Representing a concept by the distribution of names of its instances

Matthijs Westera, Gemma Boleda and Sebastian Padó
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Abhijeet Gupta & Matthijs Westera, Gemma Boleda and Sebastian Padó
Interest in Distributional Semantics (etc.)
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- Relation to formal semantics;
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- Relevance to experimental linguistics;
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- Relation to formal semantics;
- Relevance to experimental linguistics;
- Relation between language and the world.
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• Relevance to experimental linguistics;

• Relation between language and the world.
Language and the world
Language and the world

… that dog ate my shoe …
Language and the world

... that dog ate my shoe ...

... a young dog is called a puppy ...
Language and the world

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Language and the world

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Language and the world

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Distributional Semantics (DS)

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“cat”

“animal”
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Should Distributional Semantics account for *entailment*?

No.

“cat”

“animal”
“cat”

“animal”
Language and the world are not perfectly aligned

“cat”

“animal”
Language and the world are not perfectly aligned

- A cat ~ "cat"
- Various animals ~ "animal"
Language and the world are not perfectly aligned
Language and the world are not perfectly aligned

• This is not (just) a technical challenge, but interesting.
Language and the world are not perfectly aligned

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- Are some parts of language closer to the world than other parts? Does this show in DS? Can we exploit this?
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• Are some parts of language closer to the world than other parts? Does this show in DS? Can we exploit this?

Some expressions are used more rigidly than others... (Kripke, '80)
Approach
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  - **Predicate-based:**
    Word vector of a predicate that is used to denote the category.
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    *E.g.*, for *scientist*, the word vector of "scientist"
  
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  *E.g.*, the mean of vectors for “Albert Einstein”, “Emmy Noether”, …
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    *E.g.*, the mean of vectors for “Albert Einstein”, “Emmy Noether”, ...

• Evaluation against human judgments of category relatedness.
Representing a concept by the distribution of names of its instances

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Existing data/model we use
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- The **Instantiation** dataset (Boleda, Gupta, and Padó, 2017, EACL):
  - e.g., *<Emmy Noether, scientist>* , *<Edinburgh, capital>*
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  – derived from WordNet’s ‘instance hyponym’ relation.

• We focus on the 159 categories that have at least 5 entities.

• As DS representations of the entities’ names and categories’ predicates we use the **Google News** embeddings (Mikolov, Sutskever, et al., 2013, ANIPS).
Evaluation: gathering human judgments
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- We semi-randomly sampled 1000 category pairs (out of 12.5K).
- ‘Comparative’ task: which pair of categories are more related to each other?
- Also same way of computing aggregated ‘relatedness’ scores.
In this HIT you will see 70 items like the following, each presenting two pairs of categories:

Which pair of categories are more related to each other?

1. wheel ← car

2. building ← crane (type of bird)
Main result
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• Spearman (ranking) correlations between:
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- Spearman (ranking) correlations between:
  - cosine similarities from Name-based / Predicate-based and
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  − cosine similarities from Name-based / Predicate-based
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• Result:
  − Predicate-based: 0.56
  − Name-based: 0.74
Artist’s impression

predicate-based model
Artist’s impression

**predicate-based model**

**name-based model**

model scores

human scores
How many names do we need?
How many names do we need?
How many names do we need? Surprisingly few!

[Graph showing the trend of Spearman's R with the number of names used, comparing Name-based and Predicate-based methods.]

- Name-based: Shows an increasing trend from 0.4 to 1.0 as the number of names increases.
- Predicate-based: Stays relatively flat at 0.6, indicating less variability as the number of names increases.

Legend:
- Name-based
- Predicate-based
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  - William Cowper
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Discussion
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  - Not every category has *named* instances...
  - NLP relevance? Vs. sense disambiguation? Contextualized word embeddings (ELMo, BERT, …)?
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  - Not every category has named instances...
  - NLP relevance? Vs. sense disambiguation? Contextualized word embeddings (ELMo, BERT, …)?
  - Cognitive relevance? E.g., prototype theory?
Acknowledgments

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Where are predicates and names, anyway?
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Crowdsourcing task

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Crowdsourcing task instructions

*Be careful: words in this HIT can sometimes refer to multiple categories!* For instance, "crane" could mean a lifting machine or a type of bird. In this case, we mean the type of bird, and you should answer accordingly.

In this example you would probably choose pair 1, because the categories *wheel* and *car* seem more closely related than the categories *building* and (the type of bird!) *crane*.

*Don't know the meaning of a word?* Use your mouse to hover over a word to see its definitions.
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  – but this disadvantage is not an *unfair* one.
A closer look per ontological domain
A closer look per ontological domain

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Name-based:
Non-representative instances of ‘object’ categories

- capital: belfast, bridgetown, camelot, cardiff, edinburgh, george_town
- colony: cayman_islands, connecticut, delaware, demerara, georgia, gibraltar, maryland, massachusetts_bay_colony, new_amsterdam, new_hampshire, new_jersey, new_netherland, new_york, north_carolina, pennsylvania, plymouth_colony, rhode_island, rock_of_gibraltar, south_carolina, virginia (most entities used to be colonies, but no longer are.)
- region: achaea, far_east, french_west_indies, kennelly-heaviside_layer, occident, old_world, rand, transylvania, west, witwatersrand
- district: acadia, acre, american_samoa, aragon, attica, boeotia, castilla, catalonia, darfur, east_malaysia, galloway, kwazulu-natal, lake_district, louisiana_purchase, mount_athos, north_borneo, northern_mariana_islands, northern_territory, northwest_territories, nunavut, palatinate, papal_states, sarawak, yukon (I suspect US people will interpret ‘district’ as a part of a city, rather than a part of a country?)
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