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[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; Ädel, 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-Aydınlı, 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.

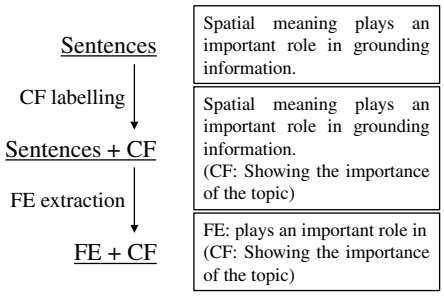

Figure 1: Process of creating FE database.

[1]http://langtest.jp/awsum/

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	Method for creating DB			DB statistics			
	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	$\simeq 2,000$
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, a host of studies extended the concept to all parts of a scientific paper. Most studies focused on very limited part 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 abstracts (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

[2] https://github.com/KMCS-NII/AASC

[3] https://www.mdpi.com/journal/molecules

[4] https://www.oncotarget.com/

[5] https://www.frontiersin.org/journals/psychology

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[6] (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

[6] https://www.semanticscholar.org/

Ulges, 2020), which sits atop the leader-board of NER tasks for scientific entities[7]. 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 an n-gram and a neighbour word. We used the local mutual information (LMI), which is formalised as follows:

$$\mathrm{LMI}(a, b) = f(a, b) \cdot \log \frac{p(a, b)}{p(a)p(b)}, \qquad (1)$$

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 $(n, k) = (2, 7)$.

[7] https://paperswithcode.com/sota/named-entity-recognition-ner-on-scierc

CF: Suggestion of future work
Sentence:
In the future, we plan to explore how to combine more features such as part-of-speech tags into our model.

Figure 2: Example of the database evaluation. An FE is underlined in the sentence, which has been retrieved from Cao et al. (2014).

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.

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

Table 4: Threshold indicates the number of annotators (out of five) who judged pairs of the sentence and CF label as correct.

Discipline	#Sentence
CL	612
Chem	644
Onc	600
Psy	687

Table 5: Numbers of sentences in the final dataset.

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.

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 6: Accuracy scores of each section (**I**ntroduction, **M**ethods, **R**esults, **D**iscussion) in each discipline. The average (Avg.) indicates the macro average.

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%

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

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

		Evaluation			
		CL	Chem	Onc	Psy
Training	CL	0.90	0.88	0.86	0.84
	Chem	0.84	0.89	0.91	0.84
	Onc	0.75	0.89	0.88	0.82
	Psy	0.88	0.89	0.88	0.84

Table 8: Average accuracy scores. The training and evaluation datasets comprise different discipline.

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 9: Accuracy scores acquire by BERT classifier.

		Evaluation			
		CL	Chem	Onc	Psy
Training	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

Table 10: Average accuracy scores by BERT.

'*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.

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

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

Section: Methods		
CF: Description of the process		#
CL	we assume that the	19
	we calculate the	17
	we also use	15
	we then use the	11
	are trained using	10
Chem	was stirred at room temperature for	104
	hrms mz m h calcd	90
	were recorded on an	89
	were purchased from	642
	the mixture was stirred for	74
Onc	were purchased from	2,972
	was used for	1,129
	was purchased from	2,129
	were maintained in	527
	were used for	548
Psy	study was carried out in accordance with the	360
	gave written informed consent in accordance with the	250
	was approved by the	165
	study was approved by the ethics committee of	156
	gave written informed consent in accordance with the declaration of helsinki	111

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 ($\leq$ 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.

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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.

[9]https://iwa2ki.com/FE/

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.

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

Table 13: CF list.

CF	FE
Section: Introduction	
Showing the importance of the topic	plays an important role in
Showing the importance of the topic	play an important role in
Showing the importance of the topic	also plays an important role in
Showing the importance of the topic	is related to
Showing the importance of the topic	plays a crucial role in
Showing limitation or lack of past work	to the best of our knowledge there is no
Showing limitation or lack of past work	to the best of our knowledge no
Showing the importance of the research	to the best of our knowledge this is the first
Showing brief introduction to the methodology	is based on
Showing brief introduction to the methodology	is based on the
Showing brief introduction to the methodology	are based on
Showing brief introduction to the methodology	is to use
Showing the outline of the paper	the paper is organized as follows

CF	FE
Showing the outline of the paper	this paper is organized as follows
Showing the outline of the paper	the paper is structured as follows
Showing the outline of the paper	this paper is structured as follows
Showing the outline of the paper	the rest of the paper is structured as follows
Section: Results	
Description of the results	there was no significant difference in
Description of the results	we found that the
Description of the results	there was no significant difference between the
Description of the results	there was no significant difference between
Description of the results	we found that
Restatement of the aim or method	we used the
Restatement of the aim or method	we compared the
Restatement of the aim or method	we used a
Restatement of the aim or method	we performed a
Restatement of the aim or method	was performed using
Reference to tables or figures	as shown in
Describing interesting or surprising results	it is interesting to note that
Describing interesting or surprising results	it is interesting to note that the
Summary of the results	these results suggest that
Summary of the results	this suggests that
Summary of the results	this suggests that the
Summary of the results	this indicates that the
Section: Discussion	
Restatement of the results	we found that the
Restatement of the results	we found that
Restatement of the results	it is interesting to note that
Restatement of the results	it is worth noting that the
Restatement of the results	it is important to note that the
Suggestion of hypothesis	our results suggest that
Explanation for findings	can be explained by the fact that
Explanation for findings	this is due to 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	to the best of our knowledge there	however * role * remains unclear	to our knowledge only one study
few attempts have been made to	to the best of our knowledge there have been	however * role * remains unknown	best of our knowledge no study has
there has been little work on	to the best of our knowledge there are few	remains to be elucidated	only a few studies have investigated
there is no	has not been reported	however * mechanism * remains unclear	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			
is an important task in	has been used in	is one of the most common	it is important to note that
there has been a growing interest in	is one of the most popular	et al reported that	is that the
in this work we are interested in	belongs to the family	et al found that	there is a growing body of research
has received a lot of attention	is used as a	et al showed that	is defined as a * cite-
the main contribution of this paper is	is widely distributed in	in this study we found that	refers to the extent to which
CF: Showing controversy within the field			
the state of the art in	it should be noted that the	role * is controversial	is still a matter of debate
this research was partially supported by	it should be noted that	is still a matter of debate	is an open question
this work was supported by the	it is important to mention that	this has led to the suggestion that	the question arises as to whether
the current state of the art	it is worth mentioning that the	is still under debate	are still a matter of debate
this work was done while the	it should be noted however that		it remains an open question whether
CF: Showing the aim of the paper			
in this paper we focus on	the aim of this study was to	the aim of this study was to	the aim of the present study was to
in this paper we propose a novel	objective of this study was to	purpose of this study was to	the aim of the present study was to investigate
in this paper we propose a	the aim of this work was to	aim of this study was to investigate the	the aim of this study was to
in this paper we present an	in this paper we report the	the aim of the present study was to	the aim of the present study was to examine
in this paper we propose an	the aim of the present study was to	purpose of this study was to investigate the	the purpose of the present study was to
CF: Showing the importance of the research			
we propose a novel	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 new	to the best of our knowledge this is the first time	in this study we * for the first time that	to our knowledge this is the first study to
to the best of our knowledge we are the first	to our knowledge this is the first time that	we demonstrate for the first time that	best of our knowledge the present study is
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 * is the first
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 is the focus of this study
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	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 a * 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		hereafter referred to as	is often referred to as
we denote by		is defined as * cite-	refer to * cite-
CF: Showing what is already done in the past work			
have been applied to	have been used as	cite- cite- cite-	et al cite-
have been proposed for	have been isolated from	accumulating evidence suggests that	and * cite-
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- cite- cite-	a growing body of evidence suggests that	it has been argued that the
CF: Showing the outline of the paper			

CL	Chem	Onc	Psy
of this paper is organized as follows			the rest of the paper is organized as follows
the rest of * paper is organized as follows			the remainder of the paper is organized as follows
remainder of this paper is structured as follows			the rest of this paper is organized as follows
paper is organized as follows section 2			can be divided into
the contributions of this paper are as follows			remainder of this paper is organized as follows
Section: Methods			
CF: Using methods used in past work			
we propose a	the title compound was prepared from	was performed as previously described cite-	was calculated using the
is based on	characterization data is in accordance with that reported in cite-	were performed as previously described cite-	was based on the
is based on the	was calculated according to the following equation	was performed as described previously cite-	was adapted from cite-
in this section we describe our	was calculated using the following equation	were performed as described previously cite-	is based on the
is based on a	was prepared according to the general procedure	conducted in accordance with the * according to the	was developed by cite-
CF: Showing reasons why a method was adopted or rejected			
is used for	was used for	was used to analyze the relationship between	was used to assess
are used for	was used as a positive control	was used to evaluate the association between	was used to measure
can be used for	was used for the	was used to analyze the correlation between	et al cite- was used to assess
is used as the	was used as the	was used to assess the association between	version * was used
is that the	were used for	were used to estimate	was used as a measure of
CF: Showing the characteristics of samples or data			
are shown in table 1	are listed in cite-	experiments were repeated at least three times	all participants had
are added to the	are shown in cite-	all experiments were performed in triplicate	had normal or corrected to normal vision
submission are marked with an asterisk	used in this study are listed in cite-	of at least three independent experiments	ranged in age from 18 to
are listed in table 1	were used as positive controls	each experiment was performed in triplicate	participants * were excluded

CL	Chem	Onc	Psy
are shown in table 2	s singlet d doublet t 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-	is how to formulate a	et al cite-
we adopt a	has been routinely and widely used in	has been widely recognized and increasingly * to examine the quality of * see eg cite-	and * cite-
we use the following	cite- cite- cite-	here the * ratio	has been shown to have good
we consider two	cite- lists the	described in cite- * there is no need to repeat	it should be noted that the
there are two	is one of the most widely used	are needed as elaborated in cite-	has been shown to be a
CF: Showing criteria for selection			
figure 1 the	were maintained in	p 005 was considered statistically significant	was defined as
is shown in figure 1	was defined as the amount of enzyme	p values 005 were considered statistically significant	was defined as the
figure 2 the	was defined as the lowest concentration of	005 was considered to be statistically significant	were selected from the * cite-
figure 1 a	in accordance with the * care and use of laboratory animals	p 005 was considered significant	is defined as
is a set of	cells were cultured in	value * was considered statistically significant	were defined as
CF: Description of the process			
we assume that the	was stirred at room temperature for	were purchased from	study was carried out in accordance with the
we calculate the	hrms mz m h calcd	was used for	gave written informed consent in accordance with the
we also use	were recorded on an	was purchased from	was approved by the
we then use the	were purchased from	were maintained in	study was approved by the ethics committee of
are trained using	the mixture was stirred for	were used for	gave written informed consent in accordance with the declaration of helsinki
Section: Results			
CF: Comparison of the results			
we compare our	cite- compares the	analysis of the	at each measurement point showed that
we compare the	comparison * is shown in cite-	comparison of the	in this section we present the

CL	Chem	Onc	Psy
table 3 comparison of	a comparison of the	comparison of * revealed	conditions there was an effect of condition with
table 2 comparison of	summary * is presented in cite-	comparison of * cite-	it can be seen that
table 1 comparison of	cite- shows the comparison of	analysis of the * cite-	inspection * indicated a significant influence of
CF: Reference to tables or figures			
table 2 shows the	cite- shows the	as shown in figure cite-	figure cite- shows the
table 1 shows the	are shown in cite-	figure cite- shows the	are presented in table cite-
table 3 shows the	it can be seen that the	are shown in table cite-	table cite- shows the
results are shown in table 2	the results are shown in cite-	are summarized in table cite-	are shown in table cite-
figure 2 shows the	is shown in cite-	are shown in figure cite-	table cite- presents the
CF: Description of the results			
achieves the highest	et al cite- reported that the	it has been reported that	revealed a significant main effect of
performs better than	indicated the presence of	our results showed that	there was a significant main effect of
significantly outperform 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 cite-	there was a main effect of
CF: Describing interesting or surprising results			
this is due to the fact that	it is worth noting that the	interestingly we found that	et al cite-
is due to the fact that the	it is important to mention that	interestingly we observed that	it should be noted that the
it should be noted that the	it is worth mentioning that the	indeed we found that	and * cite-
we call this	best of our knowledge this is the first report	interestingly we found that the	however it is important to note that
this can be explained by the fact that	it is important to note that	moreover * figure cite-	et al cite- found
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	these results are in agreement with those	taken together these results demonstrated that	this pattern is consistent with the
from these results we can conclude that	these results are in accordance with	taken together these findings indicate that	therefore hypothesis 3 is supported
this suggests that for	this indicated that the	taken together our data suggest that	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	Chem	Onc	Psy
CF: Restatement of the aim or method			
we use the	was used as a positive control	were treated with	was conducted on
we use a	was reacted with	was confirmed by	was conducted on the
we evaluate our	was used as the positive control	investigate * we performed	were submitted to a
we evaluate the	were used as positive controls	determine * we 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	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
		this suggests the possibility that	the present study contributes to the
		these results raise the possibility that	it is assumed that
		highlights the importance of	limit the generalizability of our findings
		there are several important implications in this	our findings also have implications for
CF: Restatement of the results			
we would like to thank	was found to be	to the best of our knowledge this is the first	it is important to note that
the experimental results show that our	were characterized by	et al found that	the results showed that
experimental results show that the proposed	was found to be the most potent	to our knowledge this is the first	cite- found that
in this paper we have shown that	were tested for their ability to inhibit	in this study we found that	we did not find any significant
i would like to thank	were evaluated for their	in this study we demonstrated that	it is important to note * the current study

CL	Chem	Onc	Psy
CF: Showing background provided by past work			
in this paper we have presented a	include * cite-	et al reported that	et al cite-
in this paper we presented a	in the present study	it has been reported that	cite- cite- cite-
in this paper we propose a	it has been reported that	et al demonstrated that	it has been argued that
in this paper we proposed a	will be reported in due course	it was reported that	it has been argued that the
we presented a	et al reported that	it has been shown that	and * cite-
CF: Suggestion of hypothesis			
we have presented a	best of our knowledge this is the first report	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			
we have presented a simple and effective	was successfully applied to the	is a promising	we used a
we achieved an	in summary we have successfully developed	may be a promising strategy for	is that the
we expect the	was successfully applied for the	is a promising strategy for	on the one hand * on the other hand
acknowledgements we are grateful to	has been successfully applied to the	might be a promising strategy for	declares that despite being affiliated to * 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			
this can be explained by the fact that the	can be attributed to the	may be involved in	it should be noted that the
this is due to the fact that the	can be explained by the presence of	therefore it is possible that the	however it should be noted that
we believe that this is due to the	can be attributed to the presence of	however * mechanism * is unclear	it should be noted however that
one reason for this is that	this could be explained by the fact that	this may explain why	it is also possible that 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			
in the future we plan to	studies * are in progress	this study has several limitations	it would be interesting to compare
in the future we would like to	are currently underway in our laboratory	our study has several limitations	further research is needed to clarify

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
in future work we would like to	are in progress in our laboratory	our study has some limitations	beyond the scope of this paper
as future work we plan to	are in progress and will be reported in due course	it remains to be determined whether	it would be interesting to examine 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 given that		it is not surprising that	however this was not the case
what are kinds of		unexpectedly we found that	this was not observed
it ports easily to new language pairs the		thus it is not surprising that	this was not the case for
is slightly different from * official one because * this figure if		interestingly we observed that	this was not the case in the present study

Table 15: Discipline-specific FEs.