Licensing Sentence-internal Readings in English: An Experimental Study

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1. Introduction

Many languages have lexical means to compare two elements and express identity / difference / similarity between them. English uses **adjectives of comparison (AOCs)** like *same*, *different* and *similar*. Often, the comparison is between an element in the current sentence and a sentence-external element mentioned in the previous discourse, see (1a).

(1) a. Arnold saw 'Waltz with Bashir'.
b. Heloise saw *the same movie* / *a different movie* / *a similar movie*.

But AOCs can also compare *sentence-internally*, that is, without referring to any previously introduced element, see (2). This is possible if there is a semantically plural NP in the sentence.

(2) Each of the students saw *the same movie* / *a different movie*/*a similar movie*.

In the reported research we focused solely on sentence-internal readings of AOCs.

2. Contribution

[1]-[5], [8], among others, use introspective judgments to decide which NPs license sentence-internal readings of AOCs. We extend their work and look at licensors of AOCs in a grammaticality judgment task.

- We establish which NPs license which AOCs and to what extent
- We argue that using Bayesian methods to analyze the resulting experimental data has several advantages over the more traditional, frequentist approach.
- We discuss consequences of the experimental results for the semantic analysis of AOCs.

3. Experiment

Questionnaire testing:

3 AOCs:		*same*, *different*, *similar*
4 licensors:	NPs headed by	*each*, *all*, *none*, *the*
Hence, 3 × 4	=	12 conditions

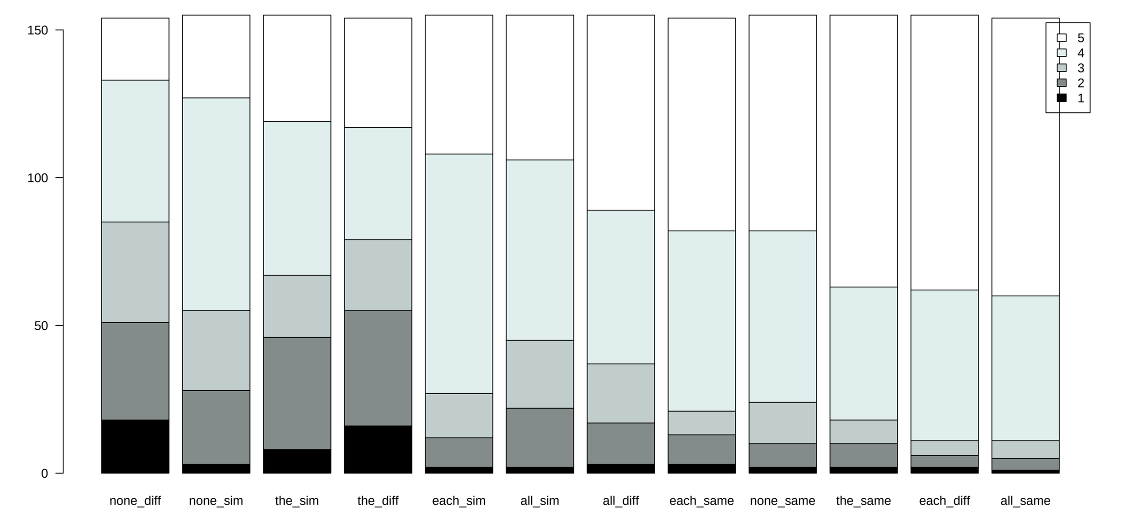
Each condition: tested 4 times (twice in a FALSE scenario, twice in a TRUE scenario), 32 fillers.

(3) Example of a scenario+test item:
Gustav, Ryan and Bill are three bank managers who share a passion for Volvo, Rolls Royce and Porsche automobiles. Last year, each of them bought a new car. Gustav bought a Volvo PY30, Ryan bought a Volvo XRT2000 and Bill bought a Volvo H4.
a. Each of the bank managers chose a similar car.

Each scenario followed by three test items and 2 fillers. Order of items and scenarios pseudo-randomized.

Task: judging (*i*) TRUTH and (*ii*) ACCEPT(ABILITY): 5=completely acceptable to 1=completely unacceptable
Subjects: 42 undergraduate students, 3 excluded, 1 subject filled in only two thirds.
Final number of observations: $n = 1856$.

4. Descriptive summary



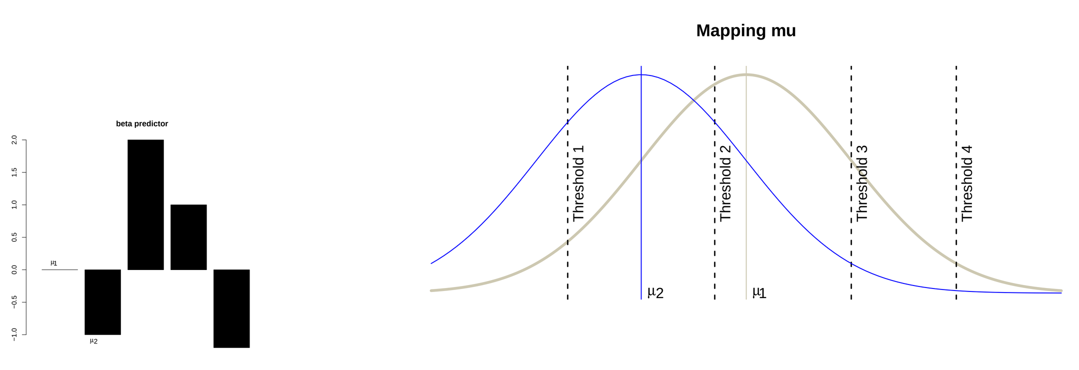
Barplots of responses by quant-AOC combination

5. Model

We use ordinal probit regression models to analyze the data. The final model has:

- 2 fixed effects (QUANT-AOC, TRUTH)
- intercept-only random effects for subjects

Reference level: EACH+DIFFERENT

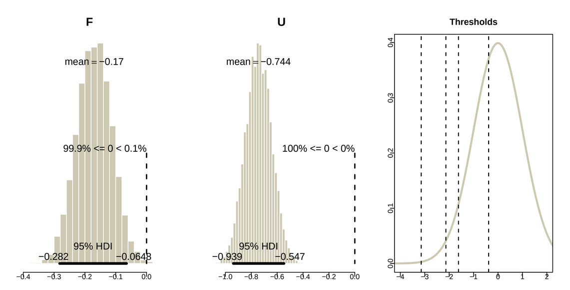


$\mu = \vec{\beta}\vec{x}$

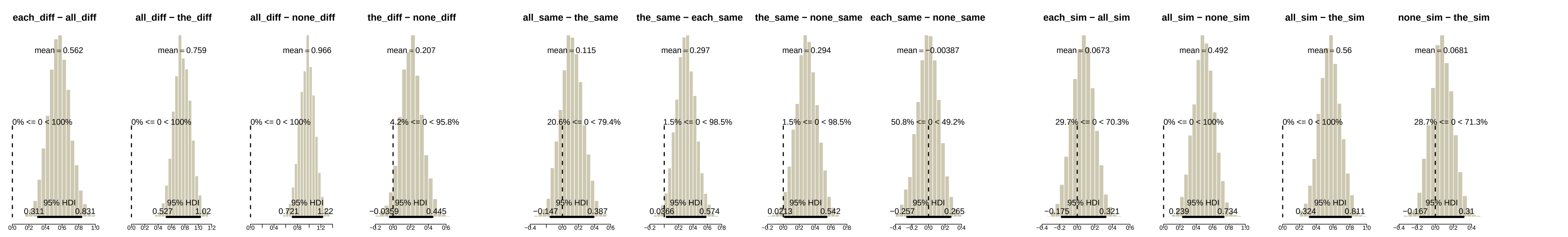
6. Multiple comparisons in a Bayesian model

We want to find which NPs license which AOCs and to what extent. Thus, we are interested in a wide range of pairwise comparisons.
Problem: Running all pairwise comparisons would require an unfeasibly large amount of data to achieve significance due to the necessary α-level corrections.
Solution: We use Bayesian modelling and check the marginal posterior distribution of each relevant pair ([6],[7])

The Bayesian model has the following structure: (*i*) vague priors for the non-reference levels of QUANT-AOC and TRUTH—independent normal distributions with mean 0 and variance 10^2; (*ii*) the subject random effects are assumed to come from a normal distribution with mean 0 and variance σ^2, with σ taken from a uniform distribution *Unif*$(0, 10)$. The range of Φ is partitioned into five intervals (since the acceptability scale was 1–5) by 4 cutoff points / thresholds; the priors for the thresholds are also independent normal distributions with mean 0 and variance 10^2.
We estimate the posterior distributions of the predictors QUANT-AOC and TRUTH, the standard deviation σ of the subject random effects and the 4 thresholds by sampling from them using Markov Chain Monte Carlo techniques (3 chains, $125,000$ iterations per chain, we discard the first $25,000$ iterations and record only every 50^{th} one).



DIFF: EACH > ALL > {THE, NONE}   SAME: {ALL, THE} > {EACH, NONE}   SIM: {ALL, EACH} > {NONE, THE}



7. Consequences

We assume that for each x in the sorting key, **dist** makes available at least some stacks which carry values of the sorting key other than x. See [3] for details.

(4) a. $\emptyset \xRightarrow{\text{Each}^{u_0}\text{boy}}$ [u_0: boy_1, boy_2, boy_3] $\xRightarrow{\textbf{dist}_{u_0}(\text{recited a}^{u_1}\,\text{different}^2_{u_1}\,\text{poem})}$

b. i. [u_0: boy_1, u_1: $poem_1$] * [u_0: boy_2, u_1: $poem_2$] & $poem_1 \neq poem_2$
ii. [u_0: boy_2, u_1: $poem_2$] * [u_0: boy_1, u_1: $poem_1$] & $poem_2 \neq poem_1$
iii. etc.

c. $\xRightarrow{\text{sum all updates}}$

u_0	u_1
boy_1	$poem_1$
boy_2	$poem_2$
boy_3	$poem_3$

We assume two **dist** operators: **dist**, **dist-COMP**

	dist	dist-Comp	no distributivity
different	✓	✓	*
same	✓	✓	✓
similar	*	✓	*

[5] argues that distributive interpretation of a predicate depends on the type of subject:

(5) **Dist: EACH > ALL > THE**

Following his work, we derive the scale of **Diff** (apart from the position of **NONE**). Furthermore, we derive the scale of **Same** if we assume that **no distributivity** is easier to interpret than **dist** and **dist-COMP**. Finally, we derive the scale of **Sim** if we assume that **ALL** and **EACH** can make use of **dist-COMP** more readily than definites and **NONE**.

References: **[1]** Barker, C. (2007). Parasitic Scope. *Ling. and Phil.* 30, 407-444. **[2]** Beck, S. (2000). The Semantics of Different. *Ling. and Phil.* 23, 101-139. **[3]** Brasoveanu, A. (2011). Sentence-internal *Different* as Quantifier-internal Anaphora. *Ling. and Phil.* 34, 93-168. **[4]** Carlson, G. (1987). *Same* and *Different*. *Ling. and Phil.* 10, 531-565. **[5]** Dotlačil, J. (2010). *Anaphora and Distributivity*. PhD diss., Utrecht Univ. **[6]** Kruschke, J. (2010). Bayesian Data Analysis. WIREs Cognitive Science 1, 658-676. **[7]** Kruschke, J. (2010). Doing Bayesian Data Analysis: A Tutorial with R and BUGS. Academic Press/Elsevier: Oxford. **[8]** Moltmann, F. (1992). Reciprocals and *Same*/*Different*. *Ling. and Phil.* 15, 411-462.