Vector-based Models of Semantic Composition

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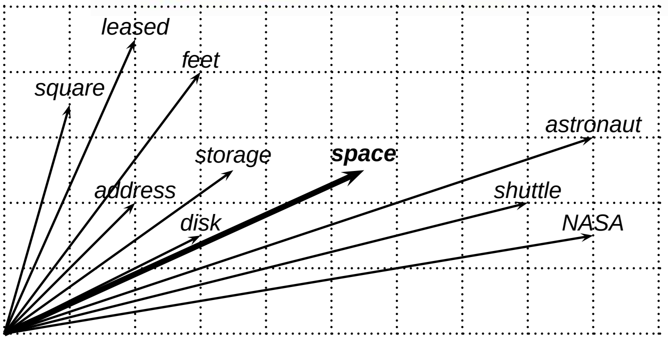
Outline

Distributional Hypothesis

You shall know a word by the company it keeps (Firth, 1957).

- A word's context provides information about its meaning.
- Words are similar if they share similar linguistic contexts.
- Distributional vs. semantic similarity.



A Simple Semantic Space

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- Five word context window each side of the target word.

A Simple Semantic Space

	vice	president	interests	insurance	...
company	1	1	1	1	...

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A Simple Semantic Space

	vice	president	tax	interests	...
company	25	103	19	55	...

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A Simple Semantic Space

	vice	president	tax	interests	...
company	0.06	0.26	0.05	0.14	...

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- Convert counts to probabilities: $p(c|w)$.

A Simple Semantic Space

	vice	president	tax	interests	...
company	1.52	2.32	1.14	1.06	...

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- Five word context window each side of the target word.
- Convert counts to probabilities: $p(c|w)$.
- Divide through by probabilities of each context word: $\frac{p(c|w)}{p(c)}$.
- Cosine similarity: $sim(\mathbf{w}_1, \mathbf{w}_2) = \frac{\mathbf{w}_1 \cdot \mathbf{w}_2}{|\mathbf{w}_1||\mathbf{w}_2|}$.

An Alternative: Topic Models

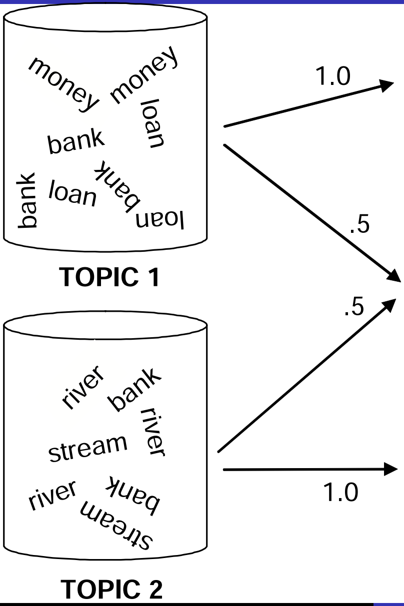
Key Idea: documents are mixtures of topics, topics are probability distributions over words (Blei et al., 2003; Griffiths and Steyvers, 2002; 2003; 2004).

Topic models are generative and structured. For a new document:

1. Choose a distribution over topics
2. Choose a topic at random according to distribution
3. draw a word from that topic

Statistical techniques used to invert the process: infer set of topics that were responsible for generating a collection of documents.

Probabilistic Generative Process

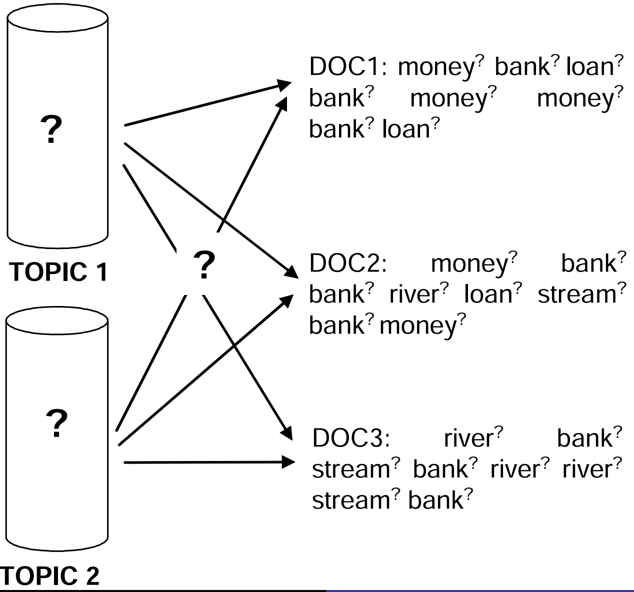


DOC1: money^1 bank^1 loan^1 bank^1 money^1 money^1 bank^1 loan^1

DOC2: money^1 bank^1 bank^2 river^2 loan^1 stream^2 bank^1 money^1

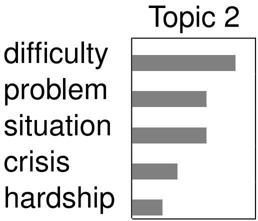
DOC3: river^2 bank^2 stream^2 bank^2 river^2 river^2 stream^2 bank^2

Statistical Inference



Meaning Representation

	Topic 1	Topic 2	Topic n
practical	0.39	0.02	...
difficulty	0.03	0.44	...
produce	0.06	0.17	...



- Topics are the dimensions of the space (500, 1000)
- Vector components: probability of word given topic
- Topics correspond to coarse-grained sense distinctions
- Cosine similarity can be used (probabilistic alternatives)

Semantic Space Models

Semantic space models are extremely popular across disciplines!

- Semantic Priming (Lund and Burgess, 1996)
- Text comprehension (Landauer and Dumais, 1997)
- Word association (McDonald, 2000)
- Information Retrieval (Salton et al., 1975)
- Thesaurus extraction (Grefenstette, 1994)
- Word Sense disambiguation (Schütze, 1998)
- Text Segmentation (Hirst, 1997)
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Catch: representation of the meaning of **single words**. What about **phrases** or **sentences**?

Quick Fix

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That day the office manager, who was drinking, hit the problem sales worker with the bottle, but it was not serious.

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- Add a neighbor to the sum: $\mathbf{p} = \mathbf{u} + \mathbf{v} + \mathbf{n}$ (Kintsch, 2001); **meaning of predicate depends on its argument**

Logic-based View

Meaning of whole is function of meaning of its parts (Frege, 1957).

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$$\begin{array}{ccc} \textbf{a} & \textbf{horse} & \textbf{ran} \\ \downarrow & \downarrow & \downarrow \\ \lambda u.\lambda v.\exists x(u@x \wedge v@x) & \lambda y.HORSE(y) & \lambda z.RUN(z) \end{array}$$

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$$\begin{tikzcd}
\textbf{a} \arrow[d] & \textbf{horse} \arrow[d] & \textbf{ran} \arrow[d] \\
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$$\exists x(HORSE(x) \wedge RUN(x))$$

- Logic can account for sentential meaning (Montague, 1974).
- Differences in meaning are **qualitative** rather than **quantitative**.
- Cannot express **degrees of similarity**.

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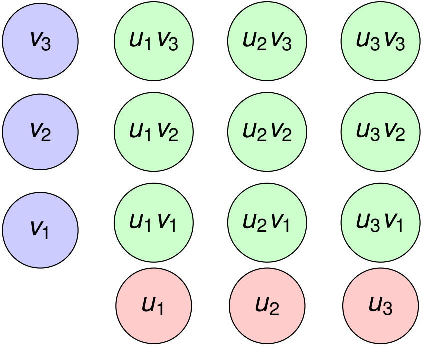
Pinker (1994): composition of simple elements must allow the construction of **novel meanings** which go beyond those of the individual elements.

Connectionism



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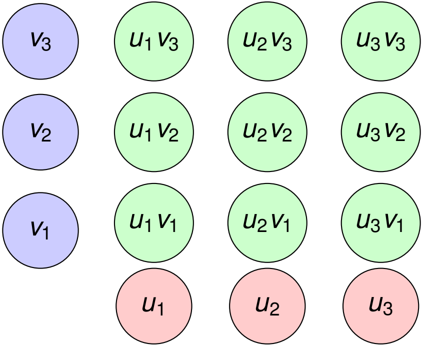

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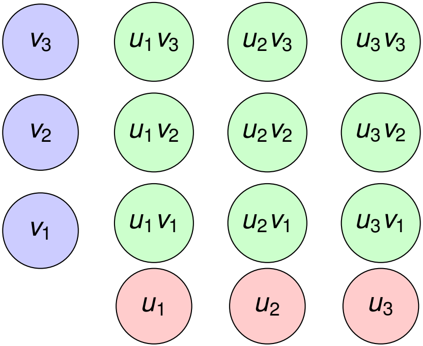

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- Spatter codes: take the XOR of two vectors (Kanerva, 1998); **components are random bits**

A Framework for Semantic Composition

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Assumptions:

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5. $f()$ is a linear function of tensor product (**multiplicative model**)

Models

Additive Models

$$\mathbf{p} = \mathbf{A}\mathbf{u} + \mathbf{B}\mathbf{v}$$

Instances

$$\mathbf{p} = \mathbf{u} + \mathbf{v}$$

$$\mathbf{p} = \mathbf{u} + \mathbf{v} + \sum_i \mathbf{n}_i$$

$$\mathbf{p} = \alpha\mathbf{u} + \beta\mathbf{v}$$

$$\mathbf{p} = \mathbf{v}$$

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	music	solution	economy	craft	create
practical	0	6	2	10	4
difficulty	1	8	4	4	0
problem	2	15	7	9	1

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Multiplicative Models

$$\mathbf{p} = \mathbf{C}\mathbf{u}\mathbf{v}$$

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$$\mathbf{p} = \mathbf{u} \odot \mathbf{v}$$
$$p_i = u_i v_i$$

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$$p_{i,j} = u_i \cdot v_j$$

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$$\textbf{practical} \otimes \textbf{difficulty} = \begin{matrix} 0 & 0 & 0 & 0 & 0 \\ 6 & 48 & 24 & 24 & 0 \\ 2 & 16 & 8 & 8 & 0 \\ 10 & 80 & 40 & 40 & 0 \\ 4 & 32 & 16 & 16 & 0 \end{matrix}$$

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$\textbf{practical} \circledast \textbf{difficulty} = [116\ 50\ 66\ 62\ 80]$

Models

Dilation Models

$$\mathbf{p} = \mathbf{C}\mathbf{u}\mathbf{v} = \mathbf{U}\mathbf{v}$$
$$U_{ij} = 0, U_{ii} = u_i$$

$$\mathbf{x} = \frac{\mathbf{u}\cdot\mathbf{v}}{\mathbf{u}\cdot\mathbf{u}}\mathbf{u} \qquad \mathbf{y} = \mathbf{v} - \mathbf{x} = \mathbf{v} - \frac{\mathbf{u}\cdot\mathbf{v}}{\mathbf{u}\cdot\mathbf{u}}\mathbf{u}$$

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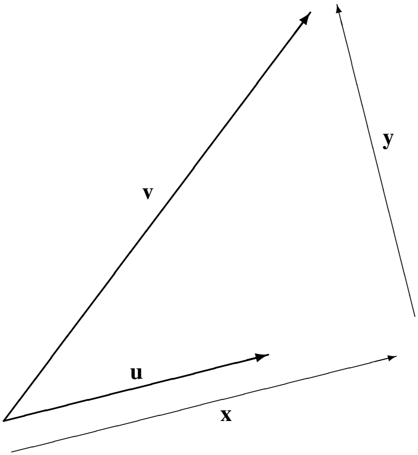

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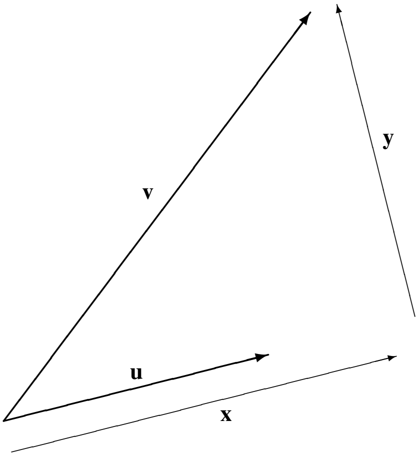

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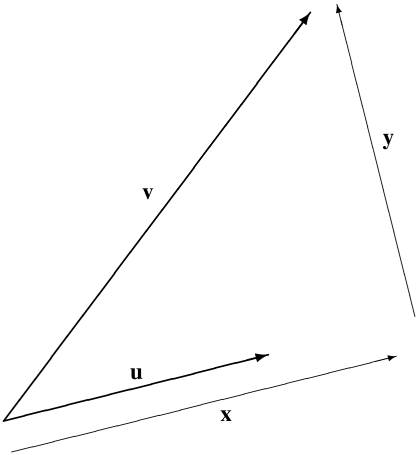

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Originally proposed in Kintsch (2002):

- Elicit similarity judgments for adjective-noun, noun-noun, verb-object combinations.
- Phrase pairs from three bands: High, Medium, Low.
- Compute vectors for phrases, measure their similarity.
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- Correlate model similarities with human ratings.

	High	**Medium**	**Low**
old person	elderly lady	right hand	small house
kitchen door	bedroom window	office worker	housing department
produce effect			

Phrase Similarity Task

Originally proposed in Kintsch (2002):

- Elicit similarity judgments for adjective-noun, noun-noun, verb-object combinations.
- Phrase pairs from three bands: High, Medium, Low.
- Compute vectors for phrases, measure their similarity.
- Correlate model similarities with human ratings.

	High	**Medium**	**Low**
old person	elderly lady	right hand	small house
kitchen door	bedroom window	office worker	housing department
produce effect	achieve result	consider matter	start work

Experimental Setup

Similarity Ratings

- 36 pairs (adj-noun, noun-noun, verb-noun) $\times$ 3 bands (324 pairs in total, created automatically, substitutability test)
- Ratings collected using Webexp (90 participants)
- Participants use 7-point similarity scale

Semantic Space

- Compare simple semantic space against LDA topic model (Blei et al. 2003)
- 2000 dimensions vs 100 topics, using cosine similarity measure
- Parameters for composition models tuned on dev set

Results (for verb-obj)

Model	Simple	LDA
Additive	0.30	0.40
Kintsch	0.29	0.33
Weighted Additive	0.34	0.40
Multiplicative	0.37	0.34
Tensor Product	0.33	0.33
Circular Convolution	0.10	0.12
Dilation	0.38	0.41
Head Only	0.24	0.17
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- Multiplicative and dilation models best for simple space
- Dilation and Additive models best for LDA model
- Circular convolution is worst performing model

Interim Summary

- General framework of semantic composition
- Different composition functions appropriate for different representations (additive vs. multiplicative)
- Dilation models overall best, syntax sensitive, parametric
- Results generalize to noun-noun, adj-noun, verb-obj combinations

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Modeling Brain Activity

Tom Mitchell and collaborators
Wang et al., 2003; Mitchell et al., 2004; Mitchell et al., 2008; Hutchinson et al., 2009; Chang et al., 2009; Rustandi, 2009

- Can we observe differences in neural activity as people think about different concepts?
- Can we use vector-based models to explain observed neural activity?

Functional MRI

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Monitors brain activity when people comprehend words or phrases.

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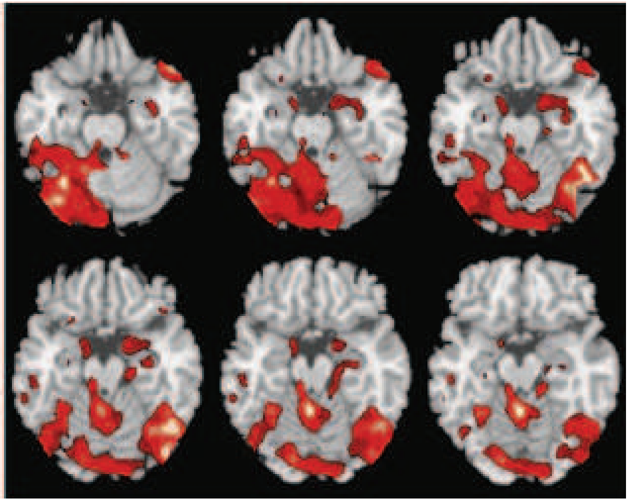
Monitors brain activity when people comprehend words or phrases.
Measures changes related to blood flow and blood oxygenation.

Functional MRI



soft bear

strong dog

Chang et al. (ACL, 2009)

- Participants see adjective-noun phrases
- Adjectives emphasize semantic properties of nouns
- Use vector-based models to account for variance in neural activity.
- Train regression model to fit activation profile of stimuli
- Multiplicative model outperforms non-compositional and additive model.

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Language Modeling

What is the next word?

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He is now president and chief operating

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'chief operating' is followed by 'officer' 99% of the time.

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'of the' is very frequent but not very predictive.

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What is the next word?

He is now president and chief operating officer of the company.

Given semantic representations for ‘president’, ‘chief’, ‘operating’ and ‘officer’ how do we combine them to make the most predictive representation of this history?

Language Modeling

- Use vector composition in a language model as a way of capturing long-range dependencies.
- Not a new idea: Bellegarda (2000), Coccaro & Jurafsky (1998), Gildea & Hofmann (1999), Deng and Khundapur (2003)
- How to combine vectors? How to construct them?
- Focus on multiplicative and additive models.

A Language Model Based on Vector Composition

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$p(company|president, chief, operating, officer)$

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$\mathbf{h}_n = f(\mathbf{w}_n, \mathbf{h}_{n-1})$
$\mathbf{h}_1 = \mathbf{w}_1$

Experimental Setup

- BLLIP Corpus
  - Training set - 38M words
  - Development set - 50K words
  - Test set - 50K words
- Numbers replaced with <NUM>
- Vocabulary of 20K word types
- Others replaced with <UNK>
- Perplexity of model predictions on test set
- Compare simple semantic space against LDA topic model

Integrating with an Ngram model

Linear interpolation

- $\lambda p_1(w) + (1 - \lambda) p_2(w)$
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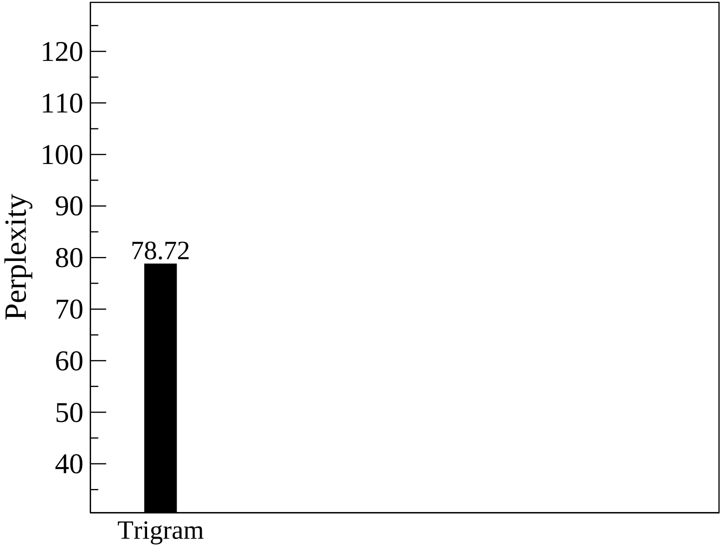
Perplexities



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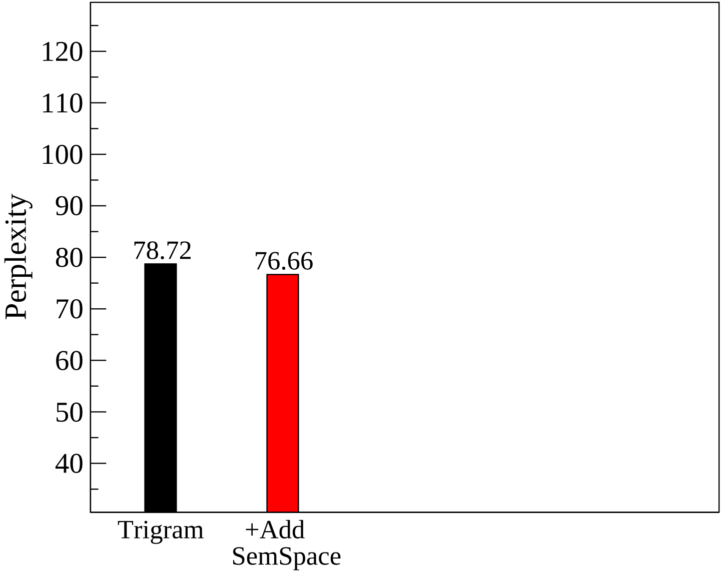

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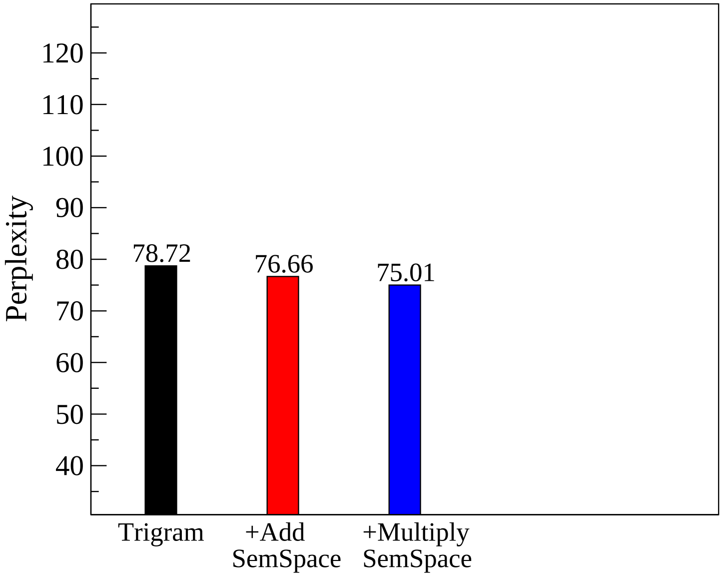

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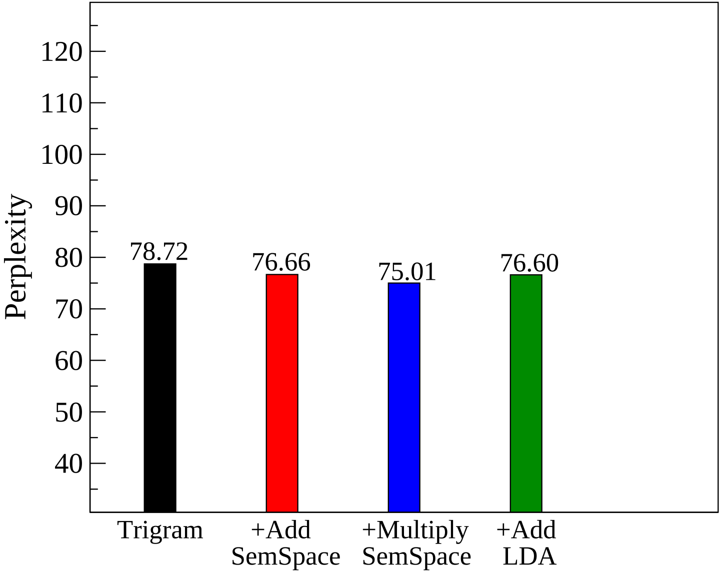

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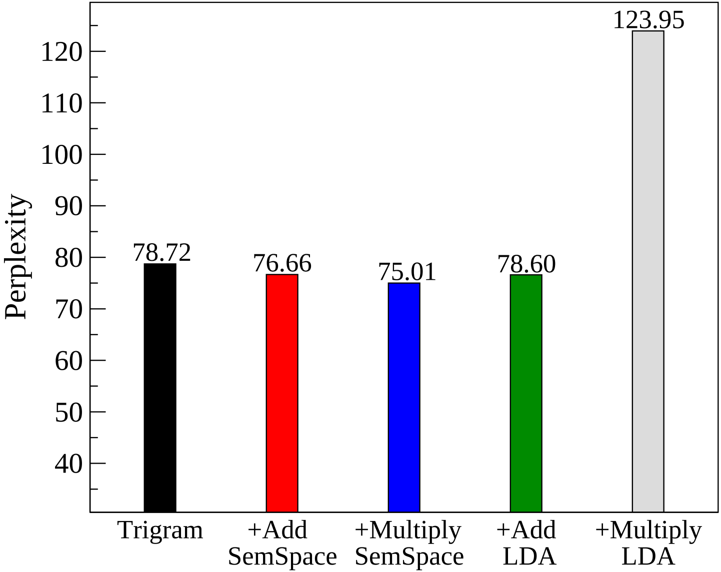

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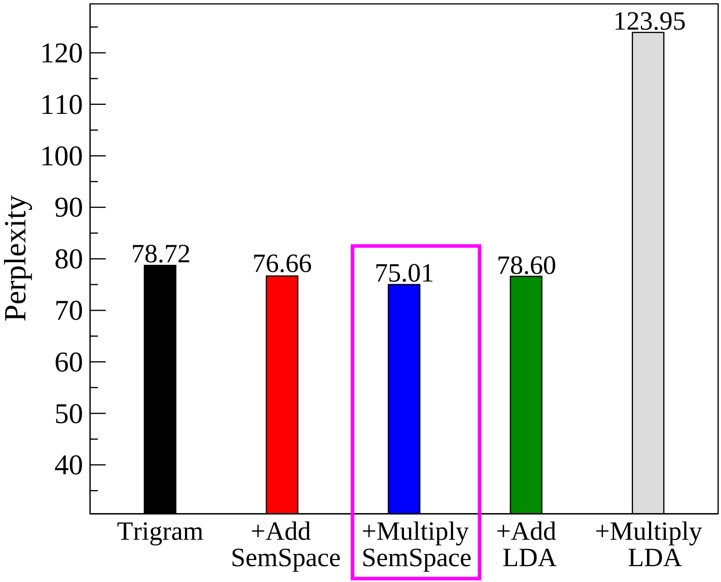
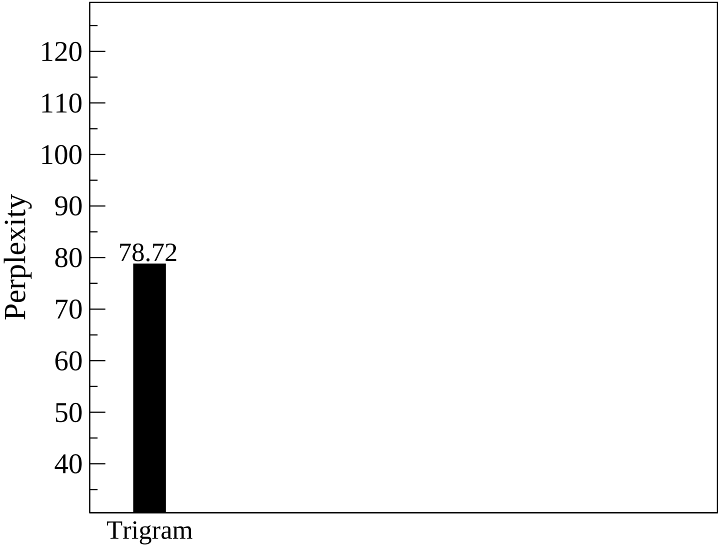


Comparison to Parsing

- Model incorporates semantic dependencies into a trigram model.
- Increases the probability of upcoming words which are semantically similar to the history.
- Syntactic information also captures long-range dependencies.
- Language models based on syntactic structure.
- Interpolate composition models with Roark's (2001) parser.

Perplexities



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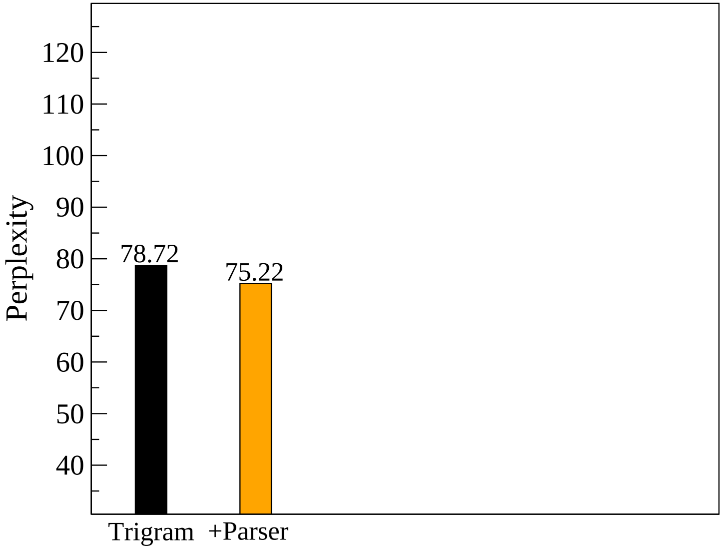

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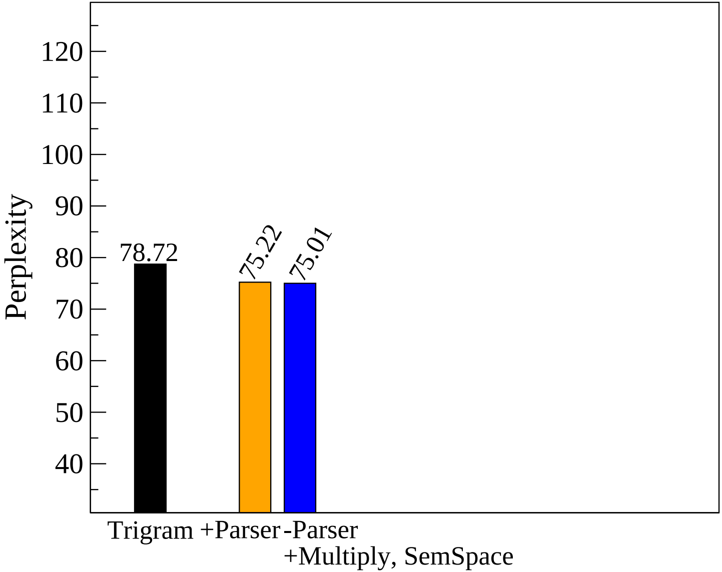

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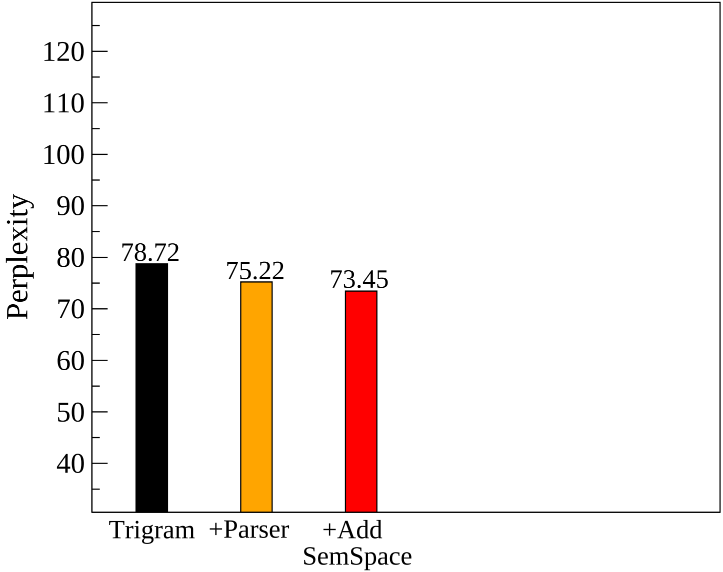

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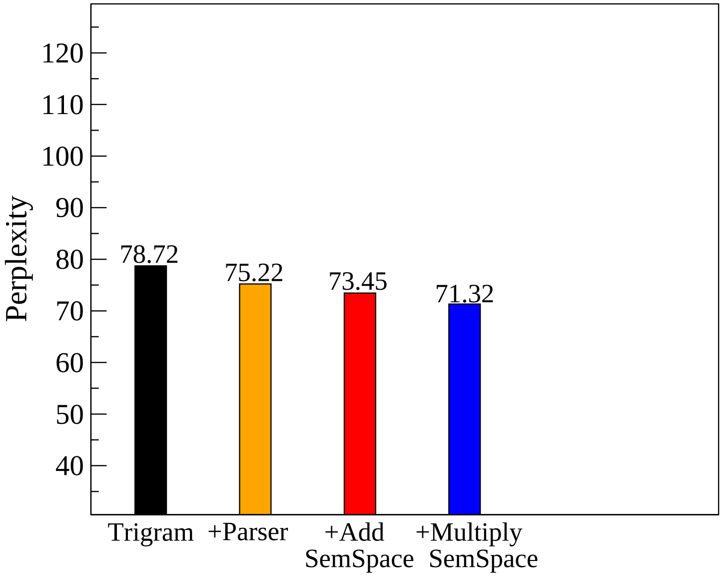

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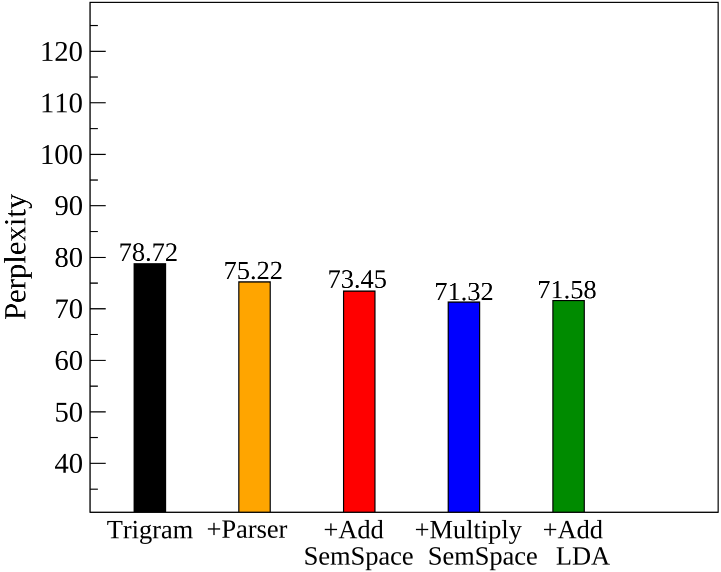

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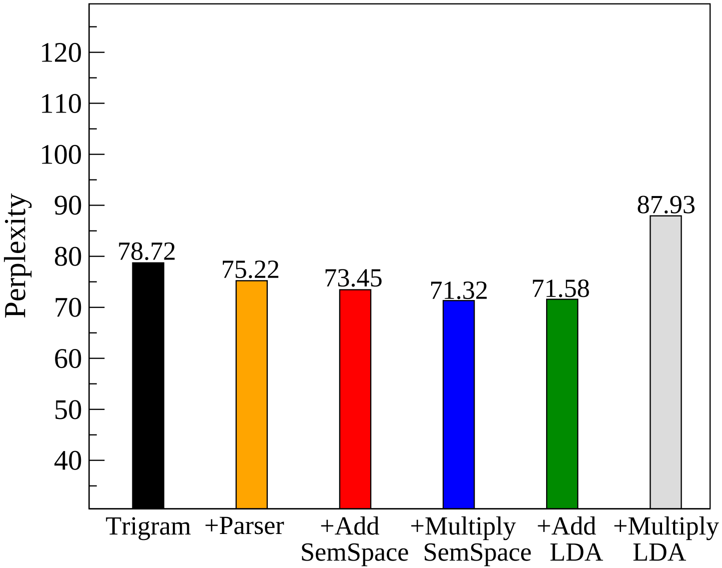

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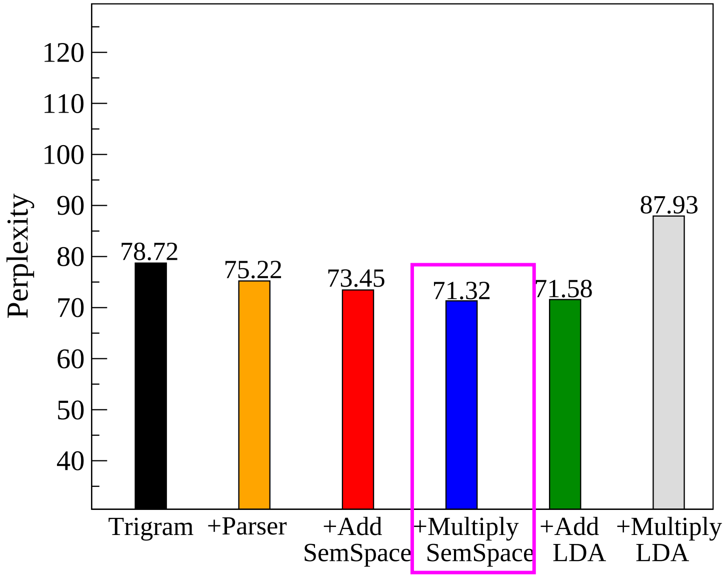


Conclusions

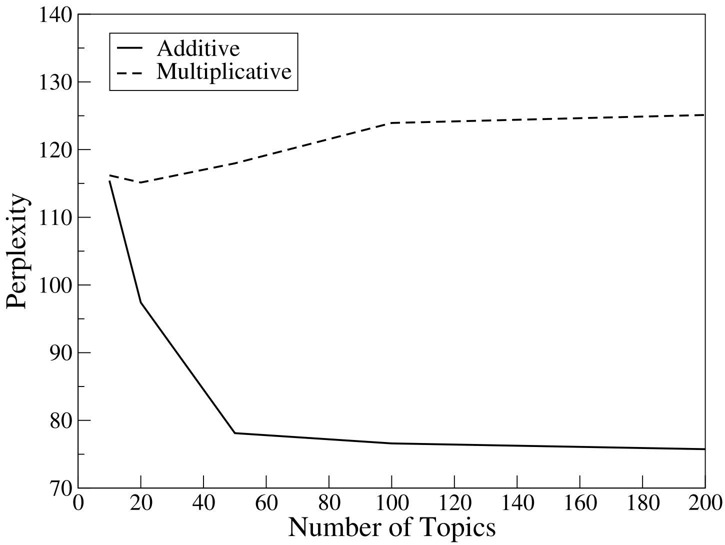
Work so far

- Vector composition for phrase similarity and language modeling
- Compared a simple semantic space to LDA
- Different composition functions appropriate for each model
- Semantic dependencies complementary to syntactic ones
- Cognitive Science (to appear), ACL 2008, EMNLP 2009.

Future work

- Incorporate syntax into composition (parser that outputs a compositional vector-based representation of a sentence)
- Optimize vectors and composition function on specific tasks

LDA Topics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