An Analysis of Multiword Expressions in the Paraphrase Database

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Abstract

We investigate whether paraphrases might be a useful resource for understanding multiword expressions (MWEs). In particular, 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). Although a small proportion of the many-to-one paraphrases in PPDB are classic MWEs, the resource contains millions of entries. We therefore train a classifier to distinguish interesting MWEs from other sorts of many-to-one paraphrases.

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. As described by Villavicencio et al. (2007), Grammar 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, Muzny and Zettlemoyer (2013) built a classifier to identify idioms, and Li and Sporleder (2010) use Gaussian Mixture Models to identify new 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

2 The Paraphrase Database

The Paraphrase Database (PPDB) is a database containing English paraphrases. PPDB was de-

veloped using alignment techniques from machine translation on bilingual parallel corpora, pivoting on a foreign language, to find English phrases that translate to the same foreign-language phrase Bannard and Callison-Burch (2005). The database takes into account syntactic information of both the English and foreign-language phrases: the entries in PPDB were found using SCFGs to come up with paraphrases that form constituents of the same syntactic category (Ganitkevitch et al., 2011; Ganitkevitch et al., 2013).

3 Related Work

Various definitions of MWEs have been used for NLP tasks. Sag et al. 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 the categories defined by Sag et al. that we investigate in this paper:

- Fixed expressions. These are expressions that don't fit standard grammatical rules and are not compositional. An exampleis the phrase "all of a sudden," which means "suddenly." The meaning of the entire phrase is not the same as the individual words in the phrase, meaning it is not compositional. Furthermore, it does not follow standard grammar rules, which can be seen by replacing the word sudden, normally an adjective, with another adjective: "all of a happy" is nonsensical. Some other examples are "in short" and "kingdom come" (Sag et al., 2001).

- Non-decomposable idioms. These are expressions that follow grammatical rules, but whose meaning is not compositional. An example is "kick the bucket," where the grammatical structure is valid (e.g., "kick the stone," which has the same grammatical structure, is an acceptable English phrase), but the meaning of the phrase is not the meaning the sum of its parts. Other examples include "to take the bull by the horns" and "to beat swords into plowshares." (Nunberg, Sag, Wasow).***

- Compoun nominal. These are noun combinations whose meaning is different than the individual nouns in the phrase. An example is "orange juice," where the meaning is juice from an orange. Other examples are "hand lotion," "street sign," and "newspaper column." The relationship between the nouns in the compound nominal cannot be deduced from their order in the phrase (orange juice is the juice from an orange, whereas hand lotion is lotion intended for hands).

- Proper nouns. These are nouns that are names for unique entities. Some examples are 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 Oakland 49ers" is not (because it is the wrong city).

- Decomposable idioms. These are phrases whose meaning is a combination of the meanings of the words they comprise. One example is the idiom "play with fire" (Wikipedia)***, whose meaning can be derived from the meaning of the individual words, but nonetheless has an idiomatic meaning. Furthermore, decomposable idioms can undergo syntactic changes, but the extent to which they can change depends on the particular idiom. For example, the phrase "let the cat out of the bag" can be modified to "the cat was out of the bag," but also to "the cat was really out of the bag," adding an adverb. On the other hand, "keep tabs on" can be modified to "keep tabs of," which is a change in the preposition of the phrase (Riehemann et al., 2001).

- 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. These are verb phrases formed of a light verb (make, give, have), followed by a noun phrase. Some examples are "make a compromise," "give a presentation," and

"have a rest." The verb of the phrase is inflected to change tense ("made a compromise"). The particular verb that a given light verb phrase will use is difficult to predict from the original verb. For example, "to walk" can be put as a light verb phrase, "to take a walk," but not "to make a walk," whereas "to make a presentation" is fine and "to take a presentation" nonsensical.

Other work has described a division of MWEs extracted from paraphrases: one-to-many, many-to-one, decomposable and non-decomposable (de Marneffe et al.,). They also investigated using paraphrases to automatically extract multiword expressions. (de Marneffe et al.,) consider dependency-based paraphrases and parallel corpora-based paraphrases as sources for MWEs, finding that 34% of the MWEs in the MSR manual word alignments of the RTE 2006 corpus were present in these resources (Brockett, 2007).

4 Analysis of PPDB

The Paraphrases Database (PPDB) contains English paraphrases. We have characterized a subset of the paraphrases found in the PPDB, according to categories of multi-word expressions (MWEs), syntactic changes in the expansion from a word to its paraphrase, and what parts of speech appear in the corpus. We also looked at how many of the paraphrases in the PPDB appear to be spurious.

The categories of MWEs we looked at were light verbs, verb-particle constructions, negation, and superlatives. We also included the categories for MWEs described in Sag et al: fixed expressions, non-decomposable idioms, compound nominals, proper names, and decomposable idioms.

In addition to MWE categories, we also included categories for syntactic changes from a word to its paraphrase: change of tense followed by a paraphrase, nominalizations, infinitival to, adverbial modifier, one or more words the same as part of the original word, determiner followed by a one-word paraphrase, determiner followed by the plural form, and change of tense. Finally, we included acronyms, hypernym-hyponym pairs, times, extra punctuation marks, and numbers as categories, as well as unspecified expansions and bad paraphrases.

PPDB is released in a series of files. The different files are divided into one-to-one (synonyms), one-to-many, many-to-many, phrasal, and syntactic files. The lexical paraphrases are from one word to one word, the one-to-many are paraphrases between one word and a multi-word expression, many-to-many paraphrases are paraphrases between two multiword expressions, and syntactic paraphrases are paraphrases are those where the syntactic category is the same for both a phrase and its paraphrase. For this analysis we investigate the one-to-many paraphrase file as a source of potential paraphrases for multiword expressions.

The PPDB files are further subdivided by size, from S to XXXL (six sizes). Each paraphrase in the PPDB is scored according to how precise of a paraphrase it is likely to be. The smaller files contain better-scoring paraphrases, while the larger files contain incrementally more paraphrases, at the cost of precision. For this analysis we chose the L corpus as a compromise point among the various sizes for both coverage and quality of paraphrases.

Of a random sample of 500 paraphrases from the L one-to-many paraphrase file, the most common types of paraphrase were expansions using the same morphological form (117 instances, or 23.4%), determiner followed by a one-word paraphrase (86 instances, or 17.2%), and paraphrases that did not fall into a particular category (62 instances, or 12.4%). Of the sample, 43 were bad paraphrases (8.6%). The full list of categories and the number of instances in each are in the table below.

Of the 500 paraphrases in the random sample, 37 (7.4%) fell into the MWE categories defined by Sag et al. (2001)l. 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.

The full list of categories with the number of instances of paraphrases in each, as well as illustrative examples for each, are in the table below (Table 1). MWEs, as defined by Sag et al. (2001), are marked in bold.

The distribution of the syntactic categories from this random sample is depicted in Table 2.

In both samples, the most common part of speech is NP, followed by VP.

Paraphrase Category	**Number of instances in sample**	**Examples**
determiner + one-word paraphrase	86	photographs, the images; duties, the responsibilities
expansion	62	suffocate, need air; cumbersome, time consuming
expansion, same morphological form	47	fun, sounds like fun; signs, signs and signals
change of tense + paraphrase	43	initiated, has undertaken; say, going to tell
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
one or more words the same as part of original word	17	anytime, any point; enslavement, slave labour
verb-particle	14	torched, burnt down; done, carried out
determiner + plural	9	gloves, the glove; militaries, the military
proper noun	7	markov, mr markov; karadzic, radovan karadzic
change of tense	7	changing, be changed; attain, be attained
fixed expression	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
decomposable idiom	4	nuts, out of your mind; sleeping, get a good night's sleep
light verb	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 '
non-decomposable idiom	2	furious, as mad as hell; entails, brings with it
alternate spelling	1	al-najaf, al nagaf
compound nominal	0	

Table 1: Number of instances from each category in random sample of 500.

In addition to categorizing a random sample of paraphrases, we searched for instances of light verbs, verb-particle constructions, negation, comparatives, and superlatives. 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. Negation instances had the word not either in the original or the expanded paraphrase. Comparatives had the word more, and superlatives had the word most.

To find instances of verb-particle constructions, we used the Linux command 'grep' and the regular expression ' particle_ to find phrases where the potential particle was not the first word, and to ensure 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 ran the following command: grep ' up_ ppdb-1.0-l-o2m

We then determined manually 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.

We used similar commands to find instances of the other paraphrase categories. A list of the commands used is in the following table:

Syntactic category	Frequency in sample	Frequency in PPDB-L
NP	254	101563
VP	109	39380
X	39	17005
ADJP	27	14513
ADVP	16	5451
S	9	4103
INTJ	3	1730
TOP	4	1476
NX	2	1113
PP	1	532
FRAG	3	388
SQ	0	305
SBAR	0	165
WHNP	0	163
WHADVP	0	66
QP	0	39
LST	0	3
SBARQ	0	3
CONJP	0	1
PRT	0	1

Table 2: Distribution of syntactic categories in random sample of 500 words from PPDB L, and in the entire PPDB L file, sorted by frequency in PPDB L.

The results from these searches are summarized in the tables below. 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').

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 corpus.

5 Building a classifier for MWEs in PPDB

There are 188,000 rules in the PPDB L one-to-many file, which is too many to manually sift through and find relevant MWEs. Therefore, we built a classifier to automatically distinguish between trivial MWEs and paraphrases that are interesting to MWE researchers.

5.1 Experimental setup

We designed features tailored to find paraphrases in the following categories of MWE: verb-particle construction; expansion, same morphological form; implicit/most common modifier; implicit type; light verb; fixed expression; non-decomposable idiom; proper noun; decomposable idiom; light verb. The methodology used in the classifier could also be applied more generally for finding relevant expressions in PPDB.

The features we used were whether a preposition appeared in the expansion of the paraphrase (feature value either 1 or 0), whether the original word appeared in the expansion, whether a light verb appeared in the expansion, and all of the scores from the PPDB (every number that appeared in the entry following an equal sign).

The prepositions and light verbs used for the features are listed in the table below.

5.2 Results

We used an SVM classifier (libsvm) with these features on our sample of 500 words from the PPDB L corpus. With ten-fold cross-validation, the accuracy of the classifier was 76.4%. By comparison, a baseline classifier that returns the majority class has an accuracy of 69.2%.

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 a sample of 33 paraphrases that fall into the categories described by Sag et al. (2001) (verb particle, fixed expression, non-decomposable idiom, compound nominal, proper name, decomposable idiom, and light verb) 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, 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 1 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 1 shows the trees for a case where the sentence containing the expansion (”leverage”) is parsed correctly, but the sentence containing the one-word paraphrase (”avail myself of”) is not. Figure 2 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 3 shows the trees for a case where both sentences are parsed incorrectly.

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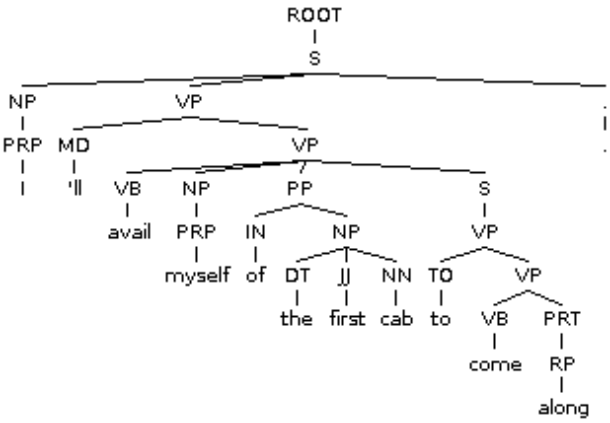
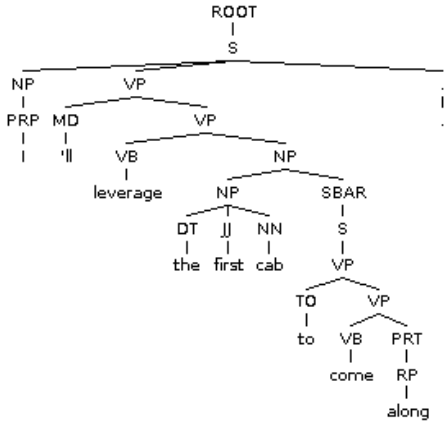
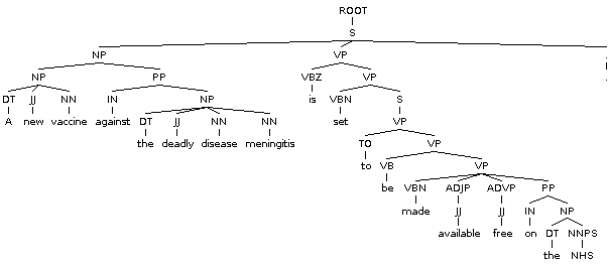


(a) Original sentence: I'll avail myself of the first cab to come along.

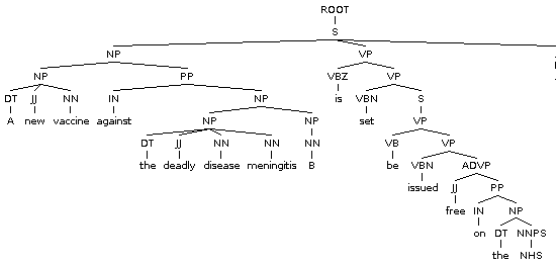


(b) Sentence with substitution: I'll leverage the first cab to come along.

Figure 1: 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)).

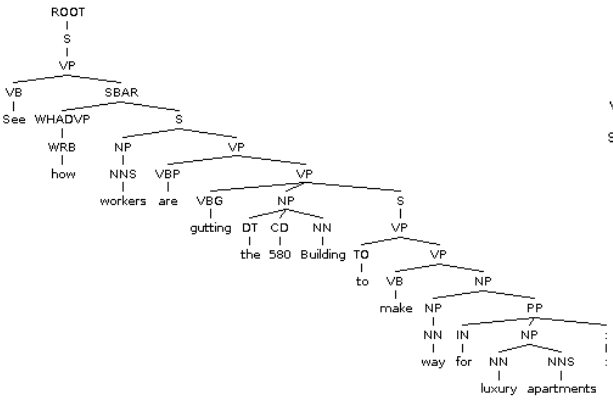


(a) Original sentence: A new vaccine against the deadly disease meningitis is set to be made available free on the NHS.

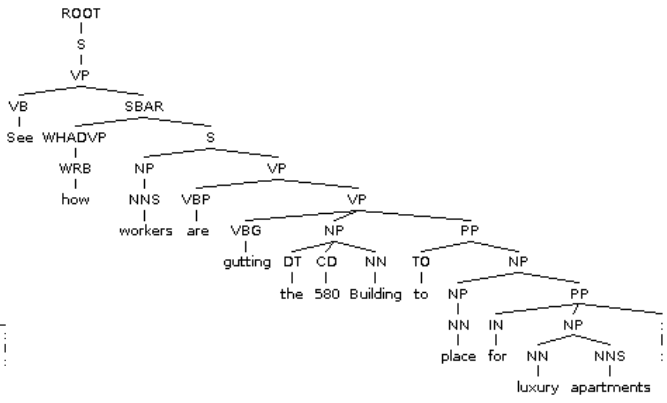


(b) Sentence with substitution: A new vaccine against the deadly disease meningitis is set to be issued free on the NHS.

Figure 2: 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)).



(a) Original sentence:See how workers are gutting the 580 Building to make way for luxury apartments.



(b) Sentence with substitution: See how workers are gutting the 580 Building to place for luxury apartments.

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 (a)).

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Paraphrase category	Search command
verb-particle construction	grep ' up \b' ppdb_filename
light verbs	grep '\b make ' ppdb_filename
negation	grep '\b not ' ppdb_filename
comparatives	grep '\b more ' ppdb_filename
superlatives	grep '\b most ' ppdb_filename

Table 3: Linux commands to search for paraphrases of different types.

Light verb	Number of light verb phrases found by grep	Number of light verb phrases	Matching verbs
make	46	35	make a call, make a decision, make a suggestion
have	105	45	have a ball, have a conversation, have a word
give	11	4	give a damn, give a reply
take	48	33	take a break, take a look, take a walk
hold	3	1	hold a debate

Table 4: Light verbs: number of potential light verb phrases found by grep, the number of these that turned out to be light-verb phrases, and some examples.

Particle	Number of verb-particle constructions found	Number of verb-particle phrases found by grep
up	439	439
about	10	115
around	44	47
back	145	156
down	190	195
in	32	207
off	134	134
on	109	196
out	383	383
over	65	67

Table 5: Verb-particle constructions.

prepositions	'about', 'around', 'back', 'down', 'in', 'off', 'on', 'out', 'over', 'up'
light verbs	'give', 'have', 'hold', 'make', 'take'

Table 6: Words used as features for classifier.