CiteBART: Learning to Generate Citations for Local Citation Recommendation

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Abstract

Citations are essential building blocks in scientific writing. The scientific community is longing for support in their generation. Citation generation involves two complementary subtasks: Determining the citation worthiness of a context and, if it's worth it, proposing the best candidate papers for the citation placeholder. The latter subtask is called local citation recommendation (LCR). This paper proposes CiteBART, a custom BART pre-training based on citation token masking to generate citations to achieve LCR. In the base scheme, we mask the citation token in the local citation context to make the citation prediction. In the global one, we concatenate the citing paper's title and abstract to the local citation context to learn to reconstruct the citation token. CiteBART outperforms state-of-the-art approaches on the citation recommendation benchmarks except for the smallest FullTextPeerRead dataset. The effect is significant in the larger benchmarks, e.g., Refseer and ArXiv. We present a qualitative analysis and an ablation study to provide insights into the workings of CiteBART. Our analyses confirm that its generative nature brings about a zero-shot capability.

1 Introduction

Citations are essential building blocks in scientific writing. Their accurate placements indicate quality, as one should know the literature to claim contributions and put the current study in the context of the existing work from different aspects, such as background information, method, and result comparison (Cohan et al., 2019).

The first citation-related task in natural language processing (NLP) has been citation impact prediction, where a paper's future scientific impact is predicted on the basis of the number of times a paper gets cited after publication (Gehrke et al., 2003). Unlike the first approaches that relied on paper metadata and abstract, the recent work (van Dongen et al. (2020), Huang et al. (2022)) exploit the whole content of scientific papers to achieve the goal.

Citation prediction is defined as a two-step process where the former focuses on where in the sentence to place the citation (Buscaldi et al., 2024), while the latter (citation recommendation) obtains a set of candidate papers once there is a specified citation placeholder in a given context. In this sense, citation recommendation serves as a citation suggestion mechanism. For a given scientific text, it can suggest additional papers on a similar topic. These suggestions can be considered additional reading material alongside the targeted paper, corresponding to the ground-truth citation.

There are two levels of citation recommendation: the first, whom to cite, and the second, whom to cite in what context. The former is global citation recommendation, traditionally performed based on paper metadata such as author names, paper titles, abstracts, conference venues, publisher information, etc. Recently, custom citation-aware language models (SciBERT (Beltagy et al., 2019), SPECTER (Cohan et al., 2020)) learn good citation-aware embeddings for full papers to perform well in this task. The latter task is local citation recommendation (LCR), aiming to determine the target paper for a citation placeholder. Additionally, the local citation contexts can be leveraged for citation impact prediction. How a paper frames its work through citations is predictive of the citation count it will receive (Jurgens et al., 2018).

Language model pre-training based on Transformers (Vaswani et al., 2017) provided new state-of-the-art performances in many downstream tasks. Masked language modeling (MLM) is the primary learning strategy behind BERT (Devlin et al., 2019) and its variants (RoBERTa (Liu et al., 2019) etc.).

LCR has been addressed in a few works. BERT-GCN (Jeong et al., 2020) utilizes a feedforward neural network to combine local citation context

representations using BERT with citation encodings through Graph Convolutional Neural Networks (GCN). The most recent solutions to the problem adopt a two-step process that consists of pre-fetching and re-ranking. DualEnh (Medić and Snajder, 2020) enhances a local citation context with the citing article's title and abstract and uses this enhanced context as the query vector to retrieve the most similar candidate articles using their titles and abstracts. It performs this ranking through BiLSTM representations of inputs with attention layers on top. On the other hand, HAtten (Gu et al., 2022) initially pre-fetches a set of papers using the nearest neighbor search between local citation context extended with the citing paper's title and abstract (query text as a whole) and the title and abstracts from a given pool of papers. Afterward, it re-ranks the selected candidate papers using a fine-tuned SciBERT (Beltagy et al., 2019) model where the input is the query text concatenated with a candidate paper's title and abstract.

The existing LCR works are not built upon Transformers but benefit from it indirectly, such as re-ranking the results (using fine-tuned SciBERT). Distinctively, we propose CiteBART, a custom pre-training approach based on Transformer. We mask citation tokens in the local contexts to learn to reconstruct them effectively during pre-training.

BART (Lewis et al., 2020) is a generative model that is pre-trained using a seq-to-seq objective while employing a mask-filling mechanism similar to that of BERT. Its MLM objective allows for a random subset of the tokens to be masked and multiple tokens to be predicted. Due to this capability, BART is particularly well-suited to our approach, aiming to generate complex parenthetical author-date citations without requiring further architectural modifications. Furthermore, BART's encoder, like BERT, effectively captures contextual information bidirectionally. Additionally, BART's generative nature permits the adjustment of generation parameters, providing greater control over the evaluation of the generated citations without further pre-training.

In CiteBART, the base scheme learns through the masked citation context. In a second technique, we extend the masked context with the citing paper's global information, e.g., title and abstract (Table 1). Inspiring from pre-training under the REALM framework (Guu et al., 2020), we append this global information to the local context, allowing backpropagation through the global information to learn associations with the pool of papers from the corpus.

CiteBART achieves superior performance without relying on a pre-fetch and re-rank pipeline. It is an end-to-end learning system. On the other hand, a pre-fetch and re-rank pipeline, such as HAtten, utilizes the citing papers' titles and abstracts with the local contexts to form the query encoding and the titles and abstracts of cited papers for the candidate papers' representations. Thus, it exploits the titles and abstracts of papers from the test set to determine the cited papers for a citation placeholder. On the contrary, we do not use the global information (titles and abstracts) of target papers to make the recommendation. CiteBART learns solely from the relation of citing papers' global information with local citation contexts. The underlying assumption is one can find out the cited papers from the enhanced citation contexts, citation contexts that are concatenated with citing papers' titles and abstracts. In the test phase, we feed these enhanced contexts to predict the target papers to be cited. Furthermore, CiteBART can be fine-tuned for any downstream task. We share our code[1] publicly for supporting reproducibility.

We summarize our contributions as follows:

- We propose an end-to-end learning system, CiteBART, with citation objectives for local citation recommendation.

- CiteBART-Global outperforms state-of-the-art approaches on the citation recommendation benchmarks except for the smallest FullTextPeerRead dataset. The effect is significant in the larger benchmarks, e.g., Refseer and ArXiv. CiteBART-Base still performs good as a baseline.

- We provide a qualitative analysis to gain insight into the working of the approach, including the zero-shot capability through hallucination.

- Our ablation study confirms the central role of local citation contexts in the learning process. It also shows the effectiveness of the Global training scheme over Base.

[1] https://anonymous.4open.science/r/CitationRecommendation-5FA1

Table 1: An example for input and target formats for pre-training and evaluation with CiteBART. Due to space constraints, we present the contexts and abstracts in an abbreviated form.

Strategy	Input	Target
Base	... error rate of 5.8% and a word error rate of 28.7%, which are on par with previous reported results **<mask>** . Unlike prior work, we do not use a language model during decoding and ...	**Yao and Zweig, 2015**
Global	... error rate of 5.8% and a word error rate of 28.7%, which are on par with previous reported results **<mask>** . Unlike prior work, we do not use a language model during decoding and ... *</s>* Deep Voice: Real-time Neural Text-to-Speech *</s>* We present Deep Voice, a production-quality text-to-speech system constructed entirely from deep neural ...	**Yao and Zweig, 2015**

2 Related Work

BERT (Devlin et al., 2019) is an encoder-only pretraining model that adopts the MLM objective. MLM masks tokens in a uniformly random fashion and predicts them, allowing the generation of learning signals bidirectionally. Some BERT variants were released to meet the requirements for masking a group of tokens. SpanBERT (Joshi et al., 2020) builds on this objective by masking random contiguous text spans. In the same direction, PMI-Masking (Levine et al., 2021) masks word n-grams based on their PMI (Pointwise Mutual Information) scores. Pretraining encoder decoders, e.g., BART (Lewis et al., 2020), combine the strengths of bidirectional learning of encoders with the autoregressive nature of decoders, capturing the local patterns of tokens within their generative capabilities.

Most of the past works in citation prediction have focused on citation count prediction. Citation counts refer to the number of times a paper gets cited after publication. Brody et al. (2006) aim to predict the future citations of a paper using web usage statistics. NNCP (Abrishami and Aliakbary, 2019) uses a SimpleRNN model to predict long-term citations using short-term citations. Bai et al. (2019) propose the Paper Potential Index based on a combination of manually acquired features. SChuBERT (van Dongen et al., 2020) leverages the entire contents of papers to accomplish the task. FGCCP (Huang et al., 2022) performs a fine-grained analysis to attribute citation frequencies to individual parts of papers.

Yu et al. (2012) learn citation relations through a meta path-based approach. Their approach combines authorship metadata with discriminative term features to calculate citation probabilities on the DBLP network. Tanner and Charniak (2015) combine LDA-Bayes with metadata features under a logistic regression classifier to recommend citations.

Similar to citation recommendation, the recent work of Luo et al. (2023) predicts provisions of the U.S. Code by pretraining RoBERTa (Liu et al., 2019) and LegalBERT (Chalkidis et al., 2020) on the curated dataset (PACER (Luo et al., 2023)) of the US federal court documents where each provision source text is given with its associated target citation.

In scientific document understanding, learning better representations for scientific papers has been a focus. In such an effort, SciBERT (Beltagy et al., 2019) performs pretraining exclusively on scientific texts. Specifically, it is pre-trained on a randomly sampled dataset of $1.14M$ from the Semantic Scholar database. It is built upon an in-domain vocabulary (SCIVOCAB), which brings about superior performance compared to BERT in downstream tasks that involve scientific data.

SPECTER (Cohan et al., 2020) learns citation-aware global representations for scientific papers using a citation-based pretraining objective. Starting from the initial SciBERT weights, the system adopts a triplet loss function based on document similarities. The first component in this objective is the source document's similarity to one of its citations. In contrast, the second component is its similarity to a negative paper not cited by the source, and finally, there is an additional term of loss margin hyperparameter. SPECTER-produced representations introduced remarkable results in the paper classification and global citation recommendation tasks.

LCR has four benchmark datasets for evaluation. BERT-GCN (Jeong et al., 2020) introduced the FullTextPeerRead dataset, extended from the original PeerRead (Kang et al., 2018). Throughout this paper, we refer to the FullTextPeerRead dataset as PeerRead for brevity. An additional dataset is

ACL-ARC (Bird et al., 2008), derived from the ACL Anthology Reference Corpus. We run our experiments on its ACL-200 subcategory, analogous to DualEnh (Medić and Snajder, 2020) and HAtten (Gu et al., 2022). Finally, Refseer (Huang et al., 2015) and ArXiv (Gu et al., 2022) are the largest benchmarks for this task.

BERT-GCN (Jeong et al., 2020) utilizes two encoders for citation recommendation. The first encoder generates local context embeddings using BERT, while the second one creates the graph embeddings of citation networks using a GCN model (Kipf and Welling, 2017). The approach combines these embeddings to produce representations for papers. It was evaluated exclusively on the PeerRead dataset.

DualEnh (Medić and Snajder, 2020) trains a Bi-LSTM model to leverage similarity between a target paper and its candidate papers. The target paper provides a context with a citation placeholder, and the model utilizes the titles and abstracts of candidate papers to calculate their semantic similarity scores. The authors calculate semantic and bibliographic scores to acquire the final recommendation scores as a weighted average. The bibliographic score is acquired by utilizing metadata such as author names and citation counts. The authors performed their experiments on the ACL-200 and Refseer datasets.

HAtten (Gu et al., 2022) uses a Hierarchical Attention Text Encoder and SciBERT-based Re-ranking scheme for LCR. It starts by pre-fetching potential candidate papers from a pool of citations. It accomplishes this filtering through a nearest neighborhood search between the local citation context plus the citing paper's title and abstract (query text as a whole) and the title and abstracts from candidate target papers. In the re-ranking phase, the authors assign scores to candidate papers using a SciBERT model with a classification layer on top. HAtten achieves state-of-the-art results on all of the benchmark datasets.

Lastly, GM-s2orc-H (Buscaldi et al., 2024) proposes two approaches for predicting citation placeholders within a given context. Their first approach employs the GPT-2 model to determine whether a token could be part of a citation. The second approach performs a similar task using the BERT model, framing it as a Named Entity Recognition (NER) task. Their results confirm the superiority of the generative GPT-2 model over the second one. Although their results are not directly comparable to CiteBART due to differences in the task objectives, their findings highlight the advantages of generative models in citation-related tasks.

3 Methodology

We propose CiteBART, a novel pre-training strategy designed to predict citations within the contexts of scientific papers. We mask placeholder tokens, which replace ground-truth citations in the parenthetical author-date style, for the continual pre-training of a vanilla seq-to-seq model (BART-base) to generate the correct parenthetical author-date citation for a given context. CiteBART is trained on the benchmark datasets, learning to recommend citations during its generation process.

3.1 Pre-training BART with Citation Objectives

We propose a citation learning strategy using BART. BART employs a variant of MLM to effectively reconstruct the masked contexts where a random subset of the words has been masked. With this MLM objective, it can predict multiple tokens for a single mask. Thus, after custom pre-training for citation tokens, CiteBART can generate complex parenthetical author-date citations without requiring further architectural modifications.

We propose two training schemes for CiteBART: Base and Global. In CiteBART-Base, the model gets the masked context with the ground-truth citation as input. This setting tests the model's performance in a local context-only situation (Table 1). With the underlying idea that good citation recommendation requires relating local citation contexts with the citing papers' global information, such as titles and abstracts, we devised an innovative way to accomplish it. Inspiring from pre-training under the REALM framework (Guu et al., 2020), in CiteBART-Global, we append the citing paper's title and abstract to the local context, allowing backpropagation through the global information that considers the pool of papers from the corpus. Specifically, we used the "</s>" token designated by the pre-trained BART-base model as the separator.

3.2 Dataset Preprocessing

We conduct our experiments on the existing citation recommendation benchmarks of ACL-200, PeerRead, RefSeer, and Arxiv. Table 2 presents the statistics of these datasets. They provide citation

Table 2: Statistics of LCR benchmarks.

Dataset Name	ACL-200	PeerRead	RefSeer	Arxiv
Train Size	30,390	9,363	3,521,582	2,988,030
Validation Size	9,381	492	124,911	112,779
Test Size	9,585	6,184	126,593	104,401
# of Papers	19,776	4,837	624,957	1,661,201
Publication Years	2009-2015	2007-2017	-2014	1991-2020

Table 3: Statistics of the preprocessed datasets.

Dataset Name	ACL-200	PeerRead	RefSeer	Arxiv
# of local contexts	63,365	16,669	3,739,189	3,205,210
Size of the training split	50,692	13,335	2,991,351	2,564,168
Size of the test split	12,673	3,334	747,838	641,042
# of removed contexts	403	0	39,577	0
# of unique citations	5,266	2,043	351,896	368,284

contexts from various articles where all contexts have a target citation in the middle. The context sizes are in terms of characters, which causes some incomplete words at the start and end of the contexts.

The datasets originally include a "TARGETCIT" marker as a placeholder for citations within each context. We replaced these markers with "<mask>" tokens to align with our pretraining process. Additionally, to ensure CiteBART focuses solely on predicting target citations, we removed any non-target citations from all four datasets.

We encountered some issues during the preprocessing of ACL-200 and RefSeer. First, they include local contexts with author name conflicts in the citation tokens. For example, the "Petrović et al., 2010" citation token was incorrectly written as "Petrovic et al., 2010" in the target citation column of ACL-200. Another problem is the incorrect ordering of two-author citations. For instance, the local citation context provides the citation "Rivera and Zeinalian, 2016"; the paper metadata includes "Zeinalian and Rivera, 2016". There are also a few cases of incorrect citations. Moreover, there are some contexts with empty author names. We removed all these cases from the aforementioned datasets to ensure consistency.

After the preprocessing, we split the benchmark datasets into training and test partitions using a conventional ratio of $8:2$. As CiteBART involves continual pre-training, we perform it on the training partition and evaluate the performance on the test partition. Consequently, we only require two partitions instead of the original three. Table 3 shows the final statistics of our preprocessed datasets[2] including the training and test partition sizes for all the benchmarks.

4 Experiments

We conducted our experiments on devices with NVIDIA RTX6000 Ada GPU and NVIDIA V100 GPU[3]. The following hyperparameters were utilized in all our experiments. The number of epochs was set to 15, as the change in loss values between epochs became negligibly small beyond this point. Only the PeerRead Global dataset has been trained for 30 epochs since the generative model requires longer training for the relatively smaller PeerRead dataset. We employed a learning rate of $2e-5$ and an attention dropout rate of 0.12. Given that BART is a generative model, we adjusted its generation parameters to produce outputs that align with our requirements. Specifically, we utilized the grouped beam search with 20 beams and applied a diversity penalty of 1.5 to generate more diverse results. The maximum number of generated tokens was 25 since the generated citations should not exceed it. Apart from these specific modifications, we did not alter the architecture of the BART model.

4.1 Results

We report our results using Recall@10 (R@10), Exact Match (EM), and Mean Reciprocal Rank (MRR)[4] and compare with the state-of-the-art approaches in Table 4. As can be seen from the table, CiteBART-Global outperforms others on the existing benchmarks except for the smallest PeerRead dataset, while the base scheme still performs as a good baseline, surpassing BERT-GCN on PeerRead, DualEnh, and HAtten on Refseer. The table includes the best-reported results of HAtten with $2k$ pre-fetched candidates. As for DualEnh (Medić and Snajder, 2020), we chose their superior "DualEnh-ws" model for the comparison. BERT-GCN's (Jeong et al., 2020) results are available only on the PeerRead dataset. None of the past works have provided their Exact Match scores.

As shown in Table 4, CiteBART demonstrates its advantage over HAtten on Refseer most since Refseer includes more training contexts compared to ArXiv. Given that CiteBART is a generative

[2]Please find information on token limits in Appendix A.

[3]Please find information on training and evaluation times in Appendix B.

[4]Please refer to Appendix C for metric definitions.

model, access to a larger training set contributes to its improved results.

4.2 Qualitative Analysis

To provide insights into the working of CiteBART, we present some top 10 prediction examples. We analyze three different scenarios shown in Table 5. Since CiteBART is a generative model, it is prone to hallucination. In the examples, the hallucinated predictions are designated with the * symbol. Furthermore, we provide another qualitative analysis on the performance of LLMs in LCR in Appendix D.

We first present an example context that is tested on a model pre-trained on the PeerRead Base dataset. It belongs to the test set of PeerRead Base and receives top 10 citation predictions for the mask. As demonstrated below, the model fails to predict the correct citation in the top 10 predictions. Actually, the ground-truth citation is the $18th$ entry in the ranked prediction list.

In a deeper analysis of the recommended citations for the first example, we bring up their connections with the ground-truth citation. The ground truth citation, "Hu et al., 2015", focuses on sentence-level semantics using convolutional neural networks (CNNs) with an application in dialogue generation. Similarly, the second prediction, "Vinyals and Le, 2015" leverages the sequential structure of sentences in dialogue systems. The fourth prediction, "Serban et al., 2015", also aims to model the hierarchical structure of sentences (utterances) for building an end-to-end dialogue system. The first prediction, "Shang et al., 2015," is still concerned with capturing sentence connections for a generative motivation. However, the primary reason for its top placement should be related to its experiments on Twitter data since the term Twitter appears in the local citation context. Analogously, the predictions $3, 5, 7$, and 9 utilize Twitter as the data source. Lastly, the model may have proposed the entries 6 and 10 due to their overlaps in authors' names with 7.

The second example has the same context as the first one, but this time, the citing paper's global information (title and abstract) is attached to it. Moreover, the model pre-trained on the PeerRead Global dataset makes the prediction, returning the ground truth citation in the first index. One can observe that the citations "Vinyals and Le, 2015", "Tan et al., 2015", and "Dhingra et al., 2016" still appear in the top-10 prediction list. There are also some hallucinated responses. The newly recommended "Bing et al., 2015" in the third position is also relevant since it tackles constructing sentences from fine-grained textual units.

The third example highlights our model's cross-dataset capabilities and zero-shot performance. We input a context from the PeerRead Global dataset into a model pre-trained on ACL-200 Global. The model fails to predict the correct citation as it is missing in the training dataset. Its predictions are NLP papers since ACL-200 is an NLP corpus. On the other hand, PeerRead includes both vision and text papers. The ground-truth citation, "Radford et al., 2015," focuses on image classification using CNNs, emphasizing unsupervised learning. Our analysis reveals that multiple predicted citations, among the top ten, are relevant to the ground-truth citation. For example, the papers in predictions 1 and 2 also employ CNNs but with a focus on sentence modeling. The papers from predictions 3 and 5 are about conditional random fields (CRFs). While their primary research areas differ significantly from the ground truth, terms such as 'conditional' and 'random' frequently appear in the ground truth paper. Moreover, the paper in Prediction 7 closely aligns with the ground-truth paper by strongly emphasizing unsupervised learning.

4.3 Ablation Study

We conducted an ablation study to show different components' contributions to the overall results. The analysis was carried out on the ACL-200 dataset. Table 6 shows the results for CiteBART-Global with a model pre-trained on the ACL-200 Global dataset in 15 epochs.

The first three experiments test the contribution of the local context, title, and abstract to the overall performance. First, we remove the local context to see the performance due to the global information-only training (#1 in Table 6). We discard the title and abstract in the second and third configurations (#2 and #3 in Table 6). The results show that excluding the local context brings about a sharp reduction in the performance metrics (a drop from 0.739 to 0.588 in Recall@10), confirming its decisive role in generating citations. On the other hand, removals of title or abstract do not lead to a statistically significant decrease in performance.

In the fourth ablation study, we further expand the global information with the cited paper's title and abstract during pre-training (#4 in Table 6). The evaluation stays the same, feeding the local

Table 4: Comparison with state-of-the-art.

Model	ACL-200			PeerRead			Refseer			Arxiv		
	R@10	EM	MRR	R@10	EM	MRR	R@10	EM	MRR	R@10	EM	MRR
BERT-GCN[a]	-	-	-	0.529	-	0.418	-	-	-	-	-	-
DualEnh-ws	0.703	-	0.366	-	-	-	0.534	-	0.280	-	-	-
HAtten	0.633	-	-[c]	**0.757**	-	-[c]	0.454[b]	-	-[c]	0.439[b]	-	-[c]
CiteBART-Base	0.686	**0.422**	0.504	0.570	0.363	0.424	0.606	0.382	0.449	0.355	0.184	0.240
CiteBART-Global	**0.739**	0.417	**0.513**	0.669	**0.430**	**0.502**	**0.652**	**0.404**	**0.479**	**0.502**	**0.230**	**0.305**

[a] BERT-GCN performs evaluation by excluding the papers cited less than five times in each dataset.
[b] The reported results are based on a $10k$ subset of the test set.
[c] The authors did not report their MRR scores.

context with the citing paper's title and abstract during inference. Contrary to expectations, adding the ground-truth paper's global information during pre-training does not help; the model falls in its performance. This failure may be explained by the model learning to associate the citation token with the global information of both the citing and cited article in the training phase. However, lacking the cited paper's global information in the test phase confuses the model's predictions.

The previous studies (Medić and Snajder (2020), Gu et al. (2022)) utilize an all-including training and inference configuration where citing and cited paper's global information is concatenated with the local citation context. Their pre-fetch and re-ranking pipeline is well-suited to this setup and benefits from it as the inference step also allows incorporating the cited paper's title and abstract, which is not the case in a classification approach like ours'. Nevertheless, CiteBART outperforms them without exploiting global information about the cited papers.

5 Discussion and Conclusion

This work proposes CiteBART, a custom language model pre-training with citation objectives for LCR. In CiteBART-Base, we mask the citation tokens in the local contexts to make citation predictions. This local context-only pre-training performs as a good baseline, superior to BERT-GCN on PeerRead, and DualEnh-ws and HAtten on Refseer. CiteBART-Global concatenates the title and abstract of the citing paper to the local context during the citation-masked pre-training. Its superior performance proves the effectiveness of global information, such as titles and abstracts, in the citation learning task.

CiteBART is distinctive as it performs LCR by end-to-end learning. On the other hand, the recent approaches adopt pre-fetch and re-rank pipelines where their system first retrieves a set of papers and then ranks the retrieved by matching queries (citing papers' titles and abstracts, local citation contexts) with candidate papers' representations (cited papers' titles and abstracts). While our model does not use global information about cited papers during testing, these systems require titles and abstracts of the cited papers for inference. In CiteBART-Base, we rely solely on local citation contexts, while CiteBART-Global incorporates the citing paper's global information to make predictions. Across all benchmark datasets except for the smallest PeerRead, CiteBART-Global outperforms the state-of-the-art.

Compared to the existing approaches, CiteBART possesses zero-shot capabilities. As a generative language model, its predictions may craft a new group of tokens to form a citation. The crafted citation tokens exhibit some good propeties, e.g., they share the author names with the ground-truth citation token, the date part hallucinated.

CiteBART can still be fine-tuned for any downstream task. We hypothesize that it should perform better in downstream tasks involving citations and scientific papers than other language models without citation-specific learning signals during pre-training, an area we intend to explore in future work. Furthermore, with the release of new citation recommendation datasets, it will be sufficient to continually pre-train the model to acquire knowledge about the new scientific papers with no need to pre-train from scratch.

Finally, we comment on the advantages of using BART over encoder-based pre-training models such as RoBERTa. BART's MLM objective is flexible and allows the masking of all the tokens in the parenthetical author-date style. RoBERTa cannot add citation tokens to its vocabulary by its MLM.

Table 5: Three example top-10 citation predictions using CiteBART. Due to space limitations, contexts and abstracts have been abbreviated.

#	Context	Ground Truth	Pretraining Dataset of the Model	Predicted Citations
1	... Twitter. Previously, a series of NLP tasks have tried to utilize the social annotations like followers , emoticons and responses **<mask>** etc. two kinds of common social labels, i.e., hyper-links and hashtags are leveraged for ...	Hu et al., 2015	PeerRead Base	1. Shang et al., 2015 2. Vinyals and Le, 2015 3. Baqapuri, 2015 4. Serban et al., 2015 5. Sordoni et al., 2015 6. Tan et al., 2015 7. Tan et al., 2014 8. Yin and Schutze, 2015 * 9. Dhingra et al., 2016 10. Tan et al., 2016
2	... Twitter. Previously, a series of NLP tasks have tried to utilize the social annotations like followers , emoticons and responses **<mask>** etc. two kinds of common social labels, i.e., hyper-links and hashtags are leveraged for ... </s> TGSum: Build Tweet Guided Multi-Document Summarization Dataset </s> The development of summarization research has been significantly hampered by the ...	Hu et al., 2015	PeerRead Global	**1. Hu et al., 2015** 2. Vinyals and Le, 2015 3. Bing et al., 2015 4. Tan et al., 2014 5. Dhingra et al., 2016 6. Xiao and Cho, 2016 7. Qu and Hovy, 2016 * 8. Bing et al., 2014 * 9. Lei et al., 2015 10. Qu and Zuidema, 2015 *
3	... in some latent space. There are many ways to structure G. The DCGAN **<mask>** uses fractionally-strided convolutions to upsample images instead of ... </s> Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking </s> Traditional generative adversarial networks (GAN) and many of its variants are trained by minimizing the KL or JS-divergence loss ...	Radford et al., 2015	ACL-200 Global	1. Kalchbrenner et al., 2014 2. Kalchbrenner and Blunsom, 2013 3. Sha and Pereira, 2003 4. Mikheev et al., 2013 * 5. Finkel et al., 2008 6. Mikheev et al., 1999 7. Gimpel and Smith, 2012 8. Kim et al., 2014 9. Blitzer et al., 2006 10. Henderson, 2004

Table 6: Ablation study results on ACL-200 Global dataset under four different configurations.

	Approach	Training Input	Recall@10	EM	MRR
	Base	Context	0.686	**0.422**	0.504
	Global	Context + Citing Title & Abstract	**0.739**	0.417	**0.513**
1	No context	Citing Title & Abstract	0.588	0.205	0.311
2	No title	Context + Citing Abstract	0.731	0.415	0.509
3	No abstract	Context + Citing Title	0.712	0.396	0.490
4	All-including	Context + Citing Title & Abstract + Cited Title & Abstract	0.111	0.039	0.056

Moreover, in the prediction phase, constraining predictions to citation tokens for RoBERTa is not straightforward. While BART is prone to hallucination, its capabilities significantly enhance LCR performance.

As shown in our ablation study, extending the local citation context with both the citing and cited paper's title and abstract during the continual pre-training does not produce a better result, which can be evaluated counter-intuitive as one has all the information to learn a citation relationship. The missing global information for the cited paper in the test phase complicates finding out the associated citation token.

For future work, we plan to investigate further the all-including configuration given in the ablation study. Conceptually, exploiting the cited paper's title and abstract during the continual pre-training should have been complementary. However, the empirical evidence proves the contrary. More sophisticated masking strategies besides citation token masking should connect the dots by combining the information from the citing paper's title and abstract, local citation context, and the cited paper's title and abstract. Additionally, we should investigate the potential solutions to the citation-specific hallucinations and tackle a way to reduce the number of hallucinated recommendations in the top k.

Limitations

We recognize the following limitations in this study. First, CiteBART addresses the task of LCR, and given context with a citation placeholder, it predicts the best candidates for the placeholder. As a citation placeholder indicates that the context is worth citation, CiteBART builds upon the assumption of the citation worthiness of a local context.

Second, CiteBART necessitates pre-training on a specific dataset to recommend citations from the pool of papers in it. Thus, it may omit to cite some work or authors if they are not included in its training corpus. However, unlike the past works, as CiteBART is generative, it can recommend unseen papers, hallucinating. Although the fabricated citations in the top k predictions show that they capture the author names of the ground-truth citations, hallucination is still a problem.

There can be a bias towards citing papers as CiteBART-Global learns from both local context and citing papers. Leveraging all the parts of a citation relationship, citing paper, local context, and cited paper should provide a more balanced learning process once it can be made learning. We leave this possibility for future exploration.

Ethics Statement

CiteBART is a tool to support the scientific community in paper writing; it in no way replaces a researcher or alternates the thoughtful process of choosing the most appropriate references to cite in a local context.

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A Token Limits

Before pre-training with citation objectives, we ensured that each context has its "<mask>" token in its middle position after tokenization. Another critical aspect was the determination of correct lengths for citation contexts. We limited citation contexts in each dataset to an optimal number of tokens to avoid increasing time and memory costs. An exploratory analysis of context lengths shows that the contexts of ACL-200 and Peerread are significantly longer than those of the other datasets. After tokenization, we observed that $200 - 400$ tokens

were optimal for all base datasets. This limit allows sufficiently long contexts without a need for excessive amounts of padding tokens. As an exception, ACL-200 has 607 contexts that exceed the 400 limit. We have shortened them to the 400 token limit as they correspond to a small proportion of the whole number of contexts and also because the number of discarded tokens is negligible.

Table 7: Maximum token limits for the preprocessed datasets.

Dataset Name	Base Token Limit	Global Token Limit
ACL-200	400	350
FullTextPeerRead	400	350
Refseer	200	350
Arxiv	300	350

For each global dataset, we chose the token limit as 350. Since abstracts require a higher number of tokens, we limited the local context sizes to 100 for the global versions of the datasets. We also ensured that there are 50 tokens each on the left and right sides of the <mask> tokens. We used a token limit of 200 for abstracts for all datasets since most abstracts can fit into it. Table 7 shows the maximum token limits for both the base and global training schemes.

B Training and Evaluation Times

We conducted our experiments on devices with NVIDIA RTX6000 Ada GPU and NVIDIA V100 GPU for Global and Base datasets, respectively. For global datasets, the pre-training for Peerread and ACL-200 lasts for 2 and 6 hours, respectively. The larger datasets, Arxiv and Refseer, take up to $8-9$ days since they have similar sizes. For base datasets, the training for the smaller datasets, Peerread and ACL-200, lasts for 8 and 20 hours, respectively. The larger datasets, Arxiv and Refseer, take up to 14-15 days. However, we believe these relatively longer times are the result of training on the device with NVIDIA V100 GPU.

Our evaluation of the corresponding test sets takes considerable time since generating the top 10 predictions for each example is resource-intensive. Especially with our limited hardware resources, acquiring the results on the larger datasets takes up to 2 days. The smaller datasets require less time, 20 minutes for Peerread and 2 hours for ACL-200. We performed our evaluations on the device with NVIDIA RTX6000 Ada GPU.

The issue of slow evaluation for larger datasets is not exclusive to our work. Gu et al. (2022) reported their results using only a smaller subsection ($10K$) of the test sets due to long evaluation times.

C Metrics

To evaluate CiteBART, we used the Recall@10, Exact Match and Mean Reciprocal Rank metrics. The past works on citation recommendation have generally used Recall@10 and Mean Reciprocal Rank as evaluation metrics.

Recall@10 is the ratio of the correctly predicted items in the top k recommendations. The benchmark datasets have only one actual target for each context. Therefore, recall@10 measures whether the target citation matches any recommendations in top k.

Exact match (EM) calculates whether the first prediction of the model is the same as the target citation. It is the same as accuracy since there is only one ground-truth citation for each context.

Mean Reciprocal Rank (MRR) considers the position of the ground-truth label in a top-k ranked recommendation list. It is the mean of the reciprocal rank of the correctly recommended citation in the recommendation list. Thus, in Equation 1, U corresponds to the total number of contexts in the dataset (test set size), and i is the position of the ground-truth citation for context u in the top-k results. We used k as 10 in our experiments.

$$MRR = \frac{1}{U}\sum_{u=1}^{U}\frac{1}{rank_i} \quad (1)$$

D Qualitative Analysis on Large Language Models' Performances in LCR

We conducted experiments on a Large Language Model (LLM) to evaluate its performance in local citation recommendation. We prompted the open-source "Llama-2-70b-chat" model for our trials. In each prompt, we first list a set of citation tokens (200, due to the limits of chat windows) from our dataset, followed by a few examples of masked contexts with the corresponding ground truth mask values. Subsequently, we ask the model to fill in the mask for a new context by selecting a citation from the initially provided list.

We present four examples in Figures 1 and 2 to illustrate the workings of the base and global pre-training schemes, respectively. Due to space

constraints, we partially display the list of citations, example contexts, and citing abstracts in the prompts. Each example consists of three parts: the prompt, the LLM's answer, and the ground truth value of the masked citation token provided at the end of the prompt.

Figure 1 includes a correct prediction in Part (a) and an incorrect one in (b). Indeed, the correct prediction is the only successful example in several trials using the base approach. The model responds to the prompt by "Shwartz et al., 2016" explaining its choice. On the other hand, the model fills in the mask by "Bahdanau et al., 2016" in Part (b), where "Bluche, 2016" is expected. Its reasoning sheds light on its wrong choice as it strongly associates the term "attention-based mechanisms" in the local context with Bahdanau et al.'s seminal paper on attention-based sequence modeling.

In Figure 2, Part (a) presents a successful example based on the global dataset where the prompt includes the citing paper's title and abstract with the local citation context. The LLM generates the correct citation without an explanation, unlike other predictions. The second example in Part (b) belongs to an incorrect prediction, yet the LLM makes a plausible choice here, judging from its grounding. We can conclude from the observed behavior that LLMs need custom pre-training for the citation tokens to perform well in the task of local citation recommendation.

Our further trials with LLMs demonstrate that they tend not to restrict their predictions to the provided list of citations but to recommend the best choice based on their prior knowledge. They also exhibit a known deficiency. They sometimes ask for confirmation when they provide an answer, and even if you confirm, they lean towards changing the answer. In conclusion, they suffer from hallucinations.

PROMPT:

Here is a list of citations:
"Stalzer, 2017"
"Langford et al., 2008"
"Zhao et al., 2015"
…

There are example context windows taken from scientific papers below. Each of them has a <mask> inside. Actual values of masks have been provided as well. They are filled using one the citations listed above.

An example context window: "… compared with hand-crafted networks.The recent work MetaQNN <mask> and ral Architecture Search with reinforcement learning reported surprising …"
Actual value of the mask: "Baker et al., 2016"
…

Now, find the following context window's actual mask using one of the citations listed above:

An example context window: "… relation between the words . Recently, presented xNET, an extension of HypeNET <mask>. This method integrates both path-based and …"
What is the actual value of the mask?

ANSWER:

The actual value of the mask in the given context window is "**Shwartz et al., 2016**".

Here's how you can identify the correct citation: The context window mentions "xNET" and "HypeNET", which are both neural network models used for semantic relation classification. The authors mention that the approach presented in the paper integrates both path-based and distributional information for semantic relation classification. The paper was published recently, relative to the publication date of the paper containing the context window. All of these clues point to the citation being "Shwartz et al., 2016", which is indeed the correct answer.

Ground Truth Citation: Shwartz et al., 2016

(a) Base approach - Successful example

PROMPT:

Here is a list of citations:
"Stalzer, 2017"
"Langford et al., 2008"
"Zhao et al., 2015"
…

There are example context windows taken from scientific papers below. Each of them has a <mask> inside. Actual values of masks have been provided as well. They are filled using one the citations listed above.

An example context window: "… compared with hand-crafted networks.The recent work MetaQNN <mask> and ral Architecture Search with reinforcement learning reported surprising …"
Actual value of the mask: "Baker et al., 2016"
…

Now, find the following context window's actual mask using one of the citations listed above:

An example context window: "… follow-up work solves this problem with attention based mechanisms <mask> , this will be investigated in future work. The recognizer is trained on both …"
What is the actual value of the mask?

ANSWER:

The actual value of the mask in the given context window is likely to be "**Bahdanau et al., 2016**". This citation is mentioned in the list of references provided earlier and fits the context of the sentence where it mentions "attention-based mechanisms". Therefore, the complete reference for the context window would be:

"… follow-up work solves this problem with attention-based mechanisms Bahdanau et al., 2016, this will be investigated in future work. The recognizer is trained on both …"

Ground Truth Citation: Bluche, 2016

(b) Base approach - Unsuccessful example

Figure 1: Prompt examples on a Large Language Model for Base dataset.

PROMPT:

Here is a list of citations:
"Mirowski et al., 2016"
"Lowe et al., 2017"
"Walsh, 2014"
…

There are example context windows taken from scientific papers below. Each of them has a <mask> inside. Alongside the context windows, the titles and abstracts of citing papers, which contain the context windows, are provided. Actual values of masks have been provided as well. They are filled using one the citations listed above.

An example context window, citing title and abstract: "... that it searches for critical points rather than local optima <mask> . Therefore, it is more common to use natural gradient or updates... </s> A Kronecker-factored approximate Fisher matrix for convolution layers </s> Second-order optimization methods such as natural gradient descent have the potential to speed up ..."
Actual value of the mask: "Pascanu et al., 2014"
…

Now, find the following context window's actual mask using one of the citations listed above:

An example context window, citing title and abstract: "… for generating specific responses, inspired by the semi-supervised deep generative model <mask> . The principle idea is to generate the next response … </s> A Conditional Variational Framework for Dialog Generation </s> Deep latent variable models have been shown to facilitate the response generation for open-domain dialog …"
What is the actual value of the mask?

ANSWER:

The actual value of the mask is "**Kingma et al., 2014**".

Ground Truth Citation: Kingma et al., 2014

(a) Global approach - Successful example

PROMPT:

Here is a list of citations:
"Mirowski et al., 2016"
"Lowe et al., 2017"
"Walsh, 2014"
…

There are example context windows taken from scientific papers below. Each of them has a <mask> inside. Alongside the context windows, the titles and abstracts of citing papers, which contain the context windows, are provided. Actual values of masks have been provided as well. They are filled using one the citations listed above.

An example context window, citing title and abstract: "... that it searches for critical points rather than local optima <mask> . Therefore, it is more common to use natural gradient or updates... </s> A Kronecker-factored approximate Fisher matrix for convolution layers </s> Second-order optimization methods such as natural gradient descent have the potential to speed up ..."
Actual value of the mask: "Pascanu et al., 2014"
…

Now, find the following context window's actual mask using one of the citations listed above:

An example context window, citing title and abstract: " ... stacked Denoising Auto-encoders to extract meaningful representations. <mask> main adaptation from multiple sources. For domain adaptation ... </s> Knowledge Adaptation: Teaching to Adapt </s> Domain adaptation is crucial in many real-world applications where the distribution of the training data differs from the distribution of ..."
What is the actual value of the mask?

ANSWER:
Based on the context window, I'm going to take a guess that the actual value of the mask is "**Nguyen et al., 2016**". My reasoning is as follows:
The context window mentions "domain adaptation" and "learning domain-invariant representations", which suggests that the paper is related to domain adaptation.
The sentence with the mask mentions "main adaptation from multiple sources", which suggests that the paper is discussing a method for adapting to multiple sources or domains.
The citation "Nguyen et al., 2016" is listed in the original list of citations, and the title of the paper is not provided, but the abstract mentions "domain adaptation" and "multiple sources", which matches the context of the context window.

Ground Truth Citation: Chen et al., 2012

(b) Global approach - Unsuccessful example

Figure 2: Prompt examples on a Large Language Model for Global dataset.