The Pragmatics of Quantifier Scope: A Corpus Study

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Scope Prediction

- we as semanticists generally do not weigh in on the **actual patterns of usage** of a given possible reading
- that is, semantics is not concerned with the problem of *quantifier scope disambiguation* (QSD)

Pragmatics of Quantifier Scope

In order to develop a model for QSD, we examine the factors influencing quantifier scope in a controlled, but naturally occurring body of text: LSAT Logic Puzzles.

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- in particular, we're interested in those aspects of a quantifier's usage that are correlated with its wide vs. narrow scope . . .
- . . . e.g., its position (before or after the other quantifier/s), its grammatical function (S, O etc.), its lexical realization (each, all etc.)

Linguistically & Psychologically Plausible Predictors

We designed the tagging scheme to reflect the features that have been argued to bias QSD in (some of) the psychological and computational literature, which we summarize now.

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2. A student saw every professor. *a* $\gg$ *every*

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- it is difficult in English to separate the effect of linear order from the next predictor, grammatical function

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Grammatical function hierarchy

3. Joan told a child the story at every intersection. *every* $\gg$ *a*
4. Joan told everyone the story at an intersection. *a* $\gg$ *every*

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Kutzman & McDonald (1993), Tunstall (1998), Micham et al. (1980)

Ioup's (1975) Quantifier Hierarchy

5. She knows a solution to every problem. *every* $\gg$ *a*
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Tunstall (1998), Van Lehn (1978)

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7. A doctor lives in every city.

- the narrow scope reading of *every* is dispreferred because it would require an individual to participate in the *living-in* relation with an atypically large number of cities.

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- applied to a handpicked corpus of 46 items
- information about numerical typicality significantly improves prediction, especially for inverse scope

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Corpus Worries

- leave out NPs headed by *a/an*
- do not separate conjoined or appositive clauses, so the two quantifiers do not interact in 61% of the corpus

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Three models (Naive Bayes, Maximum Entropy, Single Layer Perceptron) were trained on a subset of the corpus and each had an accuracy of 70%-80% on the remaining corpus.

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- conjoined or appositive clauses were not separated, so other important predictors were intervening comma or colon, intervening conjunct node, intervening quotation mark etc.

Summary of Predictors in Previous Literature

Scope predictors in the previous computational and (psycho)linguistic literature:

- Linear order/C-command
- Grammatical hierarchy
- Particular quantificational item
- Intervening clause boundaries
- World knowledge

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- our corpus is drawn from one particular type of question: analytical reasoning questions, a.k.a. logic puzzles
- logic puzzles follow a particular format as follows

Structure of a Logic Puzzle

In the course of one month Garibaldi has exactly seven different meetings. Each of her meetings is with exactly one of five foreign dignitaries: Fuentes, Matsuba, Rhee, Soleimani, or Tbahi. The following constraints govern Garibaldi's meetings:

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She has exactly three meetings with Fuentes, and exactly one with each of the other dignitaries.
She does not have any meetings in a row with Fuentes.
Her meeting with Soleimani is the very next one after her meeting with Tbahi.
Neither the first nor last of her meetings is with Matsuba.

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(A) Garibaldi's second meeting is with Soleimani.
(B) Garibaldi's third meeting is with Matsuba.
(C) Garibaldi's fourth meeting is with Soleimani.
(D) Garibaldi's fifth meeting is with Matsuba.
(E) Garibaldi's sixth meeting is with Soleimani.

} Answers

Minimal ambiguity

- test takers are expected to select a single correct answer, so ambiguity must be minimal.

Why Logic Puzzles?

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Minimal world knowledge

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- in essence, the entire discourse context is made linguistically explicit, allowing us to abstract away from world knowledge

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Multiple quantifiers frequent

- sentences with two or more quantifiers are (unsurprisingly) quite frequent in this register

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- however, it is often clear that a sentence consists of multiple separate scopal domains
- e.g., if two quantifiers appear in a coordinate structure . . .

8. **[** Joe ate three oranges **]** and **[** Pam ate two apples **]**.

- . . . the example is best treated as two separate scopal domains, one per sentential conjunct

Scopal Domains

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- therefore, we consider *scopal domains* with multiple quantifiers, rather than *sentences*
- this is consistent with our stated goal of studying the *pragmatics* of quantifier scope
- the lack of relative scope between quantifiers in different conjuncts of a coordinate clause is largely an observation about the syntax/semantics of quantifiers, not their pragmatics

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- based on Higgins & Sadock's (2003) study, we would expect to find fairly high variability

Response variable

Scope: the relative scope of the 2 or more quantifiers in a scopal domain

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Predictors:

1. Linear order
2. Grammatical function
3. Lexical identity of quantifier

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The beginning of a tag is marked by **&**, the end of a tag is marked by #, subtags are separated by _.

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9. Exactly six**&1#** employees must be assigned to exactly three**&1#** committees.

Scope (ctd.)

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10. Exactly six**&2#** of seven**&1#** jugglers are each**&3#** assigned to exactly one**&4#** of three**&1#** positions.

In cases where no truth conditional difference was clear, we used the felicity of "such that" paraphrases as our ultimate criterion.

Linear order

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Grammatical function

- we distinguished four syntactic roles as follows: **S**ubject, **O**bject, **P**ivot, **A**djunct
- for prepositions, we tagged individual prepositions separately (today, we only analyze S and O)

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Lexical identity

- if the determiner / pre-restrictor material was complex, we tagged it as a unit – e.g., **more.than.two**, **a.different** etc.

11. Each**&1_S_each#** tape is to be assigned to a different**&2_to_a.different#** time slot, . . .
12. . . . and no**&1_S_no#** tape is longer than any**&2_than_any#** other tape.

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13. Each**&1_S_each#** professor has one or**&2_O_or#** more specialities.

14. The judge of the show awards exactly four**&1_O_exactly.four#** ribbons to four**&1_to_four#** of the dogs.

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- 139 doubly counted sentences
- we randomly sample one quantifier from each of them

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Fixed effects

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2. GRAM.FUN: factor with 2 levels (S, O); reference level: S

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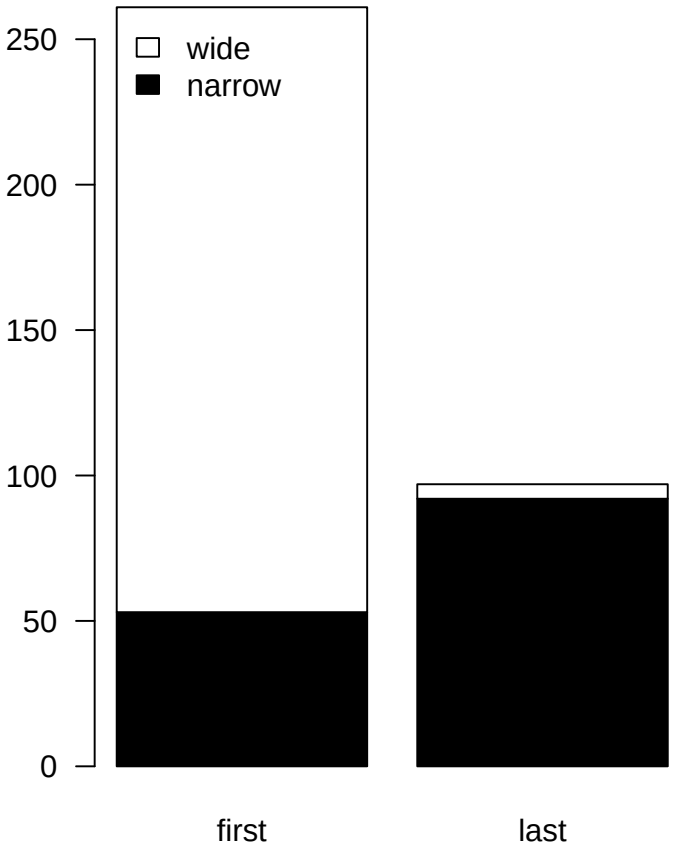
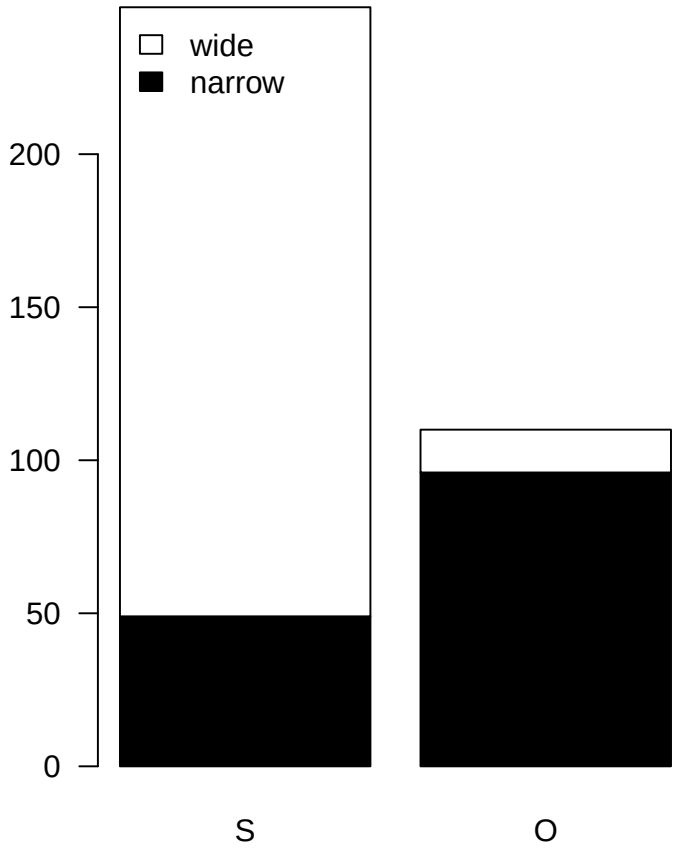
Random effects

1. LEX.REAL: factor with 17 levels (a, a.different, all, ...)
2. LEX.REAL.OTHER: factor with 19 levels (a, a.different, a.time, all, ...)

LIN.ORD by SCOPE



GRAM.FUN by SCOPE



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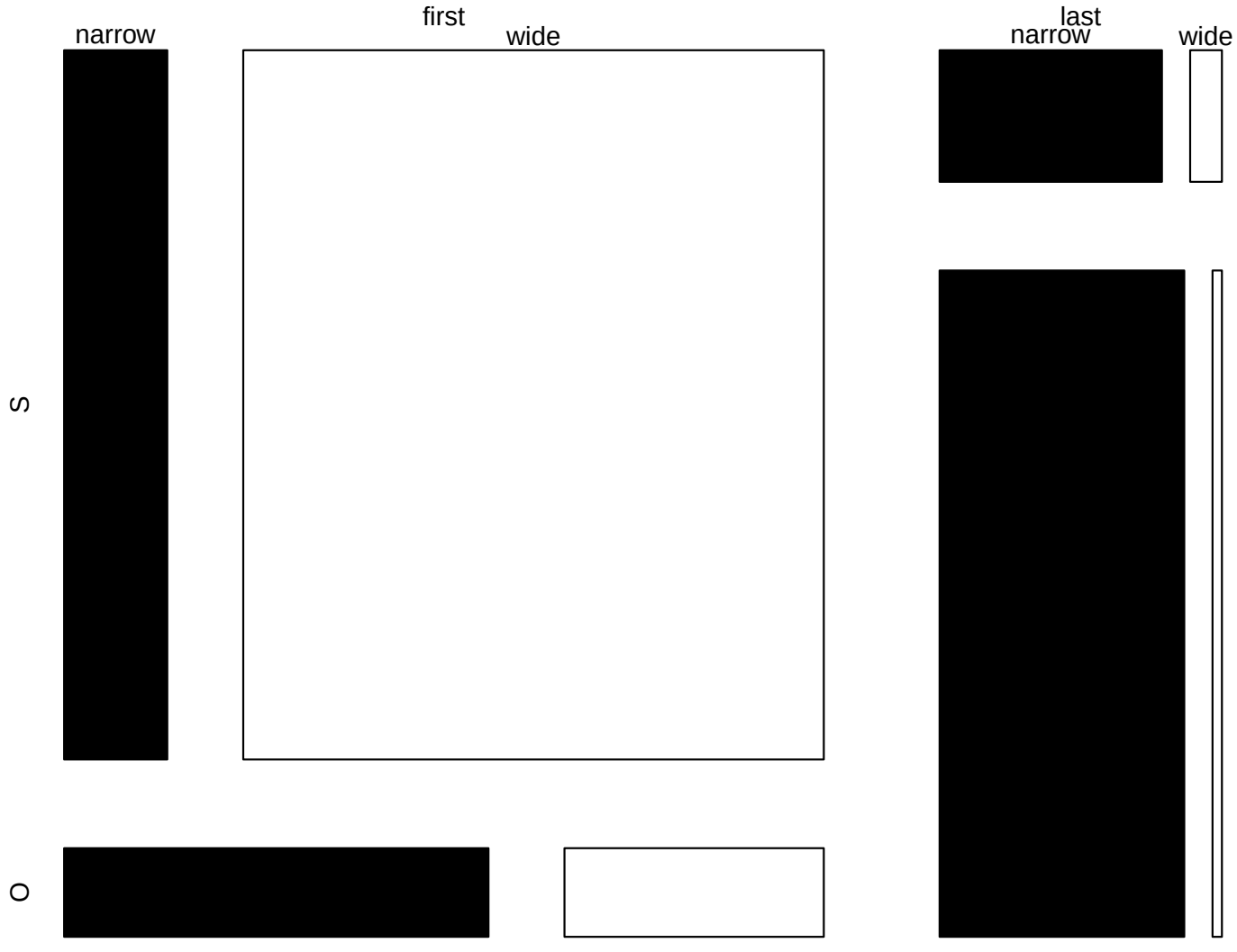
LIN.ORD by GRAM.FUN by SCOPE
first
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narrow
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S
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GRAM.FUN=S, LIN.ORD=last

- SCOPE=wide:
  Every week **six crews** – A,B,C,D,E,F – were ranked from first (most productive) to sixth (least productive).

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GRAM.FUN=S, LIN.ORD=last

- SCOPE=wide:
  Every week **six crews** – A,B,C,D,E,F – were ranked from first (most productive) to sixth (least productive).
- SCOPE=narrow:
  On each day of other days of hiring, **exactly one** worker was hired.

Examples for various conditions

GRAM.FUN=0, LIN.ORD=first

Examples for various conditions

GRAM.FUN=O, LIN.ORD=first

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  The nine flowers used in the corsages must include **at least one flower** from each of the four types.

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GRAM.FUN=O, LIN.ORD=last

- SCOPE=wide:
  Exactly three girls perform **each dance**.

Examples for various conditions

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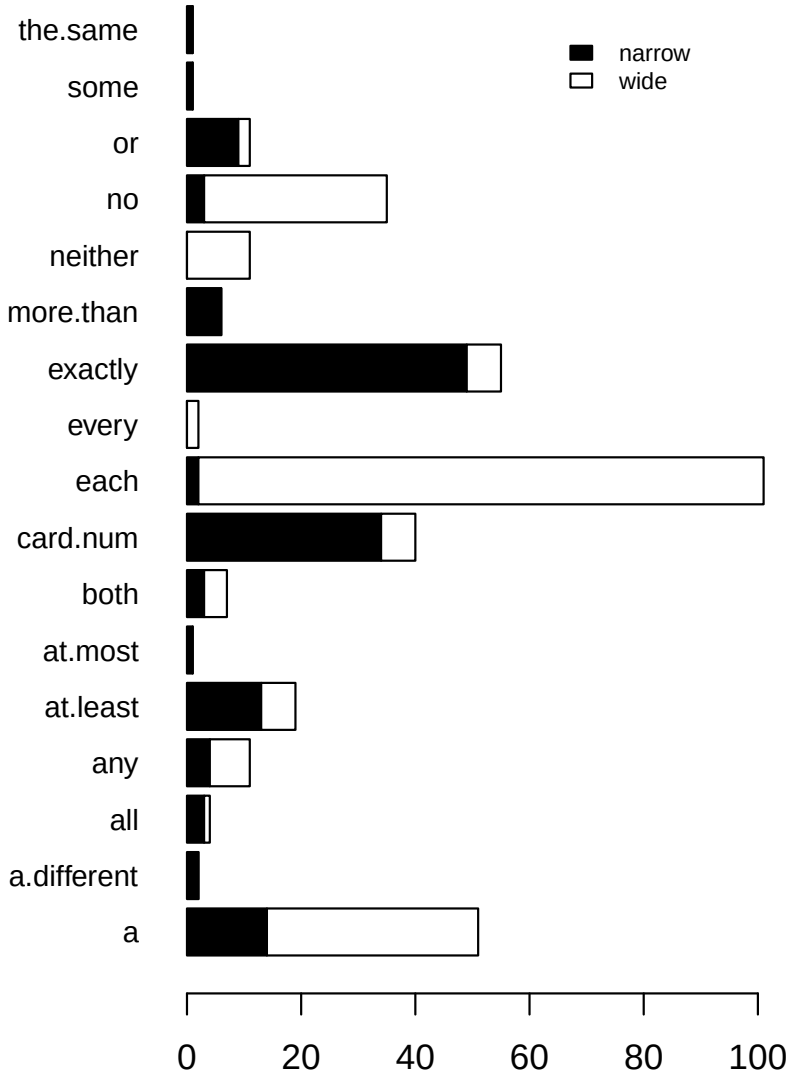
- SCOPE=wide:
  He did not wash **any two of the objects** at the same time.
- SCOPE=narrow:
  The nine flowers used in the corsages must include **at least one flower** from each of the four types.

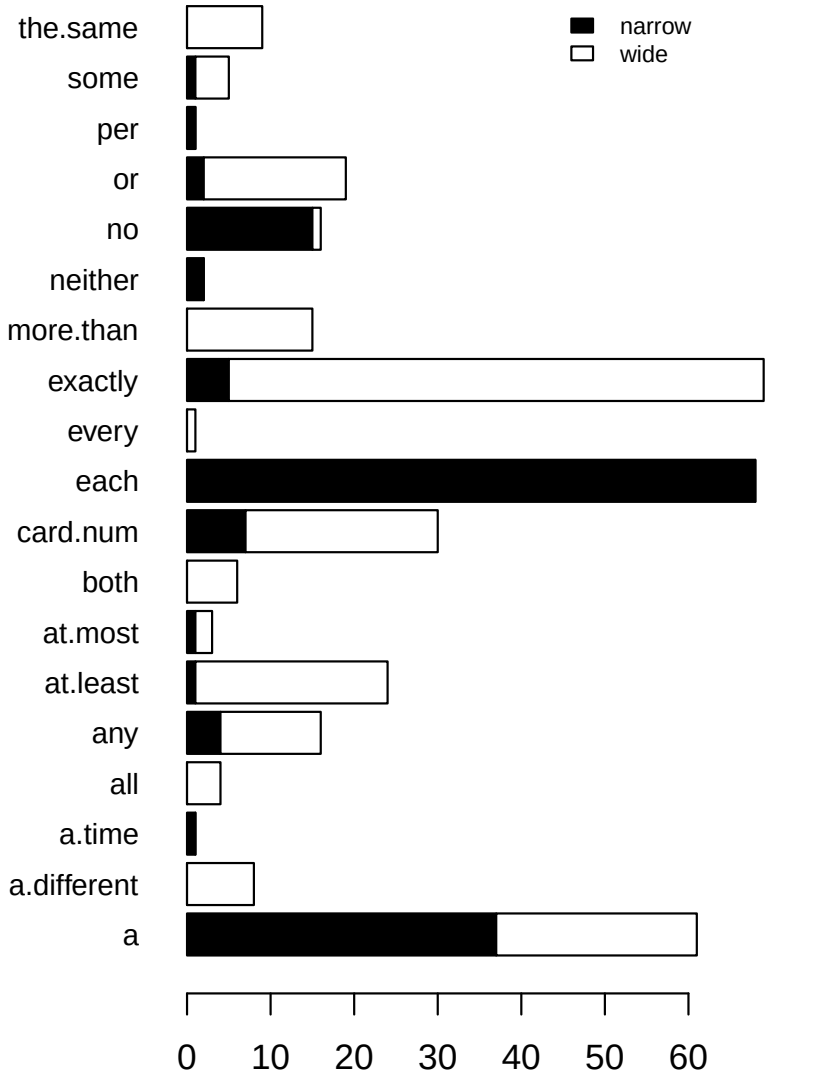
GRAM.FUN=0, LIN.ORD=last

- SCOPE=wide:
  Exactly three girls perform **each dance**.
- SCOPE=narrow:
  The official will also assign each runner to represent **a different charity**.

LEX.REAL by SCOPE



LEX.REAL.OTHER by SCOPE



Modeling and Resulting Generalizations

- we start with the full model for the fixed effects (the two main effects and their interaction) and intercept-only random effects for LEX.REAL and LEX.REAL.OTHER

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- but dropping the intercept random effects for LEX.REAL or LEX.REAL.OTHER significantly increases deviance (p= 3.21e-11 and p=2.08e-13, respectively)

Final Mixed-effects Logistic Regression Model

- intercept random effects for both LEX.REAL and LEX.REAL.OTHER
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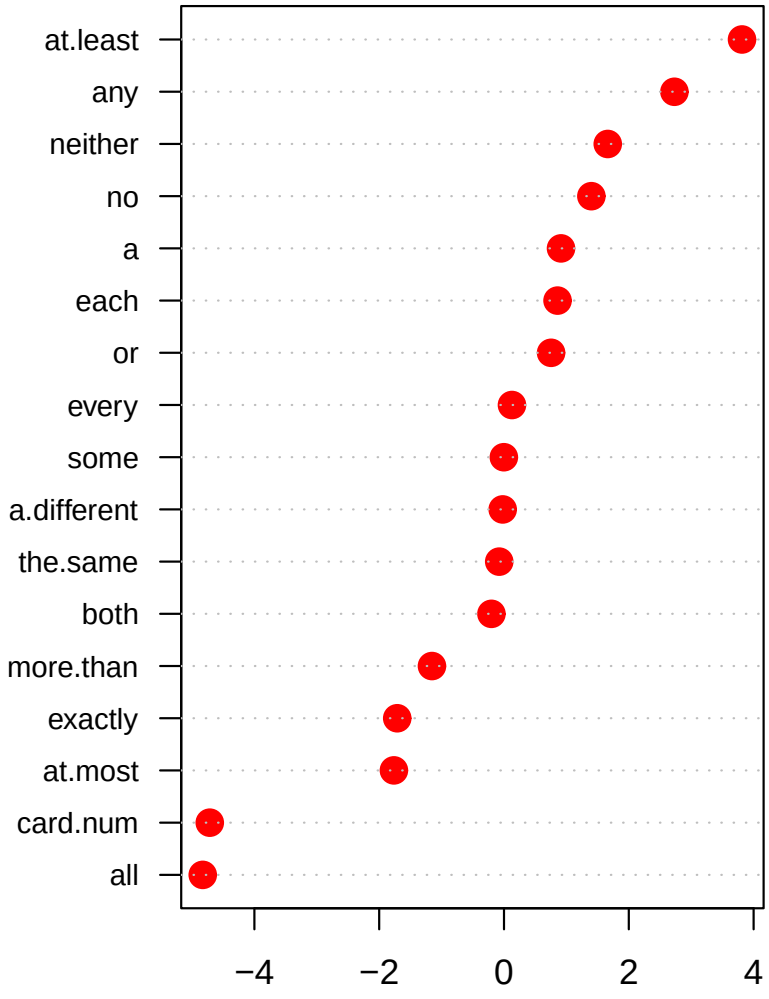
Maximum Likelihood Estimates (MLEs):

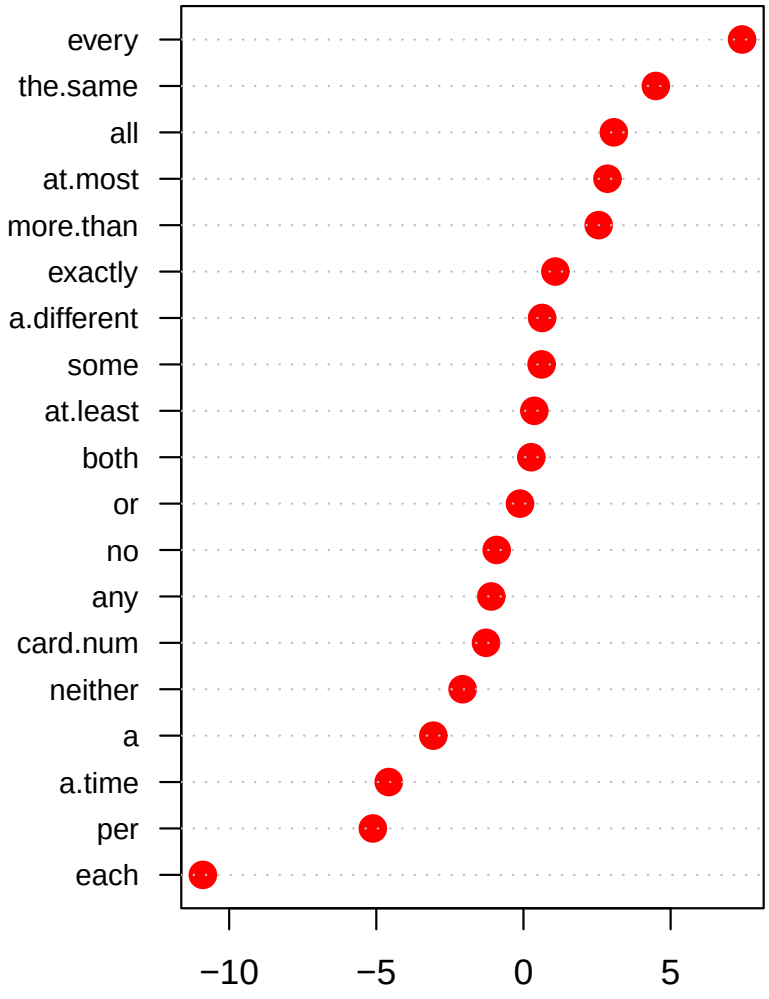
RANDOM EFFECTS		std.dev.		
	LEX.REAL	3.45		
	LEX.REAL.OTHER	5.55		
FIXED EFFECTS		**estimate**	**std.error**	**p-value**
	INTERCEPT	4.60	1.86	0.014
	LIN.ORD-LAST	-6.16	1.42	1e-05
	GRAM.FUN-O	-2.49	0.93	0.007

MLEs for Random Effects

LEX.REAL



LEX.REAL.OTHER



Main Results

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- lexical effects on scoping preferences seem more important than linear order or grammatical function
- in particular, the relational aspect of these lexical effects is important: LEX.REAL.OTHER seems to be at least as good a predictor of scope as LEX.REAL
- this provides a new kind of empirical support for *relational* theories of quantification that derive scopal behavior by focusing on the way in which one quantifier affects the context of interpretation for another quantifier, e.g., (in)dependence logic or dynamic plural logic

- the notion of interpretation context formalized in these logics is inherently relational because it focuses on context change
  - i.e., on the way in which an expression sets up the context of interpretation for a subsequent expression

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- the notion of interpretation context formalized in these logics is inherently relational because it focuses on context change
  - i.e., on the way in which an expression sets up the context of interpretation for a subsequent expression
- syntactic scoping mechanisms that focus on hierarchies of (classes of) quantifiers, e.g., Beghelli & Stowell (1997), are also supported

Semantics and processing

- identifying patterns of scoping behavior for quantifiers should ultimately enable us to group them into classes
- we might want our semantic theories to assign different kinds of semantic representations to these classes . . .
- . . . and / or we might want to hypothesize different processing strategies for these classes

Typology

- looking at the system of quantifiers in English opens the way towards examining cross-linguistic variation at system level, not only between individual (classes of) quantifiers

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Applied linguistics

- identifying and examining quantifier usage patterns is important for designing education and assessment materials in mathematics and sciences

Acknowledgments

First of all, we would like to thank the Law School Admission Council (LSAC) for access to practice test materials used in the analysis. We would also like to thank Pranav Anand, Donka Farkas, Matt Wagers and the participants in the UCSC Corpus Linguistics Group and the audiences at CUSP 3, MIT Syntax Square, ESSLLI 2011 PUQOL and SuB 2011 for helpful feedback.

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Appendix: Model Fit

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The final mixed-effects logistic regression model

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Compare with the fixed-effects only model

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Compare with the fixed-effects only model

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Compare with the random-effects only model

- C: 0.982
- Dxy: 0.965

Appendix: Model Fit

- Nagelkerke R2: a common pseudo-R2 measure for (mixed-effects) logit models assessing how much of the 'variance' in the response is accounted for by the predictors

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Nagelkerke R2

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Nagelkerke R2

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- the mixed intercept model relative to the ordinary intercept model: 0.743

Appendix: Bayesian Estimates

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MCMC estimation: 3 chains, 3.5e+06 iterations per chain, 1e+06 burnin, 2500 thinning.

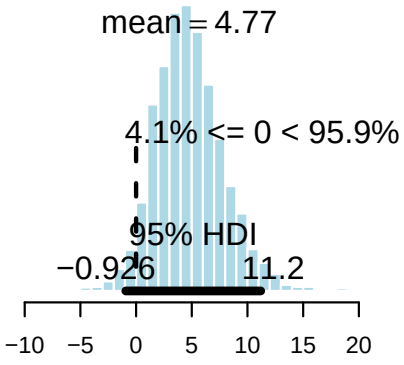
Summaries of the posterior distributions

The means and standard deviations of the posterior distributions for the random and fixed effects are fairly close to the MLEs:

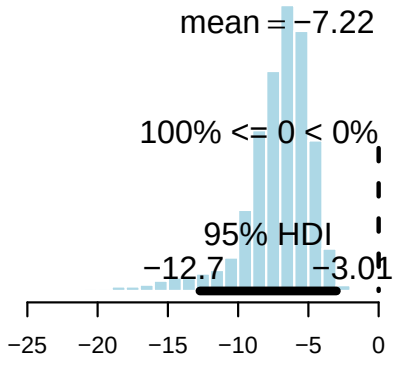
RANDOM EFFECTS		mean	std.dev.
	σ	5.37	2.48
	τ	9.65	4.32
FIXED EFFECTS		mean	std.dev.
	INTERCEPT	4.77	3.13
	LIN.ORD-LAST	-7.22	2.64
	GRAM.FUN-O	-2.67	1.07

Posteriors for Fixed Effects and Random Effect Std.Dev.s

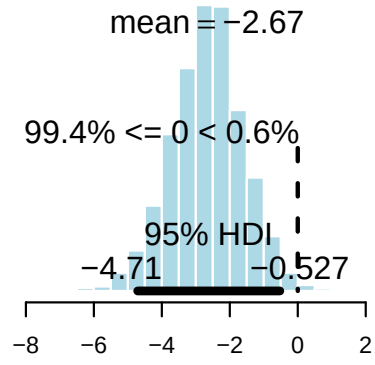
INTERCEPT



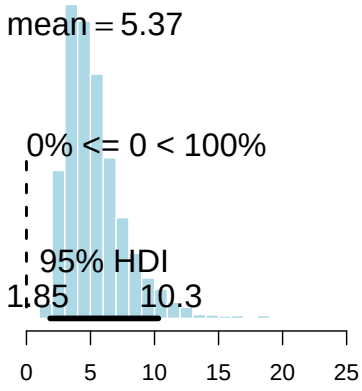
LIN.ORD-LAST



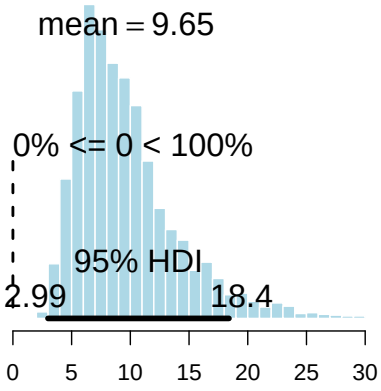
GRAM.FUN-O



LEX.REAL std.dev.

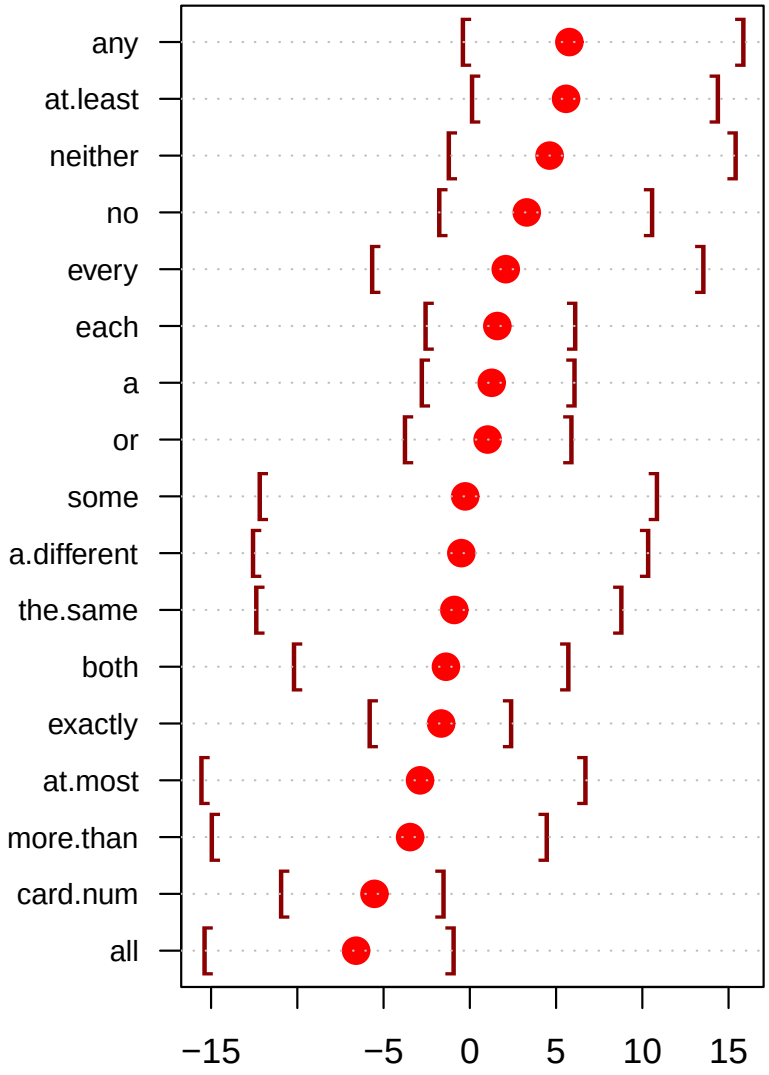


LEX.REAL.OTHER std.dev.

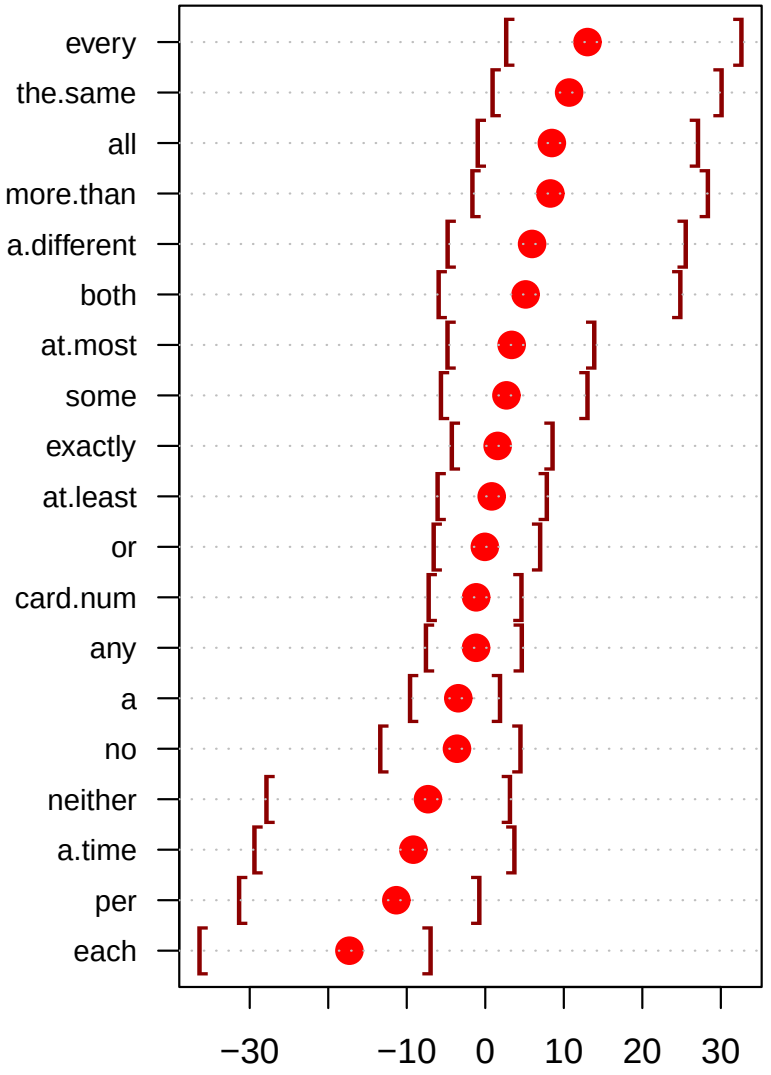


Random Effects (Means and 95% CRIs)

LEX.REAL

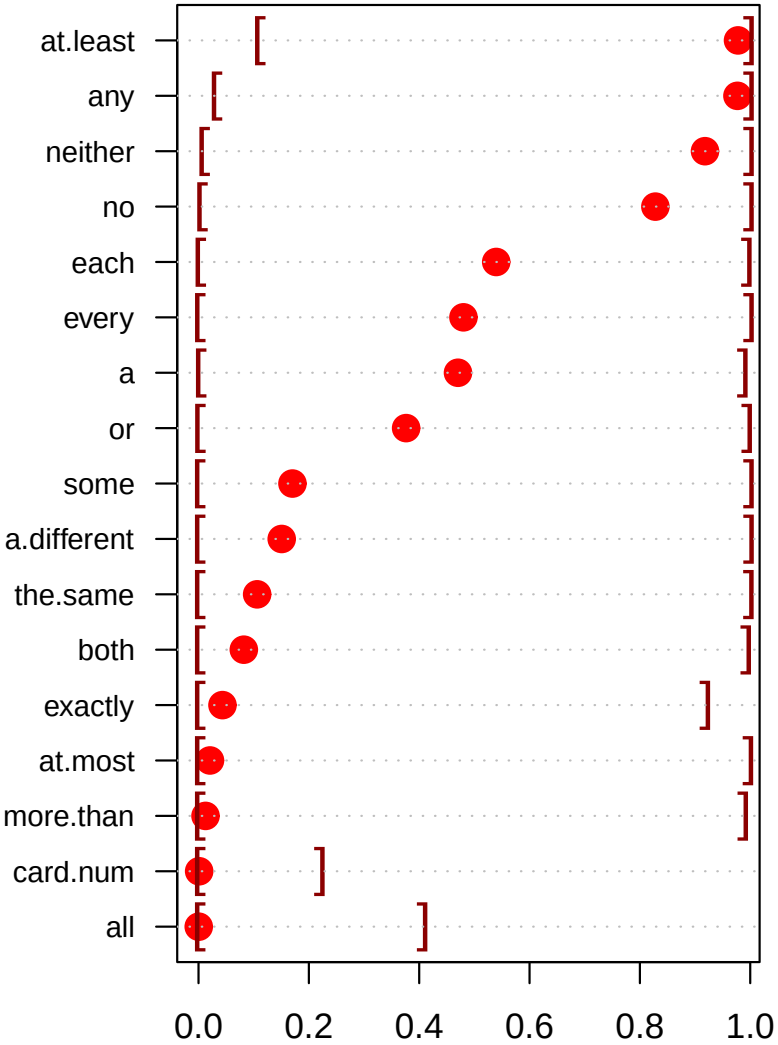


LEX.REAL.OTHER



Lex. Pref.s for Wide Scope (Median Prob.s and 95% CRIs)

LEX.REAL



LEX.REAL.OTHER