Data center resource management for in-network processing

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Contents

Chapter 1

Introduction

This Master's thesis has been written at the Technische Universität Darmstadt, Germany, during a six-month Erasmus+ exchange and under the supervision of Prof. Patrick Eugster [†], M.Sc. Marcel Blöcher [†] and Prof. Fulvio Risso [‡].

1.1 Abstract

Data centers distributed systems can nowadays make use of in-network computation to improve several factors: DAIET [14] inventors claim to achieve a 86.9%-89.3% traffic reduction by performing data aggregation entirely in the network data plane. Other solutions like NETCHAIN [9] and INCBRICKS [11] let programmable switches store data and process queries in order to cut end-to-end latency. It is now even possible to provide guarantees to applications with specific requirements: for instance, CLOUDMIRROR [10] enables applications to reserve a minimum bandwidth.

For the time being, it seems that there is still no valid resource allocation algorithm that takes into account the presence of a network having a data plane that is (in part o completely) capable of basic In-Network Processing (INP) operations. The objective of this thesis is to model and evaluate an Application Programming Interface (API) through which applications can ask for resources in a data center exploiting INP capabilities while providing guarantees (e.g., bandwidth).

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1.2 Problem statement

Using INP to keep scaling data centers' performance seems a promising idea: Daiet [14] inventors claim to achieve a 86.9%-89.3% traffic reduction, hence reducing servers' workload; NetChain [9] can process queries entirely in the network data plane, eliminating the query processing at servers and cutting the end-to-end latency to as little as half of an RTT.
Current data center Resource Managers (RMs) (e.g., Apache YARN [17], Google Omega [15]) are not completely network-unaware: for instance, some of them are capable of satisfying affinity rules. CloudMirror [10] even provides bandwidth guarantees to tenant applications. Still, current RMs do not consider INP resources.
As a consequence, tenant applications cannot request INP services while asking for server resources.

1.2.1 Modeling INP resources

This Master's thesis goal consists in investigating how to model INP resources and how to integrate them in RMs.

In order to offer INP services to a tenant application, the latter should be capable of asking for INP resources through an API. To do that, INP resources must be modeled not only to support currently existing INP solutions such as [14] [9] [11] [7], but also to support future ones. It might be convenient to derive a single model to describe both server and INP resources.

Classic tenant application requests can often be modeled as a key-value data structure. CloudMirror [10] requires a Tenant Application Graph (TAG) as an input, which is a directed graph where each vertex represents an application component and links' weights represent the minimum requested bandwidth. One possible model could be based on a TAG, describing network resources and/or INP services as vertexes or links. Tenants applications could either use the same model used within the data center or a simplified one, adding another level of abstraction.

Finally, a network-aware placement algorithm in the Resource Manager should then be able to allocate the requested resources accordingly.

Chapter 2

Background

The aim of this chapter is to introduce currently existing technologies exploited in data centers nowadays. This chapter starts with a general description of how resource are managed in a data center § 2.1 (e.g., Virtual Machines) and ends with a brief introduction to network techniques and concepts which are strictly related to Resource Managers.

2.1 Resource management in data centers

In a data center, resources of any kind are being virtualized in order to achieve higher flexibility, portability and availability. Usually both compute and storage resources are virtualized by means of Virtual Machines (VMs) and containers. Flexibility and portability are both automatically achieved thanks to this resource virtualization, resulting in some software that can be deployed dynamically, run by multiple platforms and even live migrated; availability is usually simply achieved by not co-locating VMs in a single server or rack.

Furthermore, a Resource Manager's aim is to manage all resources in a cluster and to schedule applications (sometimes referred as *jobs*) assigning the corresponding VMs/containers to the *best* subset of servers.

Today there are multiple Resource Managers that are using different approaches to solve different design issues. This section examines these existing RMs, trying to categorize them based on how they face different scheduling problems.

2.1.1 Data center terminology

The elementary computational unit in a data center is called *node*. As mentioned in § 2.1, nodes are being virtualized by means of VMs and

containers. Nodes are run on *servers*, which are grouped in *racks*. Servers within a rack are usually connected between themselves thanks to the so-called Top of Rack (ToR) switch. Racks of servers are then grouped into *cells*, that some times may be special-purpose. Usually a cell is grouped with a few small test ones to form up a *cluster*. Most of the RMs manage resources in one cluster. One or more clusters form a *data center*, which together form a *site*.

2.1.2 Scheduling architectures

Monolithic. Probably the most simple scheduler architecture out there: a monolithic scheduler consists in a single instance scheduler applying the same scheduling algorithm for every incoming job (so there is no concurrency between resource requesters). A centralized scheduling logic can support a more refined job placement. On the other hand, the absence of parallelism causes an higher latency with respect to other architectures. Although the single instance could distinguish among different job types hence treating those differently, its maintenance is not trivial, due to its single instance (and code base) nature.

Two-level. This architecture requires computer clusters to be dynamically partitioned in sub-clusters, each having a dedicated scheduler. A centralized resource allocator determines which and how many resources should made be available to each scheduler: this is done by sending *offers* to schedulers (*pessimistic concurrency*). Obviously conflicts can be avoided by not offering the same resource to multiple schedulers at the time. The same entity is in charge of dynamically divide clusters into sub-clusters: this is done to avoid resource fragmentation.

Shared-state. Schedulers are not mapped to sub-clusters anymore. Multiple schedulers have access to the entire cluster and there is no centralized resource allocator assigning resources to schedulers. In this architecture, schedulers will try to acquire resources (*optimistic concurrency*), having not only the possibility of choosing between all the resources in the cluster, but also to ask for those who have been already acquired by another scheduler. To do this, a centralized data structure called *cell state* maintains all the resource allocation information in the cluster, providing in fact a *shared-state* of it. Schedulers will try to acquire resources by atomically

modifying this cell state, that will actually be modified only if the request does not cause any conflict. Each scheduler makes its own resource-allocation decision on a private copy of the cell state, which is updated every time the scheduler tries to acquire some resource, no matter what the outcome of the attempt is.

2.1.3 Taxonomy

This section tries to underline the different scheduling design issues that RMs must face by building a simple short taxonomy, following the guidelines provided by Google in their Omega [15] paper.

Scheduling work partitioning. The workload can be distributed across schedulers basically in three different ways: (i) workload-type unaware load balancing, (ii) workload partitioning to specialized clusters and, (iii) a combination of the two.

Interference. Schedulers can concurrently ask for the same resources. In the pessimistic approach different resources are offered to different schedulers, making it impossible for them to compete for the same resource: this of course represents a lack of parallelism, since resource offers are made by a logically centralized entity. The optimistic approach instead lets every scheduler claim the desired resources and just conflicting requests are denied, which of course introduces an overhead. Of course, there could be no interference in case there is only one scheduler.

Choice of resources. Schedulers can pick amongst (i) all cluster resources or (ii) a subset of those. When resources are divided into disjoint sets there will be no concurrency by definition. Making all resources available to all scheduler will make it easier for schedulers to place jobs with particularly stringent needs, and it is also useful when the scheduling decision must be taken based on overall state (e.g., the amount of free resources in the cluster).

Preemption. Schedulers can be either allowed to preempt other schedulers' job assignments or not. Allowing preemption brings a greater flexibility at the cost of interrupting an already-running job.

Allocation granularity. Considering that jobs contain multiple tasks that can be scheduled on different resources, schedulers can either (i) incrementally schedule tasks as soon as new resources become free or (ii) schedule a job only when all tasks can be scheduled on the spot. Not all job types can exploit the incremental resource acquisition. This technique can also bring the system to a deadlock if there is no back-off mechanism that releases resources once a job cannot acquire all resources in a reasonable amount of time.

2.2 In-network processing

2.2.1 A definition

2.2.2 Examples

2.3 Network Function Virtualization

2.3.1 Examples

Chapter 3

Analysis

Chapter 2 introduced how resources can be managed in a data center and different network techniques such as INP and Network Function Virtualization (NFV). This chapter's aim is to dig into the details of these systems and to extract common patterns between similar INP solutions in order to be able to derive a model capable of fully describing INP resources.

3.1 Resource management frameworks

After having described the basics behind resource management in § 2.1, it is time now to dig into the details of existing RMs currently out there and to categorize them following the taxonomy introduced in § 2.1.3.

3.1.1 Borg [18]

Borg [18] is the first container-management system developed by Google. Jobs are divided in two groups depending on their workload type (long-running and batch) and they were initially scheduled by a logically centralized controller called *Borgmaster*. After Google developed the shared-state Omega [15] scheduler (analyzed in § 3.1.2), Borg [18] adopted the shared-state architecture as well, hence being no more a monolithic solution.

3.1.1.1 Scheduling

Each cell has its own logically centralized controller called *Borgmaster*, which is essentially split in two parts: (i) the scheduling part, consisting in one or more schedulers differentiated by the workload type they handle and (ii) a management unit in charge of handling client Remote Procedure Calls (RPCs) and communicating with all other Borg [18] agents. Schedulers

mainly work on tasks rather than jobs. Tasks are scanned in a round-robin fashion and their priority is also taken into account. Schedulers must first find all available machines for the task to be scheduled (also considering those currently acquired by a task with lower priority) and then find the best machine amongst them all. This second part is done by taking into consideration not only user-specified preferences, but also data center global goals like minimizing of preempted tasks and allocating tasks on machines which already have the needed packages installed in order to reduce the installation time, which usually takes about 80% of the total start-up latency.

3.1.1.2 Details

Jobs. Jobs in Borg [18] are split into multiple tasks which run within a single cell: tasks belonging to one job cannot be spread amongst multiple cells in the same cluster. In fact, Borg [18] only operates on cells. Each job has some properties such as a name, an owner, and most importantly, constraints about *machines* (e.g., processor architecture, etc.) which will determine where its tasks will be scheduled. Tasks instead have *resource* requirements (e.g., CPU cores, RAM, etc.) expressed in terms of *quotas* (an array of resource quantities). Task properties can be modified at run-time by the job owner: this is done by pushing a new job configuration file to Borg [18] and ordering the scheduler to update the involved tasks via a non-atomic transaction. Most of the workload in Borg [18] run in containers rather than VMs to avoid the virtualization overhead.

Fairness. Jobs have a priority expressed as an integer. Workload types are even more differentiated with the definition of non-overlapping priority bands, one for a different kind of workload. Borg [18] schedulers are preemptive, and in order to contain the negative effects of preemption cascades the system does not allow internal preemption for certain priority bands.

Resource reclamation. Tasks do not fully use their resources for their entire lifespan. This is why the *Borgmaster* estimates every few seconds what is the actual amount of resources that each task needs and reclaims the unused resources to make them available for other tasks. This is done by periodically contacting Borg [18] agents running on each cluster machine,

requesting for fine-grained resource consumption information. The initial estimated amount of resources actually needed by a task corresponds with its maximum limit, and it then slows according to the actual consumption. If the actual resource usage exceeds the estimation, than the latter is rapidly increased. This technique justifies why Borg [18] inventors have noticed that dedicating clusters for different workload types is inconvenient. They showed how segregating long-running and batch jobs in different specialized clusters requires 20% to 30% more machines than having clusters who run both type of jobs using resource reclamation.

3.1.2 Omega [15]

Omega [15] is a parallel, lock-free and optimistic cluster scheduler by Google. As said in [3], it was born after Borg [18] with the aim of improving its software engineering. There is no central resource allocator: all of the resource-allocation decisions take place in the schedulers. Multiple schedulers were first introduced in Omega [15] and then in Borg [18], making the latter scheduler no more monolithic.

3.1.2.1 Scheduling

This solution makes use of a data structure called *cell state* containing information about all the resource allocation in the cluster. Each cell has a shared copy of this data structure, and each scheduler is given a private, local, frequently-updated copy of cell state that it uses for making scheduling decisions. According to the optimistic concurrency technique, once a scheduler makes a placement decision, it updates the shared copy of cell state with a transaction. Whether or not the transaction succeeds, a scheduler re-syncs its local copy of cell state afterwards and, if necessary, re-runs its scheduling algorithm and tries again. Omega [15] supports specialized schedulers: authors have showed the advantages of a MapReduce [6] specialized scheduler in [15].

3.1.3 Apache™ Hadoop© YARN [17]

Apache™ Hadoop© YARN [17] (for the sake of brevity: Apache™ YARN [17]) is the Resource Manager of Apache™ Hadoop©, a framework for distributed processing across clusters.

Apache™ Hadoop© was initially an open source implementation of MapReduce [6], but then the programming model has been separated from the resource management function, resulting in an application-independent RM known as Apache™ YARN [17].

3.1.3.1 Entities

For each tenant application there is an *Application Master* whose task is to (i) manage the application life cycle and (ii) negotiate the resources that the application needs with the central RM, making Apache™ YARN [17] a monolithic scheduler with no interference between tenant applications. Each node then has a *Node Manager* thanks to which the RM can allocate tasks on it. The *Node Manager* must also periodically monitor resource availability and report failures.

3.1.3.2 Scheduling

Application Masters issue resource request to the RM, containing containers properties and locality preferences. Upon receiving a resource request, the centralized scheduler generates containers using available resources periodically advertised by the nodes themselves. The outcome of this procedure is reported to the Application Master corresponding to the tenant application who initiated the request. Application Masters are also informed upon inserting new nodes into the system.

3.1.3.3 Details

Preemption. The RM can also ask to Application Masters to revoke some resources in case of a shortage. The application will then have a few choices: for instance it can yield containers that are less important or checkpoint its current status. If an application does not collaborate with the RM upon receiving a *revoking request*, the RM will forcibly terminate those targeted containers.

Failures. The RM represents a single point of failure for the system and its restart causes the termination of all containers in the cluster, including all their Application Masters. Node failures are detected by the RM using timeouts (nodes have to periodically contact the RM). The RM will then inform all Application Masters who are responsible for responsible for the application life cycle.

3.1.3.4 Conclusions

Undoubtedly, Apache™ YARN [17] dedicates less attention to scalability due to its de facto monolithic scheduler: there are multiple Application Masters who just take care of the application life cycle and do not perform scheduling, which is done instead by a single RM.

However, Apache™ YARN [17] authors state that the centralized RM can assure fairness, capacity and locality thanks to the central and global view that it has on the system. They justify this by pointing out that Apache™ Hadoop© is an open platform which lets different independent sources share the same cluster, unlike other "*closed-world*" schedulers like Google Omega [15].

3.1.4 Mesos [8]

Mesos [8] is a two-level cluster scheduler based on *resource offers*. It has multiple schedulers since Mesos [8] has been conceived to share clusters between different cluster computing frameworks since the beginning of its development. By contrast, Apache™ YARN [17] was initially embedded in the first version of MapReduce [6] and subsequently became independent out of the necessity to scale Apache™ Hadoop©.

3.1.4.1 Entities

This scheduler has a logically centralized resource *allocator* in charge of offering resources to different schedulers. It is called *Mesos master* and it is replicated for fault tolerance. A scheduler with its *executor* (worker) node are together called *framework*. Nodes running on cluster nodes are called *Mesos slaves*.

3.1.4.2 Scheduling

Initially, every cluster node reports to the master node its own available resources. Based on this data, the master node can then offer resources to application frameworks based on a particular policy. The master node does not offer the same subset of resources to each scheduler. Obviously resource conflicts can be avoided by not offering the same resource to multiple schedulers at the time. Upon receiving resources offers, application frameworks can either reject the offer (in case it does not satisfy all framework's constraints) or tell the master which tasks need to be run on the dedicated resources. Mesos [8] already knows that certain types of frameworks always reject certain resource offers characterized by some factors, so frameworks can specify *filters* in order for the master to automatically avoid proposing certain kind of resources.

The resource allocation logic can be customized, and Mesos [8] includes an allocation module based on priority and one based one fairness. Tasks can be preempted, however frameworks can be offered *guaranteed* resources on which tasks cannot be preempted.

3.1.5 Guarantee provisioning: CloudMirror [10]

CloudMirror [10] allows client applications to specify bandwidth and high availability guarantees.

3.1.5.1 Motivation

Prior models are not suitable to represent interactive non-batch applications with very stringent bandwidth requirements. Both the hose and the Virtual Oversubscribed Cluster (VOC) model are inefficient as they overallocate bandwidth. The main reason of why this happens is that both models *aggregate* bandwidth requirements between different application components into a single hose: as a consequence, the VM scheduler does not get to know the actual bandwidth needed between application components. At the opposite extreme there is the pipe model which, besides not exploiting statistical multiplexing, is not scalable since it requires a list of all bandwidth guarantees between pairs of VMs. This led CloudMirror [10] inventors to come up with a new model.

3.1.5.2 Tenant Application Graph

The TAG is a directed graph where each vertex represents an application component and links' weights represent the minimum requested bandwidth. Each vertex can have an optional *size*, denoting the number of VMs belonging to the component.

There are two types of edges: (i) self-loop edges, that are equivalent a hose model and (ii) standard vertex-to-vertex edges. A standard edge from vertex a to vertex b is labeled with an ordered pair of numbers $< S, R >$, indicating respectively the guaranteed bandwidth with which VMs in a can send traffic to VMs in b and the guaranteed bandwidth with which VMs in b can receive traffic from VMs in a:

3.1.5.3 Model advantages

The edge label format $< S, R >$ allows the model to exploit statistical multiplexing, since S can represent the peak of the sum of VM-to-VM demands instead of the (typically larger) sum of peak demands needed by the pipe model. ***TO BE CONTINUED*** ...

3.1.6 Resource managers comparison

The table below contains a quick comparison amongst RMs previously analyzed. In order to categorize those, the taxonomy introduced in § 2.1.3 has been used.

Resource Managers: quick summary		
Borg [18]	Scheduling architecture	Shared-state
	Scheduling work partitioning	Specialized clusters
	Interference	Optimistic approach
	Choice of resources	All cluster resources
	Preemption	Yes
	Allocation granularity	
Omega [15]	Scheduling architecture	Shared-state
	Scheduling work partitioning	Specialized clusters
	Interference	Optimistic approach
	Choice of resources	All cluster resources
	Preemption	Yes
	Allocation granularity	Per-scheduler policy
Apache^{TM} YARN [17]	Scheduling architecture	Monolithic
	Scheduling work partitioning	—
	Interference	No interference
	Choice of resources	All cluster resources
	Preemption	Yes
	Allocation granularity	
Mesos [8]	Scheduling architecture	Two-level
	Scheduling work partitioning	
	Interference	Pessimistic approach
	Choice of resources	Subset of resources
	Preemption	Yes
	Allocation granularity	All-or-nothing

Table 3.1: Resource Managers comparison table using the taxonomy introduced in § 2.1.3

3.2 Existing in-network processing solutions

State-of-the-art INP solutions will be discussed in this section with the aim of deriving a model capable of fully describing INP resources. To that end, it is necessary to dig into the details and to recognize common patterns between them.

3.2.1 In-network aggregation: Daiet [14]

Daiet [14] is a system that performs in-network data aggregation for partition/aggregate data center applications (big data analysis such as MapReduce [6], machine learning, graph processing and stream processing). Instead of letting worker servers entirely perform computation on the data and then communicate with each other to update shared state or finalize the computation, the system let network devices perform data aggregation in order to achieve traffic reduction, thus reducing the processing load at the destination.

The inventors have proven that in-network data aggregation can reduce the network traffic significantly for machine learning algorithms (e.g., TensorFlow [1]) and for graph analytics algorithms (e.g., GPS [13]), hence justifying the usefulness of this system. The system has been designed for P4 [2] and programmable ASICs, and it can be used on any other Software Defined Networking (SDN) platform.

3.2.1.1 Details

Controller. When executing a MapReduce program, the job allocator informs the network controller of the job allocation to the workers. Then, the network controller pushes a set of rules to network devices in order to (i) establish one aggregation tree for each reducer and (ii) perform per-tree aggregation. An aggregation tree is a spanning tree from all the mappers to the reducer.

Packets. Since every reducer has its own aggregation tree associated with it, network devices should know how to correctly forward traffic according to the corresponding tree: to achieve this, a special *tree ID* (that could coincide with the *reducer ID*) packet field allows network devices to distinguish different packets belonging to different aggregation trees. Obviously, they must also know the output port towards the next network device in

the tree and the aggregation function to be performed on the data. Packets are sent via UDP (therefore communication is not reliable) with a small preamble that specifies (i) the number of key-value pairs contained in the packet and (ii) the *tree ID* whose packet belongs to. They payload is not serialized to achieve a faster computation by network devices.

3.2.1.2 Algorithm

To store the key-value map, network devices use two hash tables for each tree: one for the keys and one for the values. Upon a collision, the algorithm checks whether the key is matching or just the hash is. In the former case, data aggregation is performed. In the latter case, the conflicting pair will end up in a *spillover bucket* that will be flushed to the next node as soon as it becomes full: this is done since this data is more likely to be aggregated by the next network device if it has spare memory. A network device will also flush its data as soon as all its children (according to the aggregation tree) have sent their data: this is made possible by forcing network devices to send a special *END* packet after transmitting all key-value pairs to their successor.

Used indexes are stored in a *index stack* to avoid scanning the whole hash table when flushing.

3.2.1.3 Implementation

The network data plane has been programmed using P4 [2], which brings two main drawbacks: (i) a match-action table cannot be applied more than once for the same packet, forcing the programmer to perform loop unrolling in case of multiple headers in the same packet that need to be modified by the same rule table and (ii) keys must have a fixed size, causing a big waste of memory in applications where keys have variable-lengths (e.g., strings). The second drawback will also cause arrays to have fewer but bigger cells, thus increasing the probability of collisions. If these collisions involve pairs having different keys (section 3.2.1.2), data will not be aggregated, causing traffic to increase.

3.2.1.4 Minimum system requirements

For each aggregation tree (i.e., for each reducer), network devices must form a tree whose root is connected to the reducer and whose leaves are

connected to mappers. Each mapper has to be connected to exactly one network device of the lowest level. Network devices must (i) store two arrays (one for the keys and one for the values) and (ii) be able to hash keys. The solution requires that the system has a centralized SDN controller connected to all switches. The SDN controller must push flow rules to all switches belonging to at least one tree.

3.2.1.5 Conclusions

Besides all the drawbacks brought by P4 [2] listed in section 3.2.1.3, inventors claim to achieve a 86.9%-89.3% traffic reduction, causing the execution time at the reducer to drop by 83.6% on average.

3.2.2 Coordination services: NetChain [9]

NetChain [9] is an in-network solution for coordination services, such as distributed locking, barriers, etc. All these services are realized on top of a strongly-consistent and fault-tolerant key-value store, which is entirely implemented in the network data plane. The network device in charge of storing the distributed store is a programmable switch: this brings an obvious limitation in terms of storage size, that makes NetChain [9] an acceptable solution only when a small amount of critical data must be stored in the network data plane, e.g., coordination services.

NetChain [9] can process queries entirely in the network data plane, causing the end-to-end latency to drop from multiple RTTs to as little as half of one RTT since servers are not involved in query processing anymore.

3.2.2.1 Details

Packets. Custom UDP packets are used for queries, containing fields like *operation*, *key* and *value*. Read and write queries only involve the network data plane, while insert and delete queries involve the network controller to set up entries in switch tables and to perform garbage collection, respectively. This is acceptable since coordination services usually perform read and write queries on already-existing objects, e.g., locks. Each switch has its own IP address, and packet headers contain the list of addresses of switches to be traversed, allowing those to properly forward packets to the their successors (from head to tail for write queries and the opposite for read queries). This list of IP addresses is inserted by the client (a NetChain [9] agent).

Consistency. A variant of Chain Replication [16] is used in the data plane to handle read and write queries and to ensure strong consistency, while switches reconfiguration is handled by the network control plane. The main difference with the standard Chain Replication [16] protocol is that objects are stored on programmable switches instead of servers. Switches are logically connected together in order to form an oriented chain: read queries are processed by the *tail* switch while write queries are sent to the *head* switch, which will forward the updated state to the rest of the chain. The key-value store is partitioned amongst *virtual nodes* using consistent hashing, mapping keys to a hash ring. Each ring segment is stored by

$f+1$ virtual nodes allocated on different physical switches, hence tolerating faults involving up to f switches.

3.2.2.2 Implementation

The network data plane has been programmed in P4 [2] while the controller has been coded in Python, it runs on a server and communicates with switches through the standard Python RPC library. Switches agents are Python processes who run in the switch OS. Some P4 [2] drawbacks were already discussed in section 3.2.1.3.

The out-of-order UDP delivery problem is resolved by adding sequence numbers to write queries, hence serializing those operations, while the loss of packets is coped by *client-side retries* based on timeouts.

3.2.2.3 Minimum system requirements

Network devices must form a chain of length $f + 1$ in order to tolerate f failures. The client must include the list of IP addresses of all the $f + 1$ switches to be traversed in each query packet header (from head to tail for write queries and the opposite for read queries; storing the entire backward list for read queries is only necessary in case of tail failures).

Network devices must dedicate some local storage to NetChain [9]: more specifically, they need to store a (i) register array to store values and a (ii) match-action table to store the keys' location in the register array and the corresponding action to be performed. The solution requires that the system has a centralized SDN controller connected to all switches. The SDN controller must handle switches reconfigurations.

3.2.2.4 Conclusions

NetChain [9] inventors state that the on-chip memory of programmable switches in enough for coordination services. Assuming a 10 MB partition allocated on each NetChain [9] switch, a data center with 100 switches can provide a $(10\,\text{MB} \cdot 100)/3 = 333\,\text{MB}$ storage with a replication factor of three: that would be enough for the average number of files (22k, from 0 to 1 byte) managed by a typical Chubby [4] lock service instance, as cited by Google in their corresponding paper. Likewise, inventors claim that switches total memory is enough for a distributed locking system:

assuming 30 B locks, the previously-mentioned example would be capable of storing $333\,\mathrm{MB}/30\,\mathrm{B} = 10M$ concurrent locks.

3.2.3 In-network caching fabric: IncBricks [11]

IncBricks [11] is a hardware-software co-designed system for in-network caching: it makes use of network accelerators attached to programmable switches whenever complicated operations should be performed on payloads. Supporting multiple gigabytes of memory, network accelerators overcome the limited storage problem typical of programmable switches, which usually have a memory of tens of megabytes.

3.2.3.1 Details

Hardware. IncBricks [11] is composed by two components: (i) IncBox, an hardware unit consisting of a network accelerator and a programmable switch, and (ii) IncCache, a software system for coherent key-value storage. Packets arriving to an IncBox device are first managed by the switch, which forwards the packet to the network accelerator only if it is labeled as an in-network cache one. If there is a match, the programmable switch will check whether the packet has been already cached by the network accelerator or not, and will forward the packet to the right network accelerator attached to it in the former case.

Logic. The system has been designed having a multi-rooted tree topology in mind. For each key the centralized SDN controller comes up with a set of *designated* IncBox units allowed to cache that key. Any other IncBox unit placed between these designated units won't cache data with that specific key. Then, for a given key and a given destination node, the SDN controller establishes a unique path of designated IncBox units. Every IncBox unit in the system will get to know (i) the set of immediate designated successors (according to the tree topology) for every key it is responsible of and (ii) the unique successor used for a given destination and a given key. This data is stored in the so-called *global registration table*. Storing the former information can be useful in case of failures since it is possible to build alternative paths immediately, making the whole system more reliable. As soon as a failure is detected, the SDN controller updates all the involved tables.

3.2.3.2 Implementation

The storage has been implemented using a bucket spilling hash table plus a hash index table ***TO BE CONTINUED*** ...

3.2.3.3 Minimum system requirements

Communicating nodes (VMs) represent the leaves of the tree. Each path must include exactly one root switch. All things considered, it seems reasonable to state that the actual required topology is a chain starting from a leaf, passing through a root node and ending on another leaf. IncBox units must dedicate some local storage to realize the caching system. The solution requires that the system has a centralized SDN controller connected to all switches. The SDN controller must set configure network devices in order for them to forward IncBricks [11] packets accordingly.

3.2.3.4 Conclusions

3.2.4 Aggregation protocol: SHArP [7]

SHArP [7] stands for *Scalable Hierarchical Aggregation Protocol*, and it defines a protocol for reduction operations. This solutions aims to accelerate High Performance Computing (HPC) applications by offloading some operations to the network. SHArP [7] is targeted to support the two most used APIs in the HPC area today: MPI [19] and OpenSHMEM [5]. The kind of operations that can be offloaded to the network are: (i) MPI [19] barrier, reduce and allreduce, (ii) logic operands like sum, min, max, or, xor, and, (iii) integer and floating-point operations.

3.2.4.1 Details

Entities. Aggregation Nodes (ANs) are logical entities performing reduction operations. Such a node can either execute on a network device or on a server, and it is implemented as a daemon, namely `sharpd`. All ANs must form an aggregation tree. Multiple trees are allowed in a system. Similarly to other in-network aggregation solutions like Daiet [14], data is aggregated along the aggregation tree by ANs, until it reaches a root AN that is in charge of distributing the result.

The protocol also introduces the concept of *group*, consisting in a subset of physical hosts that are connected to the tree leaves: for instance, in MPI [19] a group coincides with a *communicator*. One aggregation tree supports multiple groups.

Resources are managed by a special management entity called Aggregation Manager (AM). Faults and errors are always notified to this node, that will also take care of freeing all resources belonging to the tree in which the error occurred. The detection of faults and errors cannot be done using timeouts since HPC APIs do not bound the duration of aggregation operations: this is why faults must be necessarily detected by monitoring.

Data flow. Eventually, an host program will need to execute a job on multiple nodes. When the job is launched and all host processes have been created (e.g., a communicator in MPI [19]), either the cluster resource manager (like Slurm [20] or IBM® Spectrum LSF) or an MPI [19] launcher like `mpirun` will contact the AM, which will dedicate SHArP [7] resources to the job and return back the list of these allocated resources. At this point,

a SHArP [7] group has been created. Each SHArP [7] daemon `sharpd` running on every group member will establish a reliable connection to the dedicated leaf switch. The AM informs the ANs about the switch resources allocated to the application, not allowing it to exceed the allocation.

Once connections have been established, all group members send an aggregation request message to their parent AN. Each AN waits for all its children requests before sending the aggregated data piggybacked on another aggregation request to the parent node. ANs temporarily maintain a data structure to track an aggregation operation's progress.

As soon as the tree root node receives data from all its children, it performs the final aggregation and it sends the result to a destination, that could be (i) one or more process belonging to one or more groups or (ii) an external process not belonging to any reduction group. In the former case, the aggregation tree is used to redistribute the result.

3.2.4.2 Implementation

SHArP [7] has been implemented using InfiniBand [12] as communication standard with Mellanox's SwitchIB-2^{TM} devices, which provide support for data reduce operations and for barriers. Nodes in the SHArP [7] tree are InfiniBand [12] end nodes, and links are implemented using InfiniBand's [12] *Reliable Connection*s. When distributing a result using a multicast address, though, an unreliable delivery mechanism is used. One AN can participate to at most 64 different aggregation trees.

3.2.4.3 Minimum system requirements

ANs (usually run by network devices) must form a tree whose leaves are connected to data producers (a *communicator* in MPI [19]). Each data producer is connected to only one tree leaf. The root AN, instead, is connected to the data consumer, which receives the final aggregated result. ANs must dedicate part of their local memory to the system. The special management unit (AM) must act as a SHArP [7] RM, dedicating SHArP [7] resources to those entities who request for them.

3.2.4.4 Conclusions

For MPI [19] applications SHArP [7] brings a significant advantage in terms of latency: tests show that the latency improvement factor (latency expe-

rienced without SHArP [7] divided by the one experienced with SHArP [7]) is proportional to the message size. Even in the worst case, with a message size of just 8 MB, an MPI [19] execution with SHArP [7] is twice as fast as the one without using it.

Chapter 4

Requirements

4.1 In-network key-value store

Examples:

- NetChain [9] for coordination services
- IncBricks [11] for in-network caching

Network devices must:

- form a chain
  - NetChain [9]: the NetChain [9] agent must explicitly specify the list of IP addresses of all switches belonging to the chain, since its order depends on the query type (read or write).
  - IncBricks [11]: the chain must connect the two communicating nodes, having just one switch connected per node (the ToR switch).
- dedicate part of their local memory to store a key-value map
  - NetChain [9]: distributed map, hash segments are repeated across multiple physical switches. Servers are never involved.
  - IncBricks [11]: cache, zero or more switches can store the pair. Servers may be involved in case no switch has cached the pair.

Data consumers:

- execute queries
- are VMs

Data producers:

- own data
- are VMs
  - NetChain [9]: are data consumers
  - IncBricks [11]: are not data consumers

The SDN controller:

- must be connected to all the network devices
  - NetChain [9]: must form the chain and handle switches reconfigurations
  - IncBricks [11]: must configure network devices in order for them to forward IncBricks [11] packets accordingly

4.2 In-network data aggregation

Examples:

- Daiet [14]
- SHArP [7]

Network devices must:

- form a tree whose root is connected to data consumers and whose leaves are connected to data producers
  - Daiet [14]: just one data consumer
  - SHArP [7]: one or more data consumers
- dedicate part of their local memory to store a key-value map
- be able to perform basic operations on data, such as writing and hashing

Data producers must:

- be connected to exactly one tree leaf
- wait for all its children to send aggregated data

Data consumers must:

- be connected to the tree root

A special unit:

- Daiet [14]: must push flow rules to all switches belonging to at least one tree. It is the SDN controller.
- SHArP [7]: must act as a RM, dedicating SHArP [7] resources to those entities who request for them. It must not necessarily be the SDN controller.

4.3 INP aspects of interest to RMs

- (Aggregation) Tree
  - **Leaf aggregator switches fan**: since aggregator switches in Daiet [14] need to wait data from all its children, the higher the fan is, the more time a switch will need to wait, the slower the system will perform
  - **Tree height** and the **number of switches**: the higher, the more messages, the smaller messages are; the shorter, the less messages, the bigger messages are
  - **Data producers distribution**: data producers sending data with the same key should be connected to "close" leaves in order for them to perform data aggregation lower in the tree
  - **Tree balance**: an extremely unbalanced tree could cause some parts of it to wait for data to be aggregated in the deepest parts
- Chain
  - **Chain length**: the longer, the more reliable the system is, the higher the latency for write queries in NetChain [9]

Chapter 5

System

Chapter 6

Evaluation

Chapter 7

Conclusions

Acronyms

AM Aggregation Manager. 28, 29

AN Aggregation Node. 28, 29

API Application Programming Interface. 5, 6, 28

HPC High Performance Computing. 28

INP In-Network Processing. 5, 6, 11, 20

NFV Network Function Virtualization. 11

RM Resource Manager. 6–9, 11, 15, 16, 19, 29, 33

RPC Remote Procedure Call. 11

SDN Software Defined Networking. 20, 22, 24, 26, 27, 32, 33

TAG Tenant Application Graph. 6, 18

ToR Top of Rack. 8, 31

VM Virtual Machine. 7, 12, 18, 27, 31, 32

VOC Virtual Oversubscribed Cluster. 18

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