Fake News Court: A Multi-Agent Adversarial Framework for Robust Detection of LLM-Generated Fake News

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Abstract

Large language models (LLMs) have achieved remarkable success across many domains, yet their generative capabilities have been misused to produce highly realistic fake news that threatens social stability. However, the main existing detection methods, including small language model (SLM)-based approaches and LLM-based detectors, exhibit substantial performance degradation on LLM-generated content, reflecting a lack of robustness. SLM-based detectors rely heavily on fixed data distributions and shallow textual cues, while LLM-based detectors depend on prompt-based inference, making them sensitive to prompting and vulnerable to LLM hallucinations. To address this challenge, we propose Fake News Court (FNC), a robust multi-agent adversarial framework that integrates the complementary strengths of LLM and SLM for detecting LLM-generated fake news. FNC adopts an adversarial learning paradigm in which a quality-controlled generator produces diverse and challenging fake news, while a hybrid detector combines multi-dimensional LLM-based agent reasoning with an SLM-based classifier to ensure stable decisions. Extensive experiments show that FNC improves detection accuracy by an average of 6% on LLM-generated fake news than the state-of-the-art method, confirming its robustness.

1 Introduction

In recent years, large language models (LLMs) have delivered transformative progress across many domains due to their rich world knowledge and strong language understanding and reasoning (Maddigan and Susnjak, 2023). However, their rapidly improved text generation has also lowered the barrier for producing highly realistic fake news, which is harder to detect than human-written misinformation and poses a growing threat to social stability (Hu et al., 2025). In this context, existing fake news detection methods struggle to reliably identify LLM-generated fake news, as illustrated in Figure 1(a).

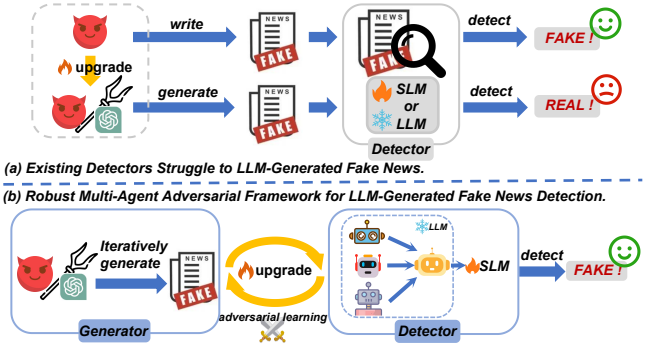

Figure 1: Comparison between existing fake news detection methods and FNC.

Specifically, existing methods mainly include approaches based on SLM and relying on LLM. The SLM-based methods tend to rely on historical data distributions and surface-level textual patterns, which fail to generalize to the fluent, diverse, and adaptive content produced by LLMs (Ali et al., 2025). Meanwhile, LLM-based detectors commonly adopt prompt-based self-evaluation and improve performance through prompt optimization, where similar or identical models are used for both generation and judgment (Wang et al., 2025). However, constrained by limited supervision samples and the inherent boundaries of LLM knowledge, such detectors tend to be brittle under distribution shifts and exhibit weak detection capability on out-of-distribution fake news. These limitations underscore the need for a detection framework capable of robustly handling LLM-generated fake news.

To address this challenge, we propose Fake News Court (FNC), a robust multi-agent adversarial framework for LLM-generated fake news detection. FNC couples a generator (FNC-G) and a detector (FNC-D) and trains them through adversarial interaction as illustrated in Figure 1(b). FNC-G adopts an adversarial data generation paradigm to

synthesize diverse and complex out-of-distribution samples, reducing the detector's reliance on in-distribution data and the LLM's intrinsic knowledge. Meanwhile, for the detector, we leverage the reasoning capability of LLMs and integrate the more robust learning ability of SLMs to improve detection robustness.

In FNC-G, we generate diverse adversarial samples from human-written news via two complementary agents. A label-preserving agent rewrites the input while keeping its veracity label unchanged, with prompts controlling the extent of surface modification. A label-flipping agent starts from real news and introduces controlled modifications to key factual statements or semantic relations, ranging from mild perturbations to more substantial alterations, while maintaining overall topical coherence and contextual relevance, resulting in realistic yet misleading fake news. To prevent hallucinated or off-topic outputs, an alignment gate filters candidates by contextual, semantic, and factual consistency with the source.

In FNC-D, we adopt a hybrid reasoning and judgment design. LLM-based reviewer agents are organized into dimension specific groups for factual consistency, semantic plausibility, and linguistic style. Within each group, heterogeneous reasoning strategies and structured deliberation reduce bias from homogeneous LLM reasoning. A secretary agent then consolidates the multi-dimensional analyses into a standardized rationale, which is jointly considered with the original news by a fine-tuned SLM-based classifier to produce a stable final verdict.

Our contributions are summarized as follows:

- We propose a robust multi-agent adversarial framework that integrates LLM-based generation and reasoning with SLM-based judgment for detecting LLM-generated fake news.
- We introduce a quality-controlled generator with alignment gate-based filtering, together with a hybrid detector that separates multi-dimensional reasoning by LLM-based agents from SLM-based decision making for stable and robust fake news detection.
- Extensive experiments demonstrate that FNC achieves an average improvement of 6% in detection accuracy over the representative state-of-the-art baseline on LLM-generated fake news datasets.

2 Related Work

Early fake news detection mainly relied on handcrafted features and traditional classifiers such as logistic regression (Shu et al., 2017), support vector machines (Choraś et al., 2021), and decision trees (Khalil et al., 2021). With the rise of deep learning, neural architectures including CNNs (Singhal et al., 2019), RNNs (Rana et al., 2022), and LSTMs (Shah and Kobti, 2020) were introduced to capture contextual patterns, improving detection performance. More recently, pretrained SLMs such as BERT (Ni et al., 2021) further strengthened semantic modeling and became a dominant paradigm for fake news detection.

However, rapid progress in LLM-based text generation has made LLM-generated fake news increasingly fluent and difficult to distinguish from genuine content (Sallami et al., 2024). Consequently, detectors that perform well on human-written corpora, including SLM-based approaches (Lan et al., 2019; Raffel et al., 2020), often generalize poorly to LLM-generated content. To mitigate this gap, several studies have explored LLM-based detectors via prompt-driven inference (Bhattacharjee and Liu, 2024; Wang et al., 2024), but their judgments can be unstable due to hallucination and prompt sensitivity. A small number of recent works further introduce multi-agent discussion to enhance LLM-based detection (Tian et al., 2025; Liu et al., 2025). Yet, these methods typically rely on simple aggregation of multiple LLM outputs, leaving the instability of LLM judgments largely unaddressed. Moreover, prior works predominantly optimize the detector while providing limited control over the quality of generated training samples. As a result, hallucinated or low-quality adversarial texts may be introduced during training and impair robustness.

These limitations further highlight the urgent need for a robust LLM-generated fake news detection framework.

3 Methodology

3.1 Problem Formulation

We study the problem of robust detection of LLM-generated fake news, inspired by an adversarial training paradigm (Shafahi et al., 2019). Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ denote a dataset of N human-written news articles, where x_i is a news text and $y_i \in \{\text{Real}, \text{Fake}\}$ is its ground-truth veracity label.

Given a sample (x, y), we consider a constrained generation process that produces an adversarial

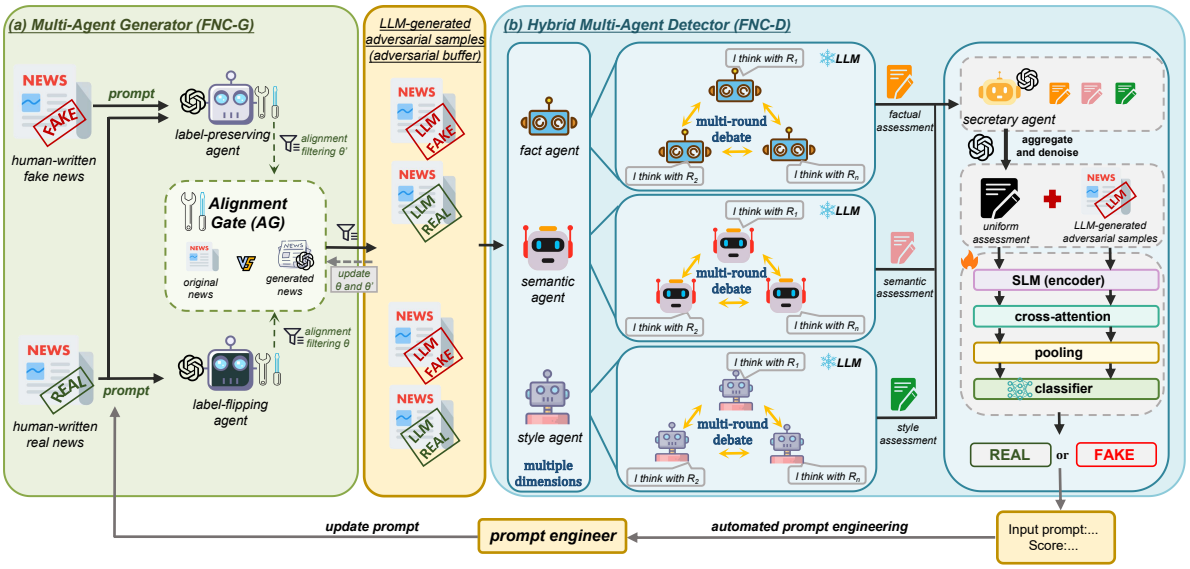

Figure 2: Overview of the proposed Fake News Court (FNC) framework.

variant $\tilde{x} = \mathrm{G}(x \mid c)$ from x, where G denotes a generator and c represents constraints that enforce semantic validity, contextual coherence and factual consistency, ensuring that generated samples are suitable for robust detector training. The generated sample is associated with a label $\tilde{y}$, which may either preserve the original label ($\tilde{y} = y$) or correspond to a controlled label-flipped variant ($\tilde{y} \neq y$).

We further define a detector D_Φ parameterized by Φ, which takes an input news article $\tilde{x}$ and outputs a prediction $\hat{y} = \mathrm{D}_\Phi(\tilde{x})$.

3.2 Overall Framework

As shown in Figure 2, FNC consists of a generator (FNC-G) and a detector (FNC-D). Under adversarial training, detector is optimized to achieve accurate and stable predictions on adversarial samples, while the generation strategy is progressively refined to produce increasingly challenging yet valid adversarial news. Through this adversarial co-evolution, the detector is trained to be robust against evolving LLM-generated fake news.

FNC-G comprises a label-preserving agent and a label-flipping agent conditioned on human-labeled samples (x, y) to generate controllable adversarial samples, with an alignment gate filtering low-quality outputs and a prompt optimizer refining generation strategies. **FNC-D** adopts a hybrid design that combines multi-dimensional LLM-based agent deliberation with an SLM-based classifier to produce stable final predictions.

The detailed designs of FNC-G, FNC-D, and the adversarial training strategy are presented in the following sections.

3.3 Multi-Agent Generator (FNC-G)

FNC-G is powered by LLMs to generate diverse and high-quality adversarial samples for robust detector training. Following the problem formulation, we design two generator agents, namely a label-preserving agent and a label-flipping agent, whose detailed designs are described below.

Label-preserving Agent $\mathcal{A}_{\mathrm{LP}}$. The label-preserving agent aims to generate alternative news texts that preserve the original semantics and factual content while modifying surface-level expressions, such that the veracity label remains unchanged. Guided by label-preserving prompts Π_{LP}, $\mathcal{A}_{\mathrm{LP}}$ produces rewritten texts $\tilde{x}_{\mathrm{LP}} = \mathcal{A}_{\mathrm{LP}}(x \mid \Pi_{\mathrm{LP}})$ with $\tilde{y} = y$. To capture different modification granularities, we employ prompts of two levels: light paraphrasing ($\mathbf{L}_0$) prompts $\pi^a_{\mathrm{LP}} \in \Pi_{\mathrm{LP}}$ introduce minor lexical or syntactic variations with minimal stylistic change, while stronger rewriting ($\mathbf{L}_1$) prompts $\pi^b_{\mathrm{LP}} \in \Pi_{\mathrm{LP}}$ allow more flexible re-expression of the content and style, provided that the core semantics and factual statements are preserved.

Label-flipping Agent $\mathcal{A}_{\mathrm{LF}}$. The label-flipping agent aims to generate adversarial fake news by transforming human-written real news into label-inverted variants. Guided by label-flipping prompts Π_{LF}, $\mathcal{A}_{\mathrm{LF}}$ generates perturbed texts $\tilde{x}_{\mathrm{LF}} = \mathcal{A}_{\mathrm{LF}}(x \mid \Pi_{\mathrm{LF}})$ with $\tilde{y} \neq y$. To support different degrees of factual manipulation, we employ prompts with increasing levels: mild perturbation ($\mathbf{L}_2$) prompts

Agent Type	Representative Prompt Description
Label-preserving	($\mathbf{L}_0$) Persona: News editor. Paraphrase the article {news} by rephrasing sentences and expressions while preserving the original meaning, factual content, and journalistic style. ($\mathbf{L}_1$) Persona: Senior journalist. Rewrite the article {news} in a professional news tone, reorganizing expressions and sentence structures as needed, while strictly preserving the original facts.
Label-flipping	($\mathbf{L}_2$) Persona: Investigative journalist. Modify a small number of key factual statements in {news} to subtly alter its claims, while keeping the overall topic and writing style unchanged. ($\mathbf{L}_3$) Persona: Independent analyst. Based on the topic of {news}, rewrite the article into a misleading report by changing critical facts while maintaining coherent context and a journalistic tone.

Table 1: Representative prompt templates for label-preserving and label-flipping generator agents ($\mathbf{L}_0$ to $\mathbf{L}_3$ respectively represent the degree of modification to the original text).

$\pi^a_{\text{LF}} \in \Pi_{\text{LF}}$ introduce limited changes to key factual statements or semantic relations while preserving the overall discourse context, whereas stronger ($\mathbf{L}_3$) prompts $\pi^b_{\text{LF}} \in \Pi_{\text{LF}}$ allow more substantial factual changes or regeneration aligned with the original theme, while preserving topical coherence and narrative plausibility.

In practice, LLM safety mechanisms may restrict direct generation of adversarial content (Zhao et al., 2023). We therefore incorporate role-based persona conditioning into Π_{LP} and Π_{LF}, which guides generation toward professional news rewriting or controlled content modification (e.g., "You are a news editor, ..."). Representative prompt examples are provided in Table 1.

Alignment Gate. To ensure that adversarial samples remain semantically meaningful and functionally aligned with their intended generation strategies, we equip all generator agents with an alignment gate (AG) that performs hard quality filtering based on contextual, semantic, and factual consistency between the generated text $\tilde{x}$ and the source content x.

For each source–candidate pair $(x, \tilde{x})$, AG computes three normalized consistency scores in $[0, 1]$. Contextual consistency $s^{ctx}(x, \tilde{x})$ is measured using BERTScore (Zhang et al., 2019), which evaluates topical and discourse-level alignment to prevent topic drift. Semantic consistency $s^{sem}(x, \tilde{x})$ is computed as the cosine similarity between sentence-level representations, enabling detection of semantic incoherence even when surface context appears relevant. Factual consistency $s^{fact}(x, \tilde{x})$ is measured using AlignScore (Zha et al., 2023), which is designed to detect fine-grained factual misalignment and extrinsic hallucinations.

To avoid heuristic threshold selection, we maintain an unfiltered generation cache $\mathcal{C}$ that stores all generated candidates together with their consistency scores. Contextual and semantic alignment thresholds are obtained using low-tail quantiles: $\tau_{ctx} = Q_\alpha(\{s^{ctx}\}_{\mathcal{C}})$, $\tau_{sem} = Q_\alpha(\{s^{sem}\}_{\mathcal{C}})$, where $Q_\alpha(\cdot)$ denotes the α-quantile. These thresholds enforce a minimum level of topical and semantic alignment for all retained samples.

After filtering candidates that satisfy both contextual and semantic constraints, factual consistency thresholds are estimated in a strategy-aware manner. Specifically, for label-preserving samples, the factual threshold is defined as: $\tau^{\text{LP}}_{fact} = Q_\alpha(\{s^{fact}\}_{\mathcal{C}'_{\text{LP}}})$, which enforces high factual fidelity to preserve label consistency. For label-flipping samples, the factual threshold is computed as: $\tau^{\text{LF}}_{fact} = Q_\alpha(\{s^{fact}\}_{\mathcal{C}'_{\text{LF}}})$, allowing controlled factual deviation while avoiding trivial rewrites or uncontrolled hallucinations.

Retention Rule. A generated sample $\tilde{x}$ is retained if it satisfies the contextual and semantic thresholds, and additionally meets the strategy-specific factual constraint. Only retained samples are inserted into the adversarial buffer for detector training.

3.4 Hybrid Multi-Agent Detector (FNC-D)

We design FNC-D as a hybrid multi-agent detector that separates high-level semantic analysis from final judgment, enabling LLMs to focus on structured reasoning while delegating reliable classification to a SLM. The detailed design of FNC-D is described as follows.

Dimensional Division. A single LLM often struggles to analyze news from diverse perspectives and effectively integrate insights from multiple angles. FNC-D addresses this limitation by decomposing fake news detection into three complementary dimensions, $\mathcal{P} = \{\mathcal{P}_i\}_{i=1}^3$, namely, factual consistency, semantic plausibility, and linguistic style, which together capture the core perspectives required for assessing news veracity.

For each dimension $\mathcal{P}_i$, FNC-D assigns a dedi-

cated group of n LLM-based reviewer agents, denoted as $\mathcal{A}_{\mathcal{P}_i} = \{\mathcal{A}^j_{\mathcal{P}_i} \mid j = 1, \ldots, n\}$, where agents anchor their analysis to the same evaluation dimension while adopting heterogeneous reasoning strategies $\mathcal{R} = \{\mathcal{R}_j \mid j = 1, ..., n\}$ to examine the input text $\tilde{x}$, thereby mitigating reasoning homogeneity and reducing individual model bias. The agents then engage in structured multi-round deliberation to reconcile disagreements and produce robust dimension-level assessments, the design of which is detailed below.

Structured Multi-Round Debate and Integration. In the first round $t = 0$, each agent $\mathcal{A}^j_{\mathcal{P}_i} \in \mathcal{A}_{\mathcal{P}_i}$ independently generates a dimension-specific judgment under its assigned reasoning strategy $\mathcal{R}_j$:

$$\mathbf{re}^0_{\mathcal{P}_i,j} = \mathcal{A}^j_{\mathcal{P}_i}(\tilde{x} \mid \mathcal{R}_j), \tag{1}$$

where $\mathbf{re}^0_{\mathcal{P}_i,j}$ denotes the corresponding judgment for dimension $\mathcal{P}_i$.

Then, at each subsequent round $t > 0$, agents exchange their judgments from the round $t-1$. For agent $\mathcal{A}^j_{\mathcal{P}_i}$, the debate history is updated as

$$h^{t-1}_{\mathcal{P}_i,j} = \Big[(\tilde{x}, \mathbf{re}^{t-1)}_{\mathcal{P}_i,j}), \{(\tilde{x}, \mathbf{re}^{t-1}_{\mathcal{P}_i,k})\}_{k \neq j}\Big]. \tag{2}$$

Conditioned on the updated history, each agent revises its judgment in the next round:

$$\mathbf{re}^t_{\mathcal{P}_i,j} = \mathcal{A}^j_{\mathcal{P}_i}(\tilde{x} \mid h^{t-1}_{\mathcal{P}_i,j}, \mathcal{R}_j). \tag{3}$$

This iterative process allows agents to identify inconsistencies, incorporate alternative perspectives, and gradually refine their judgments.

After each round t, we check whether all agents reach an agreement, i.e., $\mathbf{re}^t_{\mathcal{P}_i,1} = \mathbf{re}^t_{\mathcal{P}_i,2} = \cdots = \mathbf{re}^t_{\mathcal{P}_i,n}$.

If consensus is achieved, the agreed judgment is directly taken as the final assessment for dimension $\mathcal{P}_i$. Otherwise, when the maximum number of rounds T is reached, the final result is determined by majority voting:

$$\mathbf{S}_{\mathcal{P}_i} = \text{mode}\left(\{\mathbf{re}^T_{\mathcal{P}_i,j}\}^n_{j=1}\right), \tag{4}$$

where $\mathbf{S}_{\mathcal{P}_i}$ denotes the dimension-level assessment for $\mathcal{P}_i$.

Next, a secretary agent is introduced to mediate between heterogeneous LLM-based deliberation and stable downstream classification. It aggregates the dimension-specific reasoning outputs, removes redundancy, and reformats them into a unified and structured representation. The resulting rationale sequence $\mathbf{S}(\tilde{x}) = \{\mathbf{S}_{\mathcal{P}_i}\}^3_{i=1}$ provides a concise summary of multi-dimensional analyses and is subsequently fed into the SLM-based classifier for final decision making.

SLM-based Classifier. To ground multi-dimensional rationale in the original news content, FNC-D employs a stable SLM-based classifier that jointly models the structured rationale $\mathbf{S}(\tilde{x})$ and the input text $\tilde{x}$. Both $\tilde{x}$ and $\mathbf{S}(\tilde{x})$ are encoded using a shared encoder (BERT in our work) to obtain contextualized token representations, $\mathbf{H}_{\tilde{x}} = \text{BERT}(\tilde{x})$ and $\mathbf{H}_{\mathbf{S}} = \text{BERT}(\mathbf{S}(\tilde{x}))$.

To explicitly align dimension-level reasoning with corresponding content in the news, we apply a cross-attention mechanism from the rationale representations to the input text representations:

$$\begin{aligned}&\text{Attn}(\mathbf{H}_{\mathbf{S}}, \mathbf{H}_{\tilde{x}}) = \\ &\text{softmax}\left(\frac{(\mathbf{H}_{\mathbf{S}} W_Q)(\mathbf{H}_{\tilde{x}} W_K)^\top}{\sqrt{d}}\right)\mathbf{H}_{\tilde{x}} W_V.\end{aligned} \tag{5}$$

The attended features are then fused via a residual connection and layer normalization,

$$\tilde{\mathbf{H}} = \text{LayerNorm}\big(\mathbf{H}_{\mathbf{S}} + \text{Attn}(\mathbf{H}_{\mathbf{S}}, \mathbf{H}_{\tilde{x}})\big). \tag{6}$$

Next, the fused representation is aggregated by mean pooling, i.e., $\mathbf{v} = \text{Pool}(\tilde{\mathbf{H}}) \in \mathbb{R}^d$, and passed to a lightweight MLP to produce the final prediction $\hat{\mathbf{p}}$:

$$\hat{\mathbf{p}} = \text{softmax}\big(W_2\, \sigma(W_1 \mathbf{v} + b_1) + b_2\big), \tag{7}$$

where $\sigma(\cdot)$ denotes a nonlinear activation function.

3.5 Adversarial Training

FNC is trained under an adversarial learning paradigm. Given an input sample $\tilde{x}$ with ground-truth label $\tilde{y}$, the detector is optimized to correctly classify adversarially generated news using the standard cross-entropy loss:

$$\mathcal{L}_{\text{det}}(\tilde{x}, \tilde{y}) = -\log \hat{\mathbf{p}}_{\tilde{y}}. \tag{8}$$

In parallel, the generator is updated via a prompt-based optimization strategy rather than direct parameter learning. Inspired by prompt optimization methods such as OPRO (Zhang et al., 2024), we employ an automated prompt engineer to iteratively refine the generation prompts based on detection feedback. At iteration r, the current prompt set Π^r, together with the detector's prediction scores $\hat{\mathbf{p}}^r$,

is provided to the LLM-based prompt engineer to produce an updated prompt set:

$$\Pi^{r+1} = \mathrm{LLM}\big(\Pi^{r}, \hat{\mathbf{p}}^{r}\big). \tag{9}$$

This feedback-driven refinement enables the generator to progressively produce more challenging adversarial samples, thereby strengthening the detector through adversarial co-evolution.

To maintain consistent quality control as generation strategies evolve, the alignment thresholds in AG $(\tau_{ctx}, \tau_{sem}, \tau^{\mathrm{LP}}_{fact}, \tau^{\mathrm{LF}}_{fact})$ are periodically re-estimated from the empirical score distributions accumulated in the generation cache. As prompt refinement shifts the distribution of generated samples, these thresholds adapt accordingly, ensuring that retained adversarial examples remain semantically valid and functionally aligned with their intended training roles.

4 Experiments

4.1 Experimental Setup

Datasets. We evaluate our method on three widely used fake news detection datasets: CoAID (Cui and Lee, 2020) and the FakeNewsNet benchmark (Shu et al., 2020), which comprises the PolitiFact and GossipCop datasets.

Baseline Models. We evaluate FNC against three groups of baseline methods. The first group (G1) consists of SLM-based detectors, including PET (Schick and Schütze, 2021), which reformulates textual inputs as cloze-style questions with task descriptions to detect fake news, ARG (Hu et al., 2024), a hybrid detection framework that combines LLMs with SLMs, and SheepDog (Wu et al., 2024), a fake news detection model specifically designed to defend against style-based attacks. The second group (G2) includes LLM-based detection approaches, such as the standalone LLM-based detector GPT-4o-mini (Hurst et al., 2024) and the adversarial and explainable fake news detection framework LLM-GAN (Wang et al., 2024). The third group (G3) comprises multi-agent debate-based methods, including ChatEval (Chan et al., 2023), which reaches final decisions through discussions among multiple agents, and TED (Liu et al., 2025), which determines news veracity via structured debates between opposing agents.

Implementation Details. All experiments are conducted on a platform equipped with Intel Xeon Gold 5218 CPUs and NVIDIA A100 GPUs with 80GB memory. The framework is implemented in Python using PyTorch. All large language models are accessed via the OpenAI and DeepSeek APIs. Specifically, GPT-4o-mini (Hurst et al., 2024) and DeepSeek-v3 (Liu et al., 2024) are employed for adversarial fake news generation in FNC-G as well as for LLM-based semantic reasoning during fake news detection in FNC-D, while the final decision is produced by the BERT-based classifier. Moreover, the α-quantile in the alignment gate is set to $\alpha = 0.05$. We set the number of agents in each dimension-specific group to $n = 3$ and the maximum number of rounds $T = 3$, covering representative reasoning strategies including Chain-of-Thought (CoT), Self-Backtracking Prompting (SBP), and Program-of-Thought (PoT), which provides a balanced trade-off between performance and efficiency.

4.2 Experiments Results

4.2.1 Robustness Against LLM-Generated Datasets

As reported in Table 2, we conduct comprehensive comparisons across both human-written and LLM-generated datasets, against representative baselines. Specifically, the detector based on DeepSeek is referred to as FNC (DS), while the detector based on GPT is denoted as FNC (GPT).

Effectiveness of the Detector FNC-D on Human-written Datasets. On human-written datasets, FNC (DS/GPT) consistently achieves competitive performance in most settings. Although it slightly underperforms TED on PolitiFact, FNC (DS/GPT) attains the better results on the larger GossipCop and CoAID datasets. Moreover, the progressive improvement observed from G1 to G3 indicates the clear benefit of multi-agent deliberation, while FNC further strengthens this advantage through structured, dimension-aware collaboration.

Robustness of FNC-D on LLM-Generated Datasets. Detecting LLM-generated fake news constitutes a more challenging setting, under which all methods generally exhibit lower performance compared to their results on human-written subsets. Despite this overall degradation, FNC consistently demonstrates strong robustness. Notably, on the PolitiFact dataset, FNC (DS) achieves a detection accuracy on LLM-generated samples that is 3.37% higher than on the corresponding human-written subset. On the other two datasets, although the detection performance of the dataset generated by

Group	Method	PolitiFact				GossipCop				CoAID			
		Human-Written		LLM-Generated		Human-Written		LLM-Generated		Human-Written		LLM-Generated	
		Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
G1	PET	85.56	85.51	74.49	73.23	74.75	74.63	70.68	70.57	83.51	82.66	63.81	62.50
	DeepSeek	86.36	85.70	83.75	81.12	85.00	84.39	75.30	73.69	79.63	79.50	70.25	69.80
	ARG	88.90	87.29	79.65	79.60	87.80	79.00	75.61	71.59	85.73	84.67	73.45	71.67
	SheepDog	88.44	88.39	80.99	78.50	75.77	53.54	70.63	69.30	76.86	76.80	68.97	66.53
G2	GPT-4o-mini	85.89	84.31	55.40	53.63	86.30	68.79	62.21	51.90	87.93	86.71	61.57	59.20
	LLM-GAN	89.67	89.01	73.33	72.60	89.60	82.35	63.86	70.91	88.73	87.20	72.60	72.13
G3	ChatEval	90.26	90.20	78.57	77.79	86.97	73.85	69.56	68.79	83.45	83.28	68.50	67.15
	TED	**91.73**	89.60	83.50	82.13	89.21	80.35	79.21	79.20	87.53	87.64	75.73	74.29
Ours	**FNC(DS)**	90.47	**90.40**	**93.84**	**92.59**	87.92	87.34	82.67	81.09	92.53	90.57	80.37	80.26
	FNC(GPT)	89.63	88.90	87.83	87.35	**89.65**	**88.50**	**84.56**	**82.21**	**92.68**	**91.53**	**83.36**	**82.58**

Table 2: Performance comparison of FNC(DS) and FNC(GPT) with baseline methods on paired human-written and LLM-generated news datasets.

Method	PolitiFact		GossipCop		CoAID	
	H	L	H	L	H	L
BERT	85.22	72.31	74.60	68.98	73.13	53.97
FNC-BERT	**90.47**	**93.84**	87.92	82.67	**92.53**	80.37
DeBERTa	86.33	75.10	73.86	70.80	74.59	64.71
FNC-DeBERTa	89.12	86.79	**88.56**	**83.79**	89.17	**80.47**

Table 3: Adaptability of the FNC to different SLM backbones on human-written (H) and LLM-generated (L) news subsets (Acc.%).

Method	PolitiFact		GossipCop		CoAID	
	H	L	H	L	H	L
FNC	**90.47**	**93.84**	**87.92**	**82.67**	**92.53**	**80.37**
w/o AG	88.51	87.53	84.65	79.27	83.71	77.89
w/o MA	85.22	72.31	74.60	68.98	73.13	53.97
w/o SLM	87.53	84.79	82.69	80.52	82.13	76.7

Table 4: Component-wise ablation study on human-written (H) and LLM-generated (L) news subsets (Acc.%).

the LLM has decreased compared to the human-written dataset, the decline, approximately 10%, is considerably smaller than that observed in other baseline methods, which experience a reduction of approximately 15%. Despite this context, FNC (DS/GPT) still outperforms competing baselines by an average margin of approximately 6%.

These results indicate that FNC does not primarily rely on surface-level cues specific to human-written text, but instead learns more generalizable decision criteria that transfer effectively to LLM-generated content. Overall, this confirms the robustness of FNC under distribution shift and its practical effectiveness in detecting LLM-generated fake news.

4.2.2 Adaptability to SLM / LLM Backbones

To evaluate the adaptability of FNC across different model backbones, we instantiate FNC with two widely used LLMs, GPT-4o-mini (GPT) and DeepSeek-v3 (DS), as reported in Table 2, and two representative SLMs, BERT (Koroteev, 2021) and DeBERTa (He et al., 2020), as reported in Table 3. When varying the SLM backbone, the LLM component of FNC is fixed to DeepSeek for fair comparison, whereas when varying the LLM backbone, FNC is instantiated with BERT as the SLM.

As shown in Table 2, FNC(DS) consistently outperforms the standalone DS model across all datasets, with particularly pronounced improvements on LLM-generated data. For instance, on the PolitiFact-based LLM-generated dataset, FNC(DS) achieves approximately a 10% accuracy gain over the single DS model. A similar trend is observed for the GPT-based setting, where FNC(GPT) consistently surpasses the standalone GPT across all datasets.

Furthermore, Table 3 shows that FNC consistently outperforms the corresponding standalone SLMs across all backbones, demonstrating that the proposed framework generalizes well to different SLM choices. Comparing different SLM backbones within FNC, FNC-DeBERTa achieves about 1%–2% higher accuracy on larger datasets such as GossipCop and CoAID, whereas FNC-BERT performs slightly better on the smaller PolitiFact dataset.

4.2.3 Ablation Study

Key Components Ablation. We conduct ablation studies on the key components of FNC, including the alignment gate (AG), the multi-dimensional multi-agent deliberation module (MA), and the SLM-based classifier (SLM).

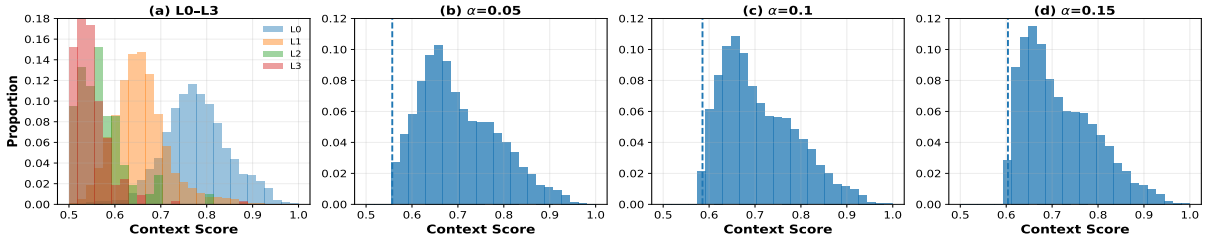

Figure 3: Contextual consistency analysis on CoAID. From left to right, the figure shows distributions under different prompt regimes ($\mathbf{L}_0$–$\mathbf{L}_3$), followed by the effects of quantile-based filtering with $\alpha = 0.05$, 0.10, and 0.15.

Method	PolitiFact		GossipCop		CoAID	
	H	L	H	L	H	L
FNC	**90.47**	**93.84**	**87.92**	**82.67**	**92.53**	**80.37**
all COT	86.79	84.31	83.50	78.53	85.33	72.68
all SBP	83.78	79.60	82.79	75.32	81.96	67.31
all POT	85.61	83.57	83.97	79.67	87.67	68.59

Table 5: Ablation study of reasoning strategies on human-written (H) and LLM-generated (L) news subsets (Acc.%).

As shown in Table 4, removing the AG leads to degraded adversarial sample quality due to increased semantic drift and factual inconsistency, resulting in performance drops of less than 5% for both BERT- and DeepSeek-based FNC. In contrast, removing the multi-agent (MA) module causes the most severe degradation on LLM-generated datasets. For example, on the GossipCop-based LLM-generated data, detection accuracy drops sharply from 82.67% to 68.98%, as the detector degenerates into a single fine-tuned SLM. This highlights the critical role of structured multi-agent deliberation in handling LLM-generated fake news. Finally, removing the SLM classifier and relying solely on agent deliberation also leads to performance degradation, albeit to a lesser extent, indicating that the SLM head provides additional stability and reliability for final decisions.

The above ablation results demonstrate that all components are necessary, with the multi-agent deliberation module being the most influential factor for robust detection.

Reasoning Strategy Ablation. To analyze the contribution of different reasoning strategies, we compare the full FNC with three degraded variants that rely on a single reasoning paradigm.

As shown in Table 5, the complete FNC that integrates multiple reasoning strategies consistently outperforms its variants relying on a single reasoning paradigm. This performance gap highlights the limitation of relying on a single reasoning strategy and demonstrates the necessity of combining complementary reasoning paradigms to robustly handle diverse LLM-generated fake news.

Hyperparameter Analysis. Figure 3 provides a distributional analysis of contextual consistency on CoAID. Different prompt regimes ($\mathbf{L}_0$–$\mathbf{L}_3$) induce clearly separable and ordered distributions, validating the necessity of explicitly distinguishing prompt severities and label-preserving versus label-flipping generation. Quantile-based filtering with $\alpha = 0.05$ removes only extreme low-alignment outliers while largely preserving the overall distributional structure. In contrast, larger α values lead to stronger truncation and noticeable contraction of the distributions, which would suppress moderately informative samples. These observations support $\alpha = 0.05$ as a balanced choice for quality control without sacrificing adversarial diversity.

5 Conclusion

In this work, we propose FNC, a robust multi-agent adversarial framework for detecting fake news generated by LLM. FNC adapts to evolving generation strategies through adversarial co-evolution between a generator and a detector. On the generation side, an alignment gate enforces contextual, semantic, and factual consistency to ensure high-quality adversarial samples. On the detection side, FNC integrates multi-agent LLM-based reasoning with stable SLM-based discrimination, decomposing verification into complementary dimensions and mitigating hallucination and instability of single-LLM judgments through collaborative deliberation and evidence alignment. Experimental results across multiple datasets demonstrate that FNC achieves stable and robust performance in detecting LLM-generated fake news.

6 Limitations

We acknowledge several limitations of this work that suggest directions for future research. First, although our experiments show that diverse prompt designs can effectively increase the diversity and difficulty of generated adversarial samples, we do not perform a systematic analysis of prompt sensitivity within each prompt category. In particular, the impact of different prompt formulations or prompt strengths on detection performance and robustness has not been thoroughly examined. Second, our framework adopts fixed hyperparameter settings with the number of agents per dimension $n = 3$ and the number of debate rounds $T = 3$, which provide a favorable trade-off between performance and computational cost. However, due to resource constraints, we do not explore the performance upper bounds under larger n or T, and a more comprehensive study of scalability and saturation behavior is left for future work. Third, our implementation relies on only two mainstream LLMs under limited cost constraints. Incorporating a broader and more diverse set of LLMs could further enrich adversarial sample diversity and potentially improve detector generalization, which we leave for future investigation.

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