Learning From Demonstrations via Structured Prediction

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Abstract

Demonstrations from a teacher are invaluable to any student trying to learn a given behavior. Used correctly, demonstrations can speed up both human and machine learning by orders of magnitude. An important question, then, is how best to extract the knowledge encoded by the teacher in these demonstrations. In this paper, we present a method of learning from demonstrations that leverages some of the structured prediction techniques currently under investigation in the literature. We report encouraging results in Wargus, a real-time strategy game.

Introduction

Humans learn to interact with the world in a variety of complex ways. One of these ways is *learning by demonstration*. In this paradigm, a "teacher" presents a "student" with a plan to accomplish a given goal, usually formalized in machine learning literature as a sequence of actions. The student can then generalize the world state to which the demonstrated plan applies to other states where the plan may also apply.

Often, the demonstration plan is one of an exponential number of plans that may satisfy a given goal set, and in many domains (such as routing and scheduling), satisfying the goals of planning may be almost trivial. The higher achievement then, is to find a plan that satisfies the goal set optimally, or at least much better than the average, randomly drawn, goal-satisfying plan. Implicit in the above description is the notion that the demonstrated plan is one such "optimal" or "much better than average" plan.

In the reinforcement learning literature, the student typically learns through exploration. The student is allowed to take random actions in the world, and whenever one of these actions is taken, a reward is given. Over the course of many thousands of random actions, it becomes clear to the student which actions and world states generate the most reward. The best sequence to accomplish the given goal, then, becomes the sequence of actions that takes the student through the sequence of world states with the highest reward. In this setting, learning by demonstration guides exploration by "showing" the student a number of high-utility states, thus eliminating the need to discover them by random action.

This presents us with a problem, however, when we are faced with a world state not seen in the demonstration plans. In this case, the student has no notion of how to proceed and can do no better than to act randomly. Clever, feature-based representations of the value function allow generalization over the state space, but we are still learning the objective function *indirectly*. That is, the above approach learns a value function over the entire state space and then attempts to maximize the value of constructed path.

As an alternative approach, we propose direct, discriminative learning of this function. Rather than ask the question, "What is the value of each state in the state space" we will ask, essentially, "What separates 'good' states from 'bad' ones?". Recent work in structured prediction has given us a framework to do exactly this.

In the next section we describe this work and relate it to our approach. We later derive our gradient boosting method and give experimental results in a sub-domain of Wargus, a real-time strategy game. The results show that our system learns to plan effectively from a small number of demonstrations even when there are many irrelevant features.

Related Work

This work is related to three threads of work in machine learning. One is *structured prediction* (Taskar 2004), and particularly the work on cutting-plane methods as seen in (Tsochantaridis *et al.* 2004) and in (Parker, Fern, & Tadepalli 2006). In the vocabulary of supervised, multi-class learning, this work focuses on problems where there are an exponentially large number of negative classes for each training example. The approach is essentially to choose one of the best misclassifications for each positive example, and to update the model so that the correct class is chosen over this misclassification. In this way, problems having exponentially large numbers of classes can be solved efficiently.

The second strand is inverse reinforcement learning (Ng & Russell 2000). Here we assume that the demonstrated behavior is the result of optimally solving a Markov Decision Process (MDP). The task is to learn the unknown reward or cost function of the MDP from the demonstrated trajectories of its optimal solution. One approach to this problem is to assume that all the other trajectories to be suboptimal and learn reward functions which maximally distinguish the optimal trajectories from the suboptimal ones. Since the number of

suboptimal solutions is exponential in the size of relevant parameters, this problem is similar to the structured prediction task and is tackled by a similar iterative constraint generation approach. In each iteration, the MDP is solved optimally for the current reward function, and if the optimal solution generates a trajectory different from the demonstrated trajectory, it is used to train the next version of the reward function which maximally separates the optimal trajectories from the suboptimal trajectories (Abbeel & Ng 2004; Ratliff, Bagnell, & Zinkevich 2006).

The task we study in this paper is more naturally formulated as learning to act from demonstrations (Khardon 1999). Unlike inverse reinforcement learning that tries to learn the reward function, thus indirectly defining an optimal policy, here we directly seek to distinguish good state-action pairs from bad state-action pairs. Each state-action pair is described by a feature vector, and the optimal state-action pairs are assumed to maximize a weighted sum of its features. Thus, learning the weights of this optimizing function is sufficient to generate optimal behavior. Unlike in inverse reinforcement learning, the weights need not correspond to reward values. They merely need to distinguish good actions from bad actions as well as possible.

Gradient Boosting for Plan Optimization

Our problem can be formulated as a four-tuple $\{S, A, \mathcal{T}, R\}$, where S is a set of possible world states, A is a set of possible actions, and R is a reward function such that $R : s \in S \times a \in A \mapsto \Re$ gives the reward for taking action a in state s. $\mathcal{T}$ is our training set of demonstrations, composed of pairs of the form $\{s, a\}$ where s is a world state and a is the optimal (or near-optimal) action to take given this state. Our ultimate goal, then, is to build a function f that chooses the correct action for any given state, so that $f(s) = \text{argmax}_{a \in A} R(s \in S, a)$. To build f, we will rely on the techniques of structured prediction as stated above. In particular, we use a gradient boosting technique first used in (Dietterich, Ashenfelter, & Bulatov 2004) and later applied to structured prediction in (Parker, Fern, & Tadepalli 2006).

Our approach proceeds as follows: We are given a set of "demonstrations" that take the world from one state to another in a way that is optimal or near-optimal. We then attempt to iteratively learn a parameterized linear function that correctly discriminates the optimal demonstration action from one drawn at random. In each iteration, we select, from a group of random actions, the best "alternative" to each demonstration action given the current function. Based on the demonstrations and the alternatives (that we hope to avoid), we compute a gradient at each parameter and take a step in this direction, ideally away from the alternatives and toward the demonstrations. Furthermore, the gradient is *margin-based* so that demonstrations that are already highly ranked against their alternatives receive less attention than ones that are not as highly ranked.

To formalize this, we first define the function $\Psi(s, a)$ extracts a *joint feature vector* that may depend on s, a, and/or the state of the world that results from the execution of a in s. We seek a set of weights $\mathbf{w}$ that gives a higher value to the demonstration action than to all other actions, given the state s_i, with optimal action a_i. Specifically, suppose that $\hat{a}_i \in A$ is the best non-optimal action given the current weights:

$$\hat{a}_i = \underset{a \in A, a \neq a_i}{\text{argmax}} \langle \mathbf{w} \cdot \Psi(s_i, a) \rangle \quad (1)$$

Our weights, then, must be engineered so that, for s_i,

$$\langle \mathbf{w} \cdot \Psi(s_i, \hat{a}_i) \rangle < \langle \mathbf{w} \cdot \Psi(s_i, a_i) \rangle \quad (2)$$

for all demonstrations $\{s_i, a_i\} \in \mathcal{T}$.

It is possible that there are zero or infinitely many choices for $\mathbf{w}$ that accomplish this goal. We will then attempt to find a $\mathbf{w}$ that minimizes some notion of loss and maximizes a notion of margin. Our margin at each training example $\{s_i, a_i\} \in \mathcal{T}$ is clearly

$$\langle \mathbf{w} \cdot \Psi(s_i, a_i) \rangle - \langle \mathbf{w} \cdot \Psi(s, \hat{a}_i) \rangle \quad (3)$$

We use a margin-based based loss function defined in previous work (Friedman, Hastie, & Tibshirani 2000), $\log(1 + \exp(-m))$, where m is the margin. The cumulative loss L over the training set is

$$L = \sum_i \log[1 + \exp(\langle \mathbf{w} \cdot \Psi(s_i, \hat{a}_i) \rangle - \langle \mathbf{w} \cdot \Psi(s_i, a_i) \rangle)] \quad (4)$$

If there are n features in $\Psi(s, a)$, and $\Psi_j(s, a)$ gives the value of the jth feature, we note that

$$\langle \mathbf{w} \cdot \Psi(s, a) \rangle = \sum_j^n w_j \Psi_j(s, a) \quad (5)$$

Define the following notation for convenience:

$$\Psi_{\Delta j}(s_i) = \Psi_j(s_i, \hat{a}_i) - \Psi_j(s_i, a_i) \quad (6)$$

Finally, suppose our current cost function is $\mathbf{w}_k$. The gradient for the loss expression can be derived at each feature in the representation as follows:

$$\begin{aligned}
\delta_{k+1}(j) &= \frac{\partial L}{\partial \Psi_j(s, a)} \\
&= \sum_i \frac{\Psi_{\Delta j}(s_i) \exp(\langle \mathbf{w}_k \cdot \Psi(s_i, \hat{a}_i) \rangle - \langle \mathbf{w}_k \cdot \Psi(s, a_i) \rangle)}{1 + \exp(\langle \mathbf{w}_k \cdot \Psi(s_i, \hat{a}_i) \rangle - \langle \mathbf{w}_k \cdot \Psi(s, a_i) \rangle)} \\
&= \sum_i \frac{\Psi_{\Delta j}(s_i)}{1 + \exp(\langle \mathbf{w}_k \cdot \Psi(s_i, a_i) \rangle - \langle \mathbf{w}_k \cdot \Psi(s, \hat{a}_i) \rangle)}
\end{aligned}$$

The new cost function is then $\mathbf{w}_{k+1} = \mathbf{w}_k - \alpha \delta_{k+1}$ where α is a step size parameter. We can then choose a new $\hat{a}$ for each training example and recompute the gradient to get an iteratively better estimate of $\mathbf{w}$. Once the iterations are complete, and we have a final weight vector, $\mathbf{w}_f$, we have successfully constructed the function f from the problem formulation above:

$$f(s) = \underset{a \in A}{\text{argmax}} \langle \mathbf{w}_f \cdot \Psi(s, a) \rangle \quad (7)$$

(a) An example of poor base cohesion. (b) An example of good base cohesion.

Figure 1: Examples of floor plans in the Wargus domain.

Empirical Evaluation

We perform our experiments in the *Wargus floor planning* domain described below. Our general approach is to design several, not necessarily linear, objective functions in this domain and attempt to learn them using the method described above. We show that learning a linear function in several simple features is sufficient to approximate the behavior of these more complex objectives, even where many of the features given are irrelevant.

The Wargus Floor Planning Domain

Wargus is a real-time strategy game simulating medieval warfare. A subproblem in Wargus is the planning of a military base whereby the layout of the buildings maximizes certain quantitative objectives. In general, the goals are to maximize the influx of resources and to survive any incoming attack. Figure 1 shows some examples.

More specifically, we consider a simplified version of Wargus in which there are two types of natural features on the map, which is an $n \times n$ grid. The first is a gold mine, and the second is a forested area. On each generated map, there is one randomly placed mine and four randomly placed forested areas. Our goal is to place four buildings on the map so that our objective quantities given below are optimized. These buildings are a town hall, a lumber mill, and two guard towers. The town hall is a storage building for mined gold. The lumber mill serves the same function for cut lumber. The towers are able to fire cannon in a given radius, providing defenses for the base.

We postulate three such quantitative objectives based on user experience. For a given map and placement of buildings, we calculate a number between zero and one as a measure of how well each of these goals are satisfied.

- **Defensive Structure:** In the case where there is a clear part of the map from which an attack might originate, as much of this area as possible should be covered by the attack area of the guard towers. Formally, suppose that $t_x(g)$ returns 1 if grid square g within the attack radius of tower x and zero otherwise. If the battle front of a given map is composed of squares $g_1, \ldots, g_m$, then the defensive quality d of a map with two towers is

$$d = \frac{\sum_{i=1}^{m} t_1(g_m) + t_2(g_m)}{2m} \tag{8}$$

- **Base Cohesion:** It is beneficial to locate buildings close to one another. This makes the base easier to defend from attack. Formally, if the locations of the buildings are $b_1, \ldots, b_4$ then the cohesion quality c is computed as

$$c = \frac{\sum_{i=1}^{4} \sum_{j=i+1}^{4} 2n - ||\mathbf{b}_i - \mathbf{b}_j||_1}{12n}. \tag{9}$$

  The factor $2n$ is the maximum distance possible between any two entities on the map.

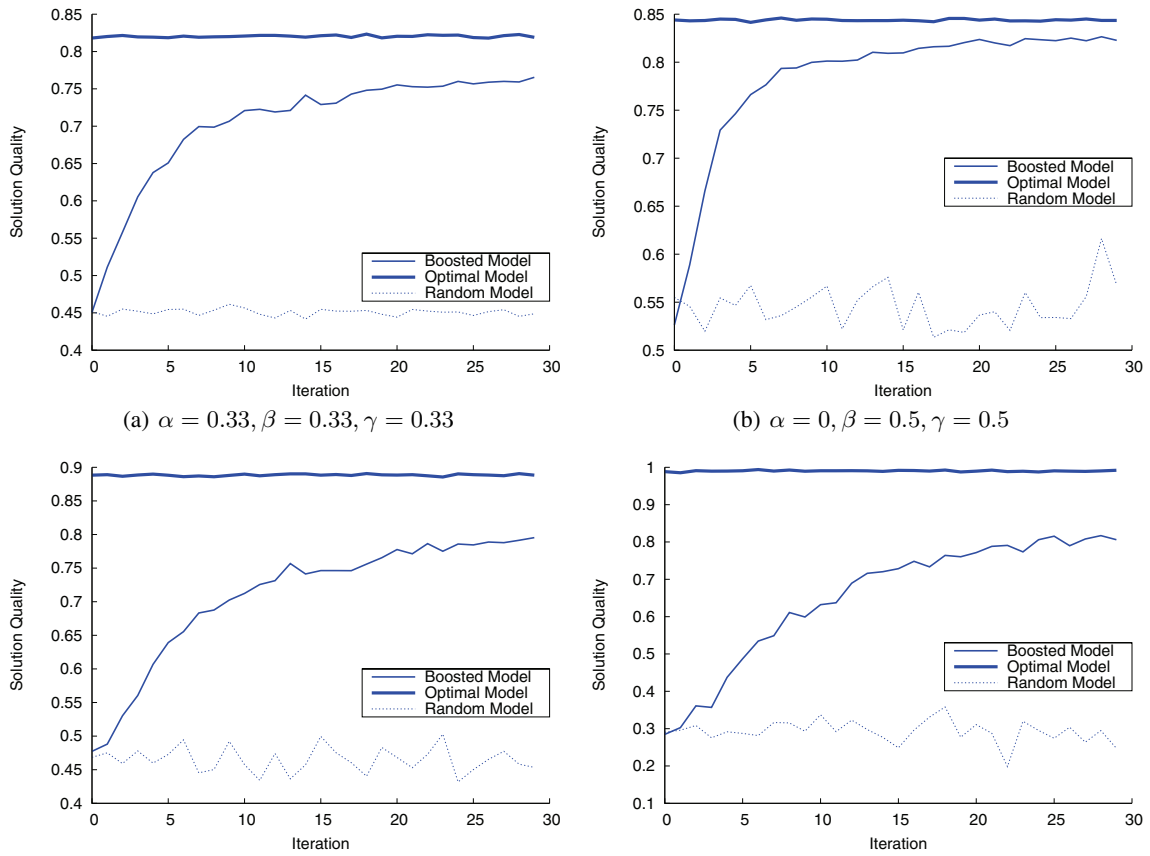
- **Resource Gathering:** The lumber mill should be located to minimize the average distance between itself and the various forested areas, and the town hall should be located as closely as possible to the mine. Formally, suppose the town hall is at $\mathbf{t}$, the gold mine at $\mathbf{m}$, the lumber mill at $\mathbf{l}$, and the four forested areas at $\mathbf{a}_1, \ldots, \mathbf{a}_4$. The resource gathering quality r of the base is then:

$$r = \frac{\frac{\sum_{i=1}^{4} 2n - ||\mathbf{l} - \mathbf{a}_i||_1}{8n} + \frac{2n - ||\mathbf{t} - \mathbf{g}||_1}{2n}}{2} \tag{10}$$

Domain Specifics

First note that in this domain, an entire plan, from start to finish, consists of a single, factored action (the placement of all buildings). Thus, we are in a special case of general MDPs which allows us to unify reward function and discriminant action-value function. However, our approach directly applies to general MDPs where we can design a feature space that allows a linear discriminant function to nearly optimal and suboptimal actions in any relevant states.

Our experiments are done on a 10×10 grid. Thus, there are tens of millions of possible plans to consider for a given map. To generate a negative example for each iteration of



(a) $\alpha = 0.33, \beta = 0.33, \gamma = 0.33$

(b) $\alpha = 0, \beta = 0.5, \gamma = 0.5$

(c) $\alpha = 0.5, \beta = 0, \gamma = 0.5$

(d) $\alpha = 1, \beta = 0, \gamma = 0$

Figure 2: Boosting curves for two objective functions in the Wargus floor planning domain. The training set contains 15 maps.

the algorithm (the $\hat{a}_i$ of Equation 2), we generate 10000 random plans and choose the best one according to the current model. The plans are pre-screened so that they are valid placements (i.e., so that multiple buildings are not located on the same grid square).

Given this, note that it is impossible to receive a perfect quality score of one on all of these measures. For example, to achieve perfect quality on the resource gathering measure, the lumber mill would have to be located on the same grid square as all of the forested areas, which would also have to be located on the same grid square.

The features in the model are of two types. First, there is a feature for the Manhattan distance between each building and each other entity on the map, resulting in $4 \times 9 = 36$ features. We also give features for the distance from each building on the map to the closest battle front square, which results in four more features, for a total of 40 features. Note that many of these features (the distance from either tower to any of the forested areas, for example) are irrelevant to plan quality.

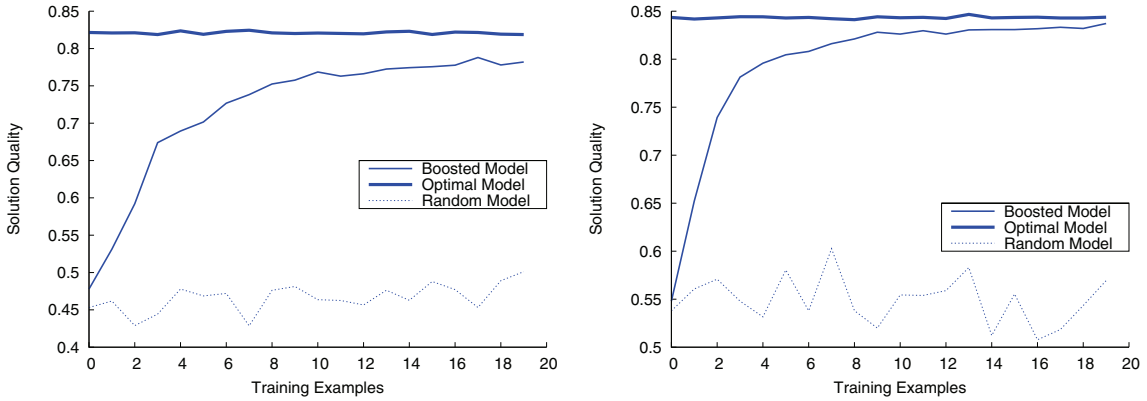
To generate several objective functions in this domain, we compute the total quality $q = \alpha d + \beta c + \gamma r$. We then vary α, β, and γ to obtain a variety of functions.

Experimental Results

In Figure 2 we see the results of boosting a random model for 30 iterations according to our algorithm. We evaluate the model at each iteration on 20 different random maps by choosing for each map, according to the model, the best in a random sample of 10000 plans. The chosen plans are then evaluated according to the optimal model. As the iterations of the algorithm progress along the horizontal axis, the quality of the plan chosen by the model increases, as expected.

For reference, we plot the performance of the optimal model as well as the performance of a linear model with its weights randomly initialized, evaluated in the same way as the boosted model. Note that the score of the optimal model varies due to the fact that first, the optimal score of a map varies from map to map, and second, the optimal plan may not be in the random sample. As can be seen from the plots in Figure 2, however, much of this variability is removed as our experiments are repeated and averaged over ten trials.

We first note that, in every case, the boosted function is able to learn a floor planning algorithm that is closer to optimal than random. This is true in particular for Figure 2(b), where the performance of the model converges to performance extremely close to the optimal. This is because the cohesion and resource gathering quality measures are almost



(a) $\alpha = 0.33, \beta = 0.33, \gamma = 0.33$ (b) $\alpha = 0, \beta = 0.5, \gamma = 0.5$

Figure 3: Learning curves for two objective functions in the Wargus floor planning domain.

directly expressible as linear functions of the given features. The defense measure is not readily expressible as a linear function. However, we see in Figure 2(d) that we are even able to learn a reasonable model when the defense measure is the only component of the objective. Finally, in 2(a), we see that that model performs admirably when it is forced to trade off all of the various components of the objective against one another.

Figure 3 shows learning curves for two of the objective functions from Figure 2. The number of training maps is plotted along the horizontal axis. Again, as expected, more training examples improves performance. We see that, again, we are able to learn more quickly when the defense measure is removed from the objective. More important to note, however, is the scale of the horizontal axis. For both objective functions, we are able to learn good models with only 10 to 15 training traces, even in the presence of many irrelevant features.

Conclusion and Future Work

We have presented here a method for learning via demonstration that leverages the structured prediction techniques currently under investigation in the literature. We use these techniques to discriminatively learn the best action to perform in a given world state even when there are an exponential number of states and actions. We have demonstrated the effectiveness of this techniques in the Wargus floor planning domain. Specifically, we have shown that this approach is able to learn to satisfy a variety of objective functions with only a small number training examples, even in the presence of irrelevant features.

An important future challenge is to relate this work to other discriminative reinforcement learning techniques such as inverse reinforcement learning (Ng & Russell 2000) and max-margin planning (Ratliff, Bagnell, & Zinkevich 2006). We suspect that these three approaches have a great deal in common mathematically, and we would like to establish exactly what these similarities are.

Turning to the particulars of our work, there is certainly room for improvement in the inference portion of the algorithm. As stated before, a best plan is chosen by drawing randomly from the space of possible plans and choosing the best one. This is both highly inefficient and unreliable: Depending on the domain, we may have to evaluate thousands or millions of plans before coming across a reasonable one, and even then there is no guarantee of quality. This not only makes inference unreliable, but has a detrimental effect on learning, as the inference algorithm rebuilds the training set at each iteration. A better inference routine may improve the quality of learning and will certainly make it more efficient.

Finally, it is possible that other methods of structured prediction can be specialized for learning via demonstration. Given the close relationship of gradient boosting (Parker, Fern, & Tadepalli 2006) to SVM-Struct (Tsochantaridis *et al.* 2004), we feel that SVM-Struct is a likely candidate.

Acknowledgments

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