**Learning the Value of Teamwork to Form Efficient Teams**

**Summary:**

Team Formation (TF) is a fundamental concept that underpins many multi-agent systems where heterogeneous agents with individual properties (e.g., roles, capabilities, costs) come together to undertake tasks. TF involves the evaluation of different sets of agents in order to determine how well they will, individually or collectively, perform their tasks. By so doing, it is then possible to pick sets of agents that form the most effective teams. In this paper, we consider how such directed interactions between agents can be valued and considered in the prediction of team performance.

The paper proposes a novel approach to forming teams using patterns that appear in a network of interactions between agents. We then validate and evaluate our approach by applying our models and algorithms to a real-world team formation problem presented by the domain of football (soccer). We show that our teamwork-focused model outperforms other player-focused approaches at predicting the teams that would be chosen by human-expert managers across 64 games from the 2018 FIFA World Cup. We also show that our model is better at predicting the performance of teams from real-world data. Thus, this paper advances the state of the art in the following ways:

1. We propose a novel approach to team formation based on the value of inter-agent interactions. Specifically, we propose a model of teamwork that considers the outcomes of the chains of such interactions.

2. Based on our model, we propose a number of network metrics to capture the contributions of individuals and sets of agents.

3. We show how the value of teamwork can be learnt from data and then applied to the

prediction of team performance. When taken together, our results establish the first benchmarks for team formation based on the learnt value of teamwork.

The TF model is based on our observations of many real world team-based systems, such as football teams or teams of emergency responders, as follows:

• Many teams operate through directed (one-to-one, one-tomany, or many-to-many) interactions. For example, in a football team, a player would pass a ball to another. However, team members will not always interact equally with every other team member. In this paper, as a first step, we will focus on one-to-one interactions. Indeed, we show that such a setup gives rise to complex interactions that pose difficult computational challenges.

• Team members may have different roles and abilities to perform tasks. For example, emergency response teams will have members with different skill sets, equipment, and training. In a football team, each player will have a position on the pitch and specific abilities.

• Team actions can have multiple consequences. In the simplest case, they may have binary outcomes (succeed in achieving a mission or failing to do so). In many cases, however, team success is more nuanced (e.g. the achievement of a sub-ideal goal). • Team formation typically involves picking a subset of agents that work well together, using some metric of efficiency. For example, emergency responders will choose a subset of available partners that are most fitting to the task or have the right skills. Similarly, a football manager will pick the best team (measured by their likelihood to win a match) of 11 players out of a squad of 23

Two methods are used to form efficient teams using values . Firstly, we form teams based on the values of singleton agents. Secondly, we form teams based on the value of agent pairs p, so that teams are formed between agents who communicate and work well together. Agent-Centred Approach To form the efficient team based on singleton agents, we use the values v(ai) for each agent ai. Given constraints on the number of agents to be picked overall and the number of agents per role allowed in the team , this results in a combinatorial optimisation problem that is solved using standard mixed integer programming (MIP) techniques. Team-Centred Approach Here we consider how the team works effectively and hence only consider the walk frequency metric. Specifically, we reconstruct the value of teamwork based on two core concepts which we call the strength of teamwork and interactional alignment which we describe as follows.

• Strength of Teamwork: This is based on the contribution of the pairwise interactions, which in this case is shown by a high frequency of directed successful interactions between the agents. We calculate this in

• Interactional Alignment: This is the measure of the strength of teamwork between overlapping pairs within the selected team. This values the strength of teamwork that the selected agents in a pair will bring when paired with other selected agents in the team. This helps us avoid selecting pairs of agents which have a strong value between themselves but are weak when combined with the rest of the team.

We combine these two measures to maximise the values of the selected pairs (pi) while also maximising the value of the pairs that they overlap with in the selected team as a whole.

To validate the models we apply our techniques to the problem of team formation in football. In this section, we first give a background of the related work in football team formation and we then highlight how this relates to our model. To calculate the values of the players in the network, we first create the weighted graph that we need for our model. We do this using the walks (patterns of play) which happen in a game. We can then calculate their values for each of the possible walk events using each of the metrics. The possible walk events we use are: a goal, a shot on target, a shot off target and a lost possession. Firstly, we do this for singleton players so that we have values based on their centrality, walk frequency and distance from the outcome. We then value the player pairs based on their frequency in the network. This gives us the values for both players and pairs from each match which we can then use to learn the impact weights of the outcomes.

To calculate the weights of the walk events we use logistic regression. sing the values for the players/pairs 7067 for each walk event in each game we use the match outcome (team win, loss or draw) as the y value in our logistic regression formula. This means that we train the model to calculate the weights based on what impact it will have on the match outcome and, therefore, the overall team performance. The final value for the players/pairs will then be a weighted sum (defined in Equation 1) which uses these learned weights and will inform the team formation process)

The two methods we take to form teams using both the singleton player values and the pair values. Singleton Agents The first method uses the values of singleton players calculated using the centrality, walk frequency and distance from outcome (as discussed in Section 3). We use these values alongside constraints over players’ positions to form the optimal team.

Secondly, using the values of the player pairs we form teams using the MIP formula. When forming teams we ensure that all the pairs of players are part of the same squad and can be selected together. We also consider the positions of the players so that we pick a team in a reasonable positional formation. This is represented by position range constraints.

We evaluate our model using all games from the 2018 FIFA World Cup and compare both the singleton approach and the pairs approach with the teams selected by the human-expert manager (focusing on both the starting 11 players and the 11 players who finish the game after substitutes). The results are presented in Figure 3 (where error bars represent a 95% confidence interval). The approaches used to form teams are:

• Model 1: Player values calculated using the centrality and team formed using an MIP.

• Model 2: Player values calculated using the walk frequency and team formed using an MIP.

• Model 3: Player values calculated using the distance from an event and team formed using an MIP. • Model 4: Pair values are calculated and Equation 6 is used to form the team.

Secondly, We see that in there is a positive correlation between the teamwork values and the number of goals scored by the teams and we see similar results for the correlation of the team value for other metrics. Hence, to evaluate the strength of our methods, we use the valuations as a predictor of the actual real7068 world performance of the selected teams. We focus on match outcomes and other team performance metrics.

Conclusion:

In this paper, we describe a novel approach to team formation based on directed interactions between agents. Our model of teamwork considers event outcomes of the chains of interactions shown as walks within graphs. We defined and tested multiple network metrics to value the contribution of agents and sets of agents and show how the value of teamwork (including interactional alignment) can be learnt from data and then applied to predict the performance of teams. We tested and validated our models of valuing agents and forming teams by applying our models to problems posed by football and using data from the 2018 FIFA World Cup. We showed that our model is can produce similar team selections to an international level human-expert manager while also being suggesting changes to the team. We also showed how our valuation methods are an effective predictor of the key team performance metrics in football.

Why is this important:

Data collection has become one of the fastest and most valuable asset used by team managers across the globe, across various sports. In their strive to improve their teams, managers are employing all sorts of methods to improve results.

The conclusions from this paper show the value of data analytics in helping managers achieve this goal, and also provide several interesting insights that would’ve otherwise gone unnoticed. This leads to better decision making and overall progress in the sport.

This technique is still in its early stages, and already rivals the top coaches in improving teamwork in a team. The prospect of improvement and development of this model provides a very interesting future for this field.

My critiques:

It is well known that the amount of data available in the football is very limited. The results that we obtain from the current data is astounding, however, the prospect of growth is limited by the availability of data in this field. The need of the hour is better and more public data collection to improve model building across all sectors.

As good as our model is today, it is based on a set of factors that are chosen by the author. While talking about team building, it is a common fact that no two people will give the same parameters for better team building, some of these factors even being contradictory. The whole field of team-building is a growing field in itself, and this model, although well build, will over time need to undergo a lot of changes to the parameters used.

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