Automatic Approach for Building Dataset of Citation Functions for COVID-19 Academic Papers

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Abstract
This paper develops a new dataset of citation functions of COVID-19-related academic papers. Because the preparation of new labels of citation functions and building a new dataset requires much human effort and is time-consuming, this paper uses our previous citation functions that were built for the Computer Science (CS) domain, which consists of five coarse-grained labels and 21 fine-grained labels. This paper uses the COVID-19 Open Research Dataset (CORD-19) and extracts 99.6k random citing sentences from 10.1k papers. These citing sentences are categorized using the classification models built from the CS domain. The manually check on 475 random samples resulted accuracies of 76.6% and 70.2% on coarse-grained labels and fine-grained labels, respectively. The evaluation reveals three findings. First, two fine-grained labels experienced meaning shift while retaining the same idea. Second, the COVID-19 domain is dominated by statements highlighting the importance, cruciality, usefulness, benefit, consideration, etc. of certain topics for making sensible argumentation. Third, discussing State of The Arts (SOTA) in terms of their outperforming previous works in the COVID-19 domain is less popular compared to the CS domain. Our results will be used for further dataset development by classifying citing sentences in all papers from CORD-19.

Keywords: citation function, citing sentence, COVID-19, state of the art.

1. Introduction
 Citation functions represent the reason why authors of academic papers cite previous works. Valenzuela et al. (2015) stated that the citations should not be treated equally. This is because citations indicate different roles, e.g., introducing the background, comparing and contrasting between studies, using or extending of existing methods, criticizing the previous works, etc. The existence of citations plays an important role in the preparation of a research manuscript since it helps the authors understand the big picture of a topic (Qayyum & Afzal, 2018), position their proposed research in the broad literature (Lin & Sui, 2020), and show their research novelty (Tahamtan & Bornmann, 2019). Moreover, citations can indicate the quality of proposed research (Casey et al., 2019; Raamkumar et al., 2016). Therefore, providing appropriate citations requires serious attention to support research dissemination.

There is a continuous development in designing labels for Rhetorical Structures (RS) and building datasets in the medical domain. Existing works have designed RS and developed the dataset (Aliheedi et al., 2019; Dayrell et al., 2012; Dernoncourt & Lee, 2017; Green, 2015; Jia, 2018; Kim et al., 2011; Liakata, 2010; Shatkay et al., 2008; Wilbur et al., 2006). However, several issues appear in these works. The first issue is that not all these RS were developed based on full text papers; several works built the RS using only papers’ abstracts. The second issue is that most of the RS were not specifically designed for citing sentences (i.e., sentences which contain citation marks). Since the existing RS covers both citing sentences and non-citing sentences, the number of labels is considered small, which causes several potential missing citation functions being accommodated—the last issue. Moreover, due to the COVID-19 pandemic, the number of published papers covering this topic has significantly increased. Existing RS is not designed specifically for this purpose, and this has become an additional issue. Considering this, we aim to develop a new dataset of citation functions that contains more detailed labels, covers full text papers, and is specific for the COVID-19 domain.

Designing new labels of citation functions and building a new dataset is challenging. This is because we need to provide large, labeled training data, which is time-consuming, expensive, and requires much human effort. To obtain the labeled instance with less effort, this paper uses our previous labels of citation functions that have been built based on Computer Science (CS) papers. Note that the process to design the labels was accomplished prior to and has not become part of this paper. The developed labels consist of five coarse-grained labels and 21 fine-grained labels. By using these labels, we obtained classification models with accuracies of 83.6% and 90.1% for coarse-grained labels and fine-grained labels, respectively. This paper uses these models to categorize citing sentences on COVID-19-related papers obtained from the COVID-19 Open Research Dataset (CORD-19) (Lu Wang et al., 2020). Through completing this research, we deliver several contributions:

- The automatic classification of citation functions on COVID-19 domain achieved accuracies of 76.6% for coarse-grained label and 70.2% for fine-grained labels.
- The experimental results show that several fine-grained labels experienced a meaning shift (the expansion of the labels’ definition while remaining in the same idea).
- The COVID-19 domain is dominated by statements highlighting the importance, cruciality,
usefulness, benefit, consideration, etc. of certain topics for making sensible argumentation.

- We noticed that discussing State of The Arts (SOTA) in terms of outperforming previous studies in the COVID-19 domain is less popular compared to the CS domain.
- Lastly, we released a final dataset consisting of 99.6k labeled citing sentences\(^1\).

This paper uses two main terms: citing paper, which is used to define the paper citing other papers, and cited paper, which is used to define the papers cited by the citing paper.

2. Dataset Development

This section describes how our proposed dataset of citation functions is developed. The dataset consists of several parts, the first of which concerns the obtainsment of data sources of COVID-19-related papers. The second part describes the labels of citation functions, and the last part builds the dataset of citation functions on COVID-19 domains.

2.1 COVID-19-related Papers

This paper uses a collection of papers from the COVID-19 Open Research Dataset (CORD-19) (Lu Wang et al., 2020). Initially, this dataset provided 28k papers. The present number of papers has significantly increased during the continuous development. The CORD-19\(^2\) collected papers from several sources (e.g., PubMed Central (PMC), PubMed, and the World Health Organization’s COVID-19 Database). Moreover, it contains a collection from preprint servers such as bioRxiv, medRxiv, and ArXiv. This paper uses the latest version of the dataset (version: 2021-12-20) from JSON parsed from the full text of 314,391 (PDF) and 243,652 (PMC) papers. The distribution of CORD-19 is shown in Figure 1.

![Figure 1: The paper distribution in CORD-19. The x axis depicts year, and the y axis depicts the number of papers. This figure is taken from Lu Wang et al.'s work (2020).](https://www.semanticscholar.org/cord19/download)

2.2 The Labels of Citation Functions

The labeling scheme of citation functions used in this paper is obtained from our previous research. The dataset used to develop the scheme is obtained from Färber et al. (2018), which provided 90,278 papers from ArXiv in the CS domain from January 1993 until December 31, 2017. Since this data source provides all parsed sentences from research papers, we perform filtering to separate the citing sentences and non-citing sentences. The filtering is performed using regular expressions based on certain citations tags. In this stage, we obtained around 1.6 million instances of citing sentences.

Our proposed labels of citation functions are developed through three steps: top-down analysis, bottom-up analysis, and annotation experiment. While the top-down analysis reviews the definitions of the labels from existing works, e.g., background, usage, and comparison, the bottom-up analysis is performed to identify the citing sentence patterns on the dataset. At this point, we obtained an initial dataset consisting of 5,669 samples. Next, we conducted the pre-annotations experiment to develop and finalize both labels of citation guidance and the annotation guidance. The final labels themselves consist of two categories: five coarse-grained labels and 21 fine-grained. The coarse-grained labels represent the generic idea of the citation functions, which are divided into background for stating certain topics, citing paper work for focusing on what is done by author, cited paper work to show what has been done by previous works, compare and contrast to discuss the similarity between the citing paper and the cited paper, and other for all categories that do not match the above criteria. To obtain more specific functions, these coarse-grained categories are broken down into fine-grained categories.

The annotation step was performed by two annotators who have master’s degrees in Computer Science. They were provided with annotation guidance which covers an introduction to the task, labeling examples, and checking mechanism for the annotators’ understanding. For the real experiment, the annotators are supplied with an excel spreadsheet that consisted of 421 random unlabeled citing sentences. Our experiment shows that the inter-annotator agreement shows 88.59% for coarse-grained labels and 72.44% for fine-grained labels. Moreover, Cohen’s Kappa shows 0.85 for coarse-grained labels and 0.71 for fine-grained labels.

| Coarse-grained Label: Background |
|----------------------------------|
| Describes the citing sentences referring to the theory, principle, concept, topic, problem, etc. from cited papers. |

| Fine-grained Label: |
|---------------------|
| (atr0) definition: explains the definition of general theory, principle, concept, topic, problem, etc. example: Gianna <citation> is a precursor visual environment for modeling CSP. |
| (atr1) suggest: provides the reader with suggestions to refer, see more details, and explore other cited papers. example: The interested reader may dig deeper on this subject by referring to <citation>. |
| (atr2) judgment: highlights the positivity/negativity, usefulness/non-usefulness, etc. of concepts, topics, problems, etc. example: The n-coalescent has some interesting statistical properties <citation>. |
| (atr3) technical: explains how a theory, principle, concept, topic, problem, etc. is applied. example: The WMF model <citation> learns the latent factors by preserving the personalized rankings. |
| (atr4) trend: explains the significance of the research topic, theory, principle, concept, topic, problem, etc. example: CNN has been gaining attention and is now used in many text classification tasks <citation>. |

| Coarse-grained Label: Citing Paper Work |
|----------------------------------------|
| What is proposed by the author? |

| Fine-grained Label: |
|---------------------|

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\(^1\) https://github.com/tutcsis/COVID-19

\(^2\) https://www.semanticscholar.org/cord19/download
dataset of the CS domain. These models were obtained by experimenting with several machine learning (ML) approaches such as Logistic Regression and Deep Learning based on Long Short-Term Memory (LSTM) architecture. Considering the limitations of available instances, we consider using pre-trained word embedding that is both non-contextual, such as Glove (Pennington et al., 2014), word2vec (Mikolov et al., 2013), and fasttext (Bojanowski et al., 2017) and contextual such as the Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) and work by Beltagy et al. (2019). The last step is verifying the automatically labeled citing sentences by performing a random selection of 475 instances and checking the predicted labels manually.

3. Experiment Results

This section explains the results of the automatic classification used to build a dataset of citation functions of the COVID-19 domain. The results are divided into several parts: brief information about classification models developed using the CS domain, the automatic classification of citing sentences of the COVID-19 domain, and the evaluation of classification through a manual label check. Note that, the classification in the CS domain and the COVID-19 domain is done through two stages, namely the filtering stage and the fine-grained stage. While the filtering stage is used to classify the citing sentences into two categories, i.e., Other (atr18) and No-Other (atr0-atr17), the fine-grained stage is applied to classify the citing sentences belonging to No-Other class into 18 fine-grained classes. Finally, the proportional distribution of labeled instances and a discussion of results are also presented.

3.1 Classification Results for CS Domain

Here, we demonstrate the best results for classifications in the CS domain. In the filtering stage, BERT and SciBERT showed identical accuracies of 90.12%, as shown in Table 2. To achieve these accuracies, both methods used different settings as shown in Table 3.

| Methods     | Accuracy | Macro avg precision | Macro avg recall | Macro avg F1 |
|-------------|----------|---------------------|------------------|--------------|
| BERT        | 90.12    | 71.58               | 85.15            | 75.99        |
| SciBERT     | 90.12    | 74.53               | 82.72            | 77.73        |

Table 2: The best results on filtering stage.

| Techniques | Parameters |
|------------|------------|
| BERT       | 2e-5; batch 64; imbalance |
| SciBERT    | 3e-5; batch 32; balance |

Table 3: Best parameters on the filtering stages.

In the fine-grained stage, the best result was obtained by using SciBERT by 83.64%, as shown in Table 4 and the hyperparameters is shown in Table 5.

| Methods     | Accuracy | Macro avg precision | Macro avg recall | Macro avg F1 |
|-------------|----------|---------------------|------------------|--------------|
| BERT        | 80.95    | 80.95               | 82.40            | 81.06        |
| SciBERT     | 83.64    | 83.46               | 85.55            | 84.07        |

Table 4: The best results on fine-grained classification.

2.3 Dataset Development in COVID-19 Domains

The proposed dataset of COVID-19 domains is built using an automatic approach by following several steps. The first step is preparing the source of the papers. In this step, we do a simple data analysis to gather a deep understanding of the parsed JSON structures of CORD-19. Following this, the analysis is accompanied by filtering to select only citing sentences. The second step is classifying all extracted citing sentences using the best models obtained from the
The classification experiment is conducted on 99.6k instances generated from 10.1k parsed paper files (JSON format). The automatic classification begins with the extraction of all the sentences in the JSON files. Next, all extracted sentences are filtered to keep only citing sentences. Similar to the dataset on the CS domain, the classification is then applied by following two classification stages, namely the filtering stage and the fine-grained stage. To measure the accuracy of labeled instances, we perform a manual label check on 25 random samples for each label, for a total of 475 samples (18 fine-grained labels + 1 other label).

After completing the manual label check, we obtained accuracies 76.63% and 70.20% for coarse-grained labels and fine-grained labels, respectively. The accuracy of coarse-grained labels is easily obtained by summing the proportion of correctly and wrongly fine-grained labels. Since each label in the fine-grained labels has the same number of instances, it is easy to use the confusion matrix to compare each label’s accuracy, as shown in Figure 2. The highest number of correctly predicted labels is achieved by the label technical, with 24 correct predictions and only a single incorrect prediction. In contrast, the label cited_paper_dominant has the lowest number of correctly predicted labels with only nine correct and 16 incorrect predictions.

| Techniques | Parameters |
|------------|------------|
| BERT       | 3e−5; batch 32; imbalance |
| SciBERT    | 3e−5; batch 32; balance |

Table 5: Best parameters on the fine-grained classification.

### 3.2 Dataset on the COVID-19 Domain

| Fine-grained Labels | Number of Instances | Label Proportion |
|---------------------|---------------------|------------------|
|                     | CS Domain | COVID-19 Domain | CS Domain | COVID-19 Domain |
| definition          | 55,508    | 3,151           | 4.18%     | 3.77%     |
| suggest             | 51,987    | 355             | 3.91%     | 0.42%     |
| judgment            | 215,428   | 37,885          | 16.21%    | 45.34%    |
| technical           | 85,374    | 5,557           | 6.42%     | 6.65%     |
| trend               | 66,594    | 6,579           | 5.01%     | 7.87%     |
| citing_paper_corroboration | 113,488 | 2,571          | 5.34%     | 3.08%     |
| citing_paper_based_on | 55,878   | 531             | 4.20%     | 0.64%     |
| citing_paper_use    | 115,215   | 1,114           | 8.67%     | 1.33%     |
| citing_paper_extend | 28,779    | 241             | 2.17%     | 0.29%     |
| citing_paper_dominant | 24,823   | 294             | 1.87%     | 0.35%     |
| citing_paper_future | 5,439     | 424             | 0.41%     | 0.51%     |
| cited_paper_propose | 243,031   | 5,442           | 18.29%    | 6.51%     |
| cited_paper_success | 34,505    | 2,128           | 2.60%     | 2.55%     |
| cited_paper_weakness | 15,054   | 1,072           | 1.13%     | 1.28%     |
| cited_paper_result  | 154,394   | 15,063          | 11.62%    | 18.03%    |
| cited_paper_dominant | 3,215     | 31              | 0.24%     | 0.04%     |
| compare             | 39,364    | 677             | 2.96%     | 0.81%     |
| contrast            | 20,909    | 439             | 1.57%     | 0.53%     |
| Total               | 1,328,985 | 83,554          | 100%      | 100%      |

Table 6: The distribution comparison of automatically labeled instances in CS domain and COVID-19 domain. The comparison consists of two parts: (a) the number of instances on each label and (b) the proportion of instance on each label to the total instances in the dataset.

Applying classification models built from CS papers to COVID-19 related papers results in two consequences. The first consequence is that there is a decrease of fine-grained label accuracy from 83.64% in CS domain to 70.2% in COVID-19 domain. The second consequence is that two fine-grained labels experienced a meaning shift: the label citing_paper_dominant and the label citing_paper_future. The definition of the label citing_paper_dominant changed
from expressing the citing paper’s performance over cited paper to discussing the success of citing paper, with or without comparison. On the other hand, the definition of the label citing paper future changed from stating the future plan of the citing paper to a general recommendation without specifying whether it is done by citing paper or cited paper.

3.3 Citation Functions Distribution
To give more analysis on the current COVID-19 dataset, in Table 6 we show a comparison of the distribution datasets in the CS domain and COVID-19 domains. Note that, the distribution in this table represents the number of automatically labeled citing sentences in the datasets. The current dataset in this paper consists of 99,691 labeled instances, of which No-Other label has 83,554 instances and the Other label 16,137 instances. Since the labels of citation functions are designed for CS papers, it is worth determining whether the classification models are effective for domains related to COVID-19. Instead of using the number of instances to compare both datasets, this paper uses the proportion of labels as indicators due to the datasets having different sizes.

Figure 3: Proportion Comparison between No-Other and Other labels.

Figure 4: The average number of citing sentences in each paper

First, the comparison is done on the filtering stage to show the percentage of No-Other vs Other labels as depicted in Figure 3. In this figure, it is seen that both domains share the same trend in that the proportion of No-Other label much higher than Other label. Surprisingly, the label judgment in the COVID-19 domain has a proportion of almost half at 45.34%. In second place, the label cited_paper_result has 18.03% of proportion. The rest of labels constitute less than 10% of the proportion. Furthermore, there are eight labels have only under 1% of the proportion, with the lowest proportion obtained by the label cited_paper_dominant with 0.04%, which is equivalent with 31 instances. The CS domain faces a similar situation in that this label has the lowest proportion at 0.24%. However, this proportion is not as severe as in the COVID-19 domain. In the dataset of CS domain, the distribution trend is varied among labels, and no single label exceeds 20% of the proportion.

Another comparative indicator between both domains is the average number of citing sentences in each paper. Figure 4 demonstrates that the CS domain has a higher number of citing sentences than the COVID-19 domain. To be more specific, the dataset of CS domain consists of 1,840,815 citing sentences extracted from 90,278 papers, while the dataset of COVID-19 domain contains 99,691 citing sentences extracted from 10,102 papers.

3.4 Discussion
The experiments conducted in this paper reveal several notable findings. The first finding is a phenomenon of meaning shift in two fine-grained labels. This corroborates the assertion that even as this paper achieves acceptable accuracies, there still exists an issue regarding the labels’ compatibility between two domains. Next, the large proportion of label judgment (constituting almost half of dataset) indicates that citation functions in the COVID-19 papers are dominated with statements highlighting the importance, cruciality, usefulness, benefit, consideration, etc. of certain topics for making sensible argumentation. Conversely, the smallest proportion, represented by the label cited_paper_dominant, which is followed by several labels with proportions less than 1% (e.g., compare, citing_paper_extend, contrast, citing_paper_dominant, and citing_paper_based_on) indicates that discussing State of the Arts (SOTA) in the COVID-19 domain is less popular compared to the CS Domain. This trend is supported by the average number of citing sentences in the CS domain being higher than in the COVID-19 domain, which emphasizes the fact that discussing the SOTA needs more citing sentences and cited papers.

4. Conclusion
This paper developed the dataset of citation functions using citing sentences extracted from COVID-19 related papers. Instead of designing new labels of citation functions from scratch and preparing training data, this paper uses our previously developed labels and applied the best ML models that have been built from the CS domain. The experiments show that the application of labels of the CS domain to the COVID-19 domain is promising. Furthermore, the evaluation for obtaining the automatic labeling accuracies uncovers several notable patterns such as label compatibility between two domains, the dominant citation roles on each domain, and the relation between a citing paper and the SOTA. For future work, we intend to apply the labels and the models to all papers in the CORD-19 dataset.

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