Lexical Semantic Analysis in Natural Language Text

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Abstract

Computer programs that make inferences about natural language are easily fooled by the often haphazard relationship between words and their meanings. This thesis develops **Lexical Semantic Analysis** (LxSA), a general-purpose framework for describing word groupings and meanings in context. LxSA marries comprehensive linguistic annotation of corpora with engineering of statistical natural language processing tools. The framework does not require any lexical resource or syntactic parser, so it will be relatively simple to adapt to new languages and domains.

The contributions of this thesis are: a formal representation of lexical segments and coarse semantic classes; a well-tested linguistic annotation scheme with detailed guidelines for identifying multi-word expressions and categorizing nouns, verbs, and prepositions; an English web corpus annotated with this scheme; and an open source NLP system that automates the analysis by statistical sequence tagging. Finally, we motivate the applicability of lexical semantic information to sentence-level language technologies (such as semantic parsing and machine translation) and to corpus-based linguistic inquiry.
I, Nathan Schneider, do solemnly swear that this thesis is my own work, and that everything therein is, to the best of my knowledge, true,* accurate, and properly cited, so help me Vinken.

To my parents, who gave me language.

In memory of Charles “Chuck” Fillmore, one of the great linguists.

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* Except for the footnotes that are made up. If you cannot handle jocular asides, please recompile this thesis with the \jnote macro disabled.
Acknowledgments

As a fledgling graduate student, one is confronted with obligatory words of advice, admonitions, and horror stories from those who have already embarked down that path. At the end of the day, though, I am forced to admit that my grad school experience has been perversely happy. Some of that can no doubt be attributed to my own bizarre priorities in life, but mostly it speaks to the qualities of those around me at CMU, who have been uniformly brilliant, committed, enthusiastic, and generous in their work.

First and foremost, I thank my Ph.D. advisor, Noah Smith, for serving as a researcher role model, for building and piloting a resplendent research group (ARK), and for helping me steer my research while leaving me the freedom to develop my own style. I thank the full committee (Noah, Chris, Lori, Ed, and Tim), not just for their thoughtful consideration and feedback on the thesis itself, but for their teaching and insights over the years that have influenced how I think about language and its relationship to technology.

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2“day” being a euphemism for 6 years
Sim, Waleed Ammar, Sam Thomson, Lingpeng Kong, Jesse Dodge, Swabha Swayamdipta, Rohan Ramanath, Victor Chahuneau, Daniel Mills, and Dallas Card—it was an honor. My officemates in GHC 5713—Dipanjan, Tae, Dani, Waleed, and (briefly) Sam and Lingpeng—deserve a special shout-out for making it an interesting place to work. It was a privilege to be able to work with several different ARK postdocs—Behrang Mohit, (pre-professor) Chris Dyer, and Fei Liu—and always a pleasure to talk with Bryan Routledge at group meetings.

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The summer of 2012 was spent basking in the intellectual warmth of USC’s Information Sciences Institute, where I did an internship under the supervision of Kevin Knight, and had the good fortune to cross paths with Taylor Berg-Kirkpatrick (and his cats), Daniel Bauer, Bevan Jones, Jacob Andreas, Karl Moritz Hermann, Christian Buck, Liane Guillou, Ada Wan, Yaqin Yang, Yang Gao, Dirk Hovy, Philipp Koehn, and Ulf Hermjakob. That summer was the beginning of my involvement in the AMR design team, which includes Kevin and Ulf as well as Martha Palmer, Claire Bonial, Kira Griffitt, and several others; I am happy to say that the collaboration continues to this day.

The inspiration that pushed me to study computational linguistics and NLP in the first place came from teachers and mentors at UC Berkeley, especially Jerry Feldman and Dan Klein. I am happy to have remained connected to that community during my Ph.D., and to have learned a great deal about semantics from the likes of Collin Baker, Miriam Petruck, Nancy Chang, Michael Ellsworth, and Eve Sweetser.

Finally, I thank my family for being there for me and putting up with my eccentricities. The same goes for my friends mentioned above, as well as from the All University Orchestra (Smitha Prasadh, Tyson Price, Deepa Krishnaswamy), from Berkeley linguistics (Stephanie Shih, Andréa Davis, Kashmiri Stec, Cindy Lee), and from NLP conferences.

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establishments, especially Tazza d’Oro, the 61C Café, and Little Asia.

There are undoubtedly others that I should have mentioned above, so I hereby acknowledge them.

If in this document contains any errors, omissions, bloopers, dangling modifiers, wardrobe malfunctions, etc., it is because I screwed up. It is emphatically not the fault of my committee or reviewers if a bug in my code caused low numbers to round up, high numbers to round down, or expletives to be inserted in phonologically suspect syllable positions.

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Computers are getting smarter all the time: scientists tell us that soon they will be able to talk to us. (By “they” I mean “computers”: I doubt scientists will ever be able to talk to us.)


### CHAPTER 1

### Setting the Stage

The seeds for this thesis were two embarrassing realizations.¹

The first was that, despite established descriptive frameworks for syntax and morphology, and many vigorous contenders for relational and compositional semantics, I did not know of any general-purpose linguistically-driven computational scheme to represent the contextual meanings of *words*—let alone resources or algorithms for putting such a scheme into practice.

My embarrassment deepened when it dawned on me that I knew of no general-purpose linguistically-driven computational scheme for even *deciding* which groups of characters or tokens in a text qualify as meaningful words!

Well. Embarrassment, as it turns out, can be a constructive

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¹In the Passover Haggadah, we read that two Rabbis argued over which sentence should begin the text, whereupon everyone else in the room must have cried that four cups of wine were needed, stat.

This thesis is similar, only instead of wine, you get footnotes.
motivator. Hence this thesis, which chronicles the why, the what, and the how of analyzing (in a general-purpose linguistically-driven computational fashion) the lexical semantics of natural language text.

The intricate communicative capacity we know as “language” rests upon our ability to learn and exploit conventionalized associations between patterns and meanings. When in Annie Hall Woody Allen’s character explains, “My raccoon had hepatitis,” English-speaking viewers are instantly able to identify sound patterns in the acoustic signal that resemble sound patterns they have heard before. The patterns are generalizations over the input (because no two acoustic signals are identical). For one acquainted with English vocabulary, they point the way to basic meanings like the concepts of ‘raccoon’ and ‘hepatitis’—we will call these lexical meanings—and the grammatical patterns of the language provide a template for organizing words with lexical meanings into sentences with complex meanings (e.g., a pet raccoon having been afflicted with an illness, offered as an excuse for missing a Dylan concert). Sometimes it is useful to contrast denoted semantics (‘the raccoon that belongs to me was suffering from hepatitis’) and pragmatics (‘…which is why I was unable to attend the concert’) with meaning inferences (‘my pet raccoon’; ‘I was unable to attend the concert because I had to nurse the ailing creature’). Listeners draw upon vast stores of world knowledge and contextual knowledge to deduce coherent interpretations of necessarily limited utterances.

As effortless as this all is for humans, understanding language production, processing, and comprehension is the central goal of the field of linguistics, while automating human-like language behavior in computers is a primary dream of artificial intelligence. The field of natural language processing (NLP) tackles the language automation problem by decomposing it into subproblems, or tasks; NLP tasks with natural language text input include grammatical analysis with linguistic representations, automatic knowledge base or database construction, and machine translation. The latter two are considered applications because they fulfill real-world needs, whereas automating linguistic analysis (e.g., syntactic parsing) is sometimes called a “core NLP” task. Core NLP systems are those intended to provide modular functionality that could be exploited for many language processing applications.

This thesis develops linguistic descriptive techniques, an English text dataset, and algorithms for a core NLP task of analyzing the lexical semantics of sentences in an integrated and general-purpose way. My hypothesis is that the approach is conducive to rapid high-quality human annotation, to efficient automation, and to downstream application.

A synopsis of the task definition, guiding principles, methodology, and contributions will serve as the entrée of this chapter, followed by an outline of the rest of the document for dessert.

1.1 Task Definition

We define Lexical Semantic Analysis (LxSA) to be the task of segmenting a sentence into its lexical expressions, and assigning semantic labels to those expressions. By lexical expression we mean a word or group of words that, intuitively, has a “basic” meaning or function. By semantic label we mean some representation of...
the expression’s contextual meaning, selected from a predefined categorization scheme.

The flavor of LxSA pursued here incorporates multiword expression identification (to determine the lexical segmentation) and supersense classification (to choose labels for noun, verb, and preposition expressions). For example, Groucho Marx’s famous aphorism is analyzed thusly:⁴

(1) a. *Time flies like an arrow.*

   TIME\(^∗\) MOTION\(^∗\) MANNER\(^∗\) ARTIFACT\(^∗\)

b. *Fruit flies like a banana.*

   ANIMAL\(^∗\) COGNITION\(^∗\) FOOD\(^∗\)

The lexical segmentation is indicated by underlining: every token belongs to exactly one lexical expression.⁵ Observe that *fruit flies* is analyzed as a multiword expression because it is deemed to have a sufficiently “atomic” meaning (see ch. 3 for criteria). This expression and other nouns, verbs, and prepositions in the sentence receive supersense labels. There are 26 supersense categories for nouns, 15 for verbs, and 70 for prepositions (see ch. 4: p. 65 and ch. 5: table 5.1 on p. 102). These coarse senses provide a measure of word sense disambiguation (contrast the two senses of *like* in (1)), even beyond the part-of-speech disambiguation (e.g., *liking a post on Facebook* would involve a COMMUNICATION sense of the verb). Supersenses also group together semantically related tokens: *like*, *prefer*, *think*, *decide*, etc. can also function as COGNITION verbs.

1.2 **Approach**

To build a system that automatically performs lexical semantic analysis, we adopt a workflow of human annotation and supervised machine learning. The research described in this thesis employs the following methodologies:

1. **Representation**: Designing the formal scheme for encoding analyses. We specify a space of possible multiword expression groupings and a mapping from lexical expression tokens to possible semantic labels.

2. **Annotation**: Devising a usable annotation scheme and applying it to a corpus with human annotators. This includes providing linguistic guidelines (categories, definitions, criteria, and examples), as well as an annotation interface and quality control procedures. Our result is a fully annotated 56,000-word corpus of English reviews from the web.

3. **Automation**: Developing a system that performs the analysis given new sentences. We implement a discriminative sequence tagger, train it on the labeled corpus, and evaluate its accuracy compared to human annotations on held-out data.

While this endeavor requires a certain amount of human expertise and intuition, we can test our hypotheses in part by quantifying several aspects of the process, including: the number of sentences that seem to violate our representational constraints; the degree to which annotators agree with one another when working independently; the extent to which system output on held-out data matches the gold standard; the runtime of the system; and, ultimately, the impact of lexical semantic analyses on performance measures for subsequent tasks.

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⁴Supersenses are part-of-speech–specific. To avoid visual clutter, we render parts of speech as symbols: \(^∗\) for verbs, \(^\prime\) for nouns, and \(^\prime\) for prepositions.

⁵Ch. 3 introduces a distinction between strong and weak multiword expressions. The definition of “lexical expression” assumed here disregards weak groupings.
1.3 Guiding Principles

We believe LxSA is worth pursuing as a general-purpose NLP task for several reasons:

• **Coverage & Informativeness:** Our approach integrates three existing representations/tasks, or **components:** MWE identification, noun and verb supersense tagging, and preposition classification. All of these can be independently motivated and are associated with existing resources. The depth and coverage of semantic labels lies somewhere between named entity annotation (limited to a small proportion of tokens) and fine-grained word sense annotation (broad-coverage in principle, but expensive to produce). We hypothesize that interactions between lexical grouping and kinds of lexical meaning can be exploited in a joint model for improved accuracy, and that predicting a single analysis that is consistent between the facets of meaning will be more useful to applications than multiple possibly inconsistent layers of analysis.

• **Corpus-comprehensiveness:** Ideally, all of the text in a corpus should be analyzed so corpus statistics can be maximally useful to machine learning algorithms. In our data, all sentences have been annotated in full for multiword expressions, and all expressions meeting simple syntactic criteria (headed by a noun, verb, or preposition) have been annotated with supersenses. This contrasts with resources whose annotations are limited to certain types (e.g., particular high-frequency words, or expressions realizing concepts from a domain ontology).

• **Annotateability:** In our experience, it takes some training—but not an advanced linguistics degree—to learn the annotation schemes as we have formulated them. The annotation process is fairly rapid, as it involves mostly local (rather than long-distance or structural) decisions; uses a relatively small, interpretable label vocabulary; and does not require reference to external resources or layers apart from the tokenized sentence.

• **Universality:** The principle of identifying and classifying “semantic words” should apply crosslinguistically. Without making light of the typological differences between languages that would affect the methodology (e.g., a polysynthetic language would likely require splitting words into lexical morphemes), some kind of mismatch between units of sound or writing and units of meaning is expected to be universal, along with many of the categories in our supersense inventory.

• **Robustness:** Our annotation scheme is reasonably domain-general, though the guidelines and even the supersense inventory could be customized to meet the needs of a particular domain. The cost of coarse LxSA annotation in a new domain (on which new domain-specific models could be trained) should not be prohibitive.

• **Simplicity:** Formally, the representation has straightforward properties and well-formedness conditions. This matters for verifying the structural consistency of annotations, measuring inter-annotator agreement, and establishing a search space for automated tools.

• **Accuracy & Efficiency:** Computationally, the LxSA framework permits leveraging and extending well-known efficient and accurate supervised discriminative sequence modeling techniques.
• **Evaluability:** Because the representation permits a closed set of labels and grouping operations, the similarity between two analyses of a text can be quantified automatically.

### 1.4 Contributions

The contributions of this thesis are primarily methodological and practical rather than theoretical. There are no radical new ideas about computational lexical semantics in this thesis. Rather, several previous lines of work are woven together into a novel framework; the prior approaches are revised, expanded, and integrated into what we hope is a helpful conceptual paradigm within the broader landscape of computational semantics, as well as a useful practical tool in the NLP toolbox. Through trial and error, we have developed an annotation scheme that can be applied rapidly with acceptable inter-coder agreement, and shown that statistical models trained on the annotated data obtain far superior performance to heuristic lexicon lookup procedures. The artifacts produced in this work—datasets, annotation guidelines, software—are shared publicly for the benefit of further research on this and related tasks.

### 1.5 Organization

Following some background on computational lexical semantics tasks and techniques in ch. 2, we will turn to the core contributions of the thesis. Their primary mode of organization is methodological; the secondary mode is by analysis component:

<table>
<thead>
<tr>
<th>COMPONENTS</th>
<th>MWEs</th>
<th>Nouns &amp; Verbs</th>
<th>Prepositions</th>
</tr>
</thead>
<tbody>
<tr>
<td>I Representation &amp; Annotation</td>
<td>Ch. 3</td>
<td>Ch. 4</td>
<td>Ch. 5</td>
</tr>
<tr>
<td>II Automation</td>
<td>Ch. 6</td>
<td>Ch. 7</td>
<td></td>
</tr>
</tbody>
</table>

Ch. 8 concludes with a discussion of broader issues, future work, and the prospects of applying lexical semantic analysis to downstream tasks.
“Good morning!” said Bilbo, and he meant it. The sun was shining, and
the grass was very green. But Gandalf looked at him from under long
bushy eyebrows that stuck out further than the brim of his shady hat.

“What do you mean?” he said. “Do you wish me a good morning, or
mean that it is a good morning whether I want it or not; or that you feel
good this morning; or that it is a morning to be good on?”

J.R.R. Tolkien, *The Hobbit*
2.1 The Computational Semantics Landscape

Human language facilitates communication of just about any idea that can be imagined—and each language does so in its own peculiar way and with a finite set of symbols. Accordingly, part of the enterprise of building a scientific understanding of human language is understanding understanding of language. The study of linguistic meaning is called semantics. There are many nuances and facets to meaning, and different semantic frameworks approach these from different angles.

Computational semantics, which aims to enable computers to detect aspects of meaning in language and to encode formally represented ideas as language, is similarly diverse. While it is impossible to do justice here to such a broad (and growing) field, it is worth mentioning a few of the paradigms in use:

- **Lexical semantics and ontologies**: The question of how to model entities and concepts and their relationship to one another and to language. As this area is directly relevant to this thesis, we discuss it in some detail below.

- **Grammaticalization semantics**: Several recent studies have been concerned with isolating aspects of linguistic meaning/function that are conveyed by grammatical categories and constructions, where languages differ in the mappings between these functions and their morphological and syntactic categories. Examples in NLP for English include semantic classification for tense/aspect (Reichart and Rappoport, 2010; Friedrich and Palmer, 2014), modality (Prabhakaran et al., 2012), definiteness functions (Bhatia et al., 2014), core vs. non-core arguments (Abend and Rappoport, 2010), argument structure constructions (Hwang et al., 2010b), and preposition senses/functions (O’Hara and Wiebe, 2003; Hovy et al., 2010; Srikumar and Roth, 2013b, *inter alia*; see ch. 5 for details).

- **Relational semantics**: This covers various attempts to model the nature of links between (usually lexically-associated) concepts in a sentence or discourse. Canonical NLP tasks include semantic role labeling (Gildea and Jurafsky, 2002; Palmer et al., 2010), relational semantic parsing (Tratz and Hovy, 2011; Das et al., 2014; Flanigan et al., 2014; Oepen et al., 2014), and coreference resolution (Stede, 2011, ch. 3).

- **Logical semantics**: An outgrowth of analytic philosophy, these approaches (sometimes called “formal semantics” in linguistics) represent concepts as predicates in formal logic and seek to describe the linguistic correlates of compositional operations that allow for predicates to be combined to form complex meanings. The logical expressions allow for truth relationships to be deduced, possibly with regard to a world model or database. In NLP, logic parsing (a variety of semantic parsing) seeks to produce logical forms for sentences, much like (and often in tandem with) syntactic parsing (e.g., Zelle and Mooney, 1996; Asudeh and Crouch, 2001; Bos et al., 2004; Zettlemoyer and Collins, 2005; Copestake et al., 2005).

- **Deep meaning and reasoning systems**: These are most closely associated with the label “artificial intelligence,” and involve substantial human-like reasoning about the world, with natural language as the input or output. Such systems are of-

1 The semantics of individual words and utterances in isolation is sometimes distinguished from meaning that requires wider communicative context (pragmatics). We do not need to reach the theoretical question of whether a line can be drawn between semantics and pragmatics, but the approaches taken in this thesis generally treat sentences in isolation.
ten associated with applications such as question answering, computer-assisted dialogue, and language-directed robotics (e.g., Carbonell, 1978; Narayanan, 1999; Branavan et al., 2010; Tellex et al., 2011; Ferrucci, 2012). They may use representations based on expert knowledge, mined from language data, or grounded in the physical/sensory domain.

2.2 Lexical Semantic Categorization Schemes

The contributions of this thesis belong to the area of lexical semantics, i.e., accounting for natural language words (lexical items) and their individual meanings. The inventory of lexical items available to speakers of a language, whether in the abstract or documented in dictionary form, is known as the lexicon. Lexicons hold information about word types; instances in context are called tokens. For example, a lexicon may record that the word type seal is polysemous (has multiple senses), and it might therefore be useful to disambiguate which of those senses is meant by a particular token in context. Lexical semantics includes both the study of the organization of the lexicon, and the study of how words convey meaning in context.

In this thesis, we will propose/adapt categorization schemes for lexical items and apply those categories (manually or automatically) in corpora. A primary consideration in developing a categorization is granularity. This is true in linguistics whether the categorization is grammatical (Croft, 2001, ch. 2) or semantic. When it comes to categorizing the meanings of lexical items, there are two major traditions in NLP. These are illustrated in figure 2.1. Traditionally, word sense disambiguation (WSD) is concerned with choosing among multiple senses of a word in a lexicon given a use of the word in context. The semantic representation adds information by refining the word into multiple lexicalized senses (figure 2.1a). Named entity recognition (NER), on the other hand, is concerned with marking and classifying proper names, most of which will not be listed in a lexicon; in this way the task is unlexicalized and contributes information by grouping together multiple lexical items that belong to the same (coarse) semantic class.

The following sections will elaborate on those traditions and introduce machine learning techniques that can be applied to automatically categorize lexical meanings in text.

2.3 Lexicons and Word Sense Classification

This section provides a brief introduction to fundamentals of word sense lexicons and word sense disambiguation that are essential to understanding the thesis. (For a recent survey of corpora and tools for word senses, see Agirre et al., 2013.)

2.3.1 WordNet

Princeton WordNet (Fellbaum, 1998, http://wordnet.princeton.edu/) is a free and open source computational semantic network of the lexicon of English. A graph-structured database of lexical concepts organized into synsets (synonym sets), it includes natural
language descriptions and examples, and several types of taxonomic links between concepts (such as inheritance and part–whole relations). As of version 3.0, 118,000 synsets account for 155,000 lexical entries of nouns (including some proper names), verbs, adjectives, and adverbs.

Figure 2.1b is a flattened, partial view of the taxonomy of the WordNet lexicon. This approach both groups and refines lexical items in mapping them to synsets and defining groupings over synsets. WordNet is fundamentally lexicalized: every semantic category is associated with at least one lexical item.

WordNet additionally defines categorizations of noun and verb senses that are known as "supersenses"; we introduce these in §4.2. In our systems, we make use of WordNet and several other available lexical resources, as discussed in §6.4.2.1 and §7.3.2.

Princeton WordNet has been imitated or adapted in many other languages: a list of these projects and related resources can be found at http://globalwordnet.org.

2.3.2 SemCor

SemCor (Miller et al., 1993) is a 360,000 word sense-tagged subset of the Brown Corpus (Kučera and Francis, 1967) that was created as part of the development of WordNet. Miller et al. contrast two approaches to developing a lexicon and sense-tagged corpus: a "targeted" approach, traditional in lexicography, of considering one word type at a time to develop a sense inventory and label all instances in a corpus with the appropriate sense—we will call this a type-driven approach; and a "sequential" (in our terms, token-driven) approach which proceeds token by token in a corpus, labeling each with an existing sense or revising the sense inventory as necessary. This second approach was preferred for constructing SemCor. Miller et al. observe that the token-by-token strategy naturally prioritizes corpus coverage. Nearly all of SemCor’s content words are tagged with a fine-grained WordNet sense: figure 2.2 shows an example annotated sentence. Named entities not in WordNet (most of them) were tagged with a coarse class.

2.3.3 Beyond WordNet

Though WordNet and similar resources record relationships such as taxonomic inheritance between senses, they do not offer an account of how a listener can infer details of the meaning that depend on multiple senses being exploited in combination—e.g., they can explain that have a banana can decompose into have ‘consume’ + banana ‘long yellow edible fruit’, and similarly for have a milkshake and have a cigarette, but not that consuming a banana entails eating it, consuming a milkshake entails drinking it, consuming a cigarette entails smoking it, and so forth. WordNet-style lexicons also do not explain word choice constraints/preferences, e.g., that heavy rain is idiomatic, while big rain may seem marked or nonnative—as
descriptors of intensity, heavy and big are simply not on an equal footing with respect to rain. Generative Lexicon Theory (Pustejovsky, 1998) and the theory of lexical functions (Mel’čuk, 1998) posit richer structure to lexical entries in order to explain their combinatorial behavior.

2.3.4 Word Sense Disambiguation as Classification

Assuming we have a list of known senses for one or more ambiguous words, we can set out to build algorithms that will choose the one that is most contextually appropriate. This is the classic word sense disambiguation (WSD) task (see Agirre and Edmonds, 2006 andNavigli, 2009 for comprehensive surveys). WSD is a type of discrete multi-class classification problem, where every input (such as a word within a sentence) is associated with a desired output, or label, to be predicted automatically. Mathematically, we can represent a classifier as a function \( h(x) \) that, when presented with an input \( x \), chooses a label \( \hat{y} \in Y \) (for now, we assume the set of labels \( Y \) is discrete, finite, and predetermined) as the prediction. For datasets where the “true” label, \( y^* \), is known for every input, the accuracy of the classifier can be estimated as the proportion of inputs for which \( h(x) = y^* \).

Classifiers can use various characteristics of the input that may be predictive of particular labels; the input–output combinations that factor into classification decisions are known as the classifier’s features. For example, a word token’s distributional context (in terms of the words that appear nearby) is known to be an important cue of its sense. If seal occurs near the word aquatic in a text, chances are it is being used in its animal sense. These cues could be hardcoded into the classification algorithm; or, they can be specified at an abstract level (e.g., "all words up to 5 words away from the word being classified") and the predictive ones for each label learned from data. In particular, supervised learning algorithms mine labeled examples for statistical associations between inputs and outputs. Because of the complexities of natural language, data-driven semantic classifiers are generally much more robust than non-statistical (rule-based) systems.

For purposes of this thesis, we focus on linear classifiers, which model the prediction function \( h(x) \) as:

\[
h(x) = \arg\max_y \text{score}(x, y; \theta)
\]

(2.1)

where

\[
\text{score}(x, y; \theta) = \theta^T g(x, y) = \sum_{j=1}^{g} \theta_j \cdot g_j(x, y)
\]

(2.2)

I.e., the classifier chooses a label that maximizes a real-valued scoring function that quantifies the compatibility between \( x \) and \( y \) as a weighted sum of feature values \( g_j(x, y) \).\(^2\) The weighting \( \theta \) of the features is what is learned from data: thus, the weights are the parameters of the model. In our example, the weight linking context word aquatic to the animal sense of seal will receive a large positive weight if the feature is a good predictor in the training data. Of course, even if aquatic is contextually present, the classification function aggregates evidence from all its features, so it is possible that enough of the other active features will influence the classifier to choose some other label.

Many learning algorithms estimate parameters for linear classifiers given labeled data. The perceptron (Freund and Schapire, 1999) is one such algorithm; Smith (2011) discusses others and elucidates

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\(^2\)For discrete data, most of these feature values are binary: the characteristics described in the feature (e.g., a particular word appearing nearby) either apply for the current instance, or not.
how they effectively solve different optimization problems. For this thesis, we require structured learning and classification algorithms, which will be introduced in the next section.

2.4 Named Entity Recognition and Sequence Models

2.4.1 NER

Named entity recognition (NER) is the task of detecting and categorizing named entities (primarily proper names) in text. The precise set of entity categories of interest varies with different formulations of the task (and annotated corpora), but the set of categories is typically small: one canonical scheme categorizes names as PERSON, ORGANIZATION, LOCATION, or MISCELLANEOUS (Tjong Kim Sang and De Meulder, 2003); others (e.g., Sekine et al., 2002; Weischedel and Brunstein, 2005; Grouin et al., 2011) consist of dozens of types. NER therefore uses an unlexicalized grouping scheme analogous to figure 2.1c.

2.4.2 Chunking

Many instances of names contain multiple words: thus, detecting such named entities requires reasoning across spaces. A chunking representation encodes how sequence elements (tokens) group together into units. The most popular flavor, BIO chunking, accomplishes this by assigning each token one of three tags: B indicates that the token begins a chunk; I (“inside”) indicates that it continues a multi-token chunk; and O (“outside”) indicates that it is not a part of any chunk (Ramshaw and Marcus, 1995). The distinction between B and I allows for a boundary between adjacent chunks. Only contiguous chunks are allowed by this representation (a constraint that we relax in §6.3). This representation facilitates statistical models that make token-level predictions, though most commonly in a joint fashion.

For tasks such as NER, in-chunk tags are commonly decorated with a class label categorizing the chunk: for example, “non-initial word of a PERSON chunk” can be denoted as I PERSON, and this is only permitted to follow B PERSON or I PERSON. When a statistical model is used to predict the tags (and therefore the chunking), the decoding algorithm is constrained to only consider compatible tag bigrams. With C classes, the number of tags is $2^C + 1$, and the number of legal token tag bigrams is $2^C + 5C + 1$. At each time step the Viterbi algorithm considers all tag bigrams, so decoding time is linear in the number of possible bigrams and also linear in the length of the sentence.

2.4.3 Structured Perceptron

The linear classifier described in §2.3.4 can be modified to incorporate a scoring function over structures such as a sequence of tags for a sentence: this is known as structured prediction. Let x denote the observed sequence of inputs (tokens) and y the sequence of predicted tags. The goodness of the tagging for the observed sequence is modeled as a linear function (again, with a real vector–valued score...
feature function \( g \) and parametrized by a real weight vector \( \theta \):

\[
\text{score}(x, y; \theta) = \theta^T g(x, y)
\]

(2.3)

The decoding (structured classification) problem given the weights \( \theta \) and input \( x \) is to construct the tag sequence \( y \) which maximizes this score. To facilitate efficient exact dynamic programming inference with the Viterbi algorithm we make a Markov assumption, stipulating that the scoring function factorizes into local functions over label bigrams:

\[
g(x, y) = \sum_{j=1}^{|x|+1} f(x, y_j, y_{j-1}, j)
\]

(2.4)

Various supervised structured learning algorithms are available for linear models (Smith, 2011). The input to such an algorithm is a training corpus of labeled sequences, \( D = \{(x^{(1)}, y^{(1)}), \ldots, (x^{(N)}, y^{(N)})\} \); the output is the feature weight vector \( \theta \).

One popular structured learning algorithm is the structured perceptron (Collins, 2002). Its learning procedure, algorithm 1, generalizes the classic perceptron algorithm (Freund and Schapire, 1999) to incorporate a structured decoding step (for sequences, the Viterbi algorithm) in the inner loop. Thus, training requires only max inference, which is fast with a first-order Markov assumption. In training, features are adjusted where a tagging error is made. The result of learning is a weight vector that parametrizes a feature-rich scoring function over candidate labelings of a sequence.

2.4.4 Cost Functions

Algorithm 1 is a cost-augmented version of the structured perceptron: it assigns different values to different kinds of errors made during training. The cost function, \( \text{cost}(y, y', x) \geq 0 \), encourages the learner to be especially careful to avoid certain kinds of mislabelings; worse errors incur a greater cost than milder errors during training (correct predictions should have a cost of 0). What counts as a “better” or “worse” error is stipulated according to the needs of the application. For example, in NER, the cost function can be defined to encourage

---

6Note that in contrast to the independence assumptions of a generative hidden Markov model, local feature functions are allowed to see the entire observed sequence \( x \).

7Conditional random fields (Lafferty et al., 2001) are another popular technique for discriminative sequence modeling with a convex loss function. We prefer the structured perceptron for its speed: learning and inference depend mainly on the runtime of the Viterbi algorithm, whose asymptotic complexity is linear in the length of the input and (with a first-order Markov assumption) quadratic in the number of tags.
recall by penalizing false negatives more than false positives (Mohit et al., 2012). The cost for each possible erroneous labeling is the minimum difference in score, or margin, between that labeling and the true labeling for the learner’s prediction to be considered acceptable. The optimization performed by the cost-augmented structured perceptron algorithm approaches the same result as that of structured SVMs (Tsochantaridis et al., 2005)—in both cases the learning objective is the structured hinge loss.

### 2.5 Conclusion

This chapter has introduced the field of computational semantics and provided background on concepts in lexical semantics that will be crucial to understanding the rest of the thesis. These include the representation of semantic senses and classes in lexicons, the canonical tasks of word sense disambiguation and named entity recognition tasks, and linear models and algorithms for multi-class classification and sequence tagging.
SONJA: It warmed the cockles of my heart!
BORIS: That's just great, nothing like hot cockles!

_Q. Please explain the expression “this does not bode well.”
A. It means something is not boding the way it should. It could be boding better._

_Dave Barry, Dave Barry Is Not Making This Up. “Punctuation ‘R Easy”_

CHAPTER 3

Multiword Expressions

This chapter:

• Reviews the literature on the linguistics and annotation of multiword expressions

• Proposes a formal representation of multiword lexical units in context that allows for (a) gaps, and (b) a strength distinction

• Develops a resource-agnostic linguistic understanding of which multiword combinations cohere strongly enough to count as units

• Designs a corpus annotation procedure for MWEs, documented with exemplar-based guidelines

• Describes a comprehensively annotated corpus of multiword expressions
3.1 Introduction

Language has a knack for defying expectations when put under the microscope. For example, there is the notion—sometimes referred to as compositionality—that words will behave in predictable ways, with individual meanings that combine to form complex meanings according to general grammatical principles. Yet language is awash with examples to the contrary: in particular, idiomatic expressions such as awash with NP, have a knack for VP-ing, to the contrary, and defy expectations. Thanks to processes like metaphor and grammaticalization, these are (to various degrees) semantically opaque, structurally fossilized, and/or statistically idiosyncratic. In other words, idiomatic expressions may be exceptional in form, function, or distribution. They are so diverse, so unruly, so difficult to circumscribe, that entire theories of syntax are predicated on the notion that constructions with idiosyncratic form-meaning mappings (Fillmore et al., 1988; Goldberg, 1995) or statistical properties (Goldberg, 2006) offer crucial evidence about the grammatical organization of language.

Here we focus on multword expressions (MWEs): lexicalized combinations of two or more words that are exceptional enough to be considered as single units in the lexicon. As figure 3.1 illustrates, MWEs occupy diverse syntactic and semantic functions. Within MWEs, we distinguish (a) proper names and (b) lexical idioms. The latter have proved themselves a “pain in the neck for NLP” (Sag et al., 2002). Automatic and efficient detection of MWEs, though far from solved, would have diverse applications including machine translation (Carpuat and Diab, 2010), information retrieval (Acosta et al., 2011; Newman et al., 2012), opinion mining (Berend, 2011), and second language learning (Ellis et al., 2008); see also §8.3.

It is difficult to establish any comprehensive taxonomy of mul-

1. MW named entities: Chancellor of the Exchequer Gordon Brown
2. MW compounds: red tape, motion picture, daddy longlegs, Bayes net, hot air balloon, skinny dip, trash talk
3. conventionally SW compounds: snapdragon, overlook (v. or n.), blackjack, shootout, sunscreen, somewhere
4. verb-particle: pick up, dry out, take over, cut short, hold hostage, take seriously
5. verb-preposition: refer to, depend on, look for, prevent from
6. verb-noun-(preposition): put attention (to), go bananas, lose it, break a leg, make the most of
7. support verb: make decisions, take breaks, take pictures, have fun, perform surgery
8. other phrasal verb: put up with, miss out (on), get rid of, look forward to, run amok, cry foul, add insult to injury
9. predicative or modifier PP: above board, beyond the pale, under the weather, at all, from time to time
10. coordinated phrase: cut and dried/dry, more or less, up and leave
11. conjunction/connective: as well as, let alone, in spite of, on the face of it/on its face
12. semi-fixed VP: smack <one>’s lips, pick up where <one> left off, go over <thing> with a fine-tooth(ed) comb, take <one>’s time, draw <oneself> up to <one>’s full height
13. fixed phrase: easy as pie, scared to death, go to hell in a handbasket, bring home the bacon, leave of absence
14. phatic: You’re welcome. Me neither!
15. proverb: Beggars can’t be choosers. The early bird gets the worm. To each his own. One man’s <thing1> is another man’s <thing2>.

Figure 3.1: Some of the classes of idioms in English. The examples included here contain multiple lexicalized words—with the exception of those in (3), if the conventional single-word (SW) spelling is used.
tiword idioms, let alone develop linguistic criteria and corpus resources that cut across these types. Consequently, the voluminous literature on MWEs in computational linguistics—see § 3.4.1, Baldwin and Kim (2010), and Ramisch (2012) for surveys—has been fragmented, looking (for example) at subclasses of phrasal verbs or nominal compounds in isolation. To the extent that MWEs have been annotated in existing corpora, it has usually been as a secondary aspect of some other scheme. Traditionally, such resources have prioritized certain kinds of MWEs to the exclusion of others, so they are not appropriate for evaluating general-purpose identification systems.

This chapter introduces a shallow form of analysis for MWEs that is neutral to expression type, and that facilitates free text annotation without requiring a prespecified MWE lexicon. The scheme applies to gappy (discontinuous) as well as contiguous expressions, and allows for a qualitative distinction of association strengths. We apply this scheme to fully annotate a 56,000-word corpus of English web reviews (Bies et al., 2012), a conversational genre in which colloquial idioms are highly salient.

We start off with background on the linguistics of MWEs (§ 3.2) and on available corpus resources (§ 3.3). Then we motivate the gist of our approach (§ 3.4), formalize the representational space of structures that can comprise an analysis (§ 3.5), and give an overview of the annotation guidelines (§ 3.6). The annotation process is discussed in § 3.7, and the resulting dataset in § 3.8. The chapter incorporates material from Schneider et al. (2014b), which described the MWE-annotated corpus, and Schneider et al. (2014a), which includes a formal description of the representation.

### 3.2 Linguistic Characterization

Much ink has been spilt over the definition of multiword expressions, idioms, collocations, and the like. The general consensus is that many combinations of two or more wordforms are “word-like” in function. Following Baldwin and Kim (2010), we broadly construe the term idiomatic to apply to any expression with an exceptional form, function, or distribution; we will say such an expression has unit status. **Idiomaticity can be viewed relative to a constellation of criteria, including:**

**syntactic criteria:** For example, if the combination has a syntactically anomalous form or is fossilized (resistant to morphological or syntactic transformation), then it is likely to be considered a unit (Huddleston, 2002; Baldwin and Kim, 2010). A construction exemplifying the former is the X-er, the Y-er (Fillmore et al., 1988); an example of the latter is the idiom kick the bucket, which only behaves like an ordinary verb phrase with respect to the verb’s inflection: *the bucket was kicked/??kick swiftly the bucket?*/the kicking of the bucket.

---

1 Gries (2008) discusses the closely related concepts of phraseologism in phraseology, word cluster and n-gram in corpus linguistics, pattern in Pattern Grammar, symbolic unit in Cognitive Grammar, and construction in Construction Grammar. In the language acquisition literature various terms for multiword expressions include formulaic sequence, lexical phrase, routine, pattern, and prefabricated chunk (Ellis, 2008; Moon, 1998). See also Moon (1998); Wray (2000).

2 Moon’s (1998, p. 6) criteria of “institutionalization, lexicogrammatical fixedness, and non-compositionality” correspond roughly to our criteria of distribution, form, and function, respectively. *Institutionalization is the process by which a string or formulation becomes recognized and accepted as a lexical item of the language* (Moon, 1998, p. 7). Moon requires all three criteria to be present in a multiword sequence to consider it a unit; we treat sequences meeting any of these criteria as MWEs, but further distinguish those that are exceptional only in distribution from those that are idiosyncratic in form and/or function.
**semantic criteria:** These often fall under the umbrella of compositional vs. lexicality, which can refer to the notion that an expression's meaning may differ from the natural combination of the meanings of its parts. This may be interpreted as a categorical or gradient phenomenon. More specifically, the meaning of the whole expression vis-a-vis its parts is said to be transparent (or analyzable) vs. opaque when considered from the perspective of a hypothetical listener who is unfamiliar with it, and predictable vs. unpredictable from the perspective of a hypothetical speaker wishing to express a certain meaning. The expressions kick the bucket and make sense are neither predictable nor transparent but likely to be fairly transparent in context. We will count all unpredictable or opaque expressions as units. The term idiom is used especially for an expression exhibiting a high degree of figurativity or proverbiality (Nunberg et al., 1994).

**statistical criteria:** An expression may be considered a unit because it enjoys unusually high token frequency, especially in comparison with the frequencies of its parts. Various association measures aim to quantify this in corpora; the most famous is the information-theoretic measure mutual information (MI) (Pecina, 2010). The term collocation generally applies to combinations that are statistically idiomatic, and an institutionalized phrase is idiomatic on purely statistical grounds (Baldwin and Kim, 2010).

**psycholinguistic criteria:** Some studies have found psycholinguistic correlates of other measures of idiomaticity (Ellis et al., 2008). Idiomatic expressions are expected to be memorized and retrieved wholesale in production, rather than composed on the fly (Ellis, 2008).

Some examples from Baldwin and Kim (2010) are as follows:

<table>
<thead>
<tr>
<th>Syntactically idiomatic</th>
<th>Semantically idiomatic</th>
</tr>
</thead>
<tbody>
<tr>
<td>to and fro</td>
<td>traffic light; social butterfly; kick the bucket; look up (= ‘search for’)</td>
</tr>
<tr>
<td>(cf. ?pepper and salt); many thanks; finish up(^4)</td>
<td></td>
</tr>
</tbody>
</table>

Unlike eat chocolate and swallow down, which are not regarded as idiomatic, all of the above expressions exhibit statistical idiomaticity (Baldwin and Kim, 2010). For instance, traffic light is more frequent than plausible alternatives like traffic lamp/road light/intersection light (none of which are conventional terms) or streetlight/street lamp (which have a different meaning). While traffic light, being an instance of the highly productive noun-noun compound construction, is not syntactically idiomatic, it is semantically idiomatic because that construction underspecifies the meaning, and traffic light has a conventionalized “ordinary” meaning of something like ‘electronic light signal installed on a road to direct vehicular traffic’. It could conceivably convey novel meanings in specific contexts—e.g., ‘glow emanating from car taillights’ or ‘illuminated wand used by a traffic officer for signaling’—but such usages have not been conventionalized.

\(^3\)Whether an expression is “compositional” or “noncompositional” may be considered either informally, or more rigorously in the context of a formalism for compositional semantics.

\(^4\)The completive meaning of ‘up’ is redundant with ‘finish’ (Gonnerman and Blais, 2012).
'create, constitute' (4): make you drinks, make an army of [corpses], the kind of thing [potion] you ought to be able to make, tricky to make [potion]

'cause (event, result, or state)' (9): make your ears fall off, make a nice loud noise, make your brain go fuzzy, make a sound, make himself seem more important than he is, make Tom Riddle forget, make anyone sick, make you more confident, make trouble

'be good or bad in a role' (2): make a good witch, make a good Auror

verb-particle constructions (2): from what Harry could make out (make out = 'reckon'), make up to well-connected people (make up to = 'cozy/kiss/suck up to'; this idiom is not present in WordNet)

light verb with eventive noun (13): make any attempt, make the Unbreakable Vow (×2), make a suggestion, make the introduction, odd comment to make, make a quick escape, make further investigations, make an entrance, make a decent attempt, make mistakes (×2)

miscellaneous multiword expressions (9): make different arrangements, make sure (×5), make do, make sense, make any sign of recognition

Figure 3.2: Occurrences of the bare verb make in a small text sample.

3.2.1 Polysemy

Figure 3.2 lists the occurrences of the highly polysemous verb make in the first 10 chapters (about 160 pages) of Harry Potter and the Half-Blood Prince (Rowling, 2005). Of the 39 occurrences in this sample, no more than 15 ought to be considered non-idiomatic.

Even knowing the extent of the MWE is often not sufficient to determine its meaning. The verb lemma make up has no fewer than 9 sense entries in WordNet, as shown in figure 3.3. Some of these senses are radically different: making up a story, a bed, a missed exam, one's face, and (with) a friend have very little in common⁶. Reassuringly, the supersenses attest to major differences, which suggests that the MWE grouping and supersense tags offer complementary information (in ch. 7 we exploit this complementarity in a unified model).

3.2.2 Frequency

Sources in the literature agree that multiword expressions are numerous and frequent in English and other languages (Baldwin and Kim, 2010; Ellis et al., 2008; Ramisch, 2012). Table 3.1 (p. 40) quantifies the frequency of MWEs in three corpora from different domains. (Appendix A takes an in-depth look at a subset of the SemCor data.) These corpora use different criteria for marking MWEs, so the relative frequencies are not directly comparable, but they show that frequency of MWE tokens is nothing to sneeze at. For example, in

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⁶Arguably, senses 7 and 8 ought to be listed as prepositional verbs: make up for and make up with, respectively.
our corpus (§3.8), the proportion of word tokens belonging to an MWE is nearly as large as the proportion of words that are common nouns.

3.2.3 Syntactic Properties

Multiword expressions are diverse not only in function, but also in form. As noted above, some idioms are anomalous or highly inflexible in their syntax. But more commonly they exploit productive syntactic patterns. In the computational literature, studies generally focus on individual classes of English MWEs, notably:

- complex nominals, especially noun-noun and adjective-noun compounds (Lapata and Lascarides, 2003; Michelbacher et al., 2011; Hermann et al., 2012a, b)
- determinerless prepositional phrases (Baldwin et al., 2006)
- verbal expressions, including several non-disjoint subclasses: **phrasal verbs** (Wulff, 2008; Nagy T. and Vincze, 2011; Tu and Roth, 2012), generally including **verb-particle constructions** (where the particle is intransitive, like *make up*) (Villavicencio, 2003; McCarthy et al., 2003; Bannard et al., 2003; Cook and Stevenson, 2006; Kim and Baldwin, 2010) and **prepositional verbs** (with a transitive preposition, like *wait for*); **light verb constructions/support verb constructions** like *make... decision* (Calzolari et al., 2002; Fazly et al., 2007; Tu and Roth, 2011; Bonial et al., 2014b); and **verb-noun constructions** like *pay attention* (Ramisch et al., 2008; Diab and Bhutada, 2009; Diab and Krishna, 2009; Boukobza and Rappoport, 2009; Wulff, 2010)

By convention, the constructions referred to as multiword expressions have two or more lexically fixed morphemes. Some are completely frozen in form, or allow for morphological inflection only. Other MWEs permit or require other material in addition to the lexically specified portions of the expression. Of particular interest in the present work are **gappy multiword expressions**. In our terminology, gappiness is a property of the surface mention of the expression: a mention is gappy if its lexicalized words are interrupted by one or more additional words. This happens in the following scenarios:

- When the expression takes a lexically unspecified argument, such as an object or possessive determiner, occurring between lexicalized parts (the **argument gap** column of figure 3.4);\(^7\)

- When an internal modifier such as an adjective, adverb, or determiner is present (the **modifier gap** column of figure 3.4);

- When the expression is transformed via some syntactic process such that other words intervene. This is relatively rare; examples we found in the SemCor involved fronting of prepositional verb complements (e.g. *those if any on whom we can rely*) and coordination (*grade and high schools*).\(^8\)

One final point worth making is that multiword expressions create syntactic ambiguity. For example, someone might *make [up to]*

---

\(^7\)This is not to suggest that the syntactic arguments MWEs always fall between lexicalized words: with prepositional verbs and verb-particle constructions, for instance, the open argument typically follows the verb and preposition (*make up a story, rely on someone*)—but we will not refer to these as gaps so long as the lexically fixed material is contiguous.

\(^8\)In the coordination example the word *schools* is really shared by two MWEs. Another case of this might be a phrase like *fall fast asleep*, where *fall asleep and fast asleep* are arguably MWEs. But this sharing is extremely rare, so in the interest of simplicity our representation will prevent any word token from belonging to more than one MWE mention.


**Figure 3.4:** Examples of gappy MWEs in the SemCor corpus. See §A.1 for further analysis.

*a million dollars* or *make up [to a friend]*. This is further complicated by expressions that license gaps. In the context of describing one’s ascent of Kilimanjaro, *make the climb up* probably cannot be paraphrased as *make up the climb*. Heuristic matching techniques based on n-grams are likely to go awry due to such ambiguity—for some kinds of MWEs, more sophisticated detection strategies are called for (see ch. 6).

### 3.2.4 Multiword Expressions in Other Languages

Though our presentation of multiword expressions has focused on English, MWEs are hardly an English-specific phenomenon. Studies in other languages have included Basque compound prepositions (Díaz de Ilarraza et al., 2008), German determinerless PPs (Dömges et al., 2007; Kiss et al., 2010), German complex prepositions (Trawinski, 2003), Hebrew noun compounds (Al-Haj and Wintner, 2010), Japanese and English noun-noun compounds (Tanaka and Baldwin, 2003), Japanese compound verbs (Uchiyama and Ishizaki, 2003), Korean light verb constructions (Hong et al., 2006), Persian compound verbs (Rasooli et al., 2011), and Persian light verb constructions (Salehi et al., 2012). The new multiword datasets we propose below will be in English, but we intend to evaluate our system on the multiword expressions in the French Treebank (Abeillé et al., 2003), as discussed below.

### 3.3 Existing Resources

Annotated corpora do not pay much attention to multiword expressions. On the one hand, MWEs are typically not factored into the syntactic and morphological representations found in treebanks. On the other, the MWE literature has been driven by lexicography: typically, the goal is to acquire an MWE lexicon with little or no supervision, or to apply such a lexicon to corpus data. Studies of MWEs in context have focused on various subclasses of constructions in isolation, necessitating special-purpose datasets and evaluation schemes.

Without getting into the details of automatic multiword analysis tasks here just yet (they will appear in ch. 6), we take the position that a comprehensive treatment requires corpora annotated for a broad variety of multiword expressions. A canonical corpus resource would offer to the multiword expressions community a benchmark dataset comparable to datasets used for problems such as NER and parsing.

To our knowledge, only a few existing corpora approach this goal of marking heterogeneous MWEs in context:

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9 Some datasets mark shallow phrase chunks (Tjong Kim Sang and Buchholz, 2000), but these are not the same as multiword expressions: syntactically, *green dye* and *green thumb* are both noun phrases, yet only the second is idiomatic. 10 Estimates are for version 2.0, which is annotated for MWEs and noun and verb supersense. Version 3.0, which will add preposition supersenses, is under development. Statistics for CMWE version 1.0 (MWEs only) appear in §3.8. 11 SEMCOR counts include 166 documents/17k sentences/386k words that have
Table 3.1: Comparison of two existing English lexical semantic corpora with the one created in this work. Counts of documents, sentences, and space-separated tokens are rounded.

<table>
<thead>
<tr>
<th></th>
<th><strong>SemCor</strong> (Miller et al., 1993)</th>
<th><strong>Wiki50</strong> (Vincze et al., 2011)</th>
<th><strong>STREUSLE</strong> (this work)</th>
</tr>
</thead>
<tbody>
<tr>
<td>text source</td>
<td>Brown Corpus</td>
<td>Wikipedia</td>
<td>EWTB</td>
</tr>
<tr>
<td>genre</td>
<td>published texts</td>
<td>crowdsourced articles</td>
<td>user reviews</td>
</tr>
<tr>
<td>docs · sents · words</td>
<td>352 · 37k · 820k (^{11})</td>
<td>50 · 4.4k · 11.4k (^{12})</td>
<td>723 · 3.8k · 56k</td>
</tr>
<tr>
<td>words/sents</td>
<td>22</td>
<td>26</td>
<td>15</td>
</tr>
<tr>
<td>syntactic parses</td>
<td>139 docs in PTB</td>
<td></td>
<td>EWTB</td>
</tr>
<tr>
<td>NE instances</td>
<td>9700</td>
<td>9000</td>
<td>—</td>
</tr>
<tr>
<td>MW NEs</td>
<td>3900</td>
<td>3600</td>
<td>(\approx 500) (^{13})</td>
</tr>
<tr>
<td>other MWEs</td>
<td>3900</td>
<td>3600</td>
<td>3000</td>
</tr>
<tr>
<td>contiguous</td>
<td>30,000</td>
<td>3600</td>
<td>2500</td>
</tr>
<tr>
<td>gappy</td>
<td>not explicit (^{14})</td>
<td>220 LVCs, 40 VPCs</td>
<td>500</td>
</tr>
<tr>
<td>total LEs</td>
<td>780k</td>
<td>100k</td>
<td>51k</td>
</tr>
<tr>
<td>NE classes</td>
<td>PER, ORG, LOC, MISC (^{15})</td>
<td></td>
<td>not distinguished from supersenses</td>
</tr>
<tr>
<td>other classes</td>
<td>NOTAG, COMPLEXPREP, FOREIGNWORD,</td>
<td>COMPOUND_ADJ, COMPOUND_NOUN,</td>
<td>strong, weak</td>
</tr>
<tr>
<td></td>
<td>IDIOM, METAPHOR, NONCEWORD (^{16})</td>
<td>IDIOM, LVC, VPC, OTHER (^{17})</td>
<td></td>
</tr>
<tr>
<td>semantic senses</td>
<td>32k WordNet synsets</td>
<td>—</td>
<td>41 supersenses (^{18})</td>
</tr>
<tr>
<td>labeled instances</td>
<td>235k synsets+NEs</td>
<td>9k NEs</td>
<td>17k N/V mentions</td>
</tr>
</tbody>
</table>

3.3.1 SemCor

As discussed in §2.3.2, **SemCor** \(^{19}\) includes named entities and many other multiword expressions, most of which are tagged with WordNet senses. Exactly how the lexicographic decisions were made is not documented, but WordNet seems to prioritize complex nominals and verb-particle constructions over other kinds of multiword constructions.

Statistics and further details on lexical expressions in SemCor appear in table 3.1 and appendix A.

3.3.2 Wiki50

The **Wiki50** corpus (Vincze et al., 2011) \(^{20}\) consists of 50 English Wikipedia articles fully annotated for named entities as well as several classes of other MWEs—principally compound nominals, discussed in §A.1.

\(^{11}\) In SemCor the respective labels are PERSON, GROUP, LOCATION, and OTHER.

\(^{12}\) These special designations apply to lexical expressions with no appropriate WordNet synset. Token frequencies in SemCor: 39,401 NOTAG (1,827 of which are contiguous MWEs), 320 COMPLEXPREP (312 contiguous MWEs), 77 FOREIGNWORD (18 contiguous MWEs), 270 IDIOM (215 contiguous MWEs), 155 METAPHOR (29 contiguous MWEs), 21 NONCEWORD (4 contiguous MWEs). Two caveats: (a) NOTAG is not a well-defined class. It contains some miscellaneous lexical expressions (function words and MWEs such as a lot and such as), as well as many apparently spurious multiword chunks, such as many of and must not. It also contains many named entities and other expressions that presumably belong to another category but were never reviewed. (b) A handful of these labels apply to an obviously gappy MWE—e.g., due (in large part) to as COMPLEXPREP—but these cannot be counted automatically because the part after the gap is not annotated.

\(^{13}\) See table 3.2.

\(^{14}\) SemCor’s file format does not directly mark gappy MWEs, though sometimes only the first part of one is tagged with the synset (e.g., of a particle verb). See

\(^{15}\) See table 3.2.

\(^{16}\) 26 noun supersenses and 15 verb supersenses, including a special verb category for auxiliaries. The WEATHER supersense for verbs is not attested in the corpus.

\(^{17}\) Our STREUSLE dataset does not explicitly mark NEs, but we estimate the number of multiword NEs by counting the number of strong MWEs containing a proper noun.

\(^{18}\) The WEATHER supersense for verbs is not attested in the corpus.

\(^{19}\) http://lit.csci.unt.edu/~rada/downloads/semcor/semcor3.0.tar.gz

\(^{20}\) http://www.inf.u-szeged.hu/rgai/project/nlp/research/mwe/attachments.zip
Table 3.2: Categories and tokens in the *Wiki* corpus for named entities (single-word and multiword) and other MWEs. (Above, **COMPOUND** is abbreviated as **CMPD**.)

<table>
<thead>
<tr>
<th>NEs</th>
<th>SW</th>
<th>MW</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>P. G. Wodehouse</em> PER</td>
<td>2743</td>
<td>1344</td>
</tr>
<tr>
<td><em>Monty Python</em> ORG</td>
<td>647</td>
<td>849</td>
</tr>
<tr>
<td><em>Kii Province</em> LOC</td>
<td>978</td>
<td>579</td>
</tr>
<tr>
<td><em>Kentucky Derby</em> MISC</td>
<td>975</td>
<td>844</td>
</tr>
<tr>
<td><strong>total</strong></td>
<td>5343</td>
<td>3616</td>
</tr>
</tbody>
</table>

MWEs

light verb constructions (LVCs),\(^{21}\) and verb-particle constructions (VPCs). The LVC (VPC) annotations specifically designate the word tokens that belong to the verb and the words that belong to the noun (particle)—there may be a gap between the verb part and the noun (particle) part, but nested annotations within the gap are not allowed. There are also two rare categories: phrasal idioms such as *come out of the closet* (**IDIOM**), and **OTHER**, which consists of compound verbs and foreign phrases.\(^{22}\) Examples and counts of these expressions appear in table 3.2, and a comparison to other corpora in table 3.1. In §6.5.8 we use this corpus for out-of-domain evaluation of our MWE identification system.

### 3.3.3 Other English Corpora

The *Prague Dependency Treebank* (PDT) (Hajič, 1998) and the *Prague Czech-English Dependency Treebank* (PCEDT) (Čmejř et al., 2005)\(^{23}\) contain rich annotations at multiple levels of syntactic, lexical, and morphological structure. *Bejček and Straňák* (2010) describe the technical processes involved in multiword expression annotation in the (Czech) PDT; notably, their corpus annotation benefited from and informed a multiword lexicon, SemLex, whereas our annotation procedure is not tied to any lexicon. The PCEDT contains parallel annotations for English (source) and Czech (translated) versions of the WSJ corpus (Marcus et al., 1993). Morphosyntactic structures for several classes of multiword expressions are detailed in the manual for the English tectogrammatical annotation layer (Činková et al., 2006). These annotations are complex, but it is possible to automatically extract some shallow multiword groupings for named entities, light verb constructions (marked **CPHR**), phrasal idioms (**DPHR**), and certain other MWEs (for an explanation of the **CPHR** and **DPHR** functors, see Urešová et al., 2013).

Several other corpus resources describe English LVCs (Tan et al., 2006; Hwang et al., 2010a; Tu and Roth, 2011; Vincze, 2012; Rácz et al., 2014; Bonial et al., 2014a) or named entities (§2.4.1).

### 3.3.4 The French Treebank

Though this thesis focuses on English, the *French Treebank* is notable for having facilitated several evaluations of MWE identification systems (Constant and Sigogne, 2011; Constant et al., 2012; Candito

---

\(^{21}\)The definition of LVC is controversial. Vincze et al. (2011) broadly define LVCs as constructions “where the noun is usually taken in one of its literal senses but the verb usually loses its original sense to some extent e.g. *to give a lecture, to come into bloom, the problem lies (in)*.” Some examples in the data, such as *change... mind and draw... ire*, might better be classified as support verb constructions (Calzolari et al., 2002) or verb-noun idiomatic combinations; see discussion in Baldwin and Kim (2010).

\(^{22}\)Namely: *down played, drink and drive, double teamed, free fall, test fire, voice acted, alter ego, de facto, fait accompli, modus operandi, non sequitur, per capita, and status quo.*

\(^{23}\)http://ufal.mff.cuni.cz/pcedt2.0/index.html
It designates syntactic constituents that correspond to a subclass of MWEs, which it terms **compounds**:

Compounds also have to be annotated since they may comprise words which do not exist otherwise (e.g. *insu* in the compound preposition *à l’insu de*= unbeknownst to) or exhibit sequences of tags otherwise non-grammatical (e.g. *à la va vite* = Prep + Det + finite verb + adverb, meaning ‘in a hurry’), or sequences with different grammatical properties than expected from those of the parts: peut-être is a compound adverb made of two verb forms, a *peau rouge* (American Indian) can be masculine (although *peau* (skin) is feminine in French) and a *cordon bleu* (master chef) can be feminine (although *cordon* (ribbon) is masculine in French). (Abeillé et al., 2003, p. 167)

Contiguity up to simple internal modification is given as a criterion (Abeillé and Clément, 2003, p. 44):

Les composants sont contiguës. Seule quelques petites insertions sont possibles (en général un petit adverbe ou adjectif).

*à force de* [by repeated action of, due to]
*un maillot <doré> deux-pièces* [a <gold> bikini/2-piece swimsuit]
*?? un maillot <de ma soeur> deux pièces* [a 2-piece <my sister’s> swimsuit]

The compounds are contiguous. Only some small insertions are possible (in general a short adverb or adjective).

Compounds are semi-automatically detected based on preexisting lexical resources (Abeillé et al., 2003, pp. 170, 172). This category appears to be rather narrow, excluding (for example) support verbs except in frozen idioms (Abeillé et al., 2004, p. 23):

Dans certains cas on peut trouver un verbe support suivi d’un nom et d’un complément prépositionnel : *avoir peur de, avoir envie de*, etc.
On ne compose pas le verbe parce que le nom peut former un syntagme plus complexe (*avoir une peur bleue de, avoir la plus grande envie de*), et parce qu’on peut le déplacer (la peur que j’ai eue), ce qui montre que ce type de construction n’est pas figé.

In some cases you can find a support verb followed by a noun and a prepositional complement: ‘be afraid of’ [lit. ‘have fear of’], ‘want to’ [lit. ‘have desire of’], etc. We do not compose the verb because the noun can form a more complex phrase (‘be deathly afraid of’ [lit. ‘have a blue fear of’], ‘have the greatest desire to’), and because it can be moved (‘the fear that I had’), which shows that this type of construction is not fixed.

The morphosyntactic guidelines further elaborate on the limitations of the compound verb category (Abeillé and Clément, 2003, p. 52):

**Les verbes composés**: Compound verbs: We chose to retain very few in the corpus, as most are discontinuous, and...
continus, et suivent une syntaxe régulière. We retained verbal expressions that involve a component that does not otherwise exist [i.e., a fossil word] or those which are firmly frozen [...] and non-compositional. [...] We do not fix the Prep at the end of the expression, because [it syntactically heads a PP complement].

The last sentence apparently indicates that prepositional verbs are not marked as compounds.

3.4 Taking a Different Tack

The remainder of this chapter is devoted to the design of an annotation scheme and corpus that offers a more comprehensive treatment of multiword expressions in context. Applied to a 56,000-word corpus of English web text with the aim of full corpus coverage, our novel scheme emphasizes:

- **heterogeneity**—the annotated MWEs are not restricted by syntactic construction;
- **shallow but gappy grouping**—MWEs are simple groupings of tokens, which need not be contiguous in the sentence; and
- **expression strength**—the most idiomatic MWEs are distinguished from (and can belong to) weaker collocations.

We examine these characteristics in turn below. Details of the formal representation appear in §3.5, the annotation guidelines in §3.6, and the annotation process in §3.7. §3.8 gives an overview of the resulting annotated corpus. The annotations are available for download at [http://www.ark.cs.cmu.edu/LexSem](http://www.ark.cs.cmu.edu/LexSem).

### 3.4.1 Heterogeneity

By “multiword expression,” we mean a group of tokens in a sentence that cohere more strongly than ordinary syntactic combinations: that is, they are idiosyncratic in form, function, or frequency. As figure 3.1 shows, the intuitive category of MWEs or idioms cannot be limited to any syntactic construction or semantic domain. The sheer number of multiword types and the rate at which new MWEs enter the language make development of a truly comprehensive lexicon prohibitive. Therefore, we set out to build a corpus of MWEs without restricting ourselves to certain candidates based on any list or syntactic category. Rather, annotators are simply shown one sentence at a time and asked to mark all combinations that they believe are multiword expressions. Examples from our corpus appear in figures 3.5 (below) and 3.6 (p. 56).

### 3.4.2 Shallow token groupings

Concretely, we represent each MWE as a grouping of tokens within a sentence. The tokens need not be contiguous: gappy (discontinuous) uses of an expression may arise due to internal arguments, internal modifiers, and constructions such as passives (see §3.2.3). For example, sentence (2) in figure 3.5 contains a gappy instance of
My wife had taken her '07 Ford Fusion in for a routine oil change.

He was willing to budge a little on the price which means a lot to me.

Figure 3.5: Two sentences from the corpus. Subscripts and text coloring indicate strong multiword groupings; superscripts and underlining indicate weak groupings. Angle brackets indicate gaps.

the verb–particle construction take in. It also contains two contiguous MWEs, the named entity '07 Ford Fusion and the noun-noun compound oil change. Syntactic annotations are not used or given as part of the MWE annotation, though MWEs can be syntactically categorized with part-of-speech tags (as in appendix C and figure 3.7) or syntactic parses.

3.4.3 Strength

Qualitatively, the strength of association between words can vary on a continuum of lexicality, ranging from fully transparent collocations to completely opaque idioms (Bannard et al., 2003; Baldwin et al., 2003; McCarthy et al., 2003; Baldwin, 2006, inter alia). In the interest of simplicity, we operationalize this distinction with two kinds of multiword groupings: strong and weak. For example, the expression close call describes a situation in which something bad nearly happened but was averted (He was late and nearly missed the performance—it was a close call). This semantics is not readily predictable from the expression: the motivation for call in this expression is opaque; and moreover, *near call and *far call are not acceptable variants,24 nor can the danger be described as *closely calling or *calling close. We therefore would treat close call as a strong MWE.

On the other hand, the expression narrow escape is somewhat more transparent and flexible—one can narrowly escape/avoid an undesirable eventuality, and the alternative formulation close escape is acceptable, though less conventional—so it would therefore qualify as a weak MWE. Along the same lines, abundantly clear and patently obvious (patently clear, abundantly obvious) would be considered mostly compositional but especially frequent collocations/phrases, and thus marked as weak MWEs.

While there are no perfect criteria for judging MWE-hood, several heuristics tend to be useful when a phrase’s status is in doubt. The strongest cues are semantic opacity and morphosyntactic idiosyncrasy: if a word has a function unique to a particular expression, or an expression bucks the usual grammatical conventions of the language, the expression is almost certainly an MWE. It often helps to test how fixed/fossilized the expression is, by substituting words with synonyms/antonyms, adding or removing modifiers, or rearranging the syntax. Another strategy is to search large corpora for the expression to see if it is much more frequent than alternatives. In practice, it is not uncommon for annotators to disagree even after considering these factors, and to compromise by marking something as a weak MWE.

For purposes of annotation, the only constraints on MWE groupings are: (a) a group must consist of two or more tokens; (b) all tokens in a group must belong to the same sentence; (c) a given token may belong to at most one strong group and at most one weak group; and (d) strong groups must cohere when used inside weak groups—i.e., if a token belongs to both a strong group and a weak group, all other tokens in the strong group must belong to the same weak group.

24But note that close shave and near miss are other idioms using the same “proximity to danger” metaphor.
3.5 Formal Representation

With these principles in mind, it is time to lay out formally the space of possible MWE analyses given a sentence.

We define a lexical segmentation of a sentence as a partitioning of its tokens into segments such that each segment represents a single unit of lexical meaning. A multiword lexical expression may contain gaps, i.e. interruptions by other segments. We impose two restrictions on gaps that appear to be well-motivated linguistically:

- **Projectivity**: Every expression filling a gap must be completely contained within that gap; gappy expressions may not interleave.

- **No nested gaps**: A gap in an expression may be filled by other single- or multiword expressions, so long as those expressions do not themselves contain gaps.

**Formal grammar.** Our scheme corresponds to the following extended context-free grammar (Thatcher, 1967), where $S$ is the full sentence and terminals $w$ are word tokens:

$$
S \rightarrow X^* \\
X \rightarrow w^+ (Y^+ w^+)^* \\
Y \rightarrow w^+
$$

Each expression $X$ or $Y$ is lexicalized by the words in one or more underlined variables on the right-hand side. An $X$ constituent may optionally contain one or more gaps filled by $Y$ constituents, which must not contain gaps themselves.\(^{25}\)

\(^{25}\)MWEs with multiple gaps are rare but attested in data: e.g., putting me at my ease. We encountered one violation of the gap nesting constraint in the reviews data: I have\(^1\) nothing\(^2\) but\(^3\) fantastic things\(^2\) to say.\(^4\) Additionally, the interrupted phrase great gateways never\(^1\) before\(^4\), since\(^1\) far\(^2\) as\(^2\) Hudson knew\(^2\), seen\(^1\) by Europeans was annotated in another corpus.

Denoting multiword groupings with subscripts, My wife had taken\(^1\) (her\(^0\) Ford\(_1\) Fusion\(_2\)\) in\(_3\) for a routine oil\(_3\) change\(_3\) contains 3 multiword groups—\{taken, in\}, \{'07, Ford, Fusion\}, \{oil, change\}—and 7 single-word groups. The first MWE is gappy: a single word and a contiguous multiword group fall within the gap. This corresponds to the following derivation in terms of the formal grammar:

$$
\begin{align*}
X' & \quad X' & \quad X' & \quad X' & \quad X' & \quad X' & \quad X' & \quad X' \\
\text{My wife had taken her '07 Ford Fusion in for a routine oil change ...}
\end{align*}
$$

The projectivity constraint forbids an analysis like taken\(_1\) her\(_0\) Ford\(_1\) Fusion\(_2\), while the gap nesting constraint forbids taken\(_1\) (her\(_2\) (\{'07\} Ford\(_3\) Fusion\(_2\))\) in\(_1\).

3.5.1 Two-level Scheme: Strong vs. Weak MWEs

Our annotated data distinguish two strengths of MWEs as discussed in §3.6. Augmenting the grammar of the previous section, we therefore designate nonterminals as strong ($\tilde{X}, \tilde{Y}$) or weak ($\hat{X}, \hat{Y}$):

$$
\begin{align*}
S & \rightarrow \tilde{X}^* \\
\tilde{X} & \rightarrow \tilde{X}' (\tilde{Y}^+ \tilde{X}')^* \\
\tilde{Y} & \rightarrow \tilde{Y}' \\
\hat{X} & \rightarrow w^+ (\hat{Y}^+ w^+)^* \\
\hat{Y} & \rightarrow w^+
\end{align*}
$$

A weak MWE may be lexicalized by single words and/or strong multiwords. Strong multiwords cannot contain weak multiwords except in gaps. Further, the contents of a gap cannot be part of any multiword that extends outside the gap.\(^{26}\)

\(^{26}\)This was violated 6 times in our annotated data: modifiers within gaps are sometimes collocated with the gappy expression, as in on\(_2\) a\(_2\) tight\(_1\) budget\(_2\) and

\[50\]
For example, consider the segmentation: he was willing to budge, a little on the price which means a lot to me. Subscripts denote strong MW groups and superscripts weak MW groups; unmarked tokens serve as single-word expressions. The MW groups are thus \{budge, on\}, \{a, little\}, \{a, lot\}, and \{means, a, lot, to, me\}. As should be evident from the grammar, the projectivity and gap-nesting constraints apply here just as in the 1-level scheme.

3.6 Annotation Scheme

The previous section outlined a fairly simple formal representation to describe what annotations can encode: A sentence's lexical segmentation is formed by grouping together space-separated tokens, subject to a few constraints, with the option to distinguish between strong and weak groupings. To keep the scheme fully general-purpose, the annotator is not tied to any particular taxonomy or syntactic structure when marking MWEs. This simplifies the number of decisions that have to be made for each sentence.

Now we turn to a much thornier issue: what our annotations should encode. How is the annotator to decide which tokens should belong to the same MWE instance? This is a question of linguistic conventions; the contours of our answer were arrived at over time and set down in roughly a dozen pages of annotation guidelines rife with examples.

Reproduced in appendix B, the guidelines document describes general issues and considerations (e.g., inflectional morphology; the spans of named entities; date/time/address/value expressions; overlapping expressions), then briefly discusses about 40 categories of constructions such as comparatives (as X as Y), age descriptions (N years old), complex prepositions (out of, in front of), discourse connectives (to start off with), and support verb constructions (make a decision, perform surgery).

Some further instructions to annotators include:

- Groups should include only the lexically fixed parts of an expression (modulo inflectional morphology); this generally excludes determiners and pronouns: made the mistake, pride themselves on. 27

- Multiword proper names count as MWEs.

- Misspelled or unconventionally spelled tokens are interpreted according to the intended word if clear.

- Overtokenized words (spelled as two tokens, but conventionally one word) are joined as multiwords. Clitics separated by the tokenization in the corpus—negative n’t, possessive ’s, etc.—are joined if functioning as a fixed part of a multiword (e.g., T’s Cafe), but not if used productively.

- Some constructions require a possessive or reflexive argument (see semi-fixed VP examples in figure 3.1). The possessive or reflexive marking is included in the MWE only if available as a separate token; possessive and reflexive pronouns are excluded because they contain the argument and the inflection in a single token. This is a limitation of the tokenization scheme used in the corpus. 28

27 In some cases idiosyncratic constructions were rejected because they did not contain more than one lexicalized element: e.g., the construction have, <evaluative adjective> + <unit of time> (have an excellent day, had a bad week, etc.).

28MWE annotators were not permitted to modify the sentence and word tokenizations supplied by the treebank. Because we use treebank data, syntactic parses are available to assist in post hoc analysis. Syntactic information was not shown to annotators.
• A handful of cases of apparent MWE overlap emerged during the course of our annotation: e.g., for *threw a surprise birthday party*, the groups \{*threw, party*\}, \{*surprise, party*\}, and \{*birthday, party*\} all would have been reasonable; but, as they share a token in common, the compromise decision was to annotate \{*birthday, party*\} as a strong MWE and \{*threw, birthday, party*\} as a weak MWE.

While annotators’ understanding of the task and conventions developed over time, we hope to have documented the conventions well enough that a new annotator could learn them reasonably well without too much difficulty.

3.7 Annotation Process

Over the course of 5 months, we fully annotated the 56,000-word REVIEWS section of the English Web Treebank (Bies et al., 2012). MWE annotation proceeded document by document, sentence by sentence. **Annotators** were the first six authors of (Schneider et al., 2014b). All are native speakers of English, and five hold undergraduate degrees in linguistics.

The annotation took three forms: (a) **individual** annotation (a single annotator working on their own); (b) **joint** annotation (collaborative work by two annotators who had already worked on the sentence independently); and (c) **consensus** annotation (by negotiation among three or more annotators, with discussion focused on refining the guidelines). In joint and consensus annotation, differences of opinion between the individual annotations were discussed and resolved (often by marking a weak MWE as a compromise). Initially, consensus annotation sessions were held semi-weekly; the rate of these sessions decreased as agreement improved. Though consensus annotations are only available for 1/5 of the sentences, every sentence was at least reviewed independently and jointly. The annotation software recorded the full version history of each sentence; during some phases of annotation this was exposed so that analyses from different annotators could be compared.

The judgment of whether an expression should qualify as an MWE relied largely on the annotator’s intuitions about its semantic coherence, idiosyncrasy, and entrenchment in the language. As noted in §3.4.3, the decision can be informed by heuristics. Judgments about the acceptability of syntactic manipulations and substitution of synonyms/antonyms, along with informal web searches, were often used to investigate the fixedness of candidate MWEs; a more systematic use of corpus statistics (along the lines of Wulff, 2008) might be adopted in the future to make the decision more rigorous.

**Annotation guidelines.** The annotation conventions discussed in §3.6 were developed and documented on an ongoing basis as the annotation progressed.

**Annotation interface.** A custom web interface, figure 3.6, was used for this annotation task. Given each pretokenized sentence, annotators added underscores (_) to join together strong multiwords and tildes (~) for weak MWEs. During joint annotation, the original annotations were displayed, and conflicts were automatically detected.

**Inter-annotator agreement.** Blind inter-annotator agreement figures show that, although there is some subjectivity to MWE judgments, annotators can be largely consistent. E.g., for one measurement over a sample of 200 sentences, the average inter-annotator
Figure 3.6: MWE annotation interface. The user joins together tokens in the textbox, and the groupings are reflected in the color-coded sentence above. Invalid markup results in an error message (b). A second textbox is for saving an optional note about the sentence. The web application also provides capabilities to see other annotations for the current sentence and to browse the list of sentences in the corpus (not shown).

Table 3.3: Annotated corpus statistics over 723 documents (3,812 sentences). 8,060,55,579 = 15% of tokens belong to an MWE; in total, there are 3,024 strong and 459 weak MWE instances. 82 weak MWEs (18%) contain a strong MWE as a constituent (e.g., means a lot to me in figure 3.5 and get in touch with in figure 4.5).

F1 over all 10 pairings of 5 annotators was 65%.29 When those annotators were divided into two pairs and asked to negotiate an analysis with their partner, however, the agreement between the two pairs was 77%, thanks to reductions in oversights as well as the elimination of eccentric annotations.

Difficult cases. Prepositions were challenging throughout; it was particularly difficult to identify prepositional verbs (speak with? listen to? look for?). We believe a more systematic treatment of preposition semantics is necessary, and undertake to provide one in ch. 5. Nominal compounds (pumpkin spice latte?) and alleged support verbs (especially with get: get busy? get a flat?) were frequently controversial as well.

29 Our measure of inter-annotator agreement is the precision/recall-based MUC criterion (Vilain et al., 1995), described in §6.2. Originally developed for coreference resolution, it gives us a way to award partial credit for partial agreement on an expression.
Figure 3.7: Distribution of tokens in the corpus by gold POS grouping and whether or not they belong to an MWE. Overall, 8,060 tokens are within an MWE; this not much less than the total number of common nouns (left). The rarest POS categories are not shown; of these, the only ones with large proportions of MWE tokens are hyphens (79/110) and incomplete words (28/31).

3.8 The Corpus

The MWE corpus (Schneider et al., 2014b) consists of the full reviews subsection of the English Web Treebank (Bies et al., 2012), comprising 55,579 words in 3,812 sentences. Each of the 723 documents is a user review of a service such as a restaurant, dentist, or auto repair shop. The reviews were collected by Google, tokenized, and annotated with phrase structure trees in the style of the Penn Treebank (Marcus et al., 1993). Most reviews are very short; half are 1–5 sentences long and only a tenth of the reviews contain 10 or more sentences. The writing style of these reviews is informal, so we would expect a lot of colloquial idioms, perhaps for dramatic effect (especially given the strong opinions expressed in many reviews).31

<table>
<thead>
<tr>
<th>Topical category</th>
<th># docs</th>
<th>Perceived sentiment</th>
<th># docs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food/restaurant</td>
<td>207</td>
<td>+ + strongly positive</td>
<td>310</td>
</tr>
<tr>
<td>Retail</td>
<td>115</td>
<td>+ positive</td>
<td>214</td>
</tr>
<tr>
<td>Home services</td>
<td>74</td>
<td>− negative</td>
<td>88</td>
</tr>
<tr>
<td>Automotive</td>
<td>73</td>
<td>−− strongly negative</td>
<td>111</td>
</tr>
<tr>
<td>Medical/dental</td>
<td>52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entertainment/recreation</td>
<td>45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel</td>
<td>44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health/beauty</td>
<td>30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pet</td>
<td>16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>65</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unsure</td>
<td>2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.4: Distribution of review topics and sentiment as coded by one of the annotators.

As the Web Treebank does not provide metadata for reviews, one of our annotators coded all the documents for topic and perceived sentiment. The distribution is shown in table 3.4.

Summary statistics of the MWEs in the corpus are given in table 3.3. Among the highlights:

- The 3,483 MWEs include 15% of all tokens in the corpus. As a point of reference, 17% of all tokens are common nouns.
- 57% of sentences (72% of sentences over 10 words long) and 88% of documents contain at least one MWE.
- 87% of the MWEs are strong/13% are weak.

of familiarity...[they can] increase solidarity between the speaker/writer and hearer/reader", and Simpson and Mendis (2003, p. 434: "possible communicative effects [of idioms] include exaggeration, informality, and rhetorical flair").
• 16% of the MWEs are strong and contain a gold-tagged proper noun—most of these are proper names.

• 73% of the MWEs consist of two tokens; another 21% consist of three tokens.

• 15% of the MWEs contain at least one gap. (Only 6 contain two gaps.\textsuperscript{32})

• 65% of the gaps are one word long; another 25% are two words long.

• 1.5% of tokens fall within a gap; 0.1% of tokens belong to an MWE nested within a gap (like ‘07 Ford Fusion and a little in figure 3.5).

These figures demonstrate (i) that MWEs are quite frequent in the web reviews genre, and (ii) that annotators took advantage of the flexibility of the scheme to encode gappy expressions and a strength distinction.

Figure 3.7 shows the distribution of intra-MWE and extra-MWE words by part of speech. The MWE words are syntactically diverse: common nouns, verbs, proper nouns, prepositions, adverbs, adjectives, determiners, and particles account for most of them. Nearly all particles and nearly two thirds of proper nouns were marked as part of an MWE.

Categorizing MWEs by their coarse POS tag sequence, we find only 8 of these patterns that occur more than 100 times: common noun–common noun, proper noun–proper noun, verb-preposition, verb-particle, verb-noun, adjective-noun, and verb-adverb. But

there is a very long tail—460 patterns in total. For the interested reader, appendix C shows the most frequent patterns, with examples of each.

Many patterns are attested with and without gaps; a handful occur more frequently with gaps than without. About 78% of gaps are immediately preceded by a verb.

There are 2,378 MWE types.\textsuperscript{33} 82% of these types occur only once; just 183 occur three or more times. The most frequent are highly recommend(ed), customer service, a lot, work with, and thank you. The longest are 8 lemmas long, e.g. do n’t get catch up in the hype and do n’t judge a book by its cover.

3.9 Conclusion

We have described a process for shallow annotation of heterogeneous multiword expressions in running text. With this process, we have created a dataset of informal English web text that has been specifically and comprehensively annotated for MWEs, without reference to any particular lexicon. 6 annotators referred to and improved the guidelines document on an ongoing basis. Every sentence was seen independently by at least 2 annotators, and differences of opinion were discussed and resolved collaboratively. The annotation guidelines and our annotations for the English Web Treebank can be downloaded at: http://www.ark.cs.cmu.edu/LexSem.\textsuperscript{34}

To the best of our knowledge, this corpus is the first to be freely annotated for more than a handful of kinds of MWEs (without refer-

\textsuperscript{32}They are: offers\textsuperscript{3} a decent bang\textsuperscript{3} for\textsuperscript{3} the buck\textsuperscript{3}; take\textsubscript{3} this as\textsubscript{3} far\textsubscript{3} as\textsubscript{3} we can\textsubscript{3}; passed\textsubscript{4} away\textsubscript{4} silently in\textsubscript{5} his sleep\textsuperscript{5}; asked\textsubscript{6} Pomper for\textsubscript{6} my money back\textsubscript{6}; putting\textsubscript{7} me at\textsubscript{7} my ease\textsubscript{7}; tells\textsubscript{8} me BS to\textsubscript{8} my face\textsubscript{8}.

\textsuperscript{33}Our operational definition of MWE type combines a strong or weak designation with an ordered sequence of lemmas, using the WordNet API in NLTK (Bird et al., 2009) for lemmatization.

\textsuperscript{34}Licensing restrictions prevent us from publishing the full text of every sentence, so we provide annotations in terms of token offsets in the original corpus. Tokens within the span of an MWE are retained.
ence to a lexicon or a set of targeted constructions). The most similar English corpora with shallow lexical semantic representations are not quite as comprehensive in their treatment of MWEs because they focused on a few subclasses (WIKI, §3.3.2) or were created primarily for sense annotation with an existing lexicon (SEMCOR, §3.3.1). Our representation, though also shallow, allows far more flexibility in the configuration of MWEs (arbitrary gaps with limited nesting) and also provides for subclassing in the form of a strong/weak contrast. Our corpus thus creates an opportunity to tackle general-purpose MWE identification, such as would be desirable for use by high-coverage downstream NLP systems. An MWE identification system trained on our corpus is presented in ch. 6.

Ch. 4 and 5 offer an approach to enriching lexical segments (single-word or multiword) with semantic class annotations. Future work includes extending the annotation scheme to new datasets; developing semi-automatic mechanisms to detect or discourage inconsistencies across sentences; and integrating complementary forms of annotation of the MWEs (such as syntactic classes). These improvements will facilitate NLP tools in more accurately and informatively analyzing lexical semantics for the benefit of downstream applications.

SPAULDING: I was sittin’ in front of the cabin, smoking some meat—
RITTENHOUSE: Smoking some meat?
SPAULDING: Yes, there wasn’t a cigar store in the neighborhood.

BORIS: Sonja—are you scared of dying?
SONJA: Scared is the wrong word. I’m frightened of it.
BORIS: Interesting distinction.

CHAPTER 4

Noun and Verb Supersenses

This chapter:

• Motivates the use of WordNet’s supersense labels for coarse lexical semantic analysis in context
• Repurposes the existing noun and verb supersense inventories for direct human annotation
• Provides detailed descriptions of the supersense categories in annotation guidelines
• Demonstrates the practicality of supersense annotation in two languages
• Enriches the English multiword expressions corpus (§3.8) with noun and verb supersenses
4.1 Introduction

The previous chapter concerned the determination of units of lexical meaning in context. Now we turn to the issue of categorizing each lexical expression with semantic labels.

As detailed in ch. 2, two major traditions of lexical semantic labeling are (a) lexicon senses, and (b) named entity classes. In this work we instead use supersenses, which like named entities are coarse in granularity, making them practical for rapid token annotation with high coverage in a variety of languages/domains. Supersenses, however, are neither restricted to names nor tied to lexicon coverage, which makes for high annotation density. This chapter elaborates on an existing inventory of supersenses for nouns and verbs, turning superordinate categories within the WordNet hierarchy into a practical annotation scheme that we then tested for Arabic (nouns only, §4.3) and English (nouns and verbs, §4.4). The approach to nouns as applied to Arabic has already been published (Schneider et al., 2012). Working within the same framework, the next chapter tackles the considerably thornier problem of prepositions.

4.2 Background: Supersense Tags

WordNet’s supersense categories are the top-level hypernyms in the taxonomy (sometimes known as semantic fields) which are designed to be broad enough to encompass all nouns and verbs (Miller, 1990; Fellbaum, 1990).¹

¹WordNet synset entries were originally partitioned into lexicographer files for these coarse categories, which became known as “supersenses.” The lexname function in WordNet/attribute in NLTK returns the lexicographer file of a given synset. A subtle difference is that a special file called noun .tops contains each noun supersense’s root synset (e.g., group .n.01 for GROUP) as well as a few miscellaneous synsets, such as living .thing .n .81, that are too abstract to fall under any single

The 25 main noun supersense categories are:

(4) NATURAL OBJECT, ARTIFACT, LOCATION, PERSON, GROUP, SUBSTANCE, TIME, RELATION, QUANTITY, FEELING, MOTIVE, COMMUNICATION, COGNITION, STATE, ATTRIBUTE, ACT, EVENT, PROCESS, PHENOMENON, SHAPE, POSSESSION, FOOD, BODY, PLANT, ANIMAL

Appendix D gives several examples for each of these noun tags. (A very small category, OTHER, is sometimes used for miscellaneous cases like organism, which include both plants and animals; see footnote 1.) There are 15 tags for verbs:

(5) BODY, CHANGE, COGNITION, COMMUNICATION, COMPETITION, CONSUMPTION, CONTACT, CREATION, EMOTION, MOTION, PERCEPTION, POSSESSION, SOCIAL, STATIVE, WEATHER

Though WordNet synsets are associated with lexical entries, the supersense categories are unlexicalized. The PERSON category, for instance, contains synsets for principal, teacher, and student. A different sense of principal falls under the category POSSESSION. The supersense categories are listed with examples in table 4.1.

As far as we are aware, the supersenses were originally intended only as a method of organizing the WordNet structure. But Ciaramita and Johnson (2003) pioneered the coarse WSD task of supersense tagging, noting that the supersense categories provided a natural broadening of the traditional named entity categories to encompass all nouns. Ciaramita and Altun (2006) later expanded the task to include all verbs, and applied a supervised sequence modeling supersense. In §4.4 we treat the latter cases under an OTHER supersense category and merge the former under their respective supersense when processing SemCor (which uses the top-level synsets to mark named entities that are not in WordNet).
Table 4.1: Summary of noun and verb supersense tagsets. Each entry shows the label, the count and the most frequent lexical item in the STREUSLE 2.0 corpus, and the frequency rank of the supersense in the SEMCOR corpus.

<table>
<thead>
<tr>
<th>Noun</th>
<th>Count</th>
<th>Verb</th>
<th>Count</th>
<th>Item</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>GROUP</td>
<td>1469</td>
<td>place</td>
<td>6</td>
<td>STATIVE</td>
<td>2922</td>
</tr>
<tr>
<td>PERSON</td>
<td>1202</td>
<td>people</td>
<td>1</td>
<td>COGNITION</td>
<td>193</td>
</tr>
<tr>
<td>ARTIFACT</td>
<td>797</td>
<td>car</td>
<td>2</td>
<td>COMMUNICATION</td>
<td>974</td>
</tr>
<tr>
<td>COGNITION</td>
<td>771</td>
<td>way</td>
<td>4</td>
<td>SOCIAL</td>
<td>944</td>
</tr>
<tr>
<td>FOOD</td>
<td>766</td>
<td>food</td>
<td>21</td>
<td>MOTION</td>
<td>602</td>
</tr>
<tr>
<td>ACT</td>
<td>700</td>
<td>service</td>
<td>3</td>
<td>POSSESSION</td>
<td>309</td>
</tr>
<tr>
<td>LOCATION</td>
<td>638</td>
<td>area</td>
<td>8</td>
<td>CHANGE</td>
<td>274</td>
</tr>
<tr>
<td>TIME</td>
<td>530</td>
<td>day</td>
<td>9</td>
<td>EMOTION</td>
<td>249</td>
</tr>
<tr>
<td>EVENT</td>
<td>431</td>
<td>experience</td>
<td>14</td>
<td>CONSUMPTION</td>
<td>143</td>
</tr>
<tr>
<td>COMMUNICATION</td>
<td>417</td>
<td>review</td>
<td>5</td>
<td>FEELING</td>
<td>67</td>
</tr>
<tr>
<td>POSSESSION</td>
<td>339</td>
<td>price</td>
<td>16</td>
<td>BODY</td>
<td>82</td>
</tr>
<tr>
<td>ATTRIBUTE</td>
<td>265</td>
<td>quality</td>
<td>7</td>
<td>CREATION</td>
<td>64</td>
</tr>
<tr>
<td>QUANTITY</td>
<td>102</td>
<td>amount</td>
<td>13</td>
<td>CONTACT</td>
<td>46</td>
</tr>
<tr>
<td>ANIMAL</td>
<td>88</td>
<td>dog</td>
<td>18</td>
<td>COMPETITION</td>
<td>11</td>
</tr>
<tr>
<td>BODY</td>
<td>87</td>
<td>hair</td>
<td>11</td>
<td>WEATHER</td>
<td>0</td>
</tr>
<tr>
<td>STATE</td>
<td>56</td>
<td>pain</td>
<td>10</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>NATURAL OBJECT</td>
<td>54</td>
<td>flower</td>
<td>15</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>RELATION</td>
<td>35</td>
<td>portion</td>
<td>19</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>SUBSTANCE</td>
<td>34</td>
<td>oil</td>
<td>12</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>FEELING</td>
<td>34</td>
<td>discomfort</td>
<td>20</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>PROCESS</td>
<td>28</td>
<td>process</td>
<td>22</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>MOTIVE</td>
<td>25</td>
<td>reason</td>
<td>25</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>PHENOMENON</td>
<td>23</td>
<td>result</td>
<td>17</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>SHAPE</td>
<td>6</td>
<td>square</td>
<td>24</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>PLANT</td>
<td>5</td>
<td>tree</td>
<td>23</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>OTHER</td>
<td>2</td>
<td>stuff</td>
<td>26</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

all 26 NSSTs 9018
The Arabic Wikipedia dataset has subsequently been used to evaluate noun supersense tagging in Arabic via a machine translation projection method (Schneider et al., 2013). That work is not discussed in this thesis—the system presented in ch. 7 is only trained and evaluated for English—but we examine the Arabic annotation process because the methodology was then adapted for English (§4.4).

4.3.1 Arabic Data

28 Arabic Wikipedia articles in four topical domains (history, science, sports, and technology) were selected from Mohit et al.’s (2012) named entity corpus for supersense annotation. The corpus is summarized in figure 4.1.

Wikipedia articles validated this approach.3

The Arabic Wikipedia dataset has subsequently been used to evaluate noun supersense tagging in Arabic via a machine translation projection method (Schneider et al., 2013). That work is not discussed in this thesis—the system presented in ch. 7 is only trained and evaluated for English—but we examine the Arabic annotation process because the methodology was then adapted for English (§4.4).

4.3.2 Arabic Annotation Process

This project focused on annotating the free text Arabic Wikipedia data with the 25 noun supersenses of (4) and appendix D. The goal was to mark all common and proper nouns, including (contiguous) multiword names and terms. Following the terminology of NER, we refer to each instance of a supersense-tagged unit as a mention. Figure 4.2 shows an annotated sentence (the English glosses and translation were not available during annotation, and are shown here for explanatory purposes only).

We developed a browser-based interactive annotation environment for this task (figure 4.3). Each supersense was assigned an

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3In an unpublished experiment, Stephen Tratz, Dirk Hovy, Ashish Vaswani, and Ed Hovy used crowdsourcing to collect supersense annotations for English nouns and verbs in specific syntactic contexts (Dirk Hovy, personal communication).
ASCII symbol; typing that symbol would apply the tag to the currently selected word. Additional keys were reserved for untagging a word, for continuing a multiword unit, and for an “unsure” label. Default tags were assigned where possible on the basis of the previously annotated named entities as well as by heuristic matching of entries in Arabic WordNet (Elkateb et al., 2006) and OntoNotes (Hovy et al., 2006).

Annotators were two Arabic native speakers enrolled as undergraduates at CMU Qatar. Neither had prior exposure to linguistic annotation. Their training, which took place over several months, consisted of several rounds of practice annotation, starting with a few of the tags and gradually expanding to the full 25. Practice annotation rounds were interspersed with discussions about the tagset. The annotation guidelines, appendix E, emerged from these discussions to document the agreed-upon conventions. The centerpiece of these guidelines is a 43-rule decision list describing and giving (English) examples of (sub)categories associated with each supersense. There are also a few guidelines regarding categories that are particularly salient in the focus domains (e.g., pieces of software in the TECHNOLOGY subcorpus).

Inter-annotator mention $F_1$ scores after each practice round were measured until the agreement level reached 75%; at that point we started collecting “official” annotations. For the first few sentences of each article, the annotators worked cooperatively, discussing any differences of opinion. Then the rest of the article was divided between them to annotate independently; in most cases they were assigned a few common sentences, which we use for the final inter-annotator agreement measures. This process required approximately 100 annotator-hours to tag 28 articles. The resulting dataset is available at: http://www.ark.cs.cmu.edu/ArabicSST/

4.3.2.1 Inter-Annotation Agreement

Agreement was measured over 87 independently-annotated sentences (2,774 words) spanning 19 articles (none of which were used in practice annotation rounds). Our primary measure of agreement, strict inter-annotator mention $F_1$ (where mentions are required to match in both boundaries and label to be counted as correct), was 70%. Boundary decisions account for a major portion of the disagreement: $F_1$ increases to 79% if the measure is relaxed to count a match...
for every pair of mentions that overlap by at least one word. Token-level $F_1$ was 83%. Further analysis of the frequent tags revealed that the **Cognition** category—probably the most heterogeneous—saw much lower agreement rates than the others, suggesting that revising the guidelines to further clarify this category would be fruitful. We also identified some common confusions, e.g. for words like book annotators often disagreed whether the physical object (**Artifact**) or content (**Communication**) was more salient.4

### 4.4 Supersense Annotation for English

As suggested above, supersense tags offer a practical semantic label space for an integrated analysis of lexical semantics in context. For English, we have created the **STREUSLE**5 dataset, version 2.0 of which fully annotates the **Reviews** corpus for WordNet’s noun and verb supersenses as well as multiword expressions (ch. 3). (A new inventory of supersenses for prepositions will be applied to the same corpus: ch. 5.)

In developing the methodology for supersense annotation with Arabic Wikipedia, we predicted that it would port well to other languages and domains. Experience with English web reviews has borne this out. We generally adhered to the same supersense annotation process; the most important difference was that the data had already been annotated for MWEs, and supersense labels apply to any strong MWEs as a whole. The same annotators had already done the MWE annotation; whenever they encountered an apparent mistake from an earlier stage (usually an oversight), they were encouraged to correct it. The more sophisticated annotation interface used for English supports modification of MWEs as well as supersense labels in one view.

Most of the supersense annotation was broken into separate rounds: first we annotated nearly the entire **Reviews** corpus for noun supersenses; then we made another pass to annotate for verbs. This was decided to minimize cognitive load when reasoning about the tagsets. Roughly a tenth of the sentences were saved for a combined noun+verb annotation round at the end; annotators reported that constantly switching their attention between the two tagsets made this mode of annotation more difficult.

#### 4.4.1 Nouns

**Targets.** According to the annotation standard, all noun singletons6 and noun-headed7 MWEs should receive a noun supersense label. Annotation targets were determined heuristically from the gold (PTB-style) POS tags in the corpus: all lexical expressions containing a noun8 were selected. This heuristic overpredicts occasionally because it does not check the syntactic head of MWEs. For this round, the backtick symbol (’’) was therefore reserved for MWEs (such as light verb constructions) that should not receive a noun label.9 The annotation interface prohibited submission of blank annotation targets to avoid oversights.

**Interface.** Instead of the interface used for Arabic annotation, we extended the online MWE annotation tool (figure 3.6) to also support modification of MWEs as well as supersense labels in one view. Additional details and analysis are reported by Schneider et al. (2012).

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4 Additional details and analysis are reported by Schneider et al. (2012).

5 Supersense-Tagged Repository of English with a Unified Semantics for Lexical Expressions

6 But not pronouns.

7 Headedness within lexical expressions is not marked as part of our annotation scheme, but annotators are expected to be able to recognize the head in order to determine the set of supersense candidates for the full expression.

8 Specifically, any POS tag starting with N or ADD (web addresses).

9 Pronouns like **anything** also fall into this category because they are POS-tagged as nouns.
port supersense labeling of units. This is visualized in figure 4.4. Specifically, singletons and strong MWEs may receive labels (subject to a POS filter). This allows the two types of annotation to be worked on in tandem, especially when a supersense annotator wishes to change a multiword grouping. Additionally, the tool provides a complete version history of the sentence and a “reconciliation” mode that merges two users’ annotations of a sentence, flagging any differences for manual resolution; these features are extremely useful when breaking the annotation down into several rounds among several annotators.

Before any annotation is saved, the tool will validate that its MWE analysis and labels are valid and compatible with one another. The set of valid labels is prespecified to consist of the supersenses, ` to mark the supersenses as not applicable to a lexical expression, and ? to indicate uncertainty. As the user begins to type a label, an autocomplete dropdown menu with possible matches will be displayed. Every identified target must receive some label.

Tagset conventions. Even though the annotation guidelines were already established from the Arabic effort, the English annotators were new to the scheme, so we devoted several brief annotation rounds to practicing it and reaching agreement in the reviews domain. Metonymy posed the chief difficulty in this domain: institutions with a premises (such as restaurants, hotels, schools, and offices) are frequently ambiguous between a GROUP reading (institution as a whole), an ARTIFACT reading (the building), and a LOCATION reading (site as a whole). Our convention was to choose whichever reading seemed most salient in context: for example, a statement about the the quality of a restaurant’s service would be

![Figure 4.4: Interface for noun supersense annotation. Previous annotation versions can be browsed in the gray box.](image_url)
the GROUP “reading of restaurant.¹⁰ Many of these decisions may
be subjective, however, which probably indicates a limitation of the
scheme in that it cannot always capture multifaceted frame-based
concepts.

4.4.2 Verbs

Targets. The set of lexical expressions that should receive a verb
supersense label consists of (a) all verb singletons that are not aux-
iliaries, and (b) all verb-headed MWEs. Again, simple but overly
liberal heuristics were used to detect annotation targets,¹¹ so where-
ever the heuristics overpredicted, annotators entered:

- ‘a for auxiliary verbs
- ‘j for adjectives (some -ing and -ed adjectives are POS-tagged
  as VBG and VBD, respectively)
- ‘ for all other cases

Interface. The same interface was used as for nouns. Figure 4.5
shows the dropdown list for verbs. For MWEs containing both a
noun and a verb, all the noun and verb labels were included in the
dropdown and accepted as valid.

Tagset conventions. We developed new guidelines to characterize
the verb supersenses for use by annotators. The guidelines docu-
ment appears in appendix F. It is similar to the guidelines for nouns
(appendix E), but is shorter (as there are only 15 verb supersenses)
and formulates priorities as precedence relations between the cat-

¹⁰This rule is sometimes at odds with WordNet, which only lists ARTIFACT for
hotel and restaurant.
¹¹All lexical expressions containing a POS tag starting with v.
several weeks and informed by annotation difficulties and disagreements.

4.4.3 Corpus Statistics

A total of 9,000 noun mentions and 8,000 verb mentions incorporating 20,000 word tokens are annotated. Table 4.1 displays supersense mention counts as well as the most frequent example of each category in the corpus. As a point of reference, it also shows the frequency rank of the supersense in **SEM**COR—note, for instance, that **FOOD** is especially frequent in the **REVIEWS** corpus, where it ranks fifth among noun supersenses (vs. 21st in SemCor).

4.5 Related Work: Copenhagen Supersense Data

An independent English noun+verb supersense annotation effort targeting the Twitter domain was undertaken by the COASTAL lab at the University of Copenhagen (Johannsen et al., 2014). The overarching goal of annotating supersenses directly in running text was the same as in the present work, but there are three important differences. First, general-purpose MWE annotation was not a goal in that work; second, sentences were pre-annotated by a heuristic system and then manually corrected, whereas here the MWEs and supersenses are supplied from scratch; and third, Johannsen et al. (2014) provided minimal instructions and training to their annotators, whereas here we have worked hard to encourage consistent interpretations of the supersense categories. Johannsen et al. have released their annotations on two samples of tweets (over 18,000 tokens in total).  

Johannsen et al.’s (2014) dataset provides a good illustration of why supersense annotation by itself is not the same as the full scheme for lexical semantic analysis proposed here. Many of the expressions that they have supersense-annotated as single-word nouns/verbs probably would have been considered larger units in MWE annotation. However, examining the Johannsen et al.’s in-house sample, multiword chunks arguably should have been used for verb phrases such as *gain entry*, *make sure*, and *make it* (‘succeed’), and for verb-particle constructions such as *take over*, *find out*, and *check out* (‘ogle’). In the traditional supersense annotation scheme, there are no chunks not labeled with a supersense; thus, e.g., PPs such as *on tap*, of **ALL-Time**, and *up to [value limit]* are not chunked.

Many of the nominal expressions in Johannsen et al.’s (2014) data appear to have overly liberal boundaries, grouping perfectly compositional modifiers along with their heads as a multiword chunk; e.g., *Panhandling Ban*, *Loudoun Firefighters*, *Panda Cub*, *farm road crash*, *Sri Lanka’s west coast*, and *Tomic’s dad*. Presumably, some of these were boundary errors made by the heuristic pre-annotation system that human annotators failed to notice.

4.6 Conclusion

This chapter has described WordNet-based noun and verb supersenses from the perspective of annotation. Supersenses offer coarse-grained and broadly applicable semantic labels for lexical expressions and naturally complement multiword expressions in lexical semantic analysis. We have developed detailed annotation criteria using the existing supersense categories and applied them to annotate text corpora in Arabic and English. Our representation of supersenses dovetails with the scheme for multiword expressions...

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proposed in the previous chapter. English annotations for the "RE-
VIEWS" corpus will be released as the STREUSLE 2.0 dataset, which
forms the basis of our integrated lexical semantic analyzer in ch. 7.

You can leave in a taxi. If you can’t get a taxi, you can leave in a huff. If
that’s too soon, you can leave in a minute and a huff.

Firefly in *Duck Soup*

JOSH: You went over my head, and you did it behind my back.
AMY: Quite the contortionist am I.

*The West Wing,* “Dead Irish Writers” (Season 3, Episode 15)

## Preposition Supersenses

This chapter:

- Illustrates the extreme semantic polysemy of English prepositions
- Summarizes resources and NLP approaches to preposition semantics developed to date, and their limitations
- Argues for treating preposition semantics in the framework of supersenses, which can be integrated with multiword expressions and noun and verb supersenses in a lexical semantic analysis
- Proposes a novel supersense taxonomy and annotation scheme for prepositions, drawing on an existing non-hierarchical coarse grouping of English preposition senses and an existing hierarchy for semantic roles of verbs
- Offers concrete criteria for selecting annotation targets
- Describes notable decisions in the new supersense scheme, including new portions of the hierarchy devoted to temporal, path, value, and comparison subcategories
Prepositions are perhaps the most beguiling yet pervasive lexical-syntactic class in English. They are everywhere (figure 5.1); their functional versatility is unrivaled and largely idiosyncratic (7). They are nearly invisible, yet present in some of the most quoted lines of text.  

In a way, prepositions are the bastard children of lexicon. The lexical item "to" serves a wide range of functions, from functioning as a preposition in "I'm happy to make the batter" (nonfinite adjectival complement) to a verb in "If you want I can treat you to a meal." (recipient)  

Sometimes a preposition specifies a relationship between two entities or quantities, as in (7h). In other scenarios it serves a case-marking sort of function, marking a complement or adjunct—principally to a verb, but also to an argument-taking noun or adjective (7g). As we have seen in ch. 3, prepositions play a key role in multiword expressions, as in (7a), (7l), the prepositional verbs in (7b) and (7k), and arguably (7e).  

This chapter briefly introduces the preposition from syntactic, semantic, and multilingual perspectives, then reviews the literature on resources and NLP for preposition semantics (§5.1). §5.2 then

\[ \begin{array}{|c|c|c|c|c|} 
\hline
\text{word} & \text{count} & \text{count} & \text{count} & \text{count} \\
\hline
\text{in} & 635 & \text{very} & 255 & \text{as} & 160 \\
\text{to} & 1,528 & \text{be} & 219 & \text{food} & 165 \\
\text{of} & 660 & \text{he} & 195 & \text{of} & 163 \\
\text{was} & 644 & \text{were} & 193 & \text{is} & 633 \\
\text{for} & 1,175 & \text{but} & 265 & \text{at} & 191 \\
\text{with} & 384 & \text{had} & 246 & \text{from} & 171 \\
\text{it} & 573 & \text{not} & 351 & \text{with} & 185 \\
\text{be} & 236 & \text{we} & 305 & \text{for} & 181 \\
\text{is} & 633 & \text{had} & 246 & \text{so} & 185 \\
\hline
\end{array} \]

\textbf{Figure 5.1:} Counts of the top 50 most frequent words in Reviews. Prepositions are bolded; others in the top 100 include up (#61), about (#68), back (#74), by (#86), and after (#96).
introduces our approach. Its main components are (a) integrating the multiword expression analysis developed in ch. 3; (b) targeting a broad range of tokens based on syntactic and lexical criteria, as detailed in §5.3; and (c) proposing in §5.4 a hierarchical taxonomy of preposition supersenses that combines the preposition inventory of Srikumar and Roth (2013a) with VerbNet's (Kipper et al., 2008) taxonomy of thematic roles (Bonial et al., 2011; VerbNet Annotation Guidelines; Hwang, 2014, appendix C), while also drawing insights from AMR's (Banarescu et al., 2013) inventory of non-core roles (Banarescu et al., 2014).

A wiki documenting our scheme in detail can be accessed at http://tiny.cc/prepwiki. It contains mappings from fine-grained senses (of 34 prepositions) to our supersenses, as well as numerous examples. The structured format of the wiki is conducive to browsing and to exporting the examples for display in our annotation tool. From our experience with pilot annotations, we believe that the scheme is fairly stable and broadly applicable: preposition tokens for which it is difficult to choose a supersense label are relatively rare. Ultimately, we aim to annotate the English REVIEWS corpus to augment the MWE and verb/noun supersense annotations in our STREUSLE dataset (§4.4) with preposition supersenses for version 3.0.

5.1 Background

5.1.1 What is an English Preposition?

It is generally understood that the category of English prepositions includes such words as to, for, and with. As with much in grammar, however, the precise contours of this category are difficult to pin down.

An early definition comes from a 1668 treatise by English clergyman and philosopher John Wilkins entitled An Essay Towards a Real Character And a Philosophical Language. We read on p. 309:³

That is, prepositions are connectives that join together content words³ (as opposed to sentences) to express “some respect of Cause, Place, Time, or other circumstance.”

A contemporary articulation of the traditional grammar view of prepositions can be found in the Merriam-Webster Learner’s Dictionary, where it is defined as “a word or group of words that is used with a noun, pronoun, or noun phrase to show direction, location, or time, or to introduce an object.” The Oxford English Dictionary gives a similar definition: “An indeclinable word or particle governing (and usu. preceding) a noun, pronoun, etc., and expressing a relation between it and another word.”

The traditional definition applies uncontroversially to the underlined PPs in the following passage:

(8) She’s gonna meet him at the top of the Empire State Building. Only she got hit by a taxi…. And he’s too proud to find out why she doesn’t come. But he comes to see her anyway…he doesn’t even notice that she doesn’t get up to say hello. And

³Image from Google Books.

³Per the Oxford English Dictionary, the term integral is “Applied by Wilkins to those words or parts of speech which of themselves express a distinct notion, as distinct from those which express relations between notions.”
he’s very bitter. And you think that he’s just gonna—walk out
the door and never know why, she’s just lying there, you know,
like on the couch with [this blanket over her shriveled little
legs]…. And he, he like goes into the bedroom. And he looks
and he comes out and he looks at her, and he kinda just—they
know, and then they hug. [Sleepless in Seattle]

Those PPs express several spatial relations (on the couch, out the
doors, etc.), and one expresses a causal relation (hit by a taxi). However,
the traditional definition leaves out instances of to, up, with,
and out in (8) that do not take a noun phrase complement:

- *to* followed by a verb phrase, where the *to* marks the verb as
  an infinitive
- *up* used following get (traditional grammar might deem this an
  adverb)
- *with* marking a state of affairs expressed in a clause (this is
  traditionally called a subordinating conjunction)
- *out* in comes out (of the bedroom), which is not followed by a
  noun phrase

Pullum and Huddleston (2002, p. 603) argue for a more inclusive
definition of preposition, pointing out that alternatives such as *walk
out the door* vs. *come[] out*—where *out* has the same semantic func-
tion, expressing that the room was exited—are possible for many of
the prepositions. Emphasizing the class of word types rather than
the syntactic environment, they define preposition as:

> a relatively closed grammatically distinct class of words
> whose most central members characteristically express
> spatial relations or serve to mark various syntactic func-
> tions and semantic roles.

In Pullum and Huddleston’s terminology, if *out, up, down, off*, etc.
appears with no complement, it is an *intransitive* preposition form-
ing a one-word PP—not a member of an entirely distinct word class.
Some prepositions are always transitive (e.g., *at, beside, Pullum
and Huddleston, 2002, pp. 635–6*), or almost always (e.g., *to, for⁵*).
Others—such as *together and back*, both closed-class items with
schematic spatial meanings—can never take NP complements (Pullum
and Huddleston, 2002, p. 614). (This is similar to the case with
verbs, some of which are always transitive, some of which are always
intransitive, and some of which are, shall we say, transiflexible.⁶)
Thus, they use the term *particle* to describe a word’s role in a partic-
ular construction, not (*pace* Penn Treebank’s RP) as a distinct part of
speech.⁷

All of this is just a flavor of the descriptive challenges raised by
prepositions; see Saint-Dizier (2006b) for an assortment of syntactic
and semantic issues.

As noted above, prepositions figure prominently in several well-
studied classes of multiword expressions: verb-particle construc-
tions, prepositional verbs, and determinerless PPs (§3.2.3). In our
MWE annotation, the category of prepositional verbs proved espe-
cially troublesome (§3.7). Undertaking to systematically analyze the
functions of prepositions may therefore help us to separate the pro-

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⁵The only exceptions that we know of are the lexical idioms *come to* ‘regain
consciousness’ and *pull*…to ‘pull (a door, etc.) closed’ (Pullum and Huddleston, 2002,
p. 613); *done for* ‘doomed’, and *talking to and what for*, compound nouns meaning
‘scolding’.

⁶Some linguists prefer the term *ambitransitive*. They are not much fun at par-
ties.

⁷The literature on verb-particle constructions (see ch. 3) sometimes takes a more
inclusive view, equating “particle” with “intransitive preposition.” Huddleston (2002,
p. 280) instead refer to the verb-particle-object construction (in which the particle
may be positioned either before or after the verb’s object NP), pointing out a few
non-prepositions that can serve as particles in this construction. For instance: *cut
short* (adjective) and *let go* (verb).
ductive and compositional cases from the exceptional, MWE-worthy cases.

5.1.2 Linguistic Approaches

Studies of prepositions appear to be relatively rare in the linguistics literature, especially outside of the spatial domain. E.g., I am aware of but a few edited volumes on the subject (Rauh, 1991; Zelinsky-Wibbelt, 1993b; Cuycvens and Radden, 2002; Feigenbaum and Kurzon, 2002; Saint-Dizier and Ide, 2006; Kurzon and Adler, 2008).

The lexical-vs.-functional dimension and, relatedly, the degree of association between prepositions and other words (especially verbs) used in combination has received some theoretical attention (e.g., Bolinger, 1971; Vestergaard, 1977; Rauh, 1993; O’Dowd, 1998; Tseng, 2000) but without (it seems to me) any clear and robust diagnostics that could be incorporated into an annotation scheme.

The structured polysemy analysis of over put forward by Brugman (1981) and elaborated by Lakoff (1987, pp. 416–461), Dewell (1994), Tyler and Evans (2003, ch. 4), and Deane (2005) has been influential within cognitive linguistics. (See also footnote 28.) Working in this tradition, Lindstromberg (2010) examines over 90 English prepositions, considering in detail the schematic spatial situations that can be expressed and the ways in which these motivate non-spatial extensions. Chapter 21 gives an inventory of about 75 “non-spatial notions”—these are not unlike the categories we will adopt below, though some are quite fine-grained: e.g., BEING RESOLVED, FIXED as in pin him down vs. BEING UNRESOLVED, UNDECIDED as in everything’s still up in the air. The extent to which annotators could be trained to agree on Lindstromberg’s detailed categorization is unknown.

5.1.3 Other Languages

Crosslinguistic variation in prepositions and spatial categorization systems has received considerable attention from theorists (Bowerman and Choi, 2001; Hagège, 2009; Regier, 1996; Xu and Kemp, 2010; Zelinsky-Wibbelt, 1993a) but is of practical interest as well, especially when it comes to machine translation (see §8.3.3) and second language acquisition (§8.3.4). A corpus creation project for German preposition senses (Müller et al., 2010, 2011) is similar in spirit to the supersense approach taken below. Finally, the PrepNet resource (Saint-Dizier, 2006a) aimed to describe the semantics of prepositions across several languages; however, it seems not to have progressed beyond the preliminary stages.

5.1.4 Preposition Resources

The following corpus resources contain semantic categorizations that apply to English prepositions:

The Penn Treebank. As detailed by O’Hara and Wiebe (2009), the PTB since version II (Marcus et al., 1994) has included a handful of coarse function tags (such as LOCATION and TIME) that apply to constituents, including PPs.

FrameNet. Semantic relationships in FrameNet (Baker et al., 1998) are organized according to scenes, known as frames, that can be evoked by predicates in a sentence. Each frame defines roles, or frame elements, which indicate possible facets along which the description of the scene can be elaborated with arguments in the

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8 This excludes the many dictionaries and pedagogical materials (especially, for second language learners) on preposition-bearing constructions such as phrasal verbs.
sentence. Many roles are highly specific to a single frame, while others are quite generic. Arguments are often realized as PPs, thus the frame element labels can be interpreted as disambiguating the function of the preposition.

The Preposition Project (TPP). This is an English preposition lexicon and corpus project (Litkowski and Hargraves, 2005) that adapts sense definitions from the Oxford Dictionary of English and applies them to prepositions in sentences from corpora. A dataset for the SemEval-2007 shared task on preposition WSD (Litkowski and Hargraves, 2007) was created by collecting FrameNet-annotated sentences (originally from the BNC) and annotating 34 frequent preposition types with a total of 332 attested senses. The SemEval-2007 sentences—of which there are over 25,000, each with a single preposition token annotated—were collected from FrameNet’s lexicographic annotations that had been selected by a FrameNet lexicographer to illustrate, for a given lexical unit, a valence pattern with a particular kind of PP. In FrameNet data, such sentences are grouped under a $\text{ppX}$ label ($\text{ppto}$, $\text{ppfor}$, etc.). Preposition types having too few of these PP exemplars were filtered out, leaving 34 types in the SemEval-2007 data (Litkowski, 2013).

The FrameNet lexicographic exemplars were handpicked from the BNC to illustrate, e.g., the range of valence patterns for a predicate; usages with few arguments are underrepresented and rare patterns are overrepresented. Biases in the lexicographic exemplars have been found to distort statistical models trained on them (e.g., Das et al., 2014). Further, only a fraction of PPs from these exemplars constitute frame element fillers (arguments to an annotated frame), and only a small proportion of those were highlighted under a $\text{ppX}$ label. Therefore, while the SemEval-2007 sentences illustrate a great variety of preposition usages, it is important to note that the dataset is not statistically representative—ans evaluation data it is not a realistic yardstick for performance on a real corpus, and it cannot be assumed to capture the full semantic range of PPs in FrameNet, let alone prepositions in English.

Recognizing this, Litkowski (2013) has initiated an effort to extend TPP annotations to a new, statistically representative corpus. Our approach is intended to complement that effort by facilitating rapid and comprehensive annotation of corpora at a coarser level of granularity. By recording many-to-many correspondences between TPP senses and supersenses, we can ensure partial (but nondeterministic) compatibility between the two annotation schemes, which should allow models to make use of additional prepositions and resources, with new annotated corpora under development (Litkowski, 2013, 2014).

Dahlmeier et al. To learn and evaluate their joint model of semantic roles and preposition senses, Dahlmeier et al. (2009) annotated TPP senses in the PropBank WSJ corpus for 7 high-frequency prepositions (of, in, for, to, with, on, and at). This amounted to 3,854 statistically representative instances in the news domain. The inter-annotator agreement rate was estimated at 86%, which suggests that clearly applicable TPP senses are available for the preponderance of tokens, but gives little insight into TPP’s suitability for rare or borderline usages.10

Tratz. Tratz (2011, ch. 4) refined the TPP sense inventory for the SemEval-2007 corpus with the goal of improving its descriptive adequacy and measuring inter-annotator agreement for all 34 prepositions. The refinement was performed by two annotators, who reorganized and rewrote the sense definitions and reannotated instances in an iterative fashion until agreement was qualitatively high. The total number of senses was reduced from 332 to 278, though a few prepositions gained additional senses. A third annotator was then added for final estimation of inter-annotator agreement. Pairwise agreement rates, Fleiss’ $\kappa$, and per-annotator sense entropies are reported for each preposition. Tratz also reports supervised classification results with the original vs. refined sense inventories.

Srikumar and Roth (S&R). Srikumar and Roth (2013b) confront the problem of predicting preposition token relations, i.e., the prepo...
sition’s governor, object, and semantic label. For their experiments, Srikumar and Roth coarsen the original TPP SemEval-2007 sense annotations into 32 categories determined semi-automatically (the fine-grained senses were clustered automatically, then the clusters were manually refined and given names). Detailed in Srikumar and Roth (2013a), those categories cut across preposition types to combine related TPP senses for better data-driven generalization. Cohen’s k for inter-annotator agreement was an estimated 0.75, which is encouraging, though it is unclear whether the disagreements were due to systematic differences in interpretation of the scheme or to difficulty with rare preposition usages. We shall return to this scheme in § 5.4 below.

5.1.5 Prepositions in NLP

Despite a steady trickle of papers over the years (see Baldwin et al., 2009 for a review), there is no apparent consensus approach to the treatment of preposition semantics in NLP. Studies have examined preposition semantics within multiword expressions (Cook and Stevenson, 2006), in spatial relations (Hying, 2007), across languages (Saint-Dizier, 2006a), in nonnative writing (Chodorow et al., 2007), in semantic role labeling (Dahlmeier et al., 2009), in vector space models (Zwarts and Winter, 2000), and in discourse (Denand and Rolbert, 2004).

Preposition sense disambiguation systems have been evaluated against one or more of the resources described in § 5.1.4 (O’Hara and Wiebe, 2003, 2009; Ye and Baldwin, 2007; Dahlmeier et al., 2009; Tratz and Hovy, 2009; Hovy et al., 2010, 2011; Srikumar and Roth, 2013b). Unfortunately, all of these resources are problematic. Neither the PTB function tags nor the FrameNet roles were designed with prepositions in mind: the former set is probably not comprehensive enough to be a general-purpose account of prepositions, and the latter representation only makes sense in the broader analytical framework of frame semantics, which we believe should be treated as a separate problem (Das et al., 2014, § 8.3.2). The Preposition Project data, though extensive, were selected and annotated from a lexicographic, type-driven perspective—i.e. with the goal of describing and documenting the uses of individual prepositions in a lexical resource rather than labeling a corpus with free-text preposition annotations (footnote 9; cf. SEMCOR, § 2.3.2). A token-driven approach would be more in line with the philosophy advocated here for lexical semantic annotation and modeling.11

5.2 Our Approach to Prepositions

As a “sweet spot” between linguistic descriptiveness and practicality for annotation, we approach preposition semantics much like the noun and verb supersenses in the previous chapter. The descriptive steps are therefore:

1. **Lexical segmentation:** Mark any multiword expressions, as in ch. 3.

2. **Preposition targets:** Identify any single-word prepositions, as well as any MWEs headed by a preposition, as candidates for receiving a preposition tag.

11A technical reason that the type-driven approach to annotation is not ideal for learning NLP systems is the i.i.d. assumption typically made in machine learning. If a sample is not random but biased by an annotator’s interest in covering as many phenomena as possible, this bias will be evident in predictions made by a learned model. As an example, Das et al. (2014) mention that including a large number of FrameNet lexicographic annotations (on handpicked sentences from a corpus) in the training data for a frame-semantic parser actually hurt performance when evaluated on a statistically representative corpus.
3. **Preposition tagging:** Assign a preposition supersense label to each of the preposition targets.

The procedure for identifying targets is described in §5.3, and the supersense inventory in §5.4.

### 5.3 Preposition Targets

From a lexical segmentation, we first have to decide which lexical expressions should be considered as candidates for receiving a preposition annotation. Though for the reviews corpus (Bies et al., 2012) we have Penn Treebank–style part-of-speech tags, those tags do not entirely line up with our definition of preposition (see §5.1.1)—for example, *apart* is consistently tagged as an adverb, but most adverbs are not prepositions. Given that prepositions form a relatively closed class (Pullum and Huddleston, 2002), we have compiled a list of 235 single words that can function as prepositions. It is as follows:

![List of 235 single words that can function as prepositions](https://en.wikipedia.org/wiki/List_of_English_prepositions)

Note that this list includes alternate/nonstandard spellings (e.g., 2 for *to*) and words that are more commonly other parts of speech, but can act as prepositions in certain constructions (*like*, *post*, etc.). We therefore use POS tags in combination with lexical matching to automatically identify preposition candidates, according to the following rule:

\[(10)\] A single-word token is considered a preposition target if it meets either of the following criteria:

a. Its POS tag is *RP* (verb particle) or *TO* (the word *to*)

b. Its POS tag is *IN* (transitive preposition or subordinator) or *RB* (adverb), and the word is listed in (9).

We are also interested in analyzing multiword prepositions (i.e., multiword expressions that function as prepositions). While this is a more difficult class to circumscribe, it is difficult to come up with an example of a multiword preposition that does not contain a word from (9)—in fact, the TPP and Wikipedia lists include several dozen multiword prepositions, all of which indisputably contain a...
single-word preposition type: these include out of, next to, on top of, in lieu of, along with, due to, thanks to, except for, such as, and as regards. Therefore, we adopt the procedure in (11):

(11) A strong MWE instance is considered a preposition target if it meets either of the following criteria:

a. The MWE begins with a word that matches the criteria of (10).

b. The MWE contains a word matching the criteria of (10), and begins with one of the following words (all of which begin a multiword preposition in TPP): a, according, all, bare, because, but, care, complete, contrary, courtesy, depending, due, exclusive, instead, irrespective, little, more, next, nothing, other, outboard, owing, preparatory, previous, prior, pursuant, regardless, relative, short, subsequent, thanks, this

The main reason to use a whitelist in (11b) is to avoid identifying prepositional verbs as preposition supersense candidates. Thus far, these heuristics applied to our data seem to be successful at identifying everything we want to annotate as a preposition (good recall) without too many false positives (good precision).

5.3.1 Special Syntactic Categories

There is a certain amount of lexical and semantic overlap between prepositions that serve as heads of prepositional phrases, and the category of subordinators (or subordinating conjunctions), which serve to link clauses. Words in the overlapping group include for, with, and as. The IN POS category includes such cases; however, we have decided to prioritize in our annotation (a) prepositions with NP complements, (b) intransitive prepositions, and (c) infinitival to. For all other cases automatically flagged as targets—including words with clausal complements, and connectives like as well as—anctors are instructed to mark the expression as not applicable to preposition annotation. Special cases include:

5.3.1.1 Infinitival to

We are interested in infinitival to where it marks a purpose or function. More commonly, however, infinitival to serves a purely syntactic function, which we designate with a special label (‘1).

5.3.1.2 Subordinating for, with, and as

In sentences like Unity is not possible with John sitting on the throne and For him to abdicate would have been unprecedented, we analyze with and for as subordinators: these constructions are unlike intransitive particles or transitive PPs. The ` label is used to mark these as non-prepositions.

5.3.1.3 Discourse Connectives

We do not consider discourse connectives as prepositions, even those that are prepositional phrases (e.g., apart from that, in other

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13Where to is governed by a verb, we use the acceptability of an in order to paraphrase as a diagnostic for purpose. I bought a TV in order to watch the election returns, but 'I want in order to suck your blood. Governed by a noun, infinitival to can also mark a function for which an entity can serve as an instrument (a bed to lie on); these receive the label function, a subtype of purpose.

14In the first example, the complement of with is arguably a clause. Likewise with as in Unity is not possible as John is on the throne. For with but not as, the clause may be verbless: with/as [John on the throne]. The second example is not to suggest that for can never head an adjective's PP complement—in Abidication would have been unbearable for him, we consider for to be a preposition with the experiencer function. Further discussion of the subtleties of for as subordinator can be found on the wiki.
words, of course). Annotators are instructed to annotate such expressions with the `label.

5.4 Preposition Tags

To characterize preposition meanings/functions in context with broad coverage, we would like an inventory of a manageable number of coarse categories in the manner of nouns and verbs (§4.2). We take Srikumar and Roth’s (2013a) inventory (hereafter, S&R) as a starting point: as noted in §5.1.4, it clusters fine-grained dictionary senses of 34 English prepositions into 32 labeled classes. Many of the classes resemble semantic roles (e.g., TEMPORAL, LOCATION, AGENT) or spatial relations (PHYSICAL, SUPPORT, SEPARATION).

We revise and extend S&R to improve its descriptive power and deploy it directly as an annotation scheme. The main areas of improvement are highlighted below; final annotation guidelines will be published at a later date.

5.4.1 Broadening

S&R provides a type-level resource: a labeled clustering of dictionary senses for 34 prepositions. Besides improving these sense groupings, we ultimately intend to annotate all preposition tokens in a corpus. Disregarding MWE annotations, the REVIEWS corpus contains 87 single-word preposition types over 5,637 tokens.

5.4.2 Harmonization and Hierarchy

Two other semantic annotation schemes offer similarly sized inventories of roles/relations: VerbNet (Kipper et al., 2008) and AMR (Banarescu et al., 2013). Many of the categories in those schemes overlap (or nearly overlap) with S&R labels. Others characterize semantic categories that are absent from S&R, but plausibly apply to English prepositions. A comparison of the three inventories is given in table 5.1. The new hierarchy, comprising 70 preposition supersenses, appears in the middle column of the table, and also in figure 5.2.

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15Improved coarse semantic categories for prepositions are the result of ongoing collaborations; they reflect the efforts of myself and others including Vivek Srikumar, Jena Hwang, Martha Palmer, Tim O’Gorman, Katie Conger, Archana Bhattachar, Carlos Ramirez, Yulia Tsvetkov, Michael Mordowanec, Matt Gardner, Spencer Onuffer, and Nora Kazour, as well as helpful conversations with Ed Hovy, Lori Levin, Ken Litkowski, and Orin Hargraves.

16Unfortunately, because S&R used the original TPP dictionary, we were unable to benefit from Tratz’s (2011) sense refinements (§5.1.4).
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<td>VALUECOMPARISON (’VALUE)</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>APPROXIMATOR</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>TEMPORAL</td>
<td>Time</td>
</tr>
<tr>
<td>✓</td>
<td>FREQUENCY</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>DURATION</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>AGE (’ATTRIBUTE)</td>
<td>A</td>
</tr>
<tr>
<td>✓</td>
<td>TIME</td>
<td>A</td>
</tr>
<tr>
<td>✓</td>
<td>RELATIVE TIME</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>START_TIME</td>
<td>Initial_time</td>
</tr>
<tr>
<td>✓</td>
<td>END_TIME</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>DEICTIC_TIME</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>CLOCKTIME_CXN</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>CIRCUMSTANCE</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>ATTRIBUTE +2</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>MANNER +1</td>
<td>V</td>
</tr>
<tr>
<td>✓</td>
<td>INSTRUMENT (’UNDERGOER)</td>
<td>V</td>
</tr>
<tr>
<td>≈Instrument</td>
<td>MEANS (’ACTIVITY)</td>
<td>V</td>
</tr>
</tbody>
</table>

100
In designing our supersense label set, we decided to modify S&R where possible to be more closely compatible with the other schemes. On a descriptive level, this allows us to take advantage of the linguistic analyses and explanations motivating those categories. On a practical level, this will make it easier to combine resources (lexicons and annotated corpora enriched with semantic role labels).

Following VerbNet, our preposition supersense categories are organized into a hierarchical (multiple inheritance) taxonomy. Not only does this explicate some of the distinctions between related categories that were described textually in S&R (e.g., the relationship between STARTSTATE and SOURCE), but it also provides a practical strategy for annotators who are unsure of how to apply a category—there is often a less specific label to fall back on.

The preposition label set proposed here is noticeably larger than the noun and verb supersenses. This might warrant concern that it will be too difficult for annotators to learn. However, there are arguments in favor of a larger set when it comes to prepositions:

- Because prepositions range from the lexical to the grammatical, they perhaps cover a wider/higher-dimensional semantic space than verbs or nouns. Thus, more categories might be needed for comparable descriptive adequacy.
- The hierarchy should help guide annotators to the right category or small set of related categories. They will not have to consider all of them one by one.
- The presence of more and less abstract categories gives annotators flexibility when they are uncertain.
- Because prepositions are closed-class, we envision that the annotation process will be guided (to a much greater extent

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**Table 5.1: Harmonization of the S&R inventory, VerbNet thematic role hierarchy, and AMR non-core roles.** In the middle column, categories with multiple parents indicate one of them in parentheses, and categories with $n$ children listed under some other parent have a $+n$ designation. In the right column, role names starting with ":" are from AMR and others are from VerbNet. (Some of the above are new in VerbNet, having been added subsequent to the latest published guidelines. Several roles only in AMR are not shown.)

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17 This S&R category has a substantially different meaning from the one in VerbNet and the new scheme.
than for nouns and verbs) by the word type. Consequences include:

- Having several dozen categories at multiple levels of granularity should mean that the number of prepositions associated with each category is small.
- For TPP prepositions (with fine-grained senses mapped to the new scheme), it will be possible to suggest a filtered list of supersenses to the annotator, and these should suffice for the vast majority of tokens.
- It may even be desirable to annotate a corpus by type rather than by token, so the annotator can focus on a few supersenses at a time.

Based on preliminary rounds of annotation—a mix of type-driven and token-driven—by several annotators, we are optimistic that the general approach will be successful. The preliminary annotation has also uncovered shortcomings in the annotation guidelines that have informed revisions to the categories and hierarchy. More extensive annotation practice with the current scheme is needed to ascertain its adequacy and usability. Should the size of the hierarchy prove too unwieldy, it will be possible to remove some of the finer-grained distinctions.

Below, we examine some of the areas of the hierarchy that are being overhauled.

### 5.4.3 Temporal Refinement

In S& R, all temporal preposition usages fall under a single label, TEMPORAL. VerbNet is slightly more discriminative, with an equivalent Time supercategory whose daughters are INITIAL_TIME, FINAL_TIME, DURATION, and FREQUENCY.

We have refined this further, as shown in figure 5.3, after coming to the conclusion that the major temporal prepositions cluster neatly into finer-grained subcategories. Relations that situate a time as before or after another time are under RELATIVE_TIME; special cases are START_TIME', END_TIME', times implicitly situated relative to the present (DEICTIC_TIME'), and constructions for telling time that express an offset in minutes relative to the hour (CLOCK_TIME_CN'). We also follow AMR’s lead in creating a dedicated AGE' category, which inherits from both TEMPORAL' and ATTRIBUTE'.

Note that most of the prepositions in figure 5.3 are only associated with one or two temporal supersenses; only in and at are known to occur with three. Therefore we do not expect that the subcategories will impose too much of a burden on annotators.
5.4.4 Values and Comparisons

Many prepositions can be used to express a quantitative value (measuring attributes such as a quantity, distance, or cost), to compare to another value, or to compare to something qualitatively.\footnote{Temporal expressions, though sometimes considered values, are here treated separately, as described in the foregoing section.} S\&R define a broad category called NUMERIC for preposition senses that mark quantitative values and classify some qualitative comparison senses as OTHER. We have developed a finer-grained scheme, seen in figure 5.4. The main categories are COMPARISON/CONTRAST', and VALUE'.

COMPARISON/CONTRAST' applies to qualitative or quantitative analogies, comparisons, and differentiations: e.g., he used to have a car like mine; he was screaming like a banshee; the club’s nothing to what it once was; the benefits must be weighed against the costs; the difference between income and expenditure; these fees are quite distinct from expenses. Where these are relative to a specific scale or ranking, the subcategory SCALAR/RANK' is used. Qualitative SCALAR/RANK' examples include: the firm chose profit above car safety; a woman who placed duty before all else; at a level above the common people; warm weather for the time of year.

VALUE' applies to points on a formal scale—e.g., prices start at $10; the drunken yobbos who turned up by the cartload; my car only does ten miles to the gallon. It also covers prepositions used as mathematical operators: a map measuring 400 by 600 mm; she multiplied it by 89; three into twelve goes four; ten to the minus thirty-three.

SCALAR/RANK' and VALUE' share a subtype, VALUECOMPARISON', for comparisons/differentiations on a formal scale—e.g., the hill was above/below sea level. A special case of this, APPROXIMATOR', is discussed in some detail below.

VALUE' and PATH' share a subtype, EXTENT', which is described in §5.4.5.

5.4.4.1 Approximate Values

We propose a new category, APPROXIMATOR', for cases such as:

(12) a. We have about 3 eggs left.
    b. We have around 3 eggs left.
    c. We have in the vicinity of 3 eggs left.
    d. We have over 3 eggs left.
    e. We have between 3 and 6 eggs left.

Reference sources take several different approaches to such expressions. Dictionaries disagree as to whether these senses of about and around should be considered prepositions or adverbs. Pullum and Huddleston (2002, p. 646) distinguish the syntactic behavior of over in “She wrote [over fifty] novels” vs. “I spent [over a year] here.”
Whatever the syntactic evidence, semantically these are all similar: they take a measurement, quantity, or range as an argument and “transform” it in some way into a new measurement, quantity, or range. Prepositional expressions under, more than, less than, greater than, fewer than, at least, and at most fit into this category as well. Note that these can all be paraphrased with mathematical operators: \( \approx \leq \geq \).

APPROXIMATOR is a subtype of VALUECOMPARISON in the hierarchy. It applies regardless of the semantic type of the thing measured (whether it is a spatial extent, temporal duration, monetary value, ordinal count, etc.). Thus APPROXIMATOR also applies to the highlighted prepositions in:

(13)  
- a. It took about/over 1 year.
- b. It took about/over a year.
- c. We swam about half a lap. (no explicit marker of EXTENT)
- d. We swam for about a lap. (for marks EXTENT)
- e. I outpaced him by over a mile.
- f. We ate in under 5 minutes.
- g. I was there for over a year.
- h. I heard from over a mile away.

We are only annotating preposition expressions, so words that are morphologically more like adverbs—nearly, roughly, approximately—are not included though they may bear the same semantics.

It should be noted that several spatiotemporal prepositions involve a semantics of imprecision. APPROXIMATOR is not intended to cover all imprecise preposition senses. As a test, we check which of near and nearly can be substituted:

(14)  
- a. He lives somewhere around/by/near/*nearly where I used to live.: LOCATION
- b. He left around/by/near/*nearly midnight.: TIME
- c. He left at around/*by/*near/nearly midnight.: APPROXIMATOR

5.4.5 Paths

Extensive discussion has gone into developing a section of the hierarchy for paths, which were not accounted for to our satisfaction in any of the existing schemes. Our analysis draws upon prior and concomitant studies of caused motion constructions in the context of improving their treatment in VerbNet. Those studies address the basic scenarios of CHANGE OF LOCATION, CHANGE OF STATE, TRANSFER OF POSSESSION, TRANSFER OF INFORMATION, and CHANGE IN VALUE ON A SCALE with regard to their syntactic and semantic argument structures (Hwang et al., 2014; Hwang, 2014, ch. 5). A proposed subhierarchy for paths—closely related to the approach adopted...
for VerbNet, but in some respects more detailed—is shown in figure 5.5. Taking PATH to be the intermediate part of literal or abstract/metaphoric motion, we distinguish the following subtypes:

- **Traversed**: A stretch of physical space that the figure inhabits during the middle of motion (not necessarily where the event as a whole is located, which be marked with a simple LOCATION preposition). This category is a subtype of LOCATION as it describes the "where" of the intermediate phase of motion. It is further refined into:
  - **1D Trajectory**: A one-dimensional region of space that is traversed, such as by following a path or passing a landmark. Examples: I walked along the river, over the bridge, and past the castle
  - **2D Area**: The two-dimensional region of space that is "covered", though there is less of a notion of completeness than with a one-dimensional trajectory. Examples: I walked about/through/around the room
  - **3D Medium**: Volumetric material that the figure moves through, and which may exert a facilitatory or opposing force on the figure. Examples: I waded through the swamp; the fish swim with the current

It is expected to be rare that an event will have phrases expressing more than one of these dimension-specific subclasses.

19 Our notion of path does not include the endpoints, which are captured by INITIAL LOCATION and DESTINATION in the motion domain, START STATE and END STATE for changes of state, and SOURCE and GOAL in more abstract domains.

20 Figure is a term for an entity that moves or is spatially situated with respect to another entity, the ground. Alternate terms in the literature are trajector and landmark, respectively. See (Evans and Green, 2006).

- **Direction**: This covers prepositions marking how the motion of the figure, or the figure itself, is aimed/oriented. This category contrasts with DESTINATION, where the preposition expressly indicates an intended endpoint of motion. Examples: walk toward the door, kick at the wall, toss the ball up, Step away from the cookie jar.

- **Contour**: This describes the shape, but not the location, of a path; it is also a kind of MANNER. Examples: walk in a zigzag

- **Extent**: Also a subtype of VALUE, this is the size of a path: the physical distance traversed or the amount of change on a scale. Examples: ran for miles, the price shot up by 10%

- **Via**: Prepositions in this category mark something that is used for translocation, transfer, or communication between two points/parties. It is a subtype of PATH because it pertains to the intermediate phase of (literal or figurative) motion, and also a subtype of INSTRUMENT because it is something used in order to facilitate that motion. S&R used the label VIA for the spatial domain and MEDIUM OF COMMUNICATION for communication devices; we instead use the VIA supersense directly for cases that are not physical motion, e.g.: talk by phone, talk on/over the phone, make an appearance on TV; order by credit card via/on the Internet; I got the word out via a friend. Enablers expressed metaphorically as paths, e.g. Hackers accessed the system via a security hole, are included as well. There are two subcases:

21 Communication is systematically framed as transfer of ideas; this is known as the conduit metaphor (Reddy, 1979).
– **Transit**: The vehicle/mode of conveyance that facilitates physical motion traversing a path. It is also a subtype of **Location** because it specifies where the figure was during the motion. The category helps distinguish the concrete cases of **Via** from non-concrete cases. Examples: *I went to Paris by plane*

– **Course**: The roadway, route, or stopping point on a route that facilitates physical motion traversing a path. It is also a subtype of **1DTrajectory** because it specifies a one-dimensional path for the figure's motion. The category, along with **Transit**, helps distinguish the concrete cases of **Via** from non-concrete cases. Examples: *I went to Paris via London; drive via back roads; connected via Mediterranean shipping routes; sent a letter by snail mail*

A heuristic for **Via** and its subtypes **Transit** and **Course** is the ability to construct a paraphrase with the word *via*.

### 5.4.5.1 Fictive Motion

There are spatial usages of certain prepositions that portray static scenes as motion: these fall under the term **fictive motion** (Talmy, 1996). Our conventions are as follows:

- With a figure whose shape/spatial extent is being described with respect to a landmark:
  - **1DTrajectory** for the extent of a one-dimensional shape: *a cable runs above the duct; the bridge [that goes] across the river; cars were parked along the grass verge; the tear runs all the way down my pants; the sun was streaming in through the window; etc.*
  - **2DArea** for the extent of a two-dimensional shape: *She wore her dark hair in plaits about her head*
  - **InitialLocation** for the “starting point”: *There is a lovely road which runs from Ixopo into the hills; single wires leading off the main lines*
  - **Destination** for the “ending point”: *There is a lovely road which runs from Ixopo into the hills; every driveway to the castle was crowded*

- For the spatial orientation of a figure: **Direction**: *the gun was aimed at his head; they faced away from each other*

- Suggesting the spatial path that may be traversed to access a place starting from a reference point (such as the speaker’s location): **Location**: *in a little street off Whitehall; He must have parked around the front of the motel; the ambush occurred 50 metres from a checkpoint; they lived across the street from one another; the auditorium is through a set of double doors; he lives a dozen miles or so down the Thames; over the hill is a small village*

- For a physical path of perception (line of sight, hearing, etc.): **1DTrajectory**: *Lily peeped around the open curtain; he looked across at me; glance over her shoulder*

- For a perspective in perception or communication: **Location**: *I can see Russia from my house; views over Hyde Park; she rang him at home from her hotel*

\[22\]Note that the spatial extent trajectories can be used with verbs like goes and runs.
5.4.6 Manner and Means

In our supersense hierarchy, we place MANNER as a parent of INSTRUMENT (see figure 5.5). We also propose to distinguish MEANS for prepositions that mark an action that facilitates a goal (S&R include these under INSTRUMENT). We define MEANS as a subtype of both INSTRUMENT and ACTIVITY. Contrast:

(15) a. He broke up the anthill with enthusiasm.: MANNER
   b. He broke up the anthill with a stick.: INSTRUMENT
   c. He broke up the anthill by hitting it with a stick.: MEANS

(16) a. We coordinated over Skype.: VIA
   b. We coordinated by setting up a Skype call.: MEANS

(17) a. The system was compromised by hackers via a security hole.: VIA
   b. The system was compromised through an exploitation of the security hole by hackers.: MEANS

(18) a. I drove in a zigzag to avoid the traffic.: CONTOUR
   b. I avoided the traffic by driving in a zigzag.: MEANS

In general, the MANNER category is for prepositions that mark the "how" of an event. For all of the above examples, the PP would be a valid answer to a "how" question (How did we coordinate? Over Skype. How did you drive? In a zigzag).

5.4.7 Communication

Communication is a frequent and important domain in many genres of text, and English systematically invokes language of motion and transfer to describe communication (Reddy, 1979). S&R includes a specific MEDIUM OF COMMUNICATION category, but its boundaries are not entirely clear. Similarly, AMR incorporates a MEDIUM role, though this conflates communicative mediums with what we have called 3D MEDIUM above. In the previous section, we have proposed using VIA in a way that includes instruments of communication but is slightly more general.

There are also cases where the preposition marks an entity involved in communication, but that entity is not really framed as an intermediary between two parties:

(19) a. I got the scoop from a friend/the Internet. (source of information)
   b. I uploaded the cat picture to icanhascheezburger.com. (abstract destination of abstract information)
   c. I put the file on your computer. (concrete destination of abstract information)
   d. I put it down on paper. (destination of concretely encoded information)
   e. The answer is somewhere in this book/room. (location of concretely encoded information)
   f. The rumor spread around the school. (information metaphorically covering an area metonymically associated with a group of people)

While it would be potentially useful to know that all of these involve communication, we want to avoid creating a proliferation of communication-specific categories where our current abstract categories—LOCUS, SOURCE, GOAL—would suffice. The same goes for communication with a concrete component, such as writ-
ing, where we can use LOCATION', INITIALLOCATION', DESTINATION', etc. Moreover, both nouns and verbs have a COMMUNICATION supersense, which should be enough to identify an associated preposition as functioning in the communication domain. Therefore, we will refrain from including any communication-specific preposition supersenses, though some (such as non-motion Via') will be primarily communication-oriented in practice.

A related set of cases involve a language or code of communication:

(20) a. “Shampooing” means "shampoo" in French.
b. I am writing a book in French.
c. I translated the book from English to French.

Again, rather than applying a communication-specific role, we can exploit existing categories: ATTRIBUTE', STARTSTATE', and ENDSATE'.

5.4.8 Part-Whole and Set-Element Relations

S&R's PARTWOLE category is broadly defined to include prepositions whose object is a whole or containing set relative to another entity, as well as for of in construction with a partitive, collective, or measure word.25 We decided that it would be more straightforward to designate three distinct categories: WHOLE', SUPERSET', and PARTITIVE'. SUPERSET' is a subtype of WHOLE'.

Part-whole and set-element relations can also occur in reverse order: e.g., the shower of the bath vs. the bath with a shower. We do not create a special label for parts because the object can usually be interpreted as an attribute, such that it would be difficult to develop distinguishing criteria for the ATTRIBUTE' category. But we create ELEMENTS' for cases where the object of the preposition exemplifies a set (used with like/ such as/ including) or notes items excluded from it (except (for)/excluding).

5.4.9 States

S&R has categories STARTSTATE and ENDSATE for changes of state, but no label for states in general. We create STATE' as a supertype of STARTSTATE' and ENDSATE', which accommodates usages such as in love (moved from S&R MANNER), on morphine (moved from OTHER), and off work (moved from SEPARATION). In general, STATE* prepositions can be paraphrased as “in a state of” or “in a state induced by”: in love → in a state of love, on morphine → in a state induced by morphine, etc.

5.4.10 Accompaniment vs. Joint Participation

The preposition with is frustratingly promiscuous. It often marks an entity that is associated with a main entity or event; what is frustrating is that the nature of the association seems to lie on a continuum from physical copresence to active counterpart in an event.26

(21) a. Tim prefers [tea with crumpets].
b. Tim sat with his computer.
c. Tim walked with Lori.
d. Tim had dinner with Lori.
e. Tim talked to Lori.
f. Tim talked with Lori.

25For some of these the first noun can be thought of as “light” or “transparent” in designating a familiar unit of some material; the object of the preposition is not necessarily a “whole” at all—e.g., a loaf of bread.

26We exclude cases like Tim walked in with [his hat on], where with serves as a subordinator of a verbless clause. See §5.3.1.2.
g. Tim argued with Lori.
h. Tim fought with Lori.
i. Tim fought against Lori.
j. Tim fought against/with the idea.

S&R provides two relevant categories: PARTICIPANT/ACCOMPANIER and OPPONENT/CONTRAST. The former includes cases of physical copresence (as well as attachment, for onto); the latter includes several senses of against and TPP sense 6(4) of with, defined as “in opposition to.” But neither S&R nor TPP (on which it is based) provides an obvious home for the (quite frequent) use of with as in talk with Lori, which implies that Lori is engaged in a conversation (viz.: #I talked with Lori, but she didn’t say anything).27

VerbNet does not provide a role for physical copresence, which would be considered non-core. On the other hand, it has roles CO-AGENT, CO-THEME, and CO-PATIENT for “events with symmetrical participants”: CO-AGENT is defined as “Agent who is acting in coordination or reciprocally with another agent while participating in the same event” (VerbNet Annotation Guidelines, p. 20), and applies for talk to/with someone (the talk-37.5 class) and fight with/against someone (meet-36.3-2). However, VerbNet has no entry mapped to the WordNet sense of fight where the enemy can be an idea occurring as the direct object or marked with against (“The senator said he would oppose the bill”—oppose is in the same synset as sense 2 of fight).

Thus, the S&R’s OPPONENT/CONTRAST category emphasizes the commonalities between argue with, fight with, and fight against, while ignoring the similarity between talk with and argue with;

VerbNet instead groups those together under CO-AGENT when the second party is a person, but would likely distinguish fighting against a person from fighting against an idea.28 On balance, something closer to VerbNet’s strategy is probably preferable for compatibility with existing parts of the hierarchy.

We therefore propose:

- **CO-AGENT**, CO-PATIENT, and CO-THEME, following VerbNet, where both participants are engaged in the same event in the same basic capacity, as in (21e–21l);

- **THEME** for (21j), where the thing being fought is not fighting back; and

- **ACCOMPANIER** for (21a–21d), where the two participants are physically colocated or performing the same action in separate (but possibly inferentially related) events. The inclusion of together seems more natural for these: Tim walked/talked together with Lori.

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27There seems to be a reading of talk to where the talking is unidirectional—I talked to Lori, but she didn’t say anything—is acceptable—but the more common case is probably no different from talk with. Note that speak to/with is similar, but tell/say to/*with are strictly unidirectional.

28This is an interesting case where there are seemingly two dimensions of meaning captured in the prepositions, and the previous schemes encode different ones in their categorizations. VerbNet encodes thematic roles relating the object of the preposition to an event, whereas S&R’s OPPONENT/CONTRAST is reminiscent of an image schema (Johnson, 1977) in the parlance of cognitive linguistics, and also falls within the scope of Talmy’s (1988) force dynamics. That is, the “opponent” part of OPPONENT/CONTRAST can be understood as schematically encoding situations where two forces come into opposition, whatever their roles (agent, cause, theme, …) in the event framing that opposition. The notion of “attachment” covered by PARTICI-
PANT/ACCOMPANIER is another example of an image schema. For in-depth analyses of prepositions and spatial and causal categories in cognitive linguistics, see Brugman (1981); Lakoff (1987, pp. 416–461); Tyler and Evans (2003); Lindstromberg (2010); Croft (2012); and the survey in Evans and Green (2006, ch. 10).
5.4.11 Abandoned or Modified S&R Categories

We list the examples from Srikumar and Roth (2013a) for the categories that have been removed or undergone major restructuring in our supersense hierarchy:

**Direction** has been narrowed due to the creation of other **Path** subcategories (§5.4.5).

- driving **along** the road → **1DTrajectory**
- drive **by** the house → **1DTrajectory**
- tears streaming **down** her face → **1DTrajectory**
- wander **down** the road → **1DTrajectory**
- roll **off** the bed → **InitialLocation**
- swim **with** the current → **3DMedium**

**Experiencer** in S&R has a different meaning than the category by the same name in VerbNet. We therefore remove it.

- focus attention **on** her → **Goal**
- he blamed it **on** her → **Beneficiary**
- he was warm **toward** her → **Beneficiary**
- felt angry **towards** him → **Stimulus**

**Manner** has been narrowed due to new categories:

- to be **in** love → **State**
- a woman **in** her thirties → **Age**
- planets move **in** ellipses around the sun → **Contour**
- plummet **like** a dive-bomber → **Comparison/Contrast**
- obtained **through** fraudulent means → **Means**
- freedom of expression **through** words → **Via**

**Instrument** has been narrowed due to new categories including **Means**.

- provide capital **by** borrowing → **Means**
- banged his head **on** the beam → **Location**
- voice **over** the loudspeaker → **Via**
- heard **through** the grapevine → **Via**
- fill the bowl **with** water → **Theme**

**MediumOfCommunication** has been removed in favor of more abstract categories such as **Via** and **Attribute** (§5.4.5).

- say it **in** French → **Attribute**
- put your idea down **on** paper → **Destination**
- saw the new series **on** TV → **Via**

**Numeric** has been largely renamed to **Value**, per VerbNet, and reinterpreted as described in §5.4.4. Some senses are reassigned to **Extent** or the new **Temporal** subcategories as appropriate.

- driving **at** 50mph → **Frequency**
- missed the shot **by** miles → **Extent**
- crawled for 300 yards → **Extent**
- a boy of 15 → **Age**

**ObjectOfVerb** was awkwardly defined and has been removed; other categories (or MWEs) should accommodate its senses.

- inquired **after** him → **inquire after** as MWE
- chase **after** something → **chase after** (and **go after**) as MWE, following WordNet
- sipped **at** his coffee → **Direction**
- considerations **for** the future → **Topic**, following FrameNet
• saved from death → Activity'
• the wedding of his daughter → Agent'
• it was kind of you → Possessor'
• she tells of her marriage → Topic'
• presided over the meeting → preside over as MWE
• scan through document → 2DArea'
• a grant towards the cost → Purpose'
• a threat to world peace → Theme'
• cross with her → Stimulus'

Opponent/Contrast is removed in favor of VerbNet-inspired categories Co-Agent', Theme', Co-Theme', etc.; see §5.4.10.

• fight against crime → Theme'
• gave evidence against him → Beneficiary' (maleficiary)
• the match against Somerset → Co-Agent'
• fought with another man → Co-Agent'
• the wars between Russia and Poland → Agent'
• fees are distinct from expenses → Separation'
• turned up his collar against the wind → Direction'

Other is retained for truly miscellaneous senses, such as:

• drinks are on me (responsibility—cf. (7e))

However, we note that many of the original examples can be relocated to another category or solved by treating the preposition as part of an MWE:

• at a level above the people, married above her, the director is over him, he was rather beneath the princess → Scalar/Rank'
• health comes after housing, placed duty before everything → Scalar/Rank'

• heard above the din → Stimulus'
• felt clumsy beside [=compared to] her → Comparison/Contrast'
• a drawing after Millet’s The Reapers, named her Pauline after her mother → Comparison/Contrast'
• married for over a year → Approximator'
• he is on morphine → State'
• he smiled to her astonishment → EndState'
• leave it with me → Location'
• swap for that → Co-Theme'
• ‘F’ is for fascinating → Function'
• tall for her age → Scalar/Rank'
• works like [=such as] Animal Farm → Contents'
• picked up tips along the way → along the way as MWE marking Path'
• swear by God → swear by as MWE

Participant/Companion seemed to conflate attachment, co-presence, and co-participation; the new Companion category has a narrower meaning (see §5.4.10).

• a nice steak with a bottle of red wine → Companion'
• his marriage with Emma → Companion'
• he is married to Emma → married to (and wedded to) as MWEs
• he pinned the map to the wall → Co-Patient'
• a map pinned to the wall → Location'
• stick the drawings onto a large map → Destination'

Co-Participants has been removed.

• drop in tooth decay among children → Locus'
• divide his kingdom among them → Recipient'
• links between science and industry → Co-Theme'
• the difference between income and expenditure → COMPARISON/CONTRAST
• choose between two options → COMPARISON/CONTRAST

PARTWHOLE has been removed in favor of the narrower categories WHOLE', SUPERSET', and PARTITIVE' (§5.4.8).

• sleeve of the coat → WHOLE'
• see a friend among them → SUPERSET'
• a slice of cake → PARTITIVE'
• cup of soup → PARTITIVE'

PHYSICALSUPPORT has been removed in favor of LOCATION' on the grounds that it is too narrow.

• stood with her back against the wall → LOCATION'
• a water jug on the table → LOCATION'

SEPARATION has been removed.

• the party was ousted from power → STARTSTATE'
• tear the door off its hinges → INITIALLOCATION'
• burden off my shoulders → STARTSTATE'
• I stay off alcohol → STATE'
• part with possessions → part with as MWE

SOURCE has been narrowed slightly due to INITIALLOCATION'.

• I am from Hackeney → INITIALLOCATION'

VIA has been made more abstract; the new subcategories TRANSIT' and COURSE' cover most previous VIA cases (§5.4.5).

• traveling by bus → TRANSIT'
• he is on his way → COURSE'
• sleep on the plane → LOCATION' (the plane does not represent a path of sleeping)
• got on the train → DESTINATION'
• go through the tube → 1DTRAJECTORY'

5.5 Conclusion

English prepositions are a challenging class, given that there are so many of them and they are put to so many uses. As Orin Hargraves put it to me: “They are without a doubt the most chameleonlike of all parts of speech.” In the interest of uncovering the chameleon’s palette, we have built on prior work to propose a new hierarchical taxonomy of preposition supersenses, so that (like nouns and verbs) their semantics can be modeled in a coarse WSD framework. The taxonomy will hopefully port well to adpositions and case markers in other languages, though we have not investigated that yet. Our annotation scheme is, to our knowledge, the first to engage deeply with multiword expressions, and intends to capture a broader selection of preposition types than the most similar previous approach (Srikanmar and Roth, 2013a). Having piloted preposition annotations for sentences in the REVIEWS corpus, the next step will be full-fledged annotation.
Part II

Automation
To curry favor, favor curry.

—P.D.Q. Bach, *The Seasonings*

Q. What about “yore?”
A. That refers to “the days of yore,” when there was a lot of yore lying around, as a result of pigs.

—Dave Barry, “Mr. Language Person on nitches, yores and defective sea lions” (Dec. 5, 1999)

**CHAPTER 6**

**Multiword Expression Identification**

Ch. 3 introduced a representation, annotation scheme, and comprehensive corpus of MWEs. This chapter:

- Shows how lexical semantic segmentations (allowing for gaps and a strength distinction) can be encoded with word-level tags
- Describes a supervised model of MWE identification
- Introduces an evaluation measure for the MWE identification task
- Analyzes the model’s performance on held-out data from our corpus, and on a corpus in another domain
- Measures the impact of features that use external resources (lexicons, clusters)
- Compares against a simpler baseline consisting of heuristic lexicon lookup
6.1 Introduction

Ch. 3 presented our comprehensive annotation approach for MWEs: unlike most existing MWE corpora, it neither targets specific varieties of MWEs nor relies upon any preexisting lexical resource. The annotations are shallow, not relying explicitly on syntax (though in principle they could be mapped onto the parses in the Web Treebank). In this chapter we use that corpus (version 1.0) to train and evaluate statistical MWE identification models. This reprises work that appeared as Schneider et al. (2014a). Additionally, we conduct an out-of-domain evaluation on the WIKI50 corpus (Vincze et al., 2011), which was likewise annotated for named entities and several kinds of idiomatic MWEs.

6.2 Evaluation

6.2.1 Matching Criteria

Given that most tokens do not belong to an MWE, to evaluate MWE identification we adopt a precision/recall-based measure similar to one in the coreference resolution literature. The MUC criterion (Vilain et al., 1995) measures precision and recall of links in terms of groups (units) implied by the transitive closure over those links.1 Our measure can be defined as follows.

Let \( a \rightarrow b \) denote a link (undirected) between two elements in the gold standard, and let \( a \leftarrow b \) denote a link in the system prediction. Let the * operator denote the transitive closure over all links, such that \([a \rightarrow b]\) is 1 if \( a \) and \( b \) belong to the same (gold) set, and 0 otherwise. Assuming there are no redundant2 links within any annotation (which in our case is guaranteed by linking consecutive words in each MWE), we approximate the MUC precision and recall

---

1As a criterion for coreference resolution, the MUC measure has perceived shortcomings which have prompted several other measures (see Recasens and Hovy, 2011 for a review). It is not clear, however, whether any of these criticisms are relevant to MWE identification.

2A link between \( a \) and \( b \) is redundant if the other links already imply that \( a \) and \( b \) belong to the same set. A set of \( N \) elements is expressed non-redundantly with exactly \( N-1 \) links.
We combine precision and recall using the standard which all weak links have been converted to strong links, and want to penalize weak-link-vs.-no-link and weak-link-vs.-strong-links constitute an MWE in the prediction, forming a cluster. This awards partial credit when predicted and gold expressions overlap in part. Requiring full MWEs to match exactly would arguably be too stringent, overpenalizing larger MWEs for minor disagreements.

We combine precision and recall using the standard \( F_1 \) measure of their harmonic mean. This is the link-based evaluation used for most of our experiments. Figure 6.1 presents a worked example. For comparison, we also report some results with a more stringent exact match evaluation where the span of the predicted MWE must be identical to the span of the gold MWE for it to count as correct.

### 6.2.2 Strength Averaging

Recall that the 2-level scheme (§3.5.1) distinguishes strong vs. weak links/groups, where the latter category applies to reasonably compositional collocations as well as ambiguous or difficult cases. We want to penalize weak-link-vs.-no-link and weak-link-vs.-strong-link disagreements less than strong-link-vs.-no-link disagreements.

To accommodate the 2-level scheme, we therefore average \( F_1^s \), in which all weak links have been converted to strong links, and \( F_1^p \), in which they have been removed: \( F_1 = \frac{1}{2}(F_1^p + F_1^s) \).

### 6.3 Tagging Schemes

Following (Ramshaw and Marcus, 1995), shallow analysis is often modeled as a sequence-chunking task, with tags containing chunk-positional information. The BIO scheme and variants (e.g., BILOU; 4} Overall precision and recall are likewise computed by averaging “strengthened” and “weakened” measurements.\footnote{4}
No gaps, 1-level (3 tags). This is the standard contiguous chunking representation from Ramshaw and Marcus (1995) using the tags \{OBI\} (introduced in §2.4.2 above). O is for tokens outside any chunk; B marks tokens beginning a chunk; and I marks other tokens inside a chunk. Multiword chunks will thus start with B and then I. B must always be followed by I; I is not allowed at the beginning of the sentence or following O.

No gaps, 2-level (4 tags). We can distinguish strength levels by splitting I into two tags: \(\bar{I}\) for strong expressions and \(\tilde{I}\) for weak expressions. To express strong and weak contiguous chunks requires 4 tags: \{OBI\}. (Marking B with a strength as well would be redundant because MWEs are never length-one chunks.) The constraints on \(\bar{I}\) and \(\tilde{I}\) are the same as the constraints on I in previous schemes. If \(\bar{I}\) and \(\tilde{I}\) occur next to each other, the strong attachment will receive higher precedence, resulting in analysis of strong MWEs as nested within weak MWEs.

Gappy, 1-level (6 tags). Because gaps cannot themselves contain gappy expressions (we do not support full recursivity), a finite number of additional tags are sufficient to encode gappy chunks. We therefore add lowercase tag variants representing tokens within a gap: \{OoBbIi\}. In addition to the constraints stated above, no within-gap tag may occur at the beginning or end of the sentence or immediately following or preceding O. Within a gap, b, i, and o behave like their out-of-gap counterparts.

Gappy, 2-level (8 tags). 8 tags are required to encode the 2-level scheme with gaps: \{OoBbIi\}. Variants of the inside tag are marked for strength of the incoming link—this applies gap-externally (capitalized tags) and gap-internally (lowercase tags). If \(\bar{I}\) or \(\tilde{I}\) immediately follows a gap, its diacritic reflects the strength of the gappy expression, not the gap’s contents.

6.4 Model

With the above representations we model MWE identification as sequence tagging, one of the paradigms that has been used previously for identifying contiguous MWEs (Constant and Sigogne, 2011, see §6.6). Constraints on legal tag bigrams are sufficient to ensure the full tagging is well-formed subject to the regular expressions in figure 6.2; we enforce these constraints in our experiments. For learning we use the framework of the cost-augmented structured
perceptron, reviewed in §2.4.3 and §2.4.4. Below we detail our cost function, features, and experimental setup.

6.4.1 Cost Function

To better align the learning algorithm with our \( F \)-score–based MWE evaluation (§6.2), we use a cost-augmented version of the structured perceptron that is sensitive to different kinds of errors during training (§2.4.4). When recall is the bigger obstacle, we can adopt the following cost function: given a sentence \( x \), its gold tagging \( y^* \), and a candidate tagging \( y' \),

\[
\text{cost}(y^*, y', x) = \sum_{j=1}^{\vert y^* \vert} c(y^*_j, y'_j) \quad \text{where}
\]

\[
c(y^*_j, y'_j) = \begin{cases} 1 & y^*_j \neq y'_j \\ 0 & \end{cases}
\]

A single nonnegative hyperparameter, \( \rho \), controls the tradeoff between recall and accuracy; higher \( \rho \) biases the model in favor of recall (possibly hurting accuracy and precision). This is a slight variant of the recall-oriented cost function of Mohit et al. (2012). The difference is that we only penalize \textit{beginning-of-expression} recall errors. Preliminary experiments showed that a cost function penalizing all recall errors—i.e., with \( \rho [y^* \neq o \land y' = o] \) as the second term, as in Mohit et al.—tended to append additional tokens to high-confidence MWEs (such as proper names) rather than encourage new MWEs, which would require positing at least two new non-outside tags.

6.4.2 Features

6.4.2.1 Basic Features

These are largely based on the sequence model features of Constant and Sigogne (2011); Constant et al. (2012): they look at word unigrams and bigrams, character prefixes and suffixes, and POS tags, as well as lexicon entries that match lemmas\(^7\) of multiple words in the sentence.\(^8\)

Some of the basic features make use of \textit{lexicons}. We use or construct 10 lists of English MWEs: all multiword entries in \textit{WordNet} (Fellbaum, 1998); all multiword chunks in \textit{SEMCor} (Miller et al., 1993); all multiword entries in English \textit{Wiktionary};\(^9\) the \textit{WikiMwe} dataset mined from English Wikipedia (Hartmann et al., 2012); the \textit{SAID} database of phrasal lexical idioms (Kuiper et al., 2003); the named entities and other MWEs in the WSJ corpus on the English side of the \textit{PCEDT} (Hajič et al., 2012); the \textit{verb-particle constructions} (VPCs) dataset of Baldwin (2008); a list of \textit{light verb constructions} (LVCs) provided by Claire Bonial; and two idioms websites.\(^{10}\)

After preprocessing, each lexical entry consists of an ordered sequence of word lemmas, some of which may be variables like \texttt{<something>}. Given a sentence and one or more of the lexicons, lookup for the lexicon features proceeds as follows: we enumerate entries whose lemma sequences match a sequence of lemmatized tokens, and

\(^7\)The WordNet API in NLTK (Bird et al., 2009) was used for lemmatization.

\(^8\)Our MWE system, like the sequence model (but unlike the reranking model) of Constant et al. (2012), does not include any features derived from the output of a syntactic parser, as explained in §6.1.3.

\(^9\)http://en.wiktionary.org; data obtained from https://toolserver.org/~enwikt/definitions/enwikt-defs-20130814-en.tsv.gz

\(^{10}\)http://www.phrases.net/ and http://home.postech.ac.kr/~oyz/doc/idiom.html
build a lattice of possible analyses over the sentence. We find the shortest path (i.e., using as few expressions as possible) with dynamic programming, allowing gaps of up to length 2.\textsuperscript{11}

In detail, the basic features are:

<table>
<thead>
<tr>
<th>All are conjoined with the current tag, $y_i$.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tag Features</strong></td>
</tr>
<tr>
<td>1. previous tag (the only first-order feature)</td>
</tr>
<tr>
<td><strong>Token Features</strong></td>
</tr>
<tr>
<td>2. $i = {1, 2}$</td>
</tr>
<tr>
<td>3. $i =</td>
</tr>
<tr>
<td>4. capitalized $\land [i = 0]$</td>
</tr>
<tr>
<td>5. word shape $\land$ Lowercased token</td>
</tr>
<tr>
<td>6. prefix: $[w_i]_{j=1}^{i+1} \land</td>
</tr>
<tr>
<td>7. suffix: $[w_i]_{j=1}^{i+1} \land</td>
</tr>
<tr>
<td>8. has digit $\land$ has non-alphanumeric c</td>
</tr>
<tr>
<td>9. context word: $w_i^{j+2}$</td>
</tr>
<tr>
<td>10. context word bigram: $w_i^{j+1}$</td>
</tr>
<tr>
<td><strong>Lemma Features</strong></td>
</tr>
<tr>
<td>12. lemma + context lemma if one of them is a verb and the other is a noun, verb, adjective, adverb, preposition, or particle: $\lambda_j \land \lambda_j$</td>
</tr>
</tbody>
</table>

\textsuperscript{11}Each top-level lexical expression (single- or multiword) incurs a cost of 1; each expression within a gap has cost 1.25.

| Part-of-speech Features |
| 13. context POS: $pos_j^{|j+2}$ |
| 14. context POS bigram: $pos_j^{i+1\mid j+1}$ |
| 15. word + context POS: $w_i \land pos_{i+1}$ |
| 16. context word + POS: $w_{i+1} \land pos_i$ |

| Lexicon Features (unlexicalized) |
| 17. OOV: $\lambda_i$ is not in WordNet as a unigram lemma $\land pos_i$ |
| 18. compound: non-punctuation lemma $\lambda_i$ and the [previous, next] lemma in the sentence (if it is non-punctuation; an intervening hyphen is allowed) form an entry in WordNet, possibly separated by a hyphen or space $\land$ pos $i$ |
| 19. compound-hyphen: $pos_{j+1} = HYPH$ previous and next tokens form an entry in WordNet, possibly separated by a hyphen or space |
| 20. ambiguity class: if content word unigram $\lambda_j$ is in WordNet, the set of POS categories it can belong to; else pos $i$ if not a content POS $\land$ the POS of the longest MW match to which $\lambda_j$ belongs (if any) $\land$ the position in that match (B or I) $\land$ pos $i$ |

For each multiword lexicon

| 21. lexicon name $\land$ status of token $i$ in the shortest path segmentation (O, B, or I) $\land$ subcategory of lexical entry whose match includes token $i$, if matched $\land$ whether the match is gappy $\land$ POS tags of the first and last matched tokens in the expression |

Over all multiword lexicons

| 22. at least $k$ lexicons contain a match that includes this token (if $n \geq 1$ matches, $n$ active features) |
| 23. at least $k$ lexicons contain a match that includes this token, starts with a given POS, and ends with a given POS |

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6.4.2.2 Unsupervised Word Clusters

Distributional clustering on large (unlabeled) corpora can produce lexical generalizations that are useful for syntactic and semantic analysis tasks (e.g.: Miller et al., 2004; Koo et al., 2008; Turian et al., 2010; Owoputi et al., 2013; Grave et al., 2013). We were interested to see whether a similar pattern would hold for MWE identification, given that MWEs are concerned with what is lexically idiosyncratic—i.e., backing off from specific lexemes to word classes may lose the MWE-relevant information. Brown clustering\(^ {12}\) (Brown et al., 1992) on the 21-million-word Yelp Academic Dataset\(^ {13}\) (which is similar in genre to the annotated web reviews data) gives us a hard clustering of word types. To our tagger, we add features mapping the previous, current, and next token to Brown cluster IDs. The feature for the current token conjoins the word lemma with the cluster ID.

6.4.2.3 Part-of-Speech Tags

We compared three PTB-style POS taggers on the full REVIEWS subcorpus (train+test). The Stanford CoreNLP tagger\(^ {14}\) (Toutanova et al., 2003) yields an accuracy of 90.4%. The ARK TweetNLP tagger v. 0.3.2 (Owoputi et al., 2013) achieves 90.1% with the model\(^ {15}\) trained on the Twitter corpus of Ritter et al. (2011), and 94.9% when trained on the ANSWERS, EMAIL, NEWSGROUP, and WEBLOG subcorpora of WTB. We use this third configuration to produce automatic POS tags for training and testing our MWE tagger. (A comparison condition in §6.5.3 uses oracle POS tags.)

\(^{12}\)With Liang’s (2005) implementation: https://github.com/percyliang/brown-cluster. We obtain 1,000 clusters from words appearing at least 25 times.

\(^{13}\)https://www.yelp.com/academic_dataset

\(^{14}\)v. 3.2.0, with the english-bidirectional-distsim model

\(^{15}\)http://www.ark.cs.cmu.edu/TweetNLP/model.ritter.ptb.alldata.fixed.20130723

6.4.3 Experimental Setup

The corpus of web reviews described in §3.8 is used for training and evaluation. 101 arbitrarily chosen documents (500 sentences, 7,171 words) were held out as a final test set. This left 3,312 sentences/48,408 words for training/development (train). Feature engineering and hyperparameter tuning were conducted with 8-fold cross-validation on train. The 8-tag scheme is used except where otherwise noted.

In learning with the structured perceptron (§2.4.3: algorithm 1), we employ two well-known techniques that can both be viewed as regularization. First, we use the average of parameters over all timesteps of learning. Second, within each cross-validation fold, we determine the number of training iterations (epochs) \(M\) by early stopping—that is, after each iteration, we use the model to decode the held-out data, and when that accuracy ceases to improve, use the previous model. The two hyperparameters are the number of iterations and the value of the recall cost hyperparameter (\(\rho\)). Both are tuned via cross-validation on train; we use the multiple of 50 that maximizes average link-based \(F_1\). The chosen values are shown in table 6.3. Experiments were managed with the ducttape tool.\(^ {16}\)

6.5 Results

We experimentally address the following questions to probe and justify our modeling approach.\(^ {17}\)

\(^{16}\)https://github.com/jhclark/ducttape/

\(^{17}\)But first, if our calculations are correct, it has been approximately 800 pages since the last diversion, and is therefore time for a Strategic Jocular MWE-Themed Footnote (SIMMETF) courtesy of Mister Language Person:

Q. Please explain the correct usage of “exact same.”
6.5.1 Is supervised learning necessary?

Previous MWE identification studies have found benefit to statistical learning over heuristic lexicon lookup (Constant and Sigogne, 2011; Green et al., 2012). Our first experiment tests whether this holds for comprehensive MWE identification: it compares our supervised tagging approach with baselines of heuristic lookup on preexisting lexicons. The baselines construct a lattice for each sentence using the same method as lexicon-based model features (§6.4.2). If multiple lexicons are used, the union of their entries is used to construct the lattice. The resulting segmentation—which does not encode a strength distinction—is evaluated against the gold standard.

Results are shown in tables 6.1 and 6.2. Even with just the labeled training set as input, the supervised approach beats the strongest heuristic baseline (that incorporates in-domain lexicon entries extracted from the training data) by 30 precision points, while achieving comparable recall. For example, the baseline (but not the statistical model) incorrectly predicts an MWE in places to eat in Baltimore (because eat in, meaning ‘eat at home,’ is listed in WordNet). The supervised approach has learned not to trust WordNet too much due to this sort of ambiguity. Downstream applications that currently use lexicon matching for MWE identification (e.g., Ghoneim and Diab, 2013) likely stand to benefit from our statistical approach.

<table>
<thead>
<tr>
<th>preexisting lexicons</th>
<th><em>lookup</em></th>
<th>Supervised Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>none</td>
<td>74.39</td>
<td>44.43</td>
</tr>
<tr>
<td>WN + SemCor (71k)</td>
<td>46.15</td>
<td>28.41</td>
</tr>
<tr>
<td>6 lexicons (420k)</td>
<td>35.05</td>
<td>46.76</td>
</tr>
<tr>
<td>10 lexicons (437k)</td>
<td>33.98</td>
<td>47.29</td>
</tr>
</tbody>
</table>

Table 6.1: Use of preexisting lexicons for lookup-based vs. statistical segmentation. Supervised learning used only basic features and the structured perceptron, with the 8-tag scheme. Results are with the link-based matching criterion for evaluation. “6 lexicons” refers to WordNet and SemCor plus SAID, WikiMwe, Phrases.net, and English Wiktionary; “10 lexicons” adds MWEs from CEDT, VNC, LVC, and Oyz. (In these lookup-based configurations, allowing gappy MWEs never helps performance.) All precision, recall, and $F_1$ percentages are averaged across 8 folds of cross-validation on train; standard deviations are shown for the $F_1$ score. The highest overall value in each column is bolded. The boxed row indicates the configuration used as the basis for subsequent experiments.

6.5.2 How best to exploit MWE lexicons (type-level information)?

For statistical tagging (right portion of table 6.1), using more preexisting (out-of-domain) lexicons generally improves recall; precision also improves a bit.

A lexicon of MWEs occurring in the non-held-out training data at least twice \(^{18}\) (table 6.2, bottom row) is marginally worse (better precision/worse recall) than the best result using only preexisting lexicons.

---

| (Dave Barry, *Dave Barry Is Not Making This Up*: “Punctuation ‘R Easy”) |

---

\(^{18}\) If we train with access to the full lexicon of training MWEs, the learner credulously overfits to relying on that lexicon—after all, it has perfect coverage of the training data!—which proves fatal for the model at test time.
**Table 6.2**: Best lookup-based and supervised configurations using an in-domain lexicon. These are cross-validation averages. The in-domain lexicon is derived from MWEs annotated in the training portion of each cross-validation fold at least once (lookup) or twice (model). Results that are superior to analogous configurations without an in-domain lexicon (table 6.1) are bolded. Because the best average $F_1$ score for the supervised model is slightly lower, we do not use the in-domain lexicon in subsequent experiments.

| configuration   | $M$   | $\rho$ | $|\theta|$ | $P$  | $R$  | $F_1$ | $\sigma$ |
|-----------------|-------|--------|------------|-----|-----|-------|---------|
| base model      | 5     | —      | 1.765k     | 69.27 | 50.49 | 58.35 | 60.99 48.27 53.85 |
| + recall cost   | 4     | 150    | 1.765k     | 61.09 | 57.94 | 59.41 | 53.09 55.38 54.17 |
| + clusters      | 3     | 100    | 2,146k     | 63.98 | 55.51 | 59.39 | 56.34 53.24 54.70 |
| + oracle POS    | 4     | 100    | 2,145k     | 66.19 | 59.35 | 62.53 | 58.51 57.00 57.71 |

**Table 6.3**: Comparison of supervised models on test (using the 8-tag scheme). The base model corresponds to the boxed result in table 6.1, but here evaluated on test. For each configuration, the number of training iterations $M$ and (except for the base model) the recall-oriented hyperparameter $\rho$ were tuned by cross-validation on train.

### 6.5.4 What are the highest-weighted features?

An advantage of the linear modeling framework is that we can examine learned feature weights to gain some insight into the model’s behavior.

In general, the highest-weighted features are the lexicon matching features and features indicative of proper names (POS tag of proper noun, capitalized word not at the beginning of the sentence, etc.).

Despite the occasional cluster capturing collocational or idiomatic groupings, as described in the previous section, the clusters appear to be mostly useful for identifying words that tend to belong (or not) to proper names. For example, the cluster with *street*, *road*, *freeway*, *highway*, *airport*, etc., as well as words outside of the cluster vocabulary, weigh in favor of an MWE. A cluster with every-

- **Recall-oriented cost.** The recall-oriented cost adds about 1 link-based $F_1$ point, sacrificing precision in favor of recall.

- **Unsupervised word clusters.** When combined with the recall-oriented cost, these produce a slight improvement to precision/degradation to recall, improving exact match $F_1$ but not affecting link-based $F_1$. Only a few clusters receive high positive weight; one of these consists of *matter*, *joke*, *biggie*, *pun*, *avail*, *clue*, *corkage*, *frills*, *worries*, etc. These words are diverse semantically, but all occur in collocations with *no*, which is what makes the cluster coherent and useful to the MWE model.

- **Oracle part-of-speech tags.** Using human-annotated rather than automatic POS tags improves MWE identification by about 3 $F_1$ points on test (similar differences were observed in development).
day destinations (neighborhood, doctor, hotel, bank, dentist) prefers non-MWEs, presumably because these words are not typically part of proper names in this corpus. This was from the best model using non-oracle POS tags, so the clusters are perhaps useful in correcting for proper nouns that were mistakenly tagged as common nouns. One caveat, though, is that it is hard to discern the impact of these specific features where others may be capturing essentially the same information.

### 6.5.5 How heterogeneous are learned MWEs?

On test, the final model (with automatic POS tags) predicts 365 MWE instances (31 are gappy; 23 are weak). There are 298 unique MWE types.

Organizing the predicted MWEs by their coarse POS sequence reveals that the model is not too prejudiced in the kinds of expressions it recognizes: the 298 types fall under 89 unique POS+strength patterns. Table 6.4 shows the 14 POS sequences predicted 5 or more times as strong MWEs. Some of the examples (major award, a deal, tip on) are false positives, but most are correct. Singleton patterns include PropN Verb (god forbid), Prep Det (at that), Adj Pron (worth it), and Prep Verb Prep (to die for), all of which were matched in at least 2 lexicons.

True positive MWEs mostly consist of (a) named entities, and (b) lexical idioms seen in training and/or listed in one of the lexicons. Occasionally the system correctly guesses an unseen and OOV idiom based on features such as hyphenation (walk-in) and capitalization/OOV words (Chili Relleno, BIG MISTAKE). On test, 244 gold MWE types were unseen in training; the system found 93 true positives (where the type was predicted at least once), 109 false positives, and 151 false negatives—an unseen type recall rate of 38%. Removing types that occurred in lexicons leaves 35 true positives, 61 false positives, and 111 false negatives—a unseen and OOV type recall rate of 24%.

### 6.5.6 What kinds of mismatches occur?

Inspection of the output turns up false positives due to ambiguity (e.g., Spongy and sweet bread); false negatives (top to bottom); and overlap (get high quality service, gold get high quality service; live up to, gold live up to). A number of the mismatches turn out to be problems with the gold standard, like having our water shut off (gold having our water shut off). This suggests that even noisy automatic taggers might help identify annotation inconsistencies and errors for manual correction.
6.5.7 Are gappiness and the strength distinction learned in practice?

Three quarters of MWEs are strong and contain no gaps. To see whether our model is actually sensitive to the phenomena of gappiness and strength, we train on data simplified to remove one or both distinctions—as in the first 3 taggings in figure 6.2—and evaluate against the full 8-tag scheme. For the model with the recall cost, clusters, and oracle POS tags, we evaluate each of these simplifications of the training data in table 6.5. The gold standard for evaluation remains the same across all conditions.

If the model was unable to recover gappy expressions or the strong/weak distinction, we would expect it to do no better when trained with the full tagset than with the simplified tagset. However, there is some loss in performance as the tagset for learning is simplified, which suggests that gappiness and strength are being learned to an extent.

6.5.8 How does the model fare out of domain, and on particular MWE classes?

As detailed in §3.3.2, the Wiki50 corpus similarly annotates sentences of running text for several kinds of MWEs (plus named entities). There are two major differences between Wiki50 and our corpus. First, the domains are different: Wiki50 contains Wikipedia articles written in a scholarly style, whereas our corpus is of online reviews written in a conversational style. We observe that the former tends to contain long sentences (table 3.1) and advanced terminology/jargon, whereas the latter contains short sentences and a great number of colloquialisms. Second, Wiki50 treats a more limited inventory of MWE classes, but explicitly categorizes each annotated instance, which allows us to quantify system recall by MWE class.

Testing our REVIEWS-trained model on the full Wiki50 dataset (the “distilled” version) gives the results in table 6.6. The system’s recall is worst on compounds, light verb constructions, and miscellaneous named entities, likely because these are more frequent in the Wikipedia genre than in web reviews. It is important to note that annotation conventions between the two corpora differed in many subtle ways, so the domain difference does not fully account for the measured differences between the two datasets. A comparison of example predictions vs. the gold standard for selected sentences, figure 6.4, reflects several of the differences in annotation conventions.

6.6 Related Work

In terms of modeling, the use of machine learning classification (Hashimoto and Kawahara, 2008; Shigeto et al., 2013) and specifically BIO sequence tagging (Diab and Bhutada, 2009; Constant and Sigogne, 2011; Constant et al., 2012; Vincze et al., 2013a; Le Roux
Even though H.C.P. Bell did a very careful and thorough research on the Maldivian documents, Prime Minister Ibrahim Nasir’s intention was to have a book on the ancient script of the Maldives written by a Maldivian.

He does, however, have an affair with Clotho, the youngest aspect of Fate.

A few months later, he was served with divorce papers by his new wife.

In 1976, Mixner began the process of coming out of the closet, and soon thereafter was a founding member of the Municipal Elections Committee of Los Angeles (MECLA), the nation’s first gay and lesbian Political Action Committee.

The common feature of all these routine screening procedures is that the primary analysis is for indicator organisms rather than the pathogens that might cause concern.

Edwards picked on nitric oxide synthase inhibition which was also a failure.

Table 6.6: Tag-level recall of the MWE identification model on the full Wiki150 corpus. The denominator is the number of tokens with gold tags other than 0 or o, and the numerator is the number of those tokens that also have a predicted tag other than 0 or o. (No Wiki150 data was used for training. Excludes single-word NEs and sentences of ≥100 words.)

Figure 6.4: Wiki150 gold standard annotations (Vincze et al., 2011; shown with underlining and category labels) versus our model’s predictions (shown by color and underscores).
MWEs, though the sequence model treats the non-adjacent component supertags like other tags—it cannot enforce that they mutually require one another, as we do via the gappy tagging scheme (§3.5.1). Gimpel and Smith's (2011) shallow, gappy language model allows arbitrary token groupings within a sentence, whereas our model imposes projectivity and nesting constraints (§3.5).

There are syntax-based approaches that do seek to identify gappy MWEs. Some MWE-enhanced syntactic parsers (but not others: e.g., Green et al., 2012; Candito and Constant, 2014) allow gaps to be described as constituents (Green et al., 2011) or skipped over by MWE dependency links (Vincze et al., 2013b). Techniques based on lexicon lookup and/or syntactic pattern matching can, in some cases, also match gappy MWEs; heuristic lookup may be followed by a statistical idiomatic vs. literal classification step (e.g., Kim and Baldwin, 2010; Fothergill and Baldwin, 2012) or face a high error rate (e.g., Bejček et al., 2013). Unlike these, our approach does not depend on syntactic parsing (see further discussion in §8.1.3).

Another major thread of research has pursued unsupervised discovery of multiword types from raw corpora, such as with statistical association measures (Church et al., 1991; Pecina, 2010; Ramisch et al., 2012; Brooke et al., 2014, inter alia), parallel corpora (Melamed, 1997; Moirón and Tiedemann, 2006; Tsvetkov and Wintner, 2010), or a combination thereof (Tsvetkov and Wintner, 2011; Pichotta and DeNero, 2013; Salehi et al., 2014—the first of these uses almost no supervision, while the other two involve both unsupervised and supervised steps). This may be followed by a lookup-and-classify approach to contextual identification (Ramisch et al., 2010). Though preliminary experiments with our models did not show benefit to incorporating such automatically constructed lexicons, we hope these two perspectives can be brought together in future work.

6.7 Conclusion

This chapter has presented the first supervised model for identifying broadly heterogeneous multiword expressions in English text. Our feature-rich discriminative sequence tagger performs shallow chunking with a novel scheme that allows for MWEs containing gaps, and includes a strength distinction to separate highly idiomatic expressions from collocations. It is trained and evaluated on a corpus of English web reviews that are comprehensively annotated for multiword expressions. Beyond the training data, its features incorporate evidence from external resources—several lexicons as well as unsupervised word clusters; we show experimentally that this statistical approach is far superior to identifying MWEs by heuristic lexicon lookup alone. In the next chapter, ch. 7, we enhance the lexical representation with semantic tags. Future extensions might integrate additional features (e.g., exploiting statistical association measures computed over large corpora), improve the expressiveness of the model (e.g., with higher-order features and inference), or integrate the model with other tasks (such as parsing and translation).
Four days later saw me standing at the gates of Castle Dracula, weary and travel-stained. Prudence had demanded that I leave her behind, so I was alone. Night was just falling as I knocked… and Count Dracula’s manservant stood before me. Of all the hideously disfigured spectacles I have ever beheld, those perched on the end of this man’s nose remain forever pasted into the album of my memory.


CHAPTER 7

Full Supersense Tagging

*This chapter:*

- Shows that the integrated lexical semantic representation set forth in Part I can be mapped to a tagging-chunking representation
- Trains a statistical model that subsumes the traditional supersense tagging task, but with a broader view of multiword expressions
- Evaluates the impact of features that generalize beyond individual word types
- Examines the model’s ability to cope with supersense-ambiguous nouns and verbs
Having annotated English sentences with lexical semantic analyses consisting of a segmentation component (multiword expressions) and a categorization component (supersense labels), we now turn to automating this task in a single statistical model.

7.1 Background: English Supersense Tagging with a Discriminative Sequence Model

The model of Ciaramita and Altun (2006) represents the state of the art for full\(^1\) English supersense tagging on the standard SemCor test set, achieving an \(F_1\) score of 77%. It is a feature-based discriminative \textit{tagging-chunking} sequence model learned in a supervised fashion with the structured perceptron, as described in §2.4.3, much like the model deployed in ch. 6 for multiword expressions.

For Ciaramita and Altun (2006) and hereafter, sequences correspond to sentences, with each sentence pre-segmented into words according to some tokenization.\(^2\) Figure 7.1 shows how token-level tags combine BIO flags with supersense class labels to represent the segmentation and supersense labeling of a sentence. These tags are observed during training, predicted at test time, and compared against the gold standard tagging of the test data.

Ciaramita and Altun’s (2006) model uses a simple feature set capturing the lemmas, word shapes, and parts of speech of tokens in a small context window, as well as the supersense category of the first WordNet sense of the current word. (WordNet senses are ordered roughly by frequency.) On SemCor data, the model achieves a 10% absolute improvement in \(F_1\) over the first sense baseline.

Though our focus in this chapter is on English, supersense tagging has also been explored in Italian (Picca et al., 2008, 2009; Attardi et al., 2010, 2013; Rossi et al., 2013), Chinese (Qiu et al., 2011), and Arabic (Schneider et al., 2013).

7.2 Piggybacking off of the MWE Tagger

I hope I will not cause any fragile readers to fall off their chairs in surprise by announcing that the methodologies employed and resources created in the foregoing chapters shall be brought to bear on the supersense tagging problem, now somewhat enhanced thanks to a broader and more sophisticated treatment of multiword expressions. The corpus developed in ch. 3 and used to build a lexical semantic segmenter in ch. 6 has since been enriched with semantic class labels for nouns and verbs (ch. 4) to the point that we can build a lexical semantic analyzer in the manner of Ciaramita and Altun (2006). This analyzer has the advantage of being able to represent a more comprehensive assortment of MWEs, including those with gaps, and unlike the classical supersense tagging task is not limited to noun and verb MWEs (though for now, those are the only ones that receive a semantic category label). Despite the fact that many of the annotated expressions in existing supersense datasets contain...
multiple words, the relationship between MWEs and supersenses has not received much attention (though Piao et al. (2003, 2005) investigated MWEs in the context of a lexical tagger employing a finer-grained taxonomy of semantic classes).

7.3 Experiments: MWEs + Noun and Verb Supersenses

The STREUSLE 2.0 dataset, as described in §4.4, is annotated for multiword expressions as well as noun and verb supersenses and auxiliary verbs. We use this dataset for training and testing an integrated lexical semantic analyzer. The experimental setup mostly follows that of ch. 6, which used the CMWE 1.0 dataset—i.e., the same REVIEWS sentences, but annotated only for MWEs. For simplicity, we use oracle POS tags and learn without the recall-oriented cost function.

7.3.1 Tagset

In the STREUSLE dataset, supersense labels apply to strong noun and verb expressions—i.e., singleton nouns/verbs as well as strong nominal/verbal MWEs. Weak MWEs are present in the dataset, but not as a unit labeled with a supersense. To convert to token-level tags, we use the 8-way scheme from §6.3 for positional flags to mark the lexical segmentation, and decorate beginners of strong lexical expressions—everything but I and I—with supersense labels. This is illustrated in figure 7.2. Under this formulation, bigram constraints are sufficient to ensure a globally consistent tagging of the sentence.4

Recall from ch. 4 that there are \(|N| = 26\) noun supersense classes and \(|V| = 16\) verb classes (including the auxiliary verb class, abbreviated ‘a’). In principle, then, there are

\[
(6 + 43 + 2) = 146
\]

possible tags encoding chunk and class information, allowing for chunks with no class because they are neither nominal nor verbal expressions. In practice, though, many of these combinations are nonexistent in our data; for experiments we only consider tags occurring in train, yielding \(|Y| = 146\).

For comparison, we also run a condition where the substantive supersenses are collapsed to a coarse POS category—i.e., \(N\)

---

3Here we use the same splits (train/test, and 8 cross-validation folds within test for tuning the number of training iterations \(M\)). A handful of the MWE analyses changed between versions of the data.

4Unlike prior work, we do not include the class in strong continuation tags though the class label should be interpreted as extending across the entire expression. This is for a technical reason: as our scheme allows for gaps, the classes of the tags flanking a gap in a strong MWE would be required to match for the analysis to be consistent. To enforce this in a bigram tagger, the within-gap tags would have to encode the gappy expression’s class as well as their own, leading to an undesirable blowup in the size of the state space.

5Including OTHER
in the above formula is replaced with \{\text{NOUN}\} and $V$ is replaced with \{'\text{VERB}', 'a'\}, yielding 26 tags in principle of which 22 are seen in training\(^6\) and a condition where the supersense refinements are collapsed entirely, i.e. $\mathcal{Y}$ consists of the 8 MWE tags.

### 7.3.2 Features

We contrast three feature sets for full supersense tagging: (a) the basic MWE features (§6.4.2.1); (b) the basic MWE features plus Brown clusters (§6.4.2.2); and (c) the basic MWE features, Brown clusters, plus several new features shown below. Chiefly, these new features consult the supersenses of WordNet synsets associated with words in the sentence; there is also a feature aimed at distinguishing auxiliary verbs from main verbs, and new capitalization features take into account the capitalization of the first word in the sentence and the majority of words in the sentence. As with the MWE-only model, we refrain from including any features that depend on a syntactic parser (see §8.1.3 for an explanation).

#### New Capitalization Features

25. capitalized $\land \ [i = 0] \land \ [ \text{majority of tokens in the sentence are capitalized}]$

26. capitalized $\land \ i > 0 \land w_0$ is lowercase

#### Auxiliary Verb vs. Main Verb Feature

27. $pos_i$ is a verb $\land \ [pos_{i+1} \text{ is a verb } \lor \ (pos_{i+1} \text{ is an adverb } \land pos_{i+2} \text{ is a verb})]$

---

\(^6\)The 4 unattested tags in this condition are 1, \text{b}, \text{b}'a, \text{a}, and a'.

---

Most of the model's percepts (binary or real-valued functions of the input\(^7\)) can be conjoined with any tag $y \in \mathcal{Y}$ to form a feature

---

\(^7\)We use the term percept rather than “feature” here to emphasize that we are talking about functions of the input only, rather than input–output combinations that each receive a weight during learning.

---
that receives its own weight (parameter). To avoid having to learn a model with tens of millions of features, we impose a percept cutoff during learning: only those zero-order percepts that are active at least 5 times in the training data (with any tag) are retained in the model (with features for all tags). There is no minimum threshold for first-order percepts. The resulting models are of a manageable size: 3–4 million parameters.

7.3.3 Results

Table 7.1 shows full supersense tagging results, separating the MWE identification performance (measured by link-based precision, recall, and F1; see §6.2) from the precision, recall, and F1 of class labels on the first token of each expression (segments with no class label are ignored). Exact tagging accuracy is also shown—this number is higher because it gives credit for true negatives, i.e. single-word segments with no nominal or verbal class label (the 0 and o tags).

The sequence tagging framework makes it simple to model MWE identification jointly with supersense tagging: this is accomplished by packing information about both kinds of output into the tags. But there is a risk that the larger tag space would impair the model's ability to generalize. By comparing the top and bottom sections of the results, we can see that jointly modeling supersenses along with multiword expressions results in only a minor decrease in MWE identification performance. Thus, we conclude that it is empirically reasonable to model these lexical semantic phenomena together.

8Zero-order percepts are those percepts which are to be conjoined with only the present tag to form zero-order features. First-order percepts are to be conjoined with the present and previous tags.

9We count the class label only once for MWEs—otherwise this measure would be strongly dependent on segmentation performance. However, the MWE predictions do have an effect when the prediction and gold standard disagree on which token begins a strong nominal or verbal expression.

<table>
<thead>
<tr>
<th>Feature Set</th>
<th>MWE ID</th>
<th>Class labeling</th>
<th>Tag</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Y]</td>
<td>[θ]</td>
<td>P</td>
</tr>
<tr>
<td>MWE</td>
<td>8</td>
<td>1,937k</td>
<td>72.97</td>
</tr>
<tr>
<td>MWE</td>
<td>22</td>
<td>5,330k</td>
<td>73.26</td>
</tr>
<tr>
<td>MWE+Brown</td>
<td>146</td>
<td>3,555k</td>
<td>67.77</td>
</tr>
<tr>
<td>MWE+Brown+SST</td>
<td>146</td>
<td>4,388k</td>
<td>68.55</td>
</tr>
</tbody>
</table>

Table 7.1: Results on test for lexical semantic analysis of noun and verb supersenses and MWEs. All of these results use a percept cutoff of 5 and no recall-oriented cost. The first two result rows use a collapsed tagset (just the MWE status, or MWE status conjoined with coarse POS) rather than predicting full supersense labels, as described in §7.3.1. The best result in each column and section is bolded.

Comparing the bottom three rows in the table suggests that features that generalize beyond lexical items lead to better supersense labeling. The best model has access to supersense information in the WordNet lexicon; it is 3 F1 points better at choosing the correct class label than its nearest competitor, which relies on word clusters to abstract away from individual lexical items.

To better understand the model's behavior, it behooves us to inspect its learned parameters. The highest-weighted parameters suggest that the best model relies heavily on the supersense lookup features (table 7.2), whereas the second-best model—lacking the supersense lookup features—in large part relies on Brown clusters (cf. Grave et al., 2013). The auxiliary verb vs. main verb feature in

10Incidentally, this sentence provides an alternative solution to a challenge once posed to Mister Language Person (Q. Like most people, I would like to use the words “parameters” and “behoove” in the same sentence, but I am not sure how. A. According to the Oxford English Cambridge Dictionary Of Big Words, the proper usage is: “Darlene, it frankly does not behoove a woman of your parameters to wear them stretch pants.” Dave Barry, “Mister Language Person Is Ready To Take Your Calls”, Jan. 15, 1996).
the best model is highly weighted as well, helping to distinguish between ‘a and STATIVE’. Table 7.3 shows the top-weighted features that pertain to the nominal and verbal communication categories: we see a mixture of cues in these features, including known WordNet supersenses associated with the current word, the noun subsequent to a verb (linking the verbal and nominal varieties of communication), character prefixes and suffixes, word clusters, and matches against the Wiktionary-derived MWE lexicon.

We have motivated the task of supersense tagging in part as a coarse form of word sense disambiguation. Therefore, it is worth investigating the extent to which the learned model in fact succeeds at choosing the correct supersense for nouns and verbs that are ambiguous in the data. A handful of lemmas in test have at least two different supersenses predicted several times; an examination of four such lemmas in table 7.4 shows that for three of them the tagging accuracy exceeds the majority baseline. In the case of look, the model is clearly able to distinguish between COGNITION or COMMUNICATION. Weights are omitted, but range from 30.3 to 7.7.

Table 7.2: Highest positively-weighted features in the best supersense tagging model.

<table>
<thead>
<tr>
<th>( y )</th>
<th>Feature Name</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>'FOOD'</td>
<td>WN_has_supersense(( y ))</td>
<td>37.1</td>
</tr>
<tr>
<td>'FOOD'</td>
<td>pos_0: (NNP, NNP)</td>
<td>35.2</td>
</tr>
<tr>
<td>'FOOD'</td>
<td>auxverb</td>
<td>31.3</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_1st_supersense: COMMUNICATION</td>
<td>30.3</td>
</tr>
<tr>
<td>'PERSON'</td>
<td>WN_1st_supersense: PERSON</td>
<td>29.0</td>
</tr>
<tr>
<td>'PERSON'</td>
<td>suffix_4: hing</td>
<td>26.4</td>
</tr>
<tr>
<td>'TIME'</td>
<td>WN_has_supersense(( y ))</td>
<td>25.7</td>
</tr>
<tr>
<td>'STATIVE'</td>
<td>mainverb</td>
<td>24.6</td>
</tr>
<tr>
<td>'GROUP'</td>
<td>WN_1st_supersense: GROUP</td>
<td>23.6</td>
</tr>
<tr>
<td>'EMOTION'</td>
<td>WN_1st_supersense: EMOTION</td>
<td>23.3</td>
</tr>
<tr>
<td>'ARTIFACT'</td>
<td>WN_has_supersense(( y ))</td>
<td>23.2</td>
</tr>
<tr>
<td>'PERSON'</td>
<td>WN_1st_supersense</td>
<td>22.5</td>
</tr>
<tr>
<td>'PERSON'</td>
<td>WN_has_supersense(( y ))</td>
<td>22.0</td>
</tr>
<tr>
<td>'PERSON'</td>
<td>pos_0: IN</td>
<td>20.5</td>
</tr>
<tr>
<td>'ARTIFACT'</td>
<td>WN_1st_supersense: ARTIFACT</td>
<td>20.4</td>
</tr>
<tr>
<td>'ARTIFACT'</td>
<td>WN_1st_supersense: ARTIFACT</td>
<td>20.4</td>
</tr>
<tr>
<td>'ARTIFACT'</td>
<td>WN_1st_supersense: ARTIFACT</td>
<td>20.3</td>
</tr>
<tr>
<td>'ARTIFACT'</td>
<td>WN_1st_supersense: ARTIFACT</td>
<td>19.5</td>
</tr>
<tr>
<td>'ARTIFACT'</td>
<td>WN_1st_supersense: ARTIFACT</td>
<td>19.5</td>
</tr>
</tbody>
</table>

Table 7.3: Highest positively-weighted features involving COMMUNICATION or COMMUNICATION. Weights are omitted, but range from 30.3 to 7.7.

<table>
<thead>
<tr>
<th>( y )</th>
<th>Feature Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_1st_supersense: COMMUNICATION</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_1st_supersense: COMMUNICATION</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_has_supersense(( y ))</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>cpos: V, WN_next_N_1st_supersense: COMMUNICATION</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_has_supersense(( y ))</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_has_supersense(( y ))</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_1st_supersense: COMMUNICATION</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>cpos: V, WN_next_N_1st_supersense: COMMUNICATION</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_1st_supersense: COMMUNICATION</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>cpos: I, WN_next_N_1st_supersense: COMMUNICATION</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>suffix_4: te</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>prefix_4: com</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>prefix_4: read</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>WN_1st_supersense: ARTIFACT</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>cpos: V, WN_next_N_1st_supersense: COGNITION</td>
</tr>
<tr>
<td>'COMMUNICATION'</td>
<td>prefix_4: call</td>
</tr>
<tr>
<td>lemma</td>
<td>gold supersense distribution</td>
</tr>
<tr>
<td>-------</td>
<td>-------------------------------</td>
</tr>
<tr>
<td>get</td>
<td>STATIVE* 12, SOCIAL* 5,</td>
</tr>
<tr>
<td></td>
<td>COGNITION* 3, POSSESSION* 3,</td>
</tr>
<tr>
<td></td>
<td>BODY* 2, MOTION* 2,</td>
</tr>
<tr>
<td></td>
<td>COMMUNICATION* 1</td>
</tr>
<tr>
<td>look</td>
<td>PERCEPTION* 8, COGNITION* 5</td>
</tr>
<tr>
<td>take</td>
<td>SOCIAL* 8, MOTION* 7,</td>
</tr>
<tr>
<td></td>
<td>POSSESSION* 1, STATIVE* 4,</td>
</tr>
<tr>
<td></td>
<td>EMOTION* 1</td>
</tr>
<tr>
<td>time(s)</td>
<td>TIME* 8, EVENT* 5,</td>
</tr>
<tr>
<td></td>
<td>COGNITION* 1</td>
</tr>
</tbody>
</table>

Table 7.4: Four lemmas and counts of their gold vs. predicted supersenses in test (limited to cases where both the gold standard tag and the predicted tag included a supersense).

looking for a company with decent rates) and PERCEPTION* (as in sometimes the broccoli looks browned around the edges).

7.4 Conclusion

We have integrated the lexical semantic segmentation task formulated in ch. 6 with the supersense tagging task of Ciaramita and Altun (2006), and applied the annotated English dataset of §4.4 to learn and evaluate a discriminative lexical semantic analyzer. Aside from experimenting with new features, richer models, and indirect forms of supervision (cf. Grave et al., 2013; Johannsen et al., 2014) for this task, the time will soon be ripe for broadening it to include preposition supersenses (ch. 5). Once the preposition supersense annotations are complete for the corpus, retraining the model described in this chapter should provide a strong baseline for future studies of coarse lexical semantics in context.
PART III

Wrapping Up
Conclusion

8.1 Lessons, Limitations, and Possible Extensions

8.1.1 Summary of Contributions

This thesis has provided a framework for describing the lexical units and semantic classes within text sentences, manually and automatically, with broad coverage. Because the general framework does not depend on any preexisting lexical resource, it is expected to be suitable for a wide range of text domains and languages. The foregoing chapters have motivated and detailed approaches to the representation of lexical semantics, a practical approach to human annotation of corpora, and statistical techniques for the automation of the analysis using said corpora. The primary case study concerning sentences from English web reviews allowed for each of these steps to be understood and documented qualitatively and quantitatively. It has also produced an annotated corpus resource and
analysis software, both of which will be released to facilitate further linguistic investigation, computational modeling, and application to other tasks.

The main specific methodological contributions are:

- a shallow but comprehensive approach to analyzing heterogeneous **multword expressions**, including those containing gaps—manually through linguistic annotation (ch. 3) and automatically through a discriminative sequence model with a modified chunking scheme (ch. 6);

- an approach to labeling semantic classes of noun and verb expressions using the **WordNet supersenses**, in a way that builds upon the MWE analysis and still lends itself to automatic sequence tagging (ch. 4, ch. 7); and

- an approach to describing the semantic functions of **prepositions** via a well-documented hierarchical taxonomy of **preposition supersenses** (ch. 5).

The operational details of this framework having been described in the aforementioned chapters, the following sections will elaborate on some of the broader issues raised by the thesis.

### 8.1.2 Limitations and Difficult Cases

The framework put forward here can be thought of as a compromise between the desire for explicit representations of meaning in context and the desire for practical and rapid corpus annotation with broad coverage. That the approach advocates a shallow treatment of multiword expressions and a coarse treatment of sense disambiguation should not be interpreted as an argument that finer distinctions and details are irrelevant.\(^1\)

As a reminder, here are some of the particular difficulties encountered during annotation that may reflect limits on our representation’s expressive power:

- There is no way to mark MWEs with overlapping words (§3.6).
- There is no way to mark that an MWE requires a possessive or reflexive constituent that might be a pronoun (§3.6).
- It can be extremely difficult to decide whether a preposition is selected by its governor, forming (e.g.) a prepositional verb (§3.7).\(^2\)
- There is no way to mark constructions with only one lexicalized element (§3.6: footnote 27).
- For nouns referring to complex concepts such as businesses with a physical premises and staff, it is often difficult (and possibly misleading) to choose between **ARTIFACT\(^*\)**, **GROUP\(^*\)**, and **LOCATION\(^*\)** supersenses (§4.4.1).
- Prepositions can be viewed as having several “facets” of meaning, some of which are orthogonal. This complicates any ap-

---

\(^1\)As an example of a subtle nuance of (prepositional) meaning, Fillmore (1985) considers the circumstances under which someone can be described as being **in** a bus vs. **on** a bus: excluding the reading of **on** as ‘atop’, the same spatial configuration is implicated—but **on** is felicitous only if the bus is in service, i.e., the individual is inside the bus on the occasion of a scheduled trip for transporting passengers. Children playing in an abandoned bus are better described as **in** (Fillmore, 1985, p. 235).

\(^2\)We had hoped that semantic categorization of preposition functions would suggest a solution, namely that prepositions with anomalous functions would count as selected by their head. But this hope was not entirely borne out; it seems that many preposition functions are associated with clusters of semantically similar verbs (e.g., **look at**, **gaze at**, **glance at**, **take a gander at**, etc.). To decide which prepositions are selected may require attention to the equally hairy issue of arguments vs. adjuncts (Hwang, 2011).
proach based on assigning a single category label, even with a hierarchy over those labels.³

### 8.1.3 Regarding MWEs and Syntax

Syntax plays only a minor role in our MWE annotation scheme (ch. 3) and identification system (ch. 6). We use part-of-speech tags to detect candidate annotation targets and in features for the identification tool. But no step of the process relies on syntactic parses (even though gold phrase structure trees are available for the REVIEWS sentences).

There were several reasons behind this design decision. First, we see MWEs as primarily a phenomenon of lexical semantics, so we did not want our judgments of MWE-hood to be constrained or influenced by syntactic treebanking conventions. Second, we wanted to highlight that our framework is feasible for domains (and in principle, languages) without syntactic treebanks or parsers. Third, sequence models are computationally more efficient than parsing models. (Though our system requires POS tagging as preprocessing, that is also accomplished with an efficient sequence model.) And finally, including a parser in the pipeline would open up a large number of methodological possibilities to explore: What kind of syntactic formalism (e.g., phrase structure or dependency)? What kind of parsing algorithm (e.g., graph-based or transition-based dependency parsing)? Should the parser be trained in the domain of interest, and if not, how much would performance suffer? How should the parser output be exploited in features for MWE identification (see, e.g., Constant et al., 2012)? Is it better to identify MWEs first, as a preprocessing step for improved syntactic parsing (Nivre and Nilsson, 2004; Korkontzelos and Manandhar, 2010; Constant et al., 2012; Candito and Constant, 2014; de Lhoneux, 2014)? Or is MWE information best integrated into the syntax (à la Green et al., 2011, 2012; Vincze et al., 2013b; Candito and Constant, 2014), or can the MWE analyzer and the parser work simultaneously for mutual benefit (Le Roux et al., 2014)? These questions have been investigated to an extent in existing resources—primarily, for compounds in the French Treebank (see §3.3.4). We believe they are worth exploring thoroughly with heterogeneous MWEs, and so we leave this to future work, save for a brief comment in §8.3.1 below on the potential role of MWE identification in enhancing parsers.

NLP strategies aside, readers interested in linguistic theory are likely wondering what the present approach to lexical semantics means for a broader theory of grammar and compositionality (the “syntax-lexis nexus”, if you will). Though ch. 3 describes MWEs using some of the formal tools that have been applied to syntax, I have made no claims about the status of these lexical semantic units in a syntactic analysis.

For theorists, MWEs challenge traditional assumptions about the separation between lexicon and grammar. The arguments have been made elsewhere (Fillmore et al., 1988; Nunberg et al., 1994; Sag et al., 2002), but to briefly list some of the possibilities: there are MWEs with
• special component vocabulary, completely opaque form and meaning: *ceteris paribus*
• familiar component vocabulary, idiosyncratic syntax, and opaque meaning: *by and large*
• frozen and partially idiosyncratic syntax, and partially opaque meaning: *All your base are belong to us*
• familiar component vocabulary, familiar but frozen syntax, the head word inflecting regularly, and opaque meaning: *kick the bucket (kicked the bucket, but *the bucket was kicked)*
• familiar and partially flexible syntax, requiring arguments and agreement, and mostly transparent meaning: *<one1> give <something> <one2>'s best shot (John gave the project his/*Mary's/*her best shot)*
• familiar and flexible syntax and figurative but decomposable meaning: *spill the beans (the beans were spilled, spill all the beans, etc.)*
• familiar but somewhat noncompositional parts arranged according to special syntactic rules: *Rev. Dr. Martin Luther King, Jr.*
• recognizable but frozen syntax and transparent semantics, but institutionalized with a special rhetorical function: *all things being equal*

In short, a full account of these expressions would need to mark what aspects of form and meaning are fixed vs. flexible and regular vs. idiosyncratic.

The philosophy of Construction Grammar—namely, that lexicon and grammar are endpoints on a spectrum of learned pattern/meaning associations, rather than separate mechanisms (Hoffmann and Trousdale, 2013)—seems a necessary background to such a theory. A construction (conventionalized form-meaning unit) can in principle map complex lexical and/or syntactic configurations to a single meaning. Representing a language's lexicon-grammar as a network of constructions, with inheritance links between constructions that overlap in form and/or meaning, is a way to account for partially predictable but partially idiosyncratic patterns (Lakoff, 1987; Goldberg, 1995).

Computational Construction Grammar formalisms such as Embodied Construction Grammar (Bergen and Chang, 2005; Feldman et al., 2009) and Fluid Construction Grammar (Steels et al., 2011; Steels, 2012) have been implemented on a small scale, but lack a corpus for data-driven learning of broad-coverage parsers. On the other hand, approaches to parsing MWE structures with Tree Substitution Grammars (Green et al., 2011, 2012) have not incorporated any meaning representation, while for Combinatory Categorial Grammar (Steedman, 2000), semantics-enabled broad-coverage parsers (e.g., Bos et al., 2004) are not (yet) equipped to treat most kinds of multiword expressions (de Lhoneux, 2014). Thus, computationally efficient and data-driven parsing of complex, meaning-bearing constructions—MWEs as well as nonlexicalized constructions (Hwang et al., 2010b)—still presents a considerable challenge for future research (Schneider and Tsarfaty, 2013).

8.1.4 Regarding Empirical Support for Claims about Linguistic Theory and Annotation

When making hypotheses about natural language, applying relevant annotations to corpora, and building computational models to test those hypotheses, it is possible to fall into a trap of circular logic. Riezler (2013) raises several concerns about empirical validity in computational linguistics, some of which are on point here.

One concern is about the reproduceability of annotations. When, as in this thesis, a group of annotators are trained over a period of
time—and especially when they are involved in shaping the guidelines themselves—it is likely that some of the consensus that emerges from that experience will be in the form of an unwritten understanding, rather than due to “pure” intuitions or articulated principles and conventions of the annotation scheme. Thus, high inter-annotator agreement may mask reliability that is due to factors outside of the annotation guidelines. Riezler suggests that ideally, naïve (even non-linguist) annotators be trained directly from the annotation guidelines to test the robustness of the scheme. Because of resource limitations, this was not possible for most aspects of the scheme proposed in this thesis, though we did find qualitatively that the noun supersense guidelines developed first for Arabic ported well to English with a different set of annotators.

Riezler also argues that extrinsic evaluations with a theory-neutral measure of “usefulness” are a valuable way to test an NLP system that produces theory-specific output. Of course, applications such as machine translation are also a major motivation for building linguistic analyzers in the first place. §8.3 considers the expected relevance of lexical semantic analysis to several extrinsic tasks.

8.1.5 Future Directions in Broad-Coverage Lexical Semantic Analysis

This thesis has not, of course, solved the lexical semantic analysis problem once and for all; much of the journey awaits. As the next step, we intend to deploy the preposition supersense scheme (ch. 5) to fully annotate a corpus and integrate preposition supersenses into the joint lexical analyzer (ch. 7). This should not require any major deviations from the approach taken for noun and verb supersenses.

Several technical directions hold promise for making models more robust. It should be possible to leverage additional unlabeled, labeled, and type-level data sources, including data from other domains (much like Johannsen et al., 2014 have recently done for Twitter supersense tagging). We have not thoroughly inspected our annotations for consistency across sentences, so making existing data more consistent is a possible direction whose value should be weighed against the value of annotating new data. Of course, we hope that the annotation scheme will be applied to new corpora and languages, and that the guidelines can be improved where necessary to work across languages. The value of incorporating syntactic information into models deserves further investigation, as discussed in §8.1.3.

Finally, this thesis has only proposed supersense inventories for nouns, verbs, and prepositions, but the framework could be extended to additional parts of speech—ideally to the point that it is capable of covering most of the lexical semantic units in any sentence. Preliminary steps have already been taken to develop a supersense scheme for adjectives (Tsvetkov et al., 2014).

8.2 Linguistic Applications

We briefly point out that gold annotations (by humans) and silver annotations (by systems trained on the gold annotations) made possible by this thesis have the potential to enable new forms of corpus-based linguistic inquiry in lexical semantics. In particular, supersenses provide a level of abstraction that is often more conducive than words for positing and testing generalizations about language. In fact, similar schemes have been used by corpus linguists in the past (Zaenen et al., 2004). Furthermore, linguists studying idiomaticity in English will be in a much better position to use corpora (Moon, 1998, p. 51: “Ideally, the FEIs [fixed expressions and idioms] in a corpus would be identified automatically by machine, thus re-
moving human error or partiality from the equation”). Of course, neither our annotated data nor our system is perfect. Still, we hope that our contributions will reduce the amount of manual coding required in new corpora and make possible linguistic analyses with much broader lexical coverage.

8.3 NLP Applications

With regard to other NLP tasks, prior work and future opportunities for applying broad-coverage lexical semantic analysis are worthy of comment.

8.3.1 Syntactic Parsing

MWEs. There has been some work connecting MWEs to parsing, either using parsing as a tool for identifying MWEs or using knowledge of MWEs to influence overall parsing accuracy (e.g., Nivre and Nilsson, 2004; Korkontzelos and Manandhar, 2010; Green et al., 2011, 2012; Constant et al., 2012; Candito and Constant, 2014; Le Roux et al., 2014; de Lhoneux, 2014; cf. §8.1.3 above). These attempts have met with mixed success. A concern is that it is not always clear which MWEs should be considered as syntactically idiosyncratic and which of them are merely semantically idiosyncratic, and how they should therefore be represented in a syntactic parse. One way to sidestep this issue would be to use the syntactic parse as a means to an end (such as semantic parsing or machine translation), and measure whether improved identification of MWEs in the parser correlates with downstream improvements.

Supersenses. Semantic senses and semantic classes such as the WordNet supersenses have been explored as additional information for improving syntactic parsers (Agirre et al., 2008, 2011; Fujita et al., 2010; Bengoetxea et al., 2014). This line of work has been somewhat inconclusive, but may benefit from more accurate supervised statistical (rather than unsupervised or heuristic) supersense tagging, especially with semantic tags for prepositions as proposed in ch. 5. There has also been work specifically on the task of PP attachment (Hindle and Rooth, 1993; Niemann, 1998; Coppola et al., 2011; Greenberg, 2014, inter alia), which would obviously stand to benefit from a system that could semantically classify the preposition, its object, and its potential governors with high accuracy.

8.3.2 Semantic Parsing

As mentioned in §2.1, one goal in computational semantics is to analyze relationships among words or lexically-denoted concepts in a sentence via some meaning representation that provides abstraction and supports some sort of inference. Broadly speaking, this challenge is known as semantic parsing.

This section considers how lexical semantic analysis might aid semantic parsers. For concreteness, we focus on two of the computational representations for relational semantics in English: frame semantics and AMR.

FrameNet (Baker et al., 1998) is a linguistically rich semantic lexicon and corpus for predicate-argument structures that instantiates the theory of frame semantics (Fillmore, 1982) for English. The FrameNet lexicon is organized in terms of conceptual scenes, or frames. Associated with each frame definition is a list of lexical units (predicates) known to evoke the frame, as well as frame elements—roles that reflect conceptual attributes of the frame that may be elaborated when the frame is used. Each annotated sentence in FrameNet records one or more evoked frames; each frame
Another reader takes Christine Sutton to task on a semantic point.

Figure 8.1: Example from the FrameNet lexicographic annotations. The gappy expression takes... to task is the frame-evoking target: it maps to the lexical unit take to task.v of the JUDGMENT_DIRECT_ADDRESS frame. The frame elements (roles) of this frame include COMMUNICATOR, ADDRESSEE, TOPIC, MEDIUM, and REASON, a subset of which are expressed overtly in the sentence. Other lexical units for this frame include chide.v, compliment.(n,v), harangue.v, tell off.v, telling off.n, tongue-lashing.n, and upbraid.v.

AMR (Banarescu et al., 2013) is a graph-based representation that canonicalizes certain aspects of logical meaning so as to abstract away from surface words and syntax, in a way that is human-readable and conducive to rapid annotation with broad coverage. Figure 8.2 displays an example. Designed primarily for English, AMR describes each sentence with a graph that encodes entity and predicate concepts as nodes, and semantic roles/relations as typed edges between concepts. Nodes can be shared to indicate within-sentence coreference (including implicit coreference implied by the syntax, such as with control structures and relative clauses). Event predicates and associated semantic roles are drawn from PropBank (Kingsbury and Palmer, 2002); the predicate-specific core roles from PropBank are supplemented with an inventory of non-core roles such as LOCATION, TOPIC, and POSS(ESSOR). There are also special conventions for named entities, time and value expressions, derivational morphology, modality and negation, and a host of special phenomena. In contrast to FrameNet, an AMR graph is not aligned to the source sentence, and is structurally richer (hierarchical, covering more phenomena), but uses shallower lexical and relational labels.

Corpora annotated with both of these representations exist⁴ and have been used to train statistical semantic parsers that take English sentences as input and predict meaning structures. The state-of-the-art system for frame-semantic parsing is SEMAFOR (Das et al., 2010, 2014).⁵ To date, the only published system for AMR parsing

⁵http://www.ark.cs.cmu.edu/SEMAFOR/; https://github.com/sammthomson/semafor/
is JAMR (Flanigan et al., 2014). Both of these systems attempt to build fairly rich structures but have limited data for supervision. Evaluations show there is a great deal of room for improvement in accuracy. A lexical semantic analyzer trained on other data could be incorporated as a preprocessing step to obtain additional features for the parser, alongside features derived from the output of other preprocessing steps already required by the tools.

SEMAFOR and JAMR both consist of two main stages, executed in sequence. First, words/word sequences in the sentence are each mapped to a canonical conceptual representation—essentially, this entails word sense disambiguation of predicates. It should not be hard to see how supersenses could help such a system to disambiguate starkly polysemous lexical predicates, and (in the case of AMR) to add the appropriate semantic class for each named entity. Likewise, it is necessary to identify various kinds of multiword predicates, some of which are canonicalized to a multiword concept (e.g., take to task in FrameNet) while others are simplified to a single-word concept (take to task → scold-01 in AMR; light verb constructions in both AMR and FrameNet). Second, typed links are added to indicate semantic relations—essentially, semantic role labeling. Lexical semantic analysis could help the parser avoid structural errors that would split MWEs across arguments, and the supersenses would inform relation labeling of non-core arguments (which oftencorrespond closely to preposition supersenses⁶) as well as core arguments (whose selectional preferences could be modeled in terms of supersenses).

6https://github.com/jflanigan/jamr/

7Both SEMAFOR and JAMR require dependency parsing as a preprocessing step. JAMR additionally uses the output of a named entity recognizer.

8See table 5.1 (p. 1022) for correspondences between preposition supersenses and AMR's non-core role labels. Similar correspondences should apply for FrameNet labels as well.

8.3.3 Machine Translation

Knowledge of lexical expressions and their meanings is surely integral to humans’ ability to translate between two languages. But of course, machines and people work very differently. In practice, the modern statistical machine translation (SMT) systems with enormous amounts of data at their disposal may be coping indirectly with most of these phenomena. Would a monolingual computational model of lexical semantics be relevant to machine translation?

An example from an SMT system will be instructive. In Google Translate—for which English-French is the best language pair—both inputs in (28) are mapped to the nonsensical French output (29a) instead of to (29b), suggesting that mind is being translated separately from make up:

(28) a. She was unable to make up the Count’s mind.
    b. She was unable to make up the mind of the Count.

    roughly: ‘She was incapable of compensating for the spirit of the Count.’
    b. Elle était incapable de convaincre le comte.
    ‘She was incapable of convincing the Count.’

Failures such as these provide evidence that better treatment of lexical items is at least plausible as a path to better translation quality.

At the lexical level, current systems face the twin challenges of sense ambiguity and multiword expressions. The English WordNet senses of make up were enumerated on page 35 above. Among its major French translations are constituer (sense #1), composer (#1, #2), fabriquer, faire, and préparer (#2), compenser (#3, #7), rattraper (#4), inventer (#5), ranger (#6), pallier (#7), se réconcilier (#8), and maquiller (#9). Further, the idiom make up...mind translates to
se décider. If the local context is insufficiently informative for the language model, an MT system might easily translate the wrong sense of make up. And if make up is not translated as part of the same unit (especially likely if it contains a gap), the overall bias for make translating as faire would probably prevail, and the up ignored entirely—or worse, mistranslated as a spatial term. Verb-noun constructions such as make up... mind are even more prone to disaster because they are more likely to be realized with a gap, as shown above.

Analysis and experimentation is therefore needed to establish the extent to which the explicit information in an English lexical semantic representation is orthogonal to, or redundant with, translation units learned and selected by a full-scale MT system.

Supersenses vs. WSD. Several attempts have been made to integrate word sense disambiguation into SMT systems. The disambiguation problem has been formulated with an explicit sense inventory (Carpuat and Wu, 2005), with lexical-level translations (Cabezas and Resnik, 2005; Chan et al., 2007; Carpuat and Wu, 2007), and with unsupervised topics (Xiong and Zhang, 2014; Hasler et al., 2014). In all of these methods, WSD is performed on the source side in order to capture wider context than is allowed in translation rules (cf. Gimpel and Smith, 2008). We are unaware of any WSD-for-SMT studies that have used prespecified coarse-grained senses such as supersenses, which would perhaps lead to better generalizations.

Name translation is a major obstacle in SMT due to unknown words (see Hermjakob et al., 2008 for a review), a problem which we do not expect supersenses to solve.

Prepositions. Prepositions are known to be especially challenging for machine translation (Gustavii, 2005), and are a high-value target due to their frequency. Yet surprisingly, adpositions have received little attention in the SMT paradigm (Baldwin et al., 2009). Exceptions are the work of Toutanova and Suzuki (2007), who use a target side reranker for Japanese case-marking postpositions in an English-to-Japanese system, and the work of Shilon et al. (2012), who incorporate information about prepositions into translation rules for an Arabic-to-Hebrew system. Preposition supersenses, one hopes, would go a long way toward disambiguating the translation. For example, two of the French equivalents of for are the prepositions pour (goal, destination) and pendant (duration).

MWEs. Recent quantitative evaluations of MWEs in machine translation systems (especially for verb-particle constructions, prepositional verbs, and support verb constructions) underscore the challenges noted above (Barreiro et al., 2013, 2014; Ramisch et al., 2013). For instance: Barreiro et al. (2014), analyzing the performance of two MT systems across five language pairs (English into Portuguese, Spanish, French, Italian, and German), find that anywhere from 27% to 70% of support verb constructions are erroneously translated.

Techniques for adapting SMT systems to capture MWEs have included altering the tokenization of the text so MWEs constitute a single token; expanding the training data with monolingual paraphrases of MWEs; expanding the phrase table with a bilingual MWE lexicon; marking phrase table entries that capture MWEs with a feature that rewards their use in decoding; and constraining reorderings of words belonging to MWEs (Nakov, 2008; Ren et al., 2009; Carpuat and Diab, 2010; Ramisch, 2012; Ghoneim and Diab, 2013; Simova and Kordoni, 2013). Some of these strategies have been more successful than others, and different strategies work well for different kinds of MWEs. Because most of these methods rely on token-level identification of MWEs, it is hoped that upstream improvements to
lexical semantic analysis will drive further gains.

8.3.4 Other Applications

Multiword chunks are an important phenomenon of study in both first language acquisition (Bannard and Lieven, 2012) and second language acquisition and education (Wray, 2000; Ellis et al., 2008). Prepositions are notoriously difficult for second language learners, especially given their prevalence in multiword expressions, so they occupy a central place in the literature on automatic grammatical error correction (Chodorow et al., 2007; Hermet and Alain, 2009; Leacock et al., 2014). It would be interesting to see how well a lexical semantic analyzer trained on native English text would perform on nonnative writing, and whether supersense tagging could draw attention to anomalous usages.

Spatial and temporal analysis tasks such as SpaceEval and TempEval (e.g., UzZaman et al., 2013), and related applications in robotics and computer vision (e.g., Dobnik and Kelleher, 2013, 2014), may benefit from the supersense analysis of prepositions, particularly the temporal (§5.4.3) and path (§5.4.5) portions of the hierarchy.

For information retrieval, segmenting or extracting multiword units in a text has been explored under various guises, including keyphrase extraction and query segmentation (e.g., Tomokiyo and Hurst, 2003; Tan and Peng, 2008; Acosta et al., 2011; Newman et al., 2012). Keyphrase extraction also has application to opinion mining (Berend, 2011). Segmentation of text on a semantic basis (though with looser criteria than proposed here) has been explored for distributitional semantic models (Srivastava and Hovy, 2014).

A colleague in Pittsburgh reports that his young daughter says upside up by analogy to upside down, rather than the usual right-side up. Children are sometimes more logical than adults.

http://alt.qcri.org/semeval2015/task8/
A subset of Brown Corpus documents are both fully sense-tagged in SemCor (Miller et al., 1993; see §2.3.2) and parsed in version 3 of the Penn Treebank (Marcus et al., 1999). We will refer to this collection as PARSEDSEMCOR. A profile of the dataset appears in figure A.1.

Looking at the SemCor annotations of the 93 documents in the PARSEDSEMCOR collection, we find 220,933 words in 11,780 sentences. There are 5590 named entity mentions; of these, 1861 (1240 types) are multiword NEs, spanning 4323 word tokens (2% of the data).¹ An additional 6368 multiword expression mentions (3047 types) are annotated, encompassing 13,785 words (6% of the data). About 87% of these mentions (and 87% of types) are tagged

¹For the type counts in this paragraph, mentions were grouped by their lower-cased surface string.
with a WordNet sense. All told, 8% of tokens in \textsc{parsedsemcor} belong to a SemCor-annotated MWE, with a 3-to-1 ratio of multiword idioms to multiword NEs.

\section*{A.1 Gappy MWEs}

To identify gappy MWEs in the \textsc{parsedsemcor} collection, including those in figure 3.4, we extracted the sense-tagged items for which the number of words in the lemma differed from the number of words in the tagged surface span—this usually indicates a gap.\footnote{The 30 most frequent MWEs to be annotated without a sense tag are: \textit{going to} \textit{(62)}, \textit{had to} \textit{(34)}, \textit{have to} \textit{(32)}, \textit{most of} \textit{(28)}, \textit{of it} \textit{(23)}, \textit{no one} \textit{(19)}, \textit{as well as} \textit{(15)}, \textit{as long as} \textit{(13)}, \textit{of this} \textit{(13)}, \textit{in order} \textit{(13)}, \textit{in this} \textit{(13)}, \textit{in front of} \textit{(12)}, \textit{in that} \textit{(10)}, \textit{got to} \textit{(9)}, \textit{as soon as} \textit{(9)}, \textit{even though} \textit{(9)}, \textit{many of} \textit{(9)}, \textit{used to} \textit{(8)}, \textit{as though} \textit{(8)}, \textit{rather than} \textit{(8)}, \textit{of what} \textit{(7)}, \textit{up to} \textit{(7)}, \textit{a lot} \textit{(6)}, \textit{such as} \textit{(6)}, \textit{as much as} \textit{(6)}, \textit{want to} \textit{(6)}, \textit{of that} \textit{(6)}, \textit{out of} \textit{(6)}, \textit{in spite of} \textit{(5)}, \textit{according to} \textit{(5)}. These include complex prepositions, comparative expressions, and discourse connectives not in WordNet. The expression \textit{a lot} is in WordNet, but is missing a sense tag in some of the documents.}

There are 336 occurrences of mismatches, with 258 distinct lemma types. Of these types, a majority—about 160—are particle verbs or prepositional verbs. About 20 types are verb-noun constructions; 7 are verb-PP idioms. Roughly 30 are complex nominals, some of which are legitimately gappy and some of which have a lemma slightly more specific than the surface word (e.g. \textit{the Church} mapped to \texttt{Roman\_Catholic\_Church.01}). Finally, 11 types are non-standard spellings (\textit{suns of biches} is mapped to \texttt{son\_of\_a\_bitch.01}), and 2 types were variant forms of the lemma: \textit{physiotherapist} as \texttt{physical\_therapist.01} \texttt{co\_as\_commanding\_officer.01}.

From these results we estimate that fewer than 2 gappy MWEs are annotated for every 1000 words of SemCor. However, we suspect SemCor annotators were conservative about proposing canonically gappy expressions like verb-noun constructions.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
\textbf{# docs} & \textbf{genre} \\
\hline
16 & F POPULAR LORE \\
15 & G BELLES-LETTRES (biographies, memoirs) \\
28 & K FICTION (General) \\
11 & L FICTION (Mystery/Detective) \\
2 & M FICTION (Science) \\
10 & N FICTION (Adventure/Western) \\
5 & P FICTION (Romance/Love Story) \\
6 & R HUMOR \\
\hline
\end{tabular}
\caption{Composition of the \textsc{parsedsemcor} dataset, which is the parsed and fully sense-tagged subset of the Brown corpus. Parses and sense tags are gold standard. The 93 documents in this sample consist of about 2200–2500 words each, a total of 220,933 words in the SemCor tokenization.}
\end{table}
MWE Annotation Guidelines

These guidelines, published at https://github.com/nschneid/nanni/wiki/MWE-Annotation-Guidelines, document the conventions of grouping tokens of text into multiword expressions. See §3.6 for discussion.
This document gives a detailed description of a linguistic annotation scheme for multiword expressions (MWEs) in English sentences. A conference paper summarizing the scheme and a dataset created with it are available at http://www.ark.cs.cmu.edu/LexSem/.

**Markup**

The input to annotators is a tokenized sentence. The goal is to join tokens where appropriate; this is done with the special characters underscore (_) for strong multiword links, a tilde (~) for weak links:

- This is a highly ~ recommended fast _ food restaurant .

Weak links can join strongly-linked expressions, such as fast_food + chain:

- This is a highly ~ recommended fast _ food _ chain .

Where an expression is interrupted by other tokens, use trailing and leading joiners:

- Do n't give _ Jon such _ a _ hard _ time !

This even works when contiguous expression can fall within the gap:

- Do n't give _ Jonathan _ Q. _ Arbuckle such _ a _ hard _ time !

On rare occasion it may be necessary to use multiple gappy expressions, in which case indexing notation is available: a|1|b|2|c|3 implies two strong expressions—a_c and b_d—and one weak expression, a_c~e. An example:

```
put_!whole$1!_heart_in$1
```

(amounts to: put_heart_in~whole). Also:

```
make_a_!big$1!_to_do$1
```

**Figurative language**

While many idioms/MWEs are figurative, not all figurative language is used in a lexically specific way. For example, “my Sicilian family” referring to a pizza community may be nonliteral, but is not an MWE.

**Foreign languages**

We do not annotate foreign sentences, but foreign names within an English sentence are MWEs.

**Collocations vs. “strong” MWEs**

A collocation is a pairing between two or more words that is unexpectedly frequent, but not syntactically or semantically unusual.

- eternally~grateful, can~not~wait, place~is~packed

- what s.o. has~to~say [is willing to say, brings to the conversation; not obligation (compare: I have to say good things to my boss to get promoted)]
A collocation may include components that are themselves MWEs:

- after-all-was_said_and_done

Drawing the line between free combination, collocation, and multiword is often difficult; annotators' opinions will vary.

### Borderline/ambiguous cases

**TODO** (join with ~)

- Cj~and_company (ambiguous whether it is actually the name of a company or a guy and his crew)

### Constructions with only 1 lexicalized word

Some semi-productive idioms are not well captured as lexicalized multiwords. These should not be joined:

- have + GOODNESS.ADJ + TIME.PERIOD: had a bad day, have a great year, etc.
- EVALUATIVE.ATTRIBUTE of s.o.: (real) Christian of you
- NUMERIC.QUANTITY PLURAL.TIME.NOUN running: two years running
- come + MENTAL.CHANGE.INFINITIVE: come to realize, believe, learn, adapt, have faith, ...

### Overlapping expressions

Rarely, a token will seemingly participate in multiple MWEs, which cannot be represented in our annotation scheme. Use your best judgment in such cases.

- I recently threw a surprise birthday party for my wife at Fraiser’s.

### Syntactically perverted expressions

Don’t worry if the parts of an expression are noncanonically ordered: gave ~ estimates, give ~ an estimate, the estimate ~ that was given

If one of the lexicalized parts is repeated due to coordination, attach the instance closest to the other lexicalized part: talked_to Bob and to Jill; North and South_America

### Special kinds of expressions

- DO join Dr., Mr., etc. and other titles to a personal name: Dr._Lori_Levin,
  Henry~Prince_of_Wales, Captain_Jack_Sparrow
- DO join Ave., Rd., St., etc. in street names: Forbes_Ave.
- DO join city-state-region expressions: Bellevue~WA or Bellevue~Washington (include the comma if there is one). Likewise: Ohio~State_Park~Pennsylvania;
  Miami~University~Ohio; Amsterdam~The_Netherlands
- DON’T join normal dates/times together (but: Fourth_of_July for the holiday)
- Symbols
  - DON’T join normal % sign
  - DO join letter grade followed by plus or minus: A_+
  - DON’T join mathematical operators: 3 x the speed, 3 x 4 = 12 [x meaning “times”]
  - DO join # sign when it can be read as “number”; #_1
  - DO join a number and “star(s)” in the sense of a rating: 5~star
  - When in doubt, join cardinal directions: north_east, north_west, south_east, south_west, north~northeast...
  - DO attach ‘s if part of the name of a retail establishment: Modell’s
  - DO join product expressions such as car Year/Make/Model or software Name/Version
  - excludes appositions that are not in a standard format (McDonald’s Dollar_Menu
    Chicken Sandwich)
- DO join names of foods/dishes if (a) the expression is noncompositional in some way, or (b) there is well-established cultural knowledge about the dish. Use ~ if unsure. For example:
  - General~Tso’s_chicken, macaroni_and_cheese, green_tea, red_velvet cake,
    ice_cream_sandwich, chicken_salad salad
  - triple_chocolate_chunk brownie [multiplier+chocolate, chocolate_chunk]
  - pizza~roll, ham~and~cheese, cheese~and~crackers, spaghetti~with~meatballs
  - grilled BBQ chicken, pumpkin_spice latte, green pepper, turkey sandwich, eggplant
    parmesan, strawberry banana milkshake
- DO join established varieties of animals/natural kinds: yellow_lion, desert_chameleon,
  Indian_elephant, furcifer_pardalis; BUT: brown dog
- DO join slogans: Trust_The_Midas_Touch, Just_Do_It, etc.
By construction

A+[P+Pobj]
- pleased/happy/angry_with, mad_at
- good_for s.o. [healthy, desirable]

affective on

This is a special use of the preposition 'on', but it does not generally join to form an MWE:
- drop_the_ball on s.o. [not literally], die on s.o.
- hang_up~on s.o. [collocation]
- 'step on s.o.' is different: here it is the semantics of 'step on' that could convey negativity in certain contexts, not 'on' by itself)

age
- (appropriate) for_ {one's, a certain, ...} _age (of child)

age construction: TEMPORAL.QUANTITY old

3 years_old, month_old project. (Note that ago should NOT be joined because it is always postpositional.)

all + A

Join unless 'all' is paraphrasable as 'completely' or 'entirely':
- participle: all gone, all done, all_told [overall, in total]
- other adj: all ready, all_right well, OK

as X as Y

Do not join, even though the as PPs are correlated. Exceptions:
- as_long_as [while]

X by Y
- one_by_one [one at a time]
- Don't join if by indicates a product, as in a multidimensional measurement: three by five

classifiers: MEASURE.WORD of N

A few English nouns take idiosyncratic measure words: 3 sheets~of~paper, 2 pairs~of~pants, a piece~of~information

clear/straight/right + P

Do not attach the modifier if it has an ordinary meaning, e.g. go clear through the wall

complex adjective phrases
- highly--recommended, highly--trained
- family--owned company

complex nominals: A+N, N+N
- capital_punishment
- big_rig [slang for truck]
- road_construction [the road isn't actually being constructed, but reconstructed!]
- silver,_ Mariott _member [rewards program]
- electric_blanket
- last_minute
- price_range
- second_chance
- grocery_stores
- pizza_parlor, pizza place, burger joint [diagnostic: does "favorite X" occur on the web? [to filter out proper names]]
- little--danger/risk
- public--wellfare
- this place is a hidden--gem
- strike_one/two/three (unusual syntax!)

complex prepositions

Cf. Quirk pp. 669–670
- out_of, in_between, in_front_of, next_to
- along_with
- as_well, as_well_as
- in_addition_to, in_light_of, on_account_of
- due_to, owing_to, because_of
complex subordinators

From Quirk et al. 1972:

- but, that, in, that, in order that, insofar as, in the event that, save, that, so, that, such, that, except, that, for all, that, now, that
- as (far, long, soon) as, inasmuch as, insofar as, as if, as though, in case
- Do NOT mark the participial ones: assuming, considering, excepting, ... that

discourse connectives

- to start off with
- that is said
- of course

else

Though as a postmodifier it is a bit odd syntactically (anything else, who else, etc.), it does not generally participate in lexicalized idioms.

- "What does 'else' even mean?" - Henrietta

exhortative, emotive, expletive, and proverb idioms

- do_X_a_favor_and Y
  - do_X_a_favor_and V
  vs. plain do_favor
- you get what you pay for (NOT: you get what you purchase)
- get the hell out
- why in the hell (can be any WH word)
- do n't forget, forget it !, never mind
- I have-to-say, gotta-say, etc.: semantics = obligation on self to say something, pragmatics = can't restrain self from expressing an opinion
- Who knows [rhetorical question]
- no way
- Phatic expressions: I 'm sorry, Thank you

existential there

We do not mark ordinary there be existentials as multiwords.

get + "accomplishment" V

get + destination

In the sense of 'arrive', not really a multiword:

- get back home, got to the school

get + result A

- get_ready, get_done, get_busy, get_older
- get_a_flat
- get_correct

infinital to

If a verb, adjective, or noun typically takes an infinitival complement, and the infinitive verb is not fixed, don't join to:

- little to say
- important to determine his fate
- able/ability to find information
- chose/choice to do nothing
- willing/ness to sail

But if it is a special construction, the to should be joined:

- in order to VP
- at liberty to VP
- ready to rumble
- special modal/tense constructions: ought_to, have_to (obligation or necessity), going_to, about_to (but want to, need to, try to)

long + TIME.PERIOD

- a long-(day, week, year) (long in the sense of bad/difficult; cannot be referring to an actual duration because the noun is a time unit with precise duration)

negative polarity items

Join these (including n't and a, but not do) if sufficiently conventional: did n't sleep_a_wink, did n't charge_a_cent/penny/dime, did n't eat_a_morsel/scrap/bite/scrumb (of food)
on: see affective on

prepositional phrase idioms

These include the so-called determiner-less PPs (in_town vs. in the town).

- in a nice/good/... way
- out of site
- on staff
- at all
- at liberty to
- mediocre at best
- to boot
- in town
- on earth, on-the-planet, in-the-world, in the country/universe

in + method of payment

- in cash/quarters/Euros

to + mental state

- to her amusement, to our chagrin, to the surprise of all present
- to my satisfaction

prepositional nouns: N+[P+Pobj]

- capacity for love
- his problem with the decision
- extensive damage to the furniture

Sometimes these participate in verb-noun constructions:

- have a problem with [be annoyed with], have a problem with [have trouble with something not working]
- do damage to the furniture

prepositional verbs: V+[P+Pobj]

- TODO: explain principles
- talk with/to, speak with/to, filled with
- NOT: learn about, booked at (hotel)
- wait for

- lock for
- test for
- (a)rising from
- disposed of
- take care of
- trust with
- listen to, pay attention to
- compare X to Y, X compared to Y
- been to LOCATION/doctor etc.
- trip over, trip on
- do damage to the furniture
- take in [bring to an establishment for some purpose, e.g. a car for service]
- focus on
- nibble/snack/munch on
- kept up with [keep pace, manage not to fall behind]
- looking for my friend [seeking out my friend] vs. looking for my friend [on behalf of]
- not multword:
  - stay at hotel
  - supply with, fit out with [‘with’ marks the thing transferred/given]

proximity expressions: A+P, A+P+P

Join: close to, close by(to), far from, far away(from)

same

- Join article if not followed by a noun (paraphrasable with ‘identical’): his objective was the same each time / each time he had the same objective
- exact same

there: see existential there

verbs with intransitive there

V+P

- walks around (path covering an area)
- stay away = keep away
- run out [get used up] vs. run out of the filter [leak]
- back
  - Generally do not include literal uses: go back [motion], came/headed back [returned to a location]
- money_back, cash_back [change of medium: overpaying with credit card so as to receive the difference in cash]
- s.o.'s money_back, CONDITION or your_money_back [refund]
- pay_s.o._back, get_money_back [returning a loan; get money back is possible but not really idiomatic with this meaning]
- brought_back [taking a car to the shop again for further repairs] vs. brought_back [returning a purchase for a refund]
- turned_back [turned around to travel back]
- get_back_to_s.o. [return to communicate information to s.o.]
- TODO: explain principles
- rent_out
  - with 'out', disambiguates the landlord/permanent owner vs. tenant/temporary user
  - (BUT: rent out an entire place?)
- turn_on, turn_off
- pick_up [retrieve from store]
- If prenominal, don't join of: a_lot/little/bit/couple/few (of), some/plenty of
  - EXCEPTION: a_number_of (TODO: why?) check what H did in xxxx5x
- Join 'square' or 'cubic' within a unit of measurement: square_miles/yards/..., cubic_centimeter/...
- Join half_a when modifying a quantity: half_a day's work, half_a million
- cf. classifiers

quantifiers/quantity modifiers
- If prenominal, don't join of: a_lot/little/bit/couple/few (of), some/plenty of
  - EXCEPTION: a_number_of (TODO: why?) check what H did in xxxx5x
- Join 'square' or 'cubic' within a unit of measurement: square_miles/yards/..., cubic_centimeter/...
- Join half_a when modifying a quantity: half_a day's work, half_a million
- cf. classifiers

quantity comparisons
- less than, more than: Join if functioning as a relational "operator." Heuristic: can '<' or '>' be substituted?
  - less than a week later ('< a week')
  - more happy than sad (NOT: '>' happy than sad')
  - I agree with him more than with you (NOT: '>' with you')

VP idioms
- trying_to_say (with implication of dishonesty or manipulativeness)
- went_out_of_their_way (went to extra effort)
- go_on_and_on [= talk endlessly] (cf. go_on by itself meaning 'continue')
- went_so_far_as_to_say: include 'say' because it has a connotation of negativity (beyond 'went_so_far_as_to (do something)')

support verb constructions

A support verb is a semantically "light" (mostly contentless) verb whose object is a noun that by itself denotes a state, event, or relation; the noun can be thought of as providing the bulk of the meaning/determining the meaning of the verb [FN Book 2010, p. 31]. We join the verb to the noun in question:
- make_a_decision/statement/request/speech/lecture
- take_a(n)_test/exam
- take_a_picture/photo
- give_speeches/lectures/interviews
- undergo/have/receive/get_an_operation
- do/perform_surgery

Some useful properties:
1. Most commonly, support verbs are extremely frequent verbs that exhibit a certain degree of grammaticalization: have, get, give, make, take, etc.
2. One indication of lightness is when the noun cannot felicitously be omitted in a question (She made a decision. / #What did she make?; She had an operation. / #What did she have?; They perform surgery on newborns. / #What do they perform on newborns?)
3. Support verb constructions can often be paraphrased with a semantically "heavy" verb, which may be derivationally related to the noun: make_a_decision = decide, give_an_interview = be interviewed, undergo_an_operation = be operated_on. (The noun surgery has no verb in English, but we could imagine "surgure" as a word! In other cases it would be not unreasonable to incorporate the noun into a verb: take_a_test = test-take.)
4. Caution is required: some expressions are not support verbs, though they appear to be at first blush:
  - get a donation: donation refers to the money donated, not the act of donating. (What did she get in the mail? A donation.)
  - have a barbecue: here have has the sense of hold (an organized event). (What did she have at her house? A barbecue.)
have a disease/an illness
witnessed an operation: the verb and the noun refer to distinct events.

5. NOTE: We exclude the copula from our definition of support, though on rare occasions an idiom lexicalizes a copula: be_the_case.

Following [Calzolari et al. 2002], we distinguish “Type II” support verbs which do contribute some meaning, though it is understood in the context of the event/scenario established by the noun:

- start~a~race
- most aspectual verbs—begin/end/start/stop/continue/finish/repeat/interrupt etc.—would qualify when used with an eventive noun
- pass~an~exam
- keep~a~promise
- answer~a~question
- execute~a~program, evaluate~a~function

Type II support verbs are lower priority for us than “core” support verbs.

verb-noun idioms

Some verb-object combinations are idiomatic, though they do not qualify as support verb constructions. We count these as multisyllables as well:

- pay_attention
- take...time: There are several related idioms involving use of one’s time for some purpose. Include the for the “extra effort” sense: take_the_time to help. Include a preposition for took_time_out_of (sacrifice), took_time_out/off (scheduled vacation).
- waste/spend/save/lose_time/money
- give_an_estimate, give_a_quote: Typically includes the process of estimation as well as offering that estimate to the customer

well V-ed

Typically, don’t join:

- my hamburger is well done

Exceptions:

- that was a job well done
- a well-oiled machine
- he is well read
- well fed

Changes requiring revisions of old annotations

- a_lot
- N_star
- in_cash
- possibly: get/ have_done (hair, etc.)
- highly-recommended, highly-trained
- city, state, etc. locations: _ => ~
- waste_time, spend_time => ~

TODO

- good job, great job, look good
- good job, good work, hard work (I’d be OK with – for these but we decided previously that good/great work should be left alone)
- ‘look at it’: include ‘it’? could be specific or not
- Short of that, One more thing – ?
- fix problem – I’d say this is a collocation, so fix_problem
- best restaurant out_there
- fast and friendly (sounds slightly better than ‘friendly and fast’, but that probably reflects a preference for the word with fewer syllables to come first)
- walk_in_the_door: entering a room or establishment
- have/get done (hair, etc.) _ done (grooming)
- ?? have/get done [work/repairs]
- ?? do~work/job (cf. surgery)
- ?? do~dishes
The following table shows all POS sequences occurring in at least 10 MWEs in version 1.0 of the CMWE corpus (49 patterns). Contiguous and gappy MWE instances are counted separately. POS groupings are abbreviated with a single character (N for common nouns, ` for proper nouns, T for particles, etc.). Strong MWEs are joined with _ and weak MWEs with ~; weak MWE examples are italicized. MWE types occurring at least 10 times are bolded.

<table>
<thead>
<tr>
<th>POS</th>
<th>MWEs</th>
<th>pattern</th>
<th>contig</th>
<th>gappy</th>
<th>most frequent types (lowercased lemmas) and their counts</th>
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</thead>
<tbody>
<tr>
<td>N,N</td>
<td>331</td>
<td>1</td>
<td>customer service: 31  oil change: 9  wait staff: 5  garage door: 4</td>
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<td><code>.</code></td>
<td>325</td>
<td>1</td>
<td>santa fe: 4  dr. shady: 4</td>
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<tr>
<td>V,P</td>
<td>217</td>
<td>44</td>
<td>work with: 27  deal with: 16  look for: 12  have to: 12  ask for: 8</td>
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<td></td>
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<tr>
<td>V,T</td>
<td>149</td>
<td>42</td>
<td>pick up: 15  check out: 10  show up: 9  end up: 6  give up: 5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>V,N</td>
<td>31</td>
<td>107</td>
<td>take time: 7  give chance: 5  waste time: 5  have experience: 5</td>
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<td></td>
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<tr>
<td>A,N</td>
<td>133</td>
<td>3</td>
<td>front desk: 6  top notch: 6  last minute: 5</td>
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<tr>
<td>V,R</td>
<td>103</td>
<td>30</td>
<td>come in: 12  come out: 8  take in: 7  step in: 6  call back: 5</td>
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<td>D,N</td>
<td>83</td>
<td>1</td>
<td>a lot: 30  a bit: 13  a couple: 9</td>
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<tr>
<td>P,N</td>
<td>67</td>
<td>8</td>
<td>on time: 10  in town: 9  in fact: 7</td>
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<tr>
<td>R,N</td>
<td>72</td>
<td>1</td>
<td>at least: 10  at best: 7  as well: 6  of course: 5  at all: 5</td>
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<tr>
<td>V,D,N</td>
<td>46</td>
<td>21</td>
<td>take the time: 11  do a job: 8</td>
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<tr>
<td>V,N</td>
<td>7</td>
<td>56</td>
<td>do job: 9  waste time: 4</td>
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<tr>
<td>POS pattern</td>
<td>MWIs</td>
<td>most frequent types (lowercased lemmas) and their counts</td>
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<tr>
<td>B-V</td>
<td>63</td>
<td>home delivery service: 3  take forest tckt: 3</td>
<td></td>
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<td></td>
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<tr>
<td>P_D_N</td>
<td>33</td>
<td>highly recommend: 43  well spend: 1  pleasantly surprise: 1</td>
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<td>P_P</td>
<td>39</td>
<td>pleased with: 7  happy with: 6  interested in: 5</td>
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<tr>
<td>P_V</td>
<td>39</td>
<td>out of: 10  due to: 9  because of: 7</td>
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<tr>
<td>V_V</td>
<td>38</td>
<td>thank you: 20  get it: 2  trust me: 2</td>
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<tr>
<td>N-N</td>
<td>34</td>
<td>channel guide: 2  drug seeker: 2  room key: 1</td>
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<tr>
<td>A-P</td>
<td>16</td>
<td>take care of: 14  have problem with: 5</td>
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<td></td>
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<tr>
<td>N_V</td>
<td>18</td>
<td>mind blow: 2  test drive: 2  home make: 2</td>
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<tr>
<td>V_V</td>
<td>28</td>
<td>bj s: 2  fraiser 's: 2  ham s: 2  alan 's: 2</td>
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<tr>
<td>R_V</td>
<td>25</td>
<td>all over: 3  even though: 3  instead of: 2  even if: 2</td>
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<td>V_A</td>
<td>19</td>
<td>make sure: 14  get busy: 2  get healthy: 2  play dumb: 1</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>V_P_N</td>
<td>14</td>
<td>go to school: 2  put at ease: 2  be in hands: 2</td>
<td></td>
<td></td>
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<tr>
<td>N_S</td>
<td>20</td>
<td>5 star: 9  2 star: 2  800 number: 1  one bit: 1</td>
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<tr>
<td>N_A</td>
<td>18</td>
<td>year old: 9  month old: 3  years old: 2  cost effective: 1  lightning fast: 1</td>
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<tr>
<td>V_R</td>
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<td>stay away: 3  go in: 2  bring back: 2  recommend highly: 2  work hard: 1</td>
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<td>N_P_R</td>
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<td>chest of drawers: 2  man of word: 1  hang for buck: 1  sister in law: 1</td>
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<td>N_V</td>
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<td>job do: 2  work do: 2  picture take: 1  care receive: 1  operation run: 1</td>
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<tr>
<td>N_R</td>
<td>15</td>
<td>Troll: 4  never mind: 2  better believe: 1  well know: 1</td>
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<td>N_R</td>
<td>15</td>
<td>night out: 3  hands down: 3  thanks again: 3</td>
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<tr>
<td>N_A</td>
<td>14</td>
<td>a f: 2  a little: 11  a few: 13  a little: 13</td>
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<td>V_R_P</td>
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<td>look forward to: 3  talk down to: 2  have yet to: 1</td>
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<td>A_A</td>
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<td>west indi: 3  old fashioned: 1  up front: 1  spot on: 1  tip top: 1  dead on: 1</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>P_P_N</td>
<td>11</td>
<td>go out for: 2  make up for: 2  put up with: 2  turn over to: 1</td>
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<tr>
<td>P_V</td>
<td>10</td>
<td>out of business: 3  out of town: 2  out of date: 1</td>
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<tr>
<td>N_P</td>
<td>12</td>
<td>nothing but: 2  increase in: 1  damage to: 1</td>
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<tr>
<td>A_N_R</td>
<td>11</td>
<td>search engine optimization: 2  kung pao chicken: 1</td>
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<tr>
<td>G_A</td>
<td>10</td>
<td>over priced: 4  over cooked: 1  miss informed: 1</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>P_R</td>
<td>10</td>
<td>by far: 8  if ever: 1  if late: 1</td>
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<td></td>
</tr>
</tbody>
</table>

Here is the complete supersense tagset for nouns. Each tag is briefly described by its symbol, name, short description, and examples.

**O NATURAL OBJECT**  natural feature or nonliving object in nature  barrier reef  nest  neutron_star  planet  sky  fishpond  metamorphic_rock  Mediterranean  cave  stepping_stone  boulder  Orion  ember  universe

**A ARTIFACT**  man-made structures and objects  bridge  restaurant  bedroom  stage  cabinet  toaster  antidote  aspirin

**L LOCATION**  any name of a geopolitical entity, as well as other nouns functioning as locations or regions  Cote_d'Ivoire  New_Yourk_City  downtown  stage_left  India  Newark  interior  airspace

**P PERSON**  humans or personified beings; names of social groups (ethnic, political, etc.) that can refer to an individual in the singular  Persian_deity  glasscutter  mother  kibbutznik  firstborn  worshiper  Roosevelt  Arab  consumer  appellant  guardian  Muslim  American  communist

**G GROUP**  groupings of people or objects, including: organizations/institutions; followers of social movements  collection  flock
**Science** chemicals, molecules, atoms, and subatomic particles are tagged as SUBSTANCE

**Sports** championships/tournaments are EVENTS

(Information) **Technology** Software names, kinds, and components are tagged as COMMUNICATION (e.g. kernel, version, distribution, environment). A connection is a RELATION; project, support, and a configuration are tagged as COGNITION; development and collaboration are ACTs.

**Arabic conventions** Masdar constructions (verbal nouns) are treated as nouns. Anaphora are not tagged.

Noun Supersense Annotation Guidelines
Supersense Tagging Guidelines

What should be tagged?

What counts as a noun?

For the current phase of annotation, we should be strict about only tagging things that (as a whole) serve as nouns. Though semantic categories like ATTRIBUTE (modifiable), LOCATION (southwestern, underneath), RELATION (eleventh), and TIME (earlier) may seem relevant to adjectives, adverbs, prepositions, or other parts of speech, worrying about those would make our lives too complicated.

Special cases:

- **Anaphora** (pronouns, etc.): if the supersense is clear in context—e.g. it has a clear nominal referent or obviously refers to a specific category (e.g. someone referring to a PERSON)—that supersense may be applied; leave blank otherwise (e.g. dummy it; others if too vague).
- Never tag WH- or relative pronouns like who or which.
- Never tag quantifiers in the gray area between determiners, adjectives, and pronouns: some, all, much, several, many, most, few, none, each, every, enough, both, (n)either, and generic senses of one. (These quantifiers often show up in partitives: all/some/none of the X, etc.)
- For Arabic annotation we are not supersense-tagging ANY anaphora.
- **Verbal nouns/gerunds**
  - In Arabic, we have decided to tag masdar instances as nouns.
- **Mentions** of words (e.g., The word "physics" means...) should be tagged as COMMUNICATION because they are about the linguistic item.

Determining item boundaries

It is often difficult to determine which words should belong together as a unit (receiving a single supersense tag) vs. tagged separately. Some guidelines:

- Try to treat **proper names** as a unit. (Lack of capitalization makes this especially difficult for Arabic.)
  - Names of titles SHOULD be included if they appear as they might be used in addressing that person:
    - President Obama
    - United States President Obama
    - Barack Obama, president of the United States
  - Honorific prefixes and suffixes should be included: Dr. Fred Jelinek, Ph.D., King Richard III
- **Other multword phrases** can be treated as a unit if they “go together strongly”.
  - For example, *lexical semantics* is a standard term in linguistics and should therefore be considered a single unit. Note that *lexical* is not a noun, but it may be included as part of a term that overall functions as a noun.
  - Indications of whether an expression should be treated as a unit might include: conventionality (is it a particularly common way to refer to something?), predictability (if you had to guess how to express something, would you be likely to guess that phrase?), transparency (if you hadn't heard the whole expression before, would its meaning be clear from the individual words?), substitutability (could you replace a word with a similar word to get an equally normal expression meaning the same thing?).
  - Consider: would you want to include the expression as a unit in a dictionary?

Vagueness and figurativity

Context and world knowledge should be used only to disambiguate the meaning of a word where it actually has multiple senses, not to refine it where it could refer to different things in context. For example, consider the sentences

1. She felt a sense of shock at the outcome.
2. She expressed her shock at the outcome.

The word ‘shock’ is ambiguous: as a technical term it could refer to a mechanical device, or to a medical state, but in the context of (1) and (2) it clearly has a sense corresponding to the FEELING tag.

You might notice that in (2) ‘shock’ is part of the content of a communication event. However, we do not want to say that ‘shock’ is ambiguous between an emotional state and something that is communicated; in (2) it is merely a feeling that happens to be communicated, while in (1) it is not communicated. Thus, we do not mark it as COMMUNICATION, because this meaning is not inherent to the word itself.

A similar problem arises with metaphor, metonymy, iconicity, and other figurative language. If a building is shaped like a pumpkin, given

3. She lives in a pumpkin.

you might be tempted to mark ‘pumpkin’ as an ARTIFACT (because it is a building). But here ‘pumpkin’ is still referring to the normal sense of pumpkin—i.e. the PLANT—and from context you know that the typical appearance of a pumpkin plant is being used in a novel (non-standard) way to describe something that functions as a building. In other words, that buildings can be shaped like pumpkins is not something you would typically associate with the word ‘pumpkin’ (or, for that matter, any fruit). Similarly, in the sentence

4. I gave her a toy lion.

‘toy’ should be tagged as ARTIFACT and ‘lion’ as ANIMAL (though it happens to be a nonliving depiction of an animal).

On the other hand, if it is highly conventional to use an expression figuratively, as in (5), we can decide that this figurative meaning has been lexicalized (given its own sense) and tag it as such:

5. The White House said it would issue its decision on Monday.

According to WordNet, this use of ‘White House’ should be tagged as GROUP (not ARTIFACT) because it is a standard way to refer to the administration.

Highly idiomatic language should be tagged as if it were literal. For example, *road in the phrase road to success should be tagged as ARTIFACT, even if it is being used metaphorically. Similarly, in an expression like

6. behind the cloak of the Christian religion

(i.e., where someone is concealing their religious beliefs and masquerading as Christian), cloak should be tagged as an ARTIFACT despite being used nonliterally.
Supersense classification

Below are some examples of important words in specific domains, followed by a set of general-purpose rules.

Software domain

- pieces of software: COMMUNICATION
  - version, distribution
  - (software) system, environment
  - (operating system) kernel
- connection: RELATION
- project: COGNITION
- support: COGNITION
- a configuration: COGNITION
- development: ACT
- collaboration: ACT

Sports domain

- championship, tournament, etc.: EVENT

Science domain

- chemicals, molecules, atoms, and subatomic particles (nucleus, electron, particle, etc.): SUBSTANCE

Other special cases

- world should be decided based on context:
  - OBJECT if used like Earth/planet/universe
  - LOCATION if used as a place that something is located
  - GROUP if referring to humanity
  - (possibly other senses as well)
- someone’s life:
  - TIME if referring to the time period (e.g. during his life)
  - STATE if referring to the person’s (physical, cognitive, social, ...) existence
  - STATE if referring to the person’s physical vitality/condition of being alive
  - (possibly others)
- reason: WordNet is kind of confusing here; I think we should say:
  - MOTIVE if referring to a (putative) cause of behavior (e.g. reason for moving to Europe)
  - COGNITION if referring to an understanding of what caused some phenomenon (e.g. reason the sky is blue)
  - COGNITION if referring to the abstract capacity for thought, or the philosophical notion of rationality
  - STATE if used to contrast reasonableness vs. unreasonableness (e.g. within reason)
  - WordNet also includes COMMUNICATION senses for stated reasons, but I think this is splitting hairs. It makes more sense to contrast MOTIVE/COGNITION vs. COMMUNICATION for explanation, where communication seems more central to the lexical meaning. FrameNet seems to agree with this: the Statement frame lists explanation but not reason.]

Decision list

This list attempts to make more explicit the semantic distinctions between the supersense classes for nouns. Follow the directions in order until an appropriate label is found.

1. If it is a natural feature (such as a mountain, valley, river, ocean, cave, continent, planet, the universe, the sky, etc.), label as OBJECT
2. If it is a man-made structure (such as a building, room, road, bridge, mine, stage, tent, etc.), label as ARTIFACT
   - includes venues for particular types of activities: restaurant, concert hall
   - tomb and crypt (structures) are ARTIFACTS, cemetery is a LOCATION
3. For geopolitical entities like cities and countries:
   - If it is a proper name that can be used to refer to a location, label as LOCATION
   - Otherwise, choose LOCATION or GROUP depending on which is the more salient meaning in context
4. If it describes a shape (in the abstract or of an object), label as SHAPE: hexahedron, dip, convex shape, sine curve groove, lower bound, perimeter
5. If it otherwise refers to a space, area, or region (not specifically requiring a man-made structure or describing a specific natural feature), label as LOCATION: region, outside, interior, cemetery, airspace
6. If it is a name of a social group (national/ethnic/religious/political) that can be made singular and used to refer to an individual, label as PERSON (Arab, Muslim, American, communist)
7. If it is a social movement (such as a religion, philosophy, or ideology, like Islam or communism), label as COGNITION if the belief system as a “set of ideas” sense is more salient in context (esp. for academic disciplines like political science), or as GROUP if the “set of adherents” is more salient
8. If it refers to an organization or institution (including companies, associations, teams, political parties, governmental divisions, etc.), label as GROUP: U.S. State Department, University of California, New York Mets
9. If it is a common noun referring to a type or event of grouping (e.g., group, nation, people, meeting, flock, army, a collection, series), label as GROUP
10. If it refers to something being used as food or drink, label as FOOD
11. If it refers to a disease/disorder or physical symptom thereof, label as STATE: measles, rash, fever, tumor, cardiac arrest, plague (= epidemic disease)
12. If it refers to the human body or a natural part of the healthy body, label as BODY: ligament, fingerprint, nervous system, insulin, gene, hairstyle
13. If it refers to a plant or fungus, label as PLANT: acorn squash, Honduras mahogany, genus Lepidobotrys, Canada violet
14. If it refers to a human or personified being, label as PERSON: Persian deity, mother, kibbutznik, firstborn, worshiper, Roosevelt, consumer, guardian, glasscutter, appellant
15. If it refers to non-plant life, label as ANIMAL: lizard, bacteria, virus, tentacle, egg
16. If it refers to a category of entity that pertains generically to all life (including both plants and animals), label as OTHER: organism, cell
17. If it refers to a prepared drug or health aid, label as ARTIFACT: painkiller, antidepressant, ibuprofen, vaccine, cocaine
18. If it refers to a material or substance, label as SUBSTANCE: aluminum, steel (= metal alloy), sand, injection (= solution that is injected), cardboard, DNA, atom, hydrochloric acid
19. If it is a term for an entity that is involved in ownership or payment, label it as POSSESSION: money, coin, a payment, a loan, a purchase (= thing purchased), debt (= amount owed), one's wealth/property (= things one owns)
   - Does NOT include *acts* like transfer, acquisition, sale, purchase, etc.
20. If it refers to a physical thing that is necessarily man-made, label it as ARTIFACT: weapon, hat, cloth, cosmetics, perfume (= scented cosmetic)
21. If it refers to a nonliving object occurring in nature, label it as OBJECT: barrier reef, nest, stopping stone, ember
22. If it refers to a temporal point, period, amount, or measurement, label it as TIME: instant/moment, 10 seconds, 2011 (year), 2nd millennium BC, day, season, velocity, frequency, runtime, latency/delay
   - Includes names of holidays: Christmas
   - age = 'period in history' is a TIME, but age = 'number of years something has existed' is an ATTRIBUTE
23. If it is a (non-temporal) measurement or unit/type of measurement involving a relationship between two or more quantities, including ordinal numbers not used as fractions, label it as RELATION: ratio, quotient, exponential function, transitivity, fortieth
24. If it is a (non-temporal) measurement or unit/type of measurement, including ordinal numbers and fractional amounts, label it as QUANTITY: 7 centimeters, half, 1.8 million, volume (= spatial extent), volt, real number, square root, decimal, digit, 180 degrees, 12 percent/12%
25. If it refers to an emotion, label it as FEELING: indignation, joy, eagerness
26. If it refers to an abstract external force that causes someone to intend to do something, label it as MOTIVE: reason, incentive, urge, conscience
   - NOT purpose, goal, intention, desire, or plan
27. If it refers to a person's belief/idea or mental state/process, label it as COGNITION: knowledge, a dream, consciousness, puzzlement, skepticism, reasoning, logic, intuition, inspiration, muscle memory, theory
28. If it refers to a technique or ability, including forms of perception, label it as COGNITION: a skill, aptitude/talent, a method, perception, visual perception/sight, sense of touch, awareness
29. If it refers to an act of information encoding/transmission or the abstract information/work that is encoded/transmitted—including the use of language, writing, music, performance, print/visual/electronic media, or other form of signaling—label it as COMMUNICATION: a lie, a broadcast, a contract, a concert, a code, an alphabet, an equation, a denial, discussion, sarcasm, concerto, television program, software, input (= signal)
   - Products or tools facilitating communication, such as books, paintings, photographs, or televisions, are themselves ARTIFACTS when used in the physical sense.
30. If it refers to a learned profession (in the context of practicing that profession), label it as ACT: engineering, law, medicine, etc.
31. If it refers to a field or branch of study (in the sciences, humanities, etc.), label it as COGNITION: science, art history, nuclear engineering, medicine (= medical science)
32. If it refers to the abstract to a philosophical viewpoint, label it as COGNITION: socialism, Marxism, democracy
33. If it refers to a physical force, label it as PHENOMENON: gravity, electricity, pressure, suction, radiation
34. If it refers to a state of affairs, i.e. a condition existing at a given point in time (with respect to some person/thing/situation), label it as STATE: poverty, infamy, opulence, hunger, opportunity, disease, darkness (= lack of light)
   - heuristic: in English, can you say someone/something is "in (a state of) X" or "is full of X)?
   - let's exclude anything that can be an emotion (though WordNet also lists a STATE sense of happiness and...
Verb Supersense Annotation Guidelines
Beginning of document content:

Verb Supersense Tagging

Using WordNet as a guide, we should develop a tagging scheme for verbs along the lines of the one for nouns. (Verb tag names are lowercased to distinguish them from noun tags.)

- a (auxiliary)
  - might/aux have/aux been/aux Ving

- j (adjectival)
  - the written/adj message, a sinking/adj feeling

- body (grooming, dressing, bodily functions and care)
  - exercise = work out, cry (shed tears), wear (clothes), sweat, shiver, faint, burp, ache, tire, sleep, recuperate = convalesce, reproduce (biologically), die = cease to live [though WN puzzlingly has change], injure (physically)

- change (size, temperature change, intensifying, etc.)
  - grow (increase in size, age, or value), remove (physically), modify, revert, adjust, pop = burst
  - includes verbs derived with -ify, -ize, -en, etc.: humidify, magnetize, strengthen

- cognition (thinking, judging, analyzing, doubting)
  - decide, think, rate (assign rating), respect = have respect for, memorize, learn, see = understand
  - contrast with perception, communication

- communication (verbal/linguistic or nonverbal gesturing: telling, asking, ordering)
  - speak, talk, write = communicate by writing, announce, type (on a keyboard), cry out, describe, argue, contest, petition, stammer, beg, mandate, veto, libel, preach, teach (education), fax, moe (animal noise)
  - WN lists music production (a person singing/playing an instrument) as creation
  - noises from inanimate objects (‘creak’, etc.) are perception
  - contrast with perception, cognition

- competition (fighting, athletic activities)
  - compete, fight (with someone), play (sports), referee, duel (supersedes social?; superseded by communication for rhetorical senses of ‘attack’, ‘contend’, etc.; superseded by contact for moments of physical contact: ‘wrestle’, ‘box’, ‘punch’, ‘beat up’)

- consumption (ingesting, using, exploiting)
  - eat, picnic, thirst for (drink), digest (food), smoke (cigarette), use, waste [supersedes change and body?]
    - we tasted the food (BUT: the food tastes yummy is perception)

- contact (touching, hitting, tying, digging)
  - fasten, overlay, slice, rub, pinch, box, punch, shoulder, yank, bump, release, lug, airlift, use/operate (an instrument or machine) [supersedes static and motion, e.g. move something by vehicle or by carrying it]

- creation (sewing, baking, painting, performing)
  - create, bake (a cake), grow (agriculture), invent, write = produce a book, perform (give a performance)

- emotion (feeling)
  - fear, anger, hope = wish, trust [difficult to separate from social and communication, e.g. ‘amuse’, ‘encourage’]
    - some lists of emotions:

- motion (walking, flying, swimming)
  - travel, leap (physically), fly, vibrate, rotate (physically) [some synsets, e.g. for ‘reach’, conflates literal and metaphorical senses under motion (metaphorical should be change?)]

- perception (seeing, hearing, feeling)
  - see (visually), witness, feel (by touch), seem, thirst = feel thirsty, ache = feel physical pain, hallucinate, clang, twinkle (candle or bulb), creak (inanimate noise source)
    - the food tastes yummy (BUT: we tasted the food is consumption)
    - contrast with communication, cognition

- possession (buying, selling, owning)
  - receive = acquire, lend, sell, purchase, rob, want/ask=charge (an amount for), have = own, possess (a piece of property)

- social (social activities and events: law, politics, economy, education, family, religion, etc.)
  - meet (socially), celebrate, divorce, succeed (achieve success, or be successor to), respect = show respect towards, gerrymander, cheat (except in the competitive sense), spoil = mollycoddle

- static (being, having, spatial relations)
  - be, have = feature, stagnate, equal, necessitate, lack, span, contain (physically), underlie [superseded by contact? encircle/surround, cover = serve as cover for]
    - what separates these things is...
• X compared to Y
• active subject usually a theme??
  weather (raining, snowing, thawing, thundering)
         rain, thunder, twinkle (star), warm up (climate)

Differentiation

perception, communication, cognition

• communication if there is necessarily a transfer of information from one party to another
  • showing me various options
• perception if the focus is on taking in information by one party (can often substitute "seem" or "feel")
  • they seemed more interested
  • it sounded like it's done every day
  • it will look beautiful
• cognition if about mentally processing information
  • rate as five stars (no communication necessarily implied)
  • difficult to see what you're paying for (= understand)

Precedence relations

• {perception, consumption} > body > change
• motion > social > change
• emotion > change
• motion > {body, possession} (e.g., stand up, bring)
• contact > {static, motion}
• {contact, communication} > competition > social
• emotion > cognition

Groupings

• GENERAL
  • motion, change, creation
  • contact

• stative
• weather

• PERSONS
  • body, consumption
  • perception
  • cognition
    • emotion
  • social
    • possession
    • communication
    • competition

Specific decisions

• fall_ill, fall_asleep, die, injure, give_birth: body
• fall_in_love: emotion

12/4

• haveBeen_to - as in visiting a location: motion
• cleft and existential 'be': stative
• give/receive a tattoo: possession; give/take a lesson: social

12/10

• wait: cognition if emphasis on expectation, stative if emphasis on not acting

12/12

• be_the epitome_of or the epitome_of?
• feel: cognition if having an opinion, emotion if experiencing a feeling, perception if experiencing a physical stimulus

12/19

• deal_with = come to grips with: emotion; deal_with = interact with somebody: social
• found something to be adj: cognition
• require/take/let/permit with an inanimate subject (i.e., it took 1 hour) stative, but when the subject and object are both people it is social
• pass time: ??
• save/keep/prevent from: stative
• like/hate etc. when conveying an opinion: emotion
• get/receive/give—service: social
• bother_with meaning go to the trouble to do something: social
• We need to revisit die and fall ill (body vs. change)
• have_pedicure, have_hair_done: body
  • We need to revisit give/receive tattoo, which is currently possession
• any commercial act (i.e., using their services): possession
• We need to revisit MWEs with be
• have_experience: stative

1/2
• revision of body to take precedence over change (for changes in health, etc.)
• use/operate an instrument/machine: contact

1/14
Several changes above, new section contrasting perception / communication / cognition, as well as:
• recommend, itemized (receipt), get_in_touch_with (a manager): communication
• beware of: cognition
• avoid:
  • (purposefully) avoid restaurant at all costs: cognition
  • something was avoided = it fortunately failed to happen: change
• social:
  • sabotaging
  • went_above_and_beyond
  • baffle_and_switching
  • helped me through difficult times
  • she makes you feel
  • worst service I ever experienced
• arrive/get=made_it/leave/brought_in (= carried): motion
• got upgraded_to (a corner suite): change
• sports related, including (parts): stative

1/16
• grab a cab: possession
• hard to find (restaurant): cognition
• do_research about a restaurant: social
• have_issues/problems: cognition
• use (someone’s services): possession
• pay_attention: perception

Remarks
When tagging in context, note that (unless it is an MWE) only the meaning of the verb should be characterized. So the verb ‘rising’ in ‘temperatures are rising’ should be tagged as a change verb, NOT as a weather verb.

Inherently negative verbs like ‘avoid’, ‘remove’, and ‘refuse’ receive a sense depending on the sort of activity that is not performed.

Issues:
• modals, quasi-modals, count as auxes: be_supposed_to, be_going_to, do not V
• all uses of ‘do’, other weakly collocated light verbs not contributing their own meaning??
• have warning about s.t.: perception?
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