Idiomify - Building a Collocation-supplemented Reverse Dictionary of English Idioms with Word2Vec for non-native learners

Eu-Bin KIM
Supervised by Professor Goran Nenadic
Bsc Artificial Intelligence
Department of Computer Science
University of Manchester

May 2021
1. Introduction

1.1. Why build a reverse dictionary of idioms?

Table 1: Definitions of some idioms. (Adapted from: *Oxford Advanced Learner’s Dictionary of Current English*, 1995)

| idiom                  | definition                                           |
|------------------------|------------------------------------------------------|
| beat around the bush   | to talk about something for a long time without      |
|                        | coming to the main point                            |
| leave no stones unturned| to try every possible course of action in order to   |
|                        | find or achieve something                            |
| ring a bell            | to sound familiar to you, as though you have heard it|
|                        | before                                               |

Idioms are figures of speech. That is, they are phrases that are more often meant to be taken figuratively than to be taken literally (Caro & Edith, 2019). Table 1 above introduces some examples of English idioms. For instance, when people say *do not beat around the bush!*, that does not necessarily mean they are asking someone to stop poking around the bush, but it means more to ask to get “to the main point”. Likewise, when people say *does not ring a bell*, this means that something does not “sound familiar” to them, rather than to mean that they have a malfunctioning bell on their hands.

The figurative nature of idioms helps us communicate more effectively. Idioms can help people describe a potentially complicated concept with a relatively comprehensible analogy, thereby boosting their conversational skills. For instance, It is much more comprehensible and elegant to say *They have left stones unturned* to achieve this end than to rather wordly say *They have tried every possible course of action in order to achieve this end*. They are not just a fun way of expressing something, they efficiently enrich the way we communicate.

Despite the benefits, non-native learners of language find it hard to leverage idioms. This is because they significantly lack idiomatic fluency, compared with the natives (Thyrab, 2016). As for the non-natives, not many idioms come to their mind to begin with. Therefore, rarely do they voluntarily try to use idioms to communicate more effectively.

![a good luck in making unexpected discoveries](image)

Figure 1: Reverse-searching the word *serendipity* with its definition, *a good luck in making unexpected discoveries* on *OneLook* (Beeferman, 2003).

We build a reverse dictionary of English idioms to help the non-native learners of English leverage the idioms on demand. As opposed to a forward dictionary, a reverse-dictionary allows us to search for words, given a definition (Sierra, 2000). For example, *OneLook* is a reverse dictionary that we can use to, say, reverse-search *serendipity* with its definition, *a good luck in making unexpected discoveries* (Figure 1). if there was a reverse dictionary as such but for idioms, it would be much helpful for the non-natives, as they would be now able to explore how they could paraphrase a sentence with an idiom, on demand. However, no reverse-dictionaries have ever been built for idioms.
1.2. Why supplement it with the collocations of idioms?

Figure 2: The verb, noun, adjective and adverb collocations of the word *serendipity* (bottom right), compiled by *COCA* (Davies, 2008)

Collocations are words that frequently and uniquely co-occur with each other. Differently put, they are combination of words “that happens very often and more frequently than would happen by chance” (*Oxford Advanced Learner’s Dictionary of Current English*, 1995) For example, discover, occur and strike are collocates of the word *serendipity* (Figure 2 above), because they would co-occur frequently more often *serendipity* than would co-occur by chance. Likewise, we could also have noun, adjective and adverb collocations of words, as in *rufus serendipity, pure serendipity* and *partly serendipitous*.

Table 2: Some responses of the native and non-native speakers to word-combining test (adapted from: Granger, 1998).

| native                     | non-native                              |
|----------------------------|----------------------------------------|
| bitterly cold(40)          | bitterly cold(7), bitterly aware(3), bitterly miserable(2) |
| blissfully happy(19)       | blissfully happy(4), blissfully ignorant(20) |

Collocational knowledge is highly beneficial to non-native learners because they serve to guide them on using words naturally and precisely. This is partly because L2 learners tend to lack native-like heuristics on collocation. Granger (1998) demonstrated this by having native and non-native speakers of English take “word-combing test”, where they were asked to choose adjectives that acceptably collocate with a given amplifier (e.g. *bitterly*). As Table 2 illustrates, L2 learners showed misguided sense of collocation (e.g. *blissfully ignorant*). This indicates that L2 learners struggle to acquire collocational knowledge, which is why collocations dictionaries are effective supplements to them. The editors of *Oxford Collocations Dictionary for Students of English* (2002) well exemplify the benefits; *strong rain* does get the idea across, but it would be more natural if it were revised to *heavy rain*. Likewise, a *fascinating book* is more precise than a *good book* because *fascinating* collocates with *book* and communicates more than *good*.

Whilst collocations of singular words are widely available, collocations of idioms are unavailable even though they do collocate. Idioms themselves are extremely strong collocations that have nearly fixed forms. Therefore, it is plausible to identify idioms as a “word” in a sentence, in which case collocation inevitably occurs. For example, the government intends to seize power by hook or by crook sounds more natural than *I’ll assist you by hook or by crook*, and in both cases *by hook or by crook* effectively behaves as an atomic unit. Yet, no major dictionary publishers have attempted to compile collocations of idioms.

We supplement the reverse dictionary of idioms to assist the non-natives in using idioms naturally and precisely. If we had “Collocations Dictionary of English Idioms”, the non-natives would benefit from it in using idioms in an appropriate context, in a more natural way. There are however no dictionaries as such available. This motivates us to supplement the reverse-search engine with the collocations of retrieved idioms.
1.3. Aim

Project Idiomify aims to suggest a list of idioms that best describe a given phrase to non-native learners of English, while supplementing the results with the collocations of the idioms. Figure 3 illustrates how we might use Idiomify with an example scenario. Say we write They are waiting excitedly, anxiously and hopefully to see the results to describe the people in the images above. If we were non-native learners of English (e.g. a Korean learning English), we may want to explore how we could paraphrase the sentence with an idiom (discussed in section 1.1), as it would make the sentence more native-like. We therefore give the phrase as the input to Idiomify: excitedly, anxiously and hopefully. Given the input, Idiomify suggests with bated breath, hold one’s breath and don’t hold your breath as the idioms that are most likely to capture the meaning of the phrase, of which with bated breath is found to be the most appropriate one. We thereby learn to rephrase the sentence to They are waiting with bated breath to see the results. As being non-native learners, we may also wonder how we could use with bated breath more adequately than the first try (discussed in Section 1.2.). Here, consulting “verb collocates” helps us in doing so. That is, we see that with bated breath collocates with watch and whisper, and we indeed notice that the people in the pictures are watching something while possibly whispering their wishful thinking. We therefore learn to revise the first try into a more precise and communicative one: They are waiting, watching and whispering with bated breath.

As a result of the project, we have developed the following deliverables:

- **identify-idioms**: A Python library for reliably identifying and collecting idiomatic expressions
- **idiom2vec**: A Python library for training a Word2Vec model on idiomatic expressions
- **idiom2collocations**: A Python library for modeling and extracting collocations of idioms.
- **idiomify**: A python library for reverse-searching idioms
2. Related Work

2.1. Identifying Idioms

Table 3: Examples of the six variation cases of idioms. The idioms are chosen from SLIDE (Jochim et al., 2018).

| base form                  | variation                        | case            |
|----------------------------|----------------------------------|-----------------|
| balls-out                  | balls-out                        | optional hyphen |
| find one’s feet            | finding her feet                 | inflection      |
| add fuel to the fire       | throw gasoline on the fire       | alternatives    |
| grasp at straws            | grasp desperately at straws      | modification    |
| open the floodgates        | the floodgates were opened       | passivisation   |
| keep someone at arm’s length | keep his old friends at arm’s length | open slot       |

It is challenging to identify idioms because they extensively vary in forms. We need a reliable way of identifying idioms to collect as many idiomatic expressions from corpora. However, while some idioms are syntactically frozen (e.g. by hook or by crook), many of the idioms vary. We could categorize their variations into 6 cases: optional hyphen, inflection, alternatives, modification, open slot and passivisation. Table 3 exemplifies each case. We often omit the hyphen (e.g. balls-out), the verbs and possessive pronouns inflect (e.g. finding her feet), some idioms have alternative forms (e.g. throw gasoline on the fire). In addition to these cases, Hughes et al. point out (2021) that there are three more cases; some constituent words could be modified with modals (e.g. grasp desperately at straws), idioms could be passivised (e.g. the floodgates were opened), pronouns could be substituted with a set of words (e.g. keep his old friends at arm’s length). We can by no means reliably identify idioms unless we come up with a way of addressing all of these variations.

At the late stages of this project, Hughes et al. have published (2021) their approach on identifying idioms. They do so by leveraging a search query API provided by a flexible and scalable search engine called ElasticSearch (Gormley & Tony, 2015); As will be discussed in later sections, they generate a set of queries for each idiom, each of which is specifically designed to address the aforementioned six variation cases, and hence their paper’s name: “leaving no stones unturned”.

The set of idioms offered by SLIDE project is worthy of extracting the collocations for and building a reverse-dictionary for. This is because SLIDE offers a shortlist of frequently used idioms (Jochim et al., 2018). They first collected 8772 idioms from Wiktionary, then compiled only the 5000 most frequently occurring idioms in news articles, publications, etc. Therefore, one could get the most out of their exploration on idioms if they do so with the set of idioms included in SLIDE.

2.2. Modeling collocations of Idioms

Researchers have attempted to model the notion of collocations with statistical metrics that can measure pairwise significance. That is, if a metric can statistically determine that, for example, the pairwise significance of heavy rain is larger than that of strong rain, people have used the metric to mathematically model collocations. This is a reasonable approach, as the notion of pairwise significance as such well echoes with the aforementioned definition of collocations - “Words that uniquely and frequently co-occur each other” (Section 1.2). The pairwise significance metrics that have been used to model collocations include: T-score, Pearson’s X-square Test, Log-likelihood Ratio and Pointwise Mutual Information (Thanopoulos et al., 2002).

\[
PMI(w_1, w_2) = \log_2 \frac{P(w_1, w_2)}{P(w_1) \cdot P(w_2)}
\]

Equation 1 The equation of Pointwise Mutual Information (PMI) for bigrams. (adapted from: Church & Hanks, 1989)
Point-wise Mutual Inclusion (PMI) is one of the most widely used measures for modeling collocations. First proposed by Church & Hanks in 1989, PMI has long been used to model collocations and extract them from corpora. Equation 1 shows the mathematical definition of PMI. Here, we see that PMI is proportional to the $P(w_1, w_2)$ conjugation probability. This means that the more frequently the words co-occur in a corpus, the higher the PMI score gets. We also see that PMI is inversely proportional to the product of $P(w_1)$ and $P(w_2)$. This means that the more rarely each word independently occurs in a corpus, the higher the PMI score gets. All in all, PMI favors rarely but frequently co-occurring pairs of words, which is a good fit for collocations.

$$\text{tf} \times \text{idf}_{t,d} = (1 + \log_{10} \text{tf}_{t,d}) \times \log_{10}(N/df_t)$$

Equation 2: The equation of TF-idf weighting (adapted from: Manning et al., 2008)

Term Frequency - Inverse Document Frequency (TF-IDF) is also a popular metric for pairwise significance, which could be used to model collocations. TF-IDF has long been used in information retrieval to measure the significance (the weight) of a word in a specific document, so that the weight can be used to rank documents (Manning et al., 2008). In the regime of TF-IDF weighting (Equation 2), the weight of a term $t$ is proportional to its term-frequency $tf$ in a document $d$ and inversely proportional to its document-frequency $df$ in $d$. In qualitative terms, this means that the more $t$ frequently and uniquely co-occurs with $d$, the higher tf-idf weight of $t$ with respect to $d$ gets. Here, if we think of $t$ as a word and $d$ as another word that co-occurs with the word $t$, we can see that TF-IDF is conceptually just as suitable a model for collocations as PMI. Extracting collocations from corpora involves retrieving documents and ranking them in terms of their collocative significance after all, so it is worth exploring TF-IDF as a candidate for the model of collocations.

2.3. Reverse-searching Idioms

| forward index                          | inverted index                                      |
|----------------------------------------|----------------------------------------------------|
| Grandma’s tomato soup: leaves, tomatoes, basil | basil: Grandma’s tomato soup                        |
| African tomato soup: tomatoes, leaves, baobab | leaves: African tomato soup, Grandma’s tomato soup |
| Good ol’ tomato soup: tomato, salt, garlic | salt: African tomato soup, Good ol’ tomato soup     |

People have taken three approaches to engineering a reverse-dictionary of words: inverted index, graphs and distributional semantics. The simplest approach of all is populating a def-to-word inverted index. As opposed to a forward index, an inverted index maps a term to documents, which allows us to search documents by terms (Ingebrigsten, 2013). For instance, as illustrated in Table 4 above, the inverted index of recipes allows us to search them by their ingredients (e.g. leaves -> *African tomato soup*). If we think of words as the recipes and each term in their definitions as the ingredients, if we populate a def-to-word inverted index that is, we can conceivably implement a simple reverse-dictionary of words. *OneLook*, introduced in Section 1.1, is an example of a reverse-dictionary that takes this approach. While *OneLook* works fairly well, Thorat & Choudhari (2016) attempted to improve upon *OneLook* by taking a graph-based approach. Their idea was to leverage *WordNet* (Miller, 1995), from which they extracted hypernym-hyponym relations of words (e.g. *parent* is a hypernym for *father*), to search the word that is nearest to all the terms of a given phrase. For example, as illustrated in Figure 4 below, on searching their graph with the phrase *Son of my parents*, the word *brother* would be retrieved as it is the one that is closest to both *Son* and *Parents* with respect to their similarity measure. It has also been attempted to take a distributional semantics approach. Distributional semantics assumes that the semantics are distributed across contexts. That is, they aim to find the meaning of words from a corpus rather than a dictionary. For example, Hill et al. attempts to build a reverse dictionary by having a Recurrent Neural Network learn the mapping from definition to words. Unlike how Thorat & Choudhari et al. carefully engineered a way to leverage *Word2Net*, Hill et al. simply provide their model features and labels. And yet, their RNN turns out to perform just as good as *OneLook*.
The distributional semantics approach is the most flexible approach of all. One reason for this is that they do not require a domain-specific feature engineering. This is especially useful for building a reverse-dictionary of idioms, since we don’t have any “IdiomNet” to leverage features from. Another reason for the flexibility is that distributional semantics allows for a semantics-aware search. For instance, Hill et al.’s aforementioned RNN model can reverse-search words not only given a definition, but also given a concept description; their model can find the word \textit{prefer} given \textit{when you like one thing more than another thing}, although this is a paraphrased version of the definition of \textit{prefer}.

Word2Vec is a good baseline for the distributional approach to building a reverse-dictionary. In their landmark paper, Mikolov et al. (2013) devised a text-based language model that can work out word analogies. The model, now known as Word2Vec, was capable of finding X such that \textit{Woman is to Man as Queen is to X}, in which case it would output a list words related to \textit{King}. Perhaps due to this remarkable of numerically capturing semantics of words, Hill et al. also uses (2016) Word2Vec to set up a baseline model for their reverse-dictionary. They use Word2Vec to get the word embeddings vectorize a phrase by averaging the word embeddings of each word in the phrase. Despite its simplicity, this way of Word2Vec-averaging a sentence is a “A simple but tough-to-beat baseline for sentence embeddings” (Arora et al., 2017). Hence, it would not be a terrible idea to implement a reverse-dictionary by first Word2Vec-average an input phrase, and then finding the nearest word neighbours to the average vector.
3. Implementation

As overviewed in Figure 5 above, the main goal of project Idiomify is broken down into the following five subgoals:

1. identify idioms: identify and collect idiomatic expressions from corpora
2. pre-process data: prepare the data needed for step 3, 4 and 5, from the data collected in step 1.
3. extract collocations of idioms: extract the collocations of idioms with TF, PMI and TFIDF from the data processed in step 2.
4. train an Idiom2Vec Model: train a Word2Vec model on the data processed in step 2.
5. reverse-search idioms (Idiomify): idiomify a given phrase using the Idiom2Vec trained in step 4.

In this chapter, we elaborate on how we implement each step.

3.1. Identifying idioms

We get a vocabulary of idioms to identify from SLIDE project. This is because it offers 5000 most frequently used idioms, as discussed in Section 2.1. We however do not identify all the 5000 idioms; we exclude the short ones. This is because they either hold little significance or often used literally rather than figuratively (e.g. I do, I wish, add up, etc). However, we include hyphenated idioms in the vocabulary regardless of their lengths because they are almost always taken figuratively (e.g. catch-22, need-to-know, back-to-back, etc). All things considered, this leaves us with 2746 idioms to identify, which is still a large set of idioms to explore.

The list of all the identifiable idioms is viewable on identify-idioms library, which we will discuss at the end of this section.

Table 5: Examples of the matching rules for identifying idioms.

| base form / variation case | matching rule |
|----------------------------|---------------|
| down-to-earth / optional hyphen | [[[TEXT:down]; [TEXT:to]; [TEXT:earth]], [[TEXT:down]; [TEXT:-]; [TEXT:to]; [TEXT:-]; [TEXT:earth]] |
We handle the case of optional hyphen, inflection and alternatives by defining idiom-matching rules that address each case. We do this by automatically deriving matching rules from the base forms of each idiom, an illustration of which is shown in Table 5. As for hyphenated idioms, we logical-or the rules with and without the hyphen (denoted as ,), each of which is the constituent texts sequentially joined with logical-and, denoted as ; (e.g. down-to-earth). Similarly, as for the idioms with alternatives, we logical-or all the possible alternatives, each of which is the constituent lemmas sequentially joined with logical-and. Here, defining the rules in terms of LEMMA ensures the rules to cover any possible inflection of the constituent words. As for the idioms with inflecting personal pronouns, we include a rule that is defined in terms of part-of-speech (e.g. [POS:$PRP$]). The automatic derivation of the matching rules were made possible with minimal boilerplate code by spaCy’s (Honnibal & Montani, 2017) easy-to-use Language pipeline and Matcher API.

Table 6: Example entries of idiom2sent.tsv with the original sentences.

| column 1 (idiom) | column 2 (tokens) |
|------------------|-------------------|
| down-to-earth    | [She, 's, so, cool, and, [IDIOM]] |
| add insult to injury | [For, God, 's, sake, man, do, not, [IDIOM]] |
| find one's feet  | [drift, back, in, time, and, [IDIOM]] |

With the matching rules, a Python library, identify-idioms, was developed and used to collect idiomatic expressions from two corpora. The library is published with pip for open use. Hence, anyone can install it (pip3 install identify-idioms) and use it to identify idioms as atomic tokens. We use the library to identify idioms from two corpora - the spoken data of Corpus of Contemporary American English, otherwise known as COCA(Davis, 2008), and OpenSubtitles (Tiedmann, 2012). This is because they are both rich with spoken contexts (e.g. movie subtitles), wherein idiomatic expressions are frequently uttered. As such, we were able to collect more than 3 million idiomatic utterances from the two corpora. We save this into a tab-separated values named idiom2sent.tsv, some examples of which are represented in Table 6 above.

3.2. Pre-processing data

Table 7: Some example entries of idiom2lemma2pos.tsv

| col 1 (idiom) | col 2 (lemma-pos pairs) |
|---------------|-------------------------|
| out_of_touch  | [[o’reilly, X], [well, INTJ], [then, ADV], [you, PRON], [be, VERB], [[IDIOM], X]] |
| on_one's_toes | [[they, PRON], [keep, VERB], [you, PRON], [[IDIOM], X]] |
| get_to_the_point | [[let, VERB], ['s, PRON], [[IDIOM], X]] |

In Pre-processing step, we prepare the data needed for training an Idiom2Vec. That is, we lemmatise and postag the set of idiomatic expressions, idiom2sent.tsv. The result of this is saved in idiom2lemma2pos.tsv, some examples of which are shown in Table 7 above. This is later used to produce idiom2bows.tsv.
We also prepare the data to extract the collocations of idioms from. That is, we collect verb, noun, adjective and adverb lemmas that are in vicinity to idioms from `idiom2lemma2pos.tsv`. We process them into a bag-of-words dictionaries, the result of which is saved in `idiom2bows.tsv` (e.g. Table 8). This data is later used as the source for collocations of idioms, from which we extract collocations in the following step 3.

### 3.3. Modeling and extracting the collocations of idioms

We model the collocations with PMI, TF-IDF and Term Frequency (TF). The reason for modeling collocations with PMI and TF-IDF is because PMI has been widely used to model collocations, and TF-IDF is also a popular metric of pairwise significance that we can conceivably use to model collocations, as discussed in Section 2.2. In addition, we also explore Term Frequency (TF) to have a reasonable baseline with which we can compare the other two models. The three models are implemented as Python classes, the UML diagram of which is illustrated in Figure 6. Given `idiom2bows.tsv` as the input, the three models extract four types of collocations: noun, verb, adjective and adverb collocations. This is to produce the same outcome as the collocations offered by COCA, which was introduced in Section 1.2.

```python
@staticmethod
def pmi(p_x_y: float, p_x: float, p_y: float) -> float:
    ""
```
Point-wise Mutual Information

\[ \log_p_{x,y} = \text{math.log}(p_{x,y}, 2) \]
\[ \log_p_x = \text{math.log}(p_x, 2) \]
\[ \log_p_y = \text{math.log}(p_y, 2) \]

return \( \log_p_{x,y} - (\log_p_x + \log_p_y) \)

Code 1: The python implementation of PMI. This is one of the methods of PMICollModel class.

We implement PMICollModel by writing the definition of PMI from scratch, and implement TFIDFCollModel with Gensim library. Code 1 shows the python implementation of PMI, which is the core method of the PMICollModel class. Although the original definition of PMI is \( PMI(x, y) = \log(p(x, y)/(p(x)p(y))) \), we use the product & quotient rule of logarithms (i.e. \( \log(a \times b) = \log(a) + \log(b) \) and \( \log(a/b) = \log(a) - \log(b) \)) to translate it into additions and subtractions: \( \log(p(x, y)) - \left( \log(p(x)) + \log(P(y)) \right) \), for faster and more precise computation of PMI. As for our TFIDFCollModel class, it is implemented with Gensim (Rehurek & Sojka, 2011) library’s TfidfModel API.

A python library, idiom2collations, was developed to house the collocation model classes and use them to extract collocations. Given idiom2bows.tsv as the input, TFCollModel, TFIDFCollModel and PMICollModel extract the collocations of idioms and save them to three tsv files: idiom2colls_tf.tsv, idiom2colls_tfidf.tsv, idiom2colls_pmi.tsv. These files are used to compile top 5 collocations of idioms, some examples of which can be found in Appendix 1A, 2A, 3A and 4A.

3.4. Train Idiom2Vec

We choose to use Word2Vec for implementing the reverse-dictionary of idioms. This is because distributional semantics approach is flexible, for which Word2Vec is a simple yet strong baseline, as discussed in Section 2.3.

Table 9: The three versions of Idiom2Vec that were trained. each model was trained on a slightly different training set.

| Idiom2Vec | corpora         | stopwords | lemmatisation |
|-----------|----------------|-----------|---------------|
| V1        | COCA (spok)    | not removed | lemmatised   |
| V2        | COCA (spok) + OpenSubtitles | not removed | lemmatised   |
| V3        | COCA (spok) + OpenSubtitles | removed    | lemmatised   |

In order to get dense vector representations of idioms, we train Word2Vec models on a set of idiomatic expressions. Since the goal is to vectorize idioms, we call them “Idiom2Vec”. We train Idiom2Vec on different versions of idiom2lemma2pos.tsv (obtained from step 2) to explore the effect of corpus size and stopwords. We therefore have three versions of Idiom2Vec, as shown in Table 9. V1 is trained on COCA only, while V2 and V3 are trained on OpenSubtitles as well as COCA. This is to see if increasing the size of the training data results in any improvement on the performance of Idiomify (the last step). Stopwords are a set of words that hold little semantic significance (Ganesan, 2020), which are generally filtered out to focus on the meaningful words. However, whether they are useless or not is domain-dependent. We therefore do not remove stopwords for training V1 and V2, but remove them for training V3, to experiment on the effect of stopwords on the performance of Idiomify. Training & serialising the three models were implemented with Gensim (Rehurek & Sojka, 2011) library’s Word2Vec API.
Aside from epoch, the three models are trained with the same set of hyper parameters, as shown in Table 10. Ideally, all of them should be optimised to each model. This however was not feasible as training the models would take over four hours. Therefore, as for vector size, window size, min count, learning rate and the type of Word2Vec, we fix them with their conventional values. We however do optimise epoch by monitoring the cumulative log loss. That is, we stop the training as soon as the cumulative loss starts to plateau. For example, the number of epochs for V1 is set to 50 (Table 10), because the loss of V1 starts to plateau at 50 epoch, as illustrated in Figure 7.

Table 11: The top 5 nearest idioms to catch-22. The results are obtained with Idiom2Vec V2. The definitions are adapted from Oxford Learner’s Dictionary of English (1995).

| rank / idiom           | cosine similarity | definition                                                                 |
|------------------------|-------------------|---------------------------------------------------------------------------|
| 1 / catch-22           | 1.0               | an unpleasant situation from which you cannot escape                       |
| 2 / life-or-death      | 0.3943            | extremely serious, especially when there is a situation in which people might die |
| 3 / apples and oranges | 0.3924            | two people or things are completely different from each other              |
| 4 / rocket science     | 0.38              | used to emphasize that something is easy to do or understand              |
| 5 / double-edged sword | 0.3801            | to be something that has both advantages and disadvantages                |

A python library, idiom2vec, was developed to train & explore Idiom2Vec models. The library offers a way of exploring the nearest idioms (in terms of cosine similarity) to a given idiom that an Idiom2Vec model has learned. An example of this with catch-22 as the input is illustrated in Table 11 above. Here, we see that the model has learned the juxtaposing nature of catch-22, and thus infer that life-or-death (live or die), apples and oranges (two different things) and double-edged sword (pros and cons) are similar in the semantics.
# 4. abort if nothing has been learnt
if len(avail_tokens) == 0:
    return None

# 3. vectorize the tokens
token_vectors = [
    self.idiom2vec_wv.wv.get_vector(token)
    for token in avail_tokens
]

# 5. return their average
return np.array(token_vectors).mean(axis=0)

Code 2: The Python implementation for vectorizing an input phrase

We reverse-search idioms by averaging the Idiom2Vec embeddings of a given phrase to get a phrase vector, then searching for the nearest idiom neighbours to the phrase vector. **Code 2** above shows how the phrase vector is obtained: First, the input phrase is refined and tokenised. Any numbers, punctuations are removed, and each word in a phrase is lemmatised. Next, we get only the tokens that the Idiom2Vec has seen in the training. For example, if tokens were [excitedly, and, anxiously] but self.idiom2vec were Idiom2Vec V3, then only [excitedly, anxiously] would be saved in avail_tokens because V3 is trained with non-stopwords data (as discussed in Section 3.4.). If no tokens are available, the method returns None to abort the process. Otherwise, we vectorize the available tokens, the average of which is then returned to give the phrase vector.

| # | Idiomifying: wait, anxiously, excitedly, hopefully | cols mode: tfidf | noun collocates |
|---|--------------------------------------------------|-----------------|----------------|
| 1 | with_bated_breath                               | 0.482485        | ['wait', 'watch', 'whisper', 'giggle'] |
| 1 | hold_one’s_breath                               | 0.441661        | ['wait', 'a', 'gon', 'underwater'] |
| 1 | don’t hold your_breath                          | 0.397863        | ['wait', 'grace', 'sweetie', 'apologise'] |
| 1 | touch_ankl_pe                                  | 0.398585        | [] |
| 1 | at_the_cool_face                               | 0.378592        | [] |
| 1 | ride_one’s_luck                                 | 0.369976        | [] |

Figure 8: The results of idiomifying wait, anxiously, excitedly, hopefully

| # | Idiomifying: difficult, dilemma | cols mode: tfidf | noun collocates |
|---|--------------------------------|-----------------|----------------|
| 1 | catch-22                        | 0.391952        | ['submit', 'emerge', 'catch', 'lie'] |
| 1 | hard-pressed                     | 0.38318         | ['find', 'straphanger', 'accommodate', 'match'] |
| 1 | hit_the_buffers                  | 0.38089         | [] |
| 1 | time_and_material                | 0.37259         | ['save'] |
| 1 | come_to_grasp_with               | 0.361348        | ['try', 'we', 'help', 'mourn'] |
| 1 | life-or-death                    | 0.354887        | ['deal', 'struggle', 'talk', 'haver'] |

Figure 9: The results of idiomifying difficult, dilemma

A python library, idiomify, was developed to amalgamate idiom2vec and idiom2collocations into Idiomify, a collocation-supplemented reverse-dictionary of idioms. **Figure 8** and **Figure 9** each illustrate an example usage of Idiomify. On idiomifying wait, anxiously, excitedly and hopefully, we get with bated breath as the most semantically similar idiom to the set of words (**Figure 8**). Likewise, on idiomifying difficult, dilemma, we get catch-22 as the most relevant (**Figure 9**). The results are supplemented with the verb, noun, adjective and noun collocations of each idiom in the result. Although the adjective and adverb collocations are truncated in the figures, they are observable by horizontally dragging to the right on the results.
4. Evaluation

4.1. Identifying idioms

4.1.1. Measures

We evaluate the flexibility of the idiom-matching rules by testing them on an example of each variation case of idioms (total of six, discussed in Section 2.1). For this, a representative example for each of case are chosen from SLIDE (introduced in Section 3.1). We test if the matching rules can identify the idioms from their exemplar use cases. For instance, as for testing for the alternatives case, we test if the rules can identify add fuel to the fire from others in the media threw gasoline on the fire by blaming farmers, where throw gasoline on the fire is an alternative form to add fuel to the fire. The results of the tests are presented in Table 12 and Table 13 below.

4.1.2. Results & analysis

Table 12: The test results of the three positive cases: optional hyphen, inflection and alternatives.

| case                        | sentence                                                                 | filtered idiom lemma             |
|-----------------------------|---------------------------------------------------------------------------|----------------------------------|
| optional hyphen(hyphenated) | in terms of rhyme, meter, and balls-out swagger.                         | ['balls-out']                    |
| optional hyphen(hyphen omitted) | in terms of rhyme, meter, and balls out swagger.                     | ['balls-out']                    |
| inflection(someone's)       | they were teaching me a lesson for daring to complain.                  | ['teach someone a lesson']       |
| inflection(one’s)           | Jo is a playwright who has always been ahead of her time                 | ['ahead of one's time']          |
| alternatives(original)       | others in the media have added fuel to the fire by blaming farmers      | ['add fuel to the fire']         |
| alternatives(1)             | others in the media have added fuel to the flame by blaming farmers      | ['add fuel to the fire']         |
| alternatives(2)             | others in the media have poured gasoline on the fire by blaming farmers  | ['add fuel to the fire']         |
| alternatives(3)             | others in the media have threw gasoline on the fire by blaming farmers   | ['add fuel to the fire']         |
| alternatives(4)             | others in the media have threw gas on the fire by blaming farmers        | ['add fuel to the fire']         |

The matching rules are able to identify idioms with an optional hyphen, those with inflecting words and those in their alternative forms. As can be seen from the first two rows of Table 12, the patterns can correctly identify balls-out regardless of whether the hyphen is omitted or not. The patterns can also handle the case of inflections; they can identify teach someone a lesson from teaching me a lesson (personal pronoun inflection, the third row) and ahead of one’s time from ahead of her time (possessive pronoun inflection, the fourth row). Lastly, we see that the patterns can identify add fuel to the fire from its four alternative forms: add fuel to the flame, pour gasoline on the fire, throw gasoline on the fire, throw gas on the fire.
Table 13: The test results of the three negative cases: modification, open slot and passivisation.

| case                | sentence                                                                 | filtered idiom lemma                  |
|---------------------|-------------------------------------------------------------------------|---------------------------------------|
| modification        | *He grasped at straws* - *He grasped desperately at the floating straw.* | ['grasp at straws'] - []              |
| passivisation       | *And with him gone, they opened the floodgates.* - *And with him gone, the floodgates were opened.* | ['open the floodgates'] - []          |
| open slot           | *They preferred to persist in keeping them at arm’s length.* - *They preferred to persist in keeping both Germans and Russians at arm’s length.* | ['keep someone at arm’s length'] - ['at arm’s length'] |

Despite the three positive cases, the idiom-matching rules are unable to cover the case of modification, passivisation and open slot. Although idioms could be modified with modals, be passivised, and their open slots, i.e. one’s and someone’s, could be replaced with a set of words (as discussed in Section 2.1), the rules do not take into account all the three cases. For instance, as can be seen in Table 13, The rules can no longer identify *grasp at straws* when it is modified to *grasped desperately at the floating straw* (the first row). Likewise, they can no longer identify *open the floodgates* when it is written in a passive tense, as in *the floodgates were opened* (the second row). While they can identify *at arm’s length* from ...keeping both Germans and Russians at arm’s length, the identified idiom is nonetheless not the correct idiom at use (the third row); It should identify *keep someone at arm’s length*, not just *at arm’s length*.

4.1.3. Discussion

Table 14: A summary of ElasticSearch query generation for retrieving idioms (Adapted from: Hughes et al., 2021)

| variation                      | solution | Example ElasticSearch query                                                                 |
|--------------------------------|----------|---------------------------------------------------------------------------------------------|
| modification                   | slop     | {"query": "call someone’s bluff", "slop": 4}                                               |
| open slot                      | wildcard + slop | {"query": "call * bluff", "slop": 5}                                                      |
| passivisation with modification | reordering + slop | {"query": "someone’s bluff * call", "slop": 5}                                           |
| passivisation with an open slot| reordering + wildcard + slop | {"query": "* bluff * call", "slop": 6}                                                   |

We could improve the idiom-matching rules if we incorporate slop, wildcard and reordering techniques into the patterns. This could have them cover modification, open slot and passivisation cases. Table 14 illustrates how Hughes et al. (2021) achieve this, with *call someone’s bluff* as an example. Although they use ElasticSearch to implement their solutions, we could still adopt the techniques to address the three negative examples introduced in Table 13 above. For instance, we could match *grasped desperately at the floating straw* with “grasp (slop) at (slop) straws” as “slop” would allow rooms for any words in between the constituent words of an idiom, thereby addressing the modification case. We could also match *keeping both Germans and Russians at arm’s length* with “keeping (slop) * (slop) at arm’s length”, as the wildcard would allow for the open slot to be substituted with any word. We should also be able to match *the floodgates*
were opened with “* the floodgates * open” as the position of the main verb is now reordered to address passivisation.

4.2. Modeling Collocations of Idioms

4.2.1. Measures

Table 15: Examples of idioms from group A(1-2), B(77-78), C(195-199) D(555-567) and E(23115-142905) with their definitions. There are 20 idioms in each group, 100 idioms in total, but here we show one example from each frequency group. This test dataset is used to evaluate both the collocation of idioms, and the reverse-dictionary of idioms (as will be discussed in Section 4.3.1).

| idiom                  | frequency/group | definition                                                                 |
|------------------------|-----------------|-----------------------------------------------------------------------------|
| from a to z             | 2/A             | over the entire range                                                        |
| spectator sport        | 77/B            | something that people watch something that people watch other people do without becoming involved themselves |
| best of both worlds    | 195/C           | all the advantages of two different situations and none of the disadvantages |
| have one’s hands full  | 555/D           | To be busy or thoroughly preoccupied.                                        |
| tell you what          | 23115/E         | used to introduce a suggestion                                               |

We evaluate the quality of the collocations of idioms by checking if they agree with the use cases of idioms as stated in dictionaries. Inspecting the collocations of idioms manually is costly. There are no ready-made test set for collocations of idioms either. However, compilers of dictionaries tend to put the most collocative use cases when they compile example sentences for words or idioms. Therefore, we can assume that the words used in dictionary-stated use cases of idioms are collocates of the idioms, and thus use them as the ground truth to evaluate the extracted collocations with. We evaluate in this way the top 5 collocations of the five idioms listed in Table 15 above. For instance, we collect the example sentences for have one’s hands full from Oxford, Cambridge and Merriam-Webster dictionaries (Table 16), with which we evaluate the top 5 extracted collocations of have one’s hands full (Table 17). The collocates that show agreement with the example sentences are bolded (e.g. the noun collocate at the moment agrees with ... I have my hands full right now). The results for other idioms are included in Appendix at the end of the report: from a to z (Appendix A1 & A2), spectator sport (Appendix B1 and B2), best of both worlds (Appendix C1 and C2), and tell you what (Appendix D1 and D2).

4.2.2. Results & analysis

Table 16: The representative use cases of have one’s hands full(freq 555, group D).

| oxford                               | cambridge                               | merriam webster                             |
|--------------------------------------|-----------------------------------------|---------------------------------------------|
| She certainly has her hands full with four kids in the house | I’m sorry I can’t help you – I have my hands full right now | She’ll have her hands full with the new baby. |
PMI & TF-IDF generally rank the collocations better than TF does. One example that shows this is the collocations extracted for *have one’s hands full*, which are represented in **Table 17**. From the Cambridge’s example of the idiom (**Table 16**), we know that the idiom collocates with the word *now*, which is in agreement with the verb collocates extracted with TFIDF & PMI (since they both ranked *at the moment* high). We however do not see *at the moment* in the verb collocates extracted with TF. This is reassuring, as TF can only measure “frequently co-occur” part of the definition of collocation, while PMI and TF-IDF can take into account “uniquely co-occur” part of it as well.

It is nonetheless hard to discern whether PMI is more suitable than TF-IDF or vice versa. Although this may be partly due to a lack of reliable test data, the two metrics are hardly different in the way they have ranked the ground truth collocates. For example, both PMI and TF-IDF ranked *certainly* the same for the adjective collocates of *have one’s hands full*. Though PMI ranked *new* higher than TF-IDF did for the adjective collocates, the marginal difference between PMI and TF-IDF is well observable also in the collocations extracted for the idioms in other frequency groups as well (e.g. Appendix 1A, 2A, 3A.).

### 4.2.3. Discussion

**Table 18**: The representative use cases of *from a to z* (freq 1, group A).

| Oxford | Cambridge | Merriam-Webster |
|--------|-----------|-----------------|
| *He knew his subject from A to Z* | *This book tells the story of her life from A to Z.* | *The book is titled “Home Repairs From A to Z.”* |

**Table 19**: Top 5 collocations and use cases for *from a to z* (freq 1, group A).

```
model  verb         noun                     adj          adv
-------+---------------+----------------+--------------+--------------|
   tf   scan       -             -             -             |
 tfidf  scan       -             -             -             |
   pmi  -             -             -             -             |
```

We should collect more data for the idioms in frequency group A. As can be seen from **Table 18** above, the three example sentences of *from a to z* clearly indicate that the noun *book* collocates with *from a to z*. However, there were only one instance found for *from a to z*. It is for this reason we were unable to discover the obvious collocate *book*, let alone any noun, adjective or adverb collocates (**Table 19**).
If the problem is that we are torn between PMI and TF-IDF, machine learning could help us get the best of both worlds. As discussed earlier, it is hard to tell which of the two metrics are better than the other. Hence, it is not ideal to pick a single measure for modeling collocations. However, it is impossible for humans to determine the optimal preference for PMI and TF-IDF. In his paper, *Machine Learning For Collocation Identification*, Yang argues (2003) that this is a “niche for machine learning”. That is, we can take advantage of multiple measures of collocations if we can learn the optimal preference for each metric from data. Yang does exactly that; he uses the two-word pair entries in *WordNet* as the ground-truth for collocations, from which a Decision Tree model learns the optimal preferences for TF, T-test score, PMI, dice coefficient, log-likelihood ratio, and I-score. This can be directly transferable to our case because the notion of collocations is the same for words and idioms. We could try replicating the same approach, and use the class weights of PMI and TF-IDF learned by a Decision Tree model to retrieve the optimal collocations of idioms.

### 4.3. Reverse-searching idioms (Idiomify)

#### 4.3.1. Measures

We evaluate the performance of Idiomify (the reverse dictionary) with median ranks as the evaluation metric. That is, for each idiom in *Table 15* (from Section 4.2.1), we reverse-search them on Idiomify with their definitions (e.g. search “To be busy or thoroughly preoccupied” to find the rank of *have one’s hands full*), sum of their ranks in the list of suggested idioms that Idiomify suggests, and compute their median. While there are many other metrics for evaluating a search engine, such as MMR, NDCG and MAP (cite professor Nenadic’s slide - which slide was this?), we use median ranks here because it is what Hill et al. used (2016) to evaluate their reverse-dictionary. By having the same metric as theirs, we can have a concrete reference with which we can compare the performance of Idiomify. The result of this is represented in *Table 20* below.

#### 4.3.2. Results & Analysis

| model                        | method | median rank | variance |
|------------------------------|--------|-------------|----------|
| Idiomify (Idiom2Vec)         | avg    | 128         | 4310     |
| Word2Vec (Hill et al., 2016) | add    | 923         | 163      |
| Word2Vec (Hill et al., 2016) | mul    | 1000        | 10       |
| OneLook                      | -      | 0           | 67       |
| RNN cosine (Hill et al., 2016)| - | 12          | 103      |

Idiomify sets itself as a reasonable baseline for the reverse dictionary of idioms. As can be seen in *Table 20* above, Idiomify seems to perform better than all the Word2Vec model that Hill et al. devised (2016), although this is encouraging, it should be noted that this is not a fair comparison; the test set and search space is vastly different (2714 idioms vs. all the words), and the large variance might be marring the median. When compared with the RNN cosine model, it is also by no means an outstanding reverse-dictionary of words. However, when it comes to that of idioms, it could be argued that Idiomify is clearly a good baseline to improve upon, as it is the only one of its kind at the moment.

#### 4.3.3. Discussion
| Idiom2Vec | corpora                          | stopwords       | median rank |
|-----------|---------------------------------|-----------------|-------------|
| V1        | COCA (spok) not removed          |                 | 276.5       |
| V2        | COCA (spok) + Opensubtitles not removed |     | 128.0       |
| V3        | COCA (spok) + Opensubtitles     | removed         | 156.0       |

In future work, stopwords should not be excluded in building a reverse-dictionary. This is because, as shown in Table 20 above, we see that median rank of Idiomify increases by 28 when we switch from Idiom2Vec V2 to V3, where V3 is trained on non-stopwords corpus. That is, the performance of Idiomify drops when we exclude stopwords from the training data. It is speculated that this is because the stopwords do hold semantic significance when they are used to defining idioms or words. For example, all the advantages of two different situations and none of the disadvantages clearly means best of both worlds, but it is less clear if advantages, two, different, situation, disadvantages would mean precisely the same idiom. Despite being stopwords, the meaning of all and none are just as integral to the meaning of best of both worlds as the non-stopwords. Hence, as far as reverse-dictionaries are concerned, stopwords are useful and therefore should not be removed from any data.

We could further improve Idiomify by taking a mixture of inverted index and distributional semantics approach. Although a purely distributional semantics approach allows for semantic search, they require a large amount of quality data to work properly. Without enough data, it would perform even worse than a simple inverted index. Figure 10 well illustrates this problem. It attempts to idiomify a set of keywords from the definition of spectator sport, but spectator sport is not even on the list. This is as it should be, as Idiom2Vec V2 was trained on only 75 instances of the idiom. In contrast to this, we would only need a dictionary of idioms if we were to take an inverted index approach. That way, reverse searching idioms with their exact definitions, as is the case in Figure 10, would be trivial. However, semantic search would not be possible if we only use an inverted index. All things considered, then, the best approach would be to use both. That is, if we could have Idiomify first search on a pre-populated def-to-idiom inverted index, and later rank the retrieved idioms with respect to their similarity to Idiom2Vec-averaged phrase vector, We could conceivably improve both the accuracy and flexibility of Idiomify.

Figure 10: the result of Idiomifying people, watch, without, involve.

We could further improve Idiomify by taking a mixture of inverted index and distributional semantics approach. Although a purely distributional semantics approach allows for semantic search, they require a large amount of quality data to work properly. Without enough data, it would perform even worse than a simple inverted index. Figure 10 well illustrates this problem. It attempts to idiomify a set of keywords from the definition of spectator sport, but spectator sport is not even on the list. This is as it should be, as Idiom2Vec V2 was trained on only 75 instances of the idiom. In contrast to this, we would only need a dictionary of idioms if we were to take an inverted index approach. That way, reverse searching idioms with their exact definitions, as is the case in Figure 10, would be trivial. However, semantic search would not be possible if we only use an inverted index. All things considered, then, the best approach would be to use both. That is, if we could have Idiomify first search on a pre-populated def-to-idiom inverted index, and later rank the retrieved idioms with respect to their similarity to Idiom2Vec-averaged phrase vector, We could conceivably improve both the accuracy and flexibility of Idiomify.
5. Conclusion

The aim of idiomify is to build a collocation-supplemented reverse dictionary of idioms for the non-native learners of English. We aim to do so because the reverse dictionary could help the non-natives explore idioms on demand, and the collocations could also guide them on using idioms more adequately. The cornerstone of the project is a reliable way of mining idioms from corpora, which is however a challenge because idioms extensively vary in forms. We tackle this by automatically deriving matching rules from their base forms. We use Point-wise Mutual Inclusion (PMI), Term Frequency - Inverse Document Frequency (TF-IDF) to model collocations, since both of them are popular metric for pairwise significance. We also try Term Frequency (TF) as the baseline model. As for implementing the reverse-dictionary, three approaches could be taken: inverted index, graphs and distributional semantics. We choose to take the last approach and implement the reverse dictionary with Word2Vec, because it is the most flexible approach of all and Word2Vec is a simple yet strong baseline. Evaluating the methods has revealed rooms for improvement. We learn that we can better identify idioms with the help of slop, wildcard and reordering techniques. We also learn that we can get the best of both PMI and TF-IDF if we use machine learning to find the sweet spot. Lastly, We learn that Idiomify could be further improved with a mixture of inverted index and distributional semantics approach. The limits aside, the proposed methods are feasible, and their benefits to the non-natives are apparent, which therefore can be used to aid the non-natives in acquiring English idioms.
6. References

Arora, S. Liang, Y. Ma, T. (2017). A Simple but tough-to-beat baseline for sentence embeddings

Beeferman, D. (2003). OneLook reverse dictionary. Available at: http://onelook.com/reversedictionary.shtml.

Caro, R. Edith, E. (2019). The Advantages and Importance of Learning and Using Idioms in English.

Church, K. Hanks, P. (1989). Word Association Norms, Mutual Information, and Lexicography

Davies, M. (2008). The Corpus of Contemporary American English (COCA). Available online at https://www.english-corpora.org/coca/.

Ganesan, K. (2020). What are Stop Words?. Available at: https://kavita-ganesan.com/what-are-stop-words/#.YKfXMy0Rr_Q

Granger, S. (1998). Prefabricated patterns in advanced EFL writing: collocations and formulae. In: Phraseology: Theory, Analysis and Applications. Clarendon Press: Oxford. 145-160.

Gormley, C. Tony, Z. (2015). Elasticsearch: The Definitive Guide. O’Reilly Media. In: Sebastopol, CA, USA.

Hill, F. Cho, K. Korhonen, A. Bengio, Y. (2016). Learning to Understand Phrases by Embedding the Dictionary

Honnibal, M. Montani, I., (2017). spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing.

Hughes, C. Filimonov, Maxim. Wray, Alison. Spasić, Irena. (2021). Leaving No Stone Unturned: Flexible Retrieval of Idiomatic Expressions from a Large Text Corpus.

Ingebrigsten, M. (2013), Indexing for Beginners, Part 3. Available at: https://www.elastic.co/blog/finding-indexing-for-beginners-part3

Jochim, C. et al. (2018). SLIDE: a Sentiment Lexicon of Common Idioms. Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC'2018). European Languages Resources Association (ELRA)

Manning, D., et al. (2008). Tf-idf weighting. Viewed on 23th of February 2021. Available at: https://nlp.stanford.edu/IR-book/html/htmledition/tf-idf-weighting-1.html

Miller, G. (1995). WordNet: A Lexical Database for English. Communications of the ACM Vol. 38, No. 11: 39-41.

Oxford Advanced Learner’s Dictionary of Current English. (1995). Oxford University Press

Oxford Collocations Dictionary for Students of English. (2002). Oxford University Press

Rehurek, R. Sojka, P. (2011). Gensim–python framework for vector space modelling. NLP Centre, Faculty of Informatics, Masaryk University, Brno, Czech Republic, 3(2).

Sierra, G. (2000). The onomasiological dictionary: a gap in lexicography. In Proceedings f the Ninth EURALEX International

Tiedmann, J. (2012). Parallel Data, Tools and Interfaces in OPUS. Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC’2012). European Language Resources Association (ELRA)

Thorat, S. Choudhari, V. (2016). Implementing a Reverse Dictionary, based on word definitions, using a Node-Graph Architecture.

Thyrbab, R. (2016). The Necessity of idiomatic expressions to English Language learners

Yang, S. (2003). machine learning for collocation identification
7. Appendix

| model | verb | noun | adj | adv |
|-------|------|------|-----|-----|
| tf    | grow, know, fledge, die, mean | number, suit, form, courtesy, today | great, popular, complete, big, large | exactly, especially, fast, kind, long |
| tfidf | moneymake, fledge, grow, recommend, die | tutoring, form, courtesy, suit, spectacle | popular, unlocal, great, dry, mathematical | exactly, generally, especially, fast, definitely |
| pmi   | grow, know | suit, form, number | popular, great | exactly |

Appendix 1A. Top 5 collocations and use cases for *spectator sport* (freq 77, group B).

| oxford | cambridge | merriam webster |
|--------|-----------|-----------------|
| What is the country’s most popular spectator sport? | Football is certainly the biggest spectator sport in Britain. | For many, politics has become a spectator sport.” |

Appendix 1B. The representative use cases of *spectator sport* (freq 77, group B).

| model | verb | noun | adj | adv |
|-------|------|------|-----|-----|
| tf    | want, chill, laugh, let, m | way, milk, combination, future, pajama | old, salty, fashioned, wonderful, able | right, kind, inside |
| tfidf | chill, laugh, embody, gettin, want | combination, milk, pajama, future, city | - | inside, kind, right |
| pmi   | chill, laugh, want, let, m | way | - | - |

Appendix 2A. Top 5 collocations and use cases for *best of both worlds* (freq 195, group C).

| oxford | cambridge | merriam webster |
|--------|-----------|-----------------|
| If you enjoy the coast and the country, you’ll get the best of both worlds on this walk | She works in the city and lives in the country, so she gets the best of both worlds | I have the best of both worlds—a wonderful family and a great job. |

Appendix 2B. The representative use cases of *best of both worlds* (freq 195, group C).

| model | verb | noun | adj | adv |
|-------|------|------|-----|-----|
| tf    | happen, let, want, gon, think | time, people, man, problem, guy | wrong, good, great, right, little | right, kind, maybe, actually, probably |
| tfidf | happen, let, gon, want, think | problem, wrong, relief, pleasure | wrong, great, good, right, able | right, kind, actually, maybe |
| pmi   | -i’ll, privilege, irk, do-, to_do_with, transpire | barbecu, technicality-, stooling, musve, memahon’il | DON’T, youtryto, uriel, cess, exploitable | montero, mackowes, it’about, vega, weenie |
Appendix 3A. Top 5 collocations and use cases for *tell you what* (freq 23115, group E).

| oxford | cambridge | merriam webster |
|--------|-----------|-----------------|
| *I’ll* tell you what— *let’s* stay in instead. | *I’ll* tell you what— *we’ll* split the money between us. | *(I’ll)* Tell you what— *I’ll let* you borrow the car if you fill it up with gas. |

Appendix 3B. The representative use cases of *tell you what* (freq 23115, group E)