Intelligent Decision-Making in Distributed Dynamic VM Consolidation Using Fuzzy Q-Learning

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ABSTRACT

A cloud manager deals with a dynamic multi objective optimization problem. Indeed, this problem lies in the fact that there is always a tradeoff between energy and performance in a virtualized data center. Therefore, a cloud manager must be equipped with a strategy to consolidate virtual machines and configure them dynamically in a way that optimizes energy-performance tradeoff in an online manner. Distributed dynamic VM consolidation strategy can be an effective one to tackle this problem. The procedure of this strategy can be decomposed into four decision-making tasks.1) Host overloading detection; 2) VM selection; 3) Host underloading detection; and 4) VM placement. The dynamic optimization is achieved when each of aforementioned decisions are made optimally in an online manner. In this paper with concentration on host overloading detection and VM selection task, we propose the Fuzzy Q-Learning (FQL) as an intelligent and online machine learning approach in order to make optimal decisions towards dynamic energy-performance tradeoff optimization.

Categories and Subject Descriptors

D.4.7 [**Operating Systems**]: Organization and Design—*Distributed systems*; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Intelligence Agent,Multiagent systems*

General Terms

Algorithms,Management

Keywords

Dynamic VM Consolidation, Energy Efficient Cloud Manager, Fuzzy Q-Learning

1. INTRODUCTION

Unfortunately, server consolidation enabled by virtualization introduces a new problem to the cloud environment. Since the size of Virtual Machines (VMs) inside a physical server might change due to dynamic workloads, resource underutilization or overutilization might occur, causing either inefficient energy consumption or unwanted performance degradation. Consequently, the cloud managing system needs to employ a strategy to reallocate resources to virtual machines by live migration dynamically in order to maximized per-server utilization while attaining the promised non-functional qualities of the service guaranteed in the Service Level Agreements (SLA). In other word, this strategy must be able to optimize energy-performance trade-off in an online manner. Distributed dynamic VM consolidation can be an effective strategy to tackle this problem [1]. The procedure of this strategy can be decomposed into four decision-making tasks: (1) Host overloading detection, here deciding when a host must be considered as overloaded. In this situation, one or more VMs must be migrated away from this host. (2) Host underloading detection, here deciding when a host must be considered to be underloaded. In this situation, the host is ready to switch to sleep mode and all VMs must be migrated away from this host. (3) VM selection, here deciding, which VMs should be migrated away from overloaded hosts, and (4) VM placement, here deciding about which host must be selected to receive migrating VMs. Indeed, the energy-performance trade-off optimization is achieved when each of aforementioned decisions are made optimally in an online manner.

Q-learning as a model free Reinforcement Learning (RL) is an effective approach to design dynamic system managements and consequently produce dynamic decision-making tasks. In principle, Q-learning can automatically learn high-quality decision making tasks without an explicit model, and with little or no built-in system specific knowledge. Fuzzy Q-Learning (FQL) [2] is the fuzzy extension of Q-Learning. It is capable of handling continuity in the state space; in addition, it is powerful enough to tackle the curse of dimensionality and other ordinary RL issue rising in real life and industrial problem. In this work we employ FQL approach in order to give an intelligent behavior to the physical hosts for making optimal decision into the dynamic VM consolidation procedure towards energy-performance tradeoff optimization. Several researches have been done so as to enhance the dynamic VM consolidation and several algorithms and policies have been proposed for host overloading detection and selecting VM until now. In contrast to previous studies, our proposed approach can achieve better result in improving energy-performance tradeoff in cloud data center.

2. DATA CENTER AND FQL AGENTS

In our data center each physical host is associated with two FQL agents. One of them is responsible for making decision about when a host must be considered as an overloaded host and another one is responsible for making decision about which VM must be selected to migrate when a host is overloaded. All the agents inside data center by interacting whit their own corresponding host learn how to make decisions and consequently take actions according to dynamic characteristics of physical host state towards energy-performance trade-off optimization. Since the agents inside data center may experiment similar states to make decision during their lifetime; thus, we propose a cooperative learning strategy by sharing learning knowledge among agents. It can help to increase learning convergence rate and consequently make better decisions.

3. INTELLIGENT DECISION-MAKING IN HOST OVERLOADING DETECTION

Each learning agent i at each time-step t, observes the current state of its own corresponding host S_{t_i}, and gathers some information including average CPU utilization and number of VMs residing on the host as the input state X_{t_i}, where $1 \leq i \leq N$ and N is the number of hosts inside the data center. Further, the learning agent immediately chooses a threshold value as an action from the actions set $A(X_t)$. The threshold value is used in the host overloading detection procedure, if the CPU utilization exceeds the threshold; it means the host is overloaded and one or more VMs must be selected to migrate. One time-step later, in parts of a consequence action, the FQL agent receives a numerical reward, $Reward_{i_{t+1}}$ and finds itself in a new state S_{t+1_i}. The reward is a feedback on the resulted new threshold value from the actions set. The feedback is provided by a tradeoff model (we will address it in section 5) that is able to capture both energy and performance at each interval in a host. In a trial and error interaction, finally the FQL agent learns how to map the sates to the actions, so as to maximize the discounted sum of reward obtained. In other words, the FQL agent learns the best sequence of selecting thresholds, corresponding to the states observed during its lifetime.

4. INTELLIGENT DECISION-MAKING IN VM SELECTION

When a host becomes overloaded, a VM selection task is called so as to remedy this situation by choosing one or more VMs for migration. Several criteria have been proposed to select VMs in the previous literatures until now .The FQL agent is able to make decision about which criterion can be effective at each state of its corresponding host for selecting VM towards energy-performance tradeoff optimization. The FQL procedure is like what we discussed in the previous section; however, the definition of action set is different. In fact, each element of the actions set $A(X_t)$ is a criterion for selecting VM, such as minimum CPU utilization and maximum CPU utilization. The FQL agent in a trial and error interaction learns the best sequence of criteria, corresponding to the states observed during its lifetime.

5. ENERGY-PERFORMANCE TRADE-OFF MODEL

To represent the energy-performance trade-off, we use the product combination of SLA Violation (SLAV) and energy consumption (EC). The SLAV [1] is a metric , which can

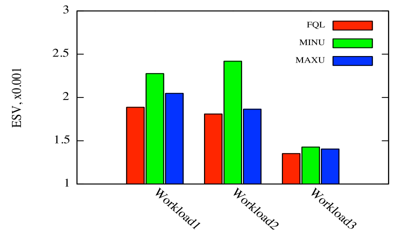

Figure 1: Comparision of VM slection strategies

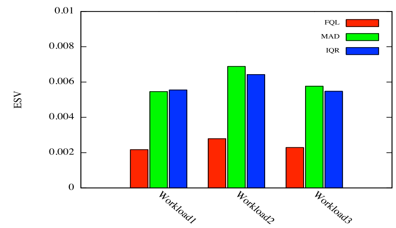

Figure 2: Comparison of host overloading detection strategies

encompass both performance degradation due to host overloading and VM migration in each host.The EC [1] is defined as a linear function of the CPU utilization of each host.

$$ESV_i = SLAV_i \times EC_i \qquad 1 \leq i \leq N \tag{1}$$

6. EXPERIMENTAL RESULTS

We used CloudSim toolkit to evaluate our experiments. At the first experiment, we have compared the result of the dynamic VM consolidation procedure when its VM selection task uses the FQL strategy with ones use minimum utilization and maximum utilization as a fixed criterion. At the second experiment, we have compared the result of the dynamic VM consolidation procedure when its host overloading detection task uses the FQL strategy with the state of the art algorithms [1] that use some adaptive heuristics, based on statistical analysis of historical data for estimating CPU utilization threshold. In the comparison we have measured the ESV (Energy SLA Violation) value [1]. These experiments have been evaluated by three different workloads in tree different days. The results of these experiments have been illustrated in figure 1 and 2 respectively.Both results show the superiority of the FQL as an intelligent decision making strategy in improving energy-performance trade-off in comparison with the state of the art strategies.

7. REFERENCES

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