

Paper: The Game Imitation: Deep Supervised Convolutional Networks for Quick Video Game AI

Summary

In this paper, the authors present a study of teaching a computer to play modern video games purely through imitation learning; i.e. pure behavioral mimicry of human actions viewed through gameplay screenshots. Imitation learning provides several advantages over its deep-Q learning. First, one does not have to depend on a carefully crafted loss function or an a priori notion of the game score. Their model also provides a reasonable performance at a significantly lower cost in terms of hardware and time and can be implemented with minimal fine-tuning at inference. Therefore, their main goal is not to dethrone deep-Q learning in terms of performance but rather to demonstrate that a significantly more lightweight approach using CNNs can yield reasonable results.

They propose a purely supervised learning classification for fully vision-based gaming AI. Their classification pipeline takes as input a concatenation of four temporarily sequential gameplay images, each of dimension (128, 128, 3). They then use a CNN to output 30 class softmax scores, each corresponding to a different possible input command on the Nintendo 64 console. The data was collected by the authors via a combination of Nintendo 64 emulation and screen capture tools. For the full dataset, 60 5-minute games were played of Super Smash Bros, giving approximately 600,000 frames of gameplay with corresponding key presses. For Mario tennis, 25 single games were played of Mario Tennis, giving approximately 125,000 frames of data. Image preprocessing was kept minimal to keep the training pipeline as end-to-end as possible. Each frame of the video was downsampled from an original size of (334, 246) to (128, 128) in pixels.

The authors trained main CNN architectures: a single frame CNN, an Early Integration CNN, and a late integration CNN. The foundational architecture of all three models is AlexNet. They take the standard softmax loss as classification loss in our system and train with Adam and standard learning hyperparameters.

They used two metrics they test their performance: validation accuracy and live games of their neural network player.

First, they note that after 2 epochs of training, their top 3 validation score for Super Smash Bros exceeds 96%, which shows that their model is learning correct behavior but that this behavior might not produce the maximal softmax score.

Second, on the live gameplay, they found out that their model runs at test time with a latency of 300ms which is only slightly below the average human reaction time. They pit their fully CNN controlled Pikachu against the pre-packaged Mario game AI. They run 10 games against a level 9 Mario AI and 10 games against each a level 3 and level 6 Mario AI and record damage dealt in each game. They note that the CNN Pikachu handily defeats a level 3 CPU, is just barely outside the margin of error for being better than a level 6 CPU, and is quite competitive with the level 9 CPU. However, they reported that their performance on Mario Tennis is not as good.

Strengths

- They have provided a detailed explanation of their models and methods.
- They have also included a video of their model playing game.
- They have also included the limitation of their model.

Weaknesses

- Even though the visualization was colorful and fancy, they were not very appealing to me.
- I was not very convinced of their evaluation metric.

Discussions

- What may be the reason that their model did not do so well in Mario Tennis?
- How will CNN based models perform on very high-resolution complicated games such as FIFA and Call of Duty?