Combined Task and Action Learning from Human Demonstrations for Mobile Manipulation Applications

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Abstract—Learning from demonstrations is a promising paradigm for transferring knowledge to robots. However, learning mobile manipulation tasks directly from a human teacher is a complex problem as it requires learning models of both the overall task goal and of the underlying actions. Additionally, learning from a small number of demonstrations often introduces ambiguity with respect to the intention of the teacher, making it challenging to commit to one model for generalizing the task to new settings. In this paper, we present an approach to learning flexible mobile manipulation action models and task goal representations from teacher demonstrations. Our action models enable the robot to consider different likely outcomes of each action and to generate feasible trajectories for achieving them. Accordingly, we leverage a probabilistic framework based on Monte Carlo tree search to compute sequences of feasible actions imitating the teacher intention in new settings without requiring the teacher to specify an explicit goal state. We demonstrate the effectiveness of our approach in complex tasks carried out in real-world settings.

I. INTRODUCTION

In order to operate intelligently in unstructured domestic environments, service robots should be able to handle a wide spectrum of situations and tasks, which makes it infeasible for an expert to pre-program a robot with sufficient knowledge to solve everyday tasks a-priori. In this context, learning from demonstrations is a promising paradigm as it allows non-expert users to instruct robots in an intuitive manner [1]. Ideally the learning is performed by observing a human teacher, as this avoids the restrictions posed by kinesthetic teaching in terms of limited motion of the robot base as well as requiring knowledge about the robot's kinematics. However, whereas this allows learning complex actions on a trajectory level, it introduces the necessity to map the observed human motion trajectories to the robot.

In this work, we consider learning sequential mobile manipulation tasks that can be modeled geometrically based on the spatial relations between the involved objects, e.g., arranging objects on a table, tidying up, or operating doors. In this context, it is insufficient to learn the motion associated with executing each step of the task. Instead, the robot should also reason about the relevant spatial relations between the objects that it should achieve to solve the task and generalize the demonstrations in new settings. Without prior knowledge of the task, this introduces ambiguity with respect to the intention of the teacher and the goal of the task. For example, the pose of an object relative to the table might be more



Fig. 1: Our approach enables a robot to learn complex mobile manipulation tasks involving sequences of actions by observing teacher demonstrations (top row). By observing each step in the demonstrations, the robot is able to infer flexible models of the relevant spatial relations between the objects for each action and for the overall goal of the task (middle row). At the same time, our approach enables the robot to learn action models on the trajectory level in order to execute the motions necessary to reproduce the task in new settings and without needing the teacher to specify a concrete goal of the task (bottom row).

relevant for a task like setting the table than for a task like opening a box on the table. This makes it challenging to commit to one model for each action and for the overall goal of the task based on a few training examples. At the same time, without the user or an expert specifying an explicit goal to achieve in each situation, we cannot leverage existing task planning techniques to sequence the learned actions.

In our previous work [2], we presented a novel approach to learning models of mobile manipulation actions that enables the robot to adapt complex human teacher demonstrations to account for the robot's kinematics and grasping capabilities. This allows the robot to learn motion models to reproduce the demonstrated actions by generating feasible trajectories. However, this approach considered one action at a time, and required the teacher to manually specify a reference frame (e.g., object on the table) to generate the motion. As opposed to that, in [3] we introduced *teach-and-improvise*, a novel approach that builds on Monte Carlo tree search (MCTS) to enable the robot to compute sequences of demonstrated actions to achieve a goal state that aligns with the intention of the teacher. In contrast to existing planning techniques, our approach does not require committing to one model for each action or for the goal of the task. Instead, our

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algorithm disambiguates the demonstrations by considering several interpretations of the actions and the task with respect to the relevant spatial relations in a probabilistic framework. This allows the robot to improvise task solutions based on the starting state. One limitation of our work in [3], however, was relying on existing motion planners to execute point-to-point actions for each step of the plan. This limited the imitation to tasks consisting of non-mobile and unconstrained actions.

In this work, we extend our previous works by combining the mobile manipulation action models developed in [2] with the teach-and-improvise framework presented in [3]. Specifically, we present the following contributions: i) our approach enables jointly learning models of a mobile manipulation task and its actions from a small number of markerless teacher demonstrations, and ii) our approach enables the robot to imitate complex mobile manipulation tasks involving geometrically-constrained actions without requiring motion planners that depend on prior semantic knowledge of the task or an explicit goal representation. We evaluate our contributions thoroughly in real-world experiments with a PR2 robot. Note that an earlier version of this work with preliminary results was presented in [4].

II. RELATED WORK

In the field of learning actions on a trajectory level from demonstrations, different methods have been proposed over the last years [5], [6]. In contrast to previous approaches we focus on adapting human demonstrations of mobile manipulation actions to the robot in terms of grasping capabilities and kinematic feasibility.

Complementary to the learning of individual actions, there are also a number of approaches addressing imitation learning on a task level. Calinon et al. [7], [8] extract spatial and temporal constraints and their relevance to each part of the task from demonstrations, while [9] automatically selects task spaces for modeling demonstrated motions. The work by Niekum et al. leverages a Bayesian nonparametric model to identify repeated structure in trajectories, and accordingly represents the high-level structure of the task using a finite state machine where each learned skill is encoded relative to the most consistent reference frame [10]. Such approaches rely on simple heuristics, statistical measures, or a teacher to determine relevant frames of reference for learning and executing motion primitives. In contrast to that, our method allows for considering several reference frames for each action in a Monte Carlo tree search framework.

Most current work on learning the integration of action models in tasks builds on existing predicates to instantiate or extract symbolic or logical rules from teacher demonstrations such as the work by Höfer and Brock [11]. Other approaches extract relevant preconditions and effects of actions from experience in a reinforcement learning domain [12]. Related to that, Pasula *et al.* introduced a probabilistic, relational planning rule representation that compactly models noisy, non-deterministic action effects [13]. Recently, Paxton *et al.* proposed an approach that relies on a symbolic description of a task to perform sampling-based motion planning based on actions learned from expert demonstrations [14]. Rather than extracting symbolic action representations for planning or relying on prior semantic knowledge such as a library of predicates or a planning domain, our approach addresses learning a continuous representation of actions and tasks from a small number of demonstrations. Accordingly, our action goal distributions encode multi-modal spatial relations between the objects.

To compute feasible sequences of actions when solving a task using our continuous representation, our algorithm builds on heuristic-based MCTS [15], [16]. However, we extend the traditional tree structure of MCTS to leverage our flexible action models that encode several interpretations (possible reference frames) for each action.

Planning for robotics is typically addressed with task and motion planning techniques [17]-[19]. These integrate geometric reasoners into forward-chaining state-space search, Hierarchical Task Network planning, or knowledge-based planning. Such planning-based approaches require a description of the symbolic and geometric domain as well as a concrete goal state or formula. As opposed to this, our approach does not assume such prior semantic knowledge about the task as we build our models on a continuous representation modeling spatial relations between objects. Accordingly, rather than planning to achieve a pre-specified symbolic goal, we formulate task imitation as an optimization problem in which we maximize the likelihood that the final goal state aligns with the intention of the teacher. Similar to task and motion planning methods, our approach integrates feasibility checks (e.g., collision checking) directly into the search. Additionally, we perform full feasibility checks when a plan is found to ensure it can be executed by the robot in practice. However, in contrast to the above planning approaches, we do not assume prior geometric models of actions (e.g., manipulating articulated doors) as we enable the robot to learn feasible trajectories from demonstrations that encode such constraints inherently.

Similar to us, Toussaint *et al.* formulate sequential manipulation tasks as an optimization problem without an explicit goal state [20], [21]. However, they do not consider learning from teacher demonstrations, and leverage logic-geometric programming and continuous path optimization while considering symbolic, kinematic, and geometric constraints. Furthermore, Medina *et al.* also tackle learning sequential tasks from demonstrations and focus on stable control policies and action transitions [22].

III. PROBLEM STATEMENT

We aim to enable a robot to learn a manipulation task from a small number of teacher demonstrations such that the robot can generalize the task in new settings. We define a task as a tuple $\mathcal{T} = \langle \mathcal{O}, \mathcal{A}, \Psi \rangle$ describing the involved objects \mathcal{O} , the set of applicable manipulation actions \mathcal{A} and a function Ψ modeling the teacher's intended task goal. We represent the state \mathbf{s}_t at time t based on the 6-dof poses of all objects involved in the task. We use ${}^lT_k(t)$ to denote the pose of object o_k relative to object o_l at time t. We consider learning tasks that involve several manipulation actions. We do not explicitly address the problem of segmenting demonstrated trajectories in this work. We assume that each manipulation action can be modeled based on three steps: reaching for and grasping an object, manipulating the object, and releasing the object. Accordingly, we automatically segment demonstrations based on co-occurring motion of objects and the teacher's hand. Beyond this we provide 3D models of all objects involved but make no assumptions about the semantics of the task or its actions. Note that the teacher can choose to demonstrate the task using a different order of actions in each case. We assume that each task demonstration ends in a goal state that represents the teacher's intention for the task. Accordingly, we aim to solve two joint problems, see Fig. 2: First, given the segmented demonstrations, we aim to learn a set of actions \mathcal{A} by adapting the observed trajectories such that the robot can reproduce them. Second, given all task demonstrations, we aim to learn a model $\Psi(s)$ that captures how well a goal state s aligns with the intention of the teacher for the task. Accordingly, given a new starting state s_0 , we aim to compute a feasible plan consisting of actions $a_{0:T-1}$ from \mathcal{A} and their subsequent goal states $\mathbf{s}_{1:T}$ such that the robot can achieve a final goal state s_T that maximizes $\Psi(\mathbf{s}_T)$. As there can be several ways of solving the same task, we aim to do so without assuming knowledge of the goal state s_T or the number of steps T needed to achieve it.

IV. APPROACH

In this section, we present our approach for solving the problems in Sec. III. We first describe how we model the intention likelihood Ψ of the task in (Sec. IV-A). In Sec. IV-B, we describe our approach for learning action models that allow the robot to imitate the manipulation trajectories demonstrated by the teacher. In Sec. IV-C, we describe how we leverage those models in our teach-and-improvise framework to allow the robot to compute a feasible plan for solving the task starting in an arbitrary state.

A. The Intention Likelihood of the Task

One challenge of learning the demonstrated task is inferring the intention of the teacher with respect to the desired final goal state, see Fig. 3. Rather than committing to one goal state s_T^* to reach for all cases, we introduce the intention likelihood function $\Psi(s_T)$, which models the extent to which a goal state s_T aligns with the intention of the teacher for solving the task. As we do not assume to have any prior semantic knowledge about the task, we assume that Ψ can be modeled based on the pairwise spatial relations between all pairs of objects in the task as follows:

$$\Psi(\mathbf{s}_T) = \eta \sum_{\substack{o_k \in O(\mathbf{s}_T) \\ o_k \neq o_l}} \sum_{\substack{o_l \in O(\mathbf{s}_T) \\ o_k \neq o_l}} \omega_{(k,l)} p(^l \mathbf{T}_k(T)), \quad (1)$$

where $O(\mathbf{s}_T)$ is the set of objects in \mathbf{s}_T and $p({}^{l}\mathbf{T}_k)$ is the likelihood that the pose of o_k relative to o_l in state \mathbf{s}_T aligns with the corresponding training poses at the end of the



Fig. 2: Our approach uses the teacher demonstrations to learn models of the individual actions as well as the overall task goal. Each action manipulates one object to achieve desirable spatial relations between it and other objects in the scene. We learn an action goal distribution to sample likely goal states s_{t+1} to achieve when applying the action *a* in s_t . We leverage a Gaussian mixture model (colored spheres) to encode the motion of the action and generate feasible trajectories for executing it (magenta line). Our algorithm computes sequences of actions to imitate the task driven by maximizing the likelihood of the final task goal state achieved.



Fig. 3: The left column shows the final goal states for three different demonstrations of arranging objects on the table. The right column illustrates the inherent ambiguity in the demonstrations by showing the corresponding distributions of three pairwise relations from this task. We model these relations using multi-modal distributions we construct from the demonstrated poses. This flexible model allows us to encode multiple modes of solving the task by computing solutions that maximize the intention likelihood of the task.

teacher demonstrations. The weights $\omega_{(k,l)}$, normalized by η capture the importance of the pairwise relation between o_k and o_l for the task, which we estimate from the consistency in the demonstrations by assuming that more relevant relations show a lower dispersion than less relevant ones. We define $\omega_{(k,l)} = \frac{1}{\epsilon_H + H_{(k,l)}}$, where $H_{(k,l)}$ is the entropy based on the object relations seen in the task demonstrations. We ensure that all weights $\omega_{(k,l)}$ are finite and positive by setting $\epsilon_H = 0.01 - \min(0, H_{min})$, where H_{min} is the minimum entropy over all pairwise relations. We estimate the entropy of this distribution numerically by drawing samples from its N modes as proposed by [23]. We aim to model the distributions $p({}^{l}\mathbf{T}_{k})$ from a small number of demonstrations and yet capture fine details of the teacher intention. Accordingly, we adopt a data-driven approach based on kernel density estimation to model these distributions from N demonstrations:

$$p({}^{l}\mathbf{T}_{k}) = \frac{1}{N} \sum_{n=1}^{N} k({}^{l}\mathbf{T}_{k}^{(n)}(T_{n}), {}^{l}\mathbf{T}_{k}), \qquad (2)$$

where k(.,.) is the Gaussian kernel function capturing the similarity between ${}^{l}\mathbf{T}_{k}$ and the corresponding relative pose ${}^{l}\mathbf{T}_{k}^{(n)}(T_{n})$ at the end of the *n*-th demonstration.

Our model of the intention likelihood is flexible and allows us to consider a continuous distribution of valid goal states for solving the task. This addresses the ambiguity in the demonstrations, where it can be unclear what the intention of the teacher is, see Fig. 3. Rather than committing to a predefined goal state for reproducing the task using classical planning approaches, we show in Sec. IV-C how our MCTSbased framework enables the robot to *improvise* feasible solutions that maximize Ψ .

B. Action Model Learning

Whereas Ψ captures the intention of the teacher with respect to the final goal state of the task, we also aim to learn a library of actions \mathcal{A} using the segmented demonstrations such that the robot can later sequence those actions to achieve a state maximizing Ψ . We assume that each action $a \in \mathcal{A}$ is associated with a unique object o_k and consists of three steps: reaching for and grasping the object, manipulating the object, and releasing the object. We therefore seek to learn a model that enables the robot to manipulate o_k starting in a state \mathbf{s}_t by defining: 1) how to sample a goal state \mathbf{s}_{t+1} such that o_k satisfies desirable *spatial relations* between o_k and other objects in the scene after applying the action, and 2) how to generate a *feasible trajectory* for moving o_k to achieve \mathbf{s}_{t+1} starting from \mathbf{s}_t .

1) Action Templates and Goal Distributions: We aim to model a goal distribution $p(\mathbf{s}_{t+1} \mid \mathbf{s}_t, a)$ that captures the likelihood to achieve state s_{t+1} when applying action a to move o_k in state s_t . We assume that the intention of the teacher is to achieve desirable spatial relations between o_k and other objects in the scene. Analogous to the intention likelihood of the whole task Ψ , we adopt a non-parametric mixture model for $p(\mathbf{s}_{t+1} \mid \mathbf{s}_t, a)$ based on the training poses before and after each teacher demonstration of the action. Specifically, we consider the poses of o_k relative to all other objects. This enables us to tackle the ambiguity in the demonstrations and not commit to a single model of the action (e.g., always moving o_k relative to o_l). However, we also aim for an efficient way to sample from this distribution when searching for a solution to the task (Sec. IV-C). Therefore, we propose to decompose it by considering several action *templates* Γ^a , where each template $\gamma \in \Gamma^a$ conditions moving o_k relative to only one other object in the scene, i.e., $p(\mathbf{s}_{t+1} \mid \mathbf{s}_t, a) = \sum_{\gamma \in \Gamma^a} p(\mathbf{s}_{t+1} \mid \mathbf{s}_t, a, \gamma) \ p(\gamma \mid \mathbf{s}_t, a).$ Without any prior knowledge about the action, we assume $p(\gamma \mid \mathbf{s}_t, a) = \frac{1}{|\Gamma^a|}$ for all $\gamma \in \Gamma^a$. We construct a mixture distribution $p(\mathbf{s}_{t+1} \mid \mathbf{s}_t, a, \gamma)$ for each template (analogous to Eq. (2)) based on the poses ${}^{l}\mathbf{T}_{k}$ of o_{k} relative to one object o_l in \mathbf{s}_{t+1} as seen in the action demonstrations. This allows the robot to explore a different subset of spatial relations at a time depending on the situation. For example, it might be more beneficial to move a cup to achieve a desired pose relative to a bowl (γ_1) than to the door (γ_2). Note that Γ^a includes the special template of moving an object relative to itself (e.g., the cabinet door in the second row of Fig. 5). In Sec. IV-C.2.b, we describe how our algorithm samples from this distribution when solving the task.

2) Learning the Action Trajectory: In addition to reasoning about a likely goal state s_{t+1} of the action, we aim to learn the motion associated with executing the action in state s_t to achieve s_{t+1} on the trajectory level. For this, we adopt the approach we introduced in [2] for learning mobile manipulation actions directly from human demonstrations. This allows the robot to adapt the demonstrations to its capabilities to achieve successful grasps of the manipulated object while considering kinematic constraints between the robot's mobile base and end-effector. We formulate this as a graph optimization problem that incorporates these constraints and generates robot-suited trajectories for grasping, moving and releasing the object by following the human demonstrations as close as possible while deviating as necessary to meet the robot's capabilities. We use the adapted demonstrated trajectories to learn models for a combined motion of the robot's base and end-effector described by their pose, velocity, and acceleration. The motion is assumed to be driven by a second order differential system encoded as a Gaussian Mixture Model. Fig. 2 and Fig. 5 include visualizations of the learned time dependent models.

For details on the graph structure and the implementation of our mobile manipulation action models, we refer to our work in [2], [24]. The learned models can generate trajectories to grasp, move and release the action-relevant object o_k on demand. However, one limitation of our prior work is assuming that the reference frame for the motion and accordingly, the goal pose for the manipulation is provided by the teacher. In the next section, we discuss how this work addresses this issue by enabling the robot to automatically select different reference frames based on the action templates Γ^a and sample goal states from the corresponding distributions (Sec. IV-B.1) while computing a task plan.

Algorithm 1 The proposed teach-and-improvise algorithm based on the initial state s_0 and intention likelihood Ψ with feasibility checking for the applied action models A.

1:	procedure SOLVETASK(Ψ , \mathcal{A} , \mathbf{s}_0 , K)
2:	$n_a \leftarrow CreateRootNode(\Psi, \mathbf{s}_0)$
3:	// Run k iterations or root is solved ($\rho(n_a) = true$)
4:	$k \leftarrow 0$
5:	while $k < K$ and $\rho(n_a) = false$ do
6:	$n_a^* \leftarrow \text{SelectLeafNode}(n_a)$
7:	$ExpandNode(n_a^*,\Psi,\mathcal{A})$
8:	UPDATEVALUES (n_a^*)
9:	$k \leftarrow k + 1$
10:	// Find best plan with feasible actions
11:	$found \leftarrow false$
12:	while not found do
13:	$bestPlan \leftarrow \text{RecommendBestPlan}(n_a)$
14:	$found \leftarrow CHECKFEASIBILITY(bestPlan)$
15:	if not found then UPDATEVALUES (n_a^*)
16:	else return bestPlan



Fig. 4: An illustration of our Monte Carlo tree search structure. The red circles represent action-selection nodes, which are used to reason about which action to apply from state s, i.e., which object should be moved. Template selection nodes are depicted as blue squares and are used to select templates for the corresponding actions, i.e. given the selected action (or object to move, illustrated inside the squares) they select which object should be used as a reference frame for the motion. The green hexagons depict goal-selection nodes used for selecting new goal poses, i.e., given the state s_t of their grand-parent, the selected action a of their parent, and the selected reference frame γ (illustrated inside the hexagons), they sample new possible goal states s_{t+1} from the learned action goal distribution. The branch on the right depicts the special no-op action used to ensure termination.

C. Solving the Task through Search-Based Optimization

In this section, we describe our approach for solving a task given the intention likelihood and action models learned above. For this, we build on the teach-and-improvise framework we introduced in [3]. Rather than planning to achieve a predefined goal state, we formulate solving the task as the problem of computing a feasible plan that maximizes the intention likelihood, i.e.,

$$\max_{\substack{a_{0:T-1}\\\gamma_{0:T-1}\\\mathbf{s}_{1:T}}} \Psi(\mathbf{s}_{T}) - \sum_{t=0}^{T-1} cost(a_{t}).$$
(3)

The plan consists of a sequence of actions $a_{0:T-1}$, the corresponding templates $\gamma_{0:T-1}$ used to apply each action, as well as the intermediate goal states $s_{1:T}$ resulting from applying each action. We additionally pose the constraint that the computed plan must be executable by the robot. We do not assume the best number of actions T to solve the task is known beforehand. Accordingly, we use a constant $cost(\cdot)$ for each action to favor more efficient plans. This formulation enables the robot to use the learned models and improvise a suitable goal state s_T for solving the task depending on the starting state s_0 . The optimization involves discrete (actions and templates) and continuous (goal states) variables, as well as a non-convex objective function Ψ and feasibility constraints. To tackle these challenges, our algorithm builds on Monte Carlo tree search as described next.

1) Tree Structure: Classical MCTS iteratively grows a search tree starting from s_0 to approximate the returns of states and actions using Monte Carlo simulations while trading off exploration and exploitation, see [15]. In the context of Markov Decision Processes, MCTS typically considers two types of tree nodes: decision and chance nodes.

Decision nodes select actions to apply in their associated states. Chance nodes reason about potential outcomes of the action, usually reflecting the stochasticity of the domain. In our context of imitating a demonstrated task, we assume that the stochasticity stems from the ambiguity in the goals of the actions and the task. Given our approach to leverage several interpretations (templates) of each action as in Sec. IV-B.1, we propose a tree structure involving three types of nodes, see Fig. 4. Action-selection nodes reason about which action $a \in \mathcal{A}$ to apply in a certain state. Subsequently, *template*selection nodes reason about which template $\gamma \in \Gamma^a$ to use for applying the action a of their parent nodes. Each child of a template-selection node considers one template (reference frame) for the action, and is referred to as a goalselection node. Each such node is responsible for sampling goal states (new action-selection nodes) of the action from its goal distribution conditioned on the template and starting state as described in Sec. IV-B. This structure allows us to tackle the dimensionality of the problem and disambiguate the demonstrations by efficiently searching through the space of potential action interpretations and their intended goals. As the optimal number of steps for solving the task is unknown beforehand, we address the stopping problem by incorporating a special no-op action a^0 in the set A, which does not change the current state and leads to a goal state that cannot be further expanded.

2) Anytime Tree Search: We adopt an anytime search approach with a budget of K iterations. Alg. 1 summarizes our algorithm. After initializing the tree with the starting state as root (line 2) we iteratively select a promising leaf actionselection node (line 6) and expand it by applying all possible actions from the set of actions A in its state s_t (line 7). For each action, this adds subsequent template-selection, goalselection, and action-selection children nodes (new leaves representing the resulting goal states s_{t+1}). Each node is associated with a value continuously updated to reflect its utility for the solution. Therefore, each iteration initializes the values of newly-added nodes and backpropagates them to the root (line 8). Those values guide the selection of new leaf nodes in subsequent iterations based on explorationexploitation considerations. We repeat this process for Kiterations or until no leaf can be further expanded. Due to space limitations, we now briefly describe the idea behind each of these steps, and refer the reader to our work in [3] for all variations and implementation details of the algorithm.

a) Node Selection: Selecting a promising node to expand (line 6) involves traversing the tree from the root by sampling one child of each node iteratively until a leaf node is reached. For action-selection and template-selection nodes, rather than greedily selecting the child with the highest value, in this work we employ a Boltzmann Exploration strategy to trade off exploration with exploitation. This initially encourages a more uniform sampling of children, and gradually converges to greedily selecting the child with the highest value as the visit count of the parent increases. For goal-selection nodes, we sample a child with a probability proportional to that of its goal state based on the goal

distribution of the action and template of its parent, as we describe in the next section.

b) Node Expansion: Expanding the selected leaf node (line 7) involves adding its successors of template-selection, goal-selection, and action-selection nodes based on the corresponding actions, templates, and sampled goal states. For the latter, we do so by sampling states s_{t+1} from the mixture distribution $p(\mathbf{s}_{t+1} | \mathbf{s}_t, a, \gamma)$ of the corresponding action aand template γ , which encodes moving an object o_k relative to one other object o_l specified by the template γ (Sec. IV-B.1). To restrict the branching factor while exploring several modes of the action, we first draw S poses ${}^{l}\mathbf{T}_{k}$ from the set of poses of o_k relative to o_l seen in the demonstrations of this action. We use each sample and the pose of o_l in \mathbf{s}_t to compute a corresponding state \mathbf{s}_{t+1} by transforming the pose of o_k to the goal pose $(\mathbf{T}_k(t+1) = \mathbf{T}_l(t) \ ^{l}\mathbf{T}_k)$ as o_k is the only object that moves between t and t + 1. The resulting samples define the goal distribution, which we discretize by clustering the goal states with respect to \mathbf{T}_k using agglomerative hierarchical clustering such that the state of each cluster is based on the mean pose of o_k over its members. Finally, each cluster is added as a new leaf node to the tree, with a goal probability proportional to the number of samples used to create it. In summary, each node expansion step explores several modes of moving objects relative to each other based on the demonstrations, see Fig. 4.

c) Value Initialization and Backpropagation: We follow a heuristic-based MCTS approach and gauge how good a newly-added leaf node is as a final goal of the task by initializing its value to the intention likelihood $\Psi(\mathbf{s}_{t+1})$ of its state \mathbf{s}_{t+1} . Through backpropagation, we then update all affected node values back to the root such that a node's value depends on those of its children. For this, we use a max-value strategy, which sets the value of a node as the max value of its children while subtracting the constant cost of the action for goal-selection nodes.

3) Retrieving the Best Feasible Plan: The procedure described in Sec. IV-C.2 corresponds to the MCTS-based algorithm we introduced in [3]. This relies on a lazy approach of checking inverse kinematic constraints and collisions in the state of a leaf node only after it gets selected for expansion to prevent expanding infeasible states. This guarantees the feasibility of the intermediate goal states $s_{1:T}$, but not of the trajectory between each two states. Additionally, we assumed the existence of a suitable motion planner to generate a trajectory for each step consisting of the current state s_t , the action to be applied a_t , the corresponding template γ_t and the new desired state s_{t+1} . In this work, we address these limitations by incorporating our action trajectory models when generating the solution plan.

After building the search tree, we traverse it to retrieve the best plan found so far (lines 12-16 of Alg. 1) while ensuring that the robot can generate and execute feasible action trajectories in each step. Procedure RECOMMENDBESTPLAN greedily traverses the tree from the root to a leaf node while always selecting the child node with the largest value. Each step in the resulting plan corresponds to one level in this path,



Fig. 5: This figure shows the three tasks used in the evaluation. The first row shows the task of removing the lid of a box and placing a second box inside it. In the second task, the robot has to open a cabinet door, take out a cereal box and place it next to a bowl on the table. In the third task, the robot has to open and move through a door before performing the same task as before. The respective action models are shown as colored spheres representing the centers of the Gaussian mixture models used to encode the motion. The generated trajectories for the end-effector are shown in magenta and are used to ensure collision-free solutions that satisfy inverse kinematic constraints when executing each action.

which represents applying and action a_t in state s_t using template γ_t to move the relevant object and achieve the next state s_{t+1} . To check the feasibility of the resulting plan, we generate the corresponding grasping, moving and releasing trajectories for each action $a_t \in a_{0:T-1}$ using the motion models learned as described in Sec. IV-B.2. The grasping trajectory is generated based on the current pose in s_t of the object associated with action a_t (the grasp pose is learned as part of the model, see [2]), and the motion is performed with respect to the reference frame of the object defined by the corresponding template γ_t . We set the end pose of each trajectory as the initial state of the next motion model. While generating trajectories, we perform inverse kinematic and collision checks for each pose using 3D models of the robot and the scene. If any trajectory is found to be infeasible, we update the tree by assigning a value of $-\infty$ to the leaf, backpropagating, and repeating.

V. EXPERIMENTAL EVALUATION

In this section, we present the experimental evaluation of our proposed approach in both simulation and with a real robot. To record teacher demonstrations, we rely on [25] to track the hand of the teacher using RGB-D images, and on *Simtrack* [26] to detect the objects in the scene and estimate their 6-dof poses. We segment the demonstrations automatically based on which object is being manipulated as described in Sec. III. We use our approach (Sec. IV-B) to learn the motion model of each action. Additionally, we use the final state after each task demonstration to learn a model of the intention likelihood of the task as in Sec. IV-A.



Fig. 6: Examples of the robot executing the sequences of actions generated by our approach for solving the tasks in Fig. 5. Our approach allows the robot to generate feasible trajectories for each step of the plan using the learned action models and without requiring an existing motion planner.

Finally, we rely on the *MoveIt*! library ¹ to perform collision and inverse-kinematics checks.

Our previous work and extensive evaluation focused on either learning complex motion models of individual actions [2], or on generalizing sequential tasks consisting of simple point-to-point, pick-and-place actions that can be executed using standard motion planners [3]. In [3], we also discuss computation cost and search efficiency for different variants of our teach-and-improvise algorithm. Therefore, in this work, we conducted experiments to demonstrate the benefits that our proposed integrated system brings: i) the ability to jointly learn task and action models from a few demonstrations; ii) the ability to imitate tasks involving geometricallyconstrained manipulation actions without requiring an existing motion planner that depends on articulated object models (e.g., a model of a door); and *iii*) the ability to improvise task solutions in previously unseen settings. We investigate three tasks of increasing complexity, see Fig. 5.

Task 1: In this task, the teacher demonstrated grasping the lid of a box, opening the box, placing the lid next to the box, grasping a second box, and placing it inside the opened box (see Fig. 1). We provided the robot with five demonstrations to learn both the task goal and the involved action models.

Task 2: The second task consists of opening a cabinet door, taking a cereal box from the cabinet, and placing it next to a bowl on the table. Note that our proposed approach enables the combined learning of the actions and the task intention likelihood from the same set of task demonstrations as in Task 1. However, in this work, we do not explicitly address the perception problem. For this task, we provided the robot with demonstrations of the actions independently of the demonstrations of the final task state, as the scene is often not fully observable from a single perspective. Overall, we provided five demonstrations of the task goals and for each

action. Beyond the recorded state during the demonstrations, we did not provide the robot with further information such as a model of the articulated cabinet door.

Task 3: This task involves the same goal as in the previous task. Here however, the robot is initially outside of the room and has to first enter through a door to reach the cabinet and the table. For this task, we use the demonstrations from *Task 2*, and additionally provide the robot with 10 teacher demonstrations of the door opening action only.

A. Generalizing the Learned Tasks in New Settings

To demonstrate the ability of our system to learn applicable models of the task and actions and use them to generate plans starting from new states s_0 , we evaluated our approach on *Task 1* and *Task 2* each for 50 different simulated settings. The starting poses of the objects were sampled from the space of reachable poses, e.g., pose of the box inside the cabinet is geometrically constrained by robot's grasping capabilities. Besides the learned models no additional information or explicit goal state was provided. In this experiment the generated action sequences are checked for feasibility, the execution of the generated plans is addressed in Sec. V-B.

For Task 1 our approach generated feasible solutions for 43 trials and for Task 2 in 41 trials. Note that the computed plan was not always the same as our approach explores different action sequences and interpretations, e.g., the robot may choose to move the lid relative to itself or to the box to solve the task. Failures occurred due to the infeasibility of the required actions, i.e., there was no collision-free plan. Out of the seven failures for Task 1, two still resulted in a partial solution of removing the lid of the box. For Task 2, the nine failures included six results with a partial solution. When, for instance, the grasping of the box inside the cabinet with the learned action model is not possible due to collisions, our approach proposed to open the cabinet and stop afterwards as this is the best achievable solution. This highlights the advantage of our approach in improvising solutions by maximizing the intention likelihood of the task.

B. Task Imitation on the Robot

To demonstrate that the plans generated by our approach are executable in practice, we evaluated the tasks on our PR2 robot in real-world and simulation experiments. The three rows in Figures 5 and 6 show examples of the planning process and the execution of the three tasks, respectively. For Task 1, the object poses were detected before generating the plan using Simtrack [26]. We reproduced the task from five different starting states. As no navigation with the mobile base was required here, we used a fixed robot position to minimize the errors induced from object detection and localization. Task 2 was planned and executed in five trials in both simulated and real-world settings, each with different starting poses of the objects and the robot. For Task 3, we performed three repetitions both in simulation and real-world settings. For Tasks 2 and 3, we manually provided the initial object poses to the robot as some of them were initially occluded, e.g., behind the respective doors.

¹[Online] Available:http://moveit.ros.org

For all tasks, our approach was able to compute feasible solutions from each initial state and to successfully execute them on the robot. This demonstrates that our approach enables transferring human demonstrations to the robot such that it can reproduce them based on its own constraints. In Task 3, our algorithm always selected action sequences that require the robot to first apply the door opening action as all other solutions resulted in collisions with the door (see attached video). The robot is able to achieve this by generating feasible trajectories from the learned action models without requiring a motion planner as in [3], i.e., our approach enables incorporating such constrained mobile manipulation actions when learning from non-expert teachers. Furthermore, the imitation performed in Task 3 highlights the flexibility of our approach in incorporating actions learned in a different context to solve a different task.

VI. CONCLUSION

In this paper, we presented a novel approach to learning sequential mobile manipulation tasks demonstrated by a human teacher. Our work combines learning action models that allow reasoning about feasibility on a geometric level with a probabilistic planning framework based on Monte Carlo tree search. Our approach adopts flexible, probabilistic models of each action and the overall goal of the task based on the spatial relations between the involved objects. This allows the robot to reason about different valid ways of imitating the task, thus tackling the ambiguity in the demonstrations. As opposed to standard planning approaches that can leverage this prior knowledge, we formulate solving the task as an optimization problem to maximize the intention likelihood given the demonstrations, thus avoiding the need for the teacher or an expert to specify an explicit goal state in each situation, i.e., the robot would do what it can to generalize the demonstrations given a new initial state. Furthermore, our approach enables the robot to reproduce complex, geometrically-constrained action trajectories and to automatically select a suitable reference frame for each motion without the need for a motion planner that requires prior semantic knowledge of the task and its constraints. This makes our approach unique in its ability to imitate sequential manipulation tasks demonstrated by a non-expert teacher without a formal planning domain description of the task or expert knowledge about the relevant reference frames for each action. In experiments we demonstrate the effectiveness of our approach in computing and executing feasible sequences of actions to solve complex mobile manipulation tasks and generalize them in new settings.

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