *tournament*|NN *at*|IN *Wembley*|NNP ,|, *North*|NNP *London*|NNP .|.

Dependency relations

(ncmod _ *goal first*)
(det *goal the*)
(ncmod _ *tournament football*)
(det *tournament the*)
(ncmod _ *London North*)
(dobj *at Wembley*)
(ncmod _ *scored at*)
(dobj *of tournament*)
(ncmod _ *goal of*)
(dobj *scored goal*)
(ncsubj *scored Giggs* _)

Context: a fine-grained representation

target word - *goal*

Different contexts

Contextual elements for target word *goal* using a 7-word window method:
{*scored, the, first, of, football*}

Contextual elements with parts-of-speech:
{*scored*|VBD, *the*|DET, *first*|JJ, *of*|IN, *football*|NN}

Contextual elements with direction (L for left, R for right):
{*scored*|L, *the*|L, *first*|L, *of*|R, *the*|R, *football*|R}

Contextual elements with position (e.g. 1L is 1 word to the left):
{*scored*|3L, *the*|2L, *first*|1L, *of*|1R, *the*|2R, *football*|3R}

Contextual elements as grammatical relations:
{*first*|`ncmod`, *the*|`det`, *scored*|`dobj`}

Context: more fine-grained?...

Extend syntactic relations

- Create dependency paths
- Basis vectors = whole sequencies of syntactic relation between target and context

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Example

$\{\textit{first}|\textit{ncmod}, \textit{the}|\textit{det}, \textit{scored}|\textit{obj}, \textbf{Giggs}|\textbf{subj}\}$

Context: more fine-grained?...

Extend syntactic relations

- Create dependency paths
- Basis vectors = whole sequencies of syntactic relation between target and context

Example

{*first*|*ncmod*, *the*|*det*, *scored*|*obj*, **Giggs**|**subj**}

Problem

Data sparsity: too detailed representation → too small counts

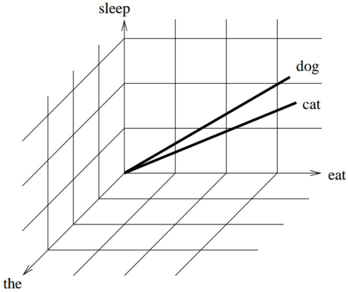
Weighting

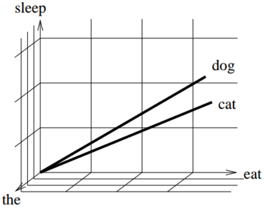
Not all basis vector are equally useful!

A simple approach

- Word frequency / number of document in which word occurs (remember *inverse document frequency (IDF)*?)
- Decrease the weight of highly frequent words

Weighting:IDF





Weighting

An issue with IDF

the same effect to all target words

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Why problematic?

we want to weight different words differently:

wear → jacket

~~wear → car~~

gasoline → car

wear → jacket

Weighting: collocations

The basic idea

Use collocation[a] statistics to discriminate between more and less useful context words

[a] a collocation is a sequence of words which co-occur more often than it would be expected by chance

- make use of parameters (e.g., collocation window)
- set the parameters empirically

Similarity

$$Sim(\vec{q}, \vec{d}) = \frac{\vec{q}.\vec{d}}{||\vec{q}|| \;\; ||\vec{d}||}$$
$$= \cos(\vec{q}, \vec{d})$$

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looks familiar?

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looks familiar?

do not forget the importance of normalization!

Corpus

Which corpus to use?

- depends on the application: web data, query logs, research paper, dictionaries, etc.
- popular: British National Corpus (BNC) $\approx$ 100 million words
- general rule: the more data, the better quality

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Efficient processing of very large corpora is a big issue in academia

An example output

Ranked synonyms

introduction: launch, implementation, advent, addition, adoption, arrival, absence, inclusion, creation, departure, availability, elimination, emergence, use, acceptance, abolition, array, passage, completion, announcement, ...

evaluation: assessment, examination, appraisal, review, audit, analysis, consultation, monitoring, testing, verification, counselling, screening, audits, consideration, inquiry, inspection, measurement, supervision, certification, checkup, ...

context: perspective, significance, framework, implication, regard, aspect, dimension, interpretation, meaning, nature, importance, consideration, focus, beginning, scope, continuation, relevance, emphasis, backdrop, subject, ...

similarity: resemblance, parallel, contrast, flaw, discrepancy, difference, affinity, aspect, correlation, variation, contradiction, distinction, divergence, commonality, disparity, characteristic, shortcoming, significance, clue, hall-mark, ...

An example output

What can we say about automatically extracted data?

- Not always correlates with the competence of humans
  advent for *introduction*
- Errors
  elimination $\neq$ *introduction*
- Decisions that are hard to explain
  array for *introduction*

Evaliuation

Intrinsic

- Compare against a manually created gold standard
- Disadvantage: some results can be marked as incorrect because of lack of coverage/errors
- Standard measure: precision (accuracy)
  How many synonyms for target words were found and ranked correctly?
- Example: 68% at rank 1 means that 68% top-ranked synonyms from the output were created and top-ranked in the gold standard

Evaliuation

Extrinsic

- Apply the output to a practical task
- Psycholinguistic experiments, crowdsourcing
- An example: semantic priming
- Higher similarity between word and related prime
- Correlation between similarity and reading time

Final wrap-up

Now we know how to...

- **Represent word meanings in vector space**
  Context = basis vectors which define space
  Words to describe = vectors in space

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- **Define context of a word**
  Sentence, few words, one word

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- **Represent word meanings in vector space**
  Context = basis vectors which define space
  Words to describe = vectors in space
- **Define context of a word**
  Sentence, few words, one word
- **Weight context words**
  IDF, collocation statistics

Final wrap-up

Now we know how to...

Measure similarity of vectors

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Conduct experiments

Define corpus, application, etc.

Special features of the data obtained from corpora automatically

Final wrap-up

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Conduct experiments

Define corpus, application, etc.

Special features of the data obtained from corpora automatically

Evaluate experiments' results

Intrinsic vs. extrinsic, precision

Final wrap-up

We also learned that...

Vector models' design depends on the application

e.g., lexical realtions can help in a search engine

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Defining context might be complicated

...and also depends on the application

Final wrap-up

We also learned that...

Vector models' design depends on the application
e.g., lexical realtions can help in a search engine

Defining context might be complicated
...and also depends on the application

We can use differently fine-grained methods to define context
Window method (directed and undirected)
Syntactic relations (PoS tags, dependency relations)

Final wrap-up

Moreover...

Vector representation of word meanings help to extact lexical realtions

synonymy, antonymy, hyponymy, etc.

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Vector representation of word meanings help to extact lexical realtions

synonymy, antonymy, hyponymy, etc.

We can go into details

...see references

Final wrap-up

Finally...

We learnt more about distributional models in computational semantics!

References

- Clark, Stephen (2015), Vector Space Models of Lexical Meaning. Handbook of Contemporary Semantic Theory — second edition, edited by Shalom Lappin and Chris Fox. Chapter 16, pp.493-522. Wiley-Blackwell.
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Thanks for your attention!

Questions?