The Serverless Scheduling Problem and NOAH

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Abstract

The serverless scheduling problem poses a new challenge to Cloud service platform providers because it is rather a job scheduling problem than a traditional resource allocation or request load balancing problem. Traditionally, elastic cloud applications use managed virtual resource allocation and employ request load balancers to orchestrate the deployment. With serverless, the provider needs to solve both the load balancing and the allocation.

This work reviews the current Apache OpenWhisk serverless event load balancing and a noncooperative game-theoretic load balancing approach for response time minimization in distributed systems. It is shown by simulation that neither performs well under high system utilization which inspired a noncooperative online allocation heuristic that allows tuning the trade-off between for response time and resource cost of each serverless function.

1 Introduction

Serverless is an emerging Cloud Service model that provisions event processing on demand. In place of traditional VM rental, the providers service dispatching and execution of events registered with user-provided functions. This radically changes the deployment model from resource allocation to on-demand execution. Serverless only charges for the number of dispatched events and the resource-time covered by the event execution. Amazon[1] has made its serverless platform generally available in Apr’15 and Google[6], IBM[9] and Microsoft[2] have released similar offerings within a year. As data center inefficiency had previously been criticised for comatose and idling servers [12, 11], the shift from a rental model to pay per use would allow providers to increase server utilization and customers to fit the cost of a service deployment closer to its actual demand.

This flexibility comes with an overhead to the application execution. Firstly, serverless applies the stateless worker model, which requires each function to externalize all context that needs to persist between two consecutive invocations as the context is not guaranteed to remain in use after event completion. Secondly, part of the billed execution time is spent on code initialization and data access at the start of processing, which is small compared to VMs, but can still be significant in comparison to the total runtime of a function (100ms-5min). Thirdly, the setup time contributes a substantial overhead to the response time (up to 1-2s if it scales to an additional container). The service model devolves responsibility to solve this scheduling challenge to the provider. Traditionally, cloud-native application orchestration would require development of application-specific load balancers and engineering to find a suitable trade-off between response time guarantees, data locality and proactive resource allocation. The serverless provider is entrusted with scaling and would ideally adapt to the demand.

Serverless is supposed to ease the orchestration and operation automation challenge as it finds the application decomposed into a functional (i.e. event-, or data-driven) set of non-blocking stateless executions that are structurally similar tasks which can be scaled independently. The provider challenge is to find a demand scheduling that fits all applications’ performance requirements. The decomposition into stateless, short-lived executions that perceive increased (context) data access latency and initialization time calls for locality-aware scheduling to maximize cache hit rates. Affinity scheduling is common in high throughput computing. It can be found in VM placement policies for network colocation in NFV Clouds and at task level in microbatching platforms. But locality poses a challenge when providers aim for high resource utilization whereas customers strive for minimum response times. The balance between maximizing resource utilization and minimizing response time is a multi-objective problem. This work reviews state-of-the-art demand scheduling approaches and introduces a non-
cooperative online allocation heuristic (NOAH) as a parameterizable approach to configure the serverless scaling behaviour.

Section 3 classifies the serverless scheduling problem and describes the optimization problem, followed by a review of the current OpenWhisk scheduling heuristic and a game-theoretic approach to response time minimization. Section 4 introduces the new allocation heuristic NOAH to solve the serverless scheduling problem. Section 5 describes the simulation used to evaluate the presented approaches. Section 2 discusses related work and section 6 concludes the findings.

2 Related Work

Amazon Lambda has recently introduced a limit to concurrent executions per functions, which would contain the number of started instances but neither considers response time nor scaling behaviour. Microsoft Azure, IBM Cloud Functions and Google Cloud Functions provide a quota of concurrent executions per user or namespace but not for individual functions.

McGrath and Brenner [15] design a classful system that lets instances poll for work. NOAH makes no specific assumptions about the messaging and can be implemented with polling. CaaS-based serverless platforms such as Kubeless [13], Fission [5], OpenFaaS [4] adhere to container resource allocation, scale by resource monitoring and use hash-based reverse proxy load balancing as best practices of cloud-native platforms.

Multiple works have inspired NOAH, i.e. smoothing of online virtual resource allocation to save reallocation cost [10], game-theoretic optimally controlled load balancing [7,8], multi-objective game-theoretic job scheduling [3], distributed, classful optimal control demand reallocation [18] and integration of queuing theory with scheduling [17].

3 The Serverless Scheduling Problem

In serverless platforms, the scheduling subsystem dispatches events from their occurrence (at a gateway or within the platform) to the designated resource that performs the function execution. The demand follows an open arrival process, is distributed across the platform and has multiple users per function. All tasks have a similar structure and are, in principle, processes with moldable execution time in an OS-sharing model. The problem can be classified as distributed job scheduling applying the taxonomy by Lopez and Menascé [14], which positions it quite uniquely among popular research.

Traditional Cloud VM scaling is sluggish and separates the allocation control loop from request load balancing. On the contrary, emerging serverless platforms decide upon every event whether they can reuse an available instance (warm container) or simply launch a new one (cold container). As a result, bursts of events cause the launch of many parallel instances as the heuristic provides no control over the scaling behaviour and is only constrained by resource quota.

When an event is dispatched to a site, the container to host the instance may need initialization (cold start), it may miss only the function code (pre-warmed) or have already run the function (warm). The first cold start of its type may require the host to load custom function code (and library dependencies), which may require network transfer or disk access. Other techniques may provide fast copies of an instance (e.g. forking) or its container context. The total setup time of an instance may vary significantly w.r.t. the function execution time under dynamic workloads.

Execution time starts with the handover of the event message to the function instance. Depending on its content, named data are accessed from the platform’s data store, e.g. remote or host-local replica, residing on disk or in memory. Although the function runtime is typically memory-heavy compared to the data transfers in question, data access and concurrent modification can cause access latency that varies based on the location. Content population of cold caches incurs additional execution overhead.

The serverless provider bears the resource cost of the setup time and the customer pays for access latency, so both the platform and the function share a common contractual objective to reduce the makespan of executions while keeping the resource use to a required minimum. Each function competes against others for colocation to reduce access latencies.

3.1 Noncooperative Load Balancing

Grosu and Chronopoulos [7] have designed a noncooperative game approach to balance multi-user flow allocations for optimal response time in a distributed server environment. Each user (e.g. distributed controller) collects information on the service time and allocations at every host to calculate an optimal split of its own perceived arrival rate in response to the other players’ allocations.

The noncooperative approach yields Nash Bargaining Solutions for a set of heterogenous M/M/1-type servers (a cooperative version is described in [8] that creates Pareto-optimal solutions). It is a queuing-analytic, distributed, multi-user solution but remains classless. To apply it to the OpenWhisk controller architecture, each function is made a player in the noncooperative game to compete in the allocation for minimum response time.

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3.2 OpenWhisk Heuristic

The Apache OpenWhisk serverless platform implements event scheduling in a distributed controller architecture that shares common host state information, including the number of concurrently active invocations on each host. A function name’s hash $h$ is used to identify a starting point in the pool of sites $I$. If the number of active events at the target exceeds a threshold ($\alpha$), the controller tries the next host in pseudo-random order using pairwise coprime generators as the following pseudo-code illustrates.

```plaintext
select_host (h=hash, I=[]) {
  lvl=α=16, G=[]
  for (i=0,...,|I|) {// create generators
    if (\forall g ∈ G, gcd(i,g) == 1)
      G=G ∪ i
  }
  g=G[h mod |G|] // select generator
  while (lvl ≤ 3α) {//try up to 3 times busy threshold
    for (k=0,...,|I|) {
      x = I[h+k*g (mod |I|)]
      if (events at(x) < lvl)
        return x
    }
    lvl += α
  }
  return random site
}
```

If no host is below the busy level, the threshold is increased and the pool is progressed again. Eventually, a random site would be picked. This compelling first-fit, hash-based load balancing heuristic solves statistically the locality, distribution and overflow of function allocations across hosts, as it ensures that all resource slots are in use before the system starts to oversubscribe its resources. However, the host progression does not consider the instance setup time when scaling out a function type to a host that hasn’t previously been employed. For some events, it may be beneficial to enqueue rather than scale out.

4 NOAH

The two approaches of hash-based and queue-analytical minimum-response time balancing presented in section 3 face high churn rates of instances when demand increases: noncooperative load balancing tries to statistically distribute events across hosts, so different function types evict each other’s instances upon changes in allocation, resulting in an increased occurrence of instance setup times. OpenWhisk uses pseudo-random progression to find a free spot where it also would evict an idling container.

This has inspired the design of a noncooperative online allocation heuristic (NOAH), which uses both an analytic allocation and a minimum completion time heuristic to design a configurable solution to the serverless scheduling problem. The heuristic estimates for each function type the required number of instances to keep expected request waiting time below a chosen threshold. The resulting allocations are then placed with sites, but no actual instances are spawned by an allocation. Instead, each site manages the instance pool to handle arriving requests, deciding autonomously whether to enqueue a request or spawn a new instance. Event dispatching tries to schedule events to idling instances for minimum completion time and otherwise balances requests according to the allocations of the function.

**Allocation.** Each function uses an analytical model to contain the expected average waiting time that an event would face in the system. Estimating the arrival rate $\hat{\lambda}_k$ for a function type $k$ and the current average service time of function executions $\mu_k$, the number of required (warm) instances $c_k$ can be chosen, such that the expected waiting time of queuing remains below threshold $\alpha$.

For example, assuming an M/M/c model, i.e. a Poisson arrival process and exponentially distributed service times, the allocation should at least satisfy the stability condition: $\frac{k}{c_k \mu_k} < 1 \implies c > \frac{\hat{\lambda}_k}{\frac{\mu_k}{c_k}}$. To contain the probability that an arriving event finds all instances active, the Erlang C formula can be used to find $c_k$ such that $c(k, \frac{\hat{\lambda}_k}{\frac{\mu_k}{c_k}}) < \alpha$.

Having identified the required number of allocations $c_k$ for class $k$ events, the system needs to place allocations $c'_k: \Sigma_i c'_i = c_k$ to sites $I$ with a maximum number of allocations per site $c'$ such that $\Sigma_k c'_i <= c'$.

**Dispatching.** Following the OpenWhisk example of distributed host state information, the controller can obtain if any host has an idling instance for the given function type to schedule the event. If there is no idling instance, the event is dispatched to the host with the lowest ratio of active instances over allocations.

**Execution.** Each site measures separate setup and execution time of a function type starting from shared experience values. If an arriving event finds an empty queue and an idling instance, it is immediately scheduled. If the maximum number of actively processing events is reached, events are queued. But, if the host can chose between queuing the event or starting a new container, it checks whether the estimated queue waiting time (given the estimated completion of concurrent events) would exceed the estimated setup time, in which case it would opt to launch a new container.

4.1 Allocation Heuristic

While the allocation control loop of every event class contains the average waiting time, the concerted allo-
cation management needs to select hosts when a class wants to scale-out or scale-in.

The allocation control for each event class constitutes a player in a noncooperative game for the location of the allocations. Depending on the effect of access latency on the response time of events, classes benefit differently from instance colocation, e.g. when synchronizing shared context. When it scales out, allocation management tries to colocate allocations. This heuristic reduces the setup time overhead to transfer dependencies and populate caches to occasions when it is inevitable. When a function scales in, the host with the least allocations is reduced. This keeps the bulk of events colocated and decreases both expected waiting time of an arriving event and may be used to reduce data synchronization latency. Classes with a shared data context have a stronger incentive to aggregate allocations, so coalitions to swap allocations (tit-for-tat) between classes are possible and defragmentation strategies are possible, but currently not implemented.

5 Simulation

To evaluate the approach, a serverless simulation tool was developed using SimPy (v3.0.1) to mimic the Apache OpenWhisk architecture which dispatches events via a controller to invokers that manage local container pools with a maximum size each.

The simulation execution uses processor sharing and memory caching. Executions can be purely processing or read/write accesses to named data items which requires replication from the least loaded copy to local memory. Transfer incurs execution at both ends and honors solid state disk, memory and network speed.

Work-conserving scheduling has been verified using several queuing models. Data transfer, access and eviction has been verified with a set of tests that assert precedence. Ultimately, the simulation tool has been verified running designed workloads on both OpenWhisk and the simulation tool. Simulation timing of container setup and function initialization has been directly obtained from OpenWhisk invoker logs.

Noncooperative load balancing is implemented as an alternative controller (noncoop). For NOAH, modifications to both the controller as well as the invoker simulation were necessary.

5.1 Evaluation

The simulated system has ten homogenous hosts with 16 cores each, 711MB/s disk speed (SSD), 1,135MB/s network speed (10GBe) and 12.8GB/s memory speed with sufficient capacities each. The evaluation scenario simulates ten function types, each with an independent Poisson arrival process. To measure the scaling behaviour, a series of simulations has been run with different slopes and load maxima \( \Lambda \). The arrival rate of function types equally increases as depicted in figure 1 for different simulations. In each simulation, the interarrival rate to each function scales within 20 s from zero to the maximum arrival rate \( \Lambda \) and then stops. The simulation is run until all messages have been processed. Each function is single-threaded and has an ideal execution time of 200 ms - unless processor sharing slows execution, thus the upper bound system arrival rate is 10hosts * 16cores * 5 \( \frac{\text{msg}}{\text{sec}} \) = 800. Simulations are run with 10 functions and \( \Lambda = \{1, 2, \ldots, 80\} \frac{\text{msg}}{\text{sec}} \) each. Due to container setup (500 ms), message transfer and suboptimal balance, the approaches start struggling at about 50-60 messages per second per function.

The remainder discusses the performance of NOAH with waiting time thresholds \( \alpha \) set to 10 ms, 1 ms, 100 \( \mu \)s and 10 \( \mu \)s, against default OpenWhisk ow and noncooperative load balancing noncoop.

**Cold starts.** OpenWhisk invokers manage a configurable maximum of 32 containers. The default busy threshold causes the controller to scale-out at 16 concurrently processing events. Only 16 containers can be active in parallel to avoid processor sharing and context switching. The gap prevents a host from evicting con-
tainers every time a function does not run on its primary host target. The default holding time for an unused container is 5 min unless the container needs to be evicted earlier. The more often controllers use overflow progression, the more eviction occurs and in consequence, the more cold starts occur. Noncooperative load balancing noncoop almost equally balances each function’s load across sites, which likewise evicts idling containers to keep a maximum of 32 instances. With noncoop, flows spread across the whole pool for minimum latency, which causes at least one instance of a function type at every server and a high container churn under high load. NOAH invokers limit the number of concurrent events and the total number of containers separately. The total number of instances (active and inactive) is bound by the number of allocations and the host memory capacity.

Figure 2 shows the total number of containers started in each simulation. At $\Lambda = 50$, the load causes OpenWhisk to resort for some events to random site selection and therefore, eviction. NOAH can maintain stable increase of cold starts proportional to the workload increase.

Hosts covered by request processing counts only those sites that have been employed to process at least one event. Load balancing approaches ow and noncoop always try to utilize the entire pool. OpenWhisk may in rare cases see hosts that would only be used for excess load, which explains why low rates keep 1-2 hosts unused. NOAH’s allocation tuning covers only the required minimum set of hosts and scales out when necessary. NOAH allows unused hosts (e.g. VMs) to be released entirely, reducing resource cost to the required minimum. Tuning $\alpha$ to low expected waiting times requires more hosts whereas an allowance for longer waiting times covers less hosts in total.

Average response time is best when instances can be reused (fig. 5). OpenWhisk maintains the best response times under moderate load, but suffers tragically under high utilization, because it can not contain the container churn. NOAH’s allocation tuning of the waiting time using the Erlang-C formula shows clear increments between tuning for low response times ($\alpha=10\mu s$) to high response times ($\alpha=10\text{ ms}$) antiproportional to the resource coverage.

Container utilization (fig. 4) is the ratio between the time a container actively processes an event (execution time) and the total time that it remains in the system (including setup and idle overhead). Regardless the container timeout (which would add 5 min idle time to the 20 s experiment), only the time from a container’s creation until the last processing of a message is considered here as the total container life time. Overall, NOAH yields higher container utilization. For ow and noncoop, increasing eviction reduces utilization. Under high load, the allowance for a longer queuing delay ($\alpha=10\text{ ms}$) conversely shows lower utilization than stringent requirements ($\alpha=10\mu s$). Notice also, that a ($\alpha=10\text{ ms}$) covers less hosts than ($\alpha=10\mu s$) (cmp. fig. 3), which leads to higher churn of instances as can also be seen in the number of container creations (cmp. fig. 2).

6 Conclusion

For serverless event scheduling, NOAH shows several benefits over the current OpenWhisk controller[16] and the game-theoretic load balancing approach[7]. By virtually allocating demand, NOAH can contain instance churn and remains responsive under high system utilization. Furthermore, it limits execution to required sites which allows scaling of the resource pool and provides means to balance the trade-off between resource cost and response time by tuning for allowed queue waiting times of individual functions.
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