When redundancy is useful: A Bayesian approach to 'overinformative' referring expressions

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September 4, 2019

Author note: The earliest precursor of this work (the core idea of a continuous semantics RSA model and Exp. 1) was presented as a talk at the RefNet Round Table Event in 2016 and at AMLaP 2016. Exp. 2 and the corresponding model were presented as a submitted talk at the CUNY Conference on Sentence Processing in 2017 and as a poster at the Experimental Pragmatics (XPrag) Conference in 2017. An earlier version of Exp. 3 and an earlier version of the corresponding model were published in the Proceedings of CogSci 38 as Graf, C., Degen, J., Hawkins, R. X. D., & Goodman, N. D. (2016). Animal, dog, or dalmatian? Level of abstraction in nominal referring expressions. In A. Papafragou, D. Grodner, D. Mirman, & J. Trueswell (Eds.), Proceedings of the 38th Annual Conference of the Cognitive Science Society (pp. 2261?2266). Austin, TX: Cognitive Science Society. All experiments and models have been presented by the first author in various invited talks at workshops and colloquia in Linguistics, Psychology, Philosophy, and Cognitive Science since 2016.
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Abstract

Referring is one of the most basic and prevalent uses of language. How do speakers choose from the wealth of referring expressions at their disposal? Rational theories of language use have come under attack for decades for not being able to account for the seemingly irrational overinformativeness ubiquitous in referring expressions. Here we present a novel production model of referring expressions within the Rational Speech Act framework that treats speakers as agents that rationally trade off cost and informativeness of utterances. Crucially, we relax the assumption that informativeness is computed with respect to a deterministic Boolean semantics, in favor of a non-deterministic continuous semantics. This innovation allows us to capture a large number of seemingly disparate phenomena within one unified framework: the basic asymmetry in speakers' propensity to overmodify with color rather than size; the increase in overmodification in complex scenes; the increase in overmodification with atypical features; and the preference for basic level nominal reference. These findings cast a new light on the production of referring expressions: rather than being wastefully overinformative, reference is usefully redundant.

Keywords: language production; reference; overinformativeness; experimental pragmatics; Bayesian modeling

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1 Overinformativeness in referring expressions

Reference to objects is one of the most basic and prevalent uses of language. In order to refer, speakers must choose from among a wealth of referring expressions they have at their disposal. How does a speaker choose whether to refer to an object as *the animal*, *the dog*, *the dalmatian*, or *the big mostly white dalmatian*? The context within which the object occurs (other non-dogs, other dogs, other dalmatians) plays a large part in determining which features the speaker chooses to include in their utterance – speakers aim to be sufficiently informative to establish unique reference to the intended object. However, speakers' utterances often exhibit what has been claimed to be *overinformativeness*: referring expressions are often more specific than necessary for establishing unique reference, and they are more specific in systematic ways. For instance, speakers are likely to produce referring expressions like *the small blue pin* instead of *the small pin* in contexts like Figure 1a, even though the color modifier is not strictly speaking required for identification (Gatt, van Gompel, Krahmer, & van Deemter, 2011; Gatt, Krahmer, van Deemter, & van Gompel, 2014; Arts, Maes, Noordman, & Jansen, 2011; Koolen, Gatt, Goudbeek, & Krahmer, 2011). Similar use of redundant *size* modifiers, in contrast, is rare. Providing a unified theory for speakers' systematic patterns of overinformativeness has so far proven elusive.

This paper is concerned with accounting for these systematic patterns in overinformative referring expressions. We restrict ourselves to definite descriptions of the form *the (ADJ?)+ NOUN*, that is, noun phrases that minimally contain the definite determiner *the* followed by a head noun, with any number of restrictive adjectives occurring between the determiner and the noun.[1] A model of such referring expressions will allow us to unify two domains in language production that have been typically treated as separate. The choice of adjectives in (purportedly) overmodified referring expressions has been a primary focus of the language production literature (Herrmann & Deutsch, 1976; Pechmann, 1989; Nadig & Sedivy, 2002; Sedivy, 2003; Maes, Arts, & Noordman, 2004; Engelhardt, Bailey, & Ferreira, 2006; Arts et al., 2011; Koolen et al., 2011; Rubio-Fernandez,

[1] In contrast, we will not provide a treatment of pronominal referring expressions, indefinite descriptions, names, definite descriptions with post-nominal modification, or non-restrictive modifier uses, though we offer some speculative remarks on how the approach outlined here can be applied to these cases.

2016), while the choice of noun in simple nominal expressions has so far mostly received attention in the concepts and categorization literature (Rosch, 1973; Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976) and in the developmental literature on generalizing basic level terms (Xu & Tenenbaum, 2007; but see Dale & Reiter, 1995 for a treatment of basic level terms in natural language generation).

In the following, we review some of the key phenomena and puzzles in each of these literatures. We then present a model of referring expression production within the Rational Speech Act framework (M. C. Frank & Goodman, 2012; Goodman & Frank, 2016; Franke & Jäger, 2016), which treats speakers as boundedly rational agents who optimize the tradeoff between utterance cost and informativeness. Our key innovation is to relax the assumption that informativeness of utterances is computed with respect to a deterministic Boolean semantics. Under this relaxed semantics, certain terms may apply better than others to an object without strictly being true or false. This idea has its oldest modern precursor in fuzzy logic (Zadeh, 1965). It is similar in spirit to recently proposed models of meaning in both computational semantics, which assign probabilities rather than truth conditions to sentences (Bernardy, Blanck, Chatzikyriakidis, & Lappin, 2018), and in NLP, which treat word and sentence meanings as vectors of real numbers (Pennington, Socher, & Manning, 2014; Peters et al., 2018; Devlin, Chang, Lee, & Toutanova, 2018). As we will show, computing utterance informativeness with respect to these more graded meanings can make adding seemingly overinformative modifiers or using nouns that are seemingly too specific useful and informative; not doing so might lead the listener to go astray, or to invest too much processing effort in inferring the speaker's intention. This model provides a unified explanation for a number of seemingly disparate phenomena from the modified and nominal referring expression literature.

We spend the remainder of the paper demonstrating how this account applies to various phenomena. In Section 1 we spell out the problem and introduce the key overinformativeness phenomena. In Section 2 we introduce the basic Rational Speech Act framework with deterministic Boolean semantics and show how it can be extended to a relaxed semantics. In Sections 3 - 5 we evaluate the relaxed semantics RSA model on data from interactive online reference game experiments that exhibit the phenomena introduced in Section 1: size and color modifier choice under varying conditions of scene complexity; typicality effects in the choice of color modifier; and choice of nominal level of reference. We wrap up in Section 6 by summarizing our findings and discussing the

(a) Size sufficient. (b) Color sufficient.

Figure 1: Example contexts where (a) size only (e.g., *the small pin*) or (b) color only (e.g., *the blue pin*) is sufficient for unique reference. Thick border marks the intended referent.

far-reaching implications of and further challenges for this line of work.

1.1 Production of referring expressions: a case against rational language use?

How should a cooperative speaker choose between competing referring expressions? Grice, in his seminal work, provided some guidance by formulating his famous conversational maxims, intended as a guide to listeners' expectations about cooperative speaker behavior (Grice, 1975). His maxim of Quantity, consisting of two parts, requires of speakers to:

1. *Quantity-1:* Make your contribution as informative as is required (for the purposes of the exchange).

2. *Quantity-2:* Do not make your contribution more informative than is required.

That is, speakers should aim to produce neither under- nor overinformative utterances. While much support has been found for the avoidance of underinformativeness (Brennan & Clark, 1996; R. Brown, 1958; Olson, 1970; Levinson, 1983; Engelhardt et al., 2006; Davies & Katsos, 2013), speakers seem remarkably willing to systematically violate Quantity-2. In modified referring expressions, they routinely produce modifiers that are not necessary for uniquely establishing reference (e.g., *the small blue pin* instead of *the small pin* in contexts like Figure 1a). In simple nominal expressions, speakers routinely choose to refer to an object with a basic level term even when a superordinate level term would have been sufficient for establishing reference (e.g., *the dog* instead of *the animal* in contexts like Figure 3; Rosch et al., 1976; Hoffmann & Ziessler, 1983; Tanaka & Taylor, 1991a; Johnson & Mervis, 1997; R. Brown, 1958).

These observations have posed a challenge for theories of language production, especially those positing rational language use (including the Gricean one): why this extra expenditure of useless

effort? Why this seeming blindness to the level of informativeness requirement? Many have argued from these observations that speakers are in fact not economical (Engelhardt et al., 2006; Pechmann, 1989). Some have derived a built-in preference for referring at the basic level from considerations of perceptual factors such as shape (Rosch et al., 1976; Rosch, 1973; Murphy & Smith, 1982). Others have argued for salience-driven effects on willingness to overmodify (Gatt et al., 2014; Westerbeek, Koolen, & Maes, 2015). In all cases, it is argued that informativeness cannot be the key factor in determining the content of speakers' referring expressions.

Here we revisit this claim and show that systematically relaxing the requirement of a deterministic Boolean semantics for referring expressions also systematically changes the informativeness of utterances. The intuition, using the example from Figure 1a, is that *blue* and *small* do not apply equally well to all roughly blue, roughly small objects, and that a speaker might opt to include more modifiers when any one alone might not be a perfectly apt descriptor. Assuming that *blue* is more precise than *small* leads the speaker to overmodify more with color than with size – and further, the more variability is present in the scene, the more the precision of color helps weed out non-intended referents, i.e., the more color overmodification occurs. This results in a reconceptualization of what have been termed *overinformative referring expressions* as *usefully redundant referring expressions*. We begin by reviewing the phenomena of interest that a revised theory of definite referring expressions should be able to account for.

1.2 Modified referring expressions

Most of the literature on overinformative referring expressions has been devoted to the use of overinformative modifiers in modified referring expressions. The prevalent observation is that speakers frequently do not include only the minimal modifiers required for establishing reference, but often also include redundant modifiers (Pechmann, 1989; Nadig & Sedivy, 2002; Maes et al., 2004; Engelhardt et al., 2006; Arts et al., 2011; Koolen et al., 2011). However, not all modifiers are created equal: there are systematic differences in the overmodification patterns observed for size adjectives (e.g., *big, small*), color adjectives (e.g., *blue, red*), material adjectives (e.g., *plastic, wooden*), and others (Sedivy, 2003). Here we review some key patterns of overmodification that have been observed, before spelling out our account of these phenomena in Section 2.

1.2.1 Asymmetry in redundant use of color and size adjectives

In Figure 1a, singling out the object highlighted by the thick border requires only mentioning its size (*the small pin*). But it is now well-documented that speakers routinely include redundant color adjectives (*the small blue pin*) which are not necessary for uniquely singling out the intended referent in these kinds of contexts (Pechmann, 1989; Belke & Meyer, 2002; Gatt et al., 2011). However, the same is not true for size: in contexts like Figure 1b, where color is sufficient for unique reference (*the blue pin*), speakers overmodify much more rarely. Though there is quite a bit of variation in proportions of overmodification, this asymmetry in the propensity for overmodifying with color but not size has been documented repeatedly (Pechmann, 1989; Sedivy, 2003; Gatt et al., 2011; Rubio-Fernandez, 2016; Westerbeek et al., 2015; Koolen, Goudbeek, & Krahmer, 2013).

Explanations for this asymmetry have varied. Pechmann (1989) was the first to take the asymmetry as evidence for speakers following an incremental strategy of object naming: speakers initially start to articulate an adjective denoting a feature that listeners can quickly and easily recognize (i.e., color) before they have fully inspected the display and extracted the sufficient dimension. However, this would predict that speakers routinely should produce expressions like *the blue small pin*, which violate the preference for size adjectives to occur before color adjectives in English (Bloomfield, 1933; Sproat & Shih, 1991). While Pechmann did observe such violations in his dataset, most cases of overmodification did not constitute such violations, and he himself concluded that incrementality cannot (on its own) account for the asymmetry in speakers' propensity for overmodifying with color vs. size. We discuss the role of incrementality further in the General Discussion.

Another explanation for the asymmetry is that speakers try to produce modifiers that denote features that are reasonably easy for the listener to perceive, so that, even when a feature is not fully distinguishing in context, it at least serves to restrict the number of objects that could plausibly be considered the target. Indeed, there has been some support for the idea that overmodification can be beneficial to listeners by facilitating target identification (Arts et al., 2011; Rubio-Fernandez, 2016; Paraboni, van Deemter, & Masthoff, 2007). We return to this idea in Section 2 and the General Discussion.

There have been various attempts to capture the color-size asymmetry in computational natural language generation models. The earliest contenders for models of definite referring expressions like the Full Brevity algorithm (Dale, 1989) or the Greedy algorithm (Dale, 1989) focused only on

discriminatory value – that is, an utterance's informativeness – in generating referring expressions. This is equivalent to the very simple interpretation of Grice laid out above, and consequently these models demonstrated the same inability to capture the color-size asymmetry: they only produced the minimally specified expressions. Subsequently, the Incremental algorithm (Dale & Reiter, 1995) incorporated a preference order on features, with color ranked higher than size. The order is traversed and each encountered feature included in the expression if it serves to exclude at least one further distractor. This results in the production of overinformative color but not size adjectives. However, the resulting asymmetry is much greater than that evident in human speakers, and is deterministic rather than exhibiting the probabilistic production patterns that human speakers exhibit. More recently, the PRO model (van Gompel, van Deemter, Gatt, Snoeren, & Krahmer, 2019) has sought to integrate the observation that speakers seem to have a preference for including color terms with the observation that a preference does not imply the deterministic inclusion of said color term. In PRO, the uniquely distinguishing property (if there is one) is first selected deterministically. In additional steps, additional properties are added probabilistically, depending on both a salience parameter associated with the additional property and a parameter capturing speakers' eagerness to overmodify. If both properties are uniquely distinguishing, a property is selected probabilistically depending on its associated salience parameter. The second step proceeds as before. This model successfully captures speakers' overmodification patterns in contexts with one target and two distractors, in the choice of two properties (color, size) and three properties (color, size, border presence).

While the PRO model – the most state-of-the-art computational model of human production of modified referring expressions – can capture the color-size asymmetry discussed above, it does not straightforwardly account for the more subtle systematicity with which the preference to overmodify with color changes based on various features of context, which we turn to next.

1.2.2 Scene variation

Speakers' propensity to overmodify with color is highly dependent on features of the distractor objects in the context. In particular, as the variation present in the scene increases, so does the probability of overmodifying (Davies & Katsos, 2013; Koolen et al., 2013). How exactly scene variation is quantified differs across experiments. One very clear demonstration of the scene vari-

ation effect was given by Koolen et al. (2013), who quantified scene variation as the number of feature dimensions along which objects in a scene vary. Over the course of three experiments, they compared a low-variation condition in which objects never differed in color with a high-variation condition in which objects differed in type, color, orientation, and size. They consistently found higher rates of overmodification with color in the high-variation (28-27%) than in the low-variation (4-10%) conditions. Similarly, Davies and Katsos (2013) found that listeners judge overmodified referring expressions in low-variation scenes of four objects as less natural than in high-variation scenes of 4 potentially compositional 'objects-on-objects' (e.g., a button on a sock). And finally, Gatt, Krahmer, Van Deemter, and van Gompel (2017), while not reporting differences in overmodification behavior, did find that when size and color are jointly disambiguating, speech onset times for non-redundant *color-and-size* utterances increased as the number of distractors in the display increased.

The effect of scene variation on propensity to overmodify has typically been explained as the result of the demands imposed on visual search: in low-variation scenes, it is easier to discern the discriminating dimensions than in high-variation scenes, where it may be easier to simply start naming features of the target that are salient (Koolen et al., 2013).

Above, we have considered three different ways of quantifying scene variation: the number of dimensions along which objects differ, whether objects are 'simple' or 'compositional', and the number of distractors present in a scene. A model of referring expression generation should ideally capture all of these types of variation in a unified way.

1.2.3 Feature typicality

Modifier type and amount of scene variation are not the only factors determining overmodification. Overmodification with color has been shown to be systematically related to the typicality of the color for the object. Building on work by Sedivy (2003), Westerbeek et al. (2015) (and more recently, Rubio-Fernandez (2016)) have shown that the more typical a color is for an object, the less likely it is to be mentioned when not necessary for unique reference. For example, speakers never refer to a yellow banana in the absence of other bananas as *the yellow banana* (see Figure 2a), but they sometimes refer to a brown banana as *the brown banana*, and they almost always refer to a blue banana as *the blue banana* (see Figure 2b). Similar typicality effects have been shown for

(a) Typical color, type sufficient. (b) Atypical color, type sufficient.

Figure 2: Example contexts where type (*banana*) is sufficient for unique reference and color is (a) typical or (b) atypical. A thick border marks the intended referent.

other (non-color) properties. For example, Mitchell (2013) showed that speakers are more likely to include an atypical than a typical property (either shape or material) when referring to everyday objects like boxes when mentioning at least one property was necessary for unique reference.

Whether speakers are more likely to mention atypical properties over typical properties because they are more salient to *them* or because they are trying to make reference resolution easier for the listener, for whom presumably these properties are also salient, is an open question (Westerbeek et al., 2015). Some support for the audience design account comes from a study by Huettig and Altmann (2011), who found that listeners, after hearing a noun with a diagnostic color (e.g., *frog*), are more likely to fixate objects of that diagnostic color (green), indicating that typical object features are rapidly activated and aid visual search. Similarly, Arts et al. (2011) showed that overspecified expressions result in faster referent identification. Nevertheless, the benefit for listeners and the salience for speakers might simply be a happy coincidence and speakers might not, in fact, be designing their utterances for their addressees. We return to this issue in the General Discussion.

1.3 Nominal referring expressions

Even in the absence of adjectives, a referring expression can be more or less informative: *the dalmatian* communicates more information about the object in question than *the dog* (being a dalmatian entails being a dog), which in turn is globally more informative than *the animal*. Thus, this choice can be considered analogous to the choice of adding more modifiers – in both cases, the speaker has a choice of being more or less specific about the intended referent. However, the choice of reference level in simple nominal referring expressions is also interestingly different from that of adding modifiers in that there is no additional word-level cost associated with being more

(a) Subordinate level term necessary. (b) Superordinate level term sufficient.

Figure 3: Example contexts in which different levels of reference are necessary for establishing unique reference to the target marked with a thick border. (a) subordinate (*dalmatian*) necessary; (b) superordinate (*animal*) sufficient, but basic (*dog*) or subordinate (*dalmatian*) possible.

specific – the choice is between different one-word utterances, not between utterances differing in word count.

Nevertheless, cognitive cost affects the choice of reference level: in particular, speakers prefer more frequent words over less frequent ones (Oldfield & Wingfield, 1965), and they prefer shorter ones over longer ones (Degen, Franke, & Jäger, 2013; Rohde, Seyfarth, Clark, Jäger, & Kaufmann, 2012). This may go part of the way towards explaining the well-documented effect from the concepts and categorization literature that speakers prefer to refer at the *basic level* (Rosch et al., 1976; Tanaka & Taylor, 1991b). That is, in the absence of other constraints, even when a superordinate level term would be sufficient for establishing reference (as in Figure 3b), speakers prefer to say *the dog* rather than *the animal*. Early computational work in natural language generation hard-coded a preference to refer at the basic level where possible (Dale & Reiter, 1995).

Contextual informativeness is another factor that has been shown to affect speakers' nominal production choices (e.g., Brennan & Clark, 1996). For instance, in a context like Figure 3a, speakers should use the subordinate level term *dalmatian* to refer to the target marked with a thick border, because a higher-level term (*dog*, *animal*) would be contextually underinformative. However, there are nevertheless cases of contexts where either the superordinate *animal* or the basic level *dog* term would be sufficient for unique reference, as in Figure 3b, in which speakers nevertheless prefer to use the subordinate level term *the dalmatian*. This is the case when the object is a particularly good instance of the subordinate level term or a particularly bad instance of the basic level term, compared to the other objects in the context. For example, penguins, which are rated as particularly atypical birds, are often referred to at the subordinate level *penguin* rather than at the basic level *bird*, despite the general preference for the basic level (Jolicoeur, Gluck, & Kosslyn, 1984).

Table 1: List of effects a theory of referring expression production should account for and paper section(s) in which they are treated.

Section	Effect	Description
2 & 3	Color/size asymmetry	More redundant use of color than size [2]
2 & 3	Scene variation	More redundant use of color with increasing scene variation [3]
4	Color typicality	More redundant use of color with decreasing color typicality [4]
5	Basic level preference	Preference for basic level term when superordinate sufficient [5]
5	Subordinate level use	Unnecessary use of subordinate level term [6]

1.4 Summary

In sum, the production of modified and simple nominal referring expressions is governed by many factors, including an utterance's informativeness, its cost relative to alternative utterances, and the typicality of an object or its features. Critically, these factors are all in play at once, potentially interacting in rich and complex ways. In the next section, we provide an explicit computational account of these different factors and how they interact, with a focus on cases where speakers appear to be overinformative – either by adding more modifiers or by referring at a more specific level than necessary for establishing unique reference. A summary of the effects we will focus on in the remainder of the paper is provided in Table 1.

To date, there is no theory to account for all of these different phenomena; and no model has attempted to unify overinformativeness in the domain of modified and nominal referring expressions. We touched on some of the explanations that have been proposed for these phenomena. We also indicated where computational models have been proposed for individual phenomena. In the next section, we present the Rational Speech Act modeling framework, which we then use to capture these disparate phenomena in one model.

[2]Reported by many (e.g., Pechmann, 1989; Engelhardt et al., 2006; Gatt et al., 2011; Rubio-Fernandez, 2016)

[3]Multiple replications reported (e.g., Davies & Katsos, 2013; Koolen et al., 2013)

[4]Multiple replications reported (e.g. Sedivy, 2003; Westerbeek et al., 2015; Rubio-Fernandez, 2016)

[5]Originally reported by Rosch et al. (1976), dozens of replications.

[6]Reported by Jolicoeur et al. (1984)

2 Modeling speakers' choice of referring expression

Here we propose a computational model of referring expression production that accounts for the phenomena introduced above. The model is formulated within the Rational Speech Act (RSA) framework (M. C. Frank & Goodman, 2012; Goodman & Frank, 2016).[7] It provides a principled explanation for the phenomena reviewed in the previous section and holds promise for being generalizable to many further production phenomena related to overinformativeness, which we discuss in Section 6. We proceed by first presenting the general framework in Section 2.1, and show why the most basic model, as formulated by M. C. Frank & Goodman, 2012, does not produce the phenomena outlined above due to its strong focus on speakers maximizing the informativeness of expressions under a deterministic Boolean semantics. In Section 2.2 we introduce the crucial innovation: relaxing the semantics. We show that the model can qualitatively account both for speakers' asymmetric propensity to overmodify with color rather than with size and (in Section 2.3) for speakers' propensity to overmodify more with increasing scene variation.

2.1 Basic RSA

The production component of RSA aims to soft-maximize the utility of utterances, where utility is defined in terms of the contextual informativeness of an utterance, given each utterance's literal semantics. Formally, this is treated as a pragmatic speaker S_1 reasoning about a literal listener L_0, who can be described by the following formula:

$$P_{L_0}(o|u) \propto \mathcal{L}(u, o). \tag{1}$$

The literal listener L_0 observes an utterance u from the set of utterances U, consisting of single adjectives denoting features available in the context of a set of objects O, and returns a distribution over objects $o \in O$. Here, $\mathcal{L}(u, o)$ is the lexicon that encodes deterministic lexical meanings such that:

[7] All RSA models and Bayesian data analyses reported in this paper were implemented in the probabilistic programming language WebPPL (Goodman & Stuhlmüller, electronic) and can be viewed at `https://github.com/thegricean/RE_production`. All experimental materials and analysis scripts are available in the same repository. An interactive browser-based toy model is provided at `http://forestdb.org/models/overinf.html`.

$$\mathcal{L}(u, o) = \begin{cases} 1 & \text{if } u \text{ is true of } o \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Thus, $P_{L_0}(o|u)$ returns a uniform distribution over all contextually available o in the extension of u. For example, in the size-sufficient context shown in Figure 1a, $U = \{big, small, blue, red\}$ and $O = \{o_{\text{big\_blue}}, o_{\text{big\_red}}, o_{\text{small\_blue}}\}$. Upon observing *blue*, the literal listener therefore assigns equal probability to $o_{\text{big\_blue}}$ and $o_{\text{small\_blue}}$. Values of $P_{L_0}(o|u)$ for each u are shown on the left in Table 2.

The pragmatic speaker in turn produces an utterance with probability proportional to the utility of that utterance:

$$P_{S_1}(u|o) \propto e^{U(u,o)} \tag{3}$$

The speaker's utility $U(u, o)$ is a function of both the utterance's *informativeness* with respect to the literal listener $P_{L_0}(o|u)$ and the utterance's *cost* $c(u)$:

$$U(u, o) = \beta_i \ln P_{L_0}(o|u) - \beta_c c(u) \tag{4}$$

Two free parameters, β_i and β_c enter the computation, weighting the respective contributions of informativeness and utterance cost, respectively.[8] In order to understand the effect of β_i, it is useful to explore its effect when utterances are cost-free. In this case, as β_i approaches infinity, the speaker increasingly only chooses utterances that maximize informativeness; if β_i is 0, informativeness is disregarded and the speaker chooses randomly from the set of all available utterances; if β_i is

[8] M. C. Frank and Goodman (2012) fixed $\beta_i = 1$ and did not include cost in their formulation, because they assumed equal costs for all utterances. Subsequent work has demonstrated the importance of taking into account utterance cost in modeling interpretation phenomena like cost-based quantity implicatures (Degen, Franke, & Jäger, 2013) and M-implicature (Bergen, Levy, & Goodman, 2016). We include it here because of the importance that cost has played in explanations of overinformative referring expressions, where it typically surfaces as the idea that speakers have different overall preferences for mentioning color vs. size modifiers (Dale & Reiter, 1995; Koolen et al., 2011; van Gompel et al., 2019). At this point we remain agnostic about the factors that contribute to an utterance's cost $c(u)$. In later sections we allow cost to be a function of properties (e.g. color & size) mentioned in the utterance, or of an utterance's empirical length and corpus frequency; our policy for these cases is to introduce free cost parameters for each linear component of the cost function.

1, the speaker probability-matches, i.e., chooses utterances proportional to their informativeness (equivalent to Luce's choice rule, Luce, 1959). Applied to the example in Table 2, if the speaker wants to refer to $o_{\text{small\_blue}}$ they have two semantically possible utterances, *small* and *blue*, where *small* is twice as informative as *blue*. They produce *small* with probability 1 when $\beta_i \to \infty$, probability 2/3 when $\beta_i = 1$ and probability 1/4 when $\beta_i = 0$.[9]

Conversely, disregarding informativeness and focusing only on cost, any asymmetry in costs will be exaggerated with increasing β_c, such that the speaker will choose the least costly utterance with higher and higher probability as β_c increases.

As has been pointed out by van Gompel et al. (2019), the basic Rational Speech Act model described so far (M. C. Frank & Goodman, 2012) does not generate overinformative referring expressions for two reasons. One of these is trivial: U only contains one-word utterances. We can ameliorate this easily by allowing complex two-word utterances. We assume an intersective semantics for complex utterances u_{complex} that consist of a two adjective sequence $u_{\text{size}} \in \{big, small\}$ and $u_{\text{color}} \in \{blue, red\}$, such that the meaning of a complex two-word utterance is defined as

$$\mathcal{L}(u_{\text{complex}}, o) = \mathcal{L}(u_{\text{size}}, o) \times \mathcal{L}(u_{\text{color}}, o). \tag{5}$$

The resulting renormalized literal listener distributions for our example size-sufficient context in Figure 1a are shown in the middle columns in Table 2.[10]

Unfortunately, simply including complex utterances in the set of alternatives does not solve the problem. Let's turn again to the case where the speaker wants to communicate the small blue object. There are now two utterances, *small* and *small blue*, which are both more informative than *blue* and equally informative as each other, for referring to the small blue object. Because they are equally contextually informative, the only way for the complex utterance to be chosen with greater probability than the simple utterance is if it was the *cheaper* one. While this would achieve the desired mathematical effect, the cognitive plausibility of complex utterances being cheaper than

[9] Note that instead of a β_i parameter weighting informativeness *inside* the utility function, other recent formulations have used an α parameter modulating the entire utility function, i.e. $P_{S_1}(u|o) \propto \exp \alpha U(u, o)$. These parameterizations are equivalent. In the present work, where informativeness and cost both play important roles, we chose the 'flattened' linear combination with independent weights for simplicity.

[10] 'Normalization' refers to the process of turning a set of numbers into a probability distribution by dividing each number by the sum of all the numbers in the set, such that they add up to 1.

Table 2: Row-wise literal listener distributions $P_{L_0}(o|u)$ for each utterance u in the size-sufficient context depicted in Figure 1a, allowing only simple one-word utterances (left) or one- and two-word utterances (middle, right) under a deterministic Boolean semantics (left, middle) or under a continuous semantics (right) with $x_{\text{size}} = .8$, $x_{\text{color}} = .99$. Bolded numbers indicate crucial comparisons between literal listener probabilities in correctly selecting the intended referent $o_{\text{small\_blue}}$ in response to observing the sufficient *small* and the redundant *small blue* utterances.

	deterministic (simple)			deterministic (complex)			non-deterministic		
	$o_{\text{big\_blue}}$	$o_{\text{big\_red}}$	$o_{\text{small\_blue}}$	$o_{\text{big\_blue}}$	$o_{\text{big\_red}}$	$o_{\text{small\_blue}}$	$o_{\text{big\_blue}}$	$o_{\text{big\_red}}$	$o_{\text{small\_blue}}$
big	.5	.5	0	.5	.5	0	.44	.44	.11
small	0	0	1	0	0	**1**	.17	.17	**.67**
blue	.5	0	.5	.5	0	.5	.50	.01	.50
red	0	1	0	0	1	0	.01	.99	.01
big blue	NA	NA	NA	1	0	0	.79	.01	.20
big red	NA	NA	NA	0	1	0	.01	.99	.00
small blue	NA	NA	NA	0	0	**1**	.20	.00	**.80**

simple utterances is highly dubious (see also the discussion of cost functions in Krahmer, van Erk, & Verleg, 2003, who explicitly introduce this monotonicity constraint as a constraint on the search space of possible referring expressions within a graph-based framework). Even if it wasn't dubious, as mentioned previously proportions of overinformative referring expressions are variable across experiments. The only way to achieve that variability under the basic model is to assume that the costs of utterances vary from task to task. This also seems to us an implausible assumption. Thus we must look elsewhere to account for overinformativeness. We propose that the place to look is the computation of informativeness itself.

2.2 RSA with continuous semantics – emergent color-size asymmetry

Here we introduce the crucial innovation: rather than assuming a deterministic Boolean semantics that returns true (1) or false (0) for any combination of expression and object, we relax to a continuous semantics that returns real values in the interval $[0, 1]$. Formally, the only change is in the values that the lexicon can return:

$$\mathcal{L}(u, o) \in [0, 1] \subset \mathbb{R} \tag{6}$$

That is, rather than assuming that an object is unambiguously big (or not) or unambiguously blue (or not), this continuous semantics captures that objects count as big or blue to varying degrees (similar to approaches in fuzzy logic, prototype theory, and recent developments in NLP; Zadeh,

1965; Rosch, 1973; Bernardy et al., 2018).

Another approach to relaxing the deterministic Boolean semantics would be to relax the determinism. That is, to assume a semantics which is fundamentally Boolean, but whose truth-values contain an element of randomness. (Or even a fully deterministic Boolean semantics with intensional parameters that are themselves random variables.) This is appealing because if would clearly preserve the existing machinery of (truth-functional) compositional semantics. It can be shown that using continuous semantic values in the RSA model is equivalent to using Boolean values that are chosen non-deterministically. Conversely, marginalizing over the randomness in a Boolean semantics yields a probability of truth, which is a value between 0 and 1. For this reason we will sometimes refer to the relaxed semantics as a "noisy" semantics, and the deviation of the semantic value from 0 or 1 as the degree of noise. We will generally treat the relaxed semantics in its continuous value guise, as it simplifies exposition and development.

To see the basic effect of switching to a continuous semantics, and to see how far we can get in capturing overinformativeness patterns with this change, let us explore a simple semantics in which all colors are treated the same, all sizes are as well, and the two compose via a product rule. That is, when an object o is in the extension of a size adjective under a Boolean semantics – i.e., when the size can be truthfully predicated of o – we take $\mathcal{L}(u, o) = x_{\text{size}}$, a constant; when it is not in the extension of the adjective – i.e., when the size cannot be truthfully predicated of o – $\mathcal{L}(u, o) = 1 - x_{\text{size}}$. Similarly for color adjectives. This results in two free model parameters, x_{size} and x_{color}, that can take on different values, capturing that size and color adjectives may apply more or less well/reliably to objects. Together with the product composition rule, Eq. 5, this fully specifies a relaxed semantic function for our reference domain.[11]

Now consider the RSA literal listener, Eq. 1, who uses these relaxed semantic values. Given an utterance, the listener simply normalizes over potential referents. As an example, the resulting renormalized literal listener distributions for the size-sufficient example context in Figure 1a are shown for values $x_{\text{size}} = .8$ and $x_{\text{color}} = .99$ on the right in Table 2.[12] Recall that in this context, the speaker intends for the listener to select the small blue pin. To see which would be the best

[11] An interactive toy version of this model is provided at `http://forestdb.org/models/overinf.html`.

[12] These values were chosen for the demonstration because they are the ones that result in the best approximation of the proportion of redundant referring expressions reported in van Gompel et al. (2019): 80% in size-sufficient contexts; 8% in color-sufficient contexts.

utterance to produce for this purpose, we compare the literal listener probabilities in the $o_{\text{small\_blue}}$ column. The two best utterances under both the Boolean and the continuous semantics are bolded in the table: under the Boolean semantics, the two best utterances are *small* and *small blue*, with no difference in listener probability. In contrast, under the continuous semantics *small* has a smaller literal listener probability (.67) of retrieving the intended referent than the redundant *small blue* (.80). Consequently, the pragmatic speaker will be more likely to produce *small blue* than *small*, though the precise probabilities depend on the cost and informativeness parameters β_c and β_i.

Crucially, the reverse is not the case when color is the distinguishing dimension. Imagine the speaker in the same context wanted to communicate the big red pin. The two best utterances for this purpose are *red* (.99) and *big red* (.99). In contrast to the results for the small blue pin, these utterances do not differ in their capacity to direct the literal listener to the intended referent. The reason for this is that we defined color to be almost noiseless, with the result that the literal listener distributions in response to utterances containing color terms are more similar to those obtained via a Boolean semantics than the distributions obtained in response to utterances containing size terms. The reader is encouraged to verify this by comparing the row-wise distributions under the Boolean and continuous semantics in Table 2.

To gain a wider understanding of the effects of assuming continuous meanings in contexts like that depicted in Figure 1a, we visualize the results of varying x_{size} and x_{color} in Figure 4. To orient the reader to the graph: the Boolean semantics of utterances is approximated where the semantic values of both size and color utterances are close to 1 (.999, top right-most point in graph). In this case, the simple sufficient (*small pin*) and complex redundant utterance (*small blue pin*) are equally likely, around .5, because they are both equally informative and utterances are assumed to have 0 cost. All other utterances are highly unlikely. The interesting question is under which circumstances, if any, the standard color-size asymmetry emerges. This is the yellow/orange/red space in the 'small blue' facet, characterized by values of x_{size} that are lower than x_{color}, with high values for x_{color}. That is, redundant utterances are more likely than sufficient utterances when the redundant dimension (in this case color) is less noisy than the sufficient dimension (in this case size) and overall is close to noiseless.

Thus, when size adjectives are noisier than color adjectives, the model produces overinformative referring expressions with color, but not with size – precisely the pattern observed in the literature

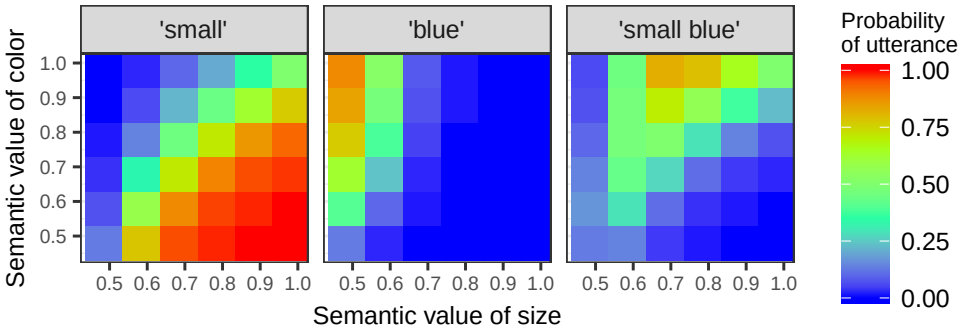


Figure 4: Probability of producing sufficient *small pin*, insufficient *blue pin*, and redundant *small blue pin* in contexts as depicted in Figure 1a, as a function of semantic value of color and size utterances (for $\beta_i = 30$ and $\beta_c = 0$). For a visualization of model behavior under varying αs, see Appendix A.

(Pechmann, 1989; Gatt et al., 2011). Note also that no difference in adjective *cost* is necessary for obtaining the overinformativeness asymmetry, though assuming a greater cost for size than for color does further increase the observed asymmetry. We defer a discussion of costs to Section 3.2, where we infer the best parameter values for both the costs and the semantic values of size and color, given data from a reference game experiment.

We defer a complete discussion of the important potential psychological and linguistic interpretation of these continuous semantic values to the General Discussion in Section 6. However, it is worth reflecting on why size adjectives may be inherently noisier than color adjectives. Color adjectives are typically treated as *absolute adjectives* while size adjectives are inherently *relative* (Pechmann, 1989; Kennedy & McNally, 2005). That is, while both size and color adjectives are vague, size adjectives are arguably context-dependent in a way that color adjectives are not – whether an object is big depends inherently on its comparison class; whether an object is red does not.[13] In addition, color as a property has been claimed to be inherently salient in a way that size is not (Arts et al., 2011; van Gompel et al., 2019). Finally, we have shown in recent work that color adjectives are rated as less subjective than size adjectives (Scontras, Degen, & Goodman, 2017). All of these suggest that the use of size adjectives may be more likely to vary across people and contexts than color.

[13]This is not entirely true, as has been repeatedly pointed out (e.g., Cohen & Murphy, 1984): red hair has a very different color than red wine, which in turn has a different color from a red bell pepper. If presented out of context, only the last red is likely to be judged as red. For our purposes, it suffices that one can give a color judgment but not a size judgment for an object presented in isolation.

To summarize, we have thus far shown that RSA with continuous adjective semantics can give rise to the well-documented color-size asymmetry in the production of overinformative referring expressions when color adjectives are closer to deterministic Boolean truth-functions than size adjectives. The crucial mechanism is that when modifiers are relaxed, adding additional, 'stricter' modifiers adds information. From this perspective, these redundant modifiers are not *over*informative; they are usefully redundant, or sufficiently informative given the needs of the listener.

2.3 RSA with continuous semantics – scene variation

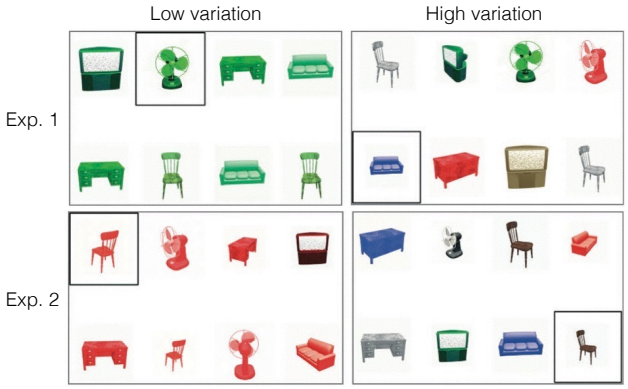
As discussed in Section 1, increased scene variation has been shown to increase the probability of referring expressions that are overmodified with color. Here we simulate the experimental conditions reported by Koolen et al. (2013) and explore the predictions that continuous semantics RSA – henceforth *cs-RSA* – makes for these situations. Koolen et al. (2013) quantified scene variation as the number of feature dimensions along which pieces of furniture in a scene varied: type (e.g., chair, fan), size (big, small), and color (e.g., red, blue).[14] Here, we simulate the high and low variation conditions from their Experiments 1 and 2, reproduced in Figure 5a.

In both conditions in both experiments, color was not necessary for establishing reference; that is, color mentions were always redundant. The two experiments differed in the dimension necessary for unique reference. In Exp. 1, only type was necessary (*fan* and *couch* in the low and high variation conditions in Figure 5a, respectively). In Exp. 2, size and type were necessary (*big chair* and *small chair* in Figure 5a, respectively). Koolen et al. (2013) found lower rates of redundant color use in the low variation conditions (4% and 9%) than in the high variation conditions (24% and 18%).

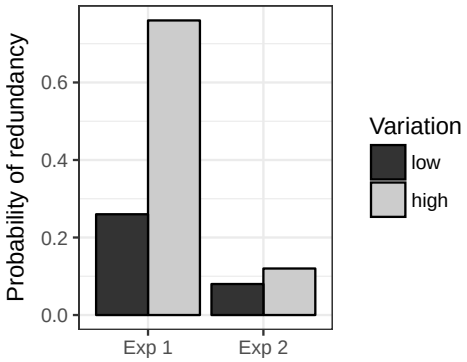
We generated model predictions for precisely these four conditions. Note that by adding the type dimension as a distinguishing dimension, we must allow for an additional semantic value x_{type}, which encodes how noisy nouns are.

Koolen et al. (2013) counted any mention of color as a redundant mention. In Exp. 1, this includes the simple redundant utterances like *blue couch* as well as complex redundant utterances

[14] They also included orientation (left-facing, right-facing) as a dimension along which objects could vary in certain cases. We ignore this dimension here for the sake of simplicity.



(a) Contexts from Koolen et al. (2013)'s low variation (left column) and high variation (right column) conditions in Exp. 1 (top row) and Exp. 2 (bottom row).



(b) Predicted probability of redundant color utterance in Koolen et al. (2013) conditions for $\beta_i = 30$, $\beta_c = c(u_{\text{size}}) = c(u_{\text{color}}) = 1$, $x_{\text{size}} = .8$, $x_{\text{color}} = .999$, $x_{\text{type}} = .9$.

Figure 5: Visual contexts employed in experiments by Koolen et al. (2013) alongside RSA model predictions for the use of redundant modifiers in those contexts.

like *small blue couch*. In Exp. 2, where size was necessary for unique reference, only the complex redundant utterance *small brown chair* was truly redundant (*brown chair* was insufficient, but still included in counts of color mention). The results of simulating these conditions with parameters $\beta_i = 30$, $\beta_c = c(u_{\text{size}}) = c(u_{\text{color}}) = 1$, $x_{\text{size}} = .8$, $x_{\text{color}} = .999$, and $x_{\text{type}} = .9$ are shown in Figure 5b, under the assumption that the cost of a two-word utterance $c(u)$ is the sum of the costs of the one-word sub-utterances.[15] For both experiments, the model exhibits the empirically-observed qualitative effect of variation on the probability of redundant color mention: when variation is greater, redundant color mention is more likely. Indeed, this effect of scene variation is predicted by the model anytime the semantic values for size, type, and color are ordered as: $x_{\text{size}} \leq x_{\text{type}} < x_{\text{color}}$. If, on the other hand, x_{type} is greater than x_{color}, the probability of redundantly mentioning color is close to zero and does not differ between variation conditions (in those cases, color mention reduces, rather than adds, information about the target).

To further explore the scene variation effect predicted by RSA, turn again to Figure 1a. Here, the target item is the small blue pin and there are two distractor items: a big blue pin and a big red pin. Thus, for the purpose of establishing unique reference, size is the sufficient dimension and color the insufficient dimension. We can measure scene variation as the proportion of distractor items that do not share the value of the insufficient feature with the target, that is, as the number

[15] These parameter values were chosen merely for convenience in illustrating the qualitative model predictions. We reused values from the previous example, where possible, but also included a cost per word.

of distractors n_{diff} that differ in the value of the insufficient feature divided by the total number of distractors n_{total}:

$$\text{scene variation} = \frac{n_{\text{diff}}}{n_{\text{total}}}$$

In Figure 1a, there is one distractor that differs from the target in color (the big red pin) and there are two distractors in total. Thus, scene variation $= \frac{1}{2} = .5$. In general, this measure of scene variation is minimal when all distractors are of the same color as the target, in which case it is 0. Scene variation is maximal when all distractors except for one (in order for the dimension to remain insufficient for establishing reference) are of a different color than the target. That is, scene variation may take on values between 0 and $\frac{n_{\text{total}}-1}{n_{\text{total}}}$.[16]

Using the same parameter values as above, we generate model predictions for size-sufficient and color-sufficient contexts, manipulating scene variation by varying number of distractors (2, 3, or 4) and number of distractors that don't share the insufficient feature value. The resulting model predictions are shown in Figure 6. The predicted probability of redundant adjective use is largely (though not completely) correlated with scene variation. Redundant adjective use increases with increasing scene variation when size is sufficient (and color redundant), but not when color is sufficient (and size redundant). The latter prediction depends, however, on the actual semantic value of color—with slightly lower semantic values for color, the model predicts small increases in redundant size use. In general: increased scene variation is predicted to lead to a greater increase in redundant adjective use for less noisy adjectives.

RSA with a continuous semantics thus captures the qualitative effects of color-size asymmetry and scene variation in production of redundant expressions, and it makes quantitative predictions for both. Testing these quantitative predictions, however, will require more data. In Sections 3, 4, and 5 we quantitatively evaluate cs-RSA on datasets capturing the phenomena described in the Introduction (Table 1): modifier type and scene variation effects on modified referring expressions, typicality effects on color mention, and the choice of taxonomic level of reference in nominal choice.

[16]Some readers might find this unintuitive: shouldn't scene variation be maximal when there is an equal number of same and different colors? Or when the different colors are also all different from one another? As discussed in the Introduction, there are many ways of quantifying (different aspects of) scene variation. We choose to explore this aspect of variation here as a reasonable first step; RSA makes predictions for other kinds of variation that would be equally straightforward to test.

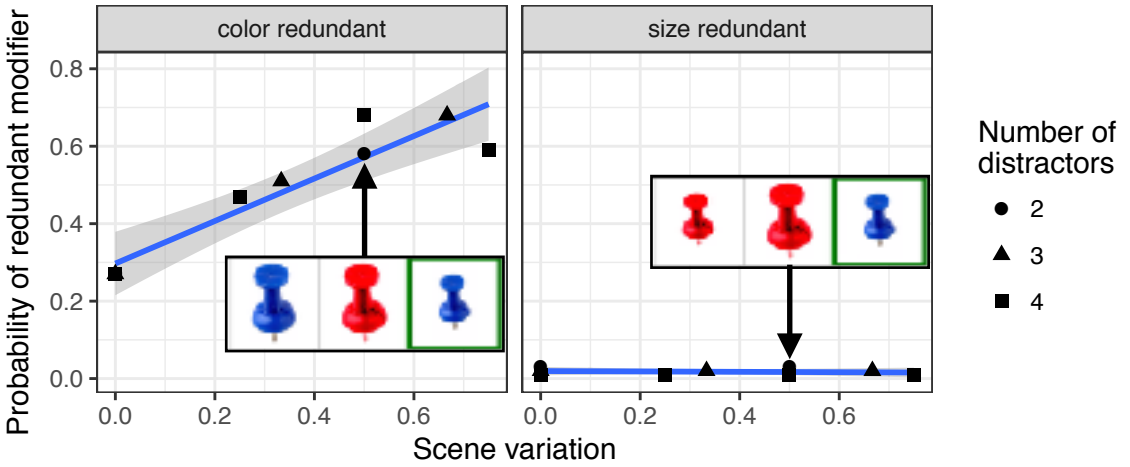


Figure 6: Predicted probability of redundant utterance (*small blue pin*) as a function of scene variation when size is sufficient (and color redundant, left) and when color is sufficient (and size redundant, right), for $\beta_i = 30$, $\beta_c = c(u_{\text{size}}) = c(u_{\text{color}}) = 1$, $x_{\text{size}} = .8$, $x_{\text{color}} = .999$. Linear smoothers overlaid.

3 Modified referring expressions: size and color modifiers under different scene variation conditions

Adequately assessing the explanatory value of RSA with continuous semantics requires evaluating how well it does at predicting the probability of various types of utterances occurring in large datasets of naturally produced referring expressions. We first report the results of a web-based interactive reference game in which we systematically manipulate scene variation (in a somewhat different way than Koolen et al. (2013) did). We then perform a Bayesian data analysis to both assess how likely the model is to generate the observed data – i.e., to obtain a measure of model quality – and to explore the posterior distribution of parameter values – i.e., to understand whether the assumed asymmetries in the adjectives' semantic values and/or cost discussed in the previous section are validated by the data.

3.1 Experiment 1: scene variation in modified referring expressions

We showed in Section 2.3 that cs-RSA correctly predicts qualitative effects of scene variation on redundant adjective use. In particular, we showed that color is more likely to be used redundantly when objects vary along more dimensions. To test the model predictions, we conducted an interactive web-based production study within a reference game setting. Speakers and listeners were

shown arrays of objects that varied in color and size. Speakers were asked to produce a referring expression to allow the listener to identify a target object. We manipulated the number of distractor objects in the grid, as well as the variation in color and size among distractor objects.

3.1.1 Method

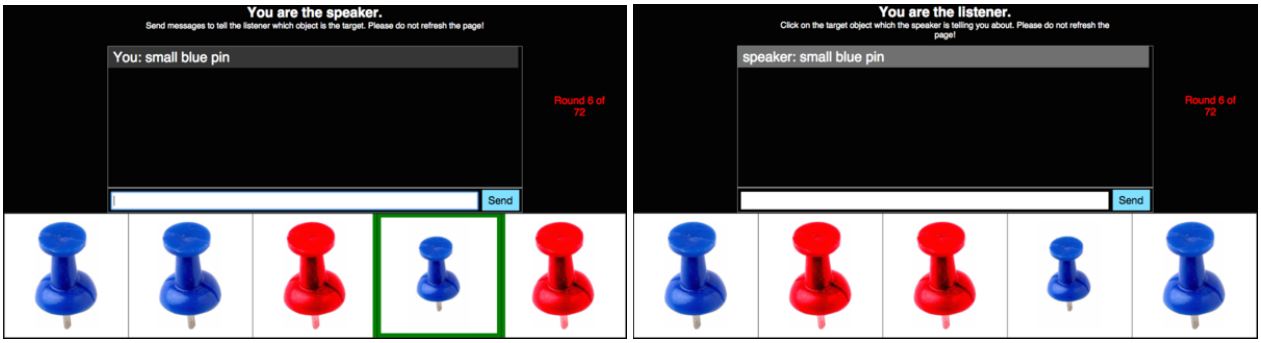
Participants We recruited 58 pairs of participants (116 participants total) over Amazon's Mechanical Turk who were each paid $1.75 for their participation.[17] Data from another 7 pairs who prematurely dropped out of the experiment and who could therefore not be compensated for their work, were also included. Here and in all other experiments reported in this paper, participants' IP address was limited to US addresses and only participants with a past work approval rate of at least 95% were accepted.

Procedure Participants were paired up through a real-time multi-player interface (Hawkins, 2015). For each pair, one participant was assigned the speaker role and one the listener role. They initially received written instructions that informed participants that one of them would be the Speaker and the other the Listener. They were further told that they would see some number of objects on each round and that the speaker's task is to communicate one of those objects, marked by a thick border, to the listener. They were explicitly told that using locative modifiers (like *left* or *right*) would be useless because the order of objects on their partner's screen would be different than on their own screen. Before continuing to the experiment, participants were required to correctly answer a series of questions about the experimental procedure. These questions are listed in Appendix B.

On each trial participants saw an array of objects. The array contained the same objects for both speaker and listener, but the order of objects was randomized and was typically different for speaker and listener. In the speaker's display, one of the objects – henceforth the *target* – was highlighted with a thick border. See Figure 7 for an example of the listener's and speaker's view on a particular trial.

The speaker produced a referring expression to communicate the target to the listener by typing into an unrestricted chat window. After pressing Enter or clicking the 'Send' button, the speaker's

[17] We aim to pay Mechanical Turk workers at a rate of $12 - $14.



(a) Speaker's perspective. (b) Listener's perspective.

Figure 7: Example displays from the (a) speaker's and the (b) listener's perspective on a *size-sufficient 4-2* trial.

message was shown to the listener. The listener then clicked on the object they thought was the target, given the speaker's message. Once the listener clicked on an object, a red border appeared around that object in both the listener and the speaker's display for 1 second before advancing to the next trial. That is, both participants received feedback about whether the intended referent was selected. This was done in order to allow participants to notice if their referential strategies weren't working, in which case they could self-correct or discuss what had gone wrong. Both speakers and listeners could write in the chat window, allowing listeners to request clarification if necessary. Listeners could only click on an object to advance to the next trial once the speaker sent an initial message.

At the end of the experiments, participants completed a questionnaire in which they indicated whether their native language was English, whether they thought their partner was human, and whether they liked their partner.

Materials Participants proceeded through 72 trials. Of these, half were critical trials of interest and half were filler trials. On critical trials, we varied the feature that was sufficient to mention for uniquely establishing reference, the total number of objects in the array, and the number of objects that shared the insufficient feature with the target.

Objects varied in color and size. On 18 trials, color was sufficient for establishing reference. On the other 18 trials, size was sufficient. Figure 7 shows an example of a size-sufficient trial. We further varied the amount of variation in the scene by varying the number of distractor objects in each array (2, 3, or 4) and the number of distractors that did share the redundant feature value

with the target. That is, when size was sufficient, we varied the number of distractors that shared the same color as the target. This number had to be at least one, since otherwise the redundant property would have been sufficient for uniquely establishing reference, i.e. mentioning it would not have been redundant. Each total number of distractors was crossed with each possible number of distractors that shared the redundant property, leading to the following nine conditions: *2-1, 2-2, 3-1, 3-2, 3-3, 4-1, 4-2, 4-3,* and *4-4*, where the first number indicates the total number and the second number the shared number of distractors. Each condition occurred twice with each sufficient dimension. Objects never differed in type within one array (e.g., all objects are pins in Figure 7) but always differed in type across trials. Each object type could occur in two different sizes and two different colors. We used photo-realistic objects of intuitively fairly typical colors. The 36 different object types and the colors they could occur with are listed in Appendix C.

Fillers were target trials from Exp. 2, a replication of Graf, Degen, Hawkins, and Goodman (2016). Each filler item contained a three-object grid. None of the filler objects occurred on target trials. Objects stood in various taxonomic relations to each other and required neither size nor color mention for unique reference. See Section 5 for a description of these materials.

3.1.2 Data pre-processing and exclusion

We collected data from 2177 critical trials. Because we did not restrict participants' utterances in any way, they produced many different kinds of referring expressions. Testing the model's predictions required, for each trial, classifying the produced utterance as an instance of a *color*-only mention (e.g., *blue pin*), a *size*-only mention (e.g., *big pin*), or a redundant *color-and-size* mention (e.g., *big blue pin*). To this end we applied a semi-automatic data pre-processing procedure in which a script first checked whether the speaker's utterance contained a color or size term. In a second step, one of the authors (CG) manually checked and, if necessary, corrected the automatic classification. If no classification was possible, the trial was excluded. After exclusions, 2076 cases entered the analysis. See Appendix D for details on the pre-processing procedure.

3.1.3 Results

Proportions of redundant *color-and-size* utterances are shown in Figure 8 alongside model predictions (to be explained further in Section 3.2). There are three main questions of interest: first, do

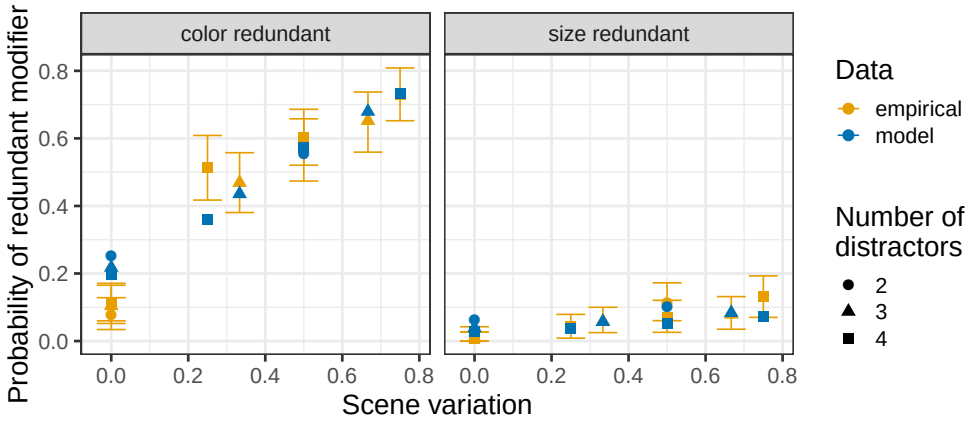


Figure 8: Empirical redundant utterance proportions (orange) alongside point-wise maximum a posteriori (MAP) estimates of the RSA model's posterior predictives for redundant utterance probability (blue) as a function of scene variation in the color redundant (left) and size redundant (right) condition. Here and in all following plots, error bars indicate 95% bootstrapped confidence intervals.

we replicate the color/size asymmetry in probability of redundant adjective use? Second, do we replicate the previously established effect of increased redundant color use with increasing scene variation? Third, is there an effect of scene variation on redundant size use and if so, is it smaller compared to that on color use, as is predicted under asymmetric semantic values for color and size adjectives?

We addressed all of these questions by conducting a single mixed effects logistic regression analysis predicting redundant over minimal adjective use from fixed effects of sufficient property (color vs. size), scene variation (proportion of distractors that do not share the insufficient property value with the target), and the interaction between the two.[18] All predictors were centered before entering the analysis. The model included the maximal random effects structure that allowed the model to converge: by-speaker and by-item random intercepts.

We observed a main effect of sufficient property, such that speakers were more likely to redundantly use color than size adjectives ($\beta = 3.54$, $SE = .22$, $p < .0001$), replicating the much-documented color-size asymmetry. We further observed a main effect of scene variation, such that redundant adjective use increased with increasing scene variation ($\beta = 4.62$, $SE = .38$, $p < .0001$). Finally, we also observed a significant interaction between sufficient property and scene variation

[18] All mixed effects analyses reported in this paper were conducted with the `lme4` package (Bates, Mächler, Bolker, & Walker, 2015) in R (R Core Team, 2017).

($\beta = 2.26$, $SE = .74$, $p < .003$). Simple effects analysis revealed that the interaction was driven by the scene variation effect being smaller in the *color-sufficient* condition ($\beta = 3.49$, $SE = .65$, $p < .0001$) than in the *size-sufficient* condition ($\beta = 5.75$, $SE = .38$, $p < .0001$), as predicted if size modifiers are noisier than color modifiers. That is, while the *color-sufficient* condition indeed showed a scene variation effect—and as far as we know, this is the first demonstration of an effect of scene variation on redundant size use—this effect was tiny compared to that of the *size-sufficient* condition.[19]

3.2 Model evaluation

In order to evaluate RSA with continuous semantics we conducted a Bayesian data analysis. This allowed us to simultaneously generate model predictions and infer likely parameter values, by conditioning on the observed production data (coded into *size*, *color*, and *size-and-color* utterances as described above) and integrating over the five free parameters. To allow for differential costs for size and color, we introduce separate cost weights ($\beta_{c(\text{size})}, \beta_{c(\text{color})}$) applying to size and color mentions, respectively, in addition to semantic values for color and size (x_{color}, x_{size}) and an informativeness parameter β_i. We assumed uniform priors for each parameter: $x_{\text{color}}, x_{\text{size}} \sim \mathcal{U}(0, 1)$, $\beta_{c(\text{size})}, \beta_{c(\text{color})} \sim \mathcal{U}(0, 40)$, $\beta_i \sim \mathcal{U}(0, 40)$. Inference for the cognitive model was exact. We used Markov Chain Monte Carlo (MCMC) with a burn-in of 10000 and lag of 10 to draw 2000 samples from the joint posteriors on the five free parameters.

Point-wise maximum a posteriori (MAP) estimates of the model's posterior predictives for just redundant utterance probabilities are shown alongside the empirical data in Figure 8. In addition, MAP estimates of the model's posterior predictives for each combination of utterance, sufficient dimension, number of distractors, and number of different distractors (collapsing across different items) are plotted against all empirical utterance proportions in Figure 9. At this level, the model

[19] In order to address convergence issues with `lmer` when specifying the full random effects structure – i.e., by-speaker and by-item random intercepts and slopes for all fixed effects and their interactions – we ran a Bayesian binomial mixed effects model with weakly informative priors using the `brms` package (Bürkner, 2017) that included the same fixed effects structure as the lmer model and the full random effects structure. The results were qualitatively identical, yielding evidence for main effects of redundant feature (posterior mean $\beta = 5.91$, 95% CI = [4.15,8.10], $p(\beta > 0) = .98$), scene variation (posterior mean $\beta = 6.18$, 95% CI = [4.30,8.24], $p(\beta > 0) = 1$), and their interaction (posterior mean $\beta = 3.31$, 95% CI = [-0.54,7.23], $p(\beta > 0) = .96$).

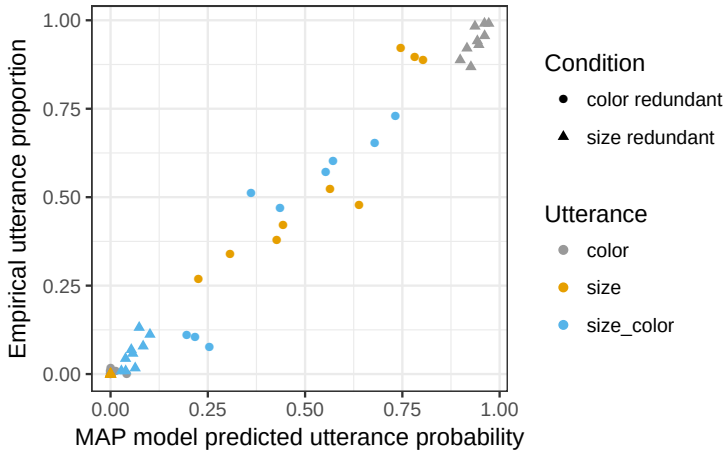


Figure 9: Scatterplot of empirical utterance proportions against point-wise maximum a posteriori (MAP) estimates of the RSA model's posterior predictives. Each dot represents a condition mean.

achieves a correlation of $r = .99$. Looking at results additionally on the by-item level yields a correlation of $r = .85$ (this correlation is expected to be lower both because each item contains less data, and because we did not provide the model any means to refer differently to, e.g., *combs* and *pins*). The model thus does a very good job of capturing the quantitative patterns in the data.

Posteriors over parameters are shown in Figure 10. Crucially, the semantic value of color is inferred to be higher than that of size – there is no overlap between the 95% highest density intervals (HDIs) for the two parameters. That is, size modifiers are inferred to be noisier than color modifiers. The high inferred β_i (MAP $\beta_i = 31.4$, HDI = [30.7,34.5]) suggests that this difference in semantic value contributes substantially to the observed color-size asymmetries in redundant adjective use and that speakers are maximizing quite strongly. As for cost, there is a lot of overlap in the inferred weights of size and color modifiers, which are both skewed very close to zero, suggesting that a cost difference (or indeed any cost at all) is neither necessary to obtain the color-size asymmetry and the scene variation effects, nor justified by the data. Recall further that we already showed in Section 2.2 that the color-size asymmetry in redundant adjective use requires an asymmetry in semantic value and cannot be reduced to cost differences. An asymmetry in cost only serves to further enhance the asymmetry brought about by the asymmetry in semantic value, but cannot carry the redundant use asymmetry on its own.

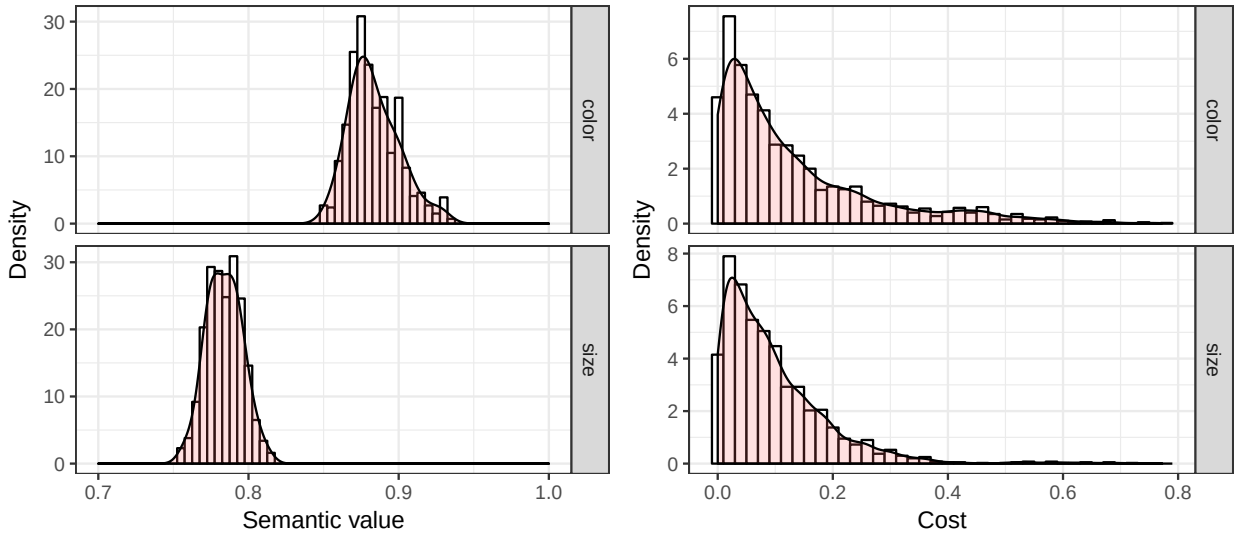


Figure 10: Posterior model parameter distributions for semantic value (left column) and cost (right column), separately for color (top row) and size (bottom row) modifiers. Maximum a posteriori (MAP) $x_{\text{size}} = 0.79$, 95% highest density interval (HDI) = [0.76,0.80]; MAP $x_{\text{color}} = 0.88$, HDI = [0.85,0.92]; MAP $\beta_{c(\text{size})} = .02$, HDI = [0, 0.26]; MAP $\beta_{c(\text{color})} = 0.03$, HDI = [0,0.45].

3.3 Discussion

In this section we reported the results of a dataset of freely collected referring expressions that replicated the well-documented color-size asymmetry in redundant adjective use, the effect of scene variation on redundant color use, and showed a novel effect of scene variation on redundant size use. We also showed that cs-RSA provides an excellent fit to these data. In particular, the crucial element in obtaining the color-size asymmetry in overmodification is that size adjectives be noisier than color adjectives, captured in RSA via a lower semantic value for size compared to color. The effect is that color adjectives are more informative than size adjectives when controlling for the number of distractors that each would rule out under a Boolean semantics. Asymmetries in the cost of the adjectives were not attested, and would only serve to further enhance the modification asymmetry resulting from the asymmetry in semantic value. In addition, we showed that asymmetric effects of scene variation on overmodification straightforwardly fall out of cs-RSA: scene variation leads to a greater increase in overmodification with less noisy than with more noisy modifiers because the less noisy modifiers (colors) on average provide more information about the target.

These results raise interesting questions regarding the status of the inferred semantic values: do color modifiers have inherently higher semantic values than size modifiers? Is the difference

constant? What if the color modifier is a less well known one like *mauve*? The way we have formulated the model thus far, there would indeed be no difference in semantic value between *red* and *mauve*. Moreover, the model is not equipped to handle potential object-level idiosyncracies such as the typicality effects discussed in Section 1.2.3. We defer a fuller discussion of the status of the semantic value term to the General Discussion (Section 6.5) and turn first to cs-RSA's potential for capturing these typicality effects.

4 Modified referring expressions: color typicality

In Section 3 we showed that cs-RSA successfully captures both the basic asymmetry in overmodification with color vs. size as well as effects of scene variation on overmodification. In Section 1.2.3 we discussed a further characteristic of speakers' overmodification behavior: speakers are more likely to redundantly produce modifiers that denote atypical rather than typical object features, i.e., they are more likely to refer to a blue banana as a *blue banana* rather than as a *banana*, and they are more likely to refer to a yellow banana as a *banana* than as a *yellow banana* (Sedivy, 2003; Westerbeek et al., 2015). So far we have not included any typicality effects in the semantics of our RSA model, hence the model so far would not capture this asymmetry.

A natural first step is to introduce a more nuanced semantics for nouns in our model. In particular, we could imagine a continuous semantics in which *banana* fits better (i.e. has a semantic value closer to 1 for) the yellow banana than the brown, and fits the brown better than the blue; specific such hypothetical values are shown in the first row of Table 3. Let us further assume that modifying the noun with a color adjective leads to uniformly high semantic values close to 1 for those objects that a simple truth-conditional semantics would return 'true' for (see diagonal in Table 3) and a very low semantic value close to 0 for any utterance applied to any object that a simple truth-conditional semantics would return 'false' for.

The effect of running the speaker model forward with the standard literal listener treatment of the values in Table 3 for the three contexts in Figure 11, where *banana* is the strictly sufficient utterance for unique reference (i.e., color is redundant under the standard view) is as follows: with $\beta_i = 12$ and $\beta_c = 5$,[20] the resulting speaker probabilities for the minimal utterance *banana* are .95,

[20]The results hold qualitatively for any informativeness weight > 1 and any cost weight > 0.

Table 3: Hypothetical semantic values for utterances (rows) as applied to objects (columns). Values where a Boolean semantics would return 'true' are bolded.

	yellow banana	brown banana	blue banana	other
banana	**.9**	**.35**	**.1**	.01
yellow banana	**.99**	.01	.01	.01
brown banana	.01	**.99**	.01	.01
blue banana	.01	.01	**.99**	.01
other	.01	.01	.01	**.99**

(a) Typical color. (b) Mid-typical color. (c) Atypical color.

Figure 11: Three hypothetical contexts where color is redundant for referring to the target banana. Banana varies in typicality from left to right. Each context contains one distractor of the same color as the target, and one of a different color.

.29, and .04, to refer to the yellow banana, the brown banana, and the blue banana, respectively. In contrast, the resulting speaker probabilities for the redundant *yellow banana*, *brown banana*, and *blue banana* are .05, .71, and .96, respectively. That is, redundant color mention increases with decreasing semantic value of the simple *banana* utterance.

This shows that cs-RSA can predict typicality effects if the semantic fit of the noun (and hence also of color-noun compounds) to an object is modulated by typicality. The reason the typicality effect arises is that, with the hypothetical values we assumed, the gain in informativeness between using the unmodified *banana* and the modified *COLOR banana* is greater in the blue than in the yellow banana case.

This example is somewhat oversimplified. In practice, speakers sometimes mention an object's color without mentioning the noun. In the contexts presented in Figure 11 this does not make much sense because there is always a competitor of the same color present. In contrast, in the contexts in Figure 13a and Figure 13c, color alone disambiguates the target. This suggests that we should consider among the set of utterance alternatives not just the simple type mentions (e.g., *banana*) and color-and-type mentions (e.g., *yellow banana*), but also simple color mentions (e.g., *yellow*). The dynamics of the model proceed as before.

An additional, more theoretically fraught, simplification concerns where typicality can enter into

the semantics and how compositions proceeds. In the above, we have assumed that the semantic value of the modified expression is uniformly high, which is qualitatively what is necessary (and, as we will see below, empirically correct) in order for the typicality effects to emerge. However, there is no straightforward way to compositionally derive such uniformly high values from the semantic values of the nouns and the semantic values of the color modifiers, which we have not yet discussed. Indeed, compositional semantics of graded meanings is a well known problem for theories of modification (Kamp & Partee, 1995; Osherson & Smith, 1981). Rather than try to solve it here, we note that RSA works at the level of whole utterances. Hence, if we can reasonably measure the semantic fit of each utterance to each possible referent, then cs-RSA will make predictions for production without the need to derive the semantic values compositionally. That is, if we can measure the typicality of the phrase *blue banana* for a banana, we don't need to derive it from *blue*, *banana*, and a theory of composition. This separates pragmatic aspects of reference, which are the topic of this paper, from issues in compositional semantics, which are not; hence we will take this approach for experimentally testing the predictions of relaxed semantics RSA for typicality effects.

The stimuli for Exp. 1 were specifically designed to be realistic objects with low color-diagnosticity, so they did not include objects with low typicality values or large degrees of variation in typicality. This makes the dataset from Exp. 1 not well-suited for investigating typicality effects.[21] We therefore conducted a separate production experiment in the same paradigm but with two broad changes: first, objects' color varied in typicality; and second, we did not manipulate object size, focusing only on color mention. This allows us to ask three questions: first, do we replicate the typicality effects reported in the literature – that is, are less color-typical objects more likely to lead to redundant color use than more color-typical objects? Second, does cs-RSA with empirically elicited typicality values as proxy for a continuous semantics capture speakers' behavior? Third, does the semantic value depend only on typicality, or is there still a role for modifier type noise of the kind we investigated in the previous section? In addition, we can investigate the extent to which utterance cost, which we found not to play a role in the previous section, affects the choice of referring expression.

[21] We did elicit typicality norms for the items in Exp. 1 and replicated the previously documented typicality effects on the four items that did exhibit variation in typicality. See Appendix E for details.

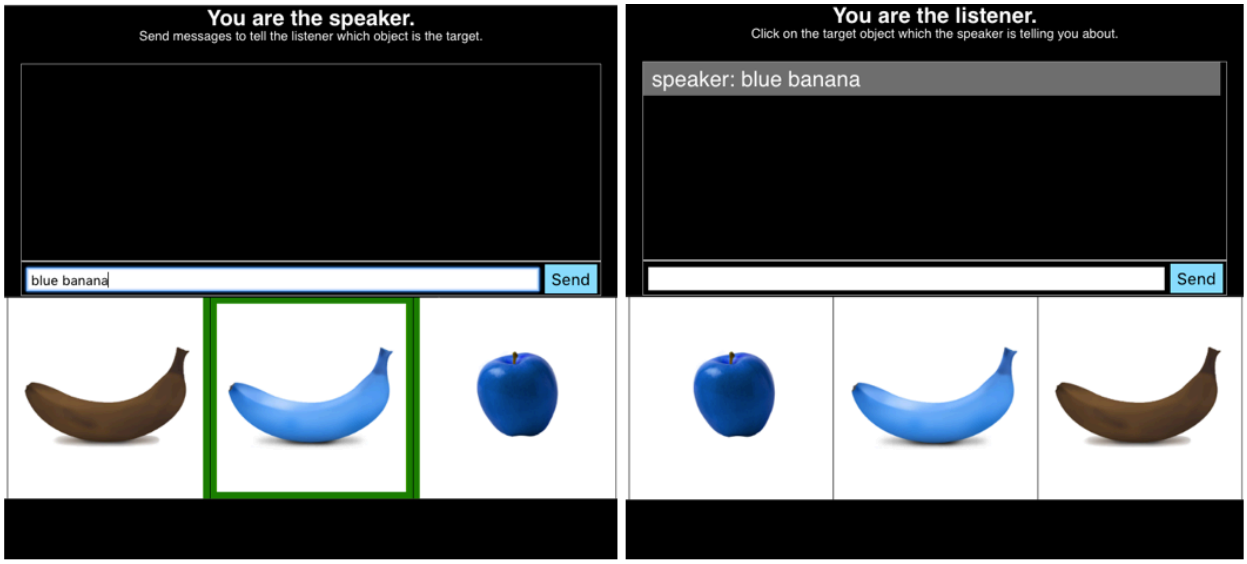


Figure 12: Example displays from the speaker's (left) and listener's (right) perspective in an informative-cc (i.e., presence of another object of the same type and one with the same color) condition.

4.1 Experiment 2: color typicality effects

4.1.1 Method

Participants We recruited 61 pairs of participants (122 participants total) over Amazon's Mechanical Turk who were each paid $1.70 for their participation.

Procedure The procedure was identical to that of Exp. 1. See Figure 12 for an example speaker and listener perspective.

Materials Each participant completed 42 trials. In this experiment, there were no filler trials, since pilot studies with and without fillers delivered very similar results. Each array presented to the participants consisted of three objects that could differ in type and color. One of the three objects functioned as a target and the other two as its distractors.

The stimuli were selected from seven color-diagnostic food items (apple, avocado, banana, carrot, pear, pepper, tomato), which all occurred in a typical, mid-typical and atypical color for that object. For example, the banana appeared in the colors yellow (typical), brown (midtypical), and blue (atypical). All items were presented as targets and as distractors. Pepper additionally occurred in a fourth color, which only functioned as a distractor due to the need for a green color

(a) informative (without color competitor)

(b) informative-cc (with color competitor)

(c) overinformative (without color competitor)

(d) overinformative-cc (with color competitor)

Figure 13: Examples of the four different context conditions in Exp. 2. They differed in the presence of an object of the same type (informative vs. overinformative) and in the presence of another object of the same color as the target (with color competitor vs. without color competitor). The thick border marks the intended referent.

competitor (as explained in the following paragraph).

We refer to the different context conditions as "informative", "informative-cc", "overinformative", and "overinformative-cc" (see Figure 13). A context was "overinformative" (Figure 13c) when mentioning the type of the item, e.g., banana, was sufficient for unambiguously identifying the target. In this condition, the target never had a color competitor. This means that mentioning color alone (without a noun) was also unambiguously identifying. In contrast, in the overinformative condition with a color competitor ("overinformative-cc", Figure 13d), color alone was not sufficient. In the informative conditions, color and type mention were necessary for unambiguous reference. Again, one context type did (Figure 13a) and one did not (Figure 13d) include a color competitor among its distractors.

Each participant saw 42 different contexts. Each of the 21 items (color-type combinations) was the target exactly twice, but the context in which they occurred was drawn randomly from the four possible conditions mentioned above. In total, there were 84 different possible configurations (seven target food items, each of them in three colors, where each could occur in four contexts). Trial order was randomized.

4.1.2 Data pre-processing and exclusion

We collected data from 1974 trials. The utterance produced on each trial was classified as belonging to one of the following categories: *type-only* (e.g., *banana*), *color-and-type* (e.g., *yellow banana*),

and *color-only* (e.g., *yellow*). Referring expressions that could not be classified were excluded. See Appendix D for further details on exclusion criteria and the data pre-processing procedure. Overall, 1827 utterances entered the analysis.

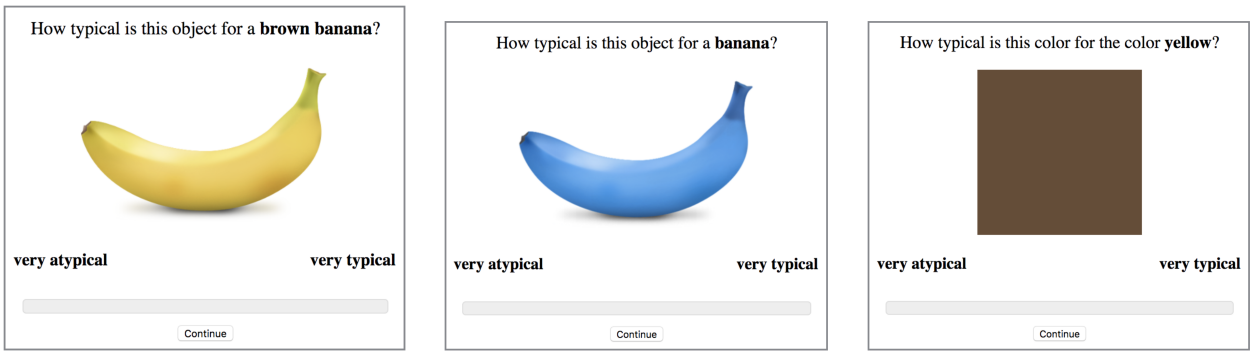
4.1.3 Typicality norming

In order to test for typicality effects on the production data and to evaluate cs-RSA's performance, we collected empirical typicality values for each utterance/object pair in three separate studies. The first study collected typicalities for *color-and-type*/object pairs (e.g., *yellow banana* as applied to a yellow banana, a blue banana, an orange pear, etc., see Figure 14a). The second study collected typicalities for *type-only*/object pairs (e.g., *banana* as applied to a yellow banana, a blue banana, an orange pear, etc., Figure 14b). The third study collected typicalities for *color*/color pairs (e.g., *yellow* as applied to a color patch of the average yellow from the yellow banana stimulus or to a color patch of the average orange from the orange pear stimulus, and so on, for all other colors, Figure 14c).

On each trial of the *type* or *color-and-type* studies, participants saw one of the stimuli used in the production experiment in isolation and were asked: "How typical is this object for a *utterance*", where *utterance* was replaced by an utterance of interest. In the *color* typicality study, they were asked "How typical is this color for the color *color*?", where *color* was replaced by one of the relevant color terms. They then adjusted a continuous sliding scale with endpoints labeled "very atypical" and "very typical" to indicate their response. A summary of the the three typicality norming studies is shown in Table 4.[22]

Slider values were coded as falling between 0 ('very atypical') and 1 ('very typical'). For each utterance-object combination, we computed mean typicality ratings. As an example, the means for the banana items and associated color patches are shown in Table 5. The values exhibit the same gradient as those hypothesized for the purpose of the example in Table 3. The means for all

[22]The typicality elicitation procedure we employed here is somewhat different from that employed by Westerbeek et al. (2015), who asked their participants "How typical is this color for this object?" We did this because the semantic values that enter into the RSA model are best conceptualized as the typicality of an object as an instance of an utterance, rather than a feature-category relation. See Appendix E for a comparison of our question and the Westerbeek question as applied to typicality norms for the items in Exp. 1. In general, the TYPE-object values are highly correlated with the Westerbeek question values.



(a) color-and-type norming. (b) type-only norming. (c) color-only norming.

Figure 14: Example stimuli exemplifying the three different typicality norming studies.

Utterances	Example	Images	Participants	Trials	Items	Excluded participants
Adj Noun	*yellow banana*	object	174	110	484	14
Noun	*banana*	object	75	90	154	1
Adj	*yellow*	color patch	110	90	176	None

Table 4: Overview of the typicality norming studies for Exp. 2. Column 'Items' contains the number of unique utterance-object pairs that we elicited responses for.

Table 5: Mean typicalities for banana items. Combinations where Boolean semantics would return 'true' are marked in boldface.

	Banana items			Other
Utterance	yellow	brown	blue	
banana	**.98**	**.66**	**.42**	.05
yellow banana	**.97**	.30	.15	.05
brown banana	.22	**.91**	.15	.04
blue banana	.16	.15	**.92**	.06
yellow	**.77**	.05	.06	.09
brown	.11	**.87**	.01	.12
blue	.06	.06	**.92**	.07

items are visualized in Figure 15. Mean typicality values for utterance-object pairs obtained in the norming studies are used in the analyses and visualizations in the following.

4.1.4 Results and discussion

Proportions of type-only (*banana*), color-and-type (*yellow banana*), color-only (*yellow*), and other (*funky carrot*) utterances are shown in Figure 16a as a function of the described item's mean

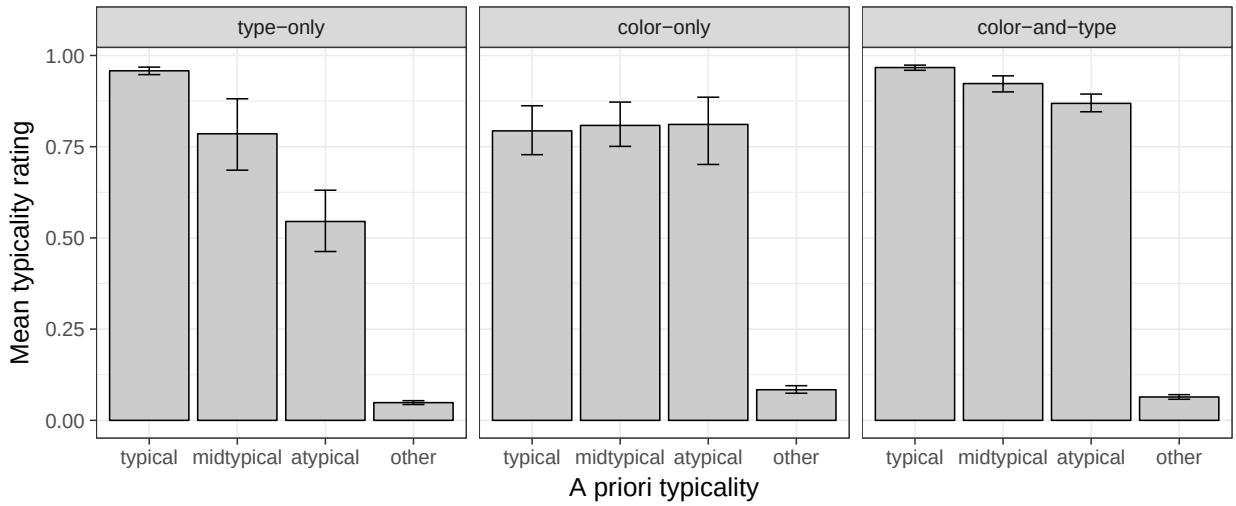
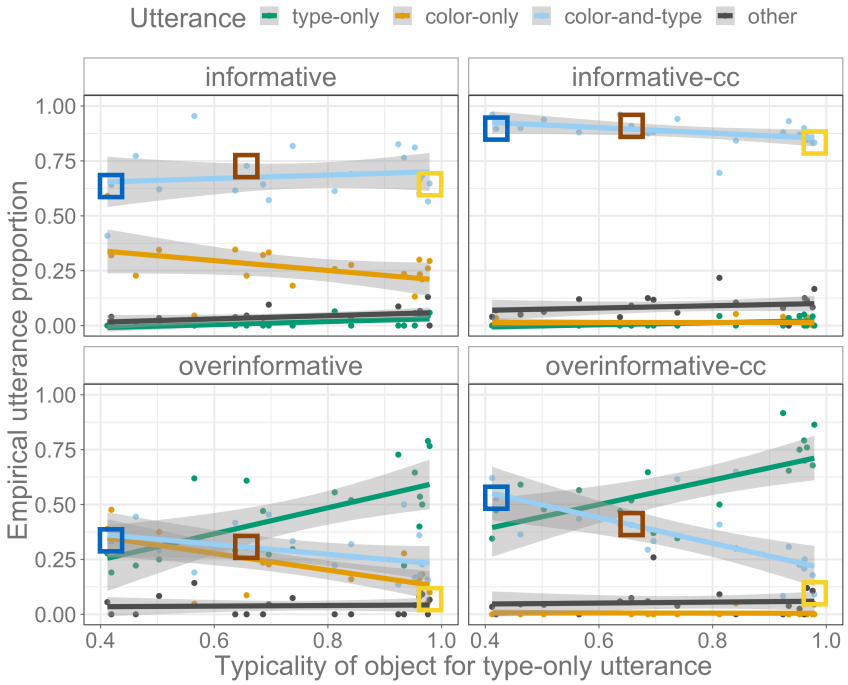


Figure 15: Mean typicality ratings for the three norming studies (type-only, color-only, color-and-type). The results are categorized according to the objects' a priori typicality as determined by the experimenters (yellow banana = typical, brown banana = midtypical, blue banana = atypical). The category *other* comprises all utterance-object combinations where a Boolean semantics would return false (e.g. a pepper). Error bars indicate bootstrapped 95% confidence intervals.

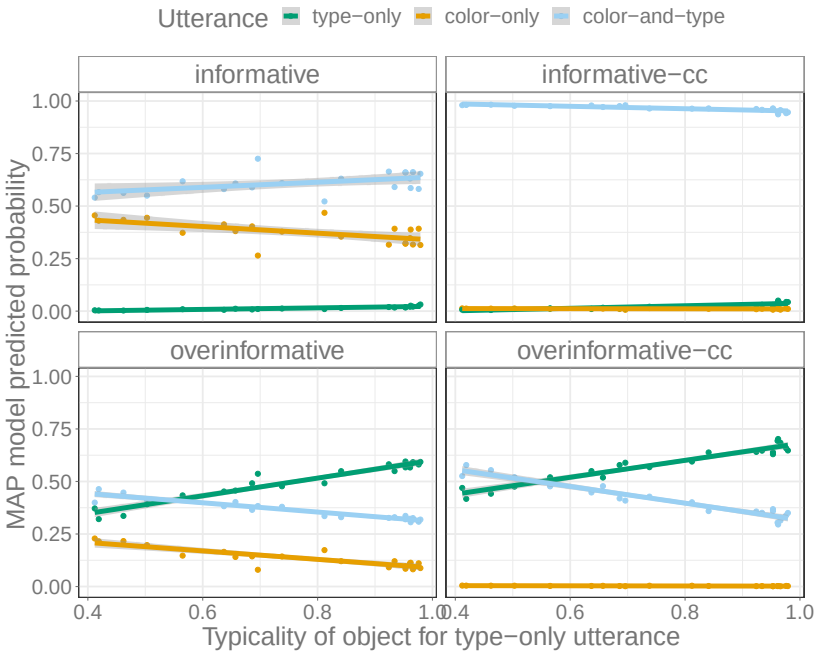
type-only (*banana*) typicality. Visually inspecting just the explicitly marked *yellow banana*, *brown banana*, and *blue banana* cases suggests a large typicality effect in the overinformative conditions as well as a smaller typicality effect in the informative conditions, such that color is less likely to be produced with increasing typicality of the object.

The following questions are of interest. First, do we replicate the previously documented typicality effect on redundant color mention (as suggested by the visual inspection of the banana item)? Second, does typicality affect color mention even when color is informative (i.e., technically necessary for establishing unique reference)? Third, are speakers sensitive to the presence of color competitors in their use of color or are typicality effects immune to the nature of the distractor items?

To address these questions we conducted a mixed effects logistic regression predicting color use from fixed effects of typicality, informativeness, and color competitor presence. We used the typicality norms obtained in the *type*/object typicality elicitation study reported above (see Figure 14b) as the continuous typicality predictor. The informativeness condition was coded as a binary variable (color informative vs. color overinformative trial) as was color competitor presence (absent vs. present). All predictors were centered before entering the analysis. The model included by-speaker and by-item random intercepts, which was the maximal random effects structure that



(a) Empirical utterance proportions



(b) MAP model predicted utterance probabilities

Figure 16: (a) Empirical utterance proportions in Exp. 2 and (b) MAP model predicted utterance probabilities for each target as a function of mean object typicality for the type-only utterance (e.g., *banana*). Color indicates utterance type: type-only (*banana*), color-only (*yellow*), color-and-type (*yellow banana*), and other (*funky carrot*). Facets indicate conditions. Modified utterance data points for the banana items are circled in the banana's respective color in (a).

allowed the model to converge.

There was a main effect of typicality, such that the more typical an object was for the type-only utterance, the lower the log odds of color mention (β = -4.17, SE = 0.45, $p < .0001$), replicating previously documented typicality effects. Stepwise model comparison revealed that including interaction terms was not justified by the data, suggesting that speakers produce more typical colors less often even when the color is in principle necessary for establishing reference (i.e., in the informative conditions). This is notable: speakers sometimes call a yellow banana simply a *banana* even when other bananas are present, presumably because they can rely on listeners drawing the inference that they must have meant the most typical banana. In contrast, blue bananas' color is always mentioned in the informative conditions.

There was also a main effect of informativeness, such that color mention was less likely when it was overinformative than when it was informative (β = -5.56, SE = 0.33, $p < .0001$). Finally, there was a main effect of color competitor presence, such that color mention was more likely when a color competitor was absent (β = 0.71, SE = 0.16, $p < .0001$). This suggests that speakers are indeed sensitive to the contextual utility of color – color typicality alone does not capture the full set of facts about color mention, as we already saw in Section 3.

4.2 Model evaluation

We evaluated the cs-RSA model on the obtained production data from Exp. 2. In particular, we were interested in using model comparison to address the following issues: First, can RSA using elicited typicality as the semantic values account for quantitative details of the production data? Second, are typicality values sufficient, or is there additional utility in including a noise offset determined by the type of modifier, as was used in the previous section? Third, does utterance cost explain any of the observed production behavior.

While the architecture of the model remained the same as that of the model presented in Section 2.2, we briefly review the minor necessary changes, some of which we already mentioned at the beginning of this section. These changes concerned the semantic values and the cost function.[23]

[23]See Table 7 for an overview of the models reported in the paper.

4.2.1 Lexicon

Whereas for the purpose of evaluating the model in Section 3 we only considered the utterance alternatives *color*, *size*, and *color-size*, collapsing over the precise attributes, here we included in the lexicon each possible color adjective, type noun, and combination of the two. This substantially increased the size of the lexicon to 37 unique utterances. For each combination of utterance u and object o that occurred in the experiment, we included a separate semantic value $x_{u,o}$, elicited in the norming experiments described in Section 4.1.3 (rather than inferred as done for Exp. 1, to avoid overfitting). For any given context, we assumed the utterance alternatives that correspond to the individually present features and their combinations. For example, for the context in Figure 13d, the set of utterance alternatives was *yellow, green, pear, banana, avocado, yellow pear, yellow banana*, and *green avocado*.

4.2.2 Semantics

We compared two choices of semantics for the model. In the *empirical semantics* version, the empirically elicited typicality values were directly used as semantic values. In the more complex *fixed plus empirical semantics* version, we introduce an additional parameter interpolating between the empirical typicality values and inferred values for each utterance type as employed in Section 3 (e.g. one value for color terms and another for type terms, which are multiplied when the terms are composed in an utterance). Note that this allows us to perform a nested model comparison, since the first model is a special case of the second.

4.2.3 Cost function

For the purpose of evaluating the model in Section 3 we inferred two constant costs (one for color and one for size), and found in the Bayesian Data Analysis that the role of cost in explaining the data was minimal at best. Here, we compared two different versions of utterance cost. In the *fixed cost* model we treated cost the same way as in the previous section and included only a color and type level cost, inferred from the data. We then compared this model to an *empirical cost model*, in which we included a more complex cost function. Specifically, we defined utterance cost $c(u)$ as follows:

$$c(u) = \beta_F \cdot p(u) + \beta_L \cdot l(u) \tag{7}$$

Here, $p(u)$ is negative log utterance frequency, as estimated from the Google Books corpus (years 1950 to 2008); $l(u)$ is the mean empirical length of the utterance in characters in the production data (e.g., sometimes *yellow* was abbreviated as *yel*, leading to an $l(u)$ smaller than 6); β_F is a weight on frequency; and β_L is a weight on length. Both $p(u)$ and $l(u)$ were normalized to fall into the interval $[0, 1]$.[24] The empirical cost function thus prefers short and frequent utterances (e.g., *blue*) over long and infrequent ones (*turquoise-ish bananaesque thing*). We compared both of these models to a simpler baseline in which utterances were assumed to have no cost.

4.2.4 Model comparison

To evaluate the effect of these choices of semantics and cost, we conducted a full Bayesian model comparison. Specifically, we computed the Bayes Factor for each comparison, a measure quantifying the support for one model over another in terms of the relative likelihood they each assign to the observed data. As opposed to classical likelihood ratios, which only use the maximum likelihood estimate, the likelihoods in the Bayes Factor integrate over all parameters, thus automatically correcting for the flexibility due to extra parameters (the "Bayesian Occam's Razor"). Because it was intractable to analytically compute these integrals for our recursive model, we used Annealed Importance Sampling (AIS), a Monte Carlo algorithm commonly used to approximate these quantities. To ensure high-quality estimates, we took the mean over 100 independent samples for each model, with each chain running for 30,000 steps. The marginal log likelihoods for each model are shown in Table 6. The best performing model used *fixed plus empirical* semantics and did not include a cost term. Despite the greater number of parameters associated with adding the fixed semantics to the empirical semantics, the *fixed plus empirical* semantics models were preferred across the board compared to their empirical-only counterparts ($BF = 3.7 \times 10^{48}$ for fixed costs, $BF = 2.1 \times 10^{60}$ for empirical costs, and $BF = 1.4 \times 10^{71}$ for no cost). In comparison, additional cost-related parameters were not justified, with $BF = 5.7 \times 10^{21}$ for no cost compared to fixed cost and $BF = 2.1 \times 10^{27}$ for compared to empirical cost.

The correlation between empirical utterance proportions and the best model's MAP predictions at the by-item level was $r = .94$. Predictions for the best-performing model are visualized alongside

[24] Note that we changed the sign on frequency, which means that values closer to 1 in the normalized space reflect greater cost on both the length and the frequency dimension.

Table 6: Marginal log likelihood for each model. Best model is in bold. Parentheses indicate number of free parameters.

		Semantics	
		empirical	*fixed plus empirical*
Cost	*empirical*	-1474.6 (4)	-1354.4 (7)
	fixed	-1434.8 (4)	-1321.9 (7)
	none	-1372.9 (2)	**-1209.8 (5)**

empirical proportions in Figure 16b. The model successfully reproduces the empirically observed typicality effects in all four experimental conditions, with a reasonably good quantitative agreement. The interpolation weight between the fixed and empirical semantic values β_{fixed} (Figure 17) is in the intermediate range: this provides evidence that a noisy truth-conditional semantics as employed in Exp. 1 is justified, but that taking into account graded category membership or typicality in an utterance's final semantic value is also necessary.

There is one major, and interesting, divergence from the empirical data in conditions without color competitors. Here, *color-and-type* utterances are systematically somewhat underpredicted in the informative condition, and systematically somewhat overpredicted in the overinformative condition. The reverse is true for *color-only* utterances. It is worth looking at the posterior over parameters, shown in Figure 17, to understand the pattern. In particular, the utterance type level semantic value of type is inferred to be systematically higher than that of color, capturing that type utterances are less noisy than color utterances.[25] An increase in *color-only* mentions in the overinformative condition could be achieved by reducing the semantic value for type. However, that would lead to a further and undesirable increase in *color-only* mentions in the informative condition as well. That is, the two conditions are in a tug-of-war with each other.

4.3 Discussion

In this section we demonstrated that cs-RSA predicts color typicality effects in the production of referring expressions. The model employed here did not differ in its architecture from that employed in Section 3, but only in that a) semantic values were assumed to operate at the individual utterance/object level in addition to at the utterance type/object level; b) semantic values for individual utterances were empirically elicited via typicality norming studies; and c) an utterance's

[25]Interestingly, the inferred semantic value for color is very similar in absolute terms to that in Exp. 1.

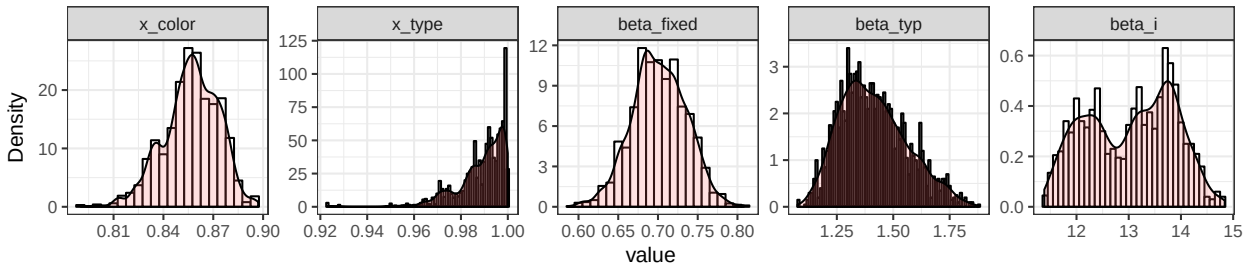


Figure 17: For best model, posterior model parameter distributions for utterance type level semantic values (color, type), interpolation weight on fixed vs. empirical semantics, typicality stretching parameter, and weight on informativity. Maximum a posteriori (MAP) $x_{\text{color}} = 0.86$, 95% highest density interval (HDI) = [0.82,0.89]; MAP $x_{\text{type}} = 0.998$, HDI = [0.97,1.00]; $\beta_{\text{fixed}} = .69$, HDI = [0.64, 0.77]; MAP $\beta_{\text{typ}} = 1.34$, HDI = [1.19,1.75]; MAP $\beta_i = 13.74$, HDI = [11.58,14.37].

cost was allowed to be a function of its mean empirical length and its corpus frequency instead of having a constant utterance type level value, though utterance cost ultimately was found not to play a role in predicting utterance choice.[26]

This suggests that the dynamics at work in the choice of color vs. size and in the choice of color as a function of the object's color typicality are very similar: speakers choose utterances by considering the fine-grained differences in information about the intended referent communicated by the ultimately chosen utterance compared to its competitor utterances. For noisier utterances (e.g., *banana* as applied to a blue banana), including the 'overinformative' color modifier is useful because it provides information. For less noisy utterances (e.g., *banana* as applied to a yellow banana), including the color modifier is useless because the unmodified utterance is already highly informative with respect to the speaker's intention. These dynamics can sometimes even result in the color modifier being left out altogether, even when there is another—very atypical—object of the same type present, simply because the literal listener is expected to prefer the typical referent strongly enough.

Model comparison demonstrated the need for assuming a semantics that interpolates between a noisy truth-conditional semantics as employed in Exp. 1 and empirically elicited typicality values. This may reflect semantic knowledge that goes beyond graded category membership, additional effects of compositionality, or perhaps simply differences between our empirical typicality measure and the "semantic fit" expected by RSA models. Perhaps surprisingly, we replicated the result from Exp. 1 that utterance cost does not add any predictive power, even when quantified via a

[26]See Table 7 for a more extensive overview of the ways in which the models reported across sections differed.

more sophisticated cost function that takes into account an utterance's length and frequency.

In the next section, we move beyond the choice of modifier and ask whether cs-RSA provides a good account of referring expression production more generally.

5 Unmodified referring expressions: nominal taxonomic level

In this section we investigate whether cs-RSA accounts for referring expression production beyond the choice of modifier. In particular, we focus on speakers' choice of taxonomic level of reference in nominal referring expressions. A particular object can be referred to at its subordinate (*dalmatian*), basic (*dog*), or superordinate (*animal*) level, among other choices. As discussed in Section 1.3, multiple factors play a role in the choice of nominal referring expression, including an expression's contextual informativeness, its cognitive cost (short and frequent terms are preferred over long and infrequent ones, Griffin & Bock, 1998; Jescheniak & Levelt, 1994), and its typicality (an utterance is more likely to be used if the object is a good instance of it, Jolicoeur et al., 1984). Thus, we explore the same factors as potential contributors to nominal choice that we explored in previous sections for modification.

In order to evaluate cs-RSA for nominal choice, we proceeded as in Section 4: we collected production data within the same reference game setting, but varied the contextual informativeness of utterances by varying whether distractors shared the same basic or superordinate category with the target (see Figure 18). We also elicited typicality ratings for object-utterance combinations, which entered the model as the semantic values via the lexicon. We then conducted Bayesian data analysis, as in previous sections, for model comparison.

5.1 Experiment 3: taxonomic level of reference in nominal referring expressions

5.1.1 Method

Participants We recruited 58 pairs of participants (116 participants total, the same participants as in Exp. 1) over Amazon's Mechanical Turk who were each paid $1.75 for their participation.

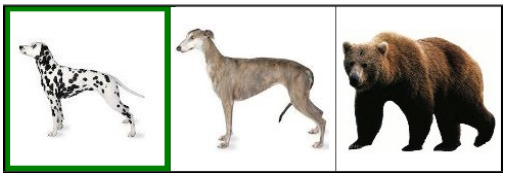
Procedure and materials The procedure was identical to that of Exp. 1.[27] Participants proceeded through 72 trials. Of these, half were critical trials of interest and half were filler trials (the critical trials from Exp. 1). On critical trials, we varied the level of reference that was sufficient to mention for uniquely establishing reference.

Stimuli were selected from nine distinct domains, each corresponding to distinct basic level categories such as *dog*. For each domain, we selected four subcategories to form our target set (e.g. *dalmatian*, *pug*, *German Shepherd* and *husky*). See Table 9 in Appendix F for a full list of domains and their associated target items. Each domain also contained an additional item which belonged to the same basic level category as the target (e.g., *greyhound*) and items which belonged to the same supercategory but not the same basic level (e.g., *elephant* or *squirrel*). The latter items were used as distractors.

Each trial consisted of a display of three images, one of which was designated as the target object. Each pair of participants saw each target exactly once, for a total of 36 trials. These target items were randomly assigned distractor items which were selected from three different context conditions, corresponding to different communicative pressures (see Figure 18). The *subordinate necessary* contexts contained one distractor of the same basic category and one distractor of the same superordinate category (e.g., target: *dalmatian*, distractors: *greyhound* (also a dog) and *squirrel* (also an animal)). The *basic sufficient* contexts contained either two distractors of the same superordinate category but different basic category as the target (e.g., target: *husky*, distractors: *hamster* and *elephant*) or one distractor of the same superordinate category and one unrelated item (e.g., target: *pug*, distractors: *cow* and *table*). The *superordinate sufficient* contexts contained two unrelated items (e.g., target: *German Shepherd*, distractors: *shirt* and *cookie*).

This context manipulation served as a manipulation of utterance informativeness: any target could be referred to at the subordinate (*dalmatian*), basic (*dog*) or superordinate (*animal*) level. However, the level of reference necessary for uniquely referring differed across contexts.

[27] A separate earlier data set was reported at the annual meeting of the Cognitive Science Society (Graf et al., 2016), and serves as a close replication of the reported study.



(a) subordinate necessary

(b) basic sufficient (two superordinate distractors)

(c) basic sufficient (one superordinate distractor)

(d) superordinate sufficient

Figure 18: Example contexts in which different levels of reference are necessary for establishing unique reference to the target marked with a thick border: (a) subordinate necessary (*dalmatian*); (b, c) basic sufficient (*dog*) and subordinate possible (*husky*, *pug*); (d) superordinate sufficient (*animal*) and basic or subordinate possible (*dog*, *German Shepherd*).

5.1.2 Typicality norming

In order to test for typicality effects on the production data and to evaluate cs-RSA's performance, we collected empirical typicality values for each utterance/object pair. See Appendix G for details.

5.1.3 Data pre-processing and exclusion

We collected data from 2193 critical trials. Each referring expression was classified as containing the target's correct *sub*(ordinate, e.g., *dalmatian*), *basic* (e.g., *dog*), or *super*(ordinate, e.g., *animal*) level term, or excluded if classification was not possible. See Appendix D for details on exclusion criteria and the pre-processing procedure. After exclusions and pre-processing, 1872 cases entered the analysis.

5.1.4 Results and discussion

Proportions of sub, basic, and super level utterances are shown in Figure 19. Overall, super level mentions are highly dispreferred ($< 2\%$), so we focus in this section only on predictors of sub over basic level mentions. The clearest pattern of note is that sub level mentions are only preferred in the most constrained context that necessitates the sub level mention for unique reference (e.g., target: dalmatian, distractor: greyhound; see Figure 18a). Nevertheless, even in these contexts there is a non-negligible proportion of basic level mentions (28%). This includes cases of using just the basic

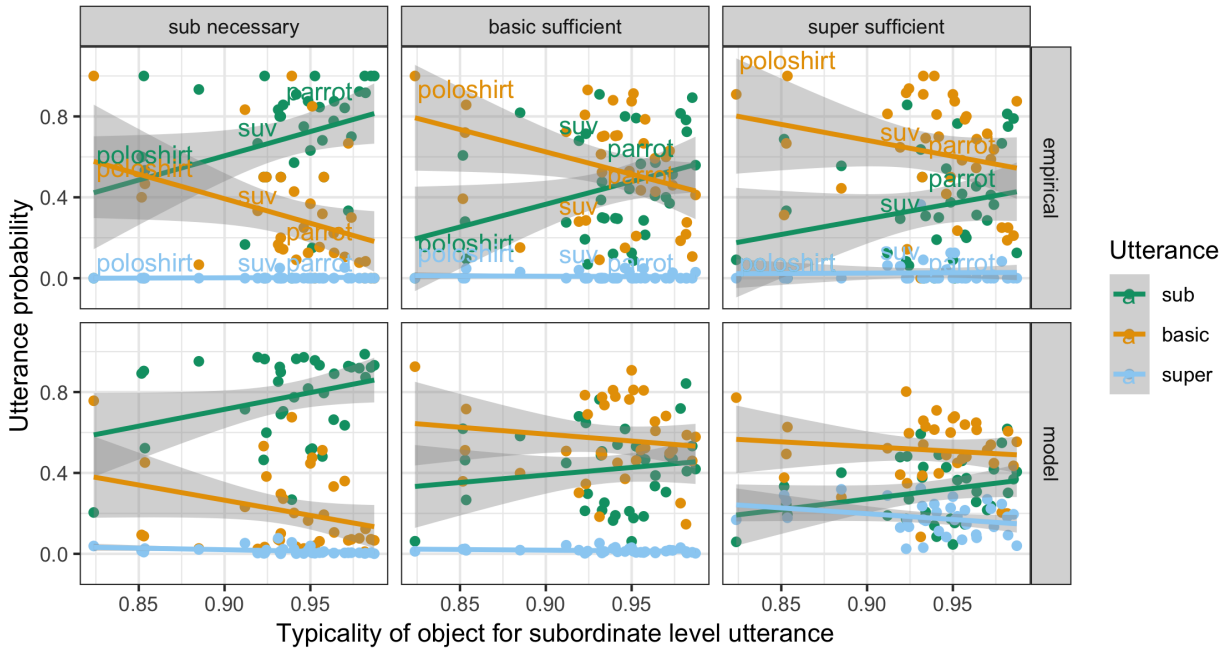


Figure 19: Top: utterance proportions for each target item across different informativeness conditions as a function of the object's subordinate level typicality. Example target items *polo shirt* (basic: *shirt*, super: *clothes*), *SUV* (basic: *car*, super: *vehicle*), and *parrot* (basic: *bird*, super: *animal*) that were characteristic of relatively low to relatively high sub typicality items are labeled explicitly. Bottom: MAP model predicted utterance probabilities.

level term (6%, e.g., *dog* for the German Shepherd when one of the distractors was a greyhound, an atypical dog, akin to the unmodified cases in the informative conditions discussed in Section 4.1.4) as well as basic level terms with additional modifying material (22%). In the remaining contexts, where the sub and basic level are equally informative, there is a clear preference for the basic level. In addition, mitigating this context effect, sub level mentions increased with increasing typicality of the object as an instance of the sub level utterance.

What explains these preferences? In order to test for effects of informativeness, length, frequency, and typicality on nominal choice we conducted a mixed effects logistic regression predicting sub over basic level mention from centered predictors for the factors of interest and the maximal random effects structure that allowed the model to converge (random by-speaker and by-target intercepts).

Frequency was coded as the difference between the sub and the basic level's log frequency, as extracted from the Google Books Ngram English corpus ranging from 1960 to 2008.

Length was coded as the ratio of the sub to the basic level's length. We used the mean empirical

lengths in characters of the utterances participants produced. For example, the minivan, when referred to at the subcategory level, was sometimes called "minivan" and sometimes "van" leading to a mean empirical length of 5.71. This is the value that was used, rather than 7, the length of "minivan". That is, a higher frequency difference indicates a *lower* cost for the sub level term compared to the basic level, while a higher length ratio reflects a *higher* cost for the sub level term compared to the basic level.[28]

Typicality was coded as the ratio of the target's sub to basic level label typicality.[29] That is, the higher the ratio, the more typical the object was for the sub level label compared to the basic level; or in other words, a higher ratio indicates that the object was relatively atypical for the basic label compared to the sub label. For instance, the panda was relatively atypical for its basic level "bear" (mean rating 0.75) compared to the sub level term "panda bear" (mean rating 0.98), which resulted in a relatively *high* typicality ratio.

Informativeness condition was coded as a three-level factor: *sub necessary*, *basic sufficient*, and *super sufficient*, where *basic sufficient (two superordinate distractors)* and *basic sufficient (one superordinate distractor)* were collapsed into *basic sufficient*. Condition was Helmert-coded: two contrasts over the three condition levels were included in the model, comparing each level against the mean of the remaining levels (in order: *sub necessary*, *basic sufficient*, *super sufficient*). This allowed us to determine whether the probabilities of type mention for neighboring conditions were significantly different from each other, as suggested by Figure 19.

The log odds of mentioning the sub level term were greater in the *sub necessary* condition than in either of the other two conditions ($\beta = 2.11$, $SE = .17$, $p < .0001$), and greater in the *basic sufficient* condition than in the *super sufficient* condition ($\beta = .60$, $SE = .15$, $p < .0001$), suggesting that the contextual informativeness of the sub level mention has a gradient effect on utterance choice.[30] There was also a main effect of typicality, such that the sub level term was preferred for objects that were more typical for the sub level compared to the basic level description ($\beta = 4.82$, $SE = 1.35$,

[28] We replicate the well-documented negative correlation between length and log frequency ($r = -.49$ in our dataset).

[29] Typicalities were elicited in a separate norming study that was identical in procedure to that of Exp. 1a. See Appendix G for details about the study.

[30] Importantly, model comparison between the reported model and one that subsumes basic and super under the same factor level revealed that the three-level condition variable is justified ($\chi^2(1) = 12.82$, $p < .0004$), suggesting that participants do not simply revert to the basic level when no basic-level distractor is in context.

$p < .001$). In addition, there was a main effect of length, such that as the length of the sub level term increased compared to the basic level term ("chihuahua"/"dog" vs. "pug"/"dog"), the sub level term was dispreferred ("chihuahua" is dispreferred compared to "pug", $\beta = -.95$, $SE = .27$, $p < .001$). The main effect of frequency did not reach significance ($\beta = .08$, $SE = .11$, $p < .45$).

Unsurprisingly, there was also significant by-participant and by-domain variation in sub level term mention. For instance, mentioning the sub over the basic level term was preferred more in some domains (e.g. in the "candy" domain) than in others. Likewise, some domains had a greater preference for basic level terms (e.g. the "shirt" domain). Using the super term also ranged from hardly being observable (e.g., *plant* in the "flower" domain) to being used more frequently (e.g., *furniture* in the "table" domain and *vehicle* in the "car" domain).

We thus replicated the well-documented preference to refer to objects at the basic level, which is partly modulated by contextual informativeness and partly a result of the basic level term's cognitive cost and typicality compared to its sub level competitor, mirroring the results from Exp. 2.

Perhaps surprisingly, we did not observe an effect of frequency on sub level term mention. This is likely due to the modality of the experiment: the current study was a written production study, while most studies that have identified frequency as a factor governing production choices are spoken production studies. It may be that the cognitive cost of typing longer words may be disproportionately higher than that of producing longer words in speech, thus obscuring a potential effect of frequency. Support for this hypothesis comes from studies comparing written and spoken language, which has found that spoken descriptions are likely to be longer than written descriptions and, in English, seem to have a lower propositional information density than written descriptions (van Miltenburg, Koolen, & Krahmer, 2018).[31]

[31] In order to address convergence issues with `lmer` when specifying the full random effects structure – i.e., by-speaker and by-item random intercepts and slopes for all fixed effects – we also ran a Bayesian binomial mixed effects model with weakly informative priors using the `brms` package (Bürkner, 2017) that included the same fixed effects structure as the lmer model and the full random effects structure. The results were qualitatively identical, yielding evidence for main effects of context (sub vs basic sufficient: posterior mean $\beta = 2.44$, 95% CI = [1.87,3.06], $p(\beta > 0) = 1$; basic vs super sufficient: posterior mean $\beta = 0.70$, 95% CI = [0.32,1.09], $p(\beta > 0) = 1$), typicality (posterior mean $\beta = 9.96$, 95% CI = [3.55,17.51], $p(\beta > 0) = 1$), and length (posterior mean $\beta = -1.12$, 95% CI = [-2.00,-0.31], $p(\beta < 0) = 1$).

5.2 Model evaluation

We evaluated cs-RSA on the production data from Exp. 3. The architecture of the model is identical to that of the model presented in Section 4.2. The only difference is that the set of alternatives contained only the three potential target utterances (i.e., the target's sub, basic, and super label).[32] Whereas the modifier models from the previous sections treat all individual features and feature combinations represented in the display as utterance alternatives, for computational efficiency we restrict alternatives in the nominal choice model, considering only the three different levels of reference to the target as alternatives, e.g., *dalmatian*, *dog*, *animal*. (So, when a German Shepherd is a distractor, *German Shepherd* is *not* considered an alternative. This has minimal effects on model predictions as long as *German Sheperd* has low semantic fit to the dalmatian target.)

For the previous dataset, we tested which of three different semantics was most justified – a fixed compositional semantics with type-level semantic values, the empirically elicited typicality semantics, or a combination of the two. For the current dataset, this question did not arise, because we investigated only one word utterances (all nouns). We hence only considered the *empirical* semantics. However, like in the previous dataset, we evaluated which cost function was best supported by the data: the one defined in (7) (a linear weighted combination of an utterance's length and its frequency) or a simpler baseline in which utterances were assumed to have no cost.

We employed the same procedure as in the previous section to compute the Bayes Factor for the comparison between the two cost models, and to compute the posteriors over parameters. Priors were again $\beta_i \sim \mathcal{U}(0, 20)$, $\beta_F \sim \mathcal{U}(0, 5)$, $\beta_L \sim \mathcal{U}(0, 5)$, $\beta_t \sim \mathcal{U}(0, 5)$.

Despite the greater number of parameters associated with adding the cost function, the model that includes non-zero costs was preferred compared to its no-cost counterpart ($BF = 2.8 \times 10^{77}$). Posteriors over parameters are shown in Figure 20. It is worth noting that the weight on frequency is close to zero. That is, in line with the results from the mixed effects regression, it is an utterance's length, but not its frequency, that affects the probabilitiy with which it is produced in this paradigm.[33]

MAP model predictions are shown alongside empirical utterance proportions in Figure 19. The

[32] See Table 7 for an overview of the models reported in the paper.

[33] As discussed in previous sections, the lack of importance of a word's frequency may well be attributable to the written modality within which participants generated referring expressions.

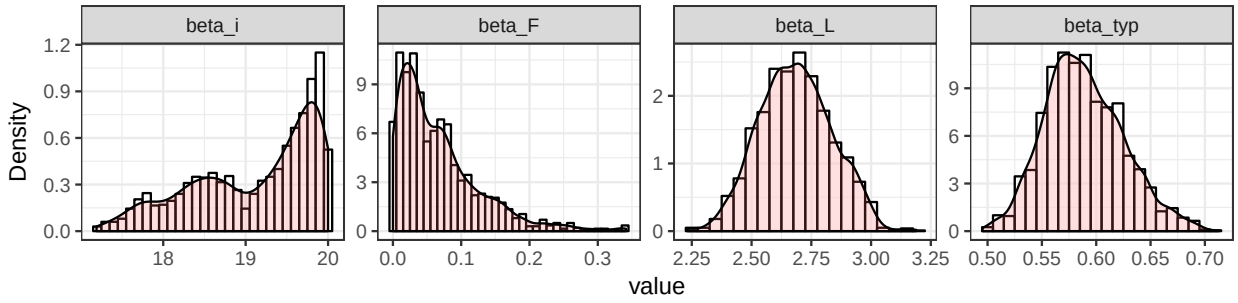


Figure 20: Posterior model parameter distributions for informativity weight (β_i), frequency cost weight (β_F), length cost weight (β_L), and typicality weight (β_t). Maximum a posteriori (MAP) β_i = 19.8, 95% highest density interval (HDI) = [17.71,20.0]; MAP β_F = 0.0.02, HDI = [0.00,0.19]; MAP β_L = 2.69, HDI = [2.42,2.99]; MAP β_t = 0.57, HDI = [0.53,0.67].

correlation between empirical utterance proportions and the model's MAP predictions at the level of targets, utterances, and conditions was $r = .86$. Further collapsing across targets yields a correlation of $r = .95$. The model captures the qualitative patterns well, though it somewhat overpredicts subordinate level and underpredicts basic level choices. It also accounts for the strong preference against super level mentions. The reason for this is that the semantics for each utterance (eg., *dalmatian*, *dog*, *animal*) is taken from the empirically elicited typicality values for each utterance-object pair. As can be seen in the left panel of Figure 25, the target images used in this experiment were generally rated as less typical instances of the superordinate level term than of the basic or subordinate level term. This difference is enough to lead to a general bias against using the superordinate level term, especially when coupled with the fact that superordinate terms tend to be costlier than basic level terms.

6 General Discussion

In this paper we have provided a unified account of referring expression choice that solves a long-recognized puzzle for rational theories of language use: why do speakers' referring expressions often and systematically exhibit seeming overinformativeness? We have shown here that by allowing contextual utterance informativeness to be computed with respect to a continuous (or noisy) rather than a Boolean semantics, utterances that seem overinformative can in fact be sufficiently informative. This happens when what seems like the prima facie sufficiently informative utterance is in fact noisy and may lead a literal listener astray; adding redundancy ensures successful communication.

This simple modification to the Rational Speech Act approach allowed us to capture: the basic well-documented asymmetry for speakers to be more likely to redundantly use color adjectives than size adjectives; the interaction between sufficient dimension and scene variation in the probability of redundancy; and typicality effects in both color modifier choice and noun choice.

We have thus shown that with one key innovation – a continuous semantics – one can retain the assumption that speakers rationally trade off informativeness and cost of utterances in language production. Rather than being wastefully overinformative, adding redundant modifiers or referring at a lower taxonomic level than strictly necessary *is* in fact appropriately informative. This innovation thus not only provides a unified explanation for a number of key patterns within the overinformative referring expression literature that have thus far eluded a unified explanation; it also extends to the domain of nominal choice. And in contrast to previously proposed computational models, it is straightforwardly extendable to any instance of definite referring expressions of the sort we have examined here.

6.1 Comparison of model components across experiments

In order to address the possible concern that the different models employed are too different from one another to be comparable, we begin by providing an overview of the parts of the model that remained the same or differed across experiments. While the core architecture with relaxed semantics remained constant throughout the paper, some peripheral components were adjusted to accommodate the aims of the different experiments. These different choices are fully consistent with one another, and many of them were justified against alternatives via model comparison. We have provided an overview of the best-fitting RSA models for each of the three reported production datasets in Table 7.

Most prominently, Exps. 2 and 3 aimed to predict patterns of reference via typicality at the *object-level*; in those cases the model thus required semantic values for each utterance-object pair in the lexicon. While these values could have in principle been inferred from the data, as we inferred the two type-level values in Exp. 1, it would have introduced a large number of additional parameters (see *size of lexicon*). Instead, we addressed this problem by empirically eliciting these values in an independent task and introducing a single free concentration parameter β_t that modulated their strength. In the case of Exp. 2, we found that the best-fitting model smoothly integrated these

Table 7: Overview of the best-performing models used for the three different production datasets Color/size (Exp. 1), Color typicality (Exp. 2), and Nominal choice (Exp. 3). Parameter names: x_{color}: semantic value of color; x_{size}: semantic value of size; $\beta_{c(\text{color})}$: cost of color; $\beta_{c(\text{size})}$: cost of size; β_i: weight on informativity; β_F: weight on cost (as estimated by utterance frequency); β_L: weight on cost (as estimated by utterance length); β_t: weight on elicited typicality values; β_{fixed}: interpolation weight between fixed type-level and empirical semantic values

	Color/size	Color typicality	Nominal choice
Semantic values	at type-level (inferred)	at type-level (inferred) + object-level (elicited)	at object-level (elicited)
Size of lexicon $\mathcal{L}(u, o)$	8 (all combinations of *size* and *color*)	814 (1 for each utterance-object pair)	51 (1 for each utterance-object pair)
Set of alternatives	8 contextually available feature combinations (size, color)	8 or 9 contextually available feature combinations (type, color)	3 target alternatives (level of reference: *sub, basic, super*)
Cost	type-level (color and size)	none necessary	empirical (length and frequency)
Free parameters	x_{color}, x_{size}, $\beta_{c(\text{color})}$, $\beta_{c(\text{size})}$, β_i	x_{color}, x_{type}, β_i, β_t, β_{fixed}	β_F, β_L, β_i, β_t

empirical values with type-level values used in Exp. 1.

The need to make object-level predictions also drove decisions about what to use as the cost function and the set of alternative utterances. For instance, in Exp. 3 we could have inferred the cost of each noun but this again would have introduced a large number of free parameters and risked overfitting. Instead we used the empirically estimated *length* and *frequency* of each word. For Exp. 2, we tested models both using fixed costs for each modifier as in Exp. 1 and empirical length and frequency costs as in Exp. 3, but our model comparison showed that neither sufficiently improved the model's predictions.

Finally, the set of alternative utterances differed slightly across the three experiments for computational reasons. Because Exp. 1 collapsed over the particular levels of size and color, it was practical to consider all utterances in the lexicon for every target. In Exp. 2 and Exp. 3, however, the space of possible utterances was large enough that this exhaustive approach became impractical. We noticed that the probability of using some utterances (e.g. 'table' to refer to a Dalmatian) was low enough that we could prune the utterance space to only those that could plausibly apply to the objects in context without substantially altering the model's behavior. Future work must address how predictions may change as more complex referring expressions outside the scope of this paper

enter the set of alternatives (e.g. the option of combining adjectives with nominal expressions, as in *the cute, spotted dog*).

In the following we discuss a number of intriguing questions that this work raises and avenues for future research it suggests.

6.2 Comparison with PRO

While a detailed comparison of cs-RSA with PRO (van Gompel et al., 2019), the hitherto most state-of-the-art computational model of human production of modified referring expressions, is outside the scope of this paper, we include some comparative remarks here. PRO has the advantage of being computationally more efficient than cs-RSA, partly because it aims to be an algorithmic-level model, which may be of importance for applications. PRO may further have the advantage of having fewer parameters, though this is a bit harder to evaluate in general: while PRO as applied to the choice of color and size in principle involves 2 parameters, s (size preference) and e (overspecification eagerness), in the 2019 paper the maximum likelihood parameter values are estimated on each of the experimental conditions separately, effectively resulting in 6 parameters. In the extension to 3 properties, this results in 14 parameters, and this number increases further as more properties and conditions are added. If the parameter values had been estimated on all conditions jointly, which is what we did in the evaluation of cs-RSA instead of separately, then indeed PRO would have fewer effective parameters than cs-RSA, though it iss unclear how this would affect the data fit. One advantage of the cs-RSA approach is greater generality. For instance, it is not immediately clear how PRO should be extended to contexts that vary in the number and nature of distractors, where empirical overmodification proportions change, but the PRO predictions would not. We see this as one of the great strengths of cs-RSA: scene variation effects fall out of the model directly. Finally, we have proposed here a way to account for typicality effects. PRO may be able to accommodate typicality effects if its preference parameters can be made to be sensitive to typicality. In general, a systematic comparison and possible combination of these models is an important next step.

6.3 'Overinformativeness'

This work challenges the traditional notion of overinformativeness as it is commonly employed in the linguistic and psychological literature. The reason that redundant referring expressions are

interesting for psycholinguists to study is that they seem to constitute a clear violation of rational theories of language production. For example, Grice's Quantity-2 maxim, which asks of speakers to "not make [their] contribution more informative than is required" (Grice, 1975), appears violated by any redundant referring expression – if one feature uniquely distinguishes the target object from the rest and a second one does not, mentioning the second does not contribute any information that is not already communicated by the first. Hence, the second is considered 'overinformative', a referring expression that contains it 'overspecified.'

This conception of (over-)informativeness assumes that all modifiers are born equal – i.e., that there are no a priori differences in the utility of mentioning different properties of an object. Under this conception of modifiers, there are hard lines between modifiers that are and aren't informative in a context. However, what we have shown here is that under a continuous semantics, a modifier that would be regarded as overinformative under the traditional conception may in fact communicate information about the referent. The more visual variation there is in the scene, and the less noisy the redundant modifier is compared to the modifier that selects the dimension that uniquely singles out the target, the more information the redundant modifier adds about the referent, and the more likely it therefore is to be mentioned. This work thus challenges the traditional notion of utterance overinformativeness by providing an alternative that captures the quantitative variation observed in speakers' production in a principled way while still assuming that speakers are aiming to be informative, and is compatible with other efficiency-based accounts of 'overinformative' referring expressions (e.g., Sedivy, 2003; Rubio-Fernandez, 2016).

But this raises a question: what counts as a truly overinformative utterance under RSA with a continuous semantics? Cs-RSA shifts the standard for overinformativeness and turns it into a graded notion: the less expected the use of a redundant modifier is contextually, the more the use of that modifier should be considered overinformative. For example, consider again Figure 8: the less scene variation there is, the more truly overinformative the use of the redundant modifier is. Referring to *the big purple stapler* when there are only purple staplers in the scene should be considered overinformative. If there is one red stapler, the utterance should be judged less overinformative, and the more non-purple staplers there are, the less overinformative the utterance should be judged. We leave a systematic test of this prediction for our stimuli for future research, though we point to some qualitative examples where it has been borne out previously in the next

subsection.

6.4 Comprehension

While the account proposed in this paper is an account of the *production* of referring expressions, it can be extended straightforwardly to *comprehension*. RSA models typically assume that listeners interpret utterances by reasoning about their model of the speaker. In this paper we have provided precisely such a model of the speaker. In what way should the predicted speaker probabilities enter into comprehension? There are two interpretations of this question: first, what is the ultimate interpretation that listeners who reason about speakers characterized by the model provided in this paper arrive at, i.e. what are the predictions for referent choice? And second, how do the production probabilities enter into online processing of prima facie overinformative utterances? The first question has a clear answer. For the second question we offer a more speculative answer.

6.4.1 Choice of referent

Most RSA reference models, unlike the one reported in this paper, have focused on comprehension (M. C. Frank & Goodman, 2012; Degen, Franke, & Jäger, 2013; Qing & Franke, 2015; Franke & Degen, 2016). The formula that characterizes pragmatic listeners' referent choices is:

$$P_{L_1}(o|u) \propto P_{S_1}(u|o) \cdot P(o) \tag{8}$$

That is, the pragmatic listener interprets utterance u (e.g., *the big purple stapler*) via Bayesian inference, taking into account both the speaker probability of producing *the big purple stapler* and its alternatives, given a particular object o the speaker had in mind, as well as the listener's prior beliefs about which object the speaker is likely to intend to refer to in the context. For the situations considered in this paper, in which the utterance is semantically compatible with only one of the referents in the context, this always predicts that the listener should choose the target. And indeed, in Exps. 1-3 the error rate on the listeners' end was always below 1%. From a referent choice point of view, then, these contexts are not very interesting. They are much more interesting from an online processing point of view, which we discuss next.

6.4.2 Online processing

The question that has typically been asked about the online processing of redundant utterances is this: do redundant utterances, compared to their minimally specified alternatives, help or hinder comprehenders in choosing the intended referent? 'Help' and 'hinder' are typically translated into 'speed up' and 'slow down', respectively. What does the RSA model presented here have to say about this?

In sentence processing, the current wisdom is that the processing effort spent on linguistic material is related to how surprising it is (Hale, 2001; Levy, 2008). In particular, an utterance's log reading time is linear in its surprisal (Smith & Levy, 2013), where surprisal is defined as $-\log p(u)$. In these studies, surprisal is usually estimated from linguistic corpora. Consequently, an utterance of *the big purple stapler* receives a particular probability estimate independent of the non-linguistic context it occurred in. Here we provide a speaker model from which we can derive estimates of *pragmatic surprisal* directly for a particular context. We can thus speculate on a linking hypothesis: the more expected a redundant utterance is under the pragmatic continuous semantics speaker model, the faster it should be to process compared to its minimally specified alternative, all else being equal. We have shown that redundant expressions are more likely than minimal expressions when the sufficient dimension is relatively noisy and scene variation is relatively high. Under our speculative linking hypothesis, the redundant expression should be easier to process in these sorts of contexts than in contexts where the redundant expression is relatively less likely.

Is there evidence that listeners do behave in accordance with this prediction? Indeed, the literature reports evidence that in situations where the redundant modifier does provide some information about the referent, listeners are faster to respond and select the intended referent when they observe a redundant referring expression than when they observe a minimal one (Arts et al., 2011; Paraboni et al., 2007). However, there is also evidence that redundancy sometimes incurs a processing cost: both Engelhardt, Demiral, and Ferreira (2011) and Davies and Katsos (2013) (Exp. 2) found that listeners were slower to identify the target referent in response to redundant compared to minimal utterances. It is useful to examine the stimuli they used. In the Engelhardt et al study, there was only one distractor that varied in type, i.e., type was sufficient for establishing reference. This distractor varied either in size or in color. Thus, scene variation was very low and redundant expressions therefore likely surprising. Interestingly, the incurred cost was greater

for redundant size than for redundant color modifiers, in line with the RSA predictions that color should be generally more likely to be used redundantly than size. In the Davies et al study, the 'overinformative' conditions contained displays of four objects which differed in type. Stimuli were selected via a production pre-test: only those objects that in isolation were not referred to with a modifier were selected for the study. That is, stimuli were selected precisely on the basis that redundant modifier use would be unlikely.

While the online processing of redundant referring expressions is yet to be systematically explored under the cs-RSA account, this cursory overview of the patterns reported in the existing literature suggests that pragmatic surprisal may be a plausible linking function from model predictions to processing times. Excitingly, it has the potential for unifying the equivocal processing time evidence by providing a model of utterance probabilities that can be computed from the features of the objects in the context.

6.5 Continuous semantics

The crucial component of the model that allows for capturing 'overinformativeness' effects is the continuous semantics. In this section, we consider what the nature is of these continuous semantic values. Readers already convinced of the utility of a continuous semantics are invited to skip to the next section.

For the purpose of Exp. 1 (modifier choice), a semantic value was assigned to modifier *type*. The semantics of modifiers was underlyingly truth-conditional and the semantic value captured the probability that a modifier's truth conditions would accidentally be inverted. This model included only two semantic values, one for size and one for color, which we inferred from the data. For the datasets from Exps. 2 and 3, we then extended the continuous semantics to apply at the level of utterance-object combinations (e.g., *banana* vs. *blue banana* as applied to the blue banana item, *dalmatian* vs. *dog* as applied to the dalmatian item) to account for typicality effects in modifier and nominal choice. In this instantiation of the model, the semantic value differed for every utterance-object combination and captured how good of an instance of an utterance an object was. These values were elicited experimentally to avoid over-fitting, and for the dataset from Exp. 2 we found further that a combination of a noisy truth-conditional semantics and the empirically elicited semantics best accounted for the obtained production data.

What we have said nothing about thus far is what determines these semantic values; in particular, which aspects of language users' experience – perceptual, conceptual, communicative, linguistic – they represent. We will offer some speculative remarks and directions for future research here.

First, semantic values may represent the difficulty associated with verifying whether the property denoted by the utterance holds of the object. This difficulty may be perceptual – for example, it may be relatively easier to visually determine of an object whether it is red than whether it it is big (at least in our stimuli). Similarly, at the object-utterance level, it may be easier to determine of a yellow banana than of a blue banana whether it exhibits banana-hood, consequently yielding a lower semantic value for a blue banana than for a yellow banana as an instance of *banana*. Further, the value may be context-invariant or context-dependent. If it is context-invariant, the semantic value inferred for color vs. size, for instance, should not vary by making size differences more salient and color differences less salient. If, instead, it is context-dependent, increasing the salience of size differences and decreasing the salience of color differences should result, e.g., in color modifiers being more noisy, with concomitant effects on production, i.e., redundant color modifiers should become less likely. This is indeed what Viethen, van Vessem, Goudbeek, and Krahmer (2017) found. Similarly, van Gompel, Gatt, Krahmer, and van Deemter (2014) found that the asymmetry in redundant use of color vs. with size disappeared when participants were shown displays with very noticeable size contrasts and barely noticeable color contrasts.

Another possibility is that semantic values represent aspects of agents' prior beliefs (world knowledge) about the correlations between features of objects. For example, conditioning on an object being a banana, experience dictates that the probability of it being yellow is much greater than of it being blue. This predicts the relative ordering of the typicality values we elicited empirically, i.e., the blue banana received a lower semantic value than the yellow banana as an instance of *banana*.

Another possibility is that the semantic values capture the past probability of communicative success in using a particular expression. For example, the semantic value of *banana* as applied to a yellow banana may be high because in the past, referring to yellow bananas simply as *banana* was on average successful. Conversely, the semantic value of *banana* as applied to a blue banana may be low because in the past, referring to blue bananas simply as *banana* was on average unsuccessful (or the speaker may have uncertainty about its communicative success because they have never encountered

blue bananas before). Similarly, the noise difference between color and size modifiers may be due to the inherent relativity of size modifiers compared to color modifiers – while color modifiers vary somewhat in meaning across domains (consider, e.g., the difference in redness between *red hair* and *red wine*), the interpretation of size modifiers is highly dependent on a comparison class (consider, e.g., the difference between a *big phone* and a *big building*). In negotiating what counts as *red*, then, speakers are likely to agree more often than in negotiating what counts as *big*. That is, size adjectives are more subjective than color adjectives. If semantic values encode adjective subjectivity, speakers should be even more likely to redundantly use adjectives that are more objective than color. In a study showing that adjective subjectivity is almost perfectly correlated with an adjective's average distance from the noun, Scontras et al. (2017) collected subjectivity ratings for many different adjectives and found that material adjectives like *wooden* and *plastic* are rated to be even more objective than color adjectives. Thus, under the hypothesis that semantic values represent adjective subjectivity, material adjectives should be even more likely to be used redundantly than color adjectives. This is not the case. For instance, Sedivy (2003) reports that material adjectives are used redundantly about as often as size adjectives. Hence, while the hypothesis that semantic values capture the past probability of communicative success in using a particular expression has yet to be systematically investigated, subjectivity alone seems not to be the determining factor.

Finally, it is also possible that semantic values are simply an irreducible part of the lexical entry of each utterance-object pair. This seems unlikely because it would require a separate semantic value for each utterance and object token, and most potentially encounterable object tokens in the world have not been encountered, making it impossible to store utterance-token-level values. However, it is possible that, reminiscent of prototype theory, semantic values are stored at the level of utterances and object *types*. This view of semantic values suggests that they should not be updated in response to further exposure of objects. For example, if semantic values were a fixed component of the lexical entry *banana*, then even being exposed to a large number of blue bananas should not change the value. This seems unlikely but merits further investigation.

The various possibilities for the interpretation of the continuous semantic values included in the model are neither independent nor incompatible with each other. Disentangling these possibilities presents an exciting avenue for future research.

What is highlighted by the above possibilities for which aspects of experience the semantic values encode is that we have been using the term 'semantics' here loosely, to refer to the representations that the literal listener performs computations on. These real valued representations can be conceived of either as semantic primitives themselves – which would constitute a fundamentally different basic semantics than has been previously assumed in formal semantics – or as the result of adding the right kind of use or world knowledge related noise to a standard Boolean truth-conditional semantics. The continuous semantics posited as the basis for the literal listener's computation thus follows the recent NLP trend in distributional semantics of blurring the meaning/use boundary in the basic representations that further computations are performed on (see Potts, 2019, for an overview). Whether one conceives of these values as semantic primitives or as the result of a complex function that combines Boolean truth conditions with the right kinds of use conditions, they provide the right basis for capturing the production choices explored in this paper. When to assume a relaxed semantics, and what the implications of such a relaxation are for other phenomena that RSA has successfully captured, are interesting questions for future research.

6.6 Audience design

One question which has plagued the literature on language production is that of whether, and to what extent, speakers actually tailor their utterances to their audience (Clark & Murphy, 1982; Horton & Keysar, 1996; Brown-Schmidt & Heller, 2014). This is also known as the issue of *audience design*. With regards to redundant referring expressions, the question is whether speakers produce redundant expressions because it is helpful to them (i.e., due to internal production pressures) or because it is helpful to their interlocutor (i.e., due to considerations of audience design). For instance, Walker (1993) shows that redundancy is more likely when processing resources are limited. On the other hand, there is evidence that redundant utterances are frequently used in response to signs of listener non-comprehension, when responding to listener questions, or when speaking to strangers (Baker, Gill, & Cassell, 2008), suggesting at least some consideration of listeners' needs.

RSA seems to make a claim about this issue: speakers are trying to be informative with respect to a literal listener. That is, it would seem that speakers produce referring expressions that are tailored to their listeners. However, this is misleading. The ontological status of the literal listener is as a "dummy component" that allows the pragmatic recursion to get off the ground. Actual

listeners are, in line with previous work and briefly discussed above, more likely fall into the class of pragmatic L_1 listeners; listeners who reason about the speaker's intended meaning via Bayesian inference (M. C. Frank & Goodman, 2012; Goodman & Stuhlmüller, 2013).[34]

Because RSA is a computational-level theory (Marr, 1982) of language use, it does not claim that the mechanism of language production requires that speakers actively consult an internal model of a listener every time they choose an utterance, just that the distribution of utterances they produce reflect informativity with respect to such a model. It is possible that this distribution is cached or computed using some other algorithm that doesn't explicitly involve a listener component.

Thus, the RSA model as formulated here remains agnostic about whether speakers' (over-) informativeness should be considered geared towards listeners' needs or simply a production-internal process. Instead, the claim is that redundancy emerges as a property of the communicative situation as a whole.

6.7 Other factors that affect redundancy

RSA with a continuous semantics as presented in this paper straightforwardly accounts for effects of typicality, cost, and scene variation on redundancy in referring expressions. However, other factors have been identified as contributing to redundancy. For example, Rubio-Fernandez (2016) showed that colors are mentioned more often redundantly for clothes than for geometrical shapes. Her explanation is that knowing an object's color is generally more useful for clothing than it is for shapes. It is plausible that agents' knowledge of *goals* may be relevant here. For example, knowing the color of clothing is relevant to the goal of deciding what to wear or buy. In contrast, knowing the color of geometrical shapes is rarely relevant to any everyday goal agents might have. While the RSA model as implemented here does not accommodate an agent's goals, it can be extended to do so via projection functions, as has been done for capturing figurative language use (e.g., Kao, Wu, Bergen, & Goodman, 2014) or question-answer behavior (Hawkins, Stuhlmüller, Degen, & Goodman, 2015). This should be explored further in future research.

One factor that has been repeatedly discussed in the literature and that we have not taken up here is the *incrementality* of language production, both at the conceptual level of content or prop-

[34] But see Franke and Degen (2016) for an evaluation of the distribution of listener and speaker types in Quantity inferences.

erty selection and at the level of linguistic realization. For instance, according to Pechmann (1989), incrementality is to blame for redundancy: speakers retrieve and subsequently produce words as soon as they can. Because color modifiers are easier to retrieve than size modifiers, speakers produce them regardless of whether or not they are redundant. The problem with this account is that it predicts that the preferred adjective order should be reversed, i.e., color adjectives should occur before size adjectives. Pechmann does observe some, but not many, instances of this. An interesting test case for the incrementality hypothesis are cases where adjective ordering preferences are weak. Fukumura (2018) reports one such case in which speakers prefer to order more discriminative and more available properties before less discriminative and less available ones, highlighting incrementality as an important factor affecting the choice of referring expression. On the other hand, it is unclear how incrementality could account for the systematic increase in color redundancy with increasing scene variation and decreasing color typicality, unless one makes the auxiliary assumption that the more contextually discriminative or salient color is, the more available (i.e., easily retrievable) the modifier is. Indeed, Clark and Bangerter (2004) emphasize the importance of *salience against the common ground* in speakers' decisions about which of an object's properties to include in a referring expression. There are other ways incrementality could play a role in modifier choice. For example, mentioning the color adjective may buy the speaker time when the noun is hard to retrieve. This predicts that in languages with post-nominal adjectives, where this delay strategy cannot be used for noun planning, redundant color mention should be less frequent; indeed, this is what Rubio-Fernandez (2016) shows for Spanish. In sum, the incrementality of language production clearly affects the choice of referring expression; the ways in which considerations of incrementality should be incorporated in RSA are yet to be explored (but see Cohn-Gordon, Goodman, & Potts, 2018, for an incremental extension of RSA).

6.8 Extensions to other language production phenomena

In this paper we focused on providing a computationally explicit account of definite modified and nominal referring expressions in reference games, focusing on the use of prenominal size and color adjectives as well as on the taxonomic level of noun reference. The cs-RSA model can be straightforwardly extended to different nominal domains and different properties. For instance, the literature has also explored 'overinformative' referring expressions that include material (*wooden,*

plastic), other dimensional (*long, short*), and other physical (*spotted, striped*) adjectives.

However, beyond the relatively limited linguistic forms we have explored here, future research should also investigate the very intriguing potential for this approach to be extended to any language production phenomenon that involves a choice in which aspects of an event or entity to mention (content selection) and how to realize that content linguistically, including in the domain of reference (pronouns, names, definite descriptions with post-nominal modification) and event descriptions. For example, in investigations of optional instrument mentions, P. Brown and Dell (1987) showed that atypical instruments are more likely to be mentioned than typical ones – if a stabbing occurred with an icepick, speakers prefer *The man was stabbed with an ice pick* rather than *The man was stabbed*. If instead a stabbing occurred with a knife, *The man was stabbed* is preferred over *The man was stabbed with a knife*). This is very much parallel to the case of atypical color mention.

Similarly, the approach outlined here might be extended to the case of non-restrictive modifiers. In these cases, the modifier is not used to distinguish a target referent from possible competitors. Instead, the speaker may intend to communicate an aspect of an already contextually established referent, as in *Sit by the newly painted table*, where the speaker is warning the listener not to put their elbows on the table (Dale & Reiter, 1995); or *Forrest looks at the massive crowd*, where the speaker is commenting on the extraordinary size of the crowd (Hahn, Degen, Goodman, Jurafsky, & Futrell, 2018). In these cases, the table and the crowd are contextually given referents; the modifiers *newly painted* and *massive* are used to highlight informative aspects of these referents. The approach proposed in this paper could be extended to these cases by allowing the speaker to be informative with respect to goals other than getting the listener to infer the intended referent. For instance, the speaker may want to be informative with respect to the goal of highlighting task-relevant properties of contextually given referents, as in the newly painted table case.

More generally, the approach should extend to any phenomenon that affords a choice between a more or less specific utterance. Whenever the more specific utterance adds relevant information compared to the less specific one, it should be produced. This is related to surprisal based theories of production like Uniform Information Density (UID, Jaeger, 2006; Levy & Jaeger, 2007; A. Frank & Jaeger, 2008; Jaeger, 2010), where speakers have been found to be more likely to omit linguistic signal if the underlying meaning or syntactic structure is highly predictable to the listener. Importantly, UID diverges from our account in that it is an account of the choice between

meaning-equivalent alternative utterances and includes no pragmatic reasoning component.

6.9 Conclusion

In conclusion, we have provided an account of redundant referring expressions that challenges the traditional notion of 'overinformativeness', unifies multiple language production literatures, and has the potential for many further extensions. We take this work to provide evidence that, rather than being wastefully overinformative, speakers are usefully redundant.

A Effects of semantic value on utterance probabilities

Here we visualize the effect of different adjective types' semantic value on the probability of producing the insufficient color-only utterance (*blue pin*), the sufficient size-only utterance (*small pin*), or the redundant color-and-size utterance (*small blue pin*) to refer to the target in context Figure 1a under varying β_i values, in Figure 21. This constitutes a generalization of Figure 4, which is duplicated in row 6 ($\beta_i = 30$).

B Pre-experiment quiz

Before continuing to the main experiment, each participant was required to correctly respond "True" or "False" to the following statements. Correct answers are given in parentheses after the statement.

- The speaker can click on an object. (False)
- The listener wants to click on the object that the speaker is telling them about. (True)
- The target is the object which has the red circle around it. (False)
- Only the speaker can send messages. (False)
- There are a total of 72 rounds. (True)
- The locations of the three objects are the same for the speaker and the listener. (False)

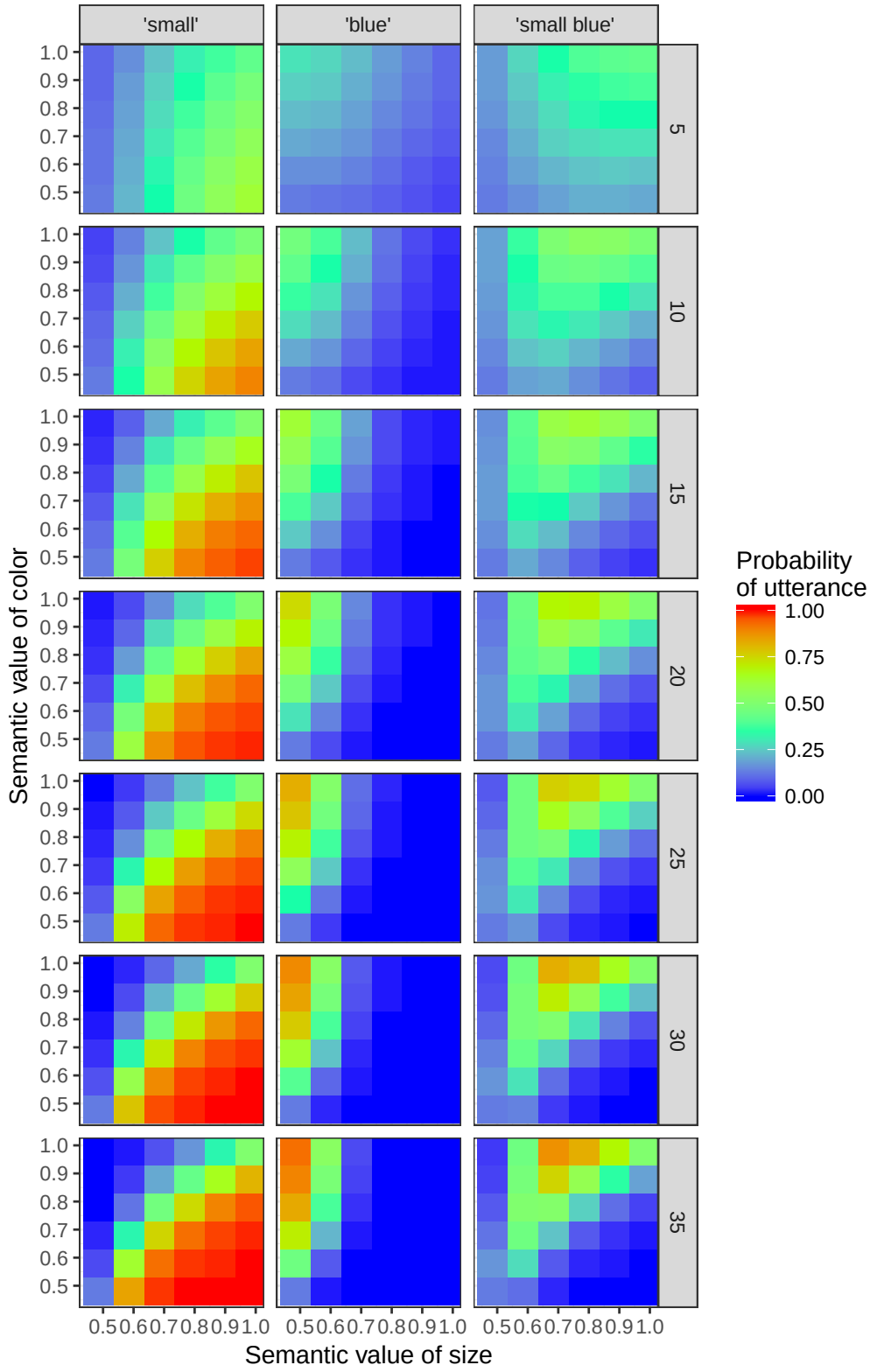


Figure 21: Probability of producing sufficient *small pin*, insufficient *blue pin*, and redundant *small blue pin* in contexts as depicted in Figure 1a, as a function of semantic value of color and size utterances and varying β_i row-wise (for $\beta_c = 0$).

C Exp. 1 items

The following table lists all 36 object types from Exp. 1 and the colors they appeared in:

Object	Colors	Object	Colors
avocado	black, green	balloon	pink, yellow
belt	black, brown	bike	purple, red
billiard ball	orange, purple	binder	blue, green
book	black, blue	bracelet	green, purple
bucket	pink, red	butterfly	blue, purple
candle	blue, red	cap	blue, orange
chair	green, red	coat hanger	orange, purple
comb	black, blue	cushion	blue, orange
flower	purple, red	frame	green, pink
golf ball	blue, pink	guitar	blue, green
hair dryer	pink, purple	jacket	brown, green
napkin	orange, yellow	ornament	blue, purple
pepper	green, red	phone	pink, white
rock	green, purple	rug	blue, purple
shoe	white, yellow	stapler	purple, red
thumb tack	blue, red	tea cup	pink, white
toothbrush	blue, red	turtle	black, brown
wedding cake	pink, white	yarn	purple, red

D Data pre-processing and exclusions

D.1 Exp. 1

Median completion time was 10 minutes. One participant was excluded because their native language was not English (but they participated in the listener role, so their exclusion was of no consequence to the analysis). 83% of participants thought their partner was human. Participants were not excluded if they didn't believe their partner was human.

We collected data from 2177 critical trials. Because we did not restrict participants' utterances

in any way, they produced many different kinds of referring expressions. Testing the model's predictions required, for each trial, classifying the produced utterance as an instance of a *color*-only mention, a *size*-only mention, or a *color-and-size* mention (or excluding the trial if no classification was possible). To this end we conducted the following semi-automatic data pre-processing.

An R script first automatically checked whether the speaker's utterance contained a precoded color (i.e. *black, blue, brown, gold, green, orange, pink, purple, red, silver, violet, white, yellow*) or size (i.e. *big, bigger, biggest, huge, large, larger, largest, little, small, smaller, smallest, tiny*) term. In this way, 95.7 % of cases were classified as mentioning size and/or color. However, this did not capture that sometimes, participants produced meaning-equivalent modifications of color/size terms for instance by adding suffixes (e.g., *bluish*), using abbreviations (e.g., *lg* for *large* or *purp* for *purple*), or using non-precoded color labels (e.g., *lime* or *lavender*). Expressions containing a typo (e.g., *pruple* instead of *purple*) could also not be classified automatically. In the next step, one of the authors (CG) therefore manually checked the automatic coding to include these kinds of modifications in the analysis. This covered another 1.9% of trials. Most of the time, participants converged on a convention of producing only the target's size and/or color, e.g., *purple* or *big blue*, but not a determiner (e.g., *the*) or the noun corresponding to the object's type (e.g., *comb*). Determiners were omitted in 88.6 % of cases and nouns were omitted in 71.6 % of cases. We did not analyze this any further.

There were 50 cases (2.3%) in which the speaker made reference to the distinguishing dimension in an abstract way, e.g. *different color*, *unique one*, *ripest*, *very girly*, or *guitar closest to viewer*. While interesting as utterance choices,[35] these cases were excluded from the analysis. There were 3 cases that were nonsensical, e.g. *bigger off a shade*, which were also excluded. In 6 cases only the insufficient dimension was mentioned – these were excluded from the analysis reported in the next section, where we are only interested in minimal or redundant utterances, not underinformative ones, but were included in the Bayesian data analysis reported in Section 3.2. Finally, we excluded six trials where the speaker did not produce any utterances, and 33 trials on which the listener selected the wrong referent, leading to the elimination of 1.5% of trials. After the exclusion, 2076

[35]Certain participants seemed to have deliberately used this as a strategy even though simply mentioning the distinguishing property would have been shorter in most cases. In all, only 12 participants produced these kinds of utterances: one 18 times, one 8 times, one 6 times, two 3 times, one 2 times, and the remaining six only once each.

cases classified as one of *color*, *size*, or *color-and-size* entered the analysis.

D.2 Exp. 2

Median completion time was 7 minutes. All participants self-reported English as their native language. 93% of participants thought their partner was human. Participants were not excluded if they believed their partner was human.

Two participant-pairs were excluded because they did not finish the experiment and therefore could not receive payment. Trials on which the speaker did not produce any utterances were also excluded, resulting in the exclusion of two additional participant-pairs. Finally, there were 10 speakers who consistently used roundabout descriptions instead of direct referring expressions (e.g., *monkeys love...* to refer to banana).[36] These pairs were also excluded, since such indirect expressions do not inform our questions about modifier production.

We analyzed data from 1974 trials. Just as in Exp. 1, participants communicated freely, which led to a vast amount of different referring expressions. To test the model's predictions, the utterance produced for each trial was to be classified as belonging to one of the following categories: *type-only* ("banana"), *color-and-type* ("yellow banana"), and *color-only* ("yellow") utterances. Referring expressions that included superordinate categories ("yellow fruit"), descriptions ("has green stem"), color-circumscriptions ("funky carrot"), and negations ("yellow but not banana") were regarded as *other* and excluded. To this end we conducted the following semi-automatic data pre-processing.

The referring expressions were analyzed similarly to Exp. 1. First, 32 trials (1.6%) were excluded because the listener selected the wrong referent. 109 trials (5.6%) were excluded because the referring expressions included one of the exceptional cases described above (e.g., using negations). An R script then automatically checked the remaining 1833 utterances for whether they contained a precoded color term (i.e. *green, purple, white, black, brown, yellow, orange, blue, pink, red, grey*) or type (i.e. *apple, banana, carrot, tomato, pear, pepper, avocado*). This way, 96.5% of the remaining

[36] It is unclear whether these participants misunderstood task instructions, or were simply being playful. This is interestingly different from Exp. 1, where participants did not produce such descriptions, presumably because the object type was identical and therefore there were no differences between objects except for color and size. We speculate that on average the functional differences between objects that differ in type are greater than between those that differ in color or size, with the former consequently being more inspiring for the generation of creative referring expressions.

cases were classified as mentioning type and/or color.

However, this did not capture that sometimes, participants produced meaning-equivalent modifications of color/type terms for instance by adding suffixes (e.g., *pinkish*), using abbreviations (e.g., *yel* for *yellow*), or using non-precoded color and type labels (e.g., *lavender* or *jalapeno*). In addition, expressions that contained a typo (e.g., *blakc* instead of *black*) could also not be classified automatically. One of the authors (EK) therefore manually hand-coded these cases. There were 6 cases (0.3%) that could not be categorized and were excluded. Overall, 1827 utterances were classified as one of *color*, *type*, or *color-and-type* entered the analysis.

D.3 Exp. 3

We collected 2193 referring expressions. To determine the level of reference for each trial, we followed the following procedure. First, speakers' and listeners' messages were parsed automatically; the referring expression used by the speaker was extracted for each trial and checked for whether it contained the current target's correct *sub*(ordinate), *basic*, or *super*(ordinate) level term using a simple grep search. In this way, 71.4% of trials were labelled as mentioning a pre-coded level of reference. In the next step, remaining utterances were checked manually by one of the authors (CG) to determine whether they contained a correct level of reference term which was not detected by the grep search due to typos or grammatical modification of the expression. In this way, meaning-equivalent alternatives such as *doggie* for *dog*, or reduced forms such as *gummi*, *gummies* and *bears* for *gummy bears* were counted as containing the corresponding level of reference term. This covered another 15.0% of trials. 41 trials on which the listener selected the wrong referent were excluded, leading to the elimination of 2.1% of trials. Six trials were excluded because the speaker did not produce any utterances. Additionally, a total of 12.5% of correct trials were excluded because the utterance consisted only of an attribute of the superclass (*the living thing* for *animal*), of the basic level (*can fly* for *bird*), of the subcategory (*barks* for *dog*) or of the particular instance (*the thing facing left*) rather than a category noun. These kinds of attributes were also mentioned in addition to the noun on trials which were included in the analysis for 8.9% of sub level terms, 18.9% of basic level terms, and 60.9% of super level terms. On 1.2% of trials two different levels of reference were mentioned; in this case the more specific level of reference was counted as being mentioned in this trial. After all exclusion and pre-processing, 1872 cases classified as one of *sub*, *basic*, or *super*

entered into the analysis.

E Typicality effects in Exp. 1

To assess whether we replicate the color typicality effects previously reported in the literature (Sedivy, 2003; Westerbeek et al., 2015; Rubio-Fernandez, 2016), we elicited color typicality norms for each of the items in Exp. 1 and then included typicality as an additional predictor of redundant adjective use in the regression analysis reported in Section 3.1.3.

E.1 Methods

E.1.1 Participants

We recruited 60 participants over Amazon's Mechanical Turk who were each paid $0.25 for their participation.

E.1.2 Procedure and materials

On each trial, participants saw one of the big versions of the items used in Exp. 1 and were asked to answer the question "How typical is this for an X?" on a continuous slider with endpoints labeled "very atypical" to "very typical." X was a referring expression consisting of either only the correct noun (e.g., *stapler*) or the noun modified by the correct color (e.g., *red stapler*). Figure 22 shows an example of a modified trial.

Each participant saw each of the 36 objects once. An object was randomly displayed in one of the two colors it occurred with in Exp. 1 and was randomly displayed with either the correct modified utterance or the correct unmodified utterance, in order to obtain roughly equal numbers of object-utterance combinations.

Importantly, we only elicited typicality norms for unmodified utterances and utterances with color modifiers, but not utterances with size modifiers. This was because it is impossible to obtain size typicality norms for objects presented in isolation, due to the inherently relational nature of size adjectives. Consequently, we only test for the effect of typicality on *size-sufficient* trials, i.e. when color is redundant.

Figure 22: A modified example trial from the typicality elicitation experiment.

E.2 Results and discussion

We coded the slider endpoints as 0 ("very atypical") and 1 ("very typical"), essentially treating each response as a typicality value between 0 and 1. For each combination of object, color, and utterance (modified/unmodified), we computed that item's mean. Mean typicalities were generally lower for unmodified than for modified utterances: mean typicality for unmodified utterances was .67 (sd=.17, mode=.76) and for modified utterances .75 (sd=.12, mode=.81). This can also be seen on the left in Figure 23. Note that, as expected given how the stimuli were constructed, typicality was generally skewed towards the high end, even for unmodified utterances. This means that there was not much variation in the difference in typicality between modified and unmodified utterances. We will refer to this difference as *typicality gain*, reflecting the overall gain in typicality via color modification over the unmodified baseline. As can be seen on the right in Figure 23, in most cases typicality gain was close to zero.

This makes the typicality analysis difficult: if typicality gain is close to zero for most cases (and, taking into account confidence intervals, effectively zero), it is hard to evaluate the effect of typicality on redundant adjective use. In order to maximize power, we therefore conducted the analysis only on those items for which for at least one color the confidence intervals for the modified and unmodified utterances did not overlap. There were only four such cases: *(pink) golfball*, *(pink) wedding cake*, *(green) chair*, and *(red) stapler*, for a total of 231 data points.

Predictions differ for size-sufficient and color-sufficient trials. Given the typicality effects re-

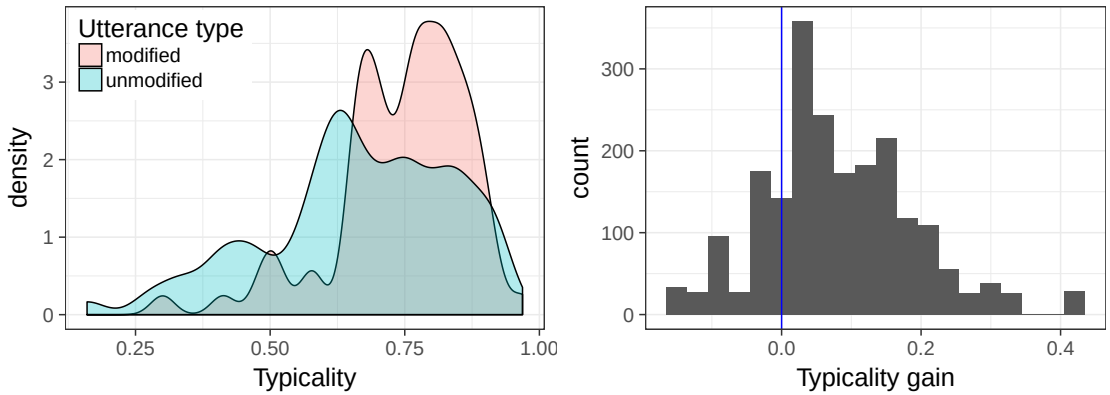


Figure 23: Typicality densities for modified and unmodified utterances (left) and histogram of typicality gains (differences between modified and unmodified typicalities, right).

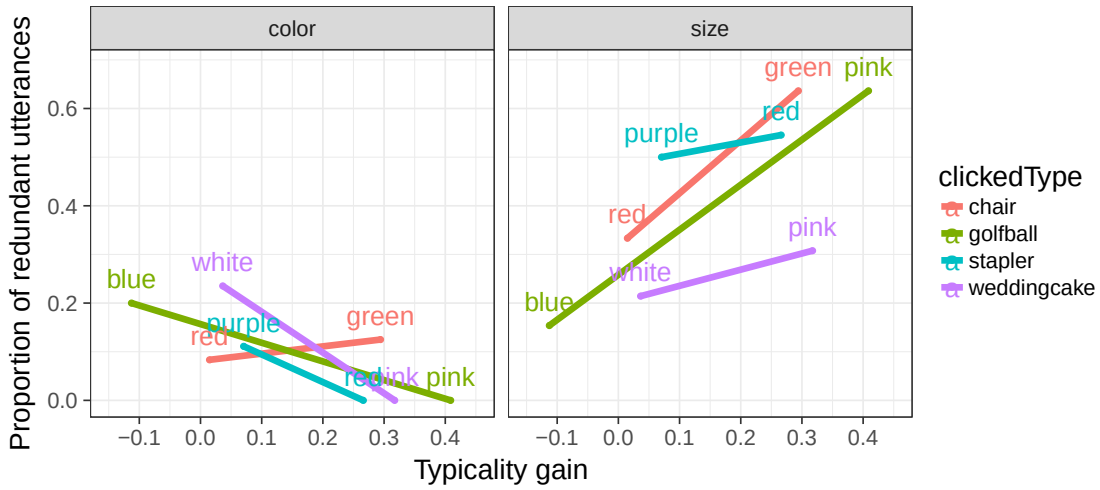


Figure 24: Utterance probability for four items as a function of difference in typicality between modified and unmodified utterance (x-axis) and sufficient dimension (columns).

ported in the literature and the predictions of cs-RSA, we expect greater redundant color use on size-sufficient trials with *increasing* typicality gain. The predictions for redundant size use on color-sufficient trials are unclear from the previous literature. Cs-RSA, however, predicts greater redundant size use with *decreasing* typicality gain: small color typicality gains reflect the relatively low out-of-context utility of color. In these cases, it may be useful to redundantly use a size modifier even if that modifier is noisy. If borne out, these predictions should surface in an interaction between sufficient property and typicality gain. Visual inspection of the empirical proportions of redundant adjective use in Figure 24 suggests that this pattern is indeed borne out.

In order to investigate the effect of typicality gain on redundant adjective use, we conducted a mixed effects logistic regression analysis predicting redundant over minimal adjective use from

Table 8: Model coefficients, standard errors, and p-values. Significant p-values are bolded.

	Coef β	SE(β)	p
Intercept	−1.85	0.34	**<.0001**
Scene variation	4.29	1.16	**<.001**
Sufficient property	2.72	0.60	**<.0001**
Scene variation : Sufficient property	0.88	2.12	<0.68
Sufficient property : Typicality gain	9.43	2.68	**<.001**

fixed effects of scene variation, sufficient dimension, the interaction of scene variation and sufficient property, and the interaction of typicality gain and sufficient property. This is the same model as reported in Section 3.1.3, with the only difference that the interaction between sufficient property and typicality gain was added. All predictors were centered before entering the analysis. The model contained the maximal random effects structure that allowed it to converge: by-participant and by-item (where item was a color-object combination) random intercepts.

The model summary is shown in Table 8. We replicate the effects of sufficient property and scene variation observed earlier on this smaller dataset. Crucially, we observe a significant interaction between sufficient property and typicality gain.[37] Simple effects analysis reveals that this interaction is due to a positive effect of typicality gain on redundant adjective use in the size-sufficient condition ($\beta = 4.47$, $SE = 1.65$, $p < .007$) but a negative effect of typicality gain on redundant adjective use in the color-sufficient condition ($\beta = -5.77$, $SE = 2.49$, $p < .03$).

An important point is of note: the typicality elicitation procedure we employed here is somewhat different from that employed by Westerbeek et al. (2015), who asked their participants "How typical is this color for this object?" We did this for conceptual reasons: the values that go into the semantics of the RSA model are most easily conceptualized as the typicality of an object as an instance of an utterance. While the typicality of a feature for an object type no doubt plays into how good of an instance of the utterance the object is, deriving our typicalities from the statistical properties of the subjective distributions of features over objects is beyond the scope of this paper. However, in a separate experiment we did ask participants the Westerbeek question. The correlation

[37] Conducting the same analysis on the entire dataset (i.e., using all of the noisy typicality estimates, replicated the scene variation and sufficient property effects. The interaction of typicality gain and sufficient property went in the same direction numerically, but failed to reach significance ($\beta = 1.52$, $SE = 1.45$, $p < .29$).

between mean typicality ratings from the Westerbeek version and the unmodified "How typical is this for X" version was .75. The correlation between the Westerbeek version and the modified version was .64. The correlation between the Westerbeek version and typicality gain was -.52.

For comparison, including typicality means obtained via the Westerbeek question as a predictor instead of typicality gain on the four high-powered items replicated the significant interaction between typicality and sufficient property ($\beta = -6.77$, $SE = 1.88$, $p < .0003$). Simple effects analysis revealed that the interaction is again due to a difference in slope in the two sufficient property conditions: in the size-sufficient condition, color is less likely to be mentioned with increasing color typicality ($\beta = -3.66$, $SE = 1.18$, $p < .002$), whereas in the color-sufficient condition, size is more likely to be mentioned with increasing color typicality ($\beta = 3.09$, $SE = 1.45$, $p < .04$).[38]

We thus overall find moderate evidence for typicality effects in our dataset. Typicality effects are strong for those items that clearly display typicality differences between the modified and unmodified utterance, but much weaker for the remaining items. That the evidence for typicality effects is relatively scarce is no surprise: the stimuli were specifically designed to minimize effects of typicality. However, the fact that both ways of quantifying typicality predicted redundant adjective use in the expected direction suggests that with more power or with stimuli that exhibit greater typicality variation, these effects may show up more clearly.

F Experiment 3 items

The following table lists all items used in Exp. 3 and the mean empirical utterance lengths that participants produced to refer to them:

G Typicality norms for Experiment 3

Analogous to the color typicality norms elicited for utterances in Exps. 1-2, we elicited typicality norms for utterances in Exp. 3. The elicited typicalities were used in the mixed effects analyses and Bayesian Data Analysis reported in Section 5.

[38] Again, conducting this analysis on the entire dataset yielded only a marginal interaction of sufficient property and color typicality in the right direction ($\beta = -1.10$, $SE = .64$, $p < .09$).

Table 9: List of domains and associated superordinate category, target stimuli, and mean length (standard deviation) in characters of actually produced subordinate level utterances in Exp. 2.

Domain	Super	Targets	Mean sub length (sd)
bear	animal	black bear	9.9 (.14)
		polar bear	8.8 (.35)
		panda bear	5.5 (.2)
		grizzly bear	9 (.98)
bird	animal	eagle	4.9 (.1)
		parrot	6.1 (.13)
		pigeon	5.9 (.22)
		hummingbird	10.1 (.5)
candy	snack	MnMs	4.4 (.49)
		skittles	6.9 (.43)
		gummy bears	8.5 (.47)
		jelly beans	9.3 (.44)
car	vehicle	SUV	3 (0)
		minivan	5.7 (.27)
		sports car	9.8 (.23)
		convertible	11.1 (.2)
dog	animal	pug	3 (.08)
		husky	4.7 (.22)
		dalmatian	8.8 (.18)
		German Shepherd	13.1 (.82)
fish	animal	catfish	6.6 (.4)
		goldfish	7.9 (.22)
		swordfish	8 (.43)
		clownfish	9.1 (.38)
flower	plant	rose	4 (0)
		tulip	4.4 (.18)
		daisy	5.9 (.55)
		sunflower	9 (.11)
shirt	clothing	T-shirt	6.4 (.48)
		polo shirt	6.7 (.79)
		dress shirt	11 (0)
		Hawaii shirt	12.6 (.46)
table	furniture	picnic table	9.7 (.58)
		dining table	12 (0)
		coffee table	9.1 (.95)
		bedside table	8.3 (.68)

G.0.1 Methods

Participants We recruited 240 participants over Amazon's Mechanical Turk who were each paid $0.50 for their participation.

Procedure and materials On each trial, participants saw one of the images used in Exp. 3 and were asked to answer the question "How typical is this for an X?" on a continuous slider with endpoints labeled "very atypical" to "very typical." X was a nominal referring expression. We did not test all utterance-object combinations, which would have led to an explosion of conditions. Instead, we tested each target object with its three utterances (e.g., the dalamtian was paired with *dalmatian*, *dog*, and *animal*; the pug was paired with *pug*, *dog*, and *animal*, etc.). That yielded a total of 108 combinations – four targets in nine domains with three utterances each. We further tested each distractor item that shared the target's superordinate category (*dist-samesuper*, e.g., elephants share the superordinate category animal with dogs) on both the basic level and the superordinate level term (e.g., *dog* for elephant and *animal* for elephant), for a total of 469 combinations. Finally, we also tested each distractor of a different superordinate category than the target on the target's superordinate level term (*dist-diffsuper*, e.g., *animal* for rose). This yielded another 168 combinations. Overall, we obtained typicality norms for 745 object-utterance combinations. All other object-utterance combinations were assumed to have typicality 0. Each participant rated 45 items: 7 targets, 10 dist-diffsuper, and 28 dist-samesuper cases. These were randomly sampled from the overall pool of items in each category.

G.0.2 Results and discussion

Each combination was rated at least 5 times and at most 27 times. We coded the slider endpoints as 0 ("very atypical") and 1 ("very typical"). In order to evaluate the model, we used each object-utterance combination's typicality mean as input.

Typicality ratings by item type (target, dist-samesuper, dist-diffsuper) and utterance type (sub, basic, super) are visualized in Figure 25. As expected, typicality was close to 0 for distractor items with a different superordinate category as the target, and for subordinate/basic level terms used with distractors of the same superordinate category. However, even for these cases, there was some variation.

For targets, typicality of the object for the utterance decreased with increasing reference level, mirroring the typicality ratings obtained for Exp. 1 – a particular object is a better instance of the more specific term than of the more general term for that object.

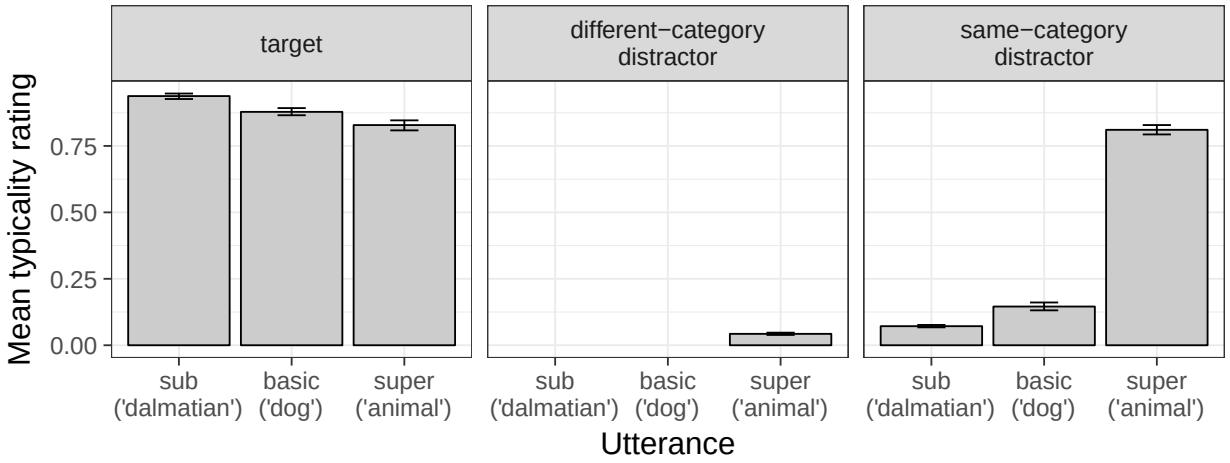


Figure 25: Mean typicality ratings by utterance (target subordinate, basic, and superordinate level term) for targets (e.g., *dalmatian*, left panel), distractors with a different superordinate category from the target (e.g., *rose*, middle panel), and distractors with the same superordinate category as the target (e.g., *elephant*, right panel). Error bars indicate bootstrapped 95% confidence intervals.

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