Pommerman Fight: A Detailed Analysis of Reinforcement Algorithms

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Abstract

Reinforcement learning is an area of machine learning that deals with software agents tending to take actions in the environment with aim to maximize the notion of cumulative reward by using state value and reward functions. It is vastly used in developing robots for manufacturing, inventory management, delivery management (to name a few). On the other hand, its abilities can also be vastly used in development of games like Pommerman, Atari, Go and Robocup.

Our research interest branches from the intention to understand the power of various Reinforcement Learning algorithms and its performances in multi-agent environment. Pommerman, a multi-agent environment based on the classic console game Bomberman provided the benchmark for our project.

Why Pommerman Fight

There are several remarkable achievements of agents learning to play games against humans and defeating them. Google's Agent57 can beat the average human at 57 classic Atari games, AlhaGo recorded a tremendous achievement by defeating Lee Sedol, a world champion in Go. Robocup is an international scientific initiative to advance the state of the art intelligent robots. However, these games are based on consensus benchmark involving two player zero sum game and there are sparsely any environment that utilizes general sum game settings with more than 2 players.

Pommerman is a multi-agent mode;-free game which typically involves 4 agents and contains both cooperative and competitive aspects and sets an epitome example for general sum game.

Few of the key notable differences between Robocup (a multi-agent two player zero sum game) and Pommerman are:

1. Pommerman includes an explicit communication channel. This changes the dynamics of the game and adds new research avenues.

2. Pommerman strips away the sensor input, which means that the game is less apt for robotics but more apt for studying other aspects of AI, games, and strategy.

3. Pommerman uses low dimensional, discrete control and input representations instead of continuous inputs. We believe this makes it easier to focus on the high-level strategic aspects rather than low level mechanics.

4. In team variants, the default Pommerman setup has only two agents per side, which makes it more amenable to burgeoning fields like emergent communication which encounter training difficulties with larger numbers of agents.

5. Pommerman promotes research that does not reduce to a 1v1 game, which means that a lot of the theory underlying such games (like RoboCup Soccer) is not applicable.

While on one hand there are a lot of researches focusing on the diverse set of tools and methods including planning, opponent/teammate modeling, game theory and communication aimed at advanced research on building state of the art technologies contributing to lasting results for years to come, our team focused on analyzing the performance of various RL algorithms in this model-free game.

There are attributes that are common to the best benchmarks beyond satisfying the community's research direction. These include having mechanics and gameplay that are intuitive for humans, being fun to play and watch, being easy to integrate into common research setups, and having a learning problem that is not too difficult for the current state of method development. Most games violate at least one of these. For example, the popular game Defense of the Ancients (OpenAI 2018) is intuitive and fun, but extremely difficult to integrate. On the other hand, the card game Bridge is easy to integrate, but it is not intuitive; the gameplay and mechanics are slow to learn and there is a steep learning curve to understanding strategy.

Multi-Agent Learning

Pommerman is very challenging model-free environment for reinforcement learning due to its sparse, delayed and deceptive rewards and it has shown that RL algorithms fail to achieve significant learning.

The game environment in pommerman changes by bombs placed by agents whose effects are observed when it explodes i.e; after 10 time steps. However, it has been noted that the action of placing bomb is highly correlated to losing and is presumably a major impediment for achieving good results using model-free reinforcement learning and could lead to catastrophic suicides when an agent intersects with an exploding bomb's flames, previously placed by itself. It has been seen that for each of the four agents, even when their configuration is different, their probabilities of ending up with suicide are ≈ 40% (0.39, 0.38, 0.46, 0.38,

Suicides can occur frequently in pommerman during learning phase because agents use intensive search to fully learn policies. Hence, it is essential to filter out actions leading to immediate negative terminal states so that model-free RL can imitate those safer actions to learn to safely explore.

According to the research paper Safer Deep RL with Shallow MCTS published by borealis AI, Pommerman is a challenging benchmark for multi-agent learning and model-free reinforcement learning, due to the following characteristics:

1. Multiagent component: the agent needs to best respond to any type of opponent, but agents' behaviors also change based on the collected power-ups, i.e., extra ammo, bomb blast radius, and bomb kick ability.
2. Delayed action effects: the only way to make a change to the environment (e.g., kill an agent) is by means of bomb placement, but the effect of such an action is only observed when the bombs explodes after 10 timesteps.

3. Sparse and deceptive rewards: the former refers to the fact that the only non-zero reward is obtained at the end of an episode. The latter refers to the fact that quite often a winning reward is due to the opponents’ involuntary suicide, which makes reinforcing an agent’s action based on such a reward deceptive.

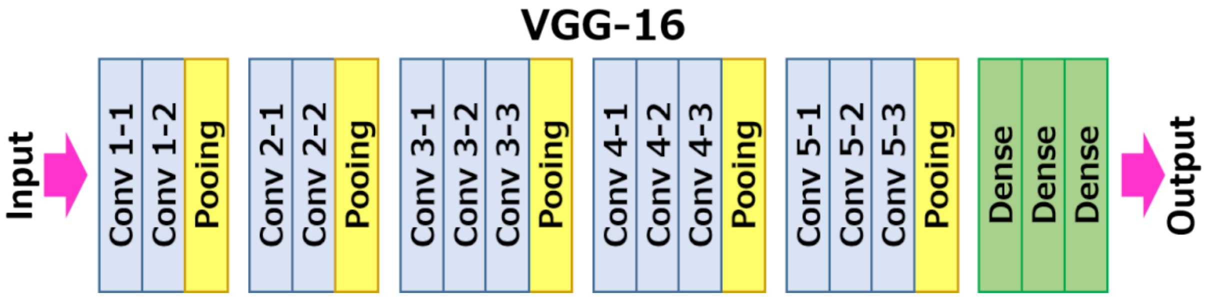
For these reasons, this game is considered to be challenging for many standard RL algorithms and a local optimum is commonly learned, i.e., not placing bombs or stay put.

Indeed, the problem of suicide stems from acting randomly without considering constraints of the environment and in extreme cases, in each time step, the agent may have only one survival action.

Prior work in this area

Prior to working on our project we researched several Github profiles and determined the tools required to efficiently train our agents. The following tools were the important amongst all available tools:

VGG



VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper “Very Deep Convolutional Networks for Large-Scale Image Recognition ". The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU’s.

Tensorflow

TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for their internal use. It was released under the Apache License 2.0 on November 9, 2015.

Pytorch

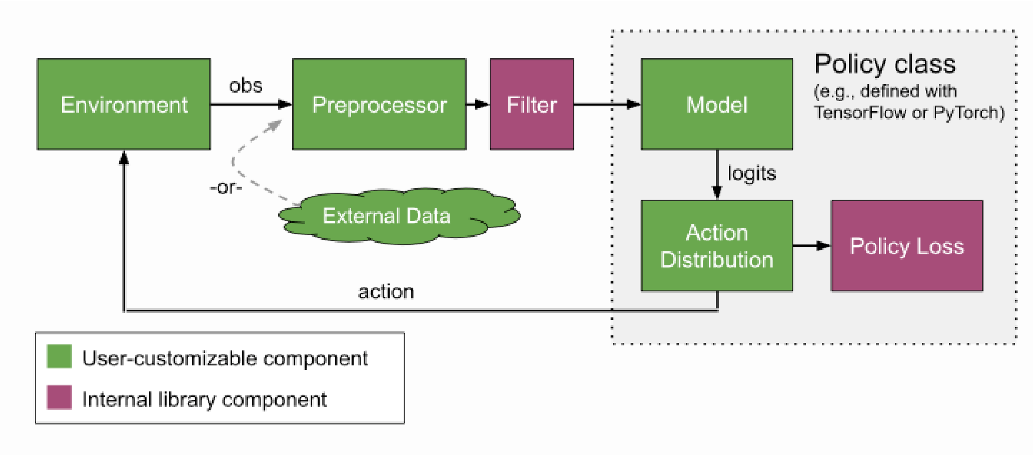
PyTorch is an open source machine learning library based on the Torch library, used for applications such as computer vision and natural language processing. It was primarily developed by Facebook's AI Research lab (FAIR).It is a free and open-source software released under the Modified BSD license. Although the Python interface is more polished and the primary focus of development, PyTorch also has a C++ interface.

A number of pieces of Deep Learning software are built on top of PyTorch, including Uber's Pyro, HuggingFace's Transformers, and Catalyst.

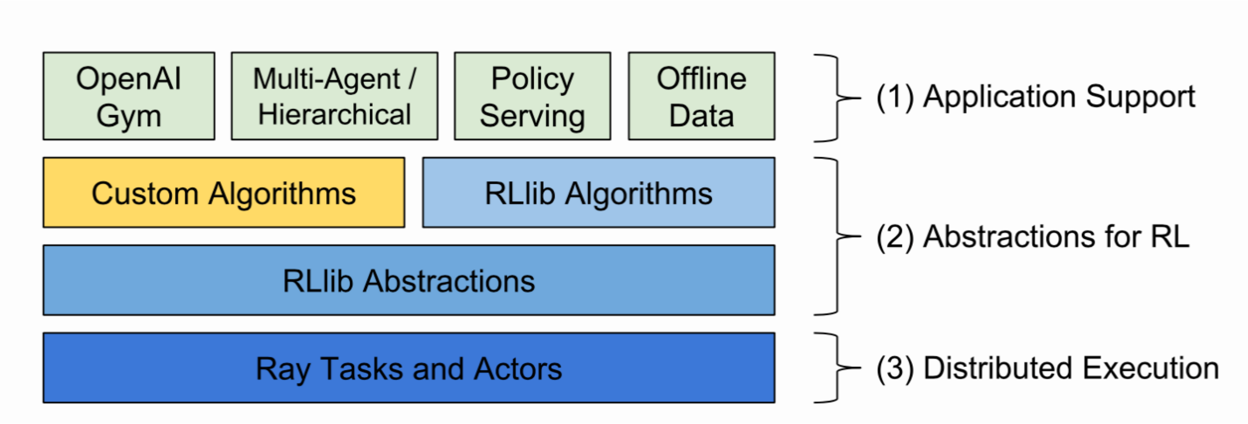
PyTorch provides two high-level features:

- Tensor computing (like NumPy) with strong acceleration via graphics processing units (GPU)
- Deep neural networks built on a tape-based autodiff system

RLlib

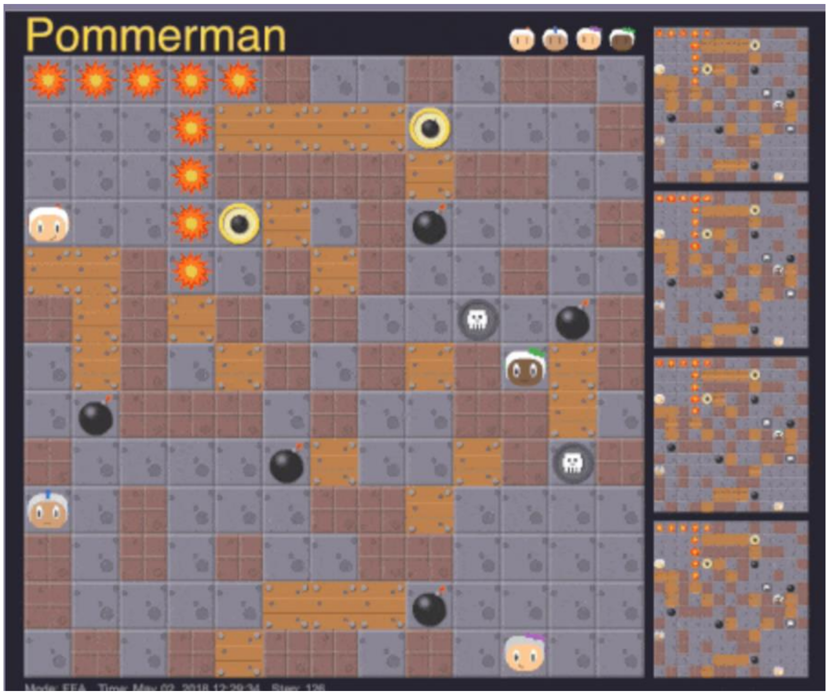


Basically, RLlib builds up a keras like api that only need us to provide a custom environment and model without worrying about the details in the RL optimization process. Also, they adopt the setting of OpenAI Gym, a widely used interface for building standard RL environments. During the execution, they allow the distributed ways to sample batch and tune hyper-parameters of algorithms based on the Ray library. In brief, we choose RLlib for it brings us the convenience in using RL algorithms to train an agent for Pommerman.



Game Layout

Bomberman is an arcade-style maze-based video game developed by Nintendo Entertainment System on 1985, it contains an agent known as Bomberman who navigates a grid like maze and places bombs to destroy enemies and surrounding wooden walls to obtain power-ups and access to the next stage through a door. Pommerman is stylistically similar to Bomberman and at a higher level it has 4 agents traversing a grid environment with a goal of their team being the last one standing on the board.



Key notable characters of the game environment are:

1. Agent – Navigates through the grid environment and communicates with the other agents either in an adversarial and cooperative fashion.

2. Bombs – placed by the agents and upon explosion can destroy anything in their vicinity except the rigid walls.
3. Rigid Walls – Indestructible and impassable walls that form both the surroundings of the game and might be present in the grid such that the agents cannot pass through these walls but should instead navigate for other passable routes.
4. Wooden Walls – Walls that are initially impassable but can be destroyed using bombs and some of them acts as containers for power-ups.

In Pommerman, each agent can execute one of 6 actions at every timestep:

1. Stop: This action is a pass.
2. Up: Move up on the board.
3. Left: Move left on the board.
4. Down: Move down on the board.
5. Right: Move right on the board.
6. Bomb: Lay a bomb (Note: This is considered a negative reward action).

Every battle starts on a randomly drawn symmetric 11x11 grid ('board') with four agents, one in each corner. In team variants, teammates start on opposite corners and the game ends when at most one agent remains alive or both players on one team have been destroyed and the winning team is the one who has remaining members.

If there is a communicative scenario, then the agent emits a message every turn consisting of two words from a dictionary of size eight. These words are passed to its teammate in the next step as part of the observation. In total, the agent receives the following observation each turn:

1. Board: 121 Ints. The flattened board. In partially observed variants, all squares outside of the 5x5 purview around the agent's position will be covered with the value for fog (5).
2. Position: 2 Ints, each in [0, 10]. The agent's (x, y) position in the grid.
3. Ammo: 1 Int. The agent's current ammo.
4. Blast Strength: 1 Int. The agent's current blast strength.
5. Can Kick: 1 Int, 0 or 1. Whether the agent can kick or not.
6. Teammate: 1 Int in [-1, 3]. Which agent is this agent's teammate. In non-team variants, this is -1.
7. Enemies: 3 Ints in [-1, 3]. Which agents are this agent's enemies. In team variants, the third int is -1.
8. Bomb Blast Strength: List of Ints. The bomb blast strengths for each of the bombs in the agent's purview.
9. Bomb Life: List of Ints. The remaining life for each of the bombs in the agent's purview.
10. Message: 2 Ints in [0, 8]. The message being relayed from the teammate. Both values are zero only when a teammate is dead or if it is the first step. This field is not included for non-cheap talk variants.

Game Play: The agent starts with one bomb ('ammo'). Every time it lays a bomb, its ammo decreases by one. Bombs placed explodes after 10 timesteps and produces flames that have a lifetime of 2 timesteps and destroys the anything in its blast radius except the rigid walls, and post the explosion agents ammo will increase by one. The agent also has a blast strength that starts at two. Every bomb it lays is imbued with the current blast strength, which is how far in the vertical and horizontal directions that bomb will affect. Bombs destroyed in this manner chain their explosions. A single game finishes when an agent dies or reaches 800 timesteps.

Power-Ups: Half of the wooden walls have hidden powerups that are revealed when the wall is destroyed. These are:

1. Extra Bomb: It increases the agent's ammo by one.
2. Increase Range: This increases the agent's blast strength by one.
3. Can Kick: Permanently allows an agent to kick bombs by moving into them. The bombs travel in the direction that the agent was moving at one unit per time step until they are impeded either by a player, a bomb, or a wall.

Reward Shape:

Initially we trained agents with default reward shape as per the pommerman playground:

1. +1: Win.
2. -1: Lost.

In this scenario it was observed that the agent being trained tend to remain safe always and executed stay put action on all steps. Hence, we made certain changes to the reward values and trained the agents to obtain smart agents that move during the game but do not plant bombs and agents that moved and also planted bombs. Reward values that resulted in the training of agents were:

1. no penalty – if an agent plants a bomb and its explosion does not kill any enemies.
2. 0.02 pts – if agent explores previously unexplored positions.
3. 0.05 pts – if the agent picks up power-up that increases bomb's blast strength.
4. 0.05 pts - if the agent picks up power-up that increases its number of ammos.
5. 0.5*number of woods – if an agent plants a bomb and its explosion destroys wooden walls.
6. 0.5/100 near the enemy - if agent moves towards its enemies.
7. 0.5*impact_of_bomb_blast based on bomb strength – If agent places a bomb and it blasts.
8. 0.5 pts – if an agent plants a bomb and kills 1 enemy.
9. 1.0 pt - if an agent plants a bomb and kills 2 enemies.
10. 1.5 pts - if an agent plants a bomb and kills 3 enemies.

Technologies Built

Software and Libraries used:

1. PyTorch – A free open source machine learning library initially developed for Facebook's AI and used for scalable distributed training and performance optimization in our research.
2. RLlib – Open Source library used for reinforcement learning offering abstractions for highly scalable and unified API for variety of applications like TensorFlow and PyTorch
3. Gym – Toolkit for developing and comparing RL algorithms. Supports in training agents to play Pommerman.
4. Github – Platform enabling our community of developers to discover, share and build Pommerman games and train the agents.

5. Ray – High performance distributed execution framework used for large scale machine learning and reinforcement learning applications like Pommerman.
6. Pip – Standard software management system used to install and manage software packages written in Python.
7. Conda – Open source cross-platform language-agnostic package manager and environment management system used to create virtual environments and install packages for Pommerman.
8. Numpy – Python library used for large multi-dimensional arrays and matrices along with collection of high level mathematical funcions to operate and performs computations in Pommerman's grid like environment.
9. TensorFlow – End-to-End open source machine learning platform used to develop and train ML models using tensors.
10. Keras – Neural Network library which is open source and capable of running on top of TensorFlow and designed to enable fast experimentations with deep neural networks.
11. Convolutional Neural Networks – Regularized versions of multilayer perceptrons used to form fully connected networks i.e; each neuron in a layer is connected to all neurons in the next layer.
12. Logging – Used to track events when pommerman runs.

Reinforcement Learning Algorithms:

Dynamic Environment, Partial Observability and self dependence on current policy due to performing actions based on agents interaction with the environment makes reinforcement learning a challenge.

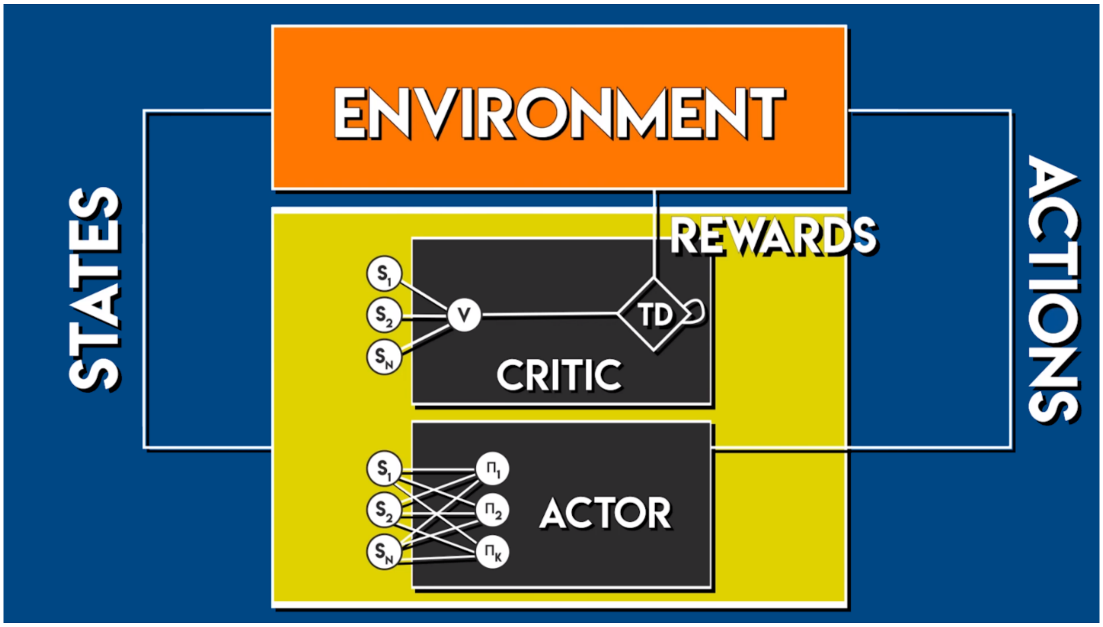
Hence, Data distributions over observations and rewards are constantly changing resulting in major instability during the training process

A2C (Advantage Actor Critic Model)

Similar to Deep Q-Network i.e; finite input and output space, we implemented A2C (Actor - Critic) algorithm to train our agent in this multi-agent game. In this algorithm, the actor takes in the current environment state and determines the best action to take i.e; actor is the policy being optimized, the critic plays the evaluation role by taking in the environment state and action performed by the actor and returns the action score i.e; critic is the value function which is being learned.

Analogy: Much like how a child playing in a park can perform multiple actions and it's parent can either compliment or critic the child's actions, our agent initially performs any randomly chosen action from the list of actions and the critic part of the algorithm evaluates the reward score for each action and hence helps in determining the best possible action.

Then, by deploying chain rule, the agent eventually learns to perform the right actions based on the feedback obtained from the critics and updates the policy distribution in the direction suggested by the critic.



In A2C: the reward functions are calculated using the formula:

$$\nabla_\theta J(\theta) \sim \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t|s_t) A(s_t, a_t)$$

[where; s: state of the environment, a: action taken by the agent, pie: expected value obtained by performing an action a on state s at time t and A is advantage function]

Method to avoid local maximum: Reward obtained by performing an action a in state s at time t is reduced by a baseline factor using Advantage Function A, which is computed as:

$$A(s_t, a_t) = r_{t+1} + \gamma V_v(s_{t+1}) - V_v(s_t)$$

[where; s: state of the environment, r: reward earned till now based on the policy generated, gamma: discounted reward and Vv is the average of Q-Values obtained for all actions in the given state at time t]

Advantages:

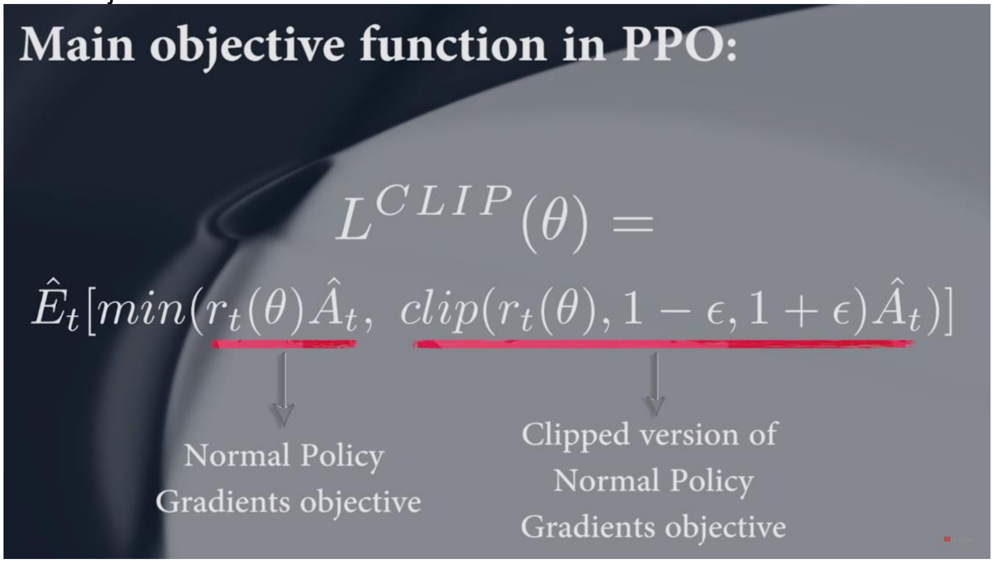
1. Actor Critic models tend to require much less training time than policy gradient methods.

PPO (Proximal Policy Optimization)

Developed at OpenAI, based on the principles of policy optimization and value based functions of A2C framework and “trusted region” of TRPO algorithm, PPO algorithm is used to overcome the disadvantages of vanilla policy gradient methods. It is also easier to implement, samples efficiencies and easy to tune.

PPO utilizes fixed-length trajectory segments and during each iteration N parallel actors, collects T timesteps of data and constructs a surrogate loss optimized with mini batch SGD or Adam optimizers for K epochs. Further, based on the rewards obtained from the N actors, an advantage function is calculated (thus involves actual computation and no guessing) and overcomes noisy advantage function values.

Main objective function of PPO is calculated as:



Main objective function in PPO:

$$L^{CLIP}(\theta) =$$

$$\hat{E}_t[min(\underbrace{r_t(\theta)\hat{A}_t}_{\text{Normal Policy Gradients objective}},\ \underbrace{clip(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t}_{\text{Clipped version of Normal Policy Gradients objective}})]$$

[where; E: Expectation objective (calculated using batches of trajectories, r: reward obtained by following the policy, A: Advantage function, epsilon: clipping factor (usually 0.2 to clip the reward function between 0.8*r and 1.2*r]

Advantage Function:

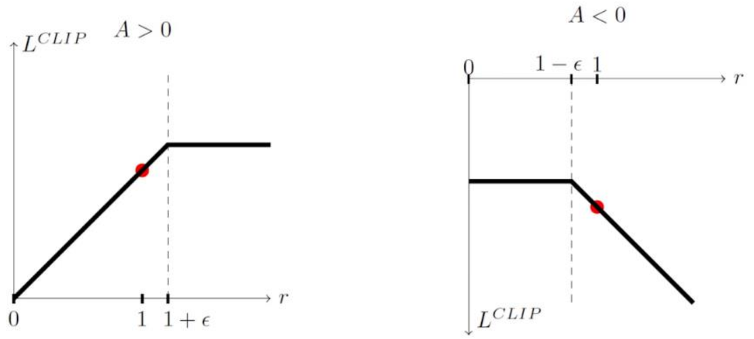
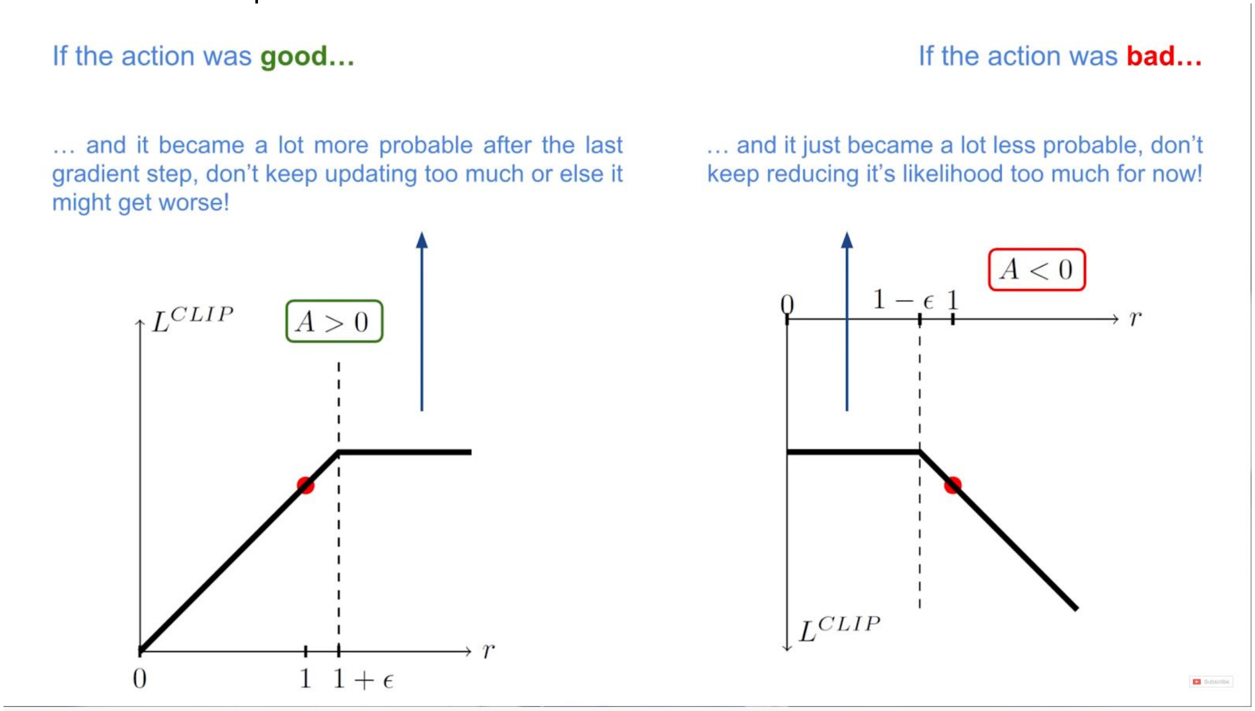


Figure 1: Plots showing one term (i.e., a single timestep) of the surrogate function L^{CLIP} as a function of the probability ratio r, for positive advantages (left) and negative advantages (right). The red circle on each plot shows the starting point for the optimization, i.e., $r = 1$. Note that L^{CLIP} sums many of these terms.

The advantage function might be positive for all the cases when our selected action has better outcome than the expected return or negative in all other cases.

Analogy:

The Advantage function helps in sampling efficiencies and leads to larger or frequent hops on flat surface and small hops on steep surface. Similar to how hopping or jumping on flat terrain is easier than on steep mountains.



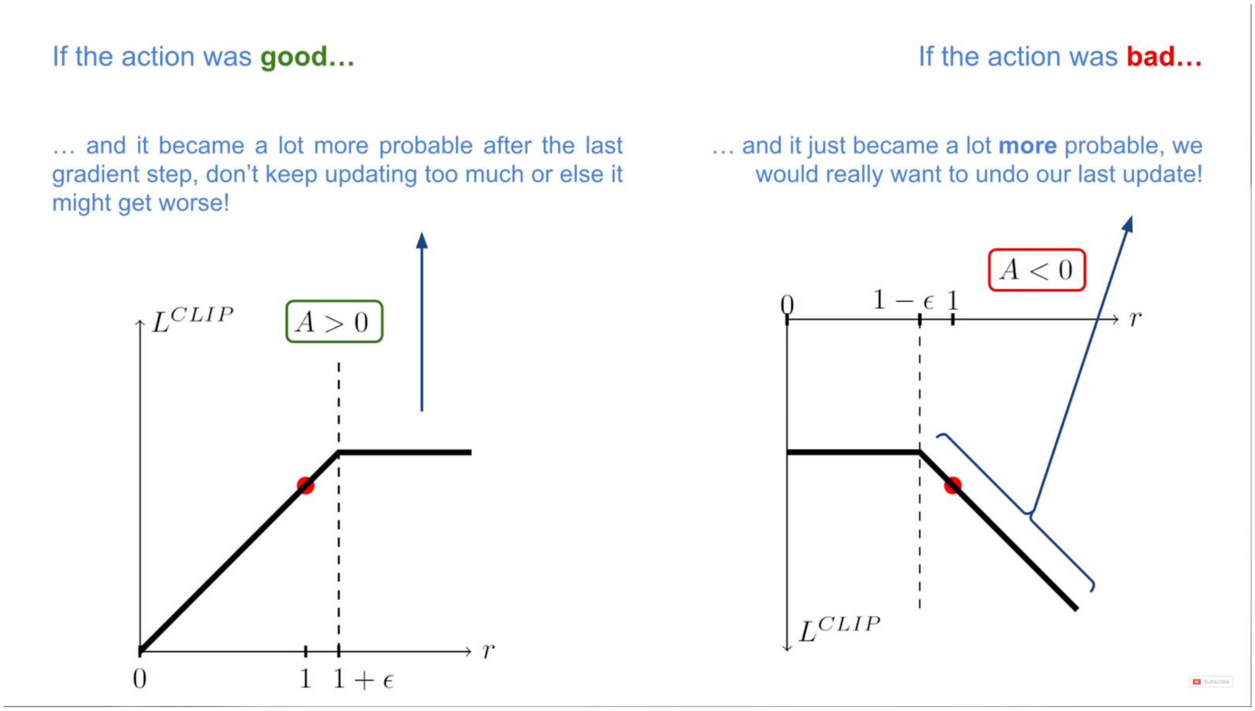
If the action was **good…**

… and it became a lot more probable after the last gradient step, don't keep updating too much or else it might get worse!

If the action was **bad…**

… and it just became a lot less probable, don't keep reducing it's likelihood too much for now!

Condition for termination of program:



If the action was **good…**

… and it became a lot more probable after the last gradient step, don’t keep updating too much or else it might get worse!

If the action was **bad…**

… and it just became a lot **more** probable, we would really want to undo our last update!

Advantages:

1. Requires less space - In contrast to Deep-Q Network, agents in PPO do not learn from past experiences saved on replay buffers but instead it learns directly from the environment.
2. Sample Efficiency - PPO algorithm can sample the efficiencies at each stage and if the advantage function does not lead to large changes in the calculated rewards then it can perform multiple or long hoppings i.e; on flatter surface and when there are large changes i.e; when the surface is steep then it can automatically perform small hops and hence attempts to the reach the optimal value.

APPO (Accelerated Proximal Policy Optimization):

An algorithm formed on the basis of PPO and Nesterov’s Accelerated Gradient (NAG) is an algorithm still under research and utilized to speed up training process using momentum. It uses the concept of training rounds i.e; series of updates to our policy network after collecting a certain number of experiences. For Example; we can define 1 training round to be 4 epochs after playing 2 episodes of the game.

$$v_t = \gamma v_{t-1} + \eta \nabla_\theta J(\theta - \gamma v_{t-1})$$

$$\theta = \theta - v_t$$

[where; vt: Exponentially Weighted Average at timestep t, gamma: decay factor, eta: learning rate, θ: weights]

Disadvantages of PPO:

1. It is a reactive algorithm and hence slows the training process. We decided to experiment with proactive algorithm to enable early learning.

   In PPO, Clipping only takes effect after the policy gets pushed outside of the range (it also depends on the sign of advantage). As such, it is a reactive algorithm because it only restricts movement once the policy has already moved outside of the specified bounds. This means that PPO does not ensure the new policy is proximal to the old policy because rt(θ)rt(θ) can easily move well below 1−ϵ1−ϵ or above 1+ϵ1+ϵ. As we will see later in this post, by using the accelerated gradient concept behind NAG, we can design a proactive algorithm which anticipates how much the policy will move. We can then use the anticipated move to better control our policy and keep it roughly within the bounds.

2. Using a ratio to measure divergence from the old policy handicaps updates for low probability actions.

The bounds that we set for the policy in PPO is based off of a ratio, which I do not like. The denominator πθoldπθold matters a lot because if it is too small, then learning is severely impaired. Let’s use an example to show you what I mean. Imagine two scenarios:

1. Low probability action: πθold(st,at)=2%πθold(st,at)=2%
2. High probability action: πθold(st,at)=70%πθold(st,at)=70%

Now let’s assume that ϵ=0.2ϵ=0.2. This means that we restrict our new policy to be 1.6%≤πθ≤2.4%1.6%≤πθ≤2.4% for the first scenario and 56%≤πθ≤84%56%≤πθ≤84% for the second scenario. Under the first scenario the policy can only move within a range that is 0.8% wide, while in the second scenario the policy can move within a range that is 28% wide. If the low probability action should actually have a high probability, then it will take forever to get it to where it should be. However, if we use an absolute difference, then the range in which the new policy can move is the exact same regardless of how small or large the probability of taking an action under our old policy is.

After calculating πθpred, we can see if it moves outside of the bounds πθold(at|st)±ϵ. If so, then we can use Mean Squared Error (MSE) as the loss function for those samples and move πθ towards the bound that it crossed. On the other hand, if it is within the range, then you can update πθ with the regular policy gradient method.

It can be noticed that by using the method above, an if statement splits the mini-batch into two smaller batches: one to be trained with MSE and the other to be trained with a policy gradient loss. If you don't want to split up your mini-batch with an if statement during training, then you can update the whole mini-batch with the following loss function:

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}\left(\pi_{\theta}^{(i)} - \mathrm{clip}(\pi_{\theta_{\mathrm{pred}}}^{(i)}, \pi_{\theta_{\mathrm{old}}}^{(i)} - \epsilon, \pi_{\theta_{\mathrm{old}}}^{(i)} + \epsilon)\right)^{2}$$

Randomized Agent:

General Deep RL algorithm that performs exploration through a stochastic policy. Actions are randomly sampled from the action likelihood distribution provided by the neural network resulting in apparently random selection of actions.

Though a naïve method to train an agent, we attempted this method to understand how agent would behave and it was observed that in most of the cases the agent executes stay put action and does not perform any action or it randomly moves across the board without placing any bombs.

It was extremely difficult to train the agents using this method because of the large batch size and epochs required and it did not result in sufficient performance and hence we explored other RL algorithms.

Results and Analysis

Limitations

There are, however, limitations to this environment. One difficulty is that a local optimum arises where the agent avoids exploding itself by learning to never use the bomb action. In the long term, this is ineffective because the agent needs to use the bomb to destroy other agents.

These demonstrate that the environment is challenging and we do not yet know what are the optimal solutions in any of the variants. Preliminary analysis suggests that the game can be very challenging for reinforcement learning algorithms out of the box. Without a very large batch size and a shaped reward (Ng, Harada, and Russell 1999), neither of Deep QLearning (Mnih et al. 2013) nor Proximal Policy Optimization (Schulman et al. 2017) learned to successfully play the game against the default learning agent ('SimpleAgent'). One reason for this is because the game has a (previously mentioned) unique feature in that the bomb action is highly correlated with losing but must be wielded effectively to win.

Conclusions

<Conclusions…>

Future Work

Research game competitions disappear for two reasons - either the administrators stop running it or participants stop submitting entrants. This can be due to the game being ‘solved’, but it could also be because the game just was not enjoyable or accessible enough. We view Pommerman as having a long life ahead of it.

Beyond the surface hyperparameters like board size and number of walls, early forays suggest that there are many aspects of the game that can be modified to create a rich and long lasting research challenge and competition venue. These include partial observability of the board, playing with random teammates, communication among the agents, adding power-ups, and learning to play with human players.

We consider Asynchronous Advantage Actor-Critic (A3C) as a baseline algorithm and we propose a new framework based on diversifying some of the workers of A3C with MCTS based planners

(serving as non-expert demonstrators) by using the parallelized asynchronous training architecture. This has the effect of providing action guidance, which in turns improves the training efficiency

measured by higher rewards.

Safe Reinforcement Learning tries to ensure reasonable system performance and/or respect safety constraints during the learning and/or deployment processes. Roughly, there are two ways of doing safe RL: some methods adapt the optimality criterion, while others adapt the exploration mechanism. Since classical approaches to exploration like ε-greedy or Boltzmann exploration do not guarantee safety, the research area of safe exploration deals with the question – how can we build agents that respect the safety constraints not only during normal operation, but also during the initial learning period?

Hester et al. used demonstrator data by combining the supervised learning loss with the Q-learning loss within the DQN algorithm to pre-train and showed that their method achieves good results on Atari games by using a few minutes of game-play data.

Cruz et al. employed human demonstrators to pre-train their neural network in a supervised learning fashion to improve feature learning so that the RL method with the pre-trained network can focus more on policy learning, which resulted in reducing training times for Atari games.

AlphaGo defeated the strongest human Go player in the world on a full-size board. It uses imitation learning by pretraining RL’s policy network from human expert games with supervised learning. Then, its policy and value networks keep improving by self-play games via DRL. Finally, an MCTS search skeleton is employed where a policy network narrows down move selection (i.e., effectively reducing the branching factor) and a value network helps with leaf evaluation (i.e., reducing the number of costly rollouts to estimate state-value of leaf nodes).

In this section, firstly, we present our framework PI-A3C (Planner Imitation - A3C) that extends A3C with a lightweight search-based demonstrator through an auxiliary task based loss refinement

Domains where rewards are delayed and sparse are difficult exploration RL problems and are particularly difficult when learning tabula rasa. Imitation learning can be used to train agents much faster compared to learning from scratch.

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5. TensorFlow – An end-to-end open source machine learning library used to develop and train models.
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