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# DISTRIBUTED FUNCTION CACHE FOR HETEROGENEOUS SERVERLESS CLOUD

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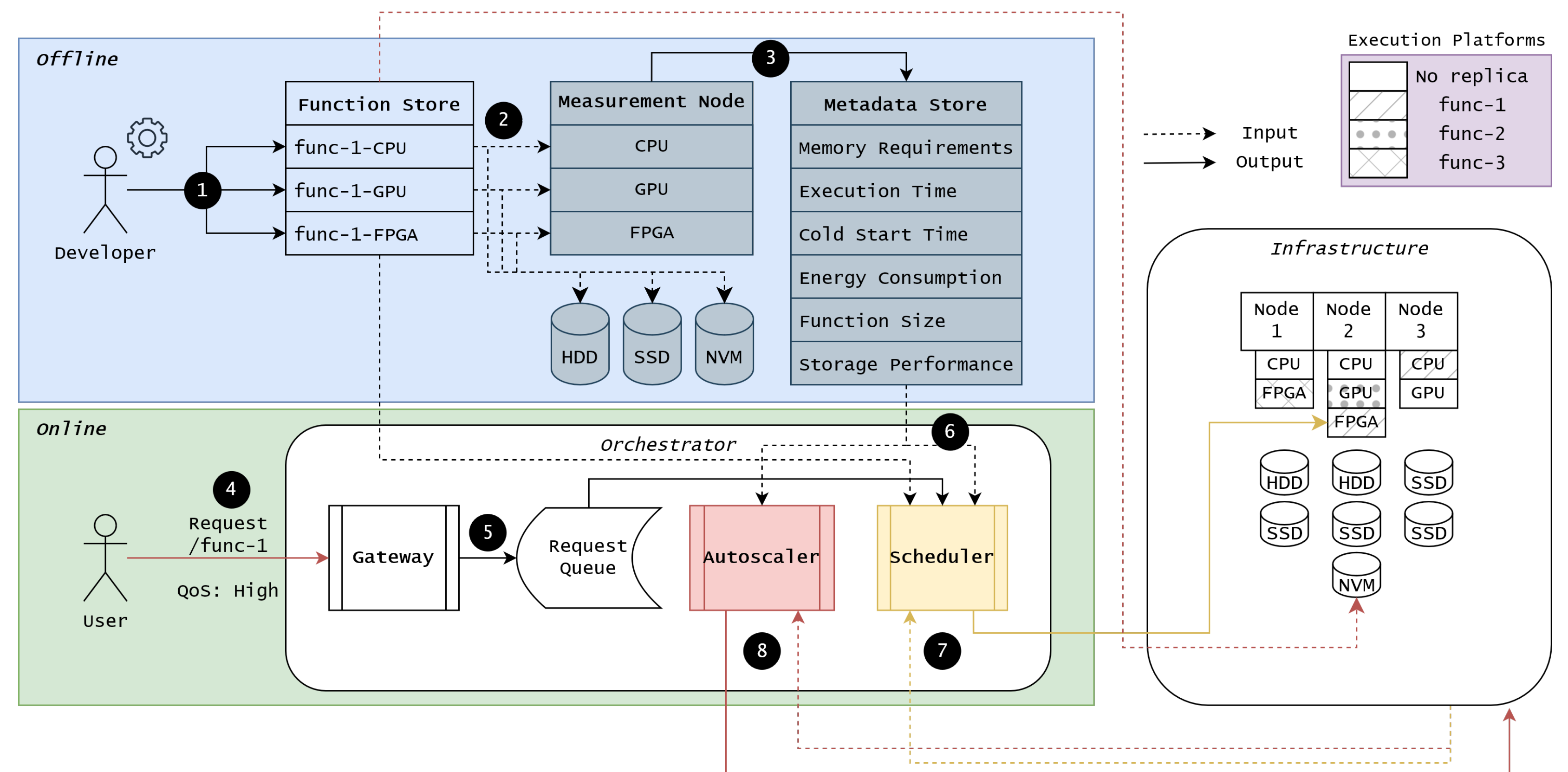
## 1 – Serverless Cloud Challenges [5]

Characteristic	Serverful (IaaS, PaaS)	Serverless (FaaS)
Provisioning	Customer responsibility	Fully <b>managed</b> (i.e. by the provider)
Scaling	Customer responsibility	<b>Auto-scaling</b> built in
Availability	Depends on <b>provisioned</b> resources	Code runs in multiple high availability zones
Fault tolerance	Depends on deployment strategy	Retries of <b>stateless</b> functions
Concurrency	Depends on <b>provisioned</b> resources	Virtually <b>infinite</b>

Tab. 1: Comparison of key characteristics in serverless and serverful service models

- Serverless resources are *not reserved* [6]
  - Increased provider’s responsibility
    - \* Dynamic **allocation** (following load variations) ⑧
    - \* Dynamic **placement** (mapping requests to resources) ⑦
- Functions are *not network-addressable* [1]
  - Communications between functions use **slow storage**
  - Initialization times can **dominate** total function execution time
- Cloud resources are *heterogeneous* [3]
  - Various levels of **performance** and **cost**
- Load is *unpredictable* [7]
  - Stochastic barrier: need for an online solution
- Users have various *QoS requirements* [2]
  - Throughput-centric (batch jobs) vs. lower latency (interactive jobs)

## 2 – Platform Overview and Lifecycle of a Request [4]



**PROBLEM STATEMENT** – How to account for storage costs when deploying short-lived serverless functions in a private cloud, leveraging heterogeneous hardware to optimize for quality of service?

## 3 – Problem Justification

- Function instantiation requires **pulling the function image** (2 to 4 GB) from a remote image repository (Fig. 2)
- Functions on the same node **benefit from local storage** to achieve communications (Fig. 3)
- Short execution times (10 to 100 ms) can be offset by longer or more frequent **cold start delays** (1 to 15 s) (Fig. 2)
- There is a **contention on local storage** between function images and function data (Fig. 3)
- Risk of saturating node function cache with function images (Tab. 2)
- Local image cache starts thrashing, resulting in SLA violations (Tab. 2)

### 3a – Function Cache

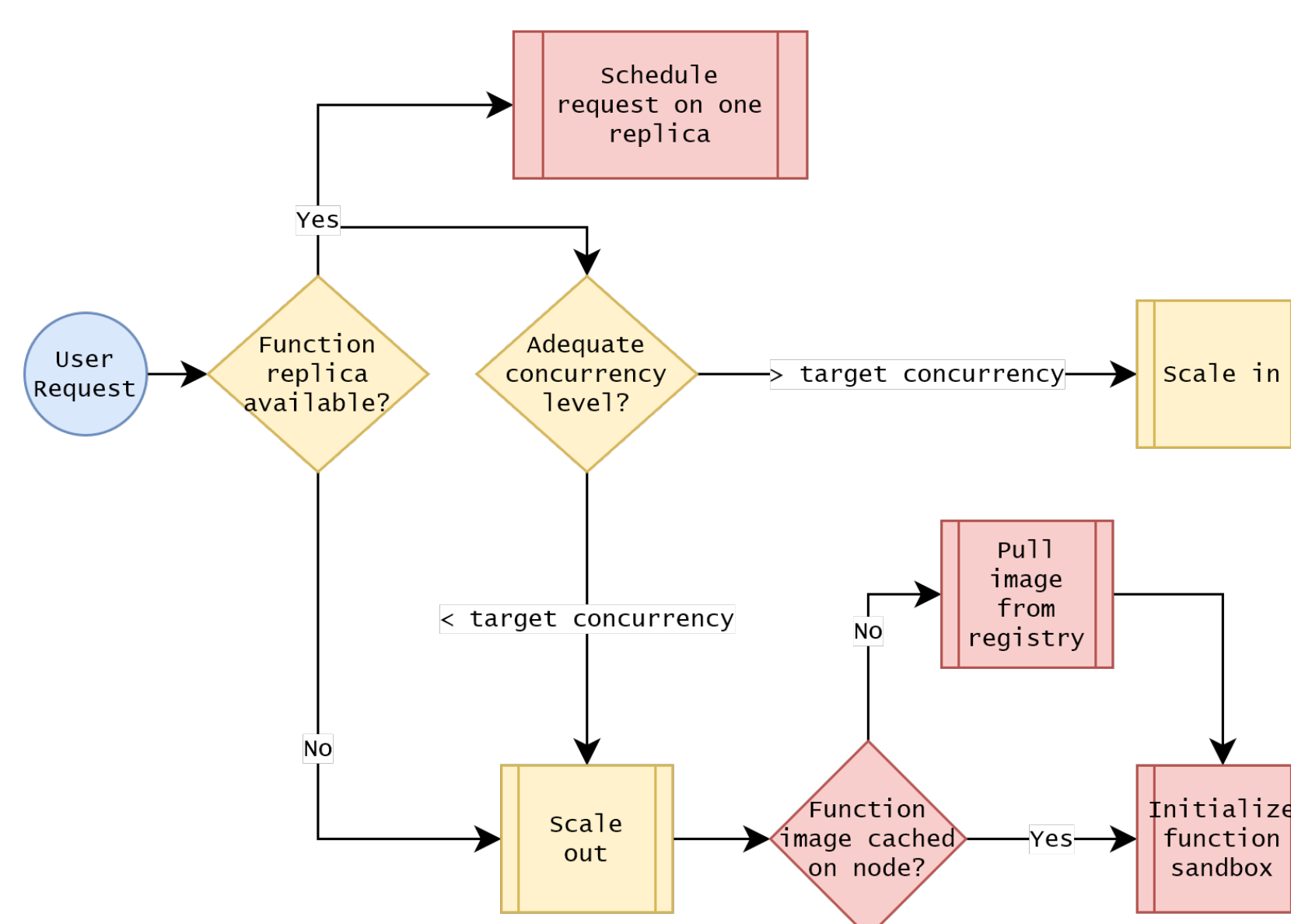


Fig. 2: Flowchart: allocation (yellow) and scheduling (red) decisions

### 3b – Function Communications

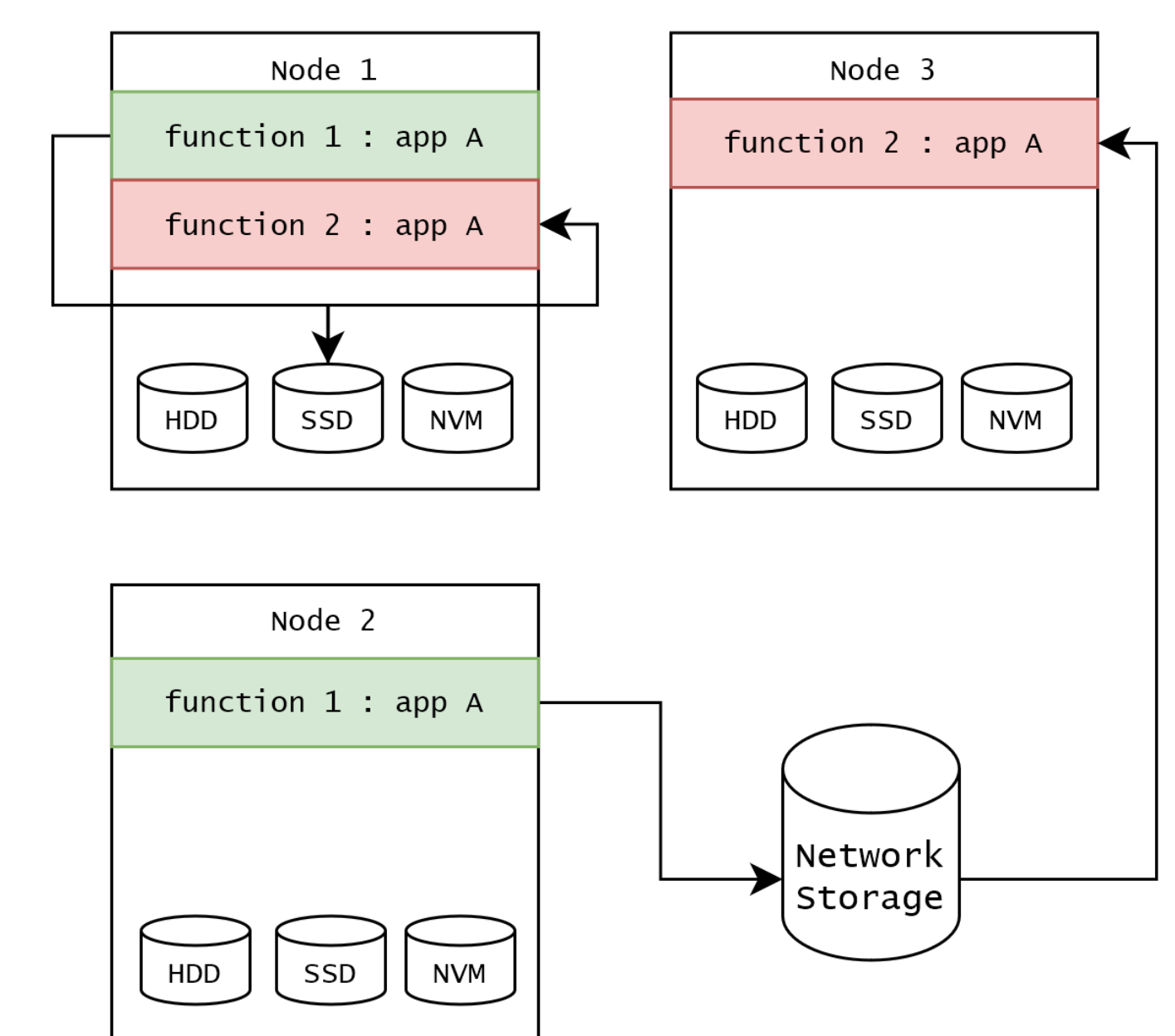


Fig. 3: Functions can achieve communications through either local or remote storage

## 4 – Thinking in Terms of Cost

We extend the cost model for resources allocation and function scheduling we published in [4]. We identify the implications of storage at each step:

	Impact	Cost
Resources allocation	Function response time	I/O bandwidth (Gbps)
	Resource contention	I/O capacity (GB)
Function scheduling	SLA penalties	I/O latency (ms)
	Tasks consolidation	I/O capacity (GB)
Application execution	Inter-function communications	I/O latency (ms)
	Output data storage	I/O capacity (MB)

Tab. 2: Breakdown of storage impacts on cost throughout the request lifecycle

$$scaleCost_{f_{N,P}} = k_{TT} \cdot TT_{f_{N,P}} + k_{EC} \cdot EC_{f_{N,P}} + k_{HP} \cdot HP_{f_{N,P}}$$

$$schedCost_{f_{N,P}} = k_{QP} \cdot QP_{f_{N,P}} + k_{EC} \cdot EC_{f_{N,P}} + k_{TC} \cdot TC_{f_{N,P}}$$

## 5 – Leveraging Node Storage

We propose to extend the platform in Fig. 1 with a **distributed, cost-aware function cache** that opportunistically leverages the heterogeneity of available disk space and memory on worker nodes to:

- accelerate function initialization by minimizing cold start delays;
- lower application response time by minimizing inter-function communications through remote storage.

$TT_{f_{N,P}}$	function response time (total execution time)
$WT_{f_{N,P}}$	duration of the scheduling decision, including queuing time
$CST_{f_{N,P}}$	initialization time for the function, including cold start
$ET_{f_{N,P}}$	execution time of the function on the platform
$TC_{f_{N,P}}$	sum of total times of all tasks in platform’s queue
$QP_{f_{N,P}}$	QoS penalty for a given scheduling
$HP_{f_{N,P}}$	hardware price for a given allocation or scheduling
$HP_{f_{N,P}}$	energy consumption for a given scheduling
$IFC_{f_{N,P}}$	inter-function communications

$CST_{f_{N,P}}$  is impacted by either pulling the function image from a repository or deploying from the local cache and increases function response time and thus potential  $QP_{f_{N,P}}$  penalties due to missed deadlines:

$$TT_{f_{N,P}} = WT_{f_{N,P}} + CST_{f_{N,P}} + ET_{f_{N,P}}$$

$TC_{f_{N,P}}$  has to be maximized for functions of a same application so as to allow node-local communications between functions of an application and minimize the use of remote storage:

$$ET_{app_{N,P}} = \sum ET_{f_{app_{N,P}}} + \sum IFC_{app}$$

$$IFC_{app} = \sum IFC_{local_{f_{N,P}}} + \sum IFC_{remote_{f_{N,P}}}$$

## 6 – Perspectives

- We are extending the simulator developed for [4] to integrate our updated cost model to the resources allocation and task scheduling policy;
- We will evaluate the relevance of the full policy using traces derived from Azure datasets [7];
- We consider exploring the use of machine learning algorithms to introduce workload prediction and/or to characterize workloads during execution instead of during an offline measurement phase.

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