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 **?**). 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 (**?**). 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 **?**; **?**) found that, among a random sample of 20,000 strings from the written portion of the British National Corpus (**?**), using the English Resource Grammar (**?**), MWEs caused 8% of all parse errors. When manually selected compound nominals were searched for as single terms it improved information retrieval results (**?**).

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, **?**) built a classifier to identify idioms, TODO - ADD SEVERAL MORE EXAMPLES. 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 developed 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 (Ganitkevich et al, 2011; Ganitkevich et al, 2013).

3 Experimental Design

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 Tim Baldwin's categories for MWEs: 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.

4 Results

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 Baldwin et al. 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 Baldwin et al., 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.

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.

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.

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

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').

After manually identifying categories, we developed a classifier to automatically find paraphrases that are interesting to MWE researchers. We built the classifier to find 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 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.

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.

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.

We used an SVM classifier (libsvm) with these features on our sample of 500 words. With ten-fold cross-validation, the accuracy of the classifier was 75.4

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 Tim Baldwin categories (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, and then created an equivalent sentence by replacing the expansion with the one-word paraphrase. We used the Berkeley parser to parse these sentence pairs and compared the parse trees.

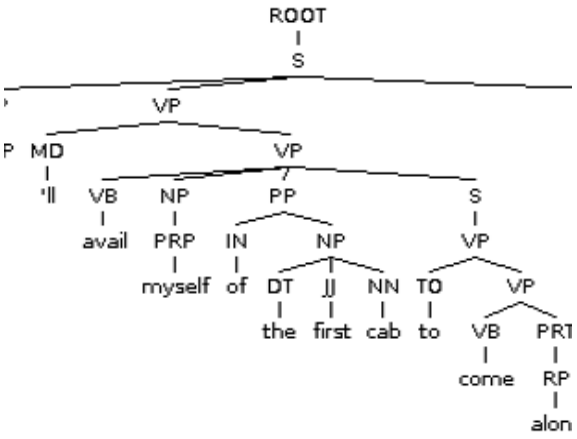
Of the 33 paraphrases sampled, 30 were correctly parsed using the one-word paraphrase, and 29 were correctly parsed using the expansion. 2 were parsed correctly for the one-word paraphrase but not for the expansion, 1 was parsed correctly for the expansion but not the one-word paraphrase, and 1 was parsed incorrectly for both. Figure 4 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.

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.



5 Analysis

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.