# NFL Playoff Prediction

# Smells Like Team Spirit

```
library(RCurl)
library(dplyr)
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
library(readr)
library(ggplot2)
library(GGally)
## Registered S3 method overwritten by 'GGally':
     method from
     +.gg
            ggplot2
library(tidyr)
## Attaching package: 'tidyr'
## The following object is masked from 'package:RCurl':
##
       complete
library(knitr)
library(factoextra)
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
library(purrr)
```

NFL teams that performed poorly in win column one year can rise to Super Bowl champions the next (like the Philadelphia Eagles). An NFL game has been sometimes referred to as a "game of inches" in which wins and losses can be determined by chance, hiding the true potential of a team. This could lead to the seemingly surprising rise of a team like the Eagles. We can use machine learning to look beyond just team record to determine which teams that performed poorly last year could compete for a Super Bowl this year. Our goal is to create a machine learning model that groups NFL teams together, predicting a set of playoff teams.

We'd look at NFL season (2000-2013) that we used to predict "Wins" with a column indicating whether a team makes the playoff or not. to test our model on predicting former playoff teams, and then later we will predict next season's.

Since we want to visualize the groupings of NFL teams, we must reduce the dimensionality of all the variable data we collected. To reduce dimensionality, we can use Principal Component Analysis (PCA), which is a statistical procedure that converts a set of variables into a new smaller set of variables that still captures the essence of all the original variables.

#### I. PCA

```
nfl_playoff_all_data <- read.csv("nfl_playoff_all_data.csv")
head(nfl_playoff_all_data)</pre>
```

##			TeamYear	Та	amName Yea	r VoorF	Plawoff	Wing Sc	coreOff	
	1	Arizona Car		Arizona Caro			0 1 1 ay	9	178	
##			Falcons 00'	Atlanta Fa			0	7	238	
##	3		Ravens 00'	Baltimore H			1	12	355	
##	-		Bills 00'	Buffalo			0		288	
##	_			Carolina Par			0	7	272	
##			Bears 00'	Chicago			0	9	216	
##				RushYdsOff Pa			Off Pas	sYdsOff	PassInt	Off
##	1	253	342	1284	554	-	316	3478		24
##	2	256	350	1214	515		285	3166		20
##	3	319	619	2480	553		309	3539		20
##	4	309	476	1921	546		312	3936		10
##	5	304	363	1186	566		340	3850		19
##	6	238	416	1736	542		304	3005		16
##		${\tt FumblesOff}$	${\tt SackYdsOff}$	PenYdsOff Pu	untAvgOff	ScoreDet	FirstD	ownDef R	RushAttI	ef
##	1	20	239	756	710	443	3	344	5	80
##	2	14	386	720	654	413	3	308	4	<del>1</del> 53
##	3	8	349	905	741	183	L	260	4	130
##	4	12	359	913	610	350	)	252	4	144
##	5	16	382	683	607	310		304	4	125
##	6	13	206	696	593	355		297		169
##		RushYdsDef	${\tt PassAttDef}$	${\tt PassCompDef}$	PassYdsDe	ef PassIr	ntDef Fu	mblesDef	SackYo	lsDef
##	1	2609	458	295	326	33	10	10	)	126
##		1983	515	306	376	66	15	10		142
##	_	1162	650	357	373		29	27		245
##		1559	480	283	317		16	13		308
##		1949	552	352	393		17	21		231
##	6	1828	530	332	363	35	11	S	)	231
##		PenYdsDef								
##	_	32								
##	_	14								
##	-	39								
##	4	27								

```
## 5     38
## 6     0

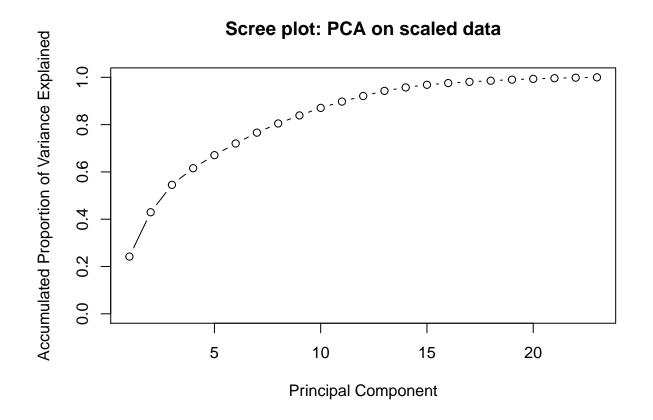
nfl_data_TY <- subset(nfl_playoff_all_data, YearF != 2013)[c(1,5:29)]

nfl_data <- subset(nfl_playoff_all_data, YearF != 2013)[c(5:29)]

nfl_2013 <- subset(nfl_playoff_all_data, YearF == 2013)[c(1,5:29)]

nfl_pca <- prcomp(nfl_data[2:24] , scale = TRUE)

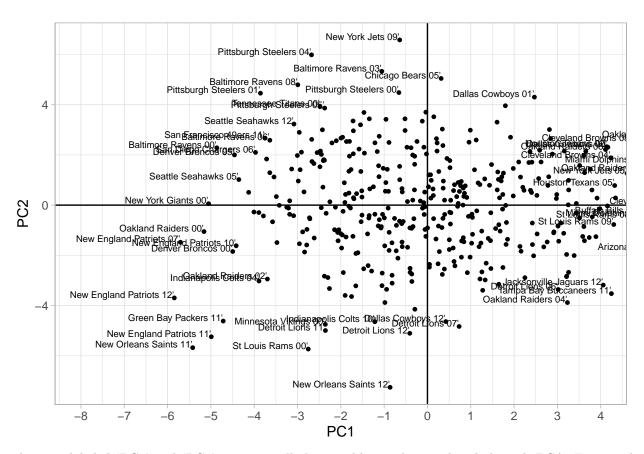
pr.var <- nfl_pca$sdev^2
pve = pr.var / sum(pr.var)
plot(cumsum(pve), xlab = "Principal Component", ylab = "Accumulated Proportion of Variance Explained", main = "Scree plot: PCA on scaled data")</pre>
```



```
nfl_pca_scores <- nfl_pca$x
low_dim_rep <- nfl_pca_scores %>%
data.frame() %>%
mutate(TeamYear = nfl_data_TY$TeamYear) %>%
select(TeamYear, everything())

ggplot(low_dim_rep, aes(x = PC1, y = PC2)) +
geom_vline(xintercept = 0) +
geom_hline(yintercept = 0) +
geom_point(size = 1) + geom_text(aes(label=ifelse(PC1^2+PC2^2 > 19 ,as.character(TeamYear),'')),hjust=
scale_x_continuous(breaks = -10:10) +
```

```
coord_cartesian(xlim = c(-8, 4)) +
theme_light()
```

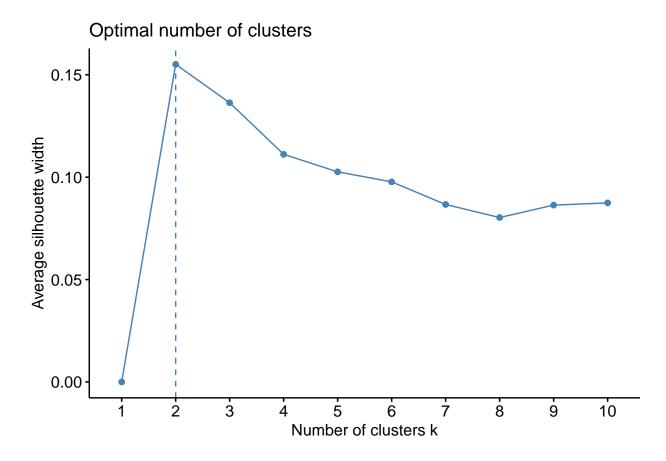


The axes labeled 'PC1' and 'PC2' represent all the variables we have reduced through PCA. For visual clarity, only some of the teams (plus year) have been labeled.

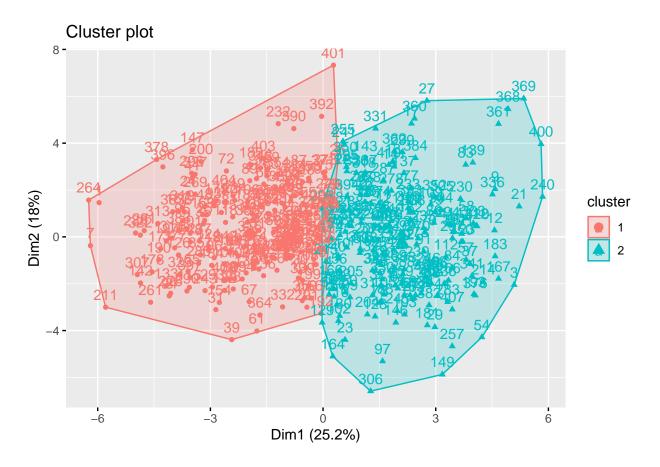
II. k-means Clustering Using the K-Means Elbow Method, we found the ideal number of clusters to be 2. Finally, we can use the K-Means Algorithm to determine and plot the clusters of different types of NFL teams, shown below:

```
#fviz_nbclust(nfl_data_TY, kmeans, method = "wss")
df <- scale(nfl_data_TY[2:25])

fviz_nbclust(df, kmeans, method = "silhouette")</pre>
```



```
final2 <- kmeans(df, 2, nstart = 25)
fviz_cluster(final2, data = df)</pre>
```

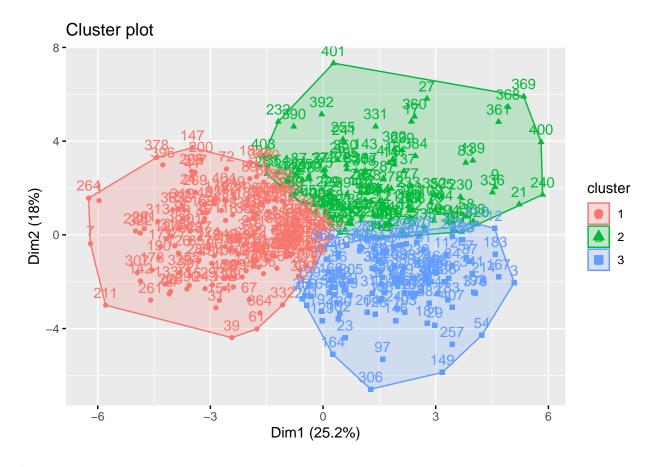


```
table(final2$cluster, nfl_data_TY$Playoff)
```

Clusters represent the quality of teams based on collected input variables. According to the table (0 and 1 represent whether the team makes the playoff, 1 = yes), cluster 1 represents the non-playoff teams and cluster 2 are playoff caliber teams. Cluster 1 contained 5/215 = 2.32% of the playoff teams, while cluster 2 contained 75.4% of the playoff teams. This indicates that teams in cluster 2 were more than 30 times more likely to make the playoffs than cluster 1 teams.

We also tried something new as we manually changed the number of clusters from 2 to 3, which gives us the following result:

```
final3 <- kmeans(df, 3, nstart = 25)
fviz_cluster(final3, data = df)</pre>
```



table(final3\$cluster, nfl\_data\_TY\$Playoff)

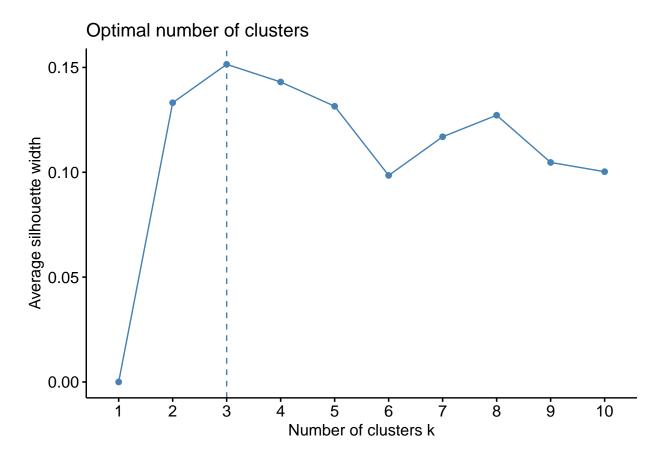
```
## ## 0 1
## 1 175 3
## 2 55 68
## 3 29 84
```

Cluster 1 represents the non-playoff teams, cluster 2 are borderline playoff teams, and cluster 3 are playoff caliber teams. Cluster 1 contained only 1.7% of the playoff teams, cluster 2 contained 44.7% of the playoff teams, while cluster 3 contained only 74.3% of the playoff teams.

The clustering method with 3 clusters provide more detailed description for mid-table teams, which could be also useful to predict whether a team can make the playoff based on its performance.

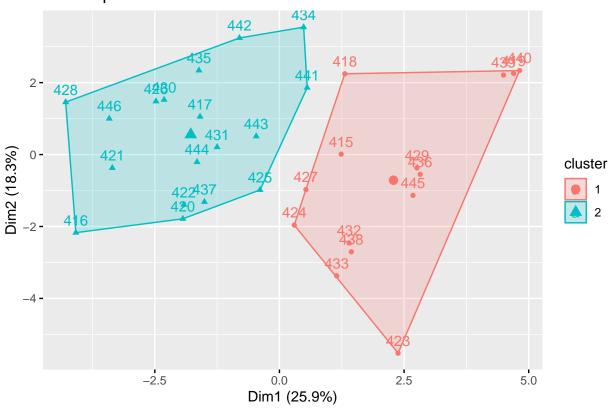
Lastly, we apply the K-Means algorithm to the 2013 season to predict its playoff teams, shown below:

```
dfnew <- scale(nfl_2013[2:25])
fviz_nbclust(dfnew, kmeans, method = "silhouette")</pre>
```



```
testCluster <- kmeans(dfnew, 2, nstart = 10)
fviz_cluster(testCluster, data = dfnew)</pre>
```





### testCluster\$cluster

```
## 415 416 417 418 419 420 421 422 423 424 425 426 427 428 429 430 431 432 433 434
##
         2
             2
                      1
                          2
                               2
                                   2
                                       1
                                            1
                                                2
                                                    2
                                                             2
                                                                      2
                                                                          2
  435 436 437 438 439 440 441 442 443 444 445 446
                               2
                                   2
                                       2
                                            2
##
                      1
                           1
```

```
nfl_2013$Playoff
```

```
## [1] 0 0 0 0 1 0 0 0 1 0 1 0 1 0 1 0 1 0 0 1 1 0 0 1 0 1 1 1 0 0 0 0 1 0
```

## table(testCluster\$cluster, nfl\_2013\$Playoff)

The result demonstrates that Cluster 1 of our model predicts 79% of the teams correctly and does represent the playoff caliber teams. Cluster 2 yields a 5.5% of playoff team, showing that clustering really gives an accurate prediction on whether a team makes the NFL playoff based on its performance.