Linguistic Intersections of Language and Gender

He, she, they, they
A first discriminative analysis of third-person pronoun semantics

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- What is missing, however, is
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  - but pronouns in general
- The present pilot study offers a first account of pronoun semantics by example of *he*, *she*, and plural and singular *they*

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Research questions

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RQ1 – Methodological Question

Can distributional semantics meaningfully capture pronoun semantics?

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RQ2 – Theoretical Question

How is singular *they* semantically related to other third-person pronouns?

Methods

discriminative learning and instance vectors

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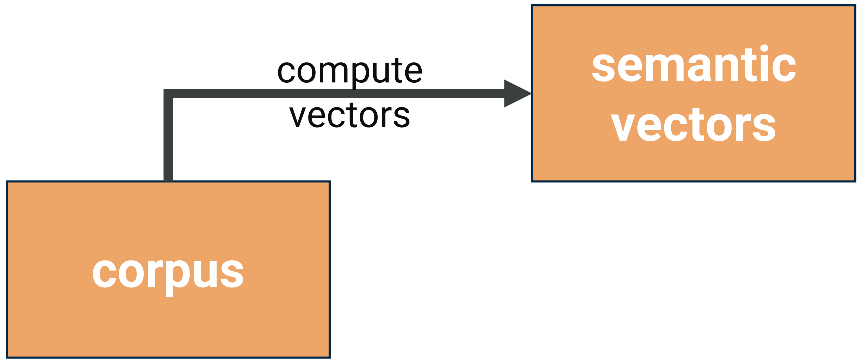

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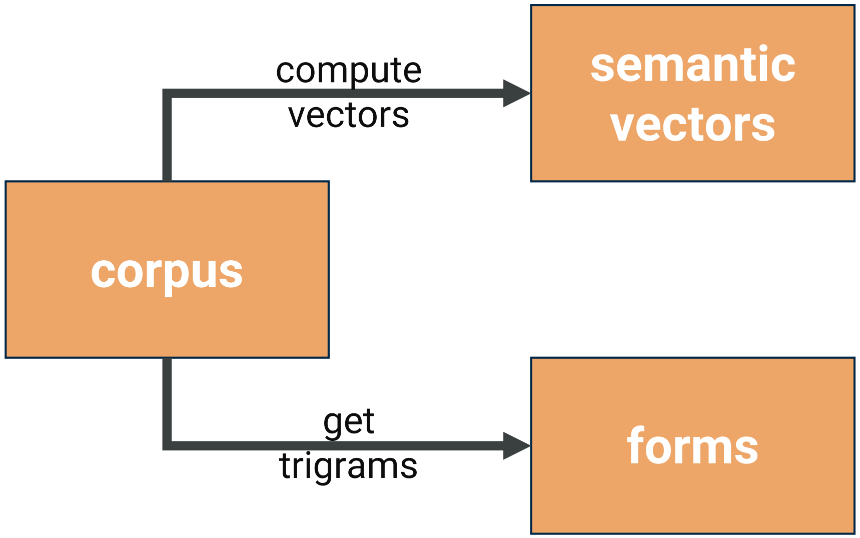

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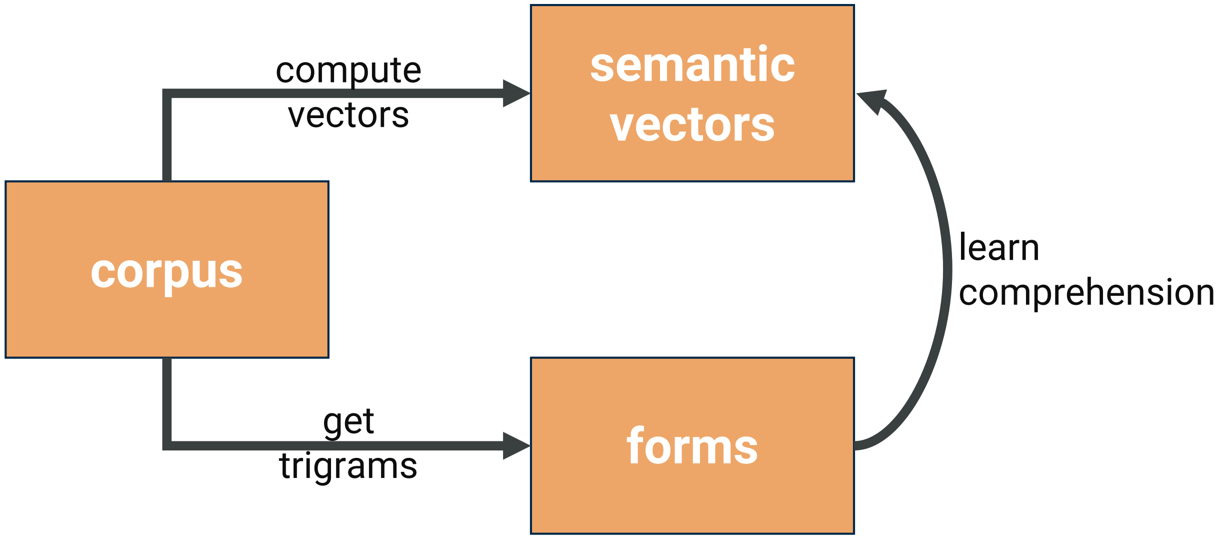

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  - 17,805 word form tokens
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- Automatically analysed and annotated for inflection using the RNNTagger software (Schmid, 1999)

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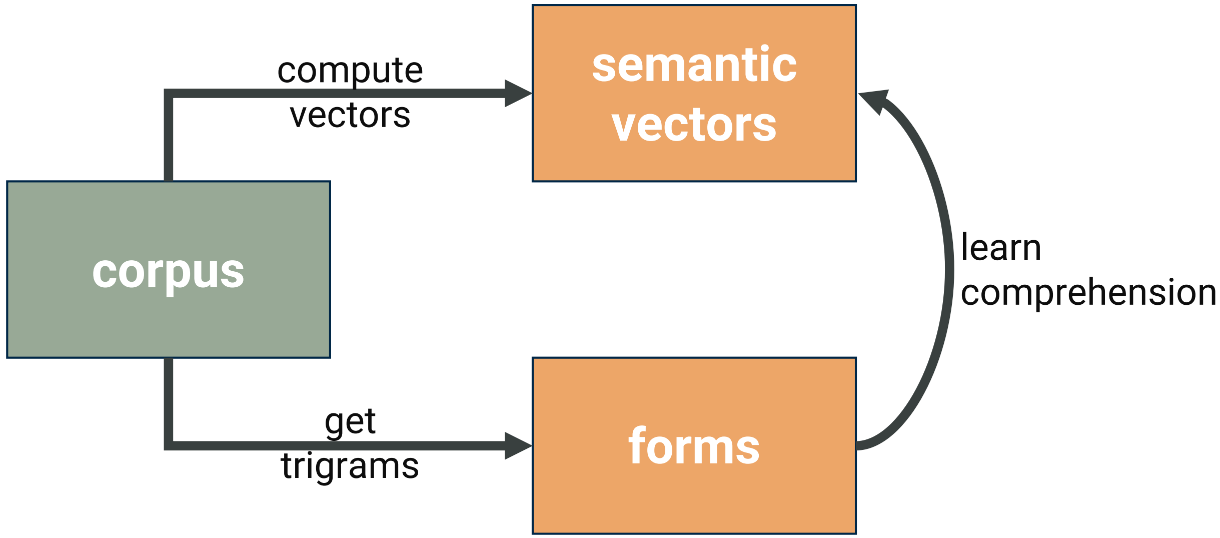

Semantic vectors

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- Difference in meaning is measured via semantic vectors
- There are different algorithms to arrive at a word's semantic vector, two of them are
  - NDL: Naive Discriminative Learning (Baayen et al., 2011)
  - Instance vectors (Lapesa et al., 2018)

Naive Discriminative Learning

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- Each sentence was used to predict each individual outcome within the sentence by the other bases/function words/inflectional functions in that sentence

Naive Discriminative Learning

cues: all, teacher, PLURAL, be, PLURAL, nice

outcomes: teacher, villain

All teachers are nice.

	all	teacher	PLURAL	be	nice	villain	evil
teacher							
villain							

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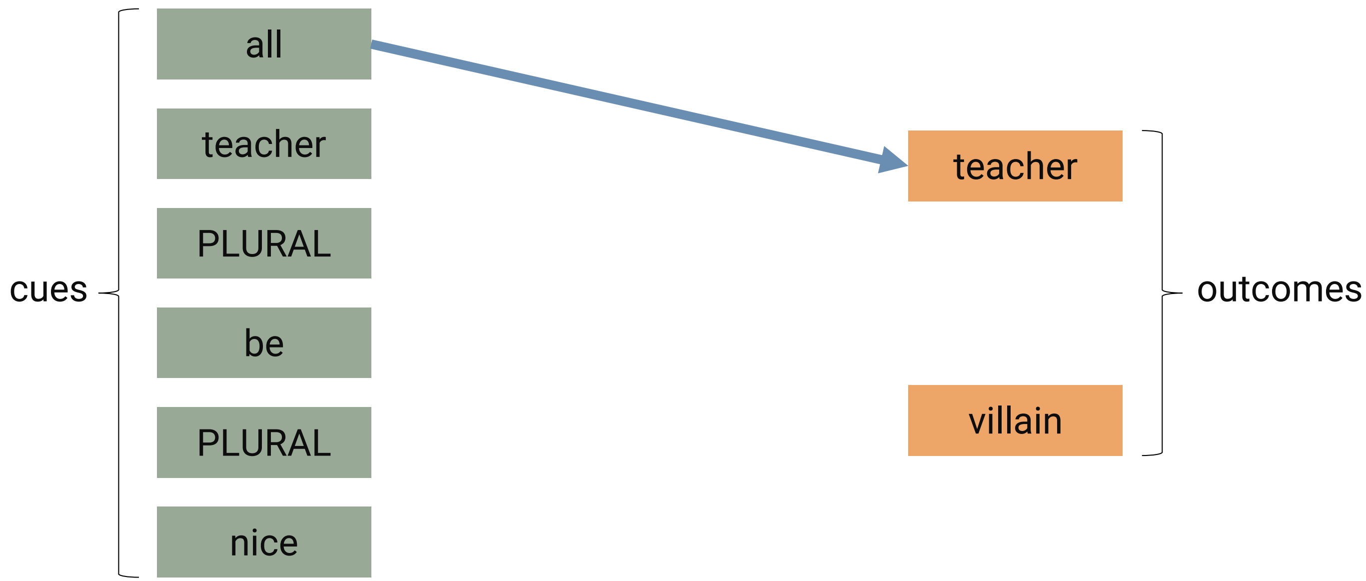

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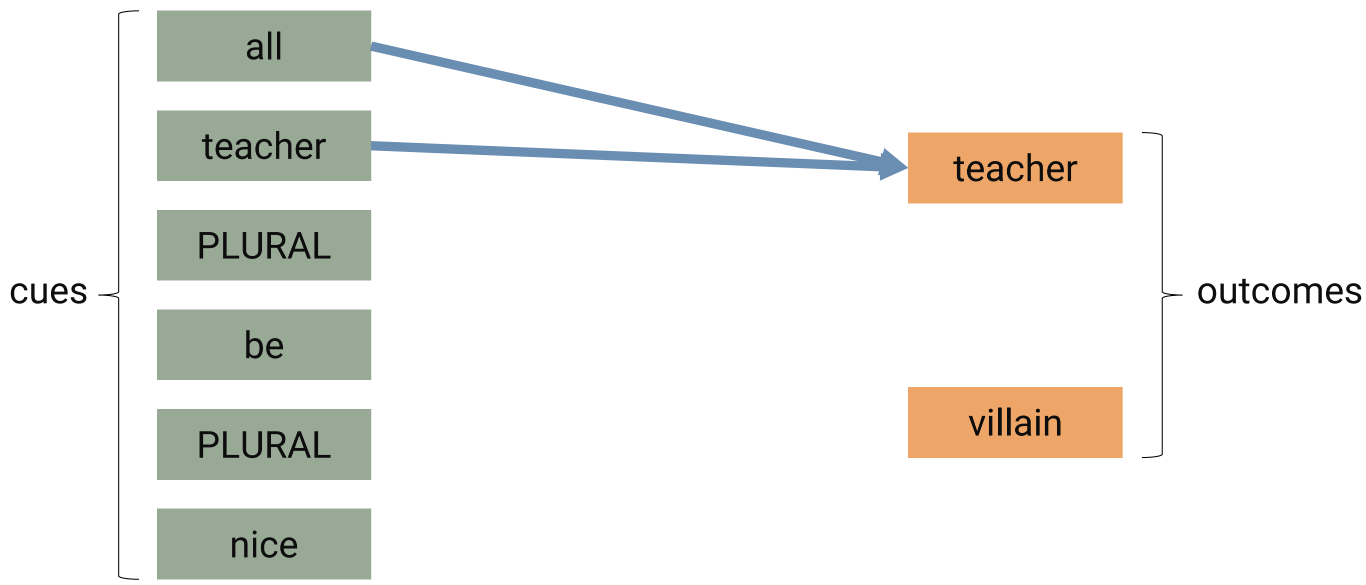

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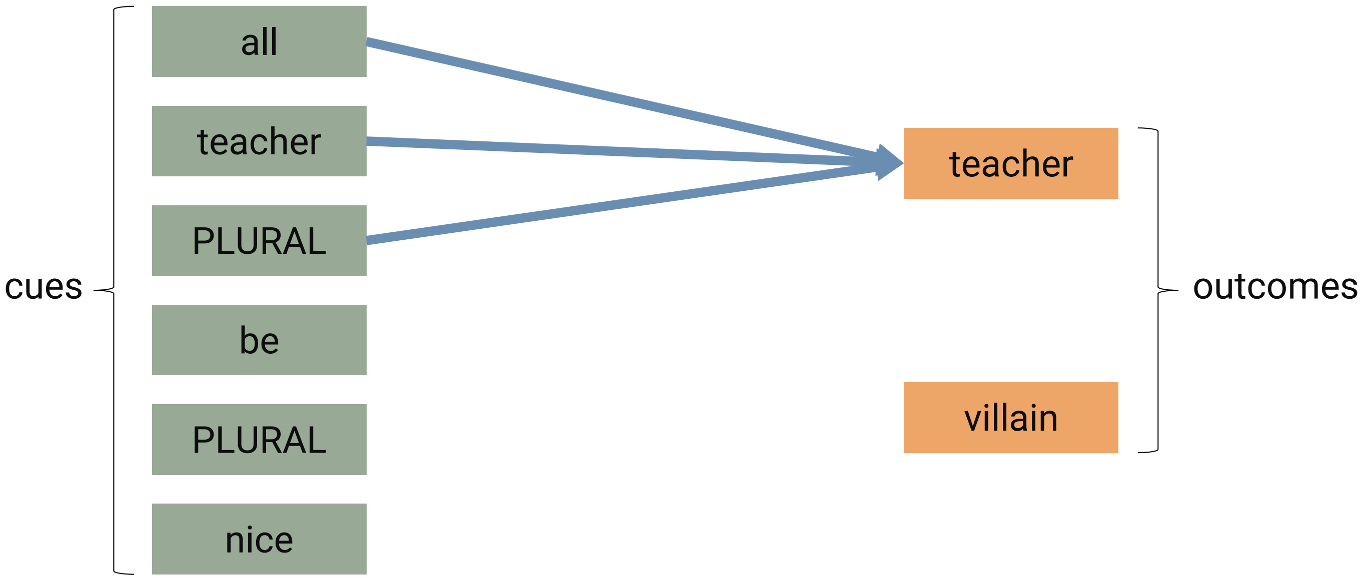

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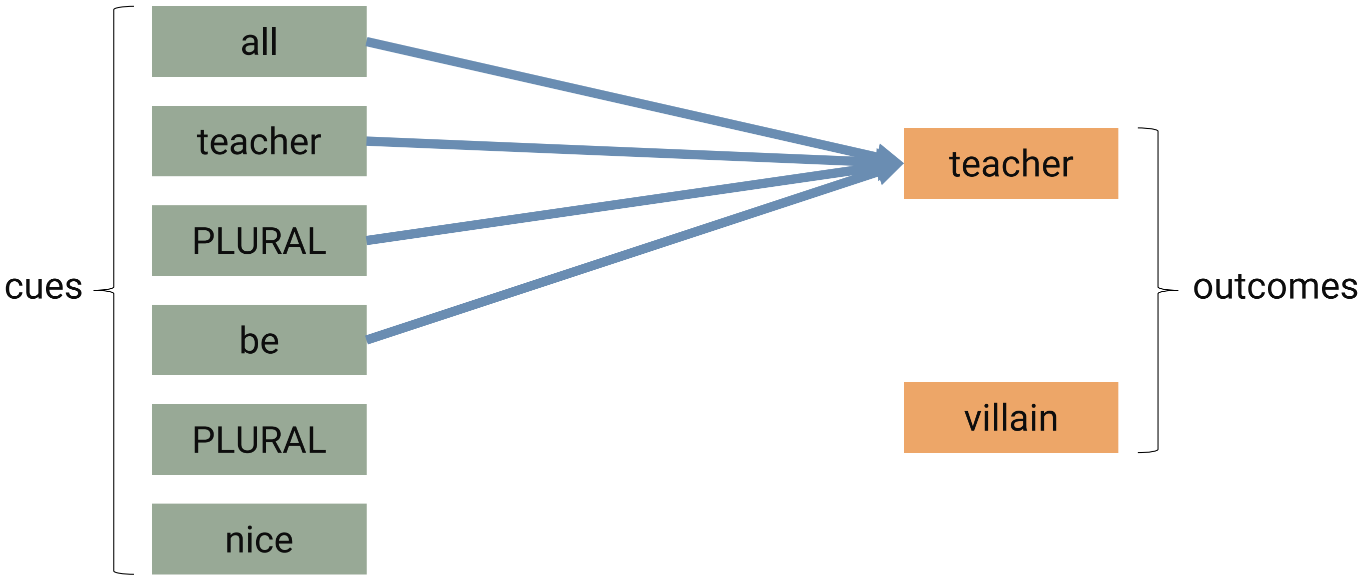

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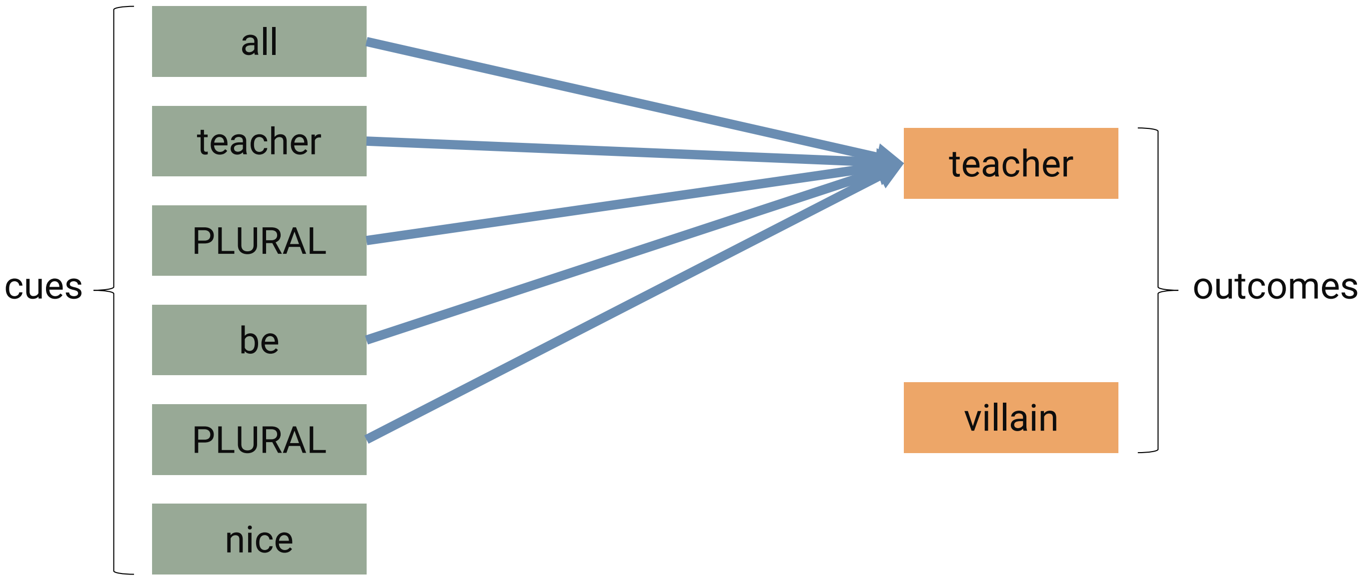

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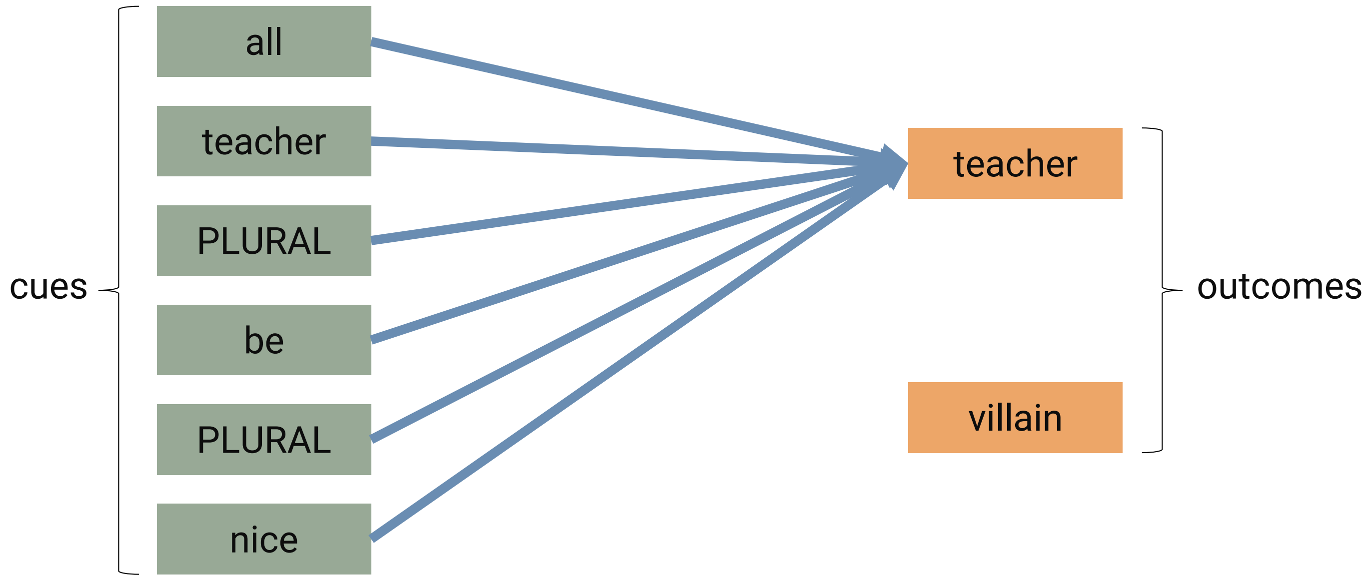

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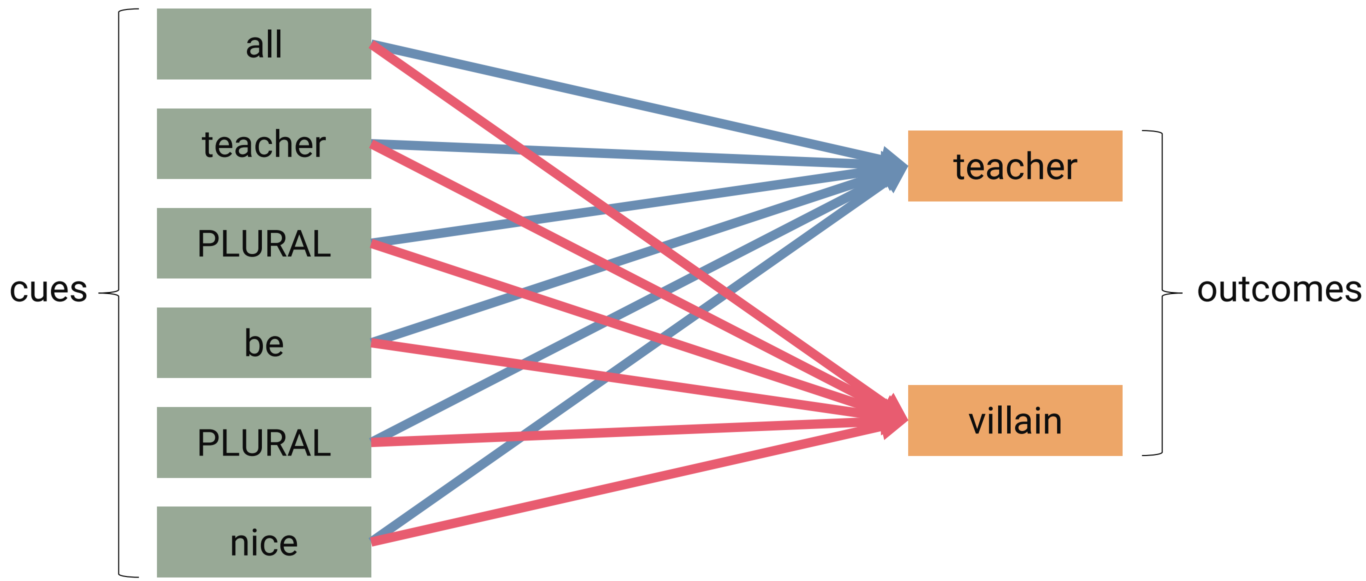

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- Potentially very different semantics of pronoun attestations are conflated into one vector representation
- This is an issue!
  → Pronouns are assumed to inherit the semantics of their referents

Instance vectors

- preceding and following words

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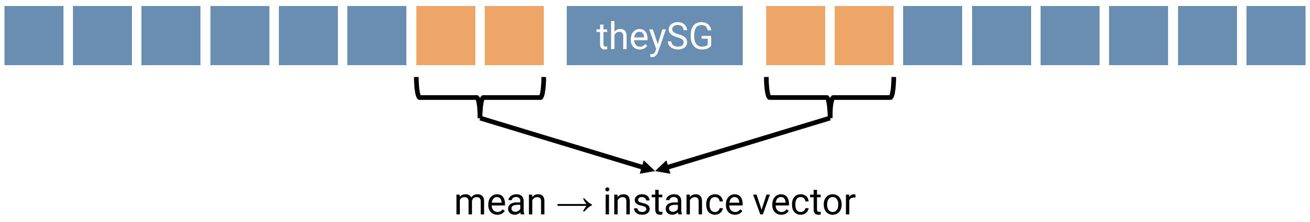

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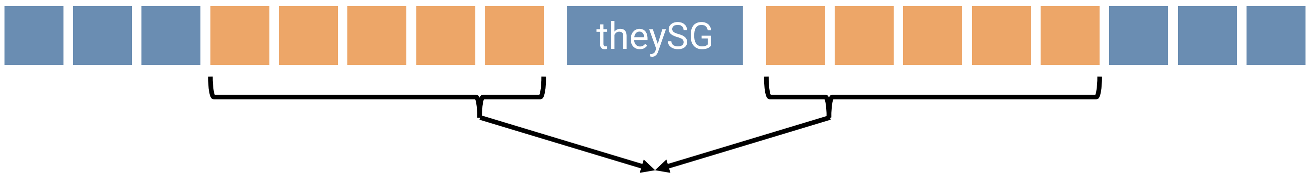

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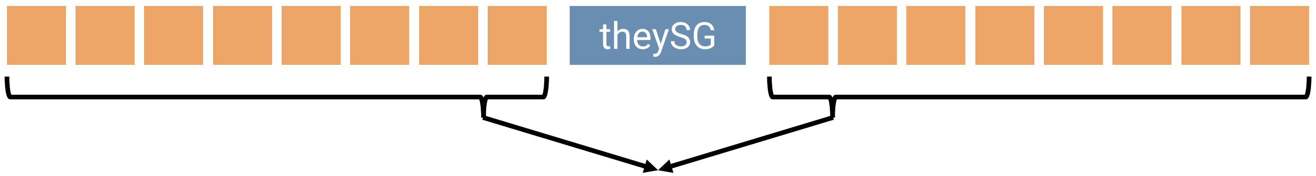

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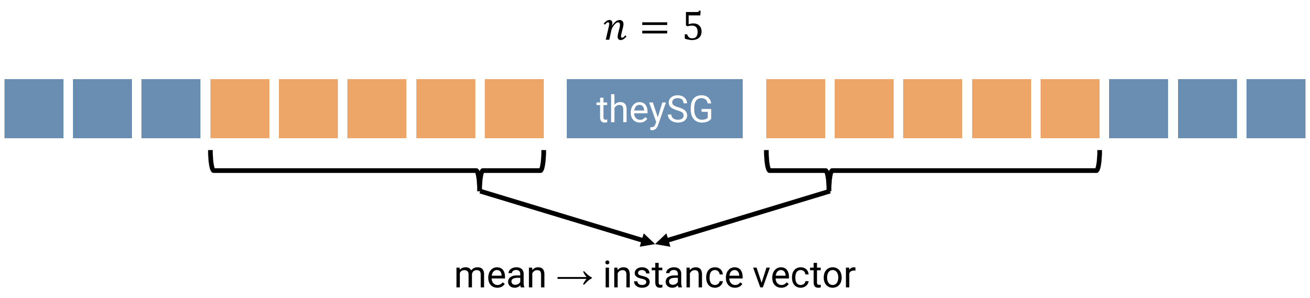
Instance vectors

- For the present study
  - $n = 5$
  - Preceding and following units: vectors for bases/function words/inflectional functions
  - Preceding and following semantic vectors: via NDL



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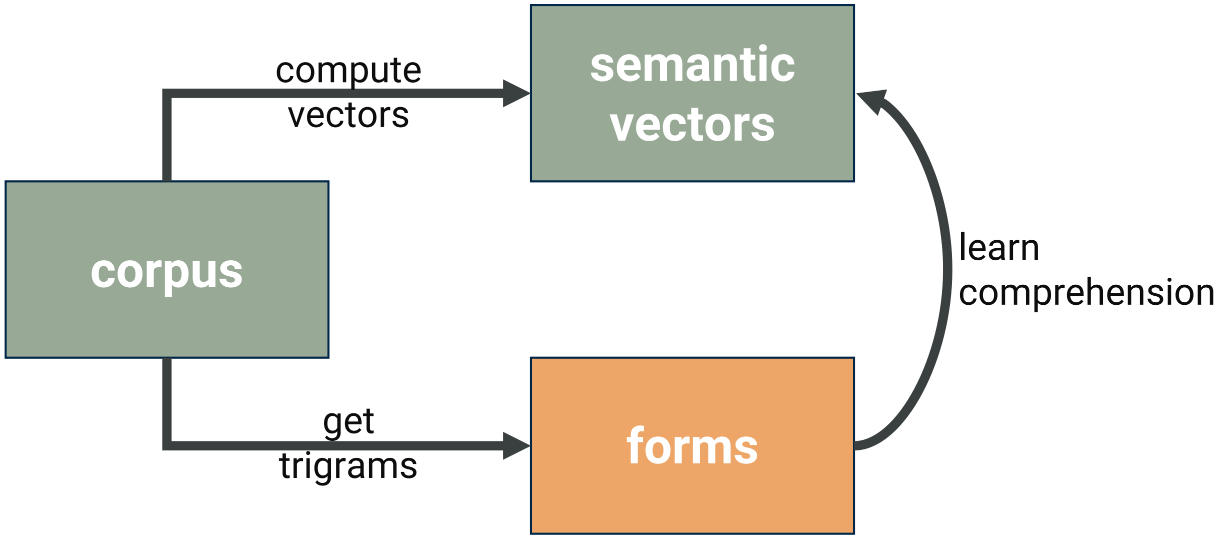

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target form	#ca	cat	at#	cap	ap#	#ba	bat
cat	1	1	1	0	0	0	0
cap	1	0	0	1	1	0	0
bat	0	0	1	0	0	1	1

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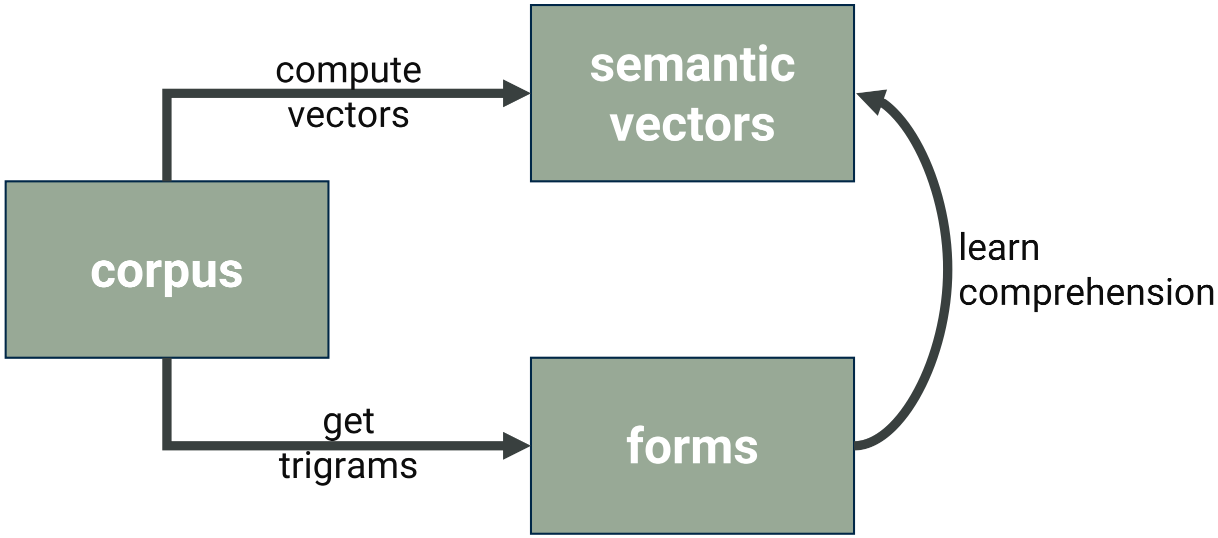

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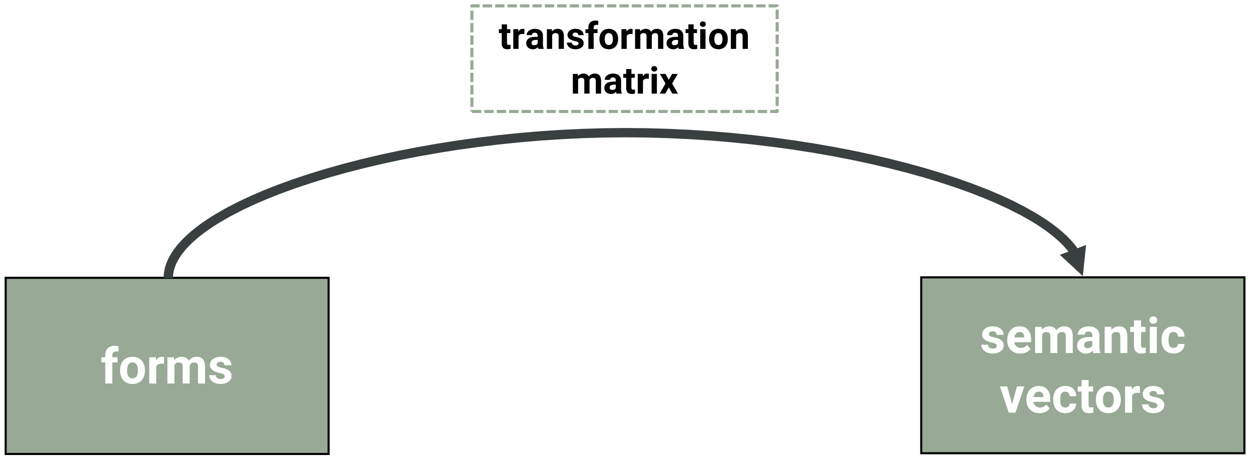

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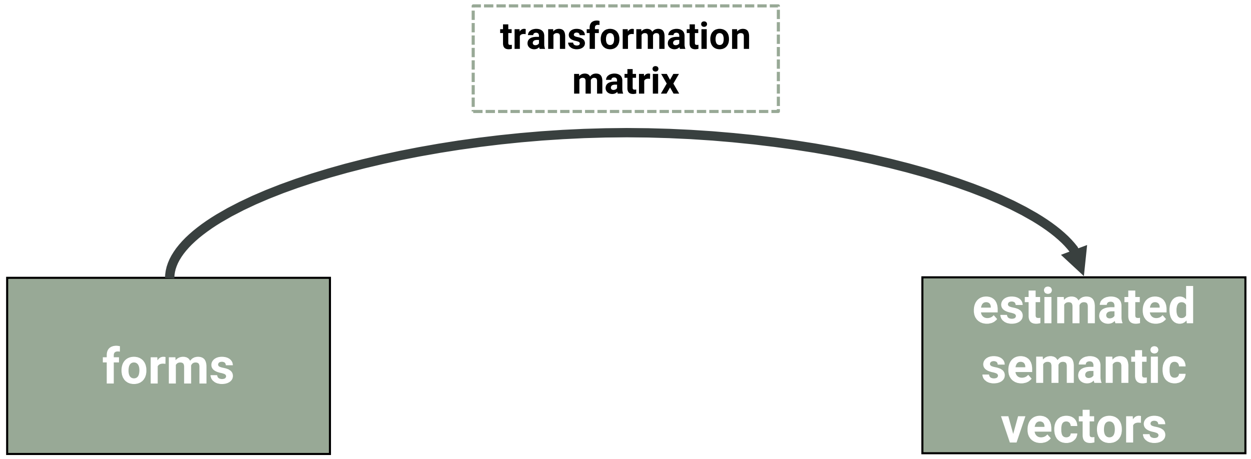
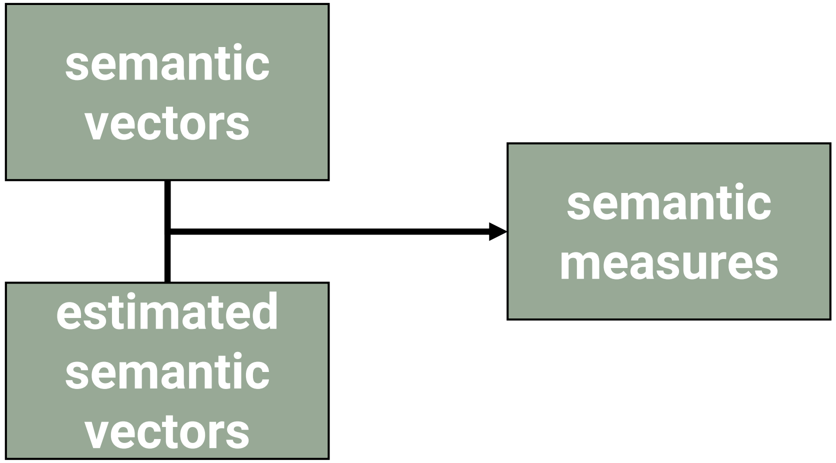


Semantic measures

- From the comprehension mapping, semantic measures can be derived



Results

Activation diversity and neighbourhood density

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Euclidian length of a target's vector

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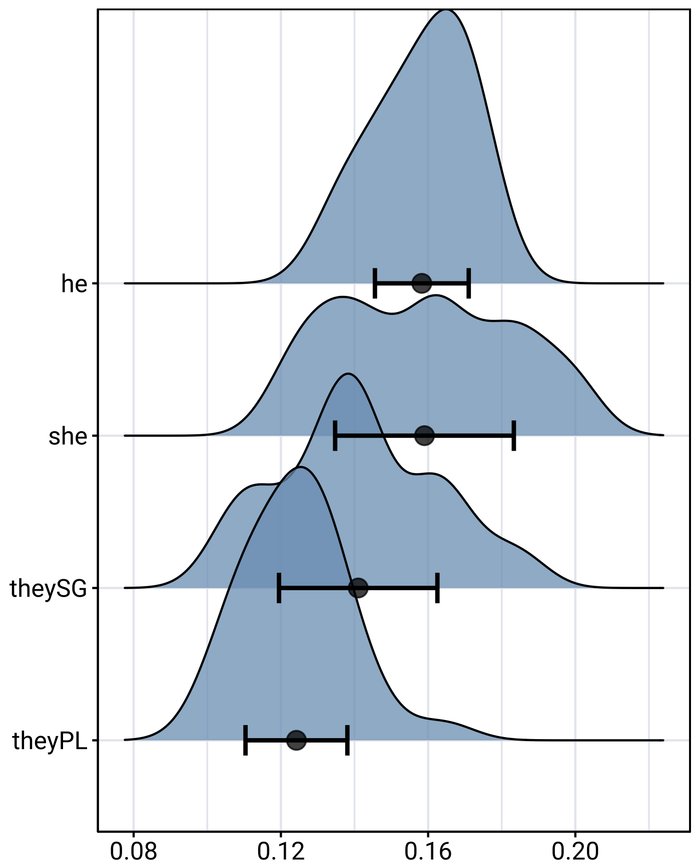

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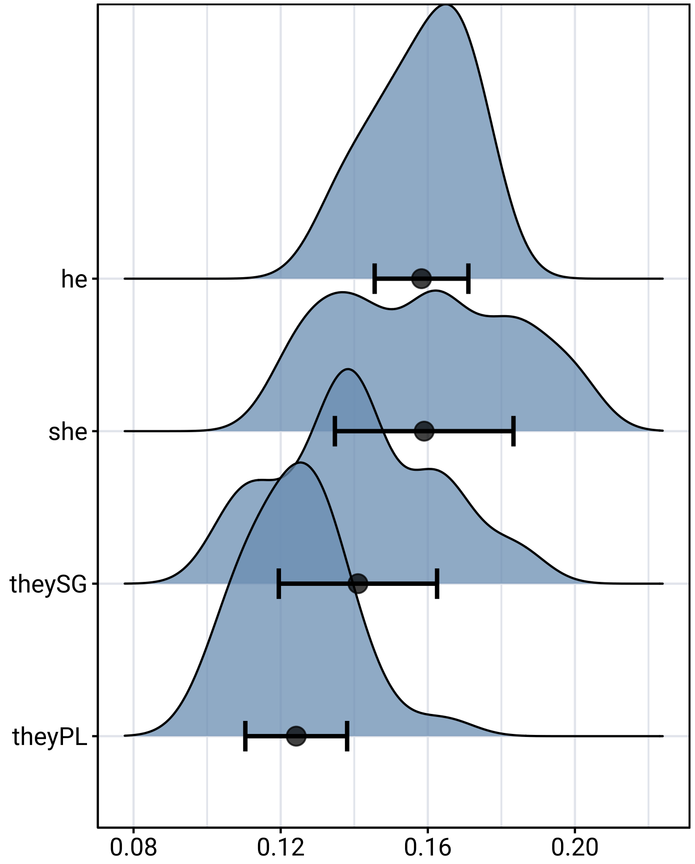

Semantic measures

SEMANTIC NEIGHBOURHOOD DENSITY

Correlation of a target with its

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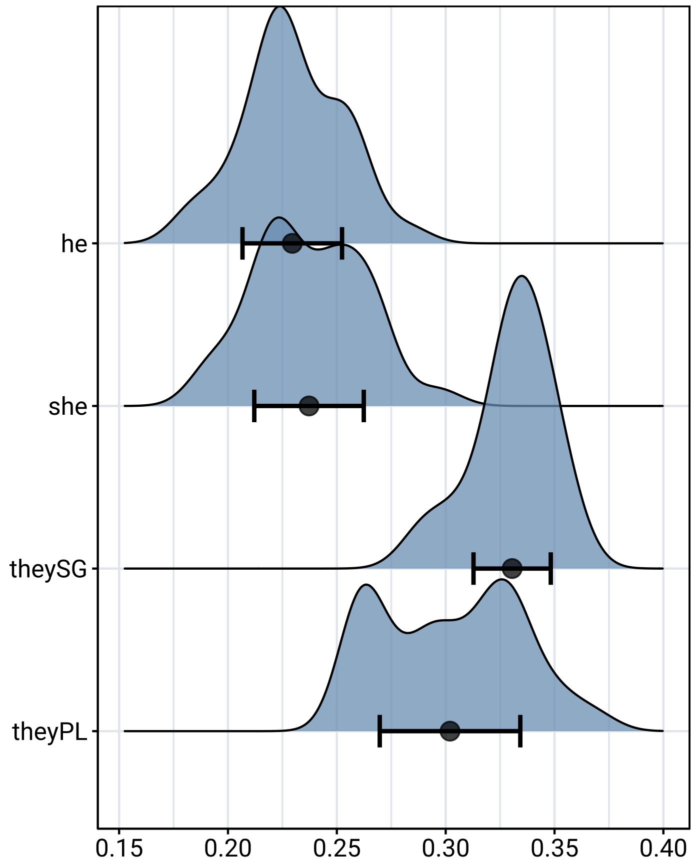

Discussion

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→ **YES**

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RQ2 – Theoretical Question

How is singular *they* semantically related to other third-person pronouns?

Research questions

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Can distributional semantics meaningfully capture pronoun semantics?

→ **YES**

RQ2 – Theoretical Question

How is singular *they* semantically related to other third-person pronouns?

→ **well…**

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capture the relation of third-person pronouns

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  - singular *they* in-between *he*, *she* and plural *they*

    = situated between its singular competitors and its plural homophone
- **SEMANTIC NEIGHBOURHOOD DENSITY**
  - singular *they* has highest neighbourhood density

    = potential effect of belonging to two "worlds" – singular and plural pronouns

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Thank you!

References

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Semantic measures

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  - regarding **SEMANTIC NEIGHBOURHOOD DENSITY**,

    singular *they* is most frequently confused with *anybody*, *anyone*, and plural *they*

Semantic space

Semantic space