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Monitoring IaaS Cloud for Healthcare Systems

Healthcare Information Management and Cloud Resources Utilization

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ABSTRACT

Healthcare functionality is enriched by cloud services which offers a perspective for broad integration and interoperability. Cloud-based facilities support healthcare systems to remain connected to remote access devices to various tasks and information. The healthcare actors should have an understanding of the risks and benefits associated with the usage of Cloud Computing resources utilization. Also, they must launch an appropriate contract-based relationship between the Cloud Service Providers and the actors of healthcare systems by means of Service Level Agreements (SLAs). The variation in both demand and supply within the healthcare information affects the use of information technology. Hence, monitoring resources can play an important role in accommodating the healthcare data. To deal with the aforementioned problems; reinforcement learning mechanisms along with the metrics has been used and experimented with the various dynamics of workload to deliver services with quality assurance.

KEYWORDS

Agents, Cloud Computing, Healthcare, Monitoring, Reinforcement Learning, Service Level Agreements

INTRODUCTION

The healthcare sector is perceiving a huge growth fueled by a growing population and results in the focused wellness to the consumers. This is due to the information technologies-enabled patient care systems. To serve the same, the organizations are migrating to the cloud-based healthcare services to strengthen their expectation to meet with the demand. The volume of data the healthcare business gathers is mind-boggling. A 2014 report from consulting corporation EMC and research firm IDC place the volume of global healthcare figures at 153 exabytes in 2013 (an exabyte equals one billion gigabytes; five exabytes is equal to the all the words ever vocalized by humans). If the information stored all that data on tablet computers, the authors noted, the stack would reach nearly 5,500 miles. The report expected a 48 percent annual progress rate, meaning that the figure would reach 2,314 exabytes by 2020 and the same has been depicted in Figure 1. Figure 2 shows healthcare cloud systems.

Cloud computing (CC) is an advance terminology; in terms of paid resources (Abdel-Basset et al., 2018). CC permits IT companies to consume the computational resources, just like storage, memory, CPU usage, etc., similar to any of the utility services such as electricity and water. Based on the usages of associated resources and cloud services the client has to pay the amount as per

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Figure 1. The size of worldwide healthcare data collected

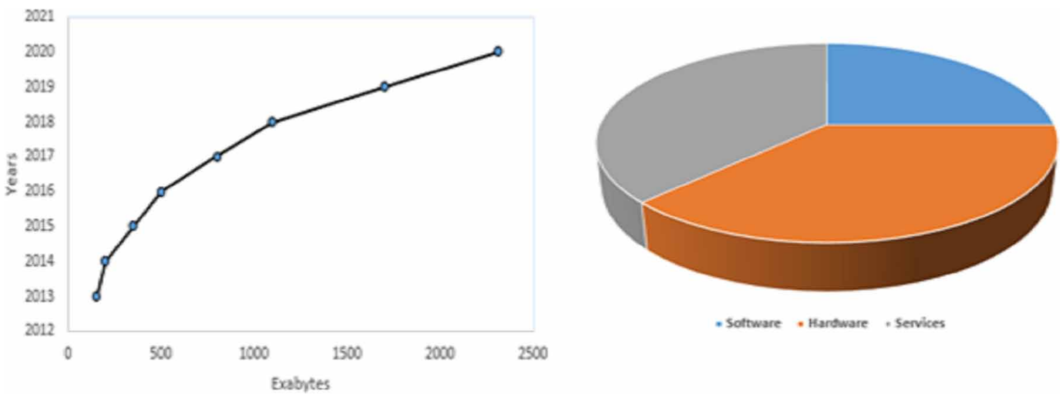
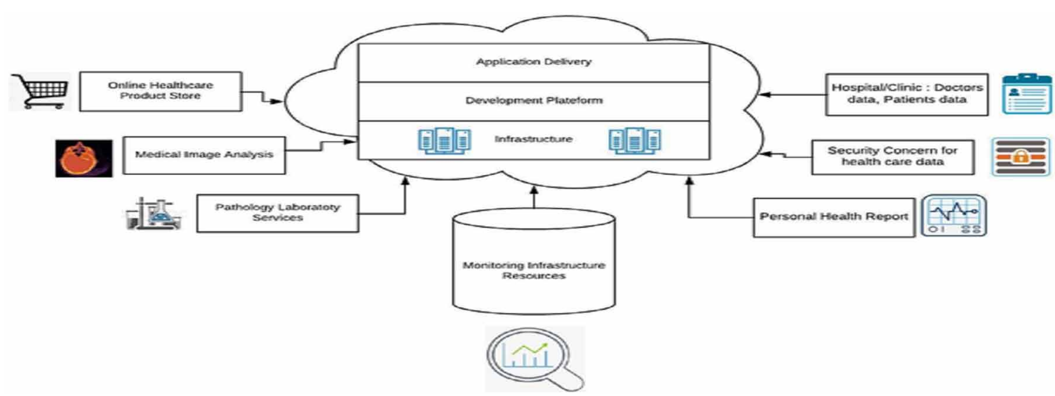


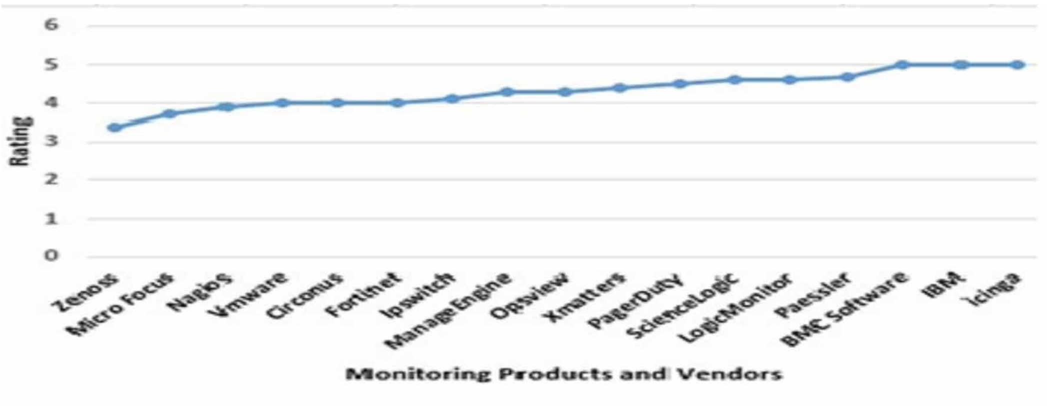
Figure 2. Healthcare cloud systems



the billings (Cao et al., 2017). There are numerous characteristics of CC and one of the important characteristics of intelligence cloud resource management (Cao et al., 2017); is automatic provisioning and de-provisioning of the resources. In other words, the end-users can automatically ask for more resources and CSP (Cloud service provider) will release the resources when they do not require the said resources then the resources will be unprovisioned (released) (Auto-scaling feature with scale in and scale out). The auto-scaling technique (Alhamazani et al., 2015) can be resolved out by applying the monitoring approach. Monitoring of the cloud infrastructure results in providing application guarantees such as security, availability, and performance. This is also crucial from the perspective of CSP to maintain the demand of the clients without any interruptions. There are various tools (cloud monitoring products and vendors) for monitoring the cloud environment. Figure 3 show the various monitoring tools and their ratings as per the survey done by the Gartner 2018 (Gartner, 2018).

Figure 2 indicates the CC usages for the healthcare systems, such as virtual care and telehealth through internet access to the systems. Medical reminder and refill ordering (automatic), monitoring of real-time supply chain and event-based alerts and logging data (counterfeit and drug theft),artificial Intelligence based decision-making process mechanism, research based on social network, maintaining the individual data privacy, such as for HIPPA(Health Insurance Portability and Accountability Act of 1996) acquiescent and offsite servers with cutting-edge encryption and undeviating medical data in terms of standard EHR (Electronic Health Record) and portability across the healthcare providers.

Figure 3. Survey of ratings: cloud monitoring tools



In the proposed approach, we have adopted the mechanism of reinforcement learning (RL) to train the agent for the cloud environment. RL is a field of machine learning as shown in Figure 4 and its working has been represented in Figure 5.

Figure 4. Reinforcement learning: a part of machine learning

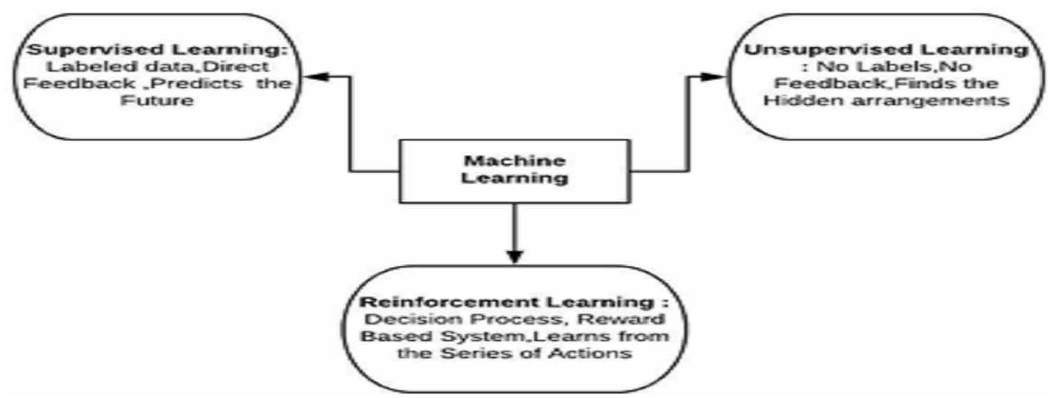


Figure 5. Working of reinforcement learning

The machine learning can be classified as:

- **Supervised Learning:** Majorly used for prediction. The established training data including output and input will be provided. Based on these data the model will be trained to predict the output from an unobserved input.
- **Unsupervised Learning:** Majorly used for pattern withdrawal. The established data will be delivered which has no output, the algorithm will attempt to abstract the nontrivial construction within the data.
- **Reinforcement Learning:** Majorly used for optimization. Representing how human learn from an infant, the trial, and error. The approach will be used to find the actions that result in a good consequence, and give favoritism to the preferences of these identified good consequences.
    - **Agent and Environment Dealings**

RL is about; how the better decision will be acquired through trial and error method, it is a communication between the agent and the respective environment. The communications can be in terms of the below-mentioned steps until the termination condition will be achieved.

- The agent witnesses the environment having the state S.
- Out of the potential activities, the agent has to identify which action to adopt. (This happens because of the term called as policy, this is a function that produces an output S' that is an action with respect to the present state).
- The agent fixes the action and environment accepts the action.
- With the help of transition matrix prototypical, the environment will determine the next state and continue for the same.
- Through the reward model, the environment regulates the reward for the agent for the specified actions (a) and states(s).
- The main aim of the agent is to determine an optimal policy which maps the corresponding states to its associated actions. So that the maximized discount for a long-term reward can be achieved.

The rest of this paper is organized as; the next section describes the background and related work, then motivation and contribution have been described, followed by Model used for communication, results and discussions, research challenges, and ended with conclusion and future work.

BACKGROUND AND RELATED WORK

RL has been cast off as a diversity of learning various tasks, such as for robotics(Cully et al., 2015), manufacturing industries (Mahadevan & Theocharous, 1998) and computer-based game playing technologies (Sutton & Barto, 2018).In the paper by Rolik et al. (Rolik et al., 2018) proposed a dynamic assignment of virtual machines based upon the learning mechanism of the RL and also considered the number of SLA violation. In another approach (Arabnejad et al., 2017) authors have proposed

a fuzzy rule-based scheme, where they have come up with two methods that is Fuzzy Q Learning and Fuzzy SARSA Learning; used for scaling down/ scaling up the Cloud resources as per the requirement of QoS and also used to reduce the cloud cost by refining the cloud resource consumption. (Yan et al., 2016) presents an approach where RL based approach has been used for dynamic decision making for resource utilization based self-management technique. Farahnakian F et al. (Farahnakian et al., 2016) presented an approach where hierarchical multi-agent-based architecture model has been used. The scheme customs novel adaptive utilization threshold and uses RL method to dynamically regulate the memory and CPU thresholds for individual Physical Machine (PM). This periodically runs a virtual machine placement optimization procedure to know the whole resource usages of the physical machine with the assigned thresholds to improve the SLA compliance. In another work (Ho & Lee, 2015), introduces the concept of model-based RL, where the system preserves a model of interaction along with the consequent environment and its associated actions, to improve the performance of the system. (Jamshidi et al., 2016) presents a control- theoretic elasticity management method which usages fuzzy control. This allows qualitative specifications of elasticity guidelines and similarly deals with the uncertainty which arises from monitoring the cloud environment. In (Hussin et al., 2015) authors have presented an approach of effective resource management using RL which emphases on refining effective execution of the resources with low computational intricacy. The said approach uses RL and Neural network to help the scheduler to observe and adapts to the dynamic environment of the cloud. Mijumbi et al. (Mijumbi et al., 2014) proposed a multiagent learning algorithm which manages substrate network resource management in a decentralized way. The agent makes use of feedback to learn the optimal policy and reserve the resources based upon the evaluative feedback learning. (Farahnakian et al., 2014) proposed a method called RL-DC (Reinforcement Learning-based Dynamic Consolidation) to decrease the number of active hosts as per the present resources usage. The RL-DC use agents to learn the optimal policy. The agents learn from the past experience to decide which hosts to sleep or activate as the workload changes.

MOTIVATION

Infrastructure as s service (IaaS) is one of the imperative CC service models that is used to provide the virtualized hardware infrastructure (such as memory, CPU, storage, etc.) to the end users. The billing will be generated based on the usages of these aforementioned resources. The providers will allocate and deallocate the resources for computation according to the requirement of the end users.

There are numerous challenges in dealing with IaaS services. The most difficult concern is the management of the whole infrastructure. The cloud management should be handled properly, if not; then this can result in a higher cost than the cost of deploying the servers in the datacenter. Which ultimately affect the return on investment (RoI) of the CSP.

Few of the challenges are mentioned below:

- As CC is commercialized with respect to the services provided and in terms of utilization of resources and like any other, subscription centered facilities; CSP and the end user have to follow the agreement known as Service Level Agreement (SLA). The SLA (Alhamazani et al., 2015) would cover the responsibilities and roles of both the parties involved such as quality, the scope of the said services and performance requirement with respect to Quality of Services (QoS). Hence QoS acts as an imperative part of creating the cloud services suitable for customers. Maintaining the SLA and QoS is a challenging task in a dynamic cloud environment.
- To make the cloud environment less susceptible to failure conditions (Sutaria et al., 2017); there should be a proposal where the computational agents should monitor and react to the conditions as under-utilization and overload of resources as per the workload being assigned to the cloud and can act intelligently to avoid the failure occurrences in an autonomous way (without any human interventions).
- Provisioning of the resources at the real-time is an important factor which determines the trust level (Gonzales et al., 2017) of the CC environment.

CONTRIBUTION

To alleviate the aforementioned issues, the subsequent contributions are presented in the paper and are mentioned below.

1. An RL based monitoring mechanism has been presented with zero knowledge of historical data, the model will learn from the dynamism of the cloud resources demand, allocation strategy and act accordingly with respect to the mentioned policy.
2. The model is designed to tune with the different workload scenarios and is based on various performance parameters of the CC.
3. The CSP has to select the policies based on the cloud metrics and the model will give the optimal solution to attain the rewards of healthcare professionals and organizations on the basis of outcome and cost-effectiveness automatic decision-making approach.
4. The computational agent's key feature will be; to become self-adapt with the dynamic workload management of medical healthcare data in a cloud environment.

MODEL USED FOR COMMUNICATION

Enthused by a current improvement in deep RL (Peng et al., 2016) for Artificial intelligence features, we consider building the systems which will learn to manage the IaaS resources of CC directly from the experiences (operations happening at the IaaS level of cloud). Now, let's discuss the equations that will help us to identify the respective states and actions to be performed to get the optimal policy. Q-Learning is the technique which can be used to identify the optimal action selection policy using a function and can be explained by using the Bellman equation (Ma et al., 2017) as mentioned below.

$$Q\left(S,A\right) = R + \gamma \max_a^{'} Q\left(S',A'\right)$$

Where Q function will contain the state and action pair, R is the reward (i.e the reward the agent receives after taking the corresponding action at the respective state S) and γ is the discount factor (To deal with the condition of never ended communication in between agent and environment, we use the term discount factor for the impending reward. This discount terminology will result from the sum of an infinite series to the finite series) and $\max_a^{'} Q\left(S',A'\right)$ is the next optimal Q state value.

The variation of the above equation can be re written as mentioned (below) equation (Ma et al., 2017).

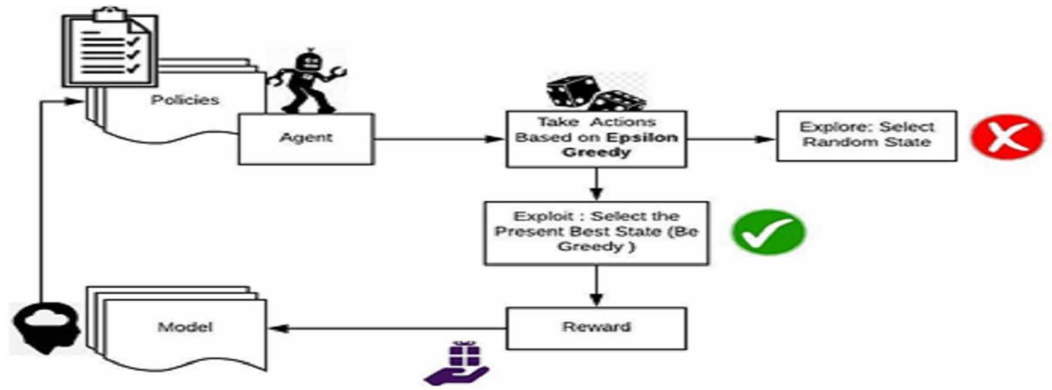
$$Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma Q(S0,A0) - Q(S,A)]$$

Where α is the learning rate and γ is the discount rate.

IDENTIFYING OPTIMAL POLICY FOR THE MODEL

For the model to learn through agent-environment interaction; the reward distribution and probability transition model has to be identified (Xiao et al., 2017). To practice all likely combinations of different state/action pairs; we use random actions to learn about the model. Once the model has passed the learning segment, we can determine the optimal policy by observing the past policy iterations. While looking for the best action; the right balance strategy has to be adopted. For this, the epsilon-greedy approach has been used. In case of the epsilon-greedy approach, exploitation decision making fundamental has to be opted as shown in Figure 6. Exploitation means the better decision given the present evidence whereas exploration indicates gathering more information. For exploitation in every decision step, we assign a minor (e) probability where we take haphazard action and (1-e) probability where we yield the best-known action we have traveled beforehand.

Figure 6. Greedy approach for learning the cloud model



The policies of CC environment can be; the reward function for the agent may be performed in terms of scheduling solution for allocation of the tasks to the resources by comparing the present execution time with the predefined baseline execution time (Orhean et al., 2018). The reward function can also be grounded upon the performance goals defined with respect to the Service Level Objectives (SLO)requirements in term of the response time, resource utilization, etc. (Rolik et al., 2018). The following metrics (Al-Ahmad et al., 2018) can be used to evaluate the aforementioned policies.

- **Metrics for performance:** queries/sec, response time, etc.
- **Metrics for utilization:** CPU, memory, disk, etc.
- **Metrics for throughput:** network, caches
- **Metrics for users:** click rates, page views, etc.
- **Data for compliance:** LA based metrics, permissions, etc.
- **Indicators of performance:** revenue per hour, prices per transaction involved, users number.

Table 1 shows different monitoring tools/products (Syed et al., 2017) along with their basic requirements (fulfillment) such as; Scalable, Cloud-aware, Fault tolerance, Time sensitive, Autonomic, and Comprehensiveness. CC owes numerous properties to its previous models of computing such as a grid, cluster, service-oriented architecture, distributed computing, etc. The aforementioned requirements (Ward & Baker, 2014) are the major challenges in terms of monitoring and have been described below

1. **Scalable:** CC resources are scalable, in the sense, the resources should scale up/down as per the user's demand and should support robustness in architecture, which allows the system to adapt to elasticity/dynamism.
2. **Cloud-aware:** The monitoring system of the cloud should be aware of the positions of the virtual machines and gathers data in a way by which can delay and cost can be minimized.
3. **Fault tolerance:** Failure is an obvious matter in any of the distributed systems. The cloud monitoring system should sense the actual failure and take necessary actions to mitigate the same in an autonomous way.
4. **Time-sensitive:** The monitoring data should sense the unusual phenomena as soon as this occurs and take necessary steps to avoid any mishaps, arise due to any number of causes. Similar to monitoring latency, which means the time between the said phenomena occurring and that phenomena being detected (close to the real-time) should be reduced.

Table 1. Gaps identified for various cloud monitoring tools/products

Different Basic Requirements of Cloud Monitoring Schemes						
Monitoring Schemes	**Scalable**	**Cloud Aware**	**Fault Tolerance**	**Time Sensitive**	**Autonomic**	**Comprehensiveness**
Astrolabe	Yes		Yes			
Catci						Yes
collectd	Yes					Yes
Ganglia	Yes		Yes			
GEMS	Yes		Yes			
Icinga						Yes
MonaLISA	Yes					Yes
Nagios						Yes
OpenNMS						Yes
Reconnoiter	Yes					
Riemann	Yes					
StatsD	Yes					
sFlow						Yes
visPerf	Yes		Yes			
Zabix						Yes
Zenoss						Yes
Cloudinit.d		Yes	Yes			
Cloudsense	Yes			Yes		
DARGOS	Yes	Yes		Yes		
GMonE	Yes	Yes				Yes
Logstash	Yes			Yes		
OpenNebula		Yes				
PCMONS	Yes	Yes				
Sensu	Yes				Yes	
SQRT-C	Yes	Yes		Yes		
Varanus	Yes	Yes		Yes		

5. **Autonomic:** The cloud monitoring system should be self-manageable/ self-optimize/ self-healing; i.e. to optimize and configure itself without any need of any human intervention. The cloud system should not require any runtime manipulations or configurations.
6. **Comprehensiveness:** The cloud monitoring tool should support data collection from different software, platforms and supplementary data sources which compromise of heterogeneous structures.

Table 2 shows some of the comparisons of the loopholes of a few of the well-known monitoring tools and the objectives covered in the proposed model. Figure 7 shows the flow of the proposed model where RL has been implemented. The detailed overview of the model is discussed below.

The agent will interact with the present status of the cloud environment and get the following details

CPU cores**:** The number of Virtualized CPU core are allowed for the provision
CPU usages in relations of MHZ
CPU usages in percentage
Memory usages in terms of KB
Disk read/write throughput in the relation of KB/s, etc.

The Agent now decides the new action be adopted based upon the policy selected and transition metrics model. The goal is to identify the optimal policy in the case where our model is unknown initially through the support of reward distribution prototypical, the environment regulates the reward to the agent; as per the agent's present action and state. The agents learn the environment and acquire a positive reward to reach its optimal state.

Based upon the model learned, the cloud environment can be classified as in terms of resource utilization; such as average resource utilization, above average and below average resource utilization. The significance of this environment creation helps the CSP for capacity planning and used for allocation of resources and identifies the circumstances of scaling up/ scaling down the resources based upon the end users resources demand.

Now the model works with an optimal policy; if we know the model beforehand, figuring out its policy will be an easy task. We just require the dynamic programming to compute its optimal policy and there is no requirement of the learning anymore. The Proposed flow chart for the scheme has been discussed in Fig 9. Table 2 indicates how our approach is better as compared to the listed approach in the table.

Table 2. Proposed monitoring scheme classification w.r.t available tools/products

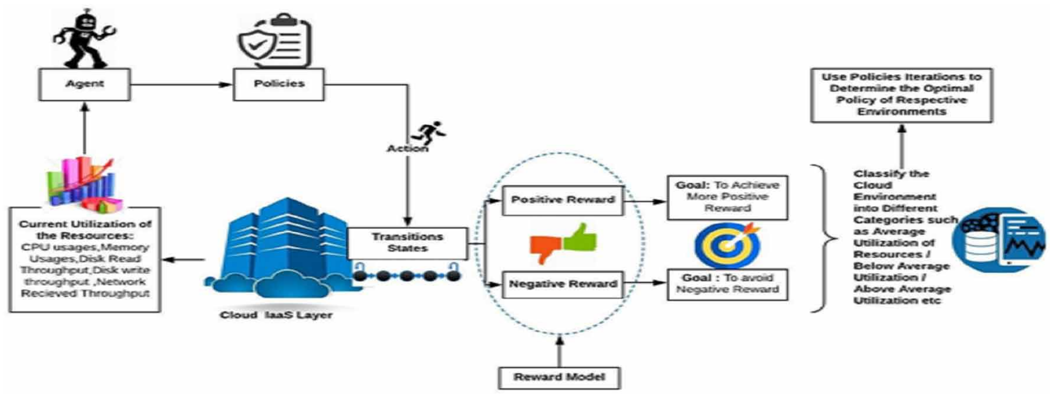
Monitoring Scheme	Gaps Identified
Ganglia	This is not designed for the highly dynamic environment
Astrolabe	Limited Capacity for performance analysis
Nagios	Extensive amount of manual configuration are required
Riemann	Requires arbitrary metrics generated by the clients
Icinga	Considered the SLA reporting scheme only
Cloudinit.d	Monitoring is done according to the scripts which are included in the plan.
Cloud Sense	Collects extensive monitoring data
Proposed Approach	**Advantages**
	Uses Reinforcement learning Can work with dynamic Cloud environment; No manual configuration required

PERFORMANCE EVALUATION

In this subsection, the implementation environment and its related components have been presented.

We have made use of a python framework for implementing the same, Figure 7 shows the environment where the agent will learn the model. States, action, and policy have already been discussed in the aforementioned sections.

Figure 7. The Architecture of the proposed model



Replay Memory: This stores the experiences or knowledge of the state transition order in the replay memory (Foerster et al., 2017), the same will be used to train the Q-network; this permits the network to learn from all the previous understandings. In our proposed model, the agent begins the learning when the replay memory is half full. The values associated with discount factor and learning rate: The value for discount factor (Okdinawati et al., 2017) chosen in our case is 0.8, the value near to 1, as if the value will be near to 0, would not achieve the optimal state. The working of the replay memory has been depicted in Figure 8. Figure 9 shows a flow chart of the monitoring technique.

Figure 8. Reinforcement learning with replay memory

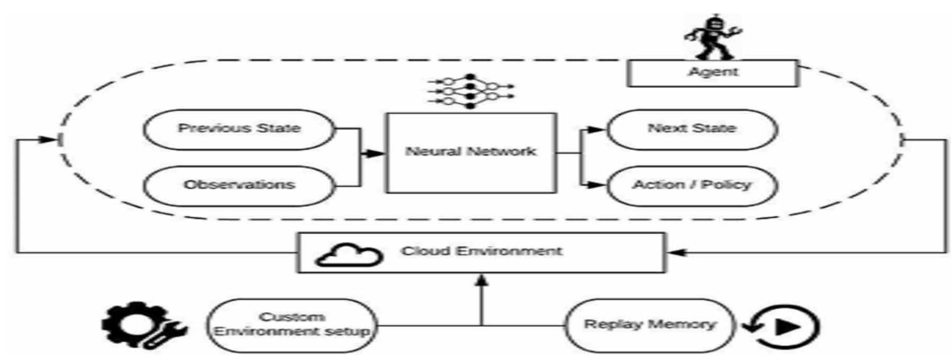
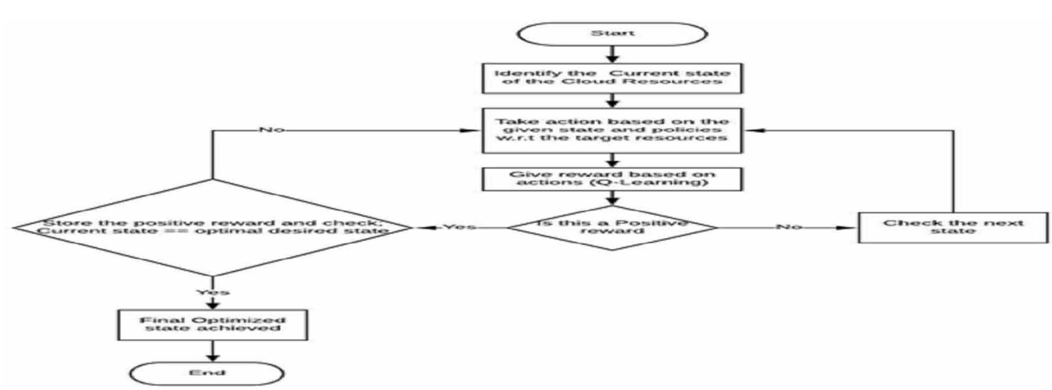


Figure 9. Flow chart of the monitoring technique



Simulation Results

For Simulation results, the parameter which has been undertaken are mentioned in Table 3.

The proposed model has been tested in the following Cloud environment where we have considered the CPU utilization only as one of the parameters.:

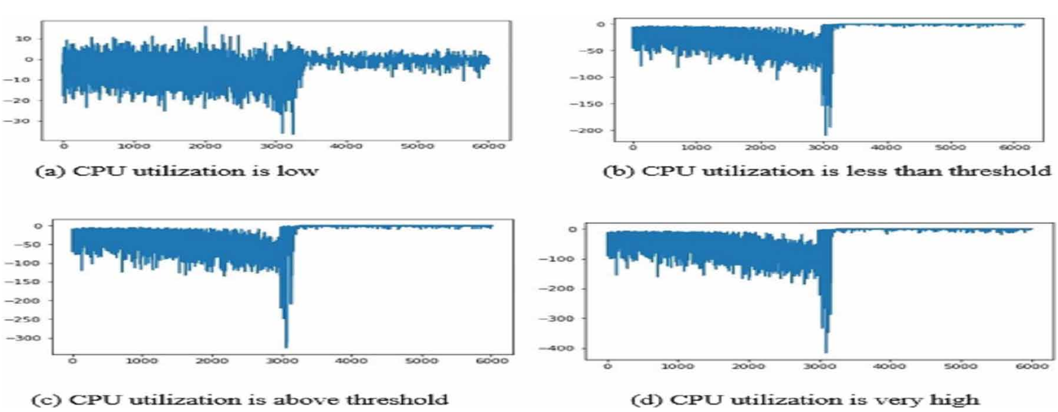
Table 3. Parameters used for the simulation and results

Parameters	Values
Discount (γ)	0.8
Tau	0.01
Batch size	32
layers	(50,50)
Learning rate	0.001
Epsilon decay fraction	0.4
Memory faction	0.80
Memory Type	Deque
Process_observation	Standardized
Process_target	Normalizer

CPU Utilization (in Percentage) is Low

a) The utilization of the CPU has been identified by the agent as 2,3,12,23, etc. CPU utilization (in percentage) is less than the threshold (i.e 50 % and 70 %)

Figure 10. With threshold 50 percent; x-axis: episodes, y-axis: rewards



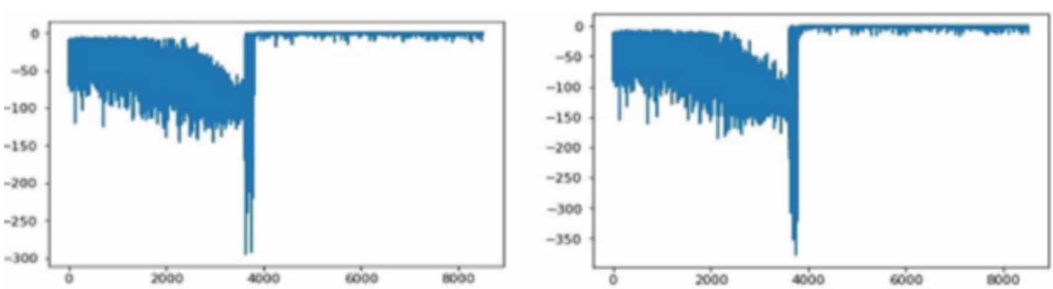
1. The utilization of the CPU has been identified by the agent as 43, 45, 42, 44, In a series of forties. CPU utilization (in percentage) is below threshold (50 and 70)

2. The utilization of the CPU has been identified by the agent as 72, 73, 72, 76, in a series of seventies and more than 70%..CPU utilization (in percentage) is just above the 70% threshold
3. The utilization of the CPU has been identified by the agent as 91, 92, 93, 95, or in a series of nineties and more than 90%. Hence it will be concluded as; the utilization of the CPU is very high. These different conditions or thresholds help to generate various workloads and will be used for the management of Cloud resources..

Figure 10(a) to 10(d) shows the results of the learning behavior of the agent with respect to the different cloud environment that is with a 50% threshold. The results displayed here shows how the RL works in different cloud workload environment. The CPU utilization is considered here as a metric. In certain cases the utilization of the CPU is just above the said threshold and in some cases, this is very high and obviously more than the 50%. These utilization factors can be used for generating workloads with slightly varying characteristics and used to perform sensitivity analysis of the application performance to the workload attributes, as a result, to the management of the infrastructure of the CC. The total revenue generated by the CC depends on its resource management. If the resource is managed optimally, more revenues will be generated and, if not managed properly, will result in the generation of low revenue and wastage of the resources.. The episodes are the finite sequence of states, actions, and rewards.

Episodes: an arrangement of (s1, a1, r1, s2, a2, r2, s3, a3, r3......sn, an, rn....sN, aN, rN) where s = state a = action, r = reward, similarly Figure 11(a) and 11(b) shows the related trend with little variations for the cloud environment with the threshold as 70%.

Figure 11. With threshold 70 percent; x-axis: episodes, y-axis: rewards



(a)CPU Utilization is above the threshold of 70%

(b)CPU Utilization is very high and above the threshold of 70%

The monitoring of the cloud resources for medical healthcare data will be used to manage the data of the health care systems as well as it can be used for real-time intelligence decision making. The cloud deals with the ability to adjust to demand and scalability. It offers seamless collaboration and communication benefits which results in optimized operational efficiency. The resources are efficiently allocated to healthcare systems. These allocations must be dynamic based on output received from grid members

The results show that monitoring of the resources for healthcare systems will allow the CSP to carefully manage the data as per the available resources of the cloud and creating a trend for adopting advanced health information technology with manager's support and through lower cost. Even this will also boost the proficiency of the rapid ubiquitous access to healthcare resources and elasticity. The benefits and open research challenges have been described below.

The benefits of using cloud computing for medical healthcare systems

- **Records in terms of electronic:** The important benefit of CC for healthcare is the cloud makes this easier to archive patients data and medical images.
- **Streamlined collaboration:** Most of the Doctors/physicians find the CC as a better tool for collaboration and offer care as a team.
- **Data Storage saving:** The occurrence of big data is an irresistible challenge for many health organizations, and CC allows the CSP to lessen the in-house storage need.
- **Cloud computing is meant for data analytics:** By data computation and tracking in CC, that too in real time the providers can harvest it for research in the medical field, generation of the referrals, spotting the trend and other personalized care.
- **Enhancing the efforts with respect to the data sharing:** The cloud is used for gathering the information and this doesn't limit to the in-house. The organization of the healthcare can combine these technologies and share with industry information to create more pools of the comprehensive bid data for one and all to learn in greater, and further complex systems.
- The cloud permits a lot of high-power data key answers, which results in the fabulous power of the research process, such as DNA sequencing, etc.
- To boost up the technologies, such as the technology of mobile, higher –tech devices and CC, which provides the information of health data from distance in reality, such as telesurgeries, consultations, and patient's health monitoring without having to come in.

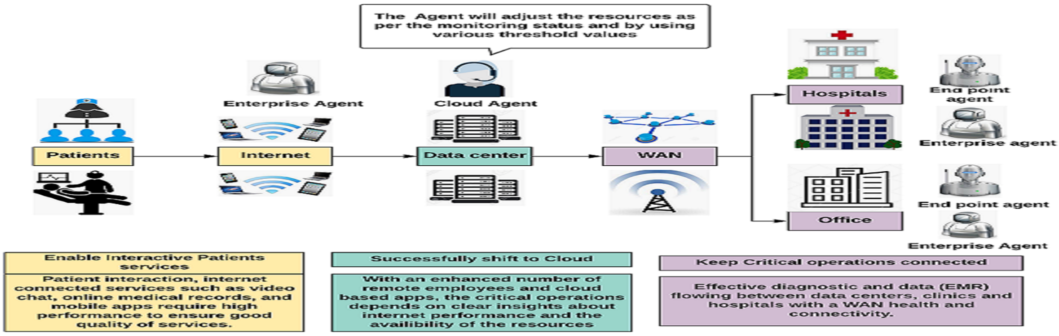
RESEARCH CHALLENGES FOR MONITORING HEALTHCARE DATA IN CLOUD COMPUTING.

- Improvement in terms of
    - Access
    - On-demand increase storage capability
    - Security Boost are required
- Patients receive the proficiency they need when they require it. Rural maintenance and disaster response have to be further realistic.
- As the information becomes reachable from different locations, and even if something happens on site, the information needs to be preserved.
- Providing resources for available medical data protection and when to replicate the medical data to increase the data security as well as offering dynamically scaled self-protective resource consolidation resilience are required.
- CSP's assurances to protect the client's medical data securely.
- Expansion of technologies and guidelines to permit the enhancement of trusted platforms by not- for- profit healthcare organizations.
- The root cause analysis for the lack of trust, lack of regulations or mandate to upkeep the full cloud adaptation have to be identified.

Case Study

The case study (Howard, n.d.) discussed here will demonstrate the usages of the monitoring needs for the cloud resources for health care systems. The architecture for the same has been depicted in Figure 12. Here the pulse of the entire networks and cloud can be measured at every linkage and based on the threshold values the alarm will be generated to scale in or scale out the resources.

Figure 12. The monitoring of resources in the cloud for medical health care systems



The data will be kept on flowing into entire architecture i.e. from patients to datacenter through the internet and from hospitals and clinic to the data centers through the WAN. At every location, the intelligent agent is located to track every moment/ status of the present zone. Such as Cloud agent, enterprise agent, and endpoint agent. The agents will monitor the present utilization of the resources and based upon the calculated metrics (Service Level Agreements) and the threshold value auto scaling decisions will be taken automatically without the human intervention. This not only solves the resource utilization problem but also useful to manage the healthcare data in a cost-effective manner. The proper monitoring with timeliness will result in rapid identification of performance issues, service quality concerns, and availability. The case study discussed here outlines the usages and benefits of the cloud's agent for managing the healthcare information.

CONCLUSION AND FUTURE WORK

CC is expertise which supports many services and is successful because of the term called elasticity; which means rapidly this can scale up and scale down as per the resources demand made by the end-user. The results discussed and presented here are of RL mechanism, which is used to deal with cloud dynamism. The proposed mechanism can solve the problem of instant resources growths (demand) in size and complexity too. As a future work; to manage the cloud infrastructure and facilitate the property of elasticity of the resources, the workload generator and model-based prediction techniques are essential. The results of the experiments done here can be used for advance reservation of the resources (supervised Learning). Besides the mentioned areas, the hierarchical RL can also be used where we have multiple policies defined to reach the same optimal goal, this too demands further research to flourish in CC field. To strengthen the forecast, LSTM (Long Short Term Memory) techniques can be used.

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