A computational model of S-selection

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Slides available at aswhite.net

Preliminary

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S-selection

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S-selection

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Challenge

These analyses can be difficult to scale to an entire lexicon

Goals

1. Demonstrate a combined experimental-computational method for scaling distributional analysis

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- Given syntactic distribution data, use computational techniques to automate inference of projection rules and verbs' semantic type, controlling for lexical idiosyncrasy

Focus

Clause-embedding predicates (~1000 in English)

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Case study

Responsive predicates: take both interrogative and declaratives

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Importance

Deep literature on S-selection properties of responsives Do they take questions, propositions, or both? (Karttunen 1977, Groenendijk

& Stokhof 1984, Heim 1994, Ginzburg 1995, Lahiri 2002, George 2011, Rawlins 2013, Spector & Egre 2015, Uegaki 2015)

Selection and clausal embedding

The MegaAttitude data set

Model fitting and results

Conclusions and future directions

Appendix

Selection and clausal embedding

Many verbs are syntactically multiplicitous

- (2) a. John knows {that, whether} it's raining.
 - b. John wants {it to rain, rain}.

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- (3) a. John knows [what the answer is]_S.
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[(3b)] = [(3a)] suggests it is possible for type([NP]) = type([S])







What do the projection rules look like?

How are a verb's semantic type signatures projected onto its syntactic type signatures (subcategorization frames)? (Gruber 1965,

Jackendoff 1972, Carter 1976, Grimshaw 1979, 1990, Chomsky 1981, Pesetsky 1982, 1991, Pinker 1984, 1989, Levin 1993)



A model of S-selection and projection



Lexical idiosyncrasy

Observed syntactic distributions are not a perfect reflection of semantic type + projection rules

Example

Some Q(uestion)-selecting verbs allow concealed questions...

- (4) a. Mary asked what time it was.
 - b. Mary asked the time.

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Example

Some Q(uestion)-selecting verbs allow concealed questions...

- (4) a. Mary asked what time it was.
 - b. Mary asked the time.

... others do not (Grimshaw 1979, Pesetsky 1982, 1991, Nathan 2006, Frana 2010, a.o.)

- (5) a. Mary wondered what time it was.
 - b. *Mary wondered the time.

Grimshaw (1979)

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Shared core

Lexical noise (idiosyncrasy) alters verbs' idealized syntactic distributions

A model of S-selection and projection



How do we represent each object in the model?

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A minimalistic answer

Every object is a matrix of boolean values

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Strategy

1. Give model in terms of sets and functions

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Strategy

- 1. Give model in terms of sets and functions
- 2. Convert this model into a boolean matrix model

A model of S-selection and projection



$\mathsf{know} \to \{[__P], [__Q]\}$
$\mathsf{know} \to \{[__P], [__Q]\} \quad \mathsf{wonder} \to \{[__Q]\}$

$\mathsf{think} \to \{[__P]\} \quad \mathsf{know} \to \{[__P], [__Q]\} \quad \mathsf{wonder} \to \{[__Q]\}$



$[_P] \rightarrow \{[_that S], [_NP], ...\} \qquad [_Q] \rightarrow \{[_whether S], [_NP], ...\}$

A boolean model of projection



 $\hat{D}(VERB, SYNTYPE) = \bigvee_{t \in SEMTYPES} S(VERB, t) \land \Pi(t, SYNTYPE)$

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 $\hat{D}(\text{know, }[__{t\in \{[P], [Q], ...\}} S(\text{know}, t) \land \Pi(t, [__{t\in \{[P], [Q], ...\}} S(\text{know}, t) \land \Pi(t, [___{t\in \{P\}, [Q], ...\}}))$



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 $\hat{D}(wonder, [_NP]) = \bigvee_{t \in \{[_P], [_Q], ...\}} S(wonder, t) \land \Pi(t, [_NP])$



A model of S-selection and projection



 $\forall t \in SYNTYPE : D(wonder, t) = \hat{D}(wonder, t) \land N(wonder, t)$

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	[that S]	[whether S]	[<u>N</u> P]			[that S]	[whether S]	[NP]	
think	/ 1	0	1	\	think	/ 1	1	1	\
know	1	1	1)	know	1	1	1	
wonder	0	1	1		wonder	1	1	0	
				.					
			:	·. /		(:		:	·.)

 $\forall t \in SYNTYPE : \mathbf{D}(wonder, t) = \hat{\mathbf{D}}(wonder, t) \land \mathbf{N}(wonder, t)$



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Question

What is this model useful for?

Answer

In conjunction with modern computational techniques, this model allow us to scale distributional analysis to an entire lexicon

Basic idea

Distributional analysis corresponds to reversing model arrows

A model of S-selection and projection



A model of S-selection and projection



The MegaAttitude data set

Ordinal (1-7 scale) acceptability ratings

Ordinal (1-7 scale) acceptability ratings for 1000 clause-embedding verbs

reassure alert alert question redo trust advise signal stress wager bet inform ask probe phone agonize prompt reaffirm affirm specify indicate panic dictate dispute worry threaten determine press lecture tease remind believe clarify admit whisper delight deligh delight attempt

Ordinal (1-7 scale) acceptability ratings for 1000 clause-embedding verbs × 50 syntactic frames

Challenge

Automate construction of a very large set of frames in a way that is sufficiently general to many verbs





















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Construct semantically bleached frames using indefinites
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- (6) Examples of responsives
 - a. know + NP V {that, whether} S
 Someone knew {that, whether} something happened.

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 Someone told someone {that, whether} something happened.

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- 5 judgments per item
 - $\cdot\,$ No annotator sees the same sentence more than once

1.	Someone	neede	d whe	ther	som	ething	happe	ened.
	1	2	3	3	4	5	6	7
2.	Someone	nated	which	n thi	ng to	do.		
	1	2	3	3	4	5	6	7
3.	Someone	was w	orrie	d ab	out s	ometh	ing.	
	1	2	3	3	4	5	6	7
4.	Someone	illow	d sor	neor	ne do	somet	hing.	
	1	2	3	3	4	5	6	7

Reward: \$0.00 per HIT HITS Available: 20 Duration: 14 weeks 2 days

Turktools (Erlewine & Kotek 2015)

Sentence Acceptability Task (expert annotation) Requester: JHU Semantics Lab

Interannotator agreement

Spearman rank correlation calculated by list on a pilot 30 verbs

Pilot verb selection

Same verbs used by White (2015), White et al. (2015), selected based on Hacquard & Wellwood's (2012) attitude verb classification

- 1. Linguist-to-linguist median: 0.70, 95% CI: [0.62, 0.78]
- 2. Linguist-to-annotator median: 0.55, 95% CI: [0.52, 0.58]

3. Annotator-to-annotator median: 0.56, 95% CI: [0.53, 0.59]

Results



Results

7 wonder know 6 NP V whether S 5 -4. • think 2 -1 want 5 7 ż 3 6 1 4 NP V S

Model fitting and results

A model of S-selection and projection



A model of S-selection and projection



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Goal

Find representations of verbs' semantic type signatures and projection rules that best explain the acceptability judgments

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Challenges

- 1. Infeasible to search over $2^{1000T} \times 2^{50T}$ possible configurations (T = # of type signatures)
- 2. Finding the best boolean model fails to capture uncertainty inherent in judgment data

Solution

Search probability distributions over verbs' semantic type signatures and projection rules

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Going probabilistic

Wrap boolean expressions in probability measures

A boolean model of idealized syntactic distribution

 $\hat{D}(VERB, SYNTYPE) = \bigvee_{t \in SEMTYPES} S(VERB, t) \land \Pi(t, SYNTYPE)$



A boolean model of idealized syntactic distribution

$$\hat{D}(\text{know}, [__\text{that S}]) = 1 - \prod_{t \in \{[_P], [_Q], ...\}} 1 - S(\text{know}, t) \times \Pi(t, [__\text{that S}])$$



 $\mathbb{P}(\mathsf{S}[\mathsf{VERB}, t] \land \mathbf{\Pi}[t, \mathsf{SYNTYPE}]) = \mathbb{P}(\mathsf{S}[\mathsf{VERB}, t])\mathbb{P}(\mathbf{\Pi}[t, \mathsf{SYNTYPE}] \mid \mathsf{S}[\mathsf{VERB}, t])$ $= \mathbb{P}(S[VERB, t])\mathbb{P}(\Pi[t, SYNTYPE])$ $\mathbb{P}\left(\bigvee_{t} \mathsf{S}[\mathsf{VERB}, t] \land \mathbf{\Pi}[t, \mathsf{SYNTYPE}]\right) = \mathbb{P}\left(\neg \bigwedge_{t} \neg(\mathsf{S}[\mathsf{VERB}, t] \land \mathbf{\Pi}[t, \mathsf{SYNTYPE}])\right)$ $= 1 - \mathbb{P}\left(\bigwedge_{t} \neg(\mathsf{S}[\mathsf{VERB}, t] \land \mathbf{\Pi}[t, \mathsf{SYNTYPE}])\right)$ $= 1 - \prod \mathbb{P}\left(\neg(\mathsf{S}[\mathsf{VERB}, t] \land \mathbf{\Pi}[t, \mathsf{SYNTYPE}])\right)$ $= 1 - \prod 1 - \mathbb{P}(\mathsf{S}[\mathsf{VERB}, t] \land \mathbf{\Pi}[t, \mathsf{SYNTYPE}])$ $= 1 - \prod [1 - \mathbb{P}(S[VERB, t])\mathbb{P}(\Pi[t, SYNTYPE])]$

Algorithm

Projected gradient descent with adaptive gradient (Duchi et al. 2011)

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Remaining challenge

Don't know the number of type signatures T

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Standard solution

Fit the model with many type signatures and compare using an information criterion, e.g., the Akaike Information Criterion (AIC)

High-level idea

Measures the information theoretic "distance" to the true model from the best model with T types signatures (Akaike 1974)

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Measures the information theoretic "distance" to the true model from the best model with *T* types signatures (Akaike 1974)

Low-level idea (cf. Gelman et al. 2013)

For each datapoint...

- 1. ...remove that datapoint from the dataset
- 2. ...fit the model to the remaining data
- 3. ...predict the held-out datapoint

In the limit, model with lowest error on step 3 has lowest AIC

Result

12 is the optimal number of type signatures according to AIC

Reporting findings

Remainder of talk: best model with 12 type signatures

Three findings

1. Cognitive predicates

1.1 Two distinct type signatures [___P] and [___Q]

Findings

[___P] [___Q]



Three findings

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2. Communicative predicates

2.1 Two unified type signatures $[_(Ent) P \oplus Q]$ (optional recipient) and $[_Ent P \oplus Q]$ (obligatory recipient)





Question

What do we mean by $P \oplus Q$?

Example

Structures with potentially both informative and inquisitive con-

tent (Groenendijk & Roelofsen 2009, a.o.)

- S-selectional behavior of responsive predicates on some accounts (Uegaki 2012; Rawlins 2013)
- Some attitudes whose content is a hybrid Lewisian (1988) subject matter (Rawlins 2013 on think v. think about)















S-selection







S-selection



S-selection





What we conclude

Proposition and question types live alongside hybrid types, and the presence of a hybrid type correlates with communicativity

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What we can exclude

Accounts that reduce (or unify) declarative and interrogative selection solely to S-selection of a single type + coercion

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Methodological point

Coercion can have measurable effects

Conclusions and future directions

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Case study

Responsive predicates and the features that underly their selectional behavior.

(7) John knows {that, whether} it's raining.

By looking at such a large data set, we can *discover* the relevant s-selectional features, and get an angle on the problem *at the scale of the entire lexicon*.

Further investigation of type signatures

Seven other type signatures that are also remarkably coherent

Example

Many nonfinite-taking verbs

Atomic v. structured type signatures

Currently treating type signatures as atomic but type signatures have rich structure

Example

Preliminary experiments with models that represent type structure suggest that our glosses for the types are correct

Homophony v. regular polysemy v. underspecification

Patterns in how semantic type signatures distribute across verbs may belie regular polysemy rules

Example

Preliminary experiments with a more elaborated model suggest responsive predicates display a regular polysemy (cf. George 2011)

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Appendix

Two functions

1. Normalize for participants' judgments so they are comparable

Two functions

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- 2. Control for lexicosyntactic noise

Why normalize judgments?

Necessary to control for differences in participants' use of scale

Why normalize judgments?

Necessary to control for differences in participants' use of scale



0 1





























Find the optimal number T of type signatures

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Goodness of $T \leftrightarrow$ model's ability to... ...fit observed judgments ...predict unobserved judgments

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• T too small
$$\rightarrow \begin{cases} bad fit \\ bad prediction \end{cases}$$

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Goodness of $T \leftrightarrow$ model's ability to... ...fit observed judgments ...predict unobserved judgments

Number of type signatures



Number of type signatures



Low extreme All verbs' syntactic distributions explained by single rule

Number of type signatures



Low extreme All verbs' syntactic distributions explained by single rule High extreme # types ≥ # frames every syntactic frame has separate rule

Find the optimal number T of type signatures

Goodness of $T \leftrightarrow$ model's ability to... ...fit observed judgments ...predict unobserved judgments

$$\begin{array}{l} \cdot \ \, T \ {\rm too} \ {\rm small} \rightarrow \begin{cases} {\rm bad} \ {\rm fit} \\ {\rm bad} \ {\rm prediction} \end{cases} \\ \cdot \ \, T \ {\rm too} \ {\rm large} \rightarrow \begin{cases} {\rm good} \ {\rm fit} \\ {\rm bad} \ {\rm prediction} \end{cases} \end{array}$$

Measure

Akaike Information Criterion (AIC) trades off fit to observed data and prediction of unobserved data

Model comparison



Model comparison

