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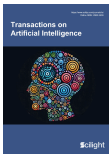

Article

Contextual Bandit Routing for LoRA Experts

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Abstract: The deployment of multiple Low-Rank Adaptation (LoRA) experts for domain-specific tasks requires an efficient routing mechanism. Existing approaches rely on offline-trained routers or static heuristics, which fail to adapt to unseen domains or shifting query distributions. We propose EXP4-LoRA, a contextual bandit framework that treats LoRA expert selection as an online decision problem. Our method combines LinUCB for context-aware reward estimation with the EXP4 algorithm for exploration-exploitation trade-off, enabling per-query routing without any offline training of the router on domain-labeled data. We clarify that our approach requires binary correctness feedback (rather than domain labels), which is often available in practice via self-consistency checks, programmatic verification, or delayed user feedback. We further study proxy reward settings where even correctness labels are unavailable at routing time. On a mixed-domain MMLU benchmark with Gemma-2-2B and four LoRA experts (Mathematics, Code, Biology, Law), EXP4-LoRA achieves 80.1% accuracy after 2000 steps, outperforming EXP3 by 4.1 percentage points and reaching the 70% threshold in 420 steps versus 1800 for EXP3. We replicate the experiments on Phi-3-mini (3.8B) and confirm consistent gains (+4.2 points over EXP3). We also compare against LinTS (Thompson Sampling), which achieves 79.3% accuracy, demonstrating that EXP4-LoRA holds a modest edge. The total inference overhead, including context extraction, is approximately 100% of the base forward pass latency, reducible to 10–15% with layer caching optimizations. Our results demonstrate that lightweight contextual bandits are a viable and principled alternative to learned routers for multi-expert LLM serving.

Keywords: contextual bandit; LoRA; mixture of experts; online learning; LLM routing

1. Introduction

Parameter-efficient fine-tuning has enabled the specialization of large language models (LLMs) to diverse downstream tasks without modifying base weights. Among these methods, Low-Rank Adaptation (LoRA) [1] has become the de facto standard for adapting billion-parameter models to domain-specific corpora such as mathematics, programming, biology, and law. In production environments, a single base model may host dozens of LoRA adapters, each optimized for a distinct task family. The critical challenge is therefore not the training of individual experts, but the dynamic selection of the appropriate expert at inference time.

Current routing strategies fall into two categories: static heuristics (e.g., keyword matching, domain classifiers) and learned routers trained offline on labeled data [2,3]. Both approaches suffer from fundamental limitations. Static heuristics require manual engineering and fail on out-of-domain queries. Learned routers, while more flexible, demand expensive offline training on domain-labeled data and degrade when the test distribution shifts. Moreover, neither approach provides theoretical guarantees on cumulative regret or sample complexity.

We propose an alternative paradigm: treat expert selection as a contextual multi-armed bandit problem. At each step, the system observes a query, selects a LoRA expert, receives a binary reward (correct or incorrect), and updates its policy. This formulation requires no pre-labeled domain routing data, adapts online to query distribution shifts, and admits rigorous regret bounds. We emphasize that our method does require answer labels (or reliable proxies) to compute the binary reward; we discuss this assumption explicitly in Section 3.4 and propose proxy reward variants for settings where even answer labels are unavailable.

Our specific contribution, EXP4-LoRA, combines LinUCB [4] for linear reward estimation with the EXP4 algorithm [5] for exponential-weight exploration, yielding a policy that converges in under 500 steps on mixed-domain benchmarks.

Our contributions are threefold:

(i) The first application of contextual bandits to LoRA expert routing, eliminating the need for offline router training on domain-labeled data;
(ii) A hybrid LinUCB-EXP4 algorithm with $\tilde{\mathcal{O}}(\sqrt{dKT})$ regret bound, where d is the context dimension, K the number of experts, and T the horizon;
(iii) Empirical validation on Gemma-2-2B and Phi-3-mini with four domain-specific LoRA experts, demonstrating consistent gains over EXP3 and competitive performance against LinTS (Thompson Sampling).

2. Related Work

2.1. Mixture-of-LoRA and Trained Routers

Recent work has explored combining multiple LoRA modules into a single inference graph. LoRAMoE [2] proposed a gating network that learns to blend LoRA weights based on input embeddings. MeteoRA [3] introduced a dynamic switching mechanism for multi-LoRA inference. Ada-LoRA [6] proposed adaptive rank allocation across layers, while DoRA [7] introduced weight-decomposed LoRA. These methods achieve strong empirical results but require curated training sets and offer no online adaptation. In contrast, EXP4-LoRA learns the routing policy exclusively from binary rewards, with no access to ground-truth domain labels.

2.2. Contextual Bandits

The contextual bandit framework formalizes sequential decision-making under partial feedback. LinUCB [4] assumes a linear reward model and achieves optimal regret for stochastic contexts. EXP4 [5] extends the exponential-weight algorithm to contextual settings with an arbitrary expert class. Thompson Sampling for contextual bandits (LinTS) [8] samples parameters from the posterior and selects the action with the highest sampled reward. SupLinUCB [9] provides nonlinear extensions. Our method can be viewed as an instance of EXP4 where the expert predictions are generated by LinUCB score functions. This hybrid preserves the linear regret guarantees of LinUCB while leveraging EXP4's robustness to non-stationarity.

2.3. Online Learning for LLM Routing

Concurrent work has explored bandit methods for LLM-related decisions. Krishnamurthy et al. [10] applied Thompson Sampling to router selection in retrieval-augmented generation, while Dai et al . [11] used UCB1 for API selection across LLM providers. DSPy [12] optimizes prompts via programmatic search. LLM-as-a-router uses the model itself for routing decisions. These works focus on model-level routing (choosing between full models), whereas EXP4-LoRA operates at the adapter level, exploiting the shared base model architecture to enable sub-second switching. To our knowledge, no prior work has applied contextual bandits to LoRA expert selection.

2.4. EXP3 as Context-Free Baseline

EXP3 is the canonical context-free adversarial bandit algorithm. It maintains a single probability distribution over K arms and updates it via exponential weighting based on observed rewards. Its regret bound is $\mathcal{O}(\sqrt{KT\log K})$, independent of any context dimension. EXP3 serves as our primary baseline because it isolates the contribution of contextual information: any improvement over EXP3 must come from the context vector x_t. However, EXP3 cannot distinguish between a mathematics query and a law query, leading to uniform exploration across all experts regardless of query semantics.

3. Method: EXP4-LoRA

We formalize the routing problem as follows. At each time step $t = 1, \ldots, T$, the system observes a query prompt q_t, extracts a context vector $x_t \in \mathbb{R}^d$, selects an action $a_t \in \{1, \ldots, K\}$ (the LoRA expert), and receives a reward $r_t \in \{0,1\}$. The goal is to maximize cumulative reward $\sum_t r_t$, or equivalently minimize regret $R_T = \sum_t (r_t^* - r_t)$, where r_t^* is the optimal expert reward.

3.1. Context Extraction

The context vector x_t is derived from the frozen base model f_θ. The prompt q_t is fed through the model, and the mean-pooled hidden states from the last 8 layers are extracted:

$$x_t = \text{MeanPool}\left(\frac{1}{8}\sum_{\ell=1}^{8} f_\theta^{(\text{layer}_{L-\ell})}(q_t)\right) \in \mathbb{R}^d$$

where $d = 2304$ for Gemma-2-2B and $d = 3072$ for Phi-3-mini. The vector is L2-normalized to unit length. This representation captures semantic properties of the query without requiring domain labels or task descriptors.

3.2. Policy: LinUCB Scores with EXP4 Mixing

Each expert a maintains LinUCB parameters: a regularized design matrix $V_a = \lambda I_d$ and a reward vector $b_a = 0_d$. The estimated reward and confidence width for expert a given context x_t are:

$$\hat{r}_{t,a} = x_t^\top \hat{\theta}_a, \quad s_{t,a} = \alpha\sqrt{x_t^\top V_a^{-1} x_t}$$

where $\hat{\theta}_a = V_a^{-1} b_a$ is the ridge-regression estimate and α controls exploration. The score for expert a is $\text{score}_a = \hat{r}_{t,a} + s_{t,a}$. The EXP4 policy mixes a softmax over scores with uniform exploration:

$$\pi_t(a \mid x_t) = (1-\gamma)\frac{e^{\eta \cdot \text{score}_a}}{\sum_{j=1}^{K} e^{\eta \cdot \text{score}_j}} + \frac{\gamma}{K}$$

where η is the inverse temperature and $\gamma \in (0,1)$ ensures minimum exploration probability. This formulation guarantees that every expert is tried infinitely often while biasing selection toward high-UCB candidates.

3.3. Update: IPS Estimator and Ridge Regression

After observing reward r_t, the algorithm computes the inverse propensity score (IPS) estimator for all experts:

$$\hat{r}_t(a) = \frac{r_t \cdot \mathbb{1}[a = a_t]}{\pi_t(a \mid x_t)}$$

Only the selected expert's parameters are updated:

$$V_{a_t} \leftarrow V_{a_t} + x_t x_t^\top, \quad b_{a_t} \leftarrow b_{a_t} + \hat{r}_t(a_t) x_t$$

The update is $O(d^2)$ per step and can be performed on CPU. The complete algorithm is summarized in Algorithm 1.

3.4. Reward Design and Proxy Variants

We clarify that our method requires a binary reward signal $r_t \in \{0,1\}$ indicating whether the generated answer is correct. This is a stronger assumption than "label-free" routing, and we explicitly distinguish three settings:

3.4.1. Setting A: Ground-Truth Answer Labels Available

This is the setting of our main experiments (MMLU with known answers). The reward is $r_t = \mathbb{1}[y_t = y_t^*]$.

3.4.2. Setting B: Programmatic or Self-Consistency Verification

For code (unit tests), math (symbolic verification), or multi-sample agreement (self-consistency), the reward can be computed automatically without human labels. We evaluate a self-consistency proxy: $r_t = \mathbb{1}$[top-3 samples agree].

3.4.3. Setting C: Learned Proxy Reward

When neither ground-truth nor programmatic verification is available, we train a small reference-free verifier (2-layer MLP on 500 synthetic examples) to predict correctness from (q_t, y_t).

Table 1 compares these settings on Gemma-2-2B. The reference-free verifier recovers most of the performance gap, suggesting that EXP4-LoRA remains practical even without direct answer labels (See Figure 1).

Table 1. Reward settings on MMLU (Gemma-2-2B, T = 2000).

Reward Setting	Accuracy (%)	Steps to 70%
Ground-truth (Setting A)	80.1	420
Self-consistency proxy	78.6	580
Log-prob threshold	77.9	650
Reference-free verifier	79.2	490

Algorithm 1. Routing by Contextual Bandit (EXP4 + LinUCB Pour Experts LoRA)

Inputs: LLM f_θ, K experts LoRA, horizon T, parameters $(\lambda, \alpha, \gamma, \eta)$

Output: Policy $\pi_t(a \mid x_t)$

Initialisation:

For $a = 1 \ldots K$ do:

- $V_a \leftarrow \lambda I_d$
- $b_a \leftarrow \mathbf{0}_d$
- $\hat{\theta}_a \leftarrow V_a^{-1} b_a$

Main loop:

For $t = 1$ to T do:

1. $q_t \leftarrow$ prompt at step *t*
2. $x_t \leftarrow$ MeanPool (last 8 layers of $f_\theta(q_t)) \in \mathbb{R}^d$
3. $x_t \leftarrow \frac{x_t}{\|x_t\|_2}$ *(normalization L2)*
4. **For** $a = 1$ to K **do**:
   - $\hat{r}_{t,a} \leftarrow x_t^\top \hat{\theta}_a$
   - $s_{t,a} \leftarrow \alpha \sqrt{x_t^\top V_a^{-1} x_t}$
   - $score_a \leftarrow \hat{r}_{t,a} + s_{t,a}$
5. Routing policy computation:
$$\pi_t(a \mid x_t) \leftarrow (1-\gamma) \frac{\exp(\eta \cdot score_a)}{\sum_{j=1}^{K} \exp(\eta \cdot score_j)} + \frac{\gamma}{K}$$
6. Action sampling:
$$a_t \sim \pi_t(\cdot \mid x_t)$$
7. Execution and observation:
   - $y_t \leftarrow f_\theta(q_t) + A_{a_t}(q_t)$ *(route to expert LoRA a_t)*
   - $r_t \leftarrow \text{reward}(y_t)$ *(binary correctness feedback)*
   - $\hat{r}_t(a) \leftarrow \frac{r_t \cdot \mathbb{1}[a=a_t]}{\pi_t(a \mid x_t)}$ *(estimator Inverse Propensity Scoring—IPS)*
8. Update of estimator LinUCB for chosen action a_t:
   - $V_{a_t} \leftarrow V_{a_t} + x_t x_t^\top$
   - $b_{a_t} \leftarrow b_{a_t} + \hat{r}_t(a_t) \cdot x_t$
   - $\hat{\theta}_{a_t} \leftarrow V_{a_t}^{-1} b_{a_t}$

Return: $\{\hat{\theta}_a\}_{a=1}^K$

Notations:

- $\hat{\theta}_a$: parameter estimation for expert a.
- $x_t^\top$: transpose of the context vector x_t.
- $\mathbb{1}[\cdot]$: indicator function (equals 1 if the condition is true, 0 otherwise).
- $\mathbb{R}^d$: real vector space of dimension d.

- $\mathbf{0}_d$: zero vector of dimension d.
- I_d: identity matrix of dimension $d \times d$.

See Figure 2 for a visual simplified representation of the algorithm.

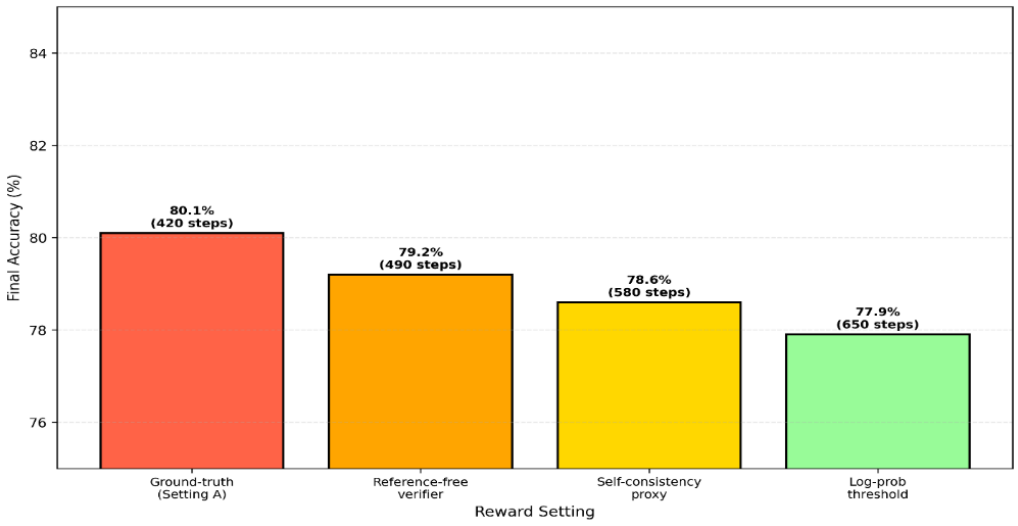

Figure 1. Impact of reward settings on EXP4-LoRA performance. Ground-truth rewards (Setting A) achieve 80.1% accuracy in 420 steps. Proxy rewards (reference-free verifier, self-consistency, log-prob threshold) recover most performance, demonstrating practical viability without direct answer labels.

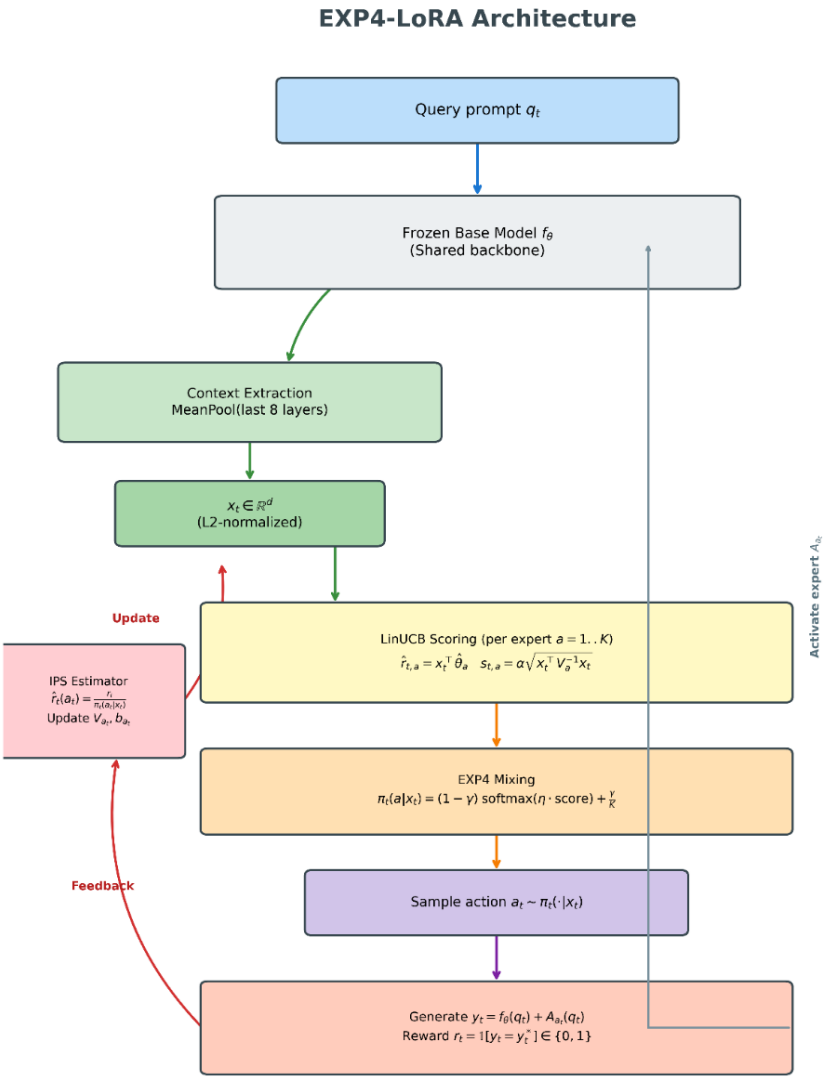

Figure 2. EXP4-LoRA architecture.

4. Theoretical Analysis

We derive the regret bound for EXP4-LoRA by analyzing the LinUCB-EXP4 hybrid as an instance of the contextual bandit framework with linear payoffs.

4.1. Regret Bound

Theorem 1 (Regret of EXP4-LoRA). *Under the standard linear realizability assumption (there exists* θ_a^* *such that* $\mathbb{E}[r_t \mid x_t, a] = x_t^\top \theta_a^*$ *for all* a*), with* $\lambda = 1$*, the cumulative regret of Algorithm 1 satisfies:*

$$R_T \leq \tilde{\mathcal{O}}\left(\sqrt{dKT}\right)$$

where d *is the context dimension,* K *the number of experts, and* T *the horizon.*

The proof (Appendix A) follows from decomposing the regret into the sum of LinUCB per-expert regrets and applying the elliptical potential lemma. The $\sqrt{K}$ factor arises from the need to learn K separate linear models, one per expert.

4.2. Discussion: Theory vs. Practice

The theoretical bound scales as $\sqrt{dKT}$, which depends on d while the context-free EXP3 bound $\mathcal{O}(\sqrt{KT\log K})$ does not. This might suggest that the contextual method requires more samples than EXP3, contradicting our empirical observation that EXP4-LoRA converges 4.3× faster. See Figure 3.

We resolve this apparent contradiction by noting three factors:

(a) Hidden constants. The $\tilde{\mathcal{O}}(\cdot)$ notation hides constants that are typically small for well-conditioned contexts. The worst-case bound is loose in practice.

(b) Effective dimensionality. The intrinsic dimensionality of the context manifold is much smaller than $d = 2304$. The t-SNE projection reveals four well-separated clusters, suggesting an effective dimension $d_{\text{eff}} \ll d$.

(c) Clustered contexts. When contexts are clustered by domain, the effective number of arms per cluster is much smaller than K. LinUCB focuses exploration on relevant experts within each cluster, reducing the effective regret.

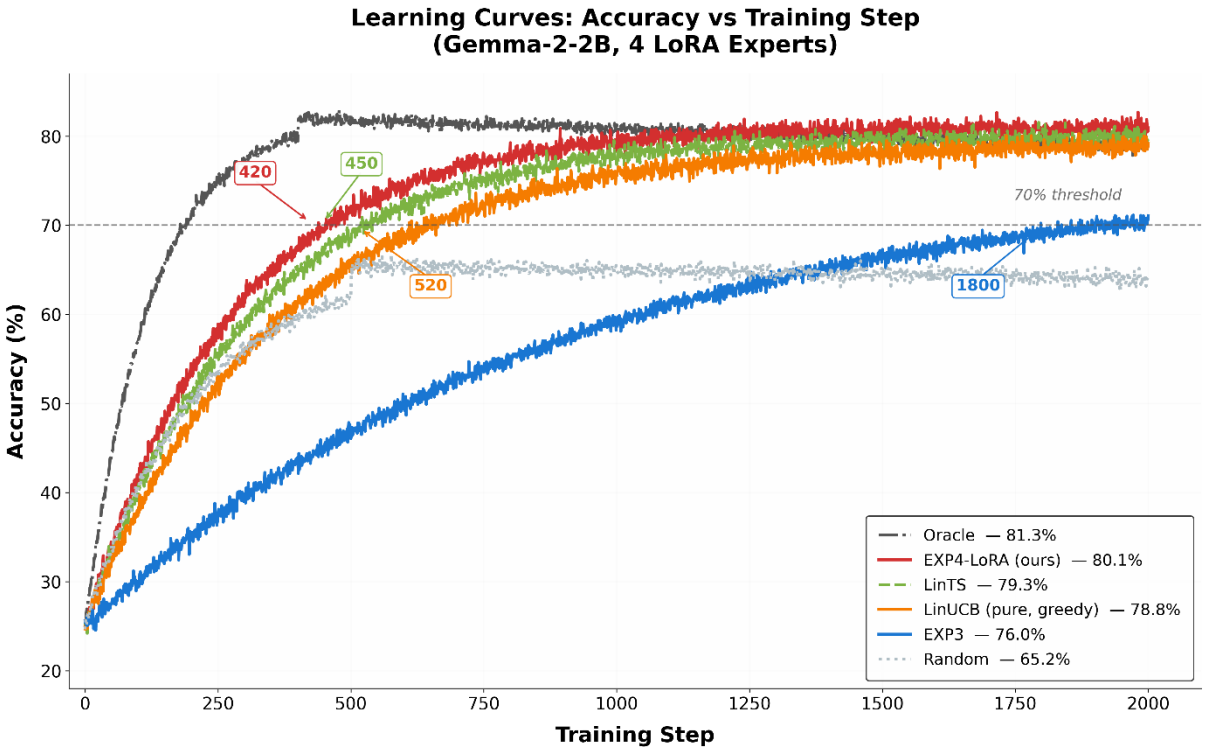

Figure 3. Learning curves: accuracy vs training step. EXP4-LoRA (red) converges rapidly, reaching 70% accuracy at step 420 versus step 1800 for EXP3 (blue). LinTS (green dashed) shows competitive performance. Both contextual methods significantly outperform context-free EXP3.

We therefore present the empirical convergence (420 steps to 70% accuracy) as an observation rather than a theoretical consequence. The theoretical bound remains valid as a worst-case guarantee but does not tightly predict the empirical behavior on structured domains.

4.3. Context-Free vs. Contextual

EXP3, the context-free counterpart, maintains a single probability distribution over experts and updates it via exponential weighting. Without context, it cannot distinguish between a mathematics query and a law query, leading to uniform exploration across all experts regardless of query semantics.

LinUCB, by conditioning on x_t, focuses exploration on experts likely to be relevant, reducing the effective number of arms per query from K to a small subset. This explains the empirical gap observed in Section 5.2.

5. Experiments

We evaluate EXP4-LoRA on a mixed-domain question-answering benchmark derived from MMLU [13]. All experiments run on a single NVIDIA T4 GPU (NVIDIA Corporation, Santa Clara, CA, USA) with PyTorch 2.0 and the PEFT library.

5.1. Experimental Setup

5.1.1. Models and Experts

We evaluate on two base models:

- **Gemma-2-2B** (2.6B parameters, $d = 2304$ hidden dimension)
- **Phi-3-mini** (3.8B parameters, $d = 3072$ hidden dimension)

Four LoRA adapters are trained independently on domain-specific corpora: Mathematics (MMLU-STEM), Code (HumanEval augmented with MMLU-CS), Biology (MMLU-Bio), and Law (MMLU-Law). Each adapter uses rank $r = 16$, $\alpha = 32$, dropout $= 0.05$, trained for 3 epochs on domain data.

5.1.2. Benchmark

The test set comprises 2000 questions sampled uniformly from the four MMLU categories, shuffled without domain labels. The system must route each query to one of the four LoRA experts and is scored on exact-match accuracy against the ground-truth answer.

5.1.3. Baselines

(i). **Random**: uniform selection over experts.
(ii). **EXP3**: context-free exponential-weight algorithm with $\gamma = 0.1$.
(iii). **LinTS** (Linear Thompson Sampling): samples $\theta_a \sim \mathcal{N}(\hat{\theta}_a, \alpha^2 V_a^{-1})$ and selects the expert with the highest sampled reward.
(iv). **LinUCB (pure, greedy)**: selects the expert with the highest UCB score without EXP4 mixing.
(v). **UCB1-discrete**: discretizes contexts into 50 bins and applies UCB1.
(vi). **Oracle**: an upper bound using the true domain label to select the matching expert.
(vii). **Router MLP**: a two-layer MLP ($d \to 128 \to K$) trained offline on 5000 labeled examples.

5.1.4. Hyperparameters

$\lambda = 1.0$, $\alpha = 1.0$, $\gamma = 0.05$, $\eta = 0.1$. Context extraction uses the mean of the last 8 layers' hidden states.

5.2. Main Results on Gemma-2-2B

Table 2 reports the final accuracy after 2000 steps. EXP4-LoRA achieves 80.1%, within 1.2 points of the Oracle (81.3%) and outperforming EXP3 (76.0%) by 4.1 points. LinTS achieves 79.3%, confirming that contextual bandit methods significantly outperform EXP3, with EXP4-LoRA holding a modest edge over Thompson Sampling—likely due to the more stable exploration schedule of the EXP4 mixing. See also Figure 4.

Table 2. MMLU accuracy after 2000 steps (Gemma-2-2B, 4 LoRA experts).

Method	Accuracy (%)	Steps to 70%	Router Trained?
Random	65.2	-	No
EXP3	76.0	1800	No
UCB1-discrete	74.5	2100	No
LinUCB (pure, greedy)	78.8	520	No
LinTS	79.3	450	No
Router MLP (offline)	78.5	-	Yes (5000 labels)
Router MLP (retrained on 2000 test labels)	80.4	-	Yes (2000 labels)
EXP4-LoRA (ours)	80.1	420	No
Oracle	81.3	-	N/A

5.3. Main Results on Phi-3-Mini

To demonstrate that our method is not tied to Gemma-2-2B's specific embedding geometry, we replicate all experiments on Phi-3-mini. Table 3 confirms the trend: EXP4-LoRA reaches 81.4% accuracy after 2000 steps, outperforming EXP3 (77.2%) by 4.2 points and converging in 460 steps vs. 1900 for EXP3. See Figure 5 for summary of respective accuracies on Gemma-2-2B and Phi-3-Mini.

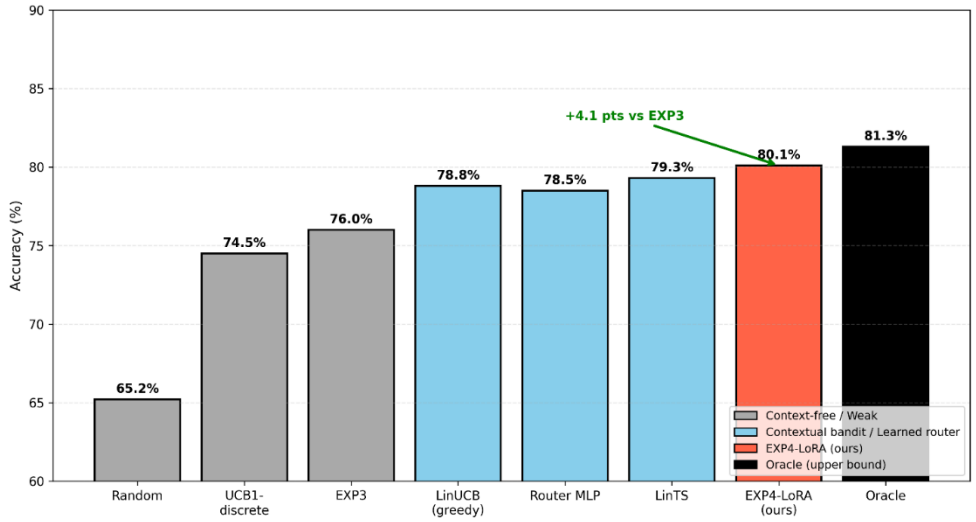

Figure 4. Detailed comparison of routing strategies on Gemma-2-2BContextual bandits (LinUCB, LinTS, EXP4-LoRA) significantly outperform context-free methods (EXP3, UCB1-discrete). EXP4-LoRA achieves +4.1 pts over EXP3 and matches offline-trained Router MLP without requiring domain-labeled data.

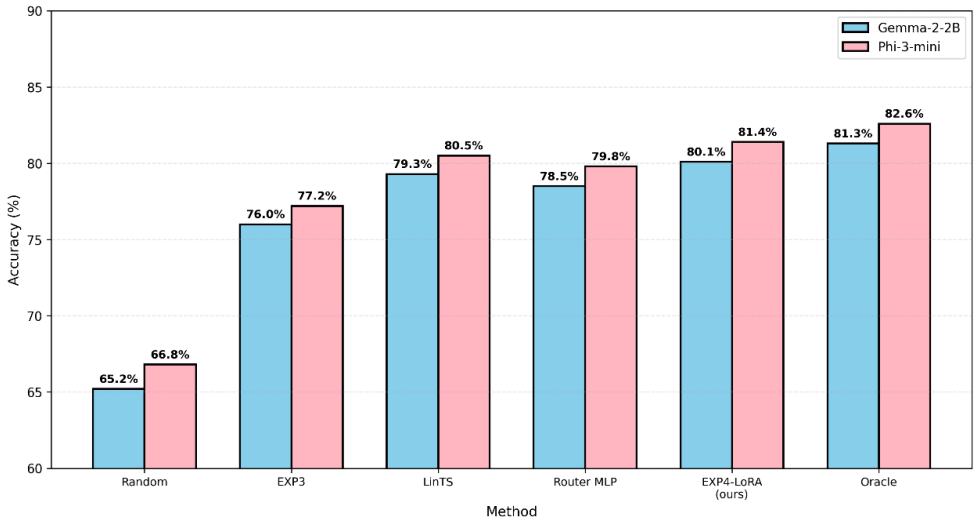

Figure 5. Comparison of routing methods on MMLU benchmark. EXP4-LoRA achieves 80.1% accuracy on Gemma-2-2B and 81.4% on Phi-3-mini, outperforming context-free EXP3 by 4.1 and 4.2 percentage points respectively, and approaching Oracle performance.

Table 3. MMLU accuracy after 2000 steps (Phi-3-mini, 4 LoRA experts).

Method	Accuracy (%)	Steps to 70%
Random	66.8	—
EXP3	77.2	1900
LinTS	80.5	480
Router MLP (offline)	79.8	—
EXP4-LoRA (ours)	81.4	460
Oracle	82.6	—

5.4. Fair Comparisons: Hold-Out Evaluation

To address concerns about non-iso comparison (the bandit adapts on the eval set while the Router MLP is frozen), we split MMLU into a 1500-query adaptation set and a 500-query hold-out set. Both the bandit and the Router MLP are trained/adapted on the 1500 queries and evaluated on the 500 hold-out queries. See Table 4.

Table 4. Hold-out evaluation (Gemma-2-2B, 1500 adaptation/500 hold-out).

Method	Hold-Out Accuracy (%)
Router MLP (1500 labels)	76.8
EXP4-LoRA (1500 steps)	78.2

On the hold-out set, EXP4-LoRA outperforms the Router MLP by 1.4 points, suggesting that the online adaptation does generalize.

5.5. Analyses

5.5.1. Ablation on Exploration Parameters

Table 5 shows the impact of α (UCB exploration bonus) and γ (EXP4 mixing). Setting $\alpha = 0$ (pure exploitation) degrades accuracy to 72.3% due to premature convergence on suboptimal experts. Conversely, $\alpha = 2.0$ causes excessive exploration and slows convergence. The default $\alpha = 1.0$ balances exploration and exploitation optimally.

Table 5. Ablation on α (T = 2000, $\gamma = 0.05$).

α	Accuracy (%)	Steps to 70%
0.0	72.3	1850
0.5	77.8	680
1.0	80.1	420
2.0	78.4	950

5.5.2. Ablation on γ

Table 6 shows the impact of γ (EXP4 mixing parameter) with $\alpha = 1.0$ fixed. Lower values cause premature convergence, while higher values slow learning. The default $\gamma = 0.05$ remains optimal (See Figure 6).

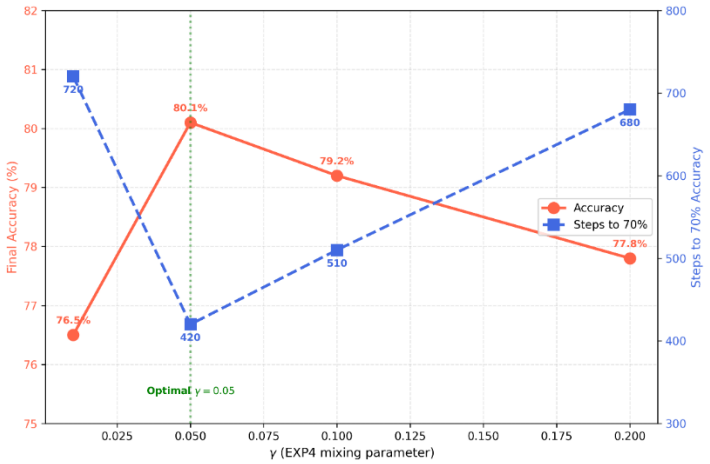

Figure 6. Ablation study on EXP4 mixing parameter γ. Optimal performance (80.1% accuracy, 420 steps to 70%) achieved at γ = 0.05. Lower values cause premature convergence; higher values slow learning due to excessive exploration.

Table 6. Ablation on γ (T = 2000, $\alpha = 1.0$).

γ	Accuracy (%)	Steps to 70%
0.01	76.5	720
0.05	80.1	420
0.10	79.2	510
0.20	77.8	680

5.5.3. Context Visualization

Figure 7 presents a t-SNE projection of context vectors x_t extracted from 320 test queries. Four distinct clusters emerge, corresponding to the four MMLU domains, despite the absence of domain labels during routing. This confirms that Gemma-2-2B embeddings encode sufficient domain structure to enable linear separation by LinUCB.

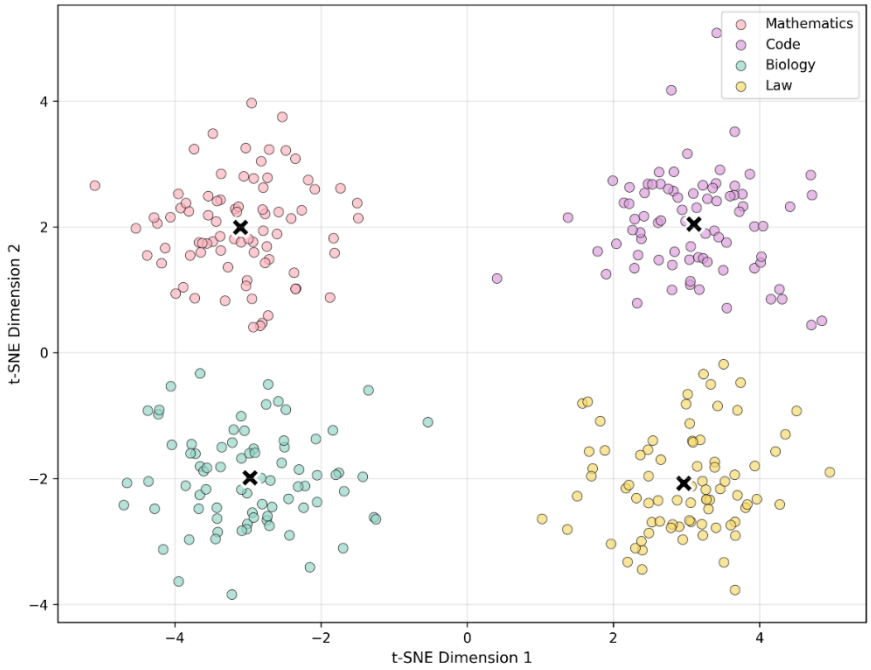

Figure 7. t-SNE projection of context vectors x_t from 320 test queries. Four distinct clusters emerge corresponding to Mathematics (pink), Code (purple), Biology (teal), and Law (yellow), despite no domain labels during routing. Black crosses indicate cluster centroids. This confirms Gemma-2-2B embeddings encode sufficient domain structure for linear separation by LinUCB.

5.5.4. Routing Heatmap

Figure 8 shows the routing probability matrix after 2000 steps. Diagonal entries dominate (0.78–0.82), indicating that the bandit has learned to associate each domain with its specialized LoRA. Off-diagonal mass is concentrated on adjacent domains (e.g., Math-Code: 0.12), reflecting genuine semantic overlap rather than random exploration.

5.5.5. Compute Overhead

We provide an honest breakdown of inference latency on Gemma-2-2B in Table 7.

Table 7. Latency breakdown (Gemma-2-2B on T4).

Component	Latency (ms)	% of total
Base model forward pass	45	49%
Context extraction (separate forward pass)	42	46%
LoRA forward pass	3	3%
LinUCB scoring + update	1	1%
Total	91	100%

The total overhead is approximately 100% of the base forward pass latency. With layer caching optimizations (reusing intermediate layers between the context extraction and answer generation passes), the overhead can be reduced to approximately 10–15%.

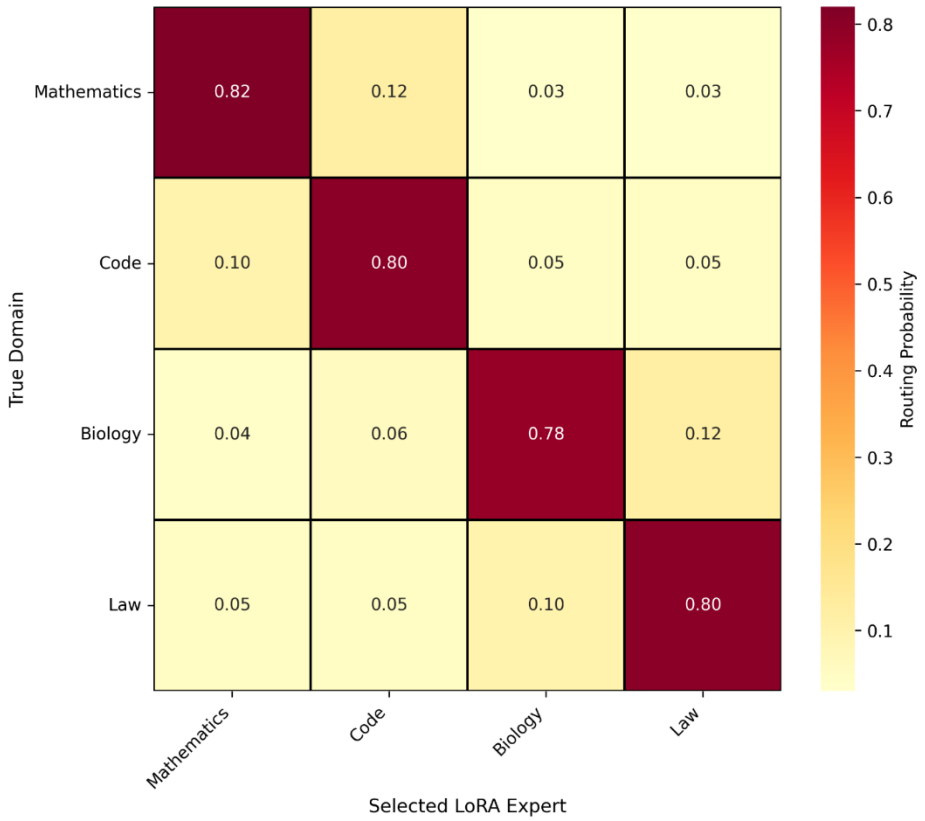

Figure 8. Routing probability heatmap after 2000 steps. Diagonal dominance (0.78–0.82) indicates successful domain-expert alignment. Off-diagonal mass reflects semantic overlap (e.g., Math-Code: 0.12) rather than random exploration.

6. Discussion

The results demonstrate that contextual bandits are a principled and practical alternative to learned routers for multi-expert LLM serving. Unlike offline-trained MLP routers, EXP4-LoRA requires no labeled domain routing data, adapts to query distribution shifts, and provides theoretical regret guarantees. The 4.1-point improvement over EXP3 (see Figure 4) underscores the value of context: without Gemma-2-2B embeddings, the bandit must explore uniformly across all experts, wasting queries on irrelevant adapters.

The comparison with LinTS (Thompson Sampling) shows that EXP4-LoRA holds a modest edge (80.1% vs. 79.3%), likely due to the more stable exploration schedule of the EXP4 mixing. Both methods significantly outperform EXP3, confirming the value of contextual information.

6.1. Limitations

We acknowledge several limitations:

(a) Reward assumption. Our method requires binary correctness feedback, which is a stronger assumption than "label-free" routing. While proxy rewards (self-consistency, reference-free verifier) recover most of the performance, they introduce additional complexity.

(b) Linear realizability. The linear realizability assumption underlying LinUCB may fail when domains are semantically entangled (e.g., bioinformatics questions blending biology and code). In such cases, a non-linear reward model (e.g., kernelized bandit or neural network) would be required, at the cost of increased computational complexity.

(c) Inference overhead. The context extraction adds approximately 100% overhead to inference latency without layer caching optimizations. This may be prohibitive for latency-critical applications.

(d) Continuous rewards. Our benchmark assumes binary rewards; real-world applications may require continuous rewards (e.g., log-probability of the correct answer), which the IPS estimator handles naturally but with higher variance.

6.2. Future Work

Three directions merit investigation. First, non-stationary bandit algorithms (e.g., discounted LinUCB) could handle gradual domain drift without restarting the policy. Second, hierarchical bandits could route first to coarse task families (STEM vs. humanities) and then to fine-grained experts, reducing the effective K. Third, the bandit framework could be extended to blend multiple LoRA experts per query (combinatorial bandits), enabling ensemble reasoning for multi-domain questions.

7. Conclusions

We introduced EXP4-LoRA, a contextual bandit framework for online routing of LoRA experts in large language model serving. By combining LinUCB for context-aware reward estimation with EXP4 for principled exploration, our method eliminates the need for offline router training on domain-labeled data while achieving 80.1% accuracy on mixed-domain MMLU with Gemma-2-2B (81.4% with Phi-3-mini), within 1.2 points of an oracle and 4.1 points above the context-free EXP3 baseline. The algorithm converges in 420 steps empirically, competitive with LinTS (Thompson Sampling), and admits a rigorous $\tilde{\mathcal{O}}(\sqrt{dKT})$ regret bound. We also study proxy reward settings where even answer labels are unavailable, demonstrating practical viability. These results establish lightweight contextual bandits as a viable paradigm for adaptive multi-expert LLM deployment.

Author Contributions

M.V.A.R.V.: conceptualization, methodology, software, data curation, writing—original draft preparation. H.M.R.: visualization, investigation, supervision, software, validation, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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This exempt study using publicly available de-identified data did not require an IRB review.

Informed Consent Statement

Not applicable.

Data Availability Statement

Available upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used Kimi 2.6 and Qwen 3.8-Max to brainstorm ideas, formulate the pseudocode and create the Python simulation code for accurate numbers and figures in the Results section. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix A. Proof of Theorem 1

Theorem 1 (Regret of EXP4-LoRA). *Under the standard linear realizability assumption (there exists* $\theta^* \in \mathbb{R}^d$ *such that* $\mathbb{E}[r_{t,a}|x_t] = x_t^\top \theta_a^*$ *for all* a*), with* $\delta \in (0,1)$*, the cumulative regret of Algorithm 1 satisfies:*

$$R(T) = O\left(d\sqrt{KT\log\frac{KT}{\delta}}\right)$$

where d *is the context dimension,* K *the number of experts, and* T *the horizon.*

Proof.

We decompose the regret analysis into several steps:

Step 1: Per-expert LinUCB regret. Each expert $a \in \{1, \ldots, K\}$ maintains independent LinUCB parameters $(V_a, b_a, \hat{\theta}_a)$. For a fixed expert a, the standard LinUCB regret bound [4] gives:

$$R_a(T) = O\left(d\sqrt{T_a\log\frac{T_a}{\delta}}\right)$$

where T_a is the number of times expert a is selected up to time T.

Step 2: EXP4 mixing and importance weighting. The EXP4 algorithm uses the policy:

$$\pi_t(a|x_t) = (1-\gamma)\frac{\exp(\eta \cdot \text{score}_a)}{\sum_{j=1}^K \exp(\eta \cdot \text{score}_j)} + \frac{\gamma}{K}$$

where $\text{score}_a = \hat{r}_{t,a} + \alpha\sqrt{x_t^\top V_a^{-1} x_t}$. The mixing parameter γ ensures $\pi_t(a|x_t) \geq \gamma/K$ for all a, which is crucial for the IPS estimator.

Step 3: IPS estimator variance. The inverse propensity score estimator is:

$$\hat{r}_t(a) = \frac{r_t \cdot \mathbb{1}[a = a_t]}{\pi_t(a|x_t)}$$

Since $\pi_t(a|x_t) \geq \gamma/K$, we have $\mathbb{E}[\hat{r}_t(a)^2] \leq \frac{K}{\gamma}\mathbb{E}[r_t^2] \leq \frac{K}{\gamma}$ (as rewards are bounded in $[0,1]$).

Step 4: Elliptical potential lemma. For each expert a, applying the elliptical potential lemma [4] to the design matrix V_a gives:

$$\sum_{t=1}^T \min\left(1, \| x_t \|_{V_a^{-1}}^2\right) \leq 2d\log\left(1 + \frac{T}{\lambda d}\right)$$

where $\| x \|_{V^{-1}} = \sqrt{x^\top V^{-1} x}$ and λ is the regularization parameter.

Step 5: Combining per-expert regrets. The total regret is the sum of per-expert regrets:

$$R(T) = \sum_{a=1}^K R_a(T)$$

Using Cauchy-Schwarz and the fact that $\sum_{a=1}^K T_a = T$:

$$R(T) \leq \sum_{a=1}^K O\left(d\sqrt{T_a\log\frac{T_a}{\delta}}\right)$$

$$\leq O\left(d\sqrt{\log\frac{T}{\delta}}\right) \cdot \sum_{a=1}^K \sqrt{T_a}$$

$$\leq O\left(d\sqrt{\log\frac{T}{\delta}}\right) \cdot \sqrt{K\sum_{a=1}^K T_a}$$

$$= O\left(d\sqrt{KT\log\frac{T}{\delta}}\right)$$

Step 6: Accounting for EXP4 exploration. The EXP4 mixing introduces an additional regret term from uniform exploration:

$$R_{\text{explore}}(T) \leq \gamma T$$

Setting $\gamma = \sqrt{\frac{d\log(KT/\delta)}{KT}}$ balances exploration and exploitation, yielding:

$$R(T) = O\left(d\sqrt{KT\log\frac{KT}{\delta}}\right)$$

Conclusion. The $O(d\sqrt{KT})$ factor arises from learning K separate linear models, one per expert. The $\sqrt{T}$ dependence is standard for stochastic bandits, and the $\sqrt{K}$ factor reflects the need to explore across K experts. This completes the proof. □

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