Attend, Adapt and Transfer: Attentive Deep Architecture for Adaptive Transfer from multiple sources in the same domain

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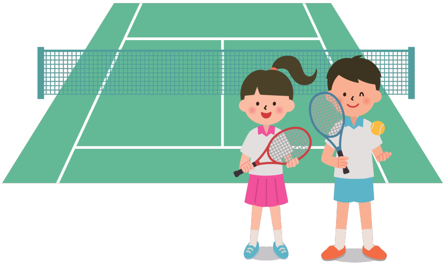
Outline

Knowledge Transfer



Knowledge Transfer

- N source tasks with $K_1, K_2, ..., K_N$ being the solutions of the source tasks (e.g. tennis coaches)
- K_B is the base solution for the target task which starts learning from scratch (tennis student's initial knowledge)
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This paper: Using combination of the solutions to obtain K_T

$$K_T(s) = w_{N+1,s} K_B(s) + \sum_{i=1}^{N} w_{i,s} K_i(s) \tag{1}$$

$w_{i,s}$ is the weight of solution i at state s (learned by a separate network)

Attention Network for Selective Transfer (A2T)

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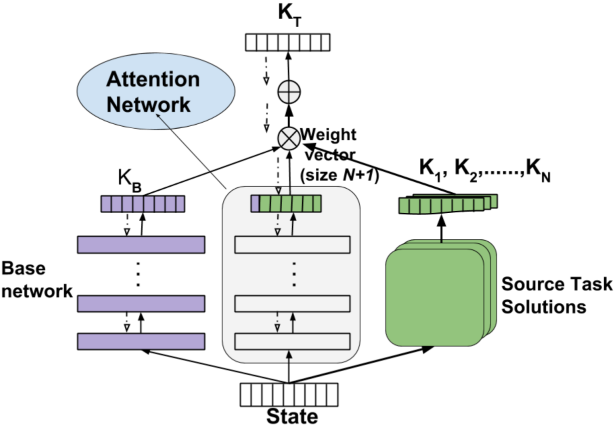

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Background: Reinforcement Learning

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- π: policy function, distribution over actions given states: $\pi(a, s) = \mathbb{P}[A_t = a | S_t = s]$
- $V(s)$: state value function, the expected return of a policy π, for every state: $V_\pi(s) = \mathbb{E}_\pi[R_t | S_t = s]$

Outline

Policy Transfer

- Transferring source task policies
- We have $K_1, ..., K_N, K_B, K_T \leftarrow \pi_i, ..., \pi_N, \pi_B, \pi_T$
- The agent acts in the target task by sampling actions from the target distribution π_T, obtained from:

$$K_T(s) = w_{N+1,s} K_B(s) + \sum_{i=1}^{N} w_{i,s} K_i(s) \tag{1}$$

Policy Transfer using REINFORCE

REINFORCE

Direct policy search by making weight adjustments along the gradient of expected reinforcement.

$$\theta_a \leftarrow \theta_a + \alpha_{\theta_a}(r - b)\frac{\partial \sum_{t=1}^{M} log(\pi_T(s_t, a_t))}{\partial \theta_a} \quad (2)$$

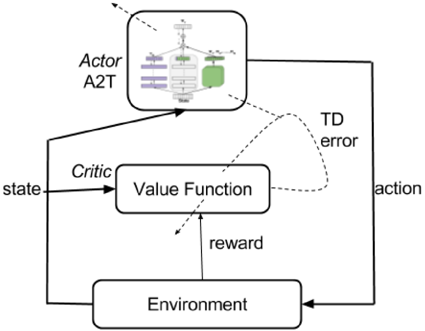
$$\theta_b \leftarrow \theta_b + \alpha_{\theta_b}(r - b)\frac{\partial \sum_{t=1}^{M} log(\pi_B(s_t, a_t))}{\partial \theta_b} \quad (3)$$

where α is learning rate, r is return obtained in the episode, b is a reinforcement baseline, M is the length of the episode

Policy Transfer in Actor-Critic

Actor-Critic

Temporal Difference (TD) method where the actor proposes a policy and the critic estimates the value function to critique the actors policy. The updates to the actor happens through TD-error



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Value Transfer

- Transferring source task's action-value functions (Q functions):

$$Q_\pi(s, a) = \mathbb{E}_\pi[R_t | S_t = s, A_t = a] \tag{4}$$

- The Q function is used to guide the agent to selecting the optimal action a at a state s.

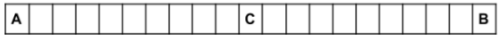
Value Transfer

Q-learning

One way to learn optimal policies for an agent is to estimate the optimal Q(s, a) for the task. Q-learning is an off-policy learning algorithm that estimates the Q function (e.g. using a deep neural net).

Outline

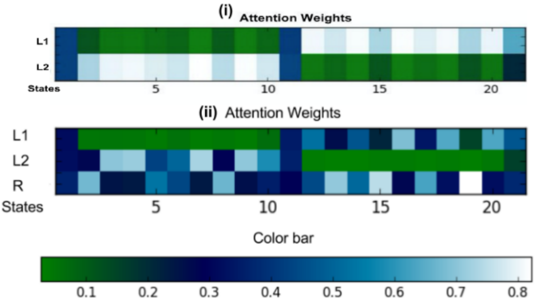
Selective Transfer with Policy Function



(a) Chain World

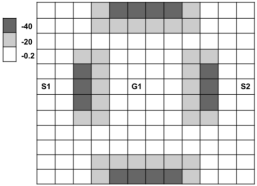
- Task LT is to start in A or B with uniform probability and end up in C in the least number of steps.
- Two source tasks, $L1$ and $L2$ are available. $L1$ has learned to reach A from B and $L2$ has learned to reach B from A.
- Model learns to solve LT using REINFORCE

Selective Transfer with Policy Function



(a) The weights given by the attention network. Selective transfer in REINFORCE

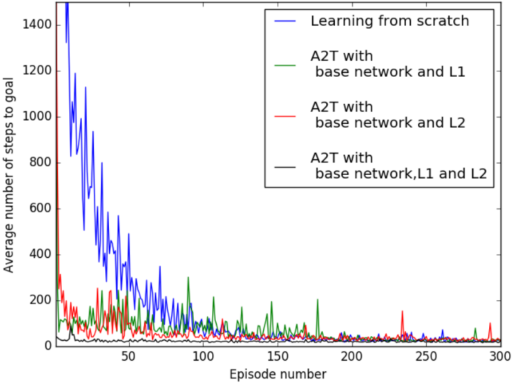
Selective Transfer with Policy Function



(c) Puddle World 2

- Task LT is to start in S1 or S2 and end up in G1 in the least number of steps
- $L1$ has learned to reach G1 from S1 and $L2$ has learned to reach G1 from S2
- Model learns to solve LT using Actor-Critic

Selective Transfer with Policy Function



(b) Selective transfer in Actor-Critic

Selective Transfer with Value Function

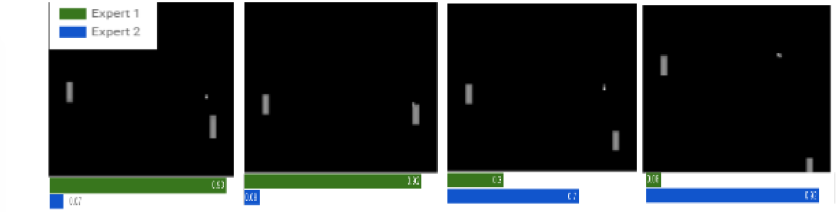


Figure 4: Visualisation of the attention weights in the Selective Transfer with Attention Network

- L1 performs poorly on upper right quadrant
- L2 performs poorly on lower right quadrant

Selective Transfer with Value Function

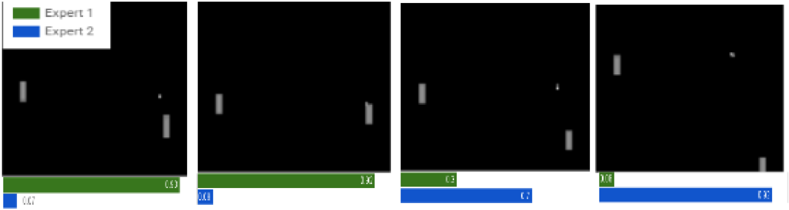
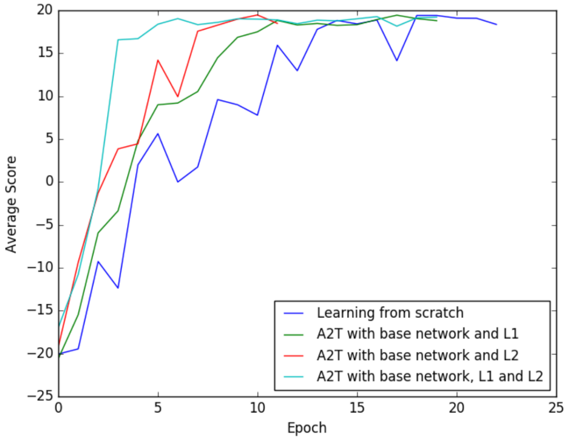


Figure 4: Visualisation of the attention weights in the Selective Transfer with Attention Network

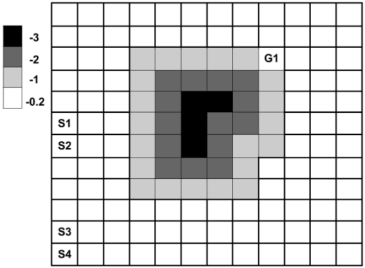
- L1 performs poorly on upper right quadrant
- L2 performs poorly on lower right quadrant
- L1 score of 9.2, L2 score of 8, LT score of 17.2 ([-21,21])

Selective Transfer with Value Function



Outline

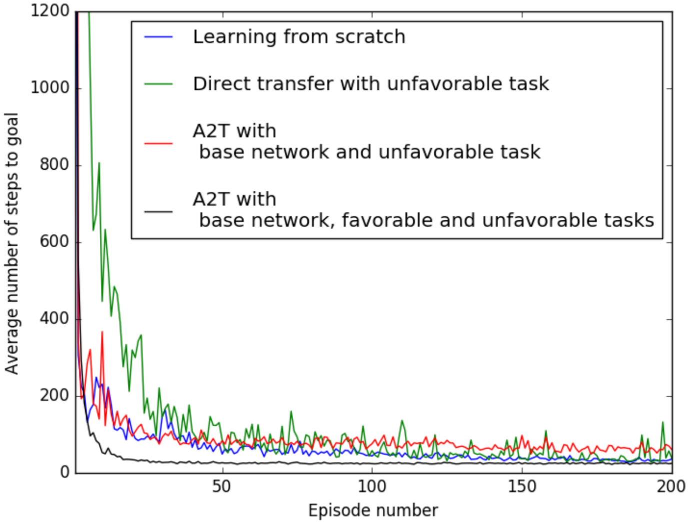
Avoiding Negative Transfer and Ability to Transfer from Favorable Task (policy transfer in puddle world)



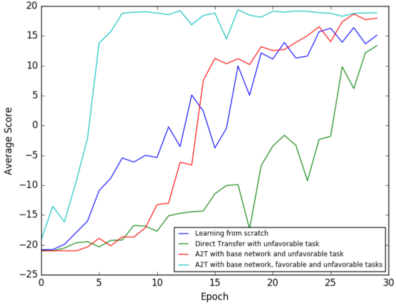
(b) Puddle World 1

- Reach goal state by starting in S1,S2,S3,S4
- L1 is favorable (good) model
- L2 is unfavorable (inverse output weights of L1)

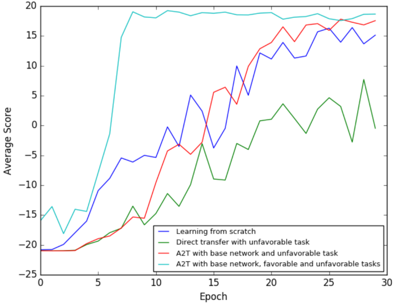
Avoiding Negative Transfer and Ability to Transfer from Favorable Task (policy transfer in puddle world)



Avoiding Negative Transfer and Ability to Transfer from Favorable Task (value transfer in pong)

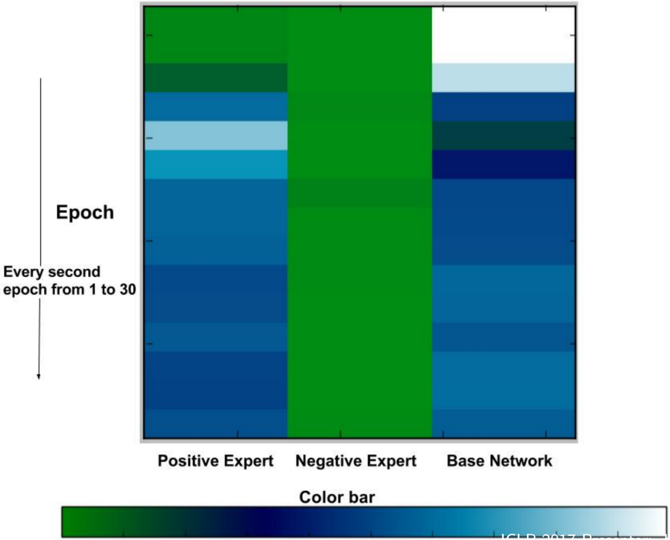


(a) Avoiding negative transfer(Pong) and transferring from a favorable task



(b) Avoiding negative transfer(Freeway) and transferring from a favorable task

Attention Map for Favorable/Unfavorable Sources (value transfer in pong)



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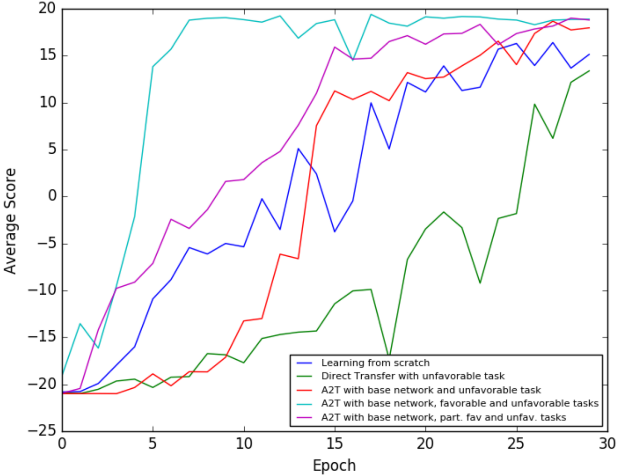
When a Perfect Expert is Not Available Among Tasks

- Pong with partially favorable and unfavorable source tasks



Conclusions

- General deep neural network architecture, A2T, for transfer learning
- A2T avoids negative transfer while enabling selective transfer from multiple source tasks in the same domain