

# Exploring Machine Learning Prediction for Soccer Outcomes

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## ABSTRACT

Sports betting is a wide-spread activity among sports fans and successful betting motivates the exploration of ways to accurately predict the outcome of soccer matches and other sporting events. In this project, we explore the use of machine learning tools and techniques to predict the outcome of soccer matches from around the world. Using various algorithms and feature sets, we were unable to obtain predictors which were able to accurately predict outcomes better than simply predicting a result for the home team. While this shows the importance of home-field advantage in soccer, it also indicates that using relevant data and appropriate hypothesis spaces impacts the performance of machine learning models. For future work, it is desirable to further explore ways to accurately represent intangible elements of sports such as injury, winning- and losing-streaks, and performance against rivals.

## 1 INTRODUCTION

Sports betting is a common activity among sports enthusiasts around the world. In this setting, it is desirable to be able to predict the outcome of matches between two given teams. Typically, sports analysts and experts gather rich sets of data on each and every game for individual teams, and sometimes gather data on individual players. In this project we will be focusing on the problem of predicting the outcome of soccer matches, which can be used in the sports betting arena. While it can be difficult for humans to accurately predict the outcome of a match, we explore whether or not it is possible to predict outcomes accurately using machine learning techniques. While it is applicable to sports betting, it is also interesting to consider whether or not machine learning can predict outcomes, even in the presence of intangible elements of the game, such as team chemistry, home-field advantage, winning- and

losing-streaks, player transfers and injuries, and other factors.

The methods utilized in this project explore a variety of algorithms, such as support vector machines (SVM), logistic regression, bagged forests, and perceptron. A large portion of this work is exploration with features, such as comparing raw statistics against derived features. We also explore the divisions of training and test data, such as comparisons between chronologically split data and randomly split data. The main lessons we learned from this project are the following:

- (1) Feature selection and the relevance of data is extremely important and can significantly impact machine learning model performance.
- (2) The selections of concept class and hypothesis space are important aspects of machine learning pursuits and can heavily impact the performance of a model. That is, the bias introduced as related to the best hypothesis in the space can be a significant limiting factor and must be monitored and controlled carefully.

## 2 RELATED WORK AND BACKGROUND

Sports betting is a common activity among avid sports fans in all sports, including soccer, basketball, football, baseball, and many other sports. To facilitate betting, many organizations publish public betting lines that describes which team is favored to win a game, and how much they are favored to win a game. However, many, or perhaps even most, of these models are strictly statistical and probabilistic. We seek to apply machine learning. Our goal is to focus on soccer, particularly in the United States, and to explore how different algorithms may produce better results, and if different train/test splits on data have an impact on learning results (e.g. explore if it is more useful to split data randomly or linearly within the course of a single season).

Feature	p-value
# of wins this season	$1.67 \times 10^{-7}$
# of ties this season	0.00321
# of losses this season	0.000267
Avg # of passes in defensive zone	$3.52 \times 10^{-10}$
Avg # of passes in forward zone	$1.19 \times 10^{-6}$
Avg # of passes from defensive to offensive zone	$2.11 \times 10^{-5}$
Avg # of accurate crosses	0.00658

**Table 1: Relevant Features and Statistical Significance**

We have explored several different studies of machine learning with sports betting. These studies explore data from NCAA (college) basketball in the United States [4], NFL (professional) football in the United States [3], and EPL (professional) soccer in England [2]. These reports have utilized Bayesian methods [2, 4], decision trees and random forests [4], and Gaussian processes [3]. An important common aspect of all of these studies is that they recognize that using simple, raw statistics is not nearly as useful in machine learning algorithms. That is, they recognize the need for alternative features to help represent matches. This includes factors like home field advantage, winning- and losing-streaks, and player injuries. We build upon these studies in our own exploration of machine learning in sports.

### 3 DESCRIPTION OF DATA

The data used in this experiment was scraped from the web from the Audi soccer data store [1]. The data from each match is identified by a unique id specified in the url. The data was compiled by the company Opta, which gathers detailed statistics on sports matches. After being scraped from the web, a SQLite database was used to aggregate and consolidate the data to allow it to be transformed into per-match feature vectors.

Once the data was in feature vectors as a CSV file, more high-level feature extraction was performed. We extracted summary statistics for each game that averaged each team’s statistics over the past games from each season. Then, we generated statistics that summarized a team’s performance during the season like total wins, ties, and losses and average points per game. In soccer, a win is worth 3 points, a tie is worth 1 point, and a loss is worth 0 points. We also added some columns that could be used for the output of the prediction like "did the home team get a result (win or tie) or not?"

and "was the outcome a win, tie, or loss for the home team"?

We separated the features into home and away because we suspected that home-field advantage would play a large role in determining who won games. We also subdivided the data into files by season and league, for example, Major League Soccer for 2016 or English Premier League for 2016. In total, there were 3300 games and 400 features from which the train and test sets could be made. However, we explored fitting models to different subsets of the data such as games from a specific year or leagues.

#### 3.1 Feature Extraction

Examples of the features include the number of completed passes in the forward third of the field, the number of failed passes in the back third of the field, the number of yellow and red cards, the average number of points per game, and the number of previous wins, ties, and losses. These features were all real-valued features. Using a Chi-Squared test, we were able to identify features as significantly different ( $p < 0.01$ ) between instances where a home team got a result and did not. These are listed in Table 1.

We also generated a set of 100 binary features that were characterized by comparisons between teams. For example, one feature represented if the home team has a higher average of points per game than the visiting team. Another feature represented if the home team had more shots on goal than the visiting team. These features were especially relevant for using Naive Bayes and Decision Tree models.

## 4 METHODS AND IMPLEMENTATION

Our implementation was designed with the goal of predicting whether or not the home team would get a result from the game. In soccer, a team gets a result if they win or tie their opponent. We chose to predict whether or not the home team got a result because it allowed us to simplify the problem to binary classification. In addition, if we could accurately predict whether or not the home team gets a result, it would be trivial to extend the classifier to predict whether the away team gets a result. This in turn would allow us to predict the outcome of a game explicitly as a home win, tie, or home loss.

We used the Python programming language for our machine learning algorithms and for our feature extraction code. In an effort to explore the various tools and methodologies, we use various algorithms. The algorithms we used for this project included Support Vector Machines, Logistic Regression, variants of the Perceptron, Decision Trees, and Naive Bayes. We performed a grid search using 5-fold cross validation to tune hyper-parameters for each algorithm, such as learning rate and regularization terms. We then evaluated the performance of each algorithm on a test set using the best set of hyper-parameters. For those models which train over epochs, the weights from the most successful epoch were used to evaluate against the test set.

We used various data sets to examine the results of each group. The MLS '16 dataset consists of the Major League Soccer games from the year 2016. This dataset was split into a training set that consisted of games from the first 90% of the season, and a test set that consisted of games from the past 10% of the season. The EPL '16 dataset consists of English Premier League matches from the year 2016. This dataset was also split into the first 90% of games as training data and the last 10% of games as test. The Random dataset consists of all the examples from every league and year. The Random dataset is split randomly between train and test sets, such that there is not consideration of time in the split. The impact of chronologically versus randomly split data is addressed in the evaluation. We also explore the impact of using the raw statistical features as opposed to the derived binary features.

## 5 EVALUATIONS

### 5.1 Raw Features

The results for running the algorithms on the various data sets using the raw statistical features are shown in Table 2. The results for the MLS '16 data set, EPL '16 data set, and comprehensive data set are shown in Tables 2a - 2c, respectively. It is interesting to note, that the results largely show that each of the algorithms learns to simply predict that the home team gets a result. The majority label for each of the three data sets is that the home team gets a result, with percentages 81.08%, 83.33%, and 75.30%, respectively. These curious results seemed to initially indicate errors in the implementation, such that the algorithms are simply guessing the majority label. However, for the SVM, logistic regression, and Perceptron variants, each algorithm is implemented twice, once by each author independently. The results are confirmed by running each set of algorithms against these data sets. Furthermore, the algorithms were run using other unrelated data sets, and non-trivial results are obtained. That is, the algorithms do not simply predict the majority label for other data sets in the same format. Nevertheless, we also rigorously inspected the code for errors, but found none. Thus, the results seem to indicate that the data and features have a significant impact on the performance of the algorithms. In addition, the results seem to show that the hypothesis spaces associated with our chosen algorithms are not expressive enough to manage the "intangible" elements of soccer and other sports.

Another interesting result which further shows the dependence on the data are the results of weights produced by individual epochs. Figure 1 shows the accuracy of individual epochs for each algorithm over the MLS '16 data set. Rather than following a generally increasing path, the accuracy of successive epochs varies wildly, depending on the shuffling of data to start each epoch. This further indicates the importance of the impact of data on the results of the algorithms.

### 5.2 Derived Features

Using the derived set of binary features over the whole data set, and training with the Naive Bayes and decision tree models, the algorithms output results similar to those above, achieving the test accuracy of 75.30%. This continues to hold for using ensemble methods

Algorithm	Best Hyper-Parameters	Train Accuracy	Test Accuracy
SVM	$r = 10, C = 10$	81.61%	81.08%
Logistic Regression	$r = 1, C = 1$	81.61%	81.08%
Perceptron	$r = 0.01$	81.61%	81.08%
Dynamic Perceptron	$r = 0.01$	81.61%	81.08%
Margin Perceptron	$r = 0.01, \gamma = 0.01$	81.61%	81.08%
Averaged Perceptron	$r = 0.01$	68.06%	81.08%

(a) MLS '16 Results

Algorithm	Best Hyper-Parameters	Train Accuracy	Test Accuracy
SVM	$r = 10, C = 0.01$	75.93%	83.33%
Logistic Regression	$r = 1, C = 100$	75.93%	83.33%
Perceptron	$r = 0.01$	75.93%	83.33%
Dynamic Perceptron	$r = 0.01$	67.77%	83.33%
Margin Perceptron	$r = 0.01, \gamma = 0.01$	75.93%	83.33%
Averaged Perceptron	$r = 0.01$	66.30%	83.33%

(b) EPL '16 Results

Algorithm	Best Hyper-Parameters	Train Accuracy	Test Accuracy
SVM	$r = 1, C = 10$	72.25%	75.30%
Logistic Regression	$r = 1, C = 1000$	72.25%	75.30%
Perceptron	$r = 0.01$	72.25%	75.30%
Dynamic Perceptron	$r = 0.01$	62.32%	75.30%
Margin Perceptron	$r = 0.01, \gamma = 0.01$	72.25%	75.30%
Averaged Perceptron	$r = 0.01$	62.32%	75.30%

(c) All Results

Table 2: Evaluation Results

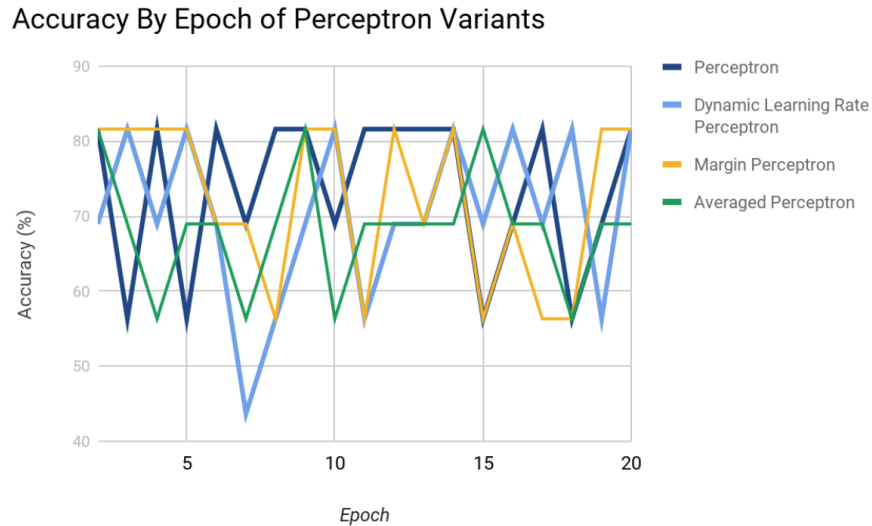
combining bagged forests with SVM and logistic regression. While we hoped that the derived features may be more expressive than the raw statistics (as discussed in related work), the results don't appear promising. Unfortunately the results again indicate the data, features, and hypothesis spaces we are using are not expressive enough to capture the results of soccer matches.

## 6 FUTURE WORK

The results of the evaluation showed significant impact on model performance based upon the data available. It would be a great future work opportunity to explore gathering different types of data and extracting much richer feature sets to see if the models are able to achieve performance better than just predicting a home team result. There are many features we were unable to capture in our data like recent performance by each team,

time since last match, injuries, and trades. It would be interesting to see if adding these features grants the model more predictive power. In addition, other high-level statistics could be found like goals per minute or considering performance against specific teams. It would also be useful to obtain a much larger set of data. In addition, it would be informative to do more spot checking on the data that was scraped and transformed into feature vectors to make sure there were no mistakes in the data gathered, such as could be caused by abnormal requests to the data API.

In order to address the issues of hypothesis space expressiveness, another important future work opportunity would be to utilize many layered neural networks and other ensemble methods to see if they are able to capture a more expressive hypothesis space, and thus better predict the outcomes of matches. It would also be an interesting exploration to compare the results of



**Figure 1: Individual Epoch Accuracy**

using our own implementation of algorithms against tools already available in Python, such as SciKit-Learn.

## 7 CONCLUSION

This project was designed as an exploratory investigation into the use of machine learning tools and techniques for predicting the outcome of soccer matches from around the world. We utilized a variety of machine learning algorithms, including both linear and non-linear algorithms to produce models which can predict the outcome of an individual match. The results from each model show that the best each of the models is able to obtain is to predict a result for the home team, which does occur for approximately 75% of our entire data set. This is consistent for different algorithms, chronologically and randomly split testing and training data, and raw statistical features and derived binary features. The results are also consistent across independent implementations of a given algorithm by each author. However, using the same implementations on other unrelated data sets yield non-trivial predictions. These results thus indicate the impact of data on limiting algorithm performance, and results seem to indicate the importance of using relevant and rich feature sets as well as appropriate and expressive hypothesis classes. However, it is interesting to note the impact of home-field advantage on the outcome of a match, as is clear from the results. Future work could improve the

performance of various models by exploring different data sets and statistics for soccer matches, as well as using different machine learning models which may be more appropriate for the concept class containing the most accurate representation of the soccer matches.

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