Project 9 | Hypothesis Testing with Men's and Women's Soccer Matches

Lawal's Project

2024-03-04

Table of contents

Figure 1: A soccer pitch for an international match.

0.1 Project Overview

You're working as a sports journalist at a major online sports media company, specializing in soccer analysis and reporting. You've been watching both men's and women's international soccer matches for a number of years, and your gut instinct tells you that more goals are scored in women's international football matches than men's. This would make an interesting investigative article that your subscribers are bound to love, but you'll need to perform a valid statistical hypothesis test to be sure!

While scoping this project, you acknowledge that the sport has changed a lot over the years, and performances likely vary a lot depending on the tournament, so you decide to limit the data used in the analysis to only official `FIFA World Cup` matches (not including qualifiers) since `2002-01-01`.

You create two datasets containing the results of every official men's and women's international football match since the 19th century, which you scraped from a reliable online source. This data is stored in two CSV files:

- `women_results.csv` – Results of every official women's international match.
- `men_results.csv` – Results of every official men's international match.

The question you are trying to determine the answer to is:

> Are more goals scored in women's international soccer matches than men's?

You assume a **10% significance level**, and use the following null and alternative hypotheses:

- H_0 : The mean number of goals scored in women's international soccer matches is the same as men's.
- H_A : The mean number of goals scored in women's international soccer matches is greater than men's.

0.2 Datasets Summary

Table 1: `men_results.csv/women_results.csv`

Column	Description
`date`	The date when the match was played (YYYY-MM-DD format).
`home_team`	The name of the team that played at home.
`away_team`	The name of the team that played away.
`home_score`	The number of goals scored by the home team.
`away_score`	The number of goals scored by the away team.
`tournament`	The type of tournament in which the match was played (e.g., FIFA World Cup, Friendly).

0.3 Project instructions

- Perform an appropriate hypothesis test to determine the p-value, and hence result, of whether to reject or fail to reject the null hypothesis that the mean number of goals scored in women's international soccer matches is the same as men's. Use a 10% significance level.
- For this analysis, you'll use Official FIFA World Cup matches since 2002-01-01, and you'll also assume that each match is fully independent, i.e., team form is ignored.
- The `p-value` and the result of the test must be stored in a dictionary called `result_dict` in the form: `result_dict = {"p_val": p_val, "result": result}` where `p_val` is the `p-value` and result is either the string `"fail to reject"` or `"reject"`, depending on the `result` of the test.

0.4 Data Source

The primary data used for this analysis is the `men_results.csv` and `women_results.csv`. Download men's dataset here and women's dataset here. See Table 1 for the column names and descriptions.

0.5 Tools

This project was conducted using `JupyterLab`, a versatile interactive development environment that facilitates data analysis, visualization, and documentation in Python.

0.6 Steps/Explanations

1. Importing Required Libraries

To begin, I imported key Python libraries to handle data processing, visualization, and statistical analysis:

- `pandas` and `numpy` for data manipulation.
- `matplotlib.pyplot` and `seaborn` for visualizations.
- `scipy.stats` and `pingouin` for statistical hypothesis testing.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import shapiro, normaltest, mannwhitneyu
import pingouin as pg
```

2. Loading and Exploring the Datasets

I analyzed two datasets:

- `women_results.csv` (Women's international match results).
- `men_results.csv` (Men's international match results).

Key Steps:

1. Loaded the datasets using `pd.read_csv()`.
2. Checked column names, data types, and missing values.
3. Converted the `date` column to a datetime format for proper filtering.
4. Inspected the `tournament` column to identify relevant tournaments.

```
# Load datasets
women_results = pd.read_csv('women_results.csv')
men_results = pd.read_csv('men_results.csv')

# Check data structure
women_results.info()
men_results.info()

# Convert 'date' column to datetime format
women_results['date'] = pd.to_datetime(women_results['date'])
men_results['date'] = pd.to_datetime(men_results['date'])
```

3. Filtering the Data

The analysis focuses only on FIFA World Cup matches played after January 1, 2002.

Filtering Steps:

1. Selected only matches from the FIFA World Cup (`tournament == "FIFA World Cup"`).
2. Filtered matches that took place after `2002-01-01`.
3. Created a new column `Total_Score` to represent the total number of goals in each match.

```
# Create a new column for total goals scored
women_results['Total_Score'] = women_results['home_score'] + women_results['away_score']
men_results['Total_Score'] = men_results['home_score'] + men_results['away_score']

# Filter for FIFA World Cup matches after 2002-01-01
women_goals = women_results.loc[
    (women_results['tournament'] == 'FIFA World Cup') & (women_results['date'] > '2002-01-01'),
```

```
    'Total_Score'
]

men_goals = men_results.loc[
    (men_results['tournament'] == 'FIFA World Cup') & (men_results['date'] > '2002-01-01'),
    'Total_Score'
]
```

4. Choosing the Right Hypothesis Test

The goal is to compare the number of goals in men's and women's FIFA World Cup matches.

Key Considerations:

- Since there are **two independent groups** (men's and women's matches), a **two-sample test** is required.
- **Normality Check**:
  - Visualized the goal distribution using a histogram.
  - Conducted statistical tests (Shapiro-Wilk and Kolmogorov-Smirnov) to check if the data follows a normal distribution.

```
# Visualize goal distributions
sns.histplot(women_goals, kde=True, label="Women's Matches", color='blue')
sns.histplot(men_goals, kde=True, label="Men's Matches", color='red')
plt.legend()
plt.title("Goal Distribution in FIFA World Cup Matches")
plt.show()

# Test for normality
print("Shapiro-Wilk Test for Women's Matches:", shapiro(women_goals))
print("Shapiro-Wilk Test for Men's Matches:", shapiro(men_goals))
```

Selecting the Test:

- If the data is **normally distributed**, an **unpaired t-test** can be used.
- If the data **does not follow a normal distribution**, the **Wilcoxon-Mann-Whitney test** (a non-parametric test) is used.

5. Performing the Hypothesis Test

Since normality assumptions were not met, the **Wilcoxon-Mann-Whitney test** was used to compare goal counts.

Using `pingouin`

```
# Perform Wilcoxon-Mann-Whitney test using pingouin
test_results = pg.mwu(x=women_goals, y=men_goals, alternative="two-sided")

# Extract p-value
p_value = test_results['p-val'].values[0]
print("P-value (pingouin):", p_value)
```

Using `SciPy`

```
# Perform Wilcoxon-Mann-Whitney test using SciPy
stat, p_value = mannwhitneyu(women_goals, men_goals, alternative="two-sided")
print("P-value (SciPy):", p_value)
```

6. Interpreting the Results

The p-value determines if there is a **statistically significant difference** between men's and women's FIFA World Cup goal counts.

Decision Rule:

- **If p-value 0.10 (10% significance level)** → Reject the null hypothesis (significant difference in goals).
- **If p-value > 0.10** → Fail to reject the null hypothesis (no significant difference).

```
# Interpret result
alpha = 0.10  # 10% significance level
if p_value <= alpha:
    print("Reject the null hypothesis: There is a significant difference in goals scored.")
else:
    print("Fail to reject the null hypothesis: No significant difference in goals scored.")
```

0.7 Data Analysis

```python
# Start code here!
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import shapiro, normaltest, probplot, mannwhitneyu
import pingouin as pg
```

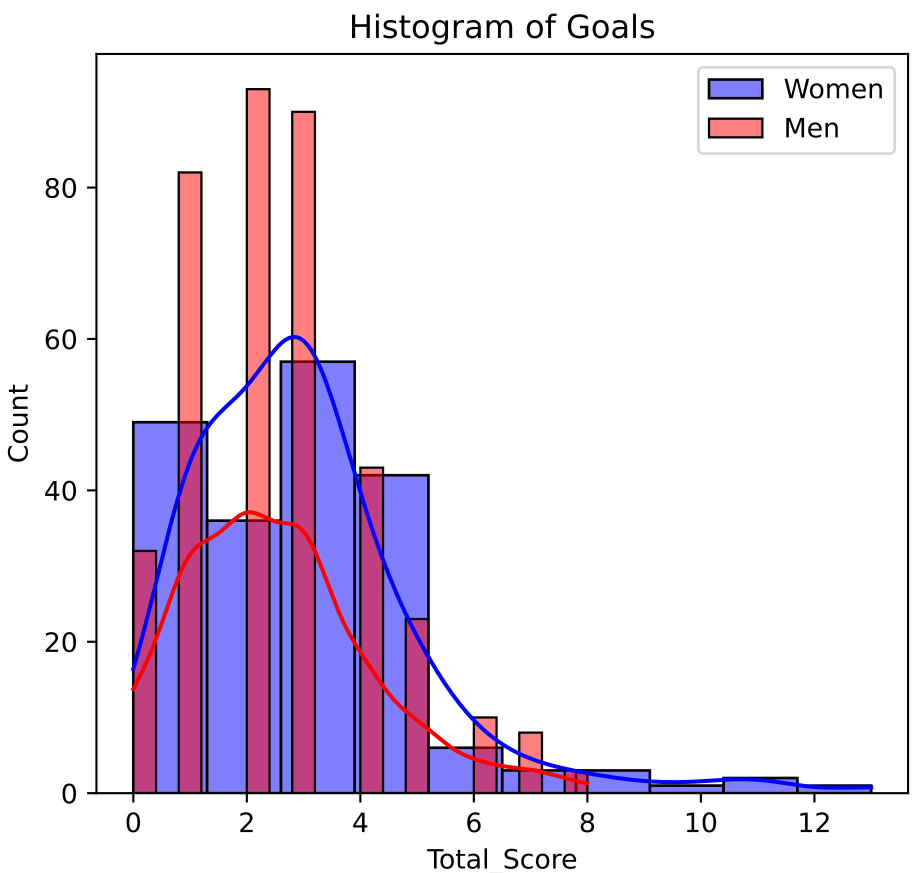
```python
women_results = pd.read_csv('women_results.csv')
men_results = pd.read_csv('men_results.csv')

# Column names and data type
women_results.info()

# Any Missing values
women_results.isna().sum()

# Convert date column from object to datetime
women_results['date'] = pd.to_datetime(women_results['date'])

# Values for tournament
women_results['tournament'].unique()

# Total Goals Scored by women
women_results['Total_Score'] = women_results['home_score'] + women_results['away_score']

# Filter for FIFA World Cup and date beyond 2002-01-01
filter_criteria = ((women_results['tournament'] == 'FIFA World Cup')
                   & (women_results['date'] > '2002-01-01'))

# Use .loc and the filter to select for goals
women_goals = women_results.loc[filter_criteria, 'Total_Score']


# Column names and data type
men_results.info()

# Any Missing values
men_results.isna().sum()

# Convert date column from object to datetime
men_results['date'] = pd.to_datetime(men_results['date'])

# Total Goals Scored by women
men_results['Total_Score'] = men_results['home_score'] + men_results['away_score']

# Filter for FIFA World Cup and date beyond 2002-01-01
filter_criteria1 = ((men_results['tournament'] == 'FIFA World Cup')
                   & (men_results['date'] > '2002-01-01'))

# Use .loc and the filter to select for goals
men_goals = men_results.loc[filter_criteria1, 'Total_Score']
```

```
# Set significance level
alpha = 0.10

# --- 1. Visualization Methods of Checking for Normality ---

# Histogram
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.histplot(women_goals, kde=True, bins=10, color="blue", label="Women")
sns.histplot(men_goals, kde=True, bins=20, color="red", label="Men")
plt.legend()
plt.title("Histogram of Goals")

# --- 2. Statistical Normality Tests ---

# Shapiro-Wilk Test
shapiro_women = shapiro(women_goals)
shapiro_men = shapiro(men_goals)

print(f"Shapiro-Wilk Test for Women's Goals: p = {shapiro_women.pvalue:.5f}")
print(f"Shapiro-Wilk Test for Men's Goals: p = {shapiro_men.pvalue:.5f}")

# Normality Decision
if shapiro_women.pvalue > alpha:
    print("Women's goals follow a normal distribution.")
else:
    print("Women's goals do NOT follow a normal distribution, hence use Wilcoxon-Mann-Whitney tes

if shapiro_men.pvalue > alpha:
    print("Men's goals follow a normal distribution.")
else:
    print("Men's goals do NOT follow a normal distribution, hence use Wilcoxon-Mann-Whitney test.


# --- Hypothesis Test Using Wilcoxon-Mann-Whitney test ---
u_stat, p_val = mannwhitneyu(women_goals, men_goals, alternative='greater')

# Alternative

# Filter the data for the time range and tournament
men_filter = men_results[(men_results["date"] > "2002-01-01") & (men_results["tournament"].isin([
women_filter = women_results[(women_results["date"] > "2002-01-01") & (women_results["tournament"

# Create group and goals_scored columns
```

```python
men_filter["group"] = "men"
women_filter["group"] = "women"

# Combine women's and men's data and calculate goals scored in each match
both = pd.concat([women_filter, men_filter], axis=0, ignore_index=True)

# Transform the data for the pingouin Mann-Whitney U t-test/Wilcoxon-Mann-Whitney test
both_subset = both[["Total_Score", "group"]]
both_subset_wide = both_subset.pivot(columns="group", values="Total_Score")

# Perform right-tailed Wilcoxon-Mann-Whitney test with pingouin
results_pg = pg.mwu(x=both_subset_wide["women"],
                    y=both_subset_wide["men"],
                    alternative="greater")

# Extract p-value as a float
p_val1 = results_pg["p-val"].values[0]

# Determine the test result
result = "reject" if p_val1 < alpha else "fail to reject"

# Store in dictionary
result_dict = {"p_val": p_val1, "result": result}

print(result_dict)  # Final dictionary output
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4884 entries, 0 to 4883
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  4884 non-null   int64
 1   date        4884 non-null   object
 2   home_team   4884 non-null   object
 3   away_team   4884 non-null   object
 4   home_score  4884 non-null   int64
 5   away_score  4884 non-null   int64
 6   tournament  4884 non-null   object
dtypes: int64(3), object(4)
memory usage: 267.2+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 44353 entries, 0 to 44352
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
```

```
 0   Unnamed: 0  44353 non-null  int64 
 1   date        44353 non-null  object
 2   home_team   44353 non-null  object
 3   away_team   44353 non-null  object
 4   home_score  44353 non-null  int64 
 5   away_score  44353 non-null  int64 
 6   tournament  44353 non-null  object
dtypes: int64(3), object(4)
memory usage: 2.4+ MB
Shapiro-Wilk Test for Women's Goals: p = 0.00000
Shapiro-Wilk Test for Men's Goals: p = 0.00000
Women's goals do NOT follow a normal distribution, hence use Wilcoxon-Mann-Whitney test.
Men's goals do NOT follow a normal distribution, hence use Wilcoxon-Mann-Whitney test.
{'p_val': 0.005106609825443641, 'result': 'reject'}
```



0.8 Result/Findings

Key Finding:

The Wilcoxon-Mann-Whitney test returned a **p-value of 0.0051**. Since this is **significantly lower than the 10% significance level (0.10)**, we **reject the null hypothesis**.

Interpretation:

This means that there is a **statistically significant difference** in the number of goals scored in men's and women's FIFA World Cup matches since 2002. In other words, the goal-scoring patterns in women's World Cup matches are **not the same as** those in men's matches.

Implications:

- If the **goal count is higher in women's matches**, this could suggest differences in playing styles, defensive strategies, or game dynamics.
- If the **goal count is lower in women's matches**, it may indicate stronger defensive tactics or other factors influencing scoring trends.

0.9 Recommendation

I will recommend further analysis, such as looking at average goals per match or considering external factors (e.g., tournament format, rule changes), could help explain why this difference exists.

0.10 References

1. For loop in Intermediate Python Course for Associate Data Scientist in Python Carrer Track in DataCamp Inc by Hugo Bowne-Henderson.

2. Hypothesis Testing in Python in Intermediate Python Course for Associate Data Scientist in Carrer Track in DataCamp Inc by James Chapman.

3. Exploratory Data Analysis in Python in Intermediate Python Course for Associate Data Scientist in Python Carrer Track in DataCamp Inc by Hugo Bowne-Henderson.

4. Python For Data Analysis 3E (Online) by Wes Mckinney Click here to preview.