# Semantic Tagging for the Penn Treebank

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#### Abstract

This paper describes the methodology that is being used to augment the Penn Treebank annotation with sense tags and other types of semantic information. Inspired by the results of SENSEVAL, and the high inter-annotator agreement that was achieved there, similar methods were used for a pilot study of 5000 words of running text from the Penn Treebank. Using the same techniques of allowing the annotators to discuss difficult tagging cases and to revise WordNet entries if necessary, comparable inter-annotator rates have been achieved. The criteria for determining appropriate revisions and ensuring clear sense distinctions are described. We are also using hand correction of automatic predicate argument structure information to provide additional thematic role labeling.

## 1. Introduction

The success of recent applications of machine learning techniques to tasks such as part-of-speech tagging and parsing has kindled the hope that these same techniques might have equal or greater success in other areas such as lexical semantics. Advances in automated and semiautomated methods of acquiring lexical semantics in particular would release the field from its dependence on welldefined subdomains with small vocabularies and enable broad-coverage natural language processing. However, supervised machine learning requires large amounts of publicly available training data, and a prerequisite for this training data is general agreement on which elements should be tagged and with what tags. With respect to lexical semantics, this type of general agreement has been strikingly elusive. The field has yet to develop a clear consensus on guidelines for a computational lexicon that could provide a springboard for training data. This is in spite of much effort being devoted to individual approaches to lexicon development such as Meaning Text Theory (Mel'cuk, 1988), the Generative Lexicon (Pustejovsky, 1991), Sensus (Hovy, 1993), MikroKosmos (Nirenburg et al., 1992), Acquilex (Copestake and Sanfilippo, 1993), Framenet (Lowe et al., 1997), Lexical Conceptual Structures (Dorr, 1997), and WordNet (Miller et al., 1990). Each takes a very different approach and makes reference to different underlying theories of semantics.

One of the most controversial areas in semantic representation has to do with polysemy. What constitutes a clear separation into senses for any one word, and how can these senses be computationally characterized and distinguished (Palmer, 1999)? The answer to this question is the key to breaking the bottleneck of semantic representation that is currently the single greatest limitation on the general application of natural language processing techniques.

SIGLEX98-SENSEVAL<sup>1</sup> shed light on the task of sense tagging, and whether or not sufficient training data could be consistently tagged with a set of pre-existing sense distinctions.<sup>2</sup> Assuming appropriate training data could

be provided, an exercise was set up to evaluate different systems on the word sense disambiguation task.<sup>3</sup> This data was prepared using a set of senses from the Hector project (Atkins, 1993), and the results of the exercise were very encouraging. By allowing for revision of senses that caused disagreements among annotators during a training period, inter-annotator agreement for the words that were tagged was well over 90%, and the best supervised systems achieved precision and recall scores in the 80's.

All of the participants in SIGLEX98-SENSEVAL agreed that they would prefer evaluations based on running text rather than corpus instances, but this is only feasible if the Gold Standard sense inventory being used for tagging can be appropriately mapped onto several different lexical resources. Inspired by the SENSEVAL results, we used similar methods for a pilot study of sense tagging 5000 words of running text from the Penn Treebank. Using the same techniques of allowing the annotators to discuss difficult tagging cases and to revise WordNet entries if necessary, comparable inter-annotator rates have been achieved.

# 2. Semantically Tagged Running Text

As a spin-off from SENSEVAL98, for SIGLEX99 we tagged running text with WordNet senses, as well as other senses. This tagged text was made available on the web prior to the workshop, and participants seemed satisfied with the quality of the sense-tagged running text. It was agreed that the next SENSEVAL should include text of this type, with two qualifications. It must be possible to revise WordNet senses along the lines of the Hector revisions when clear sense distinctions could not be made, and the running text should be augmented with sufficient corpus instances of the words chosen for training and testing.

#### 2.1. Sense Tagged Text

We sense-tagged a 5000-word corpus of running text using WordNet1.6 senses. The most obvious example of

<sup>&</sup>lt;sup>1</sup>http://www.itri.brighton.ac.uk/events/senseval

<sup>&</sup>lt;sup>2</sup>There were concerns about inter-annotator agreement for

SemCor.

<sup>&</sup>lt;sup>3</sup>The exercise was also supported by Euralex, Elsenet, ECRAN and SPARKLE. A special issue of Computers and the Humanities that includes a detailed overview of the exercise and reports of individual systems will appear shortly (Kilgarriff and Palmer, 2000).

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<wf lemma=Donald_Trump wnsn=person>Donald Trump</wf> ,
<wf lemma=who wnsn=person:DT>who</wf>
<wf cmd=arb lemma=face wnsn=?>faced</wf> rising
<wf cmd=done lemma=doubt wnsn=1>doubt</wf> about his
<wf cmd=done lemma=bid wnsn=2>bid</wf> for American Airlines parent
<wf lemma=AMR_Corp. wnsn=company>AMR Corp.</wf> even before a United Airlines
<wf cmd=done lemma=buy-out wnsn=1>buy-out</wf>
<wf cmd=done lemma=come_apart wnsn=1?>came apart</wf>
<wf cmd=done lemma=Friday wnsn=1>Friday</wf>
</wf cmd=arb lemma=withdraw wnsn=5?>withdrew</wf> his $ 7.54 billion
<wf cmd=done lemma=offer wnsn=2>offer</wf>
```

Donald Trump <person>, who faced <face7?> rising doubt <doubt1> about his bid <bid2> for American Airlines parent AMR Corp. <company>, even before a United Airlines buy-out <buy-out1> came apart <come\_apart1> Friday, withdrew <withdraw5?> his \$7.54 billion offer <offer2>.

Figure 1: Sample sense-tagged text

an existing corpus of semantically tagged running text is SemCor, in which WordNet1.5 senses were used to tag approximately 200,000 words from the Brown corpus. Unlike SemCor, which assigns WordNet senses to all the verbs, nouns, adjectives, and adverbs, we chose to sensetag only the verbs and headwords of their noun arguments and adjuncts.<sup>4</sup> In addition, proper nouns which were not in WordNet were tagged as either person, company, date, or name (indicating none-of-the-above), and, wherever possible, pronouns were tagged with the sense of their antecedents.

Corpus Selection Our corpus sample comprised five texts from the Penn Treebank II Wall Street Journal (WSJ) corpus. We chose to work on the WSJ corpus because it was already manually annotated for part of speech and bracketed for syntactic structure, and because we have developed tools to automatically extract predicate-arguments from bracketed text. The particular WSJ articles that we chose contained interesting verbs that had been discussed in previous SIGLEX meetings, and covered a range of topics, including an account of an earthquake that occurred during court proceedings, a report about insurance and claims adjusting following an earthquake, a letter to the editor about the need to fight the Columbian drug mafia, a report about a bid by Donald Trump to buy an airline, and a description of a case in which government could seize the assets of criminal defendants, including lawyers fees.

Annotation Process Our test corpus was annotated once by a linguistics graduate student, and then checked by a computer science graduate student trained in lexical semantics. The first annotator made one pass through the corpus and assigned initial sense tags for each of the relevant words, making note of problematic cases. Then the second annotator independently chose a sense for each word, checked it against the initial tag, and then assigned the "final" tag. Instances with differing initial and final tags

<sup>4</sup>WordNet1.6 SemCor includes a large number of additional files in which only the verbs are tagged.

were flagged with "arb", indicating that the second annotator could not agree with the decision of the first annotator even after reconsideration.<sup>5</sup> Tagging in the first pass was done serially and required approximately 40 hours to tag the 5000-word sample. The second pass required the same amount of time but included manual lemmatization of the tagged words (this will be done automatically in the future) so that all inflected forms of a word could be tagged at one time, allowing for more reliable results than serial annotation. We are currently developing a graphical interface that will allow more rapid and efficient annotation in the future.

Annotation Results Approximately 2100 words were sense-tagged, with an overall inter-annotator agreement rate of 89%, as measured by tokens not flagged with "arb". Of the tagged words, 700 were verbs, with an inter-annotator agreement rate of 81%. There were 350 different verb lemmas, 90 of which had at least one occurrence in the corpus in which the annotators disagreed on the correct sense. In many cases, this was because WordNet either did not have the correct sense or else did not adequately define how the different senses should be distinguished.

Figure 1 shows a sample of the tagged text, followed by a simplified form that is easier to read. Some words, such as *face*, are tagged with question marks because they did not have appropriate senses in WordNet, while others, such as *withdraw*, are tagged with question marks because the annotators were uncertain about which sense was correct based on the sense definitions. With our high interannotator agreement level we are confident that when we can allow for senses to be revised as was done for SENSE-VAL we will also get agreement in the 94% range.<sup>6</sup>

<sup>&</sup>lt;sup>5</sup>Consultation of the initial tag was done primarily to filter out some inter-annotator disagreement due to carelessness, fatigue, etc.

<sup>&</sup>lt;sup>6</sup>The method for estimating our agreement figures (i.e., counting "arb" tags) was used primarily as an indicator of which verbs required additional discussion among annotators or even revision of sense definitions. The initial goal of the task was to rapidly

#### 2.2. Automatic Tagging of Predicate-Argument Structure

We are also automatically annotating the same sentences with more explicit verbal predicate-argument structure that is closely linked to the Penn Treebank II bracketing (Marcus, 1994). Under this bracketing scheme, subscripts are appended to standard parse-tree nonterminals (such as NP, PP) to indicate approximately what semantic role a constituent plays in a sentence. For instance, the subscript SBJ is used to indicate that an NP is the subject of some verb, while the subscript TMP may be used to indicate that a prepositional phrase specifies temporal information about an event that is being described. Additionally, indexed empty constituents are used to mark extraction and movement phenomena in cases when the locus of semantic interpretation differs from the position where a constituent appears in a tree.

To induce a useful predicate-argument annotation from this parse-tree representation, however, it is necessary to perform additional analysis on the trees. For instance, when an NP is marked as a subject, there is no explicit indication of what verb it is the subject of. To link verbs and their subjects, it is necessary to determine what the semantic heads of phrases are. Morphological information is not given in the Treebank II annotation scheme, so this also must be added, and phrasal lexical entries must also be identified when they form complex semantic predicates comprising several nodes in the parse tree. Additionally, while some extraction and movement is marked in the corpus, there are often still crucial linkages which are left implicit, and which therefore must be recovered to create an unbroken chain between a predicate and its arguments.

We have developed a module to perform this additional analysis on the Treebank II materials, outputting an SGML representation of all predicate-argument relations detected.<sup>7</sup> The module consults a lexical semantic knowledge base including information about verb subcategorization, the ontology of noun-phrase referents, and complex lexical items comprising more than one word of text.

The module is also able to infer some of the information represented by the Treebank II formalism even if this information has not been explicitly coded in its input. Therefore, it can analyze parse trees produced by statistical parsers such as the one developed by Collins (Collins, 1997), the output of which lacks some of the semantic cues that have been added manually to the Treebank II by annotators.

The predicate-argument analysis is performed in three main phases. First, root forms of inflected words are identified using a morphological analyzer derived from the Word-Net stemmer and from inflectional information in machinereadable dictionaries such as the Collins English Dictionary. Also in this phase, phrasal items such as verb-particle constructions, idioms and compound nominals are identified. An efficient matching algorithm is used which is capable of recognizing both continuous and discontinuous phrases, and phrases where the order of words is not fixed. The matching algorithm makes use of hierarchical declarative constraints on the possible realizations of phrases in the lexicon, and can exploit syntactic contextual cues if a syntactic analysis of the input, such as the parse tree structure of the Penn Treebank, is present.

In the next phase, the explicit antecedents of empty constituents are read off from the Treebank annotation, and gaps are filled where implicit linkages have been left unmarked. This is done by heuristic examination of the local syntactic context of traces and relative clause heads. If no explicit markings are present (for automatically generated parses or old-style Treebank parses), they are inferred. Estimated accuracy of this phase of the algorithm is upwards of 90 percent.

Finally, an efficient tree-template pattern matcher is run on the Treebank parse trees, to identify syntactic relations that signal a predicate-argument relationship between lexical items. The patterns used are schematic tree fragments similar to the elementary trees of a Tree Adjoining Grammar, and are in part derived from the XTAG grammar (XTAG-Group, 1995). Each pattern typically corresponds to a predication over one or more arguments. There are patterns for: transitive, intransitive and ditransitive verbs operating on their subjects, objects and indirect objects; prenominal and predicate adjectives, operating on the nouns they modify; subordinating conjunctions operating on the two clauses that they link; prepositions; determiners; and so on.

Patterns are matched even if they are not contiguous in the tree, as long as the intervening material is well-formed. This allows a pattern to match the subject and main verb of a sentence even if there is an intervening auxiliary verb. The mechanism for handling such cases resembles the adjunction mechanism in Tree Adjoining Grammar.

When a pattern has been identified, it is instantiated with the lexical items that occur in its predicate and argument positions. The argument grid specified by a pattern is marked with thematic information based on the semantic class of the predicate associated with that pattern when it is instantiated. For instance, if the pattern is an intransitive verb tree and the predicate is a causative verb that takes the inchoative alternation, the subject will be assigned a Patient theta role. If however it is a verb of creation, for example, the subject will be an Agent.

To evaluate the accuracy of the automatic predicateargument analyzer, we examined 65 sentences from our sense-tagged running corpus containing 162 automatically annotated verb predicate-argument structures, and found 132 to be correct (81% precision). Hand correction of the entire 5000-word corpus took one day. Since this experiment, we have further improved the accuracy of the analyzer, though we have not yet been able to quantify the degree of this improvement.

produce an accurately sense-tagged corpus of running text using a sense inventory that could be revised. Therefore, inter-annotator agreement figures reported in this paper are not measured in the same way as the standard method in which each annotator independently assigns tags from a fixed inventory, without consulting other annotators.

<sup>&</sup>lt;sup>7</sup>Even though the module can output other predicatearguments, such as for adjectival predicates, we only considered the verbal predicates in this experiment.



WordNet: Shake

Figure 2: Mismatches between Hector and WordNet: Shake

### **3.** Defining Criteria for Sense Distinctions

We have demonstrated that, allowing for revisions, WordNet senses can be just as consistently tagged as Hector senses. However, this does not solve the problem of using training data tagged with one set in order to evaluate a system that uses a different set. To illustrate how pervasive mismatches between lexical resources can be, here are some of the discrepancies between the Hector *shake* and WordNet 1.6 *shake* definitions.

#### 3.1. Shake Mismatches

WordNet 1.6 had 8 senses for shake, with an additional 5 senses for shake up and 2 for shake off, 15 all together. Hector also has 8 main senses for shake, with the first one having 3 additional subsenses and the second one having 2. It has 3 senses for shake up instead of 5, and 2 for shake off. In addition, it has 3 for shake down and 2 for shake out. On the surface this seems fairly compatible, with Word-Net just missing a few verb particle constructions. However, looking in detail at the content of the senses reveals a more fundamental mismatch. Hector distinguishes between shaking hands with someone, and shaking one's fist and shaking one's head. This is quite legitimate, since although these are all similar in that they are communicative acts, they communicate quite different things. Hector also distinguishes between the intransitive TREMBLE sense, Myhands were shaking from the cold, and the more proactive MOVE sense, He shook the bag violently, where someone intentionally moves something back and forth. WordNet collects these together, along with She shook her cousin's hands, as WN1, and instead makes distinctions with respect to the type of action: WN2, gentle tremors; WN3, rapid vibrations; or WN4, swaying. So 3 Hector senses map onto WN1, and Hector 1 maps equally onto WN1,WN2, WN3 and WN4 (see Fig 2). Hector also includes shake out and shake off as examples of 1.1, the CLEAN subsense of 1, Richard removed her socks and shoes and shook all the

gravel out of them, The sand gets shaken off them at the knockout, then goes on to have separate entries for both of these for their more abstract variations, such as, A jittery stock market has shaken out more shareholders in United Scientific Holdings, ... unable to shake off the memories of the trenches. One could argue that shaking out shareholders is not exactly the same thing as shaking apples out of a tree, but that does not mean they are completely unconnected, either.

#### 3.2. Concrete Criteria for Sense Distinctions

In parallel with our sense tagging work we have been developing a lexical resource for verbs that uses Levin classes (Levin, 1993), as the basis of an hierarchical organization allowing for inheritance, and as a source of cross-linguistic semantic features (Dang et al., 1998). To make our resource more usable, we are mapping our verb entries to the relevant WordNet senses. In addition to class membership information, we are also augmenting the WordNet entries with explicit syntactic information such as that found in COMLEX or the XTAG Syntactic Database. Where applicable we include semantic class constraints on verb arguments and information about resulting states, and will be using corpus-based techniques and machine learning to enrich these categorizations. We expect to derive synergies from the parallel tasks of lexicon construction and corpus analysis, using the corpus to enrich the lexicon and the enhanced lexicon to analyze and annotate the corpus more effectively, in an iterative cycle of positive feedback.

The verbs covered by the Levin classes are a subset of what is covered by WordNet, and many of the senses in WordNet entries are not addressed. However, in discussing the different entries for *shake*, and in going back and forth between Hector and WordNet, we find that we often make reference to the inclusion of specific lexical items, different syntactic frames, different semantic class constraints on verb arguments, or differences in outcome to distinguish



Figure 3: High level organization for *Shake* 

the senses. The simplest and most obvious distinguishers are prepositions. *Shake down* is clearly marked as being different in meaning from *shake up*. Having access to even rudimentary syntactic structure makes it quite straightforward to tease apart all of the verb particle structures and idiomatic expressions by virtue of the presence of specific lexical items. Transitive and intransitive usages are also fairly easy to distinguish, but unfortunately they only too often cross sense boundaries.

Semantic class constraints are more subtle and more difficult to capture. However, even semantic preferences can help to distinguish senses. Verb class membership itself, if it can be determined, can play a central role, and can indicate either homonyms or polysemes that are produced through regular extensions of meaning that can apply uniformly to entire sets of verbs. Since these regular extensions, such as resultatives, are often produced by adjunctions that can be seen as extending the subcategorization frame, this highlights the fundamental role argument structure plays in distinguishing senses. For instance, the 27 Hector *shake* senses and the 15 WordNet *shake* senses can all be partitioned into the same five major divisions that are illustrated in Figure 3, each one of which corresponds to a different Levin class. Idioms are handled separately.

The basic sense is the externally controlled *shaking* motion which results when a person or an earthquake or some other major force shakes an object. This same motion can be further amplified with directional information specifying a result such as *off, down, up, out* or *away*. If a path prepositional phrase is actually specified, such as *shook the apples out of the tree* or *shook water from the umbrella*, then a change of location (CH-LOC) occurs, and these usages are now classed as Funnel verbs. The same back and forth motion can occur during Body-Internal states such as shaking from cold or fear, i.e., TREMBLING. If a particular BODY-PART is shaken in a stereotypical way, such as shaking hands or fists or fingers then a communicative act takes place and these are Crane verbs (as in craning one's neck or blinking ones eyes.) Then there are the abstract usages, which are all classified as Psych verbs, such as shaken by the news, or the attack, or his father's death, etc.. The Crane verbs and the Psych verbs are distinguished syntactically from the others in that they cannot occur in the intransitive, or even the passive.<sup>8</sup> Finally we are left with the idioms, which of course have to be listed individually. All of the Hector and WordNet senses can be categorized under one of these major divisions, providing more fine-grained distinctions if needed.

## 4. Discussion

We have presented the approach used to provide semantic tags for 5000 words of running text from the Penn Treebank. We used WordNet senses, but where we found difficulty in getting inter-annotator agreement, allowed for the revision of the WordNet senses. In determining these revisions we make recourse to additional corpus examples as well as concrete criteria for sense distinctions such as those discussed in Section 3.2.. We also tagged the same data with predicate-argument structures marked with Agent and

<sup>&</sup>lt;sup>8</sup>With the exception of his hand was shaken, which being symmetrical is something of an outlier anyway.

Patient thematic roles. This was done semi-automatically, by first running an algorithm for performing the annotation and then hand correcting the twenty percent with errors.

The Penn Treebank seems the ideal corpus for a major semantic tagging effort. It already has syntactic bracketing which can be extremely helpful, as demonstrated by the thematic role labeling, and it is widely available, and widely used.

We will continue to tag running text, but will do it more slowly, so that we can tag the additional corpus instances of each word as we come to it. This is more efficient, and more importantly, gives us sufficient data to determine if the WordNet senses need to be revised. If the Treebank itself has only a few instances of a particular word, these can always be augmented. We can automatically separate out all of the verb particle constructions and idiomatic usages which are clearly lexically marked as distinct senses. We can also automatically recognize simple predicate-argument structure, another useful indicator.

We will also be using an improved interface that simplifies the tagging itself, and displays both the sentence to be tagged and its predicate-argument structure. The interface can also be used to retrieve surrounding text, sometimes necessary in making a subtle sense distinction.

## 5. Acknowledgments

This paper reports on work supported by NSF grant IIS-9800658.

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