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DISSERTATION WORK

A Study of Reinforcement Learning for 3D Games

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Introduction

Motivation

Some of the main hobbies in my life are programming and playing computer games. Since I started to understand the basics of programming, I was wondering how the features in games are being done.

In the days when I was playing on my Nintendo Entertainment System console, I saw how the characters in the screen would be moving, how they reacted when I pressed the buttons on the controller, how the points on the screen are affected and how the enemy characters are moving. Back in those days, the behavior of the enemies were very simple. Most of the time they moved all the way to one side, hit an obstacle, then start walking to the other side.

Back then, that simple strategy was enough to keep players on the edge. Eventually better technology was available, stronger hardware was cheaper, and the demands of the players grew.

The characters in video games slowly became smarter and smarter. They are now interacting within a 3D environment, searching actively for the player and becoming more and more life-like.

Racing games would have the enemy computer drivers trying to surpass you, to be faster than you, but it has to do all sorts of complex calculations. For example how to get ahead of you, without necessarily colliding with you or the walls, while moving at relatively high speeds.

Real time strategy games such as StarCraft II give to human players the possibility to fight against one or more enemy commanders controlled by the computer. I personally do not even begin to understand the size and complexity of the code that was written for the enemy to be able to build entire bases and command their armies.

Simple tasks and routines for the enemy AIs does not take a significant effort to be written. Writing the code for a competent AI that is able to challenge even the best humans at complicated tasks is incredibly difficult. Thus I started searching for other ways of writing these AIs.

One thing that I found was how machine learning is used to train AIs that became so good they are surpassing humans and relatively complicated tasks.

A simple Google search for the term “ai defeats human” will reveal several interesting websites:

- **Google AI defeats human Go champion**
  “Google's DeepMind AlphaGo artificial intelligence has defeated the world's number one Go player Ke Jie.” (2017 May 25, https://www.bbc.com/news/technology-40042581)
- **DeepMind AI Beats Professional Human StarCraft II Players**
  “The Google-owned artificial intelligence lab announced on Thursday that its new "AlphaStar" AI had beaten two of the world's best StarCraft II players.”

(2019 January 25, https://www.forbes.com/sites/samshead/2019/01/25/deepmind-ai-beats-professional-human-starcraft-ii-players/#32d881077cec)

- **AI trained on 3500 years of games finally beats humans at Dota 2**
  "They say 10,000 hours makes an expert, but for video-game playing AIs much more is needed. After playing thousands of years' worth of the video game Dota 2, artificial intelligence is now able to beat the world's top amateurs."
  (2018 June 25, https://www.newscientist.com/article/2172612-ai-trained-on-3500-years-of-games-finally-beats-humans-at-dota-2/)

This has shown me that by applying machine learning, developers can create some incredible AIs, so good that even the humans that trained them could not create a better code by hand to beat the respective AIs.

But one more hurdle had to be surpassed, I do not have experience with machine learning, perceptrons, neural networks, reinforcement learning and so on. Trying to learn all such techniques and algorithms would be too complicated and take too much time to implement them correctly. Even then, when I will try to train whatever AI, I would not even know if the implementation I have done would be correct or not, as training them can take anywhere from minutes to days.

Here comes ML-Agents, a plugin for the Unity game engine that lets developers and hobbyists skip over the difficulty of implementing their own machine learning code and use the best implementations currently available in a popular and powerful machine learning library called TensorFlow.

No longer I have to worry about code correctness, time of training and possible hidden bugs. The respective plugin is hosted on GitHub, where everyone can see what is happening to the code base, able to report whenever they see a problem, and also able to improve it.

After copying and doing the setup for the plugin, I started trying all of the samples.

It contains several environment samples, with machine agents that were already trained to solve sample problems more efficiently then I could do by playing the games themselves, or by writing a code for an agent to solve the respective problems.

For some of the problems I cannot even begin to imagine how to solve them by writing a code. For example, there is an environment with a ragdoll model where each of the important joints are motorized and controlled by the agent, in an attempt to reach a golden target somewhere far away. How does one even take into consideration all the angles, physics and calculations that have to be done for the ragdoll to even just simply stay upright. Yet in the sample we can see the ragdoll running like

Illustration 1: Walker Agent screenshot

a crazy cartoon character towards the target. Even though it looks ridiculous, it is still a ragdoll controlled only by it’s joints, running decently fast while balancing itself!

A screenshot of the ragdoll walker agent can be seen in Illustration 1.

After trying every sample, I started following the guide for creating a brand new Learning Environment (https://github.com/Unity-Technologies/ml-agents/blob/master/docs/Learning-Environment-Create-New.md). I was beginning the grasp the idea how the scene should be organized, and how the scripts should look like. I observed how the training time was pretty slow, until I added the suggested training hyperparameters (batch_size: 10 buffer_size: 100) which indeed has reduced the number of training steps from 300000 to 20000 just like how the guide has said.

I was amazed at the significant change, it was at least 10 times faster!

Slowly, I began adding more complexity to the task, and experimented with the different hyperparameters, the reward system, how the agent gets information from the environment and so on.

I documented here my findings, in hope people will use it to get a better idea on how the different values affect the training time and the performance of the agents.

Used tools

About Unity

Unity is a game engine developed by Unity Technologies. It is currently one of the most popular engines currently used. One of the main features of this game engine is the very wide selection of platforms that it lets users to create applications in. Some of these platforms are Windows, iOS, Android, macOS, Linux, PlayStation 4 and Xbox One.

Even though this is a game engine, games are not the single things that are done in Unity. For example users have used it to create:

- renders of aesthetically pleasing car models
- high quality animations while still permitting lots of artistic freedom
- educational applications
- virtual reality and augmented reality applications

Here is a short list of popular games that were made with Unity: Cuphead, Monument Valley 2, Rick and Morty: Virtual Rick-ality, Inside, Ori and the Blind Forest, Hearthstone and Cities: Skylines.

Even though the main programming language is C#, it can be converted to C++ if the targeted platform is for example Windows.

About machine learning

Machine learning represents the science of programming computers in such a way that they learn from data and improve themselves.

Another definition would be: [Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed (Arthus Samuel, 1959).

In current days machine learning is used at things such as:

- filtering the spam that arrives in your email account
- your smartphone recognizing the position of your face when it sees you
- estimating the human body pose when viewed through Xbox Kinect

By using machine learning, humans can train computers to discover patterns in data and develop behaviors that help it solve complex problems [Hands-On Machine Learning].

About ML-Agents

ML-Agents is an open-source plugin for Unity that helps developers to add machine agents in their applications that can be trained in environments created by the developer.

All of the actual training is done inside of the TensorFlow Python API, while ML-Agents is just sending all of the data collected from the application via a socket to a TensorFlow training application instance.

The plugin is designed in a such a way to make it easier for developers to wrap and compartmentalize all of the intricacies of machine learning into abstract objects the represent things such as agents, academies, brains and brain models.

ML-Agents is currently hosted at [ML Agents GitHub page].

About TensorFlow

In this project, TensorFlow is used indirectly through the ML-Agents plugin.

TensorFlow is an open source software that enables developers to easily create machine learning models, and then just feed into it the training data. Currently it is a considered a popular choice when selecting a library for machine learning and deep learning.

The library was built by Google and offers a considerable amount of documentation that will help users understand it properly.

The TensorFlow library project can be currently found at [TensorFlow GitHub page].

About GitHub and Git

When working with large projects, there is always a need for tracking changes in the files. An application that can help with that is a Version Control Software (abbreviated to VCS).

The VCS that I chose is Git. It is fast and relatively easy to use when needed for basic functionalities such as pushing and pulling files to/from the server ([Pro Git]).

The server that stores all of the files of this project are located on GitHub, one of the most known project repositories that uses Git as the VCS. My project is a fork from the original ML-Agents plugin, to which I added my personal changes.

I decided to use a fork of the original project so that I may continue to receive updates and other possible new features that might be worth experimenting with.

Used hardware

Most of the machine learning sessions have been done on my 2 personal computers. First a desktop that has these respective hardware specifications:

- **CPU** : AMD Ryzen 7 2700X Eight-Core Processor

  8 physical cores, 16 logical cores, no overclocking, base speed 3.70 GHz
- **RAM** : 16 GB, 2400 MHz
- **GPU** : NVIDIA Geforce GTX 1080, 8GB
- **SSD #1** : KINGSTON SV300S37A120G
- **SSD #2** : Samsung SSD 850 EVO 250GB
- **OS** : Windows 10 Pro, 64-bit version

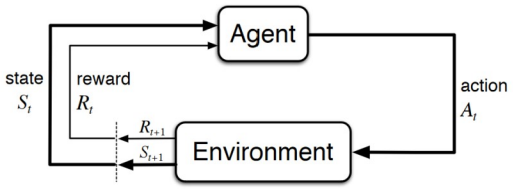
  Second, a Lenovo ideapad 330S laptop with the hardware specifications:
- **CPU** : Intel® Core(TM) i5-8250U CPU

  4 physical cores, 8 logical cores, no overclocking, base speed 1.80 GHz
- **RAM** : 8 GB, 2400 MHz
- **SSD** : SanDisk SD9SB8W512G1101
- **OS** : Windows 10 Home, 32-bit version

State of the art

What is a Markov Decision Process?

A Markov Decision Process (MDP) helps us model in a mathematical way the decision making process that is done by an agent inside of an environment with the scope of achieving the best reward possible. An abstract example of such a model can be seen in Drawing 1. [A Markovian Decision Process]



Drawing 1: Typical model of a Markov Decision Process

The agent starts from an initial state s_0, and makes actions *a* in the environment. After making an action through in environment, the agent receives a reward *R*, and its state changes from the current state s_t to s_{t+1}.

The agent will keep doing this until it reaches the a terminal state, or until the number of steps that it has done reaches a certain imposed limit called a *horizon*.

A Markov Decision Process is defined by:

- Set of states: S
- Set of actions: A
- Transition function: $P(s'|s,a)$
- Reward function: $R(s,a,s')$
- Start state: s_0
- Discount factor: γ
- Horizon: H

The goal of the agent is find a policy π, that maximizes the amount of reward that it receives when interacting trough a given environment.

Goal: $max_\pi \mathbb{E}\left[\sum_{t=0}^{H} \gamma^t R(S_t, A_t, S_{t+1})|\pi\right]$

Obtaining the best reward that an agent can receive while acting optimally can be done by using the optimal value function V^*.

$$V^*(s) = \max_\pi \mathbb{E}\left[\sum_{t=0}^{H} \gamma^t R(s_t, a_t, s_{(t+1)}|\pi, s_0 = s)\right]$$

Calculating the optimal values is done by value iteration.

When H (the horizon) is equal to 0, all the possible reward values are 0.

$$V_0^*(s)=0 \,\forall\, s$$

When H is equal to 1, the optimal values can be calculated using the results of when H was equal to 0.

$$V_1^*(s)=\max_a \sum_{s'} P(s'|s,a)(R(s,a,s')+\gamma V_0^*(s'))$$

Something of interest is the fact that only the best a that maximizes the reward is kept in the optimal values for H=1. Also the fact that γ (discount factor) is starting to be taken into consideration.

All of the next optimal values take into consideration the optimal values of the previous step.

$$V_2^*(s)=\max_a \sum_{s'} P(s'|s,a)(R(s,a,s')+\gamma V_1^*(s'))$$

$$V_k^*(s)=\max_a \sum_{s'} P(s'|s,a)(R(s,a,s')+\gamma V_{k-1}^*(s'))$$

Every time an optimal value is calculated, the policy is updated. This way the best policy can be found.

$$\pi^*(s)=\arg\max_a \sum_{s'} P(s'|s,a)[R(s,a,s')+\gamma V^*(s')]$$

One problem with this method is that it is exhaustive. It has to calculate multiple iterations for each possible combinations of state and actions of the agent. The states themselves could be combinations of data that describe for example the position and rotation of the agent in the environment, auxiliary data such as distance towards a target. The actions could be for example moving to the left, right, forwards or backwards, and maybe even jumping.

The amount of values that have be calculated explodes rapidly even after a small increase of possible actions or states.

At least one only a sufficiently large H (horizon) value is needed in order to discover the optimal policy due to the fact that value iteration eventually converges.

Theorem: Value iteration converges $\forall S \in S : V^*(s)=\max_a \sum_{s'} P(s'|s,a)[R(s,a,s')+\gamma V^*(s')]$

What is Q-Learning?

Calculating the optimal reward when starting from a certain state sometimes is not enough. It would be more helpful to introduce a way of taking into consideration the best reward that could be received by starting from a state and doing a certain action from there.

These values are known as Q-Values.

Bellman Equation: $Q^*(s,a)=\sum_{s'} P(s'|s,a)(R(s,a,s')+\gamma \max_{a'} Q^*(s',a'))$

Q-Value Iteration: $Q_{k+1}(s,a)\leftarrow\sum_{s'} P(s'|s,a)(R(s,a,s')+\gamma \max_{a'} Q_k^*(s',a'))$

From these formulas, it looks like it pretty much acts the same way as before. All optimal values still have to be calculated exhaustively. What if instead of going though every possible combination, we try to improve current optimal value by sampling random actions and starting states?

Tabular Q-Learning

The pseudocode seen in Text 1 starts from an initial state, and tries random actions from there on in order create a table with as many combinations of states and actions as possible and get their evaluated value.

Instead of simply picking random actions, another way would be to greedily choose the action that certainly takes the agent to the best final state. This greedy choice will only be used with a certain probability; sometimes it will be greedy, sometimes it will just sample as usual.

Start with $Q_0(s,a)$ for all s, a.
Get initial state s
For k = 1, 2, ... till convergence
  Sample action a, get next state s'
  If s' is terminal:
    $\text{target} = R(s,a,s')$
    Sample new initial state s'
  else:
    $\text{target} = R(s,a,s') + \gamma \max_{a'} Q_k(s',a')$
  $Q_{k+1}(s,a) \leftarrow (1-\alpha)Q_k(s,a) + \alpha[\text{target}]$
  $s \leftarrow s'$

Text 1: Tabular Q-Learning pseudocode

Though it is a bit better, there is still a problem with the exploring the vast majority of space set X action set. This algorithm generates a table where for each combination of states and actions that it has explored until now, it outputs a value.

Storing such a table becomes unfeasible very fast even in games that relatively not that complicated for humans. For example, in the Atari game screenshot seen in Illustration 2, for storing all the possible RAM states, approximately 10^308 states would be needed, and for storing all the pixel combinations, approximately10^16992 states would be needed.

Illustration 2: Atari game screenshot

Approximate Q-Learning

Instead of storing all the combinations of the states and actions and their rewards values, we would like to find a function that accepts a state and an action, and outputs a value.

Either a linear function:

$$Q_\theta(s,a)=\theta_0 f_0(s,a)+\theta_1 f_1(s,a)+...+\theta_n f_n(s,a)$$

Or a multi-layered and complicated neural network.

The learning rule would look something like this:

$$\theta_{k+1} \leftarrow \theta_k - \alpha \nabla_\theta [\frac{1}{2}(Q_\theta(s,a)-target(s'))^2]\Big|_{\theta=\theta_k}$$

Start with $Q_0(s,a)$ for all s, a.
Get initial state s
For k = 1, 2, ... till convergence
  Sample action a, get next state s'
  If s' is terminal:
    $\text{target} = R(s,a,s')$
    Sample new initial state s'
  else:
    $\text{target} = R(s,a,s') + \gamma \max_{a'} Q_k(s',a')$
  $\theta_{k+1} \leftarrow \theta_k - \alpha \nabla_\theta \mathbb{E}_{s' \sim P(s'|s,a)} \left[(Q_\theta(s,a) - \text{target}(s'))^2\right]\big|_{\theta=\theta_k}$
  $s \leftarrow s'$

Text 2: Approximate Q-Learning pseudocode

This has the advantages of longer needing an entire table with all the possible states and actions and their result. We only have to store now the parameters of the generated function or neural networks.

The pseudocode is very similar to the one in Tabular Q-Learning, as seen in Text 2.

What are Deep Q-Networks?

One problem of Q-Learning is when the target that has to be chased is non-stationary. While in environment, the target might change as time passes by. One way to help better predict and understand the moving target is to have a secondary network just for the target ([Human-level control through deep reinforcement learning]).

The target network is just an older set of weights from the main neural network.

$$L_i(\theta_i)=\mathbb{E}_{s,a,s',r\sim D}(\underbrace{r+\gamma \max_{a'} Q(s',a';\theta_i^-)}_{target}-Q(s,a;\theta_i))^2$$

Deep Q-Learning with experience replay algorithm

The algorithm shown in Text 3 uses a "replay memory", where it stores its past transitions as experiences from which it randomly selects later so that it may better alter the policy.

After a certain interval of runs through the training, the target network is updated with the currently trained so far neural network.

Even if it may sounds counter-intuitive to let a target neural network that started with random weights to guide the main neural network, this algorithm will still approach an optimal solution. This due to the fact that both neural networks still have a common ground truth, and that is the environment itself, which will always give the rewards necessary to encourage the emergence of behavior in the policies.

Algorithm 1: deep Q-learning with experience replay.
Initialize replay memory D to capacity N
Initialize action-value function Q with random weights θ
Initialize target action-value function $\hat{Q}$ with weights $\theta^{-} = \theta$
For episode = 1, M **do**
  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$
  For t = 1,T **do**
    With probability ε select a random action a_t
    otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^{-}) & \text{otherwise} \end{cases}$
    Perform a gradient descent step on $\left(y_j - Q(\phi_j, a_j; \theta)\right)^2$ with respect to the network parameters θ
    Every C steps reset $\hat{Q} = Q$
  End For
End For

Text 3: DQN learning with experience replay taken from [Human-level control through deep reinforcement learning]

Such an algorithm was successfully used to train agents that take the raw pixel input data from Atari 2600 games as input ([Playing Atari with Deep Reinforcement Learning]). In three of the Atari 2600 games, the agent was able to surpass a human expert.

Double DQN

One of the problems of the normal DQN implementation is its tendency to lose its a lot of the progress that it has done while training. This is apparently caused by action values that are overestimated in certain situations ([Deep Reinforcement Learning with Double Q-learning]).

This version of the implementation uses two sets of weights for the neural network, θ and θ^{-}, which are used for selecting and respectively evaluating the best action.

Loss function: $L_i(\theta_i) = E_{s,a,s',r\,D}\left(r + \gamma\, Q\left(s', \underset{a'}{arg\,max}\, Q(s', a'; \theta); \theta_i^{-}\right) - Q(s, a; \theta_i)\right)^2$

This implementation is better at maintaining a high reward value during training.

Prioritized Experience Replay

When selecting experiences to alter the policy, not all of them are as important as others. One way to speed up training is to select experiences that are more relevant ([Prioritized Experience

Replay]). The function to calculate the weights of each experience when selecting them is:

$$|r+\gamma \max_{a'}(s',a';\theta^{-})-Q(s,a;\theta)|$$

Dueling DQN

A dueling DQN is a new proposed neural network architecture which takes into consideration the usual state value function and additionally a state-dependent action advantage function([Dueling Network Architectures for Deep Reinforcement Learning]).

With the help of this architecture, it can learn which states in the environment are more relevant or not when it comes to deciding if an action will affect in a significant way the agent and/or environment.

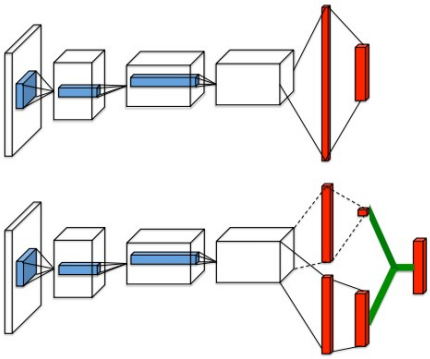


*Illustration 3: Classical DQN (**top**) Dueling DQN (**bottom**)*

Value-Advantage decomposition of Q: $Q^{\pi}(s,a)=V^{\pi}(s)+A^{\pi}(s,a)$

Dueling DQN: $Q(s,a)=V(s)+A(s,a)-\frac{1}{|action\,set|}\sum_{a}^{action\,set}A(s,a)$

where V represents the state value function and A represents the advantage function.

What is a Policy Optimization?

One disadvantage of Q-learning is that the actions that it outputs are not continuous. There is no easy way of asking the agent Q-learning to generate only subtle movements, like for example pressing the joystick towards the left 30% and upwards 75%.

Also in Q-learning, we are not directly improving the policy, we just improve the values of different actions in different states, and with that data we improve the policy. This sounds like extra steps.

The problem policy optimization can be seen as trying to solve as best as possible this function

$$\max_{\theta} E[\sum_{t=0}^{H} R(s_t)|\pi_\theta]$$

The function $\pi_\theta(u|s)$ represents the stochastic policy class, where *u* is an action in the *s* state.

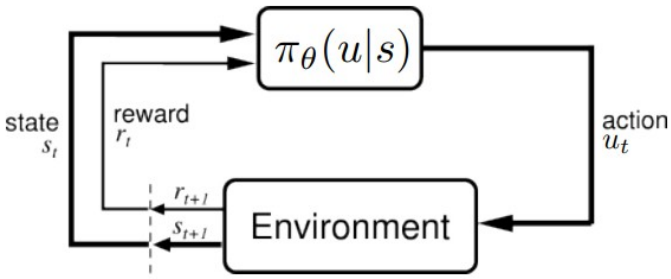


Figure 1: [Figure source: SuTon & Barto, 1998]

Lets define some values

- **τ** will represent a sequence of states and actions (typically looking like: $s_0,u_0,\ldots,s_H,u_H$)
- R is the reward function, which is defined as $R(\tau)=\sum_{t=0}^{H} R(s_t,u_t)$
- U is the utility function, it calculates how well is an agent doing by taking it through all kinds of **τ** values, and is defined as $U(\theta)=E[\sum_{t=0}^{H} R(s_t,u_t);\pi_\theta]=\sum_{\tau} P(\tau;\theta)R(\tau)$

The scope of all of this to find the best neural network weights and biases (defined as θ).

$$\max_{\theta} U(\theta)=\max_{\theta} \sum_{\tau} P(\tau;\theta)R(\tau)$$

In order to calculate the gradient of the policy, which will help us in finding the "direction" where we need to move the weights and biases in the neural network, we shall use the function:

$$\nabla U(\theta)\approx \hat{g}=\frac{1}{m}\sum_{i=1}^{m} \nabla_\theta \log P(\tau^{(i)};\theta)R(\tau^{(i)})$$

In order to better accommodate environment such as games, where the scoring system can vary wildly from from a few tens points for a successful game, all the way up to hundreds of thousands, it is indicated to subtract a bias value value from the inside the function, such as:

$$\nabla U(\theta)\approx \hat{g}=\frac{1}{m}\sum_{i=1}^{m} \nabla_\theta \log P(\tau^{(i)};\theta)(R(\tau^{(i)})-\boldsymbol{b})$$

What is Proximal Policy Optimization?

The Proximal Policy Optimization algorithm, which from now on shall be abbreviated to PPO, is an algorithm that uses a neural network to create behavior for machine agents, taking as input the observations of the environment it currently is in, and outputting the actions of the agent.

This algorithm is currently used by the ML-Agents plugin, which is implemented in TensorFlow.

Due to the fact that it is performing as good as or better than other state-of-the-art algorithms, it was also chosen by the OpenAI team as the default reinforcement learning algorithm.

This reinforcement learning technique was invented by John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford and Oleg Klimov and is described in the article named Proximal Policy Optimization Algorithms ([PPO]).

Up until recently, policy gradient methods have been mostly used for training deep neural networks with the task of controlling machine agents, such as in video games. But their main disadvantage depends on the chosen step size. If it is too small the machine agent is learning too slowly, if it is too large, the performance of the agent might suffer sudden significant drops. Even if the step size is picked carefully, the progress is still incredibly slow, taking millions (or billions) of time steps to learn simple tasks.

Other reinforcement learning techniques have been developed, such as [TRPO], and [ACER], with the hope of eliminating these flaws. But they come with disadvantages also, [ACER] is more complicated than [PPO] (even though [ACER] is a bit better than [PPO]), and [TRPO] isn't so good at solving problems that require visual input, such as video games.

Here is the objective function that is currently used in [PPO].

$$L^{CLIP}(\theta)=\hat{E}^{t}[min(r_{t}(\theta)\hat{A}^{t}, clip(r_{t}(\theta),1-\varepsilon,1+\varepsilon)\hat{A}^{t})]$$

- θ is the policy parameter
- $\hat{E}_t$ denotes the empirical expectation over time steps
- r_t is the ratio of the probability under the new and old policies, respectively
- $\hat{A}_t$ is the estimated advantage at time t
- ε is a hyperparameter, usually 0.1 or 0.2

The team at OpenAI, was able to train a human shaped ragdoll that is able to: stand up straight without falling, walk fast towards a target (it was technically not running, it's legs were never really both above the ground at the same time), turn towards a target, maintain up-right position when hit small projectiles and finally when toppled over because it couldn't balance, it was able to stand up by itself after being knocked over.

By using a keyboard, the user is able to point where the rag-doll human/robot should be walking to. The target is simply placed in direction where to agent is supposed to walk to. Even though the way it walks is amusing, it has potential to become more lifelike than currently hand-made walking and turning animations that are usually made for games.

What is Curriculum Learning?

Curriculum learning in machine learning is a way of teaching machines to become proficient at solving problem by giving them at the start easy challenges that they have to overcome, and slowly increase the difficulty of the challenges as the machine masters the problem.

This idea is based on how human children learn, they are given at the very beginning simple lessons, and once they understand the basics, they are introduced to more complex lessons.

Easing up the children to more and more complicated problem gradually helps them understand the intricacies. Seeing how well this can work in the real world, an attempt was made to simulate this for machines.

One of the ML-Agents sample training scenarios that uses curriculum learning is Wall Jump. The training scenario contains a blue cube shaped machine agent that is tasked with reaching a green target on the arena that it is placed on.

Usually between the agent and the target there is gray wall of varying heights. The machine agent is able to jump a fixed height. Sometimes the wall is small enough that a simple jump is enough to go over it, sometimes the wall is non-existent, sometimes the wall is too tall to jump over it with a simple jump.

The interesting bit in this scenario, is that there is also an orange block, that can be pushed around by the agent. The orange block is big enough for the agent to jump on it, and then over the wall if needed. The training scenario is setup in a such a way that the wall is never taller than the height the agent is able to jump while starting on top of the orange block.

It doesn’t look too difficult to learn, even for a neural network to learn. Simply generating arenas with random wall height, random starting position for the agent and random position for the target (the target is always behind where the wall generated, even if it’s height is non-existent) should be enough for the neural network to learn.

But something interesting happens when generating the arenas in a more controlled manner. If the first few arenas have a non-existent wall height, and in time the wall height increases, the neural network learns significantly faster how to jump even the tallest wall in order to reach the target. It is faster than just picking random heights every time for the wall.

In ML-Agents, Curriculum Learning defines the “lessons” that the machine agent has to go through with the help of “metacurriculum” files (explained in more detail at [Training with Curriculum Learning]).


```
{
  "measure" : "progress",
  "thresholds" : [0.1, 0.3, 0.5],
  "min_lesson_length" : 100,
  "signal_smoothing" : true,
  "parameters" :
  {
    "big_wall_min_height" : [0.0, 4.0, 6.0, 8.0],
    "big_wall_max_height" : [4.0, 7.0, 8.0, 8.0]
  }
}
```

Text 4: Curriculum structure example

Parameters have to be defined in the respective file that enables the TensorFlow API to control them.

For example, in the Wall Jump sample training scenario, there are the *big_wall_min_height* and *big_wall_max_height* parameters which are used in the Unity code to decide how tall to generate the wall.

What is Deep Reinforcement Learning?

In order to answer the question of “What is Deep Reinforcement Learning?”, first we have to understand what is Reinforcement Learning by itself.

Reinforcement Learning refers to all algorithms that are goal-oriented and learn to execute complex tasks. As we know until now, they use positive rewards to encourage an actor to do things that we deem to be correct, and negative rewards in order to discourage it from doing things that we consider bad for solving the task.

In order to make it smarter at solving tasks, Deep Learning is used. In essence Deep Learning refers to using multiple neural network layers that help the agent extract higher level features from the observation input that it is receiving. One classical example is in image processing, where the first layers are very good at extracting very basic information, such as edges in the image, which is then used by the subsequent layers to understand more complex features such faces.

Combining Deep Learning algorithms and Reinforcement Learning algorithms, one can obtain a Deep Reinforcement Learning algorithm. Such an algorithm would be able to extract meaningful information from a broad observation input, and combine with the reward system in order to better decide its next action.

The machine agents in the ML-Agents plugin for Unity use deep reinforcement learning.

For those that wish to further study more about deep reinforcement learning, there is currently an online course that can be found at the [Udacity Deep Reinforcement Learning] bibliographic entry.

Implementation

How does the training environment look like?

In order to keep the environment simple to train, I have decided to create a simple game for the agent to train with.

The idea of the game for the machine agent or the player is to control the black-and-white checkered sphere and push out of the stage all of the other colored spheres in a certain order. (seen in Illustration 4)

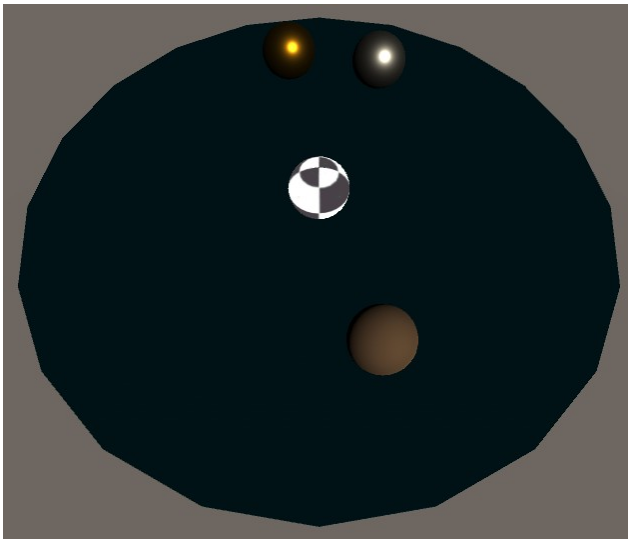


Illustration 4: Screenshot of an arena

First the brown sphere must be pushed out, then the gray-metallic sphere, then lastly the golden sphere. If all three balls are pushed out in the correct order, the agent/player has won, if any of the balls have fallen when it was not supposed to fall (for example, it has attempted to push out the golden sphere) or if the black-and-white sphere has fallen out, then the agent/player lost.

All of the spheres have the same mass, drag and angular drag. And also all of them are affected by the same gravitational force. They all have the same radius of 0,5 units.

The platform that all the spheres are standing on is a very thin cylinder with a radius of 5. From a physics point of view, it is immovable and the spheres cannot pass through it or push it no matter how hard they hit it.

How is the main sphere agent controlled?

The main sphere agent can only be controlled via two possible actions: a force applied on the X axis and a force applied on the Z axis. The code that applies these respective forces look a little like this.5

```
Vector3 controlSignal = Vector3.zero;
controlSignal.x = vectorAction[0];
controlSignal.z = vectorAction[1];
rBody.AddForce(controlSignal * speed);
```

Text 5: Force applied on the agent sphere

The physics calculations are being handled by the Unity game engine. The force is just applied, and the engine handles the rest.

Those ***vectorAction*** values that can be seen in Text 5 are being generated by the neural network after it has received the observations of the current game state. The machine agents brain does not inherently know that the first vectorAction value controls the X axis movement, and the second vectorAction value controls the Z axis movement. In the very first training steps, it will most likely just create random values that will make the main sphere run off the stage.

After many attempts of simply falling off the stage, it might accidentally knock the first brown sphere, and receive a reward value. When it starts to receive the first rewards, it might also start to understand what the vectorAction values also control.

What can the machine agent “see” in the environment?

In order for the machine agent to be able to win at the game that was proposed, it must receive information about what it is playing. One way to do that is to simply give it everything that a human player can also see, like a camera render of the entire stage.

Indeed that would be possible, but training such a machine where it is receiving as an input the entire image, frame by frame, every time it has to decide what to do would mean an astonishing amount of time for it to train to a competent performance.

Surely such a mass of information will help train the best agent, but in order for it to finish training faster, a more limited set of data must be sent.

When a human is playing this particular game, it can see where it is currently positioned in stage, where all the other spheres are positioned. It can also approximate the speed that it is currently traveling that and a pretty general idea of how far it is from the center of the stage and how close it is to other spheres.

And all of this information is unconsciously deduced by the human. In order to help the machine agent to learn faster, we shall send all of this distilled information directly to it.

Observations that are sent to machine agent:

- the agents current position on the X and Z axis
- the agents distance from the center of the stage
- the agents velocity on the X and Z axis
- the agents “mission” (a number that symbolizes which of the colored ball should it attempt to knock out)
- the position of the brown sphere relative to the agent on the X and Z axis
- the distance from the brown sphere to the agent
- the brown spheres distance from the center of the stage
- the brown spheres velocity on the X and Z axis
- the position of the gray sphere relative to the agent on the X and Z axis
- the distance from the gray sphere to the agent
- the gray spheres distance from the center of the stage
- the gray spheres velocity on the X and Z axis

- the position of the gold sphere relative to the agent on the X and Z axis
- the distance from the gold sphere to the agent
- the gold spheres distance from the center of the stage
- the gold spheres velocity on the X and Z axis

One interesting thing that can be seen is that the data that is relevant to the Y axis is never being sent. That is because for the machine agent, that information is not necessary. The Y coordinate for all of the spheres will only change when the spheres are falling out of the stage.

The information that the spheres have fallen off the stage can be deduced just from the distance observations or from the “current mission” observation.

Another thing that might be odd to some is why are all of the positions of the other spheres being sent as relative to the main sphere. This is just to help the machine agent to better understand where are the other spheres. For example it is much simpler for the machine agent to deduce that it has to go to the right to hit the golden sphere if it has received data that the relative position of it on the X axis is greater than 0. The alternative would have been for the machine agent to deduce to do additional computation, such as subtracting the absolute position of the golden sphere from the absolute position of the main sphere.

In this situation, there are in total 24 observations sent to the machine agents brain.

How is the game stage generated?

In order for the machine agent to experience as many situations as possible, the target spheres positions are randomly generated in such a way so that they do not overlap.

Inside Text 6 there is a snippet of the code that attempts to generate a valid random position for the first target sphere, the brown sphere.

```
do
{
   Vector2 r = Random.insideUnitCircle * arenaRadius;
   targetPosition = new Vector3(r.x, spawnHeight,
      r.y);
   distanceToAgent =
Vector3.Distance(transform.position, targetPosition);
} while (distanceToAgent < 1.1f);
target1.transform.position = targetPosition;
```

Text 6: Position randomizer

Attempting to move any gameObject that has a RigidBody component in such away that it overlaps another gameObject with a RigidBody will cause them to spontaneously move away from each other with great velocities. The more overlapped they are, the more violent the reaction between them will be.

This position randomizer will start to take into consideration all the previously moved spheres when generating positions for the gray and golden spheres.

There is ample room on the stage, so it doesn’t take a significant amount of retries in order to generate valid non-overlapping positions.

Another thing to take into consideration is that simply moving the spheres back on the stage is not enough, the physics engine still has data about their velocity and angularVelocity.

Simply teleporting them back on stage will cause them to keep moving with the same velocity as before, so in order to prevent that, the velocity and angularVelocity of all the target spheres must be set to Vector3.zero.

What rewards are given to the machine agent?

The reward system is simple and straight forward, every sphere that is successfully knocked off the stage in the correct order, it will give a reward of 1/3f to the agent.

When all 3 spheres are knocked off in the correct order, the agent is marked as Done, and Tensorflow will adjust the weights in the neural network in order to encourage the same behavior.

Anytime the agent does something wrong: knocking off one the spheres too early or dropping off stage; the agent will be marked as done, and it's currently accumulated reward will be taken into consideration by Tensorflow.

More complicated reward systems can be implemented, such as on every action that the machine agent is doing, add a small constant negative reward that will encourage the machine agent to finish the task faster before it accumulates a time penalty that is too big.

Another example would be to give weighted rewards for each of the spheres being dropped off, such as:

- knocking out the brown sphere: 1/7 reward
- knocking out the gray sphere: 2/7 reward
- knocking out the golden sphere: 4/7 reward

This way, making further and further progress is exponentially better that just doing the first and second task and be contempt with just that.

There is also another way that could be done. I saw that in the "Pyramids" sample from the MLAgents even though there are two tasks to be done, the positive reward is given only when both of the tasks are completed in the correct order. With this the reward system could be like this:

- knock out the brown, gray and golden spheres in the correct order: 1 reward

Speeding up the training process

One way to speed up training is by creating several agents and for each one of them to create an arena to train into. This can be seen to be also applied in several of the example scenes of the ML-Agents plugin and also described in the documentation [Making a New Learning Environment] found on the GitHub page for the ML-Agents plugin.

The responsibility of generating all of the agents and the arenas where they will train has been given to the ***RollerArenaAcademy*** class, which extends the Academy.

Inside of the InitializeAcademy method, a dynamic amount of arenas are generated.

The number of generated arenas is set with the help of the Unity Editor [Illustration 5]. The same is also said about the arena themselves, which are just copies instantiated from a prefabricated roller arena game object.

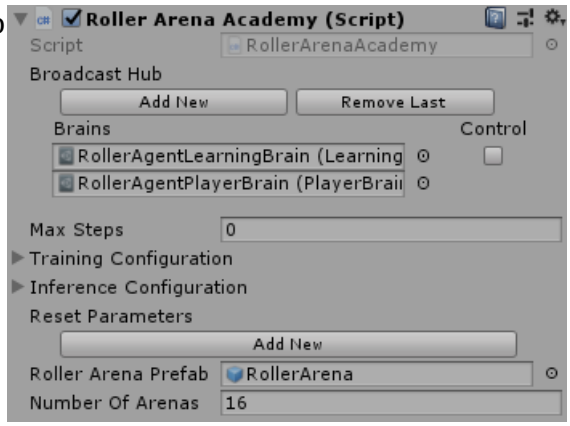


Illustration 5: Roller Arena Academy Unity settings

The code that handles the creation of the arenas is

```
public GameObject m_RollerArenaPrefab;
public int m_NumberOfArenas;
public override void InitializeAcademy()
{
  for(int i = 0; i < m_NumberOfArenas; i++)
  {
    Instantiate(m_RollerArenaPrefab, new Vector3(0, -
4*i, 0), Quaternion.identity);
  }
}
```

At the moment of writing this document, I found that creating 16 arenas is an adequate amount that does not overload my system when training and also leaves enough resources for my PC also to do something else.

What are the used training parameters?

A list of all the training parameters that can be chosen are displayed on a documentation page called [Training ML-Agents].

The ones that are currently used by default for training the roller agents are:

- *use_curiosity: true* => train using an additional intrinsic reward signal generated from Intrinsic Curiosity Module[Solving sparse-reward tasks with Curiosity]
  Seeing that the Pyramids example inside of the ML-Agents plugin was able to train to competent levels, I decided to try this value to see if it affects the training in a positive way
- *curiosity_strength: 0.01* => magnitude of intrinsic reward generated by Intrinsic Curiosity Module
- *curiosity_enc_size: 256* => the size of the encoding to use in the forward and inverse models in the Curiosity module
- *summary_freq: 2000* => how often, in training steps, to save training statistics
- *time_horizon: 128* => how many steps of experience to collect per-agent before adding it to the experience buffer

- *batch_size: 128* => the number of experiences in each iteration of gradient descent
- *buffer_size: 2048* => the number of experiences to collect before updating the policy model
- *hidden_units: 512* => the number of nodes in each of the hidden layers of the neural network
  In my attempt of making the roller agent able to learn complicated tasks, I have decided to give it a large amount of hidden nodes
- *num_layers: 3* => the number of hidden layers in the neural network
  Again, I have chosen this number in order to attempt to make the agents learn more complicated problems
- *beta: 1.0e-2* => corresponds to the strength of the entropy regularization, which makes the policy "more random."
- *max_steps: 5.0e5* => how many training steps are run in total
- *num_epoch: 3* => the number of passes through the experience buffer during gradient descent

The chosen reinforcement learning technique is called Proximal Policy Optimization. All of the above values have been chosen by either copying them from other ML-Agents examples or after reading more about them from the GitHub documentation page named [Training with Proximal Policy Optimization]

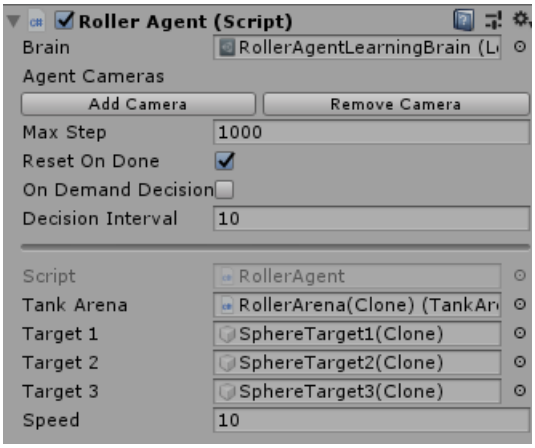
Discovered observations

Default setting used for training

Before the observations and the differences between them are being described, first there must be a common default set of settings or particularities defined for them.

Firstly, here are the training hyper-parameters that are being used

```
batch_size:     128
beta:   0.01
buffer_size:    2048
epsilon:        0.2
gamma:  0.99
hidden_units:   512
lambd:  0.95
learning_rate:  0.0003
max_steps:      5.0e5
normalize:      False
num_epoch:      3
num_layers:     3
time_horizon:   128
sequence_length:        64
summary_freq:   2000
use_recurrent:  False
memory_size:    256
use_curiosity:  True
curiosity_strength:     0.01
curiosity_enc_size:     256
```



Secondly is to describe the particularities of environment created in Unity

- all of the spheres have the same mass
- the main agent sphere moves by applying a force of 10 multiplied with vector that indicates where it desires to move
- the main agent sphere is given the relative position of all the other target spheres as observation (not the absolute position in the game world)
- the “current mission” of the main agent sphere is coded as
  - 1 => push off the brown sphere
  - 2 => push off the gray sphere
  - 3 => push off the golden sphere
- failing to push the correct sphere just sets the agent as done and does not impose a negative reward
- the main agent sphere falling of the arena sets the agent as done and does not impose a negative reward

- going over the “Max Step” value because the much time was taken trying to complete the task does not impose a negative reward
- the simple passage of time does not impose a negative reward
- in this version of the training scenario, there are in total three spheres that have to be pushed off
- rewards are given gradually and proportionally to the number of spheres that have been pushed off
    - 1/3 reward for each of the 3 spheres that have been pushed off

Training when using the default settings

By using the default training parameters, the mean reward slowly raised to these respective values:

- 0.124 at step 4000
- 0.200 at step 10000
- 0.322 at step 26000
- 0.410 at step 112000
- 0.510 at step 258000
- 0.610 at step 370000

Only stabilized mean reward values are taken into consideration. There is no need to report reaching a milestone such as for example a mean reward of 0.5 when it is not immediately improving from there on.

In this particular training session, the best mean reward that it was able to get was 0.690 at step 472000, but it was not stable. The reward did not approach maximum value of 1.

Behavior

Positive behaviors:

- it is proactively trying to always stay on the arena
- in the vast majority of times it will first chase after the brown sphere to knock it off
- after the first brown sphere is knocked off it will chase after the gray one to also knock it off
- sometimes when attempting to push the brown or gray sphere, it may avoid the gold sphere

Negative behaviors:

- when chasing the brown sphere, it sometimes moves the gray sphere by accidentally
- after successfully knocking off the gray sphere, it just moves around and around the stage, it does not actively search for the gold sphere to knock it off the arena

- sometimes when attempting to push the brown or gray sphere, it may push the gold sphere out the stage too early by mistake

Training when the reward is given only at the end

In this training scenario, instead of giving a reward of 1/3 to the agent for every sphere that is pushed out correctly, now it will receive only once a reward of 1 if it knocks out all of the spheres in the correct order.

Because of this, the chances of it ever receiving the reward are very slim when the agent just began to learn. It is highly probable that it will just knock the spheres by mistake in the wrong order. But such a strict training scenario might help it discover eventually that the task is fully complete only when pushing all of spheres in the correct order.

In the first 20000 training steps, the mean reward only reached a maximum of 0.002, most of the time it's just 0.000.

After reaching 40000 training steps, the mean reward reached a maximum of 0.017. It seems that it is starting to discover some sort of pattern or behavior.

At training step 54000, the mean reward reached a value of 0.049. The training is incredibly slow, it seems as if it's just pure luck.

When reaching training step 80000, it seems as if the mean reward does not increase, rather it decreased over time, now being at a value of 0.018.

At training step 94000, the mean reward has recovered back to 0.052. Maybe that curiosity feature is indeed exploring wider and more random weights for the neural network.

At training step 108000 it has finally reached a mean reward of 0.108. Compared to the default settings, which already had a mean reward of 0.124 at step 4000, it is 27 times slower taking into consideration the progress made so far.

While going to training step 236000, the mean reward value kept growing and shrinking, at worst being a value of 0.057, at best 0.155. Again, the curiosity feature is exploring possible solutions.

At training step 278000, it has finally reached a mean reward value of 0.206, which is still incredibly slow compared to the default settings that reached this value at training step 10000. Thus again making it around 27 times slower.

The trend of rising and lowering mean reward continues to happen. At training step 296000 it reached a mean reward of 0.265, and at 304000 it dropped to 0.194.

At training step 360000, it has reached a mean value of 0.300. It close to reaching a success rate of 33% percent.

At around training step 450000, it has managed to somewhat stabilize a mean reward value of 0.332. Thus making it able to win the game at 33% of the time.

Finally at the end of the training session, with 500000 steps done, the best mean reward that it has achieved was of 0.404, which is worse the defaults case with 0.610.

Attempting to give a reward only at the end slowed down the training significantly. It might be possible that a much longer training period will make it achieve better performance.

Behavior

In comparison to the default case, this machine agent is moving more carefully. Instead of just flinging around very fast, it seems sometimes it's slowing down before coming into contact with the spheres.

Positive behaviors:

- once it manages to start pushing a sphere, sometimes it lets it roll a bit, then starts going for another sphere while the previous one has not fallen of the stage yet; this reduces the total time for all three spheres to fall down
- it became incredibly good at not falling of the stage
- in comparison to the default case, once it pushed of the first two spheres, it is better at finding the last golden sphere to push it away
- sometimes is seen to avoid pushing other spheres thus avoiding a hard to mitigate billiard effect

Negative behaviors:

- sometimes the machine agent slams into the golden sphere at the start of a round, thus knocking it out too early
- was observed one time to be too afraid to push a brown sphere because it was incredibly close to the edge of stage and not moving (the brown sphere had no velocity because it was just spawned)
- sometimes pushes off the metallic sphere first because the brown sphere was too close to the golden sphere at the start of the round

Because the reward is now fully given only at the end of task, this agent is sometimes performing better than the default agent by making smarter decisions that take it consideration the velocity of the spheres. Sadly with an average success rate of 33-40% it is not good enough.

Training when using 4 hidden layers with 32 units each

In this training session, the number of hidden units will be change from 512 to 32, and the number of hidden layers from 3 to 4.

Having a smaller number of hidden nodes in total might make it simpler for TensorFlow to explore relevant weights for the neural network. After all, the proposed problem does not need an incredibly complicated neural network to chase some spheres.

Increasing the number of layers might help it also create some interesting and complex functions.

Let’s not forget that this training scenario still use the default training scenario, the rewards are still cumulative (1/3 for each sphere).

Instead of being 512*3 = 1536 hidden nodes, there are now only 128 hidden nodes.

Already beginning from the training step 4000, the mean reward has become 0.132. This is very similar to the default case.

At training step 12000 it has reached a mean reward of 0.200. It is slightly slower than the default case.

At training step 36000 it is now at 0.314, and it seems to have some difficulty surpassing this value. Because of the cumulative reward system, the agent has mastered pushing off the brown sphere, now it must continue to learn to push after that the metallic gray sphere.

At 54000 it’s starting to make a breakthrough, the mean reward is 0.363, so that means that some agents are starting to discover how to push off the brown sphere and gray sphere in the correct order.

The simpler neural network is starting to show it’s problems. When the training reached step 76000, the mean reward is still around 0.333. The default case reached that value at training step 26000. At this point it looks like having a network that is too simple is detrimental to learning more complex behavior.

When it reached training step 190000, the mean reward was 0.408. Reaching this mean reward took almost twice as many training steps then the default training scenario. The mean reward is now increasing only very slowly, occasionally dipping under 0.400.

Even at training step 360000, the mean reward has not changed by significant amount, only about reaching a value of 0.420.

At around training step 392000, the agent finally starts to grasp what it has to do in order to obtain the next chunk of 1/3 reward, thus approaching the mean reward of around 0.450.

At the end of the training session, the best mean reward had a value of 0.480, and the last mean reward at step 500000 had a value of 0.464.

In comparison with the default training session with a value of 0.610, it performed worse. The cause of why this happened might be because of pure bad luck, as in the possible space of values for the neural network was not explored sufficiently.

Or it might have been because the configuration of 32 hidden nodes by 4 layers was actually detrimental to generating useful behavior for the proposed problem.

Behavior

In comparison to the previous test case, where the result was given fully only at the end of a round, this machine agent is moving more chaotically. Most of the time its moving fast in circles, using it's high velocity to smack out the other spheres.

Positive behaviors:

- actively chasing the first brown sphere to push it out
- it became incredibly good at not falling of the stage
- after taking out the brown sphere, it starts it's chaotic spinning pattern, sometimes kicking out the metallic sphere
- the fact that it's moving fast helps it finish the task faster in some cases

Negative behaviors:

- sometimes the machine agent slams into the golden sphere at the start of a round, thus knocking it out too early
- due to the chaotic movement, it sometimes does mistakes at the very beginning of the round, such as knocking out the metallic or golden sphere
- does not actively search for the final golden sphere after pushing out the metallic sphere
- does not really seem to take into consideration the velocity of the other spheres

Training when using 4 hidden layers and more steps

From what I saw in the default case, the machine agent was able to reach a mean reward of around 0.600, thus I thought, what if I let it train overnight, and also give it more hidden layers.

Having more hidden layers should help it learn more complex behaviors, and letting it train more time should help it reach better average rewards.

All the training settings are the same, except that there are now 4 hidden layers, and the max steps value is now set to 5.0e6 (5 million).

At step 6000, it has already reached a mean reward of over 0.139. This looks good so far, the training started really well.

At step 50000, it was able to stabilize the mean reward to be above 0.300. It took it almost twice as many training steps than the default case, but it is expected for this to happen, taking into consideration the extra hidden layer.

After a long time, it has reached a stable mean reward of at least 0.400, at training step 214000. Again it took twice as many training steps to reach this compared to the default case.

I thought everything will be well, but something very interesting has happened, the mean reward started to drop. And it didn't stop. After it reached a decent mean reward of 0.467 at training step 272000, the mean reward just started to get lower and lower.

It dropped all the way down to a mean reward of perfectly 0.000, at training step 418000. It was as if all progress was lost. I am not completely sure why this happened, but this might be because of the curiosity flag being set to true.

When the curiosity flag is set to true it makes the agent more prone to wildly exploring different strategies, giving itself some kind of special reward to continue searching, in hope of receiving a real reward.

For a very long time, this strategy does not seem to really work. The mean reward remained under 0.020 until training step 1168000. That means 896000 training steps have been spent randomly trying bad strategies. That is an amazing amount of time, considering all my previous training setups stopped when reaching 500000.

After this long pause of trying and failing for a very long time, the agent seems to start recovering some of it's progress.

At training step 1216000 it reached a mean reward of 0.105.

At 1286000 it reached 0.200.

At 1340000 it got to 0.304.

Its now taking tens of thousands of steps to learn useful strategies.

It managed to stabilize a reward of at least 0.400 after 1538000 steps. The growth was slow, but at least it's not dropping back to zero.

At training step 1948000, it has managed to stabilize a new best mean reward of at least 0.500. Maybe the new strategy that it was discovered due to the curiosity system might help it after all.

The incredibly slow learning process is still continuing. At training step 3352000, it finally managed to stabilize to at least 0.600. It took at least 1000000 steps of training for just that little increase in performance.

My hope in leaving my computer run over night was to discover a fully developed agent that was an expert at it's task. But it was taking too much time. I stopped the training at step 3352000, the time was 19:07, the time when I started the training was 01:16, and all of that was to just reach a mean reward of 0.626.

It took almost 18 hours, only to reach that meager value.

Behavior

The movements of this agents are not chaotic, they may rather be consider to be prudent. The speed is very controlled at most times.

Positive behaviors:

- actively chasing the first brown sphere to push it out
- it became incredibly good at not falling off the stage
- sometimes is seen to chase metallic sphere in order to get the second reward
- sometimes seen to actively push on the final golden sphere if it comes into solid contact with it
- the more prudent nature of this agent makes it give a small push to the other spheres, as if it was played by a player

Negative behaviors:

- sometimes the machine agent slams into the golden sphere at the start of a round, thus knocking it out too early
- sometimes seen to be too afraid to approach the metallic sphere if the golden one is nearby to it
- in about 50% of times, it does not attempt to chase after the last golden sphere, only to spin around in the safety of the arena
- sometimes too afraid of the spheres that are very close to the edge of the arena

Training when separating the mission observation into three values

Taking into consideration the progress of the other training attempts, it always seems to have difficulty in mastering pushing all three spheres.

It only seems to be reaching an average reward value of around 0.610, which is close to the default given reward when knocking off the first two spheres.

One attempt at coercing the agent to learn better is to better split up the observations regarding the current mission for it.

Instead of just using a single float value that signals to the agent the current mission it has, now there are 3 separate values.

When the current mission is to push off the brown sphere, instead of just sending a single float value of 1, there are now the three float values 1, 0 and 0.

The same idea is used on the next spheres, for the metallic sphere being 0,1 and 0. And in the end when the agent has to push off the golden sphere, the values shall be 0,0 and 1.

Separating the values should now be easier for the agent to understand, it doesn’t have to make an awkward comparison for the mission being equal to 1, 2 or 3. Now it will have these values that plainly say which one to attempt to chase.

The training process is going pretty smoothly. The mean reward is slowly increasing and at a stable rate. There are some places where it dips down for a moment, but then it continues to increase. This phenomenon might be due to the curiosity flag being set to true, thus making it more likely to change it's strategy more radically.

Here is just a simple list of the training process:

- training step 6000, mean reward 0.117
- training step 12000, mean reward 0.219
- training step 24000, mean reward 0.329; most of the agents are now able to successfully push the first brown sphere off the stage.
- training step 84000, mean reward 0.401
- training step 242000, mean reward 0.524
- training step 326000, mean reward 0.601
- training step 400000, mean reward 0.650; now that it is close to reaching two thirds of the reward, it means most agents are proficient at proficient at pushing both the brown and metallic sphere off the stage in the correct order.
- training step 500000, mean reward 0.671; the end of this training session

The best achieved mean reward until training step 500000 was of 0.708, which is slightly better than the value of 0.690 from the default training session.

Compared to the default training session, the "milestones" are reached slightly faster. Maybe the clearer separation of mission observation value does indeed help.

Or it could just be the fact that better weights have been randomly selected by chance for the neural network of the agent.

One argument why it isn't just a random chance for the slightly faster training, is because even though they are random, they are spread over a very significant amount of time. That makes it more evenly spread in the long run.

Behavior

The movements of this agents are neither very chaotic, neither are too prudent. The speed is very controlled at most times.

Positive behaviors:

- actively chasing the first brown sphere to push it out
- the spheres tend to be more confidently pushed; not afraid to go to spheres that are on the edge of the arena

- seen one attempt of trying to stop the golden sphere from being pushed off the stage when touching it by accident; it's almost is as if it doesn't want to lose the game too early
- it became incredibly good at not falling off the stage
- observed sometimes to push multiple spheres in order to give them different velocities before they fall of the stage; the brown sphere to be pushed the fastest, metallic sphere given a medium speed, and golden sphere just a very light tap; the agent might have understood that it doesn't have to fully confirm that sphere has fallen off, and that it understands their order
- sometimes when the golden sphere is left last, the slightly chaotic movement of the machine agent might give a light tap to the respective sphere and knock it off

Negative behaviors:

- it doesn't seem to understand that when it's pushing the brown sphere and it hits another sphere there might be a chance that the second sphere is knocked off too early
- sometimes seen to be too afraid to approach the metallic sphere if the golden one is nearby to it
- has difficulty understanding how to chase the last golden sphere when it is its turn to be knocked off
- in about 50% of times, it does not attempt to chase after the last golden sphere, only to spin around in the safety of the arena
- sometimes too afraid of the spheres that are very close to the edge of the arena

Extending the training time

Taking into consideration the slightly better success of this training scenario, I was wondering what would happen if I let it train more.

Thus it was left again to train over the course of a day.

The average mean reward is sometimes decreasing significantly. This can be seen around training step 998001 where it reached a value of 0.370.

The reason why this is happening might due to the curiosity feature rewarding the agent by exploring different strategies that might help it finish the entire course.

Even though it was given copious amounts of time to train, it only reached a maximum mean reward value of 0.825 at training step 3298001.

While this is better than the default case, so much time being spent only training the agent is too much taking into consideration the simplicity of the proposed challenge.

Behavior after extending training time

The movements of the agent have become slightly more prudent than before. It seem to be pushing the sphere with a slight “scare”, as if, when it first forcefully pushes one the spheres, the next moment is seen to jolt momentarily in the other direction.

At other times is seen to over enthusiastically push the spheres off stage, thus resulting in the agent itself falling off the stage.

Positive behaviors:

- sometimes observed to expertly avoid spheres that don’t have be pushed yet in order to correctly go for the right one
- sometimes observed that it gives only a slight velocity to some of the spheres so that it may move to other spheres in the meantime to finish the task faster
- the machine agent is still good at staying on the stage
- when the last golden sphere is left alone on the stage, it seems to understand that and goes directly to it to push it off, instead of just spinning around in the stage and hitting it by accident
- most of the time not afraid to go after spheres that are near the edge of the arena

Negative behaviors:

- seen many times to push the brown sphere by mistake into the golden or metallic sphere, thus triggering a chain reaction of movement, making them fall too early
- the machine agent is seen sometimes to fall off stage because it accumulated too much velocity
- it doesn’t seem to understand that when it’s pushing the brown sphere and it hits another sphere there might be a chance that the second sphere is knocked off too early
- sometimes is seen to be too afraid to push the first brown sphere off the stage

In conclusion of this training setup, adding more training time does eventually help the machine agent become better at given tasks.

Training when using no curiosity and smaller batch_size and buffer_size values

Training these machine agents take a lot of time. Most of the time they take at least 2 hours for them reach the 500000 step.

One suggestion I found on the internet was to use smaller batch_size and buffer_size values, and because I want the training process to be more steady, I also disabled the curiosity feature.

Now that the curiosity feature is turned off, it should no longer wildly increase and decrease the mean reward over time.

All the characteristics of this training are the same as the default training scenario, with the only differences being the used hyperparameters.

The updated values are:

- use_curiosity: false
- batch_size: 64
- hidden_units: 512

Around training step 6000, the machine agent has reached a mean reward of 0.106. A pretty decent start.

At training step 12000, it reached a mean reward of 0.206. This is very similar to how the default training scenario manifested.

At training step 42000, it reached a mean reward of 0.309, which sadly didn't continue to increase. It then decrease to 0.211 when reaching training step 44000.

The mean reward seems to have reached some sort of ceiling of around 0.333, even at training step 80000. It is taking more time to train compared to the default training scenario. At around this step it seems the machine agent mastered pushing off only the brown sphere.

When reaching training step 148000, the mean reward is around 0.400. The agent is slowly learning the next step of exercise, pushing the metallic sphere after the brown sphere.

At training step 208000 it seems to be picking up the pace. The mean reward is around 0.450.

A stable mean reward of 0.500 is reached at step number 272000. It's only slowly lagging behind the default training session, which achieved this value at 258000.

When reaching the training step 416000, it's getting close to mastering pushing the first two spheres correctly, by having a stable mean reward values of approximately 0.640.

Behavior

This particular machine agent is seen to move more confidently then others but it is also seen to stagnate very often when it has to push off the last golden sphere.

Positive behaviors:

- actively chasing the first brown sphere to push it out
- sometimes observed to give a very solid hit to the other spheres when it sees that it has clear path to do that
- it became incredibly good at not falling off the stage
- seems to understand that it has to push the spheres off the stage in the correct order

- seems to understand sometimes that the velocity of the spheres is a good indicator for finding out if they are going to fall off soon

Negative behaviors:

- sometimes locks up (makes only very small movements, as if it's stuck) when it has to push the last golden sphere
- doesn't really understand that colliding spheres together might send them off the stage too early
- when the stage resets, the machine agent might have a very great velocity from the previous stage, thus accidentally slamming into a new sphere, which might not be a brown one
- sometimes seen to spin around the stage when only the golden sphere is left on stage; it doesn't seem to go directly for it

Training when using normalization

In this training session, all the training parameters and characteristics are the same as the default training session, with the exception of the normalization parameter being set to true.

Normally this is set to false, and I was curios what effects does it have when it's enabled. I saw that this parameter is set to true also in these samples: BouncerLearning, 3DBallLearning, 3DBallHardLearning, TennisLearning, CrawlerStaticLearning, CrawlerDynamicLearning, WalkerLearning and ReacherLearning.

Taking into consideration the fact that a pretty wide variety of learning environment are taking advantage of this normalize flag, I decided that it is worth a try.

The mean reward of 0.120 was reached at training step 6000, which is a similar achievement to the one made by the default training scenario.

At training step 12000, the mean reward stabilized above 0.200. This is slightly slower than the default training scenario.

At training step 92000, the mean reward stabilized above 0.333. It seems that it is significantly slower then the default scenario, which achieved this around training step 26000. It is hard to tell if this is caused by the normalize flag, or by simple bad luck during the random selection of weights for the neural network.

The trend of the slow training seems to continue. The mean reward has stabilized above 0.400 at around training step 136000.

But as time continues, this testing scenario seems to have reached the stabilization of mean reward 0.500 faster, at training step 226000.

At around training step 318000, it has achieved a mean reward of 0.594, but it has not stabilized yet. The mean reward still tends to drop down a little from time to time. The machine agent should be soon mastering pushing off the brown sphere and the metallic sphere.

Only when reaching training step 440000 it can be said that it is safely over 0.600.

At the end of this training session, after 500000 steps, the best average reward was of 0.646. Which is slightly smaller than the default training scenario.

The addition of the normalize flag does not seem to significantly improve the speed of training or the rewarding.

Behavior

The way this machine agents moves is rather peculiar. Instead of moving in a circle-like pattern, it tends to much faster in X axis, instead of the Z axis. This makes it a bit more reluctant to change its current Z axis position in order to better collide with the other spheres.

Positive behaviors:

- actively chasing the first brown sphere to push it out
- sometimes observed to give a very solid hit to the other spheres when it sees that it has clear path to do that
- it became good at not falling off the stage
- seems to understand that it has to push the spheres off the stage in the correct order

Negative behaviors:

- doesn’t really understand that colliding the goal spheres between them might result in them falling too early
- overly favoring movement on the X axis makes it very reluctant to chase rare cases when the current goal sphere is directly above or below on Z axis
- does not seem to understand the velocity of the spheres; it’s not taken into consideration so that it may finish the task faster

Training by rewarding only just touching the spheres

Just for the sake of trying, it is worth to see if a simpler mission for the machine agent can be mastered.

Here the stakes are simpler, the brown sphere, metallic sphere and golden sphere only have to be touched in the correct order. They disappear instantly after they are touched, and the reward is given as usual, as if they were pushed off the stage.

All the other training parameters and characteristics are the same as in the default training scenario.

This training scenario is significantly faster in getting a high mean reward value.

By step 4000, it has already reached a mean reward of 0.229.

At training step 12000, it reached a mean reward value of 0.362. Most of the agents are now able to reach for the first brown sphere.

At training step 70000, a mean reward of 0.668 was achieved. Now most agents are reaching one after the other the brown sphere and the metallic sphere.

From here on out it should be very straight forward for TensorFlow to discover the last adjustment to go for the golden sphere.

At training step 108000, it reached a mean reward value of 0.791, which is a considerably high value, but does not manage to raise it higher than that for a while. Occasionally dipping and increasing.

The mean reward does not increase, instead it keep increasing and decreasing for a very long time.

At training step 500000, it didn't manage to improve the mean reward over 0.791. Considering the potential of the mission being simpler, I modified the training parameter max_steps to 5.0e6.

The mean reward just doesn't seem to just go upwards, there are many times where it reaches some sort of local maximum and then starts dipping down.

Such "local maximum" and "local minimum" moments are observed around the training steps:

- 962090, mean reward 0.809
- 1132090, mean reward 0.098
- 1256090, mean reward 0.380
- 1298090, mean reward 0.175

One reason why these weird mean reward values manifest, could be because of the curiosity feature from the ML Agents plugin. It encourages the machine agent to try new strategies with the scope of discovering new interesting observations that might advantage it.

This might have paid off eventually. The best mean reward had a value of 0.956 which is incredibly close to a perfect reward value of 1. This value was reached at training step 2846090, which took almost an entire day to do so.

The training was allowed to continue in hope for it become even close to a perfect reward of 1, but I saw it started to dip again, and thus I stopped the training.

The last training step was done around 2874090, and had a mean reward value of 0.929. Currently I do not know if the model that is kept is the last one that was trained, or if it is the best one that ever performed.

Luckily the achieved performance was pretty good even if the observation values still contained the velocity of the other spheres. They were not useful at all, because once they were touched they disappear. They velocity is always 0, and it could have been removed in order to further increase the training speed.

Behavior

The machine agent is performing marvelously. It has learned how to control it's velocity, and a pretty good sense of how to dodge for example the metallic or golden sphere when it has to touch only the first brown sphere.

The only times it is losing is either due to bad luck when generating the sphere positions (for example: brown sphere is very close to edge and the rest of the spheres surround it), either due to the machine agent having too much velocity from the previous run.

Positive behaviors:

- it has learned to dodge spheres that must not be touched yet in order to chase the one that the current mission points it to
- it has learned to go the spheres in the correct order
- it became good at not falling off the stage
- when the line between the machine agent and the current mission sphere is clear, it moves with a confident speed towards it

Negative behaviors:

- sometimes it has bad luck because of the way the stage is generated; any remaining velocity from the machine agent might propel it in a newly spawned sphere that might not be correct one at that time
- sometimes seen to be too afraid of dodging both the metallic and golden sphere in order to reach the brown sphere, even though there is sufficient space between them
- sometimes seen to fall outside the stage because the remaining velocity of the machine agent after hitting the last sphere from the previous run is still too great

Training when only having to push two spheres

One obvious thing that can be seen from most of the other training sessions so far is that the machine agent has a difficulty in mastering pushing out all three spheres.

Thus it is worth seeing if simplifying the problem in different ways increases the learning rate of the machine agent.

In this session, all machine agents now only have to push the brown sphere off the stage, then the metallic sphere. There is no more a golden sphere to take into consideration.

Compared to the default training session, the number of spheres have been changed, and along with that, the reward for each sphere is now 0.5, and the number of observations have been reduced. There are no observations relevant to the golden sphere being sent, because it doesn't exist anymore.

This training session is significantly faster at gaining a good mean reward.

At training step 12000, the mean reward is already at 0.508, which mean the majority of the machines agents have figured out how to push off the brown sphere, even some of them were lucky enough to also push the metallic sphere after it.

Now that the golden sphere is out of the picture, the stage is also less cluttered and simpler. The agent can't make as many accidental movements as before.

At training step 24000, the mean reward is at 0.660. The machine agent is starting to understand how to chase metallic sphere after the brown one.

At training step 58000, the mean reward has stabilized at 0.855. It is rather interesting how after completing a small sub task, it is difficult for machine agents to continue with learning the other sub tasks successfully. Over 30000 steps were necessary in order to attain a meager extra reward of around 0.200.

At training step 200000, it was the first time the mean reward surpassed 0.9, reaching the value of 0.905. But sadly it is not stable.

The training was left to continue until the mean reward was around 0.970. Reaching a mean reward of exactly 1 is nearly impossible, as there can always be awkward cases that the agent cannot handle properly.

It can be said that the machine agent has properly mastered the task of pushing off two spheres in the correct order.

Behavior

Positive behaviors:

- it became incredible good at chasing the first brown sphere
- after the brown sphere was pushed, it immediately goes straight for the metallic sphere; it does not move around in circles trying to hit it by accident
- it became good at not falling off the stage

- it was seen to understand the velocities of the spheres; when pushing the brown sphere, if it collides with the metallic sphere, the agent can somewhat adjust its positioning so that it pushes the brown sphere faster out

Negative behaviors:

- sometimes when it tries to chase the metallic sphere, it completely misses it, and falls out of the arena
- observed a few times to continue to push off the metallic sphere and fall off the stage with it

Training when using two stacked vectors

All of the training scenarios until now only passed observations of the present state of the environment. The default machine agents have no ability to remember events from the past. Every movement that they make is always based on the exact present instance.

My original guess was that passing sufficient observation values of the present state of the spheres would be enough in order to manage to find the best way to push them off in the correct order.

While searching for ways to improve the machine agent, I discovered an interesting slider in the Unity editor (as in Illustration 6), the one named Stacked Vectors.

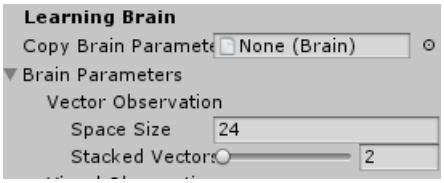


Illustration 6: Learning Brain Settings

The Stacked Vectors value represents the number of previous vector observations that will be stacked and used collectively for decision making.([Learning Environment Design Brains]).

This value lets a machine agent “remember” values from the past, and use them in current time decision calculation. But one disadvantage of this would be the vast increase in size of number of observations. This would mean a typical learning brain that would have normally 24 observations, if its stacked vector value is 2, it would now have 48 values being used as input for its neural network.

A vast amount of inputs will indeed help an agent train and gain a better performance for the task, but this results in more time being needed for the respective agent to understand the meaning of the new values.

One way the machine agent might use the values from the previous frame is to see if the distance of the target spheres has increased or decreased. With this information it can decide if it has to pursue that respective sphere to not fall yet, to let it fall off in order to begin pushing the next sphere or to push it harder if the its speed is not high enough.

But with this there might be some redundant information, having an update on the current and previous distance is nice, but is it really necessary to know the previous frame mission value? Or to know the previous distance? A lot of information might simply not be worth to be repeated, but taken into consideration the only thing that needed to be changed was that slider in the Unity editor, and no change to the script, it was a worth try to see the results.

The training scenario is all the same as the default training scenario, except that the maximum amount of steps was increased to 5.0e6, and the stacked vectors value is set to 2.

At the very beginning of the training session, it's pretty much the same as the default training session, reaching a mean reward of 0.132 at training step 6000.

The trend continues, at training step 10000, the mean reward reached a value of 0.217.

At training step 16000, we see something surprising, the mean reward already stabilized above 0.300, while the default training scenario managed this at training step 26000.

The rate at which the mean reward increase at the beginning seem to be faster at the beginning, reaching a value of 0.403 at training step 54000. In comparison the default scenario managed this at 112000. This scenario managed to master pushing off the brown sphere in almost half the training steps compared to the default training scenario (it reached that value at 112000)!

For the next few tens of thousands of steps, the mean reward value increases to 0.500, but does not stabilize yet, dipping down to 0.349 at training step 210000. It finally manages to discover a better strategy, thus stabilizing the mean reward above 0.500, beginning with training step 250000.

This is a shame that this happened so late, as the default training case managed this around training step 258000.

The stacked vector value of 2 seemed to help the machine agent learn in a very small time how to avoid the metallic and golden sphere in order to chase the brown sphere, but then got stuck with that strategy for a very long time.

When reaching training 500000, the mean reward is at 0.554. All that time it wasn't quite able to master pushing both the brown and the metallic sphere in the right order. The default training surpassed that mean value a long time ago, with a stabilized value of 0.610 at training step 370000.

The next hundreds of thousands of steps, the machine agent is still struggling to stabilize the mean reward to 0.600. The mean reward is slowly varying around the value of 0.550.

The firs time it reached a mean value of 0.602, the training step was 448000, but it quickly lost some ability and the mean reward value started to drop.

At around training step 2000000, it has finally overcome some sort of hurdle, stabilizing its mean reward over 0.600. The very fast learning speed from the beginning for the simpler task for pushing the brown sphere has been traded off for a very sluggish incrementation in the long run.

The machine agents seems to have mastered pushing off the first two spheres at around training step 2500000. This is incredibly slow compared to the default training scenario. Luckily the mean reward seem to be slowly increasing from there on.

At training step 3328000, the mean reward has stabilized over 0.700. Bigger and bigger time frames are required in order to become better.

A mean reward of over 0.750 is starting to stabilize around training step 4000000. Over 600000 steps just to increase another 0.050 in the mean reward.

When the training session has stopped, it has reached training step 4166000, where it was an average reward value of 0.786. At training step 4156000, it reached a the biggest mean reward value of 0.807. In these final training steps, the mean reward seems to have stabilized around 0.785.

This training session took almost 18 hours. Being left over night, and continuing to run during the day.

Behavior

Positive behaviors:

- it became good at chasing the first brown sphere
- it has learned knock out the spheres in the correct order
- it became incredibly good at not falling off the stage
- after pushing off the brown sphere, it was seen sometimes chasing after the metallic sphere
- it is seen sometimes to give first a small impact to the metallic sphere in order to make it move slowly, and then slam hard into the brown sphere to take it out first
- rarely seen to give a small velocity to each of the spheres in order to push them all out sequentially in the right order, even though the first brown sphere didn't even fall out yet
- seen to avoid the metallic sphere when it's current mission is to push off the brown sphere

Negative behaviors:

- when its current mission is to push off the brown or metallic sphere, the machine agent doesn't really take into consideration the position of the golden sphere, thus hitting it many times by accident, and not correcting its velocity
- seen several times that the strategy of pushing first the metallic sphere fails horribly because it doesn't chase the brown sphere fast enough after that
- when the golden sphere is the last sphere to be pushed, it doesn't go straight to it, the machine agent just moves around the stage in big circles, thus hitting it occasionally by accident
- seen sometimes to attempt to stop spheres from falling off when it's not their turn, only to push them even faster then intended out

Training when using a visual input

There are many ways of conveying information about the environment to a machine agent. Most strategies involve sending some form of distilled data to the respective agent. Such as relevant

positions, nearby walls, some distances to important things and maybe some prepossessed data that help the agent understand faster what it’s supposed to do.

There is also another way, make it see how humans see the game. That is to give an actual graphically rendered input, similar to what a human would see.

When a human plays a video game, it is constantly aware of all the queues and events that happen on the screen. Things like it’s own position in the world, the position of the enemies and their health values are conveyed visually and sometimes by sounds.

The human can deduce how well it is doing just from these queues, all there is left for it is to desire to become better.

As amazing as it may sound, there are drawbacks to send a visual input of the game itself. One of the first problems is the sheer size of such an input. Typical video games of 2019 are rendered at a resolution of 1920*1080 RGB pixels, with image refresh rates that can range from 30 Hz to 60 Hz.

That would mean the machine agent would typically have to receive and process

1920 pixels on width * 1080 pixels on height * 3 colors per pixel = 6220800 **inputs per action**

6220800 inputs per action * 30 frames per second = **186624000 inputs per second!!!**

And that value was calculated using only a refresh rate of 30 Hz, if it were 60 Hz that number would be twice as big. And if the resolution was 4K, that number would be 4 times as big!

That is simply way too much data to be processed. There must be a way to simplify the input.

The typical route that is taken, is to simply use a smaller resolution. The machine agent does not have to see the entire image in perfect clarity, it just needs enough to distinguish the important things. Another thing that could be done is to not send RGB values, just use a gray scale image. Gray scale images are typically 3 times smaller than RGB images because they only need one value per pixel, instead of 3 values per pixel, one for each color (Red,Green and Blue).

And finally that machine agent wouldn’t probably need to know everything that happens every single frame. It is enough for it to understand what is happening only when it wants to take an action. Taking into consideration that all our machine agents had a decision interval of 10, that means it’s requesting an input and sending an output every 10 frames, instead of 30Hz, 60Hz or more.

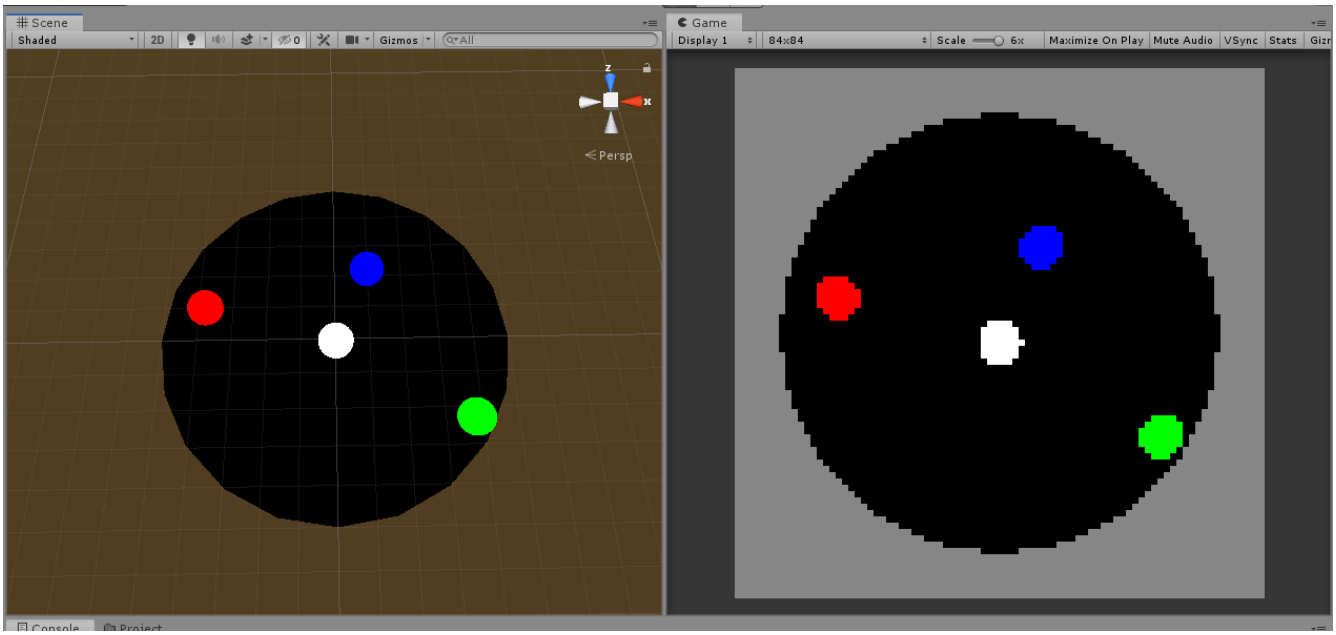


Illustration 7: Roller Camera Agent Training Environment

In this particular training scenario, several things have been changed. The colors of all of the spheres, the arena and the background have been changed. The agent sphere itself is now plain white, the arena is plain black, and the rest of spheres are plain red, green and blue.

The reason why I chose is in order to make it simpler for the agent to distinguish the objects in the arena. In this training scenario the agent does not receive any kind of other observation! It no longer receives any of the positions, distance or velocities of itself or all the spheres. Now it has to find out by itself what are each of the colored blobs on the screen.

In Illustration 7, on the left side of the screen can be seen the game world as in the editor. On the right side of the screen is game camera, but it manually selected resolution of only 84 by 84. The respective camera represents pretty accurately what the machine agent is receiving as an input.

84 pixels on width * 84 pixels on height * 3 colors per pixel= 21168 **inputs per action**

This value is relatively better than 6220800 inputs. Approximately 300 times lesser inputs per action. But still a significant amount of input.

In order to help it a bit with the training, I set up more hidden layers for the neural networks, it now uses 6 of them. More layers might help it better understand the feature of the present in the camera input.

The training was left to run over night, and sadly virtual no coherent behavior was developed, even though it was left to run for over 1600000 training steps. The mean reward value was always very close to 0. The behavior of the agent is that to simply fall of the stage, it was not able to deduce any relevant information just from the camera input.

Training when using Curriculum Learning

All the training sessions until now have attempted to teach the machine agent an unchanging task from start to finish. Some of the training sessions had simpler requirements, such as pushing out only two of the spheres instead of all three.

Teaching the machine agent a complicated task that is composed from smaller missions can be difficult and time consuming. One solution to this might be to gradually raise the difficulty of the task.

A naive approach to this would be to start the number of spheres that have to be pushed with one, and after a certain fixed amount of time, increase the number to two, then again after some time to three.

But this method does not take into consideration the fact that the machine agent has truly become good at its current task. It might become a master at pushing only one sphere off the stage in a minuscule amount of time, but then will keep repeating the task until the code finally gives the machine agent a tougher challenge.

Or the opposite problem, the machine agent might be spending some time trying to understand how to push the first two spheres correctly, still in the learning process, and suddenly it has to do it with three spheres, because the naive method has decided it's time for that to happen.

The machine agent would now have to learn how to push off three spheres, while it was still struggling with just two.

This is somewhat similar to real life, where a student is struggling to understand the previous lesson, but then gets slammed with the next lesson when it is not ready.

When it comes to machine learning, there is already a solution for such a problem, and that is Curriculum Learning. This type of training is already implemented in ML-Agents, and it only has to be configured for it to begin.

With Curriculum Learning, the machine agent is given more difficult tasks only when certain thresholds in the reward have been surpassed. Because of that, in theory, the machine agent should gradually learn how to do more difficult tasks, and train much faster than an agent that was given from the start the most difficult task.

First we have to define a curricula file (as seen in Text 7) which will describe to the Python API when we intend to increase the difficulty of the task.

For this training session I decided to use the average reward value that the machine agent receives at every 2000 episodes. By taking into consideration so many episodes, I'm making sure that the agent understands how to solve the task up to the current difficulty.

```
{
    "measure": "reward",
    "thresholds": [0.8, 0.9],
    "min_lesson_length": 2000,
    "signal_smoothing": true,
    "parameters": {
       "sphere_count": [ 1, 2, 3]
    }
}
```

Text 7: Roller Agent Curricula

The threshold values tell the Python API when to ramp up the difficulty. The first one is when the mean reward is above 0.800, which means the difficulty will be increased from one sphere at a time to two spheres at a time on the arena only when the agent has completed on average over 80% of the time the task of pushing one sphere off the arena.

The second one is when the mean reward is over 0.900 and the current task is to push off two spheres. When it manages to do so, the difficulty will increase again, and the agent will continue to train with all three spheres.

There is a possibility that simply through pure luck that the agent performs incredibly well due to a very beneficial and easy initial positioning of the target spheres. This will measure the agent as being incredibly well prepared for the current task, and thus a receive a lesson that is increased in difficulty, when in reality it wasn't ready at all to advance.

In order to try to mitigate this, the signal_smoothing value was set to true which will mix the current reward with the previous reward of a run in order to attempt to block such cases. The weighting is 0.75 for the new reward and 0.25 for the old one.

All these values until now are specific to the Python API, and now we have to give it something that also means something particular to the project. We will tell the API to change some particular values in a key-value map.

The one and single key that is defined is sphere_count, which will be read by the RollerAgent class, in order to decide what difficulty it should be aiming for. What is interesting is that the sphere_count key somehow receives three values in the curricula JSON file.

There are three values, because the very first value is for when the agent is at the very beginning of the training and it hasn't surpassed any of the thresholds yet. The rest of the values will be used only when the agent surpasses the thresholds.

For the training of this agent, all of the training parameters were left the same, except the max_steps value which was set 5.0e6, so that it may run for an extended amount of time.

The curriculum learning started with the lowest difficulty, the sphere_count value set to 1. The machine agent was quickly able to master this task at around 16000 training steps, when the mean reward has gone over the first threshold.

After the first threshold was surpassed, the difficulty was increased by the Python API by changing the sphere_count value from 1 to 2. The training step count is continuing from where it left off when it had a sphere_count value of 1.

In the beginning of this new task, the one with two spheres on the arena, the machine agent was at training step 20000, with an average reward of 0.282. This is a pretty bad average reward taking into consideration it became so good at pushing just one sphere correctly.

If it was pushing the first sphere correctly, and just ignore the second one, it should have received an average reward of around 0.500. But it seems now that the second sphere was introduced, it keeps stumbling over it. More training time might correct this.

At training step 26000, it reached a mean reward of 0.325. The reward average seems to be increasing.

The mean reward stabilized over 0.500 after training step 44000. Here the machine agent is starting to understand how push the first sphere correctly, and not push out the second sphere too early.

At training step 90000, the mean reward is 0.614. The machine agent is starting to understand how to push the two spheres out one after the other.

At training step 122000, it reached a mean reward of 0.717. Good progress is being made for the current difficulty.

The average reward starts to destabilize at 152000, dropping to a value of 0.391 at training step 154000. No clear reason why did this happen all of a sudden. It could be that TensorFlow may have hit some sort of bad local minima.

The average reward slowly increases back to around 0.700, but it is fluctuating after that, not being stable.

The mean reward managed to stabilize above 0.700 at around training step 210000. It could be that TensorFlow managed to get out of the bad local minima. At training step 246000 it managed to reach an average reward of 0.800 for pushing out the two spheres correctly.

In order to get to the next difficulty, with a sphere_count value of 3, the mean reward must be above 0.900.

The mean reward keeps fluctuating, dipping under 0.800 at training step 328000, and managing to attain back the average reward of over 0.800 only at training step 532000.

Many such dips continue to appear. Maybe the machine agent is going trough all kinds of behaviors which are incredibly hard to improve, for example one such hard to improve behavior would be when the agent is over-eager to push off the first sphere as fast as possible, but cannot correct in time its movement.

A breakthrough finally starts to appear from training step 1544000, where the mean reward steadily increases from 0.804, all the way up to 0.909, at training step 1720000. The machine agent became sufficiently good at pushing only two spheres in the correct order.

When this finally happens, it triggers the next threshold in the curriculum, and the agent now has to learn how to push all three spheres in the correct order.

The machine agent starts decently well, with a mean reward of 0.550 at training step 1726000. The machine agent seems to have managed to retain the behavior of pushing out the first sphere, and partially for pushing out the second sphere, but in the beginning it’s stumbling over the third one.

It seems that the agent is trying to understand the presence of the new third sphere, and it will need some time for that.

The mean reward starts to stabilize to 0.600 at around training step 2250000. This is still incredibly slow compared to the default case, which managed this at around training step 370000.

At around training step 2910000, it was the first time the agent reached a mean reward of 0.700, but it is not stable. A stable mean reward of over 0.700 was reached only at training step 3638000.

At the very end of training session, at training step 5000000, the mean reward reached a value of 0.813.

From what can be seen from this attempt of curriculum learning is that in this particular environment where an agent has to gradually push more and more spheres, it seems to rather stumble very hard on gaining progress.

Becoming good at pushing only one or two spheres seems to have gotten the machine agent stuck for a very long time in some sort of bad local minima, from which it was very hard to get out of.

Behavior

Positive behaviors:

- it somewhat understands the order that it has to push off the spheres
- sometimes seen to confidently push spheres in order to give them a velocity; it doesn't have to continuously push out the spheres until they are out
- it is good at staying on the stage

Negative behaviors:

- generally pushing other spheres by mistake when it is not their turn yet; causing the training episode to fail early
- does not understand that pushing one sphere might cause it to collide with another sphere and cause it to fall too early
- when it is at the last step of pushing off the golden sphere, it does not seem to go directly towards it, only to go around in wild circles while trying to stay inside the arena
- seen many times to accumulate too much velocity and fall off the arena

Source code

RollerAgent.cs

The RollerAgent.cs file contains the RollerAgent class which extends the Agent class from the ML-Agents plugin. It is responsible for collecting the observations of the environment, interpreting the action values that come from the neural network, and resetting the position and velocity of itself and the target spheres.

The class was designed to have some flexibility regarding how the training environment is handled. Features can be enabled and disabled by changing boolean and integer variables that will be shown below.

Initialization and reset

The objects and variables that every RollerAgent object needs can be seen in Text 8. The arenaPosition is needed in order to know where to set the position of all the spheres after a reset. The public modifier makes it easy for other classes, or for the developer, to set what GameObjects have to be chased and handled.

```
Rigidbody rBody;
public Vector3 arenaPosition;
public GameObject target1;
public GameObject target2;
public GameObject target3;
private Rigidbody target1RigidBody;
private Rigidbody target2RigidBody;
private Rigidbody target3RigidBody;
public float speed;
```

Text 8: RollerAgent objects and variable

All of the RigidBody objects are for convenience; it reduces further down in the code the amount of calls to the function GetComponent<Rigidbody>().

The speed variable is for controlling how fast should the RollerAgent be allowed to move.

```
private const bool giveGradualRewardForEachSphere = true;
private const bool eachMissionIsItsOwnBoolean = false;
private const bool rewardOnTouch = false;
private int numberOfTargets = 3;
private int currentMission = 1;
private bool m_UseCurriculumLearning = false;
```

Text 9: RollerAgent training environment modifiers and current mission variable

In Text 9 can be seen the variables that control how the training environment is interacting with the RollerAgent itself.

The giveGradualRewardForEachSphere flag controls whether to give a reward each time the agent pushes off a target sphere in the correct order, or to give a big reward only when all the target spheres have been pushed off in the correct order.

The eachMissionIsItsOwnBoolean flag controls whether to send only a single value for the current mission of the agent, or to send a boolean value for each of the target spheres, with a value of true only if when it has to chase it and push it off, or false when it must not push it off the stage yet.

The rewardOnTouch flag controls whether the RollerAgent has to push off the stage the target spheres or if it is enough to just simply touch them in order to get a reward and complete a mission.

The numberOfTargets value controls how many sphere targets are on the arena for the agent to push off. Currently it can only have a value between 1 and 3. The majority of the testing scenarios that were done had a numberOfTargets value of 3, thus meaning that all three target spheres were present.

When for example the numberOfTargets is 2, every target sphere being pushed off gives a reward of ½ = 0.5.

The currentMission variable stores a value that represents which one of the missions the agent must do right now. A currentMission value of 1 would mean to chase the brown sphere. A value of 2 is for the metallic sphere. And finally a value of 3 is for the golden sphere.

```
public override void InitializeAgent() {
  if(numberOfTargets < 1) {
    numberOfTargets = 1;
  }else if(numberOfTargets > 3) {
    numberOfTargets = 3;
  }
  rBody = GetComponent<Rigidbody>();
}
```

Text 10: RollerAgent initialization

The m_UseCurriculumLearning flag is necessary when we want to train the agent via curriculum learning. This tells the code to send observations of all three target spheres, even though the agent is currently training with only one or two of them.

Using a variable to store the current mission instead of inferring it from the current state of the target spheres simplifies the code.

The RollerAgent initialization is shown in Text 10. Nothing much is done here, only to check that the numberOfTargets value is clamped between 1 and 3, and to store a reference to the RigidBody component of the RollerAgent game object.

Every time an agent is initialized, or when it has been reset, it's AgentReset method is called. Usually in this method there is implemented some logic for moving everything in the training environment back to relevant positions.

The implementation of the AgentReset method can be seen in Text 11.

```
public override void AgentReset(){
  if (m_UseCurriculumLearning){
    numberOfTargets=(int)(academy.resetParameters["sphere_count"]);
  }
  if (!target1RigidBody){
    target1RigidBody = target1.GetComponent<Rigidbody>();
  }
  if (!target2RigidBody){
    target2RigidBody = target2.GetComponent<Rigidbody>();
  }
  if (!target3RigidBody){
    target3RigidBody = target3.GetComponent<Rigidbody>();
  }

  if (transform.position.y < arenaPosition.y + 0.45f){
    rBody.angularVelocity = Vector3.zero;
    rBody.velocity = Vector3.zero;
    transform.position = new Vector3(0, arenaPosition.y + 0.5f, 0);
  }
  currentMission = 1;
  ResetAllTargets();
}
```

Text 11: RollerAgent AgentReset method

If training via curriculum learning was enabled, we have to obtain the parameter stored at the "sphere_count" key.

In here the RigidBody component of every target sphere is being obtained if it wasn't obtained until now. The agent sphere is placed back in the center of the stage if it fell off stage due to any reason. The currentMission value is set back to 1 so that the agent will know to start chasing for the first target sphere. At the end of this method, the ResetAllTargets method is called.

In the ResetAllTargets method, there are many things done, the first is canceling all of the velocity and angular velocity of all the target spheres as in Text 12.

```
target1RigidBody.velocity = Vector3.zero;
target1RigidBody.angularVelocity = Vector3.zero;
target2RigidBody.velocity = Vector3.zero;
target2RigidBody.angularVelocity = Vector3.zero;
target3RigidBody.velocity = Vector3.zero;
target3RigidBody.angularVelocity = Vector3.zero;
```

Text 12: Reset target spheres velocity and angular velocity

```
target1.SetActive(numberOfTargets >= 1);
target2.SetActive(numberOfTargets >= 2);
target3.SetActive(numberOfTargets >= 3);
```

Text 13: Selective activation of the target spheres

```
float spawnHeight = arenaPosition.y + 0.5f;
float arenaRadius = 4.5f;
```

Text 14: Auxiliary variables in ResetAllTargets

In Text 13 the target spheres are selectively activated depending on the value of numberOfTarges.

In Text 14 there can be seen two auxiliary variables that simplify the code for the next lines of code. The arenaRadius value of 4.5 was hard-coded for convenience, but has to be changed if the actual size of the arena is changed.

The position of each of the target spheres is selected randomly until they have a distance of at least 1.1 between each one of them and the agent itself. (show in Text 15)

This way no training scenario will be ever start with target spheres already overlapping with others or with the agent.

After each target has been successfully placed in the environment, a check is done on the numberOfTargets variable to see if the code logic has to find a position for the next targets too.

For example, if a training environment only uses two spheres, it is not worth finding a valid position for the third sphere.

Also something to observe that the more spheres are placed in the environment, the more distance checks have to be made to ensure that they do not collide, which might make the loops last a bit longer. But they should not really be of any problem considering the radius of the arena is 5 and the radius of the agent and target spheres is 0.5, which leaves for them more than enough room to find a valid spot.

```
do{
  r = Random.insideUnitCircle*arenaRadius;
  targetPosition = new Vector3(r.x,spawnHeight,r.y);
  distanceToAgent = Vector3.Distance(
    transform.position, targetPosition);
} while (distanceToAgent < 1.1f);
target1.transform.position = targetPosition;

if (numberOfTargets < 2) return;
do{
  r = Random.insideUnitCircle*arenaRadius;
  targetPosition = new Vector3(r.x,spawnHeight,r.y);
  distanceToAgent = Vector3.Distance(
    transform.position, targetPosition);
  distanceToTarget1 = Vector3.Distance(
    target1.transform.position, targetPosition);
} while (distanceToAgent < 1.1f
         || distanceToTarget1 < 1.1f);
target2.transform.position = targetPosition;

if (numberOfTargets < 3) return;
do{
  r = Random.insideUnitCircle*arenaRadius;
  targetPosition = new Vector3(r.x,spawnHeight,r.y);
  distanceToAgent = Vector3.Distance(
    transform.position, targetPosition);
  distanceToTarget1 = Vector3.Distance(
    target1.transform.position, targetPosition);
  distanceToTarget2 = Vector3.Distance(
    target2.transform.position, targetPosition);
} while (distanceToAgent < 1.1f
         || distanceToTarget1 < 1.1f
         || distanceToTarget2 < 1.1f);
target3.transform.position = targetPosition;
```

Text 15: Finding positions for target spheres in the ResetAllTargets method

Interacting with the environment

The Goal1Achieved method, shown in Text 16, is called whenever the RollerAgent managed to push out the first target sphere. The method then deactivates the respective sphere, adds the reward if necessary and marks the agent as done if that was also the last sphere to be pushed (can only happen if the numberOfTargets

```
private void Goal1Achieved() {
  if (currentMission == 1) {
    target1.SetActive(false);
    if (giveGradualRewardForEachSphere) {
      AddReward(1f / numberOfTargets);
    }
    if(currentMission == numberOfTargets) {
      if (!giveGradualRewardForEachSphere) {
          AddReward(1);
      }
      Done();
    }
    currentMission++;
  }
  else {
    Done();
  }
}
```

Text 16: Goal1Achieved method

is set to 1). If the respective sphere was pushed out when it wasn't its turn, the agent is marked as done without it receiving the reward.

Similar methods can be seen for the other two targets spheres as well, in Text 17 and in Text 18.

```
private void Goal2Achieved() {
  if (currentMission == 2) {
    target2.SetActive(false);
    if (giveGradualRewardForEachSphere) {
      AddReward(1f / numberOfTargets);
    }
    if (currentMission == numberOfTargets){
      if (!giveGradualRewardForEachSphere){
        AddReward(1);
      }
      Done();
    }
    currentMission++;
  }
  else {
    Done();
  }
}
```

Text 17: Goal2Achieved method

```
private void Goal3Achieved() {
  if (currentMission == 3) {
    target3.SetActive(false);
    if (giveGradualRewardForEachSphere) {
      AddReward(1f / numberOfTargets);
    }
    if (currentMission == numberOfTargets){
      if (!giveGradualRewardForEachSphere){
        AddReward(1);
      }
      Done();
    }
    currentMission++;
  }
  else {
    Done();
  }
}
```

Text 18: Goal3Achieved method

Each of the 3 methods also take care of incrementing the currentMission variable each time the correct sphere is pushed off, thus better encapsulating the functionality.

```
public override void AgentAction(float[] vectorAction, string textAction) {
  Vector3 controlSignal = new Vector3(vectorAction[0], 0, vectorAction[1]);
  rBody.AddForce(controlSignal * speed);

  if (target1.activeSelf && numberOfTargets>=1 && target1.transform.position.y+1<arenaPosition.y){
    Goal1Achieved();return;
  }
  if (target2.activeSelf && numberOfTargets>=2 && target2.transform.position.y+1<arenaPosition.y){
    Goal2Achieved();return;
  }
  if (target3.activeSelf && numberOfTargets>=3 && target3.transform.position.y+1<arenaPosition.y){
    Goal3Achieved();return;
  }
  if (transform.position.y < arenaPosition.y + 0.45f){
    Done();
  }
}
```

Text 19: RollerAgent AgentAction method

The AgentAction method, shown in Text 19, is called every time TensorFlow sends the vectorAction output generated from the trained neural network to the agent running in the environment. Because in our examples all of the machine agents have been moving along the X and Z axis, only two outputs are needed and sent.

The first output is interpreted as the force applied on the X axis, and the second output is for the Z axis. After finding the vector describing the direction of the agent, a force is applied on the RigidBody component of the agent, making it move.

Taking into consideration the fact that the AgentAction method is called periodically, it is a nice place to add some code logic that normally would be put in an Update method.

In this respective method, it is checked if the target spheres have fallen of the arena, but not just by any amount. The center of the target spheres, which is normally 0.5 units above the arena, has to fall 1 unit below the arena before it is considered gone.

This will ensure that the target spheres are clearly out of bounds. While the agent sphere is given a more restrictive condition, if it drop even 0.05 units below its usual height, it is considered gone.

```
void OnCollisionEnter(Collision collision){
  if (!rewardOnTouch) { return;}
  GameObject otherGameObject = collision.gameObject;
  if(otherGameObject == target1) { Goal1Achieved();}
  if(otherGameObject == target2) { Goal2Achieved();}
  if(otherGameObject == target3) { Goal3Achieved();}
}
```

Text 20: Reward on touch alternative behavior

Punishing the agent faster might help it understand that it's most recent action has led to it falling, thus learning faster to not fall off the stage.

An alternative behavior is when enabling the rewardOnTouch flag. It causes the goal achieved methods to trigger instantly on touch instead of pushing them off the stage.

The OnCollisionEnter method (seen in Text 20) is called by the game engine whenever the RigidBody or Collider component of the current game object starts touching another game object that also has RigidBody or Collider component.

Once called, the game object that has collided with can be obtained and then checked. For each of the target spheres, a check is done, and if true, will call their respective goal methods. The goal methods will handle the rest of the logic.

This alternative was added for developers who wanted to train machine agents who only had to collide once with the target spheres instead of completely pushing them out.

Obtaining observations

In order to send observations to TensorFlow which will then use them as inputs in the neural network, the developer must implement a method called CollectObservations.

```
if(agentParameters.agentCameras.Count > 0){
  return;
}
```

Text 21: Do not add observations if camera is present

In the CollectObservations method, the developer must call the AddVectorObs method in order to send data to the input layer of the neural network.

In one training environment, a camera is the only input that is used. In order to keep it fair, no other observations are sent, the neural network must figure everything out only from the camera. (code shown in Text 21).

```
AddVectorObs(transform.position.x);
AddVectorObs(transform.position.z);
float distanceFromCenter = Vector3.Distance(
  transform.position,
  new Vector3(0, arenaPosition.y + 0.5f, 0)
);
AddVectorObs(distanceFromCenter);
AddVectorObs(rBody.velocity.x);
AddVectorObs(rBody.velocity.z);
```

Text 22: Observations of the agent itself

In the code shown at Text 22, there can be seen how the observations of the machine agent itself are sent. The coordinate and velocity on the Y axis is ignored as the agents and the target spheres are not meant to jump.

```
if (eachMissionIsItsOwnBoolean){
  for(int i = 1; i <= 3; i++){
    AddVectorObs(currentMission == i);
  }
}
else {
  AddVectorObs(currentMission);
}
```

Text 23: Mission observations

A distance value from the center of the arena helps the agent find out how far it is from center, and in how much danger is from falling out.

The next observations that have to be taken into consideration is how the agent is signaled what its current mission is. In Text 23 can be seen that there are two ways to do that. The first one is to send three boolean values, each one of them being either true or false, which is converted to 1 or 0 by the AddVectorObs method. The boolean values will be true if the current mission is equal to index of the boolean value, leaving the rest false.

The second way to do this is to simply send an integer value of 1, 2 or 3 to plainly say the current mission.

These two options can be toggled with the help of the eachMissionIsItsOwnBoolean flag.

The observations regarding the first target can be seen in Text 24. The values that are sent are the targets position, velocity, distance from the agent and the distance from the center.

Such a wealth of information should be enough for a neural network to understand how to interact with the respective target object.

```
Vector3 relativePosition = target1.transform.position -
  transform.position;
AddVectorObs(relativePosition.x);
AddVectorObs(relativePosition.z);
float distanceToTarget = Vector3.Distance(
  transform.position, target1.transform.position);
AddVectorObs(distanceToTarget);
float targetDistanceFromCenter = Vector3.Distance(
  target1.transform.position,
  new Vector3(0, arenaPosition.y + 0.5f, 0)
);
AddVectorObs(targetDistanceFromCenter);
AddVectorObs(target1RigidBody.velocity.x);
AddVectorObs(target1RigidBody.velocity.z)
```

Text 24: First target sphere observations

```
if (numberOfTargets<2&&!m_UseCurriculumLearning)
  return;
relativePosition = target2.transform.position -
  transform.position;
AddVectorObs(relativePosition.x);
AddVectorObs(relativePosition.z);

distanceToTarget =
  Vector3.Distance(transform.position,
    target2.transform.position);
AddVectorObs(distanceToTarget);

targetDistanceFromCenter = Vector3.Distance(
  target2.transform.position,
  new Vector3(0, arenaPosition.y + 0.5f, 0)
);
AddVectorObs(targetDistanceFromCenter);

AddVectorObs(target2RigidBody.velocity.x);
AddVectorObs(target2RigidBody.velocity.z);
```

Text 25: Second target sphere observations

```
if (numberOfTargets<3&&!m_UseCurriculumLearning)
  return;
relativePosition = target3.transform.position -
  transform.position;
AddVectorObs(relativePosition.x);
AddVectorObs(relativePosition.z);

distanceToTarget =
  Vector3.Distance(transform.position,
    target3.transform.position);
AddVectorObs(distanceToTarget);

targetDistanceFromCenter = Vector3.Distance(
target3.transform.position,
new Vector3(0, arenaPosition.y + 0.5f, 0)
);
AddVectorObs(targetDistanceFromCenter);

AddVectorObs(target3RigidBody.velocity.x);
AddVectorObs(target3RigidBody.velocity.z);
```

Text 26: Third target sphere observations

Similar code is defined also for the second(Text 25) and third(Text 26) target spheres, with the exception that they have an if condition at the beginning of their code section, that will stop sending observations about them if the current numberOfTargets value is small enough and the m_UseCurriculumLearning flag is set to false.

RollerArena.cs

The RollerArena class is responsible for creating instances of the RollerAgent and target sphere game objects based on the prefab game objects that are set in the Unity Editor by the developer.

In Text 27, there can be seen the objects that are being maintained by this class. A prefab for each of the needed game objects, and the game objects themselves after they are created.

```
public GameObject rollerAgentPrefab;
public GameObject target1Prefab;
public GameObject target2Prefab;
public GameObject target3Prefab;

private GameObject rollerAgentObject;
private GameObject target1Object;
private GameObject target2Object;
private GameObject target3Object;

private RollerAgent rollerAgent;
```

Text 27: Objects used by RollerArena

The Start method of the RollerArena class (seen in Text 28), is responsible for instantiating every game object that is needed for the training environment.

The RollerAgent object was intentionally generated at a specific position of the arena so that it may be valid from the very beginning.

After creating every new instance, the target sphere objects are sent as references to the freshly generated RollerAgent game object, so that it may position them accordingly.

```
private void Start() {
  rollerAgentObject = Instantiate(rollerAgentPrefab,
    new Vector3(0, transform.position.y + 0.5f, 0),
    Quaternion.identity);

  rollerAgent = rollerAgentObject.GetComponent<RollerAgent>();
  rollerAgent.arenaPosition = transform.position;
  target1Object = Instantiate(target1Prefab);
  target2Object = Instantiate(target2Prefab);
  target3Object = Instantiate(target3Prefab);
  rollerAgent.target1 = target1Object;
  rollerAgent.target2 = target2Object;
  rollerAgent.target3 = target3Object;
}
```

Text 28: RollerArena Start method

The Instantiate method is provided by the Unity game engine, and it's functionality is to simply clone whatever Unity Object is sent to it as a parameter.

If that respective Unity Object is of type GameObject, developers may set other values such as transformation and rotation so that it may be immediately placed in the game world.

Dedicating the generation of the game objects to a particular class eases the difficulty of the rest of code in the long run because it enables the developer to better compartmentalize the structure of the project.

RollerArenaAcademy.cs

The RollerArenaAcademy class extends the Academy class provided by the ML-Agents, and it's role is to dynamically generate several arenas so that multiple agent may train at the same time.

The content of this class is shown in Text 29, where we can see how the arena can receive via the Unity editor the prefab objects for the arena that it has to instantiate and how many of them.

```
public GameObject m_RollerArenaPrefab;
public int m_NumberOfArenas;
public override void InitializeAcademy() {
  for(int i = 0; i < m_NumberOfArenas; i++) {
    Instantiate(
      m_RollerArenaPrefab,
      new Vector3(0, -4 * i, 0),
      Quaternion.identity);
  }
}
```

Text 29: RollerArenaAcademy code contents

Sometimes Academy classes override the AcademyReset and AcademyStep methods in order to add more interesting interactions with the possible training environment. But in this project these are not needed as the RollerAgent class is already doing most of the important logic already.

The developer must be careful to set a prefab that will eventually generate some agents that the academy will have to train. And the m_NumberOfArenas must also be chosen according to the capabilities of the PC system that it's going to run on.

Usually more arenas can be generated if the system is particularly strong and/or the training scenarios are simple and non-intensive for the CPU.

Conclusion

After trying all the testing scenarios and collecting their data, one thing that becomes obvious is that simply letting it train more times helps in achieving a higher mean reward than the default case.

Environment name	**Best mean reward**	**Mean reward at end**	**Nr. of training steps**
Default	0.690	0.641	500000
Reward given at end	0.491	0.377	500000
4 hidden layers * 32 units	0.487	0.464	500000
4 hidden layers and more training time	0.661	0.626	3538000
Split mission observations	0.708	0.671	500000
Split mission observations with extended time	0.814	0.779	3290001
No curiosity & small batch_size and buffer_size	0.786	0.738	1927450
Normalization	0.646	0.627	500000
Touch to collect	0.956	0.929	2874090
Only two spheres	0.975	0.934	1992000
Two stacked vectors	0.807	0.786	4166000
Visual input	0.047	0.010	1606000
Curriculum Learning	0.833	0.813	5000000

Most of the training scenarios that run more than 1000000 steps were left over night to do so.

Another modification that significantly boosts the mean reward is to just simplify the task that has to solved, which is pretty obvious (such as in “Touch to collect” and “Only two spheres”).

Out of all the environments with all three spheres that had to pushed out of the arena, Curriculum Learning performed the best, with a best mean reward of 0.833, and final average of 0.813. These high reward values could have either because Curriculum Learning was used (steady difficulty increase) or simply because it was left the most time to run out of all the other scenarios.

Training by using the visual input offered by the game engine has failed completely. I personally do not know the exact reason why this happened.

One environment that affected only slightly in a negative way the reward values compared to the default case is “4 hidden layers * 32 units”. One possibility why this happened could be because of the lower number of units per layer.

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