# Serverless in the Wild: Characterizing and Optimizing the Serverless Workload at a Large Cloud Provider

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2022. 05. 31 Presented by Yejin Han yj0225@dankook.ac.kr





### What is Serverless?

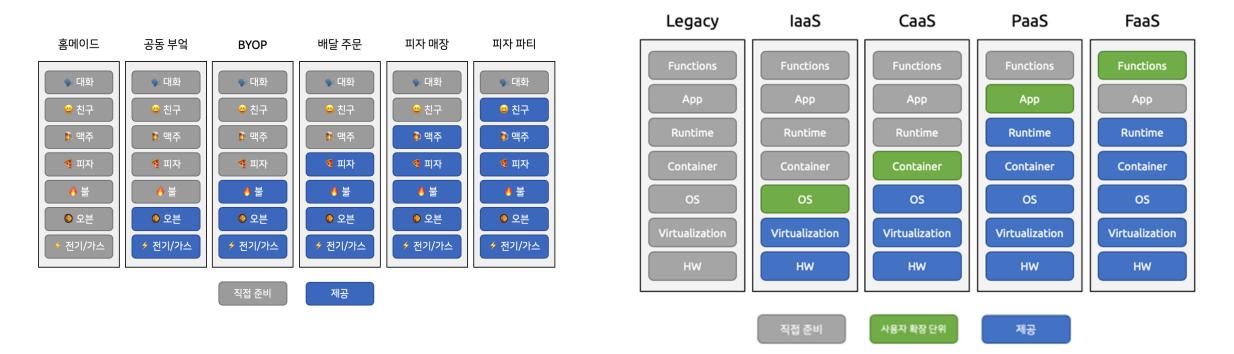
- Very attractive abtraction to users:
  - Pay for only usage
  - No worry about servers
    - Provisioning, reserving, configuring, patching, managing
- Most popular offering: Function-as-a-Service (FaaS)
  - Intuitive, event-based interface for developing cloud-based applications
  - Users upload the code, provider enables a handle for the code to run





### **FaaS**

- FaaS (Function as a Service): users do not provision or configure resources
  - Function: basic unit of deployment
  - Application: consists of multiple functions, unit of resource allocation



(source: https://futurecreator.github.io/2019/03/14/serverless-architecture/)



## Put yourself in provider's shoes...

- Challenges are:
  - You do worry about servers
    - Provisioning, scaling, allocating, securing, isolating
  - Optimize resource usage
  - Provide the illusion of always-available resources at the lowest cost
    - Fast function invocations without cold starts



**Cloud Providers** 

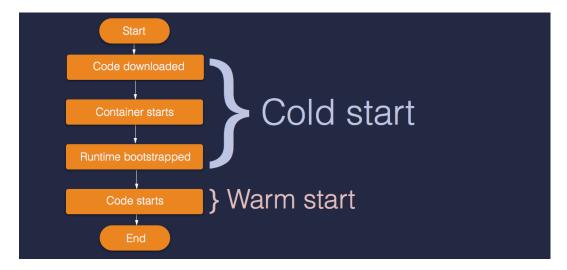




### **Cold Starts**

- Providers want to provide high function performance at the lowest cost
  - Function execution requires the needed code in memory
    - Warm start (from memory) vs cold start (from storage)
  - Keeping all resources in memory is prohibitively expensive
  - Functions have varying resource needs and invocation frequencies

a comprehensive characterization of the FaaS workload is needed!!



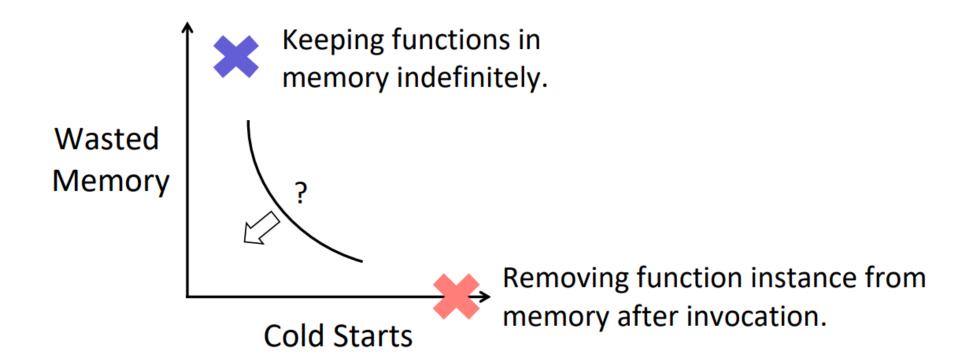
(Source: https://medium.com/ssense-tech/the-trade-offs-with-serverless-functions-71ea860d446d)





## **Problem: Cold Starts and Resource Wastage**

Trade-off between reducing cold starts and the resources they need



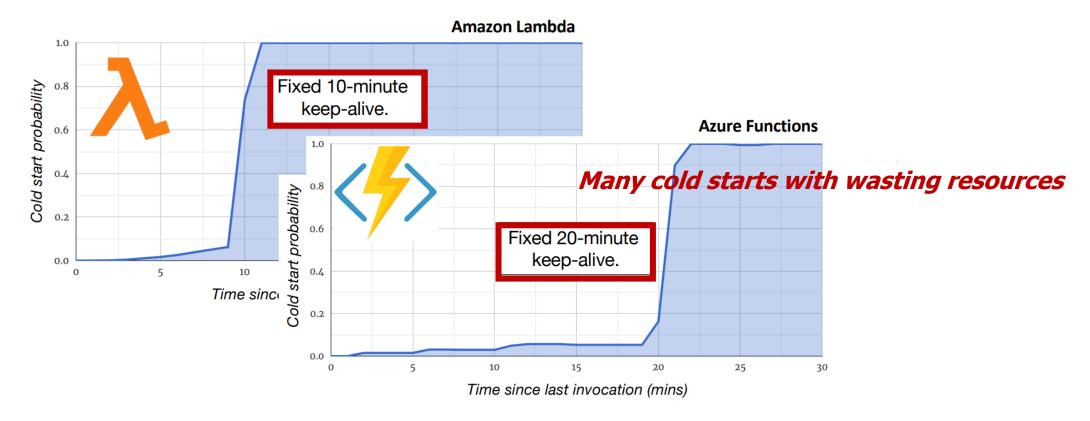
(Source: https://www.usenix.org/system/files/atc20-paper593-slides-shahrad.pdf)





## **Problem: Fixed keep-alive policy**

- Application instances are kept loaded in memory for a fixed time
  - It does not consider the wide variety of application behaviors



(Source: https://www.usenix.org/system/files/atc20-paper593-slides-shahrad.pdf)





- Functions and applications
  - 54% applications only have one function and 95% applications have at most 10 functions

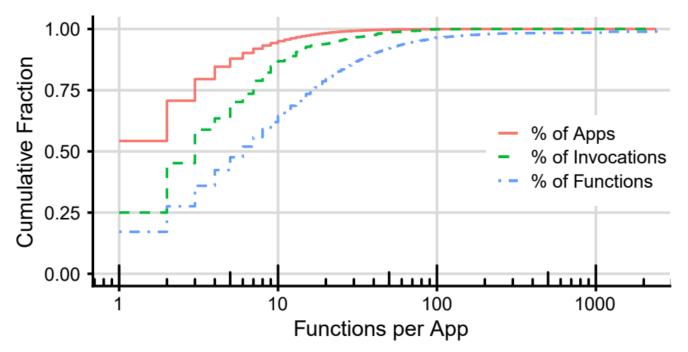


Figure 1: Distribution of the number of functions per app.

The number of functions in an applications is not useful in resource management



#### Triggers and applications

Trigger	%Functions	%Invocations	
HTTP	55.0	35.9	
Queue	15.2	33.5	
Event	2.2	24.7	
Orchestration	6.9	2.3	
Timer	15.6	2.0	
Storage	2.8	0.7	
Others	2.2	1.0	

Figure 2: Functions and invocations per trigger type.

		Trigger	Fraction of	Cum. Frac.
	_	Types	Apps (%)	(%)
		Н	43.27	43.27
Trigger Type	% Apps	T	13.36	56.63
HTTP (H)	64.07	Q	9.47	66.10
Timer (T)	29.15	HT	4.59	70.69
Queue (Q)	23.70	HQ	4.22	74.92
Storage (S)	6.83	E	3.01	77.92
Event (E)	5.79	S	2.80	80.73
Orchestration (O)	3.09	TQ	2.57	83.30
Others (o)	6.28	HTQ	2.48	85.78
		Ho	1.69	87.48
		HS	1.05	88.53
		HO	1.03	89.56

(a) Apps with  $\geq 1$  of each trigger.

(b) Popular trigger combinations.

Figure 3: Trigger types in applications.

For predicting invocations: timers are very predictable, other applications with no timers aren't



- Invocations per application
  - Daily invocations varies by over 8 orders of magnitude
  - Vast majority of functions are invoked very infrequently

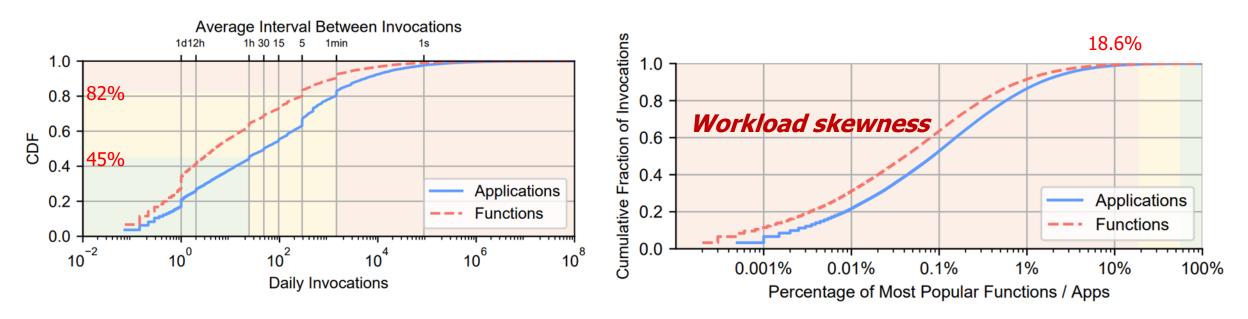


Figure 5: Invocations per application and per function for a representative sample of the dataset.

From IAT (Inter-arrival time) of invocation, we can pre-warming the application





#### Function execution times

- Same sale as the cold start times
- Execution times are short

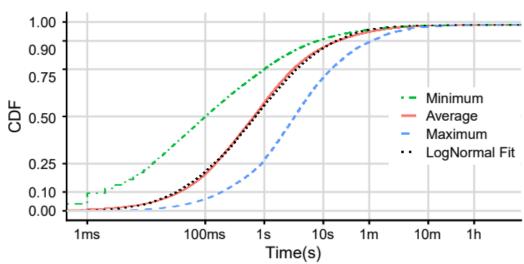


Figure 7: Distribution of function execution times. Min, avg, and max are separate CDFs, and use independent sorting.

#### Optimizing cold starts is important

### Memory Usage

Applications tend to remain memory resident for longer

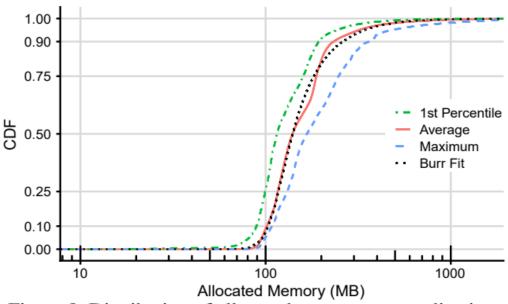


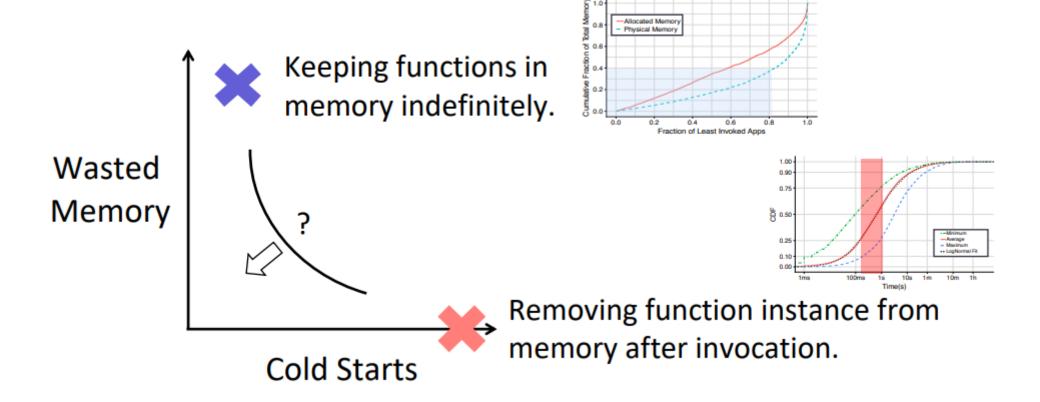
Figure 8: Distribution of allocated memory per application.

Memory is important in keep-alive decision for FaaS



## **Cold Starts and Resource Wastage**

How to manage cold starts in FaaS?



## **Hybrid Histogram Policy**

- The policy of hybrid histogram
  - Pre-warming window / keep-alive window

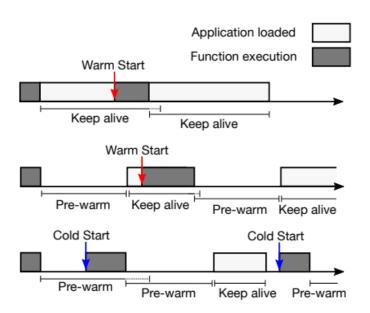


Figure 9: Timelines showing a warm start with keep alives and no pre-warming (top); a warm start following a pre-warm (middle); and two cold starts, before a pre-warm, and after a keep alive (bottom).

\* ARIMA: Autoregressive Integrated Moving Average

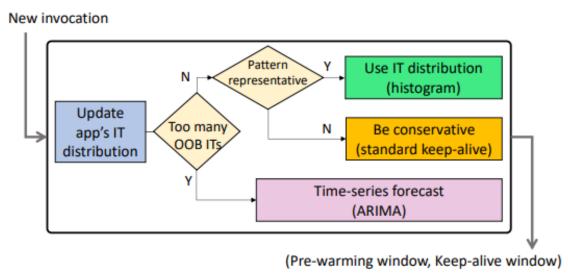


Figure 10: Overview of the hybrid histogram policy.

## **Hybrid Histogram Policy**

- Three main components of the policy
  - A range-limited histogram
  - Standard keep-alive approach
  - Time-series forecast component

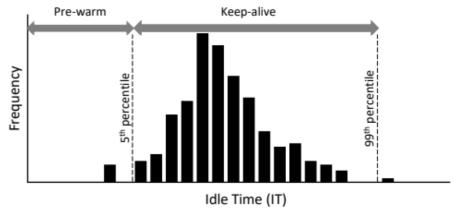


Figure 11: Example application idle time (IT) distribution used to select pre-warming times and keep-alive windows.

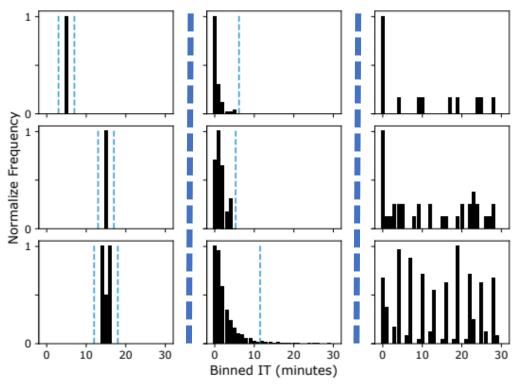


Figure 12: Nine normalized IT distributions from real FaaS workloads over a week.





## **Implementation in Apache OpenWhisk**

### Apache OpenWhisk

- Open-sourced industry-grade (IBM Cloud Functions)
- Functions run in docker containers
- Uses 10-minute fixed keep-alive
- Built a distributed setup with 19 VMs



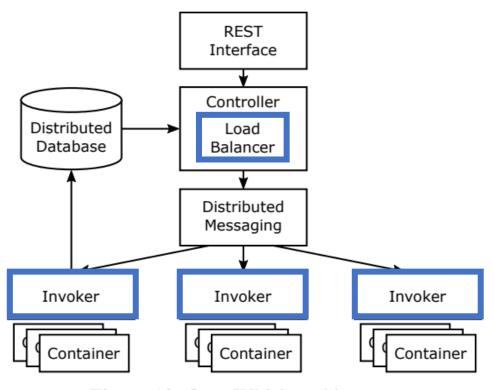


Figure 13: OpenWhisk architecture.



## **Evaluation**

- Experiment Setup
  - Simulation
    - Workload: all function invocations across Azure between July 15<sup>th</sup> and Jylu 20<sup>th</sup>
    - Generates an array of invocation times and infer whether each invocation would be a cold start
  - Real experiments
    - Workload: scaled-down version of the trace
    - 19VM: One VM with 8 cores, 8GB of memory hosts / 18 VM with 2 cores, 4 GB of memory



### **Evaluation: simulation**

#### Fixed keep-alive policy

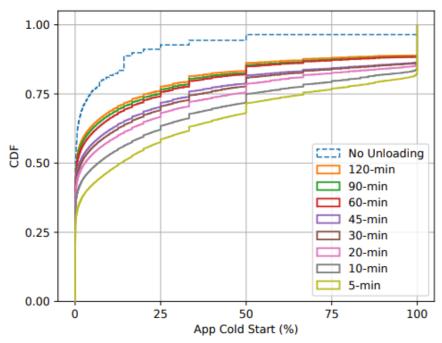


Figure 14: Cold start behavior of the fixed keep-alive policy, as a function of the keep-alive length.

Longer keep-alive reduces cold starts significantly

#### Hybrid policy using a histogram

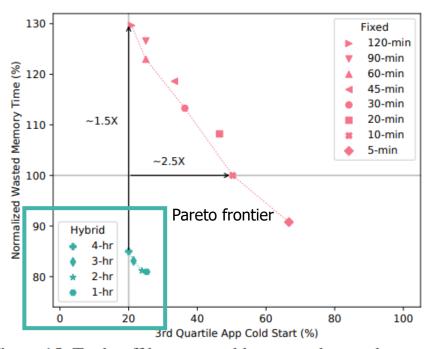


Figure 15: Trade-off between cold starts and wasted memory time for the fixed keep-alive policy and our hybrid policy.

Hybrid policies reduce cold starts significantly with lower memory waste



## **Evaluation: simulation**

Impact of the histogram cutoff percentiles

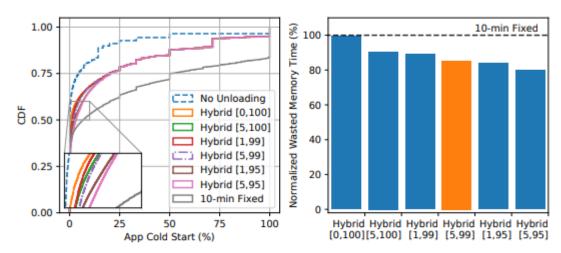


Figure 16: Wasted memory time can be significantly reduced by excluding outliers from the IT distribution.

wasted memory time goes down by 15%, compared to with no cutoff [0,100]

Impact of unloading and pre-warming

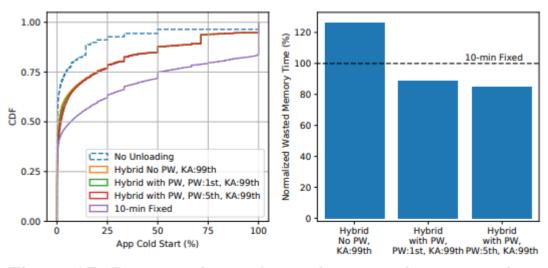


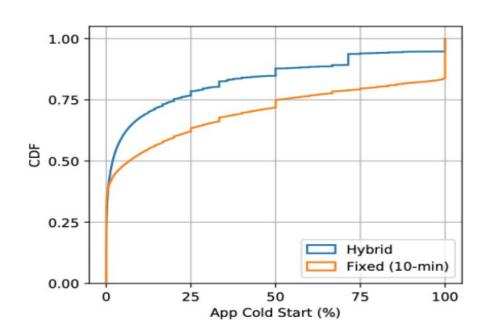
Figure 17: Pre-warming reduces the wasted memory time significantly. The cost is slight increase in cold starts.

PW (Pre-warming) reduce the wasted memory time significantly



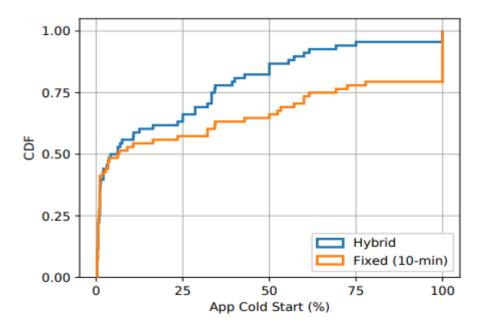
## **Evaluation: real experiment**

#### Simulation results



- Average exec time reduction: 32.5%
- 99th-percentile exec time reduction: 82.4%

#### Experimental results



- Container memory reduction: 15.6%
- Latency overhead: < 1ms (835.7us)</li>



## Conclusion



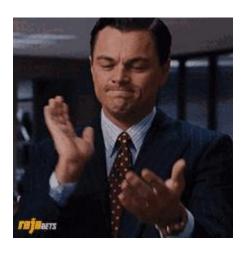
### Microsoft Research

Characterize the users' real FaaS workloads of Azure Functions from provider's perspective

A dynamic policy leveraging small histogram to reduce cold starts at a low resource cost

Azure Functions sanitized traces available:

https://github.com/Azure/AzurePublicDataset/blob/master/AzureFunctionsDataset2019.md



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Thank You!

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