Gender and language: When form meets semantics in computational models

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Master Colloquium “Phonological & Psycholinguistic Research”
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Gender meets language

- two word classes are most prominently associated with gender

(ROLE) NOUNS

e.g. *Lehrer* vs. *Lehrer*in* in German

PRONOUNS

e.g. *they* vs. *he/she* in English

Background: role nouns

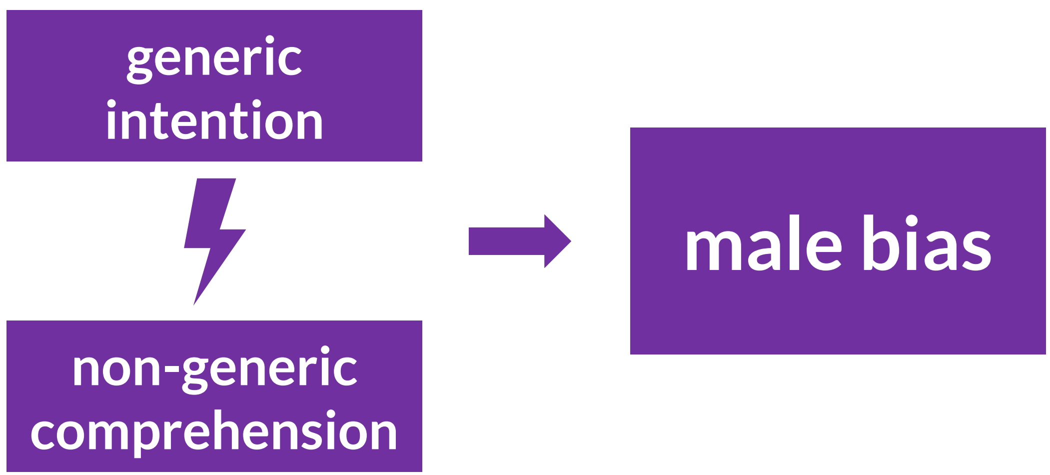
- in German, role nouns such as *Lehrer* ‘teacher’ can be used as generic forms

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 and/or female	masculine	
Lehrerinnen	female	feminine	

- 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)

Background: role nouns

- however, previous research has cast doubt on the gender-neutral use of generic masculines
- most (if not all) behavioural studies on the subject find one overall result
  → generic masculines are not gender-neutral but show a clear bias towards the explicit masculine reading (e.g. Schunack & Binanzer 2022; Gygax et al. 2008; Irmen & Kurovskaja 2010; Irmen & Linner 2005; Koch 2021; Misersky et al. 2019; Stahlberg & Sczesny, 2001)



Background: pronouns

- in recent years, the use of appropriate third-person pronouns has gained increased attention
- in contemporary English, one can differentiate at least four types of singular *they* (Conrod, 2020)
  - **generic indefinite**

    Someone ran out of the classroom, but **they** forgot **their** backpack.
  - **generic definite**

    The ideal student completes the homework, but not if **they** have an emergency.
  - **specific definite ungendered**

    The math teacher is talented, but **they** hand back grades late.
  - **specific definite gendered**

    James is great at laundry, but **they** never wash **their** dishes.

Methods in gender linguistics

- a great variety of methods has already been used to investigate gender
  - estimated proportions of women/men after reading texts (Braun et al., 1998)
  - text and sentence continuations (Heise, 2000)
  - questionnaires (Stahlberg et al., 2001)
  - sentence evaluation paradigm (Rothmund & Scheele, 2004)
  - eye-tracking (Esaulova et al., 2015)
  - event-related potentials (ERPs; Misersky et al., 2019)
  - word-picture matching tasks (Zacharski & Ferstl, 2023)
  - sociolinguistic interviews (Steriopolo & Aussoleil, 2023)
  - morphosyntactic analyses (Conrod, 2022)
  - …and much more!

Today’s aim

Today's aim

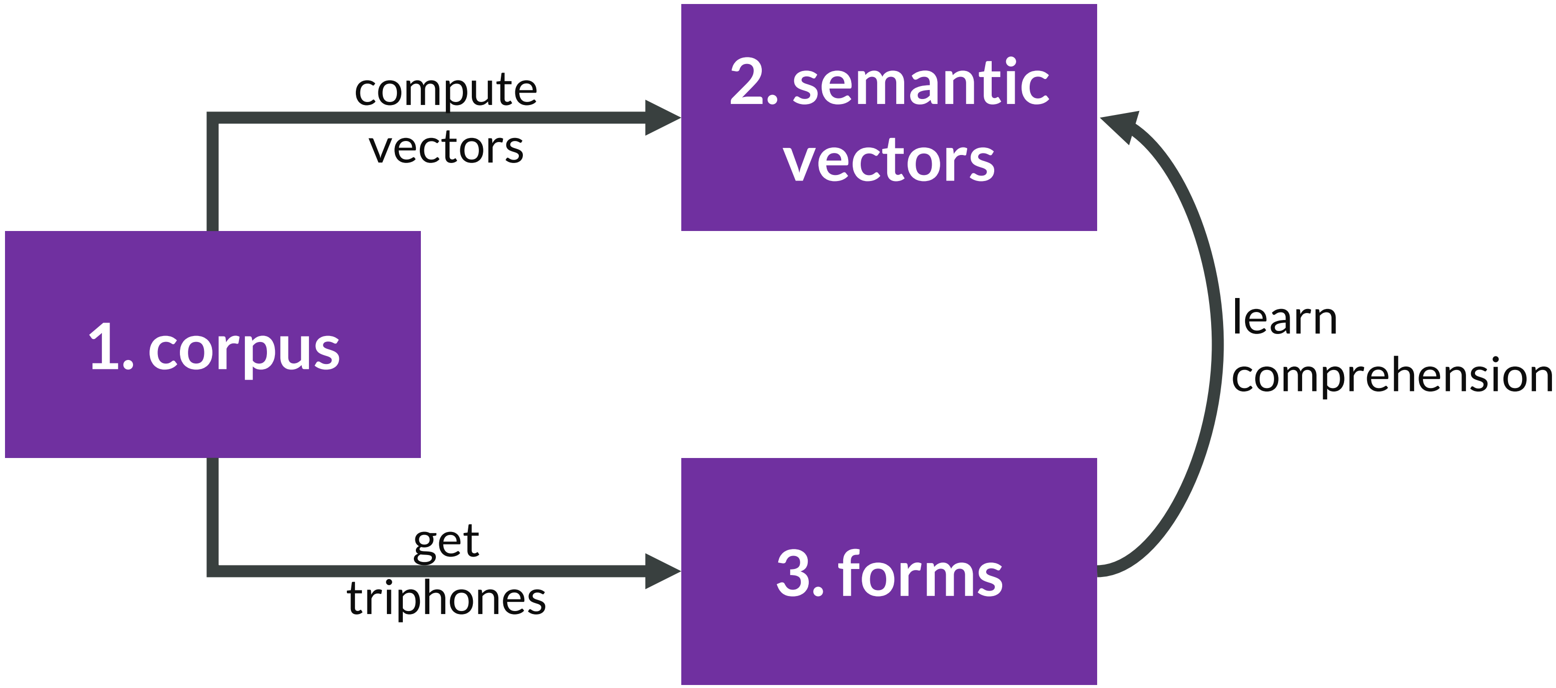
- while many methods have already been used, some were long untouched by gender linguistic research, for example
  - computational methods
- and while many questions have already been asked, some areas are still understudied, for example
  - the semantics of role nouns and pronouns

What can a computational model based on psychological theory tell us about the semantics of role nouns and pronouns?

German role nouns

Linear Discriminative Learning

- 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



Corpus: Targets

- 113 target word paradigms were adapted from a study on the influence of stereotypicality on the comprehension of generic masculines (Gabriel et al. 2008)
- all target word paradigms
  - consist of role nouns
  - have common explicit feminine forms

generic & explicit masculines	translation
Anwalt	‘lawyer’
Bäcker	‘baker’
Historiker	‘historian’
Maurer	‘mason’
Professor	‘professor’
Wärter	‘guard’

Corpus: Sentences

- 10 million sentences were extracted from the Leipzig Corpora Collection's subcorpus "News" (Goldhahn et al. 2012) → 1 million for each year from 2010 to 2019
- from the 10 million sentences, the following was sampled
  - 800,000 sentences without any target words
  - 30,000 sentences with target words
  - 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

Corpus: Annotation

- the 30,000 sentences containing target words were manually annotated by two authors and two assistants, all of which were native speakers of German
- for each target word occurrence, it was annotated whether the form was
  - masculine or feminine; singular or plural; explicit or generic
- the 800,000 sentences without and the 30,000 sentences with target words were then automatically analysed and annotated using the RNNTagger software (Schmid, 1999)
- tagged information consisted of words' base forms and information on inflectional grammar

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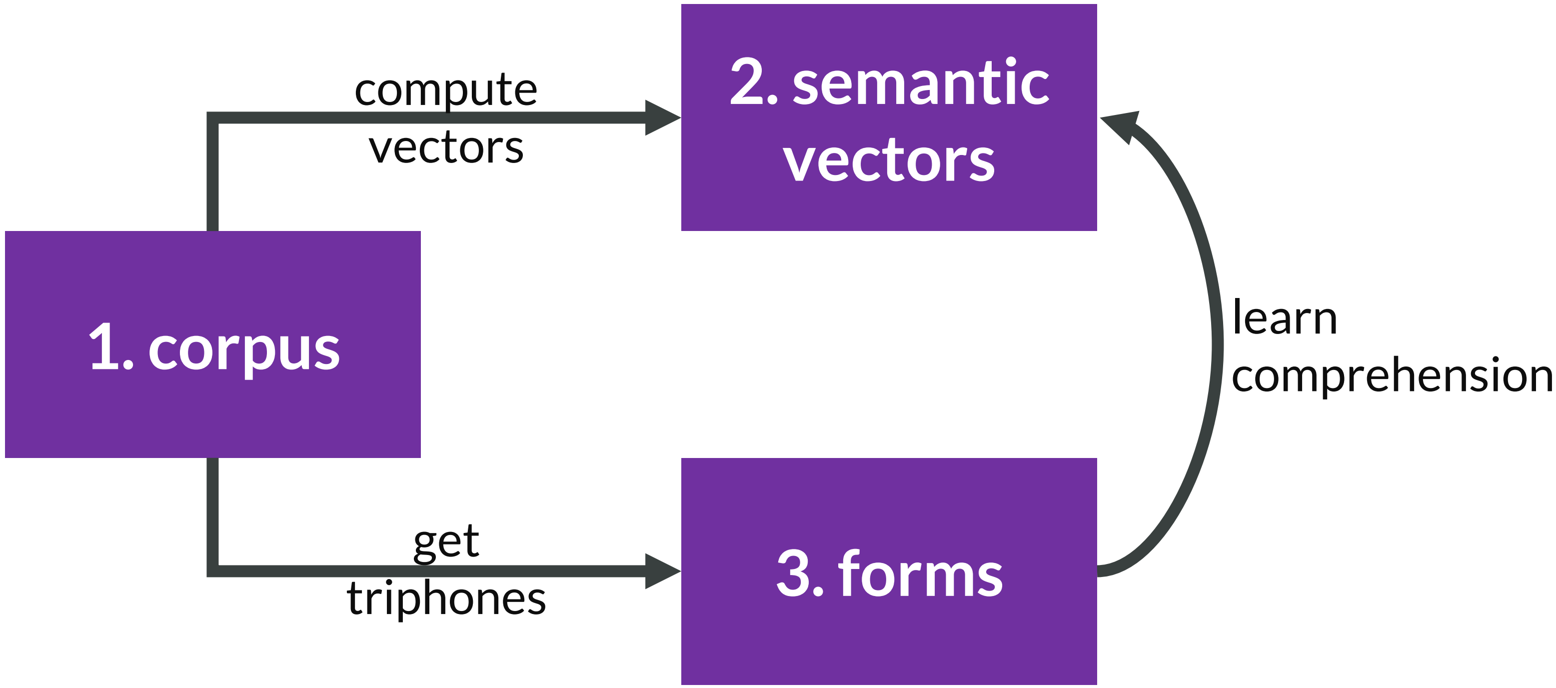
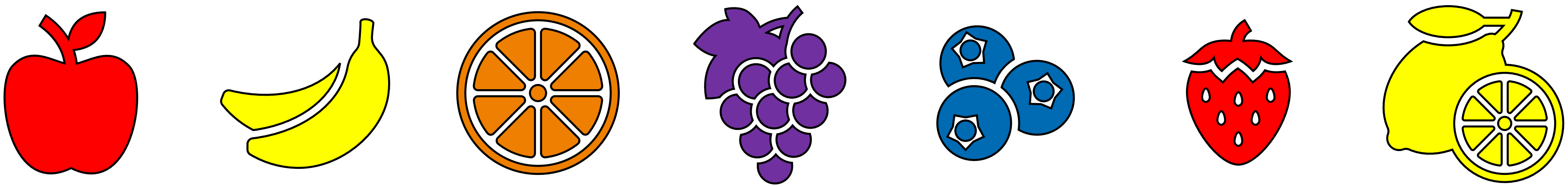


Semantic vectors

- semantic vectors were computed based on the corpus for words and inflectional functions with **Naive Discriminative Learning** (NDL; e.g. Baayen & Ramscar, 2015)
- **NDL** follows the Rescorla-Wagner rules (Rescorla & Wagner, 1972)
  - **outcomes** (word forms) are predicted by **cues** (words/inflection)
  - the **associative strength** between an outcome and a cue is represented by a single number
- 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



Naive Discriminative Learning

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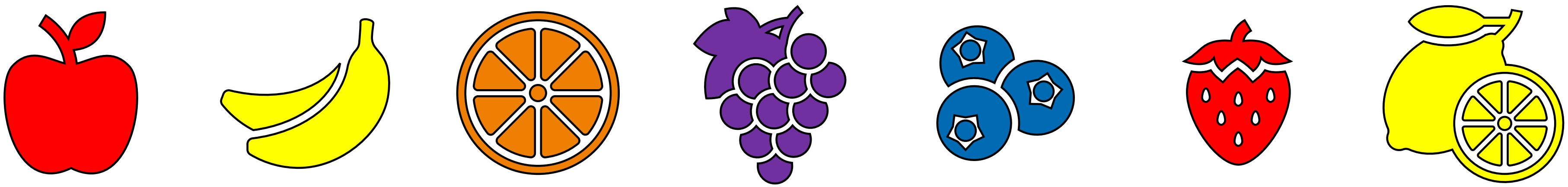

red	yellow	orange	purple	blue	red	yellow
sweet	sweet	sour	sweet	sweet	sweet	sour
round	long	round	round	round	round	round
					long	long

Naive Discriminative Learning

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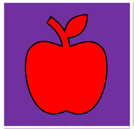
	red	yellow	orange	purple	blue	sweet	sour	round	long
	1					1		1	
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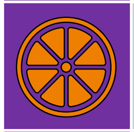
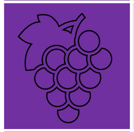
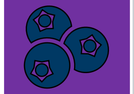
			1				1	1	
				1		1		1	
					1	1		1	
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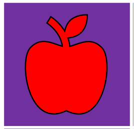
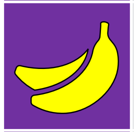
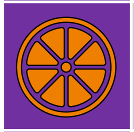
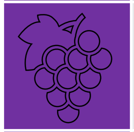
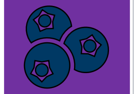
	30					30		30	
		15				15			15
			18				18	18	
				10		10		10	
					5	5		5	
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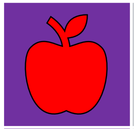
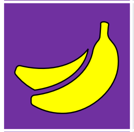
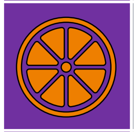
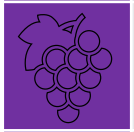
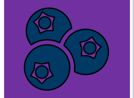
	30	1				30		30	
		15				15			15
			18				18	18	
				10		10		10	
					5	5		5	
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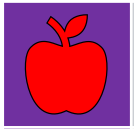	30	1				30	1	30	
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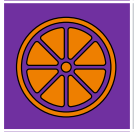
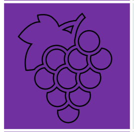
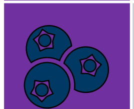
			18				18	18	
				10		10		10	
					5	5		5	
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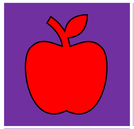
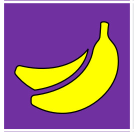
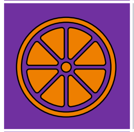
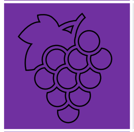
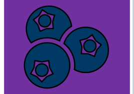
	30	1	-1	-3	-2	30	1	30	-1
		15				15			15
			18				18	18	
				10		10		10	
					5	5		5	
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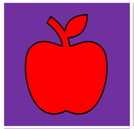	30	1	-1	-3	-2	30	1	30	-1
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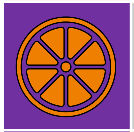
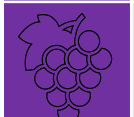
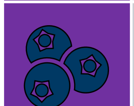
	-6	-7	18	-14	-15	3	18	18	-2
	-5	-1	-6	10	-9	10	5	10	-7
	-6	-9	-19	2	5	5	1	5	-5
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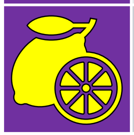	-1	20	-5	-6	-8	-4	20	20	20

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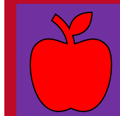	30	1	-1	-3	-2	30	1	30	-1
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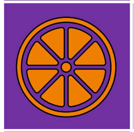
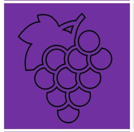
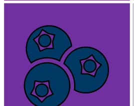
	-6	-7	18	-14	-15	3	18	18	-2
	-5	-1	-6	10	-9	10	5	10	-7
	-6	-9	-19	2	5	5	1	5	-5
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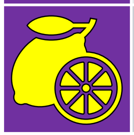	-1	20	-5	-6	-8	-4	20	20	20

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
blueberry	-6	-9	-19	2	3	4	1
strawberry	45	-6	-9	-14	-1	25	20
lemon	-1	20	-5	-6	-8	-4	20

Naive Discriminative Learning

- 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	$\overrightarrow{Lehrer}$	+	$\overrightarrow{\text{singular}}$	+	$\overrightarrow{\text{masculine}}$	+	$\overrightarrow{\text{generic}}$
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	$\overrightarrow{Lehrer}$	+	$\overrightarrow{\text{plural}}$	+	$\overrightarrow{\text{masculine}}$	+	$\overrightarrow{\text{generic}}$
Lehrer	$\overrightarrow{Lehrer}$	+	$\overrightarrow{\text{plural}}$	+	$\overrightarrow{\text{masculine}}$	+	$\overrightarrow{\text{explicit}}$
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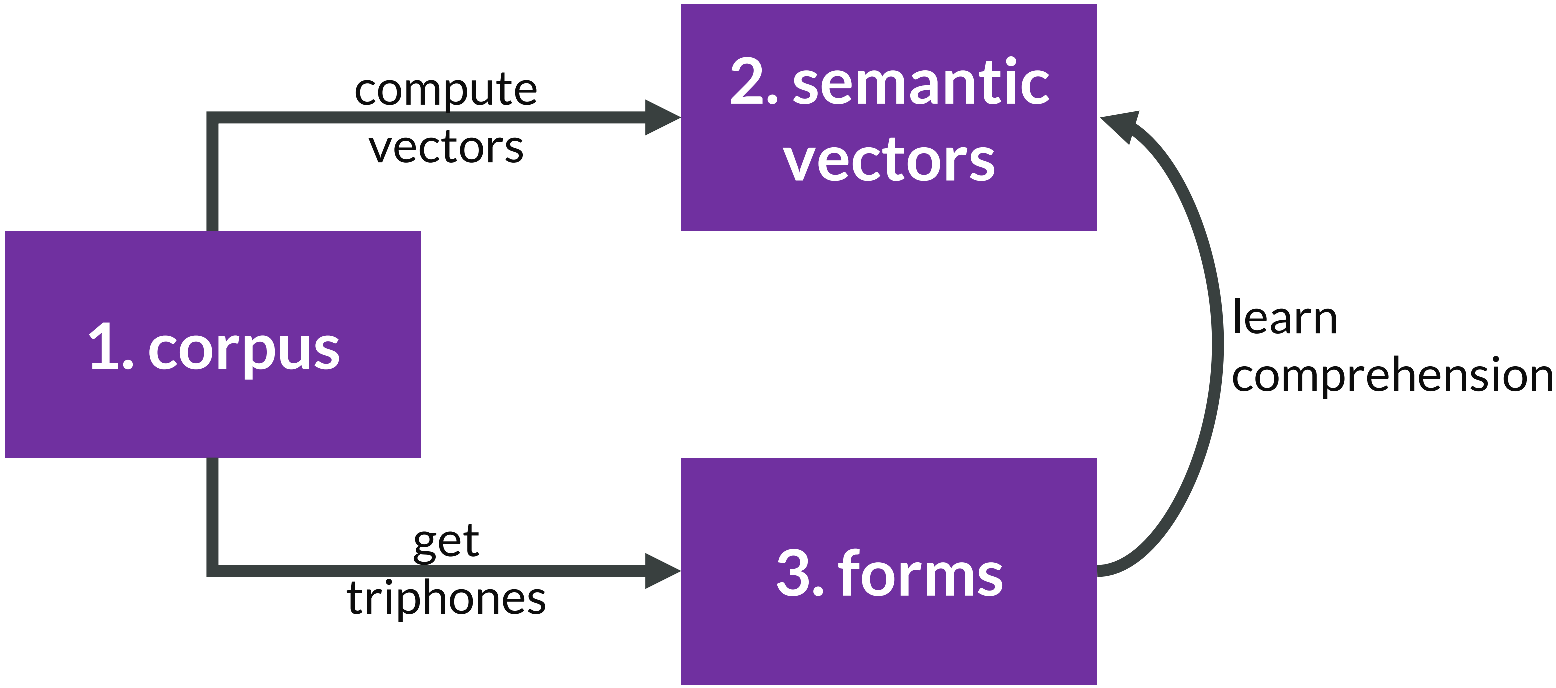

Forms

- triphones as unit for a word's form
- trigrams / triphones have been shown to capture the form variability of words well (e.g. Chuang et al., 2020; Schmitz et al., 2021; Schmitz et al., 2023)

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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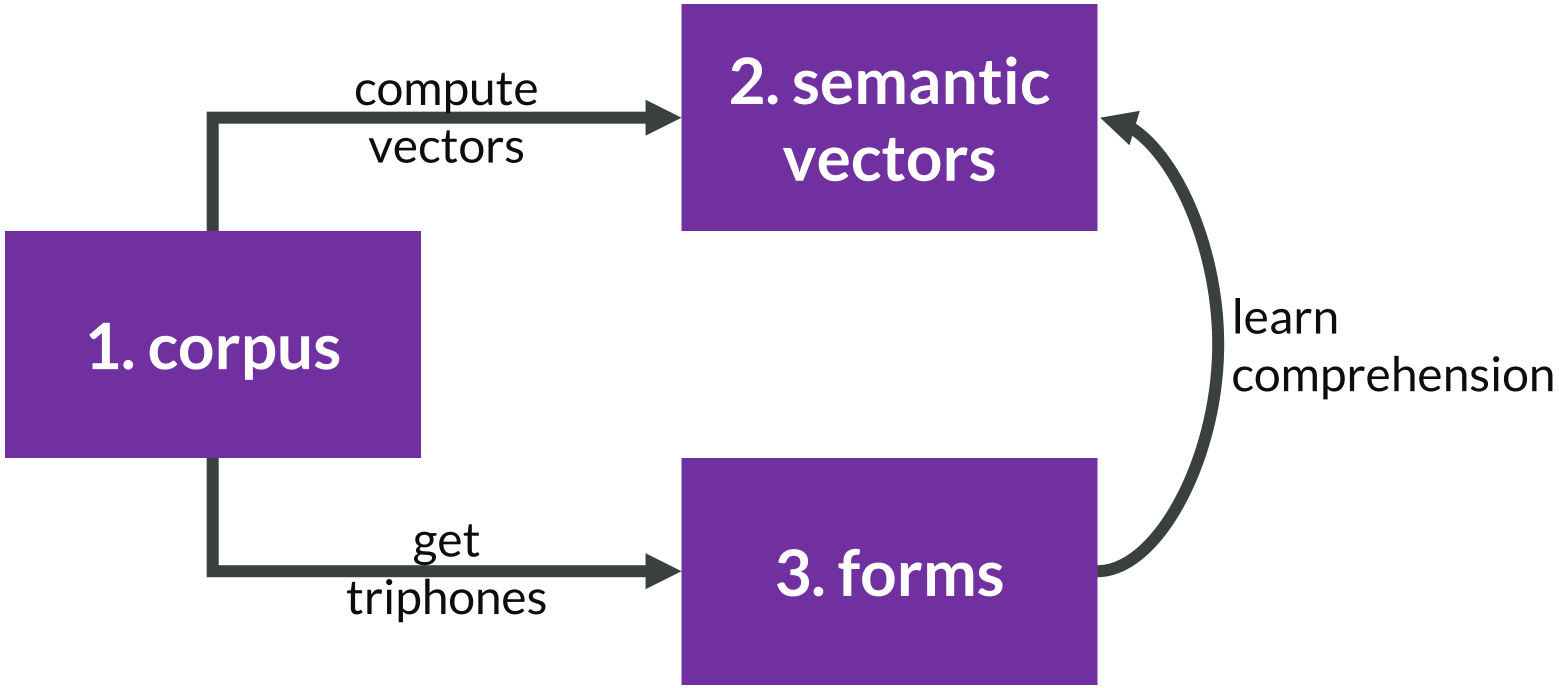
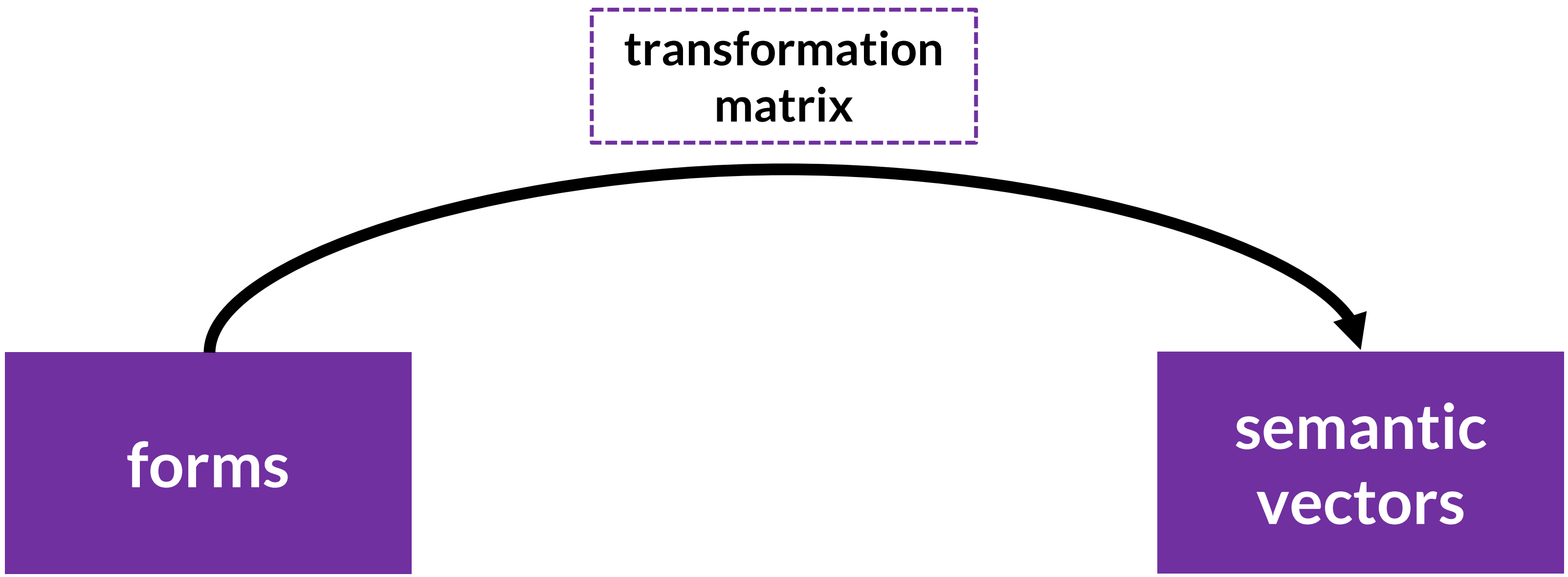


Learning comprehension

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



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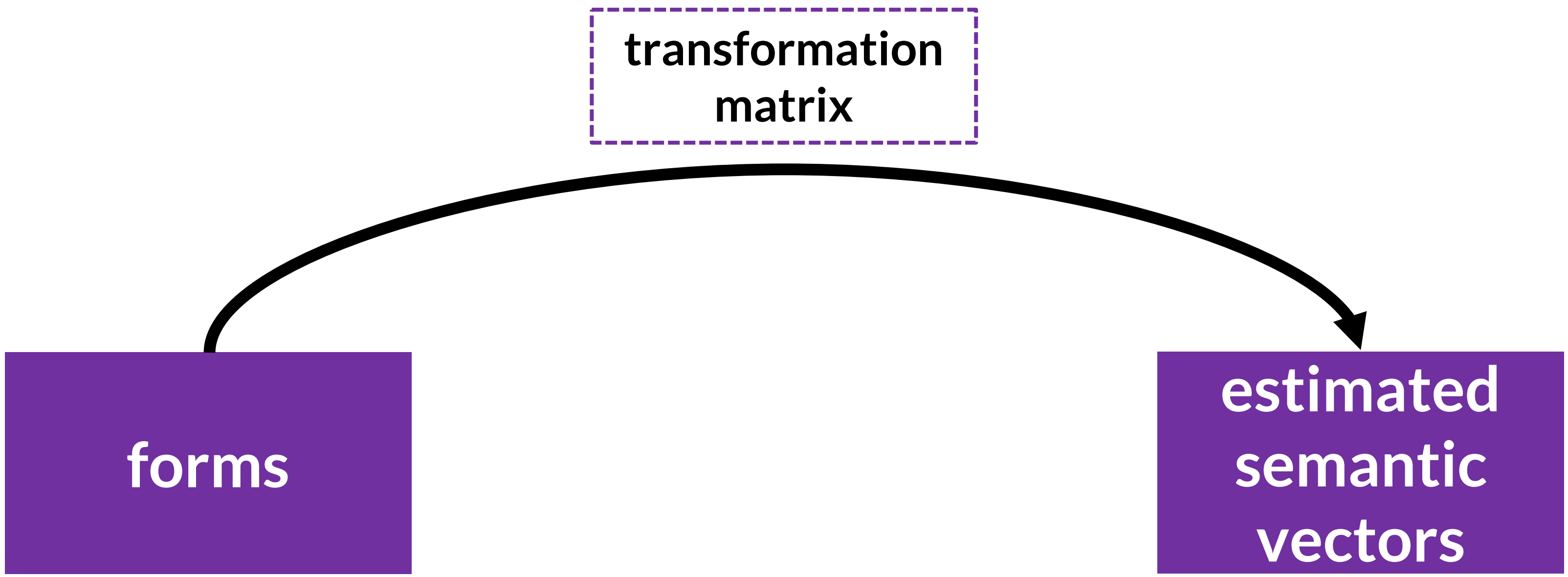

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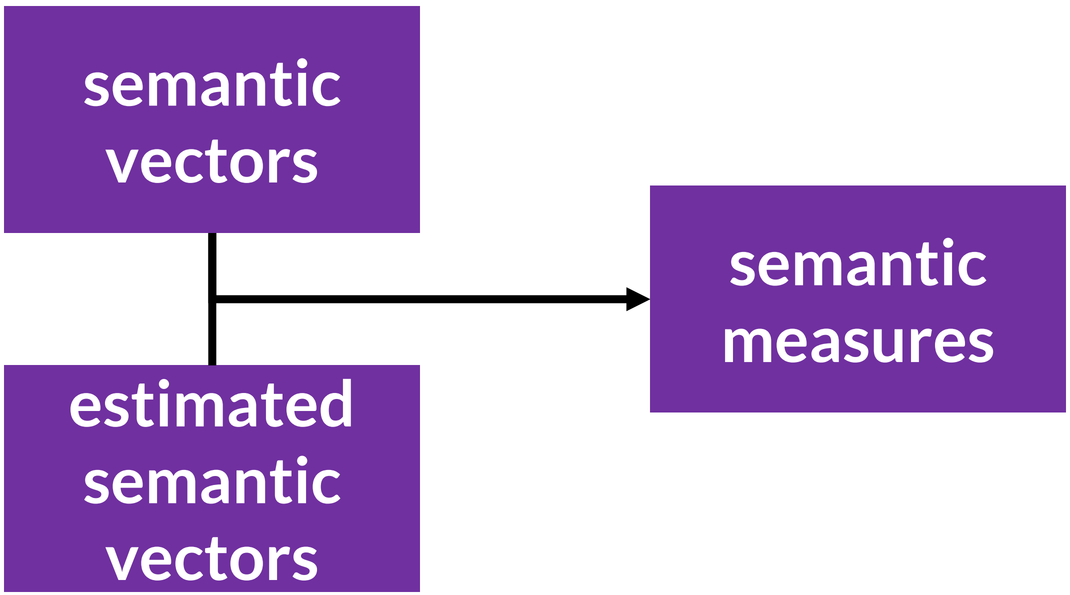


Measures

- **COMPREHENSION QUALITY**

  correlation of a target's original and estimated vectors

  higher correlation = higher comprehension quality

- **NEIGHBOURHOOD DENSITY**

  correlation of a target with its 8 nearest neighbours

  higher density = denser neighbourhood

- **ACTIVATION DIVERSITY**

  Euclidian norm of a target's vector

  higher norm = higher degree of co-activation

- **STEREOTYPICALITY**

  adopted from Gabriel et al. (2008)

Multinomial Logistic Regression Analysis

- dependent variable: **TYPE**

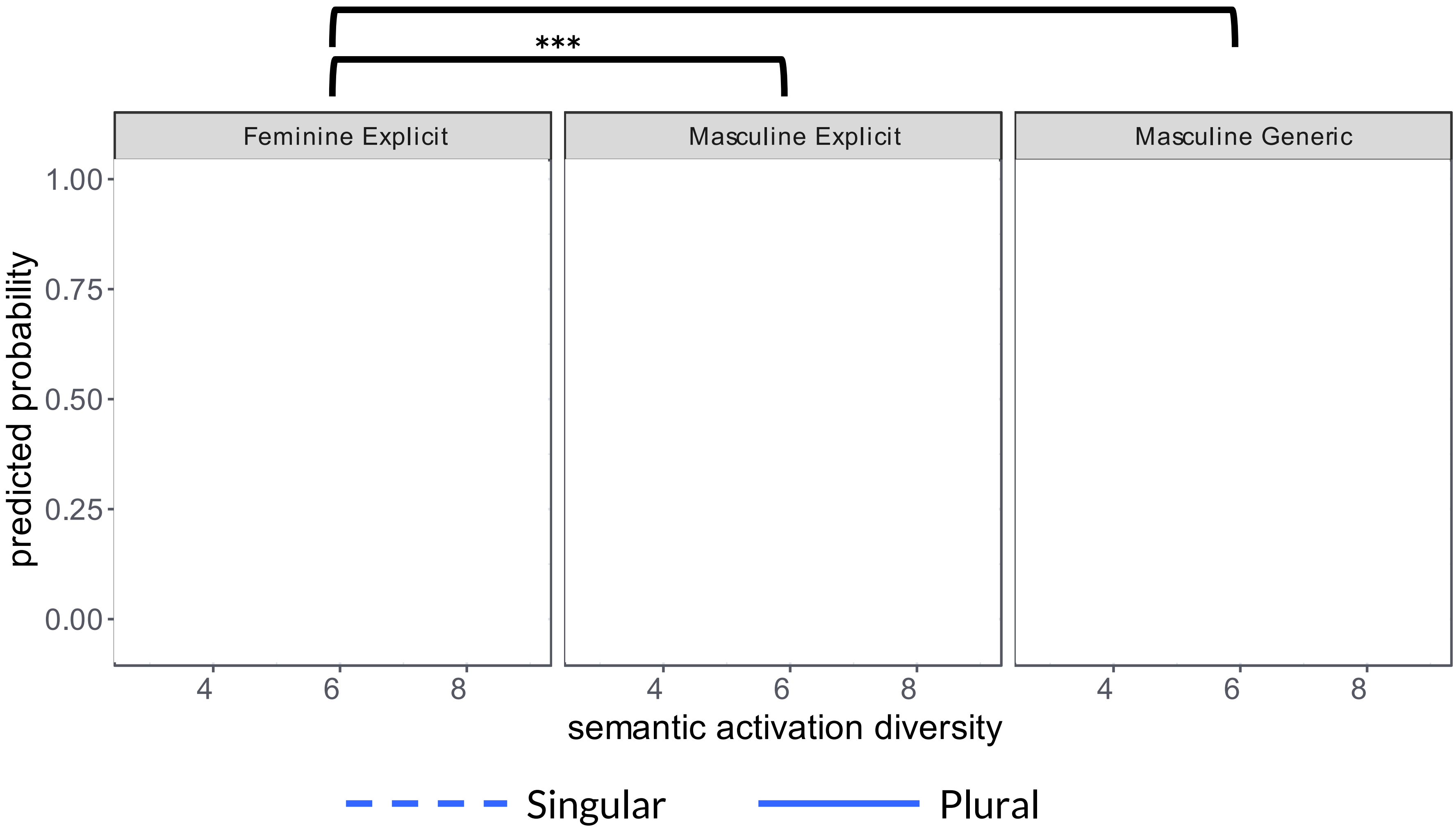
  singular generic masculine; singular explicit masculine; singular explicit feminine

  plural generic masculine; plural explicit masculine; plural explicit feminine

- explanatory variables
  - **ACTIVATION DIVERSITY**
  - **PRINCIPAL COMPONENT** (COMPREHENSION QUALITY + NEIGHBOURHOOD DENSITY)
  - **STEREOTYPICALITY JUDGEMENTS** (Gabriel et al. 2008)

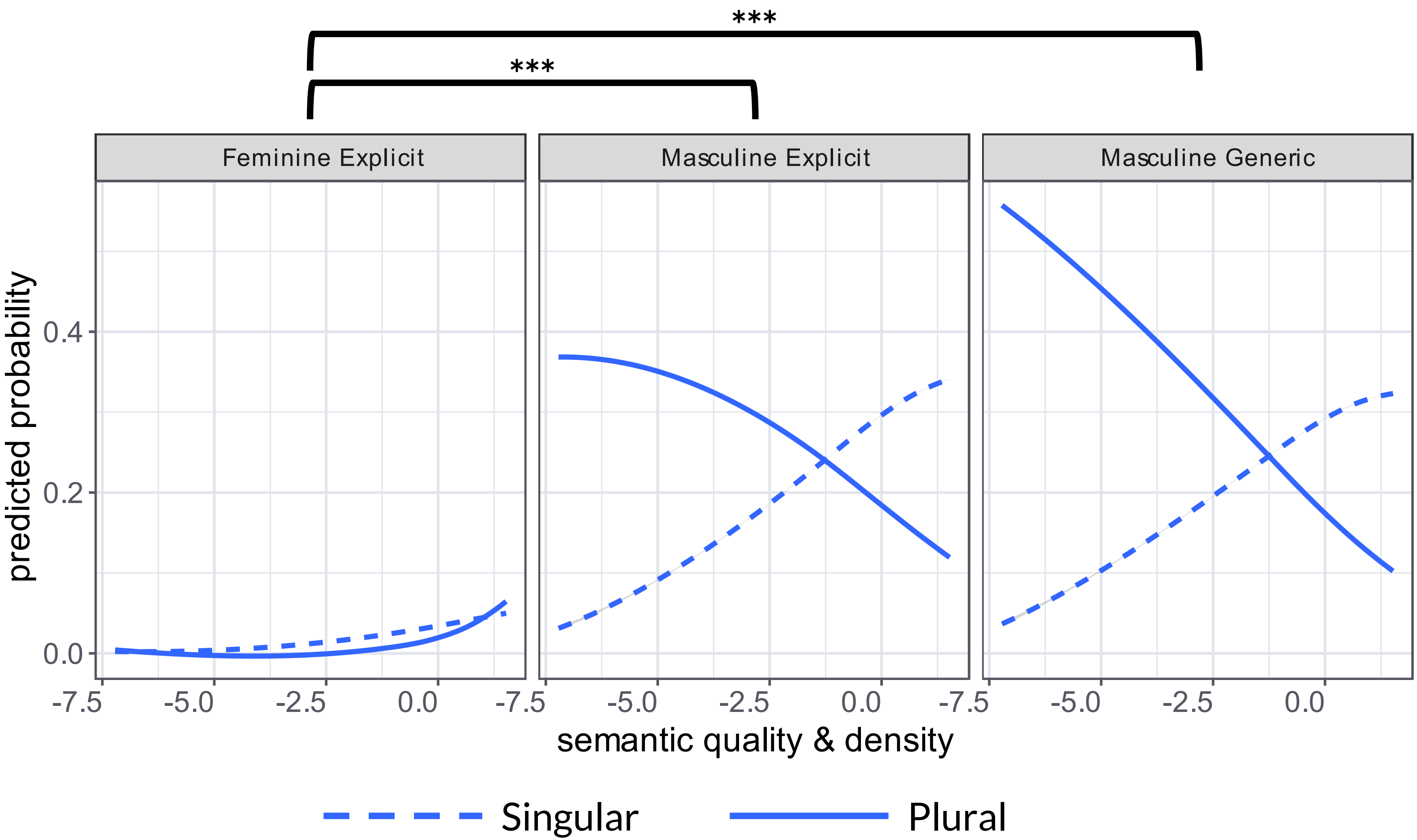
Results

ACTIVATION DIVERSITY



Results

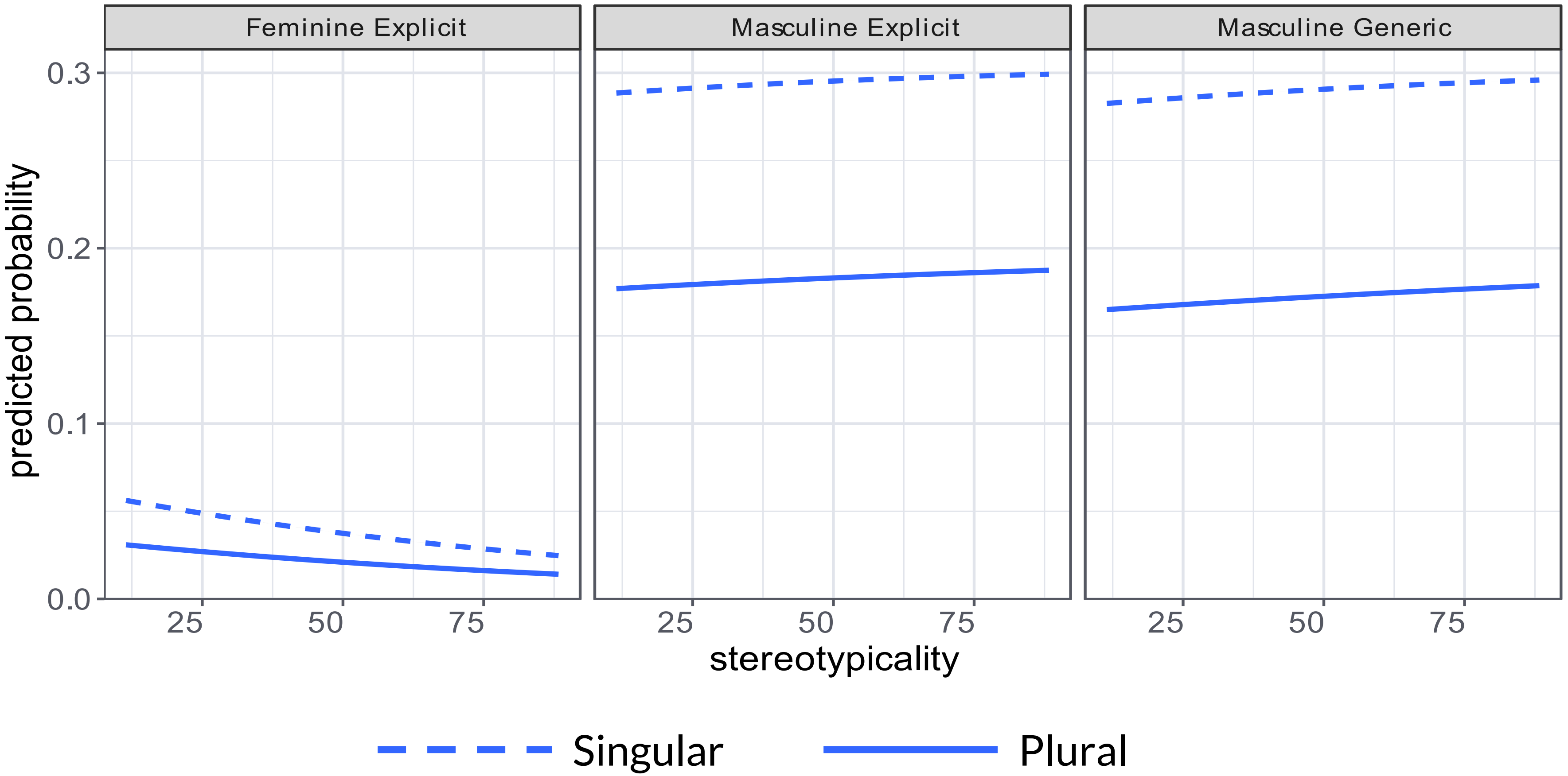
COMPREHENSION QUALITY + NEIGHBOURHOOD DENSITY



Results

STEREOTYPICALITY JUDGEMENTS

no significant effects!



Discussion

- findings are in line with assumptions found in previous research
  - Stahlberg et al. (2001)

    masculine gender of [masculine] generics has a semantic component of "maleness"
  - Irmen & Linner (2005)

    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

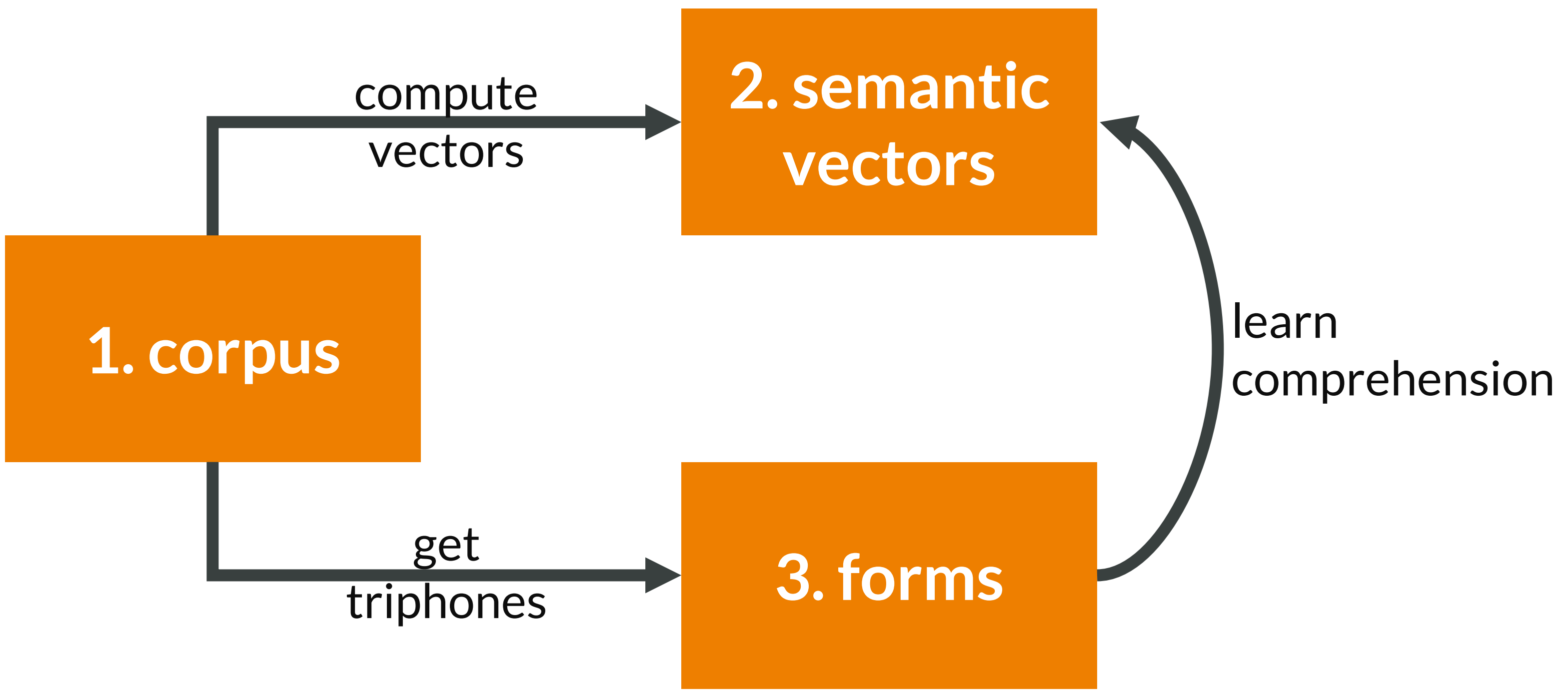
Discussion

- the masculine bias found in generic masculines is due to their underlying semantic features which they share with explicit masculines
- the language itself is the reason for the masculine bias, not any non-linguistic influences
- findings confirm the bias found in previous behavioural studies (e.g. Schunack & Binanzer 2022; Gygax et al. 2008; Irmen & Kurovskaja 2010; Irmen & Linner 2005; Koch 2021; Misersky et al. 2019; Stahlberg & Sczesny, 2001)
- 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

English pronouns

Linear Discriminative Learning

- 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



Corpus

- small corpus based on COCA (Davies, 2008-)
  - 17,805 word form tokens
  - 1,000 sentences
  - 60 + attestations of each target pronoun

    he, *she*, and plural and singular *they*
- pronoun attestations were manually checked for number and genericity
- automatically analysed and annotated for inflection using the RNNTagger software (Schmid, 1999)

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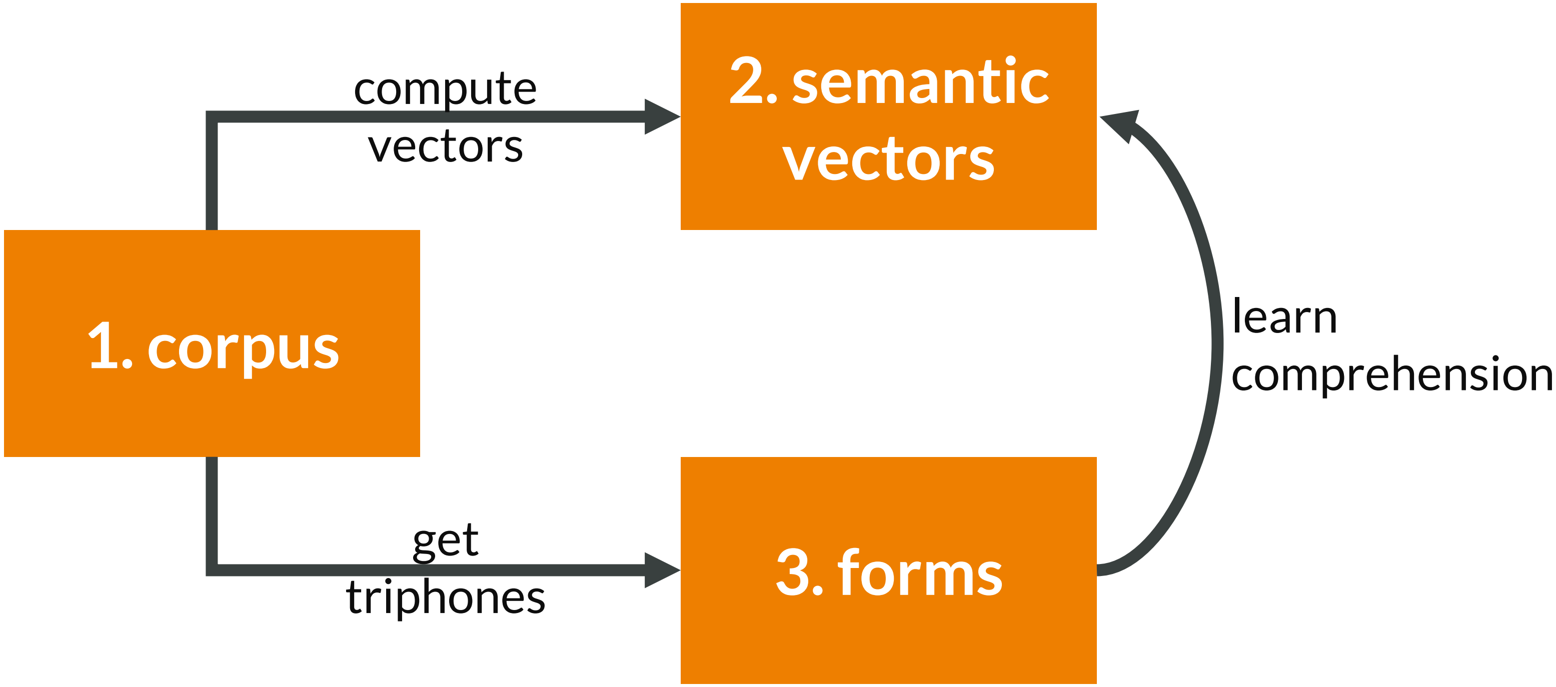

Semantic vectors

- semantic vectors were computed based on the corpus for words and inflectional functions with **Naive Discriminative Learning** (NDL; e.g. Baayen & Ramscar, 2015)
- **NDL** follows the Rescorla-Wagner rules (Rescorla & Wagner, 1972)
  - **outcomes** (word forms) are predicted by **cues** (words/inflection)
  - the **associative strength** between an outcome and a cue is represented by a single number
- we used each sentence to predict each individual word within the sentence by the other words in that sentence

Semantic vectors

- however: 1 vector per base/function word/inflectional function

  = 1 vector per pronoun

- 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

- the solution: instance vectors (Lapesa et al., 2018)
  - take n preceding and following words
  - get the semantic vectors of these words
  - compute the mean of these vectors

= instance vector

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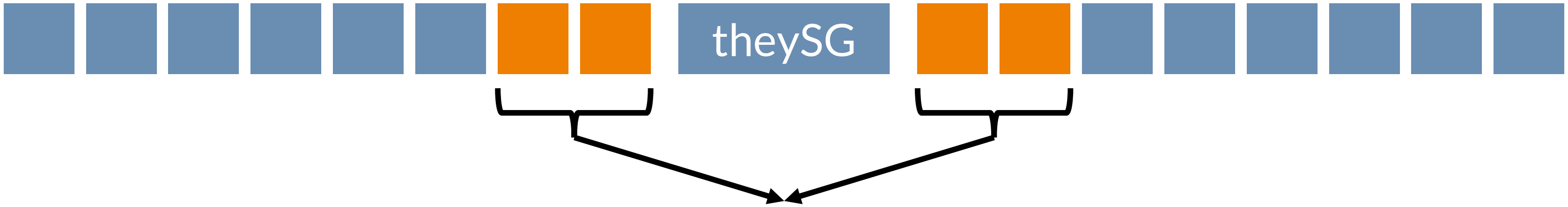
    = instance vector

$n = 2$



mean → instance vector

Instance vectors

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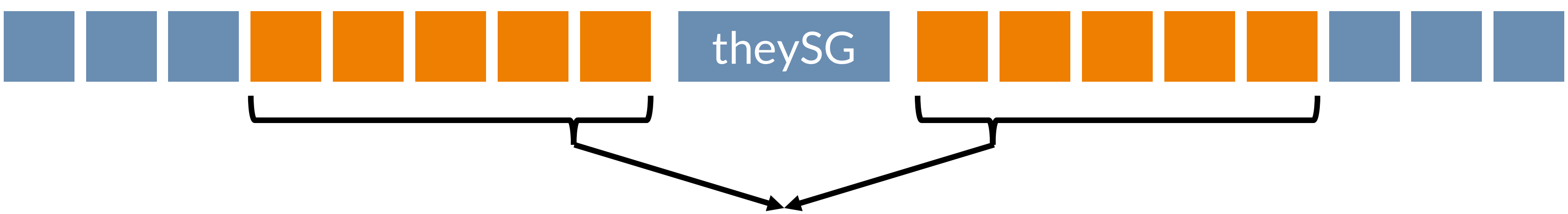
    = instance vector

$$n = 5$$



mean → instance vector

Instance vectors

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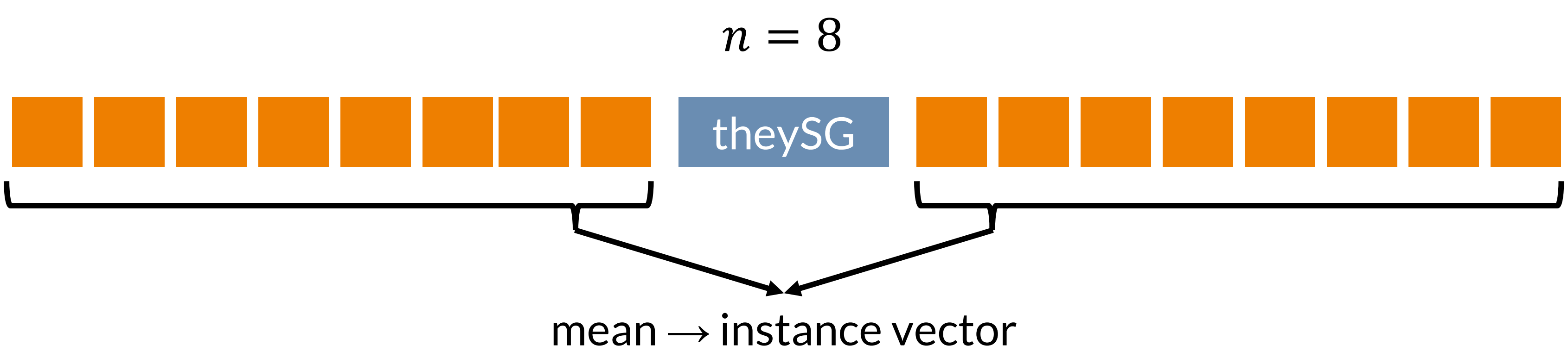
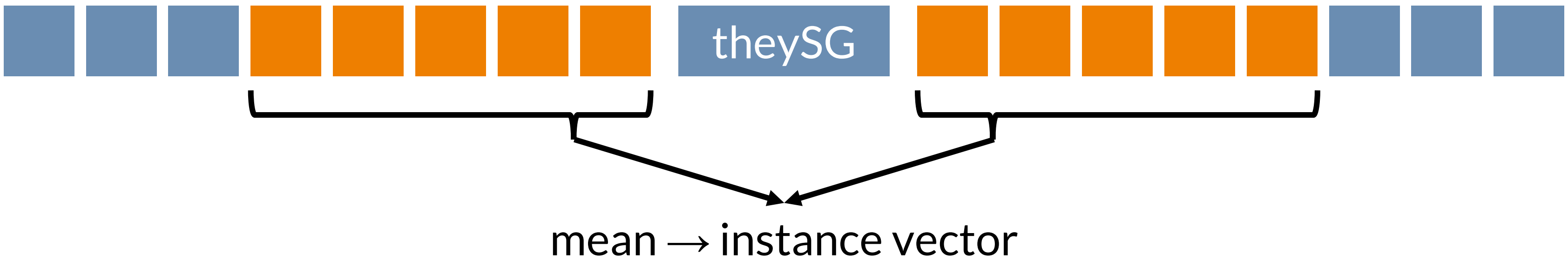


Instance vectors

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

$$n = 5$$



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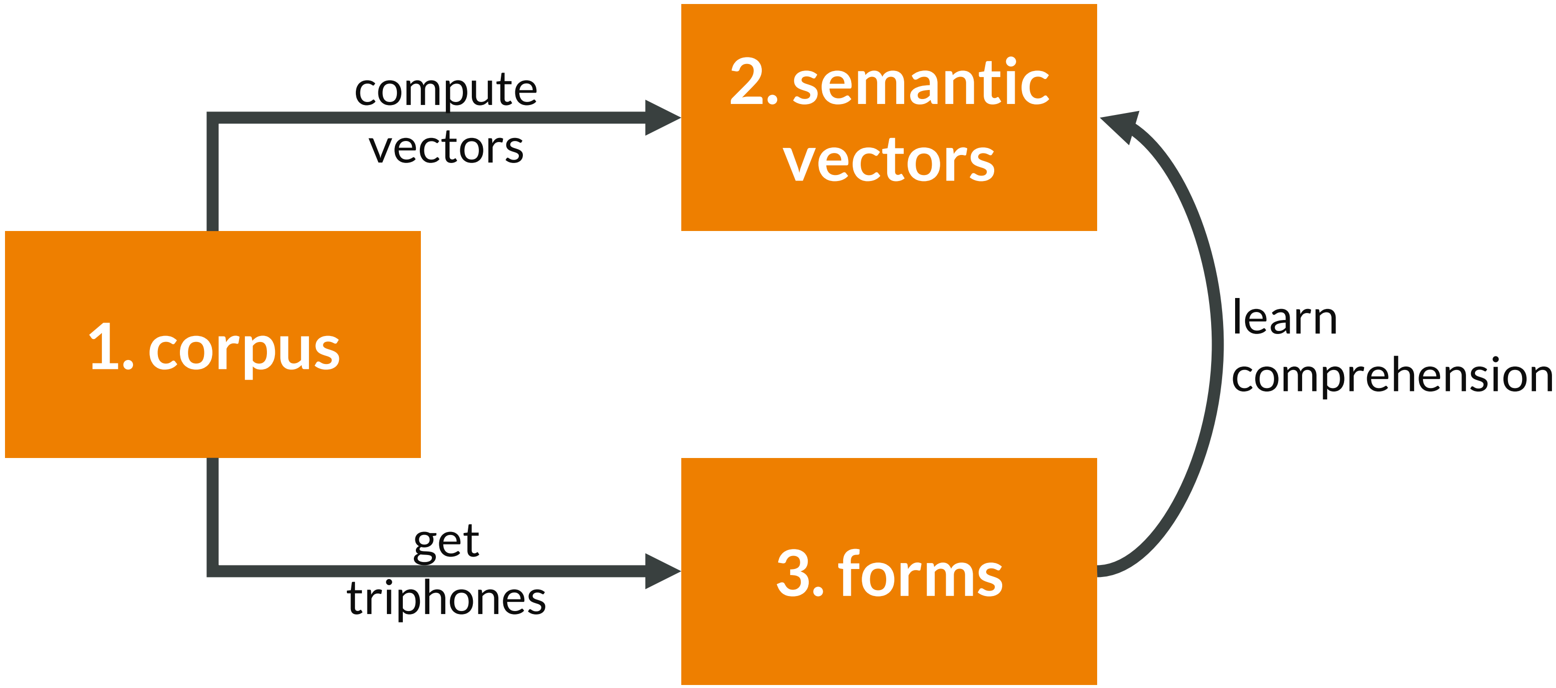

Forms

- trigrams as unit for a word's form
- trigrams / triphones have been shown to capture the form variability of words well (e.g. Chuang et al., 2020; Schmitz et al., 2021; Schmitz et al., 2023)

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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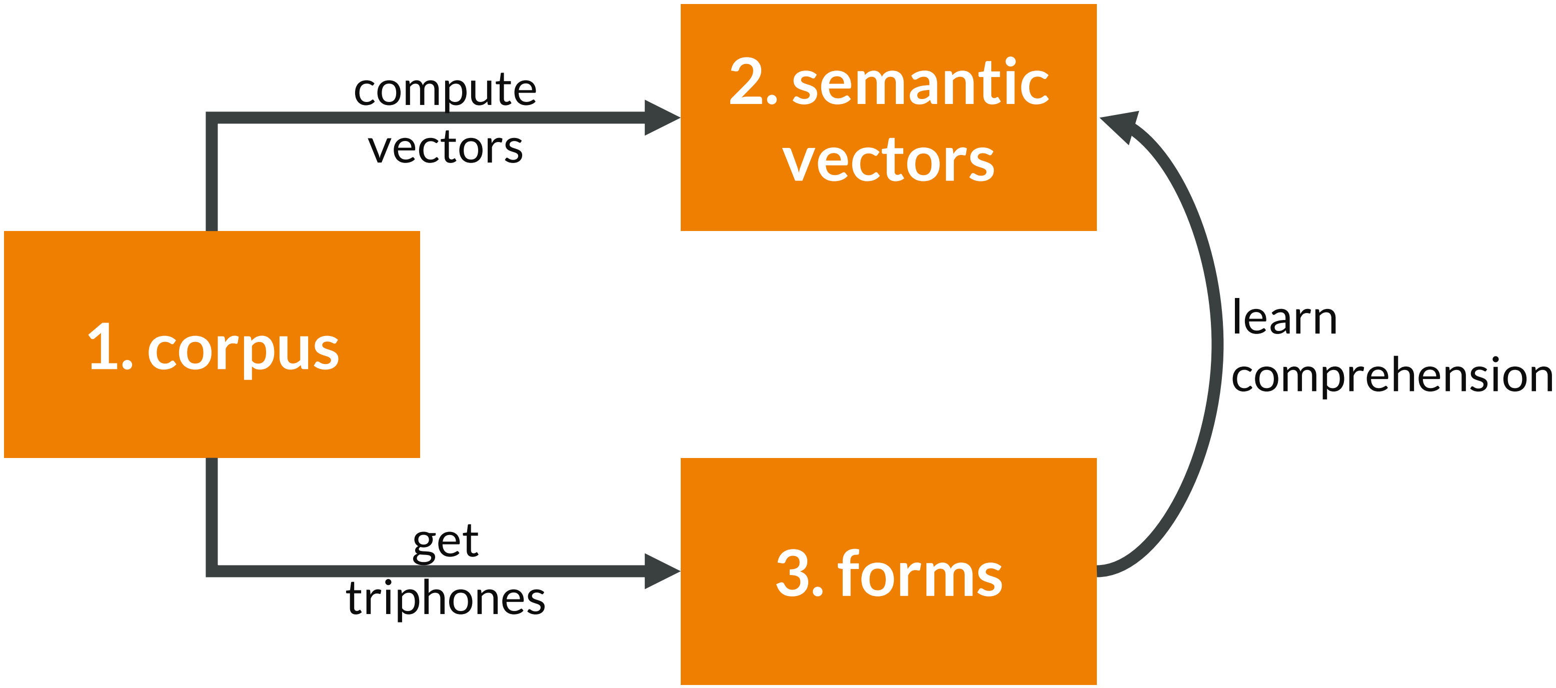
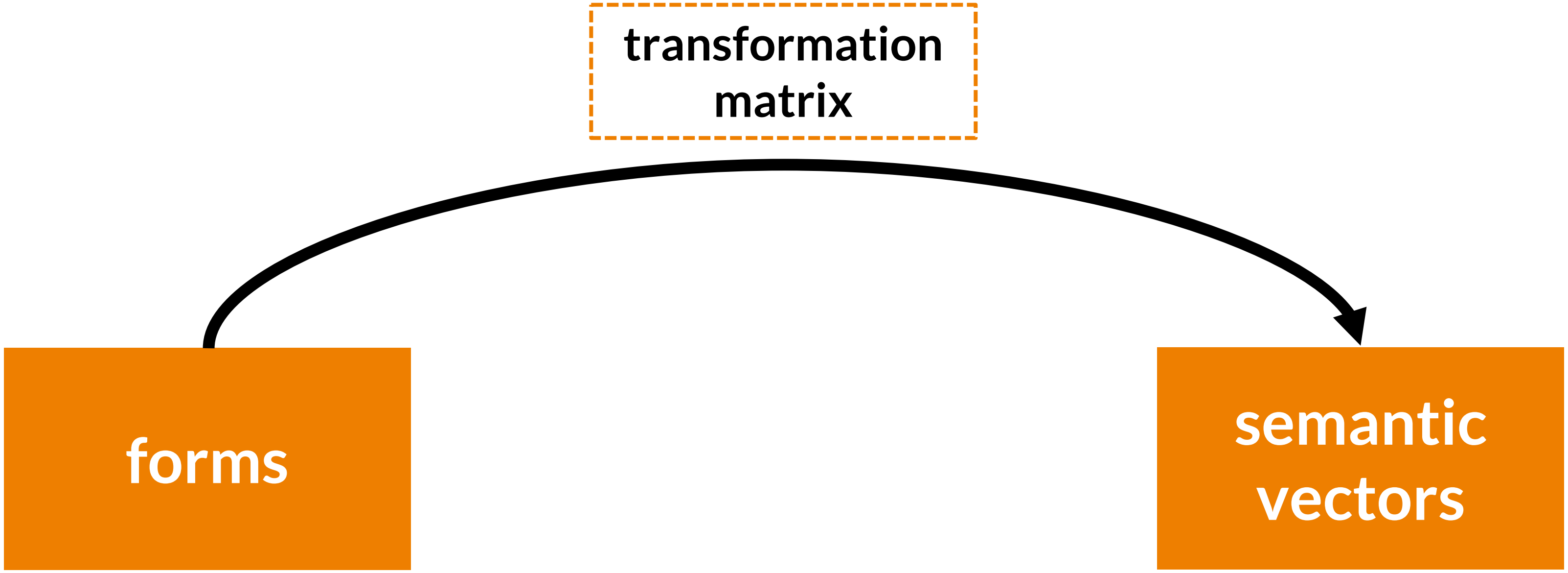


Learning comprehension

- Comprehension is learnt by linearly mapping the matrix of forms onto the matrix of semantic vectors – this done 60 times with different instance vectors for *he*, *she*, singular *they*, and plural *they*



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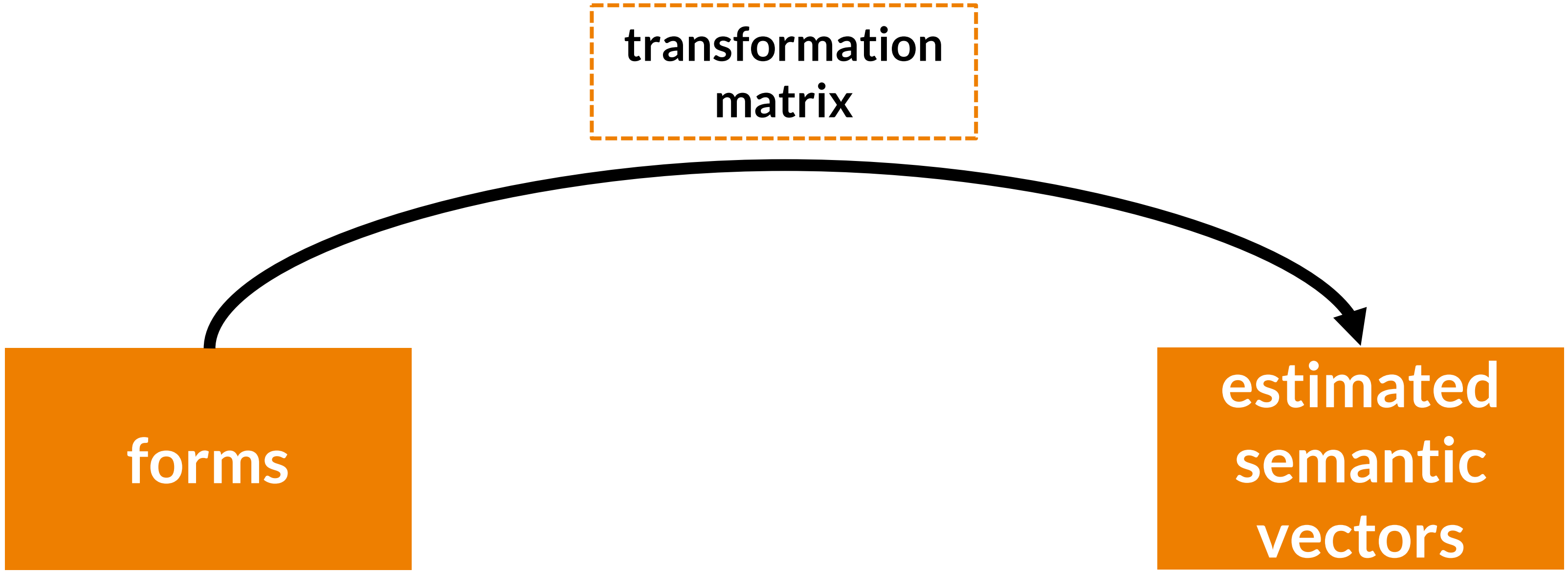

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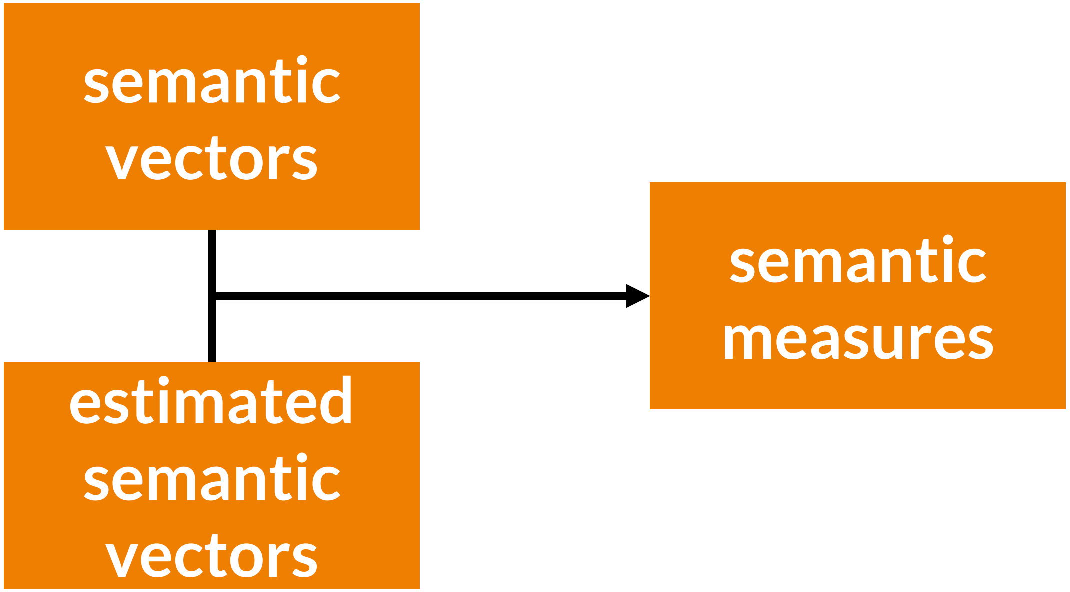
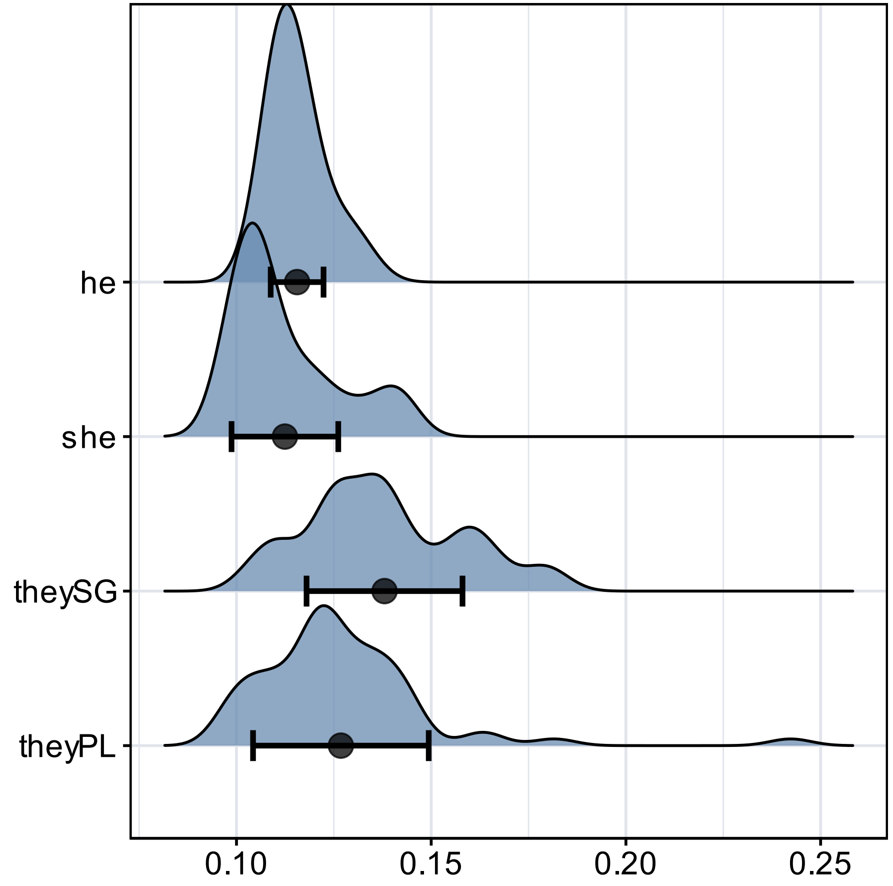


Results

DEGREE OF SEMANTIC CO-ACTIVATION

- higher = more co-activation

	he	she	theyPL
she	**		
theyPL	***	***	
theySG	***	***	**

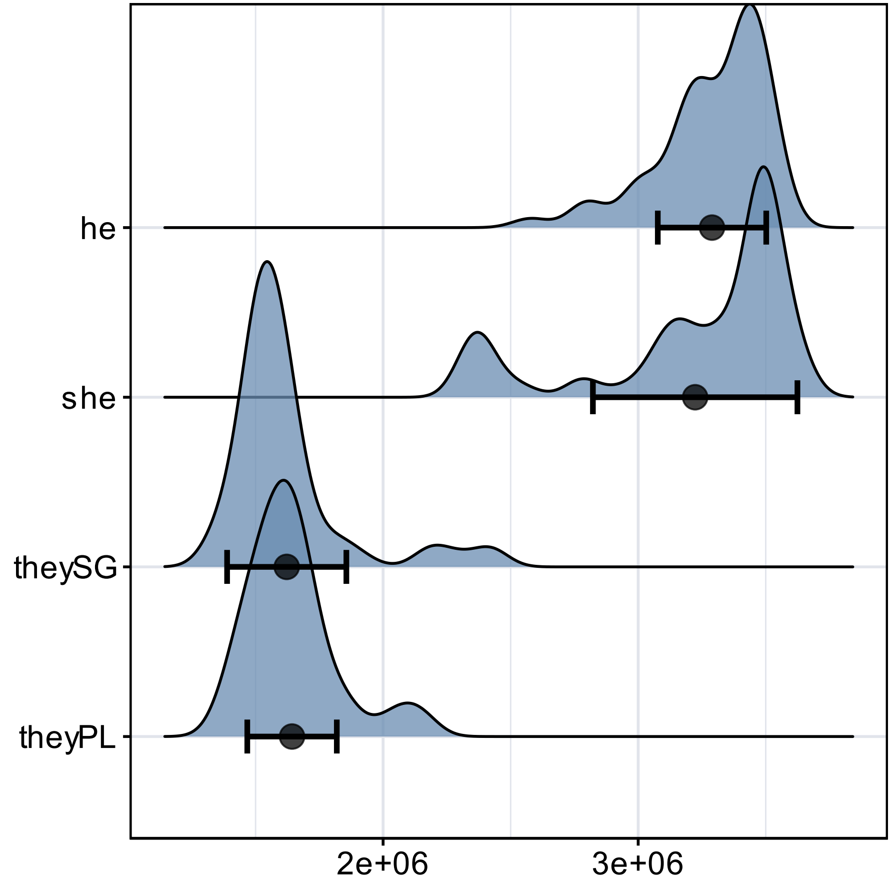


Results

SEMANTIC UNCERTAINTY

- higher = more uncertain

	he	she	theyPL
she	n.s.		
theyPL	***	***	
theySG	***	***	n.s.

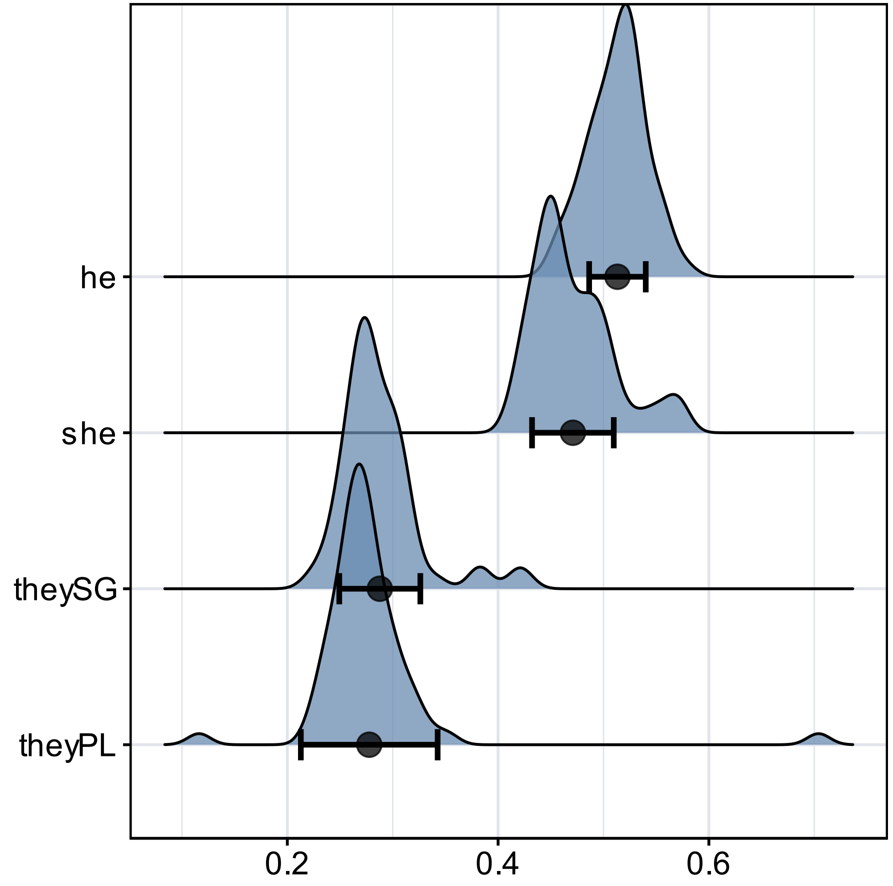


Results

SEMANTIC NEIGHBOURHOOD DENSITY

- higher = more close neighbours

	he	she	theyPL
she	***		
theyPL	***	***	
theySG	***	***	n.s.



Discussion

- *he* and *she* co-activate to a lower degree than generic and plural *they*
  - *he* and *she* are less strongly connected to other entries of the lexicon

    = generic and plural *they* are more generic (?)
- *he* and *she* are semantically less certain than generic and plural *they*
  - referents of *he* and *she* are more specific than those of generic and plural *they*, i.e. *they* is “more often correct”
- *he* and *she* have more close neighbours than generic and plural *they*
  - *he* and *she* are more specific than plural *they*, while generic and plural *they* are more generic (?)

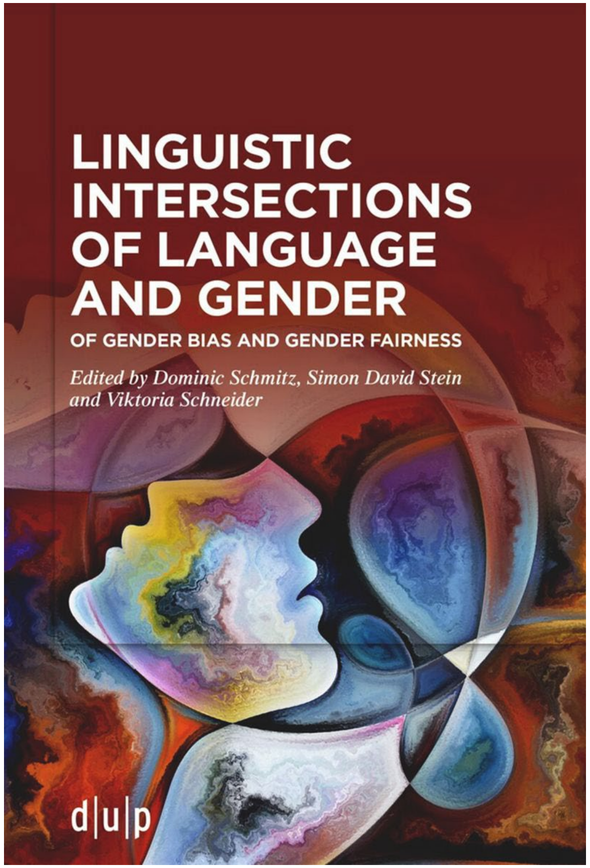
Summary

Summary

- computational methods provide novel insights into
  - generic masculines and their male bias
  - pronouns and their semantic similarities and differences
- computational methods are a fruitful addition to the field of gender linguistics
  - however, such methods only recently entered the field (Schmitz, 2023a; Schmitz, 2023b; Schmitz et al., 2023)
- more computational research is definitely called for

Summary

- a huge variety of different methodological approaches generally lead to complementary findings in gender linguistic research
- and, more generally, to new insights into the intersections of language and gender
- however: what is beyond the scope of linguistic research is what society makes of these findings



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THANK YOU!

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