A Hybrid Approach for Reinforcement Learning Using Virtual Policy Gradient for Balancing an Inverted Pendulum

Doctoral Consortium

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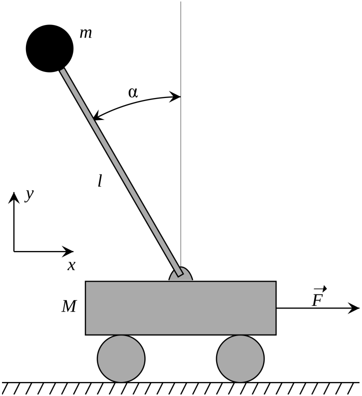
Introduction

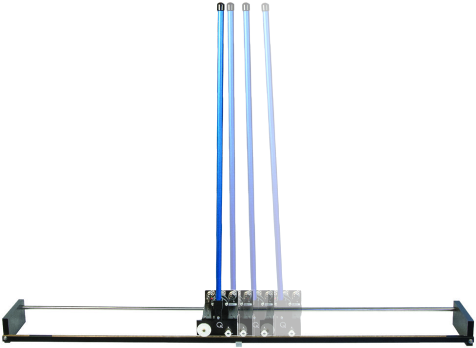
Reinforcement Learning is the process of using trial-and-error with finite rewards.

- Input state of the environment
- Output optimal action
- (Optional) Rewards

Our agent is an underactuated single-inverted pendulum on a one-dimensional track. The nonlinear equations of motion result in an unstable equilibrium that can be difficult to maintain.

Environment and Agent





Goals

- Use RL to train a realistic simulation of a virtual pole to balance itself.
- Use the trained neural network to balance a real pole in the real world.

Ultimately, training through simulation can speed up training time and increase robustness.

Literature Review

- Traditional control: Linearized systems limit the angle of deflection. Robost performance is only achieved with properly tuned weights.
- Virtual RL: Usually implemented in a simulation like OpenAI's Cartpole. Physics here are usually questionable.
- Real RL: “Nothing works; I mean, the robots will break down - they'll break down all the time.” - Dr. Tim Lillicrap

Environment

- Started with OpenAI Cartpole
- Adjusted physics, improved EOM
- Continuous action-space
- State: $[x, \alpha, \dot{x}, \dot{\alpha}]$

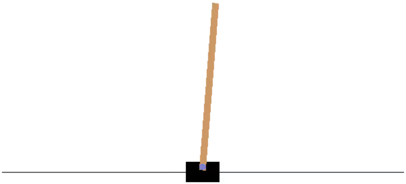
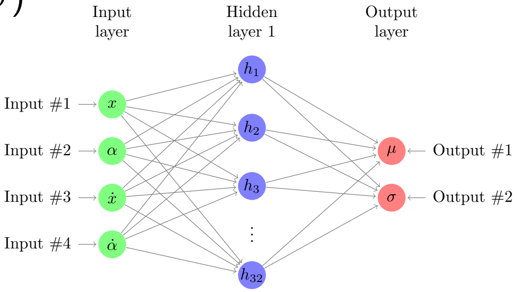


Figure: Modified Cartpole environment.

Neural Network

- Input state vector
- `ReLU` activation
- 2 outputs: $\sim N(\mu, \sigma)$

Figure: Artificial NN approximates actions.



Discounted Rewards

Rewards: $r_t = 1,\ 0 \leq t \leq T$

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$$

- $0 < \gamma < 1$ is a discount factor, intended to prioritize actions now over actions in the future.
- Larger values of γ takes a long term approach.

Loss

$$L = -R \cdot \tilde{a} + \epsilon H$$

- $R =$ normalized discounted rewards
- $\tilde{a} =$ log probability of actions
- $H =$ optional entropy parameter

This can be modified to promote optimal behaviour.

Neural Networks - Policy Gradient

Unlike supervised learning, we cannot calculate an explicit error between the neural network's output and the "correct" answer. Goal: max $\sum_i \ln p(y_i|x_i)$

- Maximize expected return:
  $J(\pi_\theta) = \int_\tau P(\tau|\theta)R(\tau) = \underset{\tau\sim\pi_\theta}{\mathbb{E}}[R(\tau)]$
- Use gradient descent:
  $\nabla_\theta J(\pi_\theta) = \underset{\tau\sim\pi_\theta}{\mathbb{E}}[\nabla_\theta \ln P(\tau|\theta)R(\tau)]$
- Normalized discounted rewards encourage and discourage half of actions.

Virtual Policy Gradient

$$\nabla_\theta J(\pi_\theta) = \underset{\tau \sim \pi_\theta}{\mathbb{E}} \left[\sum_{t=0}^{T} \nabla_\theta \ln \pi_\theta(a_t | s_t) A^{\pi_\theta}(s_t, a_t) \right]$$

The algorithm is incredibly generalizeable, allowing the same code to complete a variety of tasks.

- Balance a pole
- Play Pong
- Drive a car

You only need an updated simulation, and the appropriate number of neurons, hyperparameters...

Results

The inverted pendulum learned to balance for at least 10 seconds 91% of the time

- takes an average of 807 trials
- high variance among gradients and training time
- optimizing hyperparameters reduced this to 355
- minimum trials was only 54 ($\sim$1 minute to train)

Due to the high variance among the gradients, even the best hyperparameters had inconsistent performance.

New Work - Actor Critic and PPO

- Actor: ANN predicting the best action to take
- Critic: new head of the same ANN estimating the value of that action, $V^{\pi}(s_t)$
- Subtracting this baseline reduces the variance of Policy Gradient

Given $Q^{\pi}(s,a) = \mathop{\mathbb{E}}_{\tau\sim\pi}[R(\tau)|s_0 = s, a_0 = a]$,
set $A^{\pi}(a_t|s_t) = Q^{\pi}(s_t, a_t) - V^{\pi}(s_t)$

Then we use the same equation as before:

$$\nabla_\theta J(\pi_\theta) = \mathop{\mathbb{E}}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} \nabla_\theta \ln \pi_\theta(a_t|s_t) A^{\pi_\theta}(s_t, a_t)\right]$$

Applications

Ultimately, training in simulation could make other machine learning applications more efficient, speeding up the development of control systems that can be implemented in the real world.

- Self-driving cars
- Reusable rockets
- Complex robotics
- Healthcare treatment

Domain randomization and cross-modal learning can help make virtually trained models more robust.

Questions and Contact Info

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- Happy Birthday, Mom!