Natural Language Processing (CSEP 517): Distributional Semantics

Roy Schwartz

University of Washington
roysch@cs.washington.edu

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To-Do List

- Read: (Jurafsky and Martin, 2016a,b)

Distributional Semantics Models

Aka, Vector Space Models, **Word Embeddings**

$$\mathbf{v}_{\text{mountain}} = \begin{pmatrix} 0.23 \\ \text{-}0.21 \\ 0.15 \\ 0.61 \\ \vdots \\ 0.02 \\ \text{-}0.12 \end{pmatrix}, \mathbf{v}_{\text{lion}} = \begin{pmatrix} 0.72 \\ 0.2 \\ 0.71 \\ 0.13 \\ \vdots \\ \text{-}0.1 \\ \text{-}0.11 \end{pmatrix}$$

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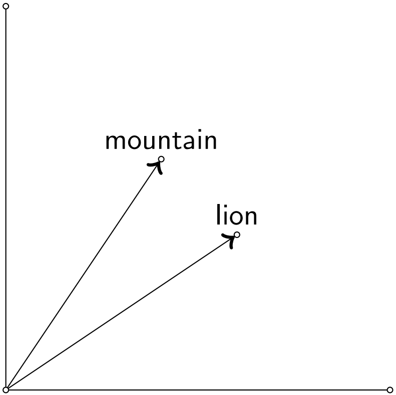

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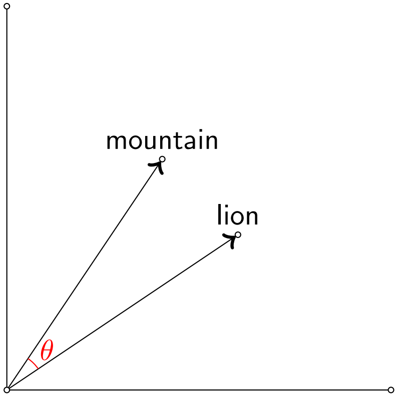

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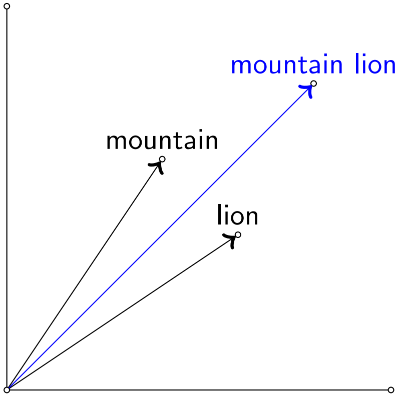

Distributional Semantics Models

Aka, Vector Space Models, **Word Embeddings**

Applications

Deep learning models:
Machine Translation
Question Answering
Syntactic Parsing
...

Linguistic Study

Lexical Semantics
Multilingual Studies
Evolution of Language
...

Outline

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Distributional Semantics Hypothesis

Harris (1954)

Words that have similar contexts are likely to have similar meaning

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Vector Space Models

- Representation of words by vectors of real numbers
- $\forall w \in \mathcal{V}, \mathbf{v}_w$ is function of the contexts in which w occurs
- Vectors are computed using a large text corpus
  - No requirement for any sort of annotation in the general case

$V_{1.0}$: Count Models

Salton (1971)

- Each element $\mathbf{v}_{w_i} \in \mathbf{v}_w$ represents the co-occurrence of w with another word i
  - $\mathbf{v}_{\text{dog}} =$ (cat: 10, leash: 15, loyal: 27, bone: 8, piano: 0, cloud: 0, ...)
- Vector dimension is typically very large (vocabulary size)
- Main motivation: lexical semantics

Count Models

Example

$$\mathbf{v}_{\mathsf{dog}} = \begin{pmatrix} 0 \\ 0 \\ 15 \\ 17 \\ \vdots \\ 0 \\ 102 \end{pmatrix}, \mathbf{v}_{\mathsf{cat}} = \begin{pmatrix} 0 \\ 2 \\ 11 \\ 13 \\ \vdots \\ 20 \\ 11 \end{pmatrix}$$

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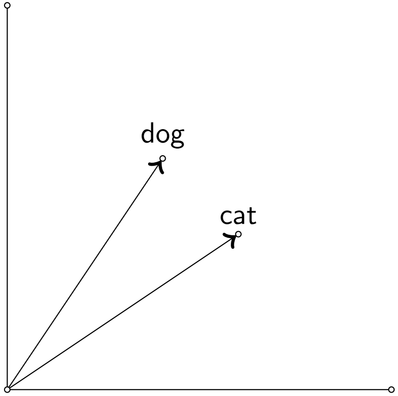

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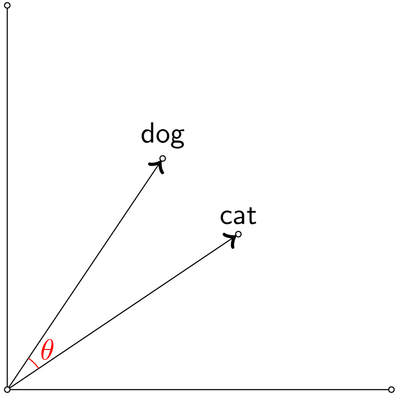

Variants of Count Models

- Reduce the effect of high frequency words by applying a weighting scheme
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  - Pointwise mutual information (PMI), TF-IDF
- Smoothing by dimensionality reduction
  - Singular value decomposition (SVD), principal component analysis (PCA), matrix factorization methods
- What is a context?
  - Bag-of-words context, document context (Latent Semantic Analysis (LSA)), dependency contexts, pattern contexts

Outline

Vector Space Models

Lexical Semantic Applications

Word Embeddings

Compositionality

Current Research Problems

Vector Space Models

Evaluation

- Vector space models as features
  - Synonym detection
    - TOEFL (Landauer and Dumais, 1997)
  - Word clustering
    - CLUTO (Karypis, 2002)

Vector Space Models

Evaluation

- Vector space models as features
  - Synonym detection
    - TOEFL (Landauer and Dumais, 1997)
  - Word clustering
    - CLUTO (Karypis, 2002)
- Vector operations
  - Semantic Similarity
    - RG-65 (Rubenstein and Goodenough, 1965), wordsim353 (Finkelstein et al., 2001), MEN (Bruni et al., 2014), SimLex999 (Hill et al., 2015)
  - Word Analogies
    - Mikolov et al. (2013)

Semantic Similarity

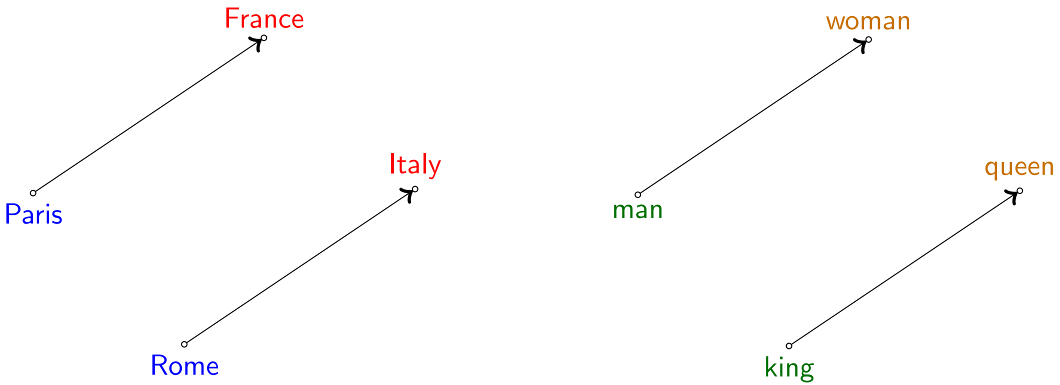
w_1	w_2	human score	model score
tiger	cat	7.35	0.8
computer	keyboard	7.62	0.54
...	...	...	...
architecture	century	3.78	0.03
book	paper	7.46	0.66
king	cabbage	0.23	-0.42

Table: Human scores taken from wordsim353 (Finkelstein et al., 2001)

- Model scores are cosine similarity scores between vectors
- Model's performance is the Spearman/Pearson correlation between human ranking and model ranking

Word Analogy

Mikolov et al. (2013)



Outline

$V_{2.0}$: Predict Models

(Aka Word Embeddings)

- A new generation of vector space models
- Instead of representing vectors as cooccurrence counts, train a supervised machine learning algorithm to predict $p(\text{word}|\text{context})$
- Models learn a latent vector representation of each word
  - These representations turn out to be quite effective vector space representations
  - *Word embeddings*

Word Embeddings

- Vector size is typically a few dozens to a few hundreds
- Vector elements are generally uninterpretable
- Developed to initialize feature vectors in deep learning models
  - Initially language models, nowadays virtually every sequence level NLP task
  - Bengio et al. (2003); Collobert and Weston (2008); Collobert et al. (2011); word2vec (Mikolov et al., 2013); GloVe (Pennington et al., 2014)

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word2vec

Mikolov et al. (2013)

- A software toolkit for running various word embedding algorithms

Based on (Goldberg and Levy, 2014)

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- Continuous bag-of-words: $\underset{\theta}{\operatorname{argmax}} \prod_{w \in \text{corpus}} p(w|C(w);\theta)$

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- Skip-gram: $\underset{\theta}{\operatorname{argmax}} \prod_{(w,c) \in \text{corpus}} p(c|w;\theta)$
- Negative sampling: randomly sample **negative** (*word,context*) pairs, then:

$$\underset{\theta}{\operatorname{argmax}} \prod_{(w,c) \in \text{corpus}} p(c|w;\theta) \cdot \prod_{(w,c')} (1 - p(c'|w;\theta))$$

Based on (Goldberg and Levy, 2014)

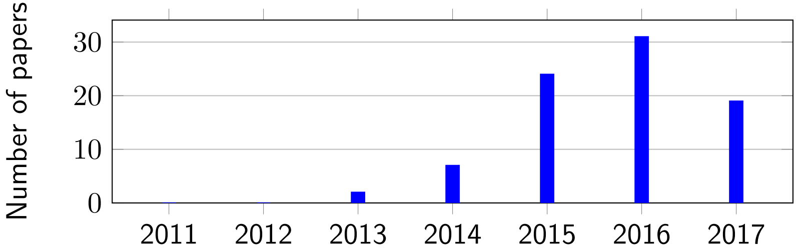
Skip-gram with Negative Sampling (SGNS)

- Obtained significant improvements on a range of lexical semantic tasks
- Is very fast to train, even on large corpora
- Nowadays, by far the most popular word embedding approach[1]

[1] Along with GloVe (Pennington et al., 2014)

Embeddings in ACL

Number of Papers in ACL Containing the Word “Embedding”



Count vs. Predict

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- So?...
  It's all about *hyper-parameter* (Levy et al., 2015)
- The bottom line:
  word2vec and GloVe are very good *implementations*

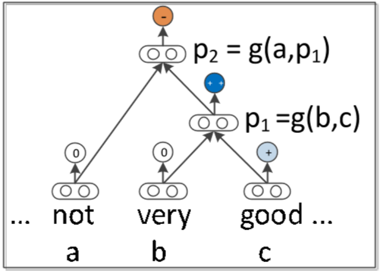
Outline

Compositionality

- Basic approach: average / weighted average
  - $\mathbf{v}_{\text{good}} + \mathbf{v}_{\text{day}} = \mathbf{v}_{\text{good day}}$

Compositionality

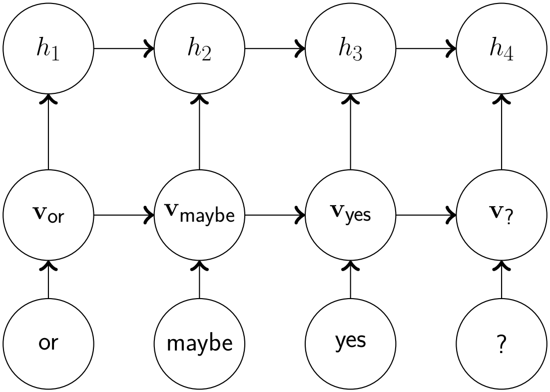
Recursive Neural Networks (Goller and Kuchler, 1996)



Picture taken from Socher et al. (2013)

Compositionality

Recurrent Neural Networks (Elman, 1990)



Recurrent Neural Networks

- In recent years, the most common method to represent sequence of texts is using RNNs
  - In particular, long short-term memory (LSTM, Hochreiter and Schmidhuber (1997)) and gated recurrent unit (GRU, Cho et al. (2014))

Recurrent Neural Networks

- In recent years, the most common method to represent sequence of texts is using RNNs
  - In particular, long short-term memory (LSTM, Hochreiter and Schmidhuber (1997)) and gated recurrent unit (GRU, Cho et al. (2014))
- Very recently, state-of-the-art models on tasks such as semantic role labeling and coreference resolution stated to rely solely on deep networks with word embeddings and LSTM layers (He et al., 2017)
  - These tasks traditionally relied on syntactic information
  - Many of these results come from the UW NLP group

Word Embeddings in RNNs

- Pre-trained embeddings (fixed or tuned)
- Random initialization
- A concatenation of both types

Alternatives to Word Embeddings

- Character embeddings
  - Machine translation (Ling et al., 2015)
  - Syntactic parsing (Ballesteros et al., 2015)
- Character n-grams (Neubig et al., 2013; Schütze, 2017)
- POS tag embeddings (Dyer et al., 2015)

Outline

50 Shades of Similarity

- What is *similarity*?
  - Synonymy: high — tall
  - Co-hyponymy: dog — cat
  - Association: coffee — cup
  - Dissimilarity: good — bad
  - Attributional similarity: banana — the sun (both are yellow)
  - Morphological similarity: going — crying (same verb tense)
  - Schwartz et al. (2015); Rubinstein et al. (2015); Cotterell et al. (2016)
- Definition is *application dependent*

What is a context?

- Most word embeddings rely on bag-of-word contexts
  - Which capture general word association
- Other options exists
  - Dependency links (Padó and Lapata, 2007)
  - Symmetric patterns (e.g., "X and Y", Schwartz et al. (2015, 2016))
  - Substitute vectors (Yatbaz et al., 2012)
  - Morphemes (Cotterell et al., 2016)
- Different context types translate to different relations between similar vectors

External Resources

- Guide vectors towards desired flavor of similarity
- Use dictionaries and/or thesauri
  - Part of the model (Yu and Dredze, 2014; Kiela et al., 2015)
  - Post-processing (Faruqui et al., 2015; Mrkšić et al., 2016)
- Multimodal embeddings

Multimodal Embeddings

- Combination of textual representation and perceptual representation
  - Most prominently visual
- Most approaches combine both types of vectors using methods such as canonical correlation analysis (CCA, e.g., Gella et al. (2016))
- The resulting embeddings often improve performance compared to text-only embeddings
  - They are also able to capture visual attributes such as size and color, which are often not captured by text only methods (Rubinstein et al., 2015)

Multilingual Embeddings

- Mapping embeddings in different languages into the same space
  - $\mathbf{v}_{\text{dog}} \sim \mathbf{v}_{\text{perro}}$
- Useful for multi-lingual tasks, as well as low-resource scenarios
- Most approaches use bilingual dictionaries or parallel corpora
- Recent approaches use more creative knowledge sources such as geospatial contexts (Cocos and Callison-Burch, 2017) and sentences ids in a parallel corpus (Levy et al., 2017)

Summary

- Distributional semantic models (aka *vector space models, word embeddings*) represent words using vectors of real numbers
- These methods are able to capture lexical semantics such as similarity and association
- They also serve as a fundamental building block in virtually all deep learning models in NLP
- Despite decades of research, many questions remain open

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Thank you!

Roy Schwartz `homes.cs.washington.edu/~roysch/` roysch@cs.washington.edu

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