Learning a Markov Model for Evaluating Soccer Decision Making

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Abstract

Reinforcement learning techniques are often used to model and analyze the behavior of sports teams and players. However, learning these models from observed data is challenging. The data is very sparse and does not include the intended end location of actions which are needed to model decision making. Evaluating the learned models is also extremely difficult as no ground truth is available. In this work, we propose an approach that addresses these challenges when learning a Markov model of professional soccer matches from event stream data. We apply a combination of predictive modeling and domain knowledge to obtain the intended end locations of actions and learn the transition model using a Bayesian approach to resolve sparsity issues. We provide intermediate evaluations as well as an approach to evaluate the final model. Finally, we show the model's usefulness in practice for both evaluating and rating players' decision making using data from the 17/18 and 18/19 English Premier League seasons.

1. Introduction

Reinforcement learning techniques are increasingly being applied to analyze sports such as ice hockey (Liu & Schulte, 2018; Luo et al., 2020; Routley & Schulte, 2015; Schulte et al., 2017), soccer (Fernández et al., 2021; Hirotsu & Wright, 2002; Liu et al., 2020; Rudd, 2011; Singh, 2019; Van Roy et al., 2021; Yam, 2019), basketball (Cervone et al., 2016; Sandholtz & Bornn, 2018; 2020; Wang et al., 2018), and American football (Goldner, 2012). These models leverage the large amounts of data that are being collected from matches, which include line-up information, specific actions or events that occur, and sometimes even include information about the location of all players at each moment of the match. Using this data, reinforcement learning techniques are able to model the observed team and player behavior. Such models have a variety of use cases including performing match analysis (Fernández et al., 2021), aiding tactical planning (Hirotsu & Wright, 2002), evaluating the effect of different strategies (Sandholtz & Bornn, 2018; 2020; Van Roy et al., 2021) and rating the actions of players which is useful for player scouting (Cervone et al., 2016; Liu & Schulte, 2018; Liu et al., 2020; Luo et al., 2020; Routley & Schulte, 2015; Rudd, 2011; Schulte et al., 2017; Singh, 2019; Van Roy et al., 2020; Yam, 2019).

In this paper, we will focus on learning a Markov model of professional soccer matches with the goal of aiding in-game decision making. The model will be learned on the basis of event stream data, which is a type of data that annotates various events such as passes, tackles, interceptions, and shots that occur during a match. Moreover, it also records information like the location of the event on the pitch, the players involved in the event, and the time the event occurred. Working with such data poses a number of challenges from a learning perspective. First, the observational nature of the data means that when an action is unsuccessful, its intended end location is not recorded and hence unknown. For example, if a player attempts a cross that the opposition clears, we are unsure of where the player was aiming. Second, the data is sparse. A season is relatively short and the dynamic nature of the game makes it such that teams rarely perform the exact same action multiple times. Finally, evaluating and validating the learned models is extremely difficult. For other tasks like rating individual actions, ground truth ratings simply do not exist. For tasks like assessing changes to in-game decision making, validation becomes even harder as the proposed changes cannot be implemented in practice solely for the sake of evaluation.

Our work uses a Markov Decision Process (MDP) to model soccer and addresses each of the aforementioned challenges when learning the model from event stream data. First, we learn a predictive model to predict the intended end locations of players' actions using a combination of domain knowledge and predictive modeling. Second, we employ a hierarchical Bayesian approach to learn the transition model which helps mitigate sparsity issues by using a prior based on a "typical team". The model is then specialized to an individual team on the basis of their data. Third, we evaluate each step and outline an approach to validate the final

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Reinforcement Learning for Real Life (RL4RealLife) Workshop in the 38^{th} International Conference on Machine Learning, 2021.