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Final Project: Algorithmic Bias in Sports Analytics

The use of AI in the sports analytics field has been growing in recent years. Many data analysts are using machine learning techniques for strategizing, recruitment, injury prevention and even fan engagement. One major use of machine learning is for player assessment, specifically with the drafting system. This is where mainly college players are recruited into professional leagues with the aim to disperse talent evenly within the league. Often, teams with the lowest ranking choose the best players first in multiple rounds. The NFL, for example, uses computer vision algorithms to analyze athlete movement to predict plays and player viability (West et al., 2022). On top of this, the NFL also uses data and statistical analysis to create strategies and increase fan engagement from certain plays or players (West et al., 2022). These are just some examples of the practical applications of using AI and machine learning.

These assessments have become commonplace when trying to recruit new players and give them a chance to play professionally. While these algorithms seem to improve sport strategies and fan enjoyment, there are certain ethical concerns when it comes to using AI. Algorithmic bias can be present when a dataset favors a particular group over another, which can lead to misrepresentation and discrimination (O’Neil, 2016). There are certain algorithms used which lack transparency, which can create uncertainty about how these algorithms actually predict values (Ausloos et al., 2018). Confusing and mysterious algorithms and data bias in general can have an array of detrimental effects.

It's important to consider how the use of AI can negatively affect players' careers and wellbeing. A deontologist might argue that assessing players based on their game stats is treating them as irrational beings instead of humans. Algorithms should not be biased since that would not be treating everyone as equal rational beings, since bias creates discrimination. A utilitarian would debate whether better strategies and more entertainment is outweighed by potential harm to athletes' wellbeing and other social implications. If an athlete feels unfairly judged or loses their position or potential spot on a team just because of an algorithm and this causes them pain, the utilitarian can argue that this pain does not outweigh the predictive accuracy of AI. Liberty ethics would argue that the uncertainty of algorithms violates the freedom of athletes in knowing how they are being assessed. Players should have freedom to be assessed fairly based on things they can control, not by being assessed by algorithms that have biases in gender, race, and other demographic measures. These are just some of the ethical concerns of algorithmic bias in sports analytics which might harm players.

To explore the potential bias in a real dataset, I found an online dataset on Kaggle that has data on players in the NBA. This data includes some demographics, game stats, and draft round and number the players were picked. This seems like a realistic dataset that actual data analysts would use when predicting draft rounds and player assessment. I performed exploratory data analysis on the data and then used a Random Forest Classifier to find out which features were used the most when predicting which draft round a player would be drafted into. This data had about 12,844 players and 22 features like stats and demographics. I attached the code I wrote as well as the data visualization. It has notes and clarifications as to what I did in more detail.

When performing a univariate analysis of the data, I found that around 83% of the players in the dataset had the USA as their country of origin. The other top countries were Canada, France, Australia and Spain, but those were all under 2% of the data. This means that there could be a bias towards players who are from the USA since there are so many players in this dataset from the USA. If we are trying to predict a player from another country, the predication might be skewed by the USA players' stats. This can create significant misrepresentation in the model as well as possible discrimination against players from minority countries.

When performing a bivariate analysis of the data, I noticed that the bottom countries (by frequency in the dataset) had a higher percentage of players being undrafted as opposed to the USA and Canada, who had higher percentages of players being drafted in rounds 1 and 2. This means that there is overrepresentation of the dominant countries performing better than the minority countries in the dataset. This is unethical since not all countries are being fairly and equally represented. This is most likely due to the fact that there isn't enough data in general, but nonetheless this still creates bias. Observing the correlations between the numerical data, it seems that points scored per game and usage percentage and highly positively correlated, which suggests that players who score more points tend to also play more. If this is a causation, that means that there will be bias towards players scoring more points, which can unfairly represent players who have more defensive positions.

Aside from the dataset bias, I found algorithmic bias when creating a model that predicts draft rounds. I used a machine learning model called the Random Forest Classifier. The data is passed through many randomized decision trees which give an output, then those outputs are voted, and the highest voted one is what the data is classified as. A decision tree has multiple splits based on features that recursively get called down branches and nodes until categories are created. An example of a node could be: "player age > 30," if the age is then it would go down the "yes" branch, and if it's not, it would go down the "no" branch and so on until it reaches the last leaf, which is the classifier. While random forests are highly accurate, one of the downsides of this algorithm is that it's hard to interpret. This means that what goes on during the algorithm is hard to understand, making figuring out how the model predicted what it did very hard to follow. This was one of the main ethical concerns mentioned before about model uncertainty.

I encoded the data so that the categorical features were compatible with the model. This doesn't change the data at all, just reformats it. I also removed the columns dealing with player names, colleges and team abbreviations. College had too many missing values for me to fill in so dropping it proved easier. The other two didn't seem relevant to predicting draft rounds. Regarding how the data got passed into the model, I split the data into 80% training data to help the model learn, and 20% testing data where the model shows how accurate it was.

I made two versions of the model. The first version was the default parameters. It was pretty accurate for both the training and testing data. The second version had the optimal parameters, such as choosing the number of leaves and number of data splits. However, there wasn't much change in accuracy, so I didn't use this model for analysis.

After I trained the model and assessed accuracy, I looked at the feature importance. This is the measure of how much a feature contributed to the final prediction. The order of importance was first draft number, then draft year, points per game, rebounds, games played, usage percentage and then assists. This ranking proved my earlier suspicion that this dataset had a bias towards points over assists when assessing which players were drafted first. This suggests that players in offensive positions were favored over defensive positions. As stated before, this is another display of misrepresentation and unfairness.

In conclusion, the data I analyzed shows overrepresentation of majority countries as well as algorithmic bias towards more offensive positions. The model itself also has some uncertainties about how it arrives at certain predictions. If not addressed, this bias could harm players and their careers if they aren't from a majority country or if they have a defensive playstyle. If the model predicts a higher draft round or even undrafted, they might not get drafted, even if they are indeed very capable and have potential.

Works Cited

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