# Scaling Up Multi-Task Robotic Reinforcement Learning

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**Abstract:** General-purpose robotic systems must master a large repertoire of diverse skills. While reinforcement learning provides a powerful framework for acquiring individual behaviors, the time needed to acquire each skill makes the prospect of a generalist robot trained with RL daunting. In this paper, we study how a large-scale collective robotic learning system can acquire a repertoire of behaviors simultaneously, sharing exploration, experience, and representations across tasks. In this framework, new tasks can be continuously instantiated from previously learned tasks improving overall performance and capabilities of the system. To instantiate this system, we develop a scalable and intuitive framework for specifying new tasks through user-provided examples of desired outcomes, devise a multi-robot collective learning system for data collection that simultaneously collects experience for multiple tasks, and develop a scalable and generalizable multi-task deep reinforcement learning method, which we call MT-Opt. We demonstrate how MT-Opt can learn a wide range of skills, including semantic picking (i.e., picking an object from a particular category), placing into various fixtures (e.g., placing a food item onto a plate), covering, aligning, and rearranging. We train and evaluate our system on a set of 12 real-world tasks with data collected from 7 robots, and demonstrate the performance of our system both in terms of its ability to generalize to structurally similar new tasks, and acquire distinct new tasks more quickly by leveraging past experience. We recommend viewing the videos at https://mt-opt.github.io/

**Keywords:** Multi-Task Reinforcement Learning, Robot Learning

## 1 Introduction

Today's deep reinforcement learning (RL) methods, when applied to real-world robotic tasks, provide an effective but expensive way of learning skills [1, 2]. While existing methods are effective and able to generalize, they require considerable on-robot training time. For example, the QT-Opt [1] system can learn vision-based robotic grasping, but it requires over $500,000$ trials collected across multiple robots. While such sample complexity may be reasonable if the robot needs to perform a single task, it becomes costly if we consider the prospect of training a general-purpose robot with a large repertoire of behaviors, where each behavior is learned in isolation, starting from scratch. Can we instead *amortize* the cost of learning this repertoire over multiple skills, where the effort needed to learn whole repertoire is reduced, easier skills serve to facilitate the acquisition of more complex ones, and data requirements, though still high overall, become low for each individual behavior?

Prior work suggests that multi-task RL can amortize the cost of single-task learning [3, 4, 5, 6, 7]. Insofar as the tasks share common structure, if that structure can be discovered by the learning algorithm, all of the tasks can in principle be learned much more efficiently than learning each of the tasks individually. In addition, by collecting experience simultaneously using controllers for a variety of tasks with different difficulty, the easier tasks can serve to "bootstrap" the harder tasks. Finally, by enabling the multi-task RL policy to learn shared representations, learning new tasks can become easier over time as the system acquires more skills and learns more widely-useful aspects of the environment.

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However, to realize these benefits for a real-world robotic learning system, we need to overcome a number of major challenges [8, 9, 10, 11], which have so far made it difficult to produce a large-scale demonstration of multi-task image-based RL in the real world. First, multi-task reinforcement learning is known to be exceedingly difficult from the optimization standpoint [8, 12]. Second, a real-world multi-task learning framework requires the ability to easily and intuitively define rewards for a large number of tasks. Third, while all task-specific data could be shared between all the tasks, it has been shown that reusing data from non-correlated tasks can be harmful to the learning process [13]. Lastly, in order to receive the benefits from shared, multi-task representation, we need to significantly scale up our algorithms, the number of tasks in the environment, and the robotic systems themselves.

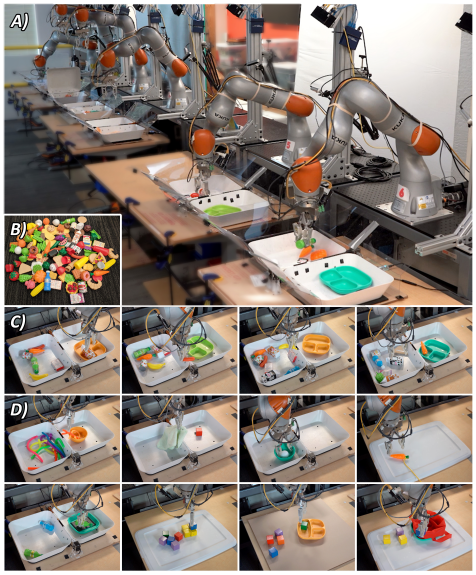


Figure 1: A) Multi-task data collection. B) Training objects. C) Sample of tasks that the system is trained on. D) Sample of behaviorally and visually distinct tasks such as covering, chasing, alignment, which we show our method can adapt to. MT-Opt learns new tasks faster (potentially zero-shot if there is sufficient overlap with existing tasks), and with less data compared to learning the new task in isolation.

The main contribution of this paper is a general multi-task learning system, which we call MT-Opt. MT-Opt realizes the hypothesized benefits of multi-task RL in a scalable real-world robotic learning system, addressing the associated challenges through a number of important design decisions, including a carefully designed multi-task data sharing strategy and multi-robot parallelized data collection. We train MT-Opt on a set of 12 real-world tasks that include data collected over the course of over 1.5 years, and provide an extensive evaluation (spanning over 500 real-robot-hours) of our method together with a number of baselines. We show that at such scale, our system can quickly acquire new tasks by taking advantage of prior tasks via shared representations, new data-sharing strategies and learned policies. Our results indicate that, by learning multiple related tasks simultaneously, not only can we increase the data-efficiency of learning each of them, but also solve more complex tasks than in a single-task setup. We present our multi-task system as well as examples of some of the tasks that it is capable of performing in Fig. 1.

## 2 Related Work

Multi-task learning, inspired by the ability of humans to transfer knowledge between different tasks [14], is a promising approach for sharing structure and data between tasks to improve overall efficiency. Multi-task architectures have been successful across multiple domains; natural language processing [15, 16, 17, 18] and computer vision [19, 20, 21, 22, 23, 24]. In this work, we apply multi-task learning concept in a RL setting to real robotic tasks.

Combining multiple task policies has been explored in RL by using gating networks [25, 26], conditioning policies on tasks [27], mapping tasks to parameters of a policy [28, 29, 30], distilling separate task policies into a shared multi-task policy [31, 32, 33, 34, 35, 36]. Advantages of multi-task learning for visual representations has been explored in [37]. Pinto and Gupta [4] use a shared multi-task neural network architecture, which is trained with separate task-specific losses. In contrast, in our work, we concentrate on tasks with a common loss structure within a Q-learning framework. Several works explore how to mitigate multi-task interference and conflicting objectives [38, 39]. In our experiments, we find that better data routing helps with not only better mitigating conflicting objectives but also improving learning efficiency through data reuse.

Learning complex skills has been addressed through hierarchical reinforcement learning with options [40, 41, 42], combining multiple sub-tasks [43, 44, 45, 46, 47, 48], reusing samples between tasks [49], relabeling experience in hindsight [50], introducing demonstrations [51, 52, 53, 54, 55, 56, 57]. A range of works employ autonomous supervision to learn diverse skills, e.g. by scaling up data collection [58], sampling suitable tasks [59] or goals [60] to practice, learning a task embedding space amenable to sampling [7], or learning a dynamics model and using model-predictive

control to achieve goals [61, 62, 63, 64]. Riedmiller et al. [5] learn sparse-reward tasks by solving easier auxiliary tasks and reusing that experience for offline learning of more complex tasks. In Cabi et al. [65], previously collected experience is relabeled with new reward functions in order to solve new tasks without re-collecting the data. In our work, we similarly design techniques for reusing experience between related tasks and apply them to large-scale data collection on real robots.

# 3 MT-Opt: a Scalable Multi-Task RL System

Our multi-task learning system is shown in Fig. 2. We devise a distributed, off-policy multi-task RL algorithm together with a multi-task visual success detector ($SD$) to learn multiple robotic manipulation tasks simultaneously. The $SD$, trained from video examples of desired outcomes, (Fig. 2A) in part determines how episodes are leveraged to train an RL policy (Fig. 2C). During evaluation and fine-tuning (Fig. 2B), at each time step, a policy takes as input a camera image and a one-hot encoding of the task, and sends a motor command to the robot. At episode end, the outcome image of this process is graded by the $SD$ that determines which tasks were accomplished successfully and assigns a sparse reward 0 or 1 for each task. The system then decides whether another task should be attempted or if the environment should be reset. We train this system with multiple robots, where each robot concurrently collects data for a different, randomly selected task. The generated episodes are used as offline data for training future policies (Fig. 2C) and are available to improve $SD$s.

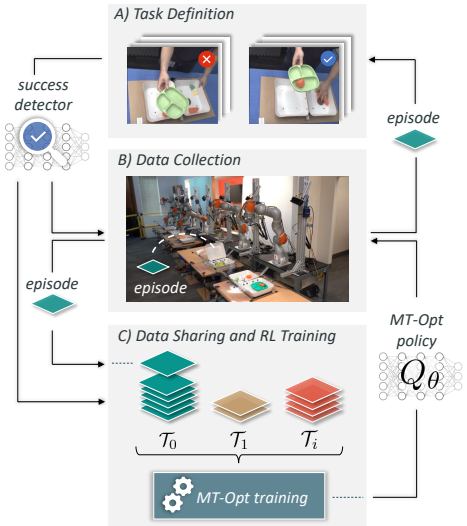


Figure 2: MT-Opt overview. A) The user defines a success detector ($SD$) for tasks through examples of desired outcomes, and relabeling outcomes of prior episodes. B) Utilizing the $SD$ and the MT-Opt policy, new episodes are collected for multiple tasks. C) Offline episodes enter the data-sharing pipeline that expands and re-balances the data used to train the MT-Opt policy, while optionally more on-policy data is collected, esp. for new tasks. This is an iterative process, which results in additional experiences that can be leveraged to define new tasks and train future policies.

In order to enable our system to take full advantage of multi-task training, we develop a number of components and evaluate their importance for overall performance. First, we use a single, multi-task deep neural network to learn a policy for all the tasks simultaneously, which enables parameter sharing between tasks. Second, we devise data management strategies that share and re-balance data across certain tasks. Third, since all tasks share data and parameters, we use some tasks as exploration policies for others, which aids in exploration. Although the individual components are based on previously studied concepts in multi-task learning, we show through our experiments that the particular choice and design of these components is essential for our large-scale multi-task learning system to effectively leverage data from all tasks to improve performance, particularly for "underrepresented" tasks that have the least available training data.

## 3.1 Multi-Task Reinforcement Learning Algorithm

We denote the multi-task RL policy as $\pi(\mathbf{a}|\mathbf{s}, \mathcal{T}_i)$, where $\mathbf{a} \in \mathcal{A}$ denotes the action, in our case, the position and the orientation of a robot arm as well as gripper commands, $\mathbf{s} \in \mathcal{S}$ denotes the state, which corresponds to images from the robot's cameras, and $\mathcal{T}_i$ denotes an encoding of the $i^{\text{th}}$ task drawn from a categorical task distribution $\mathcal{T}_i \sim p(\mathcal{T})$, which has $n$ possible categories, each corresponding to a different task. At each time step, the policy selects an action $\mathbf{a}$ given the current state $\mathbf{s}$ and the current task $\mathcal{T}_i$ set at the beginning of the episode, and receives a task-dependent reward $r_i(\mathbf{a}, \mathbf{s}, \mathcal{T}_i)$. The goal of the multi-task RL policy is to maximize the expected sum of rewards for all tasks drawn from the distribution $p(\mathcal{T})$. The episode finishes when the policy selects a TERMINATE action or reaches a step limit.

We build on the single-task QT-Opt algorithm [1], which itself is a variant of Q-learning [66], and learns a single-task optimal Q-Function by minimizing the Bellman error: $\mathcal{L}_i(\theta) =$

$\mathbb{E}_{(\mathbf{s},\mathbf{a},\mathbf{s}')\sim p(\mathbf{s},\mathbf{a},\mathbf{s}')}\big[D(Q_\theta(\mathbf{s},\mathbf{a}), Q_T(\mathbf{s},\mathbf{a},\mathbf{s}'))\big]$, where $Q_T(\mathbf{s},\mathbf{a},\mathbf{s}') = r(\mathbf{s},\mathbf{a}) + \gamma V(\mathbf{s}')$ is a target Q-value and $D$ is a divergence metric, such as cross-entropy, $\gamma$ is a discount factor, $V(\mathbf{s}')$ is the target value function of the next state computed using stochastic optimization of the form $V(\mathbf{s}') = \max_{\mathbf{a}'} Q(\mathbf{s}',\mathbf{a}')$, and the expectation is taken w.r.t. previously seen transitions $p(\mathbf{s},\mathbf{a},\mathbf{s}')$. Similarly to [1], we use the cross-entropy method (CEM) to perform the stochastic optimization to compute the target value function.

To extend this approach to the multi-task setting, let $\mathbf{s}^{(i)}, \mathbf{a}^{(i)}, \mathbf{s}'^{(i)}$ denote a transition that was generated by an episode $e^{(i)}$ for the $i^{\text{th}}$ task $\mathcal{T}_i$. As we discuss next, each transition could in fact be used for multiple tasks. In the multi-task case, the loss becomes:

$$\mathcal{L}_{\text{multi}}(\theta) = \mathbb{E}_{\mathcal{T}_i\sim p(\mathcal{T})}\left[\mathcal{L}_i(\theta)\right] = \mathbb{E}_{\mathcal{T}_i\sim p(\mathcal{T})}\Big[ \mathbb{E}_{p(\mathbf{s}^{(i)},\mathbf{a}^{(i)},\mathbf{s}'^{(i)})}\Big[D(Q_\theta(\mathbf{s}^{(i)},\mathbf{a}^{(i)},\mathcal{T}_i), Q_T(\mathbf{s}^{(i)},\mathbf{a}^{(i)},\mathbf{s}'^{(i)},\mathcal{T}_i))\Big]\Big], \tag{1}$$

where $(\mathbf{s}^{(i)}, \mathbf{a}^{(i)}, \mathbf{s}'^{(i)})$ are transitions generated by tasks $\mathcal{T}_i$.

### 3.2 Sharing Data Between Tasks

One advantage of an off-policy RL algorithm is that collected experience can be used to update the policy for other tasks, not just the task for which it was originally collected. This section describes how we effectively train with multi-task data through *task impersonation* and *data re-balancing*, as summarized in Fig. 3.

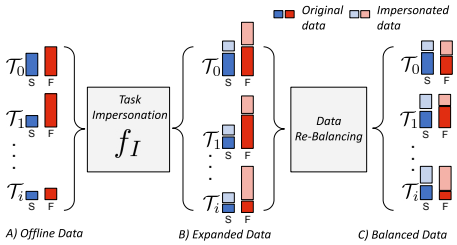


Figure 3: Task impersonation: episodes are routed to train relevant tasks, and data re-balancing where the ratio of success (S) and failure (F) episodes and proportion of data per task is controlled. Pale blue and pale red show additional training data coming from other tasks. The bar height indicates different amount of data across tasks and successful outcomes.

We leverage such experience sharing at the whole episode level rather than at the individual transition level. The goal is to use all transitions of an episode $e^{(i)}$ generated by task $\mathcal{T}_i$ to aid in training a policy for a *set of* $k_i$ tasks $\mathcal{T}_{\{k_i\}}$. We refer to this process as *task impersonation* (see Appendix, Algorithm 1), where the impersonation function $f_I$ transforms episode data collected for one task into a set of episodes that can be used to also train other tasks, i.e.: $e^{\{k_i\}} = f_I(e^{(i)})$. Note that in general case $\{k_i\}$ is a *subset* of all tasks $\{n\}$, and it depends on the original task $\mathcal{T}_i$ that the episode $e^{(i)}$ was collected for.

We can consider two ends of the data-sharing spectrum: an identity impersonation function $f_{I_{\text{orig}}}(e^{(i)}) = e^{(i)}$, where no task impersonation takes place, i.e. an episode $e^{(i)}$ generated by task $\mathcal{T}_i$ is used to train the policy exclusively for that task; and $f_{I_{\text{all}}} = e^{\{n\}}$, where each task shares data with *all* remaining $n-1$ tasks resulting in maximal data sharing. While $f_{I_{\text{orig}}}$ fails to leverage the reusable nature of multi-task data, $f_{I_{\text{all}}}$ can result in many unrelated episodes used as negative examples for the target task.

For MT-Opt, we devise a new task impersonation strategy $f_{I_{\text{skill}}}$ that makes use of more fine-grained similarities between tasks. We refer to it as a skill-based task-impersonation strategy, where we overload the term "skill" as a set of tasks that share semantics and dynamics, yet can start from different initial conditions or operate on different objects. For example, tasks such as *place-object-on-plate* and *place-object-in-bowl* belong to the same skill. Our impersonation function $f_{I_{\text{skill}}}$ allows us to impersonate an episode $e^{(i)}$ only as the tasks belonging to the same skill as $\mathcal{T}_i$. In our experiments, we conduct ablation studies comparing $f_{I_{\text{skill}}}$ (ours) with other task impersonation strategies.

While training, due to the design of our task impersonation mechanism, as well as the variability in difficulty between tasks, the resulting training data stream often becomes highly imbalanced, see Fig. 3B. To address this, we re-balance each batch both between tasks, such that the relative proportion of training data for each task is equal, and within each task, such that the relative proportion of successful and unsuccessful examples is kept constant.

## 4 SD-Based Rewards and Continuous Data Collection

We learn a discrete set of tasks evaluated on the final image of an RL episode. This sparse-reward assumption allows us to train a multi-view CNN success detector model ($SD$), which given final

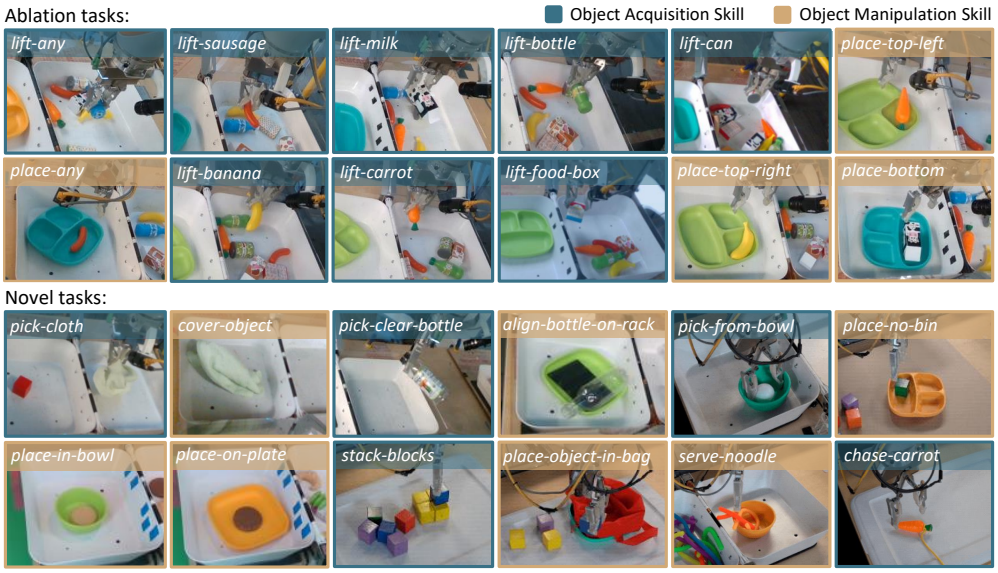


Figure 5: Top: 12 ablation tasks, giving rise to Object Acquisition and Object Manipulation skills. Bottom: examples of additional tasks that the MT-Opt policy can yield occasional success for. These additional tasks can be proactively bootstrapped using MT-Opt as an exploration process and further fine-tuned.

images from 3 perspectives, infers task success. Similarly to policy learning, we train a single multi-task success detector conditioned on task ID. Appendix 7.1 has additional details.

To generate training data for the $SD$, we ask users to collect positive and negative examples of positive and negative outcomes of a task. These examples are not demonstrations – just examples of what successful completion (i.e., the final state) looks like. We use this data to train the initial version of the multi-task $SD$, which we then continuously fine-tune given the images gathered during autonomous data collection to avoid out of distribution images that might be caused by various real-world factors such as different lighting conditions, and novel states which the robot discovers. We continue to manually label such images and incrementally retrain $SD$ to obtain the most up-to-date $SD$. In result, we label $\approx 5,000$ images per task and provide more details in the Appendix 8.

Our main observation w.r.t. the multi-task data collection process is that we can use solutions to easier tasks to bootstrap the learning of more complex tasks. In particular, an average MT-Opt policy for simple tasks might occasionally yield episodes successful for harder tasks. Over time, this allows us to start training an MT-Opt policy now for the harder tasks, and consequently, to collect better data for those tasks. To kick-start this process and bootstrap our two simplest tasks, we use two crude scripted policies for picking and placing (see Sec. 7.2 for details) following prior work [1]. To simplify the exploration problem for longer-horizon tasks, we also allow the individual tasks to be ordered sequentially, where one task is executed after another. As such, our multi-task dataset grows over time w.r.t. the amount of per-task data as well as percentage of successful episodes for all the tasks. Importantly, this fluid data collection process results in an imbalanced dataset, as shown on Fig. 4. Our data impersonation and re-balancing methods address this imbalance by efficiently expanding and normalizing data.

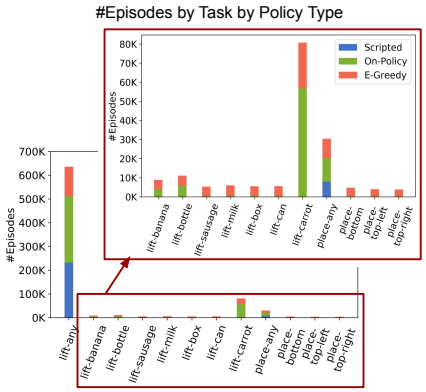


Figure 4: Offline dataset properties. Our data collection strategy collects data for multiple tasks, where it uses easier, more general tasks (e.g. *lift-any*) to bootstrap learning of more specialized tasks (e.g. *lift-carrot*). The resulting dataset is imbalanced across the distribution of exploration policies per task and success rate per task.

## 5 Experiments

The goal of our real-world experiments is to answer the following questions: **(1)** How does MT-Opt perform, quantitatively and qualitatively, on a large set of vision-based robotic manipulation tasks?

**(2)** Does training a shared model on many tasks improve MT-Opt's performance? **(3)** Does data sharing improve performance of the system? **(4)** Can we use easier tasks to bootstrap learning of more difficult tasks? **(5)** Can MT-Opt quickly learn distinct new tasks by adapting learned skills?

### 5.1 Experimental Setup

MT-Opt provides a general robotic skill learning framework that we use to learn multiple tasks, including semantic picking (i.e., picking an object from a particular category), placing into various fixtures (e.g., placing a food item onto a plate), covering, aligning, and rearranging. We focus on basic manipulation tasks that require repositioning objects relative to each other. A wide range of manipulation behaviors fall into this category, from simple bin-picking to more complex behaviors, such as covering items with a cloth, placing noodles into a bowl, and inserting bottles into form-fitted slots. In the following experiments, we use a set of 12 tasks for quantitative evaluation of our algorithm. These 12 tasks include a set of plastic food objects and divided plate fixtures and they can be split into "object acquisition" and "object manipulation" skills. Our most general object acquisition task is *lift-any*, where the goal is to singulate and lift any object. We also define 7 semantic lifting tasks, where the goal is to search for and lift a particular object, such as a plastic carrot. The placing tasks utilize a divided plate where the simplest task is to place the previously lifted object anywhere on the plate (*place-any*). Harder tasks require placing the object into a particular section of a divided plate, which could be oriented arbitrarily. See Fig. 5 for a visualization of the tasks.

All polices used in our studies are trained with offline RL from a large dataset summarized in Fig. 4. The resulting policy is deployed on 7 robots attempting each task 100 times for evaluation. In order to further reduce the variance of the evaluation, we shuffle the bins after each episode and use a standard evaluation scene (see Appendix, Fig. 17), from which all 12 evaluation tasks are feasible.

### 5.2 Quantitative and Qualitative Evaluation of MT-Opt

Fig. 6 shows the success rates of MT-Opt on the 12 evaluation tasks. We compare the MT-Opt policy to three baselines: i) single-task QT-Opt [1], where each per-task policy is trained separately using only data collected specifically for that task, ii) an enhanced QT-Opt baseline, which we call QT-Opt Multi-Task, where we train a shared policy for all the tasks but there is no data impersonation or re-balancing between the tasks, and iii) a Data-Sharing Multi-Task baseline that is based on the data-sharing strategy presented in [65], where we also train a single Q-Function but the data is shared across all tasks. Looking at the average performance across all task, we observe that MT-Opt significantly outperforms the baselines, in some cases with $\approx 3\times$ average improvement. While the single task QT-Opt baseline performs similarly to MT-Opt for the task where we have the most data (see the data statistics in Fig. 4), *lift-any*, its performance drastically drops (to $\approx 1\%$) for more difficult, underrepresented tasks, such as *lift-can*. Note, that we are not able run this baseline for the placing tasks, since they require a separate task to lift the object, which is not present in the single-task baseline. A similar observation applies to QT-Opt Multi-Task, where the performance of rare tasks increases compared to QT-Opt, but is still $\approx 4\times$ worse on average than MT-Opt. Sharing data across all tasks also results in a low performance for semantic lifting and placing tasks and, additionally, it appears to harm the performance of the indiscriminate lifting and placing tasks. The MT-Opt policy, besides attaining the $89\%$ success rate on (*lift-any*), also performs the 7 semantic lifting tasks and the 4 placing and rearrangement tasks at a significantly higher success rate than all baselines. We explain these performance gaps by the way MT-Opt shares the representations and data, and provide a more comprehensive analysis of these factors in the following experiments.

To illustrate the learned behavior, we present an example of a successful carrot grasping episode in Fig. 7, where the policy must work the carrot out of the corner before picking it up. We note that semantic picking and placing performance differs substantially between the different tasks. While this is due in part to the difficulty of the tasks, this is also caused by the quantity of data available for each object. We refer to Fig. 4, showing amounts and type of data collected for various tasks. Tasks such as *lift-carrot* and *lift-bottle*, which have more data, especially on-policy data, have higher success rates than underrepresented tasks, such as *lift-box*. The performance of these underrepresented tasks could be further improved by focusing the data collection on these tasks.

### 5.3 Sharing Representations Between Tasks

To explore the benefits of training a single policy on multiple tasks, we compare the 12-task MT-Opt policy with a 2-task policy that learns *lift-any* and *place-any*. Both of these policies are evaluated on

these two tasks (*lift-any* and *place-any*). We use the same $f_{I_{\text{skill}}}$ task impersonation strategy, and the exact same offline dataset (i.e. both policies use the data from the extra 10 narrower tasks, which is impersonated as *lift-any* and *place-any* data) without any on-policy fine-tuning, so data-wise the experiments are identical.

Table 1 shows the comparison between 12-task and 2-task policies. The 12-task policy outperforms the 2-task policy *even on the two tasks that the 2-task policy is trained on*, suggesting that training multiple tasks not only enables the 12-task policy to perform more tasks, but also improves its performance on the tasks through sharing representations. This suggests that the additional supervision provided by training on more tasks has a beneficial effect on the shared representations, which may explain the improved performance of the 12-task policy on the *lift-any* and *place-any* tasks.

| Parameter Sharing (Success Rate) | | |
|---|---|---|
| Model: | 2-Task | 12-Task |
| *lift-any* | 0.82 | **0.89** |
| *place-any* | 0.63 | **0.85** |

Table 1: Parameter sharing: the policy that learns two tasks (*lift-any*, *place any*) in addition to 10 other tasks outperforms a policy trained only for the two target tasks. Both policies are trained on the same offline dataset.

### 5.4 Data Sharing Between Tasks

To test the influence of data-sharing and re-balancing on the multi-task policy's performance, we compare our task impersonation strategy $f_{I_{\text{skill}}}$ introduced in Sec. 3.2 to a baseline impersonation function that does not share the data between the tasks $f_{I_{\text{orig}}}$, as well as a baseline where each task is impersonated for all other tasks $f_{I_{\text{all}}}$. In our skill-based task impersonation strategy $f_{I_{\text{skill}}}$, the data is expanded only for the class of tasks having similar visuals, dynamics and goals. In addition to $f_{I_{\text{skill}}}$ task impersonation, we re-balance each training batch between the tasks as well as within each task to keep the relative proportion of successful and unsuccessful trials the same.

The results of this experiment are in Table 2, with the full results reported in the Appendix, Table 4. Sharing data among tasks using our method of task impersonation and re-balancing provides significant improvement across all the tasks, with improvements of up to $10x$ for some tasks. The full data-sharing strategy performs worse than both the no-data-sharing baseline and our method, suggesting that *naïvely sharing all data across all tasks is not effective*. Because of our data-collection strategy, the resulting multi-task dataset contains much more data for broader tasks (e.g., *lift-any*) than for more narrow, harder tasks (e.g., *lift-box*), as shown in Fig. 4. Without any additional data-sharing and re-balancing, this data imbalance causes the baseline strategy $f_{I_{\text{orig}}}$ to attain good performance for the easier, overrepresented tasks, but poor performance on the harder, underrepresented tasks (see Table 2, first row), whereas our method performs substantially better on these tasks.

| Data Strategies (min, mean, max, mean of low data tasks) | | |
|---|---|---|
| Imp. Fn | Data Re-Balancing Strategy | |
| | uniform sampling | task re-balanced sampling |
| $f_{I_{\text{orig}}}$ | 0.10 / 0.32 / 0.94 / 0.18 | 0.16 / 0.55 / 0.85 / 0.42 |
| $f_{I_{\text{all}}}$ | 0.07 / 0.21 / 0.62 / 0.13 | 0.02 / 0.35 / **0.95** / 0.21 |
| $f_{I_{\text{skill}}}$ | 0.17 / 0.46 / 0.88 / 0.32 | **0.29** / **0.58** / 0.89 / **0.50** Ours |

Table 2: Min, average and max task performance across 12 tasks, as well as average performance across 6 tasks having least data ($\approx 6K$ episodes) for different data-sharing strategies. $f_{I_{\text{skill}}}$ impersonation and data re-balancing are complimentary: they both improve over the baselines, while the best effect is achieved by combining both. The effect is especially pronounced for the underrepresented tasks.

### 5.5 Using Easier Tasks to Bootstrap Harder Tasks

To explore question (4), we study whether learning an easier, broader task (*lift-any*) can help with a structurally related task that is harder but more specific (*lift-sausage*). We separate out the data for *lift-sausage* which consists of $5400$ episodes collected for that task (i.e. $4600$ failures and $800$ successes). In addition, there are $11200$ episodes of successful sausage lifting and as many as $740K$ failures that were collected during the *lift-any* task. Combining the *lift-sausage* data and the extra successes from *lift-any* yields $16600$ episodes ($12000$ successes and $4600$ failures). To investigate the influence of MT-Opt and task impersonation on the bootstrap problem, we compare our 12-task MT-Opt policy to a single-task policy trained on these $16600$ episodes. These include the same set of successful *lift-sausage* episodes as MT-Opt, but does not include the failures from other tasks.

The single-task policy learned from the $16600$ episodes yields performance of $3\%$. MT-Opt, using impersonated successes and failures, achieves $39\%$ success for the same task, a $\approx 10\times$ improvement. Both experiments use identical data representing successful episodes. The benefits of MT-Opt are twofold. First, we leverage an easier *lift-any* task to collect data for the harder *lift-sausage* task.

Second, MT-Opt benefits from the additional failures impersonated from other tasks. These failures, which often include successful grasps of non-target objects, when re-balanced as described in Sec. 3.2, results in the significant task performance boost. This demonstrates the value of both successful and unsuccessful data collected by other tasks for learning new tasks.

### 5.6 Learning New Tasks with MT-Opt

In addition to retroactive relabelling of prior data, MT-Opt can learn new tasks via *proactive* adaptation of known tasks, even ones that are visually and behaviorally different than the initial training set. To demonstrate this, we perform a fine-tuning experiment, bootstrapping from the MT-Opt 12-task model described in Sec. 5.2. We use the MT-Opt policy to collect data for previously unseen tasks: *lift-cloth* and *cover-object* (see Fig. 7 bottom row for an example episode). Unlike the *lift-sausage* tasks, prior to starting collection of these new tasks, no episodes in our offline dataset can be relabelled as successes for these tasks.

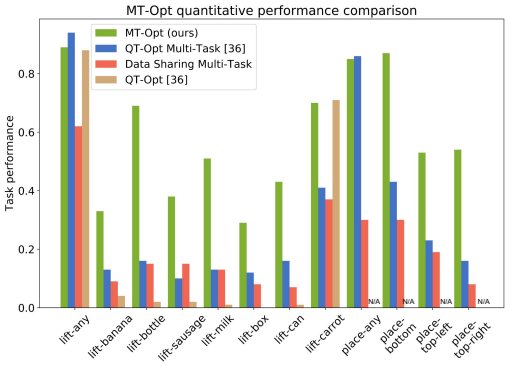


Figure 6: Quantitative evaluation of MT-Opt across 12 tasks. QT-Opt trains each task individually using only data collected for that task. QT-Opt Multi-Task trains a single network for all tasks but does not share the data between them. Data-Sharing Multi-Task also trains a single network for all tasks and shares the data across all tasks without further re-balancing. MT-Opt (ours) provides a significant improvement over the baselines, especially for the harder tasks with less data.

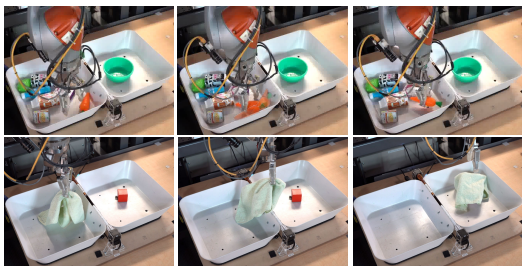

Figure 7: Top: Example of *pick-carrot*. The robot repositions the carrot out of the corner to pick it. Bottom: *cover-object*. The deformable covers the object.

We follow the continuous data collection process described in Sec. 4: we define and train the success detector for the new tasks, collect initial data using our *lift-any* and a *place-any* policies, and fine-tune a 14-task MT-Opt model that includes all prior as well as the newly defined tasks. While the new tasks are visually and semantically different, in practice the above mentioned policies give reasonable success rate necessary to start the fine-tuning. We switch to running the new policies on the robots once they are at parity with the *lift-any* and *place-any* policies. After $11K$ *pick-cloth* attempts and $3K$ *cover-object* attempts (requiring $< 1$ day of data collection on 7 robots), we obtain an extended 14-task MT policy that performs cloth picking at $70\%$ success and object covering at $44\%$ success. The policy trained only for these two tasks, without support of our offline dataset, yields performance of $33\%$ and $5\%$ respectively, confirming the hypothesis that MT-Opt method is beneficial even if the target tasks are sufficiently different, and the target data is scarce. By collecting additional $10K$ *pick-cloth* episodes and $6K$ *cover-object* episodes, we further increase the performance of 14-task MT-Opt to $92\%$ and $79\%$, for cloth picking and object covering respectively. We perform this fine-tuning procedure with other novel tasks such as previously unseen transparent bottle grasping, which reaches a performance of $60\%$ after less than $4$ days of data collection. Note that in this experiment, we additionally take advantage of the pre-trained MT-Opt policy for collecting the data for the new task. Similarly to other ablations, collecting data using the two-task policy would yield lower success rate per task, leading to larger difference in performance.

## 6 Conclusion

We presented a general multi-task learning framework, MT-Opt, that encompasses a number of elements: a multi-task data collection system, a scalable success detector framework, and a multi-task deep RL method that is able to effectively utilize the multi-task data. Our experiments show that by sharing data and parameters across various tasks we can significantly increase the data efficiency of learning individual tasks as well as learn a policy that generalizes to new skills such as placing into new fixtures, covering, aligning and rearranging. Finally, we show how MT-Opt can quickly acquire new tasks by leveraging the shared multi-task representations and exploration strategies.

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