Automaton-Guided Curriculum Generation for Reinforcement Learning Agents

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Abstract

Despite advances in Reinforcement Learning, many sequential decision making tasks remain prohibitively expensive and impractical to learn. Recently, approaches that automatically generate reward functions from logical task specifications have been proposed to mitigate this issue; however, they scale poorly on long-horizon tasks (i.e., tasks where the agent needs to perform a series of correct actions to reach the goal state, considering future transitions while choosing an action). Employing a curriculum (a sequence of increasingly complex tasks) further improves the learning speed of the agent by sequencing intermediate tasks suited to the learning capacity of the agent. However, generating curricula from the logical specification still remains an unsolved problem. To this end, we propose AGCL, Automaton-guided Curriculum Learning, a novel method for automatically generating curricula for the target task in the form of Directed Acyclic Graphs (DAGs). AGCL encodes the specification in the form of a deterministic finite automaton (DFA), and then uses the DFA along with the Object-Oriented MDP (OOMDP) representation to generate a curriculum as a DAG, where the vertices correspond to tasks, and edges correspond to the direction of knowledge transfer. Experiments in gridworld and physics-based simulated robotics domains show that the curricula produced by AGCL achieve improved time-to-threshold performance on a complex sequential decision-making problem relative to state-of-the-art curriculum learning (e.g., teacher-student, self-play) and automaton-guided reinforcement learning baselines (e.g., Q-Learning for Reward Machines). Further, we demonstrate that AGCL performs well even in the presence of noise in the task’s OOMDP description, and also when distractor objects are present that are not modeled in the logical specification of the tasks’ objectives.

1 Introduction

Deep reinforcement learning utilizes neural networks to solve complex tasks ranging from Atari games to robot manipulation (Gao and Wu 2021; Karpathy and Van De Panne 2012). Despite these advances, many tasks remain prohibitively expensive to learn from scratch, requiring large number of interactions. This problem worsens in long-horizon tasks where sparse reward settings and poor goal representations make the task difficult to solve. In many practical scenarios, the objective for a task is known before commencing learning the task, and thus it can be captured using high-level specifications that have an equivalent automaton representation (Velasquez et al. 2021; Jothirugan et al. 2021). This formulation allows decomposing the task into sub-goals, where each sub-goal can be learned by a Reinforcement Learning (RL) agent. This approach of automaton-guided RL is beneficial in scenarios where the high-level task objective is known beforehand and can be expressed using an automaton, but the low-level transition dynamics are unavailable and hence motion and symbolic planners cannot be reliably used. Recently, many approaches have made use of richer language representations (such as finite-trace Linear Temporal Logic (LTL\textsubscript{f}) (De Giacomo and Vardi 2013)) to incorporate history in the task Markovian Decision Processes (MDPs). This technique helps the RL agent to shape reward effectively to achieve the goal in sparse reward settings, eliminating the need to rely on human guidance for shaping the reward function (Camacho et al. 2018; Icarte et al. 2018; Velasquez et al. 2021). However, reward shaping falls short in complex sequential-decision making tasks as it does not generate simpler sub-tasks suited to the current knowledge of the agent, and incentivizes policies to reach local optima. In this work, we extend automaton-guided RL beyond reward shaping, by deriving a curriculum for the target objective. Curriculum Learning (CL) intends to optimize the order in which an agent attempts tasks, increasing the expected return while reducing training time for complex tasks (Narvekar et al. 2020; Foglino, Christakou, and Leonetti 2019). Nevertheless, automaton-guided curriculum generation still remains an unsolved problem in literature.

We explore representing the high-level task objective using finite-trace Linear Temporal Logic (LTL\textsubscript{f}) formulas (De Giacomo and Vardi 2013) which can be equivalently represented using Deterministic Finite Automaton (DFA). Using the structure of the DFA, we generate a curriculum for the target objective. While the DFA provides a graphical representation of the sequence in which the sub-goals must be achieved, it does not specify the individual sub-tasks of the curriculum. Thus, generating a curriculum is non-trivial as it requires the agent to reason over multiple potential curriculum environment configurations for the same sub-goal objective. Given a high-level task objective in

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the form of a DFA, we propose AGCL, Automaton-guided Curriculum Learning (Fig. 1), that generates two types of curricula: 1) A sequence of sub-tasks that increase in order of difficulty for the agent, and 2) A directed acyclic graph (DAG), where agents can transfer knowledge concurrently learned in multiple source tasks to learn a common target task\(^1\). Unlike previous graph-based curriculum approaches (Svetlik et al. 2017; Silva and Costa 2018), ours does not require access to all possible state configurations of the environment. Further, generating the curriculum does not require additional interactions with the environment, and learning through the curriculum yields quicker convergence to a desired performance compared to learning from scratch, automaton-guided reward shaping baselines - GSRS (Camacho et al. 2018), QRM (Icarte et al. 2018), and curriculum learning baselines - Teacher-Student (Matiisen et al. 2020) and self-play (Sukhbaatar et al. 2018).

We further perform an extensive evaluation on a set of challenging robotic navigation and manipulation tasks and demonstrate that AGCL reduces the number of interactions with the target environment by orders-of-magnitude when compared to state-of-the-art curriculum learning and automaton-guided reinforcement learning baselines.

### 2 Related Work

**Curriculum Learning** (CL) in RL has been studied for games (Gao and Wu 2021), robotic tasks (Karpathy and Van De Panne 2012), and self-driving cars (Qiao et al. 2018). A survey on CL (Narvekar et al. 2020) summarizes the three main elements of CL as task generation, task sequencing, and knowledge transfer. Task generation builds a set of source tasks given the target task (Kurkcu, Campolo, and Tee 2020). Task sequencing optimizes the task sequence to enhance learning in the target task (Narvekar, Sinapov, and Stone 2017; Matiisen et al. 2020), and knowledge transfer determines what information must be transferred from the source to the target to promote effective learning (Da Silva and Costa 2019; Taylor and Stone 2009). Existing graph-based CL methods (Svetlik et al. 2017; Silva and Costa 2018) assume knowledge of the set of states in the task, and thus cannot be used for complex tasks that require function approximation. Metaheuristic search methods serve as a tool to evaluate the CL frameworks (Foglini, Christakou, and Leonetti 2019). In most methods, optimizing a curriculum is still computationally expensive and sometimes takes more interactions compared to learning from scratch. Our proposed framework addresses this concern by utilizing high-level logical specification to derive an optimized graphical representation of a curriculum, eliminating the sunk cost of interactions required to optimize the curriculum.

**Automaton-guided RL** approaches specify tasks using temporal logic-based high-level language specifications (Toro Icarte et al. 2018; Velasquez et al. 2021; Jiang et al. 2021). Most approaches generate a dense reward function to speed up learning. Learning separate policies for subgoals of a task helps abstract knowledge which can be used in new tasks (Icarte et al. 2018). Another technique is to shape the reward inversely proportional to the distance from the accepting node in the automaton (Camacho et al. 2018) however, it leads to inefficient reward settings. Augmenting the reward function with a dynamic Monte Carlo Tree Search helps mitigate this problem (Velasquez et al. 2021). DRL interleaves high-level planning with RL to learn a policy for each edge, overcoming challenges introduced by poor representations (Jothimurugan et al. 2021). However, this approach becomes inefficient when there are multiple paths to the target in the graph, and other reward shaping techniques prove inefficient compared to curriculum learning (Pocius et al. 2018). In this work, we use the underlying DFA to develop a graphical representation of the curriculum, and implement a transfer learning mechanism compatible with a function-approximator, outperforming state-of-the-art baselines.

### 3 Theoretical Framework

#### 3.1 Markov Decision Processes

An episodic Markov Decision Process (MDP) \(M\) is defined as a tuple \((S, A, P, R, S_0, S_f, \gamma, L)\), where \(S\) is the set of states, \(A\) is the set of actions, \(P(s' | s, a)\) is the transition function, \(R : S \times A \times S \rightarrow \mathbb{R}\) is the reward function, \(S_0\) and \(S_f\) are the sets of starting and final states respectively, and \(\gamma \in [0, 1]\) is the discount factor. At each timestep \(t\), the agent observes a state \(s\) and performs an action \(a\) given by its policy function \(\pi_a(\theta | s)\), with parameters \(\theta\). The agent's goal is to learn an optimal policy \(\pi^*\), maximizing its discounted return \(G_t = \sum_{k=0}^K \gamma^k R(s_k, a_k, s_k)\) until the end of the episode at timestep \(K\). The labeling function \(L : S \rightarrow 2^A\) maps a state in the MDP to a set of atomic propositions that hold true for that state. For example, in Fig. 1 the set of atomic propositions, \(AP = \{\text{tree}, \text{rock}\}\).
3.2 Curriculum

Let $\mathcal{M}$ be a set of tasks, where $M_i = (S_i, A_i, P_i, R_i, S_0, i, \Sigma_i, L_i)$ is a task in $\mathcal{M}$. Let $D_i$ be the set of states associated with task $M_i : D_i = \{(s, a, r, s') | s \in S_i, a \in A_i, s' \sim P_i(\cdot | s, a), r \leftarrow R_i(s, a, s')\}$. A curriculum $T = (V, E, g, \mathcal{M})$ is a directed acyclic graph, where $V$ is the set of vertices, $E \subseteq \{(x, y) | (x, y) \in V \times V \land x \neq y\}$ is the set of directed edges, and $g : V \rightarrow \{D_i | M_i \in \mathcal{M}\}$ is a function that associates vertices to samples of a single task in $\mathcal{M}$. A directed edge $(v_j, v_k)$ indicates that samples associated with $v_j \in V$ should be trained on before samples associated with $v_k \in V$. All paths terminate on a single sink node $v_t \in V^2$.

A graph-based curriculum is a general case of a curriculum, where the indegree and outdegree of each vertex $v \in V$ can be greater than one, and there can be multiple source nodes but only one sink node. A sequence-based curriculum is a special case of a curriculum, where the indegree and outdegree of each vertex $v \in V$ is at most 1, and there is only one source node and one sink node as shown in Fig. 1. Examples of a sequence-based curriculum and a graph-based curriculum are shown in Fig. 2(a) and Fig. 2(b) respectively.

3.3 Object Oriented MDP

The Object-Oriented MDP (OOMDP) representation abstracts the task description, as to intuitively generalize the elements in the environment and their properties (Diuk, Cohen, and Littman 2008). In OOMDPs, the task space is abstracted by a set of classes $C$ where each class $C_i \in C$ has a parameter set $\text{Par}(C_i) = \{C_i.p_1, \ldots, C_i.p_{|p|}\}$. Each parameter $C_i.p_i$ has a range of values, given by $\text{Range}(C_i, p_i)$. At any given time, an environment consists of a set of objects $O = \{o_1, \ldots, o_{|o|}\}$, where each object $o_i$ is an instance of a class $C_i$ and is defined by the parameters for that class $o_i = \text{Par}(C_i.o_i)$. For a task, the OOMDP state $s_o$ is given by the union of all object states $s_o = \bigcup_{o \in O} \text{State}(o_i)$, where each object state is the value of the parameters of that object: $\text{State}(o_i) = \{o_i.p_1, \ldots, o_i.p_{|p|}\}$. Since the OOMDP representation is a high-level abstraction of the task space, we assume a many-to-one mapping between a subset of MDP states ($S_{sub}$) and the OOMDP state ($s_o$): $w : S_{sub} \rightarrow s_o$.

For the task in Fig. 1, the OOMDP description consists of classes $C = \{\text{world size}, \text{trees}, \text{rocks}\}$, with the parameters: $C(\text{world size}) = \{\text{width}, \text{height}\}$ (width and height of the grid), $C(\text{trees}) = \{\text{trees env}, \text{trees in}\}$ (number of trees in the environment and inventory of the agent), and similarly, $C(\text{rocks}) = \{\text{rocks env}, \text{rocks in}\}$. In a task, classes have objects whose parameters are assigned values within a range. Example: $\text{Par(\text{world size}[\text{height}])} = [5, 10]$ denotes that the height of the grid can have any value within the range $[5, 10]$. The MDP transition $s' = s \circ \delta$ and the OOMDP transition $s_o \rightarrow s_{o'}$ occurs synchronously.

3.4 Linear Temporal Logic and Deterministic Finite Automata (DFA)

We define the high-level specification of our task using finite-trace Linear Temporal Logic (LTLf) formulas (De Giacomo and Vardi 2013). LTLf allows us to succinctly express complex temporal tasks such as reachability, safety, recurrence, persistence or a combination of these. Most importantly, the language of any LTLf formula can equivalently be represented as a Deterministic Finite Automaton (DFA).

Given a set of atomic propositions, $AP$, a formula in LTLf is constructed inductively using the operations $p, \neg \phi, \phi_1 \lor \phi_2, X \phi, G \phi, F \phi, F_\phi, U \phi_2$ where $p \in AP$ and $\phi, \phi_1$ and $\phi_2$ are LTLf formulas. The operator $\neg$ denotes negation, $\lor$ denotes disjunction, and the operators $X, G, F, U$ denote $\text{Next}$, $\text{Always}$, $\text{Eventually}$, and $\text{Until}$ respectively. An LTLf formula can be translated into a DFA $H = (\Omega, \omega_0, \Sigma, \delta, F)$, where $\Omega$ is the set of nodes with initial node $\omega_0 \in \Omega$, $\Sigma = 2^AP$ is an alphabet defined over a set of atomic propositions $AP$, $\delta : \Omega \times \Sigma \rightarrow \Omega$ is a deterministic transition function, and $F \subseteq \Omega$ is the set of accepting nodes. Given any two states $\omega, \omega' \in \Omega$ and a symbol $\sigma \in \Sigma$, we denote the transition $\omega' = \delta(\omega, \sigma)$ as $\omega \xrightarrow{\sigma} \omega'$. A path $\zeta = \omega_0 \omega_1 \ldots \omega_n$ is a finite-length sequence of states such that, for any $i = 0 \ldots n - 1$, we have $\omega_{i+1} = \delta(\omega_i, \sigma_i)$. The occurrence operator, $\text{Occ}(\zeta)$, defined as $\{\omega \in \Omega | \omega \text{ appears in } \zeta\}$, returns the set of nodes in the path $\zeta$.

The set of atomic propositions in $AP$ is shared within the
MDP and the DFA. The labeled MDP and the automaton (DFA) operate synchronously. Specifically, a transition $s \xrightarrow{a} s'$ in the labeled MDP triggers a transition $\omega \xrightarrow{L(s')} \omega'$ in the DFA. Therefore, the high-level specification is achieved in the labeled MDP if and only if a final state is reached in the DFA. We define a one-to-many relationship using the function $P : \Omega \rightarrow M$, that given a node $\omega \in \Omega$ in the DFA, returns the set of tasks that can reach the node $\omega$ from the start node $\omega_0$. The equivalent DFA representation of the LTL$_f$ objective $F\langle tree\rangle \land F\langle rock\rangle$ is shown in Fig. 1.

3.5 Running Example

Consider the environment description shown in Fig. 1. We start with the target task MDP $M_{\text{target}}$ and its OOMDP description (described in Sec. 3.3) along with the LTL$_f$ formula for the task $(F\langle tree\rangle \land F\langle rock\rangle)$ which corresponds to the automaton shown in Fig. 1. When the agent follows a policy $\pi$ that collects a tree followed by a rock, it satisfies the path $\zeta : \omega_0 \xrightarrow{\text{tree}} \omega_1 \xrightarrow{\text{rock}} \omega_3$. Since $\omega_3$ is in the set of accepting nodes $F$, the policy produces a trajectory in the MDP that satisfies the LTL$_f$ objective. Generating curriculum given the DFA involves reasoning over the trace paths as well as the set of MDPs that can generate trajectories to reach a node in the DFA. For example, to have a trajectory (of length > 0) that reaches the node $\omega_4$, the agent must have a tree in its inventory by the end of the episode. To achieve this, at least one tree must be present in the environment when the episode starts for the agent to collect. Using this information, a potential source task of the curriculum is generated by varying the parameter values for the objects within the range specified in the OOMDP representation. Thus, a query to the function $P(\omega_1)$ will generate the set of MDPs $M_1$ that have at least 1 tree in the initial task configuration, while varying other object parameters. The set of initial and final OOMDP states for $M_1$ will be given by $w(P(\omega_1)(\mathcal{S}_0))$ and $w(P(\omega_1)(\mathcal{S}_f))$ respectively as the function $w$ maps the MDP state to an OOMDP state. An example of a sequence-based curriculum for the path $\zeta : \omega_0 \xrightarrow{\text{tree}} \omega_1 \xrightarrow{\text{rock}} \omega_3$ is shown in Fig. 2, where in the first task $M_0$, the agent learns to collect a tree in a smaller environment, while transferring the knowledge to the final task. For the graph-based curriculum in Fig. 2, two agents simultaneously learn to collect a tree and a rock separately, and transfer their knowledge to learn the target task. The curriculum for the agent that learns to collect a tree in $M_0$ is derived from the set of MDPs produced using the path $\zeta : \omega_0 \xrightarrow{\text{tree}} \omega_1 \xrightarrow{\text{rock}} \omega_3$, whereas the curriculum for the agent that learns to collect a rock in $M_1$ is derived using the path $\zeta : \omega_0 \xrightarrow{\text{rock}} \omega_2 \xrightarrow{\text{tree}} \omega_3$. The agent’s trajectory in the final target task $M_{\text{target}}$ can follow any of the paths in the DFA. The knowledge from the source tasks in the curriculum guides the agent in the final target task to make decisions based on its prior experiences. In the following sections, we discuss our automaton-guided curriculum generation approach.

3.6 Problem Formulation

CL aims to generate a curriculum, such that the agent’s convergence or its time-to-threshold performance on the final target task $(M_{\text{target}})$ improves relative to learning from scratch. Time-to-threshold ($\Delta$) metric computes how much faster an agent can learn a policy that achieves expected return $G \geq \delta$ on the target task if it learns through a curriculum, as opposed to learning from another approach (Foglino, Christakou, and Leonetti 2019). Here $\delta$ is desired performance threshold, in success rate or episodic reward. An optimal curriculum would converge to the expected return value in the target task the quickest. Formally:

$$T^* := \arg\min_{T \in \mathcal{T}} a_\delta^{M_{\text{target}}} + \sum_{M_i \in T} a^{M_i}$$

where $T$ is the set of all curricula, $a_\delta^{M_{\text{target}}}$ is the number of actions the agent took in the target task $M_{\text{target}}$ to achieve threshold performance $\delta$, and $a^{M_i}$ is the number of actions the agent took in the source task $M_i$ of the curriculum.

Our objective is to find a curriculum $T = \{V, E, g, \mathcal{M}\}$ that improves an agent’s time-to-threshold performance on the target task, given the LTL$_f$ representation and the OOMDP and MDP description of the target task.

4 Methodology

The high-level curriculum generation algorithm is given in Algorithm 1. To begin, we assume the following:

1. We have access to a high-level target task $(M_{\text{tar}})$ objective which is expressed using LTL$_f$ formulas, and can be equivalently represented using a DFA $U$.

2. We have access to the OOMDP description of the target task. The OOMDP description contains the set of classes $C$ of the environment, and for each class, the set of parameters for that class, along with the range of acceptable values for the parameters. Varying these parameters gives us different tasks of the curriculum. We also have the initial and goal OOMDP states of the final task of the environment.

3. We have access to the functions $P$ that given a node in the DFA, return the set of MDPs that can reach the node, and access to function $w$ that performs mapping between MDP states and OOMDP states.

Given the DFA, we first generate a key-value pair dictionary $K$, where each key is a node of the automaton, and the value is the set of MDPs that can reach the node, with each MDP augmented with the initial and final OOMDP state configuration of the MDP, resulting in the MDP-OOMDP tuple $(\mathcal{M}, s_{0,oo}, \mathcal{S}_{f,oo})$, lines 1-2. The function Get_Trace_Paths returns the set of all paths $(Z)$ that start from the initial node $\omega_0$ and reach an accepting node $\omega_f \in F$. We consider only acyclic DFAs, ignoring paths that contain a cycle. A curriculum designed with this consideration will prune curriculum candidates that intend to learn the same task repeatedly, ensuring progress in the curriculum. Then, for each path $\zeta \in Z$, the List_Candidates function generates an ordered-list of sequence-based curriculum candidates by choosing a MDP-OOMDP tuple from...
each node of the path, and sequencing it according to the sequence of nodes in the path $\zeta$. We repeat this until we attain a set of all possible combinations of MDP-OOMDP tuple sequences (lines 4-7). This yields an exhaustive set $\Psi$ where each element in the set is an ordered list of MDP-OOMDP tuples, and the length of the list is equal to the number of transitions in the trace path. Thus, each list corresponds to a curriculum candidate $T$ where the vertices of the graph are the MDPs in the list, and the edges are defined by the sequence of the MDPs in the list. Once we have a set of sequence-based curriculum candidates, we choose an effective curriculum from this set. We introduce the jump score, where we assign a score for each pair of consecutive source tasks in the curriculum (lines 10-16).

**Jump score:** Inspired by the difficulty scores for supervised learning (Weinshall, Cohen, and Amir 2018), we assign a jump score $J : (M_i, M_j) \rightarrow \mathbb{R} \in [0,1]$ for each pair of consecutive source tasks $M_i$ and $M_j$:

$$J_{M_i \rightarrow M_j} = 1/2 \times (\text{sim}_t(M_j, M_{\text{tar}}) - \text{sim}_t(M_i, M_{\text{tar}}) + \text{sim}_g(M_j, M_{\text{tar}}) - \text{sim}_g(M_i, M_{\text{tar}}))$$

(1)

where, $\text{sim}_t(M_i, M_{\text{tar}})$ is the task configuration similarity between the task $M_i$ and the final target task $M_{\text{tar}}$; while $\text{sim}_g(M_i, M_{\text{tar}})$ is the goal state similarity. The jump score $J_{M_i \rightarrow M_j}$ calculates how dissimilar two consecutive source tasks in the curriculum are by calculating the difference of the similarity of the task and goal configurations of each of the two consecutive tasks with the final target task.

Next, we calculate the average jump score of each curriculum candidate $\psi \in \Psi$ and store it in a Curriculum - Jump Score dictionary $J$ (line 16). For sequence-based curricula, the curriculum is determined by the candidate that yields the lowest average jump score (lines 17-18).

$$T = \arg \min_{\psi \in \Psi} J(\mathcal{J}_\psi)$$

(4)

Intuitively, the curriculum $T$ is an ordered list of MDP-OOMDP tuples that have the lowest cumulative average jump among any two consecutive source tasks, i.e. the curriculum has the lowest task and goal state dissimilarity between any two consecutive tasks. A lower dissimilarity will result in a stronger knowledge transfer.

The graph-based curriculum is determined by the set of elements in $\Psi$ that yield the cumulative average jump score lower than a predetermined threshold value $\eta$ (lines 19-21).

$$T' = \{ \psi \in \Psi \ni J(\mathcal{J}_\psi) \leq \eta \}$$

(5)

Thus, $T'$ is a set where each element is an ordered list of MDPs (each element is a sequence-based curriculum). A graph is generated by considering equivalent MDPs in $T'$ as common nodes, and the edges are given by the sequence of MDPs in each element in $T'$ (line 22). The weights on the edges denote the proportion of knowledge contribution of a source task and is discussed further below. The worst case time-complexity of the algorithm is $O(|\mathcal{V}|^3|\mathcal{E}|(|\mathcal{C}|^2|p|^2))$ and where $|\mathcal{V}|$ and $|\mathcal{E}|$ are the number of vertices and edges in the DFA’s DAG and $|\mathcal{C}|$ and $|p|$ are the number of classes and maximum number of class parameters in the OOMDP.

**Knowledge Transfer** in curriculum learning involves leveraging learned knowledge from a source task and transferring relevant knowledge to the next task in the curriculum. In our curriculum setting, each individual source task is learned using DQN (Mnih et al. 2015), and hence we perform value function transfer, where the weights of the neural network of the learned value function of a source task are initialized as the weights of the value function of the next task, i.e. $V_{M_j} \leftarrow V_{M_i}$. Thus, instead of commencing the next task $M_j$ with random $V(s)$ values, the learned value function of the source task biases action selection in the next task according to the experience already collected in the source task. In scenarios where the action spaces are continuous, the RL algorithm needs to be adapted to suit the needs of the domain. DDPG (Lillicrap et al. 2016) and PPO (Schulman et al. 2017) allow continuous action spaces and can replace the DQN as the base RL algorithm. In case of a sequence-based curriculum, where we transfer knowledge from only one source task $M_i$ to the next task $M_j$ in the curriculum, the value function of $M_j$ is initialized to be the learned value function of $M_i$. This process is continued until we reach the end of curriculum, culminating in the final target task.
Algorithm 1: AGCG (U, M_{tar}, w, P, \eta, CL-Type)  
\textbf{Output:} Curriculum: T  
\textbf{Placeholder Initialization:} Set of all acyclic trace paths Z \leftarrow \emptyset  
Node-MDP Dictionary K \leftarrow \emptyset  
Curriculum - Jump Score dictionary J \leftarrow \emptyset  
Set of curriculum candidates \Psi \leftarrow \emptyset  

\textbf{Algorithm:}  
1: for \omega \in \Omega do  
2: \quad K \leftarrow K \cup \{w : (P(w), w(\pi(S_0)), w(\pi(S_f)))\}  
3: end for  
4: Z \leftarrow \text{GetTracePaths}(U)  
5: for \omega \in Occ(\zeta) do  
6: \quad J \leftarrow J \cup \{\zeta\}  
7: \quad \Psi \leftarrow \Psi \cup \{\text{ListCandidates}(K(\omega))\}  
8: end for  
9: end for  
10: for \psi \in \Psi do  
11: \quad \text{jump}_\psi \leftarrow 0  
12: for i = 1 to |\psi| - 1 do  
13: \quad \text{jump}_\psi \leftarrow \text{jump}_\psi + J_{M_i \rightarrow M_{i+1}}  
14: end for  
15: J_\psi \leftarrow \text{jump}_\psi / |\psi|  
16: J \leftarrow J \cup \{\psi : J_\psi\}  
17: end for  
18: if CL-Type == Sequence-based then  
19: \quad T = \arg\min_{\psi \in J} J_\psi  
20: else if CL-Type == Graph-Based then  
21: \quad T^* = \{\psi \in \Psi : J(\psi) \leq \eta\}  
22: \quad T \leftarrow \text{Graph}(T^*)  
23: end if  
24: return T

\(M_{\text{tar}}\). In case of a graph-based curriculum, where we transfer knowledge from multiple source tasks \((M_i, M_{i+1}, \ldots)\) to the next task in the curriculum \((M_j)\), the value function of the next task \((M_j)\) is initialized to be a weighted sum of the value functions of its source tasks, i.e.,

\[
V_j^* = \beta_0 \cdot V_i^* + \beta_1 \cdot V_{i+1}^* + \ldots + \beta_l \cdot V_{i+l}^*
\]  

(6)

where \(V_j^*\) is the initial value function of the target task \(M_j\), \(V_i^*\) is the learned value function of the source task \(M_i\), \(l\) is the number of source tasks, and \(\beta\) is a scalar weighting factor. To calculate \(\beta\), we use the following:

\[
\beta_i \propto \frac{1}{J_{M_i \rightarrow M_j}} \quad \text{and} \quad \sum_{k=0}^{l} \beta_{i+k} = 1
\]  

(7)

i.e., the lower the jump score between tasks \(M_i\) and \(M_j\), the higher the similarity between their OOMDP task and goal configurations, thus, higher the weightage of the learned value function of the task \(M_i\), and vice versa. A higher similarity will correspond to a stronger positive transfer. In case of a graph-based curriculum, we learn the tasks that correspond to the leaf nodes initially, transferring knowledge using Equations 6 and 7, culminating in the final target task\(^5\).

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\(^5\)Link to source code and appendix: https://github.com/tufts-ai-robotics-group/Automaton-guided-CL

5 Experimental Results

We aim to answer the following questions: (1) Does AGCL yield sample efficient learning? (2) How does it perform in environments that have distractor objects that are not modeled in the LTL\(_f\) specification? (3) How does it perform when the exact OOMDP description is unknown? (4) Does it yield sample efficient learning when the OOMDP parameter space is continuous? (5) How does it perform when generating all potential curricula candidates is intractable?

5.1 AGCL - Gridworld Results

To answer our first question, we evaluated AGCL on a gridworld domain with the LTL\(_f\) objective:

\[
G((t \rightarrow \neg r \land \neg p) \land (r \rightarrow \neg t \land \neg p) \land (p \rightarrow \neg r \land \neg t)) \land \neg pU(t \land X(\neg pU)) \land (\neg pU) \land F p
\]  

(8)

where \(t, r, p\) correspond to the atomic propositions \(\text{tree}, \text{rock}\) and \(\text{pogo-stick} \) respectively. Essentially, the agent needs to collect 2 \(\text{trees}\) and 1 \(\text{rock}\) (by navigating to the objects and breaking them) before approaching the crafting table to \(\text{craft a pogo-stick}\). This is a complex sequential decision making task and requires \(\sim 10^8\) interactions to reach convergence (Shukla et al. 2022). The OOMDP description is given by:

\[
C = \{\text{world size}, \text{trees}, \text{rocks}, \text{crafting table}\}
\]

The parameters \(\text{width}\) and \(\text{height}\) can assume values in the range \([6, 12]\) and the number of \(\text{trees}, \text{rocks}\) and \(\text{crafting table}\) in the environment can assume a value in the ranges of \([0, 4], [0, 2]\) and \([0, 1]\) respectively. In this environment, the agent can move 1 cell forward if the cell ahead is clear or rotate \(\pi/2\) left or right. In the target task, the agent receives a reward of \(10^2\) upon crafting a \(\text{pogo-stick}\), and \(-1\) reward for all other steps. The agent’s sensor emits a beam at incremental angles of \(\pi/4\) to determine the closest object in the angle of the beam (i.e., the agent receives a local-view of its environment). Two additional sensors provide information on the amount of \(\text{trees}\) and \(\text{rocks}\) in the agent’s inventory (More details in Appendix B).

The learning curves in Fig. 3 depict the performance of our proposed sequence and graph-based AGCL method against five baseline approaches namely learning from scratch, automaton-guided reward shaping baslines: GSRS (Camacho et al. 2018), QRM (Icara et al. 2018), and curriculum learning baselines: Teacher-Student (Mat-isen et al. 2020) and self-play (Sukhbaatar et al. 2018), all implemented using the same RL algorithm DQN (Mnih et al. 2015). The automaton-guided reward shaping baslines do not employ a curriculum and build upon naive reward shaping by modifying the reward inversely proportional to the distance from the DFA goal state and by learning policies for each DFA state transition. The curriculum learning baseline approaches do not utilize a reward machine, and rely on optimizing the task sequence through agent’s experience\(^6\).

\(^6\)Baseline implementation details in Appendix Section C
Figure 3: Learning curves (Averaged over 10 trials): (a) Gridworld domain; (b) Gridworld - with distractor objects in the environment; (c) Gridworld - with imperfect OOMDP description of the environment; (d) Gridworld - with subset of curriculum candidates. Figs. (e) and (g) show the two robotic environments and their learning curves in (f) and (h).

The learning curve for the curriculum approaches have an offset on the x-axis to account for the interactions used to go through the curriculum before moving on to the target task, signifying strong transfer (Taylor and Stone 2009). The results in Fig. 3a show that AGCL reaches a successful policy quicker, and the graph-based curriculum proposed by AGCL outperforms the sequence-based approach. Learning source tasks in a graph-based curriculum is also parallelized, reducing the overall wall time. Furthermore, our method outperforms the five baseline approaches in terms of learning speed. The other four baseline approaches perform better than learning from scratch, but do not outperform AGCL. All approaches may converge to a higher asymptote, but will need more interactions with the environment. For this task, the curriculum generated by AGCL has $|V| = 4$ and $|V| = 6$ for the sequence-based and graph-based curricula respectively. To demonstrate that the average convergence rate of AGCL is consistently higher than the baseline approaches, we perform an unpaired t-test (Kim 2015) to compare AGCL against the best performing baselines at the end of $10^7$ training interactions and we observed statistically significant results (95% confidence). Thus, AGCL not only achieves a better success rate, but also converges faster.\(^7\)

5.2 AGCL on Tasks with Distractor Objects

Next, we test our AGCL approach (sequence and graph) on the pogo-stick task described in Sec. 5.1 but now the OOMDP description of the environment contains a new class $C(\text{distractor}) = \{\text{distractor}_{\text{env}}, \text{distractor}_{\text{inv}}\}$.

\(^7\)Statistical significance result details in Appendix Section D.

whose object $\text{distractor}_{\text{env}}$ or $\text{distractor}_{\text{inv}}$ can assume values in the range $[0, 2]$, signifying that the initial task state or the inventory may contain 0 to 2 instances of the distractor object. The agent interacts with this object the same way it interacts with trees and rocks, i.e. by navigating to the object and collecting it in inventory. However, presence of distractor objects in the inventory of the agent is not necessary to achieve the target objectives and is not modeled in the LTL$_F$ specification.

Fig. 3b demonstrates how our proposed AGCL performs against the baseline approaches. Since our curriculum generation approach models not only the goal configuration but also the initial task space configuration, it is successful in estimating the difficulty posed by the introduction of the distractor object as they are present in the initial state of the target task. The curriculum generated by AGCL guides the agent to a successful policy in fewer interactions compared to the other baselines. Approaches that design a curriculum purely from the LTL$_F$ specification will not model the distractor objects, and will thus fail to determine the complexity of a source task that contains these distractor objects.

5.3 Tasks with Imperfect OOMDP Descriptions

In certain partially observable settings, it might not be possible to obtain an accurate OOMDP description of the environment. To demonstrate the efficacy of our approach in imperfect OOMDP descriptions, we incorporate a gaussian noise over the class parameter value ranges, i.e. if the parameter range is $\text{Par}_{\text{given}}(\text{world size}|\text{height}) = [a, b]$, we assume that this range is imperfect, and the true range is given
by \( \text{Par}_{\text{noisy}}(\text{world}_\text{size}|\text{height}) = [a - \mathcal{N}(0, \sigma), b + \mathcal{N}(0, \sigma)] \), where \( \sigma = (b-a)/6 \); covering the entire range of the parameter values in six standard deviations. We incorporate a gaussian noise over all the class parameters ranges.

We test AGCL (sequence and graph) on the same task of Sec. 5.1 but now the environment’s OOMDP description is noisy over the parameter values, i.e., the exact OOMDP description is unknown. We observe that even with imperfect OOMDP descriptions, AGCL converges faster than the baselines (Fig 3c), and the graph-based AGCL converges to a successful policy the quickest, in \( 2.5 \times 10^8 \) interactions.

5.4 Tasks with Continuous OOMDP Ranges

In the gridworld, the OOMDP parameter values were integers. In this experiment, we test how our approach performs in tasks that have continuous parameter ranges. We modify the function \( P: \Omega \rightarrow \mathcal{M} \) that given a node in the DFA, samples a subset of MDPs \( \mathcal{M}_{\text{sub}} \subseteq \mathcal{M} \) such that \( |\mathcal{M}_{\text{sub}}| = b \). We test this on two challenging simulated robotic environments where the interaction cost is high.

Fig. 3e shows a robotic task with the same objective described in Sec. 5.1. Here the values for the parameters \( \text{width}, \text{height} \) for class \( \text{world}_\text{size} \) are in the continuous range \([2m, 4m]\). The move forward (backward) action causes the robot to move forward (backward) by 0.1m and the robot rotates by \( \pi/8 \) radians with each rotate action. Additionally, the objects can be placed at continuous locations in this robotic domain as compared to discrete grid locations for the gridworld task. These changes increase the number of MDP and OOMDP states the agent can attain.

The second simulated robotics environment (Fig. 3g) consists of a robotic arm performing a pick-and-place task (Gallouédec et al. 2021) with the LTL\(_f\) objective: \( F(g \wedge F(p \wedge Fq)) \) where \( g, p, q \) are the atomic propositions for ‘reach-object’, ‘pick-up-object’ and ‘place-object’. The OOMDP is modeled as \( \mathcal{C} = \{\text{world}_\text{size}, \text{objects}\} \) with \( \text{Par}(\text{world}_\text{size}) = \{\text{length}, \text{width}, \text{height}\} \) and \( \text{Par}(\text{objects}) = \{\text{no}\_\text{objects}\} \). The continuous parameters \( \{\text{length}, \text{width}, \text{height}\} \) assume values between \([10, 50] cm\). The robot has continuous action parameters for moving the arm and a binary gripper action (close/open). The robotic domains were modeled using PyBullet (Coumans and Bai 2021). For each node, we sample \( b = 25 \) different MDPs and evaluate AGCL. The results in Figs.(3f,3h), show that AGCL outperforms all other baselines in both environments. Additionally, the graph-based AGCL converges to a successful policy the quickest.

5.5 AGCL on Subset of Curriculum Candidates

In cases where the range of parameter values or the DFA representation is too large, the number of curriculum candidates can grow exponentially in terms of the number of nodes in the DFA, making it infeasible to calculate the jump-score for each curriculum candidate. For this, we evaluate AGCL on the task described in Sec. 5.1 by sampling a subset \( \Psi_{\text{sub}} \) of the total curriculum candidates \( \Psi \), such that \( |\Psi_{\text{sub}}| = |\Psi|/4 \), thus reducing the total number of curriculum candidates and the amount of computation required to determine a suitable curriculum. From the results in Fig. 3d, we observe that in this experiment, AGCL takes more interactions to converge to a desired policy as compared to Fig. 3a, as sampling a subset prunes some desirable curriculum candidates, however it outperforms the other curriculum learning and automaton-guided RL baselines in terms of learning speed.

6 Conclusion and Future Work

We proposed AGCL, a framework for curriculum generation using the high-level LTL\(_f\) specification and the OOMDP description of the environment. AGCL decomposes the target objective into sub-goals, and generates a sequence-based or a graph-based curriculum for the task. Through experiments, we demonstrated that AGCL accelerates learning, converging to a desired success rate quicker as compared to other curriculum learning and automaton-guided RL baselines. Moreover, our proposed approach improves learning performance even in the presence of distractor objects in the environment that are not modeled in the LTL\(_f\) specification. Finally, we evaluate our approach on long-horizon complex robotic tasks where the state space is large. AGCL reduces training time without relying on human-guided dense reward function nor does it require a perfect OOMDP description of the environment. The graph-based curricula produced by AGCL affords learning separate behaviors in parallel, reducing wall clock time for complex sequential decision making tasks. Thus, our proposed AGCL approach offers accelerated learning when the high-level task objective is available.

We assume that the high-level task objective is available, and can be characterized using a LTL\(_f\) formula. However, in certain cases, the target tasks can be completely novel, with no prior information on the task objective. Additionally, it might not be feasible to represent the domain using OOMDP representation, as the objects in the environment can be unknown, and the only way to get more information about the environment is through interaction with the environment. In scenarios where the LTL\(_f\) specification becomes complex, the DFA gets larger, and it might become intractable to come up with exact solutions of curriculum optimization. Future work would involve devising approximate solutions that tightly bound exact solutions. Also, our heuristic, the jump score, while it was shown to be useful here, might not perform universally well for all task objectives and environments. In future work, we plan to modify this heuristic to be more theoretically-grounded. Furthermore, we plan to extend it to settings where obtaining an accurate LTL\(_f\) specification might be difficult. Finally, we would like to extend our work to multi-agent settings, and investigate curriculum generation using even more expressive high-level languages, such as CTL\(_x\) and \( \mu \)-calculus.

Ethical Impact

AGCL aims to boost the learning speed of reinforcement learning agents for sequential decision making tasks. This will enable quicker learning for robotic applications. It will lead to an overall reduction in the training times, saving computation time and energy. On the other hand, this work can also be used for negative applications - e.g., malicious
use of RL. However, the above mentioned concerns are central to all works that deal with any aspects of AI.

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