SDCF: semi-automatically structured dataset of citation functions

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Abstract
There is increasing research interest in the automatic detection of citation functions, which is why authors of academic papers cite previous works. A machine learning approach for such a task requires a large dataset consisting of varied labels of citation functions. However, existing datasets contain a few instances and a limited number of labels. Furthermore, most labels have been built using narrow research fields. Addressing these issues, this paper proposes a semiautomatic approach to develop a large dataset of citation functions based on two types of datasets. The first type contains 5668 manually labeled instances to develop a new labeling scheme of citation functions, and the second type is the final dataset that is built automatically. Our labeling scheme covers papers from various areas of computer science, resulting in five coarse labels and 21 fine-grained labels. To validate the scheme, two annotators were employed for annotation experiments on 421 instances that produced Cohen’s Kappa values of 0.85 for coarse labels and 0.71 for fine-grained labels. Following this, we performed two classification stages, i.e., filtering, and fine-grained to build models using the first dataset. The classification followed several scenarios, including active learning (AL) in a low-resource setting. Our experiments show that Bidirectional Encoder Representations from Transformers (BERT)-based AL achieved 90.29% accuracy, which outperformed other methods in the filtering stage. In the fine-grained stage, the SciBERT-based AL strategy achieved a competitive 81.15% accuracy, which was slightly lower than the non-AL strategy. These results show that the AL is promising since it requires less than half of the dataset. Considering the number of labels, this paper released the largest dataset consisting of 1,840,815 instances.

Keywords
Active learning · Citation function · Coarse label · Fine-grained label · Semiautomatic
Introduction

Citation analysis is part of the bibliographic analysis that studies how the connection between academic publications is established in terms of one which cites and the other which is cited (Nicolaisen, 2008). Citation analysis has become widespread practice to measure the impact of academic publication. Hlavcheva and Kanishcheva (2020) stated that an academic publication’s impact comes from several directions, such as the impact of the researcher, the impact of the group or institution, the local or global academic ranking, and the quality of the publication, which are measured by citation counts. In this setting, the citation counts involve calculating the number of times a document is cited by other documents and is performed through bibliometric databases. However, there is no single database that gathers all publications together with their cited references. The analysis needs to look at several database options, such as Web of Science (WOS), Scopus, Google Scholar, etc. There are several measurements, e.g., h-index personal metric, or impact factor for journal metric, which are widely used as impact indicators because of the citation analysis.

Besides the benefit of current citation analysis, measuring the publication impact using the citation counts gets intense criticism. This is because the citation counts assume that all citations have an equal impact on the academic publication. In fact, not all citations are equal and should not be treated equally (Valenzuela et al., 2015). Treating the citations to be always a positive endorsement of the cited references is problematic because the citations are often made to show disapproval of the cited references. Moreover, the citation analysis fails to capture contextual information (Hirsch, 2005; Mercer et al., 2014) containing several citation functions, such as giving the background, using the work, making the comparison, criticism, etc. Focusing on the research paper, the contextual information can be used to dig deeper into the paper. Authors of research papers use citations to show the position of their research in broad literature (Lin & Sui, 2020). The citation functions indicate the research’s novelty (Tahamtan & Bornmann, 2019), and the quality of the research (Raamkumar et al., 2016), and help authors understand the big picture of the given topics (Qayyum & Afzal, 2018). Furthermore, the citation functions enable the research paper to obtain a higher impact when it is used, approved, and supported by other works, and less impact when other works just mention the research paper. Thus, involving the citation functions as the contextual information needs serious attention to enrich the impact analysis of the scientific publication.

There is a growing concern for works on the automatic identification of citation functions (Pride & Knoth, 2020). This trend is caused by the fact that authors provide citations to determine the important and non-important roles of citations (Nazir et al., 2020). According to (Zhu et al., 2015), previous works are considered influential if they inspire authors to propose solutions. While incidental citations refer to a previous work that does not provide a significant impact on the proposed research. In this domain, the terms important and non-important (Valenzuela et al., 2015) are identical to the terms influential and incidental (Pride & Knoth, 2020). However, most previous works have a small number of citation instances or considered few types of labels. In addition, existing works have

1 https://clarivate.com/webofsciencegroup/solutions/web-of-science/.
2 https://www.scopus.com/home.uri.
3 https://scholar.google.com/.
suffered from a lack of research variety. Most of these works were developed based on natural language processing (NLP)-related papers. Consequently, several potential *citation functions* were missing from being identified.

The contribution of this paper consists of two parts. In the first part, we propose a new annotation scheme for *citation functions* that have not been accommodated in previous works. Our proposed scheme covers all computer science (CS) fields on arXiv from the beginning to December 31, 2017. This paper uses well-organized parsed sentences of research papers from (Färber et al., 2018) and selects 1.8 million raw *citing sentences*. Based on 5668 randomly selected instances, we developed the proposed annotation scheme following three stages, i.e., top-down analysis, bottom-up analysis, and annotation experiment. Completing the first two stages reveals that there are potential newly proposed labels. We found five *fine-grained* labels related to the *background’s role of cited papers* that were not proposed by existing works. These labels are *definition*, *suggest*, *technical*, *judgment*, and *trend*. In addition, we found three new labels defining the role of a *cited paper*, i.e., *cited_paper_propose*, *cited_paper_result*, and *cited_paper_dominant*. Our final scheme consists of 5 *coarse* and 21 *fine-grained* labels. Following this, annotation experiments were conducted involving two annotators on 421 samples. We use Cohen’s Kappa (Cohen, 1960) to validate the results of the annotation experiments.

The second part of our contribution is to build a dataset of *citation functions* through a semiautomatic approach. This approach was chosen because manual labeling is time-consuming and needs enormous human effort. The proposed method consists of two development stages. In the first stage, we build two classification tasks, i.e., *filtering*, and *fine-grained* classification. The *filtering* task eliminates nonessential labels, and the *fine-grained* task categorizes the detail of the essential labels. In both tasks, we implement a classical machine learning and deep learning approach. Because of the small number of manually labeled instances, pre-trained word embedding methods should be considered here. In addition, this paper demonstrates pool-based active learning (AL) as a low-resource scenario. Following this, the next stage is to assign labels to the entire unlabeled instances using the best models from both tasks of the previous stage.

At the end of this research, this paper delivers several contributions:

- The annotation scheme for citation functions consists of five coarse and 21 fine-grained labels.
- The validity of the scheme is demonstrated in terms of Cohen’s Kappa results with 0.85 (almost perfect) for coarse labels and 0.71 (substantial agreement) for fine-grained labels.
- The low-resource scenario-based AL achieves competitive accuracies on less than half of the training data.
- While Bidirectional Encoder Representations from Transformers (BERT)-based AL outperformed other methods in the filtering task, SciBERT reached competitive performances compared to non-AL methods in the fine-grained stage.
- Considering the number of labels, we released the largest dataset consisting of 1,840,815 instances.4

4 https://github.com/tutcsis/SDCF.
The rest of this paper is organized as follows. The “Related works” section describes existing works covering three parts, namely, the annotation schemes of citation functions, the research papers’ argumentative structure, and the detection of citation functions. Next, the section “Building the dataset of citation functions” discusses how our dataset is developed. This section covers several points, i.e., scheme development, scheme comparison, annotation strategy, and text classification strategy. The section “Experiment results” presents annotation and text classification experiments, including the released dataset. Finally, in the “Conclusion and future work” section, we present other notable findings from the conducted experiments.

Related works

This section contains a review of existing works related to several points, i.e., the annotation schemes of citation functions, the argumentative structures of scientific papers, the dataset of citation functions, and the automatic identification of citation functions. For consistency, this paper uses several terminologies, namely, citing paper is an author’s work, cited paper is previous work cited by citing paper, citing sentence is a sentence containing citation marks, and citation function is a reason behind citations.

Citation function labels

The review was conducted on previous works proposing their annotation schemes. During the review, we found two major categories of citation functions, i.e., coarse label (general) and fine-grained label (detail). While several works provided both categories, other works provided a single category, either coarse or fine-grained label. The existing annotation schemes of citation functions are shown in Table 1.

We report several notable results while reviewing previous works on citation functions. The review of existing works poses the fact that most of the schemes were developed using NLP-related papers. The paper data sources were dominated by ACL Anthology, but several works used other sources such as NIPS Proceedings, PubMed, SciCite, and Computation and Language E-Print Archive. However, we identified two works that have developed the scheme based on multi-disciplinary research papers. In addition, instead of proposing new annotation schemes of citation functions, several works reproduced existing schemes. Turning to the developed scheme, most existing works have citation functions related to the background label, use-related labels, and comparison-related labels.

Reviewing the labeling scheme of citation functions in the previous works reveals several drawbacks.

- Most existing works have developed a few types of labels and the labels were considered too generic. There was a work by (Casey et al., 2019) that proposed detailed labels. However, these labels were designed not only for citing sentences but also for other sentences in the Related Work section. This situation brings a consequence that several potential citation functions are missing from being identified.
- The labels developed in the previous works were domain-specific since they were created based on Natural Language Processing (NLP)-related papers. As a result, there is an issue related to the compatibility of the labels when applied to broader computer science domains. Here, we identified two works that developed the labels based on multi-
| No. | Research paper          | Coarse classes | Fine-grained classes | Data source domain               |
|-----|-------------------------|----------------|----------------------|----------------------------------|
| 1   | Teufel et al. (2006)    | Weakness       | Weak                | Computation and language E-Print archive |
|     |                         | Contrast       | CoCoGM              |                                  |
|     |                         | Contrast       | CoCoR0              |                                  |
|     |                         | Contrast       | CoCoXY              |                                  |
|     | Agreement/usage         | PBas           |                      |                                  |
|     | Agreement/usage         | PUse           |                      |                                  |
|     | Agreement/usage         | PModi          |                      |                                  |
|     | Agreement/usage         | PMot           |                      |                                  |
|     | Agreement/usage         | PSim           |                      |                                  |
|     | Agreement/usage         | Psup           |                      |                                  |
|     | Neutral                 | neutral        |                      |                                  |
| 2   | Dong and Schäfer (2011) | Background     | Background          | ACL anthology                    |
|     |                         | Fundamental idea | Fundamental idea    |                                  |
|     |                         | Technical basis | Technical basis     |                                  |
|     |                         | Comparison     | Comparison          |                                  |
| No. | Research paper         | Coarse classes | Fine-grained classes | Data source domain |
|-----|------------------------|----------------|----------------------|--------------------|
| 3   | Li et al. (2013)       | Positive       | Based-on             | PubMed             |
|     |                        | Positive       | Corroboration        |                    |
|     |                        | Positive       | Discover             |                    |
|     |                        | Positive       | Positive             |                    |
|     |                        | Positive       | Practical            |                    |
|     |                        | Positive       | Significant          |                    |
|     |                        | Positive       | Standard             |                    |
|     |                        | Positive       | Supply               |                    |
|     |                        | Neutral        | Contrast             |                    |
|     |                        | Neutral        | Co-citation          |                    |
|     |                        | Neutral        | Neutral              |                    |
|     |                        | Negative       | Negative             |                    |
| 4   | Valenzuela et al. (2015)| Incidental    | Related work         | ACL Anthology      |
|     |                        | Incidental    | Comparison           |                    |
|     |                        | Important      | Using the work       |                    |
|     |                        | Important      | Extending the work   |                    |
| No. | Research paper                  | Coarse classes | Fine-grained classes | Data source domain |
|-----|---------------------------------|----------------|----------------------|--------------------|
| 5   | Hernández-Álvarez et al. (2016) | background     | Acknowledge          | ACL anthology      |
|     |                                 | background     | Corroboration        |                    |
|     |                                 | background     | Debate               |                    |
|     |                                 | Use            | Based-on             |                    |
|     |                                 | Use            | Supply               |                    |
|     |                                 | Use            | Useful               |                    |
|     |                                 | comparison     | Contrast             |                    |
|     |                                 | Critique       | Weakness             |                    |
|     |                                 | Critique       | Hedges               |                    |
| 6   | Jurgens et al. (2018)           | Background     | Background           | ACL anthology      |
|     |                                 | Motivation     | Motivation           |                    |
|     |                                 | Uses           | Uses                 |                    |
|     |                                 | Extension/continuation | Extension/continuation |    |
|     |                                 | Comparison/contrast | Comparison/contrast |    |
|     |                                 | Future         | Future               |                    |
| 7   | Bakhti et al. (2018)            | Useful         | Useful               | ACL anthology      |
|     |                                 | Contrast       | Contrast             |                    |
|     |                                 | Mathematical   | Mathematical         |                    |
|     |                                 | Correct        | Correct              |                    |
|     |                                 | Neutral        | Neutral              |                    |
| No. | Research paper          | Coarse classes | Fine-grained classes       | Data source domain                      |
|-----|-------------------------|----------------|-----------------------------|-----------------------------------------|
| 8   | Casey et al. (2019)     | Background     | BG-DESC-NE                 | ACL anthology (related works sections) |
|     |                         | Background     | BG-DESC-EP                 |                                         |
|     |                         | Background     | BG-EVAL-P                  |                                         |
|     |                         | Cited work     | CW-DESC                    |                                         |
|     |                         | Cited work     | CW-COMP                    |                                         |
|     |                         | Cited work     | CW-EVAL-P                  |                                         |
|     |                         | Cited work     | A-CW-BUILD                 |                                         |
|     |                         | Cited work     | A-CW-SIM                   |                                         |
|     |                         | Gap            | CW-EVAL-SC                 |                                         |
|     |                         | Gap            | BG-EVAL-SC                 |                                         |
|     |                         | Author contribution | A-DIFF                   |                                         |
|     |                         | Author contribution | A-DESC                   |                                         |
|     |                         | Author contribution | A-GAP                   |                                         |
|     |                         | Author contribution | A-CW-DIFF                |                                         |
|     |                         | Additional labels | OTHER                    |                                         |
|     |                         | Additional labels | OCR                      |                                         |
|     |                         | Additional labels | TEXT                     |                                         |
| No. | Research paper | Course classes | Fine-grained classes | Data source domain |
|-----|----------------|----------------|----------------------|--------------------|
| 9   | Rachman et al. (2019) | Problem | Use | UseModel, UseTool, UseData, Other | ACL anthology |
| 10  | Su et al. (2019) | Weakness | Compare and Contrast | Positive, Neutral, Use, Produce, Introduce, Compare, Extent, Other | ACL anthology, NIPS, and PubMed |
| 11  | Zhao et al. (2019) | Use | Produce | Introduce, Compare, Extent, Other | SciCite and ACL Anthology |
| 12  | Cohan et al. (2019) | Background | Method | Result comparison, Use, Extend, Utilize, Not utilize, Not utilize | Multiple disciplines |
| 13  | Tuarob et al. (2019) | Not utilize | Utilize | Extent, Mention, Not utilize | Not utilize |
| No. | Research paper             | Coarse classes | Fine-grained classes | Data source domain     |
|-----|---------------------------|----------------|----------------------|------------------------|
| 14  | Pride and Knoth (2020)    | Background     | background           | Multiple disciplines   |
|     |                           | Use            | Use                  |                        |
|     |                           | Compare_contrast| Similarities         |                        |
|     |                           | Compare_contrast| Differences          |                        |
|     |                           | Compare_contrast| Disagreement         |                        |
|     |                           | Motivation      | Motivation           |                        |
|     |                           | Extension       | Extension            |                        |
|     |                           | Future          | Future               |                        |
disciplinary fields (Pride & Knoth, 2020; Tuarob et al., 2019), but these works have few and too generic scopes of 8 labels, and 4 labels, respectively. In addition, it is difficult to justify the accuracy of developed labels for comprehensively analyzing the research paper when it is developed according to a wide-ranging domain, for example involving computer science and non-computer science domains. This is because each domain has its style of argumentative structure in the research papers.

To handle these issues, this paper proposed a new labeling scheme of citation functions from multiple fields in the computer science domain. Accommodating the variety of citing sentences in the multi-field paper and maintaining the scope still in the computer science domain, it is arguable that our proposed labels provide more comprehensive coverage for future citation function-related analysis tasks.

**Research paper argumentative structure**

The argumentative structure represents how information is presented, discussed, and motivated. This structure is useful to justify the scientific claim, state the existing trend, and guarantee research reproducibility (Alliheedi et al., 2019). It is worth discussing argumentative structures in this paper since our proposed annotation scheme naturally contains argumentative labels.

Argumentative structures can be applied to a section-level or sentence-level category. Sollaci and Pereira, (2004) presented the study about the adoption of section-level categories, namely, *introduction*, *methods*, *results*, and *discussion* (IMRAD). This scheme was first used in the 1940s, and since the 1980s, it became the only pattern adopted in health papers. The IMRAD scheme is considered a generic scheme since authors use it to structure a paper's sections. Teufel et al. (1999) developed the first version of *Argumentative Zone* (AZ-I) as a sentence-level category. AZ-I consists of seven labels based on 48 computational linguistics papers. Then, AZ-I was upgraded using 30 Chemistry papers and 9 Computational Linguistics papers (Teufel et al., 2009). The upgraded version, AZ-II, contains 15 labels. The next sentence-level category is *Core Scientific Concepts* (CoreSCs) proposed by (Liakata, 2010). This structure consists of 18 labels based on 265 Physical Chemistry and Biochemistry papers. Another argumentative structure is *Dr. Inventor* proposed by (Fisas et al., 2015). This scheme contains five categories and three sub-categories built based on 40 Computer Graphics papers.

**Citation function dataset**

Table 2 shows the summary of the existing datasets of citation functions together with estimation number of sample papers and number of labeled instances. The work by (Roman et al., 2021) has provided the largest dataset, consisting of 10 million instances which was labeled automatically. However, these works provided too few labels, i.e., *background*, *method*, and *result*, which are not sufficient to represent the reason behind citations.
Citation function classification

The existing works which performed citation function classification can be divided into two main categories. First, the works that proposed both labeling schemes of citation functions and datasets, second, the works that use other dataset and perform the citation functions classification.

In the first category, the work by (Teufel et al., 2006) is considered as a pioneer in citation functions development. Next, (Valenzuela et al., 2015) built a classification system using support vector machine (SVM) and random forest (RF). Similarly, the RF approach was implemented by (Jurgens et al., 2018) using several features, i.e., pattern, topic, and prototypical. Zhao et al. (2019) used long short-term memory (LSTM), along with character-based embedding, to classify citation resources (tools, code, media, etc.) and functions. Tuarob et al. (2019) proposed a system to classify algorithm citation functions on four usage labels, i.e., use, extend, mention, and notalgo. The maximum entropy-based classification was used by (Li et al., 2013) to propose coarse annotation with sentiment labels. Because of the limitation of labeled instances, Dong and Schäfer (2011) introduced ensemble-style self-training to reduce annotation efforts.

Still, in the same category, another work proposing both annotation schemes of citation functions and datasets is (Hernández-Álvarez et al., 2016). This research covered three classification tasks, i.e., citation functions, citation polarities, and citation aspects. All tasks were implemented using sequential minimal optimization. Su et al. (2019) used a convolutional neural network (CNN) for citation function and provenance classification. This task was implemented using multitask learning. Sharing a similar multitask setting. While Bakhti et al. (2018) also used a CNN, Cohan et al. (2019) proposed another multitask learning approach.

### Table 2

Existing datasets of citation functions, together with the estimation number of source papers, and citing sentences

| No. | Research paper | Estimation Number of Papers | Estimation number of labeled instances |
|-----|----------------|----------------------------|----------------------------------------|
| 1   | Teufel et al. (2006) | 300                       | 9576                                   |
| 2   | Dong and Schäfer (2011) | 122                       | 1768                                   |
| 3   | Li et al. (2013) | 91                        | 6355                                   |
| 4   | Valenzuela et al. (2015) | 20,527                   | 465                                    |
| 5   | Hernández-Álvarez et al. (2016) | 85                    | 2092                                   |
| 6   | Jurgens et al. (2018) | 185                       | 1969                                   |
| 7   | Bakhti et al. (2018) | ?                         | 8700                                   |
| 8   | Casey et al. (2019) | 95 related work sections | 1806                                   |
| 9   | Rachman et al. (2019) | Dataset 1: 160 Dataset 2: 50 | Dataset 1: 2475 Dataset 2: 1153 |
| 10  | Su et al. (2019) | ?                         | 1432                                   |
| 11  | Zhao et al. (2019) | 39,601                    | 3088                                   |
| 12  | Cohan et al. (2019) | 6627                      | 11,020                                 |
| 13  | Tuarob et al. (2019) | 8063                      | 8796                                   |
| 14  | Pride & Knoth (2020) | 883                       | 11,233                                 |
| 15  | Roman et al. (2021) | ?                         | 10 million                             |
In the second category, most of the existing works were dominated by studies focusing on classification strategies based on Valenzuela’s dataset. Hassan et al. (2017) proposed six new features combined with Valenzuela’s most important features. This work used five algorithms, i.e., SVM, naive Bayes, decision tree, K-nearest neighbor (KNN), and RF. This work outperformed Valenzuela’s performance using RF, achieving 84% accuracy. Another work, i.e., Hassan et al. (2018), reached 92.5% accuracy by implementing LSTM using 64 features. Following this, Nazir et al. (2020) proposed using citation frequencies, similarity scores, and citation count. The classification in this research was built using kernel logistic regression, SVM, and RF. Pride and Knoth (2017) used influential and non-influential citations to find highly predictive features. The classification in this work was performed using RF. Next, Wang et al. (2020) used syntactic and contextual features for important and non-important citation detection. This work applied several algorithms, namely, SVM, KNN, and RF.

Besides all these works, Rachman et al. (2019) used a dataset from (Teufel et al., 2006) with re-annotation and developed a model using SVM. Following this, (Roman et al., 2021) used the citation context dataset from CORE. This research applied BERT, depending on the three labels proposed by Sci-Cite (Cohan et al., 2019).

### Building the dataset of citation functions

This section describes how our dataset is developed using a semiautomatic approach. The entire system consists of three stages. The first stage is annotation scheme development. In this stage, we identified and reviewed the existing labels of citation functions. More potential labels are obtained by enlarging the research scopes. The goal of this stage is to develop a final version of the annotation scheme for citation functions. The second stage is building classification models based on available handcrafted instances. This paper uses several classification scenarios to build these models. The first scenario is implemented using a classical deep learning method. Next, we apply non-contextual and contextual word embedding to cope with limited available data. Furthermore, a low-resource scenario is applied using an AL approach. Finally, the third stage is assigning labels to all instances using the best models resulting from the previous stage. Figure 1 depicts how our proposed dataset is developed.

### Annotation scheme development

The proposed annotation scheme for citation functions in this paper is developed by following several steps. First, we performed top-down and bottom-up analyses. The top-down analysis elaborates on the label definitions of existing schemes, i.e., background, usage, and comparison. In this analysis, the concept of background can be expanded by questioning what, why, when, and how. The usage can be expanded by categorizing its degree into inspired, uses method, or use data. The comparison can be elaborated using the similarity and difference between citing paper and cited paper. The bottom-up analysis is used to identify the citing sentence patterns in 5,668 random instances. This paper uses a dataset from well-parsed sentences from arXiv (Färber et al., 2018). We filtered sentences containing <DBLP>, <GC>, or <ARXIV> as targeted citing sentences. This process results in 1,840,815 citing sentences of 15,534,328 sentences. The final scheme consists of 5 coarse labels and 21 fine-grained labels shown in Table 3.
Citation scheme comparison

As part of scheme development, a label comparison is performed between our scheme and existing schemes. As mentioned before, the existing schemes consist of citation functions and argumentative structures. Through comparison, we show the compatibility and contribution of our proposed scheme. In Table 4, N/A marks indicate the newly proposed labels of our scheme that were not accommodated in existing works. The comparison reveals that our labels are partially and fully compatible with existing labels. However, there exist incompatibilities here. This is caused by the fact that argumentative labels are not naturally designed for citing sentences. For example, the label AIM in (Teufel et al., 1999) and (Teufel et al., 2009) is defined as a specific research goal or hypothesis of research papers. This label is commonly stated using ordinary sentences. Another example is the label Conclusion in (Liakata, 2010). This label makes a connection between the experimental results and research hypotheses. Sentences explaining this label naturally are not citing sentences. Furthermore, another reason for incompatibility is that labels in the argumentative structure can be represented using more than one sentence.

Annotation strategy

Annotation experiments are the last part of scheme development. Two CS master’s degree graduates (annotators) are used in the experiments. Several required resources for the experiments are annotation guidance and unlabeled citing sentence samples. In the guidance, there are annotation task explanations, label definitions, and annotation examples, as well as the guidance step-by-step annotation process, best practices, and annotation schedules. After training, each annotator was provided with an Excel sheet containing 421
Table 3  The proposed annotation scheme for citation functions in this paper

| Coarse labels | Fine-grained labels | Example of citing sentences |
|---------------|---------------------|-----------------------------|
| Background: describing the *citing sentences* referring to the theory, principle, concept, topic, problem, etc. from cited papers | *Definition*: explaining the definition of general theory, principle, concept, topic, problem, etc | Warped gps <citation> are an extension of gps that allows the learning of arbitrary mappings |
| | *Suggest*: giving the reader a suggestion to refer, see more detail, and explore other cited papers | For more details on these recurrent activation units, we refer the reader to <citation> |
| | *Judgment*: highlighting the positive/negative, useful/not-useful, etc. of concept, topic, problem, etc | The *n*-coalescent has some interesting statistical properties <citation> |
| | *Technical*: explaining how a theory, principle, concept, topic, problem, etc. is applied | An initial decoding is performed with a wfst decoder, using the architecture described in <citation> |
| | *Trend*: explaining the significance of the research topic, theory, principle, concept, topic, problem, etc | However, this coherence metric is widely used for the cs scenario due to its simplicity <citation> |
| Citing paper work: research that is proposed by the author | *Citing_paper_corroboration*: while proposing a research topic, citing paper cites cited paper | In this section, we define the smoothed analog of the worst-case class and the average-case class <citation> |
| | *Citing_paper_based_on*: stating that citing paper follow, consider, is built based on, inspired by the cited paper | To overcome the difficulty, we come up with an idea inspired by <citation> |
| | *Citing_paper_use*: citing paper use, implement, employ, or adopt the concept, dataset, technique, etc | For the simulation experiments, we use the conll data <citation> as annotated data for eight languages |
| | *Citing_paper_extend*: citing paper extends, adapts, improves, adds, or modifies the cited paper’s work | In this paper, we extend the results of pauly <citation> |
| | *Citing_paper_dominant*: The performance of citing paper outperforms cited paper’s performance | Our prednet model outperforms the model by <citation> |
| | *Citing_paper_future*: mentioning the plan of citing paper | To alleviate some of these limitations, we hope to explore near-touch sensors in the future <citation> |
| Coarse labels | Fine-grained labels | Example of citing sentences |
|---------------|---------------------|-----------------------------|
| Cited paper work: what is done by cited papers | Cited_paper_propose: describing the proposed research by cited paper | In <citation> the authors propose a model for storing and using infrared images |
| | Cited_paper_success: highlighting the success of cited paper | Recently, li <citation> successfully use cnn on re-id to extract an effective feature representation |
| | Cited_paper_weakness: highlighting the weakness of cited paper | the limitation of <citation> is that the traffic is assumed to be always cross-directional |
| | Cited_paper_result: describing the result of cited paper (neutral) | However, <citation> reported that users could read text easily on a target of approximately 2 to 3 mm |
| | Cited_paper_dominant: stating the superiority of cited paper compared to citing paper | For market-1501 dataset, a recent metric learning approach <citation> outperforms ours |
| Compare and contrast: Compare and contrast is performed between citing papers and cited papers | Compare: describing the similarity between citing papers and cited papers | The bhlt algorithm <citation> is closely related to our work |
| | Contrast: describing the differences between Citing papers and cited papers | Unlike <citation> that retains cd, we adopted nce as the basic learning strategy |
| Other: This label is prepared for citing sentences that do not match the above criteria | Other_cited_paper_comparison: comparison between cited papers (whether similarities or differences between them) | Table compares the computational complexity of the proposed method with aog <citation> and ncte <citation> |
| | Other_multiple_intent: citing sentences have two or more citation marks for different intents | in <citation>, the mtd system is modeled as a game called pladd, based on flipit games <citation> |
| | Other_other: This label is designed for citing sentences that do not meet all label categories described above | c++ in ilog solver <citation> or java in gecode/j <citation>) and even term rewriting <citation> |
| Fine-grained classes of our scheme | Citation function-focused existing works | Argumentative-focused existing works |
|-----------------------------------|------------------------------------------|-------------------------------------|
|                                   | Fully related label | Partially related label | Fully related label | Partially related label |
| Definition                         | N/A                      | Dong and Schäfer (2011): background; Jurgens et al. (2018): background; Zhao et al. (2019): introduce; Cohan et al. (2019): background; Pride and Knoth (2020): background; Roman et al. (2021): background | N/A                          | Teufel et al. (1999): background; Fisas et al. (2015): background; Liakata (2010): background |
| Suggest                           | N/A                      | N/A                                    | N/A                          | N/A                          |
| Judgment                           | N/A                      | Zhao et al. (2019): introduce; Cohan et al. (2019): background; Pride and Knoth (2020): background; Roman et al. (2021): background | N/A                          | N/A                          |
| Technical                          | N/A                      | N/A                                    | N/A                          | N/A                          |
| Trend                              | N/A                      | N/A                                    | N/A                          | N/A                          |
| Citing_paper_corroboration         | Hernández-Álvarez et al. (2016): corroboration | N/A                                    | N/A                          | N/A                          |
| Citing_paper_based_on              | Pride and Knoth (2020): motivation; Teufel et al. (2006): Pb; Dong and Schäfer (2011): fundamental idea; Li et al. (2013): based_on | Su et al. (2019): positive, Casey et al. (2019): A-CW-BUILD; Li et al. (2013): corroboration; Li et al. (2013): discover | N/A                          | Teufel et al. (1999): basis; Teufel et al. (2009): support; Fisas et al. (2015): approach |
| Fine-grained classes of our scheme | Citation function-focused existing works | Argumentative-focused existing works |
|-----------------------------------|----------------------------------------|-------------------------------------|
|                                   | Fully related label | Partially related label | Fully related label | Partially related label |
| Citing_paper_use                  | Pride and Knoth (2020): use; Tuarob et al. (2019): use, extend; Teufel et al. (2006): puse; Dong and Schäfer (2011): technical basis; Hernández-Álvarez et al. (2016): based-on, supply; Jurgens et al. (2018): uses; Bakhti et al. (2018): useful; Rachman et al. (2019): useModel, useTool, useData; Zhao et al. (2019): use; Cohan et al. (2019): method | Valenzuela et al. (2015): using the work; Su et al. (2019): positive; Casey et al. (2019): A-CW-BUILD | Teufel et al. (2009): Use | Teufel et al. (1999): basis; Fisas et al. (2015): approach |
| Citing_paper_extend              | Pride and Knoth (2020): extension; Teufel et al. (2006): Pmodi; Valenzuela et al. (2015): extending the work; Zhao et al. (2019): extent; Jurgens et al. (2018): extension/continuation | N/A | N/A |
| Citing_paper_dominant            | Teufel et al. (2006): CoCo | Su et al. (2019): compare and contrast | Teufel et al. (2009): ANTISUPP; Liakata (2010): method-new-advantage | Teufel et al. (2009): NOV_ADV; Fisas et al. (2015): outcome, outcome-contribution; Liakata (2010): result |
| Citing_paper_future              | Pride and Knoth (2020): future | N/A | Teufel et al. (2009): FUT; Fisas et al. (2015): future work | N/A |
## Table 4 (continued)

| Fine-grained classes of our scheme | Citation function-focused existing works | Argumentative-focused existing works |
|-----------------------------------|------------------------------------------|-------------------------------------|
|                                   | Fully related label | Partially related label | Fully related label | Partially related label |
| Cited_paper_propose               | N/A | Valenzuela et al. (2015): related work; Hernández-Álvarez et al. (2016): acknowledge; Casey et al. (2019): CW-DESC | N/A | Teufel et al. (1999): other; Liakata (2010): method-old |
| Cited_paper_success               | Casey et al. (2019): CW-EVAL-P; Li et al. (2013): positive | N/A | Teufel et al. (2010): other; Teufel et al. (2009): OTHR; |
| Cited_paper_weakness              | Teufel et al. (2006): weak; Hernández-Álvarez et al. (2016): weakness, hedges; Su et al. (2019): weakness; Rachman et al. (2019): problem; Li et al. (2013): negative | Roman et al. (2021): result | (Liakata 2010): method-old-disadvantage | Teufel et al. (1999): other; Teufel et al. (2009): GAP_WEAK; |
| Cited_paper_result                | N/A | Roman et al. (2021): result | N/A | Teufel et al. (1999): other; |
| Cited_paper_dominant compare      | N/A | Dong and Schäfer (2011): comparison, Valenzuela et al. (2015): comparison | N/A | Teufel et al. (1999): contrast; Teufel et al. (2009): CODI |
| Contrast                          | Pride and Knoth (2020): contrast; Teufel et al. (2006): CoCoGM, CoCoR0; Hernández-Álvarez et al. (2016): contrast; Bakhti et al. (2018): contrast | Zhao et al. (2019): compare, Cohan et al. (2019): result comparison | Su et al. (2019): compare and contrast | N/A |
| Other_multiple_intent             | N/A | N/A | N/A | N/A |
| Fine-grained classes of our scheme | Citation function-focused existing works | Argumentative-focused existing works |
|-----------------------------------|----------------------------------------|--------------------------------------|
|                                   | Fully related label | Partially related label | Fully related label | Partially related label |
| Other_cited_paper_comparison      | Teufel et al. (2006): CoCoXY; Casey et al. (2019): CW-COMP; Li et al. (2013): contrast | Valenzuela et al. (2015): comparison | N/A | N/A |
| Other_other                       | Li et al. (2013): neutral Teufel et al. (2006): Neutral | Bakhti et al. (2018): neutral Su et al. (2019): neutral | N/A | N/A |
instances to be labeled. We used Inter-annotator Agreement and Kappa values (Cohen, 1960) to validate the annotation results. The Kappa is categorized into several ranges: 0.01–0.20 is stated as slight agreement, 0.21–0.40 as fair agreement, 0.41–0.60 as moderate agreement, 0.61–0.80 as substantial agreement, and 0.81–1.00 as almost perfect (Wang et al., 2019).

**Text classification strategy**

Text classification strategies contain two stages, i.e., filtering stages and fine-grained classification. The filtering stage eliminates three fine-grained instances belonging to the coarse label other. The fine-grained classification is used to categorize 18 detailed labels. These two stages are applied to a dataset containing manually labeled 5668 instances. Here, we evaluate four classification approaches. First, three classical approaches, namely Logistic Regression, Support Vector Machine (SVM), and Naïve Bayes are used as a baseline system. Then, LSTM is our deep learning method. Considering the few numbers of labeled instances, it is worth applying pretrained word embeddings. We implement two contextual models, i.e., BERT (Devlin et al., 2019) and SciBERT (Beltagy et al., 2019), and three non-contextual models, i.e., fasttext (Bojanowski et al., 2017), word2vec (Mikolov et al., 2013), and glove (Pennington et al., 2014). Note that the non-contextual models’ implementations are combined with LSTM. The labeled dataset is divided into training, development, and testing with 80%, 10%, and 10% proportions, respectively. Deep learning approaches are implemented with Keras API, whereas BERT and SciBERT are built using the ktrain python library. The best learning rates were obtained during the experiment with a range of $10^{-5}$ to $50^{-5}$, batch sizes of 32 and 64, and dataset balance or imbalance. The best epoch was specified using early stops by keeping the best model based on validation instances. Regarding the imbalance problem, we use class_weight parameter to address this issue. This parameter is applied by multiplying the proportion of minority class to make the distribution of all classes relatively balanced and force to assign higher values to the loss function. Figure 2 depicts the distribution of the development dataset for all classification strategies.

**Active learning strategy**

Active learning (AL) is subfield of Machine Learning which allows the algorithm to choose to the data from which it learns (Settles, 2010). This method is motivated by existing problems faced by machine learning where the huge unlabeled data is easily obtained but the labels are expensive and time-consuming. The AL argues that the algorithm will perform better using less data because the mechanism for asking queries to the oracle (human annotator) to label the unlabeled instances. The implementation of the AL is conducted by using scenarios in which the learner asks queries. Figure 3 shows the pool-based scenario as the most common scenario of the AL. Lewis and Gale, (1994) define the pool-based AL by assuming there is small set of labeled data $L$ and a large pool of unlabeled data $U$. The instances are selected from the pool by considering several informativeness measures. Technically, the most informative instances will be labeled by the oracle.

The mechanism to select the most informative instances is called query strategy. The most popular and simplest method of query strategy is uncertainty sampling (Lewis &
Gale, 1994) that an instance will be selected when it has the least certain how to label. The uncertainty sampling can be implemented through these sampling variants, by denoting the $x^*_A$ is the most informative instance based on selection method (Settles, 2010):

- **Least confident**
  This is the general uncertainty sampling strategy. Here, the instance will be selected if they have the least confidence in its most likely label. Here, the $\hat{y}$ is the class label having the highest posterior probability of the model $\theta$.
  \[
  x_{LC}^* = \arg\max_x 1 - P_\theta(\hat{y}|x)
  \]

![Fig. 3 Pool-based active learning scenario (Settles, 2010)](image-url)
• **Margin sampling**

Addressing the drawback of the least confident strategy that considering only the most probable label, the margin sampling selects the instance that has the smallest difference between the most and the second most probable labels. The margin sampling is defined as follows (Scheffer et al., 2001):

\[ x^*_M = \arg\min_x P_\theta(\hat{y}_1|x) - P_\theta(\hat{y}_2|x) \]

• **Entropy**

This is the most popular uncertainty sampling strategy that works by utilizing all label probabilities (\(y_i\)). Entropy works by using the following formula (Shannon, 1948) to each instance and the instance having the highest value will be queried.

\[ x^*_H = \arg\max_x - \sum_i P_\theta(y_i|x) \log P_\theta(y_i|x) \]

AL has been successfully used to reduce the manual labeling effort. This paper implements the pool-based AL strategy using a batch mode as illustrated in Fig. 4. Using BERT and SciBERT, AL is used in the filtering and fine-grained stages. The filtering stage selects seed \(L\) from 10% of training instances, whereas the fine-grained stage selects 20% for initial seed \(L\) training. The difference in seed proportion is caused by two factors, i.e., the number of available datasets and the number of labels in each stage. The rest of the unlabeled instances \(U\) will be used later in AL iterations. The AL strategy is designed to run in 20 iterations. The pretrained word embeddings are trained on seed \(L\). In each iteration, the AL strategy selects a batch consisting of 50 unlabeled instances from \(U\) and added them to \(L\) with their real labels. This means that there are 1000 new instances from \(U\) that are gradually added to \(L\). For batch selection, we compare three sampling approaches, i.e., least confident, max-margin, and entropy. Note that this paper follows the AL strategy proposed by (Ein-Dor et al., 2020; Hu et al.,

![Fig. 4 Pool-based active learning used in this paper, modified from (Settles, 2010)](image-url)
that fine-tuning is performed from scratch in each iteration to prevent overfitting data from previous rounds. The best parameters from a non-AL strategy will be used in the AL experiments.

**Statistically significant test**

Since this paper implements two classification scenarios, i.e., non-AL and AL, we computed the significance of achieved performances. The McNemar’s test (McNemar, 1947) is a statistical test for checking the significance of the difference of paired nominal data. In the case of machine learning, the McNemar’s test is used to compare two classifier performances by creating a $2 \times 2$ contingency table.

According to Table 5, the test statistic is calculated as follows:

$$X^2 = \frac{(b - c)^2}{(b + c)}$$

Under the null hypothesis where none of the compared classifiers perform better than the other, the test statistic $X^2$ should be a small value. The high value of $X^2$ indicate that there is an option to reject the null hypothesis. In addition, we need to specify the common significant threshold by 0.05 and then compute the $p$-value. If the $p$-value is larger than the threshold, then it is called *Fail to Reject Null Hypothesis* which means that none of the compared classifiers perform better than the other. In contrast, if the $p$-value is lower than the threshold, we can *Reject Null Hypothesis* because the two compared classifiers are significantly different. The $p$-value is calculated as follows:

$$p - value = 1 - cdf\left(X^2\right)$$

where $cdf$ is cumulative distribution function of the *chi-squared* distribution with 1 degree of freedom.
Table 7  Confusion matrix for Inter-annotator Agreement on fine-grained labels

|                | Definition | Suggest | Judgment | Technical | Trend | Citing_paper_corroboration | Citing_paper_based_on | Citing_paper_use | Citing_paper_extend | Citing_paper_future | Cited_paper_propose | Cited_paper_success | Cited_paper_weakness | Cited_paper_result | Cited_paper_dominant | Compare | Contrast | Multiple_intent | Cited_paper_comparison | Other_other |
|----------------|------------|---------|----------|-----------|-------|-----------------------------|-----------------------|-------------------|---------------------|---------------------|---------------------|---------------------|----------------------|---------------------|---------------------|-------------------|----------|----------|---------------|----------------------------|------------|
| Definition      | 16         | 4       | 0        | 1         | 0     | 0                           | 0                     | 0     | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 1                   | 0       | 0        | 0             | 0                                         | 0          |
| Suggest        | 0          | 21      | 2        | 0         | 1     | 0                           | 0                     | 0     | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0       | 0        | 0             | 0                                         | 0          |
| Judgment        | 1          | 1       | 12       | 5         | 0     | 0                           | 0                     | 0     | 0                   | 0                   | 0                   | 0                   | 0                   | 1                   | 1                   | 0                   | 0       | 0        | 0             | 0                                         | 0          |
| Technical       | 2          | 1       | 0        | 10        | 0     | 0                           | 0                     | 0     | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0       | 0        | 0             | 0                                         | 0          |
| Trend           | 1          | 0       | 3        | 13        | 1     | 0                           | 0                     | 0     | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0                   | 0       | 0        | 0             | 0                                         | 0          |
| Citing_paper_corroboration | 0 | 0 | 0 | 0 | 3 | 5 | 3 | 8 | 1 | 0 | 0 | 1 | 1 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| Citing_paper_based_on | 0 | 0 | 0 | 0 | 0 | 18 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Citing_paper_use | 0 | 1 | 0 | 0 | 1 | 11 | 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Citing_paper_extend | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Citing_paper_dominant | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Citing_paper_future | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Note: The table entries represent the number of agreements between annotators for each label.
| Table 7 (continued) | Definition | Suggestion | Judgment | Technical | Trend | Citing_paper_corroboration | Citing_paper_based_on | Citing_paper_use | Citing_paper_extend | Citing_paper_future | Cited_paper_propose | Cited_paper_success | Cited_paper_weakness | Cited_paper_result | Cited_paper_dominant | Compare | Contrast | Multiple_intent | Cited_paper_comparison |
|---------------------|------------|------------|----------|-----------|-------|---------------------------|----------------------|------------------|-------------------|-------------------|-------------------|---------------------|----------------------|------------------|-------------------|--------------------------|----------------------|
| Cited_paper_propose | 0          | 1          | 0        | 0         | 0     | 0                         | 0                    | 0                | 0                 | 0                 | 0                 | 0                   | 0                    | 0                | 0                 | 0                        | 0                    |
| Cited_paper_success | 0          | 0          | 0        | 0         | 0     | 0                         | 0                    | 0                | 0                 | 0                 | 1                 | 0                   | 0                    | 0                | 0                 | 0                        | 0                    |
| Cited_paper_weakness| 0          | 0          | 0        | 0         | 0     | 0                         | 0                    | 0                | 0                 | 0                 | 0                 | 0                   | 0                    | 0                | 0                 | 0                        | 0                    |
| Cited_paper_result  | 0          | 0          | 0        | 0         | 0     | 0                         | 0                    | 0                | 0                 | 0                 | 0                 | 0                   | 0                    | 0                | 0                 | 0                        | 0                    |
| Cited_paper_dominant| 0          | 0          | 0        | 0         | 0     | 0                         | 0                    | 0                | 0                 | 0                 | 1                 | 0                   | 0                    | 0                | 0                 | 0                        | 0                    |
| Compare             | 0          | 0          | 0        | 0         | 0     | 0                         | 1                    | 0                | 0                 | 0                 | 0                 | 0                   | 0                    | 0                | 0                 | 0                        | 0                    |
| Contrast            | 0          | 0          | 0        | 0         | 0     | 0                         | 0                    | 1                | 0                 | 1                 | 0                 | 1                   | 1                    | 0                | 0                 | 0                        | 0                    |
| Multiple_intent     | 0          | 0          | 0        | 0         | 0     | 0                         | 0                    | 0                | 0                 | 0                 | 0                 | 0                   | 0                    | 0                | 0                 | 0                        | 0                    |
| Cited_paper_comparison | 0       | 1          | 0        | 0         | 0     | 0                         | 0                    | 0                | 0                 | 0                 | 0                 | 0                   | 0                    | 1                | 2                 | 0                        | 0                    |
|                      | Definition | Suggest | Judgment | Technical | Trend | Citing_paper_corroboration | Citing_paper_based_on | Citing_paper_use | Citing_paper_extend | Citing_paper_future | Cited_paper_propose | Cited_paper_success | Cited_paper_weakness | Cited_paper_result | Cited_paper_dominant | Compare | Contrast | Multiple_intent | Cited_paper_dominant | Cited_paper_comparison | Other_other |
|----------------------|------------|---------|----------|-----------|-------|----------------------------|----------------------|------------------|-------------------|------------------|-------------------|-------------------|--------------------|------------------|------------------|--------------------|-------------------|---------------------|-----------|
| Other other          | 0          | 2       | 1        | 2         | 0     | 0                           | 0                    | 0                | 0                 | 0                | 0                 | 0                 | 0                  | 2                | 0                | 0                 | 1                 | 0                   | 0         |
Experiment results

This section shows the result of the annotation experiments and text classification experiments.

Annotation experiment results

The annotation experiment results contain raw agreement and Kappa values. The confusion matrix in Tables 6 and 7 show raw agreements between annotators. The diagonal bold values in the confusion matrices indicate the number of agreed instances between annotators. The raw agreements reached 88.59% (373 agreed instances) and 72.55% (305 agreed instances) for coarse and fine-grained labels, respectively. Citing paper work achieved the highest percentage of 30.56% in the coarse level, followed by background with 25.20% and then cited paper work with 24.93%. The two labels with the lowest percentage are other label with 10.19% and compare and contrast label with 9.12%. The fine-grained agreements show fairer results since each label has a relatively equal number of samples. The highest percentage in the fine-grained level was achieved by suggest with 6.89%. Next, citing_paper_corroboration and other had the two lowest percentages of 1.64% and 0.33%, respectively. The Kappa statistic on coarse labels reached 0.85 and 0.71 for the fine-grained label. The results are considered as nearly perfect and substantial agreement.

Considering the number of labels in our scheme, the obtained Kappa values are competitive compared with previous works, e.g., (Casey et al., 2019) with 0.77, (Teufel et al., 2006) with 0.72, (Dong & Schäfer, 2011) with 0.757, and (Zhao et al., 2019) with 0.47.

We highlight several sources of disagreement between annotators. The highest number of disagreements in the coarse labels occurred in 6 instances where annotator I (x-axis) predicted as background label and annotator II (x-axis) predicted as other label. The annotators have an issue to identify the motivation behind the background label through its fine-grained labels and understanding the motivation behind other labels. Focusing on the total of miss-categorized instances by each annotator, there were 15 instances labeled by annotator I and 16 instances labeled by annotator II. On the fine-grained labels, the highest disagreement happened on 8 instances where annotator I labeled as citing_paper_use and

| Methods                  | Accuracy | Macro avg precision | Macro avg recall | Macro avg f1 |
|--------------------------|----------|---------------------|------------------|--------------|
| SVM                      | 85.71    | 82.88               | 52.28            | 50.62        |
| Naïve Bayes              | 85.19    | 42.59               | 50.00            | 46.00        |
| Logistic regression      | 85.19    | 70.48               | 69.67            | 70.06        |
| LSTM + embedding layer   | 84.66    | 50.18               | 52.62            | 46.96        |
| LSTM + word2vec          | 85.19    | 50.00               | 42.59            | 46.00        |
| LSTM + fasttext          | 85.19    | 50.00               | 42.59            | 46.00        |
| LSTM + glove             | 85.36    | 50.60               | 92.67            | 47.22        |
| BERT                     | **90.12**| 71.58               | **85.15**        | 75.99        |
| SciBERT                  | **90.12**| **74.53**           | 82.72            | **77.73**    |
In this case, both labels are part of the coarse label citing paper work and our analysis shows that the disagreement on both labels occurred in ambiguous instances. To handle this, the annotation guidelines, including the labeling example, need to be improved to solve the ambiguous instances.

**Filtering stage result**

In Table 8, we show performance metrics of classification experiments without AL. Focusing on accuracy, the experiments demonstrated that contextual word embeddings, i.e., BERT and SciBERT, shared the highest performances of 90.12%. However, the SciBERT achieved higher macro avg f1 by 77.73% compared with BERT which was

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**Table 9** The hyperparameter settings were used in the filtering stage

| Techniques       | Parameters                                                                 |
|------------------|----------------------------------------------------------------------------|
| SVM              | ngram_range: (1, 2); imbalance; TF/IDF; kernel = linear                   |
| Naïve Bayes      | ngram_range: (1, 2); imbalance; TF/IDF                                     |
| Logistic regression | C: 1; penalty = 1; ngram_range: (1, 1); imbalance; solver = liblinear     |
| LSTM + embedding layer | optimizer = adam; loss = binary_crossentropy; epoch 5; batch 32; imbalance |
| LSTM + word2vec  | optimizer = adam; loss = binary_crossentropy; epoch 5; batch 32; imbalance |
| LSTM + glove     | optimizer = adam; loss = binary_crossentropy; epoch 7; batch 32; imbalance |
| LSTM + fasttext  | optimizer = adam; loss = binary_crossentropy; epoch 5; batch 32; imbalance |
| BERT             | $2 \times 10^{-5}$; batch 64; imbalance                                   |
| SciBERT          | $3 \times 10^{-5}$; batch 32; balance                                      |

---

Fig. 5 The performance metrics of individual class in the filtering stage. The x-axis depicts the classes and their performance metrics, and the y-axis depicts the performance values.
only 75.99%. Notably, classical classifiers achieved almost similar accuracies of 85%. But if we look at the macro avg f1, the Logistic Regression reached the highest value by 70.06% among three baseliners. Following this, three non-contextual word embeddings, i.e., word2vec, fasttext, glove, depicted nearly equal accuracies and macro avg precision. But, for macro avg recall and macro avg f1, the glove achieved higher values by 85.15% and 75.99%. Among all methods, the embedding layer showed the poorest performance in all metrics. Table 9 depicts the parameters used in the filtering stage.

Looking at the performance of each label in Fig. 5, all performance metrics in the noother label are lower than other label. There are extreme cases where the noother

| Methods                  | Accuracy | Macro avg precision | Macro avg recall | Macro avg f1 |
|--------------------------|----------|---------------------|------------------|--------------|
| SVM                      | 67.29    | 75.57               | 66.79            | 68.49        |
| Naïve Bayes              | 57.55    | 74.06               | 50.94            | 52.87        |
| Logistic regression      | 69.98    | 71.87               | 70.23            | 70.53        |
| LSTM + embedding Layer   | 13.87    | 10.22               | 8.09             | 6.02         |
| LSTM + word2vec          | 10.97    | 7.73                | 2.29             | 3.45         |
| LSTM + fasttext          | 14.49    | 10.02               | 4.89             | 5.75         |
| LSTM + glove             | 14.49    | 10.23               | 4.99             | 6.00         |
| BERT                     | 80.95    | 80.98               | 82.40            | 81.06        |
| SciBERT                  | **83.64**| **83.46**           | **85.35**        | **84.07**    |

Bold values show the best result in each performance metric. All metrics are measured by percentage (%).
label has zero values as in Naïve Bayes, word2vec, and fasttext. Two methods, BERT and SciBERT, relatively have balanced proportions compared with other methods.

**Fine-grained stage result**

As predicted, the performance in this stage will be lower than that in the filtering stage. Table 10 shows that there are performance gaps between contextual word embedding and other approaches. The SciBERT showed its superiority compared with other approaches in all metrics. Here, the three non-contextual word embeddings and embedding layers produced the lowest performances below 10% of accuracies and below 10% of macro avg f1. Looking at the baseliners, the best results were achieved by Logistic Regression by around 70% of all metrics. If we look at the individual performance, four approaches i.e., embedding layer, word2vec, fasttext, and glove show poor results (Fig. 6). Here, the three baseline approaches show better performances but still underperform the results from BERT and SciBERT.

All parameter settings in this stage are shown in Table 11. The full performance comparison of BERT and SciBERT in the filtering and fine-grained stages is shown in Fig. 7.

**Active learning results**

The experiments were performed using the best parameters from the non-AL results. The filtering experiment used several parameters, i.e., learning rate of $2 \times 10^{-5}$, batch size of 64, and imbalanced distribution in the BERT-based AL. For the SciBERT experiments, the best parameters were learning rate of $3 \times 10^{-5}$, batch size of 32, and balance distribution. BERT-based fine-grained experiment implemented the AL strategies based on learning rate of $3 \times 10^{-5}$, batch size of 32, and imbalanced distribution. For SciBERT, the parameters used were learning rate of $3 \times 10^{-5}$, batch size of 32, and balanced distribution.

| Techniques          | Parameters                                                                                                                                 |
|---------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| SVM                 | ngram_range: (1, 2); TF/IDF; imbalance; kernel = linear;                                                                                   |
| Naïve Bayes         | ngram_range: (1, 2); bag of word; imbalance;                                                                                              |
| Logistic regression | C: 1; penalty: 11; ngram_range: (1, 2); TF/IDF; imbalance; solver = 'liblinear'                                                           |
| LSTM + embedding layer | epoch 3; batch 32; imbalance; optimizer = adam; loss = categorical_crossentropy;                                                           |
| LSTM + word2vec     | epoch 7; batch 32; balance; optimizer = adam; loss = categorical_crossentropy;                                                           |
| LSTM + glove        | epoch 7; batch 32; imbalance; optimizer = adam; loss = categorical_crossentropy;                                                           |
| LSTM + fasttext     | epoch 7; batch 32; imbalance; optimizer = adam; loss = categorical_crossentropy;                                                           |
| BERT                | $3 \times 10^{-5}$; batch 32; imbalance                                                                                                   |
| SciBERT             | $3 \times 10^{-5}$; batch 32; balance                                                                                                     |
Filtering stage results

AL-based performance in the filtering stage is depicted in Table 12. BERT combined with least confident achieved the highest accuracy with 90.29% in the filtering stage. To obtain this result, the AL strategy requires 1,000 queried instances for training. While entropy used 500 queried instances to obtain 88.88% accuracy, max-margin required 450 queried instances to reach 88.71% accuracy. At this stage, the best accuracy reached by SciBERT was 89.59% when integrated with entropy on 850 queried instances. Integrating SciBERT with max-margin and least confident demonstrated the same accuracy of 88.88%, although they need different queried instances, 900 for max-margin and
800 for least confident. The random sampling reached the lowest accuracy of 88.35% when the AL was combined with BERT but achieved the second-highest performance by 89.41% in the SciBERT setting. In summary, the AL strategy outperformed the best result from the classification strategy without AL on the entire training instances, especially when integrating BERT with least confident and using smaller training instances. The detailed AL results for the filtering stage are shown in Fig. 8.

As the AL-based strategy in the filtering stage achieved slightly higher accuracy (90.29%) compared to the non-AL strategy (90.12%), we conducted a statistically
significant test based on the McNemar approach. Unfortunately, the accuracy achieved using the AL strategy failed to show its significance by producing a $p$-value of 0.73. Instead of relying only on accuracy, we measured alternative metrics as shown in Table 13 as performed in the non-AL setting. Even failed to reject the null hypothesis, we are still able to justify that the AL strategy achieved a better macro avg f1 of 78.89% compared to the best results in the filtering stage by 77.73% using SciBERT.

### Table 14

The best result of fine-grained AL strategies, and the bold value indicates the highest accuracy among others

| Classification strategies | Max_margin | Entropy | Least_confident | Random_sampling |
|---------------------------|------------|---------|-----------------|-----------------|
| BERT                      | 850 79.08  | 1,000 80.95 | 700 79.71 | 650 79.91 |
| SciBERT                   | 850 80.33  | 850 **81.15** | 600 **81.15** | 700 80.12 |

**Fig. 9** Result comparison of AL strategies for fine-grained classification using BERT and SciBERT with four sampling approaches. The data splitting scenario is 1039 (testing), 3858 (simulating $L$ and $U$), and 771 (seed)
Fine-grained results

The AL-based performance in fine-grained classification is depicted in Table 14. The highest accuracy of 81.15% was achieved by two AL settings, namely combining SciBERT with entropy-based sampling using 850 queries and combining SciBERT with least_confident sampling using 600 instances. Using another sampling technique, i.e., max-margin, the AL strategies reached maximum accuracy of 80.33% on 850 queried instances. At this stage, the maximum accuracy obtained by combining BERT and AL was 80.95% on 1000 queried instances. Other sampling methods only reached 79.08%, 79.71%, 79.91% on max-margin, least_confident, and random sampling, respectively. The detailed AL results for fine-grained classification are shown in Fig. 9.

AL-based strategy in the fine-grained stage achieved slightly lower accuracy (81.15%) compared to the non-AL strategy (83.64%). As in the filtering stage, the significant test conducted in the fine-grained stage compared these two accuracies. The test demonstrated that the accuracy was significantly different with a p-value of 0.011. Considering more detailed performances, the AL strategy obtained lower results in all metrics compared to the non-AL strategy, as shown in Table 15.

Here, the AL strategies required fewer instances (less than half of the total dataset) for the training process to achieve competitive accuracy in the fine-grained stage and slightly higher accuracy in the filtering stage. This proves two aspects. Firstly, not all instances in the dataset do not share the same contribution toward performance, and secondly, keeping the role of humans in the loop of machine learning using fewer instances will make better judgments than entirely processed datasets by machine learning. Focusing on query strategy, the least_confident delivered the best performances compared with other methods.

Another point worth mentioning is that the random sampling strategy reached competitive accuracies in the filtering stage when combined with SciBERT and in the fine-grained stage when combined with BERT. In this setting, the random sampling slightly outperformed least_confident as the best method in overall scenarios. However, even though it has smallest accuracies compared with all other strategies in another setting, the performances of unbiased instance selection performed by random sampling can be used to generalize the performances when using the whole dataset.

Finally, we use the best models to classify unlabeled citing sentences. Table 16 shows the label distribution in the dataset. cited_paper_propose has the highest distribution both in the cited_paper_work category and the entire dataset by 243,031 instances, whereas citing_paper_future has the lowest instance distribution by 5439. The most interesting point is that there is consistency in the highest distribution in each coarse category in the development dataset with manual labeling (See Fig. 2) and the final dataset, e.g., judgment for background class, citing_paper_use for the citing_paper_work class, cited_paper_propose for the cited_paper_work class, and compare for the compare and contrast class.
Conclusion and future work

This paper developed a dataset of citation functions consisting of 1,840,815 labeled instances. The dataset was built using a semiautomatic approach. Specifically, we trained machine learning models on manually labeled data and use these models to label unlabeled instances. Our scheme was developed through top-down analysis, bottom-up analysis, and annotation experiments. Besides our competitive Kappa results, several findings were identified during the experiments. First, assigning coarse labels first helped annotators select appropriate fine-grained labels. Second, annotation guidance needs to be upgraded to handle ambiguous instances. Third, the proposed scheme is compatible with well-known papers’ argumentative structures.

The classification experiments have shown that BERT and SciBERT achieved higher accuracies than other methods. In addition, these two methods achieved promising results using AL on less than half of the training data. SciBERT consistently outperformed BERT in the fine-grained stage in both AL and non-AL settings. However, BERT outperformed SciBERT in the filtering stage using AL. Note that there is a consistent label distribution between the initial and final datasets.

Table 16 The distribution of our new dataset of citation function. The bold values indicate the fine-grained labels which have the highest number of instances in each coarse category

| Filtering stage | Instance distribution | Coarse label | Fine-grained labels | Instance distribution |
|-----------------|-----------------------|--------------|---------------------|-----------------------|
| No-other        | 1,328,985             | Background   | Definition          | 55,508                |
|                 |                       |              | Suggest             | 51,987                |
|                 |                       |              | **Judgment**        | 215,428               |
|                 |                       |              | Technical           | 85,374                |
|                 |                       |              | Trend               | 66,594                |
| Citing paper work |                    | Citing_paper_corroboration | 113,488            |
|                 |                       |              | Citing_paper_based_on | 55,878               |
|                 |                       |              | **Citing_paper_use** | 115,215              |
|                 |                       |              | Citing_paper_extend | 28,779                |
|                 |                       |              | Citing_paper_dominant | 24,823               |
|                 |                       |              | Citing_paper_future | 5,439                 |
| Cited paper work |                    | **Cited_paper_propose** | 243,031            |
|                 |                       |              | Cited_paper_success | 34,505                |
|                 |                       |              | Cited_paper_weakness | 15,054                |
|                 |                       |              | Cited_paper_result | 154,394               |
|                 |                       |              | Cited_paper_dominant | 3,215                 |
| Compare and contrast |                | **Compare** | 39,364             |
|                 |                       |              | Contrast            | 20,909                |
| Other           | 511,830               | Other        | Other               | 511,830               |
| Total instances |                       |              |                     | 1,840,815             |
The limitation of this paper is the labels of citation functions are determined using only citing sentences themselves, without considering the surrounding sentences. These sentences will be useful during the manual labeling stage, especially when deciding on the labels of ambiguous samples. In future work, we plan to extract sentences before and after the citing sentences using the window sizes of two. Not only useful for judging labels of difficult samples, but this information is also important as classification features. Another potential research direction is to investigate the possibilities of applying our scheme of citation functions to other research areas through domain adaptation. In this case, domain adaptation becomes a potential method since creating entirely new training data on target domains is expensive, time-consuming, and needs massive human efforts.

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