Role-Based Ad Hoc Teamwork

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Abstract

An ad hoc team setting is one in which teammates must work together to obtain a common goal, but without any prior agreement regarding how to work together. In this abstract we present a *role-based approach* for ad hoc teamwork, in which each teammate is inferred to be following a specialized role that accomplishes a specific task or exhibits a particular behavior. In such cases, the role an ad hoc agent should select depends both on its own capabilities and on the roles currently selected by the other team members. We present methods for evaluating the influence of the ad hoc agent's role selection on the team's utility and we examine empirically how to select the best suited method for role assignment in a complex environment. Finally, we show that an appropriate assignment method can be determined from a limited amount of data and used successfully in similar new tasks that the team has not encountered before.

Introduction

Ad hoc teamwork is a relatively new research area (Bowling and McCracken 2005; Jones et al. 2006)—and the subject of a AAAI challenge paper (Stone et al. 2010)—that examines how an agent ought to act when placed on a team with other agents such that there was no prior opportunity to coordinate behaviors. This is in contrast to most prior research on multi-agent teamwork, which often requires explicit coordination protocols, languages, and/or shared assumptions (e.g. (Grosz and Kraus 1996; Tambe 1997)).

In some team domains, such as search and rescue missions and many team sports, the team behavior can be broken down into *roles*. In such domains, an ad hoc teamwork agent's main task is to decide which role to assume, such that the team's performance is maximized. This decision is situation-specific: it depends on the task the team is to perform, on the environment in which it will operate, and on the capabilities of the team members. One trivial approach is for an ad hoc team member to assume the role at which it is most *individually* capable. However, the choice of an optimal role—one that results in highest *team* utility—rarely depends only on the ad hoc team member, but also on the behavior of the other team members. We therefore examine the contribution of an ad hoc team member to the team by the measure of *marginal utility*, which is the increase (or decrease) in a team's utility when an ad hoc agent is added to the team and assumes a particular role. An *optimal mapping* of an ad hoc team member to a role is, therefore, one that maximizes the marginal utility, hence maximizing the contribution of the ad hoc agent to the team's utility.

The main contributions of this work are i) a formalism of role-based ad hoc teamwork scenarios, ii) a classification of types of tasks according to the patterns they exhibit in terms of marginal utilities for role mappings, and iii) detailed experiments in a new role-based ad hoc teamwork domain.

Problem Definition

In this work we study the *role-based* ad hoc teamwork problem, which is one that requires or benefits from dividing the task at hand into roles. We assume that different roles have different values to the team and each agent has some ability to perform each role. As such, an ad hoc agent must take into account both the needs of the team and its own abilities when determining what role to adopt.

Formally, let task d have roles $R(d) = \{r_0, ..., r_{m-1}\}$. Let $\mathbf{A} = \{a_0, ..., a_{n-1}\}$ be the set of ad hoc agents whose behavior we control and $\mathbf{B} = \{b_0, ..., b_{k-1}\}$ be the set of teammates such that $T = A \cup B$ is the team that is to perform task d. Let mapping $\mathbf{P} : B \to R(d)$ be the mapping of the teammates in B to roles $\{r_0, ..., r_{m-1}\}$ and let mapping $\mathbf{S}$: $A \to R(d)$ be the mapping of the ad hoc agents in A to roles $\{r_0, ..., r_{m-1}\}$. Additionally, let mapping $\mathbf{SP} : T \to R(d)$ be the combination of mappings S and P.

A team score $U(SP, d, T)$ results when the set of agents T perform a task d, with each $t_i \in T$ fulfilling some role $r_j \in R(d)$ under mapping SP. The marginal utility $MU(S, P)$ is the score improvement obtained when each ad hoc agent a_j chooses role $r_S(a_j)$ under mapping S such that $MU(S, P) = U(SP, d, T) - U(P, d, B)$. Given that mapping P is fixed, the role-based ad hoc team problem is to find a mapping S that maximizes marginal utility. In this work we focus our attention on the case where there is only one ad hoc agent.

Choosing a Role—Proposed Models

The ground truth way for an ad hoc agent to determine the marginal utility from selecting a particular role, and hence determine its optimal role, is to determine $U(SP, d, T)$ for each possible role it could adopt. However, in practice, the ad hoc agent must *predict* its marginal utility for all possible roles and then select just one role. As such, we present five models with which the ad hoc agent could do this prediction, each appropriate for a different class of role-based tasks.

Unlimited Role Mapping Model : The benefit the team receives for an agent performing a role is not dependant on the roles fulfilled by other teammates.

Limited Role Mapping Model : Each role r_i has an associated r_i^{min} value and r_i^{max} value that represent the minimum and maximum number of agents that should perform role r_i. The team receives no benefit for agents above (below) r_i^{max} (r_i^{min}) that perform role r_i.

Incremental Value Models(3) : The value added by agents performing a role may not be linearly correlated with the number of agents performing that role. In particular, it might be correlated via a (1) logarithmic function, (2) exponential function, or (3) sigmoidal function.

Model Evaluation

We empirically evaluate each of the five models in a capture-the-flag style variant of Pacman (DeNero and Klein 2010). The Pacman map (see Figure 1) is divided into two halves, and two teams compete by attempting to eat the food on the opponent's side of the map while defending the food on their home side. A team wins by eating all but two of the food pellets on the opponent's side or by eating more pellets than the opponent before three thousand moves have been made. The result of each game is the difference between the number of pellets protected successfully by the team and the number of pellets successfully protected by the opponent—we refer to this result as the *score differential*.

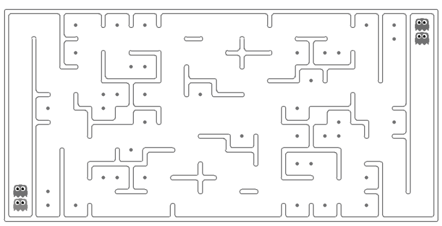

Figure 1: Sample map. The team protects the left half of the map, and the opponent protects the right half of the map.

In each experiment, we consider two roles that could be performed: $R = \{$offense, defense$\}$. These offensive and defensive behaviors are deliberately suboptimal, as we focus solely on role decisions given whatever behaviors the agents execute when performing their roles.

Choosing a Model

In order to decide which of the models is most representative of the marginal utility of a role selection in the Pacman Capture-the-Flag environment, we gather score differentials over one thousand runs for teams of zero to six offensive agents and zero to six defensive agents in three tasks. We input each score differential into the following sigmoid function $1/1 + e^{-0.13 * scoreDifferential}$ to obtain more representative data, and then use this *ground truth data* to determine the *ground truth decisions* of whether an ad hoc agent should perform an offensive role or a defensive role on any team composed of zero to five offensive agents and zero to five defensive agents in each task.

With the ground truth decisions for the ad hoc agent in three tasks, we can determine which of the five models best captures the actual marginal utility of role selection in each task. First, we input the ground truth data and the model function into a least squares curve fitting algorithm and obtain *fitted parameters* for the model function. We can then use these fitted parameters to calculate *fitted results* for all forty-nine teams. Finally, we translate these fitted results into *fitted decisions*. We can then compare the number of times the ground truth decision does not match the fitted decision for a particular team arrangement —in other words, the number of times the model made an *incorrect decision*. Our experiments found that the sigmoidal model made the fewest incorrect decisions in all three tasks. As such, we concluded that in the Pacman Capture-the-Flag domain, at least on the maps and opponents we studied, the sigmoidal incremental model most accurately models team utility.

Predictive Modeling

Once a model type has been selected, the ad hoc agent can use this model to predict the marginal utility of role selection on similar tasks for which we have limited ground truth data. Before using a model predictively, the ad hoc agent *must* obtain new fitted parameters for the model function based upon available data. Experiments show that if parameters fit on one task are used on another task, the results can be quite poor. However, fitting the parameters even with very limited data can be beneficial. In one new task we studied, fitting the model parameters to data from just one team configuration and twenty-five games yielded an average of 33.5% incorrect decisions, which is significantly better than the 50% incorrect decisions obtained if decisions are made randomly.

Future Work

This research is among the first to study role-based ad hoc teams. As such, there are many potential directions for future work. First, we plan to expand our work into more interesting and complicated environments with more than two potential roles to fulfill and more than one ad hoc agent. Additionally, we wish to consider the case in which the ad hoc agents encounter teammates that are running unfamiliar behaviors, forcing the ad hoc agents to model their teammates in order to classify their behavior into a known role and successfully collaborate.

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