Survey of Deep Reinforcement Learning Techniques

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Abstract

Deep Reinforcement Learning (RL) is a powerful approach to agent learning in complex environments. Its applications range from gaming, to robotics to financial-market trading, achieving state-of-the art results across some distinctly challenging problem spaces. The aim of this work is to survey the actor-critic based techniques that have been applied to agent learning in Atari games [1]. We profile baseline approaches and experiment with network topologies and hyper-parameter settings. We then benchmark our agents against an A3C agent implemented by Kostrikov [?] based on the asynchronous multi-agent learning described by Minh et al [2].

1 Introduction

The algorithms for RL can be categorized into policy-based (policy gradients), value-function based (Q-learning) and a hybrid of the two (actor-critic). The actor-critic paradigm is simple and logically expressive. The actor's role is to engage in some (pre-determined) policy, and the critic is responsible for evaluating this policy. Through interactions with the environment (in our case game-play) and explicit rewards (points scored) both the actor and critic are able to iteratively update the representations of their tasks.

Our goal is to profile a baseline approach which uses a single-agent advantage actor-critic model (where the actor is learning a policy through policy gradient [3] and the critic is learning a value function similar to classic Q-Learning [4]), and explores ways we can modify the network to achieve better performance. We also try to reimplement A3C [2] for asynchronous multi-agent play what has recently been shown to reduce learning time drastically. In sum, our efforts represent a survey of the state-of-the art methods, which some experimentation do understand more deeply how network topologies (architectures and convolution vs linear approaches) affect both the ability of agents to learn and the training time.

In summary, our effort is a survey of the state-of-the-art methods in deep reinforcement learning, and a study of how policy-based agents can be trained and optimized through network topology and hyperparameter optimization. It is also a comparison study of how these agents compares against the state-of-the-art A3C. ?

2 Related Works

SARSA [4](state-action-rewards-state-action) is an early reinforcement learning algorithm that updates a policy based upon an agent's interactions with its environment. The algorithm attempts to learn a Markov Decision Process by updating a Q-value function which depends on the current state s_t, the current action a_t, the current reward r_t for choosing that action, the next state s_{t+1} and the next action a_{t+1}.

Most recent work in Deep RL can be categorized into advancements in value function methods, policy search, or a hybrid mix of the two.

In the value function paradigm of RL, significant progress was made by Minh et al. [4] in their work at addressing the assumptions of deep networks. Specifically, neural networks assume that data is i.i.d. but this assumption is violated in many RL applications. Minh's work for deep Q-Networks, introduces experience replay, a mechanism for sampling previous game states. Since consecutive game frames are highly correlated, this mechanism enables practitioners to sample from a varied distribution, addressing the i.i.d violation. They show empirically that this allows the agent to learn a value function that generalizes well to unseen game states.

Policy Gradient, specifically Karpathy's REINFORCE [3], is a recent attempt of directly estimating the optimal policy, rather than extracting a policy from a value function. Exclusively an on-policy method, this approach is simple, effective and quite stable. Playing until the end of an episode, this method is able backprop the gradient of the cross-entropy loss of the action the agent selected from its distribution relative to the distribution itself, using the reward at the end of the end of the episode to indicate the direction of the gradient. However, a limitation of this approach is that the method cannot leverage off-policy data, which may be more data efficient.

Actor-Critic (AC) is a hybrid approach defining an actor (agent) which learns through Policy Gradient methods, and a critic, which measures the efficacy the agent's policy through a learned Q value function. The insight with this approach is that one can measure the advantage of a policy relative to an estimate for the rewards produced by that policy. This learned value function ($V^{\pi}(s_t)$) is then used as a baseline function to reduce the variance of the policy gradient. Specifically, the policy gradient is scaled by an Advantage Function, defined as the advantage of action a_t in state s_t:

$$\begin{aligned} A(a_t, s_t) &= Q(a_t, s_t) - V^{\pi}(s_t) \\ &\approx R_t - V^{\pi}(s_t) \end{aligned}$$

Until recently, the state-of-the art approach for actor-critic method has been the Asynchronous Advantage Actor Critic (A3C) [2] introduced by Minh et al. A3C enables multi-agent game play which results in significantly reduced training time, lower policy variance and high agent performance.

Since the creation of the DQN, there have been many extensions to the fundamental ideas. Rainbow [5] is an approach that combines insights from recent work in DQN, addressing performance and limitations of the original DQN algorithm. They introduce Double DQN to mitigate overestimation bias from the maximization step in the DQN algorithm. They also introduce prioritized replay, so that the replay emphasizes replaying memories where the real reward significantly diverges from the expected reward, allowing the agent to adjust itself in response to incorrect assumptions. A clever trick is to use multi-step learning which that looks n steps ahead to determine the action to take.

Actor Critic using Kronecker-Factored Trust Region (ACKTR) [6] is a scalable trust-region optimization algorithm for actor-critic methods. A second order method, this proposed algorithm allows for efficient inversion of the covariance matrix of the gradient; improving sample efficiency and the final performance of the agent. It applies policy gradient with a trust region on generic A3C agents, allowing them to achieve higher rewards, and a 2 to 3-fold improvement in sample efficiency over both A2C and A3C [6].

3 Methodology

3.1 Games

We are interested in profiling deep RL with Atari Games. OpenAIGym provides emulators for many Atari games. For each game, it exposes two interfaces: RAM provides the memory state of the game, and RGB provides a $210 \times 160 \times 3$ image of the screen, reflecting the pixel values that would be rendered for game-play.

We profile two games *Pong* and *Breakout* of varying difficulty. While the size of the action space varies from $[4, 20]$, the major differentiating factor for complexity comes from the delay in reward assignment. We also experimented with other games such as *Space Invaders*, but due to frame-rate difficulties (the frame-rate of the emulator matches the period of the flashing lasers), the lasers were not visible to our agent.

Game Name	Difficulty Score	Category
Pong	2	Easy
Breakout	3	Easy

Figure 1: Game Difficulties

Pong is a simple game with only two options at any given timepoint. The screen is always based on the same display, so there are no changes from round to round. The score of Pong is the difference in the amount of wins between the user and the computer, where each win is comprised of 21 point rounds. Based on this simplicity, we have assigned Pong a difficulty score of 2.

Breakout is also a relatively simple game with only two possible moves at any given point in time. In contrast to Pong, there is no built-in opponent for the user and instead the network attempts to destroy blocks on the screen to gain points. Breakout is considered more difficult than Pong, as the game involves a longer round with only positive rewards, that can trick the network into believing that it is doing well, when it is actually not making much progress.

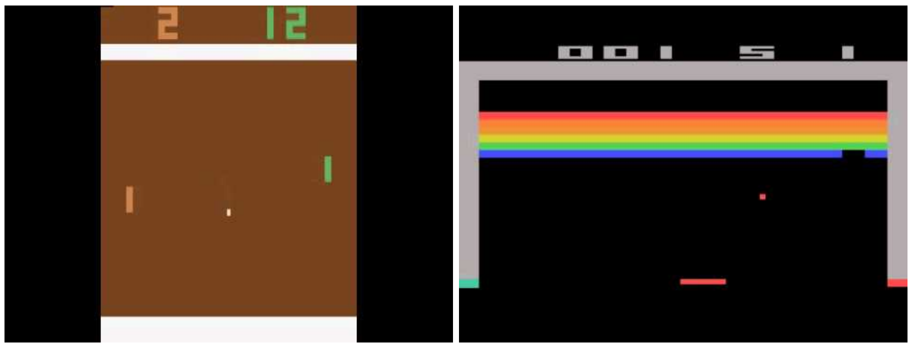

Figure 2: Sample gameplay: Pong (left), Breakout (right)

3.2 Metrics

To compare the performance across experiments, we measure *score_vs_episodes*. We explore both the number of episodes required to reach human level performance and the peak performance achieved after a certain number of episodes specific to each game. For a comparison, we thought it would be interesting to include the performance of random play, SARSA [4], human experts as reported by Minh et al [2], DQN [4], A3C [2], and ACKTOR [6].

4 Models

We implement 3 network topologies:

1. Linear + Actor/Critic (Model 1)
2. CNN + Actor/Critic (Model 2)
3. CNN + LSTM + Actor/Critic (Model 3)

Model 1: Linear + Actor/Critic

The first model is a feed-forward, fully-connected linear network. The $210 \times 160 \times 3$ image returned by the gym environment at each time step is cropped to 160×160, converted to grayscale, downsampled to 80×80, and stretched to a vector of length 6400. The input to the network is then computed as the difference between the previous frame and the current frame. The network consists of a single fully connected hidden layer with 256 nodes. The hidden layer then connects to two separate heads. The action head is connected through a softmax to a node for each of the available actions. The value head is a single node representing the value of the current state. The input is connected to the hidden layer through a ReLU activation function. This model is optimized using RMSProp with various learning rates and regularization in the form of weight decay with a coefficient of 0.01.

Model 2: CNN + Actor/Critic

The second model is a two-layer convolutional neural network. The preprocessing for this model is different from the first. Again the $210 \times 160 \times 3$ image returned by the gym environment at each time step is cropped to 160x160, converted to grayscale, downsampled to 80×80. Instead of vectorizing the frame and taking a difference, this model stacks four consecutive frames as a four channel input to the network. The first convolutional layer has a kernel of size of 8 with stride 4 and padding 2, resulting in the input image being downsized to 20×20. This layer has 16 output channels. The second convolutional layer has a kernel of size 4 with stride 2 and padding 1 which further downsizes the image to 10×10. This layer has 32 output channels. The data is then stretched to a single vector of length 3200 and fully connected to the action and value heads as in the previous model. Between each convolutional layer, batch normalization and ReLU are applied. This model is optimized using RMSProp with a learning various learning rates and regularization in the form of weight decay with a coefficient of 0.01.

Model 3: CNN + LSTM + Actor/Critic

Traditional algorithms in reinforcement learning make the Markov assumption in which the current state conditioned on all previous states is only dependent on the state from the previous time step. However, this may ignore actions and states from several time steps ago that may have contributed to some future rewards. In the case of *Breakout* and *Pong*, the previous states beyond the past four frames may be very important, and it may be the case that a long-run sequence of actions and states could better train a policy over each episode. We draw inspiration from the DQN paper, where "experience replay" is utilized to randomly sample previous transitions to train and backpropagate uncorrelated past behaviors. We hypothesize that using LSTM units with gradient descent can learn which state-action pairs far into the past may have influenced final rewards, resulting in faster and more efficient credit assignment and therefore performance.

The next model is a three layer convolutional neural network with an LSTM layer as shown in Figure 4. The preprocessing for this model is the same as for the previous convolutional model. The first convolutional layer has a kernel of size of 8 with stride 4 and padding 2 which results in the input image being downsized to 20×20. This layer has 16 output channels. The second and third convolutional layers have kernels of size 4 with stride 2 and padding 1 which further downsizes

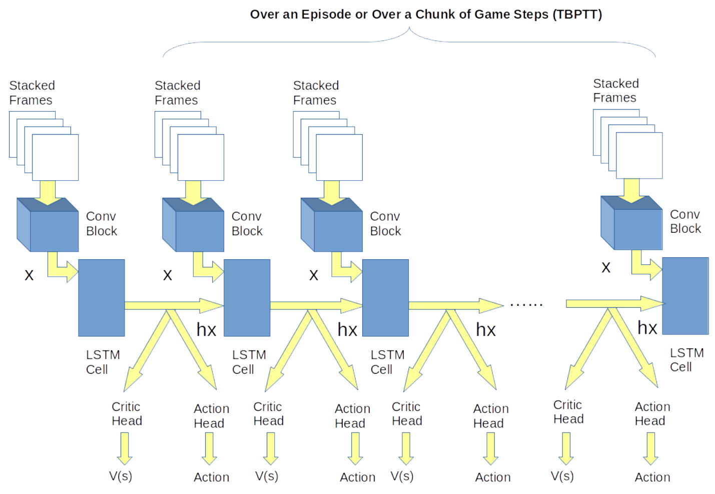

Figure 3: LSTM Network Architecture

the image to 10×10 and 5×5 respectively. Each of these layers has 32 output channels. The data is then stretched to a single vector of length 1600 an LSTM layer with 256 hidden nodes. The outputs of the LSTM layer are then fully connected to the action and value heads as in the previous model. Between each convolutional layer batch normalization and ReLU are applied. This model is optimized using RMSProp with a learning various learning rates and regularization in the form of weight decay with a coefficient of 0.01.

5 Hyperparameters

In our work, we explore the effects of various hyperparameters on our models. In this section, we report on the various hyperparameters that we experiment with and the motivations therein.

- ***Temperature:*** We used *Temperature* to anneal the state-space exploration rate of the agent. This was inspired by observing that the agent was not exploring much, failing to learn a general strategy effectively. To implement this effect, we take the the output of the network (before *softmax*) and scale by *temperature*.

$$\text{output-distribution} = \text{softmax}\left(\frac{\text{net\_output}}{temp}\right)$$

$$T = \max\left(T_{min}, T_{init} - \frac{\Delta_T \cdot \text{episode}}{C}\right)$$

  Where T is temperature, T_{min} is the smallest value we allow the temperature to get, T_{init} is the initial temperature value, $\Delta_T = T_{init} - T_{min}$ and C is the a constant, set for each game ($C_{Pong} = 10000, C_{Breakout} = 50000$).
- ***Learning-Rate:*** We tune the learning-rate, testing values at $lr = 1e-3$ and $lr = 1e-4$.
- ***Gradient Clipping:*** While LSTM units inherently mitigate the effects of vanishing gradient, they do not prevent the gradients from exploding during a long training sequence. In order to mitigate this affects of this, we experiment with gradient-clipping at various values for the gradient norm. Specifically we try clipping at $||\nabla|| \in \{1000, 2000, 5000, 80000\}$.

- ***Truncated Backprop Through Time:*** We found that our experiments with larger (deeper and wider) models had a huge memory footprint to store a full episode, and did not fit in memory. This motivated introducing *TBPTT*. Instead of running multiple forward passes and then one single backward pass though the entire game sequence, we run multiple forward passes and a single backward pass through chunks of the game sequence, while the hidden values of the LSTM hx and cx are carried forward in time between chunks. For this project, we experiment with chunks of 256,512 and 768 game steps.In tuning the *chunk-size* hyperparameter, we tried *chunk-size* $\in [256, 512, 768]$.
- ***Activation function:*** We experiment with replacing the ReLU activation function present in the rest of our models with the SiLU activation function defined as:

  $$\text{SiLU}(x) = x \cdot \sigma(x)$$

  We decided to implement the Sigmoid-Weighted Linear Unit (*SiLU*) activation function after having read through the work by Elfwing et al. 2017 [8] and examined properties of the function which show it to be similar to *ReLU*, but instead of having a global minimum of 0, it has a minimum value of -0.28. This global minimum prevents the "dying *ReLU*" issue which is fixed in the leaky *ReLU* function as well. Unlike *ReLU*, at the its minimum *SiLU* has a gradient of 0 which behaves like regularization, preventing large negative gradients. Below is an image of the *SiLU* activation function which demonstrates these properties:

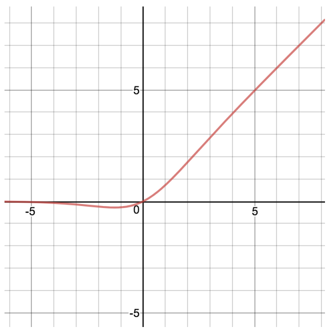

Figure 4: SiLU Activation Function

6 Results

We find that Model 3 (CNN+LSTM+Actor/Critic) is the best network topology for Deep Reinforcement Learning, with a final *running-mean* of 123% and 238% of human-expert level performance on *Pong* and *Breakout* respectively. To train the model for optimal performance, it is necessary to optimize two major hyperparameters - *temperature* and *learning-rate*. The *SiLU* activation function is comparable to *ReLU*. We find that it is important to implement Gradient Clipping and that TBPTT is a very promising way to significantly reduce demands on GPU memory.

6.1 Network Topology Experiment Results

We decided abandon further experimentation with Model 1 because the memory demands of the linear layers are extremely high (over 1.3M parameters per game step), and when gradients and intermediary values are accumulated over an episode of several thousand game steps, this results in GPU out-of-memory errors.

In addition, we discover that while the difference of two consecutive images works for *Pong* (where all of the objects on the screen are constantly in motion). This approach, however, is unsuitable for *Breakout* because the bricks are not in motion and therefore disappear in the difference image. As a result, we focus our project efforts on Models 2 and 3.

As shown in Figure 6 we can see that Model 3 (CNN+LSTM+Actor/Critic) outperforms Model 2 (CNN+Actor/Critic) in both Breakout and in Pong. This is true in both how quickly it achieves expert-human play, and in its peak performance.

6.2 Hyperparameters

In our exploration of Deep RL, we have learned a tremendous amount about sensitivity of these network setups to hyperparameters, and the trade-off space between learning-time and model generalization and various tricks-of-the-trade that can condition these models to learn better.

- ***Temperature:*** We used *Temperature* to anneal the state-space exploration rate of the agent. This was inspired by observing that the agent was not exploring much, failing to learn a a general strategy effectively. Specifically, with no temperature annealing, both the *Pong* and *Breakout* agents would get stuck at $scores = +1, +3$, respectively. Upon watching the *Breakout* agent play, we noticed it consistently moved the paddle to the corner of the board where it was able to consistently achieve small positive rewards - and once it learned this strategy, it failed to learn anything else.
- ***Learning-Rate:*** One may not be surprised to hear that our models are highly sensitive to learning rate. At $lr = 1e - 3$, the agent quickly achieves human-level performance, but its progress plateaus and the agent never achieves strong game-play strategy. At $lr = 1e - 4$, the agent is slower to reach human-level performance, but continues learning, achieving 238% and 123% on *Breakout* and *Pong* respectively.
- ***Gradient Clipping:*** We initially implemented gradient clipping to prevent exploding gradients, but we found that our models never suffered from this effect and we do not ever actually truncate our gradients.
- ***Truncated Backprop Through Time:*** We found that our experiments with larger (deeper and wider) models had a huge memory footprint for store a full episode, and did not fit in memory. This motivated introducing *TBPTT*. In exploring the impacts thereof, we find that this speeds up learning because it enables our model to do more frequent policy updates per episode. In tuning the *chunk-size* hyperparameter, we tried *chunk-size* $\in [256, 512, 768]$ and found that performance (running reward) improves with higher *chunk-size*. At *chunk-size* $= 768$ was sufficient to surpass human-level performance on both games.

  Truncated Backprop Thru Time In general, the agent learns better with higher chunk size (256 -768). We believe there is a chunk size for each game that will allow the agent to learn as well as backprop through episode, but we have not tested that out fully. TBPTT has the additional benefit of limiting the GPU memory to a very low amount, typically 1/2 to 1/3 of the memory demands of backprop through episode.

It can be seen that it is possible to beat human expert ability in both games across the various methods surveyed in our experiments. Interestingly, actor-critic without LSTM learned very quickly while plateauing around human expert level performance for both games. Meanwhile using LSTM units causes the agent to learn more slowly at first, but performed at much higher levels across both games at around 40,000 episodes. This suggests that perhaps the network may be exploiting long-run patterns across time for better gameplay performance. Furthermore, it is interesting to note that our A3C benchmarks vastly over-performed our methods with 1, 4, and 16 agents in both games.

6.3 A3C

Our A3C benchmark uses existing starter code and beats human experts very easily as shown below in Figure 6 for both Pong and Breakout.

While using various numbers of agents in the A3C code that we chose to have as a reference point, we discovered a few interesting notes about the benefits of parallelization in neural network architecture design. Even though trials with fewer agents reached higher levels of performance in fewer episodes, when we look at their performance through the lens of the number of iterations that the agents executed in tandem, the higher agent counts performed markedly better. Therefore, improving and implementing parallelism is conducive to fast and effective networks.

7 Discussion

This is a novel approach to agitating the agent towards exploration. It is interesting to note others' related work. Specifically, Mnih et al. [2] use policy entropy as an alternative method for incentivizing agent exploration.

8 Future Works

Going forward, we can explore these 2 areas in greater depths:

(1) A3C agents outperform our Actor-Critic agent in long term performance and speed of attaining these performances. Code analysis reviews three key differences between our Actor-Critic implementation from the A3C implementation:

1. Parallelism A3C is capable of parallelism (1 to 16 agents), we have not implemented parallelism in our model.

2. Advantage Function

We uses the generic advantage function defined for Actor-Critic:

$Advantage = Q_t(s, a) - V_t(s)$

A3C implements the Generalized Advantage Estimation:

$Advantage = Reward_t + \gamma * V_{t+1}(s) - V_t(s)$

3. Policy Entropy vs. Temperature

The A3C and many subsequent papers (A2C and ACKTR) adding policy entropy to policy loss to encourage exploration, where policy entropy is defined as:

$H(X) = -\sum_x P(x) log P(x)$

We on the other hand uses temperature to influence the policy distribution outputted by the softmax classifier:

```
action = torch.nn.functional.softmax(action_head(x) /temperature)
```

(2) A more thorough study of how temperature and learning rate influence the agents long term performance (running reward) and the speed of attaining this performance. The study should be run based on controlled random seeds, so that we can better replicate an agents training. In our project, we frequently run into situations where we cannot replicate an agents peak performance when training it a 2nd time using the same hyperparameters.

(3) An investigation into how TBPTT can be optimized through its hyperparameter (chunk size) to achieve comparable performance as Backprop through Episode. The use of TBPTT greatly reduces the GPU memory demand, which allows a research to run more parallel experiments on a GPU-equipped workstation.

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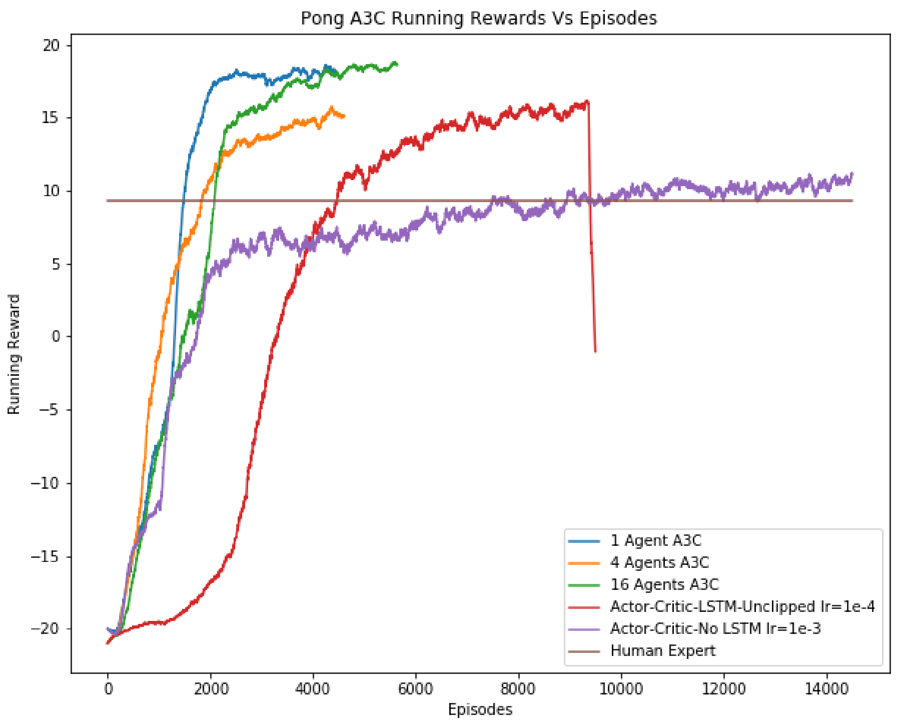

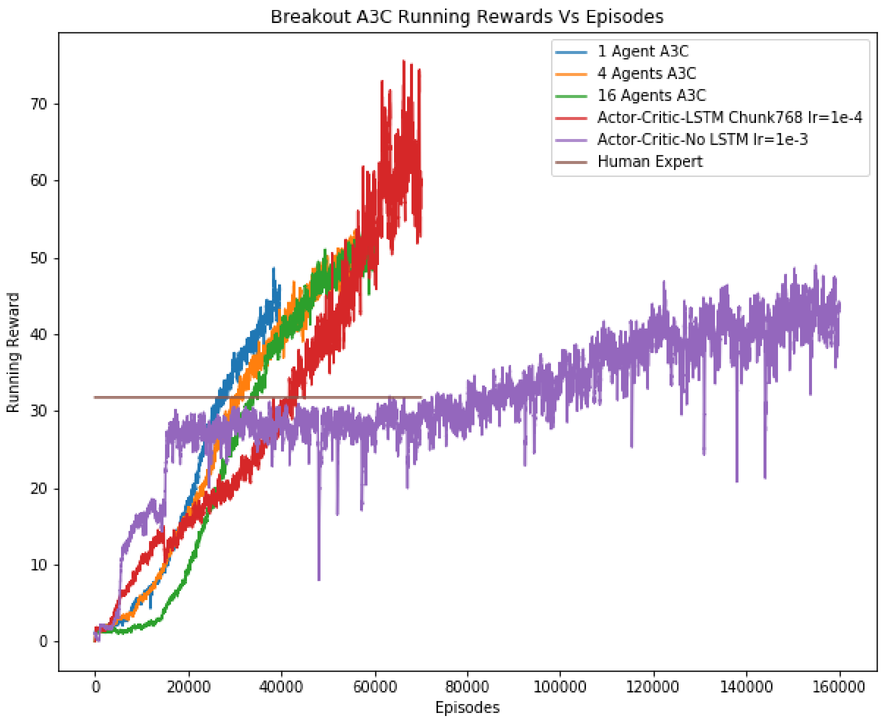

Figure 5: Pong/Breakout results

Agent	**Pong-v0**		**Breakout-v0**	
	Running Mean	% of Human Expert	Running Mean	% of Human Expert
Random Play	-20.7	1%	1.7	5%
SARSA	-17.4	12%	6.1	19%
Human Expert	9.3	100%	31.8	100%
DQN	18.9	132%	401.2	1262%
A3C (Single agent)	18.61	131%	48.62	153%
A3C (Four agents)	15.75	121%	53.58	168%
A3C (Sixteen agents)	18.77	131%	54.25	171%
ACKTR	20.9	138%	735.7	2314%
A2C (Baseline)	**11.2**	**106%**	**48.96**	**154%**
A2C-LSTM	**16.2**	**123%**	**75.6**	**238%**
A2C-LSTM (Swish)	**7.12**	**93%**	**42.32**	**133%**

Figure 6: Comparison of scores for various agents playing Pong and Breakout. * refers to our models.

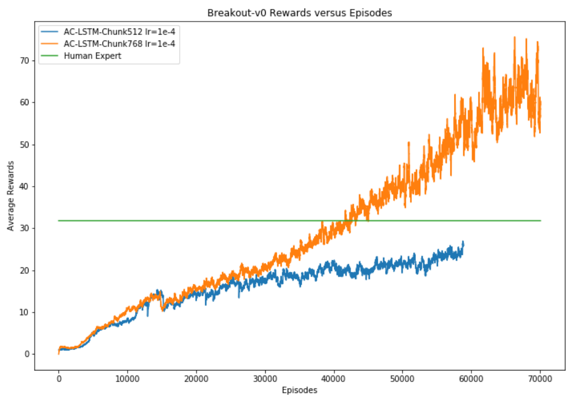

Figure 7: TBPTT