LIP: A Universal Latent Injection Protocol for Heterogeneous Model Communication

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Abstract

Since the inception of artificial intelligence, the focus has been on teaching machines to think and speak like humans. While significant advancements like Chain-of-Thought and Retrieval-Augmented Generation have improved model performance, the fundamental medium of inter-model communication remains stuck in a human-centric paradigm: natural language text. This creates a substantial bottleneck, similar to two humans exchanging handwritten letters to converse while sitting at the same table. In this work, we argue that text is an inefficient, ambiguous, and insecure medium for machine-to-machine interaction. We propose the **Latent Injection Protocol (LIP)**, a universal framework that enables heterogeneous Large Language Models (LLMs) to communicate directly via latent vectors, bypassing the tokenization/detokenization cycle. Our contributions include: (1) a standardized vector-based packet protocol; (2) an Energy Matching mechanism for signal calibration; and (3) the first validation of functional code generation transfer from a 1.1B parameter model to an 8B parameter model. Our experiments demonstrate that LIP not only preserves semantic intent with greater fidelity than text but also introduces a native layer of data obfuscation, significantly enhancing security and privacy in distributed AI systems.

1 Introduction

Since 1943, the pursuit of AI has been defined by the imitation of human cognition and communication. We have engineered sophisticated tools—vector databases, knowledge graphs, and reasoning chains—to refine this capability. However, in our quest to make machines fluent in human language, we have inadvertently imposed a human limitation on machine-to-machine (M2M) interaction: the reliance on text as the universal interface.

Current research has extensively mapped the landscape of multi-agent collaboration. Yan et al. (2025) provided a comprehensive survey of communication paradigms, highlighting that while agents effectively coordinate through natural language, the overhead of this interaction remains a persistent bottleneck [**?**]. As the field obsessively optimizes how to organize these agents, a fundamental question remains largely unaddressed: *"The whole world is asking how to organize LLMs efficiently, but why is no one talking about teaching them to speak an efficient language?"*

This work directly tackles this question by proposing a shift from human-centric text to machine-centric vectors. Current multi-agent systems operate under a paradigm of extreme inefficiency. When Model A tasks Model B, it must collapse its high-dimensional reasoning into a sequence of discrete tokens (text), which Model B must then parse, tokenize, and re-embed to recover the original intent.

This process is not only computationally expensive but also semantically lossy. Furthermore, the reliance on plaintext creates a critical security vulnerability. In a production environment, any interceptor of the network traffic gains immediate access to the raw reasoning and data of the system.

To address these fundamental flaws, we introduce the **Latent Injection Protocol (LIP)**. LIP operates on three core principles:

1. **Universal Vector Packaging:** A standardized protocol for encapsulating latent states.
2. **Energy Matching Calibration:** A mechanism to align the magnitude of incoming vectors with the recipient model's latent space.
3. **Heterogeneous Transfer:** The capability to bridge models of vastly different sizes (e.g., 2048d to 4096d), enabling "Split Computing" architectures.

In this work, we validate LIP by establishing a semantic bridge between **TinyLlama-1.1B** and **Llama-3-8B**. While both models can operate on local consumer hardware, this pairing represents a massive 7x gap in parameter size and reasoning capability [**?**]. By successfully transferring intent from the smaller to the larger model, we provide the first proof-of-concept for **Asymmetric Latent Control**.

2 Methodology

We propose a framework for heterogeneous model communication that decouples semantic intent from linguistic representation. Our approach consists of three key components: an asymmetric Dual-Encoder Adapter, a Hybrid Loss objective, and the Latent Injection Protocol (LIP).

2.1 Asymmetric Dual-Encoder Architecture

To bridge the representational gap between a source model M_S (TinyLlama-1.1B, $d_S = 2048$) and a target model M_T (Llama-3-8B, $d_T = 4096$), we introduce a bottleneck adapter A_θ. Unlike previous homogeneous approaches that maintain constant dimensionality, our architecture is explicitly asymmetric to force semantic compression. The adapter consists of an Encoder E and a Decoder D linked by a latent bottleneck $z \in \mathbb{R}^{512}$.

$$z = \sigma(LN(W_E \cdot h_S + b_E)) \tag{1}$$

$$\hat{h}_T = LN(W_D \cdot z + b_D) \tag{2}$$

where h_S is the last hidden state of M_S, LN denotes Layer Normalization, and σ is the GELU activation function. The low-dimensional bottleneck ($d = 512$) acts as a semantic filter, stripping away model-specific noise.

2.2 Hybrid Geometric Loss

Initial experiments using Mean Squared Error (MSE) alone resulted in "mode collapse," where the model predicted the mean vector of the target space (often the start-of-text token). Conversely, using only Cosine Similarity preserved direction but ignored vector magnitude, leading to "manifold degradation" (hallucinations). To address this, we employ a composite loss function $\mathcal{L}_{hybrid}$:

$$\mathcal{L}_{hybrid} = \mathcal{L}_{MSE}(\hat{h}_T, h_T) + \lambda \cdot (1 - \cos(\hat{h}_T, h_T)) \tag{3}$$

where $\lambda = 2.0$ is a hyperparameter empirically tuned to prioritize semantic alignment.

2.3 The Latent Injection Protocol (LIP)

Transferring raw vectors is insufficient for stable generation due to the sensitivity of the target model's attention mechanism. LIP introduces two stabilization mechanisms at inference time:

Energy Matching Calibration: LLMs are sensitive to the norm of input vectors. We dynamically scale the injected vector v_{inj} based on the target model's reference energy E_{ref} (the mean norm of its embedding matrix):

$$v_{calibrated} = v_{inj} \cdot \frac{E_{ref}}{||v_{inj}||_2 + \epsilon} \tag{4}$$

Context Priming and Anchoring: Injecting a latent vector at position 0 disrupts the Rotary Positional Embeddings (RoPE). To mitigate this, LIP constructs a hybrid input sequence $[t_{BOS}, t_{CTX}, v_{calibrated}]$, where t_{BOS} initializes the model state and t_{CTX} (e.g., "Code:") sets the domain context.

3 Experiments

To validate the efficacy of LIP, we designed an experimental setup that forces a high-compression transfer between a compact edge model and a large foundation model.

3.1 Experimental Setup

- **Source Model (M_S):** TinyLlama-1.1B-Chat (float32).
- **Target Model (M_T):** Llama-3-8B-Instruct (bfloat16).
- **Dataset:** A curated subset of the Alpaca dataset, filtered for programming-related instructions ($N = 1000$).
- **Hardware:** All experiments were conducted on consumer-grade hardware (Intel Core i7 CPU, 32GB RAM).

3.2 Quantitative Analysis: Ablation Study

We compared three training strategies to isolate the impact of our Hybrid Loss function. The models were evaluated on a hold-out test set of 200 unseen vector pairs.

Table 1: Comparative Results on Test Set

Architecture	Loss Strategy	Cosine Sim. (↑)	MSE Loss (↓)	Observation
Dual-Encoder	Baseline (MSE)	0.0150	**0.0287**	Mode Collapse
Dual-Encoder	Geometric (Cosine)	**0.4815**	0.9997	Hallucinations
Dual-Encoder	LIP Protocol (Hybrid)	0.4771	0.0794	**Stable Convergence**

As shown in Table 1, the **Baseline (MSE)** achieves excellent magnitude error but near-zero directional alignment. The **Geometric** approach achieves high directional accuracy but fails to match the magnitude physics ($MSE \approx 1.0$). The **LIP Hybrid** strategy achieves the optimal balance, enabling stable generation.

3.3 Qualitative Analysis

We tested the system's ability to generate functional Python code from abstract intent.

- **Input (TinyLlama):** "python function sum"
- **Output (Llama-3 via LIP):**

```
def find_max_sum_subarray(arr):
    """
␣␣␣␣This␣function␣takes␣a␣list␣of␣integers␣as␣input...
␣␣␣␣"""
```

This confirms that the adapter successfully bridged the semantic gap between the 2048d space of TinyLlama and the 4096d space of Llama-3, preserving the intent class (Code Definition) and syntax.

4 Conclusion

In this work, we introduced the **Latent Injection Protocol (LIP)**, a novel framework for heterogeneous vector-to-vector (V2V) communication. We successfully demonstrated that a resource-constrained 1.1B parameter model can drive the code generation capabilities of a powerful 8B parameter foundation model without exchanging a single token of natural language. Our experiments highlight that geometric alignment alone is insufficient; Energy Matching and Context Priming are essential for stable heterogeneous transfer. LIP paves the way for privacy-preserving "Split Computing" AI ecosystems.

References