A discriminative account of masculine generics and their masculine bias in German

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word	referent gender(s)	grammatical gender	number
Lehrer	male	masculine	singular
Lehrer	male or female	masculine	
Lehrerin	female	feminine	
Lehrer	male	masculine	plural
Lehrer	male or female	masculine	
Lehrerinnen	female	feminine	

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- generic masculines are
  - orthographically and phonologically **identical** to explicit masculines
  - used to describe individuals of **all genders** in singular and plural contexts
  - traditionally assumed to "abstract away" notions of gender, i.e. to be **gender-neutral** (cf. Doleschal 2002)

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  → generic masculines are not gender-neutral but show a clear bias towards the explicit masculine reading (e.g. Demarmels 2017; Garnham et al. 2012; Gygax et al. 2008; Irmen & Kurovskaja 2010; Irmen & Linner 2005; Koch 2021; Misersky et al. 2019; Stahlberg & Sczesny, 2001)

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- even though a generic masculine may be used with the intention of considering all genders…
- …this intention is not fully translated by the receiver's comprehension system
- instead, a reading favouring male individuals is received

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Most studies provide evidence for a masculine bias but do not deliver an explanation for the masculine bias.

→ use naive and linear discriminative learning

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RQ 2
If so, how do the semantics of masculine generics differ from the semantics of masculine explicits and feminine explicits?

Method

Discriminative Learning

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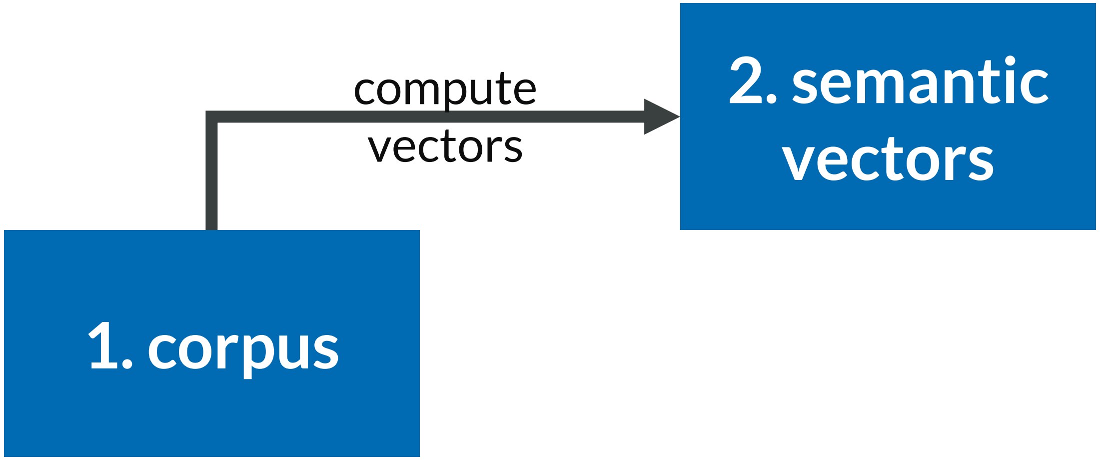

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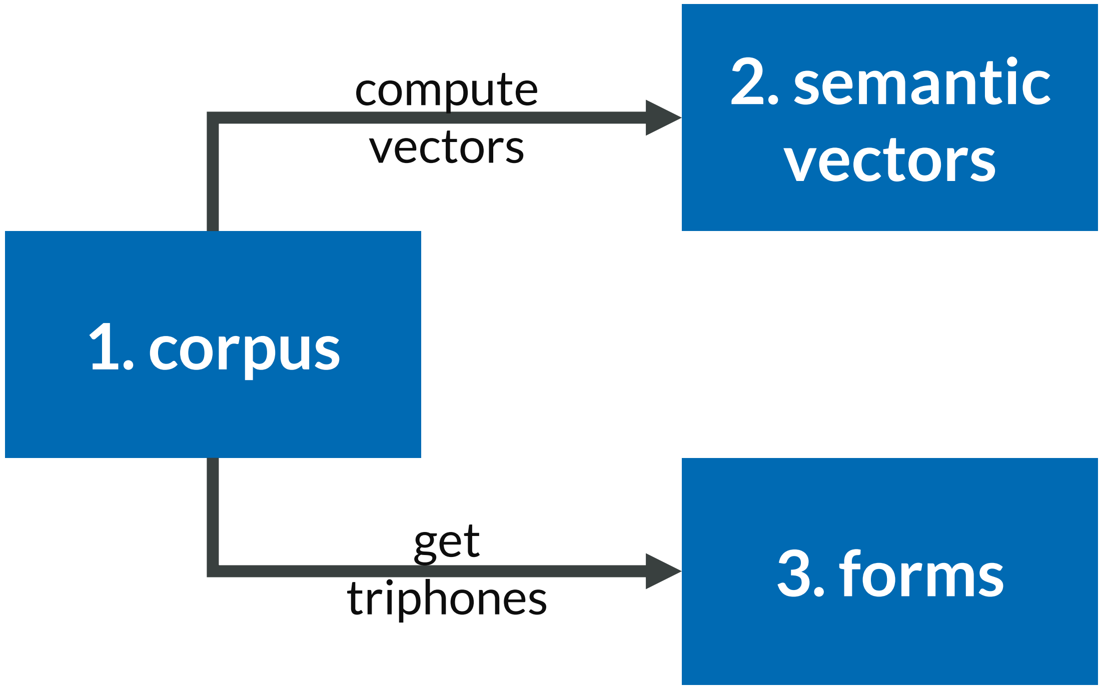

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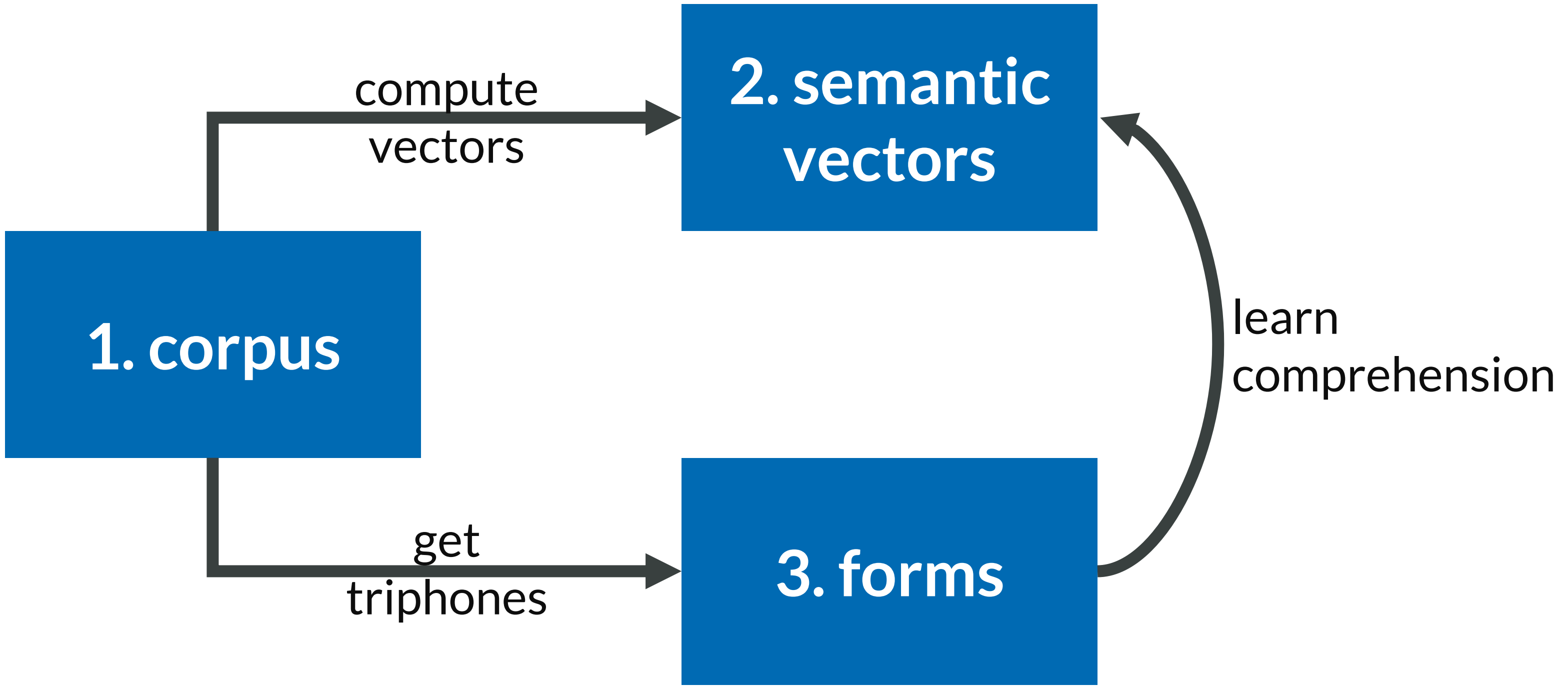

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generic & explicit masculines
Anwalt
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translation
‘lawyer’
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generic & explicit masculines	explicit feminines	translation
Anwalt	*Anwältin*	'lawyer'
Bäcker	*Bäckerin*	'baker'
Historiker	*Historikerin*	'historian'
Maurer	*Maurerin*	'mason'
Professor	*Professorin*	'professor'
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  - 30,000 sentences with target words
  - 49,044,960 words overall

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- from the 10 million sentences, the following was sampled
  - 800,000 sentences without any target words
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  - 49,044,960 words overall
- overall frequency of target word paradigms in our corpus is relative to their overall frequency in the 10 million sentences, e.g.
  - target word paradigm with 20,000+ occurrences = 600 samples
  - target word paradigm with fewer than 200 occurrences = 100 samples

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- tagged information consisted of words' base forms and information on inflectional grammar

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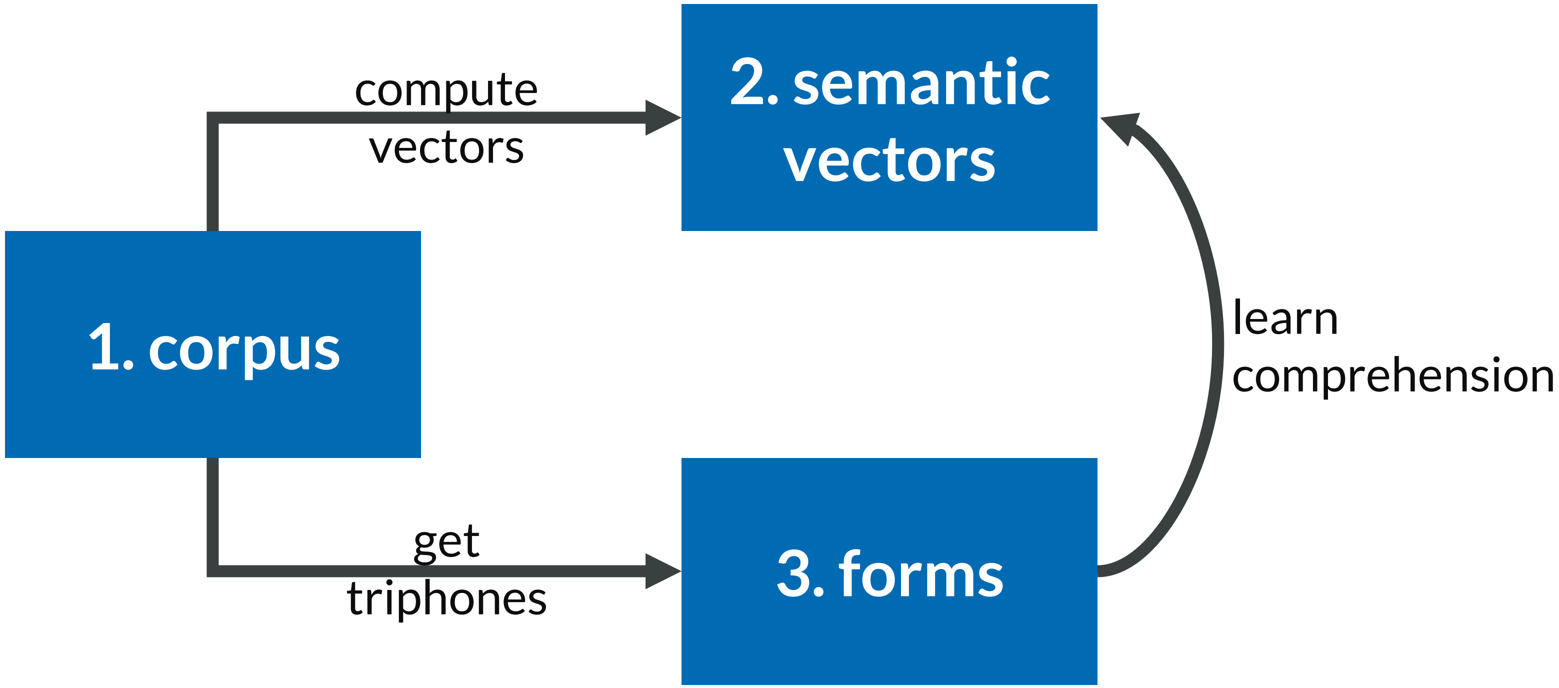

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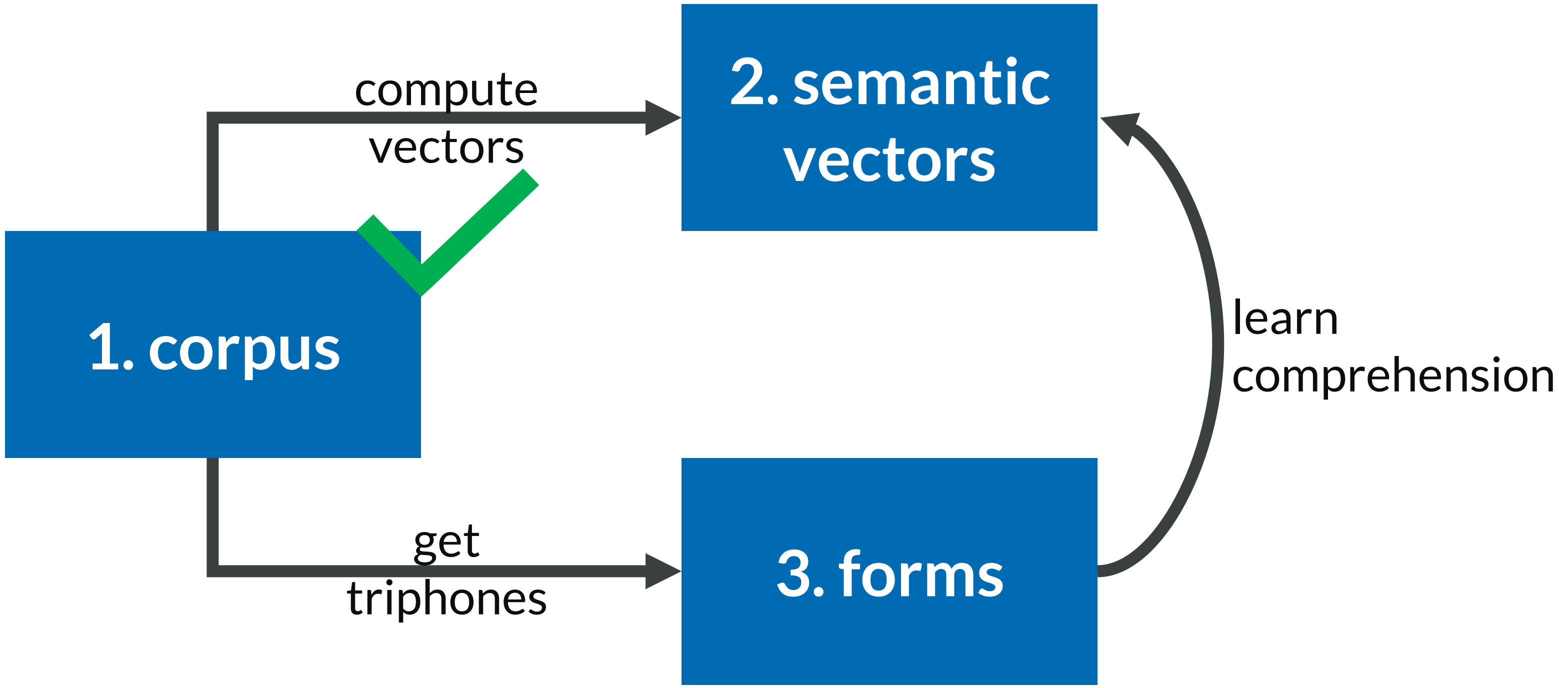

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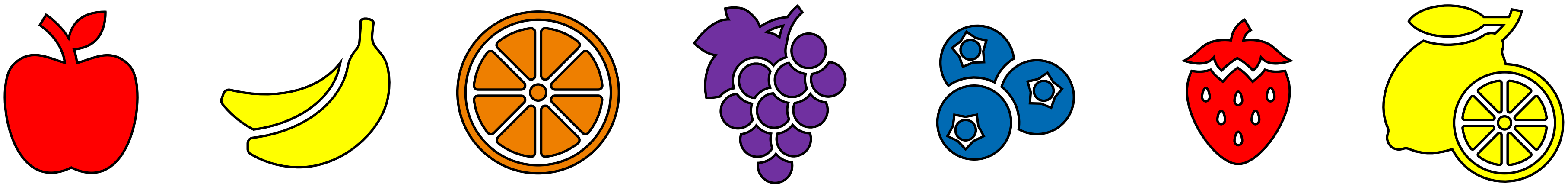
- we used each sentence to predict each individual word within the sentence by the other words in that sentence

Naive Discriminative Learning

toy example: different fruits



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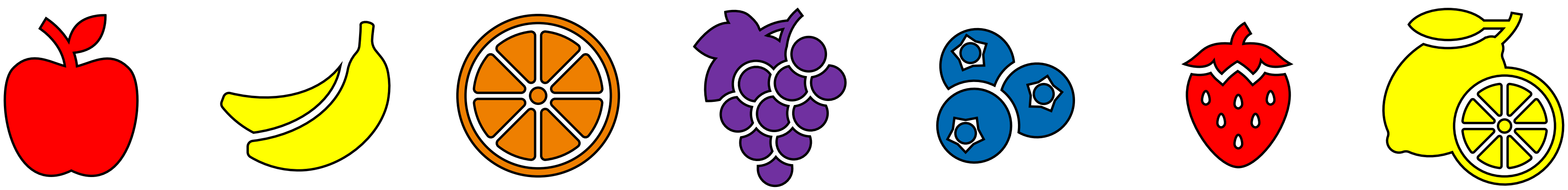

red	yellow	orange	purple	blue	red	yellow
sweet	sweet	sour	sweet	sweet	sweet	sharp
round	long	round	round	round	round	round
					long	long

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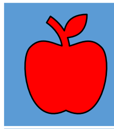
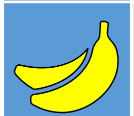
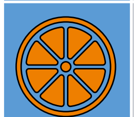
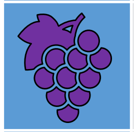
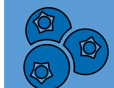
	red	yellow	orange	purple	blue	sweet	sour	round	long
	1					1		1	
		1				1			1
			1				1	1	
				1		1		1	
					1	1		1	
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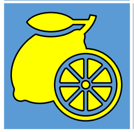		1					1	1	1

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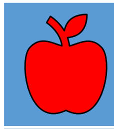
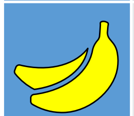
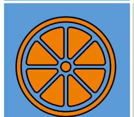
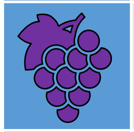
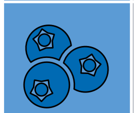
	30					30		30	
		15				15			15
			18				18	18	
				10		10		10	
					5	5		5	
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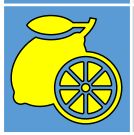		20					20	20	20

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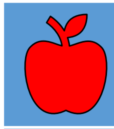	29	1				30		30	
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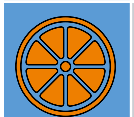
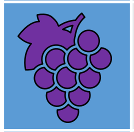
			18				18	18	
				10		10		10	
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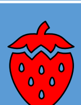
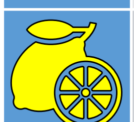
	45					45		45	45
		20					20	20	20

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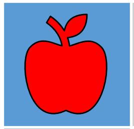
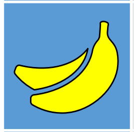
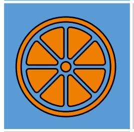
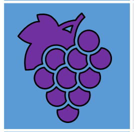
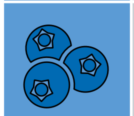
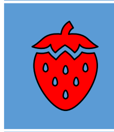
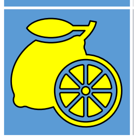
	29	1				29	1	30	
		15				15			15
			18				18	18	
				10		10		10	
					5	5		5	
	45					45		45	45
		20					20	20	20

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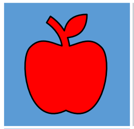
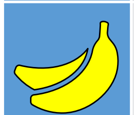
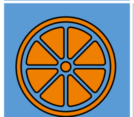
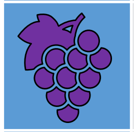
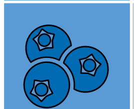
	29	1	-1	-3	-2	29	1	30	-1
		15				15			15
			18				18	18	
				10		10		10	
					5	5		5	
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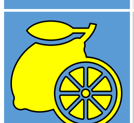
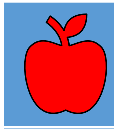
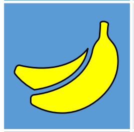
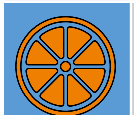
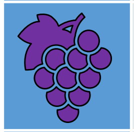
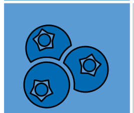
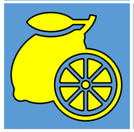
		20					20	20	20

Naive Discriminative Learning

toy example: different fruits

	red	yellow	orange	purple	blue	sweet	sour	round	long
	29	1	-1	-3	-2	29	1	30	-1
	-10	15	-10	-8	-6	15	-11	-5	15
	-6	-7	18	-14	-15	3	15	18	-2
	-5	-1	-6	10	-9	5	5	10	-7
	-6	-9	-19	2	3	4	1	5	-5
	45	-6	-9	-14	-1	25	20	45	45
	-1	20	-5	-6	-8	-4	20	20	20

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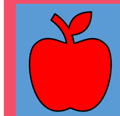	29	1	-1	-3	-2	29	1	30	-1
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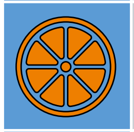
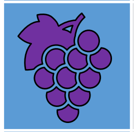
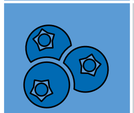
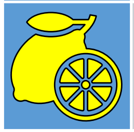
	-6	-7	18	-14	-15	3	15	18	-2
	-5	-1	-6	10	-9	5	5	10	-7
	-6	-9	-19	2	3	4	1	5	-5
	45	-6	-9	-14	-1	25	20	45	45
	-1	20	-5	-6	-8	-4	20	20	20

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Semantic vectors: Role nouns

- for content words, their semantic vector is the sum of the vectors of their parts, e.g. $\overrightarrow{apples} = \overrightarrow{apple} + \overrightarrow{plural}$

Semantic vectors: Role nouns

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- thus, e.g., the semantics of the target word paradigm *Lehrer* 'teacher' consists of

target	base		number		gender		genericity
Lehrer	$\overrightarrow{Lehrer}$	+	$\overrightarrow{\text{singular}}$	+	$\overrightarrow{\text{masculine}}$	+	$\overrightarrow{\text{generic}}$
Lehrer	$\overrightarrow{Lehrer}$	+	$\overrightarrow{\text{singular}}$	+	$\overrightarrow{\text{masculine}}$	+	$\overrightarrow{\text{explicit}}$
Lehrerin	$\overrightarrow{Lehrer}$	+	$\overrightarrow{\text{singular}}$	+	$\overrightarrow{\text{feminine}}$	+	$\overrightarrow{\text{explicit}}$
Lehrer	$\overrightarrow{Lehrer}$	+	$\overrightarrow{\text{plural}}$	+	$\overrightarrow{\text{masculine}}$	+	$\overrightarrow{\text{generic}}$
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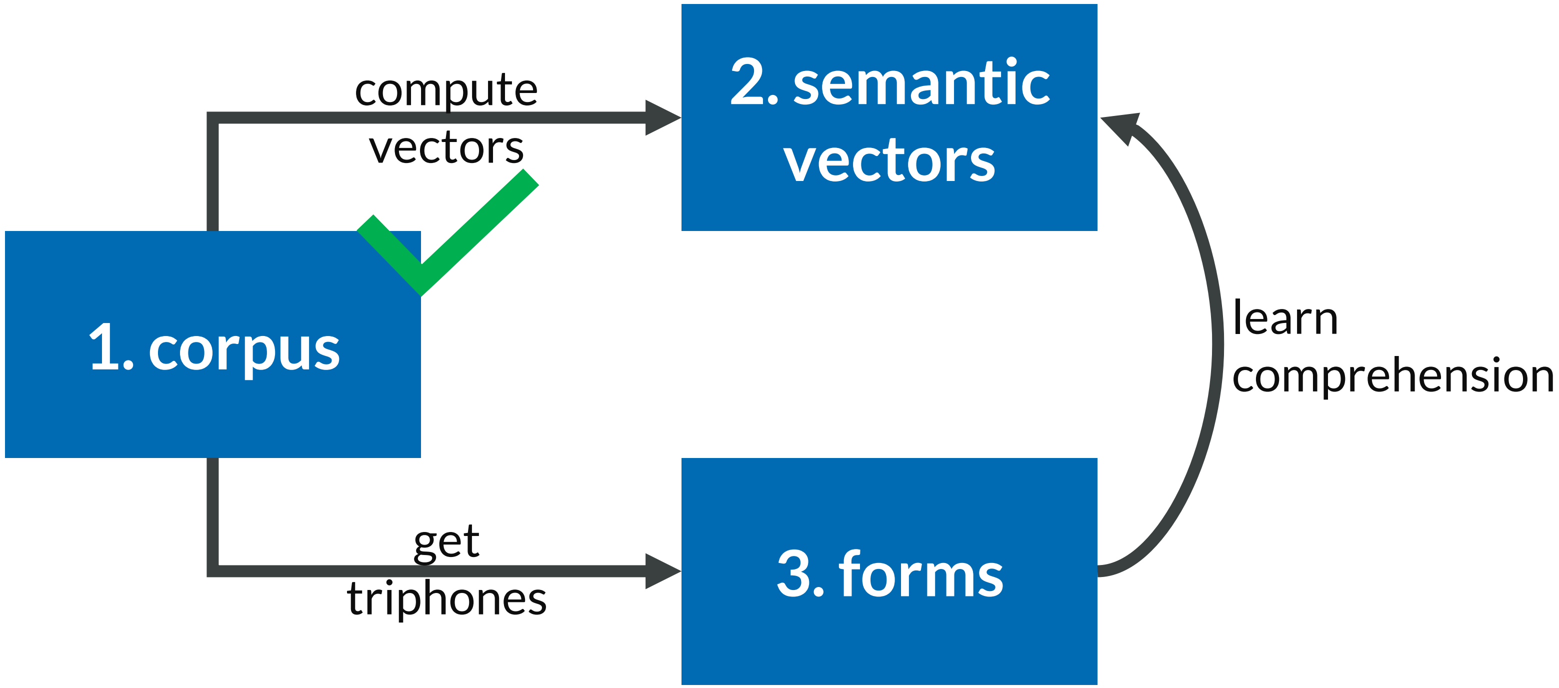
Method

- we simulate a mental lexicon by implementing a linear discriminative learning network (e.g. Baayen et al. 2019)
- using this mental lexicon, we can extract semantic measures for its entries



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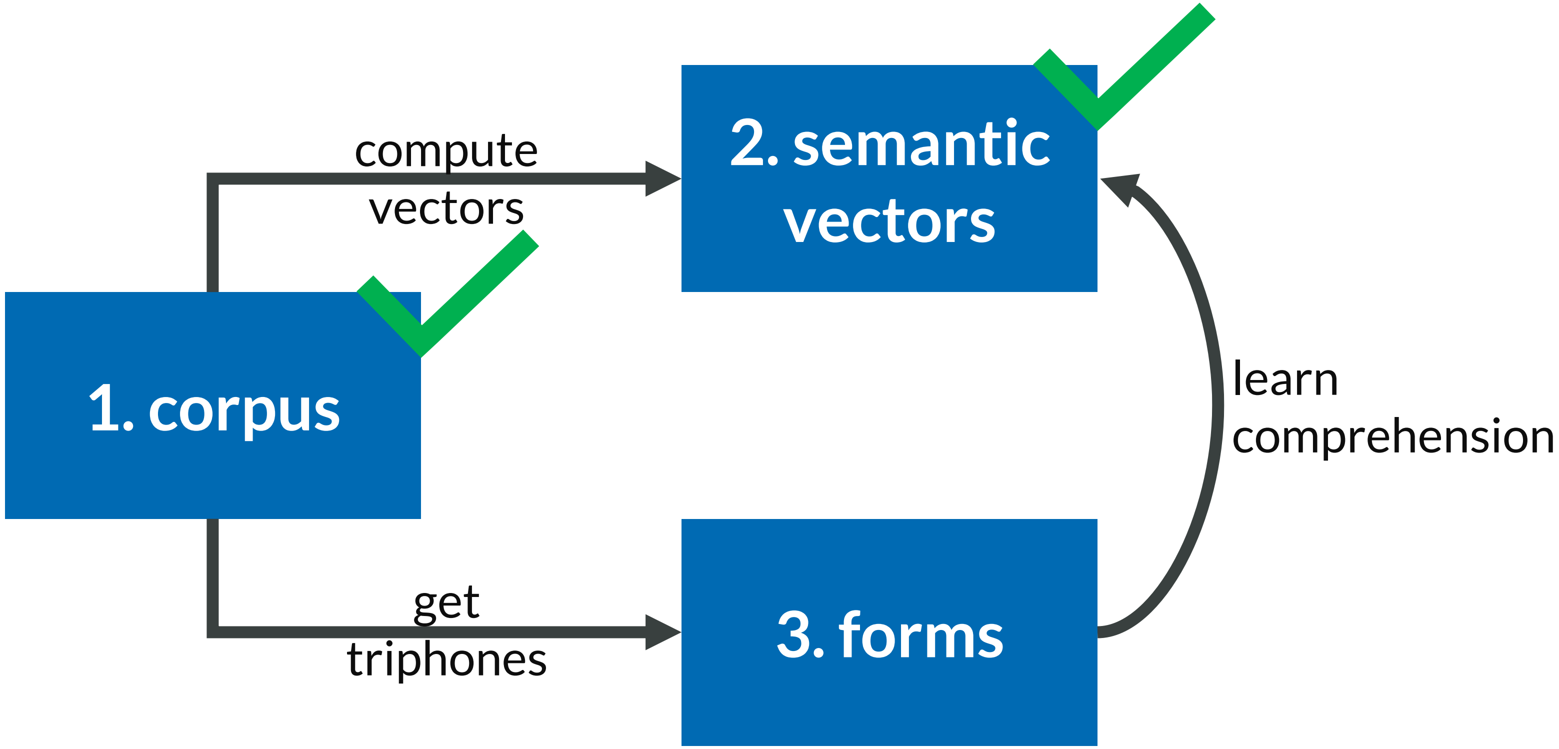

Forms

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- word forms are represented by triphones

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form	#le	ler	erA	rA#	ArI	rIn	In#
Lehrer	1	1	1	1	0	0	0
Lehrer	1	1	1	1	0	0	0
Lehrerin	1	1	1	0	1	1	1

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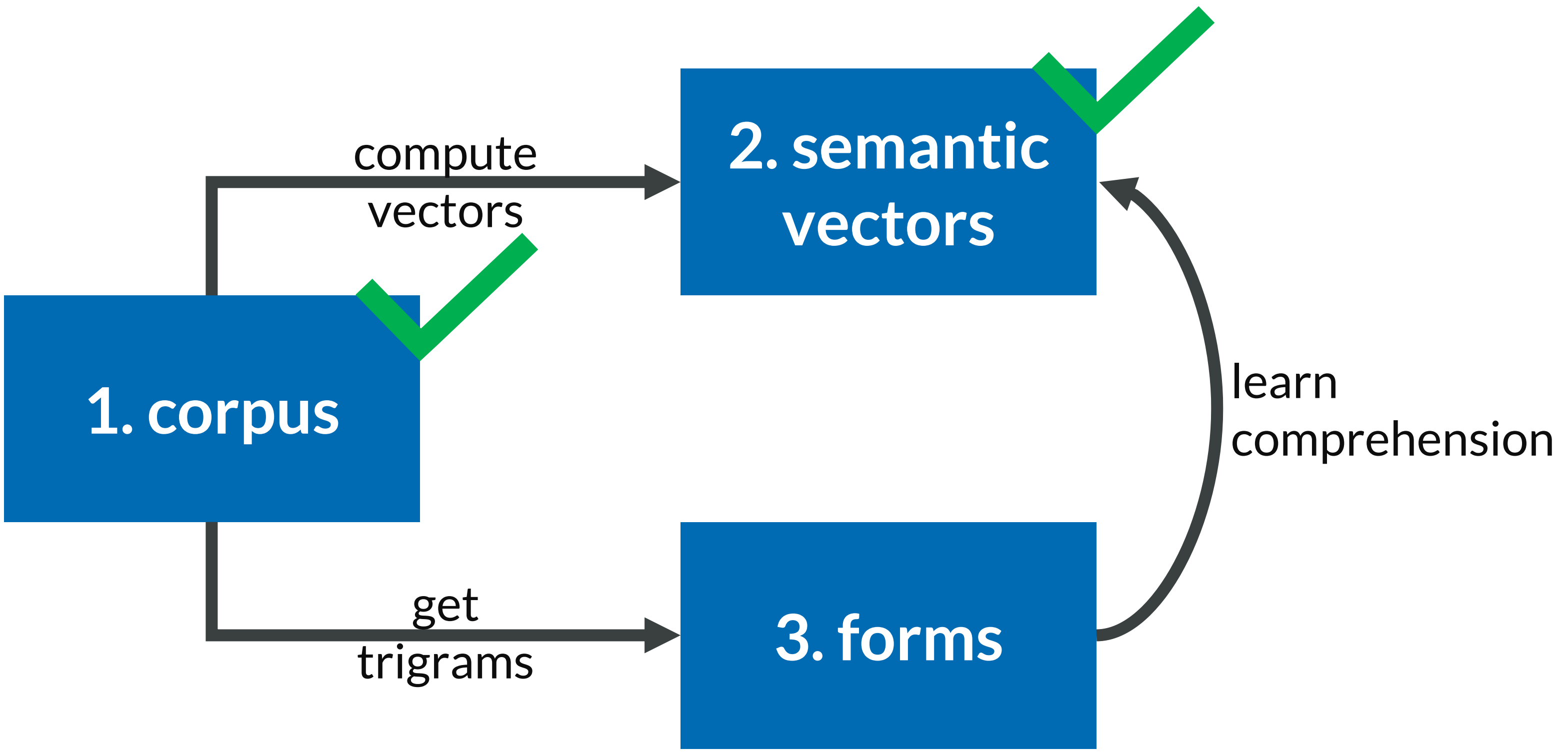

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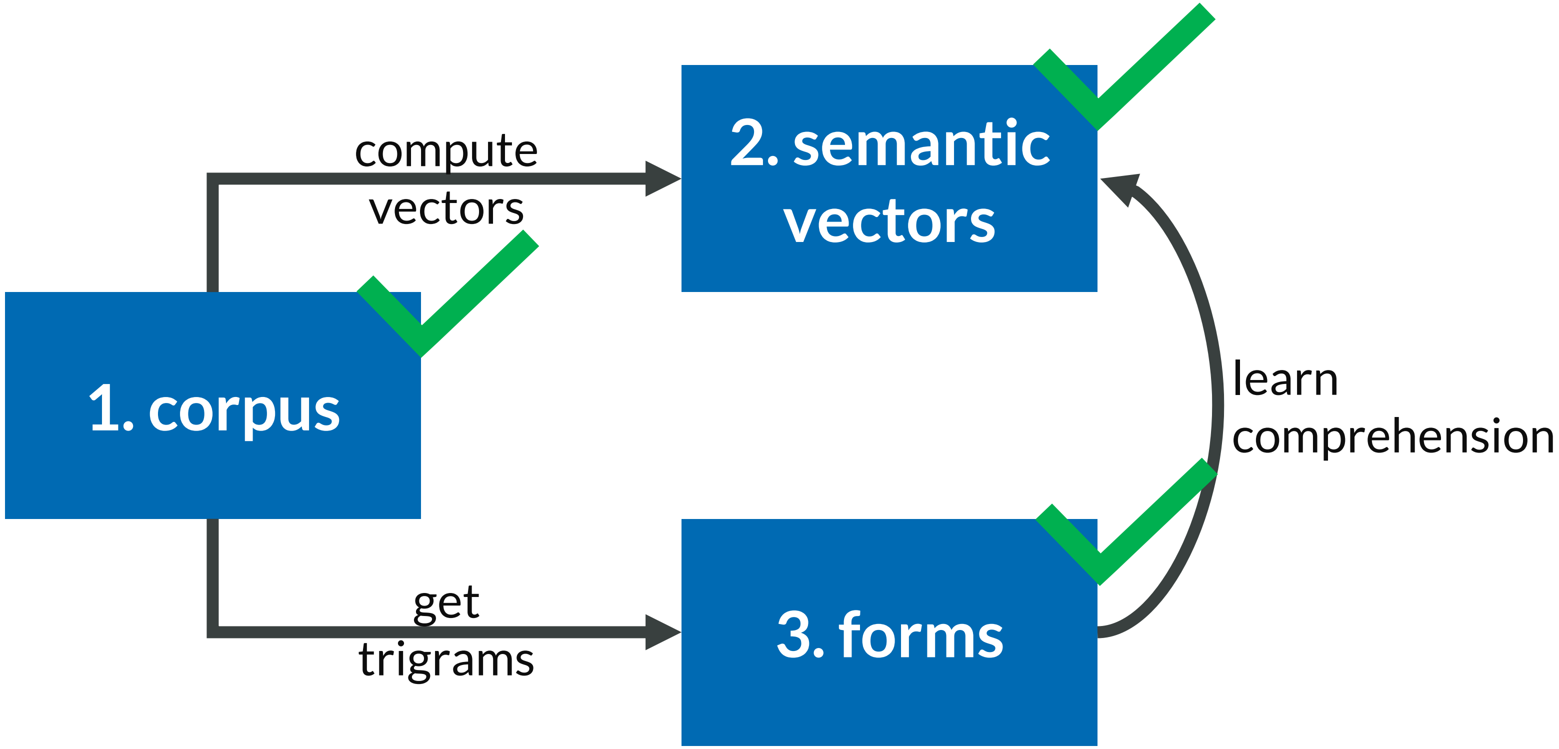

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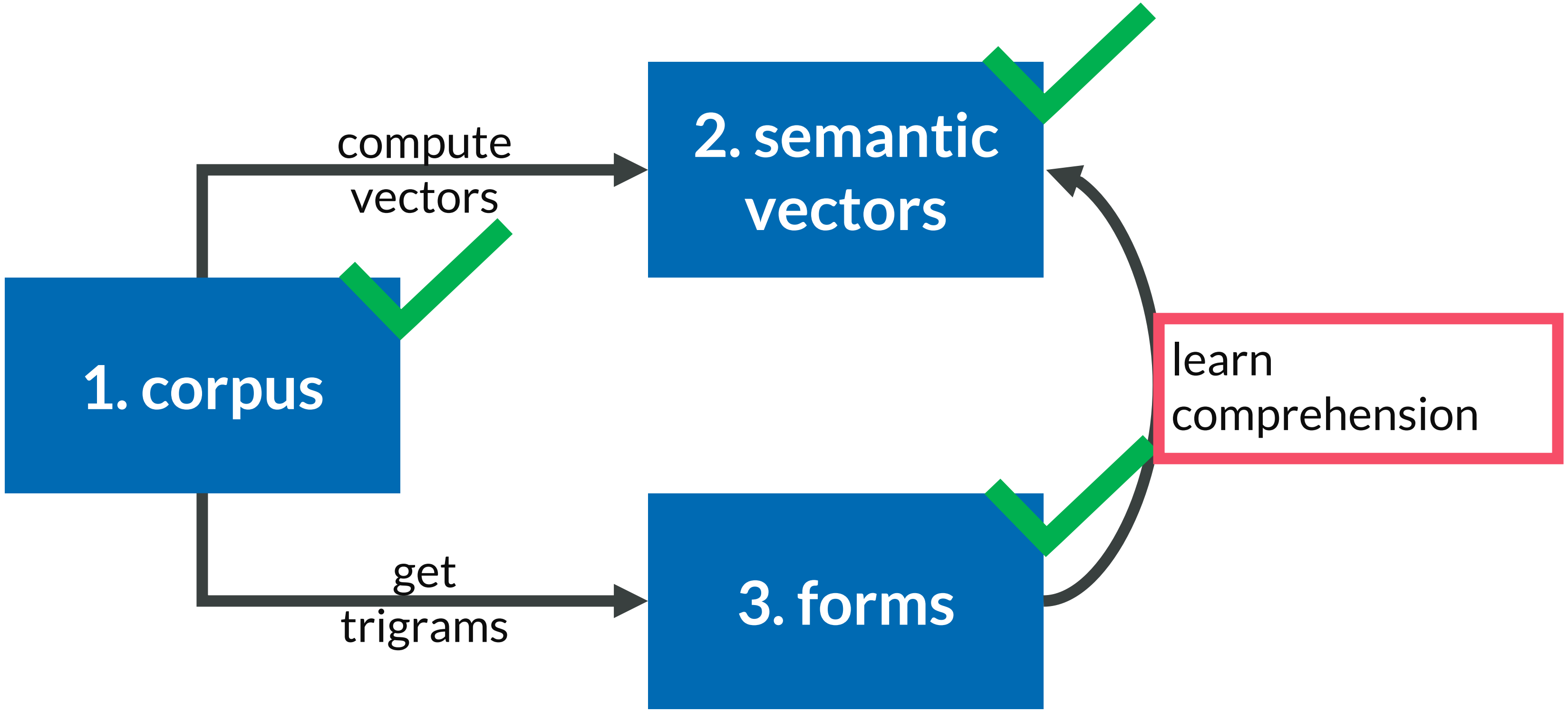

Learning comprehension

- Comprehension is learnt by linearly mapping the matrix of forms onto the matrix of semantic vectors

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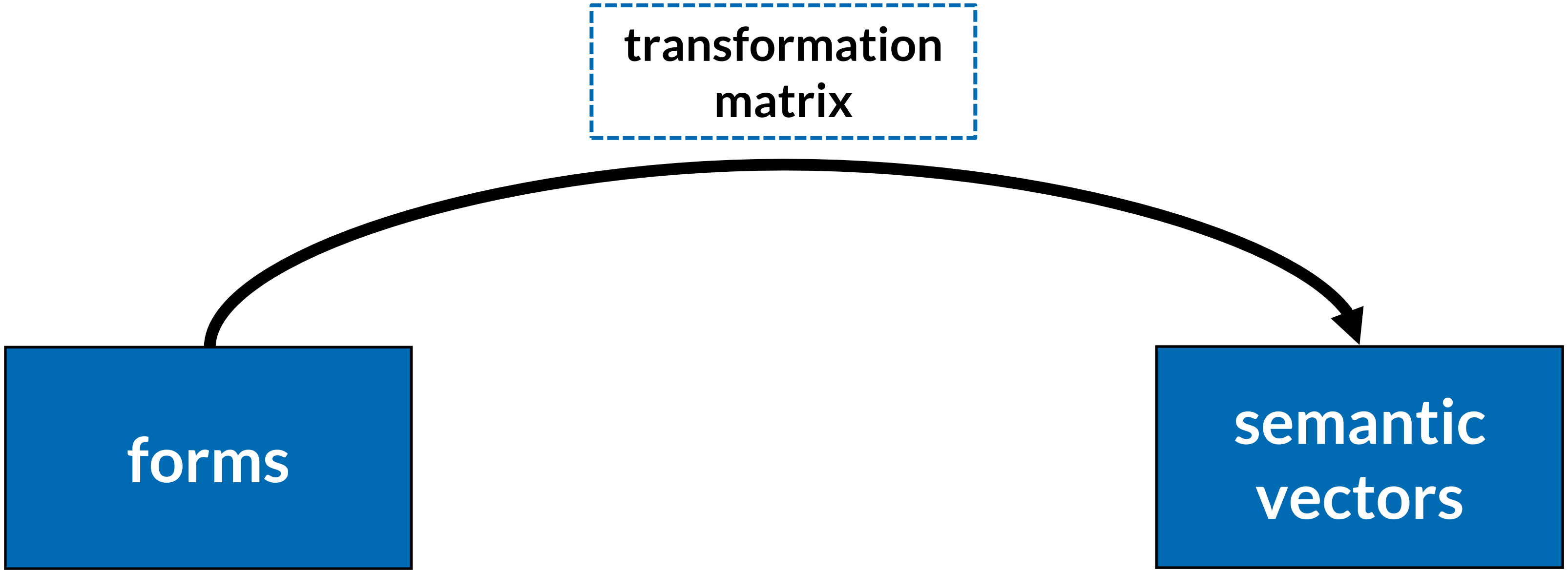

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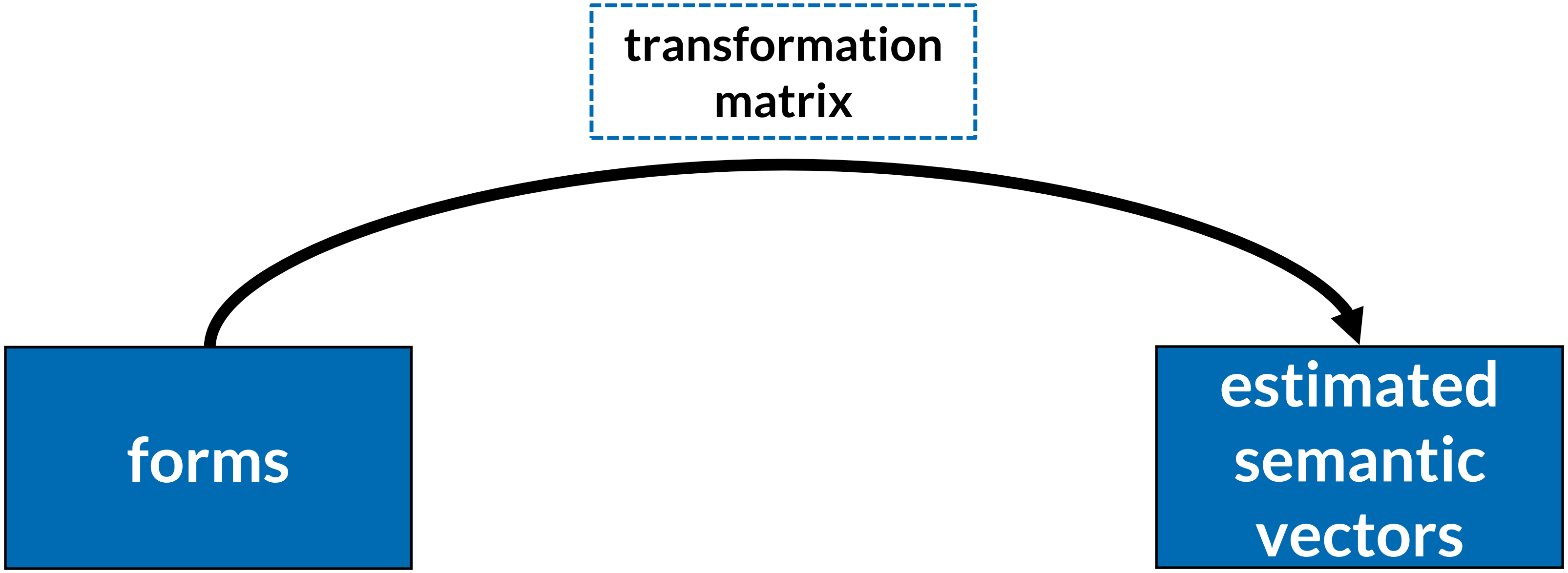

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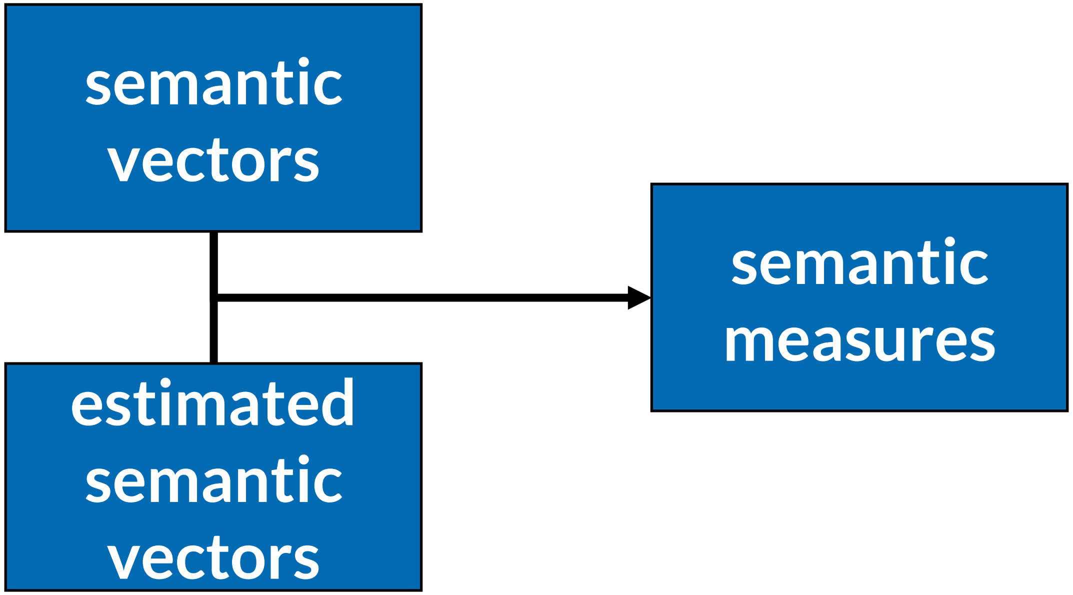

Analysis

Multinomial Logistic Regression

Variables

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  correlation of a target’s original and estimated vectors

  higher correlation = higher comprehension quality

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- **STEREOTYPICALITY**

  adopted from Gabriel et al. (2008)

Multinomial Logistic Regression

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- dependent variable: **TYPE**

  singular generic masculine; singular explicit masculine; singular explicit feminine

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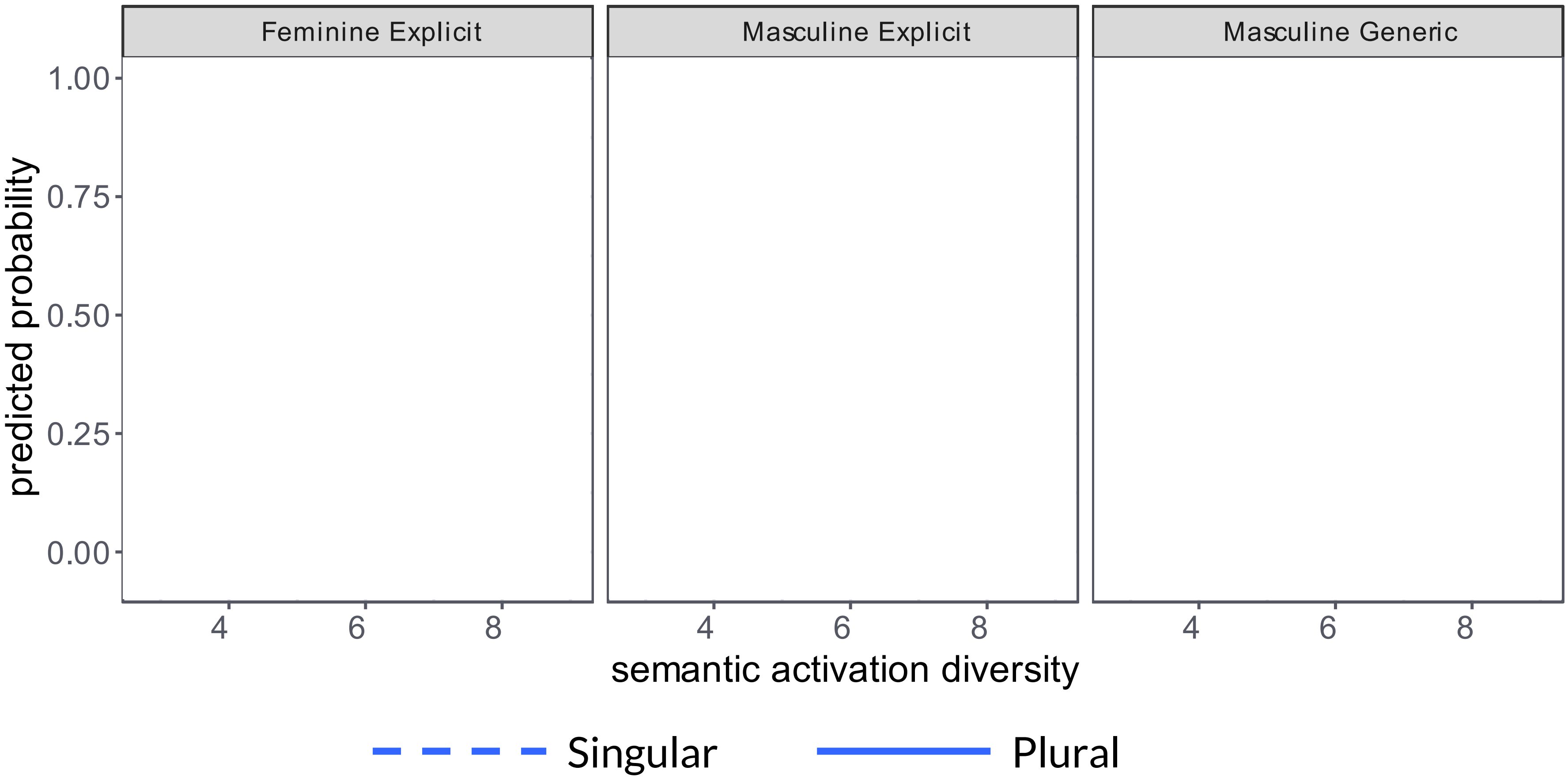
Results

ACTIVATION DIVERSITY



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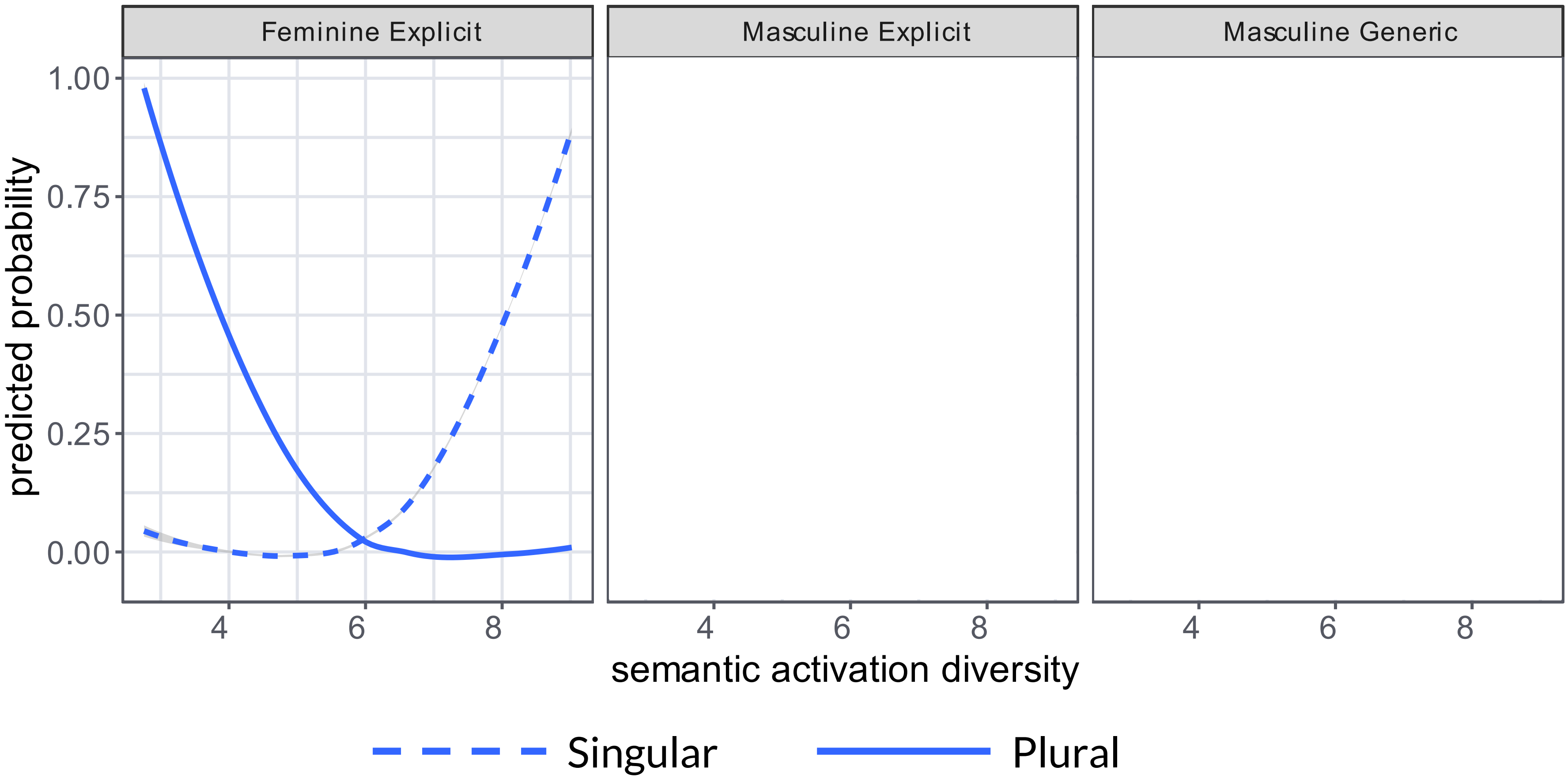

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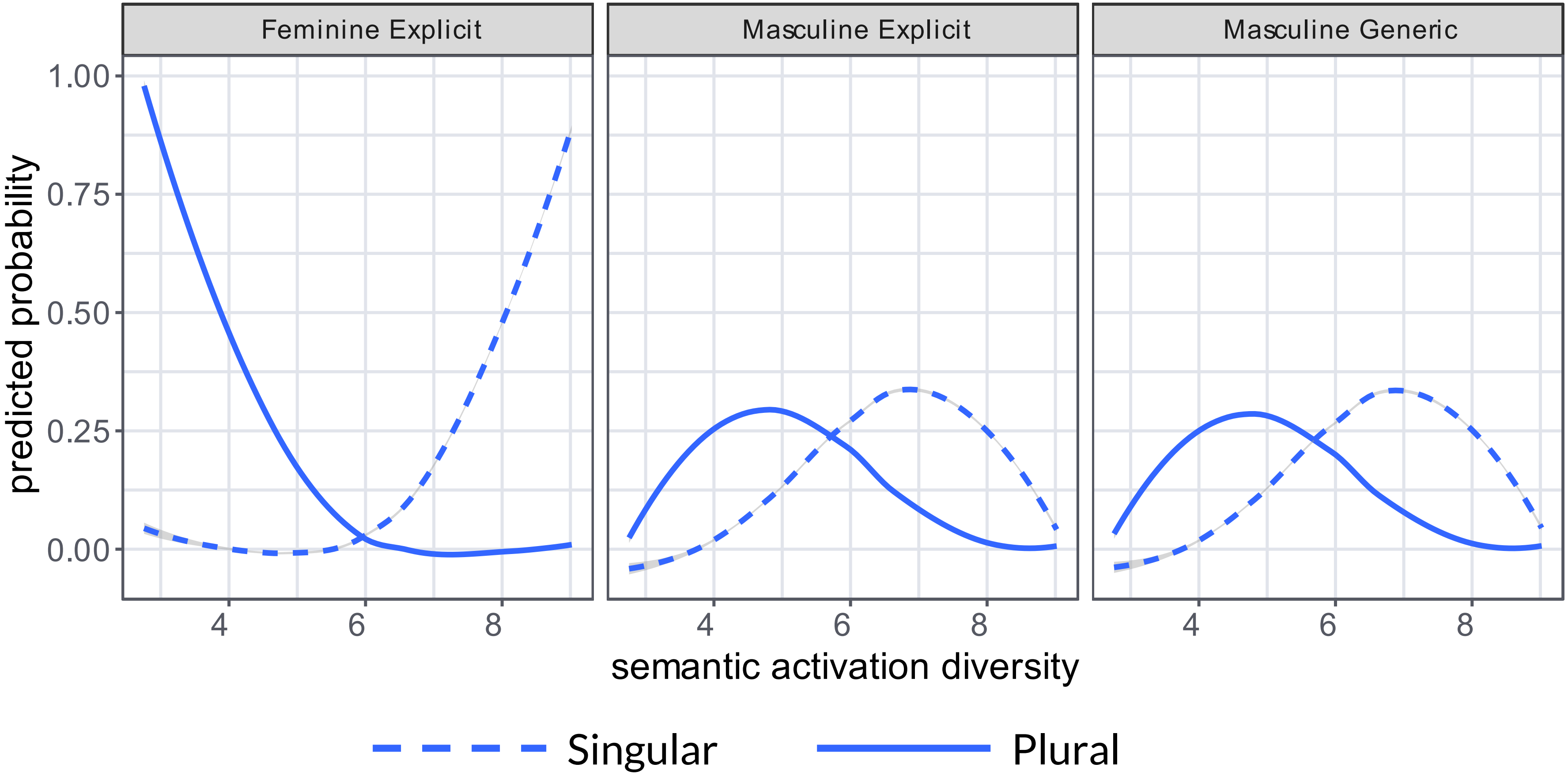

Results

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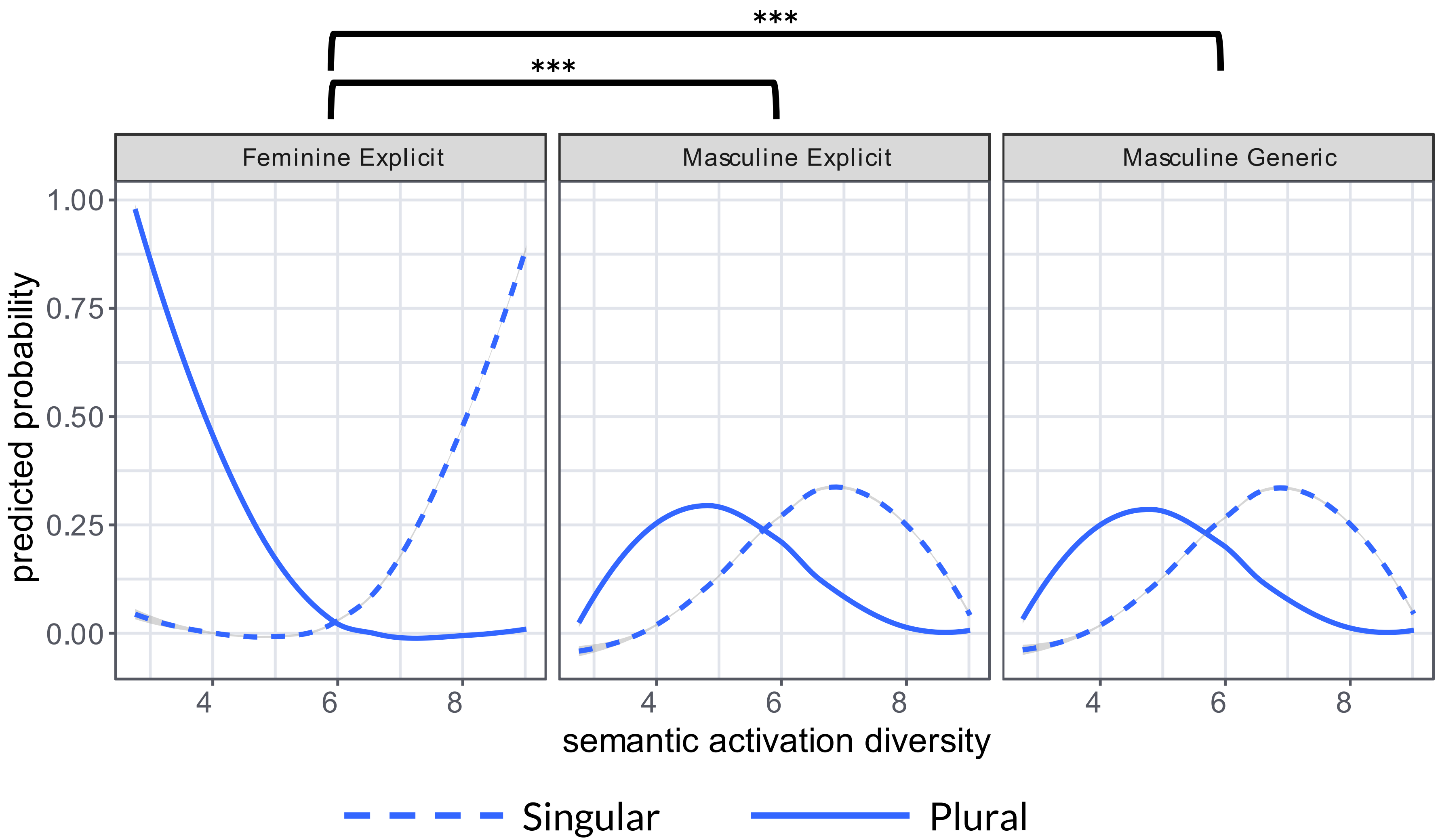
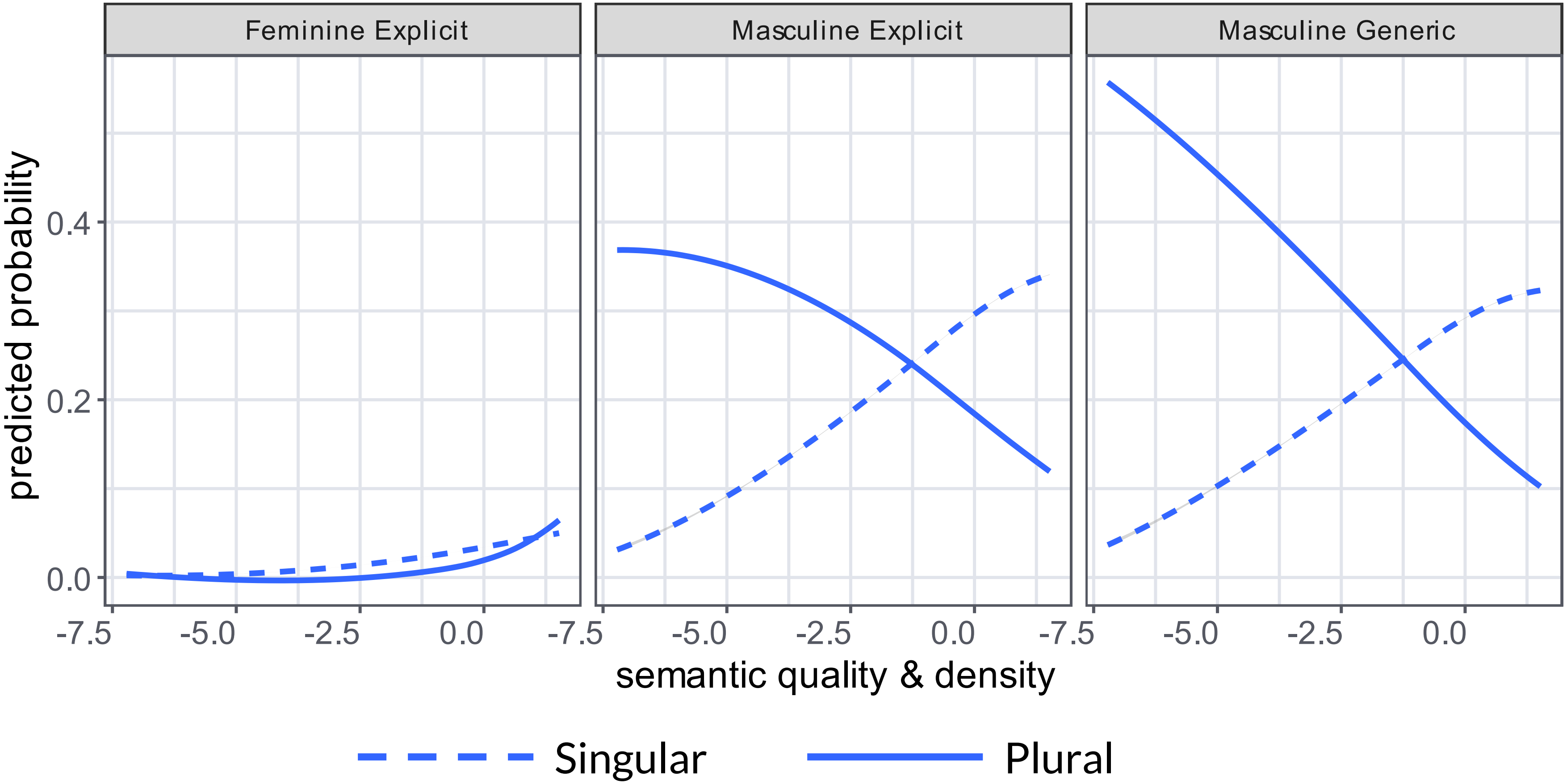


Results

COMPREHENSION QUALITY + NEIGHBOURHOOD DENSITY



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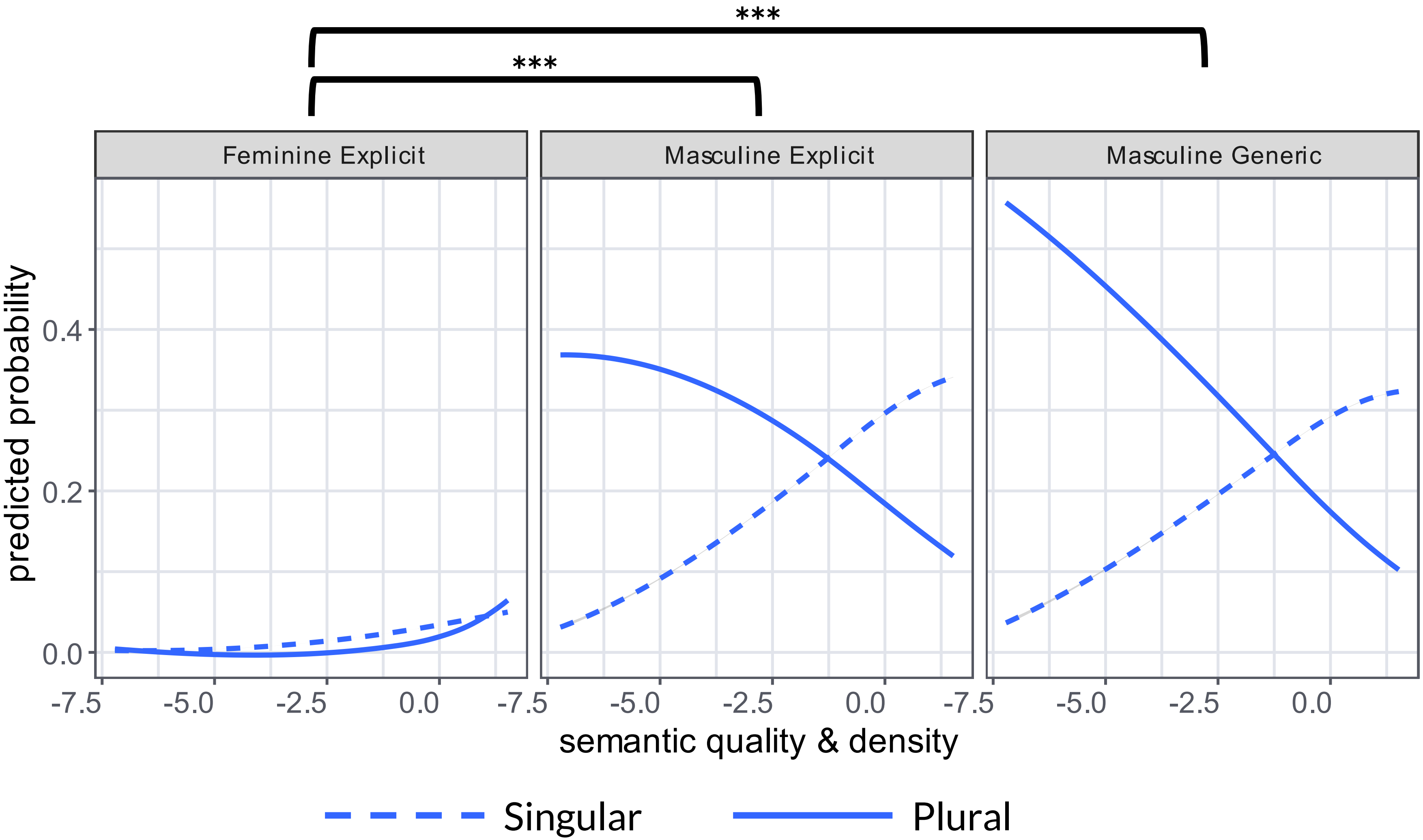
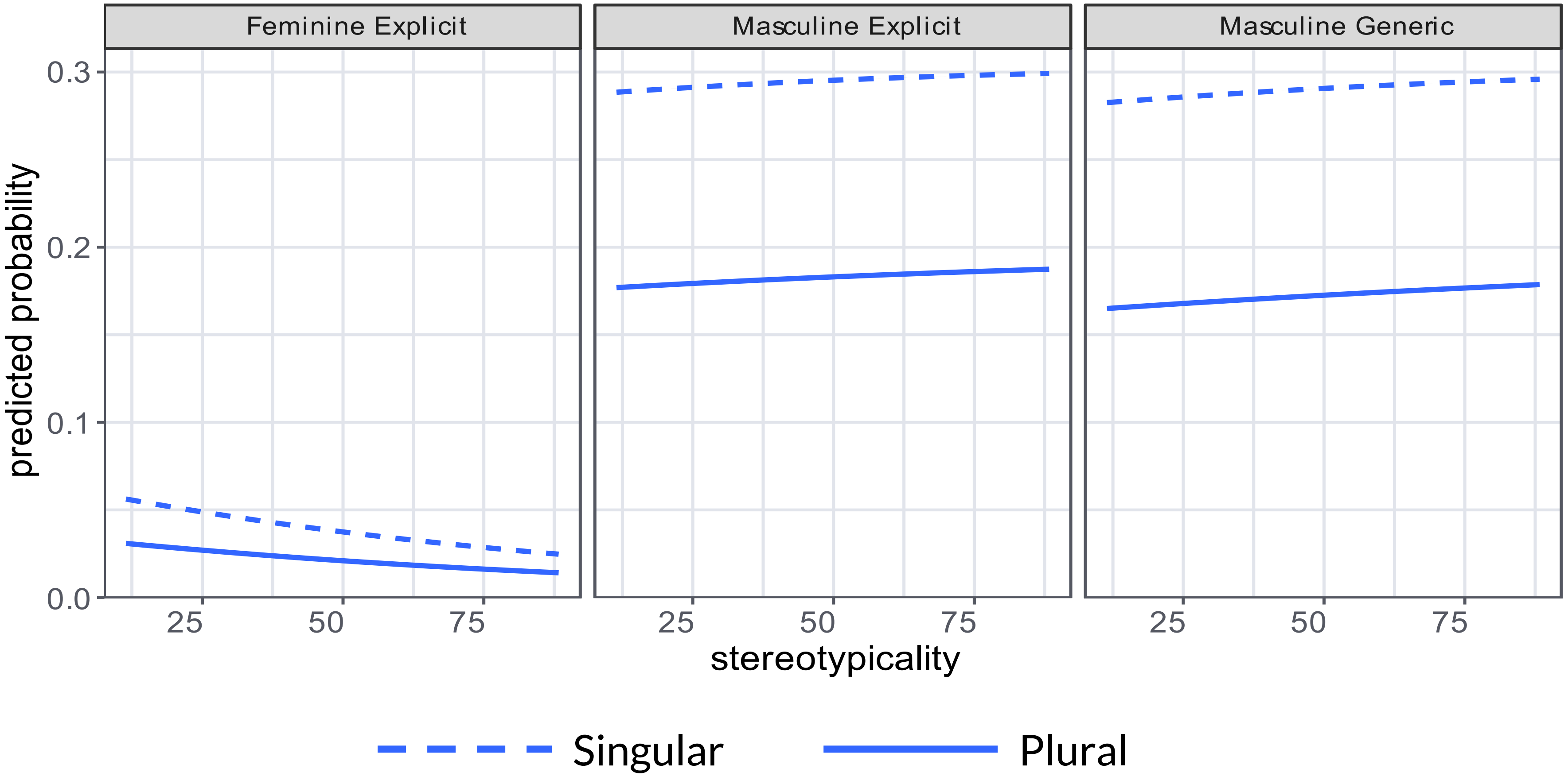


Results

STEREOTYPICALITY JUDGEMENTS

no significant effects!



Research questions

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Does discriminative learning provide insight into the semantics of masculine generics, masculine explicits, and feminine explicits?

→ **yes!**

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Discussion

So what do we learn from all of this?

Discussion

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  - feminine role nouns show interpretable exponent of their grammatical gender

    → shift in semantic space

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    semantic similarity of generic and explicit masculines due to their resonance with the lexicon and each other
  - Gygax et al. (2012) and Gygax et al. (2021)

    generic masculines activate the underlying representations of explicit masculines, leading to a semantic activation of explicit masculines, thus a male bias

Conclusion

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- future research will show
  - whether the LDL measures computed for our data are predictive of behavioural measures
  - how (new & allegedly) more neutral forms, e.g. *Lehrer*innen*, *LehrerInnen*, perform

Thank you!

Newly published in Glossa Psycholinguistics:
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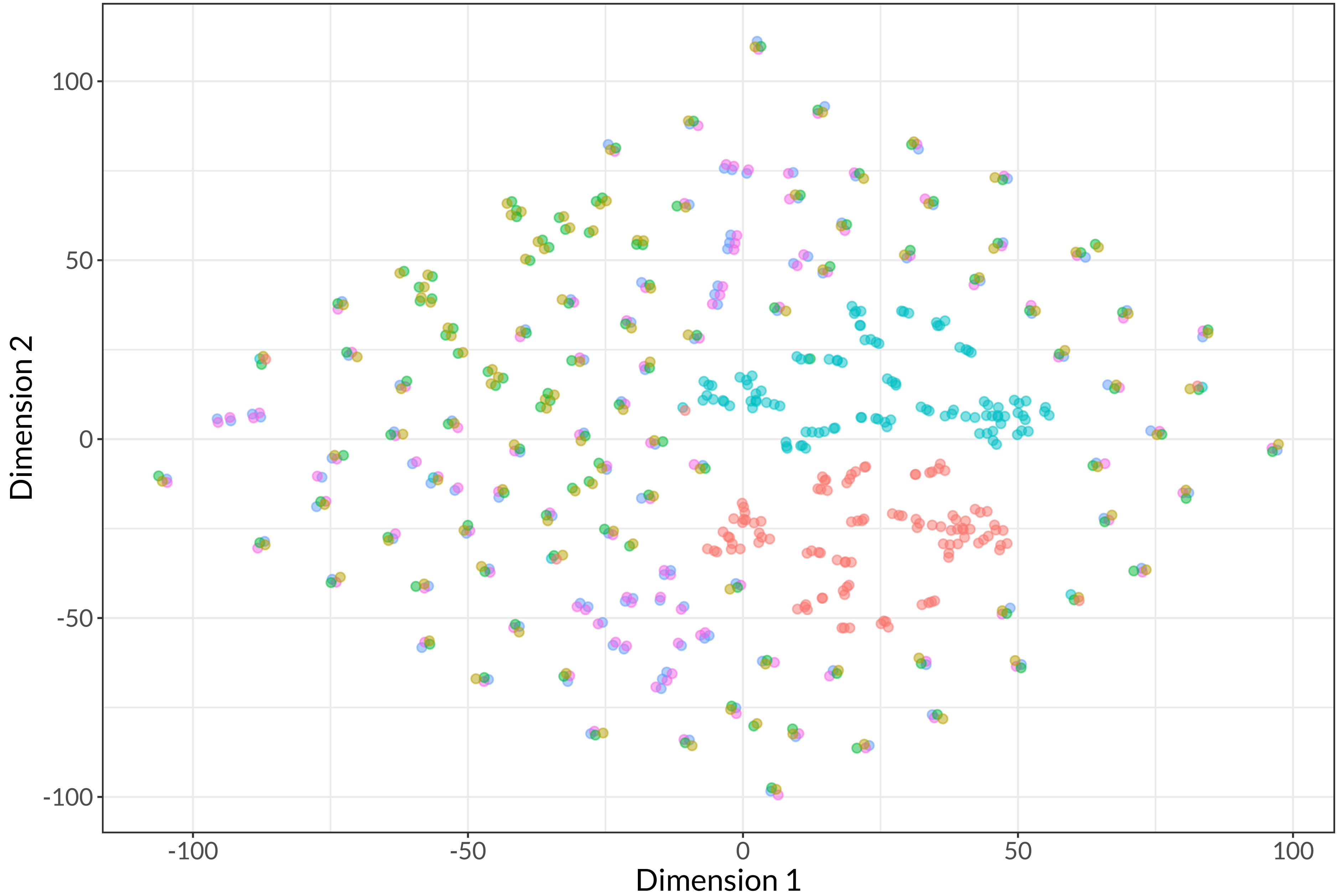
- hence our simulated lexicon will not be ‘confused’ by such forms / if the generic masculine shows a bias, it is not due to such new forms



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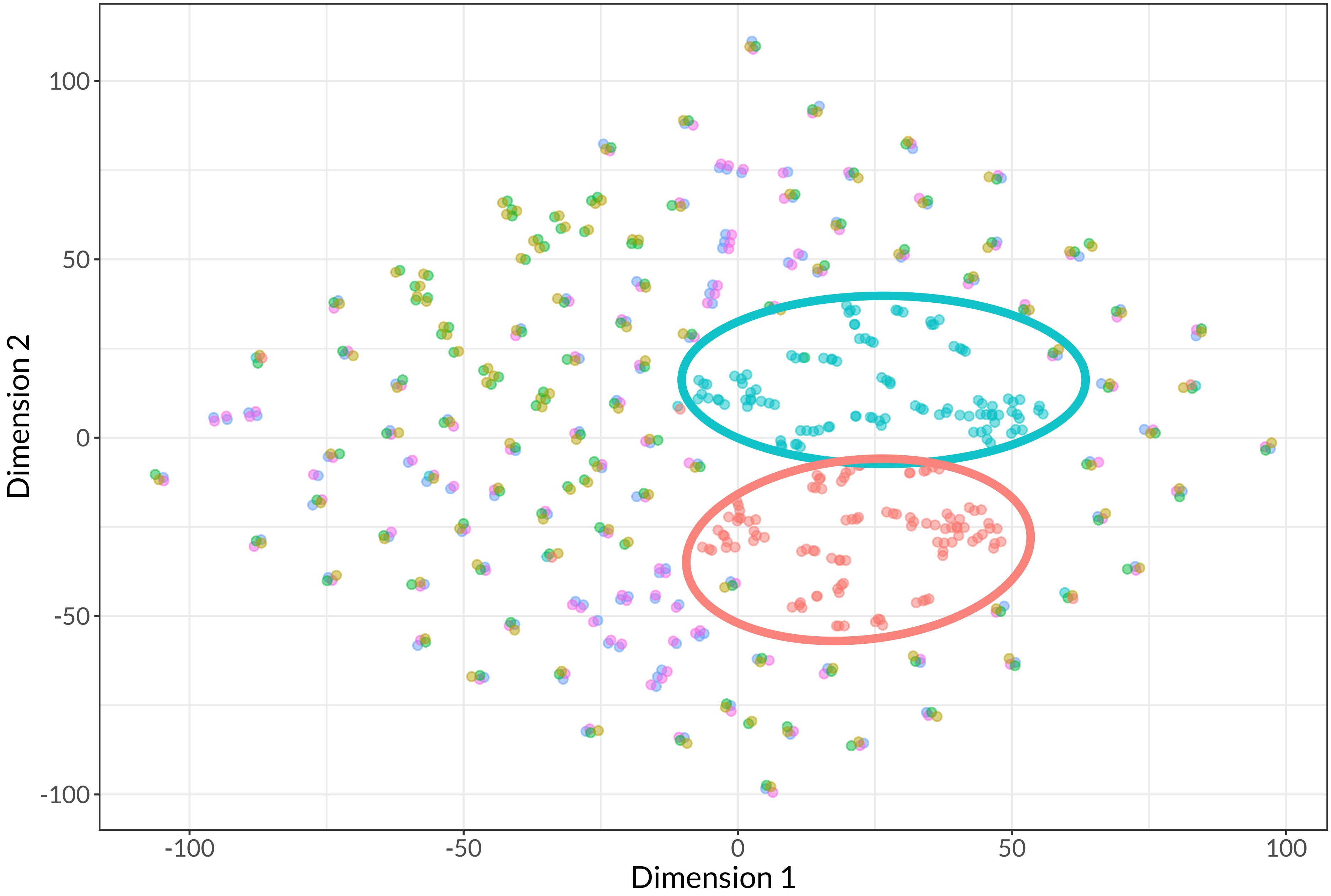

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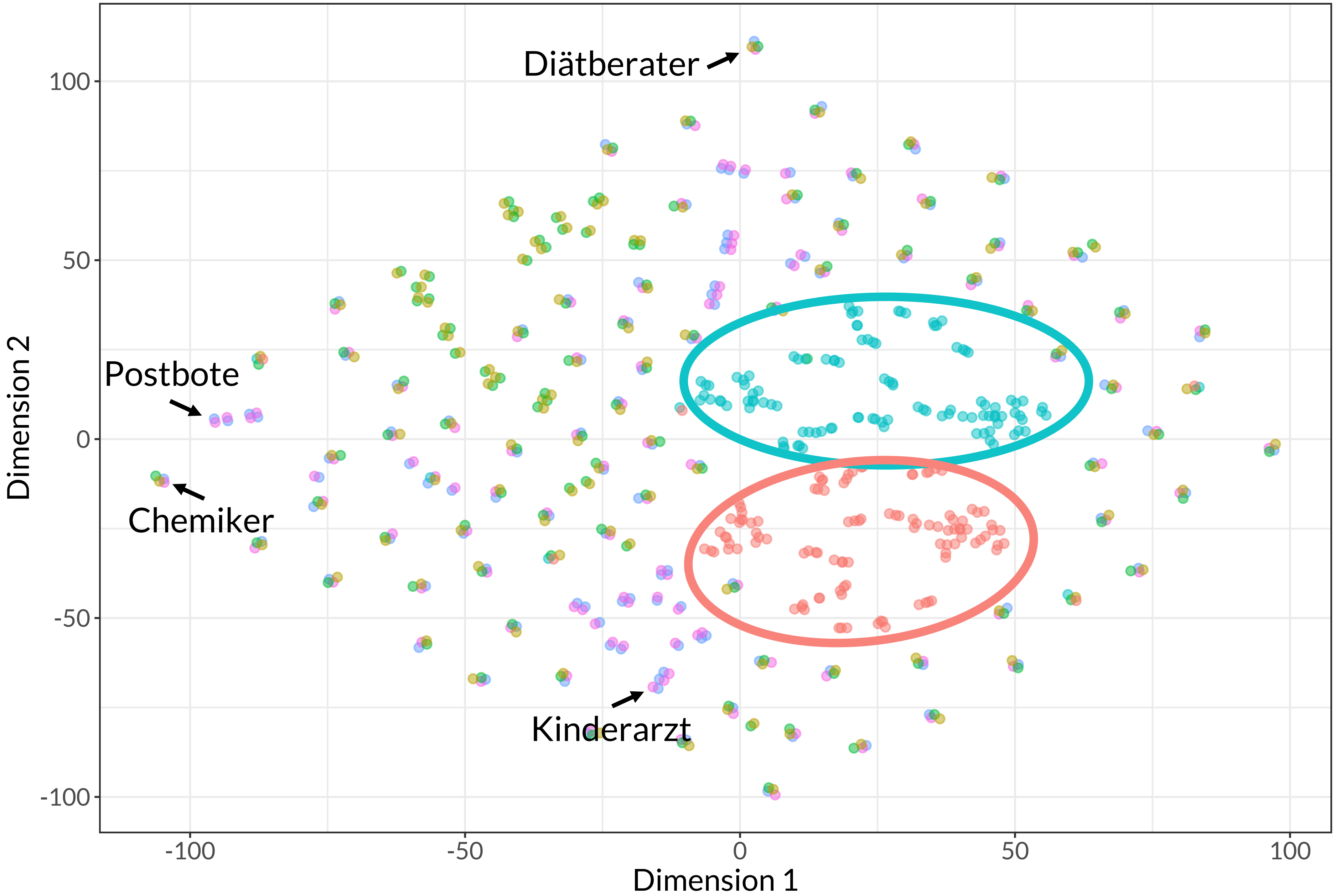
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Method

cues

- all
- teacher
- PLURAL
- be
- PLURAL
- nice

outcomes

- teacher
- villain

Example: *All teachers are nice.*

	all	teacher	PLURAL	be	nice	villain	evil
teacher							
villain							

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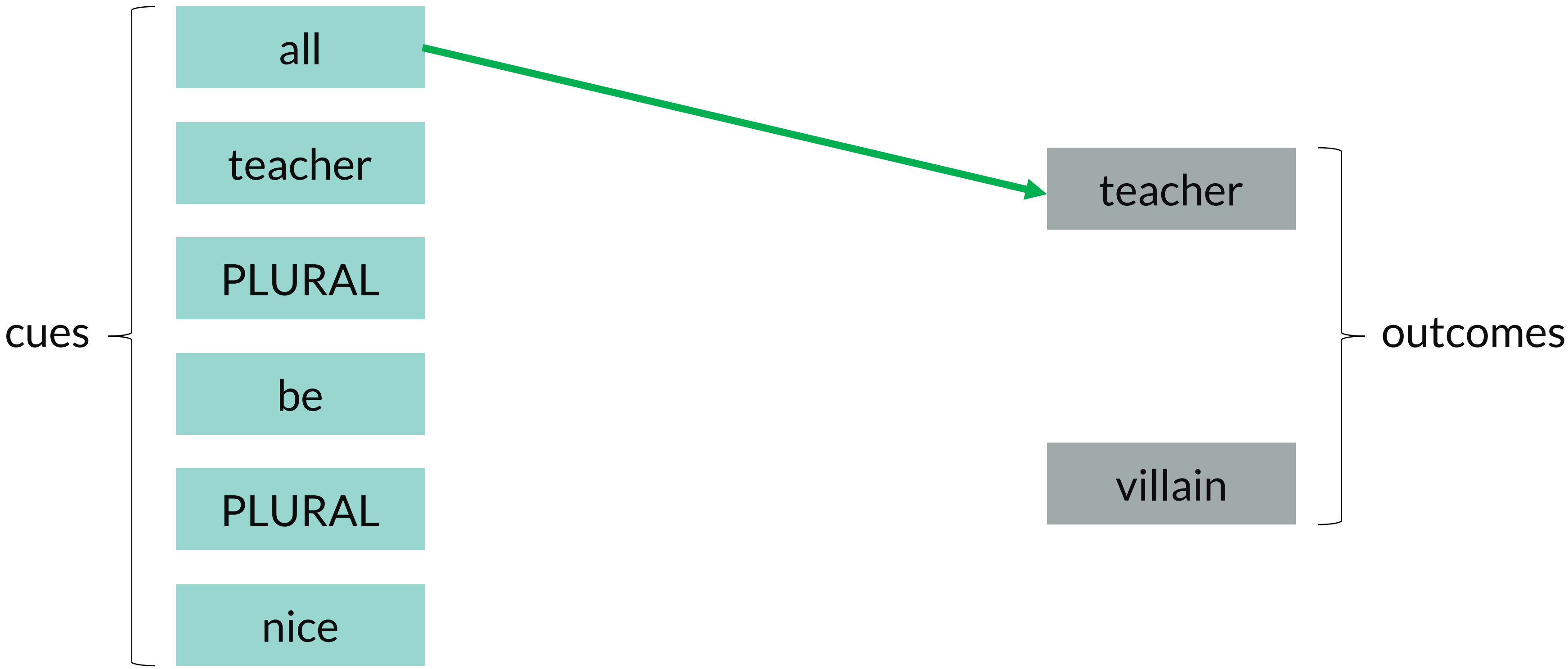

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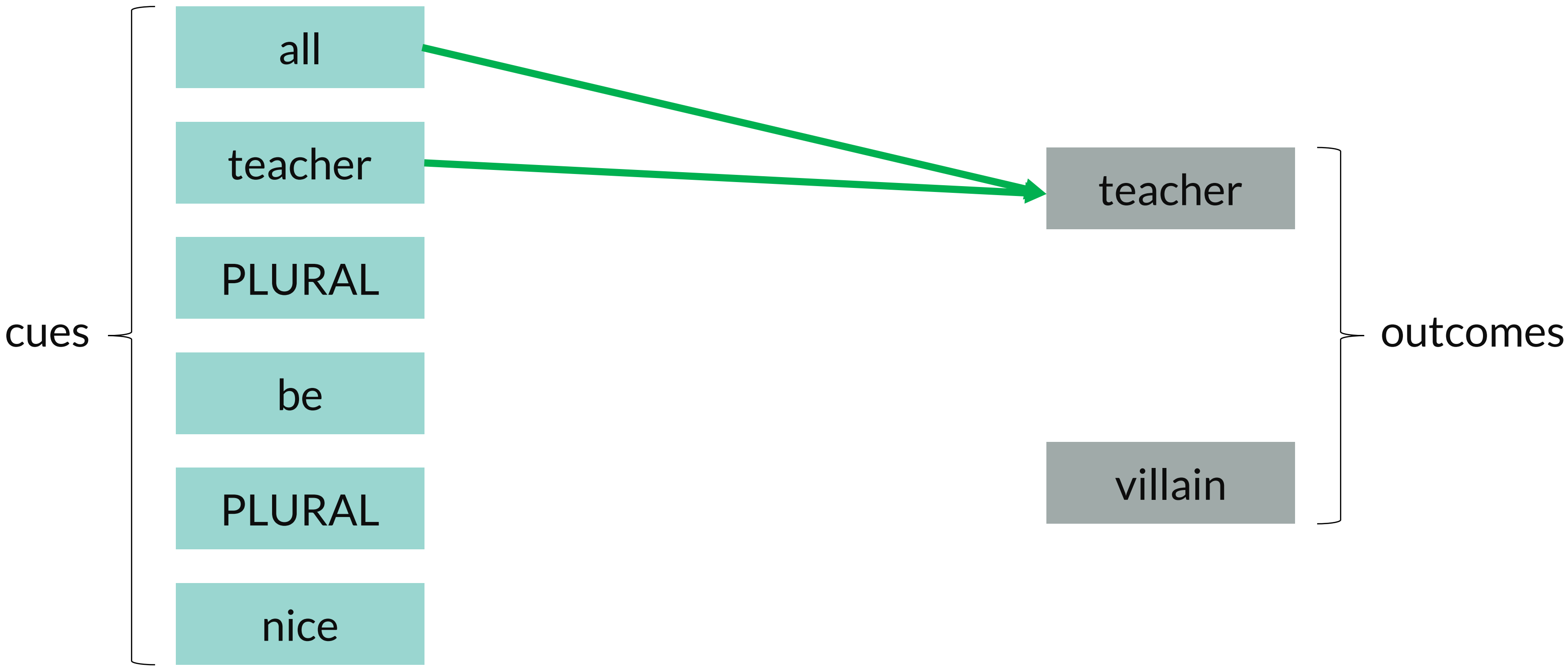

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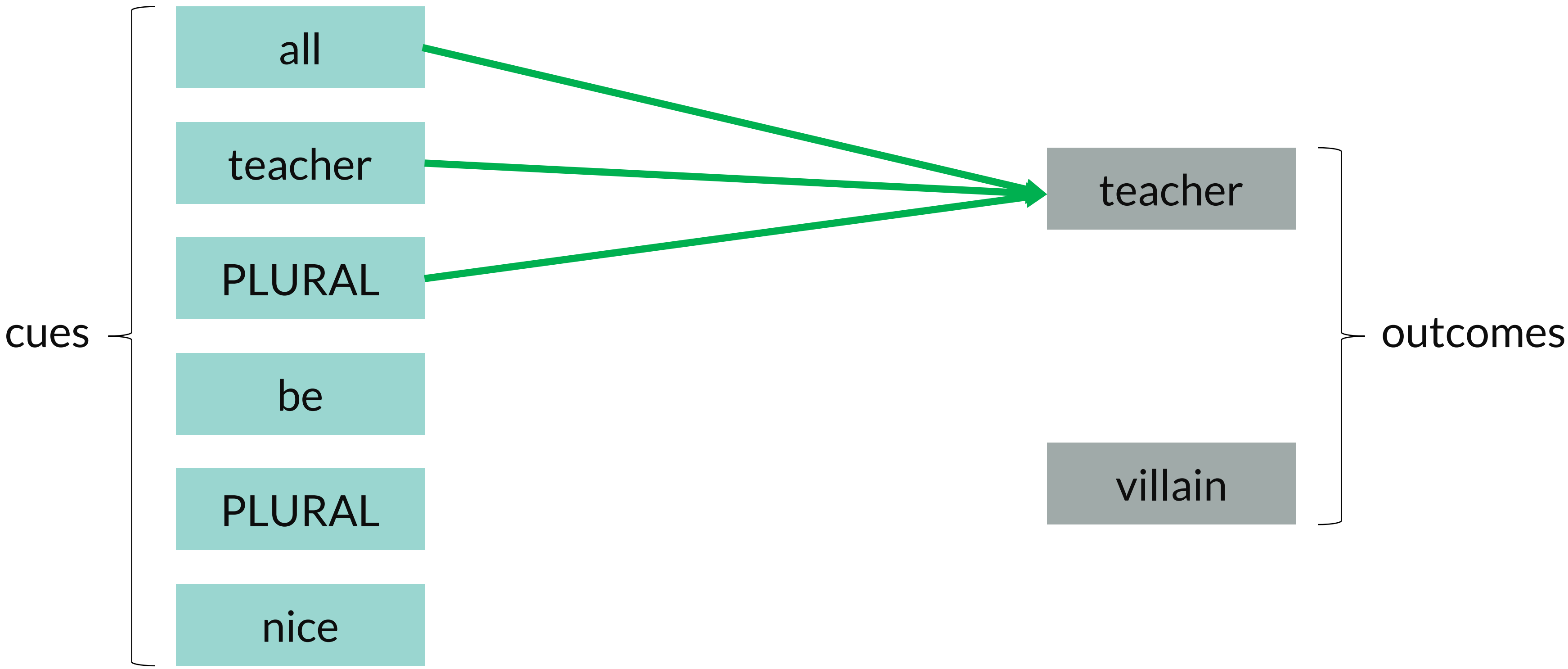

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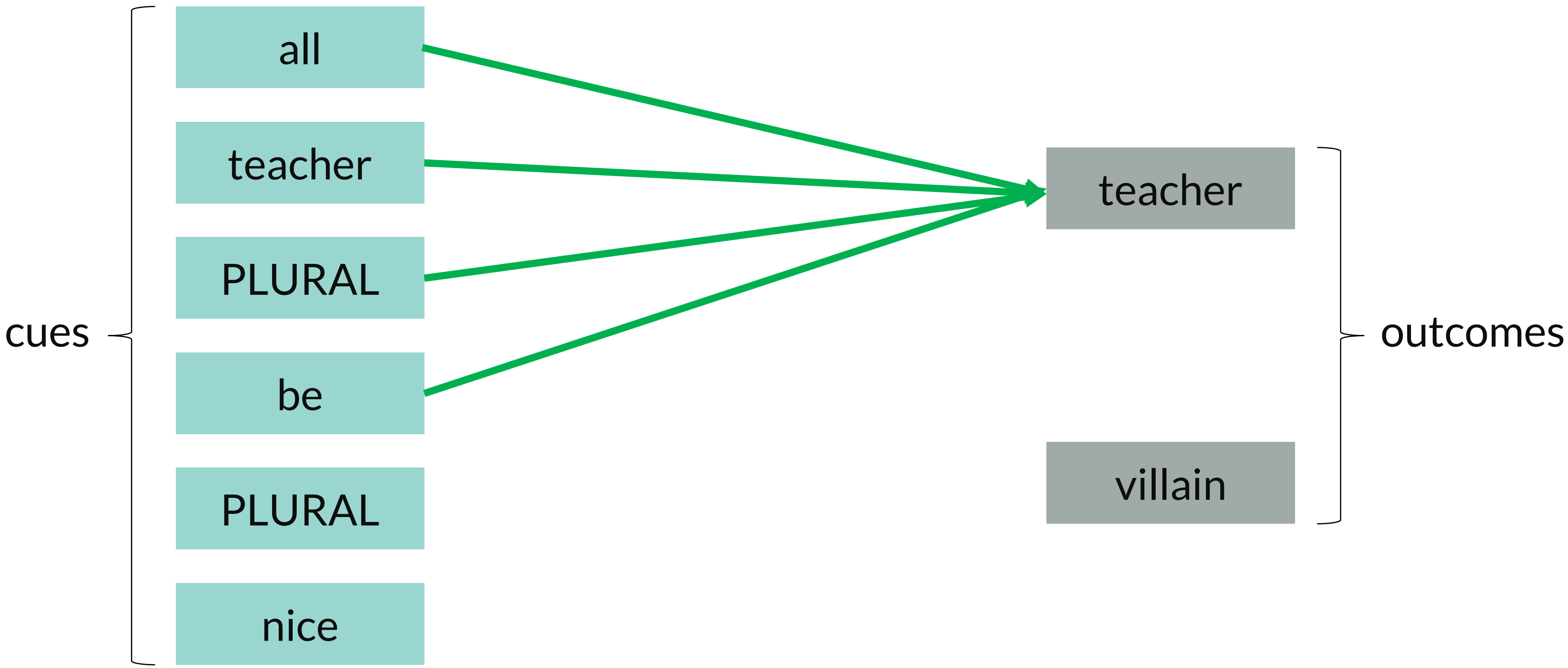

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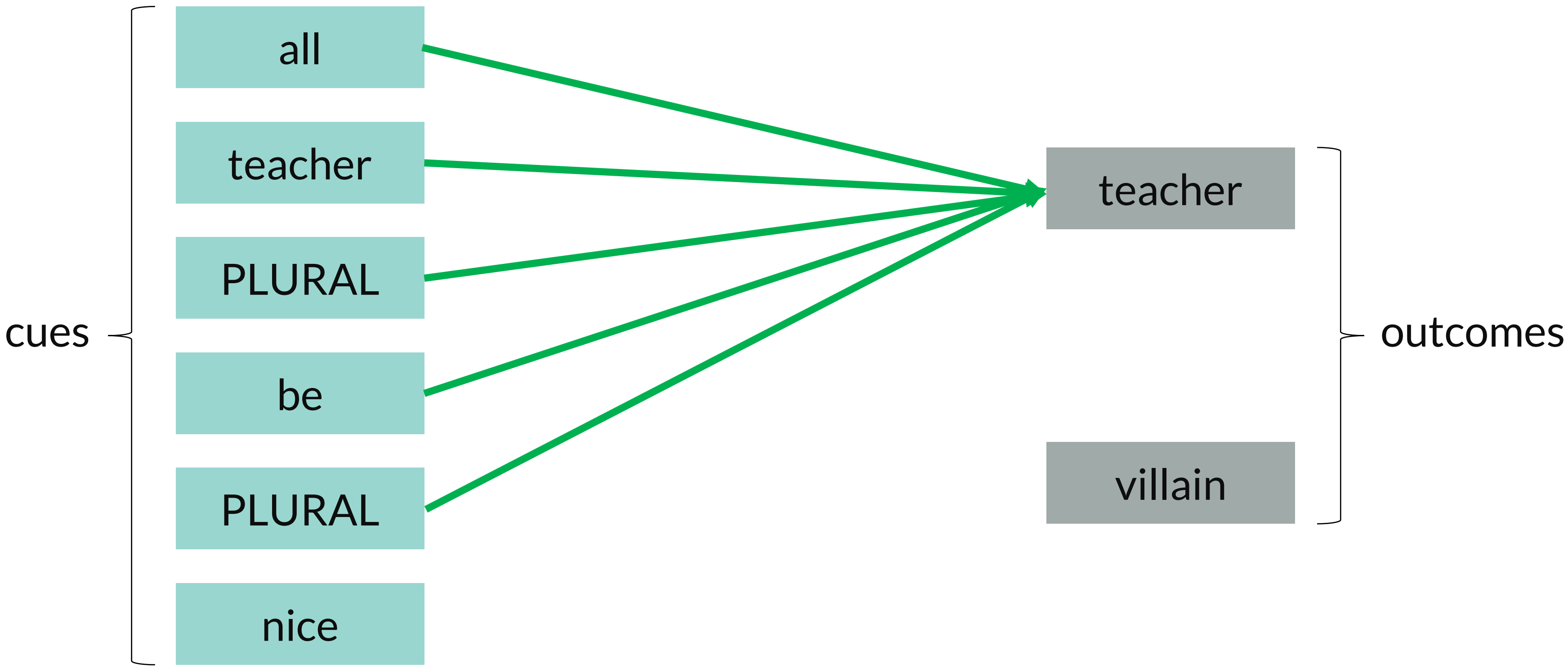

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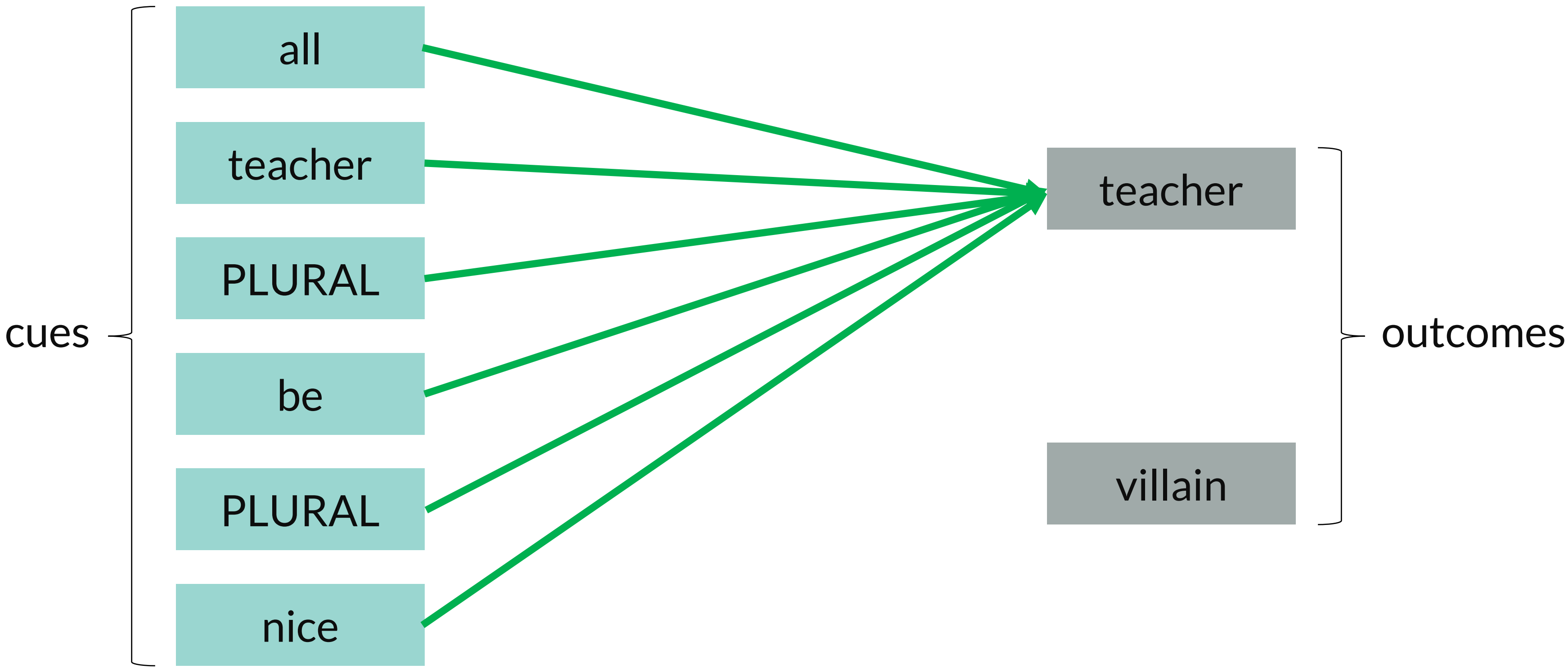

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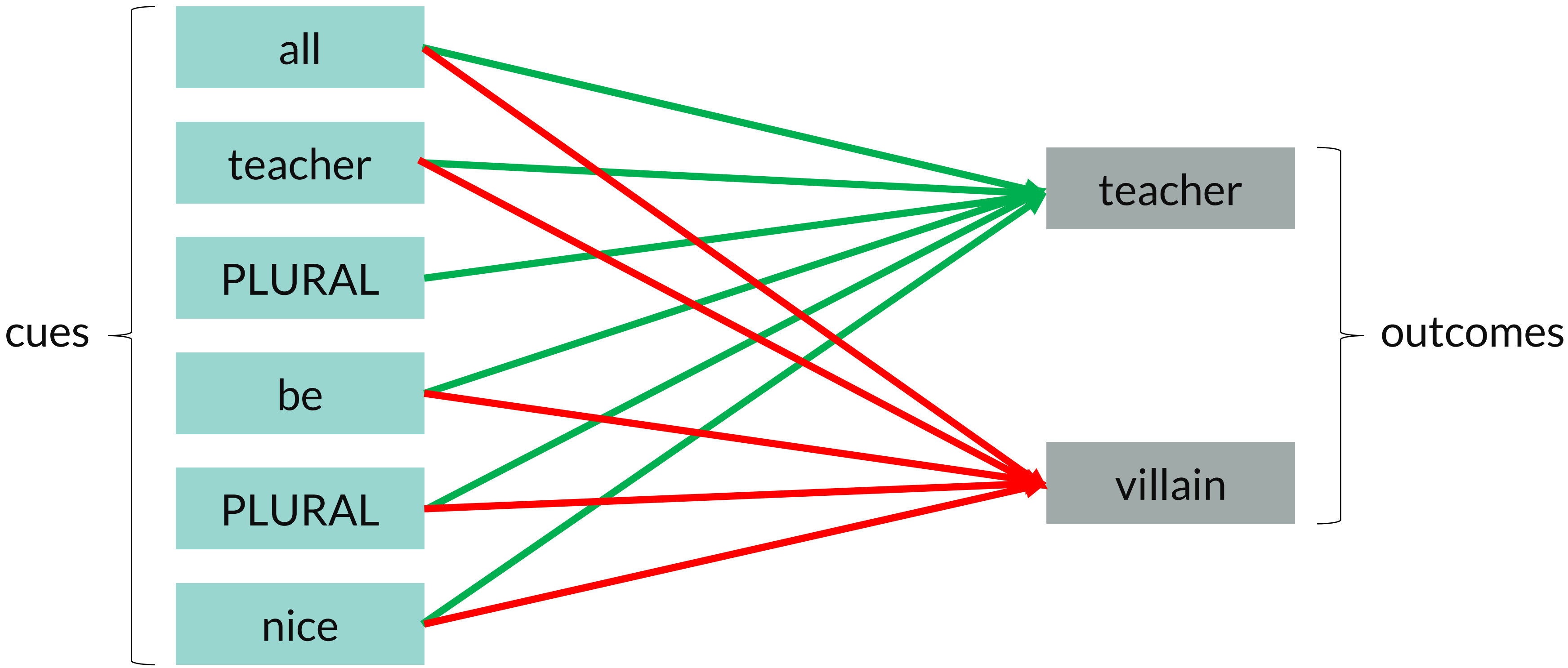

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teacher	+	+	++	+	+	-	-
villain	-	-	-	-	-		

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villain	0.0003	0.001	0.0005	0.0004	0.0091	1.0	0.96

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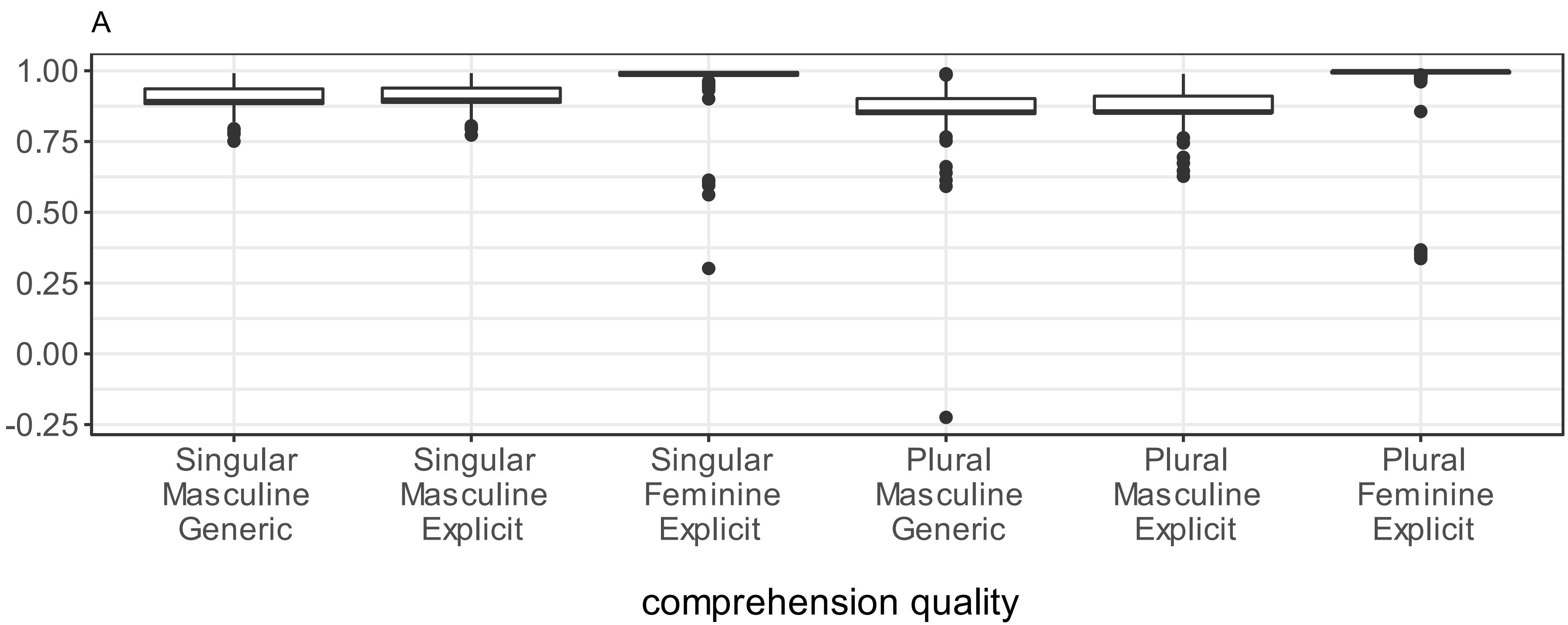
Semantic Measures

COMPREHENSION QUALITY

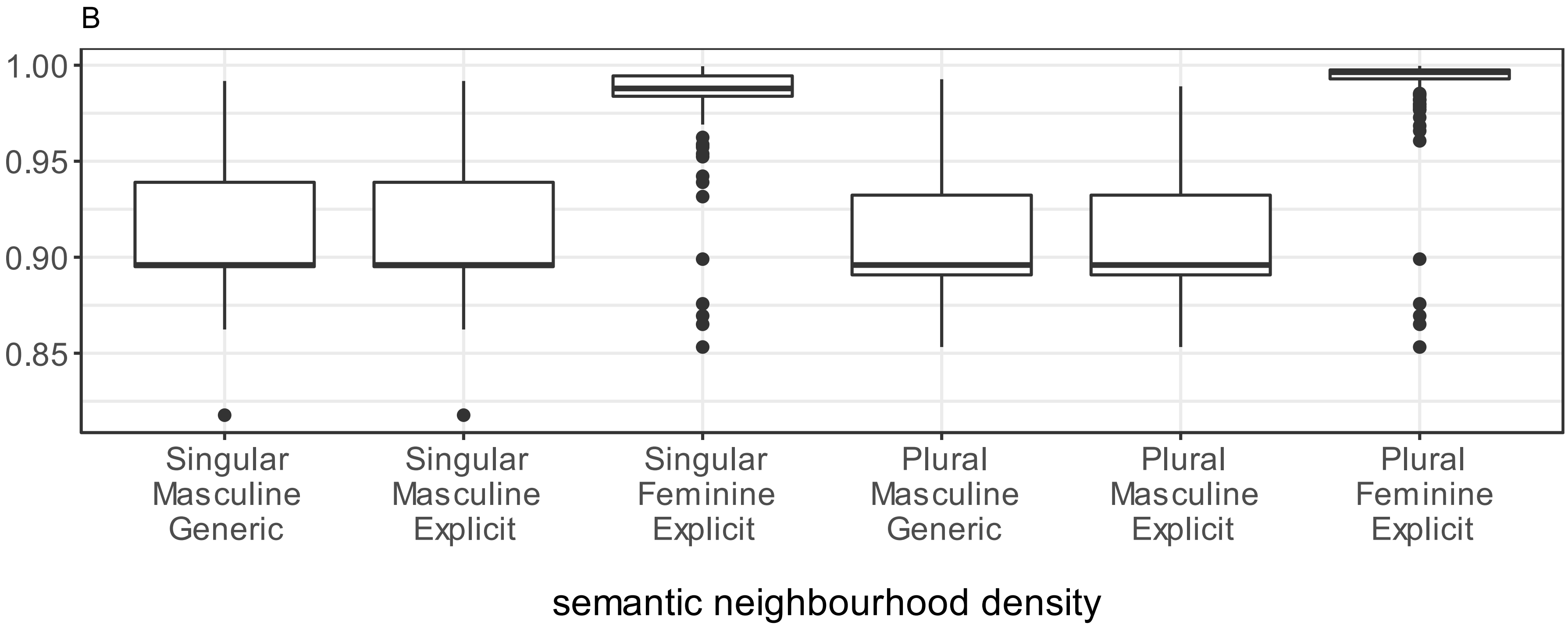
correlation of a target's original and estimated vectors
higher correlation = higher comprehension quality



Semantic Measures

NEIGHBOURHOOD DENSITY

correlation of a target with its 8 nearest neighbours
higher density = denser neighbourhood



Semantic Measures

ACTIVATION DIVERSITY

Euclidian norm of a target's vector

higher norm = higher degree of co-activation