What analogies reveal about word vectors and their compositionality

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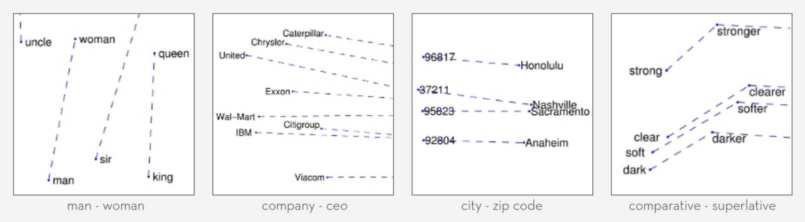
By modeling word meanings with co-occurrence statistics, we unlock linear algebra as a tool for linguistic computation.

- Cosine similarity and human judgments
- Average, add, subtract meaning between words
- Lexical $\rightarrow$ compositional?

Analogy questions

$$dog : puppy :: cat : ?$$

$$w_2 - w_1 \approx w_4 - w_3$$



Pennington *et al.*, https://nlp.stanford.edu/projects/glove/

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$$w_4 \approx w_3 + w_2 - w_1$$

$$\textit{dog} : \textit{puppy} :: \textit{cat} : \textit{?}$$

$$\begin{array}{lcl} \text{cat} + \text{puppy} - \text{dog} & \approx & \text{kitten} \\ & & \text{puppies} \\ & & \text{pet} \\ & & \text{beagle} \\ & & \quad\vdots \\ & & \text{angiography} \end{array}$$

Prior results

Given the simplicity of the solving method, surprisingly high accuracy for some types of analogy questions.

The most-used test set is probably the Google set (distributed with `word2vec`).

- Rather low diversity of categories—mostly geography and inflection
- Results often reported on "syntactic" and "semantic" subsets; this division is too coarse to be useful

Word similarity

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$$\text{hypothesis} = \text{sailboat} + \text{horses} - \text{horse} \approx \text{sailboat (!)}$$

Goal

We designed a study that:

1. addresses a wide variety of categories, and
2. controls for prior similarity.

We want to **describe** and **explain** inter-category differences.

Vectors

- `word2vec`
- Wikipedia
- no case or punctuation
- $d = 200$, CBOW

(Also experimented with GloVe, skip-gram, etc.)

Test sets

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Microsoft Research (Mikolov *et al.*, 2013a): inflectional relationships

- *cheap* : *cheaper* :: *mighty* : *mightier*
- *learn* : *learned* :: *think* : *thought*

  (etc.)

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Google (`word2vec`; Mikolov *et al.*, 2013b): adds “semantic” categories

- *paris* : *france* :: *havana* : *cuba*
- *austin* : *texas* :: *minneapolis* : *minnesota*
- *king* : *queen* :: *man* : *woman*

  (etc.)

Test sets

Better Analogy Test Set (BATS; Gladkova *et al.*, 2016): more derivational and semantic categories

- *helpful* : *helpfulness* :: *righteous* : *righteousness*
- *bottle* : *glass* :: *clothing* : *fabric*

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SemEval 2012 (Jurgens *et al.*, 2012): many, many more semantic categories

- *candy* : *sweet* :: *snow* : *cold*
- *boy* : *man* :: *gosling* : *goose*
- *bar* : *drinking* :: *church* : *worship*

(etc.)

Test sets

Source	Categories	Analogies
Microsoft Research	14	7,000
Google (`word2vec`)	14	19,544
BATS	40	95,625
SemEval2012	79	30,082
Total	147	152,251

Table 1: Summary of test data sources.

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Measure the **rank** of the correct answer in the entire vocabulary, ordered by similarity to hypothesis vector.
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Reciprocal of rank (RR) is more sensitive and forgiving than accuracy:

rank	acc	RR
1	1	1
2	0	.5
3	0	.3333
4	0	.25
⋮	⋮	⋮
10526	0	.0001

Metrics: Baseline

hypothesis vector := w_2 or w_3, whichever is better

walk : *walked* :: ***fly*** : *flew*

banana : ***yellow*** :: *cherry* : *red*

- (w_3 is better than w_2 in about 85% of cases)

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$walk : walked :: \boldsymbol{fly} : flew$

$banana : \boldsymbol{yellow} :: cherry : red$

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For each category of analogy questions, measure:

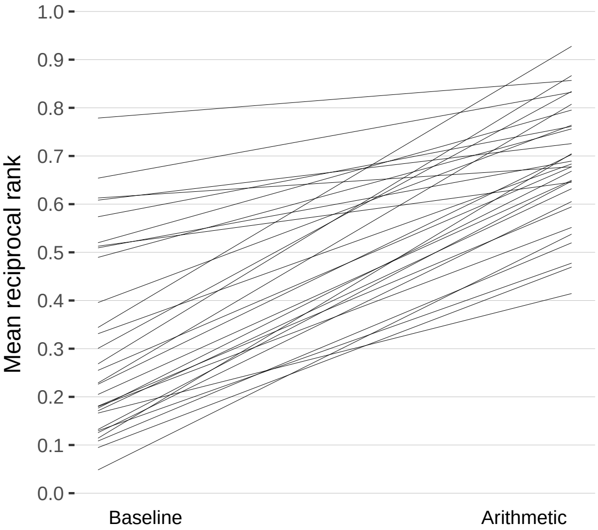
- mean RR using vector arithmetic hypothesis,
- mean RR of the baseline hypothesis,
- the difference between them.

Analogy supercategories

We have 147 distinct categories of analogical relationships.
For visualization and analysis, consider supercategories:

- **inflection:** inflectional morphological relationships (noun plural, adjective degree, verb tense)
- **derivation:** derivational morphology (*-tion*, *un-*)
- **named entity semantics:** meanings of words with a single real-world referent (*Vancouver, Beethoven*)
- **lexical semantics:** meanings of common nouns, adjectives, verbs, etc.

Results: Inflection



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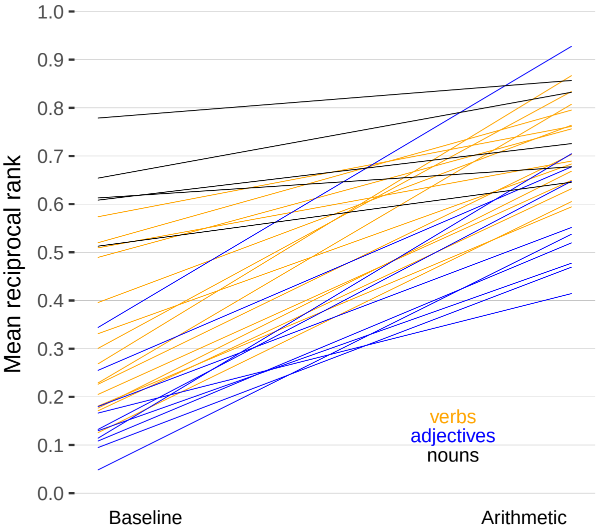

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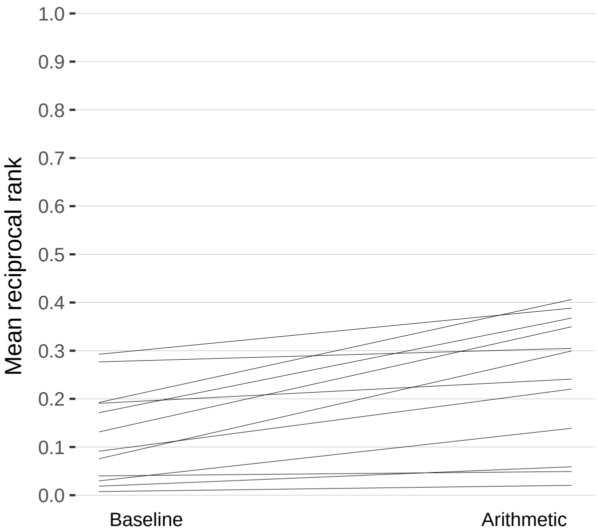

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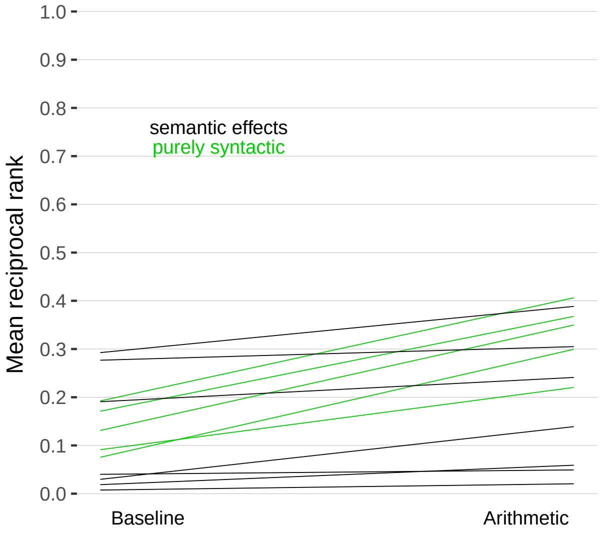

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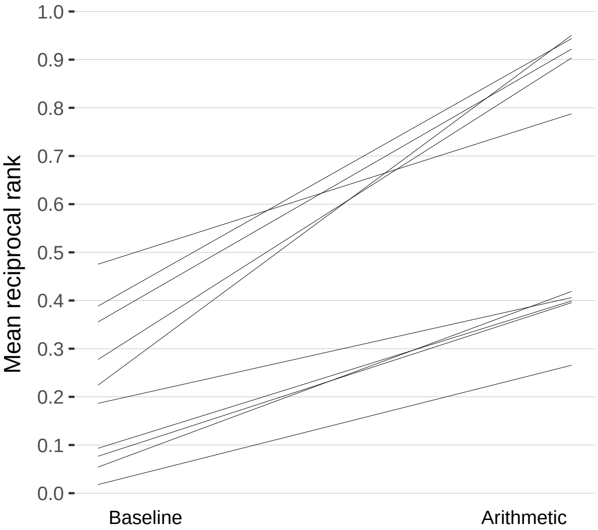

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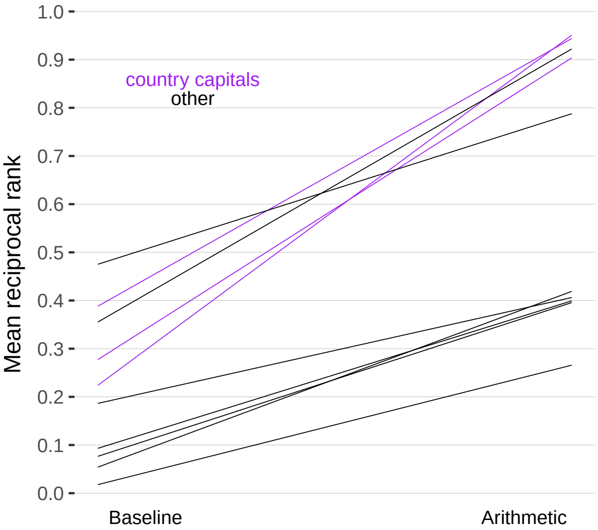

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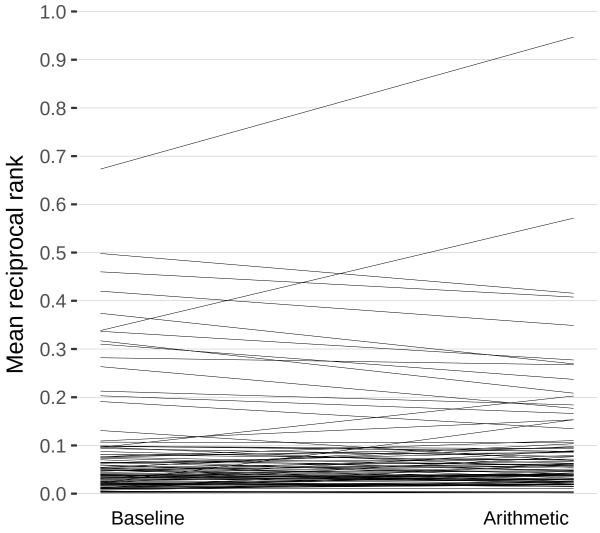

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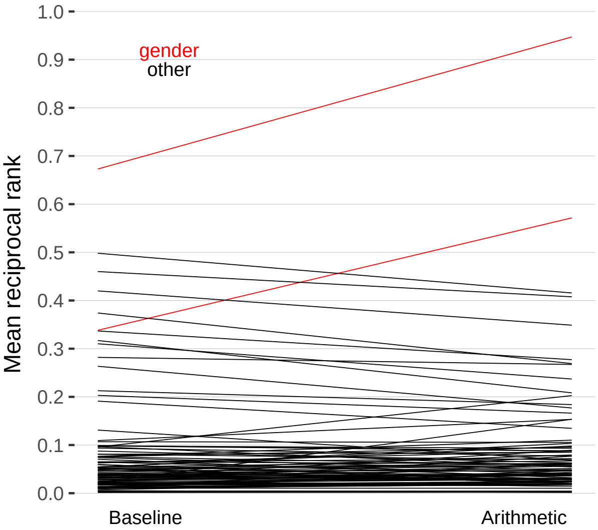

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One hallmark of derivation is changing a word's syntactic class.
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affix	syntactic?	semantic?	RR gain
-ment	V $\rightarrow$ N	minimal	.224
-tion	V $\rightarrow$ N	minimal	.218
-ly	A $\rightarrow$ Adv	minimal	.205
-ness	A $\rightarrow$ N	minimal	.129
-er	V $\rightarrow$ N	some?	.109
un-	no (A)	yes	.062
re-	no (V)	yes	.050
-able	V $\rightarrow$ A	yes	.040
-less	N $\rightarrow$ A	yes	.013
-over	no (V)	yes	.009

Discussion: Named entities

Why the stark difference between named entities and other semantic relationships?

Semantic theory supports differentiating common from named nouns. E.g., in Montagovian semantics:

- proper nouns denote **individuals** (type e)
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Polysemy/ambiguity is a known problem for distributional approaches. If every **referent** is a sense, common nouns are extremely polysemous!

Concretely: vector must *simultaneously* model the word co-occurrences for every individual in the set.

A unified account

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  *that is a **cheap** tuxedo*
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  ... and verbs too:

  she ***ran*** *out of time*
  she is ***running*** *out of time*
  she has ***run*** *out of time*

A unified account

- Derivation is less regular than inflection. More importantly, its distributional effects are less automatic and predictable:

  Billy was a ***slow*** *runner*
  Billy ran ***slowly***
  vs.
  their investments have been very ***prudent*** *this year*
  they invested very ***prudently*** *this year*

- Adverbs tend to co-occur with verbs and adjectives with nouns, but these words do not belong to **closed classes** as they tend to with inflection.

A unified account

What about semantics?

- Less polysemous nouns will have “tighter” distributions: lower diversity of co-occurrences, thus smaller sets of differences. Named entities are especially non-polysemous.
  - The relationship between every *dog* and every *puppy* is less consistent than the relationship between every *Netherlands* and every *Amsterdam*.

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- Less polysemous nouns will have "tighter" distributions: lower diversity of co-occurrences, thus smaller sets of differences. Named entities are especially non-polysemous.
  - The relationship between every *dog* and every *puppy* is less consistent than the relationship between every *Netherlands* and every *Amsterdam*.
- Gendered nouns agree with pronouns—a closed class, as seen with inflectional relationships.

*when the **boy** dropped his ice cream, he cried*
*when the **girl** dropped her ice cream, she cried*

Conclusion

We have arrived at an explanation grounded in linguistic and distributional theory that accounts for the effects observed.

- Should work further to verify the claim that certain distributional differences are more regular (although the analogy task *does* measure that directly).

Recommend: Test a wide variety of questions. Use a baseline. Don't rely on coarse splits like "syntactic/semantic."

All code, results, and figures will be available at:
https://github.com/gpfinley/analogies

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