Subjectivity predicts adjective ordering preferences

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Abstract here. . .

language | ordering preferences | subjectivity | faultless disagreement

ntoduction. . . summary of the literature on adjective ordering preferences.

Corpus Counts

Description of our corpus work.

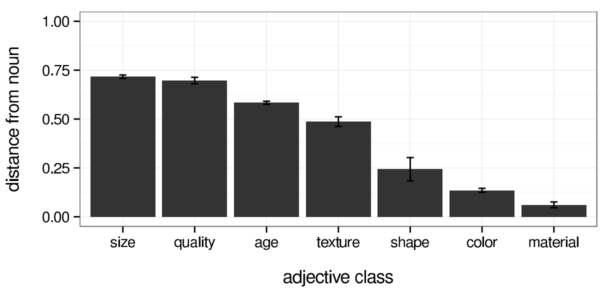

Fig. 1. Average distance from noun by adjective class for cases with at least two modifying adjectives (39,199 cases).

Based on the average distance-from-noun scores calculated in Fig. 1, we may infer the ordering preferences in 1 via pairwise comparisons between classes.

$$size \geq quality > age > texture > shape > color > material \quad [1]$$

Behavioral Experiments

Subjectivity. We conducted experiment 1 to measure the subjectivity of adjectives and the broader classes to which they belong. Participants evaluated the potential for faultless disagreement between two differing descriptions of an object (*Experiment 1a: Faultless Disagreement*). For example, an experimental trial might have Mary assert “that apple is old,” then have Bob counter with “that apple is not old.” To the extent that both Mary and Bob can be right in their descriptions of the apple, “old” admits that degree of faultless disagreement. In other words, to the extent that two people might disagree about a description without one necessarily being wrong, that description is subjective. We validated our faultless disagreement measure in a separate paradigm, which explicitly asked about the potential “subjectivity” of an object description like “old apple” (*Experiment 1b: Subjectivity*). The results of these two methods are highly correlated with each other ($r^2 = 0.89$), suggesting that the measures they invoke converge in their estimation of adjective subjectivity.

Fig. 2 plots faultless disagreement ratings for adjectives and their respective classes. Based on these aggregate scores, we infer the adjective class subjectivity raking in 2 on the basis of pairwise comparisons between classes.

$$quality \geq size > texture \geq age > color \geq shape \geq material \quad [2]$$

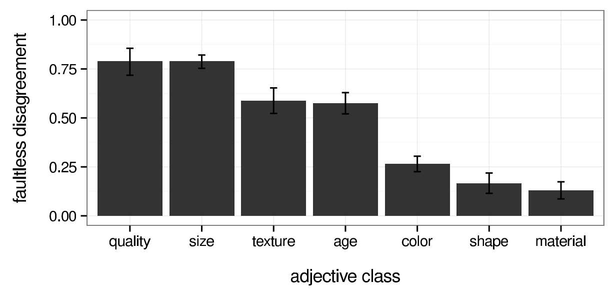

Fig. 2. Average distance from noun for each adjective class, determined by computing how often adjectives from a class occur first in preferred adjective-adjective-noun orderings.

Ordering preferences. We have so far established a connection between adjective subjectivity (measured in experiment 1) and adjective proximity to nouns (obtained from corpus counts). Our next task is to verify the adjective ordering preferences that we have inferred from the corpus and from the literature on the topic, and to evaluate the predictive power of subjectivity in determining adjective order. To that end, we elicited naturalness judgments on adjective-adjective-noun object descriptions, permuting the relative order of the adjectives (*Experiment 2: Ordering Preferences*). Participants indicated which ordering of an adjective-adjective-noun object description (e.g., “the big red apple” vs. “the red big apple”) sounded more natural.

On the basis of these naturalness ratings, we computed for each adjective-adjective pairing its preferred, canonical order. We then determined how often an adjective from a given

Significance

Speakers exhibit robust ordering preferences when it comes to modification involving more than one adjective. We present experimental and corpus results showing that these preferences track the subjectivity of the adjectives at play such that less subjective adjectives occur closer to the nouns they modify.

Reserved for Publication Footnotes

class occurred first in an adjective-adjective-noun configuration; Fig. 3 plots these average distance scores, where a value of 2 signals that a class's adjectives always occur first in preferred adjective-adjective-noun orderings, and a value of 1 indicates that a class's adjectives always occur second, closest to the noun.

$$size \geq quality > texture \geq age > color > shape > material \quad [3]$$

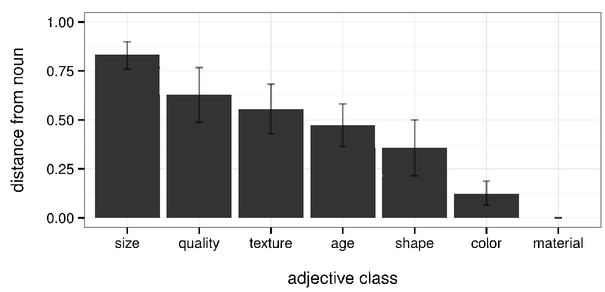

Fig. 3. Average distance from noun for each adjective class, determined by computing how often adjectives from a class occur first in preferred adjective-adjective-noun orderings.

Finally, and most directly related to our hypothesis concerning adjective subjectivity in ordering preferences, we compared acceptability ratings from the current experiment with faultless disagreement scores from Expt. 1. To do so, we first calculated a difference score for each class configuration, CLASS1–CLASS2, subtracting the average faultless disagreement score for CLASS1 from the average faultless disagreement score for CLASS2. Fig. 4 plots class configuration acceptability ratings against faultless disagreement difference scores.

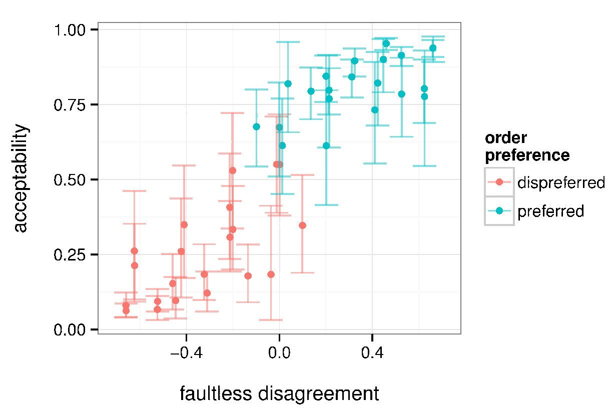

Fig. 4. By-class adjective order preferences plotted against difference in faultless disagreement.

Discussion

Materials and Methods

Corpus counts.

Pairwise comparisons using t tests with bonferroni correction age color material quality shape size color ¡ 2e-16 - - - - - material ¡ 2e-16 8.9e-05 - - - - quality ¡ 2e-16 ¡ 2e-16 ¡ 2e-16 - - - shape ¡ 2e-16 0.032 1.3e-05 ¡ 2e-16 - - size ¡ 2e-16 ¡ 2e-16 ¡ 2e-16 0.636 ¡ 2e-16 - texture 2.1e-13 ¡ 2e-16 ¡ 2e-16 ¡ 2e-16 1.9e-10 ¡ 2e-16

Experiment 1a: Faultless Disagreement. Something about our methods and how we ran the experiment

Pairwise comparisons using t tests with bonferroni correction age color material quality shape size color ¡ 2e-16 - - - - - material ¡ 2e-16 0.00161 - - - - quality 7.6e-06 ¡ 2e-16 ¡ 2e-16 - - - shape ¡ 2e-16 0.25546 1.00000 ¡ 2e-16 - - size 2.8e-10 ¡ 2e-16 ¡ 2e-16 1.00000 ¡ 2e-16 - texture 1.00000 ¡ 2e-16 ¡ 2e-16 0.00011 ¡ 2e-16 1.1e-07

Experiment 1b: Subjectivity.

Experiment 2: Ordering preferences. We recruited 50 participants through Amazon.com's Mechanical Turk crowd-sourcing service. Participants were compensated for their participation.

Participants were asked to indicate which of two descriptions of an object sounded more natural. Each description featured a noun modified by two adjectives, for example "the red small chair" or "the small red chair". Description pairs contained the same words, with relative adjective order reversed. Descriptions were random combinations of two adjectives and a noun from the list in Table (compiled via the procedure described in Section **??**), with the constraint that no description contained adjectives from the same adjective class. On each trial, participants indicated which description sounded more natural by adjusting a slider whose endpoints were labeled with the competing descriptions; an example trial appears in Fig. 5.

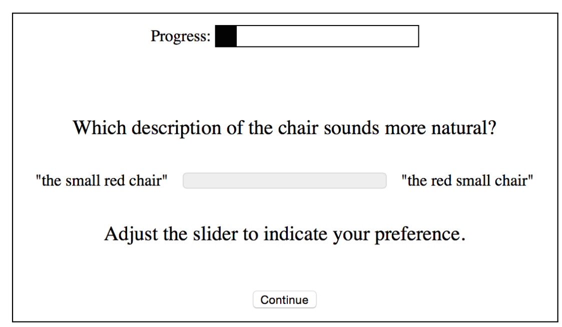

Fig. 5. Example trial from Expt. 1; participants indicated the more natural of two adjective-adjective-noun descriptions on a sliding scale.

Only native speakers of English with IP addresses located within the United States were included in the analyses; we analyzed data from 45 participants.

$<$**0.001**

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adjective	class	adjective	class	noun	class
old	age	good	quality	apple	food
new	age	bad	quality	banana	food
rotten	age	round	shape	carrot	food
fresh	age	square	shape	cheese	food
red	color	big	size	tomato	food
yellow	color	small	size	chair	furniture
green	color	huge	size	couch	furniture
blue	color	tiny	size	fan	furniture
purple	color	short	size	TV	furniture
brown	color	long	size	desk	furniture
wooden	material	smooth	texture		
plastic	material	hard	texture		
metal	material	soft	texture		

Table 0. Adjectives and nouns used in experimental stimuli.

	age	color	material	quality	shape	size
color	$<$**0.001**	-	-	-	-	-
material	$<$**0.001**	1.00	-	-	-	-
quality	0.98	$<$**0.001**	$<$**0.001**	-	-	-
shape	1.00	$<$**0.05**	$<$**0.001**	$<$**0.05**	-	-
size	$<$**0.001**	$<$**0.001**	$<$**0.001**	0.11	$<$**0.001**	-
texture	1.00	$<$**0.001**	$<$**0.001**	1.00	0.30	$<$**0.001**

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