Can We Automate Scientific Reviewing?

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Abstract

The rapid development of science and technology has been accompanied by an exponential growth in peer-reviewed scientific publications. At the same time, the review of each paper is a laborious process that must be carried out by subject matter experts. Thus, providing high-quality reviews of this growing number of papers is a significant challenge. In this work, we ask the question "can we automate scientific reviewing?", discussing the possibility of using state-of-the-art natural language processing (NLP) models to generate first-pass peer reviews for scientific papers. Arguably the most difficult part of this is defining what a "good" review is in the first place, so we first discuss possible evaluation measures for such reviews. We then collect a dataset of papers in the machine learning domain, annotate them with annotations of different aspects of each review, and train targeted summarization models that take in the paper and generate a review. Comprehensive experimental results show that system-generated reviews tend to touch upon more aspects of the paper than human-written reviews, but the generated text can suffer from lower factuality for all aspects except the explanation of the core ideas of the papers, which are largely factually correct. We finally summarize *eight* challenges in the pursuit of a good review generation system together with potential solutions, which, hopefully, will inspire more future research on this subject. We make all codes, dataset publicly available: https://github.com/neulab/ReviewAdvisor as well as a *ReviewAdvisor* system: http://review.nlpedia.ai/.

1 Introduction

The number of published papers is growing exponentially (Tabah, 1999; De Bellis, 2009; Bornmann and Mutz, 2015). While this may be positively viewed as indicating acceleration of scientific progress, it also poses great challenges for researchers, both in reading and synthesizing the relevant literature for one's own benefit, and for performing *peer review* of papers to vet their correctness and merit. With respect to the former, a large body of existing work explores automatic summarization of a paper or a set of papers for automatic survey generation (Jha et al., 2015a, 2013; Mohammad et al., 2009; Xing et al., 2020; Jha et al., 2015b; Yasunaga et al., 2019b; Cohan et al., 2018b). However, despite the fact that peer review is an important, but laborious part of our scientific process, automatic systems to aid in the peer review process remain relatively underexplored. Bartoli et al. (2016) investigated the feasibility of generating reviews by surface-level term replacement and sentence reordering etc, and Wang et al. (2020) (contemporaneously and independently) propose a two-stage information extraction and summarization pipeline to generate paper reviews. However, both do not extensively evaluate the quality or features of the generated review text.

In this work, we are concerned with providing at least a preliminary answer to the ambitious overarching question: *can we automate scientific reviewing?* Given the complexity of understanding and assessing the merit of scientific contributions, we do not expect an automated system to be able to match a well-qualified and meticulous human reviewer at this task any time soon. However, some degree of review automation may assist reviewers in their assessments, or provide guidance to junior reviewers who are just learning the ropes of the reviewing process. Towards this goal, we examine two concrete research questions, knowing the answers to which are prerequisites to building a functioning review assistant:

Q1: What are the desiderata of a good automatic reviewing system, and how can we quantify them for evaluation? Before developing an automatic review system, we first must quan-

tify what constitutes a good review in the first place. The challenge of answering this question is that a review commonly involves both objective (e.g. "lack of details necessary to replicate the experimental protocol") and subjective aspects (e.g. "lack of potential impact"). Due to this subjectivity, defining a "good" review is itself somewhat subjective.

As a step towards tackling this challenge, we argue that it is possible to view review generation as a task of *opinion-aware summarization*, where the summary not only tries to summarize the core idea of a paper, but also expresses opinions on specific aspects of that paper (e.g. novelty or potential impact). We then evaluate review quality from multiple perspectives, in which we claim a good review not only should make a good summary of a paper (summary accuracy) but also consist of factually correct (recommendation accuracy, summary-level factuality) and fair comments (bias) from diverse aspects (aspect coverage), together with informative evidence (informativeness).

To operationalize these concepts, we build a dataset of reviews from machine learning domain, making fine-grained annotations of aspect information for each review, which provides the possibility for a richer evaluation of generated reviews.

Q2: Using state-of-the-art NLP models, to what extent can we realize these desiderata? We provide an initial answer to this question by using the aforementioned dataset to train state-of-the-art summarization models to generate reviews from scientific papers, and evaluate the output according to our evaluation metrics described above. We propose different architectural designs for this model, which we dub *ASAPReview* (§4), and comprehensively evaluate them, interpreting their relative advantages.

Lastly, we highlight our main observations and conclusions:

(1) What are review generation systems (not) good at? Most importantly, we find the constructed automatic review system *generates non-factual statements* regarding many aspects of the paper assessment, which is a serious flaw in a high-stakes setting such as reviewing. However, there are some bright points as well. For example, it *can often precisely summarize the core idea* of the input paper, which can be either used as a draft for human reviewers or help them (or general readers) quickly understand the main idea of the paper to

be reviewed (or pre-print papers). It can also generate reviews that *cover more aspects* of the paper's quality than those created by humans, and provide evidence sentences from the paper. These could potentially provide a preliminary template for reviewers and help them quickly identify salient information in making their assessment.

(2) Will system generate biased reviews? Yes. We present methods to identify and quantify potential biases in reviews (§5.3.2), and that both human and automatic reviewers exhibit varying degrees of bias. (i) **regarding native vs. non-native English speakers**: papers of native English speakers tend to obtain higher scores on "`Clarity`" from human reviewers than non-native English ones,[1] but the automatic review generators are narrow this gap. Additionally, system reviewers are harsher than human reviewers when giving a score regarding the paper's "`Originality`" for non-native English speakers. (ii) **regarding anonymous vs. non-anonymous submissions:** both human reviewers and system reviewers favor non-anonymous papers, which have been posted on non-blind preprint servers such as arXiv before the review period, more than anonymous papers in all aspects.

Based on above mentioned issues, we claim that **review generation system can not replace human reviews at this time, instead, it may be helpful as part of a machine-assisted human review process**. Our research also enlightens what's next in pursuing a better methods for automatic review generation or assistance and we summarize EIGHT CHALLENGES that can be explored for future directions in §7.2.

2 What Makes a Good Peer Review?

As concluded by Jefferson et al. (2002b): "*Until we have properly defined the objectives of peer-review, it will remain almost impossible to assess or improve its effectiveness.*" Therefore we first discuss the possible objectives of peer review.

2.1 Peer Review for Scientific Research

A research paper is commonly first reviewed by several committee members , who should assign one or several *scores* and give detailed comments.

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[1]Whether this actually qualifies as "bias" is perhaps arguable. Papers written by native English speakers may be more clear due to lack of confusing grammatical errors, but the paper may actually be perfectly clear but give the impression of not being clear because of grammatical errors.

The comments, and sometimes scores, cover diverse *aspects* of the paper (e.g. "clarity," "potential impact"; detailed in §3.2.1), and these aspects are often directly mentioned in review forms of scientific conferences or journals.[2] Then a senior reviewer will often make a *final decision* (i.e., "reject" or "accept") as well as comments summarizing the decision (i.e., a *meta-review*).

After going through many review guidelines[3] and resources about how to write a good review[4] we summarize *some* of the most frequently mentioned desiderata below:

1. **Decisiveness:** A good review should take a clear stance, selecting high-quality submissions for publication and suggesting others not be accepted (Jefferson et al., 2002a; Smith, 2006).

2. **Comprehensiveness:** A good review should be well-organized, typically starting with a brief summary of the paper's contributions, then following with opinions gauging the quality of a paper from different aspects. Many review forms explicitly require evaluation of different aspects to encourage comprehensiveness.

3. **Justification:** A good review should provide specific reasons for its assessment, particularly whenever it states that the paper is lacking in some aspect. This justification also makes the review more constructive (another oft-cited desiderata of reviews), as these justifications provide hints about how the authors could improve problematic aspects in the paper (Xiong and Litman, 2011).

4. **Accuracy:** A review should be factually correct, with the statements contained therein not being demonstrably false.

5. **Kindness:** A good review should be kind and polite in language use.

Desiderata	Metrics	Range	Automated
Decisiveness	RACC	[-1, 1]	No
Comprehen.	ACOV	[0, 1]	Yes
	AREC	[0, 1]	Yes
Justification	INFO	[0, 1]	No
Accuracy	SACC	[0, 1]	No
	AFAC	[0, 1]	No
Others	ROUGE	[0, 1]	Yes
	BERTScore	[-1, 1]	Yes

Table 1: Evaluation metrics from different perspectives. "Range" represents the range value of each metric. "Automated" denotes if metrics can be obtained automatically.

Based on above desiderata, we make a first step towards evaluation of reviews for scientific papers and characterize a "good" review from multiple perspectives.

2.2 Multi-Perspective Evaluation

Given input paper D and meta-review R^m, our goal is to evaluate the quality of review R, which can be either manually or automatically generated. We also introduce a function $\text{DEC}(D) \in \{1, -1\}$ that indicates the final decision of a given paper reached by the meta-review: "accept" or "reject". Further, $\text{REC}(R) \in \{1, 0, -1\}$ represents the acceptance recommendation of a particular review: "accept," "neutral," or "reject" (see Appendix A.1 for details).

Below, we discuss automatic evaluation metrics that can be used to approximate the desiderata of reviews described in the previous section. And we have summarized them in Tab. 1.

2.2.1 D1: Decisiveness

First, we tackle the *decisiveness*, as well as accuracy of the review's recommendation, through **Recommendation Accuracy (RACC)**. Here we use the final decision regarding a paper and measure whether the acceptance implied by the review R is consistent with the actual accept/reject decision of the reviewed paper. It is calculated as:

$$\text{RAcc}(R) = \text{DEC}(D) \times \text{REC}(R) \quad (1)$$

A higher score indicates that the review more decisively and accurately makes an acceptance recommendation.

2.2.2 D2: Comprehensiveness

A comprehensive review should touch on the quality of different aspects of the paper, which we measure using a metric dubbed **Aspect Coverage (ACOV)**. Specifically, given a review R, aspect coverage measures how many aspects (e.g. `clarity`) in a predefined aspect typology (in our case, §3.2.1) have been covered by R.

In addition, we propose another metric **Aspect Recall (AREC)**, which explicitly takes the meta review R^m into account. Because the meta review is an authoritative summary of all the reviews for a paper, it provides an approximation of which aspects, and with which sentiment polarity, should be covered in a review. Aspect recall counts how many aspects in meta review R^m are covered by general review R, with higher aspect recall indicating better agreement with the meta review.[5]

2.2.3 D3: Justification

As defined in §2.1, a good peer review should provide hints about how the author could improve problematic aspects. For example, when reviewers comment: "this paper lacks important references", they should also list these relevant works. To satisfy this justification desideratum, we define a metric called **Informativeness (INFO)** to quantify how many negative comments[6] are accompanied by corresponding evidence.

First, let $n_{\mathrm{na}}(R)$ denote the number of aspects in R with negative sentiment polarity. $n_{\mathrm{nae}}(R)$ denotes the number of aspects with negative sentiment polarity that are supported by evidence. The judgement of supporting evidence is conducted manually (details in Appendix A.1). INFO is calculated as:

$$\mathrm{Info}(R) = \frac{n_{\mathrm{nae}}(R)}{n_{\mathrm{na}}(R)} \tag{2}$$

And we set it to be 1 when there are no negative aspects mentioned in a review.

2.3 D4: Accuracy

We use two measures to evaluate the accuracy of assessments. First, we use **Summary Accuracy (SACC)** to measure how well a review summarizes contributions of a paper. It takes value of 0, 0.5, or 1, which evaluates the summary part of the review as incorrect/absent, partially correct, and correct. The correctness judgement is performed manually, with details listed in Appendix A.1.

INFO implicitly requires that negative aspects should be supported with evidence, ignoring the quality of this evidence. However, to truly help to improve the quality of a paper, the evidence for negative aspects should be factual as well. Here we propose **Aspect-level Factuality (AFAC)**, the percentage of the supporting statements $n_{\mathrm{nae}}(R)$ that are judged as valid support by human annotators. If $n_{\mathrm{nae}}(R)$ is 0, we set its AFAC as 1. The details of evaluating "validity" are also described in Appendix A.1.

2.4 D5: Kindness

While kindness is very important in maintaining a positive research community, accurately measuring it computationally in a nuanced setting such as peer review. Thus, we leave the capturing of kindness in evaluation to future work.

2.5 Similarity to Human Reviews

For automatically generated reviews only we use **Semantic Equivalence** metrics to measure the similarity between generated reviews and reference reviews. The intuition is that while human reviewers are certainly not perfect, knowing how close our generated reviews are to existing human experts may be informative. Here, we investigate two specific metrics: ROUGE (Lin and Hovy, 2003) and BERTScore (Zhang et al., 2019). The former measures the surface-level word match while the latter measures the distance in embedding space. Notably, for each source input, there are multiple reference reviews. When aggregating ROUGE and BERTScore, we take the maximum instead of average since it is not necessary for generated reviews to be close to all its references.

3 Dataset

Next, in this section we introduce how we construct a review dataset with more fine-grained metadata, which can be used for system training and the multiple perspective evaluation of reviews.

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[5]Notably, this metric potentially biases towards high scores for reviews that were considered in the writing of the meta-review. Therefore, higher aspect recall is not the only goal, which should be taken together with other evaluation metrics.

[6]We only consider whether the reviewer has provided enough evidence on their negative opinion since we find that most human reviewers rarely provide evidence for their positive comments.
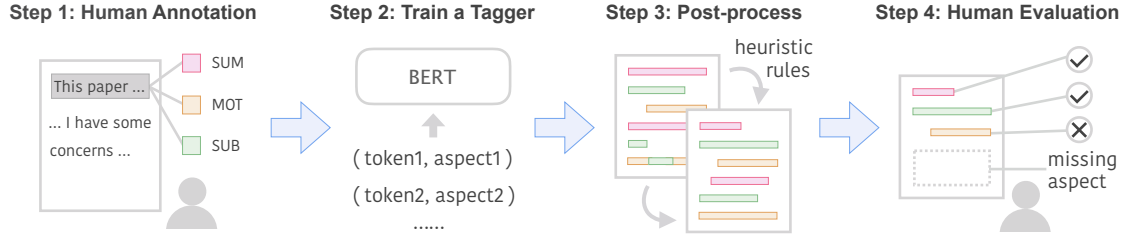
Figure 1: Data annotation pipeline.

3.1 Data Collection

The advent of the Open Peer Review system[7] makes it possible to access review data for analysis or model training/testing. One previous work (Kang et al., 2018) attempts to collect reviews from several prestigious publication venues including the Conference of the Association of Computational Linguistics (ACL) and the International Conference on Learning Representations (ICLR). However, there were not nearly as many reviews accumulated in OpenReview at that time[8] and other private reviews only accounted for a few hundred. Therefore we decided to collect our own dataset `Aspect-enhanced Peer Review` (`ASAP-Review`).

We crawled ICLR papers from 2017-2020 through OpenReview[9] and NeurIPS papers from 2016-2019 through NIPS Proceedings[10]. For each paper's review, we keep as much metadata information as possible. Specifically, for each paper, we include following metadata information that we can obtain from the review web page:

- *Reference reviews*, which are written by a committee member.
- *Meta reviews*, which are commonly written by an area chair (senior committee member).
- *Decision*, which denotes a paper's final "accept" or "reject" decision.
- *Other* information like url, title, author, etc.

We used Allenai Science-parse[11] to parse the pdf of each paper and keep the structured textual information (e.g., titles, authors, section content and references). The basic statistics of our `ASAPReview` dataset is shown in Tab. 2.

	ICLR	NIPS	Both
Accept	1859	3685	5544
Reject	3333	0[1]	3333
Total	5192	3685	8877
Avg. Full Text Length	7398	5916	6782
Avg. Review Length	445	411	430
# of Reviews	15728	12391	28119
# of Reviews per Paper	3.03	3.36	3.17

[1] Note that NIPS only provide reviews for accepted papers to the public.

Table 2: Basic statistics of `ASAPReview` dataset.

3.2 Aspect-enhanced Review Dataset

Although reviews exhibit internal structure, for example, as shown in Fig. 3 (*reviewer view*) , reviews commonly start with a paper summary, followed by different aspects of opinions, together with evidence. In practice, this useful structural information cannot be obtained directly. Considering that fine-grained information about the various aspects touched on by the review plays an essential role in review evaluation, we conduct aspect annotation of those reviews. To this end, we first (i) introducing an aspect typology and (ii) perform human annotation.

3.2.1 Aspect Typology and Polarity

We define a typology that contains 8 aspects, which follows the ACL review guidelines[12] with small modifications, which are *Summary* (SUM), *Motivation/Impact* (MOT) , *Originality* (ORI), *Soundness/Correctness* (SOU), *Substance* (SUB), *Replicability* (REP), *Meaningful Comparison* (CMP) and *Clarity* (CLA). The detailed elaborations of each aspect can be found in Appendix A.2. Inside the parentheses are what we will refer to each aspect for brevity. To take into account whether the comments regarding each aspect are positive or negative, we also mark whether the comment is

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positive or negative for every aspect (except summary).

3.2.2 Aspect Annotation

Overall, the data annotation involves four steps that are shown in Fig. 1.

Step 1: Manual Annotation   To manually annotate aspects in reviews, we first set up a data annotation platform using Doccano.[13]

We asked 6 students from ML/NLP backgrounds to annotate the dataset. We asked them to tag an appropriate text span that indicates a specific aspect. For example, "The results are new [Positive Originality] and important to this field [Positive Motivation]". The detailed annotation guideline can be found in Supplementary Material B.1.

Each review is annotated by two annotators and the lowest pair-wise Cohen kappa is 0.653, which stands for substantial agreement. In the end, we obtained 1,000 human-annotated reviews in total. The aspect statistics in this dataset are shown in Fig. 2-(a)

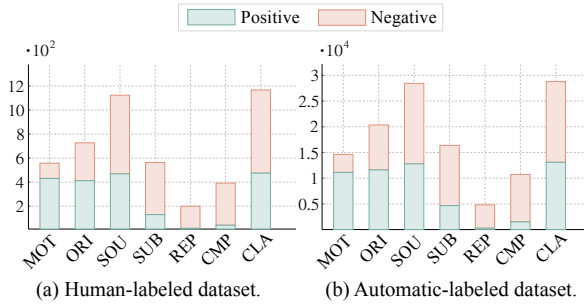(a) Human-labeled dataset.   (b) Automatic-labeled dataset.

Figure 2: (a)-(b) represent distributions over seven aspects obtained by human and BERT-based tagger respectively. Red bins represent positive sentiment while green ones suggest negative sentiment. We omit "Sum" aspect since there is no polarity definition of it.

Step 2: Training an Aspect Tagger   Since there are over 20,000 reviews in our dataset, using human labor to annotate them all is unrealistic. Therefore, we use the annotated data we do have to train an aspect tagger and use it to annotate the remaining reviews. The basic architecture of our aspect tagger contains a pre-trained model BERT (Devlin et al., 2019) and a multi-layer perceptron. The training details can be found in Appendix A.3.

Step 3: Post-processing   However, after inspecting the automatically labeled dataset, we found that

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[13]https://github.com/doccano/doccano

there appears to be some common problems such as interleaving different aspects and inappropriate boundaries. To address those problems, we used seven heuristic rules to refine the prediction results and they were executed sequentially. The detailed heuristics can be found in Appendix A.4. An example of our model prediction after applying heuristic rules is shown in Appendix A.5. Fig. 2-(b) shows the distribution of all reviews over different aspects. As can be seen, the relative number of different aspects and the ratio of positive to negative are very similar across human and automatic annotation.

Step 4: Human Evaluation   To evaluate the data quality of reviews' aspects, we conduct human evaluation. Specifically, we measure both aspect precision and aspect recall for our defined 15 aspects.

We randomly chose 300 samples from our automatically annotated dataset and assigned each sample to three different annotators to judge the annotation quality. As before, these annotators are all from ML/NLP background.

The detailed calculation for aspect precision and aspect recall can be found in Appendix A.6. Under these criterion, we achieved 92.75% aspect precision and 85.19% aspect recall. The fine-grained aspect precision and aspect recall for each aspect is shown in Tab. 3 The aspect recall for positive replicability is low. This is due to the fact that there are very very few mentions of positive replicability. And in our human evaluation case, the system identified one out of two, which results in 50%. Other than that, the precision and recall are much higher. One thing to mention is that our evaluation criterion is very strict, which can act as a lower bound for these two metrics.

4 Scientific Review Generation

4.1 Task Formulation

Based on the internal structure of a scientific review, we conceptualize review generation of scientific articles as an *opinion-aware scientific paper summarization* task. Although scientific paper summarization is not new, most current works summarize a paper (i) either from an "*author view*" that only use content written by the author to form a summary (Cohan et al., 2018a; Xiao and Carenini, 2019; Erera et al., 2019; Cohan et al., 2018a; Cachola et al., 2020b), (ii) or from a "*reader view*" that argues a paper's summary should take into account the view of those in the research community

Aspect	Polarity	Precision	Recall
Summary		95%	100%
Motivation	+	94%	89%
	–	72%	71%
Originality	+	95%	87%
	–	94%	80%
Soundness	+	95%	98%
	–	92%	79%
Substance	+	90%	94%
	–	90%	78%
Replicability	+	100%	50%
	–	77%	71%
Clarity	+	97%	92%
	–	92%	73%
Comparison	+	85%	100%
	–	94%	94%

Table 3: Fine-grained aspect coverage and aspect recall for each aspect. + denotes positive and – denotes negative.

(Qazvinian and Radev, 2008; Cohan and Goharian, 2017; Yasunaga et al., 2019a).

In this work, we extend the view of scientific paper summarization from "author" or "reader" to "reviewer". and claim that a good summary of a scientific paper can not only reflect the core idea but also contains critical comments made by domain experts. The advantages lie in: (i) *reviewers*: it can relieve them from the burden of reviewing process (ii) *readers*: help them quickly grasp the main idea of the paper and let them know what domain experts' comments on this paper are. The three views of scientific paper summarization is shown in Fig. 3.

4.2 System Design

Despite the fact that our dataset contains fewer training samples compared with other benchmark summarization datasets, the few-shot learning ability of recent contextualized pre-trained models (Radford et al., 2019; Brown et al., 2020; Cachola et al., 2020a) still put training a passable review generation system from this dataset within grasp. We use BART (Lewis et al., 2019), which is a denoising autoencoder for pretraining sequence-to-sequence models, as our pre-trained model since it has shown superior performance on multiple generation tasks.

However, even if we can take the advantage of this pre-trained model, how to deal with lengthy text in the context of using a pre-trained model
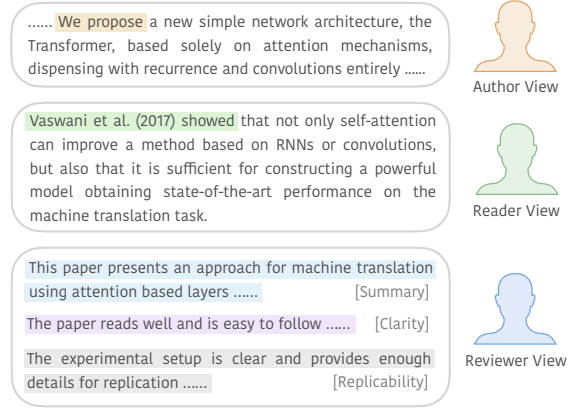

Figure 3: Summarization from three different views for the paper "Attention Is All You Need" (Vaswani et al., 2017).

(BART, for example, has a standard length limit of 1024 since it was pre-trained on texts of this size) remains challenging. After multiple trials, we opted for a two-stage method detailed below, and describe other explorations that were less effective in Appendix A.7.

4.2.1 Two-stage Systems for Long Documents

Instead of regarding text generation as a holistic process, we decompose it into two steps, and consider using an *extract-then-generate* paradigm (Chen and Bansal, 2018; Gehrmann et al., 2018; Subramanian et al., 2019). Specifically, we first perform content selection, extracting salient text pieces from source documents (papers), then generate summaries based on these extracted texts.

To search for an effective way for content selection that really matters for constructing a review generation system, we operationalize the first extraction step in diverse ways. One thing to notice is that the extraction methods we use here mainly focus on heuristics. We leave more complicated selection methods for future work.

Oracle Extraction First, for comparison purposes, we construct an oracle for each paper which is the extraction that achieves highest average ROUGE scores with respect to reference reviews, specifically using the greedy method described in Nallapati et al. (2017). Note that for each paper with multiple reviews, we construct multiple oracles for that paper. We assume that oracle extractions can reflect where reviewers pay more attention to when they are writing reviews. The selected sentence position distribution in oracles is shown in Fig. 4.
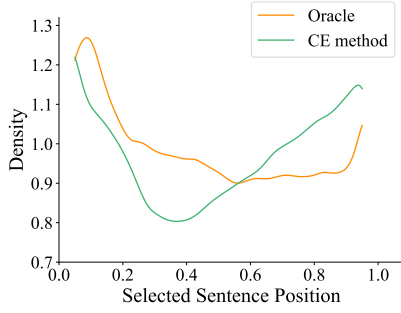
Figure 4: Selected sentence position distribution. We use the relative position of each sentence with regard to the whole article, thus taking values from 0 to 1.

Section-based Extraction Scientific papers are highly structured. As a convention, a scientific paper usually describes problem background, related work comparison, as well as its own contributions in the introduction part. Regarding this method, we only use the introduction section, which can be regarded as a baseline model.

Cross-entropy (CE) Method Extraction Here we select salient sentences from the full text range. The way we do so is through a two-step selection process, which are

1. Select sentences that contain certain keywords which are detailed in Appendix A.8. Those selected sentences form a set $\mathcal{S}$.
2. Select a subset $\mathcal{S}' \subseteq \mathcal{S}$ such that sentences in $\mathcal{S}'$ cover diverse content and satisfy certain length constraint.

In the second step, we use the cross-entropy method introduced in Feigenblat et al. (2017) where we select sentences that can jointly maximize our defined performance function. The details of this two-step process can be found in Appendix A.8. The selected sentence position distribution using this method is shown in Fig. 4. We can see that the extractor tends to select sentences from the beginning of a paper as well as the ending part of a paper just as the oracle extractor does. This makes sense because the beginning part is the introduction part which talks about the essence of the whole paper and the ending part mostly contains the analysis of experimental results and conclusions etc.

Hybrid Extraction We combine the abstract of a paper and its CE extraction to form a hybrid of both.

4.2.2 Aspect-aware Summarization

Typically in the *extract-then-generate* paradigm, we can just use the extractions directly and build a sequence-to-sequence model to generate text. Here, in order to generate reviews with more diverse aspects and be able to interpret the generated reviews through the lens of their internal structure, we make a step towards a generation framework involving *extract-then-generate-and-predict*. Specifically, instead of existing aspect-based summarization works that explicitly take aspects as input (Angelidis and Lapata, 2018; Frermann and Klementiev, 2019; Hayashi et al., 2020), we use our annotated aspects (§3.2) as additional information, and design an auxiliary task that aims to predict aspects of generated texts (reviews). Fig. 5 illustrates the general idea of this.
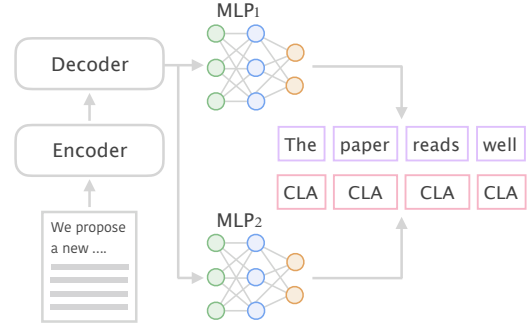

Figure 5: Aspect-aware summarization.

The loss of this model is shown in Eq. 3

$$\mathcal{L} = \mathcal{L}_{\text{seq2seq}} + \alpha \mathcal{L}_{\text{seqlab}} \tag{3}$$

where $\mathcal{L}_{\text{seq2seq}}$ denotes sequence to sequence loss which is the negative log likelihood of the correct next tokens, and $\mathcal{L}_{\text{seqlab}}$ denotes sequence labeling loss which is the negative log likelihood of the correct labels of next tokens. α is a tunable parameter, and we found $\alpha = 0.1$ works well according to aspect coverage and aspect recall.

5 Experiment

In this section, we investigate using our proposed review generation systems with state-of-the-art pre-trained models, to what extent can we realize desiderata of reviews that we defined in §2.2. We approach this goal by two concrete questions: (1) *What are review generation systems (not) good at?* (2) *Will systems generate biased reviews?*

5.1 Settings

Here we consider three extraction strategies in §4.2.1 as well as two generation frameworks, one is the vanilla sequence to sequence model, the other is jointly sequence to sequence and sequence labeling.

Dataset We use our constructed dataset `ASAPReview` described in §3 to conduct experiments. For each paper, we use full text (without Appendix) as source document.[14] And we filtered papers with full text fewer than 100 words since they don't contain enough information for models to learn. For reviews, we only use 100-1024 word reviews[15] for training, which account for 92.57% of all the reviews. Reasons are: (i) Reviews that have more than 1000 words is noisy which often contains lots of updates. (ii) Reviews that have fewer than 100 words often comes from reviewers with less confidence.

This results in 8742 unique papers and 25,986 paper-review pairs in total, the split of our dataset is shown in Tab. 4.

	Train	Validation	Test
Unique papers	6993	874	875
Paper-review pairs	20757	2571	2658

Table 4: Split of dataset.

Model As mentioned in §4.2, the pre-trained sequence-to-sequence model we used is BART. For all models, we initialized the model weights using the checkpoint: "`bart-large-cnn`" which is pre-trained on "`CNN/DM`" dataset (Hermann et al., 2015).[16] For *extract-then-generate-and-predict* framework, we add another multilayer perceptron on top of the BART decoder, and initialize it with 0.0 mean and 0.02 standard deviation. We use the Adam optimizer with a linear learning rate scheduler which increases the learning rate linearly from 0 to $4e^{-5}$ in the first 10% steps (the warmup period) and then decreases the learning rate linearly to 0 throughout the rest of training steps. We fine-tuned our models on the whole dataset for 5 epochs. We set a checkpoint at the end of every epoch and finally took the one with the lowest validation loss.

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[14] If a paper has more than 250 sentences, we truncate it and take the first 250 sentences when we do the extraction step.

[15] As measured by BART's subword tokenizer.

[16] We also tried "`bart-large-xsum`" checkpoint which is pre-trained on "XSUM dataset()", however that results in much shorter reviews, and sentences in it tend to be succinct.

During generation, we used beam search decoding with beam size 4. Similarly to training time, we set a minimum length of 100 and a maximum length of 1024. A length penalty of 2.0 and trigram blocking (Paulus et al., 2017) were used as well.

5.2 What are Systems Good and Bad at?

Based on the evaluation metrics we defined in §2.2, we conduct both automatic evaluation and human evaluation to characterize both reference reviews and generated reviews, aiming to analyze what subtasks of review generation automatic systems can do passably at, and also where they fail. The aspect information in each review is obtained using aspect tagger we trained in §3.2.

Automatic Evaluation Automatic evaluation metrics include *Aspect Coverage* (ACov), *Aspect Recall* (ARec) and *Semantic Equivalence* (ROUGE, BERTScore). Notably, for each source input, there are multiple reference reviews. When aggregating ROUGE and BERTScore[17], we take the maximum instead of average. And when aggregating other metrics for human reviews, we take the average for each source document. The results are shown in Table 5.

Human Evaluation Metrics that require human labor include *Recommendation Accuracy* (RACC), *Informativeness* (INFO), *Aspect-level Factuality* (AFAC) and *Summary Accuracy* (SACC). We select 31 papers (21 accepted, 10 rejected) from ML/NLP/CV/RL domains. None of these papers are in the training set. Details regarding human judgment are shown in Appendix A.1. The evaluation results are shown in Table 5.

Overall, we make the following observations:

(i) Using extractions from the full text range to generate reviews will result in higher aspect coverage and aspect recall compared to only using the introduction part. This is reasonable since models can receive more diverse information from the full text.

(ii) By looking at ROUGE and BERTScore, we can see that using extractive + abstractive methods can result in reviews that are much closer in meaning to reference reviews compared to pure extractive methods.

(iii) In terms of *Aspect Coverage* and *Informativeness*, reference reviews fall behind most of our

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[17] We have used our own custom baseline to rescale BERTScore, details can be found in Appendix A.1.

Desiderata		Decisive.	Comprehen.		Justification	Accuracy		Others			
Metric		RACC	ACOV	AREC	INFO	AFAC	SACC	R-1	R-2	R-L	BS
HUMAN		41.83	46.60	58.66	94.60	81.05	94.35	–	–	–	–
EXTRACTIVE											
INTRO		–	–	–	–	–	–	38.62	8.84	25.11	29.22
CE		–	–	–	–	–	–	38.56	7.81	25.94	29.11
ABSCE		–	–	–	–	–	–	37.55	8.53	25.85	31.99
EXTRACTIVE+ABSTRACTIVE											
	Aspect										
INTRO	$\times$	9.68	45.63	55.52†	99.71†	40.93†	87.10	41.39	11.53	38.52	42.29
	$\checkmark$	6.45†	46.09	58.24	98.92†	40.80†	87.10	41.31	11.41	38.38	42.33
CE	$\times$	-6.45†	54.13†	60.73	99.35†	44.22†	87.10	42.37	11.72	39.86	41.78
	$\checkmark$	-19.35†	55.06†	61.62†	99.19†	37.37†	77.42†	42.27	11.62	39.73	41.71
ABSCE	$\times$	-6.45†	48.89†	58.31	99.19†	38.19†	96.77	43.11	12.24	40.18	42.90
	$\checkmark$	-22.58†	49.90†	57.56	98.39	42.02†	93.55	42.99	12.19	40.12	42.63

Table 5: Results of the baseline models as well as different aspect-enhanced models under diverse automated evaluation metrics. "BS" represents BERTScore. † denotes that the difference between system generated reviews and human reviews are statistically significant (p-value < 0.05 using 1000 paired bootstrap resampling (Efron, 1992) tests with 0.5 sample ratio).

systems. This means that even reviews from the reviewers may also fall short on our defined criterion.

(iv) When using metrics that require higher level understanding of the source paper like *Recommendation Accuracy* and *Aspect-level Factuality*, our systems have much lower performance. This means our systems cannot distinguish high-quality papers from low-quality papers well and the evidence for negative aspects cannot be trusted most of the time.

(v) Current systems can correctly summarize the contributions of papers most of the time as shown by *Summary Accuracy*. This is what we can hope for by now, and it's obvious that there is a long way to go towards reliable automatic review generation.

(vi) Our fine-grained evaluation metrics enable us to compare different systems and interpret their relative merits. For example, our systems can achieve higher *Informativeness* than reference reviews while suffering from much lower *Aspect-level Factuality*. This means that if we want our systems to match the performance of real reviewers, we should focus on improving the factuality of our systems instead of letting it give more revision advice (which are not factually correct most of the time). Another example is that models using aspect information achieves consistently higher aspect coverage while suffering from lower *Recom-*

mendation Accuracy. This means that for aspect-enhanced models, it is much urgent to improve its ability to distinguish papers of different quality instead of letting it generate more aspects.

We conduct detailed case studies in Appendix A.9.

5.3 Will System Generate Biased Reviews?

Biases in text are prevalent while challenging to detect (Manzoor and Shah, 2020; Stelmakh et al., 2019). For example, in natural language processing, researchers are trying to identify societal biases (e.g, gender) in data and learning systems on different tasks (Bolukbasi et al., 2016; Zhao et al., 2018; Stanovsky et al., 2019). Previous works on biases analysis in scientific peer review usually focus on disparities in numerical feedback instead of text. Manzoor and Shah (2020) recently uncover latent bias in text. In this work, besides designing a model to generate reviews, we also perform bias analysis, in which we propose a method to identify and quantify biases both in human-labeled and system-generated data in a more fine-grained fashion.

5.3.1 Measuring Bias in Reviews

To characterize potential biases existing in reviews, we (i) first define *aspect score*, which calculates

the percentage of positive occurrences [18] with respect to each review's aspects. The polarity of each aspect is obtained based on our learned tagger in §3.2.2; (ii) then we aim to observe if different groups G_i (e.g., paper is anonymous during reviewing or not) of reviews R would exhibit *disparity* $\delta(R, \mathbf{G})$ in different aspects. The calculation of disparity can be visualized in Fig. 6.
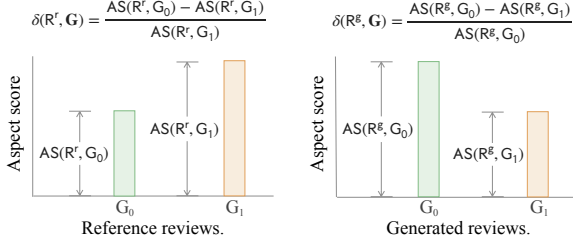

Figure 6: *Aspect score* $\mathrm{AS}(R, G_i)$ and *disparity* $\delta(R, \mathbf{G})$ in reference reviews (R^r) and generated reviews (R^g). $\mathbf{G} = [G_0, G_1]$ denotes different groups.

Based on above two definitions, we characterize bias in two ways respectively:
(1) **spider chart**, which directly visualizes aspect scores of different groups of reviews w.r.t each aspect.
(2) **disparity difference**, which represents the difference between disparities in generated reviews R^g and reference reviews R^r and can be formally calculated as:

$$\Delta(R^g, R^r, \mathbf{G}) = \delta(R^g, \mathbf{G}) - \delta(R^r, \mathbf{G}) \quad (4)$$

where $\mathbf{G} = [G_0, G_1]$ denotes different groups based on a given partition criterion. Positive value means generated reviews favor group G_0 more compared to reference reviews, and vice versa.

In this work, we group reviews from two perspectives. The basic statistics are shown in Tab. 6.

	Native	Non-native	Anonym.	Non-anonym.
Total	651	224	613	217
Acc.%	66.51%	50.00%	57.59%	78.34%

Table 6: Test set statistics based on nativeness and anonymity.

Nativeness We categorize all papers in test set into "native" (G_0) and "non-native" (G_1) based on whether there is at least one native speaker in the author list as well as whether the institution is in an English-speaking country.

Anonymity We categorize all papers in test set into "anonymous" (G_0) and "non-anonymous" (G_1) based on whether the paper has been released pre-printly before half month after the conference submission deadline[19].

5.3.2 Analysis of Spider Chart

Taking our model with introduction extraction as an example, the aspect scores of generated reviews and reference reviews are shown in Fig. 7.

Regarding *nativeness*, `native` papers receive higher score in most aspects in both reference reviews and generated reviews. Regarding *anonymity*, `non-anonymous` papers receive higher score in all aspects in both reference reviews and generated reviews. Those information reveal the favor for certain groups. Our observations are:

Nativeness Regarding human reviews:
(1) By looking at Fig. 7-(a), there is a significant gap in `Clarity`, which is reasonable since non-native authors usually have trouble conveying their ideas. (2) Scores of the two groups are much closer in other aspects.

Regarding system-generated reviews:
(1) By looking at Fig. 7-(b), Auto-review system narrows the disparity in `Clarity` but amplify it in `Originality`. (2) Scores of the two groups are much closer in other aspects.

Anonymity Regarding human reviews: we find gaps are non-negligible in `Soundness`, `Clarity` and `Meaningful Comparison`.

Regarding system-generated reviews: we observe that gaps are non-negligible in `Motivation`, `Originality`, `Soundness`. The largest gap is not as large as that in human reviews.

5.3.3 Analysis of Disparaty difference

However, through spider chart, gaps between different groups are relatively small and hard to discern. Besides, those gaps can only show the absolute favor for a certain group in different aspects. We are also interested in whether generated reviews are more in favor of a certain group **compared to reference reviews**. To do this, we calculate disparity differences and list them in Tab. 17.

Occurrences of positive numbers and negative numbers indicate that compared to reference reviews, generated reviews favor different groups in

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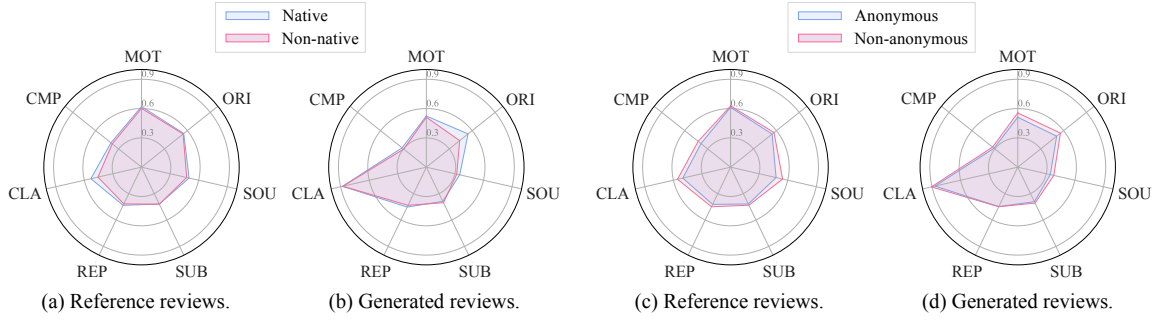
Figure 7: Spider chart of aspect scores with respect to different groups.

	MOT	ORI	SOU	SUB	REP	CMP	CLA	Total
Nativeness	-0.72	+18.71	+3.84	-3.66	+0.73	-13.32	+2.40	43.39
Anonymity	-5.69	-4.43	+2.76	-0.64	+5.65	+5.80	+3.02	28.00

Table 7: Disparity differences regarding nativeness and anonymity. Total is the sum of absolute value of disparity difference.

different aspects. This essentially means that overall our model does not particularly favor a certain group compared to reference reviews.

However, the total aspect bias regarding nativeness is much larger than anonymity. This, in some sense suggests that our model is more sensitive to nativeness compared to anonymity. We list the bias analysis for other models in Appendix A.11.

6 Related Work

Scientific Review Generation One previous work (Bartoli et al., 2016) investigated the feasibility of generating fake reviews by surface-level term replacement and sentence reordering etc. However, apart from that, there is very little work in this area, except one contemporaneous and independent work by Wang et al. (2020), who propose a two-stage information extraction and summarization pipeline to generate paper reviews. Their evaluation focuses mainly on the accuracy of information extraction, and the evaluation of the generated summaries is somewhat precursory, assessing only a single criterion "constructiveness and validity" manually over 50 papers. Our paper (1) proposes a wide variety of diagnostic criteria on review quality, (2) uses a very different summarization methodology, and (3) evaluates the generated results extensively.

Peer Review Peer review is an essential component of the research cycle and is adopted by most journals and conferences to identify important and relevant research. However, at the same time it is easy to identify many issues: expensiveness,

slowness, existence of inconsistency (Langford and Guzdial, 2015) and bias (Tomkins et al., 2017), etc.

Some efforts have been put into analyzing the peer review process including automating review assignment (Jin et al., 2017; Nguyen et al., 2018; Anjum et al., 2019; Jecmen et al., 2020), examining bias problems (Tomkins et al., 2017; Stelmakh et al., 2019), examining consistency problem (Langford and Guzdial, 2015) as well as performing sentiment analysis on reviews (Wang and Wan, 2018; Chakraborty et al., 2020). Several decision classification methods have been explored to help make accept or reject decision given a paper. Those methods are either based on textual (Kang et al., 2018; Jen et al., 2018; Qiao et al., 2018) or visual (Von Bearnensquash, 2010; Huang, 2018) information. However, they don't actually help the reviewers since reviewers still need to write reviews for both accepted papers and rejected papers. In contrast, our work starts in the interests of reviewers and try to help automate review writing.

7 Discussion

We first summarize what we have achieved in this work and how the current *ReviewAdvisor* system can render help. Then we discuss challenges and potential directions for the automatic review generation task, which, hopefully, encourages more future researchers to explore this task, and in the right direction.

7.1 Machine-assisted Review System

Instead of replacing a human reviewer, a better position for *ReviewAdvisor* is to regard it as a machine-assisted review system. Although there is still a large room for improvement, current *ReviewAdvisor* can assist reviewers from the following aspects:

(1) Based on the evaluation of §5.2, *Summary Accuracy* of our systems is quite high, suggesting that it can be either used for reviewers to finish the description of *Summary*, or help general readers to quickly understand the core idea of recently pre-printed papers (e.g., papers from arXiv[20]).

(2) Based on evaluation of §5.2, reviews generated by *ReviewAdvisor* can cover more aspects and generate more informative reviews. Although the associated opinions may suffer from the factuality problem, it still can be useful since it can provide a preliminary template for reviewers, especially enabling junior non-native English reviewers to know (i) what a review generally should include (ii) how to phrase it for each aspect, and then develop their own reviews based on the templates. Additionally, for each aspect (e.g., *Clarity*), our system can provide relevant evident sentences from the paper, helping reviewers quickly identify salient information when reviewing the paper (Detailed example in our Appendix A.9).

7.2 Challenges and Promising Directions

7.2.1 Model

(1) *Long Document Modeling*: The average length of one scientific paper is commonly larger than 5,000 words, far beyond the input text's length that mainstream neural sequence models (e.g., LSTM, Transformer) or pre-trained models (e.g., BERT, BART) normally use. This work (in §4.2.1) bypasses the difficulty by using a two-stage system, but there will be more other strategies to be explored.

(2) *Pre-trained Model for Scientific Domain*: Although previous works, as exemplified by (Beltagy et al., 2019) have pre-trained BERT on scientific domain, we observe that those models with transformer decoder perform much worse than BART on sequence generation tasks in terms of fluency and coherence, which calls for general sequence to sequence models pre-trained on scientific domain for higher-quality review generation.

(3) *Structure Information*: Review generation systems could get a deeper understanding of a given research paper if structure information can be provided. To this end, outputs from scientific paper-based information extraction tasks (Hou et al., 2019; Jain et al., 2020) can be utilized to guide review generation.

(4) *External Knowledge*: Besides the paper itself, review systems can also rely on external knowledge, such as a citation graph constructed based on more scientific papers or a knowledge graph connecting concepts across different papers.

7.2.2 Dataset

(5) *More Open, Fine-grained Review Data*: In this work, we annotate fine-grained information (aspect) of each review manually. However, this information can be relatively easily obtained from the peer review system. How to access this information appropriately would be an important and valuable step in the future.

(6) *More Accurate and powerful Scientific Paper Parser*: Existing parsing tools (e.g. science-parse, grobid) for scientific papers are commonly designed for certain specific paper templates, and also still struggle at extracting fine-grained information, such as the content of tables and figures.

7.2.3 Evaluation

(7) *Fairness and Bias in Generated Text*: In this work, we make a step towards identifying and quantifying two types of biases existing in human and system-generated reviews. Future works can explore more along this direction based on our dataset that contains fine-grained aspect annotation.

(8) *Reliability*: In addition to generating a review, a reliable system should also provide a level of confidence w.r.t the current comment. Moreover, whether review scores are calibrated is another valuable question.

Acknowledgment

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[20]https://arxiv.org/

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A Appendices

A.1 Details for Evaluation Metrics

REC In §2.2, the REC function we define corresponds to the recommendation sentiment of a review, with $\{-1, 0, 1\}$ representing negative, neutral and positive.

To decide the sentiment of a reference review, we use the rating information from reviewers: (i) if the rating corresponds to marginal accept or marginal reject, then we regard it as neutral; (ii) if the rating is above marginal accept, then we regard it as positive; (iii) otherwise, we regard it as negative.

To decide the sentiment of a generated review, two members of the project team judged the sentiment polarity of a review. If they agreed with each other, then we uses the agreed-upon sentiment, if they disagreed with each other, then we label the sentiment of that review as neutral. The Cohen kappa of two annotators is 0.5778, which is commonly referred to as "moderate" agreement.

INFO The judgement of evidence for negative aspects was conducted by a member of the project team, who judged whether each identified negative aspect was accompanied by evidence irrespective of the correctness of the evidence. In other words, as long as there is a reason, we count that as an evidence.

SACC & AFAC The judgement of summary accuracy and valid support for negative aspects are performed by one of the first authors of the reviewed paper. Summary and each negative aspect in the review should be scored 0, 0.5 or 1 which represent agree, partially agree and disagree respectively. We provide authors with the following instructions:

```
"We have created a Google
doc for your paper, and
you can score the summary
as well as each aspect
with its corresponding
comments inside the red
brackets. "1" denotes
agree, "0.5" denotes
partially agree, "0"
denotes disagree. You
only need to assign
a score based on your
judgment. For summary,
agree means that you think
```

it's factually correct.
For each aspect, agree
means that you think
the strength/weakness
the reviewer points
out is reasonable or
constructive."

BERTScore Regarding BERTScore, we apply the same rescaling procedure following Zhang et al. (2019), which does not affect the ranking ability and reliability of BERTScore, aiming to increase the score readability (not in a limited range).

A.2 Aspect Definition

We define eight aspects for reviews, which are: *Summary*, *Motivation/Impact*, *Originality*, *Soundness/Correctness*, *Substance*, *Replicability*, *Meaningful comparison* and *Clarity*. For each aspect we list several examples that are extracted from reviews.

Summary

- "The paper proposes a new
  memory access scheme based on
  Lie group actions for NTMs."

Motivation/Impact

- "The issue researched in
  this work is of significance
  because understanding the
  predictive uncertainty of a
  deep learning model has its
  both theoretical and practical
  value."
- "The method seems limited in
  both practical usefulness and
  enlightenment to the reader."

Originality

- "Novel addressing scheme as an
  extension to NTM."
- "The reviewer believes that
  the idea of the paper is
  similar to the one in [1]."

Soundness/Correctness

- "Illustrations using simulated
  data and real data are also
  very clear and convincing."

- "The proposed method is
  sensible and technically
  sound."
- "The experiments are also
  quite convincing."
- "The required condition is
  rather implicit, and it is
  unclear how this condition can
  be checked in practice."
- "There is not much theory to
  support the method."
- "Several model designs are not
  well justified."
- "There is no enough
  justification to demonstrate
  improvements."

Substance

- "This is a thorough
  exploration of a mostly
  under-studied problem."
- "The experiment section shows
  extensive experiment."
- "There are several modules
  introduced in the paper, but
  there isn't much analysis of
  them during the experiments."
- "This experimental study does
  not seem to conduct sufficient
  experiments to demonstrate the
  advantages."
- "Lack detailed and insightful
  ablation studies."
- "I would expect the authors
  to conduct some more analysis
  of their results besides acc.
  and distortion levels."

Replicability

- "Release of the dataset
  and code should help with
  reproducibility."
- "There are some technical
  ambiguities."

Meaningful Comparison

- "The authors do a good job
  of positioning their study
  with respect to related work
  on black-box adversarial
  techniques."

- "The comparison with the
  Caron-Fox approach is very
  good and useful for the
  reader."
- "The experimental study can
  have more comparison on
  challenging datasets with more
  classes."
- "Since the attention based
  aggregation is similar to GAT,
  a discussion on the difference
  is important."
- "The paper fails to locates
  itself in the literature, how
  it compares itself into other
  techniques (both analytically
  and experimentally)."
- "The comparison does not seem
  fair."

Clarity

- "The paper is well-written and
  easy to follow."
- "The presentation of the
  results is not very clear."

A.3 Training of Aspect Tagger

We formulate the annotation process as a sequence labeling problem where the input is a sequence consisting of n words $S = w_1, \cdots, w_n$, and the target is a sequence of tags one for each word $T = t_1, \cdots, t_n$. We aim to find a mapping f such that $T = f(S)$ can convey reasonable aspect information in the input sequence.

We first segment each review into multiple sentences and consider each sentence as an individual training example.[21] For a tokenized sequence contains n tokens $(w_1, w_2, \cdots, w_n)$, we use BERT to get a contextualized representation for each token $(e_1, e_2, \cdots, e_n)$, where e_i represents the vector for i-th token. Then those contextualized representations can be used as features for token classification:

$$\mathbf{p}_i = \text{softmax}(\mathbf{W}e_i + \mathbf{b})$$

where $\mathbf{W}$ and $\mathbf{b}$ are tunable parameters of the multilayer perceptron. $\mathbf{p}_i$ is a vector that represents the probability of token i being assigned to different aspects.

---

[21]We also tried using larger context such as paragraph, but found out the results less satisfying since the model identified fewer aspects.

We use the negative log likelihood of the correct labels as training loss:

$$\mathcal{L} = -\sum_{t \in \mathcal{T}} \log \mathbf{p}_{tj}$$

where j is the label of token t, and $\mathcal{T}$ denotes all the tokens.

We used 900 annotated reviews for training and 100 for validation which is equivalent to using 16,543 training data and 1,700 validation data since we consider sentence as the basic individual training sample. The initial BERT checkpoint we used is "bert-large-cased" which is the large version of BERT with an uncased vocabulary. We used Adam optimizer (Kingma and Ba, 2014) with a learning rate of $5e^{-5}$ to finetune our model. We trained for 5 epochs and saved the model that achieved lowest loss on validation set as our aspect tagger.

A.4 Heuristics for Refining Prediction Results

The seven heuristic rules used for refining the prediction results are listed below. Examples of those rules are shown in Tab. 8.

1. If there are no other tags (they are tagged as "O" which stands for *Outside*) between two "summary" tags, then replace all tags between them with "summary" tag.

2. If there are multiple discontinuous text spans tagged as "summary", we keep the first one and discard others.

3. If the punctuation is separately tagged and is different from its neighbors, we replace its tag to "O".

4. If two identical tags are separated by a single other tag, then replace this tag with its right neighbor's tag.

5. If there exists a single token with a tag and its neighbors are "O", then replace this tag to 'O'.

6. For a "non-summary" "non-O" tag span, if its neighbors are "O" and the start/end of this span is not special symbol (for example, punctuations or other symbols that have 1 length), then we expand from its start/end until we meet other "non-O" tag or special symbol.

Heuristics	Before	After
1	The authors present a method for learning Hamiltonian functions [Summary] ⋯ [O] this is [Summary] ⋯ [O] that maps past observations to a latent p, q space in a VAE-like fashion. [Summary]	The authors present a method for learning Hamiltonian functions ⋯ this is ⋯ that maps past observations to a latent p, q space in a VAE-like fashion. [Summary]
2	This paper proposes a new representation learning model for graph optimization, Graph2Seq . [Summary] ⋯ the theorems are very interesting . [Positive Originality] ⋯ The performance of Graph2Seq is remarkable. [Summary]	This paper proposes a new representation learning model for graph optimization, Graph2Seq . [Summary] ⋯ the theorems are very interesting . [Positive Originality] ⋯ The performance of Graph2Seq is remarkable. [O]
3	The proposed idea is novel [Positive Originality] . [Positive Motivation] The paper is well written and easy to follow. [Positive Clarity]	The proposed idea is novel [Positive Originality] . [O] The paper is well written and easy to follow. [Positive Clarity]
4	The overall notion of [Positive Originality] learning [O] a Hamiltonian network directly is a great one. [Positive Originality]	The overall notion of learning a Hamiltonian network directly is a great one. [Positive Originality]
5	It is [O] clearly [Positive Clarity] geared towards DNN practitioners. [O]	It is clearly geared towards DNN practitioners. [O]
6	In contrast , this aspect [O] is missing from other work on ML [Negative Meaningful Comparison] for optimization. [O]	In contrast, this aspect is missing from other work on ML for optimization. [Negative Meaningful Comp.]
7	The authors propose a novel approach to estimate unbalanced optimal transport between sampled measures that scales well in the dimension and in the number of samples ⋯ The effectiveness of the approach [Summary] is shown on some tasks. [O]	The authors propose a novel approach to estimate unbalanced optimal transport between sampled measures that scales well in the dimension and in the in the number of samples ⋯ The effectiveness of the approach is shown on some tasks. [Summary]

Table 8: Examples of seven heuristic rules used for refineing prediction results.

7. If the "summary" span doesn't end with a period, then we truncate or extend it at most five words to make it ends with a period.

A.5 An Example of Automatically Annotated Reviews

Tab. 9 illustrates an annotated review after using our trained aspect tagger and heuristic refining rules in Appendix A.4. Although here we do not add separate polarity tags to avoid visual burden, the polarity of each aspect the model predicts is correct.

A.6 Calculation of Aspect Precision and Aspect Recall

To measure aspect precision, we asked three annotators to decide whether each aspect span the model predicted is accurate. They were asked to delete a tagged span if they regarded it as inappropriate. We denote all prediction spans as $\mathcal{M}$, and the filtered spans from annotators as $\mathcal{F}_1$, $\mathcal{F}_2$ and $\mathcal{F}_3$. We represent $n_\mathcal{S}$ as the total number of text spans in $\mathcal{S}$. Here we define correct spans as

$$\mathcal{C} = \{l | l \in \mathcal{F}_1, l \in \mathcal{F}_2, l \in \mathcal{F}_3\}$$

The aspect precision is calculated using Formula 5.

$$\text{Precision} = \frac{n_\mathcal{C}}{n_\mathcal{M}} \tag{5}$$

For measuring aspect recall, we asked three annotators to label aspect spans that they identified while the model ignored. We denote the additional labeled spans from one annotator as $\mathcal{A}$ where $\mathcal{A} = \{a_1, a_2, \cdots, a_{n_\mathcal{A}}\}$, a_i represents a text span. We denote the additional labeled spans from other two annotators as $\mathcal{B}$ and $\mathcal{C}$.

We define common ignored spans for every two annotators as below. $|\cdot|$ denotes the number of tokens in a span and $\cap$ takes the intersect span

▨ summary	▨ originality	▨ clarity	▨ meaningful comparison	▨ motivation	▨ substance

This paper studies the graph embedding problem by using encoder-decoder method . The experimental study on real network data sets show the features extracted by the proposed model is good forclassification . Strong points of this paper: 1. The idea of using the methods from natural language processing to graph mining is quite interesting . 2. The organization of the paper is clear Weak points of this paper: 1. Comparisons with state-of-art-methods (Graph Kernels) is missing . 2. The problem is not well motivated, are there any application of this . What is the difference from the graph kernel methods ? The comparison with graph kernel is missing . 3. Need more experiment to demonstrate the power of their feature extraction methods . (Clustering, Search, Prediction etc.) 4. Presentation of the paper is weak . There are lots of typos and unclear statements.

Table 9: An example of automatically labeled reviews.

between two spans.

$$\mathcal{I}_1 = \{a_i \cap b_j | \frac{|a_i \cap b_j|}{\min\{|a_i|, |b_j|\}} > 0.5\}$$

$$\mathcal{I}_2 = \{b_i \cap c_j | \frac{|b_i \cap c_j|}{\min\{|b_i|, |c_j|\}} > 0.5\}$$

$$\mathcal{I}_3 = \{a_i \cap c_j | \frac{|a_i \cap c_j|}{\min\{|a_i|, |c_j|\}} > 0.5\}$$

We also define common ignored spans for three annotators as below.

$$\mathcal{I} = \{a_i \cap b_j \cap c_k | \frac{|a_i \cap b_j \cap c_k|}{\min\{|a_i|, |b_j|, |c_k|\}} > 0.3\}$$

where a_i, b_j, c_k are text spans from $\mathcal{A}, \mathcal{B}, \mathcal{C}$ respectively. We assume all the spans the model predicts are correct. Then we can calculate total number of spans using Formula 6.

$$n = n_{\mathcal{M}} + n_{\mathcal{A}} + n_{\mathcal{B}} + n_{\mathcal{C}} - n_{\mathcal{I}_1} - n_{\mathcal{I}_2} - \\ n_{\mathcal{I}_3} + n_{\mathcal{I}} \quad (6)$$

The aspect recall is calculated using Formula 7.

$$\text{Recall} = \frac{n_{\mathcal{M}}}{n} \quad (7)$$

A.7 Adjusting BART for Long Documents

The first attempts we made to directly adjust BART for long text either expanded its positional encodings or segmented the input text and dealt with each segment individually. Below are three ways we attempted.

Arc-I: Position Encoding Expanded BART Since the original BART model is pretrained on 512 sequence length and fintuned on 1024 sequence length.[22] We followed this approach and tried copying the first 1024 position encodings periodically for longer sequence and finetuned the model on our own dataset.

Arc-II: Independently-windowed BART In this architecture, we simply chunked the documents into multiple windows with 1024 window size, and then use BART to encode them separately. The final output of the encoder side is the concatenation of those window outputs. The decoder can then generate texts as normal while attending to the whole input representations.

Arc-III: Dependently-windowed BART In **Arc-II**, we ignore the interdependence between each chunk which may lead to incoherence in generated texts. Here, to model the inter-window dependencies, we followed the approach introduced in Rae et al. (2020). We kept a compressive memory of the past and used this memory to compute the representation of new window. The final output of the encoder side is the concatenation of those window outputs as in **Arc-II**.

However, we found that none of these adjustments could generate satisfying fluent and coherent texts according to our experiments. Common problems include interchanges between first and third person narration (They... Our model...), contradiction between consecutive sentences, more descriptive texts and fewer opinions, etc.

A.8 CE Extraction Details

The basic sentence statistics of our ASAP-Review dataset is listed in Table 11.

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[22]https://github.com/pytorch/fairseq/issues/1413

KEYWORDS							
find	prove	examine	address	suggest	baseline	optimize	outperform
show	design	explore	analyze	achieve	maximize	efficient	generalize
imply	reduce	propose	explain	perform	minimize	effective	understand
study	metric	observe	benefit	improve	increase	introduce	investigate
bound	better	present	compare	dataset	decrease	interpret	demonstrate
apply	result	develop	measure	evaluate	discover	experiment	state-of-the-art

Table 10: Predefined keywords for filtering sentences.

	ICLR	NIPS	Both
Avg. Sentence Num.	216	198	209

Table 11: Sentence statistics of `ASAPReview` dataset. "Avg. Sentence Num." denotes average sentence number in a paper.

We use two steps to extract salient sentences from a source document: (i) Keywords filtering, (ii) Cross-entropy method

A.8.1 Keywords Filtering

We have predefined 48 keywords and in the first stage, we select sentences containing those keywords as well as their inflections. The 48 keywords are shown in Tab. 10. After applying keywords filtering, the statistics of selected sentences are shown in Tab. 12.

	ICLR	NIPS	Both
Avg. Sentence Num.	97	85	92

Table 12: Sentence statistics of selected sentences after keywords filtering. "Avg. Sentence Num." denotes average selected sentence number in a paper.

A.8.2 Cross Entropy Method

Following Feigenblat et al. (2017)'s approach in unsupervised summaization. We formalize the sentence extraction problem as a combinatorial optimization problem.

Specifically, we define the performance function R as below.

$$R(S) = -\sum_{w \in S} p_S(w) \log p_S(w) \qquad (8)$$

$$p_S(w) = \frac{\text{Count}(w)}{\text{Len}(S)} \qquad (9)$$

Where S represents the concatenation of selected sentences, $\text{Len}(S)$ represents the number of

words in S while $\text{Count}(w)$ represents the number of times w appears in S.

The intuition behind this performance function is that we want to select sentences that can cover more diverse words. Note that when calculating $R(S)$, we do preprocessing steps (i.e. lowercasing, removing punctuation, removing stop words etc.).

For each paper containing n sentences, we aim to find a binary vector $p = (p_1, \cdots, p_n)$ in which p_i indicates whether the i-th sentence is selected such that the conbination of selected sentences achieves highest performance score and also contains fewer than 30^{23} sentences.

We did this by using Cross Entropy Method (Rubinstein and Kroese, 2013). The algorithm is shown below.

1. For each paper containing n sentences, we first assume that each sentence is equally likely to be selected. We start with $p_0 = (1/2, 1/2, ..., 1/2)$. Let $t := 1$.

2. Draw a sample $X_1, \cdots, X_N$ of Bernoulli vectors with success probability vector p_{t-1}. For each vector, concatenate the sentences selected and get N sequences $S_1, \cdots, S_N$. Calculate the performance scores $R(S_i)$ for all i, and order them from smallest to biggest, $R_{(1)} \leq R_{(2)} \leq \cdots \leq R_{(N)}$. Let γ_t be $(1-\rho)$ sample quantile of the performances: $\gamma_t = R_{(\lceil (1-\rho)N \rceil)}$.

3. Use the same sample to calculate $\hat{p}_t = (\hat{p}_{t,1}, \cdots, \hat{p}_{t,n})$ via

$$\hat{p}_{t,j} = \frac{\sum_{i=1}^N I_{\{R(S_i) \geq \gamma_t\}} I_{\{X_{ij}=1\}}}{\sum_{i=1}^N I_{\{R(S_i) \geq \gamma_t\}}} \qquad (10)$$

where $I_{\{c\}}$ takes the value 1 if c is satisfied, otherwise 0.

---

[23]This number is chosen according to our empirical observations. We need to extract sentences that can fit BART's input length (1024).

This paper studies the problem of transfer learning from a single pre-trained network onto a new task . The authors propose a method of combining the outputs of multiple pre-trainable classifiers by training on their raw predictions and then fine-tuning on the target samples . The proposed method is based on the use of (non-linear) maximal correlation analysis that originated with Hirschfeld [9] to this problem . The paper is well written and easy to follow . The experimental results show that the proposed method outperforms the state-of-the-art methods on the CIFAR-100 , Stanford Dogs , and Tiny ImageNet datasets . However , it is not clear to me how the performance of the method is affected by the number of target training samples . It would be better if the authors can provide some theoretical analysis on the effect of the size of the target dataset .

Table 13: Illustration of generated tokens associated with corresponding aspects. + denotes positive sentiment. - denotes negative sentiment.

4. Perform a smoothed update.

$$p_t = \alpha \hat{p}_t + (1 - \alpha)p_{t-1} \qquad (11)$$

5. If the value of γ_t hasn't changed for 3 iterations, then stop. Otherwise, set $t := t + 1$ and return to step 2.

The elements in p_t will converge to either very close to 0 or very close to 1. And we can sample from the converged p_t to get our extraction.

We chose $N = 1000$, $\rho = 0.05$ and $\alpha = 0.7$ when we ran this algorithm. If we happen to select more than 30 sentences in a sample, we drop this sample. Note that we slightly decrease the initial probability when there are more than 90 sentences after filtering to ensure enough sample number in the first few iterations.

A.9 Detailed Analysis and Case Study

In §5.2, we have shown that our aspect-enhanced model performs better in terms of aspect coverage and aspect recall. Here we take our aspect-enhanced model using CE extraction to do a more fine-grained analysis to diagnose advantages and disadvantages of our system.

A.9.1 Advantages of Our System

Aspect-aware In the aspect-enhanced model, we have added another multi-layer perceptron that can classify the aspect of a token. It would be interesting to see the results of the model generating a token and predicting its label simultaneously. Tab. 13 shows an example review when we do so. We can see that the model can not only generate fluent text but also be aware of what aspect it's going to generate together with a correct polarity of that aspect.

Although the generated aspects are often small segments and there are some minor alignment issues, but the model is clearly aspect-aware.

Evidence-sensitive It would also be interesting to trace back to the evidence when the model generates a specific aspect. To do that we inspect where the model attends when it generates a specific aspect by looking at the attention values with respect to the source input.[24]

And interestingly, we found that the model attends to the reasonable place when it generates a specific aspect. Fig. 8 presents the attention heatmap of several segment texts , the bottom of the figure shows aspects the model generates. There are some common patterns we found when we examined the attention values between the source input and output.

1. When the model generates summary, it will attend to sentences that contain strong indicators like "we propose" or "we introduce".

2. When it generates originality, it will attend to previous work part as well as places describing contributions of this work.

3. When it generates substance, it will attend to experiment settings and number of experiments conducted;

4. When it generates meaningful comparison, it will attend to places contains "et al."

---

[24]The way we aggregate attention values is to take the maximum, no matter is to aggregate tokens to a word or to aggregate different attention heads or to aggregate words to an aspect.

Clear organization After carefully inspecting the generated reviews, we found that their structures are very similar and typically follow the routine in Tab. 14. This is better compared to some reviews from reviewers where there are just comments concatenated together with no explicit structure.

STRUCTURE
Overview of the paper [summary]
Some advantages [Pros]
However I have some concerns: [Cons]
1. concern1 ...
2. concern2 ...
3. concern3 ...
......

Table 14: Structure of generated reviews.

A.9.2 Disadvantages of Our System

We select five examples for each aspect the model mentions and list them in Tab. 15. Although those comments seem like from real reviewers, there are common issues, which we list below.

Imitating style In §5.3.2, we observe that generated reviews achieve much higher scores in the *Clarity* aspect for model with introduction extraction. Same phenomenon occurs in other models as well. After careful inspection, we found that "The paper is well-written and easy to follow" appears in more than 90% generated reviews. This is due to the fact that in the training data, this exact sentence appears in more than 10% papers. This accounts for the high number of occurrences of *Positive Clarity*.

Lack of questioning Generated reviews struggle to ask questions which is an important component in peer reviewing. In the reference reviews, average number of questions per review ask is 2.04, while it is only 0.32 in generated reviews.

Nonconstructive In generated reviews, supportive evidences for negative aspects are often invalid. For example, when it generates "The author should compare with [1, 2, 3] and [4]", it rarely provides the reference papers beyond those random numbers. Even if it provides the related papers to be compared with, those links mostly point to papers that are not relevant to the current paper at all. Another example is that it often suggests a paper to conduct experiment in more datasets like ImageNet even if the paper is a NLP paper.

A.10 Calculation of Aspect Score

For accepted (rejected) papers, we calculate the average aspect score for each aspect.

The aspect score of a review is calculated as follows.

- If an aspect doesn't appear in a review, then we count the score for this aspect as 0.5 (which stands for neutral)

- If an aspect appears in a review, we denote its occurrences as $\mathcal{O} = \{o_1, o_2, \cdots, o_n\}$ where n is the total number of occurrences. And we denote the positive occurrences of this aspect as $\mathcal{O}_p = \{o_{p_1}, o_{p_2}, \cdots, o_{p_n}\}$ where p_n is the total number of positive occurrences. The aspect score is calculated using Formula 12.

$$\text{Aspect Score} = \frac{p_n}{n} \qquad (12)$$

A.11 Bias Analysis for All Models

Here, following the method we proposed in §5.3.1, we list the bias analysis for all models below.

B Supplemental Material

B.1 Dataset Annotation Guideline

The annotation guideline for annotating aspects in reviews can be found at https://github.com/neulab/ReviewAdvisor/blob/main/materials/AnnotationGuideline.pdf
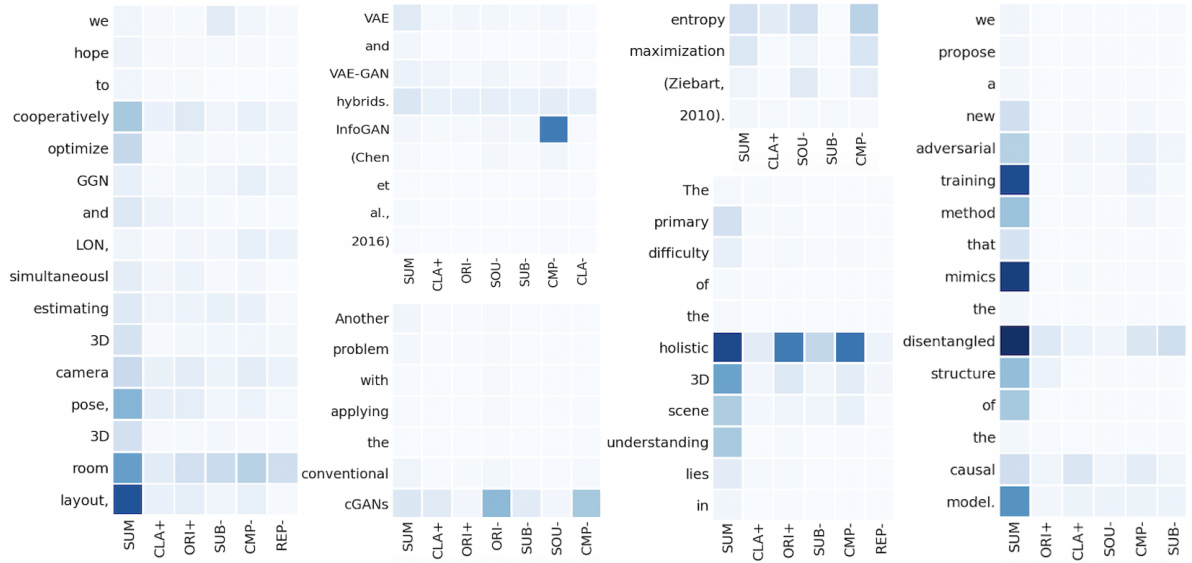
Figure 8: Attention heatmap between source document and generated reviews. $+$ denotes positive sentiment and $-$ denotes negative sentiment.
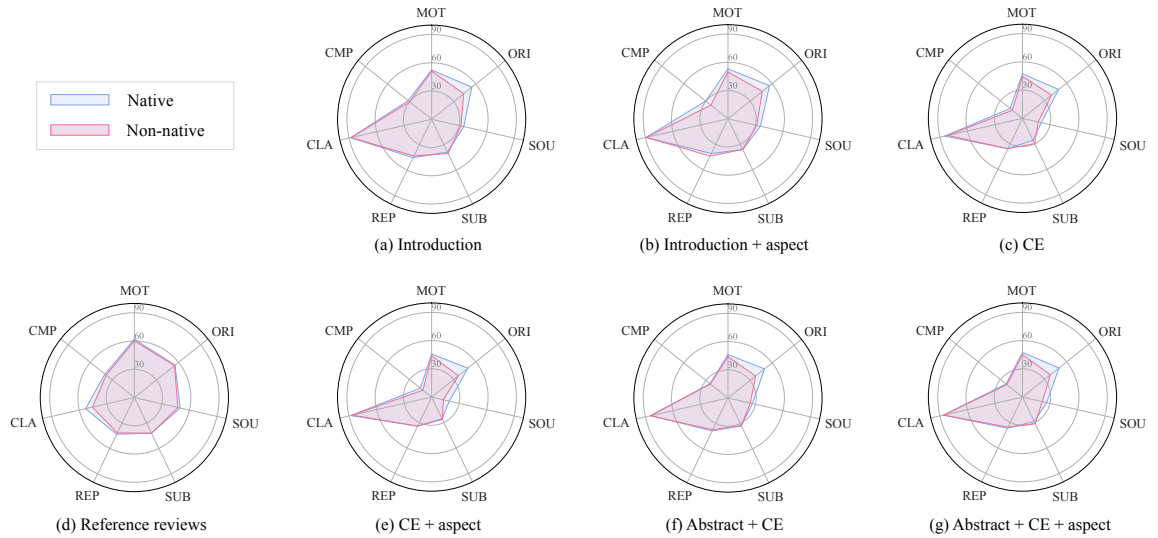

Figure 9: Spider chart of aspect scores for all models with regard to nativeness.
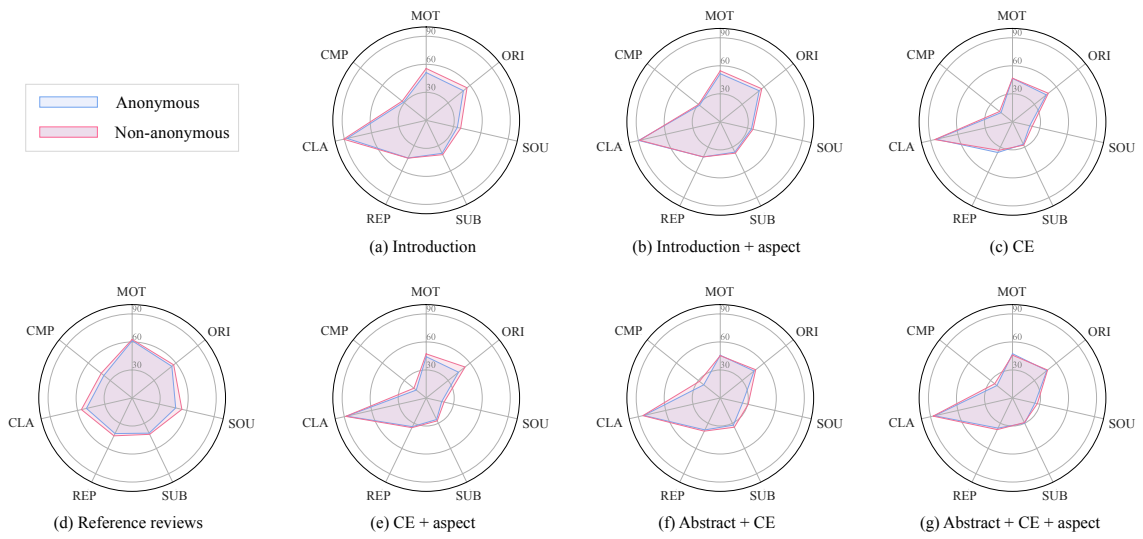
Figure 10: Spider chart of aspect scores for all models with regard to anonymity.

Motivation

1. The motivation of using the conditional prior is unclear.
2. I think this paper will be of interest to the NIPS community.
3. The idea of continual learning is interesting and the method is well motivated.
4. Overall, I think this paper is a good contribution to the field of adversarial robustness.
5. It is hard to understand the motivation of the paper and the motivation behind the proposed methods.

Originality

1. This paper presents a novel approach to cross-lingual language model learning.
2. The novelty of the paper is limited . The idea of using low rank matrices is not new.
3. The proposed method seems to be very similar to the method of Dong et al. (2018).
4. The idea of using neural networks to learn edit representations is interesting and novel .
5. The proposed method seems to be a simple extension of the batched-E-step method proposed by Shazeer et al.

Soundness

1. This assumption is not true in practice .
2. The experimental results are not very convincing .
3. But the authors do not provide any theoretical justification for this claim.
4. The theoretical results are sound and the experimental results are convincing.
5. The paper does not provide any insights on the reasons for the success of the supervised methods.

Substance

1. The experiments are well-conducted.
2. The ablation study in Section A.1.1 is not sufficient.
3. It would be better to show the performance on a larger dataset.
4. The authors should show the performance on more difficult problems.
5. The experiments are extensive and show the effectiveness of the proposed method.

Replicability

1. It is not clear how the network is trained.
2. The authors should provide more details about the experiments.
3. The authors should provide more details about the hyperparameters.
4. The authors should provide more details about the training procedure.
5. It would be better if the authors can provide more details about the hyperparameters of LST.

Meaningful Comparison

1. The author should compare with [1 , 2 , 3] and [4] .
2. The authors should compare the proposed method with existing methods .
3. It would be more convincing if the authors can compare with other methods such as AdaGrad.
4. authors should compare the performance with the state-of-the-art methods in real-world applications .
5. I also think the paper should compare the performance of intrinsic fear with the other methods proposed in [1 , 2 , 3 , 4 , 5].

Clarity

1. There are some typos in the paper.
2. The paper is well-written and easy to follow.
3. It is not clear to me how to interpret the results in Table 1.
4. It would be better if the authors can provide a more detailed explanation of the difference.
5. The paper is not well organized . It is hard to follow the description of the proposed method.

Table 15: Examples for different aspect mention from generated reviews.

	MOT	ORI	SOU	SUB	REP	CMP	CLA	Total
INTRO	-0.72	+18.71	+3.84	-3.66	+0.73	-13.32	+2.40	43.39
INTRO+ASPECT	+3.12	+15.75	+6.14	+0.66	-10.61	-13.50	+19.05	68.84
CE	+2.56	+18.33	+11.16	-13.41	-3.71	-9.94	+13.49	72.58
CE+ASPECT	+1.13	+24.77	+28.78	-2.92	-3.18	-12.02	+18.36	91.18
ABSTRACT+CE	+1.77	+23.01	+3.79	+0.44	+0.37	-15.18	-2.13	46.69
ABSTRACT+CE+ASPECT	+1.72	+22.23	+12.94	-8.30	-0.38	-13.40	+0.89	59.86

Table 16: Disparity differences regarding nativeness. Total is the sum of absolute value of disparity difference.

	MOT	ORI	SOU	SUB	REP	CMP	CLA	Total
INTRO	-5.69	-4.43	+2.76	-0.64	+5.65	+5.80	+3.02	28.00
INTRO + ASPECT	-3.53	-1.65	+7.85	+0.01	+5.93	+11.02	+4.20	34.20
CE	+1.89	-1.18	+0.05	-0.44	+13.09	+8.00	-2.56	27.21
CE+ASPECT	-4.20	-12.32	-0.52	-2.57	+2.70	+8.75	-10.31	41.37
ABSTRACT+CE	+3.18	-0.05	-7.96	-3.73	+2.25	+8.69	-12.02	37.88
ABSTRACT+CE+ASPECT	+5.45	+2.49	+2.80	+5.69	+1.33	+8.03	-3.79	29.59

Table 17: Disparity differences regarding anonymity. Total is the sum of absolute value of disparity difference.