Help Rather Than Recycle: Alleviating Cold Startup in Serverless Computing Through Inter-Function Container Sharing

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Abstract
In serverless computing, each function invocation is executed in a container (or a Virtual Machine), and container cold startup results in long response latency. We observe that some functions suffer from cold container startup, while the warm containers of other functions are idle. Based on the observation, other than booting a new container for a function from scratch, we propose to alleviate the cold startup by re-purposing a warm but idle container from another function. We implement a container management scheme, named Pagurus, to achieve the purpose. Pagurus comprises an intra-function manager for replacing an idle warm container to be a container that other functions can use without introducing additional security issues, an inter-function scheduler for scheduling containers between functions, and a sharing-aware function balancer at the cluster-level for balancing the workload across different nodes. Experiments using Azure serverless traces show that Pagurus alleviates 84.6% of the cold startup, and the cold startup latency is reduced from hundreds of milliseconds to 16 milliseconds if alleviated.

1 Introduction
Owing advantages of high maintainability and testability, serverless computing is suitable for the ever-growing Internet services (the tenants are charged per invocation). As a result, hyperscalers now provide serverless computing services (e.g., Amazon Lambda [5], Google Cloud Function [11], Microsoft Azure Functions [12], and Alibaba Function Compute [1]). Meanwhile, some open-source serverless computing solutions like Apache OpenWhisk [3] and Fission [9] have also been developed and released.

In serverless computing, user functions run in containers (or Virtual Machines), and the containers are specialized for a function (a container is not allowed to run different user functions). Warm containers refer to the keep-alive containers that serve subsequent invocations (warm startup). If there is no warm container for a function invocation, a new container is started from scratch (cold startup). The cold startup latency is more than 10× of the warm startup latency due to the container creation, software environment setup, and code initialization [40, 44, 47, 49, 59, 61]. It is ideal if all functions can run in warm containers. However, keep-alive containers are recycled to save resources once no new invocation arrives during the lifetime.

Many efforts have been devoted to speeding up the container cold startup [7, 28, 31, 32, 45, 46, 54–56, 58]. The prewarm-based methods create containers and runtime in advance, one method of which is prewarming customized containers for each function that includes all its required software packages [8, 15, 27, 28, 60]. However, it brings heavy memory consumption. Another method of prewarming containers is only installing common packages, and all functions share the prewarmed container pool [14, 45, 46]. This method is more memory space-efficient, but generating customized containers for a function from the prewarmed containers suffers from package download and installing latency overhead. Current solutions mainly adopt the second method [14, 46].

To alleviate the memory waste and minimize the function response time, instead of prewarming containers, we propose to alleviate the cold container startup through container sharing. For instance, if function A in Figure 1 can “fork or lend” the runtime checkpoint from its idle warm containers for function B, the cold startup of B is eliminated. By such means, we can leverage a function’s idle warm containers before being recycled to help others that tend to experience cold container startup.
Analyzing the container sharing logic and challenging steps.

Figure 2: The container sharing logic and challenging steps.

We propose a container management system, named Pagurus to tackle these challenges. Figure 2 shows the steps of using function A’s idle warm containers to alleviate the cold container startup of other functions. The key idea is to replace its idle containers with new containers that other functions can safely use. The new container is created through a new image that already installs the required software packages of other functions, without including the code/data of the original function A. In this way, the warm containers of a function are classified into three categories: private containers, zygote containers, and helper containers. A function’s private containers can only be used by itself. Its zygote containers are the new containers that other functions can use. Its helper containers are the containers forked from other functions’ zygotes. A helper container already loads its user code for future invocations. By using privilege control in the operating system, a function that uses a helper container cannot obtain any code, data, or package information of other functions.

Pagurus uses an intra-function container manager for each function to manage its containers, an inter-function scheduler on each node to manage the “fork” action between functions, and a sharing-aware function balancer to schedule functions across the nodes. For a function, the intra-function manager monitors the status of each container, identifies idle warm containers, and re-purposes an idle container based on a QoS-based timer. The inter-function scheduler, acting as an orchestrator, determines the to-be-helped functions of each function. We design a Similarity Filtered Weighted Random Sampling (SF-WRS) algorithm to find an appropriate set of to-be-helped functions. Besides, the sharing-aware function balancer distributes function invocations to different nodes to achieve efficient inter-function container sharing.

Pagurus requires no offline analysis or profile on the functions, thus can be easily adopted in production. The main contributions of this paper are as follows.

- **A resource-friendly design of zygote and helper container.** Zygote container enables resource-saving through package and function reclamation, without incurring any additional security issues meanwhile.
- **The design of a SF-WRS re-packing policy.** Based on the package similarity between functions and the frequency of function cold startups, SF-WRS policy reduces the number of packages to-be-installed, thus minimizing the memory needed and the overhead of creating zygote containers.
- **The design of an efficient container sharing mechanism.** Pagurus divides the warm containers of a function into three types and manages the three types of containers in different ways. The mechanism efficiently alleviates the cold container startup.

We evaluate Pagurus using both best-practice AWS serverless functions [6] and Azure traces [50]. Experiments show that Pagurus alleviates 84.6% of cold startups on average in Azure traces, and the cold startup latency is reduced from hundreds of milliseconds to 16 milliseconds if alleviated.

2 Background and Related Work

If a function is invoked for the first time or there is no alive (or warm) container for it, the serverless system starts a new container to encapsulate its function runtime, initializes the software environment, loads application-specific code, and runs the function. All these steps make up a cold startup and may even take several seconds [21, 36, 59]. The cold startup significantly increases queries’ end-to-end latency [23, 33, 47, 49]. The long latency problem worsens when the function invocation is short (e.g., hundreds of milliseconds).

Prewarm startup spawns template containers that are already initialized with the software environment. Though it skips the container startup and users only need to perform application-specific code initialization [2, 3, 32, 46], its pre-loaded packages can either make the image size too large [20, 32, 53], or cause more memory consumption for the prewarm container [24, 46, 50].
Many prior studies have been conducted to reduce the container startup latency [19, 28, 34, 48, 52, 54]. However, existing works mainly focused on seeking lightweight virtualization technologies to pursue lower overhead [17] or optimizing prewarm strategies for more accurate prediction models and less initialization cost [1]. A common optimization is to pause the container when idle to save resources consumed by function codes and packages, and then reload it for reusing when invoked [34, 44, 45, 57].

SAND [19] separated applications via containers while allowing functions of one application to run in the same container by different processes. FaasCache [31] took the caching model for objects into serverless context, and implemented the Greedy-Dual keep-alive caching mechanism to reduce the resource requirement and keep containers warm. Shahrad et al. [50] proposed to dynamically change the instance lifetime of the recycling and provisioning instances according to the time series prediction. Some researchers use C/R (Checkpoint and Restore) [7, 55, 56, 58] that restores container images from checkpoints to speed up the cold startup. For example, Catalyster [28] utilized C/R to realize on-demand recovery. However, it still incurs long latency compared with a warm startup. The above technologies are orthogonal to us, and Pagurus can be combined with them to reduce the cold startup latency further. SOCK [46] introduced a tree cache and uses the benefit-to-cost model to update packages in the prewarmed containers dynamically, but the zygote design consumes more memory when maintaining packages by a cache-tree. Moreover, the cache-tree design does not work if functions require conflicted package versions.

Pagurus resolves the problems through inter-function container sharing with conflict concerns, and needs neither pool-size tradeoffs nor time-consuming model training.

3 Investigation and Motivations

In this section, we discuss the current prewarm-based mechanism for alleviating the cold container startups, and show the possibility of eliminating the cold container startup with inter-function container sharing.

3.1 Latencies of Cold and Prewarm Startups

A cold container startup is done in three time-consuming steps: create container from the image, initialize software environment, and initialize application-specific code. With the prewarm mechanism (used in OpenWhisk [3] and production platforms), several containers that already import common libs/packages are hatched in a container pool. A function invocation with no warm container can specialize the prewarmed container by installing the extra packages.

We use prewarm-enabled OpenWhisk with local cache as the serverless platform, and use the best practice serverless applications in AWS [6] as the benchmarks, to investigate the impacts of cold and prewarm startup on the end-to-end latency of a function invocation. A benchmark may have several functions [41]. As for the hardware, we use one node to perform the computation and one node to generate function invocations. The benchmarks, software, and hardware setups are described in Section 8.

Figure 3 shows the time of generating a container when it is started from the image, or is specialized from a common prewarmed container. As shown, the cold container startup takes about 500 milliseconds. The prewarm startup takes 15 milliseconds in the best case, but takes more than 1500 milliseconds in the worst case (e.g., function union in the benchmark ddns). This is because union requires to load/install many additional packages in the prewarmed containers, and the package loading is time-consuming.

Intuitively, a prewarmed container may install all the software packages required by all the functions on a physical node to speed up the prewarm startup. It is possible because for most serverless systems, the packages needed by a function (besides the private ones) are usually given by its user in a requirements.txt file, and are publicly accessible for FaaS providers. However, many functions require software packages of contradicting versions. In addition, such a solution may expose the package information of other functions. The pre-imported requirements will implicitly embody user privacy. Due to the software conflict and privacy concerns, it is not a good option to install packages for all functions in the prewarmed containers.

3.2 Limitations of Prewarm Schemes

We then explore the effectiveness of the prewarm schemes in alleviating the cold startup. In this experiment, we run all the benchmarks on a single node, and the invocation patterns of the functions are the same as the patterns in the Azure serverless traces. The invocation patterns actually follow the Pareto distribution (most of the invocations are for a small part of the functions) [15]. By default, a prewarm container pool has two prewarmed containers on a node [2].

Figure 4 shows the percentage of the remaining cold startups with the prewarm mechanism. Many cold startups are not eliminated (e.g., functions in eco and cart). This phe-
nomenon attributes to the inappropriate pool size of the pre-
warm container pool. For eco and cart, their functions are in-
voked simultaneously or in short intervals to satisfy complex
business logic, such as workflows [18, 22, 25]. For instance,
five functions are triggered simultaneously by a caller in eco.
These functions contend for the prewarmed containers.

It is nontrivial to appropriately configure the prewarm
scheme due to two considerations. 1) Pool-size and mem-
ory overhead trade-off. If we prewarm more containers,
larger additional memory space is used. In our experiment,
the prewarmed containers use more than 1GB of memory
(on a node with 16GB memory) to eliminate 80% of the cold
startup. The prewarm mechanism is not able to effectively
eliminate the cold startup with reasonable memory overhead.
2) User experience and system efficiency contradiction.
As discussed, most of the invocations are from a small part
of the functions [15], and a prewarmed container can only
cache a small number of packages for the low memory over-
head. Caching packages for frequently invoked functions
improves the system efficiency (frequent invocations have
low startup time), but results in poor user experience (invoca-
tions of most functions tend to suffer from the long package
installation time), and vice versa.

The current container prewarm scheme is not efficient due
to several inevitable trade-offs. It is beneficial to alleviate
cold startups without trapping in the same dilemmas.

### 3.3 Opportunity of Reusing Idle Containers

We therefore propose to alleviate cold startup without relying
on prewarming containers. The key idea is leveraging the
warm but idle containers of some functions to alleviate the
cold startups. A function invocation that requires cold startup
may “steal” an idle warm container from other functions.

The proposed scheme is effective only when there are idle
warm containers in some functions when an invocation tends
to suffer from the cold container startup. In principle, only
underutilized warm containers that are active due to the keep-
alive strategy can be used by other functions. Otherwise,
always stealing a warm container directly may result in the
cold container startup of the victim function.

We analyze the day07 trace of Azure serverless plat-
form [50] (the trace contains invocations of over 44,000
functions) to verify the above requirement. If a container
triggers recycling, it must be an idle warm container because
of no new invocation during its lifetime. By replaying the
trace, we find that the warm containers for some functions
are idle (no invocation is received during this idle time),
while some other functions suffer from cold startup. We refer
to idle warm containers as idle containers.

Figure 5 shows the number of idle containers and cold
startups when replaying the trace. As observed, the time that
idle containers and cold startup happen are similar, and there
are more idle containers than the cold startups. If the time
does not match, the functions that suffer from cold startup
cannot find idle containers from other functions.

The time matches because many containers are prepared
and invoked to serve the high load, and they become inactive
when the load drops. We can observe a significant discon-
 tinuity at the beginning of each hour as there is a certain
number of functions with a 1-hour timer trigger, and they
are invoked once and will keep idle during the rest of their
lifetime. In this case, excessive idle containers are pervasive.

In summary, serverless computing systems usually adopt
a keep-alive strategy (e.g., 15 minutes) to reduce the cold
startup. The kept-alive containers are idle before they are re-
cycled. The widely-existed diurnal load pattern also makes
containers over-provisioned at the high load. These contain-
ers will become idle when the load drops as well.

Based on the investigation, we observe the opportunity to
leverage the idle containers of some functions to help others
that suffer from cold startup on the same node.

### 4 Design of Pagurus

There are two prerequisites to alleviate the cold container
startup with the warm containers of other functions. First, the
container manager has to identify the actual idle warm con-
tainers. Otherwise, the “steal” results in the container cold
startup of the victim function. Second, the proposed strategy
should not expose any information of a function (e.g., data,
code, package requirements) to other functions from the con-
sideration of security.

We propose and implement Pagurus, a container man-
agement system that fulfills the two prerequisites. Figure 6
shows the design of Pagurus. It comprises an intra-function container manager for each function, an inter-function container scheduler on each node, and a sharing-aware function balancer at the cluster level. The intra-function container manager of a function manages its three types of containers (private containers, zygote containers, and helper containers) (Section 5). The inter-function scheduler manages the zygoters sharing between functions (Section 6). The sharing-aware function balancer maps the functions across multiple nodes to minimize the system-wide cold startup (Section 7).

Based on runtime statistics, a function’s idle warm containers are replaced with its zygote containers that are newly created from its zygote image (② in Figure 6). The zygote image does not include the code or data of any functions. Pagurus uses the inter-function container scheduler on each node to generate the zygote image of each function (① in Figure 6). Creating zygote images does not introduce extra runtime latency overhead, as it is done asynchronously before replacing the idle container with a zygote container. The inter-function container scheduler determines the possible to-be-helped functions of each function based on Similarity-Filtered Weighted Random Sampling (SF-WRS) policy, which will be detailed in Section 6.1. A function’s zygote container additionally installs the required packages of its to-be-helped functions in an anonymous fashion. Based on the privilege control of the Linux operating system, a function is only able to access its own packages.

Specifically, when an invocation of a function \( f \) arrives, it obtains a container to host the invocation in four steps.

1) It first tries to obtain an idle warm private container from its own private container pool directly. Then, if its private container pool is empty, it checks whether its helper container pool has containers for queries.

2) If both the private pool and the helper pool are empty, it will further check whether its zygote container pool has some containers already adapted for other functions. If not empty, a zygote container can be used to host the invocation.

3) If its zygote container pool is also empty, Pagurus tries to find a container that includes the required packages of \( f \) from other functions’ zygote container pool. The forked zygote then joins the helper container pool of \( f \) (③ in Figure 6).

4) If all the above steps fail, the invocation of \( f \) would suffer from a cold container startup.

## 5 Intra-function Container Management

The key points of the intra-function manager are identifying the actual idle containers, and designing an efficient sharing mechanism.

### 5.1 Identifying Idle Containers

In principle, a container is idle when it does not host function invocations for a long time. For a function \( f \), we introduce a timer in each of its containers to measure the free time.

A warm container is treated to be idle if its timer exceeds threshold \( T_{idle}(f) \). The timer is reset once the container receives an invocation.

The design principle here is that most function invocations can still get warm containers, even when a container is identified to be idle and “stolen” by other functions. Different functions should have different idle thresholds because of their diverse invocation patterns. We explore the runtime invocation arrival pattern to determine the value of \( T_{idle}(f) \) for a function \( f \). Specifically, we use all the \( m \) invocations during the container lifetime, and let \( T_1, T_2, \ldots, T_m \) represent the time intervals between the adjacent invocations (the time interval is sorted in the ascending order). Equation (1) calculates the idle threshold \( T_{idle}(f) \) for the function \( f \) in the next time period.

\[
T_{idle}(f) = \begin{cases} T_{\{0.95m\}}, & m \geq 30, \\ T_{default}, & m < 30. \end{cases}
\]  

(1)

In the equation, \( T_{\{0.95m\}} \) is the 95%-ile time interval of the \( m \) samples. In this case, for frequent invoked functions (\( m \geq 30 \)), more than 95% invocations of \( f \) tend to get warm containers; if the invocation arrival patterns remain. We use 30 to be the sampling target for stability considerations. For occasionally invoked functions, \( T_{idle}(f) \) is set to be \( T_{default} \), and almost all the invocations get warm containers. \( T_{default} \) may impact the overall efficiency for idle identification, and Section 8.4.3 evaluates the sensitivity of Pagurus to it.

### 5.2 Replacing Idle Containers with Zygotes

A function’s idle containers cannot be used by other functions directly, as the data and code of the function may still reside in the memory of the idle containers. To this end, Pagurus creates a zygote container that does not include any...
data or code of the owner function, and uses the zygote container to replace the original idle warm container. The zygote container is created from an image that installs the shared packages of all the to-be-helped functions. Section 6 discusses the policies used to determine the to-be-helped functions and generate the zygote image of a function.

One may be concerned about the security and privacy of the zygote container for re-purposing. Figure 7 shows the way to avoid package information leakage in zygote containers. All the functions run as non-root users [4, 10, 16]. In the figure, \( f_B \) and \( f_C \) are the to-be-helped functions in \( f_A \)'s zygote container. In general, the common intersectant packages required by all functions are installed as a shared domain \((pkg_m, pkg_n)\) in the zygote container, and the additional complementary and private packages of to-be-helped functions are cached in different directories of the host. These directories are mounted anonymously into the zygote, thus ensuring that others cannot identify a function.

Each function that may use the zygote container is given a privilege domain and is only allowed to access its corresponding package directory. The privilege domain and privilege control are provided by Linux operating system and different non-root users. For instance, in Figure 7, when function \( f_B \) obtains the zygote container, it can only enter its own privilege domain for \( f_B \)'s packages (private packages and \( pkg_m \)) to specialize its software runtime. In this way, the zygote container serves as a safety checkpoint. Because it does not import any user-related code and data, the function privacy of the software environment is also protected.

6 Inter-function Container Scheduling

The inter-function container scheduler selects to-be-helped functions for zygotes, re-packs zygote images, and manages the fork operation for helper containers.

6.1 Selecting To-be-helped Functions

A straightforward approach is to treat all the other co-located functions as the candidate to-be-helped functions, and install all the required packages into a zygote image. However, this approach suffers from extremely high re-packing overhead, in terms of both time and resource consumption. When re-packing a zygote image, we have two important observations. On the one hand, if the set of to-be-installed packages is large, it is time-consuming and resource-unfriendly to create a giant zygote image. On the other hand, some functions tend to have more cold startups than others (as observed from Azure traces [12]), inappropriate selection of to-be-helped functions is inefficient in alleviating the system-wide cold startups. Taking the above challenges into consideration, we propose SF-WRS (Similarity Filtered Weighted Random Sampling) algorithm, which contains:

- A Similarity-based Filter to find out to-be-helped candidates based on the similarity of functions’ packages. In this way, a zygote installs fewer complementary packages, thereby lowering the re-packing overhead.
- A WRS (Weighted Random Sampling) strategy [29] to select \( K \) to-be-helped functions based on the cold startup frequency of each function on the node. Pagurus tends to prepare zygote images for the functions that suffer from more cold startups with high possibility.

Similarity-based Filter. Focusing on the package information, a function \( f \) can be viewed as a set of packages, i.e., \( f = \{ pkg_1, pkg_2, \ldots \} \), where \( pkg_i \) is assigned in the requirements.txt and refers to the required package in \( f \)'s runtime environment. Let \( \mathbb{F}_n = \{ f_1, f_2, \ldots \} \), \( \forall f_i \neq f \) represent the set of functions on node \( n \) when function \( f \) triggers re-packing. The package difference between \( f \) and \( f_i \in \mathbb{F}_n \) imposes a deep influence on the re-packing overhead. Let us denote the containment relationship of a package \( pkg \) in \( f_A \) and another function \( f_B \) as

\[
\text{con}(pkg, f_A) = \begin{cases} 
1, & \text{if } pkg \in f_A \cup f_B; \\
0, & \text{others},
\end{cases}
\]  

We can then derive the containment relationship vector of \( f \) and \( f_i \in \mathbb{F}_n \) as \( \mathbf{f} = [\text{con}(pkg, f)]\forall pkg \in f \cup f_i \) and \( \mathbf{f}_i = [\text{con}(pkg, f_i)]\forall pkg \in f \cup f_i \), respectively. The similarity between \( f \) and \( f_i \) thus can be calculated as their cosine distance by

\[
\text{Cos} (\mathbf{f}, \mathbf{f}_i) = \begin{cases} 
\frac{\mathbf{f} \cdot \mathbf{f}_i}{\|\mathbf{f}\|\|\mathbf{f}_i\|}, & \|\mathbf{f}\|\|\mathbf{f}_i\| \neq 0, \\
1, & \|\mathbf{f}\|\|\mathbf{f}_i\| = 0.
\end{cases}
\]  

Thereafter, we can obtain an initial \( f \)'s to-be-helped function candidate set \( \mathbb{C}_f \) by removing those functions with similarity lower than \( \text{TargetSimilarity} \) from \( \mathbb{F}_n \). \( \text{TargetSimilarity} \) can be set as the median similarity in default.

Note that, as discussed before, a package may be specified in different versions, and a zygote image with version conflict (i.e., the same package but different versions) could not be re-purposed by another function. Denoting the version of a package \( pkg \) in function \( f \) as \( V(pkg, f) \), we can express the version conflict relationship between \( f \) and \( f' \) as

\[
\text{Conflict}(f, f') = \begin{cases} 
1, & \exists \ pkg \in f, V(pkg, f) \neq V(pkg, f'), \\
0, & \text{others}.
\end{cases}
\]  

Figure 7: Security assurance of a zygote container.
Then, we first ensure that there is no conflict between function \( f \) and its candidates, by removing the functions with version conflict from the candidate set. However, it is still possible that some candidates conflict with each other. For instance, candidates \( f'_1 \) and \( f'_2 \) do not conflict with \( f \), but \( f'_1 \) conflicts with \( f'_2 \). In this case, they cannot be packed into a single zygote image either. The candidate set \( C'_n \) should be further updated by Equation (5), where \( C'_n \setminus f'_i \) represents the complement of \( f'_i \) in \( C'_n \).

\[
C'_n = \{ f'_i | \text{Conflict}(f, f'_i) = 0, \text{Conflict}(f'_j, C'_n \setminus f'_i) = 0, \forall f'_j \in C'_n \}, \tag{5}
\]

Take the package conflict in AWS application benchmarks as an example, function \( tcp_{\text{check_transcribe}} \) requires the package \( aws_{\text{requests-auth}} \) with version 0.4.1, while function \( ep_{\text{delivery_on_package_create}} \) requires that with version 0.4.3. It denotes that applications have various package similarities, and two functions may rely on conflicted packages. By selecting the to-be-helped functions based on package similarity, a zygote image installs fewer packages for zygote images with less re-packing overhead.

**WRS selection.** After the similarity filter and conflict recognition, the to-be-helped function candidates can be significantly reduced. However, it is still nontrivial for the inter-function scheduler to determine the appropriate number of to-be-helped functions without resulting in too large image size, too long image generation time, or failing to eliminate most cold startups. Therefore, we should choose an appropriate number, say \( K \), of functions from candidates \( C'_n \) that tends to eliminate the cold startups with high probability.

Therefore, we first remove the functions never re-invoked from \( C'_n \). Let \( I \) be the number of remaining functions that have been invoked more than once. We can calculate \( K \) as

\[
K = \frac{\sum_{n=1}^{I} K_n \cdot \left( \sum_{n=1}^{I} \text{Cold}(f'_n) + \sum_{n=1}^{I} \text{Zygote}(f'_n) \right)}{I}, \tag{6}
\]

\( K_n \) is the expected number of to-be-helped functions for \( f'_n \), \( \text{Num}(\text{Zygote}) \) is the average number of active zygotes in the system, \( \text{Zygote}(f'_n) \) and \( \text{Cold}(f'_n) \) indicate the times a function experiences zygote-based invocation and cold startups of \( f'_n \), respectively. \( K \) ensures that each to-be-helped function \( f'_n \) can be re-packed into a zygote container at least once.

**Algorithm 1** summarizes the SF-WRS algorithm. First, the inter-function scheduler filters out the candidate functions with low similarity values (lines 1-3), recognizes the package conflicts (lines 4-6), and then selects \( K \) to-be-helped ones by the A-ExpJ algorithm, which is a variation of WRS (Weighted Random Sampling) algorithm [29] (lines 9-12). Compared with naive WRS, A-ExpJ shows much lower time complexity. The time complexity of selecting \( K \) functions is \( O(K \log(\frac{K}{n})) \) with A-ExpJ, and the time complexity of naive WRS is \( O(n) \).

![Algorithm 1 SF-WRS Selection Algorithm](image)

**6.2 Re-packing a Zygote Image**

Figure 8 shows the steps of re-packing the zygote image for a function \( f \). When the intra-function container manager of \( f \) identifies an idle container, it informs the inter-function scheduler, then selects the to-be-helped functions of \( f \) based on the SF-WRS algorithm. After that, the inter-function scheduler triggers the re-packing operation, obtains the packages, and re-packs the zygote image. Only the packages shared by all the to-be-helped functions are installed in the shared domain. Finally, the re-packed zygote image is returned to the intra-function container manager of \( f \) for building zygote containers to replace \( f \)’s idle containers.

The inter-function container manager has an advantage compared with the traditional building method, where the image is built through the network from the container repository. Pagrus omits the downloading of the required packages in a zygote image through the network again, benefiting from the locally cached packages, when creating the private container images [26, 39]. By reusing cached packages, re-packing a zygote image takes a much shorter time.

Besides, the zygote image of a function is asynchronously re-packed before its to-be-helped functions actually meet in cold startups. Re-packing a zygote image does not result in long response latencies of to-be-helped function invocations.


6.3 Forking a Zygote Container

The rest undertaking is to safely and efficiently share zygote containers for other functions. To provide higher availability for multiple to-be-helped functions getting zygote containers, we fork the zygote container to be helper containers, rather than directly specializing it. The zygote container remains there for other to-be-helped functions. The forked containers also ensure software security by the anonymous mounting and privilege domain as zygote containers do.

When a zygote container is forked from function \( f_A \) to be \( f_B \)'s helper container, the code of \( f_B \) is copied into the forked one. We implement two plugins, Zygote fork and Code copy, in the inter-function scheduler. The Zygote fork plugin forks a container asynchronously, un-mounts the package directories of functions other than \( f_B \), and transfers the control access to \( f_B \)'s corresponding privilege domain. The Code copy plugin copies the code of \( f_B \) to the helper container.

Figure 9(a) shows the steps of \( f_B \) forking a zygote container of function \( f_A \). In Step 1, a zygote container of \( f_A \) is forked through the Zygote fork plugin. Then, the Code copy plugin copies the code of \( f_B \) into the forked zygote (Step 2). Lastly, the forked container joins the helper container pool of \( f_B \) (Step 3). It also provides process-level isolation for queries, as shown in Figure 9(b).

7 Sharing-aware Function Balancing

In existing serverless computing clusters, hash-based methods or resource usage-based methods are often used to route user queries [13, 30, 35, 37, 38, 42, 43]. It is possible that the functions on a node do not share many packages. In this case, the host node needs to create many private directories with many packages, resulting in poor resource efficiency. To address such a problem, a straightforward solution is checking the package similarities of all the active functions, and assigning the functions that share more packages to the same node. However, it is not always a good solution, as the functions sharing many packages may not have idle containers.

To resolve the problems above, we propose a function balancing strategy based on the statistics of zygote containers and the available resources \( U = (U_{CPU}, U_{I/O}, U_{net}, ...) \) on every node. The function balancer is implemented on the head node of the cluster, to obtain the statistics from all the nodes. For a function \( f_B \) that requires package \( pkg_a \) and \( pkg_b \), if it fails to find a zygote container during its invocation on a node, its future invocations should be redirected to another node with potential zygote images.

To this end, Pagurus runs the sharing-aware function balancer on the head node based on the resource usage \( U \), and the similarity between the redirected \( f_A \) and functions with idle containers on node \( n \). Let \( N = \{ n \mid max(U_n) \leq T_{res} \} \) represent the set of nodes where the resource utilization is under the threshold \( T_{res} \) (80% by default). The head node will select a new node with the most zygote containers from \( N \) and inform the API gateway accordingly. After that, the queries of \( f_B \) will be routed to this new node.

8 Evaluation of Pagurus

In this section, we evaluate Pagurus in reducing the cold startups and end-to-end latencies when a function does not have warm containers. Then, we evaluate Pagurus by a large-scale evaluation with Azure trace. After that, we show the integration with other techniques and overhead.

8.1 Experimental Setup

We use 10 best-practice applications with the most GitHub stars from Amazon AWS samples as the benchmarks [6]. We use these applications for revealing the performance of Pagurus for real applications. Experiments with small scale benchmarks in serverless benchmark suites, e.g., FaaS-Profiler [49] and ServerlessBench [61] show similar results. We run the benchmarks on a 6-node cluster. A node generates function invocations, and the other 5 nodes serve invocations. Table 1 shows the configurations of each node.

Pagurus does not rely on the function invocation arrival distribution. In Section 8.2-8.3, we send queries to each application following a Poisson distribution by randomly sampling \( \lambda \) between 0 and 5 queries per second. We co-locate all the benchmarks, and run 20 tests with different samples to avoid randomness. More experiments are done with the Pareto distribution-based invocation pattern of the Azure serverless trace in Section 8.4.

We compare Pagurus, prewarm-disabled OpenWhisk, prewarm-enabled OpenWhisk (OpenWhisk-Prewarm), and SOCK [46]. SOCK also prewarms containers by dynamically updating packages in the prewarmed containers to alleviate cold startups. When a function obtains a prewarmed
container, SOCK and OpenWhisk-Prewarm copy the missing packages into the prewarmed container for its invocation.

### 8.2 Alleviating Container Cold Startups

Figure 10 shows the percentages of the cold startups not eliminated by Pagurus, SOCK, and OpenWhisk-Prewarm, compared with prewarm disabled OpenWhisk. On average, Pagurus alleviate 83.1% of the cold startups, while OpenWhisk-Prewarm and SOCK alleviate 68.9% and 64.4% of that. Meanwhile, as Pagurus does not need to prewarm containers, there is no extra memory overhead introduced by the prewarm container pool with Pagurus.

As observed, SOCK and OpenWhisk-Prewarm only reduce a small percentage of cold startups for many functions (e.g., functions of eco and cart). This is because the functions tend to contend for the limited prewarmed containers. On the contrary, Pagurus alleviates the cold startups by forking other functions’ zygote containers, without trapping in the same dilemmas. We can also find that Pagurus alleviates slightly fewer container cold startups for several functions, compared with SOCK and OpenWhisk-Prewarm. This is because these functions have low cold startup frequency by default, and SF-WRS policy does not tend to re-pack them into zygotes for achieving higher system-level cold startup alleviation. The percentage looks large when the original cold startup frequency is low, even if a small number of cold container startup is not eliminated.

In our experiment, 27.8% of the warm containers are turned into zygote containers, then are forked by other functions. When a function does not have a warm container for its queries, 60.5% of the obtained containers are forked.

### 8.3 Reducing Startup and E2E Latency

Figure 11 shows the latencies of starting a container from a prewarmed one (OpenWhisk-Prewarm and SOCK), and forking a zygote container (Pagurus). As observed, all the benchmarks have the shortest startup latencies with Pagurus. If a function invocation is hosted by a helper container with Pagurus, the packages are ready beforehand, and only the user-specific code initialization is needed. Pagurus is able to fork a zygote container in 11ms, and completes the code initialization in 5ms.

With OpenWhisk-Prewarm, starting from prewarmed containers takes longer than directly cold startup a container from the image (e.g., functions in ddns, pod, and rep). SOCK reduces the latency of the prewarm startup leveraging the packages cached with higher benefit-to-cost.

Figure 12 shows the average end-to-end latency of each function normalized to its latency with prewarm-disabled
8.4 Large-scale Evaluation with Azure Trace

In this subsection, we evaluate Pagurus by replaying the Azure serverless trace [50] on a 31-node cluster. The software and hardware configuration of each node is the same as Table 1. We use all the 40,000 functions from the day07 trace [12], generate function invocations, and randomly route the invocations to the 30 nodes.

The Package similarity in Pagurus is used to shrink the searching space for identifying to-be-helped candidates and reducing the re-packing overhead. However, the Azure trace does not provide package information for the functions, but only the function duration and invocation arrival time. Lacking the package information, it is impossible to evaluate the similarity-filtered WRS selection policy in Pagurus, nor OpenWhisk-Prewarm or SOCK. With no package information and similarity-filtered re-packing for Azure trace, Pagurus identifies to-be-helped candidates based on the basic WRS policy. We therefore only compare similarity-disabled Pagurus, with the prewarm-disabled OpenWhisk for the large-scale evaluation, to show the effectiveness of alleviating cold startups by simply replacing idle containers with zygotes.

By mounting packages beforehand with privilege control, zygote containers can better reduce the startup latency, thus the end-to-end latency.

8.4.1 Alleviating Cold Startup

We report two user experience-related metrics in this experiment. First, how many cold startups are alleviated by Pagurus? Second, how many functions seldom experience cold startups (e.g., one cold startup) in one day with Pagurus?

Figure 13(a) shows the total number of cold startups with Pagurus and prewarm-disabled OpenWhisk (denoted by “OpenWhisk” for short in this subsection). In the figure, the functions are sorted in the descending order of their invocation frequencies. The smaller the function ID, the more frequent the function is invoked. As shown in the figure, Pagurus reduces the number of cold startups by 84.6%. We can also find that OpenWhisk results in the frequent cold startup for the functions of middle-popularity. It is because the warm containers of these middle-popularity functions tend to be recycled due to the relatively low invocation frequencies. Pagurus efficiently alleviates the cold startups for the middle-popularity functions through zygote containers.

Figure 13(b) shows the cumulative distribution of the functions with different container cold startup frequencies. As observed, 73.4% and 52.1% of all functions experience cold startup less than once in a day with Pagurus and OpenWhisk, respectively. Meanwhile, 90.1% of the functions experience cold startups less than 5 times daily with Pagurus.

In the figure, sudden jumps happen around 24 and 48 cold startups (e.g., one cold startup) in one day with Pagurus? Experience cold startups less than 5 times daily with Pagurus and OpenWhisk, respectively. Meanwhile, 90.1% of the functions experience cold startups less than 5 times daily with Pagurus.

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with ID smaller than 15,000) have similar 95%-ile latency with OpenWhisk and Pagurus. This is because the slowest 95%-ile invocations of these functions still experience warm startup, as these functions are frequently invoked. For the middle-popularity and low-popularity functions, their 95%-ile latencies are the latency of the function invocation that suffers from the cold container startup with OpenWhisk.

8.4.3 Impacts of Hyperparameters

In this experiment, we evaluate the impact of $T_{\text{default}}$ (the value is set as 60s by default), and the number of to-be-helped functions $K$, on Pagurus. Figure 15 shows the percentages of cold startups alleviated by Pagurus with different $T_{\text{default}}$ and different $K$. As observed, the performance of Pagurus is stable when $T_{\text{default}}$ varies. The performance of Pagurus is not sensitive to $T_{\text{default}}$.

We also find the number of to-be-helped functions, $K$, gradually converges to 8. Moreover, the appropriate value of $K$ is not affected by $T_{\text{default}}$. For Azure workloads, Pagurus should generate a zygote for 8 to-be-helped functions on average. It is consistent with the calculated one in Equation 6. We also measure the impact of larger prewarm pool size in OpenWhisk, and find that the improvement becomes marginal but with significant resource waste.

8.5 Integrating with Orthogonal Techniques

The decoupled hierarchy design of Pagurus provides easy-to-use APIs for container orchestrators. Pagurus can be integrated with prior work on speeding up the cold startup.

Table 2: Overheads of the components in Pagurus

<table>
<thead>
<tr>
<th>Sources</th>
<th>Type</th>
<th>Overheads (each node)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CPU overhead</td>
<td>0.66 core (re-packing included)</td>
</tr>
<tr>
<td></td>
<td>Memory overhead</td>
<td>485MB for each zygote image</td>
</tr>
<tr>
<td></td>
<td>Storage overhead</td>
<td>455MB</td>
</tr>
</tbody>
</table>

Pagurus brings shorter end-to-end latency when it is integrated with Checkpoint/Restore [7] (denoted by C/R) and Catalyzer [28], respectively. With C/R, a container is recovered from a checkpoint image. With Catalyzer, more data are already loaded in the image stored in memory. By replaying the evaluation, we find that C/R+Pagurus reduces the cold startup time of the benchmarks by 78.9% on average compared with C/R; Catalyzer+Pagurus reduces the cold startup time by 15.1% on average compared with Catalyzer. Even if no appropriate forked zygote container returns, Pagurus does not slow down the container startup.

8.6 Overheads of Pagurus Components

In Pagurus, packing zygote images, generating zygote containers from the images, and determining the to-be-helped functions for each function introduce runtime overhead.

According to our measurement, each container in Pagurus uses smaller memory on average than OpenWhisk. The reduction originates from the design of the zygote container. Although packages are pre-installed in zygote containers, they are imported into memory only when a zygote container is forked. On the contrary, warm containers (private containers) always keep the packages in memory for low latency. The reduction of memory usage is not affected by the number of to-be-helped functions.

Table 2 shows the CPU, memory, and storage overhead caused by the intra-container managers and the inter-function schedulers when replaying the Azure trace. As reported, less than one core is required to run all the intra-container managers and the inter-function scheduler on a node. If fewer functions are executed on a node, the overhead will be smaller.

9 Conclusion

Pagurus alleviates cold startups with inter-function container sharing rather than popular prewarm-based methods. It comprises an intra-function manager for idle container identification and management, an inter-function scheduler for safe container scheduling, and a sharing-aware function balancer for resource-aware workload balancing. Our experimental results based on both real system benchmarks and Azure trace show that Pagurus significantly alleviates the cold container startup. The cold startup latency is reduced from hundreds of milliseconds to 16ms if Pagurus alleviates it.
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A Artifact Appendix

A.1 Abstract

Our artifact includes the prototype implementation of Zygote-based mechanism in Pagurus, 10 masked applications (including 38 functions) benchmarks, and mapped functions from Azure Trace. The artifact provides experiment workflow scripts to perform the measurement.

A.2 Artifact Check-list (Meta-information)

- **Run-time Environment**: Ubuntu 18.04, Docker 20.10.6, CouchDB 3.2.2, and Python are required.
- **Data set**: The artifact uses 10 masked application benchmarks from AWS samples and Azure traces.
- **Execution workflows**: For reproducing our paper’s results, we provide the corresponding scripts for each evaluation section (from Section 8.2 to Section 8.4) to send queries, collect the execution metrics, and draw the comparison plots.
- **Time needed to complete**: see the instruction of each Exp.
- **Publicly available**: https://github.com/lzjzx1122/Pagurus
- **Code Licenses**: Apache-2.0 license

A.3 Hardware and Software Dependencies

- **Hardware**: The hardware is configured by (CPU: Intel Xeon(Ice Lake) Platinum 8369B @3.5GHz, Cores: 8, DRAM: 16GB, Disk: 200GB SSD with 4200 IOPS.)
- **Software environment**: Operating system: Linux with kernel 4.15.0, Docker: 20.10.6, Container runtime: Python-3.6.9, Linux with kernel 4.15.7, Nginx version: nginx/1.10.3, Database: Couchdb with version 3.2.2, runc version: {1.0.0–rc93}, containerd version: {1.4.4}, and Pagurus. Detailed software dependencies are all listed and scripted in the artifact.

A.4 How to Access and Install

GitHub link: https://github.com/lzjzx1122/Pagurus. Clone the GitHub repository and then run the quick setup script to deploy Pagurus.

A.5 Experiment and Expected Results

A.5.1 AWS applications (Section 8.2 and 8.3)

Under the path Pagurus/aws/trace, there are 18 different sampling test results for AWS applications, and the expected test results for each sampling are stored in the directory aws/expected_result. You can directly run aws/plot.py to generate the plots, or replay the trace using a testing script to run the AWS experiment:

$ python3 aws/run_experiments.py 1

**Experiment customization**: The above script performs the 1st sampling test with Openwhisk, Pagurus, OpenWhisk-Prewarm, and SOCK. Other sampling tests can also be performed by changing "1" to other test numbers. To fully reproduce our result, it additionally takes at least 160-hours (20 tests with different sampling parameters) to generate the execution logs for 4 platforms. To ensure that the zygote repackaging mechanism and prewarm works efficiently, the running time should be at least 2-hours for both 4 platforms (8 hours for each test number).

After running the sampling tests under four platforms, the script will generate the results under aws/result. Run the following script to generate three .csv files:

$ python3 aws/summary_from_results.py

- **cold_start.csv** shows the remained cold startups of Openwhisk, SOCK, and Pagurus. Compared with prewarm-disabled OpenWhisk (Figure 11).
- **startup_time.csv** shows latencies of starting up containers in prewarm-disabled OpenWhisk, OpenWhisk and SOCK, respectively. It also contains latencies of forking zygote containers in Pagurus (Figure 12).
e2e_latency.csv shows e2e latencies of benchmarks in Pagurus, SOCK, OpenWhisk, and prewarm-disabled OpenWhisk, respectively. (Figure 13).

Then run the following script to generate the plots:

```bash
$ python3 aws/plot_from_results.py
```

### A.5.2 Azure Trace mapping (Section 8.4)

In the Azure trace experiment (Day07), invoke more than 40,000 functions will take 24 hours and more than 800 vCPUs by default. To reduce the computation resources needed, we randomly select about 4,000 functions to generate several small-scale Azure traces under the path Pagurus/azure/trace. The functions in each small-scale trace are all different from each other. A larger trace with more functions can be replayed if only more computation resources or nodes are provided.

Considering that the experiment will take about 24 hours, we already pre-run each small-scale Azure trace and save their execution results. You can directly run azure/plot.py to generate the plots, or replay the trace using the following script:

```bash
$ python3 azure/run_experiments.py 1
```

**Experiment customization:** Each small-scale Azure trace can be replayed by changing "1" to other trace numbers. The script will replay the trace in Openwhisk and Pagurus, respectively, and then generate results under azure/result.

Run the following script to generate two .csv files:

```bash
$ python3 azure/summary_from_results.py
```

- `cold_start.csv` shows the remained cold startups of OpenWhisk and Pagurus, respectively (Figure 14).
- `e2e_latency.csv` shows end-to-end 95%-ile latencies of benchmarks in Openwhisk and Pagurus, respectively (Figure 15).

Then run the following script to generate the plots:

```bash
$ python3 azure/plot_from_results.py
```