Hypernetwork-PPO for Continual Reinforcement Learning

Final Presentation

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2022-09-29

Continual Reinforcement Learning

- Reinforcement Learning
  - Learn by interacting with an environment + getting rewards
  - Unsupervised - no training data, just an environment

Continual Reinforcement Learning

- Reinforcement Learning
  - Learn by interacting with an environment + getting rewards
  - Unsupervised - no training data, just an environment
- Continual
  - Learn multiple tasks sequentially
  - Cannot revisit old environment when learning new tasks
  - Do not forget old skills
  - Still a major issue in machine learning[2]

Proximal Policy Optimization

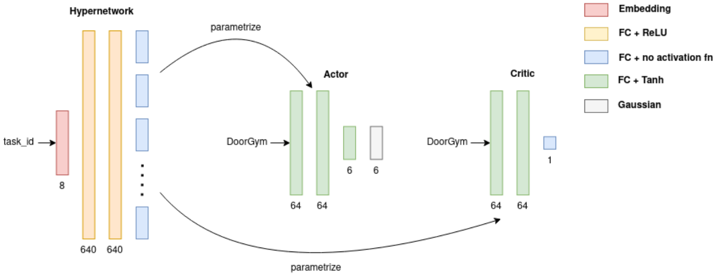
- On-line RL algorithm
- Objective is a "clipped" loss - discourages large, detrimental changes[3]

$$L_t^{clip}(\theta) = \mathbb{E}_t \left[min \left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \hat{A}_t, clip \left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}, 1+\epsilon, 1-\epsilon \right) \hat{A}_t \right) \right]$$

- Additional loss components
  - state value
  - entropy bonus

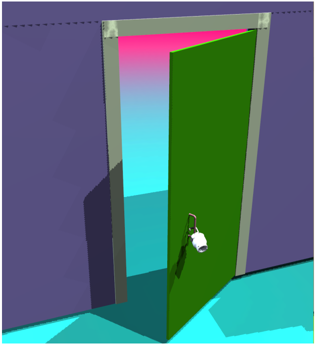
Hypernetworks

- Network that outputs a network[5]
- Task ID as input
- Target networks determine policy/dynamics
- Regularization on changes of outputs for old tasks



DoorGym

- Based on OpenAI Gym[1]
- Robot arms try to open doors
- Multiple handles, opening directions
- Our experiments
  - "Floating hook" robot
  - 6 different kinds of doors

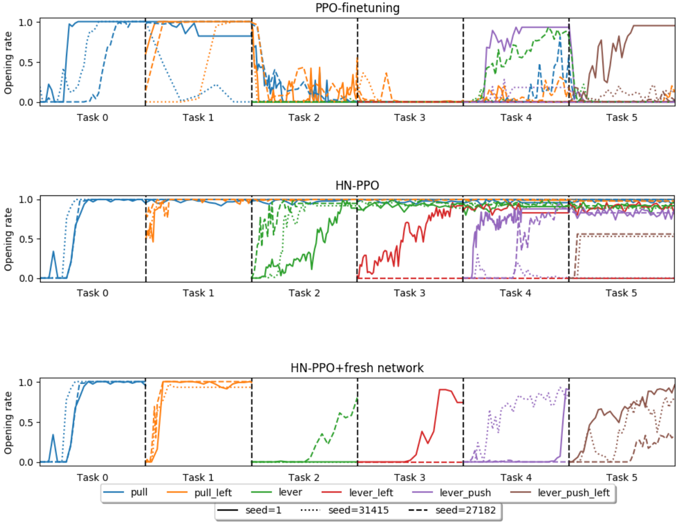


DoorGym world: `pull` handle, right hinge

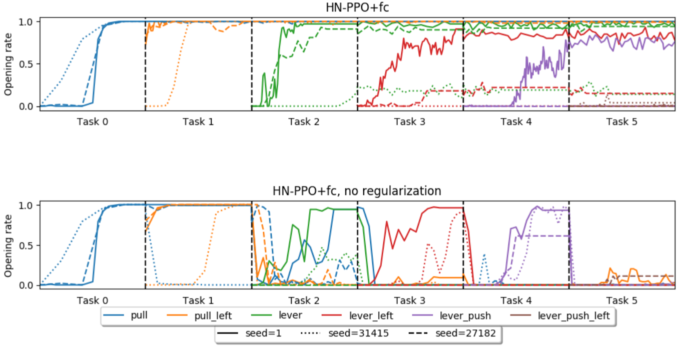
Experiments

- Baselines
  - PPO (pre-implemented in DoorGym)[4]
  - PPO-finetuning
  - HN-PPO with fresh networks for each task
- 2 hypernetwork architectures
  - HN-PPO
  - HN-PPO with fresh critic
- Ablation Study: HN-PPO without regularization

HN-PPO protects against catastrophic forgetting



HN regularization is required for CL performance



DoorGym demo

Conclusion

- HN-PPO is very effective against catastrophic forgetting
- Single-task success rate comparable to PPO
- Regularization crucial for HN-PPO's CL capability
- Limitations
  - Seed dependence
  - Checkpoint dependence

References

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