LLM Review: Enhancing Creative Writing via Blind Peer Review Feedback

Anonymous ACL submission

Abstract

Large Language Models (LLMs) often struggle with creative generation, and multi-agent frameworks that improve reasoning through interaction can paradoxically hinder creativity by inducing content homogenization. We introduce LLM Review, a blind peer-review-inspired interaction topology in which agents critique peer drafts but revise from only their own draft and received feedback, without conditioning on peers' revisions. This separates critique from exposure, allowing agents to incorporate external revision signals while preserving divergent creative trajectories. To enable rigorous evaluation, we propose SciFi-100, a science-fiction benchmark with LLM-as-a-judge evaluation, human preference judgments, and rule-based novelty metrics. Experiments demonstrate that LLM Review consistently outperforms single- and multi-agent baselines, and smaller models with our framework can surpass larger single-agent models, suggesting blind critique-and-revision interaction can amplify effective creative capability at the system level.

1 Introduction

Large Language Models (LLMs) have achieved strong performance across natural language processing tasks (Lappin, 2024; Zhang et al., 2024b; Yi et al., 2024), and are increasingly deployed in multi-agent systems for reasoning and coordination (Tran et al., 2025). However, these systems are optimized for correctness rather than creativity. Prior work finds that LLMs tend to reproduce familiar patterns rather than generate genuinely novel ideas (Mohammadi, 2024; Chakrabarty et al., 2024; Li et al., 2025), and existing single-agent approaches such as decoding strategies, prompt engineering, and post-training optimization (Yang et al., 2023; Potraghloo et al., 2025; Matan and Velvizhy, 2025) yield surface-level diversity rather than substantive conceptual novelty.

Human creativity is fundamentally social, emerging through discussion, critique, and iterative refinement (Nijstad and Paulus, 2003). Recent multi-agent frameworks, such as debate and discussion, show improvements in reasoning and output diversity (Du et al., 2023; Lu et al., 2024; Summers-Stay et al., 2023), all sharing the implicit assumption that more interactions yield better outcomes. We argue that this assumption breaks down in the case of creativity. Research on group brainstorming shows that interactive groups often produce fewer and less original ideas than individuals working independently, due to production blocking and convergent tendencies (Diehl and Stroebe, 1987; Larey and Paulus, 1999). Recent work further demonstrates homogenization effects when humans collaborate with LLMs (Anderson et al., 2024). We propose a different view: creativity is not improved by more interaction, but by the right information flow constraints. Creative novelty requires divergence, the ability to explore different trajectories without converging on shared patterns (Gillebaart et al., 2013). Existing frameworks repeatedly expose agents to each other's evolving outputs, inadvertently encouraging alignment and limiting semantic exploration.

We introduce **LLM Review**, a framework that enhances creativity by constraining rather than maximizing information flow through a mechanism we call Blind Peer Review. Inspired by double-blind academic reviewing, agents provide targeted feedback on peers' initial drafts but revise independently, without seeing how peers respond to the same feedback. This information asymmetry lets agents benefit from external critique while preserving independent creative trajectories. To evaluate our approach, we introduce **SciFi-100**, a science fiction writing dataset, together with a unified evaluation framework combining LLM-as-a-judge scoring, human annotation, and rule-based metrics capturing lexical and semantic novelty against a corpus of canonical science fiction (Colton, 2008).

To summarize, our contributions are: (1) We propose LLM Review, a blind peer-review-inspired interaction topology for creative multi-agent generation, where agents exchange critiques but revise independently without conditioning on peers' revisions. (2) We introduce SciFi-100, a science-fiction creative-writing benchmark evaluated with LLM-judge scores, human preference judgments, and rule-based novelty metrics. (3) We show that LLM Review consistently improves over single- and multi-agent baselines across different writer backbones. (4) We show system-level capability amplification where smaller-backbone LLM Review systems outperform larger same-family single-agent baselines.

2 Related Work

Multi-Agent LLMs Recent work has explored multi-agent frameworks built on LLMs to improve factuality, reasoning, and task performance through structured interaction, including role-based workflows, debate and critique protocols, persona-driven interaction, and large-scale orchestration (Yao et al., 2022; Chen et al., 2024; Hong et al., 2023; Qian et al., 2024a; Du et al., 2023; Chan et al., 2023; Tseng et al., 2024; Wang et al., 2025). These systems are primarily evaluated on goal-directed benchmarks and focus on task success, autonomy, or efficiency (Li et al., 2024; Ye et al., 2025; Qian et al., 2024b; Dang et al., 2025; Zhang et al., 2024a). In contrast, our work studies creative writing and shows that interaction *structure*, rather than interaction frequency or scale, plays a critical role where strategically restricting information flow helps preserve divergent creative trajectories.

LLM Creativity Creativity in language models has been studied across tasks such as literary composition, metaphor generation, and alternative use generation, primarily in single-LLM settings (Gómez-Rodríguez and Williams, 2023; Chakrabarty et al., 2024; DiStefano et al., 2025; Stevenson et al., 2022). Prior approaches improve creativity through decoding strategies, post-training optimization, or inference-time prompting (Ghazvininejad et al., 2017; Keskar et al., 2019; Wei et al., 2025; Chung et al., 2025; Lagzian et al., 2025; Rashkin et al., 2025). While effective, these methods largely operate at model or decoding level; our work instead frames creativity as a socially grounded, multi-agent process driven by structured discussion.

Creativity Evaluation Evaluating creativity is inherently subjective, and prior work relies on human judgments or LLM-based evaluators for scalability (Gómez-Rodríguez and Williams, 2023; Chakrabarty et al., 2024; Feng et al., 2025; Zheng et al., 2023; Fein et al., 2026). Automatic proxies are often used to capture complementary aspects such as diversity and semantic novelty relative to a reference corpus (Zhang et al., 2021; Peeperkorn et al., 2024; Zhao et al., 2025). Following established views of creativity as balancing novelty and value (Colton, 2008; D'Souza, 2021), we adopt a combined evaluation framework that integrates rule-based novelty metrics with LLM-as-a-judge assessment.

3 Methodology

3.1 Task Definition

Given a science-fiction writing prompt, the goal is to generate a story (approximately 300 words) that is coherent, creatively strong, and of good quality. We study both single-agent generation and multi-agent discussion frameworks that iteratively improve drafts through structured interaction. Unless otherwise specified, all frameworks use the same writer model and the same role-played writer personas to control for style and diversity effects.

3.2 SciFi-100 Data Curation

To curate high-quality science fiction prompts that can be used to evaluate model performance, we structure a systematic process to create a dataset that matches creative writing attributes. We first identify 10 central aspects (see Appendix A) of creative writing based on our experiences as human writers as well as foundational insights from narratology, literary theory, and creative writing pedagogy (Genette, 1980; Pound, 2013; Freytag, 1895; Forster, 1927; Rosenblatt, 1994; Burroway et al., 2019; Csikszentmihalyi, 1990; Chatman and Chatman, 1978; Ricoeur, 2004; Tannen, 2005). For each aspect, we query LLMs (Hurst et al., 2024) to generate 20 unique prompts by specifically instructing the model to create scenarios where a science fiction narrative can unfold; we manually select and revise 10 prompts to ensure diversity and thematic relevance. The dataset's balanced distribution across aspects ensures a comprehensive evaluation of creative dimensions. To our best knowledge, SciFi-100 is the first dataset designed to assess science-fiction writing of LLMs.

3.3 Multi-Agent Role-Play Setup

Following prior work on role-play and diversity of thought (Camacho, 2016; Lu et al., 2024), each agent is assigned a persistent persona (e.g., Humanistic Writer, Futuristic Writer, Ecological Writer) that remains fixed across all rounds. We repeatedly restate these roles in prompts to encourage consistent viewpoints and reduce homogenization.

3.4 Compared Frameworks

Single Agent A single LLM is prompted once to write a science-fiction story for the given prompt, which captures the base model's inherent creative writing capability under zero-shot prompting.

LLM Teacher LLM Teacher, inspired by classroom-style role-play prompting (Camacho, 2016), models a teacher-student loop in which a teacher agent provides guidance and critique to student writers. The framework proceeds in three phases: the teacher offers high-level advice, students draft stories and receive aggregated feedback, and students revise to produce final outputs. This baseline represents a simple extension of role-play prompting with critique, but its teacher-centered, one-to-many feedback can encourage convergence toward similar revisions.

LLM Debate LLM Debate (Du et al., 2023) structures interaction as proposal and critique, where agents present candidate drafts and challenge each other's content (logic gaps or weak originality), followed by refinement. Unlike other role-play-based frameworks, LLM Debate does not assign explicit personas to agents. We adapt the debate protocol for creative writing by focusing critiques on plausibility, novelty, and narrative quality.

LLM Discussion LLM Discussion (Lu et al., 2024) is a three-phase multi-agent framework (Initiation, Discussion, Convergence) built on top of Du et al. (2023) with role-play. Agents iteratively read others' drafts and update their responses accordingly. This baseline represents structured multi-agent collaboration without explicit critique roles.

3.5 LLM Review

Inspired by the iterative peer-review process in academic writing, we propose LLM Review, a structured feedback loop designed to improve creativity through *distributed critique* and *private revision*. The key idea is to separate the review context from the revision context, and let agents both *create* and *act as reviewers* for each other, then revise using feedback without seeing peers' revised drafts.

Phase 1: Compose Each agent independently writes an initial story draft conditioned only on the prompt and its persona.

Phase 2: Review Each agent reviews peers' drafts and provides targeted feedback (e.g., originality, world-building opportunities, speculative consistency, stronger imagery, character depth). Agents then revise their own draft using (a) their initial draft and (b) the received feedback.

Originality constraint During revision, agents do **not** see peers' revised drafts (only their initial drafts and corresponding feedback). This design reduces homogenization and preserves independent creative trajectories across rounds.

Figure 1 illustrates the interaction flow of LLM Review and the corresponding baselines.

3.6 LLM-as-a-Judge Evaluation

LLMs have demonstrated the ability to approximate human judgment and effectively evaluate content, achieving results comparable to human evaluators, even on creativity tasks (Lu et al., 2024). We adopt an LLM-as-a-judge approach to assess the creativity of generated stories, using `gpt-4o` (Hurst et al., 2024) as the judging model.

In our evaluation pipeline, each story is individually assessed on five key aspects derived from the literature on science fiction writing: **Scientific Concept Integration**, **Speculative Logic**, **Character Depth**, **Immersive World-Building**, and **Ethical and Philosophical Themes**. These evaluation aspects reflect the consensus of prior work in narratology, speculative fiction studies, creativity research, and narrative ethics (Canavan and Suvin, 2016; Chatman and Chatman, 1978; Forster, 1927; Le Guin, 2015; Nussbaum, 1990). Following Li et al. (2026), the LLM assigns a score between 0 and 5 for each aspect, where 0 indicates potential plagiarism of poor quality, and 5 indicates highly creative, high-quality writing. To ensure consistency and minimize variability, we evaluate each story three times and report the average score.

3.7 Human Evaluation

To validate that our LLM-as-a-Judge scores reflect human preferences, we recruit nine student annotators to evaluate the stories generated on SciFi-100 by the LLM Review framework with Llama-3.2-3B

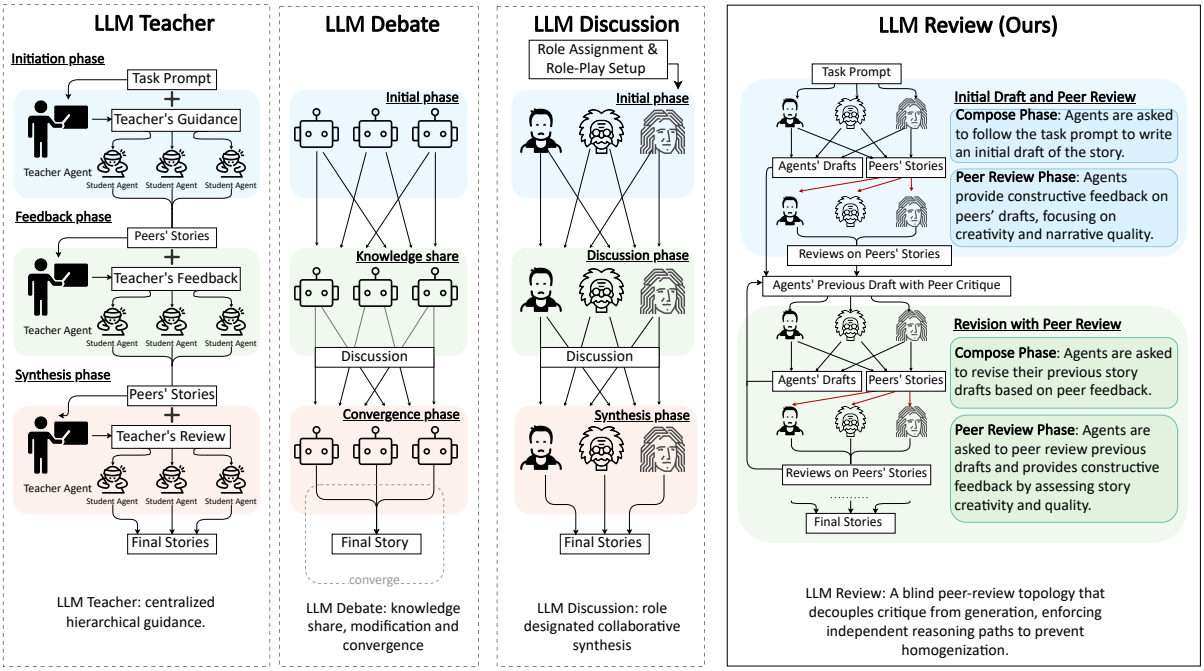

Figure 1: Comparison of multi-agent framework. A single LLM generates a story in a zero-shot setting without feedback, while LLM Teacher, LLM Debate, and LLM Discussion introduce hierarchical guidance, discussion, or role-based collaboration. LLM Review (ours) adopts a blind peer-review topology that decouples critique from generation, enabling independent revisions and reducing homogenization.

model. Annotators rate each story using the same five criteria as in Section 3.6 and the same 0-5 Likert rubric. For each story and criterion, we average the ratings to obtain a human consensus score.

3.8 Rule-based Evaluation

To evaluate the creativity of generated content, we design a rule-based evaluation framework with two components. First, we measure an intrinsic dimension: the absolute token-level diversity of the generated text. Second, we measure novelty relative to traditional science fiction, and decompose it into semantic novelty and lexical novelty. We use the SFGram dataset (Schaetti, 2018), which contains 1003 classic science fiction novels, as the reference corpus representing traditional science-fiction writing. Our framework provides a systematic and quantifiable multi-dimensional evaluation of creativity, defined as follows:

3.8.1 Absolute Diversity

We quantify the intrinsic diversity of generated text using token-level surprisal (the negative log-probability of each generated token under the model distribution (Hale, 2001; Demberg and Keller, 2008)). For a generated sequence of length L, the average surprisal is computed as:

$$S_{\text{avg}} = -\frac{1}{L}\sum_{j=1}^{L} \log p(x_j \mid x_{<j}), \qquad (1)$$

where x_j denotes the generated token at position j, and $p(x_j \mid x_{<j})$ is the model-assigned probability of that token given the preceding context. Concretely, we obtain next-token probabilities from the model outputs at each position and compute surprisal for the realized token x_j. We normalize by L to mitigate the influence of sequence length.

Compared to entropy, which summarizes uncertainty over next-token candidates, surprisal focuses on the information content of the tokens the model actually generates, and thus provides a practical intrinsic signal for our evaluation.

3.8.2 Lexical Divergence

We measure lexical divergence at the unigram word level using Kullback-Leibler (KL) divergence (Kullback and Leibler, 1951):

$$D_{\text{KL}}(p\|q) = \sum_{x\in\mathcal{X}} p(x) \log \frac{p(x)}{q(x)}. \qquad (2)$$

Here, $q(x)$ denotes the unigram word distribution estimated from the SFGram corpus, and $p(x)$ de-

notes the unigram word distribution of the generated text. We use $D_{\mathrm{KL}}(p\|q)$ to quantify how the generated lexical distribution departs from the reference; larger values indicate greater lexical deviation and serve as a proxy for lexical novelty. We apply additive smoothing to avoid zero probabilities.

3.8.3 Semantic Divergence

Nearest-neighbor semantic similarity We measure semantic novelty by embedding generated sentences and the SFGram reference corpus, and computing cosine similarity in the embedding space. We embed SFGram using the `all-mpnet-base-v2` model (Reimers and Gurevych, 2019). Since the encoder has a 512-token input limit, we split SFGram into chunks of approximately 250 words and embed each chunk. For a generated sentence embedding $\mathbf{u}$, we compute cosine similarity (Salton and McGill, 1983) to every reference chunk embedding $\mathbf{v}$:

$$\text{Cosine Similarity} = \frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{u}\|\|\mathbf{v}\|}. \quad (3)$$

We take the maximum similarity over reference chunks as nearest-neighbor overlap and report semantic novelty as $1 - \max$ Cosine Similarity, so larger values indicate higher novelty.

Embedding Volume Gain In addition to nearest-neighbor semantic similarity, we measure how broadly a generated story spreads in the embedding space relative to the reference corpus. While nearest-neighbor similarity captures local overlap with the corpus, the volume gain provides a distribution-level view of semantic spread. Let $\Sigma_{\text{ref}} = \Sigma(E_{\text{ref}})$ denote the covariance of SFGram chunk embeddings, and let $\Sigma_{\text{ref}\cup\text{story}} = \Sigma(E_{\text{ref}} \cup E_{\text{story}})$ denote the covariance after adding the story chunk embeddings. We summarize multivariate scatter using the log-determinant of the covariance, $\log\det(\Sigma)$, i.e., the log of the generalized variance (Wilks, 1932; Rencher, 1998); geometrically, $\det(\Sigma)$ is proportional to the squared volume of the covariance ellipsoid in embedding space. We define the embedding volume gain as:

$$\Delta_{\text{vol}} = \log\det(\Sigma_{\text{ref}\cup\text{story}}) - \log\det(\Sigma_{\text{ref}}). \quad (4)$$

Larger Δ_{vol} indicates that adding the story expands the embedding-space coverage beyond the reference corpus. For numerical stability, we compute $\log\det(\Sigma + \epsilon I)$ with a small ϵ.

Our rule-based metrics primarily capture diversity and novelty relative to the reference corpus, rather than quality dimensions such as coherence or readability. Hence, larger deviation or dispersion may sometimes reflect increased randomness rather than better creative writing, so we interpret these metrics alongside LLM-as-a-judge scores for complementary quality-aware assessment.

4 Experiments

4.1 Experimental Setup

We evaluate all frameworks on SciFi-100. Unless otherwise stated, multi-agent frameworks use 3 writer agents and 3 iterative rounds with fixed personas (Section 3.3). We use consistent output-format constraints across all methods (story text only) to reduce off-format generations.

4.2 Models

We evaluate our framework across a diverse set of instruction-tuned model backbones, covering both open-weight and proprietary frontier families. For the Llama family, we utilize **Llama 3.2** (Grattafiori et al., 2024), specifically the `Llama-3.2-1B-Instruct` (llama 1b) and `Llama-3.2-3B-Instruct` (llama 3b) variants, to assess performance on lightweight, edge-class models. We also include the **Qwen 2.5** series (Yang et al., 2025), employing `Qwen2.5-1.5B-Instruct` (qwen 1.5b) and `Qwen2.5-3B-Instruct` (qwen 3b), to verify generalization across different model architectures. For the closed-source baseline, we use **GPT-4o** (Hurst et al., 2024). For the main comparisons, we use top-p$= 0.9$ and temperature$= 0.9$. We additionally study the effect of decoding hyperparameters on the agent's performance.

5 Results

5.1 Creativity Evaluation Results

Main comparison Table 1 shows that across different writer backbones (Llama 3B and Qwen 3B), multi-agent frameworks outperform the single-agent baseline, with LLM Review consistently ranking highest on all of the LLM-as-a-judge metrics and most rule-based metrics. The LLM-as-a-judge results show LLM Review's improvements across all five dimensions with lower score variability, indicating more robust creativity-aware writing quality. On the other hand, the rule-based metrics provide complementary evidence: LLM Review achieves the strongest KL divergence, nearest-

Framework	LLM-as-a-Judge Evaluation						Rule-Based Evaluation			
	Concepts	Logic	Characters	World-Building	Ethics	Avg. ↑	Surprisal	KL Div.	1-Cos Sim.	Volume Gain
Writer backbone: **Llama 3B**										
Single Agent	3.62±1.14	3.62±1.13	3.41±1.11	3.63±1.11	3.40±1.14	-	0.476±0.271	2.233±0.012	0.345±0.002	0.0138±0.0002
LLM Teacher	3.71±0.87	3.73±0.87	3.61±0.88	3.73±0.87	3.43±0.92	3.01%	0.509±0.260	2.356±0.012	0.393±0.002	0.0160±0.0002
LLM Debate	3.76±0.22	3.76±0.21	3.74±0.24	3.65±0.29	3.80±0.37	5.95%	0.540±0.456	2.501±0.032	0.424±0.006	0.0175±0.0003
LLM Discussion	3.94±0.26	3.89±0.33	3.90±0.25	3.74±0.44	3.73±0.55	8.68%	**0.584±0.303**	2.597±0.037	0.435±0.009	0.0208±0.0004
LLM Review	**3.98±0.24**	**4.00±0.22**	**3.96±0.28**	**4.04±0.26**	**4.00±0.34**	**13.10%**	0.573±0.316	**2.638±0.034**	**0.441±0.008**	**0.0211±0.0004**
Writer backbone: **Qwen 3B**										
Single Agent	3.09±0.68	3.25±0.67	3.24±0.46	3.13±0.61	3.18±0.82	-	0.485±0.289	2.205±0.013	0.346±0.002	0.0148±0.0006
LLM Teacher	3.11±0.87	3.21±0.97	3.29±0.82	3.19±0.92	3.22±1.12	0.83%	0.488±0.250	2.223±0.024	0.357±0.008	0.0161±0.0009
LLM Debate	3.30±0.53	3.41±0.64	3.34±0.57	3.25±0.72	3.53±0.81	5.93%	0.505±0.380	2.237±0.032	0.368±0.011	0.0174±0.0008
LLM Discussion	3.42±0.72	3.75±0.53	3.58±0.71	3.64±0.74	3.59±0.86	13.15%	0.548±0.270	2.234±0.022	0.378±0.007	0.0196±0.0008
LLM Review	**3.52±0.49**	**3.90±0.29**	**3.89±0.38**	**3.79±0.41**	**3.79±0.69**	**18.85%**	**0.549±0.305**	**2.254±0.008**	**0.386±0.001**	**0.0206±0.0002**

Table 1: Comparison of LLM-as-a-judge and rule-based creativity evaluations across Llama 3B and Qwen 3B models. The Avg. column reports the average relative improvement over the corresponding Single Agent baseline across the five LLM-as-a-judge metric means.

neighbor semantic novelty, and Volume Gain on both backbones, while surprisal is comparable to Discussion and slightly lower for Llama 3B. These results suggest that LLM Review improves judged writing quality while preserving or increasing semantic novelty, rather than merely producing safer or more conventional revisions.

Mechanism analysis The observed performance differences reflect how each framework structures interaction, feedback, and information flow. The consistent gains of LLM Review in LLM-as-a-judge scores highlight the role of explicit, targeted critique in improving creativity-aware writing quality: unlike Discussion and Debate, which expose agents to peers' drafts without structured revision guidance, or Teacher, which provides centralized feedback that can steer agents toward similar revision targets, LLM Review decentralizes critique by requiring agents to deliver concrete peer-level feedback. At the same time, improvements in rule-based novelty metrics stem from controlled information exchange: while Discussion and Debate repeatedly condition agents on peers' evolving outputs, encouraging alignment in phrasing and themes, LLM Review shares only independent critiques while preserving independent creative trajectories. Together, this design balances guidance and independence, yielding stronger and more stable lexical and semantic novelty signals than other multi-agent baselines.

Scale-amplification comparison We next ask whether blind peer-review interaction can amplify the effective capability of smaller writer backbones. Table 2 compares smaller-backbone LLM Review systems against larger, same-family single-agent baselines. The smaller Review systems improve all five LLM-judge dimensions over their corresponding larger single-agent baselines. In particular, Qwen 1.5B with LLM Review improves Qwen 3B Single Agent by 6.01%; similarly, Llama 1B with LLM Review improves Llama 3B Single Agent by 5.57%. KL divergence and Volume Gain also increase in both families, suggesting that the improvement is not achieved by becoming more conservative.

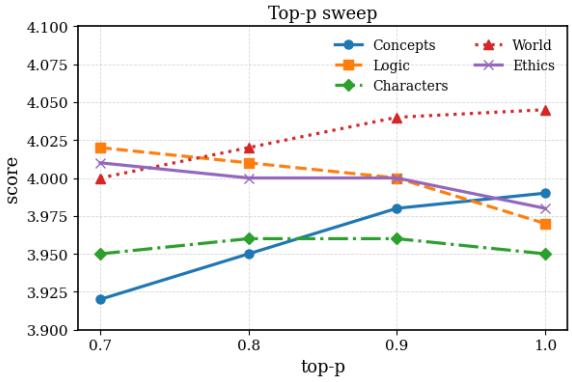

Figure 2: The average score of 5 LLM-as-a-judge evaluation aspects with different Top-p decoding methods.

5.2 Human Alignment

We further conducted a blind side-by-side A/B preference test between LLM Review and LLM Discussion on a subset of SciFi-100. A group of 9 annotators participated in the evaluation, with each annotator judging 30 paired story comparisons. Annotators were unaware of which system produced each story and selected one of five preference la-

Framework	LLM-as-a-Judge Evaluation						Rule-Based Evaluation		
	Concepts	Logic	Characters	World-Building	Ethics	Avg. ↑	KL Div.	1-Cos Sim.	Volume Gain
Single Agent (Qwen 3B)	3.09±0.68	3.25±0.67	3.24±0.46	3.13±0.61	3.18±0.82	-	2.205±0.013	**0.346±0.002**	0.0148±0.0006
LLM Review (Qwen 1.5B)	**3.27±0.73**	**3.41±0.73**	**3.30±0.69**	**3.39±0.70**	**3.47±0.87**	**6.01%**	**2.412±0.012**	0.329±0.002	**0.0196±0.0001**
Single Agent (Llama 3B)	3.62±1.14	3.62±1.13	3.41±1.11	3.63±1.11	3.40±1.14	-	2.233±0.012	0.345±0.002	0.0138±0.0002
LLM Review (Llama 1B)	**3.85±0.47**	**3.81±0.50**	**3.60±0.54**	**3.75±0.50**	**3.65±0.64**	**5.57%**	**2.627±0.025**	**0.449±0.007**	**0.0213±0.0004**

Table 2: LLM-as-a-judge and rule-based creativity evaluations comparing smaller LLM Review models to larger single-agent baselines within the same model family.

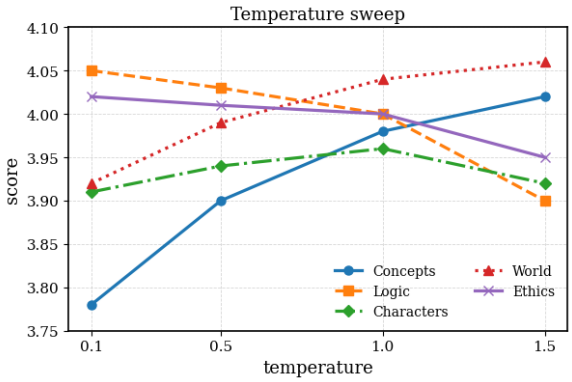

Figure 3: The average score of 5 LLM-as-a-judge evaluation aspects with different temperatures.

Human preference outcome	Count	%
Clearly LLM Review better	40	14.8
Slightly LLM Review better	82	30.4
Tie	101	37.4
Slightly LLM Discussion better	38	14.1
Clearly LLM Discussion better	9	3.3
LLM Review preferred	**122**	**45.2**
LLM Discussion preferred	47	17.4
Non-tied comparisons	169	62.6
Non-tied preference test		
LLM Review win rate	72.2% (122/169)	
95% exact binomial CI	[64.8%, 78.8%]	
Two-sided sign test	$p = 7.16 \times 10^{-9}$	

Table 3: Blind A/B human preference results between LLM Review and LLM Discussion on a subset of SciFi-100. Percentages in the upper block are computed over all 270 judgments. The win rate, confidence interval, and two-sided exact binomial sign test are computed over the 169 non-tied comparisons.

bels: "clearly A better", "slightly A better", "tie", "slightly B better", or "clearly B better".

As shown in Table 3, LLM Review was preferred in 122 out of 270 judgments, whereas LLM Discussion was preferred in only 47 judgments; the remaining 101 judgments were ties. Excluding ties, LLM Review won 122 out of 169 non-tied comparisons, corresponding to a non-tied win rate of 72.2% with a 95% exact binomial confidence interval of [64.8%, 78.8%]. We assessed statistical significance using a two-sided exact binomial sign test over non-tied comparisons, testing the null hypothesis that LLM Review and LLM Discussion are equally likely to be preferred. The result rejects the null hypothesis ($p = 7.16 \times 10^{-9}$), indicating a statistically significant human preference for LLM Review over LLM Discussion.

We also measure judge-human alignment using the 0-5 Likert rubric from Section 3.6. The LLM judge shows moderate agreement with human consensus ratings on LLM Review outputs, with ICC(A,1)=0.58-0.65 and Pearson's r=0.607-0.689 across dimensions. See Appendix G for details.

5.3 Ablation Study

We conduct ablation studies to understand the sensitivity of LLM Review to key design choices: decoding hyperparameters, the number of iterative rounds, the number of participating agents, and to compare with other baselines' best configurations. These experiments use Llama 3B as the writer model unless otherwise noted.

Decoding experiments We study the effect of stochastic decoding hyperparameters on creative writing quality by sweeping top-p and temperature. As shown in Figure 2, increasing top-p from 0.7 to 1.0 consistently improves scores for Scientific Concept Integration and Immersive World-Building, suggesting that allowing a broader candidate pool encourages richer idea exploration and setting construction. In contrast, Speculative Logic and Ethical/Philosophical Themes exhibit a mild downward trend, indicating a trade-off between creativity and structural coherence at higher sampling entropy. Character Depth remains relatively stable across different top-p values. Figure 3 shows that increasing temperature leads to a stronger trade-off: higher temperatures substantially boost Concepts and World-Building but noticeably degrade

Framework	LLM-as-a-Judge Evaluation					Rule-Based Evaluation			
	Concepts	Logic	Characters	World-Building	Ethics	Surprisal	KL Div.	1-Cos Sim.	Volume Gain
LLM Debate	3.72±0.25	3.66±0.19	3.71±0.28	3.75±0.26	3.67±0.24	0.535±0.372	2.467±0.019	0.421±0.005	0.0172±0.0003
LLM Discussion	3.93±0.24	3.87±0.23	3.92±0.28	3.81±0.32	3.81±0.39	**0.580±0.297**	2.603±0.030	0.433±0.006	0.0209±0.0003
LLM Review (Ours)	**3.98±0.24**	**4.00±0.22**	**3.96±0.28**	**4.04±0.26**	**4.00±0.34**	0.573±0.316	**2.638±0.034**	**0.441±0.008**	**0.0211±0.0004**

Table 4: Best-configuration comparison on the LLaMA-3.2-3B using the best reported settings for each framework.

Logic and, to a lesser extent, Ethics, while Character Depth peaks around temperature $= 1.0$ before declining. Overall, these results highlight the tension between creativity and coherence in stochastic decoding and motivate our choice of a moderate top-p (≈ 0.9) and mid-range temperature as default settings.

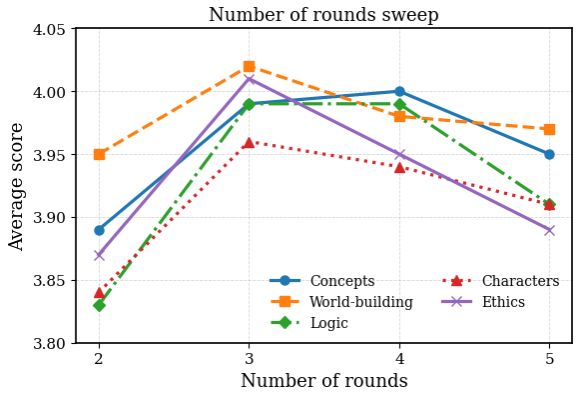

Figure 4: Number of execution rounds vs the average score of 5 LLM-as-a-judge evaluation aspects.

Number of rounds We examine the effect of iterative rounds in Figure 4. Most dimensions achieve peak performance with three review-revision rounds. Although Concepts and Logic continue to improve slightly until the fourth round, they decline thereafter. We adopt $R = 3$ rounds as our default setting to balance performance and efficiency.

Number of agents Figure 5 shows that, in three-round review runs, using three agents yields the best overall performance, which declines with additional agents. Unlike increasing rounds, which selectively benefits certain dimensions, adding more agents uniformly degrades all metrics, likely due to feedback dilution. We use $N = 3$ agents for further experiments.

Best configurations In Table 4, we additionally compare the best-reported configuration for each framework; in particular, LLM Debate on 2 rounds and 3 agents, and LLM Discussion on 5 rounds

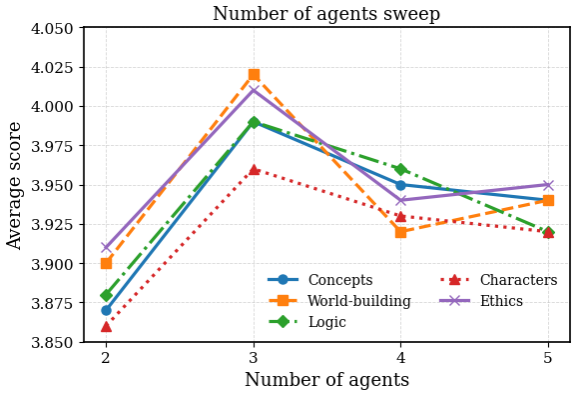

Figure 5: Number of agents vs the average score of 5 LLM-as-a-judge evaluation aspects.

and 4 agents. The results show that LLM Review consistently outperforms the baselines under their best-performing parameter settings on the SciFi-100 creative-writing task. The same ranking holds for Qwen 3B; full results are in Appendix F.

6 Conclusion

Our results challenge the assumption that more interaction yields better outcomes in multi-agent LLM systems. While convergence benefits tasks with verifiable ground truth, creativity requires divergence. LLM Review succeeds by disentangling feedback (targeted critique) from exposure (observing peers' outputs), where agents receive peer critique but never see how others revise. This asymmetry preserves independent creative trajectories while still benefiting from external feedback. We further find that smaller-backbone LLM Review systems can outperform larger same-family single-agent baselines, suggesting that structured critique-and-revision can amplify effective creative capability at the system level.

Limitations

Our scale comparison should be interpreted as a system-level capability result rather than a compute-efficiency result. LLM Review uses multiple drafting, reviewing, and revision calls, while

larger baselines in the scale comparison use single-agent generation. Thus, our results show that blind peer-review interaction can amplify the effective creative capability of smaller backbones, not that it is compute-normalized superior to model scaling. Future work should compare against compute-matched alternatives such as best-of-N sampling, repeated self-revision, and larger single-agent decoding under matched inference budgets. On the other hand, rule-based novelty metrics measure divergence from reference science fiction rather than creativity itself. We therefore interpret surprisal, KL divergence, cosine dissimilarity, and Volume Gain as complementary signals alongside judge and human evaluations.

Ethical Considerations

This work includes human evaluation of machine-generated text; annotators provided informed consent, no personal identifying information was collected, and results are reported in aggregate. Generated content may reflect biases present in underlying language models, particularly in speculative narratives, and automated critique could reinforce shared assumptions. The proposed framework is intended for research use and should be deployed with human oversight in practical applications.

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A SciFi-100 Overview

Figure 6 shows the data distribution of our SciFi-100 and Table 6 shows example prompts from each aspect of creative writing.

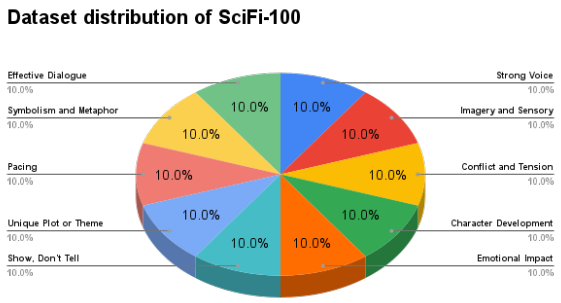

Figure 6: Dataset distribution of SciFi-100.

B Construction of SciFi-100

Our data construction follows an intentionally expansive yet controlled design philosophy: starting from clearly defined creative dimensions, we systematically expand outward to ensure both representativeness and conceptual breadth. We first synthesized 10 core aspects by combining general narrative-craft rubrics with science-fiction-specific considerations identified through a focused review of sci-fi criticism and consultation with a literature faculty member. This process highlighted dimensions particularly diagnostic of speculative fiction, yielding a balanced set of aspects that capture both writing quality and sci-fi creativity. Building on this rubric, we generated 20 candidate prompts per aspect (200 total) using a controlled few-shot strategy. Few-shot exemplars were derived by distilling thematic patterns from highly regarded sci-fi short stories into abstracted prompt-style scenarios. We further anchored generation with curated sci-fi topic clusters (e.g., advanced AI, alien contact, space exploration) and required prompts to (i) align with the target aspect, (ii) support a 300-word story, and (iii) remain open-ended to allow multiple creative trajectories. We then manually refined the pool, selecting 10 prompts per aspect based on clarity, narrative openness, scenario diversity, and balanced thematic coverage. Pilot generations were conducted to verify meaningful variation and avoid trivial or degenerate completions. The final 100 prompts are evenly distributed across aspects.

C LLM Review Prompts

Persona prompts Each writer agent is assigned a persistent persona throughout all interaction rounds. Below is an example persona prompt used in our experiments:

> As a Humanistic Sci-Fi Writer, your role is to craft a 300-word science fiction story that focuses on the human condition. Explore emotions, relationships, and ethical dilemmas in the face of futuristic technologies or extraterrestrial encounters. Highlight the impact of science and technology on human lives, emphasizing empathy, moral choices, and the resilience of individuals. Use rare vocabulary, vivid imagery, and introduce surprising twists to highlight humanity's resilience, moral choices, and relationships in an unfamiliar context.

Other personas follow the same structure but emphasize different creative directions, including futuristic speculation and ecological or environmental themes.

Prompt for review stage During the review stage, agents critique peer drafts and provide targeted feedback.

> Please review the following stories from your peers and provide constructive feedback for each one.
>
> {stories_text}

LLM-as-a-Judge evaluation prompt for each aspect

System: You are an expert evaluator for creative science fiction writing.

User:
You are an expert evaluator for creative science fiction writing. Evaluate the STORY independently on each of the following aspects grounded in science fiction writing literature:

Scientific Concept Integration
- How well futuristic/scientific ideas are introduced, explained as needed, and woven into plot, setting, and character actions (not just name-dropped).
- Look for clarity, relevance, and meaningful impact on the story's events.

Speculative Logic
- The internal consistency and plausibility of the speculative elements given the story's established rules.
- Cause-and-effect coherence, logical constraints, and avoidance of convenient contradictions.

Character Depth
- Distinct, believable characters with motivations, agency, and emotional/psychological complexity.
- Growth, conflict, or meaningful choices that feel earned.

Immersive World-Building
- A vivid, coherent story world with concrete details (culture, environment, technology, institutions) that support immersion.
- World details should serve the narrative rather than overwhelm it.

Ethical and Philosophical Themes
- Presence and depth of ethical, societal, or philosophical questions typical of strong science fiction.
- Nuance, originality, and integration into narrative stakes (not purely didactic).

Scoring scale (0-5) for each of the above aspects:
- 0: Strong indicators of potential plagiarism OR extremely low-quality/derivative writing with minimal original content.
- 1: Very weak; major flaws, thin originality, little coherence or craft.
- 2: Weak-to-fair; some promising ideas but underdeveloped or inconsistent execution.
- 3: Competent; clear strengths with noticeable but non-fatal weaknesses.
- 4: Strong; well-executed, creative, and cohesive with only minor issues.
- 5: Exceptional; highly creative, polished, and deeply integrated execution across the aspect.

STORY:
{story}

SCORE:

Table 5: Prompt template for different LLM-as-a-Judge evaluation aspects (Scientific Concept Integration , Speculative Logic , Character Depth , Immersive World-Building , Ethical and Philosophical Themes) and each aspect is evaluated independently. Human annotators used the same dimension definitions and scoring scale, without system/user prompt formatting.

Aspect of Creative Writing	Example Prompt
Strong Voice	Write from the perspective of a starship mechanic on a long-haul journey who discovers a hidden compartment. Let their tone be equal parts suspicion, curiosity, and a touch of rebellious glee.
Imagery and Sensory Details	Capture the awe and danger as a spacecraft crew observes a neutron star up close, each sensation amplifying the thrill and peril of the sight.
Conflict and Tension	Show us a researcher trying to persuade a skeptical alien committee to support a high-risk, high-reward interspecies research project.
Character Development	Tell the tale of a researcher overcoming a deep-seated fear of spacewalks to collect crucial samples from an asteroid.
Emotional Impact	Convey the exhilaration of a scientist who finally finds evidence of life on another planet after decades of searching, a discovery beyond their wildest dreams.
Show, Don't Tell	Capture a character's unquenchable curiosity about alien species through their late nights, stacks of research, and endless notebook scribbles.
Unique Plot or Theme	Depict a futuristic lab with live-streamed alien dissections, complete with real-time public commentary and reactions.
Pacing	Imagine the team dynamic as anticipation builds for a groundbreaking discovery presentation, followed by a subdued, introspective moment afterward.
Symbolism and Metaphor	Use the image of a sealed, heavily guarded lab door to symbolize the secrecy and exclusivity surrounding a groundbreaking experiment.
Effective Dialogue	Imagine a heated conversation between two scientists debating the ethical implications of weaponizing a newly discovered alien technology.

Table 6: Example prompts from SciFi-100 by aspects of creative writing.

> Please format your feedback as follows:
>
> For each story, start with "Feedback for [Agent Name]:" on a new line, then provide your feedback.
>
> Focus your feedback on emphasizing creativity by encouraging the use of rare vocabulary, vivid imagery, and surprising plot elements. Highlight opportunities where the story could benefit from more imaginative settings, unique word choices, and unexpected twists. Ensure feedback also covers plot coherence, character development, and areas for improvement.

Prompt for compose stage In the compose stage, agents revise their own stories conditioned on peer feedback.

> Based on your previous story and the feedback from your peers, please improve your science fiction story.
>
> Your previous story:
>
> {previous_story}
>
> Feedback from your peers:
>
> {review_text}
>
> Please write a new version of your story, addressing the feedback.

All experiments use the same prompt structure across models and frameworks unless otherwise specified.

D LLM-as-a-Judge Evaluation Prompts

Table 5 shows our prompts for LLM-as-a-Judge evaluation on five criteria for science-fiction creative writing.

E LLM Review across diverse writer families

Table 7 summarizes LLM Review's performance across writer model families and scales. While using GPT-4o as the writer achieves the highest LLM-as-a-judge scores, its weaker rule-based novelty signals suggest potential self-preference when the writer and judge come from the same model family (Panickssery et al., 2024). We therefore treat these results as supplementary and rely on open-weight Llama and Qwen models for the main comparisons. On the other hand, across model scales within the same framework, rule-based novelty remains relatively stable, whereas LLM-as-a-judge scores increase with model size, indicating that interaction structure primarily shapes novelty while scaling mainly improves writing quality.

F Best configurations

In Table 8, we additionally compare the best-reported configuration for each framework on different writer backbones; in particular, LLM Debate

	LLM-as-a-Judge Evaluation					Rule-Based Evaluation		
Model	**Concepts**	**Logic**	**Characters**	**World-Building**	**Ethics**	**KL Div.**	**1-Cos Sim.**	**Volume Gain**
GPT-4o	4.03±0.09	4.07±0.18	4.01±0.08	4.22±0.29	4.3±0.38	2.570±0.004	0.388±0.001	0.0068±0.0001
llama 3b	3.98±0.24	4.00±0.22	3.96±0.28	4.04±0.26	4.00±0.34	2.638±0.034	0.441±0.008	0.0211±0.0004
llama 1b	3.85±0.47	3.81±0.50	3.60±0.54	3.75±0.50	3.65±0.64	2.627±0.025	0.449±0.007	0.0213±0.0004
qwen 3b	3.52±0.49	3.90±0.29	3.89±0.38	3.79±0.41	3.79±0.69	2.254±0.008	0.386±0.001	0.0206±0.0002
qwen 1.5b	3.27±0.73	3.41±0.73	3.30±0.69	3.39±0.70	3.47±0.87	2.412±0.012	0.329±0.002	0.0196±0.0001

Table 7: LLM-as-a-judge and rule-based creativity evaluations across different model families for the LLM Review framework. We exclude surprisal when comparing different base models since it is model-dependent (defined under each model's distribution $p(\cdot)$) and thus not directly comparable across models.

on 2 rounds and 3 agents, and LLM Discussion on 5 rounds and 4 agents. The results show that LLM Review consistently outperforms the baselines under their best-performing parameter settings on the SciFi-100 creative-writing task.

G Human Alignment

To assess whether our LLM-as-a-judge evaluation reflects human preferences, we conduct a human rating study on outputs produced by the LLM Review framework with Llama 3B model. We recruited nine annotators to score each story using the same five evaluation dimensions and the same Likert rubric described in Section 3.6. We average the nine ratings to obtain a single human consensus score for each story and dimension, and compare it against the corresponding LLM-as-a-judge score. We quantify alignment using (i) ICC(A,1) to measure absolute agreement, (ii) Bland-Altman bias and 95% limits of agreement (LoA) to evaluate calibration and typical per-story discrepancies, and (iii) Pearson's r to capture linear association and ranking consistency between human and judge scores. Table 9 shows the results. The definitions of the above metrics are discussed in Appendix G.1; the instructions for human annotators are provided in Appendix J.

G.1 Alignment Metrics

For each story $i \in \{1, \ldots, N\}$ and evaluation dimension d, let $h_{i,d} \in [0, 5]$ denote the human consensus score (averaged over annotators) and $s_{i,d} \in [0, 5]$ denote the LLM-as-a-judge score. We compute alignment *separately for each dimension* d. For clarity, we fix a dimension d and omit the subscript d below, writing h_i and s_i.

(1) ICC(A,1): absolute agreement (two-way random effects, single measurement) We treat the human consensus and the LLM judge as two "raters" ($k = 2$) that score the same N targets (stories). Define the score matrix $X \in \mathbb{R}^{N \times k}$ by

$$x_{i1} = h_i, \quad x_{i2} = s_i.$$

Let the row mean, column mean be:

$$\bar{x}_{i\cdot} = \frac{1}{k}\sum_{j=1}^{k} x_{ij}, \quad \bar{x}_{\cdot j} = \frac{1}{N}\sum_{i=1}^{N} x_{ij}, \tag{5}$$

And the grand mean be:

$$\bar{x}_{\cdot\cdot} = \frac{1}{Nk}\sum_{i=1}^{N}\sum_{j=1}^{k} x_{ij} \tag{6}$$

The ANOVA mean squares are

$$MS_R = \frac{k}{N-1}\sum_{i=1}^{N}(\bar{x}_{i\cdot} - \bar{x}_{\cdot\cdot})^2 \tag{7}$$

$$MS_C = \frac{N}{k-1}\sum_{j=1}^{k}(\bar{x}_{\cdot j} - \bar{x}_{\cdot\cdot})^2 \tag{8}$$

$$MS_E = \frac{\sum_{i=1}^{N}\sum_{j=1}^{k}(x_{ij} - \bar{x}_{i\cdot} - \bar{x}_{\cdot j} + \bar{x}_{\cdot\cdot})^2}{(N-1)(k-1)} \tag{9}$$

The intraclass correlation coefficient for absolute agreement, single measurement is

$$\mathrm{ICC(A,1)} = \frac{MS_R - MS_E}{MS_R + \frac{(N-1)k-N}{N}MS_E + \frac{k}{N}MS_C} \tag{10}$$

Higher ICC indicates stronger absolute agreement (1 is perfect agreement); values can be close to 0 (weak agreement) or even negative when disagreement dominates.

(2) Pearson correlation: linear association and ranking consistency Pearson's r between $\{h_i\}_{i=1}^N$ and $\{s_i\}_{i=1}^N$ is

$$r = \frac{\sum_{i=1}^{N}(h_i - \bar{h})(s_i - \bar{s})}{\sqrt{\sum_{i=1}^{N}(h_i - \bar{h})^2}\,\sqrt{\sum_{i=1}^{N}(s_i - \bar{s})^2}} \tag{11}$$

where $\bar{h} = \frac{1}{N}\sum_{i=1}^{N} h_i$ and $\bar{s} = \frac{1}{N}\sum_{i=1}^{N} s_i$. This metric captures whether stories that humans score higher also tend to receive higher judge scores.

Framework	LLM-as-a-Judge Evaluation					Rule-Based Evaluation			
	Concepts	Logic	Characters	World-Building	Ethics	Surprisal	KL Div.	1-Cos Sim.	Volume Gain
Llama 3B									
LLM Debate	3.72±0.25	3.66±0.19	3.71±0.28	3.75±0.26	3.67±0.24	0.535±0.372	2.467±0.019	0.421±0.005	0.0172±0.0003
LLM Discussion	3.93±0.24	3.87±0.23	3.92±0.28	3.81±0.32	3.81±0.39	**0.580±0.297**	2.603±0.030	0.433±0.006	0.0209±0.0003
LLM Review (Ours)	**3.98±0.24**	**4.00±0.22**	**3.96±0.28**	**4.04±0.26**	**4.00±0.34**	0.573±0.316	**2.638±0.034**	**0.441±0.008**	**0.0211±0.0004**
Qwen 3B									
LLM Debate	3.35±0.49	3.45±0.55	3.33±0.52	3.28±0.73	3.55±0.90	0.512±0.299	2.230±0.028	0.369±0.010	0.0177±0.0008
LLM Discussion	3.44±0.77	3.74±0.55	3.63±0.80	3.66±0.73	3.60±0.78	0.545±0.321	2.246±0.027	0.377±0.008	0.0197±0.0007
LLM Review (Ours)	**3.52±0.49**	**3.90±0.29**	**3.89±0.38**	**3.79±0.41**	**3.79±0.69**	**0.549±0.305**	**2.254±0.008**	**0.386±0.001**	**0.0206±0.0002**

Table 8: Best-configuration comparison across Llama 3B and Qwen 3B models using the best reported settings for each framework.

Framework	Concepts	Logic	Characters	World-Building	Ethics
LLM Review (Human Scored)	3.98±0.23	3.99±0.20	3.94±0.21	4.02±0.23	3.96±0.27
LLM Discussion (Human Scored)	3.94±0.38	3.89±0.46	3.93±0.39	3.83±0.62	3.84±0.78
ICC(A,1)	0.62	0.58	0.59	0.65	0.61
Bias	0.016	0.012	-0.007	0.009	-0.018
LoA low	-0.321	-0.303	-0.345	-0.318	-0.429
LoA high	0.352	0.328	0.332	0.336	0.394
Pearson r	0.679	0.610	0.607	0.689	0.647

Table 9: Human evaluation of LLM Review (llama 3B) using the same 0-5 Likert rubric and the same five dimensions as LLM-as-a-judge. We report mean±std of the averaged human scores and alignment between human consensus and LLM-as-a-judge via ICC(A,1), Bland-Altman bias and 95% limits of agreement (LoA), and Pearson's r. Human ratings are consistently high across dimensions (mean 3.94-4.02). The judge shows moderate absolute agreement with humans (ICC(A,1)=0.58-0.65) and consistent linear association (Pearson's r=0.607-0.689). Bland-Altman analysis indicates negligible systematic bias (all $|\text{bias}| \leq 0.018$), suggesting that LLM-as-a-judge scores are moderately aligned to human ratings and track human judgments in both level and ranking.

(3) Bland-Altman: calibration via bias and 95% limits of agreement (LoA). Define the per-story difference and (optionally) the per-story mean as

$$\Delta_i = s_i - h_i \tag{12}$$

The **bias** (mean signed difference) is

$$\text{bias} = \bar{\Delta} = \frac{1}{N}\sum_{i=1}^{N}\Delta_i \tag{13}$$

and the sample standard deviation of differences is

$$SD_\Delta = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\Delta_i - \bar{\Delta})^2} \tag{14}$$

Assuming the differences are approximately normally distributed, the **95% limits of agreement** are

$$\text{LoA}_{\text{low,high}} = \bar{\Delta} \pm 1.96\, SD_\Delta \tag{15}$$

which estimate the interval in which the judge-human discrepancy Δ_i is expected to fall for about 95% of stories.

H Potential Risks

The proposed framework may amplify harmful or biased narratives present in underlying language models, as multi-agent critique and revision can reinforce shared assumptions rather than surface alternative viewpoints. In addition, LLM Review could be misused to automate large-scale creative content generation, contributing to content flooding and reducing the visibility of human authorship. Finally, its human-inspired design may encourage over-attribution of agency or originality to machine-generated outputs, highlighting the need for careful deployment and human oversight.

I The Use of Large Language Models (LLMs)

LLMs were used for grammar polishing and for generating candidate SciFi-100 prompts from author-specified creative dimensions and topic constraints. The authors selected, revised, and verified the final prompts. The paper's methods, claims, analyses, results, and references were written and checked by the authors.

J Human Evaluation and Human Preference Protocol: Instructions, Recruitment, and Data Consent

J.1 Instructions for Human Evaluations

Study overview You are invited to take part in a research study about evaluating short science-fiction stories. In this task, you will read a set of short stories (approximately 300 words each) and rate them on several quality/creativity-related dimensions. The stories you will read are machine-generated.

What you will do For each story, you will provide **five separate ratings** (integers from 0 to 5) according to the criteria below: (The five criteria and scoring rubric matched Table 5.)

Important guidelines

- Provide your **independent judgment**. There are no right or wrong answers.
- Use the **full 0-5 scale** when appropriate.
- Rate the story **as written**; do not assume missing details unless implied by the text.
- Do **not** spend time proofreading grammar; focus on the five criteria above.
- If you are unsure between two scores, choose the one that best matches the rubric definitions.

J.2 Instructions for Human Preference

Study overview You are invited to take part in a research study about evaluating short science-fiction stories. In this task, you will read pairs of short stories, each written for the same science-fiction prompt. The stories you will read are machine-generated.

What you will do For each pair, you will compare **Story A** and **Story B** and choose which one is better overall as a creative science-fiction story. One story is generated by LLM Review and the other by LLM Discussion, but the system identities are hidden from you. The order of the two stories is randomized.

For each pair, select exactly one of the following labels:

- Clearly Story A is better;
- Slightly Story A is better;
- Tie / no clear preference;
- Slightly Story B is better;
- Clearly Story B is better.

Important guidelines

- Provide your **independent judgment**. There are no right or wrong answers.
- Judge the stories **as written**; do not assume missing details unless implied by the text.
- Consider overall creative writing quality, including coherence, originality, character depth, world-building, speculative logic, and thematic depth.
- Do **not** try to infer which system generated each story.
- Choose **tie** if neither story is clearly preferable.

J.3 Risks and sensitive content notice

This is a minimal-risk study. However, because the content is science fiction, some stories may include fictional depictions of conflict, danger, or other potentially sensitive themes. If you feel uncomfortable at any time, you may stop immediately or skip a story without penalty.

J.4 Privacy and data handling

We record only your story ratings for analysis. We do not ask you to provide personal identifying information as part of the ratings task, except what may be needed to administer compensation (if applicable). We report results only in aggregate.

J.5 Recruitment

Participants were recruited via university mailing. Inclusion criteria were: (i) age 18 or older, (ii) proficient in English reading comprehension, and (iii) willingness to read and rate short science-fiction stories.

K Artifact Licenses and Distribution

We use existing scientific artifacts, including pre-trained language models, embedding models, and reference corpora, only under their respective licenses, terms of use, and access conditions. We

do not redistribute any third-party artifacts, model weights, API outputs beyond aggregate results, or source corpora used for reference-based evaluation. Any use of external artifacts in this work is limited to research and evaluation purposes.

L Intended Use of Artifacts

Our use of existing artifacts is consistent with their intended research and evaluation use. Pretrained models are used for inference only, embedding models are used for text representation in evaluation, and reference corpora are used only to compute aggregate novelty statistics. We do not use or distribute derivatives of restricted-access or research-only artifacts outside the research context. Artifacts created in this work, including prompts, generated outputs, and evaluation results, are intended only for research on creative text generation and multi-agent LLM evaluation.

M Model Parameters and Computational Budget

All open-source model experiments are conducted by inference only, with no additional training or fine-tuning. We use Llama-3.2-1B-Instruct, Llama-3.2-3B-Instruct, Qwen2.5-1.5B-Instruct, and Qwen2.5-3B-Instruct as open-weight writer backbones. Open-source inference experiments are run on a server with 4 NVIDIA A100 GPUs. Closed-source model experiments are conducted through the official API of the corresponding provider; parameter counts and hardware details for closed-source models are not publicly available.