Hypernetwork-PPO for Continual Reinforcement Learning

Final Presentation

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Continual Reinforcement Learning

- Reinforcement Learning
  - Learn by interacting with an environment + getting rewards
  - Training data collected from environment

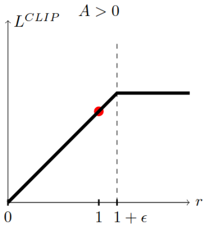
Continual Reinforcement Learning

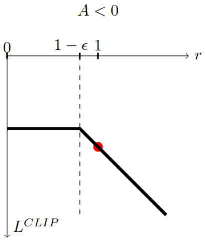
- Reinforcement Learning
  - Learn by interacting with an environment + getting rewards
  - Training data collected from environment
- Continual
  - Learn multiple tasks sequentially
  - Cannot revisit old environment when learning new tasks
  - Do not forget old skills
  - Still a major issue in machine learning

Proximal Policy Optimization

- On-policy, model free RL algorithm
- Objective is a "clipped" loss - discourages large, detrimental changes

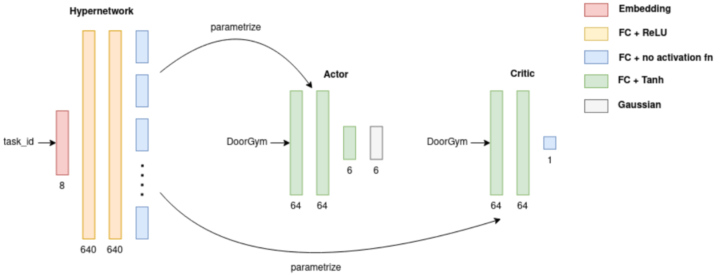
$$L_t^{clip}(\theta) = \mathbb{E}_t\left[min\left(r_t(\theta)\hat{A}_t, clip\left(r_t(\theta), 1+\epsilon, 1-\epsilon\right)\hat{A}_t\right)\right]$$





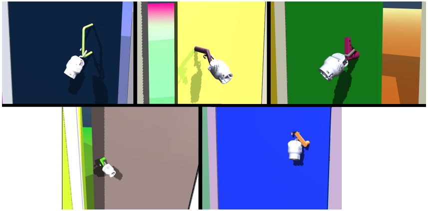
Hypernetworks

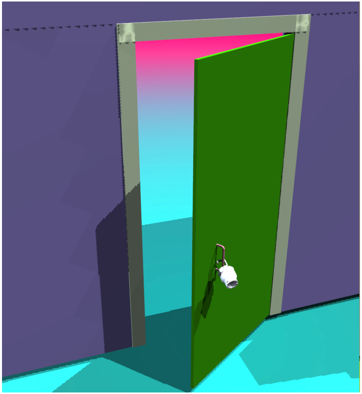
- Network that outputs a network
- Task ID as input
- Target networks determine policy/dynamics
- Regularization on changes of outputs for old tasks



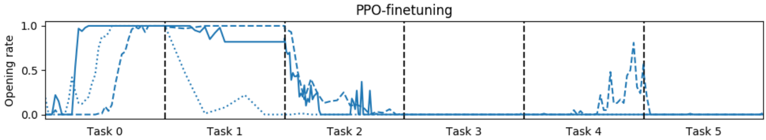
DoorGym

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





HN-PPO protects against catastrophic forgetting



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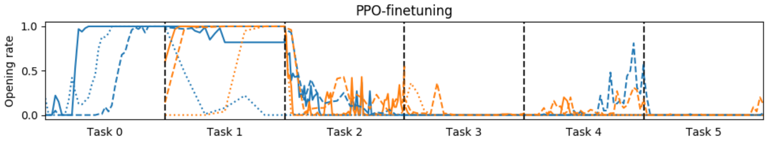

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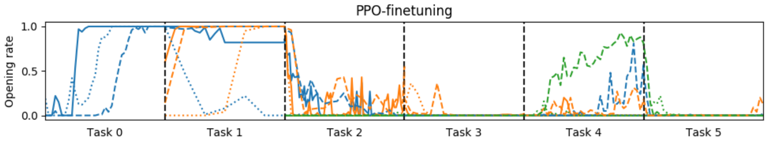

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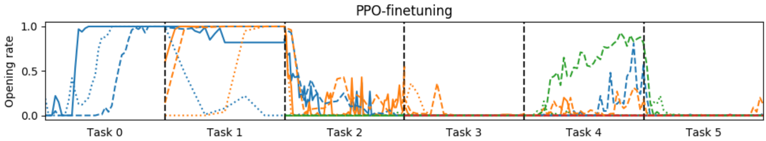

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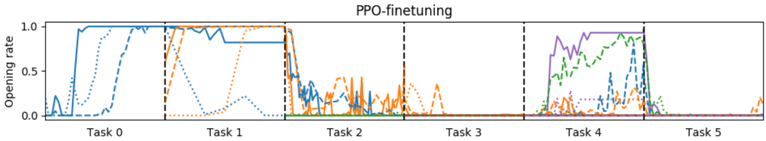

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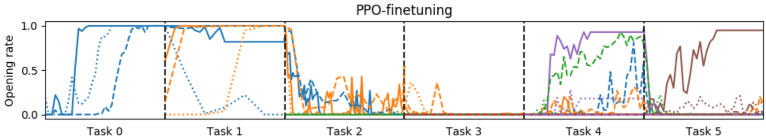

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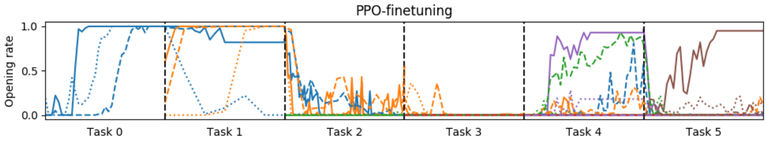

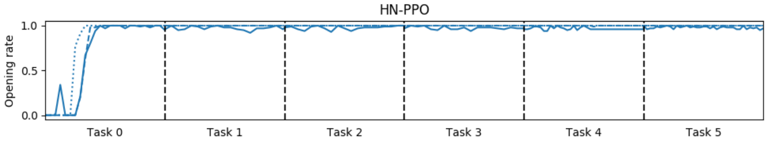

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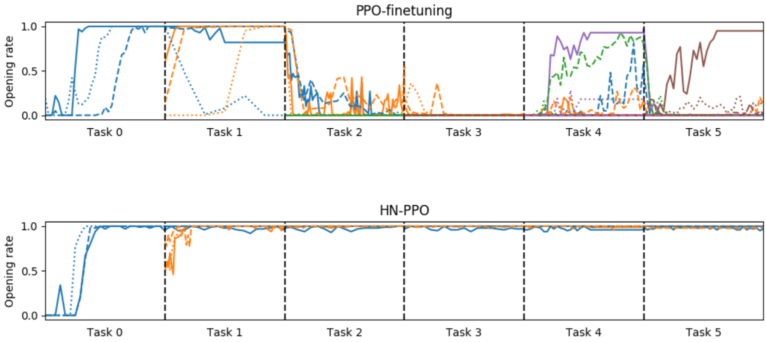

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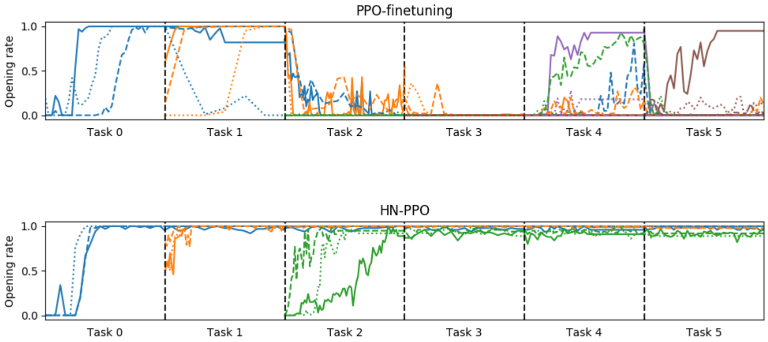

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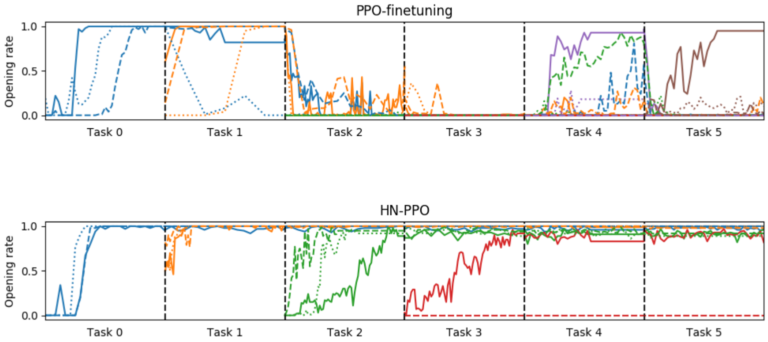

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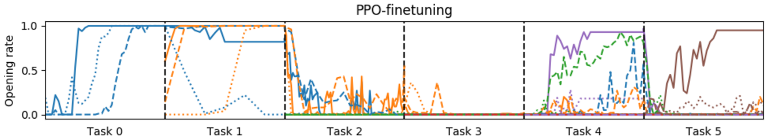

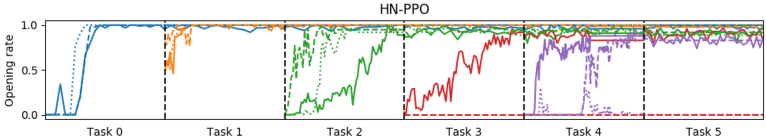

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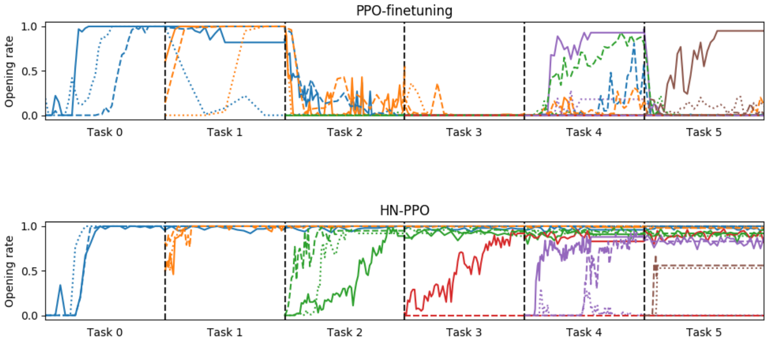
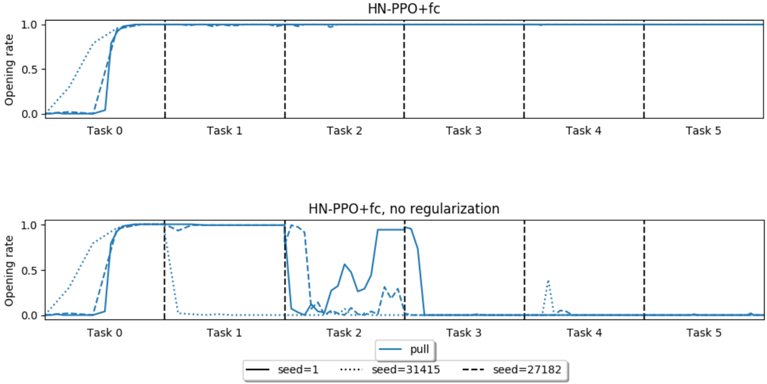


HN-PPO protects against catastrophic forgetting

Metric	PPO-finetuning	HN-PPO
Accuracy	0.20 ± 0.035	$\mathbf{0.81} \pm 0.041$
Remembering	0.47 ± 0.060	$\mathbf{1.00} \pm 0.0024$

HN regularization is required for CL performance



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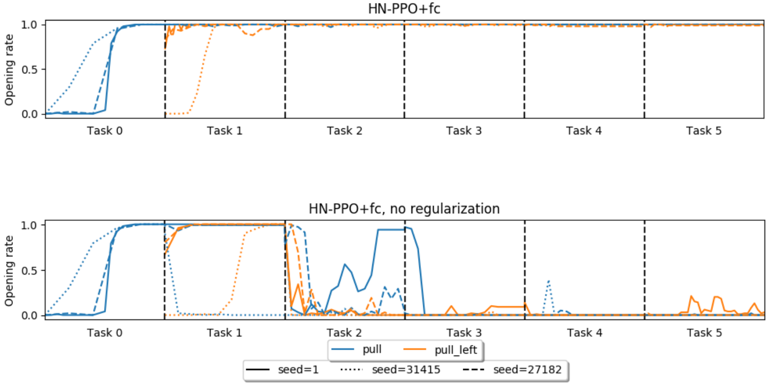

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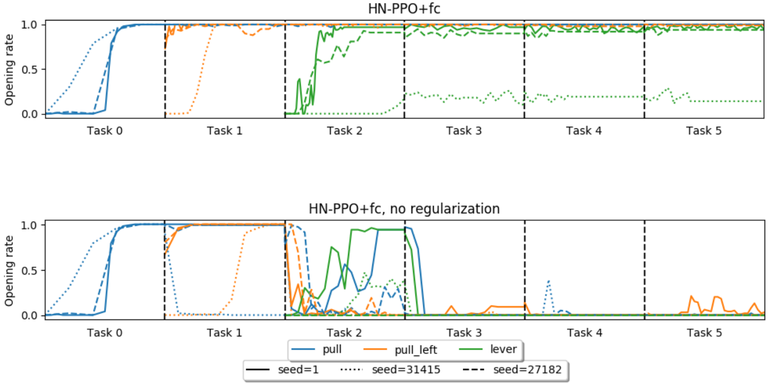

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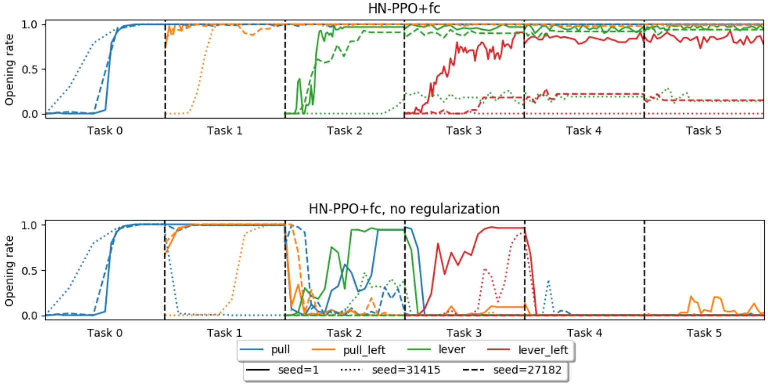

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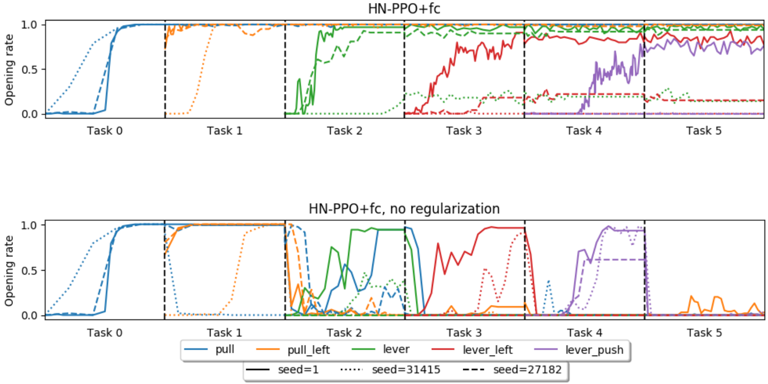

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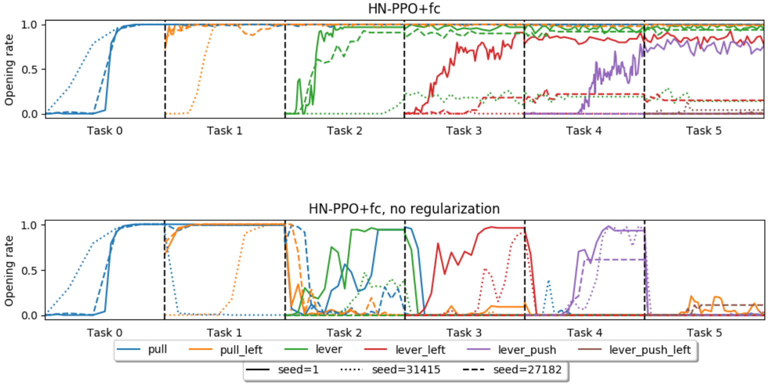
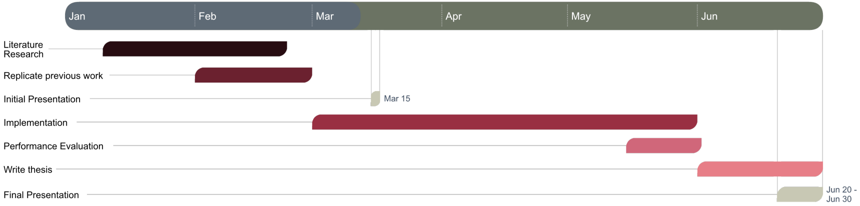


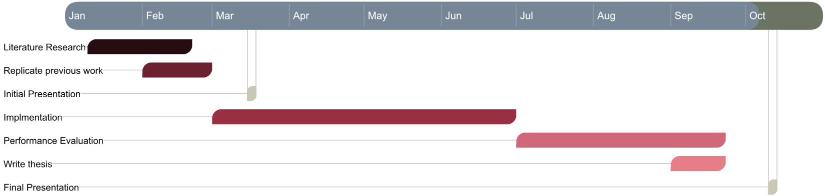
DoorGym demo

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
  - Previous task checkpoint dependence

Timeline


Jan
Feb
Mar
Apr
May
Jun
Literature Research
Replicate previous work
Initial Presentation
Mar 15
Implementation
Performance Evaluation
Write thesis
Final Presentation
Jun 20 - Jun 30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