Learning Quickly to Plan Quickly Using Modular Meta-Learning

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Abstract—Multi-object manipulation problems in continuous state and action spaces can be solved by planners that search over sampled values for the continuous parameters of operators. The efficiency of these planners depends critically on the effectiveness of the samplers used, but effective sampling in turn depends on details of the robot, environment, and task. Our strategy is to learn functions called specializers that generate values for continuous operator parameters, given a state description and values for the discrete parameters. Rather than trying to learn a single specializer for each operator from large amounts of data on a single task, we take a modular meta-learning approach. We train on multiple tasks and learn a variety of specializers that, on a new task, can be quickly adapted using relatively little data – thus, our system learns quickly to plan quickly using these specializers. We validate our approach experimentally in simulated 3D pick-and-place tasks with continuous state and action spaces.

I. INTRODUCTION

Imagine a company that is developing software for robots to be deployed in households or flexible manufacturing situations. Each of these settings might be fairly different in terms of the types of objects to be manipulated, the distribution over object arrangements, or the typical goals. However, they all have the same basic underlying kinematic and physical constraints, and could in principle be solved by the same general-purpose task and motion planning (TAMP) system. Unfortunately, TAMP is highly computationally intractable in the worst case, involving a combination of search in symbolic space, search for motion plans, and search for good values for continuous parameters such as object placements and robot configurations that satisfy task requirements.

A robot faced with a distribution over concrete tasks can learn to perform TAMP more efficiently by adapting its search strategy to suit these tasks. It can learn a small set of typical grasps for the objects it handles frequently, or good joint configurations for taking objects out of a milling machine in its workspace. This distribution cannot be anticipated by the company for each robot, so the best the company can do is to ship robots that are equipped to learn very quickly once they begin operating in their respective new workplaces.

The problem faced by this hypothetical company can be framed as one of meta-learning: given a set of tasks drawn from some meta-level task distribution, learn some structure or parameters that can be used as a prior so that the system, when faced with a new task drawn from that same distribution, can learn very quickly to behave effectively.

Concretely, in this work we focus on improving the interface between symbolic aspects of task planning and continuous aspects of motion planning. At this interface, given a symbolic plan structure, it is necessary to select values for continuous parameters that will make lower-level motion-planning queries feasible, or to determine that the symbolic structure itself is infeasible. Typical strategies are to search over randomly sampled values for these parameters, or to use hand-coded “generators” to sample them [1], [2].

Our strategy is to learn deterministic functions, which we call specializers, that map a symbolic operator (such as \textit{place}(\textit{objA})) and a detailed world state description (including object shapes, sizes, poses, etc.) into continuous parameter values for the operator (such as a grasp pose). Importantly, rather than focusing on learning a single set of specializers from a large amount of data at deployment time, we will focus on meta-learning approaches that allow specializers to be quickly adapted online. We will use deep neural networks to represent specializers and backpropagation to train them.

We compare two different modular meta-learning strategies: one, based on MAML [3], focuses on learning neural network weights that can be quickly adapted via gradient descent in a new task; the other, based on BOUNCEGRAD [4], focuses on learning a fixed set of neural network “modules” that can be quickly chosen among in a new task.

We demonstrate the effectiveness of these approaches in an object manipulation domain, illustrated in Figure 1, in which the robot must move all of the objects from one table.
to another. This general goal is constant across tasks, but different tasks will vary the object shapes and sizes, requiring the robot to learn to manipulate these different types of objects. We conjecture that the meta-learning approach will allow the system, at meta-training time, to discover generally useful, task-independent strategies, such as placing objects near the back of the available space; and, at deployment time, to quickly learn to adapt to novel object geometries. Note that our methods are agnostic to exactly which aspects of the environments are common to all tasks and which vary – these concepts are naturally discovered by the meta-learning algorithm. We show that the meta-learning strategies perform better than both a random sampler and a reasonable set of hand-built, task-agnostic, uninformed specializers.

II. RELATED WORK

Our work is focused on choosing continuous action parameters within the context of a symbolic plan. We are not learning control policies for tasks [5, 6, 7], nor are we learning planning models of tasks [8]. We assume any necessary policies and planning models exist; our goal is to make planning with such models more efficient by learning specializers via modular meta-learning. There is existing work on learning samplers for continuous action parameters in the context of task and motion planning [9], [10], [11], [12], but these works do not explicitly consider the problem of learning samplers that can be quickly adapted to new tasks. Our work addresses this problem using meta-learning. Specializers are closely related to the notion of *generators*, used in some task and motion planning systems [1], [2].

**Meta-Learning:** Meta-learning is a particularly important paradigm for learning in robotics, where training data can be very expensive to acquire, because it dramatically lowers the data requirements for learning new tasks. Although it has a long history in the transfer learning literature [13], meta-learning was recently applied with great effectiveness in the paradigm for learning in robotics, where training data can be very expensive to acquire, because it dramatically lowers the data requirements for learning new tasks.

**Learning Modular Structure:** Our approach is a modular learning approach, in the sense of Andreas et al. [14]: the learned specializers are associated with planning operators, allowing them to be recombined in new ways to solve novel problems. Andreas et al. [15] use reinforcement learning to train subtask modules in domains with decomposable goals. Unlike in their work, they assume a policy sketch (sequence of symbolic operators) is given. The challenge in their work instead stems from learning to map the symbolic language to control actions. Devin et al. [16] decompose visuomotor policies into “task-specific” and “robot-specific” modules, and show that these modules can be composed to solve new tasks. Separate lines of work have focused on learning modular parameterized skills from the perspectives of control theory [17], [18] and learning from demonstration [19], [20].

**Modular Meta-Learning:** Modular meta-learning was developed by Alet et al. [4] and forms the inspiration for this work. Their work includes an EM-like training procedure that alternates between composing and optimizing neural network modules, and also includes a mechanism for choosing the best compositional structure of the modules to fit a small amount of training data on a new task.

III. PROBLEM SETTING

In this section, we describe the class of task and motion planning meta-learning problems.

A. Task and Motion Planning

Robot task and motion (TAMP) problems are typically formulated as discrete-time planning problems in a hybrid discrete-continuous state transition system [21], [22], with discrete variables modeling which objects are being manipulated and other task-level aspects of the domain, and continuous variables modeling the robot configuration, object poses, and other continuous properties of the world.

A world state $s \in S$ is a complete description of the state of the world, consisting of $(c, o_1, \ldots, o_n, x_1, \ldots, x_m)$, where $c$ is the robot configuration, the $o_i$ are the states of each object in the domain, and the $x_i$ are other discrete or continuous state variables, such as the index of the held object. An object’s state $o = (o_1, \ldots, o_d)$ has $d$ dimensions describing its properties, including pose and shape, as well as possibly other attributes such as mass, color, or owner.

We now define a TAMP problem, using some definitions from Garrett et al. [21]. A *predicate* is a Boolean function. A fluent is an evaluation of a predicate $p$ on a tuple $(\bar{o}, \theta)$, where $\bar{o}$ is a set of discrete objects and $\theta$ is a set of continuous values. A set of basis predicates $B$ can be used to completely describe a world state. Given a world state $s$, the set of basis fluents $\Phi_B(s)$ is the maximal set of atoms that are true in $s$ and can be constructed from the basis predicate set $B$. A set of derived predicates can be defined in terms of basis predicates. A planning state $\mathcal{I}$ is a set of fluents, including a complete set of basis fluents and any number of derived fluents; it is assumed that any fluent not in $\mathcal{I}$ is false.

An action or operator $a$ is given by an argument tuple $\bar{O} = (O_1, \ldots, O_k)$ and a parameter tuple $\bar{\Theta} = (\Theta_1, \ldots, \Theta_j)$, a set of fluent preconditions $\text{pre}(a)$ on $(\bar{O}, \bar{\Theta})$, and a set of positive and negative fluent effects $\text{eff}^+(a)$ on $(\bar{O}, \bar{\Theta})$. An action instance $a(\bar{o}, \bar{\theta})$ is an action $a$ with arguments and parameters $(\bar{O}, \bar{\Theta})$ replaced with discrete objects $\bar{o}$ and continuous values $\bar{\theta}$. An action instance $a(\bar{o}, \bar{\theta})$ is applicable in planning state $\mathcal{I}$ if $\text{pre}(a(\bar{o}, \bar{\theta})) \subseteq \mathcal{I}$. The result of applying an action instance $a(\bar{o}, \bar{\theta})$ to a planning state $\mathcal{I}$ is a new state $\mathcal{I}' \cup \text{eff}^+(a(\bar{o}, \bar{\theta})) \setminus \text{eff}^-(a(\bar{o}, \bar{\theta}))$, where $\text{eff}^+$ and $\text{eff}^-$ are the positive and negative fluents in $\text{eff}$, respectively. For $a$ to be a well-formed action, $\text{eff}^+(a)$ and $\text{eff}^-(a)$ must be structured so that the planning state $\mathcal{I}'$ resulting from applying $a$ is valid (contains a complete set of basis fluents). Then $\mathcal{I}'$ determines a world state $s \in S$, and the action $a$ can be viewed as a deterministic transition on world states.

A TAMP problem $(\mathcal{A}, \mathcal{I}, \mathcal{G})$ is given by a set of actions $\mathcal{A}$, an initial planning state $\mathcal{I}$, and a goal set of fluents $\mathcal{G}$. A sequence of action instances, $\pi = (a_1(\bar{o}_1, \bar{\theta}_1), \ldots, a_k(\bar{o}_k, \bar{\theta}_k))$, is called a plan. A plan $\pi$ is a task-level solution for problem $(\mathcal{A}, \mathcal{I}, \mathcal{G})$ if $a_1(\bar{o}_1, \bar{\theta}_1)$ is applicable in $\mathcal{I}$, each $a_i(\bar{o}_i, \bar{\theta}_i)$ is...
applicable in the \((i - 1)\)th state resulting from application of the previous actions, and \(G\) is a subset of the final state.

A sequence of actions with arguments instantiated but not parameters, \(\pi = \langle a_1(\hat{o}_1, \Theta_1), \ldots, a_k(\hat{o}_k, \Theta_k)\rangle\), is called a plan skeleton. A plan skeleton \(\pi\) is task-feasible for problem \((A, I, G)\) if there exist continuous values \(\hat{o}_1, \ldots, \hat{o}_k\) such that plan \(\pi = \pi(\hat{\theta}) = \langle a_1(\hat{o}_1, \hat{\theta}_1), \ldots, a_k(\hat{o}_k, \hat{\theta}_k)\rangle\) is a task-level solution for \((A, I, G)\). A world-state trajectory \(\tau(\pi, I)\) for plan \(\pi\) and initial planning state \(I\) is the sequence of world states \(s_1, \ldots, s_k \in S\) induced by the sequence of planning states resulting from applying \(\pi\) starting from \(I\). A plan \(\pi\) is a complete solution for the TAMP problem \((A, I, G)\) if, letting \(\tau(\pi, I) = \langle s_1, \ldots, s_k\rangle\), there exist robot trajectories \(\tau_1, \ldots, \tau_{k-1}\) such that \(\tau_i\) is a collision-free path (a motion plan) from \(c_i\) to \(c_{i+1}\), the robot configurations in world states \(s_i\) and \(s_{i+1}\) respectively.

Finding good search strategies for solving TAMP problems is an active area of research, partly owing to the difficulty of finding good continuous parameter values that produce a complete solution \(\pi\). Our learning method could be adapted for use in many TAMP approaches, but for clarity we focus on a very simple one, sketched below.\[^1\] See Section [IV] for discussion of the TAMP system we use in our implementation.

**Algorithm PLAN\(\text{SKETCH}(A, I, G)\)**

1. for \(\pi\) in some enumeration of plan skeletons do
2. for \(\hat{\theta}\) s.t. \(\pi = \pi(\hat{\theta})\) is a task-level solution do
3. if motion plans exist for \(\pi\) then
   return the complete solution \(\pi\)

The problems of symbolic task planning to yield plausible plan skeletons (Line 1) and collision-free motion planning (Line 3) are both well studied, and effective solutions exist. We focus on the problem of searching over continuous values \(\hat{\theta}\) for the skeleton parameters (Line 2), to find a set resulting in a plan \(\pi = \pi(\hat{\theta})\) that is a complete solution to the TAMP problem. We first outline two simple strategies for finding \(\hat{\theta}\). In random sampling, we perform a simple depth-first backtracking search: sample values for \(\hat{\theta}\) uniformly at random from some legal set, check that there is a motion plan from \(s_{i-1}\) to \(s_i\), continue on to sample \(\hat{\theta}_{i+1}\) if so, and either sample \(\hat{\theta}_i\) again or backtrack to a higher node in the search tree if not. In the hand-crafted strategy, we rely on a human programmer to write one or more specializers \(\sigma_a^i\) for each action \(a\). A specializer is a function \(\sigma(I, \hat{o}, j)\), where \(I\) is a planning state, \(\hat{o}\) are the discrete object arguments to which \(a\) will be applied, and \(j\) is the step of the skeleton where a particular instance of \(a\) occurs. The specializer \(\sigma\) returns a vector of continuous parameter values \(\hat{\theta}\) for \(a\). So, in this hand-crafted strategy, for each plan skeleton \(\pi\) we need only consider the following discrete set of plans \(\pi_s\):

\[
\langle a_1(\hat{o}_1, \sigma_a^1(I_1, \hat{o}_1, 1)) \ldots a_k(\hat{o}_k, \sigma_a^k(I_k, \hat{o}_k, k)) \rangle,
\]

where the \(i\) values select which specializer to use for each step. Each setting of the \(i\) values yields a different plan \(\pi_s\).

\[^1]\)Generally, not all of the elements of \(\hat{\theta}\) are actually free parameters given a skeleton. Some elements of \(\hat{\theta}\) may be uniquely determined by other parameters, or by the state in which an action is applied. We will not complicate our notation by explicitly handling these cases.

Now, it is sensible to combine the search over both skeletons and specializers into a single discrete search. Let \(\Sigma(W)\) be a set of specializers (the reason for this notation will become clear in the next section) and \(A(\Sigma(W))\) be a discrete set of “actions” obtained by combining each action \(a \in A\) with each specializer \(\sigma_a^i \in \Sigma(W)\), for valid \(i\). We obtain our algorithm for planning with specializers:

**Algorithm PLAN\(\text{SPECIALIZER}(A, I, G, \Sigma(W))\)**

1. for \(\pi\) in \(\text{SYMBOLIC\(\text{PLAN}(A(\Sigma(W)), I, G)\)}\) do
2. if motion plans exist for \(\pi\) then
   return the complete solution \(\pi\)

**B. Learning Specializers**

We begin by defining our learning problem for just a single task. A single-task specializer learning problem is a tuple \((A, D, \Sigma(W))\), where \(A\) is a set of actions specifying the dynamics of the domain, \(D = \{(I_1, G_1), \ldots, (I_n, G_n)\}\) is a training set of (initial state, goal) problem instances, \(\Sigma\) is a set of functional forms for specializers (such as neural network architectures), and \(W\) is a set of initial weights such that \(\Sigma(W)\) is a set of fully instantiated specializers that can be used for planning with the PLAN algorithm.

Informally, the objective of our learning problem is to find \(W\) such that planning with \(\Sigma(W)\) will, in expectation over new \((I, G)\) problem instances drawn from the same distribution as \(D\), be likely to generate complete solutions. The function classes \(\Sigma\) of the specializers are given (just like in the hand-crafted strategy), but the weights \(W\) are learned.

Although our ultimate objective is to improve the efficiency of the overall planner, that is done by replacing the search over continuous parameter values \(\hat{\theta}\) with a deterministic choice or search over a finite set of parameter values provided by the specializers; so, our objective is really that these specializers be able to solve problems from \(D\).

Most directly, we could try to minimize \(0 - 1\) single-task loss on \(D\), so that \(W^* = \min_W L_S(W; D)\) where:

\[
L_S(W; D) = \sum_{(I, G) \in D} \left\{ \begin{array}{ll} 0 & \text{PLAN}(A, I, G, \Sigma(W)) \text{ succeeds} \\ 1 & \text{otherwise} \end{array} \right. 
\]

Unfortunately, this loss is much too difficult to optimize in practice; in Section [IV] we will outline strategies for smoothing and approximating the objective.

**C. Meta-Learning Specializers**

In meta-learning, we wish to learn, from several training tasks, some form of a prior that will enable us to learn to perform well quickly on a new task. A specializer meta-learning problem, given by a tuple \((A, (D_1, \ldots, D_m), \Sigma(W))\), differs from a single-task specializer learning problem both in that it has multiple datasets \(D_j\), and in that it has a different objective. We make the implicit assumption, standard in meta-learning approaches, that there is a hierarchical distribution over \((I, G)\) problems that the robot will encounter: we define a task to be a single distribution over \((I, G)\), and assume we have a distribution over tasks.

Let \(\text{LEARN}(A, D, \Sigma(W))\) be a specializer learning algorithm that returns \(W^*\), tailored to work well on problems
drawn from $D$. Our meta-learning objective will then be to find a value of $W$ that serves as a good prior for learn on new tasks, defined by new $(I, G)$ distributions. Formally, the meta-learning objective is to find $W^*_M = \arg\min_W \mathcal{L}_M(W)$, where the meta-learning loss is, letting $j$ index over tasks:

$$\mathcal{L}_M(W) = \frac{1}{m} \sum_{j=1}^m \mathcal{L}_S(\text{learn}(A, D^\text{train}_j, \Sigma(W)); D^\text{test}_j) \, .$$

The idea is that a new set of weights obtained by starting with $W$ and applying learn on a training set from task $j$ should perform well on a held-out test set from task $j$.

After learning $W^*_M$, the robot is deployed. When it is given a small amount of training data $D'_{\text{new}}$ drawn from a new task, it will call learn($A, D'_{\text{new}}, \Sigma(W^*_M)$) to get a new set of weights $W^*_\text{new}$, then use the planner PLAN($A, I, G, \Sigma(W^*_\text{new})$) to solve future problem instances from this new task. If the meta-learning algorithm is effective, it will have learned to

- learn quickly (from a small dataset $D'_{\text{new}}$) to
- plan quickly (using the specialists $\Sigma(W^*_\text{new})$ in place of a full search over continuous parameter values $\theta$), motivating our title.

IV. Approach

In this section, we begin by describing two single-task specialist learning algorithms, and then discuss a specialist meta-learning algorithm that can be used with any specialist learning algorithm.

A. Single-Task Specialist Learning Algorithms

Recall that an algorithm for learning specialists takes as input $(A, D, \Sigma(W))$, where $A$ are the actions describing domain dynamics, $D$ is a dataset of $(I, G)$ problem instances, $\Sigma$ is a set of functional forms for specialists, and $W$ is a set of initial weights such that $\Sigma(W)$ is a set of fully instantiated specialists. The job of a learning algorithm is to return $W^* = \arg\min_W \mathcal{L}_S(W; D)$.

We consider two algorithms: alternating descent (AD) and subset selection (SS).

a) Alternating Descent: AD adjusts the weights $W$ to tune them to dataset $D$.

If we knew, for each $(I, G) \in D$, the optimal plan skeleton and choices of specialists that lead to a complete solution $\pi$ for the TAMLP problem $(A, I, G)$, then we could adjust the elements of $W$ corresponding to the chosen specialists in order to improve the quality of $\pi$. However, this optimal set of actions and specialists is not known, so we instead perform an EM-like alternating optimization, much like the optimization performed at meta-training time in BOUNCEGRAD [4] or at meta-test time in MOMA [4]. In particular, we use the PLAN algorithm (described in detail later) to find a skeleton of $\pi$ and sequence of specialists $\sigma_j$ to be optimized. PLAN is an approximation of PLAN (Section III-A) that can return illegal plans. Then, we adjust the elements of $W$ corresponding to the $\sigma_j$ so the plan becomes “less illegal.”

More formally, we assume the existence of a predicate loss function $\mathcal{L}_p$ for each predicate $p$ in the domain, which takes the arguments of predicate $p$ ($\bar{o}$ and $\bar{\theta}$) and a world state $s \in S$, and returns a positive-valued loss measuring the degree to which the fluent $p(\bar{o}, \bar{\theta})$ is violated in $s$. If $p(\bar{o}, \bar{\theta})$ is true in $s$, then $\mathcal{L}_p(\bar{o}, \bar{\theta}, s)$ must be zero. For example, if fluent $\phi$ denotes $\text{pose}(o, v)$ asserts that the pose of object $o$ should be the value $v$, then we might use the squared distance $(v - v')^2$ as the predicate loss, where $v'$ is the actual pose of $o$ in $s$.

Consider the situation in which we run PLAN, and it returns a plan $\pi$ created from a plan skeleton $\hat{\pi}$ and the chosen specialists $\sigma_1, \ldots, \sigma_k$. From this, we can compute both the induced trajectory of planning states $I_1, \ldots, I_k$, and the induced trajectory of world states $\tau = \langle s_1, \ldots, s_k \rangle$. We can now define a trajectory loss function $\mathcal{L}_T$ on $W$ for $\pi$:

$$\mathcal{L}_T(W; I, G, \pi) = \sum_{j=1}^k \sum_{\phi \epsilon \text{eff}^+([\sigma_j, \bar{o}_j, \bar{\theta}_j])} \mathcal{L}_p(\bar{o}_j, \sigma_j(I_j, \bar{\theta}_j; W), s_j) \, .$$

This is a sum over steps $j$ in the plan, and for each step, a sum over positive fluents $\phi$ in its effects, of the degree to which that fluent is violated in the resulting world state $s_j$. Here, $p(\phi)$ is the predicate associated with fluent $\phi$. Recall that $\bar{\theta}_j = \sigma_j(I_j, \bar{\theta}_j; W)$, where we have included $W$ to expose the specialists’ parametric forms. Thus, we have:

$$\mathcal{L}_T(W; I, G, \pi) = \sum_{j=1}^k \sum_{\phi} \mathcal{L}_p(\bar{o}_j, \sigma_j(I_j, \bar{o}_j, j; W), s_j) \, .$$

If the $\mathcal{L}_p$ are differentiable with respect to the $\bar{\theta}_j$ and the functional forms $\Sigma$ generating the $\theta$ are differentiable with respect to $W$ and their continuous inputs, then $W$ can be adjusted via a gradient step to reduce $\mathcal{L}_T$. This method will adjust only the values of $W$ that were used in the specialists chosen by PLAN. We use feedforward neural networks to implement each individual $\sigma$. The overall algorithm is:

**Algorithm AD-LEARN** $(A, D, \Sigma(W), n_{\text{iters}}, n_{\text{plans}})$

1. for $t = 1$ to $n_{\text{iters}}$ do
2.  Sample $(I, G)$ from $D$.
3.  $\pi \leftarrow \text{PLAN}(A, I, G, \Sigma(W), t, n_{\text{plans}})$
4.  $W \leftarrow W - \alpha \nabla_W \mathcal{L}_T(W; I, G, \pi)$
5.  **Subroutine** PLAN$(A, I, G, \Sigma(W), t, n_{\text{plans}})$
6.  for $i = 1$ to $n_{\text{plans}}$ do
7.  6.1 $\pi_i \leftarrow \text{next SymbolicPlan}(A(\Sigma(W)), I, G)$
8.  6.2 if motion plans exist for $\pi_i$ then
9.  6.2.1 $\text{score}(\pi_i) \leftarrow -\mathcal{L}_T(W; I, G, \pi_i)$
10.  6.2 if no scores were computed then
11.  6.2.2 Randomly initialize more $\sigma$; repeat procedure.
12.  return sample $\pi_i \sim \text{score}(\pi_i)/T(t) \mid Z$

We now describe in detail the PLAN procedure, which is an approximation of PLAN. Generally, while we are learning $W$, we will not have a complete and correct set of specialists, but we will need to assemble plans in order to adjust the $W$. In addition, to prevent local optima, and inspired by the use of simulated annealing for structure search in BOUNCEGRAD [4] and MOMA [4], we do not always consider the $\pi$ with least loss early on. PLAN, rather than always trying to find a $\pi$ that is a complete solution to the problem, treats SYMBOLICPLAN as a generator, generates
We define: \( \nabla W \) best plan we can find using the given

ture on \( \nabla \) gradient, we ignore the dependence of the plan struc-

reduce the trajectory loss on \( D \) \( W \)

be chosen to go to zero as \( t \) increases.

b) Subset Selection: SS assumes that \( \Sigma(W) \) includes a

large set of specializers, and simply selects a subset of them
to use during planning, without making any adjustments to
the weights \( W \). Let \( \Sigma_a(W) \) be the set of specializers for
action \( a \) and let integer \( k \) be a parameter of the algorithm.
The SS algorithm simply finds the size-\( k \) subset \( \rho_k \) of \( \Sigma_a(W) \)
for each \( a \) such that \( L_S(\cup_{\rho_k} D) \) is minimize\(^2\) There are
many strategies for finding such a set; in our experiments, we
have a small number of actions and set \( k = 1 \), and so we
can exhaustively evaluate all possible combinations.

B. Specializer Meta-Learning Algorithm

Recall that the meta-learning problem is to take in \( m \) different
datasets \( D_1, \ldots, D_m \) and return \( W_M = \text{argmin}_W L_M(W) \), which should be a good starting point
for a learning algorithm on a new task. This ideal objective
is difficult to optimize, so we must make approximations.

We begin by describing the meta-learning algorithm,
which follows a strategy very similar to MAML. We do
stochastic gradient descent in an outer loop: draw a task
\( D_j \) from the task distribution, use some learning algorithm
\( \text{LEARN} \) to compute a new set of weights \( W_j \) for \( D_j^{\text{train}} \)
starting from \( W \), and update \( W \) with a gradient step to
reduce the trajectory loss on \( D_j^{\text{test}} \) evaluated using \( W_j \).

Algorithm MetaLEARN(\( A, D_1, \ldots, D_m, \Sigma(W) \))

1. \( \text{while not done} \)
2. \( \quad j \leftarrow \text{sample}(1, \ldots, m) \)
3. \( \quad W_j \leftarrow \text{LEARN}(A, D_j^{\text{train}}, \Sigma(W)) \)
4. \( \quad W \leftarrow W - \beta \nabla_W L_{T, D_j^{\text{test}}}(\Sigma(W_j)) \)

In practice, we drop the Hessian term in the gradient by
taking the gradient with respect to \( W_j \) rather than \( W \) (so \( \nabla W \rightarrow \nabla W_j \)); this is done successfully by many MAML
implementations, for efficiency: we define:

\[
L_{T, D}(\Sigma(W)) = \sum_{I, G \in D} L_T(I; G, \text{PLANT}(A, I, G, \Sigma(W), \epsilon, \infty)).
\]

This represents the smoothed trajectory loss for the
best plan we can find using the given \( \Sigma(W) \), summed
over all planning problems in \( D \). When we compute the
gradient, we ignore the dependence of the plan structure
on \( W \). We estimate \( \nabla W_j L_{T, D_j^{\text{test}}}(\Sigma(W_j)) \) as follows:

1. \( \text{for } t = 1 \text{ to } n_{\text{gradEst}} \)
2. \( \quad \text{Sample } (I, G) \text{ from } D_j^{\text{test}} \)
3. \( \quad \pi \leftarrow \text{PLANT}(A, I, G, \Sigma(W_j), \epsilon, \infty) \)
4. \( \quad \nabla W_j \leftarrow \nabla W_j + \nabla W_j L_T(I; G, \pi) \)
5. \( \text{return } \nabla W_j \)

\(^2\) Technically speaking, the first argument to \( L_S \) should be all the
weights \( W \); we can assume that \( \cup_{\rho_k} \rho_k \) is the following operation: leave the elements
of \( W \) that parameterize the \( \rho_k \) unchanged, and set the rest to \( 0 \).

When \( \text{LEARN} \) is the subset selection learner (SS), the
\( \text{LEARN} \) procedure returns only a subset of the \( \Sigma(W) \), corre-
spending to the chosen specializers. Only the weights in that
subset are updated with a gradient step on the test data.

V. Experiments

We demonstrate the effectiveness of our approach in an
object manipulation domain where the robot is asked to move
all of the objects from one table to another, as illustrated
in Figure 1. The object geometries vary across tasks, while
a single task is a distribution over initial configurations of
the objects on the starting table. We consider 6 tasks for
training and 3 tasks for evaluation, across 3 object types:
cylinders, bowls, and vases. The phrase “final task” will refer
to a random sample of one of the 3 evaluation tasks.

To avoid complications surrounding manipulation, we use
a KUKA iwa robot arm without a gripper. Grasp legality
is computed using a simple end effector pose test based on
the geometry (radius, height, and shape) of the object being
grasped. We require that cylinders are grasped from the side,
while bowls and vases are grasped from above, on their lip.
The robot base pose is automatically set among two legal
positions: one in front of each table.

There are four operators: \( \text{moveToGrasp} \) and
\( \text{moveToPlace} \) move the robot (and any held object)
to a configuration suitable for grasping or placing an object,
\( \text{grasp} \) picks an object up, and \( \text{place} \) places it onto
the table. All operators take in the ID of the object being
interacted with as discrete arguments, set through the search
over plan skeletons. The continuous parameters learned by
our specializers are the target end effector pose for each
operation; we employ an inverse kinematics solver to try
reaching these poses. We learn three specializers for each of
the first three operators, and one specializer for \( \text{place} \) due
to its relative simplicity. The state representation is a vector
containing the end effector pose, each object’s position,
object geometry information, robot base position, and the
ID of the currently-grasped object (if any).

All specializers are implemented as fully connected,
feed-forward deep neural networks with hidden layer sizes
[100, 50, 20], a capacity which preliminary experiments found
necessary. We use the Adam optimizer [23] with initial
learning rate \( 10^{-2} \), decaying by 10% every 1000 iterations.
We also batch our implementation and use batch size 32.

For motion planning, we use the RRT-Connect algo-
rithm [24]; we check for infeasibility crudely by giving
the algorithm a computation allotment, implemented as a
maximum number of random restarts to perform upon which
(a infeasible) straight-line trajectory is returned. We use Fast-
Forward [25] as our symbolic planner. For simulation and
visualization, we use the pybullet [26] software.

A major source of difficulty in this domain is that the end
effector poses chosen by the specializers must be consistent
with both each other (place pose depends on grasp pose,
etc.) and the object geometries. Furthermore, placing the first
few objects near the front of the goal table would impede
the robot’s ability to place the remaining objects. We should
expect that the general strategies discovered by our meta-learning approach would handle these difficulties.

To implement the discrete search over plan skeletons and specializers, we adopt the TAMP approach of Srivastava et al. [2], which performs optimistic classical planning using abstracted fluents, attempts to find a feasible motion plan, and incorporates any infeasibilities back into the initial state as logical fluents. We also set a depth limit for this iterative process, so that we only ever search over five candidate plan skeletons per training iteration. During evaluation, there is no such limit. For each skeleton, we search exhaustively over all combinations of \( k = 1 \) specializer per operator, of which there are 27 possibilities.

**Evaluation:** We evaluate the MetaLearn algorithm with both the alternating descent (AD) learner and the subset selection (SS) learner. We test against two baselines, random sampling and the hand-crafted strategy, both of which are described in Section III-A. The random sampler is conditional, sampling only end effector poses that satisfy the kinematic constraints of the operators. At final task time with the AD learner, we optimize the specializers on 10 batches of training data, then evaluate on a test set of 50 problems from this task. At final task time with the SS learner, we choose a subset of \( k = 1 \) specializer per operator that performs the best over one batch of training data, then use only that subset to evaluate on a test set. Note that we should expect the test set evaluation to be much faster with the SS learner than with the AD learner, since we are planning with fewer specializers.

**Results and Discussion** See Table I for a summary of our experimental results over various numbers of objects, and Figure 2 for corresponding learning curves.

The results show that both meta-learning approaches perform much better at the final task than the baselines do. The random sampler fails because it expends significant effort trying to reach infeasible end effector poses, such as those behind the objects. The hand-crafted specializers, though they perform better than the random sampler, suffer from a lack of context: because they are task-agnostic, they cannot specialize, and so search time is wasted on continuous parameter values that are inappropriate for the current task, making timeouts more frequent. Furthermore, the hand-crafted strategy does not adapt to the state (such as the locations of objects surrounding one being grasped). Qualitatively, we found that the general strategies we outlined earlier for succeeding in this domain were meta-learned by our approach.

Notably, the alternating descent (AD) learner performs better than the subset selection (SS) learner, likely because in the former, the specializer weights are optimized for the final task rather than held fixed. These findings suggest that this sort of fine-tuning is an important step to learning specializers in our domain. However, this improvement comes at the cost of much longer training times, since the AD learner performs an inner gradient computation which the SS learner does not. Another finding is that the SS learner spends much less search effort than the AD learner, which is expected since the SS learner plans with only one specializer per operator.

**TABLE I:** Summary of experimental results. Percentage of 50 final task problem instances solved within a 30-second timeout, number of training iterations needed to reach 50% final task solve rate, average number of plan skeletons and specializers searched over, and total training time in hours. Both meta-learning approaches learn to perform much better at the final task than the baselines do. Notably, the alternating descent (AD) learner performs better than the subset selection (SS) learner, likely because in the former, the specializer weights are optimized for the final task rather than held fixed. However, this improvement comes at the cost of much longer training times. Meta-learners were trained for 10^4 iterations.

![Learning Curves](image)

**Fig. 2:** Learning curves over 10^4 training iterations (smoothed).

**VI. CONCLUSION AND FUTURE WORK**

We used modular meta-learning to address the problem of learning continuous action parameters in multi-task TAMP.

One interesting avenue for future work is to allow the specializers to be functions of the full plan skeleton, which would provide them with context necessary for picking good parameter values in more complex domains. Another is to remove the assumption of deterministic specializers by having them either be stochastic neural networks or output a distribution over the next state, reparameterized using Gumbel-Softmax [27]. Finally, we hope to explore tasks requiring planning under uncertainty. These tasks would require more sophisticated compositional structures; we would need to search over tree-structured policies rather than sequential plans as we did in this work. This search could be made tractable using heuristics for solving POMDPs [28], [29].

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