**Soccer: One Goal = One Red Card = Six Yellow Cards**

Good Acting, Bad Refereeing, or Something Else?

Soccer players are known for being great actors. Their facial expressions and body language don’t equal the severity of their pain, but a first-time viewer can’t tell the difference. Even experienced fans and referees can be fooled. In the flurry of a scramble, with arms flailing and legs twisting, it is difficult to see what happens. The player slides to a dramatic fall, grimaces, and clutches his hamstring in sheer agony. One minute later they are back in action. In the end, soccer players get a bad rep for their acting.

Why do they do it? Why do summer league kids act tough after rough play, while grown men, professional athletes, strive for the opposite?

This analysis doesn’t strive to define the acting abilities of professional soccer players. Instead, it attempts to codify a phenomenon that soccer players seem to know intuitively – a single card can change the outcome of a match. On a broader scale, this analysis attempts to gauge the impact of match events over the course of a season, such as number of shots on goal, corner kicks, and crosses.

**Industry Impacts**

Accurately gauging these events can affect several industries. Most notably, it can affect a team’s draft picks and contracts for new players by monetizing which skills are most valuable. In the gambling world, it can affect the odds that betting houses and gambling websites place on matches. In a further reaching sense, it might also affect post-game entertaining staffing. A win means more celebration at home after the game.

For the purposes of this study, we will focus on betting houses, as the impact of wins and other game events is most immediately felt by their business.

**Introduction to the Problem**

We have limited ability to accurately forecast the outcomes of soccer matches. Paradoxically, the unpredictability of soccer matches makes the business of betting possible. Gamblers try their luck at predicting outcomes, and betting houses set odds that are profitable.

Fortunately, a lot of data is available for soccer matches, from goals and penalties per match to individual player attributes. Part of the problem is to determine which data are significant and which are not.

**Data**

The data originally comes as an SQLite database with eight tables, which are converted into eight separate data frames:

|  |  |  |  |
| --- | --- | --- | --- |
| Player | **team** | **league** | country |
| Playerattributes | teamattributes | **match** | Sqlitesequence |

***Figure 1***

Our analysis primarily focuses on the bold tables. The other data frames contain useful information, such as which league ID’s belong to which country. However, they are small and require little analysis. The focus data frames are larger and require restructuring.

The most important of these data frames is ‘match’. It contains individual match information, such as number of goals scored, fouls committed, and length of ball possession.

Data Frame: ‘match’

The variables in match can be divided into four categories – Base Data, Player Data, XML Data, and Betting House Odds. We used the **Base Data** to do a high-level exploration. We used **Base Data and XML Data** to do further analysis. Restructured and calculated data is asterisked\* and in **bold**:

|  |  |  |  |
| --- | --- | --- | --- |
| **Base Data** | Player Data | **XML Data** | Betting House Odds |

|  |  |
| --- | --- |
| country\_id | league\_id |
| season | stage |
| date | match\_api\_id |
| home\_team\_api\_id | away\_team\_api\_id |
| home\_team\_goal | away\_team\_goal |
| **goalDiff**\* | **points**\* |

|  |  |  |
| --- | --- | --- |
| goal | **goals\*** | **oppgoals\*** |
| shoton | **shotson\*** | **oppShotson\*** |
| shotoff | **shotsoff\*** | **oppShotsoff\*** |
| foulcommit | **fouls\*** | **oppFouls\*** |
| card | **Ycards\*** | **oppYcards\*** |
|  | **Rcards\*** | **oppRcards\*** |
| cross | **crosses\*** | **oppCrosses\*** |
| corner | **corners\*** | **oppCorners\*** |
| possession | **homePoss\*** | **awayPoss\*** |

***Figure 2***

Base Data:

Our highest-level analysis comes from this data frame. The dataframe 'statsMB3' contains only these variables, plus two calculated variables - goalDiff and points. It is used to show that a higher goal differential correlates to more points accumulated in a season. Because a better goal differential results in a better season outcome, we continued by focusing on what causes a better goal differential, which is the difference between goals scored and goals permitted.

XML data: The XML data allows us to focus on what causes a better goal differential. These variables possess details of shots and gameplay. Because the number of shots and plays can vary from game to game, it is stored in nested data frames which are not easily read by R. We later explain the packages and techniques necessary to extract the desired data from here.

Player Data: This data shows the position on of first, second, and third string players. The variables are coordinates on the plane of a soccer field. This was not used for our analysis.

Betting house odds: These numbers show the odds placed on games by various betting houses. Because we want to find factors contributing to wins ourselves, we don’t use these numbers in our analysis.

Limitations

This is a relatively involved data set. It has 198 variables between 8 data frames, not including calculated fields or data within nested XML data frames. The nested XML data frames contain rich information such as ball possession by team, goal types, and players who scored.

While any data set’s limitations can be defined by the data it does not have, this data set is a case where the limitations are better ascribed to the analyst’s creativity and by data that exist but aren’t complete for all observations. For example, the match data frame has ~25,000 rows. However, only 14,217 of those rows contain XML data, and 8,124 of those rows contain complete XML nested data. Because certain seasons lack complete XML data, this might restrict seeing higher-level trends.

While this data set has the benefit of already being rich, it could be further improved by including referee and external event data. For example, it does not contain information on league rules, match referees, or external events, such as league policy changes or weather during the soccer matches. Finally, no documentation exists to explain the variable names.

Cleaning and Wrangling

This data set is intended to thwart practitioners of R. It is stored in SQLite format, and many interesting variables are stored in nested XML data frames within individual observations. This requires a combination of R packages - RSQLite, DBI, XML, dplyr, and magrittr.

The initial transformation involves reading the SQLite data into R and creating a variable for each table. R plays nicer with csv files, so we wrote each table to a csv file that was stored in the project folder. We then created a variable for each csv file and read it back into R. This allowed us to move forward with base R and common R packages.

At this point, it is easy to select the non-XML data with dplyr to create simple plots and regressions. Extracting the desired data from the XML data is more involved. It requires converting the XML data into a data frame and extracting the desired data with the following process:

1. Use dplyr to create a sub-data frame with the desired columns
2. Load library(XML)
3. Remove all rows with incomplete data:

# removes all rows in matchAD1$possession with NA

test <- test[complete.cases(test$possession),]

# remove all rows where test$possession contains only "<possession />"

test <- test[!(test$possession == "<possession />"),]

# removeall rows where test$possession contains only "<possession />"

test <- test[!(test$card == "<card />"),

testALL <- testALL[!(testALL$corner == "<corner />"),]

***Figure 3***

1. Create for-loops that extracts the necessary data from XML variables and place them into new variables. All for-loops contain elements of the dplyr package, the XML package, and base R conditional coding.
   1. Some XML columns do not convert into clean data frames. Many data values are in the wrong column. This may or may not be a result of the parser. However, we mitigated this within the for-loop for all variables (except “possession”) by using “|”. Given additional time, it would be prudent to find a more efficient parser.
   2. The “possession” variable also produced incorrect variables, and the output of the for-loop contains excess characters that need to be removed. We ameliorated both of these issues outside of the for loop using substr() and magritrr().
   3. Six for-loops required a conditional statement, because some observations have a missing column.

These for loops take about 12 hours to run.

Preliminary exploration

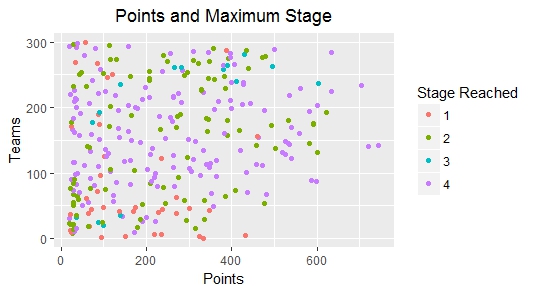
Before unpacking the XML data, we create various plots to see if teams with more points or goals proceed to further stages.

ggplot(data = statsMB3, aes(spoints, statID, col = factor(maxStage))) + geom\_point() +

labs(title = "Points and Maximum Stage") + theme(plot.title = element\_text(hjust = 0.5)) +

labs(x = "Points", y = "Teams")

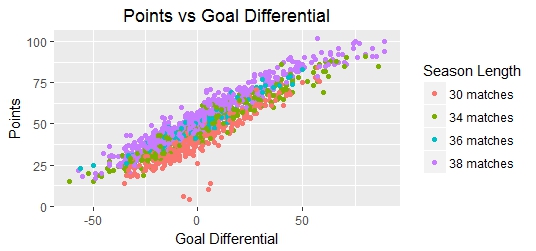
***Figure 4***



***Figure 5***

We include this chart here because we originally intended to analyze factors that contributed to stage progression, as described in the Milestone report. On further analysis, we found that the “stage” variable represented the match number in the season. For example, the teams in “Stage 3” were playing their third match of the season. The seasons varied in length from 30 matches to 38 matches (half at home and half away) for each league.

While this nullified any stage-progression style analysis, it still allowed to compare leagues with shorter seasons vs leagues with longer seasons. The following chart shows that teams with longer seasons tend to score more points (as expected), but it also shows that the dispersion of points accumulated by teams across leagues appears similar:



***Figure 6***

This chart shows expected data – more goals scored (and fewer goals permitted) lead to more wins, which directly leads to more points acquired.

The interesting part begins here. Why do certain teams score more goals, win more games, and acquire more points? This is where the nested XML data comes in handy.

Starting with summary statistics, we can see how many games are played and how events are distributed between home and away teams. The following figure shows the distribution of these events.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Games | Wins | Ties | Loss | Goals | Poss% | ShOn | ShOff | Crosses | CKicks | Fouls | YCards | RCards |
| Home | 8124 | 3741 | 2054 | 2329 | 12697 | 48.77 | 50028 | 50739 | 149923 | 47374 | 99654 | 14371 | 442 |
| % T | 50% | 61.6% | 50% | 39% | 57.3% | 48.7% | 55.6% | 55.5% | 56.1% | 56.3% | 48.9% | 45.5% | 46.8% |
| Away | 8124 | 2329 | 2054 | 3641 | 9471 | 51.23 | 39995 | 40662 | 117108 | 36819 | 104221 | 17220 | 503 |
| % T | 50% | 38.4% | 50% | 61% | 42.7% | 51.2% | 44.4% | 44.5% | 43.9% | 43.7% | 51.1% | 54.5% | 53.2% |

***Figure 7***

This figure highlights what is commonly known as “home team advantage.” 61.6% of wins are acquired by the home team. We see further that the home team typically scores more goals, and gets more shorts, crosses, and corner kicks than the away team. We see a few additional interesting numbers:

1. The home team has less ball possession than the away team
2. The away team gets 20% more yellow cards than the home team 🡪 (17,220-14371)/14371
3. The away team gets 14% more red cards than the home team 🡪 (503-442)/442

Figure 8 shows the same data, but split up amongst winning, losing, drawing teams:

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | #Matches | Home | Away | Ycards | Rcards | Fouls | Goals | Crosses | c-kicks | ShOn | ShOff |
| Wins | 6070 | 3741 | 2329 | 10706 | 185 | 73779 | 14610 | 96495 | 32558 | 35851 | 35483 |
| % of total | 74.7% | 46.0% | 28.7% | 33.9% | 19.6% | 36.2% | 65.9% | 36.1% | 38.7% | 39.8% | 38.8% |
| Draws | 2054 | 2054 | 2054 | 8317 | 202 | 52918 | 4104 | 69993 | 21657 | 22909 | 23442 |
| % of total | 25.3% | 25.3% | 25.3% | 26.3% | 21.4% | 26.0% | 18.5% | 26.2% | 25.7% | 25.4% | 25.6% |
| Losses | 6070 | 2329 | 3741 | 12568 | 558 | 77178 | 3454 | 100543 | 29978 | 31263 | 32476 |
| % of total | 74.7% | 28.7% | 46.0% | 39.8% | 59.0% | 37.9% | 15.6% | 37.7% | 35.6% | 34.7% | 35.5% |
| Totals | 8124 | 8124 | 8124 | 31591 | 945 | 203875 | 22168 | 267031 | 84193 | 90023 | 91401 |

***Figure 8***

While the home teams win fewer than half of the matches (46%), the away teams only win 29% of the matches. We see some additional expected figures. Winning teams outscore and outplay losing teams, as shown by goals, crosses, corner kicks, shots on goal, and shots off goal. Winning teams received 34% of total yellow cards, while losing teams received 40% of total yellow cards. Even more stark is red cards – winning teams received 20% of total red cards, while losing teams received 59% of total red cards.

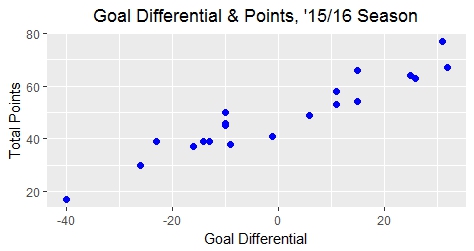
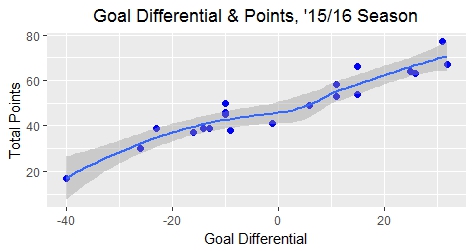
While stark, the numbers make sense. When a team receives a red card, they continue the match with a player down. Also, if the foul happens within the penalty box by the defending team, the attacking team is awarded a penalty shot. It makes sense why a team disadvantaged by a red card may have reduced chances of winning. However, further analysis would explore whether any bias exists in carding. Is it a result of aggressive play, or it a result of something else, such as referee favoritism or home field advantage?

Another interesting point can be gleaned from ratios here. Out of 8,124 matches total, 3,026 of them (or 37%) were decided by 1 goal. Out of 945 total red cards, 358 of them (38%) were awarded in a match that was determined by one goal. This seems to show that regardless of whether a match is a close victory or not, red cards appear to be evenly awarded (for this metric).

However, in matches determined by 1 goal that also have a red card, the red card is given to the losing team 68% of the time (243 matches). This compares to the overall total, where in 59% of matches with a red card, it is given to the losing team.

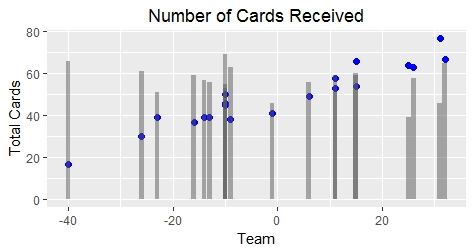
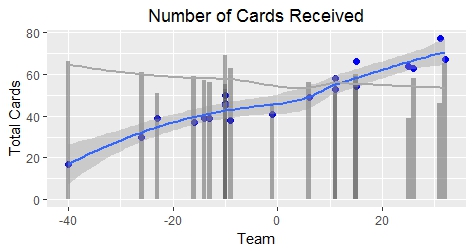
Several visuals can help show whether this is a trend between leagues and seasons.

To begin, we use the English Premier league for the 2015/2016 season as an example. Figures (9) and (10) show the relationship between goal differential and points acquired. Each point represents a team. The scatterplots naturally place the teams in rough order from left to right by those which won least to those which won most.



1. **Goal Differential vs Points Scored (10) With trendline**

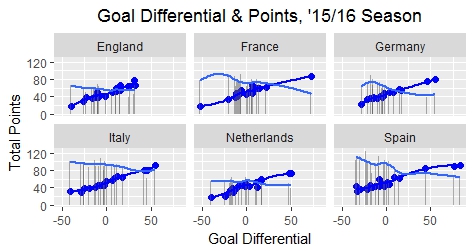
Figures (11) and (12) superimpose number of cards awarded to each team, where each bar is placed in line with its corresponding team’s point:



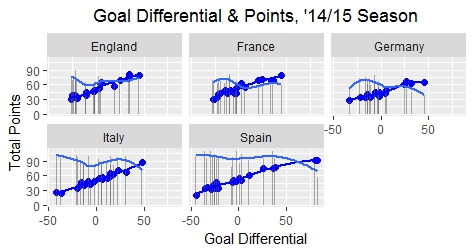
**(11) Superimposed bar chart of cards awarded to each team** **(12) With trendlines**

These plots show us that higher winning teams receive fewer yellow and red cards than lower winning teams.

The power of data allows us to see if the trends displayed in this league and season are an isolated occurrence, or if this happens on a broader scale. The following figure shows the 2015/2016 season again. Instead of just the English Premier League, it shows all leagues with available data.

Again, these plots naturally arrange the teams roughly from least winningest (left) to most winningest (right). The dark blue trendline shows the relationship between goal differential and wins. The light blue trendline shows the carding trend of teams from least to most winningest.

***Figure 13***

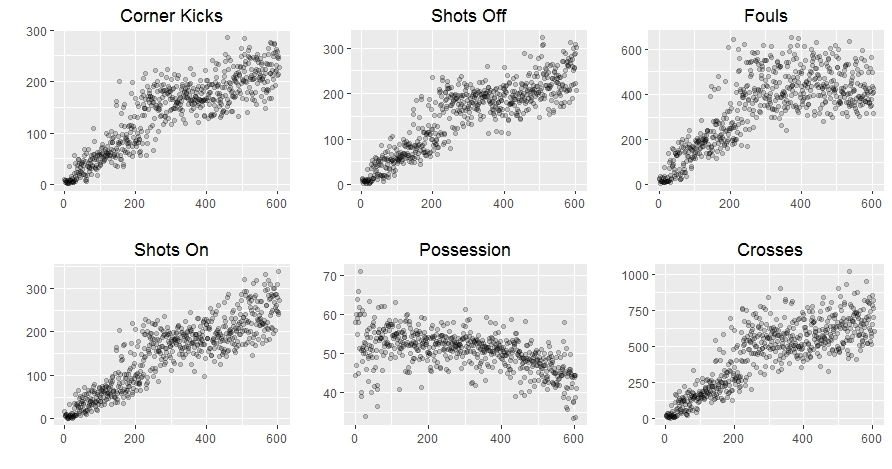


It seems to be a clear relationship. We see this same relationship in other seasons too. Figure 14 shows this relationship for available data in the 2014/2015 season.

***Figure 14***

We cannot say whether winning teams have less aggressive players or referees who call in their favor, but it warrants further investigation and special attention in the later analysis.

Do other factors show a similar relationship? We’ve included charts for remaining variables. In this case, we’ve ordered the teams along the x-axis from least to most winningest, and plotted the corresponding point on the y-axis.



***Figure 15***

Each point represents a unique season-team. Some of these plots are expected – teams that produce more chances for goals tend to win more games. Interestingly, this does not seem to be the case with ball possession. It shows that teams who win more have less ball possession time.

By how much do these variables affect match outcome? What is the effect of yellow and red cards, and is ball possession significant? This is where the benefit regression analysis appears. It can show which variables are significant, and by how much they might affect a match.

Because match outcome is measured in the number of goals a team scores minus the number of goals they permit, we ran a linear regression where the independent variables are measured by their effect on goal differential. An added benefit of our data is that it is panel or longitudinal in style. This means that we can use earlier seasons as our training data and a subsequent season as our test data.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Season | 2008/09 | 2009/10 | 2010/11 | 2011/12 | 2012/13 | 2013/14 | 2014/15 | 2015/16 |
| # of Obs | 1502 | 1714 | 1982 | 1904 | 716 | 724 | 3572 | 4134 |

***Figure 16***

We first check for multicollinearity by checking if any variables correlated with each other using the following code:

***Figure 17***

dragon\_numeric <- dragon[, sapply(dragon, is.numeric)]

cor(dragon\_numeric)

We find that the only highly correlated variables are "goals," "points," and "goal differential." This makes sense, since they are directly derived from each other. We chose goal differential as the dependent variable. There were other variables that had some correlation, but nothing approaching concern. For example, home team shots on goal correlated with corner kicks (43%) and crosses (36%). This is expected, as the intention of both plays are intended to set up a shot on goal.

We took seasons 2008/09 to 2014/15 as our training set. We set our dependent variable as goal differential and regressed it on the available variables. The benefit of regressing against goal differential is that this outcome variable is a result of both home and away team goals.

Call:

lm(formula = HTgoaldiff ~ homePoss + HTshoton + HTshotoff + HTcross +

HTcorners + ATshoton + ATshotoff + ATcross + ATcorners +

HTfouls + htYcard + htRcard + ATfouls + atYcard + atRcard,

data = dtrain)

Residuals:

Min 1Q Median 3Q Max

-9.308 -1.009 -0.014 1.043 7.755

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 3.221689 0.188725 17.071 < 2e-16 \*\*\*

homePoss -0.038811 0.002712 -14.311 < 2e-16 \*\*\*

HTshoton 0.030583 0.007630 4.008 6.19e-05 \*\*\*

HTshotoff 0.005822 0.008044 0.724 0.46925

HTcross -0.049484 0.003246 -15.247 < 2e-16 \*\*\*

HTcorners 0.036979 0.009116 4.057 5.04e-05 \*\*\*

ATshoton -0.055931 0.008637 -6.475 1.02e-10 \*\*\*

ATshotoff -0.026612 0.009157 -2.906 0.00367 \*\*

ATcross 0.041854 0.003905 10.719 < 2e-16 \*\*\*

ATcorners -0.048612 0.010467 -4.644 3.49e-06 \*\*\*

HTfouls -0.015576 0.005642 -2.761 0.00579 \*\*

htYcard -0.180150 0.018537 -9.718 < 2e-16 \*\*\*

htRcard -0.924849 0.093253 -9.918 < 2e-16 \*\*\*

ATfouls -0.001180 0.005500 -0.214 0.83018

atYcard 0.050487 0.017372 2.906 0.00367 \*\*

atRcard 0.855362 0.083332 10.264 < 2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.67 on 6039 degrees of freedom

(2 observations deleted due to missingness)

Multiple R-squared: 0.1373, Adjusted R-squared: 0.1351

F-statistic: 64.06 on 15 and 6039 DF, p-value: < 2.2e-16

***Model 1***

Because home team shots off goal and away team fouls appeared to have no significance on the model, we removed these variables and tried again.

Call:

lm(formula = HTgoaldiff ~ homePoss + HTshoton + HTcross + HTcorners +

ATshoton + ATshotoff + ATcross + ATcorners + HTfouls + htYcard +

htRcard + atYcard + atRcard, data = dtrain)

Residuals:

Min 1Q Median 3Q Max

-9.2881 -1.0057 -0.0136 1.0451 7.7742

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 3.244338 0.175565 18.479 < 2e-16 \*\*\*

homePoss -0.038927 0.002698 -14.429 < 2e-16 \*\*\*

HTshoton 0.031172 0.007585 4.110 4.01e-05 \*\*\*

HTcross -0.049019 0.003185 -15.392 < 2e-16 \*\*\*

HTcorners 0.037965 0.009018 4.210 2.59e-05 \*\*\*

ATshoton -0.056143 0.008627 -6.508 8.25e-11 \*\*\*

ATshotoff -0.026366 0.009148 -2.882 0.00396 \*\*

ATcross 0.041647 0.003893 10.698 < 2e-16 \*\*\*

ATcorners -0.048721 0.010465 -4.656 3.30e-06 \*\*\*

HTfouls -0.016168 0.005313 -3.043 0.00235 \*\*

htYcard -0.180474 0.018385 -9.816 < 2e-16 \*\*\*

htRcard -0.926692 0.093206 -9.942 < 2e-16 \*\*\*

atYcard 0.049568 0.016407 3.021 0.00253 \*\*

atRcard 0.856504 0.083284 10.284 < 2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.67 on 6041 degrees of freedom

(2 observations deleted due to missingness)

Multiple R-squared: 0.1372, Adjusted R-squared: 0.1353

F-statistic: 73.89 on 13 and 6041 DF, p-value: < 2.2e-16

***Model 2***

With this model, we have fewer variables and a slightly higher Adjusted R-squared. We can test this model accuracy for out of sample data. We did this by bringing in the data from the testing set (2015/2016 season) to see if the model maintains integrity:

predictTest = predict(dmodel2, newdata = dtest)

# check variables

predictTest

# Check R2:

SSE = sum((dtest$HTgoaldiff - predictTest)^2)

SST = sum((dtest$HTgoaldiff - mean(dragon$HTgoaldiff))^2)

1 - SSE/SST

# original adj-R2: .1353. Against the testing set: .10097. Not bad?

***Figure 18***

The model from our training set has an Adjusted R-squared of 0.1353. When we apply this model to the testing set, the R2 is 0.1009. Given that this data attempts to measure human behavior, it is not surprising that any model we attempt has a low R2, even if the variables in the model are statistically significant. Perhaps a better measure of model reliability in this case is the Sum of Squared Errors (SSE) or the Mean Squared Error (MSE). Figure 19 shows several models that we ran, the SSE, the MSE, the Adjusted R2, and the Adjusted R2 for the testing set. The MSE is a more interpretable value, as it has the same unit of measurement as the dependent variable (goals).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Variables | Adj-R2 | Test Adj-R2 | SSE | MSE |
| 1 | homePoss, HTshoton, HTshotoff, HTcross, HTcorners, ATshoton, ATshotoff, Atcross, ATcorners, HTfouls, htYcard, htRcard, ATfouls, atYcard, atRcard | .1351 | .1016596 | 6194 | 1.731 |
| 2 | homePoss, HTshoton, HTcross, HTcorners, ATshoton, ATshotoff, Atcross, ATcorners, HTfouls, htYcard, htRcard, atYcard, atRcard | .1353 | .1009683 | 6198 | 1.732 |
| 3 | homePoss, HTshoton, HTcross, HTcorners, ATshoton, ATshotoff, Atcross, ATcorners, HTfouls, htYcard, htRcard, atYcard, atRcard, (HTshoton\*HTcorners), (ATshoton\*ATcorners) | .1363 | 0.1015945 | 6195 | 1.731 |
| 4 | homePoss, HTshoton, HTcross, ATshoton, ATshotoff, ATcross, HTfouls, htYcard, htRcard, atYcard, atRcard | .1303 | .1016003 | 6193 | 1.730 |
| 5 | HTshoton, ATshoton, HTcard, ATcard | .05449 | .040111 | 6619 | 1.789 |
| 6 | HTshoton, ATshoton, htYcard, htRcard, atYcard, atRcard | .07194 | .058187 | 6494 | 1.772 |

***Figure 19***

Note: We included a model that combines yellow and red cards for each team to see its impact on SSE, MSE, and Adjusted R2. In addition to being slightly less accurate in all areas, the model loses the impact that red and yellow cards individually can have on a match.

The models above have similar Adjusted R2 values, all which tend to carry over well to the test set, and they all have similar MSE. In such a case, we prefer to take a simpler model. Model 4 had the lowest MSE and is one of the simplest. This leads us to prefer Model 4, which has the lowest MSE, or Model 6, which controls for yellow and red cards separately and is simpler yet. The formulas for these models are:

**Model 4**

***a4 = 3.339 + -.040(x1) + .039(x2) + -.041(x3) + -.066(x4) + -.031(x5) + .031(x6)+ -.016(x7) +***

***-.18(x8) + -.908(x9) + .050(x10) + .844(x11)***

**Model 6**

***a6 = 0.817 + .029(x1) + -.066(x2) + -.224(x3) + -.894(x4) + .064(x5) + .833(x6)***

It is not surprising that these variables all have some level of contribution to a match. As much as soccer may be a game of skill, it is also a game of odds. The more shots on goal a team has, the more opportunities they create to score. The more cards a team receives, the higher the chance they lose a player and play at a disadvantage.

Next, we run several logistic regressions. We use win = 1/not win = 0 and draw = 1/not draw = 0 as the dependent variables. Before conducting any regressions, we establish several baseline models.

The filtered data set we use has 16,248 observations:

|  |  |  |  |
| --- | --- | --- | --- |
| Wins | Draws | Losses | Total |
| 6,070 | 4,108 | 6,070 | 16,248 |
| .3736 | .2528 | .3736 | 1 |

***Baseline Model 1***

That means that if we always guess win for a team, we will be right 37.36% of the time. If we always guess draw, we will be right 25.28% of the time. We can improve the accuracy of our baseline model by controlling for whether the team is playing at home or away.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Home Wins | Away Wins | Home draw | Away Draws | Home Loss | Away Loss | Total |
| 3741 | 2329 | 2054 | 2054 | 2329 | 3741 | 16,248 |
| .4605 | .2867 | .2528 | .2528 | .2867 | .4605 | 1 |

***Baseline Model 2***

In this case, if we always guess “win” for the home team (or loss for the away team), we will be right 46.05% of the time. If we always guess draw for the home (or away) team, we will be right 28.67% of the time. Both figures are slightly higher than the previous baseline model.

In creating the logistic regression model, our goal is to predict a win more than 46% of the time for a home team and draw more than 28.67% of the time. The logistic regression model allows for a binary outcome – 1 or 0. However, a team has three potential match outcomes – win, loss, or draw. We mitigate this by creating the logistic regression models in pairs – a model for win and a model for draw. A model that regresses on “win” will give us the probability of a win. A model that regresses on “draw” will give us the probability of a “draw.” We can roughly calculate the probability of a loss by subtracting the sum of any pair of models from 1.

We created a total of 8 regressions models – or 4 model pairs. Odd numbered models had “win” as the dependent variable, and even numbered models have “draw” as the dependent variable.

(Note: we did not include “possession” as a variable because it contained an error that prevented us from calculating the mean in-sample prediction. Given additional time, we would like to return to this variable and find the error, since the linear regressions gave us an interesting interpretation of the variable. We would like to see if the logistic regression also finds a negative correlation between ball possession time and the likelihood of a win.)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Dep. Var | Variables | AIC | Mean Prediction |
| 1 | win | shotson, shotsoff, crosses, corners, oppShotson, oppShotsoff, oppCrosses, oppCorners, fouls, Ycards, Rcards, oppYcards, oppRcards | 14810 | .4295 |
| 2 | draw | shotson, shotsoff, crosses, corners, oppShotson, oppShotsoff, oppCrosses, oppCorners, fouls, Ycards, Rcards, oppYcards, oppRcards | 13553 | .2476 |
| 3 | win | crosses, oppCrosses, fouls, Ycards, Rcards, oppYcards, oppRcards | 15448 | .4048 |
| 4 | draw | crosses, oppCrosses, fouls, Ycards, Rcards, oppYcards, oppRcards | 13548 | .2476 |
| 5 | win | shotson, shotsoff, crosses, oppShotson, oppShotsoff, oppCrosses, Ycards, Rcards, oppYcards, oppRcards, home\_or\_away | 14683 | .4427 |
| 6 | draw | shotson, shotsoff, crosses, oppShotson, oppShotsoff, oppCrosses, Ycards, Rcards, oppYcards, oppRcards, home\_or\_away | 13573 | .2486 |
| 7 | win | crosses, oppCrosses, Ycards, Rcards, oppYcards, oppRcards, home\_or\_away | 15011 | .4265 |
| 8 | draw | crosses, oppCrosses, Ycards, Rcards, oppYcards, oppRcards, home\_or\_away | 13569 | .2487 |

***Figure 20***

These models do better than Baseline Model 1, but not as well as Baseline Model 2. This makes sense, as the outcome variables includes wins for both home teams and away teams. Adding a control variable, “home\_or\_away” did not increase the strength of these models. This makes sense, as any home field advantage may already be built into the existing variables.

Instead of controlling for field location, we ran several additional models using data where the outcome variable was “home team win” and “home team draw.” The following 8 models (4 model pairs) show the variables for each model, along with AIC, in-sample prediction mean, and out-of-sample prediction mean.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Dep Var | Variables | AIC | In-sample Prediction | Out-of-Sample |
| 1 | HTwin | HTshoton, HTshotoff, HTcross, HTcorners, ATshoton, ATshotoff, ATcross, ATcorners , HTfouls, htYcard, htRcard, ATfouls, atYcard, atRcard | 7810.3 | .5170\* | .5164\* |
| 2 | HTdraw | HTshoton, HTshotoff, HTcross, HTcorners, ATshoton, ATshotoff, ATcross, ATcorners , HTfouls, htYcard, htRcard, ATfouls, atYcard, atRcard | 6773.1 | .2592\* | .2585\* |
| 3 | HTwin | HTcross, ATcross, HTfouls, ATfouls, htYcard, htRcard, atYcard, atRcard | 8011.5 | .4994\* | .5021\* |
| 4 | HTdraw | HTcross, ATcross, HTfouls, ATfouls, htYcard, htRcard, atYcard, atRcard | 6770 | .2581\* | .2597\* |
| 5 | HTwin | HTcross, ATcross, htYcard, htRcard, atYcard, atRcard | 8029.4 | .4976\* | .5061\* |
| 6 | HTdraw | HTcross, ATcross, htYcard, htRcard, atYcard, atRcard | 6782.5 | .2561\* | .2518 |
| 7 | HTwin | htYcard, htRcard, atYcard, atRcard | 8151.8 | .4870\* | .4830\* |
| 8 | HTdraw | htYcard, htRcard, atYcard, atRcard | 6805.8 | .2527 | .2545 |

***Figure 21***

\*Baseline Model 2 predicts “win” with accuracy of .4605 and “draw” with accuracy of .2528. The asterisked figures (\*) in columns 5 and 6 had stronger predictive capability than both Baseline Models.

These are stronger logistic regression models. All 4 models in Figure 21 that regress against win have a higher in-sample and out-of-sample prediction than Baseline Model 2. Models 2 and 4 have higher in-sample and out-of-sample prediction than the draw prediction for Baseline Model 2.

**Recommendation**

Because our goal is to predict outcome of a soccer match at a profitable rate, we need to do it beyond random guessing, and we need to do it beyond simple arithmetic. To both those ends, we have succeeded. For games of chance that involve betting on the simple outcome of a game (win/loss/draw), these models will perform more strongly than the average better.

In an academic setting, we might point out how little the AIC changes for the model pairs and argue for a simpler model. However, because every little improvement in the model means additional revenue for the firm, we may opt in favor of a more complex model pair. In Figure 21, Models 1 and 2 have the highest prediction accuracy.

For games of chance that involve betting on the finer details of a game, such as by home much a team will win or lose, we turn to the linear regressions shown earlier.

Of all variables in the preferred linear regressions (Models 4 and 6), yellow and red cards have the largest coefficients. While the other variables are all statistically significant, it is worth paying close attention to cards. They occur less commonly than the other variables, but the introduction of a card to the game may signal a significant shift in the game outcome. For example, a home team red card is equal to 0.93 of an away team goal (0.18 for a yellow card), and an away team red card is roughly equal to 0.86 of a home team goal (0.05 for a yellow card). For this reason, we recommend gathering additional data on the players who receive more cards, the referees who award more cards, and seeing what the difference is between leagues.

Unfortunately for betting houses, yellow cards are not extremely common, and red cards even less so. For this reason, it is worth viewing other variables.

The variables with the next four largest coefficients are:

HTcross -0.049019

ATshoton -0.056143

ATcross 0.041647

ATcorners -0.048721

***Figure 19***

Interestingly, we see that home team crosses are negatively correlated with home team goal differential, and away team crosses are positively correlated with home team goal differential. The other two variables have the expected sign. I would recommend that gambling houses first reinspect the data to ensure that the signs are correct. Next, we would need data on the component parts of these variables, and if variations exist between various groups. Component parts include individual players, referees, or playing conditions that may contribute to corner kicks, crosses, and shots on goal. Various “groups” include leagues, seasons, or time of year.

If all else fails – bribe the refs.

If necessary, we can rearrange the model so that any of the variables acts as the dependent variable.