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

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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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- 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?

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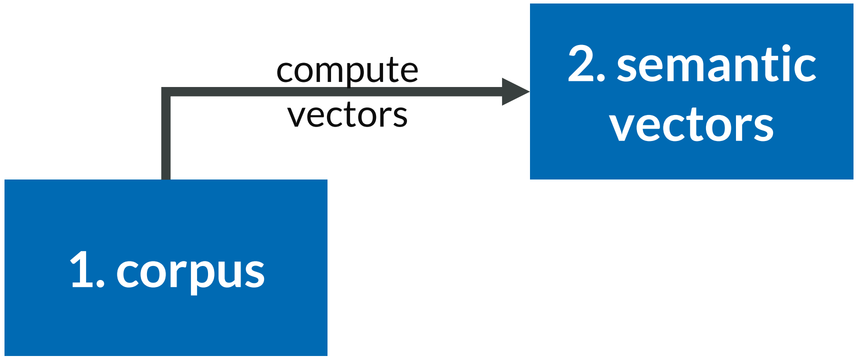

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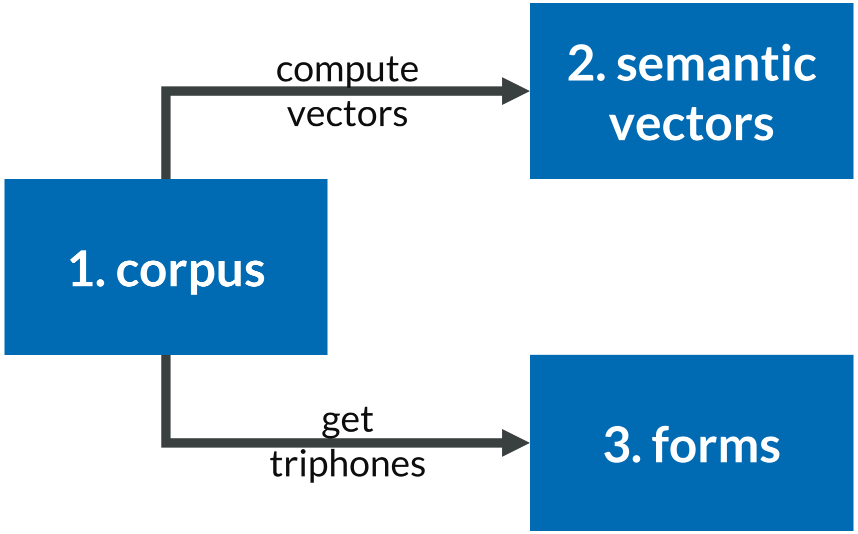

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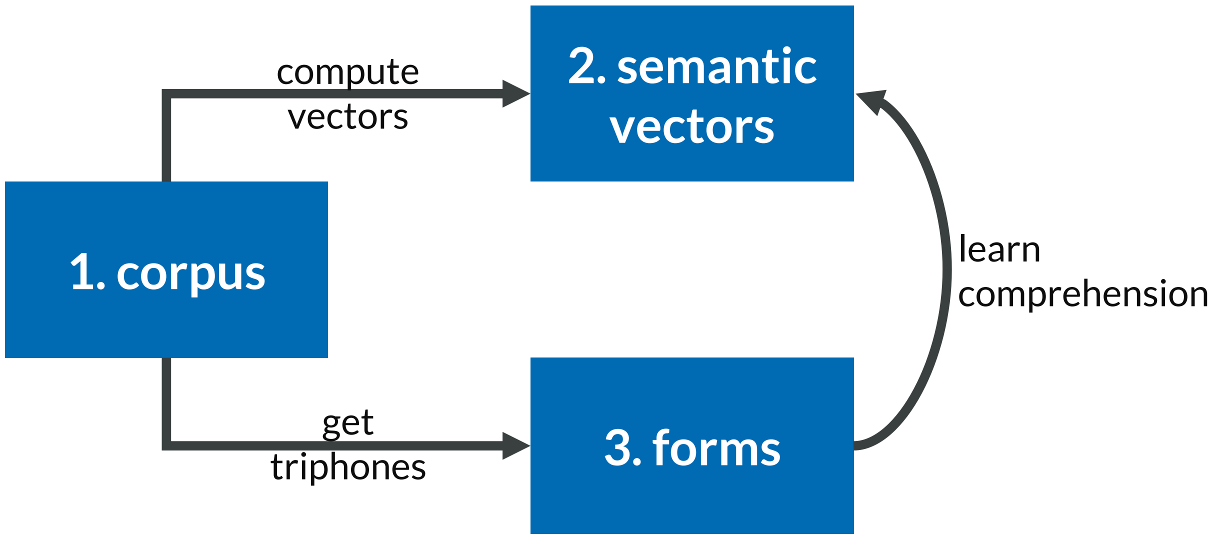

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Bäcker	‘baker’
Historiker	‘historian’
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- from the 10 million sentences, the following was sampled
  - 800,000 sentences without any target words
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  - 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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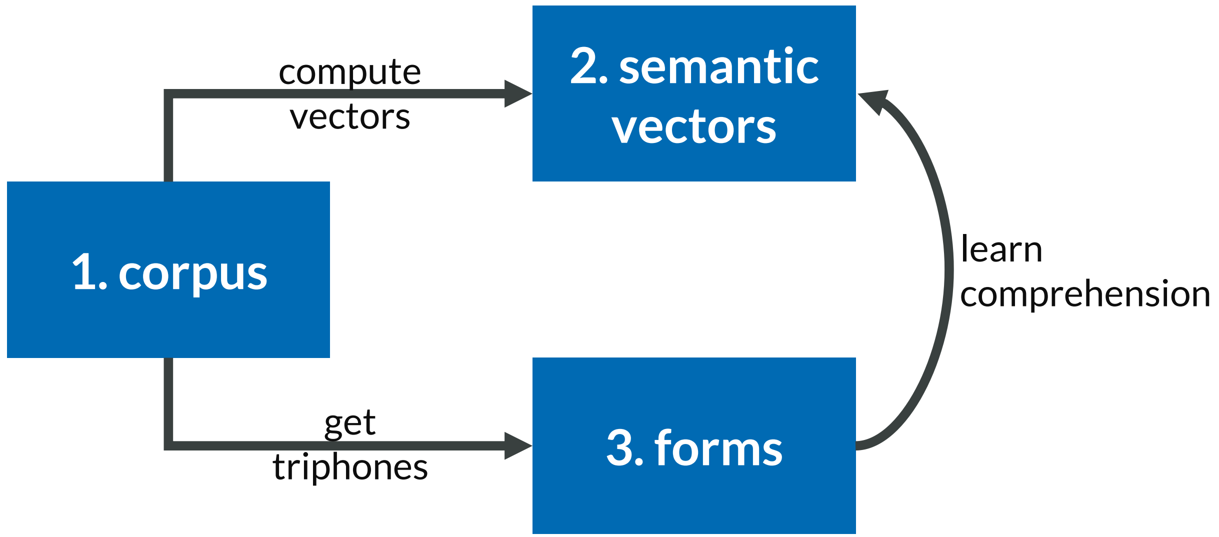

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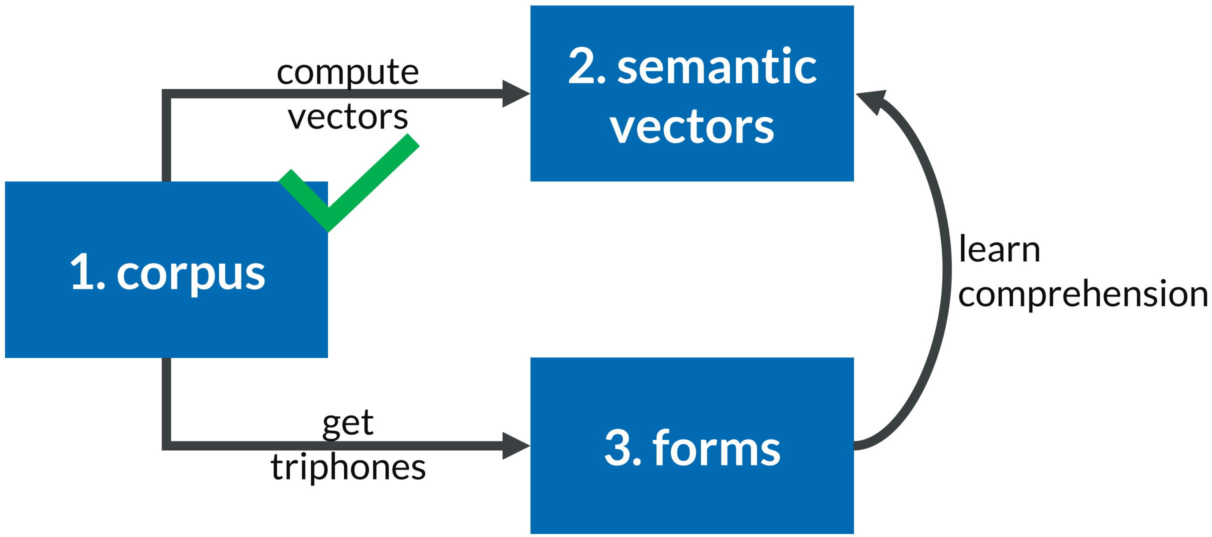

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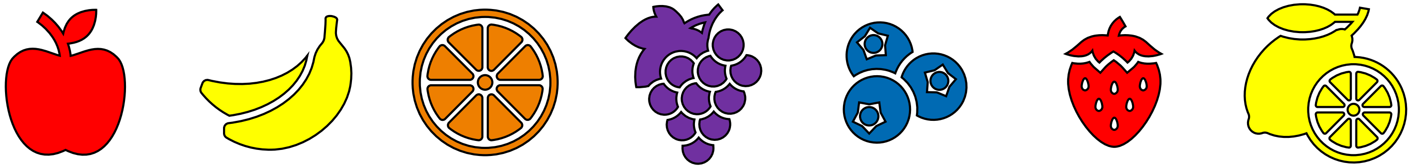
- we used each sentence to predict each individual word within the sentence by the other words in that sentence

Naive Discriminative Learning

toy example: different fruits



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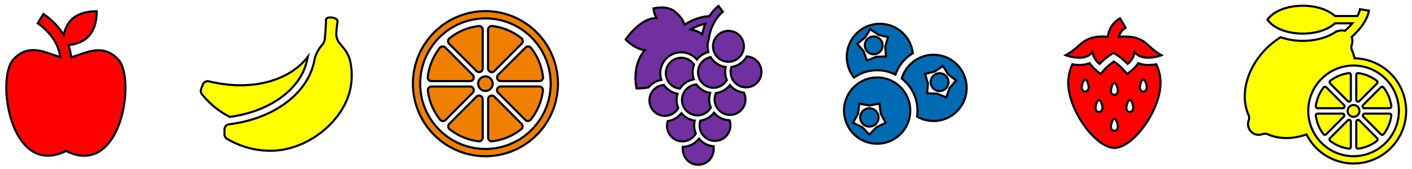

red	yellow	orange	purple	blue	red	yellow
sweet	sweet	sour	sweet	sweet	sweet	sharp
round	long	round	round	round	round	round
					long	long

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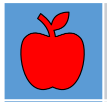
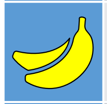
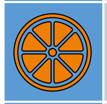
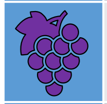
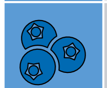
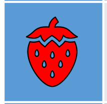
	1					1		1	
		1				1			1
			1				1	1	
				1		1		1	
					1	1		1	
	1					1			1
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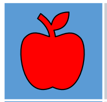
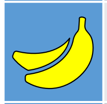
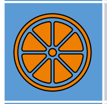
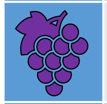
	30					30		30	
		15				15			15
			18				18	18	
				10		10		10	
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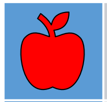
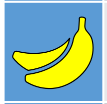
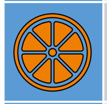
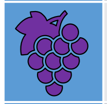
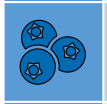
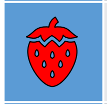
	29	1				30		30	
		15				15			15
			18				18	18	
				10		10		10	
					5	5		5	
	45					45		45	45
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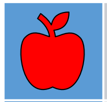
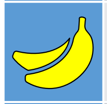
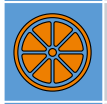
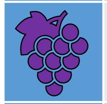
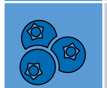
	29	1				29	1	30	
		15				15			15
			18				18	18	
				10		10		10	
					5	5		5	
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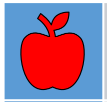
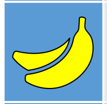
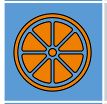
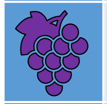
	29	1	-1	-3	-2	29	1	30	-1
		15				15			15
			18				18	18	
				10		10		10	
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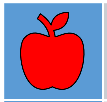
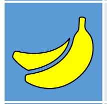
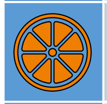
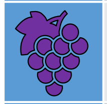
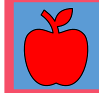
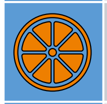
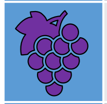
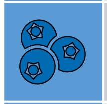
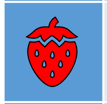
	29	1	-1	-3	-2	29	1	30	-1
	-10	15	-10	-8	-6	15	-11	-5	15
	-6	-7	18	-14	-15	3	15	18	-2
	-5	-1	-6	10	-9	5	5	10	-7
	-6	-9	-19	2	3	4	1	5	-5
	45	-6	-9	-14	-1	25	20	45	45
	-1	20	-5	-6	-8	-4	20	20	20

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
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Naive Discriminative Learning

toy example: different fruits

	red	yellow	orange	purple	blue	sweet	sour
apple	29	1	-1	-3	-2	29	1
banana	-10	15	-10	-8	-6	15	-11
orange	-6	-7	18	-14	-15	3	15
grape	-5	-1	-6	10	-9	5	5
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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

- for content words, their semantic vector is the sum of the vectors of their parts, e.g. $\overrightarrow{apples} = \overrightarrow{apple} + \overrightarrow{plural}$
- thus, e.g., the semantics of the target word paradigm *Lehrer* 'teacher' consists of

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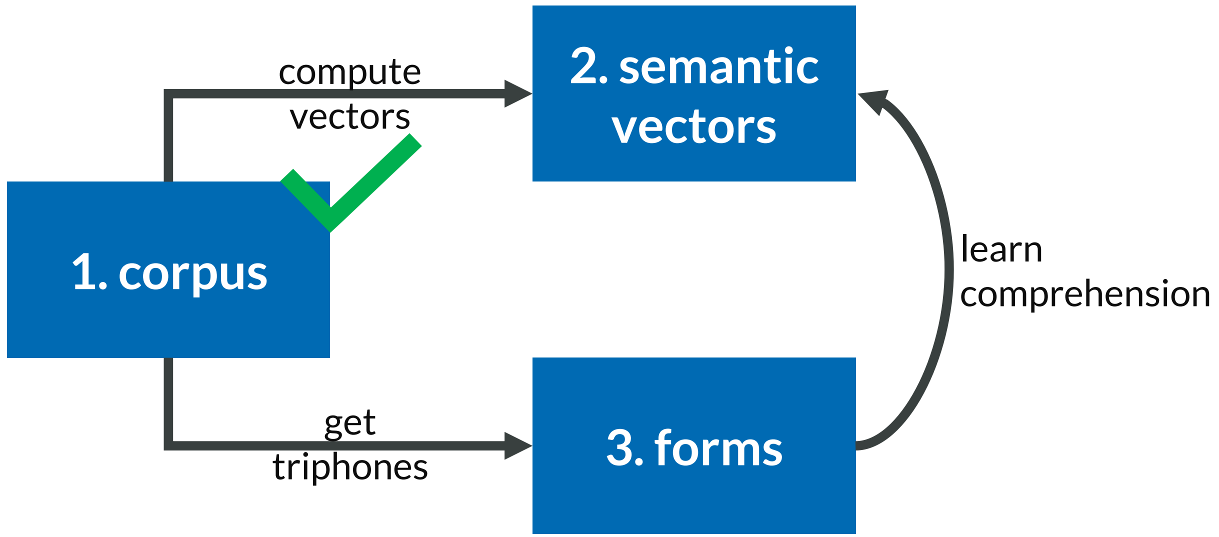
Method

- 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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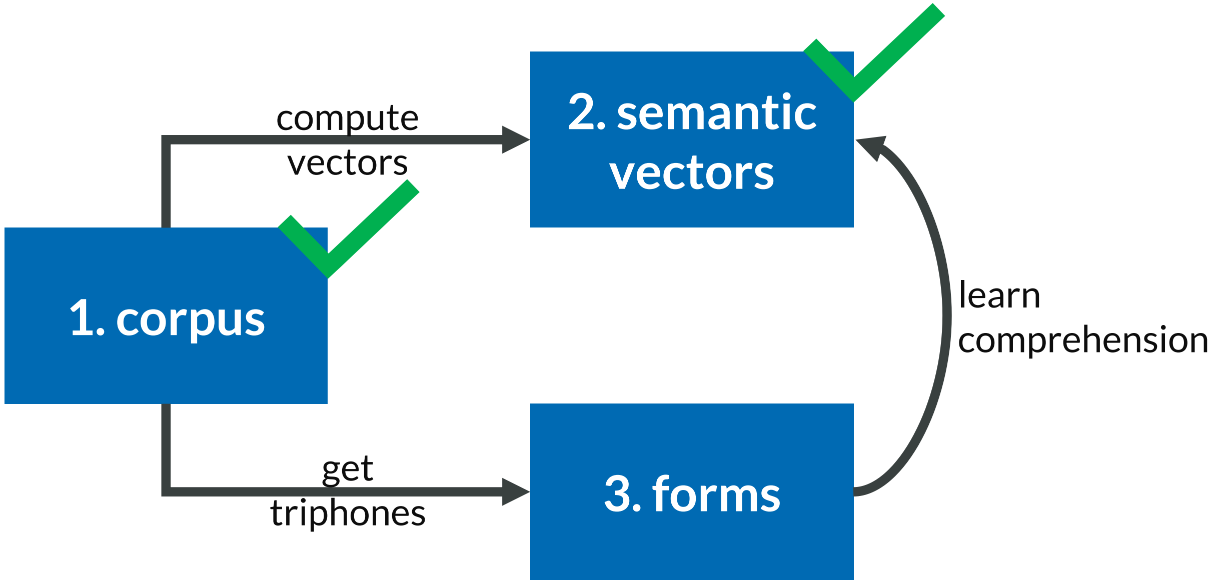

Forms

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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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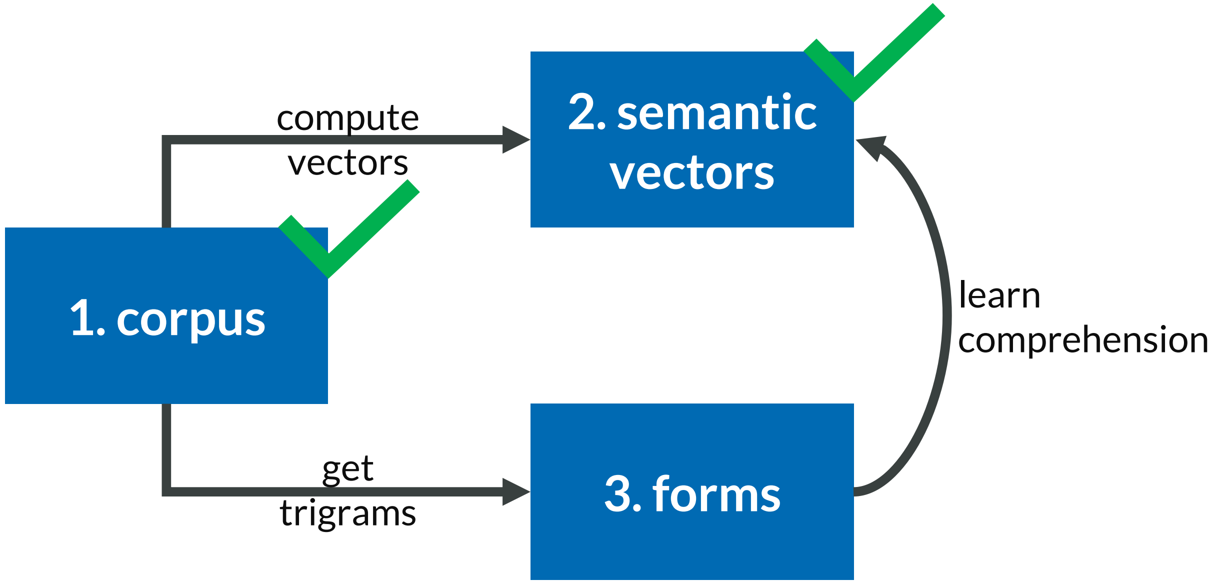

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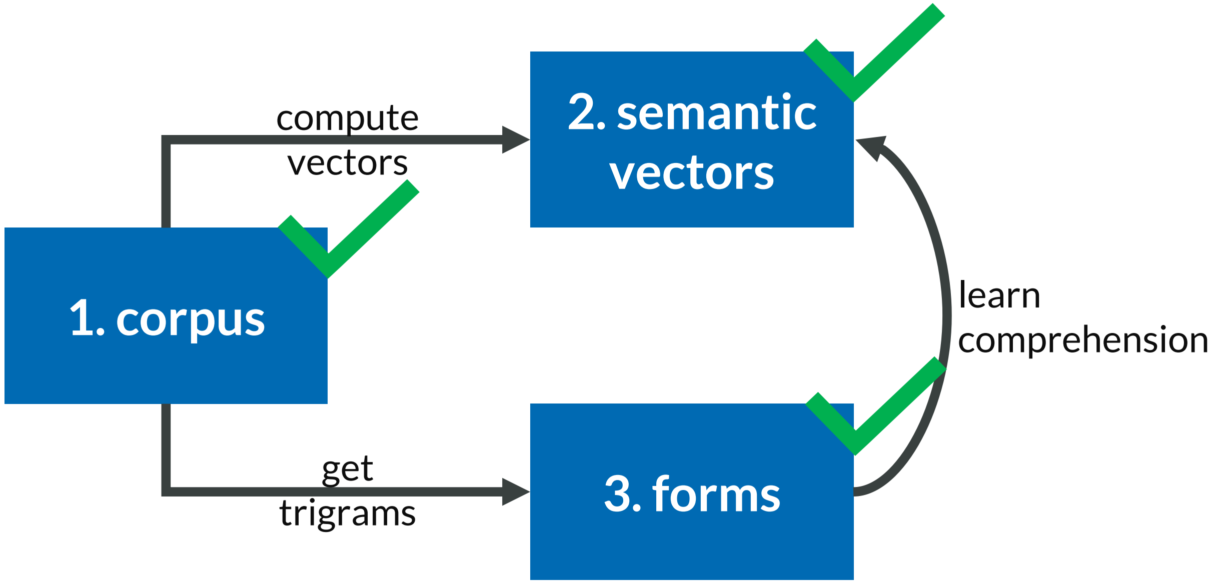

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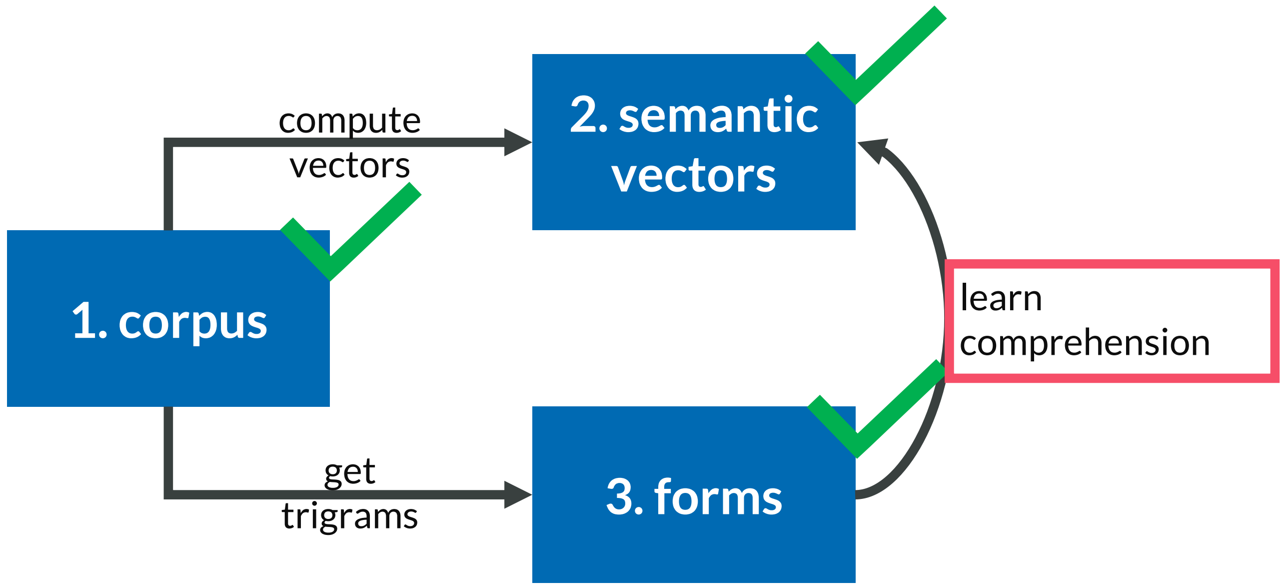

Learning comprehension

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

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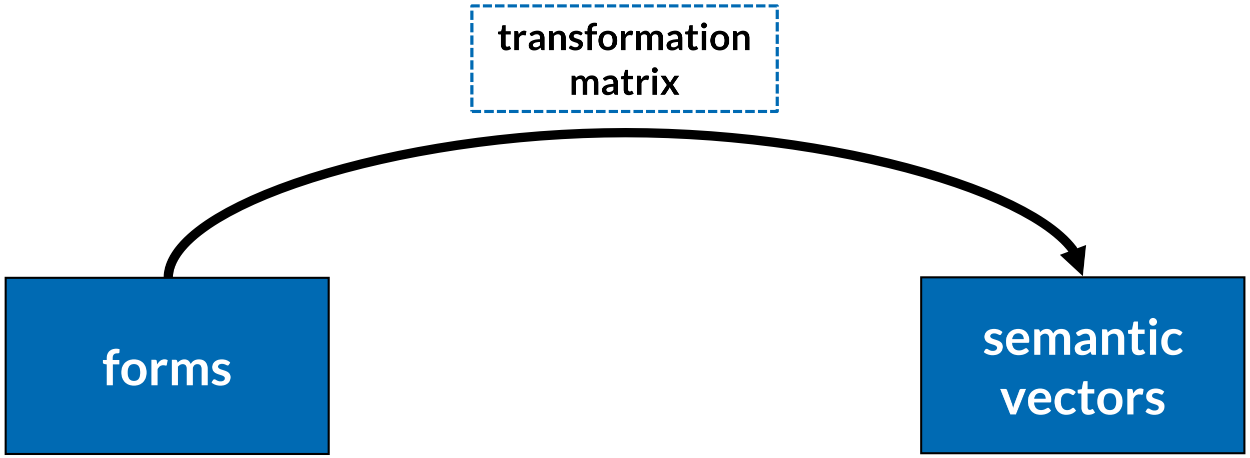

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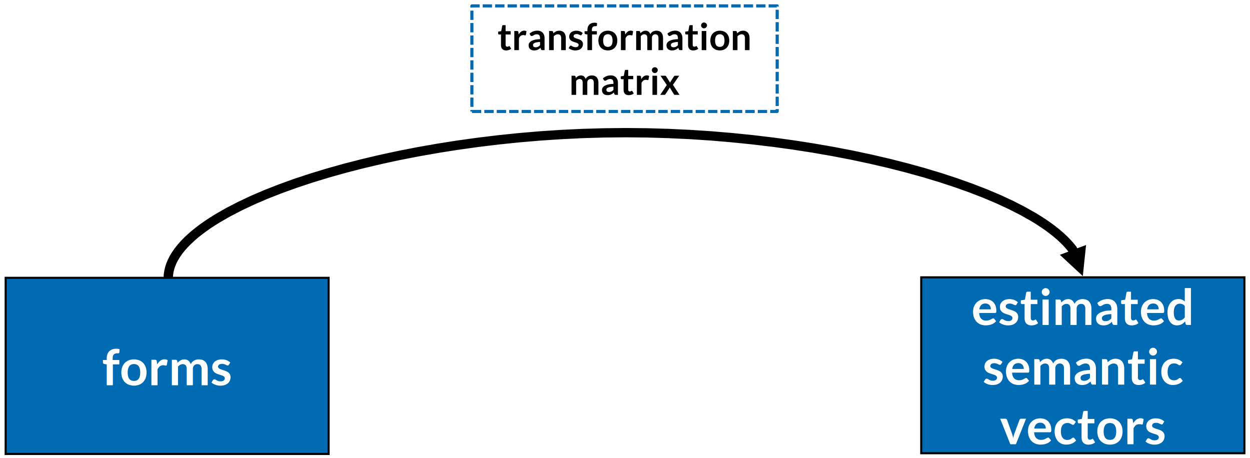

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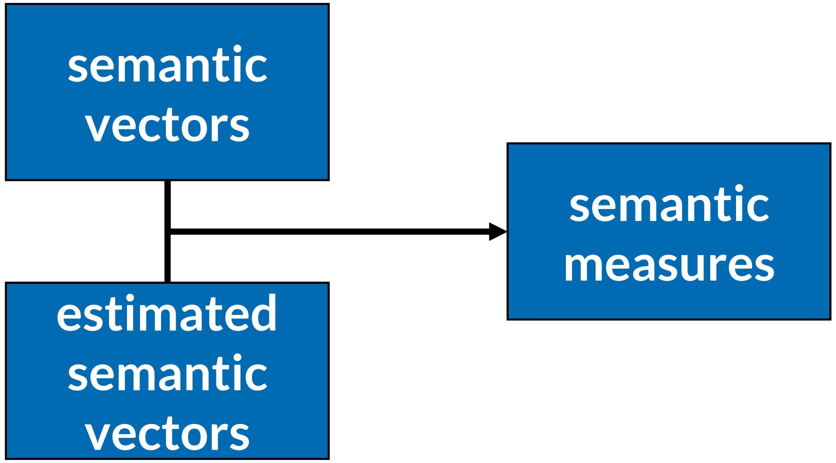

Analysis

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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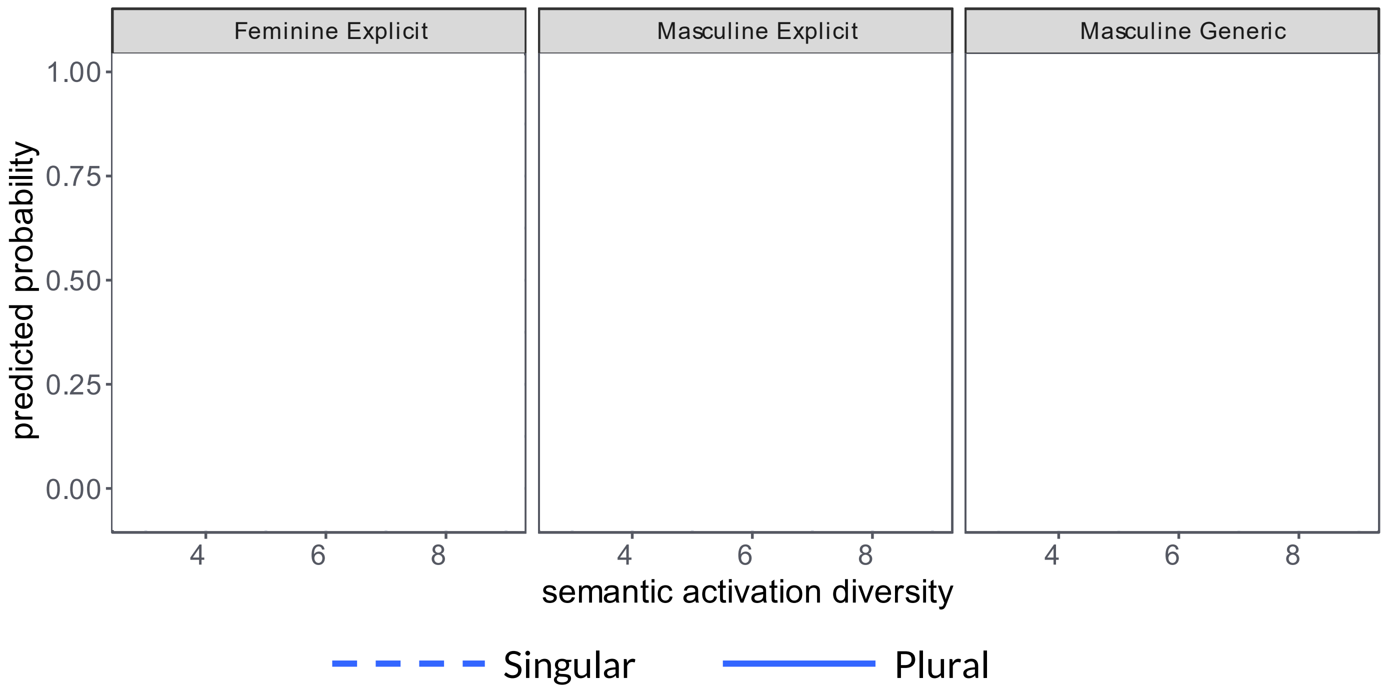
Results

ACTIVATION DIVERSITY



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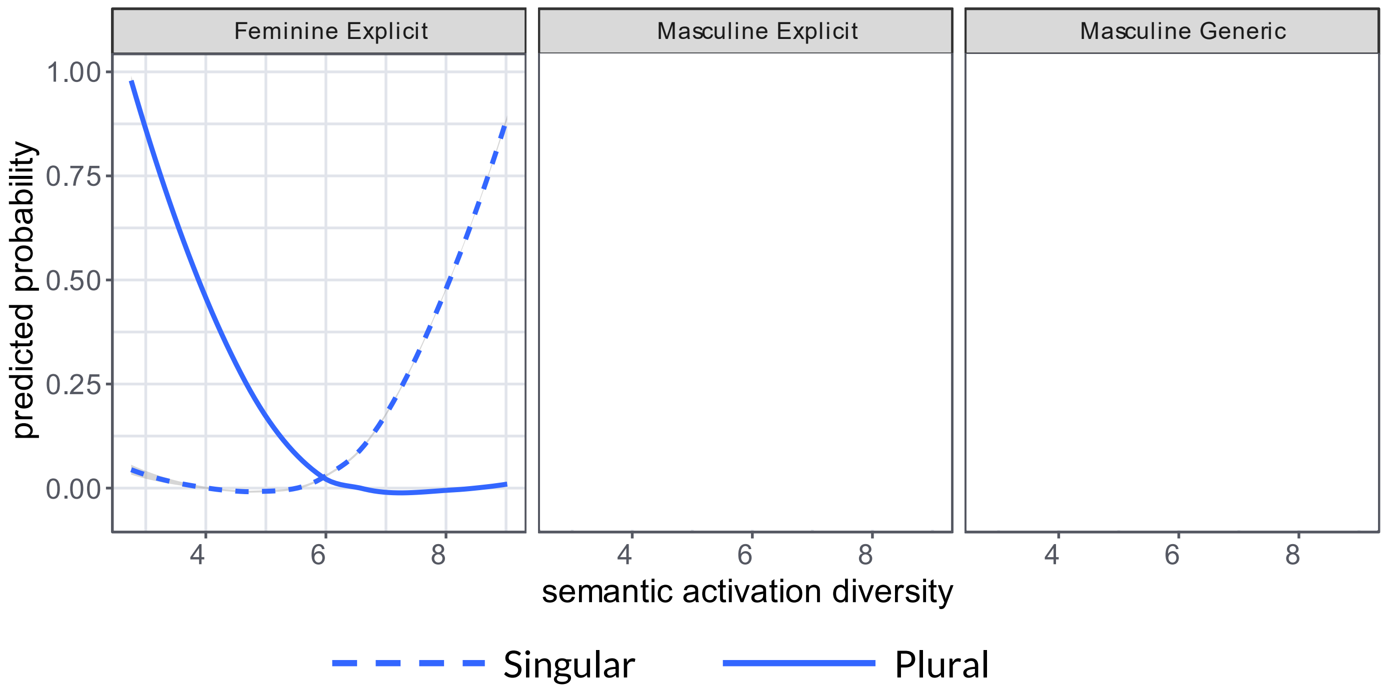

Results

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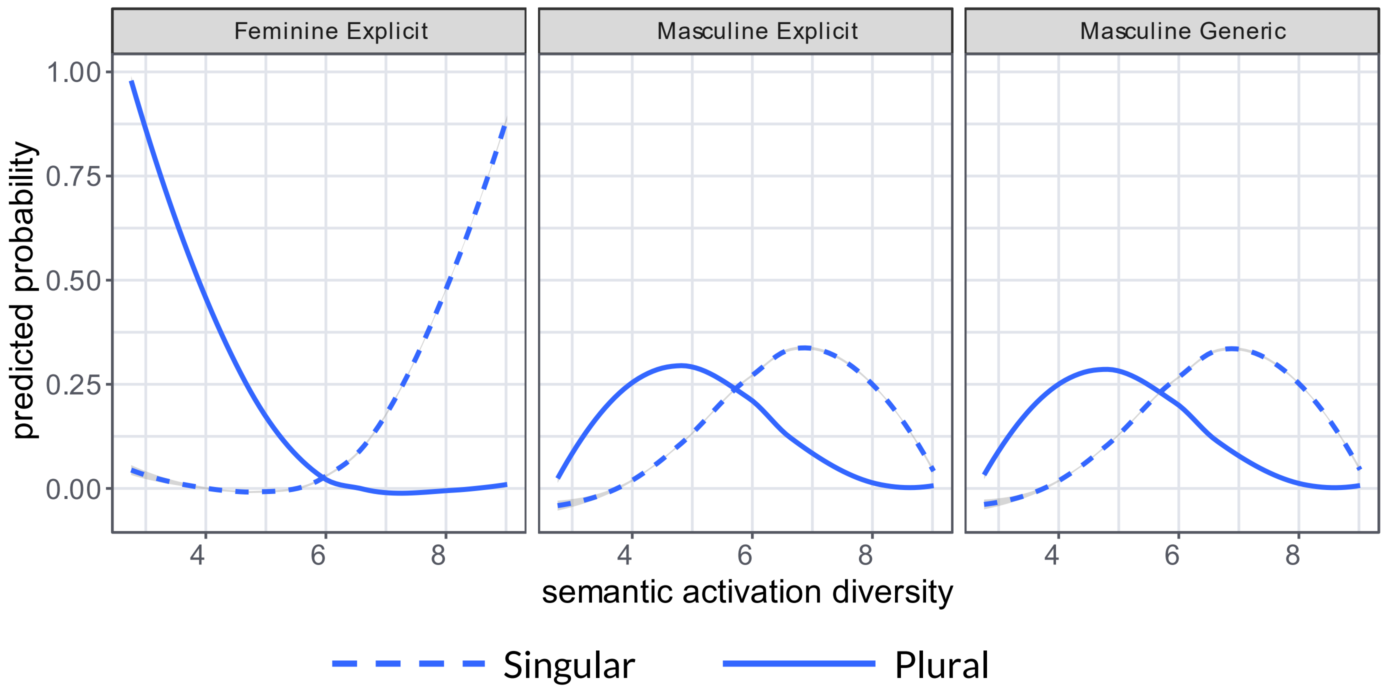

Results

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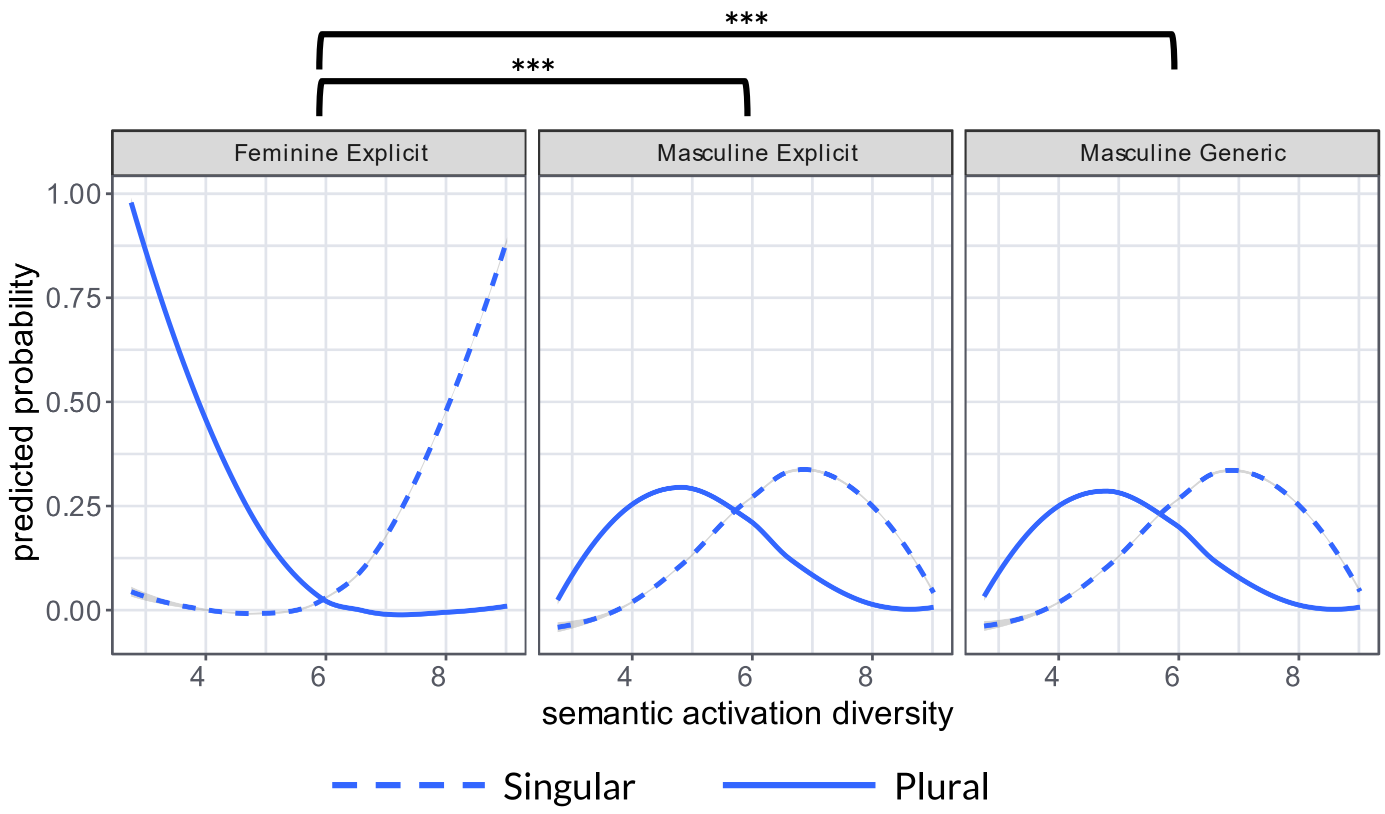
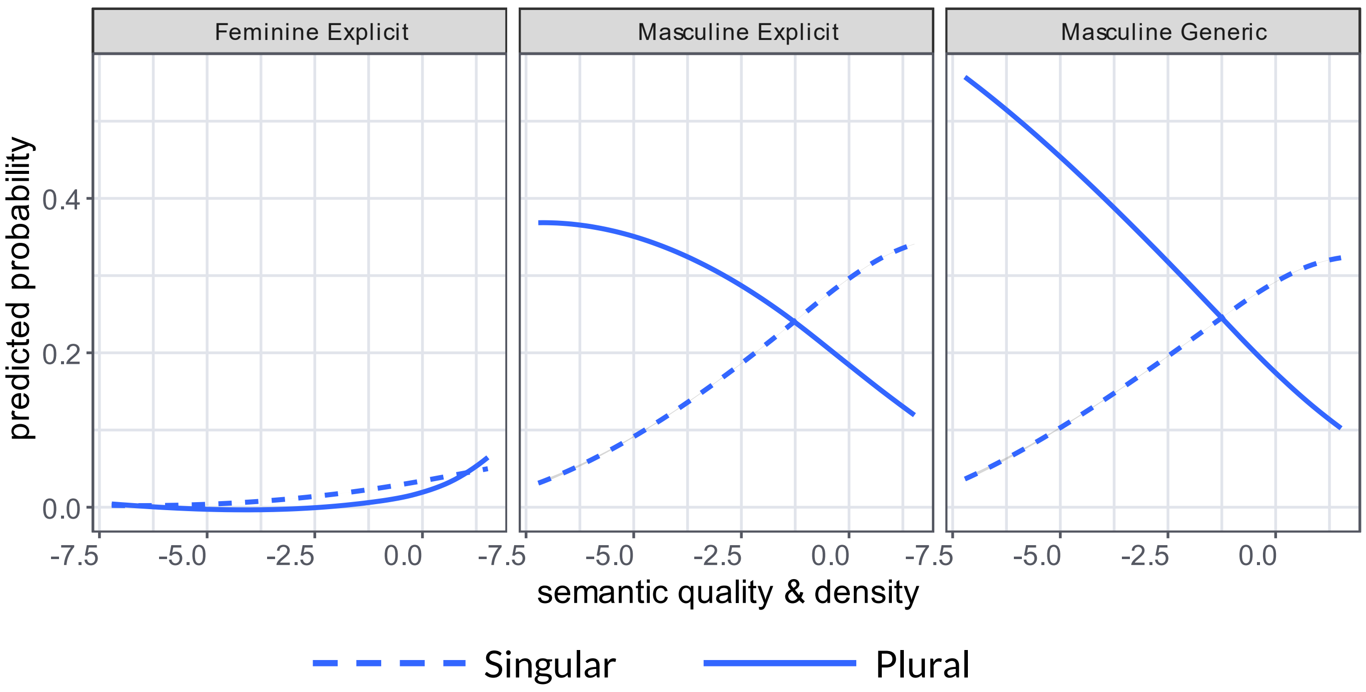


Results

COMPREHENSION QUALITY + NEIGHBOURHOOD DENSITY



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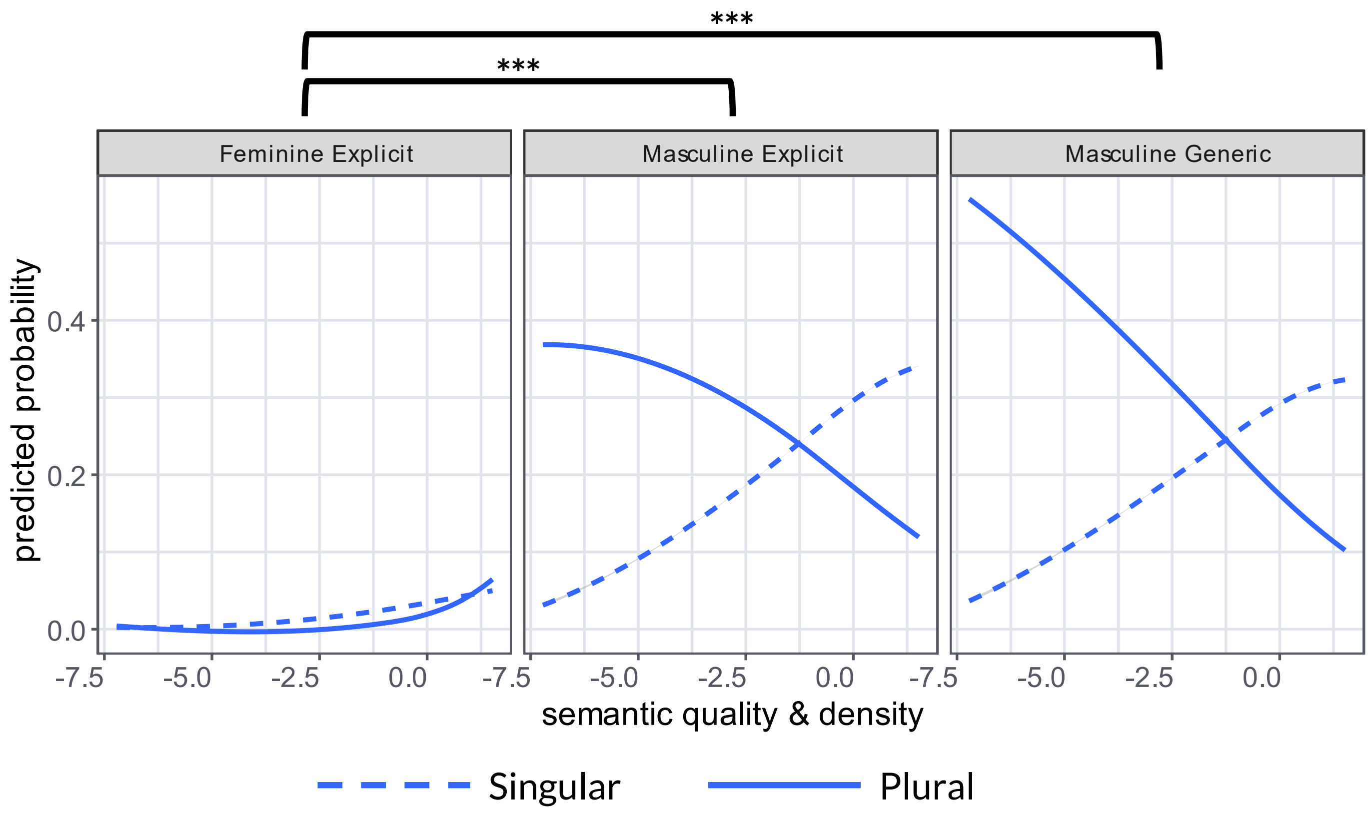
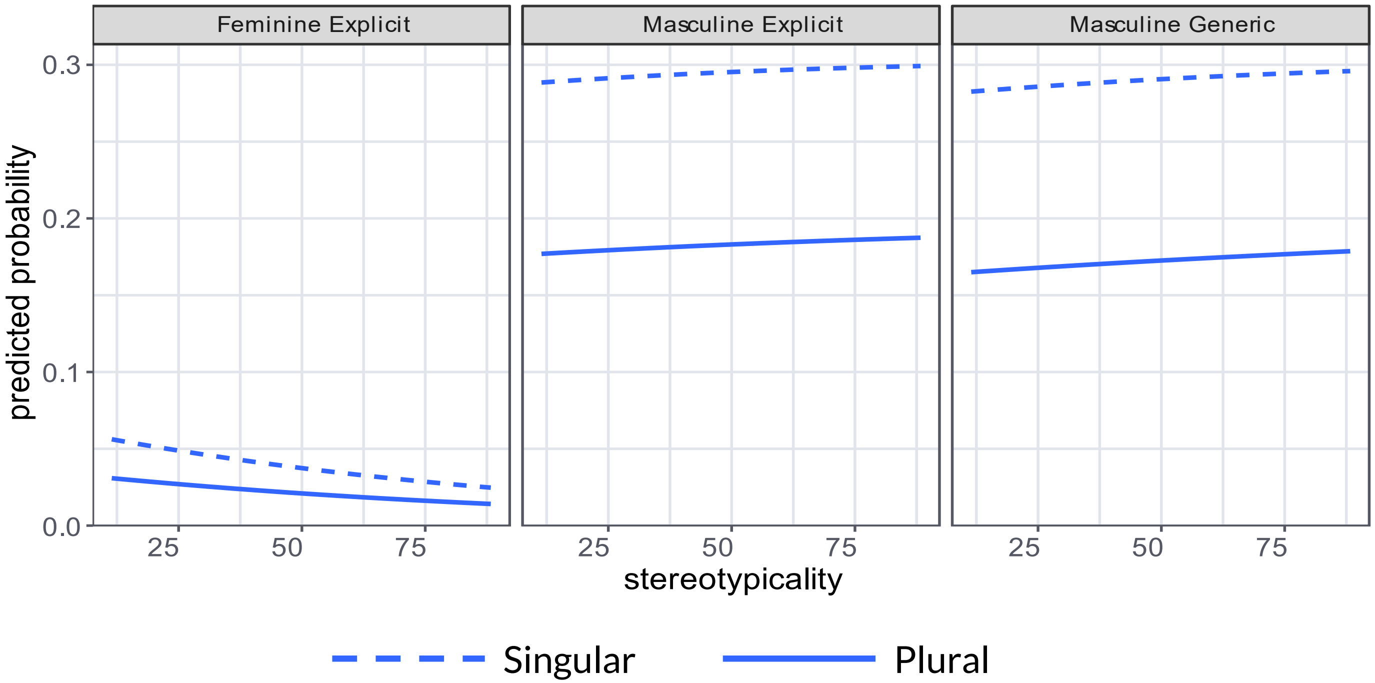


Results

STEREOTYPICALITY JUDGEMENTS

no significant effects!



Research questions

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

→ **well...**

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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:
10.5070/G6011192

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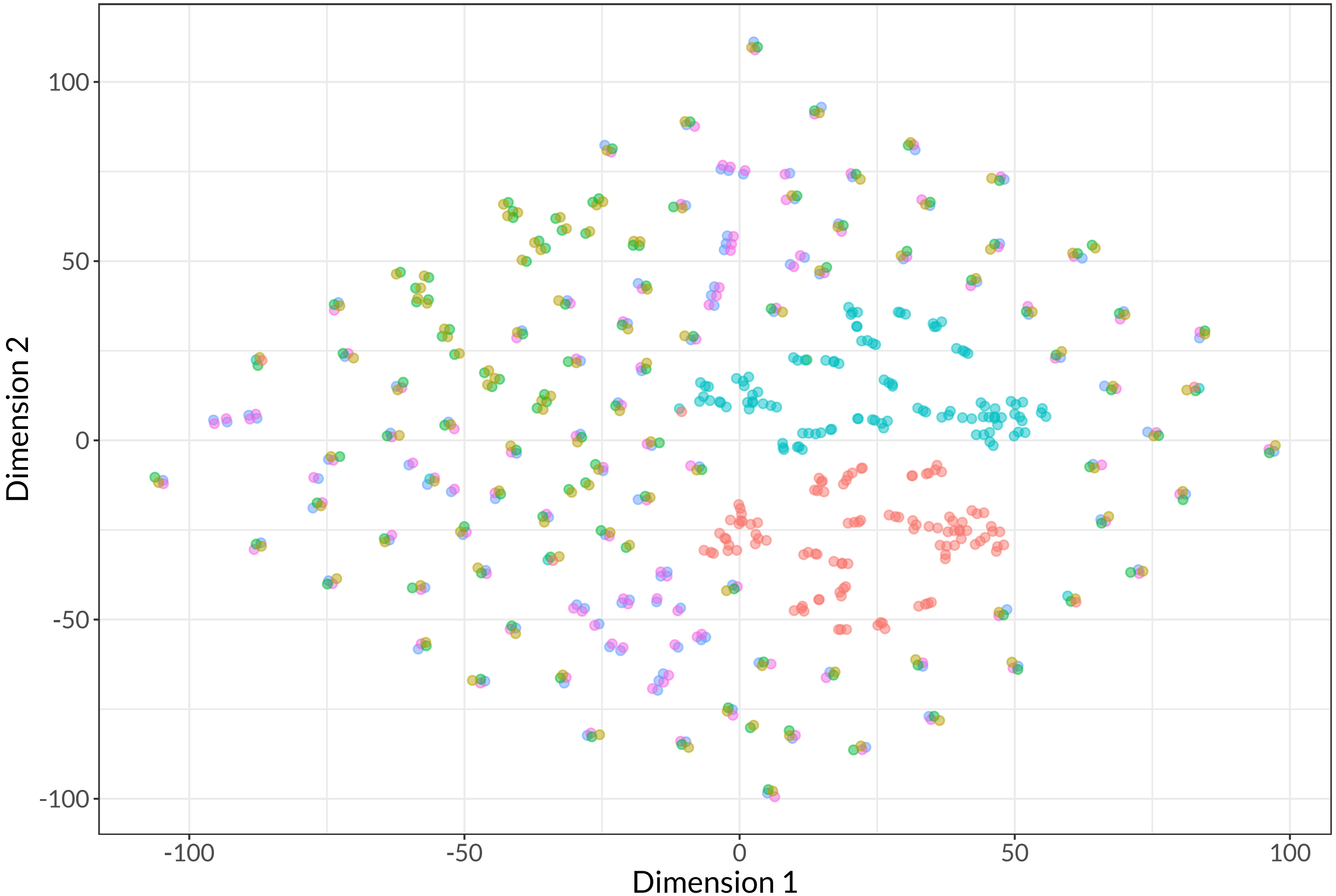
- our corpus did not contain any ‘new forms’, e.g. gender star forms or capital-I forms: *Lehrer*in* or *LehrerIn* ‘teacher (of any sex or gender)’

Corpus

- using data from news websites allowed us to strictly control for genre
- our results cannot be potential artefacts of ‘genre confusion’, i.e. of chance due to an uncontrolled mix of different styles and genres
- however, this indicates that chances are given that other sources/genres/styles might lead to different results

- our corpus did not contain any ‘new forms’, e.g. gender star forms or capital-I forms: *Lehrer*in* or *LehrerIn* ‘teacher (of any sex or gender)’
- 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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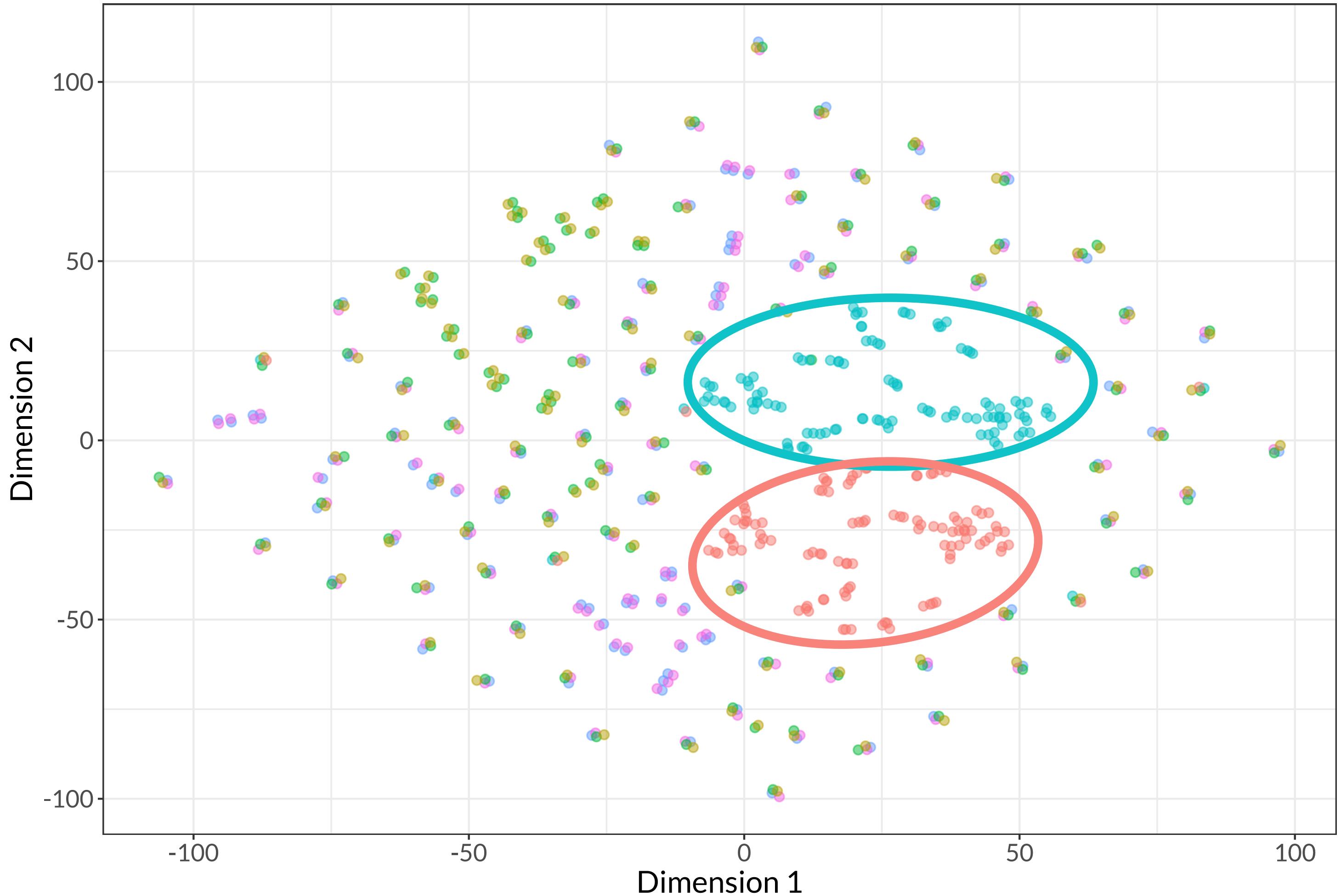
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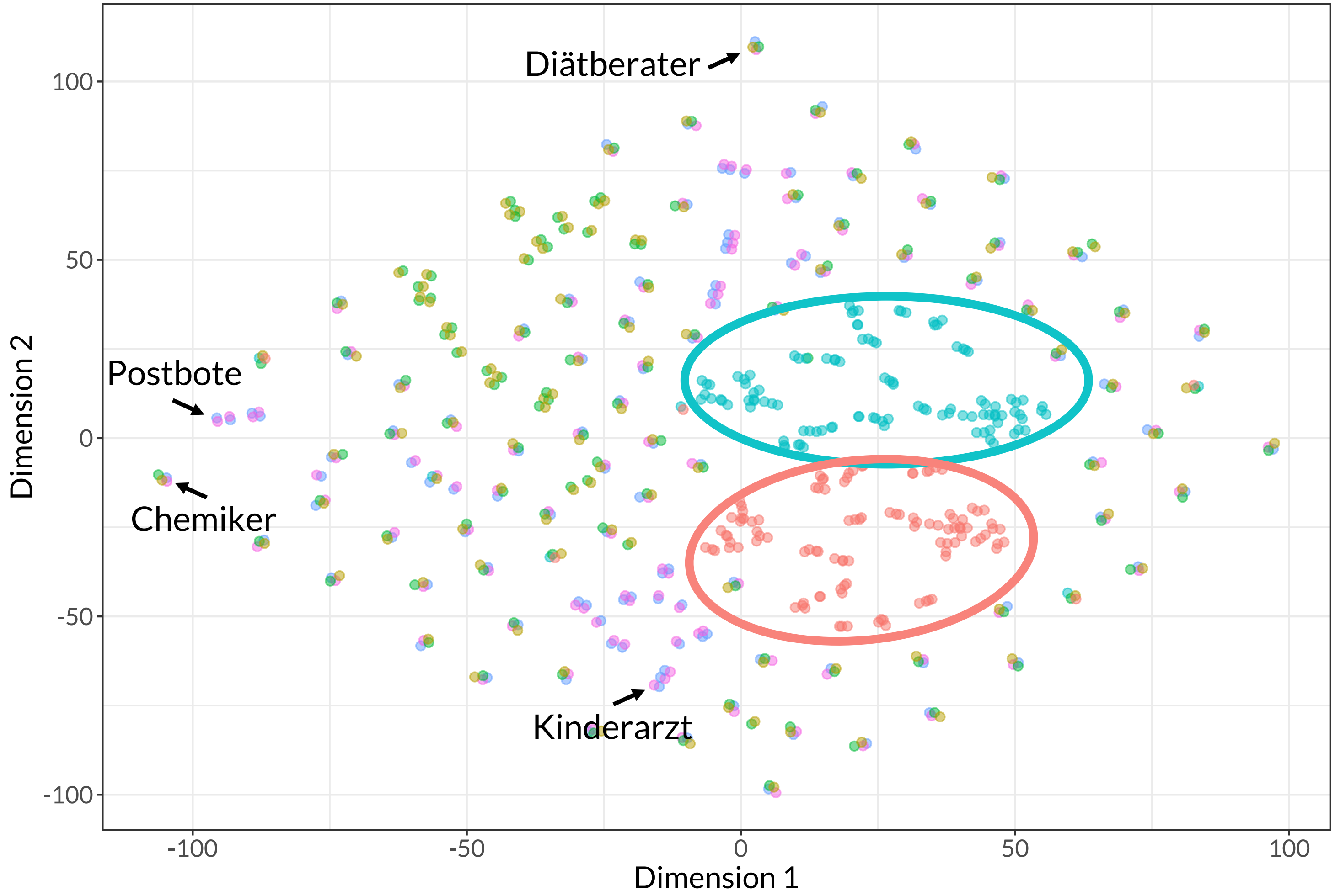
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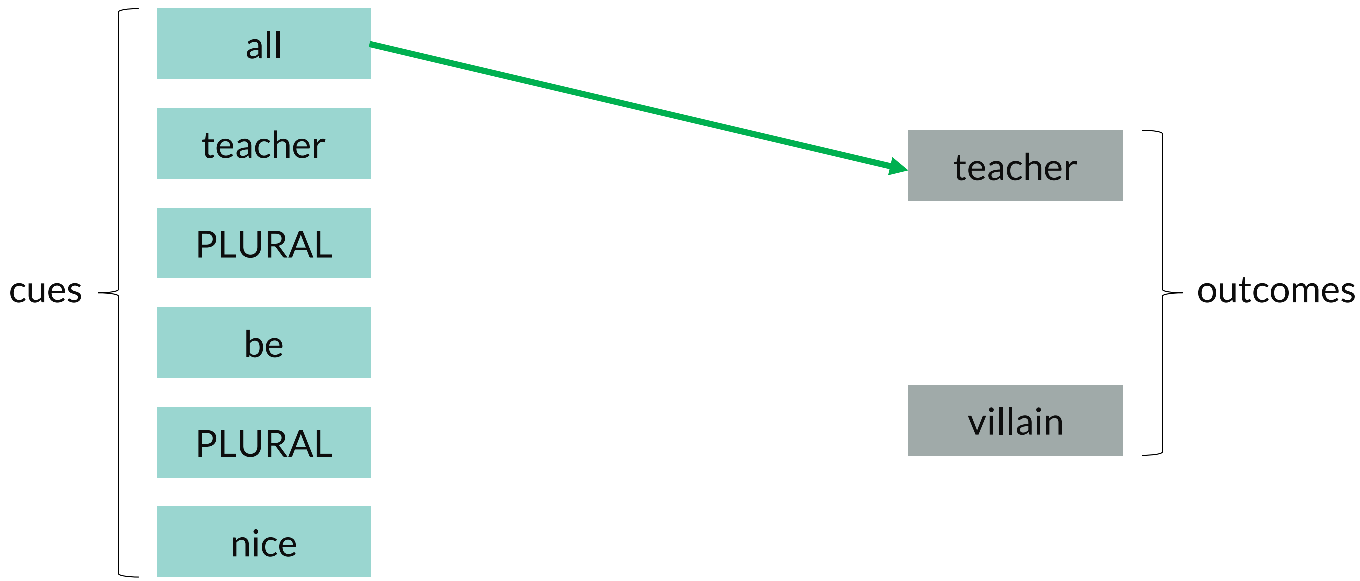
Method

Example: *All teachers are nice.*

	all	teacher	PLURAL	be	nice	villain	evil
teacher							
villain							

Method



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villain							

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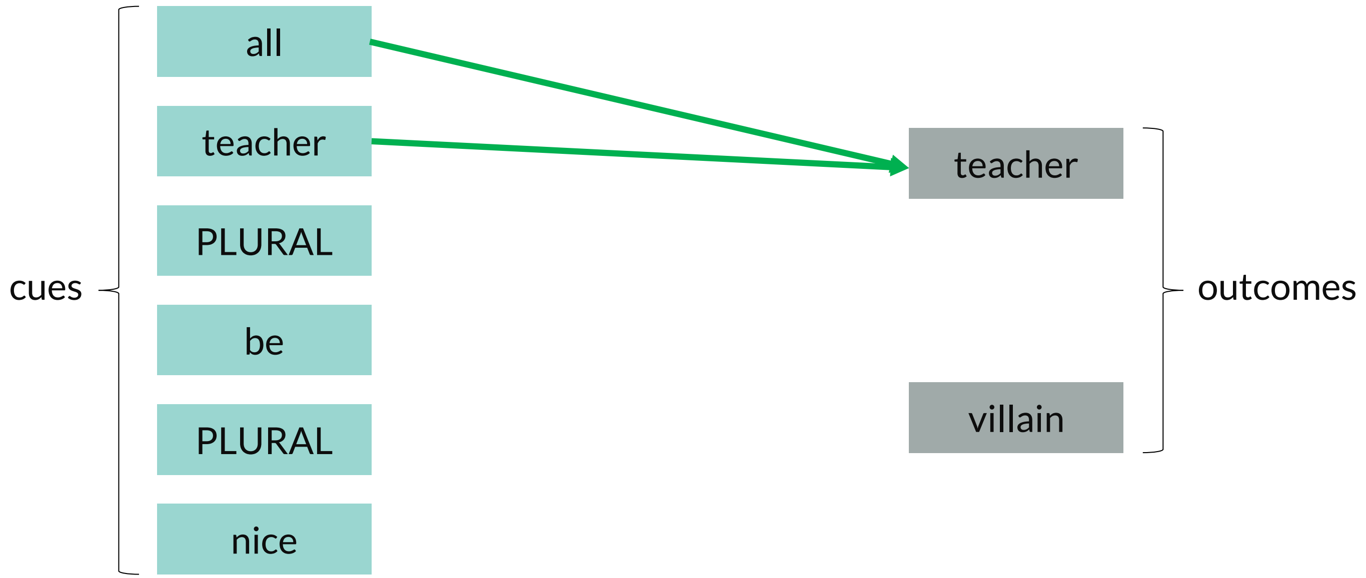

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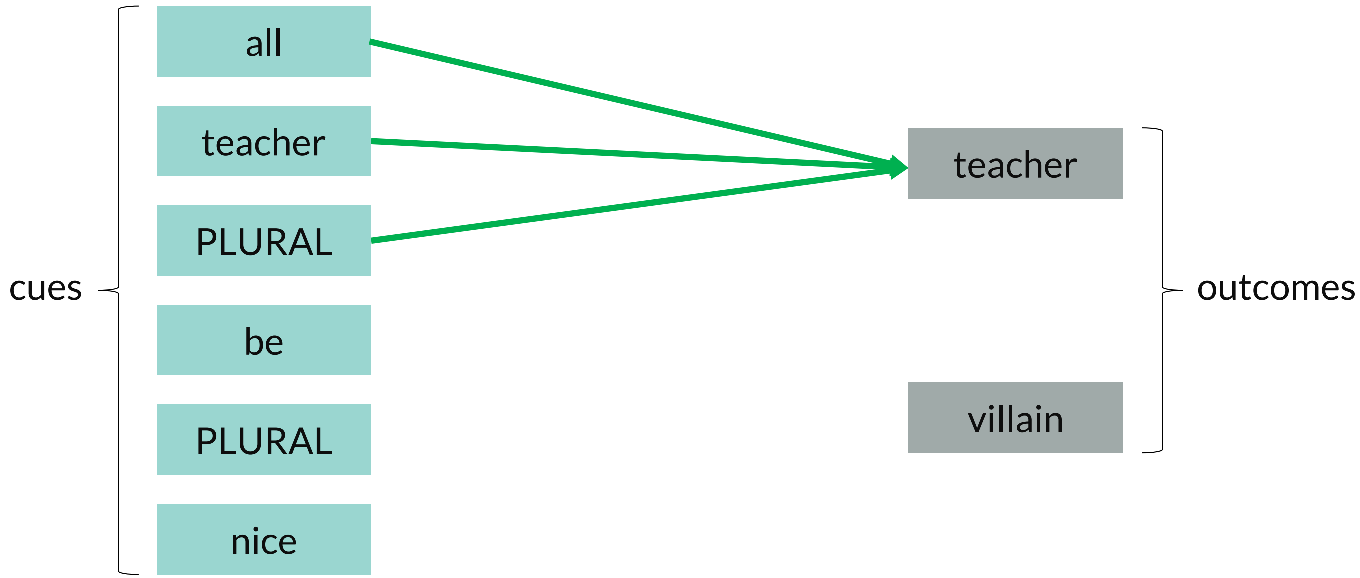

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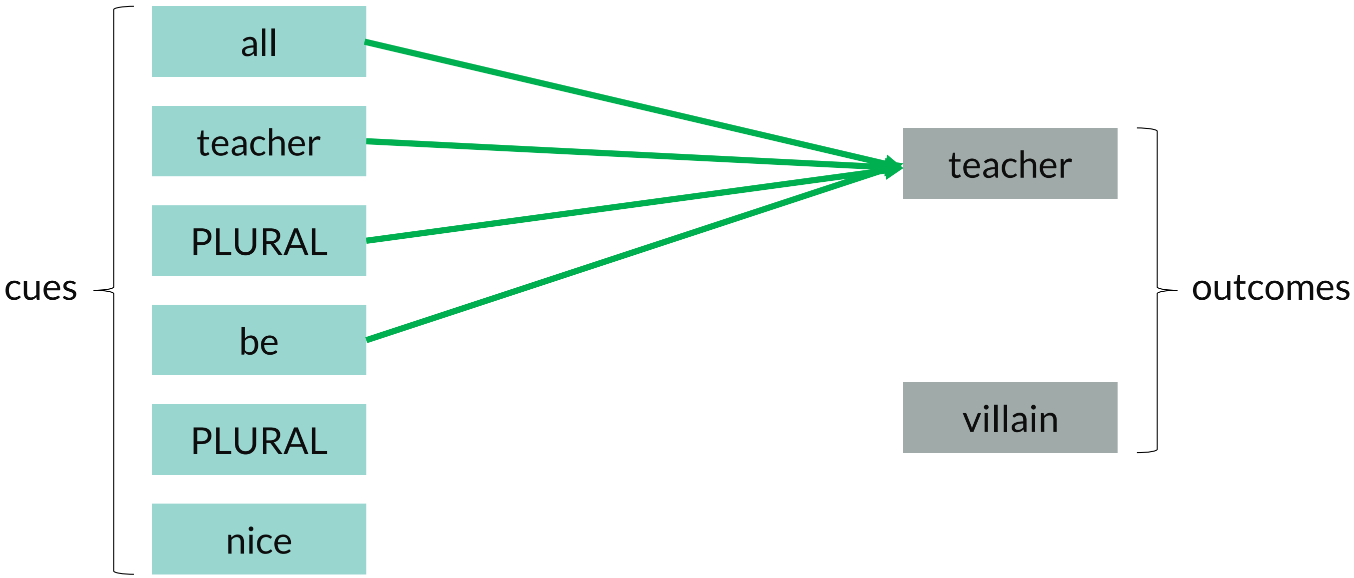

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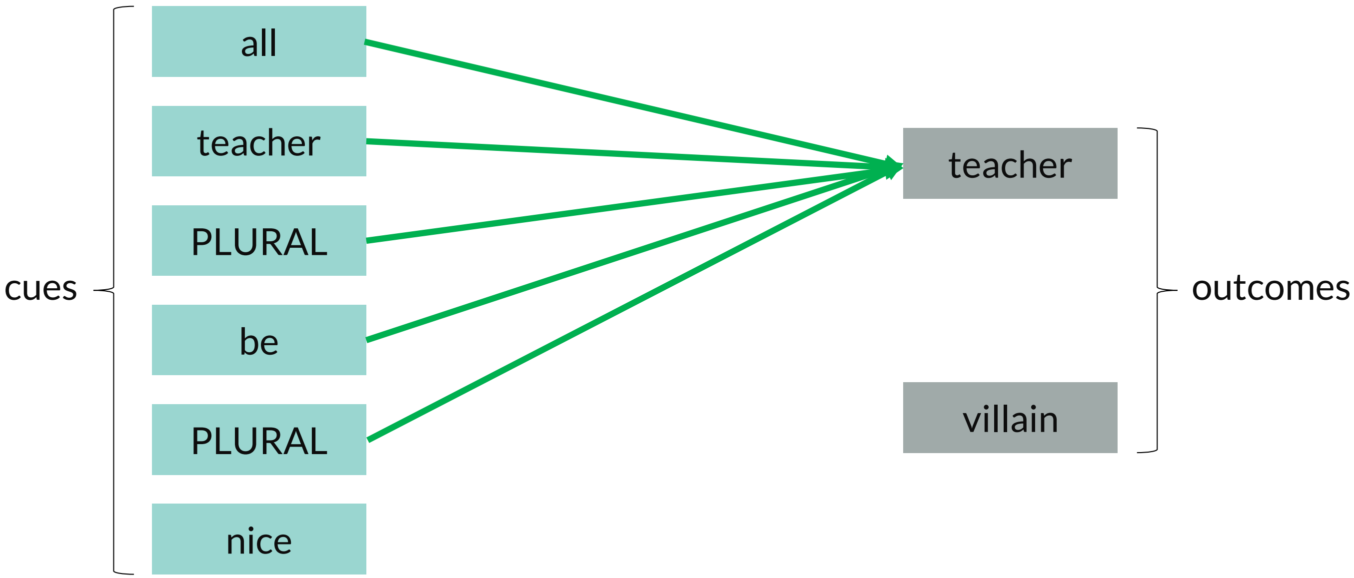

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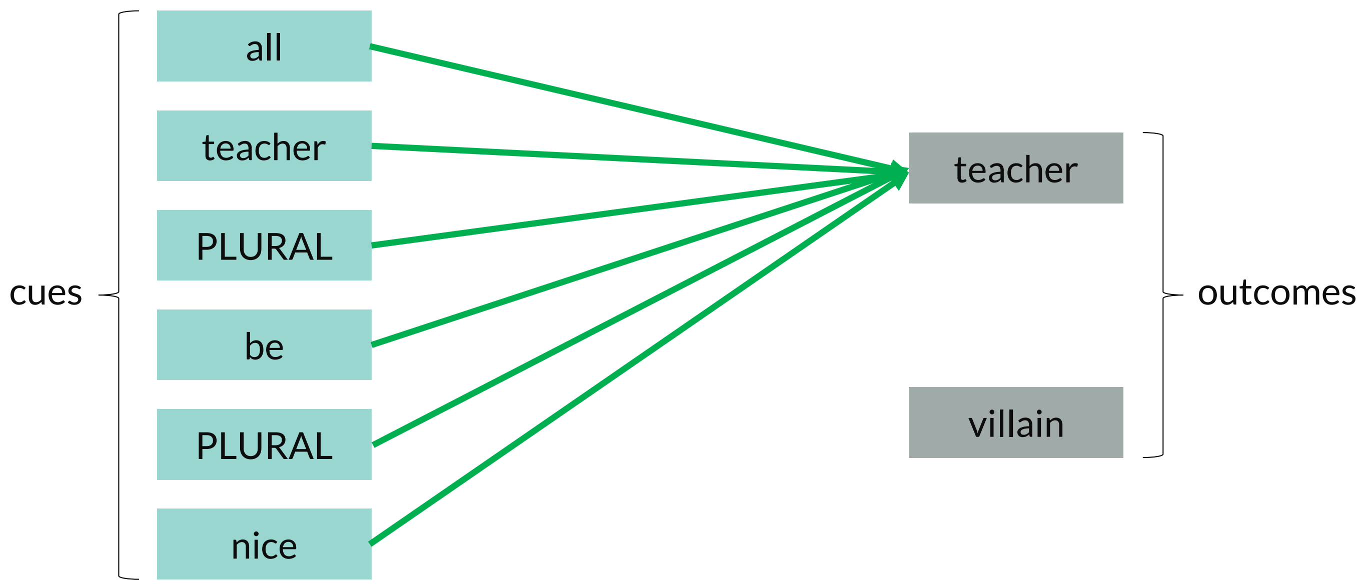

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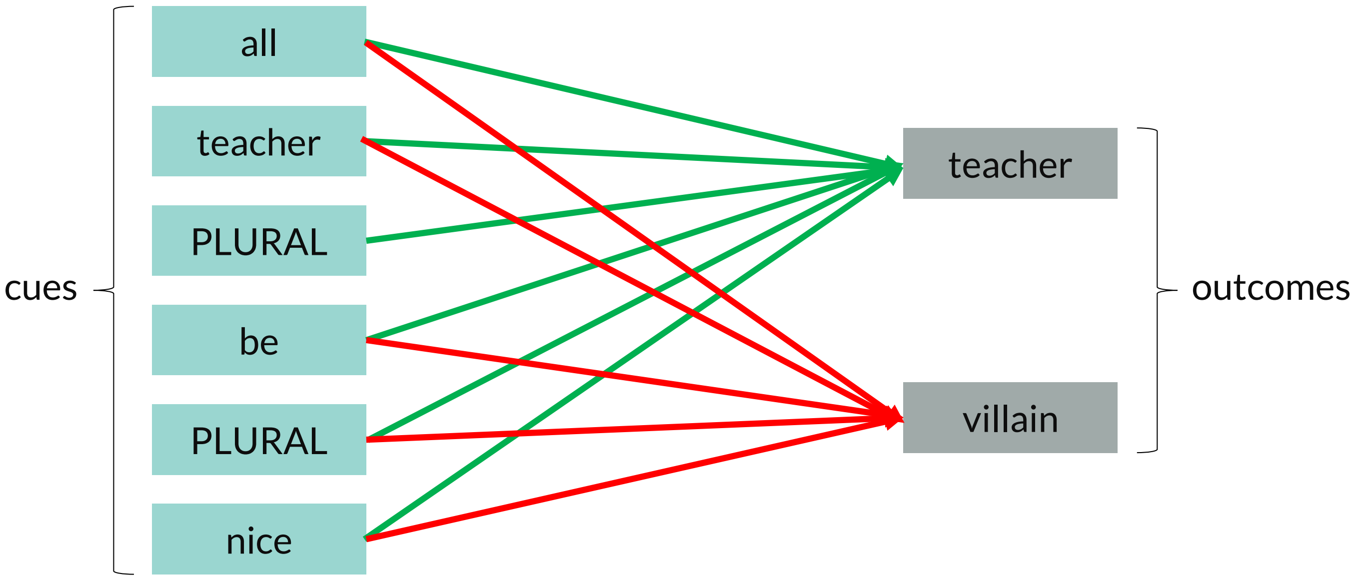

Example: *All teachers are nice.*

	all	teacher	PLURAL	be	nice	villain	evil
teacher	+	+	++	+	+	-	-
villain	-	-	-	-	-		

Method

Semantic vectors

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teacher	0.31	1.0	0.57	0.43	0.15	0.00071	0.0007
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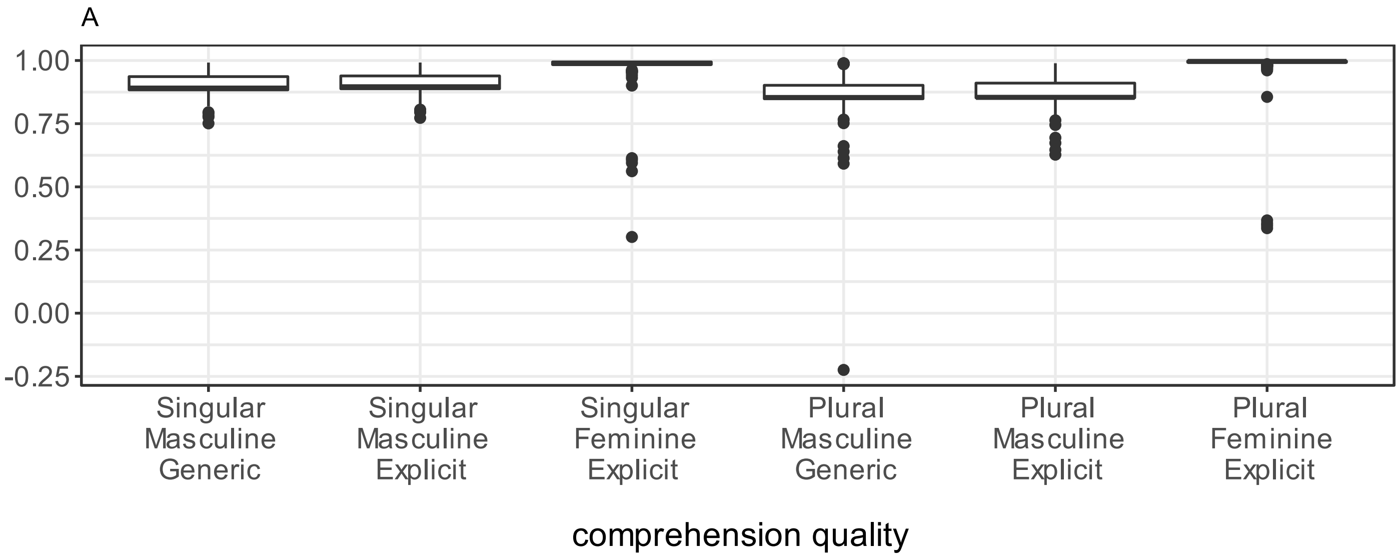
Semantic Measures

COMPREHENSION QUALITY

correlation of a target's original and estimated vectors

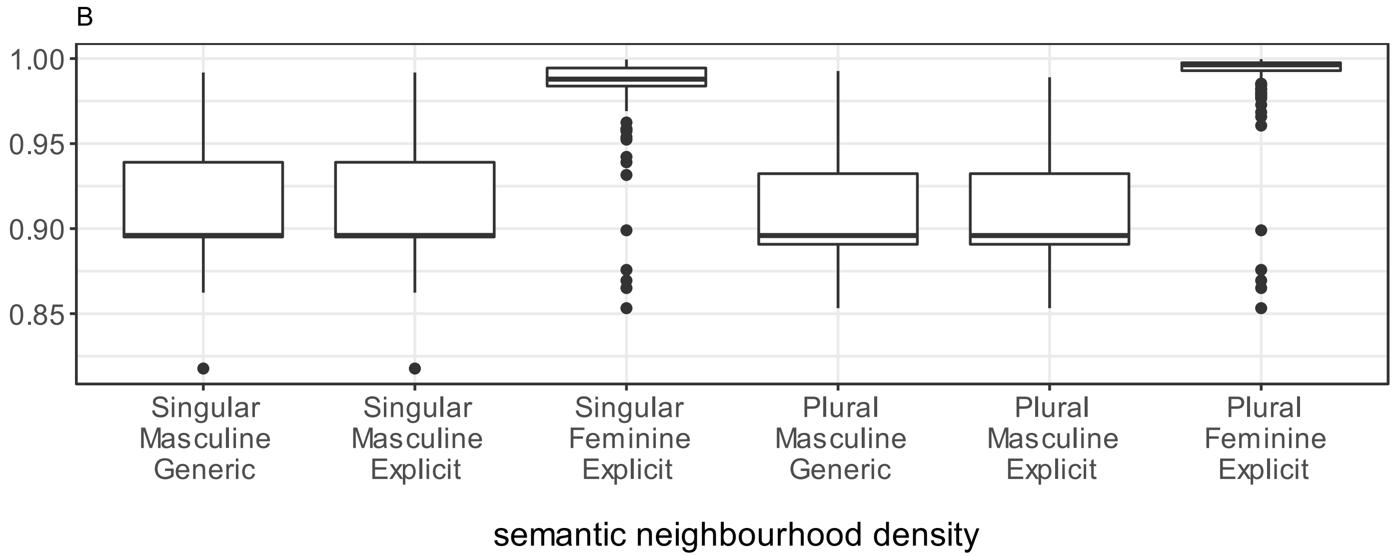
higher correlation = higher comprehension quality



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