



# Computing Chinese character ambiguity based on the variability of word formations

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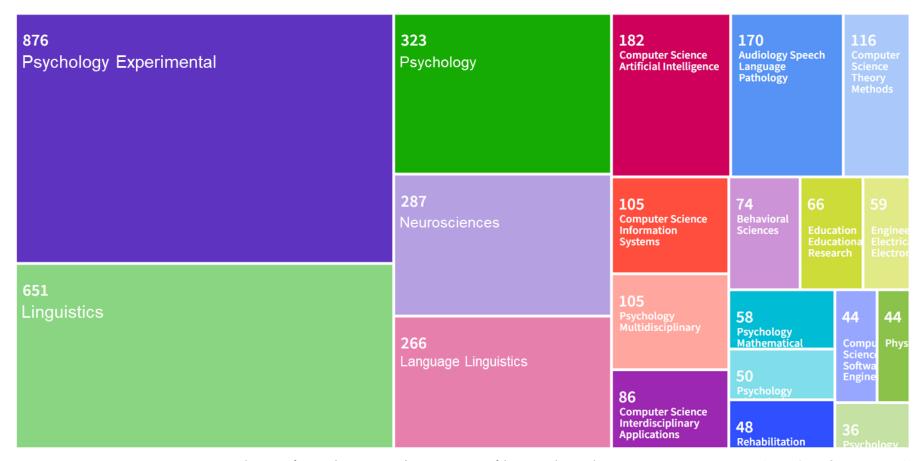
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# What is lexical ambiguity?

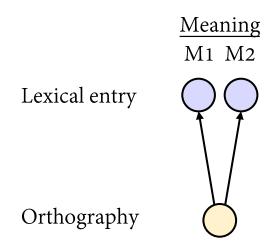
- Lexical ambiguity: one single word form with more than one meaning
  - Ubiquitous in all human language (Youn et al., 2016)
  - Enables the expression of a near-infinite set of ideas with a small finite lexicon (Piantadosi et al., 2012; Ramiro et al., 2018)
  - Comprehension becomes more challenging when its immediate language contexts are impoverished or not available

# Who are studying lexical ambiguity?



Number of studies on the topic of lexical ambiguity since 1960 (Web of Science)

- Ambiguous vs. unambiguous words: recognized *faster* and *more accurately* in lexical decision (e.g., Borowsky & Masson, 1996; Ferraro & Hansen, 2002; Hino & Lupker, 1996; but see Gernsbacher, 1984)
  - Multiple meanings are represented as *individual lexical entries* within a network (Klein & Murphy, 2001)
  - Simultaneous activation of the lexical entries results in *greater inhibition* to their competitors (Kellas et al., 1988)



Relatedness between a word's various meanings was underappreciated

#### Linguistic taxonomy of words

#### Examples

• Homonymy: words with *unrelated* meanings

"bank" { financial institution side of river

• Polysemy: words with *related* senses

"paper" { white sheet academic article document

• Monosemy: words with a *single* sense

"wacky"

funny in an odd way

▶ *Relatedness* between a word's various meanings was underappreciated

#### Linguistic taxonomy of words

Effects on word recognition

Homonymy: words with unrelated meanings
 Inhibition

• Polysemy: words with *related* senses

Facilitation

• Monosemy: words with a *single* sense

(Rodd et al., 2002; Yap et al., 2011)

▶ *Relatedness* between a word's various meanings was underappreciated

#### Linguistic taxonomy of words

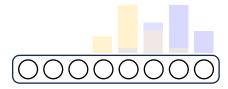
Homonymy: words with unrelated meanings

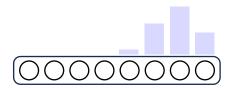
• Polysemy: words with *related* senses

• Monosemy: words with a *single* sense

#### Representation / Semantic activation







(Armstrong & Plaut, 2016; Rodd et al., 2002)

# How to characterize a word's meanings?

Number of meanings: number of dictionary meanings (dNoM)

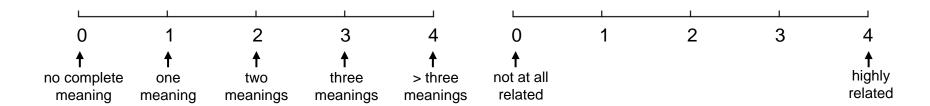
#### Critical issues

- How different must two uses of a word be to qualify as separate senses (Hoffman et al., 2013; Hoffman & Woollams, 2015)?
- Could measures based on dictionary definitions reflect native speakers' perception of the word's number of meanings (Gernsbacher, 1984)?
- ▶ *Relatedness of meanings:* distinction between homonymy, polysemy, and monosemy is a simplification of reality

homonymy	polysemy	monosemy	

### Alternative approaches to characterize a word's meanings

Norms for the perceived number of meanings (pNoM) and relatedness of meanings (pRoM)



#### Norms for Chinese characters

pNoM: 4,363 characters

pRoM: 1,052 characters (with pNoM > 1.45)

Chen, H., Xu, X., & Wang, T. (2023). Assessing lexical ambiguity of simplified Chinese characters: Plurality and relatedness of character meanings. *Quarterly Journal of Experimental Psychology*.

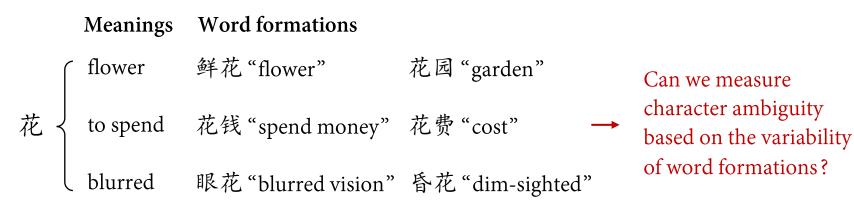
Corpus-based approaches 

The present study

# Ambiguity in Chinese characters

- Chinese is *morpho-syllabic* in nature, and there is usually a correspondence between a morpheme, a syllable, and a single character
- ▶ The mapping between characters and morphemes is *not always one-to-one* 
  - Forming a complex word based on one specific meaning of an ambiguous Chinese character makes it semantically concrete (Xu, 1994)

#### **Example**



- Computed dissimilarity of meanings (cDoM)
  - Probe the meanings of a character using its word formations
  - Measure the *dispersion* of their vector representation in a *distributional semantic space*

#### Distributional hypothesis

Words appearing in similar contexts have similar meanings

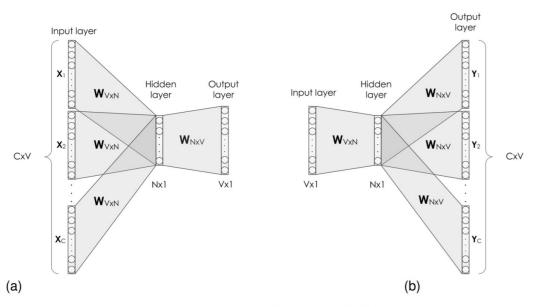
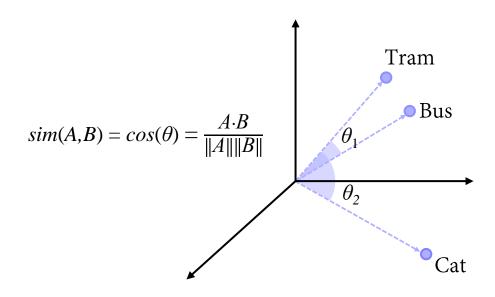


Illustration of the word2vec models: (a) CBOW, (b) skip-gram

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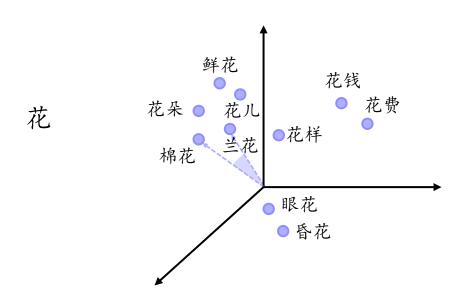
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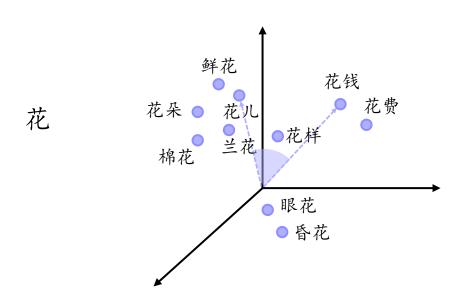
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Top 10 word formations based on frequency ⇒ Pairwise cosine similarity



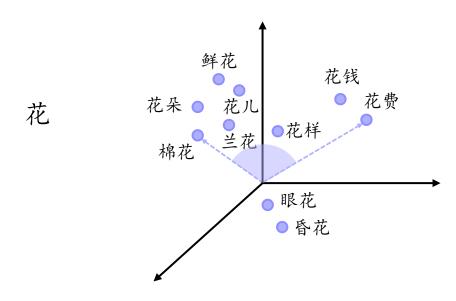
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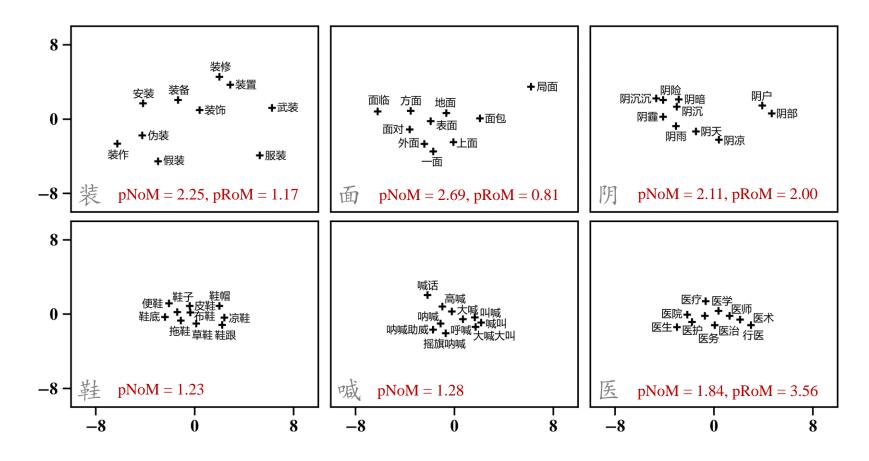
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 $cDoM = -log \ [min \ cos(\theta)]$   $cDoM \uparrow \Rightarrow$  dissimilarity between sense probes  $\uparrow$ 



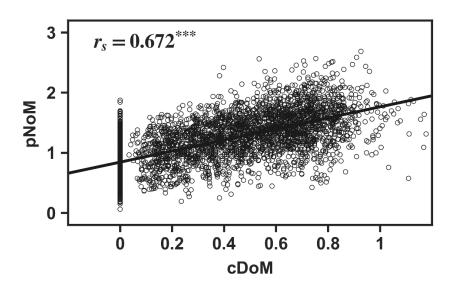
#### Visualization

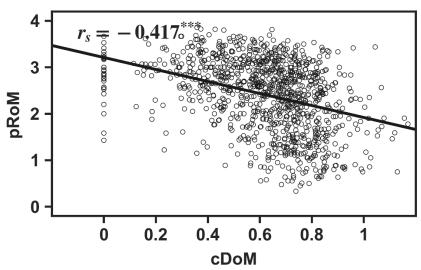
Multidimensional scaling plots for the configuration of six example characters



# Validity and efficacy of the computed metric

Correlation with pNoM and pRoM





### Validity and efficacy of the computed metric

Correlation and partial correlation with *number of word formation (NWF)* 

	pNoM	pRoM	cDoM
logNWF	0.727***	-0.123***	0.792***
logNWF (control: logFreq)	0.443***	0.016	0.523***

Partial correlation with pNoM and pRoM

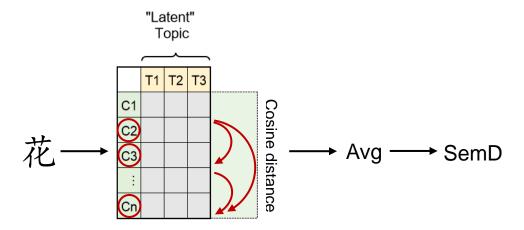
	pNoM	pRoM	
cDoM (control: logNWF)	0.214***↓	-0.427***	

- *NWF* is the "common ground" between the pNoM and cDoM
- pRoM draws upon deeper *conceptual analysis* about the meanings associated with a character rather than statistical perception about the word formations of the character
- cDoM can capture the foundation of human perception about the degree to which a character would be regarded as polysemantic, and the essence of pRoM

# Comparison to semantic diversity (SemD)

▶ SemD (Hoffman et al., 2013): semantic similarity of a word's different contexts

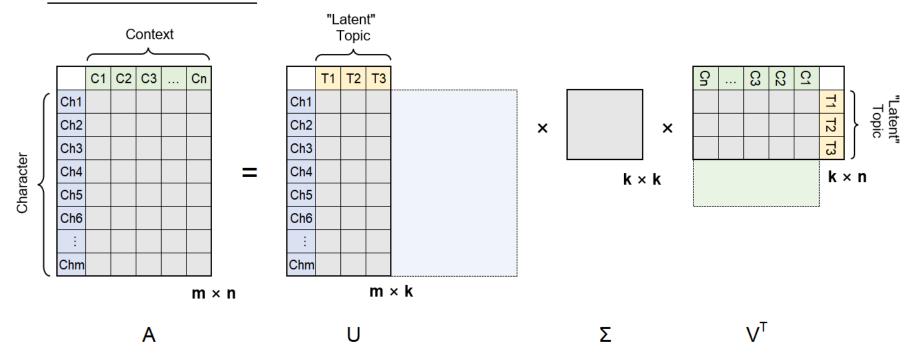
#### **Character-based SemD**



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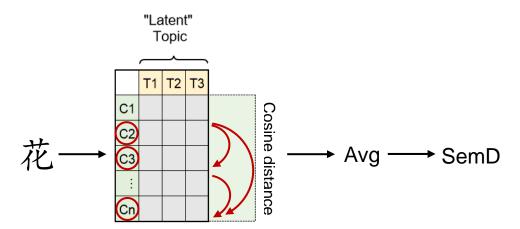
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### Comparison to semantic diversity (SemD)

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#### Character-based SemD



Correlation and partial correlation with pNoM and pRoM

	pNoM	pRoM	
SemD	0.375***	-0.225***	
SemD (Control: logNWF)	-0.007	-0.189 <sup>***</sup>	

# Summary

- We can compute lexical ambiguity in Chinese characters based on the variability of their word formations
  - cDoM could inform about the *number of the characters' meanings*
  - For characters that are definitively polysemantic, cDoM could also reflect people's conceptual knowledge about the *relatedness between these meanings*
- ▶ cDoM reflected the *graded* nature of lexical ambiguity
- Gaps between computed metrics and human performance

Thanks!