

# Project 1: NHL API Access and Analysis

Lee Pixton

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## NHL API Connection Functions

This is the first project for the course ST558 (Data Science for Statisticians) at NC State University. In this vignette, we will discuss reading data from the National Hockey League (NHL) API, and then providing summaries of the data pulled.

## Required Project Packages

In order to run the code for the project, the required packages, as well as code to install them, are below.

- httr
- knitr
- ggrepel
- RSQLite
- jsonlite
- tidyverse
- rmarkdown

### Installing required packages

To install the packages required for this project, use the code chunk below, removing the beginning #

```
#install.packages("knitr", "httr", "ggrepel", "RSQLite", "jsonlite", "rmarkdown", "tidyverse")
```

## Function to Contact Franchise API

First thing to do is create a function that can access the franchise API. This will allow us to pull any number of information about each franchise. The **extension** option in the function takes in one of the following:

- **franchise** - Returns id, firstSeasonId and lastSeasonId and name of every team in the history of the nhl
- **franchise-team-totals** - Returns total stats for every franchise (ex roadTies, roadWins, etc)
- **franchise-season-records** - Returns drill-down into season records for a specific franchise
- **franchise-goalie-records** - Returns goalie records for the specified franchise
- **franchise-skater-records** - Returns skater records, same interaction as goalie endpoint
- **franchise-detail** - Returns captainHistory, coachingHistory, generalManagerHistory and a summary of retired numbers

And the ID option is available for specifying a team.

```
# This function is used to take input from the user and return appropriate data from the NHL franchise .
franchiseAPI <- function(extension, ID = NULL){
  base <- "https://records.nhl.com/site/api/"

  if(is.null(extension)){
    return("Must include a valid franchise call")
  } else{
    if(!is.null(ID)){
      if(extension == "franchise" | extension == "franchise-team-totals"){
        warning("ID is not allowed for these calls, will return ", extension, "without ID")
        URL <- paste0(base, extension)
      } else if(extension == "franchise-detail"){
        URL <- paste0(base, extension, "?cayenneExp=mostRecentTeamId=", ID)
      } else{
        URL <- paste0(base, extension, "?cayenneExp=franchiseId=", ID)
      }
    } else{

```

```

    URL <- paste0(base, extension)
  }
}

get_nhl <- GET(URL)
nhl_text <- content(get_nhl, "text")
nhl_json <- fromJSON(nhl_text, flatten=T)
return(tbl_df(nhl_json$data))
}

```

## ID Mapping Table

Once we have the function, the next step is to put together a mapping from team name to ID number. This allows the user to input the team name without having to know the specific ID. We will use our API call to retrieve this information into a dataframe, that we can then use to complete a mapping in the wrapper function. The user will be able to use the full name, the abbreviation, or just the mascot to pull the ID.

```

team_mapping <- franchiseAPI("franchise")
team_mapping <- team_mapping %>% select(mostRecentTeamId, fullName, teamAbbrev, teamCommonName) %>% rename(
  kable(team_mapping)

```

teamID	fullName	teamAbbrev	teamCommonName
8	Montréal Canadiens	MTL	Canadiens
41	Montreal Wanderers	MWN	Wanderers
45	St. Louis Eagles	SLE	Eagles
37	Hamilton Tigers	HAM	Tigers
10	Toronto Maple Leafs	TOR	Maple Leafs
6	Boston Bruins	BOS	Bruins
43	Montreal Maroons	MMR	Maroons
51	Brooklyn Americans	BRK	Americans
39	Philadelphia Quakers	QUA	Quakers
3	New York Rangers	NYR	Rangers
16	Chicago Blackhawks	CHI	Blackhawks
17	Detroit Red Wings	DET	Red Wings
49	Cleveland Barons	CLE	Barons
26	Los Angeles Kings	LAK	Kings
25	Dallas Stars	DAL	Stars
4	Philadelphia Flyers	PHI	Flyers
5	Pittsburgh Penguins	PIT	Penguins
19	St. Louis Blues	STL	Blues
7	Buffalo Sabres	BUF	Sabres
23	Vancouver Canucks	VAN	Canucks
20	Calgary Flames	CGY	Flames
2	New York Islanders	NYI	Islanders
1	New Jersey Devils	NJD	Devils
15	Washington Capitals	WSH	Capitals
22	Edmonton Oilers	EDM	Oilers
12	Carolina Hurricanes	CAR	Hurricanes
21	Colorado Avalanche	COL	Avalanche
53	Arizona Coyotes	ARI	Coyotes
28	San Jose Sharks	SJS	Sharks

teamID	fullName	teamAbbrev	teamCommonName
9	Ottawa Senators	OTT	Senators
14	Tampa Bay Lightning	TBL	Lightning
24	Anaheim Ducks	ANA	Ducks
13	Florida Panthers	FLA	Panthers
18	Nashville Predators	NSH	Predators
52	Winnipeg Jets	WPG	Jets
29	Columbus Blue Jackets	CBJ	Blue Jackets
30	Minnesota Wild	MIN	Wild
54	Vegas Golden Knights	VGK	Golden Knights
55	Seattle Kraken	SEA	Kraken

## Function to Contact Stats API

Next we need a function to access the stats API. Though there are many modifiers available to access multiple data sets, for our purposes we will only provide access to the `?expand=team.stats` modifier. By providing an ID, it will pull specific team data, but the function alone will pull data on all the teams.

```
# This function is used to take user input and output a tibble with data from the NHL Stats API
statsAPI <- function(ID = NULL){
  base <- "https://statsapi.web.nhl.com/api/v1/teams?expand=team.stats"
  if(!is.null(ID)){
    URL <- paste0(base,"=",ID)
  } else{
    URL <- paste0(base)
  }

  get_stats <- GET(URL)
  stats_text <- content(get_stats, "text")
  stats_json <- tbl_df(fromJSON(stats_text, flatten=T))
  stats_data <- stats_json$teams$teamStats

  if(!is.null(ID)){
    stats_data <- stats_json$teams$teamStats[stats_json$teams$id == ID]
    end_data <- stats_data[[1]]$splits[[1]]
  } else{
    end_data <- stats_data[[1]]$splits[[1]]

    for(i in c(2:length(stats_data))){
      stats_data <- stats_json$teams$teamStats
      end_data <- rbind(end_data,stats_data[[i]]$splits[[1]])
    }
  }
  return(tbl_df(end_data))
}
```

## Wrapper Function for Both API Calls

Here we create a function that takes in the user input specific to either API.

```

# Allows for one function call to query either API
access_NHL_API <- function(extension, ID = NULL, ...){
  if(!is.numeric(ID) & !is.null(ID)){
    if(length(which(team_mapping$fullName == ID)) == 0){
      i <- which(team_mapping$fullName == ID)
    } else if(length(which(team_mapping$teamAbbrev == ID)) == 0){
      i <- which(team_mapping$teamAbbrev == ID)
    } else if(length(which(team_mapping$teamCommonName == ID)) == 0){
      i <- which(team_mapping$teamAbbrev == ID)
    } else{
      stop("Team ID not found!")
    }
  }

  if (extension == 'stats'){
    if(!is.null(ID)){
      ID <- team_mapping$teamAbbrev[i]
    }
    return(statsAPI(ID))
  } else {
    if(!is.null(ID)){
      ID = i
    }
    return(franchiseAPI(extension, ID))
  }
}

```

## NHL Data Analysis Using Our API

First we need to pull the data. We will pull franchise data, team totals, and current season stats. We will conduct some filtering here to make the join simpler.

```

franchise <- access_NHL_API("franchise") %>% select(!(lastSeasonId | id))
team_totals <- access_NHL_API("franchise-team-totals") %>% filter(gameTypeId == 2 & activeFranchise == 1)
stats <- access_NHL_API("stats") %>% filter(!is.na(stat.gamesPlayed))

```

## Combining Data

Next we need to combine these data together.

```

final_data <- right_join(franchise, team_totals, by = c("mostRecentTeamId" = "teamId")) %>% inner_join(stats)

```

## Adding Columns

In this section we will do some calculations to add a couple columns of interest. We will then filter on columns of interest. Six of the final columns are shown below.

- `seasonsInLeague` - How many seasons the team has been in the league
- `currentWinPerc` - Win percentage of the current season

- `currentGoalDiff` - Goal differential (team goals scored - team goals allowed) for current season
- `histWinPerc` - Historic win percentage
- `histGoalsPerGame` - Historic goals per game
- `histGoalDiff` - Historic goal differential
- `winPercDiff` - Difference between current season win percentage and historic
- `seasonGoalDiff` - Difference between current goal differential and historic
- `goalsPerGameDiff` - The difference between the current season goals per game and historic

```
final_data$firstSeason <- as.integer(substr(as.character(final_data$firstSeasonId),1,4))
central <- c("CAR","CHI","CBJ","DAL","DET","FLA","NSH","TBL")
east <- c("BOS","BUF","NJD","NYI","NYR","PHI","PIT","WSH")
west <- c("LAK","COL","ARI","SJS","ANA","MIN","VGK","STL")
north <- c("TOR","MTL","VAN","CGY","EDM","OTT","WPG")
final_data <- final_data %>%
  mutate(
    division = case_when(
      teamAbbrev %in% central ~ "Central",
      teamAbbrev %in% east ~ "East",
      teamAbbrev %in% west ~ "West",
      teamAbbrev %in% north ~ "North"
    ),
    seasonsInLeague = 2021 - firstSeason,
    currentWinPerc = as.integer(stat.wins) / stat.gamesPlayed,
    currentGoalDiff = as.numeric(stat.goalsPerGame) - as.numeric(stat.goalsAgainstPerGame),
    histWinPerc = wins / gamesPlayed,
    histGoalsPerGame = goalsFor / gamesPlayed,
    histGoalDiff = histGoalsPerGame - (goalsAgainst / gamesPlayed),
    winPercDiff = currentWinPerc - histWinPerc,
    seasonGoalDiff = currentGoalDiff - histGoalDiff,
    goalsPerGameDiff = as.numeric(stat.goalsPerGame) - histGoalsPerGame
  ) %>%
  select(fullName,teamAbbrev,division, seasonsInLeague, gamesPlayed, goalsFor, goalsAgainst, histGoalsPerGame)
kable(final_data[,1:6])
```

fullName	teamAbbrev	division	seasonsInLeague	gamesPlayed	goalsFor
Montréal Canadiens	MTL	North	104	6787	21791
Toronto Maple Leafs	TOR	North	104	6516	19980
Boston Bruins	BOS	East	97	6626	21112
New York Rangers	NYR	East	95	6560	20041
Chicago Blackhawks	CHI	Central	95	6560	19537
Detroit Red Wings	DET	Central	95	6293	19550
Los Angeles Kings	LAK	West	54	4172	13053
Dallas Stars	DAL	Central	54	2109	6022
Philadelphia Flyers	PHI	East	54	4171	13690
Pittsburgh Penguins	PIT	East	54	4171	13874
St. Louis Blues	STL	West	54	4173	12827
Buffalo Sabres	BUF	East	51	3945	12471
Vancouver Canucks	VAN	North	51	3945	12138
Calgary Flames	CGY	North	49	3154	10257
New York Islanders	NYI	East	49	3788	12045
New Jersey Devils	NJD	East	47	2993	8792
Washington Capitals	WSH	East	47	3633	11516
Edmonton Oilers	EDM	North	42	3235	10776

fullName	teamAbbrev	division	seasonsInLeague	gamesPlayed	goalsFor
Carolina Hurricanes	CAR	Central	42	1812	4914
Colorado Avalanche	COL	West	42	1978	5857
Arizona Coyotes	ARI	West	42	536	1345
San Jose Sharks	SJS	West	30	2274	6490
Ottawa Senators	OTT	North	29	2195	6250
Tampa Bay Lightning	TBL	Central	29	2194	6216
Anaheim Ducks	ANA	West	28	2111	5693
Florida Panthers	FLA	Central	28	2109	5665
Nashville Predators	NSH	Central	23	1731	4730
Winnipeg Jets	WPG	North	22	749	2209
Columbus Blue Jackets	CBJ	Central	21	1568	4092
Minnesota Wild	MIN	West	21	1567	4166
Vegas Golden Knights	VGK	West	4	291	939

## Exploratory Data Analysis

Now that we have our data set with 31 rows and 20 columns, we are able to do exploratory data analysis (EDA).

### Summary of Team Age

It can be interesting to see the spread of current teams and how long they have been in the league. Below we can see that the max is 104 seasons with the minimum being just 4. The average number of seasons in the NHL is just over 50.

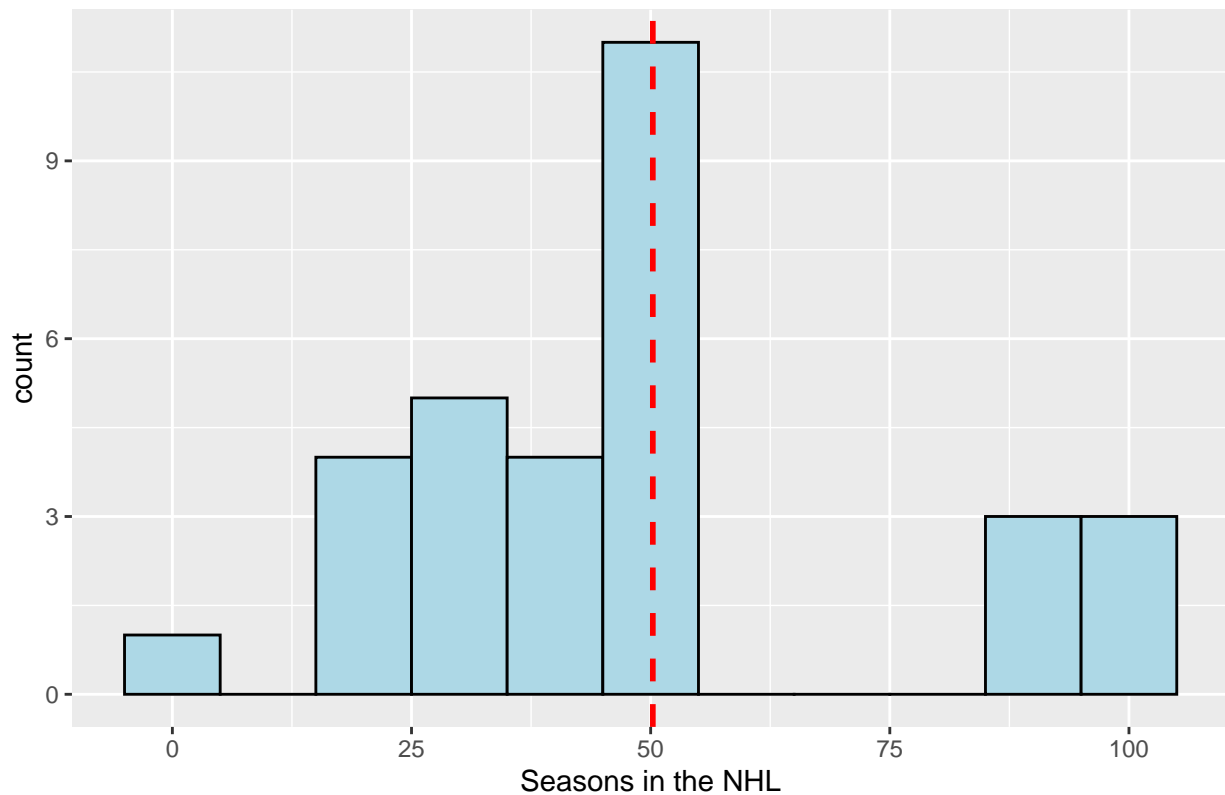
```
summary(final_data$seasonsInLeague)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      4.00   29.00   47.00   50.23   54.00   104.00
```

**Histogram of Seasons** We can further explore this with a histogram.

```
g <- ggplot(final_data, aes(x = seasonsInLeague))
g + geom_histogram(binwidth = 10, color="black", fill="lightblue") + geom_vline(aes(xintercept=mean(season
```

## Histogram of the Number of Seasons in the NHL



## Goal Differentials

Now we want to explore goal differentials, and see how goal differential affects win percentage. In the table below, we can see that having a positive goal differential in general will lead to a win percentage above 50%. There is one team that has been scored on more than they have scored and still has a win percentage above 50%, and 2 that are in the same position on the other side, but overall scoring more goals leads to winning more games.

```
kable(table(final_data %>% mutate(positiveGoalDiff = ifelse(currentGoalDiff > 0, "Positive Goal Diff", "Negative Goal Diff"),
  winsAbove500 = if_else(currentWinPerc > 0.5, "Above .500", "Below .500")) %>%
  select(positiveGoalDiff, winsAbove500)))
```

	Above .500	Below .500
Negative Goal Diff	1	15
Positive Goal Diff	13	2

## Historic Win Percentages

In this case, we will just look at the comparison between a team's historic win percentage and the current season's percentage. We can see that about half of the teams are exceeding their historic win rates, while the other half are falling behind.

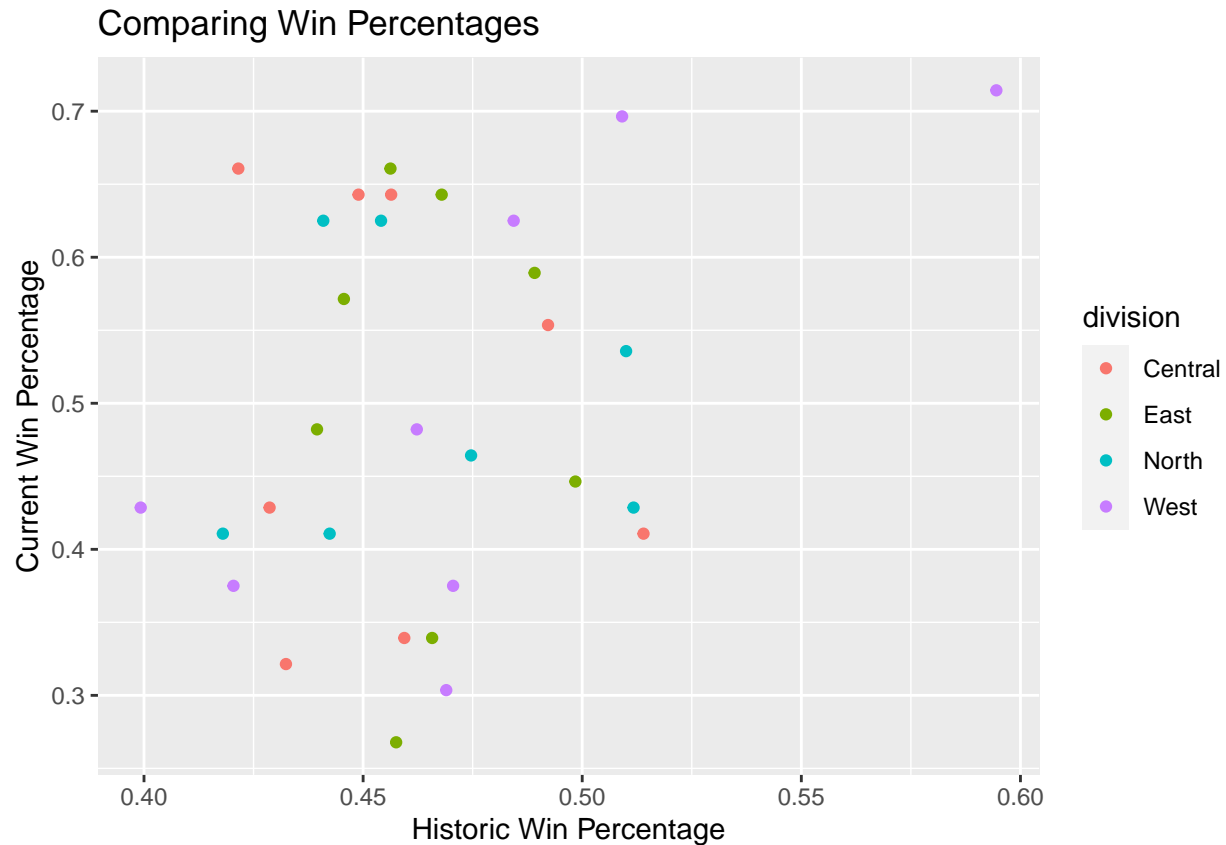


```
kable(final_data %>% select(teamAbbrev, seasonsInLeague, histWinPerc, currentWinPerc, winPercDiff) %>%
```

teamAbbrev	seasonsInLeague	histWinPerc	currentWinPerc	winPercDiff
FLA	28	0.4215268	0.6607143	0.2391875
PIT	54	0.4562455	0.6607143	0.2044688
TBL	29	0.4489517	0.6428571	0.1939055
COL	42	0.5091001	0.6964286	0.1873285
CAR	42	0.4564018	0.6428571	0.1864554
TOR	104	0.4409147	0.6250000	0.1840853
WSH	47	0.4679328	0.6428571	0.1749243
EDM	42	0.4540958	0.6250000	0.1709042
MIN	21	0.4843650	0.6250000	0.1406350
NYI	49	0.4456177	0.5714286	0.1258108
VGK	4	0.5945017	0.7142857	0.1197840
BOS	97	0.4891337	0.5892857	0.1001520
NSH	23	0.4922010	0.5535714	0.0613704
NYR	95	0.4394817	0.4821429	0.0426611
ARI	42	0.3992537	0.4285714	0.0293177
WPG	22	0.5100134	0.5357143	0.0257009
STL	54	0.4622574	0.4821429	0.0198855
CHI	95	0.4286585	0.4285714	-0.0000871
VAN	51	0.4179975	0.4107143	-0.0072832
CGY	49	0.4746354	0.4642857	-0.0103497
OTT	29	0.4423690	0.4107143	-0.0316547
LAK	54	0.4204219	0.3750000	-0.0454219
PHI	54	0.4984416	0.4464286	-0.0520130
MTL	104	0.5117136	0.4285714	-0.0831421
SJS	30	0.4705365	0.3750000	-0.0955365
DAL	54	0.5139877	0.4107143	-0.1032734
CBJ	21	0.4323980	0.3214286	-0.1109694
DET	95	0.4593993	0.3392857	-0.1201136
NJD	47	0.4657534	0.3392857	-0.1264677
ANA	28	0.4689721	0.3035714	-0.1654006
BUF	51	0.4575412	0.2678571	-0.1896840

**Win Percentages Scatter Plot** We can observe this in a scatter plot as well, using `ggplot2`. Adding the division coloring shows that some of the west division teams are the most successful in the league, at the expense of others in that division falling at the bottom of the spectrum.

```
g1 <- ggplot(final_data, aes(x = histWinPerc, y = currentWinPerc, group=division))
g1 + geom_point(aes(color=division)) + labs(x = "Historic Win Percentage", y = "Current Win Percentage")
```



## Goals by Division

Next we will look at goals scored by division. First we will subset our dataframe and group by division.

```
goals <- final_data %>% group_by(division) %>% select(division, teamAbbrev, goalsFor, goalsAgainst, his
```

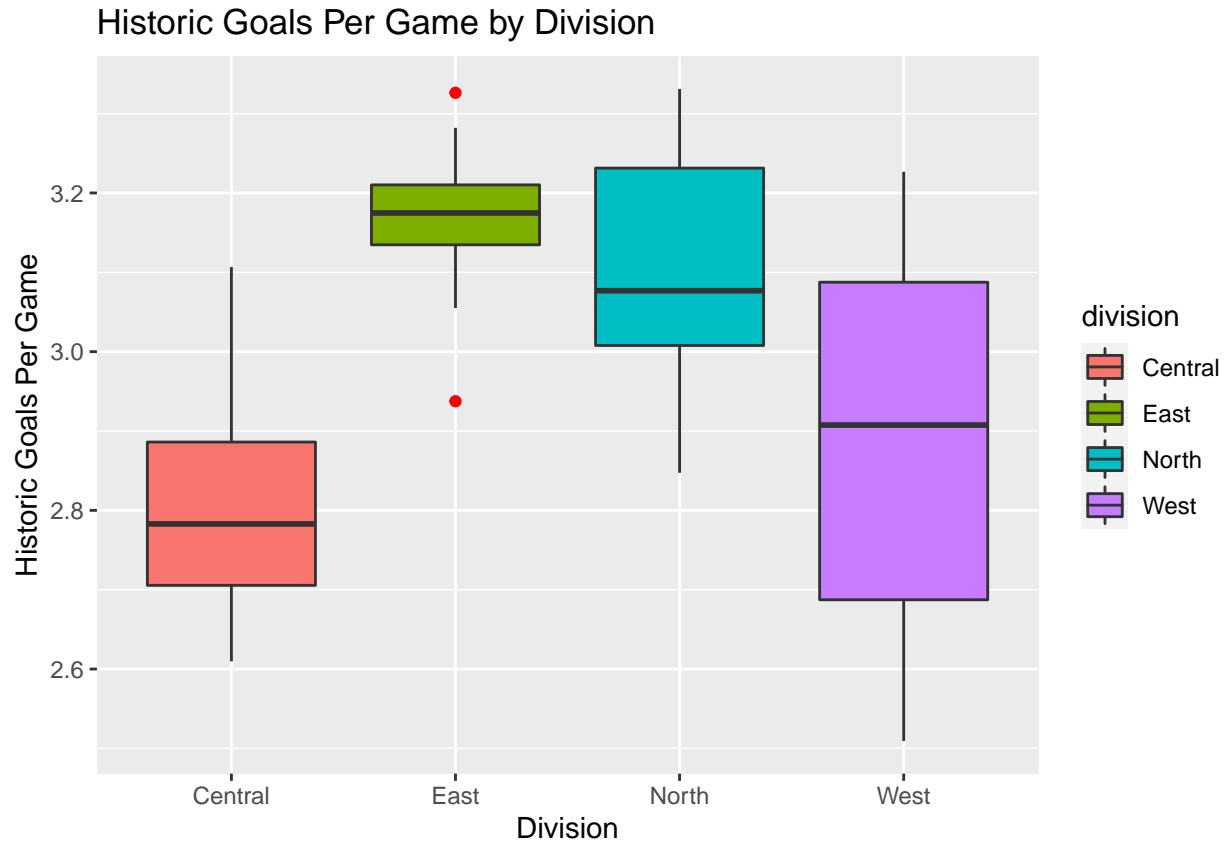
Now we can look at some data within these divisions. First we will look at the performance historically versus this season. We can see that the Central division is performing the best compared to their historical performance, but the other three divisions actually have more goals per game this season than the Central. It is interesting to see such high numbers of goals scored historically in the North and East, with the numbers down significantly this year compared to average.

```
goalDiff <- goals %>% summarise(currentGoalsPerGame = mean(as.numeric(stat.goalsPerGame)), histGoalsPerGame = mean(as.numeric(stat.goalsPerGame)), difference = currentGoalsPerGame - histGoalsPerGame)
kable(goalDiff)
```

division	currentGoalsPerGame	histGoalsPerGame	difference
Central	2.830250	2.814205	0.0160454
West	2.892875	2.888642	0.0042327
North	2.946429	3.104796	-0.1583678
East	2.928500	3.162263	-0.2337627

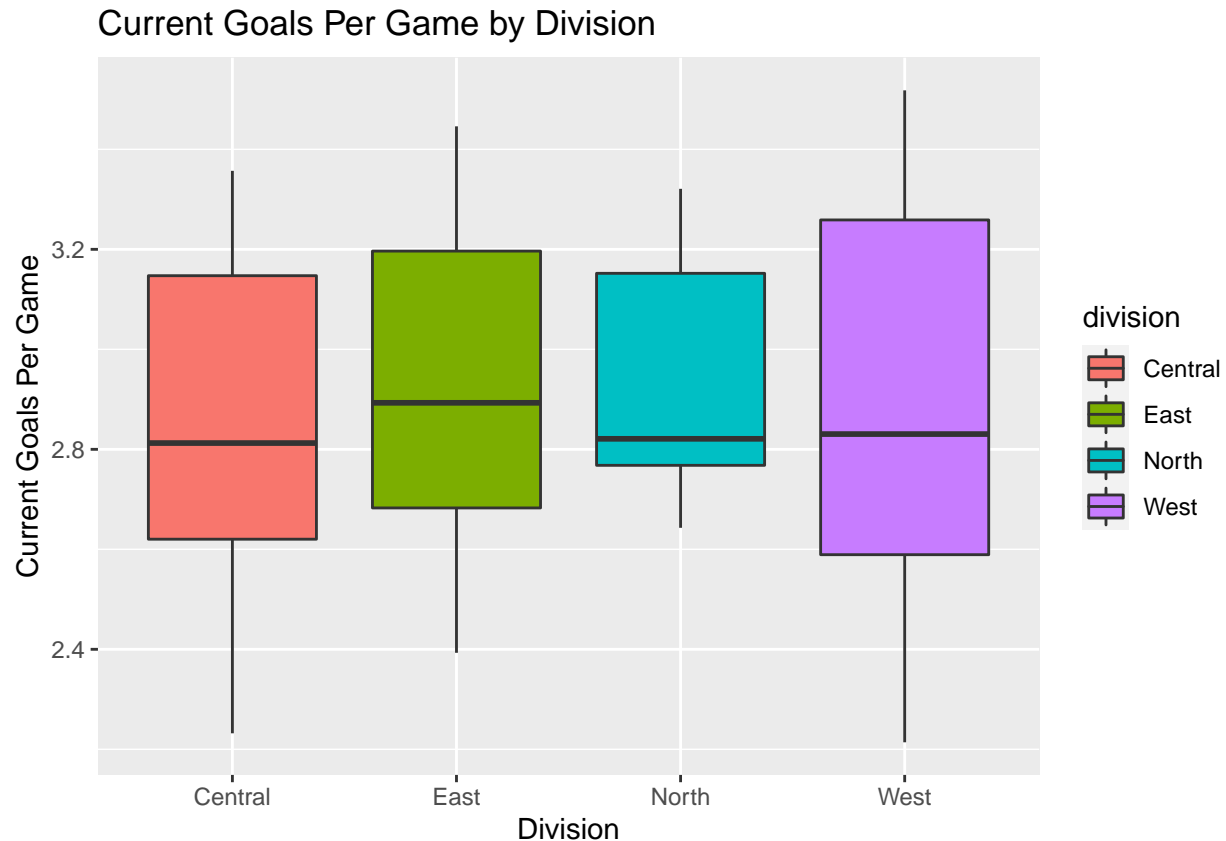
**Goals by Division Box Plots** Next we can show a box plot of this data to compare the spread of the divisions. We can look at both the historic and current data.

```
g2 <- ggplot(goals, aes(x = division, y = histGoalsPerGame, fill = division))
g2 + geom_boxplot(outlier.colour="red") + labs(x = "Division", y = "Historic Goals Per Game", title = "Historic Goals Per Game by Division")
```



The historic data has a wide IQR in the West and very slim IQR in the East. There are outliers in the east though. The current data is surprisingly uniform throughout, signifying that the average goals in the current season is similar across all divisions, and there is an even spread of high and low scoring teams in each.

```
g3 <- ggplot(goals, aes(x = division, y = as.numeric(stat.goalsPerGame), fill = division))
g3 + geom_boxplot(outlier.colour="red") + labs(x = "Division", y = "Current Goals Per Game", title = "Current Goals Per Game by Division")
```



### Number of teams per Division Because of the current state of the league, there are only 31 teams. This causes an uneven number of teams between divisions until the Seattle Kraken join next year. To explore this, we will simply display a table. As we see below, the North Division is one team short of the others. This is an interesting fact to note, as looking at the previous analysis the North division does have the smallest current IQR for goals per game. It is possible this has something to do with having fewer teams, but nothing can be concluded during this analysis. Just something to be aware of in further study.

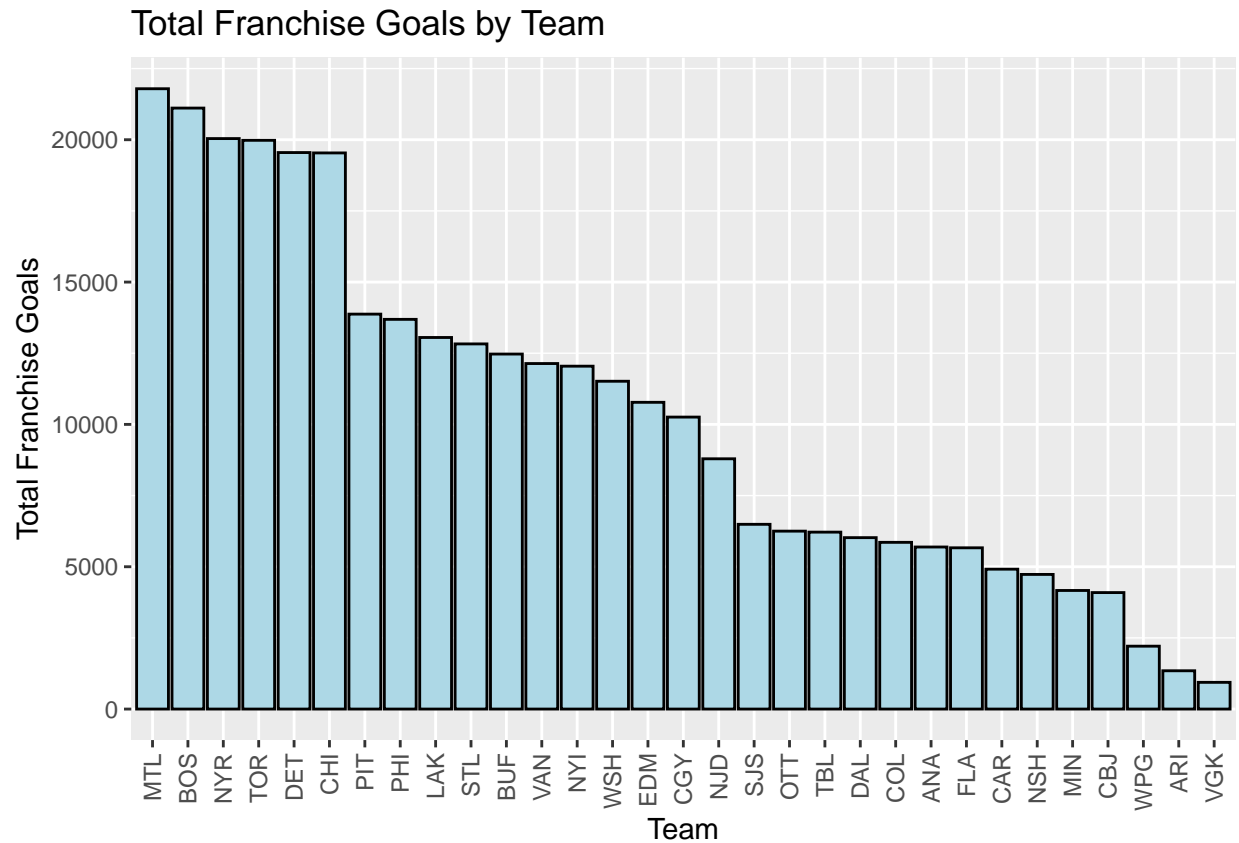
```
kable(table(goals$division),col.names = c("Division","Count"))
```

Division	Count
Central	8
East	8
North	7
West	8

## Total Franchise Goals

**Franchise Goals Bar Plot** The last thing we will explore here is historic franchise goals. This will be skewed due to the large variability between seasons in the league, but will be interesting to explore regardless. We will first use a bar plot, followed by a scatter plot to explore overachievers.

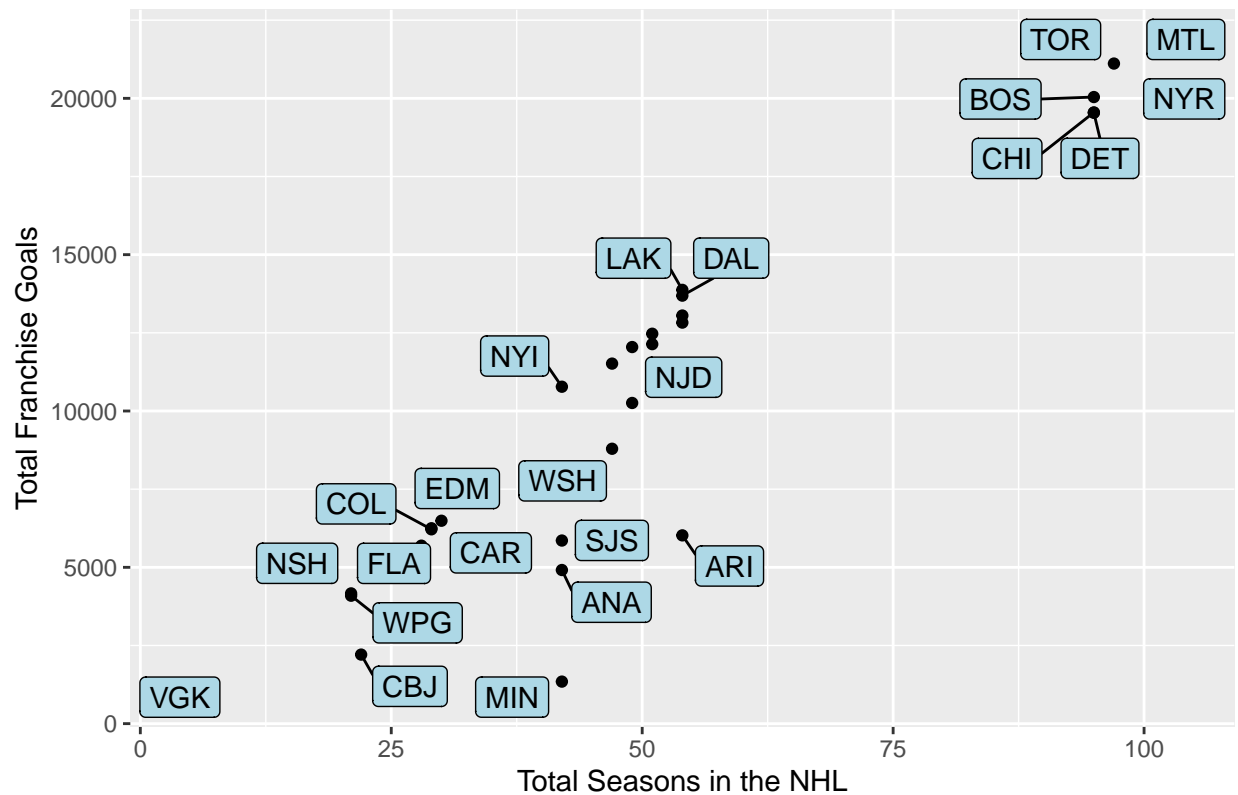
```
bar_data <- final_data %>% select(teamAbbrev, goalsFor, goalsAgainst, seasonsInLeague) %>% arrange(desc(goalsFor))
g4 <- ggplot(bar_data,aes(x = reorder(teamAbbrev, -goalsFor), y = goalsFor))
g4 + geom_bar(stat="identity", color = "black", fill = "lightblue") + theme(axis.text.x=element_text(ang
```



**Franchise Goals Scatter Plot** Finally, we will compare the number of seasons in the league per team to the total franchise goals. Here we can see as expected, those with the highest number of goals have been in the league the longest. There are a few outliers though, specifically MIN and ARI that appear to have a far fewer goals than expected for the number of seasons they have been in the league.

```
g5 <- ggplot(bar_data, aes(x = seasonsInLeague, y = goalsFor))
g5 + geom_point() + labs(x = "Total Seasons in the NHL", y = "Total Franchise Goals", title = "Comparing")
```

## Comparing Franchise Goals to Length of Tenure in the NHL



## Conclusion

This is just the beginning of what can be done with this data. Now that you know how to access this API and write your own functions to do so, you have the NHL at your fingertips! EDA is the beginning of any good data science project, and now we have a good idea behind the data we have collected here. This data can now be used for regression, prediction, any number of things! If you enjoyed this post, stay tuned to my blog as I will be posting more projects and tutorials like this one!