Hybrid Reward Architecture for Reinforcement Learning

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They achieve generalisation of their *Deep Q-Networks* (DQNs) by approximating the optimal-value function.

However, if the optimal value function is very complex, then learning an accurate low-dimensional representation can be challenging or even impossible.
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They point out that all these agents can learn in parallel on the same sample sequence by using off-policy learning (Similar to Horde architecture of Sutton, et al. (2011)).
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- Learning proceeds in parallel by all demons simultaneously so as to extract the maximal training information from whatever actions are taken by the system as a whole.
Main Idea:
Each agent gives its action-values of the current state to an aggregator, which combines them into a single value for each action. The current action is selected based on these aggregated values.
Markov Decision Process given by

\[ \langle S, A, P, R_{env}, \gamma \rangle \]

modeling an agent interacting with an environment at discrete times steps, \( t \), where:

- \( S \) is a set of states,
- \( A \) is a set of actions,
- \( R_{env} : S \times A \times S \rightarrow \mathbb{R} \) is an environment reward function,
- \( P : S \times A \times S \rightarrow [0, 1] \) is a transition probability function.
- \( \gamma \in [0, 1] \) is a discount factor.
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At time step $t$, the agent observes $s_t \in S$. 
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(Also) at time step \( t \), the agent takes action \( a_t \in A \).
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The agent observes the next state, \( s_{t+1} \) drawn from \( P(s_t, a_t, \cdot) \).
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The agent receives reward $r_t = R_{env}(s_t, a_t, s_{t+1})$. 

van Seijen et al. Hybrid Reward Architecture for RL
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The agent’s behaviour is defined by the policy

$\pi : S \times A \rightarrow [0, 1]$, representing selection probabilities over actions.
Goal:

Find a policy $\pi^*$ that maximises the expectation of the return, given by the discounted sum of the individual rewards:

$$G_t = \sum_{i=0}^{\infty} \gamma^i r_{t+i}$$
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Each policy, $\pi$, has an action-value function, giving the expected return conditioned on the state and the action:

$$Q^{\pi}(s, a) := \mathbb{E}[G_t|s_t = s, a_t = a, \pi].$$
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The optimal policy, $\pi^*$ can be found by iteratively improving an estimate of the optimal action-value function,

$$Q^*(s, a) := \max_{\pi} Q^\pi(s, a).$$
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$$L_i(\theta_i) = \mathbb{E}_{s,a,r,s'}[(y_{DQN} - Q(s, a; \theta_i))^2]$$

with

$$y_{DQN} = r + \gamma \max_{a'} Q(s', a'; \theta_{i-1})$$
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\mathcal{L}_i(\theta_i) = \mathbb{E}_{s, a, r, s'} \left[ \left( y_i^{DQN} - Q(s, a; \theta_i) \right)^2 \right] 
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Definition:
The \( Q \)-value function that minimises the loss function is called the **Training Target**.
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A training target is **Consistent** if it results in a policy that is optimal under the reward function of the environment when acting greedily with respect to the training target.

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When a training target results in a good, but suboptimal, policy when acting greedily with respect to the training target, it is called **Semi-Consistent**.
Goal:
Find an alternative training target for domains where the default training target, $Q^*_{env}$, is hard to learn.
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Proposal:
Decompose the reward function, $R_{env}$, into $n$ reward functions as follows:

$$R_{env}(s, a, s') = \sum_{k=1}^{n} R_k(s, a, s'), \quad \text{For all } s, a, s'$$

and then train a separate reinforcement learning agent on each of these reward functions.
Hybrid Reward Architecture:

Note:
Each agent, $k$, has its own reward function $R_k$, and therefore has its own $Q$-value function, $Q_k$. 

Figure 1: Illustration of Hybrid Reward Architecture.
Action selection for HRA is based on the sum of the agents’ $Q$-value functions, denoted by $Q_{HRA}$:

$$Q_{HRA}(s, a; \theta) := \sum_{k=1}^{n} Q_k(s, a; \theta), \quad \text{For all } s, a.$$
The sequence of loss functions associated with HRA is given by

\[ \mathcal{L}_i(\theta_i) = \mathbb{E}_{s,a,r,s'} \left[ \sum_{k=1}^{n} (y_{k,i} - Q_k(s, a; \theta_i))^2 \right] \] (3)

with

\[ y_{k,i} = R_k(s, a, s') + \gamma \max_{a'} Q_k(s', a'; \theta_{i-1}) \] (4)
By minimising these loss functions, the individual agents of HRA approximate the action-value functions under the reward functions: $Q_1^*, \ldots, Q_n^*$. 
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Furthermore, $Q_{HRA}$ approximates $Q_{HRA}^*$:

$$Q_{HRA}^*(s, a) := \sum_{k=1}^{n} Q_k^*(s, a) \quad \text{for all } s, a.$$
Alternative Training Target:
Evaluate the uniformly random policy, \( v \), under each component reward function:

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Q^v_{\text{HRA}}(s, a) := \sum_{k=1}^{n} Q^v_k(s, a).
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Alternative Training Target:
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This can be learned using the SARSA update rule.
\[ Q_{env}^v(s, a) = \mathbb{E} \left[ \sum_{i=0}^{\infty} \gamma^i R_{env}(s_{t+i}, a_{t+i}, s_{t+1+i}) \middle| s_t = s, a_t = a, v \right] \]

\[ = \mathbb{E} \left[ \sum_{i=0}^{\infty} \gamma^i \sum_{k=1}^{n} R_k(s_{t+i}, a_{t+i}, s_{t+1+i}) \middle| s_t = s, a_t = a, v \right] \]

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2. **Identifying terminal states.** Terminal states are states from which no further reward can be received; they have by definition a value of 0. Using this knowledge, HRA can refrain from approximating this value by the value network, such that the weights can be fully used to represent the non-terminal states.
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3. **Using pseudo-reward functions.** Instead of updating a head of HRA using a component of the environment reward, it can be updated using a pseudo-reward. In this scenario, a set of *General Value Functions* is trained in parallel using pseudo-rewards.
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- There are 10 possible fruit locations, spread out across the grid.
- For each episode, a fruit is randomly placed on 5 of those 10 locations.
- The agent starts at a random position. The reward is $+1$ if a fruit gets eaten and $0$ otherwise.
- An episode ends after all 5 fruits have been eaten or after 300 steps, whichever comes first.
Figure 2: The different network architectures used.
Figure 3: Results on the fruit collection domain, in which an agent has to eat 5 randomly placed fruits. An episode ends after all 5 fruits are eaten or after 300 steps, whichever comes first.
Test Bed: Ms. Pac-Man

Figure 4: The game Ms. Pac-Man.
Introduction

Hybrid Reward Architecture Model

Review

Hybrid Reward Architecture

Experiments

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Ms. Pac-Man

- Uses 163 “sub-agents”
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  - 154 Pellets,
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- For each object, there is a separate input channel which encodes its location with an accuracy of 4 pixels.
- Each agent has its own reward function.
- The aggregate reward functions tell the “master” agent which action is best.
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- If an object is not on-screen, all its $Q$-values are 0.
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Video
Figure 5: Training smoothed over 100 episodes. Figure 6: Training with trajectory memorisation.
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- The input state-space is in the order of $10^{77}$ states.
- However, each GVF has a state space in the order of $10^3$ states.
- This constitutes a significant reduction in dimensionality of representation, which allows the AI to learn more quickly.
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- Separating tasks into discrete targets decreases the problem size to make the problem more tractable.
- Many real-world tasks may allow for reward decomposition.