Characterizing The Impact Of Network Latency On Cloud-based Applications' Performance

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ABSTRACT

Businesses and individuals run increasing numbers of applications in the cloud. The performance of an application running in the cloud depends on the data center conditions and upon the resources committed to an application. Small network delays may lead to a significant performance degradation, which affects both the user's cost and the service provider's resource usage, power consumption and data center efficiency. In this work, we quantify the effect of network latency on several typical cloud workloads, varying in complexity and use cases. Our results show that different applications are affected by fixed and variable latency to differing amounts. These insights into the effect of network latency on different applications have ramifications for workload placement and physical host sharing when trying to reach performance targets.

Keywords

data center, network latency, performance

1. INTRODUCTION

Cloud computing has revolutionized the way businesses use computing infrastructure. Instead of building their own data centers, companies rent computing resources available from providers like Google Cloud Platform, Amazon EC2, and Microsoft Azure, and deploy their applications in the cloud. While customers are able to choose the specifications of the used computing instances according to their needs, specifying guarantees in terms of network latency for an application is not yet fully possible.

The fact that latency impacts performance is well known for wide area networks(WAN) [30, 44, 42, 33, 11], for example as it is implicitly a part of rate computations for TCP, but also for host applications. The latency studied in these works was in the order of milliseconds to hundreds of milliseconds. However, today much of the communication is within data centers, meaning that the latency is far below the WAN scale. Several studies [46, 8, 49, 35] have shown that network latency variability is common in multi-tenant data centers. There is a need to quantify the impact of network latency on an application's performance as even small amounts of delay, in the order of tens of microseconds, may lead to significant drops in application performance [54]. While past work has provided comprehensive performance studies of the effect of CPU cache and memory, the operating system or virtualization upon application performance (e.g. [51, 32, 48, 46]), a significant gap exists in evaluating the impact of networking resources, particularly network latency and network latency variation.

In this paper, we study the impact of network latency upon application performance for a set of cloud applications, ranging from a domain name server (DNS) to machine learning workloads running on Spark. We select the workloads so they represent an increasing scale of complexity, and do not target the same frameworks. Our work is both measurement and implementation driven, and is based on an extensive exploration of latency characteristics.

We describe an experimental methodology developed to evaluate the relationship between application performance and network latency. We do this by artificially injecting arbitrary network latency into a networked system. We use a bespoke hardware appliance, NRG , we specifically designed for this purpose that affords us fidelity of per-packet latency control and a precision on the order of tens of nanoseconds. Our methodology enables testing different latency magnitudes, as well as different variance magnitudes and distributions. In this manner, the injected latency may represent delay due to an increased cabling length (increased propagation delay), delay caused by end-host behaviours, or queueing within switches due to network congestion.

In order to know how we should represent latency in the system, we conduct network latency measurements for multiple cloud-operators across different data centers around the world. These measurements are used to inform the magnitude of latency and its variance in our experiments. In addition, we used well-known synthetic latency distributions to extend the understanding of latency effects. In our experiments, we use both synthetic and real workloads for our chosen applications.

The principal contributions of this paper are:

- a description of an experimental methodology to measure application performance under arbitrary network latency,
- an extensive measurement study of how the performance of a number of cloud-based applications will change under arbitrary magnitude, variance and distribution of network latency

The rest of the paper is organized as follows. In Section 2, we present the results of network latency measurements performed across six data centers from three different cloud operators. Section 3 outlines the cloud-based applications we study in this paper, while Section 4 describes our experimental setup. Section 5 presents the results of experiments of how network latency impacts application performance. Section 6 discusses the lessons learned from our study. We give an overview of related work in Section 7, with conclusions and future work in Section 8.

2. NETWORK LATENCIES IN DATA CENTERS

If in the past it was common to think about latency on the scale of milliseconds, today network elements within the data center are several orders of magnitude faster than that. In Table 2 we present some examples of the latency of different network elements. If in the past it took 640ns to transmit just 64B using 1GE technology, today it is possible to transmit five 1518B packets at the same time. Sub-microsecond, high port count, top of rack (ToR) switches are common and there is little difference in latency between different 10GE and 100GE from the same manufacturing generation. This does not preclude higher latency network elements, in the order of microseconds, from being part of the network, depending on their role (e.g. as a Layer 3 Spine switch/router). What becomes interesting is that the latency within a switch is now at the same magnitude as the latency of traversing 100m one way within the data center over fiber. All the above means that the architecture and topology of the network within the data center, the dominant factor of network latency, can significantly vary between cloud operators and expose users to different magnitudes of data center latency and variation.

To understand the scale and distribution of latency as experienced by a user in a data center, we measure the round-trip time (RTT) between multiple virtual machines (VMs) rented from different cloud operators. Our aim is to calibrate our latency exploration based upon current data center measurements and further use these values as inputs to our controlled latency environment. This permits us to evaluate the performance of an application as it is subject to varying latency values. While this is not a comprehensive study of latency within data centers, it represents several latency scenarios that might be experienced by a specific user.

For each of three cloud operators, we chose one data center from US and one from Europe, and we rented 4 VMs in each data center[1]. The VM's type is the default type recommended by each cloud operator, running Ubuntu 16.04. Since the VMs' performance may be affected by other collocated VMs and the network traffic within the data centers may be different due to diurnal and weekly patterns, we ran measurements over several days, totalling 100 million RTT measurements between each VM pair. Information regarding the hop count between our VMs is not available, and *traceroute* does not reveal any useful information, however, this does not affect our later experiments.

One of the VMs, operating as a client, measures the RTT to the three other VMs (operating as servers). The client VM sends a UDP packet to the first server VM and waits for a reply from it, measuring the time between the sending of the packet and the receipt of the reply. In one round, the client makes $100,000$ such measurements. Once a round finishes, the client VM waits 10 seconds before moving to the next server VM, and so on. The measurements are performed sequentially in a round robin fashion. Taking into account the time of each measurements round, the latency of each VM-pair is measured approximately once a minute, for a thousand consecutive minutes.

The UDP latency measurement methodology and source code are based on the tool utilized in [54]; it is intended for accurate low latency measurement, and sends a single measurement probe at a time (rather than a train of packets). As a result, the latency measurements only observe the state of the network and do not congest it. The latency measurements use the CPU's Time Stamp Counter (TSC). TSC is a 64-bit register present on recent Intel ix86 processor. It counts the number of cycles since reset and provides a useful resolution of approximately 288ps-per-cycle with tens of cycles resolution (due to CPU pipeline effects). Access to TSC is done using the *rdtsc* ix86 assembly instruction. The RTT is measured on the client VM by computing the difference between two rdtsc reads: one just before the request is sent, and one as it is received. Using the rdtsc instruction results in an error within VMs running on cloud operator C, so we use the less precise *clock_gettime* function with CLOCK_MONOTONIC instead.

The RTT CDFs for cloud operators A, B and C are presented in Figure 1. We also present in each CDF an aggregate plot using all the RTTs measured by a single VM to the three other VMs within the same data

[1]The number of VMs is cost limited.

center. We observe that there are differences between cloud operators, but on the other hand, the measured latencies within data centers of the same cloud operator share the same characteristics.

We further explore the periodicity within a data center on the minimum, median and 99^{th}percentile, per VM-pair, and find no interesting effects over time (Figure 2). Provider B maintains consistent latency in all our measurements, while other providers have noisier results (order of tens of microseconds), but on a round-to-round basis rather than for longer periodic patterns. We notice only one outlier, for the 99^{th}percentile of operator C.

We ran our measurements between 10 and 13 December 2016, and then repeated them between 8 and 10 May 2017 (Figure 3). While we observe changes between our two measurements campaigns, the data centers maintain their characteristics across operators in terms of magnitude of median latency and variance, with one exception only (Provider A US data center).

3. SELECTED CLOUD-BASED APPLICATIONS

We choose four popular applications whose performance can be analysed in our network-latency study setup (see Section 4). The choice of applications is intended to explore an increasing level of application's complexity as well as different distributed operating models. The choice of applications is not intended to represent all common data center applications, and we overtly prefer applications that are likely to be network intensive.

3.1 Domain Name System (DNS)

This is the most simple application studied, which is widely used in the cloud. It provides a domain name lookup service. As a server, we use NSD (Name Server Daemon)[2], which is an open source name server, authoritative only. DNSPerf[3] (version 2.1.0.0) is used on the client side to generate requests. We define as our application performance metric as the number of requests per second that the name server can achieve. DNS follows a client-server model, and we focus on the server side and the effect that network latency as observed by the server has on its overall performance.

3.2 Key-value Store: Memcached

Memcached[4] is a popular, in-memory, key-value store for arbitrary data. In our experiments we use on the server side, the open-source version of memcached 1.4.25.

We use the Mutilate[5] memcached load generator to evaluate the impact of network latency on memcached's application performance, measured in queries per second (QPS). The workload generator is based on a closed system model [40]; that is, each workload-generator waits for a reply before sending the next request. We use two workloads generated by the mutilate benchmark: i) a *read-only workload*, the requests follow an exponential distribution; the key size is 30 byte and the value size is 200 bytes; following [28], the keys are accessed uniformly; ii) the *Facebook "ETC" workload*, taken from [6], is considered representative of general-purpose key-value stores. The results for the two workloads are similar, and we omit for brevity the results for the read-only workload.

Memcached follows a client-server model, and we focus on the server side and the effect that network latency as observed by the server has on its overall performance.

3.3 Machine Learning Applications

Machine learning (ML) applications have become very popular in recent years, representing a common workload for data centers. Due to the huge amount of data that has to be processed, the ML applications are distributed, using either a data parallel approach (the input data is partitioned across the machines and the ML model is shared) or a model parallel approach (the ML model is partitioned across the machines and the input data is shared). In the data parallel approach, each machine can read and update all model parameters, while in the model parallel approach, each machine can access and update only its model parameter partition.

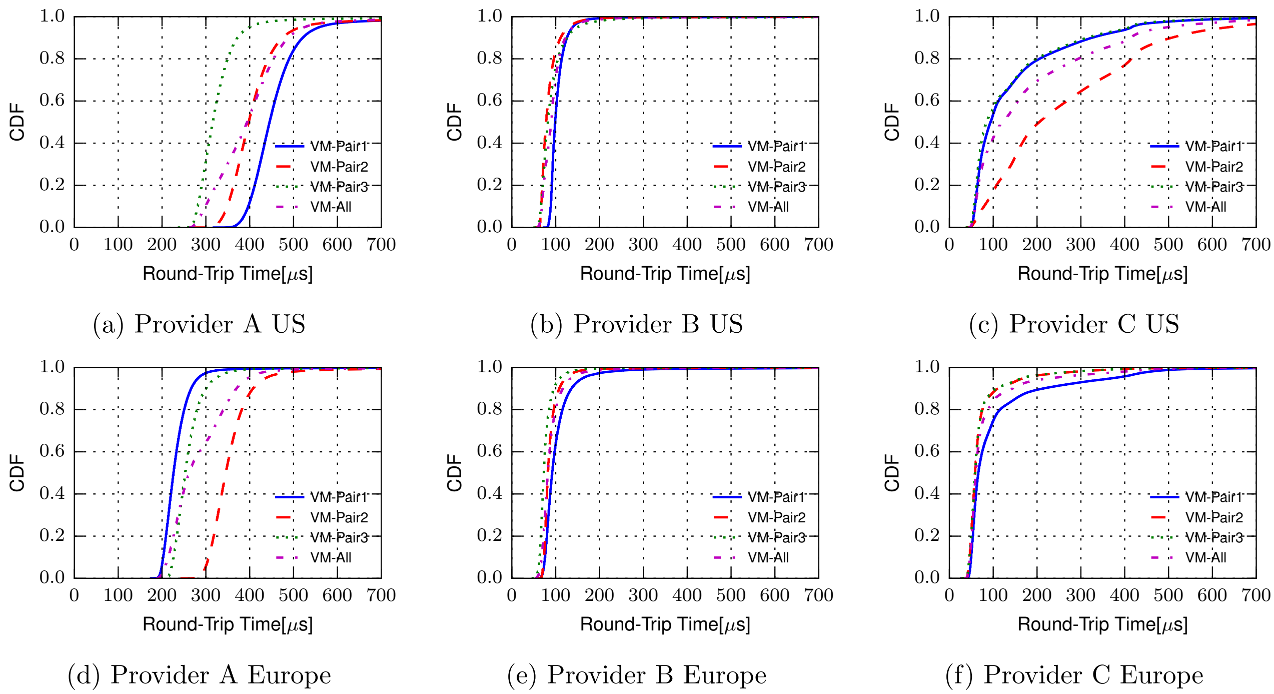
3.3.1 Distributed Machine Learning: Lasso Regression

We use the STRADS [27][6] distributed framework for machine learning algorithms. The framework is targeted for moderate cluster sizes (between 1 and 100 machines).

We evaluate the impact of network latency on the sparse Lasso (least absolute shrinkage and selection operator) regression [45] application implemented in this framework. The network communication pattern can be represented as a star in the case of the Lasso regression application, with a central coordinator and scheduler on the master server, while workers communicate only with this master server. The STRADS framework uses one coordinator, one scheduler and requires at least two workers. In our setup, the coordinator and the scheduler run on the master server (in Figure 4).

We define as application performance metric the objective function value versus time (seconds), also referred-to as *convergence time* [27]. The input to the application is represented by a N-by-M matrix and a N-by-

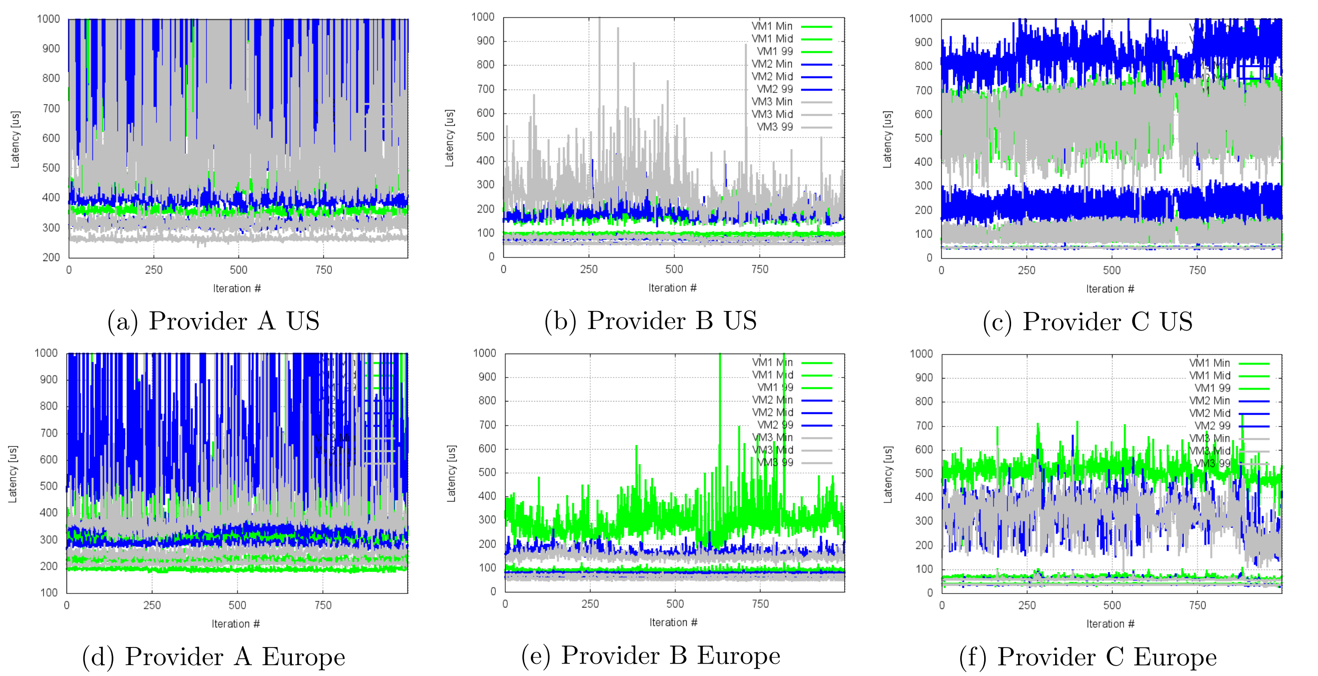
[2] `https://www.nlnetlabs.nl/projects/nsd/`
[3] `https://nominum.com/measurement-tools/`
[4] `http://memcached.org`
[5] `https://github.com/leverich/mutilate`
[6] `https://github.com/petuum/strads.git`



(a) Provider A US (b) Provider B US (c) Provider C US

(d) Provider A Europe (e) Provider B Europe (f) Provider C Europe

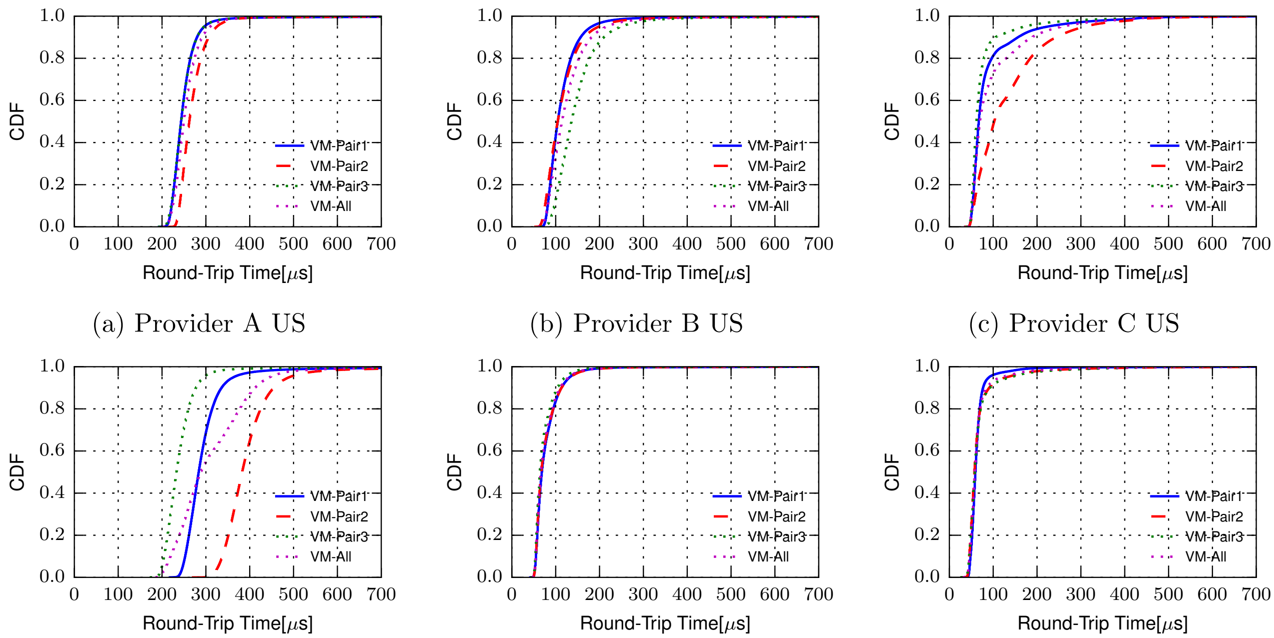
Figure 1: Measured RTTs within data centers for cloud operators A, B and C in December.



(a) Provider A US (b) Provider B US (c) Provider C US

(d) Provider A Europe (e) Provider B Europe (f) Provider C Europe

Figure 2: Measured RTTs percentiles per VM pair within data centers for cloud operators A, B and C for each iteration round.



(a) Provider A US (b) Provider B US (c) Provider C US

(d) Provider A Europe (e) Provider B Europe (f) Provider C Europe

Figure 3: Measured RTTs within data centers for cloud operators A, B and C in May.

1 observation vector, while the model parameters are represented by a M-by-1 coefficient vector. In common with papers describing the algorithm [27], we use a synthetic workload that we generated, with a number of 10K samples and 100K features, and a total of 500M non-zero values in the matrix, the data size is 9.5GB.

3.3.2 *Distributed Machine Learning: Generalized Linear Regression*

We use Spark [1]'s machine learning library (MLlib), on top of which we run benchmarks from Spark-Perf[7]. We run Spark 1.6.3 in standalone mode. We experiment with different numbers of examples (100K, 1M) and iterations (20, 100), however we notice a similar behaviour. Spark follows a master-worker model. Spark supports broadcast and shuffle, which means that the workers do not communicate only with the master, but also between themselves. We define as application performance the *training time*, e.g. the time taken to train a model.

3.4 Other applications

On top of the four applications described above, we also explored the effect of latency on the performance of other applications, which are omitted from this paper. In previous work [54] we studied the effect of static latency on Apache Benchmark[8] for a single client-server pair. However, for this use case, Apache easily saturates the link, making network bandwidth the bottleneck of the system studied. Under this scenario, even two clients are competing for network resources, thus the study of latency effect is tainted by other network effects. We also studied the effect of latency on TPC-C MySQL benchmark[9], reporting New-Order transactions per minute (where New-Order is one of the database's tables). TPC-C latency sensitivity heavily depends on its warm-up period and , which hinders the methodological reliability of repeated tests. On top of the above, we also explored a set of applications under the Spark platform, including e.g. KMeans, Gaussian Mixture Models. We omit those for brevity, as they behave similarly to other applications using the same platform.

4. EXPERIMENTAL SETUP

While characterising the performance of network latency in the cloud is ideally done within a large-scale and controlled data center, such access is granted today only to the single few who work at the world's leading data centers. Other may use the data center, but have no control over it or full visibility into it. Instead, we propose a methodology that enables characterising the effect of network latency on applications performance using a much smaller scale, well controlled environment. Our ability to control and flexibly change latency within this environment provides a new venue for studying net-

[7] `https://github.com/databricks/spark-perf`

[8] `https://httpd.apache.org/docs/2.4/programs/ab.html`

[9] `https://github.com/Percona-Lab/tpcc-mysql`

work characteristics in academic environments.

Our methodology is based on the observation that each host's experience of the network can be collapsed to the link connecting it to the Top of Rack switch (ToR). By modifying the properties of the traffic arriving through this link, the host can experience different effects of network latency, as if it was located in different data centers.

In our experiments, in each scenario one host is selected as the unit under test (UUT). This host can act as a server (DNS, memcached), master (STRADS Lasso Regression, Spark Ridge Regression) or client (memcached), depending on the application. While it can be claimed that for some distributed applications, the effect of latency on a single host becomes a statistical combination of the different values, we later show that even under such a model the latency effect on a single host is not negligible.

Between the selected host and all other parts of the setup, we use an appliance that can inject well-controlled latency into the system. The appliance is an open-source contributed NetFPGA SUME project [53], originally included in release 1.4.0. While a detailed evaluation of the latency appliance is under independent preparation [36], it is described below in Section 4.1. We abstract the network topology as a single queue, represented by the delays injected by the latency appliance and illustrated in Figure 5. This queue imposes delay, from the UUT's perspective, through the point-to-point link that connects the server to the remaining network.

The experimental setup, Figure 4, is composed of 10 hosts[10]. Each host has an Intel Xeon E5-2430L v2 Ivy Bridge CPU with six cores, running at 2.4GHz with 64GB RAM. CPU-power saving, hyper-threading and frequency scaling are disabled. The hosts run Ubuntu Server 16.04, kernel version 4.4.0-75-generic. Each host is equipped with an Intel X520 NIC with two SFP+ ports. Each host is connected at 10Gbit/s using ian Arista 7050Q switch. Table 1 describes the settings per application, and during our tests we run each application multiple times for each latency configuration.

4.1 NRG

The Network Research Gadget (NRG) is used in this work as a latency appliance that implements traffic control mechanisms in hardware, replicating the functionality of NetEm [21]. The hardware implementation provides higher resolution and better control over latency than softwareimplemented traffic control such as NetEm might afford [41, 25, 22].

The latency injection has a resolution of 5ns and can range from zero to twenty seconds (at low data rates), supporting up to 1.1ms latency for 64B packet at full 10GbE line rate. Traffic control introduces both a constant latency and variable latency to recreate a predefined latency distribution. We refrain from using terms such as jitter, which implies a difference in latency that is both above and below a certain value, as latency injected by NRG is always positive within our setup. The supported latency distributions are: none, user-defined, uniform, normal, Pareto, and Pareto-normal distributions. The definitions for the last three distributions are adapted from NetEm[21]. We refer here on to the Pareto and Pareto-normal distributions as heavy-tail distributions 1 and 2 in accordance. The user-defined distribution allows specification of any distribution, and is used to recreate the latencies measured in the cloud (Section 2).

[10]The methodology is not dependant on the number of hosts

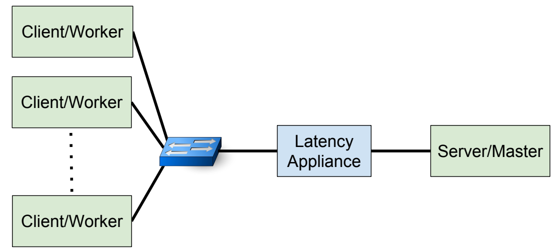


Figure 4: Experimental setup to evaluate application performance under changing network latency

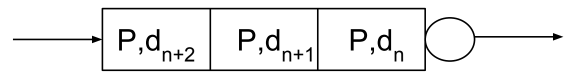


Figure 5: Each packet is P delayed by a value d chosen randomly from a certain distribution

Latencies are imposed independently for each direction of each port, thus client to server and server to client added latencies are completely independent thereby replicating the direction-independent latency experienced by packets due to in-network congestion. There is no packet reordering within NRG. As illustrated in Figure 5, a packet P is delayed in a queue inside the appliance for a given amount of time chosen from a given delay distribution. The packets delay d within the queue is independent of the inter packet gap. While inter packet gap based latency is possibly using NRG, such latency injection will impose a specific network latency distribution. As we seek to understand the effect of additive latency within the network, we impose per-packet latency control.

5. APPLICATION PERFORMANCE ANALYSIS

We study three aspects of latency effect on perfor-

Table 1: Workloads Setup. #Hosts indicates the minimum number of hosts required to saturate the UUT or the number of hosts for which we determine the best job completion time/training time when no latency is added.

Application	**UUT's Role**	**#Hosts**	**Metric**	**Runtime** Target	**Dataset**	**Dataset** Size
DNS	Server	1	Queries/sec	10M requests	*A record*	10M requests
Memcached	Server	5	Queries/sec	10 seconds	FB ETC [6]	see [6]
Memcached	Client	1	Queries/sec	10 seconds	FB ETC [6]	see [6]
STRADS Regression [27]	Coordinator	6	Convergence time time	100K iterations	Synthetic	10K samples, 100K features
Spark Regression [1]	Master	8	Training time	100 iterations	Spark-perf generator	100K samples, 10K features

mance: The scale of latency, latency variance and role of network latency from the processor perspective. For the different tests, we use a per-test setup configured to provide optimal application-performance. All results are averaged over three runs. The network latency we introduce using our appliance represents the various sources of latencies throughout a networked system: both static sources, i.e., propagation delay, and variable sources, e.g., end-host delay, and queuing in switches. The topology of the network, notably non-uniformity of latency among client-server paths, is still an unexplored factor in determining the application behaviour that we leave for future work at this time.

5.1 Setting the Baseline

Before experimenting with the effect of latency, we first find the baseline performance of each application. We set the following goals for the baseline settings:

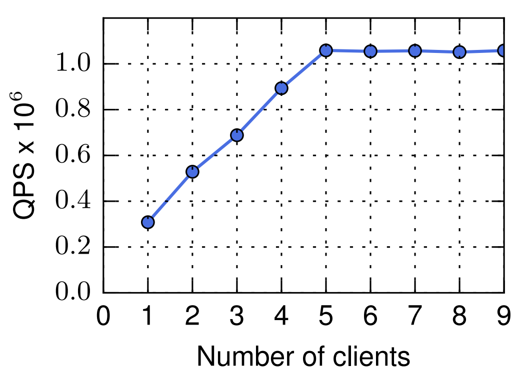
- Results must be stable. Running the same test multiple times, using the same seed, needs to produce similar results.
- Results must be reproducible. Running the same test on different (comparable) machines should produce similar results. Results should not vary over time, and should not be affected by externalities (e.g. other machines in our experimental data center.).
- Results should not be affected by our tools and methodology. For example, the number of samples should be sufficient, the latency appliance should not limit the link bandwidth and any statistics should be collected outside run time, as not to affect available computation resources.
- Baseline performance should be the maximum achievable performance of the UUT. The setup and application should be configured in a manner that achieves the maximal performance possible using the available resources.
- Baseline setup should achieve the maximum UUT performance using a minimum number of hosts. The UUT (acting as a server, worker or other) resources should be saturated, but without overloading the host.

To exemplify the last point: lets consider a client-server application, where the peak performance of the server is N queries per second. The minimum number of clients required to achieve this performance is k. Any number of clients above k can still achieve N queries, but not more. What we seek is to understand the effect of performance on such server using k clients, where any loss of performance will be due to latency rather than e.g. processing or storage. Had we picked any number of clients greater than k, it is possible that the host had maintained a performance of N queries per second, but the sensitivity to the network would not have been exposed.

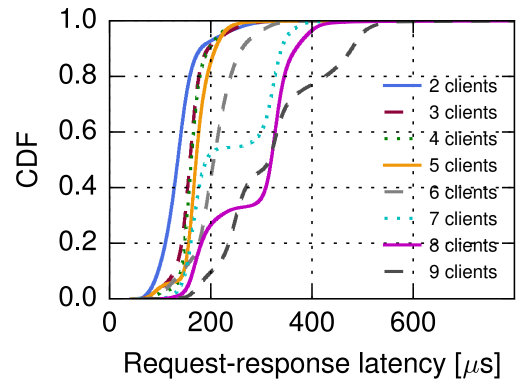
For each of the workloads, we follow the guidelines above, conducting multiple experiments required to set the aforementioned baseline. An example of such baseline analysis is provided in Figure 6 for memcached. We vary the number of client machines from 1 to 9, and one of the clients, called the master client, also takes measurements. In this configuration, memcached achieved a maximum of approximately 1.05M QPS (Figure 6(a)) using five clients machines (180 connections total). From Figure 6(a), we observe that, as we reach the maximum compute power of the memcached server, increasing the number of client machines beyond five does not increase the maximum throughput achieved. However, using more than five client machines leads to an increase in the request-response latency per client(Figure 6(b)). Based on these results, we select the setup that yields maximum performance under minimal request-response latency: four client machines to generate load, an additional client machine that keeps QPS and latency measurements, and a sixth machine - the UUT acting as a server.

5.2 Analysing the Effect of Static Latency

To consider the effect of latency on the performance of different applications, we begin by studying the scale



(a) QPS



(b) Request-response latency

Figure 6: Baseline analysis to determine the maximum QPS that can be achieved by the Memcached server.

of network latency that is enough to have a significant effect. The goal here is not to find a specific number, which is very system dependent, rather to understand what is the scale - ranging from nanoseconds to milliseconds. The scenario that we study here is most notably translated to a placement problem: what is the maximal distance between processing nodes that will not affect the performance of an application? As every $100m$ of fibre translate to $1\mu s$ of RTT, this is becoming an increasing challenge [54]. This scenario bears similarities to the median latency within data centers, and we explore the effects of those later on.

For each application, a baseline performance is determined on our setup. Next, NRG is used to introduce a constant latency between the UUT (or) and the network. A range of constant latencies, from $2\mu s$ to $1000\mu s$ is introduced, and the applications' performance is measured for each latency value.

To compare the effect of additive latency on each of the applications, we normalise their performance. The baseline performance is marked as 1, and the ratio between the measured performance at each latency point, and the baseline performance is shown in Figure 7. The x-axis is the static latency added (in μs, for RTT) while the y-axis is the normalized performance. We note that each application has a different performance metric, as shown in Table 1.

All applications are sensitive to latency, though on very different scales. For STRADS Lasso Regression, we observe performance degradation when as little as $20\mu s$ are added to the RTT ($10\mu s$ in each direction), while Ridge Regression on Spark is not affected by less than $500\mu s$ RTT. We note here that the latency is injected between the master and slaves, and not also between the slaves themselves. We also considered a scenario where we introduced additional latency using *NetEm* at the slaves, however we did not see noticeable effects below $500\mu s$ RTT. The memcached sever is also

Network Element	Typical Latency
Propagation Delay, 1m Cable / Fiber	4.3ns-4.9ns
Serialization Delay, 1518B, 100G link	125ns
ToR, L2 Switch, 10G / 100G	300ns-500ns
Propagation Delay on 100m Fiber	490ns
Low Latency NIC, 10G Serialization Delay, 1518B over 10G link	$1\mu s$ $1.25\mu s$
Spine, L3 Switch, 10G / 100G	$3.5\mu s$-$13\mu s$

Table 2: Latency of Different Network Elements - Typical Examples

very sensitive to latency: $100\mu s$ are enough for over 20% performance degradation, and the performance is halved around twice this number. DNS is also affected by latency at the scale of hundreds of microseconds, and its drop in performance is much steeper than STRADS Lasso Regression. Contrary to the memcached server case, adding static latency to a single memcached client has a minimal effect on the overall aggregated performance of the 5 clients (measured by the master client), which is likely due to the design of the benchmark.

This sensitivity to latency demonstrates two orders of magnitude difference between applications. As previous work has shown $10\mu s$ to be the scale of latency between two hosts connected back-to-back [54, 15], this certainly makes memcached and STRADS Lasso Regression very sensitive to their physical resource allocation.

5.3 Analysing the Effect of Latency Variance

The fact that latency is affecting performance (on different scales) is not new [12, 13]. The effect of latency variance, on the other hand, is rarely discussed. Latency variance changes not just in magnitude, but also in its distribution.

To study the effect of latency variance, we use NRG to introduce different variance distributions. In all experiments, we set a single median latency and vary the

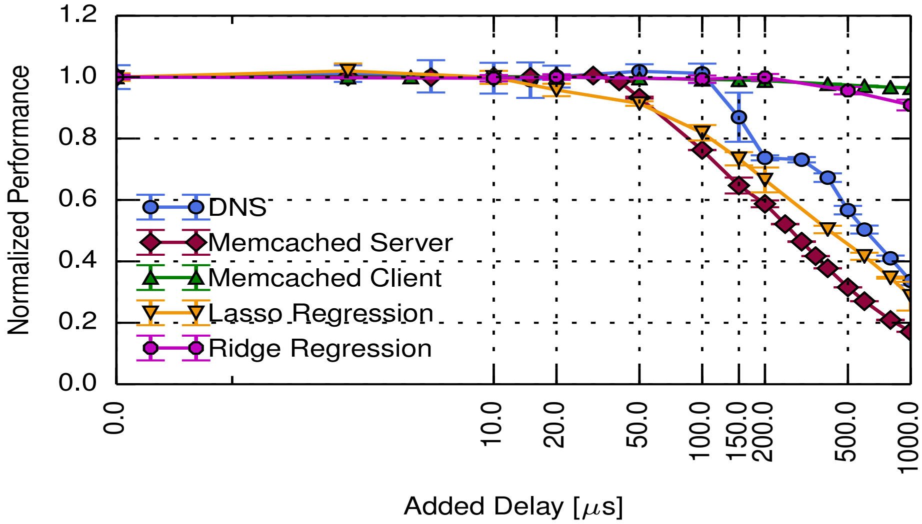


Figure 7: The effect of static latency on different applications.

magnitude and distribution of variance around this median. The value picked as the median is taken from the cloud latencies we measured, as a representative example.

Figures 8 and Figure 9 show the effect of latency variance on memcached, Lasso Regression and DNS. We omit the results for Ridge Regression, as it is not affected by latencies at the explored scales, as shown in Figure 7. Figure 8 uses 200μs as the median RTT latency, similar to the median latency of cloud operator A in Europe, while Figure 9 uses 50μs as the median RTT latency, similar to the median latency of cloud operator B in Europe. The x-axis shows the magnitude of the variance, while the y-axis is the normalized performance of the application when this variance is applied. The baseline for the performance is the same setup with no variance applied, i.e. the left most point on the graph. As can be seen, just like static latency, so does latency variance affect the performance - despite maintaining the median latency without a change.

As Figure 8(a) shows, even small scale variance, e.g. 20μs variance when the median is 200μs is enough to lead to up to 5% of performance degradation for Lasso. 160μs variance may cause 25% performance loss. Given that the variance leads to some packets with lower latency than the median, and some with higher latency - the effect of variance is even more profound.

As we have shown in Figure 7, DNS is sensitive to latency in the order of 200μs to 300μs, yet for static latency with no variance the performance of both latencies is about the same. This is likely to have the same affect as shown in Figure 8, where the maximum latency (median and variance) is in the order of 300μs RTT, therefore the performance is almost not affected by variance.

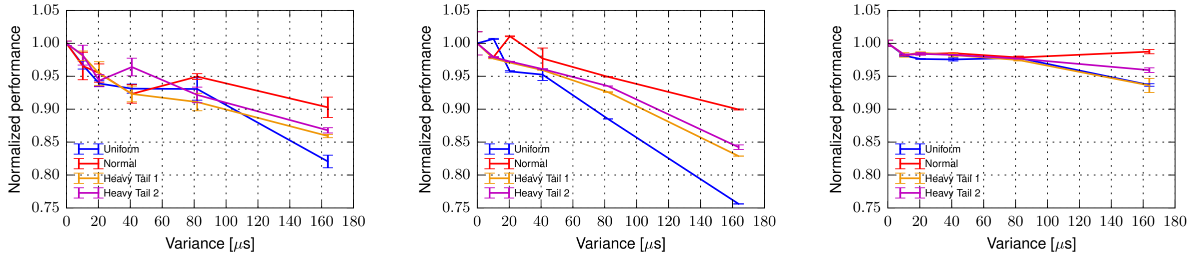
One of the results we found quite surprising is that when using similar values to cloud operator B's, where the median latency and the scale of variance are quite small, we observe non negligible effect of the variance (Figure 9) on memcached. This result is surprising as at 50μs memcached is not very sensitive to static latency (e.g. as there it is still bound by other resources).

The effect of each distribution is consistent for all applications: a normal distribution has the least effect, while a uniform distribution has the most. This is not unexpected, as for a normal distribution most of the packets experience latency that is within one standard deviation, whereas for a uniform distribution the probability of a packet experiencing tail latency is the highest. The heavy tail distributions are in between these two cases.

6. DISCUSSION

The Impact of Network Latency.

The fact that network latency affects performance is well known (e.g. [12, 9, 14]), yet our experiments expose for the first time the extent of sensitivity to latency for some applications: with 10μs latency in each direction enough to have a noticeable effect, and 50μs latency in each direction enough to significantly negatively impact the performance. Given that only a few years ago this was the scale of latency within the host alone [39], it means that much more attention must continue to be paid to the host. A second aspect is the attention to the distance between servers: with longest cable length reaching 900m [18], equivalent to 9μs RTT on the fibre alone, and expected to grow beyond the kilometre, performance can be noticeably affected. When scaling the data center comes at the cost of additional hops between servers, passing the more switches increases latency further. This has ramifications for workload placement and



(a) STRADS Lasso Regression (b) Memcached (c) DNS

Figure 8: Analysis of the effect of latency variance and distribution on STRADS Lasso Regression, memcached and DNS using the median and variance magnitude of cloud operator A in Europe.

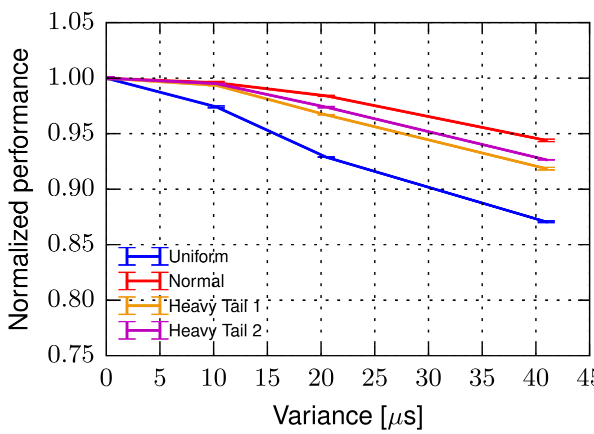


Figure 9: Analysis of the effect of small latency variance and distribution on memcached, using the median and variance magnitude of cloud operator B in Europe.

physical host sharing when trying to reach performance targets.

The Effect of Variable Latency.

Latency variance matters. Even for the same median latency, the performance is affected by the magnitude and distribution of variance. Furthermore, heavy tail distributions worsen the effect of latency on the performance. However, the tail latency or 99^{th}percentile are not necessarily an indicator of performance: for the same application and the similar tail latency, the performance may differ based on the variance distribution.

Modelling Variable Latency.

The modelling of variable latency is a challenging task, as it encapsulates a large number of traffic-affecting phenomena, some of them dependent. We take a very narrow view of the latency: the one of the end host, as it observes the latency through the single link that connects it to the rest of the network (typically through the top of rack switch). The variable latency that we introduce is consistent with our measurements and with previous studies [28, 6]. While per-packet added latency is independent, packets are still queued and reordering is not possible within a flow. Reordering of packets from different flows is still possible in our setup, within the switch, as in a real data center. Still, we assert that since each client-server pair is independent, the ordering of packets from different flows while applying a variable latency, achieves similar results to handling each flow separately. Scenarios where reordering is possible, e.g. due to load balancing, are outside the scope of this paper.

Generalizing The Results.

While the impact of latency on performance, evaluated in Section 5, is conducted on a specific setup, the results presented in this paper can be generalized to other setups and scenarios as well. While there are differences between platforms, due to their different capabilities, the results are at the same scale and follow the same trends.

Validation.

An extensive validation of NRG and the methodology used in this paper is done prior to our experiments. The characterization and evaluation of NRG are part of a different work [36].

Limitations.

In this paper, we have limited ourselves to a study of application performance and data center network latency. Our methodology may be trivially adapted to understand the impact of network bandwidth upon application performance. This adaptation would only require a derivative hardware appliance setup to constrain and control the available network bandwidth between network end-hosts.

We note that our cloud RTT measurements are not fully representative of all the cloud data centers latency, as they are a sample capture over a limited period of time and space. These measurements represent potential latency scenarios to which an application may be subjected when running in the cloud.

7. RELATED WORK

Network Latency. Network latency was identified as a crucial factor for having a good user experience several decades ago [12]. Latency is more difficult to control and improve-upon when compared with network bandwidth [38]. In recent years, tail latency has been considered an important issue for interactive applications in data centers [9, 14], because it gets magnified at scale. Multiple efforts have been proposed in this space [5, 50, 26].

In this context, it is important to have a complete breakdown of latency for common end-host systems used in data centers [54], but also of the current end-to-end network latencies in cloud data centers. Several previous works looked into the network conditions in cloud data centers, noting that network latency within data centers can vary significantly. Studies were conducted in EC2 in 2010 [8, 46] and in 2013 [49] to measure network latency, identifying as causes for the observed latency variation queuing in switches, queueing at end-hosts in the hypervisor or co-scheduling of CPU bound and latency-sensitive tasks. Mogul *et al.* [35] performed latency measurements between two pairs of VMs from several cloud operators. Pingmesh [20] reports network latency measurements for two data centers, one used for distributed storage and MapReduce, and the second used for interactive search service, observing similar ranges as ours. We performed our own cloud latency measurement study with the aim of obtaining realistic network latency ranges and distributions to use as inputs for our experiments.

The scale of latency contributions within data centers keeps shrinking: while only five years ago a switch latency of 10μs and an OS stack latency of 15μs were considered the norm [39], today's numbers are an order of magnitude smaller [54, 7]. It is within the context of these scales that we position our contribution. While previous work (e.g. [16]) considered application performance with the latency between the user to the data center to be included, our work focuses on latency within the data center and thus is focussed upon values orders of magnitude lower.[43] investigates the causes of latency inflation in the Internet, since network latency in the Internet is seen as a concern for user experience.

Several works focused on providing network latency guarantees by controlling and reducing in-network queueing [19, 23, 52]. They show the impact of network congestion on different applications' performance (for Memcached on request-response latency [19, 23], for PTPd on the clock offset [19], for Naiad barrier synchronization latency [19]). While their work gives an indication of the negative impact that network congestion has on application performance, it does not attempt to quantify its scale, their focus being on developing a solution to limit it. We performed a detailed analysis of network latency impact on application performance, where the injected network latency encompasses different causes, not only network congestion.

A different analysis than ours focuses on understanding networking requirements for data center resource disaggregation [17], using similar cloud applications. Kay *et al.* [37] analyzed Spark using different workloads, finding that improving network performance can improve job completion time by a median of at most 2%, results which are in accordance with ours, since Spark is not a network intensive application.

Memcached. Due to its popularity and extensive use by companies to provide substrates for their services, there is a large body of work that sought to improve Memcached's throughput and request latency. Leverich *et al.* [28] described techniques to co-locate latency-sensitive workloads (memcached in particular) with other workloads, while maintaining good quality-of-service for the latency-sensitive applications. IX [10], a dataplane operating system that leverages hardware virtualization to separate network processing from the other kernel functions, manages to reduce memcached's latencies to approximately half for an unloaded server. A Memcached over RDMA design has been proposed by Jose *et al.*[24], which reduces latency by considerable factors compared to the traditional design. Chronos [26] is a framework that provides predictable network latency and reduces tail latency for Memcached and other data center applications by partitioning requests based on application-level packet header fields and load balancing them across threads at the NIC. In our work, we do not propose techniques to improve the performance of Memcached. We evaluate the current performance of Memcached under arbitrary network latency, looking mainly at an aggregate metric of performance (QPS) as a measure of the overall work that a Memcached server can do, not only at individual request-response latencies.

Distributed Machine Learning. There has been an explosion of distributed machine learning frameworks and libraries in recent years: Spark MLlib [34], GraphLab [31], parameter servers [29], Bosen [47], STRADS [27]. Companies have also released libraries: Google's TensorFlow [4], Microsoft' Cognitive Toolkit [3] and Distributed Machine Learning Toolkit [2]. While considerable effort has been put in optimizing network communication and reducing the impact of network conditions on ML applications, an evaluation to understand the impact of network latency on their performance is needed in the context of the observed variability of network conditions in the cloud.

8. CONCLUSION

In this paper, we studied the effects of network latency on typical cloud applications, raging from DNS to distributed machine learning applications. We performed extensive measurements by artificially injecting controlled network latency in our experimental setup, quantifying the impact of network latency on application performance. Our results show that different applications are affected by fixed and variable latency to differing amounts. The effect of network latency is not limited to the median or tail latency, but depend on the variance distribution. Even small network delays, in the order of tens of microseconds can impact the application performance significantly.

9. ACKNOWLEDGMENTS

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