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SAS & R: A Perfect Combination for Sports Analytics

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ABSTRACT

Revolution Analytics reports more than two million R users worldwide. SAS has the capability to use R code, but users have discovered a slight learning curve to performing certain basic functions such as getting data from the web. R is a functional programming language while SAS is a procedural programming language. These differences create difficulties when first making the switch from programming in R to programming in SAS. However, SAS/IML enables integration between the two languages by enabling users to write R code directly into SAS/IML. This paper details the process of using the SAS/IML command Submit /R and the R package “XML” to get data from the web into SAS/IML. The project uses public basketball data for each of the 30 NBA teams over the past 33 years, taken directly from Basketball-Reference.com. The data was retrieved from 66 individual web pages, cleaned using R functions, and compiled into a final dataset composed of 48 variables and 895 records. The seamless compatibility between SAS and R provide an opportunity to use R code in SAS for robust modeling. The resulting model provides a clear and concise approach for those interested in pursuing sports analytics, as well as, a performance comparison between SAS and R.

INTRODUCTION

Moving from one program to another can provide challenges, especially when users have built proficiencies that do not directly translate over to the new program. SAS makes moving from R to SAS simple with SAS/IML’s integration with R. This integration allows users to write R commands directly into SAS/IML, call R packages and functions, and transfer data between the two programs seamlessly. We used this integration with R to illustrate how users can scrape data from the web using the R package XML and the function readHTMLTable within SAS/IML. This process allows for a continuous workflow and streamlined

code. Using these procedures, we analyzed 33 years of basketball data and looked at trends in the game over that span.

OBTAINING THE DATA

The data for this project came from Basketball-Reference.com, a branch of the Sports Reference family, one of the leading sources for sports statistics in the world. Data is organized according to the season in which the statistics occurred. Thus, to analyze 33 seasons of data one would have to pull statistics from 33 different web pages. Additionally, we added opponent statistics to these data sets, requiring two tables to be downloaded from each web page. An example of the data is presented in Figure 1.

Team Stats

Playoff teams are marked with an asterisk (*) ·
 [Glossary](#) ·
 [SHARE](#) ·
 [Embed](#) ·
 [CSV](#) ·
 [Export](#) ·
 [PRE](#) ·
 [LINK](#) ·
 ?

Rk	Team	G	MP	FG	FGA	FG%	3P	3PA	3P%	2P	2PA	2P%	FT	FTA	FT%	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS	PTS/G
1	Golden State Warriors*	82	19730	3410	7137	.478	883	2217	.398	2527	4920	.514	1313	1709	.768	853	2814	3667	2248	762	496	1185	1628	9016	110.0
2	Los Angeles Clippers*	82	19730	3228	6830	.473	827	2202	.376	2401	4628	.519	1468	2067	.710	784	2711	3495	2031	640	409	1012	1749	8751	106.7
3	Dallas Mavericks*	82	19880	3255	7036	.463	732	2082	.352	2523	4954	.509	1386	1843	.752	858	2608	3466	1846	663	371	1062	1644	8628	105.2
4	Oklahoma City Thunder	82	19830	3184	7119	.447	632	1864	.339	2552	5255	.486	1524	2020	.754	1052	2844	3896	1681	598	454	1205	1829	8524	104.0
5	Toronto Raptors*	82	19855	3108	6829	.455	726	2060	.352	2382	4769	.499	1585	2014	.787	881	2526	3407	1701	615	357	1057	1712	8527	104.0
6	Houston Rockets*	82	19805	3032	6832	.444	933	2680	.348	2099	4152	.506	1525	2133	.715	958	2624	3582	1820	777	407	1366	1803	8522	103.9
7	San Antonio Spurs*	82	19955	3208	6854	.468	677	1847	.367	2531	5007	.505	1368	1754	.780	806	2772	3578	2000	657	444	1146	1564	8461	103.2
8	Cleveland Cavaliers*	82	19780	3089	6739	.458	826	2253	.367	2263	4486	.504	1453	1934	.751	911	2612	3523	1814	603	340	1171	1510	8457	103.1
9	Portland Trail Blazers*	82	19855	3175	7049	.450	807	2231	.362	2368	4818	.491	1272	1589	.801	879	2881	3760	1799	525	372	1117	1494	8429	102.8
10	Atlanta Hawks*	82	19730	3121	6699	.466	818	2152	.380	2303	4547	.506	1349	1735	.778	715	2611	3326	2111	744	380	1167	1457	8409	102.5

Figure 1: Basketball-Reference.com 2014 season team statistics table (top 10 teams).

While Basketball-Reference.com allows users to easily download tables into various formats, downloading 66 of these tables individually would be quite the daunting task. Hence, the R package XML and function readHTMLTable become very useful. By applying readHTMLTable to a list of the 33 web pages, each table from those web pages is almost

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instantly read into SAS/IML. A preview of this code can be seen below in Figure 2.

```
url.list = sprintf("http://www.basketball-reference.com/leagues/NBA_%s.html",
                  c(1980:1998, 2000:2011, 2013:2014)) #create a list of the links

columnclasses = c("character", "character", rep("integer", 4), "numeric",
                  rep("integer", 2), "numeric", rep("integer", 2),
                  "numeric", rep("integer", 2), "numeric",
                  rep("integer", 9), "numeric") #vector for setting column names

library(XML)

for(i in 1:33) { #read in the tables from the urls
  nam = paste0("x", i)
  assign(nam, readHTMLTable(url.list[[i]], colClasses = columnclasses,
                            stringsAsFactors=FALSE))
}
```

Figure 2: Application of XML function readHTMLTable to Basketball-Reference.com data.

Additional work is needed to clean and join the team statistics and opponent statistics tables; however, the result is a data set of 48 variables and 836 observations, as seen below in Figure 3.

	48	SeasonEnd	Team	W	Playoffs	FG	oppFG	FGA	oppFGA	Fgpercent	oppFGpercent
895			Int	Nom	Nom	Int	Int	Int	Int	Int	Int
1	■ x²	1980	Atlanta Hawks	50		1	3261	3144	7027	0.464	0.458
2	■ x²	1980	Boston Celtics	61		1	3617	3439	7387	0.49	0.47
3	■ x²	1980	Chicago Bulls	30		0	3362	3585	6943	0.484	0.496
4	■ x²	1980	Cleveland Cavaliers	37		0	3811	3811	8041	0.474	0.501
5	■ x²	1980	Denver Nuggets	30		0	3462	3736	7470	0.463	0.492
6	■ x²	1980	Detroit Pistons	16		0	3643	3847	7596	0.48	0.496
7	■ x²	1980	Golden State Warriors	24		0	3527	3438	7318	0.482	0.493
8	■ x²	1980	Houston Rockets	41		1	3599	3658	7496	0.48	0.496
9	■ x²	1980	Indiana Pacers	37		0	3639	3693	7689	0.473	0.489
10	■ x²	1980	Kansas City Kings	47		1	3582	3328	7489	0.478	0.476
11	■ x²	1980	Los Angeles Lakers	60		1	3898	3723	7368	0.529	0.47
12	■ x²	1980	Milwaukee Bucks	49		1	3685	3456	7553	0.488	0.462
13	■ x²	1980	New Jersey Nets	34		0	3456	3480	7427	0.461	0.469
14	■ x²	1980	New York Knicks	39		0	3802	3707	7672	0.496	0.495
15	■ x²	1980	Philadelphia 76ers	59		1	3523	3444	7156	0.492	0.455
16	■ x²	1980	Phoenix Suns	55		1	3570	3563	7235	0.493	0.476
17	■ x²	1980	Portland Trail Blazers	38		1	3408	3349	7167	0.476	0.478
18	■ x²	1980	San Antonio Spurs	41		1	3856	4000	7738	0.498	0.5
19	■ x²	1980	San Diego Clippers	35		0	3524	3752	7494	0.47	0.5
20	■ x²	1980	Seattle SuperSonics	56		1	3554	3408	7565	0.474	0.459
21	■ x²	1980	Utah Jazz	24		0	3382	3559	6817	0.496	0.496
22	■ x²	1980	Washington Bullets	39		1	3574	3615	7796	0.458	0.465
23	■ x²	1981	Atlanta Hawks	31		0	3291	3401	6866	0.479	0.495
24	■ x²	1981	Boston Celtics	62		1	3581	3372	7099	0.504	0.462
25	■ x²	1981	Chicago Bulls	45		1	3457	3527	6903	0.501	0.489
26	■ x²	1981	Cleveland Cavaliers	28		0	3556	3608	7609	0.467	0.503
27	■ x²	1981	Dallas Mavericks	15		0	3204	3622	6928	0.462	0.513
28	■ x²	1981	Denver Nuggets	37		0	3784	4059	7960	0.475	0.506
29	■ x²	1981	Detroit Pistons	21		0	3236	3499	6986	0.463	0.509
30	■ x²	1981	Golden State Warriors	39		0	3560	3631	7284	0.489	0.504

Figure 3: Complete data set with 33 seasons of aggregated statistics.

PROCEDURES IN SAS/IML

To run R code in SAS/IML, users must use a special Submit statement, SUBMIT / R, followed by an ENDSUBMIT statement. All R code found between these two statements is executed in R and then passed back into SAS/IML.

submit / R;

{insert R code here}

endsubmit;

Inserting the code found in Figure 2 will run the code in R and pass it back to SAS/IML.

While it is entirely possible to run the code in R, save the data set, and read the saved dataset into SAS/IML, this integration creates continuity of workflow and allows users to work in a single window within one program. This process provides better access to robust modeling tools in SAS.

ANALYSIS

When analyzing this data set, we started by looking at trends in the NBA over the past 33 seasons. At this point, it is important to note that lockout-shortened seasons were excluded from the analyses; thus, allowing for more consistent data from season to season. Each season consisted of 82 games for each team, and the analyses were performed for regular season games.

A popular topic in the NBA has been the rise of 3-point shot attempts over the years. Players such as Ray Allen and Stephen Curry have attributed to this trend by shooting at proficiencies never before seen in the league, and teams like the Houston Rockets continue to shoot more

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and more 3s every season. The rise of analytics in sports has been a strong driver for this change. Figure 4 (below) shows the rise in 3-point attempts (3PA) since the three point line was introduced in the 1979-1980 season.

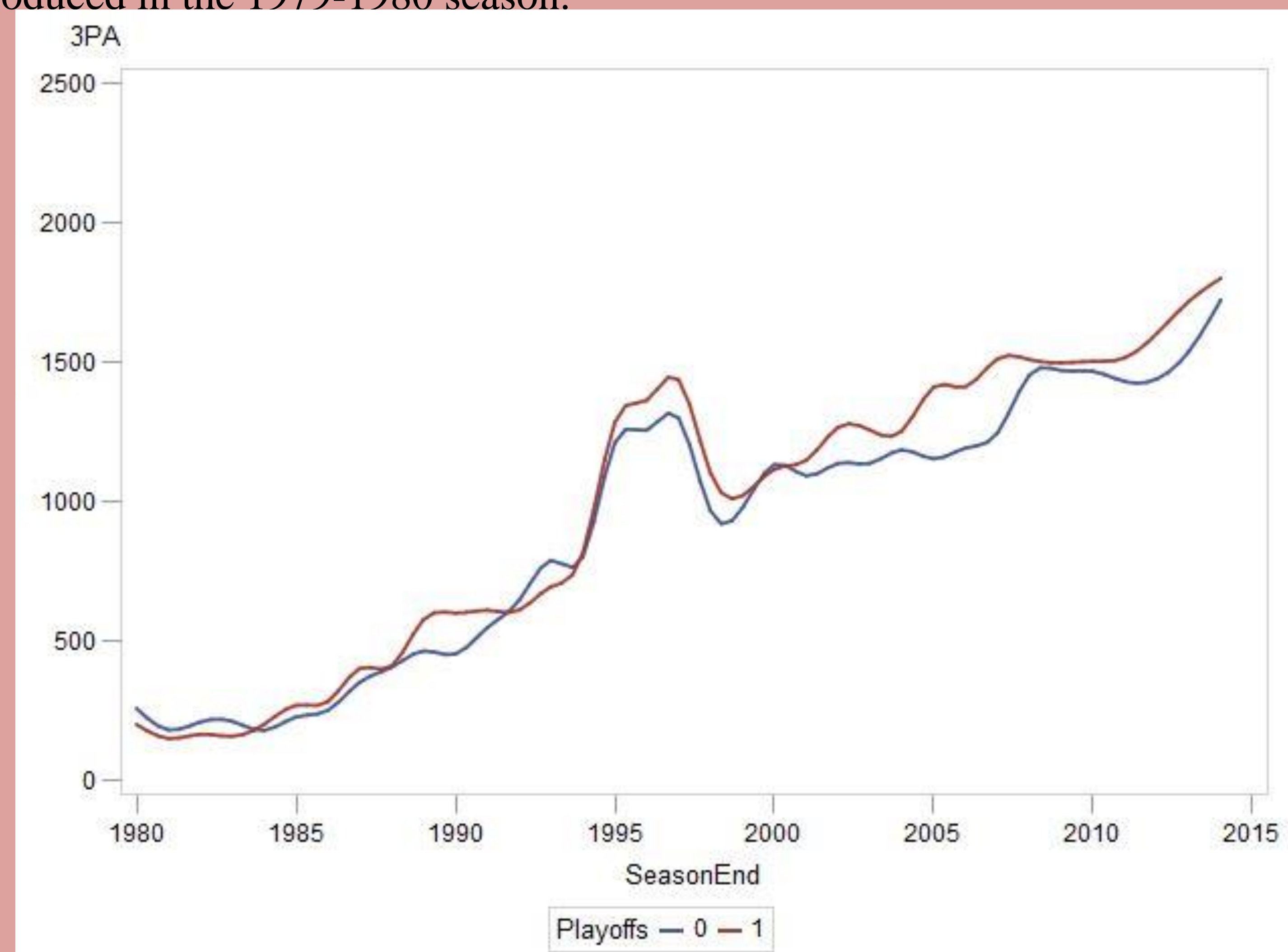


Figure 4: Rising trend of 3-point shot attempts.

It is clear that the rate at which 3-point shots are attempted has increased dramatically over this span of 35 years. Additionally, teams that make the playoffs typically attempt more three point shots than teams that do not make the playoffs. This point of interest is likely attributable to the fact that playoffs teams have better shooters, thus, allowing them the freedom to attempt more 3s.

Another topic of discussion in the NBA, recently, has been fouling, specifically the Hack-a-Player phenomenon. When a bad free throw shooter is on the floor, teams will intentionally foul that player hoping they will miss one of two free throws consistently. However, despite the introduction of these new tactics, overall fouls per team per season have declined significantly since 1980.

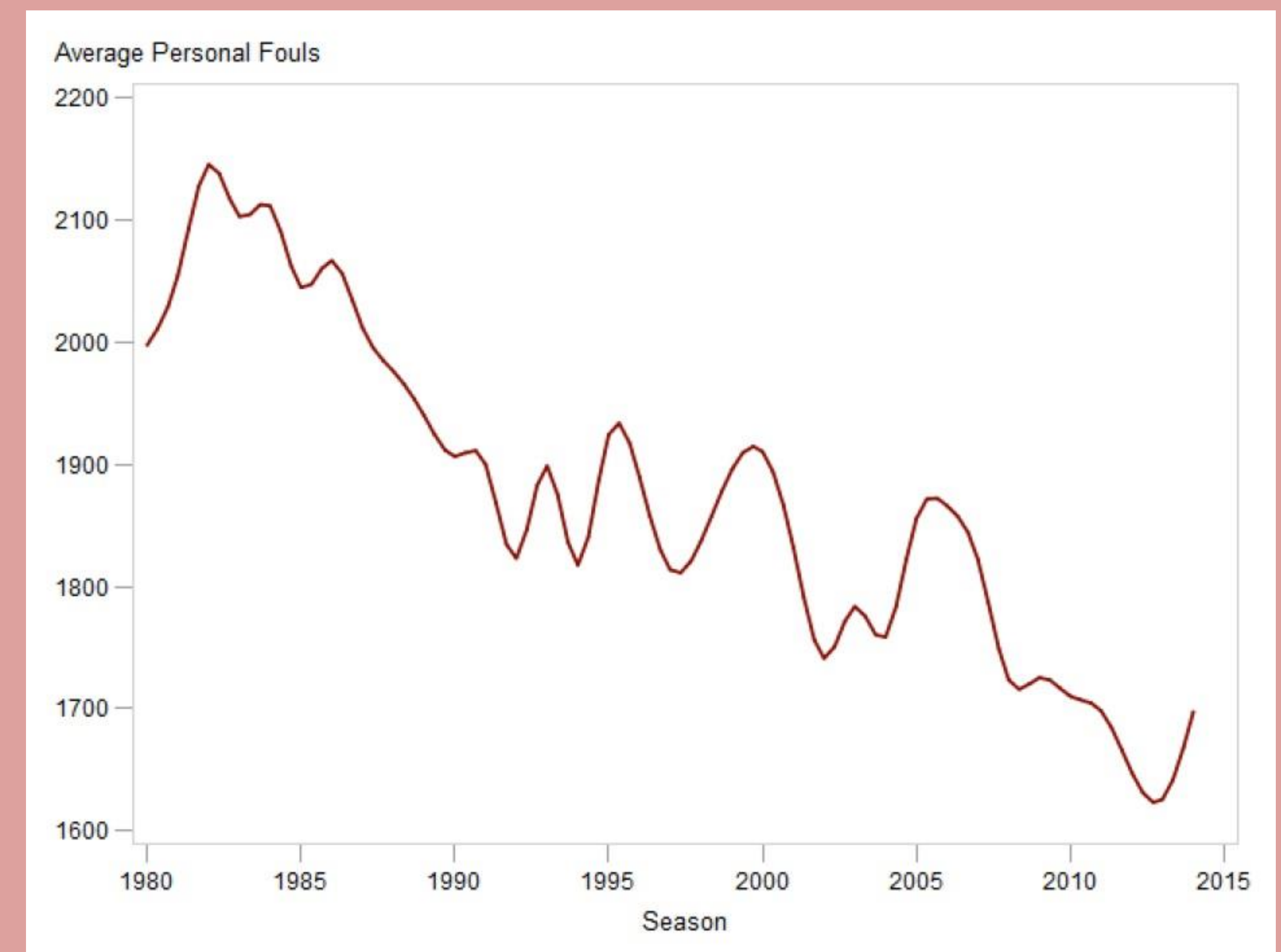


Figure 5: Declining rate of average fouls per season.

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As represented in Figure 5, the number of fouls per season has declined greatly, which could be due to the optimization of rules and increased technology and standards among referees.

Using some of the more advanced methods in SAS, the model included Effective Field Goal Percentage (a metric that compensates for 3-point attempts being worth an extra point), Turnover Percentage (the percent of possessions in which a team turns the ball over), and Wins for playoff vs. non-playoff teams in the 2014 season.

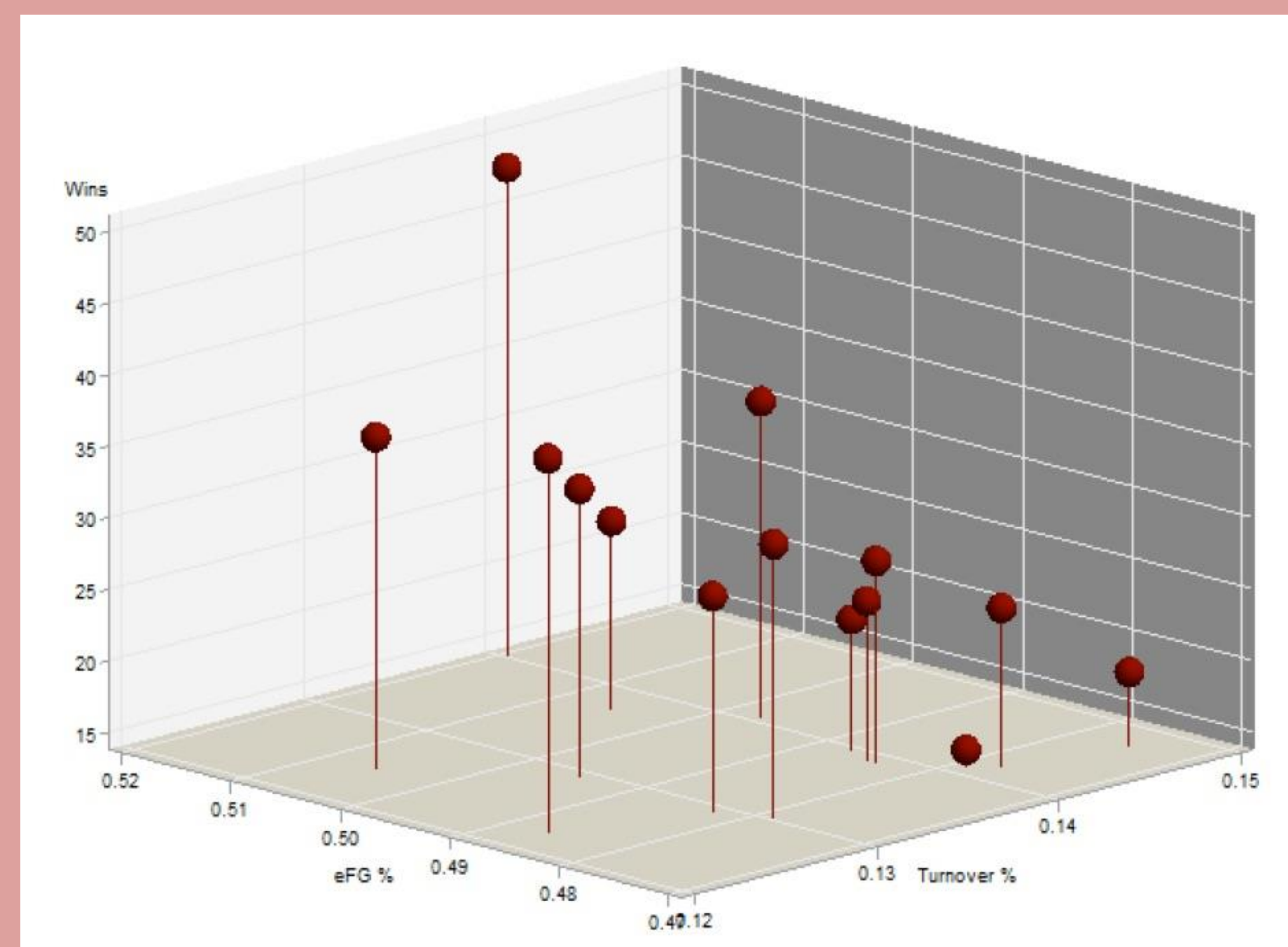


Figure 6: 3D plot of 2014 season non-playoff teams

This graph in Figure 6 shows how non-playoff teams with a low number of wins congregate toward the right of the chart, where high Turnover Percentage and low Effective Field Goal Percentage are located. One notable outlier is the team in the upper left of the graph, the Phoenix Suns. Although the Suns had a great Effective Field Goal Percentage and achieved 48 wins, they still missed the playoffs despite having more wins than some teams in the playoffs. The Suns were not in the Playoffs because each of the two conferences in the NBA are guaranteed eight playoffs and the Suns are in the Western Conference, the best of the conference in recent years.

Looking at the playoff teams for 2014, represented in Figure 7, many of the teams are clustered higher in Effective Field Goal Percentage. The team with the highest number of wins in the regular season, the San Antonio Spurs, won the NBA Finals.

The techniques presented in this paper demonstrate how R users can easily use that knowledge to begin performing analysis in SAS/IML and illustrates how the two programs work seamlessly together in the booming field of sports analytics.

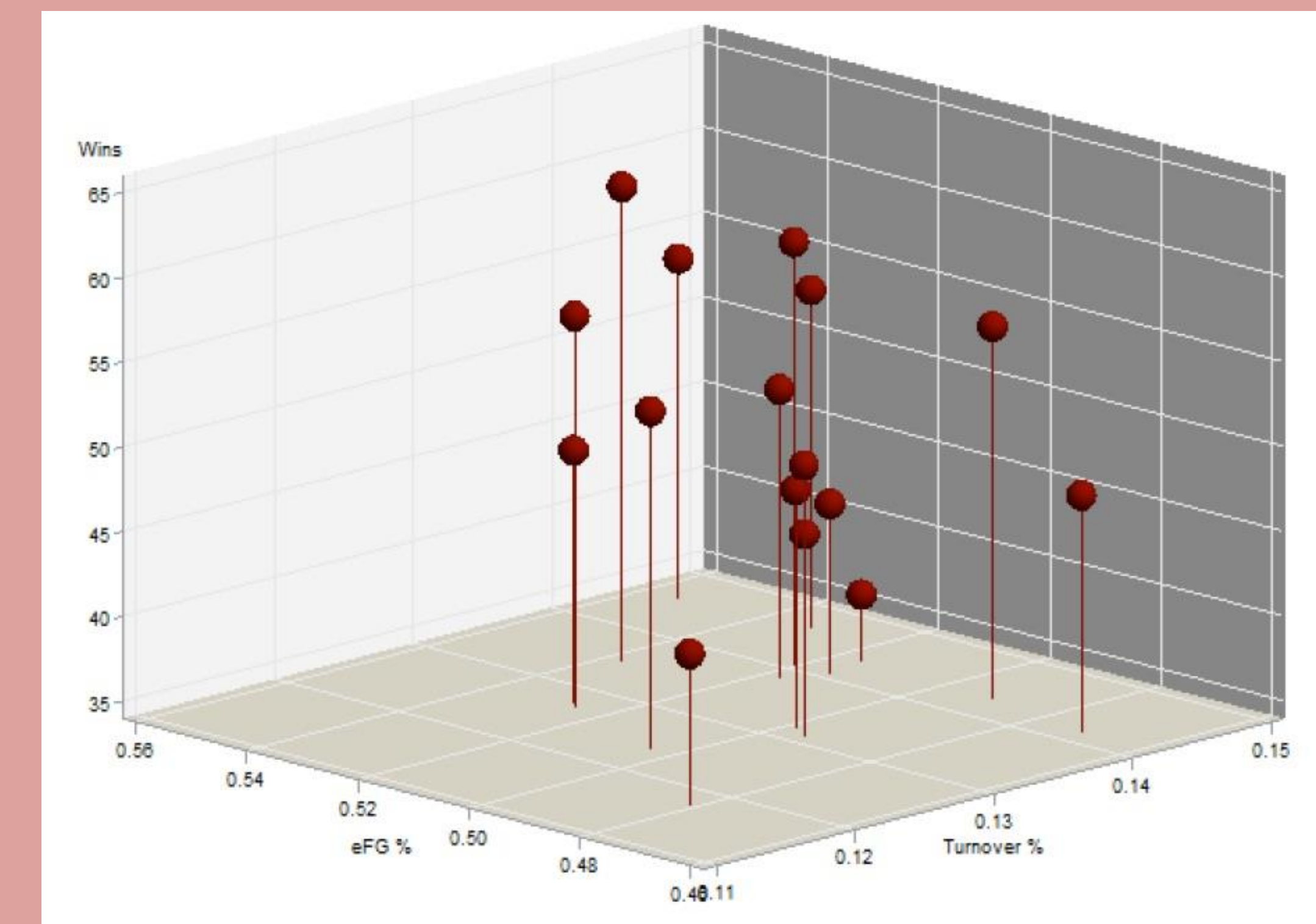


Figure 7: 3D plot of 2014 season playoff teams

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