Towards a Heuristic Categorization of Prepositional Phrases in English with WordNet

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Abstract

This document discusses an approach and its rudimentary realization towards automatic classification of PPs: the topic, that has not received as much attention in NLP as NPs and VPs. The approach is a rule-based heuristics outlined in several levels of our research. There are 7 semantic categories of PPs considered in this document that we are able to classify from an annotated corpus.

1 Introduction

Historically, prepositions have not enjoyed the attention of nouns and verbs, being until recently relegated to the status of “an annoying little surface peculiarity” [Jac73]. However, linguistics tells us that different syntactic categories contain distinct semantic characteristics which are often exclusive to members of that category [LP91]. This raises two distinct yet equally important questions: How are such categories found syntactically, and how are their characteristics expressed semantically?

The famed linguist Sir Randolph Quirk states that “a preposition expresses a relation between two entities, one being that represented by the prepositional complement” [Qui85].

In this paper we describe the development of a heuristics-based system.

2 Theoretical Foundations

Through a survey of the literature, it is clear that the study of prepositions is becoming more intricate, and is segmented into a few focussed areas. Our work is therefore motivated towards the construction of a sequential system of increasingly complex levels, each of which is representative of one of these focussed areas. The system is organized in such a way that the product of one level becomes a dependency of the next as outlined by the following sequence:

Level 0: From Part-of-Speech annotated text, minimal prepositional phrases are found at the syntactic level according to a context-free grammar (CFG), and not categorized.

Level 1: Minimal prepositional phrases are augmented with a set of labels indicating classes of semantic roles, by means of rule-based heuristics.

Level 2: The proper attachment of the prepositional phrase is attempted with shallow heuristics based on results of Levels 0 and 1, in case of ambiguity.

Level 3: Semantic characteristics of the PP and its co-predicate phrases are analyzed in order to perform attachment ‘intelligently’, and do discover more thorough semantic relations.

Each level is described in more detail in Sections 2.1 through 2.4.
2.1 Discovery of Minimal PPs - Syntactic Analysis

The first stage is to locate prepositional phrases within a text grammatically, irregardless of semantic function. For this we turn to linguistics, which studies PPs by their production and by their expansion as outlined below.

2.1.1 Production of PPs

Prepositional phrases generally attach to noun phrases and verb phrases, usually acting adjectively for the former and adverbially for the latter [Hud03], as in the example

\[
(S
  (NP
    (DET the) (HEAD boy)
    (PP
      in
      (NP
        (DET the) (HEAD shop)
        )))
  )
  (VP
    is waiting
    (PP
      at
      (NP
        (DET the) (HEAD corner)
        ))
  )))
\]

At first glance, we should be able to augment grammatical noun and verb phrases by simply adding rules of the form \( NP \leftarrow NP \ PP \) and \( VP \leftarrow VP \ PP \) [JM00]. However this can lead to overgeneration, especially in cases where there exist ambiguity with regards to the part-of-speech of a potential preposition. For example, in “Turn off/RB the light”, “off” is used as an adverb, but if we are not careful with our expansion rules for \( VP \), we could easily generate “(VP turn (PP off/IN (NP the light)))” if the tagging is done incorrectly. Some such errors in tagging cannot be avoided within the scope of this project, but careful augmentation of existing rules, such as in \( NP \leftarrow DET \ MOD \ HEAD \ PP \), can result in a more fine-tuned grammar, as will be shown in our results (see Section and \( VP \) expansions producing \( PP \)s are given in Appendix B.

2.1.2 Expansion of PPs

Though there is some debate as to the semantic function played by the prepositional phrase [FS03], the syntactic nature of a prepositional phrase is relatively universally accepted. It is very safe to define the prepositional phrase specifically as having a preposition as its head, followed by a noun phrase or an entity which is always the direct object [Hud03].

A full listing of rules for \( PP \) expansions are given in Appendix A and B.

2.1.3 Non-minimal PPs

We will often encounter sequences of contiguous prepositional phrases, as in “I saw the fool on/IN the hill with/IN the telescope”. In such circumstances, we are principally concerned with PP-attachment, which is a significant grammatical challenge, but which also involves semantic analysis, hence its discussion is delayed until Section 2.3. Suffice it to say, we will with some regularity encounter such a sequence of PPs where each PP modifies the same predicative, and hence we add the production rule \( PP \leftarrow PP \ PP \) to deal with such a circumstance.

2.1.4 The Mechanism of Discovery

The mechanism for discovering prepositional phrases is an implementation of the Earley parser in Scheme. While this provides a simple interface to grammatical tree-expansions, based purely on syntactic context-free rules – the algorithm is devoid of any stochastic or world knowledge, and hence cannot be used for more complex grammatical or semantic analysis. The instantiated grammar is an instance of a partial parser PP-chunker which searches exclusively for prepositional phrases.

2.2 Semantic Role Annotations & Categorization

Prepositions convey significant semantic relations in text, and provide “the principal means of conveying semantic roles for the supporting entities referred to in a predicative” [OW02]. They are, however, highly ambiguous - with closely related word-senses and a relatively high degree of internal polysemy. Furthermore, definitions as to
how semantic roles are conveyed, and how supporting entities relate are varied and often imprecise. At present, it is not feasible for automatic systems to attain a degree of semantic granularity comparable to that of collegiate dictionaries, but we can at least categorize different uses of the prepositional phrase by broad semantic characteristics.

2.2.1 Semantic Role Annotations

The Penn Treebank described the prepositional phrase as having semantic-role subcategorizations defined by case-style relations, the 7 most frequent of which are shown with their associated frequencies of occurrence in Table 1. Although by no means a thorough description of the semantic relations within a text, such subcategorizations allow for a suitable indication of the manner in which a prepositional phrase is used, and therefore to how they modify the semantics of the phrase to which they attach.

| tag       | Freq. | Description       |
|-----------|-------|-------------------|
| PP-LOC    | 17220 | locative          |
| PP-TMP    | 10572 | temporal          |
| PP-DIR    | 5453  | direction         |
| PP-MNR    | 1811  | manner            |
| PP-PRP    | 1096  | purpose           |
| PP-EXT    | 280   | extent            |
| PP-BNF    | 44    | beneficiary       |

Table 1: Subcategorization of augmented PPs, ordered by frequency of occurrence in the \[Bie95\].

These semantic relations can be attached to any verb complement, but more frequently occur with noun phrases and their clauses. The University of Pennsylvania provides online annotated texts from SIGLEX’99 \[sei03\] \[tru03\] with parsed examples showing each of these categories:

PP-LOC: “...a federal grand jury (PP-LOC in (NP Newark))...” \[sei03\]

PP-TMP: “The people who suffer (PP-TMP in (NP the short term))...” \[sei03\]

PP-DIR: “Citicorp had discussed lowering the offer (PP-DIR to (NP $250 a share))” \[tru03\]

PP-MNR: “He could be left (PP-MNR without (NP top-flight legal representation))...” \[sei03\]

PP-PRP: “...prosecutors told Mr. Antar’s lawyers that (PP-PRP because of (NP the recent Supreme Court rulings))...” \[sei03\]

PP-EXT: “AMR declined (PP-EXT by (NP $22.125))...” \[tru03\]

PP-BNF: “I baked a cake (PP-BNF for (NP Doug))” \[Bie95\]

It is with this simple framework of 7 semantic annotations that we choose to develop our system. Although our heuristics will be designed to suit these categories, alternative classifications of prepositional phrases can be used to help obtain insight towards this process.

2.2.2 Alternative classifications

Alternative classifications for prepositional phrases have been discussed within the domain of semantic encoding in lexica \[EAG96\] where labels are assigned to prepositions but describe whole phrases according to whether they apply to PPs modifying predicative heads (verbs and predicative nouns) or to PPs modifying nonpredicative heads (nonpredicative nouns). This distinction is justified semantically and syntactically, and most labels associated with predicative-head modifiers coincides directly with the semantic role annotations in Section 2.2.1.

The subtlety such a distinction makes is shown for modifiers of non-predicative heads, all of which describe quality modifications. Consider, for instance, the difference between a place-position (locative) modifier in “the report is ON THE TABLE” and a quality-place modifiers in “oranges FROM SPAIN” (origin) and “a road THROUGH EGYPT” (path). Even subtle semantic differences in positional modifiers can be noted depending on the predication of the head. Although such a distinction is not replicated in our system, the motivation behind the analysis of the semantic qualities of the head is applied theoretically to our heuristics.

\[From a syntactic point of view, the choice of the prepositional label modifying nonpredicative heads is much more restricted than for predicative heads, although more predominantly in the romance languages than in the germanic family. Generally, nonpredicative prepositional modifiers ‘behave’ more like adjectives, whereas predicative prepositional modifiers ‘behave’ more like adverbs. \[sei03\] \[\footnote{From a syntactic point of view, the choice of the prepositional label modifying nonpredicative heads is much more restricted than for predicative heads, although more predominantly in the romance languages than in the germanic family. Generally, nonpredicative prepositional modifiers ‘behave’ more like adjectives, whereas predicative prepositional modifiers ‘behave’ more like adverbs. \[sei03\]}\]
2.2.3 Temporal PPs (TPPs)

Of those semantic categorizations common across multiple paradigms, temporal prepositional phrases have received special attention. Ian Pratt et al. [PF97], show that temporal prepositional phrases with NP complements, and also with PP complements (validating our non-minimal grammar decision!), and even sentential complements with quantification-restrictions and structural ambiguities can be grouped into a unified theory of generalized temporal quantifiers which serve as meanings for temporal PPs specifically, but also to NPs and sentences. Their theory differs from the normal categorization theory in that their semantics rely heavily on the λ-calculus and warp functions, and hence is only used as a theoretical landmark.

It should be noted that in response to Pratt et. al, Nissim Frances et al. [FS03] argues that the unorthodox semantic operations and lack of syntactic cues in that paper makes such an approach infeasible for practical purposes, and that a simpler syntactic framework (indexical prepositional phrases), would better be employed, which is an approach somewhat closer to our implementation.

2.2.4 Categorization Heuristics

The heuristic approach to the problem of semantic categorization is easily implemented in a transformational PERL script that accepts simple PP partial parses and transforms the tag PP to PP-XXX (where XXX is one of the annotations of Section 2.2.1). Syntactic cues from the partial parse include the following:

1. The lexical entry of the head preposition
2. The head of the component noun phrase

It is tempting to produce heuristics based exclusively on the preposition alone (1), since intuitively the preposition should indicate the manner in which a PP is being used. For instance, in the examples “Put the letter IN the mailbox”, “the dog is IN the space capsule” and “The farmer IN the dell”, the preposition “in” is always used as a locative preposition. A moment’s reflection will reveal that this approach is extremely naive, because most prepositions can be used for multiple functions, as in the following examples:

- ex. “The transient sleeps WITHIN the cardboard box” (LOC) vs. “I’ll be back WITHIN three weeks” (TMP)
- ex. “I kicked the ball TOWARDS the net” (DIR) vs. “My politics tend TOWARDS the left” (MNR)
- ex. “I’ll see you IN a couple of weeks” (TMP)

Our heuristics cannot in the vast majority of cases consider the preposition alone because prepositions can often be used under different semantic relations. However, some prepositions, such as “when” or “because” are so often associated with a single semantic function (temporal and purpose, respectively), that we can make minimal use of the preposition’s lexical entry, but not exclusively. We implement a two-layer system of subsuming heuristics - the first which makes a “guess” at the class depending on lexical knowledge associating words with semantic classes. For instance,

| TMP:         | when, until, in, during, after, before, while, under, over, then, since, around, at, throughout |

This will of course lead to instances where certain ambiguous prepositions such as “for” are always guessed to be of the most frequent category - but this is excusable because of the second heuristic layer.

The second heuristic layer subsumes (overrides decisions made in) the first, and forms the most significant part of system and makes use of semantic knowledge in WordNet with regards to the head of the PP’s component noun phrase in order to guide semantic classification. Specifically, depending on the NP expansion rule that expands the direct object of the preposition, the relevant head of the noun phrase is extracted. For instance, for pronouns and proper NPs, the whole NP is considered, otherwise, only the grammatic head of the noun phrase (which has been annotated automatically) is considered.

Given the relevant head of the noun phrase, hypernyms for that word is looked up in WordNet using the command ‘wn $noun –hypen’. This will often result in multiple possible hypernym expansions due to the slightest polysemy of the noun phrase, so only the first few senses

\[3\text{In WordNet, this translates as being the few most frequent senses, as determined through corpus-based training.}\]
up to some threshold (4 or 5) are considered. The hypernym trees are then searched in decreasing frequency of sense for particular keywords indicating semantic role, for instance the hypernym “time period”, which can be derived from the noun “yesterday”, indicates a temporal relation. This search is done in such a way that the most common semantic categories are given priority.

This approach is similar to (and inspired by!) approaches using FrameNet as the semantic resource, and an evaluation of this technique follows in Section 3.2.2.

2.3 PP Attachment

Although prepositional phrases “... can appear within all the other major phrase types” [MS02], the task of achieving automatic PP-attachment syntactically has traditionally required attachment either to a verb phrase or to a noun phrase, historically accomplished by means of a specific binary decision between two particular methods:

Right Association: A constituent tends to attach to another immediately to its right. This approach favours attachment to the noun [Kim73].
(ex. “I (VP saw (NP the dog (PP with its puppies )))”)

Minimal Attachment: A constituent tends to attach to existing nonterminals using the fewest intermediate nodes. This approach favours attachment to the verb [Frz78].
(ex. “I (VP saw (NP the dog) (PP with my binoculars))”)

However, Whittemore et al. [Whi90] showed that neither of these complementary tactics can account for more than 55% of cases in general texts - and that each are poor predictors of how people resolve ambiguity [BR02]. The first solution to this shortcoming is to involve statistics and lexical knowledge. It has been shown in Brill and Resnik (1994) [BR94], “I saw the fool on the hill with the telescope”, where there exist numerous examples of ambiguity, but our concern is with the ambiguity of PP-attachment. Does the prepositional phrase “on the hill” refer to the location of the fool, or of the speaker? Does the prepositional phrase “with the telescope” attach to the verb “saw”, or to either of the nouns “the fool” or “the hill”? Both of these suggested improvements to a syntactic approach to PP-attachment - corpus-based statistical learning and world knowledge (with inference), are beyond the scope of this project.

2.4 Consideration of Semantics

Determining semantics (Level 4) is beyond the scope of this work presently due to time constraints. However, we present a few general ideas on how that could possibly be done. One (rather shallow) way is to build subcategories of the 7 classes we have used. For example, locative-type PPs may have lexical entries with semantic relations, such as “part-to-whole”, “betweenness”, and “relative distance” relations, which build up “path” and “orientation” structures for “movement-directional” and “stative-locational” interpretations according to [Nam95]. Similarly to VPs, we’ll have to look at the (semantics of) argument structure of such PPs. In general, a hierarchy of subcategories of the original classes of PPs will have to be implemented. That would possibly require more than two passes of over the parses we currently have. Tests for argument structure can be done as presented in [Ver].

3 Experiments & Analysis

In order to gauge the effectiveness of our heuristics-based approach, the evaluation of our system on corpora, and the subsequent experimental analysis must be performed. Such experiment involves a ‘training’ phase where the syntactic and semantic characteristics of the prepositional phrases are analyzed and represented by heuristics, and a ‘testing’ phase where the efficacy of those heuristics are measured statistically. The process is described in the following subsections.

3.1 Experimental Setup

3.1.1 Corpora

For the purposes of experiment, a collection of texts from the Wall Street Journal (WSJ) corpus are chosen at random to be representative of the available corpora, and are divided into two sets: The first is comprised of 20 texts (~74%) used for ‘training’ of the system - that is, our heuristics are modified to best suit these documents.
The second set is comprised of 7 texts (~26%) used for ‘testing’ the system - from which our empirical measures of performance are derived. The breakdown is shown in Tables 2 and 3.

### 3.1.2 Human Annotation

All 27 documents were hand-annotated for the occurrence and grammatical structure of prepositional phrases. This task was facilitated by two factors:

- Only prepositional phrases (and their constituents) were annotated, saving the annotators the trouble of doing full sentence parsing.
- As a consequence of the first point, PP-attachment was not taken into consideration.

Subsequently the parses were augmented with the semantic role annotations from Section 2.2.1. In cases where the prepositional phrase did not fall into one of the 7 semantic categories, the tag was left simply as PP, without additional markup.

The annotation of the 20 training documents guided the production of rules for grammatical expansion and heuristics for semantic role markup. The annotation of the 7 test documents allowed for numeric performance measures, and statistical evaluation.

### 3.1.3 Measures of Performance

Two principal measures of performance are precision and recall, defined thusly [Qui85]:

\[
\text{Precision: } P = \frac{\text{of correct answers given by the system}}{\text{of answers given by the system}} \\
\text{Recall: } R = \frac{\text{of correct answers given by the system}}{\text{of possible answers in the text}}
\]

For each of these measures, an ‘answer’ can be defined with regards to the task at hand, and will be specified in the Section 3.2. For instance, when measuring the bare PP-chunker grammar, recall would be defined as the total number of correctly identified prepositional phrases among all actual prepositional phrases in a text.

An additional statistical measure is the F-Measure, which describes the combined measure of precision and recall, and is described by

\[
F = \frac{\left(\beta^2 + 1\right) PR}{\beta^2 P + R}
\]

where we consider \(\beta = 1\) (equal weight to precision and recall). Non-statistical measures of performance include computational measures and the qualitative evaluation of rules.

### 3.2 Results & Analysis

#### 3.2.1 Evaluation of PP-grammar

The discovery of minimum non-characterized PPs, which comprises the first level of the system, is first analyzed independently, since its performance will drastically affect the performance of later stages.

The first pass of evaluation leads to a recall of \(R = \frac{302}{369} \approx 81.8\%\) and a precision of \(P = \frac{302}{409} \approx 73.8\%\). The relatively poor precision is quickly discovered to be a result of poor preprocessing of the WSJ texts, which results in errors in tagging. Specifically, erroneous prepositional phrases are found in headers of the WSJ texts and at the ends of sentences at points where punctuation causes difficulty to Brill’s Tagger, where errors are likely made during the transformational tagging stage.

With additional preprocessing steps for those circumstances listed, recall improved to \(R = \frac{302}{369} \approx 81.8\%\) and precision to \(P = \frac{302}{369} \approx 73.8\%\). Though a significant improvement, additional improvements are possible. Analysing the training corpus, we find that many potential prepositional phrases will not parse due to poor parsing of more complex noun phrases which would normally form the object of the PP. Furthermore, the rule \(PP \leftarrow INRB\), which was originally included to deal with phrases of the form “in particular”, was overgenerating many parses.
Modifying the rules for NPs to take into consideration aggregate NPs, and removing the rule $PP \leftarrow IN RB$ results in a final recall of $R = \frac{324}{369} \approx 87.8\%$ and precision to $P = \frac{324}{381} \approx 85.0\%$, which translates into an F-Measure of $F \approx 86.4\%$.

Evidently, relatively high precision and recall can be achieved for prepositional phrases with relatively few grammatical rules. This is in stark contrast to the automatic noun phrase or verb phrase chunkers, which traditionally score lower and require more numerous and more complex rules. This tends to validate the theory in the literature which paints PPs as having a basic syntactic structure, as described in Section 2.1. The improvements made at each evaluation pass are summarized in Figure 1.

3.2.2 Evaluation of Automatic Categorization

Utilizing lexical knowledge first, then subsuming it with semantic knowledge, leads to very encouraging results. Measuring the recall, precision, and $F$-measure as previously defined for all 7 test, we break down the analysis into the 4 most frequent categories, where un-annotated PPs are considered towards the total positively if they do not strictly fit into our seven categories, and negatively otherwise. This breakdown is shown in Table 4.

It is immediately recognized that our heuristics seem exceptionally well-suited for directional-PPs, and exceptionally poorly suited to manner-PPs. Such a discrepancy can of course not be linked merely to the heuristics for these two categories, since the system is not independent and heuristics for other categories play a significant role with each other.

It should be noted that as more potential categories are taken under consideration, the more error we can expect due to the relative higher rate of perplexity.

4 Future Work

Most of the future work would be dedicated to the Levels 3 and 4 outlined at the beginning, i.e. PP-attachment and Semantic Analysis of PPs. Both problems are quite difficult to solve and will require a lot of research-trial-and-error attempts of the existing and new proposals. New, more robust, tools will be required, such as stochastic methods in NLP and a lot more training and testing data. For example, we could assign probabilities to our grammar rules and encode the attachment information into the syntactic productions. Likewise, the detection of semantic roles of PPs and their arguments can be done heuristically and statistically with two or more passes.

Table 4: Evaluation of Automatic Categorization

| Category          | Recall | Precision | $F$-measure |
|-------------------|--------|-----------|-------------|
| Locative PPs only | $\frac{428}{475}$ | $\frac{428}{475}$ | $87.1\%$ |
| Temporal PPs only | $\frac{78}{88}$ | $\frac{78}{88}$ | $89.5\%$ |
| Directional PPs only | $\frac{68}{75}$ | $\frac{68}{75}$ | $91.3\%$ |
| Manner PPs only | $\frac{17}{26}$ | $\frac{17}{26}$ | $60.7\%$ |
| Total             | $\frac{293}{351}$ | $\frac{293}{351}$ | $83.5\%$ |

4 So total fractions do not necessarily equal the sum of its parts.

References

[Bie95] A. et. al. Bies. Bracketing Guidelines for Treebank II Style Penn Treebank Project. Linguistic Data Consortium, 1995. URL: http://www.ldc.upenn.edu/Catalog/docs/treebank3/PRSGUID1.PS.

[BR94] E. Brill and P. Resnik. A Rule-Based Approach to Prepositional Phrase Attachment Disambiguation. COLING-94, Kyoto, Japan, 1994.
5 Appendix

5.1 Appendix A: PP Rule Set

The rule set is quite small and simple provided the rest of the grammar has a quite a notion of what NP and VP are. This basic rule set is used for Level 0 of our work. This gives us a list of unclassified PPs from a corpus. Later on, a Perl script run to augment this information with the 7
categories outlined in 2.2.1 keeping PP as a general classification if we are unsure what kind of PP we are looking at. This second pass of annotation provides classification information of Level 1 of our work. The entire Level 0 grammar is in \texttt{pp-chunker.scm} presented in Appendix C. The Level 1 heuristic rules are presented in Appendix C, the \texttt{augment-pp.pl} Perl Script.

The below are the sample rules used:

```scheme
(PF (IN NP) ; "on new rules", "for him", "by
Doug"
(IN IN NP) ; "because of the rain"
(PF PF) ; "on new rules for covert
operations" ; (NB. we don't care about
attachment)
(TO NP) ; "to committee officials"
(IN NP VP) ; "of the top dog running the show"
; (NB. spurious, but not harmful)
```

5.2 Appendix B: PP Chunker (pp-chunker.scm)

See [pp-chunker.scm]

5.3 Appendix C: PP Augmenter Script (augment-pp.pl)

See [augment-pp.pl]