Interpretable Hierarchical Reinforcement Learning

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Hierarchical Reinforcement Learning

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- In real world, many many tasks have sub-parts which may be reused for other tasks.
- Hierarchical Learning intends to solve this by learning different sub-parts independently and having a master choose the sub-policy to be activated.

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- We propose solution based on hierarchical learning methods that include a goal specific master policy and generic sub policies
- We also maintain interpretability in regards to the sub-policies activated for different tasks/goals

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- This approach requires the environment to be complex enough to have multiple near optimal ways of solving a task

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  - Joint Update: Optimise both the shared and task specific parameters to obtain optimal values for shared sub policies ϕ_k

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- After learning a set of optimal sub policies, the model can generalise to new unseen tasks by using only warmup period updates

Meta Learning Shared Hierarchies

Algorithm 1 Meta Learning Shared Hierarchies

Initialize ϕ
repeat
  Initialize θ
  Sample task $M \sim P_M$
  for $w = 0, 1, ...W$ (warmup period) **do**
    Collect D timesteps of experience using $\pi_{\phi,\theta}$
    Update θ to maximize expected return from $1/N$ timescale viewpoint
  end for
  for $u = 0, 1, ...U$ (joint update period) **do**
    Collect D timesteps of experience using $\pi_{\phi,\theta}$
    Update θ to maximize expected return from $1/N$ timescale viewpoint
    Update ϕ to maximize expected return from full timescale viewpoint
  end for
until convergence

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  - Obtain embedding vectors $\phi(\hat{s})$ and $\psi(\hat{g})$ by performing matrix factorization of the sparsely filled value function table $V_g(s)$
  - Solve the regression problems: Map the state/goal to its target embedding i.e. state s to $\phi(\hat{s})$ and the goal g to $\psi(\hat{g})$.

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- Mutual Information Maximisation is approximate via the reconstruction loss due to the Posterior Network
- An additional reward is included: Planner Reward that assists the master network to learn a simpler relation between the goals and the latent code

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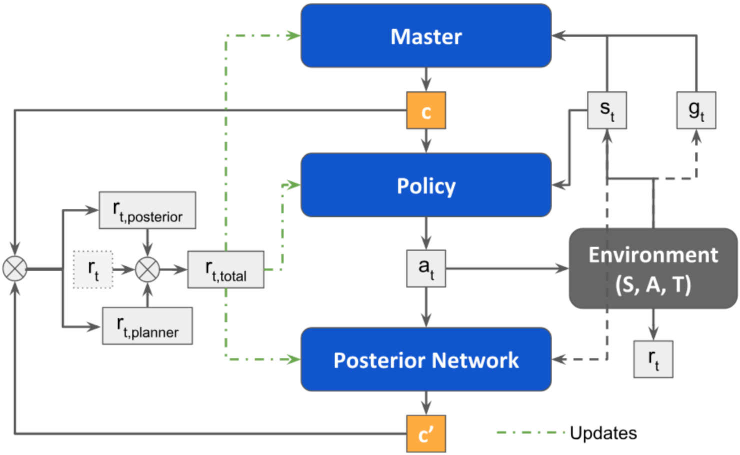

Architecture

Algorithm 1: Interpretable Hierarchical Reinforcement Learning

initialize master(ϕ_m), policy(π_θ), and posterior(ϕ_p);
repeat
- sample goal $g \sim \mathbb{G}_T$;
- $s \sim S_0$;
- c $\sim$ master_network(s, g);
- **repeat**
  - sample trajectories $\tau, s, r \sim \pi_\theta(c, s)$;
  - sample state action pairs $\xi \sim \tau$;
  - $c' \sim \phi_p(\xi)$;
  - $r = r + posterior\_reward(c, c')$;
  - update_policy(r);
  - update_master(r);
  - update_posterior(c, c');
- **until** *convergence*;

until *N times*;

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- Planner reward is added that penalises the master network for too much variance in the set of latent codes generated for the whole episode
- Both master and the policy networks choose actions at the same frequency

Environment

- 10x10 grid environment, with chooseble multiple goals.

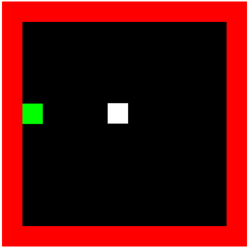

Figure: Grid Env
Green – Goal, White – Initialization

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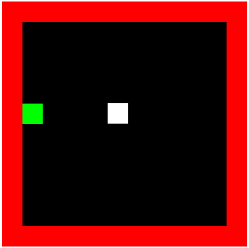
- 4 actions (U, D, L, R) allowed.



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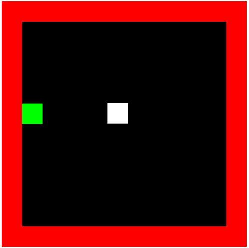

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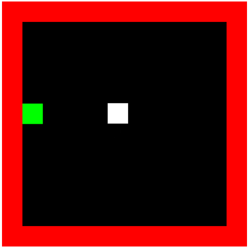
- +1 reward for getting to the goal, -1 for dying, in addition to small dense rewards.



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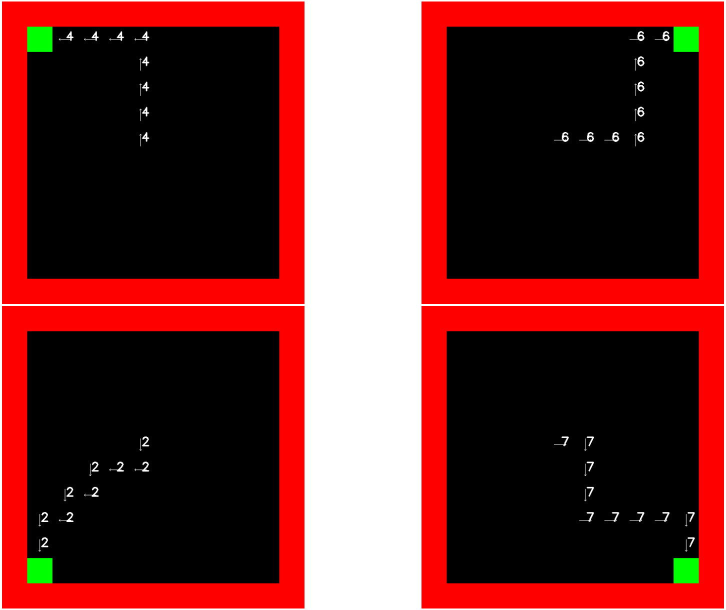
Results for training on 8 goals



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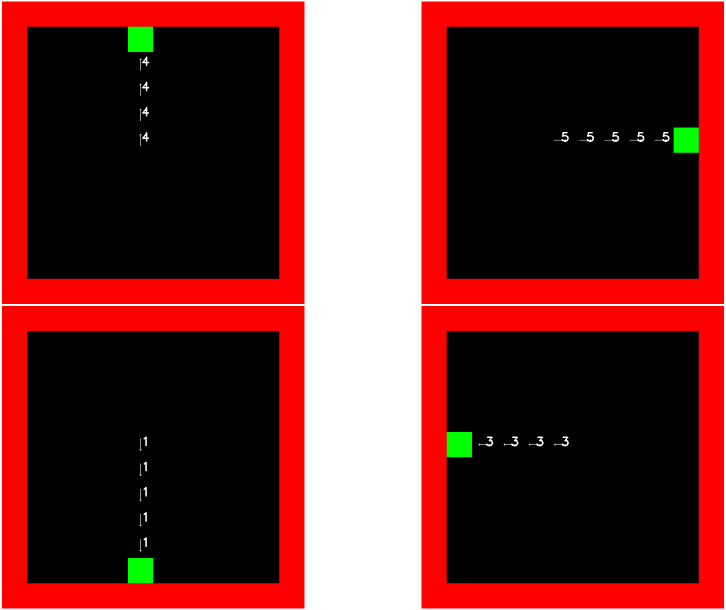
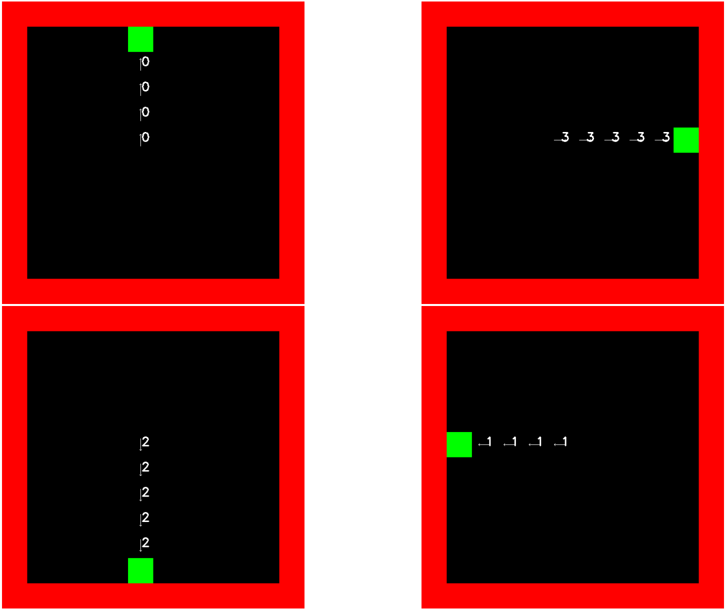


Results for training on 4 goals



Generalization Results after training on 8 goals

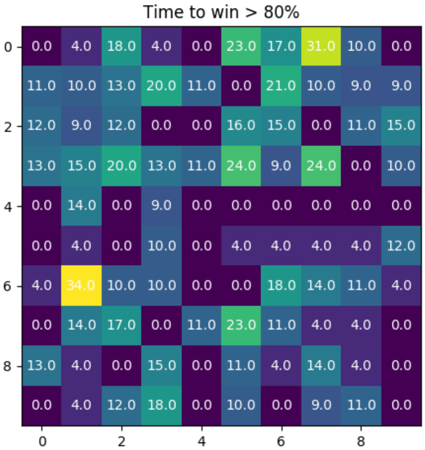


Figure: Generalization Update Steps

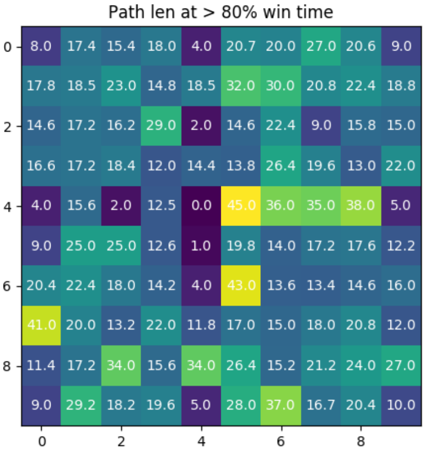


Figure: Generalization Path Length

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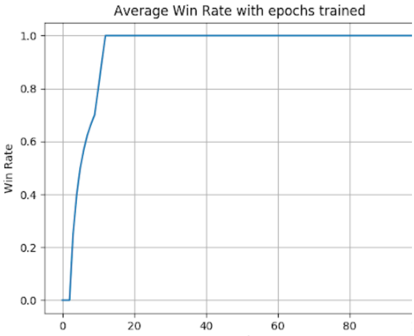
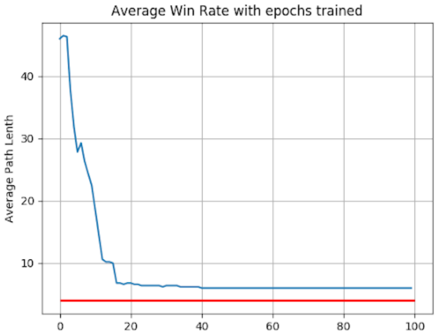


Figure: Fine-tuning time average win rate for goal(2, 2)



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- Figure 3 shows that the network does not randomly reach the goal, instead it targets the goal, though for most of the goals, the number of steps taken is larger than the optimal number.
- The results can be further improved by the use of matrix factorization techniques on the value function.

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- Test our approach in complex environments where the dynamics change and our approach generalises to new dynamics
- Compare our approach with some baseline methods like UVFA for the generalisation part

Thank You