Abstract—Lifelong-learning robots need to be able to acquire new skills and plan for new tasks over time. Prior works on planning with skills often make assumptions on the structure of skills and tasks, like subgoal skills, shared skill implementations, or learning task-specific plan skeletons, that limit their application to new and different skills and tasks. By contrast, we propose doing task planning by jointly searching in the space of skills and their parameters with skill effect models learned in simulation. Our approach is flexible about skill parameterizations and task specifications, and we use an iterative training procedure to efficiently generate relevant data to train such models. Experiments demonstrate the ability of our planner to integrate new skills in a lifelong manner, finding new task strategies with lower costs in both train and test tasks. We additionally show that our method can transfer to the real world without further fine-tuning.

I. INTRODUCTION

Lifelong-learning robots need to be able to plan with new skills and for new tasks over time [1]. For example, a home robot may initially have skills to rinse dishes and place them individually on a rack. Later, the robot might obtain a new skill of operating a dishwasher. Now the robot must plan to either wash the dishes one by one or use the dishwasher depending on the costs of each skill and the number of dishes to be cleaned. In other words, robots need to be able to obtain and use new skills over time to either adapt to new scenarios, or for new tasks that are added over time, or to improve performance on existing tasks. Otherwise, the robot designer would need to account for all potential tasks and all possible ways the robot can do them before deployment. To achieve such capabilities, we propose a task planning system that can efficiently incorporate new skills and plan for new tasks in a lifelong robot manipulation setting.

To create such a versatile manipulation system, we use parameterized skills that can be adapted to different scenarios by selecting suitable parameter values. We identify three properties of skills that are important to support in this context: 1) skills can have different implementations, 2) skills can have different parameters which can take discrete, continuous, or mixed values, and 3) skill parameters may or may not correspond to subgoals. Property one means the skills can be implemented in a variety of manners, e.g., hard-coded, learned without models, or optimized with models. This requires relaxing the assumptions placed on the skill structures made in previous works, like implementing all skills with the same skill-conditioning embedding space [2], [3], [4], [5]. Property two requires the task planner to not assume any fixed structure for skill parameters. Unlike previous works [6], [7], each skill can utilize a different number of parameters, and these parameters can be a mix of discrete and continuous values. Property three means that instead of chaining together skill subgoals, the planner needs to reason about the effects of the skills for different parameter values. For example, the home robot may need to predict how clean a plate is for different rinsing durations.

Planning for new tasks requires the task planner to be flexible about the structure of task specifications. Hence, a task should be described by either a goal condition function or goal distributions [8], instead of shared representations like task embeddings [9] or specific goal states [10], [6], [5], [11]. Using predefined task representations limit the type of tasks a robot can do, and using learned task embeddings may require additional fine-tuning on new tasks. Only having access to a goal condition function also means function approximators cannot easily take in tasks as inputs, making it difficult to learn general value or policy functions for high-level planning.

To satisfy the skill and task requirements for the lifelong manipulation planning problem, we propose a task planning system that performs search-based planning with learned skill effect models.

II. RELATED WORK

A. Search-Based Planning

Search-based planning searches in the space of a goal's state representations, and the search is guided by the effect of skills and task specifications. Learning the skill effect model allows the planner to find low-cost paths that lead to the goal state representation. The planner uses learned skill effect models to choose skill effect combination and parameter values that lead to the goal state representation.

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effects of parameterized skills. Search-based methods directly plan in the space of skill-parameter tuples. They support skills regardless of their parameter choices and implementation details, and only a general goal condition check is needed to evaluate task completion.

To efficiently use search-based planning methods in task planning, we propose to learn skill effect models (SEMs). SEMs are learned instead of hardcoded or simulated, since manually engineering models is not scalable for complex skills and simulations are too expensive to perform online during planning. Every skill has its own SEM that predicts the terminal state and costs of a skill execution given a start state and skill parameters. We interleave training SEMs with generating training data by running the planner with the learned SEMs on a set of training tasks. This efficiently collects skill execution data relevant for planning, and it supports the addition of new skills and tasks over time. The planner uses the SEMs to plan for existing tasks with different initial states, as well as new test tasks.

In summary, our contributions are 1) a search-based task planning algorithm with learned skill-effects models that 2) relaxes assumptions of skill and task representations in prior works; skill effect models are learned with 3) an iterative data collection scheme that efficiently collects relevant training data, and together they enable 4) planning with new skills and tasks in a lifelong manner. Please see supplementary materials, with additional results and experiment videos, at https://sites.google.com/view/sem-for-lifelong-manipulation

II. RELATED WORKS

Subgoal Skills. Many prior works approached planning with skills with the subgoal skill assumption. The successful execution of a subgoal skill always results in the same state or a state that satisfies the same preconditions of all skills, regardless of where the skill began in its initiation set [12]. As such, the skill effects are always known, and such approaches instead focus on learning preconditions [6] of goal-conditioned policies, efficiently finding parameters that satisfy preconditions [7], [13], or learning feasible skill sequences [11]. While subgoal planning is powerful, it limits the types of skills the robot can use.

Non-Subgoal Skills. For works that plan with non-subgoal skills, many represent the skill policy as a neural network that takes as input both the state and an embedding that defines the skill. This can be viewed as planning with one parameterized skill or a class of non-parameterized skills, each defined by a different embedding. Such skills can be discovered by experience in the real world [3] and in learned models [2], [4], or learned from demonstrations [5]. Planning with these skills is typically done via Model Predictive Control (MPC), where a short sequence of continuous skill embeddings is optimized, and replanning occurs after every skill execution. While these approaches do not assume subgoal skills, they require skills to share the same implementation and space of conditioning embeddings, and MPC-style planning cannot easily support planning with multiple skills with different parameter representations [6], [4], [3], [5].

Planning with Skills and Parameters. To jointly plan sequences of different skills and parameters, works have proposed a two-stage approach, where the planner first chooses the skills, then optimizes skill parameters [14], [15], [13]. Unlike directly searching in the space of skills and parameters, it is difficult for two-stage approaches to give guarantees on solution quality. Some also require hardcoded or learned plan skeletons [15], [13], which limits the planner’s applicability to new tasks.

Instead of planning, an alternative approach is to learn to solve Markov Decision Processes (MDPs) with parameterized skills [16], [17], [18]. However, learning value or policy functions typically requires a fixed representation for function approximators, so these methods cannot easily adapt to new skills and skills with parameters with different dimensions or modalities (e.g. mixed continuous and discrete). Doing so for search-based planning can be done by directly appending new skills when expanding a node for successors.

Obtaining Skill Effects. Many prior works used simulated skill outcomes during planning [19], [20], [21], [14]. This can be prohibitively expensive to perform online, depending on the complexity of simulation and the duration of each skill. To avoid simulation rollouts, works have used hardcoded analytical [22], [23] or symbolic [24], [25], [26] skill effect models. Manually engineering such models may not always be feasible, and they do not easily scale to changes in skills, dynamics, and tasks. Although symbolic models can be automatically learned [27], [12], [28], [29], [30], these approaches also make the subgoal skill assumption. By contrast, our method, which learns skill effect models in continuous state spaces without relying on symbolic constructions, can plan with both subgoal skills as well as skills that do not share this property.

The works most closely related to ours are [15] and [30]. In [15], the authors jointly train latent dynamics, latent preconditions, and parameter samplers for hardcoded skills and a model that proposes plan skeletons. Planning is done MPC-style by optimizing skill parameters with the fixed plan skeleton. Although this approach does not assume subgoal skills and supports skills with different parameters, learning task-specific plan skeletons and skill parameter samplers makes it difficult to use for new tasks without finetuning. The method in [30] learns to efficiently sample skill parameters that satisfy preconditions. Task planning is done using PDDLStream [31], which supports adding new skills and tasks. Though this approach does not use subgoal parameters, the desired skill outcomes are narrow and predefined, and the learned parameter sampler aims to achieve these predefined effects. As such, the method shares the limitations of works with the subgoal skill assumption, where the skill-level transition model is not learned but predefined as the skills’ subgoals.
The proposed method consists of two main components - learning skill effect models (SEMs) for parameterized skills and using SEMs in search-based task planning. These two components are interleaved together - we run the planner on a set of training tasks using SEMs to generate data, which is used to further train the SEMs. New skills and training tasks can be added to the pipeline, as the planner and the SEM models do not assume particular implementations of skills and tasks. The planner can also directly use the learned SEMs to solve test tasks. See Figure 1 for an overview.

A. Formulation of the Skill Planning Problem

Parameterized skills. Central to our approach is the options formulation of skills. Denote a parameterized skill as $o$ with parameters $\theta \in \Theta$. Parameters are skill-specific and may contain subgoal information such as the target object pose for a pick-and-place skill. We assume a fully observable state $x \in X$ that contains all information necessary for task planning, cost evaluations, and skill execution. Define the low-level action $u \in U$ as the command sent to the robot by a low-level controller shared by all skills (e.g. torque).

In our formulation, a parameterized skill $o$ contains the following five elements: an initiation set (precondition) $I_0(x, \theta) \rightarrow \{0, 1\}$, a parameter generator that samples valid parameters from a distribution $p_\theta(\theta|x(x, \theta)) = 1$, a policy $\pi_\theta(x, \theta) \rightarrow u$, a termination condition $\beta_o(x, \theta, t) \rightarrow \{0, 1\}$, and the skill effects $f_o(x_t, \theta) \rightarrow x_{t+T}$, where $T$ is the time it took for the skill to terminate. To execute skill $o$ at state $x$ with parameters $\theta$, we first check if $(x, \theta)$ satisfies the preconditions and belong to the initiation set $I_0$. If it does, then we run the skill’s policy $\pi_o$ until the termination condition is satisfied. We assume that the precondition, parameter generator, policy, and termination conditions are given, and the skill effects are unknown but can be obtained via simulating the policy. To enable reasonable planning speeds, the SEMs learn to predict these skill-level transitions.

Task planning of skills and parameters. Before specifying tasks, we first define a background, task-agnostic cost $c(x_t, u_t) \geq 0$ that should be minimized for all tasks. The background cost is accumulated at the beginning of each skill execution, so the total cost is $c_o = \sum_{t=0}^{T} c(x_t, u_t)$.

$$\min_P \sum_{n=0}^{N-1} c_{o_n}$$

s.t. $G(x_N) = 1$

\[ \forall n \in [0, N-1], G(x_n) = 0 \]

\[ I_{o_n}(x_n, \theta_n) = 1, f_{o_n}(x_n, \theta_n) = x_{n+1} \]

A task is specified by a goal condition $G(x) \rightarrow \{0, 1\}$ that classifies whether or not a state achieves the task. We denote a sequence of skills, parameters, and their incurred states as a path $P = (x_0, o_0, \theta_0, x_1, \ldots, x_n, o_n, \theta_n, x_{n+1}, \ldots, x_N)$, where $N$ is the number of skill executions, and the subscripts indicate the $n$th skill in the sequence (not time). We assume the environment dynamics and skill policies are deterministic. The task planning problem is to find a path $P$ such that the goal condition is satisfied at the end of the last skill, but not sooner, and the sequence of skill executions is feasible and valid. See equation 1. Note that $\theta$, $I_o$, and $f_o$ are all skill-specific, so if there are $M$ types of skills, then there would be $M$ different parameter spaces, preconditions, and skill effects.

B. Learning Skill Effect Models (SEMs)

Defining SEMs for manipulation skills. We learn a separate SEM for each skill, which takes as input the current state $x_t$ and a skill parameter $\theta$. The SEM predicts the terminal state $x_{t+T}$ reached by the skill when it is executed from $x_t$ using $\theta$ and the total skill execution cost $c_o$. We assume SEMs are queried only with state and parameter tuples that satisfy the precondition. Because we focus on the robot manipulation domain, we assume the state space $X'$ can be decomposed into a list of object-centric features that describe discrete objects or robots in the scene.

We model SEMs with Graph Neural Networks (GNNs), because their inductive bias can efficiently model interactions among entities through message passing, encode order-invariance, and support different numbers of nodes and edges during training and test [32], [33], [34], [35]. Each node in the SEM GNN graph corresponds to an object in the scene and contains features relevant to that object from the state $x$. We denote these object features as $s_k \in \mathbb{R}^S$, where $k$ denotes the $k$th object in the scene. Because a skill may directly affect multiple objects, each node also contains the skill parameters $\theta$ as additional node features. The full node feature is the concatenation of $[s_k, \theta]$. There are no edge features. The network makes one node-level prediction, the change in object features $\Delta s_k$, and one graph-level prediction, the total skill execution cost $c_o$. As SEMs make long-term predictions about the entire skill execution, the graph is fully connected to allow all objects the possibility of interacting with each other, not just objects that are initially nearby. The loss function to train SEMs for a single step of skill execution prediction is $L = \lambda_1 \| c_o - c_o^* \|^2 + \lambda_2 \sum_{k=1}^{K} \| \Delta s_k - \Delta s_k^* \|^2$. The hat notation denotes predicted quantities, and the $\lambda$s are positive scalars that tune the relative weights between the loss terms. The GNN is implemented with PyTorch Geometric [36].

SEMs allow a planner to efficiently plan in the space of diverse skills and parameters, and it also provides two additional benefits: First, because the model is on the skill-level, not action-level, it only needs one evaluation to predict the effects of a skill execution, which reduces planning time as well as covariance shift by reducing the number of sequential predictions [37], [38], [39], [40]. Second, a long-horizon skill-level model can leverage a skill’s ability to act as a funnel in state space during execution, which simplifies the learning problem.

Collecting diverse and relevant data for training SEMs. To learn accurate and generalizable SEMs, they must be trained on a set of skill execution data that is both diverse
and relevant to task planning. While we assume knowledge of the initial state distribution of all tasks, we do not know the distribution of all states visited during planning. As such, we obtain these state transitions and train the SEMs in an iterative fashion. First, given an initial set of skills, we generate single skill execution transitions from the known initial state distribution. This data is used to train the initial SEMs. Then, given a set of training tasks, we deploy the planner to plan for these tasks using the learned SEMs across a set of initial states. The planner terminates when it finds a path to the goal or reaches a fixed planning budget (reaching maximum number of nodes expanded, maximum search depth, or maximum planning time). Then we sample paths in the graph and simulate them in a high-fidelity physics simulator to collect skill execution data, which is then appended to a dataset of all skill data collected so far. Path sampling is biased toward longer paths and ones that have the newly added skills. The transitions added are filtered for duplicates, since multiple paths in a planning graph may share the same initial segments, and we do not want to bias the dataset toward transitions closer to the initial states. After a fixed amount of path data is collected, we continue training the SEMs on the updated dataset, before restarting the data collection process. In the beginning, it is expected that the planner performance will be highly suboptimal due to the inaccurate initial SEMs.

Planning with new skills. The above procedure supports incrementally expanding the list of skills used by the planner. Given a new skill, we first train an initial SEM by sampling from the initial state distribution, then during planning data generation the search-based planner can use the new SEM to get successors. SEMs for new and existing skills will be improved and continuously trained on this new planning data. Fine-tuning previous SEMs is needed, because the new skill might have incurred states that were previously absent from the dataset. Although this fine-tuning may not be necessary in specific cases, we leave detecting such scenarios and reducing overall training budget to future work. Learning one SEM for each skill allows for different parameter spaces (e.g. dimensions, discrete, continuous, mixed) that cannot be easily represented with a shared, common model.

Planning with new tasks. Because the planner does not rely on predefined plan skeletons, it can directly use SEMs to plan for new tasks. Two main factors about data collection affect the generalization capability of the SEMs when applied to unseen test tasks. The first is whether the states incurred while planning for training tasks are sufficiently diverse and relevant to cover the states incurred by planning for test tasks. The second is the planner itself — how greedy is its search and how much it explores the state space. Many planners have hyperparameters that can directly balance this exploration-exploitation trade-off.

C. Search-based Task Planning

We pose task planning as a graph search problem over a directed graph, where each node is a state \( x \), and each directed edge from \( x \) to \( x' \) is a tuple \((o, \theta)\) such that \( f_o(x, \theta) = x' \). Edges also contain the costs of the corresponding skill execution \( c_o \). During search, this graph is constructed implicitly. Given a node to expand, we iterate over all skills, generate up to \( B_o \) parameters per skill that satisfy the preconditions, then evaluate the skill-level dynamics on all state-parameter tuples to generate successor states. \( B_o \) decides the maximum branching factor on the graph. This number varies per skill, because some skills have a broader range of potential parameters than others, requiring more samples. The number of parameters actually sampled could be 0 if no parameters satisfy the precondition of the skill at the given state. It could also be a number between 0 and \( B_o \) if a maximum sampling budget is reached for rejection sampling with the preconditions.

To search on this graph, We apply Weighted A* (WA*), which guarantees completeness on the given graph. If the heuristic is admissible, WA* also guarantees the solution found is no worse than \( c^* \), where \( c^* \) is the cost of the optimal path and \( \epsilon \) determines how greedily the search follows the heuristic. We assume an admissible heuristic is given. This is in line with previous works that have shaped rewards or costs that guide the planner [6], [15], [3], [5].

While WA* provides guarantees on a graph, we additionally need to show the constructed graph represents the underlying problem sufficiently well. Under smoothness assumptions in the dynamics and cost functions, with large but bounded \( B_o \), the graph will contain a solution that is close to the optimal with high probability. A detailed analysis is provided in Appendix A.

The proposed search-based planning scheme enables planning with new skills and tasks. After learning the SEMs for new skills, they can be used to compute additional successors during node expansion. Planning for new tasks is done by replacing the heuristic and goal conditions, and this does not affect the graph construction procedure or the learned SEMs.

IV. Experiments

Our main experiment studies how incrementally adding new skills to the proposed method affect planning performance on both train and test tasks. We apply our method on a blocks and bin manipulation domain, chosen because it can be reliably simulated, contains a diverse set of skills, and the skills used here have broader applications in desktop manipulation and tool use. In addition, we show our approach compares favorably against planning with simulation as well as the benefits of using planning data to train SEMs. Lastly, we show the generalizability of our method by deploying it in a real-world setup. Additional experimental details for
learning SEMs and planning with them can be found in Appendix II.

A. Task Domain

The task domain has a Franka Emika Panda 7 DoF arm, a set of colored blocks, a table, a tray, and a bin. On the table, blocks of the same size and different colors are initialized in random order on a grid with noisy pose perturbations. The tray on the table can be used as a tool to carry and sweep the blocks. Beside the table is a bin, which is divided into 2 regions, the half which is closer to the robot, and the half that is farther away. The state space contains the 3D position of each block, its color, and index. We implement the task in simulation with Nvidia Isaac Gym [41].

Skills. We experiment with four distinct skills: Pick and place (Figure 1 skill 1) moves a chosen block to a target location. It has a mixed discrete and continuous parameter space — which object to pick and its placement location. Tray Slide (Figure 1 skill 2) controls the robot to grasp the tray, move it over to the bin, and tilt down the tray to empty any blocks on it into the bin. Its parameter is a continuous value defining where along the length of the bin to rotate the tray. Tray Sweep (Figure 1 skill 3) uses the tray to perform a sweeping motion along the table. Its parameter specifies where to start the sweeping motion, while the sweep motion ends at the table’s edge. Bin Tilt (Figure 1 skill 4) controls the robot to grasp the handle at the side of the bin and tilt the bin by lifting the handle, which moves blocks in the bin from the close half to the far half.

Tasks. We use 4 different tasks, shown in Figure 2 which are variations of moving specific sets of blocks to different regions in the bin. Two tasks are used to collect SEM training data: Move All Blocks to Bin (A) and Move All Blocks to Far Bin (C), while the remaining two are used to evaluate learned SEMs: Move Red Blocks to Bin (B) and Move Red Blocks to Far Bin (D). Each task has the same background cost which is the distance the robot’s end-effector travels, plus a small penalty for placing the gripper inside the bin. The admissible heuristic used is the mean distance of each block to the closest point in their target regions. While Pick and Place can make substantial progress on all tasks, it alone is not sufficient. This is due to kinematic constraints, where the robot cannot directly place blocks on the far side of the bin, so Bin Tilt or Tray Slide is needed. Additionally, using other skills can achieve lower costs; Tray Sweep can quickly move multiple blocks into the bin, but this may move blocks that were supposed to stay on the table. Planning is needed to find low-cost paths, and the sequence of skills may change depending on the initial placements of the blocks.

B. Lifelong Task Planning Results

To evaluate our approach for lifelong integration of new skills, we add the four skills over time using the iterative training procedure. We evaluate two scenarios, first in which the train-test task pair are respectively tasks A and B, and second with C and D. In each case, the robot starts with only Pick and Place, while Tray Slide, Tray Sweep, and Bin Tilt are added successively in that order at fixed times. We measure planning performance by execution costs, execution success, and planning times.

Figure 3 plots the execution costs over time for both scenarios. The proposed method is able to incorporate new skills over time, lowering execution costs when applicable. This is done by planning with new skills to generate new, lower-cost plans. For example, adding Tray Slide allows the planner to find plans with significantly reduced costs across all tasks, since multiple blocks can now be moved together. In other cases, adding a new skill does not drastically affect performance of a task, and the planner is able to find previously discovered plans and maintain the same execution costs. One example is when adding Bin Tilt to the blocks to anywhere in bin tasks, because the main use of the skill is to move blocks to the far side of the bin. Another is on adding
Fig. 5: Success on task B with SEM trained on random vs. planner data.

Tray Sweep — it significantly reduced costs for moving all blocks to the bin but less so for moving only red blocks to the bin. This is because sweeping is only useful for the latter task when multiple red blocks line up in a column near the bin, which does not always happen due to random initial state sampling.

Figure 3 plots the probability of finding successful plans (dashed) and optimal plans (solid) with new skills. Immediately after adding a new skill, there is insufficient data to learn a robust SEM, so the planner is unlikely to find optimal plans using the new skill. Over time, as more data is collected, SEMs improve and the probability of finding optimal plans increases. Figure 3 also shows how some tasks can only be accomplished when a new skill is incorporated. For instance, with just Pick and Place, the robot can accomplish blocks to bin tasks (A,B), but fails to plan for the blocks in far bin tasks (C,D). Adding new skills in the former case did not change the success rate of the task, which remained at 100%, although the composition of the plans found does change. For the latter case, adding Tray Slide enabled 100% success rate, while adding Tray Sweep did not affect plan compositions, but adding Bin Tilt did. These results show that our proposed method can learn skill effects and plan with SEMs in a lifelong manner, and that SEMs can plan for new tasks without additional task-specific learning. Qualitative results can be found in Appendix V.

Failures of the planner to find successful plans are due to inaccurate SEM predictions before SEMs are trained with sufficient data. The inaccurate next state predictions mislead the planner into planning infeasible skill sequences. Although sometimes the planner can still find paths to goal under such conditions, such plans lead to execution failures.

Planning with a Simulator. To highlight the need for learning SEMs instead of simulating skill effects for task planning, we compare their planning times in Table I. We

| Task      | Sim     | SEMs   |
|-----------|---------|--------|
| A         | 776.19  | 1.3 (0.7) |
| C         | 1736.8  | 0.98 (0.5) |

TABLE I: Comparing plan times (seconds) using simulator vs. SEMs.

| Task        | +Pick-Place | +Tray-Slide | +Tray Sweep | +Tilt Bin |
|-------------|-------------|-------------|-------------|----------|
| A           | 11.3 (3.4)  | 20.2 (7.9)  | 0.6 (0.5)   | 1.3 (0.7) |
| B           | 7.4 (2.3)   | 14.9 (8.2)  | 18.0 (14.3) | 22.1 (12.4) |

TABLE II: Plan times (seconds) using SEMs for objects to bin tasks (A, B) with an increasing number of skills.

Table III shows the plan times for SEMs with increasing number of skills. In all cases the planner is able to find plans in less than half a minute.

Training on Planner vs. Random Data. To evaluate the benefits of using planning data for the iterative training of SEMs, we compare the test-task success rate between our approach and one that generates data by executing random skill sequences. See results in Figure 5. Training on planning data achieves higher success rates faster than training on random data, which illustrates the value of using an exploration strategy informed by planning.

Real-world Results. We implemented our task domain in the real world and used the learned SEMs to plan for the test task B. Three sets of planning experiments were performed, one with only Pick and Place, one with the addition of Tray Slide, and one with the addition of Tray Sweep. We did not implement Bin Tilt in the real world. Each set of experiments consists of 10 planning trials with different initial block configurations. See Table III. These results are similar to the ones shown in the task A test curves in Figure 5. The differences are due to the small changes in real-world object locations and controller implementations. While we did not fine-tune SEMs on real-world data, this is possible and may improve real-world performance.

V. CONCLUSION

We propose an approach of using search-based task planning with learned skill effect models for lifelong robotic manipulation. Our approach relaxes prior works’ assumptions on skill and task representations, which enables the planner to plan with new skills and tasks over time. Learning skill effect models improves planning speed, while the proposed iterative training scheme efficiently collects relevant data for learning. In future work, we will scale our method to larger number of skills and parameters by utilizing partial expansions to speed up planning. We will also explore probabilistic domains by using contingency planning and planning with uncertainty.

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REFERENCES

[1] S. Thrun and T. M. Mitchell, “Lifelong robot learning,” Robotics and autonomous systems, vol. 15, no. 1-2, pp. 25–46, 1995.
[2] A. Sharma, S. Gu, S. Levine, V. Kumar, and K. Hausman, “Dynamics-aware unsupervised discovery of skills,” International Conference on Learning Representations (ICLR), 2019.
[3] K. Lu, A. Grover, P. Abbeel, and I. Mordatch, “Reset-free life-long learning with skill-space planning,” International Conference on Learning Representations (ICLR), 2021.
[4] K. Xie, H. Bhardwaj, D. Hafner, A. Garg, and F. Shkurtt, “Skill transfer via partially amortized hierarchical planning,” International Conference on Learning Representations (ICLR), 2021.
[5] T. Li, R. Calandra, D. Pathak, Y. Tian, F. Meier, and A. Rai, “Planning in learned latent action spaces for generalizable legged locomotion,” IEEE Robotics and Automation Letters, vol. 6, no. 2, pp. 2682–2689, 2021.
[6] S. Nasiriany, V. H. Pong, S. Lin, and S. Levine, “Planning with goal-conditioned policies,” Advances in Neural Information Processing Systems, 2019.
[7] A. Mandlekar, F. Ramos, B. Boots, S. Savarese, L. Fei-Fei, A. Garg, and D. Fox, “Iris: Implicit reinforcement without interaction at scale for learning control from offline robot manipulation data,” in 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020, pp. 4414–4420.
[8] A. Conkey and T. Hermans, “Planning under uncertainty to goal distributions,” arXiv preprint arXiv:2111.04782, 2020.
[9] S. Nasiriany, V. H. Pong, A. Nair, A. Khazatsky, G. Berseth, and S. Levine, “Disco rl: Distribution-conditioned reinforcement learning for general-purpose policies,” International Conference on Robotics and Automation (ICRA), 2021.
[10] A. Srivivas, A. Jabri, P. Abbeel, S. Levine, and C. Finn, “Universal planning networks: Learning generalizable representations for visual motor control,” in International Conference on Machine Learning, PMLR, 2018, pp. 4732–4741.
[11] B. Ichter, P. Sermanet, and C. Lynch, “Broadly-exploring, local-policy trees for long-horizon task planning,” arXiv preprint arXiv:2010.06491, 2020.
[12] G. Konidaris, L. P. Kaelbling, and T. Lozano-Perez, “From skills to symbols: Learning symbolic representations for abstract high-level planning,” Journal of Artificial Intelligence Research, vol. 61, pp. 215–289, 2018.
[13] A. Simeonov, Y. Du, B. Kim, F. R. Hogan, J. Tenenbaum, P. Agrawal, and A. Rodriguez, “A long horizon planning framework for manipulating rigid pointcloud objects,” Conference on Robot Learning (CoRL), 2020.
[14] Z. Pan and K. Hauser, “Decision making in joint push-grasp action space for large-scale object sorting,” International Conference on Robotics and Automation (ICRA), 2020.
[15] D. Xu, A. Mandlekar, R. Martín-Martín, Y. Zhu, S. Savarese, and L. Fei-Fei, “Deep affordance foresight: Planning through what can be done in the future,” arXiv preprint arXiv:2011.08424, 2020.
[16] W. Masson, P. Ranchod, and G. Konidaris, “Reinforcement learning with parameterized actions,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 30, no. 1, 2016.
[17] M. Hausknecht and P. Stone, “Deep reinforcement learning in parameterized action space,” International Conference on Learning Representations (ICLR), 2015.
[18] J. Xiong, Q. Wang, Z. Yang, P. Sun, L. Han, Y. Zheng, H. Fu, T. Zhang, J. Liu, and H. Liu, “Parametrized deep q-networks learning: Reinforcement learning with discrete-continuous hybrid action space,” arXiv preprint arXiv:1810.06394, 2018.
[19] S.-K. Kim and M. Likhachev, “Parts assembly planning under uncertainty with simulation-aided physical reasoning,” in 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2017, pp. 4074–4081.
[20] H. Song, J. A. Haustein, W. Yuan, K. Hang, M. Y. Wang, D. Kragic, and J. A. Stork, “Multi-object rearrangement with monte carlo tree search: A case study on planar nonprehensile sorting,” International Conference on Intelligent Robots and Systems (IROS), 2019.
[21] S.-K. Kim, O. Salzman, and M. Likhachev, “Pomdp: Search-based belief space planning using multiple heuristics,” in Proceedings of the International Conference on Automated Planning and Scheduling, vol. 29, 2019, pp. 734–744.
[22] A. Bagaria, J. Crowley, J. W. N. Lim, and G. Konidaris, “Skill discovery for exploration and planning using deep skill graphs,” 2020.
[23] J. Buzké, K. Sapkota, K. Prasad, B. MacAllister, and M. Likhachev, “Skill lattice with controllers: Augmenting lattice-based path planning with controller-based motion primitives,” in 2014 IEEE/RJS International Conference on Intelligent Robots and Systems. IEEE, 2014, pp. 258–265.
[24] L. P. Kaelbling and T. Lozano-Pérez, “Hierarchical task and motion planning in the now,” in 2011 IEEE International Conference on Robotics and Automation. IEEE, 2011, pp. 1470–1477.
[25] ——, “Integrated task and motion planning in belief space,” The International Journal of Robotics Research, vol. 32, no. 9-10, pp. 1194–1227, 2013.
[26] M. Eppe, P. D. Nguyen, and S. Wermter, “From semantics to execution: Integrating action planning with reinforcement learning for robotic causal problem-solving,” Frontiers in Robotics and AI, vol. 6, p. 123, 2019.
[27] E. Ugr and J. Piatier, “Bottom-up learning of object categories, action effects and logical rules: From continuous manipulative exploration to symbolic planning,” in 2015 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2015, pp. 2627–2633.
[28] B. Ames, A. Thackston, and G. Konidaris, “Learning symbolic representations for planning with parameterized skills,” in 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2018, pp. 526–533.
[29] A. Suárez-Hernández, T. Gaugry, J. Segovia-Aguas, A. Bernardin, C. Torras, M. Marchal, and G. Alenyà, “Leveraging multiple environments for learning and decision making: A dismantling use case,” IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020.
[30] Z. Wang, C. R. Garrett, L. P. Kaelbling, and T. Lozano-Pérez, “Learning compositional models of robot skills for task and motion planning,” The International Journal of Robotics Research, vol. 40, no. 6-7, pp. 866–894, 2021.
[31] C. R. Garrett, T. Lozano-Pérez, and L. P. Kaelbling, “Pdslstream: Integrating symbolic planners and blackbox samplers via optimistic adaptive planning,” in Proceedings of the International Conference on Automated Planning and Scheduling, vol. 30, 2020, pp. 440–448.
[32] P. W. Battaglia, R. Pascanu, M. Lai, D. Rezende, and K. Kavukcuoglu, “Interaction networks for learning about objects, relations and physics,” Advances in Neural Information Processing Systems, 2016.
[33] M. Janner, S. Levine, W. T. Freeman, J. B. Tenenbaum, C. Finn, and J. Wu, “Reasoning about physical interactions with object-oriented prediction and planning,” International Conference on Learning Representations (ICLR), 2019.
[34] R. Kartmann, F. Paus, M. Grotz, and T. Asfour, “Extraction of physically-plausible support relations to predict and validate manipulation action effects,” IEEE Robotics and Automation Letters, vol. 3, no. 4, pp. 3991–3998, 2018.
[35] A. E. Tekden, A. Erdem, E. Erdem, T. Asfour, and E. Ugr, “Object and relation centric representations for push effect prediction,” arXiv preprint arXiv:2102.02100, 2021.
[36] M. Fey and J. E. Lenssen, “Fast graph representation learning with PyTorch Geometric,” in ICLR Workshop on Representation Learning on Graphs and Manifolds, 2019.
[37] M. Y. Seker, A. E. Tekden, and E. Ugr, “Deep effect trajectory prediction in robot manipulation,” Robotics and Autonomous Systems, vol. 119, pp. 173–184, 2019.
[38] N. Naderian, G. Louda-Graham, H. J. Braviner, A. L. Caterini, J. C. Cresswell, T. L. L., and A. Garg, “C-learning: Horizon-aware cumulative accessibility estimation,” International Conference on Learning Representations (ICLR), 2021.
[39] M. Janner, I. Mordatch, and S. Levine, “Gamma-models: Generative temporal difference learning for infinite-horizon prediction,” Advances in Neural Information Processing Systems, 2020.
[40] N. O. Lambert, A. Wilcox, H. Zhang, K. S. Pister, and R. Calandra, “Learning accurate long-term dynamics for model-based reinforcement learning,” arXiv preprint arXiv:2012.09156, 2020.
[41] Nvidia. (2020) Isaac sim. [Online]. Available: https://developer.nvidia.com/isaac-gym
[42] S. M. LaValle, Planning algorithms. Cambridge university press, 2006.
[43] A. Hinrichs, D. Krieg, R. J. Kunsch, and D. Rudolf, “Expected dispersion of uniformly distributed points,” Journal of Complexity, vol. 61, p. 101483, 2020.
## APPENDIX I
### RELATED WORKS

Table IV compares the discussed related works and our proposed approach. We include this table to illustrate the subtle but important similarities and differences among prior approaches, which may be overlooked when they are compared at a more general level. This is not an exhaustive list of all works in relevant areas. See below for the list of acronyms of each column. While we list the skill policy at a more general level. This is not an exhaustive list of approaches, which may be overlooked when they are compared at a more general level. This is not an exhaustive list of approaches, which may be overlooked when they are compared at a more general level. This is not an exhaustive list of approaches, which may be overlooked when they are compared at a more general level. This is not an exhaustive list of approaches, which may be overlooked when they are compared at a more general level.

| Policy: MB - Model-Based Optimization, MF - Model-Free RL, MP - Motion Primitives, HC - Hardcoded Controllers, IL - Learned via Imitation Learning | Preconditions (PC): H - Hardcoded, L - Learned | Effects: H - Hardcoded, Sim - Simulator, L - Learned | Parameters: H - Hardcoded, L - Learned (e.g. training a CVAE parameter sampler), SG - Subgoal, N-SG - Not Subgoals |
| --- | --- | --- | --- |
| Planning State (PS): S - State (e.g. low-dimensional object features), V - Visual (e.g. images, point clouds), LE - Latent Embeddings (usually learned to encode high-dimensional visual observations), Sym - Symbols | Init Plan (if the planner uses an initial plan, where does it come from?): L - Learned (e.g. from experience or predefined plan skeleton), H - Hardcoded (e.g. a plan skeleton of a skill sequence, linear interpolation of subgoals, or randomly sampled subgoals) | Heuristics (e.g. task value functions or shaped rewards/costs that guide planning towards a goal): H - Hardcoded, L - Learned (could be from experience, analytical models, or demonstrations) |

### APPENDIX II
#### ADDITIONAL EXPERIMENTAL DETAILS

## A. SEM Implementation

The GNN model contains four learnable multilayer perceptron (MLP) modules. The first is a node feature embedding module, with two layers of sizes $[32, 32]$. The second is a message embedding module that passes messages among nodes. It has three layers of sizes $[128, 128, 128]$. The third is a node-level prediction module, with two layers of sizes $[64, S + 32]$, where $S$ is the dimension of per-object features, and the extra 32 is used to produce graph-level predictions. The fourth is a graph-level prediction module, which takes as input the sum of the last 32 dimensions of node-level predictions and passes it through an MLP with sizes $[32, 1]$ to predict skill execution costs.

The loss weight for terminal state prediction is $\lambda_s = 100$, and the weight for cost prediction is $\lambda_c = 1$. All nonlinearities are ReLU. The network is trained with the Adam optimizer with a batchsize of 128, initial learning rate of 0.01, and for 300 epochs on every training run.

Each input object feature contains the position of the block, its color, and its index. Index is needed for SEMs to identify which block is being grasped for Pick-Place. Color and indices are encoded with an offset positional encoding. For example, for the $i$th color or index, its encoding is a two-dimensional feature vector $[i, i+1]$. We found in practice that this simple approach allowed our network to capture indices well and also allowed scaling to different number of objects and colors, which cannot be done with one-hot encoding.

## B. Iterative Training

Instead of collecting all the data from the planner for training the SEM models, we use heuristics to sample the more relevant data. First, we bias data collection towards longer paths in the planning tree since these paths are more likely to be closer to the relevant task. Second, we also bias data collection towards newly added skills. Since in the beginning we would not have sufficient data for the newly added skill, this ensures that we get sufficient data for such new skills. Algorithm 1 lists the pseudo-code for the data-collection procedure including the heuristics used to sample paths from the planner.

### Algorithm 1 SEM iterative training pseudocode.

#### Input:
- Set of skills $s$, set of training tasks $\tau_s$.

#### for all new skills $o$ do
  - Sample $M_0$ initial states from $x_0 \sim p(x_0)$.
  - Sample $P_0$ parameters $\theta$ for each initial state that satisfies $\beta_0(x_0, \theta)$.
  - Simulate $\pi_o$ with all $M_0 \times P_0$ (state, parameter) tuples.

#### end for

#### for all skills $o$ do
  - Train on $D_o$ for $E$ epochs the skill’s SEM from scratch or fine-tune previous model if it exists.

#### end for

#### for all training tasks $\tau$ do
  - Sample $M_p$ initial states from $x_0 \sim p(x_0)$.

#### for all sampled initial state $x_0$ do
  - $G \leftarrow$ get planning graph by running WA* on $\tau$ with max search depth $N_d$, max node expansions $N_e$, and timeout $T_p$.
  - Sample $N_i$ nodes in $G$’s open list.
  - For each of the $N_i$ nodes, trace their optimal path found so far $P$ from $x_0$.
  - Give each of the $N_i$ paths a weight $w = n_o + 10n_s$, where $n_o$ is the number of old skills in the path, $n_s$ the number of new skills.
  - Sample without replacement $N_s$ paths from all $N_i$ paths with their normalized weights as likelihoods.
  - Simulate each $N_s$ path.
  - Add skill transitions to the corresponding dataset $D_o$ while ignoring duplicates (e.g. some paths may share identical initial segments).

#### end for

#### end for
APPENDIX III

WEIGHTED A* PLANNER

Weight A* (WA*) is a best-first graph search algorithm that expands nodes in the order of lowest $g(x) + \epsilon h(x)$, where $g(x)$ is the total cost of the current optimal path from the initial node to $x$, and $h(x)$ is a heuristic function. The hyperparameter $\epsilon$ is called the inflation factor and is usually greater than or equal to 1. If it is set to 1, then the search is no different from A*. The higher the $\epsilon$ above 1, the greedier the search becomes at following the heuristic.

A. Hyperparameters.

For all blocks in bin tasks (tasks A and C) with just the Pick-Place skill we use a high value of $\epsilon = 20$ since there are not many ways to achieve the task. With the addition of more skills i.e, Tray-Slide, Tray-Sweep and Bin-Tilt we set $\epsilon = 2$. We found that this value to be sufficient to choose optimal plans. Additionally we also set the maximum search depth for both tasks A and C to be 8, since the longest plan for these tasks should be of length 8. For the colored blocks in bin tasks (tasks B and D), we used $\epsilon = 2$ and a max search depth of 5. Additionally, we sample a larger number of parameters for Pick-Place skill as compared to the other skills. This is because the Pick-Place skill affects each block separately and thus to find optimal plans we need to sample sufficient parameters for each block. This necessitates a larger number of parameters for this skill. For Pick-Place skill we sample 24 parameters while for all other skills we sample [4, 6] parameters.

B. Guarantees on the Constructed Graph

WA* guarantees completeness and bounded suboptimality on a given graph. Here we show that under smoothness assumptions, the graph constructed with our parameter sampling approach is suitable for search-based planning. Theorem 1 is about completeness — the distance between the reached goal state by any solution path and the closest last state of a path on the graph is bounded. Theorem 2 is about solution quality — for any solution path with a certain cost, the graph will contain a solution path with a bounded cost difference.

Definition 1: The dispersion [42] of a finite set $A$ of samples in a metric space $(X, \rho)$ is defined as

$$\delta(A) = \sup_{x \in X} \min_{p \in A} \rho(x, p)$$

Intuitively, it is the radius of the largest empty ball that can be drawn around any point in $X$ without intersecting any point in $A$.

In the following discussion, we assume all preconditions and the goal set are open sets.

Theorem 1: Let the skill transition function $f_\theta : \mathcal{X} \times \Theta \to \mathcal{X}$ be Lipschitz continuous with a maximum Lipschitz constant $K$ and $\eta = (x_0, o_0, \theta_0, x_1, \cdots, x_N)$ be a solution to the planning problem. Then, $\exists$ a path $\eta' = (x_0, o_0, \theta_0', x_1', \cdots, x_N')$ on the constructed search graph such
that \( |x_N - x'_N| \leq 2\delta \kappa_N = 2\delta \frac{K(K_N - 1)}{K - 1} \) if the dispersion \( \delta \) of parameter samples is small enough.

**Proof** Consider an instance of the randomly generated search tree \( \mathcal{T} \) of depth more than \( N \). We pick a small enough \( \delta \) such that \( \mathcal{T} \) contains at least one path \( \eta' \) that has the same sequence of skills as \( \eta \). However, due to random sampling, the sampled parameters may not be the same. For every \( \theta_i \) at a state, \( \exists \) a parameter sample \( \theta'_i \) such that

\[
|\theta_i - \theta'_i| \leq 2\delta \tag{2}
\]

Using the definition of Lipschitz continuity and the triangle inequality, we have

\[
|f_o(x_i, \theta_i) - f_o(x'_i, \theta'_i)| \leq K |x_i - x'_i| + K |\theta_i - \theta'_i| \tag{3}
\]

In particular,

\[
|\eta| = |f_o(x_0, \theta_0)| = |f_o(x_0, \theta_0)| \leq K |\theta_0 - \theta'_0| \tag{4}
\]

and

\[
|x_N - x'_N| = |f_N(x_{N-1}, \theta_{N-1}) - f_{N-1}(x'_{N-1}, \theta'_{N-1})| 
\leq K |\theta_{N-1} - \theta'_{N-1}| + K |x_{N-1} - x'_{N-1}| 
\leq \sum_{i=0}^{N-1} K^{N-i} |\theta_i - \theta'_i| \leq \Delta \theta \sum_{i=0}^{N-1} K^{N-i} 
\leq 2\kappa_N \delta \text{ (Using inequality 2)} \tag{5}
\]

where \( \kappa_N = \frac{K(K_N - 1)}{K - 1} \).

To ensure that we have a path \( \eta' \) on the graph that terminates \( \epsilon \)-close to the terminal state of \( \eta \), we require that

\[
|x_N - x'_N| \leq 2\kappa_N \delta \leq \epsilon.
\]

To guarantee that \( \eta' \) will also be a solution, we additionally need to ensure that \( \epsilon < r \), where \( r \) is the radius of the largest ball we can draw around \( x_N \) in \( G \) (goal set). This is always possible if \( G \) is an open set.

**Theorem 2**: Let the cost function be Lipschitz continuous with a maximum Lipschitz constant of \( L \). Let \( \eta \) be a solution path of cost \( c(\eta) \) and \( r > 0 \), then for a sufficiently small dispersion \( \delta \), \( \exists \) a solution path \( \eta' \) on the constructed search graph with cost \( c(\eta') \leq c(\eta) + \delta NL[1 + \sum_{i=1}^{N} \kappa_i] \).

**Proof** Choose \( \delta \) such that \( 2\kappa_N \delta < r \) and \( \exists \) a path \( \eta' \) on the graph with the same sequence of skills as \( \eta \). Then, from the previous theorem, \( \exists \) a path \( \eta' \) on the graph such that

\[
|x_N - x'_N| \leq 2\kappa_N \delta < r.
\]

By the definition of \( r \), \( x'_N \in G \) and hence \( \eta' \) is a solution path. Next, we bound the cost of this path.

The cost of a path \( c(\eta) = \sum_{i=0}^{N-1} c_o(x_i, \theta_i) \). For convenience, here we write the cost function as skill-specific cost functions that vary w.r.t the initial state and skill parameters, instead of step-wise costs on state and low-level controls. Let \( c_i = c_o(x_i, \theta_i) \) and \( c'_i = c_o(x'_i, \theta'_i) \). Then, using the definition of Lipschitz continuity, we have

\[
|c_i - c'_i| \leq L(|x_i - x'_i| + |\theta_i - \theta'_i|) \leq L[2\kappa_i \delta + \delta] \tag{6}
\]

Hence,

\[
|c(\eta) - c(\eta')| = \sum_{i=0}^{N-1} |c_i - c'_i| \leq \sum_{i=0}^{N-1} |c_i - c'_i| \leq \delta NL[1 + 2 \sum_{i=1}^{N} \kappa_i] \tag{7}
\]

The dispersion of a set of sampled parameters depends on the sampling strategy used. For uniformly random sampling, we can only estimate it probabilistically. [43] prove bounds on the expected dispersion of a set of i.i.d points which tightens with more points, i.e., we are more confident of a lower expected dispersion with a larger number \( (B_n) \) of parameter samples.

**Theorem 2** provides two additional observations. First, skills with dynamics that don’t change fast, i.e., their Lipschitz constant are small, can be approximated with a sparse graph (less parameter sampling). Second, longer horizon tasks require more parameter sampling to guarantee good quality plans.

**Appendix IV**

**Task Domain Skill Details**

All skill policies are implemented by end-effector waypoint following, where trajectories between waypoints are computed via min-jerk interpolation, and low-level control is achieved by end-effector impedance control. A subset of waypoints for each skill is indirectly determined by the skill parameters. For example, for *Pick-Place*, the object index parameter determines which object to pick. Together with the current state, they are used to compute the waypoints associated with the picking motion.

**A. Pick-Place**

This skill picks up a chosen block and places it at a target location.

**Parameter**. A 4-vector consisting of an index corresponding to which block to pick and a 3D position for placement

**Parameter Sampling**. For which block to pick, we sample the index of a block on the table with collision-free grasps. For the placement position, we first sample which general placement region to use, table, bin, or tray, with probabilities \([0.2, 0.5, 0.4]\). Then, we randomly sample a position on the surface of reach placement region. The bin placement region is the half of the bin that is closer to the robot.

**Precondition**. The precondition function check returns satisfied if the placement position is collision free. It assumes the pick grasp is collision free and the placement location is reachable.
B. Tray Slide

This skill picks up the tray, brings it over the bin, rotates the tray to let blocks fall to the bin, then brings the tray back to its original pose.

Parameter. One value that determines where along the bin does the slide rotation motion. This allows dropping blocks over the close or far side of the bin.

Parameter Sampling. This is done via uniform sampling over a range of the length of the bin.

Precondition. The precondition is satisfied when there is at least one block on the tray.

C. Tray Sweep

This skill picks up the tray, rotates it 90°, brings it down toward the table, sweeps downstream objects into the bin, and returns the tray to its original pose.

Parameter. One value that determines where along the table the sweep motion begins.

Parameter Sampling. This is done via uniform sampling over a range of the width of the table.

Precondition. The precondition is satisfied when there is at least one block that will be swept by the skill and the starting location for the tray is collision-free.

D. Bin Tilt

This skill lifts one side of the bin by a desired angle, allowing objects to slip down toward the far side of the bin, before return the bin to the original configuration.

Parameter. One value that determines the angle of the tilt. With a shallow angle it is possible for some blocks to remain in the near side of the bin, or not move at all due to friction.

Parameter Sampling. This is done via uniform sampling in the range of [5°, 20°].

Precondition. The precondition is satisfied if there is at least one block in the bin.

APPENDIX V
ADDITIONAL RESULTS

A. Qualitative Planning Results

In this section we show qualitative results for our train and test tasks.

Figure 7 shows the qualitative results for the train task A with an increasing number of skills. In the above result we see that with only Pick-Place skill the planner finds a plan which needs to pick all blocks and place them in the bin. However, after adding the Tray-Slide skill (row 2) the planner finds a longer plan but with a lower cost 3. This lower cost is a result of being able to use the Tray-Slide skill to transport multiple blocks to the bin directly. Additionally, with the addition of Tray-Sweep skill we can perform the task with only 1 skill which significantly reduces the overall plan cost.

Similarly, Figure 8 and 9 show the qualitative results for both test tasks B and D respectively. Similar to before, with an increasing number of skills the overall plan and its associated cost changes significantly. For task B we observe that adding Tray-Sweep improves the performance only in some scenarios as shown in Figure 8 (rows 3 and 4). In another instance the robot can also perform Pick-Place to align the red blocks to sweep them into the bin (row 4).

Similarly, for test-task D we observe that using Pick-Place alone is not sufficient (as observed in Figure 8). However, adding the Tray-Slide skill makes the task feasible (top row). However, in contrast to tasks A and B, adding Tray-Sweep does not affect task execution since the robot cannot move the blocks to the far bin with this skill. We observe this in Figure 10 where the top two rows use the same set of skills. However, adding the Bin-Tilt skill allows the planner to use the Tray-Sweep skill, as shown in Figure 10 (row 3, second row from bottom).

B. Video Results Link

Video results for most tasks and settings can be found at the project page https://sites.google.com/view/sem-for-lifelong-manipulation

C. Failure Modes

Here we discuss examples of planning and execution failures due to insufficiently trained SEMs.

First, if SEM predictions are not sufficiently accurate, then the predicted states would do not satisfy the preconditions of necessary skills, and the planner will not find a plan. For instance, when Tray-Sweep is trained with less data, the learned SEM predictions can incorrectly predict that the blocks move to the edge of the table instead of being moved to the bin. Thus, the planner considers this to be a non-optimal action and instead resorts to using the remaining skills (Pick-Place and Tray Slide), which leads to a sub-optimal plan if one is found. Another scenario where incorrect SEM predictions lead to failure is when Tray-Slide is added. Given the previously used Pick-Place was mostly trained on moving blocks from the table to the bin (because of the train-task bias), the existing Pick-Place SEM may inaccurately predict that the skill is unable to move blocks to the tray. This results in the failure for Tray-Slide preconditions which finally results in either the planner timing out or finding sub-optimal plans.

Second, there are also scenarios where the planner is able to find a plan despite inaccurate SEM predictions, but the plan does not work in execution. One common instance is with Pick-Place, where early on with insufficient data the SEM often inaccurately predicts that the skill will move blocks to the bin, despite the target placement location being on the edge of the table. Given the incorrect prediction by the SEM, the planner mistakenly believes that the block has been placed in the bin, and it may find a plan but its execution does not lead to success.
Fig. 7: Qualitative results: Plans found for Task-A with increasing number of skills. Left most columns are the skills executed at t=0, with skills being executed as we move towards right. Each row also lists the different skills used to plan.

Fig. 8: Qualitative results: Plans found for Task-B with increasing number of skills. Left most columns are the skills executed at t=0, with skills being executed as we move towards right. Each row also lists the different skills used to plan.

D. Latent Space SEMs

In our main results we trained SEMs directly using the state space for each skill separately. We also evaluate how SEMs perform when trained with a shared latent space.

Our latent space SEMs implementation uses an encoder-decoder architecture as visualized in Figure 6. The encoder model $f_{encoder}$ uses the state as an input and outputs a latent state. The dynamics model $f_{dynamics}$ then uses this latent state...
along with the skill parameters $\theta_t$ to outputs the next latent state denoted as $z_{t+1}^j$ in Figure 6. Along with the next latent state the skill-specific dynamics model also outputs the skill execution execution cost. We note that the dynamics model is specific to each skill. The decoder is used to decode the latent states to the original state space. Separate latent-space SEMs are learned for each skill.

Figure 6 only visualizes the encoder-decoder acting on state $x_t^j$ (state at time $t$) and $z_{t+1}^j$ (latent state at $t + 1$) respectively. However, during training the encoder and decoder model are used to reconstruct all states i.e. both the current state and the next state. In our implementation, we use a latent space of size 32. Additionally all our models i.e., the encoder, decoder and dynamics model for all skills are implemented using the same GNN implementation as discussed in Appendix II-A.

Figure 10 plots the costs when using the latent-space models on the train-test task pair of $A$ and $B$, which has comparable performance to state-space models (Figure 3 left). This is a promising result since such a latent space could allow us to plan using image inputs; however, we leave image-space planning for future work.

E. Random Planner

To demonstrate the need for a guided planner to efficiently search (skill, parameter) tuples, we performed an experiment to compare planning performance with a random planner. The random planner randomly picks the next node to expand in the search graph, instead of in the order of their $f$-value (optimal cost to come + weighted heuristic). We evaluated the random planner on the following 4 planning problems:

1) Task A (all blocks to bin) w/ Pick-Place, Tray Slide
2) Task A (all blocks to bin) w/ Pick-Place, Tray Slide, and Tray Sweep
3) Task B (red blocks to bin) w/ Pick-Place, Tray Slide

![Fig. 9: Qualitative results: Plans found for Task-D with increasing number of skills. Left most columns are the skills executed at $t=0$, with skills being executed as we move towards right. Each row also lists the different skills used to plan.](image)

![Fig. 10: Execution costs for tasks $A$ and $B$ using SEMs in latent-space.](image)
TABLE V: Planning performance comparison with Random Planner. Values are averaged across 10 trials in which the random planner found a plan within 1000s, and stds are in the parenthesis

| Problem | Cost (Ours) | Cost (Random) | Planning Time (Ours) | Planning Time (Random) |
|---------|-------------|---------------|----------------------|------------------------|
| 1       | 9.1 (0.18)  | 11.63 (0.19)  | 20.2 (7.9)           | 641.90 (375.93)        |
| 2       | 1.5 (0.0)   | 2.34 (1.03)   | 0.6 (0.5)            | 5.69 (11.51)           |
| 3       | 4.3 (0.21)  | 6.67 (0.62)   | 14.9 (8.2)           | 432.22 (345.76)        |
| 4       | 3.89 (0.8)  | 5.72 (1.06)   | 18.0 (14.3)          | 311.78 (337.30)        |

4) Task B (red blocks to bin) w/ Pick-Place, Tray Slide, and Tray Sweep

See results in Table VI. In all cases the random planner took an order of magnitude longer to plan on average than a guided planner. The achieved costs are also all higher than the costs of the plans found using the guided planner. The complexity of the planning problem is caused by 1) we do not assume knowledge of a plan skeleton or the exact number of skills needed to complete the task and 2) the high branching factor (about 30-40 depending on the particular scenario) caused by sampling skill parameters.

F. Learned Precondition Model

Here we perform a small experiment to show it is possible for our method to support learned skill precondition models. These learned skill precondition models take as input a (skill, parameter) tuple and output a binary output which signifies if the given skill can be executed at the current state. We use a GNN architecture as our precondition model. To collect data for training skill preconditions we initialize the environment to a random configuration by first selecting the block to place and then selecting a place location for it. This block can be placed on the table, on the bin or on the tray. We then execute the skill with some randomly sampled parameter to note if the skill can be successfully executed in this scenario. Using this scheme we collect around 24000 data samples for the Pick-Place skill and 8000 data samples for the Tray-Slide skill. We use this to train our precondition model. No task-specific data is used to train these precondition models.

This learned precondition model is combined with the learned SEMs to plan on test task B (red blocks to bin). We execute these learned models for 20 different scenarios with 3 seeds. In addition to the average cost, we also report the average success rate since in some scenarios errors in the learned precondition models may affect task success.

See results in Table VII. The learned precondition models also allow the planner to have a high test-task success ratio, which indicates the effectiveness of the learned precondition models and learned SEMs. The precondition models were only trained with random data and their accuracy can be improved by additionally utilizing data incurred from planning for train-tasks.

G. Generalization to Object Features

In the experiment domain the state space includes the 3D position of each block, its color, and its index. Here we run two small experiments to investigate how well the learned SEMs would generalize to variations in object features not in the state space that have varying impacts on skill effects.

Generalization to object sizes: In the first experiment, we show that trained SEMs can generalize to objects of different sizes. We show this using Pick-Place and Tray Slide. Both skills have been trained on square objects of size 4 cm and we show that these models do generalize to objects of size 2 cm and 3 cm. We see similar quantitative performance on these different sized objects. See Table VII for the average costs for different sized blocks. The trained SEMs do generalize well to objects of different sizes.

| Skill                  | 4 cm | 3 cm | 2 cm |
|------------------------|------|------|------|
| Pick-Place             | 6.41 | 6.66 | 6.47 |
| Pick-Place + Tray Slide| 4.1  | 4.04 | 4.12 |

TABLE VII: Average cost for Test-Task B showing generalization of SEMs to different object sizes

Generalization to object counts: In the second experiment we show that since object color is a property included in the state representation our learned SEMs can also generalize to different numbers of colored objects. During training we always use 3 red colored blocks and 3 green colored blocks. We evaluate these learned SEMs for Test-task B and on scenes with 1 red colored block and 5 green colored blocks as well as 2 red colored blocks and 4 green colored blocks. We initially use Pick-Place skill only and then incrementally add the Tray-Slide skill. See Table VIII which shows that the learned SEMs are able to generalize well to these different settings.

| Skill                        | Scene       | Cost |
|------------------------------|-------------|------|
| Pick-Place                   | 1 Red Block | 1.91 |
| Pick-Place                   | 2 Red Blocks| 4.33 |
| Pick-Place + Tray Slide      | 1 Red Block | 1.96 |
| Pick-Place + Tray Slide      | 2 Red Blocks| 3.20 |

TABLE VIII: Average cost for Test-Task B showing generalization of SEMs to different numbers of objects.

| Skill                  | Success Rate Mean (std) | Cost |
|------------------------|-------------------------|------|
| Pick-Place             | 0.96 (0.02)             | 6.44 |
| Pick-Place + Tray Slide| 0.90 (0.04)             | 4.35 |

TABLE VI: Planning results for using learned precondition models on Task B.