

Asynchronous advantage actor-critic (A3C) method on Atari games

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Outline

- 1 Introduction
- 2 Implementation
- 3 Results
- 4 Latest progress
- 5 Conclusions

Introduction

- FF neural networks
- CNN
- RNN (LSTM)
- Actor-critic method \approx Q-learning + policy gradient
- Asynchronous gradient descent
- CPU/GPU hybrid method

Actor-critic method

Screenshots \rightarrow $\begin{cases} \text{Actor } \pi(a|s, \theta_p): \text{ probability of each action} \\ \text{Critic } V(s, \theta_v): \text{ expected discounted future reward} \end{cases}$

Basic idea of parameter updates

The parameters should be updated every few steps such that

- $V(s, \theta_v)$ should reflect the expected discounted future reward (EDFR), i.e., $(R - V(s, \theta_v))^2$ should be minimized.
- An action that gives a higher/lower EDFR than current estimated one should be encouraged/discouraged, i.e., $-\log \pi(a|s, \theta_p) (R - V(s, \theta_v))$ should be minimized.

Asynchronous gradient descent

Why not experience replay?

- Requires large memory and computation.
- Uses data from old policies to train current policy.

Asynchronous gradient descent

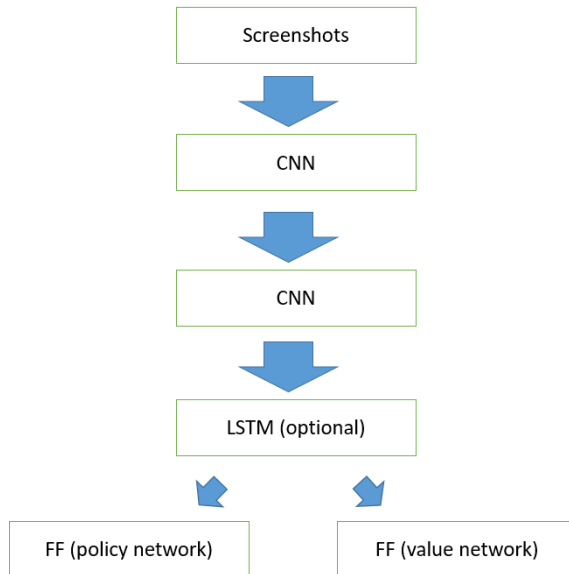
Why not experience replay?

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Then how do we get uncorrelated training data?

- Run game agents concurrently, and train independent models.
- Update the parameters for the shared model asynchronously.

Model structure



Implementation issues

- For each process/thread: run an individual game simulator, and a training model
- Shared objects:
 - Global shared model (for asynchronous updates)
 - Shared RMSprop optimizer (to enhance stability)

Implementation issues

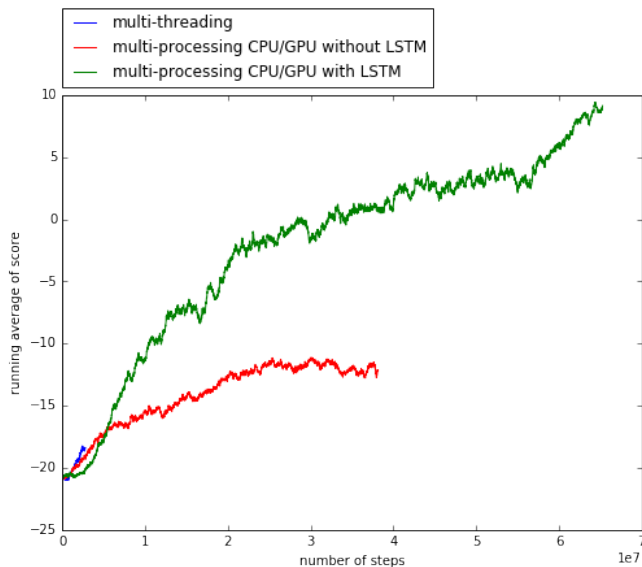
Q: How to parallelize training and do asynchronous updates?

- Multiprocessing in CPU: 6-7 h/M steps
 - Sometimes some processes get stuck and keep 'sched_yield()' (from tracing Linux kernel calls). This might be related to OpenBLAS issue (<https://github.com/scikit-learn/scikit-learn/issues/2088>)
- Multiprocessing in GPU: 0.6 h/M steps
 - Shared model does not work, multiprocessing module does not support shared arrays in GPU (<https://github.com/muupan/async-rl/issues/10>).

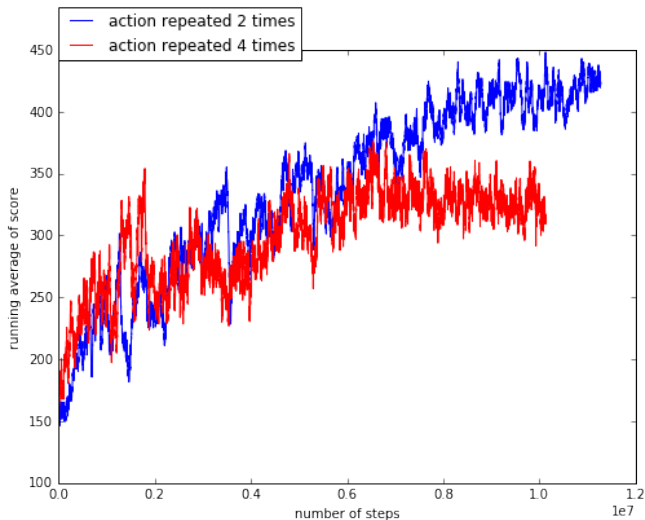
Implementation issues

- Multithreading in GPU: 5-6 h/M steps
 - Slow since only one thread can be executed each time due to GIL (global interpretation lock).
- Multiprocessing in GPU, while requesting shared weight and optimizer parameters from CPU memory in each iteration: 2 h/M steps
- Multiprocessing, with independent models in GPU, and shared model in CPU (parameters shared in CPU): 0.5 h/M steps
 - Reason: profiling shows that most time consuming part is backpropagation.

Results: Pong

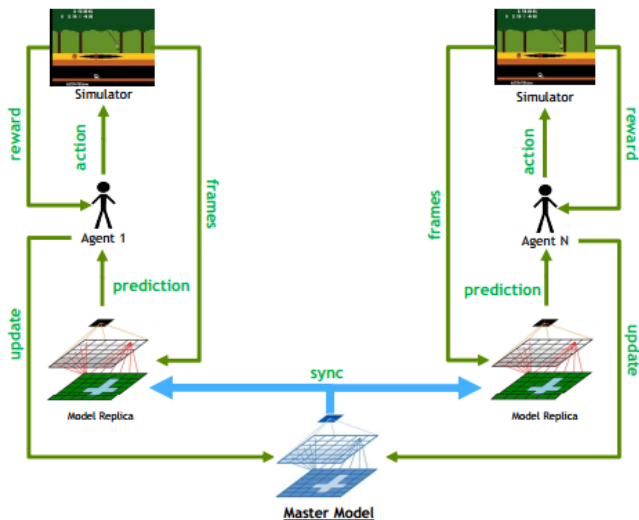


Results: Space-invaders

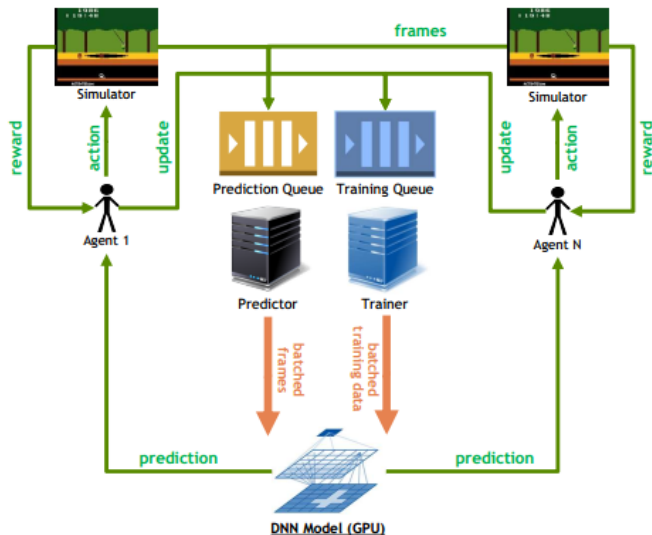


https://gym.openai.com/evaluations/eval_i57wuZpQhKHRhywgh4Ug

Latest progress: GA3C (ICLR 2017) by UIUC and Nvidia



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Conclusions

Conclusions

- A3C works for training Atari games, the implementation of training and parallelization part would significantly affect the efficiency.
- GA3C could possibly reduce training time by 1-2 order of magnitude.

Code

https://github.com/weiHelloWorld/IE598_project

Questions?