

# An Analysis of Multiword Expressions in the Paraphrase Database

## First Author

Affiliation / Address line 1  
Affiliation / Address line 2  
Affiliation / Address line 3  
email@domain

## Second Author

Affiliation / Address line 1  
Affiliation / Address line 2  
Affiliation / Address line 3  
email@domain

## Abstract

We hypothesize that paraphrases may be a useful resource for understanding multiword expressions (MWEs). We analyze the paraphrases in PPDB, the Paraphrase Database, where multiple words are re-written as a single word. By automatically mapping from multiword expressions onto single words, NLP systems could potentially process the re-written text more easily than the original text containing MWEs. We use the MWE categorization system as described in Sag et al. (2001) to identify paraphrases in PPDB that might be interesting to MWE researchers. Although only a relatively small proportion of the many-to-one paraphrases in PPDB are classic MWEs, the resource contains millions of entries. We train a classifier to distinguish the interesting MWEs from other sorts of many-to-one paraphrases. We do a pilot study on parsing paraphrased sentences, to determine whether sentences with a MWE replaced by its paraphrase are parsed correctly more often than the original.

## 1 Introduction

Multiword expressions (MWEs) are phrases whose meanings are different than the literal interpretation of the words in the phrase. MWEs include verb-particle constructions, fixed expressions, compound nominals, and decomposable idioms, to name a few (Sag et al., 2001). MWEs are difficult to process both for non-native speakers of English, as well as for NLP systems. Studies using an eye-movement paradigm have found that non-native speakers of English required more

time to retrieve figurative senses of phrases than literal ones, whereas native speakers retrieved the idiomatic meaning faster than the literal meaning (Siyanova-Chanturia and Martinez, 2014). These studies imply that L2 speakers of English may find it more difficult to understand MWEs than a similar phrase whose meaning was literal. Among NLP systems, both parsers and information retrieval systems make errors on MWEs. Baldwin et al. (2004) found that, among a random sample of 20,000 strings from the written portion of the British National Corpus (Burnard, 2000), using the English Resource Grammar (Copestake and Flickinger, 2000), MWEs caused 8% of all parse errors. When manually selected compound nominals were searched for as single terms it improved information retrieval results (Acosta et al., 2011).

Because MWEs are challenging for many NLP tasks, automatically identifying them could be useful for identifying and averting errors. Several research efforts have examined this topic. For example, Li and Sporleder (2010) and Muzny and Zettlemoyer (2013) built a classifiers to identify idioms. In this paper, we use the Paraphrase Database (PPDB) as a resource to define a MWE lexicon, which could be incorporated into other NLP systems. In addition to being a potentially useful resource for *identifying* MWEs, it has the unique feature of potentially giving an *interpretation* of the MWEs by replacing them with a one word paraphrase.

In this paper we

- Analyze the PPDB for the prevalence of various types of MWEs
- Build a classifier that distinguishes interesting MWEs in the PPDB from more generic paraphrases
- Investigate whether parse quality can be improved by substituting MWEs with one word paraphrases

---

Place licence statement here for the camera-ready version, see Section ?? of the instructions for preparing a manuscript.

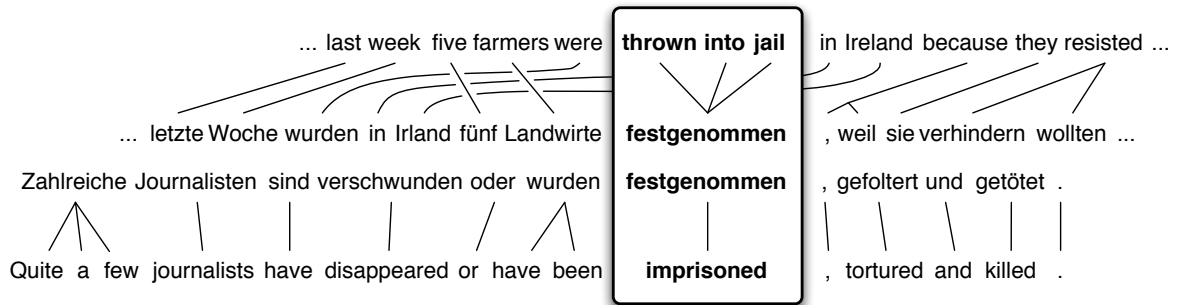


Figure 1: The paraphrase database contains one-to-many paraphrase where a single English word is paraphrased as a multiword phrase. The paraphrase of *imprisoned* as *thrown into jail* results because the shared foreign phrase *festgenommen* is sometimes translated using one word and sometimes as a phrase. We analyze PPDB’s one-to-many paraphrases for their prevalence of more interesting MWEs.

## 2 The Paraphrase Database

In this paper, we analyze paraphrases within the Paraphrase Database (PPDB) (Ganitkevitch et al., 2013), currently the largest available collection of paraphrases. Compared to other paraphrase resources such as the DIRT database (12 million rules) (Lin and Pantel, 2001) and the MSR paraphrase phrase table (13 million) (Dolan et al., 2004), PPDB contains over 150 million paraphrase rules. These rules were extracted automatically using Bannard and Callison-Burch (2005)’s “bilingual pivoting” method, in which two English phrases are assumed to be paraphrases if they both translate to the same foreign phrase. This is illustrated in Figure 1. Entries in the PPDB are represented as synchronous context free grammar rules, following Ganitkevitch et al. (2011).

PPDB has several types of paraphrases: one-to-one (synonyms), one-to-many, many-to-many phrasal paraphrases, and syntactic transformations. We examine the one-to-many paraphrases, since we wanted to analyze whether these paraphrases would be a suitable resource for interpreting multi-word expressions (MWEs).<sup>1</sup> The PPDB is distributed as a set of six increasingly large files, from Small to XXXL. Each paraphrase in the PPDB is scored according to how precise of a paraphrase it is likely to be. The smaller files con-

tain better-scoring paraphrases, while the larger files contain incrementally more paraphrases, at the cost of precision. For this analysis we chose the Large corpus as a compromise point between coverage and quality of paraphrases. PPDB-Large contains 188,000 one-to-many paraphrases, and PPDB-XXXL contains 1.5 million of such paraphrases.

## 3 Related Work

Various definitions of MWEs have been used for NLP tasks. Sag et al. (2001) define a taxonomy of multiword expressions that is widely used in computational MWE research. They define broad categories for MWEs (fixed expressions, semi-fixed expressions, syntactically flexible expressions, institutionalized phrases), and more specific categories within each of these. The following is a brief outline of their specific categories. We use an expanded set of categories to analyze the MWEs found in PPDB in section 4.

- Fixed expressions. The meaning of fixed expressions is non-compositional, and they do not follow standard grammar rules. An example is the phrase “all of a sudden,” which means “suddenly.” The word sudden cannot be replaced with another adjective: “all of a happy” is nonsensical. Other examples of fixed expressions are “in short” and “kingdom come”.
- Non-decomposable idioms. These are non-compositional expressions that do follow grammatical rules. For example, the grammatical structure of “kick the bucket,” is valid

<sup>1</sup>Many-to-many paraphrases might be interesting for examining interpretations of other MWEs like noun-noun compounds (e.g. if “hand lotion” paraphrased to “lotion for hands” or “apple juice” paraphrased to “juice made from apples”). The syntactic paraphrases might also give hints at the level of syntactic fixedness of idioms, for instance. For this analysis we investigate only the one-to-many paraphrases as a source of potential paraphrases for multiword expressions.

(e.g., there exist other acceptable English phrases with the same structure, like “kick the stone,”), however the idioms meaning is not sum of its parts. Other examples include “to take the bull by the horns” and “to beat swords into plowshares.” (Nunberg et al., 1994).

- **Compound nominals.** These are noun combinations whose meaning is not automatically inferable from the individual nouns in the phrase. Contrast “orange juice”, “hand lotion” and “newspaper column.” Without word knowledge it is not possible to know whether the nouns relationship is *is made from*, *is intended for*, or *is located in*.
- **Proper nouns.** These are nouns that are names for unique entities including places (California, the Bronx), people (President Roosevelt), and events (the Industrial Revolution). This category is included in the taxonomy because names allow for some kinds of variation but not others. For example, *the San Francisco 49ers*, *the 49ers*, and *49ers* are all valid names for the sports team, but “the Bay Area 49ers” is not.
- **Decomposable idioms.** These are phrases whose meaning is compensational from the meaning of the individual words, but which still carry an idiomatic meaning. One example is “play with fire.” Decomposable idioms can undergo syntactic changes to varying degrees. For example, the phrase “let the cat out of the bag” can be modified to “the cat was out of the bag,” and also to “the cat was *really* out of the bag,” adding an adverb.
- **Verb-particle constructions.** These are verb phrases formed of a verb followed by a particle, where the meaning of the phrase is different than that of the verb alone, or up the verb and the particle combined. Some examples are “wash out,” “break down,” and “follow up.”
- **Light verbs.** The combination of light verbs (make, give, take) followed by a normalized verb are idiosyncratic in that it is difficult to predict which light verb will be used with the original verb. “To walk” can be paraphrased as “to take a walk,” but not “to make a walk,”

whereas “to make a presentation” is fine and “to take a presentation” nonsensical.

Another piece of related work examined the possibility of using paraphrases to interpret MWEs. de Marneffe et al. (2009) examined the use of paraphrases to better align text-hypothesis pairs in the task of Recognizing Textual Entailment (Dagan et al., 2006). They analyzed paraphrase resources derived from Lin and Pantel (2001)’s DIRT algorithm and from Bannard and Callison-Burch (2005)’s bilingual pivoting method. They found that about one third of the MWEs in the RTE data set were contained in the paraphrase resources, but that the MWEs were sometimes mis-paraphrased, making it unclear whether the resources would help with RTE-alignment. Like de Marneffe et al. (2009), we do an analysis of a paraphrase resource derived from Bannard and Callison-Burch (2005)’s bilingual pivoting method, but at a larger scale.

## 4 Analysis of PPDB

We analyzed the paraphrases in PPDB to determine the prevalence of MWEs. We focused on one-to-many paraphrases, since we were interested in whether PPDB could be used to interpret MWEs by replacing them with their single word counterparts. We took a random sample of 500 paraphrases from the PPDB Large one-to-many paraphrase file. We categorized each of the items in the sample to see how many fell into the MWE categories defined by Sag et al. (2001). For phrases that did not fall within the scope of Sag et al.’s MWE definitions, we added our own categories. This allowed us to characterize the PPDB’s one-to-many.

In addition to Sag et al.’s inventories, we added 21 additional categories. 6 of our categories were meaning-preserving transformations that did not change the syntax of the phrases.

- **Acronyms.** This category captures paraphrases where one or both of the entries in a paraphrase pair are acronyms. Usually the acronym is expanded (e.g., “sme/small and medium enterprises” or “unicef/united nations children ’s fund”). Sometimes the expansion contains a variant acronym (e.g., “cmf,” “the fcm”).
- **Negation.** The phrase component of these included, “not” followed by another word.

Their single word counterpart contained a negative prefix. For instance “unacceptable/not acceptable”, “non-toxic/not toxic”, and “illegible/not readable”.

- Superlatives and comparatives. The phrase components of these included “most” or “more” followed by an adjective. The one word paraphrase contained the suffix “-est” or “-er”. For example, “most recent/latest”, “most high-ranking/highest”, “more humid/wetter”, “more sexy/sexier”.
- Time variation. Paraphrases in this category were contained either times (e.g., “9:00,” “9 a.m.”) or dates (“2003/04,” “the 2003-04 fiscal year”) in either the original word or the paraphrase. Some of these could be rewritten in many different ways. For instance, “9:00” is rewritten not only as “9 a.m.” but also as “9 hours”, “9.00 a.m.”, “9:00 am”, “nine hours” and “nine o’clock”.
- Variant use of punctuation. This category captures paraphrases where either the original word or the expansion contains a punctuation mark (e.g., apostrophe or hyphen), which is what causes the word to be interpreted as a single word (e.g., “debt-servicing,” “debt servicing”) or the expansion to be interpreted as having multiple words (e.g., “what,” “something”).
- Numbers. Paraphrases in this category contain number in either the original word or its expansion. Some examples are “20,” “twenty of,” and “5,000,” “five thousand.”

We added 6 categories for syntactic changes between the word and its paraphrase. Many of these result from the fact that the syntactic constraints that are imposed on the paraphrases are not fine grained (Callison-Burch, 2008). Each phrase and its paraphrase must have the same syntactic categories. PPDB’s syntactic categories are derived from the Penn Treebank tag set, so all verb phrases are grouped together into the label VP, regardless of their tense or whether they include modals.

- Change of tense. Paraphrases in this category both rephrased the original word and changed the tense of the phrase. An example is the pair “say”, “going to tell”.

- Nominalization. Paraphrases in this category had one of the phrases as a noun form of a verb. Two examples are “a monopoly” and “monopolization”, and “operation” and “proper functioning.”
- Infinitival to. Paraphrases in this category had the infinitival form a verb as the expansion, and either the same verb or one with similar meaning as the one-word paraphrase. One example is “answer,” “to reply.”
- Adverbial modifier. Paraphrases in this category had either the original word or a word with similar meaning, plus an adverbial modifier. Two examples are “interesting”, “very interesting,” and “teeny”, “really little.”
- Partial word overlap. This category is meant to capture paraphrases that are lexicographically related to each other even if the original word is not a substring of the paraphrase. Some examples of this category are “any-time”, “any point,” and “vice-president,” “the deputy president.”
- Added determiner. Paraphrases in this category map one word to a phrase consisting of a determiner followed by a one-word paraphrase of the original word. Some examples are “photographs,” “the images,” and “mist,” “the smoke.” This also contains generics like “loans,” “a loan.”

Finally, we defined 2 categories to capture paraphrases that did not fall under the classic MWE, syntactic change, or non-syntactic categories.

- Bad paraphrases. These are paraphrases where the original word and the expansion do not seem to be related in any way, or where there is no context where the expansion could be replaced by the original word.
- Unspecified expansions. These paraphrases do not fall under any of the other paraphrase categories defined until now.

Table 1 gives the results of our manual categorization of our 500 randomly selected examples. The two most common types of paraphrases were

Paraphrase Category	Instances in sample	Examples
paraphrastic expansions	109	suffocate, need air; cumbersome, time consuming, fun, sounds like fun; signs, signs and signals
added determiner	95	photographs, the images; duties, the responsibilities; militaries, the military
change of tense	50	initiated, has undertaken; say, going to tell; changing, be changed
inaccurate/bad paraphrase	43	iron, a par; also, do i
implicit/most common modifier	41	baghdad, iraqi capital baghdad; enrichment, uranium enrichment
implicit type	29	training, training course; customs, customs offices
adverbial modifier	27	interesting, very interesting; more, even more
acronym	21	gpa, the global programme of action; cras, credit-rating agencies
partial word overlap	17	anytime, any point; enslavement, slave labour
<b>verb-particle</b>	14	torched, burnt down; done, carried out
<b>proper noun</b>	7	markov, mr markov; karadzic, radovan karadzic
<b>fixed expression</b>	6	applied, put into effect; plenty, a whole host
superlative	5	notably, most particularly; best-known, most famous
copula	5	qualify, are eligible; reason, been right
<b>decomposable idiom</b>	4	nuts, out of your mind; sleeping, get a good night's sleep
<b>light verb</b>	4	issued, made available; place, make way
number	4	20, twenty of; 5,000, 5 000
infinitival to	3	track, to follow; answer, to reply
nominalization	3	operation, proper functioning
negation	2	unused, not utilized; non-parties, not parties
time variation	2	7:00, seven hours; 2003/04, the 2003-04 fiscal year
punctuation	2	debt-servicing, debt servicing; what, somethin '
<b>non-decomposable idiom</b>	2	furious, as mad as hell; entails, brings with it
alternate spelling	1	al-najaf, al nagaf
<b>compound nominal</b>	0	

Table 1: We manually categorized a random sample of 500 one-to-many paraphrases drawn from PPDB. The categories in bold are drawn from Sag et al. (2001)'s taxonomy of MWEs.

Light verb	Manually verb phrases found by regex	Number categorized as light verbs	Example matches, and their paraphrases
make	46	35	make a call/phone, make a decision/decide, make a suggestion/afford
have	105	45	have a ball/dream, have a conversation/discuss, have a word/talk
give	11	4	give a damn/care, give a reply/reply
take	48	33	take a break/pause, take a look/watch, take a walk/wind
hold	3	1	hold a debate/discuss

Table 2: In addition to taking a random sample of the multi-word paraphrases in PPDB, we directly searched for classic MWEs using regular expressions. This table shows examples of the light verbs that matched our regex.

paraphrastic expansions of single words into multiword phrases (109 instances, or 22%) the addition of a determiner (95 instances or 19%). Of the sample, 43 were bad paraphrases (8.6%). Of the 500 paraphrases in the random sample, only 37 (7.4%) fell into the classic MWE categories defined by Sag et al. (2001). Of these MWE paraphrases, the most common were verb-particle constructions (14 instances, or 37.8%), followed by proper names (7, or 18.9%). There were no instances of compound nominals in the sample.

#### 4.1 Directly locating MWEs

In addition to categorizing a random sample of paraphrases, we searched for instances of light verbs and verb-particle constructions in the PPDB XXL file. The light verbs were those with the verb “have”, “take”, “make”, “hold” or “give” followed by a noun phrase. The verb-particle constructions were any verbs followed by the particles “down”, “up”, “on”, “out”, “over” or “upon”.

To find instances of verb-particle constructions, we constructed a regular expression to match a list of particles at the end of a phrase. The regex `particle\b` matched phrases where the potential particle was not the first word, and ensured that it was not a substring of another word (e.g., ‘onto’ instead of ‘on’). For example, to find potential instances of verb-particle constructions with the particle ‘up’, we searched for the following regular expression: `up\b`.

We then manually determined whether the phrases found were verb-particle constructions. The potential particle was sometimes a preposition or adverb, in which case it did not fit into this MWE category. The results from these searches are summarized in the Tables 2 and 3. We considered only light verb phrases with no extra terms (e.g., ‘have a word’, but not ‘have a word with you’ or ‘can i have a word’).

### 5 Building a classifier for MWEs in PPDB

Among the 500 paraphrases in the sample, 37 fell into the category of interesting MWEs. Since the PPDB L one-to-many corpus contains 188,000 rules, based on our sample, we expect there to be around 14,000 relevant MWEs in the database. 188,000 rules is too many to manually sift through, and the PPDB XXXL corpus has far more rules (1.5 million). Therefore, we built a classifier to

automatically distinguish paraphrases that are interesting to MWE researchers.

#### 5.1 Experimental setup

We designed features tailored to find paraphrases in interesting categories of MWE. The methodology used in the classifier could also be applied more generally for finding relevant expressions in PPDB (for example, trying to automatically classify hypernym/hyponym pairs instead of MWEs).

The features we used were:

- A binary feature that indicated whether a preposition appeared in the expansion of the paraphrase (for prepositions ‘about’, ‘around’, ‘back’, ‘down’, ‘in’, ‘off’, ‘on’, ‘out’, ‘over’, ‘up’)
- A binary feature to indicate whether the original word appeared in the expansion
- A binary feature to indicate whether a light verb appeared in the expansion (for ‘give’, ‘have’, ‘hold’, ‘make’, ‘take’),
- All of the scores from the PPDB. There are 31 scores associated with each entry in the PPDB. These features help to score the goodness of paraphrases and are described in Ganitkevitch and Callison-Burch (2014).

We used the 500 manually classified examples from Table 1 as training and test data, performing a ten-fold cross-validation. We performed a binary classification to distinguish between “interesting” MWEs and the other paraphrases in the set. We denoted all of the Sag et al. (2001) MWEs (verb-particle construction; expansion, same morphological form; light verb; fixed expression; non-decomposable idiom; proper noun; decomposable idiom; light verb) as interesting plus two others implicit/most common modifier and implicit type. The majority class was paraphrases that were not interesting to MWE researchers. This consisted of 69.2% of the data, and the interesting MWEs consisted of 30.8%.

#### 5.2 Results

We used an SVM classifier (libsvm) with these features on our sample of 500 words from the PPDB L corpus. Averaged over the ten-fold cross-validation, the accuracy of the classifier was 76.4%. This improves over the majority class baseline by 7.2% absolute / 10.4% relative.

Verb particle	Found by regex	Number correct	Example matches, and their paraphrases
up	439	439	blow up/explode, cheer up/courage, dream up/imagine
about	115	10	bring about/achieve, come about/arisen, move about/scroll
around	47	44	kid around/idiot, playing around/playing, sit around/sit
back	156	145	fall back/retirement, fight back/retaliate, roll back/reverse
down	195	190	bow down/bow, break down/decompose, calm down/relax
in	207	32	break in/enter, check in/protect, dig in/eat
off	134	134	back off/back, ease off/relax, pull off/remove
on	196	109	carry on/continue, catch on/take, hang on/wait
out	383	383	back out/return, bail out/jump, single out/highlight
over	67	65	move over/push, pull over/stop, start over/zero

Table 3: Verb-particle constructions found in PPDB by our regular expression search.

## 6 Using paraphrased MWEs for an NLP task

### 6.1 Experimental design

To determine whether a lexicon of paraphrases extracted from the PPDB would be useful for the task of parsing, we took all of the 33 paraphrases from our sample that fell into the categories described by Sag et al. (2001), as well as one paraphrase from each of the other categories from the random sample of 500 words. We then did a Google search to find a sentence containing the expansion, selecting sentences where the part of speech matched that of the paraphrase, by manual inspection. We restricted the sentences to those less than 50 words long. We then created an equivalent sentence by replacing the expansion with the one-word paraphrase. We used the online demo of the Berkeley parser (Petrov et al., 2006) to parse these sentence pairs, and manually evaluated the resulting parse trees for each sentence of the pair.

### 6.2 Results

Of the 33 paraphrases sampled from MWE categories, 30 were correctly parsed using the one-word paraphrase, and 29 were correctly parsed using the expansion. 2 were parsed correctly for the one-word paraphrase but not for the expansion, 1 was parsed correctly for the expansion but not the one-word paraphrase, and 1 was parsed incorrectly for both. Figure 2 shows the trees for a

case where the sentence containing the one-word paraphrase (“leverage”) is parsed correctly, but the sentence containing the expansion (“avail myself of”) is not. Figure 3 shows the trees for a case where the sentence containing the one-word paraphrase (“issued”) is parsed correctly, but the sentence containing the expansion (“made available”) is not. Figure 4 shows the trees for a case where both sentences are parsed incorrectly.

Of the 18 other paraphrases sampled, all were parsed correctly in their original form, while 15 were parsed correctly using the one-word paraphrase. This suggests that it is important to carefully choosing which paraphrases to use and when they should be substituted. Note that this negative result may be attributable to our method for randomly sampling paraphrases. The PPDB contains many paraphrases for the same input phrase, and these can be sorted from best to worst. We randomly draw any of the paraphrases from each original phrase, suggesting that a better paraphrase may exist within the set.

## 7 Summary

We investigated whether the PPDB could be a useful source for multiword expressions. To achieve this goal, we looked at a random sample of 500 paraphrases from the database and categorized them according to widely recognized categories of multiword expressions, as well as other categories describing the relationship between the two

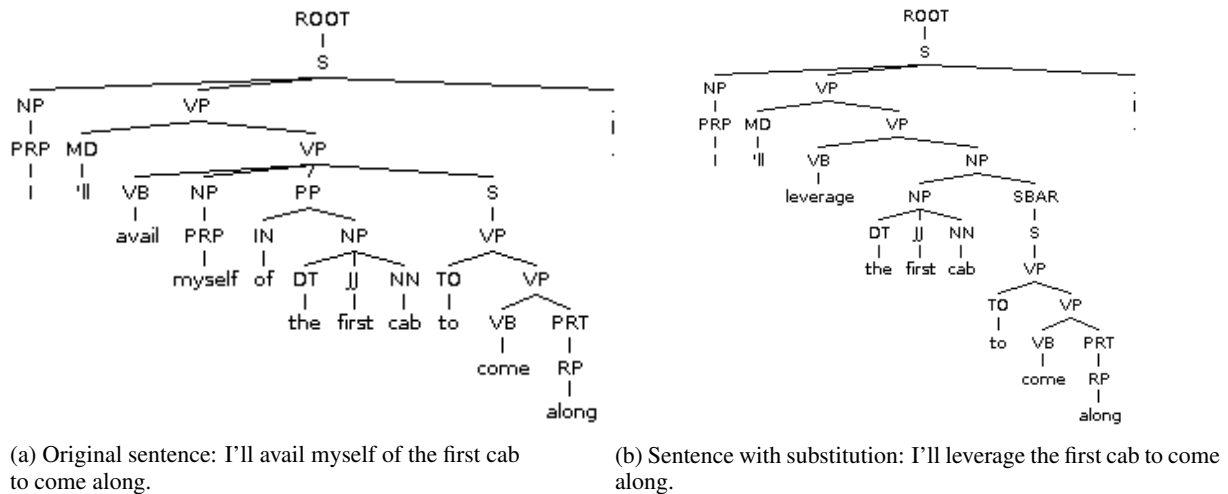


Figure 2: Parse trees for a sentence pair where substituting the single-word paraphrase for the MWE (in figure (b)) yields a better parse than the original sentence (in figure (a)). In the parse of the modified sentence, “to come along” modifies “the first cab,” which is correct, while in the parse of the original sentence it does not.

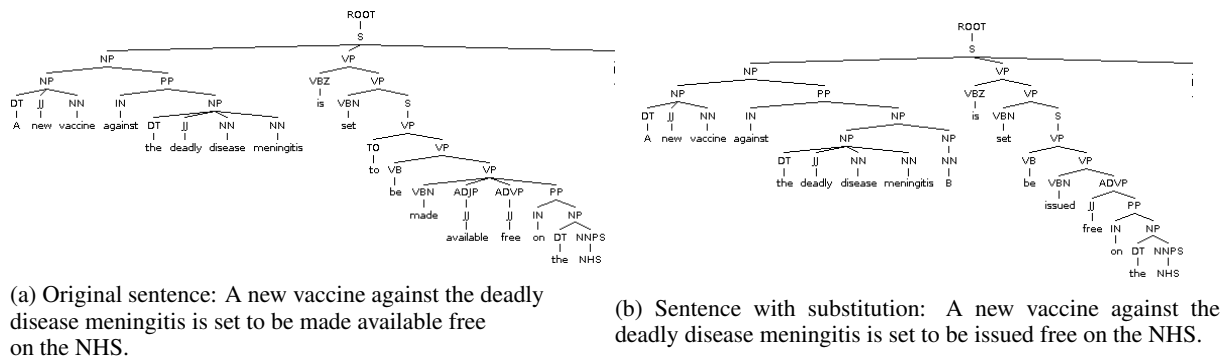


Figure 3: Parse trees for a sentence pair where the original sentence (in figure (a)) yields a better parse than substituting the single-word paraphrase for the MWE (in figure (b)). In the parse of the original phrase, “on the NHS” modifies the verb phrase headed by “issued,” which is correct, while in the parse of the modified phrase it does not.

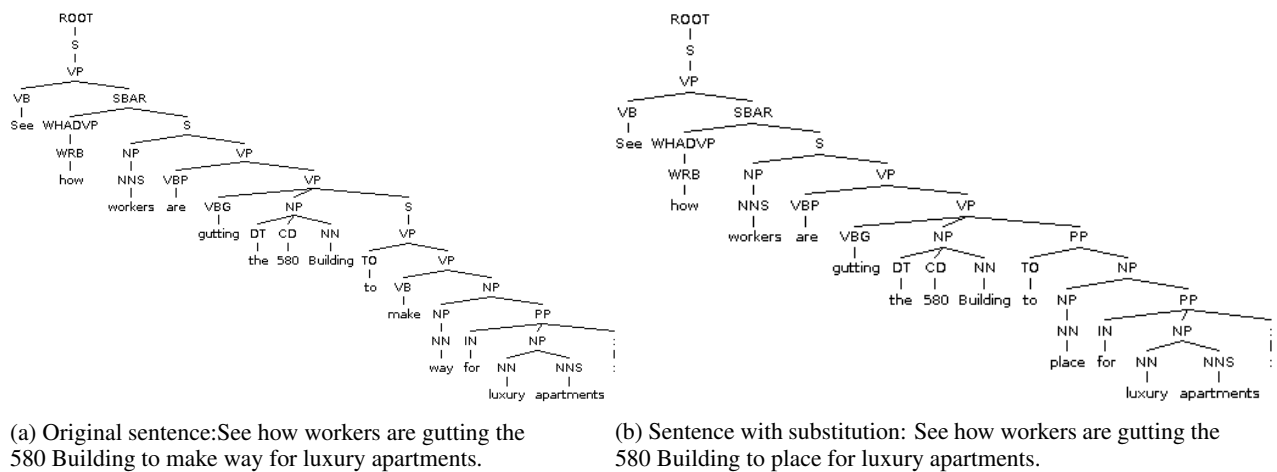


Figure 4: Parse trees for a sentence pair where the original sentence (in figure (a)) yields a better parse than substituting the single-word paraphrase for the MWE (in figure (b)). In the modified sentence, the substituted word (“place”) is misparsed as a noun.



phrases in a paraphrase. We then developed a classifier to automatically extract MWEs from PPDB that MWE researchers might find relevant, so that relevant MWEs could be found easily from the entire PPDB file, which would be too large to scan manually. Finally, we did a pilot study on the paraphrases in PPDB, replacing a multiword phrase in a sentence with its one-word paraphrase from PPDB, and then parsing both sentences to see if parsing would improve after paraphrasing. We found that there was no significant difference between the parses for either the expansions or the one-word paraphrases.

## Bibliography

## References

- Otavio Acosta, Aline Villavicencio, and Viviane Moreira. 2011. Identification and treatment of multiword expressions applied to information retrieval. In *Proceedings of the Workshop on Multiword Expressions: from Parsing and Generation to the Real World*, pages 101–109, Portland, Oregon, USA, June. Association for Computational Linguistics.
- Timothy Baldwin, John Beavers, Emily M. Bender, Dan Flickinger, Ara Kim, and Stephan Open. 2004. Beauty and the beast: What running a broad-coverage precision grammar over the BNC taught us about the grammar – and the corpus.
- Colin Bannard and Chris Callison-Burch. 2005. Paraphrasing with bilingual parallel corpora. In *Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL'05)*, pages 597–604, Ann Arbor, Michigan, June. Association for Computational Linguistics.
- Lou Burnard. 2000. User reference guide for the british national corpus, technical report. Oxford University Computing Services.
- Chris Callison-Burch. 2008. Syntactic constraints on paraphrases extracted from parallel corpora. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*.
- Ann Copestake and Dan Flickinger. 2000. An open-source grammar development environment and broad-coverage English grammar using HPSG. In *Proceedings of the second international conference on Language Resources and Evaluation (LREC-2000)*, Athens, Greece.
- Ido Dagan, Oren Glickman, and Bernardo Magnini. 2006. The pascal recognising textual entailment challenge. In *Machine Learning Challenges. Evaluating Predictive Uncertainty, Visual Object Classification, and Recognising Textual Entailment*, pages 177–190. Springer.
- Marie-Catherine de Marneffe, Sebastian Pado, and Christopher D. Manning. 2009. Multi-word expressions in textual inference: Much ado about nothing? In *Proceedings of the 2009 Workshop on Applied Textual Inference*, pages 1–9, Suntec, Singapore, August. Association for Computational Linguistics.
- Bill Dolan, Chris Quirk, and Chris Brockett. 2004. Unsupervised construction of large paraphrase corpora: Exploiting massively parallel news sources. In *Proceedings of the 20th international conference on Computational Linguistics*, page 350. Association for Computational Linguistics.
- Juri Ganitkevitch and Chris Callison-Burch. 2014. The multilingual paraphrase database. In *The 9th edition of the Language Resources and Evaluation Conference*, Reykjavik, Iceland, May. European Language Resources Association.
- Juri Ganitkevitch, Chris Callison-Burch, Courtney Napoles, and Benjamin Van Durme. 2011. Learning sentential paraphrases from bilingual parallel corpora for text-to-text generation. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 1168–1179, Edinburgh, Scotland, UK., July. Association for Computational Linguistics.
- Juri Ganitkevitch, Benjamin Van Durme, and Chris Callison-Burch. 2013. Ppdb: The paraphrase database. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 758–764, Atlanta, Georgia, June. Association for Computational Linguistics.
- Linlin Li and Caroline Sporleder. 2010. Using gaussian mixture models to detect figurative language in context. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pages 297–300, Los Angeles, California, June. Association for Computational Linguistics.
- Dekang Lin and Patrick Pantel. 2001. DIRT – Discovery of Inference Rules from Text. In *Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 323–328. ACM.
- Grace Muzny and Luke Zettlemoyer. 2013. Automatic idiom identification in Wiktionary. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1417–1421, Seattle, Washington, USA, October. Association for Computational Linguistics.
- Geoffrey Nunberg, Ivan A Sag, and Thomas Wasow. 1994. Idioms. *Language*, pages 491–538.
- Slav Petrov, Leon Barrett, Romain Thibaux, and Dan Klein. 2006. Learning accurate, compact, and interpretable tree annotation. In *Proceedings of*

*the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics*, pages 433–440, Sydney, Australia, July. Association for Computational Linguistics.

Ivan A. Sag, Timothy Baldwin, Francis Bond, Ann Copestake, and Dan Flickinger. 2001. Multiword expressions: A pain in the neck for nlp. In *In Proc. of the 3rd International Conference on Intelligent Text Processing and Computational Linguistics (CICLing-2002)*, pages 1–15.

Anna Siyanova-Chanturia and Ron Martinez. 2014. The idiom principle revisited. In *Applied Linguistics*, January.