Applying the Synergy Graph Model to Human Basketball (Extended Abstract)

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ABSTRACT

Synergy Graphs model team performance as a function of individual capabilities and inter-agent compatibility. Synergy Graphs have previously been applied to team formation problems in multi-agent systems, physical robot teams, and selecting modules for multi-robot teams. In this extended abstract, we describe how the Synergy Graph model is applied to human teams. In particular, we focus on basketball, and use data from games played in the National Basketball Association (NBA), in order to predict the game outcomes.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent systems

General Terms

Algorithms, Experimentation

Keywords

Team formation, performance modeling, learning, synergy, basketball, human teams

1. INTRODUCTION

A game of basketball is played between two opposing teams, over four quarters of fifteen minutes each. During the game, each team selects a line-up of five players to play against the five players of the opposing team. These line-ups change frequently as players are substituted. Hence, we believe that in order to predict the outcome of a game accurately, we must first be able to predict the outcome of a 5v5 lineup between the teams.

The Synergy Graph model was recently introduced, where agents are modeled as vertices in a connected graph, and edges represent the compatibility between agents, i.e., agents that are more compatible have shorter distances to each other. The performance of a team is then a function of the agent compatibility, as well as the individual agents' capabilities. The Synergy Graph model has been applied to multi-agent team formation problems [1], such as in simulated urban search and rescue [5]. Synergy Graphs have also been applied to role assignment in robot teams [2], and selecting modules for a multi-robot team [4, 3].

In this extended abstract, we consider applying the Synergy Graph model to adversarial zero-sum games. We consider human basketball as a motivating real-life example of such games. We formally define the Adversarial Synergy Graph model, and describe how the model is used to predict the outcome of two adversarial teams in a zero-sum game. We then conclude by describing how the Adversarial Synergy Graph model can be applied to human basketball.

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2. ADVERSARIAL SYNERGY GRAPH

We formally define the Adversarial Synergy Graph model:

Definition 2.1. *An* ***Adversarial Synergy Graph*** *is a tuple* (G, C)*, where:*

- $G = (V, E)$ *is a connected unweighted graph,*
- $V = \{a_{1,1}, \ldots, a_{N,M_N}\}$*, i.e., every agent* $a_{i,\alpha}$ *from team* i *is represented by a vertex,*
- E *are unweighted edges in* G*, and*
- $C = \{C_{1,1}, \ldots, C_{N,M_N}\}$*, where* $C_{i,\alpha} \in \mathbb{R}$ *is agent* $a_{i,\alpha}$*'s capability.*

G is a connected graph, so there exists a path between any pair of agents. The unweighted edges represent the compatibility among the agents, where a shorter distance between two agents represents a higher compatibility. A comprehensive description of these task-based relationships is presented in [5].

To compute the performance of two adversarial teams, we first define the pairwise synergy of two agents in the same team.

Definition 2.2. *The* ***pairwise synergy*** *of two agents* $a_{i,\alpha}$ *and* $a_{i,\beta}$ *in the* ***same team*** i *is:*

$$\mathbb{S}_{2,team}(a_{i,\alpha}, a_{i,\beta}) = \phi(d(a_{i,\alpha}, a_{i,\beta})) \cdot (C_{i,\alpha} + C_{i,\beta})$$

where $d(a_{i,\alpha}, a_{i,\beta})$ *is the shortest distance between the vertices representing the agents in the unweighted graph* G *(i.e., edges have a distance of 1), and* $\phi : \mathbb{R} \to \mathbb{R}$ *is the compatibility function.*

The compatibility function ϕ maps larger distances to lower compatibility. Examples include $\phi_{\text{fraction}}(d) = \frac{1}{d}$ and $\phi_{\text{decay}}(d) = \exp\left(-\frac{d \ln 2}{h}\right)$.

Next, we define the pairwise synergy of two agents in opposing teams.

DEFINITION 2.3. *The **pairwise synergy** of two agents $a_{i,\alpha}$ and $a_{j,\beta}$ in **adversarial teams** $i \neq j$ is:*

$$\mathbb{S}_{2,adver}(a_{i,\alpha}, a_{j,\beta}) = \phi(d(a_{i,\alpha}, a_{j,\beta})) \cdot (C_{i,\alpha} - C_{j,\beta})$$

where $d(a_{i,\alpha}, a_{j,\beta})$ is the shortest distance between the vertices representing the agents in the unweighted graph G (i.e., edges have a distance of 1), and $\phi : \mathbb{R} \to \mathbb{R}$ is the compatibility function.

The key difference between Defs. 2.2 and 2.3 is whether the agent capabilities are summed. When agents are in the same team, their capabilities aid the final team performance, and so the sum of their capabilities is used. In contrast, the difference between agent capabilities is used when the agents are in opposing teams, since they are adversarial.

Using the pairwise synergy definitions, we now define the synergy of two teams.

DEFINITION 2.4. *The **synergy** of two adversarial teams A_i and A_j ($i \neq j$) is:*

$$\mathbb{S}(A_i, A_j) = \frac{1}{\binom{|A_i|+|A_j|}{2}} \left(\sum_{\{a_{i,\alpha}, a_{i,\beta}\} \in A_i} \mathbb{S}_{2,team}(a_{i,\alpha}, a_{i,\beta}) - \sum_{\{a_{j,\alpha}, a_{j,\beta}\} \in A_j} \mathbb{S}_{2,team}(a_{j,\alpha}, a_{j,\beta}) + \sum_{a_{i,\alpha} \in A_i, a_{j,\beta} \in A_j} \mathbb{S}_{2,adver}(a_{i,\alpha}, a_{j,\beta}) \right)$$

The overall synergy of the teams A_i, A_j, i.e., which team will win in the zero-sum game, is computed using the difference of pairwise synergy of agents within A_i and within A_j (the effects of each team independently), and then by the pairwise synergy of agents across the teams (the effects of the agents interacting in the zero-sum game). Hence, the agents' capabilities and their pairwise distances play an important role in affecting the final synergy.

Differences from other Synergy Graph models

The key differences between the Adversarial Synergy Graph (AdSyn) model and previous Synergy Graphs are:

1. The AdSyn models adversarial teams;
2. The AdSyn uses unweighted edges;
3. The agent capabilities are real numbers.

Previous Synergy Graphs model multi-agent and multi-robot teams that are fully collaborative, i.e., all the agents are working towards a shared goal. The Adversarial Synergy Graph model considers two adversarial teams in a zero-sum game, hence the agents are working for competing goals.

Our Adversarial Synergy Graph model uses unweighted edges in the graph structure, and real numbers for the agent capabilities. Previous Synergy Graphs considered both unweighted [1] and weighted edges [2], and showed that some task-based relationships cannot be represented using unweighted edges [5]. However, we use unweighted edges in this work because the number of vertices are large when considering opponents (e.g., there are 450 players in the NBA), so weighted edges would increase the search space for learning. Similarly, we use real numbers for agent capabilities, instead of Normally-distributed variables in previous Synergy Graph models, due to the increase in complexity for learning an AdSyn from data.

3. MODELING HUMAN BASKETBALL

Each player in the National Basketball Association (NBA) (e.g., LeBron James) is represented as a vertex $a_{i,\alpha}$ in the Adversarial Synergy Graph model, where i is the player's team (e.g., Cleveland Cavaliers). The edges in the Adversarial Synergy Graph represent the players' compatibilities, where players that are highly compatible have shorter distances to one another.

Every agent $a_{i,\alpha}$ is also associated with its individual capability $C_{i,\alpha}$. The agent capabilities capture the contribution of each player during the basketball game, in affecting the point difference between two line-ups of five players each.

The Adversarial Synergy Graph structure (i.e., the edges in the graph) and the agent capabilities are learned completely from data. To do so, we parse the historical play-by-play data of the NBA games and extract the following:

$$((h_1, h_2, h_3, h_4, h_5), (o_1, o_2, o_3, o_4, o_5), ptd)$$

where $h_1, \ldots, h_5$ are the names of the players on the line-up of home team, $o_1, \ldots, o_5$ are the players on the line-up of the opposing team, and ptd is the point-difference between these two line-ups.

Since each basketball game consist of multiple substitutions, we can extract a large dataset of such tuples from a single season of the NBA. For example, in the 2008-2009 season, there are 60235 such tuples corresponding to 444 unique players (some players did not play any games that season).

Since we do not use any domain-specific information, such as the statistics of the players (e.g., the percentage of successful field goals), we believe that the key contribution of our Adversarial Synergy Graph approach is that it is applicable to general adversarial zero-sum games.

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