Parachute: Evaluating Interactive Human-LM Co-writing Systems

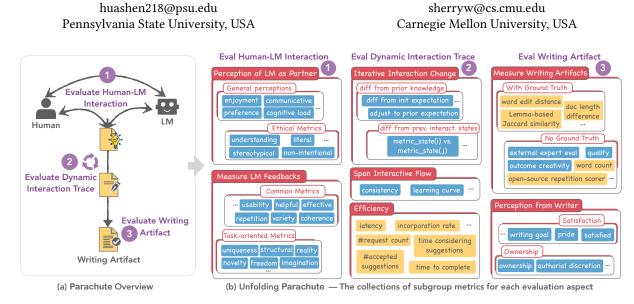


Figure 1: Parachute: human-centered integrative evaluations on interactive co-writing systems. (a) Parachute overview. (b) The subgroup metrics for each evaluation aspect. (yellow and blue indicates objective and subjective metrics, respectively.)

ABSTRACT

A surge of advances in language models (LMs) has led to significant interest in using LMs to build co-writing systems, in which humans and LMs interactively contribute to a shared writing artifact. However, there is a lack of studies assessing co-writing systems in interactive settings. We propose a human-centered evaluation framework, Parachute, for interactive co-writing systems. Parachute showcases an integrative view of interaction evaluation, where each evaluation aspect consists of categorized practical metrics. Furthermore, we present Parachute with a use case to demonstrate how to evaluate and compare co-writing systems using Parachute.

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1 INTRODUCTION

Language models (LMs) have advanced significantly, showcasing previously unheard-of capabilities in solving a wide spectrum of generation and language understanding tasks [3, 8, 9]. This has spurred great academic and public interest in using LMs to build writing assistants, in which humans collaborate with LMs to paraphrase sentences (e.g., QuillBot), autocomplete sentences [2], write stories [1], etc. Despite the interactive co-writing process, the cowriting systems are at present primarily tested in non-interactive settings [4, 12]. Specifically, current studies commonly conduct evaluations only on the final, co-written article [7], or prior- and post-human assessment on perceiving LMs [11, 12], etc. Consequently, these evaluations fail to capture the *delta* (or dynamic shift) of human-LM interactions. Consider, for instance, a scientific paper writing task involving two types participants, freshmen and a university professors. While it may not be surprising that the professor-LM team achieves significantly better writing quality, this metric does not reflect the fact the impact of the LM on its

users: Freshmen might have benefited significantly from the model in terms of the scientific paper structure, grammar correction, etc., whereas professors might have achieved similar writing performance even without the LM. In other words, the quality of the final article cannot genuinely reflect the co-writing system's influence on users. Instead, we should assess users' dynamic interaction improvements to indicate system capability, such as the relative quality change between two iterated articles from the same user.

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In spite of the importance, to the best of our knowledge, there are few studies that examine *how to assess the interaction shift in the iterative co-writing process*, and *how to depict an integrative view for evaluating interactive co-writing systems*. To close this gap, we propose Parachute: a human-centered evaluation framework for human-LM interactive co-writing systems. We identify the key components and interaction aspects for evaluating the co-writing systems. We further collect the comprehensive types of evaluation metrics under each aspect, including the novel measurements designed for dynamic interaction assessments, and the other two conventional yet important aspects (*i.e.*, human-LM interaction and writing artifact evaluation). Though a case study, we show that Parachute can be effectively used as a thinking tool for comprehensively evaluating and comparing the co-writing systems.

2 PARACHUTE FRAMEWORK

We aim to propose Parachute as a guideline that can assist researchers in evaluating and analyzing interactive co-writing systems more comprehensively and fairly.

To this end, we focus on identifying key axes for co-writing systems. To begin with, grounded on the Co-Creative Framework for Interaction Design (COFI) model [10], we identify three key **components** in human-LM co-writing systems: it involves both **human** and **LM** collaborating on a shared **writing artifact** (*e.g.*, essay, story, paper, etc.) as partners [10]. Among these three components, *humans* are the primary decision-makers for interacting with LMs and writing artifacts. To reflect its importance, we design Parachute to be a human-centered evaluation framework, meaning that the ultimate objectives of these metrics is help humans achieve their various writing needs (*e.g.*, better user experience, higher-quality writing artifact, etc.).

As shown in Figure 1, Parachute further recognizes three **aspects**, which are important around these components and also the interactions between them, including **1** *evaluate human-LM interaction*, **2** *evaluate dynamic interaction trace*, and **3** *evaluate writing artifact*. Based on existing evaluation approaches, which might capture insufficient evaluation aspects to reflect the system capability holistically [4, 7, 12] or focus much on one-time metrics that neglect dynamic interaction changes [5, 11], Parachute seeks to contribute in two folds. First, Parachute presents a more integrative view of interaction evaluation supported by practical metrics. Besides, Parachute explicitly extracts a set of metrics to assess the dynamic change along iterations.

3 PARACHUTE TO PRACTICAL METRICS

How can Parachute guide practical evaluation? We use Parachute to analyze existing evaluations, and reflect on what axes these metrics emphasize Concretely, we use an inductive approach to collect the practical metrics adopted in state-of-the-art co-writing systems (*e.g., Wordcraft* [12], *Integrative Leaps* [11], *Beyond Text Generation* [4], *Dramatron* [7], etc.) Then we categorize them into subgroups and fit into Parachute framework. Figure 1(b) depicts the categorized evaluation metrics for each Parachute aspect. We next clearly define the aspects and metric subgroups in Parachute, and briefly explain the underlying motivation. Please see Table 1 in **Appendix A.1** for more elaborated metrics and details.¹.

• Evaluating Human-LM interaction. These metrics measure interactions between the co-writers (*i.e.*, human & LM). Suppose humans perceive LM as a co-author in co-writing systems. Then their evaluations primarily derive from two dimensions: *i*) how does the human feel to collaborate with LM? (*i.e.*, "Perception of LM as Partner"). This subgroup consists of both metrics of general perceptions (*e.g.*, *enjoyment*, *preference*, etc.), and ethical metrics (*e.g.*, *stereotypical*, etc.). Meanwhile, *ii*) how credible is the LM's feedback? (*i.e.*, "Measure LM Feedbacks"), which involves common metrics for a variety tasks (*e.g.*, *usability*, etc.), or task-oriented metrics, like *imagination* preferred by storytelling, or *structural* for scientific writing, etc.

2 Evaluating dynamic interaction trace. These metrics focus on evaluating the dynamic change of interactions along iterative writing process. We identify three dimensions for evaluations. First, when human iteratively updates the artifacts, "Iterative Interaction Change" subgroup aims to compare metrics between multiple iterations, such as measuring human understanding on LM *before* start writing and when almost *finish* the article). Also, we cover **"Span Interactive Flow**" subgroup here to assess metrics that need to observe spanning multiple artifact versions (*e.g., consistency, learning curve*). Besides, the responding time affects user experience in the interactive systems. We thus include **"Efficiency"** metrics (*e.g., latency, incorporation rate*) to assess the process.

Sevaluating writing artifact. These metrics gauge the content of the final writing artifact that human and LM jointly accomplish. We broadly divide these metrics into "**Measure Writing Artifacts**", where we can compare written artifacts with ground-truth articles (*e.g.*, using *Jaccard similarity*) or recruit external experts for evaluation when without ground truth, and "**Perception from Writer**" dimensions, where writers provide subjective feedback on their outputs (*e.g., satisfaction* or *ownership*).

4 CASE STUDY: PARACHUTE FOR CO-WRITING

We consider Parachute as a framework for researchers to fairly evaluate and compare co-writing systems. Parachute can be useful for researchers to: 1) **identify key interactive evaluation aspects** among human, LM, and writing artifact interactions during the co-writing process, 2) **select appropriate metrics** to assess and compare the co-writing systems, 3) **comprehensively analyze and describe** the human-LM interactive performance of the co-writing systems. Next we present a concrete use case of re-evaluating the Beyond Text Generation (BTG) [4] system to showcase how to use Parachute for evaluation.

Suppose the researchers have built the BTG system and need to evaluate its performance in an interactive setting. Parachute can help them assess the system comprehensively and compare it to existing baselines. For example, they can use the Parachute framework to unpack their hypothesis into fine-grained evaluation requirements. A mapping may look like: "the BTG system can help humans write better articles (i.e., aspect3: evaluate writing artifact) by enabling better human-LM interactions (i.e., aspect1: evaluate human-LM interaction) in efficient ways (i.e., aspect2: evaluate dynamic interaction trace). With these aspects in mind, they can then dive into each aspect to select the appropriate metrics to support this statement. For instance, they can assess "writers' perceptions of LM" by choosing enjoyable, preference metrics, and "how writers think about LM's feedbacks" with usabiity, effective, coherence metrics, etc. Also, they can assess the dynamic interaction efficiency by analyzing the objective logging data (e.g., incorporation rate, latency). The final writing article can also be rated with a set of measures (e.g., external expert review, quality, satisfaction, ownership, etc.). Following the evaluation methods presented in Appendix A.2 (which captures the most common methods used for state-of-the-art system evaluations), they can map the metrics to actual user study designs. Note that the researchers apply all measurements to both the proposed BTG system and the baselines, and ideally with the same group of users, so that they can compare the performance of co-writing systems in a fair manner.

5 CONCLUSION

This work present Parachute: a human-centered framework to evaluate human-LM interactive co-writing systems. It provides a thinking tool for researchers to design comprehensive interaction evaluations and analyses. We further feature a use case study introducing how to use Parachute step-by-step for fair evaluations.

¹Note that we do not aim to build enumerated lists of evaluation metrics. Instead, we focus on introducing the motivation and process of creating these evaluation aspects and subgroups, which can be generalized in broader use.

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REFERENCES

- [1] Nader Akoury, Shufan Wang, Josh Whiting, Stephen Hood, Nanyun Peng, and Mohit Jyyer. 2020. STORIUM: A Dataset and Evaluation Platform for Machinein-the-Loop Story Generation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics, Online, 6470–6484. https://doi.org/10.18653/v1/2020.emnlp-main.525
- [2] Mia Xu Chen, Benjamin N Lee, Gagan Bansal, Yuan Cao, Shuyuan Zhang, Justin Lu, Jackie Tsay, Yinan Wang, Andrew M Dai, Zhifeng Chen, et al. 2019. Gmail smart compose: Real-time assisted writing. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 2287– 2295.
- [3] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. 2022. Palm: Scaling language modeling with pathways. arXiv preprint arXiv:2204.02311 (2022).
- [4] Hai Dang, Karim Benharrak, Florian Lehmann, and Daniel Buschek. 2022. Beyond Text Generation: Supporting Writers with Continuous Automatic Text Summaries. In Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology. 1–13.
- [5] Mina Lee, Megha Srivastava, Amelia Hardy, John Thickstun, Esin Durmus, Ashwin Paranjape, Ines Gerard-Ursin, Xiang Lisa Li, Faisal Ladhak, Frieda Rong, et al. 2022. Evaluating Human-Language Model Interaction. arXiv preprint arXiv:2212.09746 (2022).
- [6] Matthew B Miles and A Michael Huberman. 1994. Qualitative data analysis: An expanded sourcebook. sage.
- [7] Piotr Mirowski, Kory W Mathewson, Jaylen Pittman, and Richard Evans. 2022. Co-writing screenplays and theatre scripts with language models: An evaluation by industry professionals. arXiv preprint arXiv:2209.14958 (2022).
- [8] Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. arXiv preprint arXiv:2203.02155 (2022).
- [9] Jack W Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, et al. 2021. Scaling language models: Methods, analysis & insights from training gopher. arXiv preprint arXiv:2112.11446 (2021).
- [10] Jeba Rezwana and Mary Lou Maher. 2022. Designing Creative AI Partners with COFI: A Framework for Modeling Interaction in Human-AI Co-Creative Systems. ACM Transactions on Computer-Human Interaction (2022).
- [11] Nikhil Singh, Guillermo Bernal, Daria Savchenko, and Elena L Glassman. 2022. Where to hide a stolen elephant: Leaps in creative writing with multimodal machine intelligence. ACM Transactions on Computer-Human Interaction (2022).
- [12] Ann Yuan, Andy Coenen, Emily Reif, and Daphne Ippolito. 2022. Wordcraft: story writing with large language models. In 27th International Conference on Intelligent User Interfaces. 841–852.

A APPENDIX

A.1 Parachute Metric Details

We list the practical evaluation metrics of Parachute with details, including Interaction Aspects, Subgouprs, Metrics, Measure Questions, and References in Table 1.

A.2 Evaluation Methods in User Studies for Co-writing Systems

We summarize a list of evaluation methods that are commonly used in studying co-writing systems [7, 11, 12] for the future work reference. This summary aims to serve the purpose of providing inspirations and benchmarks for future co-writing system work to design and compare user study evaluations.

(a) **Coding users' think aloud transcripts.** Researchers can encourage the participants to articulate their thinking during interacting with the systems, such as *why they decided to use this prompt for querying LM but not others*, etc. After finishing the study, researchers can convert the video/radio into transcripts and code the transcripts for further data analysis. Some common qualitative data analysis approaches include thematic analysis, content coding, and topic modeling [6], etc.

(b) **Coding researchers' observation notes.** During the user studies, the researchers can also record their observations for later analysis. For instance, they can pre-design a set of topics (*e.g.*, user's emotion change, etc.) that are important to answer their research questions, and pay close attention to these topics during the studies.

(c) **Coding (semi-)structured interview transcripts.** Prior studies also commonly leverage (semi-)structured interviews to elicit users' experience and feedback on using the systems. Researchers can design effective interview questions and invoke participants' answers, to better support the research arguments.

(d) **Questionnaires or Surveys.** Previous studies also frequently design surveys, which include questions such as N-five-point Likert ratings, single choice or multiple choice questions, etc. These surveys can provide more accurate measures on user's assessment.

(e) **Interaction data logs.** The data logs during interaction can provide more objective analysis on user behaviors. Typical interaction data logs for co-writing systems involve artifact submission count, prompt request frequency, latency, etc.

(f) Assessment on the written artifacts. These metrics aim to directly evaluate the quality of written artifacts, commonly using automatic metrics by comparing with ground truth (*e.g., similarity*), computing the artifact properties (*e.g., word count, document length*, etc.), or having external experts to assess the outputs.

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	enjoyment	I enjoyed writing the story.	[7, 12]
• Evaluating Human- -LM Interaction	effort	I put lots of effort into getting AI suggestions.	[11]
	preference	I prefer the suggestions from the AI agent.	[7]
	communicative		[11]
	cognitive load		[11]
	collaborative		[7, 11, 12]
	ease	The AI agent is easy to learn and work with.	[7, 12]
Parasetion of IM as Partner	understanding	Lean understand the AL agent	[[11]
[Ethical Metrics]			[11]
			[7]
			[7]
	non-intentional		[11]
Measure LM Feedbacks [Common Metrics] Measure LM Feedbacks [Task-oriented Metrics]			[7, 11]
			[7, 11]
			[7, 11, 12]
			[12]
			[11]
	usability	The AI agent is useful for my writing.	[11]
	combinatorial	I feel the AI agent combines a broad set of information.	[11]
	uniqueness	The AI's suggestions are unique	[7, 11, 12]
			[7, 11]
			[11]
			[11]
			[7]
			[11]
	unexpected	The AI suggestions are often unexpected to me.	[7, 11]
Iterative Interaction Change	different from initial expectation	what's the difference before the initial expression.	[11]
[diff from prior knowledge]	adjust to prior expectation	I adjusted my expectation to prior ones.	[11]
9 Evaluating Dynamic Iterative Interaction Change Interaction Trace [diff from prev. interact. states] Span Interactive Flow Efficiency	dynamics of suggestion integra- tion	how does the suggestion integration change dynamically.	[11]
	learning curve	I can learn to use this system auickly.	[11]
	e		[7, 11]
			[7, 11]
	v		
			[4]
			[4]
			[4]
	0 00		[4]
			[4]
	time to complete	The elapsed time for human to complete the task.	[4]
Measure Writing Artifacts	word edit distance	The word edit distance between prior- and post- articles.	[7]
[With Ground Truth]	lemma-based Jaccard similarity	The similarity of ground truth and outcome article.	[7]
	document length difference	The difference between prior- and post- articles.	[7]
Magguro Writing Artifacto	outoomo areativity	The article Lewrote with ALie exection	[7, 11]
	,		
			[5] [5]
			[4]
	open-source repetition scorer	Computing repetition score using exisint tools.	[7]
Perception from Writer [Satisfaction]	writing goal	The outcome article reaches my writing goal.	[4, 7]
	pride	I'm proud of the final article.	[4, 7]
	•		
[]	satisfied	I feel satisfied with the final article.	[7]
Perception from Writer	satisfied ownership	I feel satisfied with the final article. I feel ownership over the final article.	[7]
	[General perceptions] Perception of LM as Partner [Ethical Metrics] Measure LM Feedbacks [Common Metrics] Measure LM Feedbacks [Task-oriented Metrics] Iterative Interaction Change [diff from prior knowledge] Iterative Interaction Change [diff from prior knowledge] Iterative Interaction Change [diff from prev. interact. states] Span Interactive Flow Efficiency Measure Writing Artifacts [With Ground Truth] Measure Writing Artifacts [No Ground Truth]	[General perceptions]preference communicative cognitive load collaborative easePerception of LM as Partner [Ethical Metrics]understanding literal stereotypical non-intentionalMeasure LM Feedbacks [Common Metrics]coherent variety helpful effective repetition usability combinatorialMeasure LM Feedbacks [Task-oriented Metrics]uniqueness reality novelty freedom structural imagination unexpectedIterative Interaction Change [diff from prior knowledge]different from initial expectation adjust to prior expectation 	[General perceptions] preference Tprefer the suggestions from the AT agent. communicative construiture load communicative and with the AT agent requires much cognitive load. feet the AT agent of LM as Partner Interacting with the AT agent requires much cognitive load. [Ethical Metrics] inderstanding Ican understand the AT agent. Iteral The AT agent is any to learn and work with. Interacting with the AT agent suggestions are stereotypical The AT agent is any to learn and work with. Interacting the AT agent is any to learn and work with. Interacting with the AT agent is any to learn and work with. Measure LM Feedbacks Icon understand the AT agent is any to learn any work ingestion are various. [Common Metrics] variety helpful The AT agent is any to learn any work ingestion are various. repetition The AT agent is any to learn any work ingestion are various. repetition The AT agent is any to learn any work ingestion are various. repetition The AT agent is any to learn any work ingestion are various. repetition The AT agent is any to learn any work ingestion are various. [Common Metrics] variety The AT agent is any to learn any work ingestion are various. repetition The AT agent agent any to learn any wore

Table 1: The practical subgroup metrics for each evaluation aspect in Parachute. We demonstrate the metric details of Interaction Aspects, Subgroups, Metrics, Measure Questions, and the corresponding References. (yellow and blue indicates objective and subjective metrics, respectively.)