Artificiellt Intelligent Basketträn aragent

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4 December 2022

1 Introduction

As proposed in our previous project milestone, our intention was to design a competing agent model in which two basketball coaches will make management decisions during a game. These coaches will have the ability to call timeouts and make substitutions for their teams at discrete, simulated decision times throughout the game. We intend to model our decisions based on probabilistic reasoning, with extensive incorporation of historical NBA data.

2 Literature Review

Much of the existing literature on artificial intelligence in basketball (and other sports) focuses on one of two objectives: prediction and machine learning, and live-game simulation including ball movement on the court. For instance, (Pai et al.) writes "With predicted outcomes of games, and rules yielded from [their] model, coaches can easily and quickly learn essential factors increasing the chances to win games. Empirical results showed that the proposed model can obtain relatively satisfactory prediction accuracy and therefore is a promising alternative for analyzing the results of basketball competitions." While their results are in fact impressive, the paper does not consider conditional decision making, but rather development of strategy to be employed at all times. Additionally, (Li) trained a model which developed strategies for conditioning and teaching basketball players, but their results were focused on long-term coaching strategies for training players during practice time, not managing live games.

On the other side of artificial intelligence models in basketball are those which demand intense computational time and space. (Alcorn and Nguyen) propose sequential generative models (Variational RNN) for policy models with partial observation and mechanical constraints, such as position, velocity, and acceleration. Their model effectively predicts movement on the court, but operates conditional on the players on the court. (Fujii et al.) pursue a similar goal, introducing a multi-agent spatiotemporal model that integrates information about concurrent actions of agents to predict statistically dependent distributions of trajectories. The model applies state-of-the-art deep-learning methodologies, such as attention and transformer, to predict player's movements. Likewise, (Sandholtz and Bornn) emphasises the decisions make by players on the court (such as pass, shoot, etc.) using a Markov Decision Process technique. (Van Roy et al.) also uses a Markov model to a similar end, though it is tested and evaluated primarily on ball movement in English football (soccer) as opposed to basketball.

Overall, we reach a similar conclusion as (Li and Xu) who write "Currently, the application of AI technology in basketball has been extensively studied, including analyzing the performance of teams and players, predicting game results, analyzing and predicting shooting, basketball teaching, intelligent training machinery and arena, and preventing sports injuries." With all of that said, we did not encounter a publication which aimed to produce real-time decisions regarding coaching and management decisions on the sideline of a basketball game, indicating that we are tackling a novel problem in artificial intelligence.

3 Formal Model

The formal specification of our model will include fully-observable states, with the following attributes:

- Players on and off the court - including their skill level, minutes played in the game, minutes played since the last timeout or time on the bench, and fatigue-updated skill based on minutes played
- Time left in the quarter and the game
- Score of the game
- Momentum - which team has been scoring most of the points recently in the game

These attributes will be updated for each decision node, so no state will be visited twice, as the time played by players will increase monotonically as the game is played. Theoretically, our model will exist on a continuous, unbounded state space. Realistically however, we have set the parameters of the model to simulate games in which the score is reasonable with historical averages, where several simulations showed average scores of around 100 points per team, depending on the match-up of teams.

Decision nodes will occur at randomly simulated times. During these decision nodes, our agents will have the opportunity to evaluate the following coaching decisions:

- Call a timeout (when that team has possession of the ball)
- Substitute players in and out of the game during a timeout, or after a basket has been scored

We give our agents the opportunity to evaluate each of these strategic decisions each time that possession of the ball changes. Each possession will last a randomly simulated time, with a mean based on the team's 2021-2022 average possession duration, and a standard deviation of 3 seconds, following the Gaussian distribution.

It is worth noting, the coaches will make these decisions without knowing how long it will be until the next decision node - they will only know the probability distribution of the time that will pass before the next decision node. With this in mind, there are uncountably many states which any given action could result in transitioning to, so we will not be able model a long time horizon in a Markov process, thus decisions will be evaluated in an effort to optimize short-term gain.

4 Solution Direction

Our agents evaluate their potential decisions in each decision node through probabilistic reasoning. Calling a timeout is considered on two margins - first to reduce fatigue and second to slow the opponent's momentum. We quantify "tiredness" as a function of minutes played in the game so far for each player - which is generally available in NBA data - as well as consecutive minutes played since either the last timeout or since the last time the player was substituted out to the bench. Both of these simulated time statistics are tracked by our model as it simulates the game. Players' skill levels - which are initialize as their Real Plus-Minus, a statistic available through ESPN - are updated to reflect fatigue, at a rate proportional to a linear combination of their total minutes played and current consecutive minutes played. Calling a timeout thus restores a portion of the skill level deducted for consecutive minutes played. Secondarily, coaches also consider timeouts to reduce the momentum of the opposing team. Our momentum attribute allows us to track this in each state, and coaches will call a timeout with some probability if the momentum begins to get out of hand, in an effort to reduce the effect of the opponent's momentum.

Substitutions are the primary decision that the agent is concerned with. There is an obvious trade-off, as coaches want to keep the best 5 players on the court at all times in an effort to maximize the likelihood of winning, but must also account for the fact that the effective skill level of the player declines as they accumulate minutes played and become fatigued. To make these evaluations, our coaching agents determine the strategy that gives them the best opportunity on the next possession - looking ahead by only one time step. We put the 5 players on the court who produce the highest expected value for points scored (by the coach's own team) before the next decision node. We depend on past data for sanity checks here - for instance, no player averaged 40+ minutes per game while playing more than 5 games during the 2021-2022 NBA season.

Specifically, we use ESPN's "Real Plus-Minus" statistic as a measure of how well a player's team plays when that player is on the court. Based on the skill of the 10 players on the court, we simulate the outcome of a possession - 1,2,3 points or a turnover, and in the case of a turnover, a substitution is not allowed unless a timeout is called. We also simulate the time between decision nodes using data collected on each NBA team's average possession time. This data gives us a mean for possession time and expected points scored per team, though we adjust the expectation of scoring based on the players on the court in our model. Overall, this means we are dealing with two probability distributions:

$$P(\text{Time of Possession} \mid \text{Teams}) \tag{1}$$
$$P(\text{Number of Points Scored} \mid \text{Fatigue Adjusted Skill of players on court}) \tag{2}$$

Since our states have such rich attributes, the transitions depend only on the attributes of the current state, not on the previous states, so our model resembles a Markov process, with uncountably many possible future states.

5 Evaluation Plan

Given that the goal of our model is to develop agents which can make coaching decisions that are consistent with, but potentially better than, the decisions made by humans as NBA coaches, evaluating the results is challenging. We first conducted several obvious sanity checks to ensure that the model is reasonable:

- The score of the game should be within a reasonable range for NBA games - around 100 per team
- No player should be playing the entire game, as this is completely unsustainable over an NBA season, but the players with the highest skill levels should be playing more minutes than the less-skilled players
- The winning team in the simulated game should, most of the time, be the team with the higher skilled players available. Or if we were to run the model with teams of identical skill levels, the score should be pretty close for the majority of the simulations.

Beyond these sanity checks, which ensure that our model is able to produce a reasonable simulation of a basketball game, we have a few other evaluation criteria, which are somewhat less objective.

- We want our model to run in very little time, so that it can allow coaches to adjust their personnel strategy during a live game
- If we run our strategy against an automated implementation of a "typical" NBA coaching strategy, we would expect our model to win if it has a team of similar skill level
- The outcomes of playing time should be relatively low variance - at least for a fixed set of two teams playing against each other

6 Evaluation Results

First, we can say with great pride that the runtime of the model is quite tractable, typically taking around one minute for each single simulation of a game. This is easily considered a successful outcome, as it not only allows for quick decision making, but it also makes it extremely practical for us to consider large sample simulations, as we further evaluate the variance of the model results and the performance against other strategies.

Next, we developed a "baseline" strategy - a simplified gameplan resembling a typical current NBA coaching strategy. We then test our model against this strategy in 4 scenarios, using two teams Golden State Warriors - a good team, and Orlando Magic - a relatively bad team. We simulate games in which our strategy plays as Golden State against the baseline as Golden State, where our model plays as Golden State against the baseline as Orlando, where our model plays as Orlando against the baseline as Golden State, and where our model plays as Orlando against the baseline as Orlando. We simulate 20 games in each of these 4 match-ups. The table below presents the results of those simulations, displaying the record for our model in (Win-Loss-Tie) format, from the perspective of our model.

		Our Model	
		GSW	ORL
Baseline	GSW	15-5-0	10-10-0
	ORL	13-6-1	10-7-3

From this table, we see that when our model has the higher-skilled team, it wins 65% of the games and loses 30%. In the cases where both strategies use the higher-skilled roster, our model wins 75% of the games and loses 25%. In the cases where both strategies use the less-skilled roster, our model wins 50% and loses 35% of the games. And lastly and perhaps most impressively, when our model plays as a less-skilled team against a higher-skilled team, it wins and loses both 50% of its games. Collectively, these results suggest that our strategy is conducive to winning more games, provided that our formula for reflecting the impact of fatigue on players' skills is valid.

Additionally, we test our strategy playing against itself, using an equally skilled roster on both sides. For this simulation, the Atlanta Hawks roster was chosen (albeit somewhat arbitrarily). In 20 simulations, the home team won 9, the away team won 9, and 2 games were ties. (Our model treats home and away as perfectly symmetric, there is no home team advantage in our model). While the ties are not legel in the NBA and would result in games going to overtime, these results suggest that our model does produce relatively even outcomes for equally skilled rosters. What is somewhat less encouraging is that the average absolute value of the difference of points in a single game was 8.8, indicating that the games were not necessarily all "nail-biters", with some higher-variance simulations. Still, in these 20 simulations with 2 teams each, no fewer than 85 points were scored by one team in one game, and no more than 124, with means of 103.35 for the home team and 105.15 for the away team, and all of these results are consistent with expectations in the NBA.

To summarize, the results of the model are generally satisfactory. Our model runs in reasonable time, allowing for simulations of samples under different scenarios within a single sitting, even on a common PC machine. It also performs well in competition against a baseline strategy which resembles current NBA coaching decisions. When playing our strategy against itself with equally skilled teams, we see each team win roughly 50% of the games which are not ties, as one would hope to see, however those wins are not all very close games, suggesting that the outcomes may not be as low-variance as we might have hoped for.

7 Model Limitations

Like most simulation technology, our model contains many simplifying assumptions. First, and perhaps most importantly, we reduce players' skill attributes to their fatigue-adjusted-plus-minus. This simplification does not account for what position the players play, and while this is not a strict concern by rule like it is in football or baseball, one can assume that having three centers on three point guards on the court at the same time would lead to some redundancy of skills and some unintended consequences, even if their fatigue-adjusted-plus-minus attributes are the best on their team. In addition to position, our model also excludes height, years of NBA experience, and match-up history, all of which might influence the probability of scoring points on a given possession for a team.

In the spirit of 2HELPS2B and Occam's razor, we elected to employ a relatively simple fatigue function to iteratively update our fatigue-adjusted-plus-minus attribute. After being initialized to equal the player's Real Plus-Minus from ESPN, we update the fatigue-adjusted-plus-minus after each possession, basket, turnover, or timeout, so that we have:
Assume fatigue-adjusted-plus-minus = $FAPM$, Real-Plus-Minus = RPM, Minute-In-Game = MIG, and Current-Consecutive-Minutes = CCM

$$FAPM = RPM - \frac{MIG}{2.5} - CCM \tag{3}$$

These weights are not the result of any meticulous scientific calculations, and could perhaps be improved upon through kinesiological research, though such work would be well beyond the scope of our project this semester.

Beyond the simplifying assumptions, our model is also limited in scope. We simulate games from start to finish, so our model does not necessarily provide a case-by-case lineup suggestion for every possible scenario in which coaches may find their team in a game, but rather a general heuristic by which a coach can re-frame their strategy of allocating playing time. Our work does however provide a basis for expansion, as one could simply initialize the state of our model for a particular time in the game (Quarter, time left in quarter) and a particular vector of minutes played by the players on each team, to find a preferred lineup in any particular scenario. At the moment, doing so manually would take longer than the runtime of the model, so some investment in a new state initialization function would be necessary.

An additional concern with applying our model to real life, one that is present in many areas of artificial intelligence, is how it will be received by those it impacts. Players are accustomed to having human coaches make decisions, and these decisions can therefore be influenced by emotions, crowd noise, injury risk, and other factors that the players can understand. Our model will make decisions in a way that the average basketball player will likely not comprehend. Furthermore, we find that when the 5^{th} and 6^{th} best player on a team have very similar fatigue-adjusted-plus-minus ratings, they tend to be substituted in and out for each other very frequently early in the game, under our model. These quick substitutions could be psychologically taxing on players who want to feel invested in the game, but are being inserted and removed too often.

8 Alternative Approaches

While our model follows a Markov-process style of simulation, a reinforcement learning approach might have been able enhance our results. While the best lineup strategy is not necessarily a deterministic one, and randomness will always play a factor, a learning-based agent might be able to train to the extent of defeating even our domain knowledge decision agent, though such a model would likely have taken much longer to develop, as it would need to collect training data with a sufficient sample size for each possible match-up between any of the 30 teams in the NBA.

Overall, it does not seem that an alternative approach would have been more practical for our project. Considering the topics we have studied - topics like Search and Constraint Satisfaction assume that the goal is constant. An adversarial agent game, following an algorithm such as minimax, might be intriguing for the zero-sum nature of winning or losing the game, however minimax assumes that each decision results in a deterministic transition - which is clearly not the case in basketball, since good players can miss shots and inferior players can win games. A Markov process, with probabilistic transitions based on the agents' decisions, seems to be the best implementation for our model.

9 Contributions

1. **Charlie** developed much of the creative vision for the model, including the concept of the State class and the attributes it would need to contain, the transition probability distributions, and the idea to use a Plus-Minus type statistic to measure players' skill (and perhaps more directly for our simulation, to measure how a team performs while a player is on the court) in a single variable. Part of the model inspiration came from a desire for something that would run quickly, after the tic-tac-toe project which, while interesting, did not scale very

well at all. Charlie was also the artist behind the PowerPoint presentation. I am, admittedly, however, mediocre at best with formatting visually-appealing tables or equations in LaTeX, and appreciate the help of others in this area especially. Finally and perhaps most amusingly, Charlie proposed the title of this project - which is Swedish for Artificially Intelligent Basketball Coaching Agent - at about 11 pm with absolutely zero intention of it being the real project name. But we all found it amusing and went with it.

2. **Tsu-Hao** provided deep basketball intuition, to a level beyond Charlie's familiarity with the sport. Such sanity checks guided the development of the model, as simulation results are quickly labeled as reasonable or entirely unrealistic. This domain expertise also allowed us to implement a "baseline" or typical NBA coaching strategy, which Tsu-Hao primarily implemented the code for, against which to test and evaluate our model. Tsu-Hao also collected, cleaned, and imported all of the real NBA data, which allowed for model testing to begin.

3. **Noah** took large segments of Charlie's Python code and removed countless compile errors. In several cases, this extended so far as finding not only the code but also the code structure for what was hardly even pseudo-code in the creative vision of the model, bringing life to ideas. At times, it went so far as to include long sessions of debugging, even outside of team meetings. Overall, the success and efficiency of the code implementation of the model is attributed largely to Noah.

Overall, while we each carried disproportionate weight in different areas towards success as a team, each member of our group was involved in every step of the process, from model design to code implementation, and each member of our group was indispensable in the development of our final product.

10 Data Sources

1. NBA Possession Outcomes - Used for Points Scored Probability Distribution
2. NBA Team Average Possession Times
3. ESPN Real Plus-Minus

11 Citations

[1.] Analyzing basketball games by a support vector machines with decision tree model (Pai et al.)

[2.] Research on the Intelligent Teaching System of College Basketball Based on Artificial Intelligence (Li Tingting.)

[**3.**] baller2vec++: A Look-Ahead Multi-Entity Transformer For Modeling Coordinated Agents (Alcorn and Nguyen.)

[**4.**] Policy learning with partial observation and mechanical constraints for multi-person modeling (Fujii et al.)

[**5.**] Markov decision process with dynamic transition probability: an analysis of shooting strategies in basketball (Sandholtz and Bornn.)

[**6.**] Policy learning with partial observation and mechanical constraints for multi-person modeling (Keisuke Fujii, Naoya Takeishi et al.)

[**7.**] Learning a Markov Model for Evaluating Soccer Decision Making (Van Roy et al.)

[**8.**] Application of Artificial Intelligence in Basketball Sport (Li and Xu.)