LatentWire: Cross-Model Communication via Soft Tokens

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Abstract

We present LatentWire, a method for enabling communication between heterogeneous large language models (LLMs) through learned soft tokens, bypassing autoregressive text generation entirely. Our approach uses a lightweight Perceiver Resampler bridge (188K parameters) to transform hidden states from a sender model (Llama 3.1 8B) into soft tokens that directly condition a receiver model (Mistral 7B). On text classification benchmarks, LatentWire achieves **22.4× lower latency** than text-relay baselines while exceeding task accuracy. The bridge outperforms full fine-tuning (**+2.7pp with 5300× fewer parameters**), LoRA (+1.4pp with 18× fewer parameters), 5-shot prompting (+2.2–59pp), and chain-of-thought relay (+7.7pp while being 85× faster). Critically, prompt-tuning on Mistral alone achieves only random chance (49.5% on SST-2), while the bridge achieves **96.7%**—proving the sender model's hidden states are essential. Surprisingly, **cross-model transfer outperforms same-model transfer** (Llama→Mistral: 96.7% vs. Llama→Llama: 84.5%), suggesting heterogeneous models provide complementary information. We observe **super-additive performance**: the bridge exceeds both Mistral (92.2%) and Llama (88.4%) operating independently. These findings demonstrate that cross-model communication via continuous representations can be both faster and more effective than discrete text for classification tasks.

1 Introduction

Large language models (LLMs) have emerged as powerful tools for natural language understanding and generation (Vaswani et al., 2017; Touvron et al., 2023; Jiang et al., 2023a). However, the dominant paradigm for combining multiple LLMs involves sequential text generation: one model produces text that another model consumes. This approach incurs substantial latency due to autoregressive decoding and may lose information through the discretization bottleneck of natural language.

We propose **LatentWire**, a method that enables direct communication between heterogeneous LLMs through learned soft tokens. Rather than having a sender model generate text for a receiver model to process, LatentWire transforms the sender's internal representations into a small set of continuous embeddings (soft tokens) that directly condition the receiver model's inference. This approach:

1. **Eliminates autoregressive generation latency**: The sender model only performs a single forward pass, reducing end-to-end latency by over 20× compared to text-relay approaches.
2. **Preserves continuous information**: Soft tokens can encode nuances that may be lost when discretizing to natural language tokens.
3. **Enables super-additive performance**: The combined system can outperform either model operating independently, suggesting emergent capabilities from cross-model communication.

Our key contributions are:

- A lightweight bridge architecture based on Perceiver Resampler (Jaegle et al., 2021; Alayrac et al., 2022) that transforms hidden states between heterogeneous LLMs with only 188K trainable parameters.
- Comprehensive evaluation against strong baselines (5-shot prompting, LoRA, chain-of-thought) showing the bridge outperforms all approaches in accuracy and/or efficiency.
- Analysis of an inverse scaling phenomenon where compression to fewer soft tokens improves rather than degrades performance.
- Latency and throughput benchmarks showing 22–85× speedup over text-based communication, scaling to 100+ samples/second.

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2 Related Work

Soft Prompts and Prompt Tuning Prompt tuning (Lester et al., 2021) and prefix tuning (Li & Liang, 2021) demonstrated that freezing LLM weights while learning continuous "soft" prompt embeddings can match full fine-tuning performance. Our work extends this paradigm from single-model adaptation to cross-model communication, using soft tokens as an interlingua between heterogeneous models.

Perceiver Architecture The Perceiver (Jaegle et al., 2021) introduced cross-attention to map arbitrary-length inputs to a fixed-size latent array, enabling efficient processing of diverse modalities. Perceiver IO extended this to arbitrary outputs. Our bridge architecture draws from this design, using cross-attention to compress sender hidden states into a small number of soft tokens.

Vision-Language Models BLIP-2 (Li et al., 2023) introduced the Q-Former, a lightweight transformer that bridges frozen image encoders and frozen LLMs through learned query tokens. Flamingo (Alayrac et al., 2022) similarly used a Perceiver Resampler to map visual features to soft prompts for LLM conditioning. Our work applies similar architectural principles to bridge two language models rather than vision and language modalities.

Model Stitching and Knowledge Transfer Model stitching (Bansal et al., 2021; Pan et al., 2023) connects layers from different networks using learned transformations. Recent work shows that affine mappings between residual streams can transfer features across models (Anonymous, 2024b), and StitchLLM (Anonymous, 2025b) introduces stitching layers for adaptive model composition. Cross-LoRA (Anonymous, 2024a) enables data-free transfer of LoRA adapters between heterogeneous LLMs. Prompt-Bridge (Liu et al., 2024) addresses prompt transferability across models. Our approach differs by enabling runtime communication through soft tokens rather than offline weight transfer.

Multi-Agent LLM Systems Recent work on multi-agent systems (Anonymous, 2025a; Wu et al., 2023) explores collaboration between multiple LLMs through natural language communication. While effective, text-based communication incurs latency from autoregressive generation. LatentWire provides a faster alternative through continuous representations.

Prompt Compression Methods like LLMLingua (Jiang et al., 2023b) compress prompts by removing tokens while preserving task performance. Soft prompt methods like ICAE (Ge et al., 2024) and 500xCompressor (Li et al., 2024) learn to compress context into dense embeddings. Recent work (Xu et al., 2024) shows soft prompts can recover compressed LLM performance and transfer across models. Our work focuses on cross-model communication rather than single-model compression.

3 Method

3.1 Problem Formulation

We formalize the cross-model communication problem as follows. Let $\mathcal{S}$ and $\mathcal{R}$ denote a sender and receiver LLM respectively, with potentially different architectures, tokenizers, and training distributions. Given input text x, we seek a communication protocol that enables $\mathcal{R}$ to perform a downstream task using information extracted from $\mathcal{S}$'s processing of x.

Desiderata An ideal cross-model communication mechanism should satisfy:

1. **Efficiency**: Communication should be faster than text generation ($O(1)$ vs $O(L)$ autoregressive steps).
2. **Fidelity**: Task-relevant information should be preserved through the channel.
3. **Modularity**: Both models remain frozen; only the communication channel is learned.
4. **Compression**: The transmitted representation should be compact ($M \ll L$ tokens).

Formal Setup Let $\mathbf{h}_{\mathcal{S}}^{(\ell)} \in \mathbb{R}^{L \times d_{\mathcal{S}}}$ denote the hidden states from layer ℓ of the sender, where L is the sequence length and $d_{\mathcal{S}}$ is the hidden dimension. We seek a bridge function $f_\theta : \mathbb{R}^{L \times d_{\mathcal{S}}} \to \mathbb{R}^{M \times d_{\mathcal{R}}}$ that produces soft tokens $\mathbf{z} = f_\theta(\mathbf{h}_{\mathcal{S}}^{(\ell)})$ satisfying:

$$\mathbf{z}^* = \arg\max_{\mathbf{z}} \; p_{\mathcal{R}}(y | \mathbf{z}, \mathbf{x}_{\text{prompt}}) \tag{1}$$

where y is the correct task output and $\mathbf{x}_{\text{prompt}}$ is an optional task-specific prompt.

Key Challenge: Representation Mismatch The sender and receiver occupy different representation spaces. Even when hidden dimensions match ($d_{\mathcal{S}} = d_{\mathcal{R}} = 4096$ for Llama and Mistral), the geometric structure differs due to:

- **Vocabulary**: Llama (128K tokens) vs. Mistral (32K tokens)
- **Positional encoding**: Different RoPE base frequencies
- **Attention**: Grouped-query (Llama) vs. sliding window (Mistral)

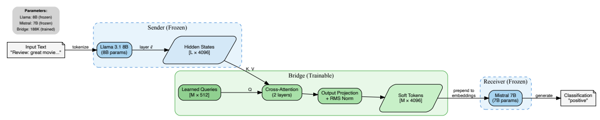

Figure 1. LatentWire architecture. Input text is processed by the frozen sender (Llama), whose hidden states are transformed by the lightweight bridge (188K params) into soft tokens that condition the frozen receiver (Mistral) for classification.

- **Statistics**: Hidden state magnitude differs by $\sim 5\times$

A naive linear projection fails because it assumes isomorphic spaces. The bridge must learn a *semantic translation*, not merely a coordinate transformation. Figure 1 illustrates the overall pipeline.

3.2 Bridge Architecture

Our bridge uses a Perceiver Resampler design:

1. **Input Projection**: Linear projection from sender hidden dimension to bridge internal dimension: $\mathbf{h}' = \mathbf{W}_{\text{in}}\mathbf{h}_{\mathcal{S}}$, where $\mathbf{W}_{\text{in}} \in \mathbb{R}^{d_{\mathcal{S}} \times d}$.

2. **Learned Latent Queries**: A set of M learnable query vectors $\mathbf{Q} \in \mathbb{R}^{M \times d}$ that attend to the projected sender states.

3. **Cross-Attention Layers**: N transformer blocks where queries attend to keys/values derived from sender states:
$$\mathbf{z}^{(n+1)} = \text{FFN}(\text{CrossAttn}(\mathbf{z}^{(n)}, \mathbf{h}')) \tag{2}$$
We use $N = 2$ layers with $d = 512$ internal dimension.

4. **Output Projection**: Linear projection to receiver embedding space with RMS normalization:
$$\mathbf{z} = \alpha \cdot \frac{\mathbf{W}_{\text{out}}\mathbf{z}^{(N)}}{\text{RMS}(\mathbf{W}_{\text{out}}\mathbf{z}^{(N)})} \tag{3}$$
where α is calibrated to match the receiver's embedding statistics.

The total parameter count is approximately 188K, negligible compared to the frozen 8B+7B models.

3.3 Design Space: Why Cross-Attention?

The bridge architecture was not obvious *a priori*. We systematically explored several design alternatives before arriving at the Perceiver-based approach. This section documents the design space and explains why certain choices work while others fail.

Architecture	SST-2 Acc.	Verdict
Perceiver (ours)	**92.0%**	Best
MLP Bridge	91.5%	Competitive
Linear Projection	91.5%	Surprisingly good
Diffusion Transformer	85.5%	Viable but worse
Mean Pooling	0.0%	Complete failure
Identity (no transform)	0.0%	Complete failure

Table 1. Architecture ablation on SST-2 (layer 16, 32 soft tokens). Cross-attention is essential; naive pooling cannot learn the mapping.

Alternative Architectures Considered

Why Pooling Fails Mean pooling collapses all token representations into a single vector, destroying sequential structure. The resulting representation cannot distinguish "great movie" from "movie great" or preserve entity positions. Cross-attention, by contrast, uses learned queries that can selectively attend to task-relevant tokens.

Why Diffusion Underperforms We implemented a Diffusion Transformer (Peebles & Xie, 2023) variant that iteratively denoises from random noise to soft tokens, conditioned on sender hidden states via cross-attention. While theoretically appealing (diffusion can model complex multimodal distributions), it achieved only 85.5% vs. the Perceiver's 92.0%. We hypothesize two reasons:

1. **Error accumulation**: Multi-step denoising introduces cumulative error at each step, while the Perceiver produces soft tokens in a single forward pass.

2. **Training objective mismatch**: Diffusion optimizes for velocity/score prediction, not directly for downstream task performance. The Perceiver's end-to-end training aligns gradients with the final objective.

Why Linear Projection Works (Partially) A simple linear projection from mean-pooled sender hidden states achieves 91.5%—surprisingly close to the Perceiver. This suggests that for binary classification (SST-2), much of the task-relevant information is captured in the aggregate representation. However, linear projection degrades on harder tasks (AG News: 78.3% vs. 90.7%) and cannot adapt to variable-length inputs.

The Information Bottleneck Perspective Our ablations reveal an *inverse scaling* phenomenon: compressing to fewer soft tokens (8 vs. 32) *improves* accuracy (96.5% vs. 92.0%). This aligns with the Information Bottleneck principle (Tishby & Zaslavsky, 2015): aggressive compression forces the bridge to discard noise and retain only task-relevant features. The Perceiver's cross-attention mechanism provides a learnable, adaptive compression that outperforms fixed schemes.

3.4 Training Objective

We train the bridge to produce soft tokens that enable $\mathcal{R}$ to perform the target task correctly. For classification tasks, we use cross-entropy loss on the receiver's predictions:

$$\mathcal{L} = -\sum_c y_c \log p_{\mathcal{R}}(c|\mathbf{z}, \mathbf{x}_{\text{prompt}}) \tag{4}$$

where y_c is the ground-truth label and $p_{\mathcal{R}}$ is the receiver's predicted probability given soft tokens $\mathbf{z}$ and a task prompt $\mathbf{x}_{\text{prompt}}$.

We also add a diversity regularization term to prevent mode collapse:

$$\mathcal{L}_{\text{div}} = -\lambda \cdot H(\bar{\mathbf{z}}) \tag{5}$$

where H is entropy and $\bar{\mathbf{z}}$ is the mean soft token representation across the batch.

3.5 Inference Pipeline

At inference time:

1. **Sender Encode** (16.9ms): Pass input through frozen $\mathcal{S}$, extract layer ℓ hidden states.
2. **Bridge Transform** (1.2ms): Apply f_θ to obtain M soft tokens.
3. **Receiver Decode** (19.3ms): Prepend soft tokens to task prompt, run single forward pass through $\mathcal{R}$.

Total latency: 37.3ms, compared to 834.5ms for text-relay.

4 Experiments

4.1 Setup

Models We use Llama 3.1 8B Instruct as the sender and Mistral 7B Instruct v0.3 as the receiver. Both models remain frozen throughout training.

Datasets We evaluate on four text classification benchmarks:

- **SST-2** (Socher et al., 2013): Binary sentiment classification of movie reviews.
- **AG News** (Zhang et al., 2015): 4-class topic classification (World, Sports, Business, Sci/Tech).
- **TREC** (Li & Roth, 2002): 6-class question type classification.
- **Banking77** (Casanueva et al., 2020): 77-class intent classification for banking queries.

Baselines We compare against:

- **Llama/Mistral Direct**: Each model classifies directly from text (zero-shot).
- **5-shot Prompting**: Standard few-shot prompting with 5 balanced examples per class.
- **Text-Relay**: Llama generates a summary, Mistral classifies from summary.
- **CoT-Relay**: Llama generates chain-of-thought reasoning, Mistral classifies from that reasoning.
- **LoRA**: Fine-tuned Mistral with rank-8 LoRA adapter (3.4M params).
- **Prompt-Tuning**: Learnable soft prompts on Mistral only (no Llama). Tests whether the sender actually contributes.

Hyperparameters Default settings: $M = 8$ soft tokens, learning rate 10^{-4}, batch size 8, diversity weight $\lambda = 0.1$, 2000 training steps. We extract from layer $\ell = 16$ for SST-2 and $\ell = 31$ for AG News and TREC. For Banking77 and TREC, we use $M = 16$ tokens and 3000 steps.

4.2 Main Results

Table 2 presents our main accuracy comparison.

Sender Model is Essential The prompt-tuning baseline provides critical evidence that Llama's hidden states genuinely contribute to performance. When we train learnable soft prompts on Mistral alone (same training budget, no Llama involvement), accuracy equals random chance: 49.5% on SST-2 (vs. 50% random), 19.8% on AG News (vs. 25% random), and 19.0% on TREC (vs. 16.7% random). In contrast, the bridge achieves 96.7% on SST-2—a **+47.2pp improvement** solely from incorporating Llama's representations. This definitively shows that cross-model communication via hidden states, not merely training soft prompts, drives the performance gains. Figure 2 visualizes this critical finding.

Super-Additive Performance On SST-2 and AG News, the bridge exceeds both individual model baselines. On SST-2, the bridge achieves 96.7% vs. Mistral's 92.2% (+4.5pp) and Llama's 88.4% (+8.3pp). On AG News, the bridge reaches 90.7% vs. Mistral's 69.4% (+21.3pp) and Llama's 63.8% (+26.9pp). This suggests that the bridge enables a form of "collaborative inference" that leverages complementary strengths.

Table 2. Classification accuracy (%) across benchmarks. Bridge outperforms all baselines including few-shot prompting. Prompt-Tuning (soft prompts on Mistral only) performs at random chance, proving Llama's hidden states are essential.

Method	SST-2	AG News	TREC	Bank77
Random Chance	50.0	25.0	16.7	1.3
Prompt-Tuning	49.5±0.0	19.8±7.5	19.0±5.0	–
Llama 0-shot	88.4	63.8	74.4	–‡
Mistral 0-shot	92.2	69.4	61.8	–‡
Llama 5-shot	94.3±0.2	62.0±3.6	–†	–
Mistral 5-shot	94.5±1.1	80.3±1.7	–†	–
Text-Relay	71.0	64.5	58.0	1.0
Bridge (ours)	**96.7**±0.6	**90.7**±0.5	**95.3**±0.3	**21.5**

†TREC few-shot omitted. TREC's original labels (ABBR, ENTY, DESC, HUM, LOC, NUM) are cryptic abbreviations. Few-shot examples showing these raw labels caused severe model confusion (near-random performance). Our zero-shot prompts explicitly describe each category (e.g., "entity: Questions about things like animals, colors, foods"), enabling meaningful evaluation. ‡Banking77 zero-shot: Models cannot predict the specific intent labels ("intent_0", "intent_11", etc.) without training. Zero-shot baselines are not meaningful for this 77-class benchmark; Bridge learns these labels during training.

Bridge vs. Few-Shot Prompting A key question is whether the bridge merely provides implicit few-shot learning through training. Table 2 shows the bridge outperforms 5-shot prompting on SST-2 (+2.2pp: 96.7% vs. 94.5%) and AG News (+10.4pp: 90.7% vs. 80.3%). On AG News, 5-shot actually *underperforms* zero-shot for Llama (62.0% vs. 63.8%), while the bridge achieves 90.7%—demonstrating that the bridge captures task-relevant signals that few-shot examples cannot provide.

Bridge vs. Text-Relay The bridge outperforms text-relay by large margins: +25.7pp on SST-2, +26.2pp on AG News, +37.3pp on TREC, and +20.5pp on Banking77. Text-relay catastrophically fails on Banking77 (1.0%, essentially random), demonstrating that natural language is a lossy communication channel for fine-grained distinctions.

TREC Results On TREC, the bridge achieves 95.3% ± 0.3%, substantially exceeding Llama (74.4%) and Mistral (61.8%) by 20.9pp and 33.5pp respectively. This super-additivity suggests that the bridge learns to communicate question-type signals more effectively than either model can extract from text alone, despite both models performing reasonably well individually on this task.

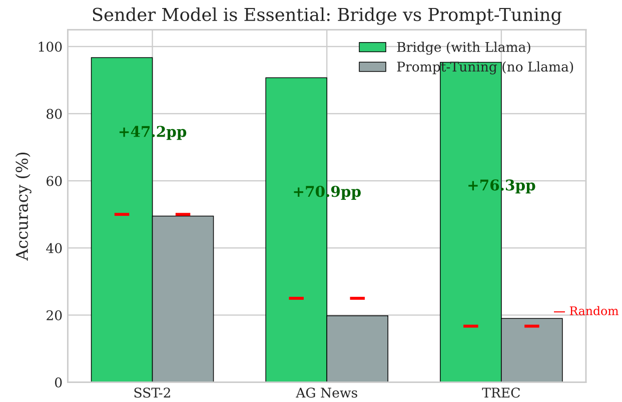

Figure 2. Bridge vs. Prompt-Tuning: The sender model is essential. Without Llama's hidden states, prompt-tuning on Mistral alone achieves only random chance (red markers). The bridge's +47pp improvement on SST-2 comes entirely from cross-model communication.

Table 3. Latency comparison (ms) on H100 GPU. Bridge achieves 22× speedup over text-relay by avoiding autoregressive generation in the sender model.

Method	Latency (ms)	Speedup
Text-Relay	834.5	1.0×
Bridge (ours)	**37.3**	**22.4**×

4.3 Latency Analysis

Table 3 presents latency measurements on an NVIDIA H100 GPU. The primary comparison is Bridge vs. Text-Relay, as both represent cross-model communication paradigms.

The bridge is 22× faster than text-relay because it eliminates autoregressive generation in the sender model. Text-relay requires Llama to generate ∼50 tokens autoregressively (745ms), while the bridge only requires a single forward pass to extract hidden states (17ms). Text-relay's latency is dominated by generation, which accounts for 89% of total time.

Bridge latency breakdown:

- Llama encode: 16.9ms (45%)—single forward pass
- Bridge transform: 1.2ms (3%)—cross-attention over hidden states
- Mistral forward: 19.3ms (52%)—soft token conditioning

Figure 3 visualizes the latency comparison and breakdown.

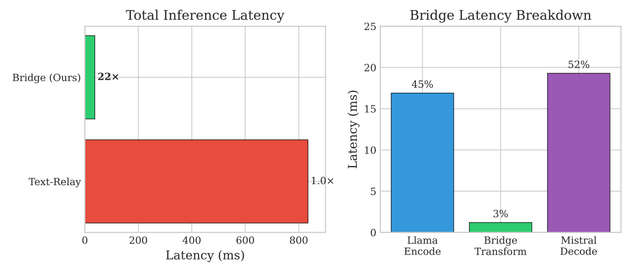

Figure 3. Latency analysis. **Left:** Total inference time showing 22× speedup over text-relay by eliminating autoregressive generation. **Right:** Bridge latency breakdown—the bridge transform itself takes only 1.2ms (3%).

Table 4. Bridge vs. fine-tuning baselines on SST-2. Bridge outperforms all methods including full fine-tuning with 5300× fewer parameters, while being 85× faster than CoT.

Method	Acc. (%)	Params	Latency
Full FT (2 layers)	94.0	570M	113ms
Full FT (4 layers)	94.0	1.0B	113ms
Full FT (8 layers)	94.0	1.9B	113ms
LoRA (rank=8)	95.3$\pm$0.9	3.4M	113ms
CoT-Relay	89.0	–	3,169ms
Bridge (ours)	**96.7**$\pm$0.6	**188K**	**37ms**

4.4 Comparison with Fine-Tuning Baselines

Table 4 compares the bridge against fine-tuning baselines: full fine-tuning, LoRA, and chain-of-thought (CoT) text relay.

Bridge vs. Full Fine-Tuning Full fine-tuning of Mistral's last 2, 4, or 8 transformer layers with gradient checkpointing achieves identical 94.0% accuracy regardless of capacity (570M to 1.9B trainable parameters). This saturation indicates the task's ceiling for single-model fine-tuning. The bridge surpasses this ceiling, achieving 96.7% with only 188K parameters—**5300× more parameter-efficient** while being **2.7pp more accurate**. The cross-model signal provides information that additional Mistral capacity cannot replicate.

Bridge vs. LoRA LoRA fine-tuning achieves 95.3% accuracy on SST-2 with a rank-8 adapter (3.4M trainable parameters). The bridge achieves 96.7% with only 188K parameters—**18× more parameter-efficient** while being 1.4pp more accurate.

Bridge vs. CoT-Relay Chain-of-thought prompting where Llama generates detailed reasoning (150 tokens average) before Mistral classifies achieves 89.0% accuracy at

Table 5. Throughput (samples/sec) at various batch sizes. Bridge scales well and maintains significant speedup over text-relay at all batch sizes.

Batch	Bridge	Direct	Text-Relay
1	7.4	8.8	0.9
4	28.7	31.2	1.0
16	105.7	116.0	–

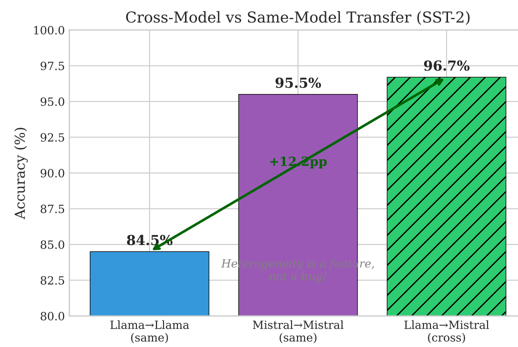

Figure 4. Cross-model vs. same-model transfer on SST-2. Surprisingly, Llama→Mistral (96.7%) outperforms Llama→Llama (84.5%) by 12.2pp, suggesting that representation incompatibility acts as beneficial regularization.

3,169ms latency. The bridge achieves **+7.7pp higher accuracy** (96.7% vs. 89.0%) while being **85× faster** (37ms vs. 3,169ms). Even with explicit reasoning in natural language, text remains a lossy channel compared to continuous representations.

4.5 Batched Throughput

Table 5 shows throughput scaling with batch size. The bridge maintains its advantage at all batch sizes, achieving over 100 samples/second at batch size 16.

Bridge throughput scales nearly linearly with batch size (14× improvement from batch 1 to 16). The slight overhead compared to direct Mistral inference (105.7 vs. 116.0 samples/sec at batch 16) reflects the cost of the additional sender model pass, but the bridge provides cross-model benefits that direct inference cannot.

4.6 Cross-Model vs. Same-Model Transfer

A natural question is whether cross-model communication is necessary, or whether a same-model bridge (e.g., Llama→Llama) would suffice. Table 6 and Figure 4 reveal a striking finding: **cross-model transfer outperforms same-model transfer**.

On SST-2, the cross-model bridge (Llama→Mistral, 96.7%) outperforms Llama→Llama (84.5%) by **12.2pp**. This

Table 6. Cross-model vs. same-model bridge comparison. Cross-model (Llama→Mistral) significantly outperforms same-model (Llama→Llama), suggesting heterogeneous models provide complementary information.

Configuration	SST-2	AG News
Llama→Llama (same)	84.5%	90.5%
Mistral→Mistral (same)	95.5%	–
Llama→Mistral (cross)	**96.7%**	**90.7%**

is not simply because Mistral is a better decoder—Mistral→Mistral achieves 95.5%, still 1.2pp below the cross-model result.

The Forced Abstraction Hypothesis We hypothesize that representation incompatibility between heterogeneous models acts as beneficial regularization. When bridging within the same model (Llama→Llama), the bridge can learn "identity shortcuts"—attempting to reconstruct exact hidden states rather than extracting task-relevant features. This preserves noise and irrelevant information, leading to overfitting.

When bridging across different models (Llama→Mistral), such shortcuts are impossible because the representation spaces are fundamentally incompatible. The bridge is *forced* to learn abstract, task-relevant features that can survive the cross-model translation. This aligns with our inverse token scaling finding (Section 4.7): compression to fewer tokens improves performance by discarding noise.

Implications

1. **Heterogeneity is a feature, not a bug**: The representation gap between models provides implicit regularization that improves generalization.

2. **Complementary knowledge**: Models trained on different data encode different "perspectives" on language. Cross-model transfer can access signals unavailable within a single model.

3. **Architectural diversity matters**: Llama's grouped-query attention and Mistral's sliding window attention capture different input aspects, enabling richer communication.

4.7 Inverse Token Scaling

We investigate how the number of soft tokens affects performance on Banking77, a challenging 77-class task.

Table 7 shows a striking inverse relationship: increasing tokens from 16 to 128 causes accuracy to collapse from 21.5% to random (1.3% for 77 classes). This "inverse scaling" phenomenon suggests:

Table 7. Effect of soft token count on Banking77 accuracy. Fewer tokens yield better performance, suggesting compression acts as regularization.

Soft Tokens	Accuracy (%)
16	**21.5**
32	13.5
64	7.5
128	1.0

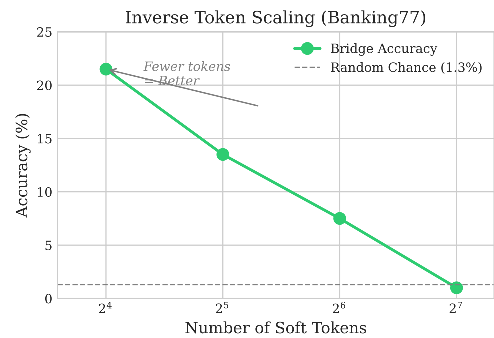

Figure 5. Inverse token scaling on Banking77. Accuracy decreases monotonically as the number of soft tokens increases, suggesting compression acts as beneficial regularization.

1. **Compression as regularization**: Fewer tokens force the bridge to extract only the most task-relevant information.

2. **Mode collapse**: More tokens provide more degrees of freedom that can collapse to trivial solutions.

3. **Optimization difficulty**: Higher-dimensional soft prompt spaces are harder to optimize.

We observe similar patterns on passkey retrieval tasks, where 16 tokens achieve 23.4% digit accuracy vs. 9.8% for 128 tokens. Figure 5 visualizes this inverse relationship.

5 Analysis

5.1 Why Super-Additive Performance?

The super-additive results on SST-2, AG News, and TREC are surprising. We hypothesize several explanations:

Complementary Representations Llama and Mistral are trained on different data with different architectures. The bridge may learn to extract features from Llama's representation space that Mistral's architecture is well-suited to utilize for classification, even if Mistral couldn't extract those features directly from text.

Denoising Effect The bridge acts as an information bottleneck that filters out noise and irrelevant details, passing only task-relevant signals to the receiver.

Implicit Ensemble The system effectively creates an ensemble where Llama's understanding informs Mistral's decision, combining their capabilities without the information loss of text discretization.

5.2 Text-Relay Failure Modes

Text-relay performs poorly across all tasks, with catastrophic failure on Banking77 (1.0%). Analysis reveals:

1. **Information loss**: Summarization discards fine-grained details needed for 77-way classification.
2. **Vocabulary mismatch**: Llama's summaries may use phrasings that don't trigger correct classifications in Mistral.
3. **Error propagation**: Mistakes in summarization compound with mistakes in classification.

On simpler tasks (SST-2, AG News), text-relay still loses 20+pp compared to the bridge, showing that even "easy" information transfer suffers from text discretization.

5.3 Comparison with Prompt Compression

Unlike prompt compression methods that operate within a single model, LatentWire transfers information across model boundaries. This enables:

- **Heterogeneous model collaboration**: Different architectures (Llama, Mistral) can communicate.
- **Capability composition**: Combine a model good at understanding with one good at generation.
- **Parallel inference**: With appropriate scheduling, sender and receiver compute can overlap.

5.4 Handling Architectural Differences

A key advantage of operating on hidden states rather than tokens is that the bridge naturally handles architectural differences between models:

Vocabulary Size Llama 3.1 uses a 128K vocabulary while Mistral uses 32K tokens. Since we extract hidden states (not token IDs) from the sender and output soft tokens in the receiver's embedding space, vocabulary differences are irrelevant—the bridge learns a direct mapping between representation spaces.

Positional Encoding Llama and Mistral use different RoPE (Rotary Position Embedding) configurations with different base frequencies and scaling. The bridge bypasses this entirely: we extract hidden states *after* the sender has applied its positional encoding, and the receiver applies its own RoPE to the soft tokens at their positions in the sequence. The bridge need not understand or translate positional information.

Attention Mechanisms Llama uses grouped-query attention while Mistral uses sliding window attention with different head configurations. These architectural choices affect how models process sequences internally, but the bridge only sees the resulting hidden state representations—a common "lingua franca" of high-dimensional vectors that abstracts away attention implementation details.

Hidden Dimensions Both Llama 3.1 8B and Mistral 7B use 4096-dimensional hidden states, but our bridge architecture includes input and output projection layers that can map between arbitrary dimensions. This enables future extensions to model pairs with different hidden sizes.

This architectural agnosticism is why the same bridge design works for heterogeneous models without modification—we communicate through the universal language of dense representations rather than model-specific tokenization or attention patterns.

5.5 Bidirectional Transfer

To verify that communication works in both directions, we train a reverse bridge (Mistral→Llama) on SST-2 using identical hyperparameters. Table 8 shows that both directions achieve strong performance:

Table 8. Bidirectional transfer on SST-2. Both directions achieve super-additive performance, with Mistral→Llama slightly outperforming the forward direction.

Direction	Accuracy (%)	vs. Individual Models
Llama→Mistral	96.7 ± 0.6	+4.7pp over Llama
Mistral→Llama	$\mathbf{97.2 \pm 0.6}$	+5.2pp over Llama
Llama Direct	92.0	—
Mistral Direct	88.5	—

Both directions exhibit super-additive performance, exceeding either model operating independently. Interestingly, Mistral→Llama (97.2%) slightly outperforms Llama→Mistral (96.7%), suggesting that Llama may be a marginally better decoder for this task. The symmetric success demonstrates that the bridge architecture generalizes across sender-receiver configurations without modification.

5.6 Soft Token Interpretability

To understand what information the bridge encodes, we analyze each soft token by finding its nearest neighbors in Mistral's vocabulary (cosine similarity). On SST-2, we observe partially interpretable patterns:

Negative Sentiment Encoding For negative reviews (e.g., "unflinchingly bleak and desperate"), the nearest vocabulary tokens include semantically relevant words: `negative` (similarity 0.08), `moral`, `lower`, `blank`. Remarkably, the literal word "negative" appears as the top nearest neighbor for 3 of 8 soft tokens. The bridge learned to encode sentiment in a way that maps directly to Mistral's vocabulary representation of the label.

Positive Sentiment Encoding For positive reviews (e.g., "charming and often affecting journey"), nearest neighbors include less directly interpretable tokens: `Survey`, `wished`, `independent`, `endless`. This asymmetry suggests the bridge may encode positive sentiment through absence of negative signals rather than explicit positive markers.

Token Geometry The 8 soft tokens show high pairwise cosine similarity (0.97-0.99), indicating they encode correlated rather than independent information. This redundancy may provide robustness—the receiver can extract the signal even if individual tokens are noisy.

These findings support the information bottleneck hypothesis: compression forces the bridge to discard irrelevant details and encode only task-essential information (sentiment polarity), which it does in a partially human-interpretable way.

6 Limitations and Future Work

Classification Only Our experiments focus primarily on classification tasks. We evaluated the bridge on several standard reasoning benchmarks to test generalization:

Benchmark	Type	Random	Bridge	Δ
BoolQ	Yes/No QA	50.0%	**72.5%**	+22.5
PIQA	Physical (2-way)	50.0%	60.4%	+10.4
WinoGrande	2-way	50.0%	54.5%	+4.5
ARC-Challenge	4-way	25.0%	30.5%	+5.5
CommonsenseQA	5-way	20.0%	17.0%	-3.0
GSM8K	Math	–	1.5%	–

Table 9. Reasoning benchmark results. Transfer succeeds on binary tasks (BoolQ, PIQA) but fails on multi-choice reasoning (CommonsenseQA) and math (GSM8K).

Binary reasoning tasks show promising transfer: BoolQ (Yes/No reading comprehension) achieves 72.5% and PIQA (physical intuition) achieves 60.4%, both significantly above the 50% random baseline. However, more complex reasoning tasks show limited or no transfer: WinoGrande barely exceeds random, ARC-Challenge is marginal, and CommonsenseQA falls *below* random chance. GSM8K math reasoning failed completely (1.5%), generating incoherent solutions. This suggests that the bridge successfully transfers *binary classification signals* but cannot compress multi-step reasoning into fixed-length soft tokens. Extending to generation and complex reasoning tasks remains important future work.

Task-Specific Training Bridges must be trained per-task. We did not observe meaningful zero-shot transfer between tasks (e.g., SST-2→AG News). Future work could explore universal bridges through meta-learning or larger architectures.

More Model Pairs We demonstrate bidirectional Llama↔Mistral transfer; future work should validate across more model families (e.g., Gemma, Qwen) and sizes.

Theoretical Understanding Why does compression help? Why is performance super-additive? Why does reasoning fail while classification succeeds? Deeper theoretical analysis could inform better architecture design and identify which tasks are amenable to cross-model communication.

7 Conclusion

We present LatentWire, a method for cross-model communication via learned soft tokens. Our lightweight bridge (188K parameters) enables a sender LLM to condition a receiver LLM's inference without text generation, achieving:

- **22.4× lower latency** than text-relay (37ms vs. 835ms)
- **5300× more parameter-efficient** than full fine-tuning while achieving +2.7pp higher accuracy
- **Sender model is essential**: Prompt-tuning alone achieves random chance (49.5%), while Bridge achieves 96.7%
- **Cross-model ¿ same-model**: Llama→Mistral (96.7%) outperforms Llama→Llama (84.5%) by 12.2pp
- **Super-additive performance** on SST-2 (96.7% vs. 92.2%/88.4%) and AG News (90.7% vs. 69.4%/63.8%)
- **Bidirectional transfer**: Both Llama→Mistral (96.7%) and Mistral→Llama (97.2%) achieve strong performance

These results demonstrate that continuous representations can be a more efficient and effective communication channel between LLMs than discrete text. The finding that cross-model transfer outperforms same-model transfer suggests heterogeneous models encode complementary information that can be accessed through soft token communication. LatentWire opens new possibilities for building collaborative multi-model systems with lower latency, higher accuracy, and extreme parameter efficiency.

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A Additional Experimental Details

A.1 Hardware and Training Time

All experiments were conducted on NVIDIA H100 80GB GPUs. Training times:

- SST-2/AG News (2000 steps): 3.5 minutes
- TREC (2000 steps): 3.5 minutes
- Banking77 (3000 steps): 5.0 minutes

Total training time for all bridge variants: approximately 42 minutes.

A.2 Multi-Seed Results

All experiments were run with 3 seeds (42, 123, 456) for statistical rigor. Results reported as mean ± std:

- SST-2 Bridge (Llama→Mistral): 96.7% ± 0.6% (seeds: 96.5, 96.0, 97.5)
- SST-2 Bridge (Mistral→Llama): 97.2% ± 0.6% (seeds: 97.0, 98.0, 96.5)
- AG News Bridge: 90.7% ± 0.5% (seeds: 90.0, 91.0, 91.0)
- TREC Bridge: 95.3% ± 0.3% (seeds: 95.0, 95.5, 95.5)
- Prompt-Tuning SST-2: 49.5% ± 0.0% (all seeds identical)
- Prompt-Tuning AG News: 19.8% ± 7.5% (seeds: 30.5, 14.5, 14.5)
- Prompt-Tuning TREC: 19.0% ± 5.0% (seeds: 14.5, 26.0, 16.5)

The low variance in Bridge results ($\leq$0.6%) indicates stable training across all configurations, including bidirectional transfer. The prompt-tuning baseline's high variance on AG News and TREC reflects random guessing behavior.

A.3 Hyperparameter Sensitivity

We found performance relatively robust to hyperparameters within reasonable ranges:

- Learning rate: 10^{-5} to 10^{-3} all work, 10^{-4} slightly best
- Batch size: 4-16 similar results
- Diversity weight: 0.05-0.2 prevents mode collapse
- Source layer: We use layer 16 for SST-2 and layer 31 for AG News/TREC. Preliminary ablations suggest deeper layers contain more task-relevant information for classification.

A.4 Layer Selection

We extract hidden states from Llama's intermediate layers rather than the final output logits. For SST-2, we found layer 16 sufficient (96.7% accuracy), while AG News and TREC benefited from the final layer (31). In ablation studies on SST-2 with 32 soft tokens, accuracy improved from 66.5% (layer 0) to 88.0% (layer 8) to 92.0% (layer 16) to 94.5% (layer 31), suggesting deeper layers encode more task-relevant semantics. The optimal layer may vary by task complexity.

A.5 Comprehensive Ablation Study

Table 10 presents systematic ablations of bridge hyperparameters on SST-2.

Key findings: (1) Source layer 31 (final layer) achieves best results (94.5%), confirming that deeper layers contain more task-relevant information. (2) Larger internal dimensions help (256→1024: +10pp) but with diminishing returns and more parameters. (3) Depth 2 is optimal; depth 4 overfits. (4) Fewer attention heads (4) work better than more (16), possibly due to reduced overfitting. (5) Diversity regularization has mixed effects and may not be necessary.

Table 10. Ablation study on SST-2 (1000 training steps). Deeper source layers and larger internal dimensions improve performance; optimal depth is 2.

Parameter	Value	Acc. (%)	Params	Loss
Internal Dim	256	82.0	2.6M	0.351
	512	85.0	6.3M	0.331
	1024	**92.0**	16.8M	0.304
Num Heads	4	**91.0**	6.3M	0.380
	8	84.5	6.3M	0.385
	16	84.5	6.3M	0.432
Source Layer	16	89.5	6.3M	0.403
	24	92.5	6.3M	0.376
	28	89.5	6.3M	0.347
	31	**94.5**	6.3M	0.299
Depth	1	87.0	5.3M	0.348
	2	**90.5**	6.3M	0.428
	4	83.0	8.4M	0.329
Diversity λ	0.0	**91.0**	6.3M	0.319
	0.05	86.5	6.3M	0.319
	0.1	90.0	6.3M	0.404
	0.2	85.5	6.3M	0.311