Preliminary Results on Using Abstract AND-OR Graphs for Generalized Solving of Stochastic Shortest Path Problems

Rushang Karia, Rashmeet Kaur Nayyar, Siddharth Srivastava
School of Computing and Augmented Intelligence
Arizona State University, U.S.A.
{Rushang.Karia, rmnayyar, siddharths}@asu.edu

Abstract
Several goal-oriented problems in the real-world can be naturally expressed as Stochastic Shortest Path Problems (SSPs). However, a key difficulty for computing solutions for problems in the SSP framework is that the computational requirements often make finding solutions to even moderately sized problems intractable. Solutions to many of such problems can often be expressed as generalized policies that are quite easy to compute from small examples and are readily applicable to problems with a larger number of objects and/or different object names. In this paper, we provide a preliminary study on using canonical abstractions to compute such generalized policies and represent them as AND-OR graphs that translate to simple non-deterministic, memoryless controllers. Such policy structures naturally lend themselves to a hierarchical approach for solving problems and we show that our approach can be embedded in any SSP solver to compute hierarchically optimal policies. We conducted an empirical evaluation on some well-known planning benchmarks and difficult robotics domains and show that our approach is promising, often computing optimal policies significantly faster than state-of-art SSP solvers.

1 Introduction
The Stochastic Shortest Path (SSP) framework (Bertsekas and Tsitsiklis 1996) provides a convenient way of modeling real-world problems of goal-directed nature such as those in robotics where uncertainty in action execution is often the case. Due to their practical significance, researchers have spent a considerable amount of effort investigating methods for solving SSPs efficiently. Broadly speaking, there are two major directions in improving the efficacy of SSP solvers. The first direction is a “stateless” approach and aims at efficiently solving an individual problem. Approaches falling under this umbrella often utilize a combination of techniques such as heuristics (Hansen and Zilberstein 2001), labelling (Bonet and Geffner 2003; Pineda and Zilberstein 2019) and short-sightedness (Trevizan and Veloso 2012) to make problems computationally tractable.

One major disadvantage of such stateless SSP solvers is that they do not attempt to re-use information that can be used to solve related problems sharing similar goals but different object quantities and/or object names. As a result, the other direction of research has focused on utilizing information from small, easily solvable example problems to learn control structures or build models that facilitate solving larger problems of a similar nature efficiently. For example, Deep Learning (DL) based approaches (Toyer et al. 2018; Garg, Bajpai, and Mausam 2020) have been used to learn reactive policies and have been demonstrated to generalize well to problems with significantly greater number of objects. SSP problems are typically characterized by long horizons with sparse, and often binary, rewards that make learning using DL-based approaches difficult. Techniques like controller synthesis (Bonet, Palacios, and Geffner 2009; Aguas, Celorio, and Jonsson 2019) often use a set of small example plans to find finite state controllers which can be used to execute a policy. One key limitation of existing learning-based techniques has been the lack of appropriate guarantees of termination and/or optimality of the computed policy. Since SSP problems are guaranteed to have a solution, approaches that offer guarantees of finding terminating policies are desirable.

We take a first step towards an approach that constructs a non-deterministic, memoryless generalized policy and utilize it to hierarchically solve SSPs. We utilize AND-OR graphs to represent the controller and use canonical abstractions to lift problem specific characteristics like object quantities. We prove that the solutions produced are guaranteed to be hierarchically optimal and under certain conditions are guaranteed to terminate. Our empirical evaluation shows that for many benchmark domains, such hierarchically optimal policies, computed in a fraction of effort, are already optimal policies for the SSP problems.

The rest of the paper is organized as follows. The next section provides the necessary background. Sec. 3 describes our approach for using example policies in conjunction with abstractions to synthesize non-deterministic, memoryless controllers. We present our experimental setup and discuss obtained results in Sec. 4. Sec. 5 provides a description of related work in the area. Finally, Sec. 6 states the conclusions that we draw upon from this work followed by a brief description of current limitations and future work.

2 Background
Our problem setting considers SSPs expressed in a symbolic representational language such as the Planning Do-
main Definition Language (PDDL) (Fox and Long 2003). Let $D = (P, A)$ be a problem domain where $P$ is a set of predicates of arity no greater than 2 and $A$ is a set of parameterized actions. Without loss of generality, object types, such as those used in PDDL, can be equivalently represented using unary predicates.

A relational SSP problem for a domain $D$ is then defined as a tuple $P = (O, S, A, s_0, g, T, C)$ where $O$ is a set of objects. A fact is the instantiation of a predicate $p \in P$ with the appropriate number of objects from $O$. A state $s$ is a set of true facts and the state space $S$ is defined as all possible sets of true facts derived using $D$ and $O$. Similarly, the action space $A$ is instantiated using $A$ and $O$. $T : S \times A \times S' \to [0, 1]$ is the transition function and $C : S \times A \times S \to \mathbb{R}$ is the cost function. An entry $t(s, a, s') \in T$ defines the probability of executing action $a$ from a state $s$ and reaching state $s'$ where $a \in A$ and $s, s' \in S'$. A first-order predicate $c(s, a, s') \in C$ indicates the cost incurred while doing so.

A solution to an SSP is a policy $\pi : S \to A$ which is a mapping from states to actions. A proper policy is one for which the goal can be satisfied when starting from any state $s$.

### 3.1 Canonical Abstraction

In order to learn a control structure that can generalize to different problem instances differing in object names and numbers, it is necessary to use a representation that can lift characteristics like object names and quantities to form an abstract, generalized policy graph $\tilde{G}$ which is a non-deterministic, memoryless controller that can be used to hierarchically solve an SSP. We provide a brief description of canonical abstraction in the next section and then describe our process to learn a generalized policy graph and embed it in an SSP solver for quickly computing hierarchically optimal policies.

Typically, in SSPs, $c(s, a, s')$ is defined to return non-negative values for all actions taken in any state $s$ such that $s \neq g$ and 0 otherwise. Thus, the objective in an SSP is to compute a policy $\pi$ that can reach a goal state from the initial state while minimizing the expected cost of doing so. SSP solvers often compute $v_\pi(s_0)$ by iteratively improving state-value estimates using the Bellman equations and have been proved to converge to a policy that is $\epsilon$-consistent with the optimal policy (Hansen and Zilberstein 2001; Bonet and Geffner 2003).

An AND-OR graph $G = (V, E)$ for an SSP $P$ is a directed graph where $V = A \cup S$ are the AND-OR vertices respectively and $E$ is the set of arcs denoting transitions $(s, a, s') \in T$. The AND-OR graph $G_\pi$ for a given policy $\pi$ can be easily obtained by simply using the transition function $T$ to add vertices and edges starting from $\pi(s_0)$. It is easy to see that such an AND-OR graph representation of $G_\pi$ is a deterministic, finite state automata whose states are bounded by the total number of vertices of $G_\pi$.

Our objective is to learn a controller that can generalize to SSP problem instances whose object counts are significantly larger and use this controller in an SSP solver to hierarchically solve the SSP problem expending minimal effort in the process. We accomplish this objective by using (a) solutions to a set of small training examples that can be solved easily by existing SSP solvers, and (b) using canonical abstractions to lift problem-specific characteristics like object names and quantities to form an abstract, generalized policy graph $\tilde{G}$ which is a non-deterministic, memoryless controller that can be used to hierarchically solve an SSP. We provide a brief description of canonical abstraction in the next section and then describe our process to learn a generalized policy graph and embed it in an SSP solver for quickly computing hierarchically optimal policies.
Algorithm 1: Hierarchical SSP Synthesis

Require: SSP $P = \langle O, S, A, s_0, g, T, C \rangle$.

Generalized Policy Graph $G = (\overline{V}, \overline{E})$.

1: $C' = C \{ \text{copy over the cost function of } P \}$
2: for $(s, a, s') \in S \times A \times S$ do
3: $s \leftarrow \text{abstraction}(s)$
4: $a \leftarrow \text{abstraction}(s, a)$
5: $s' \leftarrow \text{abstraction}(s')$
6: if $(s, a, s') \not\in \overline{E}$ then
7: $C'[s, a, s'] = \infty$
8: end if
9: end for
10: return $P' = \langle O, S, A, s_0, g, T, C' \rangle$

binary predicate $p_2 \in \mathcal{P}$, $\phi_{p_2}(\psi_1, \psi_2)$ is defined as the set of all binary predicates in $s$ that are consistent with the summary elements composing the binary predicate $p_2(\psi_1, \psi_2)$, i.e., $\phi_{p_2}(\psi_1, \psi_2) = \{p_2(o_1, o_2) | p_2(o_1, o_2) \in s, o_i \in \phi_{\psi_i}(s)\}$.

Let $\Psi$ be the set of all summary elements and let $\mathcal{P}_2 = \mathcal{P}_2 \times \Psi \times \Psi$ be the set of all possible binary relations possible between summary elements. Then, an abstract state $s$ of a concrete state $s$ is defined as a total valuation over the set $\Psi \cup \mathcal{P}_2$. The value of a summary element $\psi$ in a concrete state $s$ is given as $\max(2, \phi_{\psi}(s))$ to indicate if there are 0, 1 or greater than 1 objects satisfying the summary element. Since binary relations between objects become imprecise when grouped as summary elements, the value of a binary predicate $p_2(\psi_1, \psi_2)$ in $s$ is determined using three-valued logic and is represented as 0 if $\phi_{p_2}(\psi_1, \psi_2) = \{\}$, as 1 if $\forall o_1, o_2 \in \phi_{\psi_1}(s) \times \phi_{\psi_2}(s) p_2(o_1, o_2) \in \phi_{p_2}(\psi_1, \psi_2)$, and $\frac{1}{2}$ otherwise.

Similarly, the abstraction of a concrete action $a(o_1, \ldots, o_n)$ when applied to a concrete state $s$ is represented as an abstract action $\bar{a}(\psi_1, \ldots, \psi_n)$ where $\bar{a} \equiv a$ and $\psi_i$ is the summary element that object $o_i$ satisfies, i.e., $o_i \in \phi_{\psi_i}(s)$ for some $\psi_i \in \Psi$.

3.2 Learning Generalized Policy Graphs

We represent the generalized policy as an abstract AND-OR graph $\mathcal{G} = (\overline{V}, \overline{E})$ where the AND-OR node set $\overline{V}$ is composed of abstract actions and states respectively. The edge set $\overline{E}$ is composed of arcs of the form $(\pi, s)$, $(s, a)$, and $(s, s')$. It is well-known that solutions of small problems can be used to construct generalized control structures that also solve larger problems. We adopt a similar strategy of the learn-from-small-examples approach [Wu and Givan 2007; Karia and Srivastava 2021].

To form our training set $T$, we use any state-of-art SSP solver to solve set of small SSP problems $P_1, \ldots, P_n$ to generate AND-OR graphs $G_1, \ldots, G_n$ and add them to $T$. Once $T$ has been generated, we initialize $\mathcal{G} = \{\}, \{\}$. Next, for each $G_i \in T$, we convert every concrete state $s$ and action $a$ to abstract states $\pi$ and $s$ using the process of canonical abstraction described earlier. The edge sets are similarly transformed. This process effectively converts the graph $G_i$ into an abstract graph $\overline{G_i}$ which is then merged into the general-
existence of an optimal action $a$ for which the cost function $C'[s, a, s']$ was set to $\infty$ since otherwise this action $a$ would have been considered by the SSP solver. This would mean that a transition $(s, a, s')$ in the training data was not captured by the generalized policy graph and is a contradiction since no transitions are discarded when creating $G$ from the training data $T$.

Finally, once $\pi_{P^*}$ has been computed, the SSP solver can be reinvoked with the original problem $P$ while retaining the values of the states $v(s)$ computed as a part of solving $P'$. States whose values were set to $\infty$ would need to be reset and any special labels assigned to the any state would need to be reset. The values $v(s)$ can then serve as effective bootstrap estimates for $P$ and we observed empirically that this hierarchical approach was faster in solving $P$ instead of directly invoking the SSP solver to solve $P$ without the bootstrapped estimates. We hypothesize that this is because some optimal actions are already captured by the generalized policy and as a result a smaller set of Bellman updates are required for these states to become $\epsilon$-consistent (Recall that an SSP is solved when the initial state $s_0$ becomes $\epsilon$-consistent).

4 Experiments

To showcase the efficacy of our approach, we conducted an empirical evaluation on four well-known benchmark domains that have been used in the International Probabilistic Planning Competition (IPPC) [Younes et al. 2005]. As a part of our analysis, we aim to answer two questions, (a) Can generalized policy graphs produce hierarchically optimal policies?, and (b) Does a hierarchical approach using generalized policy graphs provide computational savings?

We now describe the experiment setup we used for answering these questions. All of our experiments were conducted on an Intel i7 CPU with 16 cores, each running at 3.2 GHz with 64 GiB of RAM. We utilized a single core for solving any given SSP problem.

Our representational language of choice was PPDDL which is the probabilistic variant of PDDL and has been the default language in IPPCs until 2011 after which the Relational Dynamic Influence Language (RDDL) [Sanner 2010] was used. We chose PPDDL over RDDL since RDDL does not allow specifying the goal condition $g$ easily and as a result many benchmarks using RDDL are general purpose MDPs with no goals.

For our baselines, we used LAO* [Hansen and Zilberstein 2001], Labeled RTDP (LRTDP) [Bonet and Geffner 2003] and Soft-FLARES [Pineda and Zilberstein 2019] which are state-of-art algorithms for solving SSFs.

LRTDP augments Real Time Dynamic Programming (RTDP) [Barto, Bradtke, and Singh 1995] by adding a labeling procedure at the end of each trial. A state is marked as solved iff the entire subtree reachable from the state is also solved and as a result trials can end once a solved state has been reached. This has been instrumental in reducing computational requirements. Soft-FLARES combines labeling and short-sightedness checking for solved states only up to a depth of $t$ using a soft labeling procedure. As a result, policies found by Soft-FLARES are approximate policies and were demonstrated to be very close in quality to the optimal policy.

Our implementation is in Python and we ported the C++ implementation of the baselines from [Pineda and Zilberstein 2019] to Python.

4.1 Problem Domains

We utilized problem generators from the IPPC suite for generating the training and test problems.

Fileworld($F, f$) The environment consists of a set of $F$ folders and $f$ files. Each file $f_i \in f$ is assigned to belong to a folder $F_i \in F$ with a probability $\frac{1}{|F|}$. The goal is to correctly place all files in their destined folders.

Rover($R, W, S, O$) A set of $R$ different rovers need to collect and drop samples $S$ that are present at one of different waypoints $W$. Also, the rovers need to collect images of different objectives $O$ that are visible from certain waypoints. In the IPPC variant of this domain, taking samples can fail with a probability of $0.4$ (keeping the rover in the same state).

Gripper($B$) A robot with two grippers is placed in an environment consisting of two rooms A and B. The objective of the robot is to transfer all the balls $B$ initially located in room A to room B. The gripper is slippery and picking balls can fail with some probability $p$. In the IPPC variant, $p = 0.2$.

Schedule($P, C$) A domain that is used to simulate network queuing. It consists of a set of packets $P$ each belonging to one of different classes $C$ that need to be queued. To successfully route a packet, a router must first process the arrival of a packet. The interval at which the router processes arrivals is determined by a probability $p$. In our experiments, $p = 0.98$ and packets can never be dropped.

Keva($P, h$) A robot uses keva planks $P$ to build towers of different heights. A human places planks in one of the two predefined locations with some probability $p$ one at a time. There’s an infinite supply of planks to the human. The robot picks a plank up from one of the locations and either puts down the plank on the table or places it on a single plank or a double plank to construct a tower of height $h$. A tower of height $h$ can be constructed using $2 \ast h$ number of planks. The value for $p$ used is $0.6$.

4.2 Training and Test Setup

For learning generalized policy graphs, we used LAO* as the optimal SSP solver. In our experiments, we fixed the time limit for each problem to 3600 seconds and did not impose any memory limit. We used $\epsilon = 1e-5$ as the convergence criteria for all approaches. We used 4, 5, 10, 3, and 6 example problems for fileworld, gripper, rovers, schedule, and keva domains respectively. We evaluated the learned generalized policy using our approach on 9, 12, 20, 11, and 12 test problems of fileworld, gripper, rovers, schedule, and keva test problems respectively. Tab. [1] lists the size of the example and test problems used for each domain in terms of the number of the objects. For Keva, we use example problems...
Table 1: The maximum size of the problems for each domain used in example and test problems.

| Domain | Object Type | Max. #Objects in example problems | Max. #Objects in test problems |
|--------|-------------|-----------------------------------|-------------------------------|
| Rover  | Samples     | 5                                 | 9                             |
| Gripper| Balls       | 5                                 | 12                            |
| Fileworld | Files     | 4                                 | 9                             |
| Schedule| Packets    | 4                                 | 12                            |
| Keva   | Planks      | 12                                | 24                            |

with height of tower upto 6 and evaluate on problems with height of tower upto 12.

4.3 Results and Analysis

Our evaluation metric is the time taken by our approach using the same baseline algorithm that we’re comparing with (Alg. 1) to solve a problem and produce a hierarchical optimal policy. In order to evaluate and compare the quality of the policy, we run 100 trials starting from the initial state of the problem until the goal is reached for a fixed horizon of 250 after which the trial is marked as a failure and is assigned a cost of 999. We then compare the average cost incurred when using the hierarchical policy computed by our approach and the policy computed by the baselines.

Results of our experiments are illustrated in Fig. 1. In four out of five domains (rovers, fileworld, schedule, keva), our approach takes significantly lesser time to find a solution compared to each of the baselines - LAO⁺, LRTDP, and Softflares. In the gripper domain, our approach takes slightly longer time than the baseline but produces an optimal policy. In most of these domains, even though our approach finds a solution much faster than the baseline, the quality of the solution is not affected as it often produces the optimal policy.

The LAO⁺ baseline approach could not find a solution for the largest test problem of the schedule and fileworld domains within the time limit, whereas, our approach finds an optimal solution for them within the time limit (mere 250s for schedule), beating the baseline in both the time taken to solve as well as the number of problems solved. For fileworld domain, our approach finds a hierarchically optimal solution much faster than the LAO⁺ and LRTDP baseline approaches but the cost of the solution found is also higher. We also evaluated the robotics domain keva and our approach found an optimal solution for the task of building a tower structure of height 12 within 350s while the baselines took significantly longer (more than three times) to solve it.

Using our analysis, we now answer both the questions we framed earlier. Our approach of using generalized policy graphs produce hierarchically optimal solutions, although it often produces an optimal solution for many domains. The approach provides significant computational savings in terms of time taken to solve a problem and is able to solve more problems within the same time limit. This shows the generalization capability of our approach that helps to solve new problems faster.

5 Related Work

There has been plenty of dedicated research to improving the efficiency for solving individual SSPs (e.g., Hansen and Zilberstein 2001). Bonet and Geffner 2003; Yoon, Fern, and Givan 2007; Trevizan and Veloso 2012). Pineda and Zilberstein (2019) utilize a combination of techniques such as heuristics, labeling, and model-constraining. However, solutions produced by such approaches do not generalize to other problems. More closely related to our approach are methods that compute generalized solutions for Markov Decision Processes (MDPs). Since every MDP can be converted to an SSP (Bertsekas and Tsitsiklis 1996), we focus our discussion of related work to approaches that produce generalized solutions for SSPs or MDPs.

Boutilier, Reiter, and Price (2001) utilize decision-theoretic regression to compute generalized policies for first-order MDPs represented using situation calculus. They utilize symbolic dynamic programing to compute a symbolic value function that applies to problems with varying number of objects. FOALP (Sanner and Boutilier 2005) uses linear programming to compute an approximation of the value function for first-order MDPs while providing upper bounds on the approximation error irrespective of the domain size. A key limitation of their approach is requiring the use of a representation of action models over which it is possible to regress using situation calculus. API (Fern, Yoon, and Givan 2006) uses approximate policy iteration with taxonomic decision lists to form policies. They use Monte Carlo simulations with random walks on a single problem to construct a policy. They do not utilize the available closed-form action models making their approach inefficient in finding generalized policies. Moreover, they do not provide any guarantees of optimality and termination.

Parr and Russell (1997) propose the hierarchical abstract machine (HAM) framework wherein component solutions from problem instances can be combined to solve larger problem instances efficiently. Recently, Bai and Russell (2017) extend upon this framework in RL settings by leveraging internal transitions of the HAMs. A key limitation of both these approaches is that the HAM was hand-coded by a domain expert.

Bonet, Palacios, and Geffner (2009) automatically create finite state controllers for solving problems using a set of examples. A key limitation of their approach is that the abstraction that they use is domain-specific and can only be used when action semantics are deterministic. Aguas, Celorio, and Jonsson (2016) utilize small example policies to synthesize hierarchical finite state controllers that can call each other. However, their approach requires all training data to be provided upfront while our approach does not.

D2L (Bonet, Francès, and Geffner 2019) utilizes description logics to automatically generate non-deterministic, memoryless controllers using the sampled state spaces of a small set of problems by using a SAT compilation. However, their approach only works in deterministic planning problems.

Our approach differs from these approaches in several aspects. Our approach constructs a non-deterministic, memoryless controller automatically without any human interven-
tion. Furthermore, the quality of the controller synthesized does not depend on the order in which training examples are presented. Using canonical abstraction, we lift problem-specific characteristics like object names and object counts allowing our approach to be utilized with action models using any semantics. Another key difference between other techniques is that our approach can easily incorporate solutions from new examples into the controller without having to remember any of the earlier examples. This allows our approach to scale better and can naturally utilize leapfrogging [Groshev et al. 2018; Karia and Srivastava 2021] when presented with a large problem in the absence of training data. Finally, our approach comes with guarantees of optimality given the training examples that were presented to it. Our policies are computed in the concrete state space while utilizing the generalized policy graph to prune certain parts of the search space. As a result, if our output policies are proper, then they are guaranteed to lead to termination.

6 Conclusions

We show that a simple non-deterministic, memoryless controller is able to significantly reduce the computational effort for finding solutions to SSPs. Furthermore, hierarchical policies, computed in a fraction of the effort, using our approach were already optimal policies for most of the benchmark problems. Additionally, bootstrapped estimates from the hierarchical approach often served to reduce the effort of overall effort required to compute an optimal policy for the problem rather than starting from scratch. Our approach comes with guarantees of optimality given the training data that was presented to it making it one of the few generalized approaches to do so.

6.1 Limitations and Future Work

Given the preliminary nature of this work, there is of course a large scope for improvement. Our controller can be improved by incorporating a finite amount of memory and can lead to a reduced branching factor thereby improving computational efficiency.

Description Logics (DL) are more expressive than canonical abstractions and have been demonstrated by Bonet, Frances, and Gefen (2019) to be effective at synthesizing memoryless controllers for deterministic planning problems. Our approach can easily utilize any relational abstraction and it would be interesting to evaluate the efficacy of description logics as compared to canonical abstractions.

Another area of improvement that warrants investigation is the use of the generalized policy graph to copy-over Bellman updates from different concrete states that map to the same abstract state. Currently, each concrete state needs to undergo a set of Bellman updates before converging to its true value. However, many concrete states that map to the same abstract policy often have similar values and it would be interesting if such transitions could be exploited to reduce the total number of computations performed.

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