Final Project Report on

**PREDICTING GOALS SCORED FOR FOOTBALL MATCHES**

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**Abstract**

Team sports can be described as dynamic systems that evolve in time and thus involve various teams from different countries and leagues for every season that are compatible with the study of dynamical systems. The study of match interaction pattern-forming the impact on the home or away matches for a country will reveal the clues to the underlying tactical behavior. The purpose of this research is to suggest quantitative assessments of the success of a team derived only from team interactions. In particular, we segment the data into events that end with a targeted attempt. Using the sequences of events obtained, we construct a coarse-grain activity model describing a network of team-to-team matches played. To show a correlation with an effort to score, we derive metrics based on information theory and total interaction behavior.

In addition, we compared various algorithms for a novel approach to machine learning to predict the probability of a team attempting to score during a section of the match. In predicting the right segmental result from matches in our dataset, our established prediction models showed an overall precision of 60.5 percent. In 66.6 percent of the matches that ended in a draw, the overall expected winner of a match associated with the actual match result.

In addition, on the largest available open set of soccer logs, the algorithm was tested. In the classification of the 42, 860 segments from 1, 941 matches, the algorithm showed an accuracy of 0.84 and correctly predicted the match outcome in 83.05 percent of matches that ended in a result. The potential performance metrics provide an insight into the underlying performance features.

There have been several studies in which researchers have sought to identify the predictability of matches during premier league depending on the location of playing. Many of these techniques relied on a qualitative methodology and lacked any quantitative analysis. This research is therefore based on bridging the difference between qualitative and quantitative approaches analyzing and recalling matches on the basis of the countries using logical regression, SVM model, Random Forest, K-NN model, Multilayer perceptron model (Neural network), decision tree. Based on these algorithms for the feature dataset, the accuracy is predicted highly is by using a gradient boosting algorithm. This research utilized algorithms for machine learning to measuring accuracy for the sports field and using them even for real-time aspects. Coachers may use data from these algorithms to even provide useful input on the efficacy of their instructional methods and pedagogies. This input can be used by the coaching staff to reinforce their teaching methods, and players can benefit from better learning and mastery of techniques during the match. Ultimately, this would lead to the improved willingness of players for doing work in their respective fields.

**Introduction**

In sports science, enhancing the perception of strategic performance and success in team competition is an essential objective. The subjective limitations (manual analysis) of the match can be easily solved by data-driven approaches and deliver better outcomes for football clubs. Statistical analysis could provide some insight for players and coaches by enabling them to optimize their match and analyze the case beyond what can be accomplished by personal observation. Traditionally, performance analysis methods drive the study of one-dimensional and discrete performance metrics towards approaches to probabilism and correlation. Although this contributes to some very limited domain expertise since the player-to-player interactions that support player activity and overall team behavior are not understood. A study of such one-versus-one strategies in team sports is fair to assume to be incomplete as multiplayer interactions are critical in evaluating success and failure. Therefore, it has been advocated that performance analysis in team sports must also concentrate on the interactions between players that maintain the overall team behavior in order to measure and clarify performance.

From the dynamic view of systems, the secret to performance analysis is the interpretation of how teamwork arises from the interaction between system components, that is, gamer interaction. Performance appraisal methods that take into account player dynamics in many multiplayer team competitions, such as football, are not well examined in team sports. Researchers have recently developed a number of techniques and models to help us understand player interaction networks in sports, inspired by empirical studies of networked systems. From the observation of ball transfer among players, interaction or passing networks can be built. To gain a practical understanding of underlying team strategies, a major challenge is to exploit the interaction networks. For example, repetitive pass sequences can be defined and connected to the playing style of a team by analyzing the structure of interaction networks. Duch et al. used the interaction networks to measure and rate player contribution relative to the overall team operation when the priority is imposed at the player level. There is no systematic software for predicting network structure due to differentiation and diversity in real-world sports data. Furthermore, there are no unique diagnostic subsets that are widely accepted. As team networks are intrinsically subjective and complex artifacts, it is often difficult to establish an acceptable way of characterizing the network that governs the creation of teams. The quantification of player-to-player contact in team sports such as football is the key to understanding the complex trends that create an incentive for scoring. This inspired us to make a strategic decision that characterizes the relationship of players in team sports quantitatively. A data-driven approach to the analysis of matches and the player interactions is used in this research from event stream data produced during football matches (hereinafter referred to as soccer). Using a machine learning approach, the proposed framework can be used to measure matches and player interactions and correlate them with the outcome.

Data-driven soccer analytics approaches are essential for the availability of the event stream data. In their work, Cintia et al. extracted pass-based performance measures to learn the association using a machine learning method to match the outcome. More recently, in their work, Pappalardo et al. have used a machine learning approach to rank players. Their analysis is founded on measuring data sets for each player from the event stream data, which are then used to learn feature weights in a supervised learning environment, i.e. relative to the outcome of the match. In order to compute a player's rank, the authors then use the learned weights.

The authors conducted a transverse analysis of different match states in another recent study by Decroos et al.to extract several associative characteristics of player results, which are then used to evaluate the winning or conceding likelihood using a classifier model.

The proposed research defines a section of a match using a series of behavior and entropy-based quantifiable markers that capture both inter-and intra-player interactions, in contrast to the above-mentioned studies that take into account individual player acts or cumulative team statistics. It is important to use appropriate measures in order to quantify the interaction between players in team sports conceived as complex processes that unfold in time. The proposed research takes into account the actions of numerous teams and the emerging nature of competition in order to create pattern-forming dynamics, i.e. the complex physical relationships that a team can build to achieve a goal with teammates and opponents.

From the ownership chain data, we created a coarse-grain activity model of player-to-player interaction, which can be used to measure the complex patterns underlying player interaction. In order to measure the complexity of a pattern describing player interactions during sub-segments of the match, we used the notions of information theory retrieval.

The format of the soccer log data is another main challenge from the analytics perspective, as different vendors use various data formats. An analyst must, therefore, build complicated pre-processors unique to a dataset. We recommend an approach that uses only a small amount of information to overcome the challenges posed by the diversity of event stream formats and to support the data science community.

The suggested method uses control details only, such as game, staff, type of action, and the outcome of the data from the event stream. Thus, during a particular module, that is a match phase, the segmental analysis was carried out using only the possession information to measure the team success and stability in team dynamics.

In addition, we built a machine learning-enabled decision support system based on the derived performance metrics to automatically predict a team's probability of a successful target attempt.

**Background / related work**

And Karlis et. In areas where I assumed independence, al (Karlis & Ntzoufras, 2003) and Rue and Salvesen (Rue & Salvesen, 2000) takes into consideration dependency, the former in terms of the correlation between the number of matches the home team scores in a match with the number of goals the away team scores, the latter created a "skill" metric that depended on all other teams in the league. And Karlis et. Al was less concentrated on the predictions and more about how well the data could match with a bivariate Poisson.

They also placed heavy focus, which I also found, on the advantages of playing at home. Rue and Salvesen found both the team's offensive potential and the team's ability to attack. There are also several articles that are looking to predict a match's result. Goddard and Asimakopoulos (2004) choose and ordered model of regression analysis, for instance. Those who not just to take past results into account, as well as the time of the season and the geographical distance between the towns of the two teams. They tried to measure the efficacy of the prices of betting companies instead of determining goals scored.

**Approach**

Dataset: We evaluated the dataset of European Soccer dataset in this analysis. The dataset is made up of data on the possession chain from more than 25,000 matches. The contact data (possession chain) contains all matches won for various teams in the home and away from the country players over time and length. The dataset also contains the type of contact that can be categorized as between teammates or opposing players. You will note international keys for when you take a look at the database. The teams and matches are the same as the sources of the original results. I've got the "API id".

Here for comparing data, I have used six algorithms:

1. Support Vector Machine

Support Vector Machine" (SVM) is a directed algorithm for machine learning that can be used for problems with classification and regression problems." In classification issues, however, it is mostly used. We map each data element in the SVM algorithm as a position in n-dimensional orbit (where n is the number of characteristics you see with the value of each characteristic becoming the value of a certain coordinate. Then by discovering the hyper-plane that distinguishes the two groups very well.

Chart, scatter chart

Description automatically generated

SVM's main objective is to divide the datasets into groups in order to find a maximum marginal hyperplane (MMH) and this can be achieved in the following stages that follow.

First, SVM will iteratively generate hyperplanes that best segregate the groups.

Then it will choose the hyperplane that correctly divides the groups.

1. Random Forest model:

Any of the individual constituent models will outperform a large number of relatively uncorrelated models (trees) working as a committee.

The secret is the low correlation between models. Just as low-correlation investments (such as stocks and bonds) come together to construct a portfolio that is larger than the sum of its components, uncorrelated models may generate ensemble predictions that are more precise than any of the individual predictions.

The explanation for this tremendous effect is that the trees defend each other as much as they do not all err in the very same way) from their individual errors. Although some trees will be wrong, there will be several other trees that are right, so the trees will move in the right direction as a group. So the basic requirements for a well-performing random forest are:

In our features, there needs to be some real signal so that models constructed using those features perform better than random guessing. The predictions made by the individual trees (and thus the errors) also have to have low correlations with each other.

Random forests or random decision forests are an effective modality, regression, and other functions that function by creating a decision tree based at training time and generating the class that is the class model (classification) or the individual trees' information prior (regression). Random decision forests correct the practice of overfitting their training set for decision trees.

Diagram

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Stimulating.

Aggregation Bootstrap (Bagging).

1. Enhancing

Boosting refers to a group of algorithms that make stronger learners using weighted averages to make weak learners. Boosting is about "teamwork" all around. What model that runs decides what characteristics the next model will concentrate on.

In developing, as the name implies, one is learning from another, which in turn improves the learning.

2. Aggregation Bootstrap (Bagging)

Bootstrap refers to sampling at random with substitution. Bootstrap helps one to understand the bias and the variance of the dataset better. Bootstrap requires randomly sampling small data sub-sets from the dataset. For certain algorithms that have high variance, usually decision trees, this is a general method that can be used to decrease the variance. Bagging independently runs each model and then aggregates the outputs at the end without preferences

1. K-NN model

The KNN algorithm assumes that in close vicinity, similar items happen. Similar objects, in other words, are close to each other.

Map

Description automatically generated

Note in the picture above that identical data points is close to each other much of the time. For the algorithm to be useful, the KNN algorithm relies on this statement being valid enough. The concept of similarity (sometimes called distance, proximity, or closeness) is captured by KNN with some geometry that we could have learned in our youth, measuring the distance on a graph between points.

We run the KNN algorithm several times with different K values to pick the K that is correct for your data and choose the K that decreases the number of errors we find while retaining the capacity of the algorithm to correctly make accurate predictions when something is given data that haven't seen before.

Our forecasts are less stable when we decrease the value of K to 1. Just think for a moment, imagine K=1 and we have a question point accompanied by a number of reds and a green one I'm thinking of the top left corner of the colored plot above but the green is the nearest neighbor alone. We should logically think that the query point is most likely red, but because K=1, KNN wrongly predicts that perhaps the query value is green.

Conversely, because of the majority casting a vote, as we calculate the quality of K, our predictions become more stable and hence more likely to make more accurate predictions (up to a certain point). We are finally starting to encounter a growing abundance of mistakes. We know we have moved the value of K too far at this stage.

We usually make Kan odd numbers to provide a tiebreaker in situations where we take a majority vote (e.g. choosing the mode in a classification problem) between labels.

As a hyperplane, the decision function dividing the two groups is taught. It is possible to formulate the optimization problem as:

Diagram, schematic

Description automatically generated

1. Neural Network based model / Multilayer Perceptron model:

A multilayer perceptron (MLP) is a perceptron that, stacked in many layers, teams up with extra perceptron to solve complex problems. An MLP with 3 levels is shown in the diagram below. Every perceptron during the first level on the left (the input layer) sends outputs to all the hybrid cryptographic perceptron (the secret layer) and all the second layer perceptron send outcomes to the final layer mostly on right (the output layer).

Diagram, schematic

Description automatically generated

It sends several signals, one signal over the next layer goes to each perceptron. The machine learning algorithm uses various weights for each signal. Every line going from a perceptron in one layer to the next layer represents a different output in the diagram above. There can be a substantial percentage of perceptron in each layer, and there can be several layers, so that the multilayer perceptron can become a very complex system quickly. There is another, more general term for the multilayer perceptron-a neural network.

This algorithm includes the following steps:

1. 1. Requires the inputs, multiplies them by numerical weights, and calculates their total Why That’s Critical The weights allow the perceptron to determine each of the outputs’ relative importance. By finding better and better weights that result in a more precise prediction, neural network algorithms learn. Several algorithms are used to fine-tune the weights, the most common being called backpropagation.
2. Keeps adding a biased factor, multiplied by a weight number 1 Why It’s Necessary This is a technical step that makes it possible to shift the curve of the activation function up and down, or on the number graph left and right. It makes it possible to fine-tune the perceptron’s numeric output.

Feeds the total with the activation feature Why That’s Critical The activation feature maps the input values to the output values needed. Input values could be between 1 and 100, for instance, and outputs can be 0 or 1. The activation feature also enables the perceptron to understand when it is part of a perceptron multilayer (MLP). Certain properties of the activation function, particularly its non-linear nature, allow complex neural networks to be trained.

1. Gradient Boosting Algorithm:

a. Distance to target:

First, we look at the most common type of GBM that optimizes the mean squared error (MSE), often referred to as the cost or loss of L2.

A GBM is a composite model that incorporates the efforts of several weak models to construct a strong model, as we can see, and each additional weak model decreases the overall model’s mean square error (MSE). For a simple data set, complete with computations and model visualizations, we give a fully-worked GBM example.

b. Going into the right direction

Optimizing a model according to MSE lets it chase outliers because extreme values are stressed by squaring the gap between goals and expected values. It’s easier to optimize the mean absolute error (MAE), also called the L1 loss or expense, when we can’t eliminate outliers.

Optimizing a model according to MSE lets it chase outliers because extreme values are stressed by squaring the gap between goals and expected values. It’s easier to optimize the mean absolute error (MAE), also called the L1 loss or expense, when we can’t eliminate outliers.

c. Gradient boosting performs gradient descent:

The previous two papers provide the intuition behind GBM and the clear formulas to explain how weak models join forces to construct a powerful model of regression. There was no attempt to demonstrate how we can abstract a generalized GBM that works for any function of loss. This last article shows that gradient boosting is really a form of gradient descent, and thus, depending on the direction vectors we use to training the weaker models, MSE or MAE is actually optimized.

Diagram

Description automatically generated

1. Decision Tree model:

a. A decision tree is an algorithm for machine learning that separates the data into subsets. With a binary split, the partitioning process begins and continues until no more splits can be made. The aim of a decision tree is to encapsulate the training data in the smallest tree possible Multiple branches of variable length are created. The conceptual rule that the simplest possible explanation for a series of phenomena is preferred over other explanations is the reason for reducing the tree size. Small trees also make choices quicker than big trees, and they are much simpler to look at and understand. To regulate the depth, or prune, of the tree, there are different methods and techniques.

These are the steps involved under a decision tree:

a. Splitting: The method in which the data set is partitioned into subsets. On a specific variable and in a specific position, splits are created. Two judgements are made for each split: the predictor variable used during the split, called the splitting variable, as well as the set of values, called the split point, for the predictor variable (which is split between the left child node and the right child node). The split is focused on a basic criterion, such as Gini (for classification) or square sums (for regression) from the data set as a whole. A small subset of the observations is found in the leaf node, often called a terminal node. Splitting proceeds until it constructs a leaf node.

b. Pruning: The shortening of tree branches. By converting certain branch nodes into leaf nodes, pruning is the method of growing the size of the tree and eliminating the leaf nodes below the original branch. Pruning is helpful since classification trees can match well with the training details but may do a bad job of classifying new values. Outliers can strongly affect lower branches. Pruning helps you to locate and mitigate the problem with the next largest tree. A simpler tree also prevents unnecessary fittings.

c. Tree Selection: The process of finding the smallest tree to match the details. This is typically the tree that yields the lowest error that is cross validated.

Diagram

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**Experiment:**

In this final project, I have used

Software: PyCharm and Sublime software are used for development

Hardware: MAC OS

Language: Python version 3.8.2

Datasets: These are taken from Kaggle website on European Soccer Datasets which has 7 CSV files with 25,000 and more matches details including player details.

Apart from these there are few other pre requirements that I have installed on my machine. Here are the details:

numpy==1.18.2

pandas==1.0.3

matplotlib==3.1.3

ipython==7.19.0

scikit\_learn==0.23.2

Algorithms:

1. Logistic Regression model
2. SVM model
3. Random Forest model
4. K-NN
5. Multi-Layer Perceptron model
6. Gradient Boosting model
7. Decision Tree model

Here are the graphs, tables and also the statistical analysis of the data for both the train and test data in the feature dataset. Also, I have used SQLite database for storing the predicted data as well as the data entries for each match played in the league.

Here is the snippet of the SQL queries that I have used for this project that I have taken from the Kaggel website for the data and the csv files and tables. By using them I have uploaded the data into the PyCharm with the help of SQL queries.

Text

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Fig.a This graph below shows the data visualization for total number of goas and seasons they played during the time period as shown.

Chart, line chart

Description automatically generated

Fig.a

Fig. b shows the average goals scored by each individual country during the league seasons played.

Chart, line chart

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Fig.b

Fig.c is the line graph which shows the data points scored by each country when they played in their home countries during the seasons.

Chart, line chart

Description automatically generated

Fig.c

Chart, line chart

Description automatically generated

Fig . d

The above Fig. d shows the total number of goals each country has scored when they were playing away from the home country during the seasons of league matches happened.

In the below fig.e shows the ratio of goals achieved by the teams when they played on home ground and away by each country during the seasons.

Chart, line chart

Description automatically generated

Fig.e

Chart, bar chart

Description automatically generated

Fig. f

Fig.f is a bar graph which represents the accuracy of all the algorithms and shows the leading one as gradient boost.

This is the confusion matrix shown below fig.g for logistic regression using true labels and predicted labels

Chart

Description automatically generated

Fig. g

Chart

Description automatically generated

Fig.h

In the fig.h shows the confusion matrix of support vector machine algorithm which plots true labels and predicted labels.

In this fig.i shown below is the confusion matrix of random forest using true labels and predicted labels.

Chart

Description automatically generated

Fig.i

The graph shown below is the fig.j using the confusion matrix true labels and predicted labels.

Chart

Description automatically generated

Fig.j

In this fig.k shown below are the confusion matrix of multilayer perceptron using the true label and predicted label.

Chart

Description automatically generated

Fig.k

In this graph the confusion matrix of gradient boosting using true labels and predicted labels and among all the algorithms this has predicted with high accuracy.

Chart

Description automatically generated

Fig.l

In this fig. m shown below, the confusion matrix is measure using decision tree for true label classes and predicted label classes.

A picture containing calendar

Description automatically generated

Fig.m

Implementations and challenges:

The most complex problems and challenges of development:

During the execution of the project, training the test data was very difficult as that datasets has to be merged using the uniquie “api\_id” for each team from various countries.

Displaying the rows and columns

Countries data: (11, 2)

League data: (11, 3)

Match data: (25979, 115)

Team data: (299, 5)

Data set is taken from Kaggle website : <https://www.kaggle.com/hugomathien/soccer> using these csv files , statistical analysis is performed on this data.

To train the data on the test dataset, it had quite a lot of challenging aspects on the features and also on the columns that are to be merged.

I merged the data using these datasets from various csv files and that resulted on feature data set. Displaying the rows and columns count of the final dataset: (25979, 9)

While training, the dataset has to be in many ratios so that the accuracy or the predictability is way better on the new or test data with minimal of the errors during the prediction. I have taken various rations as 60:40, 70:30, 80:20 and finally test data started to predict the data with recall rate good at the ratio of 80:20

Displaying the rows and columns count of the feature dataset data set:(4064, 12)

The shape of the train and test datasets are (3237, 10) and (827, 10)

How is my project unique?

This is an attempt to take machine learning algorithms to meet sports field. Team sports can be categorized as active systems that evolve over time and thus include multiple teams from different nations and leagues that are consistent with the analysis of dynamic systems for each season. The analysis of interaction pattern matches that form the effect on a nation's home or away matches can show the clues to the underlying tactical conduct. The objectives of this research is to propose objective evaluations of a team's performance extracted only from group interaction. We segment the data in particular into events that end with a goal attempt. Using the sequences of events collected, we create a model of course-grain operation representing a team-to-team match network played. We derive metrics based on information theory and total interaction activity to demonstrate a connection with an attempt to score. By using these algorithms, the teams can be well prepared and can get to learn various other techniques which will help them in their success.

Conclusion

Our research proposes quantifiable success metrics derived from data theory that can reveal the complex dynamics underlying team sports like soccer. The research demonstrates first proof of a machine learning-enabled approach for segmentally automated predictive performance analysis, offering the ability to uncover local team performance numerical markers. Our optimized predictive models display an average accuracy of gradient boost algorithm percent in determining the segmental result of the team's probability of making a successful attempt to score a goal consisting of 13 matches on our dataset. Additionally, in 66.6 percent of the matches that resulted in a winner, the segmental results could predict the right overall winner. The validation on an external dataset consisting of 42, 860 segments out of 1, 941 matches also demonstrated the robustness of the proposed method. The validation on an external dataset consisting of 42, 860 segments out of 1, 941 matches also demonstrated the robustness of the method. Finally, the study shows that the research we present will help to reveal the pattern dynamics of the system of a team generated using concentration chain data by quantitatively analyzing performance measures that have a particular distribution which can be used to estimate a team's performance.

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