Hyperparameter tuning of the PPO algorithm for OpenAI's CarRacing

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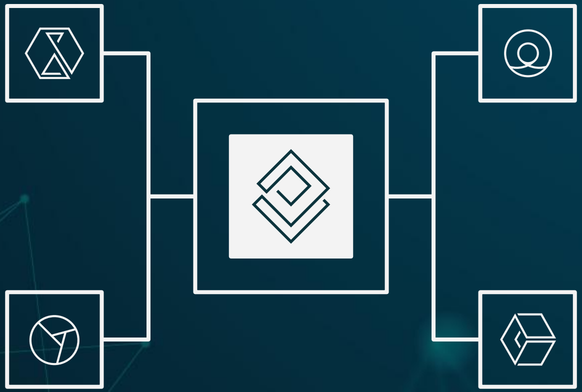
Introduction

Deep Learning & Neural Networks

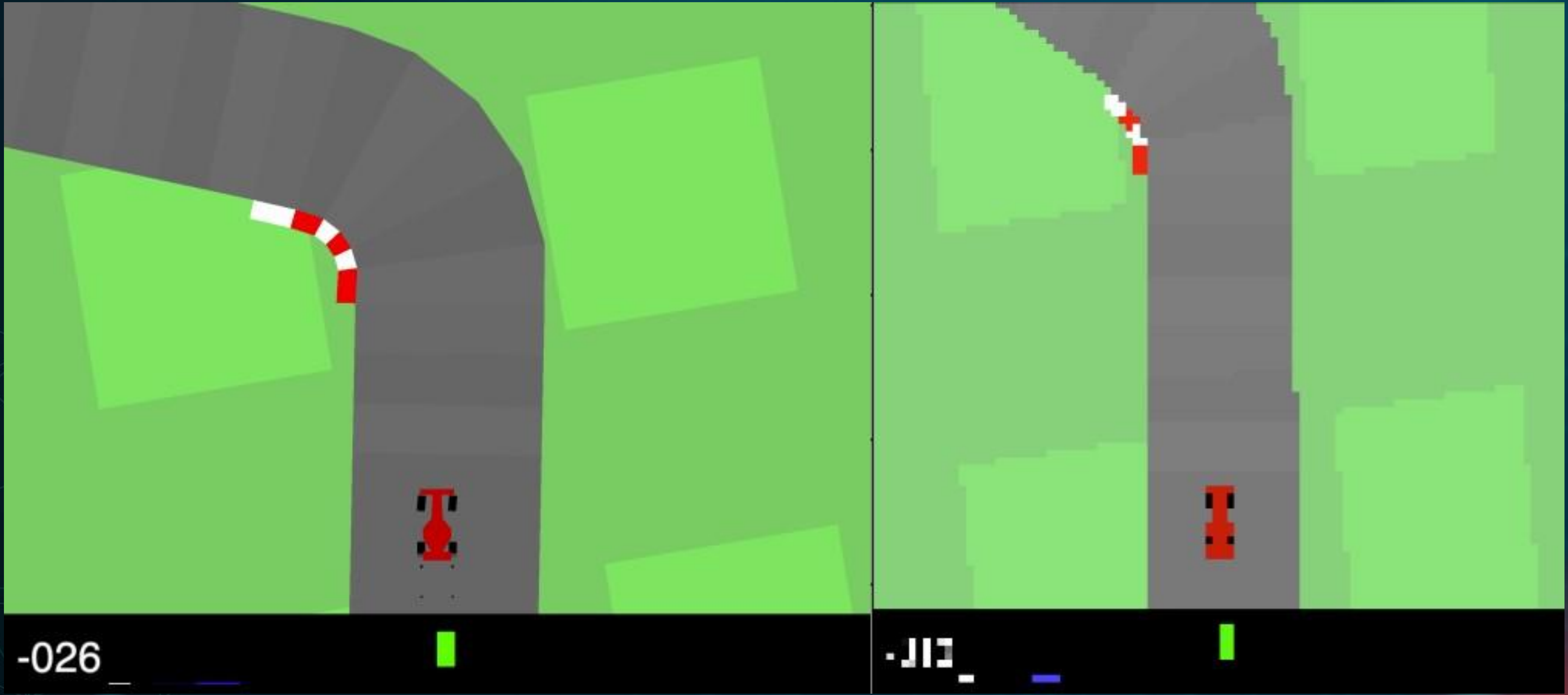
Proximal Policy Optimization



Reinforcement Learning

Autonomous Cars

Car Racing Environment



Left: Render for humans

Right: 96x96 render for agents

Car Racing Environment

- **Action Space**
  - Continuous - There are 3 actions: steering (-1 is full left, +1 is full right), throttle, and breaking
  - Real world physics
- **Observation Space**
  - Image 96x96x3 RGB
- **Reward**
  - -0.1 for every frame
  - +1000/N for every track tile visited. N is the total number of tiles visited in the track.
  - Aims = stay on track & go as fast as possible
  - 900 score is a solved environment

Proximal Policy Optimization Algorithm (PPO)

- **Stable Baseline**
- **Usable for discrete & continuous action spaces**
- **Minimizes loss → maximizes reward**
- **Policy Gradient method**
- **Proximal**
  - Stay close to previous policy
    - Stability
    - Avoid overfitting
    - Improve performance

Policy Gradient Methods

- **Learn Online** (difference from DQN)
- **Do not store past experiences in a replay buffer**
  - Learn directly after each episode
  - Once a memory is used it is discarded
- **PG methods = 1 gradient update per data sample**
  - **PPO = multiple epochs of updates from same data sample**
-

Algorithm 1 PPO, Actor-Critic Style

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for iteration$=1,2,\ldots$ **do**
  for actor$=1,2,\ldots,N$ **do**
    Run policy $\pi_{\theta_{\text{old}}}$ in environment for T timesteps
    Compute advantage estimates $\hat{A}_1,\ldots,\hat{A}_T$
  end for
  Optimize surrogate L wrt θ, with K epochs and minibatch size $M \leq NT$
  $\theta_{\text{old}} \leftarrow \theta$
end for

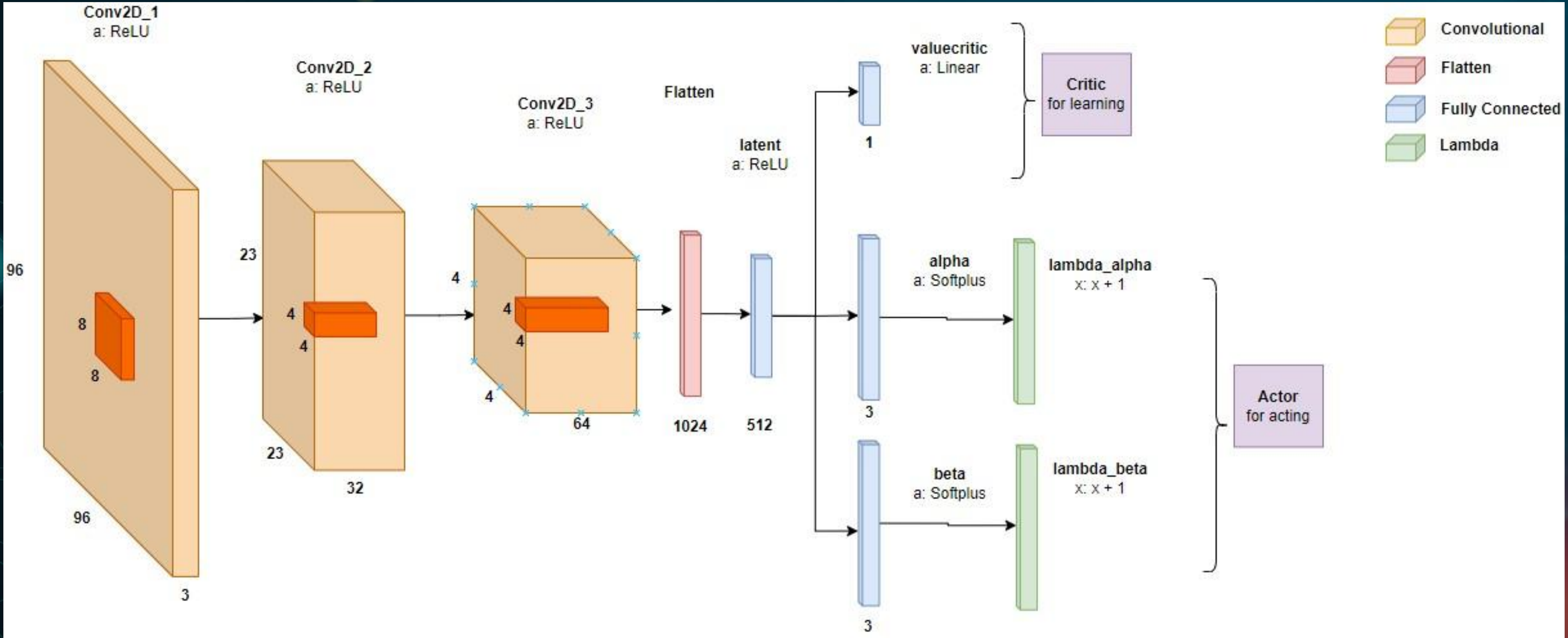
1. **Collect experiences**
2. **Run Gradient Descent on policy network**

Deep Neural Network Structure

- Convolutional Neural Network for image processing
- Actor
  - Estimate actions (using Beta distribution)
- Critic
  - Estimate value of current state

$$f(x, \alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}$$

Deep Neural Network Structure



Hyperparameter Tuning

Initial

Our initial hyperparameters were

$$\begin{aligned} \text{horizon} &= 128 \\ \text{mini-batch size} &= 256 \\ \text{epochs per episode} &= 3 \\ \text{gamma} &= 0.99 \\ \text{clipping range} &= 0.2 \\ \text{gae lambda} &= 0.95 \\ \text{value function coefficient} &= 1 \\ \text{entropy coefficient} &= 0.01 \\ \text{learning rate} &= 2.5e{-4} \end{aligned}$$

Experience Collection

Horizon

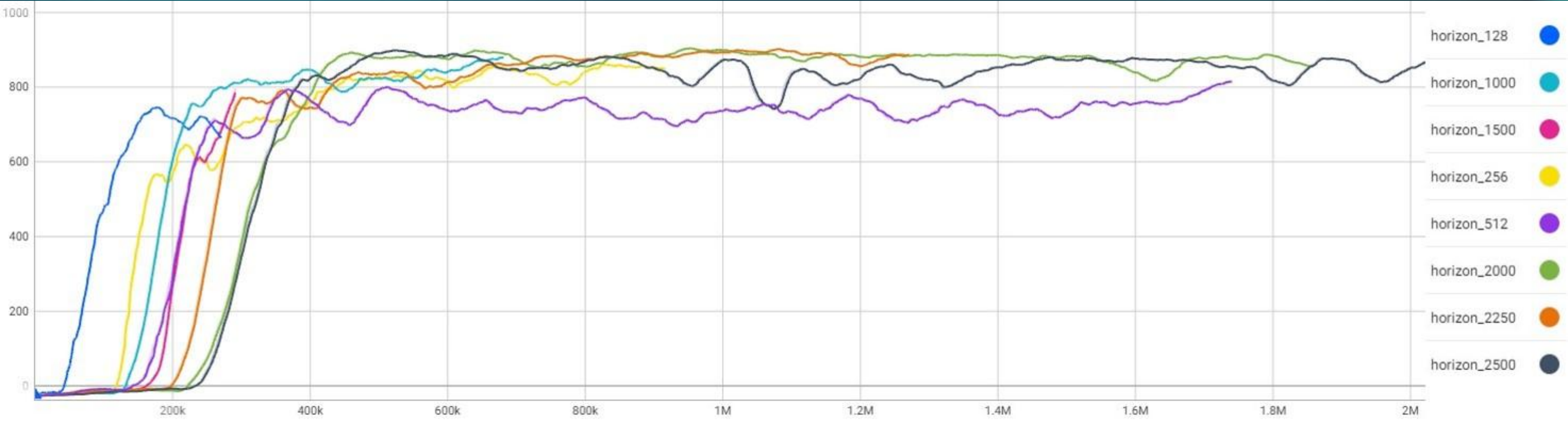
Mini-batch size

Epochs

Horizon (2250)

= The number of steps in each episode

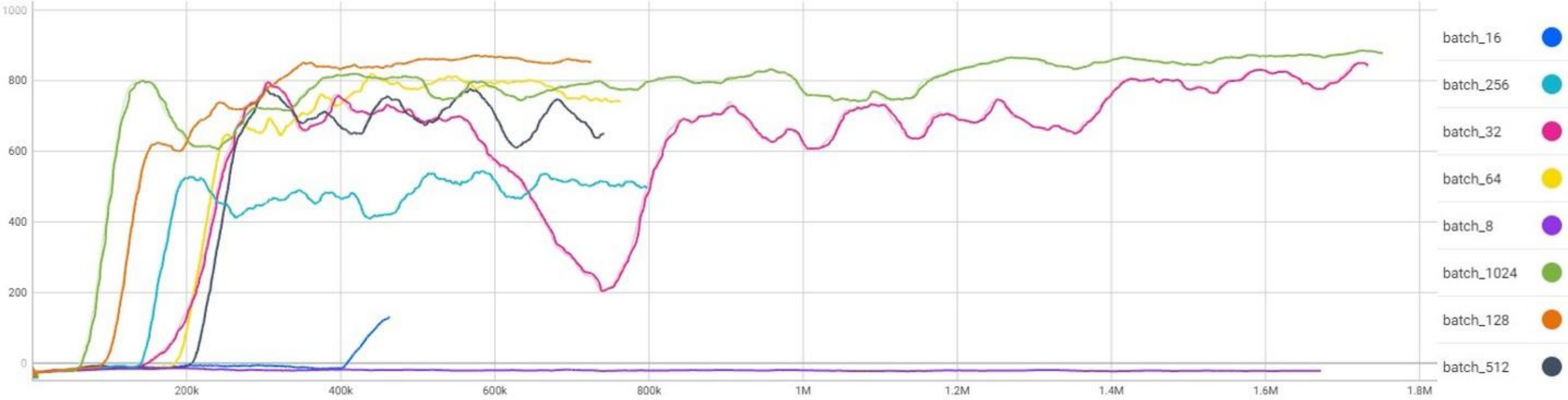
- **Low horizon**
  - Car explores only start of track
  - Learns track in smaller sections
- **High horizon**
  - Car explores turns before it knows how to drive
  - Longer initial training time



Mini-batch size (1024)

= **We optimize using gradient descent using a single batch of experiences at one time.**

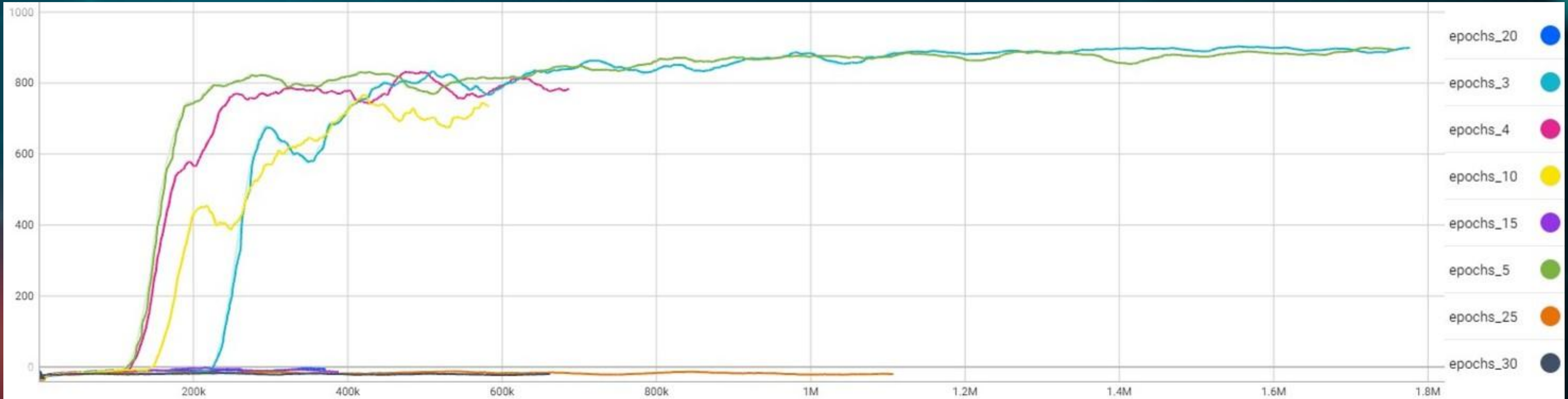
- **Small**
  - Noisy = regularizing effect, lowers generalization error
  - Fits into memory



Epochs (3)

= One cycle through the full training dataset

- **Lot of epochs**
  - overfitting



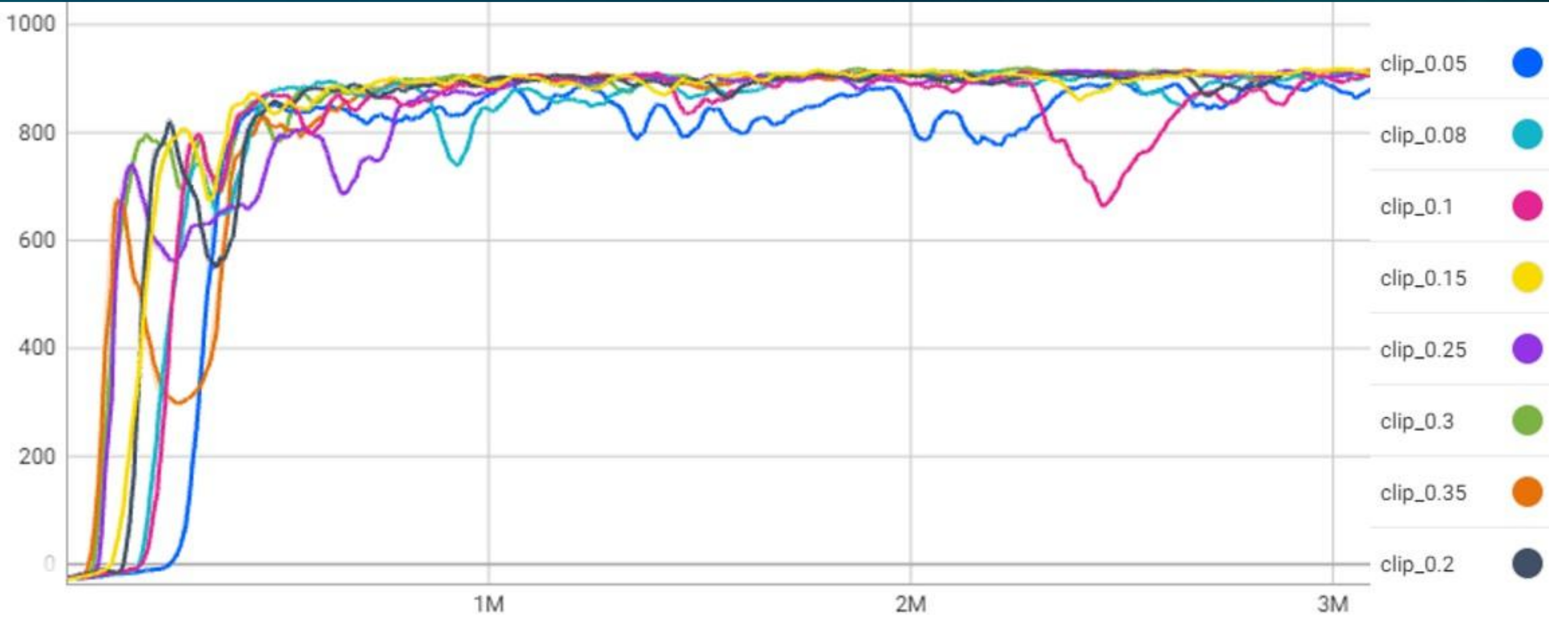
Policy Updating

Clipping Range

Gamma

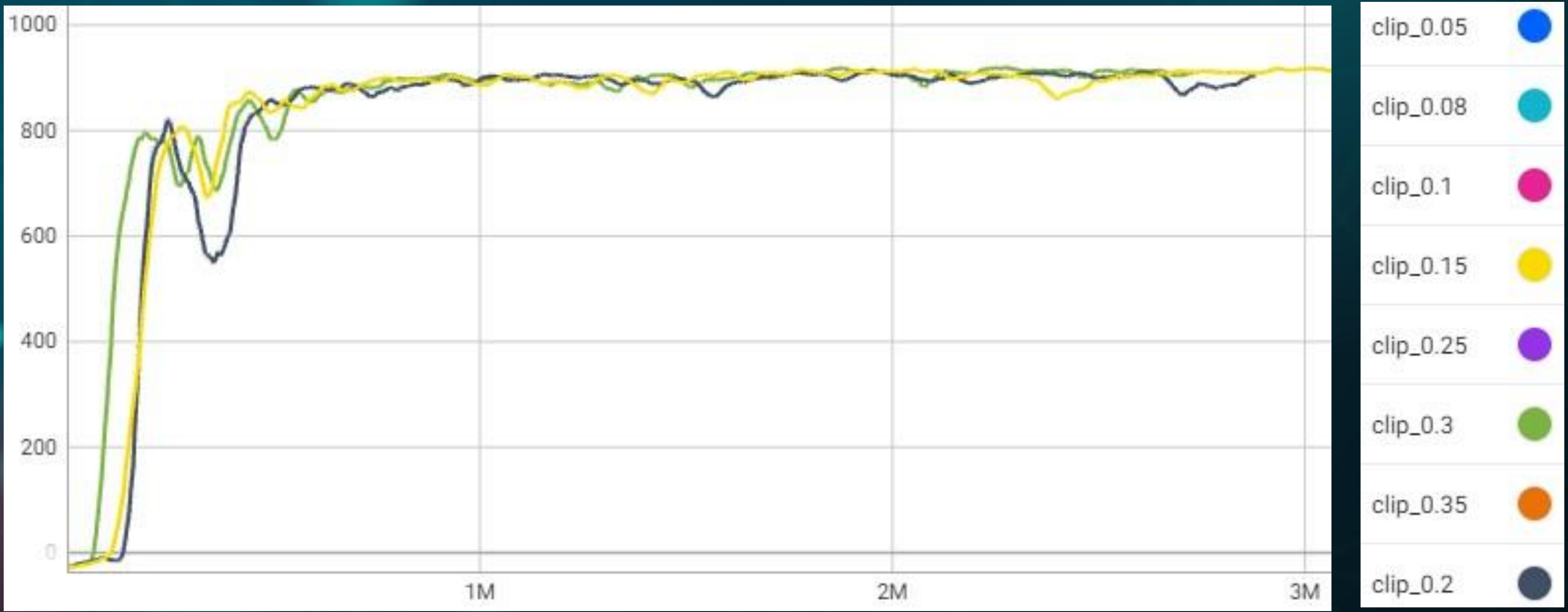
GAE Lambda

Clipping range



Clipping range (0.15)

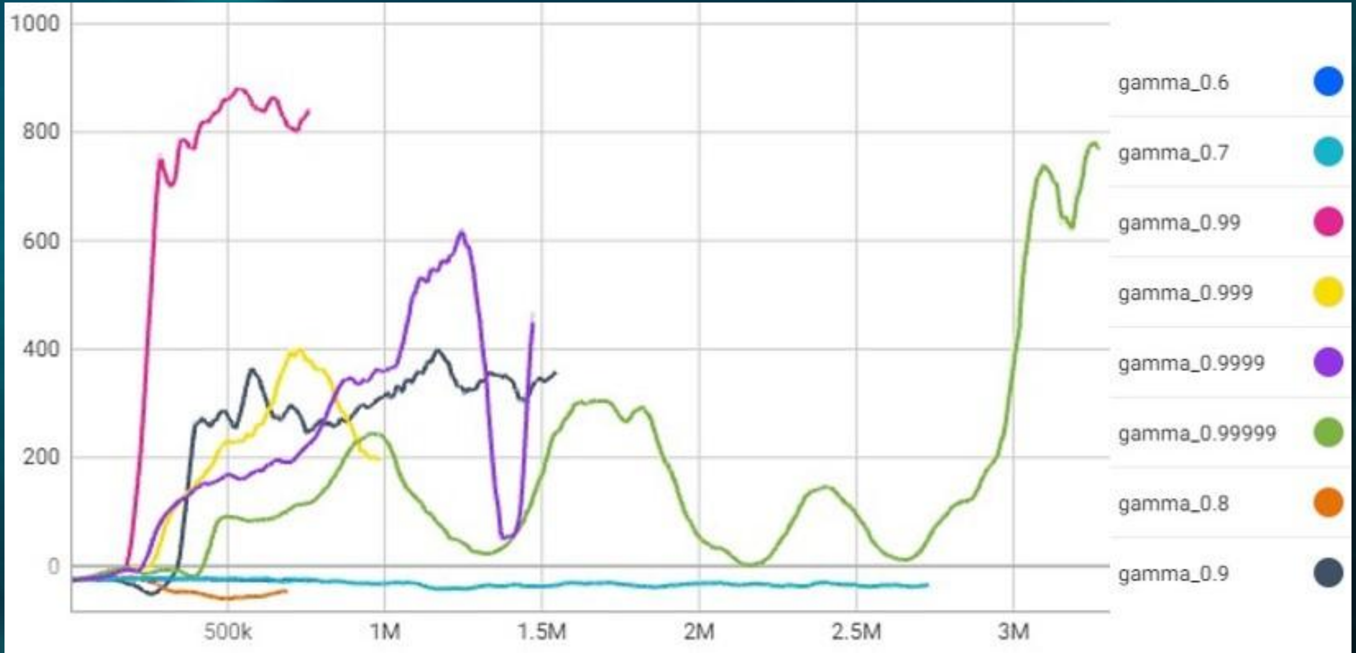
the higher the clipping range, the larger the policy update can be done, which could result in a drastic change in the policy.
To keep the policy stable, a smaller number is often used



Gamma (0.99)

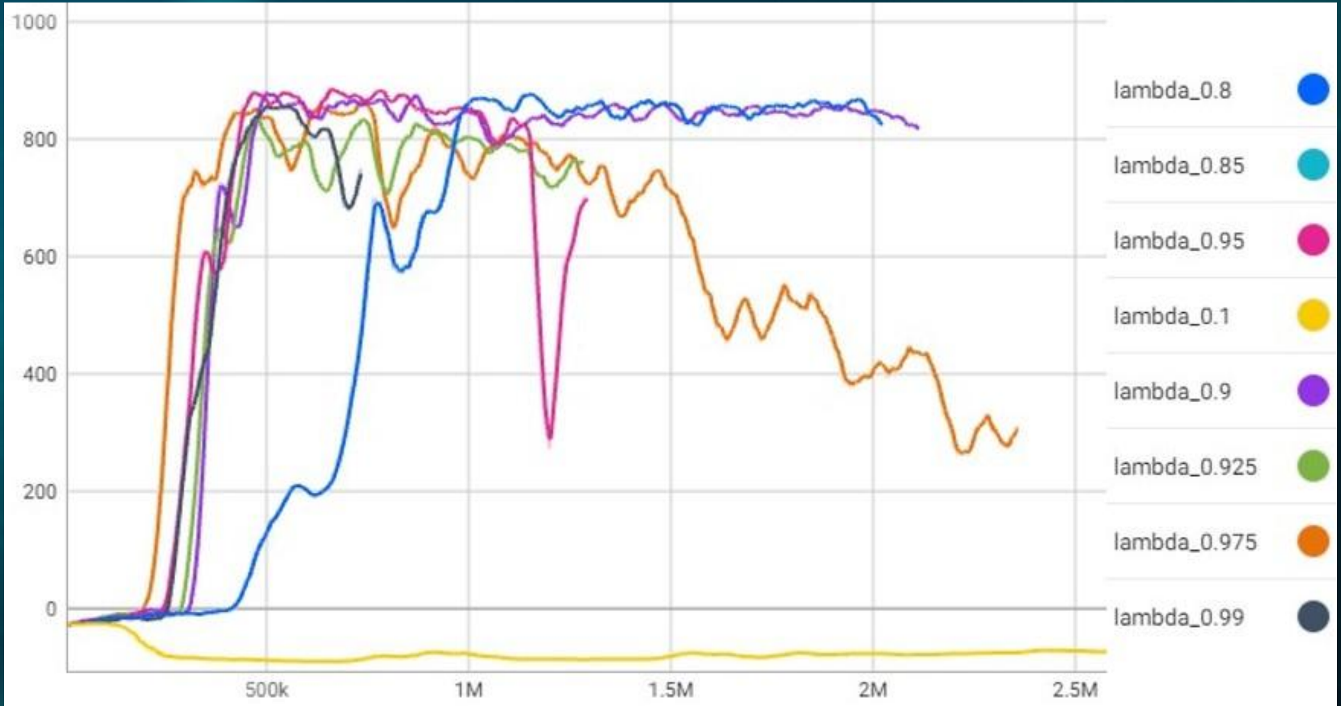
Our agent prefers rewards that it will receive now rather than the same reward further down the line

If we have gamma=0.9, the reward in 6 steps is half as important as the immediate reward, whereas, with gamma=0.99, the reward in 60 steps is half as important as the immediate reward.



GAE Lambda (0.9)

If you want to have a smoother training curve corresponding to training being more stable, choose a λ close to zero. A number close to zero means high bias and low variance, while a number close to 1 means the opposite.



Loss function coefficients

C1

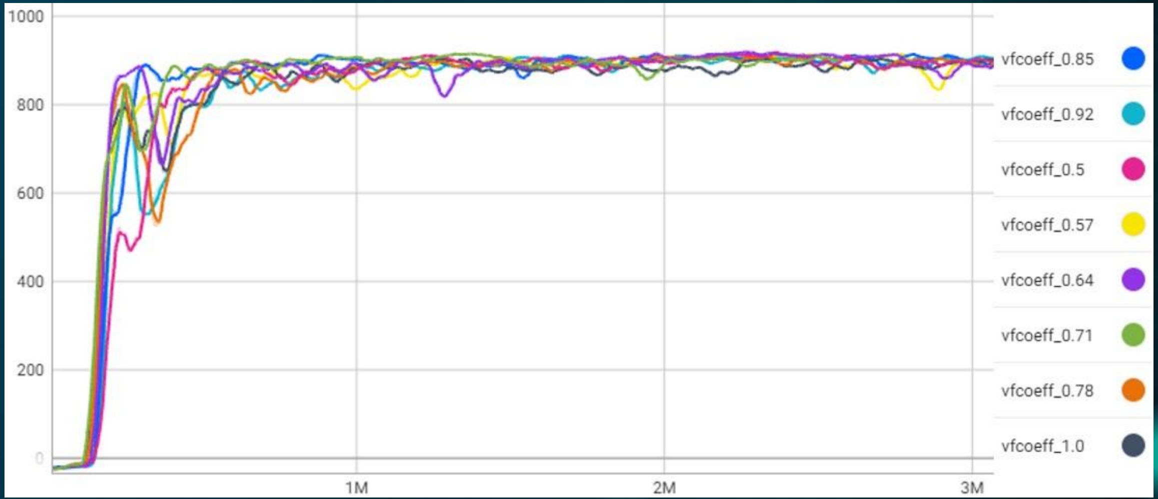
Value Function Coefficient

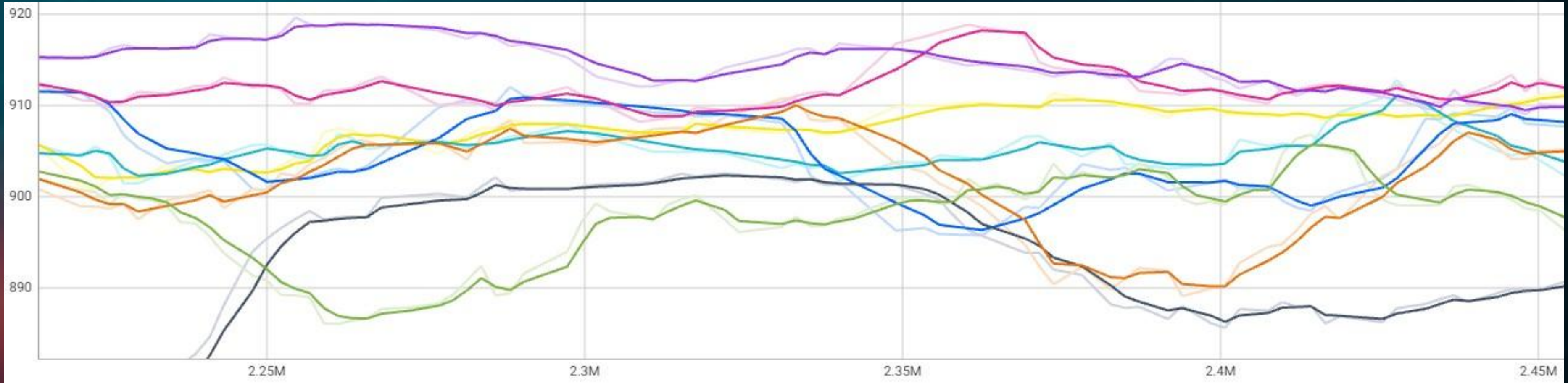
C2

Entropy Coefficient

Value Function Coefficient (0.64)

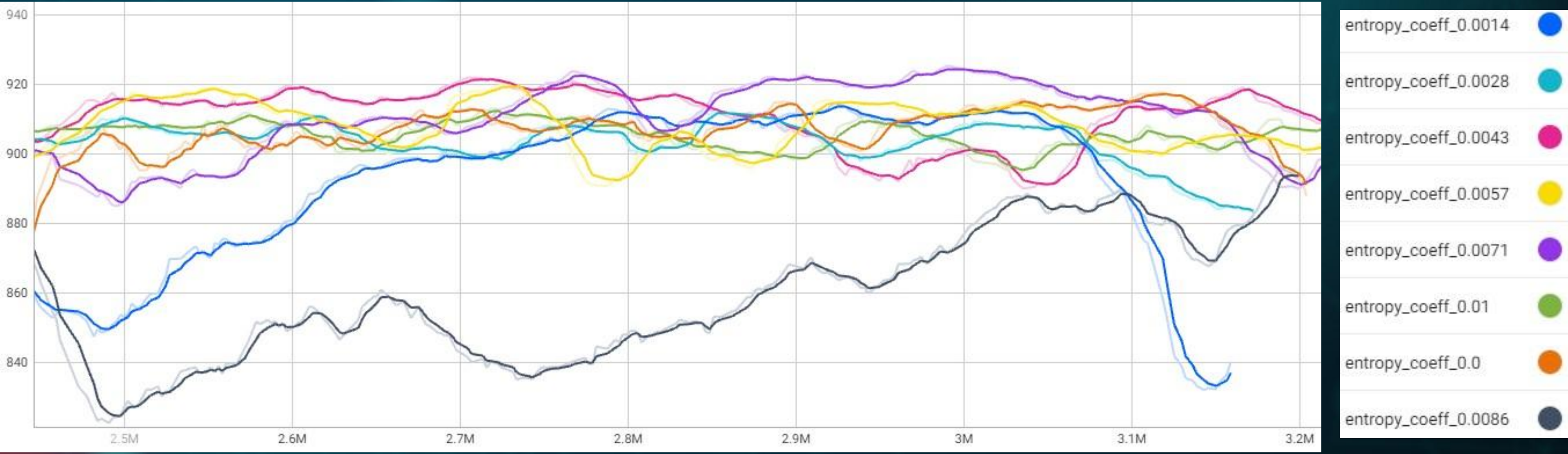
It decides how influential should our prediction, of the value of a state, be.





Entropy Coefficient (0.0071)

helps prevent premature dominance of one action probability over the policy which could prevent exploration. A policy has minimum entropy when a single action has an overly dominant probability.



General

Optimizer learning rate

Terminating Condition

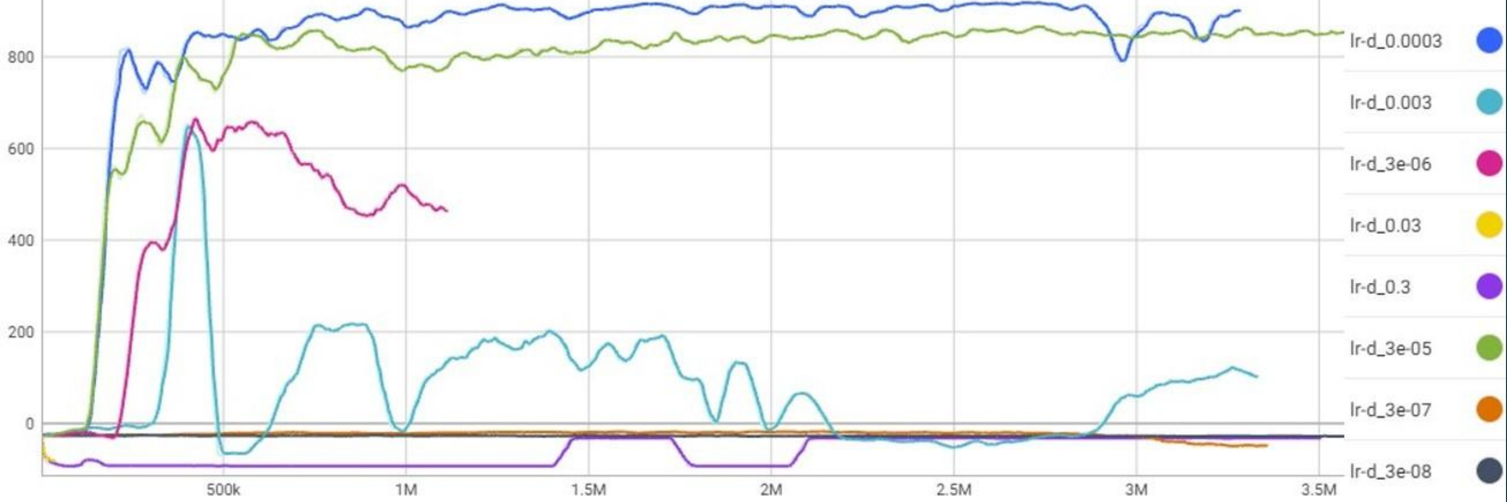
Optimizer Learning Rate (0.0003)

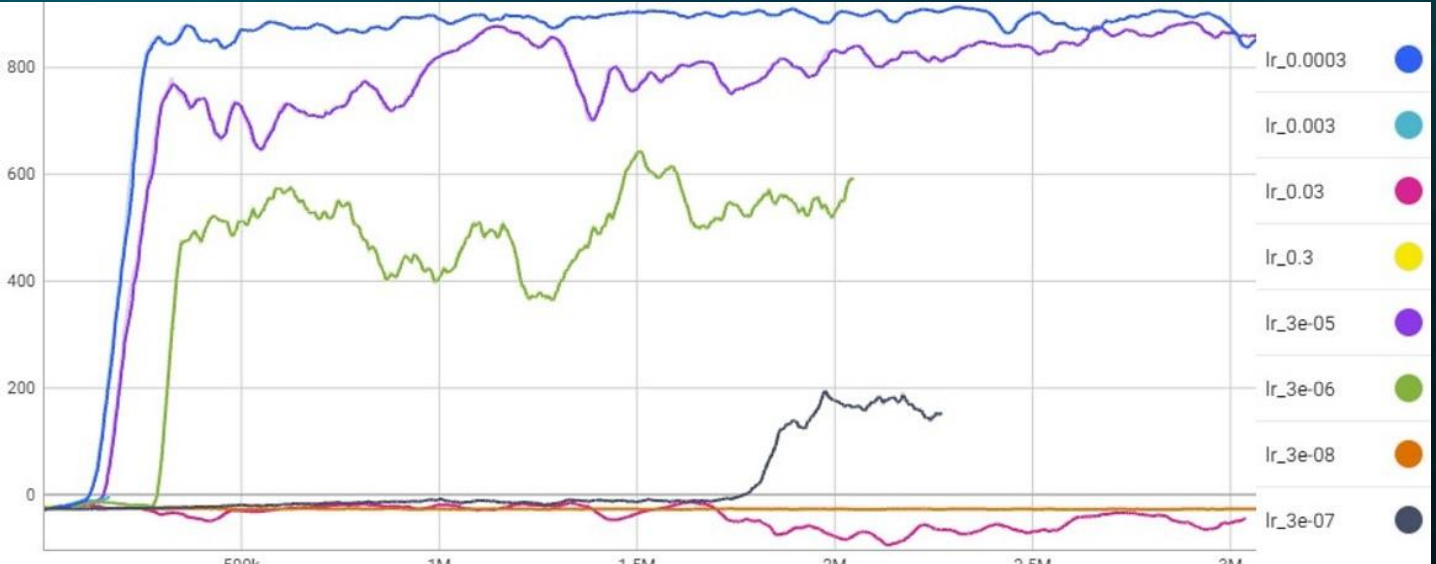
= how large of an impact should the optimizer have during a single update.

- **For our experiment we chose the Adam optimizer**
- **Discounted VS constant learning rate**
- **Discounted changes after each episode**
    - a discounted learning rate we multiplied the initial learning rate by a decreasing number $\left(1 - \frac{\text{current episode number}}{\text{final episode number}}\right)$ which fell linearly from 1 to 0

beginning of training = useful to explore and be able to escape some local minima.

Somewhat good agent = much less desirable to change the policy significantly in a single update.


800
600
400
200
0
500k
1M
1.5M
2M
2.5M
3M
3.5M
lr-d_0.0003
lr-d_0.003
lr-d_3e-06
lr-d_0.03
lr-d_0.3
lr-d_3e-05
lr-d_3e-07
lr-d_3e-08


800
600
400
200
0
lr_0.0003
lr_0.003
lr_0.03
lr_0.3
lr_3e-05
lr_3e-06
lr_3e-08
lr_3e-07

Terminating Condition

- **Environment solving score of 900**
- **We wanted to explore hyperparameters = run as long as possible**
    - **Placeholder 4000 episodes**
        - Because of hardware used

Conclusion

- Deep Reinforcement Learning, Proximal Policy Optimization
- Car Racing - Real life physics, continuous
- 10 Hyperparameters
  - Different impacts on score
  - Explainable occurrences on training graphs
- Environment solved (gained over 900 score)
- Further projects
  - Autonomous driving in more challenging environments
  - Modified CarRacing-v2
    - Wind, obstacles ...

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