Online inference is becoming a key service product for many businesses, deployed in cloud platforms to meet customer demands. Despite their revenue-generation capability, these services need to operate under tight Quality-of-Service (QoS) and cost budget constraints. This paper introduces Kairos, a novel runtime framework that maximizes the query throughput while meeting QoS target and a cost budget. Kairos designs and implements novel techniques to build a pool of heterogeneous compute hardware without online exploration overhead, and distribute inference queries optimally at runtime. Our evaluation using industry-grade deep learning (DL) models shows that Kairos yields up to 2× the throughput of an optimal homogeneous solution, and outperforms state-of-the-art schemes by up to 70%, despite advantageous implementations of the competing schemes to ignore their exploration overhead.

1 INTRODUCTION

As machine learning (ML) models are becoming widely adopted in commercial services, the service providers will utilize cloud computing resources to serve their customers, and online inference has become a highly critical application for both on-premise and public cloud computing platforms [1–3]. As a result, an increasing amount of research effort is dedicated to improving the capability of cloud systems for inference workloads [4–9]. Serving ML inference is particularly challenging because they pose additional constraints and objectives beyond meeting latency deadlines. For example, business service providers can utilize the pay-as-you-go model to rent cloud computing instances, but they seek the following desirable objectives: (1) meet quality-of-service target (QoS constraint, e.g., 99% of queries finish within 100ms); (2) efficient under a fixed cost budget; (3) process as many queries as possible per time unit (i.e., high query throughput).

Cloud platforms provide a wide range of virtual machines (VMs), each comes with different hardware types (e.g., different CPU, GPU, memory). While there have been previous attempts at providing partial solutions to exploit hardware heterogeneity in datacenter [10–12], edge [13, 14], and cloud [15–17], we lack a complete solution to achieve all the desirable properties (Sec. 2). In particular, prior schemes do not consider the full aspects of inference serving: heterogeneous resource allocation and intelligent query distribution among allocated hardware resources.

Note that a heterogeneous pool of cloud compute instances (a mix of GPUs and CPUs) appear naturally more promising for inference serving as they provide the opportunity to balance the trade-off between cost and performance (QoS target). More powerful and expensive instances can be used for executing smaller queries that will not violate their QoS on such instances, and thereby, provide a chance to reduce the overall cost of the query serving system. Consequently, many prior techniques have opportunistically taken advantage of hardware heterogeneity to improve query throughput or meet QoS target [10, 11, 13, 14, 17]. However, none of them provide a systematic methodology to efficiently optimize the heterogeneous configuration (i.e., determine the number of GPUs and CPUs of different types). Therefore, while prior works are heterogeneity-aware, they do not proactively optimize the hardware heterogeneity under a cost budget.

In fact, we show that some heterogeneous configurations can perform significantly worse than an otherwise cost- and QoS-equivalent homogeneous configuration (Sec. 4). Determining a heterogeneous configuration requires online evaluation of multiple potential candidates. Unfortunately, this approach is not suitable when the query load changes or other system parameters change, since it requires invoking the exploration process frequently and potentially evaluating configurations that are worse than homogeneous configurations. This has been the main hindrance for the community to exploit heterogeneous computing hardware. Kairos breaks this limitation and designs novel techniques to take full advantage of hardware heterogeneity while meeting QoS constraints under a given cost budget.

Summary of Contributions. We design and implement Kairos, a novel runtime framework to maximize throughput under cost budget and QoS constraints for machine learning inference tasks. Kairos breaks away from searching the complex and vast configuration space of heterogeneous hardware. Instead, Kairos devises two techniques to quickly find a high-throughput heterogeneous configuration without exploring.

First, it designs an efficient query-distribution mechanism to distribute queries among different cloud computing instances for any given heterogeneous configuration to maximize throughput — formulating this as a bipartite matching problem and solving it efficiently. Second, it approximates the upper bound of the throughput that a heterogeneous configuration can provide in the best. Then, it uses the similarity in top-ranked heterogeneous configurations to pick the most promising heterogeneous configuration without online evaluation. Our evaluation confirms that Kairos’s configuration choice is often the near-optimal configuration across different machine learning models in production, where the optimal configuration is determined via exhaustive offline search of all heterogeneous configurations.

We have leveraged industry-grade deep learning recommendation models to drive the evaluation of Kairos’s effectiveness...
2 RELATED WORK

Table 1 lists the relevant works in exploiting heterogeneous hardware and inference serving. Overall, Kairos is the only work that satisfies all the desirable properties (table header from left to right): (i) meets QoS for inference queries; (ii) has service throughput requirement; (iii) is aware of heterogeneous hardware cost; (iv) intelligently distributes (or maps) queries among resources; (v) optimizes heterogeneous resource allocation; and (vi) does not need prior knowledge to train a model or perform online exploration. While some previous works are heterogeneity-aware (i.e., can efficiently use available heterogeneous hardware), they do not proactively configure the heterogeneity to optimize other aspects: query throughput, QoS, and cost budget.

Latency-critical applications are commonly studied in large-scale datacenter and cloud systems [19–23]. Previous works such as Paragon [10] and TetriSched [11] have focused on optimizing heterogeneous resource utilization [24–27], but their resource heterogeneity is pre-determined and sub-optimal, and their target applications are long-running jobs in datacenters, which is different from online inference tasks. Some other previous works have relied on tuning by expertise [28–31], prior profiling [32–35], or historical training data from similar applications [36–39], and cannot be used to solve the Kairos problem.

Existing ML inference frameworks [1, 4, 8, 13, 14, 18, 40–46] are not suitable for exploiting heterogeneous hardware optimally and may require extensive profiling. Kairos addresses this limitation. For example, S3DNN and DART are heterogeneity-aware deep neural network (DNN) inference frameworks [13, 14], but their hardware heterogeneity is pre-determined. Additionally, their layer-based scheduling for vanilla DNNs is not suitable for more complex DL architectures. INFaaS [46] optimally selects a particular hardware type from heterogeneous devices depending on the user application, but unlike Kairos, it does not serve the model using different hardware simultaneously. Media application frameworks such as Llama [45] and Scrooge [15] allocate different hardware for different stages of the media application inference, but each query is assigned to the same sequence of hardware types, they do not distribute queries to heterogeneous resources like Kairos and are not suitable for general purpose applications.

Kairos will be open-sourced with the final version of the paper for reproducibility, community adoption, and enhancement.

Ribbon [16] optimizes the serving cost by exploring different heterogeneous configurations, but compared to Kairos, it still incurs Bayesian Optimization exploration overhead and does not exploit the heterogeneity by intelligently distributing the queries. DeepRecSys [17] explores heterogeneity between GPUs and CPUs when serving online queries. However, it does not explore the potential of different CPU/GPU ratios under a cost budget. It uses a hill-climbing algorithm to find an optimal threshold for query distribution, but it incurs tuning overhead as the threshold is different for each heterogeneous configuration. Clockwork [18] consolidates design choices in a top-down manner for deterministic inference latencies, but its central controller does not exploit heterogeneous hardware like Kairos. Compared to all previous work, Kairos delivers a full suite of heterogeneity support for cloud service and considers all key metrics (QoS, throughput, and cost).

3 BACKGROUND

Machine learning inference service. When machine learning models are trained into maturity, they will get deployed in production to provide ML inference service. The service users can submit inference request through provided interfaces (e.g., HTTP request), then get a response. The inference pipeline can have multiple stages (e.g., data pre-processing, model prediction, post-processing), and they are typically packaged into a container image along with the software dependencies. On the cloud, the inference service provider
can then allocate a set of compute instances and use a resource manager like Kubernetes to deploy the service. In this work, we focus on discussing the potential of using a heterogeneous resource instance allocation — how to efficiently distribute the inference queries and find a good heterogeneous configuration quickly.

Inference serving with QoS constraints and cost budget. The inference service has a QoS target, requiring the tail latency (e.g., 99th percentile) of queries to be within a limit for a better user experience. For flexibility reasons and the pay-as-you-go model, businesses rent the computing power from the cloud computing provider to meet the QoS target, but they also have a budget constraint. Each compute instance type, rented from the cloud, is associated with a price ($/hr). Given a cost budget, one can only allocate a limited number of instances to serve as many queries as possible — that is, maximize the query throughput. The query throughput is defined as queries served per second (QPS). Since QoS cannot be violated, we use the allowable throughput, which is the maximum throughput the allocated instances can serve without causing QoS violation. In this work, we use allowable throughput, throughput and QPS interchangeably. All of them hold the implicit condition that QoS is satisfied.

4 MOTIVATION

In this section, we first provide experimental evidence to demonstrate that a heterogeneous configuration (a configuration can be a mix of a few GPU instances, a few instances of CPU type A, and a few instances of type B) can be better than a homogeneous configuration under the same cost budget while respecting QoS. But, it is not always true — and any heterogeneous configuration is not superior by simply the virtue of heterogeneity.

First, we note that given a certain cost budget, one can choose to allocate the most cost-effective instances that can meet the QoS for all queries. We denote such instance type as base instance, and such strategy as homogeneous serving or homogeneous configuration. However, since inference queries have highly diverse batch sizes (or query sizes) [4, 16, 17], even though a cheaper but higher throughput-per-cost instance type cannot meet the QoS (so it cannot serve standalone as the allowable throughput is 0), it can still meet QoS for some smaller queries (queries with smaller batch sizes) due to the lower latency. Another choice is to replace some base instances with such cheaper instances (denoted as auxiliary instances), we denote this as heterogeneous serving or heterogeneous configuration. Unlike the base instance which comes from the optimal homogeneous instance, multiple types of auxiliary instances can be used for more flexibility and higher potential.
Exploiting heterogeneity via intelligent query distribution is the key to higher throughput. Next, we show that only finding a high-performing heterogeneous is not sufficient. Distributing diverse queries among heterogeneous instances is key to unlocking higher throughput. In previous results (Fig. 1 and 2), we used Ribbon’s [16] simple first-come-first-serve (FCFS) mechanism, which schedules the first arrived query on the best instance available. To demonstrate the impact of query distribution strategies, we employ two more complicated query distribution schemes denoted as DRS [17], CLKWRK [18], and an oracle scheme (ORCL) (details in Sec. 7) in Fig. 3. We make two observations. First, all state-of-the-art schemes Ribbon [16], DRS [17] and CLKWRK [18] are sub-optimal. Second, one is not necessarily better than the other and leaves the scope for more improvement. Kairos exploits this opportunity and bridges the gap to the oracle scheme by designing a new intelligent query distribution mechanism for heterogeneous serving.

5 KAIROS DESIGN

In this section, we provide design details of KAIROS as a complete heterogeneous serving solution, illustrated in Fig. 4. The queries submitted by users will be distributed to the processing nodes, which consist of heterogeneous compute instances built by a throughput optimizer. The first design target of KAIROS is to efficiently distribute queries to different instances in a particular heterogeneous configuration (Sec. 5.1). Since finding a promising heterogeneous configuration is also a challenging problem by itself, this is KAIROS’s second design component (Sec. 5.2).

5.1 KAIROS Query Distribution Mechanism

Overview. We introduce the query distribution mechanism as the first design component of KAIROS. The key objective is to intelligently distribute queries of different batch sizes to different instances, so that the throughput is maximized. In Sec. 8, we confirm that KAIROS’s query-distribution mechanism is indeed key to its overall effectiveness and works across different heterogeneous configurations.

We start with mathematical formulation to maximize the throughput for a given configuration. The key intuition is to distribute the queries in such a way that it maximizes the available/idle time on all the instances in the future. This maximizes the likelihood of serving more queries in the future – a higher throughput. We show that this problem can be transformed and mapped to a min-cost bipartite matching problem, which KAIROS solves to find an efficient query-distribution plan without knowledge of future query arrivals.

Mathematical formulation of query distribution for throughput maximization. Our problem objective is: given a number of queries to be served at the current time $t_0$, maximize future availability of instances until a future time instance. This is equivalent to minimizing the total resource usage since unused resources can be used to process future queries, indirectly maximizing throughput at the current time.

Suppose at $t_0$, there are $m$ queries in the serving queue, denoted as $Q_1, Q_2, ..., Q_m$, and $n$ compute instances in the heterogeneous configuration, denoted as $I_1, I_2, ..., I_n$. Table 2 summarizes the parameters used in our mathematical formulation. If distribute query $Q_i$ to instance $I_j$, the query completion time from $t_0$ ($L_{i,j}$) includes the serving latency (varies for different $i,j$) and if there is a query currently being served at $I_j$, the remaining time till $I_j$ can serve $Q_i$. For all queries and instances, this time can be represented by an $m \times n$ matrix $L$. Namely, $L_{i,j}$ represents the $I_j$ instance resource usage (measured by time) if scheduled to serve query $i$.

It is important to note that the equal wall-clock usage time on different instance types in a heterogeneous configuration do not hold the same value. That is, one second of GPU is not equivalent to one second of CPU. To account for this, KAIROS employs a heterogeneity coefficient $C_j$ for each instance type $j$.

**Definition 1.** We define $C_j \in (0,1]$ as the heterogeneity coefficient for instance $I_j$. It is used to represent the relative importance of instance $j$ compared to other instances in a heterogeneous system. It is calculated as the ratio of the largest query latency between $I_j$ and the base instance type.

To determine $C_j$, we first set the coefficient of the base instance type (e.g., lowest latency instance) to 1 as a normalization point, then calculate $C_j$ as the latency ratio. We find that using the largest query the system can serve to measure the latency ratio works well. Intuitive, larger queries are more compute demanding and more prone to violate QoS, thus, they are more suitable for evaluating the relative importance of instances in a heterogeneous system. With the introduction of heterogeneity coefficient, the revised usage time for instance $j$ can be expressed as $C_j L_{i,j}$.

This usage can be calculated for every query-instance pair. Since the time is relative to the base instance, we can directly sum the usage across all instances, and the sum is the aggregated resource usage. To maximize this, we need to carefully select which $Q_i$ to be served on which $I_j$. We define these optimization variables as an $m \times n$ binary matrix $P$:

$$P_{i,j} = \begin{cases} 1 & \text{if query } Q_i \text{ is served by instance } I_j, \\ 0 & \text{otherwise.} \end{cases}$$

Table 2: Query distribution optimizer parameters.

| List | Description |
|------|-------------|
| $L_{i,j}$ | Time needed to finish serving $Q_i$ on instance $I_j$ from $t_0$. |
| $m$ | Number of queries at time $t_0$. |
| $n$ | Number of instances in the configuration. |
| $C_j$ | Heterogeneity coefficient for instance $I_j$. |
| $QoS$ | QoS target latency. |
| $W_i$ | Query $Q_i$’s time spent waiting in queue before $t_0$. |
| $P_{i,j}$ | Query-to-instance pairing/assignment matrix. |
Then, we express the minimization objective function as:

\[ f(P) = \sum_{i=1}^{m} \sum_{j=1}^{n} C_{j} L_{i,j} P_{i,j} \]  

(2)

This formulation maps itself to the linear-sum assignment problem, or in graph theory, a min-cost bipartite matching problem. A bipartite graph has two disjoint and independent sets of vertices \( U \) and \( V \). In our case, \( U \) contains the queries as vertices, \( V \) contains the instances as vertices. An edge is available for all query-instance pairs, and a cost is associated with each edge. A typical min-cost bipartite matching would have the same number of elements in \( U \) and \( V \), the elements are one-to-one matched with the total cost minimized. However, in our situation, there is no guarantee on the number of queries. If there are fewer queries than instances, the matching is when all queries are matched to a unique instance, and vice versa when there are fewer instances than queries. The cost of each edge between \( Q_i \) and \( I_j \) corresponds to \( C_{j} L_{i,j} \) in Eq. 2.

Before solving for this bipartite matching problem to maximize the throughput, we note that processed queries can only count towards throughput when served under QoS, otherwise Kairos's idea of heterogeneous serving becomes meaningless: one can simply find the instance type with the highest throughput-to-cost ratio and do homogeneous serving. To be QoS-aware, we add an inequality constraint:

\[ (L_{i,j} + W_i) P_{i,j} \leq T_{qos} \]  

(3)

This constraint states that if serving \( Q_i \) with \( I_j \), the sum of query completion time on \( I_j \) and queue wait time before \( t_0 \) should be less than the QoS target.

In summary, Kairos formulates an optimization problem and designs its objective function and constraints for throughput maximization under QoS target. The key design principle is respecting the fact that different queries have different speedups from one instance type to another (e.g., queries with larger batch sizes have higher speedup from CPU to GPU). By prioritizing higher speedup queries on more powerful instances, Kairos minimizes resource usage and prepares maximized slack time for future queries. This is reflected in Eq. 2, where \( L \) matrix implicitly contains this information. Fig. 5 visualizes this effect with a 2-instance example. By efficiently distributing current queries without future information, Kairos leaves more slack time for the future, thus it is able to process all 4 queries while a naive scheme (e.g., FCFS) can only process 3 queries (shaded query does not count towards throughput due to QoS violation). The superior distribution scheme gives Kairos 33% higher throughput (4 queries vs. 3 queries processed in time) than the naive scheme, despite the same hardware.

Putting everything together, the query-distribution problem can be formulated as follows:

\[ \min_{P} \sum_{i=1}^{m} \sum_{j=1}^{n} C_{j} L_{i,j} P_{i,j} \]  

(4)

s.t. \( \forall i, j \) \( (L_{i,j} + W_i) P_{i,j} \leq T_{qos} \),

(5)

\[ \forall i, j \sum_{i=1}^{m} P_{i,j} \leq 1, \sum_{j=1}^{n} P_{i,j} \leq 1, \]  

(6)

\[ \sum_{i=1}^{m} \sum_{j=1}^{n} P_{i,j} \geq \min\{m, n\} \]  

(7)

where \( i \in \{1, 2, ..., m\} \) and \( j \in \{1, 2, ..., n\} \). Eq. 6 indicates one-one mapping, and Eq. 7 guarantees when there are more instances than queries, every query gets mapped to an instance; when there are more queries than instances, every instance receives a query.

A bipartite matching problem can be directly solved by the Hungarian algorithm [48] or Jonker-Volgenant algorithm [49]. However, we note that Kairos's formulated problem is not a strict min-cost bipartite matching problem because of the QoS constraint in Eq. 5. Therefore, to guarantee feasibility, Kairos integrates this constraint into the objective function by modifying the \( L \) matrix with a condition. If serving \( Q_i \) on \( I_j \) does not violate the QoS, \( L_{i,j} \) is unchanged. If it violates QoS, then \( L_{i,j} \) is penalized by a large quantity (e.g., 10x of the QoS target). Consequently, Kairos achieves min-cost solutions that avoid QoS-violating \( Q_i-I_j \) matching. With this constraint integration, the new \( L \) matrix becomes:

\[ L_{i,j} = \begin{cases} L_{i,j} & \text{if Eq. 5 is true,} \\ 10 \cdot T_{qos} & \text{otherwise.} \end{cases} \]  

(8)

Then, Eq. 5 constraint is removed, the problem with updated parameter \( L \) becomes a strict min-cost bipartite matching problem. Kairos uses the Jonker-Volgenant algorithm as it is considered more efficient than the Hungarian algorithm [50].

Remarks on assumptions and overhead. We note that Kairos requires constructing the parameter \( L \), which requires predicting the query latency of certain batch sizes on different instance types. Fortunately, DL inference is a fully deterministic process without conditional branching, thus the latency is highly predictable [18]. Kairos makes sure an instance serves one query at a time without any resource contention. Thus, the end-to-end latency has a very low variance (< 0.5% of mean). A previous work has observed that inference latency can be accurately predicted with simple features such as request batch size [51]. We have observed similar trends in our experiments as latency is highly correlated with query batch size: the Pearson correlation coefficient [52] between latency and batch size is greater than 0.99 for all models and instance types in Sec. 7. As a result, Kairos can model this completely online with a handful of queries without requiring any prior knowledge or instrumentation. Kairos starts with a linear model, but does not rely on the model accuracy because it will quickly transition into a lookup table after processing more queries. All our evaluation results include this overhead from
learning the query latencies online. In practice, as a noise safeguard, we replace \( T_{gos} \) with \( \xi T_{gos} \) in Eq. 5, and setting \( \xi \) to be 0.98 such that the completion time predicted to be within 2% range of the QoS target is considered a violation.

### 5.2 Kairos Throughput Estimation

Next, we discuss how Kairos quickly reaches a good configuration from the vast search space as the second part of its design component. Evaluating the throughput of a configuration is expensive and causes delays in finding a good configuration (Sec. 4). Kairos takes a different approach to approximate the actual throughput using an upper bound. We have explored other options such as queuing theory [53, 54] to analytically calculate the actual throughput. However, due to the dynamic service time (varying batch size), the heterogeneity in hardware, and unconventional queue discipline (Sec. 5.1), we cannot fit the problem into a classical \( M/M/c \) queue framework. Therefore, we take an approximation approach to avoid the expensive evaluations.

Designing an application-specific approximation strategy is known to be challenging [55]. This is also true for Kairos’s throughput approximation due to QoS restrictions and the complex interactions between queries and heterogeneous instances. Kairos tackles this challenge with a method to calculate a throughput upper bound for a given configuration. With this method, Kairos first finds promising candidates with high upper bounds from search space under budget without any evaluation, then performs aggregation to output a final configuration. To explain, we first demonstrate the intuition and calculation for the throughput upper-bound given a simple heterogeneous configuration – that is, one instance of base type (e.g., GPU) and one instance of auxiliary type (e.g., CPU). Then, we show how to extend this method to the cases where each instance type can have multiple instances. Eventually, we extend it to the cases where one can have multiple different types of auxiliary instances.

**Definition 2.** For an inference service, given a particular allocation of hardware resources, the throughput \( QPS \) varies with the query distribution algorithm \( \lambda \). The allowable throughput can be represented as a function \( Q(\lambda) \). We define the throughput upper bound \( QPS_{\text{max}} \) as a number that satisfies \( \forall \lambda, Q(\lambda) < QPS_{\text{max}} \).

Essentially, the upper bound of a particular hardware allocation is a throughput that cannot be exceeded no matter how the system distributes the query. A throughput number may be the upper bound for a hardware allocation, but if the allocation changes, it may not be the upper bound any more.

We estimate the throughput upper bound as follows: Kairos makes a simple observation that upper-bound estimation is akin to estimating the maximum possible throughput in an unrealistic scenario where all queries are available to us at the beginning, and we can control when each query should arrive – then there is no need to worry about latency interactions with queuing. Recall that Kairos’s query distribution mechanism efficiently accounts for the practical case when we have no control over when queries will arrive: queries may wait in the queue, instances may be idle waiting for queries. Compared to the practical case, our upper bound calculation ensures queries do not miss QoS by waiting in the queue and instances do not waste idle cycles that could have served more queries.

Using the one-base-one-auxiliary simplification example, the intuition is to determine which instance type is the bottleneck given a mix of queries and then, the bottleneck type dictates the maximum possible throughput we can achieve. Formally, let \( Q_b \) and \( Q_a \) denote the standalone throughput (QPS) achieved by the base and auxiliary instance type, respectively. Note that the auxiliary instance cannot satisfy QoS for all queries. Therefore, \( Q_a \) refers to the throughput achieved when serving only queries that do not violate QoS (i.e., queries smaller than size, say \( s \)). Queries larger than size \( s \) will then be served by the base instance. However, the base instance throughput when serving larger than \( s \) size queries will be lower than \( Q_b \) – we denote this by \( Q_b^{*} \).

We can then partition the query mix into two fractions: \( f \) for queries smaller than batch size \( s \), and \( 1 - f \) for queries larger than \( s \). If the auxiliary instance is fully occupied with smaller size queries, it implies that \( \frac{1-f}{f} \times Q_a \) needs to go to the base instance type. Sending larger queries to base and small queries to auxiliary instances also aligns well with the design principle of Sec. 5.1. However, recall all these queries are of sizes larger than \( s \) and hence, the base instance can serve them only at the rate of \( Q_b^{*} \). Fig. 6 shows a visual representation of the mathematical formulation above. Note that there are only two potential outcomes that dictate the maximum throughput we can achieve: (1) the base instance is the bottleneck, and (2) the auxiliary instance is the bottleneck.

If \( Q_b^{*} \leq \frac{1-f}{f} \times Q_a \), that means the base instance is the bottleneck. If the maximum throughput is denoted as \( QPS_{\text{max}} \), then, \( 1 - f \) fraction of these queries (queries larger than size \( s \)) will be served by the base instance at the rate of \( Q_b^{*} \). Hence, the maximum throughput can be estimated as:

\[
QPS_{\text{max}} = \frac{Q_b^{*}}{1 - f} \tag{9}
\]

If \( Q_b^{*} > \frac{1-f}{f} \times Q_a \), that means the auxiliary instance is the bottleneck and the base instance has some slack left to serve more queries. If the maximum throughput is denoted as \( QPS_{\text{max}} \), then, \( f \) fraction of these queries (queries smaller than size \( s \)) will be served by the auxiliary instance at the rate of \( Q_a \). So, the \( QPS_{\text{max}} \) is equal to \( \frac{Q_a}{f} \). However, recall that the base instance still has slack available to serve more queries. Intuitively, the slack proportion at the base instance is equal to the difference between \( Q_b^{*} \) and \( \frac{1-f}{f} \times Q_a \), divided by its total capability \( Q_b^{*} \). The total slack throughput can be mathematically expressed as:

\[
\text{Slack-at-the-base-instance} = \left( \frac{Q_b^{*} - \frac{1-f}{f} \times Q_a}{Q_b^{*}} \right) \times Q_b \tag{10}
\]
Therefore, the maximum possible throughput is:

\[
QPS_{\text{max}} = \frac{Q_a}{f} + \left(\frac{Q_b^+ - \frac{1-f}{Q_b}}{Q_b^+}\right) \times Q_b
\]  

(Kairos’ approach of query mix partition would be over-optimistic if the partitions have strong temporal locality (e.g., if all large queries arrive together before small queries, then auxiliary instance cannot contribute). However, no such cyclic behavior has been observed, and due to the law of large numbers, this upper bound is reasonable over the long term for a large number of query mixes.

We can next extend this method to the case when each instance type has multiple nodes. If the base instance has \( u_a \) nodes and the auxiliary instance has \( u_b \) nodes, then, Eq. 9 and 11 can be written as:

\[
QPS_{\text{max}} = \frac{u_a Q_a^+}{1-f}
\]

\[
QPS_{\text{max}} = \frac{u_a}{f} + \left(\frac{u_b^+ - \frac{1-f}{u_b^+}}{u_b^+}\right) \times u_b
\]

The next step is to extend this upper-bound estimation for multiple types of auxiliary instances. Multiple types of auxiliary instances accurately is more challenging since each new auxiliary instance has its own QoS-respecting region and throughput in that region. Fortunately, Kairos is not concerned with modeling the accurate throughput, instead, it only cares about the upper-bound estimation of the throughput. Therefore, it makes a relatively simple approximation that additional auxiliary instance types have the same QoS-respecting region as the type with maximum \( s \) size and \( f \) fraction. This essentially makes the upper bound estimation more optimistic since some weaker auxiliary instances are assumed to meet QoS for batch sizes larger than their limit. As our evaluation confirms (Sec. 8.5), even though this approximation results in a higher upper bound, configurations still follow similar order as the actual throughput (higher upper bound is likely to indicate higher throughput).

With this simplification, the upper bound formula (14) is guided by the estimated upper bounds and is shown to be outperforming any other traditional search space exploration (Sec. 8). The intuition to greedily start from high upper bound configurations as these configurations have better potential than others, and after evaluating a number of such instances, it is likely that the current best throughput will be high enough to filter out a large number of configurations whose upper bounds are lower. Another pruning mechanism in the algorithm is the sub-configuration pruning. If configuration \( x_1 \) can add more instances to become \( x_2 \), we define \( x_1 \) to be a sub-configuration of \( x_2 \). Every time a configuration is evaluated, all of its sub-configurations get pruned away from the search space, since these sub-configurations will not have higher throughput than the evaluated one. We note that upper bounds that are tight to the actual throughput are especially beneficial to Kairos+ since more configurations can be pruned away.

**Remarks on assumptions and overhead.** Kairos upper bound based throughput estimation has a one-time warmup phase consisting of two major steps. Firstly, it needs to compute the upper bound for all combinations of instance numbers of each type under cost budget. Fortunately, this calculation is quick using the formula in Eq. 15: for an order of 1000-configuration search space, all upper bounds can be calculated and ranked within 2 seconds, negligible compared to even one evaluation (tens of seconds for instance allocation). Secondly, Kairos’ estimation implicitly assumes that it can obtain information of the batch size distribution (fraction \( f \) of batch sizes smaller than \( s \)). This is done via query monitoring to keep track of a number of most recent queries (e.g., 10000 queries), and does not require extra profiling. In addition, to provide robustness, we demonstrate that Kairos adapts when the batch size distribution changes and continues to be effective (Sec. 8.4).

**Upper-bound-assisted search algorithm.** We also develop Kairos+, a variation of Kairos that uses minimum number of online evaluations to quickly find the optimal (Algorithm 1). The search process is guided by the estimated upper bounds and is shown to be outperforming any other traditional search space exploration (Sec. 8). The intuition to greedily start from high upper bound configurations as these configurations have better potential than others, and after evaluating a number of such instances, it is likely that the current best throughput will be high enough to filter out a large number of configurations whose upper bounds are lower. Another pruning mechanism in the algorithm is the sub-configuration pruning. If configuration \( x_1 \) can add more instances to become \( x_2 \), we define \( x_1 \) to be a sub-configuration of \( x_2 \). Every time a configuration is evaluated, all of its sub-configurations get pruned away from the search space, since these sub-configurations will not have higher throughput than the evaluated one. We note that upper bounds that are tight to the actual throughput are especially beneficial to Kairos+ since more configurations can be pruned away.
Algorithm 1: Kairos+’s pruning-based algorithm for quickly finding optimal configuration.

\[ U Bs \leftarrow \text{Sort all } Q P S_{\text{max}} \text{ high to low} \]
\[ \text{curr\_best} = 0 / \text{Highest throughput so far} \]
\[ \text{best\_config} = \text{None} \]
\[ \text{configs} \leftarrow \text{list of all configurations, each denoted as } x \]
\[ \text{foreach } UB(x) \text{ in } U Bs \text{ do} \]
\[ \text{if } x \in \text{configs} \text{ then} \]
\[ \text{eval} = f(x) // \text{Actual QPS evaluation.} \]
\[ \text{if } \text{eval} > \text{curr\_best} \text{ then} \]
\[ \text{curr\_best} = \text{eval} \]
\[ \text{best\_config} = x \]
\[ \text{Filter all } c \text{ out of } \text{configs} \text{ that satisfies} \]
\[ UB(c) \leq \text{curr\_best} \]
\[ \text{end} \]
\[ \text{Prune away all sub-configs. of } x \text{ from } \text{configs} \]
\[ \text{end} \]
\[ \text{return curr\_best, best\_config} \]

6 IMPLEMENTATION

Kairos and Kairos+ is implemented as a cloud inference server, similar to frameworks such as NVIDIA Triton [57]. Every allocated compute instance hosts a copy of the model, only one query is served by one model copy at a time. The query distribution mechanism (Sec. 5.1) resides in a central controller, which performs the optimization to decide the query-instance mapping. It acts as a client and sends the optimized inference requests to individual instances (as servers) through the gRPC protocol [58]. Compared to a traditional load balancer, the central controller is aware of the server heterogeneity and tries to avoid QoS violations. When queries arrive, the controller estimates the query latency and uses its estimated server remaining time to construct the \( L \) matrix for Eqs. 4 and 5.

Notice that the central controller needs to solve the optimization problem in real-time because the solving time is added to the inference latency. We implement this using the scipy.optimize package to solve the bipartite matching problem in polynomial time. We experimentally confirmed that the sum of network delay and algorithm runtime for a large 20-query-20-instance matching is within 0.05ms, negligible compared to QoS which is typically tens of hundreds of milliseconds. Thereby, Kairos ensures that its controller does not become the bottleneck or add significant latency. Furthermore, according to the theory from POP [59], inference service frameworks like Kairos can scale to extremely large systems by dividing the system into multiple sub-systems and running a Kairos instance on each sub-system.

7 METHODOLOGY

Models and QoS constraints. We use industry scale recommender systems to drive the evaluation of Kairos’ effectiveness. Such deep recommendation models (DRMs) have several advantages: (1) wide interest from systems research [16, 60, 61] (2) large customer demand and wide deployment in industry [62, 63] (3) availability of public trace and artifact [17]. Table 3 lists the models and QoS as 99th tail latency target.

These models are chosen because they represent a wide range of recommendation services, the internal architectures are also highly diverse across models [2, 68]. For example, NCF is a light-weighted model with limited embedding tables, but the RM2 model is dominated by large embedding tables, while the MT-WND model has large parallel DNN predictors for abstract features. The QoS constraint for these models cover a wide range and are selected strictly based on real applications. For example, Alibaba’s e-commerce service requires tens of milliseconds of response time while Facebook’s social media platform requires hundreds of milliseconds [17].

An important feature of model queries is that they arrive in different batch sizes (Sec. 4). Our evaluation is driven by the production trace of real query batches from Facebook [17]. The query inter-arrival is generated from a Poisson process, which has been commonly used in various online inference serving studies [2, 69–71]. To evaluate Kairos’s response to load change and sensitivity, we also use Gaussian distributed batch sizes because Gaussian distribution is another commonly used distribution for online services [72].

Computing hardware types and cost. We use different hardware types provided by Amazon Elastic Compute Cloud (EC2) for our evaluation. The compute instances are categorized into four classes: general purpose, compute optimized, memory optimized, and accelerated. We select an instance type of each class to form a heterogeneous pool. Table 4 summarizes the compute instance types.

These instance types create a 4-dimensional search space, each heterogeneous pool corresponds to a certain number of instances of each type. We select the instance size (indicated by .xlarge characters) so that all types have 16GBs of memory allocation to host the model. We use the g4dn.xlarge GPU instance type as the base instance type as only this instance type can meet QoS for all batch sizes. The other instance types (e.g., c5n.2xlarge) are considered as auxiliary instance types. g4dn.xlarge instance type uses NVIDIA T4 GPU. Compared to all other GPU-accelerated instance types in EC2, g4dn has the best inference performance – similar to

### Table 3: Models and QoS targets.

| Model   | Description                                      | Application          | QoS    |
|---------|--------------------------------------------------|----------------------|--------|
| NCF     | Neural Collaborative Filtering                   | Movie recommendation | 5ms    |
| RM2     | Facebook’s recommendation model class 2          | High-accuracy social media posts ranking | 350 ms |
| WND     | Google Wide and Deep recommender system          | Google App Store recommendation | 25ms   |
| MT-WND  | Multi-Task Wide and Deep, predicts multiple metrics in parallel | YouTube video recommendation | 25ms   |
| DIEN    | Alibaba Deep Interest Evolution Network          | E-commerce recommendation | 35ms   |

### Table 4: Instance types used in heterogeneous pool.

| Instance Type | Instance Category | Price ($/hr) |
|---------------|-------------------|--------------|
| g4dn.xlarge   | GPU Accelerated   | 0.526        |
| c5n.2xlarge   | Compute Optimized | 0.432        |
| r5n.large     | Memory Optimized  | 0.149        |
| t3.xlarge     | General Purpose   | 0.1664       |
p3.2xlarge instance type (NVIDIA V100 GPU). But, p3 has nearly 6x higher cost than g4dn, therefore, we use g4dn as the most cost-effective base instance type to be used in a homogeneous pool. The cost budget is set to 2.5$/hr by default for Kairos evaluation - this budget is chosen purely to ensure the cost incurred during the evaluation period remains within a reasonable limit while demonstrating the value of the idea. As our evaluation confirms, Kairos is not sensitive to cost budget (e.g., 10$/hr budget) and is not tuned to work specifically only for certain cost budget caps.

**Metrics.** Our main evaluation metric remains the throughput (QPS) under QoS (Sec. 4). To find this allowable throughput, we gradually increase the arrival rate of queries, until the QoS is violated. In addition, since evaluating a configuration in the search space is expensive, we also compare the number of iterations required to find the optimal configuration for a particular scheme. This part is only applicable to competing techniques (non-Kairos solutions) since Kairos does not require online exploration and evaluation.

**Competing query distribution techniques.** We evaluate Kairos against three recent DL inference serving schemes.

**Ribbon.** This scheme focuses only on hardware allocation, therefore it has a simple first-come-first-serve (FCFS) query distribution policy which prefers instances of the base type when multiple instances are available. However, it uses Bayesian optimization to allocate a near-optimal set of heterogeneous hardware on the cloud, which is similar to the problem Kairos tries to solve in Sec. 5.2.

**DRS.** This scheme represents the scheme used in a related work - DeepRecSys system [17]. It uses a static batch size threshold to decide whether to serve a query on a base instance (if large than a threshold) or on the auxiliary instance (otherwise). To determine the threshold, a hill-climbing sweep is used by DeepRecSys system [17] to find the threshold that yields the highest throughput.

**CLKWRK.** This scheme is a QoS-aware query distribution scheme inspired by Clockwork [18]. It has a focus on latency consolidation, but we have used its central controller for comparison with Kairos. This scheme monitors all hardware availability timings and accurately predicts query latency. A query is guaranteed to be served within its latency target unless none of the instances can meet the QoS target. Each instance maintains an individual FCFS query queue. There is a central controller to keep track of all hardware and queue timings and send new queries to the instance queues.

**ORCL.** Oracle scheme is a practically infeasible scheme only for reference to understand the limits of performance. Oracle always has higher throughput than other schemes because it knows the future query arrival patterns. It creates a sequence of queries according to batch size distribution and sorts all queries by the batch size. Whenever a base instance is available, it serves the next largest query. For auxiliary instances, it is the next smallest query. There is no wait time for queries, and queries never run on instances that violate QoS. The throughput on serving the query sequence is recorded, and among all possible heterogeneous configurations, the largest throughput is used as the Oracle throughput.

Recall that Kairos determines the near-optimal heterogeneous configuration using its upper-bound assisted method without any online configuration evaluation - unlike other competing schemes. Kairos+ is an online variation of Kairos for optimal configuration, but the number of online evaluation is limited because its guided by Kairos’s upper bound method, as our evaluation section discusses next.

### 8 Kairos: Experimental Evaluation

First, we quantitatively evaluate Kairos’s performance compared to other competing schemes and state-of-the-art approaches. We explain why Kairos works effectively, and what are the key contributing factors toward its superiority over existing methods. Finally, we demonstrate that Kairos performs effectively even under varying constraints and parameters (e.g., cost budget, QoS, and batch size distribution).

#### 8.1 Comparison with Best Homogeneous

First, our experimental results (Fig. 7) confirm that Kairos provides significant allowable throughput improvement compared to the most competitive base instance homogeneous configuration under the same QoS constraints and budget (Sec. 7). The number of instances in the homogeneous pool is determined by the maximum number of nodes that can fit within the cost budget. Note that the cost budget is not a multiple of g4dn.xlarge price. To compensate for the wasted budget, we scale up the homogeneous throughput proportionally. But, to evaluate conservatively, we allow the budget slack of Kairos to be wasted. Despite this, Kairos is still able to provide up to 2x throughput (i.e., RM2 model) and more than 1.25x in all cases.

#### 8.2 Comparison with State-of-the-Art

Next, our results show that Kairos outperforms competing schemes of Ribbon, DRS and CLKWRK in Fig. 8. Recall that the competing techniques DRS and CLKWRK only focus on distributing the queries to a set of instances following a certain strategy. They do not observe that one can build a heterogeneous configuration that is more performant than a homogeneous configuration under a cost budget. To provide these techniques an advantage, we provide each...
scheme with the best heterogeneous configuration obtained via Oracle search and compare the throughput against Kairos. Fig. 8 shows the allowable throughput for different schemes.

We make several observations. First, as expected, both DRS and CLKWRK outperform the Ribbon scheme because Ribbon uses a simple query distribution mechanism. Second, Kairos significantly outperforms all existing techniques and is close to the Oracle scheme. For all models, Kairos can provide around 1.5× the throughput of Ribbon. Kairos’ performance comes from its superior query distribution mechanism (Sec. 5) which focuses on exploiting the heterogeneity for maximum availability cycles on all resources combined, while carefully avoiding QoS violations. Note that DRS is ultimately limited by its threshold-based mechanism and misses the opportunity of utilizing different instance types for smaller queries. CLKWRK actively schedules queries on instances that do not violate QoS, thus it helps avoid more unnecessary QoS violations than Ribbon. However, unlike Kairos, it does not optimize on heterogeneous instances.

The most attractive aspect of Kairos’ superior performance and design is that Kairos does not experimentally evaluate heterogeneous configurations online – unlike other methods. It uses its unique approximation method to determine a good heterogeneous configuration in one shot. For our evaluation, we provided additional advantages to all competing schemes by allowing them to use optimal heterogeneous configuration – determined offline. Even under this conservative evaluation, Kairos outperforms the DRS and CLKWRK schemes by up to 44% (Fig. 8).

Lastly, Kairos+ performs slightly better than Kairos. This is expected because Kairos+ employs a pruning-based online approach to find the optimal heterogeneous configuration. Nevertheless, Kairos still provides approximately the same throughput as Kairos+ without any online evaluation. Next, we discuss the impact of online configuration search.

8.3 Online Optimal Config. Exploration

Among all competing schemes, only Kairos and Oracle do not require online evaluation; others need to evaluate configurations online to find the optimal one for its query distribution mechanism. One may ask: how much overhead does Kairos save from avoiding online evaluation? In our previous result (Fig. 8), the impact of online evaluation is not included. Fig. 9 shows the number of evaluations each online technique requires to find its optimal configuration (on log-scale). We observe that Ribbon and DRS often need to evaluate 5%-30% of the search space to reach the optimal configuration, and hence, the maximum throughput they can achieve is delayed by the length of this exploration period.

For fair comparison, in Fig. 9, we augment all competing techniques with the same online configuration exploration algorithm as Kairos+. We note that Kairos+ consistently evaluates less than

1% of the search space for all models, outperforming competing schemes despite using the same search algorithm. Similar trends are observed, even with other non-Kairos+ online exploration algorithms such as genetic algorithm, simulated annealing, etc.

A related inquiry is: is calculating the throughput upper bound and leveraging it toward online exploration in Kairos+ useful? Will any other alternative search methods such as Ribbon quickly find the same optimal configuration that Kairos+ finds? We use random search (RAND), genetic algorithm [73] (GENE), and Ribbon’s Bayesian Optimization as competing search algorithms and evaluate the number of evaluations compared to the Kairos+ technique. We purposely provide these competing algorithms with the same sub-configuration pruning mechanism as Kairos+ in Algorithm 1 to save some iterations. But, as Fig. 10 shows, competing methods still require significantly more online evaluations than Kairos+. These results essentially decouple the effects of Kairos’ two components of query distribution and search space evaluation, showing that they both are critical for quickly achieving a configuration that performs well. The advantages of Kairos as a technique that can quickly find a good configuration are further emphasized.

8.4 Timely Reaction to Load Changes

Previous results demonstrate that, besides a higher throughput, Kairos’s major benefit is from eliminating the time overhead to find a promising configuration. Fig. 11 provides further experimental demonstration to substantiate this. When the query load or its distribution changes, the throughput of evaluated configurations.

![Figure 9: Kairos+ has low evaluation overhead.](image)

![Figure 10: Kairos+ versus competing search algorithms.](image)

![Figure 11: When query size probability distribution changes, the throughput of evaluated configurations.](image)
Figure 12: Impact of changing query distribution scheme. The dashed horizontal line indicates Oracle.

Figure 13: KAIROS when: (a) budget is scaled by 4x; (b) using a higher QoS target. Red dot: Fig. 7 results.

8.5 Further Evaluations

To further demonstrate the effectiveness of KAIROS, in Fig. 12, we pick the RM2 model and plot the experimental throughput for KAIROS’s top upper bound configurations when changing the query distribution scheme to Ribbon, DRS, and CLKWRK. This setting is chosen to better understand how the query distribution mechanism and heterogeneous configuration search by KAIROS are co-designed, and replacing the query distribution mechanism with any other would result in worse performance of configuration search.

From this figure, we make three observations. Firstly, the upper bound (UB) is lower than but close to the Oracle throughput (dashed), indicating that the upper bound is relatively tight and meaningful to be used in practice. Secondly, the calculated (UB) and KAIROS’s experimentally observed throughput are close to each other and follow the same trend. This substantiates the design decision to approximate real throughput using the upper bound. Thirdly, KAIROS’s query-distribution mechanism is a key source of its effectiveness. If KAIROS only chooses a configuration based on the upper bound without employing its query-distribution mechanism, the actual throughput will yield far from expectation (loose bound) — underscoring the effectiveness of KAIROS’s query-distribution mechanism.

Finally, we evaluate KAIROS’s robustness against different parameters. Fig. 13(a) shows that KAIROS’s heterogeneity approach offers substantial improvement over homogeneous configurations when the cost budget scales. Notice that non-KAIROS schemes would struggle more in finding a good configuration as the search space is increased by 4x. Similarly, in Fig. 13(b), when the QoS targets are set 20% higher, KAIROS continues to offer similar improvements as before (Fig. 7 results marked in red).

Recall that the query batch size patterns may change over time, and KAIROS can quickly respond to the new patterns without on-line evaluations (Sec. 8.4). In Fig. 14(a), we show that KAIROS still yields significant benefit over homogeneous serving on Gaussian distributed batch sizes. Note that the Oracle could also yield lower improvements — hence, the relative improvement compared to the previous distribution (red dots) also decreases for some models. Lastly, since the query distribution scheme of KAIROS makes a realistic assumption that the inference latency can be accurately predicted, we also show KAIROS’s effectiveness when this assumption is relaxed. In Fig. 14(b), we intentionally inject an additive Gaussian white noise with 5% variance in latency prediction to emulate performance variability in the cloud [74]. Our results suggest that KAIROS is not sensitive to such noise that is common due to interference or transient hardware degradation, and continues to offer similar improvements.

9 CONCLUSION

KAIROS demonstrates that a mixture of heterogeneous compute instances can be effectively utilized to maximize the inference query throughput under QoS and cost constraints. KAIROS’s upper-bound based method eliminates the need for online configuration exploration, and KAIROS intelligently distributes queries among heterogeneous instances. Our evaluation shows that KAIROS significantly outperforms state-of-the-art techniques.

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