

Classifying Options for Deep Reinforcement Learning

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Abstract

In this paper we combine one method for hierarchical reinforcement learning—the options framework—with deep Q-networks (DQNs) through the use of different “option heads” on the policy network, and a supervisory network for choosing between the different options. We utilise our setup to investigate the effects of architectural constraints in subtasks with positive and negative transfer, across a range of network capacities. We empirically show that our augmented DQN has lower sample complexity when simultaneously learning subtasks with negative transfer, without degrading performance when learning subtasks with positive transfer.

1 Introduction

Recent advances in reinforcement learning have focused on using deep neural networks to represent the state-action value function (Q-function) [Mnih *et al.*, 2015] or a policy function [Levine *et al.*, 2015]. The successes of such methods are largely attributed to the representational power of deep networks. It is tempting to create an ultimate end-to-end solution to general problems with these kinds of powerful models. However, these general methods require large amount of samples in order to learn effective policies.

In order to reduce sample complexity, one can use domain knowledge to construct an algorithm that is biased towards promising solutions. The deep Q-network (DQN) [Mnih *et al.*, 2015] is an end-to-end reinforcement learning algorithm that has achieved great success on a variety of video games [Bellemare *et al.*, 2013]. In this work, we explore the possibility of imposing some structural priors onto the DQN as a way of adding domain knowledge, whilst trying to limit the reduction in generality of the DQN.

In classical reinforcement learning literature, there is a large amount of research focusing on temporal abstraction of problems, which is known under the umbrella of hierarchical reinforcement learning. The options framework [Sutton *et al.*, 1999] augments the set of admissible actions with temporally-extended actions that are called options. In this context, an option is a closed-loop controller that can execute either *primitive* actions or other options according to its

policy. The ability to use options gives the agent many advantages, such as temporally-extended exploration, allowing planning across a range of time scales and the ability to transfer knowledge to different tasks.

Another approach, MAXQ [Dietterich, 2000], decomposes a task into a hierarchy of subtasks. This decomposition allows MAXQ agents to improve performance towards achieving the main objective by recursively solving smaller problems first. Both the options and MAXQ frameworks are constructed so that prior domain knowledge can be implemented naturally. Both approaches can be viewed as constructing a main policy from smaller sub-policies with implemented prior knowledge on either the structural constraints or the behaviour of the sub-policies themselves.

We consider the class of problems where the task can be broken down into reward-independent subtasks by a human expert. The task decomposition is done such that the sub-tasks share the same state space, but can be explicitly partitioned (for different options). If the action space can similarly be partitioned, then this knowledge can also be incorporated to bound the actions available to each option policy. With this domain knowledge we decompose the DQN into a composition of smaller representations, derived from prior work on hierarchical reinforcement learning. Although there is evidence that the DQN can implicitly learn options [Zahavy *et al.*, 2016], we investigate whether there is any benefit to constructing options explicitly.

1.1 Related Work

Our “option heads” are inspired by Osband *et al.* [2016]. Their policy network is similar to ours, but without the additional supervisory network. Their network’s “bootstrap heads” are used with different motivations. They train each of the heads, with different initialisations, on the same task. This allows the network to represent a distribution over Q-functions. Exploration is done “deeply” by sampling one head and using its policy for the whole episode, while the experiences are shared across the heads. Our motivation for using option heads, however, is for allowing the use of temporally abstracted actions akin to the options framework, or more concretely, as a way to decompose the policy into a combination of simpler sub-policies. This motivates the use of a supervisory network, which is discussed in Subsection 3.2.

Although we focus on the options framework and the notion of *subtasks*, an alternative view is that of multitask learning. In the context of deep reinforcement learning, recent work has generalised *distillation* [Hinton *et al.*, 2015], applied to classification, in order to train DQNs on several Atari games in parallel [Rusu *et al.*, 2015; Parisotto *et al.*, 2015]. Distillation uses trained teacher networks to provide extra training signals for the student network, where originally the technique was used to *distill* the knowledge from a large teacher network into a smaller student network as a form of model compression. For multitask learning, Parisotto *et al.* [2015] were able to keep the student DQN architecture the same as that of the teacher DQNs, whilst Rusu *et al.* [2015] created a larger network with an additional fully connected layer. The latter explicitly separated the top of the network into different “controllers” per game, and called the architecture a Multi-DQN, and the architecture in combination with their policy distillation algorithm Multi-Dist. Both studies showed that the use of teacher networks could enable learning effective policies on several Atari games in parallel—8 on a standard DQN [Parisotto *et al.*, 2015] and 10 on a Multi-DQN [Rusu *et al.*, 2015]. The same architectures were unable to perform well across all games without teacher networks.

We note that the bootstrapped DQN and the multi-DQN have similar structures: several “heads” either directly or indirectly above shared convolutional layers. One of the baselines for evaluating the actor-mimic framework [Parisotto *et al.*, 2015] is the Multitask Convolutional DQN (MCDQN), which has the same architecture as the bootstrapped DQN. Although working from the same architecture, our goals are different due to incorporating the DQN into the options framework. The first major difference in our work is that we use a supervisory network, which allows us to infer which subtask should be attempted at each time step during evaluation. Conversely, in a multitask setting, different tasks are typically clearly separated. Secondly, our method does not rely on teacher networks, instead focusing on a DQN whose augmented training signal is based only on the knowledge of the current subtask. With respect to the latter point, we focus our analysis on controlling the capacity of the networks, as opposed to scaling parameters linearly with the number of tasks [Rusu *et al.*, 2015; Parisotto *et al.*, 2015].

Another notable success in subtask learning with multiple independent sources of reward are universal value function approximators (UVFAs) [Schaul *et al.*, 2015]. UVFAs allow the generalisation of value functions across different goals, which helps the agent accomplish tasks that it has never seen before. The focus of UVFAs is in generalising between similar subtasks by sharing the representation between the different tasks. This has recently been expanded upon in the hierarchical-DQN [Kulkarni *et al.*, 2016]; however, these goal-based approaches have been demonstrated in domains where the different goals are highly related. From a function approximation perspective, goals should share a lot of structure with the raw states. In contrast, our approach focuses on separating out distinct subtasks, where partial independence between subpolicies can be enforced through structural constraints. In particular, we expect that separate Q-functions are

less prone to negative transfer between subtasks.

2 Background

Consider a reinforcement learning problem, where we want to find an agent’s policy π which maximises the expected discounted reward, $\mathbb{E}[R] = \mathbb{E}[\sum_t \gamma^t r_t]$. The discount parameter, $\gamma \in [0, 1]$, controls the importance of immediate rewards relative to more distant rewards in the future. The reward r_t is a scalar value emitted from a state $s_t \in \mathcal{S}$. The policy selects and performs an action $a_t \in \mathcal{A}$ in response to the state s_t , which then transitions to s_{t+1} . The transition of states is modelled as a Markov decision process (MDP) where each state is a sufficient statistic of the entire history, so that the transition at time t need only depend on s_{t-1} and the action a_{t-1} . See [Sutton and Barto, 1998] for a full introduction.

The Q-learning algorithm [Watkins, 1989] solves the reinforcement learning problem by approximating the optimal state-action value or Q-function, $Q^*(s_t, a_t)$, which is defined as the expected discounted reward starting from state s_t and taking initial action a_t , and henceforth following the optimal policy π^* :

$$Q^*(s_t, a_t) = \mathbb{E}[R_t | s_t, a_t, \pi^*]$$

The Q-function must satisfy the Bellman equation,

$$Q^*(s_t, a_t) = \mathbb{E}_{s_{t+1}}[r_t + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1})].$$

We can approximate the Q-function with a function approximator $Q(s, a; \theta)$, with parameters θ . Learning is done by adjusting the parameters in such a way to reduce the inconsistency between the left and the right hand sides of the Bellman equation. The optimal policy can be derived by simply choosing the action that maximises $Q^*(s, a)$ at each time step.

2.1 Deep Q-networks

The DQN [Mnih *et al.*, 2015] is a convolutional neural network that represents the Q-function $Q(s, a; \theta)$ with parameters θ . The (online) network is trained by minimising a sequence of loss functions at iteration i :

$$\begin{aligned} L_i(\theta_i) &= \mathbb{E}_{s, a, r, s'}[(y_i - Q(s, a; \theta_i))^2] \\ y_i &= r + \gamma \max_{a'} Q(s', a'; \theta^-) \end{aligned} \quad (1)$$

The parameters θ^- are associated with a separate target network, which is updated with θ_i every τ steps. The target network increases the stability of the learning. The parameters θ_i are updated with mini-batch stochastic gradient descent following the gradient of the loss function.

Another key to the successful training of DQNs is the use of experience replay [Lin, 1992]. Updating the parameters, θ_i , with stochastic gradient descent on the squared loss function implies an i.i.d. assumption which is not valid in an online reinforcement learning problem. Experience replay stores samples of past transitions in a pool. While training, samples are drawn uniformly from this pool. This helps break the temporal correlation between samples and also allows updates to reuse samples several times.

2.2 Double Deep Q-networks

We follow the learning algorithm by van Hasselt *et al.* [2015] to lower the overestimation of Q-values in the update rule. This modifies the original target, Equation 1, to the following,

$$y_i = r + \gamma Q(s', \operatorname{argmax}_{a'} Q(s', a'; \theta_i); \theta^-).$$

2.3 The Options Framework

The original definition of options [Sutton *et al.*, 1999] consists of three components: a policy, π , a termination condition, β , and an initiation set, I . We illustrate the role of these components by following the interpretation by Daniel *et al.* [2012].

Consider a stochastic policy, $\pi(a_t|s_t)$, or a distribution over actions, a_t , given state, s_t , at time step t . We add an auxiliary variable, $o_t \in \mathcal{O}$, such that a_t is dependent on o_t , and, o_t is dependent on s_t and o_{t-1} . This variable o_t controls the selection of action a_t through their conditional dependence, $\pi(a_t|s_t, o_t)$, and can be interpreted as the policy of a Markov option o_t . The termination condition, β , can be thought of as a specific constraint of the conditional form, imposed on the transition of the option as follows:

$$\begin{aligned} \pi(o_t|o_{t-1}, s_t) &\propto \beta(s_t, o_{t-1})\pi(o_t|s_t) \\ &+ \delta_{o_t, o_{t-1}}(1 - \beta(s_t, o_{t-1})), \end{aligned}$$

where $\delta_{o_t, o_{t-1}}$ is 1 when $o_t = o_{t-1}$ and 0 otherwise. The initiation set specifies the domain of s_t available to $\pi(o_t|s_t)$.

We consider a fully observable MDP where s_t is assumed to be a sufficient statistic for all the history before t , including o_{t-1} . Therefore, we can model o_t to be conditionally independent of o_{t-1} given s_t . We define our “supervisory policy” as $\pi(o_t|s_t)$. Both the termination condition and the initiation set are absorbed into the supervisory policy. The full policy is then decomposed into:

$$\pi(a_t|s_t) = \sum_{o_t} \pi(o_t|s_t)\pi(a_t|o_t, s_t).$$

This form of policy can be seen as a combination of option policies, weighted by the supervisory policy. We will show in the next section how we decompose the DQN into separate option policies, alongside a supervisory policy.

3 Deep Q-networks with Option Heads

We augment the standard DQN with several distinct sets of outputs; concretely we use the same architecture as the bootstrapped DQN [Osband *et al.*, 2016] or the MCDQN [Parisotto *et al.*, 2015]. As with the MCDQN, we use domain knowledge to choose the number of heads a priori, and use this same knowledge to train each option head separately. A comparison between a standard DQN and a DQN with option heads that we use is pictured in Figure 1. As noted in [Rusu *et al.*, 2015], even this augmentation can fail in a multitask setting with different policies interfering at the lower levels of the network, which highlights the need for further study.

Along with other work on the DQN, we assume that the convolutional layers learn a general representation of the state space, whilst the fully connected layers at the top of the network encode most of the actual policy. In the multitask Atari

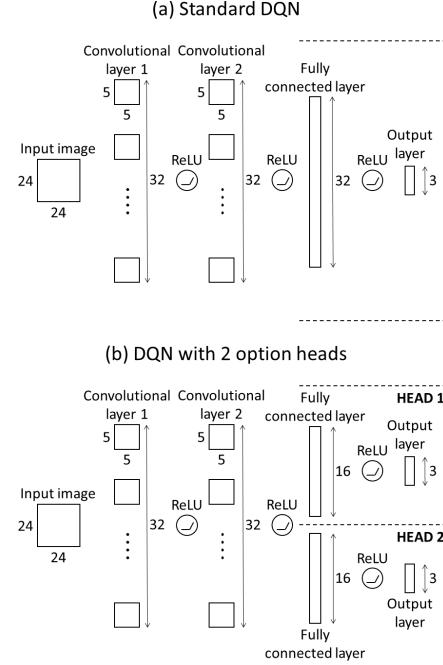


Figure 1: Comparison of DQN architectures. a) Standard DQN. b) DQN with 2 option heads.

setting, the set of games are so different that the states are unlikely to have many features in common [Rusu *et al.*, 2015], but we would assume that in a hierarchical reinforcement learning setting with subtasks this problem does not occur.

In addition to our augmented *policy network*, $Q_o(s, a) : \mathcal{O} \times \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$, where o indexes over option heads, we also introduce a *supervisory network*, $O(s) : \mathcal{S} \rightarrow \mathcal{O}$, which learns a mapping from a state to an option; this allows each option head to focus on a subset of the state space. With our networks, our full policy can be written as a deterministic mapping, $\pi(s) : \mathcal{S} \rightarrow \mathcal{A}$,

$$\pi(s) = \operatorname{argmax}_a Q_{O(s)}(s, a)$$

3.1 Option Heads

The option heads consist of fully connected layers which branch out from the topmost shared convolution layer. The final layer of each head outputs the Q-value for each discrete action available, and hence can be limited using domain knowledge of the task at hand and the desired options. While training, an oracle is used to choose which option head should be evaluated at each time step t . The action a_t is picked with the ϵ -greedy strategy on the o_t head, where ϵ is shared between all heads. The experience samples are tuples of (s_t, a_t, s_{t+1}, r_t) , and are stored in separate experience replay buffers for each head. During evaluation the oracle is replaced with the decisions of the supervisory network.

3.2 Supervisory Network

The supervisory network is an arbitrary neural network classifier which represents the supervisory policy. The input layer

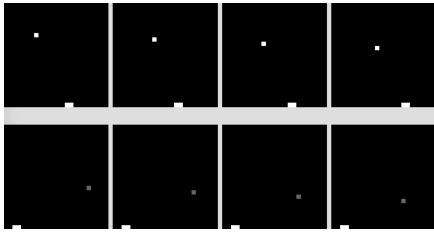


Figure 2: 8 frames of Catch. The first row shows the white ball subtask, and the second row shows the grey ball subtask.

receives the entire state. The hidden layers can be constructed using domain knowledge, e.g. convolutional layers for visual domains. The output layer is a softmax layer which outputs the distribution over options, o_t , given the state, s_t , and can be trained with the standard cross-entropy loss function. During training the targets are given from an oracle.

4 Experiments

For our experiments we reimplemented the game of ‘‘Catch’’ [Mnih *et al.*, 2014], where the task is to control a paddle at the bottom of the screen to catch falling balls (see Figure 2). The input is a greyscale 24x24 pixel grid, and the action space consists of 3 discrete actions: move left, move right and a no-op. As in [Mnih *et al.*, 2015], the DQN receives a stack of the current plus previous 3 frames. During each episode a 1 pixel ball falls randomly from the top of the screen, and the agent’s 2-pixel-wide paddle must move horizontally to catch it. In the original a reward of +1 is given for catching a white ball; we add an additional grey ball to introduce subtasks into the environment. This simple environment allows us to meaningfully evaluate the effects of the architecture on subtasks with *positive* and *negative* transfer. For the positive transfer case the subtasks are the same—catching either ball results in a reward of +1. In the negative transfer case the grey ball still gives a reward of +1, but catching the white ball results in a reward of -1. In this subtask the optimal agent must learn to catch the grey balls *and* avoid the perceptually-similar white balls; suboptimal solutions would include avoiding or catching both types of balls. In both setups the type of ball used is switched every episode.

Our baseline is the standard DQN. In order to provide a fair comparison, we impose one condition on the architecture of our policy network, and one condition on its training. For the first condition we divide the number of neurons in the hidden layer of each option head by the number of option heads, thereby keeping the number of parameters the same. For the second condition we alternate heads when performing the Q-learning update, keeping the number of training samples the same. We also construct a ‘‘half DQN’’, which contains half the parameters of the standard DQN in the fully connected hidden layer; this uses the standard architecture, not the option heads. This tests whether the sample complexity of our DQN with option heads is either the result of having fewer parameters to tune in each head, or the result of our imposed structural constraint. More details on the model architectures and training hyperparameters are given in the Appendix.

As well as investigating the effects of different kinds of transfer, we also look into the effects of varying the capacity of the network—specifically we run experiments with 16, 32, and 64 neurons in the fully connected hidden layer of the standard DQN. Correspondingly, the half DQN has 8, 16, and 32 neurons, and each of the 2 option heads in our network also has 8, 16, and 32 neurons.

As seen in Figure 3, lack of capacity has the most significant effect on performance. As capacity increases, the differences between the three networks diminishes. Besides capacity, architecture does not appear to have any significant impact on the positive transfer subtasks. However, with negative transfer subtasks the DQN with option heads is able to make significantly quicker progress than the standard DQN. When given enough capacity, our control for ‘‘head capacity’’ in this experiment—the half DQN—also converges to the same policy in terms of performance, but with a larger sample complexity. This suggests that incorporating domain knowledge in the form of structural constraints can be beneficial, even whilst keeping model capacity the same—in particular, the quicker learning suggests that this knowledge can effectively be utilised to reduce the number of samples needed in deep reinforcement learning.

Qualitatively, the convolutional filters learned by all DQNs are highly similar. This reinforces the intuition that the structural constraint imposed upon the DQN with option heads allows low-level feature knowledge about falling balls and moving the paddle to be learned in the shared convolution layers, whilst policies for catching and avoiding balls are represented more explicitly in each head.

As the classification task for the supervisory network is simple in this domain, we do not attempt to replace it with an oracle during evaluation. In practice the network learns to divide the state space rapidly.

5 Discussion

We show that with a simple architectural adjustment, it is possible to successfully impose prior domain knowledge about subtasks into the DQN algorithm. We demonstrate this idea in a game of catch, where the task of catching or avoiding falling balls depending on their colour can be decomposed intuitively into the subtask of catching grey balls and another subtask of avoiding white balls—subtasks that incur negative transfer. We show that learning the subtasks separately on different option heads allows the DQN to learn with lower sample complexity. The shared convolutional layers learn generally useful features, whilst the heads learn to specialise. In comparison, the standard DQN presumably suffers from sub-task interference with only a single Q-function. Additionally, the structural constraint does not hinder performance when learning subtasks with positive transfer.

Our results are contrary to those reported with the MCDQN trained on eight Atari games simultaneously, which was outperformed by a standard DQN [Parisotto *et al.*, 2015]. According to Parisotto *et al.* [2015], the standard DQN and MCDQN tend to focus on performing well on a subset of games at the expense of the others. We posit that this ‘‘strategy’’ works well for the DQN, whilst the explicitly con-

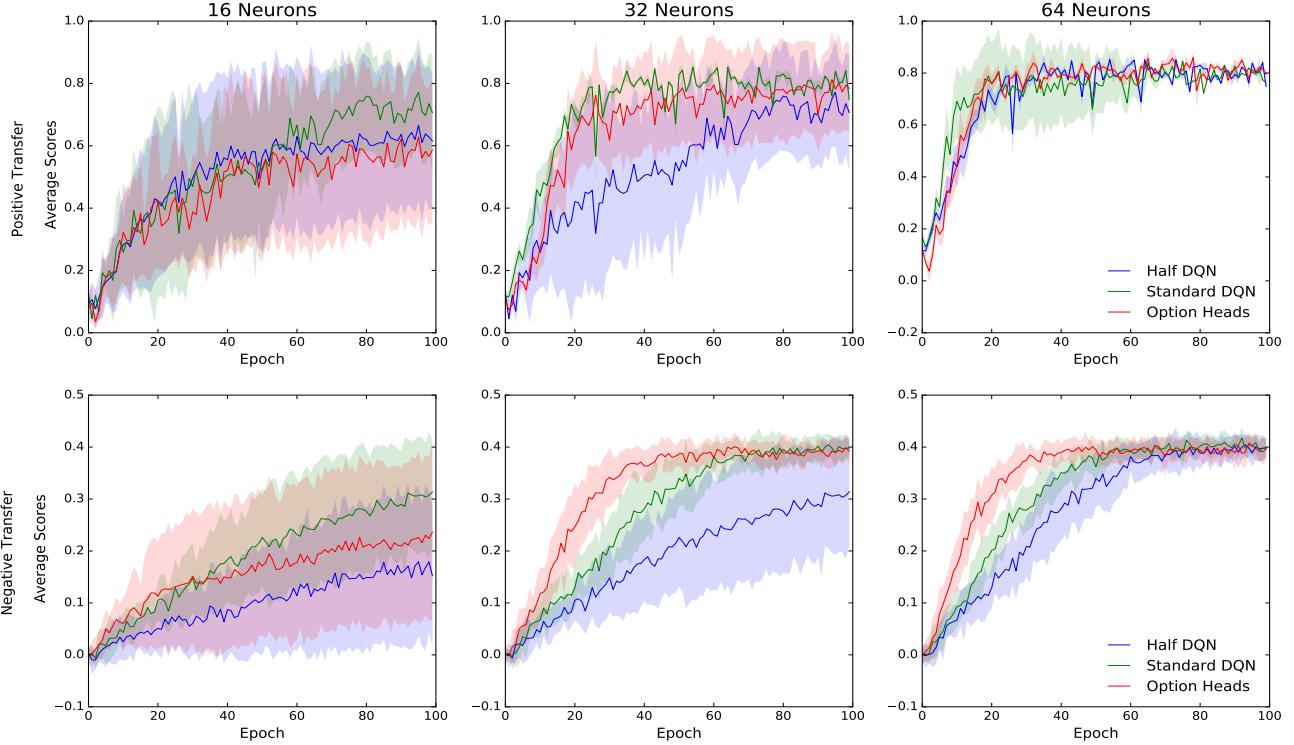


Figure 3: The average score per episode of the standard DQN, half DQN and DQN with 2 option heads. The average and standard deviation are calculated over 15 runs (with different random seeds), with the score for each run being averaged over 250 episodes. Each epoch corresponds to 10000 training steps. The number of neurons corresponds to the number of neurons in the fully connected hidden layer of the standard DQN. In the positive transfer setting the most important factor is capacity, not the architecture. As capacity increases the difference in performance between the networks diminishes. In the negative transfer setting the effect of capacity is strong when capacity is very low, but otherwise the DQN with option heads demonstrates a superior sample complexity over the baselines. Best viewed in colour.

structured controller heads on the MCDQN receive more consistent training signals, which may cause parameter gradients that interfere with each other in the shared convolutional layers [Caruana, 2012; Rusu *et al.*, 2015]. This is less of a concern in the hierarchical reinforcement learning setting as we assume a more coherent state space across all subtasks.

In the regime of subtasks rather than multiple tasks, the DQN with option heads is not as generalisable as goal-based approaches [Schaul *et al.*, 2015; Kulkarni *et al.*, 2016]. However, these methods currently require a hand-crafted representation of the goals as input for their networks—a sensible approach only when the goal representation can be reasonably appended to the state space. In contrast, our oracle mapping from states to options can be used when constructing representations of goals as inputs is not a straightforward task. This suggests future work in removing the oracle by focusing on *option discovery*, where the agent must learn options without the use of a supervisory signal.

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Appendix

A Model

We use a smaller DQN than the one specified in [Mnih *et al.*, 2015]. The baseline (standard) DQN architecture that we used in our experiments, with a capacity of “32 neurons”, is as follows:

Layer	Specification
1	32 5x5 spatial convolution, 2x2 stride, 1x1 zero-padding, ReLU
2	32 5x5 spatial convolution, 2x2 stride, ReLU
3	32 fully connected, ReLU
4	3 fully connected

As our version of Catch can be divided into 2 distinct sub-tasks, our policy network therefore has 2 option heads. Each option head has 16 neurons each in the penultimate fully connected layers—half that of the baseline DQN. The half DQN therefore also has 16 neurons in the penultimate fully connected layer. The same formula is employed when testing with a capacity of 16 and 64 neurons.

Unlike [Osband *et al.*, 2016], we do not normalise the gradients coming through each option head, as the errors are only backpropagated through one head at a time.

B Hyperparameters

Hyperparameters were originally manually tuned for the model with the original version of Catch [Mnih *et al.*, 2014] (only white balls giving a reward of +1). We then performed a hyperparameter search over learning rates $\in \{0.000125, 0.00025, 0.0005\}$, target network update frequencies $\in \{4, 32, 128\}$, and final values of $\epsilon \in \{0.01, 0.05\}$. The learning rate with the best performance for all models was 0.00025, except for the standard DQN and half DQN in the negative transfer setting, where 0.000125 was better. This is an interesting finding—with negative transfer the standard architecture requires a lower learning rate, whilst with option heads a higher learning rate can still be used. The following hyperparameters were used for all models, where only hyperparameters that differ from those used in [Van Hasselt *et al.*, 2015] for the tuned double DQN are given:

Hyperparameters	Value	Description
Replay memory size	10000	Size of each experience replay memory buffer.
Target network update frequency	4	Frequency (in number of steps) with which the target network parameters are updated with the policy network parameters.
Optimiser	Adam	Stochastic gradient descent optimiser.
Final exploration frame	10000	Number of steps over which ϵ is linearly annealed.
Replay start size	10000	Number of steps of random exploration before ϵ is annealed.
Gradient clipping	10	Max absolute value of the L2 norm of the gradients.
Validation frequency	10000	Number of steps after which evaluation is run.
Validation steps	6000	Number of steps to use during evaluation. Corresponds to 250 episodes of Catch.