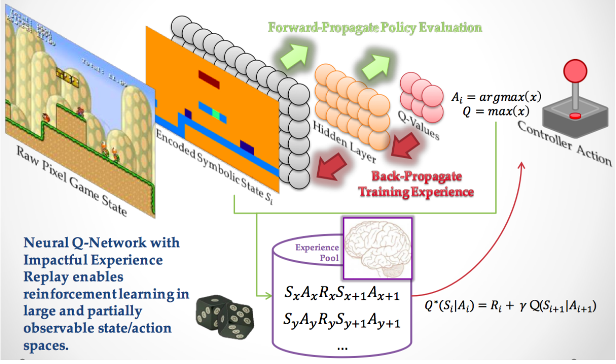
BroadMind: A Better Platforming Agent

Dave Kotfis DKOTFIS@SEAS.UPENN.EDU
Zhi Li ZHILI@SEAS.UPENN.EDU
Yesha Ouyang YESHA@WHARTON.UPENN.EDU

Abstract

Recent work in reinforcement learning has focused on building generalist video game agents, as opposed to focusing on a particular genre of games. We aim to build a more specialized agent focused on the more challenging genre of platform games, which has received less attention but quite difficult due to complex dynamics and partially observable game state. Utilizing symbolic representations of game state, we have trained fully connected Neural Q-Network agents to successfully learn to play a game with long term rewards and complex dynamics.


Forward-Propagate Policy Evaluation
Raw Pixel Game State
Encoded Symbolic State S_i
Hidden Layer
Q-Values
$A_i = argmax(x)$
$Q = max(x)$
Controller Action
Back-Propagate
Training Experience
Experience Pool
$S_x A_x R_x S_{x+1} A_{x+1}$
$S_y A_y R_y S_{y+1} A_{y+1}$
...
$Q^*(S_i|A_i) = R_i + \gamma Q(S_{i+1}|A_{i+1})$

Neural Q-Network with Impactful Experience Replay enables reinforcement learning in large and partially observable state/action spaces.

1. Background

Platform games involve a free-running avatar that jumps between suspended platforms and avoid obstacles to advance through levels in the game. As a result of the large variety of environments to parse and the huge decision space, these games are very difficult for learning agents to play well. We have built an agent that does not have to simulatenously comprehend the screen-space pixels of the game and decide optimal policies. Instead, we have decoupled these two problems, using symbolic state representations from the environment encoded for the agent. However, this symbolic representation is still very large, motivating us to utilize neural network-based Q-learning approaches.

2. Approach

2.1. Experimental Setup

We have developed a Neural Q-Network algorithm that can be extended as a reinforcement learning agent in multiple gaming environments including Generalized Mario and the Arcade Learning Environment (ALE). We utilize the RL-Glue framework to allow our agents and experiments to be used across these environments.

RL-Glue is a socket-based API that enables reinforcement learning experiments to work with software across multiple languages (Tanner & White, 2009). It allows our experiments to connect reusable Python agents across many open source game environments written in languages including C++ and Java. It also enables us to customize our experiments, such as optional game visualization, loading and saving trained policies, adjusting the game difficulty, etc.

We have trained our agents in the Generalized Mario environment. This is part of the 2009 AI Competition software package and is RL-Glue compatible (Togelius et al., 2010). The Generalized Mario game has a total control input space of 12, which we encode to integers. The raw state is made up of left/right/none motions, on/off for jump, and on/off for run. The observation interface provides the 2D screen position and velocity of the mario actor, as well as a 22x16 tile grid semantically describing the screen space with the location of coins, pipes, blocks, etc. Separately, it has a list of all enemy positions, with similar position and velocity information as provided about Mario. We use these high-level representations of game state to encode a symbolic state representation.

The Generalized Mario environment provides a positive reward of 1 for smashing enemies or collecting coins, a substantial positive reward of 100 for reaching the goal, a substantial negative reward of -10 for Mario's death, and a small negative reward of -0.01 every timestep where nothing else occurred,

We have leveraged the Arcade Learning Environment, an RL-Glue compatible framework built on top of an Atari 2600 emulator (Bellemare et al., 2013). It provides an API

Proceedings of the 31st International Conference on Machine Learning, Beijing, China, 2014. JMLR: W&CP volume 32.

for interfacing with the raw pixels, the current score, and the controller input of the game. This environment does not provide any symbolic state representations, so any agent would need to be capable of encoding the game state from raw pixel values. ALE has enabled us to use original Atari games to train and evaluate our agents. We currently support 7 Atari platformers in our experimental setup:

1. Montezumas Revenge
2. Kung-Fu Master
3. Frostbite
4. Kangaroo
5. Pitfall!
6. Pitfall! 2
7. H.E.R.O.

2.2. Learning Algorithms

2.2.1. State Representation in Mario

It is challenging to find an effective representation of the Mario game state that enables effective Q-learning. The environment observations provided by Generalized Mario contains a wealth of symbolic information, but there are many possible encodings that we have investigated. Our primary representation is a tiled grid of integers, 20x12 tiles in size. The relative value in each tile is given as a "measure of goodness", enemies are -2, obstacles are -1, coins are +2, etc. The grid is centered on Mario's current location.

We have also evaluated an alternative representation of the state with separate substrates for each class of objects, as in (Hausknecht et al., 2013), by breaking it out into separate background, enemy, and reward layers. To conserve memory and computation, this representation restricts each of the 3 substrates to an 11x7 set of tiles centered around Mario, which makes the total state size roughly equivalent to the previous representation. Note that this representation does not explicitly encode Mario's position, but it does so implicitly as the tiles are centered at Mario's position. This position will never fluctuate with tiles of odd edge lengths, so an implicit encoding should be sufficient.

It is worth nothing that none of these representations encode the important velocity information about the actors, which is important in platformers where the characters move with some inertia.

2.2.2. Neural Q-Learning

Typically, Q-Learning approaches use a table representing the Q-function. For very large state/action spaces such as platforming games, this is impractical as the space would take too many trials to explore and converge on an optimal policy. Even using optimizations such as nearest neighbor ran out of memory for our Generalized Mario state representation. We have implemented a neural-network based Q-learning algorithm (see Algorithm 1) to allow us to learn on large state/action spaces with reasonable memory uti-

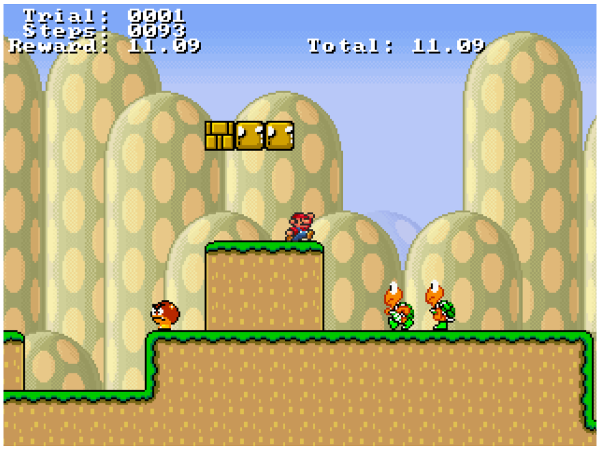
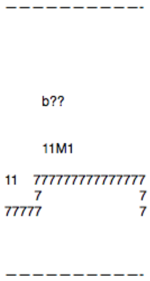


Figure 1. Raw pixels representing the state of the mario game, as it would be seen by a player.



```
-----------


     b??


     11M1

11  777777777777777
    7             7
77777             7


-----------
```

Figure 2. The equiivalent game state encoded as symbolic characters, as provided to the learning agent by the Mario environment in each timestep.

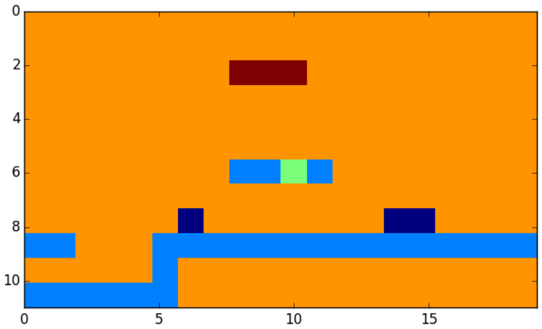


Figure 3. Our encoding of the game state in a 20x12 grid with Mario at the center, as provided to the Neural Q-Network. Larger postive values correspond to positive symbols such as coins and free space, and negative values correspond to negative symbols such as enemies and obstacles.

Algorithm 1 Neural Q-Network with Impactful Experience Replay

```
Initialize Neural Q-Network with random weights
Initialize Experience Pool to $\{\}$
for episode$= 1, m$ do
  Initialize previous state $s_0$ and previous action $a_0$ to NULL
  for $t = 1, T$ do
    Compute the mean and standard deviation of absolute value of the rewards in the experience pool, $r_{ave}, r_{dev}$.
    Observe state $s_t$ from the emulator
    With probability $\epsilon_a$, select random action $a_t$
    Else, set $a_i = \max_a Q(s_t, a)$ by forward propagating $s_t$ through Q
    if $s_{t-1}$ and $a_{t-1}$ are not NULL then
      Observe reward $r$ from emulator
      With probability $\epsilon_r * (1 + \frac{|r| - r_{ave}}{r_{dev}})$, store the experience $\{s_{t-1}, a_{t-1}, r, s_t, a_t\}$ in the pool
    end if
    for re-experience$= 1, ex$ do
      Randomly sample experience $\{s'_0, a'_0, r', s'_1, a'_1\}$ from the pool
      if using SARSA update rule then
        Compute $v = r' + \gamma Q(s'_1, a'_1)$
      else
        Compute $v = r' + \gamma \max_a Q(s'_1, a)$
      end if
      Update Q through backpropagation of value v on output $a'_0$ with state $s'_0$
    end for
    Apply action $a_i$ to emulator
    Update state $s_{t-1} = s_t$ and action $a_{t-1} = a_t$
  end for
end for
```

lization by finding a useful hidden layer.

Inspired by DeepMind's approach (Mnih et al., 2013), we have avoided multiple forward propagation steps when selecting optimal actions by using only the state as the input to the network, and a weight for each action as the output. Thus, we can select an optimal action for a state by propagating once, and selecting the max argument from the outputs. Also like DeepMind, we include an Experience Replay step that stores a history of events to re-learn. This avoids overfitting to the current situation and unlearning good behavior from earlier episodes. Our algorithm can optionally use the standard Q-Learning update, or the SARSA calculation.

We have adjusted the experience rememberance process to prioritize memorization of meaningful experiences. We observe that experiences corresponding with large positive or negative rewards are rare, but these are the experiences that provide the most value to the agent. To do this, we modify the probability of rememberance, multiplying by $1 + \frac{|r| - r_{ave}}{r_{dev}}$ to increase the chances of remembering experiences that are observed to be impactful.

2.2.3. Extension to Atari Platformers

We have setup the ALE environment, and connected default agents to it. However, we have yet to attempt to port our agents to these problems. First, we will need to develop an agent that can learn our symbolic state representations from raw pixel inputs provided by the ALE environment.

3. Results

We have found that the initial random weights in the neural network can make the early policies very flawed. To counter this, we use heavy exploration bias ($\epsilon = 1.0$) for early episodes, while transitioning to exploitation policies ($\epsilon = 0.1$) at later episodes. We have also biased the random action to prefer motion to the right, helping the agent to explore more of the game.

We have trained agents for 1,000 episodes in the Mario environment using the state encoded in the format described in section 2.2.1, and using the Neural Q-Network with experience replay of Algorithm 1. We use Mario level of difficulty 1 so that the levels provide a challenge with enemies, but not so hard that a random agent cannot make considerable progress.

Due to the variation in available rewards between each Mario level, we have compared all performance results against an agent that acts randomly. To reduce noise in our plots, we compute a running average of total rewards over 100 episodes. The Mario environment provides a substantially large reward for reaching the end of the level. When averaging this reward over 100 levels, it provides too much weight that de-emphasizes the results of the other episodes. For this reason, we have capped the max reward that a single episode can add to the running average.

3.1. Impactful Experience Rememberance

We evaluated the performance of an agent prioritizing impactful experiences in their memory pool against one that equally values all new experiences. We have found that both agents saturate at the same level of performance, though the impact-weighted experiences causes that agent to learn more slowly in earlier episodes. We suspect that the weight term makes most experiences nearly impossible to remember, and this slows down the rate at which the experience pool can be filled. A good compromise may be to deactivate the weight term until the experience pool is at max capacity.

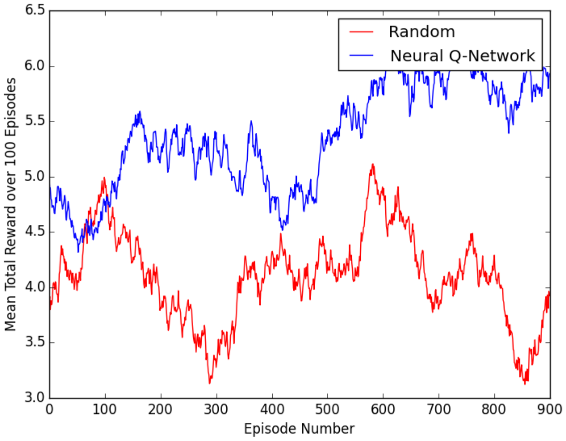


Figure 4. Mario agent trained with a neural q-network with a hidden layer of 126 nodes. The agent was trained for 1000 episodes of the same level seed 3 and difficulty 1. The initial exploration factor was 1.0, and this decreased by 0.05 every 100 episodes, until stopping at 0.1. The total reward gained by the agent was summed over each episode, and the running average of 100 episodes is shown here.

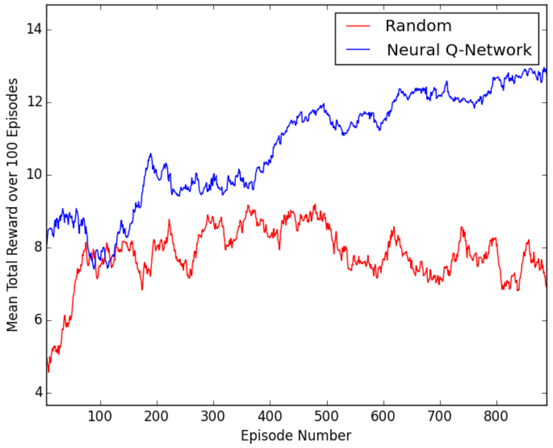


Figure 5. The same test performed with level seed 8. At its peak, the mean reward earned for the learned agent is roughly double that of random behavior

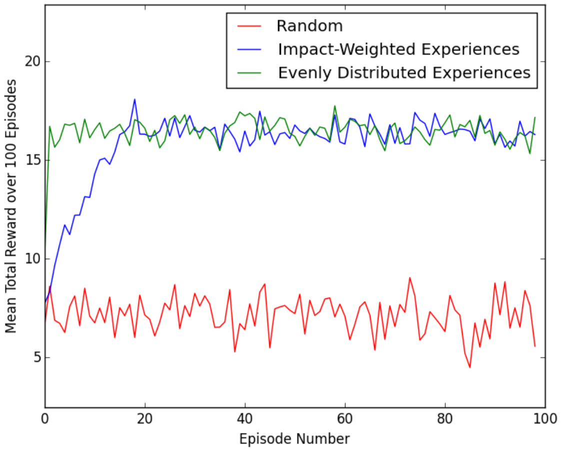


Figure 6. Level seed 8 continued out to 10,000 episodes with and without impact-weighted experience rememberance. Each point represents an average over 100 episodes.

3.2. Transfer Learning Between Levels

Our initial experiments focused on simultanous training and testing of an agent that is continuously executing the same level of the game. We are interested in training a generalist agent that can perform well on an experience that has not yet been seen. We have tested the performance of an agent that is trained for 100 episodes on each level before switching to a completely new level of similar difficulty. We have found that performance on these new levels seems to match what we would see if the agent were trained only on that level.

3.3. Multiple Substrate Representation

We have trained an agent using the multiple substrate representation with separate background, enemy, and reward layers. However, we have found that this agent does not appear to be learning as its performance remains roughly in the realm of a random agent over 1000 training episodes. We believe that the smaller grid size of these substrates is not suitable for the dynamics of the Mario game.

4. Conclusion

Our results have shown that a Q-Learning agent with a single hidden-layer neural network Q-function can learn to play a game with complex dynamics and partially observed states like Mario. This agent also performs well on unseen levels.

We have found that encoding the symbolic game state in a single layer has led to agents capable of improving their

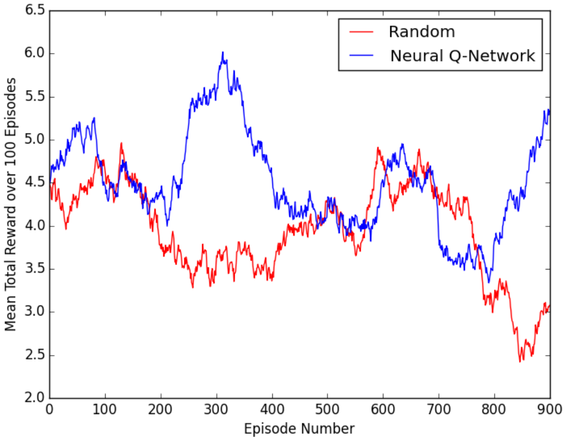


Figure 7. Mario agent on level seed 3, using the multiple substrate state representation. The performance of this agent does not reach a point where it exceeds the performance of what could be achieved by a random agent.

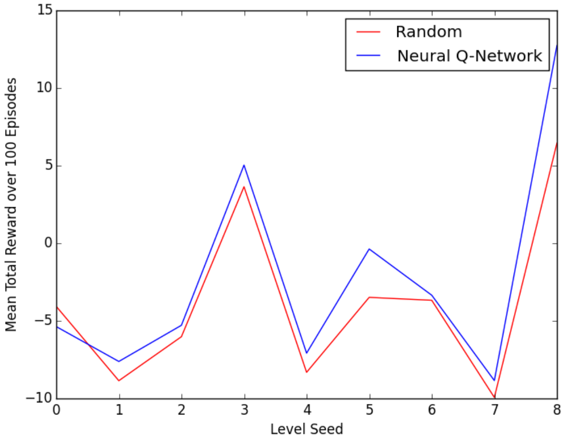


Figure 8. Here, every 100 episodes the Mario envrionment changes to a new level. For levels 3 and 8 that we previously examined, the performance of the learned agent is consistent with what we observed in tests that trained an agent only on these levels. After the first level where the agent is learning but still acting completely randomly, the learned agent exceeds random performance in every case.

performance, but splitting out the state into separate layers for background, enemies, and rewards does not exceed random performance. This may suggest that a large grid size of the state representation is important to allow the agent to plan over a longer horizon.

An experience replay mechanism is critical to ensure that the agent does not unlearn behavior. We have developed a novel method for emphasizing impactful experiences in memory. This approach may prove to be important when scaling this approach to a lifelong learning application. It should alleviate the need to increase the memory pool size by ensuring that less valuable experiences do not need to be stored. However, our early results have shown that this mechanism delays learning in early episodes as it takes longer to fill the experience pool.

Future work should focus on application of this algorithm to platforming games on a full console emulator like the Atari ALE environment where the symbolic state representation is not directly observable by the agent, and mapping raw screen space pixels into the symbolic representation must be learned.

Acknowledgments

None.

References

Bellemare, Marc G, Naddaf, Yavar, Veness, Joel, and Bowling, Michael. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47:253–279, 2013.

Hausknecht, M., Lehman, J., Miikkulainen, R., and Stone, P. A neuroevolution approach to general atari game playing. *IEEE Transactions on Computational Intelligence and AI in Games*, 2013.

Mnih, Volodymyr, Kavukcuoglu, Koray, Silver, David, Graves, Alex, Antonoglou, Ioannis, Wierstra, Daan, and Riedmiller, Martin. Playing atari with deep reinforcement learning. *NIPS Workshop on Deep Learning and Unsupervised Feature Learning*, 2013.

Tanner, Brian and White, Adam. Rl-glue: Language-independent software for reinforcement-learning experiments. *Journal of Machine Learning Research*, 10: 2133–2136, 2009.

Togelius, J., Karakovskiy, S., and Baumgarten, R. The 2009 mario ai competition. *Evolutionary Computation (CEC), 2010 IEEE Congress on.*, pp. 1–8, 2010.