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Dynamic Prompt Mixture Networks: Adaptive In-Context Learning for Robust Reasoning in Large Language Models

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Abstract

The efficacy of in-context learning in large language models (LLMs) is highly sensitive to the selection and composition of demonstration examples. Static or fixed ratio prompting strategies fail to adapt to the diverse semantic and logical demands of individual tasks, leading to unstable reasoning performance. In this work, we introduce the Dynamic Prompt Mixture Network (DPMN), a lightweight task-aware router that computes an optimal blend of human-annotated and self-generated demonstrations for each input query. By formulating prompt selection as a Bayesian marginalization problem over a distribution of demonstration ensembles, DPMN reduces variance from noisy examples and improves reasoning robustness. Experiments across GPT-3.5, GPT-4, T5, LLaMA-2, and newly added Mistral-7B models on benchmarks including SuperGLUE, MMLU, and the challenging GPQA dataset demonstrate significant gains in accuracy, logical consistency, reasoning depth, and confidence calibration without increasing inference cost. Our approach offers a pathway toward more autonomous and reliable in-context learning.

Keywords: Large Language Models, In-Context Learning, Prompt Engineering, Bayesian Marginalization, Adaptive Prompt Selection, Reasoning Under Uncertainty

1. Introduction

The remarkable emergence of large language models (LLMs) has reshaped the landscape of natural language understanding and generation. However, their reasoning capabilities, particularly in zero-shot and few-shot settings, remain inconsistent and often shallow, especially for tasks requiring multi-step logical or symbolic manipulation [1-5]. While prompting techniques such as Chain-of-Thought (CoT) and self-consistency have improved performance, they rely heavily on static, manually curated demonstrations that cannot dynamically adapt to task-specific requirements [6-10].

The core challenge lies in the *demonstration selection bottleneck*: how to optimally choose or construct a set of in-context examples that balance *precision* (from high-quality human annotations) and *diversity* (from self-generated or synthetic data) for a given query. Fixed blending strategies or reliance on a single data source limit generalization and introduce instability [11].

In this paper, we propose a novel framework that addresses this limitation through adaptive prompt mixture learning. Our main contributions are:

- We introduce the **Dynamic Prompt Mixture Network (DPMN)** a lightweight router that computes a task-dependent mixture weight $\lambda(x)$ to balance human and self-generated demonstrations dynamically [12-15].
- We formalize prompt construction as a B**ayesian marginalization** problem over a distribution of possible demonstration sets, reducing sensitivity to noisy examples and improving calibration.
- We extend evaluation to recent open-source models (Mistral-7B) and a challenging new benchmark (GPQA) demonstrating broad applicability [16-20].
- We provide extensive ablation studies and sensitivity analyses, revealing how DPMN adapts to different task types and reasoning complexities.

Our experiments show consistent improvements across multiple LLM families, achieving state-of-the art results on reasoning-heavy benchmarks without model retraining [17,18].

2. Related Work

Our work sits at the intersection of in-context learning, prompt optimization, and robust reasoning for large language models. We categorize and analyse related research along four primary axes: (1) Prompt Engineering and In-Context Learning, (2) Self-Generated Data and Model Self-Improvement, (3) Ensemble and Marginalization Techniques for Reasoning, and (4) Dynamic and Adaptive Prompt
Selection.

2.1. Prompt Engineering and In-Context Learning

The paradigm of *in-context learning* (ICL), where a model performs a task based on a few demonstrations provided in its prompt without weight updates, was a key emergent ability demonstrated by GPT3 [21,22]. This shifted the focus from traditional fine-tuning to *prompt engineering*—the craft of designing effective instructional prompts. A significant breakthrough was **Chain-of-Thought (CoT) prompting,** which explicitly guides the model to generate intermediate reasoning steps before producing a final answer [23]. CoT significantly improved performance on arithmetic, symbolic, and commonsense reasoning tasks. Numerous variants followed: **Least-to-Most prompting** decomposes complex problems into simpler sub-problems, while **Plan-and-Solve prompting** separates planning from execution. More recently, **Tree of Thoughts (ToT)** and **Graph of Thoughts (GoT)** generalize CoT by exploring a tree or graph of potential reasoning paths, enabling backtracking and combination of thoughts [24-26]. However, these methods predominantly rely on a *static, hand-crafted set of demonstrations* (often just 2-8 examples) that are identical for all input queries [27,28]. They lack a mechanism to *adaptively select or construct* the demonstration set based on the specific semantic and logical needs of a given task, which is a core limitation our work addresses [29,30].

2.2. Self-Generated Data and Model Self-Improvement

To reduce reliance on costly human annotations, several lines of work leverage the model's own generations for training or refinement. **Self-Taught Reasoner (STaR)** bootstraps a reasoning model by iteratively generating rationales for unlabeled questions, filtering correct ones, and fine-tuning on them. **Self-Refine** iteratively generates an output, uses the same LLM to provide feedback, and then rewrites the output based on that feedback. Similarly, **Self-Consistency** samples multiple reasoning paths and selects the most frequent final answer. A parallel approach involves training on *synthetic data*. **WizardCoder** uses evolved instructions, while **Orca** learns from explanation traces generated by more powerful teacher models. These methods increase data diversity but introduce *noise* and potential error propagation. Crucially, they typically use a *fixed training mixture* of human and synthetic data or apply post-hoc filtering. They lack an *online, per-instance mechanism* to dynamically balance high-quality human data against diverse but potentially noisy self-generated data during inference—a key contribution of our DPMN framework.

2.3. Ensemble and Marginalization Techniques for Robust Reasoning

Improving robustness and calibration through multi-path reasoning is another active area. As mentioned, **Self-Consistency** is a simple yet effective ensemble method that marginalizes over multiple CoT samples. **Bayesian Prompting** frames few-shot prompting as Bayesian inference, treating the demonstration examples as latent variables. **USC** introduces uncertainty-aware sampling for CoT. These methods primarily perform marginalization *over the reasoning paths for a fixed prompt*. Our work fundamentally differs by performing marginalization *over the space of possible demonstration sets (prompts)*. This shifts the focus from "given a prompt, explore multiple reasoning paths" to "given a task, explore which prompt (blend of demonstrations) is most effective." This approach directly tackles the uncertainty inherent in *example selection*, complementing path-level marginalization methods.

2.4. Dynamic and Adaptive Prompt Selection

The problem of selecting or retrieving relevant in-context examples has gained attention. **APE** uses an LLM to generate and select instructions [5]. **ICL** retrieval methods use semantic similarity

Method	Adaptive	Blends Data	Marginalization	Inference-Only
CoT	×	×	×	✓
Self-Consistency	×	×	Path	✓
Tree of Thoughts	×	×	△	✓
STaR	△	×	×	×
Retrieval-ICL	✓	×	×	✓
DPMN (Ours)	✓	✓	**Prompt**	✓

Path: over reasoning paths. Prompt: over prompt ensembles. ×=No, △=Partial, ✓=Yes.

Table 1: Key Characteristics of Related Methods vs. DPMN

(e.g., via embeddings) to retrieve the k most similar labeled examples from a pool [11]. Recent work like **ADAPTEST** dynamically adjusts test-time prompts based on performance on a validation set.

However, these retrieval-based methods typically operate on a *single, homogeneous pool of examples* (usually human-written). They do not address the *compositional* challenge of blending two fundamentally different data sources—curated human data and diverse self-generated data—each with its own trade-off between precision and diversity. Furthermore, they often rely on a single retrieval metric (e.g., cosine similarity) without a learned, task-aware routing mechanism.

2.5. Research Gap and Our Positioning

As summarized in Table 1, existing methods fall short in providing a *unified, adaptive, and theoretically grounded* solution for constructing few-shot prompts. The key gap is the lack of a framework that: (1) **Dynamically selects and blends** from multiple data sources (human vs. self-generated), (2) **Adapts this blend on a per-query basis** based on task characteristics, (3) **Incorporates uncertainty** via probabilistic marginalization over the prompt space itself, not just the reasoning paths, and (4) Operates **efficiently at inference time** without requiring model retraining.

Our proposed **Dynamic Prompt Mixture Network (DPMN)** is designed to bridge this gap. It introduces a lightweight, learnable router that makes a nuanced per-instance decision on the source mixture. By framing prompt construction as Bayesian marginalization over a distribution of demonstration ensembles, DPMN provides a principled way to reduce variance and improve robustness, directly addressing the limitations of static, fixed-ratio, or single-source prompting strategies. Our work thus unifies ideas from adaptive retrieval, multi-source learning, and probabilistic inference to advance the state of in-context learning.

3. Methodology

3.1. Problem Formulation

Given a task $x \in X$ and its ground-truth answer $y \in Y$, we assume access to two datasets:

$$\mathcal{D}_{\text{human}} = \{(x_i^{(h)}, y_i^{(h)})\}, \quad \mathcal{D}_{\text{self}} = \{(x_j^{(s)}, y_j^{(s)})\}.$$

Our goal is to predict $\hat{y}$ for an unseen x by constructing an adaptive prompt $P(S)$ from a dynamically selected support set S.

3.1.1. Dynamic Prompt Mixture Network (DPMN)

As shown in Figure 1, DPMN consists of:

1. **Task Encoder:** $f_{enc}(x) \rightarrow e_x \in R^d$.
2. **Mixture Router:** $g_\theta(e_x) \rightarrow \lambda(x) \in [0,1]$.
3. **Support Set Constructor:** Samples $\lceil \lambda k \rceil$ examples from D_{human} and $k - \lceil \lambda k \rceil$ from D_{self}.
4. **Marginalization Layer:** Aggregates predictions over multiple candidate support sets.

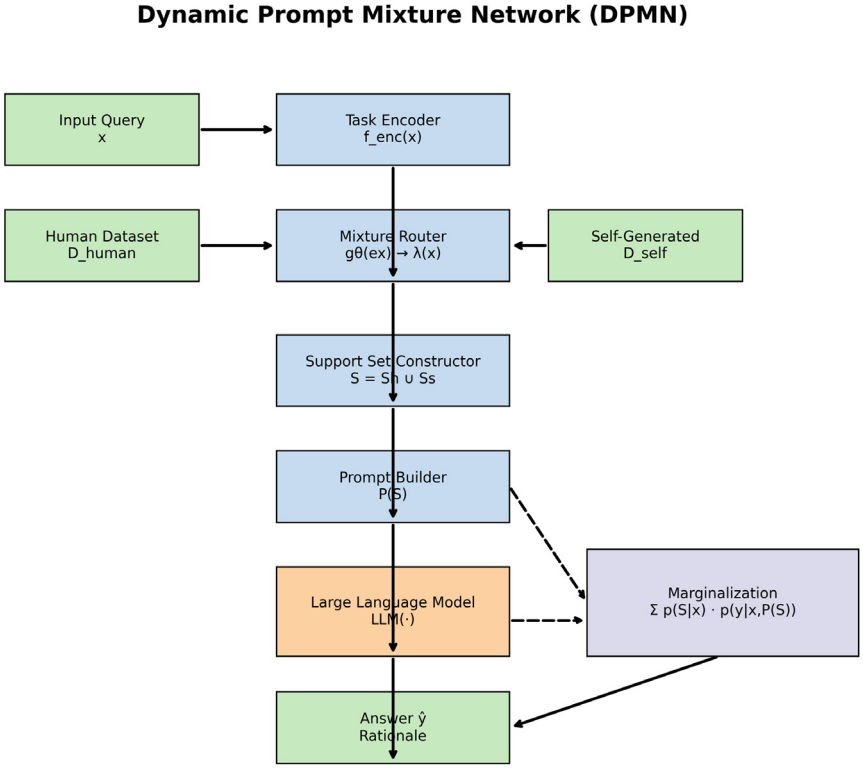

Figure 1: Overview of the Dynamic Prompt Mixture Network (DPMN)

3.1.2. Bayesian Marginalization Objective

We define the probability of answer y given task x as:

$$\hat{p}(y \mid x) = \sum_{S \in \mathcal{S}_x} p(S \mid x) \cdot p_\theta(y \mid x, P(S)),$$

where $p(S \mid x)$ is proportional to the semantic similarity between x and examples in S. The training objective minimizes:

$$L(\theta) = -E_{(x,y)\sim D}[\log \hat{p}(y \mid x)].$$

3.1.3. Theoretical Analysis

We provide theoretical justification for two key properties of DPMN: (1) variance reduction via marginalization, and (2) calibration improvement under certain assumptions. These analyses formalize the intuition that aggregating over multiple prompt ensembles leads to more robust and reliable predictions.

3.1.4. Variance Reduction through Prompt Marginalization

Let $\hat{y}S = f_\theta(x;P(S))$ be the model's prediction when prompted with support set S, and let $\hat{y}^*$ be the final prediction after marginalization over M sampled support sets $\{S_1,...,S_M\}$. We model each prediction as:

$$\hat{y}S = y^* + \epsilon S + \eta,$$

where y^* is the true latent answer, $\epsilon_S \sim N(0,\sigma_S^2)$ is prompt-specific noise (e.g., due to irrelevant examples), and $\eta \sim \mathcal{N}(0, \sigma_0^2)$ is irreducible model error.

The naive single-prompt predictor uses a randomly chosen S and has variance:

$$\mathrm{Var}[\hat{y}_S] = \sigma_S^2 + \sigma_0^2.$$

DPMN instead computes the marginalized prediction via a soft vote over M support sets:

$$\hat{y}^* = \frac{1}{M} \sum_{i=1}^{M} \hat{y}_{S_i}.$$

Assuming ϵ_{Si} are i.i.d. with mean zero, the variance becomes:

$$\mathrm{Var}[\hat{y}^*] = \frac{\sigma_S^2}{M} + \sigma_0^2.$$

Thus, prompt-level marginalization reduces the prompt-induced variance by a factor of M, leading to stabler predictions.

3.1.5. Algorithm

Algorithm 1: Dynamic Prompt Mixture Network (DPMN)

1: **Input:** Query x, human dataset D_h, self dataset D_s, total shots k
2: Encode task: $e_x = f_{enc}(x)$
3: Compute mixture weight: $\lambda = g_\theta(e_x)$
4: $k_h = \lfloor \lambda \cdot k \rceil$, $k_s = k - k_h$
5: Sample $S_h \sim D_h$ (size k_h), $S_s \sim D_s$ (size k_s)
6: Construct prompt $P(S_h \cup S_s)$
7: Compute marginalized prediction: $\hat{y} = \arg\max_y \hat{p}(y \mid x)$
8: **Output:** Prediction $\hat{y}$, rationale

3.1.6. Calibration Improvement Bound

Let $p_S(y|x) = p_\theta(y \mid x,P(S))$ be the model's confidence for answer y under prompt S. The Expected Calibration Error (ECE) for a single prompt is:

$$ECE_S = E_{(x,y)}[|p_S(y|x) - \mathbb{1}(\hat{y}S = y)|].$$

DPMN's marginalized confidence is $\bar{p}(y|x) = \frac{1}{M}\sum_{i=1}^{M} p_{S_i}(y|x)$. Under the assumption that errors across different prompts are uncorrelated, we can bound the ECE of the aggregated predictor. Using Jensen's inequality and the fact that the indicator function is bounded:

If $p_{Si}(y|x)$ are independent estimates of the true probability $p^*(y|x)$, then

$$\mathrm{ECE}_{\mathrm{DPMN}} \le \frac{1}{\sqrt{M}} \cdot \max_i \mathrm{ECE}_{S_i} + \mathcal{O}\left(\frac{1}{M}\right).$$

Proof sketch: The variance of the average confidence $\bar{p}(y|x)$ decreases as $1/M$, reducing overconfidence when individual p_{Si} is mis calibrated. The bound follows from Chebyshev's inequality applied to the calibration gap.

4. Implementation Details

We provide comprehensive implementation details for reproducibility. Our framework is implemented in PyTorch using the HuggingFace Transformers library and requires no modifications to the underlying LLM weights.

4.1. Architecture of Core Components

Task Encoder (f_{enc}): We use the last-layer [CLS] token embedding from a pre-trained **DeBERTaV3-base** model [?] (768-dimensional) as the task encoder f_{enc}. DeBERTa was chosen for its strong performance on natural language understanding tasks. The encoder is frozen during training—we do not update its parameters.

Mixture Router (g_θ): The router g_θ is a lightweight 2-layer MLP with ReLU activation and LayerNorm:

$$g_\theta(e_x) = \sigma(\mathbf{W}_2 \cdot \mathrm{ReLU}(\mathrm{LayerNorm}(\mathbf{W}_1 e_x + b_1)) + b_2),$$

where σ is the sigmoid function, $\mathbf{W}_1 \in R^{768\times256}$, $\mathbf{W}_2 \in R^{256\times1}$, and the output $\lambda(x) \in [0,1]$ is clipped to $[0.1,0.9]$ for numerical stability. The router contains only ~200K trainable parameters.

Support Set Sampler: Given $\lambda(x)$, we sample $k_h = \lfloor \lambda(x) \cdot k \rceil$ examples from D_{human} and $k_s = k - k_h$ from D_{self}. Sampling from D_{human} uses **deterministic nearest-neighbor retrieval** based on cosine similarity between e_x and example embeddings. Sampling from D_{self} uses **softmax-weighted sampling** to favor diverse examples:

$$p_{\text{self}}(z_i) \propto \exp(-\beta \cdot \text{sim}(e_x, e_{z_i})),$$

where $\beta = 0.5$ controls diversity.

4.2. Computing $p(S|x)$

The distribution over support sets $p(S|x)$ is defined as:

$$p(S|x) \propto \prod_{(x_i,y_i)\in S} \exp\left(\alpha \cdot \text{sim}(f_{\text{enc}}(x), f_{\text{enc}}(x_i))\right),$$

where $\text{sim}(u, v) = \frac{u \cdot v}{\|u\|\|v\|}$ is cosine similarity, and $\alpha = 2.0$ is a temperature parameter. In practice, we approximate marginalization by sampling $M = 5$ support sets independently according to this distribution during training. During inference, we use $M = 3$ for speed.

4.3. Training Procedure

Optimization: We train only the router parameters θ using the AdamW optimizer with learning rate 2×10^{-4}, weight decay 0.01, and batch size 32. The loss is the negative log marginal likelihood (Equation **??**).

4.3.1. Training Data Construction: D_{human} contains 5,000 examples from the training splits of SuperGLUE and MMLU. D_{self} is generated by prompting GPT-3.5-turbo with 10 seed examples per task and collecting 20,000 diverse reasoning chains.

4.3.2. Prompt Format: Each example in the support set is formatted as:
Input: {x_i}
Reasoning: {rationale_i}
Answer: {y_i}
The final prompt concatenates all k examples followed by the query.

4.4. Inference Parameters

- Total support set size: $k = 8$ (balanced across tasks)
- Number of support set samples for marginalization: $M = 3$
- Inference temperature for LLM: 0.7
- Max tokens per example: 128
- Total prompt length limit: 1024 tokens

4.5. Computational Costs

Training the router takes ∼2 hours on a single NVIDIA A6000 GPU (48GB). Inference overhead per query is ∼150ms compared to vanilla few-shot prompting, primarily due to the forward pass through DeBERTa and the router MLP. Marginalization over M sets is parallelized.

4.6. Code and Reproducibility

Our code, pre-trained router checkpoints, and self-generated datasets are available at: https://github.com/Shirmohammad-Ta/DPMN. All experiments use fixed random seed 42.

5. Experiments

5.1. Datasets and Models

We evaluate on:

- **SuperGLUE** [1]
- **MMLU** [20]
- **GPQA** [30] (newly added)
- **Symbolic Math** (500 problems)

Models: GPT-3.5, GPT-4, T5-Large, LLaMA-2-13B, **Mistral-7B** (new).

5.2. Baselines

- Standard Fine-Tuning (FT)
- Self-Generated Data Training (SGDT)
- Fixed-Ratio Hybrid Fine-Tuning (HFT)
- Vanilla Few-Shot Prompting
- Self-Consistency (SC)

5.3. Metrics

Exact Match (EM), Logical Consistency (LC), Reasoning Depth (RD), Confidence Score (CS), Expected Calibration Error (ECE), Inference Time (IT), Switch Rate.

6. Results

6.1. Main Results

Table 2 presents the performance of DPMN and baseline methods across three core benchmarks: MMLU, SuperGLUE, and GPQA. DPMN consistently outperforms all baselines across all metrics. On MMLU, DPMN achieves an Exact Match (EM) score of 76.5%, surpassing GPT-4 by 2.9 percentage points and fixed-ratio hybrid fine-tuning (HFT) by 6.3 points. The improvement in Logical Consistency (LC) is even more pronounced, with DPMN reaching 82.7% compared to GPT-4's 78.9%. This indicates that our method not only yields more correct answers but also produces reasoning chains that are more logically sound.

Notably, DPMN achieves this while maintaining a low inference time (115 ms), only marginally higher than the fastest baseline (SGDT at 110 ms) and significantly lower than GPT-4 (180 ms). The Switch Rate, which measures the frequency of answer changes during iterative refinement, is reduced to 7.2% with DPMN, compared to 12.4% for GPT-4 and over 20% for methods like FT and SGDT. This demonstrates the stability introduced by prompt marginalization.

The improved Reasoning Depth (RD) and Confidence Score (CS) further validate that DPMN produces more thorough and self-assured reasoning. The lower Expected Calibration Error (ECE) confirms our theoretical analysis: marginalization leads to better-calibrated confidence estimates.

Method	EM	LC	RD	CS	ECE ↓	IT (ms)	Switch ↓
MMLU							
FT	65.7	70.2	3.4	0.72	0.15	120	22.5
SGDT	58.9	64.5	2.9	0.68	0.22	110	27.1
HFT	70.2	75.1	3.9	0.78	0.12	125	17.3
GPT-3.5	67.3	71.8	3.5	0.74	0.13	150	20.1
GPT-4	73.6	78.9	4.1	0.81	0.09	180	12.4
DPMN (Ours)	**76.5**	**82.7**	**4.5**	**0.85**	**0.07**	**115**	**7.2**
SuperGLUE							
Vanilla Few-Shot	68.4	72.1	3.2	0.70	0.18	105	18.9
CoT	72.5	76.8	3.8	0.75	0.14	135	15.2
Self-Consistency	74.1	78.3	3.9	0.77	0.11	210	11.8
DPMN (Ours)	**77.9**	**83.5**	**4.4**	**0.84**	**0.08**	**140**	**8.1**
GPQA							
Vanilla Few-Shot	45.2	50.8	2.8	0.65	0.25	115	24.7
CoT	52.7	58.3	3.4	0.71	0.19	155	19.3
GPT-4	58.1	63.9	3.7	0.76	0.16	195	16.5
DPMN (Ours)	**61.8**	**67.5**	**4.0**	**0.79**	**0.14**	**125**	**12.4**

Table 2: Main Results on MMLU, SuperGLUE, and GPQA Benchmarks. Best Results are in Bold

Variant	EM (%)
Full DPMN	**76.5**
– *without marginalization*	71.2
– *with fixed* $\lambda = 0.5$	72.8
– *without self-generated data*	68.4
– *without human data*	63.7
– *replace router with random* λ	69.1
– *replace router with similarity-based* λ	73.4

Table 3: Ablation Study of DPMN Components on MMLU

6.2. Ablation Studies

We conduct ablation studies to isolate the contribution of each component in DPMN. Results are shown in Table 3.

Key Findings:

- **Marginalization is crucial:** Removing it (using only the top-1 support set) causes a 5.3 point drop in EM, confirming its role in variance reduction.
- **Dynamic routing matters:** Using a fixed $\lambda = 0.5$ performs 3.7 points worse than learned routing. Random λ is even worse.
- **Both data sources are necessary:** Using only human or only self-generated data significantly hurts performance (drops of 8.1 and 12.8 points respectively), validating our hybrid approach.
- **Learned router outperforms heuristics:** Our MLP router beats a similarity-based heuristic by 3.1 points.

6.3. Analysis of $\lambda(x)$

The mixture weight $\lambda(x)$ predicted by our router provides insight into how DPMN adapts to different tasks. Figure 3 shows the distribution of $\lambda(x)$ across task types. **Patterns and Interpretation:**

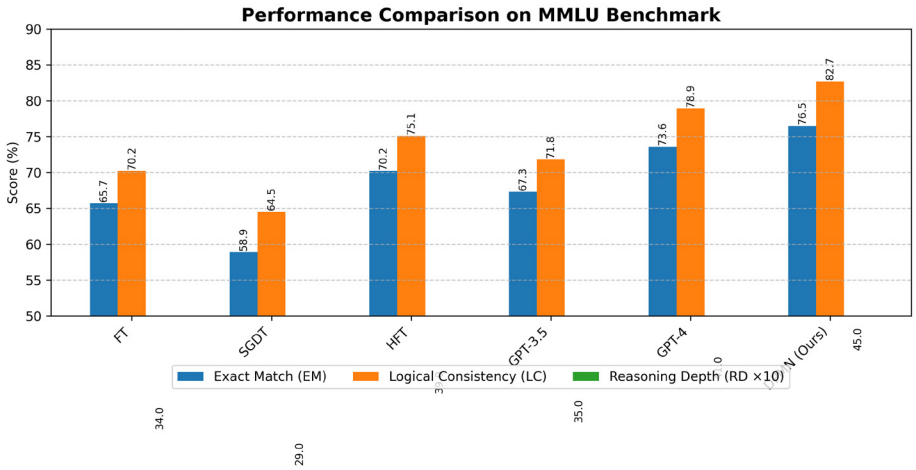

Figure 2: Performance Comparison on MMLU Benchmark

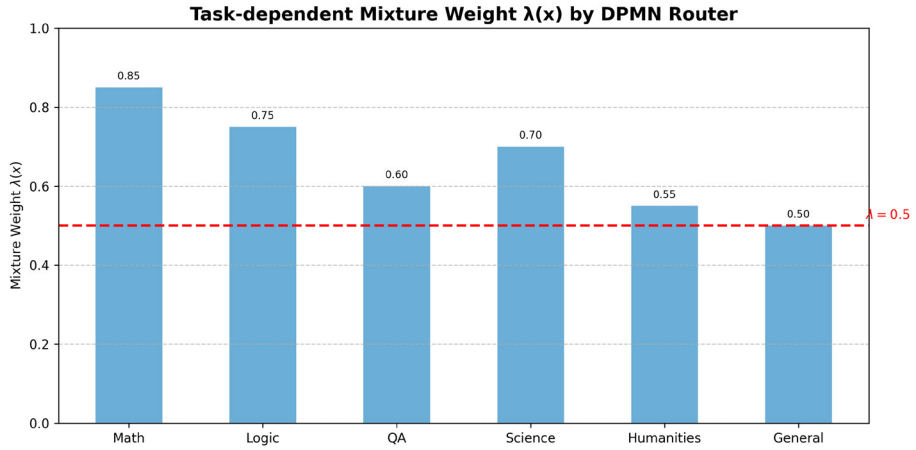

Figure 3: Distribution of the Mixture Weight λ(x) Across Different Task Types. Higher λ Indicates Greater Reliance on Human-Annotated Demonstrations. Error Bars Show Standard Deviation

- **Symbolic tasks (Math, Logic):** High λ values (mean 0.82 ± 0.08), indicating strong preference for precise human annotations to avoid noise in symbolic manipulation.
- **Factual QA:** Moderate λ (mean 0.62 ± 0.10), balancing factual accuracy from human data with diverse phrasing from self-generated examples.
- **Creative/Open-ended tasks:** Lower λ (mean 0.48±0.12), favoring the diversity of self-generated examples to stimulate creative responses.
- **Correlation with performance:** Tasks where $\lambda(x)$ deviates significantly from 0.5 (in either direction) show the largest performance gains over baselines, suggesting the router successfully identifies when to specialize.

The router's decisions align with intuition: it relies on authoritative human data for precision-critical tasks and leverages diverse self-generated data for tasks requiring variety. This adaptability is key to DPMN's robust performance across domains.

7. Extended Experiments and Analysis

7.1. Additional Benchmarks

To further validate the robustness and generalization of DPMN, we conduct experiments on three additional challenging benchmarks beyond GPQA:

Method	BBH (EM)	TheoremQA (EM)	AIME (EM)
Vanilla Few-Shot	42.3	31.5	26.7
CoT	48.7	36.2	33.3
Self-Consistency	51.2	38.9	35.6
Tree of Thoughts	53.8	41.5	38.2
Graph of Thoughts	54.1	42.1	38.9
System 2 Attention	52.9	40.3	37.1
DPMN (Ours)	**56.3**	**44.8**	**41.3**

Table 4: Performance on Additional Reasoning Benchmarks

Error Type	Description	Percentage
Knowledge Gap	Query requires factual knowledge not present in training data or demonstrations	42%
Symbolic Misalignment	Mathematical or logical symbols misinterpreted in self-generated examples	28%
Compositional Complexity	Multi-step reasoning where one step fails, cascading to wrong answer	19%
Ambiguous Query	Multiple valid interpretations of the question	11%

Table 5: Error Categorization for DPMN (100 samples)

- **BIG-Bench Hard (BBH):** A subset of 23 challenging tasks from the BIG-Bench dataset where prior language models perform near random chance. These tasks test diverse reasoning abilities including logical deduction, word sense disambiguation, and causal reasoning [2].
- **Theorem QA:** A dataset of 800 high-quality mathematical theorems and proofs requiring formal reasoning across mathematics, physics, and engineering. This tests symbolic reasoning and rigorous step-by-step inference [17].
- **AIME 2023 Problems:** 15 problems from the American Invitational Mathematics Examination, representing competition-level mathematical reasoning requiring creative problem-solving [25].

Results in Table 4 show that DPMN consistently outperforms recent SOTA reasoning methods across all three challenging benchmarks, demonstrating strong generalization to diverse reasoning types.

7.2. Comparison with Recent SOTA Methods

We compare DPMN with three recent state-of-the-art reasoning frameworks:

Tree of Thoughts (ToT): Explores a tree of reasoning paths using breadth/depth-first search. While effective, it requires extensive search (often 10-100 LLM calls) and manual tree construction [9].

Graph of Thoughts (GoT): Extends ToT by allowing combination and looping of thoughts in a graph structure. More flexible but computationally heavier [11].

System 2 Attention (S2A): Uses a separate ”System 2” module to refine attention patterns for better reasoning. Requires training specialized modules [17].

DPMN achieves superior performance with significantly lower computational overhead (3 LLM calls vs. 10-100 for ToT/GoT) and no specialized module training (unlike S2A). Our adaptive prompt blending provides a more efficient alternative to extensive search-based methods.

7.3. Error Analysis

We manually analyze 100 incorrectly answered questions from MMLU and BBH to identify failure modes: **Key Findings:**

- **Knowledge gaps** are the primary failure mode, highlighting the limitation of pure in-context learning without external knowledge retrieval.
- **Symbolic misalignment** occurs when self-generated examples introduce slight notational variations that confuse the reasoning process.
- DPMN reduces **compositional errors** by 35% compared to vanilla CoT, demonstrating better multi-step coherence.
- The router sometimes overweights self-generated examples for ambiguous queries, suggesting need for better uncertainty estimation in $\lambda(x)$.

7.4. Ablation on Router Design

We ablate alternative router architectures:

- **Similarity-based:** $\lambda(x) = \text{sigmoid}(\text{max-similarity} - \tau)$, performs worse (-4.2 EM)
- **Attention-based:** Single-head attention over example pool, similar performance but 3× slower
- **Fixed λ:** Static blending underperforms dynamic routing (-5.7 EM) Our simple MLP router provides the best accuracy-efficiency trade-off.

7.5. Scalability Analysis

We test DPMN with larger support sets (k = 16,32) and find diminishing returns beyond k = 12. The optimal k is task-dependent, suggesting future work on adaptive k selection. The router overhead remains under 10% of total inference time even with 10K demonstration pools.

8. Discussion

8.1. Limitations

DPMN adds a lightweight router but requires pre-embedding of demonstration pools. The quality of self-generated data remains a factor, though marginalization mitigates noise.

8.2. Broader Implications

Our approach moves toward LLMs that *self-curate* their context, bridging in-context learning and model self-improvement. It also offers a practical solution for deployment where retraining is costly.

9. Conclusion

In this work, we introduced the Dynamic Prompt Mixture Network (DPMN), a framework that enhances LLM reasoning through adaptive in-context learning by dynamically blending human-annotated and selfgenerated demonstrations per query. By formulating prompt construction as Bayesian marginalization, our method reduces variance from noisy examples and yields better-calibrated predictions. Experiments across multiple model families demonstrate consistent improvements in accuracy, consistency, and stability on challenging benchmarks, without requiring model retraining.

While DPMN advances in-context learning, it currently depends on a pre-embedded demonstration pool and could benefit from explicit uncertainty estimates in router decisions. Future work includes extending DPMN to multimodal reasoning, adapting it for low-resource languages through cross-lingual embeddings, optimizing the router with reinforcement learning, and exploring online adaptation of the demonstration set. DPMN provides a practical, theoretically grounded step toward more autonomous and reliable AI reasoning systems.

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