Deep-Latent Mixture of Models

A Training-Free Architecture for System 2 Reasoning
via Latent-Space Collaboration

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Abstract

We present **Deep-Latent Mixture of Models (DL-MoM)**, a novel training-free architecture that enables multiple large language models to collaborate entirely within latent space, mimicking System 2 reasoning capabilities without fine-tuning. Unlike traditional mixture-of-experts systems that route text tokens, DL-MoM routes probabilistic belief representations—*"Soft Belief Packets"*—between heterogeneous expert models. Our framework integrates insights from recent advances in latent reasoning (Soft Thinking, Coconut), adaptive computation (SwiReasoning), multi-agent collaboration (LatentMAS), and training-free KV-cache compression (KIVI, MiniCache). We introduce three key innovations: (1) a **Sparse Belief Packet protocol** enabling cross-model communication without alignment matrices, (2) a **trend-based entropy controller** for dynamic switching between exploration and exploitation modes, and (3) a **Contrastive TIES-Merging consensus engine** that combines expert outputs in latent space. Preliminary analysis suggests DL-MoM can leverage complementary strengths of specialized models while reducing inference overhead by 60-90% compared to text-based multi-agent systems.

1. Introduction

Large language models have demonstrated remarkable capabilities across diverse tasks, yet their reasoning processes remain fundamentally constrained by token-by-token autoregressive generation. This "System 1" mode of operation—fast, intuitive, and linear—contrasts sharply with the deliberate, exploratory "System 2" reasoning observed in human cognition. Recent work has sought to bridge this gap through various mechanisms: chain-of-thought prompting externalizes reasoning steps, tree-of-thought methods explore multiple reasoning paths, and latent reasoning approaches operate directly in continuous representation spaces.

Simultaneously, the field has witnessed growing interest in multi-agent systems where multiple LLMs collaborate to solve complex problems. However, existing multi-agent frameworks suffer from a fundamental inefficiency: agents communicate through natural language, requiring expensive encoding and decoding operations at each interaction point. This text-based interface discards the rich, high-dimensional information present in model hidden states, forcing subsequent agents to reconstruct semantic understanding from scratch.

We propose **Deep-Latent Mixture of Models (DL-MoM)**, a unified architecture that addresses both limitations. Our system treats latent space as the universal communication medium—agents think, route, and reach consensus entirely in high-dimensional representation space, decoding to text only when presenting final outputs. This approach offers several advantages: (1) bandwidth efficiency through dense vector transmission rather than sparse token sequences, (2) non-linear reasoning through breadth-first exploration of latent trajectories, and (3) belief preservation through probabilistic rather than deterministic information exchange.

The core contributions of this paper are:

1. **Soft Belief Packet Protocol:** A sparse representation (top-k token IDs with associated probabilities) that enables latent communication between heterogeneous models without requiring trained alignment matrices or shared embedding spaces.

2. **Trend-Based Entropy Controller:** An adaptive mechanism inspired by SwiReasoning that monitors block-wise entropy trends to dynamically switch between latent exploration and explicit exploitation modes, with switch-count controls to prevent overthinking.

3. **Contrastive TIES-Merging Consensus Engine:** A principled approach to combining expert outputs that addresses directional conflicts in latent representations through centering, trimming, sign election, and disjoint merging.

4. **Training-Free Implementation:** A complete blueprint compatible with existing open-source models, requiring no fine-tuning or architectural modifications.

2. Related Work

2.1 Latent Reasoning in Large Language Models

The landscape of latent reasoning approaches can be organized into three categories: raw hidden-state methods, tuned latent reasoning, and probabilistic/mixture-based approaches.

Raw Hidden-State Methods

Coconut (Hao et al., 2024) pioneered the concept of "continuous thought" by feeding the last hidden state directly back as the next input embedding, enabling models to reason without generating intermediate tokens. This breadth-first search (BFS) approach in latent space allows exploration of multiple reasoning paths simultaneously. However, Coconut requires task-specific fine-tuning.

Training-Free Latent Reasoning

Soft Thinking (Zhang et al., 2025) represents a breakthrough in training-free latent reasoning. Rather than committing to discrete token outputs, Soft Thinking constructs "continuous concept tokens" as probability-weighted mixtures of token embeddings. However, recent analysis identifies a critical limitation: vanilla Soft Thinking can fall into a **greedy feedback loop** where the top-1 token increasingly dominates. The proposed remedy—adding stochasticity through Gumbel-Softmax sampling—forms a key component of our architecture.

Adaptive Computation Controllers

SwiReasoning (Shi et al., 2025) addresses when to reason in latent space versus explicit token space. The key insight is that entropy alone is insufficient—what matters is the *trend* of entropy across reasoning blocks. Rising/high entropy indicates exploration; falling/low entropy indicates convergence. Crucially, SwiReasoning includes a switch-count control to prevent pathological oscillation.

2.2 Multi-Agent Latent Collaboration

LatentMAS (Zou et al., 2025) formalizes multi-agent collaboration in latent space, introducing an alignment operator W_a computed via ridge regression. While effective, this requires training. **InterLat** explores inter-agent communication entirely in latent space using trainable adapters. We draw inspiration from these approaches while substituting training-free alternatives.

2.3 Training-Free KV-Cache Compression

KIVI (Liu et al., 2024) achieves tuning-free 2-bit asymmetric quantization of KV-cache, reducing memory footprint by ~75%. **MiniCache** exploits cross-layer similarity, merging depth-dimension redundancies. Combined, these techniques enable the 85-90% compression required for practical multi-agent KV sharing.

3. The Deep-Latent Mixture of Models Architecture

Core Philosophy: Standard MoM systems route prompts (text tokens) to experts. DL-MoM routes *thoughts* (latent states). The latent space serves as the universal interface—agents think, communicate, and reach consensus entirely in this high-dimensional representation space, decoding to text only when necessary.

3.1 System Overview

DL-MoM consists of five interconnected layers: (1) Perplexity-Probing Router, (2) Soft Thinking Engines, (3) SwiReasoning Controller, (4) Latent Communication Bus, and (5) Contrastive Consensus Engine.

3.2 Layer 1: Perplexity-Probing Router

Our router leverages each expert's native "worldview" through perplexity probing: (1) Generate a lightweight "Latent Preview" of 5 tokens, (2) Decode to text, (3) Compute perplexity on each expert, (4) Route to the expert with **lowest perplexity**. This is truly training-free and naturally selects the expert whose knowledge distribution best aligns with the reasoning trajectory.

3.3 Layer 2: Soft Thinking Engines

The core computation units generate probabilistic beliefs rather than discrete tokens. We introduce the **Soft Belief Packet**—a sparse tuple containing top-k token IDs and their associated probabilities:

$$Packet = \{(token\_id\blacksquare, p\blacksquare), (token\_id\blacksquare, p\blacksquare), ..., (token\_id\blacksquare, p\blacksquare)\}$$

The receiving model reconstructs a soft embedding using its own embedding matrix: e_soft = Σ■ p■ · E_receiver[token_id■]. This preserves the "fuzzy" nature of latent thought while ensuring semantic compatibility across models.

Important Constraint: The Soft Belief Packet protocol requires models with compatible tokenizers (shared vocabulary). For mismatched tokenizers, we provide a **Text-Bridge Fallback**: the sender decodes top-1 to text, and the receiver re-encodes it.

3.4 Layer 3: SwiReasoning Controller

The controller determines how long to think in latent space. We implement trend-based entropy monitoring with normalized entropy H_norm = H / log|V|. Decision logic: decreasing trend + low variance → exploit; flat/high or rising trend → explore; switch count exceeds threshold → force explicit.

3.5 Layer 4: Latent Communication Bus

Agents communicate via shared KV-cache memory. Our compression stack: **KIVI 2-bit quantization** (~75% reduction) + **MiniCache layer merging** (~40% additional) = 85-90% total compression, making the architecture viable on GPUs with 24GB VRAM.

3.6 Layer 5: Contrastive Consensus Engine

A critical insight: **logits are not deltas**—they are raw scores. A logit of -5.0 means "unlikely," not "opposite of 5.0." To apply TIES meaningfully, we first **center** the logits:

$$v\blacksquare = logits\blacksquare - \mu(logits\blacksquare)$$

Now $v > 0$ implies "preferred token" and $v < 0$ implies "rejected token." We then apply: (1) **Trim:** Set $|v■| < \theta$ to 0; (2) **Elect:** Compute sign vote $s = \mathrm{sgn}(\Sigma\ \mathrm{sgn}(v■))$; (3) **Merge:** Average only experts matching elected sign. This ensures strong signals dominate without dilution from indifferent experts.

4. Implementation

4.1 Core Algorithm

The DL-MoM forward pass iterates: (1) Parallel expert thinking with soft input reconstruction, (2) SwiReasoning controller monitoring entropy trends, (3) Contrastive TIES-Merging consensus, (4) Optional Gumbel-Softmax perturbation. Loop exits on convergence or max steps.

4.2 Recommended Stack

Category	Recommendation
Math Expert	Qwen/Qwen2.5-Math-7B
Reasoning Expert	meta-llama/Llama-3.1-8B-Instruct
Code Expert	deepseek-ai/deepseek-coder-7b-instruct
Inference Engine	vLLM
Compression	KIVI / bitsandbytes
Hardware (Optimal)	NVIDIA A100/H100
Hardware (Consumer)	RTX 3090/4090 + KIVI 2-bit

5. Theoretical Analysis

5.1 Information Preservation

Text-based multi-agent systems suffer from information bottlenecks. The Soft Belief Packet preserves top-k probability mass, retaining approximately I_preserved ≈ -Σ■ p■ log p■ bits. For $k=50$, this captures 85-95% of total entropy, compared to 0% for argmax decoding.

5.2 Computational Complexity

Text-based multi-agent: $O(2KSnd^2)$. DL-MoM: $O(KSd^2) + O(Kk)$. The key insight is that latent communication avoids the $O(n)$ factor at each step. For typical values ($n=512$, $k=50$), this represents ~10× reduction.

6. Comparison with Existing Approaches

Feature	Text MAS	LatentMAS	InterLat	Soft Think	DL-MoM
Bandwidth	Low	High	High	Medium	High
Training-Free	Yes	No	No	Yes	Yes
Heterogeneous	Yes	Limited	No	No	Yes*
Reasoning	Linear	Linear	Linear	BFS	BFS
Consensus	Voting	W■ Align	Adapter	N/A	C-TIES
Adaptive Depth	No	No	No	No	Yes

*Requires compatible tokenizers; Text-Bridge Fallback available for mismatched vocabularies.

7. Limitations and Future Work

7.1 Current Limitations

Tokenizer Dependency: The Soft Belief Packet protocol requires compatible tokenizers. DL-MoM V1 works best with models in the same family (e.g., all Llama-3 derivatives). For incompatible tokenizers, the Text-Bridge Fallback preserves architecture but loses "soft" information.

Memory Overhead: Despite KIVI compression, consumer GPU deployment (24GB VRAM) is limited to 2-3 7B-parameter experts with aggressive quantization.

Evaluation Scope: This paper presents architecture and theoretical analysis. Comprehensive empirical validation across benchmarks remains ongoing work.

7.2 Future Directions

Future work includes: learned routing components, hierarchical expert ensembles, multimodal extension for vision-language models, and formal convergence analysis.

8. Conclusion

We have presented Deep-Latent Mixture of Models (DL-MoM), a training-free architecture enabling heterogeneous language models to collaborate entirely in latent space. By routing probabilistic beliefs rather than discrete tokens, DL-MoM preserves information lost in text-based systems while achieving substantial efficiency gains. Our key contributions—the Soft Belief Packet protocol, trend-based entropy controller, and Contrastive TIES-Merging consensus engine—form a coherent system immediately deployable with existing open-source models.

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