Efficient Provisioning of Virtual Machine Sets with Placement Constraints in IaaS Clouds with Deep Reinforcement Learning

***Abstract***–Today, cloud service providers like Amazon Web Services (AWS), Google Cloud, Microsoft Azure and more provide computing capacity on demand. A fundamental problem that arises when providing these services is that of mapping requests to physical machines in such a way as to minimise wasted space and maximise the number of requests that can be served given fixed physical infrastructure. This project explores the viability of using deep reinforcement learning to determine a solution for VM mapping problems to minimize waste, and therefore maximise revenue for the cloud service provider. Following some consideration, a proximal policy optimization (PPO) algorithm was used in conjunction with a multi-layer perceptron (MLP) network comprising 2 hidden layers of 64 nodes with input and output layers correlating with the environment size.

# INTRODUCTION

## Why should we solve this problem?

Infrastructure-as-a-service is undeniably a huge industry, and it is estimated that it will continue to grow by 23.2% year-on-year until 2027 (Gaul, 2022). As demand for these services increases, so too will the amount of work required to allocate requests in a timely fashion in terms of both time and processing power. Traditionally, these problems have been solved using complex integer linear programming techniques, or one-size-fits-all heuristics like first-fit decreasing (FFD) – I posit that by harnessing recent advances in machine learning, particularly concerning the efficiency of deep Q networks, we can reduce both the complexity of mapping these requests and the amount of space wasted. Harnessing this knowledge could not only improve efficiency at the point of allocation but also enable cloud service providers to tailor their pricing model based on their current capacity to encourage consumer behaviour in line with the optimal policy, which in turn would allow providers to offer more competitive rates.

## Why deep reinforcement learning?

To answer this question, we should first examine all of our options. Machine learning approaches can be broken down into three main categories:

1. Supervised learning.
2. Unsupervised learning.
3. Reinforcement learning.

Supervised learning requires a labelled dataset for training, for example, pictures of dogs that are tagged “dog”, and its goal is to learn the association between data and its label. This allows the agent to look at new data and determine what labels should be applied to it with varying degrees of certainty. Training this type of machine learning agent requires people to manually review data and apply the appropriate tags, which is in no way practical for the type of problem we are trying to solve.

Unsupervised learning does not require a labelled dataset; its goal is to find patterns in data which it can then use to decide how similar two pieces of data are. One application of this type of agent is anomaly detection in cases where we might want to flag data or events that differ from the norm. Again, this does not fit our use case.

Finally, reinforcement learning uses a trial-and-error approach whereby an agent takes actions in some environment; this agent is then either rewarded or penalised for these actions to reinforce the behaviour we want the agent to learn. Over time, a value mapping can be determined between states and actions. You could imagine, for example, that in a game of rock paper scissors we may have a state wherein our opponent has just played paper; in this state, we would expect a well-trained RL agent to associate a high expected reward with the action ‘scissors’, and a low reward with the action ‘rock’ (Of course, this sort of asymmetric gameplay is not traditionally encouraged in rock paper scissors…).

In complex environments where it may not be practical to map every state to the optimal action, we can introduce an artificial neural network (ANN)to estimate the value of states based on the values of similar states we have seen in the past. The addition of an ANN is what distinguishes deep reinforcement learning from reinforcement learning.

## Scope

In this paper, we are going to focus specifically on the provision of Virtual Machines (VMs), and all real-world data will be taken from Amazon’s Elastic Compute Cloud (EC2). This choice was made to both keep things consistent, and to limit the research scope to manageable levels. It is expected that other market-leading cloud service providers would operate similar pricing models to AWS to remain competitive and so the learnings from this project should be transferrable.

# METHODS

## Evaluating performance

It is challenging to benchmark the success of our approach without having some data to compare it against. As detailed revenue information from EC2 is not publicly available, I propose determining some baseline for the possible revenue generated for a given infrastructure and scoring our attempts against this. If we determine the average value per unit by dividing the cost of an instance by the sum of its dimensions, then we can multiply this value by the number of units available in our environment to estimate the value we could expect from a perfect fit of a uniform range of instances.

Using this, we may see that a heuristic-based approach achieves 80% of the benchmark or exceeds it by some percentage; this can give us a quantifiable target against which we can measure.

## Modelling the problem

There are three principal areas to consider with this problem:

1. Modelling some environment that is both analogous to the real-world problem, and conducive to machine learning approaches in the sense that we can extrude some clear value signal to optimize.
2. Finding data that is representative of the real world.
3. Determining some machine learning model which can produce meaningful insights.

I believe that we can treat this as a multi-dimensional specialization of the online knapsack problem in which our agent is given some number of servers each with fixed storage, memory, and CPU capacity. At each timestep, our agent will then receive a request for VM capacity which it must then either allocate to a server or refuse.

The modelling of the environment will be covered in more depth in the technical design document but, in short, I first reduced the problem to a 1-dimensional bin packing environment whereby we had some number of bins, or containers, each with a non-negative integer capacity. At each time step, we would generate a new item with a size between 1 and the maximum bin capacity and try to place this into one of the bins. From here, I iteratively increased the complexity of the environment first by adding a value to each item that did not necessarily correlate to its size (turning this into a knapsack-style problem), and then by increasing the dimensionality of the items.

I pulled real-world pricing data from Amazon’s EC2 service; this was taken both from the on-demand pricing[[1]](#footnote-1) and the spot pricing[[2]](#footnote-2). I collected data on the price, the number of vCPUs, memory, storage, and network performance of 392instance types (instance types were ignored where pricing information for both on-demand and spot instances was not available). While we cannot know the true distribution of these instances in the real world, we can make certain assumptions. If we compare the pricing for both instance types, we can determine some discount factor that we assume to be inversely proportional to that instance type’s popularity (David Naori, 2020).

# RESEARCH

Previous research has looked at solving this problem through approaches like integer linear programming and heuristic-based approaches like first-fit descending.

## Algorithm selection

The foundational method in the deep reinforcement learning space is DQN, or Deep Q-Network, which was proposed in the paper “Playing Atari with Deep Reinforcement Learning” (Mnih, et al., 2013). DQN uses Q-learning, whereby we seek to continually improve some reward or Q-value, with a neural network to approximate some state-value function which allows us to estimate a value for a particular action in some state. DQN also employs experience replay by storing random samples of learning steps which are later recalled and trained on; this improves data efficiency by getting the most value out of a given data set and, by breaking up the pattern with respect to time, it also aims to reduce autocorrelation which may occur in online learning environments such as ours and cause overfitting of the model.

The drawback of DQN is that it is quite unstable; that is to say, it is sensitive to changes in input data, reducing its ability to generalise solutions to problems. In well-defined environments, like the Atari games it was designed to solve, this is acceptable as each instance tends to play out in a similar way when the game is played optimally. I do not feel that this is the case in our environment. Given the stochastic nature of our inputs, no two episodes are likely to play out in the same way and so a standard DQN would find it difficult to converge on a general solution.

Improvements were made to DQN algorithms with the advent of policy gradients. The paper “Trust Region Policy Optimization” (Schulman, et al., 2015) proposed stability improvements over DQN while making minimal sacrifices to the data efficiency by utilizing a policy optimisation function that considers the change between policies at each step. This policy optimisation function considers the advantage at each timestep – that is, how much better a certain new action is as compared to the previous on-policy action – and scales this advantage by some delta coefficient which is a measure of how much this new policy differs from the previous. Once we determine which change provides the maximum advantage, we use a KL-divergence policy to mediate the reward signal by how drastically it changes the policy, helping to modulate wildly changing reward values and increase the stability of our model.

The drawback of TRPO however was its complexity. A lot of calculations needed to happen at each step, and this made it both expensive to run and challenging to implement.

Finally, Proximal Policy Optimization (Schulman, et al., 2017) was proposed as a simplification of TRPO. PPO cuts down on the number of steps and uses a hyperparameter, epsilon, to constrain the distribution change (typically between 0.8 - 1.2, using an epsilon value of 0.2). By removing the incentive for the policy to move too far at a given timestep, we increase the stability of the function without having to calculate a KL divergence[[3]](#footnote-3). This, of course, only gives us an approximation of the results we would see in TRPO, but at a reduced cost. To further reduce instability, PPO uses a minimization function taking the lower bound of the change which will produce results, therefore making the smallest effective change.

For the reasons covered above, in addition to PPO being a popular algorithm in the DRL space today meaning it has a lot of up-to-date documentation, PPO was selected as the algorithm of choice for this project.

# RESULTS

The 1-dimensional bin packing environment showed excellent results as compared to the control agent which took random choices. It was able to allocate incoming items at accuracies reaching 94%, and reach bin utilization of 98.64%.

# CONCLUSIONS

# FURTHER WORK

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1. This is the normal pricing offered for all instances. (https://aws.amazon.com/ec2/pricing/on-demand/) [↑](#footnote-ref-1)
2. This is a discounted price based on current demand, meaning that lesser-used instance types are offered at a discount. (https://aws.amazon.com/ec2/spot/pricing/) [↑](#footnote-ref-2)
3. This describes the clipping method, but it is also possible to use the KL-divergence penalty method, or indeed a hybrid method using a KL-divergence constraint wrapping our clipping method. An ablation study by OpenAI found the clipping method to work better (Engstrom, et al., 2020). [↑](#footnote-ref-3)