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Semantic Information and the Syntax of Propositional Attitude Verbs

Aaron S. White,[a] Valentine Hacquard,[b] Jeffrey Lidz[b]

[a]*Science of Learning Institute, Department of Cognitive Science, Center for Language and Speech Processing, Johns Hopkins University*

[b]*Department of Linguistics, University of Maryland*

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Abstract

Propositional attitude verbs, such as *think* and *want*, have long held interest for both theoretical linguists and language acquisitionists because their syntactic, semantic, and pragmatic properties display complex interactions that have proven difficult to fully capture from either perspective. This paper explores the granularity with which these verbs' semantic and pragmatic properties are recoverable from their syntactic distributions, using three behavioral experiments aimed at explicitly quantifying the relationship between these two sets of properties. Experiment 1 gathers a measure of 30 propositional attitude verbs' syntactic distributions using an acceptability judgment task. Experiments 2a and 2b gather measures of semantic similarity between those same verbs using a generalized semantic discrimination (triad or "odd man out") task and an ordinal (Likert) scale task, respectively. Two kinds of analyses are conducted on the data from these experiments. The first compares both the acceptability judgments and the semantic similarity judgments to previous classifications derived from the syntax and semantics literature. The second kind compares the acceptability judgments to the semantic similarity judgments directly. Through these comparisons, we show that there is quite fine-grained information about propositional attitude verbs' semantics carried in their syntactic distributions—whether one considers the sorts of discrete qualitative classifications that linguists traditionally work with or the sorts of continuous quantitative classifications that can be derived experimentally.

Keywords: Propositional attitude verbs; Syntactic bootstrapping; Verb learning; Syntax-semantics interface; Lexical semantics; Projection rules

1. Introduction

Theoretical linguists have long been interested in propositional attitude verbs—for example, *want*, *think*, and *know*—for both their syntactic properties and their semantic

Correspondence should be sent to Aaron Steven White, Johns Hopkins University, Department of Cognitive Science, 237 Krieger Hall, 3400 N. Charles Street, Baltimore, MD 21218. E-mail: aswhite@jhu.edu

properties. These verbs are syntactically interesting because, as a class, they take a wide variety of clausal complements. For instance, *think* and *know* take tensed clausal complements, and *want* takes untensed clausal complements.

(1) Mary {thought, knew} that John was happy.
(2) Mary wanted John to be happy.

They are semantically interesting because even superficially quite similar verbs, such as *think* and *know*, can have strikingly different semantic properties—for example, distinct patterns of entailment. Neither 1 nor 1 implies either 1 or 1, but both 1 and 1 (only) imply 1.

(3) a. Mary thought that John was happy.
    b. Mary didn't think that John was happy.
(4) a. Mary knew that John was happy.
    b. Mary didn't know that John was happy.
(5) a. John was happy.
    b. John wasn't happy.

Language acquisitionists have also long been interested in propositional attitude verbs, though from a different angle: Among other interesting cognitive properties, these verbs, in contrast to action verbs like *run* and *kick*, are not associated with concepts that have perceptual correlates (Gleitman, 1990; Landau & Gleitman, 1985). This *problem of observability* was key in Gleitman's (1990) argument for *syntactic bootstrapping*, wherein a learner uses a word's syntactic context in acquiring its meaning (Brown, 1957, 1973; Fisher, 1994; Fisher, Hall, Rakowitz, & Gleitman, 1994; Fisher, Gertner, Scott, & Yuan, 2010; Lidz, Gleitman, & Gleitman, 2004; Macnamara, 1972; Naigles, 1990; Naigles, 1996; Naigles, Gleitman, & Gleitman, 1993; Waxman & Lidz, 2006; Waxman & Markow, 1995).

These two traditions have largely remained separate, despite having what we believe to be closely aligned goals.[1] On the one hand, the theoretical literature has focused on understanding the fine-grained relationships that exist between word meaning and syntactic structure, without much thought to whether these relationships are robust enough to support learning. On the other hand, the acquisition literature has focused on how only very few syntactic distinctions—generally, the distinction between tensed and untensed clausal complements—are leveraged in syntactic bootstrapping. But if the problem of observability is as dire as Gleitman suggests—a view which is supported by much subsequent literature (Gillette, Gleitman, Gleitman, & Lederer, 1999; Papafragou, Cassidy, & Gleitman, 2007; Snedeker & Gleitman, 2004 among others)—understanding the strength of the correlations between syntax and fine-grained aspects of meaning is crucial.

Our goal in this paper is to test the limits of syntactic bootstrapping by quantitatively assessing correlations between syntax and word meaning in the domain of propositional attitude verbs. We do this in two parts. In the first, we assess whether the fine-grained semantic properties that are discussed in the theoretical literature are in fact predictable based purely on propositional attitude verb syntactic distributions. And to the extent that they are, we aim to find out which syntactic structures are predictive of these semantic properties. To do this, we collect a measure of propositional attitude verbs' syntactic distributions using an acceptability judgment-based methodology developed by Fisher, Gleitman, and Gleitman (1991). We show that the classifications laid out in the theoretical literature are quite well predicted by syntactic distributions and that the syntactic structures that are predictive of those properties generally match those suggested in the literature. This part is aimed mainly at the acquisitionists interested in generating hypotheses about what syntactic features learners might use in syntactic bootstrapping.

In the second part, we assess whether the semantic properties discussed in the theoretical literature exhaust the semantic information carried in propositional attitude verb syntactic distributions. To do this, we gather an independent measure of verbs' semantics—verb similarity judgments (cf. Fisher et al., 1991; Lederer, Gleitman, & Gleitman, 1995; Schwanenflugel, Fabricius, Noyes, Bigler, & Alexander, 1994; Schwanenflugel, Fabricius, & Noyes, 1996)—and ask whether semantic properties discussed in the existing theoretical literature statistically mediate the relationship between the syntactic distributions and this measure. The idea is that, insofar as the similarity judgments are predictable from syntactic distributions even after controlling for the semantic properties, we have evidence of further semantic properties that are tracked by syntactic distributions. We show that there is indeed substantial evidence for such further syntactically tracked semantic properties. This part is aimed mainly at theoreticians interested in augmenting their methodological toolbox, but we believe it is also useful for acquisitionists trying to understand how much learning could in fact be squeezed out of the syntax.

We begin in Section 2 with an overview of relevant theoretical literature on propositional attitude verbs, pointing out areas of connection with the acquisition literature. In Section 3, we present our acceptability judgment experiment, whose design draws heavily on the prior work discussed in Section 2. We then use the data from this experiment to predict the semantic properties discussed in Section 2. In Section 4, we present two similarity judgment experiments, which we compare against both the acceptability judgment data from Section 3 and the semantic properties from Section 2. In Section 5, we discuss the prospects for extending our findings to other languages. And in Section 6, we conclude.

2. Propositional attitude verb syntax and semantics

In this section, we present a brief overview of the literature on the syntax and semantics of propositional attitude verbs. Each subsection corresponds to a semantic property we attempt to predict in Section 3. Where possible, we point out cases where the property, or a related property, has been studied in the acquisition literature. Beyond laying out the properties themselves, our aim in this section is to show (a) how these semantic properties might map to syntactic distributions and (b) that there is sufficient uncertainty about these mappings to warrant the quantitative assessments we carry out in Sections 3 and 4.

2.1. Representationality and preferentiality

Perhaps the most well-known semantic distinction among propositional attitude verbs is that between verbs that express beliefs—or represent "mental pictures" or "judgments of truth" (Bolinger, 1968)—and those that express desires—or more generally, orderings on states of affairs induced by, for example, commands, laws, preferences, and so on (Anand & Hacquard, 2013; Bolinger, 1968; Farkas, 1985; Heim, 1992; Stalnaker, 1984; Villalta, 2000 2008, a.o.). Within the first class, which we henceforth refer to as the *representationals*, fall verbs like *think* and *know*; and within the second class, which we henceforth refer to as the *preferentials*, fall verbs like *want* and *order*.

There appear to be various aspects of the syntactic distribution that roughly track this distinction in English. One well-known case is finiteness: Representationals tend to allow finite subordinate clauses (6a) but not nonfinite ones (6b); preferentials tend to allow non-finite subordinate clauses (7b) but not finite ones (7a).[2]

(6) a. Bo thinks that Jo went to the store.
    b. *Bo thinks Jo to go to the store.

(7) a. *Bo wants that Jo went to the store.
    b. Bo wants Jo to go to the store.

This correlation is quite well studied in the acquisition literature, with particular focus on how it relates to theory of mind (de Villiers, 1995, 2005; De Villiers, 2007; De Villiers & De Villiers, 2000; De Villiers & Pyers, 2002; Lewis, 2013; Perner, Sprung, Zauner, & Haider, 2003; Wimmer & Perner, 1983). Children tend to reject sentences like 1 when they report false beliefs—for example, if Jo didn't go to the store—but not sentences like 1 when they report desires that are counter to fact. The relative difficulty with sentences like 1 has been blamed on conceptual difficulty with false belief (Perner et al., 2003), syntactic difficulty with finite complements (de Villiers, 1995, 2005; De Villiers, 2007; De Villiers & De Villiers, 2000; De Villiers & Pyers, 2002) or pragmatic difficulty tied to the assertivity of belief reports (Lewis, 2013; Lewis, Hacquard, & Lidz, 2017). (See below for more on assertivity.)

There are two important things to note about the representational-preferential distinction. First, though this distinction is often discussed as though it were mutually exclusive, some verbs appear to fall into both categories, and suggestively, show up in both frames. For instance, *hope p* involves both a desire that *p* come about and the belief that *p* is possible (Anand & Hacquard, 2013; Hacquard, 2014; Portner, 1992; Scheffler, 2009, but see also Portner & Rubinstein, 2013), and it occurs in both finite 1 and nonfinite 1 syntactic contexts.

(8) a. Bo hopes that Jo went to the store.
    b. Bo hopes to go to the store.

Harrigan (2015) and Harrigan, Hacquard, and Lidz (2016) show that this distribution of clausal complements affects children's interpretation of *hope*. When *hope* occurs with a finite complement, children's interpretations show properties similar to the representational *think*—for example, they overgeneralize that *hope*, like *think*, is used to report true beliefs—but when it occurs with a nonfinite complement children's interpretations show properties similar to the preferential *want*.

Second, the link between representationality and finiteness is just a tendency. Some verbs plausibly classed as representationals allow nonfinite subordinate clauses (9a)/(9b), and others plausibly classed as preferentials allow subordinate clauses that look finite (9c).[3] The roughness of this correlation is perhaps not surprising since not all languages track representationality with tense; for instance, various Romance languages track the distinction with mood—representationals tending to take indicative mood and preferentials tending to take subjunctive mood (Bolinger, 1968; Farkas, 1985; Giannakidou, 1997; Giorgi & Pianesi, 1997; Hooper, 1975; Portner, 1992; Quer, 1998; Villalta, 2000 2008, a.o.). (We return to this issue of cross-linguistic instability in Section 5.)

(9) a. Bo believes Jo to be intelligent.
b. Bo claims to be intelligent.
c. Bo demanded that Jo go to the store.

But though the correlation between representationality and tense is imperfect, even in English, finiteness does not appear to be the only associated syntactic (distributional) property. Also relevant appears to be a distinction in whether the verb's subordinate clause can be fronted—or in Ross's (1973) terms, S-lifted.[4] At least some representationals' subordinate clauses 10 appear to be able to undergo S-lifting, but many preferentials' subordinate clauses 10 cannot (Bolinger, 1968).[5]

(10) Jo already went to the store, I {think, believe, suppose, hear, see}
(11) a. *Bo already went to the store, I {want, need, demand}.
b. *Bo to go to the store, I {want, need, order}.

S-lifting may well be quite important for learning whether a verb is a representational: Diessel and Tomasello (2001) find that many of children's early uses of representationals like *think* show up in S-lifting structures.

2.2. Factivity

The representationality distinction is cross-cut by another common distinction: factivity (Hooper, 1975; Horn, 1972; Karttunen, 1971; Kiparsky & Kiparsky, 1970). Factivity is defined in terms of its discourse effects: Very roughly, a verb is factive if upon uttering a sentence containing a factive verb with a subordinate clause, a speaker takes the content of the subordinate clause for granted regardless of propositional operators placed around the propositional attitude verb: in particular, negation (13b)/(12b) or questioning (13c)/(12c). For instance, each sentence in (12) commits the speaker to (14) being true, but modulo the context, the sentences in 2 do not. That is, in uttering the sentences in (12), the speaker presupposes (14) (Stalnaker, 1973). This suggests that *know*, *love*, and *hate* are factive, while *think*, *believe*, and *say* are not.

(12) a. Bo {knew, loved, hated} that Jo went to the store.
  b. Bo didn't {know, love, hate} that Jo went to the store.
  c. Did Bo {know, love, hate} that Jo went to the store?
(13) a. Bo {thought, believed, said} that Jo went to the store.
  b. Bo didn't {think, believe, say} that Jo went to the store.
  c. Did Bo {think, believe, say} that Jo went to the store?
(14) Jo went to the store.

Factivity truly cross-cuts the representationality distinction in that there are verbs representing all four possible combinations: (a) representational (cognitive) factives, like *know*, *realize*, and *understand*, (b) preferential (emotive) factives, like *love* and *hate*, (c) representational nonfactives, like *think* and *say*, and (d) preferential nonfactives, like *want* and *prefer*.[6]

The factivity distinction appears to be tracked most closely by whether the verb allows both question and nonquestion subordinate clauses (Anand & Hacquard, 2014; Egré, 2008; Ginzburg, 1995; Hintikka, 1975; Lahiri, 2002; Sæbø, 2007; Spector & Egré, 2015; Uegaki, 2012, though see White and Rawlins, unpublished data). For instance, the factive *know* can occur with both nonquestion (15a) and question (15b) subordinate clauses, while the nonfactive *think* can occur only with nonquestion subordinate clauses (16a) and (16b).[7]

(15) a. Jo knows that Bo went to the store.
  b. Jo knows {if, why} Bo went to the store.
(16) a. Jo thinks that Bo went to the store.
  b. *Jo thinks {if, why} Bo went to the store.

This generalization has two well-known types of exceptions. First, many nonfactive communication predicates, such as *tell* and *say*, allow both question and nonquestion subordinate clauses; second, some mental predicates, such as *decide*, *assess*, and *evaluate*, also allow both question and nonquestion subordinate clauses.

(17) a. Jo hasn't {told me, said} whether Bo went to the store.
  b. Jo hasn't yet {decided, assessed, evaluated} whether to go to the store.

Little work has been done on how learners might use the syntax to learn factives or even when factivity is acquired at all (though see Dudley, Orita, Hacquard & Lidz, 2015). There is, however, some work focusing on distinctions in speaker certainty signaled by, for example, *know* versus *think* (Abbeduto & Rosenberg, 1985; Harris, 1975; Johnson & Maratsos, 1977; Moore & Davidge, 1989; Moore, Bryant & Furrow, 1989; Schwanenflugel et al., 1994 1996), which is likely correlated with factivity but which is a conceptually distinct phenomenon (though see Hopmann & Maratsos, 1978; Léger, 2008; Scoville & Gordon, 1980, for tasks that attempt to test factivity).

2.3. Assertivity

Further cross-cutting representationality and factivity is the assertivity distinction (Hooper, 1975). Like factivity, assertivity is defined in terms of its effects on discourse. Again very roughly, a verb is assertive if it can be used in situations where its subordinate clause seems to carry the main point of the utterance (see Anand & Hacquard, 2014; Simons, 2007; Urmson, 1952, for discussion). For instance, *think* and *say* seem to allow this (18a), but *hate* does not (18b).

(18) a. **A:** Where is Jo?
B: Bo {thinks, said} that she's in Florida.
b. **A:** Where is Jo?
B: # Bo loves that she's in Florida.

Assertivity tends to correlate with representationality, though not all representationals are assertive. For example, negative representationals (e.g., *deny*, *doubt*), fictive representationals (e.g., *imagine*, *pretend*) and emotive factives (e.g., *love*, *amaze*) are all nonassertive.

(19) **A:** Where is Jo?
B: # Bo {doubts, is pretending} that she's in Florida.

Assertivity correlates with the availability of S-lifting and the propositional anaphor object *so*. Assertives, like *think* and *say*, can occur with S-lifted subordinate clauses (20a) and *so* (21a), but *hate* cannot occur with either S-lifting (20b) or *so* (21b).

(20) a. She's in Florida, Bo {thought, said}.
b. *She's in Florida, Bo hated.
(21) a. Bo {thinks, said} so.
b. *Bo hates so.

Hooper (1975) claims that the assertivity distiction cross-cuts the factivity distinction to give rise to a further split between semi-factives (assertive factives), like *know*, and true factives (nonassertive factives), like *love* and *hate* (see Karttunen, 1971, for an early description of this distinction).[8] Important for our purposes is that the semi-factive verus true factive distinction appears to correlate (a) with the (semantic) representationality distinction—semi-factives also tend to be cognitive factives and true factives tend to be emotive factives—and (b) at least two sorts of syntactic distinctions.

First, semi-factives tend to allow both polar (22a) and WH (22b) questions, but true factives tend to allow only WH questions (23b), not polar questions (22a) (Karttunen, 1977).[9]

(22) a. Jo knows if/whether Bo sliced the bread.
b. Jo knows how Bo sliced the bread.
(23) a. *Jo {loves, hates} if/whether Bo sliced the bread.
b. Jo {loves, hates} how Bo sliced the bread.

Guerzoni (2007) notes, however, that this correlation is not perfect, since some canonical semi-factives like *realize* resist polar questions in many contexts.

Second, semi-factives tend to allow complementizer ommission (24a), but true factives tend not to (24b). This second correlation is less strong and is likely modulated by syntax: expletive subject emotive factives appear to be better with complementizer omission, particularly when they passivize (see Grimshaw, 2009, for further recent discussion of complementizer ommission).

(24) a. I {know, realize} (that) Jo already went to the store.
b. I {hate, love} *(that) Jo already went to the store.

(25) a. It {amazed, bothered} me ???(that) Jo already went to the store.
b. I was {amazed, bothered} ?(that) Jo already went to the store.

The idea of assertivity as a semantic property shows up in the *function codes* developed by Gelman and Shatz (1977) and Shatz, Wellman, and Silber (1983). It is also important in Diessel and Tomasello's (2001) study of parenthetical uses of propositional attitude verbs, and it is what Lewis (2013) and Lewis et al. (2017) argue is responsible for children's tendency to reject *think* sentences that report false beliefs: Children tend to over-assume assertive parenthetical uses, and thus reject *think* sentences which they believe are used to indirectly assert something false.

2.4. Communicativity

Communicativity roughly corresponds to whether a verb refers to a communicative act. This distinction cross-cuts at least the representationality distinction—there are both representational communicatives, like *say* and *tell*, and preferential communicatives, like *demand*—and perhaps other distinctions as well, such as the factive-nonfactive distinction (see Anand & Hacquard, 2014, for extensive discussion of whether communicativity truly cross-cuts factivity or not).[10]

The syntactic correlates of communicativity seem quite apparent on the surface. Communicative verbs, along with a subordinate clause, tend to take noun phrase (26a) or prepositional phrase (26b) arguments representing the recipient of the communication (see Zwicky, 1971 *et seq*).

(26) a. Bo told me that Jo went to the store.
b. Bo said to me that Jo went to the store.

But though this is often treated as a clearly marked distinction, there are various reasons to be cautious about it. For instance, note that *demand* and *tell* can occur in string-identical contexts with *want* and *believe*. These string-identical contexts appear to be be distinguished only given some parse of the string. Wanting and believing don't seem to involve anything besides a wanter/believer and a thing wanted/believed. In contrast, telling and demanding seem to require an additional role: the entity to which the communication is directed.

(27) Bo {told, demanded, wanted, believed} Jo to be happy.

This is plausibly syntactically encoded. Note that the pleonastic element *there*, which is plausibly an overt cue to the particular syntactic configuration in question, is only allowed with *want* and *believe*, but not *tell* and *demand*. This has been used to suggest that *tell* and *demand* in (27) involve an underlying object while *want* and *believe* do not (see (see Rosenbaum, 1967 *et seq*).

(28) Bo {*told, *demanded, wanted, believed} there to be a raucous party.

Further, there are some string-identical contexts that both communicative and noncommunicative verbs can appear in which plausibly have no syntactic (or perhaps even selectional) distinctions. For instance, the communicative verb *promise* and the verb *deny*, which is plausibly noncommunicative in this syntactic context, both allow constructions with two noun phrases.

(29) Bo {promised, denied} Bo a meal.

This is not to say that the semantic distinction has no syntactic correlates, of course; it is just to say that these correlates may not be apparent from the string context.

2.5. Perception

The final class we consider is the perception predicates, like *see*, *hear*, and *feel*, which were a main focus of early work on verbal syntactic bootstrapping (Gleitman, 1990; Landau & Gleitman, 1985). These predicates form a somewhat small class and tend to allow bare verb phrase subordinate clauses (30a) and participial verb phrase subordinate clauses (30b).

(30) a. Jo {saw, heard, felt} Bo leave.
b. Jo {saw, heard, felt} Bo leaving.

While bare verb phrase subordinate clauses are relatively distinctive of perception predicates, bare and participial verb phrase subordinate clauses can occur with predicates that do not clearly involve perception, such as *make* and *remember*.

(31) a. Jo made Bill leave.
b. Jo remembered Bo leaving.

This suggests that though these two syntactic contexts might be strong cues to a verb having a perception component, they are not full proof.

2.6. Discussion

There are two main take-aways from this section. First, there are some potentially promising correlations between propositional attitude verbs' semantic properties and their syntactic distributions, only some of which have been studied in any depth in the acquisition literature. Second, while these correlations are promising, it remains unclear whether they are really robust enough to support learning. This lack of clarity arises in large part because none of the correlations between particular syntactic structures and particular semantic properties are perfect. Moreover, it is difficult to assess how much these correlations improve when considering multiple syntactic structures at once without quantitative tests. In the next section, we conduct such a quantitative test.

3. Validating previous classifications

In this section, we present an experiment aimed at measuring the acceptability of a variety of propositional attitude verbs in different syntactic contexts. Our goal here is to assess the extent to which claims from traditional distributional analysis regarding correlations between syntax and semantics hold up. To do this, we compare the results of the acceptability judgment experiment against the classification of verbs discussed in the last section. This allows us to quantitatively assess how closely these previous classifications are tracked by the syntax. All materials and data are available at https://github.com/aaronstevenwhite/ProjectionExperiments.

3.1. Methodology

The methodology we use is based on one developed by Fisher et al. (1991), who were concerned that, in standard distributional analysis "only those semantic generalizations that can be readily labeled by the investigator are likely to be discerned," but that it "may well be that there are semantic abstractions which, while correlated with the syntax, are not so easy to puzzle out and name."

To address this concern, Fisher et al. (1991) obtain (a) a measure of verbs' meaning in the form of semantic similarity judgments and (b) a measure of verbs' syntactic distributions, using an acceptability judgment task.[11] They then ask to what extent the two measures are correlated. The idea here is that such quantitative representations allow one to bypass the sort of explicit labeling inherent to the traditional method, since distinctions among features salient to the participants are not explicitly invoked.

Fisher et al. (1991) use this methodology to study the high-level correlations between semantics and syntax, selecting a relatively small number of verbs from across the entire lexicon and using a fairly coarse-grained notion of syntactic frame. We further diverge from Fisher et al. (1991) in explicitly quantifying the relationship between the syntactic measure and prior semantic classifications, interpreting the relationship between the quantitative measure of the syntax and the quantitative measure of the semantics relative to these prior classifications.

3.2. Design

Thirty propositional attitude verbs were selected in such a way that they evenly spanned the classes in Hacquard and Wellwood's (2012) semantic classification. This classification is essentially a more elaborated version of the classification presented in Section 2, synthesizing much of the previous theoretical literature on the propositional attitude verb classes.[12]

We then selected 19 syntactic features based on the theoretical literature discussed in Section 2. These features consist in five broad types: clausal complement features, noun phrase (NP) complements, prepositional phrase (PP) complements, expletive arguments, and anaphoric arguments.[13]

3.2.1. Features of interest

Six types of clausal complement features were selected: finiteness, complementizer overtness, subordinate subject overtness, subordinate question type, S-lifting, and small clause type. Finiteness had two values: finite (32a) and nonfinite (32b).

(32) a. Jo thought that Bo went to the store.
b. Jo wanted Bo to go to the store.

Complementizer presence had two values: present 2 and absent 2.

(33) a. Jo thought that Bo went to the store.
b. Jo thought Bo went to the store.

Embedded subject presence had two values: present (34a) and absent (34b) and is relevant only when the clause is nonfinite and has no overt complementizer.

(34) a. Jo wanted Bo to go to the store.
b. Jo wanted to go to the store.

Embedded question type had three values: nonquestion (35a), polar question (35b), and WH question (35c). Only adjunct questions were used, since constituent questions are ambiguous on the surface between a question and a free relative reading.

(35) a. Jo knows that Bo went to the store.
b. Jo knows if Bo went to the store.
c. Jo knows why Bo went to the store.

S-lifting had two values: first person (36a) and third person (36b).

(36) a. Bo went to the store, I think.
b. Bo went to the store, Jo said.

Small clause type had two values: bare small clause (37a) and gerundive small clause (37b).

(37) a. Jo saw Bo go to the store.
b. Jo remembered going to the store.

Two NP structures were selected: single (38a) and double objects (38b). NPs were chosen so as not to have an interpretation in which they could be interpreted to have propositional content (Anand & Hacquard, 2014; Moulton, 2009a, b; Rawlins, 2013; Uegaki, 2012).

(38) a. Jo wanted a meal.
b. Jo promised Bo a meal.

A third feature relevant to NP complements—passivization—was also included (39). The availability of structures like (39) and the unavailability of structures like (34a) appear to correlate with whether a predicate is eventive and/or encodes something about the manner in which a communicative act was performed—for example, *say* does not encode manner while *yell* does (Moulton, 2009a, b; Pesetsky, 1991; Postal, 1974, 1993; see also Zwicky, 1971, for other syntactic and semantic features that track manner of speech).

(39) Bo was said to be intelligent.

Two types of PP complement were selected: PPs headed by *about* (40a) and PPs headed by *to* (40b).

(40) a. Jo thought about Bo.
b. Jo said to Bo that she was happy.

Three types of expletive arguments were selected: expletive *it* matrix subject, expletive *it* matrix object, and expletive *there* matrix object/embedded subject.

(41) a. It amazed Bo that Jo was so intelligent.[14]
b. Bo believed it that Jo was top of her class.
c. Bo wanted there to be food on the table.

Three types of anaphoric complement features were selected: *so* (42a), nonfinite ellipsis (42c), and null complement/intransitive (42b).[15]

(42) a. Jo knew so.
b. Jo remembered.
c. Jo wanted to.

3.2.2. Stimulus construction

These 19 features were then combined into 30 distinct abstract frames. These abstract frames are listed along the *y*-axis in Fig. 1. Each categorial symbol in the frame should be interpreted as follows:

NP NP constituent (e.g. *Jo*)
WH (Adjunct) WH word (e.g. *why*)
V Bare form of verb (e.g. *think*)
VP Verb phrase with verb in bare form (e.g. *fit the part*)
S Tensed clause without complementizer (e.g. *Bo fit the part*)

For each abstract frame, three instantiations were generated by inserting lexical items. This yielded 90 frame instantiations, which were then crossed with the 30 verbs to create 3,060 total items. Lexical items for these instantiations were chosen so that, when crossed with each of the 30 verbs, the frame instantiation should yield a reasonably plausible

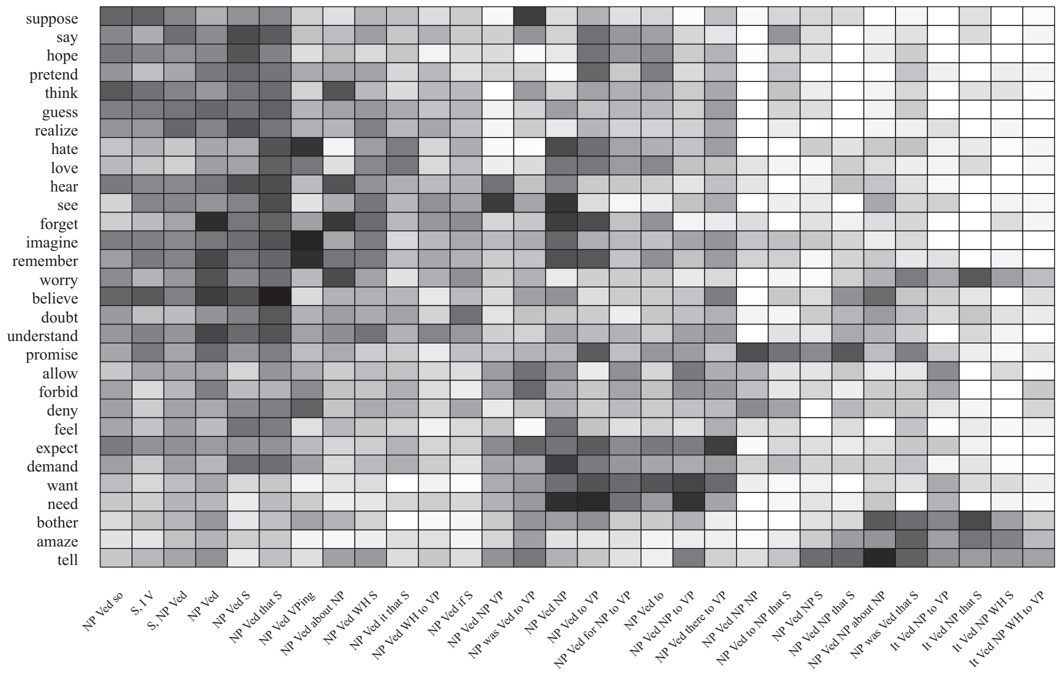

Fig. 1. Normalized verb-frame acceptability judgments. Darker shades mean higher normalized ratings.

sentence (*modulo* effects of syntactic acceptability that might make plausibility difficult to ascertain).

Thirty lists of 102 items each were then constructed subject to the restriction that the list should contain exactly three instances of each verb and exactly three instances of each frame and that the same verb should never be paired with the same frame twice in the list.[16] (That is, no verb showed up with more than one instantiation of the same frame in a single list.)

These lists were then inserted into an Ibex (version 0.3-beta17) experiment script with each sentence displayed using an unmodified `AcceptabilityJudgment` controller (Drummond, 2014). This controller displays the sentence above a discrete scale. Participants can use this scale either by typing the associated number on their keyboard or by clicking the number on the scale. A 1-to-7 scale was used with endpoints labeled *awful* (1) and *perfect* (7).

3.3. Participants

Ninety participants (48 females; age: 34.2 [mean], 30.5 [median], 18–68 [range]) were recruited through Amazon Mechanical Turk (AMT) using a standard Human Intelligence Task (HIT) template designed for externally hosted experiments and modified for the specific task. Prior to viewing the HIT, participants were required to score 7 or better on a nine-question qualification test assessing whether they were a native speaker of American English, which can be found in Supplementary Material. Along with this qualification test, participants' IP addresses were required to be associated with a location within the United States, and their HIT acceptance rates were required to be 95% or better. After finishing the experiment, participants received a 15-digit hex code, which they were instructed to enter into the HIT. Once this submission was received, participants were paid for their effort.

Prior to analysis, data were removed from participants that (a) did multiple HITs or (b) showed very low agreement with other participants that did the same list. Two participants submitted multiple HITs—one participant submitted three and another submitted two—and in both of these cases, only the first submission was used. Low agreement was determined by (a) calculating Spearman rank correlations between each participant's responses and those of every other participant that did the same list (mean $\rho = 0.63$, median $\rho = 0.64$, IQR $\rho = 0.69 - 0.58$) and then (b) excluding participants for whom all such comparisons fell outside the Tukey interval across participants. Data from two participants were removed in this way, resulting in 86 unique participants.

3.4. Results

In this section, we investigate the extent to which attitude verb classifications presented in Section 2 are predictable from our acceptability judgment data. Prior to carrying out the actual analysis, we normalize and decorrelate the acceptability judgment data. Because we are using these normalized judgments as predictors instead of dependent variables, we need a slightly more sophisticated normalization procedure than standard *z*-scoring—specifically, one that controls not only for subject variability in scale use but also item variability. We provide a detailed description of this procedure in Appendix.

3.4.1. Data decorrelation

As can be seen by the shading of each column in Fig. 1, the correlations between the normalized ratings for different subcategorization frames is quite high. This is not likely to be a consequence of the normalization procedure in any way. The rank correlations for the mean unnormalized ratings show a nearly identical pattern.

Because we would like to use these data as predictors, we decorrelate them using principal component analysis (PCA; see Jolliffe, 2002). We applied PCA to the matrix of normalized judgments depicted by Fig. 1 with the standard preprocessing step of first centering and standardizing by column. Fig. 2 shows the PCA score matrix in descending order of their eigenvalue. Black denotes positive values and red denotes negative values, with darker shades denoting higher absolute value. Note that the scores fade off as the eigenvalues get smaller. This fading, which is expected in PCA, provides a visual cue to the importance of each component in explaining variance in the normalized ratings depicted in Fig. 1.

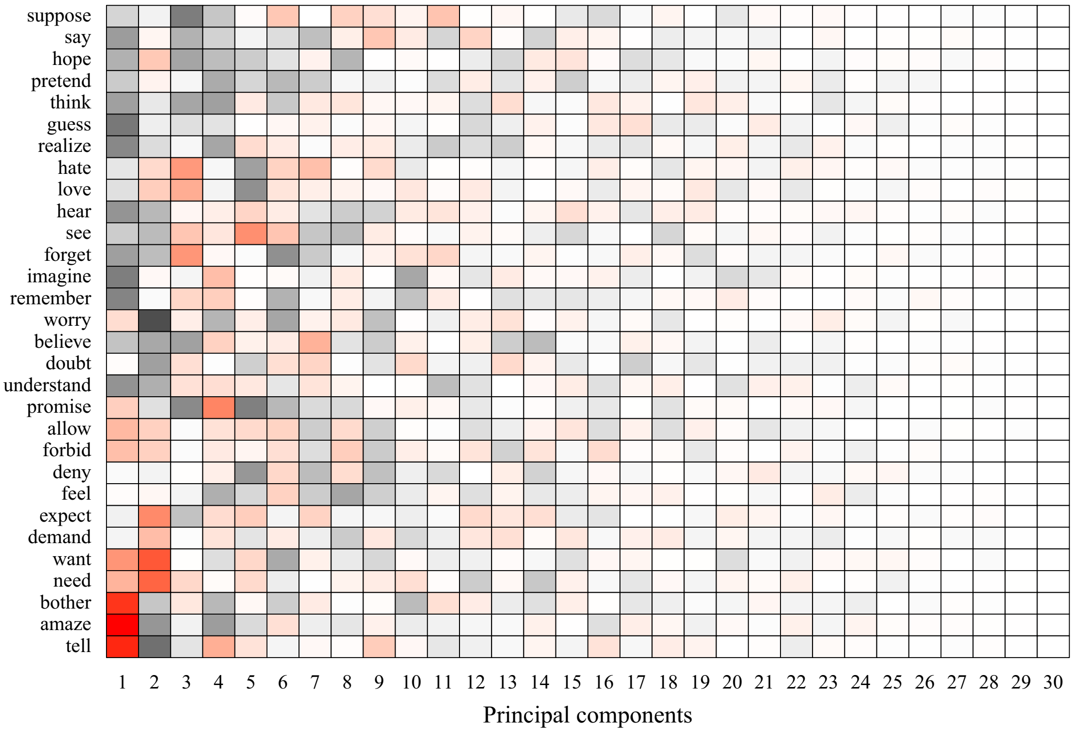

Fig. 2. PCA score matrix for acceptability matrix in Fig. 1.

3.4.2. *Predicting attitude verb semantic properties*

We now turn to our analysis of how predictable the semantic properties discussed in Section 2 are based on the normalized acceptability judgments. We consider semantic properties corresponding to the subsections of that section: REPRESENTATIONAL, PREFERENTIAL, PERCEPTION, FACTIVE, COMMUNICATIVE, and ASSERTIVE. A concise representation of which verbs have each of these properties, based on a review of the literature, is given in Table 1.

The PCA scores for each verb were entered as predictors into logistic regressions of each property.[17] To determine which principal components to include as predictors, we use a step-wise AIC-based model building procedure. (Using BIC does not change the final models selected.) For each semantic property, we begin with an intercept-only model and allow both constructive and destructive updates of a single predictor on each step. We allow the procedure access to at most two-way interactions between principal components. As is standard in step-wise model building, interactions are only considered candidates for addition when all of their constituent predictors are already currently in the model. The only model that actually includes interactions under this procedure is the one predicting ASSERTIVE. Rerunning this procedure with only simple effects as candidates does not yield a substantially worse final AIC for the ASSERTIVE model, and since it makes interpretation easier, we use this model instead of the one including interactions.

Table 1
Classification of 30 verbs in experiment based on literature reviewed in Section 1

VERB	REPR	PREF	FACT	ASSERT	COMM	PERCEPT
Allow		✓				
Amaze	✓	✓	✓			
Believe	✓			✓		
Bother	✓	✓	✓			
Demand		✓			✓	
Deny	✓				✓	
Doubt	✓					
Expect	✓			✓		
Feel	✓			✓		✓
Forbid		✓			✓	
Forget	✓		✓	✓		
Guess	✓			✓		
Hate	✓	✓	✓			
Hear	✓		✓	✓		✓
Hope	✓	✓		✓		
Imagine	✓					
Love	✓	✓	✓			
Need		✓				
Pretend	✓					
Promise	✓			✓	✓	
Realize	✓		✓	✓		
Remember	✓		✓	✓		
Say	✓			✓	✓	
See	✓		✓	✓		✓
Suppose	✓			✓		
Tell	✓			✓	✓	
Think	✓			✓		
Understand	✓		✓	✓		
Want		✓				
Worry	✓	✓		✓		

We find that, for every semantic property, our model-building procedure includes at least one principal component as a predictor: PC2 and PC7 for REPRESENTATIONAL; PC1, PC2, PC4, PC15, and PC27 for PREFERENTIAL; PC2, PC3, PC13, and PC27 for FACTIVE; PC1, PC2, PC3, PC8, PC20, and PC23 for ASSERTIVE; PC3, PC4, PC7, and PC12 for COMMUNICATIVE; and PC5 and PC8 for PERCEPTION. This suggests that all semantic properties are tracked at least to some extent in verbs' syntactic distributions.

As can be seen by the fact that the principal components that are chosen have low numbers, the most important principal components in terms of eigenvalue (i.e., variance explained) also tend to be the most important for predicting semantic properties. This is unsurprising, since these semantic properties are interesting exactly because they are the ones that are purported to correlate with major syntactic distinctions. But it is a useful sanity check, since if we had seen principal components with high numbers being selected, we would be suspicious that these models are fitting to noise.

Another way to make sure that we are not fitting to noise is to employ leave-one-out cross-validation for each semantic property, wherein we remove each verb from the data, train the model on the remaining data, and predict the held-out verb. We use L1 regularization as a variable selection method analogous to the step-wise procedure above.

Because L1 regularization requires us to set a regularization parameter, we use a nested leave-one-out cross-validation procedure. On each outer fold of this nested cross-validation, the PCA scores (depicted in Fig. 2) and semantic properties (Table 1) for a single verb are first removed from the training set, forming the outer folds. Grid search over the L1 regularization parameter is conducted using a 4-fold crossvalidation on the resulting outer fold training set. The model selected via this grid search is then used to predict the classification of the held-out verb based on its PCA scores. This was carried out for all verbs and for all semantic properties (columns of Table 1). Table 2 shows the resulting accuracies, which are all above chance relative to the particular semantic property in question.[18] Corroborating the previous result, this suggests that all six of these semantic properties—or at least some distinction correlated with each—are tracked in the syntax.

3.4.3. Predictors of attitude verb classes

Besides knowing *that* a semantic property is predictable, it is also useful to know which frames predict it best, since these are the ones a learner might be able to use for syntactic bootstrapping. To assess this, we analyze the logistic regression coefficients—which weight the principal components—in conjunction with the PCA loading matrix (not shown)—which gives the association between each principal component and each frame. We can extract the relationship between each frame and each semantic property by weighting the loading matrix by the logistic regression coefficients and summing across the latent dimensions—that is, multiplying the vector of coefficients by the PCA loading matrix. Fig. 3 shows the resulting weights for each semantic property and each frame. As for Fig. 2, black denotes positive values and red denotes negative values, with darker shades denoting higher absolute value.

Fig. 3 is somewhat hard to parse on its own, so to help with interpretation, we compute the rank (Spearman) correlation between the weights depicted in this figure and a dummy coding of each frame's syntactic features, laid out in Section 3.2.1. Fig. 4 shows all such correlations whose 95% confidence interval does not include zero. These

Table 2
Cross-validation accuracy for each transformation and attitude verb class

Semantic Property	Accuracy
REPRESENTATIONAL	86.7
PREFERENTIAL	83.3
FACTIVE	70.0
ASSERTIVE	66.7
COMMUNICATIVE	83.3
PERCEPTION	93.3

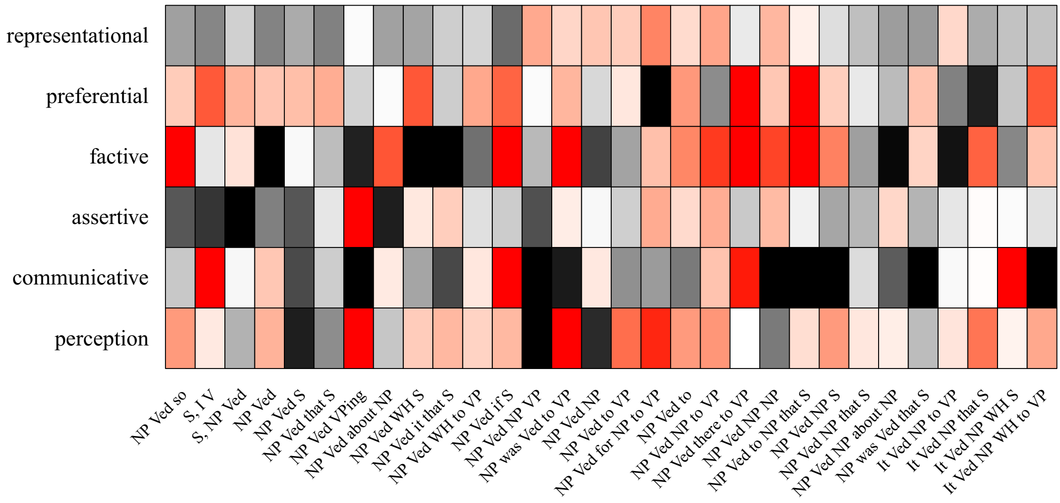

Fig. 3. Frame weights for each semantic property.

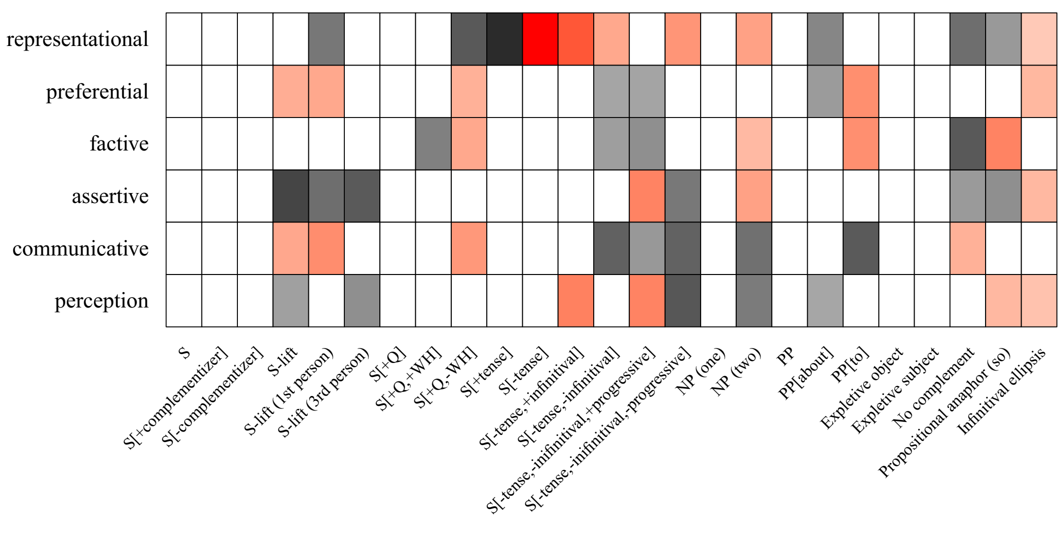

Fig. 4. Feature correlations for each semantic property.

confidence intervals are computed from a nonparametric bootstrap, resampling by frame, with 1,000 iterations.

To a large extent, these correlations corroborate the syntax-semantics relationships laid out in Section 2. Representationality tends to correlate with tensed complement clauses, propositional anaphors, and first-person S-lifting. It is also positively correlated with null complements (or intransitivity) and anticorrelated with lack of clausal tense. Preferentiality tends to show fewer such correlations overall, but it crucially does not correlate with tensed complements and what clausal complements it does correlate with are untensed. Factivity correlates with taking WH question subordinate clauses, which is consonant with the observation that factives tend to take both question and nonquestion complements. Assertivity nearly perfectly matches the distribution suggested in the literature in correlating with S-lifting and propositional anaphors. Communicativity correlates with PP [to] complements, which tend to denote recipient arguments. And perception tends to correlate with bare verb clausal complements.

3.5. Discussion

We have shown that the classification from the theoretical literature, discussed in Section 2, is indeed tracked in the syntax by many of the syntactic features that are purported in the literature to track these distinctions. But given that the accuracies in Table 2 aren't perfect, to what extent are they high enough to robustly support learning? There is no straightforward answer to this based just on these results. What we ourselves take away is that even relatively uninteresting models such as logistic regression, which have heavy constraints on the sorts of classification structures they can learn, can detect these features at least to some extent, suggesting that a more sophisticated classifier would do even better. We take it that language learners no doubt instantiate more sophisticated classifiers, and so the accuracies in Table 2 should really be seen as a strong baseline against which to test learning models.

One direction we believe would be fruitful to theoreticians and acquisitionists alike is to investigate how to account for correlations among the different semantic properties in the model. Our current setup predicts each property separately, meaning that the models we use cannot benefit from information about the space of semantic properties they are predicting. If the learner either innately knows or can somehow learn constraints on this space, it could make the classification task significantly easier. We leave this for future work—using, example, *structured prediction* methods like *conditional random fields* (Lafferty, McCallum, & Pereira, 2001)—since our goal here is not the development of a learning model, but rather the establishment of baseline results.

A major question that remains at this point is to what extent the semantic properties we investigated in this section exhaust the semantic features tracked by the syntax. As noted at the beginning of this section, this question provides the original impetus for developing the methodology we use here (Fisher et al., 1991), but linguists have a long-standing interest in how best to approach this question, which has been central in investigations of the syntax-semantic interface (Fillmore, 1970; Grimshaw, 1979, 1990; Jackendoff, 1972; Levin, 1993; Pesetsky, 1982, 1991; Pinker, 1984, 1989; Zwicky, 1971, among many others).

In the remainder of the paper, we pivot to investigating what additional semantic properties, beyond those discussed so far, might be latent in the syntax. To do this, we gather similarity judgments for each of the verbs tested in this section and ask to what extent the semantic properties from this section statistically mediate the relationship between these similarities and our normalized acceptability judgments.

4. Exhausting the semantic information

In this section, we present two experiments aimed at getting a measure of how similar in meaning naïve speakers take the propositional attitude verbs from Experiment 1 to be. Our goal here is to assess the extent to which the semantic properties discussed in Sections 2 and 3 exhaust the space of semantic properties tracked by the syntax. We use two experiments here, since as we show, different tasks seem to tap different aspects of meaning. All materials and data are available at https://github.com/aaronstevenwhite/ProjectionExperiments.

4.1. Experiment 2a: Generalized semantic discrimination task

In this first experiment, we employ a generalized semantic discrimination task—also known as a triad or "odd man out" task—in which participants are given lists of three words and asked to choose the one least like the others in meaning (Fisher et al., 1991; Wexler, 1970).

4.1.1. Design

We constructed a list containing every three-combination of the 30 verbs from Experiment 1 (4,060 three-combinations total). Twenty lists of 203 items each were then constructed by randomly sampling these three-combinations, which we refer to as triads, without replacement. These lists were then inserted into an Ibex (version 0.3-beta15) experiment script with each triad displayed using an unmodified `Question` controller (Drummond, 2014). This controller displays an optional question above a list of answers. In this case, the question was omitted and the verbs making up each triad constituted the possible answers. Participants could select an answer either by typing the number associated with each answer or clicking on the answer.

4.1.2. Participants

Sixty participants (28 females; age: 34.5 [mean], 31 [median], 18–68 [range]) were recruited through AMT using a standard HIT template designed for externally hosted experiments and modified for the specific task. All qualification requirements were the same as those described in Section 3.3. After finishing the experiment, participants received a 15-digit hex code, which they were instructed to enter into the HIT. Once this submission was received, participants were paid for their time.

We use the same data validation procedure described in Section 3.3 with the exception that we calculate Cohen's κ instead of Spearman's ρ (mean $\kappa = 0.45$, median $\kappa = 0.45$, IQR $\kappa = 0.52 - 0.37$).[19] No participant did multiple lists and no participant's agreement scores fell outside the Tukey interval of scores across participants, and so no participants were excluded.

The median agreement here is quite a bit lower than the interrater agreement found by either Fisher et al. (1991) or Lederer et al. (1995). Fisher et al. (1991) report Spearman's

$\rho = 0.81$ (Exp. 1); 0.78 (Exp. 2); 0.76 (Exp. 3), 0.79 (Exp. 4), 0.72 (Exp. 5). Lederer et al. (1995) report Spearman's $\rho = 0.81$. This is likely driven by the fact that we are investigating a much smaller portion of the lexicon and thus are bound to find that participants have less certainty about which verbs are more semantically similar.

4.2. *Experiment 2b: Ordinal similarity*

In this second experiment, we employ an ordinal scale similarity task, in which participants are asked to rate the similarity in meaning of a word pair on a 1–7 scale.

4.2.1. *Design*

We constructed a list containing every pair of the 30 verbs from Experiment 1 plus the verb *know* (460 pairs).[20] Twenty lists of 62 pairs were then constructed such that every verb was seen an equal number of times and no pair was seen twice.

These lists were then inserted into an Ibex (version 0.3.7) experiment script with each pair displayed using an unmodified `AcceptabilityJudgment` controller (Drummond, 2014). This controller displays the verb pair separated by a pipe character—for example, *think* | *want*—above a discrete scale. Participants could use this scale either by typing the associated number on their keyboard or by clicking the number on the scale. A 1-to-7 scale was used with endpoints labeled *very dissimilar* (1) to *very similar* (7). To encourage them to make a symmetric similarity judgment, participants were instructed to rate "the similarity between the meanings of the two verbs" as opposed to rating how similar the first verb was to the second (or vice versa).

4.2.2. *Participants*

Sixty (29 females; age: 32.9 [mean], 29.0 [median], 18–67 [range]) participants were recruited through AMT. All qualification requirements were the same as those described in Section 3.3. After finishing the experiment, participants received a 15-digit hex code, which they were instructed to enter into the HIT. Once this submission was received, participants were paid for their time.

The data validation procedure is the same one described in Section 3.3 (mean $\rho = 0.41$, median $\rho = 0.40$, IQR $\rho = 0.52-0.32$). No participant did multiple lists and no participant's agreement scores fell outside the Tukey interval of scores across participants, and so no participants were excluded.

4.3. *Comparison of similarity datasets*

Fig. 5 plots the generalized semantic discrimination judgments against the ordinal scale similarity judgments, both after normalization and standardization. We provide a detailed description of the respective normalization procedures in Appendix.

Overall, the correlation between responses on the generalized semantic discrimination task and those on the ordinal scale task are at about the same level as the correlations among participants within each experiment (Spearman's $\rho = 0.437$, $p < .001$). This

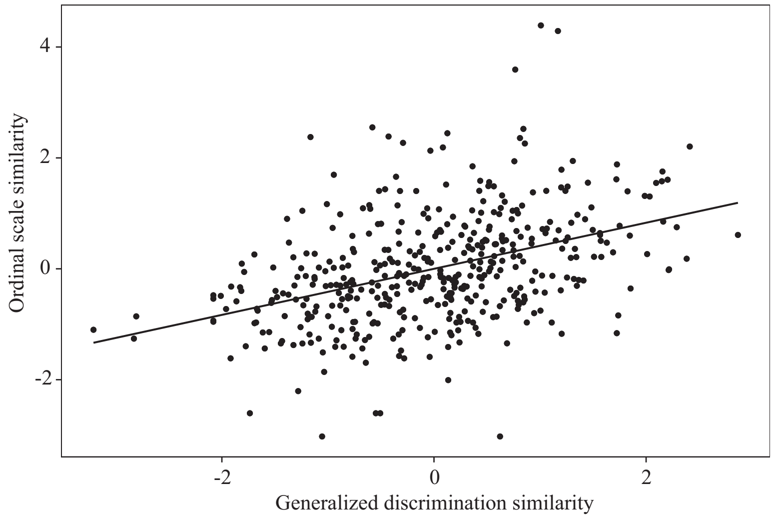

Fig. 5. Generalized semantic discrimination semantic similarity ratings (normalized and standardized) plotted against ordinal scale similarity ratings (normalized and standardized).

suggests not only that these two tasks are tapping similar aspects of participants' semantic knowledge but that they do so at the limit of what we would expect given inter-annotator agreement within each experiment. But as we show in the next section, the difference in the two tasks does not appear to be solely about interannotator noise; each task taps slightly different semantic and conceptual properties.

4.4. Exhausting the semantic information

If the syntax carried no information about semantic properties beyond those discussed in Sections 2 and 3, we would expect the relationship between the syntactic distributions and the similarity judgments to be mediated by those semantic properties. To assess the extent to which these semantic properties exhaust the space of semantic properties tracked by the syntax, we now conduct what amounts to a mediation analysis. This analysis has three components, which we apply to each similarity dataset separately: (a) establish that there is a relationship between the semantic properties and the similarity judgments (Section 4.4.1); (b) establish that there is a relationship between the syntactic distributions and the similarity judgments (Section 4.4.2); and (c) measure the extent to which the relationship between the syntactic distributions and the similarity judgments remains after controlling for the relationship between the semantic properties and the similarity judgments (Section 4.4.3).

4.4.1. Predicting similarities with semantic properties

Each normalized similarity dataset was entered into a linear regression with SIMILARITY as the dependent variable and the value of REPRESENTATIONAL, PREFERENTIAL, PERCEPTION, FACTIVE, COMMUNICATIVE, and ASSERTIVE for the two verbs whose similarity is being predicted as independent variables. We use the same stepwise model selection procedure described in the last section, allowing up to four-way interactions.

Table 3 shows the models selected by this procedure. We don't dwell on these models except to make three points. First, the fact that our model selection procedure does not select an intercept only model suggests that at least some of the semantic properties we have been employing correlate with naïve speakers judgments. This is important for the mediation analysis as a whole, since the mediation question would be moot if the semantic properties couldn't in fact be mediators. Second, we see that only a subset of the semantic properties appear to be relevant in participants similarity judgments: REPRESENTATIONAL and PERCEPTION are absent from both models. Third, PREFERENTIAL only appears to be active in the generalized discrimination judgments. This is interesting because it suggests that these two tasks pick up on distinct aspects of the semantics.

4.4.2. *Predicting similarities with syntactic distributions*

Each normalized similarity dataset was entered into a linear regression with SIMILARITY as the dependent variable and the principal components scores discussed in Section 3 (Fig. 2) as predictors. We employ the same stepwise model selection procedure used for the semantic properties, allowing up to two-way interactions. (The space of candidate predictors explodes when allowing for larger numbers of interactions.)

The resulting models are extremely large and their parameters are not particularly easy to interpret, given that their predictors are principal components, so we do not include a

Table 3
Regression coefficients for predicting SIMILARITY by semantic properties

	Dependent Variable	
	Discrimination	Ordinal
PREFERENTIAL	0.057 (0.122)	
FACTIVE	−0.334 (0.068)	−0.702 (0.101)
ASSERTIVE	0.641 (0.161)	−0.069 (0.094)
COMMUNICATIVE	−0.728 (0.182)	−0.793 (0.119)
PREFERENTIAL × ASSERTIVE	−0.686 (0.155)	
PREFERENTIAL × COMMUNICATIVE	0.355 (0.216)	
ASSERTIVE × COMMUNICATIVE	0.689 (0.205)	
ASSERTIVE × ASSERTIVE	−0.369 (0.176)	0.688 (0.124)
COMMUNICATIVE × COMMUNICATIVE		1.617 (0.225)
FACTIVE × FACTIVE		0.533 (0.158)
FACTIVE × COMMUNICATIVE		0.501 (0.182)
Observations	870	870
R^2	0.245	0.203
Adjusted R^2	0.232	0.193
Residual *SE*	0.877 (df = 854)	0.898 (df = 858)
F-statistic	18.461 (df = 15; 854)	19.880 (df = 11; 858)

table analogous to Table 3 here. It is useful, however, to compare how many simple effects are shared between the two resulting models and the semantic property model from the last section. The generalized discrimination model includes PC1, PC3, PC4, PC5, PC8, PC12, PC15, PC16, PC17, PC19, PC21, and PC28, and the ordinal scale model includes PC1, PC3, PC5, PC7, PC8, PC10, PC11, PC12, PC14, PC19, PC20, PC26, and PC28. Thus, both models share PC1, PC3, PC5, PC8, PC12, PC19, and PC28—a substantial overlap in the most important principal components. There is also substantial overlap with the semantic property models. The only semantic property for which the selected model did not share any principal components was REPRESENTATIONAL, which is predicted by PC2 and PC7. The rest share at least one component.

This is interesting because it appears to further corroborate the result mentioned in the last section that REPRESENTATIONAL does not appear to be active in participants similarity judgments. This could mean that representationality is not a coherent semantic property, though if we were to accept this interpretation, we would need to explain why the syntax correlates so well with it, as we saw in Section 3.

One thing that could be happening here is that we were too promiscuous in our original coding of representationality. As mentioned in Section 2, whether emotive predicates are representational is a contentious issue. Emotives tend to trigger inferences that involve representationality, but it is at least possible that these inferences are not semantic in nature, and thus they may not be part of emotive predicates' semantic representations. These inferences are also typically backgrounded, and so a compounding factor may be that these inferences are not very salient to naïve speakers making similarity judgments. What we take away from this result is that one cannot rely solely on similarity judgments of the kind we use here as a source of semantic properties, even though similarity judgment tasks may be useful for large-scale annotation of some properties.

The final syntactic distribution-based models selected by the step-wise procedure show nearly double the R^2 for both the generalized discrimination judgments ($R^2 = 0.477$) and the ordinal scale judgments ($R^2 = 0.457$) compared to the semantic property-based models. This of course could be due to the fact that the syntax-based models have many more parameters. We reject this hypothesis, however, based on the fact that Vuong tests for nonnested models suggest that both the syntax-based model of the generalized discrimination judgments ($z = 8.861$, $p < .001$) and the syntax-based model of the ordinal scale judgments ($z = 7.642$, $p < .001$) fit significantly better than the semantic property-based models, controlling for the number of parameters.

This is suggestive that the syntactic distributions carry semantic information beyond the semantic properties we have been discussing. In the next section, we show this directly by residualizing the syntactic distributions by the semantic properties and jointly predicting the similarity judgments.

4.4.3. Exhausting the semantic information

We now aim to predict the semantic similarity judgments given both the semantic properties and the syntactic distributions. We know from Section 3 that there are significant correlations between the semantic properties and the syntactic distributions, however, and so prior to carrying out this prediction, we remove this semantic property information from the syntactic distributions to avoid multicollinearity.

We fit a multivariate linear regression with the acceptability judgments for each syntactic frame as the dependent variables and semantic properties for each verb as the predictors. (Note that we use the normalized acceptability judgments here, since we are not worried about correlations among the acceptability judgments for each frame.) We then residualized the normalized acceptability judgments using this model. This results in a matrix with information about the semantic properties removed. This matrix still contains correlations among the residualized acceptability judgments for each frame, and so as in Section 3, we decorrelate these variables using PCA.

Next, we enter each normalized similarity dataset into a linear regression with SIMILARITY as the dependent variable and the principal components scores discussed in Section 3 (Fig. 2) as predictors. We employ the same stepwise model selection procedure used for the semantic properties and the syntactic distributions alone. We allow up to two-way interactions between variables within each type of predictor—that is, interactions between semantic properties and the decorrelated residualized syntactic distributions were not considered. We find that the models that this procedure selects are substantially better than the models predicting the similarity judgments based on the semantic properties alone, for both the generalized discrimination judgments ($\chi^2(29) = 123.16$, $p < .001$) and the ordinal scale judgments ($\chi^2(26) = 136.95$, $p < .001$). This suggests that there is further semantic information in the syntactic distributions beyond information about the semantic properties from the theoretical literature.

To assess what semantic information this is, we regress the decorrelated residualized syntactic distributions (without the semantic properties) against the similarity judgments. We then use this model to predict the similarity judgments. These predictions encode whatever semantic information lies in the syntax about the particular semantic properties participants use to make their similarity judgments in the generalized discrimination and ordinal scale tasks. We again use a stepwise model-building procedure to select this model.

Fig. 6 shows the results of applying a hierarchical clustering (Ward's method) to the predicted similarity judgments for both the generalized discrimination task (left) and the ordinal scale task (right). In both cases, there is a major split between a group that contains a combination of preferentials and verbs with negative affect (whether preferential or not)—many, though not all of which, are nonassertive. For instance, the negative affect verbs *doubt*, *forget*, and *deny* are both representational nonpreferentials that occur in this cluster along with negative affect preferentials, such as *hate*, *bother*, *forbid*, and *worry*, and nonnegative affect preferentials, such as *amaze* and *allow*.

This finding is at once surprising and unsurprising from a theoretical perspective. On the one hand, many languages that have a robust mood distinction—for example, Romance languages, like Spanish and French—group negative affect verbs together with preferentials in terms of which verbs take subjunctive subordinate clauses. (This is necessarily a rough characterization, since the distribution of subjunctive subordinate clauses turns out to be very difficult to predict precisely.) On the other hand, since English does not have the relevant distinction robustly, a property combining negative affect and

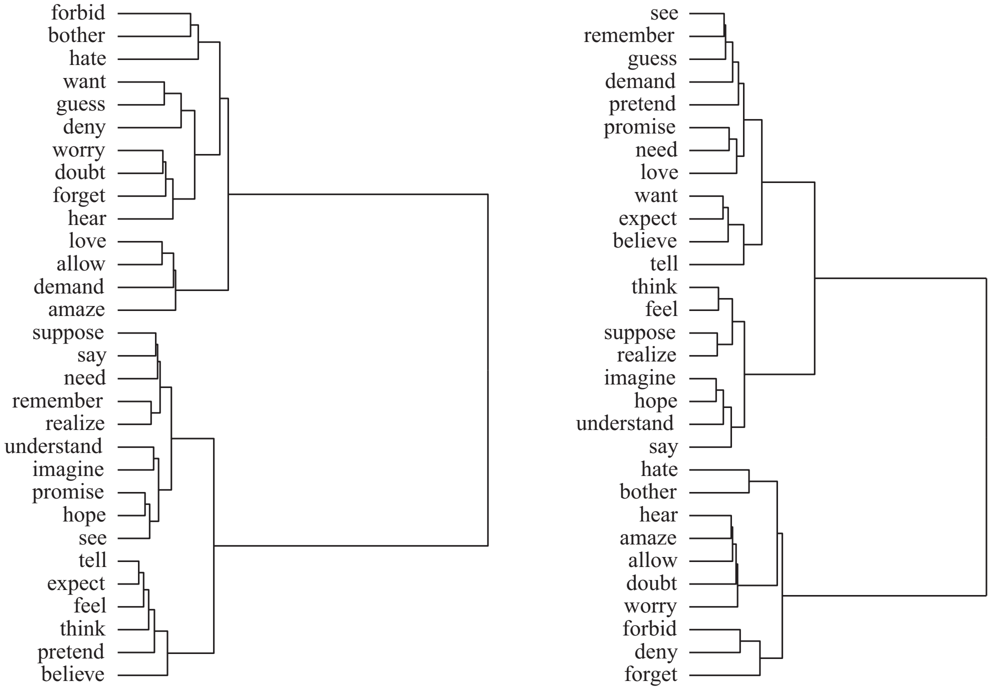

Fig. 6. Hierarchical clustering of semantic information carried by the syntax about generalized discrimination judgments (left) and ordinal scale judgments (right) after removing semantic property information.

preferential verbs together is not generally thought to determine syntactic distribution in English. Thus, this finding might be taken as preliminary evidence for this distinction being tracked by English syntax. Our final analysis in this section will thus be aimed at figuring out what syntactic structure this distinction correlates with.

To do this, we cut each of the trees in Fig. 6 at their highest level split. We then compute the rank correlation between this split and each the normalized acceptability judgments for each frame. Fig. 7 shows this rank correlation, with a positive correlation for a frame meaning that that frame correlates with the negative affect + preferential class.

What we see here is that, in general, the correlations between this class and syntactic frames is somewhat low. Rather, it is the other side of the negative affect + preferential split that seems to be tracked robustly in the syntax. Indeed, it is exactly the frames that tend to correlate with representationality and assertivity that tend to strongly correlate with this other class. What this may mean is that the negative affect + preferential class is robustly tracked in the syntax, but it is tracked in a negative sense—that is, in terms of the syntactic structures it cannot take. This is not particularly surprising, since as we noted, many negative affect + preferential verbs also tend to be nonassertive. One possibility this finding raises is that, when a language lacks a syntactic distinction that another language uses to track a particular semantic property, that language uses alternative means of encoding that distinction distributionally—for example, it encodes it as an elsewhere case.

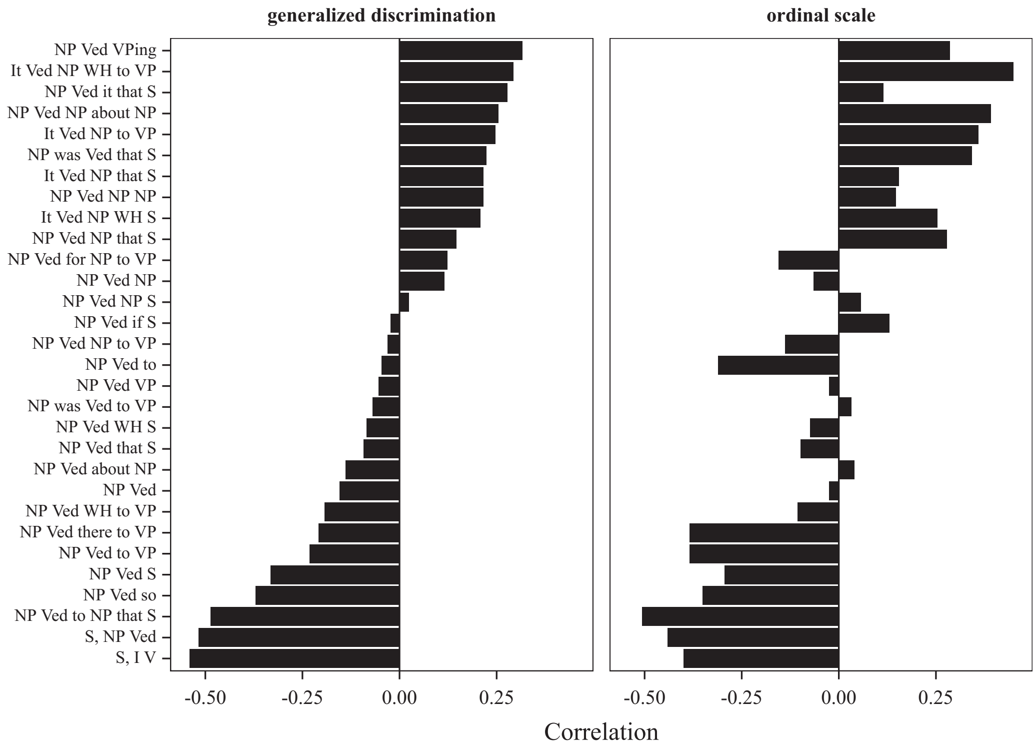

Fig. 7. Correlation with negative affect + preferential class from Fig. 6.

4.5. Discussion

We have shown that there is substantial semantic information in propositional attitude verb syntactic distributions beyond that discussed in the theoretical literature. In particular, we found that the syntax appears to track a semantic distinction that groups together preferentials and negative affect verbs, but only as an elsewhere case.

These findings raise two questions: one methodological and another empirical. First, to what extent is our ability to predict semantic similarity judgments based on syntactic acceptability judgments really an indicator of a correlation between the syntax and the semantics? And second, to what extent are the semantic properties tracked by syntactic distributions cross-linguistically stable? We end this section with a brief discussion of the first question and then turn to the second in Section 5.

It is at least a logical possibility that, when making semantic similarity judgments, participants ignore the instruction to make their judgment based on the meaning of the words at hand, and instead make their judgments based on some limited comparison of those words' syntactic distributions. Then, we should not be surprised about a correlation between the purportedly semantic similarity judgments and syntactic acceptability judgments for the uninteresting reason that the two are based on the same kind of knowledge. This possibility is recognized by Fisher et al. (1991), who argue against it on the basis that, if this were the case, we would expect even better correlations between the two types of judgments than we already see (see also Lederer et al., 1995).

An anonymous reviewer raises the counterargument that semantic similarity judgments might be based, in some cases, on true semantic representations (or more general conceptual representations) and, in others, on syntactic representations. For instance, that reviewer suggests that when a particular judgment becomes hard to make based on semantic comparison alone, participants switch to some syntax-based method—for example, selecting a frame on which to compare those verbs' respective acceptabilities.

There are various components of such a proposal that would need to be fleshed out in order to evaluate it. For instance, on what basis are some semantic similarity judgments harder to make than others? And are the syntax-based similarity judgments made with respect to words' entire syntactic distributions or only some salient subset—for example, a single frame, as under the reviewer's proposal? We believe this is an interesting question to pursue insofar as it might reveal something about the nature of and relationship between semantic representations and syntactic representations, but addressing it in any detail is beyond the scope of this paper.

5. General discussion

Our goal in this paper was to test the limits of syntactic bootstrapping by quantitatively assessing correlations between syntax and word meaning in the domain of propositional attitude verbs. We did this in two steps, which together amount to a mediation analysis. First, we validated prior theoretical claims about the relationship between semantic properties and syntactic distributions. Second, we showed that the semantic properties discussed in this prior work do not exhaust those tracked by the syntax. Together these findings reveal a best case scenario for language learners that are able to use syntactic distributions as evidence about word meanings. Learners who could track the full set of distributional facts and use them to identify clusters of semantically similar words would be rewarded for doing so. A subsequent question, then, is whether learners do, in fact, track syntactic distributions at this grain size, and whether distributional facts about a novel word lead to particular guesses about its meaning.

Moving forward, it will be important to understand whether the correlations we find in English translate straightforwardly to other languages. For instance, throughout this paper we have seen that the representational-preferential distinction is quite robustly tracked by the syntax. Indeed, even the distinction related to negative affect that we discuss in Section 4 appears to be somewhat related to the representational-preferential distinction.

One of the best indicators of this distinction in English is tense, corroborating claims in the literature on propositional attitude verbs. However, this correlation is not very stable cross-linguistically. For example, in the Romance languages, representationals tend to take indicative mood and preferentials tend to take subjunctive mood (Bolinger, 1968; Farkas, 1985; Giannakidou, 1997; Giorgi & Pianesi, 1997; Hooper, 1975; Portner, 1992;

Quer, 1998; Villalta, 2000, 2008, a.o.); in languages like German, the distinction is tracked by the availability of verb second (V2) syntax (Scheffler, 2009; Truckenbrodt, 2006). Nonetheless, learners still learn these words at similar points in development (Perner et al., 2003).

In current work, we are investigating the possibility that, rather than there being a direct mapping between, for example, belief meanings and tense there is a more abstract mapping that must be parameterized by specific aspects of the input a learner receives. In particular, belief verb take complements that share syntactic features of declarative main clauses (Dayal & Grimshaw, 2009). One reason that such a correlation might exist is that declarative main clauses are often used to assert content and many representationals are assertive. Thus, learners who can identify the hallmarks of declarative main clauses would be in a position to identify belief verbs as those whose complements resemble these declaratives.

On this view, learners begin with access to a set of unvalued syntactic features—for example, [+/− SUBJUNCTIVE], [+/− TENSE]—that a particular abstract structure—in this case, MAIN CLAUSE—will instantiate, along with a rule that tells them which semantic property verbs that embed clauses with features similar to that structure instantiate—in this case, REPRESENTATIONAL ← MAIN CLAUSE. They must then identify what the actual feature valuation for the abstract structure is in order to figure out how to use the rule (Hacquard, 2014; Hacquard & Lidz, unpublished data).

In preliminary research on English, we have found that computational models of syntactic bootstrapping that instantiate this idea not only learn the correct valuation of features for MAIN CLAUSE correctly, but they do so extremely quickly—in large part because main clauses are by definition extremely prevalent in the input (White, 2015; White et al., unpublished data). This strategy may be extendable beyond just declarative main clauses to, for example, questions and imperatives. Future work will determine if this extension is feasible.

6. Conclusion

Research on theoretical syntax is largely independent of research on language acquisition. On the one hand, the theoretical literature has focused on understanding the fine-grained relationships that exist between word meaning and syntactic structure, without much thought to whether these relationships are actually robust enough to support learning. On the other hand, the acquisition literature has focused on how only very few syntactic distinctions are leveraged in verb learning.

In this paper, we bridged this divide by combining the sort of rigorous quantitative techniques employed in experimental and computational approaches to language acquisition with close attention to theoretical proposals about linguistically relevant properties of meaning. We believe this general approach of quantitatively assessing theoretical proposals will prove to be fruitful for both our understanding of the acquisition of word meaning and for semantic theory more generally.

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Notes

1. We are, of course, not the first to say this about propositional attitude verbs (see Naigles, 2000 and references therein). As far as we can tell, however, little has been done to link these literatures in a systematic way.
2. This correlation is corroborated to some extent in Barak, Fazly, and Stevenson (2012, 2013, 2014a,b) using Alishahi and Stevenson's (2008) computational model, though caution is required here since they investigate only a small set of verbs and ignore various complications inherent to this distinction (discussed below). See White, Hacquard, and Lidz (unpublished data) for discussion of the various issues inherent to their model and ways that these issues can be surmounted. See also White (2015) and White and Rawlins (2016) for much larger scale investigations that take these complications into account.
3. Whether 1 involves a finite subordinate clause is to some extent dependent on whether what is often called the English subjunctive involves tense. On the one hand, the complementizer *that* is the same one that occurs with tensed subordinate clauses, but on the other, the verb shows up in its base (untensed) form.
4. There is a further distinction in the literature made between S-lifts involving first-person and third-person propositional attitude verb subjects (Asher, 2000; Reinhart, 1983; Rooryck, 2001). We incorporate this first-third distinction into our experiment, but the data regarding this syntactic distinction are murky at best.
5. Not all representationals allow S-lifting—for example, *doubt*. This is likely because the availability of S-lifting for a particular verb is conditioned by other semantic and pragmatic properties it has. See the discussion of *assertivity* below.
6. One question that arises here is whether, given the existence of representational + preferential verbs like *hope*, there could also be such representational + preferential factives. In a certain sense, this may be the case for the emotive factives, since it seems like sentences containing them imply that the holder of the

emotion also believes the subordinate clause to be true. If all preferential factives are emotive (and show this behavior), this might suggest that there are no non-representational factives.

One must tread carefully here, however, since not all entailments need be encoded in the meaning of the verb—that is, this belief entailment could plausibly arise via the same sorts of pragmatic processes that give rise to the factive presupposition in the first place. In the remainder of this paper, we treat all emotives—factive (e.g., *love*, *hate*) or non-factive (e.g., *hope*, *worry*)—as both representational and preferential, since we believe it to be the most consistent treatment for our purposes. We return to this in our analysis in Section 4.

7. This paradigm is filled out by what Lahiri (2002) calls rogatives, like *wonder* and (for some speakers) *ask*. *Wonder*, at least, takes only subordinate questions and not nonquestions.
8. The pragmatic effects that distinguish semi-factivity from true factivity are beyond the scope of this paper. Much ink has been spilled regarding the nature of semi-factivity in recent years, however, so the interested reader is encouraged to see, for example, Abbott, 2006; Abusch, 2002; Romoli, 2011; Simons, 2001.
9. The traditional description of this correlation concerns cognitive versus emotive factives and not necessarily semi- versus true factives. At least in the verbal domain (and possibly outside it), these two descriptions seem to be extensionally equivalent, though which distinction is relevant does matter theoretically (cf. Abels, 2004).
10. Whether *say* and *tell* are only representational is a question. Both can be used to talk about commands conditional on their taking a nonfinite subordinate clause. In any case, they plausibly have something like a representational use with finite subordinate clause.
11. Lederer et al. (1995) took a similar tack, using the same sort of semantic similarity judgment task but replacing acceptability judgments with syntactic distributions extracted from a corpus. An anonymous reviewer asks why we did not take such a tack here. Our aim here is similar to Fisher et al.'s in that we would like to assess how much information exists in syntactic distributions *in principle*, which in turn helps us to understand which particular pieces of the syntax are associated with particular semantic properties. In other work, some of which we discuss in Section 5, we ask whether this information exists in corpora (see White, 2015; White et al., unpublished data, for more details).
12. Other large-scale attitude verb classifications exist—see, for instance, the extensions to VerbNet (Kipper-Schuler, 2005) proposed in Kipper, Korhonen, Ryant, and Palmer (2006); Korhonen and Briscoe (2004) and the classifications given in FrameNet (Baker, Fillmore, & Lowe, 1998). This classification was chosen because it hews most closely to classes discussed above and in the theoretical literature more generally.
13. A sixth feature—degree modification—was also selected for investigation, from which we constructed four frames. We exclude this from our analyses since it

was pointed out to us that the information degree modification carries is likely purely—or at least mostly—semantic in nature.

14. It is difficult to force the subject in a sentence like 2 to be interpreted nonreferentially. As we see in Fig. 1, this likely affected the judgments for verbs like *tell*, which are fine in this frame if the subject is interpreted referentially—for example, if *it* refers to a repository of information, such as a book.
15. For this last feature, we cannot be sure that the structure in two involves null complements (see Depiante, 2000; Grimshaw, 1979; Hankamer & Sag, 1976; Hooper, 1975; Williams, 2012, 2015, for further discussion of these structures).
16. These lists were 102 items instead of 90 items because we are excluding four degree modification abstract frames here (see note 2).
17. See Alishahi & Stevenson, 2008; Korhonen, 2002; Merlo & Stevenson, 2001; Rooth, 1995; Schulte im Walde, 2000 2003, 2006; Schulte im Walde & Brew, 2002; Stevenson & Merlo, 1999; Vlachos, Ghahramani, & Korhonen, 2008; Vlachos, Korhonen, & Ghahramani, 2009, for alternative methods of evaluating existing classifications with respect to syntactic distributions.
18. Chance for a particular property is equal to the proportion of verbs in the majority class for that property. For instance, chance for REPRESENTATIONAL is equal to 83%.
19. An analysis of the distribution of Fleiss' κ (the multi-rater generalization of Scott's *d*) by list corroborates this analysis (median = 0.45, mean = 0.45, IQR = 0.48 − 0.40). Both Fisher et al. (1991) and Lederer et al. (1995) compute Spearman rank correlations over count matrices constructed from judgments across participants. The method they use is not available to us without significant alteration since we collected data from more than two participants per list. Instead, we opt for a more standard measure of interrater agreement here. This measure is preferable in any case since (a) it allows us to assess each participant's reliability at the same time as we assess overall agreement and (b) it can be applied to the raw data instead of a statistic of the data, as in the cases of Fisher et al. (1991) and Lederer et al. (1995)
20. *Know* was added after discussion with multiple researchers suggested it may be interesting for future uses of these data. Because we do not have data about its syntactic distribution, we do not use any ratings of any pairs including *know* in our analysis.

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Supporting Information

Additional Supporting Information may be found online in the supporting information tab for this article:
Supplementary Material: Native speaker test.

Appendix: Data normalization

Experiment 1

The standard method for normalizing ordinal scale acceptability judgements used in the psycholinguistics literature is to normalize the data by-participant—for example, using a method such as z-scoring (Schütze & Sprouse, 2014). The problem with such an approach in our case is that standard normalization methods do not control for item-based variability. Insofar as the assumptions underlying z-scoring are satisfied, this is not an issue in other studies, since acceptability is generally treated as a dependent variable, not a predictor, and thus item variability can be taken into account in whatever confirmatory analysis follows the transformation—generally, using random intercepts for item in a linear mixed model (Baayen, Davidson, & Bates, 2008). To address this issue here, we employ an ordinal mixed model similar in form to the polytomous Rasch model (Andersen, 1977; Andrich, 1978; Masters, 1982; Rasch, 1960).

There are various ways of setting up such an ordinal mixed model that vary with respect to (a) whether ordinal ratings are associated with fixed width intervals on the normalized acceptability scale (*equidistant*) or whether those intervals can vary (*varying*), (b) whether or not participants can vary with respect to where the midpoint of the scale lies on the normalized acceptability scale (*additive* participant effects), and (c) whether or not participants can vary with respect to contraction of the normalized acceptability intervals (*multiplicative* participant effects). (Within this taxonomy, z-scoring corresponds to the equidistant model with both additive and multiplicative participant effects.)

To determine which particular normalization model to use, we employ an AIC-based model selection procedure. We fit each model using gradient descent with momentum (McClelland & Rumelhart, 1986; Rumelhart & McClelland, 1986) and learning rate annealing with a *search-then-converge* schedule (Darken & Moody, 1990) to obtain the maximum likelihood estimate (MLE) for (a) the normalized acceptability of each verb-frame pair, (b) the best linear unbiased predictors (BLUPs) for each participants along with the corresponding variance estimate, and (c) the BLUPs for each item intercept along with the corresponding variance estimate. Each model was implemented in version 0.7 of the python package `theano` (Bastien et al., 2012; Bergstra et al., 2010).

Table A1 shows the log-likelihood, the Akaike information criterion (AIC; Akaike, 1974), and the Bayesian information criterion (BIC; Schwarz, 1978) for each of the six normalization models. The best model under all measures is the varying cutpoint additive-multiplicative model. This suggests that, at least for this dataset, a standard

Table A1
Comparison of normalization models for acceptability judgments

CUTPOINTS	ADDITIVE	MULTIPLICATIVE	LL	AIC	BIC
Equidistant	True	False	−8078	24254	52411
Equidistant	False	True	−8509	25116	53273
Equidistant	True	True	−7268	22808	51570
Varying	True	False	−7989	24084	52269
Varying	False	True	−8061	24228	52413
Varying	**True**	**True**	**−7084**	**22448**	**51238**

Note. Bold type indicates the best value along each respective measure.

normalization such as *z*-scoring would have been inappropriate, even controlling for item effects. We suspect this is true for many acceptability judgment tasks, suggesting the use of *z*-scoring should be discouraged in favor of ordinal mixed models. Fig. 1 shows the MLEs for the acceptability of each verb-frame pair when using this normalization model.

Experiment 2a

The fact that verbs are displayed in a list raises the worry that effects of position may arise, either as an overall preference for a particular position and/or as a participant-specific preference. We see both such preferences. Across participants, there is a bias for earlier positions—proportion for position 1: 0.36, position 2: 0.34, position 3: 0.30—but substantial variability among participants—interquartile range of participant bias for position 1: [0.33, 0.39], position 2: [0.31, 0.36], position 3: [0.27, 0.34]. Thus, as in Section 3, we normalize the data prior to analysis to control for biases a particular participant may have to choose a verb in a particular position.

To carry out this normalization, we use a multinomial logistic mixed effects model. This model predicts which verb position in a triad is chosen based on (a) the (latent) similarities between each pair in the triad and (b) the (latent) bias each participant has to choose a verb in a particular position. We furthermore impose a symmetry constraint on the similarity matrix. We find the maximum likelihood estimate (MLE) of the similarity matrix and random effects components using gradient descent implemented in version 0.7 of the python package `theano`.

Experiment 2b

Since these data are ordinal, we use the same data normalization procedure described for Experiment 1. As for the generalized semantic discrimination normalization model, we constrain the similarities inferred to be symmetric. Table A2 gives the log-likelihood and AIC for each model. As in Section 3, the best fitting model, penalizing for complexity, is the model with varying cutpoints and both additive and multiplicative subject random effects. We use the MLE of the similarities inferred by this model in the remainder of this section.

Table A2
Comparison of normalization models for ordinal similarity judgments

CUTPOINTS	ADDITIVE	MULTIPLICATIVE	LL	AIC	BIC
Equidistant	True	False	−4397	9816	12987
Equidistant	False	True	−4652	10326	13497
Equidistant	True	True	−4125	9392	12935
Varying	True	False	−4361	9752	12947
Varying	False	True	−4392	9814	13009
Varying	**True**	**True**	−**4070**	**9290**	**12858**

Note. Bolding marks the best value along each respective measure.