

Exterminating Computational Limits of Machine Learning with Merits of Serverless

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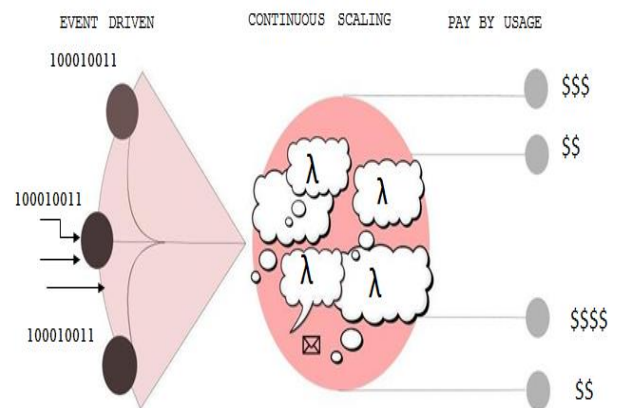
Abstract - The trend of determining patterns using the various machine-learning, data mining, deep-learning or neural networks are limited due to the computational power of machines. Sometimes the cost estimation exceeds heavily from the estimates, or the cost is not sufficient for the enterprises to get the desired infrastructure. Unexpected computational resources at times limit the accuracy and increase the cost of infrastructure to find the perfect patterns. A serverless compute may give an optimal solution to the computational resources provided by the cloud. Resources are elastic, which can expand and shrink according to the input data sets, resulting in lesser computational costs.

Index Terms – AWS (Amazon Web Service) Lambda, Amazon EC2 (Elastic Compute Cloud), Machine Learning, Neural Networks.

1. INTRODUCTION -

The Scaling of silicon behind Moores law has enabled fantastically powerful processing elements in the last twenty years. Despite this processing power, computing tasks which are elementary for a five year old child (semantic image recognition, self-learning, etc.) are still out of reach. Neuromorphic architectures incorporate key features of neurons in the brain and/or process data in a manner analogous to the human brain. Although neuromorphic computing can be classified in many ways, one divisor can be whether they emulate the neuron or not. Or in the case of integrated chips, standard chips versus neurochips. Neuron emulation has been extensively studied. For example, in [15], 16 analog chips simulate over a million neurons in real time with a power consumption of 1W. In reference [15], a practical weak point is the many required input parameters (such as bias voltages), high process variation sensibility and poor correspondence with current software applications (machine vision, machine learning, etc.). Neuromorphic computing which does not emulate the neuron is often classified as, or closely resembles, machine learning and/or artificial neural networks. Unlike neuron emulation, this type of neuromorphic computing does not attempt to simulate individual neurons or their connections, but rather model the large-scale hierarchy of the brain [1], b3 [2]. The aim is to automatically learn to identify complicated patterns and make intelligent decisions based on data. Although this type of computing does not necessarily require complex neuron emulating equations or analog memory, extremely large memory size and high memory bandwidth are still required making these algorithms inefficient when run on the Von Neumann computational model [8]. It is shown here that machine learning type neuromorphic algorithms have the

potential to be realized as single-chip implementations, although some novel breakthroughs in interconnect and memory design are required to achieve area and energy efficiency. Energy efficiency can best be achieved with an ASIC implementation, but all practical realizations require programmability. Thus, subsequent research will concentrate on determining the optimal (in an energy efficient sense) programmable architecture. Most of this type of research has been done on vector processors, such as [21]. However, the machine learning type neuromorphic algorithms pose different research problems; increased internode communication requirements, less mathematical computation due to absent non-linear equations; state-machines with branches, etc. Consider, for example, the breakdown of a load-store unit of a vector processor versus the breakdown of a single processor in a NoC. The former could lead to the inoperability of the whole system where the latter would easily be learned out be the system. There is also much work to be done in achieving energy efficiency by taking advantage of the algorithms inherent noise robustness. Algorithmic simulations are required on how much noise can be tolerated in logic, memory, and communication. These limits can then be used in designing stochastic hardware.



2. LITERATURE SURVEY

A. Mining Unstructured Processes: An Exploratory Study on a Distance Learning Domain

Maita et al. [2017] discussed to use artificial neural networks in the distance learning domain and result of paper showed that ANN was neglected in process mining. The various benefits and limitations of using ANN on unstructured processes discussed.

This paper describes a study aimed at exploring some process mining scenarios, considering the main purpose of applying ANN (Artificial Neural Network) as a technique representative of both the CI/ML fields. The study was carried out based on an unstructured process related to a distance learning supported by a Learning Management System (LMS). In particular, we address some possible benefits and limitations in mining unstructured processes.

Business process and data mining combined establish the process mining field [18], which applies data mining tasks on process data. This new field aims at extracting knowledge about process execution events, seeking to improve business processes, and discovering associations between variables, behavior or misbehavior patterns [18]. Although process mining was introduced in 1990s and it has been considerably improved in recent years, there are some types of processes for which no satisfactory mining technique has been proposed. An example of this is when dealing with unstructured processes, i.e., loosely B. Data mining and mining techniques defined processes, also known as spaghetti processes [18].

For our attempts, either, Weka presented a problem of lack of computing memory or although the tool indicated the end of the training, the results were in fact not presented. An exploration work directly on the ANN implementation provided by the tool, directly manipulating its variables, as well as the use of a more robust test environment could lead to the achievement of results also for very large dataset in terms of attributes which makes the training complexity very high[10].

B. *Learning How to Communicate in the Internet of Things: Finite Resources and Heterogeneity*

Park et al.[2016] provided an overview on the use of learning techniques within the scope of the IoT. This paper discussed about the various types of learning framework that are able to overcome a number of challenges of the IoT and in each learning techniques the main challenges, applications and results were shown. To handle the problem of heterogeneity, cognitive hierarchy theory and its applications were used in the IoT.

For a smooth and continuous deployment of the Internet of Things (IoT), there is a need for self-organizing methods to over-come IoT challenges that include data processing, resource management, coexistence with existing wireless networks, and help for IoT-wide event detection. To developed learning mechanisms for the IoT requires coping with unique IoT properties in terms of resource constraints, heterogeneity, and strict quality-of-service requirements. In this paper, there are number of learning frameworks suitable for IoT applications are presented. In particular, the advantages, limitations, IoT applications, and key results pertaining to machine learning, sequential learning, and reinforcement learning are studied [12].

The major limitation of applying ML(Machine Learning) in IoT scenarios is that ML requires an extensive data set, such as the information of sensor locations and corresponding sensor measurements [3], for good performance. Such a data set needs to be quickly processed for the IoT devices to learn the environment, but the resource-constrained IoT

devices may not be able to store and process the data set given that they have limited resources in terms of computation and memory [5].

Learning Framework	Advantage	Disadvantage
Machine Learning	I. Diversity of available techniques II. Useful in processing the massive data collected in IoT to reduce resource consumption.	I. Implementation typically centralized II. Need for significant Computational capabilities. III. Need for extensive training data.

C. *An Android Malware Detection Approach using Community Structures of Weighted Function Call graphs*

Wang et al.[2017] presented a new malware detection method that divides a function call graph into community structures and these structures were used to detect malware. By using machine learning classification the overall computation time reduced. The results shows that detection accuracy of this method is higher than that of other anti virus software.

In this paper, a new malware detection method based on the analysis of community structures of function call graphs. First, the method applies reverse engineering to obtain the function call graph of an Android application. Second, the function call graph is weighted by sensitive permissions and application programming inter-faces (APIs). Third, the community structures are extracted from the weighted function call graph. Finally, a machine learning classification process is used to detect malware. In an evaluation of 13,790 Android applications, our method achieves 96.5 accuracy in detecting unknown malware [20]. Though the method achieves good malware detection performance, the experimental results indicate that the run-time performance of our method could be improved for large function call graphs with more computational resources. In future work, more efficient computing machines should be designed for community structure generation and feature extraction.

D. *Predicting of Job Failure in Compute Cloud Based on Online Extreme Learning Machine : A Comparative Study*

Liu et al.[2017] proposed a method based on Online Sequential Extreme Learning Machine (OS-ELM) to predict online job termination status. This method has fast learning speed and good generalization.

The existing machine learning-based methods used offline working pattern, which cannot be used for online prediction in which data arrive sequentially. To solve this problem, a new method based on Online Sequential Extreme Learning Machine (OS-ELM) is used to predict online job termination status. With this method, real-time data are collected according to the sequence of job arriving, the job status could be predicted and the operation model is thus updated based on these data. The method with online incremental learning strategy has fast learning speed and good generalization [9].

The method achieves good time and accuracy performance. OSELM model updated within 0.01s, and predict the job termination with an accuracy rate of 93%. It can reduce the

storage space overhead by intelligently identifying job failure, and significantly reduce the resource waste in the cloud [9].

E. Machine Learning Based DDoS Attack Detection From Source Side in Cloud

Tianwei et al.[2017] proposed DOS attack detection system that is based on machine learning techniques in the cloud.

In this paper, machine learning techniques are used to detect DOS(Denial of Service) attack. Four types of DoS attacks are used and we achieve accuracy upto 99.7%. Attackers cannot use their own physical machines instead of their rent many virtual machines and use them as VM bolt to attack the outside world. The major limitation of this paper that it does not degrade performance and can be easily extended to broader DOS attacks.

In future work, for better performance combine different machine learning algorithms and investigate more DoS attacks and integrate their features into current system.[17].

F. Infrastructure Cost Comparison of Running Web Applications in the Cloud using AWS Lambda and Monolithic and Microservice Architectures

Villamizar et al.[2016] compared the infrastructure cost of web applications in the cloud using AWS Lambda, Monolithic and Microservice and showed that microservices reduce infrastructure cost as compared to monolithic architecture. The paper described the application deployments on the AWS infrastructure and also showed the performance test of each architecture so that to compare their infrastructure costs.

This paper compares cost of web applications developed and deployed with monolithic architecture, a microservice architecture operated by the cloud customer, and a microservice architecture operated by the cloud provider. Results show that microservices can help reduce infrastructure costs in comparison to standard monolithic architectures. Moreover, the use of services specifically designed to deploy and scale microservices reduces infrastructure costs by 70% or more [19].

The results shows that microservices can reduce up to 13.42% of infrastructure costs and AWS Lambda reduce infrastructure costs up to 77.08%. For these three architecture cost per million of requests(CMR) calculated by dividing monthly infrastructure costs by no of requests supported per month. The microservice architecture reduce upto 9.50% of cost and AWS(Amazon Web Service) Lambda help to reduce costs upto 50.43%.

The future work is to evaluate the costs incurred by companies during the process of implementing microservices. The process of defining the number of microservices to implement, and the tools required to automate the deployment of microservices in general purpose will also be evaluated [19]

G. Lambda Architecture for Cost-effective Batch and Speed Big Data processing

Kiran et al.[2015] presented an overview of the lambda architecture and how it is used with Apache Storm and Hadoop. He also showed online data collection and

processing for multiple router sensors sending data at a constant rate of 30 seconds.

The paper implemented the lambda architecture design to work on Amazon EC2(Elastic Compute Cloud) and these provide the higher throughput and minimize the cost of network. They define how to optimize the cost of data processing by examining which part of data needs online or batch processing.

For batch processing, when implemented on Amazon AWS reduce the cost and find code errors and also Amazon cloud charges for full hour even if cluster was executed for 2 minutes. For online processing, kinesis stream read data as last in first out order and Amazon cloud allocate data to multiple members of a team. This architecture also capable for big data processing problems.

In this paper, network sensor is used i.e ESnet router production network which is used to collect router in and out bytes from every 30 seconds. The lambda architecture on Amazon AWS was able to provide a proof-of-concept for data processing in data arrives. The solutions allow users to perform cost-optimised processing. Both processes can produce data aggregations which are easier to plot and reduces time for data processing through the data visualization interface [7].

H. Be Wary of the Economics of Serverless Cloud Computing

Weinman[2017] defined what is serverless and how AWS uses Lambda for Serverless Computing. This paper also discussed about the total price of serverless function based on transaction and execution time. During execution, AWS Lambda provides first 1 million hits free and 400,000GB seconds per month free. Hits per second defines the VM Infrastructure Cost and Serverless Cost. This paper defined that if we get more hits per second then we have to pay more for serverless and we have to pay less if function executes fast for serverless.

This paper shows that for 150 hits per second VM infrastructure cost is \$200/ month and serverless cost is \$167/month. Serverless might be 3x the cost of on demand compute, it might save DevOps cost in setting up autoscale, managing security patches and debugging issues with load balancers at scale Weinman [22].

I. Infra: SLO Aware Elastic Auto Scaling in the Cloud for Cost Reduction

Sidhanta and Mukhopadhyay[2016] presented SLO (Service Level Objective) Aware Elastic Auto Scaling in the cloud for cost reduction. They provide a tool that applies on existing machine learning technique to predict minimum cluster composition.

The cluster composition required to run on cloud under an SLO deadline. The degree of confidence $100 * (1 - \%)$ specifies that the probability of failure in achieving the error threshold is at most . The accuracy of prediction of minimum cluster composition ranges from 93.1% to 97.99% with a 98% degree of confidence[14]. To change application workloads, infra automatically adapts a cloud infrastructure and by using infra provisioning tools, it scales the cluster up and down. This paper also described that state-of-art auto

scaling tools require manual specification of scaling rules, and supports scaling with only fixed instance types. The - minimal cluster compositions predicted by Infra satisfies an error threshold of 0.1 with a degree of confidence 0.02 in approximating the minimum cluster composition[14].

J. Hardware for Machine Learning: Challenges and Opportunities

Sze et al.[2017] discussed that machine learning has various applications and opportunities for hardware design but during the designing's, it is important to balance accuracy, energy, throughput and cost requirements. Machine learning also transform the input data into higher dimensional space along with the programmable weights that helps to increases data movement and energy consumption.

This paper also discussed about the various challenges of hardware design for the architecture, hardware-friendly algorithms, mixed-signal circuits and advanced technologies. DNN (Deep Neural Network) delivers higher accuracy by mapping input data into higher dimensional space and increases complexity.

This paper also compared the energy and accuracy of hand crafted and DNN in which hand crafted gives higher energy efficiency as compared to DNN.

K. Predictive Analytics for Banking User Data using AWS Machine Learning Cloud Service

Ramesh[2017] developed a Machine Learning model to perform predictive analytics on the banking dataset. Data set is used to create a binary classification model using Amazon Web Service (AWS) Machine Learning platform. 70 % of the data is used to train the binary classification model and 30 % of the dataset is used to test the model[13]. The model tested by using two features in AWS Machine Learning. In first, the model was tested by using real time prediction in which real time input data is given and in second, model tested by using batch prediction in which set of customer data is used.

Amazon Machine Learning powerful algorithms create machine learning (ML) models by finding patterns in our existing data. Then, the service uses these models to process new data and generate predictions for your application[13]. To create a model various steps was used in AWS Machine Learning.

L. Study on a migration scheme by fuzzy-logic-based learning and decision approach for QoS in cloud computing

Huh and young Son[2017] presented QoS metrics of migration and proposed migration scheme based on fuzzy

logic. They we determine whether the VMs should wait or should be migrated to other active PMs for continuous service.

This paper also described that proposed scheme determining VMs which need to migrate through fuzzy system and then selecting target machine through considering QoS metrics. The goal of migration is to maximize efficiency and QoS by choosing the target machine through present scheme. The proposed scheme verified performance and reliability that can achieve much better[6]. The major goal of this paper was to apply fuzzy logic and machine learning technique for advanced migration. The future work of this paper is to improve the efficiency in the large scale service and variety of datacenter environment on live migration mechanism.

M. Cloud Computing Threats Classification Model Based on the Detection Feasibility of Machine Learning Algorithms Masetic et al.[2017] proposed that for successful threat detection in cloud computing infrastructures is the application of machine learning algorithms. This paper described that there are three types of classification type of learning algorithm, input features and cloud computing level. First considers two types of learning: supervised and unsupervised then second criterion considers system performance data and network traffic data, which are input to both types of learning.

Finally, last considers network specific and cloud environment specific threats, which are described by system performance and network traffic data[11].

N. Machine learning capabilities, limitations and implications

Armstrong[2015] discussed the various capabilities and limitations of machine learning algorithms. A model of relationship between inputs and outputs is improved by testing its predictions and correcting when wrong. Machine learning is a set of computerized techniques for recognizing patterns in data.

Machine learning algorithms are an integral part of driverless cars and will have an increasingly important role in their operational ability. These learning systems are broadly used for tasks such as image recognition or scheduling but learning in noisy real world environments is difficult. Machine learning techniques will be instrumental in providing personalized medicine and finding value in the emerging large medical and personal data sets from genomics and consumer health technologies[4].

3. COMPARISON
TABLE II
ANALYSIS OF TECHNIQUES WITH THEIR OUTCOMES

Author	Index, Year	Dataset	Technique	Purpose	Strength	Limits
Harry Armstrong	Nesta, July 2015		Discuss about capabilities limitations and implication of machine learning	Games, driverless car, medicine and healthcare	Useful in processing the massive data collected in IoT to reduce resource consumption	Need for significant computational capabilities and No security
Mariam Kiran, Peter Murphy, Sartaj Singh Baveja	IEEE, Dec 2015	ESnet network data	Lambda	To implement Lambda on Amazon EC2 and results are present on ESnet network data	Dynamo DB has \$ 0.02 per 100,000 transaction and max storage costs is \$0.09. S3 has \$ 0.005 per 1000 requests and storage costs is \$0.03 per GB	Loss of data and security
Mario Villamizar, Oscar Garces, Lina Ochoa	IEEE, July 2016		AWS lambda, monolithic and microservice	Cost comparison of a web application developed and deployed with three different approaches: 1) a monolithic architecture, 2) a microservice architecture operated by the cloud customer, and 3) a microservice architecture operated by the cloud provider	Microservices can reduce infrastructure costs as compared to standard monolithic architectures. Moreover, Microservices can reduce up to 13.42% of infrastructure costs and AWS Lambda reduce infrastructure costs up to 77.08%	To evaluate the costs incurred by companies during the process of implementing microservices
Subhajit Sidhanta, Supratik Mukhopadhyay	IEEE, 06 Oct 2016	Auto Scaling	Infra	To predict minimum cluster composition required to run on a cloud under an SLO	the accuracy of prediction of minimum cluster composition ranges from 93.1% to 97.99% with a 98% degree of confidence	State-of-the art auto scaling tools require manual specification of scaling rules, and supports scaling with only fixed instance types
Taehyeun Park, Nof Abuzainab, and Walid Saad	IEEE, 8 Nov 2016	Cognitive hierarchy Theory	Internet of things (IOT)	Self-organizing solutions for IoT challenges implementing innovative learning frameworks enables the IoT devices to operate autonomously in a dynamic environment	Determine which learning frameworks are most suitable for learning and the available resources of the IoT devices in the level of cognitive hierarchy	ML in IoT devices may not be able to store and process the data set because they have limited resources in terms of computation and memory
Joe Weinam	IEEE, April 2017		AWS	Describes what is serverless and how AWS uses Lambda	AWS Lambda offer first 1 million hits and 400,000 GB sec per month free. For 150 hits per sec VM infrastructure cost is \$200/month and serverless cost is \$167/month	Problem due to third party API system

Chunhong Liu, Jingjing Han, Yanlei Shang	IEEE, May 2017	Support Vector Machine (SVM), Extreme Learning Machine (ELM) and online Sequential Support Vector Machine (OS-SVM)	Online Sequential Extreme Learning Machine (OSELM)	To solve the problem of offline working pattern problem, OS-ELM is used to predict online termination job status.	OSELM model updated within 0.01s, and predict the job termination with an accuracy rate of 93%.	Reduce the storage space overhead by identifying job failure, reduce the resource waste in the cloud.
Z. Masetic, K. Hajdarevic, N. Dogru	IEEE, 26 May 2017	Cloud threat detection	Machine Learning	cloud computing services became a common target of cyber-attacks. So, cloud computing vendors and providers need to implement strong information security protection mechanisms on their cloud infrastructures.	99.4% detection	Accuracy
Ana R. C. Maita, Marcelo Fantinato and Sarajane M. Peres	IEEE, 3 July 2017	Id, Time and Activity	ANN (Artificial Neural Network)	ANN technique on an unstructured process related to a distance learning supported by a Learning Management System (LMS).	Training complexity very high	Weka presented a lack of computing memory
Ranjith Ramesh	IEEE, 11 July 2017	Bank	AWS Machine Learning	To develop a Machine Learning model to perform predictive analytics on the banking dataset	Prediction score is compared to the threshold and it is converted to numerical value 0 or 1. If the predicted value is above the threshold then the numerical value is 1 (yes) or else it is 0 (No)	Only 9 % of predicted data is wrong.
Zecheng He, Tianwei Zhang, Ruby B. Lee	IEEE, 24 July 2017	Internet Control Message Protocol (ICMP)	Machine learning techniques	To detect DOS (Denial of Service) attack, machine learning techniques are used. System give information from both the cloud servers hypervisor and the virtual machines, to prevent network packages from being sent out to the outside network.	DoS attacks achieves accuracy upto 99.7%.	Does not degrade performance and can be easily extended to broader DOS. attacks.
Vivienne Sze, Yu-Hsin Chen, Joel Emer	IEEE, 27 July 2017	ImageNet	Machine Learning	During the design process, it is important to balance the accuracy, energy, throughput and cost requirements		By reducing the cost of memory access, it helps in more energy efficient data flows
A-young Son, Eui-Nam Huh	IEEE, 27 July 2017	Migration	Fuzzy Logic	Apply fuzzy logic and machine learning technique for advanced migration	Decrease in migration time about 9.5%	Improve the efficiency in the large scale service.

Yao Du, Junfeng Wang	Springer, 2017	Android applications and malware samples	Malware Detection	New malware detection method based on the analysis of community structures of function call graphs. machine learning process is used to detect malware	For 13,790 Android applications, our method achieves 96.5% accuracy in detecting unknown malware	The rapid growth of new malware families presents another challenge
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3. Gaps –

- ML(Machine Learning) in IoT devices may not be able to store and process the data set because they have limited resources in terms of computation and memory.
- Online Sequential Extreme Learning Machine (OS-ELM) reduce the storage space overhead by identifying job failure, reduce the resource waste in the cloud.
- The rapid growth of new malware families presents another challenge.
- Does not degrade performance and can be easily extended to broader DOS(Denial of Service) attacks.
- By reducing the cost of memory access, Machine Learning helps in more energy efficient data flows

4. CONCLUSION -

An analysis of the various Machine Learning techniques was done with respect to their computational perspectives. From the various other limitations, lack of adequate computational resources in the machines was limiting the machine learning algorithms to flourish and perform efficiently. In some cases the large dataset was becoming a limiting factor while in others small datasets in need of larger computations became the bottleneck.

Advent of Cloud Computing , although surpassed the present day limitations to buy expensive physical machines for the data analysis, but the cloud infrastructure needs a dedicated expertise and regular observation of the virtual machines.

A serverless compute, on the other hand has become a boon for the Data Scientists in terms of computational power. The Lambda functions in AWS are automatically expanding and shrinking according to the various needs of data analysis computations, datasets and the algorithms. Resource pooling is dynamically leveraged from the cloud without any expertise and, results obtained are expected to be more accurate. The cost of analysis for the various time specific patterns (yearly/quarterly) will be reduced significantly.

A more accurate, quick, varied and cost-effective results from structured or unstructured datasets are expected with the collaboration of ServerLess and Machine Learning Techniques.

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