LLM Pipeline for Hierarchical Narrative Classification: A Traceable Approach to Multilingual Narrative Detection

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Abstract

This paper presents Agora, a configurable and reproducible framework for robust hierarchical multi-label classification using large language models. We address critical reliability challenges in LLM-based classification through a multi-agent ensemble approach with voting consensus and an optional actor-critic self-refinement loop. Our system decomposes the hierarchical classification task into manageable steps via a state-graph pipeline, providing enhanced traceability for multilingual propaganda detection. We evaluate our approach on hierarchical narrative classification benchmarks, demonstrating improved robustness and consistency compared to baseline LLM approaches.

Keywords: hierarchical classification, propaganda detection, narrative analysis, large language models, multilingual NLP

1. Introduction

Consider two statements about international relations: (1) *"Western diplomats met with Ukrainian officials to discuss potential peace negotiations,"* versus (2) *"While Western officials claim to pursue peace, their negotiations appear primarily designed to serve their own geopolitical interests rather than address regional security concerns."* While the first presents factual reporting, the second exemplifies a narrative frame: *Discrediting the West: Diplomacy*. This narrative subtly casts doubt on Western intentions through framing choices—questioning motives ("claim to pursue"), suggesting ulterior purposes ("primarily designed to serve their own interests"), and implying disregard for legitimate concerns. Detecting such narratives requires hierarchical classification: identifying the top-level frame (*Discrediting the West*), the specific narrative dimension (*Diplomacy*), and potentially nested sub-narratives (e.g., *questioning motives*, *serving own interests*). Such multi-layered structures are pervasive in online discourse, where persuasive messaging often combines several rhetorical strategies simultaneously to influence public opinion.

Text Classification (TC) is a foundational task in Natural Language Processing (NLP) (Zangari et al., 2024). While traditional approaches often model TC as a single-label problem, real-world texts frequently contain multiple overlapping themes, motivating the use of Multi-Label Classification (MLC) (Hu et al., 2025; Tidake and Sane, 2018). A particularly challenging yet crucial variant is Hierarchical Multi-Label Classification (HMLC), where labels are organized in a predefined hierarchy (e.g., a tree or DAG) (Liu et al., 2023). Narrative detection exemplifies this challenge: narratives are structured frameworks that shape how information is presented and interpreted, often appearing in nested relationships where broad themes (e.g., "climate skepticism") contain more specific sub-narratives (e.g., "scien-

tists are biased," "data is manipulated"). Accurately identifying these nested structures is essential for understanding persuasive communication in misinformation, news framing, and political discourse.

Large Language Models (LLMs) have opened new frontiers for HMLC, enabling powerful zero-shot classification without extensive labeled data. But this power comes with reliability challenges. LLMs are known to be stochastic, producing different outputs for the same input, and often exhibit low instruction fidelity, failing to consistently adhere to complex hierarchical constraints or output formats (Qin et al., 2024). These limitations hinder their deployment in high-stakes applications where robustness and verifiable reasoning are paramount.

To address these shortcomings, we introduce **Agora**, a multi-agent ensemble framework that significantly improves the robustness and accuracy of LLMs on complex HMLC tasks. By aggregating parallel classifications from multiple LLM agents via voting, Agora mitigates the inherent stochasticity of LLMs and produces more reliable results than a standard single-agent approach. We evaluate our framework on SemEval-2025 Task 10 for multilingual narrative classification (Piskorski et al., 2025), demonstrating state-of-the-art performance across five languages (Bulgarian, English, Hindi, Portuguese, Russian). Our main contributions are:

- A multi-agent ensemble framework Agora that uses consensus-based voting to improve reliability for HMLC, achieving first place in Hindi and top-3 rankings in four other languages on post-challenge SemEval-2025 Task 10.

- A comprehensive evaluation showing that consensus-based ensembles outperform both naive baselines and actor-critic self-refinement approaches, with an 11% F1-Samples improvement over single-agent classification.

- An investigation of voting strategies (union, intersection, majority vote) showing that intersec-

tion voting provides the best precision-recall balance for hierarchical narrative detection.

2. Related Work

The core challenge in Multi-Label Classification (MLC) has historically been the effective modeling of inter-label dependencies. Early methods sought to adapt single-label algorithms to this task. Approaches ranged from Binary Relevance, which simplifies the problem by training an independent classifier for each label but ignores correlations, to Classifier Chains, which attempt to capture dependencies by feeding the predictions of one classifier as features to the next in a sequence (Zhang et al., 2018; Read et al., 2011). While foundational, these methods were often superseded by deep learning models, particularly Transformers, which could learn complex label correlations implicitly from large datasets (Devlin et al., 2019).

Building on these advances, research into Hierarchical Multi-Label Classification (HMLC) focused on creating architectures that explicitly leverage the label taxonomy. A dominant paradigm involved coupling a Transformer-based text encoder with a Graph Neural Network (GNN) that operates on the label graph, allowing the model to learn hierarchy-aware representations and enforce structural consistency (Zhou et al., 2020; Xu et al., 2021). But the advent of Large Language Models (LLMs) has fundamentally shifted the landscape, enabling powerful zero-shot HMLC capabilities that bypass the need for complex, task-specific architectures and extensive supervised training (Wang et al., 2023).

The recent SemEval-2025 Task 10 on narrative detection (Piskorski et al., 2025) exemplifies this modern, LLM-driven approach. State-of-the-art systems effectively use techniques like retrieval-augmented generation and specialized prompting to classify texts within the task's two-level hierarchy (Singh et al., 2025; Younus and Qureshi, 2025). Prior work has also introduced modular "agentic" frameworks that decompose the task into parallel binary decisions (Eljadiri and Nurbakova, 2025). Yet, these pioneering systems share a fundamental vulnerability: their reliance on a single, non-deterministic generative pass, which exposes them to the inherent stochasticity of LLMs.

While ensembling is a well-established technique for improving robustness in supervised models (Jurkiewicz et al., 2020), its systematic application to mitigate the unreliability of zero-shot LLMs in HMLC remains underexplored. This represents a critical research gap: the stochasticity of individual LLM calls stands in stark contrast to the deterministic requirements of hierarchical classification systems, yet few works have investigated consensus-driven approaches to address this mismatch. Our work directly addresses this gap, proposing a multi-agent ensemble framework to produce stable, consensus-driven classifications that can reliably handle the demanding constraints of HMLC.

3. System Architecture

We address the following problem: given a multilingual news article, assign multiple labels from a two-level taxonomy of narratives and subnarratives.

A promising recent approach to HMLC, which we refer to as H3Prompting, was introduced by Singh et al. (2025). This method decomposes the hierarchical classification task into a sequence of zero-shot LLM queries, where an initial prompt determines the top-level category, and subsequent prompts classify second-level narratives conditioned on the first-level prediction. In the spirit of reproducible research, we first aimed to replicate this method. However, the lack of publicly available implementation details prevented a direct reproduction, motivating our development of an open and configurable framework to systematically investigate zero-shot HMLC strategies.

Our investigation into a robust zero-shot HMLC framework followed an iterative design process. First, we propose a traceable self-refining pipeline. Second, upon identifying its limitations, we present our more robust multi-agent ensemble approach.

3.1. Traceable Actor-Critic Pipeline

Our **Actor-Critic Pipeline** aims to improve the reliability and transparency of a single agent's output. In zero-shot classification context, simple label outputs lack traceability and auditability, and are susceptible to unverified hallucinations. To overcome this, we propose a multi-stage pipeline reframing the task from simple classification to evidence-grounded claim generation and validation.

Our implementation uses the LangGraph framework to structure the process as a cyclical state graph (LangChain AI, 2024a). The pipeline configuration is managed by a `ConfigurableGraph-Builder`, allowing components like validation to be enabled or disabled and different LLMs to be assigned to specific nodes via a YAML file. For the Actor-Critic experiments, we use Gemini 2.5 Flash as the underlying LLM for both the Actor and Critic agents. The workflow proceeds through several stages, as illustrated in Figure 1.

Category Classification. An initial node determines the document's domain (e.g. Climate Change (CC) or Ukraine-Russia-War (URW)) to focus subsequent stages on the relevant subset of the narrative taxonomy.

The Narrative Actor (Claim Generation). The "Actor" is an LLM agent prompted to act as an
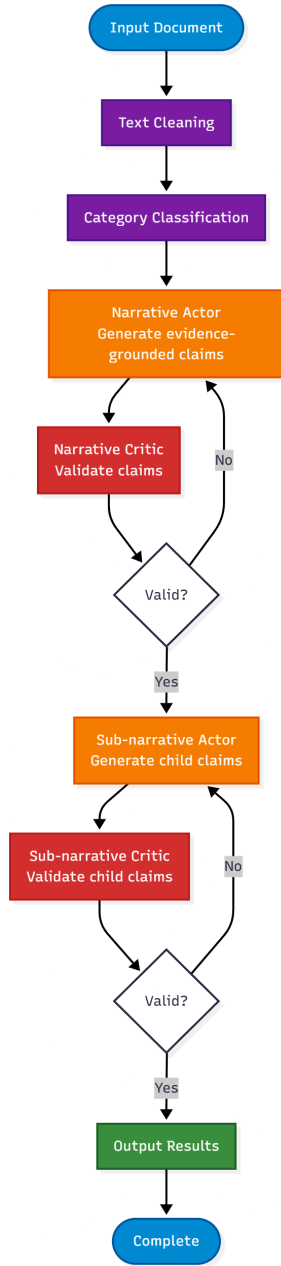
Figure 1: Actor-Critic pipeline architecture. HMLC task is decomposed into hierarchical stages where a Narrative Actor generates evidence-grounded claims, which are then validated by a Narrative Critic. Feedback loops enable iterative refinement before getting to sub-narrative classification.

expert analyst. For each narrative it identifies, it must generate a structured JSON object containing the `narrative_name`, a verbatim `evidence_quote` from the text, and reasoning that connects the two.

The Narrative Critic (Claim Validation). The Actor's output is passed to the "Critic," a separate LLM agent with a distinct, skeptical persona. The Critic validates the Actor's claims against strict crite-

ria (evidence accuracy, relevance, completeness). If the Critic finds flaws, it generates structured feedback, and the graph's conditional logic routes the state back to the Actor for a retry, incorporating the feedback into a refinement prompt.

Sub-narrative Actor and Critic. Once narratives are set, the process repeats hierarchically. A Sub-narrative Actor generates claims for each parent narrative, which are then validated by a Sub-narrative Critic, also with a self-correction loop.

This evidence-grounded architecture offers significant advantages in traceability and auditability, as every prediction is grounded in a textual `evidence_quote`, a process we enhanced using LangSmith for detailed debugging and prompt refinement (LangChain AI, 2024b). However, while this pipeline showed promise, our experiments revealed that it introduced its own form of instability. The process was highly sensitive to the quality of the Critic's feedback, which, being LLM-generated, was itself prone to stochasticity. A flawed critique could send the Actor down an unproductive refinement path, sometimes degrading performance. This reliance on a single, fallible "critic" highlighted a fundamental bottleneck and motivated our shift towards a more robust consensus mechanism.

3.2. Prompt Engineering Strategy

A critical component of both the Actor-Critic and Agora frameworks is the systematic design of prompts that guide the LLM's classification behavior. Our prompting strategy incorporates several key principles:

1. Structured Output Format. All classification prompts enforce structured JSON output with required fields (`narrative_name`, `evidence_quote`, and `reasoning`). This ensures that every classification decision is explicitly grounded in textual evidence, enabling traceability and facilitating automated validation. For example, the narrative classification prompt specifies:

> *"Your entire response MUST be a single JSON object. ALL fields in the schema below are REQUIRED. Do not omit any fields."*

This strict formatting requirement forces the model to provide explicit justifications, preventing opaque label predictions.

2. Chain-of-Thought Reasoning. Prompts explicitly instruct the model to perform step-by-step internal reasoning before producing the final classification. This approach, inspired by chain-of-thought prompting (Wei et al., 2022), encourages the model to identify key phrases, evaluate each potential label *vs.* the evidence, and formulate explicit justifications. The narrative classification prompt includes:

> *"Step 1: Chain of Thought (Internal Reasoning). First, think step-by-step to analyze the*

provided text. Identify key phrases, arguments, and themes. For each potential narrative from the list, consider if it applies. Find a specific, direct quote from the text that serves as the strongest evidence for each narrative you believe is present."

This two-step process (reasoning, then formatting) reduces impulsive classifications and improves output quality.

3. Hierarchical Prompt Design The classification process uses distinct prompts at each level of the hierarchy:

- **Category Classification**: A strict topical classifier that determines text domain (e.g. Climate Change (CC) or the Ukraine-Russia War (URW)). The prompt enforces strict labeling:

  "Output EXACTLY one label token enclosed in square brackets on the next line: [URW], [CC], or [Other]."

- **Narrative Classification**: Given the domain, the model selects from domain-specific narratives, with each narrative accompanied by its definition, examples, and classification instructions according to the template:

  "- {Category}: {Narrative Name} Definition: {Definition text} Example: {Example text} Instruction: {Instruction text}"

- **Sub-narrative Classification**: Given a parent narrative, the model identifies more fine-grained sub-narratives, including an "Other" option for cases where the text supports the parent narrative but does not fit specific sub-narrative definitions. The prompt explicitly instructs:

  "Step 2: Check for a Remainder. Are there any other phrases or arguments that support the parent narrative but were NOT used as evidence for the specific subnarratives? Step 3: Add 'Other' if Necessary."

4. Critic Prompts and Refinement. In the Actor-Critic pipeline, the Critic agent receives a specialized prompt that adopts a "meticulous and skeptical editor" persona. The Critic evaluates classifications against strict criteria: evidence accuracy (verbatim quotes), relevance (direct support for the label), and completeness (no obvious narratives missed). The critic prompt states:

"You are a meticulous and skeptical editor. Your task is to evaluate a classification of propaganda narratives applied to a text. You must be extremely strict. The classification is only valid if every narrative is strongly and explicitly supported by the provided evidence from the text."

When validation fails, a refinement prompt incorporates the Critic's feedback:

"You previously analyzed a text, but your analysis had flaws. A meticulous editor has provided the following feedback. Your task is to re-analyze the text, incorporating this feedback to produce a new, corrected classification."

This feedback loop enables iterative self-correction.

The complete prompts used in our experiments are provided in Appendix A.

3.3. Proposed Framework: Agora Multi-Agent Ensemble

To overcome the limitations of a single-critic system and the broader issue of single-agent stochasticity, we developed Agora, a multi-agent ensemble framework. The core principle of Agora is to replace the judgment of a single agent (or a single critic) with the collective "wisdom of the crowd," leveraging the consensus of multiple independent agents to arrive at a more stable and accurate classification.

Importantly, Agora uses the same core prompts as the baseline and Actor-Critic systems (without the Critic validation step). This design choice isolates the effect of the ensemble mechanism itself, allowing us to attribute performance improvements specifically to the consensus-based aggregation rather than to prompt engineering differences. For the Agora experiments, we use GPT-5-nano as the underlying LLM for all agents in the ensemble, with $N = 3$ agents by default.

The framework operates via a fan-out, fan-in process for each level of the hierarchy (e.g., Narrative classification).

Fan-Out (Parallel Classification). Instead of a single LLM call, Agora instantiates N independent agents (where N is a configurable parameter). The same input text and prompt are sent to all N agents, who perform the classification in parallel. This step effectively samples N independent points from the LLM's output distribution for the given task.

Fan-In (Aggregation via Voting). After all N agents return their individual classifications, an Aggregation node consolidates the results using a voting scheme. We implemented and evaluated three distinct aggregation strategies:

- **Union:** The final label set includes any label proposed by at least one agent. This high-recall strategy is useful for identifying all potential labels.

- **Intersection:** The final label set includes only those labels that all agents unanimously agreed upon. This high-precision strategy filters out all but the most confident predictions.

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- **Majority Vote:** The final label set includes any label proposed by more than half ($> N/2$) of the agents. This strategy provides a robust balance between precision and recall, filtering out stochastic, outlier classifications while retaining a strong consensus.

This ensemble approach directly addresses the single-point-of-failure issue observed in the Actor-Critic pipeline. Instead of relying on one critic's potentially noisy feedback, Agora relies on the statistical robustness of a majority decision, providing a more reliable and conceptually simpler method for improving classification quality.

4. Experimental setup

4.1. Dataset and its Challenges

The dataset from the SemEval-2025 Task 10, Subtask 2, a task focused on multilingual propaganda narrative detection (Piskorski et al., 2025), spans five languages. While we focus our evaluation on the English subset, our analysis of this task reveals several key characteristics that motivate our architectural choices.

First, the dataset is fundamentally multi-label in nature. A majority of documents (54.0%) are assigned more than one narrative, with an average of 2.28 labels per document. This necessitates a multi-label modeling approach.

Second, and most critically, the dataset exhibits a severe class imbalance. As illustrated in the appendix (Figure 3), the 22 narrative labels follow a classic long-tailed distribution. The most frequent narrative appears 65 times more often than the least frequent one. This sparsity poses a significant challenge for traditional supervised models, which risk overfitting on the few "head" classes and failing to generalize to the many rare but meaningful "tail" classes. This characteristic strongly motivates our adoption of a zero-shot paradigm, which does not depend on label frequencies in a training set.

Due to the multi-label nature and severe class imbalance inherent in the dataset, we decided to adopt a zero-shot learning approach. This paradigm avoids dependency on large per-class training counts and is well-suited to handle the long-tail distribution of narratives, making it ideal for this challenging classification task.

4.2. Dataset Statistics

The SemEval-2025 Task 10, Subtask 2 dataset comprises 1,699 documents spanning five languages: Bulgarian (BG), English (EN), Hindi (HI), Portuguese (PT), and Russian (RU). The dataset contains a total of 3,874 narrative annotations and 3,874 corresponding subnarrative annotations, organized in a two-level hierarchy with 22 top-level narratives and 95 subnarratives.

Multi-label Complexity. The dataset exhibits significant multi-label characteristics: 918 documents (54.0%) are assigned multiple narratives, while 781 documents (46.0%) have a single narrative label. On average, each document is annotated with 2.28 narratives and 2.28 subnarratives. The maximum complexity reaches 14 narratives in a single document, highlighting the challenge of capturing diverse narrative content.

Class Imbalance. A severe class imbalance characterizes the dataset, with the most frequent narrative (*URW: Discrediting Ukraine*) appearing 584 times, while the least frequent (*CC: Green policies are geopolitical instruments*) appears only 9 times. This yields an imbalance ratio of 64.9:1, reinforcing the motivation for zero-shot approaches that do not depend on per-class training counts.

Cross-lingual Distribution. The language-specific statistics reveal variation in annotation density: Bulgarian (401 docs, 855 annotations, avg 2.13 labels/doc), English (399 docs, 875 annotations, avg 2.19 labels/doc), Hindi (366 docs, 655 annotations, avg 1.79 labels/doc), Portuguese (400 docs, 1,217 annotations, avg 3.04 labels/doc), and Russian (133 docs, 272 annotations, avg 2.05 labels/doc). Portuguese exhibits notably higher annotation density, while Hindi shows lower average labels per document.

Text Characteristics. Document lengths vary considerably, ranging from 45 to 4,422 words, with an average of 404 words and a median of 371 words. This variation requires robust handling of both short and long-form content.

4.3. Hardware Configuration

All experiments were conducted on a machine with the following specifications: Processor: Intel Core 9 Ultra; **GPU:** NVIDIA RTX 4070 (8GB VRAM); **Memory:** 32GB RAM; **Storage:** 1TB SSD.

4.4. Evaluation Scope

We primarily evaluate the performance of our models on the English test set, providing detailed analysis and interpretation of the results on this language. However, to assess the multilingual capabilities of our approaches, we also conducted experiments on additional languages to validate the generalizability of our methods across different linguistic contexts.

5. Results

In this section, we report the empirical results of our experiments. We first provide a detailed archi-
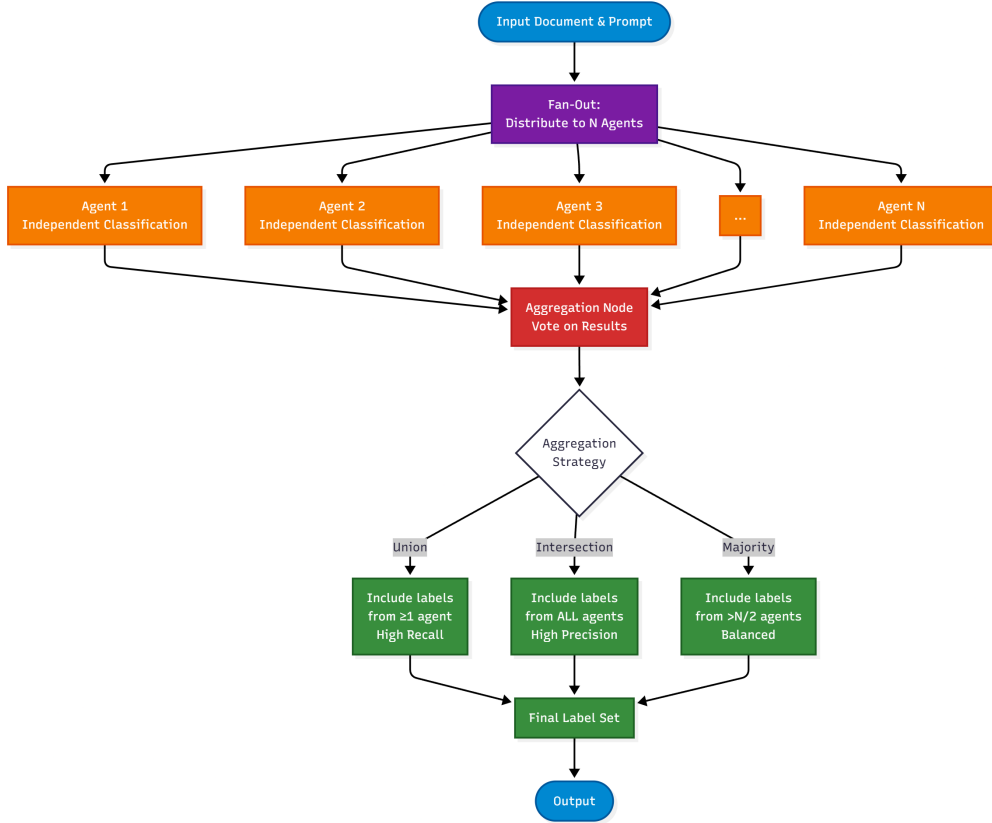
Figure 2: Agora multi-agent ensemble architecture. The classification task is distributed to N independent agents in parallel (Fan-Out), aggregates their results using a voting mechanism (Fan-In), and produces a final label set based on the chosen aggregation strategy (Union, Intersection, or Majority Vote).

tectural comparison to understand the source of improvements, analyze voting strategies, and then validate our approach through competitive performance in the official SemEval-2025 Task 10 shared task.

5.1. Architectural Comparison and Ablation Study

To understand the effectiveness of our approach, we conducted a controlled comparison on the English dataset between our final Agora system, an intermediate Actor-Critic pipeline, and a Naive Baseline. The results are presented in Table 1.

This ablation study reveals a clear performance pathway. The Naive Baseline represents the H3Prompting approach described in Section **??**: a single agent per level, applying one LLM call per hierarchical step without refinement. This baseline achieves an F1-Samples score of 0.382.

The Actor-Critic Pipeline provides a significant improvement of +0.035, demonstrating that a self-refinement loop can effectively correct errors and improve classification quality.

However, our proposed Agora framework delivers an even greater performance gain. It achieves the highest F1-Samples score of 0.424, a +0.042

point improvement (+11.0%) over the Naive Baseline. This result confirms our central hypothesis: while single-agent refinement is beneficial, the consensus-based approach of a multi-agent ensemble is a more robust and superior method for enhancing LLM reliability.

5.2. Analysis of Agora's Voting Strategies

To isolate the effect of the ensemble itself, we compared a single-agent Agora configuration ("Vanilla") against the different multi-agent voting strategies. Table 2 shows that the choice of aggregation method is critical to the ensemble's success.

This analysis provides a crucial insight: simply combining agent outputs is not enough. The Union strategy, which naively accepts all proposed labels, actually performs worse than a single agent by aggregating noise. In contrast, the consensus-based mechanisms deliver clear benefits. Both Majority Vote (+0.013) and Intersection (+0.035) significantly outperform the single agent. The Intersection strategy, requiring unanimous agreement, proves most effective for this task, successfully filtering out stochastic, low-confidence predictions to achieve the best overall performance. This demon-

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Table 1: Main Performance Comparison on the English Dataset (F1-Samples).

System Configuration	F1-Samples Score	Improvement over Baseline
1. Naive Baseline (Single-Pass)	0.382	—
2. Actor-Critic Pipeline	0.417	+0.035
3. Agora (3-Agent Intersection)	**0.424**	**+0.042**

Table 2: Ablation of Agora Configurations on the English Dataset (F1-Samples).

Agora Configuration	F1-Samples Score	Improvement over Single Agent
1. Single Agent (Vanilla)	0.389	—
2. 3-Agent Union	0.375	-0.014
3. 3-Agent Majority Vote	0.402	+0.013
4. 3-Agent Intersection	**0.424**	**+0.035**

strates that the core advantage of Agora lies in its ability to systematically reduce noise through consensus.

5.3. State-of-the-Art Performance in SemEval-2025

The ultimate validation of the Agora framework comes from its performance in the official SemEval-2025 Task 10 competition. Our submitted system, which was the Agora multi-agent ensemble, achieved top-tier rankings across all five languages, including a first-place finish in Hindi.

Table 3: Performance of the Agora Framework in SemEval-2025 Task 10 across Languages.

Language	Rank
Hindi	**1st**
English	2nd
Portuguese	2nd
Russian	3rd
Bulgarian	4th

These results confirm that the consensus-based approach is not just a theoretical improvement but a practical, state-of-the-art method for complex HMLC tasks. Achieving a first-place and two second-place finishes in a highly competitive shared task validates the robustness and generalizability of the Agora architecture.

Notably, these rankings represent a substantial improvement over our earlier submission using the Actor-Critic pipeline approach. Table 4 shows the performance of that intermediate architecture.

While the Actor-Critic approach already achieved competitive results with consistent top-5 rankings, the transition to Agora's multi-agent ensemble brought further improvements, most notably elevating Hindi from 3rd to 1st place. This progression demonstrates the value of moving from a single-critic refinement paradigm to a consensus-based ensemble approach.

Table 4: Performance of the Actor-Critic Pipeline in SemEval-2025 Task 10 across Languages.

Language	Rank
English	2nd
Portuguese	2nd
Hindi	3rd
Russian	4th
Bulgarian	5th

6. Discussion

The central finding of our work is that consensus through ensembling is a more effective strategy for improving LLM reliability than single-agent self-correction. Our experiments show a clear progression: a Naive Baseline suffers from the model's inherent stochasticity; an Actor-Critic pipeline attempts to fix this with a single "referee" but proves inconsistent, as the referee itself is an unreliable LLM. The Agora framework succeeds because it replaces this fragile, single point of correction with the statistical power of a majority vote.

By sampling multiple outputs from the LLM's distribution and aggregating them, Agora effectively averages out random hallucinations and individual agent errors. The ablation study on voting strategies (Table 2) confirms this mechanism: the noisy Union strategy underperforms, while consensus-based methods like Majority Vote and Intersection successfully filter out outlier predictions, leading to higher-quality classifications. This architectural choice directly addresses the core problem of LLM stochasticity and is the primary reason for Agora's state-of-the-art performance in the SemEval-2025 competition.

Furthermore, our initial experiments with the Actor-Critic pipeline serve as a crucial cautionary tale. The finding that the validation step often degraded performance suggests that adding architectural complexity, even when well-motivated, does not guarantee improvement. In multi-step reasoning chains, errors can accumulate, and a flawed

"critic" can be more harmful than no critic at all. This reinforces the elegance of the Agora approach: it improves robustness through a conceptually simple and statistically grounded method rather than a complex and potentially brittle reasoning loop.

7. Limitations and Future Work

Our study, while demonstrating the effectiveness of the Agora framework, is subject to several **limitations** that offer avenues for future work.

Model and API Dependency: Our zero-shot framework relies on proprietary LLMs (e.g., gpt-5-nano). This limits full reproducibility, as performance is tied to specific, closed-source model versions. Future work should explore the effectiveness of this ensemble approach with open-source models to ensure broader accessibility and control.

Prompt Sensitivity: The performance of any zero-shot system is highly sensitive to prompt engineering. While we standardized prompts across configurations, it is possible that the specific phrasing influenced the degree of stochasticity observed and the effectiveness of the voting mechanism.

Computational Cost: Deploying a multi-agent ensemble incurs a direct multiplication of inference cost and latency compared to a single-agent system. In our $N = 3$ configuration, the cost is roughly triple that of the baseline. While the performance gains justified this trade-off in a competitive setting, a critical area for future research is exploring cost-reduction techniques, such as using smaller, distilled models for some agents or implementing more sophisticated routing where an ensemble is only triggered for high-uncertainty cases.

Based on our findings, we propose several **directions for future research**. First, exploring a weighted majority vote, where agents' votes are weighted by a confidence score, could further refine the consensus mechanism. Second, a hybrid approach that uses the fast Naive Baseline for simple cases and dynamically invokes the more robust Agora ensemble for difficult or ambiguous texts could optimize the cost-performance trade-off. Finally, applying the Agora framework to other complex, hierarchical domains beyond propaganda detection, such as legal text or biomedical literature analysis, would further validate its generalizability.

Beyond the zero-shot paradigm, a promising direction involves fine-tuning LLMs on task-specific data to achieve higher performance. However, this approach faces a significant challenge in the multilingual propaganda detection context: the need for high-quality labeled data across multiple languages while preserving cultural nuances. As noted in (Eljadiri and Nurbakova, 2025), machine translation of training data often loses cultural context and domain-specific subtleties, making direct translation-based data augmentation problematic. Future work must explore methods for generating culturally-aware training data, such as collaborative annotation with native speakers or culturally-grounded synthetic data generation, to enable effective fine-tuning while respecting the nuanced differences between languages.

8. Conclusion

In this work, we addressed the critical challenge of stochasticity and unreliability in Large Language Models when applied to complex Hierarchical Multi-Label Classification tasks. While the zero-shot capabilities of LLMs are powerful, their inconsistent outputs present a significant barrier to their deployment in real-world, high-stakes applications like propaganda detection.

We introduced Agora, a multi-agent ensemble framework designed to directly mitigate this issue. By leveraging the consensus of multiple independent LLM agents through a robust voting mechanism, Agora transforms a brittle, single-pass classification into a stable, statistically-grounded decision process. Our experiments, conducted on the SemEval-2025 narrative detection task, provided three key findings: (1) a naive single-pass LLM baseline is outperformed by more sophisticated architectures; (2) a seemingly intuitive Actor-Critic self-refinement pipeline can be counterproductive, as the critic's own unreliability can introduce noise and degrade performance; (3) our Agora framework, using a 3-agent majority vote, delivers substantial and consistent performance gains over both other approaches and state-of-the-art.

The top-ranked performance of Agora on the SemEval test set, validates our central claim: ensembling is a powerful and practical method for building more robust and accurate zero-shot classification systems. Frameworks like Agora that prioritize reliability through consensus will be essential for creating trustworthy and deployable NLP solutions.

Acknowledgements

A. Appendix: Prompt Templates

This appendix provides the complete prompt templates used in our experiments to ensure full reproducibility. All prompts are designed to enforce structured JSON output with evidence grounding.

A.1. Category Classification Prompt

You are a strict topical classifier. Decide whether the given text is primarily about URW (Ukraine-Russia War topics) or CC (Climate Change topics).

Rules (follow exactly):

- First find the elements that indicate the topic, and reason through them step by step.
- Output EXACTLY one label token enclosed in square brackets on the next line: `[URW]`, `[CC]`, or `[Other]`.

Classification guidance:

- Use `[URW]` for topics clearly about the Russia-Ukraine conflict.
- Use `[CC]` for topics clearly about climate change.
- Use `[Other]` if neither topic is the primary focus.

Example outputs: `EVIDENCE: short justification` followed by `[URW]`, `[CC]`, or `[Other]`.

A.2. Narrative Classification Prompt (Template)

You are an expert propaganda narrative analyst. Your task is to analyze the given text and identify which specific propaganda narratives are present.

AVAILABLE NARRATIVES:

{Category}: {Narrative Name}

Definition: {Definition text}

Example: {Example text}

Instruction: {Instruction text}

INSTRUCTIONS:

Step 1: Chain of Thought (Internal Reasoning). Think step-by-step to analyze the text. Identify key phrases and themes. For each potential narrative, find a specific, direct quote that serves as evidence. Formulate reasoning for why that quote supports the narrative.

Step 2: Format the Final Output. Provide a single, valid JSON object with the following schema: `{"narratives": [{"narrative_name": "string", "evidence_quote": "string", "reasoning": "string"}]}`

A.3. Sub-narrative Classification Prompt (Template)

This text is known to contain the narrative: {Parent Narrative}. Your task is to identify which specific sub-narratives are present.

AVAILABLE SUBNARRATIVES: Each sub-narrative includes its definition, example, and classification instruction. An "Other" option is provided for cases where the text supports the parent narrative but does not fit specific sub-narrative definitions.

INSTRUCTIONS:

Step 1: Chain of Thought. Analyze the text step-by-step, looking for specific themes matching sub-narrative definitions. Find direct quotes as evidence.

Step 2: Check for Remainder. Re-read to identify phrases supporting the parent narrative not covered by specific sub-narratives.

Step 3: Add "Other" if Necessary. If uncovered evidence exists, include `{Parent Narrative}: Other`.

Step 4: Format Output. Provide JSON with schema: `{"narratives": [{"sub-narrative_name": "string", "evidence_quote": "string", "reasoning": "string"}]}`

A.4. Critic Validation Prompt (Narrative Level)

You are a meticulous and skeptical editor. Your task is to evaluate a classification of narratives applied to a text. You must be extremely strict. The classification is only valid if every narrative is strongly and explicitly supported by the provided evidence from the text.

EVALUATION CRITERIA (Apply Strictly):

1. **Evidence Accuracy:** Is the `evidence_quote` an exact, verbatim quote from the original text (allowing for minor formatting differences)?

2. **Relevance of Evidence:** Does the `evidence_quote` DIRECTLY support the `narrative_name`? The connection must not be a stretch.

3. **Completeness:** Does the analysis miss any obvious, high-confidence narratives clearly present in the text?

Output: Provide evaluation as a single, valid JSON object.

A.5. Refinement Prompt (After Critic Feedback)

You previously analyzed a text, but your analysis had flaws. A meticulous editor has provided the following feedback. Your task is to re-analyze the text, incorporating this feedback to produce a new, corrected classification.

EDITOR'S FEEDBACK TO CORRECT: {Critic's feedback text}

ORIGINAL TASK AND DEFINITIONS: {Original classification prompt is repeated here}

A.6. Text Cleaning Prompt

> You are a precise text cleaner. Your job is to clean raw text scraped from the web by removing UI noise and boilerplate while preserving the article's content.
> **STRICT RULES:**
> - **REMOVE:** navigation menus, cookie banners, sign-up banners, button labels (e.g., 'Accept', 'Subscribe', 'Read more'), share widgets, headers/footers, unrelated CTAs, legal disclaimers, pagination artifacts, and unrelated links.
> - **KEEP:** the main article or post content only. Preserve sentence order, punctuation, and language.
> - **DO NOT** paraphrase or summarize. Do not add or remove meaning.
> - **OUTPUT:** Return ONLY the cleaned text with no additional commentary, headings, or JSON.

A.7. Implementation Notes

All prompts are implemented as Python functions that dynamically populate templates with task-specific information (e.g., available narratives, definitions, parent narrative context). The category and narrative definitions are loaded from CSV files containing the task taxonomy. This modular design allows for easy adaptation to other hierarchical multilabel classification tasks. These prompts were specifically developed and evaluated on SemEval-2025 Task 10 for multilingual narrative classification (Piskorski et al., 2025), demonstrating the generalizability of the approach across multiple languages and narrative types.

A.8. Narrative Distribution Visualization

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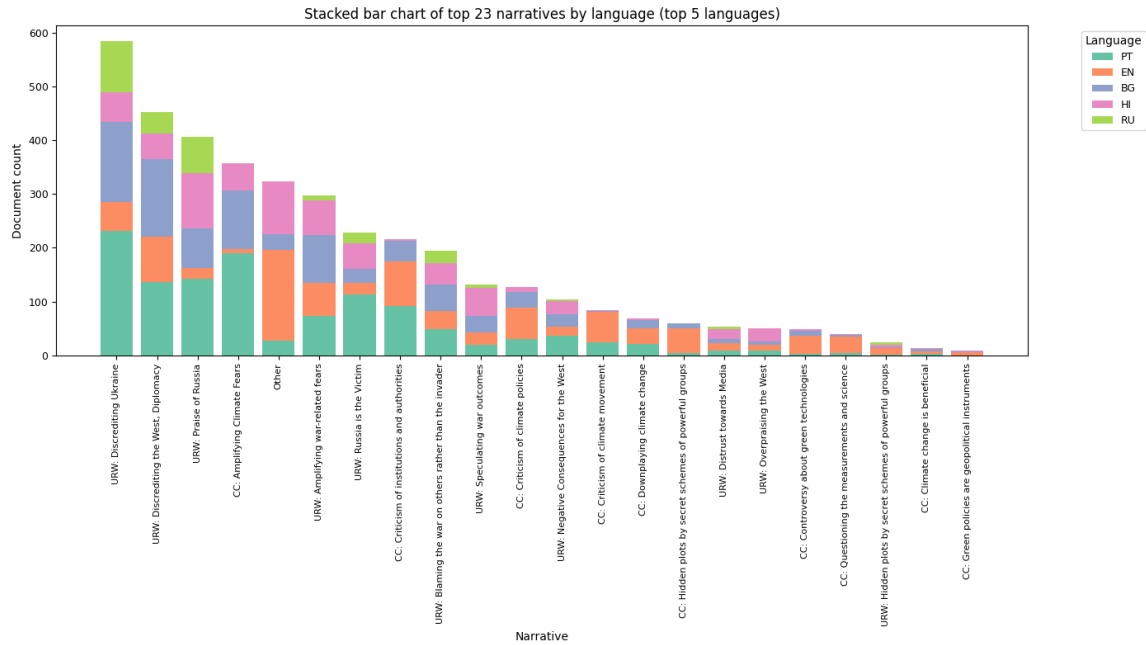
Figure 3: Long-tailed distribution of narrative labels across the dataset. A small number of frequent narratives dominate, while most are rare. This severe imbalance (64.9:1 ratio) justifies the use of zero-shot LLM approaches that do not rely on large per-class training counts.

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