AUTOREPRODUCE: Automatic AI Experiment Reproduction with Paper Lineage

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Abstract

Efficient reproduction of research papers is pivotal to accelerating scientific progress. However, the increasing complexity of proposed methods often renders reproduction a labor-intensive endeavor, necessitating profound domain expertise. To address this, we introduce the paper lineage, which systematically mines implicit knowledge from the cited literature. This algorithm serves as the backbone of our proposed AUTOREPRODUCE, a multi-agent framework designed to autonomously reproduce experimental code in a complete, end-to-end manner. To ensure code executability, AUTOREPRODUCE incorporates a sampling-based unit testing strategy for rapid validation. To assess reproduction capabilities, we introduce REPRODUCEBENCH, a benchmark featuring verified implementations, alongside comprehensive metrics for evaluating both reproduction and execution fidelity. Extensive evaluations on PaperBench and REPRODUCEBENCH demonstrate that AUTOREPRODUCE consistently surpasses existing baselines across all metrics. Notably, it yields substantial improvements in reproduction fidelity and final execution performance. The code is available at `https://github.com/AI9Stars/AutoReproduce`.

1 Introduction

The rapid advancement of artificial intelligence (AI) has heightened the demand for efficient workflow iterations, making the ability to reproduce experimental results increasingly critical (Xi et al., 2025; Li et al., 2025). While this capability is pivotal for advancing various fields, the complexity of method designs and training pipelines, often requiring specialized expertise for comprehension (Si et al., 2024; Li et al., 2024), substantially hinders automated experimental replication. For instance, developing a task-specific model often requires collaboration among experts in data processing, model design, and training pipeline (Qian et al., 2023).

Notably, the rapid evolution of AI has resulted in a substantial corpus of research papers, presenting a valuable testbed for exploring the automation of experiment replication (Erdil and Besiroglu, 2023). Prior work has typically focused utilizing large language models (LLMs) for automating in-depth analyses of existing papers (e.g., report or idea generation (Baek et al., 2024)) or assisting with discrete reproduction tasks (e.g., environment setup (Bogin et al., 2024), code repository refactor (Gandhi et al., 2025; Siegel et al., 2024)). However, comprehensive frameworks for automatic end-to-end reproduction remain unexplored. While the concurrent work (Seo et al., 2025) also attempts to address the task of automatic reproduction. They only focus on reproducing the contents introduced in the paper, without considering the executability of the generated code, which is crucial for faithful experimental reproduction (Wang et al., 2024c).

Reproducing experiments efficiently remains a significant challenge due to insufficient experimental details in research papers. We observe that distinct research domains often rely on tacit knowledge, that is, common implementation practices like specific module architectures (Chen et al., 2024) and data processing pipelines (Nie et al., 2022) that evolve into de facto standards for subsequent studies. An effective reproduction strategy must incorporate the domain-specific knowledge and practices surrounding the source paper.

Informed by the preceding analysis, we propose the paper lineage algorithm, which identifies potentially unstated details by tracing cited literature and associated code repositories of the source paper. Building upon this algorithm, we propose AUTOREPRODUCE, a multi-agent framework designed for the end-to-end reproduction of experiments in papers. AUTOREPRODUCE contains three

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key stages, *literature review*, *paper lineage* and *code development*, designed to be executed sequentially to generate valid reproductions. During code development, we propose a sampling-based unit testing strategy for rapid validation, thereby guaranteeing the code executability.

Furthermore, to rigorously evaluate the efficacy of AUTOREPRODUCE, we curate REPRODUCEBENCH, a benchmark comprising 13 research papers that span distinct AI sub-domains. For each entry, we manually construct and execute verified implementations to establish ground-truth performance. In our setup, LLM agents are tasked with reproducing the specific experiment implementations detailed in the source papers. To assess the generated code, we employ five distinct metrics spanning dimensions from structural reproduction fidelity to final execution accuracy. Experimental results demonstrate that AUTOREPRODUCE achieves superior performance on REPRODUCEBENCH across all five metrics, validating the effectiveness of our proposed approach. Our main contributions are summarized as follows:

- We propose *paper lineage*, an algorithm that enables the agent to learn implicit domain knowledge and implementation practices by analyzing the cited literature.
- We propose AUTOREPRODUCE, a multi-agent framework designed for end-to-end experiment reproduction, which achieves superior performance compared with existing methods.
- We construct REPRODUCEBENCH, a novel benchmark for evaluating the experiment reproduction capabilities, which includes manually curated reference code implementations and a suite of evaluation metrics.

2 Related Work

2.1 LLMs for Experiment Automation

Large Language Models (LLMs) are increasingly utilized to automate diverse stages within machine learning workflows, including data engineering, model selection, hyperparameter optimization, and workflow evaluation (Gu et al., 2024). For instance, in data engineering, LLMs are utilized to assist with many tasks such as dataset recommendation (Yang et al., 2025), adaptive data imputation (Zhang et al., 2023), context-aware data transformation (Liu et al., 2023a), and feature selection (Jeong et al., 2024). Also, many works explore utilizing LLM-driven approaches for model selection, for example, AutoM^{3}L (Luo et al., 2024) proposes a retrieval-based process to select the required model, while ModelGPT (Tang et al., 2024) employs generation-based methods for the same purpose. Furthermore, LLMs contribute to workflow evaluation by enabling performance prediction (Zhang et al., 2023) and supporting zero-cost proxy method development (Hollmann et al., 2022).

2.2 LLMs for Research Code

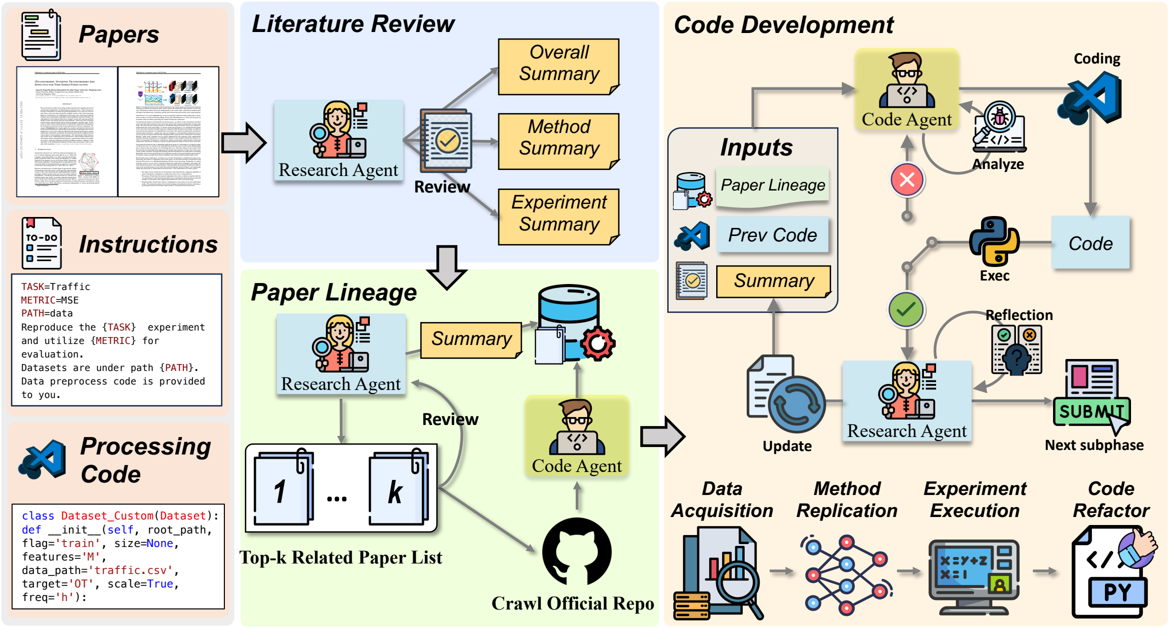
Prior works have explored using LLMs for generating novel ideas (Li et al., 2024; Weng et al., 2024). For example, Scimon (Wang et al., 2024b) focuses on scientific hypothesis discovery by elucidating relationships between variables, while ResearchAgent (Baek et al., 2024) employs an agent-based system to generate open-ended ideas accompanied by conceptual methods and experimental designs. However, these approaches typically do not generate implementation code for these novel concepts, leading to unverifiable results. More recently, many works (Schmidgall et al., 2025; Schmidgall and Moor, 2025) utilize multi-agent frameworks to generate code implementations of proposed ideas, further promoting this field. Despite this advancement, the ideas generated by these approaches often remain paper-level concepts, lacking the detailed substance described in formally proposed papers.

Achieving comparable performance in experimental reproduction hinges on the high-fidelity implementation of the methods detailed in the source paper. Recent concurrent studies (Starace et al., 2025; Seo et al., 2025; Lin et al., 2025) further underscore the significance of this research domain.

3 AUTOREPRODUCE

3.1 Problem Formulation

Rapid AI progress yields numerous novel methods, yet manual reproduction imposes prohibitive costs in time and expertise. We thus define automated experiment reproduction as the task of utilizing LLM agents to generate executable code for experiment replication, thereby automating scientific verification. Given a paper $\mathcal{P}$ and instructions about experiment $\mathcal{I}$, the agent $\mathcal{A}$ needs to reproduce the code implementation of the method and experiment proposed in the paper $\mathcal{C} = \mathcal{A}(\mathcal{P}, \mathcal{I})$, where $\mathcal{C}$ is the output code.



```
TASK=Traffic
METRIC=MSE
PATH=data
Reproduce the {TASK}  experiment
and utilize {METRIC} for
evaluation.
Datasets are under path {PATH}.
Data preprocess code is provided
to you.
```

```
class Dataset_Custom(Dataset):
def __init__(self, root_path,
flag='train', size=None,
features='M',
data_path='traffic.csv',
target='OT', scale=True,
freq='h'):
```

Figure 1: The paper content, instructions and data processing code (if necessary) are provided for each reproduction task. The workflow of AUTOREPRODUCE, which is decomposed into three subphases. (i) Literature Review, the research agent summarize the overall, method and experiment contents. (ii) Paper Lineage, the research agent lists and reviews related papers, and the code agent filters files in the corresponding repositories. (iii) Code Development, the code agent and research agent collaborate to construct executable reproduction code.

3.2 Workflow

We introduce AUTOREPRODUCE, a novel multi-agent framework for reproducing experiments from research papers. As illustrated in Figure 1, its pipeline is structured into three key phases: (i) Literature Review, (ii) Paper Lineage, and (iii) Code Development. This process is collaboratively executed by two specialized agents: a research agent for text-centric tasks such as paper summarization and related work analysis, and a code agent responsible for all code-oriented tasks, including implementation and debugging.

3.2.1 Literature Review

To mitigate the information redundancy inherent in research papers, the Research Agent employs a hierarchical three-stage summarization protocol to comprehensively extract core methodologies and experimental nuances. The process begins with a holistic paper-level overview, followed by targeted summaries that distill specific method details, such as mathematical formulations and implementation specifics, as well as the critical experimental settings required for reproduction. Acknowledging that effective summarization hinges on the quality of text extraction, where direct parsing methods (Schmidgall et al., 2025) often struggle with complex artifacts like mathematical formulas and tables, we employ MinerU (Wang et al., 2024a). This tool converts PDFs into Markdown format, significantly enhancing the fidelity of data preservation. Furthermore, to augment semantic understanding, AUTOREPRODUCE offers an optional capability to enrich summaries by integrating insights from visual structure diagrams.

3.2.2 Paper Lineage

Scientific research is an inherently cumulative process, where novel methods evolve upon the foundation of existing studies. This iterative progression fosters domain-specific conventions and implicit consensus, forming a historical context we term the *Paper Lineage*. To systematically exploit this, we propose the Paper Lineage algorithm to analyze the research landscape and uncover these prevailing practices. Specifically, the research agent identifies the top-k relevant papers (default k=3) from the source paper's references. This selection is driven by an analysis of citation relationships within the source paper's full context, where relevance is defined by the alignment of research fields and proposed methods. Notably, comparison baselines detailed in the primary experimental section are prioritized as the most critical references for analysis. Upon acquiring the relevant paper list, the research agent retrieves the manuscripts via the `ArXiv API`, summarizes their content, and identifies linked code repositories. It then employs the `GitHub API` to clone the corresponding repository. To isolate relevant files from extraneous repository content, the code agent leverages the paper summary and task instructions to selectively extract essential source files. These code segments are paired with their summaries to construct <*summary, code*> tuples, which serve as domain-aligned reference exemplars for subsequent generation. For papers lacking public repositories, their summaries alone are utilized as high-quality conceptual knowledge sources. The detailed procedure and prompts are outlined in Algorithm 1 and Figure 5, 6.

3.2.3 Code Development

The code development phase constitutes the final stage of the AutoReproduce workflow, where the research and code agents collaborate to produce a reproducible and executable implementation of the target experiment. To guarantee a high-fidelity reproduced implementation, this phase is structured into three main stages, culminating in a final refactoring of the generated code. To facilitate code execution and debugging, we provide a Docker container that encapsulates the Python runtime and common libraries such as PyTorch and Numpy. When encountering missing dependencies, the code agent can utilize ```` ```Bash\n<command>\n``` ```` to install the necessary packages.

Data Acquisition. The preliminary phase focuses on dataset curation and attribute analysis. Although off-the-shelf datasets from libraries like `torchvision` are readily available, many tasks demand the curation of custom datasets derived directly from raw data. Reproducing prior work is often impeded by the insufficient documentation of data preprocessing method and the absence of standardized data formats. To mitigate this issue, we categorize source papers based on dataset provenance: standard benchmarks or custom datasets. For papers relying on standard benchmarks, AutoReproduce generates loading code using established libraries. For those involving custom datasets, we provide corresponding preprocessing pipelines to enable seamless agent utilization. Furthermore, to prevent runtime failures arising from mismatches in critical data properties, such as tensor shape and data type, AutoReproduce employs a proactive inference mechanism. The code agent extracts these attributes by generating and executing analysis code on sampled mini-batches, thereby gathering essential context to guide the subsequent code generation process.

In response to execution errors, the code agent first diagnoses the error traceback and refines the script using the `EDIT` command, structured as ```` ```EDIT\n N M\n<new code>\n``` ````. We decouple error analysis and code editing into two distinct steps, as we observe that conducting a preliminary analysis to guide the debugging process significantly improves the success rate. The `EDIT` command facilitates targeted updates by replacing lines `N` through `M` with the generated code segment, rather than regenerating the entire file. This granular approach significantly reduces token generation overhead and is employed consistently throughout all subsequent phases of our framework. The prompt of the command is illustrated in Figure 7.

Method Replication. This stage is dedicated to implementing the method. The code agent synthesizes code snippets and resolves errors by leveraging established context, including the paper summary, inferred data attributes, and domain knowledge retrieved from the Paper Lineage. Simultaneously, the research agent validates the generated code against the method summary, providing corrective feedback while dynamically updating the summary to steer the implementation. The code agent begins by generating an initial implementation, which is then iteratively refined through a collaborative mechanism. While the code agent debugs potential errors in model computations by inspecting data flow properties, the research agent validates the code against the paper summary, updating the summary to guide the code agent in resolving any identified discrepancies The research agent chooses to submit the code once it fully aligns with the paper.

Experiments Execution This phase is dedicated to the implementation of the full experimental pipeline. Leveraging the established dual-agent loop, the system verifies that the code correctly reflects the experimental settings from the source paper. We continue to employ mini-batch sampling to accelerate debugging. To validate epoch-related configurations, the code agent generates the complete experiment script equipped with early-exit mechanisms, such as `break`. This enables a rapid dry run to validate the pipeline prior to full training.

This phase concludes with a comprehensive refactoring process to remove unnecessary debug settings and clean up the generated code.

Method	Domain	Dataset	Metrics
IEBins (Shao et al., 2023)	Monocular Depth Estimation	NYU-Depth-v2	$\delta < 1.25$
iTransformer (Liu et al., 2023b)	Time Series Forecasting	Traffic	MSE
DKD (Zhao et al., 2022)	Knowledge Distillation	CIFAR-100	Accuracy
SimVP (Gao et al., 2022)	Video Prediction	Moving MNIST	MSE
HumanMAC (Chen et al., 2023a)	Human Motion Prediction	HumanEva-I	ADE
SFNet (Cui et al., 2023)	Image Dehazing	SOTS-Indoor	PSNR
LSM (Wu et al., 2023)	Solving PDEs	Darcy	MSE
Swin-Unet (Cao et al., 2022)	Medical Image Segmentation	Synapse	DSC
TDGNN-w (Wang and Derr, 2021)	Node Classification	Citeseer	Accuracy
TimeVAE (Desai et al., 2021)	Time Series Generation	Sine 20%	Predictor
WCDM (Jiang et al., 2023)	Low-light Image Enhance	LOLv1	SSIM
BSPM (Choi et al., 2023)	Collaborative Filtering	Gowalla	Recall
DAT-S (Chen et al., 2023b)	Image Super-Resolution	DF2K/Set5	PSNR

Table 1: List of papers in REPRODUCEBENCH. To illustrate the specific experiments, we list each experimental detail, including the method names, task domains, datasets, and evaluation metrics.

4 REPRODUCEBENCH

4.1 Contributions

Our approach prioritizes experiment reproducibility by focusing on code execution and final performance. This distinguishes our work from methods like Paper2Code (Seo et al., 2025), which generate code in a single pass without considering execution. To this end, we construct REPRODUCEBENCH, a paper reproduction benchmark that establishes a comprehensive evaluation framework to assess agent fidelity and performance.

4.2 Paper Selection

We establish a rigorous curation pipeline utilizing PapersWithCode, covering diverse domains such as CV and NLP along with their respective sub-domains. Within each category, we screen 5–10 candidate papers to verify code completeness and reproducibility, culminating in the selection of at most one high-quality representative per sub-domain. Consequently, REPRODUCEBENCH comprises 13 human-curated papers spanning a broad spectrum of complexities, ranging from foundational applications like knowledge distillation (Zhao et al., 2022) to specialized challenges such as solving Partial Differential Equations (PDEs) (Wu et al., 2023). Moreover, these papers encompass varied experimental conditions, including the two primary paradigms of training from scratch and fine-tuning pre-trained models. The construction and validation of REPRODUCEBENCH follow a three-stage protocol. First, we identify representative method variants, experimental settings, and evaluation metrics specific to each paper. Next, we manually curate the official code repositories. This critical step involves excising boilerplate and refactoring the repository to isolate the core implementation from auxiliary logic. Finally, we re-execute all experiments to validate reproducibility and establish a verified baseline, ensuring fair and unambiguous evaluation. Detailed statistics are listed in Table 1. We adopt these reproduced results as the ground truth to guarantee consistent benchmarking and mitigate potential misinterpretation.

4.3 Evaluation

Given the availability of reference code and performance baselines in our curated REPRODUCEBENCH, we conduct evaluations from two key perspectives to explore: *(i) Does the generated code accurately reflect the core contributions and experimental setup as proposed in the source paper? (ii) Can the generated code fully reproduce the experimental performance metrics rerun by ourselves?* To answer these questions, we introduce two primary evaluation metrics, evaluating from alignment and execution aspects, respectively.

Align-Score: To assess alignment fidelity, we conduct a comparative analysis bridging the generated code, the core content of the paper, and the manually curated reference implementation. We examine the results across three distinct dimensions. (1) Paper-Level: Given the source paper, we utilize an LLM (default `o1`) to extract five critical components essential for experimental reproduction. Subsequently, we prompt the LLM to assess the degree to which the generated code satisfies these key objectives. (2) Code-Level: Leveraging manually annotated reference implementations, we first ensure that extraneous logic is stripped away to establish a clean ground truth. We then prompt the LLM to evaluate the generated code against this reference across four specific dimensions, encompassing overall structure, model details, training details, and experimental integrity. 3) Mixed-Level:

Baselines	LLM	Align-Score			Exec-Score (%)	
		Paper-Level	Code-Level	Mixed-Level	Exec Rate	Perf Gap (↓)
ChatDev	GPT-4o	57.33	32.80	43.33	2.56	99.62
Agent Laboratory	GPT-4o	63.47	35.32	48.64	23.08	82.31
PaperCoder	o3-mini	90.41	47.54	60.26	17.94	89.23
AutoReproduce	GPT-4o	82.13	41.52	56.24	76.92	41.77
	Claude-3.5-Sonnet	90.27	54.11	69.97	84.62	31.62
	o3-mini	90.86	58.48	75.21	92.31	24.31
	Gemini-2.5-Pro	**91.57**	**60.26**	**77.56**	**94.87**	**19.72**

Table 2: The evaluation of various agents on ReproduceBench, utilizing both o1-as-judge and execution. The presented results for each metric represent the mean value derived from three independent runs conducted across all papers in the benchmark. The best performance is indicated in **Bold**.

Our analysis reveals that paper-level evaluation often overlooks granular implementation details, potentially inflating scores, whereas code-level evaluation can be overly sensitive to syntactic variations, leading to score deflation. To address this trade-off, we propose the mixed-level evaluation strategy. This method supplies the LLM with both the key objectives extracted from the paper and the reference code context. Our evaluation results demonstrate that enabling the model to ground abstract requirements in concrete implementation patterns leads to significantly more nuanced scoring of the generated code. Consequently, this approach captures both critical features and detailed logic, demonstrating improved consistency with human judgment. Unlike Paper2Code (Seo et al., 2025), which relies on a single holistic score (1-5 scores), our framework offers a fine-grained assessment by validating individual implementation points.

Exec-Score: Given that experimental reproduction is fundamentally a code generation task, the execution outcomes of the generated code are of paramount importance. We assess this dimension by measuring the Execution Rate (Exec Rate) and the final experimental performance gap (Perf Gap). To address the heterogeneity of performance metrics across diverse research papers, we propose the relative performance gap as a unified evaluation standard. This metric quantifies the relative deviation between the final results yielded by the generated code and the reference performance established by our curated implementations.

$$\text{Performance Gap} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\mathrm{P}_i^{\mathrm{ref}} - \mathrm{P}_i^{\mathrm{agent}}|}{\max(\mathrm{P}_i^{\mathrm{ref}}, \mathrm{P}_i^{\mathrm{agent}})} \quad (1)$$

where P_{ref} and P_{agent} are the performance obtained under the reference code and agent-generated code, respectively. Since not all generated code can be executed, the $\mathrm{P}_{\mathrm{agent},i}$ is set to 0 for the non-executable instances, resulting in a maximum performance gap of 1.0. Furthermore, to prevent the performance gap from exceeding 1.0, especially in cases with small reference performance values (e.g. $\mathrm{P}_i^{\mathrm{ref}} = 0.1$ and $\mathrm{P}_i^{\mathrm{agent}} = 0.3$ when utilizing MSE as the evaluation metric), we normalize the gap by the larger performance value of $\mathrm{P}^{\mathrm{ref}}$ and $\mathrm{P}^{\mathrm{agent}}$. Reference performance values are derived by executing our verified ground-truth implementations.

5 Experiments

5.1 Baselines and Benchmarks

To better compare our proposed AutoReproduce, we compare previous work on software development and paper generation, including ChatDev (Qian et al., 2023), Agent Laboratory (Schmidgall et al., 2025) and PaperCoder (Seo et al., 2025). To our knowledge, PaperCoder is concurrent work compared to AutoReproduce. For all the metrics in the align-score, we employ o1 as the LLM judge for evaluations. Beyond ReproduceBench, we also evaluate AutoReproduce on PaperBench Code-Dev (Starace et al., 2025), which imposes requirements distinct from our primary benchmark. To align with its focus on static code generation for all experiments without execution, we streamline the AutoReproduce by omitting the iterative debugging phase and configuring the system to generate the complete experimental code including baseline methods.

5.2 Main Results

We evaluate the implementation code generated by various baselines using different LLM backbones,

Baselines	Backbone	Rep. Score (%)
BasicAgent	o3-mini	6.4
IterativeAgent	o3-mini	17.3
IterativeAgent	o1-high	43.4
PaperCoder	o3-mini	45.1
AUTOREPRODUCE		
(w/o Paper Lineage)	o3-mini	44.1
Default Setting	o3-mini	48.5
(w/ Visual Diagram)	o3-mini	49.6

Table 3: valuation results on PaperBench Code-dev are presented. Rep. Score denotes the Replication Score. The final three rows represent various configurations of AUTOREPRODUCE.

with three runs conducted for each paper. Detailed results in Table 2 demonstrate that our proposed AUTOREPRODUCE achieves superior performance across all the metrics, notably in execution rate and performance gap. By employing a sampling batch approach for efficient debugging, AUTOREPRODUCE significantly enhances the execution rate of the generated code and reduces its performance gap with the reference code. In addition, as shown in Table 3, AUTOREPRODUCE also achieves superior performance on the PaperBench Code-Dev benchmark, particularly when utilizing the paper lineage algorithm. We also observe that enabling the agents to process information from visual diagrams further improves performance, as some experimental settings are denoted within the diagrams.

Our analysis indicates that LLM judges may overrate consistency when comparing paper contents against generated code. This overestimation stems from the generality of textual descriptions, which can reward broad functional similarity rather than precise replication. Conversely, directly comparing generated code with reference implementations is also problematic, as reference code includes settings unmentioned in the paper, thereby skewing reproducibility assessments. In contrast, our proposed mixed-level scoring aligns more closely with human evaluators and offers a more reliable metric for evaluating reproduction capabilities.

5.3 Ablation Study

To explore and evaluate our proposed methods, we conduct ablation experiments to investigate: (i) the utility of the visual diagrams and the impact of content extraction MinerU during literature review, (ii) the effectiveness of our proposed Paper Lineage method and (iii) the performance difference between including debugging and refinement versus one-time code generation in the Code Development phase. Due to time constraints, we conduct only an experiment for each paper and evaluate on the Mixed-Level and Performance Gap metrics.

Ablations	Mixed-Level	Perf Gap % (↓)
w/ Visual Diagram	70.14	35.83
w/o MinerU	58.42	47.81
w/o Paper Lineage	63.15	39.59
w/o Refine	65.78	36.37
w/o Debug+Refine	68.32	88.78
AUTOREPRODUCE	69.97	31.62

Table 4: The ablation study for evaluating AUTOREPRODUCE with various subphases, the results are measured using mixed-level and performance gap metrics. We employ `Claude-3.5-Sonnet` as the LLM backbone.

The results in Table 4 demonstrate that current settings reach the optimal balanced performance. Although including the visual diagram (*w/* Visual Diagram) shows slightly better performance on the mixed-level metric, upon reviewing the scores of this particular implementation against the default setting, we observe no substantial overall difference. Furthermore, our results demonstrate that the *Paper Lineage* algorithm, coupled with debugging and refinement processes, produces significant improvements across both evaluation metrics.

5.4 Human Evaluation

To rigorously assess the reproduction results, we conduct a human evaluation study. For each instance, evaluators are presented with the task instructions, full paper content, reference code, and the generated output. They assess the code across three dimensions: methodological reproducibility, hyperparameter configuration, and the experimental pipeline, assigning maximum scores of 10, 5, and 5, respectively (see Appendix A.4). The primary objective of this study is to validate the efficacy of our Mixed-Level metric. Consequently, we calculate and report the Pearson correlation between human judgments and LLM-evaluated scores in Appendix A.4.2. Analysis of the results in Table 2, 5, and 8 reveals that mixed-level scores exhibit a stronger correlation with human evaluation than either paper-level or code-level metrics. Qualitative feedback highlights a distinct trend. While LLM agents demonstrate proficiency in reproducing high-level model architectures, their implemen-

Baselines	LLM	Method	Parameter	Experiment	Overall
ChatDev	GPT-4o	4.08 ± 1.00	2.85 ± 0.37	1.92 ± 0.15	8.86 ± 1.12
PaperCoder	o3-mini	6.84 ± 0.52	3.46 ± 0.31	2.92 ± 0.23	13.24 ± 0.68
AUTOREPRODUCE	Claude-3.5-Sonnet	7.23 ± 0.90	3.69 ± 0.37	3.27 ± 0.14	14.19 ± 0.99
AUTOREPRODUCE	o3-mini	7.36 ± 0.82	3.73 ± 0.25	3.52 ± 0.16	14.61 ± 0.84

Table 5: The comparative analysis of human evaluation scores, including the calculated mean and standard deviation.

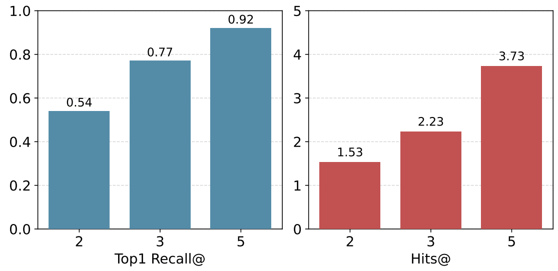


Figure 2: The correlation analysis of papers selected. We utilize `Claude-3.5-Sonnet` and calculate the mean values of the given metrics.

tations frequently deviate from the reference code regarding granular specifications, such as convolution stride and padding values. Furthermore, the precise reproduction of experimental results is often hindered by the absence of training configurations in source papers, particularly concerning learning rate decay strategies and schedulers.

5.5 Paper Lineage Analysis

In our setting, AUTOREPRODUCE constructs paper lineages by selecting related papers via content and citation analysis. To validate the relevance of the papers selected, we establish an expert-curated set of references as standard lineage papers. Specifically, for each source paper, domain experts manually curate five gold-standard references, prioritizing high research relevance and temporal proximity. Search engines such as Google Scholar and Semantic Scholar are utilized to facilitate this selection process. Given that AUTOREPRODUCE default selects k papers for each source paper, where $k \in \{2, 3, 5\}$, we evaluate under two conditions. (i) Mean Top-1 Recall@k. Whether the most relevant expert-curated reference is included among the k lineage papers selected by AUTOREPRODUCE. (ii) Mean Hits@N. The number of lineage papers selected by AUTOREPRODUCE are present within the expert-curated set. The results in Figure 2 indicate strong agreement between the LLMs and humans in selecting lineage papers.

Phase	Debugging		Refinement	
	Turns	Lines	Turns	Lines
	Claude-3.5-Sonnet			
Methods	5.78	33.52	2.16	40.53
Experiments	2.84	34.18	1.59	19.29
	o3-mini			
Methods	2.14	21.74	1.23	15.65
Experiments	0.94	30.42	0.72	24.73
	Gemini-2.5-Pro			
Methods	1.97	28.43	1.19	28.10
Experiments	0.92	26.48	0.78	19.38

Table 6: The average number of turns and lines when utilizing the `EDIT` command.

5.6 Debugging and Refinement Analysis

Given that AUTOREPRODUCE utilizes `EDIT` command for debugging and refinement, we conduct a further analysis on the details of the code editing. To characterize the editing statistics, we define two key metrics: average editing turns and average lines per turn, which are calculated by $N_{\text{turns}}/N_{\text{runs}}$ and $N_{\text{lines}}/N_{\text{turns}}$ respectively. Here, N_{lines} is the total number of edited lines, N_{turns} is the total number of edit turns, and N_{runs} is the total number of successful runs. This analysis exclusively considers executable code generated during the method replication and experiment execution subphases.

The results indicate that utilizing `o3-mini` and `Gemini-2.5-Pro` as the LLM backbone are more efficient than `Claude-3.5-Sonnet`, as evidenced by the fewer debugging and refinement iterations required to converge on high replicability and executable experiment implementations.

6 Conclusion

In this study, we explore the automatic experiment reproduction and propose AUTOREPRODUCE, a multi-agent workflow with paper lineage algorithm and unit testing with a sample batch to generate reproducible and executable code implementations. For evaluation, we introduce REPRODUCEBENCH, an experiment reproduction benchmark containing 13 papers and their human-curated implementation code. This benchmark employs multi-level criteria to assess the performance of generated code, spanning from alignment to execution fidelity. Finally, the result shows that AUTOREPRODUCE performs superior to other approaches in both REPRODUCEBENCH and PaperBench. We believe that this work will further promote research on paper reproduction and code generation.

7 Acknowledgment

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Limitations

In this work, we investigate the automatic reproducibility of AI experiments, a critical aspect we believe will significantly advance automation within the AI field. However, our current approach has certain limitations that present avenues for future research. Primarily, our method is specialized for replicating individual experimental tasks rather than performing broader code generation at the repository level. Consequently, enhancing execution capabilities within the context of repo-level code warrants further exploration. Furthermore, the inherent complexity of raw datasets often necessitates preliminary data processing. Automating this data preprocessing stage represents a substantial research challenge that must be addressed to achieve more comprehensive automation.

Ethics Statement

The primary objective of this work is to automate the replication of experiments detailed in existing, publicly available research papers. While the methodologies are drawn from the public domain, which generally implies transparency, it is important to acknowledge the potential for data leakage associated with using our system. Users should therefore be mindful of this possibility, particularly when the replication process might involve sensitive datasets or generate intermediate results that could inadvertently disclose information. We provide a license check in the Appendix for the License of papers and code in the REPRODUCEBENCH. Furthermore, LLMs are utilized for writing and refining the paper contents.

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A Appendix

A.1 Execution Error Analysis

A manual error analysis of code generated by both PaperCoder (Seo et al., 2025) and AUTOREPRODUCE reveals that the majority of issues stemmed from incorrect data shapes during internal model calculations. Intuitively, while LLMs can generate specified network structures, achieving correct data flow without test data is challenging, particularly for complex architectures. For tasks involving pre-trained models, it is often not possible to generate a completely correct model architecture implementation in a single attempts. This is mainly because LLMs still face minor challenges in accurately reproducing architectural implementations of common pre-trained models, for example, hidden layer dimensions and normalization layer configurations. Although debugging resolves numerous errors, some issues persist, particularly when encountering complex data flows.

A.2 AUTOREPRODUCE Details

For all the experiments conducted in the experiment section, AUTOREPRODUCE utilizes `claude-3-5-sonnet-20240620` version as `claude-3-5-sonnet` backbone. In the code development phase of AUTOREPRODUCE, the code agent debugs the execution errors. We set the maximum debug tries to 20 for all the subphases in the code development phase. However, further debug attempts generally do not produce more executable code, as bugs are typically fixed within 5-8 iterations. The results are also denoted in Table 6. On the REPRODUCEBENCH benchmark, the average cost for AUTOREPRODUCE to reproduce a single experiment is \$1.87 when utilising the `o3-mini` as the LLM backbone. We execuate all the generated code on the Tesla A100 GPUs.

The algorithm for paper lineage is provided in the Algorithm 1.

A.3 REPRODUCEBENCH Details

While our main text provides an overview of the research domain, datasets, and evaluation metrics integral to the REPRODUCEBENCH, this section offers a more detailed exposition of these elements.

A.3.1 Reference Code

We count the total lines of code for this reference implementation and its associated preprocessing code. Also, statistics about whether pretrained models are loaded and the reference performance rerun by ourselves are conducted. The details are shown in Table 7. Due to potential differences between our rerun settings and the experimental setup originally used by the paper authors, the reference performance may differ from the performance metric reported in their respective papers. The reference performances that we utilize in calculating performance gap metrics are obtained by rerunning the code on Tesla A100 GPUs.

Algorithm 1 Paper Lineage Algorithm

```
Input: Paper $\mathcal{P}$; research agent $\mathcal{RA}$; code agent $\mathcal{CA}$; Integer $k$ (default 3); Instructions $\mathcal{I}$.
Output: Set of paper lineage elements $K_{\text{lineage}}$.
Initialize $K_{\text{lineage}}$.
$\{P_1, ...P_k\} \leftarrow \mathcal{RA}(\mathcal{P}, k)$.   ▷ research agent identifies top-$k$ relevant papers
for each paper $P_i$ in $\{P_i, ...P_k\}$ do
    $\text{Text}_i \leftarrow \text{DownloadPaper}(P_i)$.   ▷ e.g., via ArXiv/Semantic Scholar API
    $(\mathcal{S}_i, \mathcal{U}_i) \leftarrow \mathcal{RA}(\text{Text}_i)$.   ▷ research agent extracts summary & repo URL
    $\mathcal{K}_i \leftarrow S_i$.   ▷ Initialize $\mathcal{K}_i$ with summary
    if $U_i$ is valid and accessible then
        $\text{Repo}_i \leftarrow \text{DownloadRepo}(U_i)$.   ▷ e.g., via GitHub API
        $\text{Code}_i \leftarrow \mathcal{CA}(S_i, \text{Repo}_i, \mathcal{I})$.   ▷ code agent filters for relevant code
        $\mathcal{K}_i \leftarrow \langle S_i, \text{Code}_i \rangle$.   ▷ Update $\mathcal{K}_i$ to summary-code pair
    end if
    Add $\mathcal{K}_i$ to $K_{\text{lineage}}$.
end for
Return $K_{\text{lineage}}$.
```

A.3.2 Automatic Evaluation

For the evaluation metric in the align-score, we utilize LLMs to judge the generated code from three aspects, including paper-level, code-level and mixed-level. The prompts provided to the judge LLM are generally long, requiring a powerful model for robust evaluations. Consequently, we employ `o1` for this purpose. For each level, each reproduction requires approximately \$0.5 for evaluation. Thus, an evaluation run to determine the align-score costs approximately \$20 on REPRODUCEBENCH. When evaluating the generated code in the repository (Qian et al., 2023), all the Python files are concatenated to form the gener-

Method	**Total Lines**	**Preprocess Code**	**Preprocess Lines**	**Pretrained Model**	**Evaluation Metric**	**Reference Performance**
IEBins	1877	✓	320	✗	$\delta < 1.25$	0.8854
iTransformer	610	✓	199	✗	MSE	0.4008
DKD	678	✗	0	✓	Accuracy	74.56
SimVP	544	✓	161	✗	MSE	26.19
HumanMAC	1196	✓	412	✗	ADE	0.2195
SFNet	805	✓	121	✗	PSNR	39.68
LSM	403	✓	141	✗	MSE	0.0074
Swin-Unet	1218	✓	102	✓	DSC	0.7309
TDGNN-w	310	✓	21	✗	Accuracy	0.7651
TimeVAE	711	✓	69	✗	Predictor	0.2083
WCDM	935	✓	117	✗	SSIM	0.7938
BSPM	713	✓	221	✗	Recall	0.1921
DAT-S	2047	✓	163	✗	PSNR	38.48

Table 7: More details about REPRODUCEBENCH. The Reference Performance is the rerun performance obtained by official implementations. We utilize them to calculate the performance gap.

ated code. Figure 10 denotes the prompt to extract 5 key points from the paper by utilizing `o1`. Figure 11 shows the prompt for paper-level evaluation and Figure 12 13 show the prompt for code-level evaluation. Figure 14 15 shows the prompt for mixed-level evaluation. The placeholder in each prompt is replaced with the corresponding content.

A.4 Human Evaluation Details

A.4.1 Evaluation Settings

For the human evaluations, the evaluators are given the original papers, instructions, official implementations, and generated ones. To reduce the workload of human assessment, we simultaneously generated summaries of the papers using LLMs, which helps to accelerate the evaluators' understanding of the papers. We recruit 5 students for human evaluations, including 3 PhDs, 1 master and a senior undergraduate. All the evaluators are from the EECS-related majors. The overall instructions are like the prompts for mixed-level evaluation denoted in Figure **??**, **??**. The human evaluators should score the generated code through the completeness of the method, parameters and experiment pipeline with a maximum of 10, 5, and 5. The score criteria are similar to the mixed-level evaluations in Figure 14 and 15. The minimum and maximum scores only occur in extreme circumstances where the code is totally wrong or exactly correct. For each implementation, the evaluators need around 15-25 minutes for the evaluation.

A.4.2 Human-Machine Score correlation

To evaluate the correlation of the alignment score evaluated by the LLM judge and the human evaluation scores, we calculate the Pearson correlation coefficients of these two scores. We evaluate all three runs in the main experiments. Since there is no one-to-one correspondence between the above two scores, we calculate the correlation by comparing the three alignment scores against the single average human score for each task. The results in Table 8 demonstrate that the mixed-level score aligns the best with the human scores, which proves our proposed evaluation strategy.

A.5 License Check

AUTOREPRODUCE is a non-profit project intended solely for research purposes. In constructing the REPRODUCEBENCH, we carefully curate the datasets, selecting only those licenses for research and downloading them in strict accordance with any specified requirements. For the paper and code, we have re-examined the ground-truth code for all papers and found that it is all under the MIT and Apache-2.0 licenses. The specific terms state that: Permission is hereby granted, free of charge, to any person obtaining a copy of this software and associated documentation files (the 'Software'), to deal in the Software without restriction, including without limitation the rights to use, copy, modify, merge, publish, distribute, sublicense, and/or sell copies of the Software. Secondly, we have screened the papers themselves, and their licenses

Method	LLM	Paper-level	Code-level	Mixed-level
AUTOREPRODUCE	o3-mini	0.48	0.76	0.81
PaperCoder	o3-mini	0.52	0.73	0.83
AUTOREPRODUCE	Claude-3.5-Sonnet	0.49	0.71	0.78
ChatDev	GPT-4o	0.37	0.79	0.81

Table 8: The human-machine score correlation between the human and alignment scores.

are CC BY-NC-ND (Attribution-NonCommercial-NoDerivatives International), which denotes they are free to: Share — copy and redistribute the material in any medium or format. Due to our non-profit nature, we comply with all the aforementioned terms. Additionally, we analyze the lineage papers and code for AUTOREPRODUCE. Since the lineage papers are obtained via the ArXiv API, the permissions for papers on ArXiv fall under the following licenses:

- CC BY: Creative Commons Attribution
- CC BY-SA: Creative Commons Attribution-ShareAlike
- CC BY-NC-SA: Creative Commons Attribution-Noncommercial-ShareAlike
- CC BY-NC-ND: Creative Commons Attribution-NonCommercial-NoDerivatives
- CC Zero: No Rights Reserved

Therefore, we comply with all the usage regulations given our non-commercial purpose. Furthermore, we have checked the corresponding code repositories and found that they all fall under the MIT License, Apache-2.0 licenses, and the BSD License. As our work only involves refactoring this code, our actions comply with its relevant requirements.

Input queries of AutoReproduce

```
ARXIV_ID='ArXiv ID'
TASK='Task Name'
MODEL='Model Name'
METRIC='Evaluation Metric'
INSTRUCTION=f"""You are assigned an arXiv paper to replicate.  You need to replicate the
experiment conducted for {TASK} dataset.  Utilizing {METRIC} as the evaluation metric.  The
dataset/checkpoints is under 'Relative Path'
```

Figure 3: The input quries of AutoReproduce. It contains the ARXIV ID to download the paper. TASK, MODEL and METRIC in the paper that need to be reproduced.

Iterative dialogue template of LLM agents

```
~~~~~~~~~
History: {history string}
~~~~~~~~~
Current Step: {step}, Phase: {phase}
Task instructions: {current phase prompts}
[Overall Objective] Your overall goal is to follow the instructions to replicate the method
proposed in the paper.
Instruction: {instruction}.
To achieve the objective, start by conducting a literature review, learning relevant codes, and
finally generating the method and experiment codes.
{previous step feedback}
{command instruction}
{additional notes}
When you are given commands that you can use, your reply must be selected from among the commands.
Please produce a single command below:
```

Figure 4: Prompt for the `ADD` command of code agent.

Abbreviation prompts for Paper Lineage stage of the research agent

~~~
Your task is to read the paper and identify the 3 most relevant papers from its references that
help in understanding the paper's contributions, including the proposed model architecture,
experimental settings, and other details. These papers need to be in the same research field as
the ones that need to be replicated.
You need to infer the most relevant related works based on the information such as the position
and name of the reference. Importantly, the name of the paper should be correct. Do not generate
mismatched names.
The selected papers must come from the references and be specific to the same research field
as the paper, avoiding commonly cited works like 'Attention Is All You Need'. Also, do not add
the paper in the instructions. Return the related works in the format: ['paper name 1', 'paper
name 2', ...] with only paper names (author names should not be included).
Add the most related work after reading using the following command:
```ADD\n<related code file>\n```
where <related work list> is the list of related work in the reference, the item in the list
should be the full name of the paper. ADD is just the word ADD.
You can only use a single command per inference turn.  Do not use more than one command per
inference. If you use multiple commands, then only one of them will be executed, not both.
~~~

Figure 5: Abbreviation prompts for Paper Lineage stage of the research agent

Abbreviation prompts for Paper Lineage stage of the code agent

~~~
You need to reproduce the {Task Instruction} experiment now. The code repository mentioned above
is related to the target reproduction paper. Please filter out the code files that are helpful
for the reproduction based on the instructions, and return the useful code files in the form
of a list. For example, ```python [’file1.py’, ’model/file2.py’]```. You should start from the
most relevant code file.
You could select related code files using the following command:
```ADD\n<related code file>\n```
where <related code file> is the list of related code files in the given code repo, the item in
the list should be the full name of the file path. ADD is just the word ADD.
~~~

Figure 6: Abbreviation prompts for Paper Lineage stage of the code agent

Code agent prompt for the `EDIT` command.

~~~
You can edit code using the following command:
```EDIT\n N M\n<new code>\n```
EDIT is the word EDIT, N is the first line index you want to replace, and M is the last line
index you want to replace (everything in between will also be removed), and <new code> will be
the new code that is replacing the old code.
This command allows you to replace lines indexed n through m (n:m) of the current code with as
many lines of new code as you want to add. This will be the primary way that you interact with
code.
You can only use a single command per inference turn. Do not use more than one command per
inference. If you use multiple commands, then only one of them will be executed, not both.
~~~

Figure 7: Prompt for the `EDIT` command of code agent.

Abbreviation of human evaluation instructions.

Standards for manual score evaluation

1. Overview & Objective

You are acting as an expert evaluator to assess the quality and fidelity of LLM-generated code. Your task is to compare Generated Code against the official Reference Code (Ground Truth) for a specific research paper.

Goal: Determine how accurately the generated code reproduces the specific methods, parameters, and experimental pipeline described in the paper and implemented in the reference code.

2. Scoring Criteria (Total: 20 Points)

Please evaluate the code across three specific dimensions. Use the Reference Code as the absolute standard for correctness.

A. Completeness of Method (Max 10 Points)

Focus: Does the code implement the core modeling innovation, specific algorithms, network architecture, and loss functions?

0 - 1 Points (Total Difference):

The core innovation is missing or completely incorrect. The code might implement a standard baseline (e.g., standard ResNet) instead of the paper's proposed method, or the logic is fundamentally flawed and unrunnable.

2 - 4 Points (Unsimilar):

The code attempts the method but misses critical components. Major modules are absent, or the mathematical logic (e.g., attention mechanism details, specific loss calculation) deviates significantly from the reference.

5 - 7 Points (Similar):

The core concepts are present. The implementation captures the "essence" of the method, but there are noticeable inaccuracies, over-simplifications, or structural differences compared to the reference code.

8 - 9 Points (Roughly the Same):

High fidelity. The logic and structure closely mirror the reference code. Differences are superficial (e.g., variable naming, modularization style) and do not affect the core functionality.

10 Points (Same): Functionally identical. The implementation of the key method is a near-perfect replica of the reference code logic.

B. Parameters (Max 5 Points)

Focus: Does the code use the correct hyperparameters, dimensions, and constants as specified in the reference code?

0 Points (Total Mismatch): Uses generic library defaults (e.g., ‘lr=1e-3‘, ‘hidden_dim=256‘) or random values that completely contradict the paper's specific setup.

1 Point (Significant Deviation):

Attempts to configure parameters, but critical architectural dimensions (e.g., number of layers, embedding sizes, distinct model depths) are incorrect relative to the reference.

2 Points (Partial Match):

The model architecture parameters are mostly correct, but critical training hyperparameters (e.g., specific learning rate schedules, weight decay, optimizer betas) or loss coefficients are missing or wrong.

3 Points (Moderate Match):

The majority of parameters (both model and training) align with the reference, but there are noticeable discrepancies in specific configuration details (e.g., wrong kernel size in a specific layer, incorrect temperature scaling value).

4 Points (High Fidelity):

The configuration is nearly identical to the reference code. The discrepancies are negligible and non-critical (e.g., a slightly different buffer size or a different variable name for a constant) that do not impact the main results.

5 Points (Exact Match):

Perfect replication. The generated code strictly adheres to all hyperparameters, model dimensions, and configuration settings found in the reference code without any error.

Figure 8: Prompt for human evaluation instructions.

Abbreviation of human evaluation instructions.

```
 C. Experiment Pipeline (Max 5 Points)
Focus: Is the data processing, training loop, and evaluation protocol correct?
0 Points (Broken / Wrong Task):
The pipeline is non-functional, syntax-heavy errors prevent execution, or it solves a completely
different task (e.g., generating a classification loop for a segmentation paper).
1 Point (Incorrect Data Handling):
The training loop structure exists, but the data loading or input formatting is fundamentally
wrong or hallucinated (e.g., using a fake dataset class that doesn't exist or handling data
dimensions incorrectly).
2 Points (Generic / Simplified):
The code provides a standard "boilerplate" pipeline (standard loader → model → loss). It
works, but misses all paper-specific customizations like specific data augmentations, sampling
strategies, or preprocessing steps.
3 Points (Incomplete Protocol):
The pipeline flow is correct and includes some specific steps, but misses critical evaluation
metrics or specific evaluation procedures defined in the paper (e.g., using simple Accuracy
instead of a specific mIoU calculation, or missing a required post-processing step).
4 Points (High Consistency):
The pipeline is robust and follows the correct protocol (Data Load → Model → Loss → Metric).
The logic matches the reference, with only minor deviations in non-critical areas like logging,
random seed setting, or exact validation split ratios.
5 Points (Exact Replication):
Perfect reproduction. The code includes specific preprocessing logic, exact data splits,
specific augmentation pipelines, and metric calculations exactly as implemented in the reference
code.

3. Evaluation Guidelines
1. Logic over Comments: Ignore comments in the code. Judge based on the executable logic/code
statements.
2. Functional Equivalence: If the generated code achieves the same mathematical result as the
reference but uses a slightly different coding style (e.g., 2 lines vs 1 line), consider it
correct.
3. Strictness: Do not give full marks unless the implementation is rigorous. "Looking similar"
is not enough for a max score; it must be "functionally equivalent.

4. Output Format Please provide your evaluation in the following format:

Paper Title: Title
Dimension: [Score](Justification (Briefly explain matches/discrepancies)
Method: [**/10](**)
Parameters: [**/5](**)
Pipeline: [**/5](**)
Total Score: **/20
```

Figure 9: Prompt for human evaluation instructions.

Prompt for summarizing 5 key points proposed in the paper

```
TASK = MovingMnist
METRIC = MSE
TITLE = SimVP: Simpler yet Better Video Prediction
PATH = bench/simvp/source
INSTRUCTION = You are assigned an arXiv paper {TITLE} to replicate. You need to replicate the
experiment conducted for {TASK} dataset in the paper. Training and testing datasets are under
the folder {PATH}. Code related to processing the data is provided to you to obtain the dataset.
Utilise {METRIC} as the evaluation metric.

The provided text above is the full text of the paper. The instructions for reproducing the
experiment are {INSTRUCTION} with the model {MODEL}.
Now you will evaluate whether the code has replicated the instructions about {TASK} experiments
in the paper.
Please summarise 5 key points. These 5 key points will be used to assess whether the code has
completely replicated the model, methods, and experimental setting in the paper.
Specifically, you are preferred to use 3 key points to summarise the proposed method, 1 for
hyperparameters and 1 for training setup. Do not include the dataset generation process as a
point, as the dataset has been preprocessed.
You should regard each part of the proposed method in the paper as a separate key point.
If there are formulas in the paper, you need to extract them in LaTeX format and use them as
the criteria for judging whether the code has been replicated.
Do not include some common content as the key points to be compared. Only include the key points
related to the {TASK} task. If all these 5 points are replicated exactly, the code will fully
replicate the paper. These key points are very important and should be as detailed as possible,
which could reflect the key points to reproduce the paper.
```

Figure 10: Prompt for key points summarization.

Prompt for paper-level evaluation

```
Now, I'm presenting you with a generated code. You need to check whether the details of the code
correspond to the key points.
The experiment instructions for the generated code are
{INSTRUCTION}
You just need to consider the model, task, and dataset used in the instructions.
There are a total of 5 comparison points, and each point is scored from 0 to 20. A score of 20
indicates perfect reproduction, while 0 means no reproduction at all.
Please rate each of the 5 comparison points separately and provide the reasons.
Points to compare
{Points}
Generated code
{Generated Code}
For each scoring criterion, you need to give a score between 0-20 points. The scoring criteria
are as follows:
Total difference: 0-2 points.
Unsimilar: 3-8 points.
Similar: 9-14 points.
Roughly the same: 15-18 points.
Same: 19-20 points.
You need to evaluate with a critical perspective. Don't give high scores to the mismatched
content.
Disregard all comments, as they do not pertain to the implementation of the code.
The code needs to strictly correspond to the points. Any mismatched content should result in a
deduction of points.
The scores should be presented in the form of [x/20 points]. The final score should be the sum
of the scores for each point.
```

Figure 11: Prompt for paper-level score. The Points are the 5 key points generated by the LLM judge, and the Generated Code is the code generated by LLM Agents.

Prompt for code-level evaluation

You are an expert proficient in code analysis, specialising in comparing and evaluating code structure and functionality. Now you need to judge whether the replicated code is the same as the official code.
Please analyse the following two code segments: the first is model-generated code, and the second is standard training code. You don't need to pay attention to the contents related to saving, printing and logging. Focus on the model itself and its training process instead.
Conclusion: Summarise whether the two code segments are completely equivalent in terms of model definition and Experimental Integrity, and briefly explain the significance of the scoring results.
First Code Segment (Standard Experiment Code):
{Reference Code}
Second Code Segment (Model-Generated Code):
{Generated Code}
Your task is to conduct a detailed comparison of these two code segments, focusing on the following aspects:
Overall Structure:
The overall structure of the model code includes the data flow in the forward function and the overall model structure.
Only consider the model-related code, such as the encoder-decoder structure, and ignore the data loading and other irrelevant code.
Model Structure:
Are the model architectures defined in both code segments (e.g., number of layers, activation functions, input/output dimensions) completely identical?
Specifically compare the implementation details, such as if a spatio-temporal processing module is present in the code, including but not limited to input processing, feature extraction methods, temporal dimension handling, spatial dimension handling, connection methods (e.g., residual connections, attention mechanisms), and parameter settings. Apply this level of comparison to all modules. Check for any subtle differences (e.g., convolution kernel size, pooling methods, normalisation techniques).
Training Details:
Compare whether the model hyperparameters (e.g., learning rate, batch size, optimiser type, learning rate decay strategy) are consistent. Verify whether the loss function's definition and implementation are identical, including the loss calculation formula and weight assignments.
Experimental Integrity:
Compare the implementation of the training process, including the training pipeline, data preprocessing, and gradient update logic, to determine if they are equivalent. The most crucial thing you need to pay attention to is the integrity of the experiment. Check for any functional differences (e.g., initialisation methods, early stopping mechanisms). There is no requirement for checkpoint saving, logging information and multi-GPU training. Do not consider these contents.

Pay special attention to analysing the implementation of the module in the model structure, ensuring a detailed comparison of each layer's specific parameters and computational logic.
If differences are found, clearly indicate the specific code lines or modules where they occur and analyse their potential impact on model performance or behaviour.
Ignore differences in code style (e.g., variable naming, comments) and focus on functionality and implementation logic.
You need to focus on the code implementation and don't need to consider comments and function names, and other contents irrelevant to the implementation.

Figure 12: Prompt for code-level score. The Reference Code and Generated Code are our curated official implementations and Agents' generated code, respectively.

Prompt for code-level evaluation

Scoring Criteria (Total: 100 points):
Overall Structure (25 points): Consistency in the overall structure of the model-related code, including the overall data flow pipeline in the forward function, and the overall modules are structured.
Model Details (25 points): Consistency in the implementation of the model structure. All the layers should be compared. If the names are different but the internal functions are the same, you should consider them as the same.
Training Details (25 points): Consistency in hyperparameters, loss function, learning rate decay, etc.
Experimental Integrity (25 points): Consistency in training loop, data processing, and other pipeline. You just need to compare the training, testing pipeline included in the code.

You need to analyse the code details and implementation before giving the score. Firstly, analyse the overall structure of the model and then analyse it specifically for each module.
For custom blocks, the details of how custom blocks are implemented should be analysed.
For some official implementation, you need to analyse whether the implementation of custom is the same as the official one based on your understanding. Ignoring the differences of programming languages and only considering the code implementation.

For each scoring criterion, you need to give a score between 0-25 points. The scoring criteria are as follows:
Total difference: 0-4 points.
Unsimilar: 5-10 points.
Similar: 12-16 points.
Roughly the same: 17-22 points.
Same: 23-25 points.
The MLP and a single linear layer should be considered roughly the same.
Similarly, when the functions of two codes are the same, but the implementations are different.
Unsimilar should be when the functions of two codes are different.
You need to analyse the specific implementation of the code, do not just focus on the name. Make detailed evaluations based on the details. Ignore all the comments and focus only on the code.
The scores should be presented in the form of [x/25 points]. The final score should be the sum of the scores for each point.

Figure 13: Prompt for code-level score. The Reference Code and Generated Code are our curated official implementations and Agents' generated code, respectively.

Prompt for mixed-level evaluation

You are an expert code reviewer specialising in evaluating the fidelity of research paper implementations. Your task is to meticulously compare the generated code against a set of key points from a research paper. Crucially, you will use the provided reference code as the ground truth to understand how each key point is specifically and correctly implemented.
The experiment instruction is {INSTRUCTION} You just need to consider the model, task, and dataset used in the instructions.
Inputs You Will Be Provided With:
1. Points: A list of key concepts, mechanisms, algorithms, or architectural features from the research paper that the generated code is supposed to implement.
2. Reference code: The official source code accompanying the research paper. This code serves as the benchmark for understanding the precise, intended implementation details of each key point.
3. Generated code: The generated code that needs to be evaluated for its accuracy in reproducing the key points as they are implemented in the reference code.
Your Evaluation Process:
1. Understand Key Point via Reference Code: For each key point, first, thoroughly examine the reference code. Identify and describe the specific segments of the reference code (e.g., functions, classes, logic blocks) that implement this key point. Summarize how the reference code realizes this key point. This understanding will be your basis for comparison.
2. Analyse Generated Code against Reference Implementation:Now, review the generated code (generated code) to find its implementation of the same key point. Compare this implementation directly against your understanding of how it was done in the reference code. Focus on whether the logic, structure, and functional outcome are equivalent.
3. Score the Replication: Based on your comparative analysis, assign a score from 0 to 20 to the generated code for its replication of this specific key point, using the scoring rubric below.
4. Provide Detailed Justification: Clearly articulate the reasons for your score. Specifically highlight matches and discrepancies between the generated code's implementation and the reference code's implementation of the key point. Explain why it matches or why it deviates.
Scoring Rubric:
0-2 points (Total difference): The core innovation point (as demonstrated in the reference code) is not replicated at all in the generated code, or the implementation is fundamentally flawed, missing major functional aspects, or entirely incorrect when compared to the reference code.
3-8 points (Unsimilar): The key point is replicated in the generated code, but not completely accurately or comprehensively when compared to the reference code. Some aspects of the reference code's implementation might be present, but there are noticeable inaccuracies, missing details, or differences in logic that might affect functionality or deviate from the paper's intended mechanism, as shown in the official code.
9-14 points (Similar): The key point is replicated completely and accurately in the generated code. The implementation in the generated code closely mirrors the logic, structure, and functional behavior of the corresponding implementation in the reference code, although there might be some non-critical differences or alternative approaches that achieve the same core outcome.
15-18 points (Roughly the same): The key point is replicated completely, accurately, and comprehensively in the generated code. The implementation is highly consistent with the reference code in logic, structure, and function, differing only in very minor, non-functional ways that do not impact the core mechanism.
19-20 points (Same): The implementation of the key point in the generated code is identical or functionally equivalent to the reference code, representing a code-level copy or a near-perfect replication of the relevant sections.

Figure 14: Prompt for mixed-level score. The Reference Code and Generated Code are our curated official implementations and Agents' generated code, respectively.

Prompt for mixed-level evaluation

```
Critical Evaluation Guidelines:
Conduct your evaluation with a stringent and critical perspective. Do not award high scores for superficial similarities or implementations that do not match the essence of the reference code’s approach for a given key point.
Your evaluation must be based solely on the executable code logic. Disregard all comments in both the reference code and the generated code as they do not pertain to the functional implementation.
At the same time, you need to pay attention not only to the key points themselves, but also to all the details related to them. If the key points correspond but the related implementations are different, it will still affect the reproduction effect. Please evaluate each key point in the points with the generated code. You should both determine the overall similarity and concrete scores. For example, when you decide the two codes are similar, you should also determine the level of similarity.
When evaluating specific implementations, prioritise the equivalence of core structure and function over superficial differences, such as the number of modules. If generated code achieves the same functional outcome and structural design as the reference, it should be considered equivalent, irrespective of modular composition.

Begin Evaluation:
Points to compare:{points}
Reference Code:{Reference Code}
Generated code:{Generated Code}

Output Format:
For each key point, please provide: 1. Key Point:*[Name/Description of the key point being evaluated]
2. Reference Code Implementation Summary:*[Your summary of how this key point is implemented in the reference code]
3. Generated Code Analysis & Comparison:*[Your detailed analysis of the generated code’s attempt to implement this point, comparing it directly to the reference code’s approach]
4. Score:*[x/20 points]
5. Reasoning for Score:*[Detailed justification based on the comparison]
Sum the overall scores for each key point to provide a final score out of 100 points, and include a summary of the overall evaluation.
Overall Score:*[x/100 points]
```

Figure 15: Prompt for mixed-level score. The Reference Code and Generated Code are our curated official implementations and Agents’ generated code, respectively.