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Initial parsing decisions and lexical bias: Corpus evidence from local NP/S-ambiguities

DANIEL WIECHMANN*

12 *Abstract*

13
14 *Recent research in sentence comprehension suggests that lexically specific*
15 *information plays a key role in on-line syntactic ambiguity resolution. On*
16 *the basis of an analysis of the local NP/S-ambiguity, the present study of-*
17 *fers a corpus-based approach to sentence processing that supports this view.*
18 *However, it is proposed that the relevant information used to recover the*
19 *syntactic structure of an incoming string of words is not retrieved from indi-*
20 *vidual verbs but from a more fine-grained level of form-meaning pairings*
21 *that distinguishes different verb senses. The investigation proceeds in two*
22 *steps: First, verb-general and sense-specific preferences for nominal and*
23 *sentential complementation are induced from corpus data and compared us-*
24 *ing odds ratios as a measure of association. Second, correlational analyses*
25 *are performed that relate the computed coefficients of association to read-*
26 *ing time latencies from a recent self-paced moving window experiment*
27 *(Hare et al. 2003). The results corroborate the view that individual verb*
28 *senses, rather than individual verbs, guide initial parsing decisions.*

29
30 *Keywords:* *parsing; lexical guidance; local syntactic ambiguity; distinc-*
31 *tive collexeme analysis.*
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42 (2003). Correspondence address: Institut für Anglistik und Amerikanistik, Friedrich
Schiller Universität Jena, 07743 Jena, Germany. E.mail: daniel.wiechmann@uni-jena.de.

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1 **1. Introduction**

2 Comprehending a natural language sentence is a complex process involv-
 3 ing numerous sub-processes below and above the sentence level such as
 4 recognizing words, resolving anaphoric relationships, recognizing figura-
 5 tive language, establishing discourse coherence, and various kinds of in-
 6 ferring. However, one of the most central tasks is the analysis of the
 7 syntactic structure of the signal, i.e., parsing. In languages like English,
 8 which are morphologically comparatively poor, a perceived string of
 9 words is likely to allow for more than one way of combining lexical units
 10 into larger syntactic structures, which may give rise to local syntactic am-
 11 biguities during on-line processing.

12 One of the best-studied local syntactic ambiguities involves the alterna-
 13 tion between nominal and sentential complements. In this ambiguity, a
 14 post-verbal NP cannot be straightforwardly interpreted with respect to
 15 the grammatical role that it plays in the sentence since it could either
 16 function as the direct object of the preceding verb or as the subject of an
 17 embedded clause:

- 18
 19 (1) a. Inspector Clousseau revealed [_{NP} Dreyfuss' intentions].
 20 b. Inspector Clousseau revealed [_S[_{NP} Dreyfuss' intentions] were
 21 indeed diabolic].

22 Using ambiguities of the type in (1) as an example, the present study
 23 investigates a particular hypothesis as to how such ambiguities are re-
 24 solved in on-line sentence comprehension. Specifically, what is at issue is
 25 the assumption that the process involves probabilistic subcategorization
 26 preferences that are associated with individual senses of a given verb.
 27 Corpus-linguistic evidence in support of this hypothesis is presented and
 28 compared to recent experimental results from a self-paced reading study
 29 (Hare et al. 2003). With regard to linguistic model-building, the study ar-
 30 gues that conceptions of subcategorization preferences should make refer-
 31 ence to a quite fine-grained level of representation, i.e., the individual
 32 senses of a verb. Methodologically, it is argued that such preferences can
 33 be appropriately estimated by means of quantitative corpus-linguistic
 34 methodologies.
 35

36
 37 **2. The verb sense guidance hypothesis (VSGH)**

38
 39 Early research in the field of sentence comprehension was dominated by
 40 the view that the human comprehension system employs a two-stage se-
 41 rial mechanism with different processes operating on each stage (Fodor
 42 1978; Frazier and Fodor 1978): the initial stage uses syntactic category in-

1 formation only and adopts very general parsing heuristics (like “minimal
2 attachment” or “late closure”) to recover syntactic structures. When the
3 mechanisms of the initial phase fail to detect the correct structure,
4 the parser employs a backtracking mechanism to reanalyze the string.
5 In this second stage, information from several sources (e.g., semantic or
6 discourse pragmatic properties) is integrated into the structure-building
7 process.

8 As syntactic theories put more and more emphasis on lexical represen-
9 tations (cf. Chomsky 1970; Jackendoff 1975), psycholinguistic research,
10 too, supplied more and more evidence for a parsing mechanism that is
11 guided by lexically specific information. In “lexical guidance” accounts
12 of sentence comprehension (Ford et al. 1982; Mitchell 1994), it is com-
13 monly assumed that particular lexical items, most notably verbs, exhibit
14 individual preferences for possible subcategorization patterns and that
15 these preferences enable the comprehension system to anticipate likely
16 structural continuations. Such accounts predict that sentences should be
17 easy to process if a verb’s structural expectations are met, and harder to
18 process if such expectations are violated. Consequently, these accounts
19 predict that the sentences in (2) differ significantly in terms of processing
20 difficulty:

- 21 (2) a. Inspector Clousseau suspected Sir Charles Litton was the
22 phantom.
23 b. Inspector Clousseau remembered Sir Charles Litton was the
24 phantom.
25 c. Inspector Clousseau suspected Sir Charles Litton all along.
26 d. Inspector Clousseau remembered Sir Charles Litton only vaguely.
27

28 Specifically, 2a and 2d should be easier to process than 2b and 2c, re-
29 spectively, because the structural continuations are in accordance with the
30 preferences of the verbs in these examples: *remember* is biased towards
31 nominal complements, whereas *suspect* prefers sentential continuations.

32 There is compelling evidence for such a lexically driven parsing mecha-
33 nism, which I will only briefly sketch here: Fodor (1978) predicted that a
34 verb’s preference for transitive or intransitive complementation could in-
35 fluence the initial parsing decision of whether a gap should be postulated
36 after the verb. Ford et al. (1982) generalized Fodor’s ideas and claimed
37 that each verb has associations of differing strengths to all its possible
38 subcategorization frames. These strengths reflect a combination of verb
39 frequency and contextual factors and are exploited to build up expect-
40 ations that are used in parsing. Ford et al. tested this hypothesis in an
41 off-line experiment in which subjects were asked to make a forced choice
42 between two possible interpretations of an ambiguous sentence. It could

1 be shown that a set of subcategorization preferences could be used to pre-
 2 dict subjects' choices. Although Ford and colleagues did not test for fre-
 3 quency effects themselves, it was later shown that the biases assumed in
 4 their study corresponded to frequencies in the Brown corpus (Jurafsky
 5 1996). Clifton et al. (1984) tested the approach by using the frequency
 6 norms collected by Connine et al. (1984) and showed that these fre-
 7 quencies could be used for predicting differences in processing difficulty.
 8 Tanenhaus et al. (1985) demonstrated that fronted direct objects resulted
 9 in longer reading times for verbs with a transitive bias, but not for verbs
 10 that preferred intransitive use. Trueswell et al. (1993) used a cross-modal
 11 naming paradigm to show that frequency-based subcategorization prefer-
 12 ences are relevant for on-line disambiguation. MacDonald et al. (1994)
 13 reported that the lexical bias effect was also detectable with main verb/
 14 reduced relative clause ambiguities. Jennings et al. (1997), in an extension
 15 of Trueswell et al. (1993), used a similar cross-modal naming experiment
 16 and focused on an alleged design flaw in that experiment: up to this point,
 17 previous studies had binned the verb-preferences into just two classes
 18 (high and low frequency). Jennings and colleagues demonstrated a corre-
 19 lation between the strength of the bias and reading time at the target
 20 word such that the stronger the bias, the larger the advantage they found
 21 in naming latency for the preferred over the non-preferred continuation.

22 However, it has been suggested that verb-specific preferences are not
 23 quite fine-grained enough: many verbs can express different meanings
 24 which in turn may be associated with different argument structure config-
 25 urations. Consider the examples in (3):

- 26 (3) a. Peter_{VP} [v admitted_{NP} [his ex-girlfriend]_{PP} [to the club]].
 27 b. Peter_{VP} [v admitted_S [NP [his ex-girlfriend] was hotter than his
 28 current one]].
 29 c. Peter_{VP} [v admitted_{NP} [his error]].
 30

31 The verb *admit* in (3a) roughly means 'grant entry' and takes NP ob-
 32 jects only, whereas in (3b) and (3c) it means roughly 'acknowledge to
 33 be true' and can take either nominal or sentential complements. Recent
 34 studies have therefore addressed the possibility that subcategorization
 35 preferences are in fact *sense-contingent*: Argaman and Pearlmutter (2002)
 36 showed that verbs and their derived nominals—which presumably share a
 37 number of semantic features—have similar subcategorization probabili-
 38 ties. This suggests that the semantic properties of a verb influence its sub-
 39 categorization choice. Hare et al. (2003) conducted a self-paced moving
 40 window experiment to investigate this possibility. They found increased
 41 reading times in cases in which the structural expectation after the crucial
 42 NP was not met, concluding that “[r]eaders were influenced by structural

1 expectations contingent on verb sense” (Hare et al. 2003: 294; see also
2 Hare et al. 2004). This hypothesis can be formulated as follows:

3 § Verb Sense Guidance Hypothesis (VSGH)

4
5 Each conventionalized verb sense carries probabilistic information ex-
6 pressing its bias for possible argument structure configurations. This in-
7 formation is used to guide early parsing decisions.

8 The present study investigates whether the VSGH can be corroborated
9 from a corpus-linguistic point of view. It is divided into two parts: First, a
10 distinctive collexeme analysis (henceforth DCA; Gries and Stefanowitsch
11 2004) is conducted to assess form-based and sense-contingent preferences
12 for 20 verbs in a balanced 17 million words sample of the British Na-
13 tional Corpus (BNC). This analysis supplies for each verb (sense) an as-
14 sociation score expressing the degree to which a given verb form or verb
15 sense prefers one of the two relevant complementation patterns. Second,
16 these results are compared with experimental findings from the self-paced
17 reading study reported in Hare et al. (2003) by computing correlation
18 analyses for the results of the DCA and the reading-time deltas measured
19 by Hare and colleagues.
20

21 **3. Form-based vs. sense-contingent preferences**

22
23 There are two ways of estimating lexical preferences: they can either be
24 assessed experimentally, e.g., by means of sentence completion tasks
25 (e.g., Garnsey et al. 1997) or sentence production tasks (e.g., Connine et
26 al. 1984), or via corpus investigation.¹ Both methods exhibit different
27 strengths and weaknesses: experimental techniques permit the investiga-
28 tion of a single factor in isolation by allowing the researcher to control,
29 in principle, all known factors that are not addressed in a given design.
30 By contrast, corpus data usually consist of samples of naturally occurring
31 language that is embedded in real-life communicative situations and thus
32 influenced by a multitude of factors which cannot easily be identified.
33 However, the naturalistic quality of corpus data is also what makes them
34 so attractive: experimental settings can easily produce linguistic artifacts
35 that are detached from the constraints of normal discourse. For instance,
36 since the meaning of the sentences to be produced is largely irrelevant,
37 participants in sentence completion tasks might prefer short variants
38

39
40 1. Garnsey and colleagues used a proper name followed by a verb as in “Debbie remem-
41 bered ___” and asked subjects to complete this fragment. In Connine et al. (1984), sub-
42 jects were presented with a verb and were asked to write down a sentence containing
that verb.

1 over longer ones simply to minimize their effort. However, in real life sit-
 2 uations speakers are of course bound to their communicative intentions
 3 and must thus use forms which are appropriate for the speech act to be
 4 performed. Given these respective strengths and weaknesses of experi-
 5 mentally and corpus-derived norms, it appears obvious that they should
 6 be employed in a complementary way. Nevertheless, as has been pointed
 7 out elsewhere (cf., e.g., Tummers et al. 2005), it is necessary to engage
 8 in rigorous, quantitative methodologies to make full use of the corpus-
 9 linguistic potential.

10 3.1. *Assessing form-based preferences*

11 3.1.1. *Method.* The present study employs a variant of “collostruc-
 12 tional analysis” (cf. Stefanowitsch and Gries 2003 for detailed discus-
 13 sion), a family of collocational techniques that was developed to inves-
 14 tigate the relationship between syntax and lexis. Formulated in the
 15 framework of construction grammar (Goldberg 1995; Lakoff 1987), it ad-
 16 dresses the interaction of linguistic signs of various levels of abstraction,
 17 e.g., lexical items and abstract argument structure constructions. The
 18 degree of association between such constructions—i.e., metaphorically,
 19 the “glue” between these units—is referred to as their “collostruction
 20 strength”. One of the variants of this method, “distinctive collexeme anal-
 21 ysis”, employs the general logic of the approach to compare a given
 22 word’s relative attraction to a set of constructional variants in which this
 23 item can occur. In other words, it offers a way to measure a verb’s relative
 24 preference for a given set of complementation options. In the present
 25 study, these alternatives are the nominal and the sentential complementa-
 26 tion pattern that compete in the resolution of NP/S-ambiguities. As re-
 27 gards the lexical items to be investigated in these constructions, the study
 28 covers all of the 20 verbs used in the reading experiment by Hare and col-
 29 leagues (i.e., *acknowledge, add, admit, anticipate, bet, claim, confirm, de-*
 30 *clare, feel, find, grasp, indicate, insert, observe, project, recall, recognize,*
 31 *reflect, report and reveal*), each of which can occur with both nominal
 32 and sentential complements.

33 The data were extracted from a balanced 17 million word sample of the
 34 British National Corpus which was compiled to be isomorphic to the
 35 British component of the ICE corpus.² Of interest were all instances of
 36 these verbs that are immediately followed by a noun phrase. The study is
 37 restricted to past tense forms of the verbs and lexical rather than prono-
 38 minimal NPs (pronominal realizations of the relevant NP were excluded be-
 39

40
 41
 42 2. For detailed information of the properties of that corpus cf. Nelson (1996).

1 Table 1. *Input distributions*

	verb V	other verbs	
4 nominal OBJ	O11	O12	R1
5 sentential OBJ	O21	O22	R2
	C1	C2	N

8 cause they are formally marked for case and thus do not give rise to NP/
9 S-ambiguities).³

10 As expected, the investigated verbs had markedly different frequencies
11 in the corpus. In order to attain a data set of manageable size, the follow-
12 ing procedure was applied:

- 14 – for verbs with a token frequency greater than 3,000, a random 10%
15 sample was extracted
- 16 – for verbs with a token frequency between 300 and 3,000 a random
17 sample of 300 items was extracted
- 18 – for verbs with a token frequency lower than 300, all occurrences were
19 extracted

20 This gave a set of 4,960 data-points which was then coded for the
21 grammatical role of the post-verbal NP by hand. The labels “NP” and
22 “S” were used to indicate nominal and sentential complementation, re-
23 spectively. Cases that could not be assigned to either of these two catego-
24 ries received the label “other”.

25 Having extracted and coded the data, they were submitted to the DCA
26 in order to compute association strengths between a given verb and the
27 two syntactic patterns. The figures that were required for this calculation
28 are given in Table 1.

29 Required figures include the observed frequencies of verb V in either of
30 the two constructions (O11, O21) as well as the observed frequencies of
31 these constructions occurring with other verbs (O12, O22). The labels
32 R1, R2 and C1, C2 stand for row and column totals and N denotes over-
33 all frequency, i.e., $O11 + O12 + O21 + O22$. Given these frequencies, the
34 relative attraction between verbs and the two constructions in question
35 can be computed. Generally speaking, candidate measures of the prop-
36 erty of interest (association strength) compare the observed distribution
37 with the expected distribution under the assumption of statistical indepen-
38 dence and evaluate how much evidence the observed distribution provides

41 3. The analysis was restricted to past tense forms because Hare et al. (2003) used these
42 forms in their experiment as well.

1 Table 2. *Verb preferences for nominal complements*

2 Verb	3 form-based bias (log odds ratios)
4 <i>confirm</i>	-3.66
5 <i>feel</i>	-2.04
6 <i>anticipate</i>	-1.35
7 <i>recall</i>	-1.20
8 <i>acknowledge</i>	0.11
9 <i>reflect</i>	0.27
10 <i>bet</i>	0.30
11 <i>reveal</i>	0.38
12 <i>claim</i>	0.59
13 <i>recognize</i>	0.64
14 <i>indicate</i>	0.89
15 <i>insert</i>	1.30
16 <i>observe</i>	1.38
17 <i>grasp</i>	1.40
18 <i>project</i>	1.40
19 <i>add</i>	2.22
20 <i>declare</i>	2.36
21 <i>admit</i>	2.62
22 <i>report</i>	3.38
23 <i>find</i>	4.28

24 against this assumption. On closer inspection, however, it is far from trivial
 25 to determine exactly what measure is best suited to adequately express
 26 degrees of association between linguistic units (cf. Evert 2004; Wiech-
 27 mann forthcoming).⁴ Following Gries (forthcoming), the present study
 28 makes use of a “discounted” odds ratio to express collocation strength,
 29 because a) this measure approximates the results of more accurate mea-
 30 sures (such as exact hypothesis tests) fairly well, and b) in contrast to
 31 such other measures, its estimation of the relationship in question is less
 32 dependent on sample sizes.⁵

33 3.1.2. *Results.* Table 2 and Figure 1 present the results of the DCA,
 34 specifically the preference of a given verb for NP-complementation. The

37 4. Evert (2004) provides a comprehensive overview of measures proposed in the computa-
 38 tional and corpus-linguistic literature and discusses their mathematical properties and
 39 areas of application. Wiechmann (in print) evaluates 47 scores of different mathematical
 40 types against their performance to predict eye-tracking data reported in Kennison
 (2001).

41 5. The “discounted” variant of the odds ratio adds 0.5 to each factor in order to avoid in-
 42 finite values.

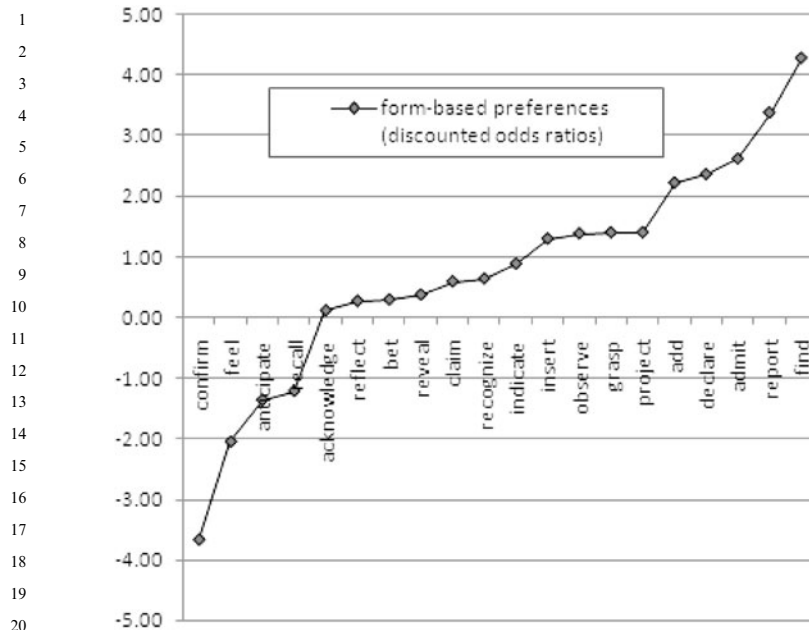


Figure 1. *Verb preferences*

left column in Table 2 lists the investigated verbs and the right column specifies the corresponding association strength coefficients, i.e., the respective (logarithmically scaled) odds ratios. These express the degree to which a given verb prefers one of the two patterns: the higher the score, the stronger the preference for NP-complementation. Negative values indicate that a verb is biased towards sentential complementation.

3.1.3. *Discussion.* Figure 1 reveals that the investigated verbs differ noticeably with regard to their structural preferences. Only four of the 20 verbs (*confirm*, *feel*, *anticipate*, *recall*) do in fact show a preference for sentential complementation. All remaining verbs have at least a tendency to prefer nominal complements. The overall preference for nominal complementation of these 20 verbs reflects a general or “global” tendency of English to favor simple monotransitive patterns (cf. Bever 1970). Other things being equal, comprehenders are thus more likely to expect NP continuations, simply because the global transitivity bias acts on the comprehension system even before the verb is being perceived. Consequently, verbs must exhibit rather strong preferences for sentential complementation to counter this effect.

1 3.2. *Assessing sense-contingent preferences*

2 3.2.1. *Method.* Different senses of the investigated verbs were identi-
 3 fied in a lexical database, WordNet 2.0, which was also used in Hare et
 4 al.'s (2003) study.⁶ Each of the 4960 items in the data set was assigned to
 5 the sense that was considered to provide the “best fit” relative to the list
 6 of senses proposed in WordNet.⁷

7 To give an example, there were 656 occurrences of [*find* NP] in the
 8 data. 608 tokens of these involve nominal complementation and 48 in-
 9 stances involve sentential complementation. A semantic subclassification
 10 of these uses revealed that 210 instances out of the 608 nominal tokens
 11 are instantiations of sense 1 (FIND₁) in WordNet, which is described as
 12 “verb of possession; come upon after searching”. Sense FIND₁ does not
 13 occur with sentential complements. This contrasts with sense FIND₂,
 14 glossed as “come to believe on the basis of emotions, intuitions, or indef-
 15 inite grounds” in WordNet, which is instantiated 180 times in the sample
 16 and has 137 occurrences in the nominal and 43 occurrences in the senten-
 17 tial pattern. The remaining tokens of *find* realize yet other senses of the
 18 verb, for which as many as 16 distinct senses are distinguished in Word-
 19 Net (however, FIND₁ and FIND₂ are the most frequent and semanti-
 20 cally different ones and account for roughly 60% of the data).

21 Having classified the data in this manner for all 20 verbs, the syntactic
 22 preference of a given verb sense could then be estimated by submitting the
 23 distributional information to a second DCA. For each verb two senses—
 24 namely the ones that fit the semantics of Hare et al.'s context sentences—
 25 were contrasted.
 26

27 3.2.2. *Results.* Table 3 presents the odds ratios expressing the sense-
 28 contingent collocation strengths:

29 As above, positive scores indicate a preference for nominal comple-
 30 mentation and negative values indicate a preference for sentential
 31 complementation.
 32

33
 34 6. WordNet was compiled by a group of psycholinguists at Princeton University in 1985—
 35 and elaborated ever since—as an attempt to investigate lexical memory. For more infor-
 36 mation on WordNet, cf. Fellbaum (1998).

37 7. The assignment of WordNet senses to a large set of novel examples is not unprob-
 38 lematic, because the sense distinctions in WordNet are very fine-grained. As a result a certain
 39 degree of misclassification had to be accepted. Note, however, that the most important
 40 semantic distinction concerns very coarse-grained contrasts: Hare and colleagues chose
 41 senses from WordNet in such a way that “[f]or each of the 20 verbs, we identified two
 42 senses that appeared to be sufficiently distinct, that we believe are known to undergrad-
 uates, and that allow different subcategorization frames according to WordNet” (p. 285).

Table 3. *Form-based vs. sense-contingent preferences*

Verb	form-based	sense1	sense2
<i>confirm</i>	-3.66	-1.63	-3.22
<i>feel</i>	-2.04	-2.15	-0.96
<i>anticipate</i>	-1.35	-0.21	-2.55
<i>recall</i>	-1.20	-0.35	-1.22
<i>acknowledge</i>	0.11	-0.35	1.76
<i>reflect</i>	0.27	-1.82	1.57
<i>bet</i>	0.30	-4.38	1.39
<i>reveal</i>	0.38	0.38	0.21
<i>claim</i>	0.59	-0.53	1.53
<i>recognize</i>	0.64	-0.91	1.61
<i>indicate</i>	0.89	-0.25	0.91
<i>insert</i>	1.30	0.93	0.79
<i>observe</i>	1.38	0.98	1.33
<i>grasp</i>	1.40	-0.07	0.85
<i>project</i>	1.40	-0.73	2.39
<i>add</i>	2.22	1.27	-0.98
<i>declare</i>	2.36	-0.75	-0.39
<i>admit</i>	2.62	1.08	0.87
<i>report</i>	3.38	-1.47	-1.04
<i>find</i>	4.28	-0.02	-1.04

Figure 2 presents the results for both form-based and sense-contingent preferences in graphical form.

3.2.3. *Discussion.* The results show that form-based and sense-contingent preferences may differ both quantitatively, i.e., in terms of association strength (cf. e.g., *bet* or *reveal*), and qualitatively, i.e., in terms of the preferred pattern at large (cf. e.g., *admit* or *confirm*). The fact that the subcategorization preferences are different for different meanings expressed by a given verb form corroborates the position advocated in Hare et al. (2004) that psychological models and, consequently, experimental protocols using subcategorization preferences should take verb senses into account. However, in order to assess their relevance for aspects of on-line processing, it is necessary to compare these off-line data to appropriate experimental observations.

3.3. *Comparing corpus-based and experimental findings*

In order to test whether the employed method, distinctive collexeme analysis, can be fruitfully applied to estimate speakers' on-line processing preferences, the computed association scores were compared with the reading time latencies of the individual items observed by Hare and colleagues.

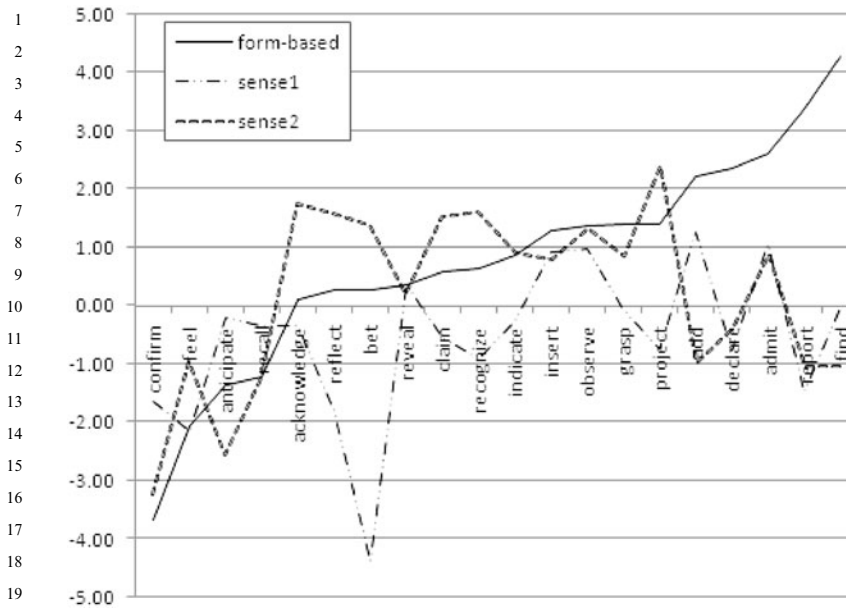


Figure 2. *Form-based vs. sense-contingent preferences*

Before I present the results, it will be helpful to provide a more detailed description of the experiment in question. As indicated, the study was designed to test whether a verb's sense-contingent subcategorization bias is exploited during on-line processing, specifically for the resolution of temporary NP/S-ambiguities. Participants were asked to read two sentences: a context sentence and the actual target sentence, which incorporated the investigated verb and always involved a sentential continuation. The context sentences were designed so as to evoke a scenario compatible with one of two maximally different senses of the verb under investigation.⁸ Having read the context sentence first, the participants then read through the test sentence, which was presented one word at a time. As an illustration, consider the stimulus set for the verb *find* in (4) and (5) (crucial NP italicized):

(4) Condition 1

- a. The intro psychology students hated having to read the assigned text because it was boring.

8. The properties of the context sentence were controlled for not directly priming the relevant syntactic patterns themselves, i.e., they did neither involve a NP V S nor a NP V NP structure.

1 b. They found *the book* was written poorly and difficult to
2 understand.

3 (5) Condition 2

4 a. Allison and her friends had been searching for John Grisham's
5 new novel for a week, but yesterday they finally were successful.

6 b. They found *the book* was written poorly and were annoyed that
7 they had spent so much time trying to get it.

8
9 Hence, having read up to the investigated verb in the target sentence,
10 subjects were predicted show a disposition to interpret this verb as instan-
11 tiating the sense that is compatible with the scenario conveyed by the con-
12 text sentence, i.e., they should expect an S-continuation once *found* was
13 been read in (4) and an NP-continuation in (5). The authors predicted a
14 context by ambiguity interaction in the disambiguation region (DR) and,
15 in fact, the strongest ambiguity effect could be measured at the second
16 word of that region (i.e., at *written* in the above example). In other words,
17 an S-biasing context sentence as (in condition 1) should lead to relatively
18 shorter reading times at the second word of the disambiguation region
19 (DR_{POS2}) of the S-target sentence. Conversely, an NP-biasing context (as
20 in condition 2) should lead to increased reading times at DR_{POS2} of the S-
21 target sentence. Averaged across verbs, these predictions were fulfilled.

22 The present study investigates whether the relevant preferences can be
23 quantified using the collostructional methodology introduced in section
24 3.1.1. To that end, the sense-contingent preferences as expressed by dis-
25 counted odds ratios were compared with the reading time latencies at the
26 second word of the disambiguation region. If collostruction strength is in
27 fact a good predictor of the relevant biases, it is expected that there is a
28 correlation between collostruction strength and reading time latency. In
29 other words: the stronger the association with nominal complementation,
30 the greater the ambiguity effect should be. Conversely, a negative correla-
31 tion is expected if reading time deltas are compared with preferences for
32 sentential complementation, the pattern that was consistently employed
33 in the experimental study by Hare and colleagues.

34
35 3.3.1. *Method.* Correlational analyses were conducted between the
36 computed association scores (discounted odds ratios) and the reading
37 time latencies at DR_{POS2} both on the level of lexical form and lexical
38 meaning using Spearman's rank order correlation.⁹

39
40
41 _____
42 9. All statistics were calculated with the R statistics package version 2.2.1.

1 3.3.2. *Results.* The analysis revealed a significant negative correlative
2 relationship between sense-contingent preferences and reading time for
3 the second word of the disambiguation region (Spearman's $\rho =$
4 -0.3136 ; $p < 0.05^*$): the weaker a sense's preference for sentential com-
5 plementation, the greater the ambiguity effect when this pattern is en-
6 countered. No such correlation could be observed for form-based prefer-
7 ences and reading time latencies (Spearman's $\rho = 0.1172$; $p = 0.471$).
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10 4. Discussion

11

12 The present study has provided corpus-linguistic evidence for the exis-
13 tence of detailed sense-specific probabilistic information that is associated
14 with particular lexical forms and that appears to guide the human lan-
15 guage comprehension system upon resolving local syntactic ambiguities.
16 In particular, the employed method of distinctive collexeme analysis as
17 well as the selected association strength measure of discounted odds ratios
18 were shown to provide a useful means for inducing the observable biases
19 from corpus data.

20 Nevertheless, some qualifications are in order: First, although verb
21 sense-specific preferences seem to play an important role in guiding com-
22 prehenders' syntactic analysis of a sentence, there are many other factors
23 that are known to influence the ambiguity resolution process, too (cf.
24 MacDonald 1997 for an overview; see also Zeschel, this volume). Fur-
25 thermore, nothing in the present study excludes the possibility that the
26 relevant expectations are in fact encoded on a more general level (i.e., a
27 level of semantically coherent verb classes) rather than stored separately
28 for particular senses of individual verbs.

29 However, wherever these preferences are encoded, the observed results
30 tie in nicely with central tenets of usage-based approaches to language.
31 First, usage-based models (Langacker 1988) predict a connection between
32 statistical patterns in the input (to be approximated by studying large-
33 scale balanced corpus data) and the mental representations that are built
34 up in response to speakers' linguistic experience. Second, usage-based ap-
35 proaches to grammar are construction-based by capitalizing on the no-
36 tion of form-meaning pairings. The present study has presented evidence
37 in support of the idea that a particular type of such form-meanings pair-
38 ings (i.e., the association between syntactic complementation patterns and
39 particular lexical meanings) indeed plays a role in determining the distri-
40 bution of verbs with different senses across grammatical constructions
41 and also seems to influence comprehenders' on-line processing decisions
42 when confronted with syntactic ambiguities involving these items.

1 One recent addition to the family of usage-based theories is Embodied
 2 Construction Grammar (Bergen and Chang 2002). Bryant (2003, 2004)
 3 has provided a parsing component for this approach, called *constructional*
 4 *analyzer*. On this approach, parsing is an analysis process which takes an
 5 input utterance in context and determines the set of constructions that are
 6 most likely to be responsible for it. The advantage of a construction-
 7 based parser is that “[...] constructions carry both phonological and
 8 conceptual content, [and] a construction[al] analyzer [...] must respect
 9 both kinds of constraint” (Bergen and Chang 2003: 19). Constructions
 10 and their constraints are regarded not as deterministic but as fitting a
 11 given utterance and context to some quantifiable degree. Bryant suggests
 12 that constructions and their constraints could be associated with connec-
 13 tion weights. The present paper is sympathetic to such a conception of
 14 language and suggests that these connections weights can be inferred
 15 from collocation strengths.

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