Automatic Discovery of Manner Relations and its Applications

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Abstract

This paper presents a method for the automatic discovery of MANNER relations from text. An extended definition of MANNER is proposed, including restrictions on the sorts of concepts that can be part of its domain and range. The connections with other relations and the lexico-syntactic patterns that encode MANNER are analyzed. A new feature set specialized on MANNER detection is depicted and justified. Experimental results show improvement over previous attempts to extract MANNER. Combinations of MANNER with other semantic relations are also discussed.

1 Introduction

Extracting semantic relations from text is an important step towards understanding the meaning of text. Many applications that use no semantics, or only shallow semantics, could benefit by having available more text semantics. Recently, there is a growing interest in text semantics (Márquez et al., 2008; Davidov and Rappoport, 2008).

An important semantic relation for many applications is the MANNER relation. Broadly speaking, MANNER encodes the mode, style, way or fashion in which something is done or happened. For example, quick delivery encodes a MANNER relation, since quick is the manner in which the delivery happened.

An application of MANNER detection is Question Answering, where many how questions refer to this particular relation. Consider for example the question How did the President communicate his message?, and the text Through his spokesman, Obama sent a strong message [. . .]. To answer such questions, it is useful to identify first the MANNER relations in text.

MANNER occurs frequently in text and it is expressed by a wide variety of lexico-syntactic patterns. For example, PropBank annotates 8,037 ARG-MNR relations (10.7%) out of 74,980 adjunct-like arguments (ARGMs). There are verbs that state a particular way of doing something, e.g., to limp implicitly states a particular way of walking. Adverbial phrases and prepositional phrases are the most productive patterns, e.g., The nation’s industrial sector is now growing very slowly if at all and He started the company on his own. Consider the following example: The company said Mr. Stronach will personally direct the restructuring assisted by Manfred Gingl, [. . .]. There are two MANNER relations in this sentence: the underlined chunks of text encode the way in which Mr. Stronach will direct the restructuring.

2 Previous Work

The extraction of semantic relations in general has caught the attention of several researchers. Approaches to detect semantic relations usually focus on particular lexical and syntactic patterns. There are both unsupervised (Davidov et al., 2007; Turney, 2006) and supervised approaches. The SemEval-2007 Task 04 (Girju et al., 2007) aimed at relations between nominals. Work has been done on detecting relations within noun phrases (Nulty, 2007),

\footnote{Penn TreeBank, file wsj_0027, sentence 10.}
named entities (Hirano et al., 2007), clauses (Szpakowicz et al., 1995) and syntax-based comma resolution (Srikumar et al., 2008). There have been proposals to detect a particular relation, e.g., CAUSE (Chang and Choi, 2006), INTENT (Tatu, 2005), PART-WHOLE (Girju et al., 2006) and IS-A (Hearst, 1992).

MANNER is a frequent relation, but besides theoretical studies there is not much work on detecting it. Girju et al. (2003) propose a set of features to extract MANNER exclusively from adverbial phrases and report a precision of 64.44% and recall of 68.67%. MANNER is a semantic role, and all the works on the extraction of roles (Gildea and Jurafsky, 2002; Giuglea and Moschitti, 2006) extracts MANNER as well. However, these approaches treat MANNER as any other role and do not use any specific features for its detection. As we show in this paper, MANNER has its own unique characteristics and identifying them improves the extraction accuracy. The two most used semantic role annotation resources, FrameNet (Baker et al., 1998) and PropBank (Palmer et al., 2005), include MANNER.

The main contributions of this paper are: (1) empirical study of MANNER and its semantics; (2) analysis of the differences with other relations; (3) lexico-syntactic patterns expressing MANNER; (4) a set of features specialized on the detection of MANNER; and (5) the way MANNER combines with other semantic relations.

3 The Semantics of MANNER Relation

Traditionally, a semantic relation is defined by stating the kind of connection linking two concepts. For example, MANNER is loosely defined by the PropBank annotation guidelines as manner adverbs specify how an action is performed [...] manner should be used when an adverb be an answer to a question starting with 'how?' We find this kind of definition weak and prone to confusion (Section 3.2). Nonetheless, to the best of our knowledge, semantic relations have been mostly defined stating only a vague definition.

Following (Helbig, 2005), we propose an extended definition for semantic relations, includ-

3.1 MANNER Definition

Formally, MANNER is represented as MNR(x, y), and it should be read x is the manner in which y happened. In addition, DOMAIN(MNR) and RANGE(MNR) are the sets of sorts of concepts that can be part of the first and second argument.

RANGE(MNR), namely y, is restricted to situations, which are defined as anything that happens at a time and place. Situations include events and states and can be expressed by verbs or nouns, e.g., conference, race, mix and grow. DOMAIN(MNR), namely x, is restricted to qualities (ql), non temporal abstract objects (ntao) and states (st). Qualities represent characteristics that can be assigned to other concepts, such as slowly and abruptly. Non temporal abstract objects are intangible entities. They are somehow product of human reasoning and are not palpable. They do not encode periods or points of time, such as week, or yesterday. For example, odor, disease, and mile are ntao; book and car are not because they are tangible. Unlike events, states are situations that do not imply a change in the concepts involved. For example, standing there or holding hands are states; whereas walking to the park and pinching him are events. For more details about these semantic classes, refer to (Helbig, 2005).

These semantic restrictions on MANNER come after studying previous definitions and manual examination of hundreds of examples. Their use and benefits are described in Section 4.

3.2 MANNER and Other Semantic Relations

MANNER is close in meaning with several other relations, specifically INSTRUMENT, AT-LOCATION and AT-TIME.

Asking how does not identify MANNER in many cases. For example, given John broke the window [with a hammer], the question how did John break the window? can be answered by with the hammer, and yet the hammer is not the MANNER but the INSTRUMENT of the broke event. Other relations that

http://verbs.colorado.edu/~mpalmer/projects/ace/PBguide lines.pdf, page 26.
may be confused as MANNER include AT-LOCATION and AT-TIME, like in [The dog jumped] x [over the fence] y and [John used to go] x [regularly] y.

A way of solving this ambiguity is by prioritizing the semantic relations among the possible candidates for a given pair of concepts. For example, if both INSTRUMENT and MANNER are possible, the former is extracted. In a similar fashion, AT-LOCATION and AT-TIME could have higher priority than MANNER. This idea has one big disadvantage: the correct detection of MANNER relies on the detection of several other relations, a problem which has proven difficult and thus would unnecessarily introduce errors.

Using the proposed extended definition one may discard the false MANNER relations above. Hammer is not a quality, non temporal abstract object or state (hammers are palpable objects), so by definition a relation of the form MNR(the hammer, y) shall not hold. Similarly, fence and week do not fulfill the domain restriction, so MNR(over the fence, y) and MNR(every other week, y) are not valid either.

MANNER also relates to CAUSE. Again, asking how? does not resolve the ambiguity. Given The legislation itself noted that it [was introduced] x “by request.” [...] (wsj_0041, 47), we believe the underlined PP indicates the CAUSE and not the MANNER of x because the introduction of the legislation is the effect of the request. Using the extended definition, since request is an event (it implies a change), MNR(by request, y) is discarded based on the domain and range restrictions.

4 Argument Extraction

In order to implement domain and range restrictions, one needs to map words to the four proposed semantic classes: situations (si), states (st), qualities (q) and non temporal abstract objects (ntao). These classes are the ones involved in MNR; work has been done to define in a similar way more relations, but we do not report on that in this paper.

First, the head word of a potential argument is identified. Then, the head is mapped into a semantic class using three sources of information: POS tags, WordNet hypernyms and named entity (NE) types. Table 1 presents the rules that define the mapping. We obtained them following a data-driven approach using a subset of MANNER annotation from PropBank and FrameNet. Intermediate classes are defined to facilitate legibility; intermediate classes ending in -NE only involve named entity types.

Words are automatically POS tagged using a modified Brill tagger. We do not perform word sense disambiguation because in our experiments it did not bring any improvement; all senses are considered for each word. isHypo(x) for a given word w indicates if any of the senses of w is a hyponym of x in WordNet 2.0. An in-house NE recognizer is used to assign NE types. It detects 90 types organized in a hierarchy with an accuracy of 92% and it has been used in a state-of-the-art Question Answering system (Moldovan et al., 2007). As far as the mapping is concerned, only the following NE types are used: human, organization, country, town, province, other-loc, money, date and time. The mapping also uses an automatically built list of verbs and nouns that encode events (verb_events and noun_events).

The procedure to map words into semantic classes has been evaluated on a subset of PropBank which was not used to define the mapping. First, we selected 1,091 sentences which contained a total of 171 MANNER relations. We syntactically parsed the sentences using Charniak’s parser and then performed argument detection by matching the trees to the syntactic patterns depicted in Section 5. 52,612 arguments pairs were detected as potential MANNER. Because of parsing errors, 146 (85.4%) of the 171 MANNER relations are in this set.

After mapping and enforcing domain and range constraints, the argument pairs were reduced to 11,724 (22.3%). The filtered subset includes 140 (81.8%) of the 171 MANNER relations. The filtering does make mistakes, but the massive pruning mainly filters out potential relations that do not hold: it filters 77.7% of argument pairs and it only misclassifies 6 pairs.

5 Lexico-Syntactic Patterns Expressing MANNER

MANNER is expressed by a wide variety of lexico-syntactic patterns, implicitly or explicitly.

Table 2 shows the syntactic distribution of MANNER relation in PropBank. We only consider relations between a single node in the syntactic tree and
Table 1: Mapping for the semantic classes used for defining DOMAIN(MNR) and RANGE(MNR).

| Class Rule | situation state || event state POStag=verb || isHypo(state.n.4) |
| --- | --- | --- | --- | --- |
| event | (POStag=verb && in(verb events)) || (POStag=noun && animate_object && isHypo(phenomenon.n.1) || isHypo(event.n.1) || in(noun events)) |
| animate_object | livingNE || (POStag=noun && (isHypo(thing.n.9) && isHypo(anticipation.n.4)) || isHypo(social_group.n.1))) |
| livingNE | neType=(human | organization | country | town | province | other-loc) |
| quality | POStag=(adverb | gerund) || headPP=(with | without) |
| non_temporal_abstract_object | abstract_object && !temporal |
| abstract_object | neType=money || isHypo(thing.n.9) || (!isHypo(social_group.n.1) && (isHypo(abstraction.n.6 | psychological_feature.n.1 | possession.n.2 | event.n.1 | state.n.4 | group.n.1 | act.n.2))) |
| temporal | TemporalNE || isHypo(time_period.n.1) || isHypo(time.n.5) |
| temporalNE | ne-type=(date | time) |

Table 2: Syntactic patterns encoding MANNER in PropBank, number of occurrences, and examples. A total of 7,852 MANNER relations are encoded in PropBank between a single node in the syntactic tree and a verb. In all examples, MNR(x, y) holds, where x is the text underlined. Syntactic annotation comes straight from the Penn TreeBank.

| Synt. pattern | #Occ. | %Occ. | Example | Sentence |
| --- | --- | --- | --- | --- |
| ADVP | 3559 | 45.3% | This story line might [resonate]y [more strongly]ADVP if Mr. Lane had as strong a presence in front of the camera as he does behind it. |
| PP | 3499 | 44.6% | NBC may yet find a way to [take]y a passive, minority interest in a program-maker [without violating the rules]PP. |
| RB | 286 | 3.6% | Backe is [a [closely]RB [held]]y ADVP media firm|NP run by former CBS Inc. President Jon Backe. |
| S | 148 | 1.9% | Salomon [posted]y an unexpectedly big gain in quarterly earnings, [aided by its securities trading and investments banking activities|S. |
| NP | 120 | 1.5% | […] he [graduated]y [Phi Beta Kappa]NP from the University of Kentucky at age 18, after spending only 2 1/2 years in college. |
| Other | 240 | 3.1% | Tokyo stocks [closed]y [former]ADVP Monday, with the Nikkei index making its fifth consecutive daily gain. |

5.1 Ambiguities of MANNER

Both ADVPs and PPs are highly ambiguous when the task is to identify their semantics. The PropBank authors (Palmer et al., 2005) report discrepancies between annotators mainly with AT-LOCATION and simply no relation, i.e., when a phrase does not encode a role at all. In their annotation, 22.2% of ADVPs encode MANNER (30.3% AT-TIME), whereas only 4.6% of PPs starting with in and 6.1% start-
Table 3: Examples of ADVPs and PPs encoding MANNER with different nodes as parents. In all examples, MNR(x, y) holds, where x is the underlined phrase. Syntactic annotation comes straight from the Penn TreeBank.

| Parent | #Occ. | Phrase | File, #sent | Example                                                                 |
|--------|-------|--------|-------------|--------------------------------------------------------------------------|
| VP     | 3306  | ADVP   | wsj_2341, 23 | The company [was [officially]ADVP [merged], with Bristol-Myers Co. earlier this month]VP. |
|        | 3107  | PP     | wsj_2320, 7  | This is something P&G would [do]y, [with or without Kao]PPVP, says Mr. Zurkuhlen. |
| S      | 215   | ADVP   | wsj_0044, 6  | [Virtually word by word]ADVP, the notes [matched], questions and answers on the social-studies section of the test the student was taking. |
|        | 339   | PP     | wsj_2454, 9  | [[Under the laws of the land]PP, the ANC [remains]y, an illegal organization, and its headquarters are still in Lusaka, Zambia.]s |
| ADJP   | 17    | ADVP   | wsj_1057, 85 | […] ABC touted “Call to Glory,” but the military drama was [[missing], [in action]PP]ADJP within weeks. |
|        | 4     | PP     | wsj_2431, 14 | Two former ministers [were]y, [[so heavily]ADVP implicated]ADJP in the Koskotas affair that PASOK members of Parliament voted […] |
| PP     | 9     | ADVP   | wsj_1249, 24 | In Japan, by contrast, companies tend to develop their talent and [promote], [from [within]PP]. |
|        | 9     | PP     | wsj_1505, 30 | London share prices were [influenced], [[largely]ADVP by declines on Wall Street and weakness in the British pound]PP. |

6 Approach

We propose a supervised learning approach, where instances are positive and negative MANNER examples. Due to their intrinsic difference, we build different models for ADVPs and PPs.

6.1 Building the Corpus

The corpus building procedure is as follows. First, all ADVPs and PPs whose parent node is a VP or S and encode a MANNER according to PropBank are extracted, yielding 3559 and 3499 positive instances respectively. Then, 10,000 examples of ADVPs and another 10,000 of PPs from the Penn TreeBank not encoding a MANNER according to PropBank are added. These negative instances must have as their parent node either VP or S as well and are selected randomly.

The total number of instances, 13,559 for ADVPs and 13,499 for PPs, are then divided into training (60%), held-out (20%) and test (20%). The held-out portion is used to tune the feature set and the final results provided are the ones obtained with the test portion, i.e., instances that have not been used in any way to learn the models. Because PropBank adds semantic role annotation on top of the Penn TreeBank, we have gold syntactic annotation for all instances.

6.2 Selecting features

Selected features are derived from previous works on detecting semantic roles, namely (Gildea and Jurafsky, 2002) and the participating systems in
CoNLL-2005 Shared Task (Carreras and Marquez, 2005), combined with new, manner-specific features that we introduce. These new features bring a significant improvement and are dependent on the phrase potentially encoding a MANNER. Experimentation has shown that MANNER relations expressed by an ADVP are easier to detect than the ones expressed by a PP.

Adverbial Phrases The feature set used is depicted in Table 4. Some features are typical of semantic role labeling, but features adverb, dictionary and ends-with-ly are specialized to MANNER extraction from ADVPs. These three additional features bring a significant improvement (Section 7).

We only provide details for the non-obvious features.

The main adverb and verb are retrieved by selecting the last adverb or verb of a sequence. For example, in more strongly, the main adverb is strongly, and in had been rescued the main verb is rescued.

Dictionary tests the presence of the adverb in a custom built dictionary which contains all lemmas for adverbs in WordNet whose gloss matches the regular expression in a .+ (manner|way|fashion|style). For example, more.adv.1: used to form the comparative of some adjectives and adverbs does not belong to the dictionary, and strongly.adv.1: with strength or in a
strong manner does. This feature is an extension of the dictionary presented in (Girju et al., 2003).

Given the sentence [...] We [work [damn hard]ADVP at what we do for damn little pay]VP, and [...] (wsj, 1144, 128), the features are: {parent-node:VP, num-leaves:2, adverb:hard, dictionary:no, ends-with-ly:no, POS-tag-bef:RB, POS-tag-aft:IN, verb:work, distance:1}, and it is a positive instance.

Prepositional Phrases PPs are known to be highly ambiguous and more features need to be added. The complete set is depicted in Table 5.

Some features are typical of semantic role detection; we only provide a justification for the new features added. Num-pp-bef and num-pp-aft captures the number of PP siblings before and after the PP. The relative order of PPs is typically manner, at-location and at-time (Hawkins, 1999), and this feature captures this idea without requiring temporal or local annotation.

PPs having quotes are more likely to encode a manner, the chunk of text between quotes being the manner. For example, use in “very modest amounts” (wsj_0003, 10) and reward with “page bonuses” (wsj_0012, 8).

head-np indicates the head noun of the NP that attaches to the preposition to form the PP. It is retrieved by selecting the last noun in the NP. Certain nouns are more likely to indicate a manner than others. This feature captures the domain restriction. For nouns, only non temporal abstract objects and states can encode a manner. Some examples of positive instances are haul in the guests’ [honor], lift in two [stages], win at any [cost], plunge against the [mark] and ease with little [fanfare]. However, counterexamples can be found as well: say through his [spokesman] and do over the [counter].

Verb-pas indicates if a verb is in passive voice. In that case, a PP starting with by is much more likely to encode an agent than a manner. For example, compare (1) “When the fruit is ripe, it [falls]y from the tree [by itself]PP,” he says. (wsj_0300, 23); and (2) Four of the planes [were purchased]y [by International Lease]PP from Singapore Airlines in a [...] transaction (wsj_0243, 3). In the first example a manner holds; in the second an agent.

Given the sentence Kalipharma is a New Jersey-based pharmaceuticals concern that [sells products [under the Purepac label]PP]VP. (wsj_0023, 1), the features are: {parent-node:VP, next-node:-, num-pp-bef:0, num-pp-aft:0, first-word:under, first-POS-tag:IN, first-prep:under, POS-tag-bef:NNS, POS-tag-aft:DT, word-aft:the, has-rb:no, has-quotes:no, head-np-lemma:label, head-is-last:yes, head-has-cap:yes, verb:sells, verb-lemma:sell, verb-pas:no}, and it is a positive instance.

7 Learning Algorithm and Results

7.1 Experimental Results

As a learning algorithm we use a Naive Bayes classifier, well known for its simplicity and yet good performance. We trained our models with the training corpus using 10-fold cross validation, and used the held-out portion to tune the feature set and adjust parameters. More features than the ones depicted were tried, but we only report the final set. For example, named entity recognition and flags indicating the presence of at-location and at-time relations for the verb were tried, but they did not bring any significant improvement.

Table 6 summarizes the results obtained. We report results only on the test corpus, which corresponds to instances not seen before and therefore they are a honest estimation of the performance. The improvement brought by subsets of features and statistical significance tests are also reported. We test the significance of the difference in performance between two feature sets i and j on a set of ins instances with the Z-score test, where $z = \frac{\text{err}_i - \text{err}_j}{\sqrt{\frac{\text{err}_i}{\text{ins}} + \frac{\text{err}_j}{\text{ins}}}}$, err$_k$ is the error made using set $k$, and $\sigma_d = \sqrt{\frac{\text{err}_i(1-\text{err}_i)}{\text{ins}} + \frac{\text{err}_j(1-\text{err}_j)}{\text{ins}}}$. ADVPs The full set of features yields a F-measure of 0.815. The three specialized features (3, 4 and 5) are responsible for an improvement of .168 in the F-measure. This difference in performance yields a Z-score of 7.1, which indicates that it is statistically significant.

PPs All the features proposed yield a F-measure of 0.693. The novel features specialized in manner detection from PPs (in bold letters in Table 5) bring an improvement of 0.059, which again is significant.
The Z-score is 2.35, i.e., the difference in performance is statistically significant with a confidence greater than 97.5%. Thus, adding the specialized features is justified.

### 7.2 Error Analysis

The mapping of words to semantic classes is data-driven and decisions were taken so that the overall accuracy is high. However, mistakes are made. Given *We want to [see] the market from the inside*, the underlined PP encodes a MANNER and the mapping proposed (Table 1) does not map inside to ntao. Similarly, given *Like their cohorts in political consulting, the litigation advisers [encourage] their clients […]*, the underlined text encodes a MANNER and yet cohorts is subsumed by social group.n.l and therefore is not mapped to ntao.

The model proposed for MANNER detection makes mistakes as well. For ADVPs, if the main adverb has not been seen during training, chances of detecting MANNER are low. For example, the classifier fails to detect the following MANNER relations: […] which together own about […] (wsj_0671, 1); and who has ardently supported […] (wsj_1017, 26) even though ardently is present in the dictionary and ends in -ly.

For PPs, some errors are due to the PropBank annotation. For example, in *Shearson Lehman Hutton began its coverage of the company with favorable ratings.* (wsj_2061, 57), the underlined text is annotated as ARG2, even though it does encode a MANNER. Our model correctly detects a MANNER but it is counted as a mistake. Manners encoded by *under* and *at* are rarely detected, as in *that have been consolidated in federal court under U.S. District Judge Milton Pollack* (wsj_1022.mrg, 10).

### 8 Comparison with Previous Work

To the best of our knowledge, there have not been much efforts to detect MANNER alone. Girju et al. (2003), present a supervised approach for ADVP similar to the one reported in this paper, yielding a F-measure of .665. Our augmented feature set obtains a F-measure of .815, clearly outperforming their method (Z-test, confidence > 97.5%). Moreover, ADVPs only represent 45.3% of MANNER as a semantic role in PropBank. We also have presented a model to detect MANNER encoded by a PP, the other big chunk of MANNER (44.6%) in PropBank.

Complete systems for Semantic Role Labeling perform poorly when detecting MANNER; the Top-10 systems in CoNLL-2005 shared task \(^3\) obtained F-measures ranging from .527 to .592. We have trained our models using the training data provided by the task organizers (using the Charniak parser syntactic information), and tested with the provided test set (test.wsj). Our models yield a Precision of .759 and Recall of .626 (F-measure .686), bringing a significant improvement over those systems (Z-test, confidence > 97.5%). When calculating recall, we take into account all MANNER in the test set, not only ADVPs and PPs whose fathers are S or VP (i.e. not only the ones our models are able to detect). This evaluation is done with exactly the same data provided from the task organizers for both training and test.

Unlike typical semantic role labelers, our features do not include rich syntactic information (e.g. syntactic path from verb to the argument). Instead, we only require the value of the parent and in the case of PPs, the sibling node. When repeating the CoNLL-2005 Shared Task training and test using gold syntactic information, the F-measure obtained is .714, very close to the .686 obtained with Charniak syntactic trees (not significant, confidence > 97.5%).

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\(^3\)http://www.lsi.upc.es/~srlconll/st05/st05.html
Even though syntactic parsers achieve a good performance, they make mistakes and the less our models rely on them, the better.

9 Composing MANNER with PURPOSE

MANNER can combine with other semantic relations in order to reveal implicit relations that otherwise would be missed. The basic idea is to compose MANNER with other relations in order to infer another MANNER. A necessary condition for combining MANNER with another relation R is the compatibility of RANGE(MNR) with DOM(R) or RANGE(R) with DOM(MNR). The extended definition (Section 3) allows to quickly determine if two relations are compatible (Blanco et al., 2010).

The new MANNER is automatically inferred by humans when reading, but computers need an explicit representation. Consider the following example: [...] the traders [place]y orders [via computers]MNR [to buy the basket of stocks ...]PRP (wsj_0118, 48). PropBank states the basic annotation between brackets: via computers is the MANNER and to buy the basket [...] the PURPOSE of the place orders event. We propose to combine these two relations in order to come up with the new relation MNR(via computers, buy the basket [...]). This relation is obvious when reading the sentence, so it is omitted by the writer. However, any semantic representation of text needs as much semantics as possible explicitly stated.

This claim is supported by several PropBank examples: (1) The classics have [zoomed]y [in price]MNR [to meet the competition]PRP, and ... (wsj_0071, 9) and (2) ... the government [curtailed]y production [with land-idling programs]MNR [to reduce price-depressing surpluses]PRP (wsj_0113, 12). In both examples, PropBank encodes the MANNER and PURPOSE for event y indicated with brackets. After combining both relations, two new MANNER arise: MNR(in price, meet the competition) and MNR(with land-idling programs, reduce price-depressing surpluses).

Out of 237 verbs having in PropBank both PURPOSE and MANNER annotation, the above inference method yields 189 new valid MANNER not present in PropBank (Accuracy .797).

MANNER and other relations. MANNER does not combine with relations such as CAUSE, AT-LOCATION or AT-TIME. For example, given And they continue [anonymously]x,MNR [attacking]y CIA Director William Webster [for being too accommodating to the committee]z,CAU (wsj_0590, 27), there is no relation between x and z. Similarly, given [In the tower]x,LOC, five men and women [pull]y [rhythmically]z,MNR on ropes attached to [...] (wsj_0089, 5) and [In May]x,TMP, the two companies, [through their jointly owned holding company]z,MNR, Temple, [offered]y [... ] (wsj_0063, 3), no connection exists between x and z.

10 Conclusions

We have presented a supervised method for the automatic discovery of MANNER. Our approach is simple and outperforms previous work. Our models specialize in detecting the most common pattern encoding MANNER. By doing so we are able to specialize our feature sets and outperform previous approaches that followed the idea of using dozens of features, most of them potentially useless, and letting a complicated machine learning algorithm decide the actual useful features.

We believe that each relation or role has its own unique characteristics and capturing them improves performance. We have shown this fact for MANNER by examining examples, considering the kind of arguments that can be part of the domain and range, and considering theoretical works (Hawkins, 1999).

We have shown performance using both gold syntactic trees and the output from the Charniak parser, and there is not a big performance drop. This is mainly due to the fact that we do not use deep syntactic information in our feature sets.

The combination of MANNER and PURPOSE opens up a novel paradigm to perform semantic inference. We envision a layer of semantics using a small set of basic semantic relations and inference mechanisms on top of them to obtain more semantics on demand. Combining semantic relations in order to obtain more relation is only one of the possible inference methods.
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