

A General Purpose Task Specification Language for Bootstrap Learning

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Abstract

Reinforcement learning (RL) is an effective framework for online learning by autonomous agents. Most RL research focuses on domain-independent learning *algorithms*, requiring an expert human to define the *environment* (state and action representation) and *task* to be performed (e.g. start state and reward function) on a case-by-case basis. In this paper, we describe a general language for a teacher to specify sequential decision making tasks to RL agents. The teacher may communicate properties such as start states, reward functions, termination conditions, successful execution traces, task decompositions, and other advice. The learner may then practice and learn the task on its own using any RL algorithm. We demonstrate our language in a simple GridWorld example and on the RoboCup soccer keepaway benchmark problem. The language forms the basis of a larger “Bootstrap Learning” model for machine learning, a paradigm for incremental development of complete systems through integration of multiple machine learning techniques.

Introduction

Traditionally, research in the reinforcement learning (RL) community has been devoted to developing domain-independent algorithms such as SARSA (Sutton & Barto, 1998), Q-learning (Watkins, 1989), prioritized sweeping (Moore & Atkeson, 1993), or LSPI (Lagoudakis & Parr, 2003), that are designed to work for any given state space and action space. However, the *modus operandi* in RL research has been for a human expert to re-code each learning environment, including defining the actions and state features, as well as specifying the algorithm to be used. Typically each new RL experiment is run by explicitly calling a new program (even when learning can be biased by previous learning experiences, as in transfer learning (Soni & Singh, 2006; Torrey *et al.*, 2005; Taylor & Stone, 2005). Thus, while standards have developed for describing and testing individual RL algorithms (e.g., RL-Glue, White *et al.* 2007), no such standards have developed for the problem of describing complete tasks to a preexisting agent.

In this paper we present a new language for specifying complete tasks, and a framework for agents to learn a new policy for solving these tasks. The language allows a user (or “Teacher”) to provide information such as start states, reward functions, termination conditions, task decompositions, successful execution traces, or relevant previously

learned tasks. An agent can then practice the task to learn a policy on its own using any RL algorithm.

The language and framework are targeted at enabling users to develop complete systems that may need to learn multiple different tasks using different learning techniques or sources of training data. Moreover, a teacher can use policies for tasks that were previously learned to “Bootstrap” learning for more complex tasks, either by suggesting earlier policies to be used as abstract actions (i.e., “options” Sutton, Precup, & Singh 1999), or by specifying that an earlier policy can serve as a source of prior experience to be transferred to learning the new task.

Why an RL Task Language?

We are motivated by the recently proposed “Bootstrap Learning” (BL) paradigm for machine learning¹, whose ambition is to integrate all forms of machine learning into a single agent with a natural human-instruction interface. In the BL setting, a human teacher provides structured, step-by-step lessons involving multiple instruction methods to a learning agent, in order to gradually build its ability to perform a variety of complex tasks. For example, rather than starting “*tabula rasa*” as in traditional machine learning, a BL agent might first be given lessons teaching it to perform various types of statistical pattern recognition or logical inference, the results of which can be used in later lessons as primitive state variables in more complex sequential decision making tasks. The final aim of the BL project is to create autonomous agents which can be taught by end users in the field to solve multiple, complex problems by combining many different teaching and learning methods.

The overall goal of BL represents a multi-year, multi-institution project. In this paper, we present a key initial component to accomplish this goal: a formal language that allows a human teacher to specify tasks to a learning agent, so that it may set up and initiate learning of new policies autonomously. We refer to our proposed language as the “Bootstrap Learning Task Learning” language, or simply the BLTL language, and likewise refer to the framework for using the BLTL language as the BLTL framework.

A key goal of the BLTL language is to enable multiple methods for instruction of processes, and multiple RL

¹Bootstrapped learning proposer information pamphlet, http://www.darpa.mil/IPTO/solicit/closed/BAA-07-04_PIP.pdf

algorithms, to be used in the same agent. Previous work on human-to-agent instruction has included task demonstrations (Schaal, 1997), task decompositions (Dayan & Hinton, 1993; Dietterich, 1998; Sutton, Precup, & Singh, 1999), general advice about actions and states which the learner can incorporate into the value function (Maclin & Shavlik, 1996; Kuhlmann *et al.*, 2004), and identification of previously acquired policies that can be used for initializing the policy to be learned for the new task (Soni & Singh, 2006; Torrey *et al.*, 2005; Taylor & Stone, 2005). Typically, research on these types of instruction has required that a human set up each individual learning task from scratch and manually invoke each one. In this paper, we allow the teacher to provide *advice*, indicate relevant previous experience (enabling *transfer learning*), and use previously taught tasks as primitive actions in new tasks (enabling *task decomposition*). Because sub-tasks can each be learned using a different technique, we enable multiple learning methods to be synergistically integrated in a single RL agent that is far more capable than an agent using any one RL algorithm.

The BL Task Learning Framework

Traditional RL research focuses on algorithms for a learning agent, behaving in a single environment, to update a policy by which it chooses actions given fixed state variables. In the BL paradigm, the automated student is responsible not just for learning a specific policy, but also for the larger problem of knowing *how* to engage in learning, provided a task specification. Thus the BL student must also be able to identify the task, and initialize, terminate, and evaluate episodes during practice. By analogy, a human student who has been given a set of practice problems, say to learn long-division, must not only learn the procedure for division, but also must know which problems to work on, how to evaluate her performance (for instance by checking the answers and noticing how long it takes to solve each problem), and that she should continue to work through the entire set of homework problems—or at least as many as it takes to master the concept and get a good grade. To enable a teacher to provide instructions to a BL student, the BLTL language must be able to address all of these elements of learning.

The standard RL definitions of agents and environments, as described in (Sutton & Barto, 1998), are as follows:

Environment: stores all the relevant details of the world, such as the current state representation, the transition probabilities, and transition rewards.

Learning Agent: both the learning algorithm and the policy maker for acting in the environment. The agent needs to decide which action to take at every step, and may update its policy as it receives experience in the world.

Experiment Program: this is the control loop, which steps the agent through the environment in multiple episodes, and collects information about performance.

A popular, freely available implementation of these components in code is the RL-Glue framework (White *et al.*, 2007), which has formed the basis of several “bakeoffs” and contests for comparing RL algorithms.

The BLTL framework encompasses the Environment and Learning Agent components identically to the traditional RL

framework (indeed we implement and connect these components using a subset of the RL-Glue package). However in the BLTL framework, the Experiment Program is incorporated into an internal component called the *Trainer*. The Trainer component monitors the environment and decides when to initiate and terminate learning of a particular policy for a particular task. It makes these choices autonomously and is not under direct external control. During a learning episode for a task, the Trainer monitors the environment and checks for the termination conditions (as specified in the task specification), combines rewards from the environment with any additional rewards specified in the task specification, and directs the Learning Agent and the Environment to the initial conditions as specified by the teacher (to the extent possible given the implementation – in a simulation environment it may be able to “teleport” to an initial condition, however in a physical implementation it may have to e.g., walk a robot to a starting position).

The BLTL framework therefore encompasses all of the concepts in traditional RL, but additionally makes the control and monitoring of the Learning Agent and Environment an integral part of the complete autonomous system, not a separate component that must be supplied by an external human user. In order to allow an external teacher to specify a task, the BLTL framework defines a common name space in which the state variables and functions (such as numerical functions or sorting routines) required to define the state and action spaces are accessible to the Teacher, Trainer, and Learning Agent.

In order to use the BLTL framework, an end user (i.e., the programmer wishing to write lessons for RL tasks) must first implement the necessary functions for the Trainer and Learning Agent to monitor and take actions in the Environment, and supply any additional learning algorithms he wishes to test if not already available. The BLTL language can then be used to set up and teach any number of lessons in the environment while the BL agent runs continually, sensing and acting in the world. While the initial setup may be no less work than in the standard approach to RL research for a *single* task, the BLTL framework makes it simple for a teacher to supply lessons for *multiple* tasks, and to reuse previously learned policies as abstract actions in new tasks.

Language Primitives

We can now specify the primitive functions needed for a teacher to describe to a BL agent how to practice a task. The specification of these functions is a main contribution of this paper. In aggregate, these functions enable a teacher to specify a completely new RL task to a BL agent for the purpose of learning. These functions involve initialization, describing the rules for termination conditions, the reward, and the state and action spaces.

When deciding how to act in the world, the Learning Agent takes as input a state vector at each time step. This state vector may be the result of complex operations on the raw world state (which may have been learned in previous lessons), therefore the language includes commands for constructing a list of functions whose outputs are concatenated into the state vector presented to the agent. Similarly, in order to allow learned actions, as well as “primitive” actions,

to be used in a policy, the language also includes commands for constructing a list of behavior functions that serve as the action space for the current RL task.

The following list of functions with informal descriptions represents our full proposed language for teacher-student interaction regarding sequential decision making problems. Though fully implemented, a complete and formal specification of the functions is beyond the scope of this paper.

BeginTaskDescription(“method”) Prepare to start learning a task, using `method` in the underlying reinforcement learning algorithm. This could for instance indicate that SARSA should be used. The specific learning algorithm must be provided by the user.

TransitionFunction(“simulator” or “function”)

Transitions to new states are either due to acting in the given `simulator`, or by directly invoking a known transition function.

BeginEpisode(“world state”) Specifies that a learning episode is to begin by initializing to the given `world state`, which must be available in the simulator.

OnEpisodeEnd(“option”) What to do when a learning episode ends. The choice of options depends on the abilities of the simulator, and might include e.g. `Restart`, `RestartFromPointX` etc. By default, the trainer will always issue the reward specified in `EpisodeReward`.

NewPolicy(“policyname”) Creates a new policy object, identified by `policyname`.

LearnedPolicy(“policyname”) Identifies which policy is to be updated through reinforcement learning. This can either be a new policy created with `NewPolicy` or a policy which already has some parameters.

SourcePolicy(“policyname”, “sourcepolicy”, “iscopy”)

Creates a new policy object, `policyname`, based on `sourcepolicy`, for transfer learning. If the boolean value `iscopy` is `TRUE`, an exact copy is made. Otherwise it is the source for a more complex transfer method.

AttachPolicy(“agent”, “policy”) Attach a policy to an agent, e.g., `AttachPolicy("agent1", "policy1")`.

EpisodeReward(“numeric function”) Attach a numeric function (binary or real valued) to the reward. For example `NumSteps(EpisodeStart)`. This will be called whenever an episode ends.

AddToStateSpace(“policy”, “function”) Add a function to the list of state space variables, which will be concatenated into the state vector. These functions generally take as input the raw sensory variables, and may have either real valued or binary output.

AddToActionSpace(“policy”, “function”) Add a function to the list of possible actions. For example in `GridWorld` this could be `MoveUp()` etc. These could also be complex options like `MoveUpUntilReachedWall()`, which might have been taught in earlier lessons.

AdviseAction(“policy”, “state”, “vals”, “function”)

Recommend to `policy` that when `state` equals `vals`, it should take the action represented by the function `function`. `vals` could be a boolean function, such as

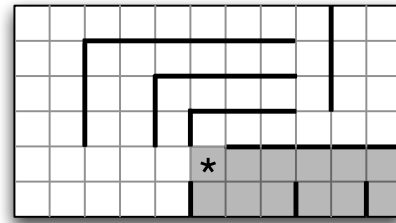


Figure 1: There are many possible tasks in this gridworld. For instance, one task may be for an agent to reach the starred location from any starting point in the shaded area.

Between $(2, 4)$. It is the responsibility of the learning algorithm to handle the advice (Maclin & Shavlik, 1996; Kuhlmann *et al.*, 2004).

SetPolicy(“policy”, “state”, “vals”, “fpolicy”, “ ϵ ”)

Used for task decomposition, this tells the agent to switch to a different policy (using its own state and action space), specified in `fpolicy`, when `state` equals `vals`. It returns to the current policy when `state` no longer equals `vals`. If $\epsilon > 0$, switching is ϵ -random. `fpolicy` could be a previously learned policy from a prior lesson.

AddStopCondition(“function”) Add a boolean function to be evaluated at each timestep, which if it evaluates to `true`, will end the episode and issue reward. It is possible to specify multiple stopping conditions.

StateSpaceDefine(“policy”, “function”, “name”) A

function that takes the raw state space as input, and places the output into a variable with `name`, to be used by state space functions. This function will be executed before calls to the state space functions.

StartLearning(“parameters”) Starts learning, and may take parameters such as `number_of_episodes`, `wait_for_stop_message`, etc.

As we show in the following sections, these functions are sufficient for specifying tasks in widely varying domains, including `GridWorld` and `RoboCup Soccer Keepaway`.

Teaching a lesson in GridWorld

As a simple example, we will teach a `GridWorld` lesson, in which the goal is to learn to get to the location marked with a star in Figure 1 from any starting point in the shaded region.

Once the Environment (call it `Example1GW`) and a Learning Agent (e.g., SARSA) have been implemented, the first step in teaching is to initialize learning and the environment:

```
BeginTaskDescription("SARSA");
TransitionFunction("Example1GW");
```

The trainer now has a reference to the agent in the common name space, which we refer to as `Agent1`. The Teacher now specifies how to start an episode, using a function provided by the simulator for starting a player at a random location within a region:

```
BeginEpisode("RandomWithinRegion(6,5,6,2)");
```

In this particular world, we only allow the actions to be moving one step in the cardinal directions. The state is the current location. The teacher commands are:

```

LearnedPolicy(NewPolicy("P1"))
AttachPolicy("P1", "Agent1")
AddToActionSpace("P1", "Up1()")
AddToActionSpace("P1", "Right1()")
AddToActionSpace("P1", "Down1()")
AddToActionSpace("P1", "Left1()")
AddToStateSpace("P1", "PositionX()")
AddToStateSpace("P1", "PositionY()")

```

An episode concludes when the agent reaches the starred location, and the reward is simply the time elapsed. The function `NumSteps()` and identifier `EpisodeStart` must be provided to indicate the number of steps since the beginning of an episode. It also must provide a function for checking the location of the agent:

```

AddStopCondition("AtLocation(theAgent, 6, 5)");
EpisodeReward("NumSteps(EpisodeStart)");
OnEpisodeEnd("Restart");

```

Finally the agent is told it may start practicing by calling `StartLearning`.

Once the agent has learned and mastered this task, we can use the learned policy `P1` as an abstract action in a future lesson, for instance to reach the upper left corner, using `P1` as an argument to either `AddToActionSpace` or `SetPolicy`.

Complex Example: The RoboCup Domain

The purpose of the BLTL framework is to be able to teach agents complex tasks by building from simpler previous tasks. Here we consider a complex domain, RoboCup soccer, and show how to describe a subtask within RoboCup to learning agents.

Robocup is a fully distributed, multiagent domain with both teammates and adversaries. There is hidden state, meaning that each agent has only a partial world view at any given moment. The agents have noisy sensors and actuators, meaning that they do not perceive the world exactly as it is, nor can they affect the world exactly as intended. Perception and action are asynchronous, prohibiting the traditional AI paradigm of using perceptual input to trigger actions.

RoboCup is a good example for the BLTL framework because mapping from the low-level state description to the low-level action language requires several levels of intermediate concepts. The primitive percepts indicate perceived distance and angle to objects in the environment, such as: (see ((goal r) 15.3 27) ((ball) 8.2 0) which indicates that the right goal is 15.3 m away and 27 degrees to the right and the ball is 8.2 m straight ahead. Meanwhile, the actions are parametric, enabling agents to dash forward with a power ranging from [0,100], turn a specified angle from [-180,180], or, when the ball is nearby, kick in a specified direction with a power ranging from [0,100].

Keepaway Soccer

Keepaway is a subtask of RoboCup soccer, in which one team, the *keepers*, tries to maintain possession of the ball within a limited region, while the opposing team, the *takers*, attempts to gain possession. Whenever the takers take possession or the ball leaves the region, the episode ends and the players are reset for another episode (with the keepers being given possession of the ball again).

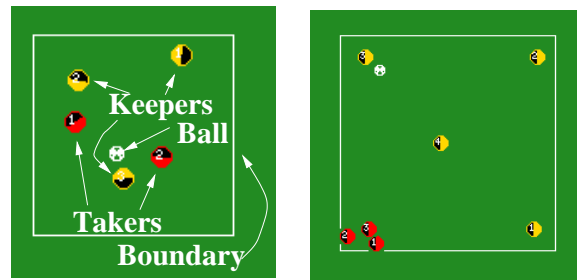


Figure 2: **Left:** A screen shot from the middle of a 3v2 keepaway game in a $20m \times 20m$ region. **Right:** A starting configuration for 4v3 keepaway in a $30m \times 30m$ region.

Parameters of the task include the size of the region, the number of keepers, and the number of takers. Figure 2 shows screen shots of episodes with 3 keepers and 2 takers (called 3 vs. 2, or 3v2 for short) playing in a $20m \times 20m$ region and 4 vs. 3 in a $30m \times 30m$ region.²

For the keepaway task, an episode ends when a taker gains possession of the ball for a set period of time or when the ball goes outside of the region. At the beginning of each episode, the location of the ball and the players are reset semi-randomly within the region of play. A sample starting configuration is shown in Figure 2.

Keepaway has received considerable attention as a testbed for RL algorithms (Pietro, While, & Barone, 2002; Torrey *et al.*, 2005; Stone, Sutton, & Kuhlmann, 2005). However, to the best of our knowledge, in all cases the task has been fully specified manually. We now focus on how the keepaway task can be taught to an agent using the BLTL framework.

In this example, our goal is for each keeper to learn a policy for what to do when it possesses the ball. When a keeper does not have the ball, it automatically follows policies that have already been specified (i.e. `Receive(GetOpen)` or `Recieve(GoToBall)`), which are described in (Stone, Sutton, & Kuhlmann, 2005). Note that these policies could be taught to the agent in prior lessons.

Required Actions, Predicates Before beginning the lesson, the student must be capable of several skills, many of which are composed of multiple primitive actions and perceptions. These skills must either be previously learned via other lessons, or be “innate” (i.e., programmed in).

Actions	Predicates
HoldBall()	CanGetToBallFaster()
PassBall(k)	HaveBall()
GetOpen()	TakerHoldsBall()
GoToBall()	BallOutOfBounds()
Receive()	dist(a, b)
PassToKThenReceive(k)	ang(a, b, c)
InitializeKeepaway(nK, nT, h, w)	min(a, b)
	SortKeeperDistances()
	SortTakerDistances()

Table 1: Actions and Predicates required for Keepaway

Table 1 summarizes the required actions and predicates for the keepaway task. The actions are implemented as their

²Flash files illustrating the task and are available at <http://www.cs.utexas.edu/~AustinVilla/sim/keepaway>

names suggest, but for clarity we provide expanded descriptions for `InitializeKeepaway(nkeepers, ntakers, h, w)`. This initializes the playing field as in Figure 2 with the specified height and width and number of keepers and takers.

Each of the actions requires several predicates, some of which define abstract mathematical relationships while other are domain related, such as `BallOutOfBounds()` which evaluates to TRUE if the ball is out of bounds.

To simplify matters, the decision for what to do when a taker does not have the ball is specified in a predefined policy, `DontHaveBallPolicy()`. In this policy the agent will calculate if it can get to the ball faster than another keeper. If so, then it calls `Receive()`, otherwise it calls `GetOpen()`. Finally, the policy for the takers will be a simple one, `ChaseBallPolicy()`, in which the player always calls `GoToBall()`.

Following the bootstrap learning philosophy, each of the above skills and primitives should have been taught to the student by the teacher previously. Those that are sequential decision making tasks, such as `GetOpen()` may be taught using the language we propose in this paper. Others, such as `BallOutOfBounds()` may be more suited to other learning approaches such as supervised learning. As such, they must be specified to the player using different communication primitives. Because this paper focuses on task specification for RL tasks, those primitives are beyond the scope of this paper. Assuming that the above skills and primitives *have* already been taught to the student, the teacher can use them to specify the keepaway task using the BLTL language.

The Keepaway lesson For the agent to learn an effective policy for keepaway, the teacher must first specify the rules of the game, then tell the student what the state and action spaces are, then allow the student to practice the game. In this case, the teacher only wants the student to learn the best policy for what to do when in possession of the ball.

Teaching three versus two Keepaway

Figure 3 shows the series of instructions needed to specify the keepaway task. Most lines are self-explanatory and are similar to those used in the GridWorld example. The 13 state variables when the keeper has the ball, defined by the series of `AddToStateSpace()` functions, are the same as the ones commonly used for learning this task (Stone, Sutton, & Kuhlmann, 2005), and consist of several distances and angles among the keepers and takers. The `StateSpaceDefs` are needed to create intermediate variables needed to define those 13 state variables.

Note that the functions are chosen so as to map relatively easily from natural language to the formal specification. For example, “learn a new soccer-related task” is represented in lines 1 and 2; “decide when to hold the ball and when to pass” is represented in lines 10 and 11; and “base your decision in part on the distances of the players to the center of the field” is represented in lines 14–18. Such NLP in a constrained domain is currently possible (Kuhlmann *et al.*, 2004) and would enable a domain expert with no special RL knowledge to express the learning task to the BL student.

```

1 BeginTaskDescription("SARSA");
2 TransitionFunction("SoccerSimulator");
3 BeginEpisode("InitializeKeepaway(3, 2, 25, 25)");
4 LearnedPolicy(NewPolicy("KeeperPolicy"));
5 AttachPolicy("Keepers", "KeeperPolicy");
6 EpisodeReward("NumSteps(kEpisodeStart)");
7 AddToStateSpace("KeeperPolicy", "HaveBall()");
8 SetPolicy("KeeperPolicy", "HaveBall()", "IsFalse()",
9           "DontHaveBallPolicy()", 0);
10 AddToActionSpace("KeeperPolicy", "HoldBall()");
11 AddToActionSpace("KeeperPolicy", "PassKThenReceive()");
12 StateSpaceDefs("KeeperPolicy", "SortKeeperDistances", "K");
13 StateSpaceDefs("KeeperPolicy", "SortTakerDistances", "T");
14 AddToStateSpace("KeeperPolicy", "dist(K[1], C)");
15 AddToStateSpace("KeeperPolicy", "dist(K[2], C)");
16 AddToStateSpace("KeeperPolicy", "dist(K[3], C)");
17 AddToStateSpace("KeeperPolicy", "dist(T[1], C)");
18 AddToStateSpace("KeeperPolicy", "dist(T[2], C)");
19 AddToStateSpace("KeeperPolicy", "dist(K[1], K[2])");
20 AddToStateSpace("KeeperPolicy", "dist(K[1], K[3])");
21 AddToStateSpace("KeeperPolicy", "dist(K[1], T[1])");
22 AddToStateSpace("KeeperPolicy", "dist(K[1], T[2])");
23 AddToStateSpace("KeeperPolicy",
24               "Min(dist(K[2], T[1]), dist(K[2], T[2]))");
25 AddToStateSpace("KeeperPolicy",
26               "Min(dist(K[3], T[1]), dist(K[3], T[2]))");
27 AddToStateSpace("KeeperPolicy",
28               "Min(ang(K[2], K[1], T[1]), ang(K[2], K[1], T[2]))");
29 AddToStateSpace("KeeperPolicy",
30               "Min(ang(K[3], K[1], T[1]), ang(K[3], K[1], T[2]))");
31 AddStopCondition("TakerHoldsBall");
32 AddStopCondition("BallOutOfBounds");
33 AttachPolicy("Takers", "ChaseBallPolicy");
34 OnEpisodeEnd("RestartFromBeginning");
35 StartLearning();

```

Figure 3: BLTL instructions for the Keepaway task.

Giving Advice At any stage during learning, the teacher may wish to give advice to influence policy learning, as in (Kuhlmann *et al.*, 2004). For example, the teacher may advise that if taker 1 is more than 50m away, the student should consider holding the ball. The command would be:

```
AdviseAction("KeeperPolicy", "dist(K[1], T[1]),
            "GreaterThan(50)", "HoldBall()");
```

Because the underlying RL algorithm is responsible for dealing with advice, algorithms such as standard SARSA will not be impacted by the above statement, so it is up to the teacher (or in the future, an automatic system) to choose an appropriate learning algorithm.

Transfer Learning If we have already trained the 3v2 example shown above, we could use it to initialize a new policy that learns 3v2 on a larger field, as in (Taylor & Stone, 2005). Lines 3, 4, and 5 in Fig. 3 would be changed to:

```
BeginEpisode("InitializeKeepaway(3, 2, 50, 50)");
LearnedPolicy(SourcePolicy("BigKP", "KeeperPolicy", true));
AttachPolicy("Keepers", "BigKP");
```

Verification

We have implemented the keepaway lesson using this protocol in the Java language, primarily using it to interface with the benchmark Keepaway code available at <http://www.cs.utexas.edu/~AustinVilla/sim/keepaway>. The soccer server remains in the C++ language, while the Trainer and Learning Agents are implemented in Java.

Since the focus of this paper is on the language for a teacher to communicate an RL task to a student, the main mark of success is whether a BL student can, with no prior knowledge of the properties of the desired task, begin learning the desired task as specified by a teacher. Indeed, using this protocol, we were able to initiate learning for keepaway

identically to the description described in Stone, Sutton, & Kuhlmann (2005). Furthermore, after having received the above instructions, the BL student is able to replicate the successful SARSA learning reported in the same paper.

After demonstrating successful learning in three versus two keepaway, Stone et al. then proceed to experiment with several task variations, including:

- Changing the the playing field to a larger or smaller size;
- Changing the state representation to a subset or a superset of the state variable specified in Figure 3; and
- Scaling up to more players (both keepers and takers).

In that previous work, each of these tasks had to be manually specified, including restarting the simulator and recompiling the players after changing their code. Using the BLTL framework, the agent can flexibly take instruction from the teacher to execute learning (and thus replicate the results reported by Stone et al.) on all of these task variations without any special-purpose preparation, on a single instance of the BL agent.

Conclusions and Future Work

The main contribution of this paper is the introduction of an architecture and interface language for teaching sequential decision making tasks to reinforcement learning agents. The BLTL language allows tasks to be specified concretely in terms of starting states, reward functions, and termination conditions. In addition, the teacher may provide advice and suggest sources for transfer learning, and may decompose complex tasks into multiple smaller lessons, allowing different policies learned with different methods to be combined synergistically. The BLTL language forms the cornerstone for the larger Bootstrap Learning project, which integrates even more machine learning methods for teaching agents to solve many different types of problems, not just sequential decision making tasks.

We have illustrated our language on a GridWorld task, and have implemented and tested the first BL agent on a specific RL task in the RoboCup soccer domain. An important next step is to test the BLTL language for other RoboCup tasks, as well as completely different domains such as flying an unmanned aerial vehicle (UAV). Future work for expanding the BLTL framework to the full Bootstrap Learning framework will include natural language mapping to the BLTL language, and adding more machine learning methods.

The BLTL language also lays the groundwork for future development of agents which can decide for themselves what tasks to learn and how to learn them, rather than waiting for task specifications and advice from a teacher. Current and future work on agents that discover new learning tasks (for example automatic subgoal discovery (McGovern & Barto, 2001)) will benefit from the ability to formulate new tasks using the BLTL language. Similarly, the introduction of BLTL exposes the important future goal of enabling an agent to automatically select, based on task characteristics, from among the large (and still growing) number of domain-independent RL algorithms and possible parameterizations thereof.

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