Augmenting Adjusted Plus-Minus in Soccer, with FIFA Ratings

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APM: State-of-the-art one number statistic in Basketball and Hockey

APM (Adjusted Plus-Minus): **one number statistic** that measures each player contribution to scoring, after controlling for the teammates and opponent strength

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APM was introduced for basketball by Rosenbaum (2004) in a blog post for 82games.com (now successfully implemented on ESPN)

Hockey has successfully adapted the APM idea (Macdonald 2011, Thomas 2013)

… But APM hasn't had the same impact in Soccer…

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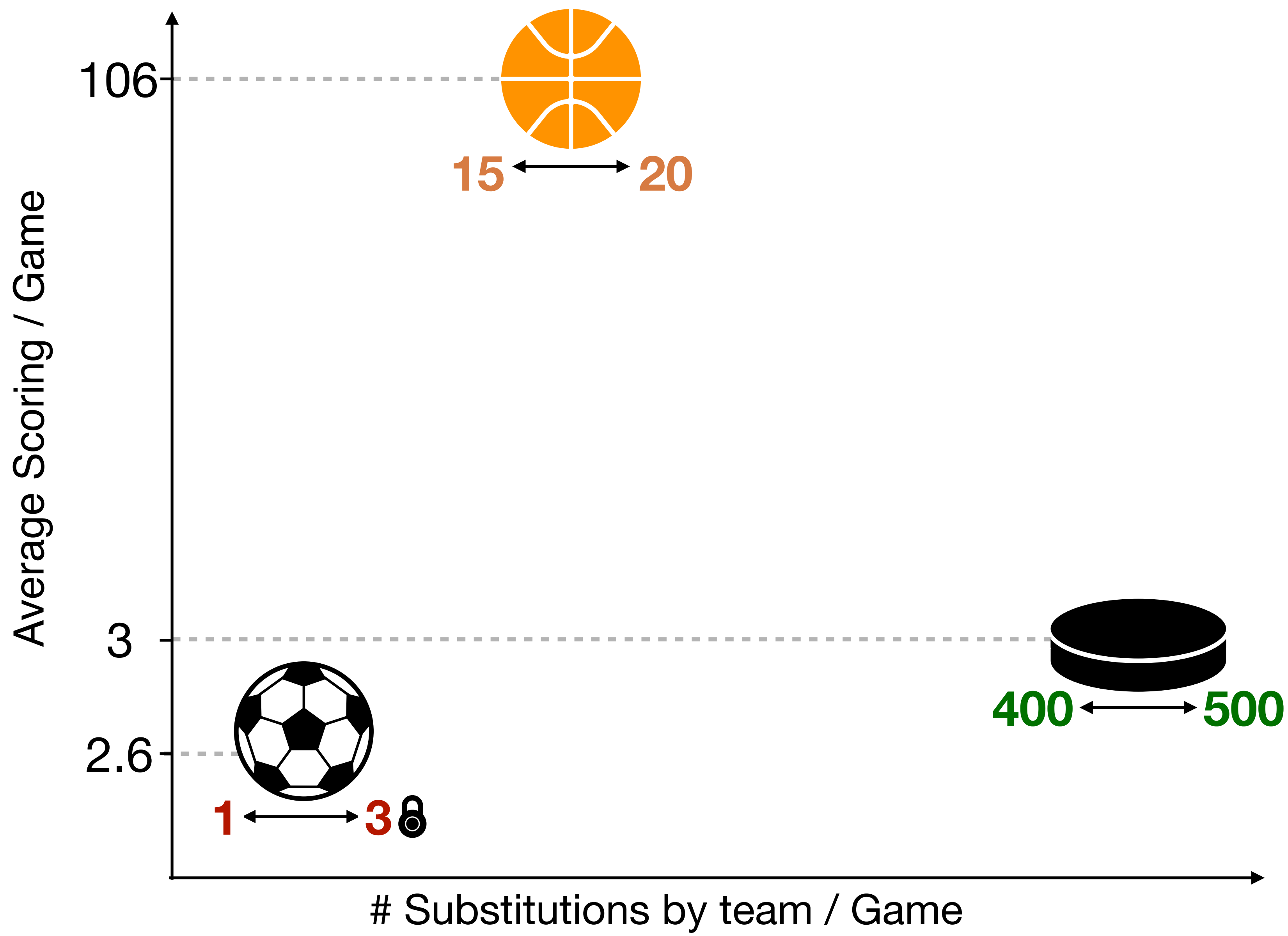

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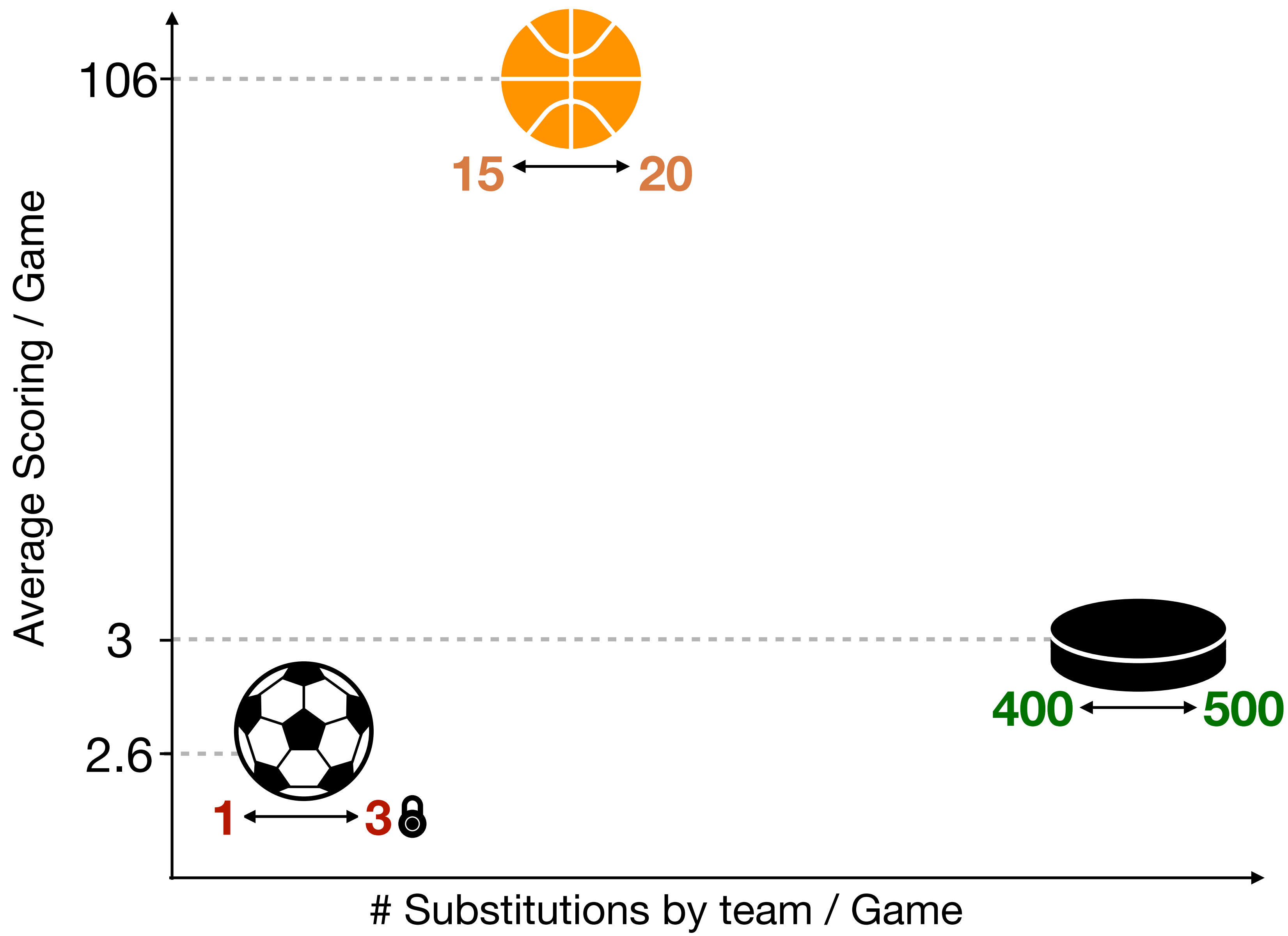

Soccer has low scoring and a low number of substitutions per game:

- multicollinearity in standard APM
- sparse response variable

FIFA provides subjective ratings for over 18,000 players/season

- A **group of 9000 “data-reviewers”**: scouts, coaches, and season-ticket holders watch games on all 18,000 players
- The **subjective ratings** are aggregated into ratings for each player
- We use each player’s overall rating

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Our goal: Augment APM with FIFA Ratings = FIFA + APM

We are interested in the following questions

- Is **Augmented APM** better in predicting games than FIFA or APM only?
- Does combining **subjective FIFA Ratings** and **APM** resolve the multicollinearity problem?
- Can we use **Augmented APM** to identify players overvalued by FIFA Ratings?

We need play-by-play data and FIFA ratings

PlusMinusData (R-package) : https://github.com/fmatano/PlusMinusData

- ⚽ downloads play-by-data from ESPN for the top 5 European Leagues (EPL, Liga, Ligue, Serie-A, Bundesliga)
- ⚽ downloads FIFA Ratings from sofifa.com
- ⚽ links players between ESPN and FIFA (interactive record linkage)

PlusMinusData returns a table with game segment data

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

Segment - t: interval of time for which the lineup did not change

Home Team	Away Team	Goal Differential	Time Start	Time End	Aguero	Salah	….	Lukaku
		2	0	60	1	**segment 1**	…	0
		-1	61	68	1	**segment 2**	…	0
		0	69	75	1	-1	…	0
		1	76	93	0	-1	…	0

Response Variable - y

Home Team	Away Team	Goal Differential	Time Start	Time End	Aguero	Salah	....	Lukaku
		2	0	60	1	-1	...	0
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Design Matrix - X

Home Team	Away Team	Goal Differential	Time Start	Time End	Aguero	Salah	....	Lukaku
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		-1	61	68	1	-1	...	0
		0	69	75	1	-1	...	0
		1	76	93	0	-1	...	0

Our goal: estimate the coefficients associated to the players

β_{Aguero} β_{Salah} β_{Lukaku}

Home Team	Away Team	Goal Differential	Time Start	Time End	Aguero	Salah	....	Lukaku
		2	0	60	1	-1	…	0
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		0	69	75	1	-1	…	0
		1	76	93	0	-1	…	0

Standard APM uses Ridge Regression to estimate the coefficients

Ridge Regression

$$\hat{\beta} = \arg\min_{\beta} \|y - X\beta\|_2^2 + \lambda\|\beta\|_2^2$$

APM uses Ridge Regression to obtain coefficients estimates

Ridge Regression (is Bayesian)

$$\hat{\beta} = \arg\min_{\beta} \|y - X\beta\|_2^2 + \lambda\|\beta\|_2^2$$

Model

$$y|\beta \sim N(X\beta, \sigma^2)$$

Subjective prior

$$\beta \sim N(0, \tau^2)$$

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Model

$$y|\beta \sim N(X\beta, \sigma^2)$$

Subjective prior

$$\beta \sim N(0, \tau^2)$$

$\hat{\beta}$ is the MAP estimate of the posterior distribution $\beta|y$

We recast Ridge Regression into a Bayesian model

$$y|\beta \sim N(X\beta, \sigma^2)$$

$$\beta \sim N(0, \tau^2)$$

We extend the model to add FIFA ratings as prior information

$$y|\beta \sim N(X\beta, \sigma^2)$$

$$\cancel{\beta \sim N(0, \tau^2)} \quad \beta \sim N(\alpha * \text{FIFA Ratings}, \tau^2)$$

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$$y|\beta \sim N(X\beta, \sigma^2)$$

$$\cancel{\beta \sim N(0, \tau^2)} \quad \beta \sim N(\alpha * \text{FIFA Ratings}, \tau^2)$$

$$\boxed{\begin{aligned} \sigma &= 1 \\ \tau &= 0.1 \\ \alpha &\sim N(0, 1) \end{aligned}}$$

The Bayesian framework offers several advantages

- Easy to specify and extend (prior uncertainty, time-weighted segments)
- Gives a measure of the uncertainty on the coefficients
- Offers an interpretation of the regularizer
- Plus-Minus Models R-package: provides features to fit and sample from these models
  https://github.com/tpospisi/PlusMinusModels

We used EPL play-by-play data

- play-by-play **EPL** data for seasons: **2015 - 2016 - 2017**
- FIFA Ratings at the beginning of each season (~August)
- We exclude goalies from the final ranking
- We measure the quality of our metric by predicting game by game goal differential from each segment, with 10 fold CV

Home Team	Away Team	Goal Differential	Time Start	Time End	$\widehat{\beta}_{\text{Augero}}$	$\widehat{\beta}_{\text{Salah}}$	....	$\widehat{\beta}_{\text{Lukaku}}$
			0	60	1	-1	...	0
			61	68	1	-1	...	0
			69	75	1	-1	...	0
			76	93	0	-1	...	0

Home Team	Away Team	Goal Differential	Time Start	Time End	$\widehat{\beta}_{\text{Augero}}$	$\widehat{\beta}_{\text{Salah}}$	....	$\widehat{\beta}_{\text{Lukaku}}$
		$\hat{y}_1$	0	60	1	-1	...	0
		$\hat{y}_2$	61	68	1	-1	...	0
		$\hat{y}_3$	69	75	1	-1	...	0
		$\hat{y}_4$	76	93	0	-1	...	0

Home Team	Away Team	Goal Differential	Time Start	Time End			....	
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		$\hat{y}_4$	76	93	0	-1	...	0

Predicted goal differential for vs $= \hat{y}_1 + \hat{y}_2 + \hat{y}_3 + \hat{y}_4$

The prediction error is the mean square error over all the games

Predict goal differential: vs

Predict goal differential: vs

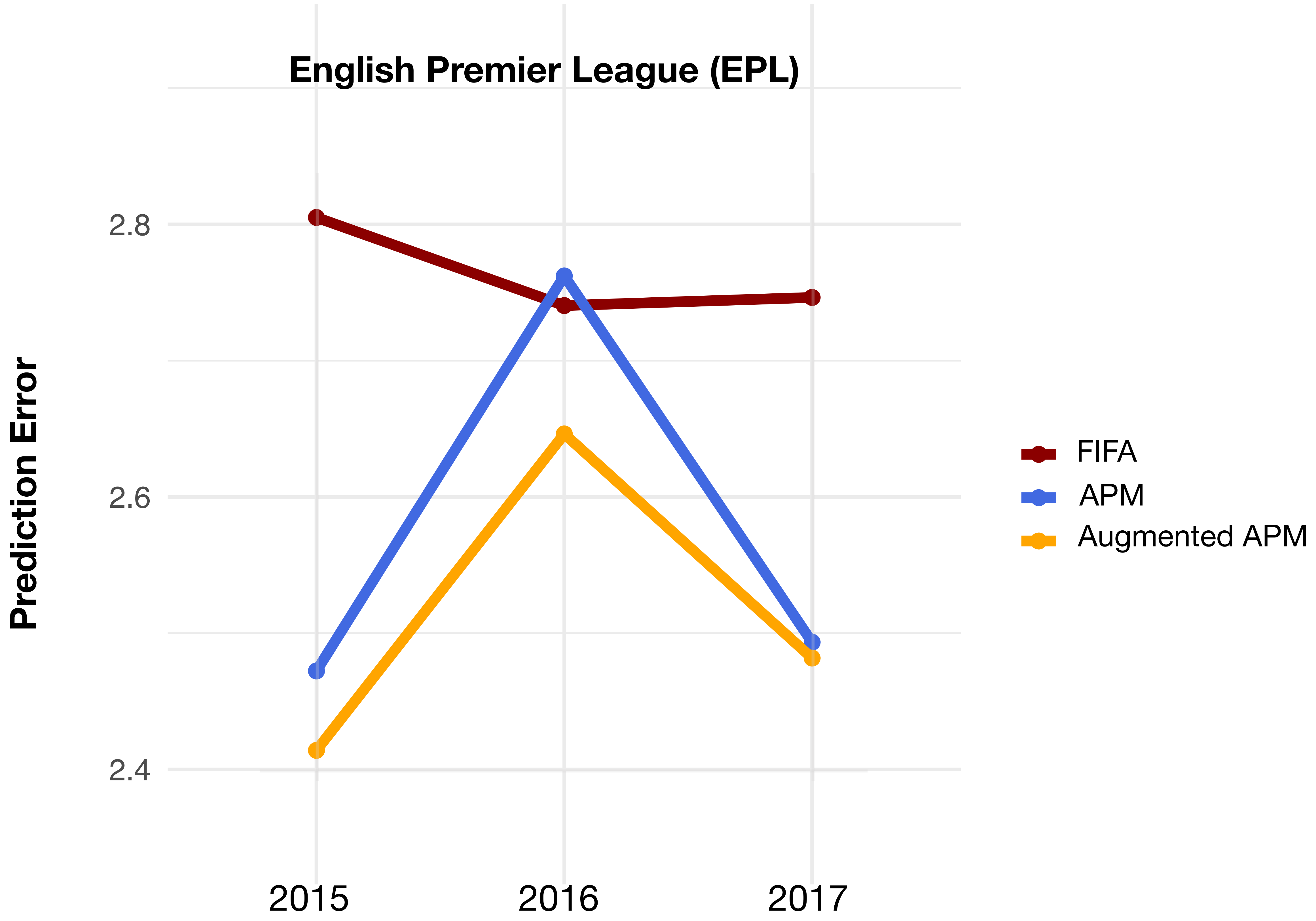
Predict goal differential: vs

.... vs ......

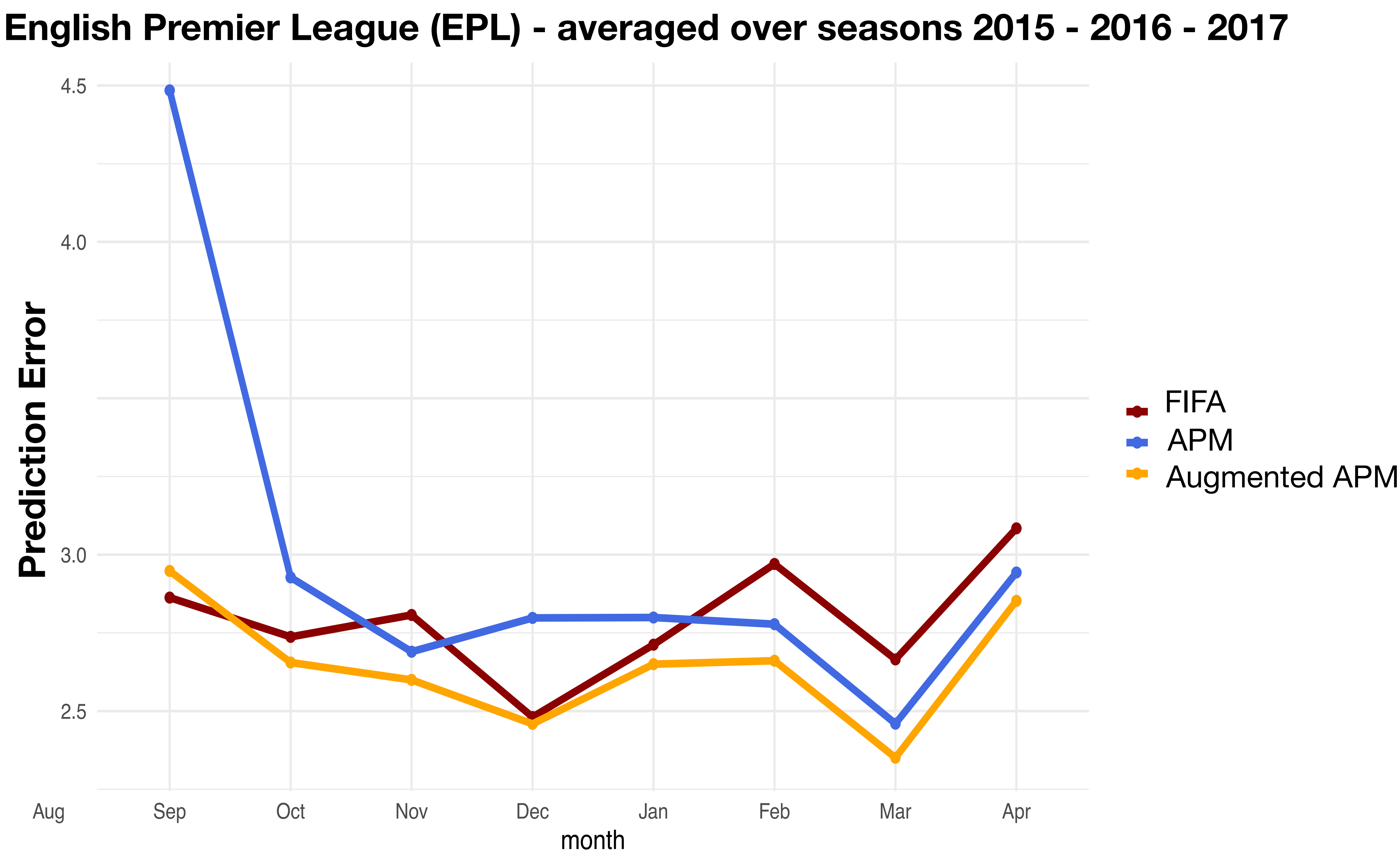
$$\textbf{Prediction Error} = \sum_{\text{games}} \frac{(\text{True goal differential} - \text{predicted goal differential})^{\mathbf{2}}}{\text{number of games}}$$


English Premier League (EPL)
Prediction Error
2.8
2.6
2.4
2015
2016
2017

Augmented APM predicts games better than APM and FIFA



Augmented APM is a more stable predictor over the season



Standard APM meets the intraocular test

APM Ranking (EPL - 2017)

espn_name	FIFA	teams_played	APM	Aug. APM
Mohamed Salah	83	Liverpool **MVP**	0.241	0.262
Son Heung	82	Tottenham Hotspur	0.222	0.198
Kevin De Bruyne	89	Manchester City	0.219	0.311
David Silva	87	Manchester City	0.215	0.291
Kyle Walker	83	Manchester City,Tottenham Hotspur	0.197	0.195
Gabriel Jesus	81	Manchester City	0.185	0.189
Sergio Agüero	89	Manchester City	0.169	0.278
Raheem Sterling	82	Manchester City	0.165	0.175
Wilfried Zaha	81	Crystal Palace	0.161	0.202
James Tomkins	76	Crystal Palace	0.161	0.136
Fernandinho	82	Manchester City	0.157	0.167
Antonio Valencia	83	Manchester United	0.152	0.169
Romelu Lukaku	86	Manchester United	0.149	0.212
Marouane Fellaini	79	Manchester United	0.146	0.14
Eric Bailly	84	Manchester United	0.144	0.216
Sadio Mané	84	Liverpool	0.142	0.219
Nemanja Matic	83	Manchester United	0.135	0.144
Bernardo Silva	84	Manchester City	0.135	0.195
Dele Alli	84	Tottenham Hotspur	0.133	0.161
Nicolás Otamendi	83	Manchester City	0.133	0.165
Andrew Robertson	75	Liverpool	0.133	0.067
Georginio Wijnaldum	82	Liverpool	0.132	0.181
Roberto Firmino	83	Liverpool	0.132	0.196

Aug. APM gives higher value to players with high FIFA Ratings

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Eden Hazard	90	Chelsea	0.068	0.192
Gabriel Jesus	81	Manchester City	0.185	0.189
Joël Matip	83	Liverpool	0.118	0.185
Alexandre Lacazette	85	Arsenal	0.121	0.184
Zlatan Ibrahimovic	90	Manchester United	-0.052	0.183
Paul Pogba	87	Manchester United	0.101	0.183
Philippe Coutinho	86	Liverpool	0.042	0.182
Christian Eriksen	87	Tottenham Hotspur	0.106	0.182
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Augmented APM de-correlates players

APM Ranking (EPL - 2017)

MVP

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Augmented APM Ranking (EPL - 2017)

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Augmented APM identifies players that are overvalued by FIFA

FIFA Ranking (EPL - 2017)

espn_name	FIFA	teams_played	value
Eden Hazard	90	Chelsea	€90.5M
Zlatan Ibrahimovic	90	Manchester United	NA
Kevin De Bruyne	89	Manchester City	€83M
Sergio Agüero	89	Manchester City	€66.5M
Alexis Sánchez	89	Arsenal,Manchester United	€67.5M
Mesut Özil	88	Arsenal	€60M
David Silva	87	Manchester City	€44M
Paul Pogba	87	Manchester United	€66.5M
Christian Eriksen	87	Tottenham Hotspur	€65M
N'Golo Kanté	87	Chelsea	€52.5M
Romelu Lukaku	86	Manchester United	€59M
Philippe Coutinho	86	Liverpool	€56M
David Luiz	86	Chelsea	€33M
Toby Alderweireld	86	Tottenham Hotspur	€40.5M
Cesc Fàbregas	86	Chelsea	€41M
Harry Kane	86	Tottenham Hotspur	€59M
Henrikh Mkhitaryan	85	Manchester United,Arsenal	€39M
Alexandre Lacazette	85	Arsenal	€48.5M
Ilkay Gündogan	85	Manchester City	€46M
Jan Vertonghen	85	Tottenham Hotspur	€28.5M
Vincent Kompany	85	Manchester City	€26M
César Azpilicueta	85	Chelsea	€37.5M
Sadio Mané	84	Liverpool	€39M

Augmented APM Ranking (EPL - 2017)

NEW

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David Silva	87	Manchester City
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We display our results on our website intraocular.net

The idea came from the way espn.com displays Real Plus Minus for NBA

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NBA Real Plus-Minus - 2017-18

Season: 2017-18

Position: All | Point Guard | Shooting Guard | Small Forward | Power Forward | Center

Last Updated: October 18, 2018 5:00:02 PM PDT

2017-18 Real Plus-Minus

RK	NAME	TEAM	GP	MPG	ORPM	DRPM	RPM	WINS
1	Chris Paul, PG	HOU	58	31.8	5.36	1.63	**6.99**	11.75
2	James Harden, PG	HOU	72	35.4	6.69	0.02	**6.71**	16.03
3	Stephen Curry, PG	GS	51	32.0	6.59	0.06	**6.65**	10.97
4	Jimmy Butler, SG	MIN	59	36.7	3.61	2.78	**6.39**	12.80
5	Nikola Jokic, C	DEN	75	32.5	4.02	1.95	**5.97**	14.03
6	Victor Oladipo, SG	IND	75	34.0	2.74	3.17	**5.91**	14.77
7	Anthony Davis, PF	NO	75	36.4	1.85	3.70	**5.55**	15.56
8	Robert Covington, SF	PHI	80	31.6	1.21	4.24	**5.45**	14.31
9	Kyle Lowry, PG	TOR	78	32.2	4.15	1.03	**5.18**	13.59
10	Russell Westbrook, PG	OKC	80	36.4	3.96	1.20	**5.16**	15.73
11	Joel Embiid, C	PHI	63	30.3	1.51	3.59	**5.10**	10.13
12	LeBron James, SF	CLE	82	36.9	5.64	-0.68	**4.96**	15.86
13	Otto Porter Jr., SF	WSH	77	31.6	2.91	2.05	**4.96**	12.51
14	Damian Lillard, PG	POR	73	36.6	5.28	-0.38	**4.90**	13.67
15	Tyus Jones, PG	MIN	82	17.9	2.38	2.40	**4.78**	7.27
16	Karl-Anthony Towns, SF	MIN	82	35.6	3.80	0.44	**4.24**	13.50
17	Giannis Antetokounmpo, PF	MIL	75	36.7	2.63	1.60	**4.23**	12.90
18	Draymond Green, PF	GS	70	32.7	0.70	3.34	**4.04**	10.98
19	Al Horford, PF	BOS	72	31.6	1.21	2.68	**3.89**	10.05
20	Rudy Gobert, C	UTAH	56	32.4	-1.24	5.06	**3.82**	8.02
21	Kemba Walker, PG	CHA	80	34.2	4.36	-0.55	**3.81**	12.27

Future Work

- Offensive and Defensive Augmented APM
- Rank players across leagues
- Model FIFA Ratings
- Extend the model using tracking data (i.e. expected goals)
- Extend the model to other sports (for instance NBA)
- "Augmenting Adjusted Plus-Minus in soccer with FIFA Ratings"
  https://arxiv.org/abs/1810.08032