Frame Skip Is a Powerful Parameter for Learning to Play Atari

Alex Braylan, Mark Hollenbeck, Elliot Meyerson and Risto Miikkulainen
Computer Science Department, The University of Texas at Austin
2317 Speedway, Austin, TX 78712

Abstract

We show that setting a reasonable frame skip can be critical to the performance of agents learning to play Atari 2600 games. In all of the six games in our experiments, frame skip is a strong determinant of success. For two of these games, setting a large frame skip leads to state-of-the-art performance.

The rate at which an agent interacts with its environment may be critical to its success. In the Arcade Learning Environment (ALE) (Bellemare et al. 2013) games run at sixty frames per second, and agents can submit an action at every frame. Frame skip is the number of frames an action is repeated before a new action is selected. Existing reinforcement learning (RL) approaches use static frame skip: HNEAT (Hausknecht et al. 2013) uses a frame skip of 0; DQN (Mnih et al. 2013) uses a frame skip of 2-3; SARSA and planning approaches (Bellemare et al. 2013) use a frame skip of 4. When action selection is computationally intensive, setting a higher frame skip can significantly decrease the time it takes to simulate an episode, at the cost of missing opportunities that only exist at a finer resolution. A large frame skip can also prevent degenerate super-human-reflex strategies, such as those described by Hausknecht et al. for Bowling, Kung Fu Master, Video Pinball and Beam Rider.

We show that in addition to these advantages agents that act with high frame skip can actually learn faster with respect to the number of training episodes than those that skip no frames. We present results for six of the seven games covered by Mnih et al.: three (Beam Rider, Breakout and Pong) for which DQN was able to achieve near- or super-human performance, and three (Q*Bert, Space Invaders and Seaquest) for which all RL approaches are far from human performance. These latter games were understood to be difficult because they require ‘strategy that extends over long time scales.’ In our experiments, setting a large frame skip was critical to achieving state-of-the-art performance in two of these games: Space Invaders and Q*Bert. More generally, the frame skip parameter was a strong determinant of performance in all six games.

Our learning framework is a variant of Enforced Subpopulations (ESP) (Gomez and Miikkulainen 1997), a neuroevolution approach that has been successfully imple-
Parameter search techniques could be used to find a ‘good enough’ frame skip for each game, but perhaps for some games there is no single best static frame skip. A more adaptive possibility is for the algorithm to adjust the frame skip based on learning progress. Taking this one step further, RL agents could be extended to specify, each time they interact with ALE, both an action and the number of frames they would like to skip before the next interaction.

A related idea has been investigated in the Atari domain with respect to Monte-Carlo Tree Search (Vafadost 2013), in which the planner can take an action repeated \( k \) times as a macro-action. In neuroevolution, one approach to this problem could be to include an additional output node whose output is mapped into a range of possible frame skips. The experiments presented above are by no means exhaustive, but they lead us to conclude that frame skip is a powerful parameter for learning to play Atari. It is currently intractable for general methods to achieve human performance on all Atari 2600 games at 60Hz. Harnessing frame skip could be a key ingredient to tractability and future success.

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**References**


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


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**Table 1: Average scores for ESP v. existing approaches.**

<table>
<thead>
<tr>
<th>Game</th>
<th>E15</th>
<th>E20</th>
<th>HNEAT</th>
<th>DQN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beam Rider</td>
<td>1663.2</td>
<td>1663.2</td>
<td>1736.8</td>
<td><strong>4092</strong></td>
</tr>
<tr>
<td>Breakout</td>
<td>30.80</td>
<td>34.20</td>
<td>43.60</td>
<td><strong>168</strong></td>
</tr>
<tr>
<td>Pong</td>
<td>13.80</td>
<td>15.40</td>
<td>15.20</td>
<td><strong>20</strong></td>
</tr>
<tr>
<td>Q*Bert</td>
<td>2020.2</td>
<td>3380.2</td>
<td>2165.0</td>
<td>1952.2</td>
</tr>
<tr>
<td>Seaquest</td>
<td>2218.0</td>
<td>2258.1</td>
<td>2508.0</td>
<td>1705.2</td>
</tr>
<tr>
<td>S. Invaders</td>
<td>1835.2</td>
<td>1912.6</td>
<td>1481.0</td>
<td>581.1</td>
</tr>
</tbody>
</table>

Breakout with frame skip 180 always scored 0. Table 1 compares our results to previous approaches.

Figure 1: ESP average scores over five runs by generation for each of the six games.