

ServerlessLLM: Locality-Enhanced Serverless Inference for Large Language Models

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Abstract

This paper presents ServerlessLLM, a locality-enhanced serverless inference system for Large Language Models (LLMs). ServerlessLLM exploits the substantial capacity and bandwidth of storage and memory devices available on GPU servers, thereby reducing costly remote checkpoint downloads and achieving efficient checkpoint loading. ServerlessLLM achieves this through three main contributions: (i) *fast LLM checkpoint loading* via a novel loading-optimized checkpoint format design, coupled with an efficient multi-tier checkpoint loading system; (ii) *locality-driven LLM inference with live migration*, which allows ServerlessLLM to effectively achieve locality-driven server allocation while preserving the low latency of ongoing LLM inference; and (iii) *locality-aware server allocation*, enabling ServerlessLLM to evaluate the status of each server in a cluster and effectively schedule model startup time to capitalize on local checkpoint placement. Our comprehensive experiments, which include microbenchmarks and real-world traces, show that ServerlessLLM surpasses state-of-the-art systems by 10 - 200X in latency performance when running various LLM inference workloads.

1 Introduction

Large Language Models (LLMs) have recently been incorporated into various online applications, including programming assistants [23], search engines [16], and conversational bots [51]. These applications process user inputs, like questions, by breaking them down into tokens (e.g., words). LLMs respond in an autoregressive fashion, predicting each subsequent token based on the combination of input tokens and those generated so far, until a sentence-ending token (EoS) is reached. To streamline this process, LLMs employ key-value caches to store intermediate results, reducing the need for repeated computations.

Serving LLM inference at scale is a challenging problem, given the substantial GPU resources it requires and the low response time constraints such interactive services need to

satisfy. Furthermore, LLM inference latency is difficult to predict because their response time depends on the output length, which can vary significantly [24, 39, 77], due to iterative output token generation. To achieve low latency, processing an LLM request often necessitates the use of several GPUs for durations ranging from seconds to minutes. In practice, LLM service providers need to host a large number of LLMs catered to different developers, leading to significant GPU consumption [15] and impeding the sustainability of LLM services [19]. As a result, LLM inference services have to impose strict caps on the number of requests sent to their services from their users (e.g., 40 messages per 3 hours for ChatGPT [51]), showing the provider’s current inability to satisfy the LLM inference demand. Researchers [19] project that LLM inference costs may increase by $> 50\times$ when it reaches the popularity of Google Search.

To reduce GPU consumption, LLM service providers are exploring serverless inference, as seen in systems like Amazon SageMaker [60], Azure [46], KServe [11] and HuggingFace [31]. In such setup, developers upload their LLM checkpoints, including model execution files and model parameter files, to a storage system. Upon receiving a request, the system uses a model loading scheduler to allocate available GPUs for starting up these checkpoints. A request router then directs the inference request to the selected GPUs. Using serverless method enables providers to efficiently multiplex LLMs on shared GPUs, enhancing utilization. Additionally, it offers cost benefits to the developers, who pay only per request processed, avoiding the expense of long-term GPU reservations.

While serverless inference holds promise for LLMs, it introduces significant latency overheads. LLM checkpoints, which range from gigabytes [4, 72, 86] to terabytes [26] in size due to their significant number of parameters, incur considerable delays when downloaded from remote storage. Moreover, these checkpoints consist of numerous tensors, each with varying structures and sizes. The process of loading tensors onto GPUs (often involving file deserialisation, memory allocation, tensor shape parsing, and more) further contributes to delays.

We aim to enhance locality in serverless inference for

LLMs. Notably, GPU-based inference servers feature multi-tier storage architecture which has substantial host memory and storage capabilities, yet these resources are underutilized in systems like KServe [11] and Ray Serve [68]. Typically, only part of the host memory is used during model inference, and SSDs are minimally employed for caching checkpoints downloaded from the model repository. This underutilization led us to a new system design approach: leveraging the multi-tier storage architecture for local checkpoint storage and utilizing their significant storage bandwidth for efficient checkpoint loading.

However, this design approach raises several open concerns: (i) Given the complex storage architecture of a GPU server, which includes multiple GPUs, DRAM, SSDs, and remote storage, all interconnected through various connections like PCIe, NVMe and networks, how can we optimize LLM checkpoint loading to fully leverage the available bandwidth? (ii) Opting for servers with pre-loaded checkpoints can improve locality in serverless inference systems, but this might cause GPU contention because these servers have ongoing LLM inferences with unpredictable completion times. How do we effectively handle such GPU contention? (iii) In a distributed cluster tasked with loading a model for request processing, what strategy should be employed to select GPUs to minimize the latency of starting up the model?

To address the above, we introduce ServerlessLLM, a locality-enhanced serverless inference system for LLMs. We make several contributions in designing ServerlessLLM:

(1) Fast LLM checkpoint loading. ServerlessLLM can maximize the storage bandwidth usage of GPU servers for LLM checkpoint loading. It introduces (i) a new *loading-optimized checkpoint* that supports sequential, chunk-based reading and efficient tensor in-memory addressing, and (ii) an *efficient multi-tier checkpoint loading system* that can harness the substantial capacity and bandwidth on a multi-tier memory hierarchy, through an in-memory data chunk pool, memory-copy-efficient data path, and a multi-stage data loading pipeline.

(2) Locality-driven LLM inference with live migration. We motivate the need for live migration of LLM inference and are the first to implement LLM live migration in serverless inference systems to enhance the performance when supporting locality-driven inference. The live migration is realized using two new mechanisms: (i) *efficient token-based migration* which determines the smallest necessary set of tokens for accurately moving LLM inference to another server, and (ii) *two-stage live migration* enabling the transfer of LLM inference without impacting the user experience in online applications.

(3) Locality-aware server allocation. ServerlessLLM aids the model loading scheduler in serverless inference systems by enabling latency-preserving, locality-driven server selection. It integrates models for accurately estimating the time of loading checkpoints from different tiers in the storage hier-

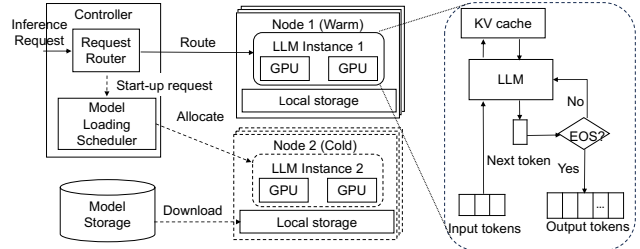


Figure 1: Overview of LLM serverless inference systems

archy and the time of migrating an LLM inference to another server. Based on the estimation results, ServerlessLLM can choose the best server to minimize model startup latency.

In our comprehensive evaluation of ServerlessLLM, we compared it against various baseline methods for running diverse LLM inference workloads in a GPU cluster. Micro-benchmark tests reveal that ServerlessLLM’s rapid LLM checkpoint loading significantly outperforms existing systems like Safetensors [32], and PyTorch [56], achieving 3.6-8.2X faster loading time performance. This is particularly notable with models such as OPT [86], LLaMA-2 [72], and Falcon [4].

Finally, we evaluated ServerlessLLM with real-world serverless workloads, modelled on the public Azure Trace [61], and benchmarked it against KServe, Ray Serve, and a Ray Serve variant with local checkpoint caching. In these scenarios, ServerlessLLM demonstrated a 10-200X improvement in latency for running OPT model inferences across datasets (i.e., GSM8K [22] and ShareGPT [78]). This shows ServerlessLLM’s effectiveness, combining fast checkpoint loading, efficient inference migration, and optimized scheduling for model loading. ServerlessLLM’s source code is in progress of releasing at <https://github.com/ServerlessLLM/ServerlessLLM>.

2 Background and Motivation

2.1 Serverless LLM Inference

Figure 1 shows the overview of a serverless LLM inference system. First, an LLM inference request carries a user-specified input prompt, i.e., a list of tokens, based on which an instance of an LLM service iteratively generates tokens, one token per iteration, based on the prompt and all the previously generated tokens, until the end-of-sentence token (denoted as EoS) is generated, making the total inference time non-deterministic [39, 53]. In each iteration, LLM caches intermediate computations in a KV cache to speed up the next token generation [39, 54].

LLM inference services are highly compute and memory-capacity intensive, often requiring many GPUs, the number of which needs to be adjusted based on demand, to satisfy the compute and memory-capacity requirements. First, LLMs have a large memory footprint featuring billions of parameters

[17, 21, 26, 71, 72]. Second, LLM inference often powers up interactive services, often characterized by highly dynamic, bursty traffic. The necessity to serve LLM inference requests under strict SLOs at a minimal cost makes LLM inference service scaling a challenge for application developers [14, 15].

To tackle the LLM inference scaling challenge, cloud providers deploy LLMs as a service, i.e., in a serverless manner where the cloud infrastructure can monitor inference request traffic to many LLM inference services deployed in a shared cluster of GPUs (or custom inference accelerators). In a typical serverless LLM inference system (as shown in Figure 1), the controller that receives inference requests and dispatches them to GPU-equipped nodes in a shared cluster running LLM inference service instances, and cloud storage that hosts model checkpoints.

The controller features two components, namely *request router* and *model loading scheduler*. The request router steers incoming requests to the nodes already running LLM inference service instances, further referred as *warm* nodes, or asking the model loading scheduler to spin up more instances of the LLM service experiencing a load spike. The model loading scheduler allocates nodes from the unallocated, *cold* node pool to start new LLM service instances. The node selected by the scheduler launches a new inference process in a container and initializes the runtime environment. The process then downloads the requested model’s checkpoint from the cloud storage and loads it into the GPU memory.

2.2 Problems with Serverless LLM Inference

A serverless inference cluster can multiplex a large number of LLMs on shared GPU servers, showing the promise of largely improving resource utilization and reducing the cost of deploying LLMs. This approach benefits from the dynamic allocation of resources, allowing for more efficient use of GPU servers and potentially lowering user expenses.

While promising, deploying LLMs onto serverless inference systems often incurs substantial latency overheads. We observed several primary reasons:

(1) Costly checkpoint download from model repositories. Serverless functions are designed to separate computation and data. AWS, for example, recommends downloading large data from S3 [5, 6]. For instance, downloading an LLM checkpoint with size 130GB (e.g., LLaMA-2-70B [72]) from S3 or blob storage takes at least 26 seconds with a fast commodity network (5GB/s [14]).

(2) Costly checkpoint loading from storage devices. Even model checkpoints can be stored locally in NVMe SSDs, loading checkpoints into GPU still takes more than tens of seconds (detailed in §7.2). For example, loading OPT-30B into 4 GPUs takes 34 seconds using PyTorch, and LLaMA-2-70b into 8 GPUs takes 84 seconds. On the other hand, the inference latency per token is around 100ms [41], which is

significantly smaller than the loading latency. Additionally, the startup latency of a serving instance (often a container or process) often takes several seconds [41], with the potential to be further reduced to below a second [42, 64, 76]. Hence, a significant component of LLM startup latency is attributed to the loading of a checkpoint.

2.3 Current Solutions

To improve the latency performance when supporting LLMs, existing solutions show a variety of issues:

(1) Over-subscribing model instances. The existing solutions [7, 79], designed to avoid model download and loading in a serverless inference cluster, often involve over-subscribing GPUs, creating an excessive number of model replicas for peak demand. For example, AWS Serverless Inference [7] can keep a certain number of warm instances to mitigate the effects of slow cold starts. While this approach is feasible for conventional small models (e.g., ResNet [30]), it becomes problematic for LLMs due to their significantly higher demand on expensive GPUs.

(2) Caching models in host memory. Additionally, there are solutions [29, 36, 83] that maintain model checkpoint caches in the host memory of GPU servers, thereby avoiding model downloads. While being effective for conventional small models (e.g., up to a couple of GBs [36]) or LoRA adapters [62], relying on a host-memory-based cache only is not sufficient for LLMs. With LLMs, cache misses are common in these systems, resulting in excessive model downloads, and compromising model startup latency (with more details presented in §7.4).

(3) Deploying additional storage servers. There are solutions [14] advocating for the deployment of additional storage servers to cache model checkpoints in a local cluster. However, recent trace studies [14] have revealed that downloading a model can take over 20 seconds through an optimized pipeline connected to local commodity storage servers, even if it is equipped with a 100 Gbps NIC. While the further adoption of high-speed networks (e.g., 200 Gbps Ethernet or InfiniBand) can reduce this latency, the cost of deploying the additional storage servers and high-bandwidth networks often incurs formidable expenses [13, 28].

3 Locality-Enhanced Serverless Inference

We now introduce ServerlessLLM – a novel low-latency serverless inference system designed for LLMs. ServerlessLLM addresses the two issues we highlighted in the previous section – very high model download time and inefficient loading the model into the GPU memory from the local storage.

Our design is motivated by a simple observation that GPU-based servers used for inference incorporate a multi-tier storage hierarchy having substantial capacity and bandwidth.

From a capacity perspective, GPU servers are integrated with substantial memory capabilities, hosting terabyte-scale memory, tens of terabytes in NVMe SSDs, and up to hundreds of terabytes in SATA SSDs [49]. From a bandwidth perspective, GPU servers often comprise several GPUs, each connected to the host memory via a dedicated PCIe link. Similarly, NVMe SSDs also connect via their own PCIe channels. For instance, an 8-GPU server with PCIe 4.0 offers 256GB/s bandwidth between host memory and GPU, and 10-30 GB/s between host memory and NVMe SSD (in RAID 0). The Grace-Hopper architecture improves CPU-GPU bandwidth to 900GB/s [48]. Additionally, we observe that in serverless inference context, a significant portion of the GPU servers’ host memory and storage devices are under-utilized, leaving a significant portion of the bandwidth and capacity unused.

Based on the above observation, we want to explore *locality-enhanced serverless inference for LLMs* where the system exploits the unused capacity and bandwidth to store the models locally and load the models faster, thereby reducing the latency. In realizing our design, we anticipate three important concerns that our design should consider.

(1) Multi-tiered storage hierarchy support. Existing checkpoint and model loaders such as PyTorch [56], TensorFlow [70], and ONNX Runtime [59] primarily focus on facilitating the training and debugging of models. However, these tools are not optimized for reading performance, which becomes a significant issue in a serverless inference environment. In such environments, model checkpoints are stored once but need to be loaded and accessed repeatedly across multiple GPUs. This lack of optimization for read operations leads to substantial loading delays, impacting overall efficiency. Solutions such as Safetensors [32] can improve loading performance. However, as we show in Section 7, they still do not exploit the full potential of the multi-tiered memory hierarchy. ServerlessLLM design needs to consider performance as a key aspect such that it can harness the entire memory hierarchy’s capacity and bandwidth efficiently. To address the concern, we discuss the design of loading optimized checkpoints and the model manager in Section 4.

(2) Strong locality-driven inference. Designing an efficient model loader is not enough; one needs to have a central entity that can recognize the checkpoint placements and the current load on each GPU server to enhance locality-driven inference. Existing serverless systems randomly assign models to available GPUs overlooking the locality factor. Despite cluster scheduling systems such as Sparrow [52] focusing on locality optimization, they cause significant queuing delays if the assigned GPU is busy. Distributed model serving systems (such as ClockWork [29] and Shepherd [85]) can consider locality. They however either rely on the accurate prediction of model inference time, making them struggle with LLMs, or they preempt ongoing model inferences, leading to significant downtime and redundant computations. Hence, Serverless-

LLM needs to accommodate a new approach that prioritizes checkpoint locality while avoiding interrupting ongoing LLM inference. We discuss the design of such an approach in Section 5.

(3) Resource allocation optimized for locality. Serverless-LLM is designed to minimize the model startup latency by leveraging the local checkpoint placement. The model loading scheduler plays a crucial role in allocating GPU resources to achieve that goal. However, the scheduler needs to allocate resources after careful consideration of the entire cluster status. Many factors may influence the overall startup latency, such as the difference in the bandwidth offered by each layer in the memory hierarchy. There may be instances where it is beneficial to move the current inference execution to a new GPU than to allocate the request to a GPU where the model may have to be loaded from the storage media. Hence, ServerlessLLM needs to accurately estimate the startup times considering the cluster status and accordingly allocate resources to minimize startup time. We discuss the design of such a startup-time-optimized allocation approach in Section 6.

Summary. ServerlessLLM ensures that the model loading time is minimal to improve the overall latency by harnessing the memory and storage capacity and bandwidth available on the local GPU. The model manager we describe next handles efficient loading of the checkpoints. ServerlessLLM relies on the modified scheduler to ensure that the inference requests are assigned to those GPUs that already have the model data stored locally to avoid downloading.

4 Fast LLM Checkpoint Loading

We create loading-optimized checkpoints for efficient loading with a model manager and further enhance performance with an efficient multi-tier checkpoint storage system.

4.1 Loading-Optimized Checkpoints

We operate under a set of assumptions about the checkpoints. The checkpoints have: (i) *Model execution files* which define the model architecture. Depending on the framework, the format varies; TensorFlow typically uses protobuf files [69], while PyTorch employs Python scripts [55]. Beyond architecture, these files detail the size and shape of each tensor and include a model parallelism plan. This plan specifies the target GPU for each tensor during checkpoint loading. (ii) *Model parameter files* which stores the binary data of parameters in an LLM. Tensors within these files can be arranged in any sequence. Runtimes such as PyTorch may also store tensor shapes as indices to calculate the offset and size for each tensor.

ServerlessLLM converts the given checkpoint into a new loading-optimized format. The conversion has two primary goals: (i) *Support sequential chunk-based reading*: To ensure

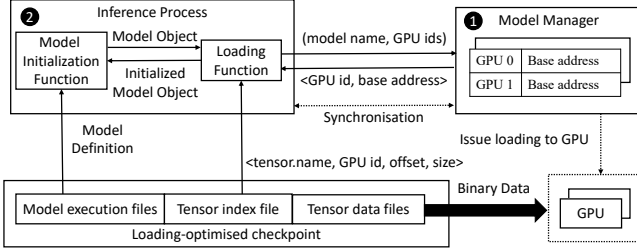


Figure 2: Checkpoint loading process.

efficient sequential reading, tensors for each GPU are grouped in separate files. These files contain only the binary data of model parameters and exclude metadata such as tensor shapes, facilitating large chunk reading. (ii) *Support efficient tensor addressing*: We create an index file that maps tensor names to a tuple of GPU id, offset, and size, facilitating the efficient restoration of tensors. The tensors are aligned with memory word sizes, facilitating direct computation of memory address and avoiding deserialization.

ServerlessLLM has an in-server model manager to load the loading-optimized checkpoints. The loading process is illustrated in Figure 2. ServerlessLLM model manager allocates memory on GPUs and preloads the binary data of the checkpoints (see ①). The preloading operation can benefit from the sequential chunk-based read design. While the model is needed, the inference process can efficiently obtain the memory address of the checkpoints in the GPU (see ②). Specifically, ServerlessLLM provides a loading function for LLM libraries. This function acquires the base addresses for each GPU (i.e., CUDA IPC handles). By querying the tensor index file, this function iterates through the model and set each tensor’s memory address (i.e., $base + offset$). To ensure the model is fully initialized before inference, the inference process and the model manager perform a synchronization.

4.2 Efficient Multi-Tier Checkpoint Loading

To boost the checkpoint loading, we design an efficient multi-tier checkpoint loading subsystem, integrated within the model manager. This subsystem incorporates several techniques:

In-memory data chunk pool. We’ve developed an in-memory data chunk pool in ServerlessLLM with three main goals: (i) *Utilizing parallel PCIe links*. To mitigate the bottleneck caused by a single PCIe link from storage when loading multiple models into GPUs, we employ parallel DRAM-to-GPU PCIe links to facilitate concurrent checkpoint loading across GPUs. (ii) *Supporting application-specific controls*. Our memory pool surpasses simple caching by providing APIs for the allocation and deallocation of memory. This enables fine-grained management of cached or evicted data chunks, based on specific requirements of the application.

(iii) *Mitigating memory fragmentation*. We address latency and space inefficiencies caused by memory fragmentation by using fixed-size memory chunks for allocation and deallocation.

Efficient data path. We’ve created an efficient data path in our model manager with two main strategies: (i) *Exploiting direct file access*. We use direct file access (e.g., ‘O_DIRECT’ in Linux) to avoid excessive data copying by directly reading data into user space. This method outperforms memory-mapped files (mmap), currently adopted in high-speed loaders such as Safetensors [32], which rely on system cache and lack consistent performance guarantees (critical for low latency scenarios). (ii) *Exploiting pinned memory*. We utilize pinned memory to eliminate redundant data copying between DRAM and GPU. This approach allows direct copying to the GPU with minimal CPU involvement, ensuring efficient use of PCIe bandwidth with a single thread.

Multi-stage data loading pipeline. We accommodate a multi-stage data loading pipeline to maximize throughput: (i) *Support for multiple storage interfaces*. ServerlessLLM offers dedicated function calls for various storage interfaces, including local storage (e.g., NVMe, SATA), remote storage (e.g., S3 object store [5]), and in-memory storage (pinned memory). It utilizes appropriate methods for efficient data access in each case. (ii) *Optimization for intra-stage throughput*. To leverage modern storage devices’ high concurrency, ServerlessLLM employs multiple threads for reading data within each storage tier, improving bandwidth utilization. (iii) *Efficient inter-stage coordination*. ServerlessLLM uses a task queue-based pipeline for extensibility and low latency. Loading threads read storage chunks and enqueue their indices (offset and size) for the loading threads in the next tier.

5 Locality-Driven LLM Inference with Live Migration

In this section, we describe how ServerlessLLM achieves live migration for LLM inference, which enables locality-driven model startup while avoiding affecting ongoing LLM inference.

5.1 Need for Live Migration

We consider a simple example to analyze the performance of different current approaches in supporting the checkpoint locality. In this example, we have two servers (named Server 1 and Server 2) and two models (named Model A and Model B), as illustrated in Figure 3. Server 1 currently has Model A in DRAM and Model B in SSD and its GPU is idle, while Server 2 currently has Model B in DRAM, and its GPU is running the inference of Model A.

In Figure 3, we analyze the performance of potential policies for starting up Model B. Our analysis is based on their

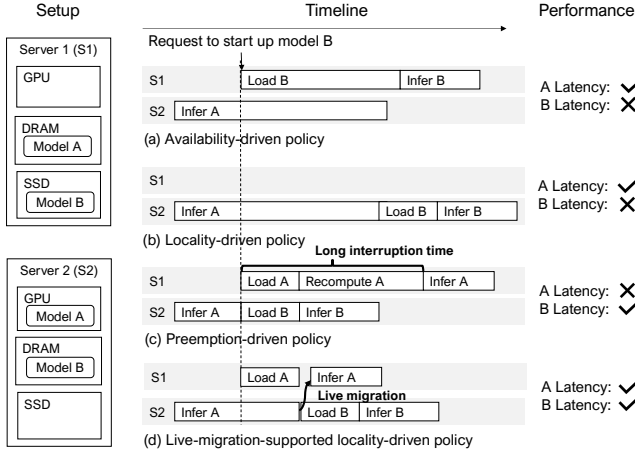


Figure 3: Analysis of different locality-driven policies

impact on the latency performance of both Model A and B:

- *Availability-driven policy* chooses Server 1 currently with an available GPU, and it is agnostic to the location of Model B. As a result, the Model B’s startup latency suffers while the Model A remains unaffected.
- *Locality-driven policy* opts for the locality in choosing the server and thus launching Model B on Server 2. However, it waits for Model A to complete, making Model B suffer from a long queuing delay. Furthermore, the locality policy leaves Server 1 under-utilized, preventing all servers from being fully utilized.
- *Preemption-driven policy* preempts Model A on Server 2 and startups Model B. It identifies that Server 1 is free and reinitiates Model A there. This policy reduces Model B’s latency but results in significant downtime for Model A when it performs reloading and recomputation.
- *Live-migration-supported locality-driven policy* prioritizes locality without disrupting Model A. It initially preloads Model A on Server 1, maintaining inference operations. When Model A is set on Server 1, its intermediate state is transferred there, continuing the inference seamlessly. Following this, Model B commences on Server 2, taking advantage of locality. This policy optimizes latency for both Models A and B.

As we can see, among the policies for enhancing locality, live migration stands out in effectively improving latency for both Model A and Model B.

5.2 Live Migration Process

In designing live migration for LLM inference, we first looked at the standard method: snapshotting the LLM inference and migrating it (similar to Singularity [66]). Yet, this approach

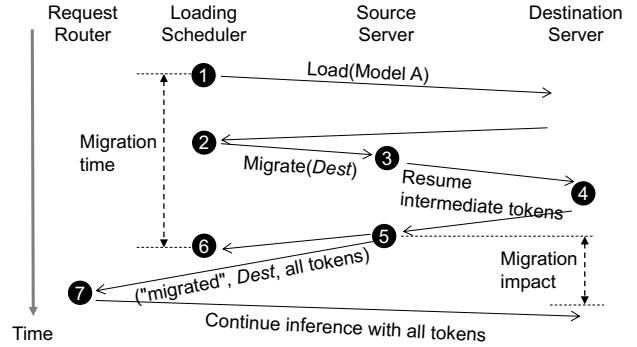


Figure 4: Live migration process for LLM inference

has notable downsides: snapshot creation and transfer are slow (taking tens of seconds [66]), as they encompass the model checkpoint, runtime states (input tokens, KV cache), and extensive GPU state.

To address the above, we propose *token-based migration*. Our proposal is based on the following insight: during inference, the model checkpoint is read-only, and the KV cache can be recalculated from tokens with low latency, usually in the range of hundreds of milliseconds. Thus, if a copy of the model checkpoint exists on another server, we can initiate the model there and then transmit all current tokens. This way, the only state transferred over the network is a list of tokens (i.e., an *int64* array). Even with a large batch size (64) and long sequence (e.g., 100k tokens for long context LLM [9]), the token size remains in the scale of MBs, significantly smaller than the typical sizes of the KV cache (e.g., GBs) and checkpoints (e.g., tens of GBs).

To avoid interrupting inference while migrating tokens, we designed a two-stage process. In stage 1, the destination server (referred to as the *dest* server) recalculates the KV cache using the intermediate tokens. Then, in stage 2, the *dest* server receives the remaining tokens that were produced after the intermediate tokens were sent. This two-stage process is depicted in Figure 4 with its steps described below:

1. The model loading scheduler sends a model loading request to *dest* server to load model A into GPUs. If there is an idle instance of model A on *dest* server, the scheduler skips this step.
2. After loading, the scheduler sends a migration request carrying the address of *dest* server to *src* server.
3. Upon receiving a migrate request, *src* server sets itself as “migrating”, sends a resume request with intermediate tokens (i.e., input tokens and the output tokens produced before step 3) to *dest* server if the inference is not completed. Otherwise, it immediately returns to the scheduler.
4. *dest* server recomputes KV cache given the tokens in the resume request.
5. Once *resume* request is done, *src* server stops inference,

returns to the scheduler, and replies to the request router with all tokens (i.e., the intermediate tokens together with the remaining tokens produced between step 3 and step 5) and a flag “migrated”. If long-context, the collection of all tokens can be very large thus resuming takes a long time, during which many new tokens are predicted. In such a case, we can repeat the above two steps to further reduce the tokens to send between *src* and *dest*.

6. The scheduler finishes the migration, unloads model A at *src* server and starts loading model B.
7. The request router checks the flag in the inference response. If it is “migrated”, the request router replaces *src* server with *dest* server in its route table and sends all tokens to *dest* server to continue inference.

5.3 Practical Concerns

Handling inference completion. The autoregressive nature of LLM inference may lead to task completion at *src* server between steps ③ and ⑤. In such cases, *src* server informs the request router of the inference completion as usual. Additionally, it notifies the loading scheduler, which then instructs *dest* server to cease resuming, terminating the migration.

Handling server failures. ServerlessLLM can manage server failures during LLM inference migration. In scenarios where *src* server fails, if the failure happens during loading (i.e., before step ② in Figure 4), the scheduler aborts the migration and unloads the model from the destination. If the failure occurs during migration (i.e., between steps ② and ③), the scheduler directs the destination to clear any resumed KV cache and unload the model.

Additionally, in cases where *src* server fails, if the failure takes place during loading, the migration is canceled by the scheduler. Should the failure occur while resuming, the source notifies the scheduler of the failure and continues with the inference.

6 Locality-Aware Server Allocation

In this section, we describe the details of achieving the locality-aware allocation of servers when scheduling a model to startup. The scheduler incorporates estimators for model loading time and model migration time to choose the best server depending on the status of each server.

6.1 Model Loading Scheduler Design

Figure 5 introduces the model loading scheduler in ServerlessLLM. The scheduler processes loading tasks from the request router and employs two key components: a model loading time estimator and a model migration time estimator. The former assesses loading times from various storage media, while the latter estimates times for necessary model

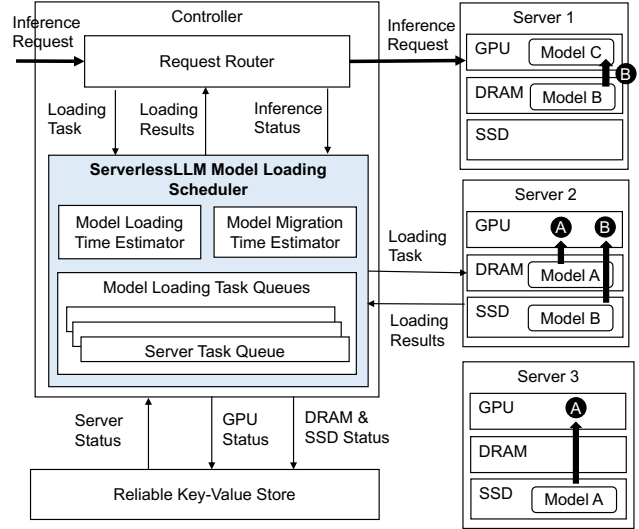


Figure 5: Model loading scheduler design

migrations. For example, as shown in Figure 5, the scheduler calculates the time to load Model A (indicated by Ⓐ) from different servers’ DRAM and SSD, aiding in server selection. Similarly, for Model B (Ⓑ), it assesses whether to migrate Model C to another server or load Model B from Server 2’s SSD.

To enhance accuracy, the ServerlessLLM scheduler maintains distinct loading task queues per server. Upon assigning a task, it updates server status, including GPU and DRAM/SSD states, in a reliable key-value store (e.g., etcd [27] and zookeeper [34]), allowing ServerlessLLM to recover from failures.

6.2 Estimating Model Loading Time

To estimate the time needed to load models from different storage tiers, we consider three primary factors: (i) *queuing time* (q), which is the wait time for a model in the server’s loading task queue. This occurs when other models are pending load on the same server; (ii) *model size* (n), the size of the model in bytes, or its model partition in multi-GPU inference scenarios; (iii) *bandwidth* (b), the available speed for transferring the model from storage to GPUs. ServerlessLLM tracks bandwidth for network, SSD, and DRAM, allowing us to calculate loading time as $q + n/b$. Here, q accumulates from previous estimations for the models already in the queue.

For precise estimations, we have implemented: (i) Sequential model loading per server, with single I/O queues for both SSD-memory and network-memory, reducing bandwidth contention which complicates estimation; (ii) In multi-tier storage, ServerlessLLM uses the slowest bandwidth for estimation because of ServerlessLLM’s pipeline loading design. For example, when SSD and DRAM are both involved, SSD bandwidth is the critical bottleneck since it is orders of magnitude

slower than DRAM; (iii) The scheduler monitors the loading latency returned by the servers. It leverages the monitoring metrics to continuously improve its estimation of the bandwidth through different storage media.

6.3 Estimating Model Migration Time

For live migration time estimation, our focus is on model resuming time (as shown in step 4 in Figure 4), as this is significantly slower (seconds) than token transfer over the network (milliseconds). We calculate model resuming time considering: (i) *input tokens* (t_{in}), the number of tokens in the LLM’s input prompt; (ii) *output tokens* (t_{out}), the tokens generated so far; and (iii) *model-specific parameters* (a and b), which vary with each LLM’s batch sizes and other factors, based on LLM system studies like vLLM [39]. With all the above factors, we can compute the model resuming time as $a \times (t_{in} + t_{out}) + b$.

However, obtaining real-time output tokens from servers for the scheduler can lead to bottlenecks due to excessive server interactions. To circumvent this, we developed a method where the scheduler queries the local request router for the inference status of a model, as illustrated in Figure 5. With the inference duration (d) and the average time to produce a token (t), we calculate $t_{out} = d/t$.

For selecting the optimal server for model migration, ServerlessLLM employs a dynamic programming approach to minimize migration time.

6.4 Practical Concerns

Selecting best servers. Utilizing our time estimation techniques, ServerlessLLM evaluates all servers for loading the forthcoming model, selecting the one offering the lowest estimated startup time. The selection includes the server ID and GPU slots to assign. If no GPUs are available, even after considering migration, the loading task is held pending and retried once the request router informs the scheduler to release GPUs.

Handling scheduler failures. ServerlessLLM is built to withstand failures, utilizing a reliable key-value store to track server statuses. On receiving a server loading task, its GPU status is promptly updated in this store. Post server’s confirmation of task completion, the scheduler updates the server’s storage status in the store. Once recorded, the scheduler notifies the request router of the completion, enabling request routing to the server. In the event of a scheduler failure, recovery involves retrieving the latest server status from the key-value store and synchronizing it across all servers.

Scaling schedulers. The performance of the loading scheduler has been significantly enhanced by implementing asynchronous operations for server status reads, writes, and estimations. Current benchmarks demonstrate its capability to

Table 1: Details of models used in cluster evaluation.

Name	Size (GB)	# Required GPUs	# Instances
OPT-6.7B	13.3	1	32
OPT-13B	25.7	2	16
OPT-30B	60	4	8

handle thousands of loading tasks per second on a standard server. Plans for its distributed scaling are earmarked for future development.

Resource fairness. ServerlessLLM treats all models with equal importance and it ensures migrations do not impact latency. While we currently adopt sequential model loading on the I/O path, exploring concurrent loading on servers with a fairness guarantee is planned for future work.

Estimator accuracy. Our estimator can continuously improve their estimation based on the monitored loading metrics returned by the servers. They offer sufficient accuracy for server selection, as shown in Section 7.

7 Evaluation

This section offers a comprehensive evaluation of ServerlessLLM, covering three key aspects: (i) assessing the performance of our loading-optimized checkpoints and model manager, (ii) examining the efficiency and overheads associated with live migration for LLM inference, and (iii) evaluating ServerlessLLM against a large-scale serverless workload, modelled on real-world serverless trace data.

7.1 Evaluation setup

Setup. We have two test beds: (i) a GPU server has 8 NVIDIA A5000 GPUs, 1TB DDR4 memory and 2 AMD EPYC 7453 CPUs, two PCIe 4.0-capable NVMe 4TB SSDs (in RAID 0) and two SATA 3.0 4TB SSDs (in RAID 0). This server is connected to a storage server via 1 Gbps networks on which we have deployed MinIO [47], an S3 compatible object store; (ii) a GPU cluster with 4 servers connected with 10 Gbps Ethernet connections. Each server has 4 A40 GPUs, 512 GB DDR4 memory, 2 Intel Xeon Silver 4314 CPUs and one PCIe 4.0 NVMe 2TB SSD.

Models. We use state-of-the-art LLMs, including OPT [86], LLaMA-2 [72] and Falcon [4] in different sizes. For cluster evaluation (§7.3 and §7.4) on test bed (ii), following prior work [41], we create different numbers of instances for each type of models. Specific configurations are detailed in Table 1.

Datasets. We use real-world LLM datasets as the input to models. This includes GSM8K [22] that contains problems created by human problem writers, and ShareGPT [78] that contains multilanguage chat from GPT4. Since the models we

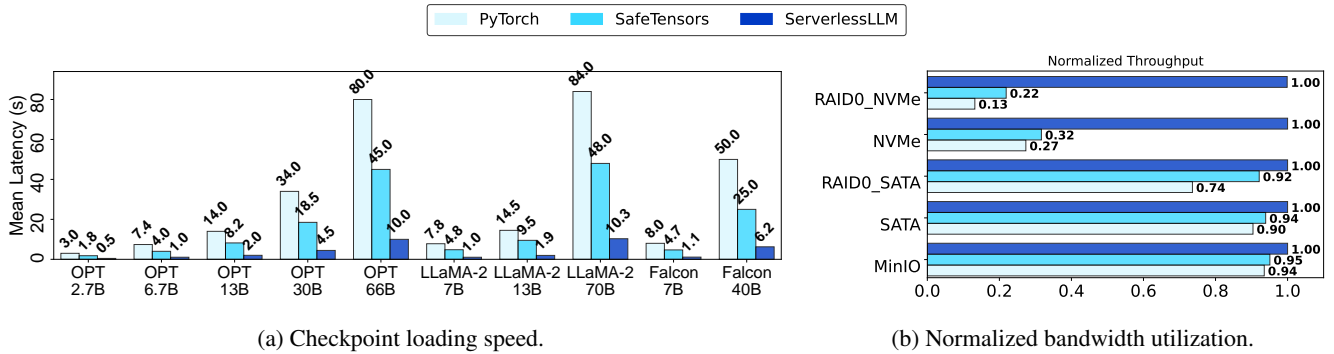


Figure 6: Checkpoint loading performance.

used can handle at most 1024 sequence lengths, we truncate the input number of tokens to the max length. For each dataset, we randomly sample 4K samples from each dataset to create a mixed workload, emulating real-world inference workloads.

Workloads. In the absence of publicly available LLM serverless inference workloads, we developed an LLM inference workload modelled on the Azure Serverless Trace [61]. This approach follows the workload generation method used in recent LLM studies, such as AlpaServe [41]. The workload designates functions to models and creates bursty request traces (CV=8 using Gamma distribution). We then scale this trace to the desired requests per second (RPS). For cluster evaluation, we replicate each model based on its popularity and distribute them across nodes’ SSDs using round-robin placement until the total cluster-wide storage limit is reached. Optimization of checkpoint placement is considered a separate issue and is not addressed in this paper. For all experiments (unless we indicate otherwise), we report the model startup latency, a critical metric for serverless inference scenarios.

7.2 Checkpoint Loading

We now evaluate the model manager’s effectiveness in reducing the model loading latency. For our experiments, we test the checkpoint read on test bed (i). We record reads from 20 copies of each model checkpoint to get a statistically significant performance report. We clear the page and inode caches after checkpoint copies are made to ensure a cold start. For each type of model, we randomly access the 20 copies to simulate real-world access patterns.

Loading performance. We aim to quantify the performance gains achieved by the ServerlessLLM checkpoint manager. We compare PyTorch [56] and Safetensors [32], representing the read-by-tensor checkpoint loading and mmap-based checkpoint loading, respectively. We use all types of models with all checkpoints in FP16 and run the test on RAID0-NVMe SSD having a throughput of 12 GB/s.

Figure 6a shows the performance comparison in terms of

mean latency for all the models¹. We observe that ServerlessLLM is 6X and 3.6X faster than PyTorch and Safetensors, respectively, for our smallest model (OPT-2.7B). We observe similar results with the largest model (LLaMA-2-70B) where ServerlessLLM is faster than PyTorch and Safetensors by 8.2X and 4.7X respectively. Safetensors is slower than ServerlessLLM due to a lot of page faults (112K for LLaMA-2-7B) on cold start. In contrast, ServerlessLLM’s checkpoint manager leverages direct I/O and realizes chunk-based parallel loading, all contributing to the significant improvement in loading throughput. PyTorch is about 2X slower than Safetensors in our evaluation, consistent with the results in a public benchmark [33] reported by Safetensors. The primary reason is that PyTorch first copies data into host memory and then into GPU memory.

Furthermore, we observe that the loading performance of ServerlessLLM is agnostic to the type of the model. For example, the performance of both OPT-13B and LLaMA-2-13B is similar signifying the fact that the performance is only dependent on the checkpoint size.

Harness full bandwidth of the storage devices. We now move to understand if ServerlessLLM can utilize the entire bandwidth that a storage medium offers to achieve low latency. We use the same setup as described above. We choose LLaMA-2-7B to represent the SOTA LLM model. We use FIO [12] with the configuration of asynchronous 4M direct sequential read with the depth of 32 as the optimal baseline and optimized throughput using the result in all storage media. We test various settings of FIO to make sure the configuration chosen has the highest bandwidth on each storage media. For object storage over the network, we use the official MinIO benchmark to get the maximum throughput.

Figure 6b shows the bandwidth utilization across different storage devices, normalized relative to the measurements obtained using FIO and MinIO. The storage device from bottom to top is ascending in maximum bandwidth. We observe that

¹The number after the model name represents the number of parameters in the figure and B stands for Billion.

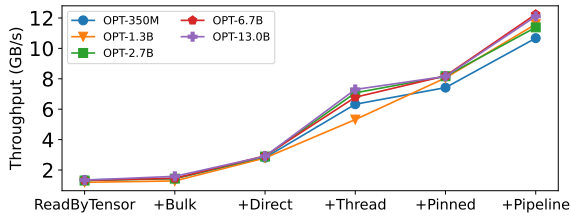


Figure 7: Performance breakdown of checkpoint loaders.

ServerlessLLM’s model manager is capable of harnessing different storage mediums and saturating their entire bandwidth to get maximum performance. Interestingly, we observe that ServerlessLLM is well suited for faster storage devices such as RAID0-NVMe compared to Pytorch and Safetensors. It shows that existing mechanisms are not adaptive to newer and faster storage technology. Despite the loading process passing through the entire memory hierarchy, ServerlessLLM is capable of saturating the bandwidth highlighting the effectiveness of pipelining the loading process.

Performance breakdown. We now move to highlight how each optimization within the model manager contributes towards the overall performance. We run an experiment using RAID0-NVMe with various OPT models. We start from the basic implementation (ReadByTensor) and incrementally add optimizations until the Pipeline implementation. Figure 7 shows the performance breakdown for each model. We observe similar contributions by different optimizations for all the models despite having different checkpoint size.

Bulk reading improves 1.2x throughput, mitigating the throughput degradation from reading small tensors one after another (on average one-third of the tensors in the model are less than 1MB). Direct IO improves 2.1x throughput, bypassing cache and data copy in the kernel. Multi-thread improves 2.3x throughput, as multiple channels within the SSD can be concurrently accessed. Pinned memory provides a further 1.4x throughput, bypassing the CPU with GPU DMA. Pipeline provides a final 1.5x improvement in throughput, helping to avoid synchronization for all data on each storage tier.

We run ServerlessLLM in a container to limit the CPU cores it can use. We find that with 4 CPU cores, ServerlessLLM can achieve maximum bandwidth utilization. We set a sufficiently large chunk size in bulk reading (16MB) to involve less number of reads and also pinned memory-based chunk pool does not need extra CPU cycles for data copy.

7.3 Model Loading Scheduler

In this section, we evaluate the performance and effectiveness of the model loading scheduler on test bed (ii). We compare ServerlessLLM against two schedulers – serverless scheduler and Shepherd [85] scheduler. The serverless scheduler randomly chooses any GPU available and does not comprise

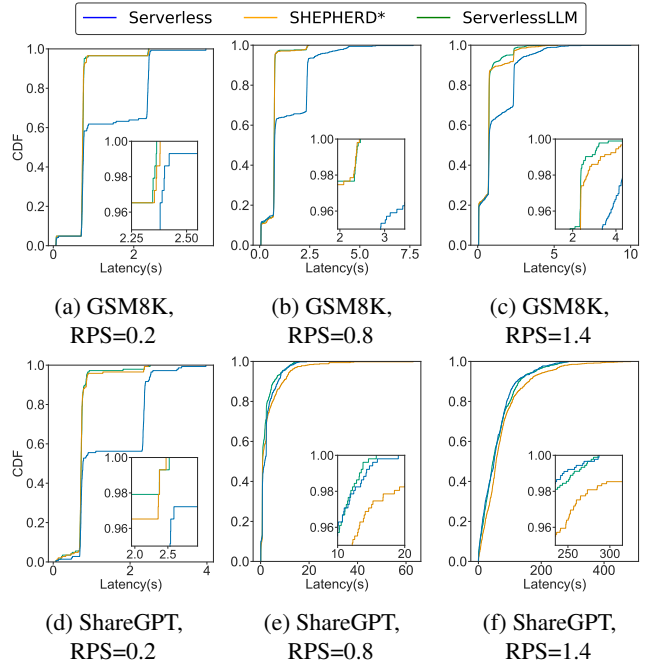


Figure 8: Impacts of RPS on model loading schedulers.

any optimization for loading time. We implement Shepherd scheduler and use ServerlessLLM’s loading time estimation strategy to identify the correct GPU. We call the modified scheduler as Shepherd*. Therefore, in principle, Shepherd* and ServerlessLLM will choose the same GPU. However, Shepherd* will continue to rely on preemption, while ServerlessLLM will rely on live migration to ensure lower latency times.

Figure 8a shows the result of a scenario where we run all three schedulers against OPT-6.7B model and GSM8K and ShareGPT dataset while increasing the requests per second. ShareGPT dataset’s inference time is 3.7X longer than GSM8K. Figure 8a and Figure 8d show the case where there is no locality contention for both datasets. The serverless scheduler cannot take advantage of locality-aware scheduling unlike ServerlessLLM and Shepherd* leading to longer latency. For 40% of the time, the model is loaded from SSD due to random allocation of the GPUs. As there is no migration or preemption, the performance of Shepherd and ServerlessLLM is similar.

When the schedulers are subjected to medium requests per second, for GSM8K (Figure 8b, without locality-aware allocation), the loading times start causing queueing latency leading with Serverless scheduler resulting in increasing the P99 latency by 1.86X. As there is no migration or preemption, the performance of Shepherd and ServerlessLLM is similar. With a longer inference time with ShareGPT (Figure 8e, the Serverless scheduler has a very long tail latency. We even observe long tail latency with Shepherd* due to preemption.

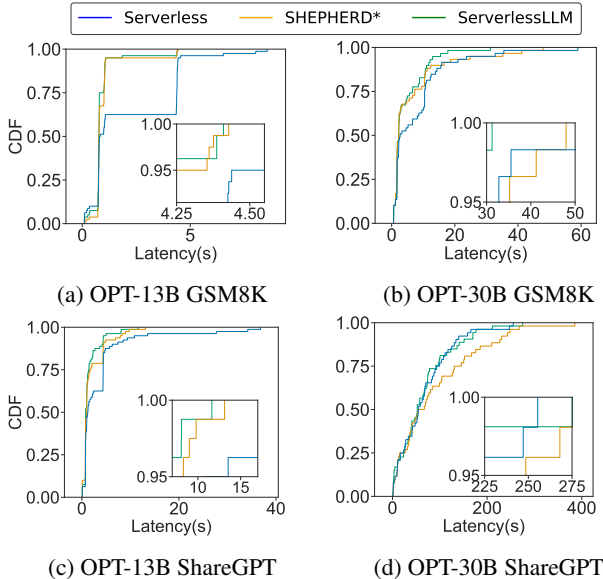


Figure 9: Impacts of datasets and models on model loading schedulers.

As ServerlessLLM relies on live migration in case of locality contention, ServerlessLLM performs better than the other schedulers despite the number of migrations is higher (114 out of 513 total requests) than the number of preemptions (40 out of 513 total requests).

On further stressing the system by increasing the requests per second to 1.4, for GSM8K, one can clearly observe the impact of live migration and preemption. ServerlessLLM outperforms Shepherd* and Serverless schedulers. There are 9 preemptions and 53 migrations respectively for a total of 925 requests. As discussed in Section 5.1, preemptions lead to longer latency compared to migrations. We also observe that with Shepherd*, the data is read from SSD 2X times more than with ServerlessLLM. With ShareGPT (figure 8f, we observe that the GPU utilization reaches 100% leading to requests timeouts with all the three schedulers². Shepherd behaves the worst compared to Serverless and ServerlessLLM schedulers. ServerlessLLM and Shepherd* issue 64 migrations and 166 preemptions, respectively for a total of 925 requests. In this scenario, ServerlessLLM’s effectiveness is constrained by resource limitations.

We further stress the system by running even larger models (OPT-13B and OPT-30B) with GSM8K and ShareGPT datasets. Figure 9 shows the results for those experiments. Locality-aware allocation is more important for larger models as caching them in the main memory can reap better performance. As ServerlessLLM and Shepherd* are both locality-aware, they can make better decisions while scheduling the requests leading to better performance. As Serverless sched-

²Based on the average inference time of OPT-6.7B on ShareGPT dataset, the maximum theoretically RPS is 1.79.

uler makes decisions randomly, for GSM8K, we observe that for 35-40% times, the model is loaded from SSD leading to poor performance. We see similar behavior for ShareGPT, OPT-13B experiment too. For the OPT-30B ShareGPT case, the model size is 66 GB. Hence, only two models can be stored in the main memory at any given time reducing the impact of locality-aware scheduling. Shepherd* performs the worst as the queue time dominates compared to the loading time. Due to the random nature of Serverless scheduler, it performs similarly to ServerlessLLM and better in several instances.

Time Estimation. The GPU time estimation error is bounded at 5ms, while the SSD loading error is bounded at 40ms. However, we do observe instability in CUDA driver calls. For instance, when migrating a model, we noted that cleaning up GPU states (e.g., KV cache) using `torch.cuda.empty_cache()` can lead to inaccurate estimations, resulting in an average underestimation of 25.78 ms. While infrequent, we observed a maximum underestimation of 623 ms during GPU state cleanup in one out of 119 migrations (as depicted in Figure 8e).

7.4 Entire ServerlessLLM in Action

We aimed to deploy the entire ServerlessLLM with a serverless workload on test bed (ii). Here, we compare ServerlessLLM against state-of-the-art distributed model serving systems: (i) Ray Serve (Version 2.7.0), a version we have extended to support serverless inference scenarios with performance that can match SOTA serverless solutions such as KServe; (ii) Ray Serve with Cache, a version we improved to adopt a local SSD cache on each server (utilizing the LRU policy as in ServerlessLLM) to avoid costly model loading and downloads; and (iii) KServe (Version 0.10.2), the SOTA serverless inference system designed for Kubernetes clusters.

For best performance, Ray Serve and its cache variant are both enhanced by storing model checkpoints on local SSDs and estimating download latency by assuming an exclusively occupied 10 Gbps network. For each system, we set the keep-alive period equal to its loading latency, following prior work [58]. We launch parallel LLM inference clients to generate various workloads, where each request has a timeout threshold of 300 seconds.

Effectiveness of loading-optimized checkpoints. We aimed to assess the effectiveness of loading-optimized checkpoints within a complete serverless workload, employing various model sizes and datasets to diversely test the checkpoint loaders.

In this experiment, as depicted in Figure 10, Ray Serve and Ray Serve with Cache utilize Safetensors. Owing to the large sizes of the models, the SSD cache cannot accommodate all models, necessitating some to be downloaded from the storage server. With OPT-6.7B and GSM 8K, ServerlessLLM starts

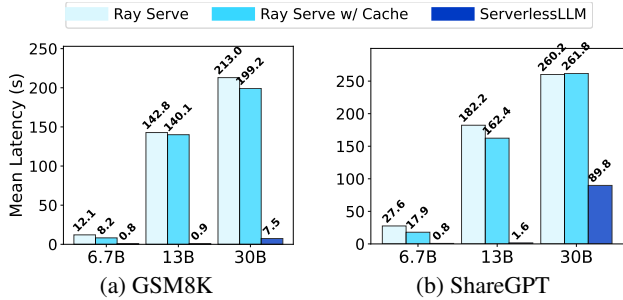
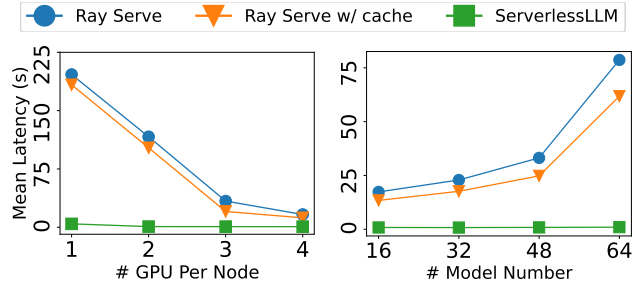


Figure 10: Impacts of datasets and models on overall serving systems.



(a) Impacts of # GPUs per node (b) Impacts of # models

Figure 12: System scalability and resource efficiency.

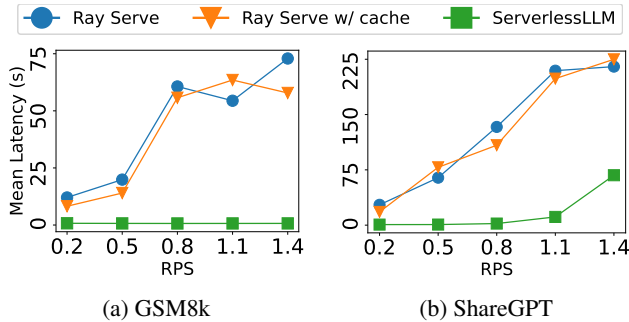


Figure 11: Impacts of RPS on overall serving systems.

models in an average of 0.8 seconds, whereas Ray Serve takes 12.1 seconds and Ray Serve with Cache 8.2 seconds, demonstrating an improvement of over 10X. The significance of the model loader becomes more pronounced with larger models, as ServerlessLLM can utilize parallel PCIe links when loading large models partitioned on multiple GPUs from pinned memory pool. For instance, with OPT-30B, ServerlessLLM still initiates the model in 7.5 seconds, while Ray Serve’s time escalates to 213 seconds and Ray Serve with Cache to 199.2 seconds, marking a 28X improvement.

This considerable difference in latency substantially affects the user experience in LLM services. Our observations indicate that ServerlessLLM can fulfill 89% of requests within a 300-second timeout with OPT-30B, whereas Ray Serve with Cache manages only 26%.

With the ShareGPT dataset (Figure 10b), which incurs a 4.2X longer inference time than GSM 8K, the challenge for model loaders becomes even more intense. For models like 6.7B and 13B, ServerlessLLM achieves latencies of 0.8 and 1.6 seconds on average, respectively, compared to Ray Serve and Ray Serve with Cache, which soar to 182.2 and 162.4 seconds. When utilizing OPT-30B, ServerlessLLM begins to confront GPU limitations (with all GPUs occupied and migration unable to free up more resources), leading to an increased latency of 89.9 seconds. However, this is still a significant improvement over Ray Serve with Cache, which reaches a latency of 261.8 seconds

Effectiveness of live migration and loading scheduler. In evaluating the effectiveness of LLM live migration and the loading scheduler, we created workloads with varying RPS levels. Scenarios with higher RPS highlight the importance of achieving load balancing and locality-driven allocation since simply speeding up model loading is insufficient to address the resource contention common at large RPS levels.

From Figure 11a, it is evident that ServerlessLLM, equipped with GSM8K, consistently maintains low latency, approximately 1 second, even as RPS increases. In contrast, both Ray Serve and Ray Serve with Cache experience rising latency once the RPS exceeds 0.5, which can be attributed to GPU resource shortages. Their inability to migrate LLM inference for locality release or to achieve load balancing, unlike ServerlessLLM, results in performance degradation.

With the more demanding ShareGPT workload, as shown in Figure 11b, ServerlessLLM maintains significant performance improvements — up to 212 times better — over Ray Serve and Ray Serve with Cache across RPS ranging from 0.2 to 1.1. However, at an RPS of 1.4, ServerlessLLM’s latency begins to rise, indicating that despite live migration and optimized server allocation, the limited GPU resources eventually impact ServerlessLLM’s performance.

Resource efficiency. A major advantage of the low model startup latency in ServerlessLLM is its contribution to resource savings when serving LLMs. We vary the number of GPUs available on each server to represent different levels of resource provisioning. As shown in Figure 12a, with just one GPU per server, ServerlessLLM already achieves a 4-second latency. In contrast, Ray Serve with Cache requires at least four GPUs per server to attain a 12-second latency, which is still higher than ServerlessLLM’s performance with only one GPU per node. With larger clusters, the resource-saving efficiency of ServerlessLLM is expected to become even more pronounced, as larger clusters offer more options for live migration and server allocation.

The resource efficiency of ServerlessLLM is further evident when maintaining a fixed number of GPUs while increasing the number of LLMs in the cluster. In Figure 12b, with a limited number of models, Ray Serve with Cache can

match ServerlessLLM in latency performance. However, as the number of models grows, the performance gap widens, showcasing ServerlessLLM’s potential suitability for large-scale serverless platforms.

KServe comparison. In our study, we assess KServe and ServerlessLLM within a Kubernetes cluster. Given that our four-server cluster is unsuitable for a Kubernetes deployment, we instead utilize an eight-GPU server, simulating four nodes with two GPUs each. Since KServe performs slower than the other baselines considered in our evaluation, we only briefly mention KServe’s results without delving into details.

With KServe, the GPU nodes initially exhibited a first token latency of 128 seconds. This latency was primarily due to KServe taking 114 seconds to download an OPT-6.7B model checkpoint from the local S3 storage over a 1 Gbps network. However, after applying the same enhancement as those for Ray Serve, we reduced the first token latency to 28 seconds. Despite this improvement, KServe’s best latency was significantly higher than those achieved by ServerlessLLM. Notably, ServerlessLLM was the only system able to reduce the latency to within one second.

8 Related Work

Serverless inference systems. Extensive research has aimed to optimize ML model serving in serverless architectures, focusing on various aspects such as batching [3, 79, 84], scheduling [58, 82], and resource efficiency [20, 40], among others [35]. Industry implementations include AWS SageMaker and Azure ML [46], while KServe [11] represents an open-source initiative. Despite these advancements, current serverless inference systems show suboptimal performance with LLMs, as evidenced by the experimental results shown in this paper. In this context, ServerlessLLM makes a significant contribution to serverless inference specifically for LLMs, addressing their unique challenges of loading, migration, and scheduling in a serverless environment.

Serverless cold-start optimizations. Cold-start latency is a critical challenge in serverless systems. Numerous strategies have been devised to mitigate this issue, such as fast image pulling [75], lightweight isolation [42, 50], snapshot and restore [10, 18, 25, 65, 73], resource pre-provision [61], elastic resource provisioning [45, 74], and fork [2, 76]. These solutions primarily address the startup latency of containers or VMs, which do not involve loading substantial external states. While recent studies [36, 83] have sought to optimize cold-starts through accelerated model swapping between GPUs and host memory, their scalability with LLMs remains limited. In contrast, ServerlessLLM effectively reduces the cold-start latency for LLMs by taking LLM-specific designs, including an LLM-optimized checkpoint format and its loading pipeline, LLM live migration and an LLM loading scheduler. ServerlessLLM’s approach is orthogonal to these optimiza-

tions specific to VMs and containers.

Exploiting locality in serverless systems. Locality plays a crucial role in various optimization strategies for serverless systems. This includes leveraging host memory and local storage for data cache [38, 57, 67], optimizing the reading of shared logs [37], and enhancing communication efficiency in serverless Directed Acyclic Graphs (DAGs) [43, 44]. ServerlessLLM, distinct from existing methods, introduces a high-performance checkpoint cache for GPUs, markedly improving checkpoint loading from multi-tier local storage to GPU memory. Recent studies [1, 81] have also recognized the need for leveraging locality in orchestrating serverless functions. Beyond these studies, ServerlessLLM leverages LLM-specific characteristics in improving the locality-based server’s selection and launching locality-driven inference.

LLM serving systems. LLM serving has recently seen significant strides, with numerous advancements optimizing inference latency and throughput. Orca [80] introduces continuous batching to enhance GPU utilization during inference. AlpaServe [41] demonstrates that model parallelism can boost throughput while adhering to SLO constraints. vLLM [39] innovates with PagedAttention for efficient KV cache management during LLM inference. SplitWise [53] capitalizes on the unique aspects of prompt and token generation in LLM inference by distributing these phases across separate machines, effectively enhancing throughput. Additionally, some systems [8, 63] explore leveraging storage devices to offload parameters from GPUs when dealing with the substantial sizes of state-of-the-art LLMs. However, these systems often neglect the model loading challenge, resulting in extended first token latencies when multiple models share GPUs for inference. ServerlessLLM’s focus on minimizing loading latency complements existing inference time optimizations.

9 Conclusions

This paper describes ServerlessLLM, a serverless inference system purposefully designed for LLMs. The design of ServerlessLLM uncovers significant opportunities for system research, including designing new loading-optimized checkpoints, discovering the need to support live migration when conducting locality-driven LLM inference, and enabling latency-preserving, locality-driven server allocation in a serverless cluster. We believe our work can be extended to ensure fairness of resources across the entire cluster and explore the possibility of smart checkpoint placement. We look forward to addressing these issues in the future. We consider ServerlessLLM as the first step towards unlocking the potential of serverless computing for LLMs and reducing the time to inference. We plan to open-source ServerlessLLM. Given its versatility, we envision it as a platform to test new research ideas.

References

- [1] Mania Abdi, Samuel Ginzburg, Xiayue Charles Lin, Jose Faleiro, Gohar Irfan Chaudhry, Inigo Goiri, Riccardo Bianchini, Daniel S Berger, and Rodrigo Fonseca. Palette load balancing: Locality hints for serverless functions. In *Proceedings of the Eighteenth European Conference on Computer Systems, EuroSys '23*, page 365–380, New York, NY, USA, 2023. Association for Computing Machinery.
- [2] Istemi Ekin Akkus, Ruichuan Chen, Ivica Rimac, Manuel Stein, Klaus Satzke, Andre Beck, Paarijaat Aditya, and Volker Hilt. SAND: Towards High-Performance serverless computing. In *2018 USENIX Annual Technical Conference (USENIX ATC 18)*, pages 923–935, Boston, MA, July 2018. USENIX Association.
- [3] Ahsan Ali, Riccardo Pinciroli, Feng Yan, and Evgenia Smirni. Batch: machine learning inference serving on serverless platforms with adaptive batching. In *SC20: International Conference for High Performance Computing, Networking, Storage and Analysis*, pages 1–15. IEEE, 2020.
- [4] Ebtesam Almazrouei, Hamza Alobeidli, Abdulaziz Alshamsi, Alessandro Cappelli, Ruxandra Cojocaru, Merouane Debbah, Etienne Goffinet, Daniel Heslow, Julien Launay, Quentin Malartic, Badreddine Noune, Baptiste Pannier, and Guilherme Penedo. Falcon-40B: an open large language model with state-of-the-art performance. 2023.
- [5] Amazon. AWS S3. <https://aws.amazon.com/s3/>, 2023. Accessed on 2024-01-22.
- [6] Amazon. AWS SageMaker Model Registry. <https://docs.aws.amazon.com/sagemaker/latest/dg/model-registry.html>, 2023. Accessed on 2024-01-22.
- [7] Amazon. Serverless inference - minimizing cold starts. <https://docs.aws.amazon.com/sagemaker/latest/dg/serverless-endpoints.html>, 2023. Accessed on 2024-01-22.
- [8] Reza Yazdani Aminabadi, Samyam Rajbhandari, Ammar Ahmad Awan, Cheng Li, Du Li, Elton Zheng, Olatunji Ruwase, Shaden Smith, Minjia Zhang, Jeff Rasley, and Yuxiong He. Deepspeed-inference: enabling efficient inference of transformer models at unprecedented scale. In *Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis, SC '22*. IEEE Press, 2022.
- [9] Anthropic. Introducing 100K Context Windows. <https://www.anthropic.com/index/100k-context-windows>, 2023. Accessed on 2024-01-22.
- [10] Lixiang Ao, George Porter, and Geoffrey M. Voelker. Faasnap: Faas made fast using snapshot-based vms. In *Proceedings of the Seventeenth European Conference on Computer Systems, EuroSys '22*, page 730–746, New York, NY, USA, 2022. Association for Computing Machinery.
- [11] The KServe Authors. Kserve. <https://github.com/kserve/kserve>, 2023. Accessed on 2024-01-22.
- [12] Jens Axboe. Flexible I/O Tester, 2022. Accessed on 2024-01-22.
- [13] Wei Bai, Shanim Sainul Abdeen, Ankit Agrawal, Krishan Kumar Attre, Paramvir Bahl, Ameya Bhagat, Gowri Bhaskara, Tanya Brokhman, Lei Cao, Ahmad Cheema, Rebecca Chow, Jeff Cohen, Mahmoud Elhaddad, Vivek Ette, Igal Figlin, Daniel Firestone, Mathew George, Ilya German, Lakhmeet Ghai, Eric Green, Albert Greenberg, Manish Gupta, Randy Haagens, Matthew Hendel, Ridwan Howlader, Neetha John, Julia Johnstone, Tom Jolly, Greg Kramer, David Kruse, Ankit Kumar, Erica Lan, Ivan Lee, Avi Levy, Marina Lipshteyn, Xin Liu, Chen Liu, Guohan Lu, Yuemin Lu, Xiakun Lu, Vadim Makherovaks, Ulad Malashanka, David A. Maltz, Ilias Marinou, Rohan Mehta, Sharda Murthi, Anup Namdhari, Aaron Ogus, Jitendra Padhye, Madhav Pandya, Douglas Phillips, Adrian Power, Suraj Puri, Shachar Raindel, Jordan Rhee, Anthony Russo, Maneesh Sah, Ali Sheriff, Chris Sparacino, Ashutosh Srivastava, Weixiang Sun, Nick Swanson, Fuhou Tian, Lukasz Tomczyk, Vamsi Vadlamuri, Alec Wolman, Ying Xie, Joyce Yom, Lihua Yuan, Yanzhao Zhang, and Brian Zill. Empowering azure storage with RDMA. In *20th USENIX Symposium on Networked Systems Design and Implementation (NSDI 23)*, pages 49–67, Boston, MA, April 2023. USENIX Association.
- [14] Anyscale Technical Blog. <https://www.anyscale.com/blog/loading-llama-2-70b-20x-faster-with-anyscale-endpoints>, 2023. Accessed on 2024-01-22.
- [15] Banana.dev Technical Blog. <https://www.banana.dev/blog/turboboot>, 2023. Accessed on 2024-01-22.
- [16] Microsoft Official Blog. Reinventing search with a new AI-powered Microsoft Bing and Edge, your copilot for the web. <https://blogs.microsoft.com/blog/2023/02/07/reinventing-search-with-a-new-ai-powered-microsoft-bing-and-edge-your-copilot-for-the-web/>, 2023. Accessed on 2024-01-22.
- [17] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen

- Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc., 2020.
- [18] James Cadden, Thomas Unger, Yara Awad, Han Dong, Orran Krieger, and Jonathan Appavoo. Seuss: skip redundant paths to make serverless fast. In *Proceedings of the Fifteenth European Conference on Computer Systems*, EuroSys '20, New York, NY, USA, 2020. Association for Computing Machinery.
- [19] Andrew A. Chien, Liuzixuan Lin, Hai Nguyen, Varsha Rao, Tristan Sharma, and Rajini Wijayawardana. Reducing the carbon impact of generative AI inference (today and in 2035). In *HotCarbon*, pages 11:1–11:7. ACM, 2023.
- [20] Seungbeom Choi, Sunho Lee, Yeonjae Kim, Jongse Park, Youngjin Kwon, and Jaehyuk Huh. Serving Heterogeneous Machine Learning Models on Multi-GPU Servers with Spatio-Temporal Sharing. In *2022 USENIX Annual Technical Conference (USENIX ATC 22)*, pages 199–216, Carlsbad, CA, July 2022. USENIX Association.
- [21] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayanan Pilla, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Aleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. Palm: Scaling language modeling with pathways. *J. Mach. Learn. Res.*, 24:240:1–240:113, 2023.
- [22] Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training verifiers to solve math word problems. *CoRR*, abs/2110.14168, 2021.
- [23] GitHub Copilot. <https://github.com/features/copilot>, 2023. Accessed on 2024-01-22.
- [24] DataBricks. LLM Inference Performance Engineering: Best Practices. <https://www.databricks.com/blog/llm-inference-performance-engineering-best-practices>, 2023. Accessed on 2024-01-22.
- [25] Dong Du, Tianyi Yu, Yubin Xia, Binyu Zang, Guanglu Yan, Chenggang Qin, Qixuan Wu, and Haibo Chen. Catalyst: Sub-millisecond startup for serverless computing with initialization-less booting. In *Proceedings of the Twenty-Fifth International Conference on Architectural Support for Programming Languages and Operating Systems*, pages 467–481, 2020.
- [26] William Fedus, Barret Zoph, and Noam Shazeer. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity. *J. Mach. Learn. Res.*, 23(1), jan 2022.
- [27] Cloud Native Computing Foundation. etcd. <https://etcd.io>, 2023. Accessed on 2024-01-22.
- [28] Yixiao Gao, Qiang Li, Lingbo Tang, Yongqing Xi, Pengcheng Zhang, Wenwen Peng, Bo Li, Yaohui Wu, Shaozong Liu, Lei Yan, et al. When cloud storage meets {rdma}. In *18th USENIX Symposium on Networked Systems Design and Implementation (NSDI 21)*, pages 519–533, 2021.
- [29] Arpan Gujarati, Reza Karimi, Safya Alzayat, Wei Hao, Antoine Kaufmann, Ymir Vigfusson, and Jonathan Mace. Serving DNNs like Clockwork: Performance Predictability from the Bottom Up. In *OSDI*, pages 443–462. USENIX Association, 2020.
- [30] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, pages 770–778. IEEE Computer Society, 2016.
- [31] HuggingFace. <https://huggingface.co>, 2023. Accessed on 2024-01-22.
- [32] HuggingFace. Safetensors: ML Safer for All. <https://github.com/huggingface/safetensors>, 2023. Accessed on 2024-01-22.
- [33] HuggingFace. Speed Comparison. <https://huggingface.co/docs/safetensors/speed>, 2023. Accessed on 2024-01-22.

- [34] Patrick Hunt, Mahadev Konar, Flavio P. Junqueira, and Benjamin Reed. Zookeeper: Wait-free coordination for internet-scale systems. In *Proceedings of the 2010 USENIX Conference on USENIX Annual Technical Conference*, USENIXATC'10, page 11, USA, 2010. USENIX Association.
- [35] Vatche Ishakian, Vinod Muthusamy, and Aleksander Slominski. Serving deep learning models in a serverless platform. In *2018 IEEE International conference on cloud engineering (IC2E)*, pages 257–262. IEEE, 2018.
- [36] Jinwoo Jeong, Seungsu Baek, and Jeongseob Ahn. Fast and efficient model serving using multi-gpus with direct-host-access. In *EuroSys*, pages 249–265. ACM, 2023.
- [37] Zhipeng Jia and Emmett Witchel. Boki: Stateful serverless computing with shared logs. In *Proceedings of the ACM SIGOPS 28th Symposium on Operating Systems Principles*, SOSP '21, page 691–707, New York, NY, USA, 2021. Association for Computing Machinery.
- [38] Ana Klimovic, Yawen Wang, Patrick Stuedi, Animesh Trivedi, Jonas Pfefferle, and Christos Kozyrakis. Pocket: Elastic ephemeral storage for serverless analytics. In *13th USENIX Symposium on Operating Systems Design and Implementation (OSDI 18)*, pages 427–444, Carlsbad, CA, October 2018. USENIX Association.
- [39] Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph Gonzalez, Hao Zhang, and Ion Stoica. Efficient Memory Management for Large Language Model Serving with PagedAttention. In *SOSP*, pages 611–626. ACM, 2023.
- [40] Jie Li, Laiping Zhao, Yanan Yang, Kunlin Zhan, and Keqiu Li. Tetris: Memory-efficient serverless inference through tensor sharing. In *2022 USENIX Annual Technical Conference (USENIX ATC 22)*, 2022.
- [41] Zhuohan Li, Lianmin Zheng, Yinmin Zhong, Vincent Liu, Ying Sheng, Xin Jin, Yanping Huang, Zhifeng Chen, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. AlphaServe: Statistical multiplexing with model parallelism for deep learning serving. In *OSDI*, pages 663–679. USENIX Association, 2023.
- [42] Zijun Li, Jiagan Cheng, Quan Chen, Eryu Guan, Zizheng Bian, Yi Tao, Bin Zha, Qiang Wang, Weidong Han, and Minyi Guo. Rund: A lightweight secure container runtime for high-density deployment and high-concurrency startup in serverless computing. In *USENIX Annual Technical Conference*, pages 53–68. USENIX Association, 2022.
- [43] Ashraf Mahgoub, Karthick Shankar, Subrata Mitra, Ana Klimovic, Somali Chaterji, and Saurabh Bagchi. SONIC: Application-aware data passing for chained serverless applications. In *2021 USENIX Annual Technical Conference (USENIX ATC 21)*, pages 285–301. USENIX Association, July 2021.
- [44] Ashraf Mahgoub, Edgardo Barsallo Yi, Karthick Shankar, Sameh Elnikety, Somali Chaterji, and Saurabh Bagchi. ORION and the three rights: Sizing, bundling, and prewarming for serverless DAGs. In *16th USENIX Symposium on Operating Systems Design and Implementation (OSDI 22)*, pages 303–320, Carlsbad, CA, July 2022. USENIX Association.
- [45] Luo Mai, Guo Li, Marcel Wagenländer, Konstantinos Fertakis, Andrei-Octavian Brabete, and Peter Pietzuch. {KungFu}: Making training in distributed machine learning adaptive. In *14th USENIX Symposium on Operating Systems Design and Implementation (OSDI 20)*, pages 937–954, 2020.
- [46] Microsoft. Azure ML. <https://learn.microsoft.com/en-us/azure/machine-learning>, 2023. Accessed on 2024-01-22.
- [47] MinIO. MinIO. <https://min.io>, 2023. Accessed on 2024-01-22.
- [48] NVIDIA. NVIDIA GH200 Grace Hopper Superchip Architecture. <https://resources.nvidia.com/en-us-grace-cpu/nvidia-grace-hopper>, 2023. Accessed on 2024-01-22.
- [49] NVIDIA. NVIDIA DGX H100. <https://resources.nvidia.com/en-us-dgx-systems/ai-enterprise-dgx>, 2023. Accessed on 2024-01-22.
- [50] Edward Oakes, Leon Yang, Dennis Zhou, Kevin Houck, Tyler Harter, Andrea Arpaci-Dusseau, and Remzi Arpaci-Dusseau. SOCK: Rapid task provisioning with Serverless-Optimized containers. In *2018 USENIX Annual Technical Conference (USENIX ATC 18)*, pages 57–70, Boston, MA, July 2018. USENIX Association.
- [51] OpenAI. ChatGPT: Optimizing Language Models for Dialogue. <https://openai.com/blog/chatgpt/>, 2022. Accessed on 2024-01-22.
- [52] Kay Ousterhout, Patrick Wendell, Matei Zaharia, and Ion Stoica. Sparrow: distributed, low latency scheduling. In *SOSP*, pages 69–84. ACM, 2013.
- [53] Pratyush Patel, Esha Choukse, Chaojie Zhang, Íñigo Goiri, Aashaka Shah, Saeed Maleki, and Ricardo Bianchini. Splitwise: Efficient generative llm inference using phase splitting, 2023.
- [54] Reiner Pope, Sholto Douglas, Aakanksha Chowdhery, Jacob Devlin, James Bradbury, Jonathan Heek, Kefan

- Xiao, Shivani Agrawal, and Jeff Dean. Efficiently scaling transformer inference. *Proceedings of Machine Learning and Systems*, 5, 2023.
- [55] PyTorch. PyTorch Documentation: Saving and Loading Models. https://pytorch.org/tutorials/beginner/saving_loading_models.html, 2023. Accessed on 2024-01-22.
- [56] PyTorch. torch.load. <https://pytorch.org/docs/stable/generated/torch.load.html>, 2023. Accessed on 2024-01-22.
- [57] Francisco Romero, Gohar Irfan Chaudhry, Íñigo Goiri, Pragna Gopa, Paul Batum, Neeraja J. Yadwadkar, Rodrigo Fonseca, Christos Kozyrakis, and Ricardo Bianchini. FaaS: A transparent auto-scaling cache for serverless applications. In *Proceedings of the ACM Symposium on Cloud Computing*, SoCC '21, page 122–137, New York, NY, USA, 2021. Association for Computing Machinery.
- [58] Francisco Romero, Qian Li, Neeraja J Yadwadkar, and Christos Kozyrakis. INFaaS: Automated model-less inference serving. In *2021 USENIX Annual Technical Conference (USENIX ATC 21)*, pages 397–411, 2021.
- [59] ONNX Runtime. API Reference, onnxruntime.backend.prepare. https://onnxruntime.ai/docs/api/python/api_summary.html, 2023. Accessed on 2024-01-22.
- [60] AWS SageMaker. Machine Learning Service - Amazon SageMaker. <https://aws.amazon.com/pm/sagemaker/>, 2023.
- [61] Mohammad Shahradd, Rodrigo Fonseca, Inigo Goiri, Gohar Chaudhry, Paul Batum, Jason Cooke, Eduardo Laureano, Colby Tresness, Mark Russinovich, and Ricardo Bianchini. Serverless in the wild: Characterizing and optimizing the serverless workload at a large cloud provider. In *2020 USENIX Annual Technical Conference (USENIX ATC 20)*, pages 205–218. USENIX Association, July 2020.
- [62] Ying Sheng, Shiyi Cao, Dacheng Li, Coleman Hooper, Nicholas Lee, Shuo Yang, Christopher Chou, Banghua Zhu, Lianmin Zheng, Kurt Keutzer, et al. S-lora: Serving thousands of concurrent lora adapters. *arXiv preprint arXiv:2311.03285*, 2023.
- [63] Ying Sheng, Lianmin Zheng, Binhang Yuan, Zhuohan Li, Max Ryabinin, Beidi Chen, Percy Liang, Christopher Re, Ion Stoica, and Ce Zhang. FlexGen: High-throughput generative inference of large language models with a single GPU. In Andreas Krause, Emma Brunskill, Kyunghyun Cho, Barbara Engelhardt, Sivan Sabato, and Jonathan Scarlett, editors, *Proceedings of the 40th International Conference on Machine Learning*, volume 202 of *Proceedings of Machine Learning Research*, pages 31094–31116. PMLR, 23–29 Jul 2023.
- [64] Jiuchen Shi, Hang Zhang, Zhixin Tong, Quan Chen, Kaihua Fu, and Minyi Guo. Nodens: Enabling Resource Efficient and Fast QoS Recovery of Dynamic Microservice Applications in Datacenters. In *USENIX Annual Technical Conference*, pages 403–417. USENIX Association, 2023.
- [65] Simon Shillaker and Peter Pietzuch. Faasm: Lightweight isolation for efficient stateful serverless computing. In *2020 USENIX Annual Technical Conference (USENIX ATC 20)*, pages 419–433. USENIX Association, July 2020.
- [66] Dharma Shukla, Muthian Sivathanu, Srinidhi Viswanatha, Bhargav Gulavani, Rimma Nehme, Amey Agrawal, Chen Chen, Nipun Kwatra, Ramachandran Ramjee, Pankaj Sharma, Atul Katiyar, Vipul Modi, Vaibhav Sharma, Abhishek Singh, Shreshth Singhal, Kaustubh Welankar, Lu Xun, Ravi Anupindi, Karthik Elangovan, Hasibur Rahman, Zhou Lin, Rahul Seetharaman, Cheng Xu, Eddie Ailijiang, Suresh Krishnappa, and Mark Russinovich. Singularity: Planet-scale, preemptive and elastic scheduling of ai workloads, 2022.
- [67] Vikram Sreekanti, Chenggang Wu, Xiayue Charles Lin, Johann Schleier-Smith, Joseph E. Gonzalez, Joseph M. Hellerstein, and Alexey Tumanov. Cloudburst: stateful functions-as-a-service. *Proc. VLDB Endow.*, 13(12):2438–2452, jul 2020.
- [68] The Ray Team. Ray serve. <https://docs.ray.io/en/latest/serve/index.html>, 2023. Accessed on 2024-01-22.
- [69] TensorFlow. TensorFlow Documentation: Using the Saved Model Format. https://www.tensorflow.org/guide/saved_model, 2023. Accessed on 2024-01-22.
- [70] TensorFlow. tf.saved_model.load. https://www.tensorflow.org/api_docs/python/tf/saved_model/load, 2023. Accessed on 2024-01-22.
- [71] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models, 2023.

- [72] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open foundation and fine-tuned chat models, 2023.
- [73] Dmitrii Ustiugov, Plamen Petrov, Marios Kogias, Edouard Bugnion, and Boris Grot. Benchmarking, analysis, and optimization of serverless function snapshots. In *Proceedings of the 26th ACM International Conference on Architectural Support for Programming Languages and Operating Systems*, ASPLOS '21, page 559–572, New York, NY, USA, 2021. Association for Computing Machinery.
- [74] Marcel Wagenländer, Luo Mai, Guo Li, and Peter Pietzuch. Spotnik: Designing distributed machine learning for transient cloud resources. In *12th USENIX Workshop on Hot Topics in Cloud Computing (HotCloud 20)*, 2020.
- [75] Ao Wang, Shuai Chang, Huangshi Tian, Hongqi Wang, Haoran Yang, Huiba Li, Rui Du, and Yue Cheng. FaaS-Net: Scalable and fast provisioning of custom serverless container runtimes at alibaba cloud function compute. In *2021 USENIX Annual Technical Conference (USENIX ATC 21)*, pages 443–457. USENIX Association, July 2021.
- [76] Xingda Wei, Fangming Lu, Tianxia Wang, Jinyu Gu, Yuhan Yang, Rong Chen, and Haibo Chen. No provisioned concurrency: Fast RDMA-codesigned remote fork for serverless computing. In *17th USENIX Symposium on Operating Systems Design and Implementation (OSDI 23)*, pages 497–517, Boston, MA, July 2023. USENIX Association.
- [77] Bingyang Wu, Yinmin Zhong, Zili Zhang, Gang Huang, Xuanzhe Liu, and Xin Jin. Fast distributed inference serving for large language models, 2023.
- [78] Ming Xu. https://huggingface.co/datasets/shibing624/sharegpt_gpt4, 2023.
- [79] Yanan Yang, Laiping Zhao, Yiming Li, Huanyu Zhang, Jie Li, Mingyang Zhao, Xingzhen Chen, and Keqiu Li. Inflex: a native serverless system for low-latency, high-throughput inference. In *Proceedings of the 27th ACM International Conference on Architectural Support for Programming Languages and Operating Systems*, ASPLOS '22, page 768–781, New York, NY, USA, 2022. Association for Computing Machinery.
- [80] Gyeong-In Yu, Joo Seong Jeong, Geon-Woo Kim, Soojeong Kim, and Byung-Gon Chun. Orca: A distributed serving system for Transformer-Based generative models. In *16th USENIX Symposium on Operating Systems Design and Implementation (OSDI 22)*, pages 521–538, Carlsbad, CA, July 2022. USENIX Association.
- [81] Minchen Yu, Tingjia Cao, Wei Wang, and Ruichuan Chen. Following the data, not the function: Rethinking function orchestration in serverless computing. In *20th USENIX Symposium on Networked Systems Design and Implementation (NSDI 23)*, pages 1489–1504, Boston, MA, April 2023. USENIX Association.
- [82] Minchen Yu, Zhifeng Jiang, Hok Chun Ng, Wei Wang, Ruichuan Chen, and Bo Li. Gillis: Serving large neural networks in serverless functions with automatic model partitioning. In *2021 IEEE 41st International Conference on Distributed Computing Systems (ICDCS)*, pages 138–148. IEEE, 2021.
- [83] Minchen Yu, Ao Wang, Dong Chen, Haoxuan Yu, Xiaonan Luo, Zhuohao Li, Wei Wang, Ruichuan Chen, Dapeng Nie, and Haoran Yang. FaaS-Swap: SLO-Aware, GPU-Efficient Serverless Inference via Model Swapping. *CoRR*, abs/2306.03622, 2023.
- [84] Chengliang Zhang, Minchen Yu, Wei Wang, and Feng Yan. MARK: Exploiting cloud services for Cost-Effective, SLO-Aware machine learning inference serving. In *2019 USENIX Annual Technical Conference (USENIX ATC 19)*, pages 1049–1062, Renton, WA, July 2019. USENIX Association.
- [85] Hong Zhang, Yupeng Tang, Anurag Khandelwal, and Ion Stoica. SHEPHERD: Serving DNNs in the Wild. In *NSDI*, pages 787–808. USENIX Association, 2023.
- [86] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona T. Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. OPT: Open Pre-trained Transformer Language Models. *CoRR*, abs/2205.01068, 2022.