FERMILAB-PUB-14-466-CD

Understanding the Performance and Potential of Cloud Computing for Scientific Applications

Iman Sadooghi, Jesús Hernández Martin, Tonglin Li, Kevin Brandstatter, Ketan Maheshwari, Tiago Pais Pitta de Lacerda Ruivo, Gabriele Garzoglio, Steven Timm,Yong Zhao, Ioan Raicu

Abstract— Commercial clouds bring a great opportunity to the scientific computing area. Scientific applications usually require significant resources, however not all scientists have access to sufficient high-end computing systems, may of which can be found in the Top500 list. Cloud Computing has gained the attention of scientists as a competitive resource to run HPC applications at a potentially lower cost. But as a different infrastructure, it is unclear whether clouds are capable of running scientific applications with a reasonable performance per money spent. This work studies the performance of public clouds and places this performance in context to price. We evaluate the raw performance of different services of AWS cloud in terms of the basic resources, such as compute, memory, network and I/O. We also evaluate the performance of the scientific applications running in the cloud. This paper aims to assess the ability of the cloud to perform well, as well as to evaluate the cost of the cloud running scientific applications. We developed a full set of metrics and conducted a comprehensive performance evlauation over the Amazon cloud. We evaluated EC2, S3, EBS and DynamoDB among the many Amazon AWS services. We evaluated the memory sub-system performance with *CacheBench*, the network performance with *iperf*, processor and network performance with the HPL benchmark application, and shared storage with NFS and PVFS in addition to S3. We also evaluated a real scientific computing application through the Swift parallel scripting system at scale. Armed with both detailed benchmarks to gauge expected performance and a detailed monetary cost analysis, we expect this paper will be a recipe cookbook for scientists to help them decide where to deploy and run their scientific applications between public clouds, private clouds, or hybrid clouds.

Index Terms— Cloud computing, Amazon AWS, performance, cloud costs, scientific computing

1 Introduction

THE idea of using clouds for scientific applications has been around for several years, but it has not gained traction primarily due to many issues such as lower network bandwidth or poor and unstable performance. Scientific applications often rely on access to large legacy data sets and pre-tuned application software libraries. These applications today run in HPC environments with low latency interconnect and rely on parallel file systems. They often require high performance systems that have high I/O and network bandwidth. Using commercial clouds gives scientists opportunity to use the larger resources on-demand. However, there is an uncertainty about the capability and performance of clouds to run scientific applications because of their different nature. Clouds have a heterogeneous infrastructure compared with homogenous high-end computing systems (e.g. supercomputers). The design goal of the clouds was to provide shared resources to multi-tenants and optimize the cost and efficiency. On the other hand, supercomputers are designed to optimize the performance and minimize latency.

However, clouds have some benefits over supercomputers. They offer more flexibility in their environment. Scientific applications often have dependencies on unique libraries and platforms. It is difficult to run these applications on supercomputers that have shared resources with pre-determined software stack and platform, while cloud environments also have the ability to set up a customized virtual machine image with specific platform and user libraries. This makes it very easy for legacy applications that require certain specifications to be able to run. Setting up cloud environments is significantly easier compared to supercomputers, as users often only need to set up a virtual machine once and deploy it on multiple instances. Furthermore, with virtual machines, users have no issues with custom kernels and root permissions (within the virtual machine), both significant issues in non-virtualized high-end computing systems.

- *I. Sadooghi, J H. Martin, T. P.P. de Lacerda Ruivo, T. Li, K. Brandstatter and I.Raicu are with the Department of Computer Science, Illinois Institue of Technology, Chicago, IL 60616. E-mail: isadoogh@iit.edu. Jhernа22@hawk.iit.edu, tonglin@iit.edu, kbrandst@iit.edu, iraicu@cs.iit.edu*
- *Y. Zhao is with ²School of Computer Science and Engineering, Univ. of Electronic Science and Technology of China, Chengdu, China E-mail: yongzh04@gmail.com*
- *K. Maheshwari is with the Argonne National Laboratory Lemont, IL 60439. E-mail: ketan@mcs.anl.gov*
- *G. Garzoglio and S. Timm are with the Fermi National Accelerator Laboratory, PO Box 500, Batavia, IL 60510. E-mail: timm@fnal.gov, garzogli@fnal.gov*

There are some other issues with clouds that make them challenging to be used for scientific computing. The network bandwidth in commercial clouds is significantly lower (and less predictable) than what is available in supercomputers. Network bandwidth and latency are two of the major issues that cloud environments have for high-performance computing. Most of the cloud resources use commodity network with significantly lower bandwidth than supercomputers [13].

The virtualization overhead is also another issue that leads to variable compute and memory performance. I/O is yet another factor that has been one of the main issues on application performance. Over the last decade the compute performance of cutting edge systems has improved in much faster speed than their storage and I/O performance. I/O on parallel computers has always been slow compared with computation and communication. This remains to be an issue for the cloud environment as well.

Finally, the performance of parallel systems including networked storage systems such as Amazon S3 needs to be evaluated in order to verify if they are capable of running scientific applications [3]. All of the above mentioned issues raise uncertainty for the ability of clouds to effectively support HPC applications. Thus it is important to study the capability and performance of clouds in support of scientific applications. Although there have been early endeavors in this aspect [10][14][16][20][23], we develop a more comprehensive set of evaluation and metrics. In some of these works, the experiments were mostly run on limited types and number of instances [14][16][17]. Only a few of the researches have used the new Amazon EC2 cluster instances that we have tested [10][20]0. However the performance metrics in those papers are very limited. This paper covers a thorough evaluation covering major performance metrics and compares a much larger set of EC2 instance types and the commonly used Amazon Cloud Services. Most of the aforementioned above mentioned works lack the cost evaluation and analysis of the cloud. Our work analyses the cost of the cloud on different instance types.

The main goal of this research is to evaluate the performance of the Amazon public cloud as the most popular commercial cloud available, as well as to ***offer some context for comparison against a private cloud solution***. We run micro benchmarks and real applications on Amazon EC2 and S3 to evaluate its performance on critical metrics including throughput, bandwidth and latency of processor, network, memory and storage [2]. Then, we evaluate the performance of HPC applications on EC2 and compare it with a private cloud solution (FermiCloud 0). We also identify the weaknesses and advantages of the cloud environment in the scientific computing area.

Finally, this work performs a detailed price/cost analysis of cloud instances to better understand the upper and lower bounds of cloud costs. Armed with both detailed benchmarks to gauge expected performance and a detailed monetary cost analysis, we expect ***this paper will be a recipe cookbook for scientists to help them decide where to deploy and run their scientific applications between public clouds, private clouds, or hybrid clouds***.

This paper is organized as follows: Section 2 provides the evaluation of the EC2, S3 and DynamoDB performance on different service alternatives of Amazon AWS. We provide an evaluation methodology. Then we present the benchmarking tools and the environment settings of the testbed in this project. Section 2.4 presents the benchmarking results and analyzes the performance. On 2.5 we compare the performance of EC2 with FermiCloud on HPL application. Section 3 analyzes the cost of the EC2 cloud based on its performance on different aspects. In section 4, we review the related work in this area. Section 5 draws conclusion and discusses future work.

2 Performance Evaluation

In this section we provide a comprehensive evaluation of the Amazon AWS technologies. We evaluate the performance of Amazon EC2 and storage services such as S3 and EBS. We also compare the Amazon AWS public cloud to the FermiCloud private cloud.

2.1 Methodology

We design a performance evaluation method to measure the capability of different instance types of Amazon EC2 cloud and to evaluate the cost of cloud computing for scientific computing. As mentioned, the goal is to evaluate the performance of the EC2 on scientific applications. To achieve this goal, we first measure the raw performance of EC2. We run micro benchmarks to measure the raw performance of different instance types, compared with the theoretical performance peak claimed by the resource provider. We also compare the actual performance with a typical non-virtualized system to better understand the effect of virtualization. Having the raw performance we will be able to predict the performance of different applications based on their requirements on different metrics. Then we compare the performance of a virtual cluster of multiple instances running HPL application on both Amazon EC2 and the FermiCloud. Comparing the performance of EC2, which we don't have much information about its underlying resources with the FermiCloud, which we know the details about, we will be able to come up with a better conclusion about the weaknesses of the EC2. On the following sections we try to evaluate the performance of the other popoular services of Amazon AWS by comparing them to the similar open source services.

Finally, we analyze the cost of the cloud computing based on different performance metrics from the previous part. Using the actual performance results provides more accurate analysis of the cost of cloud computing while being used in different scenarios and for different purposes.

The performance metrics for the experiments are based on the critical requirements of scientific applications. Different scientific applications have different priorities. We need to know about the compute performance of the instances in case of running compute intensive applications.

We also need to measure the memory performance, as memory is usually being heavily used by scientific applications. We also measure the network performance which is an important factor on the performance of scientific applications.

2.2 Benchmarking tools and applications

It is important for us to use wide-spread benchmarking tools that are used by the scientific community. Specifically in Cloud Computing area, the benchmarks should have the ability to run over multiple machines and provide accurate aggregate results.

For memory we use CacheBench. We perform read and write benchmarks on single instances. For network bandwidth, we use Iperf [4]. For network latency and hop distance between the instances, we use ping and traceroute. For CPU benchmarking we have chosen HPL benchmark [5]. It provides the results in floating-point operations per second (FLOPS).

In order to benchmark S3, we had to develop our own benchmark suite, since none of the widespread benchmarking tools can be used to test storage like this. We have also developed a tool for configuring a fully working virtual cluster with support for some specific file systems.

2.3 Parameter space and testbed

In order the better show the capability of Amazon EC2 on running scientific applications we have used two different cloud infrastructures: (1) Amazon AWS Cloud, and (2) FermiCloud. Amazon AWS is a public cloud with many datacenters all around the world. FermiCloud is a private Cloud which is used for internal use in Fermi National Laboratory.

In order to compare the virtualization effect on the performance we have also included two local systems on our tests: (1) A 6-core CPU and 16 Gigabytes of memory system (DataSys), and (2) a 48-cores and 256 Gigabytes memory system (Fusion).

2.3.1 Amazon EC2

The experiments were executed on three Amazon cloud data centers: US East (Northern Virginia), US West (Oregon) and US West (Northern California). We cover all of the different instance types in our evaluations.

The operating system on all of the US West instances and the local systems is a 64bits distribution of Ubuntu. The US East instances use 64 bits CentOS operating system. The US West instances use Para-virtualization technique on their hypervisor. But the HPC instances on the US East cloud center use Hardware-Assisted Virtualization (HVM) [7]. HVM techniques use the features of the new hardware to avoid handling all of the virtualization tasks like context switching or providing direct access to different devices at the software level. Using HVM, Virtual Machines can have direct access to hardware with the minimal overhead.

There is no information about the underlying architecture and technologies of Amazon AWS publicly available.

2.3.2 FermiCloud

FermiCloud is a private cloud providing Infrastructure-as-a-Service services internal use. It manages dynamically allocated services for both interactive and batch processing. As part of a national laboratory, one of the main goals FermiCloud is being able to run scientific applications and models. FermiCloud uses OpenNebula Cloud Manager for the purpose of managing and launching the Virtual Machines 0. It uses KVM hypervisor that uses both paravirtualization and full virtualization techniques 0. The FermiCloud Infrastructure is enabled with 4X DDR Infiniband network adapters. The main challenge to overcome in the deployment of the network is introduced when virtualizing the hardware of a machine to be used (and shared) by the VMs. This overhead slows drastically the data rate reducing the efficiency of using a faster technology like Infiniband. To overcome the virtualization overhead they use a technique called Single Root Input/Output Virtualization (SRIOV) that achieves device virtualization without using device emulation by enabling a device to be shared by multiple virtual machines. The technique involves with modifications to the Linux's Hypervisor as well as the OpenNebula manager 00.

Each server is anabled with a 4x (4 links) Infiniband card with a DDR data rate for a total theoretical speed of up to 20 Gb/s and after the 8b/10b codification 16 Gb/s. Network latency is 1 μs when used with MPI [6]. Each card has 8 virtual lanes that can create 1 physical function and 7 virtual functions via SR-IOV. The servers are enabled with 2 quad core 2.66 GHz Intel processors, 48Gb of RAM and 600Gb of SAS Disk, 12TB of SATA, and 8 port RAID Controller 0.

2.4 Performance Evaluation of AWS

2.4.1 Memory hierarchy performance

This section presents the memory benchmark results. We sufficed to run read and write benchmarks. The experiments for each instance were repeated three times.

Memory bandwidth is a critical factor in scientific applications performance. Many Scientific applications like GAMESS, IMPACT-T and MILC are very sensitive to memory bandwidth [8]. Amazon has not included the memory bandwidth of the instances. It has only listed their memory size. We also measure the memory bandwidth of each instance.

Fig. 1 shows the system memory read bandwidth in different memory hierarchy levels. The vertical axis shows the cache size. The bandwidth is very stable up to a certain cache size. The bandwidth starts to drop after a certain size. The reason for the drop off is surpassing the memory cache size at a certain hierarchy level.

As shown in the figure, the memory performance of the m1.small instance is significantly lower than other instances. The low memory bandwidth cannot be only attributed to the virtualization overhead. We believe that the main reason for that is memory throttling imposed by EC2 based on the SLA of those instances.

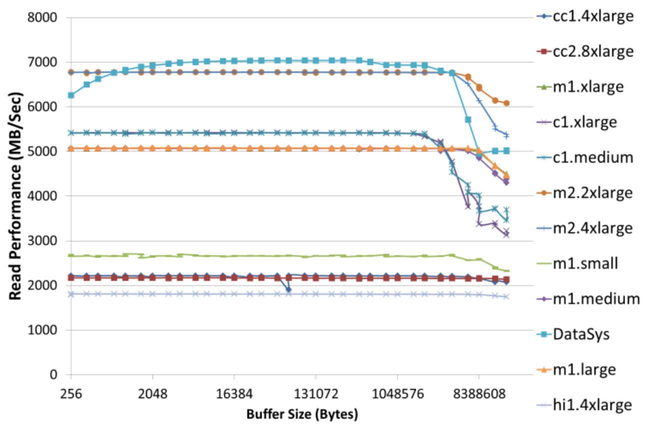


Fig. 1. CacheBench Read benchmark results, one benchmark process per instance

Another noticeable point is the low bandwidth of the cc1.4xlarge, cc2.8xlarge and hi1.4xlarge. These instances have similar performance that is much lower than normal instances. A reason for that can be the result of the different virtual memory allocation on the VMs by HVM virtualization on these instances. We have however observed an effect in large hardware-assisted virtual machines such as those on FermiCloud that it will take a while for the system to balloon the memory out to its full size at the first launch of the VM.

After all, the results show that the memory bandwidth for read operation in the larger instances is close to the local non-virtualized system. *We can conclude that the virtualization effect on the memory is low, which is a good sign for scientific applications that are mostly sensitive to the memory performance.*

Fig. 2 shows the write performance of different cloud instances and the local system. The write performance shows different results from the read benchmark. As in write, the cc2.8xlarge instance has the best performance next to the non-virtualized local system.

For each instance we can notice two or three major drop-offs in bandwidth. These drop-offs show different memory hierarchies. For example on the cc2.8xlarge instance we can notice that the memory bandwidth drops at 24 Kbytes. We can also observe that the write throughputs for different memory hierarchies are different. These data points likely represent the different caches on the processor (e.g. L1, L2, L3 caches).

Comparing the cluster instance with the local system, we observe that on smaller buffer sizes, the local system performs better. But cloud instance outperforms the local system on larger cache sizes. The reason for that could be the cloud instances residing on more powerful physical nodes with higher bandwidths. We can observe that the write bandwidth on the cloud instances drops off at certain buffer sizes. That shows the memory hierarchy effects on the write operation.

Users can choose the best transfer size for write operation based on the performance peaks of each instance type to get the best performance. This would optimize a scientific application write bandwidth.

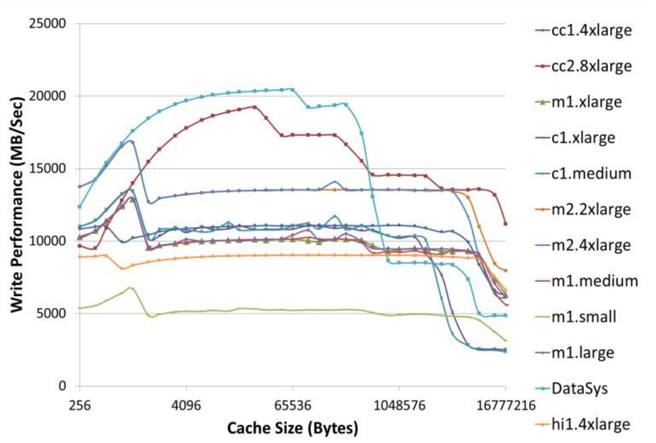


Fig. 2. CacheBench write benchmark results, one benchmark process per instance

2.4.2 Network performance

We have run many experiments on network performance of Amazon cloud. The experiments test the network performance including bandwidth and latency. We also test wide area network bandwidth of the instances.

We first test the local network bandwidth between the same types of instances. Fig. 3 shows the network performance of different types of nodes. In each case both of the instances were inside the same datacenter. The network bandwidth for most of the instances were as expected except for two instances.

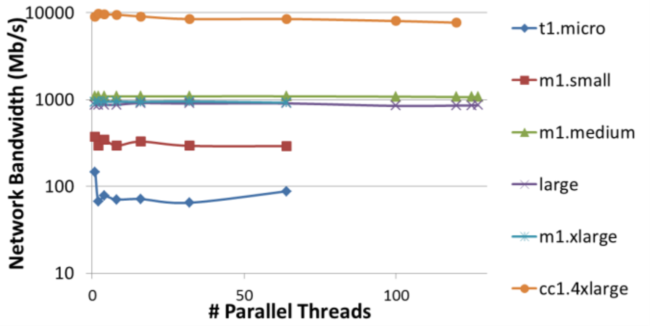


Fig. 3. iPerf benchmark results. Network bandwidth in a single client and server connection, internal network.

The lowest performance belongs to the t1.micro and m1.small instances. These two instances use the same 1 Gb/s network cards used by other instances. But they have much lower bandwidth. We believe that the reason is sharing the CPU cores and not having a dedicated core. This can affect network performance significantly as the CPU is shared and many network requests cannot be handled while the instance is on its idle time. During the idle time of the instance, the virtual system calls to the VMM will not be processed and will be saved in the queue until the idle time is over. The network performance is highly affected by processor sharing techniques. Other works had the same observations and conclusions about the network performance in these two instance types [9]. Another reason for the low performance of the m1.small and t1.micro instances could be throttling the network bandwidth by EC2. The Xen hypervisor has the ability of network throttling if needed.

Among the instances that use the slower network cards the m1.medium instance has the best performance. We did not find a technical reason for that. The m1.medium instances use the same network card as other instances do and don't have any advantage on system configuration over other instance types. We assume the reason for that is the administrative decision on hypervisor level due to their popularity among different instance types.

Another odd result is for m1.medium instance. The bandwidth in medium instance exceeds 1 Gb/Sec, which is the specified network bandwidth of these. m1.medium instance bandwidth achieves up to 1.09 Gb/sec. That is theoretically not possible for a connection between two physical nodes with 1 Gb/s network cards. We believe the reason is that both of the VMs reside in the same physical node or the same cluster. In case of residing on the same node, the packets stay in the memory. Therefore the connection bandwidth is not limited to the network bandwidth. We can also assume that not necessarily the instances have 1 Gb/s network cards. In fact the nodes that run medium instances may have more powerful network cards in order to provide better network performance for these popular instances.

The HPC instances have the best network bandwidth among the instances. They use 10 Gb/sec network switches. The results show that the network virtualization overhead in these instances is very low. The performance gets as high as 95% of ideal performance.

We also measure the network connection latency and the hop distance between instances inside the Oregon datacenter of Amazon EC2. We run this experiment to find out about the correlation of connection latency and the hop distance. We also want to find the connection latency range inside a datacenter. We measure the latency and the hop distance on 1225 combinations of m1.small instances. Fig. 4 shows the network latency distribution of EC2 m1.small instances. It also plots the hop distance of two instances. The network latency in this experiment varies between 0.006 ms and 394 ms, an arguably very large variation.

We can observe from the results that: (1) 99% of the instances which have the transmission latency of 0.24 to 0.99 ms are 4 or 6 hops far from each other. So we can claim that if the latency is between 0.24 to 0.99 ms the distance between the instances is 4 to 6 hops with the probability of 99%. (2) More than 94% of the allocated instances to a user are 4-6 percent far from each other. In other words the hop distance is 4-6 instances with the probability of more than 94%.

We can predict the connection latency based on the hop distance of instances. We have run the latency test for other instance types. The results do not seem to be dependent on instance type for the instances with the same network interconnect. *The latency variance of Amazon instances is much higher than the variance in a HPC system. The high latency variance is not desirable for scientific applications. In case of HPC instances which have the 10 Gigabit Ethernet cards, the latency ranges from 0.19ms to 0.255ms which shows a smaller variance and more stable network performance.*

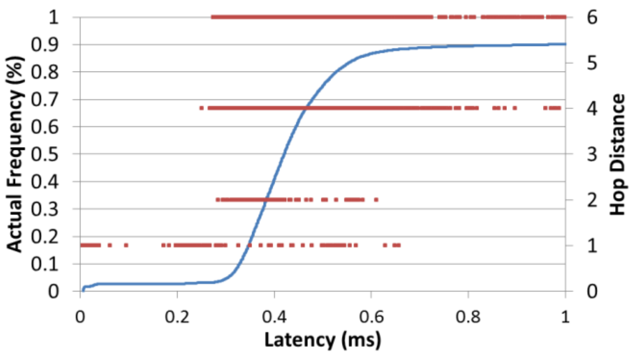


Fig. 4. Cumulative Distribution Function and Hop distance of connection latency between instances inside a datacenter.

Other researches have compared the latency of EC2 HPC instances with HPC systems. The latency of the EC2 HPC instance is reported to be 3 to 40 times higher than a HPC system with 23 Gb/s network cards [10]. The latency variance is also much higher.

2.4.3 Compute Performance

In this section we evaluate the compute performance of EC2 instances. Fig. 5 shows the compute performance of each instance using HPL as well as the ideal performance claimed by Amazon. It also shows the performance variance of instances.

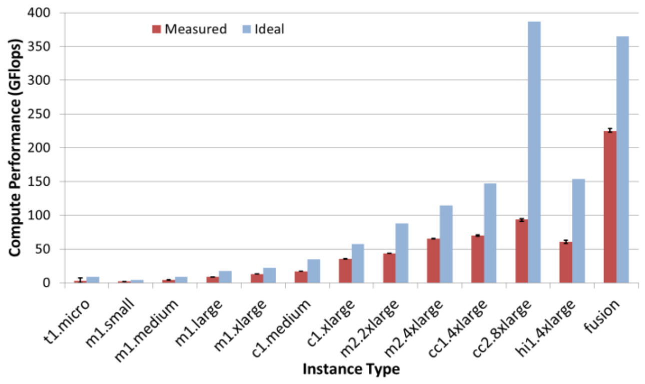


Fig. 5. HPL benchmark results: compute performance of single instances comparing with their ideal performance.

Among the Amazon instances, the cc2.8xlarge has the best compute performance. The t1.micro instance shows the lowest performance. The figure also shows the performance variance for each instance. The performance variance of the instances is low in most of the instance types. Providing a consistent performance is an advantage for cloud instances.

Among all of the instances and local nodes, the best efficiency belongs to the non-virtualized system. Overall we can observe that the efficiency of the instances is relatively low. Other papers have suggested the low performance of HPL application while running on virtualized environments [11][14]. Although the cc2.8xlarge instance has the largest compute capacity among the instances, it is the most inefficient instance. The reason for that lies behind the number of the cores in this instance. cc2.8xlarge has 16 cores. The expected performance is the aggregate performance of all of the cores of the instance. But the real performance is lower because of the communication overhead of 16 cores which is caused by the MPI application. Other papers have also reported the poor MPI performance on EC2 cloud [15][16]. Other papers have also reported the poor MPI performance on EC2 cloud [15][16].

2.4.4 I/O Performance

In this section we evaluate the I/O performance of the EBS volume and local storage of each instance. The following charts show the results obtained after running IOR on the local storage and EBS volume storage of each of the instances with different transfer sizes and storage devices. Fig. 6 shows the performance of POSIX read operation on different instances. Except for the hi1.4xlarge, which is equipped with SSDs, the throughput among other instances does not vary greatly from one another. For most of the instances the throughput is close to a non-virtualized system with a normal spinning HDD.

Fig. 7 shows the maximum write and read throughput on each instance on both EBS volumes and local storage devices. Comparing with local storage, EBS volumes show a very poor performance, which is the result of the remote access delay over the network.

Finally, to complete these micro-benchmarks, we set up a software RAID-0 with EBS volumes, varying the number of volumes from 1 to 8. We ran the same benchmark on a c1.medium instance. Fig. 8 shows the write performance on RAID0 on different number of EBS volumes.

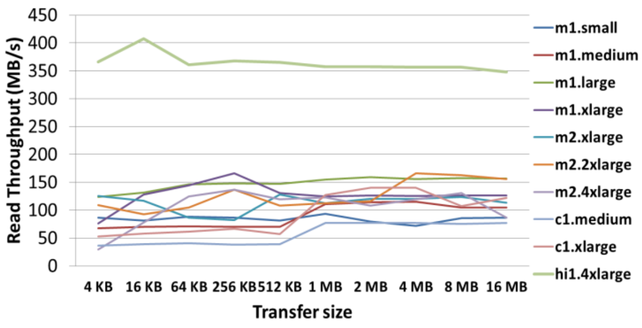


Fig. 6. Local POSIX read benchmark results on all instances

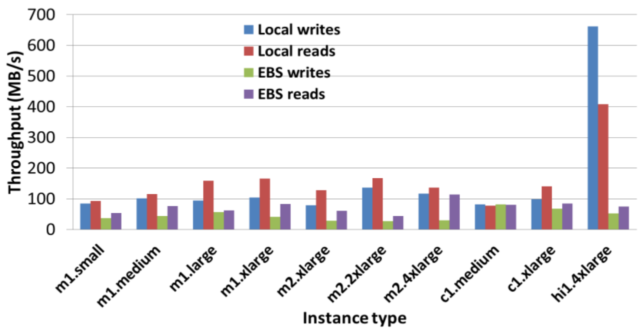


Fig. 7. Maximum write/read throughput on different instances

Looking at the write throughput, we can observe that the throughput does not vary a lot and is almost constant as the transfer size increases. That shows a stable write throughput on EBS drives. The write throughput on the RAID 0 increases with the number of drives. The reason for that is that the data will be spread among the drives and is written in parallel to all of the drives. That increases the write throughput because of having parallel write instead of serial write. Oddly, the performance does not improve as the number of drives increases from 1 to 2 drives. The reason for that is moving from the local writes to network. Therefore the throughput stays the same. For 4 EBS volumes, we can observe a 4x increase on the throughput. In case of 8 EBS volumes we expect a 2x speed up comparing with the 4 EBS experiment. However the write throughput can not scale better because of the limitation of the network bandwith. The maximum achievable throughput is around 120MB/s, which is bound to the network bandwidth of the instances that is 1 Gb/s. so we can conclude that the RAID throughput will not exceed 120 MB/s if we add more EBS volumes.

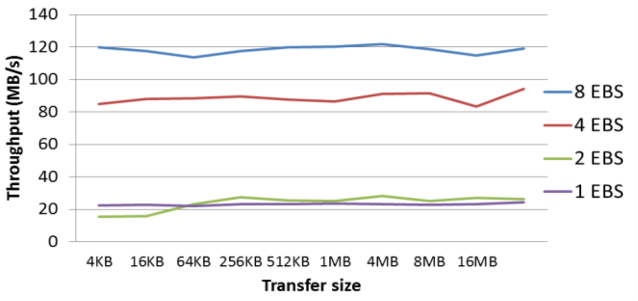


Fig. 8. RAID0 Setup benchmark for different transfer sizes – write

2.4.5 S3 and PVFS Performance

In this section we evaluate and compare the performance of S3 and PVFS. S3 is a highly scalable storage service from Amazon that could be used on multinode applications. Also, a very important requirement for most of the scientific applications is a parallel file system shared among all of the computing nodes. We have also included the NFS as a centralized file system to show how it performs on smaller scales.

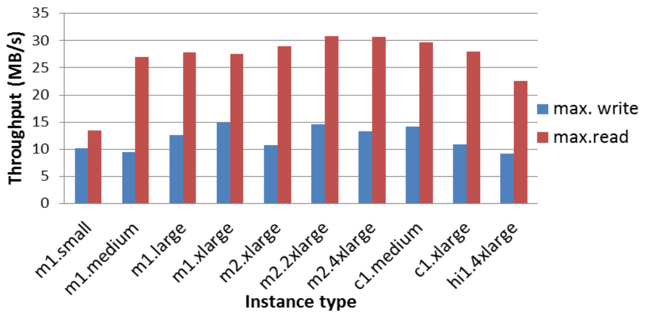


Fig. 9. S3 performance, maximum read and write throughput

First we evaluate the s3 performance on read and write operations. Fig. 9 shows the maximum read and write throughput on S3 accessed by different instance types. Leaving aside the small instances, there is not much difference between the maximum read/write throughput across instances. The reason is that these values are implictly limited by either the network capabilities or S3 itself.

Next, We compare the performance of the S3 and PVFS as two possible options to use for scientific applications.

PVFS is commonly used in scientific applications on HPC environments. On the other hand, S3 is commonly used on the multinode applications that run on cloud environment. We have only included the read performance in this paper. The experiment runs on m1.medium instances. Fig. 10 shows that the read throughput of the S3 is much lower compared to PVFS on small scales. This results from the fact that the S3 is a remote network storage while PVFS is installed and is spread over each instance. As The number of the instances increase, PVFS cannot scale as well as the S3 and the performance of the two systems get closer to each other up to a scale that S3 slightly performs better than the PVFS. Therefore it is better to choose S3 if we are using more than 96 instances for the application.

Next, we evaluate the performance of PVFS2 for the scales of 1 to 64 as we found out that it performs better than S3 in smaller scales. To benchmark PVFS2 for the following experiments we use the MPIIO interface instead of POSIX. In the configuration that we used, every node in the cluster serves both as an I/O and metadata server.

Fig. 11 shows the read operation tihroughput of PVFS2 on local storage with different number of instances and variable transfer size. The effect of having a small transfer size is significant, where we see that the throughput inceases as we make the transfer size bigger. Again, this fact is due to the overhead added by the I/O transaction.

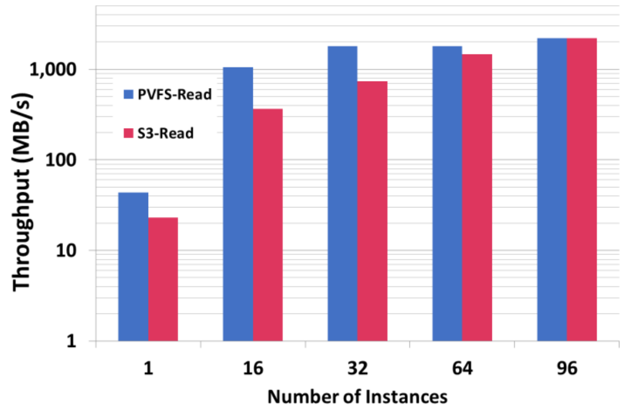


Fig. 10. Comparing the read throughput of S3 and PVFS on different scales

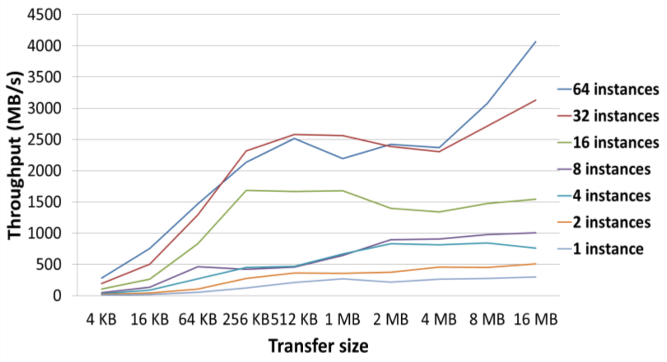


Fig. 11. PVFS read with different transfer sizes over on instance storage

Finally, Fig. 12, shows the performance of PVFS2 and NFS on memory through the POSIX interface. The results show that the NFS cluster does not scale very well and the throughput does not increase as we increase the number of nodes. It basically bottlenecks at the 1Gb/s which is the network bandwidth of a single instance. PVFS2 performs better as it can scale very well on 64 nodes on memory. But as we have shown above, it will not scale on larger scales.

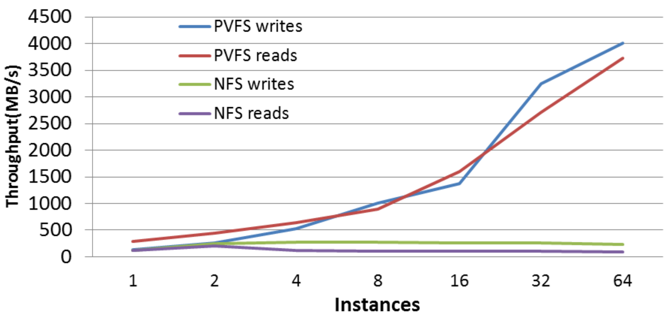


Fig. 12. Scalability of PVFS2 and NFS in read/write throughput using memory as storage

2.4.6 *DynamoDB performance*

In this section we are evaluating the performance of Amazon DynamoDB. DynamoDB is a commonly used NoSql database used by commercial and scientific applications 00. We conduct micro benchmarks to measure the throughput and latency of insert and look up calls scaling from 1 to 96 instances with total number of calls scaling from 10000 to 960000 calls. We conduct the benchmarks on both m1.medium and cc2.8xlarge instances. The provision capacity for the benchmarks is 10K operations/s which is the maximum deault capacity available. There is no information released about how many nodes are used to offer a specific throughput. We have observed that the latency of DynamoDB doesn't change much with scales, and the value is around 10ms. This shows that DynamoDB is highly scalable. Fig. 13 shows the latency of look up and insert calls made from 96 cc2.8xxlarge instances. The average latency for insert and look up are respectively 10 ms and 8.7 ms. %90 of the calls had a latency of less than 12 ms for insert and 10.5 ms for look up.

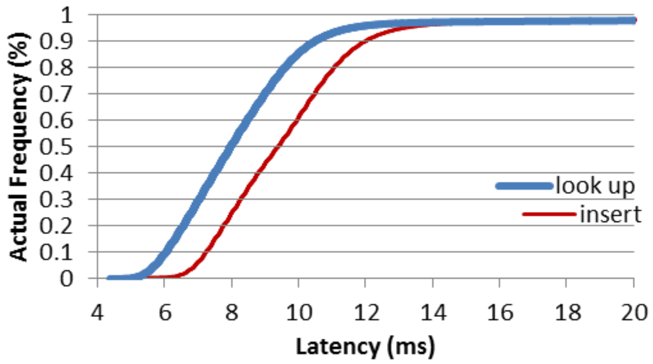


Fig. 13. CDF plot for insert and look up latency on 96 8xxl instances

We compare the throughput of DynamoDB with ZHT 0 on EC2. ZHT is an open source consistent NoSql database providing a service which is comparable to DynamoDB in functionality. We conduct this experiment to better understand the available options for having a scalable key-value store. We use both m1.medium and cc2.8xlarge instances to run ZHT. On 96 nodes scale with 2cc.8xlarge instance type, ZHT offers 1215.0 K ops/s while DynamoDB failed the test since it saturated the capacity. The maximum measured throughput of DynamoDB was 11.5K ops/s which is found at 64 cc2.8xlarge instance scale. For a fair comparison, both DynamoDB and ZHT have 8 clients per node.

Fig. 14 shows that the throughput of ZHT on m1.medium and cc2.8xlarge instances are respectively 59x and 559x higher than DynamoDB on 1 instance scale. On the 96 instance scale they are 20x and 134x higher than the DynamoDB. We can conclude that the ZHT has a significantly higher throughput than DynamoDB up to 96 instance scale and is a better option than DynamoDB for normal AWS users. In the Cost Analysis section we will compare the costs of running workloads over DynamoDB and ZHT.

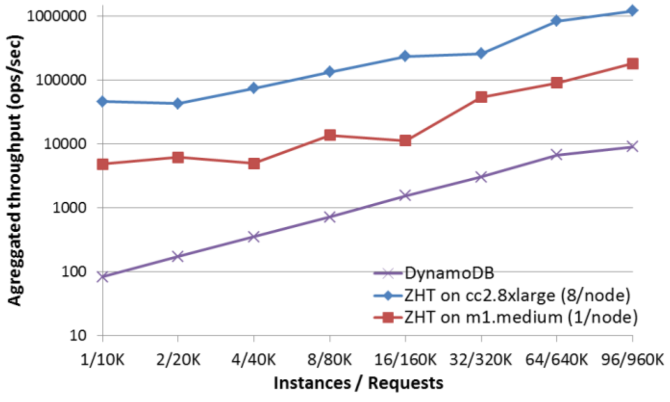


Fig. 14. Throughput comparison of DynamoDB with ZHT running on m1.medium and cc2.8xlarge instances on different scales.

2.4.7 Workflow Application Performance

In this section we analyze the performance of a complex scientific computing application on the Amazon EC2 cloud. The application investigated is Power Locational Marginal Price Simulation (LMPS), and it is coordinated and run through the Swift parallel programming system [12]. Optimal power flow studies are crucial in understanding the flow and price patterns in electricity under different demand and network conditions. A big computational challenge arising in power grid analysis is that simulations need to be run at high time resolutions in order to capture effect occurring at multiple time scales. For instance, power flows tend to be more constrained at certain times of the day and of the year, and these need to be identified.

The power flow simulation application under study analyzes historical conditions in the Illinois grid to simulate instant power prices on an hourly basis. The application runs linear programming solvers invoked via an AMPL (A Mathematical Programming Language) 0 model representation andcollects flow, generation, and price data with attached geographical coordinates. A typical application consists of running the model in 8760 independent executions corresponding to each hour of the year. Each application task execution spans in the range between 25 and 80 seconds as shown in the application tasks time distribution graph in Fig. 15.

A snapshot of one such result prices plotted over the map of Illinois is shown in Fig. 16. The prices are in US dollars per megaWatt-hour shown as interpolated contour plots across the areas connected by transmission lines and generation stations shown as lines and circles respectively. A series of such plots could be post processed to give an animated visualization for further analysis in trends etc.

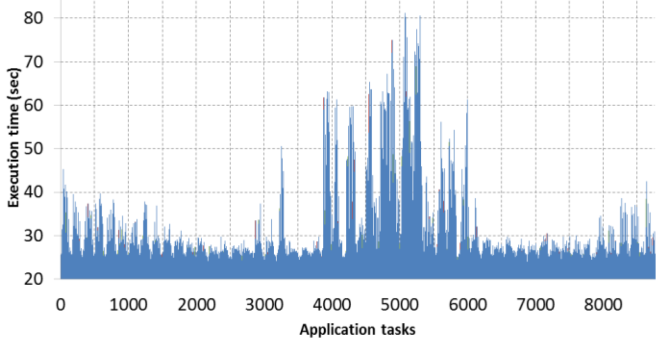


Fig. 15. The LMPS application tasks time distributions.

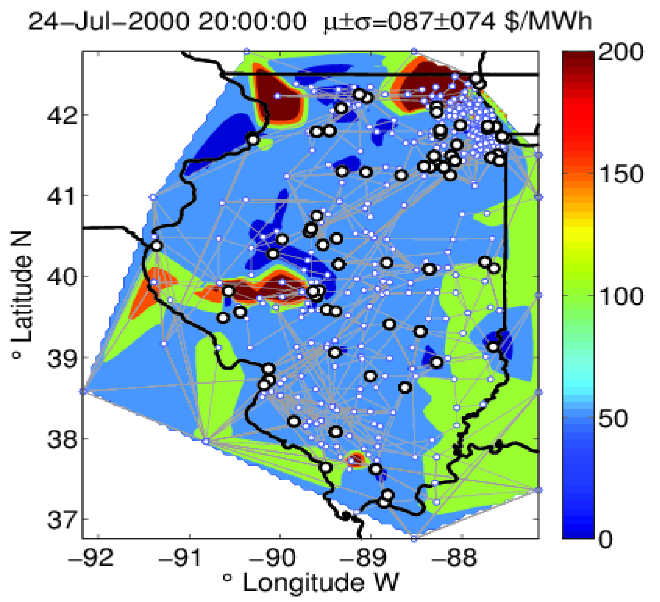


Fig. 16. A contour plot snapshot of the power prices in $/MWh across the state of Illinois for an instance in July 2000

The execution of the application was performed on an increasing number of m1.large instances (see Fig. 17). For data storage, we use S3. Given that the application scales well to 80 instances, but not beyond that. The performance saturation is a salient point that comes out of Fig. 17. With S3 object store being remote, at 100 VMs it takes long enough to fetch the data that its dominating execution time. More scalable distributed storage subsystem should be investigated that is geared towards scientific computing, such as PVFS, Lustre, or GPFS.

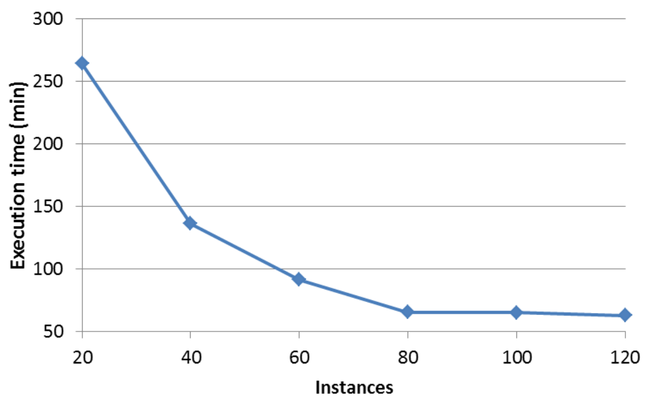


Fig. 17. The runtime of LMPS on m1.large instances in different scales.

2.5 Performance Comparison of EC2 vs. FermiCloud

In this section we want to compare the performance of the EC2 as a public cloud with FermiCloud as a private cloud on HPL benchmark which is a real HPC application. Before comparing the performance of Amazon on real Applications, we need to compare the raw performance of the two resources.

2.5.1 Raw performance comparison

Before comparing the performance of the two infrastructures on real applications like HPL, we need to compare their raw performance on the essential metrics in order to find the root causes of their performance difference. The most effective factors on HPL performance are compute power and Network. We need to compare these factors on the instances with similar functionalities.

On both of the Clouds, we chose the instances that can achieve the highest performance on HPL applications. On EC2, we use cc1.4xlarge instances that are enabled with an 8 core 2.6 GHz Intel processors and a 10 Gigabit network adapter. On FermiCloud, each server machine is enabled with with 2 quad core 2.66 GHz Intel processors, and 8 port RAID Controller.

The CPU efficiency is defined as the performance of the VM running HPL on a single VM with no network connectivity, divided by the the theoritical peak performance of the CPU.

Fig. 18 compares the raw performance of the Amazon EC2 with FermiCloud on CPU and network performance.

The results show that the virtualization overhead on FermiCloud instances are significantly lower than the EC2 instances. This would be an effective factor while running applications on simultaneously on multiple nodes.

The FermiCloud instances are enabled with infiniband network adapters and are able to provide hogher performance compared to the EC2 instances that have 10 Gigabit network cards. The efficiency of both of the systems on network throughput is high. The network throughput efficiency is defined as the VM network performance divded by the theoritical peak of the device. FermiCloud and EC2 network adapters respectively achieve %97.9 and %97.4 efficiency.

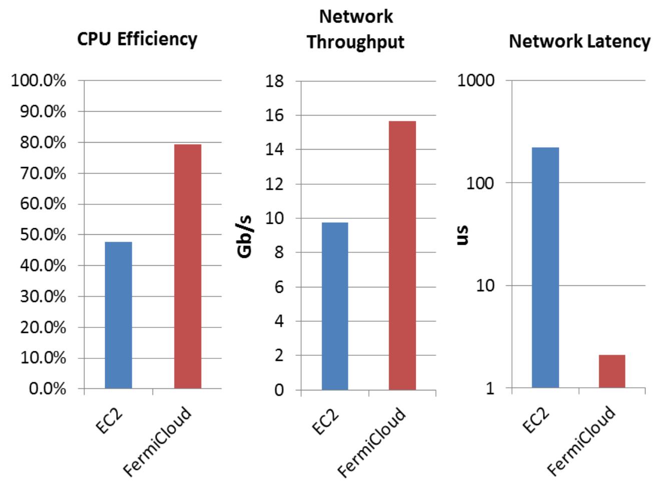


Fig. 18. Raw performance comparison overview of EC2 vs. FermiCloud

There is a huge gap between the network latency of the two clouds. The latency of the FermiCloud instance is 2.2 us as compared to the latency of EC2 instance which is 222 us. Another important factor is the latency variance. The latency variance on both systems is within %20 which is stable. HPL application uses MPI for communication among the nodes. The network latency can decrease the performance of the application by affecting the MPI performance.

2.5.2 HPL performance comparison

In this section we evaluate the performance of HPL application on both on a virtual cluster on both FermiCloud and EC2. The main difference on the two infrastructures is on their virtualization layer and the network performance. FermiCloud uses KVM and is enabled with infiniband network adapters. EC2 uses its own type of virtualization which is based on Xen hypervisor and has 10 Gigabit network adapters.

The best way to measure the efficiency of a virtual cluster on a cloud environment is defining it as the performance of the VM which include the virtualization overhead divided by the host performance that doesn't include virtualization overhead. We can measure the efficiency as defined for FermiCloud since we have access to the host machines. But that is not possible for EC2 since we don't have access to the host machines. Therefore we compare the scalability efficiency of the two clouds which is defined as the overhead of the application performance as we scale up the number of cloud instances.

Fig. 19 compares the efficiency of EC2 and FermiCloud running HPL application on a virtual cluster. Due to budget limitations we run the experiment up to 32 instances scale.

The results show that the efficiency is majorly dependent on the network performance. On the 2 instances scale, both cloud show good efficiency and only lose %10 efficiency that is due to the MPI communications latency added between the instances. Since both of the clouds have powerful network adapters, the communication overhead is still not a bottleneck on 2 instances scale. As the number of instances increase, the applications processes make more MPI calls to each other and start saturating the network bandwidth. Having infiniband network, the FermiCloud loses less efficiency than the EC2. The efficiency of EC2 drops to %78 as the FermiCloud effiency drops to %87. We can notice that the efficiency of the EC2 decreases significantly on 8 instances scles. The reason for that is that the network gets saturated due to too many MPI communications.

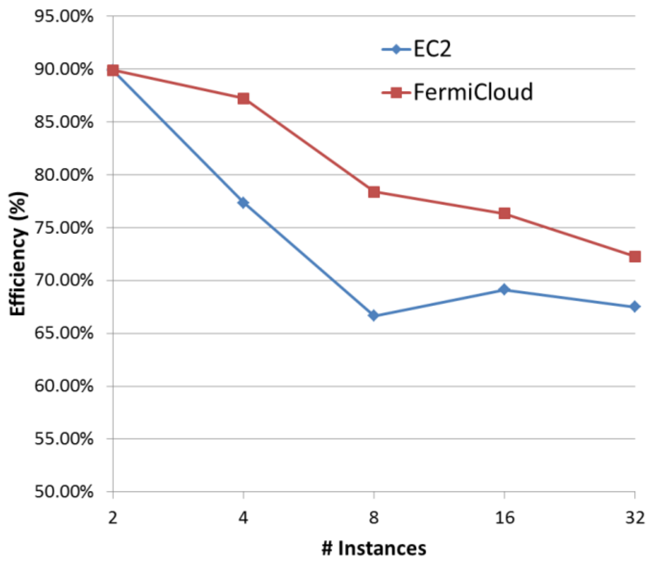


Fig. 19. Efficiency comparison of EC2 and FermiCloud running HPL application on a virtual cluster.

3 Cost Analysis

In this section we analyze the cost of the Amazon EC2 cloud from different aspects. We analyze the cost of instances for compute intensive applications as well as for data intensive applications. Our analysis provides suggestions to different cloud users to find the instance type that fits best for certain application with specific requirements. Next section compares the instances based on their memory capacity and performance.

3.1 Memory Cost

This section compares the cost of the memory on Amazon EC2 instances. Fig. 20 compares the cost of instances based on their memory capacity and bandwidth.

The GB/Dollar metric on the left hand side shows the capacity cost effectiveness of the instances. The most cost effective instances for memory capacity are the high memory (m2.2xlarge & m2.4xlarge) instances. But looking at the cost of the memory bandwidth, we can observe that these instances don't have the best memory bandwidth efficiency. The most cost effective instances based on the memory bandwidth efficiency are the m1.small and m1.medium instances.

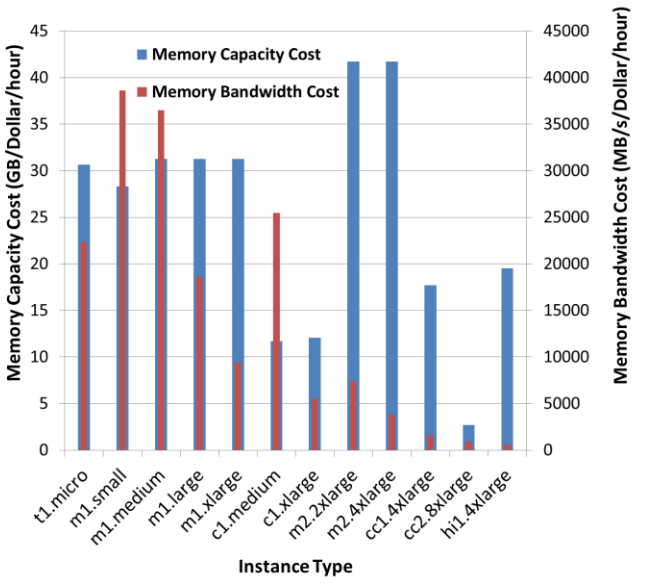


Fig. 20. Memory capacity and memory bandwidth cost.

3.2 CPU Cost

In this section we analyze the cost-effectiveness of instances based on the performance of the instances while running compute intensive applications. The metric for our analysis is GFLOPS/Dollar.

Fig. 21 compares the ideal performance cost of the instances based on Amazon claims with their actual performance while running HPL benchmark. The results show that although the cc2.8xlarge is expected to be the most cost-effective instance, the best compute type is c1.medium. This instance is listed as a High CPU instance.

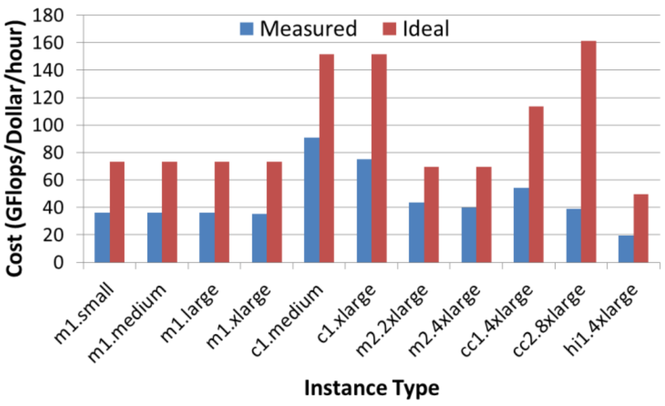


Fig. 21. CPU performance cost of instances

3.3 Cluster Cost

We analyze the cost of the virtual clusters set up by m1.medium and cc1.4xlarge instances in different sizes. Fig. 22 compares the cost of the virtual clusters based on their compute performance.

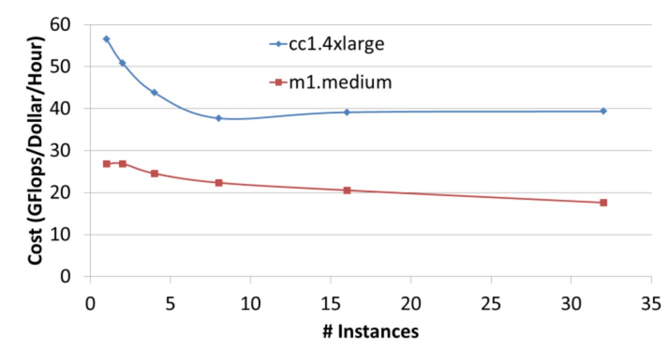


Fig. 22. Cost of virtual cluster of m1.medium and cc1.4xlarge.

3.4 DynamoDB Cost

Finally in this section we evaluate the cost of DynamoDB. In order to better understand the value of offered service, we compare the cost with the cost of running ZHT on EC2 on different instance types.

Fig. 23 shows the hourly cost of 1000 ops/s capacity offered by DynamoDB compared to the equal capacity provided by ZHT from the user point of view.

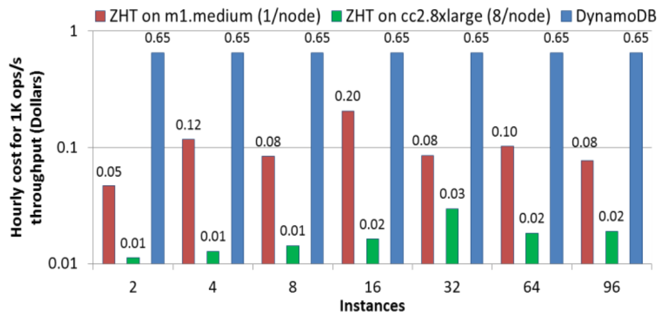


Fig. 23 Cost Comparison of DynamoDB with ZHT

We are comparing the two different scenarios of cost of using a free application on rented EC2 instances versus getting the service from DynamoDB. In case of DynamoDB, since the users pays for the capacity that they get, the number of instances doesn't affect the cost. That's why the cost of DynamoDB is always constant. For ZHT, the system efficiency and performance varies on different scales hence the variation in costs for ZHT at different scales. Since the cc2.8xlarge instances provide much better performance per money spent, the cost per operation is as good as 65X lower than DynamoDB. However, the better costs come at the complexity of managing a virtual cluster of machines to operate ZHT. It is likely that for low loads including sporadic requirements for DynamoDB, it makes financial sense to run on Amazon AWS services, but for higher performance requirements it is much more beneficial to simply operate a dedicated ZHT system over EC2 resources.

3.5 Performance and Cost Summary

This section summarizes the performance and the cost efficiency of Amazon EC2 and other services of AWS. Table 1 shows the performance overview of the different instance types on EC2. The performance results of the instances mostly match with the prediction based on the claims of Amazon. There have been anomalies in some of the specific instance types. Instances like m1.xlarge have average performance while m1.medium instance has shown a performance that was higher than expected.

TABLE 1: Performance summary of EC2 instances

	CPU bw	Mem. bw	Net. bw	Disk I/O
m1.small	Low	Low	Low	Low
m1.med	Low	Avg	Avg	Low
m1.lrg	Avg	Avg	Avg	Avg
m1.xlrg	Avg	Avg	Avg	Avg
c1.med	Avg	Avg	Avg	Low
c1.xlrg	Avg	High	Avg	Avg
m2.2xlrg	High	High	Avg	Avg
cc1.4xlrg	High	High	High	Avg
cc2.8xlrg	High	High	High	Avg
hi1.lrg	High	Avg	High	High

Table 2 summarizes the cost-efficiency of instance types of EC2. As it is noticeable from the table, the cost efficiency of the high end instances that are better fits for HPC and scientific applications is lower than the small instances. Finally table 3 summarizes the performance of S3 and DynamoDB.

TABLE 2: Cost-efficiency summary of EC2 instances

	CPU bw	Mem. Cap.	Mem. bw	Net. bw
m1.small	Avg	Avg	High	High
m1.med	Avg	Avg	High	High
m1.lrg	Avg	Avg	Avg	Avg
m1.xlrg	Avg	Avg	Low	Low
c1.med	High	Low	High	Low
c1.xlrg	High	Low	Low	Low
m2.2xlrg	Low	High	Low	Low
cc1.4xlrg	Avg	Low	Low	Low
cc2.8xlrg	Low	Low	Low	Low
hi1.lrg	Low	Low	Low	Low

TABLE 3: Performance and Cost-efficiency summary of AWS services

	Scalability	Cost-efficiency	Data Granularity
S3	High	High	Large data
DynamoDB	High	Low	Small data

4 RELATED WORK

There have been many efforts to investigate the usefulness of cloud computing and virtualization for scientific applications. Researchers have tried to evaluate the performance of clouds in order to understand the weaknesses and benefits of them when used for scientific applications.

There have been many researches that have tried to evaluate the performance of Amazon EC2 cloud [14][16][17]. However the experiments were mostly run on limited types and number of instances. Therefore they lack the generality in their results and conclusions, as they have not covered all instance types. Unlike these previous works, we cover all instance types in order to give a general view of the instances and enable users to choose the best instances for different use case scenarios.

Ostermann et al. have evaluated Amazon EC2 using micro-benchmarks in different performance metrics. However their experiments do not include the more high-end instances that are more competitive to HPC systems. Moreover, the Amazon performance has improved since then and more features have been added to make it useful for HPC applications [14]. In addition to the experiments scope of that paper, our work provides the evaluations of the raw performance of a variety of the instances including the high-end instances, as well as the performance of the real applications.

He et al. have deployed a NASA climate prediction application into major public clouds, and compared the results with dedicated HPC systems results. They have run micro-benchmarks and real applications [15]. However they only run their experiments on small number of VMs. We have evaluated the performance of EC2 on larger scales.

Jackson has deployed a full application that performs massive file operations and data transfer on Amazon EC2 [18]. The research mostly focuses on different storage options on Amazon. Our work covers the storage services performance both on micro-benchmarks as well as the performance while being used by data-intensive applications.

Only a few of the researches that measure the applicability of clouds for scientific applications have used the new Amazon EC2 cluster instances that we have tested [10][20]0. Mehrotra compares the performances of Amazon EC2 HPC instances to that of NASA's Pleiades supercomputer [10]. However the performance metrics in that paper is very limited. They have not evaluated different performance metrics of the HPC instances. Ramakrishnan have measured the performance of the HPCC benchmarks [20]. They have also applied two real applications of PARATEC and MILC. They have compared the performance of Amazon EC2 with Magellan cloud while running the same applications.

Juve investigates different options of data management of the workflows on EC2 0. The paper evaluates the runtime of different workflows with different underlying storage options. It uses a limited number of instance types. It also evaluates the cost of running workflow applications. The aforementioned works have not provided a comprehensive evaluation of the HPC instances. Their experiments are limited to a few metrics. Among the works that have looked at the new HPC instances, our work is the only one that has evaluated all of the critical performance metrics such as memory, compute, and network performance. Our paper has evaluated the performance of the new HPC instances and also has shown the compute performance of a virtual cluster that is using MPI and is made of such instances. This experiment is very useful in that it shows the performance of EC2 while running scientific applications using MPI.

Many works have covered the performance of public clouds without having an idea about the host performance of the nodes without virtualization head [14][15][16]. Younge has evaluated the performance of different virtualization techniques on FutureGrid private cloud [11]. The focus of that work is on the virtualization layer rather than the cloud infrastructure. Our work compares the performance of the public cloud and a private cloud on different aspects running both micro-benchmarks and real scientific applications. Being able to measure the virtualization overhead on the FermiCloud private cloud, we could provide a better comparison of the two cloud environments.

Many papers have analyzed the cost of the cloud as an alternative resource to dedicated HPC resources [18][19]0. However this paper is the only work that compares the cost of different instances based on major performance factors in order to find the best use case for different instances of Amazon EC2.

5 Conclusion

In this paper, we present a quantitative study to evaluate the performance of the Amazon EC2 for the goal of running scientific applications. We evaluate the performance of various instance types by running micro benchmarks on memory, compute, network and storage. In most of the cases, the actual performance of the instances is lower than the expected performance or what Amazon claims. Most of the instances have stable memory bandwidth, which is comparable with non-virtualized systems. The compute performance of the instances is affected by virtualization overhead on the larger instances. We also run different types of network benchmarking. The results show stable internal network performance of single client-server connections. However we notice the poor performance and scalability in wide area connections between datacenters. The network latency is higher and less stable than what is available on the supercomputers.

We also compare the performance of EC2 as a commonly used public cloud with FermiCloud, which is a higher end private cloud that is tailored for scientific for scientific computing. We compare the raw performance as well as the performance of the real applications on virtual clusters with multiple HPC instances. The results show that the performance of the MPI applications is highly dependent on network performance of the infrastructure. In this case, FermiCloud is able to achieve higher performance and efficiency due to having infiniband network cards. We can conclude that the cloud infrastructures with more powerful network capacity are more suitable to run scientific applications.

We evaluated the I/O performance of Amazon instances and storage services like EBS and S3. The I/O performance of the instances is lower than performance of dedicated resources. The only instance type that shows promising results is the high-IO instances that have SSD drives on them. The performance of different parallel file systems is lower than performance of them on dedicated clusters. The read and write throughput of S3 is lower than a local storage. Therefore it could not be a suitable option for scientific applications. However it shows promising scalability that makes it a better option on larger scale computations. The performance of PVFS2 over EC2 is convincible for using in scientific applications that require a parallel file system.

Amazon EC2 provides powerful instances that are capable of running HPC applications. However, the performance a major portion of the HPC applications are heavily dependent on network bandwidth, and the network performance of Amazon EC2 instances cannot keep up with their compute performance while running HPC applications and become a major bottleneck. Moreover, having the TCP network protocol as the main network protocol, all of the MPI calls on HPC applications are made on top of TCP protocol. That would add a significant overhead to the network performance. Although the new HPC instances have higher network bandwidth, they are still not on par with the non-virtualized HPC systems with high-end network topologies. The cloud instances have shown to be performing very well, while running embarrassingly parallel programs that have minimal interaction between the nodes [10]. The performance of embarrassingly parallel application with minimal communication on Amazon EC2 instances is reported to be comparable with non-virtualized environments [21][22].

Armed with both detailed benchmarks to gauge expected performance and a detailed price/cost analysis, we expect that this paper will be a recipe cookbook for scientists to help them decide between dedicated resources, cloud resources, or some combination, for their particular scientific computing workload.

ACKNOWLEDGEMENT

This work was supported in part by the National Science Foundation grant NSF-1054974. It is also supported by the US Department of Energy under contract number DE-AC02-07CH11359 and by KISTI under a joint Cooperative Research and Development Agreement. CRADA-FRA 2013-0001/KISTI-C13013. This work was also possible in part due to the Amazon AWS Research Grants. We thank V. Zavala of ANL for power grid application.

REFERENCES

[1] Amazon EC2 Instance Types, Amazon Web Services, [online] 2013, http://aws.amazon.com/ec2/instance-types/ (Accessed: 2 November 2013)

[2] Amazon Elastic Compute Cloud (Amazon EC2), Amazon Web Services, [online] 2013, http://aws.amazon.com/ec2/ (Accessed: 2 November 2013)

[3] Amazon Simple Storage Service (Amazon S3), Amazon Web Services, [online] 2013, http://aws.amazon.com/s3/ (Accessed: 2 November 2013)

[4] Iperf, Souceforge, [online] June 2011, http://sourceforge.net/projects/iperf/ (Accessed: 2 November 2013)

[5] A. Petitet, R. C. Whaley, J. Dongarra, A. Cleary. "HPL", (netlib.org), [online] September 2008, http://www.netlib.org/benchmark/hpl/ (Acessed: 2 November 2013)

[6] J. J. Dongarra, S. W. Otto, M. Snir, and D. Walker, \An introduction to the MPI standard," Tech. Rep. CS-95-274, University of Tennessee, Jan. 1995

[7] Release: Amazon EC2 on 2007-07-12, Amazon Web Services, [online] 2013, http://aws.amazon.com/releasenotes/Amazon-EC2/3964 (Accessed: 1 November 2013)

[8] K. Yelick, S. Coghlan, B. Draney, and R. S. Canon, "The Magellan report on cloud computing for science," U.S. Department of Energy, Tech. Rep., 2011

[9] L. Ramakrishnan, R. S. Canon, K. Muriki, I. Sakrejda, and N. J. Wright. "Evaluating Interconnect and virtualization performance for high performance computing", ACM Performance Evaluation Review, 2012

[10] P. Mehrotra, et al. 2012. "Performance evaluation of Amazon EC2 for NASA HPC applications" In *Proceedings of the 3rd workshop on Scientific Cloud Computing* (ScienceCloud '12). ACM, New York, NY, USA, pp. 41-50

[11] A. J. Younge, R. Henschel, J. T. Brown, G. von Laszewski, J. Qiu, and G. C. Fox, "Analysis of virtualization technologies for high performance computing environments," International Conference on Cloud Computing, 2011

[12] Y. Zhao, M. Hategan, B. Clifford, I. Foster, G. von Laszewski, I. Raicu, T. Stef-Praun, and M. Wilde. "Swift: Fast, reliable, loosely coupled parallel computation", IEEE Int. Workshop on Scientific Workflows, pages 199–206, 2007

[13] I. Raicu, Z. Zhang, M. Wilde, I. Foster, P. Beckman, K. Iskra, B. Clifford. "Towards Loosely-Coupled Programming on Petascale Systems", IEEE/ACM Supercomputing 2008

[14] S. Ostermann, A. Iosup, N. Yigitbasi, R. Prodan, T. Fahringer, and D. Epema. "A Performance Analysis of EC2 Cloud Computing Services for Scientific Computing". In Cloudcomp, 2009

[15] Q. He, S. Zhou, B. Kobler, D. Duffy, and T. McGlynn. "Case study for running HPC applications in public clouds," In *Proc. of ACM Symposium on High Performance Distributed Computing*, 2010

[16] G. Wang and T. S. Eugene Ng. "The Impact of Virtualization on Network Performance of Amazon EC2 Data Center". In IEEE INFOCOM, 2010

[17] S. L. Garfinkel, "An evaluation of amazon's grid computing services: Ec2, s3 and sqs," Computer Science Group, Harvard University, Technical Report, 2007, tR-08-07

[18] K. R. Jackson et al. "Performance and cost analysis of the supernova factory on the amazon aws cloud". Scientific Programming, 19(2-3):107-119, 2011

[19] J.-S. Vockler, G. Juve, E. Deelman, M. Rynge, and G.B. Berriman, "Experiences Using Cloud Computing for A Scientific Workflow Application," 2nd Workshop on Scientific Cloud Computing (ScienceCloud), 2011

[20] L. Ramakrishnan, P. T. Zbiegel, S. Campbell, R. Bradshaw, R. S. Canon, S. Coghlan, I. Sakrejda, N. Desai, T. Declerck, and A. Liu. "Magellan: experiences from a science cloud". In *Proceedings of the 2nd international workshop on Scientific cloud computing*, pages 49–58, San Jose, USA, 2011

[21] K. Jackson, L. Ramakrishnan, K. Muriki, S. Canon, S. Cholia, J. Shalf, H. Wasserman, and N. Wright, "Performance Analysis of High Performance Computing Applications on the Amazon Web Services Cloud," in *2nd IEEE International Conference on Cloud Computing Technology and Science*. IEEE, 2010, pp. 159–168

[22] J.-S. Vockler, G. Juve, E. Deelman, M. Rynge, and G.B. Berriman, "Experiences Using Cloud Computing for A Scientific Workflow Application," *2nd Workshop on Scientific Cloud Computing* (ScienceCloud), 2011

[23] J. Lange, K. Pedretti, P. Dinda, P. Bridges, C. Bae, P. Soltero, A. Merritt, "Minimal Overhead Virtualization of a Large Scale Su-

percomputer," In *Proceedings of the 2011 ACM SIGPLAN/SIGOPS International Conference on Virtual Execution Environments* (VEE 2011), 2011

[24] G. Juve, E. Deelman, G.B. Berriman, B.P. Berman, and P. Maechling, 2012, "An Evaluation of the Cost and Performance of Scientific Workflows on Amazon EC2", *Journal of Grid Computing*, v. 10, n. 1 (mar.), p. 5–21

[25] R. Fourer, D. M. Gay, and B. Kernighan, "Algorithms and model formulations in mathematical programming," Ed. New York, NY, USA: Springer-Verlag New York, Inc., 1989, ch. AMPL: a mathematical programming language, pp. 150–151

[26] T. Li, X. Zhou, K. Brandstatter, D. Zhao, K. Wang, A. Rajendran, Z. Zhang, I. Raicu. "ZHT: A Light-weight Reliable Persistent Dynamic Scalable Zero-hop Distributed Hash Table", *IEEE International Parallel & Distributed Processing Symposium* (IPDPS) 2013

[27] FermiCloud, Fermilab Computing Sector, [online], http://fclweb.fnal.gov/ (Accessed: 25 April 2014)

[28] R.Moreno-vozmendiano, S. Montero, I. Llorente." IaaS Cloud Architecture: From Virtualized Datacenters to Federated Cloud Infrastructures: Digital Forensics", Computer (Long Beach, CA)

[29] K. Hwang, J. Dongarra, and G. C. Fox, Distributed and Cloud Computing: From Parallel Processing to the Internet of Things. Morgan Kaufmann, 2011

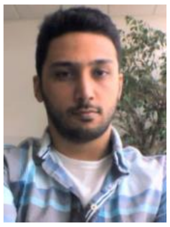
[30] W. Voegels. "Amazon DynamoDB—a fast andscalable NoSQL database service designed for Internet-scale applications." http://www.allthingsdistributed.com/2012/01/amazon-dynamodb.html, January 18, 2012

[31] I. Sadooghi et al. "Achieving Efficient Distributed Scheduling with Message Queues in the Cloud for Many-Task Computing and High-Performance Computing." *In Proc. 14th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGrid'14).* 2014

[32] T. Lacerda Ruivo, G. Bernabeu Altayo et al. "Exploring Infiniband Hardware Virtualization in OpenNebula towards Efficient High-Performance Computing." *CCGrid'14.* 2014

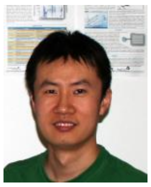
[33] Macleod, D. (2013). OpenNebula KVM SR-IOV driver.

[34] K. Maheshwari et al. "Evaluating Cloud Computing Techniques for Smart Power Grid Design using Parallel Scripting"*In Proc. 14th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGrid'13).* 2013



Iman Sadooghi is a 3rd year PhD student in the department of the Computer Science of Illinois Institute of Technology and a member of DataSys laboratory. He received his MS degree in Software Engineering from San Jose State University. Iman's research interest is Distributed Systems and Cloud Computing. He has two publications in the area of Cloud Computing. Iman is also is a member of the IEEE and the IEEE Computer Society.

Jesus Hernandez is a data engineer at Lyst. He obtained his MS degree in Computer Science from Illinois Institute of Technology in 2012. He also received a BS + MS degree in Computer Engineering from Technical University of Madrid during the same year. His interests range from distributed systems, data processing, and analytics to high performance client-server architectures.



Tonglin Li is a 5th year PhD student working in Datasys Lab, computer science department at Illinois Institute of Technology, Chicago. His research interests are in Distributed systems, Cloud computing, Data-intensive computing, Supercomputing, and Data management. He received his B.E and M.E in 2003 and 2009 from Xi'an Shiyou University, China. Tonglin Li is an IEEE and ACM member.

Kevin Brandstatter Kevin Brandstatter is a 4th year undergraduate student in the department of Computer Science at Illinois Institute of Technology. He has worked as a Research Assistant in the Datasys lab under Dr. Raicu for the past 3 years. His research focus is primarily related to distributed storage systems such as distributed file systems and distributed key value storage.

Ketan Maheshwari is a postdoctoral researcher in the Mathematics and Computer Science Division at Argonne National Laboratory. His research is focused on applications for parallel scripting on distributed and High Performance resources. His main activities in recent years involve design, implementation and execution of parallel applications on clouds, XSEDE, Cray XE6 and IBM supercomputers at University of Chicago. The applications include massive protein docking, weather and soil modeling, earthquake simulations, andpower grid modeling funded by DOE and NIH.

Yong Zhao is professor at the University of Electronic Science and Technology of China. His research interests are in big data, cloud computing, grid computing, data intensive computing, extreme large scale computing, and cloud workflow. He has published more than 40 papers in international computer books, journals and conferences, which are referenced more than 4000 times; He has chaired/co-chaired ACM/IEEE Workshop on Many Task Computing on Grids Clouds and Supercomputers, Workshop on Data Intensive Computing in the Clouds, and IEEE International Workshop on CloudFlow 2012, 2013.

Tiago Pais is a MS graduate in Computer Science by the Illinois Institute of Technology and former Graduate Research Intern in the Fermi National Accelerator Laboratory. His research interests are in network virtualization and mobile technologies.

Gabriele Garzoglio is the head of the Grid and Cloud Services Department of the Scientific Computing Division at Fermilab and he is deeply involved in the project management of the Open Science Grid. He oversees the operations of the Grid services at Fermilab. Gabriele has a Laura degree in Physics from University of Genova, Italy, and a PhD in Computer Science from DePaul University.

Steven Timm is an Associate Department Head for Cloud Computing in the Grid and Cloud Services Department of the Scientific Computing Division at Fermi National Accelerator Laboratory. He received his Ph.D in Physics from Carnegie Mellon. Since 2000 he has held various positions on the staff of Fermilab relating to Grid and Cloud Computing. He has been the lead of the FermiCloud project since its inception in 2009.

Ioan Raicu is an assistant professor in the Department of Computer Science at Illinois Institute of Technology, as well as a guest research faculty in the Math and Computer Science Division at Argonne National Laboratory. He is also the founder and director of the Data-Intensive Distributed Systems Laboratory at IIT. His research work and interests are in the general area of distributed systems. His work focuses on a relatively new paradigm of Many-Task Computing (MTC), which aims to bridge the gap between two predominant paradigms from distributed systems, HTC and HPC. His work has focused on defining and exploring both the theory and practical aspects of realizing MTC across a wide range of large-scale distributed systems. He is particularly interested in resource management in large scale distributed systems with a focus on many-task computing, data intensive computing, cloud computing, grid computing, and many-core computing.