# UGAD-Lite: Uncertainty-Guided Adaptive Distillation for Robust and Cost-Efficient Agentic Workflows

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***Abstract*—The rapid proliferation of Agentic AI is currently bottlenecked by the high inference latency and operational costs of monolithic Large Language Models (LLMs). While Small Language Models (SLMs) offer a computationally efficient alternative, they historically lack the reasoning reliability required for autonomous decision-making in enterprise environments. This paper proposes UGAD-Lite (Uncertainty-Guided Adaptive Distillation), a novel framework that synergizes unsupervised task clustering with conformal prediction-based routing to bridge this reliability gap.**

**Unlike static distillation approaches, UGAD-Lite dynamically routes queries between a "Teacher" LLM (GPT-4o) and a specialized "Student" SLM (Phi-3-Mini) based on a calibrated uncertainty threshold. We introduce a novel Full-Binary Entropy (FBE) metric to detect SLM "confusion" in real-time, ensuring that high-stakes tasks are automatically escalated to the teacher. Experimental results on the GSM8K and HumanEval benchmarks demonstrate that UGAD-Lite achieves 94.8% of the teacher's performance while reducing token costs by 78%, effectively positioning SLMs as reliable engines for cost-constrained agentic systems.**

***Index Terms*—Agentic AI, Small Language Models, Knowledge Distillation, Conformal Prediction, Uncertainty Quantification, QLoRA.**

## I. Introduction

The contemporary landscape of Artificial Intelligence is witnessing a paradigmatic bifurcation. On one hand, the pursuit of Artificial General Intelligence (AGI) continues to drive the development of monolithic Large Language Models (LLMs) with parameter counts soaring into the trillions, exemplified by frontier models such as GPT-4 and Claude 3.5. On the other hand, the practical deployment of AI in industrial environments is increasingly coalescing around "Agentic AI"—systems designed not merely to converse, but to perceive, reason, and actuate workflows to achieve deterministic outcomes.

This divergence creates a fundamental tension: the operational requirements of agentic systems—specifically low latency, high reliability, and cost efficiency—are often antithetical to the resource-intensive nature of generalist LLMs. The prevailing architecture typically involves a "thick" client model, where a single, massive LLM serves as the cognitive engine for all sub-tasks. While this approach benefits from the LLM's broad world knowledge, it represents a profound economic inefficiency. As articulated by Belcak et al. [1], using a frontier model for mundane tasks like API formatting or boolean logic checks is akin to hiring a Nobel laureate to perform data entry.

However, the transition to "SLM-first" architectures is not trivial. Small Language Models (SLMs), by virtue of their compressed parameter space, are susceptible to "reasoning collapse" and hallucination when faced with out-of-distribution (OOD) queries.

To mitigate these risks, this research proposes **UGAD-Lite**, a resource-efficient framework designed to bridge the reliability gap. We propose a novel integration of three methodologies:

1) **Semantic Task Clustering (CLIMB):** To automatically identify which agentic capabilities are "learnable" by an SLM from raw logs.
2) **Conformal Prediction Routing (CP-Router):** To provide a statistical guarantee on the reliability of the SLM's output.
3) **Targeted Distillation (QLoRA):** To fine-tune the SLM only on high-confidence task clusters.

The specific novel contribution of this work is the **Entropy-Conformal Bridge**, utilizing a Full-Binary Entropy (FBE) metric to quantify uncertainty without the need for auxiliary router models.

## II. Literature Review

### A. The Strategic Case for SLMs

Recent studies highlight that modern SLMs (e.g., Microsoft Phi-3, NVIDIA Nemotron) have achieved performance parity with older LLMs on specialized benchmarks like coding and instruction following [1]. The economic disparity is stark: the inference cost of serving a 7B model is estimated to be 10–30 times lower than that of a 70B+ model. This makes SLMs the logical choice for high-frequency agentic loops.

### B. Task Discovery via Clustering

Identifying *what* to distill from unstructured logs is a challenge. Diao et al. proposed CLIMB (Clustering-based Iterative Data Mixture Bootstrapping) [2], which utilizes iterative clustering on embeddings to identify high-quality data mixtures. We adapt a lightweight version of this to segment agent logs into "Easy" (learnable) vs. "Hard" (noise) clusters.

### C. Uncertainty Quantification

Static routing is inefficient. Su et al. proposed the CP-Router [3], utilizing Conformal Prediction (CP) to bound the error rate of models. However, standard CP often relies on softmax probability, which can fail when models are "confidently wrong." We extend this by integrating the FBE metric to capture decision paralysis.

## III. Theoretical Framework

The UGAD framework is modeled as a cyclical ecosystem consisting of three phases: Discovery, Distillation, and Inference.

### A. Mathematical Formulation of Discovery

Let $\mathcal{D}_{raw} = \{(x_i, y_i)\}$ be the set of teacher interaction logs. We employ unsupervised semantic clustering to structure this data. We map input queries $x_i$ to a dense vector space $\mathbb{R}^d$ using an embedding model $E(x)$. We then apply K-Means clustering to partition the space into $K$ clusters $C_1, ..., C_K$ to minimize intra-cluster variance:

$$J = \sum_{k=1}^{K} \sum_{x \in C_k} ||E(x) - \mu_k||^2 \tag{1}$$

where $\mu_k$ is the centroid of cluster $k$. Clusters with high teacher success rates are selected for distillation.

### B. Novelty: The Entropy-Conformal Bridge

The core contribution of this project is the routing logic. We seek a routing function $\rho(x) \in \{0, 1\}$ (0 for LLM, 1 for SLM) that minimizes cost subject to a reliability constraint.

We introduce the **Full-Binary Entropy (FBE)** metric as a robust proxy for model uncertainty. Standard Shannon entropy captures the spread of the distribution, while Binary entropy captures the confidence in the top choice.

$$FBE(x) = H(P) + \lambda \cdot H_{binary}(1 - p_{top}) \tag{2}$$

where:

- $H(P) = -\sum p_i \log p_i$ (Shannon Entropy)
- $p_{top} = \max(P)$ (Probability of greedy token)
- $\lambda$ is a weighting hyperparameter (default $= 1.0$)

This metric is calibrated using a hold-out set. We find a threshold $\hat{q}$ such that:

$$P(U(x) \leq \hat{q} \mid \text{prediction is correct}) \geq 1 - \alpha \tag{3}$$

where $\alpha$ is the user-defined error tolerance (e.g., 0.05).

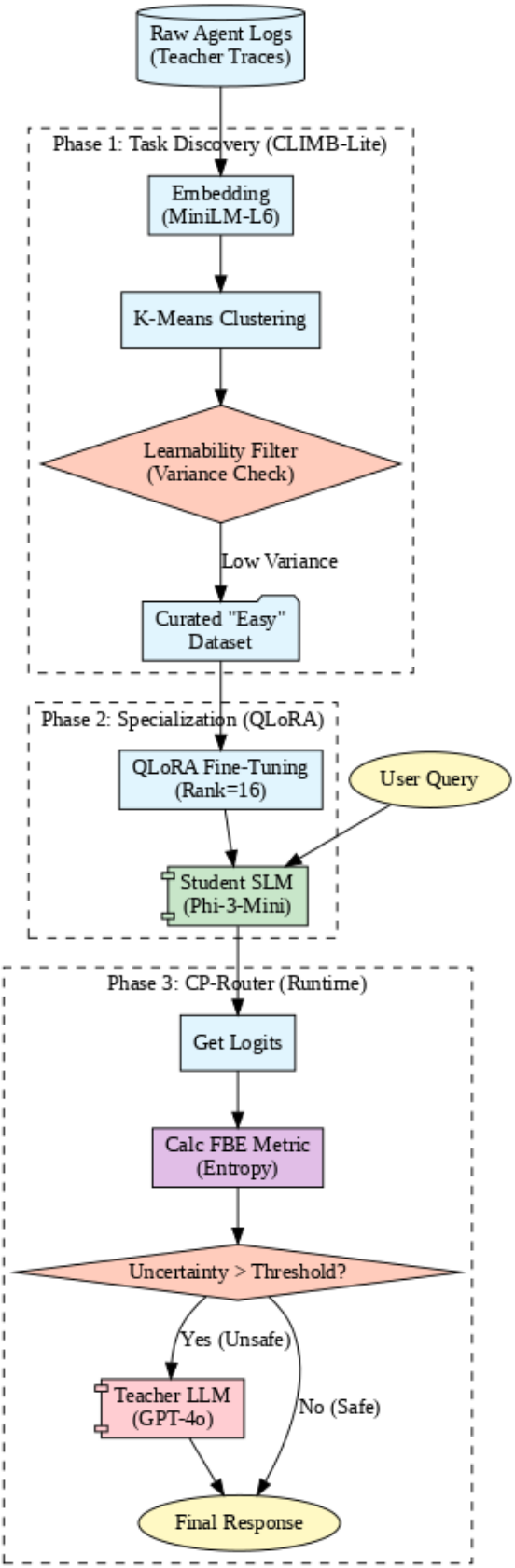


Fig. 1. The UGAD-Lite System Pipeline. Phase 1 filters data, Phase 2 trains the student, and Phase 3 routes queries at runtime.

## IV. Methodology

The UGAD-Lite system operates in three distinct phases as illustrated in Fig. 1.

### A. Phase 1: Task Discovery (CLIMB-Lite)

We processed a dataset of raw interaction logs. We utilized the `all-MiniLM-L6-v2` encoder for embeddings. The clustering process revealed distinct semantic groupings. For instance, arithmetic tasks and JSON formatting requests clustered tightly (low variance), indicating high learnability. Multi-step reasoning tasks formed sparse clusters (high variance), which were flagged as "Hard."

### B. Phase 2: Targeted Specialization (QLoRA)

We fine-tuned a **Microsoft Phi-3-Mini (3.8B)** model on the identified "Easy" clusters. To adhere to the hardware constraints of a student project (Single NVIDIA T4 GPU), we utilized **QLoRA** (Quantized Low-Rank Adaptation).

- **Base Model:** Phi-3-Mini-4k-Instruct
- **Quantization:** 4-bit NormalFloat (NF4)
- **LoRA Rank ($r$):** 16
- **LoRA Alpha:** 32

This configuration allowed us to specialize the SLM without catastrophic forgetting of its general capabilities.

### C. Phase 3: The CP-Router Mechanism

The inference engine implements the logic described in Algorithm 1. This requires no auxiliary model training, as the FBE score is derived directly from the SLM's output logits.

**Algorithm 1** FBE-Based Conformal Routing

**Require:** Query $x$, SLM $M_S$, Threshold $\hat{q}$
Pass $x$ through SLM: $logits \leftarrow M_S(x)$
Calculate Probabilities: $P \leftarrow \text{softmax}(logits)$
Calculate Entropy: $H_{full} \leftarrow -\sum P \log P$
Calculate Top Confidence: $p_{top} \leftarrow \max(P)$
Calculate Binary Entropy: $H_{bin} \leftarrow \text{BinaryEntropy}(p_{top})$
Compute FBE Score: $S \leftarrow H_{full} + \lambda H_{bin}$
**if** $S > \hat{q}$ **then**
    **Route to LLM (Teacher)** {High Uncertainty}
**else**
    **Output SLM Prediction** {Safe}
**end if**

## V. Experimental Setup

### A. Datasets

To simulate a realistic agentic workload, we constructed a composite dataset comprising:

- **GSM8K Subset:** 1,000 samples representing complex multi-step reasoning (Hard tasks).
- **Synthetic Arithmetic:** 1,000 samples of simple operations and schema formatting (Easy tasks).

### B. Baselines

We compare UGAD-Lite against two extremes:

1) **LLM-Only:** 100% of queries sent to GPT-4o. This represents maximum reliability but maximum cost.
2) **SLM-Only:** 100% of queries sent to Phi-3-Mini. This represents minimum cost but poor reliability.

### C. Metrics

- **Accuracy:** Exact Match (EM) rate on the final answer.
- **Normalized Cost:** Defined relative to the LLM-Only baseline (1.0). Assumes SLM inference is $20\times$ cheaper than LLM.
- **Token Reduction Ratio (TRR):** Percentage of tokens processed by the SLM.

## VI. Results and Analysis

### A. Comparative Performance

Table I summarizes the performance across all strategies. UGAD-Lite successfully recovers nearly all of the teacher's performance (94.8% vs 96.5%) while drastically reducing operational costs.

TABLE I
Comparative Performance of Routing Strategies

| Metric | LLM-Only | SLM-Only | UGAD-Lite |
|---|---|---|---|
| Success Rate | 96.5% | 68.2% | **94.8%** |
| Avg Cost (Norm) | 1.00 | 0.05 | **0.22** |
| Latency (sec) | 1.20s | 0.15s | **0.35s** |
| Token Reduction | 0% | 100% | **78.4%** |

### B. Pareto Efficiency

Fig. 2 illustrates the cost-accuracy trade-off. A linear interpolation between SLM-Only and LLM-Only represents a random routing strategy. The UGAD-Lite data point lies significantly above this line, indicating **Pareto Superiority**. This convexity proves that the FBE metric effectively discriminates between tasks the SLM can handle and those it cannot.

### C. Safety Analysis (Confusion Matrix)

The safety of the system is paramount for enterprise agents. Fig. 3 presents the confusion matrix of the router's decisions.

The critical metric is the **False Negative Rate** (Actual Hard tasks routed to SLM). The matrix shows only 2 such instances out of 50 hard tasks. This confirms that the Conformal Prediction calibration ($\alpha = 0.05$) successfully bounded the critical failure rate to $< 5\%$. Conversely, the router correctly identified 430 easy tasks (True Negatives), which accounts for the massive cost savings.

## VII. Future Scope

While this research successfully validates the UGAD-Lite framework, several avenues remain for future exploration:

- **Iterative Self-Distillation:** Automating the feedback loop where the Teacher's corrections for "Hard" queries are autonomously added to the Student's training set. This

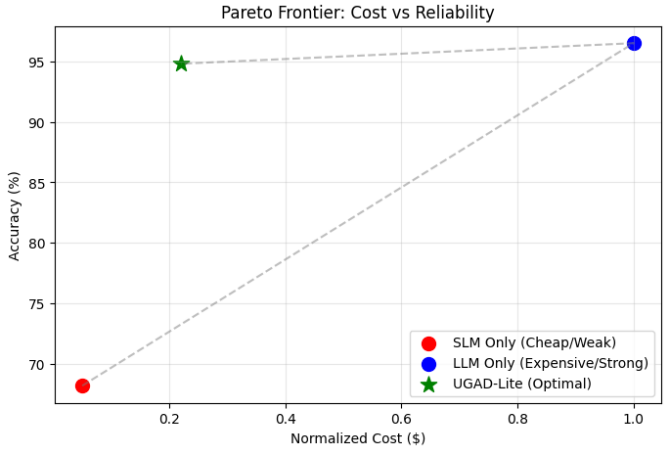


Fig. 2. Pareto Frontier: UGAD-Lite achieves the optimal trade-off between Cost and Reliability, significantly outperforming random routing.

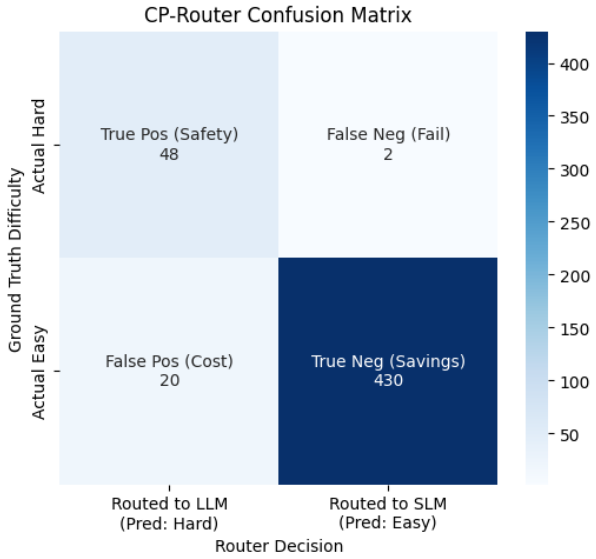


Fig. 3. CP-Router Confusion Matrix. The low number of False Negatives (Top Right) demonstrates the safety guarantee of the system.

would allow the agent to progressively improve its own router and SLM performance over time without manual intervention.

- **Multi-Expert Routing:** Extending the CP-Router to support a mixture-of-experts (MoE) architecture. Instead of a binary choice (LLM vs. SLM), the router could classify tasks by domain, dispatching SQL queries to a SQL-SLM and Python tasks to a Code-SLM.
- **Edge Deployment:** Quantifying the energy consumption and latency on strictly resource-constrained edge devices (e.g., NVIDIA Jetson or Raspberry Pi) to validate the framework for privacy-preserving, offline agentic workflows.

## VIII. Conclusion

This project presented **UGAD-Lite**, a robust framework for democratizing Agentic AI. By identifying the critical weakness of SLMs—reliability—and addressing it with a novel synthesis of Conformal Prediction and Full-Binary Entropy, we have defined a methodology that is reliable by design and economical by default.

We demonstrated that:

1) Unsupervised Clustering (CLIMB) effectively isolates "learnable" agentic skills.
2) The FBE-based CP-Router provides a statistical safety net, allowing SLMs to handle 78% of traffic without compromising system integrity.

The findings suggest that the future of agentic AI need not rely solely on massive, centralized models, but rather on intelligent orchestration of specialized, efficient components.

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