SNF: Serverless Network Functions

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Abstract— It is increasingly common to outsource network functions (NFs) to the cloud. However, no cloud providers offer NFs-as-a-Service (NFaaS) that allows users to run custom NFs. Our work addresses how a cloud provider can offer NFaaS. We use the emerging serverless computing paradigm as it has the right building blocks - usage-based billing, convenient event-driven programming model and automatic compute elasticity. Towards this end, we identify two core limitations of existing serverless platforms to support demanding stateful NFs - coupling of the billing and work assignment granularities, and state sharing via an external store. We develop a novel NFaaS framework, SNF, that overcomes these issues using two ideas. SNF allocates work at the granularity of *flowlets* observed in network traffic, whereas billing and programming occur on the basis of packets. SNF embellishes serverless platforms with ephemeral state that lasts for the duration of the flowlet and supports high performance state operations between compute units in a peer-to-peer manner. We demonstrate that our SNF prototype dynamically adapts compute resources for various stateful NFs based on traffic demand at very fine time scales, with minimal overheads.

1 Introduction

Infrastructure- and compute-as-a-service relieves cloud users from the burden of managing physical compute resources and scaling capacity. A recent exciting advancement in the cloud evolution is serverless computing, which further reduces the burden of managing, provisioning, and scaling infrastructure (servers, VMs, etc.). Now all a user has to focus on is the application logic, which tremendously reduces the barrier to entry. In this model, users write and upload programs called "functions" that can be dynamically scaled up and down based on user specified event triggers. The functions run in stateless and short-lived computing instances/containers, and the user is billed for exactly the computing cycles used for a function, providing significant cost advantages. While this is a big step in the right direction towards offering services that are cost-effective for users, serverless computing today is rather narrowly focused. It targets stateless, short-lived, batch mode, and/or embarrassingly parallelizable workloads. It leaves behind stateful streaming workloads, which form our focus.

Rather than consider general stateful streaming applications, we consider the specific and important example of network functions (NFs) that perform stateful operations on packet streams in enterprises and telecommunication infrastructures. These workloads in recent years have emerged as part of the Network Functions Virtualization (NFV) transformation in telco service provider networks and still face significant challenges in simultaneously achieving the goals of low cost (to both the user and the infrastructure provider), and scalable performance, while supporting programming ease. In many ways, serverless computing provides a key set of building blocks to address these issues impacting NFV, but important gaps remain (§2).

Our high-level goal is to address the challenges of supporting NF workloads with serverless computing infrastructures by adding in the missing abstractions and mechanisms to support stateful computation effectively. Also, we should not have to compromise on preserving the unique benefits of the serverless paradigm, such as simplified management, event-driven compute triggering which is central to usage-based pricing, autoscaling, and cost-effectiveness. This is in contrast to prior works that *retrofitted* applications onto today's serverless platforms [19, 23].

Network functions are a resource intensive workload with fine grained latency and throughput performance needs. We examine limitations imposed by two naive realizations of support for such workloads over today's serverless platforms invoking a function to process each individual packet, or invoking a function instance per *flow*. We make two key observations, and argue, correspondingly, for two key design changes. First, we observe that, in today's platforms, "events" (e.g., each incoming request) are used for both the granularity of work allocation as well as the granularity against which functions are programmed and billing is performed. This coupling imposes a hard trade-off between resource use efficiency, performance, and billing granularity for stateful applications. We argue for breaking this coupling, and allowing work allocation to happen at a different granularity than that at which a program launched in a function operates. Second, we observe that given state externalization in today's platforms (externalization is key to keeping functions stateless, enabling rapid scaleout) the only way state can be shared across events and functions is by using a remote storage service. State sharing is crucial to stateful applications and, for NFs, externalization substantially worsens packet processing latency. Thus, we advocate for *ephemeral statefulness*, where state is bound to function instances for the duration of the computation corresponding to a single unit of work allocation.

We leverage these two ideas in designing, SNF, a new serverless platform that allows cloud providers to provide NFs-as-a-service (NFaaS) wherein users can outsource NFs to enjoy the benefits of the cloud [31, 37]. Users of SNF (e.g., NFV operators) can program many different NFs as functions. For a given NF, SNF transparently distributes the packet processing work in an incoming traffic stream across an elastically scalable set of compute units; each unit has a function corresponding to the given NF deployed in it. SNF maintains high utilization of compute units, and ensures that

minimal number of units are used, both of which are attractive to the cloud provider. SNF also ensures that a given NF deployment's packet processing throughput is high, tail latency is low, and that billing only captures the work done processing traffic, all of which are appealing to users (NFV operators).

To achieve these, SNF relies on the following ideas:

- We note that the packet processing workloads in a flow can be naturally granularized into flowlets [39]. In SNF, we use flowlets as the units of our workload assignment, whereas NF programs that run in function instances operate on a packet at a time, preserving the NF programming abstraction today and ensuring billing only for work done.
- We store NF-internal state in the local memory of a compute unit where a given flowlet is being processed. We develop protocols that uses inter flowlet gaps to proactively replicate ephemeral state to a new compute unit where the processing of a subsequent flowlet in the same flow is to occur, while avoiding inconsistent updates.
- To achieve efficiency, our work assignment algorithm aims to keep all active compute units at the maximum possible utilization via a novel weighted greedy bin-packing algorithm that maximally packs flowlets into few compute units, while ensuring performance targets are met, and while preferring instances to which state has been proactively replicated.

We implement and evaluate a standalone prototype of SNF and deploy on CloudLab [1]. Our experimental results with real traffic traces and five stateful NFs demonstrate the viability of our architecture and validate the core decisions to use flowlets and ephemeral state. With SNF, we are able to simultaneously achieve efficiency, performance and fault tolerance for NF processing. We are able to closely match the packet processing demand and provisioned resources dynamically at fine grained timescales of 100ms, whereas naive NF implementations over serverless architectures result in both over and underload. Our results show that SNF reduces 75%ile processing latency by 2.9K-19.6Kx over alternatives that operate at flow granularity. Our proactive state management improves the 99%-ile tail latency of NF processing by 12-15x over state-of-the-art state management solutions. Additionally, our simple fault tolerance protocol supports fast recovery (22.8x-183.6x reduction in comparison to alternatives).

2 Motivation

2.1 Why Serverless Computing for NF-as-a-Service?

NFs examine and modify packets to ensure security, improve performance, and provide other diverse functionalities: examples include network address translators (NAT), intrusion detection systems (IDS), firewalls, load balancers, etc. Many NFs are stateful in nature, for example, NAT maintains address mappings, IDS maintains string matches, etc. Over the last few years, researchers have advocated outsourcing NFs to the cloud [31,37]. These works have observed that such outsourcing to realize NFaaS can enable NF users to enjoy the

benefits provided by the cloud such as leveraging the scale, elasticity, and availability of the cloud, pay-as-you-go billing that is intrinsic to the cloud, and the built-in management and operational expertise available at cloud providers.

However, as of today, no cloud provider offers NFaaS. There exists limited support wherein an end user can use specific out-of-the-box NFs provided by the cloud provider, such as a load balancer, or a firewall [9,10]. But, the user does not have the flexibility of running custom NFs. Our work addresses how a cloud provider can offer NFaaS and realize the goal of outsourcing NFs.

Ideally, an NFaaS platform should provide an intuitive programming model that allows users to write custom NF logic and delivers good performance (low packet processing latency) while automatically managing the infrastructure (scaling up/down) to meet the traffic demand and charging users only for the work performed, i.e., usage-based billing.

Recently, a new cloud computing paradigm known as function-as-a-service, or serverless computing, has garnered a lot of attention, primarily due to its attractive features such as event-driven programming model, usage based billing, and automatic compute elasticity. Additionally, serverless computing with fine-grained functions is also beneficial to the cloud provider as it can facilitate higher resource utilization, both in terms of short execution time and small resource footprint in comparison to other compute alternatives such as VMs. Thus, on the face of it, it appears that serverless computing has the right building blocks to meet the aforementioned requirements of NFaaS, which a cloud provider could leverage.

2.2 Drawbacks of other realizations of NFaaS

It is possible for a provider to use VM- or container-based compute platforms to realize NFaaS. However, there are a few fundamental impediments that arise. First, today's native VM- or container-based compute platforms' interface does not allow users to simply supply high-level functions; users are responsible for managing the lifecycle of compute units (e.g., launch the compute unit, install appropriate NF logic and other software dependencies etc) which imposes significant management burden.¹ Second, existing compute platforms charge on the basis of the amount of time that a compute unit is assigned to the user. This used to be in hourly increments, but has more recently been made more fine-grained. Despite this improvement, pay-as-you-go charging today is fundamentally not tied to actual usage - in true usage-based pricing, the user is charged only when the compute unit is actively processing user data or running user's compute logic. This undermines the cost effective reasons for users wanting to leverage NFaaS. Third, VM and container-based compute platforms were designed with the notion of virtualizing entire servers, with the aim of eliminating physical server deployment/management and to support consolidation. Because of

¹It is possible to provide abstractions that allow users to simply supply functions, but this is precisely what serverless platforms already support.

this, the platforms are most useful in supporting batch style stateful, server-like computations. However, similar to applications such as database services and web services, the NFaaS workload can be bursty, and consequently the cloud provider would suffer from low resource utilization as resources are typically provisioned for peak load [24].

2.3 Issues with Serverless Computing

Given that the goal of outsourcing NFs aligns with the features of serverless computing, we now briefly provide an overview of the paradigm and then go through a thought experiment of running NFaaS on existing serverless platforms to see if the manageability, efficiency, and billing benefits of serverless hold while meeting the performance requirements of NFs.

Serverless Background. In FaaS or serverless computing, the user writes a function, uploads it to the serverless platform and registers for an event (e.g., object uploads, incoming HTTP request) to trigger function execution. The event is the granularity at which the platform does both work assignment (event routing decisions) as well as billing. When an event arrives, the platform routes the event to a compute unit that runs this function. An event may cause setting up of a compute unit from scratch which involves launching the unit and downloading the relevant run-time and the function code from a data store; alternatively, an event may be sent to an already launched and "warmed up" compute unit. The platform provider can choose from a wide array of available virtualization technologies to realize the compute unit abstraction, e.g., containers, microVMs, or containers-within-VMs. Additionally, the platform elastically scales computation up/down by based on incoming event rate.

A key aspect of serverless platforms today is that functions are stateless. Thus, all state needed to process an event is read from an external store (e.g., S3 [5]), and any generated state is written back to the store. The statelessness simplifies the elasticity logic as it does not need to worry about state and can trivially setup/teardown compute units.

Serverless platforms can be viewed to have early roots in Platform- as-a-service (PaaS) offerings (e.g., Heroku [12], Google's App Engine [11] etc) with the key differences being that they support a broader range of applications, have more fine-grained autoscaling and billing support, and adopt usage-based billing instead of time-based (e.g., [11] charges by the hour), in comparison to PaaS [24].

Gaps in serverless platforms today. While NFaaS atop serverless platforms, a key design decision that needs to be taken is the *event granularity*, as it decides both the work assignment and billing granularities. There are two obvious granularities of incoming events -

 Per-packet. The platform performs work assignment for every packet, and NF function execution is triggered for each packet. This mode efficiently utilizes compute units, which helps the cloud provider, and also ensures that users are billed exactly for just the compute cycles used. But it comes at the cost of extreme reordering as packets are sprayed across the compute units in an independent manner. Also, for stateful NFs, state would need to be accessed via an external store for each packet due to the stateless nature of functions today, leading to high latencies.

• Per-flow. The platform receives an event when a new flow arrives, which triggers NF function execution. All packets from this flow are handled by this running function. This causes no reordering, and state can be maintained/cached locally. But, it impacts billing, efficiency and performance. It leads to the user being charged for periods even when no packets are being processed by the function as it busy-waits for packets pertaining to the still active "event" (flow) to arrive. Also, this mode enforces a long-term commitment between a flow and a running function, which can lead to overload, affecting performance, or under utilization, affecting efficiency, depending on the assigned flow's rate.

In conclusion, naively trying to run NFs atop serverless platforms leads to a trade-off between the manageability, efficiency, and billing benefits while meeting our performance targets. These trade-offs are fundamental and intrinsic to the two gaps present in serverless platforms today, namely: (a) the tight coupling between workload assignment and billing granularities and (b) the stateless function abstraction.

2.4 SNF Key Ideas

Given the issues that serverless platforms face today, we now describe our two key ideas that overcome these limitations and enable us to meet our goals.

1. Decouple work assignment and billing granularities: As seen above, the coupling between the two granularities leads to fundamental trade-offs between our goals. Thus, we advocate for decoupling the two granularities. The key question that needs to be addressed is what are the new granularities at which the platform should operate? We next discuss the granularities that we choose -

Billing and programming at per-packet granularity. Having events as packet arrivals leads to ideal billing as discussed earlier. Additionally, the notion of having packets as events also naturally aligns with the way developers typically implement NFs - take a packet as input and execute the processing function (process_pkt()).

Work assignment at per-flowlet granularity. Rather than making decisions at a flow granularity (as done by NF platforms today [20]), we advocate doing it at a *flowlet* granularity. A flowlet [39] is a burst of packets that is separated from other bursts of packets from the same flow by a sufficient gap called the flowlet timeout. Acting at this granularity provides more opportunities to assign/allocate work which limits the negative impacts of operating at the flow granularity.

While operating at a flow granularity, multiple flows are assigned to the same compute unit which can lead to under utilization/overload² and head of line blocking (HOL): packets

²Impact varies depending on whether flow migration is supported or not.

from an earlier elephant flow can cause those from mice flows later to wait in buffers at the unit, degrading latency (see §9.1). On the other hand, while operating at the flowlet granularity, large flows are "broken up" into many flowlets that can now be assigned at many units. This mitigates HOL blocking and over-utilization. Also, the smaller size of flowlets than flows enables better packing of work to compute units, and hence is better at avoiding under utilization.

2. Eschew complete statelessness and adopt ephemerally stateful functions: Complete statelessness due to the external store overheads [23]. While efforts have been made to reduce overheads by using low latency networking [25,26], they still experience a hold up of packets in queues when a flow is reallocated to a new compute unit (waiting for state to be made available before processing begins). This exacerbates tail packet processing latencies by 15x (see §9.2).

At the other extreme is the option of making functions fully stateful by simply keep state locally at the compute unit and routing all the appropriate packets to the same unit (similar to [21]). We eschew this option as it places strict constraints on event routing and defaults to doing flow level work allocation, which has several negative impacts as discussed above.

Instead, we choose a middle ground. We leverage the fact that all packets in a flowlet are going to be processed at the same compute unit (as work assignment is done at flowlet granularity) and maintain state locally just for the duration of the flowlet's processing. We leverage the flowlet inactivity period to opportunistically transfer ephemeral state from one compute unit to another (in case subsequent flowlets of the same flow are assigned to different compute units) helping us curtail delays and bring down tail latencies due state unavailability. With access to such state, functions now become *ephemerally stateful*; this makes packet processing latencies comparable to when state is maintained locally.

3 SNF Architecture Overview

We now give an overview of SNF, a serverless NFaaS platform. It has two main components: controller and NF runtime. The underlying compute units on which the NF logic runs can be anything - VMs, containers etc.

Controller. When registered events (packets) arrive at the platform, the controller forwards them to the appropriate compute unit where the function (NF logic) executes and the event is processed. The controller consists of three main modules: (a) the workload granularization module (WGM), (b) the work assignment module (WAM) and (c) the state management module (SMM).

When packets from different flows arrive at the controller, the WGM is granularizes the incoming flows into flowlets. Specifically, given a packet it determines which flowlet it belongs to (also involves detecting if this packet starts a new flowlet). If it belongs to an existing flowlet, then it is routed to the appropriate compute unit. If not, the WAM determines the appropriate compute unit to which this new flowlet should

be assigned, so as to meet our goals of performance and efficiency. The SMM encodes a small amount of metadata to each packet - which compute units use to push/pull state to/from and logical clock to prevent stale state updates.

NF Runtime. This runtime realizes the notion of ephemeral stateful functions (but NF developers are not aware about the ephemeralness) and is responsible for state management at each compute unit. It transparently handles updates and transfers among compute units in a peer-peer manner. The state management transparently is not visible to the NF developers. Programming Model. Given that packet arrivals are events in SNF, the NF developers operate in a familiar model wherein the process_packet() routine is called whenever a packet arrives. Also, the NF runtime exposes simple put(key, value) and get(key) APIs which the developers use to access state.

Next we describe the novel compute and state management approaches adopted by SNF that maximize utilization without sacrificing performance.

4 Compute Management

The SNF controller is responsible for the compute management. We begin by describing the approach adopted by SNF to granularize the incoming workload into flowlets (§4.1) and then explain the work assignment algorithm (§4.2). The overall logic of the WGM and WAM is shown in Pseudocode 1.

4.1 Workload Granularization Module (WGM)

The incoming workload is assumed to be an aggregate of packet flows, which are identified by the 5-tuples in the packet header. Without loss of generality, we assume in this discussion that the entire packet workload needs to be processed by a single NF type although we can easily accommodate different NF types.

In SNF, when a packet arrives, a new flowlet is detected if one of the following two criteria is met - (a) if the gap between the current packet and the previous packet of the same flow is greater than the flowlet inactivity timeout; or (2) if the size of the existing flowlet exceeds the flowlet size threshold (lines 14-25 in Pseudocode 1). We elaborate on the benefits provided by detecting flowlets in this manner below (§4.2). Both the timeout and size thresholds are configurable parameters and poor choices will impact the overall efficiency and performance. We carry out sensitivity analysis in §9.6. In case a new flowlet is not detected, then the controller forwards the packet to the appropriate compute unit (already associated with the flowlet the packet belongs to).

The WGM is also responsible for estimating the rate of incoming new flowlets, which is needed while making work assignment decisions. The aggregate workload, and the individual flows within it, arrive dynamically, and the flows' rates vary. Thus it is hard to make good resource assignment decisions without having a reasonable estimate of the incoming flowlet demands. For our prototype, we estimate the demand of the first flowlet of a flow to be the average load of all flowlets (across all flows) seen in the past. For

Pseudocode 1 SNF Compute Management

```
1: ⊳ Given a packet P, decide which compute unit to send to
2:
   procedure EVENTROUTING(Packet P)
       M
                                       4:
       T = EXTRACTTUPLE(P)
5:
       if FLOWLETDETECTOR(T, P) then
                                                              Detects new flowlet
6:
           ▷ Call WORKLOADASSIGNER as new flowlet is detected
7:
           ComputeID = WorkloadAssigner(T, P)
8
           ▷ Use the existing assignment as P is within current flowlet
9.
10:
            ComputeID = M[T]
11:
        end if
12:
        return ComputeID
13: end procedure
14: ▷ Given a flowlet F and packet P, detect new flowlet
15: procedure FLOWLETDETECTOR(Flowlet F, Packet P)
        if currTime - F.LASTPKTTIME > timeout then
            > New flowlet detected as timeout criteria met
            return TRUE
19:
        else if P.SIZE + F.SIZE > sizeThreshold then
20:
            > New flowlet detected as size criteria met
            return TRUE
22:
23:
           return False
        end if
25: end procedure
26: ▷ Given a flowlet F, assign a compute unit
27: procedure WorkloadAssigner(Flowlet F)
                                                      ▷ Candidate compute unit IDs
29:
                                                   > Sorted active compute unit IDs
30:
        for all g \in \mathbb{G} do
31:
            if F.DEMANDESTIMATOR(F) + g.LOAD() > g.CAPACITY() then
32:
               score = g.UTILIZATION() + \alpha * g.STATEEXIST(F)

\triangleright Add the computed score to \overrightarrow{C}
33.
34:
               \overrightarrow{C}.ADD(g, score)
35:
            end if
36:
        end for
37:
        ▷ Pick the compute unit ID which has the maximum score
38:
        return max(\overrightarrow{C})
39: end procedure
40: ▷ Given a flowlet F, estimate the rate
41: procedure Demandestimator(Flowlet F)
42:
        if IsNewFlow(F) then
            > Estimate is average across all flowlets load seen until now
43.
44:
            return globalaverage
45.
        else
            \triangleright EWMA(F, ID) = \delta * F_{ID-1}.Load + (1 - \delta) * EWMA(F_{ID-2}, ID - 2)
46.
47:
            return EWMA(F, ID)
48.
        end if
49: end procedure
```

subsequent flowlets, we use an estimate that computes an exponentially weighted moving average (EWMA) over the previous flowlet's *measured* rate and the previous estimate (lines 40-49 in Pseudocode 1).

4.2 Work Assignment Module (WAM)

If the WGM has detected the start of a new flowlet, it sends an assignment request to the workload assignment module (WAM) along with its load estimate. WAM is responsible for assigning the new flowlet to the appropriate compute unit running a single NF's code as in [37] or a composed NF chain code [43]. In the future, we plan to consider the handling of NF chains spread across compute units in SNF.

Depending on the actual NF logic, the packet processing demands may vary. We make a practical assumption that each NF compute unit is provisioned with adequate CPU and memory resources to support a packet workload up to $BW_{max}bps^3$. As long as the incoming aggregate rate to the compute unit is less than BW_{max} , the NF will be able to provide the requisite performance. Typically, small amounts of overload can be tolerated when there will be some queuing at the NF and the latency will increase. The goal of SNF is to avoid overload situations even in the face of highly dynamic workloads.

Our work assignment algorithm greedily packs flowlets to active compute units so as to maximize their utilization. This is analogous to bin packing: balls are flowlets, and bins reflect the network processing capacity at compute units (line 34). But the "greedy" aspect arises from the fact that in our approach the compute units are considered in a *deterministic* sorted order of their IDs; the smallest ID unit with room is chosen, which leads to units with lower IDs being packed first (lines 26-39 in Pseudocode 1). This determinism makes the algorithm simple and easy to implement scalably. Also, we show that it makes it easy to take state availability into account while making assignment decisions and accounting for ephemeral state (line 32 in Pseudocode 1 - see §5.2.2); this is crucial to balance utilization against per-packet latency.

Apart from requiring the load estimate of the flowlet that is being packed, the algorithm also requires the current load of the compute units to make decisions (line 31 in Pseudocode 1). To obtain the current compute load, given that each compute unit is managed by a single controller, the controller measures the rate at which packets are drained for a particular compute unit as it is representative of its load.

The controller adds new compute units if the existing ones are saturated, and existing compute units are made inactive if they do not receive any packets for a fixed amount of time. The start-up times of compute units also need to be considered while scaling. Given that there is significant effort ongoing to reduce this overhead [32], we do not focus on this issue in this paper. Instead, we use the simple strategy of proactively starting them when existing units start to get heavily utilized (say all have load > 90%) to mask the overhead.

Adversarial Flowlets: A key issue in packing arises when traffic demand spikes suddenly on certain, or all, flow subspaces. These flowlets that we term as adversarial flowlets, have actual flowlet load that is significantly higher than the estimate provided by the WGM; in such a situation the adversarial flowlet can degrade the performance of other flowlets that are assigned to the same compute unit by building up queues. If flowlets are detected by just using the inactivity timeout, the impact of an *adversarial flowlet* can last for an arbitrarily long duration. Thus, in SNF, we bound the negative impact of adversarial flowlets by forking a new flowlet from the current flowlet if the current flowlet's size exceeds a predefined size threshold. By bounding size in this manner, we ensure that adversarial flowlets are drained quickly and

³This maximum rate could also be specified in packets per second at a specific packet size, say 64-bytes. For the sake of simplicity, and without loss of generality, we specify this in bps.

their impact on the overall processing at a compute unit is mitigated. The new flowlet forked after exceeding the size threshold undergoes the process of assignment using an updated load estimate, wherein the moving average (lines 26-47 in Pseudocode 1) accounts for the rate spike observed in the previous adversarial flowlet.

5 State Management

A stateful NF's actions on a packet depend on the current state, and for correct and high performance operation, fast access to correct updated state information is crucial. NFs may maintain per-flow or cross-flow state. We focus on perflow state since it is the common case and plan to consider cross-flow state in the future. Also, NFs have configuration state which is often static (e.g., an IDS has string matching rules) and does not vary at packet-scale timelines. In SNF, such state is stored in an external store and is pulled during the compute unit setup phase leading to no visible overheads.

In SNF, per-flow state management is done *transparently using the NF runtime*. NF developers build NFs using well defined APIs that are exposed by the NF runtime, using which they read/update state, and without worrying about state management across compute instances. The run time makes the current values of state available where needed.

We begin by describing *ephemeral state* and how it enables fast state operations (§5.1). We then discuss how to ensure state is available locally at a compute unit even when subsequent flowlets are assigned to different units. We end with how updates to stale state information are prevented (§5.3).

5.1 Ephemeral State

A compute unit in SNF maintains state locally while processing a flowlet. This state is ephemeral as it is bound to a unit from just before the first packet of the flowlet is processed till the time the last packet is done being processed. Once the flowlet has ended, this state is no longer associated with its compute unit. Ephemeral state ensures that packets within a flowlet are processed quickly as state access is always local and fast for each arriving packet.

Ephemeral state is initialized when the first packet of a flowlet arrives at a compute unit as follows: if the flowlet is the first one of the flow, then the state is set to null; otherwise, if the state has already been copied over to the compute unit's memory (as described next), then this state value is used; else, the compute unit pulls state from the remote unit where the previous flowlet was processed. The controller sends the processing location of the previous flowlet of the same flow as metadata along with the packet belonging to the new flowlet.

5.2 Peer-to-Peer In-Memory State Storage

Different flowlets of a flow may be processed by different compute units depending on the decisions taken by the work assignment algorithm. This could lead to a scenario where a flowlet f_1 of a flow F arrives at a different compute unit from the one that the prior flowlet f_0 of the same flow F

was processed. Clearly state information is needed at the new compute unit before packet processing can begin. When state is not available, packets are held up in buffers at the compute unit until the state is initialized, affecting latency.

With SNF, we adopt a *peer-to-peer in-memory state storage service* to minimize stalls. Here, ephemeral state is replicated *proactively* in a peer-to-peer fashion by leveraging the *gaps that exist between flowlets* of a flow. This solution works well if the amount of per-flow state maintained by an NF is small enough that it can be transferred during the inter-flowlet gap and not cause stalls. Luckily, prior work [27] has shown that per-flow state size in commercial NFs like PRADS [6] and Snort [35] is under just a few KB for the entirety of a flow's lifetime; even smaller fraction of this may be updated per flowlet. Note, however, that proactive replication is unlikely to help with flowlets that were created from packets exceeding the size threshold (as opposed to the inactivity timeout).

A key issue is that the above idea requires compute units to communicate with each other directly. This is a substantial departure from existing serverless platforms, where units (e.g., lambdas [2]) are disallowed from communicating with each other, and all communication can happen only via the external state store. We do not view this constraint as fundamental, and for performance reasons, relax it to enable communication between cooperating compute units.

However, to ensure the peer-to-peer in-memory state store is performant and useful, two key questions need to be addressed - (1) when should a compute unit proactively initiate state transfer? and (2) where should it transfer state to?

5.2.1 When to transfer?

Every time there is a period of inactivity in a flowlet, the compute unit could assume that the flowlet is coming to an end and initiate state transfer. However, it is difficult to accurately predict when a flowlet will end. Replicating state whenever there is a small period of inactivity for a flow may lead to unnecessarily doing proactive state transfers if the flowlet does not end and more packets arrive. Waiting till the end of the inactivity timeout would default to reactively pulling the state, which has performance implications. Deciding how early to proactively replicate state has implications on the additional bandwidth used to transfer state.

In SNF, we proactively replicate state once the period of inactivity exceeds *half* of the flowlet inactivity timeout to balance minimizing wait times against making unnecessary state transfers. In case this flowlet does not end, processing can carry on without interruption at the primary compute unit which still holds a copy of the latest state. However, this can lead to inconsistent state updates, which we discuss and address in §5.3. In case a new flowlet arrives at a new compute unit before the proactive transfer begins, we first reactively pull relevant state (from the compute unit with state for the immediate preceding flowlet). If the flowlet arrives while the proactive transfer is occurring, we hold off processing.

Pseudocode 2 SNF State Management

```
1: ▷ Given a replication factor R, decide where replication should occur
   procedure DETERMINISTICREPLICATOR(ReplicationFactor R)
3:

    Candidate unit IDs

4:
                                                                     > Sorted active unit IDs
5.
        > Return the first R active compute units
        return \overrightarrow{G}[1:R]
7: end procedure
8: Pick R units using a weighted (inversely to IDs) randomized distribution
9: procedure WEIGHTEDRANDOMIZEDREPLICATOR(ReplicationFactor R)
10:

⊳ Sorted active unit IDs

                                                        ▶ Weights assigned inversely to IDs
12:
                                                                        Candidate unit IDs
         while len(\overrightarrow{C}) < R do
13:
14:
             \triangleright Pick a compute unit from \overrightarrow{G} where units are weighed by \overrightarrow{W}
             replicationSite = WEIGHTEDRANDOMIZER(\overrightarrow{G}, \overrightarrow{W})
15:
                .ADD(replicationSite)
         return \overrightarrow{C}[1:R]
19: end procedure
```

5.2.2 Where to transfer?

Once it is time to proactively push state, the runtime at a compute unit needs to decide where to replicate state. A strawman solution would be to broadcast to all other active units but this has the overhead of doing unnecessary transfers. Instead, in SNF, the controller estimates the top K compute units where the next flowlet of this flow could likely be assigned to and it keeps track of this information for each flowlet. The reason for picking the top K and not the exact one is because it is not possible to know ahead of time as to where the next flowlet would be assigned. The reason is that a compute unit that is available currently may be saturated by the time the new flowlet arrives (due to flowlets of other flows being assigned in the interim). The question is how to pick the "top K" such that the probability of the compute unit chosen by the WAM for the next flowlet already having the necessary state is high.

We could replicate state to the K least loaded units, expecting that the WAM would assign the next flowlet to them. However, the load can change by the time the next flowlet of this flow starts. Also, implementing a load-aware strategy is complex, as we need up to date load information at scale.

Since the WAM deterministically processes compute units (lines 2-7 in Pseudocode 2), one simple load-unaware strategy is to pick the least K ID compute units, i.e., units with IDs from 1 to K, to replicate to (the WAM would preferentially allocate a new flowlet amongst these). But doing this for every flowlet's replication would render proactive replication ineffective when the least K ID units become overloaded, which is likely especially for a small K. In such cases, future flowlets are assigned outside these K units, and thus they would have to pull state reactively.

SNF uses a simple variant of the above strategy that allows for some error in the estimated location where a future flowlet goes to. We pick the top-K compute units to replicate state to, with probability inversely proportional to the units' IDs (lines 8-19 in Pseudocode 2). Doing so ensures we pick the lower ID units' with higher probability as is done by WAM.

The next question is how should the controller make the

next assignment decision to account for state availability and maximize the potential benefits of proactive replication? A strawman solution would be for the controller to check if any of the K compute units (which have the required state) could handle this flowlet. If yes, the flowlet is assigned to one of the units in question and processing can proceed without any wait time. If not, then we assign the flowlet to an available compute unit and the state is pulled reactively. Unfortunately, this approach ignores load, which affects utilization. It can cause compute units to become fragmented with many compute units poorly utilized.

Instead we extend the work assignment algorithm to make decisions using a weighted scoring metric (line 32 in Pseudocode 1) for choosing from the available compute units using both utilization and state availability. The weighted metric is $S = utilization + \alpha \times \beta$, where β is 1 if the compute unit has the replicated state, otherwise it is 0. α is a balancing knob between 0 and 1, and balances utilization against proactive benefits: $\alpha = 0$ results in the controller making assignment decisions to improve utilization (and ignoring state) and $\alpha = 1$ biases more in favor units where replicated state is available.

5.3 Preventing Updates on Stale State

While the above techniques minimize packet wait time, we need to ensure that a flowlet does not make updates on stale state that is present at its corresponding compute unit. This can occur when the optimistic approach of using half the flowlet timeout as the deadline to proactively replicate state from an old to a new unit was erroneous in assuming a flowlet would end. Here, the NF runtime would proactively copy state, but a few lingering packets from the original flowlet continue to arrive at the old unit and update state there. State updates due to such packets should be reflected in the state copied over to the new location before *any* processing begins there.

To prevent a new flowlet from acting on stale per-flow state at the new unit, we introduce the notion of *monotonically increasing logical clocks* for each packet of a flow. These are assigned by the controller. Each packet carries its logical clock as metadata. This prevents flowlets from making update on stale state in the following manner. The NF runtime tags the state that is proactively replicated with the logical clock of the last packet of this flow that was received by the old unit. When a new flowlet of this flow arrives at the new compute unit, before making updates to the state, the NF runtime verifies if the latest state is available by checking the logical clock of the packet (i.e., first packet of the new flowlet) is one more than the value with which the copied-over state is tagged; if not, state update due to the new packet is stalled, fresh state pulled reactively, and then the update proceeds.

The above technique also works in the rare event of packets arriving out of order. As is done today, if the NF logic requires packets to be processed in order, then the NF developer needs provide appropriate reordering logic. This typically involves storing the out-of-order packet until the intermediate packet

arrives and then processing them in order. Thus, out-of-order packets become a part of the ephemeral NF state (which is tagged appropriately to prevent stale updates as described above) and are processed per the logic defined.

6 Fault Tolerance

Given that NFs are stateful and the latest state is required for correctness, we need to ensure that SNF is fault tolerant in maintaining per-flow state. When the originally assigned (or primary) compute unit for an NF fails while processing a flowlet, a new recovery unit takes over the flowlet's remaining processing. The key property we desire is that the per-flow state initialized at the recovered unit have the same value as under no failure. We assume the standard fail-stop model in which a compute unit can crash at any point and that the other units in the system can immediately detect the failure.

Traditional recovery mechanisms do not work in the NF context due to the performance constraints as well as the presence of non-deterministic state update operations in the logic (e.g., "random") [36]. Thus, we sketch a solution that builds on prior work on fault tolerance for NFs [26,36]. While past solutions covered general NF chains, where different types of NFs were deployed across different units, our solution is simpler owing to our design choices. Specifically, recall that SNF handles only composed chains that are run in the same unit. Also, our NF units have a single packet processing thread. This leads to the following approach.

In SNF each NF compute unit is coupled with a separate output logger (OL) unit, which is launched on a different physical machine. Once a packet has been processed by an NF, the packet along with its *state delta* is sent to its OL; delta is the change to the value of a piece of state. It is the responsibility of the OL to use the delta to locally update state it maintains in memory for the NF, and only then forward the packet externally. Thus, the OL maintains a consistent copy of the state of the primary NF compute unit. Note that the output logger can also be implemented using the same packet-based programming model as NFs in SNF.

We assume that the NF and its OL do not fail at the same time. To protect against simultaneous failures, the state must be replicated at multiple OLs before the packet is released. This increases overhead and we do not consider it here. If warranted by specific use cases, additional OL resources can be added to ensure correctness even under simultaneous failures.

A recovery unit can take over a failed unit's processing by pulling the state from the associated OL. On the other hand, if the OL fails, then another OL is brought up and initialized by pulling state from its associated NF compute unit. The controller provides the necessary metadata to the failover NF/OL to pull state from the relevant compute unit⁴.

While this approach would generally provide the property we desire, a corner case may still occur: say a packet has been processed by an NF (the state has been updated at the NF), but the packet along with the state delta gets lost en route to the OL, as well as the NF unit fails. During recovery, the failover NF unit would be initialized based on the state pulled from the OL (which does not have the latest state of the NF prior to the failure, because it does not reflect the update made by the lost packet). Nevertheless, using this state offers reasonable semantics: it is no different than the state value when the lost packet is dropped by the network *before* it is processed by the original NF unit. The lost packet does not reach the destination and the sender will eventually retransmit it.

If an OL fails before transmitting a processed packet, is not different from the packet being dropped by the network between the OL and the destination. The NF unit still has the most up to date state; a recovered OL can pull this state.

The above protocol provides state fault tolerance but at the cost of an additional latency of half an RTT, and the additional bandwidth usage to ship state deltas to OLs. We believe that this overhead is reasonable, especially given that prior work [27] has shown that the deltas across successive updates to state objects are typically small.

Finally, to handle controller failure, given that it is stateful (e.g., logical clock, flowlet to compute unit mapping), we can write the state to an external store (as in [26]) and have the new controller read the latest values from the external store. Alternatively, the operator may opt to replicate the controller using Apache ZooKeeper [8].

7 Controller Scalability

Though the latency overhead introduced by the controller is minimal §9.7, as the input workload scales (e.g., 100 Gbps), having a single (even powerful) controller would lead to it being a bottleneck eventually. Thus, to support large scale workloads, we would need to have multiple controllers. One approach is for controllers to operate on dedicate sets of compute units. But this impacts compute efficiency due to resource fragmentation as controllers do not share units. Alternatively, the controllers can share the underlying compute units by using a state store to share compute unit load information. But imposes the overhead of coordinating over store access for every work allocation decision, i.e., every flowlet.

Instead, in SNF, we use a global resource manager (RM) that manages a pool of compute units. The various controllers ask for the required processing capacity based on the load seen in the last epoch (say 100ms). The RM allocates the requested capacity, which can be fractional; e.g., the RM could allocate 2.5 units, which requires spinning up 3 units with the full first two units and half the capacity of the third unit allocated to the requestor. When load in the current epoch is nearing requested capacity, the controller requests for more capacity so as to avoid performance degradation. The controllers give back resources once they become inactive as described earlier. The

⁴We differ from [26, 36] in that we don't need an input logger. They had multi-threaded NFs, and complex cross flow state, recovery of which requires packet replay from an input logger. Recovery of per-flow state simply requires state copy from the OL.

RM ensures that resource fragmentation across controllers is reduced as it strives to pack (fractional) units to their capacity.

8 Implementation

We built our prototype from scratch in C++ (20K LOC) rather than building off existing platforms such as AWS Lambda due to their blackbox nature [38,41]. It consists of -

RM. Implemented as a standalone process, it establishes TCP connections with controllers and handles resource requests.

Controller. Implemented as a multithreaded process, it establishes TCP connections with compute units and runs the compute management algorithm. It measures the compute unit load by monitoring the rate at which packets are drained. It measures this load at fixed buckets (of 500us) and considers the load over multiple buckets when packing (last 200 buckets, i.e., the last 100ms). The #buckets considered indicates the minimum time for which a change in traffic pattern should exist for the system to react. We choose the above values because smaller values made our system unstable by reacting to minor bursts, and larger values cause it to react too slowly. External Datastore and NF Runtime. Implemented as multithreaded processes. The former is used to hold NF configuration state and the latter does ephemeral state management. Packet reception, transmission, processing and datastore connection are handled by different threads. Protobuf-c [7] is used to encode and decode state transferred between units. Also, the NF runtime exposes APIs using which we reimplemented five different NFs of varying complexity -

NAT. Performs address translation and the list of available ports is the NF configuration state. When a new connection arrives, it obtains an available port and it then maintains the per-connection port mapping.

LB. Performs hash-based load balancing. The servers' list constitute the NF configuration state. When a new connection arrives, it obtains the server based on hash, and then maintains per-connection (a) server mapping and (b) packet count.

IDS. Monitors packets using the Aho-Corasick algorithm [14] for signature matching. The string matching rules (e.g., Snort [35] rules) constitute the NF configuration state. Also, the NF maintains per-connection automaton state mapping. **UDP Whitelister.** Prevents UDP-based DDoS attacks [18] by recording clients who send a UDP request.

QoS Traffic Policer. Implements the token bucket algorithm. The per-connection (a) committed rate and (b) token bucket size constitute the NF configuration state. Also, the NF maintains per-connection mapping of (a) time since previous packet and (b) current available tokens.

9 Evaluation

We evaluate SNF to answer the following questions:

- Can SNF provision compute as per the incoming traffic demand at fine time scales? Do we meet our goal of maximizing utilization without sacrificing performance?
- Does proactive state replication help curtail tail latencies?
- How does SNF perform when adversarial flowlets occur?

- How quickly can SNF recover in the presence of failures?
- Is SNF able to reduce resource fragmentation when multiple controllers are being used?
- How does SNF perform with different system parameters?

Experimental Setup: We use 30 CloudLab [1] servers each with 20-core Intel Skylake CPUs and a dual-port 10G NIC. The SNF RM and controller run on dedicated machines. The controller receives the replayed traffic from traces (details below) while the compute units run within LXC containers [13] on the remaining machines. For all our experiments, we use one controller and each compute unit is configured to process incoming packets at BW_{max}=1 Gbps, enabling 10 compute instances per machine. The default parameters are: flowlet inactivity timeout $T = 500\mu s$, the flowlet size threshold B = 15KB, the balancing knob $\alpha = 0.25$ and the replication factor K = 3. Real Packet Traces: We use two previously collected packet traces on the WAN link between our institution and AWS EC2 for a trace-driven evaluation of our prototype. One trace has 3.8M packets with 1.7K connections whereas the other trace has 6.4M packets with 199K connections. The median packet sizes are 368 Bytes and 1434 Bytes. All the experiments were conducted on both the traces with similar results; we only show results from the latter trace for brevity. Given that the load of the collected traces was not high, we scale the trace files by reducing the packet inter-arrival times.

9.1 Compute Management Performance

We first evaluate SNF's approach of performing flowlet-level work allocation. We measure (1) the provisioning efficiency with changes in traffic demands by recording the number of active compute units at 100 ms time intervals (referred to as an epoch hereafter), (2) the NF packet processing latencies incurred and (3) compute unit utilizations.

We compare against two other baselines that act at the flow-level: (1) **Vanilla Flow Allocation:** work allocation is done when flows arrive, and once a flow is assigned to a compute unit, it is associated with that unit for its entire lifetime. This mimics existing out-of-the-box work allocation techniques (when optimized state reallocation schemes [21] are not used). (2) **Smart Flow Allocation (X ms):** work allocation is done when flows arrive, and if required, flows are reallocated every X ms to avoid overload/underutilization at any compute unit. This is similar to a work allocation scheme that uses state reallocation schemes and thus supports flow migration [21].

Figs. 1a-1d show a runtime snapshot of SNF's provisioned bandwidth and the packet processing demand⁵. We see that acting on flowlets enables SNF to closely match the incoming load, which is not the case when acting at the flow granularity, irrespective of whether flow migration is supported or not.

In the vanilla allocation mode, we see that the system does not adapt well to the incoming load as it can react only when new flows arrive. In the smart flow allocation mode, when we

⁵Since each compute instance has BW_{max}=1 Gbps, the provisioned bandwidth is 1x #instances.

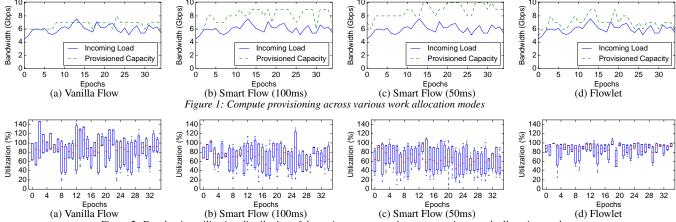


Figure 2: Epoch-wise utilization distribution of the active compute units across various work allocation modes

reallocate, if required, every X ms (X being 50ms or 100ms) the system is more adaptive in comparison to the vanilla flow mode as it gets more opportunities to reallocate flow. Acting at the flowlet granularity gives us **3.36X** more opportunities to assign work as compared to the alternatives, enabling SNF to better react to variations in the incoming load.

Additionally, when operating in the smart flow mode, there is over provisioning of units (greater when we are more aggressive to reallocate, i.e., smart flow (50ms)) due to the poor packability of flows which are larger work allocation units (in comparison to flowlets). However, even when acting in the flowlet mode, at times, additional 1-2 compute units are used in order to extract the benefits of proactive replication (§9.2). **Packet Processing Latencies.** Fig. 3 shows that the packet processing latency for the NAT NF while using the vanilla

processing latency for the NAT NF while using the vanilla flow mode is significantly worse in comparison to the flowlet mode: the 75th%-ile latency is 275.4ms, which is **19.6K** times worse than for flowlet mode. Once flows are pinned to a compute unit, the association continues until flows end and the presence of elephant flows (5% of the flows in our trace have a size greater than 10KB) causes input queues at compute units to build up. The trends for the other NFs are similar.

In the smart flow mode when we reallocate every 100ms (50ms), the latency is still worse than flowlets: the 75th%-ile latency is 64.5ms (41.1ms), which is **4.6K** (**2.9K**) times worse than the flowlet mode. This is due to (1) the mode being unable to handle overloads that occur at lower timescales than the reallocation frequency (50ms or 100ms) and (1) hold up of packets once reallocated until the relevant state is pulled from the prior compute unit. In the flowlet case the 99%-ile latency is 2.8ms, while the median is 5μ s. The tail is contributed by micro bursts⁶ leading to queuing occurring at the compute units as well as due to flowlets for which the NF runtime has to reactively pull state from the previous compute units where the prior flowlet in the flow was processed.

Utilization. While we have seen that operating in the flowlet

mode has the best performance, we need to verify that this improved performance is not coming at the cost of simply using more compute units. To do so, we delve deeper and look at the epoch-wise distribution of the active compute unit utilizations under the various modes (see Figs. 2a-2d).

As expected, while operating in the vanilla flow mode we experience maximum number of overloaded compute units as the system is the least reactive. Interestingly, in the smart flow (100ms) mode, even though over-provisioning occurs, we do see certain compute units being overloaded and this is due to the fact that the system can react only every 100ms. Consequently, in the smart flow (50ms) mode, we see lesser overload. Moreover, in all these modes wherein we act the flow level, we do experience more underutilization as well due to the poor packability of flows.

On the other hand, operating at the flowlet granularity rarely experiences overload as we get far more opportunities to react and has lesser underutilization as flowlets being smaller work allocation units pack better in comparison to flows.

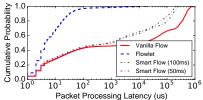
9.2 State Management Performance

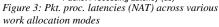
We now evaluate SNF's approach of proactively replicating ephemeral state. We compare it against two other baselines: (1) Optimized External: state is proactively pushed (rather than waiting for the flowlet end) to an external in-memory store and is read at the beginning at the flowlet. This baseline is an optimization to how state is transferred across compute units in today's serverless platforms⁷. (2) Reactive: state is pulled on the arrival of a flowlet from the previous compute unit that the flow was processed at.

We measure the per-packet processing latencies for the various NFs (Figure 4). For the NAT, the median latencies across the three modes, external, reactive and proactive are more or less similar $(0.67\mu s, 0.61\mu s \text{ and } 0.44\mu s)$ due to the fact that state for most flowlets is eventually locally available in all the three models. However, the tail latencies improve while

 $^{^6}$ Since the prototype cannot detect traffic changes that last < 100ms

⁷Today serverless platform don't write to external stores by default; such stores would have to be provisioned by the application.





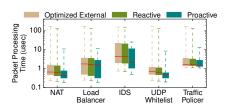


Figure 4: Pkt. proc. Latencies (1-25-50-75-99%-iles) for different storage modes

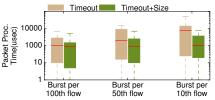


Figure 5: Pkt. proc. Latencies (1-25-50-75-99%-iles) in the presence of adversarial flowlets

shifting from the external to reactive and finally to proactive ($168.18\mu s$, $132.74\mu s$ and $11.01\mu s$ respectively). In both the baselines, upon arrival of the new flowlet, the updated state needs to be pulled from the external store and the previous compute unit respectively, thus the latencies are dominated by the network RTT 8 . In the proactive mode, state is made available prior to the arrival of a new flowlet (unless there is a delay due to network anomalies or the flowlet has been scheduled to a unit which does not have replicated state) due to which processing is not stalled due to state unavailability. Similar latency trends are noticed for the other NFs.

Proactive State Replication: We carry out deeper analyses to understand where the benefits of proactive replication arise from. For the flowlets that were assigned to different units than the immediate previous units for the various NFs, proactive state replication ensured that 90.43% of flowlets (on average across the NFs) were able to proceed seamlessly without any wait time whereas the remaining 9.57% reactively pulled state. This indicates that proactive replication comes into effect the majority of time helping to vastly reduce the tail.

Thus, with state optimizations in place, SNF can achieve median latencies similar to when state is maintained locally which reduces the tail in comparison to existing alternatives.

9.3 Tackling Adversarial Flowlets

In order to evaluate if SNF can tackle adversarial flowlets we use three synthetic workloads with varying frequency of such flowlets: we create these flowlets every 100th, 50th and 10th flow by adding bursts of 20 packets (~1400 bytes) on average. Other aspects of the experimental setup remain the same. For brevity, we only present results for NAT below.

Recall that SNF should be able to mitigate the impacts of adversarial flowlets as it uses a size threshold in addition to inactivity timeout to detect flowlets. To study whether this helps, we compare detecting flowlets using both the criteria (timeout + size) with a baseline mode of using just the timeout (timeout) in terms of the packet processing latencies.

We see in Fig. 5, that it is indeed beneficial to use both timeout and size in comparison to just using the timeout - from the least aggressive to the most aggressive workload we observe that the median (tail) latency reduces from $101\mu s$ (677.9 μs) to $87\mu s$ (504.4 μs), 201.2μ (1.5 μs s) to $93\mu s$ (702.4 μs) and 752μ (5.2ms) to $102\mu\text{s}$ (756.2 μs). Using both helps SNF bound the impact of adversarial flowlets by starting a new flowlet as soon as the size threshold has been met, which happens quickly for an adversarial flowlet and gives us the opportunity to reallocate such flowlets (does not occur while using just timeout) leading to reduced packet processing latencies.

9.4 Fault Tolerance

We study the performance of SNF under failure recovery and compare it against state of the art NF fault tolerance solutions - FTMB and CHC [26, 36]. The main metric of interest is the recovery time, i.e., the amount of time it takes to ensure that a new NF unit is available with up to date state. We fail a single NAT unit and measure the recovery times for FTMB, CHC and SNF at 50% load. We assume that the failover compute unit is launched immediately in all cases.

In case of FTMB, the recovery time is 25.7ms (assuming that FTMB does checkpointing every 50ms) and includes the time taken to load the latest checkpoint as well as the time taken to process the packets that need to be replayed to bring the new NAT instance up to date. CHC under the same failure scenario takes 3.2ms during which the latest state is fetched from the datastore and the in-transit packets are replayed. On the other hand, in SNF the recovery time is 140µs which accounts for the amount of time taken to transfer the state from the OL of the failed NAT unit to this newly launched NAT unit. Unlike FTMB and CHC, given that SNF stores a copy of the latest state at the OL, it does not need to replay packets during recovery leading to a faster recovery time.

9.5 Multiple Controllers

In order to evaluate the performance of SNF at scale when using multiple controllers we compare our approach of using a RM to the baseline mode of operating the controllers independently. We use 10 controllers and the cumulative input load is on average 93.5 Gbps. We record the per-controller provisioned capacity and actual load received and look at their difference (see Fig. 8a-8b). The Y-axis value being 0 represents the ideal case (provisioned capacity equals load), > 0 indicates over provisioning (reducing efficiency).

As seen in Figs. 8a-8b, the amount of over provisioning is minimal in case of SNF as opposed to using independent controllers. The reason being that in the baseline mode there is more resource fragmentation due to controllers provisioning compute units independently. With SNF, since the RM "leases out" capacity of compute units, resource fragmentation is reduced as multiple controllers can send traffic to the same

⁸The tail latencies in case of using an external store are slightly higher than when reactively pulling state in a peer-peer fashion as there may be scenarios where in a flowlet makes a reactive request to the external store and its not available, and thus has to wait longer

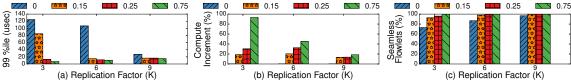


Figure 6: Impact of varying K and \(\text{on} \) on (a) packet processing time, (b) compute instances and (c) flowlets that can be processed seamlessly.

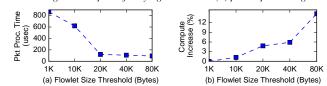


Figure 7: Impact of size threshold on latency and compute provisioning

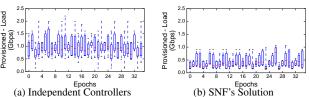


Figure 8: Comparison of epoch-wise overprovisioning distribution by each controllers while using independent controllers and our approach

shared compute unit (up to their allocated share).

9.6 Sensitivity Analysis

Flowlet Inactivity Timeout (T): Setting the flowlet inactivity timeout plays a crucial role in SNF as the value decides how closely SNF can adapt to traffic changes. Additionally, it impacts the efficiency of proactive replication.

We consider two timeout thresholds: $T=100\mu s$ and $T=500\mu s$. In comparison to allocation at the per flow level, we see 5.18X and 4.66X more opportunities to do work allocation when $T=100\mu s$ and $T=500\mu s$, respectively. While $T=100\mu s$ clearly has benefits, we choose $T=500\mu s$ in SNF. This improves the benefits of proactive replication, given that to replicate state of our NFs takes about $160\mu s$.

Flowlet Size Threshold (B): We consider multiple thresholds for B to study the impact on both performance and utilization for the NAT NF. As the flowlet size increases, the processing latencies improve (see Figs. 7a) primarily because the number of reactive state pulls decrease. On the other hand, this decrease in latency comes at the cost of increased usage of compute units (see Figs. 7b) due to poor packability of the larger work allocation units.

Replication Factor (K) and Balancing Knob (α):

Figs. 6a-6c show the impact of changing the value of K and α while having a maximum of 15 compute units in use. Here the NF capacity used is 500 Mbps. For a given K, on increasing α , the number of flowlets that can be processed without state unavailability delays increases, as our scoring metric gives more importance to units that have the state (§5.2.2). However, this comes at the cost of using some amount of additional compute units. Needless to say, the tail latencies improve as the value of α increases as more flowlets are scheduled on units where their state is present (e.g., for K=3, the latency decreases from 107μ s to 6.8μ s when α changes from

0 to 0.75). While for smaller values of α , the latencies are dominated by reactive state pulls, for larger values of α we see that as K increases, the latency increases from 6.8 μ s to 15.2 μ s (when K changes from 3 to 9) reflecting the overhead involved in proactively replicating state.

9.7 Overheads

Work Allocation Overhead. The SNF controller calls into the work allocation algorithm for every new flowlet. This adds an additional latency of 1μ s, but this is once per flowlet and hence the cost is amortized across the packets of the flowlet.

Proactive Replication. In our current prototype, we proactively replicate state to K compute units every 250us (half of the flowlet timeout). For the said trace with K = 3, the proactive replication for NAT, LB, IDS, UDP Whitelister and QoS Traffic Policer uses up an additional bandwidth of 3.62 Mbps, 4.13 Mbps, 3.12 Mbps, 2.9 Mbps and 4.8 Mbps respectively.

10 Other Related Work

Some recent studies have show the benefits of using *existing* serverless platforms in unmodified form for "non-standard" applications, e.g., scalable video encoding [19], and parallelized big data computations [23,34]. Other works instead focus on improving key aspects of serverless computing, e.g., reducing container start-up times [16,32], improved system performance [15], new storage services [28,29], which proposed elastic ephemeral storage for serverless, and security [17]. Our work falls into this second category.

Our work adds to the long line of literature on network functions and NFV. Improving performance in standalone software environments is the goal of several papers [3, 4, 22, 33, 40]. Several other systems tackle state management issues [21, 25, 42]. There has also been significant efforts in failure resiliency for NFV environments [26, 30, 36].

11 Conclusions

This paper shows the benefits of leveraging serverless computing for streaming stateful applications, using the example of NFs. Our system SNF effectively tracks varying NF workload demands by elastically allocation fine grained lambda-style compute resources, while ensuring good efficiency. SNF decouples the unit at which functions operate and the unit of serverless work allocation, using flowlets for the latter. Additionally, we develop a peer-peer in-memory state storage service that proactively replicates state during inter-flowlet gaps, realizing ephemeral storage which is key to ensuring low per packet processing latency.

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