RESEARCHARCADE: GRAPH INTERFACE FOR ACADEMIC TASKS

Anonymous authors
Paper under double-blind review

ABSTRACT

Academic research generates diverse data sources. As researchers increasingly use machine learning to assist research tasks, a crucial question arises: *Can we build a unified data interface to support the development of machine learning models for various academic tasks?* Models trained on such a unified interface can better support human researchers throughout the research process and eventually accelerate knowledge discovery. In this work, we introduce RESEARCHARCADE, a graph-based interface that connects multiple academic *data sources*, unifies *task definitions*, and supports a wide range of *base models* to address key academic challenges. RESEARCHARCADE utilizes a coherent multi-table format with graph structures to organize data from different sources, including academic corpora from ArXiv and peer reviews from OpenReview, while capturing information with multiple modalities, such as text, figures, and tables. RESEARCHARCADE also preserves temporal evolution at both the manuscript and community levels, supporting the study of paper revisions as well as broader research trends over time. Additionally, RESEARCHARCADE unifies diverse academic task definitions and supports various models with distinct input requirements. Our experiments across six academic tasks demonstrate that combining cross-source and multi-modal information enables a broader range of tasks, while incorporating graph structures consistently improves performance over baseline methods. This highlights the effectiveness of RESEARCHARCADE and its potential to advance research progress.

1 INTRODUCTION

Academic research represents a pinnacle of human knowledge discovery. Diverse research tasks such as forecasting research trends and debugging scientific papers (Sundar et al., 2024; Lin et al., 2024; Tian et al., 2025; Feng et al., 2024; 2025a; Liu et al., 2025) demand access to comprehensive data from multiple sources. To accomplish these tasks, various models are employed. These complexities raise an important research question: *Can we build a unified data interface to support the development of machine learning models for various academic tasks?*

Building such an interface for research tasks is challenging. In terms of data, firstly, academic data is sourced from diverse platforms such as ArXiv and OpenReview, encompassing complex relationships among entities like authors, papers, citations, and reviews. This requires a flexible framework capable of managing highly relational data. Secondly, the data representations themselves span multiple modalities—from textual content to visual and tabular data. Holistically integrating these varied representations is a significant challenge. Additionally, the dynamic and ever-evolving nature of academic data further complicates the task, as continuous growth and maintenance of the framework are required to keep pace with ongoing research developments. In terms of tasks, defining different academic tasks demands significant effort in data preprocessing and task formulation. In terms of models, different types of models require distinct interfaces. For example, Large Language Models (LLMs) require text-based data as input, while Graph Neural Networks (GNNs) utilize graph-structured data.

Despite existing efforts to benchmark scientific research, developing a unified and dynamic representation of research activities remains an open challenge. While existing academic datasets have systematically collected and organized academic data (Kang et al., 2018; Lo et al., 2019), they mainly focus on single-source data, such as academic corpora or peer reviewing conversations. Although multi-modal data (e.g., figures and tables within scientific papers) have been incorporated to construct valuable datasets (Xia et al., 2024; Tian et al., 2025), these approaches do not fully exploit the multi-modal relations among different data types. Recent works have used graphs to model academic data and define academic tasks (Li & Tajbakhsh, 2023; Zhang et al., 2024). However, each academic task is still formulated individually, requiring repetitive developmental efforts.

In this paper, we propose RESEARCHARCADE, a graph-based interface that links diverse academic *data sources*, with unified *task definitions*, and supports a large variety of *base models* to solve valuable academic tasks. Overall, RESEARCHARCADE exhibits four core features that make it ideal for solving academic tasks: *Multi-Source*, *Multi-Modal*, *Highly Structural and Heterogeneous*, and *Dynamically Evolving*. RESEARCHARCADE integrates academic data from multiple sources, including research papers from ArXiv and peer reviews with revisions from OpenReview, while collecting multi-modal information, including text, figures, and tables. These distinct entities are organized in a coherent multi-table format, with selected tables designated as nodes and edges, enabling RESEARCHARCADE to efficiently handle the highly relational and heterogeneous data as graphs within academic communities. Moreover, RESEARCHARCADE models academic evolution at two scales: microscopically, it preserves paper revisions with temporal information to track individual manuscript development, and macroscopically, its extensible framework enables continuous data incorporation, supporting analysis of research trends over time. Furthermore, we unify diverse academic tasks within the academic graphs in RESEARCHARCADE, enabling straightforward formulation of new tasks across both predictive and generative paradigms. Additionally, the structured knowledge in RESEARCHARCADE can be easily exported to standardized formats, such as CSV and JSON, facilitating integration with various models, including LLMs and GNNs.

To demonstrate the key advantages of RESEARCHARCADE, we define six academic tasks: figure/table insertion, paragraph generation, revision retrieval, revision generation, acceptance prediction, and rebuttal generation. Extensive experiments show that models benefit from the multi-source, multi-modal, heterogeneous, and dynamic information in RESEARCHARCADE.

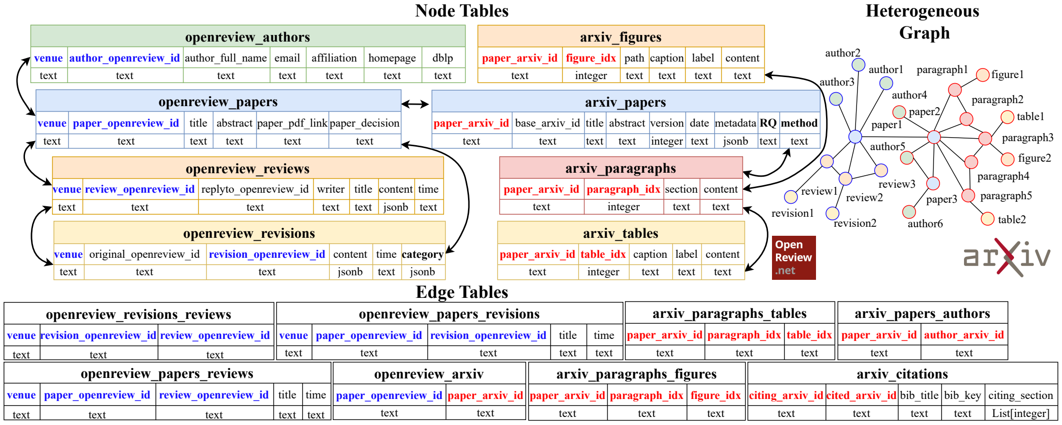
Overall, our key contributions include: First, RESEARCHARCADE enables diverse task definitions by integrating multiple data sources, multi-modal information, and supporting the inclusion of temporal and up-to-date data. Second, RESEARCHARCADE facilitates the academic task solving by unifying the task formulations and supporting the training of various models. Finally, RESEARCHARCADE shows that incorporating graph structures consistently enhances model's performance compared to baseline approaches.

2 RELATED WORK

Academic data as graphs. Existing research on academic graphs employs various decompositions on academic data. OAG-BENCH (Zhang et al., 2024) defines nodes such as authors, papers, and affiliations, modeling academic communities as heterogeneous graphs. UNARXIVE (Saier et al., 2023) and DOCGENOME (Xia et al., 2024) create finer-grained graphs by further decomposing academic corpora into paragraphs. UNARXIVE focuses on paragraph-level citations and DOCGENOME considers multi-modal elements (e.g., figures and tables). In RESEARCHARCADE, we integrate all these heterogeneous entities and extend them with comprehensive and elaborated graphs.

Dynamic modeling of academic data. Academic data are evolving dynamically, and their evolution is broadly classified into two parts: community research trends and individual manuscript evolution. For inter-paper evolution, Gollapalli & Li (2015) analyzes twenty years of ACL and EMNLP proceedings using topic distributions to trace venue convergence and divergence, while Tian et al. (2023) models scientific subcommunity evolution as event prediction, detecting growth, splits, and merges in collaboration graphs. For intra-paper evolution, Kuznetsov et al. (2022); D'Arcy et al. (2024) align revisions at the sentence level while Jourdan et al. (2025) focuses on the paragraph level. In RESEARCHARCADE, both evolutions are modeled simultaneously.

Solving academic tasks with deep learning. Various deep learning models are utilized to solve the academic tasks. Yu et al. (2025a;b) conducted end-to-end scientific discovery based on LLMs. Zhang et al. (2024) leveraged CNNs, GNNs, and LLMs to solve diverse academic tasks. However,



Node Tables

openreview_authors

venue	author_openreview_id	author_full_name	email	affiliation	homepage	dblp
text	text	text	text	text	text	text

arxiv_figures

paper_arxiv_id	figure_idx	path	caption	label	content
text	integer	text	text	text	text

openreview_papers

venue	paper_openreview_id	title	abstract	paper_pdf_link	paper_decision
text	text	text	text	text	text

arxiv_papers

paper_arxiv_id	base_arxiv_id	title	abstract	version	date	metadata	**RQ**	**method**
text	text	text	text	integer	text	jsonb	text	text

openreview_reviews

venue	review_openreview_id	replyto_openreview_id	writer	title	content	time
text	text	text	text	text	jsonb	text

arxiv_paragraphs

paper_arxiv_id	paragraph_idx	section	content
text	integer	text	text

openreview_revisions

venue	original_openreview_id	revision_openreview_id	content	time	**category**
text	text	text	jsonb	text	jsonb

arxiv_tables

paper_arxiv_id	table_idx	caption	label	content
text	integer	text	text	text

Edge Tables

openreview_revisions_reviews

venue	revision_openreview_id	review_openreview_id
text	text	text

openreview_papers_revisions

venue	paper_openreview_id	revision_openreview_id	title	time
text	text	text	text	text

arxiv_paragraphs_tables

paper_arxiv_id	paragraph_idx	table_idx
text	text	text

arxiv_papers_authors

paper_arxiv_id	author_arxiv_id
text	text

openreview_papers_reviews

venue	paper_openreview_id	review_openreview_id	title	time
text	text	text	text	text

openreview_arxiv

paper_openreview_id	paper_arxiv_id
text	text

arxiv_paragraphs_figures

paper_arxiv_id	paragraph_idx	figure_idx
text	text	text

arxiv_citations

citing_arxiv_id	cited_arxiv_id	bib_title	bib_key	citing_section
text	text	text	text	List[integer]

Figure 1: **ResearchArcade uses a multi-table format with graph structures to collect data from different sources with multiple modalities.** Tables are classified into node tables (colored) or edge tables (black and white). The blue (denoting the OpenReview part) or red (denoting the ArXiv part) columns represent the unique identification of each node or edge, and the remaining columns represent the features of the nodes or edges. And the black bold columns are generated by LLM. The conversion from the multiple tables to heterogeneous graphs is straightforward.

their efforts are scattered and require specialized data for different models. ResearchArcade offers a general graph interface to unify input data and task definitions for academic tasks.

3 ResearchArcade Data Description

ResearchArcade is an inclusive mapping of real-world research knowledge, featuring four key attributes: (1) multi-source, (2) multi-modal, (3) highly relational and heterogeneous, (4) dynamically evolving. An overview is illustrated in Figure 1, with further details in Appendix Figure 3.

3.1 Multi-source & Multi-modal

ResearchArcade is primarily sourced from computer science papers in ArXiv and available peer review data from conferences in OpenReview. Beyond text-based data, ResearchArcade also integrates multi-modal data (e.g., figures and tables), supporting more complex multi-modal tasks.

ArXiv: ResearchArcade includes 66,918 papers from ArXiv across 11 scientific fields, comprising 569,501 sections, 8,014,095 paragraphs, 876,636 figures, 324,648 tables. Relevant connections between these entities are also captured by ResearchArcade. Detailed statistics are provided in Table 5, and the procedure of data collection is in Appendix A.2.1. Research Arcade also supports continuous crawling, which updates the ArXiv dataset on a routine basis (e.g. weekly, daily). The detailed description is included in Appendix A.2.2

OpenReview: ResearchArcade also includes data from OpenReview, which comprises 57,278 submissions from ICLR, NeurIPS, ICML, and EMNLP conferences, contributed by 189,038 authors. We have also explored CVPR, ECCV, AAAI, IJCAI, ACL, and NAACL conferences, but their peer review data are unavailable. In addition, the corresponding 884,875 reviews and 54,467 submission revisions during the rebuttal process are included. These entities are enriched with valuable connections. Detailed statistics are given in Table 6 to Table 9, and the step-by-step data collection procedure is described in Appendix A.2.3.

Connect ArXiv and OpenReview: Connecting the data from the ArXiv and OpenReview contributes to more comprehensive academic graphs, allowing the definition of more diverse academic tasks. To achieve this goal, each submission in OpenReview is associated with its corresponding paper in ArXiv based on the title. Note that 25,969 (about 45.34%) submissions from OpenReview are successfully connected to papers from ArXiv. The statistics are shown in Table 10 to Table 13.

LLM-Generated Content: To facilitate the use of ResearchArcade for more academic tasks (e.g., Contradiction Detection, Theory Synthesis), we used Llama-3.1-70B-Instruct (Grattafiori

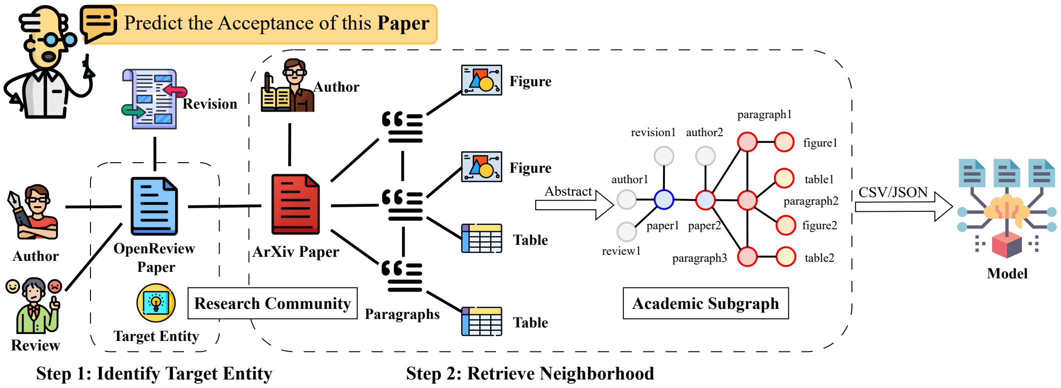


Figure 2: **RESEARCHARCADE unifies the academic task definitions in a two-step scheme**: (i) Label: Identify the task's target entity and assign its attribute as label; (ii) Input: Retrieve the target entity's neighborhood to construct an academic graph that supports task solving.

et al., 2024) for data preprocessing. The submission revisions are classified according to the categories outlined in Jourdan et al. (2025). The detailed descriptions of these categories are provided in Table 14. Additionally, we apply the same model to generate research question summaries and method descriptions for ArXiv papers. The specific prompts used are listed in Table 15 to Table 17.

3.2 HIGHLY RELATIONAL AND HETEROGENEOUS

Research activities in academic communities are modeled by interactions among typed entities. RESEARCHARCADE stores data in a multi-table node–edge schema, consisting of node tables and edge tables, which directly map to heterogeneous graphs. An illustration is shown in Figure 1.

Using data from ArXiv, RESEARCHARCADE constructs a two-scale graph representation of the literature. At the intra-paper level, each paper is decomposed into a paragraph-scale content graph including paper, paragraphs, figures, and tables nodes, linked by typed edges (e.g., paper-paragraph, paragraph-figure/table). At the macro inter-paper level, we include authors, subject categories, and citation links, adding edges for authorship, category assignment, and paper-to-paper citations.

The academic graphs built on data from OpenReview mainly model the academic activities that happen during the peer review process. It encompasses diverse types of nodes, such as papers, authors, paragraphs, reviews, and revisions. Some key relationships are also included: the authorship, which connects papers and authors; the comment-under-paper relation, which connects papers and reviews; the revision-of-paper relation, which connects papers and revisions; the revision-caused-by-review relation, which connects reviews and revisions, etc.

3.3 DYNAMICALLY EVOLVING

As the academic community continuously evolves, RESEARCHARCADE records temporal information (e.g., paper upload dates and paper revision timestamps), enabling a realistic simulation of scholarly dynamics. This includes tracing the evolution of research trends and modeling paper updates driven by the rebuttal process. Moreover, RESEARCHARCADE can be continuously updated to reflect the ongoing development in the academic community.

4 ACADEMIC TASKS ON RESEARCHARCADE

Defining different academic tasks often requires repetitive work, such as data collection, cleaning, and task specification. With RESEARCHARCADE, these tasks can be unified and conveniently defined on our academic graphs.

4.1 ACADEMIC GRAPH AS A HETEROGENEOUS GRAPH

A heterogeneous graph can be defined as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where each node $v \in \mathcal{V}$ and each edge $e \in \mathcal{E}$ is assigned a type through mapping functions. Specifically, the node type is defined by $\tau(v) : \mathcal{V} \to \mathcal{C}$,

Table 1: **Summary of six academic tasks studied with ResearchArcade.** Abbreviations include "or": openreview, "ar": ArXiv, CE: Cross-entropy Loss, BCE: Binary Cross-entropy Loss.

Task	Target Entity (Step 1)	Neighborhood (Step 2)	Loss	Type
Citation Prediction	ar_citation edge: content of the citing paragraph	ar_section nodes, ar_paragraph nodes, ar_figure nodes, ar_table nodes, ar_paragraph nodes, ar_paper nodes	CE	Predictive
Paragraph Generation	ar_paragraph node: Textual content of the paragraph	ar_paragraph nodes, ar_table nodes, ar_figure nodes, ar_citation edges	SFT	Generative
Revision Retrieval	or_revision node: Index list of modified paragraphs	or_paragraph nodes from the original paper, or_review nodes	InfoNCE	Predictive
Revision Generation	or_paragraph node: Textual content of the revised paragraph	or_paragraph node of the original paper, or_review nodes	SFT	Generative
Acceptance Prediction	or_paper node: Paper decision	or_paper nodes, ar_paper nodes, ar_paragraph nodes, ar_figure nodes, ar_table nodes	BCE	Predictive
Rebuttal Generation	or_review node: Textual content of the author's response	or_review node of the official review being replied to, ar_paper node, ar_paragraph nodes, ar_figure nodes, ar_table nodes	SFT	Generative

and the edge type is defined by $\phi(e) : \mathcal{E} \rightarrow \mathcal{D}$, where $c \in \mathcal{C}$ and $d \in \mathcal{D}$ represent the set of node types and the set of edge types. An edge e connecting a pair of nodes is denoted as $e = (v, u)$.

Data from ResearchArcade can be represented as an academic graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, which is heterogeneous. In this context, each node $v \in \mathcal{V}$ corresponds to a row in the node table, while each edge e corresponds to a row in the edge table. Furthermore, each node table V_c is associated with a unique node type c, and each edge table E_d is linked to a unique edge type d.

4.2 Unified Academic Task Definition

As is shown in Figure 2, ResearchArcade unifies the academic task definitions in the following two steps: (1) identifying the target entity and (2) retrieving the neighborhood of the target entity.

Step 1: Identifying the target entity of an academic task. The target entity is either a node v or an edge e, with attributes that define the labels for the task. Let t denote the target entity with attributes $\mathbf{a}_t$. Its certain attributes, denoted as $\mathbf{y}_t \subseteq \mathbf{a}_t$, are the labels implied in the task.

Step 2: Retrieving the neighborhood of the target entity. To support the academic task solving, the multi-hop neighborhood of the target entity t is retrieved, constructing an academic graph $\mathcal{G}_t$ centered at t. The one-hop neighborhood $\mathcal{N}_t^{(1)}$ of t consists of entities directly connected to t. If $t \in \mathcal{V}$, then $\mathcal{N}_t^{(1)} = \{k \,|\, k \in \mathcal{V},\, (t,\, k) \in \mathcal{E}\}$. If $t \in \mathcal{E}$, then $\mathcal{N}_t^{(1)} = \{k,\, u \,|\, k,\, u \in \mathcal{V},\, t = (k,\, u)\}$. For $i > 1$, the i-hop neighborhood is defined as $\mathcal{N}_t^{(i)} = \{k \,|\, k \in \mathcal{V},\, k' \in \mathcal{N}_t^{(i-1)},\, (k, k') \in \mathcal{E}\}$, which extends the $(i-1)$-hop neighborhood by one additional hop. Hence, the academic graph is constructed as $\mathcal{G}_t = (\mathcal{V}_t,\, \mathcal{E}_t)$, where $\mathcal{V}_t$ contains nodes in the multi-hop neighborhood of t, and $\mathcal{E}_t$ represents the edges between these nodes. Thus, an academic task is defined as follows:

$$f_\theta(\mathcal{G}_t) \rightarrow \mathbf{y}_t, \tag{1}$$

where f_θ represents a model with parameters θ. Furthermore, the academic tasks are broadly classified into predictive and generative tasks. If the label $\mathbf{y}_t$ is from a limited set of possible outcomes, this task is categorized as a predictive task; If the label $\mathbf{y}_t$ is in an open-ended output space, this task is categorized as a generative task. **For predictive tasks**, models (specified in Section 5.1) are considered as MLP-based, Embedding-based, GNN-based, or GWM-based, where the GWM framework efficiently integrates graph-structured data with LLM (Feng et al., 2025b). The training loss varies across different predictive tasks. **For generative tasks**, models are primarily based on LLMs. Supervised fine-tuning (SFT) is used for training, with the loss defined as follows:

$$\mathcal{L}_{\mathrm{SFT}}(\theta) = -\frac{1}{\sum_{t=1}^{T} L_t} \sum_{t=1}^{T} \sum_{i=1}^{L_t} \log p_\theta\big(y_{t,i} \,\big|\, y_{t,<i},\, \mathcal{G}_t\big), \tag{2}$$

where L_t is the length of $\mathbf{y}_t = [y_{t,\,1},\, ...,\, y_{t,\,L_t}]$, and $\log p$ is the log-likelihood. In this paper, six academic tasks are defined to demonstrate the four key features of ResearchArcade. Table 1 summarizes the tasks under the two-step scheme with detailed task definitions in Appendix A.3.

4.2.1 CITATION PREDICTION

Citation prediction requires the model to identify the appropriate paper to cite for a given paragraph, reflecting real-world needs like reference recommendation. While previous work (Arthur Brack, 2021) focuses on paper-level citation, we conduct the task at the paragraph level using the fine-grained academic graphs in RESEARCHARCADE. We formulate this task as a multi-class classification problem. Given an academic graph $\mathcal{G}_t$ that contains all paragraphs and existing citations of a paper, along with a candidate paragraph, the model predicts the paper $\hat{y}_t$ that should be cited by the target paragraph $\mathbf{y}_t$. The ground truth $\mathbf{y}_t$ corresponds to the paper that was actually cited in the target paragraph. Here, we optimize the model using the contrastive cross-entropy loss:

$$\mathcal{L}_{\text{CE}}(\theta) = -\log \frac{\exp\left(\text{sim}(h_t, z_{\mathbf{y}_t})/\tau\right)}{\sum_{j=1}^{M} \exp\left(\text{sim}(h_t, z_j)/\tau\right)}, \tag{3}$$

where θ denotes the model parameters, h_t is the embedding of the target paragraph, z_j is the embedding of the j-th candidate cited paper, M is the total number of candidate cited papers, $\mathbf{y}_t$ is the index of the ground-truth cited paragraph, τ is a temperature hyperparameter, and $\text{sim}(\cdot, \cdot)$ denotes cosine similarity between ℓ_2-normalized embeddings. This objective encourages the model to assign higher similarity to the true cited paper than to other candidate papers.

4.2.2 ACADEMIC TASK 2: PARAGRAPH GENERATION

Understanding how to generate specific paragraphs within their proper context in academic corpora is essential for assisting scientific writing. The inherent graph structures within RESEARCHARCADE offer relational signals among paragraphs, which are valuable for models to comprehend structural dependencies within corpora. This generative task is defined as follows: given the input, an academic graph $\mathcal{G}_t$ including surrounding paragraphs, referenced figures and tables, and cited literature, generate the missing paragraph content $\hat{\mathbf{y}}_t$. The original paragraph content serves as the ground truth label $\mathbf{y}_t$. To train the LLM, SFT loss (Eq. 2) is utilized. The prompt designed to help the LLM better understand the document completion task is shown in Table 22.

4.2.3 ACADEMIC TASK 3: REVISION RETRIEVAL

Identifying the precise location of revisions from reviewers' comments is essential for paper refinement. This captures intra-paper dynamics during peer review and demonstrates RESEARCHARCADE's ability to model evolving content based on graph structures. We formulate this as a top-k ranking task: given an academic graph $\mathcal{G}_t$ containing paper paragraphs and reviews, predict the top-k modified paragraphs $\hat{\mathbf{y}}_t$, with ground truth $\mathbf{y}_t$ denoting the actual revised paragraphs. Training employs the InfoNCE loss (He et al., 2020), which minimizes embedding distance between reviews and revised paragraphs while maximizing distance from unchanged ones:

$$\mathcal{L}_{\text{InfoNCE}}(\theta) = -\frac{1}{R}\sum_{r=1}^{R} \log \frac{\sum_{i=1}^{M^+} \exp\left(\text{sim}(q_r, k_i^+)/\tau\right)}{\sum_{i=1}^{M^+} \exp\left(\text{sim}(q_r, k_i^+)/\tau\right) + \sum_{j=1}^{M^-} \exp\left(\text{sim}(q_r, k_j^-)/\tau\right)}, \tag{4}$$

where θ denotes the model parameters; q_r is the model-generated embedding of the r-th review ($r = 1, ..., R$); k_i^+ and k_j^- are the embeddings of the i-th modified and j-th unchanged paragraph, respectively; M^+ and M^- are their counts; $\text{sim}(\cdot, \cdot)$ is the similarity function; and τ is the temperature in the InfoNCE loss.

4.2.4 ACADEMIC TASK 4: REVISION GENERATION

Building on Section 4.2.3, this task focuses on generating quality-enhancing revisions of localized paragraphs conditioned on reviewer feedback, further demonstrating RESEARCHARCADE's dynamic evolution capability based on graph structures. Unlike previous works on revision generation (D'Arcy et al., 2024; Jourdan et al., 2025), based on the academic graphs in RESEARCHARCADE, we can conveniently retrieve the corresponding comments from the reviewer to facilitate the task. Formally, given an academic graph $\mathcal{G}_t$ containing the original paragraph and its reviews, the goal is to generate a revised paragraph $\hat{\mathbf{y}}_t$, with the actual revision $\mathbf{y}_t$ as the label. Training uses SFT loss (Eq. 2), supported by a task-specific prompt (Table 25) to guide the LLM in leveraging graph structures. Since LLMs have limited context length, reviews are first summarized using Qwen3-8B with the prompt in Table 24.

Table 2: **Promising new tasks enabled by RESEARCHARCADE for future works.**

Task	Target Entity (Step 1)	Neighborhood (Step 2)	Loss	Type
Idea Generation	ar_paper node: Abstract	ar_citation edges, ar_paper nodes	SFT	Generative
Experiment Planning	ar_table node: Table text in experiment section	ar_paper node, ar_section nodes, ar_paragraph nodes, ar_figure nodes, ar_table nodes	SFT	Generative
Abstract Writing	ar_paper node: Abstract	ar_paper node, ar_section nodes, ar_paragraph nodes, ar_figure nodes, ar_table nodes	SFT	Generative
Review Generation	or_review node: Textual content of the official review	or_paper node, or_paragraph nodes	SFT	Generative

4.2.5 ACADEMIC TASK 5: ACCEPTANCE PREDICTION

Predicting the acceptance of academic papers is a meaningful but challenging task. Different from previous work (Feng et al., 2025a), which focuses only on text-based academic graphs, we fuse ArXiv's comprehensive multi-modal paper graph with OpenReview's ground-truth acceptance labels and temporal information to define the task. This reflects RESEARCHARCADE's multi-source, multi-modal, and dynamically evolving nature. We design the task as a binary classification problem: given the input, an academic graph $\mathcal{G}_t$ containing papers from conferences in previous years and their corresponding paragraphs with figures and tables, predict the paper acceptance $\hat{\mathbf{y}}_t$ (Accept or Reject) for the future year. The real paper acceptance is the label $\mathbf{y}_t$. Binary cross-entropy loss is utilized as the training loss:

$$\mathcal{L}_{\text{BCE}}(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\Big[\mathbf{y}_t \log \hat{\mathbf{y}}_t + (1-\mathbf{y}_t)\log(1-\hat{\mathbf{y}}_t)\Big]. \tag{5}$$

where θ represents the model's parameters and T the total number of papers.

4.2.6 ACADEMIC TASK 6: REBUTTAL GENERATION

Generating rebuttal responses to official reviews is critical, as response quality strongly influences paper acceptance. Based on the academic graph in RESEARCHARCADE, this task conveniently leverages textual and multi-modal information from ArXiv along with official reviews from OpenReview. Formally, given an academic graph $\mathcal{G}_t$ containing the review and its related paragraphs with figures and tables from ArXiv, the goal is to generate the author's response $\hat{\mathbf{y}}_t$, with the true response $\mathbf{y}_t$ as the label. Training uses SFT loss (Eq. 2), guided by a task-specific prompt (Table 27) to help the LLM capture graph structure and task requirements. To address token length limits, only the top-3 related paragraphs, selected via cosine similarity between review and paragraph embeddings using Qwen3-Embedding-0.6B, are included.

4.3 PROMISING NEW TASKS ENABLED BY RESEARCHARCADE

The versatility of RESEARCHARCADE extends beyond the tasks defined above, supporting additional stages of the research pipeline such as idea brainstorming, experiment planning, scientific writing, and peer reviewing—core activities in the academic process. These promising new tasks are illustrated in Table 2, with detailed specifications provided in Appendix A.4.

5 EXPERIMENT

5.1 EXPERIMENT SETUP

Dataset: We conduct experiments based on a subset of data in RESEARCHARCADE. For data from ArXiv, we mainly focus on papers in the Computer Science field and published within the last two years. For data collected from OpenReview, we primarily focus on the ICLR conferences within the past five years. Further detailed information is provided in Appendix A.5.

Base Models: To demonstrate the compatibility of RESEARCHARCADE with diverse models, experiments are conducted across various base models.

(1) Embedding model (EMB): Considering the relatively long token input for our academic tasks, we utilize Longformer (Beltagy et al., 2020), a model designed for processing long documents.

(2) Graph neural network (GNN): Since the academic graphs constructed from our database are highly relational and heterogeneous, we consider HANConv (Wang et al., 2019), a heterogeneous graph attention neural network, as our GNN-based model.

(3) Large language model (LLM): We mainly leverage Qwen3-0.6B and Qwen3-8B (Yang et al., 2025) as our LLM-based models, as they outperform models with an approximate number of parameters and are comparable to larger models in various evaluation tasks. We also validate our tasks on GPTOSS-120B (Agarwal et al., 2025), a larger state-of-the-art model.

(4) Graph world model (GWM): To efficiently integrate graph-structured data with LLMs, we employ the embedding-based GWM (Feng et al., 2025b). It adopts a multi-hop aggregation to perform an embedding-level message passing, yielding an enhanced graph representation, which facilitates better LLM comprehension of the graph-structured data. Qwen3-0.6B (Yang et al., 2025) is utilized as the LLM module for the GWM-based models.

Encoders: For the **text modality**, we represent text data as vector embeddings for integration with GNN-based and GWM-based models. Specifically, Longformer (Beltagy et al., 2020) is used for downstream GNNs, while Qwen3-Embedding-0.6B (Zhang et al., 2025) is adopted in GWM-based models to align with the Qwen3 LLM module. For the **visual modality**, LLaVA-1.5-7B (Liu et al., 2024) converts figures into textual descriptions, which are then encoded using the same text encoders. While we experimented with CLIP, our current approach is more effective and simpler to implement. This encoding framework remains flexible and can accommodate alternative multimodal encoders.

Evaluation Metrics: To systematically evaluate the performance of different models on our academic tasks, different evaluation metrics are considered for each task.

(1) Predictive Tasks: For the top-k ranking task, we report the top-5 precision, top-5 recall, and top-5 F-1 score to assess the model's performance. For the classification task, accuracy, AUC-ROC score, and Matthews correlation coefficient (MCC) are computed for evaluation.

(2) Generative Tasks: The semantic similarity between generated and reference answers is measured using the SBERT similarity score (Reimers & Gurevych, 2019). Lexical overlap is assessed with Rouge-L (Lin, 2004). Moreover, we leverage GPT-4o-mini (Hurst et al., 2024) to judge the clarity and the appropriateness of the output. Instead of hand-crafted evaluation metrics, we ask LLM to express pairwise preferences between the generated output and the ground truth and define the quantitative score as the preference proportion in which the generated output is preferred (including ties) over the reference.

$$\text{LLM-as-a-judge Score} = \frac{N_{\text{generated}} + N_{\text{tied}}}{N_{\text{generated}} + N_{\text{tied}} + N_{\text{truth}}}. \tag{6}$$

The specific prompt usages are shown in Appendix A.6.1.

5.2 EXPERIMENT RESULTS

The conclusive analysis of the experiment results is as follows, with detailed analysis of each task provided in Appendix A.7 and case studies provided in Appendix A.8.

5.2.1 RESEARCHARCADE IS GENERAL

Table 3 shows that RESEARCHARCADE enables diverse tasks by integrating academic corpora with multi-modal information from ArXiv and peer reviews with revisions from OpenReview, while supporting various models by converting the data into CSV or JSON formats. EMB-based, GNN-based, and GWM-based models are capable of performing predictive tasks, while LLM-based models handle generative tasks. Furthermore, the data quality in RESEARCHARCADE is validated, with trained smaller LLMs approaching the performance of larger ones. In *Revision Generation*, Qwen3-0.6B's

Table 3: **Evaluation results across six academic tasks.** Each base model follows (Backbone, Training, Hop), where Backbone is the specific model, Training is Fixed or Trained, and #-hop is the number of hops of neighbors that a model can observe. (0-hop indicates no neighbors are observed)

Citation Prediction				**Paragraph Generation**			
Model\Metric	Accuracy	AUC - ROC	MCC	Model\Metric	SBERT	Rouge-L	GPT-4o-mini
EMB (Longformer, Fixed, 1-hop)	0.970	0.427	0.050	GWM (Qwen3-0.6B, Trained, 0-hop)	0.581	0.163	0.009
GNN (HANConv, Trained, 1-hop)	**0.989**	**0.995**	0.396	GWM (Qwen3-0.6B, Trained, 1-hop)	0.624	**0.167**	0.244
GNN (HANConv, Trained, 3-hop)	0.987	0.993	**0.705**	GWM (Qwen3-0.6B, Trained, 3-hop)	0.638	0.166	0.404
GNN (HANConv, Trained, 5-hop)	**0.989**	0.993	**0.705**	GWM (Qwen3-0.6B, Trained, 5-hop)	**0.642**	0.165	0.344
Revision Retrieval				**Acceptance Prediction**			
Model\Metric	Precision@5	Recall@5	F-1@5	Model\Metric	Accuracy	AUC - ROC	MCC
EMB (Longformer, Fixed, 1-hop)	0.183	0.154	0.145	MLP (Linear, Trained, 1-hop)	0.513	0.479	0.025
GNN (HANConv, Trained, 1-hop)	**0.307**	0.325	**0.265**	GNN (HANConv, Trained, 1-hop)	0.507	0.465	0.000
GNN (HANConv, Trained, 3-hop)	**0.307**	0.324	**0.265**	GNN (HANConv, Trained, 3-hop)	**0.550**	**0.526**	**0.115**
GWM (Qwen3-0.6B, Trained, 1-hop)	0.304	0.325	0.264	GWM (Qwen3-0.6B, Trained, 1-hop)	0.470	0.478	-0.063
GWM (Qwen3-0.6B, Trained, 3-hop)	0.306	**0.326**	**0.265**	GWM (Qwen3-0.6B, Trained, 3-hop)	0.527	0.524	0.052
Revision Generation				**Rebuttal Generation**			
Model\Metric	SBERT	Rouge-L	GPT-4o-mini	Model\Metric	SBERT	Rouge-L	GPT-4o-mini
LLM (Qwen3-0.6B, Fixed, 1-hop)	0.321	0.210	0.447	LLM (Qwen3-0.6B, Fixed, 1-hop)	0.604	0.125	0.011
LLM (Qwen3-0.6B, Trained, 1-hop)	**0.733**	**0.554**	0.572	LLM (Qwen3-0.6B, Trained, 1-hop)	0.638	0.131	0.022
LLM (Qwen3-8B, Fixed, 1-hop)	0.704	0.446	0.889	LLM (Qwen3-8B, Fixed, 1-hop)	0.700	**0.154**	0.208
LLM (GPTOSS-120B, Fixed, 1-hop)	0.669	0.265	**0.999**	LLM (GPTOSS-120B, Fixed, 1-hop)	**0.703**	0.152	**0.884**

SBERT similarity score and LLM-as-a-judge score (Eq. 6) improve from 0.321 to 0.733 and 0.447 to 0.572, approaching the scores of Qwen3-8B and GPTOSS-120B. And in *Rebuttal Generation*, Qwen3-0.6B's SBERT similarity score and LLM-as-a-judge score improve from 0.604 to 0.638 and 0.011 to 0.022, approaching the scores of Qwen3-8B and GPTOSS-120B.

5.2.2 ResearchArcade Models Dynamic Evolution

As shown in Table 3, ResearchArcade effectively captures dynamic evolution at both the intra-paper and inter-paper levels by incorporating temporal data from ArXiv and OpenReview. The tasks of *Revision Retrieval* and *Revision Generation* highlight ResearchArcade's ability to model intra-paper evolution, predicting and generating revisions that reflect the continuous development of manuscripts. In particular, the top-5 F1 scores achieved by GNN-based and GWM-based models (0.265 each) outperform the EMB-based model (0.145), underscoring the framework's effectiveness. In contrast, the *Acceptance Prediction* task reflects inter-paper evolution, aiming to identify promising papers for acceptance by learning from historical data. Here, performance was much poorer, with the best accuracy reaching only 0.55, barely above random chance. This emphasizes the inherent difficulty of predicting research trends.

5.2.3 Relational Graph Structure Delivers Consistent Gains

To assess the effectiveness of ResearchArcade's graph-centric design, we compare graph-based models (GNN-based and GWM-based) with non-graph models (EMB-based and MLP-based) across two tasks, observing performance gains of 67%, and 7.2% in *Revision Retrieval*, and *Acceptance Prediction*, respectively, in Table 3. Multi-hop aggregation further improves performance, particularly in *Acceptance Prediction*: while 1-hop aggregation yields weak results (accuracies of 0.507 and 0.47), expanding to 3 hops raises both GNN-based and GWM-based models to 0.55, surpassing the MLP baseline (0.513). This indicates that acceptance decisions depend on higher-order context, such as venue affiliation and temporal trends, captured by multi-hop neighborhoods. The *Citation Prediction* task also investigates the impact of varying hops of aggregation. For *Citation Prediction*, although 1-hop performance is already high, expanding the neighborhood substantially improves robustness, as MCC score increases by 30.9%. However, for other tasks (e.g., *Revision Retrieval*, *Paragraph Generation*), additional hops provide little benefit or even make performance fluctuate. In *Paragraph Generation*, GPT-4o-mini score declines from 40.4% (3-hop) to 34.4% (5-hop), as larger neighborhoods may introduce irrelevant or noisy information.

5.2.4 Multi-Modal Information Is Critical

Table 4 shows that incorporating figures and tables consistently enhances model performance compared to text-only baselines for the *Rebuttal Generation* and *Citation Prediction* tasks. Specifically,

Table 4: **Ablation Study on multi-model and review information.** Each base model follows (Backbone, Training, Modality), where Backbone is the specific model, Training is Fixed or Trained, Modality is with Figure & Table, with Figure, with Table, without Figure & Table, with Review, or without Review.

Rebuttal Generation				**Citation Prediction**			
Model\Metric	SBERT	Rouge-L	GPT-4o-mini	Model\Metric	Accuracy	AUC-ROC	MCC
LLM (Qwen3-8B, Fixed, w/o F&T)	0.671	0.140	0.134	GNN (HANConv, Trained, 5-hop, w/o F&T)	0.977	0.990	0.542
LLM (Qwen3-8B, Fixed, w F)	0.692	0.150	0.178	GNN (HANConv, Trained, 5-hop, w F)	0.977	0.990	0.542
LLM (Qwen3-8B, Fixed, w T)	0.693	0.152	0.191	GNN (HANConv, Trained, 5-hop, w T)	0.980	0.990	0.564
LLM (Qwen3-8B, Fixed, w F&T)	0.700	0.154	0.208	GNN (HANConv, Trained, 5-hop, w F&T)	0.989	0.993	0.705

Revision Retrieval				**Revision Generation**			
Model\Metric	Precision@5	Recall@5	F-1@5	Model\Metric	SBERT	Rouge-L	GPT-4o-mini
EMB (Longformer, Fixed, w/o R)	0.067	0.043	0.046	LLM (Qwen3-0.6B, Fixed, w/o R)	0.570	0.401	0.596
EMB (Longformer, Fixed, w R)	0.183	0.154	0.145	LLM (Qwen3-0.6B, Fixed, w R)	0.321	0.210	0.447
GNN (HANConv, Trained, w/o R)	0.290	0.329	0.260	LLM (Qwen3-8B, Fixed, w/o R)	0.712	0.473	0.873
GNN (HANConv, Trained, w R)	0.307	0.324	0.265	LLM (Qwen3-8B, Fixed, w R)	0.704	0.446	0.889
GWM (Qwen3-0.6B, Trained, w/o R)	0.301	0.320	0.260	LLM (GPTOSS-120B, Fixed, w/o R)	0.672	0.369	0.924
GWM (Qwen3-0.6B, Trained, w R)	0.306	0.326	0.265	LLM (GPTOSS-120B, Fixed, w R)	0.669	0.265	0.999

both figures and tables are critical, as adding either alone yields consistent gains, while using both together gives the best performance. This suggests that the inclusion of visual and tabular data augments the model's understanding of textual content, leading to clear performance gains. For *Rebuttal Generation*, SBERT similarity score and LLM-as-a-judge score (Eq. 6) increase from 0.671 to 0.700 and from 0.134 to 0.208. Similarly, in *Citation Prediction*, the MCC increased from 0.542 to 0.705 when full modalities are included. These results validate RESEARCHARCADE's multi-modal design and highlight the effectiveness of its approach to encoding multi-modal information.

5.2.5 REVIEW INFORMATION COULD BE AMBIGUOUS

We conduct ablation studies on the review information in *Revision Retrieval* and *Revision Generation*. For *Revision Retrieval*, we remove the review information by replacing all the review content with the same prompt listed in Table 28. According to results in Table 4, incorporating specific review content delivers gains for all models. In particular, the EMB-based model exhibits a larger performance gain compared to the GNN-based and GWM-based models. The GNN-based model can exploit the review graph structure for better predictions, and the GWM-based model can further leverage the reasoning ability of its LLM module to achieve higher absolute performance. For the ablation study for *Revision Generation*, we directly prompt the model to produce a revised paragraph from the original, without incorporating the review information. Surprisingly, Qwen3-0.6B performs even worse when reviews are included, likely because the small model struggles with the longer context. And the larger models, such as Qwen3-8B and GPTOSS-120B, only show modest improvements. One reason is that many reviews lack explicit revision instructions, so the models tend to make superficial edits rather than substantial changes that would markedly improve the paragraph. In addition, some requested revisions require the author to add domain-specific content, which is difficult for the models to generate.

6 CONCLUSION

We introduced RESEARCHARCADE, a graph-based interface that unifies multi-source (ArXiv, OpenReview), multi-modal (text, figures, tables), and temporally evolving academic data into a coherent multi-table format. Furthermore, RESEARCHARCADE demonstrates strong scalability and supports the continuous crawling of new data on a routine basis. Building on a simple two-step scheme, (i) identify the target entity (label) and (ii) retrieve a task-specific academic graph (neighborhood), RESEARCHARCADE standardizes the definition of both predictive and generative academic tasks. RESEARCHARCADE is compatible with various models, serving as a valuable platform for studying research progress and developing models that facilitate automated scientific research. Experiments across six representative tasks show that the graph structure delivers consistent gains.

Ethics Statement

We developed this work in accordance with the ICLR Code of Ethics and have carefully considered its broader impacts on the academic research community. Our system aims to contribute positively to research automation by providing tools for paper discovery, review assistance, and research trend analysis that could democratize access to academic insights and support researchers across different resource levels.

Potential Risks and Mitigation: We acknowledge several areas of concern regarding our academic task automation capabilities. Automated features such as paper completion and response drafting could potentially be misused for academic misconduct. We emphasize that our system is intended as a research assistance tool to augment human judgment, not replace academic thinking or writing. Additionally, our reliance on existing academic data sources (ArXiv, OpenReview) may perpetuate existing biases in publication patterns and review processes. The acceptance prediction capabilities could inadvertently influence submission strategies in ways that prioritize predicted acceptance over scientific merit rather than encouraging methodological rigor and novelty.

Data and Privacy: Our system uses exclusively publicly available academic data from ArXiv and OpenReview platforms. We respect the existing terms of use for these platforms and do not attempt to de-anonymize review processes or access private information. No human subjects are directly involved in our research process, and no additional ethical approvals were required.

Transparency and Responsible Use: We acknowledge that our graph construction and task formulation choices embed assumptions about academic workflows that may not generalize across all research domains. We encourage users to employ our system as an exploratory and assistance tool rather than for automated decision making, particularly for high-stakes academic decisions. Any research assistance provided should be subject to appropriate human oversight and verification to maintain research integrity.

Reproducibility Statement

To ensure reproducibility of our results, we have made extensive efforts to document our methodology and provide necessary resources. Complete implementation details for our graph construction process, including multi-source data integration from ArXiv and OpenReview, are provided in A.2.1 and A.2.3. The two-step task formulation scheme is fully specified in Section 4 with concrete examples. All experimental configurations, hyperparameters, and model architectures used across the six representative tasks are detailed in 5.1 and A.5. We provide comprehensive ablation studies and statistical significance testing procedures in 5.2. Code for data processing, graph construction, model implementation, and evaluation will be made available upon publication. The constructed heterogeneous graph dataset, along with task-specific splits and evaluation protocols, will also be released to facilitate future research.

References

Sandhini Agarwal, Lama Ahmad, Jason Ai, Sam Altman, Andy Applebaum, Edwin Arbus, Rahul K Arora, Yu Bai, Bowen Baker, Haiming Bao, et al. gpt-oss-120b & gpt-oss-20b model card. *CoRR*, 2025.

Ralph Ewerth Arthur Brack, Anett Hoppe. Citation recommendation for research papers via knowledge graphs. *CoRR*, 2021.

Iz Beltagy, Matthew E Peters, and Arman Cohan. Longformer: The long-document transformer. *CoRR*, 2020.

Mike D'Arcy, Alexis Ross, Erin Bransom, Bailey Kuehl, Jonathan Bragg, Tom Hope, and Doug Downey. Aries: A corpus of scientific paper edits made in response to peer reviews. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2024.

Tao Feng, Chuanyang Jin, Jingyu Liu, Kunlun Zhu, Haoqin Tu, Zirui Cheng, Guanyu Lin, and Jiaxuan You. How far are we from AGI: are llms all we need? *Trans. Mach. Learn. Res.*, 2024.

Tao Feng, Yihang Sun, and Jiaxuan You. Grapheval: A lightweight graph-based llm framework for idea evaluation. *CoRR*, 2025a.

Tao Feng, Yexin Wu, Guanyu Lin, and Jiaxuan You. Graph world model. *CoRR*, 2025b.

Sujatha Das Gollapalli and Xiaoli Li. EMNLP versus ACL: Analyzing NLP research over time. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pp. 2002–2006, Lisbon, Portugal, 2015. Association for Computational Linguistics.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *CoRR*, 2024.

Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 9729–9738, 2020.

Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, et al. Gpt-4o system card. *CoRR*, 2024.

Léane Jourdan, Florian Boudin, Richard Dufour, Nicolas Hernandez, and Akiko Aizawa. Pararev: Building a dataset for scientific paragraph revision annotated with revision instruction. In *Proceedings of the First Workshop on Writing Aids at the Crossroads of AI, Cognitive Science and NLP (WRAICOGS 2025)*, 2025.

Dongyeop Kang, Waleed Ammar, Bhavana Dalvi, Madeleine Van Zuylen, Sebastian Kohlmeier, Eduard Hovy, and Roy Schwartz. A dataset of peer reviews (peerread): Collection, insights and nlp applications. *CoRR*, 2018.

Ilia Kuznetsov, Jan Buchmann, Max Eichler, and Iryna Gurevych. Revise and resubmit: An intertextual model of text-based collaboration in peer review. *Computational Linguistics*, 2022.

Shengzhi Li and Nima Tajbakhsh. Scigraphqa: A large-scale synthetic multi-turn question-answering dataset for scientific graphs. *CoRR*, 2023.

Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pp. 74–81, 2004.

Guanyu Lin, Tao Feng, Pengrui Han, Ge Liu, and Jiaxuan You. Paper copilot: A self-evolving and efficient LLM system for personalized academic assistance. *CoRR*, 2024.

Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved baselines with visual instruction tuning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 26296–26306, 2024.

Yaowenqi Liu, BingXu Meng, Rui Pan, Jerry Huang, and Tong Zhang. GUIDE: towards scalable advising for research ideas. *CoRR*, 2025.

Kyle Lo, Lucy Lu Wang, Mark Neumann, Rodney Kinney, and Dan S Weld. S2orc: The semantic scholar open research corpus. *CoRR*, 2019.

Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. *CoRR*, 2019.

Tarek Saier, Johan Krause, and Michael Färber. unarxive 2022: All arxiv publications pre-processed for nlp, including structured full-text and citation network. In *2023 ACM/IEEE Joint Conference on Digital Libraries (JCDL)*, pp. 66–70. IEEE, 2023.

Anirudh Sundar, Jin Xu, William Gay, Christopher Richardson, and Larry Heck. cpapers: A dataset of situated and multimodal interactive conversations in scientific papers. *Advances in Neural Information Processing Systems*, 37:66283–66304, 2024.

Yang Tian, Zheng Lu, Mingqi Gao, Zheng Liu, and Bo Zhao. Mmcr: Benchmarking cross-source reasoning in scientific papers. *CoRR*, 2025.

Yunpei Tian, Gang Li, and Jin Mao. Predicting the evolution of scientific communities by interpretable machine learning approaches. *Journal of Informetrics*, 17(2):101399, 2023.

Xiao Wang, Houye Ji, Chuan Shi, Bai Wang, Yanfang Ye, Peng Cui, and Philip S Yu. Heterogeneous graph attention network. In *The world wide web conference*, pp. 2022–2032, 2019.

Renqiu Xia, Song Mao, Xiangchao Yan, Hongbin Zhou, Bo Zhang, Haoyang Peng, Jiahao Pi, Daocheng Fu, Wenjie Wu, Hancheng Ye, et al. Docgenome: An open large-scale scientific document benchmark for training and testing multi-modal large language models. *CoRR*, 2024.

An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, Chujie Zheng, Dayiheng Liu, Fan Zhou, Fei Huang, Feng Hu, Hao Ge, Haoran Wei, Huan Lin, Jialong Tang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jian Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keqin Bao, Kexin Yang, Le Yu, Lianghao Deng, Mei Li, Mingfeng Xue, Mingze Li, Pei Zhang, Peng Wang, Qin Zhu, Rui Men, Ruize Gao, Shixuan Liu, Shuang Luo, Tianhao Li, Tianyi Tang, Wenbiao Yin, Xingzhang Ren, Xinyu Wang, Xinyu Zhang, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yinger Zhang, Yu Wan, Yuqiong Liu, Zekun Wang, Zeyu Cui, Zhenru Zhang, Zhipeng Zhou, and Zihan Qiu. Qwen3 technical report. *CoRR*, 2025.

Haofei Yu, Zhaochen Hong, Zirui Cheng, Kunlun Zhu, Keyang Xuan, Jinwei Yao, Tao Feng, and Jiaxuan You. Researchtown: Simulator of human research community. *CoRR*, 2025a.

Haofei Yu, Keyang Xuan, Fenghai Li, Kunlun Zhu, Zijie Lei, Jiaxun Zhang, Ziheng Qi, Kyle Richardson, and Jiaxuan You. Tinyscientist: An interactive, extensible, and controllable framework for building research agents. *CoRR*, 2025b.

Fanjin Zhang, Shijie Shi, Yifan Zhu, Bo Chen, Yukuo Cen, Jifan Yu, Yelin Chen, Lulu Wang, Qingfei Zhao, Yuqing Cheng, et al. Oag-bench: a human-curated benchmark for academic graph mining. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 6214–6225, 2024.

Yanzhao Zhang, Mingxin Li, Dingkun Long, Xin Zhang, Huan Lin, Baosong Yang, Pengjun Xie, An Yang, Dayiheng Liu, Junyang Lin, Fei Huang, and Jingren Zhou. Qwen3 embedding: Advancing text embedding and reranking through foundation models. *CoRR*, 2025.

A Appendix

A.1 Data Description in ResearchArcade

The detailed description of ResearchArcade is shown in Figure 3.

The statistical overview of data collected from ArXiv is illustrated in Table 5.

The statistical overview of data collected from OpenReview is illustrated separately in Table 6 (ICLR), Table 7 (NeurIPS), Table 8 (ICML), and Table 9 (EMNLP).

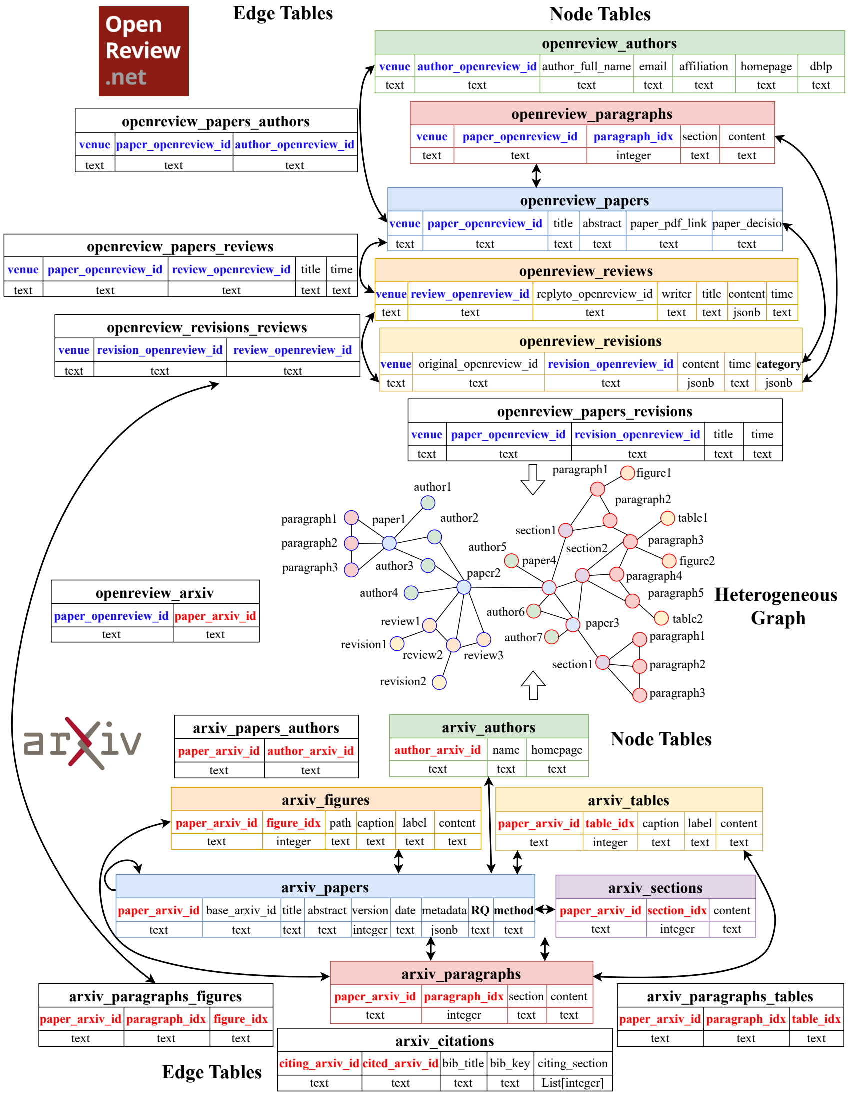
The statistical overview of openreview_arxiv table is shown in Table 10 (ICLR), Table 11 (NeurIPS), Table 12 (ICML), and Table 13 (EMNLP).

A.2 Data Collection Procedure

A.2.1 ArXiv

We develop a multi-stage pipeline to collect and structure papers from ArXiv. The process begins by selecting target papers using ArXiv IDs or publication date ranges. Using the ArXiv API, we download the LaTeX source files together with basic metadata. The sources are then processed through a seven-stage pipeline that converts raw LaTeX into structured graph representations.

Stage 1: Paper Source File Downloading For each paper, we download and unpack the LaTeX source archive into a working directory. We also collect metadata including author names, paper categories, submission dates, paper version, and abstracts.



openreview_authors

venue	author_openreview_id	author_full_name	email	affiliation	homepage	dblp
text	text	text	text	text	text	text

openreview_papers_authors

venue	paper_openreview_id	author_openreview_id
text	text	text

openreview_paragraphs

venue	paper_openreview_id	paragraph_idx	section	content
text	text	integer	text	text

openreview_papers

venue	paper_openreview_id	title	abstract	paper_pdf_link	paper_decisio
text	text	text	text	text	text

openreview_papers_reviews

venue	paper_openreview_id	review_openreview_id	title	time
text	text	text	text	text

openreview_reviews

venue	review_openreview_id	replyto_openreview_id	writer	title	content	time
text	text	text	text	text	jsonb	text

openreview_revisions_reviews

venue	revision_openreview_id	review_openreview_id
text	text	text

openreview_revisions

venue	original_openreview_id	revision_openreview_id	content	time	**category**
text	text	text	jsonb	text	jsonb

openreview_papers_revisions

venue	paper_openreview_id	revision_openreview_id	title	time
text	text	text	text	text

openreview_arxiv

paper_openreview_id	paper_arxiv_id
text	text

arxiv_papers_authors

paper_arxiv_id	author_arxiv_id
text	text

arxiv_authors

author_arxiv_id	name	homepage
text	text	text

arxiv_figures

paper_arxiv_id	figure_idx	path	caption	label	content
text	integer	text	text	text	text

arxiv_tables

paper_arxiv_id	table_idx	caption	label	content
text	integer	text	text	text

arxiv_papers

paper_arxiv_id	base_arxiv_id	title	abstract	version	date	metadata	**RQ**	**method**
text	text	text	text	integer	text	jsonb	text	text

arxiv_sections

paper_arxiv_id	section_idx	content
text	integer	text

arxiv_paragraphs

paper_arxiv_id	paragraph_idx	section	content
text	integer	text	text

arxiv_paragraphs_figures

paper_arxiv_id	paragraph_idx	figure_idx
text	text	text

arxiv_paragraphs_tables

paper_arxiv_id	paragraph_idx	table_idx
text	text	text

arxiv_citations

citing_arxiv_id	cited_arxiv_id	bib_title	bib_key	citing_section
text	text	text	text	List[integer]

Figure 3: **A comprehensive overview of RESEARCHARCADE.** RESEARCHARCADE uses a multi-table format with graph structures to collect data from different sources with multiple modalities. Tables are classified into node tables (colored) or edge tables (black and white). The blue (denoting the OpenReview part) or red (denoting the ArXiv part) columns represent the unique identification of each node or edge, and the remaining columns represent the features of the nodes or edges. And the black bold columns are generated by LLM. The conversion from the multiple tables to heterogeneous graphs is straightforward.

Stage 2: Author Information Processing Author names are first obtained from ArXiv metadata, which provides plain-text names without persistent identifiers. To enrich this information, we query the Semantic Scholar API using the ArXiv ID. We extract author identifiers, names, and optional auxiliary information (e.g., homepages). Authors are stored in a dedicated table, and paper–author relationships are recorded with sequence numbers to preserve author order.

Stage 3: Section-Level Decomposition We identify paper sections by recursively traversing the LaTeX structure. The system assumes a three-level hierarchy (`section`, `subsection`, `subsubsection`). When sectioning commands (e.g., `\section...`, `\subsection...`, `\subsubsection...`) are detected, we extract section titles, store section content, and record their positions within the paper.

Table 5: **Statistic overview of the data collected from ArXiv by primary category.** Note that some papers may belong to multiple subdomains within a category. Counts are aggregated by top-level category prefix.

Category	**#papers**	**#sections**	**#paragraphs**	**#figures**	**#tables**	**#authors**
cs	57357	849448	11306247	1309302	528055	14385
stat	9938	106751	1879176	177750	47557	613
physics	8421	69334	1013456	122287	18395	349
math	5263	50397	1293357	71226	14666	766
eess	5069	37376	479536	54377	19070	1511
q-bio	2797	24588	353634	34342	10722	220
cond-mat	1991	16794	256023	22744	2905	81
astro-ph	690	6858	97977	10352	1962	47
nlin	388	3009	49485	4559	429	17
econ	300	2683	63133	3920	1371	30
q-fin	253	2468	42267	5360	1287	45
Total	66918	569501	8014095	876636	324648	14391

Table 6: **Statistic overview of the data collected from ICLR conferences, sourced from the OpenReview.** Note that no ICLR conference was held in 2015 and 2016. Additionally, revisions of submissions from the ICLR 2013 and 2014 conferences are not accessible on the OpenReview.

Year	**#papers**	**#authors**	**#reviews**	**#paragraphs**	**#revisions**	**#papers_authors**	**#papers_reviews**	**#papers_revisions**	**#reviews_revisions**
2025	8701	27742	190934	1526799	13989	42541	190934	13989	97051
2024	5750	18077	99525	389973	1251	25297	99520	1251	11971
2023	3793	11819	55301	893211	9445	15742	55301	9445	39871
2022	2617	8155	39750	614294	6508	10505	39750	6508	28321
2021	2594	7661	32113	566963	6593	9782	32113	6593	22786
2020	2213	6963	21132	556021	6878	9117	21132	6878	14773
2019	1419	4387	16620	306915	3671	5618	16620	3671	11503
2018	935	2820	9164	352761	4929	3512	9164	4929	8374
2017	490	606	6988	104648	1203	869	6988	1203	4206
2014	69	65	548	2803	/	84	548	/	/
2013	67	56	373	2691	/	74	373	/	/
Total	28648	88351	472448	5317079	54467	123141	472443	54467	238856

Stage 4: Paragraph-Level Information Extraction Within each section, text is segmented into paragraphs based on blank lines, explicit line breaks, and environment boundaries. Content belonging to figures, tables, or display-math environments is excluded to preserve clean textual paragraphs. Each paragraph is assigned paper-level and section-level ordering. We detect citation commands (e.g., `\cite...`) and extract citation keys and titles. References to figures and tables are identified through cross-reference commands (e.g., `\ref...`). These links are stored in relational tables that connect paragraphs to citations, figures, and tables.

Stage 5: Citation Information Processing Citation metadata is collected from BibTeX files and compiled bibliography environments (e.g., `.bbl` files or `\beginthebibliography` blocks). We extract citation keys, titles, authors, and venue information, and detect ArXiv identifiers when present. For references without explicit ArXiv IDs, we apply a two-step resolution process. First, we query Semantic Scholar to retrieve reference lists with external identifiers. Second, we align these references with local entries using normalized title similarity with a conservative threshold. Unmatched references are retained in the database without ArXiv IDs.

Stage 6: Figure and Table Extraction Figures and tables are detected and indexed using their environment labels and captions at both document and section levels. Each figure or table is stored as a structured object linked to its parent paper and, when applicable, its enclosing section. At the paragraph level, cross-references to figures and tables are resolved using a global label index. Only figures and tables that are referenced in the text are retained, ensuring semantic grounding. This enables fine-grained links between paragraphs and the visual or tabular content they describe.

Table 7: **Statistic overview of the data collected from NeurIPS conferences, sourced from the OpenReview.** Note that no NeurIPS conference data before 2021 is available on OpenReview. Additionally, no revision is allowed during the rebuttal process.

Year	#papers	#authors	#reviews	#paragraphs	#papers_authors	#papers_reviews
2025	5529	21687	125739	370664	30352	125739
2024	4236	15430	75588	279708	21673	75588
2023	3394	11191	64528	218856	15863	64528
2022	2824	9102	46915	180202	12561	46915
2021	2768	7600	37952	167213	11744	37952
Total	18751	65010	350722	1216643	92193	350722

Table 8: **Statistic overview of the data collected from ICML conferences, sourced from the OpenReview.** Note that no ICML conference data before 2023 is available on OpenReview. Additionally, peer review data is only available for the year 2025, no revision is allowed during the rebuttal process, and no extracted paragraph data because the ICML PDFs are double-column-structured.

Year	#papers	#authors	#reviews	#papers_authors	#papers_reviews
2025	3422	13279	38974	17871	38974
2024	2610	9516	/	13050	/
2023	1828	6186	/	8121	/
Total	7860	28981	38974	39042	38974

Stage 7: Graph Construction and Storage All extracted elements are organized into a heterogeneous graph. Nodes represent papers, sections, paragraphs, figures, tables, and authors. Edges encode relationships such as paper–section, section–paragraph, paragraph–citation, paragraph–figure, paragraph–table, paper–author, paper–paper citations, and paper–category links. Citation edges are deduplicated and store both original bibliographic metadata and resolved ArXiv identifiers. This graph serves as the foundation for downstream tasks.

A.2.2 Continuous Crawling from ArXiv

ResearchArcade supports continuous and automated data acquisition through a fault-tolerant crawling and processing pipeline. The pipeline design reflects the multi-stage extraction procedure described above and enables the dataset to remain synchronized with newly released ArXiv papers while preserving consistency of the existing heterogeneous graph.

The major stages of the pipeline are as follows:

1. **ArXiv Identifier Retrieval.** A scheduled job (e.g., daily or weekly) queries the ArXiv API to collect newly published paper identifiers within a predefined time window, supporting both incremental updates and recovery from transient failures.
2. **Source Archive Downloading.** For each new ArXiv ID, the compressed LaTex source archive is automatically downloaded and unpacked into a staging directory to support parsing and processing.
3. **Incremental Graph Construction and Update.** Each paper is processed using the same pipeline described in Appendix A.2.1, converting source files into structured graph entities, including papers, sections, paragraphs, figures, tables, citations, and their relations.
4. **External Metadata Enrichment.** Additional metadata are added using external services, including author enrichment via the Semantic Scholar API and citation resolution through title and ArXiv ID based matching.

This automated pipeline allows ResearchArcade to evolve continuously by integrating newly published content in a consistent and reproducible way, supporting longitudinal analysis of academic structures and relationships.

Table 9: **Statistic overview of the data collected from EMNLP conferences, sourced from the OpenReview.** Note that only the EMNLP conference in 2023 is available on OpenReview. Additionally, no revision is allowed during the rebuttal process.

Year	#papers	#authors	#reviews	#paragraphs	#papers_authors	#papers_reviews
2023	2019	6696	22731	118184	10015	22731

Table 10: **Statistic overview of** openreview_arxiv **table on ICLR.** Note that no ICLR conference was held in 2015 and 2016. Additionally, revisions of submissions from the ICLR 2013 and 2014 conferences are not accessible on the OpenReview.

Year	2025	2024	2023	2022	2021	2020	2019	2018	2017	2014	2013
#openreview_arxiv	3077	2033	1469	1050	1068	866	583	424	248	53	50

The pipeline also supports two interchangeable storage backends: a PostgreSQL database and a CSV-based file store. PostgreSQL provides efficient querying and scalability for large-scale experiments, while the CSV backend offers a lightweight, portable option that requires no database deployment and can be easily used across different computing environments.

A.2.3 OpenReview

The detailed procedures used to collect and compile data from OpenReview are as follows.

Firstly, by providing a conference ID, we utilize the OpenReview API to retrieve the authors' IDs, titles, abstracts, decisions, PDF links, and unique submission IDs for each paper presented at the conference. Note that we do not collect the withdrawn papers. This step mainly contributes to the construction of the or_papers table and the or_papers_authors table.

Given the author IDs, the OpenReview API returns detailed author metadata, including full name, email domain, institutional affiliation, homepage URL, and DBLP entry. Note that, for some authors, the homepage and DBLP fields are missing from the metadata. These records constitute the authors table. Moreover, each author in OpenReview has a unique author ID, although they might have the same name.

The OpenReview API also provides access to official reviews and comments associated with each paper submission. For each review, we retrieve its ID, the ID of the review it responds to, and its timestamp. It is important to note that the official review, meta-review, and paper decision directly reply to the submission ID. The collected data is then used to form the or_reviews table and the or_papers_reviews table.

To construct the or_paragraphs table, we first download the PDF files and utilize pdfminer to extract the text from papers. The extracted text is then organized into paragraphs with unique paragraph_idx within each paper based on the distance between consecutive words.

For the or_revisions table and the or_papers_revisions table, we focus on the content of the revisions. Therefore, we begin by downloading the PDFs of all the revised papers and storing their content in the or_paragraphs table. Note that each revised paper also has a unique submission ID. Then, based on the timestamp of each revised submission, we identify pairs of original and revised papers and use difflib to extract the differences between the original and the revised texts. Finally, the locations of these differences are linked back to each paragraph.

Finally, to construct the or_revisions_reviews table, we assume that each revision is created as a result of discussions between the reviewers and the authors. And the specific discussions are identified if they occurred within the time period between the previous revision and the current revision. Thus, this table is constructed by leveraging the time information from the or_revisions table and or_reviews table.

Table 11: **Statistic overview of** openreview_arxiv **table on NeurIPS.** Note that no NeurIPS conference before 2021 is available on OpenReview.

Year	**2025**	**2024**	**2023**	**2022**	**2021**
#openreview_arxiv	2898	2303	1808	1430	1368

Table 12: **Statistic overview of** openreview_arxiv **table on ICML.** Note that no ICML conference before 2023 is available on OpenReview.

Year	**2025**	**2024**	**2023**
#openreview_arxiv	1828	1398	998

A.2.4 LLM-Generated Content

To facilitate more diverse tasks, we further preprocess the collected data using Llama-3.1-70B-Instruct (Grattafiori et al., 2024). Specifically, we classify the entities for each revision in the or_revisions table, and summarize the research question and method for each academic paper in the ar_papers table.

Revision Classification: We follow the previous work (Jourdan et al., 2025) to classify the revisions into 9 categories described in Table 14. And the specific prompt is listed in Table 15.

To validate whether the model is capable of classifying the revision, we test three state-of-the-art LLMs, Llama-3.1-70B-Instruct (Grattafiori et al., 2024), GPTOSS-120B (Agarwal et al., 2025), and GPT-4o-mini (Hurst et al., 2024) on the revision dataset Pararev from Jourdan et al. (2025). It contains 641 human-annotated examples. The evaluation results are shown in Table 18. Since Llama-3.1-70B achieves the best performance, we use it to classify the revision to the best of our knowledge.

Research Question and Method Summarization: Similarly, in order to facilitate tasks like scientific claim verification, document-level retrieval, and hypothesis synthesis, we preprocess the data by generating structured research questions and method descriptions for each paper. The specific prompts are shown in Table 16 and Table 17. These LLM-generated summaries provide a normalized, compact representation of a paper's core intent and technical approach, enabling more reliable cross-paper comparison, semantic indexing, and graph-based reasoning in downstream tasks. By transforming unstructured section text into standardized question–method pairs, we improve both the efficiency and interpretability of higher-level analytical modules built on top of ResearchArcade.

A.3 Evaluation Task Definitions

A.3.1 Citation Prediction

Step 1: The target entity t is an arxiv_paragraph_citation edge, representing a citation made by a source paragraph. The label $\mathbf{y}_t$ denotes the index of the ground-truth cited paper that the target paragraph should reference.

Step 2: The academic graph $\mathcal{G}_t$ corresponds to the full paper containing the target paragraph. It includes arxiv_section, arxiv_paragraph, arxiv_figure, and arxiv_table nodes. Paragraphs are sequentially linked. arxiv_section nodes provide the section title; arxiv_citation nodes represent external cited papers and are connected to citing paragraphs via arxiv_paragraph_citation edges.

A.3.2 Paragraph Generation

Step 1: The target entity t is an arxiv_paragraph node, with its textual content serving as the ground truth label $\mathbf{y}_t$.

Step 2: The academic graph $\mathcal{G}_t$ for this task includes the adjacent arxiv_paragraph nodes retrieved from the k-hop neighborhood (with k as a parameter), sequentially connected according to their

Table 13: **Statistic overview of** openreview_arxiv **table on EMNLP.** Note that only the EMNLP conference in 2023 is available on OpenReview.

Year	**2023**
#openreview_arxiv	1017

Table 14: **Category description of** category **column in** openreview_revisions **table.** It follows the category description in Jourdan et al. (2025).

Category	**Description**
Rewriting Light	Minor changes in word choice or phrasing.
Rewriting Medium	Complete rephrasing of sentences within the paragraph.
Rewriting Heavy	Significant rephrasing, affecting at least half of the paragraph.
Concision	Same idea, stated more briefly by removing unnecessary details.
Development	Same idea, expanded with additional details or definitions.
Content Addition	Modification of content through the addition of a new idea.
Content Substitution	Modification of content through the replacement of an idea or fact.
Content Deletion	Modification of content through the deletion of an idea.
Unusable	Issues due to document processing errors (e.g., segmentation problems, misaligned paragraphs, or footnotes mixed with the text).

order in the paper. Multi-modal nodes arxiv_figure and arxiv_table are also given, each linked to their corresponding paragraphs. arxiv_citation is added as external nodes connected to the citing paragraphs.

A.3.3 Revision Retrieval

Step 1: The target entity t in this task is an openreview_revision node, where the index list of the modified paragraphs in its attributes is the label $\mathbf{y}_t$ for this task.

Step 2: The academic graph $\mathcal{G}_t$ constructed in this task consists of two parts: First, the paragraphs from the original paper, with node type openreview_paragraph, are retrieved from the 2-hop neighborhood, according to the openreview_paper_revision and the openreview_paragraph table. These paragraphs are sequentially connected based on their order; Second, the reviews, with node type openreview_review, are also retrieved from the 2-hop neighborhood, according to the openreview_paper_revision and the openreview_papers_review table. They are connected based on their review_openreview_id and replyto_openreview_id attributes.

A.3.4 Revision Generation

Step 1: The target entity t in this task is a paragraph that has been revised. A revised paragraph is obtained based on the revision_openreview_id and the index list of the modified paragraphs for each openreview_revision node. The textual content of the revised paragraph is the label $\mathbf{y}_t$.

Step 2: To construct the academic graph $\mathcal{G}_t$ for this task, two types of nodes from t's neighborhood need to be retrieved: First, the corresponding paragraph from the original paper, with node type openreview_paragraph, is retrieved from the 2-hop neighborhood based on the corresponding openreview_revision node and the openreview_paragraph table; Second, the reviews, with node type openreview_review, are also retrieved from the 2-hop neighborhood based on the corresponding openreview_revision node, along with the openreview_paper_revision and the openreview_papers_review tables. These reviews are connected via their review_openreview_id and replyto_openreview_id attributes.

A.3.5 Acceptance Prediction

Step 1: Node or_paper is the target entity t in this task, and the paper's decision (Accept or Reject) is the label $\mathbf{y}_t$.

Role	Content
System	You are an experienced academic researcher. You will receive an original paragraph and its corresponding revised paragraph. Your task is to analyze the revision and determine its taxonomy. The revision can receive at most two taxonomies. The description of each taxonomy is as follows. [Rewriting Light]: Minor changes in word choice or phrasing. [Rewriting Medium]: Complete rephrasing of sentences within the paragraph. [Rewriting Heavy]: Significant rephrasing, affecting at least half of the paragraph. [Concision]: Same idea, stated more briefly by removing unnecessary details. [Development]: Same idea, expanded with additional details or definitions. [Content Addition]: Modification of content through the addition of a new idea. [Content Substitution]: Modification of content through the replacement of an idea or fact. [Content Deletion]: Modification of content through the deletion of an idea. [Unusable]: Issues due to document processing errors (e.g., segmentation problems, misaligned paragraphs, or footnotes mixed with the text). Please give concrete evidence while being concise. DO NOT repeat or summarize the revision's content or similarities; focus on their differences and YOUR ANALYSIS. Output [START]{{[Taxonomy]}}[END] or [START]{{[Taxonomy 1], [Taxonomy 2]}}[END]
User	<Original Paragraph>: {original_paragraph}, <Revised Paragraph>: {revised_paragraph}

Table 15: **Prompt for Revision Classification.**

Role	Content
User	Based on the following sections from a research paper, identify and summarize the main research question(s) or objective(s). Your summary should: - Be concise (2-4 sentences) - Clearly state what problem the paper addresses - Mention the key contributions or goals Do not include methodology details. Paper Sections: {section_text} Summary:

Table 16: **Prompt for Paper Research Question Generation.**

Step 2: The academic graph $\mathcal{G}_t$ is constructed using the data from ArXiv: First, relevant paragraphs, with node type arxiv_paragraph, are retrieved from the 2-hop neighborhood, according to the openreview_arxiv and the arxiv_paragraph tables, with sequential connections reflecting their order. Second, the related figures, with node type arxiv_figure, are retrieved through the arxiv_paragraph_figure table, with each figure connected to a specific paragraph. Finally, relevant tables, with node type arxiv_table, are retrieved via the arxiv_paragraph_table table.

A.3.6 Rebuttal Generation

Step 1: The author's rebuttal response (can be inferred from the openreview_review node's title), with node type openreview_review, is the target entity t in this task. The label $\mathbf{y}_t$ is the textual content of the response.

Step 2: The academic graph $\mathcal{G}_t$ is constructed as follows: Initially, the related official review, with node type openreview_review, is retrieved based on the replyto_openreview_id attribute of t. Then, the corresponding paper graph is retrieved from ArXiv data using the same procedure as in Section 4.2.5, which contains the relevant paragraphs with figures and tables.

A.4 Promising New Tasks

In this part, we list out and describe what tasks can be performed on ResearchArcade in each research stage.

Role	Content
User	Based on the following sections from a research paper, summarize the main methodology or approach used. Your summary should: - Be concise (3-5 sentences) - Describe the key techniques, algorithms, or frameworks - Mention any novel components or modifications - Briefly note the experimental setup if relevant Do not include research questions or results. Paper Sections: {section_text} Summary:

Table 17: **Prompt for Paper Method Description Generation.**

Table 18: **Evaluation results on Revision Classification.**

Model	Accuracy
Llama3.1-70B-Instruct	**0.541**
GPTOSS-120B	0.468
GPT-4o-mini	0.512

A.4.1 Idea Generation

Brainstorming research ideas based on existing works is an essential skill for any researcher. Enhancing the model's ability to support this task facilitates the idea brainstorming stage in the research pipeline. This generative task is defined as follows: given the input, an academic graph $\mathcal{G}_t$ containing the abstract of the papers that are being cited, generate the abstract of the citing paper $\hat{\mathbf{y}}_t$. The label $\mathbf{y}_t$ is the real abstract of the paper.

A.4.2 Experiment Planning

Planning an experiment to verify the effectiveness of the work is a necessary part of doing research. This generative task is defined as follows: given the input, an academic graph $\mathcal{G}_t$ consisting of paragraphs with figures and tables before the experiment section, generate the main experiment table text $\hat{\mathbf{y}}_t$. The real experiment table text is the label $\mathbf{y}_t$.

A.4.3 Abstract Writing

Writing a high-quality abstract is a challenging but meaningful task. This generative task is defined as follows: given the input, an academic graph $\mathcal{G}_t$ including all paragraphs with figures and tables from the paper, generate its abstract $\hat{\mathbf{y}}_t$. The label $\mathbf{y}_t$ is the real abstract.

A.4.4 Review Generation

Automatic generation of reviews can serve as a paper copilot, aiding the improvement of the manuscript. The task reflects the peer reviewing stage in the research pipeline. This generative task is defined as follows: given the input, an academic graph $\mathcal{G}_t$ containing paragraphs of the paper, generate its official review $\hat{\mathbf{y}}_t$. The real official review is the label $\mathbf{y}_t$.

A.5 Data Usage in Experiments

A.5.1 Citation Prediction

In this task, we use $1{,}267$ $\mathrm{ar\_paper}$ nodes containing $41{,}31$ sampled $\mathrm{ar\_citation}$ edges. Each paper also includes $\mathrm{ar\_section}$ nodes and $\mathrm{ar\_citation}$ edges. The $\mathrm{ar\_citation}$ edges are split into $33{,}048$ for training and 827 for testing.

Table 19: **LLM-as-a-judge Prompt for Rebuttal Generation.**

Role	Content
System	You are an experienced academic paper reviewer. You will receive a review of an academic paper in computer science, and two responses from the authors. (Response 1 & Response 2) Your task is to evaluate the responses and decide which response is better. The response may address the reviewer's several comments. You should compare the responses to each comment individually. When comparing the responses, you can refer to the following criteria: - 1. Does the author's response validate their work with clear arguments and coherent logic? - 2. Does the author provide sufficient evidence or reasoning to support their claims? - 3. Is the author's response consistent with the content of the original paper? Please give concrete evidence while being concise. DO NOT repeat or summarize the responses' content or similarities; focus on their differences and YOUR ANALYSIS. Output [START]{{I think Response X (1 or 2) is better}}[END] or [START]{{I think Response 1 and Response 2 are similar in quality}}[END]

User	[Review]: {official_review}
	[Response 1]: {target}
	[Response 2]: {predic}

A.5.2 Paragraph Generation

In this task, we use 1,200 ar_paragraph nodes together with their connected ar_figure, ar_table, ar_citation nodes and edges, and adjacent ar_paragraph nodes.

A.5.3 Revision Retrieval

The set of target entities for this task comprises 5,000 or_revision nodes from ICLR 2025, split into 4,000 for training and 1,000 for testing.

A.5.4 Revision Generation

Using 5,000 or_revision nodes from ICLR 2025—split 4,000/1,000 into train/test—yields 27,892 and 8,821 revised paragraphs, with node type or_paragraph for training and testing, respectively.

A.5.5 Acceptance Prediction

In this task, the test set comprises 300 or_paper nodes from ICLR 2025 that are linked to an ar_paper via the or_ArXiv table. The training set contains 1,200 nodes—300 each from ICLR 2021–2024—selected under the same linkage criterion.

A.5.6 Rebuttal Generation

We select 3,077 and 2,898 or_paper nodes and their corresponding official reviews and author rebuttals from ICLR 2025 and NeurIPS 2025, respectively, each or_paper node is connected to an ar_paper node via the openreview_arxiv table. For the training and test sets, we split them into 2,779/298 and 2,680/290 papers.

A.6 Prompt Usage

A.6.1 LLM-as-a-judge

The prompt for LLM-as-a-judge in rebuttal generation is in Table 19.

The prompt for LLM-as-a-judge in revision generation is in Table 20.

The prompt for LLM-as-a-judge in paragraph generation is in Table 21.

A.6.2 Paragraph Generation

The prompt used for the GWM-based models in the paragraph generation task is in Table 22. Specifically, {title}, {abstract}, {title}, {section name}, {figure labels and captions}, {citation bib}, {title} are text-based tokens, where {paper_graph} is the embedding-based tokens that are processed by multi-hop aggregation.

Table 20: **LLM-as-a-judge Prompt for Revision Generation.**

Role	Content
System	You are an experienced academic peer reviewer. You will receive reviews of an academic paper in computer science, a paragraph in the original paper, and two revised paragraphs of the original paragraph. (Revision 1 & Revision 2) Your task is to evaluate the revisions and decide which revision is better. The revision may address the reviewer's several comments. You should compare the two revisions to each comment individually. When comparing the revisions, you can refer to the following criteria: - 1. Does the author's revision solve the problem stated in the reviews? - 2. Does the author's revision validate their work with clear arguments and coherent logic? - 3. Is the author's revision consistent with the content of the original paper? Please give concrete evidence while being concise. DO NOT repeat or summarize the responses' content or similarities; focus on their differences and YOUR ANALYSIS. Output [START]{{I think Revision X (1 or 2) is better}}[END] or [START]{{I think Revision 1 and Revision 2 are similar in quality}}[END]

User	[Reviews]: {reviews}
	[Original Paragraph]: {original_paragraph}
	[Revision 1]: {target}
	[Revision 2]: {predic}

Table 21: **LLM-as-a-judge Prompt for Paragraph Generation.**

Role	Content
System	You are an experienced academic peer reviewer. You will receive: (1) the surrounding context of an academic paper, (2) the ground-truth paragraph that was originally masked out, and (3) four model-generated regenerated paragraphs (Revision 1, Revision 2, Revision 3, Revision 4). Your task is to evaluate the four regenerated paragraphs and decide which one is the best reconstruction of the masked paragraph. You should compare the revisions against the ground-truth paragraph and the surrounding paper context. When comparing the revisions, use the following criteria: - 1. Fidelity: How accurately does the revision preserve the meaning, technical content, and intent of the ground-truth paragraph? - 2. Coherence: How well does the revision fit logically and stylistically with the surrounding paper context? - 3. Clarity: How clear, precise, and academically appropriate is the writing? - 4. Completeness: Does the revision capture all key points without adding unsupported information? Provide concrete evidence while being concise. DO NOT repeat or summarize the revision contents; focus only on their differences and YOUR ANALYSIS. Output format (strict): [START]{I think Revision X (1, 2, 3, or 4) is better}[END] or [START]{I think the revisions are similar in quality}[END]

User	Paper Context:
	{context}
	Ground-Truth Paragraph:
	{ground_truth}
	Revision 1 (hop0):
	{generated_paragraph[0]}
	Revision 2 (hop1):
	{generated_paragraph[1]}
	Revision 3 (hop3):
	{generated_paragraph[2]}
	Revision 4 (hop5):
	{generated_paragraph[3]}
	Please evaluate which revision best reconstructs the ground-truth paragraph.

A.6.3 Revision Retrieval

The prompt used for the GWM-based models in the revision retrieval task is in Table 23. Specifically, {review_graph} is an embedding-based token that is processed by multi-hop aggregation.

A.6.4 Revision Generation

The prompt used to let LLM summarize the review is in Table 24. Specifically, {review} is the text-based content of a single review.

The following prompt used in the rebuttal generation task is in Table 25. Specifically, {review_graph} is the text-based token that sequentially connects the reviews. (e.g., Official Review by Reviewer, ...; Response by Authors: ...)

A.6.5 Acceptance Prediction

The prompt used for the GWM-based models in the acceptance prediction task is in Table 26. Specifically, {paper_graph} is an embedding-based token that is processed by multi-hop aggregation.

Table 22: **Prompt for Paragraph Generation.**

Role	Content

User	{paper_graph} You are reconstructing one missing LaTeX paragraph in a research paper.
	Title: {title}
	Abstract: {abstract}
	Section: {section name}
	Figure (optional): {figure labels and captions}
	Table (optional): {table labels and captions}
	Citation (optional): {citation bib}
	Generate the missing paragraph between the next paragraphs and previous paragraphs in the embedding space; feel free to use the given figure, table and citation information.

Table 23: **Prompt for Revision Retrieval.**

Role	Content
User	{review_graph}. Analyze the rebuttal process between the reviewer and the authors to identify information suggesting necessary modifications to the paper.

A.6.6 Rebuttal Generation

The prompt used in the rebuttal generation task is in Table 27. Specifically, {paper_graph} are text-based tokens that sequentially link paragraphs, while figures and tables explicitly denote their connections to the paragraphs (e.g., Paragraph 1: {paragraph content}, Figure: {figure description}, Table: {table text}; Paragraph 2: ...).

A.6.7 Ablation Study on Review Information

The prompt used in the ablation study on review information is in Table 28.

A.7 Experiment Results Analysis

A.7.1 Citation Prediction

In this subsection, we present the evaluation results for citation prediction.

Baselines. We compare embedding-based models with GNN-based models using 1-, 3-, and 5-hop neighborhood aggregation.

Experimental Results. Table 3 reveals two key findings: (1) incorporating adjacent neighborhoods provides sufficient contextual information and substantially improves prediction accuracy; and (2) expanding the receptive field to larger neighborhoods yields additional performance gains, although these improvements stop when increasing from 3-hop to 5-hop neighborhoods. This trend is likely due to the sparsity of the paper graph and the incomplete coverage of citation, figure, and table information during data processing, which limits the benefits of incorporating more distant nodes.

A.7.2 Paragraph Generation

In this subsection, we present the evaluation results for generating missing paragraphs.

Ablation Study We conducted two types of ablation studies for this task. The first evaluates multi-hop paragraph generation by varying the amount of neighborhood information provided across different hops. The second test involved multi-modal inputs using four conditions: both figures and tables, figures only, tables only, and neither component.

Experiment Results Table 3 reveals two main findings for neighborhood information: (1) models achieve their best performance when given the most comprehensive neighborhood context, and (2) removing neighborhood information leads to substantial performance degradation.

Table 24: **Prompt for Review Summarization.**

Role	Content
User	REVIEW: {review} INSTRUCTIONS: - Summarize the following review into fewer than 150 words. - Output only the summarization, enclosed between [START] and [END], without any extra explanation or analysis. OUTPUT: [START]{{your summarization here}}[END]

Table 25: **Prompt for Revision Generation.**

Role	Content
User	REVIEW: {review_graph} ORIGINAL PARAGRAPH: {original_paragraph} INSTRUCTIONS: - Please revise the paragraph according to the provided reviews. - Output only the revised paragraph, enclosed between [START] and [END], without any extra explanation or analysis. REVISED PARAGRAPH: [START]{{your revised paragraph here}}[END]

For multi-modal information, the results show that (1) complete multi-modal input (both figures and tables) yields the strongest performance, and (2) partial multi-modal input offers no clear benefit over omitting multi-modal data entirely.

Human analysis further indicates that paragraphs generated with larger-hop neighborhoods tend to contain more specific details (e.g., correctly named methods, datasets, and figure/table references) and exhibit smoother connections to adjacent paragraphs. This makes the generated text better integrated into the full paper rather than resembling a stand-alone summary. At 5 hops, however, the text often becomes more verbose and less focused, with repeated points, additional concepts, and overly detailed explanations, so although it is richer than 0- or 1-hop outputs, it also exhibits more topical drift and redundancy.

GPT-4o-mini, used as an LLM-as-a-judge, shows a clear preference for models with richer graph context: its scores increase from 0-hop (0.009) to 1-hop (0.244) and 3-hop (0.404), indicating that multi-hop information yields outputs it rates as higher quality. However, the score decreases at 5-hop (0.344), suggesting that expanding the neighborhood beyond 3 hops does not provide additional gains in judged quality and may slightly reduce it.

A.7.3 REVISION RETRIEVAL

Baselines. Embedding-based, GNN-based, and GWM-based models are selected as our baselines. Specifically, we consider 1-hop and 3-hop aggregation for GNN-based and GWM-based models.

Experimental Results. From Table 3 we can observe that: (1) Models optimized with InfoNCE (GNN-/GWM-based) outperform the untrained embedding baseline, confirming the effectiveness of our training and the quality of RESEARCHARCADE. (2) Graph-aware models consistently exceed non-graph baselines (EMB-based), indicating that relational structure provides a valuable signal for the task. (3) Increasing the message-passing radius yields little to no additional gain; we attribute this to the sparsity and near-sequential topology of review-centered graphs for most samples, which limits the benefits of multi-hop aggregation and may introduce noise or over-smoothing.

A.7.4 REVISION GENERATION

Baselines. For the generative task, we use LLM-based models as baselines. Qwen3-8B and GPTOSS-120B are evaluated in a zero-shot setting, while Qwen3-0.6B is evaluated under both zero-shot and supervised fine-tuning (SFT) settings.

Table 26: **Prompt for Acceptance Prediction.**

Role	Content
User	{paper_graph}. Analyze whether this academic paper is suitable for acceptance at the ICLR conference.

Table 27: **Prompt for Rebuttal Generation.**

Role	Content
User	REFERENCES: {paper_graph} QUESTIONS: {official_review} INSTRUCTIONS: - You are the author responding to the reviewer's comments during the rebuttal process. - Generate the author's response based on the provided references from the paper (include paragraphs, figures, and tables). - Provide ONLY the final response enclosed between [START] and [END], without any additional explanation or analysis. Generated Rebuttal: [START]{{author's response here}}[END]

Experimental Results. The results are displayed in Table 3, with the following observations: (1) There are substantial performance gaps between zero-shot Qwen3-0.6B and Qwen3-8B or GPTOSS-120B, which are reasonable in view of their different sizes of parameters. Human analysis indicates that larger models provide more relevant technical details based on their own knowledge than smaller models, thereby achieving higher performance. (2) After supervised fine-tuning Qwen3-0.6B, its performance is significantly enhanced, approaching the zero-shot performance of Qwen3-8B and GPTOSS-120B, highlighting the effectiveness of RESEARCHARCADE in facilitating LLMs' understanding of the dynamic evolution within a paper. (3) The GPTOSS-120B and Qwen3-8B obtain significantly high LLM-as-a-judge scores (Eq. 6). Human analysis of the examples suggests that compared with ground truth revisions, the LLM-generated revisions only make superficial changes to the original paragraphs. And GPT-4o-mini prefers the revised paragraphs that are similar to the original paragraphs. However, authors typically make more substantial edits to improve the paragraph, such as strengthening the logic by changing the narrative sequence or emphasizing the viewpoint by adding new information.

A.7.5 ACCEPTANCE PREDICTION

Baselines. MLP-based, GNN-based, and GWM-based models are adopted as the baselines for this binary classification task. Here, 1-hop and 3-hop aggregation are considered for GNN-based and GWM-based models.

Experimental Results. As shown in Table 3, the results yield the following findings: (1) The best baseline achieves only 0.550 accuracy, highlighting the challenge of predicting paper acceptance. (2) Graph-based models (GNN-based, GWM-based) outperform the non-graph-based model (MLP-based), which suggests that containing graph-structured data improves models' performance. This also confirms the validity of the highly relational and heterogeneous feature of RESEARCHARCADE. (3) The GNN-based model and GWM-based model with multi-hop aggregation achieve performance gain, indicating that multi-hop message passing further enhances the utilization of the graph-structured data.

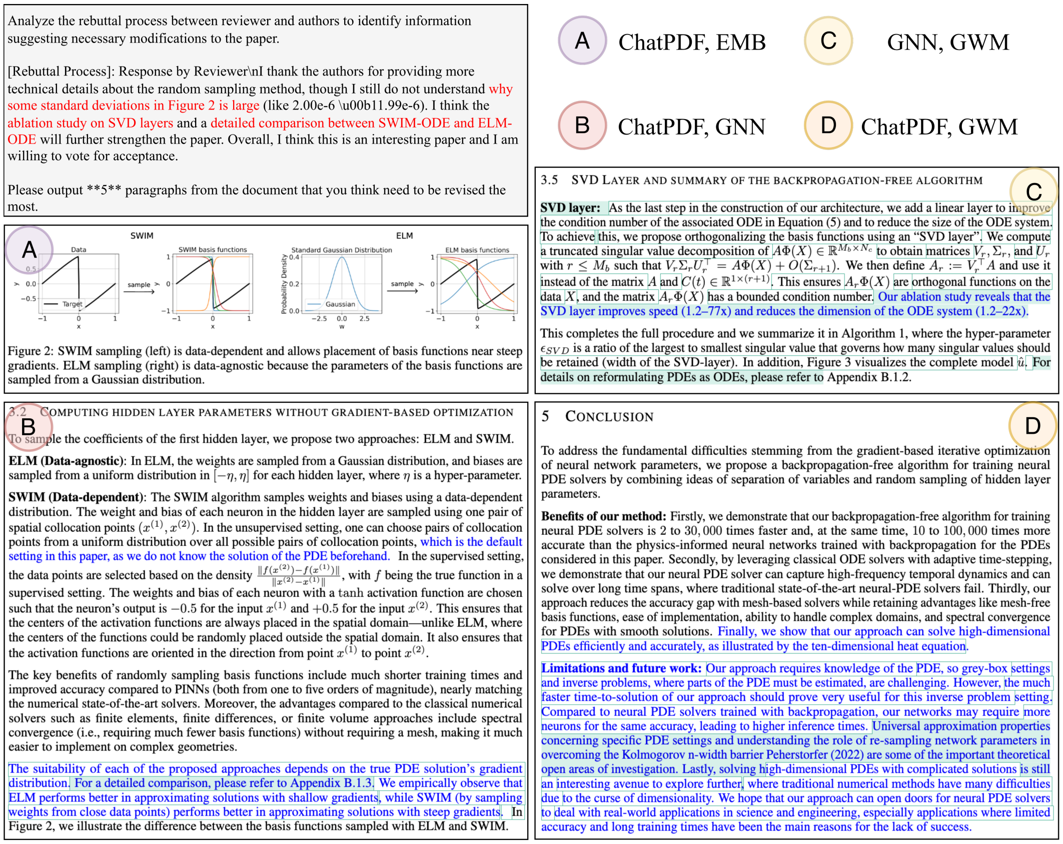
A.7.6 REBUTTAL GENERATION

Baselines. In the generative setting, LLM-based models are adopted as our baselines. Specifically, Qwen3-8B and GPTOSS-120B are assessed under a zero-shot manner, whereas Qwen3-0.6B is evaluated in both zero-shot and supervised fine-tuning (SFT) manners.

Experimental Results. The results in Table 3 reveal the following insights: (1) There exists substantial performance gaps between Qwen3-0.6B and Qwen3-8B or GPTOSS-120B in the zero-shot setting, which meets our expectations given their different parameter sizes. (2) After supervised fine-tuning, the Qwen3-0.6B shows enhanced performance, underscoring the efficacy of RESEARCHARCADE. (3) GPTOSS-120B achieves a significantly higher LLM-as-a-judge scores (Eq. 6) than other

Table 28: **Prompt for Revision Retrieval Ablation Study.**

Role	Content
User	Please revise the paper for better quality.



Analyze the rebuttal process between reviewer and authors to identify information suggesting necessary modifications to the paper.

[Rebuttal Process]: Response by Reviewer\nI thank the authors for providing more technical details about the random sampling method, though I still do not understand why some standard deviations in Figure 2 is large (like 2.00e-6 \u00b11.99e-6). I think the ablation study on SVD layers and a detailed comparison between SWIM-ODE and ELM-ODE will further strengthen the paper. Overall, I think this is an interesting paper and I am willing to vote for acceptance.

Please output **5** paragraphs from the document that you think need to be revised the most.

Figure 2: SWIM sampling (left) is data-dependent and allows placement of basis functions near steep gradients. ELM sampling (right) is data-agnostic because the parameters of the basis functions are sampled from a Gaussian distribution.

3.2 COMPUTING HIDDEN LAYER PARAMETERS WITHOUT GRADIENT-BASED OPTIMIZATION

To sample the coefficients of the first hidden layer, we propose two approaches: ELM and SWIM.

ELM (Data-agnostic): In ELM, the weights are sampled from a Gaussian distribution, and biases are sampled from a uniform distribution in $[-\eta, \eta]$ for each hidden layer, where η is a hyper-parameter.

SWIM (Data-dependent): The SWIM algorithm samples weights and biases using a data-dependent distribution. The weight and bias of each neuron in the hidden layer are sampled using one pair of spatial collocation points $(x^{(1)}, x^{(2)})$. In the unsupervised setting, one can choose pairs of collocation points from a uniform distribution over all possible pairs of collocation points, which is the default setting in this paper, as we do not know the solution of the PDE beforehand. In the supervised setting, the data points are selected based on the density $\frac{\|f(x^{(2)})-f(x^{(1)})\|}{\|x^{(2)}-x^{(1)}\|}$, with f being the true function in a supervised setting. The weights and bias of each neuron with a $\tanh$ activation function are chosen such that the neuron's output is -0.5 for the input $x^{(1)}$ and $+0.5$ for the input $x^{(2)}$. This ensures that the centers of the activation functions are always placed in the spatial domain—unlike ELM, where the centers of the functions could be randomly placed outside the spatial domain. It also ensures that the activation functions are oriented in the direction from point $x^{(1)}$ to point $x^{(2)}$.

The key benefits of randomly sampling basis functions include much shorter training times and improved accuracy compared to PINNs (both from one to five orders of magnitude), nearly matching the numerical state-of-the-art solvers. Moreover, the advantages compared to the classical numerical solvers such as finite elements, finite differences, or finite volume approaches include spectral convergence (i.e., requiring much fewer basis functions) without requiring a mesh, making it much easier to implement on complex geometries.

The suitability of each of the proposed approaches depends on the true PDE solution's gradient distribution. For a detailed comparison, please refer to Appendix B.1.3. We empirically observe that ELM performs better in approximating solutions with shallow gradients, while SWIM (by sampling weights from close data points) performs better in approximating solutions with steep gradients. In Figure 2, we illustrate the difference between the basis functions sampled with ELM and SWIM.

3.5 SVD LAYER AND SUMMARY OF THE BACKPROPAGATION-FREE ALGORITHM

SVD layer: As the last step in the construction of our architecture, we add a linear layer to improve the condition number of the associated ODE in Equation (5) and to reduce the size of the ODE system. To achieve this, we propose orthogonalizing the basis functions using an "SVD layer". We compute a truncated singular value decomposition of $A\Phi(X) \in \mathbb{R}^{M_b \times N_c}$ to obtain matrices $V_r, \Sigma_r,$ and U_r with $r \leq M_b$ such that $V_r \Sigma_r U_r^\top = A\Phi(X) + O(\Sigma_{r+1})$. We then define $A_r := V_r^\top A$ and use it instead of the matrix A and $C(t) \in \mathbb{R}^{1\times(r+1)}$. This ensures $A_r\Phi(X)$ are orthogonal functions on the data X, and the matrix $A_r\Phi(X)$ has a bounded condition number. Our ablation study reveals that the SVD layer improves speed (1.2–77x) and reduces the dimension of the ODE system (1.2–22x).

This completes the full procedure and we summarize it in Algorithm 1, where the hyper-parameter ϵ_{SVD} is a ratio of the largest to smallest singular value that governs how many singular values should be retained (width of the SVD-layer). In addition, Figure 3 visualizes the complete model $\hat{u}$. For details on reformulating PDEs as ODEs, please refer to Appendix B.1.2.

5 CONCLUSION

To address the fundamental difficulties stemming from the gradient-based iterative optimization of neural network parameters, we propose a backpropagation-free algorithm for training neural PDE solvers by combining ideas of separation of variables and random sampling of hidden layer parameters.

Benefits of our method: Firstly, we demonstrate that our backpropagation-free algorithm for training neural PDE solvers is 2 to $30,000$ times faster and, at the same time, 10 to $100,000$ times more accurate than the physics-informed neural networks trained with backpropagation for the PDEs considered in this paper. Secondly, by leveraging classical ODE solvers with adaptive time-stepping, we demonstrate that our neural PDE solver can capture high-frequency temporal dynamics and can solve over long time spans, where traditional state-of-the-art neural-PDE solvers fail. Thirdly, our approach reduces the accuracy gap with mesh-based solvers while retaining advantages like mesh-free basis functions, ease of implementation, ability to handle complex domains, and spectral convergence for PDEs with smooth solutions. Finally, we show that our approach can solve high-dimensional PDEs efficiently and accurately, as illustrated by the ten-dimensional heat equation.

Limitations and future work: Our approach requires knowledge of the PDE, so grey-box settings and inverse problems, where parts of the PDE must be estimated, are challenging. However, the much faster time-to-solution of our approach should prove very useful for this inverse problem setting. Compared to neural PDE solvers trained with backpropagation, our networks may require more neurons for the same accuracy, leading to higher inference times. Universal approximation properties concerning specific PDE settings and understanding the role of re-sampling network parameters in overcoming the Kolmogorov n-width barrier Peherstorfer (2022) are some of the important theoretical open areas of investigation. Lastly, solving high-dimensional PDEs with complicated solutions is still an interesting avenue to explore further, where traditional numerical methods have many difficulties due to the curse of dimensionality. We hope that our approach can open doors for neural PDE solvers to deal with real-world applications in science and engineering, especially applications where limited accuracy and long training times have been the main reasons for the lack of success.

Figure 4: **Case Study on Revision Retrieval.**

baselines. According to human analysis of the examples, GPTOSS-120B tends to directly incorporate generated technical details and experimental results into its response, different from real authors, who usually refer reviewers back to specific portions of the paper. While other LLMs often generate shorter responses that only point to parts of the paper without further explanation, resulting in worse performance.

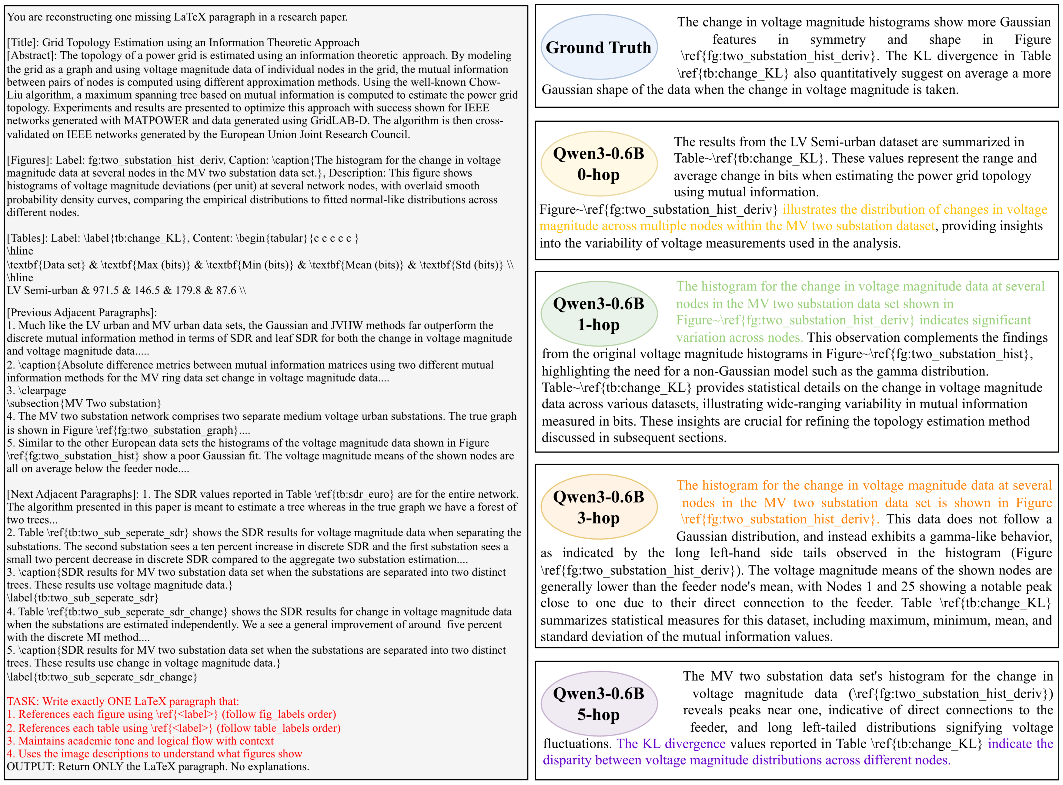
A.8 CASE STUDY

We conduct several case studies across various models, including EMB-based, GNN-based, LLM-based, GWM-based models, and ChatPDF, a powerful AI-powered app proficient in comprehending PDFs.

A.8.1 REVISION RETRIEVAL

In this section, we compare EMB-based, GNN-based, and GWM-based models on RESEARCHARCADE with ChatPDF for the Revision Retrieval task. The examples are shown in Figure 4.

In Figure 4, the comments from the reviewer focus on three aspects: (1) Standard deviations in Figure 2; (2) Ablation Study on SVD layers; (3) Comparison between SWIM-ODE and ELM-ODE. These correspond to four components in the paper: A. Figure 2; B. Section 3.2 (including



```
You are reconstructing one missing LaTeX paragraph in a research paper.

[Title]: Grid Topology Estimation using an Information Theoretic Approach
[Abstract]: The topology of a power grid is estimated using an information theoretic approach. By modeling the grid as a graph and using voltage magnitude data of individual nodes in the grid, the mutual information between pairs of nodes is computed using different approximation methods. Using the well-known Chow-Liu algorithm, a maximum spanning tree based on mutual information is computed to estimate the power grid topology. Experiments and results are presented to optimize this approach with success shown for IEEE networks generated with MATPOWER and data generated using GridLAB-D. The algorithm is then cross-validated on IEEE networks generated by the European Union Joint Research Council.

[Figures]: Label: fg:two_substation_hist_deriv, Caption: \caption{The histogram for the change in voltage magnitude data at several nodes in the MV two substation data set.}, Description: This figure shows histograms of voltage magnitude deviations (per unit) at several network nodes, with overlaid smooth probability density curves, comparing the empirical distributions to fitted normal-like distributions across different nodes.

[Tables]: Label: \label{tb:change_KL}, Content: \begin{tabular}{c c c c c }
\hline
\textbf{Data set} & \textbf{Max (bits)} & \textbf{Min (bits)} & \textbf{Mean (bits)} & \textbf{Std (bits)} \\
\hline
LV Semi-urban & 971.5 & 146.5 & 179.8 & 87.6 \\

[Previous Adjacent Paragraphs]:
1. Much like the LV urban and MV urban data sets, the Gaussian and JVHW methods far outperform the discrete mutual information method in terms of SDR and leaf SDR for both the change in voltage magnitude and voltage magnitude data.....
2. \caption{Absolute difference metrics between mutual information matrices using two different mutual information methods for the MV ring data set change in voltage magnitude data....
3. \clearpage
\subsection{MV Two substation}
4. The MV two substation network comprises two separate medium voltage urban substations. The true graph is shown in Figure \ref{fg:two_substation_graph}....
5. Similar to the other European data sets the histograms of the voltage magnitude data shown in Figure \ref{fg:two_substation_hist} show a poor Gaussian fit. The voltage magnitude means of the shown nodes are all on average below the feeder node....

[Next Adjacent Paragraphs]: 1. The SDR values reported in Table \ref{tb:sdr_euro} are for the entire network. The algorithm presented in this paper is meant to estimate a tree whereas in the true graph we have a forest of two trees...
2. Table \ref{tb:two_sub_seperate_sdr} shows the SDR results for voltage magnitude data when separating the substations. The second substation sees a ten percent increase in discrete SDR and the first substation sees a small two percent decrease in discrete SDR compared to the aggregate two substation estimation....
3. \caption{SDR results for MV two substation data set when the substations are separated into two distinct trees. These results use voltage magnitude data.}
\label{tb:two_sub_seperate_sdr}
4. Table \ref{tb:two_sub_seperate_sdr_change} shows the SDR results for change in voltage magnitude data when the substations are estimated independently. We a see a general improvement of around  five percent with the discrete MI method....
5. \caption{SDR results for MV two substation data set when the substations are separated into two distinct trees. These results use change in voltage magnitude data.}
\label{tb:two_sub_seperate_sdr_change}

TASK: Write exactly ONE LaTeX paragraph that:
1. References each figure using \ref{<label>} (follow fig_labels order)
2. References each table using \ref{<label>} (follow table_labels order)
3. Maintains academic tone and logical flow with context
4. Uses the image descriptions to understand what figures show
OUTPUT: Return ONLY the LaTeX paragraph. No explanations.
```

Ground Truth

The change in voltage magnitude histograms show more Gaussian features in symmetry and shape in Figure \ref{fg:two_substation_hist_deriv}. The KL divergence in Table \ref{tb:change_KL} also quantitatively suggest on average a more Gaussian shape of the data when the change in voltage magnitude is taken.

Qwen3-0.6B 0-hop

The results from the LV Semi-urban dataset are summarized in Table~\ref{tb:change_KL}. These values represent the range and average change in bits when estimating the power grid topology using mutual information.
Figure~\ref{fg:two_substation_hist_deriv} illustrates the distribution of changes in voltage magnitude across multiple nodes within the MV two substation dataset, providing insights into the variability of voltage measurements used in the analysis.

Qwen3-0.6B 1-hop

The histogram for the change in voltage magnitude data at several nodes in the MV two substation data set shown in Figure~\ref{fg:two_substation_hist_deriv} indicates significant variation across nodes. This observation complements the findings from the original voltage magnitude histograms in Figure~\ref{fg:two_substation_hist}, highlighting the need for a non-Gaussian model such as the gamma distribution. Table~\ref{tb:change_KL} provides statistical details on the change in voltage magnitude data across various datasets, illustrating wide-ranging variability in mutual information measured in bits. These insights are crucial for refining the topology estimation method discussed in subsequent sections.

Qwen3-0.6B 3-hop

The histogram for the change in voltage magnitude data at several nodes in the MV two substation data set is shown in Figure \ref{fg:two_substation_hist_deriv}. This data does not follow a Gaussian distribution, and instead exhibits a gamma-like behavior, as indicated by the long left-hand side tails observed in the histogram (Figure \ref{fg:two_substation_hist_deriv}). The voltage magnitude means of the shown nodes are generally lower than the feeder node's mean, with Nodes 1 and 25 showing a notable peak close to one due to their direct connection to the feeder. Table \ref{tb:change_KL} summarizes statistical measures for this dataset, including maximum, minimum, mean, and standard deviation of the mutual information values.

Qwen3-0.6B 5-hop

The MV two substation data set's histogram for the change in voltage magnitude data (\ref{fg:two_substation_hist_deriv}) reveals peaks near one, indicative of direct connections to the feeder, and long left-tailed distributions signifying voltage fluctuations. The KL divergence values reported in Table \ref{tb:change_KL} indicate the disparity between voltage magnitude distributions across different nodes.

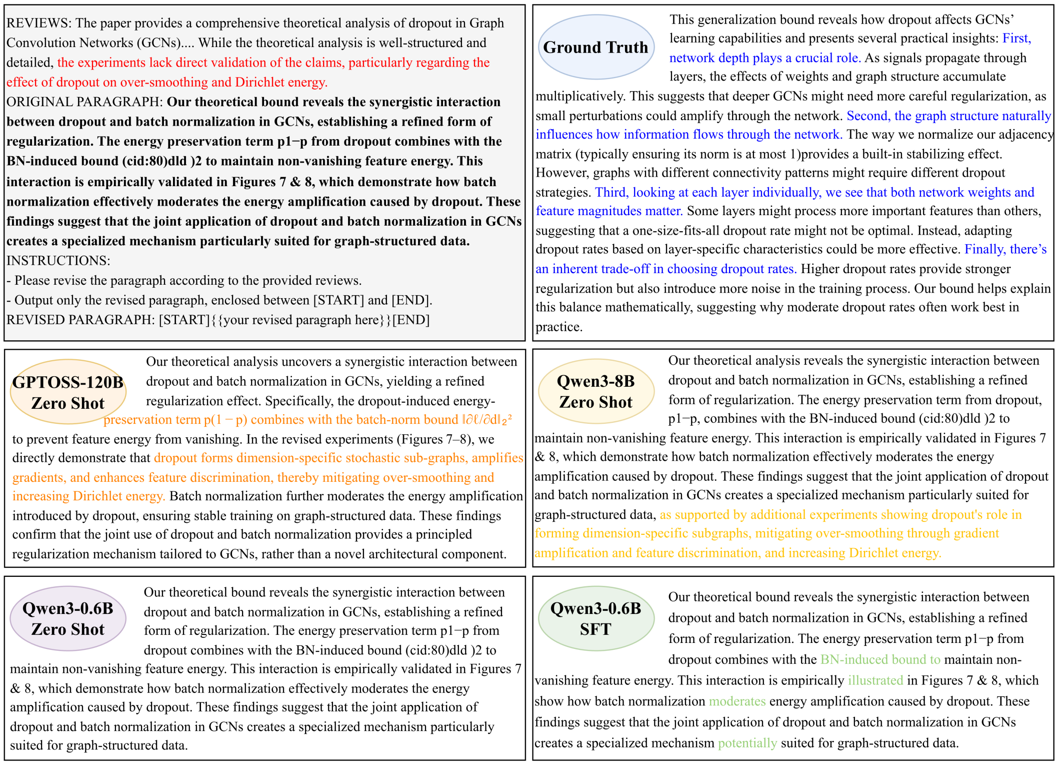
Figure 5: **Case Study on Paragraph Generation.**

the discussion on SWIM-ODE and ELM-ODE); C. Section 3.5 (including the discussion of the SVD-layers); D. Conclusion. The actual post-review revisions made by the authors are highlighted in light green (Note that the blue text is the overall revisions compared to the initial submission). Among them, although Figure 2 is explicitly mentioned by the reviewer, it remains unchanged. Most revisions, especially in Sections 3.2 and 3.5, add content directly addressing comments (2) and (3).

Examining the performance of different models, ChatPDF achieves the best results by correctly identifying three relevant components, demonstrating its superior ability to comprehend PDF files. The EMB-based model identifies only one relevant component, suggesting that it struggles with the mixed semantic information in the reviewer comments. For the GNN-based and GWM-based models, they exploit the graph structure within the paper and the rich semantic information at the embedding level to locate the two relevant components. Overall, while ChatPDF, as a state-of-the-art tool-augmented system, shows the strongest ability to understand PDF files, the graph modeling in RESEARCHARCADE is also valuable, as the graph-based models (GNN-based, GWM-based) outperform the non-graph-based model (EMB-based).

A.8.2 PARAGRAPH GENERATION

The case study is shown in Figure 5. We analyze the generated paragraphs across different hop settings and observe a clear progression in how structural and semantic context is incorporated. The 0-hop answer primarily restates generic dataset-level information and provides weak grounding to the target figure and table, indicating limited contextual awareness. With 1-hop, the model begins to align the histogram in the figure with surrounding voltage magnitude discussions and introduces more meaningful connections to the KL statistics in the table, but still relies on high-level descriptions. The 3-hop setting demonstrates a substantial qualitative improvement: it correctly characterizes the non-Gaussian, gamma-like behavior of the distributions, links node-level behavior to feeder proximity, and integrates figure–table semantics in a logically coherent manner. At



REVIEWS: The paper provides a comprehensive theoretical analysis of dropout in Graph Convolution Networks (GCNs).... While the theoretical analysis is well-structured and detailed, the experiments lack direct validation of the claims, particularly regarding the effect of dropout on over-smoothing and Dirichlet energy.
ORIGINAL PARAGRAPH: **Our theoretical bound reveals the synergistic interaction between dropout and batch normalization in GCNs, establishing a refined form of regularization. The energy preservation term p1−p from dropout combines with the BN-induced bound (cid:80)dld)2 to maintain non-vanishing feature energy. This interaction is empirically validated in Figures 7 & 8, which demonstrate how batch normalization effectively moderates the energy amplification caused by dropout. These findings suggest that the joint application of dropout and batch normalization in GCNs creates a specialized mechanism particularly suited for graph-structured data.**
INSTRUCTIONS:
- Please revise the paragraph according to the provided reviews.
- Output only the revised paragraph, enclosed between [START] and [END].
REVISED PARAGRAPH: [START]{{your revised paragraph here}}[END]

Ground Truth

This generalization bound reveals how dropout affects GCNs' learning capabilities and presents several practical insights: First, network depth plays a crucial role. As signals propagate through layers, the effects of weights and graph structure accumulate multiplicatively. This suggests that deeper GCNs might need more careful regularization, as small perturbations could amplify through the network. Second, the graph structure naturally influences how information flows through the network. The way we normalize our adjacency matrix (typically ensuring its norm is at most 1)provides a built-in stabilizing effect. However, graphs with different connectivity patterns might require different dropout strategies. Third, looking at each layer individually, we see that both network weights and feature magnitudes matter. Some layers might process more important features than others, suggesting that a one-size-fits-all dropout rate might not be optimal. Instead, adapting dropout rates based on layer-specific characteristics could be more effective. Finally, there's an inherent trade-off in choosing dropout rates. Higher dropout rates provide stronger regularization but also introduce more noise in the training process. Our bound helps explain this balance mathematically, suggesting why moderate dropout rates often work best in practice.

GPTOSS-120B Zero Shot

Our theoretical analysis uncovers a synergistic interaction between dropout and batch normalization in GCNs, yielding a refined regularization effect. Specifically, the dropout-induced energy-preservation term p(1 − p) combines with the batch-norm bound $\|\partial\ell/\partial d\|_2{}^2$ to prevent feature energy from vanishing. In the revised experiments (Figures 7–8), we directly demonstrate that dropout forms dimension-specific stochastic sub-graphs, amplifies gradients, and enhances feature discrimination, thereby mitigating over-smoothing and increasing Dirichlet energy. Batch normalization further moderates the energy amplification introduced by dropout, ensuring stable training on graph-structured data. These findings confirm that the joint use of dropout and batch normalization provides a principled regularization mechanism tailored to GCNs, rather than a novel architectural component.

Qwen3-8B Zero Shot

Our theoretical analysis reveals the synergistic interaction between dropout and batch normalization in GCNs, establishing a refined form of regularization. The energy preservation term from dropout, p1−p, combines with the BN-induced bound (cid:80)dld)2 to maintain non-vanishing feature energy. This interaction is empirically validated in Figures 7 & 8, which demonstrate how batch normalization effectively moderates the energy amplification caused by dropout. These findings suggest that the joint application of dropout and batch normalization in GCNs creates a specialized mechanism particularly suited for graph-structured data, as supported by additional experiments showing dropout's role in forming dimension-specific subgraphs, mitigating over-smoothing through gradient amplification and feature discrimination, and increasing Dirichlet energy.

Qwen3-0.6B Zero Shot

Our theoretical bound reveals the synergistic interaction between dropout and batch normalization in GCNs, establishing a refined form of regularization. The energy preservation term p1−p from dropout combines with the BN-induced bound (cid:80)dld)2 to maintain non-vanishing feature energy. This interaction is empirically validated in Figures 7 & 8, which demonstrate how batch normalization effectively moderates the energy amplification caused by dropout. These findings suggest that the joint application of dropout and batch normalization in GCNs creates a specialized mechanism particularly suited for graph-structured data.

Qwen3-0.6B SFT

Our theoretical bound reveals the synergistic interaction between dropout and batch normalization in GCNs, establishing a refined form of regularization. The energy preservation term p1−p from dropout combines with the BN-induced bound to maintain non-vanishing feature energy. This interaction is empirically illustrated in Figures 7 & 8, which show how batch normalization moderates energy amplification caused by dropout. These findings suggest that the joint application of dropout and batch normalization in GCNs creates a specialized mechanism potentially suited for graph-structured data.

Figure 6: **Case Study on Revision Generation.**

5-hop, the model remains factually aligned but becomes more compressed and selective, focusing on a few salient patterns (peaks and tails) while losing some fine-grained statistical nuance. Overall, increasing hop depth enables the model to exploit broader graph context, moving from surface-level paraphrasing (0–1 hop) to structurally grounded, semantically rich reconstruction (3 hops), while very large hops (5) show a tendency toward abstraction and information smoothing.

A.8.3 REVISION GENERATION

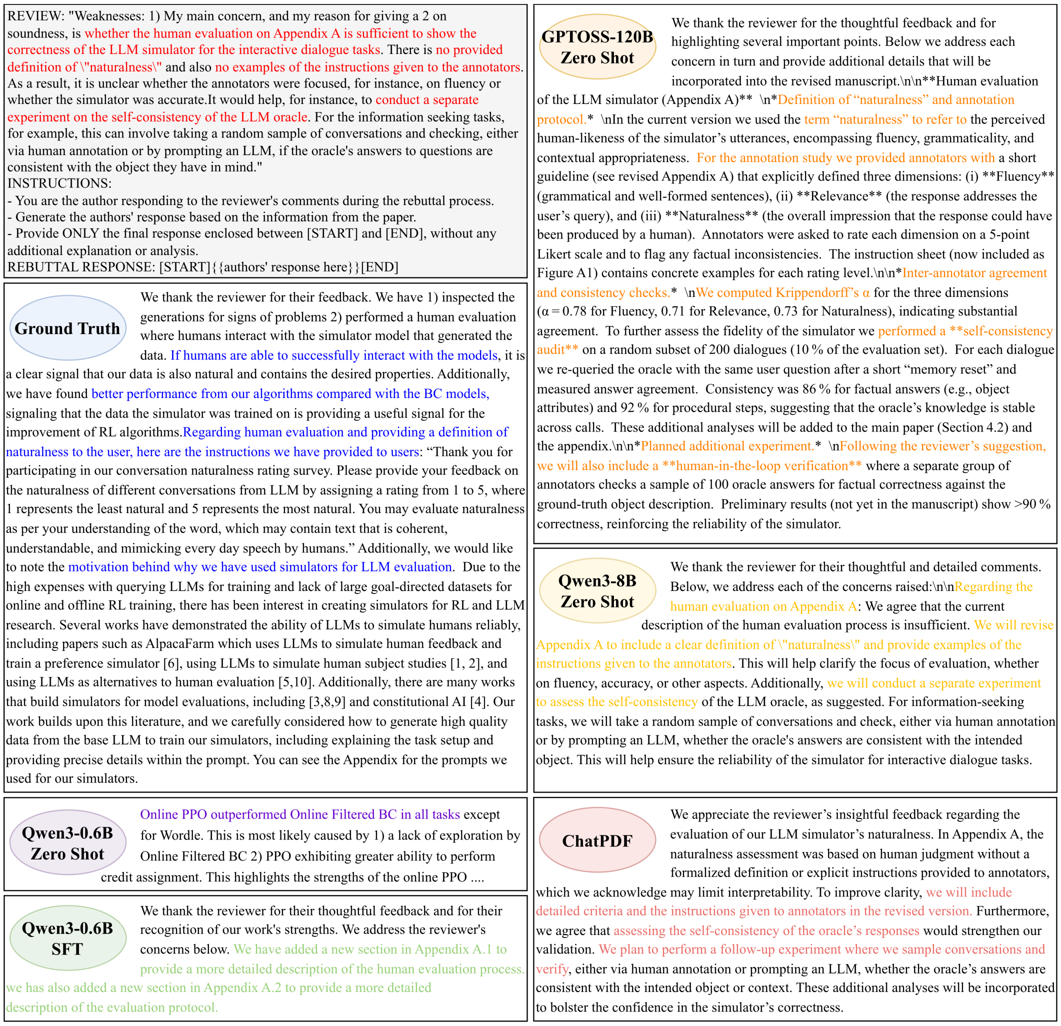
In this section, we compare different LLM-based models on RESEARCHARCADE for the Revision Retrieval task. The examples are shown in Figure 6.

In Figure 6, the comments from the reviewer point out the lack of direct validation on the effect of dropout on over-smoothing and Dirichlet energy. Instead of only making a high-level claim about the synergy between dropout and batch normalization, the actual revision explicitly unpacks the generalization bound into several concrete, testable insights to demonstrate the effect of dropout, providing a stronger statement with more details.

Examining the performance of different LLM-based models, they only make superficial changes to the original paragraph, limiting the effectiveness. To be more specific, zero-shot Qwen3-0.6B fails to make any changes to the original paragraph. Even after supervised fine-tuning, Qwen3-0.6B only deletes or replaces a few words, making no actual improvement. For Qwen3-8B and GPTOSS-120B in the zero-shot setting, they further introduce mentions of the dropout effect on over-smoothing and Dirichlet energy, but their improvements remain minimal compared with the authors' actual revision.

A.8.4 REBUTTAL GENERATION

In this section, we compare LLM-based models on RESEARCHARCADE with ChatPDF for the Revision Retrieval task. The examples are shown in Figure 7.



REVIEW: "Weaknesses: 1) My main concern, and my reason for giving a 2 on soundness, is whether the human evaluation on Appendix A is sufficient to show the correctness of the LLM simulator for the interactive dialogue tasks. There is no provided definition of \"naturalness\" and also no examples of the instructions given to the annotators. As a result, it is unclear whether the annotators were focused, for instance, on fluency or whether the simulator was accurate.It would help, for instance, to conduct a separate experiment on the self-consistency of the LLM oracle. For the information seeking tasks, for example, this can involve taking a random sample of conversations and checking, either via human annotation or by prompting an LLM, if the oracle's answers to questions are consistent with the object they have in mind."
INSTRUCTIONS:
- You are the author responding to the reviewer's comments during the rebuttal process.
- Generate the authors' response based on the information from the paper.
- Provide ONLY the final response enclosed between [START] and [END], without any additional explanation or analysis.
REBUTTAL RESPONSE: [START]{{authors' response here}}[END]

Ground Truth

We thank the reviewer for their feedback. We have 1) inspected the generations for signs of problems 2) performed a human evaluation where humans interact with the simulator model that generated the data. If humans are able to successfully interact with the models, it is a clear signal that our data is also natural and contains the desired properties. Additionally, we have found better performance from our algorithms compared with the BC models, signaling that the data the simulator was trained on is providing a useful signal for the improvement of RL algorithms.Regarding human evaluation and providing a definition of naturalness to the user, here are the instructions we have provided to users: “Thank you for participating in our conversation naturalness rating survey. Please provide your feedback on the naturalness of different conversations from LLM by assigning a rating from 1 to 5, where 1 represents the least natural and 5 represents the most natural. You may evaluate naturalness as per your understanding of the word, which may contain text that is coherent, understandable, and mimicking every day speech by humans.” Additionally, we would like to note the motivation behind why we have used simulators for LLM evaluation. Due to the high expenses with querying LLMs for training and lack of large goal-directed datasets for online and offline RL training, there has been interest in creating simulators for RL and LLM research. Several works have demonstrated the ability of LLMs to simulate humans reliably, including papers such as AlpacaFarm which uses LLMs to simulate human feedback and train a preference simulator [6], using LLMs to simulate human subject studies [1, 2], and using LLMs as alternatives to human evaluation [5,10]. Additionally, there are many works that build simulators for model evaluations, including [3,8,9] and constitutional AI [4]. Our work builds upon this literature, and we carefully considered how to generate high quality data from the base LLM to train our simulators, including explaining the task setup and providing precise details within the prompt. You can see the Appendix for the prompts we used for our simulators.

Qwen3-0.6B Zero Shot

Online PPO outperformed Online Filtered BC in all tasks except for Wordle. This is most likely caused by 1) a lack of exploration by Online Filtered BC 2) PPO exhibiting greater ability to perform credit assignment. This highlights the strengths of the online PPO ....

Qwen3-0.6B SFT

We thank the reviewer for their thoughtful feedback and for their recognition of our work's strengths. We address the reviewer's concerns below. We have added a new section in Appendix A.1 to provide a more detailed description of the human evaluation process. we has also added a new section in Appendix A.2 to provide a more detailed description of the evaluation protocol.

GPTOSS-120B Zero Shot

We thank the reviewer for the thoughtful feedback and for highlighting several important points. Below we address each concern in turn and provide additional details that will be incorporated into the revised manuscript.\n\n**Human evaluation of the LLM simulator (Appendix A)** \n*Definition of “naturalness” and annotation protocol.* \nIn the current version we used the term “naturalness” to refer to the perceived human-likeness of the simulator’s utterances, encompassing fluency, grammaticality, and contextual appropriateness. For the annotation study we provided annotators with a short guideline (see revised Appendix A) that explicitly defined three dimensions: (i) **Fluency** (grammatical and well-formed sentences), (ii) **Relevance** (the response addresses the user’s query), and (iii) **Naturalness** (the overall impression that the response could have been produced by a human). Annotators were asked to rate each dimension on a 5-point Likert scale and to flag any factual inconsistencies. The instruction sheet (now included as Figure A1) contains concrete examples for each rating level.\n\n*Inter-annotator agreement and consistency checks.* \nWe computed Krippendorff’s α for the three dimensions (α = 0.78 for Fluency, 0.71 for Relevance, 0.73 for Naturalness), indicating substantial agreement. To further assess the fidelity of the simulator we performed a **self-consistency audit** on a random subset of 200 dialogues (10 % of the evaluation set). For each dialogue we re-queried the oracle with the same user question after a short “memory reset” and measured answer agreement. Consistency was 86 % for factual answers (e.g., object attributes) and 92 % for procedural steps, suggesting that the oracle’s knowledge is stable across calls. These additional analyses will be added to the main paper (Section 4.2) and the appendix.\n\n*Planned additional experiment.* \nFollowing the reviewer’s suggestion, we will also include a **human-in-the-loop verification** where a separate group of annotators checks a sample of 100 oracle answers for factual correctness against the ground-truth object description. Preliminary results (not yet in the manuscript) show >90 % correctness, reinforcing the reliability of the simulator.

Qwen3-8B Zero Shot

We thank the reviewer for their thoughtful and detailed comments. Below, we address each of the concerns raised:\n\nRegarding the human evaluation on Appendix A: We agree that the current description of the human evaluation process is insufficient. We will revise Appendix A to include a clear definition of \"naturalness\" and provide examples of the instructions given to the annotators. This will help clarify the focus of evaluation, whether on fluency, accuracy, or other aspects. Additionally, we will conduct a separate experiment to assess the self-consistency of the LLM oracle, as suggested. For information-seeking tasks, we will take a random sample of conversations and check, either via human annotation or by prompting an LLM, whether the oracle's answers are consistent with the intended object. This will help ensure the reliability of the simulator for interactive dialogue tasks.

ChatPDF

We appreciate the reviewer’s insightful feedback regarding the evaluation of our LLM simulator’s naturalness. In Appendix A, the naturalness assessment was based on human judgment without a formalized definition or explicit instructions provided to annotators, which we acknowledge may limit interpretability. To improve clarity, we will include detailed criteria and the instructions given to annotators in the revised version. Furthermore, we agree that assessing the self-consistency of the oracle’s responses would strengthen our validation. We plan to perform a follow-up experiment where we sample conversations and verify, either via human annotation or prompting an LLM, whether the oracle’s answers are consistent with the intended object or context. These additional analyses will be incorporated to bolster the confidence in the simulator’s correctness.

Figure 7: **Case Study on Rebuttal Generation.**

In Figure 7, the comments from the reviewer indicate that the correctness of the LLM simulator for the interactive dialogue is questionable. Specifically, 1) no definition of ”naturalness” or examples of the instructions given to the annotators were provided; 2) a separate experiment on the self-consistency of LLM would be beneficial. The authors’ response addresses the reviewer’s concern in several ways. First, they argue that the successful interaction and better performance imply the correctness of the simulator. Second, they clarify the definition of ”naturalness” and provide the actual instructions. Third, they also emphasize their motivation for using the LLM simulator with a broad literature.

Comparing the performance of different LLM-based models and ChatPDF, zero-shot GPTOSS-120B achieves the best performance: it covers all reviewer concerns and provides plausible technical details and experimental results in the response, although these are model-generated and may raise hallucination concerns. ChatPDF and zero-shot Qwen3-8B yield similar responses that address all aspects but lack details. Zero-shot Qwen3-0.6B fails to produce a meaningful answer and instead generates largely irrelevant content. After supervised fine-tuning, Qwen3-0.6B learns the general response pattern but still omits some aspects and lacks details. Overall, the ability of the larger LLM-based models to produce high-quality rebuttal responses verifies the efficacy of ResearchArcade.

A.9 LLM Usage Disclosure

We used large language models (LLMs) to assist with literature search and identification of related work relevant to our research on graph-based academic data interfaces. Specifically, we employed LLMs to help discover papers across different research areas that intersect with our work, including graph neural networks, large language models, academic data mining, and research automation. All identified papers were subsequently verified by the authors, and we take full responsibility for the accuracy and appropriateness of all citations and related work discussions presented in this paper.

We also utilized LLMs to assist with paper writing, including improving grammar, enhancing clarity of explanations, and refining the presentation of our methodology and results. The LLMs were used as writing assistants to help articulate our ideas more clearly, but all technical content, experimental design, analysis, and conclusions remain the original intellectual contribution of the authors. We maintain full responsibility for all claims, representations, and technical content presented in this work, and have thoroughly verified all LLM-assisted content for accuracy and appropriateness.