Towards Generating Citation Sentences for Multiple References with Intent Control

Jia-Yan Wu*  Alexander Te-Wei Shieh*  Shih-Ju Hsu*  Yun-Nung Chen
National Taiwan University, Taipei, Taiwan
{b06701216,b05401009,b07902076}@ntu.edu.tw  y.v.chen@ieee.org

Abstract

Machine-generated citation sentences can aid automated scientific literature review and assist article writing. Current methods in generating citation text were limited to single citation generation using the citing document and a cited document as input. However, in real-world situations, writers often summarize several studies in one sentence or discuss relevant information across the entire paragraph. In addition, multiple citation intents have been previously identified, implying that writers may need control over the intents of generated sentences to cover different scenarios. Therefore, this work focuses on generating multiple citations and releasing a newly collected dataset named CiteMI to drive the future research. We first build a novel generation model with the Fusion-in-Decoder approach to cope with multiple long inputs. Second, we incorporate the predicted citation intents into training for intent control. The experiments demonstrate that the proposed approaches provide much more comprehensive features for generating citation sentences.

1 Introduction

Every month, more than ten thousand papers are submitted to platforms such as arXiv (McKerrnan, 2000). The amount of scientific literature have grown enormously in recent years (Ginsparg, 2011), so as the amount of citations needed to compose a new publication nowadays. Hence, literature review has become time-consuming, and increasing effort is needed to write them into the “related work” section. The development of automatic citation text generation system can relieve scientific researcher’s burden on tracking and editing citations. Automatic summarization already accelerated this process, but systems that can fully automate citation text generation are yet to be explored. Also, different from summarization systems, which typically involve one source document at a time, citation text generation systems need to consider both the citing and the cited documents.

However, current citation text generation systems have several limitations. They focused on generating a single sentence for a single citation, and the intent of citation were not controllable (Xing et al., 2020; Luu et al., 2020). Previous work demonstrated that citations can be classified into several intentions, such as background information, method or result comparison Cohan et al. (2019). They are crucial for studying citation behavior and evaluating the impact of a certain publication (Small, 2018). As for authors, they often need citation sentences with different intent for the same cited document depending on the current context.

This work proposes methods that address these two problems. First, we collect a new dataset that supports multiple cited documents as its input. Second, we train a model to predict citation intents for previous single citation generation data and our newly collected corpus containing examples with multiple citations. The predicted citation is incorporated into the input of citation sentence generation, providing control over intents in generation. Third, we use the Fusion-in-Decoder (FiD) model (Izacard...
and Grave, 2021) for citation text generation. The FiD model was originally used in generative open domain question answering, but we found it useful for generating sentences as well. We choose FiD for its capability of reading long inputs from multiple documents while benefiting from the prowess of large pre-trained contextual language models such as T5 (Raffel et al., 2020) for generation.

Our contributions are three-fold: (i) we identify the problem of multiple cited documents and intent control in the citation sentence generation task; (ii) we collect a new dataset, named CiteMI (stands for Cite Multiple References with Intent Control), that addresses two problems discussed above; and (iii) we leverage the Fusion-in-Decoder approach to build a model that can serve the above features. The entire workflow is depicted in Figure 1. We further evaluate our model with enriched features and discuss future directions on improving this general citation text generation task.

2 Related Work

2.1 Citation Text Generation

Xing et al. (2020) defined citations into two types: explicit and implicit citations, meaning citations with or without the author’s direct reference respectively. They built a citation text generation dataset based on the ACL Anthology Network corpus (Radev et al., 2013; Jurgens et al., 2018). In addition, they manually labeled 1,000 citation texts as either explicit or implicit, and used this dataset to train a BERT-based (Devlin et al., 2019) model that extracts more implicit citations. Then they used a PG-net (See et al., 2017) with a cross attention model for generating the final citation text, given the citing paper’s context and the cited paper’s abstract. In the data, they used the “[refer]” token to indicate explicit citation and the “[otherrefer]” token to replace references other than the one in the input.

Followingly, the work by Luu et al. (2020) also investigated citation text generation given one source document and one cited document. They tried using combinations of the abstract, introduction from the source and cited documents as input. Their training set was based on the computer science articles collected by the S2-GORC dataset (Lo et al., 2020), which is significantly larger than the prior work. Instead of PG-net, they used GPT-2 (Radford et al., 2019) as their generation model. Their results showed better automatic evaluation scores for the retrieval baseline, and the generation models performed better in human evaluation.

2.2 Citation Intents

The work by Cohan et al. (2019) produced the SciCite dataset, which provided 11,020 instances of citations with crowdsourced intents. The intents are categorized into three types: “Background”, “Method” and “Result comparison”. Compared to earlier work in the ACL-ARC dataset (Jurgens et al., 2018), the SciCite dataset has fewer categories but comes from more diverse domains and includes much more instances. They leveraged section title prediction and citation worthiness prediction for improving the intention prediction task in a multi-task setting, showing that three tasks have correlation so that they can benefit each other. Another recent work on citation intent classification asked the authors to classify their own reasons for citation (Pride and Knoth, 2020) and finally form a dataset containing six types of of citations with 11,233 instances.

2.3 Extreme Summarization

A similar task related to citation text generation is extreme summarization. The recent study by Cachola et al. (2020) introduced the SciTLDR dataset. TLDRs are short sentence with only 15-25 words that capture the key aspects of papers. These TLDR sentences resembled citations that provide background information, but are not conditioned on the citing document. They proposed the CATTS approach that utilizes control codes (Keskar et al., 2019; He et al., 2020) to generate either the title or the TLDR sentence given the abstract, introduction and conclusion of a paper.

3 Task Description and Data

The input of the CiteMI task include: the citing document’s title and abstract, several consecutively cited documents’ titles and abstracts and the intent $I_{(A,B_i)}$ for their citation, respectively. The output of this task is the citation sentences of the corresponding cited documents. We define consecutively citation as two explicit citation sentences with only one sentence sentence without explicit citations in-between. The citation sentences were extracted using handcrafted regular expressions.

We obtained the multiple reference citation sentences from the online proceedings of ACL anthology published during 2015-2020. In addition, we
This paper presents a neural network system where we participate in the first task of SemEval-2020 shared task 7 Assessing the Funniness of Edited News Headlines. Our target is to create a neural network model that can predict the funniness of edited headlines. We build our model using a combination of LSTM and TF-IDF, then a feed-forward neural network. The system manages to slightly improve RSME scores regarding our mean score baseline.

The main challenges for irony generation are the lack of large-scale irony dataset and difficulties in modeling the ironic pattern. In this work, we first systematically define irony generation based on style transfer task. To address the lack of data, we make use of twitter and build a large-scale dataset. We also design a combination of rewards for reinforcement learning to control the generation of ironic sentences.

We introduce the Self-Annotated Reddit Corpus (SARC), a large corpus for sarcasm research and for training and evaluating systems for sarcasm detection. The corpus has 1.3 million sarcastic statements. We evaluate the corpus for accuracy, construct benchmarks for sarcasm detection, and evaluate baseline methods.

Table 1: An example the CiteMI task: given the intent, citing paper’s abstract and cited papers’ abstracts, the model needs to output the corresponding citation text. We showed the actual generation result of the FiD models with and without intent.

| Model                     | BLEU  | ROUGE-1 | ROUGE-2 | ROUGE-L | BLEURT | Meteor |
|---------------------------|-------|---------|---------|---------|--------|--------|
| Retrieval (oracle)        | 7.13  | 10.63   | 1.17    | 7.92    | -0.76  | 4.31   |
| Retrieval (baseline)      | 4.11  | 7.34    | 0.63    | 5.38    | -1.42  | 3.42   |
| CiteMI (FiD, without intent) | 15.94 | 22.96   | 3.05    | 15.76   | -0.86  | 11.15  |
| CiteMI (FiD, with intent) | 17.13 | 23.62   | 3.37    | 16.06   | -0.73  | 11.67  |

Table 2: Automatic evaluation results of the proposed CiteMI task.

We added single reference citation examples from Xing et al. (2020), which includes papers until 2014 from the latest ACL Anthology Network release (Radew et al., 2013), and the SciCite intent corpus (Cohan et al., 2019) to our training set. We then crawled the abstracts of the papers in SciCite, since they were not included in the original release.

Other than the examples from SciCite, which intent labels were provided, we used a BERT-based (Devlin et al., 2019) model trained on SciCite to predict citation intents using the target citation text for the rest of the CiteMI dataset. The BERT-based model used in this step obtained 84% testing accuracy on the SciCite dataset. Currently, the CiteMI dataset has 56,955 examples with single citation and 4,189 examples with multiple citations. An example of CiteMI’s input and output is shown in Table 1.

4 Methods and Experiments

4.1 Retrieval Baseline

We first made an oracle retrieval model that returns the most semantically similar sentence from the cited document compared to the ground truth target. The mean of token embeddings from the BERT model (Devlin et al., 2019) was used to represent each sentence in the cited paper’s abstract. The sentence that has the highest cosine similarity compared with the ground truth citation text was returned. Another baseline model was made with the same method but sentences were compared with the citing paper’s abstract instead of the target.

4.2 Generative Models

Our generative model augmented the T5 (Raffel et al., 2020) model with the Fusion-in-Decoder...
(FiD) architecture (Izacard and Grave, 2021). For the nth encoder block in FiD, we encode the citing document $A$’s abstract, together with the code "$B_n\)" followed by the nth cited document $B_n$’s title and abstract. Additionally, we prepended "$I(A,B_n)\)”, where $I(A,B_n)$ is either “background”, “method”, “supportive” or “not_supportive”, to the abstract of $A$ to specify the current citation intent. Efficacy of controlling general summarization was discussed in Fan et al. (2018) and He et al. (2020). The decoder then performs attention over the encoder blocks that represented citing and the cited papers. Note that the “supportive” and “not_supportive” labels are additional labels provided by Cohan et al. (2019) for the “Result comparison” intent. As for the target citation text, we replaced the nth citation with $<B_n>$. By leveraging the FiD architecture, we can include longer data, i.e., more cited documents, to the input. The computation time of our model grows linearly with the number of cited documents, instead of quadratically when using a single encoder block. This is beneficial for scaling to examples with multiple citations in the CiteMI task. For all generation experiments, we used 80% of the CiteMI data for training, 10% for validation and 10% for testing.

5 Results and Analysis

In addition to conventional automatic evaluation scores BLEU (Papineni et al., 2002) for machine translation and ROUGE (Lin, 2004) for summarization, we also evaluate the generated citation sentences using Meteor (Denkowski and Lavie, 2014) and BLEURT (Sellam et al., 2020). The BLEURT score currently achieves state-of-the-art agreement with human judgement on machine translation benchmarks. Our automatic evaluation results were presented in Table 2. Apparently, adding intent labels further boosted FiD’s performance on the CiteMI task. The improvement was unanimous across all evaluation metrics that we evaluated, suggesting a role for explicitly specifying citation intent in generation.

We also performed a round-trip intent prediction on the generated citation text. When the intent was specified, the generated citation text achieved a micro-average accuracy of 86.39%. On the other hand, when the intent was not given the accuracy decreased to 70.14%. These results indicated that explicitly specifying the intent could effectively change the intent expressed by the generation model. Also, it showed that providing only the abstracts without intent could still reveal some clues about the underlying intent.

6 Future Work

We suggest further augmentation of the CiteMI data in the near future. Our work here only included papers related to computer science and natural language processing. However, there are more publications emerging in fields such as medicine. Further inclusion of multi-domain data is needed to build a more comprehensive model. Also, since some of the citation intents in our work were predicted, more accurately labeled citation intent should be added.

On the other hand, since an abstractive model was used in our study, pitfalls for evaluating such systems could occur. For instance, hallucinations, or contents that are not faithful or factual to the input could appear (Maynez et al., 2020). Scientific facts should be presented accurately, methods to examine the correctness of the generated results should therefore be included. Moreover, there are increasing research results regarding to citation recommendation (Nogueira et al., 2020; Giosa and Di Caro, 2020; Ali et al., 2020; Khadka, 2020; Ali et al., 2021). Pipelines combining citation recommendation and generation can make the workflow of reviewing scientific literature more efficient.

7 Conclusion

In conclusion, we addressed the problem of multiple consecutively cited documents in citation text generation by building a new dataset named CiteMI, which contains both single and multiple citation examples in the computer science domain. Also, we added predicted intention labels to provide intent control over the generated content. Although dealing with long inputs containing multiple abstracts could be difficult with Transformer-based models, we demonstrated the feasibility of building a model that can realize both features using the Fusion-in-Decoder approach. Empirically, we observed that adding intent labels improved the generation model’s performance on various automatic evaluation metrics. We expect future work on improving the accuracy of the intent labels and increasing the amount of examples with multiple citations can further enhance the overall quality of the generated citation text.
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