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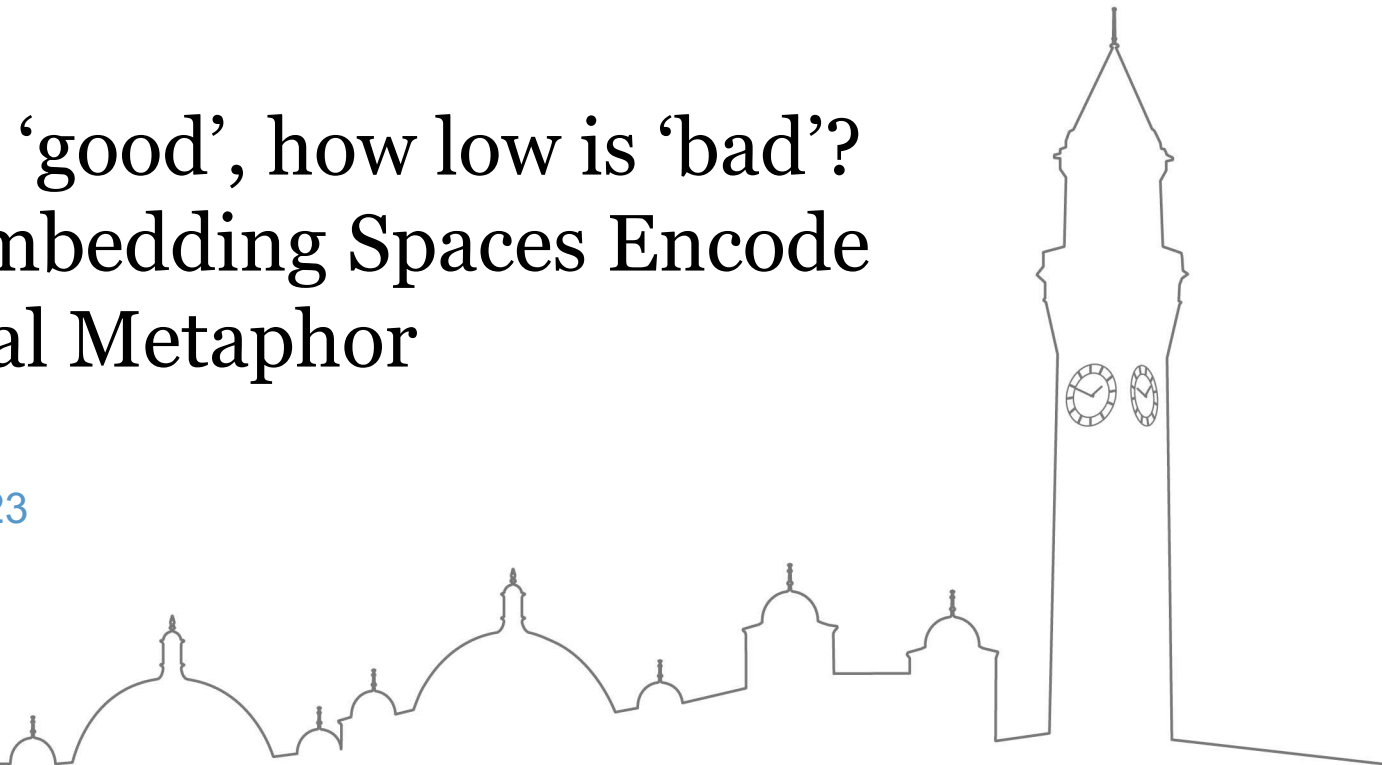
How high is 'good', how low is 'bad'? Do Word Embedding Spaces Encode Conventional Metaphor

Sara Bartl

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Lancaster University

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Motivation

1) Better understanding word embeddings

- word embeddings aim to model meaning in language
- figurative meaning is a part of how language means

2) Application: studying metaphor at scale

- more language data available
- semantic projection for modeling metaphor



Outline

- Word Embeddings
- Semantic Projection for Literal Meaning
- Semantic Projection for Metaphor
- Results
- Conclusion and Future Directions

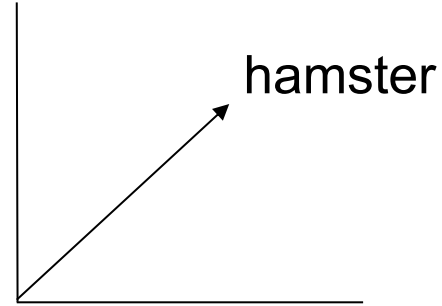


Word Embeddings



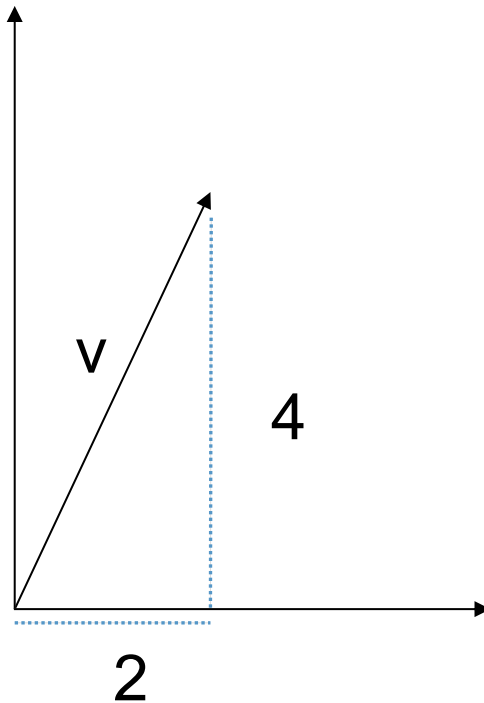
words as vectors

hamster



What is a Vector?

$$\mathbf{v} = (2, 4)$$



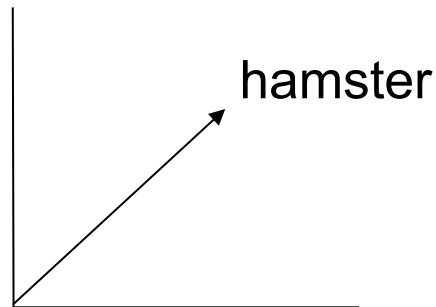
Word Embeddings



words as vectors

hamster

?



meaning in
language

?



spatial, numeric
representation



From Words to Vectors

The **particular shape** of a word's vector is learned from the word's **distribution** in a corpus.

Pre-trained GloVe embeddings:

- CommonCrawl corpus
- 42 billion tokens
- 300 dimensional vectors



Distributional Hypothesis

Words with **similar distributions** tend to have **similar meanings** (Firth, 1957; Harris, 1954)



(The vectors of) words that **have similar distributions** are **closer** together in the word embedding space.



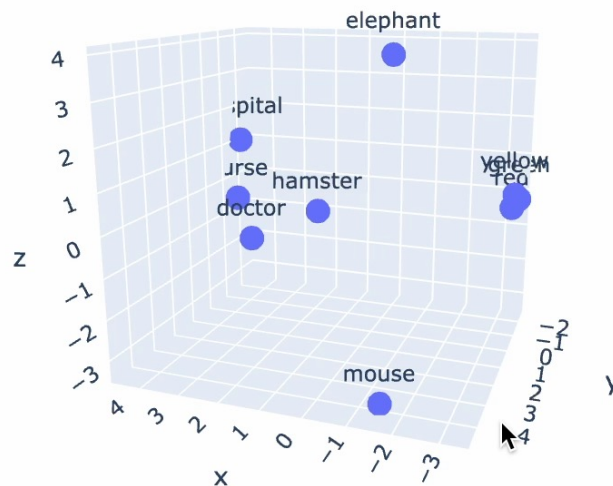
Word Embeddings in Action

Some Words

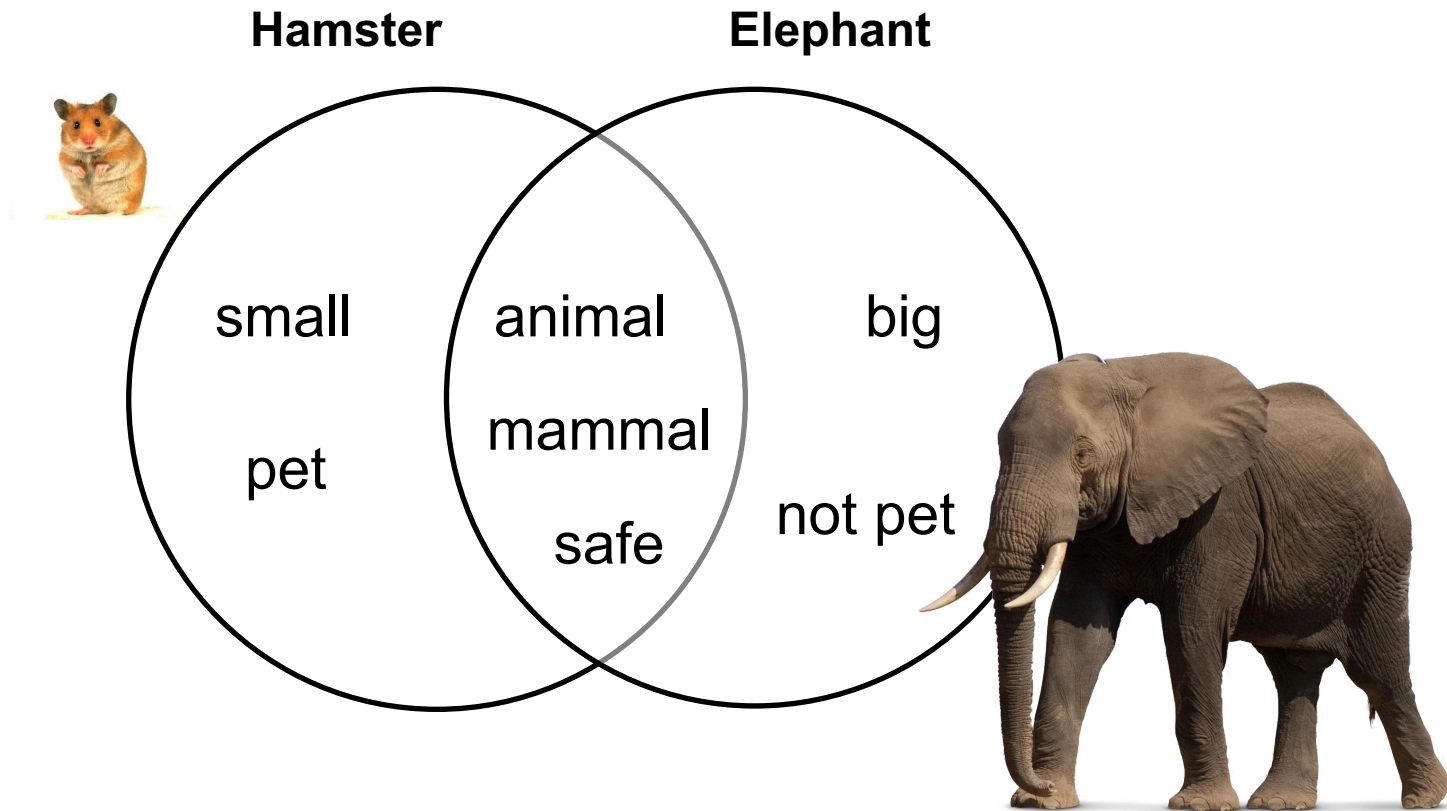
hamster, elephant,
mouse

yellow, green, red

hospital, nurse,
doctor



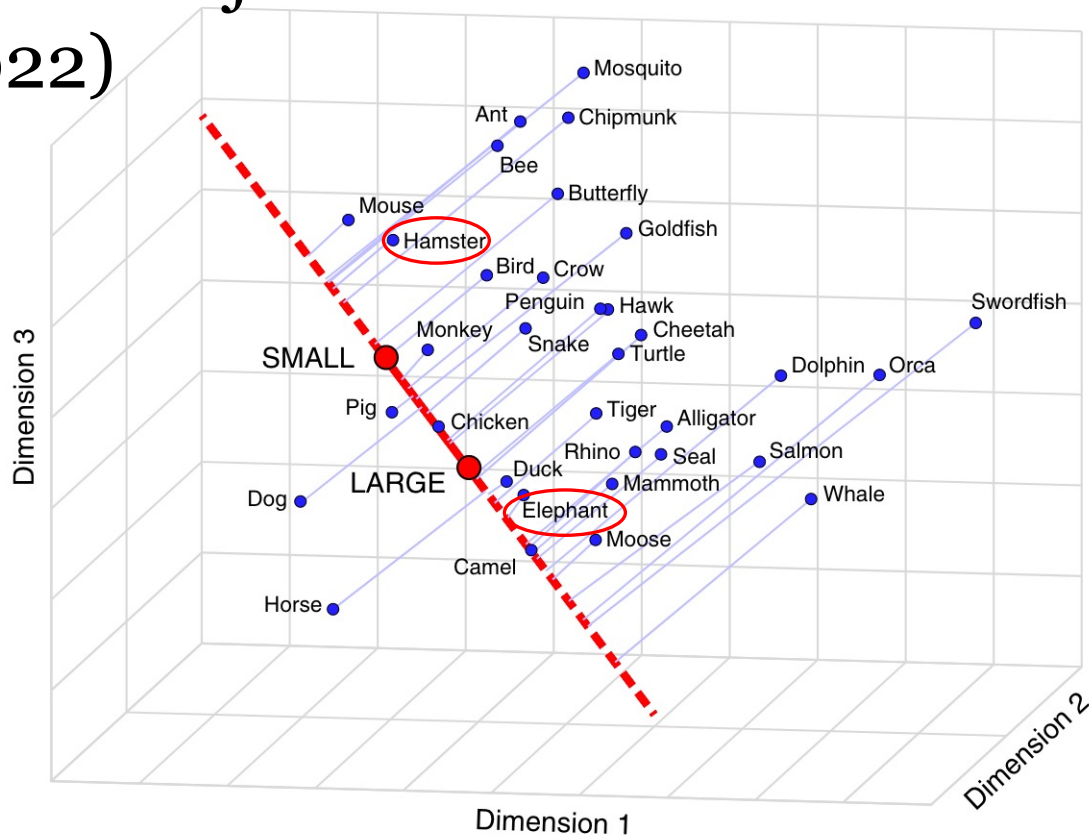
Problem: Similarity is Context-Dependant



Solution: Semantic Projection (Grand et al., 2022)

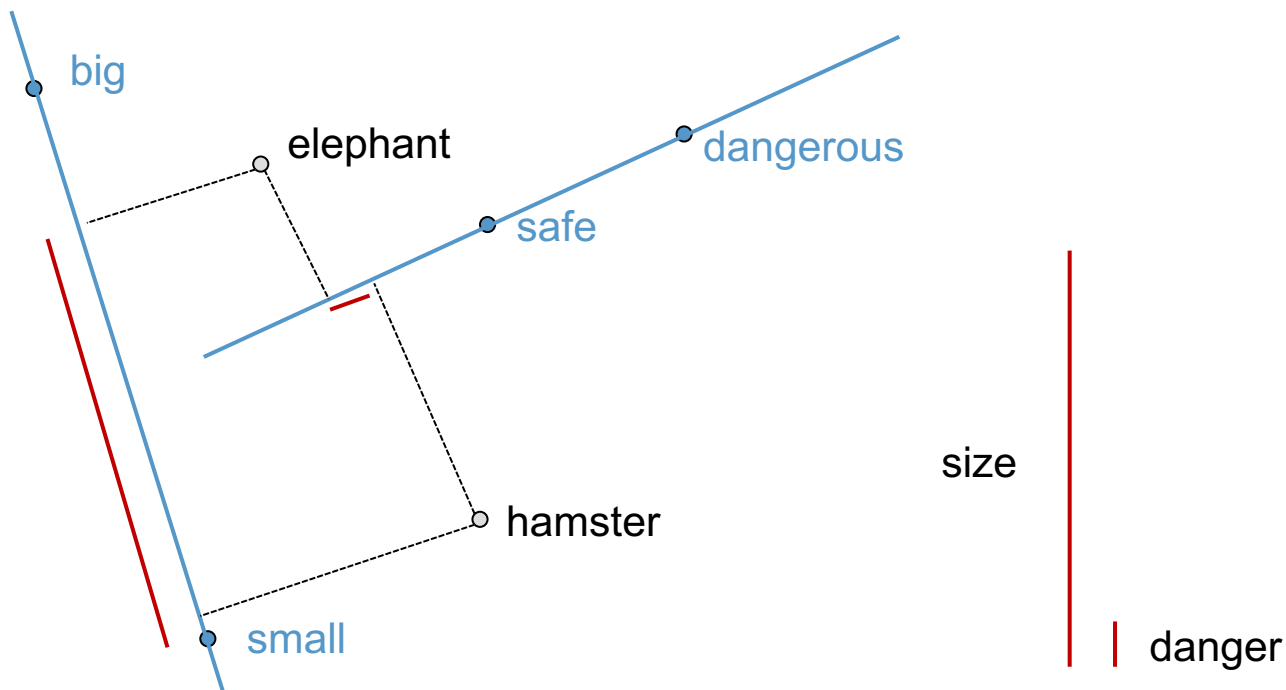
Category: Animals

Feature: Size

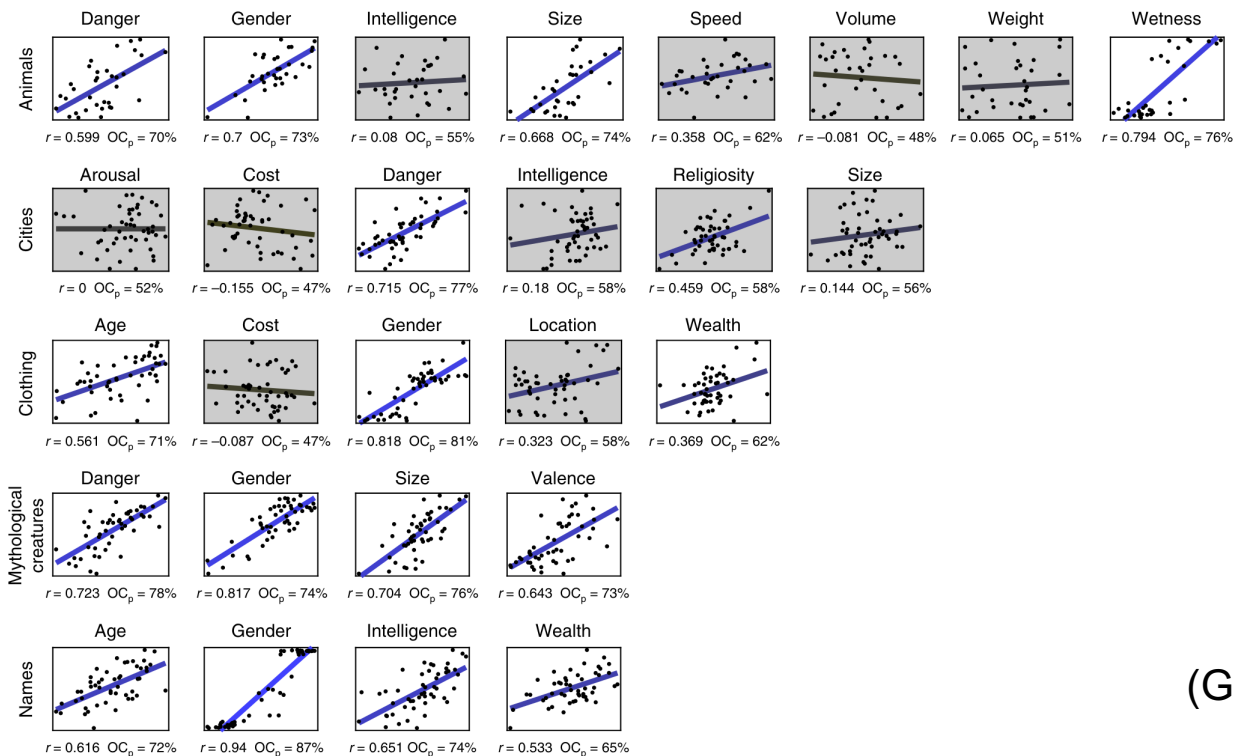


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Solution: Semantic Projection (Grand et al., 2022)



Do Word Embeddings Correlate with Human Ratings? (Grand et al., 2022)



(Grand et al., 2022, p. 5)

Grand et al. (2022) Findings

“These results demonstrate that semantic knowledge about context-dependent similarities is explicitly represented in the structure of word embeddings.”

(Grand et al., 2022, p. 7)



Semantic Projection for Conventional Metaphor?

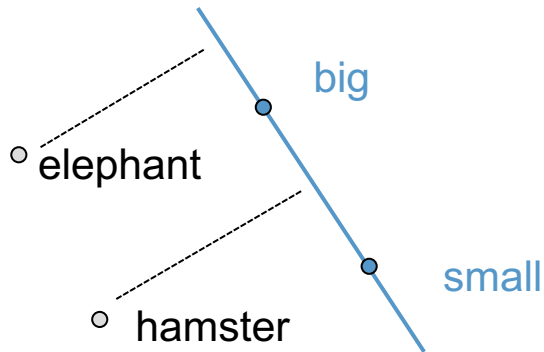
- Case Study: UP/HIGH IS GOOD, DOWN/LOW IS BAD
- feeling *up*, feeling *low*; thumbs *up*, thumbs *down*
- vertical orientation (source domain) → emotional valence (target domain)
- experimental evidence: participants prefer *vertical axis* when ordering emotional valence words *best*, *better*, *worse*, *worst* (Woodin and Winter, 2018)



Literal

Feature: literal attribute
(e.g. size)

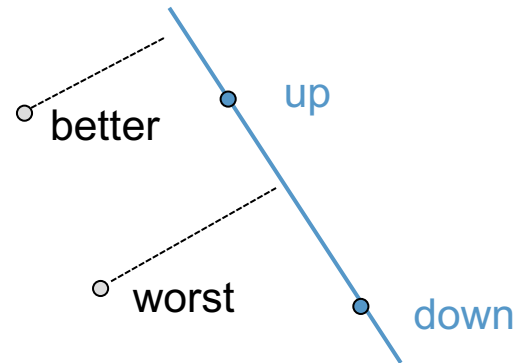
Category: objects (e.g.
animals)



Figurative

Feature: source domain (e.g. vertical
orientation)

Category: target domain vocabulary (e.g.
emotional valence words)



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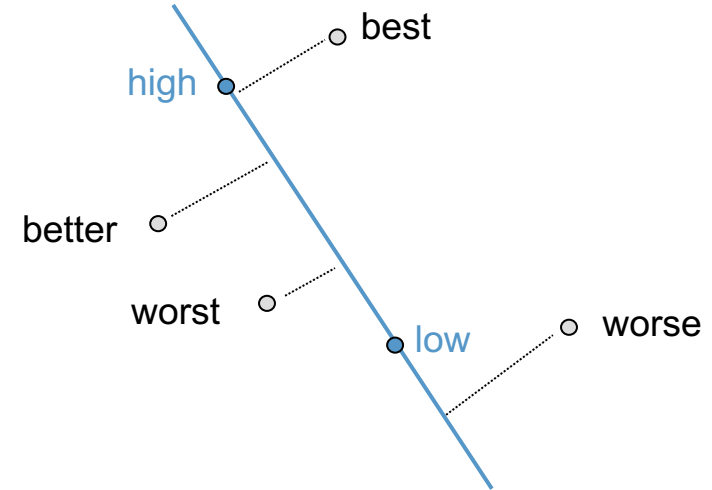
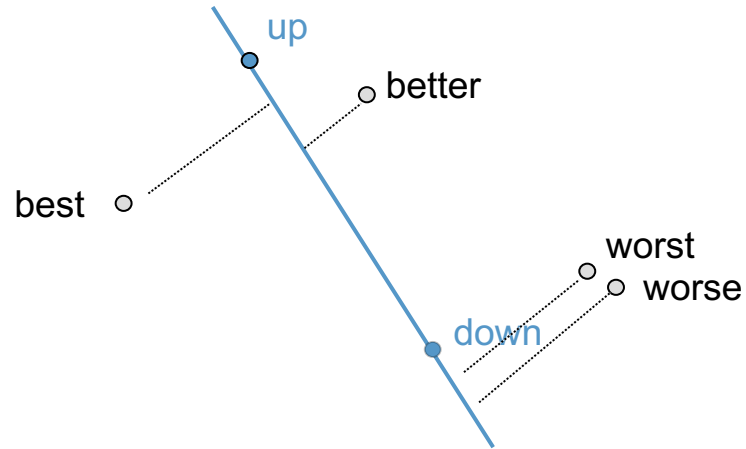
Methods

- Semantic scales: *up-down, high-low*
- Words projected: *worst, worse, better, best*
- *good* and *bad* excluded following Woodin and Winter (2018)



Results

best, better, worst, worse



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Conclusion

The GloVe word embedding space explicitly represents the context-dependent semantic relationship between source domain and target domain.



Conclusion

Semantic projection as a method for analysing metaphor at scale.

- develop and test semantic projection "in the wild"
- study metaphor variation at scale across two sub-reddits:
r/depression and r/depression_partners



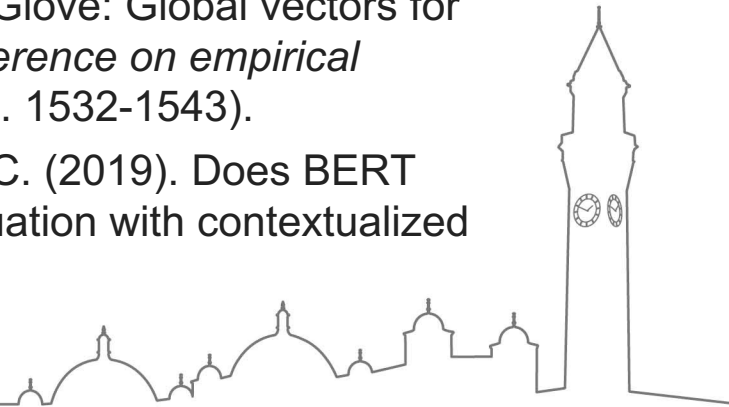
Thank you.



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References

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- Grand, G., Blank, I. A., Pereira, F., & Fedorenko, E. (2022). Semantic projection recovers rich human knowledge of multiple object features from word embeddings. *Nature human behaviour*, 6(7), 975-987.
- Harris, Z. S. (1954). Distributional structure. *Word*, 10(2-3), 146-162.
- Pennington, J., Socher, R., & Manning, C. D. (2014). Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)* (pp. 1532-1543).
- Wiedemann, G., Remus, S., Chawla, A., & Biemann, C. (2019). Does BERT make any sense? Interpretable word sense disambiguation with contextualized embeddings. *arXiv preprint arXiv:1909.10430*.

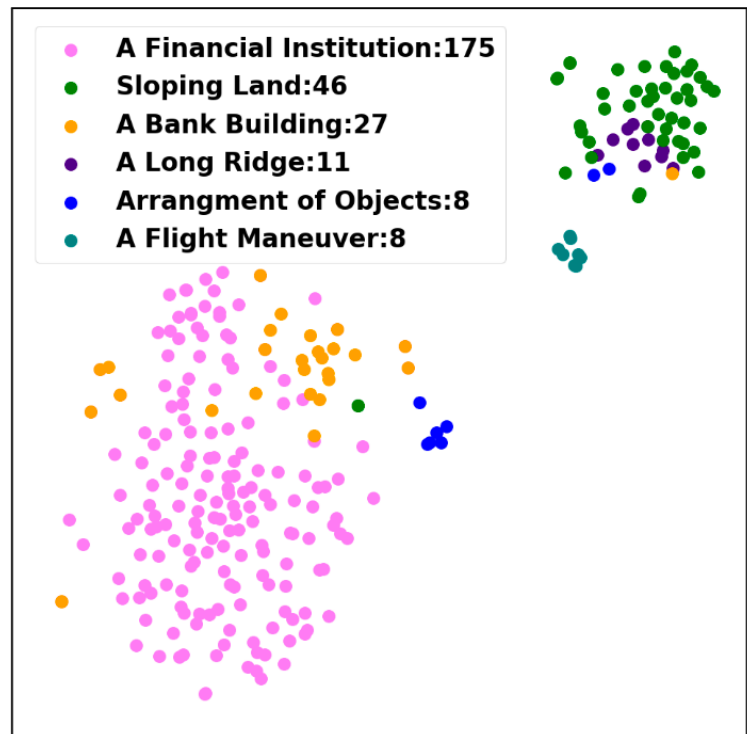
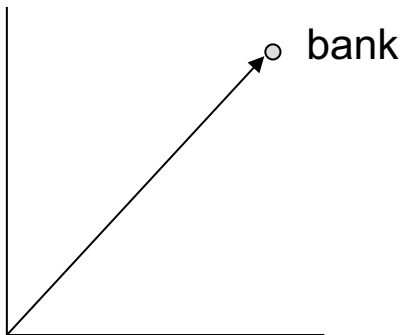


Additional Slides



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Type vs. Token Based Word Embeddings



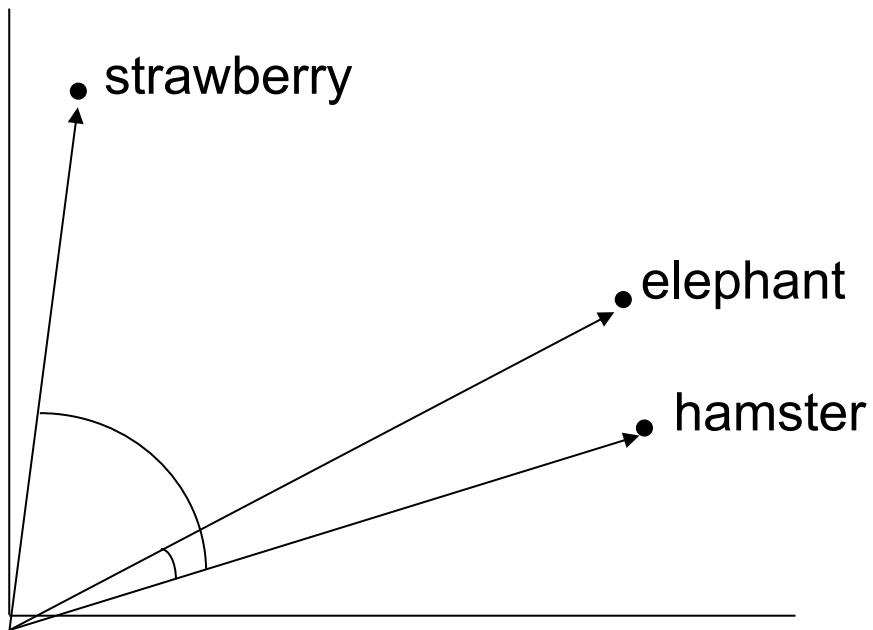
(a) BERT

(Wiedemann et al. 2019, p.8)



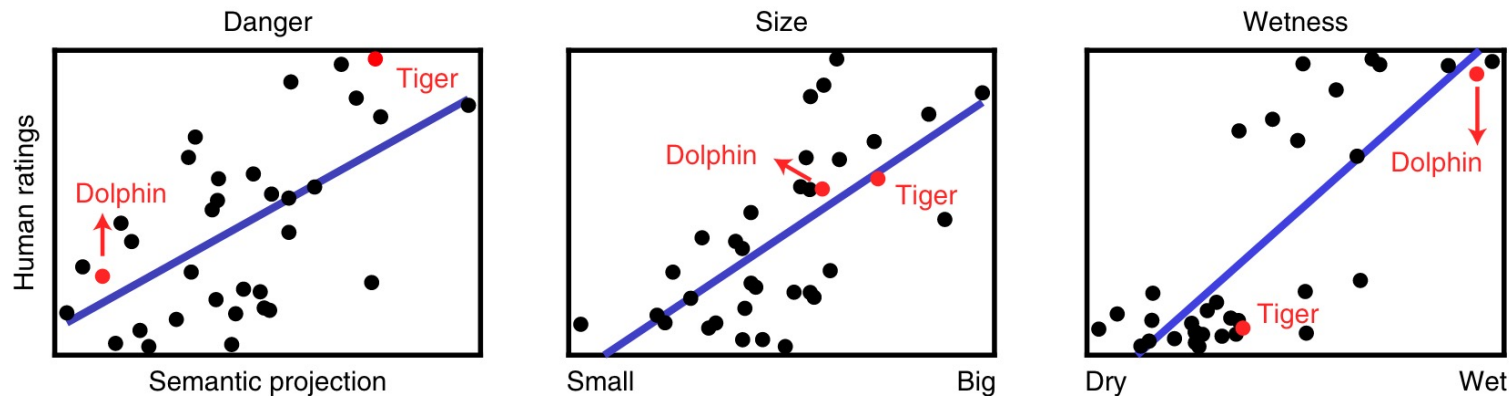
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Measuring Word Similarity



Do Word Embeddings Correlate with Human Ratings? (Grand et al., 2022)

a Same category (animals), different features



(Grand et al., 2022, p. 3)



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