Communicative-Function-Based Sentence Classification for Construction of an Academic Formulaic Expression Database

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Abstract

Formulaic expressions (FEs), such as ‘in this paper, we propose’ are frequently used in scientific papers. FEs convey a communicative function (CF), i.e. ‘showing the aim of the paper’ in the above-mentioned example. Although CF-labelled FEs are helpful in assisting academic writing, the construction of FE databases requires manual labour for assigning CF labels. In this study, we considered a fully automated construction of a CF-labelled FE database using the top–down approach, in which the CF labels are first assigned to sentences, and then the FEs are extracted. For the CF-label assignment, we created a CF-labelled sentence dataset, on which we trained a SciBERT classifier. We show that the classifier and dataset can be used to construct FE databases of disciplines that are different from the training data. The accuracy of in-disciplinary classification was more than 80%, while cross-disciplinary classification also worked well. We also propose an FE extraction method, which was applied to the CF-labelled sentences. Finally, we constructed and published a new, large CF-labelled FE database. The evaluation of the final CF-labelled FE database showed that approximately 65% of the FEs are correct and useful, which is sufficiently high considering practical use.

1 Introduction

Formulaic expressions (FEs), such as ‘in this paper we propose’, are a type of multi-word expressions and are repeatedly used in scientific papers. Some FEs convey a communicative function (CF) of a sentence, which represents intentions of authors. For example, ’in this paper, we propose’ conveys the CF of ‘showing the aim of the paper’.

Databases comprising CF-labelled FEs are required from a pedagogical perspective (Martinez and Schmitt, 2012), and a computer-based academic writing assistance system\textsuperscript{1} that uses such CF-labelled FEs has been proposed (Mizumoto et al., 2017). Several attempts have been made to extract FEs from scientific corpora and categorise them based on CFs (Cortes, 2013; Adel, 2014; Mizumoto et al., 2017; Morley, n. d.; Simpson-Vlach and Ellis, 2010; Lu et al., 2018). A CF-labelled FE database can be constructed using two main approaches: top–down and bottom–up approaches (Biber et al., 2007; Durrant and Mathews-Aydinli, 2011). By using the top–down approach, sentences are first assigned CF labels, and then FEs are extracted, while in the case of the bottom–up approach, FEs are first extracted and then assigned CF labels. To date, both the approaches have been adopted because CF assignment is performed manually (Table 1). In this paper, we propose a fully automated construction of the CF-labelled FE database, where we consider the top–down approach to be more beneficial (Figure 1). This is because the bottom–up approach requires FEs to be classified, which is difficult because a perfect FE-extraction technique is yet to be realised, and FE embeddings have not been investigated intensively. The top–down approach requires sentence classification, which has highly improved with the recent advancements on pre-trained models.

\textsuperscript{1}http://langtest.jp/awsum/

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig1.png}
\caption{Process of creating FE database.}
\end{figure}
Method for creating DB

| Approach          | CF     | FE    | Discipl. | #CFs | #Docs | #FEs |
|-------------------|--------|-------|----------|------|-------|------|
| Simpson-Vlach and Ellis (2010) | bottom–up | manual | corpus   | mixed | 15    | 200  |
| Morley (n. d.)    | -      | manual | manual   | mixed | 146   | 100  | ≃ 2,000 |
| Mizumoto et al. (2017) | top–down | manual | corpus   | specific | 52    | 1,000 | -    |
| Lu et al. (2018)  | bottom–up | manual | corpus   | mixed | 12    | 600  | 454  |
| Ours              | top–down | automated | sentence | specific | 32    | 61,728 | 86,931 |

Table 1: Properties of the existing and proposed methods for the construction of CF-labelled FE databases and the statistics of the databases. The approach of Morley (n. d.) is unknown. For the CF assignment (CF), we adopted supervised machine-learning. The FE extraction (FE) was conducted manually using a corpus- or sentence-level method. Either FEs specific to one discipline were extracted or FEs used in a corpus in which several disciplines were mixed were extracted. The number of documents used for extraction and the extracted FEs of the existing and presented database were shown. Some studies did not disclose the number of documents or FEs. Morley (n. d.) constantly revises the database, and therefore the number of FEs is not fixed.

For CF-based sentence classification, we created a dataset for supervised learning. The dataset consists of a small number of sentences that were assigned CF labels. We collected the sentences from scientific papers of multiple disciplines. By using this dataset, we fine-tuned SciBERT (Beltagy et al., 2019). Additionally, because there are preferences for CF usage depending on disciplines and as the preparation and coverage of all CFs of every discipline are difficult, sentences to which any prepared CF label should not be assigned may appear in a corpus (no-CF sentences). These no-CF sentences will have a negative effect on the classification performance. Based on the recent work on out-of-distribution detection in natural language processing (Hendrycks and Gimpel, 2017; Hendrycks et al., 2020), we used the maximum value of the softmax layer as the threshold to filter no-CF sentences in order to improve the final precision. The experimental results show that the maximum value of the softmax layer works well as the threshold to filter out undesirable sentences.

We carefully considered multidisciplinary problems in the classification. Although the development of a training dataset for every discipline in the world is obviously impossible, demonstrating a successful classification using a single disciplinary dataset is not sufficient for practical use. In this study, we determined whether a model trained on a corpus of one discipline can be applied to that of another discipline. Moreover, the effects of a pre-training dataset were examined by comparing SciBERT and BERT (Devlin et al., 2019). The experimental results show that the classifiers performed fairly well in terms of both in-discipline and cross-discipline data, and the performance was only slightly affected when scientific papers were not used as pre-training data.

For the FE-extraction process, one FE should be extracted from one sentence because CF labels are assigned to each sentence; this is termed as sentence-level approach (see Section 2.2). Therefore, we propose a sentence-level FE extraction method that is based on an existing method (Iwatsuki et al., 2020b). The method consists of three steps: named and scientific entity removal, dependency-structure-based word removal, and word-association-measure-based word removal.

Finally, we created a new, large, multidisciplinary CF-labelled FE database and evaluated it by asking human evaluators whether each instance was assigned a correct CF label and whether an FE was useful for writing a paper. The results show that approximately 65% of the collected FEs are appropriate.

The contributions of our study are as follows:

- we created and published the CF-labelled sentence dataset, which is the first dataset for training and evaluation of CF-based classification;
- we showed that a simple SciBERT-based neural classifier performed reasonably well for the CF labelling problem;
- we showed that the SciBERT classifier can be used even though the discipline of the training data is different from the inferred one;
- we proposed an FE extraction method; and
we constructed a CF-labelled FE database with the top–down approach, which is larger than the existing databases but still maintains high quality.

2 Related Work

2.1 CFs in Scientific Papers

The CFs of scientific papers were first introduced by Swales (1990), who focused on the CFs in the introduction section. The author proposed a hierarchical structure of CFs, in which move was considered a larger unit of CF and step was a smaller unit belonging to move. He found that the introduction section consists of three moves: ‘establishing a territory’, ‘establishing a niche’, and ‘occupying the niche’. Each move has several steps, such as ‘claiming centrality’ and ‘presenting research questions or hypotheses’ (Swales, 2004). Following his work, many studies extended the concept to all parts of a scientific paper. Most studies focused on very limited parts of scientific papers; only the introduction (Ozturk, 2007), methods (Lim, 2006; Cotos et al., 2017), results (Basturkmen, 2009; Lim, 2010), discussion sections (Peacock, 2002; Basturkmen, 2012), or the abstract (Lorés, 2004; Darabad, 2016; Rashidi and Meihami, 2018; Saboori and Hashemi, 2013).

The concept was extended to all parts of a scientific paper. For example, Kanoksilapatham (2005) proposed the CF structure of all the sections in biochemistry papers. Cotos et al. (2015) proposed a CF set for all four sections, i.e. introduction, methods, results, and discussion sections. Maswana et al. (2015) compared the usage of the CFs in five engineering fields and found that certain CFs are preferred depending on the discipline.

Argumentative Zoning is a similar concept based on the rhetorical moves (Teufel, 1999). It had seven categories, which were later extended to 15 categories by Teufel et al. (2009).

Previous studies on CF-based classification used conditional random fields (Hirohata et al., 2008), a classifier chain with sequential minimum optimisation, Rakel with the J48 algorithm (Dayrell et al., 2012), a Bayes classifier, and a decision tree (Soonklang, 2016). However, these studies only focused on abstracts of scientific papers. Therefore, existing CF-labelled FE lists were created by manually assigning CF labels (Table 1), complicating the construction of a large CF-labelled FE database. Recently, Fiacco et al. (2019) used a hierarchical Bi-LSTM+CRF to classify sentences. However, CF-labelled sentence corpora are yet to be made available to the public.

2.2 FE-Extraction Methods

Two approaches are used for extracting FEs: corpus- and sentence-level approaches. Based on the intuition that FEs appear frequently or words composing FE are strongly associated, most studies use the corpus-level approach, in which statistical metrics, such as frequency or mutual information, are applied to a whole corpus. To extract FEs, word n-grams were collected from a whole corpus by using the metrics (Biber et al., 2004; Simpson-Vlach and Ellis, 2010; Kermes, 2012; Mizumoto et al., 2017). However, this approach results in the extraction of an explosive number of overlapping n-grams, thus causing a serious problem in the CF-labelled FE database construction. For instance, suppose ‘in this paper we propose’, ‘this paper we propose a’, and ‘in this paper we propose a new method’ are extracted, a criterion is needed to determine which of these are regarded as FEs; however, determining such a criterion is difficult.

The n-gram lattice method (Brooke et al., 2017) is one approach to address this problem; here, scores of various aspects of formulaicity are first calculated for all word n-grams. Next, an objective function that contains all scores of the n-grams is maximised to determine which n-grams should be disregarded and which should remain. However, this method is still not focused on FEs conveying CFs but on general phrasal expressions; thus, it is thus not suitable for our setting.

The sentence-level approach assumes that one FE occurs in one sentence. Thus, ‘in this paper we propose a new method’ can be extracted, but ‘this paper we propose a’ cannot be extracted from a sentence. This approach is also useful for extracting FEs with a slot (Vincent, 2013), into which some words can be inserted, such as ‘however, *have not been reported’. This setting is regarded as a sequence-labelling problem, in which each word of a sentence is labelled as either formulaic or non-formulaic. Liu et al. (2016) proposed removing topic-specific words as non-formulaic words, using latent Dirichlet allocation. They used a corpus consisting of papers from various disciplines, and tried to remove discipline-specific vocabulary. Thus, this is not suitable for extracting discipline-specific FEs. Iwatsuki et al. (2020b) proposed re-
moving scientific and named entities in addition to dependency-based word removal.

The evaluation of the FE extraction model is another problem. Brooke et al. (2015) pointed out that the comparison of newly extracted FEs with existing reference is unreasonable because if a reference is on point, a new lexicon need not be created. Thus, Iwatsuki et al. (2020b) proposed evaluating FE extraction methods by a CF-based sentence retrieval task as an extrinsic task based on the idea that FEs convey a CF of a sentence.

2.3 CF-Labelled FE Databases

Table 1 describes the existing CF-labelled FE databases. Previous studies have shown that FEs are discipline-specific, and the resource of academic vocabulary should be presented for each discipline (Hyland and Tse, 2007; Liu, 2012). Thus, the development of CF-labelled FE databases for each discipline is important; however, many studies have focused on general FEs, which were extracted from a mixed corpus consisting of scientific papers on multiple disciplines. Some studies adopted the discipline-specific approach; Mizumoto et al. (2017) considered only the journals on applied linguistics, while Lu et al. (2018) used only the introductions of social-science papers. Moreover, only a small number of documents were used because the existing resources require manual labour for assigning CF labels.

Hence, we contend that the automated CF-based classification is helpful for constructing a large, comprehensive CF-labelled FE database. In this study, we developed a discipline-specific database based on large corpora of scientific papers from four disciplines.

3 Methods

3.1 Corpora and Datasets

3.1.1 Corpora of Scientific Papers

In this study, we considered the corpora which satisfy the following conditions. First, because we use full text of scientific papers and have made all the data public, papers must be open access. Second, to construct a comprehensive database, the corpora size is important. Third, for cross-discipline analyses, a discipline-specific journal is preferred to a multidisciplinary journal. We selected a corpus containing at least 10,000 papers.

Under these three conditions and based on the diversity of the disciplines, we selected four corpora: ACL Anthology Sentence Corpus\(^2\) for computational linguistics (CL), Molecules\(^3\) for chemistry (Chem), Oncotarget\(^4\) for oncology (Onc), and Frontiers in Psychology\(^5\) for psychology (Psy). Each corpus comprises more than 10,000 papers and is open access to full text (creative commons licence).

For pre-processing, we performed sentence splitting using ScispaCy (Neumann et al., 2019) and replaced citations and mathematical formulae with a special token. By using a simple rule-based method, section labels were normalised into five classes: introduction, methods, results, discussion, and other. Each sentence was assigned a section label; we did not use sentences belonging to the ‘other’ class. The numbers of sentences and documents are listed in Table 2.

| Corpus | #Doc. | #Sent. | #Words |
|--------|-------|--------|--------|
| CL     | 13,921| 1,612,921| 32,698,072|
| Chem   | 15,949| 1,703,902| 39,303,460|
| Onc    | 19,541| 3,029,285| 68,719,634|
| Psy    | 12,317| 1,948,082| 49,329,526|

Table 2: Number of documents (doc), sentences (sent), and words in each corpus.

3.1.2 CF Set and CoreFEs

Till date, there is no established CF set, and some CFs are not used or are frequently used in a specific discipline. Proposing a new CF set is beyond the scope of this study; however, we must select a CF set. We adopted the CF set proposed by Iwatsuki et al. (2020a), which was based on CFs used in Academic Phrasebank (Morley, n. d.). Table 3 describes the numbers of CFs in each section. (All the CFs are listed in Table 13 in the appendix.)

CoreFE is an FE that is shortened so that it can be used as a query for sentence retrieval (Generally, longer phrases result in few or no results in sentence retrieval). We used CoreFEs to create the CF-labelled sentence dataset.

3.1.3 CF-Labelled Sentence Dataset

For the CF-based classification, we created a sentence dataset by using the aforementioned corpora. To effectively collect labelled sentences, we used the following procedures. First, the CoreFEs were
Section | #CFs
--- | ---
Introduction | 11
Methods | 6
Results | 6
Discussion | 9

Table 3: Numbers of CFs for each section.

used as queries to retrieve sentences from the corpora. Although the CoreFEs have CF labels, the retrieved sentences may not always have the same CFs.

Next, we used Amazon Mechanical Turk (AMT) to check if each sentence was assigned correct labels; this process was three-fold. First, a correct set of sentences was prepared. Two experts were asked whether the sentences in the correct set were correctly labelled, and the sentences whose labels were judged incorrect by at least one expert were removed. Another set of sentences, called the incorrect set, was prepared, in which the same sentences were randomly assigned incorrect labels. Second, by using these sets, a pilot test was conducted on AMT. Five annotators were recruited and asked to check whether the labels were correct or not. Based on this pilot test, we determined the threshold to cut off sentences. Finally, a larger set of sentences was prepared, which was different from the set used in the pilot test. Another five annotators were asked to perform the same task on the set. The final dataset comprises the sentences satisfying the threshold.

3.2 Sentence Classification

3.2.1 Classifier

We assigned each sentence a CF label, and this task can be regarded as a CF-based sentence-classification problem. In addition, we used SciBERT (Beltagy et al., 2019) with an additional linear layer for classification. We split the CF-labelled sentence dataset into training/development and evaluation sets so that four sentences for each CF were in the evaluation set. Then, we conducted five-fold cross validation using the training/development set for parameter tuning. Subsequently, we fine-tuned the classifier and evaluated the classification accuracy.

Because CF sets in scientific papers have not been established, the CF set we used cannot satisfactorily cover all sentences written in papers. Additionally, pre-processing errors, such as sentence splitting, sometimes result in no-CF sentences. Thus, in some scenarios, no CF should be assigned to a sentence and no-CF sentences must be removed. The no-CF class is not contained in the training dataset; this problem is regarded as the out-of-distribution detection problem. Although the maximum value of the softmax layer is not a perfect metrics for out-of-distribution detection, pre-trained transformers, such as BERT and RoBERTa, with a softmax layer are good detectors of out-of-distribution data (Hendrycks and Gimpel, 2017; Hendrycks et al., 2020).

To manage the no-CF sentences, we used the maximum softmax value of the classifier, and verified its performance. The verification was performed in the same manner as the creation of the CF-labelled sentence dataset. That is, we asked five AMT annotators whether the output label was correct. The threshold was also the same: 5/5.

3.2.2 Multidisciplinary Perspectives

To create a multidisciplinary database, the classification must be applied to various disciplinary texts. As it is costly to create a training dataset manually for each discipline, we tested whether the classifier trained on a dataset of one discipline can be immediately applied to the datasets of other disciplines.

SciBERT was trained on scientific papers from Semantic Scholar (Beltagy et al., 2019). The corpora used in this study are open access and were also included in Semantic Scholar. Thus, we hypothesise that the cross-disciplinary adaptation is successful because the sentences are (partly) contained in the pre-training dataset. Therefore, the method cannot be applied to disciplines that are not covered by the pre-training dataset. To verify this hypothesis, we compared SciBERT to BERT, which was pre-trained on the book corpus and Wikipedia and not on scientific papers (Devlin et al., 2019), for cross-discipline sentence classification.

3.3 FE Extraction

To extract FEs, we propose a method based on Iwatsuki et al. (2020b), which is a sentence-level method; one FE was extracted from one sentence. We applied this method, which comprises three steps, to the classified sentences.

In the first step, the named and scientific entities are removed from a sentence. The entity recognition was performed using SpERT (Eberts and

*https://www.semanticscholar.org/
Ulges, 2020), which sits atop the leader-board of NER tasks for scientific entities⁷. For training, we used CoNLL04 (Roth and Yih, 2004), a corpus labelled with general-purpose named entities, and SciERC (Luan et al., 2018), a corpus of scientific papers labelled with scientific entities. The CoNLL04 labels are location, organisation, people, and other; SciERC labels are task, method, evaluation metric, material, other scientific terms, and generic. By removing the named entities, a sentence was split into several spans.

In the second step, we used the dependency structure of a sentence analysed by Stanford CoreNLP (Qi et al., 2018). Words that were neither in the span containing a sentence’s root nor organised by the root were then removed. The assumption here was that FEs representing CFs of sentences appeared in the structural centres in the sentence dependency structures (Iwatsuki et al., 2020b).

Steps 1 and 2 work well if several named entities are contained in a sentence; otherwise, an almost full sentence is produced, which is too long to be an FE. Thus, we propose an additional filtering step that further removes non-relevant generic terms from the candidate FE spans. This is based on the assumption that each word of an FE is strongly associated with each other. Thus, the association between fragments of an FE should be strong. For instance, ‘in this paper we’ and ‘propose’ are strongly associated, while ‘in this paper we’ and ‘talk’ are not.

On the basis of this observation, we first extracted all pairs of an n-gram and its neighbour word from each candidate span obtained after Step 2. For example, pairs such as (‘in this’, ‘paper’) or (‘paper we’, ‘propose’) are obtained when n = 2. Next, for each pair, we calculated the association measures between a n-gram and a neighbour word. We used the local mutual information (LMI), which is formalised as follows:

\[
\text{LMI}(a, b) = f(a, b) \cdot \log \frac{p(a, b)}{p(a)p(b)},
\]

where \(a\) and \(b\) denote a word, \(a, b\) denotes the co-occurrence of the words, \(p(a)\) is a probability of occurrence of \(a\), and \(f(a)\) is a frequency of \(a\) in a corpus (Evert, 2005). Finally, the pairs with the top \(k\) scores were labelled as an FE. To avoid generating FEs that are too short, this third process was applied only when the length of the resulting word sequence of Step 2 was more than \(k\) words. From our preliminary experiments, we determined to use \((n, k) = (2, 7)\).

Because FEs are assumed to be used as they are, we did not lemmatise them. Formulaicity sometimes does not allow the replacement of a word in an FE with another word or flection. For example, tenses can be section-specific (present or past): ‘in this paper we proposed’ rarely occurs in the introduction sections. Formulaicity also avoids grammatical errors such as ‘little researches have been done’. Many previous studies did not lemmatise FEs (Simpson-Vlach and Ellis, 2010; Mizumoto et al., 2017; Pan et al., 2016; Esfandiari and Barbary, 2017).

3.4 Constructing CF-Labelled FE Database

We created the CF-labelled FE database using the following steps. Step 1: CF labels were assigned to each sentence in a corpus and no-CF sentences were removed. Step 2: FEs were extracted from each sentence. Step 3: Noisy FEs were filtered out. If an FE was assigned multiple CF labels, only one CF was selected by majority voting. If none of the CFs took the majority, the FE was removed. Any CF-labelled FE occurring less than three times was also removed.

We evaluated the final database from two perspectives: whether a sentence was assigned a correct label and whether an FE was useful for writing a scientific paper.

The evaluation was conducted on the AMT. A sentence and its CF label were shown to evaluators, and an FE was highlighted in the sentence (see Figure 2). The evaluators were asked whether the sentence conveyed the CF and whether the FE was useful. Each FE was annotated by five evaluators, and if it was not evaluated by all as correct or useful, it was regarded as incorrect or useless.
Table 4: Threshold indicates the number of annotators (out of five) who judged pairs of the sentence and CF label as correct.

| Threshold | Precision | Recall |
|-----------|-----------|--------|
| 5/5       | 0.94      | 0.80   |
| 4/5       | 0.79      | 0.98   |
| 3/5       | 0.62      | 1.00   |
| 2/5       | 0.54      | 1.00   |
| 1/5       | 0.50      | 1.00   |

Discipline I M R D Avg.

| Discipline | I    | M    | R    | D    | Avg. |
|------------|------|------|------|------|------|
| CL         | 0.83 | 0.83 | 1.00 | 0.91 | 0.90 |
| Chem       | 0.95 | 0.79 | 0.88 | 0.89 | 0.89 |
| Onc        | 0.92 | 0.63 | 0.92 | 0.92 | 0.88 |
| Psy        | 0.93 | 0.88 | 0.96 | 0.81 | 0.84 |
| ALL        | 0.97 | 0.92 | 0.98 | 0.94 | 0.95 |

Table 5: Numbers of sentences in the final dataset.

| Discipline | Sentence |
|------------|----------|
| CL         | 612      |
| Chem       | 644      |
| Onc        | 600      |
| Psy        | 687      |

Table 7: Accuracy scores of each range of the maximum value of the softmax layer, and the proportion of sentences in the corpora.

| Range            | Accuracy | Proportion |
|------------------|----------|------------|
| (0.99, 1.00]     | 0.69     | 76.1%      |
| (0.90, 0.99]     | 0.67     | 12.4%      |
| (0.80, 0.90]     | 0.74     | 3.7%       |
| (0.70, 0.80]     | 0.51     | 2.4%       |
| (0.60, 0.70]     | 0.51     | 2.1%       |
| (0.00, 0.60]     | 0.43     | 3.3%       |

4 Results

4.1 CF-Labelled Sentence Dataset

The correct and incorrect sets consist of 55 sentences. The results of the pilot test are shown in Table 4. Accordingly, we set the threshold to 5/5 because high precision was important for creating the FE database rather than recall, and the strictest threshold did not significantly reduce the sentences. Table 5 lists the total number of sentences.

4.2 CF-Based Sentence Classification

The classification results are shown in Table 6. SciBERT worked well, which implies that this BERT-based classifier has the ability to capture CFs of sentences.

We also verified with SciBERT whether the maximum value of the softmax layer can be used as the threshold to filter out no-CF sentences. We first classified all the sentences in the corpora, and then split the classified sentences into six categories based on the maximum softmax score: [0.00, 0.60], (0.60, 0.70], (0.70, 0.80], (0.80, 0.90], (0.90, 0.99], (0.99, 1.00]. Next, we randomly sampled 100 sentences from each range, and the sentences were evaluated by five annotators on AMT. The evaluation method was the same as that used for collecting the CF-labelled sentences. The accuracy of each range is shown in Table 7. For database construction, we removed the sentences with a score of 0.80 or lower.

4.3 Multidisciplinary Perspective

We tested whether SciBERT trained on one discipline can be applied to different disciplines. The results are shown in Table 8.

We also tested the effects of the pre-trained dataset by comparing the results of SciBERT and BERT. Table 9 and 10 show the BERT results; compared with the results shown in Table 6 and 8, the two models did not show a considerable difference.

4.4 Constructing CF-Labelled FE Database

The CF-labelled FE database was evaluated by sampling 200 FEs. The results are shown in Table 11. Incorrect sentence–CF pairs were obtained because the classifier made errors and some sentences were not a complete sentence. An example of an incomplete sentence is ‘of three independent experiments.’; this was produced because of the error of sentence splitting. Examples of useful FEs are
Table 9: Accuracy scores acquire by BERT classifier.

| Discipline | I   | M   | R   | D   | Avg. |
|------------|-----|-----|-----|-----|------|
| CL         | 0.90| 0.84| 0.96| 0.93| 0.88 |
| Chem       | 0.93| 0.87| 0.93| 0.93| 0.89 |
| Onc        | 0.92| 0.66| 0.94| 0.95| 0.86 |
| Psy        | 0.92| 0.88| 0.95| 0.89| 0.92 |

Table 10: Average accuracy scores by BERT.

| Training | Evaluation |
|----------|------------|
|          | CL | Chem | Onc | Psy |
| CL       | 0.88| 0.87| 0.82| 0.85|
| Chem     | 0.85| 0.89| 0.91| 0.86|
| Onc      | 0.74| 0.91| 0.86| 0.82|
| Psy      | 0.87| 0.92| 0.88| 0.92|

‘plays a crucial role in’ (CF: Showing the importance of the topic) and ‘no significant differences were detected in’ (CF: Description of the results), while ‘et al demonstrated that’ (CF: Showing background provided by past work) and ‘is to use a’ (CF: Showing brief introduction to the methodology) were judged useless.

The statistics of the database are shown in Table 2. To show discipline-specific FEs, we calculated odds ratio for each CF of each discipline. Table 12 illustrates the top 5 high odds ratio FEs in the ‘description of the process’ CF in the introduction section. These FEs are not considered rare, as some of them occur more than a thousand times in a corpus. The differences between disciplines are relative, and these results may change if another corpus of a different discipline is added; however, preference for FEs still exists across disciplines. This reinforces the previous claim that FEs are discipline-specific (Hyland and Tse, 2007; Hyland, 2008; Durrant, 2015; Jalilifar et al., 2016). All the discipline-specific FEs are listed in Table 15 in the appendix.

Table 11: Results of the evaluation of the constructed CF-labelled FE dataset.

| Sentence | Correct | Incorrect | Total |
|----------|---------|-----------|-------|
| FE       |         |           |       |
| Useful   | 130     | 12        | 142   |
| Useless  | 34      | 24        | 58    |
| Total    | 164     | 36        | 200   |

Table 12: Examples of discipline-specific FEs. The complete list is provided in the appendix. All the FEs are lower-cased. The number of occurrences of each FE in the corpus is also shown.

5 Discussion

5.1 CF-Based Sentence Classification

The classification accuracy was quite high, and thus the results can be a good baseline for a CF-based sentence classification task. We published the dataset so that other researchers can tackle the classification task.

The no-CF detection worked fairly. From Table 7 it can be said that the maximum value is often too high; 30% of the CF labels assigned scores higher than 0.99 were incorrect. However, much lower (≤ 0.80) scores tended to cause lower accuracy. Thus, this approach is useful to improve overall precision, which is more important to construct a FE-CF database than recall.
5.2 Problems in Multidisciplinary Data

We raised two questions: Can the classifier trained on one discipline be applied to other disciplines? Does the pre-training data affect the classification performance?

The results of the sentence classification imply that the SciBERT classifier trained on a dataset of one discipline can be applied to datasets of other disciplines. This mitigates the labour of creating a training dataset for all other disciplines. Therefore, we argue that to create another FE-CF database of another discipline, the CF-labelled sentence dataset we created can be used as a training dataset.

The comparison of SciBERT (Table 6) and BERT (Table 9) denied our hypothesis that the cross-discipline adaptation worked as long as the discipline was included in pre-training data. Therefore, the ability of discipline adaptation does not come from the pre-training dataset, which implies that the classifier could be used irrespective of whether a discipline is covered by the pre-training dataset.

5.3 Quality of the FE-CF Database

The results of the evaluation (Table 11) imply that if five CF-labelled FEs are retrieved, approximately three (130/200) are good FEs. Considering scenarios where users search for FEs to write a scientific paper, the selection of one FE from five candidates containing two incorrect FEs can be considered realistic.

Consider another case in which users use an FE as a query to obtain some example sentences that play the role of a specific CF. In this case, the evaluation results imply that approximately 90% (130/142) of the retrieved sentences are satisfying results. In some cases, the same FEs appear in different CF categories. For example, ‘play critical roles in’ is used in ‘Showing the importance of the topic (introduction)’ and ‘Showing background provided by past work (discussion)’. Thus, compared to the mere collection of FEs, the addition of CF labels to FEs is proved to be more helpful.

6 Conclusion

In this paper, we proposed the fully-automated construction of a CF-labelled FE database, by solving the problem of CF-based sentence classification. We carefully considered a practical case of creating a FE database of other disciplines. The experimental results showed that the proposed classification method and dataset can be utilised to construct FE databases for disciplines different from those that we used. We proposed the FE extraction method that utilised the named and scientific entity removal, dependency-structure-based word removal, and word-association-measure-based word removal. Combining the proposed methods, we finally constructed the new CF-labelled FE database. The CF-labelled sentence database and the CF-labelled FE database are available on our website\(^8\). We expect that the proposed database could be used by pedagogical practitioners and for computer-aided academic-writing assistance such as sentence retrieval and automated proofreading.

Acknowledgements

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\(^8\)https://iwa2ki.com/FE/

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A Dataset and Databases

On our website\(^9\), we published the following dataset and databases:

1. The CF-labelled sentence dataset for training and evaluation,

2. The CF-labelled sentence database, which was constructed by applying SciBERT classifier to every sentence in the corpora we used, and

3. The CF-labelled FE database, which was constructed by applying the proposed FE extraction method to the CF-labelled sentence database.

These data were formatted in tab-separated text. In the CF-labelled sentence dataset, a line consists of an ID and a sentence. In the CF-labelled sentence database, a line consists of a sentence ID (from the corpora), an ID, the maximum softmax value, and a sentence. In the CF-labelled FE database, a line consists of a CF, an FE, and the number of appearance in the corpus.

B CF Set

Table 13 lists the CF we used. The ID in the table corresponds to the ID used in the sentence dataset and database.

C General and Discipline-Specific FEs

General FEs are FEs that appear commonly in multiple disciplines. We calculated the average rank of each FE and Table 14 lists the top-5 general FEs for each CF. For most of the CFs, general FEs were not found. We also calculated the odds ratio and Table 15 lists the top-5 discipline-specific FEs for each CF. Some CFs did not happen in a corpus.

\(^9\)https://iwa2ki.com/FE/
| Section ID | CF |
|------------|----|
| 0          | Showing the importance of the topic plays an important role in |
| 1          | Showing the main problem in the field |
| 2          | Showing what is already done in the past work |
| 3          | Showing controversy within the field |
| 4          | Showing limitation or lack of past work |
| 5          | Showing the aim of the paper |
| 6          | Showing brief introduction to the methodology |
| 7          | Showing the importance of the research |
| 8          | Showing the limitation of the research |
| 9          | Showing the outline of the paper |
| 10         | Showing explanation or definition of terms or notations |
| 0          | Showing methodology used in past work |
| 1          | Showing reasons why a method was adopted or rejected |
| 2          | Using methods used in past work |
| 3          | Showing the characteristics of samples or data |
| 4          | Showing criteria for selection |
| 5          | Description of the process |
| 0          | Restatement of the aim or method |
| 1          | Reference to tables or figures |
| 2          | Description of the results |
| 3          | Describing interesting or surprising results |
| 4          | Comparison of the results |
| 5          | Summary of the results |
| 0          | Showing background provided by past work |
| 1          | Restatement of the results |
| 2          | Unexpected outcome |
| 3          | Comparison of the results and past work |
| 4          | Explanation for findings |
| 5          | Suggestion of hypothesis |
| 6          | Implications of the findings |
| 7          | Comments on the findings |
| 8          | Suggestion of future work |

Table 13: CF list.
Section: Results

Description of the results: There was no significant difference in...

Restatement of the aim or method: We found that the...

Reference to tables or figures: As shown in...

Describing interesting or surprising results: It is interesting to note that...

Summary of the results: These results suggest that...

Section: Discussion

Restatement of the results: We found that the...

Suggestion of hypothesis: Our results suggest that...

Explanation for findings: Can be explained by the fact that...

Unexpected outcome: It is not surprising that the...

Implications of the findings: This raises the possibility that...

Table 14: General FEs.

CL | Chem | Onc | Psy
---|------|-----|-----
Section: Introduction

CF: Showing limitation or lack of past work

To the best of our knowledge there have been few attempts made to...

There has been little work on...

There is no information on...

To our knowledge only one study has investigated...

Best of our knowledge no study has investigated...

Only a few studies have investigated...

Little attention has been paid to...
| CL | Chem | Onc | Psy |
|----|------|-----|-----|
| it is not clear how to | to the best of our knowledge the | has not been reported | studies * are scarce |

**CF: Showing the importance of the topic**

| has been used in | is one of the most common | it is important to note |
|-----------------|---------------------------|------------------------|
| is one of the most popular | et al reported that | that the |
| belongs to the family | et al found that | there is a growing body |
| et al showed that | | of research |
| is used as a | refers to the extent to which |
| in this study we found that | |

**CF: Showing controversy within the field**

| it should be noted that | role * is controversial | is still a matter of debate |
|------------------------|------------------------|----------------------------|
| it should be noted that | is still a matter of debate | is an open question |
| it is important to mention that | this has led to the suggestion that | the question arises as to whether |
| it is worth mentioning that | is still under debate | are still a matter of debate |
| it should be noted however that | | it remains an open question whether |

**CF: Showing the aim of the paper**

| the aim of the study was to | the aim of the study was to | the aim of the present study was to |
|----------------------------|----------------------------|----------------------------------|
| the objective of this study was to | purpose of this study was to | investigate |
| the aim of this work was to | the aim of the present study was to | |
| the aim of the present study was to | | examine |
| the purpose of this study was to investigate the | | |

**CF: Showing the importance of the research**

| to our knowledge this is the first report on | we show for the first time that | to our knowledge the present study is the first |
|-------------------------------------------|---------------------------------|------------------------------------------|
| we propose a novel to the best of our knowledge this is the first time | in this study we * for the first time that | is the first study to |
| we propose a new to the best of our knowledge this is the first time | we demonstrate for the first time that | best of our knowledge the present study is |
| to the best of our knowledge we are the first | | |
| we present a novel was reported in * cite- | we report for the first time that | should be able to discriminate between |
| we present a new was reported in | here we show for the first time that | as far as we are aware |

**CF: Showing the limitation of the research**

| | | |
| | | |
| CL | Chem | Onc | Psy |
|----|------|-----|-----|
| is not limited to beyond the scope of this review | beyond the scope of this paper | beyond the scope of this article | in the absence of any * that could be |

**CF: Showing brief introduction to the methodology**

| page numbers and proceedings footer are added | were characterized by | in this study we investigated the | in the present study we focus on |
| we evaluate our | were also investigated | in the present study we investigated the | in the present study we investigated |
| cite- proposed a | was used as the | in this study we aimed to | cite- cite- cite- cite- |
| section 3 describes the | et al cite- used | in this study we evaluated the | et al cite- used |
| we propose a | was used as a | in this study we investigated the role of | the present study was designed to |

**CF: Showing the main problem in the field**

| is that the | is one of the most common | is the leading cause of | is one of the most common |
| is a fundamental problem in | is the most common form of | is the second leading cause of | there are two reasons for this |
| is the lack of | is one of the most serious | is the third leading cause of | however is that |
| there are two main reasons for this | therefore it is necessary to develop | is the leading cause of death | this is one of the reasons why the |
| the main contribution of this work is | is one of the most frequent | there is an urgent need to identify | for this reason it is necessary to |

**CF: Showing explanation or definition of terms or notations**

| we call this | is defined as * cite- | are defined as * cite- | refers to * cite- |
| we call such | are defined as * cite- | is also called | refers to the * cite- |
| is called a | is defined as | is defined as a * cite- | this is referred to as the |
| is called the | we denote by | hereafter referred to as | is often referred to as |
| | | | refer to * cite- |

**CF: Showing what is already done in the past work**

| have been applied to | have been used as | cite- cite- cite- accumulate evidence suggests that | et al cite- and * cite- |
| have been proposed for | have been isolated from | accumulating evidence suggests that | |
| have been developed for | et al reported that | increasing evidence suggests that | et al cite- found that |
| have been proposed | have been used in | several lines of evidence suggest that | for example it has been shown that |
| there have been a number of | have been reported cite- cite- cite- | a growing body of evidence suggests that | it has been argued that |

**CF: Showing the outline of the paper**

| | | | |
| | | | |
| | | | |

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of this paper is organized as follows

the rest of this paper is organized as follows

remainder of this paper is structured as follows

paper is organized as follows section 2

the contributions of this paper are as follows

### Section: Methods

**CF: Using methods used in past work**

| Use(s) | Details |
|--------|---------|
| we propose a is based on | the title compound was prepared from characterization data is in accordance with that reported in cite- |
| is based on the in this section we describe our is based on a | was calculated according to the following equation |
| | was performed as previously described cite- was performed as previously described cite- |
| | was based on the |
| | was adapted from cite- is based on the |
| | was developed by cite- |

**CF: Showing reasons why a method was adopted or rejected**

| Use(s) | Details |
|--------|---------|
| is used for | was used for was used to analyze the relationship between |
| are used for | was used as a positive control was used to evaluate the association between |
| can be used for | was used for the was used to analyze the correlation between |
| is used as the | was used as the was used to assess the association between |
| is that the | were used for were used to estimate |
| | was used to assess was used to measure |
| | et al cite- was used to assess version * was used |

**CF: Showing the characteristics of samples or data**

| Use(s) | Details |
|--------|---------|
| are shown in table 1 | are listed in cite- experiments were repeated at least three times |
| are added to the submission are marked with an asterisk | are shown in cite- all experiments were performed in triplicate of at least three independent experiments |
| are listed in table 1 | were used as positive controls each experiment was performed in triplicate |
| | | had normal or corrected to normal vision |
| | | ranged in age from 18 to |
| | | participants * were excluded |
| CL | Chem | Onc | Psy |
|----|------|-----|-----|
| are shown in table 2 | singlet, doublet, triplet | experiment was repeated at least three times | all participants were native speakers of |

**CF: Showing methodology used in past work**

- we use two include * cite-
- we adopt a has been routinely and widely used in
- we use the following cite- cite- cite-
- we consider two cite- lists the described in cite- 
- there are two is one of the most widely used

**CF: Showing criteria for selection**

- figure 1 the were maintained in p 005 was considered statistically significant
- is shown in figure 1 was defined as the amount of enzyme p values 005 were considered statistically significant
- figure 2 the was defined as the lowest concentration of 005 was considered to be statistically significant
- figure 1 a in accordance with the * care and use of laboratory animals p 005 was considered significant
- is a set of cells were cultured in value * was considered statistically significant

**CF: Description of the process**

- we assume that the was stirred at room temperature for study was carried out in accordance with the gave written informed consent in accordance with the declaration of helsinki
- we calculate the hrms mz m h calcd was used for
- we also use were recorded on an we were purchased from study was approved by the ethics committee of gave written informed consent in accordance with the declaration of helsinki
- we then use the were purchased from were maintained in
- are trained using the mixture was stirred for
- were used for

**Section: Results**

**CF: Comparison of the results**

- we compare our cite- compares the analysis of the at each measurement point showed that in this section we present the
| CL | Chem | Onc | Psy |
|----|------|-----|-----|
| table 3 comparison of conditions there was an effect of condition with it can be seen that | revealed | comparison of * revealed | inspection * indicated a significant influence of |
| table 2 comparison of summary * is presented in citation | analysis of the * citation shows the comparison of | |
| table 1 comparison of citation shows the comparison of | |

**CF: Reference to tables or figures**

| table 2 shows the results are shown in table 2 shows the results are shown in | as shown in figure citation shows the results are shown in | figure citation shows the results are presented in table citation shows the results are shown in |
| table 1 shows the results are shown in table 2 shows the results are shown in | | |
| table 3 shows the results are shown in table 2 shows the results are shown in | are shown in table citation are summarized in table citation are shown in figure citation | |
| figure 2 shows the results are shown in figure citation shows the results are shown in | |

**CF: Description of the results**

| achieves the highest et al cited reported that it has been reported that revealed a significant main effect of | |
| performs better than the indicated the presence of our results showed that there was a significant main effect of | |
| significantly outperforms the was determined to be was observed in showed a significant main effect of | |
| is significantly better than the was confirmed by we have previously shown that there was a significant interaction between | |
| outperforms all other was assigned to the showed * figure citation revealed a significant main effect of | |

**CF: Describing interesting or surprising results**

| this is due to the fact that it is worth noting that interestingly we found that et al cited- it should be noted that | |
| is due to the fact that the it is important to mention that interestingly we observed that and * citation | |
| the it should be noted that the it is worth mentioning that the indeed we found that | |
| it should be noted that the best of our knowledge this is the first report it is important to note that | |
| we call this moreover * figure citation however it is important to note that | |
| this can be explained by the fact that it is worth noting that interestingly we found that et al cited- | |

**CF: Summary of the results**

| this shows that our the results indicated that taken together these data demonstrate that this indicates that * likely | |
| this result shows that the proposed from these results we can conclude that this suggests that for this pattern is consistent with the the therefore hypothesis 3 is supported | |
| this suggests that for these results demonstrate that the results show that the these results suggest that * promotes this suggests that during both meditation conditions saline | |
| these results demonstrate that the proposed the results show that the these results suggest that * promotes this suggests that the * had | |
| CL: Restatement of the aim or method | Chem | Onc | Psy |
|-------------------------------------|------|-----|-----|
| we use the was used as a positive control | were treated with | was conducted on |
| we use a was reacted with was used as the positive control | was confirmed by | was conducted on the |
| we evaluate our were treated with were confirmed by investigate | were submitted to a |
| we evaluate the were used as positive controls determine were performed | we conducted a |
| we use the same were evaluated for their we next examined the effect of | was conducted with |

**Section: Discussion**

| CF: Comparison of the results and past work | |
|-------------------------------------------|-----------------------------------|
| material is based upon work supported in part by et al showed that et al cite- also reported that is in line with previous research |
| this material is based in part on research sponsored by the et al found that our results also showed that is in line with previous studies |
| material is based upon work supported by the et al demonstrated that these findings are consistent with previous reports these findings are in line with |
| this is also the case for et al cite- our results are consistent with previous reports is in line with previous findings |
| this paper is * upon work supported in part by et al indicated that our results are consistent with those this finding is in line with |

| CF: Implications of the findings | |
|---------------------------------|-------------------------------------------------|
| these findings raise the possibility that these findings have important implications for the present study contributes to the it is assumed that limit the generalizability of our findings our findings also have implications for |
| this suggests the possibility that these results raise the possibility that highlights the importance of there are several important implications in this these results raise the possibility that these results raise the possibility that highlights the importance of there are several important implications in this these results raise the possibility that these results raise the possibility that highlights the importance of there are several important implications in this |

| CF: Restatement of the results | |
|-------------------------------|---------------------|
| we would like to thank to the best of our knowledge this is the first it is important to note that |
| the experimental results show that our et al found that the results showed that |
| experimental results show that the proposed were characterized by our knowledge this is the first cite- found that |
| in this paper we have shown that were tested for their ability to inhibit we did not find any significant |
| i would like to thank were evaluated for their in this study we found that it is important to note the current study |

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| CL | Chem | Onc | Psy |
|----|------|-----|-----|
| CF: Showing background provided by past work | inclusion et al reported that | et al reported that | et al cite- |
| in this paper we have presented a | in the present study | it has been reported that | cite- cite- cite- |
| in this paper we presented a | it has been reported that | et al demonstrated that | it has been argued that |
| in this paper we propose a | will be reported in due course | it was reported that | it has been argued that |
| in this paper we proposed a | et al reported that | it has been shown that | the |
| we presented a | | and * cite- |
| CF: Suggestion of hypothesis | best of our knowledge | in conclusion our study demonstrates that | this finding supports the notion that |
| we have presented a novel | it can be concluded that the | these data suggest that | suggests that the |
| we have proposed a | in summary we have developed a | in conclusion our data suggest that | the present findings suggest that the |
| we have presented a new | in conclusion we have developed a | our results showed that | this finding supports the idea that |
| we have shown that it is possible | it is known that | in summary our results indicate that | the present study provides the first |
| CF: Comments on the findings | was successfully applied to the | is a promising | we used a |
| we have presented a simple and effective | in summary we have successfully developed | may be a promising strategy for | is that the |
| we achieved an | | is a promising strategy for | on the one hand * on the other hand |
| we expect the | was successfully applied for the | might be a promising strategy for | declares that despite being affiliated to * |
| acknowledgements we are grateful to | has been successfully applied to the | | same institution as |
| has several advantages | has been successfully applied to a | in the present study we successfully | the aim of the present study was to |
| CF: Explanation for findings | can be attributed to the | may be involved in | it should be noted that the |
| this can be explained by the fact that the | can be explained by the presence of | therefore it is possible that the | however it should be noted that |
| this is due to the fact that | can be attributed to the | however * mechanism | it should be noted however that |
| we believe that this is due to the | presence of | * is unclear | it is also possible that |
| one reason for this is that | this could be explained by the fact that | this may explain why | the |
| this can be explained by the fact that | may be due to the presence of | mechanism * is unknown | could be due to the fact that the |
| CF: Suggestion of future work | studies * are in progress | this study has several limitations | it would be interesting to compare |
| in the future we plan to | studies * are in progress | our study has several limitations | further research is needed to clarify |
| in the future we would like to | in our laboratory | | |

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| CL | Chem | Onc | Psy |
|----|------|-----|-----|
| in future work we plan to | studies * are currently underway | this study has some limitations | further research is needed to determine beyond the scope of this paper |
| in future work we would like to | are in progress in our laboratory | our study has some limitations | it would be interesting to examine whether |
| as future work we plan to | are in progress and will be reported in due course | it remains to be determined whether | |

**CF: Unexpected outcome**

| | government is authorized to reproduce and distribute reprints for | therefore it is not surprising that | this was not the case |
| | this is not surprising | it is not surprising that | however this was not |
| | given that | unexpectedly we found that | the case |
| | what are kinds of | thus it is not surprising that | this was not observed |
| | it ports easily to new language pairs the | interestingly we observed that | this was not the case for |
| | is slightly different from * official one | | this was not the case in the present study |
| | because * this figure if | | |

Table 15: Discipline-specific FEs.