Introduction

There was a thought back to my playing days that revolved around a quote by or about Wayne Gretzky that I'll do my best not butcher. It involved why he would take such a long first shift, or why his coach would double shift him on his first shift. It was so he could catch his "Second Wind", meaning that since he was tired after his first shift, he would catch his breath, and then have more endurance thereafter and would play better.

The coach or Wayne would do this intentionally to get into the game and play better throughout the rest of the game. I want to see if this has any credence or is just some myth that a coach made up to play his best player more often at the beginning of the game.

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Would love to talk about Hockey and Data Science.

Hypothesis

Null Hypothesis: The first shift length for a player has no impact on the players goal that game.

Alternative Hypothesis: A longer first shift improves the player goals for that game.

Measurement:

There are plenty of ways to measure effect on a game, but we are going to keep it limited to goals for that game.

To consider a shift "long" we're going to calculate the average shift length for all players in the league and view how those fits on the distribution.

Then the first shift long for each game for each player we are going to compare its duration to the average length. We will place the player in a bin (Long shift, Short Shift).

Then compare the goals for all players over a season to see if the first shift had an impact on goals for, for a game on average.

Bias/Assumptions

Outcomes/Goals: We know that all players aren't the same, for example Conner McDavid is going to be more valuable during his shifts and is going to have more shifts than a below average player in the NHL, but the hope is that by viewing the entire NHL population we're going to average the outlier players like Connor McDavid and his less talented counter parts to the population.

Inputs/Shifts:

I had quite a few thoughts around this one: The first one being is a shift long if it is just higher than the average or is there some point that makes a shift long? If say for example the average shift is 40 seconds should a shift that is 41 seconds be considered long? To help keep the experiment simple the first attempt I'm going to consider it as yes, that shift is "long". In the future, an adaptation might be to only include shifts that are "long" to be 1 standard deviation from the average shift. Roughly speaking, in a normal distribution, a shift that is 1 standard deviation above the mean is equivalent to the 84th percentile. Now that's a long shift.

Another thought I had from my playing days was that I took a short first shift and then my second shift would be "long" to help me get into the game. But for the sake of the experiment, we're only going to focus on the first shift. The thought here being that in an NHL game, if you are a forward on the 4th line you second shift might not occur until, (40 (sec) *4 (# of lines)* 2 (Iterations/Shifts)) = 320 Seconds / 60 Sec = 5.3 Minutes into the game. Within that time so many "events" (Goals, powerplays, penalties against, TV Timeouts) might occur to affect how shifts might be distributed.

Finally, we're only going to consider the first shift of the first period. NHL intermissions are rather long (18 minutes), but we are going to assume that the players are into the game at that point.

Considerations

Do we want to consider removing outliers from the data, the top and bottom percent of shifts.

Do we want to consider standarizining the shifts? So that they are easier to view if they are above average?

Do we want to consider one stD away from the mean to be higher than average?

Experiment

Type: Difference in Means

Since we have a category of short versus long first shift, I am going to do a diff from diff for the means. My assumption is that the population of players and their outcomes are standard and even. The only difference is going to be their first shift length. Then I can compare the outcomes on average (Goals/Game Average) to see if first shift length has an impact.

Type: Linear Regression

After I have decided in the null hypothesis is true or not, I am going to run a linear regression to see the first shift affects the goal outcomes

Data

In [1]:
```
# Pandas for Dataframes
import pandas as pd
# Numerical Py to do some calculations
import numpy as np
# Hockey Scrapper will import the data for us
import hockey_scraper as hs
# Matplotlib for plotting charts
import matplotlib.pyplot as plt
# Seaborn for some advanced visual
import seaborn as sns
```

In [2]:
```
# Prior to this I imported the shift and pbp data for 2015 and 2016 Seas
on
# Instead of rescrapping everytime, I had the hockey_scraper package wri
te to my local so I can reference later
# See documentation for assistance on how to do this https://github.com/
HarryShomer/Hockey-Scraper

# 2015 Shift Data
shift2015 = pd.read_csv("../hockey_scraper_data/csvs/nhl_shifts_2015201
6.csv")
# 2015 Play by Play Data
pbp2015 = pd.read_csv("../hockey_scraper_data/csvs/nhl_pbp_20152016.cs
v")
```

In [3]:
```
#show full output on DataFrame Rows
pd.set_option('display.max_rows', 500)
# Show full number on describes
pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

In [4]:
```
shift2015[:1]
```

Out[4]:

	Unnamed: 0	Game_Id	Period	Team	Player	Player_Id	Start	End	Duration	Date
0	0	20001	1	MTL	ANDREI MARKOV	8467496	0.00000	36.00000	36.00000	2015-10-07

In [5]:
```
shift2015RowNumber = shift2015.shape[0]
print("2015 Total Shifts:",shift2015RowNumber)
```

```
2015 Total Shifts: 1058700
```

In [6]:
```
pbp2015[:1]
```

Out[6]:

	Unnamed: 0	Game_Id	Date	Period	Event	Description	Time_Elapsed	Seconds_Elapsed	Stren
0	0	20001	2015-10-07	1	PSTR	Period Start- Local time: 7:20 EDT	0:00	0.00000	

1 rows × 57 columns

In [7]:
```
pbp2015RowNumber = pbp2015.shape[0]
print("2015 Total Number of Plays:",pbp2015RowNumber)
```

```
2015 Total Number of Plays: 413656
```

Metrics for our experiment:

shift data: Need every first shift for every player in that that. (For every game (gameID), find the the first shift (Unnamed: 0) for every player (playerId). Add that player to the category "Long" or "Short" category

pbp2015: For every game, and every player, calculate if they scored (Go through every PBP entry for every game, and every player).

In [8]:
```
shift2015.dtypes
```

Out[8]:
```
Unnamed: 0       int64
Game_Id          int64
Period           int64
Team            object
Player          object
Player_Id        int64
Start          float64
End            float64
Duration       float64
Date            object
dtype: object
```

In [9]:
```
pbp2015.dtypes
```

Out[9]:
```
Unnamed: 0            int64
Game_Id               int64
Date                 object
Period                int64
Event                object
Description          object
Time_Elapsed         object
Seconds_Elapsed     float64
Strength             object
Ev_Zone              object
Type                 object
Ev_Team              object
Home_Zone            object
Away_Team            object
Home_Team            object
p1_name              object
p1_ID               float64
p2_name              object
p2_ID               float64
p3_name              object
p3_ID               float64
awayPlayer1          object
awayPlayer1_id      float64
awayPlayer2          object
awayPlayer2_id      float64
awayPlayer3          object
awayPlayer3_id      float64
awayPlayer4          object
awayPlayer4_id      float64
awayPlayer5          object
awayPlayer5_id      float64
awayPlayer6          object
awayPlayer6_id      float64
homePlayer1          object
homePlayer1_id      float64
homePlayer2          object
homePlayer2_id      float64
homePlayer3          object
homePlayer3_id      float64
homePlayer4          object
homePlayer4_id      float64
homePlayer5          object
homePlayer5_id      float64
homePlayer6          object
homePlayer6_id      float64
Away_Players          int64
Home_Players          int64
Away_Score            int64
Home_Score            int64
Away_Goalie          object
Away_Goalie_Id      float64
Home_Goalie          object
Home_Goalie_Id      float64
xC                  float64
yC                  float64
Home_Coach           object
```

```
Away_Coach          object
dtype: object
```

Data Clean Up

In [10]:

```
# Rename column "Unnamed: 0" to shift_Id
shift2015.rename(columns = {"Unnamed: 0" : "Shift_Id"}, inplace = True)
```

In [11]:

```
# Rename column "Unnamed: 0" to Pbp_Id
pbp2015.rename(columns = {"Unnamed: 0" : "Pbp_Id"}, inplace = True)

# Replace NaN and infinite values with a suitable value (e.g. 0)
pbp2015['p1_ID'].replace([np.inf, -np.inf, np.nan], 0, inplace=True)

# Convert player_ids to ints not floats
pbp2015['p1_ID'] = pbp2015['p1_ID'].astype(int)
```

Remove Unwanted Data

In [12]:

```
# Drop columns
# Need to keep goalie IDs to drop the goal from the Shift Data
pbp2015.drop(columns = {'Description','Type','Ev_Team', 'Home_Zone', 'Aw
ay_Team', 'Home_Team',
        'Time_Elapsed', 'Seconds_Elapsed', 'Strength', 'Ev_Zone','awayPla
yer1', 'awayPlayer1_id',
        'awayPlayer2', 'awayPlayer2_id', 'awayPlayer3', 'awayPlayer3_id',
        'awayPlayer4', 'awayPlayer4_id', 'awayPlayer5', 'awayPlayer5_id',
        'awayPlayer6', 'awayPlayer6_id', 'homePlayer1', 'homePlayer1_id',
        'homePlayer2', 'homePlayer2_id', 'homePlayer3', 'homePlayer3_id',
        'homePlayer4', 'homePlayer4_id', 'homePlayer5', 'homePlayer5_id',
        'homePlayer6', 'homePlayer6_id', 'Away_Players', 'Home_Players',
        'Away_Score', 'Home_Score', 'xC', 'yC', 'Home_Coach',
        'Away_Coach'}, inplace = True)
```

In [13]:

```
print("Play by Play 2015", pbp2015.shape)
```

```
Play by Play 2015 (413656, 15)
```

In [14]:

```
# We want to remove Goalies from the shift Data
# Their shifts will skew the data

# Find all the unique goalie IDs from the Home and Away Goalie Ids in th
e Play By Play Data
# Union will drop duplicates
allGoalies2015 = np.union1d( pd.unique(pbp2015["Away_Goalie_Id"]), pd.un
ique(pbp2015["Home_Goalie_Id"]))
# Drop the empty fields
allGoalies2015 = allGoalies2015[~np.isnan(allGoalies2015)]
```

In [15]:
```
print("Goalie Shifts in 2015:", allGoalies2015.shape[0])
```

```
Goalie Shifts in 2015: 92
```

In [16]:
```
# We want to drop all goalies from the shift data
shift2015 = shift2015[~shift2015["Player_Id"].isin(allGoalies2015)]
```

In [17]:
```
print("Shifts without Goalies 2015:", shift2015.shape[0])
print("Row dropped from 2015:",  str(shift2015RowNumber - shift2015.shap
e[0]) , "Rows Dropped")
```

```
Shifts without Goalies 2015: 1048232
Row dropped from 2015: 10468 Rows Dropped
```

Subset Data

In [18]:
```
# Subset Play by play data to be only goal data for counting later on.
goalEvents2015 = pbp2015.loc[pbp2015["Event"]== "GOAL", :].copy()
# Rename the Play by Play Id to be Goal_Id
goalEvents2015.rename(columns={'Pbp_Id': 'Goal_Id'}, inplace=True)
# Drop all non-goal columns (Keep the assist columns p2_ID, p3_ID to cou
nt points)
goalEvents2015.drop(columns=["Date",
                             "Period",
                             "Event",
                             "p1_name",
                             "p2_name",
                             "p2_ID",
                             "p3_name",
                             "p3_ID",
                             "Away_Goalie",
                             "Away_Goalie_Id",
                             "Home_Goalie",
                             "Home_Goalie_Id"], inplace = True)
```

In [19]:
```
print("Goals in 2015:", goalEvents2015.shape[0])
```

```
Goals in 2015: 7278
```

In [20]:
```
# Limit the Shifts to the first period
firstPeriodShift2015 = shift2015.loc[shift2015["Period"] == 1, :].copy()
```

In [21]:
```
# Get a list of all the Game Ids
gameIds2015 = firstPeriodShift2015["Game_Id"].unique()
print("Games in 2015:", gameIds2015.shape[0])
```

```
Games in 2015: 1320
```

In [22]:
```
def getFirstShift(gameIds, shifts):
    #Go through every game
    firstShift = []
    # For every gameId in the game IDs
    for game in gameIds:
        # Find all the shifts that game
        gameShifts = shifts[(shifts["Game_Id"] == game)]
        # Find the first shift for every player_id
        # Group by the Player Ids
        # Then take out the Shift_Id, Player_Id, Duration and Game_Id fi
elds
        # Then take the first instance of that
        playerShifts = gameShifts.groupby("Player_Id")[["Shift_Id","Game
_Id", "Player_Id", "Duration"]].first()
        # Add on the first shift for all those players
        firstShift.append(playerShifts)
    return pd.concat(firstShift)
```

In [23]:
```
# Find all the first shifts for 2015
firstShift2015 = getFirstShift(gameIds2015, firstPeriodShift2015)
```

In [24]:
```
firstShift2015.head()
```

Out[24]:

Player_Id	Shift_Id	Game_Id	Player_Id	Duration
8467496	0	20001	8467496	36.00000
8468504	15	20001	8468504	40.00000
8469521	1	20001	8469521	36.00000
8469707	22	20001	8469707	37.00000
8470039	12	20001	8470039	41.00000

Understanding Data

In [25]:
```
print("All Shift Data 2015")
shift2015[["Duration"]].describe()
```

```
All Shift Data 2015
```

Out[25]:

	Duration
count	1048232.00000
mean	44.94805
std	21.32265
min	0.00000
25%	31.00000
50%	44.00000
75%	56.00000
max	1003.00000

In [26]:
```
print("All First Shift Data 2015")
firstShift2015[["Duration"]].describe()
```

```
All First Shift Data 2015
```

Out[26]:

	Duration
count	47517.00000
mean	41.65610
std	15.74502
min	0.00000
25%	32.00000
50%	41.00000
75%	51.00000
max	219.00000

Distributions

Skewness is a measure of asymmetry of a distribution.In a normal distribution, the mean divides the curve symmetrically into two equal parts at the median and the value of skewness is zero. When the value of the skewness is negative, the tail of the distribution is longer towards the left hand side of the curve. When the value of the skewness is positive, the tail of the distribution is longer towards the right hand side of the curve

Kurtosis is one of the two measures that quantify shape of a distribution. Kutosis determine the volume of the outlier. Kurtosis describes the peakedness of the distribution, if the distribution is tall and thin it is (Kurtosis > 3). Values with high peakness distribution are near the mean or at the extremes. A flat distribution where the values are moderately spread out.

All Player Shifts

In [27]:
```
print( "Distribution skew of 2015 Shifts", shift2015["Duration"].skew())
print( "Distribution peakness of 2015 Shifts", shift2015["Duration"].kur
tosis())
```

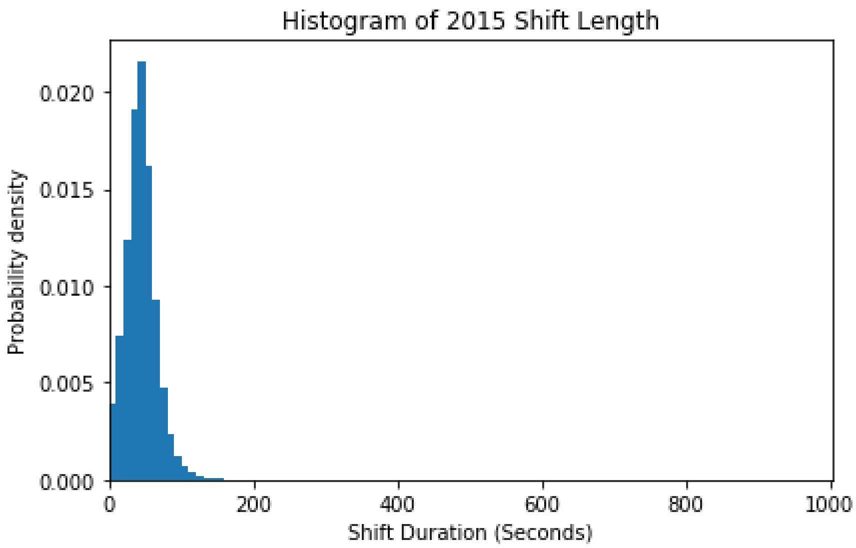
```
Distribution skew of 2015 Shifts 1.6312278238576077
Distribution peakness of 2015 Shifts 36.04838717756141
```

With the the skewness being greater than 1 at 1.63, the data is highly skewed.

If the distribution is tall and thin it is called a leptokurtic distribution(Kurtosis > 3).

In [28]:
```
fig, ax = plt.subplots()
ax.hist(shift2015["Duration"], bins= 100, density = True)
ax.set_xlabel('Shift Duration (Seconds)')
ax.set_ylabel('Probability density')
ax.set_title(r'Histogram of 2015 Shift Length')

fig.tight_layout()
plt.xlim(xmin=int(shift2015[["Duration"]].min()), xmax = int(shift2015
[["Duration"]].max()))
plt.show()
```



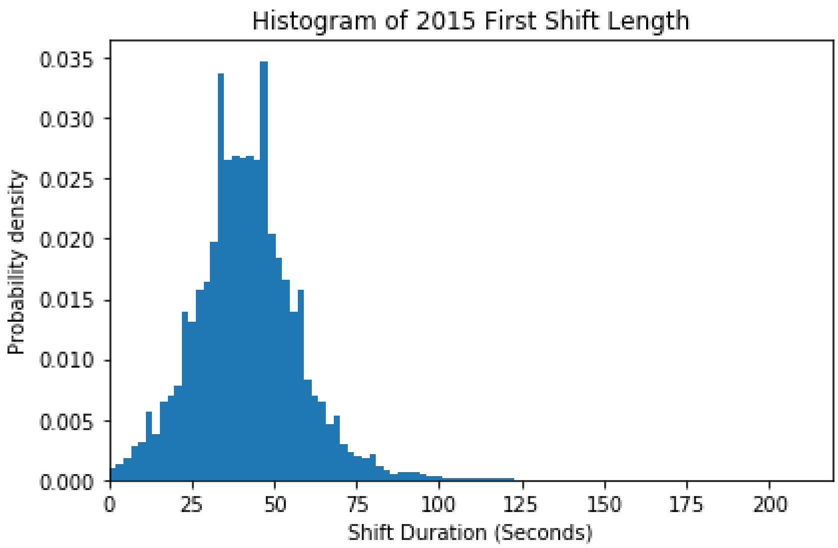
First Shifts

In [29]:
```
print( "Distribution skew of 2015 First Shifts", firstShift2015["Duratio
n"].skew())
print( "Distribution peakness of 2015 First Shifts", firstShift2015["Dur
ation"].kurtosis())
```

```
Distribution skew of 2015 First Shifts 0.5981245820475164
Distribution peakness of 2015 First Shifts 2.2456785868017164
```

In [30]:
```
fig, ax = plt.subplots()
ax.hist(firstShift2015["Duration"],bins= 100, density = True)
ax.set_xlabel('Shift Duration (Seconds)')
ax.set_ylabel('Probability density')
ax.set_title(r'Histogram of 2015 First Shift Length')

fig.tight_layout()
plt.xlim(xmin=int(firstShift2015[["Duration"]].min()), xmax = int(firstS
hift2015[["Duration"]].max()))
plt.show()
```



Outlier Removal

Since my data is right tailed, meaning there are som shifts that are extremely long, they will drag my mean to the right of the median, the middle point of the data. I propose removing any shifts longer than 128 seconds. Although that is double the average shift (44 Seconds) that would be the equal of doubling shifting your best player, which is what gretzky supposedly did.

In [31]:
```
withOutliers2015 = shift2015.shape[0]
shift2015= shift2015[shift2015["Duration"] < 128.0 ]
print("All Shifts Rows dropped:", withOutliers2015 -  shift2015.shape
[0])
```

```
All Shifts Rows dropped: 3741
```

In [32]:
```
FSOutliers2015 = firstShift2015.shape[0]
firstShift2015 = firstShift2015[firstShift2015["Duration"] < 128.0 ]
print("First Rows dropped:", FSOutliers2015 -  firstShift2015.shape[0])
```

```
First Rows dropped: 24
```

All Shifts

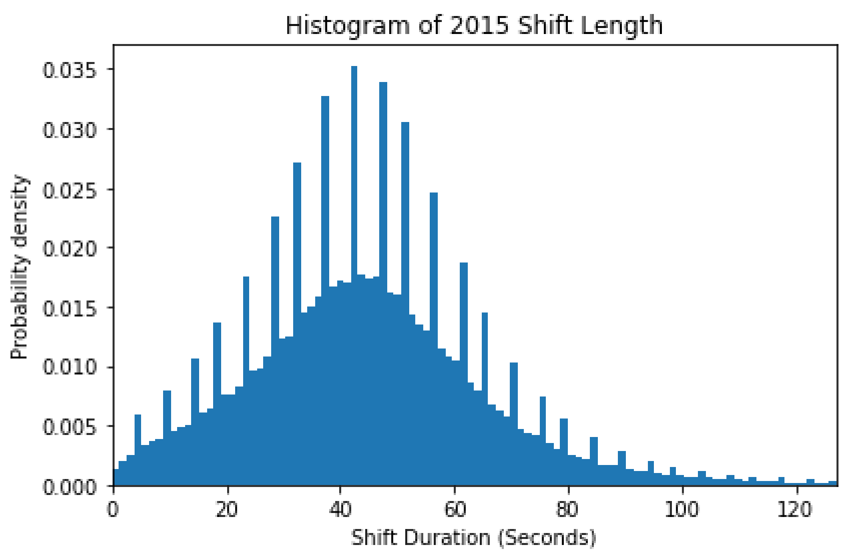
In [33]:
```
print( "Distribution skew of 2015 Shifts", shift2015["Duration"].skew())
print( "Distribution peakness of 2015 Shifts", shift2015["Duration"].kur
tosis())
```

```
Distribution skew of 2015 Shifts 0.5072239994853199
Distribution peakness of 2015 Shifts 0.6943492541825886
```

We seem to have normalized the data to a relatively acceptable skewness of .59 and a peakness value of 2.24. We don't want to normalize the data to much because we need enough long shifts to represent a double shift and see the shift's affect on the player's game.

In [34]:
```
fig, ax = plt.subplots()
ax.hist(shift2015["Duration"], bins= 100, density = True)
ax.set_xlabel('Shift Duration (Seconds)')
ax.set_ylabel('Probability density')
ax.set_title(r'Histogram of 2015 Shift Length')

fig.tight_layout()
plt.xlim(xmin=int(shift2015[["Duration"]].min()), xmax = int(shift2015
[["Duration"]].max()))
plt.show()
```



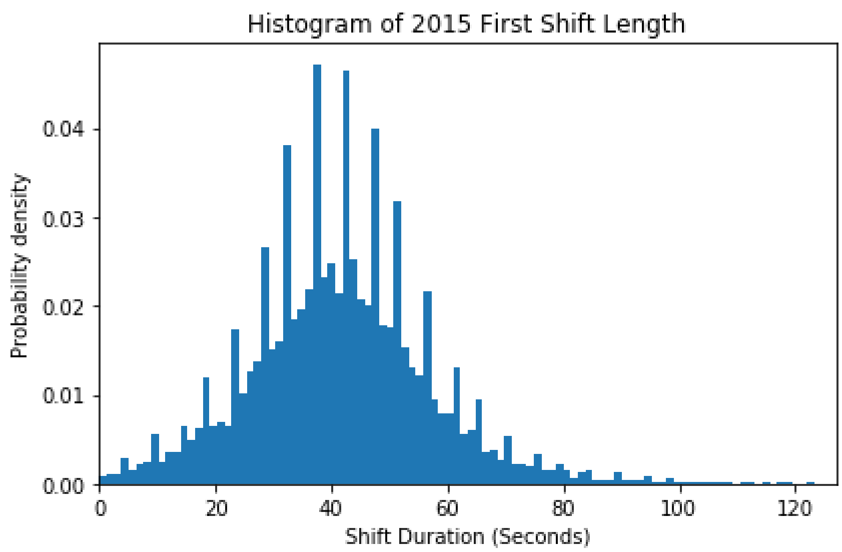
First Shift

In [35]:
```
print( "Distribution skew of 2015 First Shifts", firstShift2015["Duratio
n"].skew())
print( "Distribution peakness of 2015 First Shifts", firstShift2015["Dur
ation"].kurtosis())
```

```
Distribution skew of 2015 First Shifts 0.47824815856867253
Distribution peakness of 2015 First Shifts 1.3750862695135977
```

In [36]:
```
fig, ax = plt.subplots()
ax.hist(firstShift2015["Duration"],bins= 100, density = True)
ax.set_xlabel('Shift Duration (Seconds)')
ax.set_ylabel('Probability density')
ax.set_title(r'Histogram of 2015 First Shift Length')

fig.tight_layout()
plt.xlim(xmin=int(firstShift2015[["Duration"]].min()), xmax = int(firstS
hift2015[["Duration"]].max()))
plt.show()
```



Experiment

After removing the unwanted data, removing the outliers, we can progress with creating our experiment of difference in means. Here we're going to break out shift entries into two groups, "Long" and "Short". After that we are going to compare the Goal totals per game per player for the two groups. We are going to average out these Goals per game to try and smooth out any differences in the players and leave the only difference being their first shift length.

Data Preperation

In [37]:
```
# Decide the average shift
avgShift2015 = round(shift2015["Duration"].mean())
print("Average Shift 2015:", avgShift2015)
```

```
Average Shift 2015: 45
```

In [38]:
```
# If the shift is greater than the average make it Long outcome
# Else the shift is less than or equal to the average and we will make i
t Short Outcome
firstShift2015["Shift_Category"] = np.where(firstShift2015["Duration"] >
avgShift2015, 'Long', 'Short')
```

In [39]:
```
# In order to effectively join the two data sets I needed to reset the i
ndex for the shift data
firstShift2015.reset_index(drop = True, inplace= True)
```

In [40]:
```
# In order to effectively join the two data sets I needed to reset the i
ndex for the shift data
firstShift2015.reset_index(drop = True, inplace= True)
# Count all the goal events by game id and then by player id
playerGoalsPer2015 = goalEvents2015.groupby(["Game_Id", "p1_ID"]).count
().reset_index()
# Merge the data on a left join
# This will keep the values in the shift data where the player did not h
ave a goal that game
# The rows without goals for the game will have NaN
mergedGame2015 = firstShift2015.merge(playerGoalsPer2015, how='left', le
ft_on=["Game_Id",'Player_Id'], right_on = ["Game_Id","p1_ID"])
# Lets fill those NaNs with 0 values
mergedGame2015.fillna(0, inplace=True)
# I am going to drop the extra player ID column
mergedGame2015.drop(columns = ["p1_ID"], inplace = True)
mergedGame2015.head()
```

Out[40]:

	Shift_Id	Game_Id	Player_Id	Duration	Shift_Category	Goal_Id
0	0	20001	8467496	36.00000	Short	0.00000
1	15	20001	8468504	40.00000	Short	0.00000
2	1	20001	8469521	36.00000	Short	0.00000
3	22	20001	8469707	37.00000	Short	0.00000
4	12	20001	8470039	41.00000	Short	0.00000

Experiment Execution

In order to reject my null hypothesis I will need to have sufficent evidence to to say that outcome I am observing is not due to chance. That the year 2015 is not a random occurence. In order to do this I will take random samples from my group, compare the groups long and short and then see how many instances are similar to what I found in the NHL for 2015.

2015 NHL

In [41]:
```
mergedGame2015.groupby("Shift_Category")["Goal_Id"].count()
```

Out[41]:
```
Shift_Category
Long     17609
Short    29884
Name: Goal_Id, dtype: int64
```

In [42]:
```
grouped2015 = mergedGame2015.groupby("Shift_Category")["Goal_Id"].mean()
grouped2015Short = grouped2015[1]
grouped2015Long = grouped2015[0]
grouped2015Diff = grouped2015Long - grouped2015Short
print(grouped2015)
print(grouped2015Diff)
```

```
Shift_Category
Long     0.15112
Short    0.15440
Name: Goal_Id, dtype: float64
-0.0032810951014108913
```

2015 Experiment Outcome

This is our observed outcome.

Just looking at the total counts of Goals and the mean of Goals for 2015 the first shift duration does not influence the number of goals on average. It looks like the shorter the shift the more goals players score throughout the game.

We will look to see if shift duration and goals/game average is correlated.

Finally, we will look to see what we are observing for 2015 if it is truly accurate or up to random chance. Using our data set we will randomly sample 10,000 seasons and compare the groups to see how many instances we will find like ours.

In [43]:
```
mergedGame2015.corr()
```

Out[43]:

	Shift_Id	Game_Id	Player_Id	Duration	Goal_Id
Shift_Id	1.00000	0.56105	0.02271	-0.01023	0.00439
Game_Id	0.56105	1.00000	-0.02023	-0.04848	-0.00376
Player_Id	0.02271	-0.02023	1.00000	0.00925	-0.00785
Duration	-0.01023	-0.04848	0.00925	1.00000	-0.00944
Goal_Id	0.00439	-0.00376	-0.00785	-0.00944	1.00000

Goals/Game average does not appear to be correlated with First Shift Duration with a Correlation Coefficient of -0.00944. Based on these findings it does not appear that First Shift Duration has any relationship with Goals/Game average.

Bootstrap of Difference in Means

We are going to recreate our experiment conducted on the 2015 data on many different random samples of that 2015 data to see all the possible outcomes from that data. We will take a sample of the first shift data, and group the shifts to be Long or Short. We will match it up with the goal data for those games and players. Finally, take the means of the two groups, Long/Short and then show the difference for 10,000 samples.

In [44]:
```
# a good sample size is around 10% of the population
## But that is too large. It is greater than 1000
rows = firstShift2015.shape[0]
print("Population of First Shifts", rows)
print("10% of First Shift Rows", rows * .1)
```

```
Population of First Shifts 47493
10% of First Shift Rows 4749.3
```

Sample Size

Let’s determine our sample size (n) for First Shift Data. We will want to have a large enough sample to represent the population of first shifts in the NHL but not large enough that the sample mirrors the current population I have in the data. The goal of the random sample is to create a selection of data that could represent a population out there that we don't have access to in our current data set.

Your confidence level corresponds to something called a "z-score." A z-score is a value that indicates the placement of your raw score (meaning the percent of your confidence level) in any number of standard deviations below or above the population mean.

Z-scores for the most common confidence intervals are:

90% = 2.576 95% = 1.96 99% = 2.576

In [45]:
```
## Our intended level of confidence will be 95%
## where Z is the Z-score corresponding to your desired confidence level
## p is the estimated proportion of the population with a certain charac
teristic
## E is the maximum error you are willing to tolerate in your estimate.
## N population size

Z = 1.96
E = 0.05
N = rows
p = .05
n = round(((Z**2 * p * (1-p))/ E**2)/(1 + ((Z**2 * p *(1-p))/((E**2) *
N))))
print("Sample First Shifts:", n)
```

```
Sample First Shifts: 73
```

In [46]:
```
# Lets try one iteration
sample = firstShift2015.sample( n = n, replace = True)
sample.head()
```

Out[46]:

	Shift_Id	Game_Id	Player_Id	Duration	Shift_Category
15510	344789	20432	8470041	70.00000	Long
14525	322302	20405	8476191	36.00000	Short
13095	290405	20365	8478528	45.00000	Short
28270	626574	20790	8475795	50.00000	Long
36140	801000	21008	8474688	29.00000	Short

In [47]:
```
sampleMerged2015 = sample.merge(playerGoalsPer2015,
                                    how='left',
                                    left_on=["Game_Id",'Player_Id'],
                                    right_on = ["Game_Id","p1_ID"])
sampleMerged2015.fillna(0, inplace=True)
sampleMerged2015.drop(columns=["p1_ID"], inplace = True)
sampleMerged2015.head()
```

Out[47]:

	Shift_Id	Game_Id	Player_Id	Duration	Shift_Category	Goal_Id
0	344789	20432	8470041	70.00000	Long	1.00000
1	322302	20405	8476191	36.00000	Short	1.00000
2	290405	20365	8478528	45.00000	Short	0.00000
3	626574	20790	8475795	50.00000	Long	0.00000
4	801000	21008	8474688	29.00000	Short	0.00000

In [48]:
```
sampleGrouped2015 = sampleMerged2015.groupby("Shift_Category")["Goal_I
d"].mean()
sampleGrouped2015Short = sampleGrouped2015[1]
sampleGrouped2015Long = sampleGrouped2015[0]
sampleGrouped2015Diff = sampleGrouped2015Long - sampleGrouped2015Short
print(sampleGrouped2015)
print(sampleGrouped2015Diff)
```

```
Shift_Category
Long     0.10345
Short    0.11364
Name: Goal_Id, dtype: float64
-0.010188087774294668
```

We find here in this sample that the short shift group scored on average .08 more goals per game. This is just one sample, 73 shifts out of all the available first shifts in the data. It is rather close to our observed result in all of the 2015 data. Lets attempt this on many samples.

Many Seasons

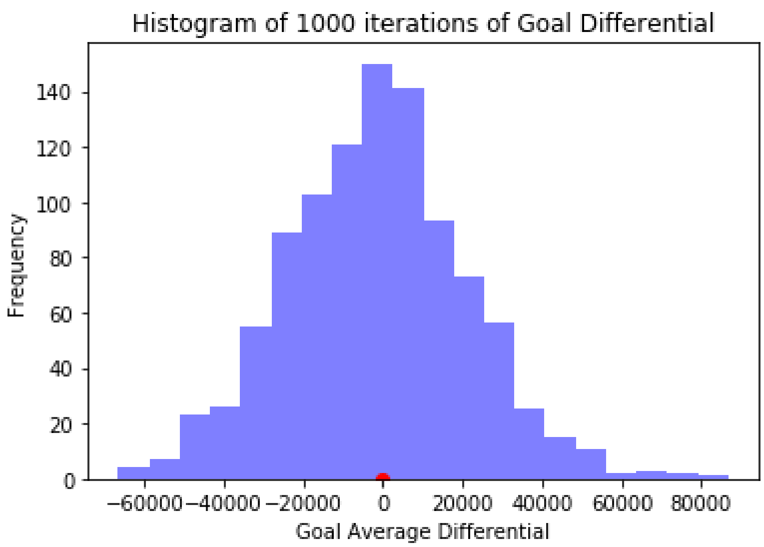
We would like to see over thousands of seasons how much the Goals/Game average would differ for our "Long" first shift group versus our "Short" first shift group. For 2015 the Goals/Game average would differ for our "Long" first shift group versus our "Short" first shift group was -0.08 Goals per game. Meanings on average the Short first shift group scored .08 more goals per games than the Long first shift group.

In [49]:
```
def goalsPerGameDiffBoot(shifts, goalsGame, sampleSize, iterations):
    # Collect Differences
    goalDiffs = []
    # Iterate through the range of all the iterations
    for i in range(iterations):
        # Take a random sample
        sample = shifts.sample(n = sampleSize, replace = True)
        # Merge the shift and goal data
        sampleMerged = sample.merge(goalsGame,
                                    how='left',
                                    left_on=["Game_Id",'Player_Id'],
                                    right_on = ["Game_Id","p1_ID"])
        # Fill the NaNs with 0 values for no goals for that game
        sampleMerged.fillna(0, inplace=True)
        # Take a mean of all the goals
        sampleGrouped = sampleMerged.groupby("Shift_Category")["Goal_I
d"].mean()
        # Calculate the difference
        sampleGroupedShort = sampleGrouped[1]
        sampleGroupedLong = sampleGrouped[0]
        sampleGroupedDiff = sampleGroupedLong - sampleGroupedShort
        # Append on to the collector
        goalDiffs.append(sampleGroupedDiff)

    return goalDiffs
```

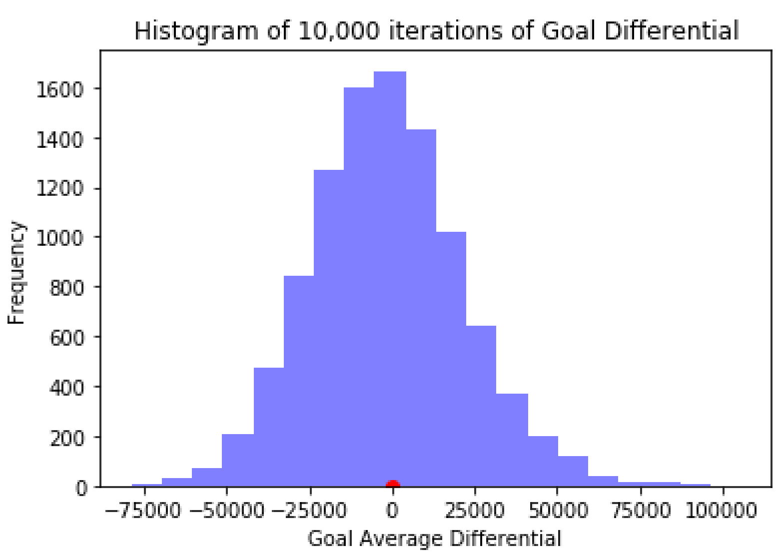
In [50]:
```
diffBootData1000 = goalsPerGameDiffBoot(shifts = firstShift2015,
                                    goalsGame = goalEvents2015,
                                    sampleSize = n,
                                    iterations = 1000)
```

In [51]:
```
plt.hist(diffBootData1000, bins=20, color='blue', alpha=0.5)
plt.xlabel('Goal Average Differential')
plt.ylabel('Frequency')
plt.title('Histogram of 1000 iterations of Goal Differential')
plt.plot(grouped2015Diff , 0, 'ro')
plt.show()
```



In [52]:
```
diffBootData10000 = goalsPerGameDiffBoot(shifts = firstShift2015,
                                    goalsGame = goalEvents2015,
                                    sampleSize = n,
                                    iterations = 10000)
```

In [53]:
```
plt.hist(diffBootData10000, bins=20, color='blue', alpha=0.5)
plt.xlabel('Goal Average Differential')
plt.ylabel('Frequency')
plt.title('Histogram of 10,000 iterations of Goal Differential')
plt.plot(grouped2015Diff , 0, 'ro')
plt.show()
```



Experiment Outcome

Final thoughts, we have failed to reject the null hypothesis. I feel that we have almost confirmed the null hypothesis, that the first shift duration does not have an effect on the average goals per game outcome for a player. I know that is this wrong terminology to use in data science but we ran through a random experiment on 1,000 and 10,000 iterations and found that our observed outcome in 2015 is likely to occur.

It turns out that some coach in the 80s and 90s just wanted an excuse to play the best player of all time more often in the first couple shifts of a game. Having that in your back pocket as a coach must have been really nice.

Possible future experiments

- I wonder if we decided the shift category on the median and instead of the mean.

The median would be the 50th percentile of the shift data and would be less affected by the outliers or long shifts. The mean gets dragged away from the median towards the tail of the data. For the shift data we found that the distribution was right tailed, some players got stuck out on the ice for some long shifts. If we used median it would not allow those shifts to affect how we categorize our first shifts.

- I wonder if the first shift duration has anything to do with the point totals, not just goals.

All hockey players know, and many coaches know that players have an impact on the game without scoring goals, specifically defenseman. If a defenseman is taking a long shift to get into the game, he might be more affective at making great outlet passes or great defensive stops. All of that can't be measured in goals.

- I wonder if the second shift should be long.

This idea came from my playing days. I always wanted to take a short first shift, touch the puck, hit someone, and get off the ice before anything bad happened. Then my next shift I would try to get good and tired, and I was in the game for the rest of it. I know this might suprise you but I'm not an NHL player, it would still be interesting to see if how I took an outlook on the game had any true affect beyond just how I felt in my head.

In [ ]:

```

```