KID-Review: Knowledge-Guided Scientific Review Generation with Oracle Pre-training

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Abstract
The surge in the number of scientific submissions has brought challenges to the work of peer review. In this paper, as a first step, we explore the possibility of designing an automated system, which is not meant to replace humans, but rather provide a first-pass draft for a machine-assisted human review process. Specifically, we present an end-to-end knowledge-guided review generation framework for scientific papers grounded in cognitive psychology research that a better understanding of text requires different types of knowledge. In practice, we found that this seemingly intuitive idea suffered from training difficulties. In order to solve this problem, we put forward an oracle pre-training strategy, which can not only make the KID-REVIEW better educated but also make the generated review cover more aspects. Experimentally, we perform a comprehensive evaluation (human and automatic) from different perspectives. Empirical results have shown the effectiveness of different types of knowledge as well as oracle pre-training. We make all code, relevant datasets available: https://github.com/yyy-Apple/KIDReview as well as the KID-REVIEW system: http://nlpeer.reviews.

Introduction
The rapid growth of research publication not only requires scientists to devote more time to the literature review (Luu et al. 2020; Jha, Abu-Jbara, and Radev 2013; Mohammad et al. 2009; Xing, Fan, and Wan 2020), but brings difficulties to peer review (Yuan, Liu, and Neubig 2021). To address this problem, a small handful of works make a preliminary exploration towards automatic scientific review generation. Wang et al. (2020) perform template-based comment generation for each fine-grained aspect. Yuan, Liu, and Neubig (2021) first answer what the desiderata of a good automatic reviewing system are, and then design an end-to-end auto-review system using current state-of-the-art summarization models.

Despite making a good first step, it is still far from a well-qualified automated reviewing system that can match a human reviewer (Yuan, Liu, and Neubig 2021). Inspired by research in the context of cognitive psychology (Kintsch and Walter Kintsch 1998; Kamide, Altmann, and Haywood 2003; Mumper 2013; Chen et al. 2018), that human comprehend text from (i) general world knowledge (long-term memory) (ii) temporary knowledge (working memory). We claim that a better understanding of scientific papers also requires these two types of knowledge and operationalize this idea by proposing a knowledge-guided framework for scientific review generation (KID-REVIEW).

Specifically, as shown in Fig. 1, knowledge is incorporated by using diverse graphs, where concept graph carries the information of entities (e.g., method) associated with their relations (e.g., a method is used for a task) for a given paper. By contrast, citation graph expresses the whole citation topology within a specific domain. Architecturally, we propose an end-to-end framework where a citation graph is first encoded using a large-scale node representation learning algorithm (Tang et al. 2015) and incorporated with the paper content itself. Then we use Graph Neural Networks (Veličković et al. 2017) to represent entities and their interactions within a paper to guide the review generation process.

Practically, to make KID-REVIEW better educated from training data, we propose an oracle pre-training strategy. The basic idea is that instead of directly training KID-REVIEW with the whole content of a paper as input, we pre-train it by feeding oracle texts (Nallapati, Zhai, and Zhou 2017), which are sentences from the paper that achieve large lexical

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Figure 1: Two types of knowledge: citation graph and concept graph. Squares represent concepts, circles represent papers.
overlap with human reviews.\footnote{We use the greedy method to get oracle texts as described in (Nallapati, Zhai, and Zhou 2017).} We then fine-tune pre-trained KID-REVIE\textsuperscript{W} with different types of paper contents (e.g., introduction) so that during the inference stage, KID-REVIE\textsuperscript{W} does not need to rely on information from human reviews.

Experimentally, we find the\textit{ oracle pre-training} strategy not only facilitates the optimization process but also makes generated reviews cover more aspects. Additionally, we observe that using different flavors of knowledge will bring diverse benefits. For example, using citation graphs will help distinguish the paper quality, while introducing concept graphs will lead to more detailed and critical reviews.

Our contributions can be summarized: (1) This is the first work that neuralizes (i.e., end-to-end system) scientific review generation task with different types of knowledge, and present an\textit{ oracle pre-training} method to make the parameter optimization more approachable. The work opens the door to this challenging task and connecting it with the latest neural techniques (e.g., BART (Lewis et al. 2020) , GNNs) so that it can enjoy the latest research success. (2) Our work not only shows the complementarity between pre-trained knowledge (e.g., BART) and diverse types of knowledge graphs (e.g., citation graph) for scientific review generation, which could provide a reference for other generation tasks, but also presents how different types of knowledge play different roles. (3) We release our systems and provide a demo service.

\section*{Preliminaries}

\textbf{Task Definition}

Scientific review generation is conceptualized as an \textit{aspect-based scientific paper summarization} task. Given input paper $D$, the aim is to generate a review whose high-level objectives are (1) selecting high-quality submissions for publication and (2) improving different aspects of a paper by providing detailed comments (Jefferson et al. 2002; Smith 2006).

\textbf{Systems \& Evaluation Metrics}

\textbf{Systems} Existing best-performing systems approach scientific review generation as a two-stage (extract-then-generate) summarization problem. Specifically, the first step is to extract salient text pieces from source documents (papers), then generate reviews based on these extracted texts with a state-of-the-art pre-trained sequence-to-sequence model.

\textbf{Metrics} We follow the definition proposed by Yuan, Liu, and Neubig (2021) about what desiderata of a good peer review are: (1) A good review should take a clear stance, selecting high-quality submissions (2) well-organized (3) provide specific reasons for assessment (4) constructive. We briefly the core idea of each metric we will use, and detailed formulation could refer to the original paper.

\begin{itemize}
  \item \textit{Recommendation Accuracy}: Whether the acceptance implied by the review is consistent with the reviewed paper.
  \item \textit{Aspect Coverage}: How many aspects in a pre-defined typology have been covered in a review.
\end{itemize}

\textbf{Knowledge-guided Review Generation}

Our proposed framework is illustrated in Fig. 2. The backbone of our model is a pre-trained sequence-to-sequence model BART (Lewis et al. 2020) due to its superior performance in text generation.\footnote{We also explored other pre-trained models like T5 (Raffel et al. 2019) while the performance is worse.} We introduce two types of knowledge into BART through different ways. Citation embeddings are learned through a large-scale node representation learning algorithm and are held fixed during training. Concept graph knowledge is encoded through Graph Attention Network (GAT) (Veličković et al. 2017) and is jointly trained with BART. We detail each knowledge component below.

\textbf{Concept Graph}

We first introduce how we construct a concept graph for each paper and then detail the graph propagation process.

\textbf{Graph Construction} We define concept graph as $G^p = \{V^p, E^p\}$ where $V^p$ stands for nodes one for each entity and $E^p$ represents relation edges between entities.

\textbf{Attributes of Nodes and Edges} Specifically, we follow the entity types (\textit{task}, \textit{material}, \textit{method}, \textit{metric}, \textit{generic}, \textit{other scientific term}) and relation types (\textit{part of}, \textit{used for}, \textit{compare}, \textit{feature of}, \textit{evaluate for}, \textit{conjunction}) defined in SciERC (Luan et al. 2018) for concept graph construction.
Edges as Graph Nodes  Since the raw entity nodes and relation edges typically cannot form a connected graph, we further adopt the method introduced in Koncel-Kedziorski et al. (2019) to restructure the graph where we convert relation edges into nodes and introduce a global node to connect all nodes. This transformation can be visualized in Fig. 3-(a) and Fig. 3-(b).

Graph Initialization  The initial representation for an entity node is obtained using the $l$ lower layers ($l$ is a hyperparameter) of BART encoder as shown in Fig. 4. Specifically, given an entity, we first tokenize it and add a [BOS] token as well as a [EOS] token, which results in a sequence of tokens $\{t_1, \cdots, t_n\}$ where $t_1$ is the [BOS] token and $t_n$ is the [EOS] token. We then use the $l$ lower layers of BART encoder to get the contextualized representations for each token therefore obtaining $\{e_1, \cdots, e_n\}$, which are the rectangles above BART encoder layers in Fig. 4. Finally, we take $e_n$ (the rectangle inside a circle), which is the representation learned for [EOS] token as the initial entity embedding.

The initializations for relation nodes and global nodes are similar. For a relation node, we encode the descriptive text (Chai et al. 2020) for that specific relation to get its initial representation (e.g. “is used to evaluate for” for “evaluate for”). For a global node, we encode the title of its associated paper to get the initial representation. Detailed descriptive texts for each relation can be found in Appendix.

Graph Propagation Layer  We learn the concept graph representations using Graph Attention Network (GAT). We refer to $e_i \in \mathbb{R}^d, i \in \{1, \cdots, m\}$ as the initial node embeddings in a graph containing $m$ nodes, $d$ is the embedding dimension. We use a multi-head self-attention setup with $N$ attention heads. The updated embedding for node $i$ after going through a GAT layer can be calculated as:

Figure 3: Restruction of the original concept graph. N denotes an entity node, R denotes a relation node. R-inv denotes an inverse relation node, G denotes a global node.

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\[
\tilde{e}_i = e_i + \frac{1}{N} \sum_{n=1}^{N} \alpha^n_{ij} W^n_v e_j
\]

(1)

\[
\alpha^n_{ij} = \frac{\exp(z^n_{ij})}{\sum_{k \in N(i)} \exp(z^n_{ik})}
\]

(2)

\[
z^n_{ij} = (W^n_v e_i) \cdot (W^n_v e_j)/\sqrt{d}
\]

(3)

Where $\|N\|$ denotes the concatenation of $N$ attention heads, $N(\cdot)$ denotes the neighbor nodes of a given node. $W_q, W_k, W_v$ are trainable parameters. Following the Transformer architecture (Vaswani et al. 2017), we add a feed-forward network to further enrich the graph representations. The final representation for node $i$ is calculated using Eq. 4.

\[
e'_i = \text{LN}(\text{FFN}(\tilde{e}_i) + \tilde{e}_i)
\]

(4)

LN($\cdot$) denotes layer normalization and FFN($\cdot$) represents feed-forward neural network.

Graph Into BART  After getting graph representations, we need to infuse such knowledge into our BART decoder. As shown in Fig 2, the way we do so is to add another cross attention module inside each BART decoder layer to attend to entity representations in our constructed concept graph. We refer to $x$ as encoded representations for input paper, $y^l$ as the representations of output in $l$-th BART decoder layer, $e$ as the entity representations got from GAT. The $(l+1)$-th decoder layer output is obtained as follows:

\[
y^{l+1} = \text{LN}(y^l + \text{SelfAttn}(y^l))
\]

(5)

\[
y^{l+1} = \text{LN}(y^{l+1} + \text{CrossAttn}(y^{l+1}, x))
\]

(6)

\[
y^{l+1} = \text{LN}(y^{l+1} + \text{CrossAttn}(y^{l+1}, e))
\]

(7)

\[
y^{l+1} = \text{LN}(y^{l+1} + \text{FFN}(y^{l+1}))
\]

(8)

Where LN($\cdot$) denotes layer normalization, SelfAttn($\cdot$) and CrossAttn($\cdot$) represent self-attention module and cross-attention module in BART decoder layer respectively, FFN($\cdot$) denotes feed-forward neural network.
Although our proposed system can be directly optimized with the citation embedding of a paper. Formally, we refer to vector spaces. Once learned, the citation embedding for each paper is fixed afterward.

**Graph Into BART** We incorporate citation graph knowledge into BART to enrich the original BART encoder output with the citation embedding of a paper. Formally, we refer to $x'$ as regular encoder output given a source paper, $c$ as citation embedding of that paper. The final encoder output $x$ is $[W_c, c|x']$, where $W_c$ is a trainable parameter and $\parallel$ denotes concatenation. The newly concatenated encoder output will be fed into the BART decoder to be further attended.

**Oracle Pre-training**
Although our proposed system can be directly optimized by feeding input texts and targeted reviews, in practice, we found it challenging to find a satisfying local optimum when training the newly initialized GAT and pre-trained BART together when feeding non-oracle texts. We speculate that this may be caused by the complicated mapping between lengthy input texts to targeted reviews, making it hard to train the knowledge graph component from scratch.

Inspired by the recent idea of oracle guided training (Dou et al. 2020), which has achieved the state-of-the-art performance on the task of summarization, we propose an oracle pre-training mechanism, which, (i) engineeringly, ensures a smoothing training process, (ii) experimentally, provides better results w.r.t some evaluation metrics. The basic idea is first to pre-train Kid-REVIEW by feeding it with oracle texts (Nallapati, Zhai, and Zhou 2017), which are sentences from the paper with large lexical overlap with human reviews, and then fine-tune systems using different paper contents extracted by diverse strategies (e.g., cross-entropy based methods).

**Setup**

**Information Extraction over scientific papers** To get desired types of entities and relations, we apply the method introduced in Wadden et al. (2019) to extract that information in the abstract section. The reason is that we aim to build a salient concept graph, where entities serve for the main idea of the paper to be reviewed (Jain et al. 2020). We collapse co-referential entities into a single entity associated with the longest mention since we assume it to be more informative than others.

**Model Settings** We initialize BART’s parameters using the checkpoint “bart-large-cnn” which is pre-trained on “CNNDM” dataset (Hermann et al. 2015). We set the embedding size to be 128 when learning citation embeddings. We use two GAT layers for the concept graph, each with 4 attention heads, and we set the hidden size to be 200. To get the initial concept graph embeddings, we set $l = N_{enc}/2$, where $N_{enc}$ denotes the total number of layers in BART encoder. For each BART decoder layer, we add another cross-attention module to attend to entity node representations on top of the regular cross-attention module.

**Training Settings** Following Yuan, Liu, and Neubig (2021), we adopt the extract-then-generate paradigm to deal with lengthy input texts and investigate two extraction strategies, which are (i) extracting sentences to maximize unigram entropy using cross-entropy method (Feigenblat et al. 2017); (ii) combining the abstract part of a paper as well as the extraction in (i). Besides, we also consider oracle extraction for comparison reason, which is the extraction that achieves the highest average ROUGE scores (Lin and Hovy 2003) with respect to reference reviews, specifically using the greedy method described in Nallapati, Zhai, and Zhou (2017).
training for systems using oracle extraction is from scratch, while others are fine-tuned based on the pre-trained models using oracle extraction. See Appendix for more details.

**Generation Settings** We use beam search decoding during generation and adopt the same parameters following Yuan, Liu, and Neubig (2021) for all systems.

### Results and Analysis

In all our experiment results, we use the following notations. “cit.” and “con.” denote citation and concept knowledge. “Pre.” stands for oracle pre-training.

**Automatic & Human Evaluation** As mentioned before, we use the following metrics to characterize human-written reviews and system-generated reviews: Recommendation Accuracy, Aspect Coverage, Aspect Recall, Summary Accuracy and Constructiveness. The former three can be naturally fed abstract as input text at our extraction stage, while the latter two require human annotations. We follow the aspect topology introduced by Yuan, Liu, and Neubig (2021) and use their provided aspect tagger to get aspect information within each review. More details can be found in Appendix. Automatic evaluation metrics are performed on ASAP-Review test set, the results are shown in Tab. 2.

Overall, we make the following observations: (i) pre-training on oracle texts and then fine-tuning on other input texts can significantly improve Aspect Coverage and Aspect Recall compared to directly training with other input texts, with the largest improvement 8.1 for Aspect Coverage and 4.69 for Aspect Recall respectively. (ii) For systems that have been equipped with oracle pre-training, using citation graph and concept graph can both achieve consistently higher Recommendation Accuracy than vanilla system without knowledge enhancement. The observed largest improvements are 7.66 and 4.46 for adding citation knowledge and concept knowledge, respectively. Besides, the combination of both knowledge can get an even higher Recommendation Accuracy boost, at most 11.88. (iii) Training directly based on oracle texts of a paper can reach the highest Aspect Coverage and Aspect Recall scores, which suggests that it is still valuable to explore more effective content selection strategies when dealing with lengthy source input.

However, to better assess the helpfulness of peer reviews, human judgements are necessary. Therefore, we also conduct human evaluation to measure Summary Accuracy and Constructiveness. We take three systems into comparison: (i) vanilla system without oracle pre-training (Yuan, Liu, and Neubig 2021), (ii) vanilla system with oracle pre-training, (iii) system equipped with both citation knowledge and concept knowledge, as well as oracle pre-training. We select 40 papers from CV/NLP domain that have not been included in the training set and use abstract plus cross-entropy extraction to get system-generated reviews. For each paper, we ask one of the co-authors to annotate the generated reviews. More specifically:

- For Summary Accuracy, we ask them to rate the summary part in a review, with a score of 1 denoting agree, 0.5 denoting partially agree, and 0 denoting absent or disagree.
- For Constructiveness, we pair the system-generated reviews for each paper and asked the author to give a pairwise ranking based on how constructive he or she thinks each review is.

The **Summary Accuracy** for three systems are shown in Tab. 3. All systems can correctly summarize the core idea of given papers almost always. This may be because we have explicitly fed abstract as input text at our extraction stage, which will better guide the summary generation.

The pairwise comparison results for Constructiveness are shown in Tab. 4. By pairwise comparison, the vanilla system without oracle pre-training performs worse than its counterpart with oracle pre-training, while the system enhanced with knowledge can outperform the vanilla system with oracle pre-training. This suggests that adding knowledge can generate more informative and constructive texts.

**Fine-grained Analysis** Results from the above section present a holistic view of how different knowledge (e.g.,

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- | Pre. | Knowledge | RACC | ACOV | AREC |
--- | --- | --- | --- | --- | --- |
- | Human | – | – | 49.25 | 50.83 | 58.35 |
- | Oracle | – | vanilla | 2.40 | 67.51 | 65.28 |
- | – | + citation | 10.06 | 68.66 | **67.48** |
- | – | + concept | 6.86 | **71.77** | 65.74 |
- | – | + cit. & con. | 5.03 | 67.67 | 64.09 |
- | CE | × | vanilla | 13.94 | 62.64 | 60.73 |
- | – | vanilla | 11.43 | **67.39** | **62.56** |
- | – | + citation | 12.80 | 66.90 | 62.49 |
- | – | + concept | 12.11 | 62.01 | 60.85 |
- | – | + cit. & con. | **23.31** | 61.00 | 61.99 |
- | Abs.+CE | × | vanilla | 15.54 | 55.37 | 58.31 |
- | – | vanilla | 17.03 | 63.47 | 63.00 |
- | – | + citation | 21.14 | **64.69** | **63.53** |
- | – | + concept | 18.06 | 60.64 | 59.80 |
- | – | + cit. & con. | **25.03** | 58.46 | 60.90 |

**Table 2:** Results on automatic evaluation metrics. **RACC:** Recommendation Accuracy, **ACOV:** Aspect Coverage, **AREC:** Aspect Recall. “Oracle” represents oracle pre-training. “CE” denotes content selection of input papers with cross-entropy method. “Abs.” stands for the abbreviation for abstract. The results for vanilla systems without pre-training are taken from Yuan, Liu, and Neubig (2021).

---

- | Vanilla | Vanilla (Pre.) | + cit.&con. (Pre.) |
--- | --- | --- | --- |
- | SACC | 39/40 | 40/40 | 39.5/40 |

**Table 3:** **Summary Accuracy** for three systems.
Table 4: Pair-wise comparisons for three systems. Sys.1 represents vanilla system without oracle pre-training. Sys.2 represents vanilla system with oracle pre-training. Sys.3 represents citation graph knowledge and concept graph knowledge enhanced system with oracle pre-training. Each \((i, j)\) entry in the table means the percentage of times system \(i\) is preferred than system \(j\).

|       | Sys.1 | Sys.2 | Sys.3 |
|-------|-------|-------|-------|
| Sys.1 | ×     | 47.73 | 45.45 |
| Sys.2 | 52.27 | ×     | 42.86 |
| Sys.3 | 54.55 | 57.14 | ×     |

Table 5: The frequency of certain words/phrases in reviews from different systems.

|                | Vanilla | + cit. | + con. |
|----------------|---------|--------|--------|
| for example    | 615     | 616    | 680    |
| e.g.           | 740     | 757    | 741    |
| such as        | 255     | 261    | 282    |
| for instance   | 294     | 294    | 394    |
| should compare | 90      | 115    | 170    |
| questions      | 22      | 25     | 38     |
| ?              | 378     | 347    | 411    |

Figure 6: Fine-grained Aspect Coverage for different extraction strategies equipped with different knowledge. M1: vanilla; M2: citation graph; M3: concept graph; M4: citation + concept graph. MOT: Motivation, ORI: Originality, SOU: Soundness, SUB: Substance, REP: Replicability, CMP: Meaningful Comparison, CLA: Clarity. “Pre.” denotes oracle pre-training.

Figure 7: Citation embeddings for accepted/rejected papers using T-SNE visualization.

Knowledge Understanding Besides holistic and fine-grained evaluation, in this section, we aim to understand how different types of knowledge work in KID-REVIEW.

Citation graph From Tab. 2, the improvements on Recommendation Accuracy are consistent by adding citation graph. To explore the potential reasons, we use T-SNE visualization (Van der Maaten and Hinton 2008) to understand the underlying citation embedding space. Specifically, The plot is shown in Fig. 7, red dots represent rejected papers while blue dots denote accepted papers. It is clear that certain region contains more accepted (rejected) papers (e.g., the upper left region contains almost exclusively accepted papers). Therefore, providing citation embeddings would suggest information about the quality of a paper, thus helping the system distinguish papers of different quality. Intuitively, the citation graph will place a paper within context. If a paper has not cited its most relevant papers, it probably lacks many necessary comparisons with prior works.

Concept graph Based on human judgments for Constructiveness, reviews with more specific details are considered to be more constructive. We speculate that with the addition of the concept graph, a model can generate more detailed and specific reviews due to its awareness of salient entities and their relations. To understand how a concept graph would generate more informative reviews, we characterize the generated reviews by looking at how frequently certain words or phrases appear. This is performed on ASAP-Review test set using oracle extraction and the results are shown in Tab. 5. It is evident that by adding a concept graph, the generated
reviews are more likely to give specific examples and are more prone to ask questions. These may account for the better review-level constructiveness observed in Tab. 4.

**Bias Analysis** Here we also conduct bias analysis to see if adding different knowledge will result in a bias for certain groups. We consider bias analysis regarding nativeness, which measures whether there is at least one native English speaker in the author list. We split the papers in the test set into “native” and “non-native”. We follow the **aspect score** and **disparity difference** defined by Yuan, Liu, and Neubig (2021) to characterize the bias of different systems. **Aspect score** is the percentage of positive occurrences for a specific aspect, and **disparity difference** measures the system bias compared to human reviewers.

In particular, we look at disparity difference which measures the distance between system preferences and human preferences for certain groups. Here we consider two extraction strategies which are (i) cross-entropy extraction and (ii) abstract part of a paper plus cross-entropy extraction. The results are shown in Tab. 6. Although adding citation graph knowledge and concept graph knowledge individually may not result in smaller disparity difference to human reviews, adding both will consistently result in smaller disparity difference to human reviews. This also demonstrates the complementarity between different knowledge.

### Table 6: Total disparity difference between generated reviews and reference reviews in terms of native bias. All systems have been oracle pre-trained. “CE” denotes content selection of input papers with cross-entropy method. “Abs.” is the abbreviation for abstract.

| Scheme                  | Vanilla | + cit. | + con. | + cit.&con. |
|-------------------------|---------|--------|--------|-------------|
| CE                      | 51.37   | 85.79  | 76.53  | 50.82       |
| Abs.+CE                 | 61.85   | 66.17  | 56.70  | 54.01       |

**Related Work**

**Knowledge-guided Text Generation** For text generation tasks, knowledge beyond the input sequence is often required to produce informative output text. Researchers have tried to incorporate different flavors of knowledge to guide text generation, including topic information (Wei et al. 2019b; Xu et al. 2020), keywords (Wei et al. 2019a; Li et al. 2020), linguistic features (Zhou et al. 2017; Dong et al. 2020), knowledge base (Yang et al. 2019; Feng et al. 2020), knowledge graph (Guan, Wang, and Huang 2019; Huang, Wu, and Wang 2020), etc. Benefits of incorporating knowledge into text generation have been observed in different tasks. For example, it can greatly alleviate hallucination problem in abstractive summarization (Zhu et al. 2020), generating more appropriate and informative responses in conversation generation (Zhou et al. 2018), etc. In our work, we consider two types of knowledge for scientific review generation: citation graph and concept graph.

**Peer Review** Peer review is an essential component in the research community and has been studied from multiple perspectives including bias analysis (Tomkins, Zhang, and Heavlin 2017; Stelmakh, Shah, and Singh 2019), aspect-based sentiment analysis (Chakraborty, Goyal, and Mukherjee 2020), decision classification (Kang et al. 2018; Qiao, Xu, and Han 2018), automatic review generation (Wang et al. 2020; Yuan, Liu, and Neubig 2021). Relevant dataset includes PeerRead (Kang et al. 2018) and ASAP-Review (Yuan, Liu, and Neubig 2021). Our work extends Yuan, Liu, and Neubig (2021) and provide a novel framework for incorporating external knowledge into pre-trained systems. As far as we know, this is the first work that proposes an end-to-end knowledge-fused system for scientific review generation.

**Implications and Future Directions**

**More Nuanced General World Knowledge** In this work, we only use a single citation embedding for each paper to incorporate domain background knowledge. It has been proven to work in terms of distinguishing papers of different quality as well as detecting more missing comparisons. However, our systems still suffer from constructiveness due to factuality errors. If a system can understand the more fine-grained relationships between papers (e.g., paper A is a combination of existing work B and C), then it can better judge the novelty of submission and give more constructive comments.

**Connecting Text Editing Research with Scientific Review Generation** Text editing (Iso, Qiao, and Li 2020), as exemplified as grammar error correction (Ng et al. 2014; Dong et al. 2019), has been studied in different settings. We claim that editing text towards grammatically correct descriptions is crucial for a high-quality scientific review generation system. For example, although our current systems can generate descriptions like “There is a typo in the abstract.”, these claims are usually not factual since current systems do not have the sufficient ability to judge the quality of the text, which, however, matters for the evaluation of “Clarity” aspect.

**Ethics Statement**

We discuss ethical issues from the following aspects:

**Intended Use** If the system is functioning as intended, both reviewers and paper authors could benefit since our model aims to make research papers better by generating informative comments.

**Failure Modes** While our system may be helpful in some cases, it is not a replacement for a skilled human reviewer. Completely relying on it will result in unfair reviews since, based on our observations, there are still many factually incorrect comments being generated.

**Biases** Biases commonly exist in peer reviews (Manzoor and Shah 2020). In this work, we have quantified biases in generated reviews and found that adding knowledge graphs will lead to lower total disparity difference. Moreover, based on some evidence that bias even exists in human reviews (Manzoor and Shah 2020), we believe the advantage of a review generation system is: reviews can be given in a more controllable way. For example, quantify biases of generated reviews first and then (i) either filter biased systems (ii) or biased aspects (e.g., originality).
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