Augmenting Adjusted Plus-Minus in Soccer with FIFA Ratings

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October 19, 2018

Abstract

In basketball and hockey, state-of-the-art player value statistics are often variants of Adjusted Plus-Minus (APM). But APM hasn’t had the same impact in soccer, since soccer games are low scoring with a low number of substitutions. In soccer, perhaps the most comprehensive player value statistics come from video games, and in particular FIFA. FIFA ratings combine the subjective evaluations of over 9000 scouts, coaches, and season-ticket holders into ratings for over 18,000 players. This paper combines FIFA ratings and APM into a single metric, which we call Augmented APM. The key idea is recasting APM into a Bayesian framework, and incorporating FIFA ratings into the prior distribution. We show that Augmented APM predicts better than both standard APM and a model using only FIFA ratings. We also show that Augmented APM decorrelates players that are highly collinear.

1 Introduction

Decision making in sports typically requires player comparison. For example, teams decide which players to draft, who to offer a contract, etc. While not a panacea, one-number statistics of individual player value are useful decision making tools. With one-number statistics, teams can quickly rank free agents, evaluate trades, simulate future outcomes, and more.

In basketball and hockey, the best one-number statistics are typically variants of Adjusted Plus-Minus (APM). APM is a regression technique that measures each player’s contribution to winning, while controlling for the quality of teammates and opponents.

While unadjusted plus-minus has existed since the 1950’s, adjusted plus minus was first used by Wayne Winston and Jeff Sagarin while consulting for the Dallas Mavericks (Leonhardt (2003)). The first public APM calculation is due to Rosenbaum (2004), followed shortly after by Ilardi and Barzilai (2008), who separated APM into offensive and defensive components. The next big advance was Sill (2010), who replaced linear regression with ridge regression, and validated the improvement through out-of-sample predictions. APM is now mainstream in basketball; ESPN produces a “Real Plus-Minus” (RPM) statistic on their website (Ilardi (2014)), and the RPM co-creator Jeremias Engelmann has written a book chapter on the subject (Engelmann (2017)). Recently, APM in basketball was extended to...
a “win-probability” framework (Deshpande and Jensen (2016)), which removes the effects of “garbage time” minutes.

APM appeared in hockey shortly after basketball, with a series of papers by Brian Macdonald (Macdonald (2011b,a, 2012b,a)). Since then, many variants have been proposed that adapt to the specifics of hockey. Schuckers and Curro (2013) proposed the “Total Hockey Rating” (THoR), which models not only shots, but also events such as turnovers. Gramacy et al. (2013) uses logistic regression to model the probability of a goal scoring event, and Thomas et al. (2013) uses hazard functions to model separate goal scoring processes for each team.

Compared with basketball and hockey, APM hasn’t had a substantial impact in soccer. Since soccer has a low number of substitutions and a low number of scoring chances (see Figure 1), standard APM has issues with collinearity and a sparse response variable. Two players who are almost always on the pitch together (consider two backs) will be indistinguishable to the APM model, since almost all of the segments which they play have been shared. Likewise, even for segments where one of these two backs is absent, we only observe a potentially small goal differential.

Figure 1: APM in basketball, hockey, and soccer, depends on the amount of scoring and substitutions. APM works best in basketball, which has by far the most scoring out of the three sports. Hockey has much less scoring than basketball, but has the most substitutions. Compared with hockey and basketball, soccer has both low scoring and low substitutions. This is the fundamental reason why APM is difficult in soccer.
That said, several authors have proposed versions of APM for soccer. ClimbingTheLadder (2009) first produced unweighted plus-minus statistics for the MLS in 2009. Bohrmann (2011) calculated adjusted plus-minus for the English Premier League in 2011, and cited Rosenbaum (2004), further demonstrating the cross-sport impact of APM. Hamilton (2014) gives a detailed calculation of APM in soccer, questions its utility, but concludes on an optimistic note, saying “Adjusted plus/minus in football could become a valuable metric over time, but it will require a lot of care in its formulation, implementation, and interpretation.” The first academic article on APM in soccer was Kharrat et al. (2017), who imports some of the best ideas from hockey and basketball into soccer.

But, APM isn’t the only way to compute one-number statistic. One popular alternative is video game ratings, for example from FIFA. FIFA provides ratings for over 18,000 players using the subjective evaluations of over 9,000 data-reviewers, who consist of coaches, scouts, and season ticket holders (Lindberg (2016)). FIFA ratings are widely respected, and have recently been used to quantify the value of positions in soccer (Pelechrinis and Winston (2018)). In some sense, FIFA ratings are the epitome of the “Intraocular”, or “eye test”.

So, APM works well in basketball and hockey, but not soccer, and in soccer, FIFA ratings are respected one-number statistics. Putting it together, we propose Augmented APM, a Bayesian regression approach that combines FIFA ratings with APM.

The rest of this paper is organized as follows. Section 2 details the Augmented APM model, Section 3 describes the data we use, Section 4 summarizes our results, and Section 5 concludes with a brief discussion.

2 Methodology

We extend the standard Adjusted Plus-Minus (APM) model, which solves the following ridge regression problem:

\[
\hat{\beta} = \arg \min_\beta \|y - X\beta\|^2 + \lambda \|\beta\|^2
\]

(1)

We can recast this ridge regression problem as a maximum a posterior estimate from a Bayesian model

\[
y|\beta \sim N(X\beta, \sigma^2) \\
\beta \sim N(0, \tau^2)
\]

(2)

for particular \(\sigma\) and \(\tau\) values. This recasting into a Bayesian framework gives us several advantages:

- The tuning parameters become easier to fit and interpret. Under the optimization framework (Equation 1), we use cross-validation to select an appropriate value of \(\lambda\) that minimizes prediction error. Under a Bayesian interpretation, the similar parameter \(\tau\) can be interpreted as the standard deviation of player abilities. This can either be selected intuitively (for the following results we set the values at \(\tau = 0.1\) and \(\sigma = 1\)) or given a hyperprior that specifies a wider range of plausible values.
• We can obtain uncertainties for our estimates of $\beta$ by sampling from the posterior distribution. Many presentations of plus-minus scores neglect to publish measures of uncertainty in the estimates. This is particularly important in the context of comparing players as it’s desirable to know whether differences in players reflect true differences in performance or simply a noisy estimation procedure. Likewise, we can express uncertainty in player rankings by drawing from the joint posterior for betas.

• We can easily extend the model to accommodate further information. We discuss two particular extensions of this model: including FIFA ratings and time-weighted segments. However, this does not exhaust the potential flexibility of these models, which are often easy to fit using standard Bayesian software (Carpenter et al. (2017)).

We take advantage of the last point to incorporate subjective ratings into the model. One problem with the traditional ridge penalty for players is that it assumes all players should be regularized towards zero: the effect of the “average” player. This is implicit in the prior which sets the prior mean for all players $\beta$ coefficients to be zero. But intuitively, priors should be different for more or less talented players: we would expect Lionel Messi to perform better than your typical player. Determining these prior values, however, could be difficult.

We can, however, use subjective assessments such as FIFA scores as an approximation for this prior. The Augmented APM model has the following multi-level form:

$$
\begin{align*}
\text{Equation 3 is a hierarchical model where the “prior” for player ratings is no longer zeroed, and is instead centered at a scaled value of their subjective ratings score. We shift the ratings so that they have mean zero, which means that the $\beta$ values can still be interpreted as an effect compared to the “average” player (in the sense of having the average FIFA rating).}

\text{This model allows us to distinguish between players who are perfectly collinear in the existing data set. While under a ridge regression model both players would receive the same attribution of credit for game results, the Augmented APM model gives the higher subjectively rated player a greater share of the credit.}

\text{We also can introduce “weights” for the time length of a segment. Intuitively a longer segment will produce larger responses: scaling both the magnitude and variance of the differential $y$. To accommodate these effects we simply introduce the time of the segment into the model}

\text{This can be achieved in the standard APM optimization problem by estimating $yt^{-1}$ and introducing weights proportional to $\sqrt{t}$.}
\end{align*}
$$
Figure 2: Play-by-play data, after pre-processing, for an example game between Manchester City and Liverpool. Each row corresponds to a game segment where no substitutions take place. The response variable is the goal differential in that game segment. Each player has a column, which is 1 when the player plays for the home team, -1 for the away team, and 0 if the player is not playing.

| Home Team | Away Team | Goal Differential | Time Start | Time End | Aguero | Salah | .... | Lukaku |
|-----------|-----------|--------------------|------------|----------|--------|-------|------|--------|
| Man City  | Liverpool | 2                  | 0          | 60       | 1      | -1    | ...  | 0      |
| Man City  | Liverpool | -1                 | 61         | 68       | 1      | -1    | ...  | 0      |
| Man City  | Liverpool | 0                  | 69         | 75       | 1      | -1    | ...  | 0      |
| Man City  | Liverpool | 1                  | 76         | 93       | 0      | -1    | ...  | 0      |

Figure 3 compares the models in each season using 10 fold cross-validation. Our Aug-

3 Data

We fit and evaluate our models on three English Premier League (EPL) seasons: 2015-16, 2016-17, and 2017-18. To fit these models, we need two sources of data: play-by-play and FIFA ratings. Play-by-play data records all events (e.g. goals, substitutions) in a game. We convert this play-by-play data into a matrix where each row corresponds to a game segment without any substitutions. An example is shown in Figure 2.

We collect preseason FIFA ratings for each EPL season. The preseason FIFA ratings are typically released in late August of each year, on the website sofifa.com. While FIFA rates many player characteristics, such as speed and agility, this paper keeps things simple, and only uses each player’s overall rating.

4 Results

This section compares our Augmented APM model against the models listed in Table 1. We use a criteria similar to Sill (2010), in that we measure each model’s ability to predict out-of-sample game results. Game result predictions are simply the sum of predictions for each game segment (e.g. each row of Figure 2). Our accuracy is the mean squared error (MSE) of the sum of predicted game segments with the actual game results.

Figure 3 compares the models in each season using 10 fold cross-validation. Our Aug-
Model | Description
---|---
**Zero** | A naive model that predicts every game segment will have a 0 goal differential. 

**Intercept** | A naive model that predicts every game segment will have the average home advantage point differential (learned on training data).

**FIFA** | Uses the difference in teams overall FIFA ratings as predictors.

**APM** | Standard ridge regression APM (Equation 1)

**Augmented APM** | Equation [3] of Section 2

Table 1: The five models we compare in this paper.

mented APM model has the best predictive accuracy. The FIFA only model improves on the intercept model, which shows that FIFA ratings are a valuable predictor. We were surprised, however, that standard APM out-predicts the FIFA only model in 2015 and 2017, due to the limitations of APM in soccer discussed in the introduction.

![Average game-result prediction error for EPL, seasons 2015–2016–2017](image)

Figure 3: The MSE of our models in three EPL seasons using 10 fold cross-validation.

We were also interesting in how our models performed at different times in the season. Intuitively, we expected that FIFA would predict better in the beginning of the season, and APM would predict better at the end of the season. To test this, we trained each model with all data up until a particular month, then predicted game results for the next two months.
The results of this are shown in Figure 4, which demonstrates that FIFA starts the season as the best predictor, and both APM and Augmented APM out-predict FIFA by February. This suggests APM picks us useful information over the course of the season.

Figure 4: The MSE of each model over the course of the season. We train our models all data up until a month, then measure the prediction error over the next two months. The MSE for each month is averaged across the three seasons in our dataset.

Adjusted Plus-Minus models are often validated by an “Intraocular” test, in that, it’s better if the results make intuitive sense to soccer fans. Here, we expect the FIFA ratings to be very helpful. Figure 5 compares the top 15 players from the APM and Augmented APM models in the 2017-18 season. As expected, Augmented APM gives higher value to players with higher FIFA ratings. We also see that Mohamed Salah, the EPL player of the year, ranks first in the APM model, and fourth in the Augmented APM model. This is a good sign for the intraocular test.

Finally, an additional benefit of Augmented APM is that it “de-correlates” players who play most of their minutes together. To show this, Figure 5 shows that players on Manchester City and Manchester United “cluster” together in the APM model. While some clustering still occurs in the Augmented APM ratings, it is less pronounced, since now players on the same team must also have similar FIFA ratings.
Discussion

This paper introduces Augmented APM, which incorporates FIFA ratings into the standard APM framework. The key idea was recasting APM into a Bayesian framework, then incorporating FIFA ratings into the prior distribution. We showed that Augmented APM has better out-of-sample prediction accuracy than models using only FIFA ratings, and standard APM. In addition, Augmented APM helps “de-correlate” players that play the majority of their minutes together.

There are many directions for future work. One direction is simply adding more data and seasons into our estimates. This would allow us to rank players across leagues, especially if we used cross-league tournament data. Another direction we tried to include in this project is using “Expected Goals” instead of goal differential as the response variable. Unfortunately, our play-by-play data was too coarse, and our expected goals model did not boost our predictive accuracy. This is certainly an area where player tracking data would help. Finally, nothing conceptually prevents extending Augmented APM to other sports.

We make both the software to generate the results, and the final results, available online. The software is in two separate R-packages:

- `PlusMinusModels`, R-package that fits the Augmented APM and APM models.
- `apm`, R-package that scrapes play-by-play data, FIFA ratings, and prepares the for modeling.

The modeling results are available as sortable tables online at [www.intraocular.net/apm](http://www.intraocular.net/apm).
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