Bayesian Approach to the Prediction of Football Match Outcome in Africa

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ABSTRACT

Football holds profound cultural and economic significance in Africa, captivating millions and transcending geographical boundaries. This research investigates the application of Bayesian analysis to predict football match outcomes on the continent, examining the intricate interplay of factors shaping the game. Motivated by Bayesian analysis's success in handling uncertainty, the study explores its potential in predicting match outcomes, acknowledging football's unpredictability influenced by team strength, player form, and tactical strategies. This paper presents a comprehensive overview of the project's findings, employing Bayesian networks, Jeffrey prior, and logistic regression to enable nuanced predictions, including teams' probabilities of qualifying and securing positions based on FIFA rankings.

Emphasizing a comprehensive, data-driven approach to football match prediction in Africa, the study contributes valuable insights and paves the way for further research, highlighting the game's multifaceted nature and the necessity of considering diverse variables for accurate predictions.

(Keywords: Bayesian, football match prediction, sports statistics, prior probability, De Finetti distance)

INTRODUCTION

Football is a widely beloved sport in Africa, with millions of fans across the continent. It is an essential source of income and pleasure for many African countries. Football holds a special place in the hearts of millions of Africans, transcending national borders and uniting diverse cultures. It is not just a sport; it is a way of life. With packed stadiums, enthusiastic fans, and grassroots passion, Africa is a powerhouse in the global football community. The continent's rich football heritage has produced legendary players who have left an indelible mark on the world stage. Predicting match outcomes is a cherished pastime for many football enthusiasts, and such insights can also hold crucial significance for sports analysts and coaches. In recent years, sports forecasts have become an area where advances in statistics are being applied to improve the accuracy of prediction.

One of these approaches is Bayesian analysis, which has attracted attention over its ability to represent uncertainty and integrate previous knowledge into new evidence in a seamless manner. The use of Bayesian analysis to predict the outcome of soccer matches in Africa offers an intriguing opportunity for combining sports dynamics with rigorous probabilistic reasoning and has received a high level of interest due to advances in statistical methods and the increasing trend toward data-driven decision-making. This study showcases the richness of Bayesian analysis and how it significantly contribute to sports analytics in predicting African football matches. Also, coaches and teams can benefit from the insights derived from this study. Understanding the factors contributing to match outcomes can inform training regimens, tactical approaches, and overall team strategy. Lastly, this research contributes to advancing Bayesian methodologies in African sports analytics.

LITERATURE REVIEW

Football is more than just a game in Africa; it is an essential component of the continent's culture. The activity offers a universal language that cuts over linguistic, tribal, and geographic barriers (Akindes and Kirwin, 2017). The passion exhibited in stadiums during these tournaments is a testament to the power of football to forge connections and build bridges between cultures (Bale, 2004).

The application of Bayesian methods in sports prediction has gained considerable traction in recent years. Research by Smith and Johnson (2019) emphasizes the advantages of Bayesian approaches in quantifying uncertainty and integrating prior knowledge with observed data. One notable advantage of Bayesian methods is their capacity to effectively account for uncertainty, a critical aspect in sports prediction where numerous variables and unpredictable events influence outcomes.

A notable advancement in the application of Bayesian methods is the use of Bayesian networks. These graphical models provide a visual representation of probabilistic relationships between various variables in the context of football prediction (Araújo, *et al.*, 2019). They serve as a visual representation of the probabilistic relationships between various variables pertinent to football prediction. For instance, a Bayesian network can seamlessly incorporate factors such as player fitness levels, prevailing weather conditions, and historical performance data.

Football matches are inherently multi-dimensional, characterized by a multitude of factors that interact in intricate and often unpredictable ways. Bayesian networks excel in capturing these interdependencies, allowing for a more complex analysis. For instance, the performance of individual players is intricately linked with the tactical strategies implemented by the team. Similarly, environmental conditions, such as weather, can significantly impact player stamina, potentially influencing the ultimate outcome.

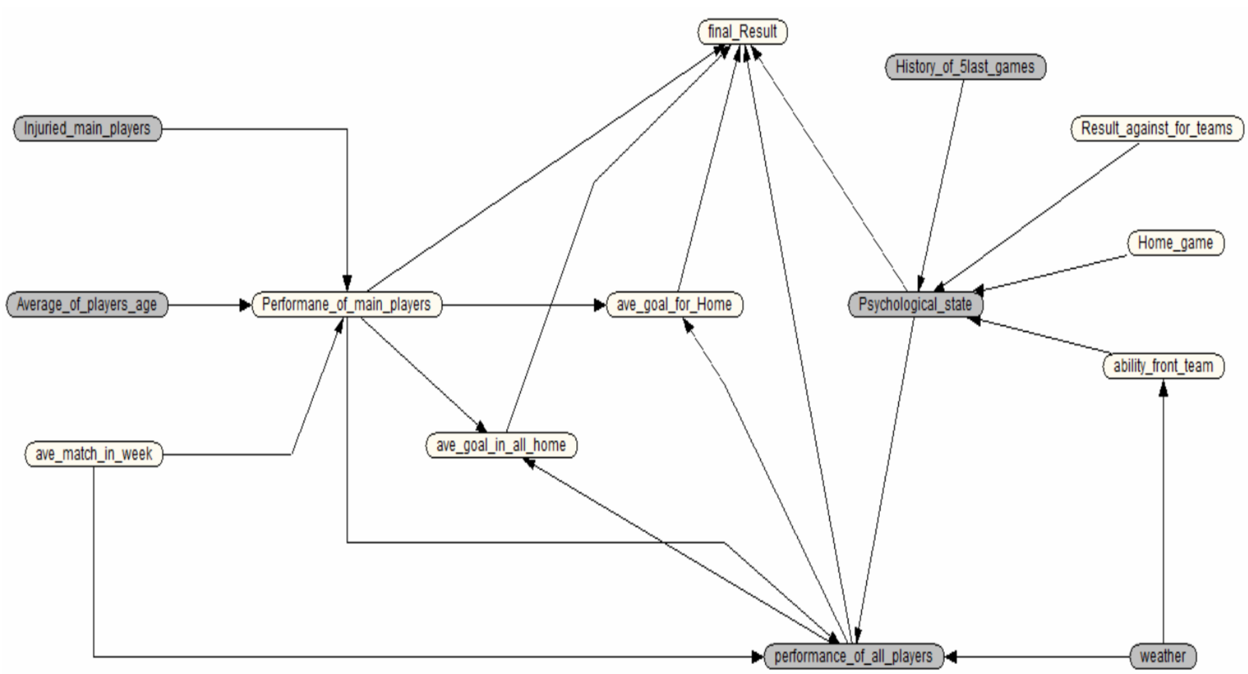

Figure 1: Bayesian Network for Football Match Prediction.

Bayesian methods in football prediction represent a significant advancement in sports analytics. The superiority of Bayesian models, as demonstrated by studies like that of Rossi and Mumford (2018), attests to their efficacy in handling the complexities of football matches. The incorporation of Bayesian networks further enriches this approach by capturing the intricate interdependencies between various factors.

METHODOLOGY

A large number of factors could affect the outcome of a football match from the perspective of one of the teams involved. One of the difficulties in any investigation of the relationships involved in a given effect is that, to a large extent, the assumption of a particular model determines the attributes to study and predetermines the possible relationships that can be found. So, choosing which model and attributes to study sets a boundary on what can be discovered. We try to find the main factors that affect the outcome of a football match.

We divide them into two groups:

i. Non-psychological factors
ii. Psychological factors

Football Analytics experts use them to predict match results.

In goal scoring, teams exhibit a range of performance levels, leading us to categorize their scoring patterns into three groups: 'Less than one', 'Between one and three', and 'More than three'. Additionally, several other crucial factors influence the final prediction. These include the average age of players, which falls into three categories: 'young', 'mid', and 'old'. We also consider the team's performance in their last five games, which can result in 'win', 'draw', or 'lost' classifications. The availability of main players, particularly regarding injuries, is another pivotal factor, categorized as 'Yes' or 'No'. Psychological state, which can be classified as 'Very good', 'good', or 'bad', also plays a significant role. Moreover, we analyze the performance levels of all players, segmented into 'high', 'medium', and 'low'. Lastly, weather conditions are considered as 'good' or 'bad'.

Bayesian Networks

Bayesian networks are a graphical model for reasoning under uncertainty, where the nodes represent discrete or continuous variables, and arcs represent direct connections between them. This direct connection means a causal connection. The strength of BNs is that it quantitatively models relationships among variables, whereby the probability of the belief will be automatically updated as new information becomes available. The main idea of Bayesian networks comes from Thomas Bayes' works called Bayes theorem. Bayes theorem technically is stated in Equation 1:

$$P(X|Y) = \frac{P(Y|X).P(X)}{P(Y)} \quad \textbf{(1)}$$

Where:

• $P(X)$ *is the prior probability or marginal probability of X.*

• $P(X|Y)$ *is the posterior probability or conditional probability of X given Y.*

• $P(Y|X)$ *is the conditional probability of Y given X (the likelihood of data Y).*

• $P(Y)$ *is the prior or marginal probability of data Y (the evidence).*

A Bayesian network consists of two components: quantitative and qualitative. The quantitative components of BNs can be represented in network parameters called conditional tables, while the qualitative components of BNs can be represented in network structure. There are sets of conditional probability for discrete data or probability density functions for continuous data in conditional tables.

A qualitative component of Bayesian networks (BNs) is represented by its directed acyclic graph (DAG) network structure. A directed acyclic graph comprises a set of nodes representing random variables from the domain and directed edges connecting nodes to represent the conditional dependencies between nodes. The directed edges cannot form any directed cycles (no loop).

When building a Bayesian network from prior knowledge alone, the probabilities will be based on Bayes' rule or Bayes' theorem. When learning this network from data, the probabilities will be physical, and the values may be uncertain.

Implementing Bayesian Network

We implement our Bayesian Network in NETICA software. NETICA is a software tool for creating, editing, and analyzing Bayesian networks. It is widely used in various fields, including artificial intelligence, machine learning, healthcare, finance, and more. Bayesian networks, also known as belief networks or causal probabilistic networks, are graphical models that represent probabilistic relationships among a set of variables. In this approach, we consider every match separately because every match has different values for factors, and they change based on their situations in matches.

Predictions for the Whole Tournament - Prior Distribution

In Bayesian statistics, the prior distribution represents your initial beliefs about the model's parameters before observing any data. It serves as a foundation for the likelihood (incorporating the data) to update these beliefs. We use the Jeffreys Prior for the logistic regression model for this project. The Jeffreys Prior is a non-informative prior that is invariant under reparameterization. It is chosen for its desirable properties of non-informativeness and scale invariance.

Parameters Used in Jeffreys Prior:

i. Intercept (β_0): The intercept term in the logistic regression model represents the log odds of the event occurring when all predictor variables are zero.

ii. Regression Coefficient (β_1): The regression coefficient associated with the team ratings represents the change in log odds for a one-unit change in the team rating.

Formulas for Jeffreys Prior: A Student's t-distribution with 3 degrees of freedom, centered at 0, and with a scale parameter of 2.5, is a decision made based on a combination of mathematical convenience and the desire for a non-informative prior.

For the regression coefficient (β_1), the Jeffreys Prior is specified using a Student's t-distribution:

$$P(\beta_1) \sim t(3,0,2.5)$$

This means the prior belief about the regression coefficient follows a Student's t-distribution with 3 degrees of freedom, centered at 0, and a scale parameter of 2.5. Similarly, for the intercept term (β_0), the Jeffreys Prior is also specified using a Student's t-distribution:

$$P(\beta_0) \sim t(3,0,2.5)$$

This implies that the prior belief about the intercept follows a Student's t-distribution with the same parameters as above. The Jeffreys Prior is chosen for its non-informativeness and invariance properties. It does not impose strong assumptions or biases on the model, primarily allowing the data to influence the results. The use of a Student's t-distribution provides for some flexibility, accommodating potential variability in the parameters. This choice of prior ensures that the prior beliefs do not unduly influence the results, especially in cases where prior information is limited. It provides a baseline level of regularization while allowing the data to guide the inference.

Likelihood Function

In Bayesian statistics, the likelihood function quantifies how likely the observed data is, given the model parameters. In this case, the likelihood involves determining the probability of observing certain match outcomes (wins, draws, losses) given the input features (team ratings).

For this project, we used a logistic regression model to relate the team ratings to the probability of different match outcomes. The logistic regression model is appropriate for binary outcomes, such as Qualified or Not-Qualified.

The logistic regression model is defined as follows:

$$P(Y_i = 1) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_i)}} \qquad \textbf{(2)}$$

$P(Y_i = 0) = 1 - P(Y_i = 1)$

Where:

Y_i Represents the binary outcome (1 for Qualified, 0 for Not-Qualified).

X_i Represents the team rating.

β_0 is the intercept term.

β_1 is the regression coefficient associated with team ratings.

Likelihood Function for Logistic Regression

The likelihood function for the logistic regression model is derived from the probability mass function (PMF) of the Bernoulli distribution, which is used to model binary outcomes:

$$L(\beta_0, \beta_1) = \prod_{i=1}^{n}[P(Y_i = 1)^{y_i}.(1 - P(Y_i = 1)^{(1-y_i)}] \ldots \quad \textbf{(3)}$$

Where:

n is the total number of observations.
y_i is the observed outcome for observation.

The likelihood function evaluates how well the logistic regression model, with a given set of model parameters (β_0 and β_1), explains the observed grouping outcomes (Qualified and Not-Qualified). It quantifies the probability of observing the actual outcomes based on the team ratings. The goal of Bayesian inference is to find the combination of model parameters that maximizes this likelihood function, which represents the best fit of the model to the observed data.

The choice of likelihood function is crucial in Bayesian analysis as it directly connects the model to the observed data. In logistic regression, the likelihood captures the relationship between the predictor variable (team ratings) and the binary outcomes (qualified and not qualified). By maximizing the likelihood function, Bayesian inference aims to find the parameter values that make the observed data most probable, given the model. This, in turn, informs the posterior distribution and, ultimately, the final inferences. This concludes the detailed explanation of the likelihood function for our Bayesian analysis in predicting football match outcomes in Africa.

Posterior Distribution

In Bayesian statistics, the posterior distribution represents updated beliefs about the model's parameters after observing the data. It is obtained by combining the prior distribution (representing prior beliefs) with the likelihood function (representing the likelihood of the data given the model).

For this research, the posterior distribution is calculated using Bayes' theorem:

$$P(\beta_0,\beta_1|X_i) = \frac{P(X_i \mid \beta_0,\beta_1).P(\beta_0,\beta_1)}{P(X_i)} \quad \textbf{(4)}$$

Where:

$P(\beta_0,\beta_1|X_i)$ is the posterior distribution of the model parameters given the observed data X_i.

$P(X_i \mid \beta_0, \beta_1)$ is the likelihood of the data given the model parameters

$P(\beta_0, \beta_1)$ is the prior distribution of the model parameters (Jeffreys Prior in this case).

$P(X_i)$ is the marginal likelihood, which serves as a normalization constant.

The posterior distribution combines our prior beliefs about the model parameters with the information provided by the observed data. It represents the updated probability distribution for the model parameters. The posterior distribution reflects the plausibility of different combinations of model parameters (intercept and regression coefficient) after considering both the prior beliefs and the observed match outcomes. It provides a probabilistic description of the uncertainty associated with the model parameters, considering both prior knowledge and empirical evidence from the data. The posterior distribution allows for a probabilistic approach to statistical modelling, providing a more nuanced understanding of the parameters and their uncertainty than frequentist methods.

Testing the Efficiency of our Prediction using De Finetti Distance

It is helpful to consider the set of all possible forecasts given by the simplex set.

$$S = \{(P_W, P_D, P_L) \in [0,1]^3 : P_W + P_D + P_L = 1\}.$$

Observe that the vertices (1, 0, 0), (0, 1, 0) and (0, 0, 1) of S represent the outcomes of win, draw and loss, respectively. Thus, a method used to measure the goodness of a prediction is to calculate the De Finnetti distance (De Finetti, 1972), which is the Euclidean distance between the point correspondent to the outcome and that one correspondent to the prediction, for example if a prediction is (P_1, P_2, P_3).

The outcome is a draw $(0,1,0)$, then the DeFinetti distance is $(P_1 - 0)^2 + (P_2 - 1)^2 + (P_3 - 0)^2$. Also, we can associate the average of its De Finetti distances to a set of predictions, known as the De Finetti measure. So, the best method among some prediction methods is the one with the least De Finetti measure.

ANALYSIS AND RESULTS

Data Set

The dataset used in this work is the 2023 Africa Cup of Nations qualification statistics collected from Wikipedia. The dataset is accessible and contains information on the 24 teams that qualified for the tournament, divided into six groups of 4. Each team plays the other teams in their group once. The top two teams from each group advance to the knockout stage, where 16 teams compete in four rounds: Round of 16, Quarterfinals, Semifinals, and the Final. Teams play single elimination matches in each round until one team emerges as the AFCON champion.
The data for the team ranking was obtained from the official FIFA website.

Predictions of Single Matches

The data used in computing the outcome of Team A (Nigeria) and Team B (São Tomé and Príncipe) match was obtained from the final group stage match between Nigeria and São Tomé and Príncipe, and it was analyzed using a Bayesian Network.

Table 1: A Data Set from the AFCON Qualification Match between Nigeria and Sao Tome.

Attributes	TEAM A	TEAM B	DATA TYPE
Goals in last three games	4	2	Numeric
Home Advantage	Yes	No	Nominal
Injury	No	No	Nominal
Weather	Good	Good	Ordinal
Average of player age	Normal	Normal	Nominal
Injuries and Suspensions	No	No	Ordinal
Player Motivation / Fan Support	Yes	No	Ordinal

The Bayesian network model above depicts a set of interdependent factors influencing the outcome of a football match. Specifically, player motivation is influenced by several variables, including the injury status of the team's main player, the average age of players, and any suspensions within the team. This level of player motivation subsequently impacts the psychological state of the team, which, in turn, affects the overall performance of all players. In a cascading effect, this collective performance plays a critical role in determining the final match result.

Notably, the model incorporates two significant constants: a 100% home game advantage and a player motivation factor set at 90%. Additionally, historical data from the last three games, demonstrating a win rate exceeding 80%, is integrated into the model.

The Bayesian network's predictive accuracy reveals a 59.5% success rate in forecasting match outcomes. This percentage surpasses the combined likelihood of a draw (36.9%) and a loss (3.58%). Moreover, the model illuminates the influence of external factors. For example, weather conditions directly impact the front team's performance. Furthermore, player motivation is revealed to significantly affect the main players' performance, demonstrating an 83.9% correlation.

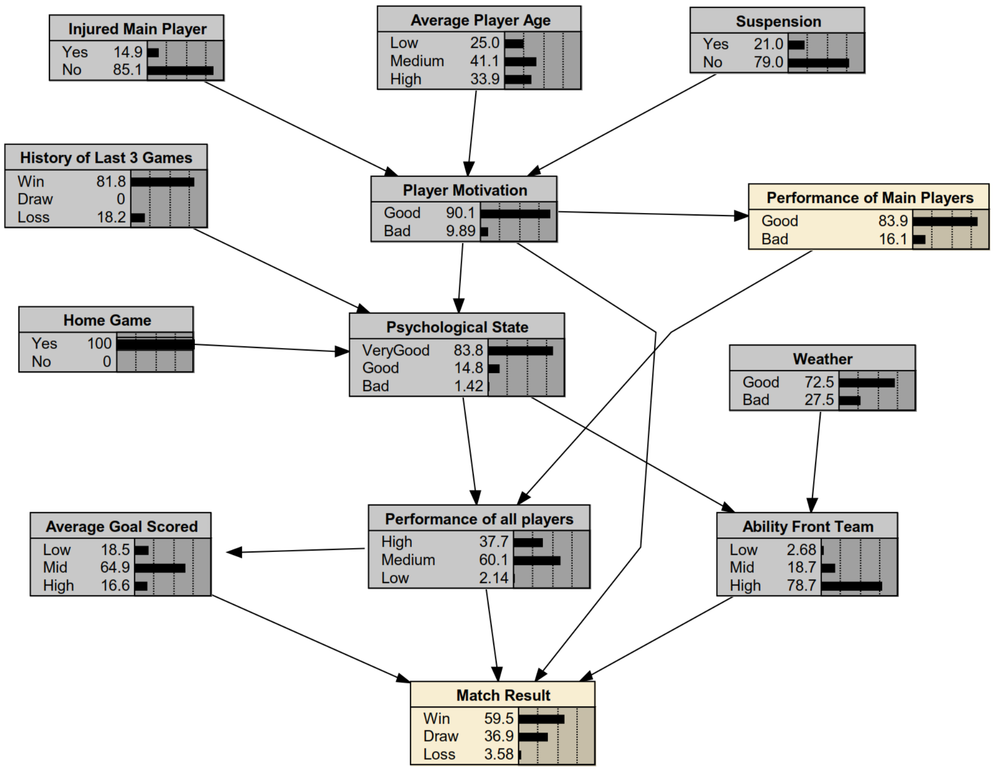

Figure 2: A Bayesian Network for Nigeria vs São Tomé and Príncipe Group Stage Match (Team A).

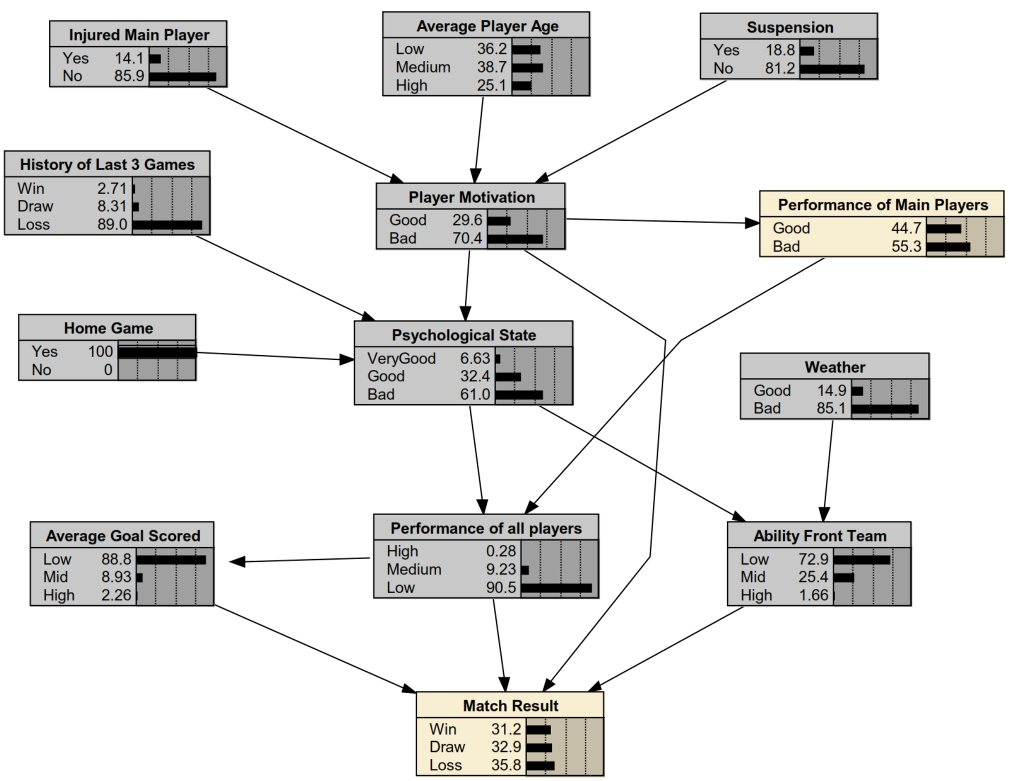

Figure 3: A Bayesian Network for Nigeria vs São Tomé and Príncipe Group Stage Match (Team B).

In the Bayesian network for Team B (representing São Tomé and Príncipe), notable differences emerge. Home advantage was absent, weather conditions differed, and factors like average goal scores varied significantly compared to Team A. The predictive accuracy of this Bayesian network indicates that Team B has a 31% chance of winning, a 33% chance of a draw, and a 36% chance of losing the match.

Additionally, the model sheds light on the impact of external influences. For instance, the history of the team's performance in the last three games affects the psychological state, subsequently influencing player performance. Notably, the front team's ability and average goal scored were both low, contributing to the final match result.

Evaluating Prediction Accuracy in Comparison with Actual Match Results

Actual Match result

Team A (Nigeria) – 6
Team B (São Tomé and Príncipe) – 0

Using De Finetti distance: Team A Prediction Result

$$S = \{(P_w, P_D, P_L) \in [0,1]^3 : P_w + P_D + P_L = 1\}.$$

From the observation of our Bayesian network model for team A

$\boldsymbol{P_w}$ **= 0.595,** $\boldsymbol{P_D = 0.369}$ **and** $\boldsymbol{P_L = 0.0358}$

The match is a win for team A

$$\mathbf{(0.595 - 1)^2 + (0.369 - 0)^2 + (0.0358 - 0)^2}$$

$$\mathbf{= 0.33}$$

Using De Finetti distance:

Team B Prediction Result

$$S = \{(P_w, P_D, P_L) \in [0,1]^3 : P_w + P_D + P_L = 1\}.$$

From the observation of our Bayesian network model for team B

$\boldsymbol{P_w}$ **= 0.312,** $\boldsymbol{P_D = 0.329}$ **and** $\boldsymbol{P_L = 0.358}$

The match is a loss for team B

$$\mathbf{(0.312 - 0)^2 + (0.329 - 0)^2 + (0.358 - 1)^2}$$

$$\mathbf{= 0.62}$$

Interpretation

The De Finetti distance of 0.33 for Team A's match prediction indicates reasonably accurate probability estimates. However, there is room for improvement in fine-tuning the model's calibration.

Conversely, Team B's prediction accuracy exhibits a higher De Finetti distance of 0.62. This suggests a notable discrepancy between predicted probabilities and actual outcomes. The unexpected heavy loss in the away games (6-0) may have contributed to this challenge in accurately estimating probabilities for Team B's matches.

Predictions for the Whole Tournament

In this section, we illustrate how the simulation is applied to obtain the classification of probabilities in group A. Table 3 displays for each team the probabilities of reaching any of the four group positions (the classification probabilities) for each team. From Table 3, we can clearly see that, with no matches played, Nigeria's squad is the favorite team in this group, which can be explained by the highest FIFA rating in the group and the Guinea-Bissau squad has the lowest qualification probability, which can be justified by the lowest FIFA ranking (106th) in this group.

Table 2: Classification of Probability before First Round for Teams in Group A.

Team	1st Place	2nd Place	3rd Place	4th Place
Ivory Coast	0.44	0.47225	0.1475	0.04475
Nigeria	0.5695	0.7495	0.1305	0.02975
Equatorial Guinea	0.136	0.04875	0.42675	0.46525
Guinea-Bissau	0.126	0.03325	0.56825	0.78725

Table 3: Classification of Probability before First Round for Teams in Group B.

Team	1st Place	2nd Place	3rd Place	4th Place
Egypt	0.92025	0.45175	0.28375	0.003
Ghana	0.3575	0.30975	0.26575	0.0225
Cape Verde	0.05325	0.2455	0.2605	0.32975
Mozambique	0.00825	0.206	0.39875	0.97975

Table 4: Classification of Probability before First Round for Teams in Group C.

Team	1st Place	2nd Place	3rd Place	4th Place
Senega	0.8415	0.5135	0.18175	0.0175
Cameroon	0.424	0.35025	0.20225	0.04075
Guinea	0.044	0.19225	0.37125	0.4095
Gambia	0.01525	0.165	0.50775	0.87175

Table 5: Classification of Probability before First Round for Teams in Group D.

Team	1st Place	2nd Place	3rd Place	4th Place
Algeria	0.8345	0.5335	0.0995	0.04275
Burkina Faso	0.41225	0.37675	0.12075	0.06225
Mauritania	0.032	0.16825	0.4735	0.50525
Angola	0.0245	0.16675	0.5665	0.713

Table 6: Classification of Probability before First Round for Teams in Group E.

Team	1st Place	2nd Place	3rd Place	4th Place
Tunisia	0.86125	0.504	0.315	0.00075
Mali	0.39025	0.35425	0.27275	0.00675
South Africa	0.0755	0.22975	0.27725	0.328
Namibia	0.01075	0.1565	0.34075	0.99425

Table 7: Classification of Probability before First Round for Teams in Group F.

Team	1st Place	2nd Place	3rd Place	4th Place
Morocco	0.99925	0.32975	0.17725	0.0125
Democratic Republic of Congo	0.32425	0.26225	0.2365	0.09825
Zambia	0.0045	0.2815	0.32275	0.36
Tanzania	0	0.34725	0.48825	0.88825

In Table 3, we observe significant variations in the classification probabilities within the groups. Notably, Egypt, with a remarkable record of seven AFCON titles, exhibits a high probability of 0.92 to secure the first place in their group. Conversely, In Table 7, Tanzania faces lower probabilities, particularly in the 4th place.

In Table 4, Senegal, the reigning African champions, maintains their status as favorites in Group C, boasting a higher FIFA ranking compared to other teams in the group.

In Table 5, Algeria's team has seen an increase in their qualification probability, rising to 0.83 for securing the first place. Burkina Faso emerges as the second-favorite team in the group. While in Table 6, Tunisia enjoys a high favoritism with a probability of 0.86 in Group E, Mali remains a contender for the first-place spot.

Lastly in Table 7, Morocco solidifies their position at the top of the table with a strikingly high probability of 0.99. In contrast, Tanzania's chance of securing either the first or second place in the group is notably low, indicating a likelihood of finishing at the bottom.

CONCLUSION AND RECOMMENDATION

This project marks an essential step in football match prediction in the African context by employing Bayesian networks and statistical models, we've unearthed a wealth of insights into the intricate web of factors influencing match outcomes. We've illuminated the significance of variables ranging from player demographics and psychological states to team performances and external influences. The Bayesian approach and the Jeffrey prior have empowered us to make nuanced predictions, enhancing our understanding of African football.

In conclusion, our findings underscore the importance of adopting a comprehensive and data-driven approach to match prediction. Football is a multifaceted game, and our study emphasizes that it's essential to account for numerous variables when forecasting match outcomes. We've contributed to the body of knowledge surrounding football match prediction in Africa and have set the stage for more in-depth research in this field.

Additionally, leveraging machine learning techniques contributes to the establishment of a robust prediction framework. Collaboration with football clubs, national teams, and governing bodies is essential to gain access to proprietary data, enriching the depth and quality of analysis. Ultimately, this research not only signifies a milestone for professionals and researchers in sports competition but also serves as a valuable reference point for advancements in the field.

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