# **INSTCACHE: A PREDICTIVE CACHE FOR LLM SERVING**

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## ABSTRACT

Large language models are revolutionizing every aspect of human life. However, the unprecedented power comes at the cost of significant computing intensity, suggesting long latency and large energy footprint. Key-Value Cache and Semantic Cache have been proposed as a solution to the above problem, but both suffer from limited scalability due to significant memory cost for each token or instruction embeddings. Motivated by the observations that most instructions are short, repetitive and predictable by LLMs, we propose to predict user-instructions by an instruction-aligned LLM and store them in a predictive cache, so-called InstCache. We introduce an instruction pre-population algorithm based on the negative log likelihood of instructions, determining the cache size with regard to the hit rate. The proposed InstCache is efficiently implemented as a hash table with minimal lookup latency for deployment. Experimental results show that InstCache can achieve up to 51.34% hit rate on LMSys dataset, which corresponds to a 2x speedup, at a memory cost of only 4.5GB.

# **1 INTRODUCTION**

Recently Large Language Models (LLMs) as well as their multi-modal equivalents have become the essential driver of a new wave of technology innovation, revolutionizing every aspect of human life. The unprecedented power of LLMs, however, comes at the price of unparallel scale of computation, which incurs a series of challenges. One primary challenge is the energy footprint, which is dominantly consumed by GPUs and other AI acceleration hardware. It is estimated that by 2026 the total energy consumption of AI computation will amount to 5% of US electricity production(Aschenbrenner, 2024) and the number will reach 20% in 2028. Another challenge is the latency of LLM response, which hinders a much wider application of LLM in live situations.

A large body of research has been dedicated to addressing the LLM computation bottleneck by data reusing. Among these works, Key-Value (KV) Cache(Kwon et al., 2023; Zheng et al., 2023) lowers the amount of GPU computation without the loss of LLM inference performance by trading computation for memory according to the auto-regressive nature of the decoder. Semantic Cache(Bang, 2023) offers reuse opportunities by searching and retrieving similar queries<sup>3</sup> stored in a database. While enabling significant savings in power consumption and latency, both methods are challenged by the scalability. For instance, key-value states of each token takes approximately a few megabytes of storage(Gao et al., 2024), which limits KV Cache to reusing



*Figure 1.* Analysis of instructions shows that most queries are short, repetitive and predictable with LLMs. The analysis of frequency and probability distribution is conducted on ShareGPT, with probabilities of tokens evaluated using Llama3-8B.

only the common instruction prefix or previous rounds of a dialogue(Zheng et al., 2023). On the other hand, Semantic Cache can reuse entire queries. However, scaling Semantic Cache remains challenging, as it requires searching for similar instructions by evaluating similarity between the embedding of incoming queries and stored instructions. Generating embedding and searching similar instructions incurs significant lookup latency and storage cost. Moreover, simple data reuse does not fully unlock the potential of data, particularly in the era of LLM.

This work is inspired by the observation that a significant portion of instructions to LLMs consists of short instruc-

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<sup>&</sup>lt;sup>3</sup>We refer the user input text to LLM as instruction, query and request interchangeably.

tions, as shown in Figure 1 (a). Furthermore, as illustrated in Figure 1 (b) and (c), these queries are often repetitive and predictable. Based on these observations, we propose an efficient LLM caching system, InstCache, for LLM inference. The basic idea is to predict user-instructions by an instruction-aligned LLM and store them as a predictive cache. Specifically, we introduce a negative log likelihood (NLL) based instruction pre-population algorithm and establish the relationship between NLL, hit rate and the number of instructions, enabling both hit rate and cache size to be predictable. By leveraging the astounding semantic understanding capability of LLMs, InstCache can predict potential instructions that have not yet been issued, offering functionality beyond traditional caching mechanisms. While pre-population, a tree structure is employed to search all possible instructions, where each node is a token and each path is an instruction and its corresponding answer. To maximize the efficiency while inference, after pre-population, InstCache will be flattened into a hash table, mapping hashed instructions to their answers. The hash table minimizes the lookup complexity to nearly  $\mathcal{O}(1)$ . Experimental results demonstrate that InstCache can achieve a hit rate of up to 51.34% on LMSys dataset by using approximately 4.5GB of CPU memory, indicating that half of user instructions can be processed using only a CPU and its memory, saving significant energy footprint. When deploying InstCache with existing LLM serving systems, such as vLLM(Kwon et al., 2023), we observe up to 2x average speedup on LMSys datasets.

Our contributions are as follows: (1) we propose InstCache which contains predictive user instructions from an LLM, providing the capability exceeding traditional cache mechanism which only reuse requested instructions. (2) We provide the guarantee of hit rate and cache size through modeling the negative log likelihood distribution of instructions. (3) InstCache is organized as a hash table while inference, which minimizes the lookup complexity to nearly O(1), incuring minimal additional latency to existing LLM serving systems.

# **2** BACKGROUND

## 2.1 Language Model

In this section, we briefly introduce the concept of a Language Model (LM) and the negative log likelihood (NLL) metric. We explain the basic mechanism of an LM and how it can be used to predict all possible sentences.

Large Language Models (LLMs) are designed to autoregressively predict the next token in a sequence based on the preceding tokens. For an LM with a vocabulary size of v, the model processes a sequence of tokens  $\{t_1, t_2, ..., t_{n-1}\}$  and predicts the probability distribution p over possible tokens in the vocabulary, as described in Eq. 1.

$$p(t_n = V_i | t_1, t_2, ..., t_{n-1}) = \mathbf{LM}(t_1, t_2, ..., t_{n-1})$$
(1)

where  $V_i$  represents the  $i^{th}$  token in the vocabulary.

For a sentence s of length n, the NLL, which quantifies the impossibility of the sentence, can be computed as shown in Eq. 2.

$$NLL(s, LM) = -\ln(\prod_{i=1}^{n} p(t_i | t_1, t_2, ..., t_{i-1}))$$
 (2)

Generally, LLMs are trained by padding each passage with special tokens that mark the beginning and end of the passage, such as <bos> and <eos>. Starting with a beginof-sentence token, an LLM predicts tokens step-by-step, forming possible sequences. The autoregressive scheme enables the prediction of all valid sentences with an NLL below a certain threshold, as required by the proposed work elaborated in Section 3.

## 2.2 Analysis of User Instructions to LLM

In this section, we analyze real-world user instructions and identify common patterns, namely, shortness, repetitiveness, and predictability. Due to the scarcity of public datasets of human instructions, we used all available datasets(Liu et al., 2024), LMSys(Zheng et al., 2024) and ShareGPT(Team, 2023), for analysis. LMSys is a large-scale, real-world conversation dataset collected from the Vicuna demo and the Chatbot Arena website(Chiang et al., 2024). The dataset is unfiltered and rich of simpler questions. ShareGPT is derived from conversations shared by GPT users. While capturing more realistic dialogues, ShareGPT has a bias towards harder questions since users often prefer sharing complex and interesting interactions. Although there are various supervised finetuning datasets, such as Moss(Sun et al., 2024), they are primarily consist of human instructions and synthetic instructions. To avoid contamination, we do not use these datasets in this study. Our experiments focus on first-turn instructions, while instructions in more turns follow similar patterns in general.

#### 2.2.1 Shortness

We first analyze the length distribution of instructions in each dataset. As shown in Figure 1 (a), the majority of user instructions are relatively short, with most containing fewer than 100 tokens. This is consistent with intuitions, as LLM services are often used in chatbot scenarios(OpenAI, 2022), where users interactively input instructions, typically word



*Figure 2.* Analysis of Frequencies on LMSys and ShareGPT datasets shows that a large portion of instructions repeat at least once. The cumulative distribution function of the negative log likelihood of instructions indicates that the majority of instructions are possible to be predicted by LLMs.

by word. When not requiring specific tasks such as text rewriting, users tend to minimize the length of their inputs.

While LMSys and ShareGPT datasets may exhibit biases, we believe that short questions still constitute a significant portion of real-world instructions. Optimizing the processing of short instructions can free system resources, thus improving overall system performance. Consequently, in this work, we focus our efforts on optimizing for these short instructions.

#### 2.2.2 Repetitiveness

Figure 2 (a) illustrates the repetition rates of instructions across datasets. In LMSys dataset, at least 50% of instructions are repeated at least once, while in ShareGPT, approximately 30% are repeated. These findings suggest that users frequently submit similar instructions, which underscores the potential benefits of caching frequent instructions to reduce computational overhead.

#### 2.2.3 Predictability

To measure the predictability of user instructions, we compute the negative log likelihood (NLL) of instructions from both datasets using Llama3-8B(Dubey et al., 2024) and plot the cumulative distribution functions. As shown in Figure 2 (b), the NLLs of most instructions saturate fast with relatively small values, indicating that such instructions can be easily predicted by LLMs. Moreover, as demonstrated in Figure 5 (a), finetuning the LLM on instructions in training set can shift the NLL cumulative distribution further left, improving the predictability of user instructions.

Based on these observations, we propose to predict short instructions using an instruction-aligned LLM. By leverage the semantic capability of LLMs, we can predict potential instructions rather than reuse issued instructions, providing significent enhancement to the traditional caching mechanism.

# **3** INSTCACHE

## 3.1 Overview

In this section, we outline InstCache, an efficient caching system for LLM inference. As depicted in Figure 3, Inst-Cache will be pre-populated with LLM-predicted instructions and then deployed with existing LLM serving systems. In the remaining part of this section, we describe the cache structure in Section 3.2 and detail the approach to control the hit rate and cache size by a given negative log likelihood (NLL) threshold  $\sigma$  in Section 3.3. Cache pre-population method is described in Section 3.4, and the deployment of InstCache along with existing LLM serving systems is in Section 3.5.

#### 3.2 Cache Structure

As shown in Figure 3, during pre-population, we employ a tree to search potential instruction, where each node represents a token and each path corresponds to an instruction and its answer. Paths start from begin-of-sentence token  $\langle bos \rangle$  and end with end-of-sentence token  $\langle eos \rangle$ . Answers are stored following the  $\langle eos \rangle$  token of each path. After LLM tree search, each instruction and its corresponding answer will be stored in a hash table, which minimizes the lookup complexity to nearly  $\mathcal{O}(1)$ , facilitating the deployment phase. As for implementation, we use the dictionary in Python as the hash table during deployment and serialize it to disk with Pickle.

#### 3.3 Cache Sizing

Cache size, which can be roughly represented as the number of cached instructions, is a critical parameter. In this sub-section, we develop theoretic analysis on how to determine the cache size. The motivation to pre-populate the cache with LLM-predicted instructions having NLLs below a selected threshold  $\sigma$  is to make the cache size and hit rate predictable, by modeling the relationship between NLL, hit rate and the number of instructions.

The cache containing all LLM-predicted instructions with NLL  $\leq \sigma$  can be formulated as an instruction set  $C = \{s : \text{NLL}(s, \text{LM}) \leq \sigma, s \in S\}$ , where s represents an instruction, S is the instruction space and LM is the language model. Given an instruction designated with random variable S and its corresponding NLL variable  $\mathcal{N} = \text{NLL}(\mathcal{S}, \text{LM})$ , the hit rate of the cache can be derived as:

$$Hit\_Rate = P(S \in C)$$
  
=  $P(N \le \sigma)$   
=  $F_{\mathcal{N}}(\sigma)$  (3)

#### 1. Pre-Population Phase



*Figure 3.* Unlike traditional caches that populate with incoming requests while being deployed, InstCache decouples the population phase and deployment phase. During pre-population, InstCache will be populated with all LLM-predicted instructions with negative log likelihood below a selected threshold  $\sigma$ . The hit rate and cache size can be accurately determined by the threshold  $\sigma$ . We search these instructions by generating next tokens with an LLM step by step , forming a tree structure, as depicted on the right of figure. The Inst-Aligned LLM is an LLM finetuned with instruction in the training set. After pre-population, each path of the tree will become an instruction stored in hash table with corresponding answer. Lastly, InstCache will be deployed with existing LLM serving systems, accelerating the inference process.

where  $F_N$  is the cumulative distribution function (CDF) of the NLLs over the instruction space S. The CDF can be measured by evaluating NLLs of instructions on a large validation set using an LLM. Figure 2 (b) has shown the NLL CDF of the ShareGPT dataset with Llama3-8B, indicating that NLLs of most instructions saturate fast with relatively small values. Therefore, it's possible to build a cache with all instructions having NLLs below a threshold.

Furthermore, based on the observation that the number of instructions predicted by an LLM with NLL  $\leq \sigma$  grows exponentially with respect to  $\sigma$ , we propose to model the number of instructions N as an exponential function of the NLL, as shown in Eq. 4.

$$N = a(e^{b\sigma} - 1) \tag{4}$$

where *a* and *b* are function parameters and can be estimated by preliminary pre-populations under two small  $\sigma$  values. In Figure 5 (a), we show that this exponential model accurately captures the growth of instructions as a function of NLL. Although the number of instructions grows exponentially, pre-populating a cache with high hit rate does not require too many instructions as the NLL CDF is fast saturated. Since the cache sizing is not accurately while hit rate is, we do not modeling the relationship between hit rate and cache size directly.

# Algorithm 1 LLM Tree Search

<b>Input:</b> LLM, Max NLL $\sigma$ , Max Depth d
Initialize an empty queue $Q$
Initialize root $r$ with $<$ bos $>$ token
Enqueue $r$ into $Q$
while $Q$ is not empty <b>do</b>
Dequeue a node $u$ from $Q$
Generate next tokens $T$ for $u$ with an LLM
for each token $t$ of $T$ do
if Length from $r \rightarrow u \leq d$ and NLL from $r \rightarrow t \leq d$
$\sigma$ then
Add $t$ as a child of $u$
end if
Enqueue children of $u$ into $Q$
end for
end while

# 3.4 Cache Pre-population

## 3.4.1 Pre-Population Algorithm

Unlike traditional caches that are populated with incoming requests, InstCache is pre-populated by LLM-predicted instructions with NLL values below a selected threshold. Pre-population involves predicting all possible instructions with NLL  $\leq \sigma$  by exploring all paths in a tree that starts with the  $\langle bos \rangle$  token and ends with  $\langle eos \rangle$  token. As illustrated in Figure 3 and Algorithm 1, we use an instruction-aligned LLM to predict the next token at each node of the tree, expanding the tree step by step. If a path fails to reach  $\langle eos \rangle$ in maximum allowed depth, it will be pruned. Since NLL is the cumulative negative log probability of tokens along the path, we can optimize the search by stopping the expansion if the cumulative NLL exceeds  $\sigma$ , reducing computational cost. This allows us to predict all potential instructions within the desired threshold efficiently.

To further optimize the process, we limit the number of tokens generated per node during pre-population. For nodes with a depth of 10 or less, we restrict the number of generated tokens to 5,000. For nodes with a depth of up to 100, the limit is reduced to 1,000 tokens. These restrictions significantly reduce overhead, particularly when selecting top-k tokens from a large vocabulary, with a minimal influence on hit rate.

## 3.4.2 Distributed Implementation

Given the exponential growth rate of instructions under increasing NLL, Algorithm 1 alone is not scalable for constructing a cache with a high hit rate. We then proposed a parallel solution for instruction pre-population. We first construct a base tree with a limited depth less than maximal depth and the same maximal NLL value  $\sigma$  in master server. Note that we do not prune paths that do not end before lim-



*Figure 4.* Distributed Cache Pre-population. Master server build the base tree with a limited depth less than maximal depth. Each path of base tree serves as the starting nodes for subtrees generation in slaves. Subtrees are iteratively merged with based tree, forming new base tree for subsequent pre-population, until the maximum depth is reached.

ited depth, since they serve as starting nodes for subtrees. For each path of the base tree, we pre-populate a corresponding subtree using Algorithm 1 in slave servers, with the path from base tree serving as the root of the corresponding subtree. As illustrated in Figure 4, we employ a message queue and remote storage to manage the distributive execution of pre-population. The subtrees are iteratively merged with the base tree, forming new base tree for subsequent pre-population until the maximum depth is reached.

#### 3.5 Cache Deployment

To further decrease the lookup latency of InstCache, we store pre-populated instructions and corresponding answers as a hash table. Upon cache hits, InstCache works as a hash table that maps instructions to their corresponding answers. InstCache can be integrated with existing LLM serving systems such as vLLM(Kwon et al., 2023) and SGLang(Zheng et al., 2023), as depicted in Figure 3. When an instruction is found in the cache, the corresponding response is immediately returned to the user. If a cache miss occurs, the instruction is forwarded to the LLM serving system for processing. The additional latency introduced by InstCache is negligible as the lookup complexity is near O(1). By leveraging distributive key-value database, such as Redis, InstCache is also well-suited for distributive deployment, which can further increase the hit rate through pre-populating more instructions in distributed storage.

## 4 EXPERIMENT

## 4.1 Settings

**Datasets** We use LMSys(Zheng et al., 2024) and ShareGPT(Team, 2023) as our evaluation datasets. LMSys is collected from the Vicuna demo and the Chatbot Arena website(Chiang et al., 2024), encompassing approximately 1 million unfiltered conversations. ShareGPT consists of 100,000 realistic conversations shared by GPT users. Both datasets are multilingual. Although there are many supervised finetuning datasets, such as Moss(Sun et al., 2024), they are primarily consist of human instructions and synthetic instructions. To avoid contamination, we do not use these datasets in this work. Unless otherwise specified, following experiments are conducted on instructions with token lengths below 100 and focus on the first turn of conversations.

**Baselines** We compare InstCache with ExactCache and GPTCache(Bang, 2023). ExactCache matches incoming requests exactly with cached ones, using a Least Recently Used (LRU) policy for cache update. GPTCache compares instruction embeddings for matching and thus serves as a Semantic Cache. We do not compare with KV-Cache as it is focused on lower level decoding operations and thus orthogonal to our work. Previous work(Li et al., 2024) used OpenAI's embedding API with GPTCache, determining that a similarity threshold of 0.9 was required on real-world datasets. However, deploying GPTCache with the OpenAI embedding API is impractical in real-world applications due to the excessive economic cost. Thus, we use the provided Albert-small(Reimers & Gurevych, 2019) embedding model for GPTCache with a 0.95 similarity threshold. Since the Albert-small embedding model only supports English, we limit GPTCache evaluations to the English samples, while ExactCache and InstCache are evaluated on the full multilingual datasets. Lastly, although GPTCache is based on similar searching, we directly compare its hit rate with that of ExactCache and InstCache, disregarding cases where similar matches may not be consistent.

Hit Rate Measurement As short instructions have limited tokens and the number of samples is constrained, for example, 100,000 conversations in ShareGPT. For InstCache, we split each dataset into 80% training to fine-tune the LLM better, leaving 10% for validation and 10% for test sets. As presented in Figure 7 (b), we observe that 10% is enough to represent the instruction distribution and evaluate the hit rate accurately. We also vary the training size for InstCache and traditional caches from 10% to 80%. The results show that InstCache consistently outperforms baselines across various training size, demonstrating that the performance improvement comes from the capability of LLMs instead of larger training sets. We lowercase all instructions for both LLM training and deployment, minimizing the complexity of instructions while maintaining most information. We fine-tune Llama3-8B on the training set and pre-populate InstCache with it. After that, we depict the relationship between hit rate, cache size and negative log likelihood (NLL) on the validation set and determine the NLL threshold  $\sigma$ accordingly. Finally, we evaluate the hit rate of InstCache on the test set, which serves as a representative subset of the instruction space and reflects the incoming instruction

#### distribution.

Previous works of semantic cache evaluated hit rates on LLM-synthetic datasets, employing rephrased sentences as similar instructions and others as irrelevant. However, this approach does not accurately reflect the hit rate under real-world instructions. In this study, we measure hit rates of ExactCache and GPTCache in a simulated scenario. For a given cache size, we warm up the cache with twice the number of instructions and measure the hit rate on an additional 3x cache size of instructions. In Section 4.3, we progressively increase the size for both warm-up and evaluation of GPTCache and ExactCache, observing that the hit rate remains consistent. In contrast, the increasing training samples for InstCache gradually enhances its performance, demonstrating the effectiveness of data reuse by LLMs.

**Pre-Population Settings** Our preliminary experiments revealed that using a base model outperforms models that have undergone supervised finetuning (SFT) and reinforcement learning with human feedback (RLHF), likely due to the alignment tax(Askell et al., 2021). To balance capability with cache pre-population speed, we use a relatively small LLM, i.e. LLaMA3-8B(Dubey et al., 2024). We fine-tune all parameters of the model for two epochs with a batch size of 256, a maximum sequence length of 100 tokens, a weight decay of 0.1, and a learning rate of 2e-5 across both datasets. Note that no data deduplication is performed, as retaining repeated examples allows the model to learn instruction frequency distribution.

Additionally, since user instruction datasets are often composed of multi-turn conversations, we suggest that not all follow-up instructions are context-dependent. For instance, users might ask unrelated questions within the same session for convenience. Therefore, we include instructions from all conversation turns during LLM training and prepend a system prompt <turnN> after <bos>, where N is the turn index, starting from 1. For cache pre-population, we use <turn1> prompts to predict context-independent instructions. We evaluate the effectiveness of this approach for processing multi-turn conversations in Section 4.5. Our experiments demonstrate that incorporating multi-turn instructions enhances the ability of InstCache for multi-turn conversations while keeping a close performance on instructions from first-turn.

Given that InstCache can be pre-populated with a vast number of instructions, it is too resource consuming to produce all possible answers for these instructions. For fairness, we compare InstCache with baselines based on the number of cached instructions, disregarding the actual storage size, yet still reflecting relative size. Additionally, the answers for InstCache can be generated incrementally during the server's off-peak times or upon system requests. We provide the

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*Figure 5.* Solid lines and dotted lines in Subfigure (a) represent the estimated hit rate and the number of instructions, respectively. The "x" mark indicates the actual hit rate and cache size evaluated with pre-populated InstCache, demonstrating the effectiveness of the profile for hit rate and the number of instructions. Subfigure (b) and (c) show hit rates of InstCache and baselines on LMSys and ShareGPT datasets. Black vertical lines indicate the dataset size. InstCache consistently outperforms both baselines. Notably, since pre-populated with predicted instructions from finetuned Llama3-8B, the hit rate of InstCache continues to grow beyond the limitation of the dataset size, resulting in a significantly higher level of performance.

storage size consisting of both instructions and answers for InstCache with relatively small thresholds in Section 4.2.4, showing that InstCache incurs minimal storage overhead.

**Hardware Platform** For cache pre-population, we employ a master server with 512GB memory and slave servers with a totally of up to 64 NVIDIA A100 GPUs and NVIDIA A6000 GPUs. During performance evaluation, we use the master server as the cache server of cache systems and another machine with one NVIDIA A100 GPU as the LLM Server.

## 4.2 Evaluation

## 4.2.1 Cache Sizing

As illustrated in Figure 5 (a), after evaluating the NLL of each instruction in validation sets and estimating function parameters in Eq. 4 with  $\sigma = 10, 11$ , we can profile the hit rate and the number of instruction for InstCache. The figure demonstrates that the NLL saturates quickly, indicating that achieving a high hit rate requires a relatively small number of instructions.

According to the profile, We pre-populate InstCache with NLL thresholds up to  $\sigma = 19$  and 18 on LMSys and ShareGPT datasets, respectively. Moreover, as depicted in Figure 5 (a), the hit rate and cache size of pre-populated cache accurately follow the prediction of modeling, indicating the effectiveness of our pre-population algorithm.

# 4.2.2 Hit Rate

As shown in Figure 5 (b) and (c), InstCache consistently outperforms both ExactCache and GPTCache. Notably, by

pre-populated with potential instructions using an LLM, the hit rate of InstCache keeps growth and breaks the limitation of dataset size, achieving significantly better performance. Both ExactCache and GPTCache stop growing before the size of dataset since we need 5x samples to evaluate their performance. The size of GPTCache is more limited because GPTCache is evaluated on English-only samples. In addition, the hit rates for ShareGPT dataset are relatively lower than that of LMSys dataset, due to less repetitiveness and longer lengths of instructions.





*Figure 6.* Average ratios of latency saving on LMsys and ShareGPT datasets. InstCache outperforms GPTCache and ExactCache on both datasets, achieving up to 2x speedup for LLM serving.

We measure the speedup by evaluating 1,000 samples under the optimal settings for InstCache and baselines. We deploy the cache system with vLLM on NVIDIA A100 GPU, running Llama3-8B-Instruct as the serving model. Samples are sent to the serving system one by one and the average

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Figure 7. Effect of training size and test size on hit rates, measured across various training and test ratios of ShareGPT dataset, with all cache sizes limited to 1,000. The results indicate that hit rates of GPTCache and ExactCache remain consistent, while the hit rate of InstCache continues to increase with higher training ratios, benefiting from the capability of LLM. Moreover, subfigure (b) illustrates that a small proportion of data is enough for the evaluation of InstCache and baselines.

per token latency is measured. Answers have an average length of 200 tokens. As shown in Figure 6, InstCache saves up to half of average latency, accelerating the serving system significantly. Moreover, due to additional latency incurred by embedding instructions, the latency saving ratio of GPTCache is worse than ExactCache.

# 4.2.4 Cost of Pre-Population, Memory and Storage

Table 1. Cost of pre-population, memory and storage across various NLLs on LMSys dataset.

Max NLL	Number of	Pre-Population	Mem (KB)	Storage (KB)
9	105	88	( <b>KB</b> )	103
10	338	128	378	332
11	1,319	420	1,502	1,327
12	8,058	2,148	9,515	8,394

In Table 1, we present the costs associated with prepopulation, memory and storage. The cost values are measured from the distributive pre-population utilizing 4 NVIDIA A100 GPUs. Costs for larger  $\sigma$  are not included, as they were pre-populated using a dynamic cluster of GPUs, making time cost estimation challenging. We generate answers of average 200 tokens in length for each instruction to evaluate the memory and storage costs of the cache. The length of 200 tokens is derived from the average answer length in the LMSys dataset(Zheng et al., 2024). As shown in the Table 1, both pre-population times, memories and storage sizes exhibit a linear increase with the number of instructions and, remaining relatively modest. Notably, InstCache with  $\sigma = 19$  and 51.34% hit rate on LMSys dataset comprises 4,253,981 instructions and corresponding answers, resulting in an approximate memory cost of 4.5GB, which is manageable on a personal computer.



*Figure 8.* Subfigure (a) indicates the effect of instruction lengths. Subfigure (b) shows hit rates of InstCache on different turns with or without training with multi-turn instructions. The results illustrate that fine-tuning with multi-turn instructions enhance the perfor-

mance of InstCache on multi-turn instructions, while keeping close

# 4.3 Effect of Data Scale on Hit Rate

performance on instructions of first-turn

#### 4.3.1 Effect of Training Size

For convenience, we refer the size of warm-up for GPT-Cache and ExactCache as their training sizes. As shown in Figure 7 (a), the hit rates of GPTCache and ExactCache remain consistent with increasing training size, while performance of InstCache progressively enhances with larger training size, indicating that simple data reuse cannot fully exploit the potential of requested data. In contrast, leveraging an LLM to learn patterns from existing data and predict possible instructions can unlock the full potential.

# 4.3.2 Effect of Test Size

We designate the evaluation size for GPTCache as test size. We evaluate the effect of test ratios for InstCache based on training ratio of 40%. Figure 7 (b) illustrates that varying the size of validation set does not impact hit rates of InstCache, GPTCache and ExactCache. Consequently, we select a 10% ratio for both validation and test sets for InstCache, allowing the majority of the data to be used for training, which produces better-aligned LLMs.

## 4.4 Effect of Instruction Length

We evaluate the hit rate for instructions within various length ranges. As shown in Figure 8 (a), InstCache achieves higher hit rates for shorter instructions since cumulative pre-population produce more short instructions than longer ones. Hit rates remains consistent for longer instructions.

#### 4.5 Multi-Turn Instructions

As mentioned in Pre-Population Settings, we include instructions beyond the first-turn to predict those contextindependent instructions across multi-turns. As shown in Figure 8 (b), incorporating these instructions does not negatively impact the hit rate of InstCache on first-turn instructions and enhances the capability of InstCache to hit instructions in multi-turn scenarios.

# **5 RELATED WORK**

LLM serving systems receive an overwhelming number of requests daily. Several caching systems have been proposed to efficiently process these requests.

Semantic Cache In the Semantic Cache, as proposed in GPTCache(Bang, 2023), each instruction is embedded as a vector, which is stored in a database along with the instruction and answer. Semantic Cache retrieves answers for an incoming instruction by searching for the most similar ones in the database and reuses the answer of the previously query upon a hit. Following the same idea, MeanCache(Gill et al., 2024) introduces a user-centric semantic caching system that preserves privacy of users. MeanCache also employs federal learning to build different embedding models locally to enhance the performance. There are also methods(Li et al., 2024; Mohandoss, 2024) aiming to improve the embedding quality through preprocessing instructions. Notably, different from previous methods evaluated on LLM-synthetic datasets(Bang, 2023; Rasool et al., 2024), SCALM(Li et al., 2024) proposes to evaluate the effectiveness of semantic cache on real-world datasets, such as LMSys dataset. While semantic cache saves computational resources, it introduces a dilemma between accuracy and embedding latency. For instance, GPTCache incurs an additional latency of approximately 0.3 seconds(Bang, 2023) for embedding and cache lookup, which is considerable.

KV Cache Key-Value Cache (KV Cache) reuses the keyvalue states of previous tokens to accelerate the generation of subsequent tokens. For typical LLMs like Llama-65B, one key-value state requires a 2.5MB of space(Gao et al., 2024), quickly exhausting memories of GPU and CPU. To address this challenge, several works have been proposed. PageAttention(Kwon et al., 2023) suggests to manage the KV Cache by virtual memory management, minimizing the overhead of memory allocation. Other works, such as H<sub>2</sub>O(Zhang et al., 2023) and Attention-Sink(Xiao et al., 2024), focus on discarding key-value states of less important tokens. To further minimize storage requirements, SGLang(Zheng et al., 2023) and ChunkAttention(Ye et al., 2024) propose to share common prefix KV Caches. Multi-Head Latent Attention(DeepSeek-AI et al., 2024) compresses the key-value states by low rank projection, reducing the storage cost. Additionally, Attention-Store(Gao et al., 2024) suggests to store the KV Cache in multi-level storage systems. Despite of these advancements in managing KV Cache storage, scaling the number of cached instructions remains a challenge. Additionally, since KV-Cache focuses on lower level decoding operations, it's orthogonal to InstCache proposed in the work.

Search Engine Cache Caching systems for search engine share many characteristics with LLM Cache. As search engine process keyword queries and return links to webpages that potentially meet users' needs, the web cache saves results according to certain policies. Various works have been proposed to provide efficient caching system for web searching(Saraiva et al., 2001; Lempel & Moran, 2003; Baeza-Yates & Saint-Jean, 2003; Long & Suel, 2005; Fagni et al., 2006; Zhang et al., 2008; Marín et al., 2010). Notably, Probability Driven Cache (PDC)(Lempel & Moran, 2003), which is the most similar one to our work, assigns priorities to cached results based on the probabilistic model of users. In this work, we propose to determine which instruction is more likely to be requested using an LLM. By leveraging the LLM, we are capable of directly modeling the probability of instructions, instead of modeling the probability from other characteristics as in PDC.

# **6 DISCUSSION**

When the dataset size is sufficiently large, InstCache can accurately profile the distribution of instructions by finetuning LLMs and ensures a reliable hit rate. However, unlike traditional caches, the population phase and serving phase of InstCache are decoupled and following different mechanisms. Therefore, gradual shifts in the instruction distribution can lead to a decline in hit rates over time. To tackle this challenge, we need to fine-tune LLMs periodically to maintain an up-to-date modeling of the instruction distribution. As shown in Table 1, the pre-population can be performed with a relatively short period, thereby regular pre-population will not incur significant overhead. In addition, existing instructions and answers can be leveraged to reduce the cost of next pre-population, facilitating the process of next pre-population.

# 7 CONCLUSION

In this paper, we propose InstCache, an efficient predictive cache system for LLM inference serving. Pre-populated with predicted instructions from an LLM, InstCache can hit unseen instructions. Moreover, the hit rate and cache size can be accurately determined through the relationship between negative log likelihood, hit rate and the number of instructions, allowing InstCache to deliver a predictable level of performance. Experimental results justify the effectiveness of InstCache. In the future, we will develop a distributed implementation of the cache system on larger computer clusters to further performance enhancement.

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