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BeBOP – Combining Reactive Planning and Bayesian Optimization to Solve Robotic Manipulation Tasks

Jonathan Styrud*‡, Matthias Mayr†, Erik Hellsten†, Volker Krueger† and Christian Smith‡

***Abstract*— Robotic systems for manipulation tasks are increasingly expected to be easy to configure for new tasks. While in the past, robot programs were often written statically and tuned manually, the current, faster transition times call for robust, modular and interpretable solutions that also allow a robotic system to learn how to perform a task. We propose the method Behavior-based Bayesian Optimization and Planning (*BeBOP*) that combines two approaches for generating behavior trees: we build the structure using a reactive planner and learn specific parameters with Bayesian optimization. The method is evaluated on a set of robotic manipulation benchmarks and is shown to outperform state-of-the-art reinforcement learning algorithms by being up to 46 times faster while simultaneously being less dependent on reward shaping. We also propose a modification to the uncertainty estimate for the random forest surrogate models that drastically improves the results.**

***Index Terms*— Behavior Trees, Bayesian Optimization, Task Planning, Robotic manipulation**

I. Introduction

Modern robots are capable of solving complex tasks in controlled environments with high reliability and precision. However, recent trends are towards smaller product batches and more frequent updates of robot programs. Meanwhile, the market share of collaborative robots is growing steadily, where shared workspaces create more unpredictable environments. As a result, it is becoming increasingly important to create robot programs/policies quickly without the need for advanced programming skills and for those programs to be reactive to changes in the environment. There are two main groups of methods to generate policies automatically, both with their own advantages and drawbacks. Firstly, automated planners [2] can be very efficient, but require that the planning domain is modelled sufficiently well. As an example, a planner can only avoid obstacles that are in the model. Planners also tend not to scale well to higher task complexity. The second group, colloquially known as Machine Learning (ML), typically builds a model by interacting with the environment and is thus not limited by preexisting knowledge. There are also cases where ML methods scale better than planners, as they can use a probabilistic instead of an exhaustive approach. However, the learning is often not very efficient and for smaller tasks, an automated planner can be many orders of magnitude faster. This hampers the use of ML-based methods as even state-of-the-art methods can take hours to days of interaction time to learn a task. As an example, *MAPLE* for the benchmarks in this paper takes several days on a normal workstation to run. Another considerable drawback is that many of the ML algorithms, often in the Reinforcement Learning (RL) subgroup, are designed to use neural networks that are known to lack the transparency and modularity of other architectures.

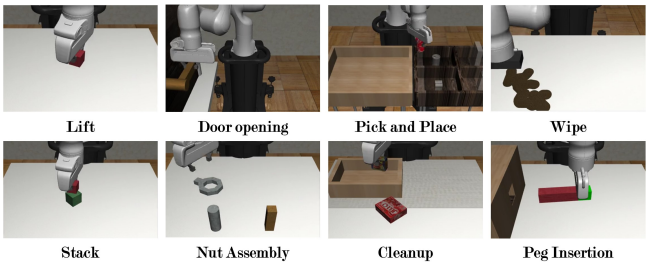

Fig. 1: The eight simulation environments with the Franka Emika Robot (Panda). They range from easy tasks like a lifting a cube to sequential multi-step tasks like picking up a peg and inserting it into a hole.

An increasingly popular alternative in robotics is to instead represent the policy with Behavior Trees (BTs) [3], [4]. The main advantages of BTs are explicit support for task hierarchy, action sequencing, reactivity and inherent modularity. They are also transparent and readable, which enables manual and automated analysis and validation [5] as well as manual editing. Those are strong advantages when compared to neural networks, especially in an industrial setting.

In this work we present Behavior-based Bayesian Optimization and Planning (*BeBOP*) that generates BTs by building a reactive tree structure using a planner and then subsequently learns the BT parameters with Bayesian Optimization (BO). With the tree structure as a prior, BO can then focus on tuning parameters that are difficult to plan and reason about. The method is evaluated in a simulation environment with eight different manipulation tasks.

It drastically outperforms the award-winning state-of-the-art RL algorithm *MAPLE* [1] in the number of simulation steps needed to learn to solve the tasks while using the same behavior primitives. By induction this also means that *BeBOP* is much more efficient than popular algorithms like *HIRO* [6] and *DAC* [7]. The speedup could even enable training on real robot systems instead of just simulation as a lot fewer evaluations are needed. Furthermore, it is also shown that our method is less dependent on reward shaping in the form of affordances compared to the benchmark.

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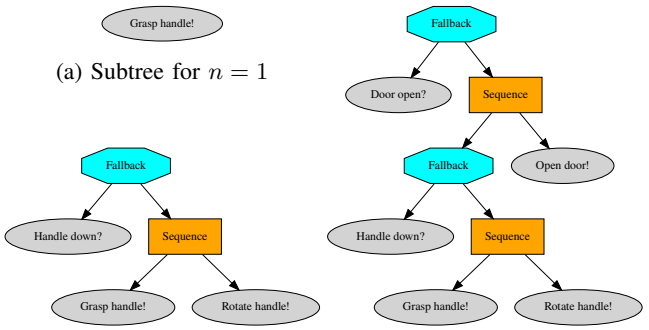
*ABB Robotics, Västerås, Sweden
†Lund University, Lund, Sweden
‡Division of Robotics, Perception and Learning, Royal Institute of Technology (KTH), Stockholm, Sweden



(a) Subtree for $n = 1$

(b) Subtree $n = 2$

(c) Full tree

Fig. 2: Different subtrees for a door opening scenario. In a cascaded learning setup, the method starts by learning how to grasp the handle (a) before the tree gets extended by the handle rotation (b) and finally the full tree is constructed (c).

Lastly, another advantage of the modular tree structure is that it also allows the task to be divided into subtasks and learned in sequence for even faster progress.

The main contributions of this paper are:

- A novel method, *BeBOP*, that combines reactive planning with efficient parameter tuning to yield state-of-the-art learning performance, while leading to an interpretable and robust policy.
- A new method to calculate the uncertainty of a random forest surrogate model within BO that outperforms the standard method on several tasks.
- A set of experiments verifying and validating our approach in comparison to the state-of-the-art RL method *MAPLE* [1], showing that *BeBOP* learns to solve the given tasks up to 46 times faster.

II. Background and Related Work

In this section we provide relevant background on behavior trees and Bayesian optimization and discuss related work.

A. Behavior Trees

Behavior Trees (BTs) were first used in the computer game industry, but have recently seen increased use in robotics [3], [4]. A BT is a directed tree where a tick signal propagates from the root node down to the leaves. The nodes are executed only when they receive the tick signal and return one of the states *Success*, *Failure* and *Running*. The non-leaf nodes are called *control flow nodes*. The flow nodes most commonly used are *Sequence*, which ticks children sequentially from left to right, returning once all succeed or one fails, and *Fallback* (or *Selector*) which also runs sequentially but returns when one succeeds or all fail. Leaves are called *execution nodes* or *behaviors* and are usually separated into the types *Action*("!") and *Condition*("?"). Conditions encode status checks and sensory readings, only returning *Success* or *Failure* while actions encode robot skills that can take more than one tick to complete and therefore can also return *Running*. Figure 2 shows three example BTs for a door opening scenario.

The main advantages of BTs are that they are readable and have inherent support for task hierarchy, action sequencing and reactivity. They are also inherently modular [4], in fact even optimally modular [8]. The *Running* return state grants the reactivity property because a running action can be preempted by higher priority ones. BTs have been shown to improve on other representations, such as finite state machines, especially in terms of modularity and reactivity [5], [9], [10].

B. Bayesian Optimization

In many practical optimization problems, there is no closed form expression available for the function to optimize. Instead, the user can only interact with the system by first selecting a configuration to evaluate and subsequently observing its performance. Often this black-box function is also expensive to evaluate; in the particular setting used in this paper, it amounts to running a simulation of a robot performing the specified task.

Bayesian optimization (BO) is a paradigm developed to efficiently optimize such problems, while limiting the number evaluations. It has recently shown great performance in a variety of applications, such as robotics [11]–[13], hyperparameter tuning [14]–[16], and material design [17]–[19].

We consider the problem of finding a global maximum of an unknown black-box objective function f: $\mathbf{s}^* \in \arg\max_{\mathbf{s}\in\mathbb{S}} f(\mathbf{s})$, over some pre-specified domain $\mathbb{S}$ in D dimensions. The variables defining $\mathbb{S}$ can be real, integer, ordinal and categorical [20]. We further assume that the evaluations of f are disturbed by observation noise and do not provide information on the function gradients.

BO is a sequential approach that iteratively selects new configurations to evaluate, trading off exploration and exploitation. It uses a surrogate model of the objective function and effectively learns the function as it gathers more data. The most common models are Gaussian Processes (GPs) [21] for their natural ability to quantify uncertainty on top of yielding accurate predictions and Random Forests (RFs) [22], [23] for their versatility and scalability to a higher number of samples. Which configuration to select next is chosen by maximizing an acquisition function that quantifies the exploration-exploitation trade-off. Common examples are the *expected improvement* or *upper confidence bound*. For a more thorough introduction to BO, see [24].

C. Related work

Various combinations of planning and RL have previously been proposed for other domains in [25]–[28]. In particular, [29] uses BTs as the underlying structure, and [30], [31] combine a planner with genetic programming. Using genetic programming to learn BTs has been done primarily for computer games [32], but there are also examples for robotic manipulation applications [29], [33], [34]. A more extensive analysis is given in [3]. The combination of a sequential planner and learning with BTs was also proposed in [12], [35] for a peg-insertion and a pushing task. In [36] it is shown

how priors defined by operators or based on experience can accelerate learning and increase the safety during learning. As an extension, [37] learns a GP model to generalize to task variations.

Regarding automated planners, we use an adaptation of the Planning Domain Definition Language (PDDL)-style planner from [38] that creates BTs by leveraging backchaining. We build on the later adaptations of the same planner from [29], [34], [39]. The main advantage of this planner is its simplicity, but there are other more advanced planners for BTs as well. Some examples are Linear Temporal Logic (LTL) [40], [41] and Hierarchical-Task-Network (HTN) planning [42], [43]. There are also other PDDL-style planners and we refer to Section 4.2 in [3] for a more exhaustive list.

We compare our method against RL with parameterized actions [44], [45] - specifically with *MAPLE* [1]. Although these are completely different algorithms from ours, the types of problems they solve are essentially the same.

III. Approach

The key assumption in this work is that if there exists a set of parameterized actions that a robot can execute, these actions were likely designed with an intended use and effect on the robots environment. It is then possible to create a plan by using the actions under the assumption that for some values of the action's parameters, the actions will succeed and work in the intended way. Utilizing this, our proposed method consists of using a planner to obtain the structure of the BT and then employing a BO algorithm in an RL framework to tune the parameters of the nodes of the BT. The complete code of the planner and all other algorithms are available online[1].

A. Planner

In this paper we use a PDDL planner adapted from [38] that was later extended in [29], [34], [39]. As input to the planner, all behaviors have a set of pre-conditions that must be fulfilled in order to execute the behavior successfully and a set of post-conditions that can be expected to be fulfilled when the behavior is done. A set of goal conditions defines the robot's task. Starting with goal conditions and proceeding backwards, the actions that complete the task or fulfill the necessary conditions for other actions are found iteratively and expanded until all conditions have been met. As an example, a place skill will have the pre-condition that the object is grasped and the post-condition that the object is at the place position. A complete list of conditions is available in the code repository[1].

In this work, we improve the planner from [39] with some additions. Mainly, we trim the resulting tree by *a)* removing any control nodes with only a single child and by *b)* removing any post-condition nodes that are placed directly before the corresponding action. The latter step assumes that all behaviors check post-conditions internally before executing. We further introduce the concept of composite subtrees where, after planning, certain leaves can be expanded into subtrees with multiple nodes or replaced by another behavior. This allows us to exploit the fact that, e.g., the behaviors *Reach* and *Open* together comprise a *Place* skill and that *Reach* can generalize different behaviors at planning time such as opening a door or moving a grasped object. Fig. 2 shows an example for the door scenario where *Open door* and *Rotate handle* are both generalized by the *Reach* behavior. For the other BTs we refer to the code repository[1].

[1]https://github.com/jstyrud/BeBOP

B. Optimization

In order to optimize a policy, we follow the policy-search formulation [46]–[48]. The goal is to find a policy $\pi, \mathbf{u} = \pi(\mathbf{x}|\boldsymbol{\theta})$ with policy parameters $\boldsymbol{\theta}$ such that we maximize the expected long-term reward when executing the policy for T time steps. Here, we use BO to tune the parameters. A given (planned) BT has a set of action nodes, such that each node can have zero or more parameters that can be learned for a given task. To construct a learning problem, we automatically examine a BT to obtain these adjustable parameters, their domains and dependencies.

We use a customized version of the BO implementation in *hypermapper* [20] as it supports a wide range of variable types and user priors for the optimum [49].

To provide a robust reward measure for the surrogate model and to prevent BO from overfitting to the training data, we evaluate each set of parameters in up to 20 episodes using *robotsuite's* domain randomization of the tasks with different seeds. We initially run each set of parameters for three episodes in different randomizations of the task simulation. After that, we estimate the variance after each episode and calculate the probability that this policy will outperform the current best policy. We then continue with more episodes as long as the probability is above 5 percent or until we have reached 20 episodes. We evaluate the parameter sets on the same random seeds for the training episodes to increase consistency of the evaluation results when training the surrogate model.

C. Improved Random Forest Surrogate

While GPs are the most common choice of surrogate models in BO, they assume a certain level of smoothness of the objective function, that is often not satisfied in the robotics tasks we consider. For example when inserting a peg into a hole, a millimeter change in offset in a movement primitive can result in a drastic difference in reward. Because of this, we instead use random forests which are more amenable to non-smooth objective functions. However, in contrast to GPs, RFs do not innately provide a variance estimate for its predictions, which is an essential building block in the BO selection process. Hutter et al. proposed the use of the empirical prediction variance across trees [50], but this suffers from that the uncertainty does not inherently grow further away from previously observed data. This, in turn, hampers exploration.

To improve the performance of the optimization, we propose two adjustments to the RF model. First, we use

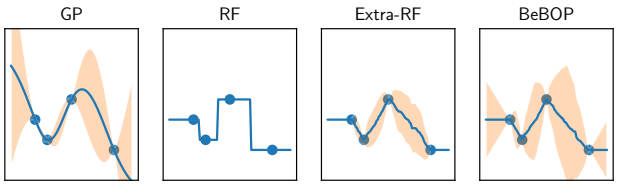


Fig. 3: The predicted mean and standard deviation on a toy example for 4 different models: Gaussian Processes (GP), Random Forests (RFs), Extremely randomized RFs and our proposed uncertainty measure with an additional linear standard deviation term.

extremely randomized trees which randomize among all optimal splits in each tree [51]. This makes the prediction surface much smoother, which makes for a richer predicted function surface. This was previously used by, for example, [20] and [52]. Secondly, we propose a new uncertainty metric, that extends the standard deviation estimate proposed by Hutter et al. by a term proportional to the distance to the closest previous observation. This incentivizes the optimization to continue exploring. To the best of our knowledge, this is the first paper to suggest such a modification in a BO setting. In Fig. 3, we show the impact of the modifications. As we will see in Section V, this significantly improves the results.

D. Combining Planning and Bayesian Optimization

To combine the planner with the BO algorithm, we first run the planner on each task to obtain the BT structure. The planner, however, leaves a number of parameters unsolved for each behavior, and during planning it assumes that there exists some set of parameters for which the behaviors will succeed. These parameters are then given as input to BO. For each parameter, the behaviors also specify an upper and lower bound and these limits should be grounded in the actual application.

Cascaded Learning: We also note that because of the hierarchical nature of the BTs that are output from the planner, the BTs can be divided into a number of subtrees that can be run sequentially with gradually larger subtrees, representing subtasks. For example, grasping would be a sub-task of moving an object. In this way, we can learn the smaller subtask first, using parameters from the solution as priors for the optimum to the next, larger subtree. This way we can potentially speed up the optimization as the learning time typically scales super-linearly with the number of parameters. We call this version of our method *cascaded BeBOP*. Starting with $n = 1$, to find subtree n we start with the first action node and traverse the tree left to right, depth first, counting the action nodes. Continue up to but not including the action node $n + 1$. The last node before the action node $n + 1$ will be the last node in the subtree. Action nodes without free parameters are omitted, as they do not increase the complexity of our optimization problem. All subtrees for smaller n will also be included in subtree n. Fig. 2 shows examples of the resulting subtrees for a door opening scenario. Note that the subtree for $n = 1$ consists of only one node and that the behaviors in the figure are only aliases during planning of more generic behaviors, as listed in Section IV-A. For every n-th subtree, we run the BO in batches of 50 iterations until no improvement is seen since the last batch. We then use the best solution found as priors and run BO on the subtree $n + 1$. Splitting learning tasks into subtrees has also been proposed in [53], but a) without an automated procedure to do this and b) while keeping the previously learned parameters fixed when combining trees. The advantage we get by *not* fixing the parameters of previous subtrees is that the optimal values might be different in the context of the complete tree.

IV. Experimental Setup

We benchmark our algorithm using *robosuite* [54] in the eight simulated robot manipulation scenarios shown in Fig. 1 that are used in *MAPLE* [1], the method that we compare against. One feature of *robosuite* is that it supports slight domain randomizations of the task environments to allow for the evaluation of the robustness of policies. In the *Door* scenario in the original benchmark the robot was incapable of grasping the door handle in all instances of domain randomization. Therefore we made a small change by allowing the gripper to rotate in the same way as in the other tasks. This change had no noticeable impact on the performance of *MAPLE* on the task.

In this paper, we refrained from performing additional validation of the resulting policies learned in simulation on real robot systems. It has been shown previously, including in the referred *MAPLE* paper which uses the same behaviors [1], that policies acting at this abstraction level are easily transferable from simulation [12], [29], [35]–[37], [53].

A. Behaviors

We use the same action primitives as *MAPLE* and only communicate with the simulation using the same action and observation vectors as the neural networks in the original benchmarks. We wrap the input and output vectors of the simulation with behaviors that can be used by a behavior tree. The five behaviors correspond to the five primitives used by *MAPLE* and call the corresponding behavior primitives when executing. The listed parameters are the ones that are learned.

- **Reach:** The robot moves to some position relative to an object or the origin of the coordinate frame. The offset (x, y, z) is specified by the behavior parameters.
- **Grasp:** The robot moves to some position relative to a graspable object and closes the gripper. The offset (x, y, z) and yaw angle are the behavior parameters.
- **Push:** The robot attempts to push an object towards an x, y position by moving to the opposing side of the object and pushing toward the goal position. The behavior parameters are the coordinates x and y.
- **Open:** The robot opens the gripper. No parameters.
- **Atomic:** The robot applies an atomic action for one step, moving a delta calculated from the relative distance between some object position and some (x, y, z) and yaw angle as specified by the behavior parameters.

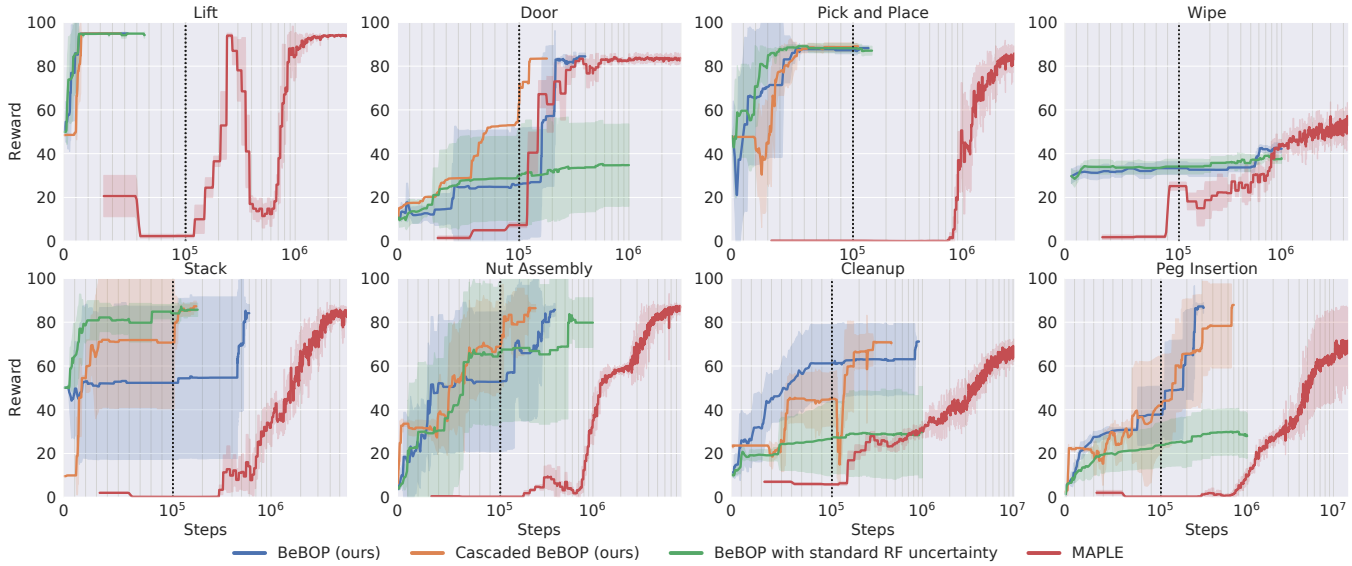


Fig. 4: Episodic reward learning curves for the eight tasks with the mean as solid lines and shaded areas denoting standard deviations. The x-axis is linear until 10^5 steps and logarithmic thereafter, as marked by the dotted vertical line. The results highlight the importance of our new uncertainty measure and that our approaches outperform *MAPLE* by a large margin.

In addition to behaviors, the BT also needs conditions that process the information in the observation vector. In the experiments, we make use of three different condition nodes.

- **At:** Returns *Success* if the object is at a given position. This is exclusively used for goal conditions and the parameters are therefore fixed.
- **Angle >:** Checks if the angle of some object is larger than a value parameter.
- **Aligned:** Checks the observation vector to see if the object is aligned. No parameters except the object identifier. Used only in the peg-insertion task.

We use pre- and post-conditions of the behaviors for planning and because the behaviors work with relative coordinates, we claim that in most real robot applications and frameworks, such as [55], this knowledge will be readily available. The BTs are implemented using the *PyTrees* framework[2].

B. Reward

The reward for the episodes is the same dense rewards with affordances as the original benchmark [1]. However, since BTs have a natural stop condition when the tree returns *Success* or *Failure*, we can also handle that. We want to avoid solutions where the tree returns *Failure*, so we add a negative reward of -500.0 for any such episode. If the BT stops before the maximum number of steps in the environment, we assume that the same reward that was given for the last step would be given for the rest of the episode and extrapolate it until the maximum number of steps. As in [1] we evaluate the policy in 20 validation episodes with different random seeds than during training. We only validate the currently best BT found, based on the reward of the training episodes. The affordances and failure penalty are not used for the validation. The affordance penalty as described in [1] is a form of reward shaping where a penalty is given for an action that is performed outside a manually specified region. In [1] it is shown that *MAPLE* is unable to make progress even on the simple *Pick and Place* task without the affordances.

[2]`https://github.com/splintered-reality/py_trees`, version 2.2.2. Specifically, we use a forked version with slightly changed visuals: `https://github.com/jstyrud/py_trees`

V. Results

Figure 4 shows learning curves for all eight tasks as the mean of five repetitions (same as in [1]) for each method with shaded areas denoting the standard deviation. We run the experiments until the task is solved, or at most 10^6 time steps. The figure shows that our method outperforms *MAPLE* in 7 of the 8 benchmarks. The number of steps needed to solve a task is often an order of magnitude less than for *MAPLE*. By outperforming *MAPLE* [1] we consequently also outperform other RL algorithms like *HIRO* [6] and *DAC* [7] which are not shown here but are discussed in detail in [1]. We also note that our new uncertainty measure as described in Section III-B performs equally or better than the standard RF uncertainty measure (green) for all benchmark tasks except *Stack*. We believe that is simply because *Stack* is easy enough to solve without it. However, BO with the standard measure fails to solve the more difficult tasks even with more iterations.

The cascaded version of *BeBOP* (orange) performs even better on several benchmarks, especially those that can be logically divided into a sequence of subtasks.

For the *Wipe* task none of the methods, including *MAPLE*, are able to solve the task. It is likely that the allowed time is in fact insufficient to perform the task reliably. The markers to wipe are randomly placed, and it is possible that MAPLE can statistically learn their positions, giving it a slight edge in this benchmark. However, with the only observation of the markers being their average position, not enough information is given to make an efficient wiping pattern.

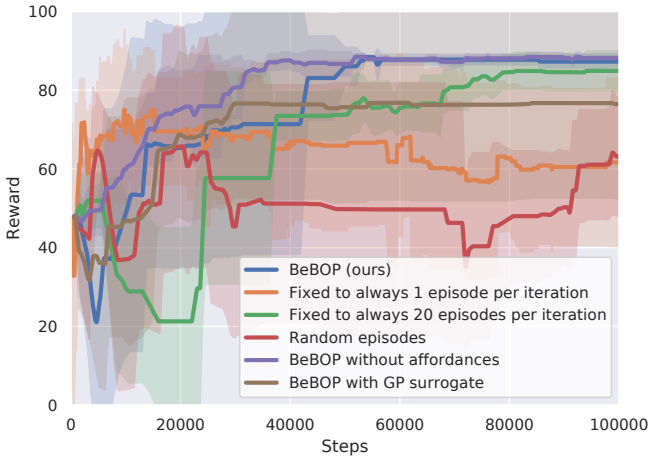


Fig. 5: The reward of the best policy on the validation data for the *Pick and Place task*. It shows that our evaluation strategy (blue) does not only learn the fastest and most robust, but our method can also learn without the special affordances (purple).

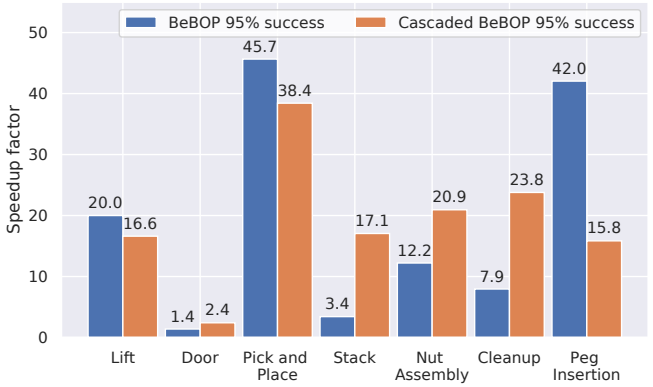


Fig. 6: The speedup factor when compared to *MAPLE* on the 7 tasks that are solved. The factor is computed at reaching a mean 95% success rate in the validation data.

We also studied how the evaluation procedure impacts *BeBOP*'s performance. In Fig. 5 we see that solving the *Pick and Place* task without affordances (purple) has no significant impact on the learning rate when compared to *BeBOP* with affordances (blue), while *MAPLE* [1] was reported to make no progress at all without affordances. We also show learning curves for variants of choosing the training episodes. Fixing the number of episodes to 1 (orange) quickly finds a good solution on the training data, but fails to generalize to the validation episodes. Fixing it to always run 20 (green) generalizes to the validation episodes but wastes steps on poor solutions which results in slow learning. Choosing 20 random environments for evaluation means that each policy randomly gets a set of easy or hard environments, which makes comparison difficult. Such inconsistencies also makes it harder to fit the BO surrogate model. The red curve in Fig. 5 shows how this negatively affects learning performance. We also show how the popular GP surrogate (brown) does not perform as well on this task. Also note that GP models have cubic computational complexity and are considerably slower per iteration.

In Fig. 6 we show the actual speedup factor to reach the specified task success rates for *BeBOP* and *Cascaded BeBOP* compared to *MAPLE* for the 7 tasks that were solved. The plot compares the point where the mean success rate of the five repetitions has reached 95% for the first time. In our experiments *MAPLE* failed to solve *Peg Insertion* task in one of the repetitions, so we only use the other four. As shown in the figure, even the smallest speedup of *BeBOP* compared to *MAPLE* in the *Door* task is still 1.4. For many tasks, *BeBOP* learns more than 15 times faster and reaches a speedup of up to 46 times. This not only saves a lot of compute time when learning in simulation, but also makes learning on a real robotic system much more realistic.

VI. Conclusions

We present *BeBOP*, a method for combining reactive task planning and Bayesian optimization to create behavior-tree policies. We show that our method for learning these policies outperforms state-of-the-art RL algorithms such as *MAPLE, HIRO* and *DAC* by a large margin. While using exactly the same behavior primitives, our method solves the robotic manipulation benchmarks using on average only 5% of the steps needed by *MAPLE*. The results are further improved by utilizing the structure of the BTs to divide the task into a sequence of sub-tasks, which makes *BeBOP* solve many of the benchmarks even faster. An ablation analysis indicates that *BeBOP* is also less dependent on reward shaping in the form of special affordances compared to the benchmark method, instead using more easily obtained conditions in planning. Our new uncertainty measure for the random forest surrogate model accelerates and robustifies the learning with Bayesian optimization in robotics tasks significantly.

At the same time, the obtained BT policies are deterministic as well as interpretable and modifiable by humans. This makes them much more attractive for sensitive environments such as in industrial manufacturing or private households.

VII. Future work

One natural direction for future work is to use a more advanced planner and to combine it with platforms that support reasoning such as [55], [56], as both leave less for the optimization algorithm to learn. In addition, it would be interesting to study the possibility of re-planning the BT structure in case of changes in the environment without having to re-learn all parameters from scratch as well as studying transfer learning to new tasks.

We believe that our method can generalize to many other types of task, perhaps also outside the robotic domain and confirming that would be an intuitive next step.

Certain tasks are well suited for neural networks, such as when decisions need to factor in many different variables. In those cases, it could be a good approach to include a network as part of a BT policy. That way, the advantages of a transparent and modular BT are kept for the majority of the policy, while still enjoying the strength of the neural network [57].

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