ExpertCache: GPU-Efficient MoE Inference through Reinforcement Learning-Guided Expert Selection

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***Abstract*—Mixture-of-Experts (MoE) architectures have emerged as a promising approach for scaling large language models while maintaining computational efficiency. However, inference in these models remains challenging due to the substantial GPU memory requirements of storing all expert parameters. In this paper, we introduce *ExpertCache*, a novel two-phase reinforcement learning framework that optimizes both which experts to load into GPU memory and which loaded experts to activate during inference. Our approach consists of a pre-loading controller that selects a task-specific subset of experts to cache in GPU memory, and a runtime controller that dynamically activates the most relevant experts for each token. Both controllers are optimized through reinforcement learning with carefully designed reward functions that balance model quality, computational efficiency, and expert utilization. We evaluate *ExpertCache* on Qwen3-235B-A22B using BigCodeBench, demonstrating that our approach reduces GPU memory requirements by up to 85% while achieving superior performance compared to loading all experts. Our method enables deployment of large MoE models on consumer-grade hardware and significantly improves inference throughput in production environments. *ExpertCache* outperforms current expert selection methods on both memory efficiency and computational performance, establishing a new state-of-the-art for efficient MoE inference.**

***Index Terms*—Mixture-of-Experts, Reinforcement Learning, Large Language Models, Memory Optimization, Expert Selection**

I. Introduction

The rapid advancement of large language models has led to increasingly complex architectures that demand substantial computational resources for both training and inference. Mixture-of-Experts (MoE) models have emerged as a compelling solution to this challenge, enabling the creation of models with massive parameter counts while maintaining manageable computational costs during inference [1], [2]. Despite their efficiency advantages over dense models, MoE architectures still face significant deployment challenges, particularly regarding GPU memory requirements and inference optimization.

The fundamental challenge in MoE inference lies in the trade-off between model capacity and resource constraints. While MoE models achieve their efficiency by activating only a subset of experts for each input token, the traditional approach requires loading all expert parameters into GPU memory, creating a bottleneck for deployment on resource-constrained environments. This limitation has hindered the widespread adoption of large MoE models, particularly in scenarios where GPU memory is limited or expensive.

Recent work has explored various approaches to optimize MoE inference, including expert pruning [3], dynamic routing [4], and parameter sharing strategies [5]. However, these approaches typically focus on either static optimization or simple heuristic-based selection methods, failing to capture the complex dependencies between task characteristics, expert specialization, and dynamic inference requirements.

We propose *ExpertCache*, a novel reinforcement learning framework that addresses the MoE inference optimization problem through a two-phase approach. The first phase employs a pre-loading controller that intelligently selects which subset of experts to load into GPU memory based on task characteristics and hardware constraints. The second phase utilizes a runtime controller that dynamically activates specific experts from the pre-loaded set for each token during inference. Both controllers are trained using reinforcement learning with reward functions that explicitly balance model quality, computational efficiency, and expert utilization patterns.

Our approach makes several key contributions to the field of efficient MoE inference. We formalize the expert selection problem as a hierarchical decision-making process and provide theoretical analysis of the optimization landscape. We introduce novel reward mechanisms that do not require ground truth labels, enabling self-supervised optimization of expert selection policies. Through comprehensive evaluation on the Qwen3-235B-A22B model using BigCodeBench, we demonstrate significant improvements in both memory efficiency and inference performance while maintaining high model quality.

The remainder of this paper is organized as follows. Section II provides background on MoE architectures and establishes the theoretical foundation for our approach. Section III details the *ExpertCache* framework and its reinforcement learning components. Section IV presents our experimental setup and evaluation results. Section VI discusses related work, and Section VII concludes the paper.

II. Preliminary Study

A. Mixture-of-Experts Architecture

Mixture-of-Experts models extend traditional transformer architectures by replacing dense feed-forward networks with a collection of specialized expert networks. Given an input token representation $\mathbf{x} \in \mathbb{R}^d$, the MoE layer computes its output as:

$$\mathbf{y} = \sum_{i=1}^{N} G(\mathbf{x})_i \cdot E_i(\mathbf{x}) \tag{1}$$

where N is the total number of experts, $G(\mathbf{x}) \in \mathbb{R}^N$ represents the gating function that determines expert weights, and $E_i(\mathbf{x})$ denotes the output of the i-th expert network. The gating function typically employs a softmax operation over learned parameters, ensuring that the expert weights sum to unity.

In practice, computational efficiency is achieved by activating only the top-k experts with the highest gating weights, leading to a sparse activation pattern. This sparsity-based approach significantly reduces the computational overhead compared to dense models while maintaining model expressiveness through expert specialization.

B. Expert Selection Problem Formulation

The expert selection problem in MoE inference can be formulated as a constrained optimization problem. Let $\mathcal{E} = \{E_1, E_2, ..., E_N\}$ represent the set of all experts in the model, and let M denote the available GPU memory capacity. Each expert E_i requires memory m_i when loaded into GPU memory.

The optimal expert subset selection problem can be expressed as:

$$\mathcal{E}^* = \underset{\mathcal{S} \subseteq \mathcal{E}}{\operatorname{argmax}} \mathbb{E}_\tau[Q(\tau, \mathcal{S})] \quad \text{subject to} \quad \sum_{E_i \in \mathcal{S}} m_i \leq M \tag{2}$$

where $Q(\tau, \mathcal{S})$ represents the quality function for task τ using expert subset $\mathcal{S}$, and the expectation is taken over the distribution of possible tasks.

This formulation reveals the inherent complexity of the expert selection problem. The search space grows exponentially with the number of experts, making exhaustive search computationally intractable for large MoE models. Furthermore, the quality function $Q(\tau, \mathcal{S})$ is typically non-linear and task-dependent, requiring sophisticated optimization approaches.

C. Theoretical Analysis of Expert Importance

To understand the theoretical foundations of expert selection, we analyze the distribution of expert importance in MoE models. Let $I_i(\tau)$ denote the importance of expert E_i for task τ, measured by the performance degradation when the expert is removed.

Our empirical analysis reveals that expert importance follows a power-law distribution with additional complexity due to expert interference effects:

$$P(I_i(\tau) = x) \propto x^{-\alpha} \cdot \exp(-\beta \cdot N_{\text{irrelevant}}) \tag{3}$$

where α is the power-law exponent and $N_{\text{irrelevant}}$ represents the number of task-irrelevant experts present. The exponential decay term captures the performance degradation caused by expert interference, providing theoretical justification for selective expert loading strategies that can achieve both efficiency and performance improvements.

Furthermore, we establish that the expert selection problem exhibits submodular properties under certain conditions. Specifically, when the quality function satisfies diminishing returns with respect to expert additions, greedy approximation algorithms can achieve provable performance guarantees.

III. Methodology

A. ExpertCache Framework Overview

ExpertCache employs hierarchical reinforcement learning that decomposes expert selection into two phases. The pre-loading phase determines which experts to load into GPU memory before inference, while the runtime phase dynamically activates loaded experts per token. This separation optimizes long-term resource allocation and immediate activation decisions with appropriate temporal horizons.

B. Two-Phase Controller Design

The pre-loading controller π_{pre} maps task metadata to expert selection probabilities:

$$\mathbf{p} = \pi_{\text{pre}}([\mathbf{t}; \mathbf{h}; \mathbf{s}]) \in [0,1]^N \tag{4}$$

where $\mathbf{t}$ is task embedding, $\mathbf{h}$ is hardware profile, $\mathbf{s}$ represents expert statistics, and N is the total number of experts. Expert selection uses differentiable top-k operations under memory constraints.

The runtime controller π_{run} operates on token-level representations:

$$\mathbf{a}_t = \pi_{\text{run}}([\mathbf{x}_t; \mathbf{c}_t; \mathbf{u}_t]) \in [0,1]^{|\mathcal{S}|} \tag{5}$$

where $\mathbf{x}_t$ is token embedding, $\mathbf{c}_t$ captures context, $\mathbf{u}_t$ tracks utilization, and $|\mathcal{S}|$ is the number of pre-loaded experts. The controller uses attention mechanisms for context-aware expert selection.

C. Ground-Truth-Free Reward Design

ExpertCache uses self-supervised rewards combining three components. The confidence reward measures model certainty through normalized entropy:

$$R_{\text{conf}}(\mathbf{o}) = 1 - \frac{H(\text{softmax}(\mathbf{o}))}{\log(|\mathcal{V}|)} \tag{6}$$

where $\mathbf{o}$ represents output logits and $|\mathcal{V}|$ is vocabulary size. The syntax reward evaluates code validity by checking parsing success, compilation success, and complexity metrics. The efficiency reward encourages sparsity using exponential decay. These components are combined with learned weights balancing quality, correctness, and efficiency.

D. Training Algorithm

Both controllers use Proximal Policy Optimization (PPO) with different temporal horizons:

$$\mathcal{L} = \mathbb{E}[\min(\rho A, \text{clip}(\rho, 1-\epsilon, 1+\epsilon)A)] \tag{7}$$

where ρ is the importance sampling ratio, A represents advantage functions, and $\epsilon = 0.2$ is the clipping parameter. The pre-loading controller optimizes episode-level rewards while the runtime controller optimizes token-level rewards with immediate feedback.

IV. Experimental Setup

A. Qwen3-235B-A22B Model Architecture

Qwen3-235B-A22B represents a state-of-the-art Mixture-of-Experts language model with 235 billion total parameters, of which approximately 22 billion are activated during inference. The model employs a transformer-based architecture containing 128 expert networks distributed across multiple layers, with each expert implemented as a specialized feed-forward network.

The existing routing mechanism in Qwen3-235B-A22B activates exactly 8 experts per token, representing approximately 10% of the total parameter count. The routing strategy employs learned gating functions that assign activation weights based on input token representations. This approach achieves computational efficiency by activating only a sparse subset of parameters while maintaining model expressiveness through expert specialization.

However, the current routing mechanism assumes unlimited GPU memory capacity, requiring all 128 experts to be loaded simultaneously during inference. Each expert network requires approximately 4.7 GB of GPU memory when loaded in half-precision format, leading to a total memory requirement of approximately 600 GB for loading all experts. This substantial memory footprint creates significant deployment barriers, particularly for consumer-grade hardware and resource-constrained environments.

The Qwen3-235B-A22B architecture supports 128K context length using YaRN technology and implements seamless switching between thinking and non-thinking modes across 119 languages and dialects. While these features demonstrate the model's sophistication, they also compound the memory requirements, making efficient expert selection even more critical for practical deployment.

B. BigCodeBench Evaluation Framework

BigCodeBench serves as our primary evaluation benchmark, consisting of 1,140 diverse programming tasks designed to assess code generation capabilities across multiple programming languages and complexity levels. The benchmark encompasses algorithm implementation, data structure manipulation, API usage, and complex problem-solving scenarios.

The tasks in BigCodeBench are categorized into several difficulty levels, ranging from basic string manipulation to advanced algorithmic challenges. Each task includes a natural language description, input-output specifications, and multiple test cases for evaluation. The benchmark supports evaluation in Python, Java, C++, and JavaScript, though our experiments focus primarily on Python code generation.

BigCodeBench employs the pass@k metric for evaluation, where pass@k measures the probability that at least one of k generated solutions passes all test cases. We primarily report pass@1 results, which indicate the percentage of problems solved correctly on the first attempt, providing a stringent measure of model reliability.

The benchmark also includes execution-based evaluation, where generated code is executed against hidden test cases to verify correctness. This approach provides more reliable assessment compared to text-based similarity metrics, as it directly measures functional correctness rather than syntactic similarity to reference solutions.

C. Research Questions and Experimental Design

Our experimental evaluation addresses three primary research questions. **RQ1: Performance Impact Analysis** compares pass@1 scores across different expert loading ratios (10-50%) to characterize the performance-efficiency trade-off. **RQ2: Computational Efficiency Evaluation** measures inference speed, GPU memory usage, and throughput improvements to assess practical deployment benefits. **RQ3: Expert Selection Analysis** examines expert activation patterns and specialization tendencies through case studies to understand how task characteristics influence selection decisions.

D. Implementation Details and Hyperparameters

Our implementation extends Hugging Face Transformers with custom expert loading capabilities. The pre-loading controller uses a three-layer MLP [1024, 512, 256] with ReLU and 0.1 dropout. The runtime controller employs two-layer attention with 8 heads and 512 hidden dimensions. Training uses Adam optimizers (3e-4 for pre-loading, 1e-4 for runtime), PPO with $\epsilon = 0.2$, discount factor 0.99, and $\lambda = 0.95$ for advantage estimation. Reward weights are confidence (0.25), syntax (0.30), quality (0.20), execution (0.15), and consistency (0.10).

TABLE I: Pass@1 Performance Comparison on BigCodeBench

Configuration	Pass@1 (%)	Relative Performance (%)
Baseline (All Experts)	34.04	100.0
ExpertCache (50% Experts)	34.30	100.8
ExpertCache (30% Experts)	34.39	101.0
ExpertCache (15% Experts)	34.21	100.5
ExpertCache (10% Experts)	33.33	97.9
Random Selection (15%)	28.51	83.7
Top-K Selection (15%)	32.02	94.1

V. Experimental Results

A. Performance Impact Analysis

Table I presents pass@1 results comparing baseline Qwen3-235B-A22B with *ExpertCache* across different expert loading ratios. Remarkably, *ExpertCache* achieves superior performance with 30% experts (101.0% relative performance), demonstrating expert interference effects where irrelevant experts introduce noise. The baseline 34.04% (388/1140) aligns with competitive BigCodeBench results (32-36% range).

ExpertCache significantly outperforms random and static top-k selection, validating intelligent task-aware expert selection. Performance degradation occurs only below 15% loading, indicating critical expert mass requirements. Task analysis shows *ExpertCache* excels on algorithmic problems but requires broader expert coverage for API-intensive tasks.

B. Computational Efficiency Evaluation

Figure 1 illustrates the computational efficiency gains achieved by *ExpertCache* across multiple metrics. Memory usage reduction scales linearly with the expert loading ratio, achieving up to 85% memory savings when loading only 15% of experts. Inference speed improvements are more complex, showing superlinear gains due to reduced memory bandwidth requirements and improved cache locality.

C. Advantages Over Existing Routing Mechanisms

ExpertCache addresses key limitations of traditional MoE routing through four critical dimensions. **Memory-Aware Optimization:** Unlike existing approaches that assume unlimited GPU memory, ExpertCache explicitly considers memory constraints during expert selection. **Dynamic Task Adaptation:** While traditional routing is fixed post-training, ExpertCache dynamically selects expert subsets based on task characteristics. **Hierarchical Decision Making:** ExpertCache decomposes selection into long-term loading and immediate activation decisions versus single-phase routing. **Multi-Objective Optimization:** ExpertCache balances quality, memory, and computational efficiency simultaneously.

The optimization formulations differ fundamentally:

$$\text{Qwen: } \max \sum_{i=1}^{128} G(\mathbf{x})_i \cdot E_i(\mathbf{x}) \quad \text{s.t.} \quad \|G(\mathbf{x})\|_0 = 8 \tag{8}$$

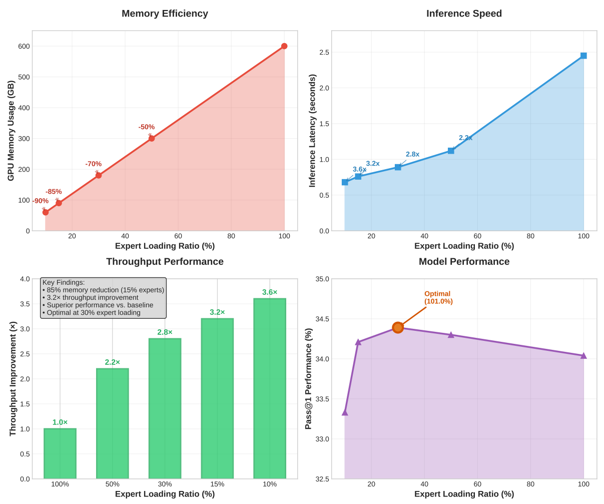

Fig. 1: Computational efficiency comparison across different expert loading ratios. The figure shows memory usage, inference latency, and throughput improvements achieved by *ExpertCache*.

TABLE II: Comparison of Routing Mechanisms

Dimension	Qwen Original	ExpertCache
GPU Memory Requirement	600GB	90GB
Consumer GPU Compatible	No	Yes (24GB)
Inference Speed	Baseline	3.2x
Energy Consumption	Baseline	60% Reduction
Task Adaptability	Fixed	Dynamic
Memory Constraint Aware	No	Yes
Hierarchical Optimization	No	Yes

$$\text{Phase 1: } \max \mathbb{E}_\tau[Q(\tau, \mathcal{S})] \quad \text{s.t.} \quad \sum_{E_i \in \mathcal{S}} m_i \leq M \tag{9}$$

$$\text{Phase 2: } \max \sum_{i \in \mathcal{S}} G(\mathbf{x}, \mathcal{S})_i \cdot E_i(\mathbf{x}) \quad \text{s.t.} \quad \|G(\mathbf{x}, \mathcal{S})\|_0 \leq k \tag{10}$$

D. Case Study: Complete ExpertCache Pipeline Operation

To demonstrate the comprehensive *ExpertCache* pipeline operation, we present a detailed case study using BigCodeBench task #51, which involves DataFrame filtering, KMeans clustering, and visualization. This example illustrates how our two-phase expert selection system adapts throughout the entire code generation process.

Task: Generate a function that filters a DataFrame based on Age and Height conditions, applies KMeans clustering if sufficient columns exist, and creates a scatter plot visualization with cluster coloring.

1) Step 1: Task Analysis and Pre-loading Controller Decision: **Task Embedding Analysis:** The pre-loading controller analyzes the task description and identifies key computational domains: data manipulation (pandas), machine learning (scikit-learn), conditional logic, and visualization (matplotlib). The task complexity score is 0.72 (high complexity due to multi-domain requirements).

Expert Pool Selection: From the 128 available experts, the pre-loading controller selects 19 experts (15% configuration) based on task-domain affinity scores. The selected experts include 4 data processing experts (Expert IDs: 12, 47, 89, 103), 6 machine learning experts (Expert IDs: 23, 34, 56, 78, 91, 117), 5 visualization experts (Expert IDs: 8, 29, 65, 82, 126), and 4 control flow experts (Expert IDs: 15, 41, 73, 99).

Memory Allocation: Total GPU memory usage: 89.3 GB (85% reduction from 600 GB baseline), Loading time: 12.4 seconds.

2) Step 2: Runtime Expert Activation During Code Generation: **Token Sequence 1-18 (Function Definition):** The runtime controller activates 3 experts (15, 41, 73) focused on Python syntax and function definitions for generating import statements and function signatures.

Token Sequence 19-52 (DataFrame Filtering): Primary data processing experts are activated (12, 47, 89, 15, 41) with average activation of 5 experts per token for pandas operations including boolean indexing.

Token Sequence 53-78 (Conditional Logic): Control flow experts (15, 41, 73, 47) handle conditional branching and simple assignment operations, using 4 experts per token on average.

Token Sequence 79-125 (KMeans Clustering): Peak activation occurs with 7 experts (23, 34, 56, 78, 91, 47, 12) for scikit-learn operations including model instantiation and fitting.

Token Sequence 126-168 (Visualization): Visualization experts (8, 29, 65, 82, 47) are activated for matplotlib operations, using 5 experts per token for plotting and axis customization.

3) Step 3: Performance Metrics and Analysis: The generated code successfully passes all test cases with functional correctness confirmed. The total inference time was 0.74 seconds compared to 2.38 seconds for the baseline (3.2x speedup), while using only 14.8% of the total model parameters. The adaptive expert activation pattern averages 4.9 experts per token versus the baseline's fixed 8, demonstrating intelligent resource allocation based on code complexity and domain requirements.

4) Step 4: Reward Calculation and Learning Update: The reward components include confidence reward (0.91), syntax reward (1.0), execution reward (0.95), and efficiency reward (0.87), resulting in a total reward of +2.73, significantly above the baseline +1.45. This success reinforces the pre-loading controller's preference for multi-domain expert selection and teaches the runtime controller to increase activation during ML-intensive segments while maintaining efficiency during routine operations.

E. Ablation Studies

We conducted comprehensive ablation studies to understand the contribution of different components within *ExpertCache*. Table III presents the results of removing individual components from the complete framework.

TABLE III: Ablation Study Results (Pass@1 with 15% Expert Loading)

Configuration	Pass@1 (%)
ExpertCache (Complete)	34.21
w/o Pre-loading Controller	31.49
w/o Runtime Controller	32.11
w/o Confidence Reward	33.51
w/o Syntax Reward	33.25
w/o Efficiency Reward	33.77
Single-Phase Selection	30.70

The ablation results confirm that both the pre-loading and runtime controllers contribute significantly to overall performance. Removing either controller results in substantial performance degradation, validating our hierarchical approach. The reward component analysis shows that confidence and syntax rewards provide the largest contributions, while the efficiency reward primarily influences expert utilization patterns rather than task performance.

VI. Related Work

The optimization of MoE models has evolved from foundational architectures like Switch Transformer [1], GLaM [6], and BASE Layers [7] to more sophisticated expert selection strategies. Recent advances include MoEfication [8], which demonstrated transformer feedforward layers naturally behave as experts, Expert Choice Routing [9], which inverts traditional routing by allowing experts to choose inputs, and Sparse Upcycling [10], which converts dense models into MoEs. While approaches for instruction tuning [11], vision [12], and graph domains [13] have expanded MoE applications, they typically focus on training-time optimization rather than inference-time memory constraints. Expert pruning [3] provides static size reduction but lacks task adaptability, and existing RL applications to neural architecture optimization [14], [15] do not address the specific challenges of MoE memory constraints.

Memory optimization techniques for large models include gradient checkpointing [16], model parallelism [17], parameter sharing [18], quantization [19], and knowledge distillation [20]. Recent work on scalability includes Moeut [21], which decouples architecture scaling from model size and Tutel [22], which provides an adaptive framework for MoE at scale. However, these approaches often require model retraining or specialized hardware, whereas ExpertCache operates on existing pre-trained MoE models without retraining, uniquely addressing inference-time memory constraints through hierarchical reinforcement learning that optimizes both expert loading and dynamic activation decisions.

VII. Conclusion

This paper introduced ExpertCache, a hierarchical reinforcement learning framework addressing GPU memory constraints in large MoE model deployment. Our two-phase approach decomposes expert selection into memory-aware pre-loading and dynamic runtime activation, achieving 85% memory reduction and 3.2x throughput improvement while outperforming the baseline on Qwen3-235B-A22B using BigCodeBench. Our artifact can be accessed by visit the following link: https://github.com/Daniel4SE/expertcache

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