Comparing the Multidimensional Mental Representations of Object Images and Object Nouns

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BACKGROUND

- We can think of semantics as composed of different dimensions
- Previous work showed that object images can be differentiated by a set of interpretable dimensions [1]
- These dimensions may vary for object words, which are not related to meaningful visual input

What are the core dimensions underlying object-word representations?

How do these dimensions differ from image-derived dimensions?

METHODS

- 1388 diverse, unambiguous object words, sampled from the **THINGS database** [2]

Word similarity task

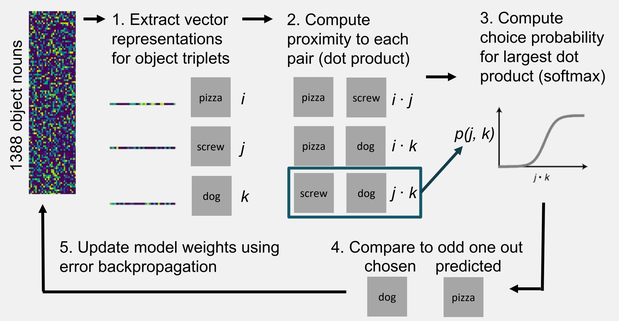
Large-scale online crowdsourcing, 5015 individuals (post exclusion)

Which is the odd-one-out?

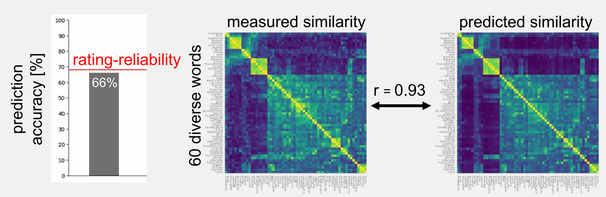
soup | jeep | snake

- ~1.3 mio. random combinations
- 1000 noise ceiling triplets (25-40 samples)
- All triplet combinations of 60 words

SPoSE model: computational model trained to capture similarity choices [1]

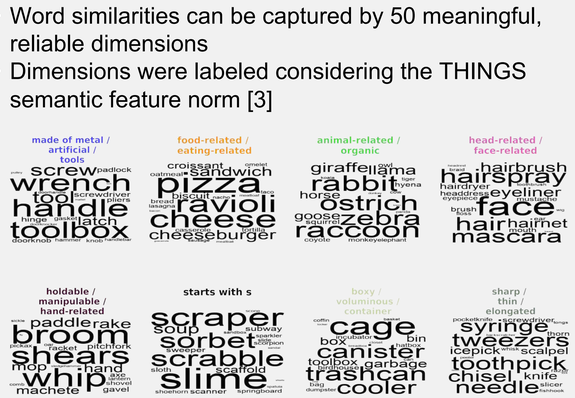


- Stable and predictive model of similarity choices

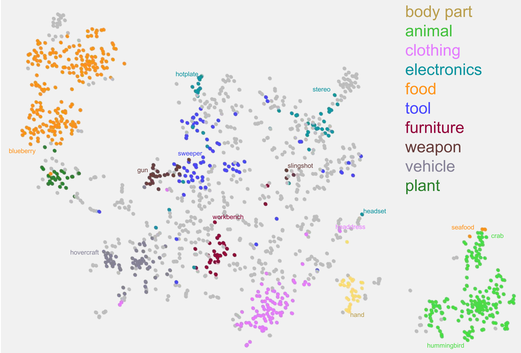


What are the core dimensions underlying object-word similarities?

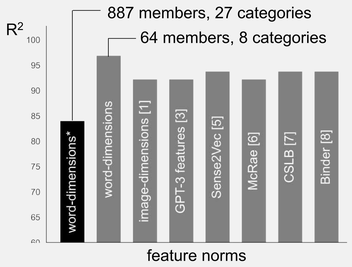
- Word similarities can be captured by 50 meaningful, reliable dimensions
- Dimensions were labeled considering the THINGS semantic feature norm [3]



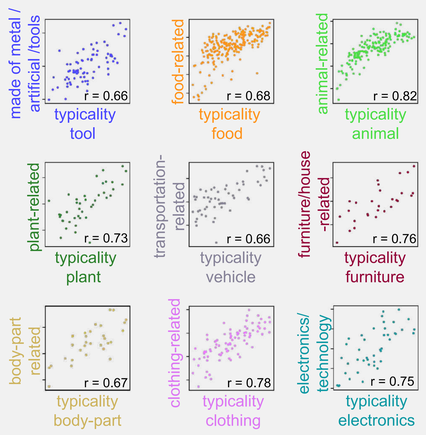
Do these dimensions capture known semantic relationships?



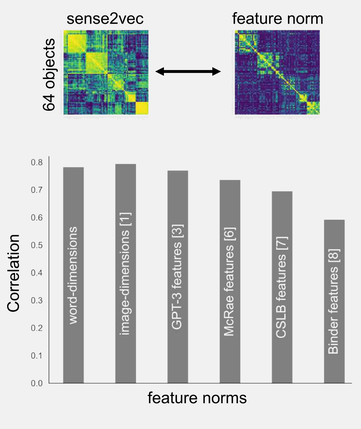
- Word-derived dimensions best predict memberships to **higher-level categories** [2, 4] (cross-validated nearest-centroid classifier)



- **Typicality** [4] of higher-level category members correlates with their loading on category-related dimensions → word-derived dimensions capture the richness of higher-level categories

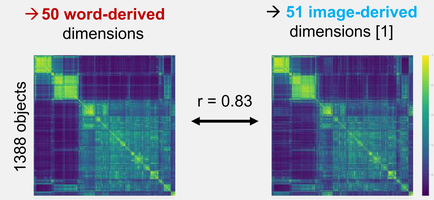


- **Sense2vec** [5] representations are best captured by image- and word-derived dimensions (RSA)



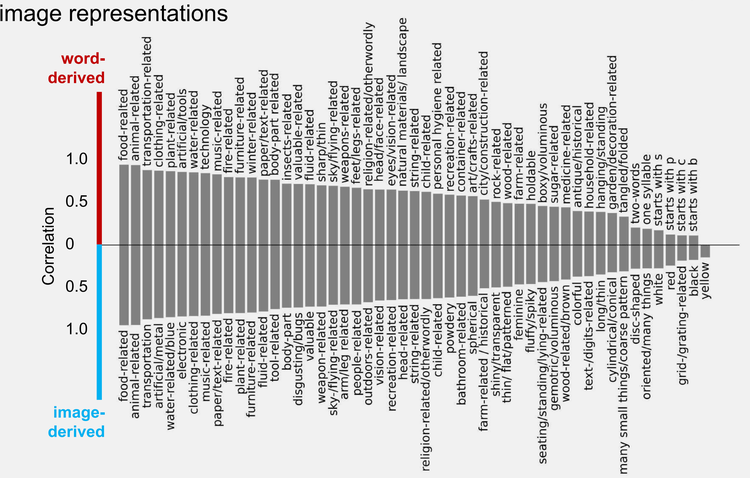
How do image and word representations differ?

- Word-representations capture much, but not all, of image-representations
- Differences remain after excluding dimensions tied to lexical-form and visual properties, or averaging image-derived dimensions across the estimated scores [9] for several images depicting the same concept



- without lexical-form dimensions: r = 0.84
- without dimensions related to visual properties: r = 0.84
- without both: r = 0.85
- when averaging image-dimensions across image examples: r = 0.84

- Correlations of word-derived dimensions with any image-derived dimensions and vice versa → color and texture dimensions are unique to image representations



CONCLUSION

- We identified **50 interpretable dimensions** underlying word similarity judgements
- These dimensions more effectively **capture higher-level categories** and known **semantic relationships** compared to other semantic norms
- **Word and image representations are very similar, but not the same** and their differences are not necessarily driven by **image-specific effects**
- Words are represented by only a **subset of visual-semantic** dimensions related to shape, but not color or texture

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PERCEPTION & ACTION: Vision

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