
GoodServe: Towards High-Goodput Serving of Agentic LLM Inferences over Heterogeneous Resources

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Abstract

Large Language Models (LLMs) play a critical role in emerging agentic applications, where the timely completion of each entire inference is critical. Meanwhile, agentic LLM inferences are increasingly served on heterogeneous GPUs in operators’ resource pools. Therefore, it is crucial to route incoming inference requests to appropriate GPUs so that their end-to-end latency requirements are satisfied whenever possible, thereby achieving high *goodput*. In this paper, we propose *GoodServe*, a goodput-optimized serving system for agentic inferences over heterogeneous resources. *GoodServe* performs inference routing in a *predict-and-rectify* manner. It estimates the request output lengths as well as the GPU serving status in an accurate and also practical manner. Based on information from both the demand and resource sides, it then makes high-quality routing decisions using a *just-enough* instance selection heuristic. It also periodically monitors SLO-violation risks of active requests and triggers runtime request migrations to address unexpected dynamics. Our evaluations show that *GoodServe* improves goodput by up to 27.4% over existing routing methods.

1 Introduction

Agentic applications driven by Large Language Models (LLMs), like code generation [18] and database management [22], are increasingly popular. Unlike chatbot-style inference serving [23], agentic applications often require a *fully-formed* output before downstream tasks can proceed [39, 15]; therefore, service quality is crucially affected by the *end-to-end inference latency* rather than time-to-first-token or time-per-output-token latency. Users often associate end-to-end latency requirements with agentic LLM inferences [37, 39, 5, 3, 1], and it is desirable for the serving system to attain high *goodput*, i.e., to complete as many inferences within their E2E-SLOs as possible. In the meantime, agentic LLM service providers often aggregate all GPUs they own—even across *heterogeneous* generations—into a resource pool to serve a massive number of requests [20, 1]; each request, upon arrival, is routed by the service proxy to a specific GPU instance for execution. Given the output uncertainty and resource heterogeneity, it is challenging to make routing decisions that achieve the best goodput performance.

Regarding multi-instance request routing, existing methods are not designed to optimize the end-to-end SLO performance of agentic LLM inferences, failing to attain high goodput. For example, some routing strategies, like *random* [25], *round-robin* [25], *least-request* [25] and *Llumnix* [30], seek to balance the loads on different instances; some other methods, like *prefix-cache* [25] and *Preble* [29], seek to maximize the local execution efficiency of individual requests. In essence, without awareness

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of end-to-end request SLOs, those methods lack the flexibility to route less-urgent requests to inferior instances; that is, they are incapable of making *locally-suboptimal yet globally-optimal* routing decisions. Therefore, when serving agentic LLM inferences, we need to exploit information from both the *demand* and *resource* aspects, so as to perform *SLO-adaptive* routing to optimize overall goodput.

In this paper, we propose *GoodServe*, a goodput-centric routing system for agentic LLM inferences over heterogeneous GPUs. To that end, we need to acquire the SLO performance of each request if it were routed to any GPU instance, which requires several pieces of future information such as the request decode length, the expected GPU queuing time, and the prefill/decode speed. While it is possible to estimate such information, it is, however, impossible to make fully accurate predictions due to the built-in algorithm and system dynamicity. Therefore, we adopt a *predict-and-rectify* methodology.

Specifically, *GoodServe* consists of three core designs. First, to predict request decode length in an accurate yet also light-weight manner, given that the agentic task type is essentially an implicit precondition crucially affecting the output length, we design a *Mixture-of-Experts* style prediction model, which ensembles multiple *simple-yet-professional* MLPs to make a weighted prediction. Second, in estimating request execution efficiency after being routed to a given GPU, for practicality, we design an *EMA-smoothed, black-box* profiling method, which turns out to be sufficiently accurate for production use. Third, given the estimated demand and resource information, to work out a high-goodput request routing scheme, we propose the *just-enough* instance selection heuristic, which is efficient and also of high quality; to further address the potential demand-prediction error and system-status drift, *GoodServe* periodically re-evaluates the SLO-violation risk of active requests, and launches light-weight, token-ID based request migration when necessary.

We have implemented *GoodServe* in 2.5k LoC, and further evaluated its performance with both testbed measurements and large-scale simulations. Our measurements over heterogeneous GPUs show that, when serving popular agentic LLM workloads, *GoodServe* consistently achieves the best goodput performance under diverse SLO scales, surpassing the second best by up to 27.4%. Meanwhile, our deep-dive experiments do confirm the effectiveness of each *GoodServe* innovation. Moreover, large-scale simulations emulating a 512-instance cluster show that *GoodServe*'s routing overhead is still negligible even under a very high load intensity (5 ms at 10,000 requests per second).

2 Background and Motivation

2.1 Serving Agentic LLM Inferences in Multi-Instance GPUs

In the coming era of agentic AI, LLM inference has become a workhorse workload supporting emerging agentic applications like mathematical reasoning [35], code generation [18] and database management [22]. Compared with conventional LLM inferences supporting chatbot conversations [2], the LLM inferences supporting agentic applications—which we call *agentic LLM inferences*—exhibit two distinct characteristics. First, agentic LLM inferences typically have much longer decode lengths than chatbot inferences, which is highly uncertain a priori. For instance, reasoning models like DeepSeek-R1 [6] generate extensive Chain-of-Thought tokens, where decode lengths vary significantly depending on task difficulty. Second, while for chatbot inferences it is the Time-to-First-Token (TTFT) or Time-Per-Output-Token (TPOT) that matters most, for agentic LLM inferences it is the *end-to-end inference latency* (i.e., Time-to-Last-Token or TTLT) that truly matters for the application-level performance. This shift arises because the downstream agentic executors require fully formed outputs for execution, making their utility binary upon completion [39, 15]. In practice, agentic LLM inferences are often associated with explicit *end-to-end latency* (i.e., E2E-SLO) requirements [37, 39, 5, 3, 1]. When

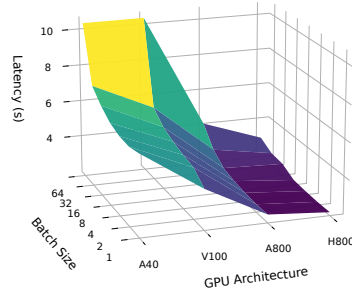


Figure 1: Inference latency across four GPU architectures under varying batch sizes, for a fixed sequence comprising 100 input tokens and 200 output tokens.

serving agentic LLM inferences, it is increasingly significant for the serving system to maximize *goodput* (i.e., the number of requests that satisfy their E2E-SLO requirements).

Meanwhile, confronting booming LLM inference demands, production service providers often maintain a pool of LLM serving instances for parallel request processing; upon the arrival of each LLM inference request, the LLM service proxy needs to route it to one inference backend for execution. In particular, the inference serving capabilities across different instances are often *inconsistent*—due to static hardware heterogeneity and dynamic resource fluctuations. Regarding hardware heterogeneity, since LLM service providers need to persistently purchase new GPUs and the available GPU types keep evolving, the resultant GPU resources available for agentic LLM serving naturally become heterogeneous [20, 1]. For example, Microsoft reports maintaining a heterogeneous cluster comprising diverse (e.g., NVIDIA H100, A100 and AMD MI300X) GPUs to serve its LLM inference workloads supporting Office 365 Copilot function [1]. Regarding resource fluctuations, depending on the instantaneous request intensity (which affects the request batch size served in one iteration), the inference serving speed on a GPU instance is also inconstant at runtime. We note that both the GPU hardware type and batch size configuration do affect the per-iteration inference time; this can be demonstrated by Fig. 1, which shows the per-iteration LLM inference latency across different GPU architectures (A40, V100, A800, and H800) under varying batch sizes.

In summary, when serving agentic LLM inferences in typical multi-instance clusters, given the potential service-backend heterogeneity and the inherent decode-length uncertainty, it is crucial yet also challenging to optimize the request routing policies for the best E2E-SLO goodput. Next, we study the effectiveness of existing request routing methods with regard to that objective.

2.2 Lessons Learned from Existing Request-routing Methods

For request routing, in practice a series of methods has already been proposed. For example, the *random* (Power of Two Choices) [24] and *round-robin* [38] strategies are classical routing methods that seek to evenly distribute requests across instances. Meanwhile, *least-request* and *prefix-cache* are also core routing strategies supported in production frameworks like AIBrix [31]: the former routes incoming requests to the backend with the minimum number of pending requests, and the latter preferentially routes requests to the server with a high cache hit ratio. Besides, the *lowest-TPM* strategy, which is adopted by the LiteLLM system [4], dispatches requests to the backend with the minimum Tokens-Per-Minute (TPM) utilization. The *Preble*-style method [29, 23] further jointly considers prefix cache hits and compute load when selecting the best-performing instance for a request. Moreover, Llumnix [30] is a more advanced scheduler that preferentially routes requests to the instance with the maximum available memory, which also supports runtime migration to alleviate load imbalance during the execution process.

However, the above routing strategies all fall short for our problem in that they are agnostic to the end-to-end SLO requirement of agentic LLM inferences. Specifically, given the highly-uncertain inference output length as well as the dynamic backend status, existing strategies essentially choose to implement simple heuristics that are hardware-aware only (e.g., for balanced hardware utilization). In that sense, they treat all the incoming requests indiscriminately, failing to identify and prioritize those requests that have more urgent SLO requirements. Consequently, given a set of agentic LLM requests with their respective SLO requirements, greedily routing each request to the currently most efficient (lightly loaded) serving instance often leads to suboptimal performance in terms of the overall goodput. To demonstrate this, we conduct a testbed experiment with 4 heterogeneous GPUs. As shown in Fig. 2, compared to an oracle request router that has the ground-truth knowledge of

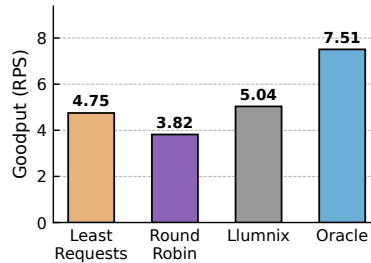


Figure 2: Performance inferiority of existing routing strategies. In total, 600 requests (with an arrival rate of 10 requests per second) are jointly served by four heterogeneous (V100, A40, A800, H800) GPUs. Each request has 100 input tokens and has its output token length randomly sampled from [100, 500]. The E2E-SLO is set to 6s.

the inference generation length and hardware processing capability (routing policy detailed later in Sec. 3.4), those existing routing policies perform substantially worse as measured by goodput.

Given the above study, we learn that to attain good SLO performance for agentic LLM inferences, instead of relying on fixed heuristics, we need to perform SLO-aware request-adaptive routing—by properly exploiting auxiliary information from both demand (i.e., request decode length) and resource (i.e., GPU inference capability) aspects. However, given the inherent dynamicity of inference length and GPU capability aforementioned, it is challenging to make near-optimal routing decisions in practical systems. We next present our solution to address that challenge.

3 Solution

3.1 Overview

Problem formulation. For clarity, we first mathematically formulate our research problem (a detailed symbol table is included in Appendix A.1). Given the request set \mathcal{R} and the GPU instance set \mathcal{G} , we let $x_{r,g} \in \{0, 1\}$ indicate whether request r is routed to GPU- g , and also let $T(r, g)$ be the end-to-end inference latency of request- r when served on GPU- g . Then our optimization objective is to maximize the overall goodput, i.e.,

$$\max_{\{x_{r,g}\}} \sum_{r \in \mathcal{R}} \mathbb{I} \left[\sum_{g \in \mathcal{G}} x_{r,g} T(r, g) \leq D_r \right], \quad (1)$$

where D_r is the E2E-SLO of request- r . Meanwhile, there are two types of constraints. First, a request can only be served by one GPU, i.e., $\sum_{g \in \mathcal{G}} x_{r,g} = 1, \forall r \in \mathcal{R}$. Second, the number of requests that can be concurrently served on each GPU is bounded by its memory capacity [32] (for symbolic clarity we skip the formula here, but this constraint is always complied with in our system).

We further take a closer look at $T(r, g)$, which is jointly affected by the demand volume of request- r as well as the execution status of GPU- g . Specifically, regarding the request demands, we let L_r^{in} and L_r^{out} respectively be the input and output lengths of request- r ; regarding the GPU status, we let p_g and d_g respectively be the average per-token prefill/decode latencies on GPU- g , and q_g be its average request queuing delay. We also take the effect of prefix caching into consideration, which can eliminate the prefill delay upon a cache hit and is therefore commonly adopted in production systems [23]. Suppose $H_{r,g}$ is the hit prefix token length, then we obtain

$$T(r, g) \triangleq q_g + p_g \cdot (L_r^{\text{in}} - H_{r,g}) + d_g \cdot L_r^{\text{out}}. \quad (2)$$

GoodServe workflow. To solve the above optimization problem, a prerequisite is to obtain the coefficients in $T(r, g)$, i.e., q_g, p_g, d_g and L_r^{out} . We note that it is possible to estimate the demand volume and hardware status in advance [14, 33, 7], yet, on the other hand, it is impossible to make 100% accurate prediction. Therefore, in this paper we propose *GoodServe*, which routes agentic LLM inferences in a *predict-and-rectify* manner for the highest goodput. As shown in Fig. 3, *GoodServe* introduces a *RequestStatusMonitor* and a *GPUStatusMonitor* on the proxy router that respectively maintain the demand- and resource-side information. In particular, the *RequestStatusMonitor* predicts request output token lengths (L_r^{out}) with an accurate and light-weight *Mixture-of-Expert-style* predictor (Sec. 3.2); the *GPUStatusMonitor* estimates the average execution status of each GPU (q_g, p_g, d_g) in an *EMA-smoothed, black-box* manner (Sec. 3.3). For each incoming request, the proxy first routes it to the GPU following an effective *just-enough-selection* heuristic, and may also trigger request migrations later based on the refreshed demand and

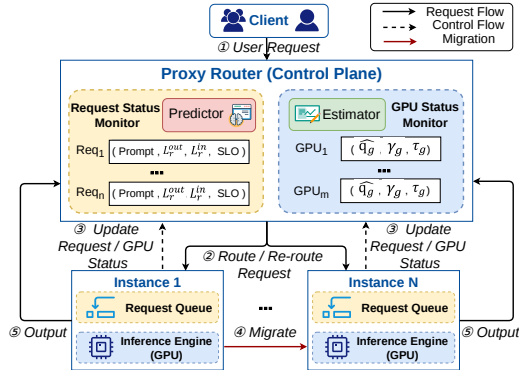


Figure 3: *GoodServe* architecture and workflow.

resource status to ensure SLO attainment (Sec. 3.4). Next we will elaborate on each component in greater detail.

3.2 Mixture-of-Expert-style Output-length Prediction

Output-length prediction is essential for goodput optimization; while 100% accurate prediction is impossible, it is still important to predict as accurately as possible. Compared with conventional chatbot inferences, agentic inferences typically have a much broader output length range (due to diverse task types); meanwhile, given the high request-arrival rate on a proxy router, output length prediction must be simultaneously made light-weight. In the literature, multiple output-length prediction methods have already been proposed. The S^3 work [14] predicts with another fine-tuned large language model (DistilBERT), the *Past-Future* work [7] predicts by referring to historical requests, and the *STAR* work [33] predicts with a 4-layer MLP model. However, all those works fall short for our problem: the DistilBERT-based prediction method incurs high training and inference overheads, whereas history-based and single-MLP-based methods fail to attain high prediction accuracy; to predict the output length of agentic inferences, we need to avoid introducing complex Transformer-like architectures, yet at the same time maintain the flexibility to adapt to diverse task types.

To that end, in *GoodServe* we design a *Mixture-of-Experts*-style predictor. Given the remarkable impact of the inference task type on the output-length distribution, for accuracy we need to treat the task type as a prediction condition: for example, inferences generating database-operating commands [22] usually have short outputs, whereas those for code-generation [18] usually have long outputs. Moreover, such preconditions (sensible from prompts) should be handled *implicitly*, without assuming the recurrence of a fixed task set. Therefore, for high accuracy and efficiency, we use an ensemble of small models and automatically select the best ones for runtime prediction. We note that this aligns well with the design philosophy of *Mixture-of-Experts* architecture [27], which has been widely adopted in modern LLMs [6] given its *Pareto-superiority* in model capability and compute efficiency.

As shown in Fig. 4, our output-length prediction model contains a gating router ($R(\cdot)$) and multiple (K) experts. Given the feature vector \mathbf{h}_r (obtained by conducting *TF-IDF* vectorization [28] over the token window so far) for request r , the router outputs a probability distribution $\mathbf{p}_r \in \Delta^K$ over experts: $\mathbf{p}_r = \text{softmax}(R(\mathbf{h}_r))$, and the final prediction is obtained via a weighted combination of expert outputs: $\hat{y}_r = \sum_{k=1}^K p_{r,k} E_k(\mathbf{h}_r)$. Specifically, the gating router is a two-layer MLP and each expert is a four-layer MLP; in total there are only 45.1M parameters.

Moreover, that predictor is trained in two phases. In the first phase, we partition one half of the dataset into K distinct subsets—by discretizing query (input) and answer (output) lengths into \sqrt{K} tiers (in practice we set K to 9), with each MLP expert trained separately using a specific data subset. In the second phase, with expert parameters frozen, we train the router on the other half of the dataset. Our later evaluations in Sec. 4.3 demonstrate that such a MoE-style predictor can perform well in terms of both accuracy and efficiency.

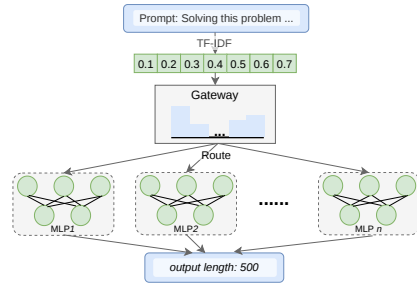


Figure 4: MoE-style output-length predictor.

3.3 EMA-smoothed, Black-box Instance-Capability Estimation

Apart from request-demand prediction, for goodput-optimal serving, we also need to estimate the average execution efficiency after a request is routed to a GPU instance. Specifically, we need to perform *comprehensive* instance status monitoring, covering all the hardware-related coefficients in Eq. 2: q_g , p_g and d_g . However, there are essentially two challenges. First, given the *batched* serving mode in mainstream LLM frameworks like vLLM [32], the actual execution efficiency of request- r on GPU- g is jointly affected by the shape (i.e., L^{in} and L^{out} in Eq. 2) of request- r and the competing requests on GPU- g , making it hard to calculate precisely with the instance configuration

information. Second, an agentic LLM inference may have many decode steps, during which the processing capability of the instance is usually not a constant.

We note that execution efficiency estimation does not need to be highly accurate (it suffices if the instance preference order is valid), but must be *practical*, i.e., easy to implement and adopt in a production environment. Therefore, we make some necessary approximations, trading accuracy slightly for much better practicality. First, since a GPU instance batches many inferences in one iteration and its local configuration rarely changes, given the *Law of Large Numbers* [26], we can view a GPU’s per-iteration time as relatively stable during a short period. Therefore, the estimation of q_g , p_g and d_g can be made in a *black-box* manner—directly from their recent past values, instead of relying on runtime request specifics or engine configurations (e.g., batch size, GPU type and queuing policy). That said, to tackle temporal system jitter, we still adopt *exponential moving average* (EMA) to obtain a smoothed estimation. As shown in Fig. 5, when replaying the realistic Mooncake trace [23] with a mixed BIRD-bench [16] and LiveCodeBench [10] dataset on an NVIDIA A40 GPU, such an *EMA-smoothed, black-box* estimation method indeed works quite well. This way, we can achieve comprehensive and practical estimation of instance serving efficiency.

3.4 Just-enough Instance Selection with Runtime Migration

Even after we have obtained both the demand- and resource-side information, it is still challenging to find the goodput-optimal request routing scheme. First, the exact optimization problem behind Eq. 1 is NP-hard: with binary routing variables and bounded GPU memory/compute capacities, it becomes an integer linear program that couples request assignments across GPUs, and thus cannot be directly solved in polynomial time [39]. Second, our previous request length prediction and resource capability estimation may not be persistently accurate, and a one-shot routing scheme may turn out to fail to meet the E2E-SLO requirement. Now we address these two challenges in turn, with the overall algorithm summarized in Appendix A.2.

First, we propose the *just-enough* heuristic for instance selection to efficiently obtain a near-optimal solution to Problem 1. In fact, while we notice from Fig. 1 that higher-end GPUs in general yield better efficiency for all the requests, completing a request faster than its E2E-SLO requirement, however, does not help improve the overall goodput, which is essentially a waste of high-end resources. Therefore, among the set of candidate instances that can all meet the E2E-SLO requirement of a request, *GoodServe* chooses to route that request to the instance *with the worst computing capability*, thereby opportunistically facilitating the fast completion of other SLO-urgent requests. The per-request routing-decision complexity in this way is only $\mathcal{O}(M)$ in an M -instance cluster.

Second, to tackle the demand prediction error and runtime resource drift, after making the initial routing decision, we continuously track each active request’s SLO-violation risk. Specifically, after every τ (set to 50 by default) inference iterations, we re-estimate the future generation length as well as the GPU processing speed with the methods respectively in Sec. 3.2 and Sec. 3.3. For each ongoing request, if its expected finish time based on the latest estimations exceeds the E2E-SLO, the LLM proxy reroutes that request to another GPU with stronger processing capability (still following the *just-enough* heuristic). In particular, when migrating a pending request to another instance, we choose to transfer the *token IDs* instead of the *intermediate KV cache states*. Since typical agentic LLM inferences have large context lengths and massive decoding iterations [34], the KV cache volume is substantial yet the prefilling time portion is negligible. Therefore, by transferring token IDs instead of the KV cache, we can trade a small prefill overhead for substantially lower communication cost and achieve higher migration efficiency (which we will confirm later in Fig. 9).

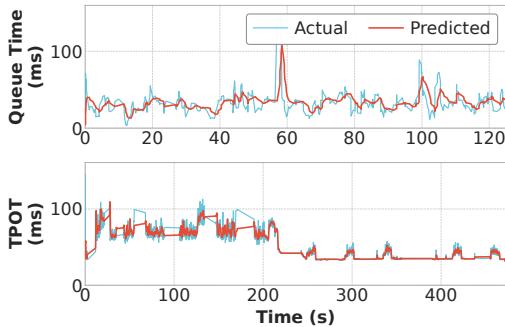
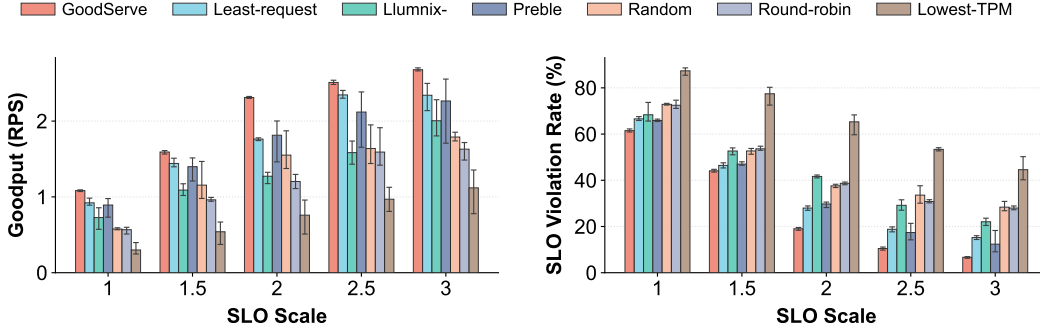
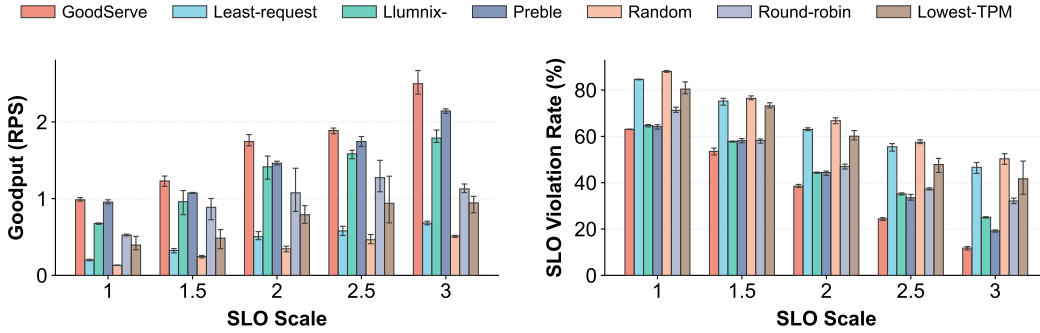


Figure 5: Effect of the EMA-smoothed, black-box estimation method on queuing time and TPOT.



(a) Performance results on Llama3.1-8B-Instruct



(b) Performance results on Qwen2.5-14B-Instruct

Figure 6: End-to-end performance under different request routing methods.

4 Evaluation

4.1 Experimental Setup

Implementation. We implemented *GoodServe* in around 2.5k LoC, and the source code is attached as a supplementary file. The demand predictor was trained on 8680 samples, for 500 epochs with a training time of 25 minutes. Meanwhile, for each ongoing request, its future output length is re-predicted directly on its assigned GPU instance, and all such predictions are batched; such measures can help mitigate the prediction overhead (Fig. 11).

Hardware and models. Our experiments are conducted on a heterogeneous cluster of four instances, each equipped with distinct NVIDIA GPUs: H800 (80GB), A800 (80GB), A40 (48GB), and V100 (32GB, with a TP level of 2). These instances are interconnected by a 10Gbps Ethernet network, and the proxy router is hosted on the A40 instance. We use two representative instruction-tuned models, Llama3.1-8B-Instruct [8] and Qwen2.5-14B-Instruct [36], as backend LLMs.

Workloads. We construct a mixed workload suite from three popular agentic benchmarks: BIRD-bench [16], SWE-bench [13] and LiveCodeBench [10]. We replay the Mooncake production traces [23] to set the request submission time. To set the E2E-SLOs, following established methodologies [17, 21, 40], we first measure the median request execution time by running each request alone on a mid-tier GPU (NVIDIA A800), and then scale that base latency by multiple relaxation factors ($1\times$, $1.5\times$, $2\times$, $2.5\times$ and $3\times$) to emulate diverse SLO urgency levels. The temperature is set to 0 to ensure output consistency across the deadline-setting stage and the testbed-measurement stage.

Baselines and Metrics. We compare *GoodServe* with diverse baselines described in Sec. 2.2: the built-in *random* and *least-request* methods in AIBrix [31], as well as the *round-robin* [38], *lowest-TPM* [4], *Preble* [29] and *Llumnix* [30] methods. Meanwhile, we adopt two metrics: (1) *goodput*, which is the average number of requests completing within their E2E-SLO *per second*, and (2) *SLO violation ratio*, which is the overall ratio of requests failing to satisfy the E2E-SLO requirements.

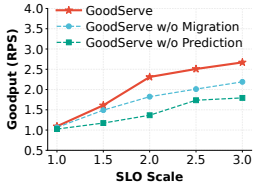
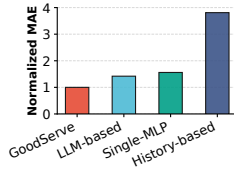


Figure 7: Effectiveness of prediction and migration innovations in *GoodServe*.



(a) Prediction error. Figure 8: Accuracy and overhead comparison among different prediction methods.

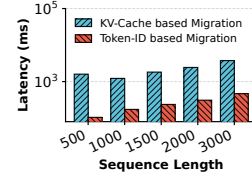
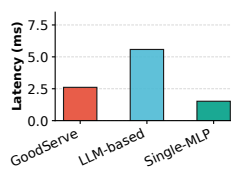


Figure 9: Average migration latency under different state transferring methods.

4.2 End-to-End Performance

In Fig. 6, we depict the end-to-end results across different SLO scales for both 8B and 14B models. We repeat each experiment five times and report the max/min values as error bars. As shown in Fig. 6, *GoodServe* consistently delivers the best goodput and the lowest SLO violation rate. For example, for the 8B model at a medium SLO scale of 2, *GoodServe* surpasses the second-best (*Preble*) by 27.4% in goodput. Meanwhile, we note that under looser SLO requirements the benefit of *GoodServe* generally becomes larger: as the SLO scale increases from 1 to 3 for the 14B model, the goodput improvement of *GoodServe* over the second best increases from 3.1% to 16.6%. This is because a looser SLO requirement allows for more *locally-suboptimal* yet *globally-optimal* routing decisions, which existing SLO-unaware methods all fail to make.

4.3 Deep Dive Experiments

In this part, we conduct a series of deep-dive experiments. Unless otherwise specified, we use the 8B model at an SLO scale of 3.

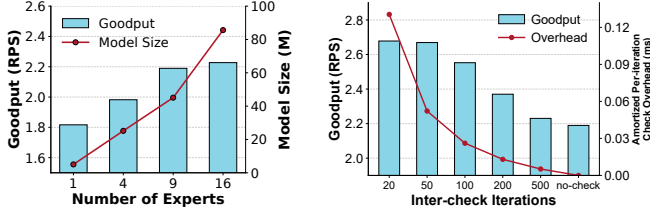
Ablation study. Recall that we have adopted an MoE-style request length predictor and also enabled runtime migration to improve robustness. To evaluate their necessity, we create two variants of *GoodServe*: (1) *GoodServe without prediction*, which replaces the original predictor with a history-based one [7] (for our problem, prediction itself cannot be disabled), and (2) *GoodServe without migration*, which disables runtime request migration. As shown in Fig. 7, both innovations are indispensable. For example, at an SLO scale of 3, removing the MoE-style predictor reduces the goodput by 32.8%, and removing the runtime migration functionality reduces the goodput by 18.0%. We note that their importance increases under looser SLOs, because a looser SLO allows for more flexible routing optimizations.

Superiority of our MoE-style demand predictor. We check the superiority of our MoE-style predictor over the other ones discussed in Sec. 3.2, in terms of both accuracy and overhead. Fig. 8 shows the normalized *Mean Absolute Error* (MAE) for different predictors. It suggests that our MoE-style predictor adopted in *GoodServe* can yield the best accuracy—with an error reduction of 1.4 \times compared to the LLM-based one [14], and up to 3.8 \times compared to the history-based one [7]. Meanwhile, its prediction latency (around 2.5 ms per request) is lower than the LLM-based one. Furthermore, replacing our predictor with the LLM-based, Single-MLP, and history-based ones reduces the goodput by 13.8%, 17.0%, and 18.1%, respectively.

Superiority of our Token-ID based request migration method. Recall that in Sec. 3.4, for request migration we choose to transfer the Token-IDs instead of the KV cache. To evaluate its superiority, we refer to Fig. 9, which shows the average migration latency for requests of different lengths. Compared with the KV-cache-based method, token-ID based migration achieves 7.1 \times to 15.3 \times lower latency.

Hyper-parameter sensitivity analysis. *GoodServe* introduces two hyper-parameters: the number of experts K in the predictor (Sec. 3.2), and the status checking frequency τ (Sec. 3.4). Here we evaluate *GoodServe*'s performance by varying their values. As shown in Fig. 10a, while adopting more experts can yield higher accuracy and consequently higher goodput, $K = 9$ can already yield sufficiently good performance, much better than $K = 4$ yet comparable to $K = 16$. Meanwhile, regarding τ , Fig. 10b suggests that a higher checking frequency does improve goodput.

Overhead analysis with large-scale simulation. In production clusters, there may be hundreds of instances. Since our core innovation lies in the proxy router instead of on the serving engine, to check



(a) Number of experts. (b) Status recheck interval.

Figure 10: Hyper-parameter sensitivity analysis.

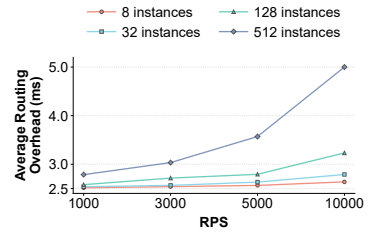


Figure 11: Routing overheads at varying cluster size and request intensity.

GoodServe's scalability we resort to large-scale simulations. Specifically, we configure a set of virtual IPs each corresponding to a simulated local inference engine. We respectively simulate 8, 32, 128 and 512 instances, and for each case we vary the RPS from 1000 to 10000—all requests handled by a single router. As shown in Fig. 11, thanks to the lightweight prediction model (Sec. 3.2), the simple heuristic (Sec. 3.4) as well as the implementation optimizations (distributed and batched predictor execution), the routing overhead of *GoodServe* is indeed quite small: the per-request routing latency is still marginal (5.0 ms) even when serving highly-intense workloads (RPS=10000) over 512 nodes.

5 Additional Related Works and Discussions

Related works on cost-efficient provisioning of heterogeneous GPU resources. While we focus on request routing over heterogeneous GPUs, in the literature some other works have explored how to compose a heterogeneous cluster for the best cost-efficiency. Specifically, Mélange [9] formulates GPU selection as a cost-aware bin-packing problem, and recent MILP-based studies [12] co-optimize GPU composition, deployment configuration, and workload assignment. SageServe [11] and *llm-d* [19] further use traffic forecasts or autoscaling signals to decide how many model variants or GPU instances should be provisioned. *GoodServe* addresses a complementary problem where the GPU composition is an *input condition* rather than an *optimization target*. It minimally intrudes on the instance-level LLM service engine. Moreover, *GoodServe* is also the first routing-optimization work to target agentic LLM inferences for which TTLT is the primary efficiency concern.

Compatibility of *GoodServe* with diverse scenarios: for inferences without E2E-SLOs, in homogeneous clusters, and for PD-disaggregated setups. While in this paper we focus on serving agentic LLM inferences with E2E-SLO requirements, *GoodServe* can work smoothly for inferences without E2E-SLOs. For those LLM inferences, we can still follow the conventional routing methods, which do not affect the functionality of each *GoodServe* component. Moreover, by proactively scheduling non-urgent agentic LLM inferences to inferior instances, we can in fact help to attain better TTFT or TPOT performance for chatbot-style inferences. Meanwhile, we note that our solution can also be used in homogeneous clusters, because at each instant, the local queuing time and batch size may still be inconsistent across different GPU instances, rendering their computing capacities still heterogeneous for an individual request. Besides, PD-disaggregated serving is also a popular technique that can avoid prefill-decode interference [23]. While we assume PD-multiplexed setups in this paper, we note that *GoodServe* can be extended to work in PD-disaggregated setups: by modifying Eq. 2, we can respectively model the true prefill (decode) time on the prefill-only (decode-only) instance for each candidate routing scheme, and our *just-enough* heuristic can be similarly applied.

Limitation: no admission control mechanism. For requests that are impossible to meet the SLO requirements based on the predicted information, *GoodServe* chooses to route them to the most capable instance to provide best-effort service. However, since completing a request later than its E2E-SLO does not help improve goodput, a better choice is simply to eliminate it from being served. We do not implement that mechanism because we admit that our predictions are not always accurate, and thus admission control itself can be risky. We will explore that in the future.

6 Conclusion

In this paper, we present *GoodServe*, a goodput-oriented serving system for agentic LLM inferences over heterogeneous GPUs. *GoodServe* works in a *predict-and-rectify* manner. It first uses an *MoE-style* predictor to predict the request output lengths in a light-weight and accurate manner. It then adopts an *EMA-smoothed, black-box* method to comprehensively and also practically estimate the instance serving efficiency. Finally, it applies the *just-enough* instance selection heuristic to optimize the overall service goodput, which is strengthened by a runtime request migration mechanism for robustness against prediction errors and system instability. Evaluation results show that *GoodServe* can enhance the overall goodput by up to 27.4%, with negligible overhead even in large-scale clusters.

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A Appendix

A.1 Notations used in *GoodServe*

Notation	Description
r	Request index
g	GPU index
\mathcal{R}	Set of requests
\mathcal{G}	Set of available GPU backends
D_r	End-to-end latency deadline (SLO) of request r
L_r^{in}	Input (prompt) length of request r
L_r^{out}	Predicted output tokens of request r
$H_{r,g}$	Reusable prefix cache length on backend g
q_g	Estimated queuing delay on backend g
p_g	Average per-token prefill latency on backend g
d_g	Average per-token decode latency on backend g
$x_{r,g}$	Binary routing variable: 1 if request r is assigned to backend g
$T(r, g)$	Predicted end-to-end latency if routing request r to backend g
$\mathbb{I}[\cdot]$	Indicator function, equals 1 if the condition holds

Table 1: Notation used in the routing formulation of *GoodServe*.

Table 1 summarizes the key notations used in the routing problem formulation and instance selection described in Section 3.1.

A.2 Scheduling Algorithm

Algorithm 1 Backend Selection Algorithm

```

1:  $\mathbf{h}_r \leftarrow \text{BUILDFEATURES}(r); L_r^{\text{out}} \leftarrow \mathcal{P}(\mathbf{h}_r)$ 
2:  $\mathcal{C} \leftarrow \emptyset$ 
3: for all  $g \in \mathcal{G}$  do
4:    $w_g \leftarrow \text{AVGWAITTIME}(g)$ 
5:    $q_g \leftarrow \alpha w_g + (1 - \alpha)q_g$ 
6:    $H_{r,g} \leftarrow \text{REUSEPREFIX}(r, g)$ 
7:    $T(r, g) \leftarrow q_g + p_g \cdot (L_r^{\text{in}} - H_{r,g}) + d_g \cdot L_r^{\text{out}}$ 
8:   if  $T(r, g) \leq D_r$  then
9:      $\mathcal{C} \leftarrow \mathcal{C} \cup \{g\}$ 
10:  end if
11: end for
12: if  $\mathcal{C} \neq \emptyset$  then
13:    $g^* \leftarrow \arg \max_{g \in \mathcal{C}} d_g$ 
14: else
15:    $g^* \leftarrow \arg \min_{g \in \mathcal{G}} (T(r, g) - D_r)$ 
16: end if
17: return  $g^*$ 

```

As discussed in Section 3.4 and shown in Algorithm 1, given an incoming request r , *GoodServe* first constructs the request feature vector \mathbf{h}_r , and uses the predictor $\mathcal{P}(\cdot)$ to estimate the remaining output length L_r^{out} . For each backend $g \in \mathcal{G}$, the scheduler continuously maintains an estimated queuing delay q_g using exponential smoothing over the observed waiting time. It then computes the reusable prefix length $H_{r,g}$ and estimates the prefill latency as $T^{\text{prefill}}(r, g) = p_g(L_r^{\text{in}} - H_{r,g})$. Based on the estimated queuing delay, prefill latency, and decoding cost, the scheduler predicts the end-to-end latency as $T(r, g) = q_g + T^{\text{prefill}}(r, g) + d_g \cdot L_r^{\text{out}}$.

A backend is considered feasible if $T(r, g) \leq D_r$. Among all feasible backends, *GoodServe* selects the backend with the largest TPOT d_g to maximize serving efficiency while satisfying the latency

deadline. If no feasible backend exists, the scheduler falls back to the backend that minimizes the deadline violation, i.e., $\arg \min_{g \in \mathcal{G}} (T(r, g) - D_r)$.