ML – Capstone Project

Predicting the Results of Soccer Matches

1. Definition

Project Overview

Sports Analytics in the past 10-15 years has increasingly become a part of every sport as teams begin to make analytical, data-driven decisions rather than a conventional or instinctual feeling that coincides with traditional beliefs. As a result, statistics about games have become increasingly available to the average fan. With these statistics, we’re looking to use machine learning to help predict the results of a soccer match.

Problem Statement

Predicting soccer matches is unique compared to other sports because soccer can have one out of three results, win, lose, or draw. The result of a draw happens very often in the sport where as with other sports if a draw is possible it happens very rarely. In the other top 4 sports in the US NBA and NHL games cannot end in a tie. There have only been 3 ties in the [NFL](https://en.wikipedia.org/wiki/List_of_NFL_tied_games) since the 2008 season and in the [MLB](https://en.wikipedia.org/wiki/Tie_(draw)) ties only occur due to weather or other extremely rare cases. Having ties as an additional result increases the complexity of creating a predictive model for soccer matches. In doing research on the topic I found this [project](https://github.com/GoogleCloudPlatform/ipython-soccer-predictions/blob/master/predict/wc-final.ipynb) by Felipe Hoffa and Jordan Tigani of Google during the 2014 World Cup. They looked to predict the winner of each match in the tournament and in their initial run of the data they don’t train on results that end in a draw since ‘they have less signal’ so all of their matches end up with either of the two teams winning. Which on some levels invalidates lowers their accuracy percentage since they are assuming that the winner of the penalty kicks (deciding factor on who continues to the next match) is considered to be the winning result of the match when in actuality the match result is a draw.

Not only does soccer have an extra result that makes predicting matches difficult, it’s also a difficult sport to return statistical analysis on because it lack statistical history outside of standard stats and because of it’s non-stop, free flowing nature. Other sports such as baseball naturally has more stats to utilize since box scores have been published for decades now and these stats can break a game down to the pitch. Also, due to licensing terms of the data on [Sportradar](http://sportradar.us/) I was only able to pull a minimal amount of games and it’s data. There may be more data that they provide for a paid version but I’

Having a minimal amount of stats and having one more outcome to predict makes predicting soccer matches more difficult than other sports. A combination of approaches might have to be taken as we explore the data and begin to break the data down to what is needed.

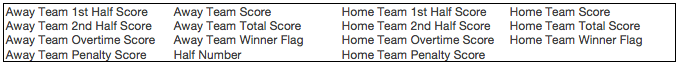
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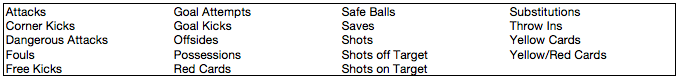
Teams can win, draw, or lose a soccer match meaning they can earn 3, 1, or 0 points respectively. This will be the target or label of the dataset. We are going to test a variety of models but initial assumption is that accuracy will need to be determined based off of a combination of a few models and not just one. One model might not be able to clearly predict wins/losses and ties (as the project above suggested) so we’ll need to identify and determine which matches might end in a draw and which matches will clearly have an outright winner.

1. Analysis

Data Exploration

Using data pulled in from [SportRadar’s](http://sportradar.us/) API I was able to pull Boxscore Information and Team Match Statistics in all previous MLS matches in the 2016 season.





From this data, I’m able to pull all matches in the current MLS season. With this data, I’m able to predict upcoming matches based on all previous matches that the two teams have previously played. The data inputted into the database wasn’t filled 100% and had some missing data. But since averages are taken on the previous games of a team, we use numpy to ignore that ‘null’ space and not factor in that game for that feature. Also note that because our model uses previous game stats to determine the outcome of the current game, we need previous data so therefore the matches start in our data at week 2.

Because all matches are contained within one MLS season, all data should be relevant and ‘outliers’ should still be considered. There are some adjustments that could be made in the future to the data that could help balance out ‘blowout’ games. For instance, you could lessen the weight of ‘Goals Scored’ if the margin is greater than 2 goals. Since this means the other team likely isn’t trying as hard the goal isn’t as significant as a goal to put a team ahead.

With this data from the API, I looked to modify and enhance the given statistics into relevant features that can help predict the result of an upcoming soccer match. Essentially these features can be grouped into 3 categories (not including the Target and Non-Feature Columns): Standard/Cumulative Features, Home/Away Features, and Extended Features Columns.

- Standard/Cumulative Features – Features that include