MA388 Sabermetrics: SCORE Project

Module Proposal

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1. Learning Goals
   A student who successfully completed this module should have the ability to:

a. Apply the six steps of the statistical investigation method to comparing two groups on a quantitative response.
b. Calculate the five-number summary (quartiles) and create histograms and boxplots to explore the data from two groups with a quantitative response variable.
c. Develop a null and alternative hypothesis for a research question for comparing two means.
d. Assess the statistical significance of the observed difference between two groups.
e. Apply the 3S Strategy to assess whether two sample means differ enough to conclude that there is a genuine difference in the population means or long-run means of a process.
f. Use the 2SD method to estimate a confidence interval for the difference in two means.
g. Determine the strength of evidence using the theory-based approach (two-sample t-test) for comparing two means.

2. Introduction
   Soccer, also known as football in other countries, is one of the most popular sports in Europe. In soccer, a player can either be right foot dominant or left foot dominant, and this can lead to differences in how players play. One question that might come up is whether or not foot dominance affects free-kick accuracy, as people may not be used to left-footed shots and as a result, may not be able to block them as effectively as right-footed shots.

To put it in clearer terms, the question that we are trying to answer using the data and our statistical exploration is: "Is there an association between dominant foot and free kick accuracy for players in the European Soccer League?"

In order to answer this question, we can use data collected from soccer games all over Europe to determine each player's preferred foot, group the players by their preferred foot, and calculate the mean free-kick accuracy score for each group. Knowing the calculated difference, we can use statistical analysis to determine if the difference in free-kick accuracy score between right-footed and left-footed players is due to a difference between the two groups or just due to chance. In statistics, such an analysis is known as a two-sample t-test for a difference in means. This module will guide you through exploring the data, developing hypotheses, and determining the strength of evidence provided by the data.

3. Data
   The data for this project comes from the Kaggle Database titled "European Soccer Database: 25k+ matches, players & teams attributes for European Professional Football" uploaded by Hugo Mathien. The data for this dataset comes from multiple sources, including http://football-data.mx-api.enetscores.com/ The data for this dataset comes from multiple sources, including http://football-data.mx-api.enetscores.com/ (includes scores, lineup, team formation and events), http://www.football-data.co.uk/ (betting odds), and (player and team attributes).

The data includes a total of seven tables: Country, League, Match, Player, Player_Attributes, Team, and Team_Attributes, and these seven tables have a total of 199 columns. According to the description, the database contains data from 2008 to 2016 on more than 25,000 matches, 10,000 players their attributes, 11 European countries and their lead championship, team line ups, betting odds, and detailed match events (goal types, possession, corner, cross, fouls, cards, etc.)

The code for loading the SQLite database and selecting the data of interest will be included in the appendix. This code loads the seven tables from the SQLite database into a separate data frame for each table. Once we have the data frames, we can narrow it down to the data that we actually need in order to conduct the analysis. Through looking at the data in each table, we can determine that the only table that applies to the question we are trying to answer is the Player_Attributes table. The code in the appendix writes the data in this table to a csv file, which is read using the code shown below.

```r
library(tidyverse)
library(knitr)
library(janitor)

Player_Attributes <- read_csv("Player_Attributes.csv")
```

Now that we know what table we want to focus on, we can take a closer look and select possible variables of interest. In addition, we can create some summary statistics and display them in a well-organized table.

```r
#Data frame with some interesting attributes
select_player_attributes <- Player_Attributes %>%
  drop_na() %>%
  select(preferred_foot, ball_control, free_kick_accuracy, overall_rating)

#Table to show interesting attributes
select_player_attributes %>%
  group_by(preferred_foot) %>%
  summarize(mean_BC = mean(ball_control), mean_FCA = mean(free_kick_accuracy), mean_OR = mean(overall_ra
  kable(col.names = c("Preferred Foot", "Mean Ball Control Score", "Mean Free Kick Accuracy", "Mean Rati
```

Preferred Foot	Mean Ball Control Score	Mean Free Kick Accuracy	Mean Rating	Number of Observations
left	65.44723	53.29136	68.65282	44107
right	62.80853	48.13070	68.62965	136247

4. Methods/Instructional Content
   The two instructional content we picked were Introduction to Statistical Investigations, 2nd Edition and Intermediate Statistical Investigations, 1st Edition.
   Scholarly reference 1: Introduction to Statistical Investigations (Chapter 8: Comparing more than two proportions)
   This chapter provides theoretical knowledge of the key components of our module as the chapter includes all basic information. We used this reference to refresh our knowledge of the process of comparing multiple proportions. It also includes information on generalization and causation.
   Scholarly reference 2: Intermediate Statistical Investigations (Section 6.1 Comparing Proportions)
   This scholarly reference provides a detailed explanation of the different methods to compare proportions, including the two-sample t-test. This source was helpful to the process of developing the model as it provides multiple examples of various cases of statistical investigations involving categorical datasets. By reading through the examples, we were able to develop the module by following the general question/exercise format as the examples, as it provides a very well-developed flow to guide readers through a problem.

5. Exercises/Activities
   The following are main topics related to the module. We will assign data exploration projects to prac-

tice the following skills to familiarize the students with the topic and ensure their success in this module.

Step 1: Ask a research question

The step to any statistical analysis is to ask a research question. In this case, we are trying to ask a research question relating a player's preferred foot and their free-kick accuracy score. What is a possible research question that can be used for this?

For our statistical investigation, we chose to use the question: Is there an association between preferred foot and free kick accuracy score in the European Soccer League?

Step 2: Design a Study and Collect Data

The first two parts to this step include identifying the observational units in this study and determining the null and alternative hypotheses. An observational unit is what is actually being observed in the study. In this case, it would be a European Soccer Player. As for the Hypotheses, there are two that need to be made for purposes of statistical analysis. The first is the Null Hypothesis, which states that there is no real statistical evidence for anything and the second is the alternative hypothesis, which says that the data provides evidence for some sort of conclusion. In this case, we need to craft the hypotheses for our question regarding a difference in means. The two null hypotheses we came up with for this study are stated below.

Null Hypothesis: There is no association between preferred foot and free kick accuracy score in the European Soccer League

Alternative Hypothesis: There is an association between preferred foot and free kick accuracy score in the European Soccer League.

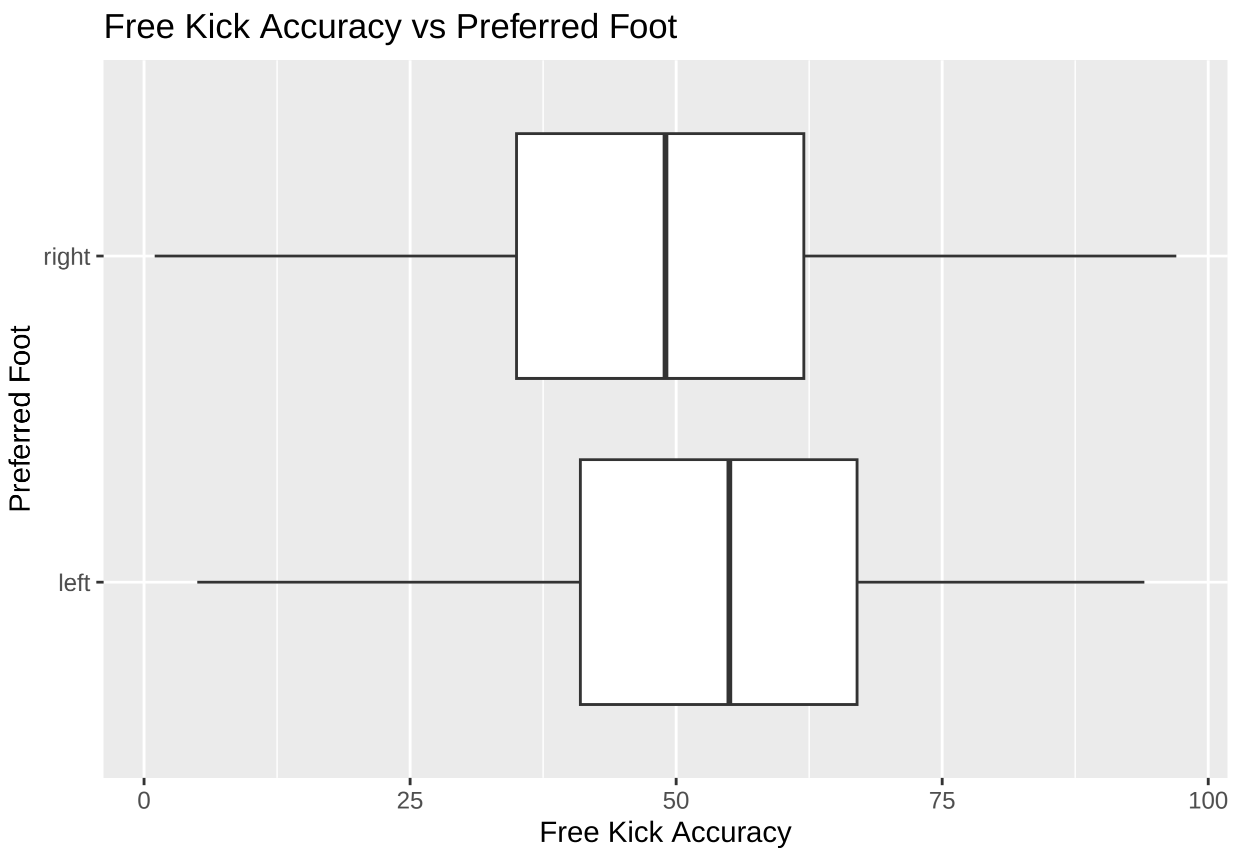
Step 3: Explore the Data

In the Data section, we took a look at the data and selected the variables that we needed in order to conduct the statistical analysis, so now all we need to do is do some data exploration and visualization. One way to do this for comparing two means s to create the five-number summary and correspondng box-plot.

```
#Five number summary of each of the two populations
select_player_attributes %>%
  group_by(preferred_foot) %>%
  summarize(Minimum = min(free_kick_accuracy),
            LowerQuartile = quantile(prob =.25, free_kick_accuracy),
            Median = median(free_kick_accuracy),
            UpperQuartile = quantile(prob=.75, free_kick_accuracy),
            Maximum = max(free_kick_accuracy))
```

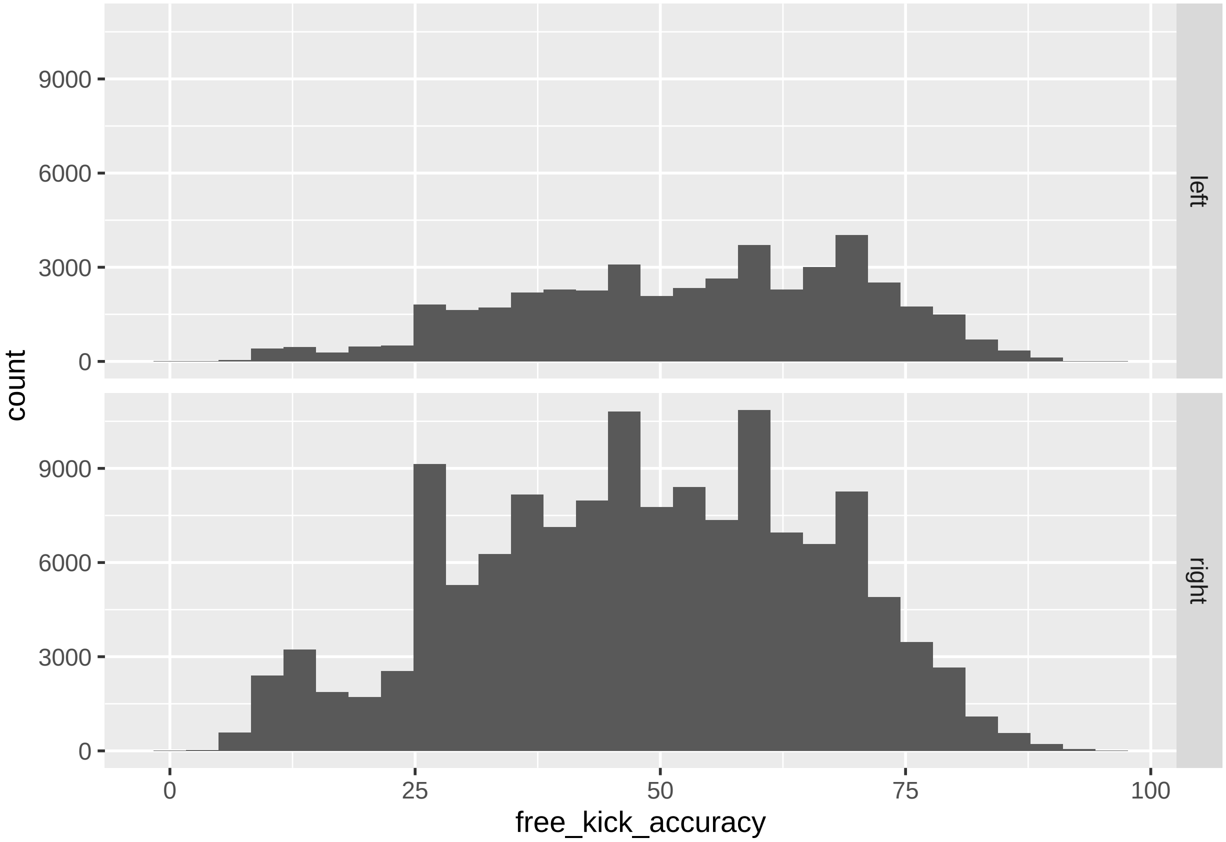
```
## # A tibble: 2 x 6
##   preferred_foot Minimum LowerQuartile Median UpperQuartile Maximum
##   <chr>            <dbl>         <dbl>  <dbl>         <dbl>   <dbl>
## 1 left                 5            41     55            67      94
## 2 right                1            35     49            62      97
```

```
#Boxplot to illustrate the five-number summary
select_player_attributes %>%
  ggplot(aes(x = free_kick_accuracy,
             y = preferred_foot)) +
  geom_boxplot()+
  labs(y = "Preferred Foot",
       x = "Free Kick Accuracy",
       title = "Free Kick Accuracy vs Preferred Foot")
```

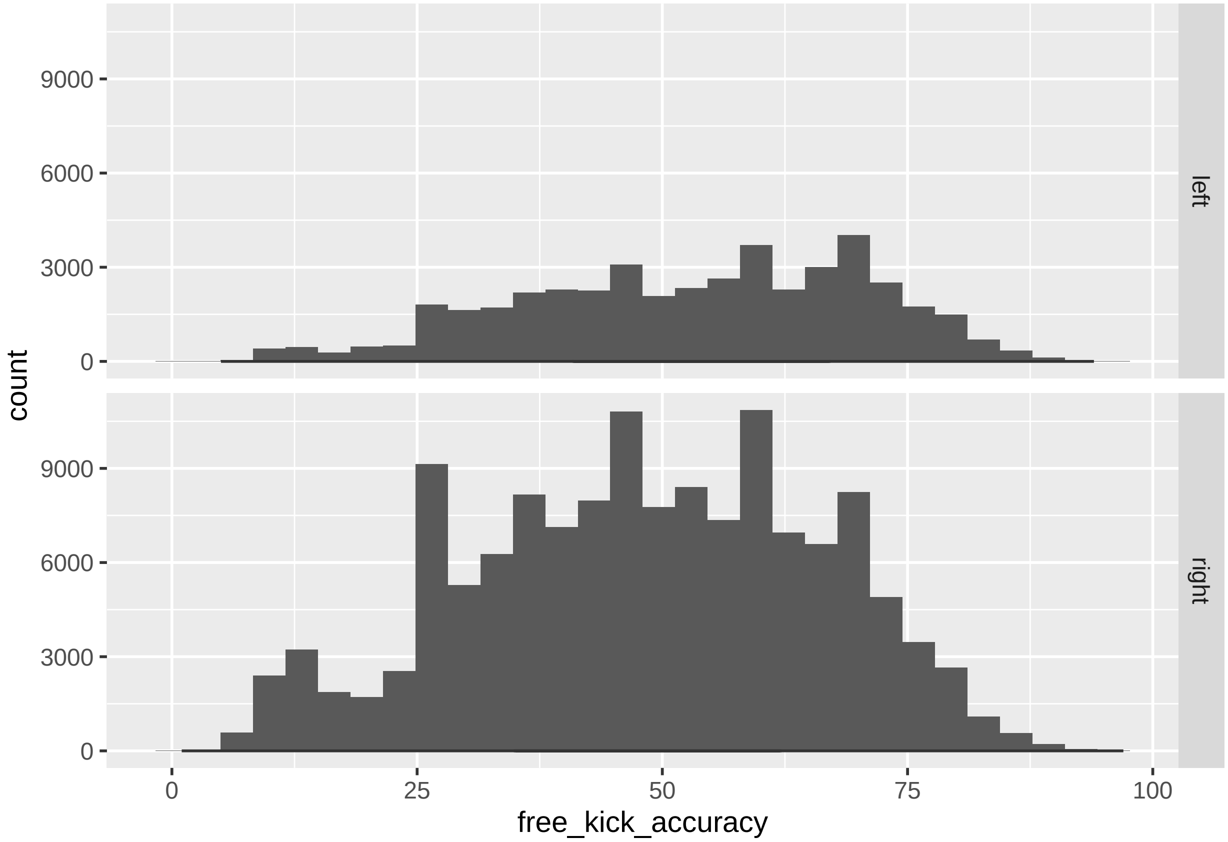


What does the five-number summary and box plot show about the distribution of free-kick accuracy score between the two groups? Does it show evidence of a significant difference? Another way to visualize the data is to use a histogram, which may help better illustrate how the data is actually distributed.

```
#Histogram to visualize data
select_player_attributes %>%
  ggplot(aes(x=free_kick_accuracy)) +
  geom_histogram() +
  facet_grid(preferred_foot~.)
```



```
#combination of boxplot and histogram
select_player_attributes %>%
  ggplot(aes(x=free_kick_accuracy)) +
  geom_histogram() +
  geom_boxplot() +
  facet_grid(preferred_foot ~.)
```



What does the distribution of the histogram show? How does this add to the information shown by the boxplot?

From the two visualizations we created, there does seem to be a difference between the mean free-kick accuracy score between the two groups, which means that it is probably worth investigating further using a statistical test.

Step 4: Draw Inferences beyond the Data In order to make conclusions beyond what is shown in the data, we must conduct a t-statistic test of the two groups and figure out if our observed difference is statistically significant.
Conduct the Two Sample T-Test: To conduct the two-sample t-test for a difference in means, we first need to calculate summarized statistics for each group, and using these statistics, we can calculate the standardized statistics needed in order to perform the statistical analysis.

```
#Calculate Summarized Statistics
select_player_attributes %>%
  group_by(preferred_foot) %>%
  summarise(xbar = mean(free_kick_accuracy),
            s = sd(free_kick_accuracy),
            n = n())
```

```
## # A tibble: 2 x 4
##   preferred_foot  xbar     s      n
##   <chr>          <dbl> <dbl>  <int>
## 1 left            53.3  17.3  44107
## 2 right           48.1  17.8 136247
```

There are a few standardized statistics we need for the two-sample t-test. xbar is the observed statistic for each group, n is the sample size of each group, and s is the observed standard deviation of each group. Using the s value from each group, we can create a value that accounts for the differing sample size and standard deviations of each group, and this sd value is what we use to determine the value of the t-statistic for our analysis.

```
#Calculate Standardized Statistics
xbar_left = 53.291
xbar_right = 48.131
s_left = 17.325
s_right = 17.796
n_left = 44107
n_right = 136247
sd = sqrt(s_left^2/n_left+s_right^2/n_right)
null = 0
statistic = xbar_left-xbar_right
t = (statistic-null)/sd
t
```

```
## [1] 54.00372
```

What is our calculated t-statistic? What does this t-statistic represent and what kind of evidence does it provide for our hypotheses?
Now that we have the t-statistic calculated, we can use it to determine the p-value, or the probability that the observed difference in means between the two groups was caused by chance alone. In order to do this, we use R's pt function with n-2 degrees of freedom, as there are two groups being compared. In addition to this, we need to multiply whatever value we get from the pt function by two, as we are trying to check if there is any difference between the two means, meaning that it doesn't matter which one is higher or which one is lower than the other, just that the two are different. When we do this, it is called a two-tailed test, as we are adding up the probabilities from both "tails" of the distribution.

```
#Calculate P-Value with n-2 degrees of freedom, two-tailed test
n = n_left+n_right
pvalue = 2*pt(t,n-2, lower.tail = FALSE)
pvalue
```

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

What is the p-value? When the p-value is compared to the significance level of 0.01, what does it show? Because our p-value is very small (less than the significance level of 0.01), we can conclude that th probability of getting our observed difference in means is very small as well, providing evidence for the fact that there actually exists a difference between the means of the two populations.
Finally, we'll calculate a confidence interval to determine what we think the actual difference between the two means is. Because we are using a 0.01 significance level, we will calculate the confidence interval with 99% confidence.

```
#calculate Confidence interval at 99% confidence
multiplier = qt(.995,n-2)
se = sd
CI = c(statistic - multiplier*se, statistic + multiplier*se)
CI
```

```
## [1] 4.91388 5.40612
```

What does the 99% level of confidence represent? It shows that we are 99% confident that the actual difference between the two means falls between the two numbers presented in the confidence interval.

5. Wrap-Up/Conclusions:

Conclusions: Through an exploration of the data and the usage of a two-sample t-test to analyze the data, we were able to reject the null hypothesis that there is no difference in free kick accuracy score between right-footed and left-footed players and show evidence for the alternative that there is a difference in average free-kick accuracy between these two groups.
The p-value of 0 is less than our significance level of 0.01, and it shows that it is extremely unlikely that the observed difference between these two groups was due to chance alone. The confidence interval calculated shows that we can be 99% confident that the actual difference in free kick accuracy score between right-footed and left-footed players is between the values of 4.91388 and 5.40612, with left-footed kickers performing better.

Wrap-Up:
Recap the lessons learned both in terms of statistical techniques and in terms of the sports research question. Provide the reader at least one other sports application (could be the same sport) for this particular skill and at least one idea for a future skill to learn that builds on what you've presented.
In this lesson, students learned to conduct a statistical investigation by following the six-step statistical investigation method. The module targeted to answer the research question of whether there exists a correlation between dominant foot and free kick accuracy in the European Soccer League by comparing two population proportions using a two-sample t-test.

6. Appendix:

```
library(tidyverse)
library('RSQLite') # SQLite package for R
library(DBI) # R Database Interface.
library(knitr)
library(janitor)

#Connect to Database
databaseConnection <- dbConnect(drv=RSQLite::SQLite(), dbname="database.sqlite")
#List Tables
tables <- dbListTables(databaseConnection)
#exclude sqlite_sequence (contains table information)
tables <- tables[tables != "sqlite_sequence"]
lDataFrames <- vector("list", length=length(tables))
#Create Dataframe for each table
for (i in seq(along=tables)) {
  lDataFrames[[i]] <- dbGetQuery(conn=databaseConnection, statement=paste("SELECT * FROM '", tables[[i]]
}
#label all of the dataframes
Country <- lDataFrames[[1]]
League <- lDataFrames[[2]]
Match <- lDataFrames[[3]]
Player <- lDataFrames[[4]]
Player_Attributes <- lDataFrames[[5]]
Team <- lDataFrames[[6]]
Team_Attributes <- lDataFrames[[7]]

Country %>%
  head(5) %>%
  kable()
League %>%
  head(5) %>%
  kable()
Match %>%
  head(5) %>%
  kable()
Player %>%
  head(5) %>%
  kable()
Player_Attributes %>%
  head(5) %>%
  kable()
Team %>%
  head(5) %>%
  kable()
Team_Attributes %>%
  head(5) %>%
  kable()

write.csv(Player_Attributes,file='./Player_Attributes.csv')
#https://sparkbyexamples.com/r-programming/r-export-csv-using-write-csv/
```