

# Unsupervised Task Clustering for Multi-Task Reinforcement Learning

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**Abstract.** Meta-learning, transfer learning and multi-task learning have recently laid a path towards more generally applicable reinforcement learning agents that are not limited to a single task. However, most existing approaches implicitly assume a uniform similarity between tasks. We argue that this assumption is limiting in settings where the relationship between tasks is unknown a-priori. In this work, we propose a general approach to automatically cluster together similar tasks during training. Our method, inspired by the expectation-maximization algorithm, succeeds at finding clusters of related tasks and uses these to improve sample complexity. We achieve this by designing an agent with multiple policies. In the expectation step, we evaluate the performance of the policies on all tasks and assign each task to the best performing policy. In the maximization step, each policy trains by sampling tasks from its assigned set. This method is intuitive, simple to implement and orthogonal to other multi-task learning algorithms. We show the generality of our approach by evaluating on simple discrete and continuous control tasks, as well as complex bipedal walker tasks and Atari games. Results show improvements in sample complexity as well as a more general applicability when compared to other approaches.

## 1 Introduction

Imagine we are given an arbitrary set of tasks. We know that dissimilarities and/or contradicting objectives can exist. However, in most settings we can only guess these relationships and how they might affect joint training. Many recent works rely on such human guesses and (implicitly or explicitly) limit the generality of their approaches. This can lead to impressive results, either by explicitly modeling the relationships between tasks as in transfer learning [42], or by meta learning implicit relations [15]. However, in some cases an incorrect similarity assumption can slow training [19]. With this paper we provide an easy, straightforward approach to avoid human assumptions on task similarities.

An obvious solution is to train a separate policy for each task. However, this might require a large amount of experience to learn the desired behaviors.

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\* Equal contribution. Johannes Ackermann did his part while visiting ETH Zurich.

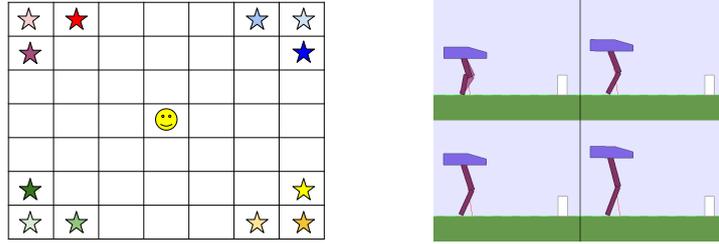


Fig. 1: **Left:** An agent (smiley) should reach one of 12 goals (stars) in a grid world. Learning to reach a goal in the top right corner helps it to learn about the other goals in that corner. However, learning to reach the green stars (bottom left corner) at the same time gives conflicting objectives, hindering training. **Right:** When all tasks are very similar, treating them as independent is disadvantageous. Task clustering allows us to perform well in both cases.

Therefore, it is desirable to have a single agent and share knowledge between tasks. This is generally known as multi-task learning, a field which has received a large amount of interest in both the supervised learning and reinforcement learning (RL) community [41]. If tasks are sufficiently similar, a policy that is trained on one task provides a good starting point for another task, and experience from each task will help training in the other tasks. This is known as *positive transfer* [19]. However, if the tasks are sufficiently dissimilar, *negative transfer* occurs and reusing a pre-trained policy is disadvantageous. Here using experience from the other tasks might slow training or even prevent convergence to a good policy. Most previous approaches to multi-task learning do not account for problems caused by negative transfer directly and either accept its occurrence or limit their experiments to sufficiently similar tasks. We present a hybrid approach that is helpful in a setting where the task set contains clusters of related tasks, amongst which transfer is helpful. To illustrate the intuition we provide a conceptualized example in Figure 1 on the left. Note however that our approach goes beyond this conceptual ideal and can be beneficial even if the clustering is not perceivable by humans a-priori.

Our approach iteratively evaluates a set of policies on all tasks, assigns tasks to policies based on their respective performance and trains policies on their assigned tasks. This leads to policies naturally specializing to clusters of related tasks, yielding an interpretable decomposition of the full task set. Moreover, we show that our approach can improve the learning speed and final reward in multi-task RL settings. To summarize our contributions:

- We propose a general approach inspired by Expectation-Maximization (EM) that can find clusters of related tasks in an unsupervised manner.
- We provide an evaluation on a diverse set of multi-task RL problems that shows the improved sample complexity and reduction in negative transfer.
- We show the importance of meaningful clustering and the sensitivity to the assumed number of clusters in an ablation study.

## 2 Related Work

Expectation-Maximization (EM) has previously been used in RL to directly learn a policy. By reformulating RL as an inference problem with a latent variable, it is possible to use EM to find the maximum likelihood solution, corresponding to the optimal policy. We direct the reader to the survey on the topic by Deisenroth et al. [9]. Our approach is different: We use an EM-inspired approach to cluster tasks in a multi-task setting and rely on recent RL algorithms to learn the tasks.

In supervised learning, the idea of subdividing tasks into related clusters was proposed by Thrun and O’Sullivan [34]. They use a distance metric based on generalization accuracy to cluster tasks. Another popular idea related to our approach that emerged from supervised learning is the use of a mixture of experts [16]. Here, multiple sub-networks are trained together with an input dependent gating network. Jordan and Jacobs [18] also proposed an EM algorithm to learn the mixture of experts. While those approaches have been extended to the control setting [17, 26, 4, 33], they rely on an explicit supervision signal. It is not clear how such an approach would work in an RL setting. A variety of other methods have been proposed in the supervised learning literature. For brevity we direct the reader to the survey by Zhang et al. [41], which provides a good overview of the topic. In contrast, we focus on RL, where no labeled data set exists.

In RL, task clustering has in the past received attention in works on transfer learning. Carroll and Seppi [5] proposed to cluster tasks based on a distance function. They propose distances based on  $Q$ -values, reward functions, optimal policies or transfer performance. They propose to use the clustering to guide transfer. Similarly, Mahmud et al. [25] propose a method for clustering Markov Decision Processes (MDPs) for source task selection. They design a cost function for their chosen transfer method and derive an algorithm to find a clustering that minimizes this cost function. Our approach differs from both in that we do not assume knowledge of the underlying MDPs and corresponding optimal policies. Furthermore, the general nature of our approach allows it to scale to complex tasks, where comparing properties of the full underlying MDPs is not feasible. Wilson et al. [38] developed a hierarchical Bayesian approach for multi-task RL. Their approach uses a Dirichlet process to cluster the distributions from which they sample full MDPs in the hope that the sampled MDP aligns with the task at hand. They then solve the sampled MDP and use the resulting policy to gather data from the environment and refine the posterior distributions for a next iteration. While their method is therefore limited to simple MDPs, our approach can be combined with function approximation and therefore has the potential to scale to MDPs with large or infinite state spaces which cannot be solved in closed form. Lazaric and Ghavamzadeh [20] use a hierarchical Bayesian approach to infer the parameters of a linear value function and utilize EM to infer a policy. However, as this approach requires the value function to be a linear function of some state representation, this approach is also difficult to scale to larger problems which we look at. Li et al. [22] note that believe states in partially observable MDPs can be grouped according to the decision they require. Their model infers the parameters of the corresponding decision state

MDP. Their approach scales quadratically with the number of decision states and at least linearly with the number of collected transitions, making it as well difficult to apply to complex tasks.

More recent related research on multi-task RL can be split into two categories: Works that focus on very similar tasks with small differences in dynamics and reward, and works that focus on very dissimilar tasks. In the first setting, approaches have been proposed that condition the policy on task characteristics identified during execution. Lee et al. [21] use model-based RL and a learned embedding over the local dynamics as additional input to their model. Yang et al. [39] train two policies, one that behaves in a way that allows the easy identification of the environment dynamics and another policy that uses an embedding over the transitions generated by the first as additional input. Zintgraf et al. [43] train an embedding over the dynamics that accounts for uncertainty over the current task during execution and condition their policy on it. Our approach is more general than these methods as our assumption on task similarity is weaker. In the second group of papers, the set of tasks is more diverse. Most approaches here are searching for a way to reuse representations from one task in the others. Riemer et al. [30] present an approach to learn hierarchical options, and use it to train an agent on 21 Atari tasks. They use the common NatureDQN network [27] with separate final layers for option selection policies, as well as separate output layers for each task to account for the different action spaces. Eramo et al. [11] show how a shared representation can speed up training. They then use a network structure with separate heads for each task, but shared hidden layers. Our multi-head baseline is based on these works. Bräm et al. [2] propose a method that addresses negative transfer between multiple tasks by learning an attention mechanism over multiple sub-networks, similar to a mixture of experts. However, as all tasks yield experience for one overarching network, their approach still suffers from interference between tasks. We limit this interference by completely separating policies. Wang et al. [36] address the problem of open-ended learning in RL by iteratively generating new environments. Similar to us, they use policy rankings as a measure of difference between tasks. However, they use this ranking as a measure of novelty to find new tasks, addressing a very different problem. Hessel et al. [14] present PopArt for multi-task deep RL. They address the issue that different tasks may have significantly different reward scales. Sharma et al. [31] look into active learning for multi-task RL on Atari tasks. They show that uniformly sampling new tasks is suboptimal and propose different sampling techniques. Yu et al. [40] propose Gradient Surgery, a way of projecting the gradients from different tasks to avoid interference. These last three approaches are orthogonal to our work and can be combined with EM-clustering. We see this as an interesting direction for future work.

Quality-Diversity (QD) algorithms [7, 29] in genetic algorithms research aim to find a diverse set of good solutions for a given problem. One proposed benefit of QD is that it can overcome local optima by using the solutions as "stepping stones" towards a global optimum. Relatedly in RL, Eysenbach et al. [12] and Achiam et al. [1] also first identify diverse skills and then use the learned skills to

solve a given task. While we do not explicitly encourage diversity in our approach, our approach is related in that our training leads to multiple good performing, distinct policies trained on distinct tasks. This can lead to a policy trained on one task becoming the best on a task that it was not trained on, similar to the "stepping stones" in QD. However, in our work this is more a side-effect than the proposed functionality.

### 3 Background and Notation

In RL [32] tasks are specified by a Markov Decision Process (MDP), defined as tuple  $(\mathcal{S}, \mathcal{A}, P, R, \gamma)$ , with state space  $\mathcal{S}$ , action space  $\mathcal{A}$ , transition function  $P(\cdot|s, a)$ , reward function  $R(s, a)$  and decay factor  $\gamma$ . As we are interested in reusing policies for different tasks, we require a shared state-space  $\mathcal{S}$  and action-space  $\mathcal{A}$  across tasks. Note however that this requirement can be omitted by allowing for task specific layers. Following prior work, we do allow for a task specific final layer in our Atari experiments to account for the different action spaces. In all other experiments however, tasks only differ in their transition function and reward function. We therefore describe a task as  $\tau = (P_\tau, R_\tau)$  and refer to the set of given tasks as  $\mathcal{T}$ . For each task  $\tau \in \mathcal{T}$  we aim to maximize the discounted return  $G_\tau = \sum_{t=0}^{t=L} \gamma^t r_t^\tau$ , where  $r_t^\tau \sim R_\tau(s_t, a_t)$  is the reward at time step  $t$  and  $L$  is the episode length. Given a set of policies  $\Pi = \{\pi_1, \dots, \pi_n\}$ , we denote the return obtained by policy  $\pi_i$  on task  $\tau$  as  $G_\tau(\pi_i)$ .

### 4 Clustered Multi-Task Learning

Before we introduce our proposed clustering approach, we first want to briefly discuss the straight forward, yet often disregarded limitation that exists when learning multiple task with a single policy.

**Proposition 1.** *The optimal policy of a jointly learned task set  $\mathcal{T} = \{\tau_1, \tau_2\}$  can be arbitrarily far from the optimal policy on task  $\tau_1$ .*

To see this, consider task  $\tau_2$  given as  $\tau_2 = (P_{\tau_1}, -2 \cdot R_{\tau_1})$ . Optimizing a policy  $\pi$  to maximizing the joint objective  $G_{\tau_1}(\pi) + G_{\tau_2}(\pi)$  is equivalent to optimizing  $\pi$  to minimize  $G_{\tau_1}(\pi)$  as for any policy  $\pi$  we have  $G_{\tau_1}(\pi) + G_{\tau_2}(\pi) = -G_{\tau_1}(\pi)$ .

On the other hand, as the growing body of literature on meta-, transfer- and multi-task learning suggests, we can expect a gain through positive transfer if we train a single policy  $\pi_i$  on a subset of related tasks  $\mathcal{T}_k \subset \mathcal{T}$ .

We incorporate these insights into our algorithm by modeling the task set  $\mathcal{T}$  as a union of  $K$  disjoint task clusters  $\mathcal{T}_1, \dots, \mathcal{T}_K$ , i.e.,  $\mathcal{T} = \bigcup_{k=1}^K \mathcal{T}_k$  with  $\mathcal{T}_i \cap \mathcal{T}_j = \emptyset$  for  $i \neq j$ . Tasks within a cluster allow for positive transfer while we do not assume any relationship between tasks of different clusters. Tasks in different clusters may therefore even have conflicting objectives. Note that the assignment of tasks to clusters is not given to us and therefore needs to be inferred by the algorithm. Note also that this formulation only relies on minimalistic assumptions. That

is, we do not assume a shared transition function or a shared reward structure. Neither do we assume the underlying MDP to be finite and/or solvable in closed form. Our approach is therefore applicable to a much broader range of settings than many sophisticated models with stronger assumptions. As generality is one of our main objectives, we see the minimalistic nature of the model as a strength rather than a weakness.

Given this problem formulation, we note that it reflects a clustering problem, in which we have to assign each task  $\tau \in \mathcal{T}$  to one of the clusters  $\mathcal{T}_k$ ,  $k \in \{1, \dots, K\}$ . At the same time, we want to train a set of policies  $\Pi = \{\pi_1, \dots, \pi_n\}$  to solve the given tasks. Put differently, we wish to infer a latent variable (cluster assignment of the tasks) while optimizing our model parameters (set of policies).

An EM [10] inspired algorithm allows us to do just that. On a high level, in the expectation step (E-step) we assign each of the tasks  $\tau \in \mathcal{T}$  to a policy  $\pi_i$ , representing an estimated cluster  $\tilde{\mathcal{T}}_i$ . We then train the policies in the maximization step (M-step) on the tasks they got assigned, specializing the policies to their clusters. These steps are alternately repeated — one benefiting from the improvement of the other in the preceding step — until convergence. Given this general framework we are left with filling in the details. Specifically, how to assign tasks to which policies (E-step) and how to allocate training time from policies to assigned tasks (M-step).

For the assignment in the E-step we want the resulting clusters to represent clusters with positive transfer. Given that policy  $\pi_i$  is trained on a set of tasks  $\tilde{\mathcal{T}}_i$  in a preceding M-step, we can base our assignment of tasks to  $\pi_i$  on the performance of  $\pi_i$ : Tasks on which  $\pi_i$  performs well likely benefited from the preceding training and therefore should be assigned to the cluster of  $\pi_i$ . Specifically, we can evaluate each policy  $\pi_i \in \{\pi_1, \dots, \pi_n\}$  on all tasks  $\tau \in \mathcal{T}$  to get an estimate of  $G_\tau(\pi_i)$  and base the assignment on this performance evaluation. To get to an implementable algorithm we state two additional desiderata for our assignment: (1) We do not want to constrain cluster sizes in any way as clusters can be of unknown, non-uniform sizes. (2) We do not want to constrain the diversity of the tasks. This

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**Algorithm 1:** Task-Clustering
 

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Initialize  $N$  policies  $(\pi_1, \dots, \pi_N)$   
 Initialize  $N$  buffers  $(\mathbf{D}_1, \dots, \mathbf{D}_N)$   
**while not converged do**

▷ E-Step

$\tilde{\mathcal{T}}_i \leftarrow \emptyset$  for  $i \in \{1, \dots, n\}$

**for**  $\tau \in \mathcal{T}$  **do**

$k \leftarrow \arg \max_i G_\tau(\pi_i)$

$\tilde{\mathcal{T}}_k \leftarrow \tilde{\mathcal{T}}_k \cup \tau$

$\tilde{\mathcal{T}}_i \leftarrow \mathcal{T}$  where  $\tilde{\mathcal{T}}_i = \emptyset$

▷ M-Step

**for**  $\pi_i \in \{\pi_1, \dots, \pi_n\}$  **do**

$t \leftarrow 0$

**while**  $t < T_M$  **do**

$\tau \sim \tilde{\mathcal{T}}_i$

        Run  $\pi_i$  on  $\tau$  for  $L$  steps,  
         store transitions in  $\mathbf{D}_i$

        Update  $\pi_i$  from  $\mathbf{D}_i$

$t \leftarrow t + L$

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implies that the assignment has to be independent of the reward scales of the tasks, which in turn limits us to assignments based on the relative performances of the policies  $\pi_1, \dots, \pi_n$ . We found a greedy assignment — assigning each task to the policy that performs best — to work well. That is, a task  $\tau_k$  is assigned to the policy  $\pi = \arg \max_{\pi_i} G_{\tau_k}(\pi_i)$ . A soft assignment based on the full ranking of policies might be worth exploring in future work. Given the greedy assignment, our method can also be seen as related to k-means [24], a special case of EM.

In the M-step, we take advantage of the fact that clusters reflect positive transfer, i.e., training on some of the assigned tasks should improve performance on the whole cluster. We can therefore randomly sample a task from the assigned tasks and train on it for one episode before sampling the next task. Overall we train each policy for a fixed number of updates  $T_M$  in each M-step with  $T_M$  independent of the cluster size. This independence allows us to save environment interactions as larger clusters benefit from positive transfer and do not need training time proportional to the number of assigned tasks.

Note that the greedy assignment (and more generally any assignment fulfilling desiderata 1 above) comes with a caveat: Some policies might not be assigned any tasks. In this case we sample the tasks to train these policies from all tasks  $\tau \in \mathcal{T}$ , which can be seen as a random exploration of possible task clusters. This also ensures that, early on in training, every policy gets a similar amount of initial experience. For reference, we provide a pseudo code of our approach in Algorithm 1. Note that we start by performing an E-Step, i.e., the first assignment is based on the performance of the randomly initialized policies.

#### 4.1 Convergence Analysis

We now show that both, the E- and M-step yield a monotonic improvement. Thereby, our algorithm improves the objective monotonically in every iteration.

We denote our overall objective function that we aim to maximize as  $o(\Pi, \tilde{\mathcal{T}}) = \sum_{\pi_i \in \Pi} \sum_{\tau_j \in \tilde{\mathcal{T}}_i} G_{\tau}(\pi_i)$ , as a function of our policy set  $\Pi = \{\pi_1, \dots, \pi_n\}$  and their corresponding task assignments  $\tilde{\mathcal{T}} = \{\tilde{\mathcal{T}}_1, \dots, \tilde{\mathcal{T}}_n\}$ . In the E-step, we evaluate all policies on all tasks to determine the returns  $G_{\tau}(\pi_i)$ . Using the greedy assignment strategy, we assign each task to the policy that achieves the respective highest return  $\arg \max_i G_{\tau}(\pi_i)$  and obtain a new assignment set  $\tilde{\mathcal{T}}'$ . It is easy to see that this assignment step can only improve the objective, as

$$o(\Pi, \tilde{\mathcal{T}}') = \sum_{\tau \in \mathcal{T}} \max_{\pi_i \in \Pi} G_{\tau}(\pi_i) \geq \sum_{\tau \in \mathcal{T}} \sum_{\pi_i \in \Pi} \mathbf{1}_{[\tau \in \tilde{\mathcal{T}}'_i]} G_{\tau}(\pi_i) = o(\Pi, \tilde{\mathcal{T}})$$

for any previous assignments  $\tilde{\mathcal{T}}$ , since the indicator function  $\mathbf{1}_{[\tau \in \tilde{\mathcal{T}}'_i]}$  will only indicate one cluster.<sup>1</sup> Note that this derivation relies on a deterministic evaluation of policies, i.e. deterministic task environments. For stochastic environments we can take the average over multiple evaluations, trading off the computational

<sup>1</sup> Note that assigning all tasks to a cluster that did not get any tasks assigned is only done for exploration. In the evaluation of our objective these clusters remain empty.

overhead with the accuracy of the evaluation. In our experiments we found that a relatively small number of evaluations is sufficient for the algorithm to converge.

During the M-step the assignments are fixed, and every policy  $\pi_i$  is trained on its assigned tasks  $\tau \in \tilde{\mathcal{T}}_i$  by sampling from them uniformly. We derive the case for shared transition dynamics  $P_\tau = P \forall \tau \in \mathcal{T}$  here and extend it to the case of tasks with distinct transition dynamics in Appendix A.<sup>2</sup>

The value of policy  $\pi_i$  on task  $\tau$  can be defined recursively as

$$V_\tau^{\pi_i}(s) = \mathbb{E}_{a \sim \pi_i}[R_\tau(s, a) + \gamma \mathbb{E}_{s' \sim P(\cdot|s, a)}[V_\tau^{\pi_i}(s')]]$$

such that  $V_\tau^{\pi_i}(s_0) = G_\tau(\pi_i)$  for the starting state  $s_0$ . We further note that the expected value  $V_{\mathcal{M}}^{\pi_i}(s) = \mathbb{E}_{\tau \sim \tilde{\mathcal{T}}_i}[V_\tau^{\pi_i}(s)]$  is in itself a value function over an MDP  $\mathcal{M}$  defined by the expected reward with

$$\begin{aligned} V_{\mathcal{M}}^{\pi_i}(s) &= \mathbb{E}_{a \sim \pi_i}[\mathbb{E}_{\tau \sim \tilde{\mathcal{T}}_i}[R_\tau(s, a) + \gamma \mathbb{E}_{s' \sim P(\cdot|s, a)}[\mathbb{E}_{\tau \sim \tilde{\mathcal{T}}_i}[V_\tau^{\pi_i}(s')]]]] \\ &= \mathbb{E}_{a \sim \pi_i}[\mathbb{E}_{\tau \sim \tilde{\mathcal{T}}_i}[R_\tau(s, a) + \gamma \mathbb{E}_{s' \sim P(\cdot|s, a)}[V_{\mathcal{M}}^{\pi_i}(s')]]] \end{aligned}$$

Policy iteration on  $\mathcal{M}$  will yield an improved policy  $\pi'_i$  with  $V_{\mathcal{M}}^{\pi'_i}(s) \geq V_{\mathcal{M}}^{\pi_i}(s) \forall s \in \mathcal{S}$ . More generally, any off-policy RL algorithm that samples uniformly over collected  $(s, r, a, s')$  transition tuples will implicitly optimize  $\mathcal{M}$ . Note that  $V_{\mathcal{M}}^{\pi_i}(s_0) = \mathbb{E}_{\tau \sim \tilde{\mathcal{T}}_i}[G_\tau(\pi_i)] = \frac{1}{|\tilde{\mathcal{T}}_i|} \sum_{\tau \in \tilde{\mathcal{T}}_i} G_\tau(\pi_i)$  for uniformly sampled tasks. Any improvement in  $V_{\mathcal{M}}^{\pi_i}$  therefore directly translates into an improvement in our overall objective. While we focus on off-policy RL in this paper, we conjecture that a similar optimisation can be done on-policy.

## 5 Experiments

As a proof of concept we start the evaluation of our approach on two discrete tasks. The first environment consists of a chain of discrete states in which the agent can either move to the left or to the right. The goal of the agent is placed either on the left end or the right end of the chain. This gives rise to two task clusters, where tasks within a cluster differ in the frequency with which the agent is rewarded on its way to the goal. The second environment reflects the 2-dimensional grid-world presented in Figure 1. Actions correspond to the cardinal directions in which the agent can move and the 12 tasks in the task set  $\mathcal{T}$  are defined by their respective goal. We refer an interested reader to Appendix B.1 for a detailed description.<sup>2</sup>

We train policies with tabular Q-learning [37] and compare our approach to two baselines: In the first we train a single policy on all tasks. We refer to this as SP (Single Policy). In the other we train a separate policy per task and evaluate each policy on the task it was trained on. This is referred to as PPT (Policy per Task). Our approach is referred to as EM (Expectation-Maximization).

The results and task assignment over the course of training are shown in Figure 2 and Figure 3. Looking at the assignments, we see that in both environments

<sup>2</sup> The Appendix and implementations of all our experiments can be found at <https://github.com/JohannesAck/EMTaskClustering>

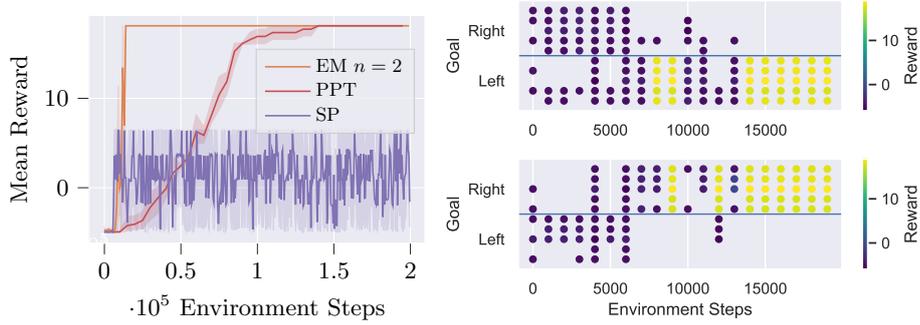


Fig. 2: **Left:** Mean reward and 95% confidence interval (shaded area) from 10 trials when training on the chain environment. **Right:** Task assignment (dots) and task specific reward (color) over the course of training the two policies in our approach. Each plot shows one of the policies/estimated clusters. The assignments converge to the natural clustering reflected by the goal location.

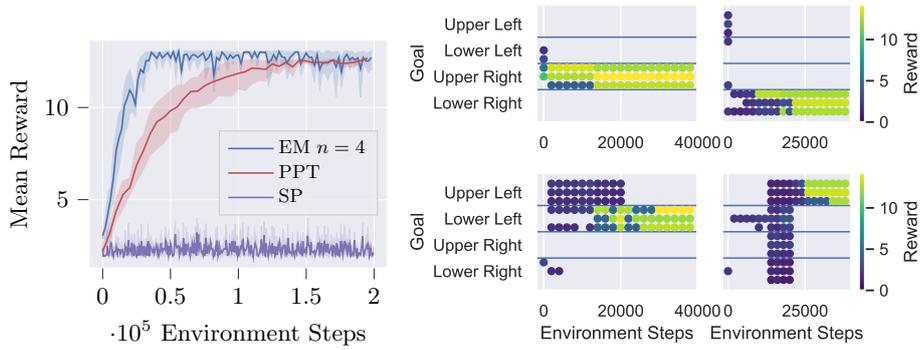


Fig. 3: **Left:** Mean reward and 95% confidence interval (shaded area) from 10 trials when training on the grid-world environment depicted in Figure 1. **Right:** Task assignment (dots) and task specific reward (color) over the course of training for the  $n=4$  policies (estimated clusters) in our approach. The assignment naturally clusters the tasks of each corner together.

our approach converges to the natural clustering, leading to a higher reward after finding these assignments. Both our EM-approach and PPT converge to an optimal reward in the chain environment, and a close to optimal reward in the corner-grid-world. However, PPT requires a significantly higher amount of environment steps to reach this performance, as it does not share information between tasks and therefore has to do exploration for each task separately. SP fails to achieve a high reward due to the different tasks providing contradicting objectives.

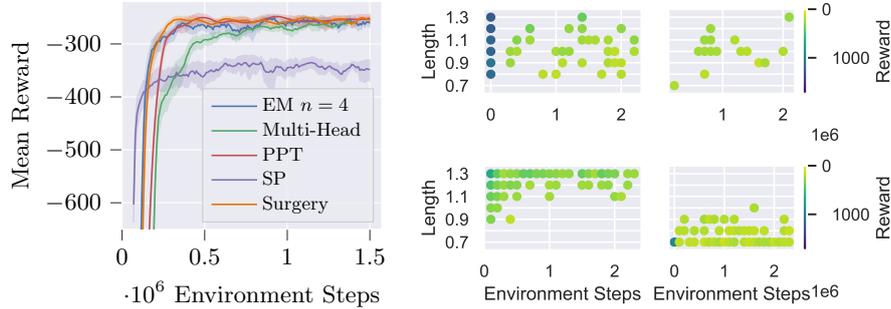


Fig. 4: **Left:** Mean reward and 95% confidence interval (shaded area) from 10 trials when training on the pendulum environment. The curves are smoothed by a rolling average to dampen the noise of the random starting positions. For [40] we used 12 trials out of which 3 failed to converge and were excluded. **Right:** Task assignment (dots) and task specific reward (color) from a sample run. Two policies focus on long and short, while the others focus on medium lengths.

## 5.1 Pendulum

Next we consider a simple continuous control environment where tasks differ in their dynamics. We use the pendulum gym task [3], in which a torque has to be applied to a pendulum to keep it upright. Here the environment is the same in all tasks, except for the length of the pendulum, which is varied in the range  $\{0.7, 0.8, \dots, 1.3\}$ , giving a total of 7 tasks. Note that there is no obvious cluster structure here and the experiment therefore serves as an edge-case to test the applicability of our approach.

We use Twin Delayed Deep Deterministic Policy Gradient (TD3) [13] with hyperparameters optimized as discussed in Appendix B.2. By default, we use  $n = 4$  policies and did not tune this hyperparameter. This was done to give a fair comparison to baseline approaches which do not have this extra degree of freedom. For application purposes the number of clusters can be treated as a hyperparameter and included in the hyperparameter optimization. We compare against SP, PPT, gradient surgery [40] and a multi-head network structure similar to the approach used by Eramo et al. [11]. Each policy in our approach uses a separate replay buffer. The multi-head network has a separate replay-buffer and a separate input and output layer per task. Surgery uses a separate replay-buffer and output layer per task. We adjust the network size of the multi-head baseline, surgery and SP to avoid an advantage of our method due to a higher parameter count, see Appendix B.2 for details. The results are shown in Figure 4.

We observe that EM, PPT, multi-head and surgery all achieve a similar final performance, with EM and surgery achieving a high reward earlier than PPT or multi-head. The multi-head approach requires significantly more experience to converge than even PPT in this setup. We believe this is due to the inherent interference of learning signals in the shared layers. Our approach manages to

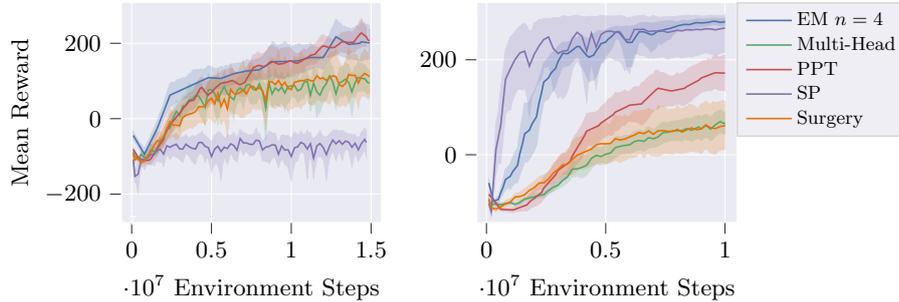


Fig. 5: Evaluation of the BipedalWalker experiments. The shaded areas show the 95% confidence interval on the mean task reward. **Left:** Track and field task set; 6 tasks with varying objectives. Results reflect 20 trials of each approach. **Right:** Task set with varying leg lengths and obstacles; 9 tasks with the same reward function. Results reflect 10 trials of each approach.

avoid this interference, as does surgery. SP is unable to achieve a high reward as it cannot specialize to the tasks. In contrast to the surgery baseline, our approach can give further insights by producing intuitive cluster assignments, see Figure 4.

## 5.2 Bipedal Walker

As a more complex continuous control environment we focus on *BipedalWalker* from the OpenAI Gym [3], which has previously been used in multi-task and generalization literature [28, 35, 36]. It consists of a bipedal robot in a two-dimensional world, where the default task is to move to the right with a high velocity. The action space consists of continuous torques for the hip and knee joints of the legs and the state space consists of joint angles and velocities, as well as hull angle and velocity and 10 lidar distance measurements. Examples are shown in Figure 1 on the right.

To test our approach, we designed 6 tasks inspired by track and field sports: Jumping up at the starting position, jumping forward as far as possible, a short, medium and long run and a hurdle run. As a second experiment, we create a set of 9 tasks by varying the leg length of the robot as well as the number of obstacles in its way. This task set is inspired by task sets in previous work [28]. Note that we keep the objective — move forward as fast as possible — constant here. We again use TD3 and tune the hyperparameters of the multi-head baseline and our approach (with  $n = 4$  fixed) with grid-search. Experiment details and hyperparameters are given in Appendix B.3.

The results in Figure 5 (left) on the track and field tasks show a significant advantage in using our approach over multi-head TD3, surgery or SP and a better initial performance than PPT, with similar final performance. SP fails to learn a successful policy altogether due to the conflicting reward functions. In contrast, the results in Figure 5 (right) from the second task set show that SP can learn

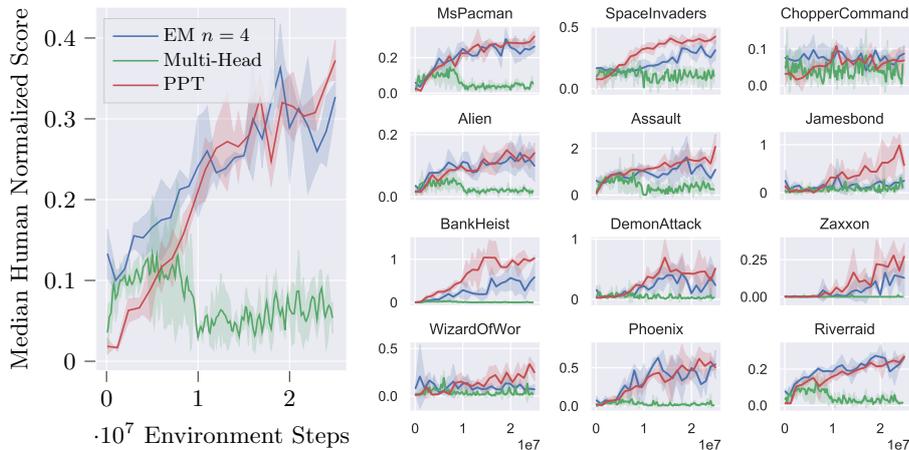


Fig. 6: The results of our experiments on a subset of the Atari Learning Environment games. The reward is averaged across 3 trials and the shaded region shows the standard deviation of the mean.

a policy that is close to optimal on all tasks here. The multi-head, surgery and PPT approaches suffer in this setup as each head/policy only gets the experience from its task and therefore needs more time to converge. Our approach can take advantage of the similarity of the tasks, converging significantly quicker. We note that the experiments presented here reflect two distinct cases: One in which it is advantageous to separate learning, reflected by PPT outperforming SP, and one where it is better to share experience between tasks, reflected by SP outperforming PPT. Our approach, unlike surgery or multi-head, demonstrates general applicability as it is the only one performing competitively in both. We provide an insight into the assignment of tasks to policies in Appendix C.1.

### 5.3 Atari

To test the performance of our approach on a more diverse set of tasks, we evaluate on a subset of the Arcade Learning Environment (ALE) tasks [23]. Our choice of tasks is similar to those used by [30], but we exclude tasks containing significant partial-observability. This is done to reduce the computational burden as those tasks usually require significantly more training data. We built our approach on top of the Implicit Quantile Network (IQN) implementation in the Dopamine framework [6, 8]. We chose IQN due to its sample efficiency and the availability of an easily modifiable implementation. As the different ALE games have different discrete action spaces, we use a separate final layer and a separate replay buffer for each game in all approaches. We use the hyperparameters recommended by [6], except for a smaller replay buffer size to reduce memory requirements. As in the Bipedal Walker experiments we fix the number of policies in our approach without tuning to  $n = 4$ . We choose the size of the network

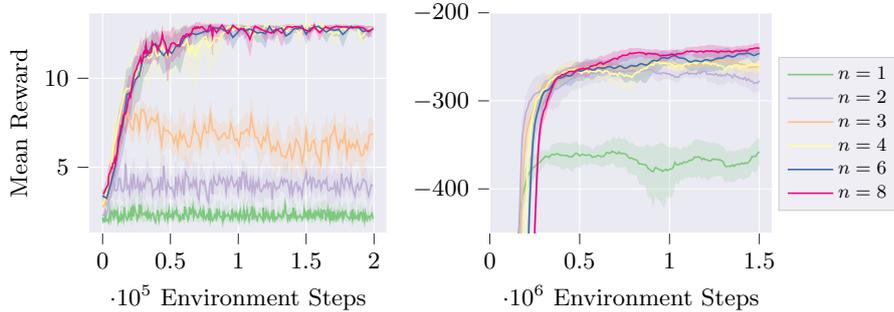


Fig. 7: Ablations for different number of policies  $n$ . Shaded areas show the 95% confidence interval of the mean reward from 10 trials each. **Left:** Corner-grid-world tasks. **Right:** Pendulum tasks, learning curves smoothed.

such that each approach has the same number of total tunable parameters. We provide the details in Appendix B.4.

The results are given in Figure 6. The multi-head approach is unable to learn any useful policy here due to negative transfer between tasks. This is in line with experiments in other research [14] and is due to the large variety of the tasks. On the other hand, both our EM-approach and PPT are able to achieve significantly higher reward. However, our approach does not perform better than PPT. Note that we can only expect a better performance than PPT if there are clusters of tasks that benefit from positive transfer. The diverse set of Atari games seems to violate this assumption. While we cannot benefit from positive transfer, our approach avoids the negative interference impacting the multi-head approach, even with just 4 clusters. Task assignments in our approach are given in Appendix C.2.

#### 5.4 Ablations

To gain additional insight into our approach, we perform two ablation studies on the discrete corner-grid-world environment and the pendulum environment.

First, we investigate the performance of our approach for different numbers of policies  $n$ . The results in Figure 7 show that using too few policies can lead to a worse performance, as the clusters cannot distinguish the contradicting objectives. On the other hand, using more policies than necessary increases the number of environment interactions required to achieve a good performance in the pendulum task, but does not significantly affect the final performance.

As a second ablation, we are interested in the effectiveness of the clustering. It might be possible that simply having fewer tasks per policy is giving our approach an advantage compared to SP or multi-head TD3. We therefore provide an ablation in which task-policy assignments are determined randomly at the start and kept constant during the training. Results from this experiment can be seen in Figure 8, with additional results in Appendix D. The results show

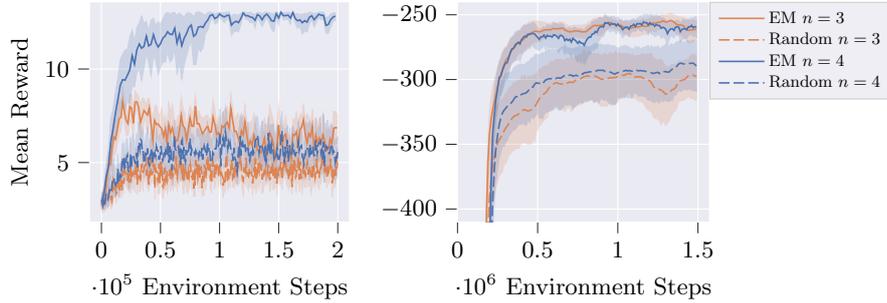


Fig. 8: Comparison of our approach against randomly assigning tasks to policies at the start of training. Shaded areas show the 95% confidence interval of the mean reward. **Left:** Corner-grid-world tasks, 10 trials each. **Right:** Pendulum tasks, 10 trials each, learning curves smoothed.

that using random clusters performs significantly worse than using the learned clusters. This highlights the importance of clustering tasks meaningfully.

## 6 Conclusion

We present an approach for multi-task reinforcement learning (RL) inspired by Expectation-Maximization (EM) that automatically clusters tasks into related subsets. Our approach uses a set of policies and alternately evaluates the policies on all tasks, assigning each task to the best performing policy and then trains the policies on their assigned tasks. While the repeated evaluation of policies adds a small computational overhead, it provides an effective way to mitigate negative transfer. Our algorithm is straightforward and can easily be combined with a variety of state-of-the-art RL algorithms. We evaluate the effectiveness of our approach on a diverse set of environments. Specifically, we test its performance on sets of simple discrete tasks, simple continuous control tasks, two complex continuous control task sets and a set of Arcade Learning Environment tasks. We show that our approach is able to identify clusters of related tasks and use this structure to achieve a competitive or superior performance to evaluated baselines, while additionally providing insights through the learned clusters. We further provide an ablation over the number of policies in our approach and a second ablation that highlights the need to cluster tasks meaningfully.

Our approach offers many possibilities for future extensions. An adaption to on-policy learning and combination with orthogonal approaches could improve the applicability further. Another interesting direction would be hierarchical clustering. This could prove helpful for complicated tasks like the Atari games. It would also be interesting to see how our approach can be applied to multi-task learning in a supervised setting. Further, different assignment strategies with soft assignments could be investigated. Overall, we see our work as a good stepping stone for future work on structured multi-task learning.

## References

1. Achiam, J., Edwards, H., Amodei, D., Abbeel, P.: Variational Option Discovery Algorithms (2018), <https://arxiv.org/abs/1807.10299>
2. Bräm, T., Brunner, G., Richter, O., Wattenhofer, R.: Attentive Multi-task Deep Reinforcement Learning. In: ECML PKDD (2019)
3. Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., Zaremba, W.: Openai gym (2016), <http://arxiv.org/abs/1606.01540>
4. Cacciatore, T.W., Nowlan, S.J.: Mixtures of controllers for jump linear and non-linear plants. In: NeurIPS (1993)
5. Carroll, J.L., Seppi, K.: Task similarity measures for transfer in reinforcement learning task libraries. In: IJCNN (2005)
6. Castro, P.S., Moitra, S., Gelada, C., Kumar, S., Bellemare, M.G.: Dopamine: A Research Framework for Deep Reinforcement Learning (2018), <http://arxiv.org/abs/1812.06110>
7. Cully, A., Demiris, Y.: Quality and Diversity Optimization: A Unifying Modular Framework. *IEEE Trans. Evol. Comput.* **22**, 245–259 (2018)
8. Dabney, W., Ostrovski, G., Silver, D., Munos, R.: Implicit quantile networks for distributional reinforcement learning. In: ICML (2018)
9. Deisenroth, M.P., Neumann, G., Peter, J.: A Survey on Policy Search for Robotics. *Found. Trends Robot.* **2**(1-2), 1–142 (2013)
10. Dempster, A.P., Laird, N.M., Rubin, D.B.: Maximum likelihood from incomplete data via the em algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)* **39**(1), 1–38 (1977)
11. Eramo, C.D., Tateo, D., Bonarini, A., Restelli, M., Milano, P., Peters, J.: Sharing Knowledge in Multi-Task Deep Reinforcement Learning. In: ICLR (2020)
12. Eysenbach, B., Gupta, A., Ibarz, J., Levine, S.: Diversity is all you need: Learning skills without a reward function. In: ICLR (2018)
13. Fujimoto, S., van Hoof, H., Meger, D.: Addressing Function Approximation Error in Actor-Critic Methods. In: ICML (2018)
14. Hessel, M., Soyer, H., Espenholt, L., Czarnecki, W., Schmitt, S., Van Hasselt, H.: Multi-Task Deep Reinforcement Learning with PopArt. In: AAAI (2019)
15. Hospedales, T., Antoniou, A., Micaelli, P., Storkey, A.: Meta-learning in neural networks: A survey (2020), <https://arxiv.org/abs/2004.05439>
16. Jacobs, R.A., Jordan, M.I., Nowlan, S.E., Hinton, G.E.: Adaptive mixture of experts. *Neural Comput.* **3**, 79–87 (1991)
17. Jacobs, R., Jordan, M.: A competitive modular connectionist architecture. *NeurIPS* (1990)
18. Jordan, M.I., Jacobs, R.A.: Hierarchical mixtures of experts and the EM algorithm. In: IJCNN (1993)
19. Lazaric, A.: Transfer in Reinforcement Learning : a Framework and a Survey. In: Wiering, M., van Otterlo, M. (eds.) *Reinforcement Learning - State of the art 12*, pp. 143–173. Springer (2012)
20. Lazaric, A., Ghavamzadeh, M.: Bayesian Multi-Task Reinforcement Learning. In: ICML (2010)
21. Lee, K., Seo, Y., Lee, S., Lee, H., Shin, J.: Context-aware Dynamics Model for Generalization in Model-Based Reinforcement Learning. In: ICML (2020)
22. Li, H., Liao, X., Carin, L.: Multi-task reinforcement learning in partially observable stochastic environments. *J. Mach. Learn. Res.* **10** (2009)

23. Machado, M.C., Bellemare, M.G., Talvitie, E., Veness, J., Hausknecht, M.J., Bowling, M.: Revisiting the arcade learning environment: Evaluation protocols and open problems for general agents. *JAIR* **61**, 523–562 (2018)
24. MacQueen, J.: Some methods for classification and analysis of multivariate observations. In: *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, Volume 1: Statistics. pp. 281–297 (1967)
25. Mahmud, M.M.H., Hawasly, M., Rosman, B., Ramamoorthy, S.: Clustering Markov Decision Processes For Continual Transfer (2013), <http://arxiv.org/abs/1311.3959>
26. Meila, M., Jordan, M.I.: Learning fine motion by markov mixtures of experts. In: *NeurIPS* (1995)
27. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.a., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., Hassabis, D.: Human-level control through deep reinforcement learning. *Nature* (2015)
28. Portelas, R., Colas, C., Hofmann, K., Oudeyer, P.Y.: Teacher algorithms for curriculum learning of Deep RL in continuously parameterized environments. In: *CoRL* (2019)
29. Pugh, J.K., Soros, L.B., Stanley, K.O.: Quality diversity: A new frontier for evolutionary computation. *Front. Robot. AI* **3** (2016)
30. Riemer, M., Liu, M., Tesauro, G.: Learning abstract options. In: *NeurIPS* (2018)
31. Sharma, S., Jha, A.K., Hegde, P.S., Ravindran, B.: Learning to multi-task by active sampling. *ICLR 2018 - Conference Track* (2018)
32. Sutton, R.S., Barto, A.G.: *Reinforcement learning: an introduction*. MIT Press (2017)
33. Tang, G., Hauser, K.: Discontinuity-sensitive optimal control learning by mixture of experts. In: *ICRA* (2019)
34. Thrun, S., O’Sullivan, J.: Discovering Structure in Multiple Learning Tasks : The TC Algorithm. In: *ICML* (1996)
35. Wang, R., Lehman, J., Clune, J., Stanley, K.O.: Paired Open-Ended Trailblazer (POET): Endlessly Generating Increasingly Complex and Diverse Learning Environments and Their Solutions (2019), <http://arxiv.org/abs/1901.01753>
36. Wang, R., Lehman, J., Rawal, A., Zhi, J., Li, Y., Clune, J., Stanley, K.O.: Enhanced POET: Open-Ended Reinforcement Learning through Unbounded Invention of Learning Challenges and their Solutions. In: *ICML* (2020)
37. Watkins, C.J.C.H.: *Learning from delayed rewards*. Ph.D. thesis, King’s College, Cambridge (1989)
38. Wilson, A., Fern, A., Ray, S., Tadepalli, P.: Multi-task reinforcement learning: A hierarchical Bayesian approach. In: *ICML* (2007)
39. Yang, J., Petersen, B., Zha, H., Faissol, D.: Single Episode Policy Transfer in Reinforcement Learning. In: *ICLR* (2020)
40. Yu, T., Kumar, S., Gupta, A., Levine, S., Hausman, K., Finn, C.: Gradient Surgery for Multi-Task Learning (2020), <http://arxiv.org/abs/2001.06782>
41. Zhang, Y., Yang, Q.: A Survey on Multi-Task Learning (2017), <https://arxiv.org/abs/1707.08114>
42. Zhu, Z., Lin, K., Zhou, J.: Transfer learning in deep reinforcement learning: A survey (2020), <http://arxiv.org/abs/2009.07888>
43. Zintgraf, L., Shiarlis, K., Igl, M., Schulze, S., Gal, Y., Hofmann, K., Whiteson, S.: VariBAD: A Very Good Method for Bayes-Adaptive Deep RL via Meta-Learning. In: *ICLR* (2020)