A Taxonomy, Dataset, and Classifier for Automatic Noun Compound Interpretation

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Abstract

The automatic interpretation of noun-noun compounds is an important subproblem within many natural language processing applications and is an area of increasing interest. The problem is difficult, with disagreement regarding the number and nature of the relations, low inter-annotator agreement, and limited annotated data. In this paper, we present a novel taxonomy of relations that integrates previous relations, the largest publicly-available annotated dataset, and a supervised classification method for automatic noun compound interpretation.

1 Introduction

Noun compounds (e.g., ‘maple leaf’) occur very frequently in text, and their interpretation—determining the relationships between adjacent nouns as well as the hierarchical dependency structure of the NP in which they occur—is an important problem within a wide variety of natural language processing (NLP) applications, including machine translation (Baldwin and Tanaka, 2004) and question answering (Ahn et al., 2005). The interpretation of noun compounds is a difficult problem for various reasons (Spärck Jones, 1983). Among them is the fact that no set of relations proposed to date has been accepted as complete and appropriate for general-purpose text. Regardless, automatic noun compound interpretation is the focus of an upcoming SEMEVAL task (Butnaru et al., 2009).

Leaving aside the problem of determining the dependency structure among strings of three or more nouns—a problem we do not address in this paper—automatic noun compound interpretation requires a taxonomy of noun-noun relations, an automatic method for accurately assigning the relations to noun compounds, and, in the case of supervised classification, a sufficiently large dataset for training.

Earlier work has often suffered from using taxonomies with coarse-grained, highly ambiguous predicates, such as prepositions, as various labels (Lauer, 1995) and/or unimpressive inter-annotator agreement among human judges (Kim and Baldwin, 2005). In addition, the datasets annotated according to these various schemes have often been too small to provide wide coverage of the noun compounds likely to occur in general text.

In this paper, we present a large, fine-grained taxonomy of 43 noun compound relations, a dataset annotated according to this taxonomy, and a supervised, automatic classification method for determining the relation between the head and modifier words in a noun compound. We compare and map our relations to those in other taxonomies and report the promising results of an inter-annotator agreement study as well as an automatic classification experiment. We examine the various features used for classification and identify one very useful, novel family of features. Our dataset is, to the best of our knowledge, the largest noun compound dataset yet produced. We will make it available via http://www.isi.edu.

2 Related Work

2.1 Taxonomies

The relations between the component nouns in noun compounds have been the subject of various linguistic studies performed throughout the years, including early work by Jespersen (1949). The taxonomies they created are varied. Lees created an early taxonomy based primarily upon grammar (Lees, 1960). Levi’s influential work postulated that complex nominals (Levi’s name for noun compounds that also permits certain adjectival modifiers) are all derived either via nominalization or
by deleting one of nine predicates (i.e., CAUSE, HAVE, MAKE, USE, BE, IN, FOR, FROM, ABOUT) from an underlying sentence construction (Levi, 1978). Of the taxonomies presented by purely linguistic studies, our categories are most similar to those proposed by Warren (1978), whose categories (e.g., MATERIAL+ARTEFACT, OBJ+PART) are generally less ambiguous than Levi’s.

In contrast to studies that claim the existence of a relatively small number of semantic relations, Downing (1977) presents a strong case for the existence of an unbounded number of relations. While we agree with Downing’s belief that the number of relations is unbounded, we contend that the vast majority of noun compounds fits within a relatively small set of categories.

The relations used in computational linguistics vary much along the same lines as those proposed earlier by linguists. Several lines of work (Finin, 1980; Butnariu and Veale, 2008; Nakov, 2008) assume the existence of an unbounded number of relations. Others use categories similar to Levi’s, such as Lauer’s (1995) set of prepositional paraphrases (i.e., OF, FOR, IN, ON, AT, FROM, WITH, ABOUT) to analyze noun compounds. Some work (e.g., Barker and Szpakowicz, 1998; Nastase and Szpakowicz, 2003; Girju et al., 2005; Kim and Baldwin, 2005) use sets of categories that are somewhat more similar to those proposed by Warren (1978). While most of the noun compound research to date is not domain specific, Rosario and Hearst (2001) create and experiment with a taxonomy tailored to biomedical text.

2.2 Classification

The approaches used for automatic classification are also varied. Vanderwende (1994) presents one of the first systems for automatic classification, which extracted information from online sources and used a series of rules to rank a set of most likely interpretations. Lauer (1995) uses corpus statistics to select a prepositional paraphrase. Several lines of work, including that of Barker and Szpakowicz (1998), use memory-based methods. Kim and Baldwin (2005) and Turney (2006) use nearest neighbor approaches based upon WordNet (Fellbaum, 1998) and Turney’s Latent Relational Analysis, respectively. Rosario and Hearst (2001) utilize neural networks to classify compounds according to their domain-specific relation taxonomy. Moldovan et al. (2004) use SVMs as well as a novel algorithm (i.e., semantic scattering). Nastase et al. (2006) experiment with a variety of classification methods including memory-based methods, SVMs, and decision trees. Ó Séaghdha and Copestake (2009) use SVMs and experiment with kernel methods on a dataset labeled using a relatively small taxonomy. Girju (2009) uses cross-linguistic information from parallel corpora to aid classification.

3 Taxonomy

3.1 Creation

Given the heterogeneity of past work, we decided to start fresh and build a new taxonomy of relations using naturally occurring noun pairs, and then compare the result to earlier relation sets. We collected 17509 noun pairs and over a period of 10 months assigned one or more relations to each, gradually building and refining our taxonomy. More details regarding the dataset are provided in Section 4.

The relations we produced were then compared to those present in other taxonomies (e.g., Levi, 1978; Warren, 1978; Barker and Szpakowicz, 1998; Girju et al., 2005), and they were found to be fairly similar. We present a detailed comparison in Section 3.4.

We tested the relation set with an initial inter-annotator agreement study (our latest inter-annotator agreement study results are presented in Section 6). However, the mediocre results indicated that the categories and/or their definitions needed refinement. We then embarked on a series of changes, testing each generation by annotation using Amazon’s Mechanical Turk service, a relatively quick and inexpensive online platform where requesters may publish tasks for anonymous online workers (Turkers) to perform. Mechanical Turk has been previously used in a variety of NLP research, including recent work on noun compounds by Nakov (2008) to collect short phrases for linking the nouns within noun compounds.

For the Mechanical Turk annotation tests, we created five sets of 100 noun compounds from noun compounds automatically extracted from a random subset of New York Times articles written between 1987 and 2007 (Sandhaus, 2008). Each of these sets was used in a separate annotation round. For each round, a set of 100 noun compounds was uploaded along with category defini-
| Category Name | % Example | Approximate Mappings |
|---------------|-----------|----------------------|
| Causal Group  |           |                      |
| COMMUNICATOR OF COMMUNICATION | 0.77 court order | BGN:Agent, L:Act, Product, V:Subj |
| PERFORMER OF ACTIVITY | 2.07 police abuse | BGN:Agent, L:Act, Product, V:Subj |
| CREATOR/PROVIDER/CAUSE OF | 2.55 ad revenue | BGV:Cause(d-by), L:Cause, N:Effect |
| Purpose/Activity Group | | |
| PERFORM/ENGAGE_IN | 13.24 cooking pot | BGV:Purpose, L:For, ≈N:Purpose, W:Activity |
| CREATE/PROVIDE/SELL | 8.94 nicotine patch | BV:Purpose, BG:Result, G:Make-Produce, GNV:Cause(s), NC:For, BGN:Product, W:Activity |
| OBTAIN/ACCESS/SEEK | 1.50 shrimp boat | BGNV:Purpose, L:For, W:Activity |
| MODIFY/PROCESS/CHANGE | 1.50 eye surgery | BGNV:Purpose, L:For, W:Activity |
| MITIGATE/OPOSE/DESTROY | 2.34 flak jacket | BGV:Purpose, L:For, ≈N:Detraction, W:Activity |
| ORGANIZE/SUPERVISE/AUTHORITY | 4.82 ethics board | BGNV:Purpose/Topic, L:For/About, W:Activity |
| PROPEL | 0.16 water gun | BGNV:Purpose, L:For, W:Activity |
| PROTECT/CONSERVE | 0.25 screen saver | BGNV:Purpose, L:For, W:Activity |
| TRANSPORT/TRANSFER/TRADE | 1.92 freight train | BGNV:Purpose, L:For, W:Activity |
| TRAVERSE/VISIT | 0.11 tree traversal | BGNV:Purpose, L:For, W:Activity |
| Ownership, Experience, Employment, and Use | | |
| POSSESSOR + OWNED/POSSESSED | 2.11 family estate | BGNVW:Possess*, L:Have |
| EXPERIENCER + COGNITION/MENTAL | 0.45 voter concern | BGNVW:Possess*, ≈G:Experience, L:Have |
| EMPLOYER + EMPLOYEE/VOLUNTEER | 2.72 team doctor | BGNVW:Possess*, L:For/Have, BGN:Beneficiary |
| CONSUMER + CONSUMED | 0.09 cat food | BGNVW:Purpose, L:For, BGN:Beneficiary |
| USER/RECIPIENT + USED/RECEIVED | 1.02 voter guide | BGNVW:Purpose, G:Recipient, L:For, BGN:Beneficiary |
| OWNED/POSSESS + POSSESSION | 1.20 store owner | ≈G:Possession, L:Have, ≈W:Belonging-Possessor |
| EXPERIENCE + EXPERIENCER | 0.27 fire victim | ≈G:Experience, L:Have |
| THING CONSUMED + CONSUMER | 0.41 fruit fly | ≈W:Obj-SingleBeing |
| THING/MEANS USED + USER | 1.96 faith healer | ≈BNV:Instrument, ≈G:Means, L:Use, W:MotivePower |
| Temporal Group | | |
| TIME [SPAN] + X | 2.35 night work | ≈BNV:Time(At), G:Temporal, L:In, T:W:Time |
| X + TIME [SPAN] | 0.50 birth date | G:Temporal, ≈W:Obj-Time |
| Location and Whole+Part/Member of Location/Geographic Scope of X | 4.99 hillside home | ≈BNV:Location(From), L:In, ≈B:Source, N:Location(A), W:Place-Obj, PlaceOfOrigin |
| WHOLE + PART/MEMBER OF | 1.75 robot arm | ≈B:Possess*, ≈G:Part-Whole, L:Have, N:Part, W:Whole-Part, ≈W:Obj-Part, Group:Member |
| Composition and Containment Group | | |
| SUBSTANCE/MATERIAL/INGREDIENT + WHOLE | 2.42 plastic bag | BNVW:Material*, G:Source, L:From, ≈L:Have, ≈L:Make, ≈N:Content |
| PART/MEMBER + COLLECTION/CONFIG/SERIES | 1.78 truck convoy | ≈L:Make, ≈N:Whole, ≈V:Part-Whole, W:Parts-Whole |
| X + SPATIAL CONTAINER/LOCATION/BOUNDS | 1.39 shoe box | ≈B:Content, L:Located, L:For, L:Have, N:Location, W:Obj-Place |
| Topic Group | | |
| TOPIC OF COMMUNICATION/IMAGERY/INFO | 8.37 travel story | BGNV:Topic, L:About, W:SubjectMatter, G:Depiction |
| TOPIC OF PLAN/DEAL/ARRANGEMENT/RULES | 4.11 law terms | BGNV:Topic, L:About, W:SubjectMatter |
| TOPIC OF OBSERVATION/STUDY/EVALUATION | 1.71 job survey | BGNV:Topic, L:About, W:SubjectMatter |
| TOPIC OF COGNITION/EMOTION | 0.58 jazz fan | BGNV:Topic, L:About, W:SubjectMatter |
| TOPIC OF EXPERT | 0.57 policy wonk | BGNV:Topic, L:About, W:SubjectMatter |
| TOPIC OF SITUATION | 1.64 oil glut | BGNV:Topic, L:About |
| TOPIC OF EVENT/PROCESS | 1.09 lava flow | G:Theme, V:Subj |
| Attribute Group | | |
| TOPIC/THING + ATTRIB | 4.13 street name | BNV:Possess*, ≈G:Property, L:Have, ≈W:Obj-Quality |
| TOPIC/THING + ATTRIB VALUE CHAR OF | 0.31 earth tone | BNV:Possess*, ≈G:Property, L:Have, ≈W:Obj-Quality |
| Attributive and Coreferential | | |
| COREFERENTIAL | 4.51 fighter plane | BV:Equative, G:Type, IS-A, ≈L:BE, ≈N:Equality, ≈W:Copula |
| PARTIAL ATTRIBUTE TRANSFER | 0.69 skeleton crew | ≈W:Resemblance, G:Type |
| MEASURE + WHOLE | 4.37 hour meeting | G:Measure, N:TimeThrough, W:Size-Whole |
| Other | | |
| HIGHLY LEXICIALIZED / FIXED PAIR | 0.65 pig iron | |
| OTHER | 1.67 contact lens | |

Table 1: The semantic relations, their frequency in the dataset, examples, and approximate relation mappings to previous relation sets. ≈-approximately equivalent; ⊂-super/sub set; ∪-some overlap; -union; initials BGLNVW refer respectively to the works of (Barker and Szpakowicz, 1998; Girju et al., 2005; Girju, 2007; Levi, 1978; Nastase and Szpakowicz, 2003; Vanderwende, 1994; Warren, 1978).
tions and examples. Turkers were asked to select one or, if they deemed it appropriate, two categories for each noun pair. After all annotations for the round were completed, they were examined, and any taxonomic changes deemed appropriate (e.g., the creation, deletion, and/or modification of categories) were incorporated into the taxonomy before the next set of 100 was uploaded. The categories were substantially modified during this process. They are shown in Table 1 along with examples and an approximate mapping to several other taxonomies.

3.2 Category Descriptions

Our categories are defined with sentences. For example, the SUBSTANCE category has the definition \( n_1 \) is one of the primary physical substances/materials/ingredients that \( n_2 \) is made/composed out of from. Our LOCATION category’s definition reads \( n_1 \) is the location / geographic scope where \( n_2 \) is at, near, from, generally found, or occurs. Defining the categories with sentences is advantageous because it is possible to create straightforward, explicit definitions that humans can easily test examples against.

3.3 Taxonomy Groupings

In addition to influencing the category definitions, some taxonomy groupings were altered with the hope that this would improve inter-annotator agreement for cases where Turker disagreement was systematic. For example, LOCATION and WHOLE + PART/MEMBER OF were commonly disagreed upon by Turkers so they were placed within their own taxonomic subgroup. The ambiguity between these categories has previously been observed by Girju (2009).

Turkers also tended to disagree between the categories related to composition and containment. Due this apparent similarity they were also grouped together in the taxonomy.

The ATTRIBUTE categories are positioned near the TOPIC group because some Turkers chose a TOPIC category when an ATTRIBUTE category was deemed more appropriate. This may be because attributes are relatively abstract concepts that are often somewhat descriptive of whatever possesses them. A prime example of this is street name.

3.4 Contrast with other Taxonomies

In order to ensure completeness, we mapped into our taxonomy the relations proposed in most pre-

vious work including those of Barker and Szpakowicz (1998) and Girju et al. (2005). The results, shown in Table 1, demonstrate that our taxonomy is similar to several taxonomies used in other work. However, there are three main differences and several less important ones. The first major difference is the absence of a significant THEME or OBJECT category. The second main difference is that our taxonomy does not include a PURPOSE category and, instead, has several smaller categories. Finally, instead of possessing a single TOPIC category, our taxonomy has several, finer-grained TOPIC categories. These differences are significant because THEME/OBJECT, PURPOSE, and TOPIC are typically among the most frequent categories.

THEME/OBJECT is typically the category to which other researchers assign noun compounds whose head noun is a nominalized verb and whose modifier noun is the THEME/OBJECT of the verb. This is typically done with the justification that the relation/predicate (the root verb of the nominalization) is overtly expressed.

While including a THEME/OBJECT category has the advantage of simplicity, its disadvantages are significant. This category leads to a significant ambiguity in examples because many compounds fitting the THEME/OBJECT category also match some other category as well. Warren (1978) gives the examples of soup pot and soup container to illustrate this issue, and Girju (2009) notes a substantial overlap between THEME and MAKE-PRODUCE. Our results from Mechanical Turk showed significant overlap between PURPOSE and OBJECT categories (present in an earlier version of the taxonomy). For this reason, we do not include a separate THEME/OBJECT category. If it is important to know whether the modifier also holds a THEME/OBJECT relationship, we suggest treating this as a separate classification task.

The absence of a single PURPOSE category is another distinguishing characteristic of our taxonomy. Instead, the taxonomy includes a number of finer-grained categories (e.g., PERFORM/ENGAGE_IN), which can be conflated to create a PURPOSE category if necessary. During our Mechanical Turk-based refinement process, our now-defunct PURPOSE category was found to be ambiguous with many other categories as well as difficult to define. This problem has been noted by others. For example, Warren (1978)
points out that tea in tea cup qualifies as both the content and the purpose of the cup. Similarly, while WHOLE+PART/MEMBER was selected by most Turkers for bike tire, one individual chose PURPOSE. Our investigation identified five main purpose-like relations that most of our PURPOSE examples can be divided into, including activity performance (PERFORM/ENGAGE_IN), creation/provision (CREATE/PROVIDE/CAUSE_OF), obtainment/access (OBTAIN/ACCESS/SEEK), supervision/management (ORGANIZE/SUPERVISE/AUTHORITY), and opposition (MITIGATE/OPPOSE/DESTROY).

The third major distinguishing different between our taxonomy and others is the absence of a single TOPIC/ABOUT relation. Instead, our taxonomy has several finer-grained categories that can be conflated into a TOPIC category. Unlike the previous two distinguishing characteristics, which were motivated primarily by Turker annotations, this separation was largely motivated by author dissatisfaction with a single TOPIC category.

Two differentiating characteristics of less importance are the absence of BENEFICIARY or SOURCE categories (Barker and Szpakowicz, 1998; Nastase and Szpakowicz, 2003; Girju et al., 2005). Our EMPLOYER, CONSUMER, and USER/RECIPIENT categories combined more or less cover BENEFICIARY. Since SOURCE is ambiguous in multiple ways including causation (tsunami injury), provision (government grant), ingredients (rice wine), and locations (north wind), we chose to exclude it.

4 Dataset

Our noun compound dataset was created from two principal sources: an in-house collection of terms extracted from a large corpus using part-of-speech tagging and mutual information and the Wall Street Journal section of the Penn Treebank. Compounds including one or more proper nouns were ignored. In total, the dataset contains 17509 unique, out-of-context examples, making it by far the largest hand-annotated compound noun dataset in existence that we are aware of. Proper nouns were not included.

The next largest available datasets have a variety of drawbacks for noun compound interpretation in general text. Kim and Baldwin’s (2005) dataset is the second largest available dataset, but inter-annotator agreement was only 52.3%, and the annotations had an usually lopsided distribution; 42% of the data has TOPIC labels. Most (73.23%) of Girju’s (2007) dataset consists of noun-preposition-noun constructions. Rosario and Heart’s (2001) dataset is specific to the biomedical domain, while Ó Séaghdha and Copestake’s (2009) data is labeled with only 5 extremely coarse-grained categories. The remaining datasets are too small to provide wide coverage. See Table 2 below for size comparison with other publicly available, semantically annotated datasets.

| Size    | Work                           |
|---------|--------------------------------|
| 17509   | Tratz and Hovy, 2010            |
| 2169    | Kim and Baldwin, 2005          |
| 2031    | Girju, 2007                    |
| 1660    | Rosario and Hearst, 2001       |
| 1443    | O Séaghdha and Copestake, 2007 |
| 505     | Barker and Szpakowicz, 1998    |
| 600     | Nastase and Szpakowicz, 2003   |
| 395     | Vanderwende, 1994              |
| 385     | Lauer, 1995                    |

Table 2: Size of various available noun compound datasets labeled with relation annotations. Italics indicate that the dataset contains n-prep-n constructions and/or non-nouns.

5 Automated Classification

We use a Maximum Entropy (Berger et al., 1996) classifier with a large number of boolean features, some of which are novel (e.g., the inclusion of words from WordNet definitions). Maximum Entropy classifiers have been effective on a variety of NLP problems including preposition sense disambiguation (Ye and Baldwin, 2007), which is somewhat similar to noun compound interpretation. We use the implementation provided in the MALLET machine learning toolkit (McCallum, 2002).

5.1 Features Used

WordNet-based Features

- (Synonyms, Hypernyms) for all NN and VB entries for each word
- Intersection of the words’ hypernyms
- All terms from the ‘gloss’ for each word
- Intersection of the words’ ‘gloss’ terms
- Lexicographer file names for each word’s NN and VB entries (e.g., n1:substance)
• Logical AND of lexicographer file names for the two words (e.g., n1:substance ∧ n2:artifact)
• Lists of all link types (e.g., meronym links) associated with each word
• Logical AND of the link types (e.g., n1:hasMeronym(s) ∧ n2:hasHolonym(s))
• Part-of-speech (POS) indicators for the existence of VB, ADJ, and ADV entries for each of the nouns
• Logical AND of the POS indicators for the two words
• ‘Lexicalized’ indicator for the existence of an entry for the compound as a single term
• Indicators if either word is a part of the other word according to Part-Of links
• Indicators if either word is a hypernym of the other
• Indicators if either word is in the definition of the other

Roget’s Thesaurus-based Features

• Roget’s divisions for all noun (and verb) entries for each word
• Roget’s divisions shared by the two words

Surface-level Features

• Indicators for the suffix types (e.g., de-adjectival, de-nominal [non]agentive, de-verbal [non]agentive)
• Indicators for degree, number, order, or locative prefixes (e.g., ultra-, poly-, post-, and inter-, respectively)
• Indicators for whether or not a preposition occurs within either term (e.g., ‘down’ in ‘breakdown’)
• The last {two, three} letters of each word

Web 1T N-gram Features

To provide information related to term usage to the classifier, we extracted trigram and 4-gram features from the Web 1T Corpus (Brants and Franz, 2006), a large collection of n-grams and their counts created from approximately one trillion words of Web text. Only n-grams containing lowercase words were used. 5-grams were not used due to memory limitations. Only n-grams containing both terms (including plural forms) were extracted. Table 3 describes the extracted n-gram features.

5.2 Cross Validation Experiments

We performed 10-fold cross validation on our dataset, and, for the purpose of comparison, we also performed 5-fold cross validation on Ó Séaghdha’s (2007) dataset using his folds. Our classification accuracy results are 79.3% on our data and 63.6% on the Ó Séaghdha data. We used the $\chi^2$ measure to limit our experiments to the most useful 35000 features, which is the point where we obtain the highest results on Ó Séaghdha’s data. The 63.6% figure is similar to the best previously reported accuracy for this dataset of 63.1%, which was obtained by Ó Séaghdha and Copestake (2009) using kernel methods.

For comparison with SVMs, we used Thorsten Joachims’ $\text{SVM}^{\text{multiclass}}$, which implements an optimization solution to Cramer and Singer’s (2001) multiclass SVM formulation. The best results were similar, with 79.4% on our dataset and 63.1% on Ó Séaghdha’s. $\text{SVM}^{\text{multiclass}}$ was, however, observed to be very sensitive to the tuning of the C parameter, which determines the tradeoff between training error and margin width. The best results for the datasets were produced with C set to 5000 and 375 respectively.

| Trigram Feature Extraction Patterns |
|-------------------------------------|
| text | $<n_1>$ | $<n_2>$ |
| $<^*>$ | $<n_1>$ | $<n_2>$ |
| $<n_1>$ | $<^*>$ | text |
| $<^*>$ | $<n_2>$ | $<^*>$ |

| 4-Gram Feature Extraction Patterns |
|-------------------------------------|
| $<n_1>$ | $<n_2>$ | text | text |
| $<^*>$ | $<n_1>$ | $<n_2>$ | $<^*>$ | text |
| text | $<^*>$ | $<n_1>$ | $<n_2>$ | text |
| text | text | $<^*>$ | $<n_2>$ | $<^*>$ |
| $<^*>$ | text | $<^*>$ | $<n_2>$ | $<^*>$ |
| $<n_1>$ | $<^*>$ | $<^*>$ | $<n_2>$ | $<^*>$ |
| $<^*>$ | $<n_1>$ | $<^*>$ | $<^*>$ | $<n_2>$ |
| $<n_2>$ | $<^*>$ | text | $<^*>$ | $<n_1>$ |
| $<^*>$ | text | $<^*>$ | $<n_2>$ | $<^*>$ |

Table 3: Patterns for extracting trigram and 4-Gram features from the Web 1T Corpus for a given noun compound ($n_1$, $n_2$).

To assess the impact of the various features, we ran the cross validation experiments for each feature type, alternating between including only one
feature type and including all feature types except that one. The results for these runs using the Maximum Entropy classifier are presented in Table 4.

There are several points of interest in these results. The WordNet gloss terms had a surprisingly strong influence. In fact, by themselves they proved roughly as useful as the hyponym features, and their removal had the single strongest negative impact on accuracy for our dataset. As far as we know, this is the first time that WordNet definition words have been used as features for noun compound interpretation. In the future, it may be valuable to add definition words from other machine-readable dictionaries. The influence of the Web 1T n-gram features was somewhat mixed. They had a positive impact on the Ó Séaghdha data, but their affect upon our dataset was limited and mixed, with the removal of the 4-gram features actually improving performance slightly.

| Feature Type   | Our Data | Ó Séaghdha Data |
|----------------|----------|-----------------|
| synonmys       | 0.674    | 0.773           |
| hyponyms       | 0.753    | 0.787           |
| hyponyms<λ>    | 0.250    | 0.791           |
| gloss terms    | 0.741    | 0.785           |
| gloss terms<λ>| 0.226    | 0.793           |
| lexnames       | 0.583    | 0.792           |
| lexnames<λ>    | 0.480    | 0.790           |
| linktypes      | 0.328    | 0.793           |
| linktypes<λ>   | 0.277    | 0.792           |
| pos            | 0.146    | 0.793           |
| pos<λ>         | 0.146    | 0.793           |
| part-of terms  | 0.372    | 0.793           |
| lexicalized    | 0.132    | 0.793           |
| part of other  | 0.132    | 0.793           |
| gloss of other | 0.133    | 0.793           |
| hyponym of other | 0.132   | 0.793           |
| | | |

Table 4: Impact of features; cross validation accuracy for only one feature type and all but one feature type experiments, denoted by 1 and M-1 respectively. ∩ - features shared by both n₁ and n₂; ∧ - n₁ and n₂ features conjoined by logical AND (e.g., n₁ is a ‘substance’ ∧ n₂ is a ‘artifact’)
who annotated the compound. Finally, the label with the highest rating was selected.

6.4 Inter-annotator Agreement Results

The raw agreement scores along with Cohen’s $\kappa$ (Cohen, 1960), a measure of inter-annotator agreement that discounts random chance, were calculated against the authors’ labeling of the data for each Turker, the weighted-voting annotation set, and the automatic classification output. These statistics are reported in Table 5 along with the individual Turker “quality” scores. The 54 Turkers who made fewer than 3 annotations were excluded from the calculations under the assumption that they were not dedicated to the task, leaving a total of 49 Turkers. Due to space limitations, only results for Turkers who annotated 15 or more instances are included in Table 5.

We recomputed the $\kappa$ statistics after conflating the category groups in two different ways. The first variation involved conflating all the TOPIC categories into a single topic category, resulting in a total of 37 categories (denoted by $\kappa^*$ in Table 5). For the second variation, in addition to conflating the TOPIC categories, we conflated the ATTRIBUTE categories into a single category and the PURPOSE/ACTIVITY categories into a single category, for a total of 27 categories (denoted by $\kappa^{**}$ in Table 5).

6.5 Results Discussion

The .57-.67 $\kappa$ figures achieved by the Voted annotations compare well with previously reported inter-annotator agreement figures for noun compounds using fine-grained taxonomies. Kim and Baldwin (2005) report an agreement of 52.31% (not $\kappa$) for their dataset using Barker and Szpakowicz’s (1998) 20 semantic relations. Girju et al. (2005) report .58 $\kappa$ using a set of 35 semantic relations, only 21 of which were used, and a .80 $\kappa$ score using Lauer’s 8 prepositional paraphrases. Girju (2007) reports .61 $\kappa$ agreement using a similar set of 22 semantic relations for noun compound annotation in which the annotators are shown translations of the compound in foreign languages. Ó Séaghdha (2007) reports a .68 $\kappa$ for a relatively small set of relations (BE, HAVE, IN, INST, ACTOR, ABOUT) after removing compounds with non-specific associations or high lexicalization. The correlation between our automatic “quality” scores for the Turkers who performed at least three annotations and their simple agreement with our annotations was very strong at 0.88.

The .51 automatic classification figure is respectable given the larger number of categories in the taxonomy. It is also important to remember that the training set covers a large portion of the two-word noun compound instances in recent New York Times articles, so substantially higher accuracy can be expected on many texts. Interestingly, conflating categories only improved the $\kappa$ statistics for the Turkers, not the automatic classifier.

7 Conclusion

In this paper, we present a novel, fine-grained taxonomy of 43 noun-noun semantic relations, the largest annotated noun compound dataset yet created, and a supervised classification method for automatic noun compound interpretation.

We describe our taxonomy and provide mappings to taxonomies used by others. Our inter-annotator agreement study, which utilized non-experts, shows good inter-annotator agreement

| Id | N  | Weight | Agree  | $\kappa$ | $\kappa^*$ | $\kappa^{**}$ |
|----|----|--------|--------|---------|-----------|-------------|
| 1  | 23 | 0.45   | 0.70   | 0.67    | 0.67      | 0.74        |
| 2  | 34 | 0.46   | 0.68   | 0.65    | 0.65      | 0.72        |
| 3  | 35 | 0.34   | 0.63   | 0.60    | 0.61      | 0.61        |
| 4  | 24 | 0.46   | 0.63   | 0.59    | 0.68      | 0.76        |
| 5  | 16 | 0.58   | 0.63   | 0.59    | 0.59      | 0.54        |
| Voted | 150 | NA | 0.59 | 0.57 | 0.61 | 0.67 |
| 6  | 52 | 0.45   | 0.58   | 0.54    | 0.60      | 0.60        |
| 7  | 38 | 0.35   | 0.55   | 0.52    | 0.54      | 0.56        |
| 8  | 149 | 0.36 | 0.32 | 0.49 | 0.53 | 0.58 |
| Auto | 150 | NA | 0.51 | 0.47 | 0.47 | 0.45 |
| 9  | 48 | 0.33   | 0.48   | 0.45    | 0.49      | 0.59        |
| 10 | 36 | 0.42   | 0.47   | 0.43    | 0.48      | 0.52        |
| 11 | 104 | 0.29 | 0.46 | 0.43 | 0.48 | 0.52 |
| 12 | 38 | 0.33   | 0.45   | 0.40    | 0.46      | 0.47        |
| 13 | 66 | 0.31   | 0.42   | 0.39    | 0.39      | 0.49        |
| 14 | 15 | 0.27   | 0.40   | 0.34    | 0.31      | 0.29        |
| 15 | 62 | 0.23   | 0.34   | 0.29    | 0.35      | 0.38        |
| 16 | 150 | 0.23 | 0.30 | 0.26 | 0.26 | 0.30 |
| 17 | 19 | 0.24   | 0.26   | 0.21    | 0.17      | 0.14        |
| 18 | 144 | 0.21 | 0.25 | 0.20 | 0.22 | 0.22 |
| 19 | 29 | 0.18   | 0.21   | 0.14    | 0.17      | 0.10        |
| 20 | 22 | 0.18   | 0.18   | 0.12    | 0.10      | 0.16        |
| 21 | 51 | 0.19   | 0.18   | 0.13    | 0.20      | 0.26        |
| 22 | 41 | 0.02   | 0.02   | 0.00    | 0.00      | 0.01        |

Table 5: Annotation results. Id – annotator id; N – number of annotations; Weight – voting weight; Agree – raw agreement versus the author’s annotations; $\kappa$ – Cohen’s $\kappa$ agreement; $\kappa^*$ and $\kappa^{**}$ – Cohen’s $\kappa$ results after conflating certain categories. Voted – combined annotation set using weighted voting; Auto – automatic classification output.
given the difficulty of the task, indicating that our
category definitions are relatively straightforward.
Our taxonomy provides wide coverage, with only
2.32% of our dataset marked as other/lexicalized and 2.67% of our 150 inter-annotator agreement
data marked as such by the combined Turker (Voted) annotation set.

We demonstrated the effectiveness of a straightforward, supervised classification approach to
noun compound interpretation that uses a large variety of boolean features. We also examined the
importance of the different features, noting a novel and very useful set of features—the words comprising the definitions of the individual words.

8 Future Work

In the future, we plan to focus on the interpretation
of noun compounds with 3 or more nouns, a problem that includes bracketing noun compounds into
their dependency structures in addition to noun-noun semantic relation interpretation. Furthermore, we would like to build a system that can handle longer noun phrases, including prepositions and possessives.

We would like to experiment with including features from various other lexical resources to determine their usefulness for this problem.

Eventually, we would like to expand our data set and relations to cover proper nouns as well. We are hopeful that our current dataset and relation definitions, which will be made available via http://www.isi.edu will be helpful to other researchers doing work regarding text semantics.

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