XtraGPT : LLMs FOR HUMAN-AI COLLABORATION ON CONTROLLABLE SCIENTIFIC PAPER REFINEMENT

This work does not advocate using LLMs to replace human creativity or ethical standards in research.

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ABSTRACT

The increasing volume of scientific publications highlights the growing need for high-quality academic writing. However, while groundbreaking ideas are often present, many papers fail to meet academic writing standards. Unlike open-ended applications of large language models (LLMs) in research, which delegate creative tasks to AI, we emphasize a human-centered approach where researchers provide ideas and drafts while LLMs strictly follow user instructions for refinement. The XtraGPT training and evaluation processes, and models will be **open-sourced**.

We propose **XtraGPT**, LLMs designed to assist authors by delivering instruction-driven, context-aware revisions that (1) adhere to user instructions, (2) align with general academic writing standards, and (3) are consistent with the whole paper. Leveraging a dataset of 7,040 ICLR 24 papers and 140,080 question-answer pairs, XtraGPT enhances specific sections without compromising the paper's integrity. Experimental results show XtraGPT-7B surpass similar size models and is competitive with GPT-4o-mini in providing high-quality, context-aware refinements. We also found that scaling up model parameters provides limited improvement for the difficulty of paper scoring. Modifying six sections with XtraGPT can improve the paper's rating according to the predictor.

By prioritizing controllability in the task of paper refinement, XtraGPT empowers researchers to focus on innovation while relying on the system to handle the demands of academic writing with context understanding and adherence to academic standards and user instructions.

1 INTRODUCTION

Hercules, the hero who achieved great deeds through the persecution of Hera, took on the twelve labors commanded by Eurystheus. Each task was not only a challenge to his courage and wisdom, but also a journey of growth and self-overcoming, much like the process of constantly refining and improving a paragraph in the creation of a paper.

The rapid growth of scientific publications has created an increasing demand for high-quality academic writing tools. While many papers present groundbreaking ideas, their overall clarity, coherence, and writing quality often fall short of meeting academic standards. Large language models (LLMs) have shown remarkable capabilities in general-purpose text generation and question-answering (Dubey et al., 2024; Liu et al., 2024a; Achiam et al., 2023; Bai et al., 2023), but their potential in assisting fine-grained and controllable paper refinement remains underexplored.

Existing research in applying LLMs to academic writing focuses on four main areas: (1) *full-paper generation without user intervention*, which lacks fine-grained refinement or user-instruction alignment (Shao et al., 2024; Jiang et al., 2024; Anonymous, 2024a; Asai et al., 2024; Schmidgall et al., 2025); (2) *idea generation*, where LLMs propose research ideas directly, raising ethical concerns over authorship and creative responsibility (Baek et al., 2024; Ghafarollahi & Buehler, 2024; Li et al., 2024a; Si et al., 2024; Gu et al., 2024); (3) *paper review and domain-specific question-answering*, with little emphasis on directly improving the overall quality of writing (D'Arcy et al., 2024; Liang et al., 2024; Lu et al., 2024; Anonymous, 2024b; Asai et al., 2024; Chen et al., 2024b; Lála et al., 2023; Song et al., 2024; Lin et al., 2024); and (4) *polishing tools*, such as AI-assisted writing apps,

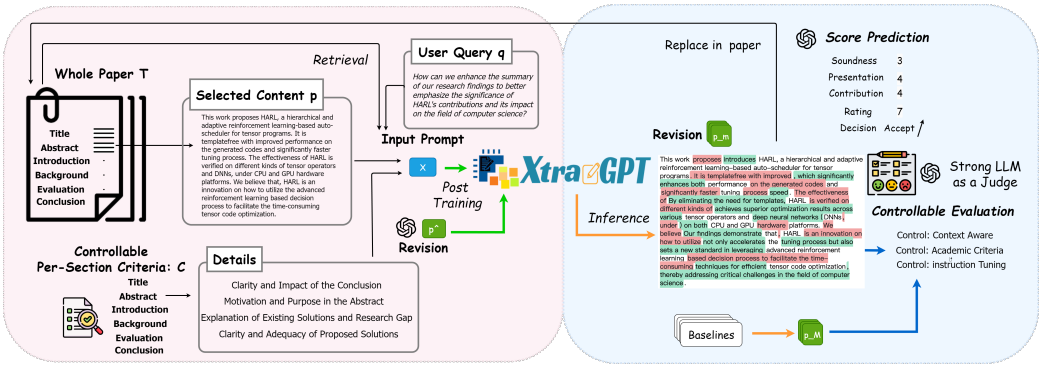


Figure 1: The schematic process of XtraGPT. The post training and evaluation processes ensure controllable section-level fine-grained paper refinement.

which focus on superficial improvements without understanding the context of the paper or the academic writing standards (CoWriter, 2025; van Zeeland, 2023).

The controllable generation of large models is emphasized (Ge et al., 2025). Despite advancements in leveraging llms for academic writing, none of the existing approaches address the necessity of a fine-grained, controllable paper refinement process. Scientific writing requires more than polished language — it demands a deep understanding of a paper's ideas and general academic writing standards to provide meaningful revisions. Human authors must retain control over the creative process, generating ideas and drafts while using tools that enhance their work in targeted and specific ways. Our approach, akin to a powerful code editor (Cursor, 2024), empowers authors to select specific sections of their paper for refinement and receive reliable, context-aware suggested revisions that align with their intent while preserving the core ideas of the work.

Developing such a paper refinement framework faces significant challenges: 1) *The lack of paired training data for instruction and refinement.* Most available datasets contain completed papers, offering little insight into pre- and post-improvement versions, making it difficult to model the refinement process effectively. 2) *The limited capability of LLMs to refine based on the context of an entire paper.* Current models struggle to deeply understand a paper's global structure, interconnected ideas, and nuanced context, which are essential for meaningful revisions. *The absence of a comprehensive summarization of general academic writing standards.* While academic writing relies on clarity, coherence, sound argumentation, and adherence to specific formats, an LLM-understandable and representative summarization of these qualities is lacking, complicating the evaluation and refinement of papers.

To address these challenges, we propose **XtraGPT** (Figure 1), a framework for controllable, fine-grained paper refinement that bridges the gap between human creativity and AI-assisted writing. XtraGPT enables authors to improve their drafts with minimal writing overhead by understanding the structure and context of scientific papers, providing section-level revisions tailored to user instructions, and maintaining the core ideas while enhancing clarity, coherence, and adherence to academic standards. By addressing the three major challenges mentioned above, XtraGPT sets a new direction in scientific writing tools.

Our key contributions include:

(1) **XtraQA**: a dataset of 7,040 research papers enriched with over 140,000 question-answer pairs for section-grained paper refinement by extracting high-quality data tailored for academic papers;

(2) **XtraGPT**: the first LLMs explicitly designed for fine-grained, controllable paper refinement, with its controllability demonstrated across three dimensions: contextual refinement, section-level fine-grained standards, and instruction-following ability;

(3) We qualify the effect of controllable paper refinement through a testset of 7000 question-answer pairs. Through detailed experiments, we provide several insights on paper refinement and scoring.

(4) XtraGPT adheres to the principle that human creatively generates ideas, while AI minimizes the mechanical burden of writing.

Table 1: Comparison of current full-paper AI generators on quality issues, full-paper In-Context Learning (ICL), Retrieval-Augmented Generation (RAG) or not, evaluation, controllability and whether include Human-Computer Interaction (HCI) or generate paper from scratch. Controllability refers to a generative system's ability to adapt to user needs, provide fine-grained control over content, and allow dynamic interaction and adjustment during the generation process.

Full-Paper AI Generator	Quality Issues	ICL	Evaluation	Control	HCI
PaperRobot (Wang et al., 2019)	Not LLM based, bad QA quality	✔	Human	✔	✔
August et al.(August et al., 2022)	Only definition	✗	Human	✗	✗
STORM (Shao et al., 2024)	Biased & Factual Hallucination	✔	Automatic & Human	✗	✗
CO-STORM (Jiang et al., 2024)	Lack of Consistency	✔	Automatic & Human	✗	✔
CycleResearcher (Anonymous, 2024a)	Reward Hacking & Outdated	✗	Automatic & Human	✗	✗
OpenScholar (Asai et al., 2024)	Disorganized Logic & Overlength	✔	Automatic & Human	✗	✗
Agent Lab (Schmidgall et al., 2025)	Structure Rigidity	✗	Automatic & Human	✗	✗
(Ifargan et al., 2024)	from scratch	✗	Automatic	✔	✔
AI Scientist (Lu et al., 2024)	no control idea	✗	Automatic	✗	✗
XtraGPT	**Controllable Refinement** 😎	✔	Automatic & Human	✔	✔

Experiments demonstrate that XtraGPT delivers context-aware, high-quality revisions that strictly follow user instructions, with comparable results to GPT-4o-mini (OpenAI et al., 2024) but using only 7 billion parameters. Additionally, we found that LLMs struggle with paper scoring even with scaling, and it is hard to achieve a rating MAE below 1.5. Moreover, modifying six sections with XtraGPT can enhance the paper's rating according to the predictor.

Our philosophy is that when the core idea of paper is strong enough, we assist authors in producing smooth and polished writing, turning the writing process into a minimal overhead task.

2 Background and Motivation

2.1 Limitations of Current AI Paper Generation Methods

Why Can't Existing LLMs Excel in Paper Generation? Table 1 provides a comparative analysis of existing AI paper generators, which are designed to generate entire papers. These systems struggle to simultaneously ensure comprehensive retrieval, fine-grained control, and effective human-computer interaction. Additionally, they often exhibit various quality issues, making it challenging to achieve **Controllable AI Paper Refinement**.

Why do we need Section-Level Fine-Grained Control? The success of o1 (OpenAI, 2024) and r1 (DeepSeek-AI et al., 2025) models lies in their ability to explore problems from multiple perspectives with fine-grained reasoning.

Academic Papers are inherently complex and sparse, making them difficult for models and even human experts to learn and evaluate effectively. As demonstrated in our experiments in Section 5.2, even models with substantial capacity find it challenging to directly learn and comprehend entire papers. Fortunately, the success of o1(OpenAI, 2024) and r1 (DeepSeek-AI et al., 2025) models lies in their ability to explore problems from multiple perspectives with fine-grained reasoning. To address this, we target on the paper into 6 **sections** (title, abstract, introduction, background, evaluation, conclusion) and establish **fine-grained criteria** for selected content across six key paragraphs. This approach is akin to *Hercules* completing 12 meticulous tasks. However, a significant challenge remains: **the lack of labeled data** or paired examples showing pre- and post-improvement versions of papers, leaving us with only the final versions for evaluation.

What criteria influence the overall evaluation of a research paper? According to the review form provided in NeurIPS 2024, **full-paper level** evalaution of paper contains soundness, presentation and contribution, which is positively correlated with the acceptance rate. However, to effectively evaluate the improvements made to a paper, we need to move beyond **section-level** assessments.

Therefore, we collaborated with experts in the AI field to develop fine-grained principles which is specifically tailored for AI papers. The criteria are detailed in Figure 10, 11, 13, 14, 15, 12, and 16.

2.2 Motivation and Philosophy

The motivation of this paper is to assist researchers in improving the quality of their AI-generated academic writing while ensuring that the necessary academic standards and language precision are maintained. The goal is to address the issues highlighted in Table 1, where existing full-paper AI generators struggle with quality control and limitations in adaptability.

We argue that revising a paper is a meticulous process, akin to *the heroism of Hercules*, overcoming numerous obstacles and challenges. Paper writing should not be done without **proper quality control**, and that directly generating a full paper without refinement is not the best approach. We believe that when the core idea of a paper is solid, using the controllable refinement capabilities of XtraGPT can help authors quickly **revise the writing**, turning the rewriting process into a task that involves minimal effort. This allows authors to leverage AI's capabilities for rapid revisions while maintaining the integrity of their work.

3 Data Collection

As outlined in Section 2.1, a significant challenge in implementing HCI paper refinement is the lack of high-quality QA data. To address this, we introduce **XtraQA**, the first dataset designed to assist authors in improving their paragraphs. XtraQA comprises 140,800 QA pairs, with 133,800 pairs allocated for training.

We initially collected all 6,994 PDFs (after excluding 64 excessively long PDFs from a total of 7,042) in ICLR 2024 and converted them into parsable markdown format. For each article, we generated 20 criteria-based questions for user-selected paragraphs, resulting in 140,800 QA pairs. Subsequently, we employed GPT-4o-mini (only 1.7% hallucination rate from (Hong et al., 2024)) to generate improved versions of these paragraphs, denoted as $\hat{p}$. As analyzed in Table 9, human annotators confirmed that the dataset is sufficiently robust to compete with GPT-o1-mini.

To evaluate the paragraph improvement capabilities of LLMs, we randomly sampled 5% of the dataset (350 papers, comprising 7,000 QA pairs) to create the QA benchmark. We used length-controlled win rate (Dubois et al., 2024) to establish an LLM arena, with XtraGPT as the anchor, avoiding the widely criticized ROUGE and BLEU metrics for direct answer evaluation. In the QA benchmark, the distribution of QAs across six sections—title, abstract, introduction, background, evaluation, and conclusion—is 2:4:6:2:3:2, corresponding to 700, 1,400, 2,100, 700, 1,050, and 700 QAs, respectively. Throughout the data collection process, we maintained stringent quality control measures to ensure the reliability of the dataset.

3.1 Submission Data Analysis

We analyzed all ICLR 2024 submissions, finding that 64.71% received replies, with 82.4% of those reaching a final decision and a 36.3% acceptance rate among the filtered and parsed PDFs. The full-paper score distribution is shown in Figure 2, and paper length distribution is shown in Section C, with a maximum of around 16,384 tokens.

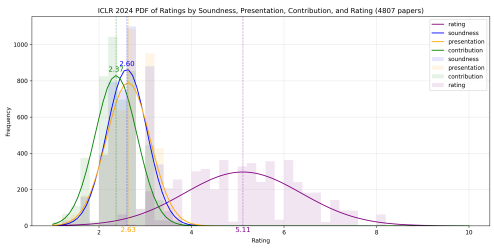


Figure 2: ICLR 2024 PDF ratings of full-paper criterias

3.2 XtraQA Data Generation

The XtraQA dataset was constructed using parsed text T from ICLR 2024 submissions. Queries q were generated based on predefined criteria c. Leveraging the full text T, the GPT-4o-mini model was employed to produce the revised paragraph $\hat{p}$.

The dataset for supervised fine-tuning (SFT) is defined as:

$$D_{SFT} = \{(q, T, p, \hat{p})\}$$

3.2.1 CONTROLLABILITY ASSURANCE OF $q, p, \hat{p}$

The queries q were guided by section-level improvement criteria (Table 2), ensuring the enhancement of selected paragraph quality, with detailed criteria illustrated in Figures 10 through 12. The improved paragraphs $\hat{p}$ were generated using a carefully designed prompt (6). The quality of both the supervised fine-tuning dataset D_{SFT} and the enhanced paragraphs $\hat{p}$ was rigorously validated by human annotators, as listed in Table 9 and detailed in Table 8.

Domain Style-Invariant Assumption To address whether varying writing styles and development speeds across different domains affect the overall evaluation of articles, we engaged three human evaluators from the fields of inference speedup, graph and FPGA. They used a specialized interface (Figure 17,18) to annotate the data on criteria definition 16 with different colors. Our findings suggest that our models do not need to be designed separately for different domains and perform consistently well across them.

Table 2: Evaluation Criteria for Title, Abstract, Introduction, Background, Evaluation, and Conclusion

Aspect	Comments
Title	Consistency and Alignment of Title with Content Conciseness and Clarity of Title
Abstract	Clarity and Impact of the Conclusion Motivation and Purpose in the Abstract Explanation of Existing Solutions and Research Gap Clarity and Adequacy of Proposed Solutions
Introduction	Strength and Clarity of Motivation in the Introduction Review of Existing Approaches in Introduction Audience Alignment and Appropriateness Clarity and Visibility of Contributions Clarity and Specificity of Problem Definition Integration of State-of-the-Art in Problem Framing
Background	Contextual Relevance and Clarity of Background Coverage of Key Preliminary Concepts Clarity and Consistency of Terminology
Evaluation	Experimental Setup Clarity and Reproducibility Depth and Clarity of Figures and Tables Analysis Experimental Support for Main Innovations
Conclusion	Broader Impact and Future Directions Clarity and Impact of Key Innovations and Findings

Table 3: Human evaluation on improvement acceptance rates before and after paragraph. We asked 3 human evaluators based on 5, 3, 5 papers, with about 100, 60, 100 questions scored from 1-5. The **Aggregated** column averages the results of the 3 human evaluators.

QA Controllability Assurance	**Judge 1**	**Judge 2**	**Judge 3**	**Aggregated**
GPT-4o-Mini				
-Instruction Following	76.6	74.3	77.4	76.1
-Criteria Following	73.6	74.7	76.6	74.9
-In-Context Ability	59.4	66.3	72.8	66.2
-Agree revision?	49.2	61.7	71.6	60.8
—				
GPT-o1-mini				
-Instruction Following	76.4	79.0	74.8	76.7
-Criteria Following	74.0	77.0	74.2	75.1
-In-Context Ability	62.0	68.0	73.6	67.9
-Agree revision?	56.0	66.3	72.8	65.0

3.2.2 QUALITY ASSURANCE OF T

We analyzed 6,994 after-filtered PDFs from ICLR 2024 using the deep learning-based academic paper parser nougat (Blecher et al., 2023), which converts PDFs into tokenizable markdown text T. To ensure the quality of T, we chose nougat, as its performance outperforms rule-based tools like pymupdf (PyMuPDF, 2024), and Marker (Paruchuri, 2024) according to (Li et al., 2024d), which were used in the ICLR analyses by Lu et al. (2024), Anonymous (2024b), and Anonymous (2024a) (using MagicDoc (Magic-Doc, 2024)). Afterward, we will perform post-processing, keeping only the content before the service and removing the acknowledge information, so that T can remain length within 16384.

4 XtraGPT

4.1 EXPERIMENT SETTINGS

We post train D_{SFT} on Qwen-2.5-1.8B-Instruct and Qwen-2.5-7B-Instruct to get XtraGPT using the LLaMA-Factory (Zheng et al., 2024) framework on a setup consisting of 4 NVIDIA H100 GPUs, with 80 GB of memory and inference on XtraQABench using the vLLM (Kwon et al., 2023) framework on a setup consisting of 1 NVIDIA A100 GPUs, with 80 GB of memory. The computing environment was configured with CUDA 12.2 and cuDNN 9.1 for optimized deep learning performance. Detailed parameters are listed in Table 10.

4.2 CONTROLLABLE INSTRUCTION POST TRAINING

We train on the XtraQA training set $D_{SFT} = \{(q, T, p, \hat{p})\}$, which consists of 133,800 QA pairs. This fine-tuning process enhances the base model's **controllability** to follow instructions, ensure criteria compliance, and maintain contextual understanding.

4.3 HOW TO EVALUATE THE MODEL'S QUALITY ON CONTROLLABLE PAPER REFINEMENT?

Previous papers including (Anonymous, 2024b) have used simple metrics like ROUGE to evaluate the full-text generation capabilities in the AI research process. However, such metrics only ensure adherence to raw text-level answers and fail to provide controllability over specific capabilities. To address this, we adopt the concept of Length Controlled Win Rate (Dubois et al., 2024) against XtraGPT as anchor and utilize alpaca_eval_gpt4_turbo_fn as a judge (Zheng et al., 2023), which reaches 68.1% human agreement according to (Tatsu-lab, 2023), with a slight modification focused on evaluating the controllability of outputs using the instruction 8, 7. Length Controlled Win Rate calculates how many times XtraGPT (m) can win against baseline models (M).

Why LLM as a controllable paper revision judger? Previous work demonstrates high alignment with automated reviewers (Lu et al., 2024), while (Schmidgall et al., 2025) say still needs both.

In this study, we chose GPT-4o-mini to generate data instead of Openai o1 or Deepseek R1 (DeepSeek-AI et al., 2025) because our task does not rely on complex reasoning or deep thinking, planning but rather focuses on the ability to handle long-context understanding. GPT-4o-mini excels in this area, effectively understanding and generating coherent paragraphs. For sequence-level tasks like paragraph rewriting, the evaluation criteria are often subjective. Using LLM as an evaluator of the generated content provides consistent quality feedback, a method proven effective in the development of InstructGPT and ChatGPT. Therefore, LLM as a judge is well-suited for quality evaluation in our scenario, avoiding the high cost of manual annotation while providing efficient feedback.

The reliability of Instruction and the bias of LLM paper revision We identified several issues with LLM-based paper revisions: overuse of certain GPT-style words like "comprehensive" to exaggerate the paper's impact, making superficial changes, and a tendency to generate excessively long revision segments. To address these issues, we meticulously designed 6 to avoid such problems during generation, along with 8 and 7 to emphasize these concerns during evaluation.

While win rate effectively reflects the relative performance of our model compared to others in paragraph rewriting tasks, it becomes unreliable due to length bias, as shown in Table 11. This issue has also been noted in other studies. To mitigate this, we employ length-controlled win rates (Dubois et al., 2024), which adjust for the bias introduced by varying lengths of generated content, ensuring a fairer evaluation, supported by methods from AlpacaEval (Tatsu-lab, 2023).

Definition of LC win rate Let b represent the baseline model and xtra represent our model. Let θ denote the prediction value. The length-controlled win rate is defined as:

$$q_{\theta,\phi,\psi}(y = m \mid z_m, z_M, x) := \text{logistic}\left(\text{model} + \text{length}\right)$$

where the model term is $\theta_m - \theta_M$ and the length term is $\phi_{M,b} \cdot \tanh\left(\frac{\text{len}(z_m) - \text{len}(z_M)}{\text{std}(\text{len}(z_m) - \text{len}(z_M))}\right)$

We omit the instruction difficulty term as we focus solely on the improvement effect. The length-controlled win rate is then calculated as:

$$\text{winrate}^{LC}(m, M) = 100 \cdot \mathbb{E}_x \left[q_{\theta,\phi,\psi}(y = m \mid z_m, z_M, x)\right]$$

When lengths are inconsistent, the length term adjusts the final estimated value to account for this bias. This approach ensures a fair comparison by controlling for length variations.

Table 4: Length-controlled (LC) win rates of various models against XtraGPT (*anchor*) across different evaluation categories. Models are ranked in descending order based on their weighted LC win rates. The judge is modified alpaca_eval_gpt4_turbo_fn (Prompt 7).

Models	Title (2)	Abstract (4)	Introduction (6)	Background (3)	Evaluation (3)	Conclusion (2)	Overall↑
Qwen2-72B-Instruct	35.93	63.43	67.63	71.18	77.26	64.77	65.31
Deepseek-v3-671B	52.36	57.33	62.08	56.26	73.23	50.00	59.75
GPT-4o-Mini	50.97	50.00	52.29	58.49	51.35	45.96	51.86
XtraGPT (*anchor*↑)							
Qwen-2.5-7B-Instruct	50.41	47.11	43.71	46.56	46.05	49.79	46.44
Qwen-QWQ-32B-Preview	37.83	34.57	32.13	40.58	30.04	32.91	34.22
Llama-3.1-8B-Instruct	34.78	30.64	35.31	41.60	40.29	18.36	33.51
Qwen2.5-1.5B-Instruct	36.07	30.87	25.80	21.34	24.18	24.27	26.80
GPT-3.5-Turbo	25.73	23.99	21.52	23.16	30.97	17.39	24.24
Llama-3.2-3B-Instruct	19.93	6.45	9.35	3.80	8.26	4.64	8.73

5 Analasis

5.1 Q1: How about the win rate of baselines against XtraGPT?

Based on the data in Table 4, the XtraGPT model demonstrates superior performance compared to several baseline models, especially in categories like Introduction, Abstract, and Background, surpassing many open-source 7B models.

While Qwen2-72B-Instruct leads in some categories, such as Introduction and Evaluation, XtraGPT remains highly competitive across all dimensions, showing reliability and strength in various tasks. Compared to Deepseek-v3-671B (59.75%) and GPT-4o-Mini (51.86%), XtraGPT's overall win rate of 65.31% surpasses both, highlighting its advantage in comprehensive performance. Moreover, XtraGPT significantly outperforms smaller models like Qwen-2.5-7B-Instruct (46.44%) and Llama-3.1-8B-Instruct (33.51%), demonstrating its consistent strength across multiple evaluation criteria.

In conclusion, XtraGPT not only leads among open-source 7B models but also shows strong competitive capabilities against larger models like GPT-4o-Mini in paper revision tasks.

The table 5 shows the quality ratings of XtraGPT by humans as judges, and combined with Table 4's LLM as a judge, it highlights XtraGPT's outstanding performance.

Table 5: Expert evaluation of XtraGPT results.

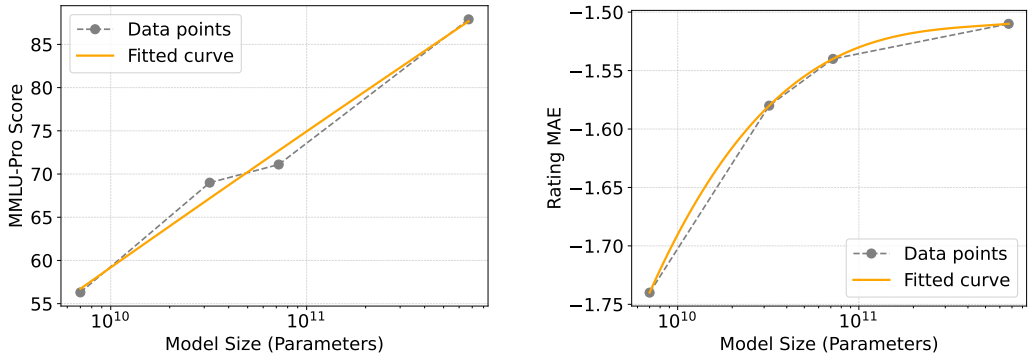
XtraGPT	Judge 1	Judge 2	Judge 3	Aggregated
Instruction Following	65.0	79.7	81.8	75.5
Criteria Following	66.8	74.0	81.8	74.2
In-Context Ability	55.8	68.0	81.2	68.3
Agree revision?	49.2	64.5	80.2	64.6

5.2 Q2: Can LLMs Score Full Papers? Scaling Laws of LLMs as Review Judges

In the context of academic paper evaluation, the only available human expert review labels at full-paper granularity come from OpenReview. Unfortunately, due to the high cost and inherent biases of human reviews—evidenced by a standard deviation of 1.26 in reviewer ratings for each paper in 2024— it is impractical to invite expert reviewers for every benchmarking scenario that requires full-paper scoring.

To address this limitation, several studies (Lu et al., 2024; Anonymous, 2024a;b) have explored the use of LLMs for predicting full-paper scores. A key question remains: are LLMs suited to be a reliable reviewer? To investigate this, we follow the approach of Lu et al. (2024), applying NeurIPS review guidelines and few-shot examples to assess our test set.

As shown in Figure 3, scaling up model parameters is significantly more challenging for paper scoring compared to MMLU-Pro. We can infer that the bottleneck in the paper scoring task **cannot be simply**



(a) MMLU-Pro scores on multi-task understanding across different # of model parameters

(b) MAE scores on paper scoring across different # of model parameters

Figure 3: Scaling trends of Qwen-2.5-7B/32B/72B/Max-Instruct performance. (a) MMLU-Pro scores stably improve with model size. Scaling is effective on multi-task understanding. (b) In the paper scoring task, the rating MAE struggles to go below 1.5. As the model size increases, the reduction in MAE becomes smaller, indicating that scaling offers limited performance improvement.

solved by scaling the model. LLMs struggle with paper scoring, which is already quite challenging even for human experts (1.16 rating MAE per paper according to Anonymous (2024a)).

Table 6: Different LLMs as scorer on the evaluation of 404 ICLR2024 papers. MAE measures the Mean Absolute Error of the avg rating of human and llm reviewers.

Criteria	Soundness			Presentation			Contribution			Rating ↑				Accept Rate
	Min.	Max.	Avg.	Min.	Max.	Avg.	Min.	Max.	Avg.	Min.	Max.	Avg.	MAE ↓	Acc.
Human Reviewer on ICLR 2024 original papers														
Human Reviewer	1.00	4.00	2.60±0.43	1.00	4.00	2.63±0.48	1.00	4.00	2.37±0.45	1.00	9.00	5.11±1.26	-	36.3%
Human R. - Rejected paper	1.00	3.75	2.46±0.40	1.00	4.00	2.50±0.46	1.00	3.50	2.20±0.39	1.00	7.50	4.53±0.97	-	-
Deepseek-V3 Reviewer as Scorer on ICLR 2024 original papers														
Deepseek-V3-64k	2.00	6.00	3.38±0.70	2.00	6.00	3.42±0.72	2.00	6.00	3.71±0.62	4.00	8.00	6.49±0.95	1.45	75.0%
Qwen (Above 7B) as Scorer on ICLR 2024 original papers														
Qwen-2.5-7B-Instruct	2.00	6.00	3.00±0.37	2.00	6.00	2.78±0.59	2.00	6.00	3.03±0.36	6.00	7.00	6.92±0.27	1.74	95.2%
Qwen-2.5-32B-Instruct	2.00	4.00	2.90±0.33	2.00	4.00	2.69±0.49	2.00	4.00	2.97±0.34	4.00	8.00	6.73±0.63	1.58	81.9%
Qwen-2.5-72B-Instruct	2.00	6.00	3.00±0.32	2.00	6.00	2.66±0.58	2.00	6.00	3.28±0.53	3.00	8.00	6.67±0.73	1.54	78.4%
Qwen-2.5-Max-LongContext	2.00	4.00	3.03±0.29	2.00	4.00	2.70±0.59	2.00	4.00	3.09±0.31	3.00	8.00	6.68±0.73	1.51	74.3%
GPT-4o as Scorer on ICLR 2024 original papers														
GPT-4o	1.00	4.00	3.05±0.53	2.00	4.00	3.13±0.61	2.00	4.00	3.43±0.54	3.00	8.00	6.79±0.85	1.60	88.0%

We list different LLMs as paper scorer in Table 6. We can derive that LLMs as reviewers tend to give higher accept rate than human. The rating MAE of Deepseek-V3 is competitive against other models, which reaches near the 1.16 human bias of a specific data (Anonymous (2024a)). Based on these findings, and thanks to the success of DeepSeek (Liu et al., 2024a; DeepSeek-AI et al., 2025), we adopt DeepSeek-V3 (Liu et al., 2024a) as our scoring model to evaluate the quality of our own models.

5.3 Q3: Does XtraLLM revision impact the full paper?

To evaluate the quality of papers at the full paper level, we randomly sampled a passage from each section (6 passages total) and brought it back for evaluation. Our findings show that even modifying just a single passage per section leads to an increase in the overall score. Additionally, the acceptance rate after revision also improved. This highlights the effectiveness of XtraGPT in enhancing paper quality.

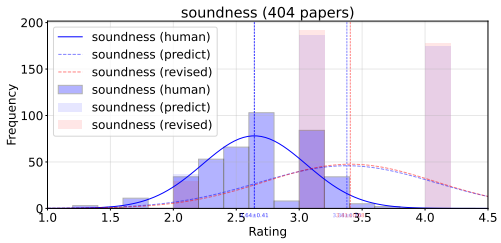
We test on 404 paper which have rating in the QA benchmark. From the data presented in Table 7, it can be observed that after replacement, the AcceptRate improved from 75.0% to 75.8% (same LLM Deepseek-V3 as reviewer). Additionally, the average scores for soundness, presentation, and contribution all saw increases of 0.03, 0.02, and 0.02 respectively. The overall rating improved by

0.02. These results demonstrate that modifying just six sections of the paper can significantly enhance the quality of the full paper, showcasing the effectiveness of XtraGPT in improving the overall paper.

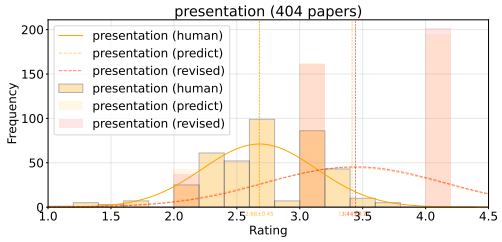
According to the overrating bias from LLM scorer in Section 5.2, we calculate the bias from Deepseek-V3 against human by the sum of the differences in ratings (without absolute values). The average bias of Deepseek-V3 is 1.03 across all 404 papers. After minusing the 1.03 bias caused by Deepseek-V3 as the scorer, the revision from XtraGPT against origin paper is 0.03 (before minus 1.05). It means after revision, the overall rating improves 0.02. Detailed results of different paper-level criteria are shown in Figure 4.

Table 7: Evaluation of 404 XtraGPT improved papers. We replace the revised paragraph back to the paper to re-evaluate the paper score by paper score classifier. The predictor is DeepSeek-V3.

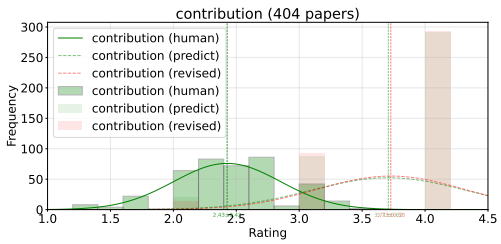
Criteria	Soundness			Presentation			Contribution			Rating ↑				Accept Rate
	Min.	Max.	Avg.	Min.	Max.	Avg.	Min.	Max.	Avg.	Min.	Max.	Avg.	MAE ↓	Acc. R.↑
Human Reviewer on ICLR 2024 original papers														
Human Reviewer	1.00	4.00	2.60±0.43	1.00	4.00	2.63±0.48	1.00	4.00	2.37±0.45	1.00	9.00	5.11±1.26	-	36.3%
Human R. - Rejected paper	1.00	3.75	2.46±0.40	1.00	4.00	2.50±0.46	1.00	3.50	2.20±0.39	1.00	7.50	4.53±0.97	-	-
Deepseek-V3 Reviewer as Scorer on ICLR 2024 original papers														
Deepseek-V3-64k	2.00	6.00	3.38±0.70	2.00	6.00	3.42±0.72	2.00	6.00	3.71±0.62	4.00	8.00	6.49±0.95	**1.45**	75.0%
Deepseek-V3 Reviewer as Scorer on XtraGPT improved papers														
XtraGPT (ours)	2.00	6.00	**3.41±0.68**	2.00	6.00	**3.44±0.71**	2.00	6.00	**3.73±0.58**	4.00	8.00	6.51±0.91	1.47	**75.8%**



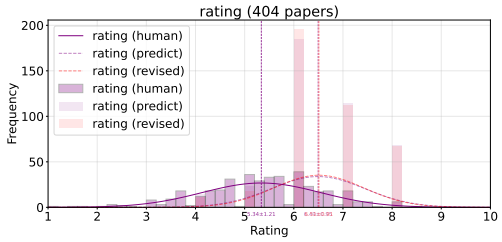
(a) Soundness score predict



(b) Presentation score predict



(c) Contribution score predict



(d) Rating predict

Figure 4: Comparison of human-assigned, predicted, and revised ratings for four evaluation criteria across 404 papers. (a) Soundness, (b) Presentation, (c) Contribution, and (d) Overall Rating. Each subfigure shows the distribution of ratings along with fitted density curves

6 Conclusion

In this work, we introduce XtraGPT, a series of LLM designed to help researchers refine scientific papers through fine-grained, controllable revisions. Leveraging a dataset of 7,040 ICLR 2024 papers and over 140,000 question-answer pairs, XtraGPT provides context-aware, instruction-driven revisions that improve clarity, coherence, and adherence to academic standards while preserving the integrity of the original work. Our experiments show that XtraGPT-7B outperforms similarly sized models and competes with larger models like GPT-4o-mini in delivering high-quality refinements. We also find that scaling model parameters beyond 100 billion is necessary for LLMs to achieve human-level paper scoring capabilities.

XtraGPT's ability to enhance sections such as the introduction, abstract, and conclusion positively impacts paper quality and acceptance rates. By enabling human-AI collaboration, XtraGPT allows researchers to maintain creative control while reducing the mechanical burden of writing, ensuring high academic standards without deviating from core ideas. We believe XtraGPT offers a significant step forward, providing researchers with a practical solution to produce high-quality papers with minimal effort.

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A Related Work

LLMs Assist Academic Writing Research on LLMs for academic writing falls into four primary categories. First, *automated paper generation* attempts to produce complete papers but often lacks user control and academic rigor (Shao et al., 2024; Jiang et al., 2024; Anonymous, 2024a; Asai et al., 2024; Schmidgall et al., 2025). Second, *research ideation* employs LLMs to propose novel ideas and methodologies, though concerns regarding authorship and originality persist (Baek et al., 2024; Ghafarollahi & Buehler, 2024; Li et al., 2024a; Si et al., 2024). Third, thanks to the success of retrieval by instruction (Sun et al., 2024), *automated reviewing and research question answering* assist in literature searches and manuscript evaluations but do not directly refine writing quality (D'Arcy et al., 2024; Liang et al., 2024; Lu et al., 2024; Anonymous, 2024b; Asai et al., 2024; Chen et al., 2024b; Lála et al., 2023; Song et al., 2024; Lin et al., 2024). Lastly, *LLM-assisted writing tools* enhance grammar and style and Shi et al. (2023) improves a small paragraph of paper, they lack deep contextual awareness necessary for high-quality academic discourse (CoWriter, 2025; van Zeeland, 2023).

LLMs Assist Research Beyond writing, LLMs are increasingly utilized in autonomous research. (Swanson et al., 2024) introduced LLM agents functioning as research assistants, integrating human feedback into scientific workflows. ChemCrow (M. Bran et al., 2024) and Coscientist (Boiko et al., 2023) highlight LLM-led ideation and experimentation in chemistry, while ResearchAgent (Baek et al., 2024) automates research generation, iterative refinement, and review. AI Scientist (Lu et al., 2024) extends automation to coding, experimentation, and manuscript review. Despite these advancements, studies caution that LLMs require human oversight to ensure reproducibility and scientific rigor (Si et al., 2024).

Gaps and Contributions LLMs also contribute to research tasks such as code generation (Chen et al., 2021; Nijkamp et al., 2022), literature search (Ajith et al., 2024; Kang & Xiong, 2024; Press et al., 2024; Li et al., 2024b), and automated paper reviewing (D'Arcy et al., 2024; Liang et al., 2024; Lu et al., 2024; Weng et al., 2024). While they support ideation (Si et al., 2024), concerns about reduced creativity and homogenization persist (Chakrabarty et al., 2024; Anderson et al., 2024). Hybrid human-LLM approaches are seen as the most effective way to enhance research workflows (Ashkinaze et al., 2024; Liu et al., 2024b; Padmakumar & He, 2024).

Recently, the controllable generation of LLMs have been emphasized (Ge et al., 2025). While much work has focused on using LLMs for idea generation, review, and automation, little research directly addresses refining research papers to enhance coherence, clarity, and adherence to academic standards. Our work bridges this gap by leveraging LLMs specifically for structured refinement, allowing researchers to focus on deeper reasoning tasks while ensuring scholarly rigor.

LLM simulation Researchers have increasingly utilized Large LLMs to construct simulations, treating LLM agents as proxies for humans to perform actions and interactions (Park et al., 2023; Lin et al., 2023; Kong et al., 2024; Wang et al., 2024). These simulations have shown promise in diverse fields such as society, economics, policy, and psychology (Park et al., 2023; Li et al., 2024c; Chen et al., 2024a), while also serving as data generators and evaluators for LLM training (Tang et al., 2024; Zhang et al., 2024). However, LLMs face significant limitations in simulation tasks. Studies (Ai et al., 2024; Petrov et al., 2024; Hu & Collier, 2024; Lee et al., 2024) highlight their inability to maintain contextual consistency and produce fine-grained outputs. For example, Lee et al. (2024) found that LLMs exhibit consistent values and preferences even when role-playing diverse personas, underscoring their lack of adaptability and nuanced understanding.

B Prompts

Figure 5 shows the prompt for QA.

C ICLR 2024 markdown Token Distribution

ICLR 2024 markdown Token Distribution showed in Figure 9.

The Prompt for QA

Act as an expert model for improving articles **PAPER_CONTENT**.
<SELECTED_CONTENT>
User Selected
</SELECTED_CONTENT>
<QUESTION>
<User Question>
</QUESTION>

Figure 5: Prompts for QA

D HUMAN LABEL DETAILS

QA Controllability Assurance	**Judge 1**	**Judge 2**	**Judge 3**
GPT-4o-Mini -Instruction Following	(78+77+72+78+78)/500	(76+68+79)/300	(75+81+80+78+73)/500
-Criteria Following	(79+74+63+77+75)/500	(77+68+79)/300	(76+81+77+74+75)/500
-In-Context Ability	(73+53+48+62+61)/500	(67+57+75)/300	(69+76+74+73+72)/500
-Agree revision?	(48+48+44+53+53)/500	(65+56+64)/300	(67+74+74+72+71)/500
—-			
GPT-o1-mini -Instruction Following	(79+71+76+76+80)/500	(79+81+77)/300	(75+80+78+77+64)/500
-Criteria Following	(72+70+74+74+80)/500	(79+77+75)/300	(74+80+78+76+63)/500
-In-Context Ability	(74+53+58+65+60)/500	(68+68+68)/300	(73+75+81+75+64)/500
-Agree revision?	(58+50+53+59+60)/500	(66+66+67)/300	(72+76+78+76+62)/500

Table 8: Human evaluation on improvement acceptance rates before and after paragraph. we ask 3 human evaluators based on 5,3,5 paper, about 100,60,100 questions in score 1-5. The **Aggregated** column aggregates the results of 3 human evaluators.

XtraGPT	**Judge 1**	**Judge 2**	**Judge 3**
Instruction Following	(62+61+72+76+74)/500	(80+80+79)/300	(86+80+83+82+78)/500
Criteria Following	(60+60+69+72+73)/500	(74+74)/300	(82+82+82+81+82)/500
In-Context Ability	(58+51+48+61+61)500	(67+69)/300	(85+80+82+79+80)/500
Agree revision?	(50+45+44+55+52)/500	(65+64)/300	(83+79+82+80+77)/500

Table 9: our model human evaluation.

E SECTION-LEVEL CRITERIA DETAILS

Section-level criterias are detailed in Table 10,11,13,14,15,12.

The Prompt for Generating QA pairs

You are an advanced language model designed to assist users in improving their articles. Users will provide an article in LaTeX or Markdown format and specify a **section** along with **criteria** for improvement. Your task is to identify a specific selected content from the provided section, align it with the given criteria, and offer actionable feedback to improve the content.
Instructions:
1. **Role 1**: We have a paper improvement task with a specific criteria 'criteria['prompt']'. Now play a role as an author of the provided paper content. Select a specific content from the section 'section' (or equivalent), and ask a chatbot assistant to help you improve that selected content.
- **The selected paper content must be a worth-improving paragraph(s)** that might not achieve the standards of the criteria 'criteria['prompt']', and that content should come from the section 'section'. The selected content will be labeled as **BEFORE IMPROVEMENT**.
- Provide a concise, conversational improvement-related question labeled as **QUESTIONS**. These questions should not explicitly tell what rules or standards to follow or what the specific goal should be. Instead, offer a high-level instruction that may hint at the criteria without stating them directly. The aim is to allow for creativity and subtle alignment with the criteria.
- Keep the question short and conversational.
2. **Role 2**: Act as an expert model for improving articles.
The revised version of the selected content should be labeled as AFTER IMPROVEMENT and specifically address the QUESTIONS on BEFORE IMPROVEMENT above. Avoid adding unnecessary length, unrelated details, overclaims, or vague statements. Focus on clear, concise, and evidence-based improvements that align with the overall context of the paper.
Provide a detailed explanation of the changes made, labeled as EXPLANATION, with clear references to the paper's content. Ensure the explanation demonstrates how the revisions align with the context and criteria of the paper.
— PAPER CONTEXT STARTS
paper_latex
— PAPER CONTEXT ENDS
Response Format (must be strictly followed):
— BEFORE IMPROVEMENT STARTS
<Selected content>
— BEFORE IMPROVEMENT ENDS
— QUESTIONS START
<Concise, improvement-related question based on the criteria 'criteria['prompt']'>
— QUESTIONS END
— AFTER IMPROVEMENT STARTS
<Revised version of the selected content to answer the **Questions** above> — AFTER IMPROVEMENT ENDS
— EXPLANATION STARTS
<An explanation of the changes made, showing how they align with the context of the article and address the criteria. Include references from the paper context where relevant.>
— EXPLANATION ENDS

Figure 6: Prompts for Generate XtraQA

The Prompt for Judging

You are a highly efficient assistant, who evaluates and rank large language models (LLMs) based on the quality of their responses to given prompts. This process will create a leaderboard reflecting the most accurate and human-preferred answers.
I require a leaderboard for various large language models. I'll provide you with prompts given to these models and their corresponding responses. Your task is to assess these responses, ranking the models in order of preference from a human perspective. Once ranked, please output the results in a structured JSON format for the make_partial_leaderboard function.
Prompt

```
{
    "instruction": "{instruction}",
}
```

Model Outputs
Here are the unordered outputs from the models. Each output is associated with a specific model, identified by a unique model identifier.

```
{
    {
        "model": "m",
        "output": "{output\_1}"
    },
    {
        "model": "M",
        "output": "{output\_2}"
    }
}
```

Task
Evaluate based on the quality and relevance to the instructions. The following is the definition of the quality on the section `<section>`: `<criteria["prompt"]>`. If the model's output refers to information beyond `<Selected content>`, it receives a slightly higher score.

Figure 7: Prompts for Judging (modified from alpaca_eval_gpt4_turbo_fn).

F HYPERPARAMS

Hyperparameter	**value**
Batch Size	{1,2}
Cut-off Len	16384
max_new_tokens	512
Epoch	{10,20}
Learning Rate	{1e-5,2e-5}
Details	
Weight Update Per	{4 Step, 6 Step}

Table 10: Hyperparameters

G WINRATE

Table 11 shows the win rate without length control, which is unreasonable compared to Table 4.

The Prompt for ranking

Human: I want you to create a leaderboard of different large-language models. To do so, I will give you the instructions (prompts) given to the models, and the responses of two models. Please rank the models based on which responses would be preferred by humans. All inputs and outputs should be Python dictionaries.
Here is the prompt:

```
{
    "instruction": "{instruction}",
}
```

Here are the outputs of the models:

```
{
    "model": "model_1",
    "answer": "{output_1}"
},
{
    "model": "model_2",
    "answer": "{output_2}"
}
```

Now please rank the models by the quality of their answers, so that the model with rank 1 has the best output. Then return a list of the model names and ranks, i.e., produce the following output:

```
[
    {'model': \texttt{<model-name>},
    'rank': \texttt{<model-rank>}},
    {'model': \texttt{<model-name>},
    'rank': \texttt{<model-rank>}}
]
```

Your response must be a valid Python dictionary and should contain nothing else because we will directly execute it in Python. Please provide the ranking that the majority of humans would give.

Figure 8: Prompts for Scoring.

Models	**Title**	**Abstract**	**Introduction**	**Background**	**Evaluation**	**Conclusion**	**Average↑**
qwen2-72B-Instruct	53.57	70.93	77.52	86.76	91.90	73.71	75.73
GPT-4o-Mini	65.57	59.71	70.05	67.81	70.86	62.14	66.02
Qwen-QWQ-32B-Preview	62.97	66.42	61.33	73.24	72.48	74.29	69.88
Deepseek-V3-671B Liu et al. (2024a)	63.79	59.29	66.19	61.24	88.95	58.57	66.33
Qwen-2.5-7B-Instruct	60.79	70.93	60.52	56.48	74.48	70.43	65.60
PaperCursor (base Qwen-2.5-7b-instruct) (*anchor*↑)							
Llama-3.1-8B-Instruct	47.41	39.64	41.24	55.24	55.71	30.29	44.92
Qwen2.5-1.5B-Instruct	34.36	32.39	26.14	21.24	26.48	31.29	28.65
GPT-3.5-Turbo	28.57	20.79	19.38	20.95	23.05	11.43	20.70
Llama-3.2-3B-Instruct	27.43	9.29	10.90	9.71	14.67	6.43	13.07

Table 11: Win rates of various models against XtraGPT (*anchor*) across different evaluation categories. Models are ranked in descending order based on their averaged win rates.

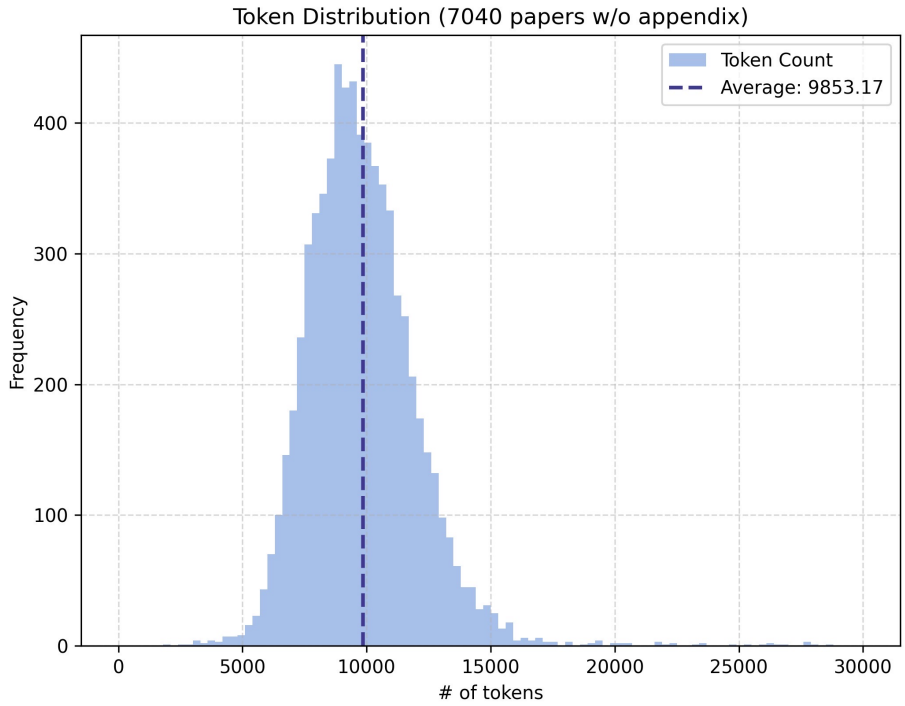

Figure 9: ICLR 2024 Paper Token Distribution (without Appendix)

Criteria Details of Section Title

1. Consistency and Alignment of Title with Paper's Content:
Evaluate the degree to which the paper's title accurately captures its principal topics, arguments, or findings. Does the title reflect the scope and focus of the paper, and is it consistent with the main concepts and keywords presented in the abstract and introduction? Identify any discrepancies or misalignment between the title and the content.

2. Conciseness and Clarity of Title:
Evaluate the paper's title for redundancy. Are there repeated words or concepts that could be removed without changing the core meaning? Does the final title remain succinct, clear, and accurately convey the paper's main focus or contribution?

Figure 10: Criteria Details of Section Title

H Annotators for Controllable Quality Assurance

I Case Study

We chose HARL Zhang et al. (2023) in Figure 19 as a case study to demonstrate the application of XtraGPT in human-AI collaboration. XtraGPT helps the author of MegaAgent refine the paper in a controllable manner.

Criteria Details of Section Abstract

1. Clarity and Impact of the Conclusion:
Evaluate the clarity and impact of the conclusion in the abstract. Does it clearly summarize the research steps, highlight key outcomes, and explain the significance of these outcomes for the field of computer science? Are the primary technical advancements and their contributions presented in a concise and unambiguous manner?

2. Motivation and Purpose in the Abstract:
Evaluate how well the abstract communicates the research's motivation. Does it clearly articulate the broader issue, concept, or problem in Computer Science that the work addresses? Does it explicitly state the specific research problem being solved and why it is important?

3. Explanation of Existing Solutions and Research Gap:
Assess how well the abstract explains the shortcomings of current solutions and highlights the corresponding research gap. Does it clearly articulate why existing methods are insufficient and how the proposed approach addresses these limitations? Is the explanation comprehensible to a wide audience, from domain experts to non-specialists?

4. Clarity and Adequacy of Proposed Solutions:
Assess how effectively the abstract communicates the proposed solutions. Does it clearly identify the research gap or problem being addressed, and explain how the proposed solution tackles this gap? Does it highlight the novelty or contribution of the solution, demonstrating its relevance or improvement over existing work? Rate the clarity, completeness, and significance of the explanation provided in the abstract.

Figure 11: Criteria Details of Section Abstract

Criteria Details of Section Conclusion

1. Broader Impact and Future Directions:
Assess the thoroughness of the paper's conclusion or discussion sections in addressing the broader impact of the research. Does the paper provide specific and clear avenues for future work?

2. Clarity and Impact of Key Innovations and Findings:
Evaluate whether the conclusion effectively highlights the paper's key innovations.

Figure 12: Criteria Details of Section Conclusion

J Baseline Model Details

K Controllability Annotation Criterias and Interface

To ensure our data and model quality, We invited three AI experts specializing in inference speedup, graph neural networks (GNN), and Field Programmable Gate Arrays (FPGA) to annotate 5, 3, and 5 papers, respectively. Each paper includes 20 question-answer pairs per model, focusing on section-level improvements. These pairs are distributed across different sections of the paper as follows: 2 for the title, 4 for the abstract, 6 for the introduction, 3 for the background, 3 for the evaluation, and 2 for the conclusion. The controllable criteria used for evaluation are presented in Figure 16. The annotators' operating interface and the interface of XtraGPT are listed in Figure 17,18.

Criteria Details of Section Introduction

1. Strength and Clarity of Motivation in the Introduction:
Evaluate whether the motivation in the Introduction is specific and convincing. Does the paper avoid over-generalization and clearly articulate the significance of the issue? Are concrete examples, statistics, or contextual details used to establish why the problem matters?

2. Review of Existing Approaches in Introduction:
Assess the thoroughness and clarity of the literature review within the introduction. Does the paper cite and critique relevant prior works, highlighting both their methodologies and limitations? Does the introduction establish how the proposed work builds upon or differentiates itself from existing research, and is there sufficient context provided to demonstrate the significance of the current study? Are any quantitative or qualitative comparisons made where appropriate?

3. Audience Alignment and Appropriateness:
Evaluate whether the introduction is effectively tailored to its target audience. Is the complexity, depth, and choice of terminology suitable for the presumed background knowledge of the readership? Does the introduction provide sufficient context without oversimplifying or overwhelming the intended audience?

4. Clarity and Visibility of Contributions:
Assess the clarity and visibility of the paper's contributions. Are the core contributions explicitly stated in a dedicated paragraph or section toward the end of the introduction? Are they understandable to a broad scientific audience, presented succinctly, and positioned logically following the problem statement and background information?

5. Clarity and Specificity of Problem Definition:
Evaluate the paper's problem definition in terms of four key elements: current situation, ideal situation, the gap between them, and how the research aims to address this gap. Are these components clearly stated, distinct, and directly tied to the research objectives? Does the definition provide sufficient clarity and focus for the research?

6. Integration of State-of-the-Art in Problem Framing:
Evaluate how effectively the introduction incorporates the State-of-the-Art (SOTA) to frame the research problem. Does it include explicit references to key works, methodologies, or findings that highlight relevant gaps or limitations in the field? Is there a clear logical link between the SOTA discussion and the stated research objectives, demonstrating how the proposed work builds upon or extends existing research?

Figure 13: Criteria Details of Section Introduction

Criteria Details of Section Background

1. Contextual Relevance and Clarity of Background:
Assess how effectively the background section establishes context for the research. Does it provide a clear overview of the broader field in computer science, then narrow down to the specific problem? Does the paper avoid making unwarranted assumptions about the reader's prior knowledge? Finally, does it clarify why addressing the problem is important to the field?

2. Coverage of Key Preliminary Concepts:
Evaluate the thoroughness and clarity of the paper's background or preliminary section. Does it introduce and define all the critical concepts, algorithms, or theorems necessary to understand the technical contributions? Are these concepts clearly explained, logically organized, and accessible to readers who are not experts in the field? Does the paper use consistent terminology and adequately explain symbols, abbreviations, or specialized terms before their first usage?

3. Clarity and Consistency of Terminology:
Assess the clarity and consistency of the key terms introduced in the background section. Are all critical terminologies defined at their first occurrence and used consistently throughout the paper? Does the paper avoid undefined shifts or redefinitions of terms, and does it align terminology with standard conventions in the field?

Figure 14: Criteria Details of Section Background

Criteria Details of Section Evaluation

1. Experimental Setup Clarity and Reproducibility:
Evaluate how clearly and thoroughly the experimental setup is described. Does the paper provide all necessary information on hardware/software configurations, parameter settings, data preprocessing steps, and any contingency procedures, such that others could replicate the experiments with the same resources?

2. Depth and Clarity of Figures and Tables Analysis:
Evaluate the thoroughness and clarity of the paper's analysis of figures and tables. Are the data clearly explained and linked to the research objectives or hypotheses? Do the authors discuss trends, patterns, or anomalies, and interpret quantitative metrics in a way that highlights their significance? Is there a clear comparison to baselines or related work, demonstrating how the results fit into or advance the field? Do the authors emphasize key takeaways and practical or theoretical implications arising from the findings?

3. Experimental Support for Main Innovations:
Evaluate how thoroughly the paper's main innovations or contributions are backed by experimental evidence. Does the paper provide direct tests or comparisons to validate each innovation? Are quantitative or qualitative results clearly linked to the claims made, with appropriate metrics and comparisons against baselines or existing methods? Are ablation studies or sensitivity analyses included to demonstrate the significance of each component? If certain claims are not experimentally supported, have the authors either provided additional experiments or adjusted their claims accordingly?

Figure 15: Criteria Details of Section Evaluation

Criteria

Each QA pair is evaluated based on four metrics, each scored from 1 to 5:
Evaluation Metrics (1-5 Scoring Criteria)
1. **Instruction Following:** Evaluate whether the answer correctly follows the given instruction.
1 – The answer completely ignores or contradicts the instruction.
2 – The answer only partially follows the instruction, with major missing elements.
3 – The answer follows the instruction but lacks completeness or clarity.
4 – The answer mostly follows the instruction with minor inconsistencies.
5 – The answer strictly follows and fully satisfies the instruction.
2. **Criteria Following:** Evaluate whether the revised text improves the original content based on predefined criteria.
1 – The revision does not follow any criteria and worsens the content.
2 – The revision attempts to follow the criteria but makes the content unclear.
3 – The revision follows the criteria but does not provide a significant improvement.
4 – The revision improves clarity and correctness while adhering to the criteria.
5 – The revision strictly follows the criteria and significantly improves the original content.
3. **In-Context Ability:** Evaluate whether the model's output appropriately references information within Selected Content.
1 – The output ignores Selected Content and adds irrelevant external information.
2 – The output relies on external information without justification.
3 – The output primarily references Selected Content but includes minor unrelated details.
4 – The output correctly refers to Selected Content with minimal external additions.
5 – The output strictly remains within Selected Content while providing a relevant and precise response.
4. **Agree Revision:** Evaluate whether the revision is convincing enough for the user to adopt it as a replacement.
1 – The revision is clearly worse than the original text.
2 – The revision is slightly better but has major flaws, making it unlikely to be adopted.
3 – The revision is neutral or slightly better, but adoption is uncertain.
4 – The revision is clearly better, and most users would likely adopt it.
5 – The revision is significantly better, and users would confidently adopt it.

Figure 16: The criteria for human instructors.

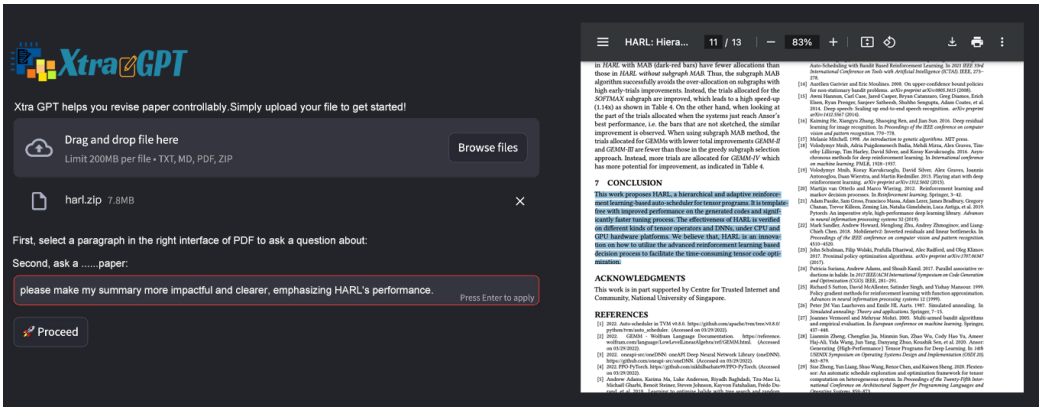

Figure 17: Demo of XtraGPT.

```
This work proposes HARL, a hierarchical and adaptive
reinforcement learning-based auto-scheduler for tensor
programs. It is templatefree with improved performance
on the generated codes and significantly faster tuning
process. The effectiveness of HARL is verified
on different kinds of tensor operators and DNNs, under
CPU and GPU hardware platforms. We believe that, HARL
is an innovation on how to utilize the advanced
reinforcement learning based
decision process to facilitate the time-consuming
tensor code optimization.
```

```
In this paper, we introduce HARL, a hierarchical and
adaptive reinforcement learning-based auto-scheduler
that significantly enhances tensor program exploration.
By employing a hierarchical RL architecture, HARL
enables learning-based decisions at various levels of
search granularity, leading to a $22\%$ improvement in
tensor operator performance and a $4.3\mathrm{x}$
increase in search speed compared to the state-of-the-
art auto-scheduler, Ansor. Our experiments reveal that
HARL not only outperforms Ansor in both tuning speed
and final program performance but also achieves up to
$8\%$ improvement in inference performance on end-to-
end neural networks. These results underscore the
effectiveness of HARL in addressing the challenges of
neural network optimization, providing a robust
framework for future research in this domain.
```

Figure 18: A comparison of the paragraph before and after revision.

Selected Content: This work proposes HARL, a hierarchical and adaptive reinforcement learning-based auto-scheduler for tensor programs. It is templatefree with improved performance on the generated codes and significantly faster tuning process. The effectiveness of HARL is verified on different kinds of tensor operators and DNNs, under CPU and GPU hardware platforms. We believe that, HARL is an innovation on how to utilize the advanced reinforcement learning based decision process to facilitate the time-consuming tensor code optimization.
User Interaction: How can we effectively summarize the key innovations of HARL and their contributions to the field of neural network optimization? What specific results and comparisons to existing methods should we include to demonstrate the significance of our findings?

Responses: In this paper, we introduce HARL, a hierarchical and adaptive reinforcement learning-based auto-scheduler that significantly enhances tensor program exploration. By employing a hierarchical RL architecture, HARL enables learning-based decisions at various levels of search granularity, leading to a 22% improvement in tensor operator performance and a $4.3\mathrm{x}$ increase in search speed compared to the state-of-the-art auto-scheduler, Ansor. Our experiments reveal that HARL not only outperforms Ansor in both tuning speed and final program performance but also achieves up to 8% improvement in inference performance on end-to-end neural networks. These results underscore the effectiveness of HARL in addressing the challenges of neural network optimization, providing a robust framework for future research in this domain.
Explanations: The revised conclusion emphasizes the key innovations of HARL, specifically highlighting the 22% performance improvement and $4.3\mathrm{x}$ speed increase over Ansor. By including quantitative results and comparisons to existing methods, we demonstrate the significance of our findings in the context of neural network optimization. The hierarchical RL architecture is clearly linked to these improvements, showcasing how it facilitates more efficient exploration of tensor programs. This alignment with the criteria of effectively summarizing key innovations and providing concrete results is crucial for advancing the field.

Figure 19: A use case on XtraGPT.

Models	Backbone	GitHub Stars	Huggingface Download
	Closed-Source		
GPT-4-Turbo (OpenAI et al., 2024)		/	
GPT-4o-mini (OpenAI et al., 2024)		/	
GPT-3.5-Turbo (Brown et al., 2020)		/	
	Open-Source (> 8B)		
Deepseek-R1 (DeepSeek-AI et al., 2025)	Llama	50K	285K
Deepseek-V3-671B (Liu et al., 2024a)	DeepSeek-V3-Base	63K	374K
Deepseek-V3-32B (Liu et al., 2024a)	DeepSeek-V3-Base	63K	374K
Qwen-2-72B-Instruct (Yang et al., 2024)	Qwen-2-72B-Instruct	45.3K	374K
QwQ-32B-Preview (Team, 2024)	Qwen2.5-32B-Instruct	15K	198K
Phi-4 (14B) (Abdin et al., 2024)	-	-	557K
	Open-Source (≤8B)		
Llama-3.1-8B-Instruct (Grattafiori et al., 2024)	Llama-3.1-8B-Instruct	28.1K	5.75M
Qwen-2.5-7B-Instruct (Yang et al., 2024)	Qwen-2.5-7B	12.6K	1.27M
Llama-3.2-3B-Instruct (Grattafiori et al., 2024)	Llama-3.2-3B	28.1K	1.48M
Qwen-2.5-1.5B-Instruct (Yang et al., 2024)	Qwen-2.5-1.5B	12.6K	551K

Table 12: Details information of baseline models. Data collected at 30.1.2025. The "/" indicates that the model uses a private download link or that its download statistics on HuggingFace are not disclosed.