

ServeGen: Workload Characterization and Generation of Large Language Model Serving in Production

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Abstract

With the widespread adoption of Large Language Models (LLMs), serving LLM inference requests has become an increasingly important task, attracting active research advancements. Practical workloads play an essential role in this process: they are critical for motivating and benchmarking serving techniques and systems. However, the existing understanding of real-world LLM serving workloads is limited due to the lack of a comprehensive workload characterization. Prior analyses remain insufficient in scale and scope, thus failing to fully capture intricate workload characteristics.

In this paper, we fill the gap with an in-depth characterization of LLM serving workloads collected from our worldwide cloud inference serving service, covering not only language models but also emerging *multimodal* and *reasoning* models, and unveiling important *new* findings in each case. Moreover, based on our findings, we propose ServeGen, a principled framework for generating realistic LLM serving workloads by composing them on a per-client basis. A practical use case in production validates that ServeGen avoids 50% under-provisioning compared to naive workload generation, demonstrating ServeGen’s advantage in performance benchmarking. We will open-source ServeGen to foster future research.

1 Introduction

In recent years, the rapid evolution of Large Language Models (LLMs) [16, 33, 36, 49] has enabled fundamentally new applications, with large-scale deployment in production clusters serving substantial user traffic every day [3]. To accommodate this growing demand, a large body of research has focused on optimizing LLM serving in terms of model serving latency [22, 47], resource utilization [4, 20, 28], service quality [30, 55], and beyond [21, 46, 54].

Inference serving workloads play an important role in this innovation process: they motivate the design of new optimization techniques and systems, and the effectiveness of the latter must be validated under respective workloads. Yet, there is an absence of comprehensive, production-scale characterization of real-world serving workloads. The status quo is a mixture of (*i*) adapted workloads from general deep-learning or cloud computing tasks [23–25, 39, 45] (e.g., using function invocations in serverless workloads as inference

requests), and (*ii*) optimization- [10, 19, 20, 35] or pattern-specific [18, 44] analyses (e.g., detailing only certain patterns), which remain insufficient in scale and scope.

The lack of practical workload characterization poses two obstacles to the innovation process of LLM serving systems. First, the many uncharacterized aspects of real-world workloads hinder new insights and motivations, especially for emerging scenarios such as serving multimodal [11, 50] and reasoning [13, 32] models. Second, even for serving normal (i.e., non-reasoning) language models that have been extensively studied, the inadequate understanding of real-world workloads may still result in unrealistic benchmarking when evaluating emerging optimizations. The *de facto* approach (referred to as NAIVE) adopted by many studies [29, 46, 47, 52] generates workloads by simply combining certain arrival traces (e.g., sampled from Poisson or Gamma processes, or scaled from published traces [39]) with datasets (e.g., ShareGPT [38]).¹ However, prior experience in cloud workload modeling [9, 41] has highlighted more intricate workload patterns, such as “heterogeneity” [37] and “imbalance” [31], revealing that “naively-generated workloads are misleadingly easier to serve than real historical ones” [9]. In practice, scaling serving optimizations to deployment has been met with unforeseen difficulties, such as performance degradation [26] and major revisions in system design [1].

As a large cloud inference service provider, we aim to fill this gap with an extensive and detailed characterization of real-world LLM serving workloads, analyzing a diverse range of models (see Table 1) and billions of requests collected from our production clusters over four months. We provide a comprehensive analysis of LLM serving workloads that covers language (§3), multimodal (§4), and reasoning (§5) workloads, unveiling important *new* findings. We release a principled framework, ServeGen, which allows practitioners to incorporate our findings and generate realistic workloads that better reflect system performance compared to NAIVE workload generation (§6), thus facilitating the motivation and evaluation of ongoing research.

Characterizing language model workloads. We begin with a characterization of various (non-reasoning) language model workloads based on their arrival patterns (§3.1) and

¹Prior work has used the terms “trace”, “dataset”, and “workload” interchangeably. In our discussion, “trace” denotes request arrival timestamps, while “dataset” refers to request data distributions exclusively.

Table 1. The list of workloads and models in our study.

Category	Name	Model	Description	Workload Information
Language	M-large	Qwen-Max	Largest, general-purpose	February
	M-mid	Qwen-Plus	Balanced, general-purpose	February
	M-small	Qwen-Turbo	Cheapest, general-purpose	February
	M-long	Qwen-Long with a 10M context length	Long-document comprehension	January (one week)
	M-rp	Tongyi-Xingchen	Role-playing	January (one week)
	M-code	Tongyi-Lingma	Code completion	January (one week)
Multimodal	mm-image	Qwen2.5-VL-72B	Image & text input	March
	mm-audio	Qwen2-Audio-7B	Audio & text input	March
	mm-video	Qwen2.5-VL-72B	Video & text input	March
	mm-omni	Qwen2.5-Omni-7B	Omni-modal input	April (one week)
Reasoning	deepseek-r1	DeepSeek-R1-671B	Full reasoning model	March (one week)
	deepqwen-r1	DeepSeek-R1-distill-Qwen-32B	Distilled reasoning model	March (one week)

input/output lengths (§3.2). While there is prior work analyzing language model workloads, our analysis yields important new findings: (i) request arrivals exhibit a complex bursty pattern that goes beyond any single stochastic process (e.g., a gamma process is not necessarily the best fit in all cases); and (ii) the input/output length distributions can be modeled by combinations of classic distributions, but the corresponding parameters vary significantly over time. Considering these findings, we further conduct a deep-dive analysis by decomposing the workloads by clients (§3.3). This decomposition reveals a causal modeling of real-world workloads: most nondeterministic patterns in request arrivals (e.g., bursts) and length distributions (e.g., high dynamics over time) are caused by several top clients, while the behaviors of most clients remain stable and predictable. This finding is valuable for generating realistic workloads.

Characterizing multimodal and reasoning workloads. We also analyze inference serving workloads of emerging multimodal and reasoning models, highlighting their unique characteristics. For multimodal workloads, we report significant load variance across modalities (§4.1) and substantial request heterogeneity (§4.2), unveiling inefficiencies in the prefill phase of LLM inference. For reasoning workloads, the long and bimodal distribution of reasoning lengths (§5.1) and the more stable arrival pattern from multi-turn conversations (§5.2) present both challenges and opportunities in optimizing the decoding phase. In both scenarios, similarly, we analyze the workloads with client decomposition (§4.3 and §5.3) to deepen our characterization, again capturing the diverse patterns through causal modeling.

Workload generation. While the aforementioned findings help motivate the design of next-generation LLM serving systems, it remains crucial for practitioners to be able to evaluate said systems with realistic workloads. However, full-scale production workloads are not always available due to privacy concerns, particularly in emerging serving scenarios. Moreover, the few published workloads [10, 19, 20, 35, 44]

are limited to a specific scale and are subject to the so-called “workload churn” [8]. To better share our insights and further facilitate the community, we build and release ServeGen, a workload generation framework to generate realistic serving workloads. ServeGen performs principled modeling of workloads on a per-client basis based on our findings to generate realistic workloads, and is easy to use (§6.1). Our evaluation shows that ServeGen outperforms the NAIVE generation approach by producing workloads that better align with real ones (§6.2). Additionally, we demonstrate that ServeGen is beneficial for performance benchmarking of serving systems in production by studying a practical instance-provisioning use case. We show that ServeGen avoids 50% under-provisioning compared to naive workload generation.

Contributions. Our main contributions are as follows.

- We provide a comprehensive study of real-world LLM serving workloads in a large-scale production environment, which not only covers language models, but also emerging multimodal and reasoning models.
- We characterize production-level LLM serving workloads and conduct in-depth analysis by client decomposition, revealing important new findings.
- We release ServeGen, a principled framework for generating realistic serving workloads based on our findings to help motivate and benchmark future research.

2 Background

2.1 LLM Basics

Basic LLM inference. The typical inference workflow for an LLM request comprises two key phases: *prefill* and *decoding*. In the prefill phase, all *input* tokens in the user prompt are processed to generate the first *output* token. Subsequently, the decoding phase auto-regressively generates the rest of the output tokens sequentially, until either the generation of an end-of-sequence (EOS) token or a predefined maximum output length is reached. In both phases, requests are commonly batched [51] and processed simultaneously to

enhance the serving throughput. Consequently, the arrival pattern and input/output lengths of requests are strongly relevant to LLM inference performance, as they impact the batching result and computational load during execution.

Multimodal models. Multimodal LLMs [11, 50] are extended with the ability to process and integrate multiple types of data beyond text prompts, such as images, audio, and video, allowing for richer user interactions. In a typical multimodal inference workflow, a model must first process its multimodal inputs through a series of *downloading* (fetching data from URLs), *normalizing* (e.g., resizing images or resampling audio), and *encoding* (through modality-specific adapters, such as ViT [14]) stages to obtain their embeddings, which are fused with the text embeddings. The inference then proceeds in a process identical to basic LLM serving. As such, multimodal data distributions play a crucial role in the inference performance of multimodal LLMs.

Reasoning models. A significant recent progress in LLMs is the rise of reasoning models [13, 32], which have shown remarkable capabilities in conducting complex coding, math, and problem-solving tasks. These models exhibit a unique “thinking” behavior—their output tokens are divided into two sections²: first the *reason* tokens, where the model performs test-time computation [2], and second the *answer* tokens that actually answer the input prompt. This behavior makes reasoning workloads stand out from normal language model workloads, altering the workload statistics (e.g., longer outputs) while also potentially enabling new optimizations.

2.2 LLM Serving Workloads

Workload characterization and generation. Optimization of LLM serving systems promises significant performance gains and substantial cost reductions. However, achieving this goal requires a deep understanding of real-world workloads, which is often unavailable due to the absence of a comprehensive production-scale workload characterization. Table 2 summarizes related work on LLM inference workload characterization, omitting various brief analyses found in other work [10, 19, 20, 35] that are optimization-specific and more limited in scope. As shown by the comparison, state-of-the-art characterizations are lacking in terms of scale, and leave many workload patterns *uncharacterized*. Furthermore, this inadequacy results in *unrealistic* workload generation approaches, restricting practitioners to workloads that cannot fully capture real-world patterns. Thus, we are motivated to perform a more comprehensive and detailed characterization of real LLM serving workloads in production. We then share our insights by building and releasing ServeGen, a principled framework for generating realistic serving workloads to foster future research.

²The reasoning models we serve output special tokens to explicitly separate the reason and answer tokens, which we utilize during analysis.

Table 2. Comparison between our work and prior characterizations of LLM serving workloads. Dashes indicate unavailable data.

	Ours	BurstGPT [44]	LMM [18]
Characterization ▷ Scale			
Duration	4 months	4 months	2 days
#Models	12	2	-
#Requests	3.54B	5.29M	-
Characterization ▷ Scope			
Workloads	Language Multimodal Reasoning	Language	Image-modal
Patterns	Variant burstiness Distribution shifts Conversations	Variant burstiness	Image data distribution
Workload Generation			
Approach	Parameterized clients	Parameterized burstiness	NAIVE

Workload source. Alibaba Bailian is a cutting-edge AI model service platform that enables users to build and use various kinds of custom model services. Its model repository contains over 200 foundation models and thousands of fine-tuned models. More than hundreds of enterprises have deployed their applications based on Bailian, and millions of requests are served each day. To support such a high and diverse model-serving workload, Bailian maintains O(10K) GPUs distributed in dozens of regions and zones, making Bailian a world-wide large model service platform.

Our characterization is supported by real inference workloads running in Bailian. The analyzed workloads span four months from January to April 2025, containing 12 different models and billions of requests from datacenters in different geolocations, as shown in Table 1. We source request metadata from our logging database for the backend inference engines, collecting detailed information including request arrival and execution times, payload (e.g., input and output lengths, chat histories, and multimodal inputs), and other relevant data, all sanitized to respect client privacy. The synergy of these dimensions enables us to gain a deep and comprehensive understanding of LLM serving workloads.

3 Characterizing Language Workloads

This section analyzes language model workloads listed in Table 1. We characterize and report a series of findings for arrival times (§3.1) and input/output length distributions (§3.2), two essential traits that affect the performance of an LLM serving system. Importantly, we show that much of the complex underlying patterns behind our findings can be explained by client decomposition (§3.3).

3.1 Request Arrival Pattern

Bursty short-term arrival patterns. Figure 1 characterizes the inter-arrival time (IAT) distributions for M-large,

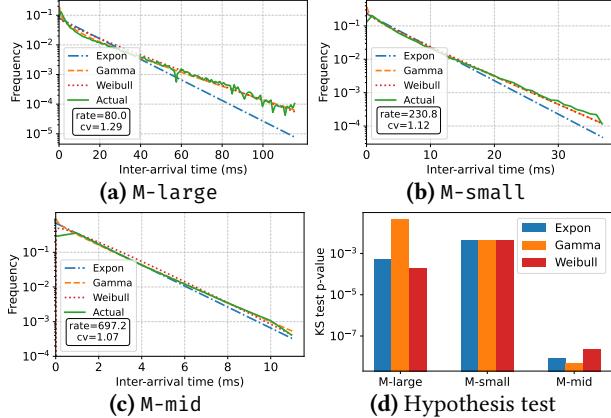


Figure 1. Inter-arrival time characterization.

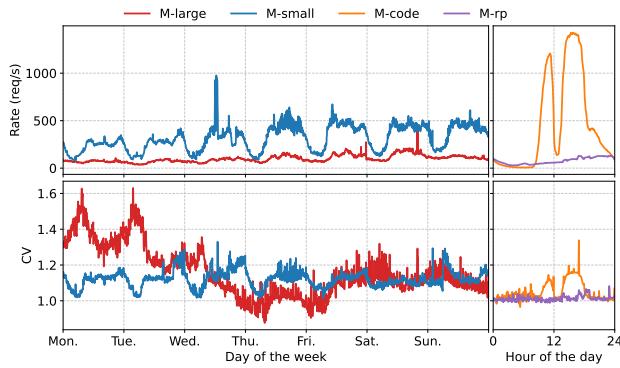


Figure 2. Long-term rate and CV shifts.

M-small, and M-mid within a 20-minute window. Conforming to existing analyses [39, 44], we find that the arrival patterns exhibit notable *burstiness*, indicated by CVs greater than 1. Consequently, Poisson processes (which have a CV of 1) often poorly model the IATs in bursty workloads (such as in Figure 1(a)), where Gamma and Weibull processes are better alternatives. However, we note that there is not a single stochastic process that best describes realistic arrivals in every case, which is validated in Figure 1(d), where we apply the Kolmogorov-Smirnov (KS) test to check whether the measured IATs came from Exponential, Gamma, or Weibull distributions.³ None of the distributions has the largest p-value consistently, indicating variable goodness of fit. In fact, the best-fit choices are different for the three workloads: Gamma for M-large, Weibull for M-mid, and even Exponential is not necessarily inferior for M-small. Practically, this implies that arrival patterns in real-world workloads should be modeled flexibly using different distributions to better preserve their characteristics.

Finding 1: The short-term arrival of LLM requests is often bursty ($CV > 1$), exhibiting complex patterns beyond any single stochastic process.

Shifting rate and burstiness. Figure 2 depicts the request rate and CV computed in 5-minute windows for multiple workloads, ranging from general-purpose (over a week) to task-specific ones (over a day). We observe evident diurnal fluctuations for the arrival rate: the load peaks during the afternoons while dropping significantly in the early mornings, resulting in potentially extreme rate shifts (as shown for M-code). Moreover, Figure 2 also displays diverse and shifting CV patterns for different workloads, underscoring the instability of burstiness [44] in real-world workloads. For instance, M-large was continuously bursty for two days (Mon. and Tue.) before turning stable (Thu. and Fri.). Meanwhile, request arrivals in M-rp remain non-bursty for the entire day of analysis. We believe such diversity is partly caused by the invocation pattern associated with each workload: while role-playing (M-rp) typically involves human interaction (*i.e.*, invoked via chatbots), where bursts are less common, general-purpose workloads (M-large) likely include API invocations with bursts of batched request submission.

These shifts in rate and burstiness have strong implications for LLM serving systems in production. On one hand, rate shifts demonstrate the importance of *auto-scaling* mechanisms in order to properly provision and utilize resources. On the other hand, CV shifts provide both challenges and opportunities for designing *request scheduling* policies, which should acknowledge and adapt to different levels of burstiness. In contrast, systems that assume static workload patterns may not perform well in practice.

Finding 2: The arrival of LLM serving requests shows a diverse shifting pattern in terms of rate and burstiness, calling for adaptive system design.

3.2 Input and Output Length Distribution

We now characterize the input and output lengths of requests by examining their distributions in Figure 3. Figure 4 further presents the correlation between input and output lengths by binning similar input lengths and showing the 90% percentile range and median of the respective output lengths.

Modeling length distributions. Existing studies [44] have advocated modeling request input lengths with the Zipf distribution, acknowledging an implicit power law: input lengths have large standard deviation and a long upper tail (*i.e.*, existence of requests with exceedingly long prompts). In our analysis, we find that input lengths in general-purpose workloads are best modeled by *Pareto* distributions mixed with *Log-normal* distributions (both of which are also power-law distributions) for handling the fat tail, as shown in Figure 3(a) and 3(b) with the *Input Fit* and *Input Tail Fit* curves.

³Indeed, these p-values are too small to deny the null hypothesis (that the arrival is modeled by some distribution) with statistical significance. This is a commonly recognized limitation of the KS test when the sample size is large. However, comparing the p-values remains helpful.

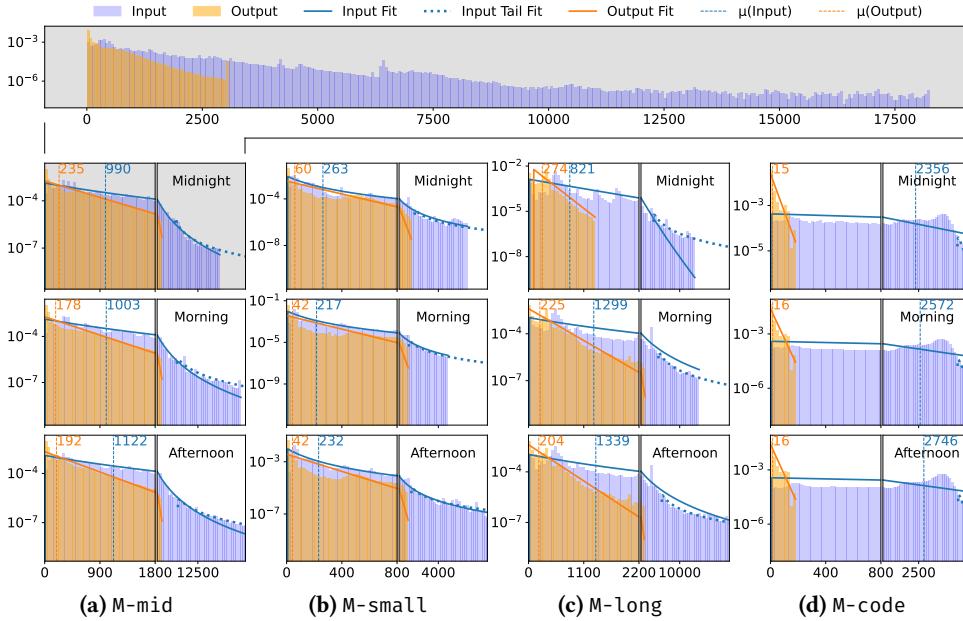


Figure 3. Input and output length distribution. *x-axis*: # tokens; *y-axis*: frequency. Each subfigure corresponds to a specific workload and time period, split to two consecutive x-scales to better visualize the shift in average lengths (left) as well as the tail distribution (right).

For task-specific workloads, the aforementioned model is less accurate due to domain-specific bias, such as the usage of common system prompts or templates.

Surprisingly, we find that *Exponential* distributions fit remarkably well for output lengths, with the only obvious exception of M-small in Figure 3(b). While it is difficult to pinpoint the exact reason behind this phenomenon (likely a combined result of training and workload semantics), the implication is worth noting: the remaining output length of an LLM request is not conditioned on the generated length so far, *i.e.*, the output length distribution is *memoryless*.

Lastly, while Figure 4 exhibits a rough positive correlation between input and output lengths (*i.e.*, long prompts lead to long responses), the relation is not as pronounced as reported in previous studies [44]. We believe that in practice, the correlation is diminished by complicated workload semantics, such as prompt templates or structured outputs.

Finding 3: The input length distribution can be modeled with a mixture of Pareto and Log-normal distributions, and the output with Exponential distributions. Correlation between input and output lengths is weak.

Shifting length distributions. Motivated by our Finding 2, we repeat the preceding analysis over time, using data sampled from three different periods in a day, as shown in the three rows of Figure 3 and 4. While the correlation appears independent of time, the actual distribution, contrary to common beliefs, *does* shift with time. Notably, the range of such shifts can be up to 1.63 \times for input lengths (Figure 3(c)) and

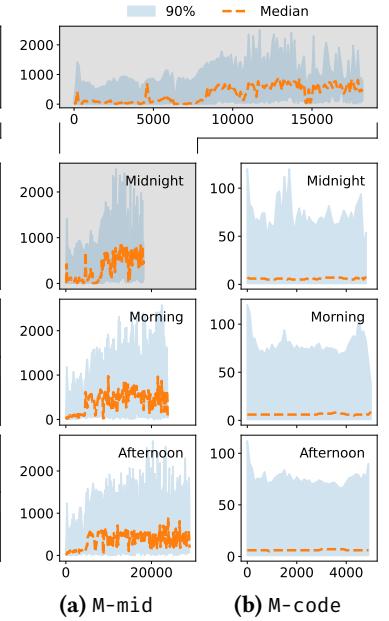


Figure 4. Input and output length correlation. *x-axis*: input length; *y-axis*: output length.

1.46 \times for output lengths (Figure 3(d)), measured by the maximal average length over the minimal.

Further, input and output length shifts occur *independently*, as demonstrated by M-mid in Figure 3(a): from *Midnight* to *Afternoon*, M-mid’s input length increases by 13% on average, while its output length drops by 18%. Intertwined with the request rate shifts, this observation translates to diverse load on the prefill and decoding phases of LLM serving, thus directly impacting system performance. Non-disaggregated serving systems may face variable performance interference between the two phases [55], while disaggregated systems must support independent resource auto-scaling for prefill and decoding.

Finding 4: The input and output length distributions shift dynamically and independently over time, leading to diverse load fluctuations for prefill and decoding.

3.3 Client Decomposition

Thus far, we have uncovered several shifting patterns in LLM serving workloads with concrete real-world implications. These patterns are non-trivial to model because they are the aggregate of requests from multiple *clients*, each corresponding to an individual end user or upstream application (*e.g.*, a chatbot that relies on our service). To gain more insights, we conduct a decomposition analysis of the M-small workload on a *per-client* basis. We report substantial heterogeneity and stability in client behaviors, and further reveal that the aforementioned shifting patterns are largely attributable to rate fluctuations among top clients.

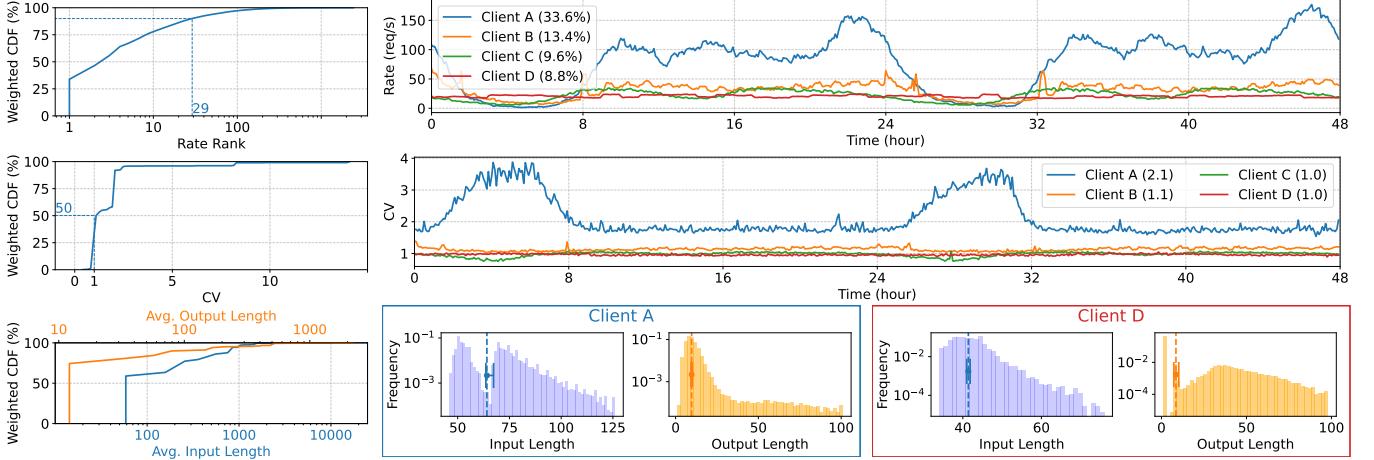


Figure 5. Client heterogeneity in terms of rate, burstiness, and input/output length distribution, using the first 48-hour data from Figure 2 (Mon. to Wed.). All CDFs are weighted by client rates.

Figure 6. Characterization of the top four clients in the M-small workload in isolation, using the first 48-hour data from Figure 2. Vertical lines in the last-row subfigures indicate average input/output lengths, and error bars show the range of average lengths in 1-hour windows.

Client heterogeneity and stability. Figure 5 characterizes the client behaviors in terms of their rate, burstiness, and input/output length distribution, using the first 48-hour data from Figure 2 (Mon. to Wed.). We observe highly skewed client rates: out of 2,412 clients, the top 29 clients (ranked by their rate in descending order) are responsible for 90% of the requests. Furthermore, client burstiness and input/output lengths span a diverse range, indicating the fundamental heterogeneity of clients.

Meanwhile, when considered separately, top clients exhibit notable stability in all aspects other than their request rate, as shown in Figure 6. For example, the burstiness of Clients B, C, and D remains mostly stable within 48 hours, and the burstiness of Client A only deviates in the early mornings when the rate drops exceedingly low. Additionally, Clients A and D display stable input and output lengths, as indicated by the small error bars in the last-row subfigures, which visualize the range of average lengths during the entire period of our analysis.

Impact of top clients. Combining these observations suggests the following *causal modeling*: characteristics of the whole workload are likely steered by a few top clients, whose rate fluctuations effectively cause the workload to shift towards different patterns.

This modeling indeed accounts for many previously found patterns in M-small. For example, note that in Figure 2, the workload temporarily bursts on Tuesday night. This matches the fact that in Figure 6, the rate of Client A (which is bursty) also sees a peak at around the same time. As for request lengths, the average input length of M-small decreases from *Midnight to Morning* in Figure 3, aligning with the increase of request rate from Client A (whose input lengths are shorter than average) from hour 1 to hour 9 in Figure 6.

We rely on the same causal modeling in §6 for generating realistic workloads that encompass the intricate shifting patterns, where we evaluate the accuracy and benefits of our approach quantitatively.

Finding 5: Real-world workloads consist of heterogeneous clients with skewed arrival rates. The top clients and their rate fluctuations largely explain the shifting workload patterns.

4 Characterizing Multimodal Workloads

We next examine workloads for multimodal models. Our characterization reveals that the tokenized length distributions are irregular across image, audio, and video modalities, contributing to highly variable multimodal load that also shifts over time (§4.1). Together with the overhead from downloading, normalizing, and encoding (§4.2), multimodal inference is prone to considerable request *heterogeneity* between modalities, leading to prolonged time-to-first-token (TTFT). We report how client decomposition helps capture these patterns and facilitates a deeper understanding of multimodal workloads (§4.3).

4.1 Modality Load Variance

Load variance in different modalities. Figure 7 characterizes data distributions in mm-image, mm-audio, and mm-video, focusing specifically on the image, audio, and video parts of request inputs. Unlike text prompts, multimodal inputs are more likely to have standard sizes depending on upstream applications. As such, in all three workloads, the tokenized lengths of multimodal inputs exhibit irregularly shaped distributions, clustering around certain values (e.g., around 2,500 for mm-video in (b)) instead of following typical power-law distributions like the text modality (see Figure 3). In addition, given the diverse number of multimodal inputs

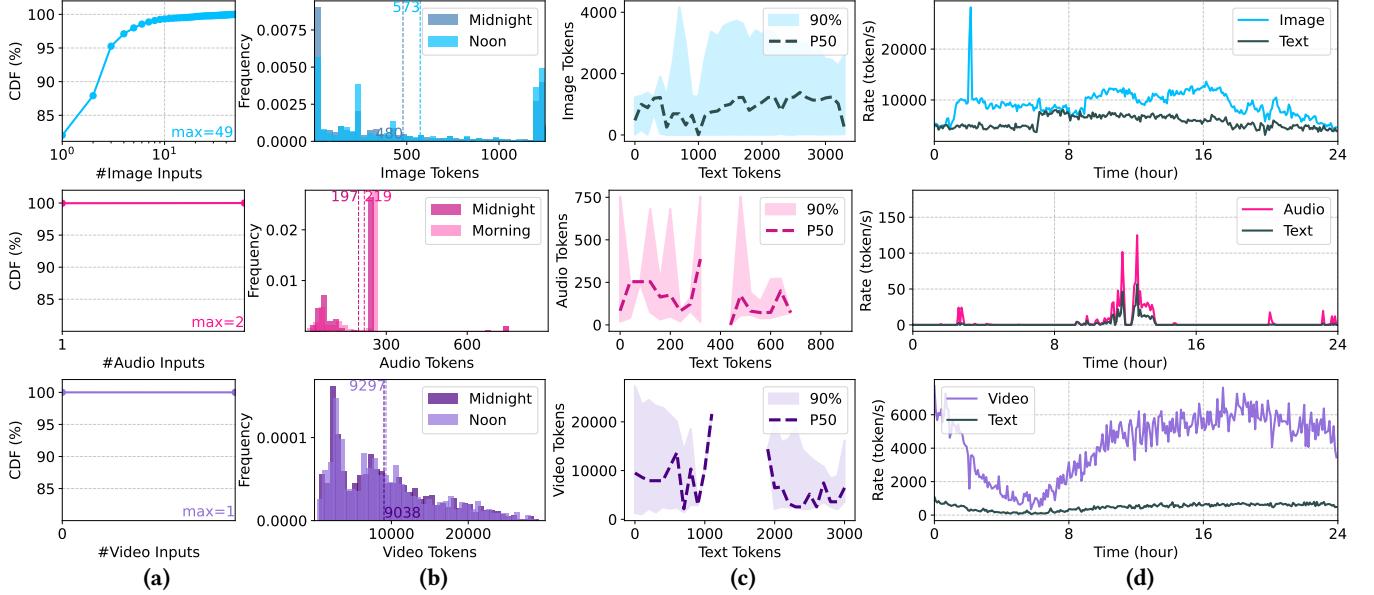


Figure 7. Characterization of multimodal inputs in three different workloads. Rows: mm-image, mm-audio, and mm-video, respectively. Columns: (a) number of multimodal inputs per request; (b) tokenized length distribution of multimodal inputs; (c) correlation between text tokens and multimodal tokens; (d) overall arrival rate of multimodal and text tokens.

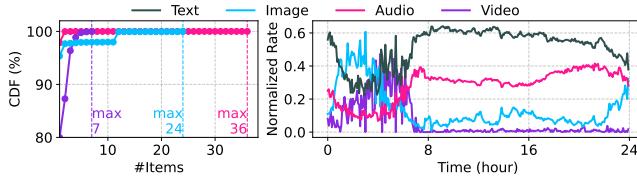


Figure 8. Characterization of omni-modal inputs in mm-omni. Left: number of multimodal inputs per request. Right: arrival rate of multimodal and text tokens, normalized by the total input rate.

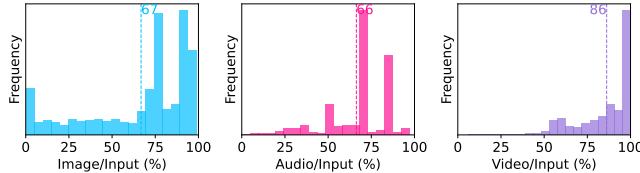


Figure 9. Ratio of multimodal input tokens per request in mm-image, mm-audio, and mm-video. Numbers indicate the average ratio.

per request (shown in (a))⁴ and the lack of correlation between text and multimodal tokens (shown in (c)), we observe highly *varied* load on modality encoders, as illustrated in (d).

Two observations further complicate the load variance in multimodal workloads. (i) The variance of multimodal load can be independent of the load from text tokens. For example, nine hours into the mm-image workload, an abrupt increase in the image token rate occurs, while the text token rate remains constant. (ii) Similar to the input/output distributions in language workloads, the distributions of multimodal data also shift over time, as revealed in Figure 7(b). For instance,

the average image length in mm-image varies by up to 19% over the course of a day.

Load variance in omni-modality. Figure 8 presents the same analysis on mm-omni, an omni-modal workload where requests can contain multiple modalities in addition to text. Unsurprisingly, the workload exhibits more complex variability, featuring a greater number of multimodal inputs per request and more diverse shifting patterns in input load (e.g., audio load rises during the day, while image load becomes prominent past midnight). Moreover, as new applications of omni-modal LLMs change how customers use our service, we anticipate that the load variance in omni-modal workloads will continue to evolve.

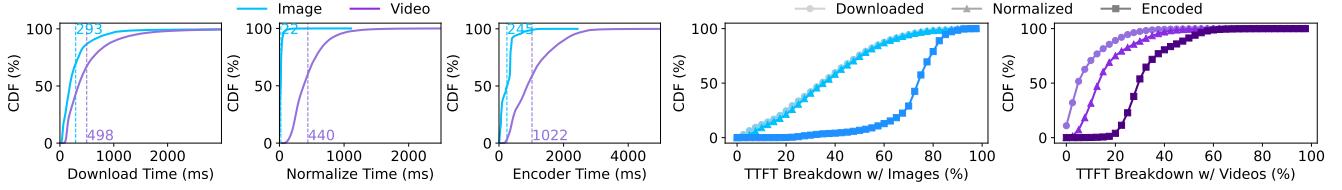
In both cases, load variance presents challenges to the resource efficiency of multimodal inference, necessitating serving systems that can scale resources (e.g., encoder instances) for each modality independently.

Finding 6: Multimodal data distributions exhibit irregular and independent shifts, underscoring significant load variance across modalities.

4.2 Request Heterogeneity

Multimodal inputs introduce complexity not only to the overall load, but also to individual requests. Figure 9 presents a breakdown of each request's input tokens in the mm-image, mm-audio, and mm-video workloads, revealing a flat distribution in every case. This indicates that real multimodal requests are *heterogeneous*, naturally ranging from text-heavy to multimodal-heavy in terms of input composition.

⁴We expect mm-audio and mm-video to have more multimodal inputs per request as their applications continue to mature.



(a) Per-stage time during first-token generation.

(b) CDF of cumulative time after each stage.

Figure 10. Breakdown of first-token time when serving requests with image or video inputs (mm-image and mm-video).

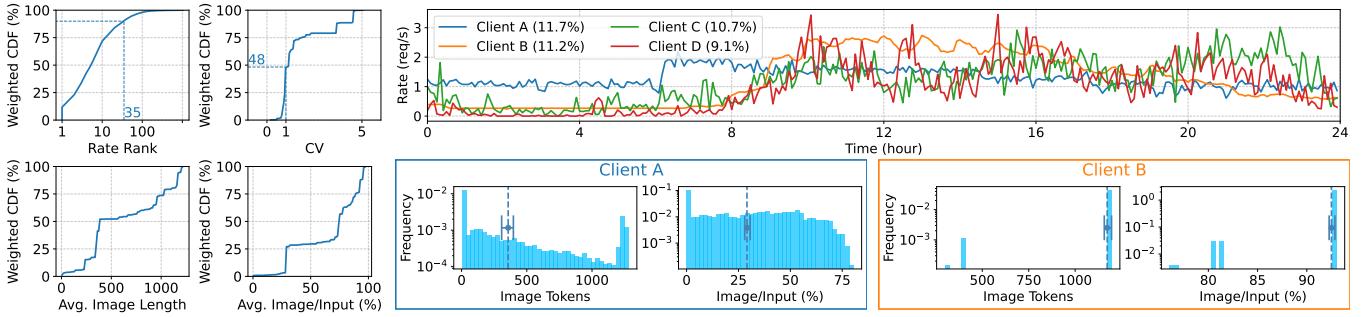


Figure 11. Client characterization for **Figure 12.** Behavior of top clients in mm-image in isolation. Vertical lines in the last-row subfigures mm-image. CDFs are weighted by rates. indicate average lengths, and error bars show the range of average lengths within a day.

In practice, such heterogeneity is challenging for serving systems, as it translates into prolonged TTFT during inference, as shown in Figure 10. On one hand, for multimodal-heavy requests, the *download*, *normalization*, and *encoding* stages for tokenizing multimodal inputs all contribute to considerable extra overhead (reported in Figure 10(a)) in the first-token generation process, directly lengthening the TTFT, as illustrated in Figure 10(b). For instance, half of the mm-image requests spend 75% of their TTFT before LLM prefilling. On the other hand, the extremely long-tailed distribution of encoder time in Figure 10 signifies potential queuing that affects text-heavy requests as well. For example, a request with few image tokens in mm-image may be blocked at the encoding stage, waiting for previously scheduled image-heavy requests; or it may experience a longer encoding time due to suboptimal batching that only considers prefill execution. This highlights the need for more advanced scheduling and batching strategies.

Finding 7: Multimodal requests are heterogeneous with diverse ratios of multimodal inputs per request, which leads to prolonged TTFTs that necessitate tailored optimizations.

4.3 Multimodal Client Decomposition

Given the involved patterns in multimodal workloads, we present a client decomposition of mm-image similar to that in §3.3 to further complement our characterization. Notably, our causal modeling proposed by Finding 5 still applies, as we verify that load variance and request heterogeneity are explainable by the multimodal client behaviors.

Characterization of multimodal clients. Figure 11 summarizes the behaviors of 1,036 multimodal clients in mm-image, which are heterogeneous in terms of rate, burstiness, image length distributions, and image-to-input ratios per request. Interestingly, the last two CDFs concerning image data in Figure 11 exhibit a *staircase-like* pattern, hinting at the existence of text-heavy or multimodal-heavy clients.

Indeed, some of the top clients show remarkably skewed data distributions, as represented by Client B in Figure 12, who exclusively sends images of the same size (around 1,200 tokens each) and requests that are similarly structured for the entire 24 hours during our measurement. In general, top-client behaviors remain stable and predictable, as indicated by the narrow error bars in the lower part of Figure 12.

Explaining workload patterns. We emphasize that the top clients presented in Figure 12 have a straightforward impact on the previously presented workload patterns. On one hand, the heterogeneity of clients directly contributes to the diverse image-to-input ratios across all requests. On the other hand, Client B's rate ramps up roughly nine hours into the workload, resulting in a surge of image-heavy requests (typical for this client) that exactly matches the load variance of image tokens, as mentioned in §4.1.

Finding 8: Top clients in multimodal workloads exhibit diverse behaviors, and characterizing them helps explain the overall workload patterns.

5 Characterizing Reasoning Workloads

This section focuses on analyzing reasoning workloads. Our characterization shows that the unique “thinking” behavior of reasoning models (§2.1) results in longer, more variable

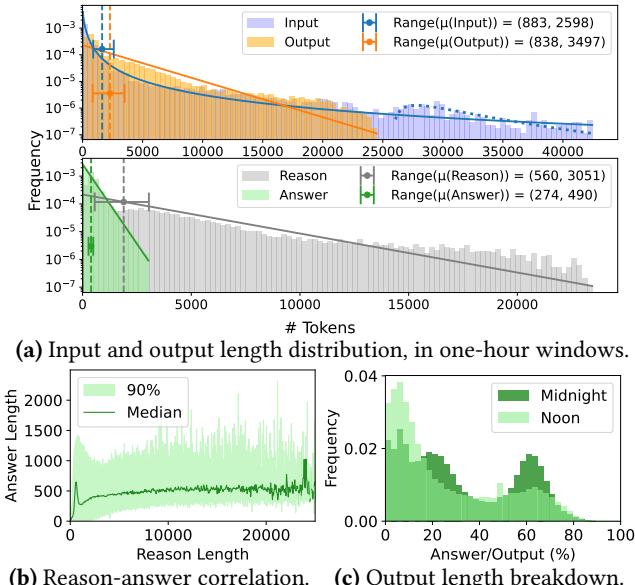


Figure 13. Characterization of input and output lengths for the deepseek-r1 workload in one day. Error bars in (a) indicate the range of average lengths over the day.

output lengths and a distinct ratio of *reason* and *answer* tokens (§5.1). In addition, request arrivals in reasoning workloads are less bursty, partly owing to a considerable proportion of multi-turn conversations, which alter the request arrival pattern (§5.2). We conclude with client decomposition to extend our causal modeling to reasoning workloads (§5.3).

5.1 Understanding Reason and Answer Lengths

Figure 13 characterizes request lengths in the deepseek-r1 workload, depicting also the reason and answer parts of outputs. In the upper part of Figure 13(a), we observe similar power-law distributions and shifting patterns (Finding 3 and 4) in terms of input and output lengths, as indicated by the fitting curves and error bars. However, output lengths are significantly longer and more variable than those found in non-reasoning workloads, due to the long reason lengths. In fact, as shown in the lower part of Figure 13(a), reason lengths can be on average 4× longer than answer lengths, and contribute more to the shifting of output lengths. The different matching levels of Exponential fitting curves suggest that, to some extent, the reason part of requests behaves more like further inputs for LLMs, while the answer section remains akin to traditional model outputs.

Moreover, Figures 13(b) and 13(c) reveal a non-trivial relation between reason and answer lengths: there exists a clearer correlation between them (compared with Figure 4), while their per-request ratio exhibits a consistent *bimodal* distribution. The bimodality originates from two dominating task patterns adopted by a reasoning model (*i.e.*, reasoning for either a more complete or more concise answer), which future serving optimizations may be able to leverage.

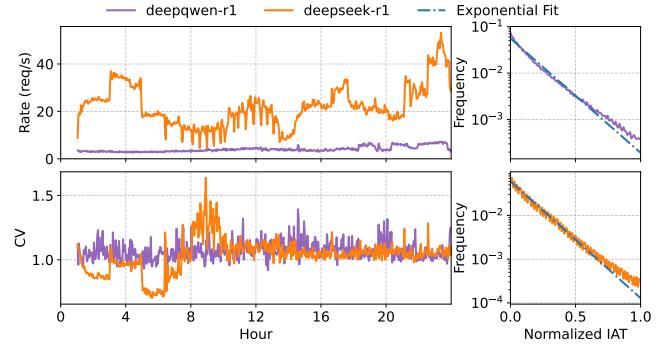


Figure 14. Characterization of request arrival patterns in deepseek-r1 and deepqwen-r1. *Left:* Rate and burstiness shifts over a day. *Right:* Normalized inter-arrival time distributions.

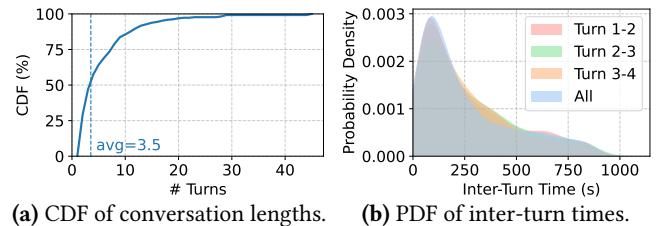


Figure 15. Characterization of conversations in deepseek-r1.

Finding 9: Reasoning workloads exhibit longer and more variable output lengths, due to the reason tokens. In relation, reason and answer lengths display stronger positive correlation, as well as a unique bimodal ratio.

5.2 Arrival Pattern and Multi-Turn Conversations

Non-bursty arrivals. Figure 14 illustrates the arrival pattern for both deepseek-r1 and deepqwen-r1 over a day. On the left, the CV of request arrivals remains mostly close to or even less than 1 despite the diurnal rate shift, indicating that both workloads are non-bursty (especially compared with those in Figure 2). The right side of Figure 14 further validates this fact, showing that the Exponential distribution fits the inter-arrival time distribution quite well (*i.e.*, the arrival is roughly modeled by Poisson processes).

Characterizing multi-turn conversations. Engaging in multi-turn conversations is an essential capability of LLMs [43, 48], and it also introduces a special pattern to request arrivals: intuitively, earlier requests foretell the *reoccurrence* of follow-up conversations, which may alter the workload burstiness.

We thus conduct a dedicated characterization of multi-turn requests found in deepseek-r1. Within our 12-hour

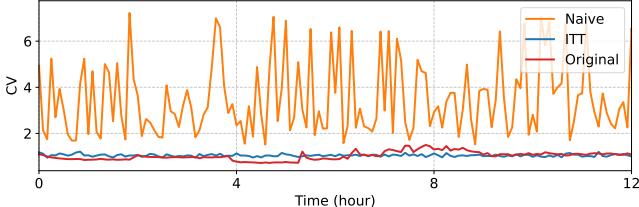


Figure 16. Comparison of two upsampling methods for a workload containing only multi-turn requests.

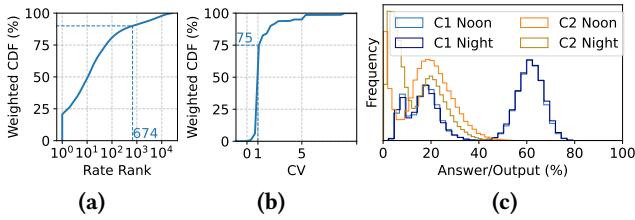


Figure 17. Client decomposition for deepseek-r1. (a) weighted CDF of client arrival rate. (b) weighted CDF of client burstiness. (c) output length breakdown of top clients (C1 and C2).

analysis window, we have identified⁵ 188,986 multi-turn requests out of 1,964,415 total requests, forming 57,205 conversations. Figure 15(a) shows the distribution of the conversation lengths, averaging 3.5. The distribution of inter-turn time (ITT), *i.e.*, the time between the arrival of consecutive turns, is detailed in Figure 15(b). In general, ITTs concentrate around 100 seconds, with an extremely long tail (the figure is truncated at the 75th percentile for visualization).

Impact of multi-turn conversations. Since multi-turn requests constitute almost 10% of the deepseek-r1 workload, their pattern has a specific impact on workload characteristics. To demonstrate this, we apply two upsampling methods to the identified multi-turn requests, scaling them to the same size as the original workload. The *Naive* method is agnostic about the conversations and simply scales the inter-arrival time, while the *ITT* method works by scaling the arrival time between conversations, leaving the ITT distribution unchanged. Figure 16 compares the upsampled and original workloads by measuring the workload burstiness over time, highlighting a substantial difference: *Naive* produces a highly bursty workload, while the *ITT*-workload is even more stable than the original. It is thus essential for realistic workloads to faithfully reflect the multi-turn conversation pattern by adhering to ITT distributions in Figure 15(b).

Finding 10: Request arrival in reasoning workloads is impacted by the reoccurring pattern of multi-turn conversations and appears less bursty.

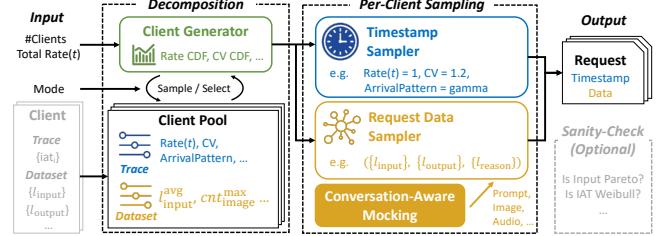


Figure 18. Overview of the ServeGen framework. The color gray indicates optional requirements; *e.g.*, users can still use ServeGen without providing additional client information.

5.3 Client Decomposition of Reasoning Workloads

Figure 17 presents client behaviors in the reasoning workload deepseek-r1. Interestingly, according to Figure 17(a), top clients in deepseek-r1 are shown to be less substantial in comparison with other workloads (Figures 5 and 11): out of 25,913 clients, the top 10 clients only constitute half of the requests. Furthermore, the proportion of non-bursty clients (Figure 17(b)) is also significantly higher, likely contributing to the overall non-burstiness of the workload. In addition, we observe again the bimodal distribution in the breakdown of request output lengths across multiple top clients, as depicted in Figure 17(c). This implies that the pattern revealed in Figure 13(c) can still be causally modeled on a per-client basis, where the day-and-night shift of the answer length ratio is attributed to the fluctuation of client rates.

Finding 11: Clients in reasoning workloads exhibit less skewed rates and less bursty arrivals, while also showing the bimodal pattern in terms of data distributions.

6 Workload Generation

Motivated by the many findings in our characterization, we build ServeGen, a principled framework for generating workloads that incorporate the realistic characteristics revealed in previous sections. Next, we describe our framework (§6.1), validate its accuracy (§6.2), and show its benefits for benchmarking serving systems with a real-world use case (§6.3).

6.1 ServeGen Framework

Figure 18 presents an overview of ServeGen, which is centered around *clients*. Essentially, ServeGen samples requests on a *per-client* basis, and aggregates them to compose realistic workloads. Each client in ServeGen is described by its trace and dataset, both of which can be either parameterized (*e.g.*, modeling a trace with the Gamma distribution) or provided as data samples (*e.g.*, a set of prompt lengths).

To use ServeGen, a user starts by providing the total number of clients, as well as a target total arrival rate. ServeGen then relies on the **Client Generator** to characterize

⁵Our method is not accurate for many reasons: parts of conversations could fall out of the analyzed window, or the messages could be altered or filtered by the log store. Still, the resulting workload is reasonably large for analysis.

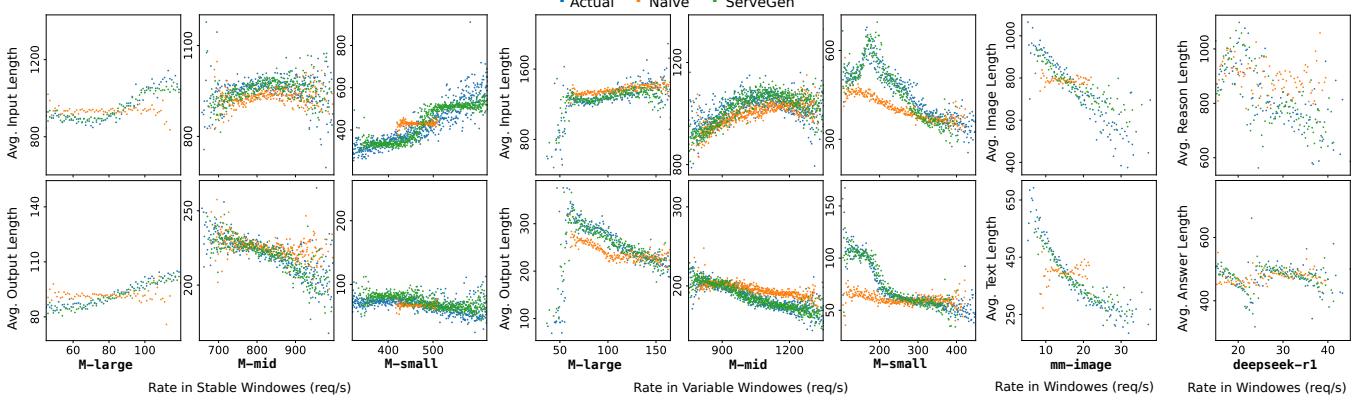


Figure 19. Comparison of workload generation accuracy.

each client, either by sampling from the Client Pool pre-configured with realistic client behaviors, or by selecting from a set of user-specified clients with custom traces and datasets. Next, ServeGen samples the request timestamps and data for each client with the Timestamp Sampler and Request Data Sampler, scaling client rates according to the total rate and generating data via conversation-aware mocking to preserve conversation histories. Lastly, ServeGen combines the timestamps and data to produce a workload.

ServeGen holistically utilizes the findings reported in previous sections to generate realistic workloads and ensure ease of use. For example, given Finding 2, the client rates and the total rate in ServeGen are parameterized over the current time t , enabling ServeGen to generate workloads with varying rates. Furthermore, we apply Finding 5 in the Client Generator to produce heterogeneous clients (*i.e.*, sampling clients according to real rates and CV rankings) and incorporate the other findings on trace and data distributions to configure the Client Pool with parameterized real-world clients⁶. Users may optionally use Findings 1 and 3 to sanity-check the statistics of generated workloads.

6.2 Generation Accuracy

We validate that the per-client generation approach in ServeGen captures the realistic characteristics of our workloads by measuring the generation accuracy with respect to Findings 2, 4, 6, and 9. Specifically, since the workload arrival patterns and data distributions undergo significant shifts over time, we aim to demonstrate that ServeGen produces workloads that exhibit similar characteristics.

Setups and metrics. For this set of experiments, we target the variability of data distributions across different workloads in 3-hour time periods. In each time period, we calculate the average values of relevant request data (*e.g.*, average input lengths for M-large) in 3-second windows, and plot

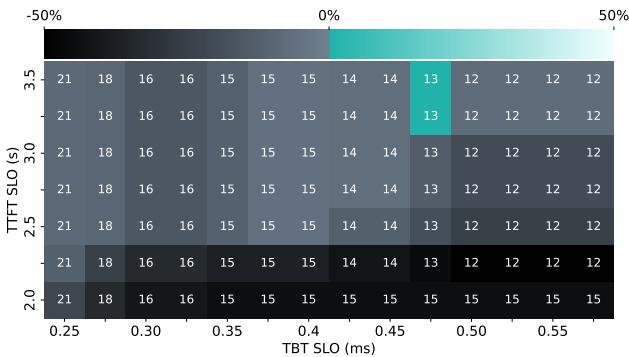
them against the request rates in those windows. For language workloads, we explicitly differentiate between stable (*i.e.*, the request rate fluctuates around a certain value) and variable (*i.e.*, the overall request rate is rising or dropping) periods. Intuitively, the shifting patterns in actual workloads should result in visible variability, which ServeGen should be able to match with generated workloads.

Configurations and baselines. We configure ServeGen to select real clients and match the corresponding total rate in each evaluated workload, effectively resampling them based on client decomposition. In contrast, the baseline approach, referred to as NAIVE, directly resamples each workload as a whole to match the rate and other overall statistics (*e.g.*, burstiness), which is representative of the workload generation method used in many existing works [29, 46, 47, 52]. For variable periods, the total rate in NAIVE is also parameterized by time to ensure a fair comparison.

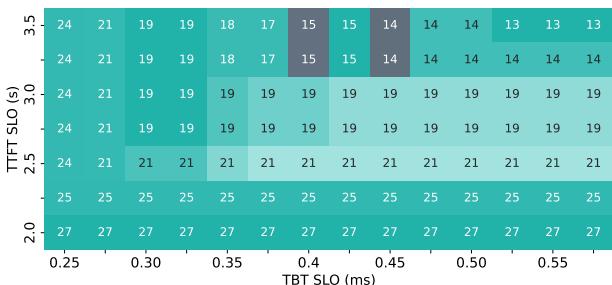
Results. Figure 19 demonstrates the generation accuracy of the two approaches. In every case, the workload produced by ServeGen is shown to be more realistic: the green scatter plot (ServeGen) matches the actual plot much better compared with the NAIVE plot.

Furthermore, the results reveal two major drawbacks of the NAIVE workloads. (i) They can be less variable in terms of request rate, despite their overall burstiness. This is particularly evident during stable periods, where the blue and green scatter plots span considerably wider horizontally, indicating more extreme values for the arrival rate. (ii) They barely capture the correlation between rates and data distributions, which is non-trivial in real workloads (see the blue scatter plot). Such correlations are not surprising given our per-client characterization—large or small short-term rates are likely caused by bursty top clients, and the workload data distributions are expected to shift correspondingly toward or away from the client data distributions.

⁶Due to confidentiality obligations, we release parameterized and sanitized data instead of full data samples.



(a) Provisioning with NAIVE.



(b) Provisioning with ServeGen.

Figure 20. Provisioning results using the NAIVE approach and ServeGen. In each cell, the number indicates the provisioned instances, while the color shows the over-provisioning percentage.

6.3 Use Case: Instance Provisioning

We now put ServeGen to use, illustrating how it helps with benchmarking LLM serving systems by running the generated workloads on vLLM [28], a representative LLM serving system with wide adoption. Particularly, we investigate an *instance-provisioning* scenario, *i.e.*, determining the minimum number of instances required to serve a workload while maintaining certain service-level objectives (SLOs). Next, we benchmark a vLLM instance with workloads produced by both ServeGen and the NAIVE approach (as defined in §6.2) to obtain provisioning results, and then evaluate how well these results scale when serving real workloads.

Detailed setups. We select a 10-minute period of M-large comprising 30,000 requests as the target workload, and set each instance to consist of 2 NVIDIA A100 (80GB) GPUs running a Qwen2.5-14B model⁷ with pipeline parallelism [29, 40]. Next, for a grid of target time-to-first-token (TTFT) and time-between-token (TBT) SLOs, we benchmark one instance with workloads generated via both ServeGen and NAIVE, adjusting the workload rate to find the maximum rate each instance can (supposedly) sustain without violating the SLOs (measured as P99 values), and thus derive the number of instances needed in each case. Lastly, we check the results by running the actual M-large workload with the provisioned number of instances, recording the actual SLO delivered.

⁷We opt for a smaller model than M-large due to budget constraints.

Results. Figure 20 reports the provisioning results, where the number in each heatmap cell represents the provisioned instance count using either NAIVE or ServeGen, and the cell color indicates the over- or under-provisioning percentage. For example, when the target P99 TTFT is 2.25s and TBT is 0.5s, ServeGen results in provisioning 25 instances (4% over the actual number needed), while NAIVE results in only 12 instances (50% under-provisioning). Overall, Figure 20(a) verifies that the NAIVE workloads are *misleadingly easier to serve* than real workloads. Meanwhile, Figure 20(b) fits the actual provisioning results much better, highlighting that the workloads generated by ServeGen can better reflect the system performance in real-world deployment.

7 Discussion

Fostering future research. The aforementioned findings have already benefited several development teams in Bailian, including those focused on inference engine optimization, resource planning, and request scheduling. Meanwhile, ServeGen can guide further research in many other areas, and we discuss two possible directions here. First, our multi-modal workload analysis reveals that a significant portion of TTFT stems from preprocessing (*i.e.*, downloading, normalization, and encoding). This highlights the importance of conducting full-stack optimizations (*e.g.*, decoupling the modality encoders and scaling them independently according to Finding 6), rather than solely improving the prefill performance. Second, our analysis of multi-turn conversations in reasoning workloads reveals that the arrival pattern for these requests is non-bursty (Finding 10), providing valuable insights for improving short-term workload predictability in conversational scenarios.

Limitations of ServeGen. While ServeGen covers mainstream LLM serving workloads, there are several aspects that require further study. First, some complex LLM serving applications adopt *plugin calls*, where a series of functions are called prior to model inference, performing web searches, database queries, or calling external APIs. The dependent execution of different functions collectively determines the end-to-end execution time, and the output length is influenced as well. We leave characterizing LLM serving with plugin calls as an important area for future work. Second, prefix caching [54] enables sharing intermediate KV cache between requests with common prompt prefixes. However, characterizing prefix caching requires full access to the content of requests. As a public cloud service provider, we prioritize user privacy and currently do not obtain full authorization to conduct such an analysis.

8 Related Work

LLM serving workload analysis. Prior work has characterized various workloads in alternative scenarios, such as HPC systems [5, 6, 17, 34], virtual machine management [9,

[12, 31, 37, 41], serverless computing [39, 53], GPU deep learning [23, 25, 42, 45], and LLM development [24], providing many valuable insights. Specific to LLM inference, Burst-GPT [44] and LMM [18] have characterized language and image-text-to-text model serving workloads, while a series of other studies have performed brief analyses from certain viewpoints such as burstiness [15], computational load [20, 55], prefix-sharing [10, 35], and energy efficiency [19]. In this work, we provide a comprehensive characterization of LLM serving workloads with a larger scale and scope.

Workload modeling and generation. Following the many findings revealed in prior cloud workload analysis, some works [7, 9, 12, 27, 45] have proposed generating realistic workloads by modeling them with historical data. Most efforts in this regard target generic cloud workloads for virtual machines. BurstGPT [44] is a recent work on LLM serving workloads, which uses a parameterized Gamma process to account for variant burstiness in LLM serving. Meanwhile, a large body of prior research [29, 46, 47, 52] has relied on the NAIve approach and simply combined traces and datasets. We hope the release of ServeGen can foster LLM serving research by covering multiple workload categories and modeling them more accurately with client decomposition, while ensuring ease of use for practitioners.

9 Conclusion

We present a comprehensive study of real-world serving workloads for language, multimodal, and reasoning models. We unveil various characteristics and summarize meaningful findings. Based on these findings, we provide ServeGen, a principled framework for generating realistic LLM serving workloads by composing them on a per-client basis. We show the benefits of ServeGen via a case study of instance provisioning.

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