

NHL Playoff Wins Analysis

Ethan Greig

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NHL Playoff Wins Analysis

First, determine which variables are most strongly correlated with playoff success (measured in # of playoff wins). This will be done on a 5 year and 10 year timeframe. Each metric will be represented as a difference wrt the league average of that metric during that season.

Since the correlation coefficient is location-scale invariant, we can directly compare how much these statistics correlate with playoff success, even when the statistics are percentages, counting totals, points-based, etc.

Independent Variables:

1. GF% (Corsica2)
2. AdjGF% (morehockeystats)
3. 5v5 GF% (Corsica1)
4. 5v5 xGF% (Corsica1)
5. 5v5 CF% (Corsica1)
6. Time_Leading (morehockeystats)
7. 5v5 Shooting% (Corsica1)
8. 5v5 Save% (Corsica1)
9. PP% (NHL.com)
10. PK% (NHL.com)
11. Regular Season Wins (NHL.com)
12. Regular Season Regulation+Overtime Wins (NHL.com)

Note that 1-3 are measurements of how many goals were scored by the team vs how many goals were allowed by the team. 4-6 constitute a variety of indicators of how many scoring opportunities a team generates compared to other teams during the season. 7 measures how effective a team is at gaining and maintaining leads in hockey games. 8-9 are primarily measurements of luck, but can be skewed by relatively strong shooters or goalies. 10-11 are special teams indicators, which also have a luck component, and tend to be less important in the playoffs. 12-13 are overall indicators of regular season performance.

Dependent Variables:

1. Playoff Wins (NHL.com)

Import Data

```
corsica1 <- read.csv("input_csvs/corsica_5v5_08-17.csv", check.names=FALSE)
corsica1$Season <- strtoi(substr(corsica1$Season, 6, 9))
corsica1 <- corsica1[, c('Team', 'Season', 'CF%', 'GF%', 'xGF%', 'Sh%', 'Sv%')]

corsica2 <- read.csv("input_csvs/corsica_all_08-17.csv", check.names=FALSE)
corsica2$Season <- strtoi(substr(corsica2$Season, 6, 9))
corsica2 <- corsica2[, c('Team', 'Season', 'allGF%', 'allGF', 'allGA')]
```

```

morestats <- read.csv("input_csvs/misc_stats_playoffwins_08-17.csv", check.names=FALSE)
morestats <- morestats[, c('Team', 'Season', 'HDCF', 'Time Led', 'Playoff Wins', 'GF_EN', 'GA_EN', 'PP%

raw_data <- merge(merge(corsica1, corsica2, by=c("Team", "Season")), morestats, by=c("Team", "Season"))
raw_data$`AdjGF%` <- with(raw_data, round(100*(allGF-GF_EN)/(allGF-GF_EN+allGA-GA_EN),2))
raw_data <- raw_data[, c('Team', 'Season', 'allGF%', 'AdjGF%', 'GF%', 'xGF%', 'CF%', 'HDCF', 'Time Led'
colnames(raw_data) <- c('Team', 'Season', 'GF%', 'AdjGF%', '5v5_GF%', '5v5_xGF%', '5v5_CF%', '5v5_HDCF%'
head(raw_data)

```

```

## Team Season GF% AdjGF% 5v5_GF% 5v5_xGF% 5v5_CF% 5v5_HDCF% Time_Led
## 1 ANA 2008 51.71 51.76 52.97 48.73 50.71 49.45 18.70
## 2 ANA 2009 50.32 50.87 52.73 51.10 50.96 53.54 19.13
## 3 ANA 2010 48.95 49.13 50.34 45.83 47.35 45.10 20.77
## 4 ANA 2011 50.21 50.66 46.53 44.08 44.35 44.88 20.58
## 5 ANA 2012 47.29 47.56 47.26 47.13 48.54 47.70 24.53
## 6 ANA 2013 53.82 52.97 55.28 50.07 47.93 48.77 19.98
## 5v5_Sh% 5v5_Sv% PP% PK% Wins ROWins Playoff_Wins
## 1 7.30 93.62 16.6 83.1 47 39 2
## 2 8.40 92.42 23.6 79.7 42 35 7
## 3 8.23 92.75 21.0 79.3 39 34 -1
## 4 7.87 92.31 23.5 81.3 47 43 2
## 5 7.99 91.66 16.6 82.0 34 31 -1
## 6 8.59 93.01 21.5 81.5 30 24 3

```

Finalize Data

```

adj_data <- raw_data
adj_data_10 <- adj_data[adj_data$`Playoff_Wins`>=0,]
head(adj_data_10)

```

```

## Team Season GF% AdjGF% 5v5_GF% 5v5_xGF% 5v5_CF% 5v5_HDCF% Time_Led
## 1 ANA 2008 51.71 51.76 52.97 48.73 50.71 49.45 18.70
## 2 ANA 2009 50.32 50.87 52.73 51.10 50.96 53.54 19.13
## 4 ANA 2011 50.21 50.66 46.53 44.08 44.35 44.88 20.58
## 6 ANA 2013 53.82 52.97 55.28 50.07 47.93 48.77 19.98
## 7 ANA 2014 56.44 56.17 58.44 51.45 49.80 52.62 23.92
## 8 ANA 2015 50.78 50.35 51.47 52.13 50.96 52.19 21.32
## 5v5_Sh% 5v5_Sv% PP% PK% Wins ROWins Playoff_Wins
## 1 7.30 93.62 16.6 83.1 47 39 2
## 2 8.40 92.42 23.6 79.7 42 35 7
## 4 7.87 92.31 23.5 81.3 47 43 2
## 6 8.59 93.01 21.5 81.5 30 24 3
## 7 9.83 92.62 16.0 82.2 54 51 7
## 8 8.48 91.82 15.7 81.0 51 43 11

```

```

adj_data_5 <- adj_data_10[adj_data_10$Season>2012,]
head(adj_data_5)

```

```

## Team Season GF% AdjGF% 5v5_GF% 5v5_xGF% 5v5_CF% 5v5_HDCF% Time_Led
## 6 ANA 2013 53.82 52.97 55.28 50.07 47.93 48.77 19.98
## 7 ANA 2014 56.44 56.17 58.44 51.45 49.80 52.62 23.92
## 8 ANA 2015 50.78 50.35 51.47 52.13 50.96 52.19 21.32

```

```
## 9   ANA   2016 53.35 52.59 49.42 53.01 52.42 52.22 23.55
## 10  ANA   2017 52.76 52.48 53.11 52.02 49.67 52.26 22.53
## 30  BOS   2013 54.51 54.30 55.42 53.24 54.39 54.22 24.35
##      5v5_Sh% 5v5_Sv% PP% PK% Wins ROWins Playoff_Wins
## 6      8.59 93.01 21.5 81.5 30 24 3
## 7      9.83 92.62 16.0 82.2 54 51 7
## 8      8.48 91.82 15.7 81.0 51 43 11
## 9      6.69 92.39 23.1 87.2 46 43 3
## 10     7.77 92.98 18.7 84.7 46 43 11
## 30     7.31 93.18 14.8 87.1 28 24 14
```

Correlations With Playoff Wins

```
stats <- colnames(adj_data_10)[4:ncol(adj_data_10)-1]
correlations_5_10 <- data.frame(matrix(ncol=13, nrow=2))
colnames(correlations_5_10) <- stats
rownames(correlations_5_10) <- c("5 years", "10 years")

correlations_5_10[1,] <- cor(adj_data_5[,4:ncol(adj_data_5)-1], adj_data_5$`Playoff_Wins`)
correlations_5_10[2,] <- cor(adj_data_10[,4:ncol(adj_data_10)-1], adj_data_10$`Playoff_Wins`)

write.csv(correlations_5_10, 'output_csvs/correlations.csv')
correlations_5_10
```

```
##      GF%   AdjGF%   5v5_GF% 5v5_xGF% 5v5_CF% 5v5_HDCF%
## 5 years 0.3458189 0.3358988 0.2745515 0.2436887 0.2310239 0.2050112
## 10 years 0.3416835 0.3317128 0.2426668 0.2060818 0.1818608 0.1710590
##      Time_Led   5v5_Sh%   5v5_Sv%      PP%      PK%      Wins
## 5 years 0.06812042 -0.07465011 0.1704371 -0.10292430 0.2153303 0.1373872
## 10 years 0.20747087 -0.03171249 0.1122820 0.06001718 0.2038975 0.1417614
##      ROWins
## 5 years 0.1154794
## 10 years 0.1488450
```

Correlations With Each Other

```
# correlations_5 <- cor(adj_data_5[,3:ncol(adj_data_5)])
# correlations_10 <- cor(adj_data_10[,4:ncol(adj_data_10)-1])
#
# eigenspace <- eigen(correlations_10) ## 6 or 9 factors
# n <- 6
# C <- as.matrix(eigenspace$vectors[,1:n])
# D <- matrix(0, dim(C)[2], dim(C)[2])
# diag(D) <- eigenspace$values[1:n]
# loadings <- C %>% sqrt(D)
# loadings
#
# S.h2 <- rowSums(loadings^2)
# S.h2
#
# S.u2 <- diag(correlations_10) - S.h2
```

```
# S.u2
```

Calculate Differences in Each Stat for Every Playoff Matchup

```
series <- read.csv("input_csvs/all_playoff_series.csv")
series$Home_Won <- round(series$Home_W., 0)

stats <- c('GF%', '5v5_xGF%', 'PK%', 'Time_Led', 'ROWins')
dStats <- stats
for (i in 1:length(stats)) {
  stat <- stats[i]
  dStat <- paste0('d', stat)
  dStats[i] <- dStat
  series[dStat] <- NA
}

regular_season_data <- adj_data_10[, c('Team', 'Season', stats)]

getDifferences <- function(row, df) {
  df_year <- df[df$Season==row$Year,]
  a1 <- df_year[as.character(df_year$Team)==as.character(row$Home),]
  a2 <- df_year[as.character(df_year$Team)==as.character(row$Away),]
  for (i in 1:length(stats)) {
    stat <- stats[i]
    dStat <- dStats[i]
    row[dStat] <- a1[[stat]] - a2[[stat]]
  }
  return(row)
}

for (row in 1:nrow(series)) {
  series[row,] <- getDifferences(series[row,], regular_season_data)
}

head(series)
```

```
##   Year Home Away Home_W. Home_Won  dGF% d5v5_xGF% dPK% dTime_Led dROWins
## 1 2008  ANA  DAL    0.33         0 -2.03    -0.89 -2.5    -3.52     -1
## 2 2009  DET  ANA    0.57         1  4.28     1.46 -1.4     5.17     10
## 3 2010  ARI  DET    0.43         0 -0.02    -0.78  0.6     0.70     -2
## 4 2011  ANA  NSH    0.33         0 -2.64    -6.48 -3.6    -2.45      5
## 5 2012  ARI  CHI    0.67         1  0.92    -2.27  7.4    -2.30     -2
## 6 2013  ANA  DET    0.43         0  1.23    -2.32 -0.2    -0.64      2
```

```
colMeans(series[,dStats])
```

```
##      dGF% d5v5_xGF%      dPK% dTime_Led  dROWins
## 2.3687333 0.5541333 0.4493333 1.8223333 4.6400000
```

Logistic Regression

The binary model runs regression only on whether the higher-seeded team won or lost. The weighted model is an abuse of glm because it uses non-integer success variables (win% in the series)

```
regression_binary <- function(dataset) {
  return(suppressWarnings(glm(`Home_Won` ~ `dGF` + `d5v5_xGF` + `dPK` + `dTime_Led` + `dROWins`, data=
})

regression_weighted <- function(dataset) {
  return(suppressWarnings(glm(`Home_W.` ~ `dGF` + `d5v5_xGF` + `dPK` + `dTime_Led` + `dROWins`, data=
})

binary_model <- regression_binary(series)
weighted_model <- regression_weighted(series)
summary(binary_model)

##
## Call:
## glm(formula = Home_Won ~ `dGF` + `d5v5_xGF` + `dPK` + dTime_Led +
##      dROWins, family = binomial(link = "logit"), data = dataset)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.1695  -1.0734   0.5740   0.9754   2.0140
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.21550    0.24496  -0.880  0.37901
## `dGF`        0.29415    0.09988   2.945  0.00323 **
## `d5v5_xGF`   0.08469    0.05674   1.493  0.13555
## `dPK`        0.08976    0.05551   1.617  0.10586
## dTime_Led   -0.02325    0.08080  -0.288  0.77357
## dROWins     -0.05652    0.05089  -1.110  0.26679
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 206.23  on 149  degrees of freedom
## Residual deviance: 181.49  on 144  degrees of freedom
## AIC: 193.49
##
## Number of Fisher Scoring iterations: 3
write.csv(binary_model$coefficients, 'output_csvs/initial_model.csv')
```

Cross Validation

```
logLoss <- function(pred, actual){
  -1*mean(log(pred[model.matrix(~ actual + 0) - pred > 0]))
}
```

```

mse <- function(pred, actual){
  mean((pred-actual)^2)
}

ten_fold_cross_validate <- function(dataset){
  series_shuffled <- dataset[sample(nrow(dataset)),]
  folds <- cut(seq(1,nrow(series_shuffled)),breaks=10,labels=FALSE)

  log_loss_binary <- NA
  log_loss_weighted <- NA
  mse_binary <- NA
  mse_weighted <- NA

  for (i in 1:10) {
    testRows <- which(folds==i,arr.ind=TRUE)
    test_data <- series_shuffled[testRows,]
    train_data <- series_shuffled[-testRows,]

    fold_binary_model <- regression_binary(train_data)
    fold_weighted_model <- regression_weighted(train_data)

    test_data$bin_pred <- predict(fold_binary_model, test_data[,dStats], type='response')
    test_data$wgt_pred <- predict(fold_weighted_model, test_data[,dStats], type='response')

    log_loss_binary[i] <- logLoss(test_data$bin_pred, test_data$Home_Won)
    log_loss_weighted[i] <- logLoss(test_data$wgt_pred, test_data$Home_Won)
    mse_binary[i] <- mse(test_data$bin_pred, test_data$Home_Won)
    mse_weighted[i] <- mse(test_data$wgt_pred, test_data$Home_Won)
  }
  return(c(mean(log_loss_binary), mean(log_loss_weighted), mean(mse_binary), mean(mse_weighted)))
}

ten_fold_metrics <- matrix(NA, nrow=200, ncol=4)
colnames(ten_fold_metrics) <- c("Log Loss Binary", "Log Loss weighted", "Mean Squared Error Binary", "Mean Squared Error weighted")
for(j in 1:200) {
  ten_fold_metrics[j,] <- ten_fold_cross_validate(series)
}

colMeans(ten_fold_metrics)

##           Log Loss Binary           Log Loss weighted
##           0.5596033           0.5941415
## Mean Squared Error Binary Mean Squared Error weighted
##           0.2262093           0.2310608

Binary-trained model always has lower log-loss, but that metric rewards conservative (40% to 60%) predictions.
### 2016 Comparison

seasons_for_2016 <- series[series$Year<2016,]
binary_model_2016 <- glm(`Home_Won` ~ `dGF` + `d5v5_xGF` + `dPK` + `dROWins`, data=seasons_for_2016,

playoffs_2016 <- series[series$Year==2016,]
playoffs_2016$bin_pred <- predict(binary_model_2016, playoffs_2016, type='response')

summary(binary_model_2016)

```

```
##
## Call:
## glm(formula = Home_Won ~ `dGF%` + `d5v5_xGF%` + `dPK%` + dROWins,
##      family = binomial(link = "logit"), data = seasons_for_2016)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.1770  -1.0267   0.4940   0.9986   1.7497
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.45420     0.28561  -1.590  0.11176
## `dGF%`       0.31137     0.10725   2.903  0.00369 **
## `d5v5_xGF%`  0.05215     0.06022   0.866  0.38650
## `dPK%`       0.11176     0.06390   1.749  0.08030 .
## dROWins      -0.03327     0.05468  -0.608  0.54293
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 165.52  on 119  degrees of freedom
## Residual deviance: 140.87  on 115  degrees of freedom
## AIC: 150.87
##
## Number of Fisher Scoring iterations: 4
playoffs_2016[c('Home', 'Away', 'Home_Won', 'bin_pred')]
```

```
##      Home Away Home_Won bin_pred
## 9      ANA  NSH         0 0.6518886
## 19     STL  CHI         1 0.5548607
## 29     DAL  STL         0 0.3689273
## 39     DAL  MIN         1 0.6356171
## 49     T.B  DET         1 0.7555869
## 59     FLA  NYI         0 0.3930856
## 69     L.A  S.J         0 0.4015320
## 79     S.J  NSH         1 0.5072879
## 89     T.B  NYI         1 0.4749745
## 99     PIT  NYR         1 0.8140909
## 109    WSH  PHI         1 0.8478197
## 119    WSH  PIT         0 0.4244600
## 129    PIT  T.B         1 0.5772182
## 139    PIT  S.J         1 0.5948153
## 149    STL  S.J         0 0.4036199
```

```
logLoss(playoffs_2016$bin_pred, playoffs_2016$Home_Won)
```

```
## [1] 0.4650487
```

```
mse(playoffs_2016$bin_pred, playoffs_2016$Home_Won)
```

```
## [1] 0.1686403
```

FACTOR ANALYSIS

Calculate Differences in Each Stat for Every Playoff Matchup

```
series <- read.csv("input_csvs/all_playoff_series.csv")
series$Home_Won <- round(series$Home_W., 0)

stats <- c('GF%', 'AdjGF%', '5v5_xGF%', '5v5_CF%', 'Time_Led', '5v5_Sh%', '5v5_Sv%', 'PP%', 'PK%', 'ROW')
dStats <- stats
for (i in 1:length(stats)) {
  stat <- stats[i]
  dStat <- paste0('d', stat)
  dStats[i] <- dStat
  series[dStat] <- NA
}

regular_season_data <- adj_data_10[, c('Team', 'Season', stats)]

getDifferences <- function(row, df) {
  df_year <- df[df$Season==row$Year,]
  a1 <- df_year[as.character(df_year$Team)==as.character(row$Home),]
  a2 <- df_year[as.character(df_year$Team)==as.character(row$Away),]
  for (i in 1:length(stats)) {
    stat <- stats[i]
    dStat <- dStats[i]
    row[dStat] <- a1[[stat]] - a2[[stat]]
  }
  return(row)
}

for (row in 1:nrow(series)) {
  series[row,] <- getDifferences(series[row,], regular_season_data)
}

head(series)
```

```
##   Year Home Away Home_W. Home_Won  dGF% dAdjGF% d5v5_xGF% d5v5_CF%
## 1 2008  ANA  DAL    0.33         0 -2.03  -2.25    -0.89   -1.00
## 2 2009  DET  ANA    0.57         1  4.28   3.46     1.46    6.35
## 3 2010  ARI  DET    0.43         0 -0.02   0.95    -0.78   -2.05
## 4 2011  ANA  NSH    0.33         0 -2.64  -1.28    -6.48   -4.79
## 5 2012  ARI  CHI    0.67         1  0.92   1.90    -2.27   -3.16
## 6 2013  ANA  DET    0.43         0  1.23   0.76    -2.32   -5.64
##   dTime_Led d5v5_Sh% d5v5_Sv% dPP% dPK% dROWins
## 1    -3.52   -1.59    1.94 -1.5 -2.5      -1
## 2     5.17   -0.37   -0.94  1.9 -1.4      10
## 3     0.70    1.15    1.00 -4.6  0.6      -2
## 4    -2.45   -0.30   -1.08  8.3 -3.6       5
## 5    -2.30   -0.08    2.08 -1.7  7.4      -2
## 6    -0.64    1.94   -0.45  3.1 -0.2       2
```

```
colMeans(series[,dStats])
```

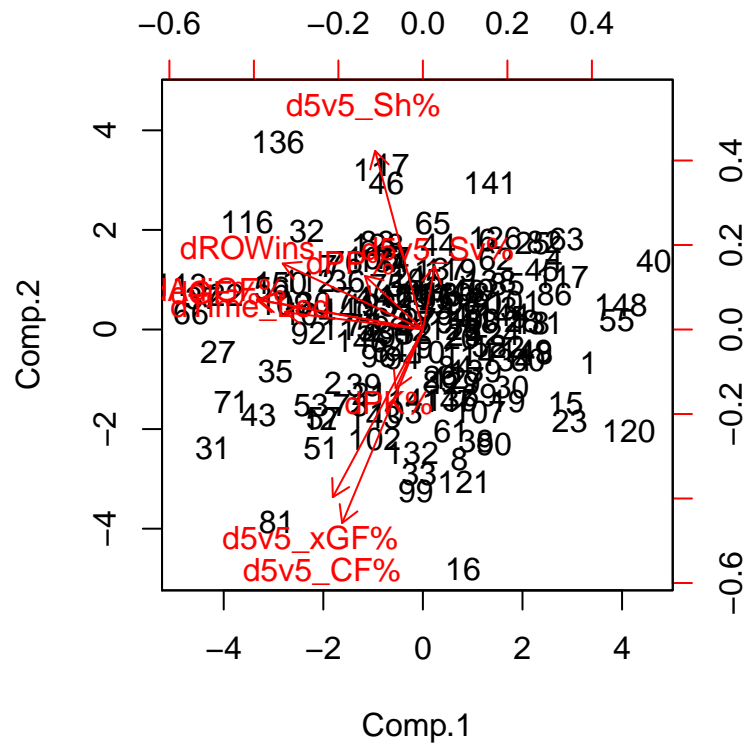
```
##      dGF%   dAdjGF% d5v5_xGF% d5v5_CF% dTime_Led d5v5_Sh% d5v5_Sv%
```



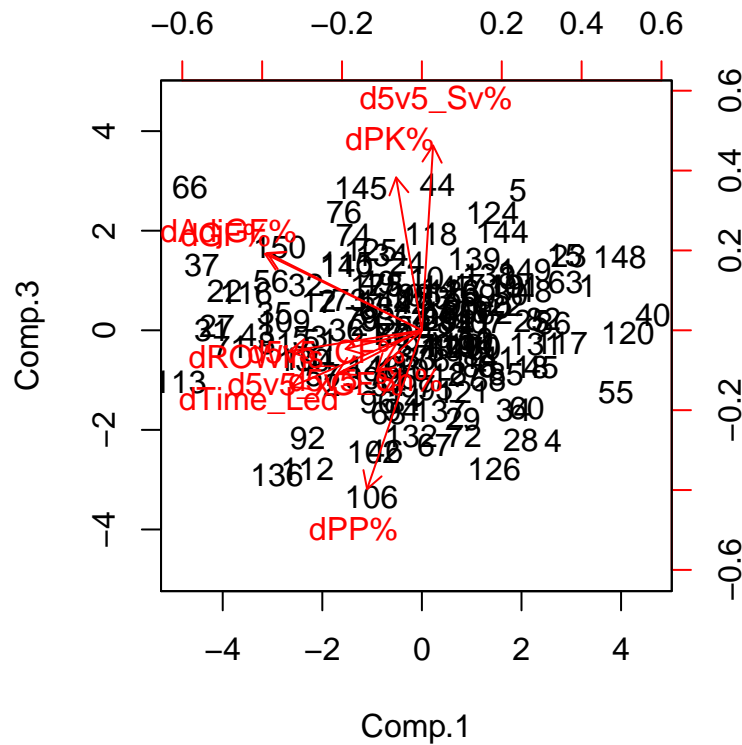
```
## 2.3687333 2.2268000 0.5541333 0.4273333 1.8223333 0.4026667 0.1891333
##      dPP%      dPK%      dROWins
## 0.9120000 0.4493333 4.6400000
```

Factor Analysis

```
dStat_table <- series[,dStats]
pca <- princomp(dStat_table, cor=TRUE)
biplot(pca,choices=c(1,2),scale=0)
```



```
biplot(pca,choices=c(1,3),scale=0)
```



```
prin_data <- series[,c('Year', 'Home', 'Away', 'Home_W.', 'Home_Won')]
prin_data <- cbind(prin_data, pca$scores)
prin_data
```

##	Year	Home	Away	Home_W.	Home_Won	Comp.1	Comp.2	Comp.3
## 1	2008	ANA	DAL	0.33	0	3.33137969	-0.675487442	0.899279981
## 2	2009	DET	ANA	0.57	1	-1.80309521	-1.078059899	-1.100219655
## 3	2010	ARI	DET	0.43	0	1.72804151	0.437142489	1.059109264
## 4	2011	ANA	NSH	0.33	0	2.63410295	1.423305261	-2.221396030
## 5	2012	ARI	CHI	0.67	1	1.93141678	0.235265070	2.810133113
## 6	2013	ANA	DET	0.43	0	1.29309473	1.790010634	-0.724809223
## 7	2014	ANA	DAL	0.67	1	-1.89700832	1.276124736	0.577418751
## 8	2015	ANA	CGY	0.80	1	0.73014833	-2.604865345	-0.850901268
## 9	2016	ANA	NSH	0.43	0	0.02224916	-0.350206755	0.524543996
## 10	2017	ANA	CGY	1.00	1	0.09088942	-0.451716518	1.056582535
## 11	2008	MTL	BOS	0.57	1	-1.04194874	3.211576021	0.529538924
## 12	2009	S.J	ANA	0.33	0	-2.06793540	-1.795221340	0.588061673
## 13	2010	BUF	BOS	0.33	0	-0.73632575	1.447217394	-0.068390753
## 14	2011	DET	ARI	1.00	1	-0.35282168	-1.406359516	-1.387160969
## 15	2012	ARI	NSH	0.80	1	2.86955128	-1.474580022	1.514993341
## 16	2013	BOS	TOR	0.57	1	0.80568749	-4.816701206	0.797446770
## 17	2014	ANA	L.A	0.43	0	-0.62157972	3.311121482	-1.011292804
## 18	2015	ANA	WPG	1.00	1	2.19697093	0.137168579	-0.741146660
## 19	2016	STL	CHI	0.57	1	1.70351822	-1.434716084	0.882828547
## 20	2017	ANA	NSH	0.33	0	0.76330389	-0.171992878	0.438139235
## 21	2008	S.J	CGY	0.57	1	-1.07264095	-1.281756851	0.121001609

##	22	2009	BOS	MTL	1.00	1	-3.96086507	0.691133621	0.784871409
##	23	2010	BOS	PHI	0.43	0	2.94993629	-1.837191573	1.487977119
##	24	2011	BOS	MTL	0.57	1	-0.29333016	1.068748299	1.360630812
##	25	2012	ARI	L.A	0.20	0	2.20210509	1.743394051	0.177314093
##	26	2013	BOS	NYR	0.80	1	0.35979015	-0.950240340	0.206395830
##	27	2014	BOS	MTL	0.43	0	-4.11453363	-0.448554804	0.083547609
##	28	2015	ANA	CHI	0.43	0	1.98960753	0.161113369	-2.195823588
##	29	2016	DAL	STL	0.43	0	0.82166355	-0.120314351	-1.783346737
##	30	2017	ANA	EDM	0.57	1	1.78134190	-1.153885311	0.725336856
##	31	2008	DET	COL	1.00	1	-4.21842406	-2.375645365	0.003540189
##	32	2009	BOS	CAR	0.43	0	-2.32962036	1.969881083	0.908936731
##	33	2010	CHI	VAN	0.67	1	-0.07171977	-2.894831041	-0.570748841
##	34	2011	PHI	BOS	0.00	0	1.84291134	-0.620802438	-1.603421817
##	35	2012	BOS	WSH	0.43	0	-2.95852083	-0.833465144	0.349855614
##	36	2013	CHI	BOS	0.67	1	-1.51480523	0.981839137	-0.004652587
##	37	2014	BOS	DET	0.80	1	-4.41889840	0.625096796	1.319623460
##	38	2015	VAN	CGY	0.33	0	1.06959724	-2.244179702	-0.252301286
##	39	2016	DAL	MIN	0.67	1	-1.18414478	-1.124931522	-0.954981313
##	40	2017	OTT	BOS	0.67	1	4.63820533	1.374343901	0.302015838
##	41	2008	MIN	COL	0.33	0	1.05583496	0.168727727	0.073139006
##	42	2009	CHI	CGY	0.67	1	-0.21495987	0.002764835	0.546007566
##	43	2010	CHI	NSH	0.67	1	-3.30510825	-1.725578995	-0.091935463
##	44	2011	BOS	T.B	0.57	1	0.31041277	1.696060095	2.920709683
##	45	2012	NSH	DET	0.80	1	2.39763684	1.197578014	-0.742306406
##	46	2013	PIT	BOS	0.00	0	-0.73200083	2.940545401	-2.432091553
##	47	2014	STL	CHI	0.33	0	0.92496000	0.282358131	0.918403087
##	48	2015	CHI	MIN	1.00	1	2.26185948	-0.469475781	0.783252080
##	49	2016	T.B	DET	0.80	1	-0.88932483	-0.134860827	0.965418850
##	50	2017	CHI	NSH	0.00	0	1.08184992	0.790864362	-0.174757759
##	51	2008	DET	DAL	0.67	1	-2.03965639	-2.372810903	-0.197403394
##	52	2009	N.J	CAR	0.43	0	-0.16668466	-0.074839248	0.071818637
##	53	2010	CHI	PHI	0.67	1	-2.24306445	-1.523838919	-0.128171277
##	54	2011	VAN	BOS	0.43	0	-0.66365278	-0.431486059	-1.096477242
##	55	2012	FLA	N.J	0.43	0	3.90073079	0.181905713	-1.252955449
##	56	2013	CHI	DET	0.57	1	-3.03038562	0.825916635	0.987748449
##	57	2014	CHI	MIN	0.67	1	-1.98616164	-1.774140803	-0.902281658
##	58	2015	NSH	CHI	0.33	0	1.34076284	-0.340656699	-1.001708148
##	59	2016	FLA	NYI	0.33	0	0.46324187	0.550969917	-0.400275207
##	60	2017	PIT	CBJ	0.80	1	2.10780534	-0.621721952	-1.570195454
##	61	2008	S.J	DAL	0.33	0	0.56988620	-2.042810886	-0.604474690
##	62	2009	PIT	CAR	1.00	1	1.47296516	1.414977763	0.341241249
##	63	2010	S.J	CHI	0.00	0	2.88518521	1.824356405	0.967937316
##	64	2011	PHI	BUF	0.57	1	-0.19288844	0.681900462	0.224938827
##	65	2012	VAN	L.A	0.20	0	0.20516424	2.129736302	0.061192810
##	66	2013	CHI	MIN	0.80	1	-4.65659138	0.320222629	2.875375392
##	67	2014	CHI	L.A	0.43	0	0.26135917	0.701347495	-2.295093867
##	68	2015	T.B	CHI	0.33	0	-0.66902280	0.214148280	-1.662622333
##	69	2016	L.A	S.J	0.20	0	1.13372853	-1.316441765	0.699605950
##	70	2017	EDM	S.J	0.67	1	1.23592785	0.523725391	-0.361417393
##	71	2008	DET	NSH	0.67	1	-3.84326521	-1.456033460	-0.324581623
##	72	2009	DET	CHI	0.80	1	0.85183297	-0.007820049	-2.121254155
##	73	2010	S.J	COL	0.67	1	-1.44924073	-1.519151251	0.605213081
##	74	2011	VAN	CHI	0.57	1	-1.37367634	0.639408334	1.922824575
##	75	2012	STL	L.A	0.00	0	-0.71757136	0.884720520	0.909734274

## 76	2013	CHI	L.A	0.80	1	-1.56244776	1.359823807	2.368431159
## 77	2014	COL	MIN	0.43	0	-0.60787296	1.434659760	-0.071169885
## 78	2015	T.B	DET	0.57	1	-1.19055685	0.092110677	0.245011310
## 79	2016	S.J	NSH	0.57	1	0.25869907	0.153449256	-0.293048372
## 80	2017	MIN	STL	0.20	0	-0.58513665	-0.073874982	-0.094752612
## 81	2008	DET	PIT	0.67	1	-2.93581780	-3.863735815	-0.259422834
## 82	2009	VAN	CHI	0.33	0	2.43911127	1.750421995	0.218855016
## 83	2010	S.J	DET	0.80	1	-0.90902853	1.757415144	0.446882630
## 84	2011	S.J	DET	0.57	1	0.65718519	-0.749033556	0.139816743
## 85	2012	N.J	L.A	0.33	0	1.69455209	0.918832748	-0.882122703
## 86	2013	STL	L.A	0.33	0	2.64343476	0.717078283	0.154886522
## 87	2014	PIT	CBJ	0.67	1	-0.15833882	0.144124100	-0.509241409
## 88	2015	STL	MIN	0.33	0	1.16563323	0.144704261	-0.724087762
## 89	2016	T.B	NYI	0.80	1	0.34739766	-1.054013903	0.239494405
## 90	2017	MTL	NYR	0.33	0	1.42949296	-2.292230068	0.473691949
## 91	2008	MTL	PHI	0.20	0	-0.03684089	0.772866327	-0.335921531
## 92	2009	DET	CBJ	1.00	1	-2.29367793	-0.061575614	-2.172207759
## 93	2010	VAN	L.A	0.67	1	-0.88046306	0.501100624	0.211162035
## 94	2011	S.J	L.A	0.67	1	-0.40446268	-0.580621745	-1.598834564
## 95	2012	PHI	N.J	0.20	0	0.27288484	0.602344827	-1.185630133
## 96	2013	L.A	S.J	0.57	1	-0.88632994	-0.526605777	-1.431554686
## 97	2014	S.J	L.A	0.43	0	-0.08150886	0.216153690	-1.125484098
## 98	2015	MTL	OTT	0.67	1	0.80633248	0.528917186	0.531414889
## 99	2016	PIT	NYR	0.80	1	-0.14038893	-3.248090019	0.715128734
## 100	2017	STL	NSH	0.33	0	1.03200562	0.196819377	-0.298484103
## 101	2008	PIT	OTT	1.00	1	1.83669983	0.543930543	0.897210590
## 102	2009	DET	PIT	0.43	0	-0.97068933	-2.196865697	-2.436678885
## 103	2010	PHI	MTL	0.80	1	-0.54321229	-1.665687774	-0.742268068
## 104	2011	VAN	NSH	0.67	1	-2.27730552	0.303871215	-0.575475782
## 105	2012	NYR	N.J	0.33	0	-0.13481290	0.998016628	0.716008352
## 106	2013	MTL	OTT	0.20	0	-1.00879980	1.440418106	-3.359077640
## 107	2014	L.A	NYR	0.80	1	1.13558260	-1.661077557	0.170889520
## 108	2015	WSH	NYI	0.57	1	0.81835863	0.718788847	0.372880770
## 109	2016	WSH	PHI	0.67	1	-2.76839631	0.503967032	0.178546307
## 110	2017	PIT	NSH	0.67	1	-0.38574949	0.667462793	-0.791702583
## 111	2008	PIT	PHI	0.80	1	0.89494771	0.373533432	0.180070937
## 112	2009	WSH	NYR	0.57	1	-2.29757522	0.975642469	-2.788549518
## 113	2010	WSH	MTL	0.43	0	-4.85896947	0.894899806	-1.029785451
## 114	2011	WSH	NYR	0.80	1	0.92086223	-0.514687559	-0.278408698
## 115	2012	NYR	WSH	0.57	1	-1.51147056	0.015249735	1.359303336
## 116	2013	PIT	NYI	0.67	1	-3.53171512	2.158487803	0.741324883
## 117	2014	MTL	NYR	0.33	0	2.79797094	1.054231713	-0.255702821
## 118	2015	NYR	WSH	0.57	1	0.18465752	0.713757117	1.930901366
## 119	2016	WSH	PIT	0.33	0	0.55145314	1.191616038	-0.306593735
## 120	2017	OTT	NYR	0.67	1	4.13792145	-2.031660605	-0.057334198
## 121	2008	WSH	PHI	0.43	0	0.83112115	-3.062960515	-1.225477920
## 122	2009	PIT	PHI	0.67	1	1.51104071	-0.355724018	0.522936653
## 123	2010	N.J	PHI	0.20	0	0.63578663	0.007321301	0.787857487
## 124	2011	PIT	T.B	0.43	0	1.42074932	-0.084509562	2.353025144
## 125	2012	NYR	OTT	0.57	1	-1.02280715	0.498528497	1.603315123
## 126	2013	WSH	NYR	0.43	0	1.45181464	1.839759738	-2.786071958
## 127	2014	T.B	MTL	0.00	0	0.70218300	-0.969974931	-0.893639240
## 128	2015	NYR	PIT	0.80	1	-0.90630829	1.702819232	0.915544416
## 129	2016	PIT	T.B	0.57	1	0.62086075	-1.072768548	-0.338559269

##	130	2017	PIT	OTT	0.57	1	-2.36758043	0.530587065	-0.590407894
##	131	2008	N.J	NYR	0.20	0	2.28498609	0.125247302	-0.273298255
##	132	2009	WSH	PIT	0.43	0	-0.21434865	-2.480984174	-2.122385067
##	133	2010	PIT	OTT	0.67	1	0.05613531	0.427129112	0.655766961
##	134	2011	VAN	S.J	0.80	1	-0.80326874	1.374944102	1.509920055
##	135	2012	PIT	PHI	0.33	0	0.56703495	-1.422554496	0.346411640
##	136	2013	PIT	OTT	0.80	1	-2.90921558	3.757251673	-2.896961279
##	137	2014	PIT	NYR	0.43	0	0.36011914	1.218383009	-1.629296740
##	138	2015	NYR	T.B	0.43	0	1.34484058	0.969261849	1.116444069
##	139	2016	PIT	S.J	0.67	1	1.04918795	-0.837021356	1.426606402
##	140	2017	WSH	PIT	0.43	0	-1.51269288	0.384289711	1.296221989
##	141	2008	PIT	NYR	0.80	1	1.35326458	2.956291384	-0.557274221
##	142	2009	VAN	STL	1.00	1	-0.74442531	0.656626811	0.600682350
##	143	2010	PIT	MTL	0.43	0	-0.96841717	-1.753294475	-0.760019105
##	144	2011	WSH	T.B	0.00	0	1.61296221	0.288192726	1.975801282
##	145	2012	STL	S.J	0.80	1	-1.22655677	-0.222327378	2.860598663
##	146	2013	VAN	S.J	0.00	0	0.71591190	0.765387258	-0.369289329
##	147	2014	NYR	PHI	0.57	1	0.51642727	-1.438388743	0.880245937
##	148	2015	MTL	T.B	0.33	0	3.97702386	0.491787016	1.470717256
##	149	2016	STL	S.J	0.33	0	2.07028338	-0.442303738	1.202996010
##	150	2017	WSH	TOR	0.67	1	-2.85491131	0.924726192	1.676129690
##			Comp.4	Comp.5			Comp.6	Comp.7	Comp.8
##	1		-1.8916454436	-0.24904837	0.404419556	0.207760688	0.4628860895		
##	2		-0.2020516932	-0.03567764	-0.142807370	1.089038897	-0.7589920727		
##	3		0.5452701547	-1.14296517	-0.362378564	-0.354824253	0.1062542435		
##	4		-0.7714358006	1.82740537	0.578836091	0.355108796	-0.6447817974		
##	5		0.0520624891	0.99460742	-0.317495139	-0.844021226	0.3873847848		
##	6		0.7793908532	0.34474720	0.352000748	-0.850174719	-0.0949799002		
##	7		0.1922285156	-0.02144567	1.155401021	0.651421831	0.1691365483		
##	8		0.6041616209	-1.10341940	-0.703928983	0.879009070	0.7866094676		
##	9		0.2210451838	1.78490918	-0.495750468	0.294779030	0.3252831033		
##	10		0.2454827752	-0.29772219	-0.443929153	-0.354345492	0.9248955517		
##	11		0.4823715793	1.43439995	-0.572399584	-0.796994760	-0.1077182446		
##	12		-0.2785168532	0.79782865	0.431742467	0.805438947	0.7141519452		
##	13		0.3377952256	0.20955553	0.604504790	0.753547743	0.1079863702		
##	14		0.8385928214	1.75106534	0.598294179	-0.747366745	-0.1793811249		
##	15		0.5872958237	-1.02981078	-0.630325142	0.038486080	-0.9966238484		
##	16		-1.6561342680	-0.93242385	0.535246583	-0.193607806	0.2035836822		
##	17		1.6792726896	-0.18222939	0.481273028	0.794958243	0.0837094959		
##	18		0.8610050754	0.13616584	1.574155212	0.841214111	-0.1489061688		
##	19		0.7108491151	0.34940216	0.719790225	-1.268981732	0.3874913935		
##	20		0.5491435041	0.54028935	-0.538613765	0.405552505	0.7742693822		
##	21		0.4993716325	0.77409845	-0.616063600	-0.245629024	0.3829124527		
##	22		-1.3874084828	-0.19283577	0.055645127	0.162601571	0.6282392512		
##	23		0.3553727076	-0.14898572	-0.075041096	-0.908451685	-0.5526141364		
##	24		-0.2797516289	-1.45050349	0.385416052	-0.506486582	-0.5040755322		
##	25		0.9072991664	-0.81069799	0.678462058	-0.020120849	-0.3371419241		
##	26		1.2951096813	0.60766459	-1.746196327	0.849924157	0.1293821434		
##	27		-1.2113139359	-0.72031545	0.283408779	-0.629082356	-0.1383449288		
##	28		1.8271917000	-0.92301048	0.352083982	0.692852955	0.6387355619		
##	29		0.7794420994	-0.42604965	0.343372077	0.335171285	-0.4786300199		
##	30		0.9210768809	-0.09004316	-0.741560975	0.554524480	0.6888458289		
##	31		-1.4603534999	0.68857405	-0.927081992	0.537061165	0.2107753469		
##	32		-0.4486025930	-0.03483784	-0.880224980	-0.865966061	0.4988722660		

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## 33  1.7772764682 -0.35221831 -0.988590334 -0.102741663 -0.1561326943
## 34  1.3104175179 -0.02476257 -0.235131356 -0.014804465  0.3441232595
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## 40 -0.8691364999 -1.34980721  0.070287272  0.430171821 -0.2317684874
## 41 -0.3718340640  1.70722815 -1.378084097  0.928273725 -0.2546464334
## 42 -1.7637538184 -0.53989355 -1.065736922 -0.681264306 -0.1327978015
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## 47  0.2711624355  0.69128844 -0.608652151  0.132684083  0.5759264625
## 48 -2.4288690926  0.19598853 -0.506404080 -0.068355020 -1.1467629243
## 49  0.8356866574 -0.66603731 -0.146537152 -0.231861350  0.0354790677
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## 53  1.7533414205 -0.95028286  0.009262853  0.088502167 -0.6205497594
## 54 -0.0076806325  1.77053026 -0.195182162 -0.421223399  0.0196658210
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## 60 -0.0618100091 -0.16414739  0.492449213 -1.005220921  0.1005710982
## 61 -0.1644869046 -0.16937737  0.344439487 -0.156034522  1.1173007373
## 62  1.6489286194 -0.71347721 -0.399869577 -1.255528232  0.0743504015
## 63 -1.4790911216  0.66750912  0.179718337 -0.439334767  0.5172883170
## 64  0.5754343274 -0.78335616 -0.404763455  0.768685634 -0.0379431795
## 65 -0.0483511746  0.53850988  1.670197368 -0.341007689 -1.0780601193
## 66  0.2181316533 -0.29236799 -1.137541223 -0.538270077 -0.7185462257
## 67  1.3670799465  0.05821787  0.025427552 -0.782673262 -0.6155577583
## 68  1.8219773665 -0.36030759  0.667657263 -0.122065423  0.4750979020
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## 70 -0.6851903793  0.94384764  0.108701959 -1.383036768 -0.4442444250
## 71 -1.7572610737  0.06787137 -0.121305379 -0.012613764 -0.2887754577
## 72 -0.1599336725  0.50187707 -0.312847482 -0.016435184 -0.4911985247
## 73 -0.0919408253  0.98721383  0.756299532 -0.393049850 -0.0550146962
## 74 -0.0740060805  1.40650221  0.310408703  0.522880720  0.3182214492
## 75 -0.6020286347 -0.24577851  2.042430846 -0.248417257  0.1385267014
## 76  0.4945436793 -0.46737368 -0.634502024 -0.273343567 -0.1858565138
## 77  0.4509285531  0.86780938 -0.011244592  1.207350917 -0.1789010793
## 78  2.0775480303 -0.98686329 -0.028407262  0.590237470  0.4311031168
## 79 -0.3503737179  0.27489110  0.801246637 -0.518438076  0.0606939129
## 80 -0.0124511405 -1.13277094  0.012831809 -0.804853988  0.3407101654
## 81  0.0322002423  0.15864884  0.258321145  0.502590289 -0.5697890612
## 82  0.7142798377 -0.13347344 -0.251430786 -0.281909712  0.3438009163
## 83  0.2775862042 -0.33209569 -0.488543428 -0.385738904  0.4709604929
## 84 -1.4017927475 -0.79684323 -0.134377324 -0.671492984  0.7365041032
## 85  2.1612369128  0.42893401  0.458225835 -0.469175718 -0.0006492602
## 86  0.5324719379  0.51957022 -0.355107867  0.015237061 -0.2171830016

```

## 87	0.6047887635	1.35466468	0.281049329	-0.237838950	-0.2040136701
## 88	-1.5297413733	0.66145635	-0.193627981	-0.699578219	-0.6400538881
## 89	-0.0932724664	-0.75887305	0.055415839	0.251861940	0.0019273158
## 90	-0.7807681259	-0.11399090	-0.083934011	-0.271046906	0.4792375917
## 91	-0.0970636044	-0.07745571	-0.782152301	-0.052610890	-0.2621422371
## 92	-2.1849047557	1.23497351	-0.629680080	0.132874282	-0.6156802367
## 93	0.3419084990	-0.17324282	0.013626692	0.538339161	0.1791848352
## 94	-2.2593212248	0.02681831	0.498272721	-0.163447814	0.5051403021
## 95	-1.5026813360	-1.00977154	1.333743606	-0.032548092	-0.4185825154
## 96	0.7868459370	-0.58875179	0.055956531	0.938708408	-0.9103577704
## 97	1.4582144720	0.18460390	-0.557778515	-0.377516927	0.5664350890
## 98	-0.2394162355	0.29428105	-0.013630148	0.681443173	0.1283631352
## 99	0.5237958970	0.83579229	0.666356483	-0.982601692	0.3991462674
## 100	0.8178817489	1.13696032	-0.153971241	0.289510906	0.3505265239
## 101	-1.3342218907	0.45933333	-0.193230423	-0.545568003	0.8464771082
## 102	-1.8183695741	0.56472424	-0.350020855	0.446954371	-0.7557979845
## 103	0.4491853028	-0.44852892	0.419127255	-0.017641252	0.2444234316
## 104	-1.1262633319	1.65613302	0.607769485	-0.219702374	-0.6414476945
## 105	-1.0772475045	-0.62015828	1.493972352	0.597071622	0.2730431546
## 106	0.4520435761	-1.84094596	-0.596657330	-0.266904471	0.0350015909
## 107	-0.4163011251	-1.44610784	-0.029406451	-0.537937386	-0.2694436038
## 108	-0.6755742595	1.48116575	-0.849870989	-0.932019073	-0.1277781672
## 109	0.9910585281	0.96765234	0.613798117	0.131326515	0.2665105412
## 110	-0.2532858557	0.26082241	0.219910788	-0.131349451	0.2457629228
## 111	-0.2300189857	-1.28805857	0.007882045	-0.454389492	0.5417685989
## 112	-1.8143462370	-0.01007988	0.273028122	0.068717787	0.2091538491
## 113	-0.2812329101	-1.53770157	0.691127546	0.173429983	-0.1912486950
## 114	0.1018615619	0.82825108	0.055341252	1.353087356	0.0183126650
## 115	0.5718587639	0.53007670	0.491092686	-0.008784592	0.3092858541
## 116	-1.3636589456	-0.52737305	-1.267126195	0.382842819	0.9428193134
## 117	0.6283555096	-0.10817071	-0.501270429	0.123358931	0.2986777942
## 118	1.2116963473	-0.68459797	0.387314619	1.458186732	-0.0869725726
## 119	0.0003680733	1.10920437	0.461135183	0.418332352	-0.4889098844
## 120	-0.2546360366	-0.26831188	-0.734478409	0.260063977	0.3401733505
## 121	0.2845567584	-1.49916229	0.672223045	-0.103083711	-0.2633106060
## 122	0.7580906322	-1.50676232	0.142962617	-0.285439927	0.0688433040
## 123	-0.1494590207	-0.43330675	0.580782328	0.369710131	-0.1786323776
## 124	-0.4107630481	-0.13852656	-0.049863799	-0.075830354	-1.1287267969
## 125	0.7683046701	0.44688793	1.433785312	0.102141485	1.1544206087
## 126	-0.4991386055	1.19332056	-1.166103903	-0.188065899	-0.2261618749
## 127	-0.6836812092	-1.05627890	0.352722593	-1.052232023	-0.8804162860
## 128	0.2962648421	-0.56448219	0.698738138	0.472777088	-0.2493483089
## 129	-0.3304333055	0.16931418	0.281882831	-0.863875159	0.6040481151
## 130	-0.1610008837	0.15903497	0.253861960	-1.020161096	0.0010434599
## 131	-0.1882078037	0.10683738	0.914064497	0.539192468	-0.2396965762
## 132	-1.6869754573	1.01594301	-0.199168498	0.654695518	0.4965664845
## 133	-0.3942181062	-0.62464686	-0.775984755	-0.608789882	-0.2199118816
## 134	0.6803385385	1.24834858	-0.645747059	0.338352414	-0.7923592120
## 135	1.4107322636	0.90949129	0.013113195	-0.865568288	-0.7571506461
## 136	-0.4110933502	-1.38384139	-1.296242394	0.205594848	0.4571311196
## 137	0.8839573442	0.47543140	-0.370250538	-0.574056387	0.0316932501
## 138	-0.3471528565	-0.05322443	-0.901226536	0.661830458	-0.0670926442
## 139	0.4993829190	-0.05763321	0.088849782	0.170855412	0.1269966694
## 140	0.0838439293	0.16766030	-1.071751568	0.477471962	-0.0131629492

```

## 141 -0.4992784769 0.07269797 0.501693935 -0.196474397 0.3916468846
## 142 -0.6162674364 -1.32799092 0.080194644 0.351316523 0.0027947689
## 143 2.0563665575 -0.98137637 1.228162816 0.164048828 -0.3504494436
## 144 -0.5989294703 0.35443096 0.825046864 0.128952271 -0.7096980951
## 145 1.0107882120 0.94843155 0.885811973 0.529737782 -0.0233881470
## 146 1.1356398521 -1.14100096 -1.099809507 1.421073333 -0.5523801732
## 147 -0.8009071721 -0.12828152 0.173547559 -0.011042907 -0.0189111147
## 148 -1.0696557264 0.24701933 -0.325945878 0.103700850 -0.0895201882
## 149 0.0264591085 1.05816241 -0.131038477 0.472150258 -0.0663888390
## 150 -0.5863871558 -0.26433990 0.593617468 0.531565527 -0.1031547941
##      Comp.9      Comp.10
## 1  -0.035201590 -0.040647430
## 2   0.247254154 0.057257020
## 3  -0.259564445 -0.210404699
## 4   0.616158703 -0.376233102
## 5  -0.367732715 -0.216664954
## 6   0.086563179 0.202333293
## 7  -0.148900225 -0.010853277
## 8  -0.773825393 -0.036726607
## 9   0.025948369 0.012555487
## 10  0.023493251 0.052904641
## 11  0.128865096 -0.076546447
## 12  0.812798841 0.136433328
## 13  0.040766565 -0.232948509
## 14  0.048313828 -0.220235538
## 15 -0.181355793 -0.121809308
## 16  0.235352370 0.095402724
## 17  0.098054833 -0.129347936
## 18 -0.113569730 0.174620771
## 19 -0.661045130 -0.138788909
## 20  0.032915113 0.118708654
## 21  0.794227218 -0.223422848
## 22 -0.257190520 -0.096283008
## 23  0.079004672 0.069331470
## 24  0.045621071 0.273744275
## 25 -0.095726325 -0.121423696
## 26 -0.327863673 0.146682770
## 27 -0.524828980 0.136462715
## 28 -0.114574625 0.018813598
## 29  0.176442414 0.516755075
## 30  0.004923706 -0.026818486
## 31 -0.255432167 -0.039196565
## 32 -0.651455580 0.186386023
## 33  0.795600465 -0.089206574
## 34  0.286764008 0.003855882
## 35  0.275663499 0.069333549
## 36  0.273192758 0.115355290
## 37 -0.019355485 0.216579669
## 38 -0.430655987 0.041180722
## 39 -0.544888506 0.249607076
## 40  0.324807115 0.152446880
## 41 -0.383430493 -0.065799799
## 42  0.974142926 0.099858675
## 43  0.483668631 0.001762523

```



```

## 44  0.086329481 -0.015860215
## 45  0.592927168  0.212404817
## 46  0.039848168  0.138754400
## 47 -0.133563448 -0.085456273
## 48  0.078335123 -0.093150062
## 49  0.203490396 -0.045156295
## 50 -0.081592977  0.285044098
## 51  0.071771025  0.042342011
## 52 -0.333288415 -0.031065136
## 53  0.389843654 -0.070818678
## 54 -0.051735070  0.013293539
## 55  0.336226202 -0.047768128
## 56  0.213503737  0.063563267
## 57  0.006325543  0.171365419
## 58 -0.192666143 -0.285902335
## 59  0.342770033  0.002315869
## 60 -0.160418723  0.143531419
## 61  0.166384924 -0.090691477
## 62 -0.727026914  0.242167335
## 63 -0.773734967  0.072438269
## 64  0.322009328  0.131438681
## 65 -0.420727503 -0.112157437
## 66 -0.020383160  0.012927389
## 67  0.244182681 -0.022339141
## 68 -0.200780706  0.059642388
## 69 -0.493536428 -0.068356186
## 70 -0.095769868  0.081723664
## 71  0.249681590 -0.079098361
## 72 -0.424476465 -0.202395222
## 73 -0.822573871  0.112356902
## 74 -0.212015610  0.083145716
## 75  0.165296973 -0.172911929
## 76  0.330425324  0.023730253
## 77 -0.035847768  0.047811584
## 78  0.166257996  0.072994846
## 79  0.156686645 -0.104552400
## 80  0.575611098  0.184520513
## 81 -0.075493806 -0.110535601
## 82 -0.445228727 -0.173840786
## 83 -0.377299836 -0.140080707
## 84  0.194899678  0.081583104
## 85 -0.069374412 -0.127189154
## 86  0.234353460 -0.099418205
## 87  0.466471828  0.144448371
## 88  0.017368157  0.017010204
## 89  0.072537807 -0.217777636
## 90 -0.505462966 -0.276663720
## 91  0.227065006 -0.119135914
## 92  0.027329044 -0.055648273
## 93 -0.491914216 -0.103602116
## 94  0.304699905 -0.020519664
## 95  0.074914724  0.005413760
## 96 -0.154482489  0.103756836
## 97  0.602041604 -0.107238256

```

98 0.126246474 -0.165028139
99 0.158751088 0.126274465
100 -0.450366686 0.117822146
101 0.675145368 0.057821222
102 0.061955384 -0.099072315
103 0.190994964 -0.038363021
104 -0.010562393 -0.116948933
105 0.519993190 -0.055575381
106 -0.020869249 -0.239452433
107 -0.191507468 0.117521252
108 -0.395034937 0.088354796
109 0.031199144 0.050399979
110 0.105517052 0.113532804
111 -0.295567042 0.074086462
112 -0.307056013 0.021818372
113 -0.700384634 0.027924451
114 -0.423905898 0.156047768
115 0.700296984 0.038503117
116 -0.381795492 0.011689257
117 0.236282605 0.017234040
118 0.253526400 -0.114066698
119 -0.104414358 -0.001767086
120 0.132273881 0.094838187
121 -0.563273227 -0.032669247
122 -0.498541162 -0.140298983
123 0.091666970 0.221225333
124 0.119818491 0.022372035
125 0.725504514 -0.255352070
126 -0.327039760 0.177813004
127 -0.145138166 -0.062637124
128 0.543285569 0.132006337
129 0.116697085 0.243395310
130 -0.236514322 -0.317942578
131 0.089328529 -0.097112691
132 -0.089938639 0.018742269
133 -0.067978488 -0.194261468
134 0.017037924 -0.026238155
135 -0.162360478 0.073916343
136 0.061503068 -0.164664072
137 0.257746968 0.078331890
138 0.528515016 -0.088965177
139 -0.209739156 0.100925494
140 -0.280311603 -0.121761080
141 0.146040798 0.141997533
142 -0.470309649 -0.006587069
143 0.110872051 -0.114805544
144 0.027180928 0.207052877
145 -0.262927302 -0.059028399
146 -0.148987781 0.107364047
147 0.440899721 -0.061057946
148 0.287532908 -0.034141165
149 -0.447163334 -0.096493108
150 0.011734927 -0.080130672

pca\$loadings

```
##
## Loadings:
##      Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8 Comp.9
## dGF%      -0.491      0.240      -0.170 -0.234  0.239
## dAdjGF%    -0.484      0.242      0.101 -0.299 -0.254  0.291
## d5v5_xGF%  -0.266 -0.496 -0.137      -0.265  0.255 -0.350  0.632
## d5v5_CF%   -0.239 -0.573      -0.142      0.133 -0.496 -0.564
## dTime_Led  -0.409      -0.177  0.104 -0.212 -0.772  0.303  0.213
## d5v5_Sh%   -0.141  0.529 -0.128  0.433 -0.313      -0.279      -0.555
## d5v5_Sv%      0.187  0.578 -0.583 -0.153 -0.137      0.324 -0.375
## dPP%       -0.172  0.159 -0.497 -0.393  0.592 -0.140 -0.367      -0.178
## dPK%        -0.174  0.478  0.519  0.602 -0.178      0.160 -0.201
## dROWins    -0.415  0.195      0.209  0.496  0.657  0.221 -0.108
##      Comp.10
## dGF%       0.736
## dAdjGF%    -0.669
## d5v5_xGF%
## d5v5_CF%
## dTime_Led
## d5v5_Sh%
## d5v5_Sv%
## dPP%
## dPK%
## dROWins
##
##      Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8
## SS loadings      1.0      1.0      1.0      1.0      1.0      1.0      1.0      1.0
## Proportion Var   0.1      0.1      0.1      0.1      0.1      0.1      0.1      0.1
## Cumulative Var   0.1      0.2      0.3      0.4      0.5      0.6      0.7      0.8
##      Comp.9 Comp.10
## SS loadings      1.0      1.0
## Proportion Var   0.1      0.1
## Cumulative Var   0.9      1.0
```

pca\$center

```
##      dGF% dAdjGF% d5v5_xGF% d5v5_CF% dTime_Led d5v5_Sh% d5v5_Sv%
## 2.3687333 2.2268000 0.5541333 0.4273333 1.8223333 0.4026667 0.1891333
##      dPP% dPK% dROWins
## 0.9120000 0.4493333 4.6400000
```

pca\$scale

```
##      dGF% dAdjGF% d5v5_xGF% d5v5_CF% dTime_Led d5v5_Sh% d5v5_Sv%
## 3.0132028 3.0151295 3.4389055 3.8715881 2.8865829 1.1646033 0.9983246
##      dPP% dPK% dROWins
## 3.9198116 3.4375911 5.0731713
```

Naming of Principal Components

Comp.1: “Creating Wins”

This metric represents your team’s (negative) ability the win games. Value comes from GF%, AdjGF%, Time_Led, and ROWins. ### Comp.2: “Quantity vs Quality” The higher this metric, the more your team relies on skill and high percentage plays to score. The lower this metric, the more your team relies on controlling the possession battle and generating a higher volume of shot attempts. Value comes from 5v5_Sh%, and negatively from xGF% and CF% ### Comp.3: “Defensive vs Offensive” This metric is higher for teams which tend to play tight, low-scoring games, and lower for teams who play a shootout-style high-scoring game. Value comes from Sv% and PK%, and negatively from PP%

Logistic Regression

The binary model runs regression only on whether the higher-seeded team won or lost. The weighted model is an abuse of glm because it uses non-integer success variables (win% in the series)

```
num_factors <- 3
Comps <- NULL
for (i in 1:num_factors) {
  Comps[i] <- paste0('Comp.', i)
}

regression_binary <- function(dataset) {
  return(suppressWarnings(glm(`Home_Won` ~ `Comp.1` + `Comp.2` + `Comp.3`, data=dataset, family=binomial)
})

regression_weighted <- function(dataset) {
  return(suppressWarnings(glm(`Home_W.` ~ `Comp.1` + `Comp.2` + `Comp.3`, data=dataset, family=binomial)
})

binary_model <- regression_binary(prin_data)
weighted_model <- regression_weighted(prin_data)
summary(binary_model)
```

```
##
## Call:
## glm(formula = Home_Won ~ Comp.1 + Comp.2 + Comp.3, family = binomial(link = "logit"),
##      data = dataset)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.0246  -1.0713   0.5498   0.9913   1.8899
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.2600     0.1795   1.448 0.147505
## Comp.1       -0.3704     0.1080  -3.429 0.000605 ***
## Comp.2       -0.2019     0.1286  -1.571 0.116285
## Comp.3        0.4412     0.1549   2.848 0.004402 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
## Null deviance: 206.23 on 149 degrees of freedom
## Residual deviance: 181.99 on 146 degrees of freedom
## AIC: 189.99
##
## Number of Fisher Scoring iterations: 3
summary(weighted_model)

##
## Call:
## glm(formula = Home_W. ~ Comp.1 + Comp.2 + Comp.3, family = binomial(link = "logit"),
## data = dataset)
##
## Deviance Residuals:
## Min 1Q Median 3Q Max
## -1.29427 -0.29962 -0.02179 0.28636 1.28898
##
## Coefficients:
## Estimate Std. Error z value Pr(>|z|)
## (Intercept) 0.14774 0.16589 0.891 0.373
## Comp.1 -0.13863 0.09044 -1.533 0.125
## Comp.2 -0.09632 0.11757 -0.819 0.413
## Comp.3 0.11938 0.13690 0.872 0.383
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 43.230 on 149 degrees of freedom
## Residual deviance: 39.393 on 146 degrees of freedom
## AIC: 199.85
##
## Number of Fisher Scoring iterations: 3
```

Cross Validation

```
logLoss <- function(pred, actual){
  -1*mean(log(pred[model.matrix(~ actual + 0) - pred > 0]))
}

mse <- function(pred, actual){
  mean((pred-actual)^2)
}

ten_fold_cross_validate <- function(dataset){
  series_shuffled <- dataset[sample(nrow(dataset)),]
  folds <- cut(seq(1,nrow(series_shuffled)),breaks=10,labels=FALSE)

  log_loss_binary <- NA
  log_loss_weighted <- NA
  mse_binary <- NA
  mse_weighted <- NA

  for (i in 1:10) {
```

```

testRows <- which(folds==i,arr.ind=TRUE)
test_data <- series_shuffled[testRows,]
train_data <- series_shuffled[-testRows,]

fold_binary_model <- regression_binary(train_data)
fold_weighted_model <- regression_weighted(train_data)

test_data$bin_pred <- predict(fold_binary_model, test_data[,Comps], type='response')
test_data$wgt_pred <- predict(fold_weighted_model, test_data[,Comps], type='response')

log_loss_binary[i] <- logLoss(test_data$bin_pred, test_data$Home_Won)
log_loss_weighted[i] <- logLoss(test_data$wgt_pred, test_data$Home_Won)
mse_binary[i] <- mse(test_data$bin_pred, test_data$Home_Won)
mse_weighted[i] <- mse(test_data$wgt_pred, test_data$Home_Won)
}
return(c(mean(log_loss_binary), mean(log_loss_weighted), mean(mse_binary), mean(mse_weighted)))
}

ten_fold_metrics <- matrix(NA, nrow=200, ncol=4)
colnames(ten_fold_metrics) <- c("Log Loss Binary", "Log Loss weighted", "Mean Squared Error Binary", "Mean Squared Error weighted")
for(j in 1:200) {
  ten_fold_metrics[j,] <- ten_fold_cross_validate(prin_data)
}

colMeans(ten_fold_metrics)

```

```

##           Log Loss Binary           Log Loss weighted
##           0.5521464           0.5914924
## Mean Squared Error Binary Mean Squared Error weighted
##           0.2215097           0.2284080

```

```

# 1-13 -> 0.238
# 1-8 -> 0.232
# 1-6 -> 0.232
# 1-5 -> 0.229
# 1-4 -> 0.226 0.225
# 1,2,3 -> 0.223 0.222 0.221
# 1,2 -> 0.232 0.230
# 1,3 -> 0.222 0.220

```

Apply Current Model With Exact Specifications

```

playoff_teams_2018 <- read.csv('input_csvs/playoff_teams_2018.csv', check.names=FALSE)

predict_matchup <- function(home_team, away_team) {
  home_stats <- playoff_teams_2018[playoff_teams_2018$Team==home_team,stats]
  away_stats <- playoff_teams_2018[playoff_teams_2018$Team==away_team,stats]
  raw_diffs <- home_stats - away_stats
  colnames(raw_diffs) <- dStats
  nrm_diffs <- data.frame(0)
  for (i in 1:length(dStats)) {
    dStat <- dStats[i]
    center <- pca$center[dStat]

```

```

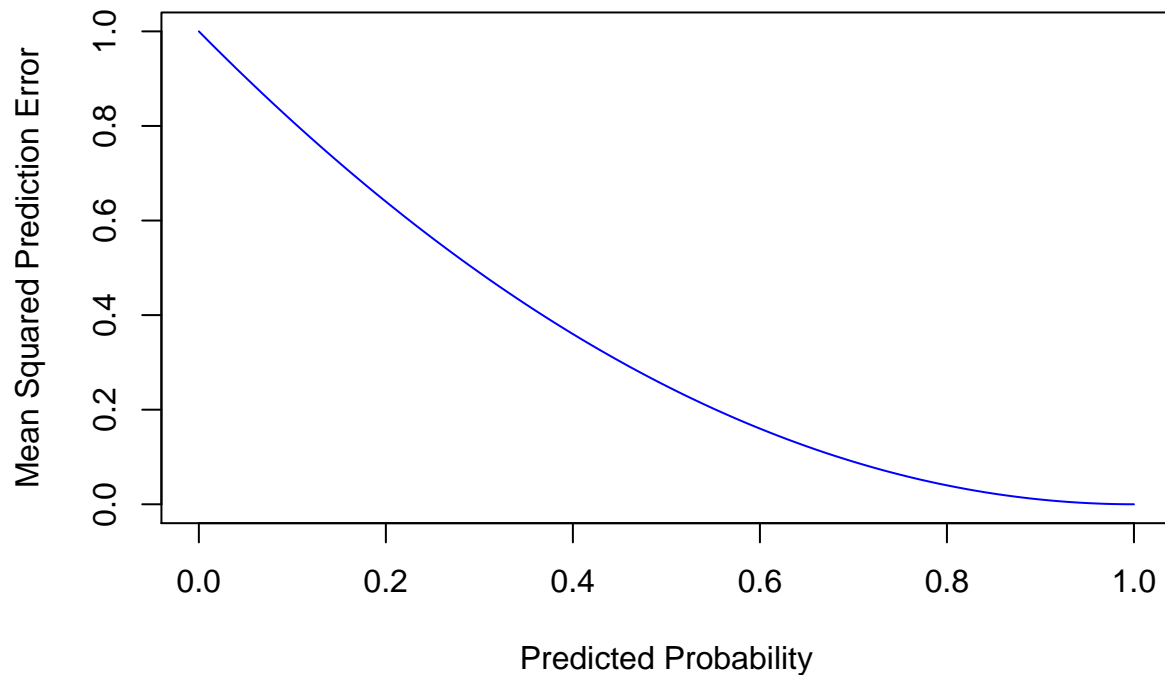
    scale <- pca$scale[dStat]
    nrm_diffs[,dStat] <- (raw_diffs[dStat]-center)/scale
  }
  component_values <- data.frame(0)
  for (j in 1:length(Comps)) {
    component <- Comps[j]
    loadings <- pca$loadings[,component]
    component_values[,component] <- 0
    for (k in 1:length(dStats)) {
      stat <- dStats[k]
      contribution <- loadings[stat] * nrm_diffs[stat]
      component_values[,component] <- component_values[,component] + contribution
    }
  }
  predict(binary_model, component_values[,Comps], type='response')
}

predict_matchup('BOS', 'ANA')

##          1
## 0.5759154
squareerror <- function(x) {(x-1)^2}
logloss <- function(x) {-log(x)}
plot(squareerror, xlim=c(0,1), ylim=c(0,1), xlab='Predicted Probability', ylab='Mean Squared Prediction Error')

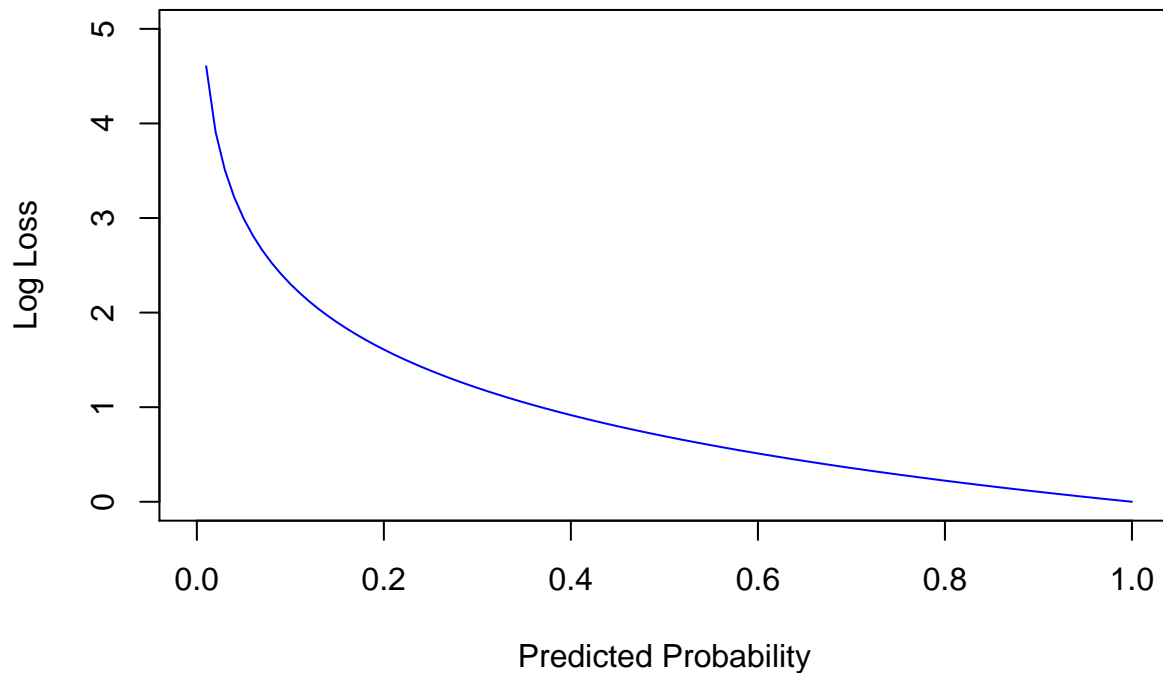
```

Mean Squared Error when True Result is 1



```
plot(logloss, xlim=c(0,1), ylim=c(0,5), xlab='Predicted Probability', ylab='Log Loss', main='Log Loss w
```

Log Loss when True Result is 1



IMPORT FOR PREDICTION

```
corsica1_pred <- read.csv("input_csvs/2018/corsica_5v5_18.csv", check.names=FALSE)
corsica1_pred$Season <- 2018
corsica1_pred <- corsica1_pred[, c('Team', 'Season', 'CF%', 'GF%', 'xGF%', 'Sh%', 'Sv%')]

corsica2_pred <- read.csv("input_csvs/2018/corsica_all_18.csv", check.names=FALSE)
corsica2$Season <- 2018
corsica2_pred <- corsica2_pred[, c('Team', 'Season', 'allGF%', 'allGF', 'allGA')]

morestats_pred <- read.csv("input_csvs/2018/misc_stats_playoffwins_18.csv", check.names=FALSE)
morestats_pred <- morestats_pred[, c('Team', 'Season', 'Time Led', 'GF_EN', 'GA_EN', 'PP%', 'PK%', 'ROW

raw_data_pred <- merge(merge(corsica1_pred, corsica2_pred, by="Team"), morestats_pred, by="Team")
raw_data_pred$`AdjGF%` <- with(raw_data_pred, round(100*(allGF-GF_EN)/(allGF-GF_EN+allGA-GA_EN),2))
raw_data_pred <- raw_data_pred[, c('Team', 'Season', 'allGF%', 'AdjGF%', 'xGF%', 'CF%', 'Time Led', 'Sh%', 'Sv%')]
colnames(raw_data_pred) <- c('Team', 'Season', 'GF%', 'AdjGF%', '5v5_xGF%', '5v5_CF%', 'Time_Led', '5v5_Sv%', 'PP%', 'PK%', 'ROW

raw_data_pred
```

```
## Team Season GF% AdjGF% 5v5_xGF% 5v5_CF% Time_Led 5v5_Sh% 5v5_Sv% PP%
## 1 ANA 2018 52.50 52.22 48.41 48.62 23.90 8.16 93.35 17.8
```


## 2	ARI	2018	45.08	45.80	46.18	48.00	16.77	7.28	92.15	16.9
## 3	BOS	2018	55.86	55.38	53.48	53.80	21.40	7.82	92.34	23.5
## 4	BUF	2018	41.68	41.83	45.05	47.58	13.30	6.16	91.63	19.1
## 5	CAR	2018	47.07	46.97	53.12	54.47	18.47	7.04	90.97	18.4
## 6	CBJ	2018	51.08	51.13	51.94	51.55	20.60	7.44	92.85	17.2
## 7	CGY	2018	47.06	46.94	52.62	53.45	17.13	6.79	91.92	16.0
## 8	CHI	2018	47.30	45.83	49.59	52.36	17.55	7.08	91.82	16.0
## 9	COL	2018	51.93	53.08	46.29	47.57	21.23	8.21	93.24	21.9
## 10	DAL	2018	50.99	51.29	53.54	51.04	19.55	7.69	92.73	19.3
## 11	DET	2018	45.34	45.88	48.58	48.80	16.95	7.53	91.98	17.5
## 12	EDM	2018	46.64	46.30	50.89	50.62	15.53	7.44	91.74	14.8
## 13	FLA	2018	50.20	50.53	48.72	49.14	20.65	7.71	92.32	18.9
## 14	L.A	2018	53.99	55.16	48.00	50.05	18.17	7.80	93.09	20.4
## 15	MIN	2018	52.19	51.32	53.58	47.18	22.35	8.19	92.72	20.4
## 16	MTL	2018	44.52	44.35	51.24	50.49	15.33	6.38	92.19	21.2
## 17	N.J	2018	50.31	51.08	50.32	48.63	19.48	7.91	91.73	21.4
## 18	NSH	2018	56.13	56.95	50.93	51.52	25.03	8.19	93.55	21.2
## 19	NYI	2018	47.11	46.74	46.87	47.47	18.58	8.84	91.71	23.2
## 20	NYR	2018	46.44	45.34	47.12	45.90	15.20	7.55	92.18	21.2
## 21	OTT	2018	43.54	42.03	45.87	47.12	14.17	7.69	90.84	16.6
## 22	PHI	2018	51.34	51.82	50.54	49.79	18.83	7.88	92.48	20.7
## 23	PIT	2018	52.12	52.00	52.69	52.23	19.47	7.29	91.03	26.2
## 24	S.J	2018	52.22	52.22	51.92	50.80	20.57	7.50	91.64	20.6
## 25	STL	2018	50.11	49.76	51.46	51.73	20.55	7.17	92.87	15.4
## 26	T.B	2018	55.34	55.58	52.76	51.62	23.67	9.35	92.93	23.9
## 27	TOR	2018	54.00	54.02	51.10	49.86	22.30	9.01	92.81	25.0
## 28	VAN	2018	45.76	47.02	46.57	47.68	16.13	7.21	92.15	21.4
## 29	VGK	2018	54.27	NA	50.67	50.96	22.28	8.38	92.19	21.4
## 30	WPG	2018	55.83	56.03	52.79	51.50	27.07	8.53	92.54	23.4
## 31	WSH	2018	51.82	51.47	46.88	47.99	21.93	9.14	92.47	22.5
##	PK%	ROWins								
## 1	83.2	40								
## 2	79.5	27								
## 3	83.7	47								
## 4	77.9	24								
## 5	77.5	33								
## 6	76.2	39								
## 7	81.8	35								
## 8	79.1	32								
## 9	83.3	41								
## 10	80.8	38								
## 11	77.5	25								
## 12	76.7	31								
## 13	80.2	41								
## 14	85.0	43								
## 15	81.3	42								
## 16	74.1	27								
## 17	81.8	39								
## 18	81.9	47								
## 19	73.2	32								
## 20	81.4	31								
## 21	76.2	26								
## 22	75.8	40								
## 23	80.0	45								

##	24	84.8	40
##	25	79.7	41
##	26	76.1	48
##	27	81.4	42
##	28	78.3	31
##	29	81.4	47
##	30	81.8	48
##	31	80.3	46