FIFA World Cup (1930-2022)

June 24, 2025

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[5]:
```python
df['Date'] = pd.to_datetime(df['Date'])
```

[7]:
```python
df['home_captain'] = df['home_captain'].fillna('Unknown')
df['away_captain'] = df['away_captain'].fillna('Unknown')
df['Officials'] = df['Officials'].fillna('Unknown')
df['Referee'] = df['Referee'].fillna('Unknown')
```

[9]:
```python
df['Attendance'] = df['Attendance'].astype(int)
```

[11]:
```python
df = pd.read_csv('../data/matches_1930_2022.csv')
print(df.head())
print(df.info())
```

```
   home_team away_team  home_score  home_xg  home_penalty  away_score  \
0  Argentina    France           3      3.3           4.0           3
1    Croatia   Morocco           2      0.7           NaN           1
2     France   Morocco           2      2.0           NaN           0
3  Argentina   Croatia           3      2.3           NaN           0
4    Morocco  Portugal           1      1.4           NaN           0

   away_xg  away_penalty      home_manager  home_captain  ...  \
0      2.2           2.0    Lionel Scaloni  Lionel Messi  ...
1      1.2           NaN      Zlatko Dalić   Luka Modrić  ...
2      0.9           NaN  Didier Deschamps   Hugo Lloris  ...
3      0.5           NaN    Lionel Scaloni  Lionel Messi  ...
4      0.9           NaN   Hoalid Regragui  Romain Saïss  ...

  home_penalty_shootout_miss_long  \
0                             NaN
1                             NaN
2                             NaN
3                             NaN
4                             NaN
```

```
                  away_penalty_shootout_miss_long  home_red_card  \
0  ['3|1:1|Kingsley Coman', '5|2:1|Aurélien Tchou...            NaN
1                                                NaN            NaN
2                                                NaN            NaN
3                                                NaN            NaN
4                                                NaN            NaN

  away_red_card   home_yellow_red_card away_yellow_red_card  \
0           NaN                    NaN                  NaN
1           NaN                    NaN                  NaN
2           NaN                    NaN                  NaN
3           NaN                    NaN                  NaN
4           NaN  Walid Cheddira · 90+3                  NaN

                               home_yellow_card_long  \
0  ['45+7&rsquor;|2:0|Enzo Fernández', '90+8&rsqu...
1                                                NaN
2                                                NaN
3  ['68&rsquor;|2:0|Cristian Romero', '71&rsquor;...
4  ['70&rsquor;|1:0|Achraf Dari', '90+1&rsquor;|1...

                               away_yellow_card_long  \
0  ['55&rsquor;|2:0|Adrien Rabiot', '87&rsquor;|2...
1  ['69&rsquor;|2:1|Azzedine Ounahi', '84&rsquor;...
2                ['27&rsquor;|1:0|Sofiane Boufal']
3  ['32&rsquor;|0:0|Mateo Kovačić', '32&rsquor;|0...
4                       ['87&rsquor;|1:0|Vitinha']

                             home_substitute_in_long  \
0  ['64&rsquor;|2:0|Marcos Acuña|for Ángel Di Mar...
1  ['61&rsquor;|2:1|Nikola Vlašić|for Andrej Kram...
2  ['65&rsquor;|1:0|Marcus Thuram|for Olivier Gir...
3  ['62&rsquor;|2:0|Lisandro Martínez|for Leandro...
4  ['57&rsquor;|1:0|Achraf Dari|for Romain Saïss'...

                             away_substitute_in_long
0  ['41&rsquor;|2:0|Randal Kolo Muani|for Ousmane...
1  ['46&rsquor;|2:1|Ilias Chair|for Abdelhamid Sa...
2  ['21&rsquor;|1:0|Selim Amallah|for Romain Saïs...
3  ['46&rsquor;|2:0|Mislav Oršić|for Borna Sosa',...
4  ['51&rsquor;|1:0|João Cancelo|for Raphaël Guer...

[5 rows x 44 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 964 entries, 0 to 963
Data columns (total 44 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
```

```
 0   home_team                        964 non-null    object 
 1   away_team                        964 non-null    object 
 2   home_score                       964 non-null    int64  
 3   home_xg                          128 non-null    float64
 4   home_penalty                     35 non-null     float64
 5   away_score                       964 non-null    int64  
 6   away_xg                          128 non-null    float64
 7   away_penalty                     35 non-null     float64
 8   home_manager                     964 non-null    object 
 9   home_captain                     644 non-null    object 
 10  away_manager                     964 non-null    object 
 11  away_captain                     644 non-null    object 
 12  Attendance                       964 non-null    int64  
 13  Venue                            964 non-null    object 
 14  Officials                        709 non-null    object 
 15  Round                            964 non-null    object 
 16  Date                             964 non-null    object 
 17  Score                            964 non-null    object 
 18  Referee                          709 non-null    object 
 19  Notes                            73 non-null     object 
 20  Host                             964 non-null    object 
 21  Year                             964 non-null    int64  
 22  home_goal                        718 non-null    object 
 23  away_goal                        571 non-null    object 
 24  home_goal_long                   718 non-null    object 
 25  away_goal_long                   571 non-null    object 
 26  home_own_goal                    39 non-null     object 
 27  away_own_goal                    17 non-null     object 
 28  home_penalty_goal                116 non-null    object 
 29  away_penalty_goal                84 non-null     object 
 30  home_penalty_miss_long           6 non-null      object 
 31  away_penalty_miss_long           9 non-null      object 
 32  home_penalty_shootout_goal_long  34 non-null     object 
 33  away_penalty_shootout_goal_long  34 non-null     object 
 34  home_penalty_shootout_miss_long  24 non-null     object 
 35  away_penalty_shootout_miss_long  30 non-null     object 
 36  home_red_card                    51 non-null     object 
 37  away_red_card                    54 non-null     object 
 38  home_yellow_red_card             23 non-null     object 
 39  away_yellow_red_card             31 non-null     object 
 40  home_yellow_card_long            621 non-null    object 
 41  away_yellow_card_long            627 non-null    object 
 42  home_substitute_in_long          740 non-null    object 
 43  away_substitute_in_long          747 non-null    object 
dtypes: float64(4), int64(4), object(36)
memory usage: 331.5+ KB
None
```

[86]:
```
continent_mapping = {
    # Europe
    'France': 'Europe', 'Germany': 'Europe', 'England': 'Europe', 'Spain':␣
 ↪'Europe',
    'Italy': 'Europe', 'Croatia': 'Europe', 'Belgium': 'Europe',

    # South America
    'Argentina': 'South America', 'Brazil': 'South America', 'Uruguay': 'South␣
 ↪America',
    'Chile': 'South America', 'Colombia': 'South America',

    # Asia
    'Japan': 'Asia', 'South Korea': 'Asia', 'Saudi Arabia': 'Asia', 'Iran':␣
 ↪'Asia',
    'Australia': 'Asia',

    # Africa
    'Nigeria': 'Africa', 'Morocco': 'Africa', 'Egypt': 'Africa', 'Cameroon':␣
 ↪'Africa',
    'Senegal': 'Africa',

    # North America
    'Mexico': 'North America', 'USA': 'North America', 'Canada': 'North America',

    # Add more as needed
}

df['home_continent'] = df['home_team'].map(continent_mapping).fillna('Other')
df['away_continent'] = df['away_team'].map(continent_mapping).fillna('Other')
```

[17]:
```
# The teams with the most wins throughout history are identified
df['winner'] = df.apply(lambda x: x['home_team'] if x['home_score'] >␣
 ↪x['away_score']
                        else (x['away_team'] if x['away_score'] >␣
 ↪x['home_score'] else 'Draw'), axis=1)
winners = df[df['winner'] != 'Draw']['winner'].value_counts()
print(winners.head(15))
```

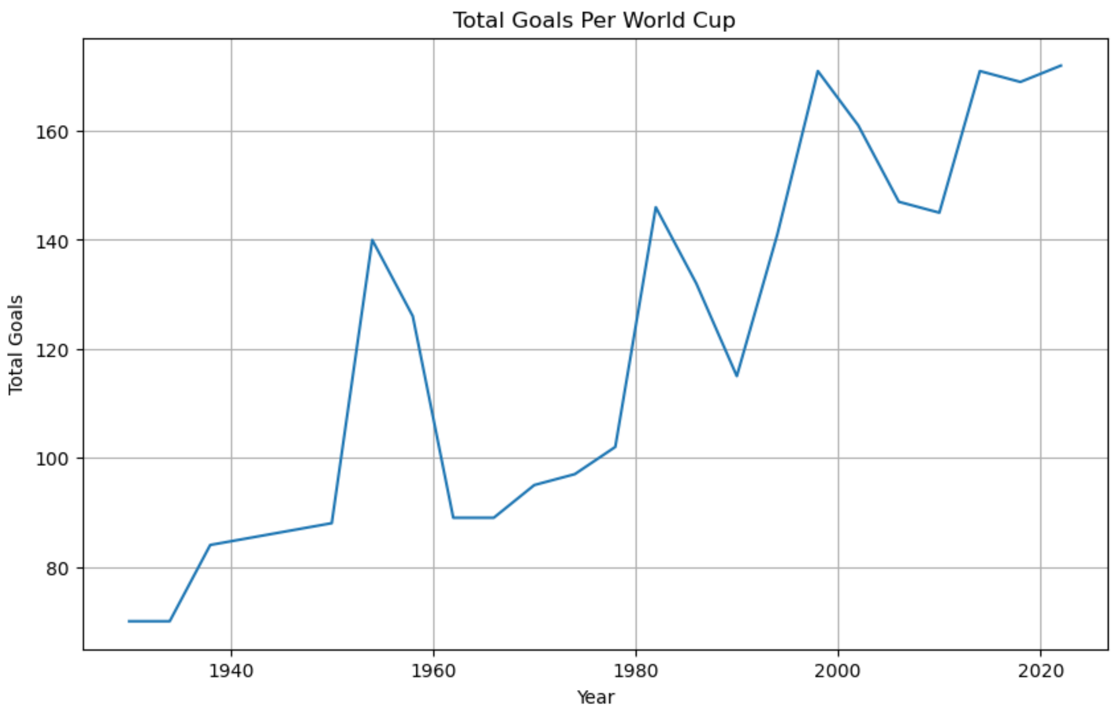
```
winner
Brazil          76
Argentina       47
Italy           45
France          39
Germany         37
England         32
Spain           31
West Germany    31
```

```
Netherlands     30
Uruguay         25
Belgium         21
Sweden          19
Poland          17
Portugal        17
Mexico          17
Name: count, dtype: int64
```

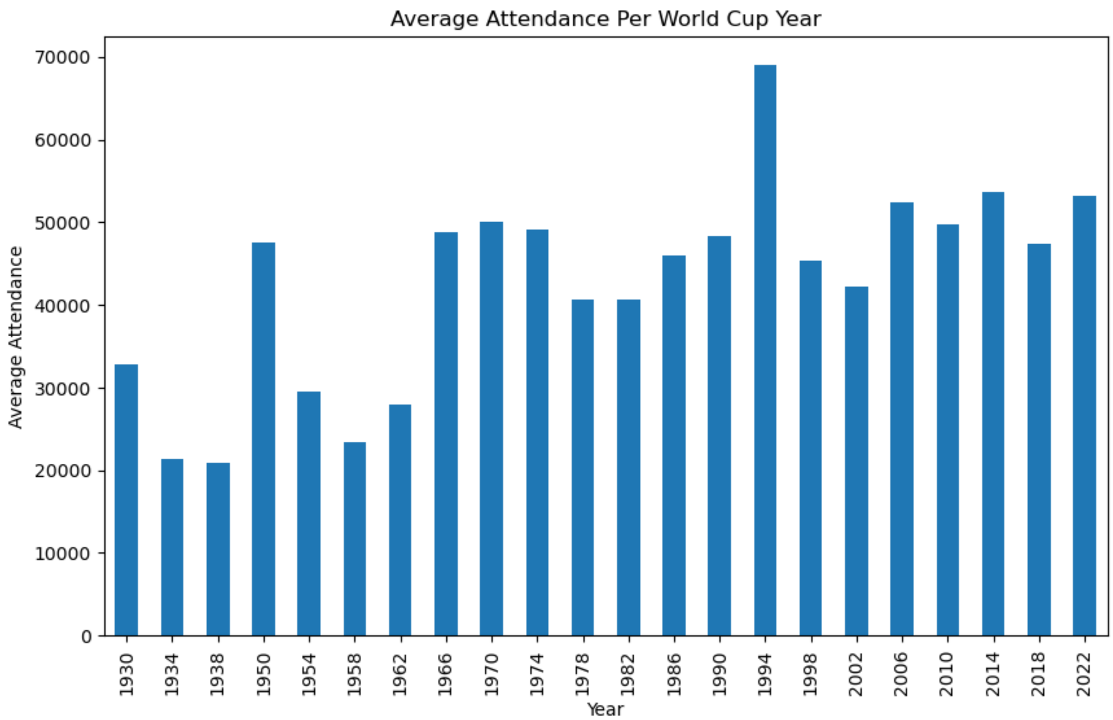
[19]:
```python
# The total number of goals for each team is calculated
goals_home = df.groupby('home_team')['home_score'].sum()
goals_away = df.groupby('away_team')['away_score'].sum()
total_goals = (goals_home + goals_away).sort_values(ascending=False)
print(total_goals.head(15))
```

```
Brazil          237.0
Argentina       152.0
France          136.0
Italy           128.0
Germany         126.0
Spain           108.0
West Germany    106.0
England         104.0
Netherlands      96.0
Uruguay          89.0
Hungary          87.0
Sweden           80.0
Belgium          69.0
Mexico           62.0
Portugal         61.0
dtype: float64
```

[21]:
```
# The total number of goals in each World Cup is calculated
df.groupby('Year')[['home_score', 'away_score']].sum().sum(axis=1).
 ↪plot(kind='line', figsize=(10,6))
plt.title('Total Goals Per World Cup')
plt.xlabel('Year')
plt.ylabel('Total Goals')
plt.grid(True)
plt.show()
```



[23]:
```python
# The evolution of average attendance is analyzed
df.groupby('Year')['Attendance'].mean().plot(kind='bar', figsize=(10,6))
plt.title('Average Attendance Per World Cup Year')
plt.ylabel('Average Attendance')
plt.show()
```



[25]:
```python
# The number of matches in which red cards were given is calculated
num_red_card_matches = df[(df['home_red_card'].notnull()) | (df['away_red_card'].
↪notnull())].shape[0]
print(f"Number of matches with red cards: {num_red_card_matches}")
```

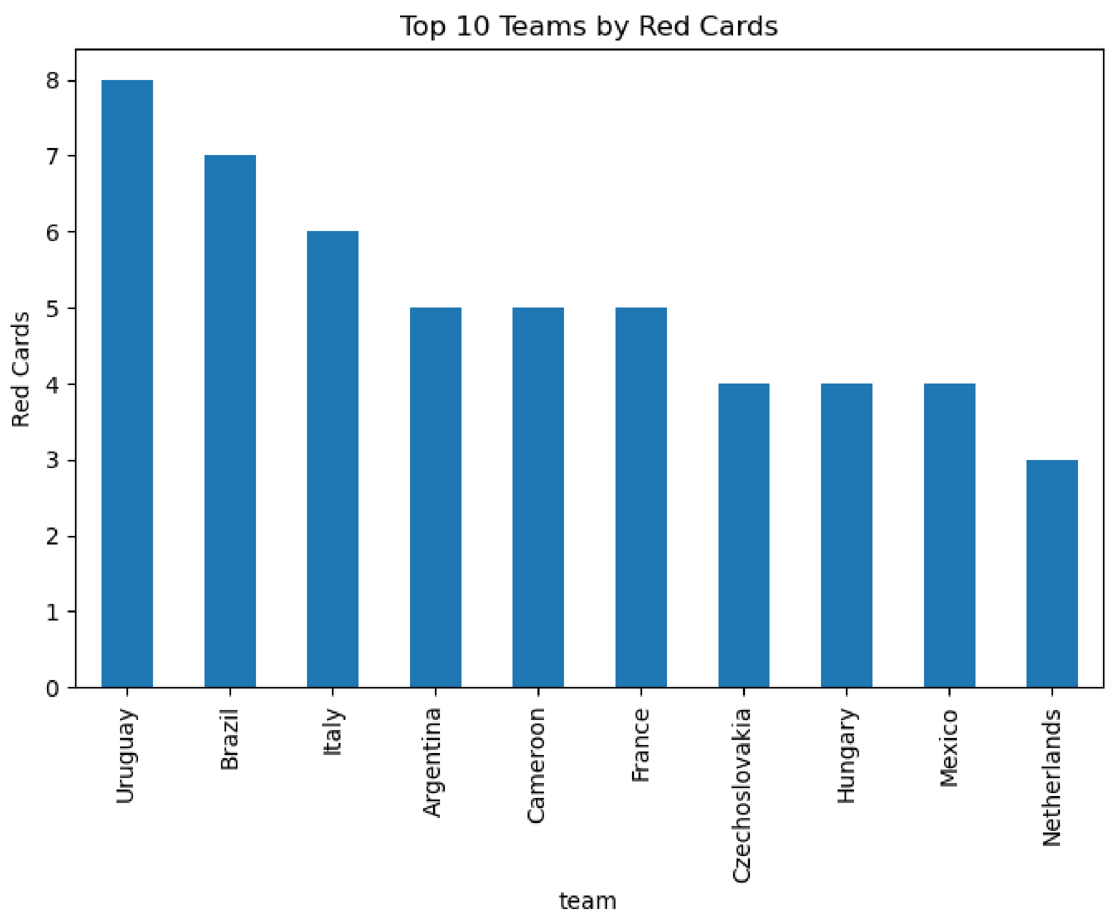
```
Number of matches with red cards: 95
```

[116]:
```python
# The teams with the most red cards are identified by counting occurrences for␣
↪each team
red_cards = pd.concat([df[['home_team', 'home_red_card']].
↪rename(columns={'home_team':'team', 'home_red_card':'red_card'}),
                       df[['away_team', 'away_red_card']].
↪rename(columns={'away_team':'team', 'away_red_card':'red_card'})])
```

```
red_cards_count = red_cards.dropna().groupby('team').size().
↪sort_values(ascending=False).head(10)
print(red_cards_count)

red_cards_count.plot(kind='bar', figsize=(8,5), title='Top 10 Teams by Red␣
↪Cards')
plt.ylabel('Red Cards')
plt.show()
```

```
team
Uruguay           8
Brazil            7
Italy             6
Argentina         5
Cameroon          5
France            5
Czechoslovakia    4
Hungary           4
Mexico            4
Netherlands       3
dtype: int64
```



[49]:
```
# The number of matches that included yellow cards is calculated
yellow_matches = df[(df['home_yellow_card_long'].notnull()) |␣
↪(df['away_yellow_card_long'].notnull())]
print(f"Number of matches with yellow cards: {yellow_matches.shape[0]}")
```

```
Number of matches with yellow cards: 725
```

[118]:
```
# The number of matches decided by penalty shootouts is calculated
penalty_shootouts = df[df['home_penalty_shootout_goal_long'].notnull()]
print(f"Number of penalty shootout matches: {penalty_shootouts.shape[0]}")
```

```
Number of penalty shootout matches: 34
```

[31]:
```
# The teams with the most appearances in the final are identified
finals = df[df['Round'].str.contains('Final', case=False, na=False)]
final_teams = pd.concat([finals['home_team'], finals['away_team']])
print(final_teams.value_counts().head(20))
```

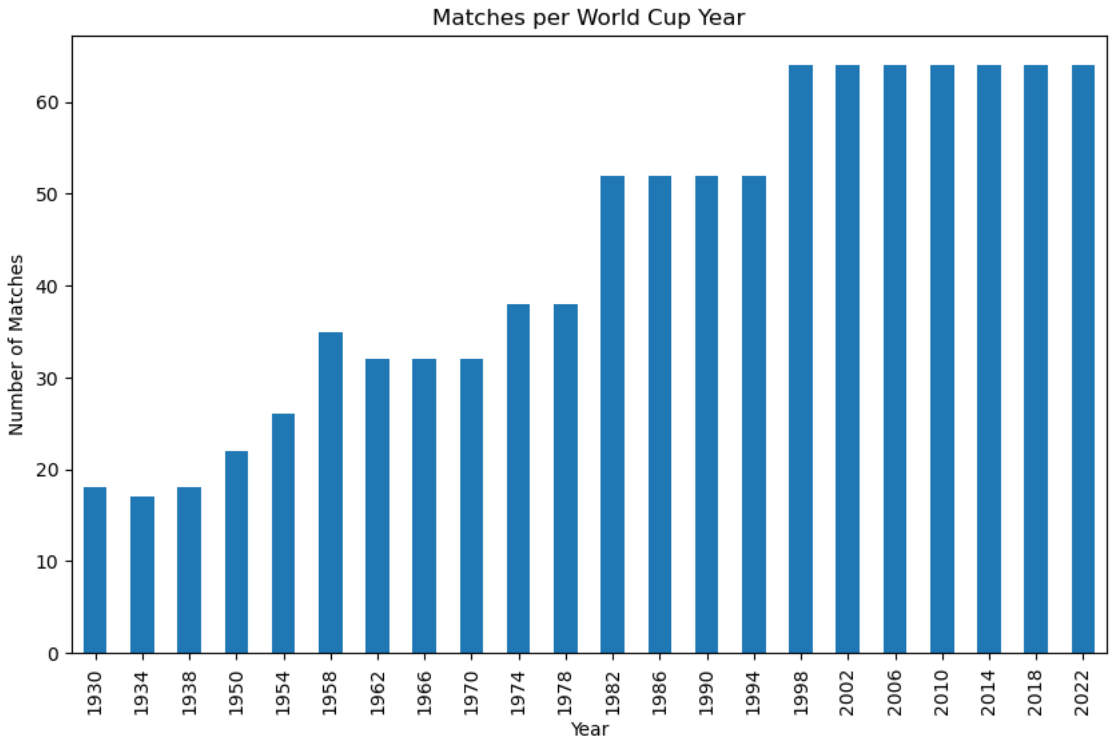
```
Brazil            32
Italy             21
Argentina         19
France            19
West Germany      17
Germany           17
England           14
Uruguay           13
Sweden            12
Netherlands       11
Spain             11
Hungary            9
Czechoslovakia     9
Croatia            7
Yugoslavia         6
Portugal           5
Belgium            5
Soviet Union       5
Austria            4
Switzerland        3
Name: count, dtype: int64
```

[35]:

```
# The average number of goals per match for each team is calculated to identify␣
↪the teams that score the most per match
goals = df.groupby('home_team')['home_score'].mean().add(
    df.groupby('away_team')['away_score'].mean(), fill_value=0)
print(goals.sort_values(ascending=False).head(20))
```

```
Türkiye                   6.250000
Hungary                   5.055556
Germany                   4.462500
Brazil                    3.878702
Russia                    3.791667
France                    3.684962
West Germany              3.637427
Czechoslovakia            3.550000
Netherlands               3.500000
Bosnia and Herzegovina    3.500000
Yugoslavia                3.386029
Spain                     3.218360
Soviet Union              3.158120
Portugal                  3.142857
Argentina                 3.119813
Austria                   3.117647
Sweden                    3.023810
Côte d'Ivoire             3.000000
Czech Republic            3.000000
Romania                   2.916667
dtype: float64
```

[39]:
```python
# The number of matches played in each World Cup edition is analyzed
matches_per_year = df['Year'].value_counts().sort_index()
matches_per_year.plot(kind='bar', figsize=(10,6), title='Matches per World Cup␣
↪Year')
plt.xlabel('Year')
plt.ylabel('Number of Matches')
plt.show()
```



[45]:
```python
# The total points (3 for a win, 1 for a draw) for the host country are␣
↪calculated across the 22 World Cup editions
df['points_home'] = df.apply(lambda x: 3 if x['home_score'] > x['away_score']
                              else (1 if x['home_score'] == x['away_score'] else␣
↪0), axis=1)
host_points = df.groupby('Host')['points_home'].sum().
↪sort_values(ascending=False)
print(host_points.head(22))
```

```
Host
Germany              166
Mexico               163
Brazil               157
France               151
Italy                142
```

```
Qatar                       102
Korea Republic, Japan        97
Argentina                    96
Spain                        95
Russia                       91
United States                89
England                      86
Chile                        86
South Africa                 85
Sweden                       82
Switzerland                  68
Uruguay                      54
Name: points_home, dtype: int64
```

[61]:

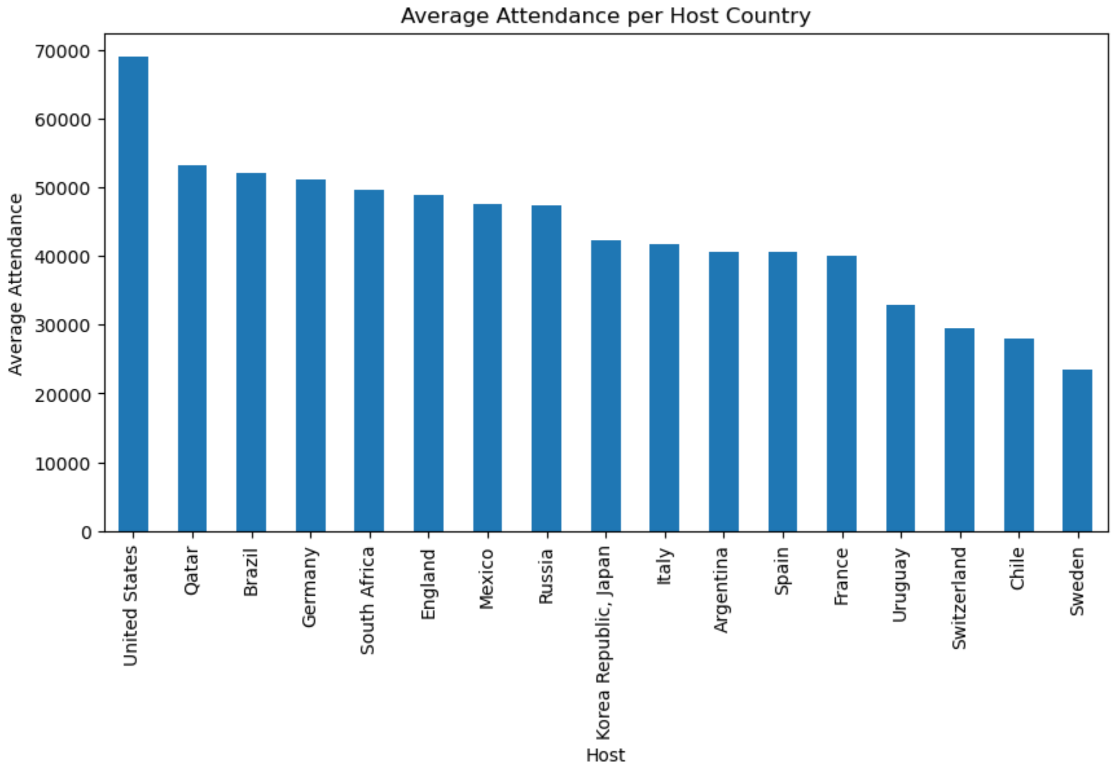
```
# The countries that have been awarded the most penalties are identified
penalties = df.groupby('home_team')['home_penalty'].sum().add(
    df.groupby('away_team')['away_penalty'].sum(), fill_value=0).
 ↪sort_values(ascending=False)
print(penalties.head(20))
```

```
Argentina                 25.0
France                    17.0
Brazil                    15.0
Croatia                   14.0
West Germany              13.0
Italy                     13.0
Spain                     13.0
England                   11.0
Netherlands               11.0
Costa Rica                 8.0
Romania                    8.0
Republic of Ireland        7.0
Russia                     7.0
Korea Republic             5.0
Sweden                     5.0
Paraguay                   5.0
Belgium                    5.0
Uruguay                    4.0
Japan                      4.0
Germany                    4.0
dtype: float64
```

[63]:
```
# The average attendance per match by host country is calculated
attendance_by_host = df.groupby('Host')['Attendance'].mean().
↪sort_values(ascending=False)
print(attendance_by_host)
```

```
Host
United States            68991.115385
Qatar                    53191.437500
Brazil                   52036.267442
Germany                  51160.372549
South Africa             49669.625000
England                  48847.968750
Mexico                   47595.309524
Russia                   47371.375000
Korea Republic, Japan    42270.890625
Italy                    41727.753623
Argentina                40678.710526
Spain                    40571.596154
France                   39989.963415
Uruguay                  32808.277778
Switzerland              29561.807692
Chile                    27911.625000
Sweden                   23423.142857
Name: Attendance, dtype: float64
```

[59]:
```
attendance_by_host.plot(kind='bar', figsize=(10, 5), title='Average Attendance␣
↪per Host Country')
plt.ylabel('Average Attendance')
plt.show()
```



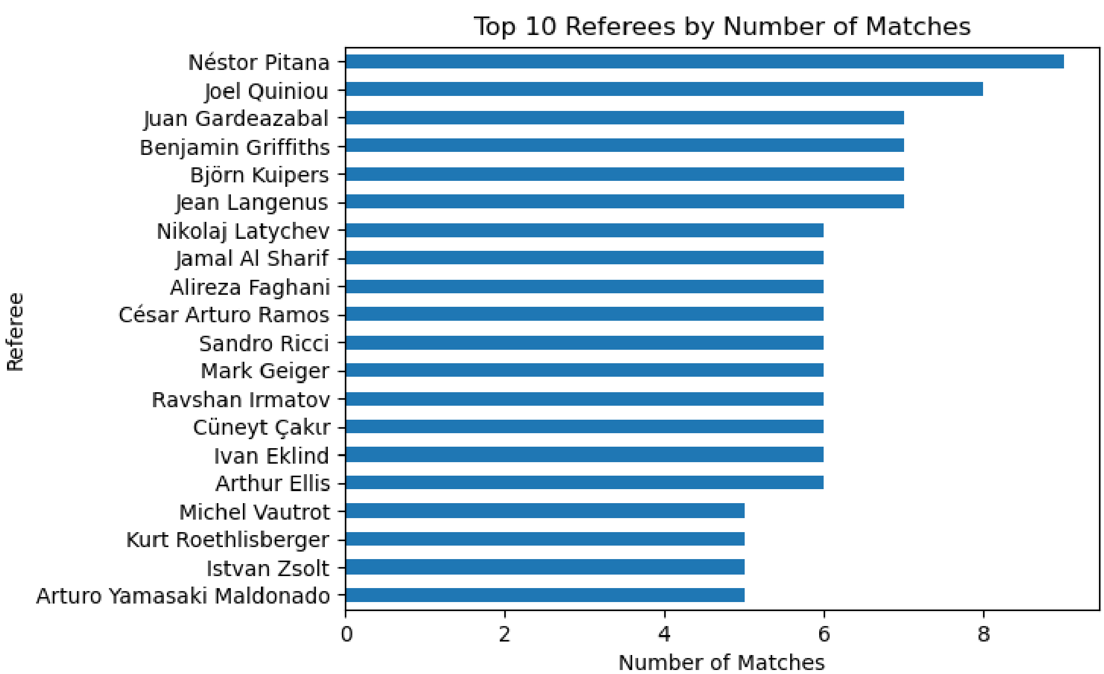
[69]:
```
# The number of matches officiated by each referee is counted, and the referees␣
↪with the most matches are identified
referee_counts = df['Referee'].value_counts().head(20)
print(referee_counts)
```

```
Referee
Néstor Pitana             9
Joel Quiniou              8
Juan Gardeazabal          7
Benjamin Griffiths        7
Björn Kuipers             7
Jean Langenus             7
Nikolaj Latychev          6
Jamal Al Sharif           6
Alireza Faghani           6
César Arturo Ramos        6
Sandro Ricci              6
Mark Geiger               6
```

```
Ravshan Irmatov            6
Cüneyt Çakır               6
Ivan Eklind                6
Arthur Ellis               6
Michel Vautrot             5
Kurt Roethlisberger        5
Istvan Zsolt               5
Arturo Yamasaki Maldonado  5
Name: count, dtype: int64
```

[71]:

```
referee_counts.plot(kind='barh', title='Top 10 Referees by Number of Matches')
plt.xlabel('Number of Matches')
plt.gca().invert_yaxis()
plt.show()
```



[80]:

```
# The matches that included penalty shootouts are extracted based on the penalty␣
↪shootout columns
shootouts = df[df['home_penalty_shootout_goal_long'].notnull() |␣
↪df['away_penalty_shootout_goal_long'].notnull()]

print(f"Number of matches decided by penalty shootout: {len(shootouts)}")
print(f"Percentage of matches decided by shootout: {100 * len(shootouts) /␣
↪len(df):.2f}%")
```

```
Number of matches decided by penalty shootout: 35
Percentage of matches decided by shootout: 3.63%
```

[108]:
```python
# The managers with the most wins are identified based on which team scored the␣
↪most goals in each match
df['winner'] = df.apply(lambda row: row['home_manager'] if row['home_score'] >␣
↪row['away_score']
                        else (row['away_manager'] if row['away_score'] >␣
↪row['home_score'] else None), axis=1)
top_managers = df['winner'].value_counts().head(10)
print(top_managers)

top_managers.plot(kind='barh', figsize=(8,5), title='Top 10 Winning Managers')
plt.xlabel('Number of Wins')
plt.show()
```

```
winner
Helmut Schoen            16
Didier Deschamps         14
Luiz Felipe Scolari      14
Joachim Löw              12
Carlos Alberto Parreira  10
Óscar Tabárez             9
Mario Zagallo             9
Enzo Bearzot              9
Sepp Herberger            9
Tele Santana              8
Name: count, dtype: int64
```

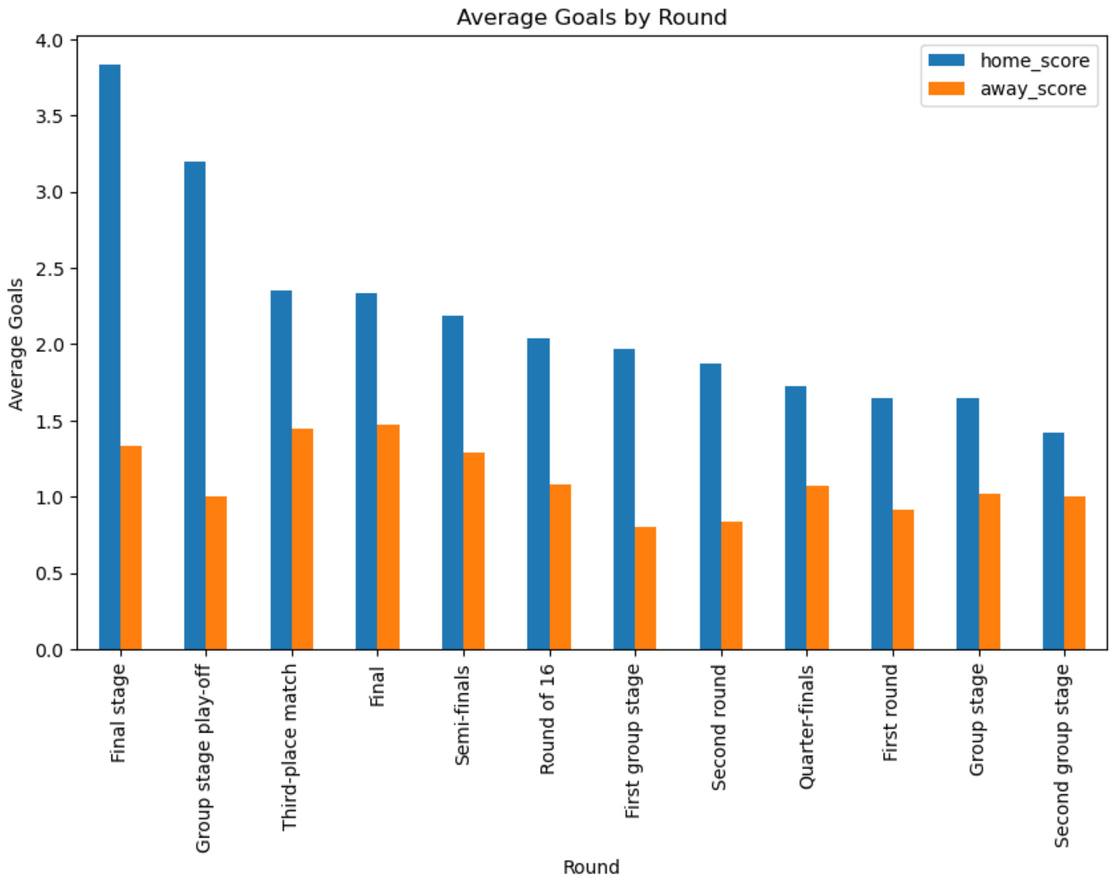
[112]:
```
# The number of matches that went to extra time is calculated
extra_time_matches = df[df['Notes'].fillna('').str.contains('Extra time|ET',␣
↪case=False)]
print(f"Number of extra time matches: {len(extra_time_matches)}")
```

```
Number of extra time matches: 73
```

[122]:
```
# The average goals in different stages of the tournament are compared
stage_goals = df.groupby('Round')[['home_score', 'away_score']].mean().
↪sort_values(by=['home_score', 'away_score'], ascending=False)
print(stage_goals)

stage_goals.plot(kind='bar', figsize=(10,6), title='Average Goals by Round')
plt.ylabel('Average Goals')
plt.show()
```

```
                        home_score  away_score
Round
Final stage               3.833333    1.333333
Group stage play-off      3.200000    1.000000
Third-place match         2.350000    1.450000
Final                     2.333333    1.476190
Semi-finals               2.184211    1.289474
Round of 16               2.041237    1.082474
First group stage         1.972222    0.805556
Second round              1.875000    0.833333
Quarter-finals            1.728571    1.071429
First round               1.645833    0.916667
Group stage               1.642249    1.022147
Second group stage        1.416667    1.000000
```



[124]:
```
# The difference between expected goals (XG) and actual results is analyzed
df['home_xg_diff'] = df['home_score'] - df['home_xg']
df['away_xg_diff'] = df['away_score'] - df['away_xg']

xg_diff = pd.concat([
    df.groupby('home_team')['home_xg_diff'].mean().rename('xg_diff'),
    df.groupby('away_team')['away_xg_diff'].mean().rename('xg_diff')
]).groupby(level=0).mean().sort_values()

print(xg_diff.head(10))  # The teams that scored fewer goals than expected are␣
↪identified
print(xg_diff.tail(10))  # The teams that scored more goals than expected are␣
↪displayed
```

```
Germany    -1.266667
Iceland    -0.875000
Brazil     -0.873810
Mexico     -0.675000
Canada     -0.650000
Wales      -0.550000
```

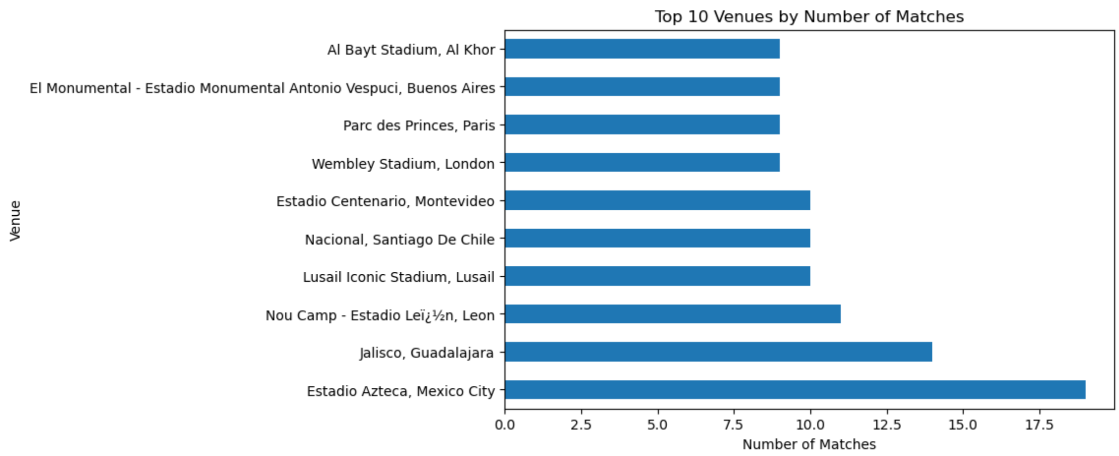
```
Peru       -0.500000
Poland     -0.433333
Uruguay    -0.303333
Denmark    -0.245833
Name: xg_diff, dtype: float64
South Africa            NaN
Soviet Union            NaN
Togo                    NaN
Trinidad and Tobago     NaN
Türkiye                 NaN
Ukraine                 NaN
United Arab Emirates    NaN
West Germany            NaN
Yugoslavia              NaN
Zaire                   NaN
Name: xg_diff, dtype: float64
```

[126]:

```
# The venues that have hosted the most matches are identified
top_stadiums = df['Venue'].value_counts().head(10)
print(top_stadiums)

top_stadiums.plot(kind='barh', figsize=(8,5), title='Top 10 Venues by Number of␣
↪Matches')
plt.xlabel('Number of Matches')
plt.show()
```

```
Venue
Estadio Azteca, Mexico City                                        19
Jalisco, Guadalajara                                               14
Nou Camp - Estadio Leï¿½n, Leon                                    11
Lusail Iconic Stadium, Lusail                                      10
Nacional, Santiago De Chile                                        10
Estadio Centenario, Montevideo                                     10
Wembley Stadium, London                                             9
Parc des Princes, Paris                                             9
El Monumental - Estadio Monumental Antonio Vespuci, Buenos Aires    9
Al Bayt Stadium, Al Khor                                            9
Name: count, dtype: int64
```

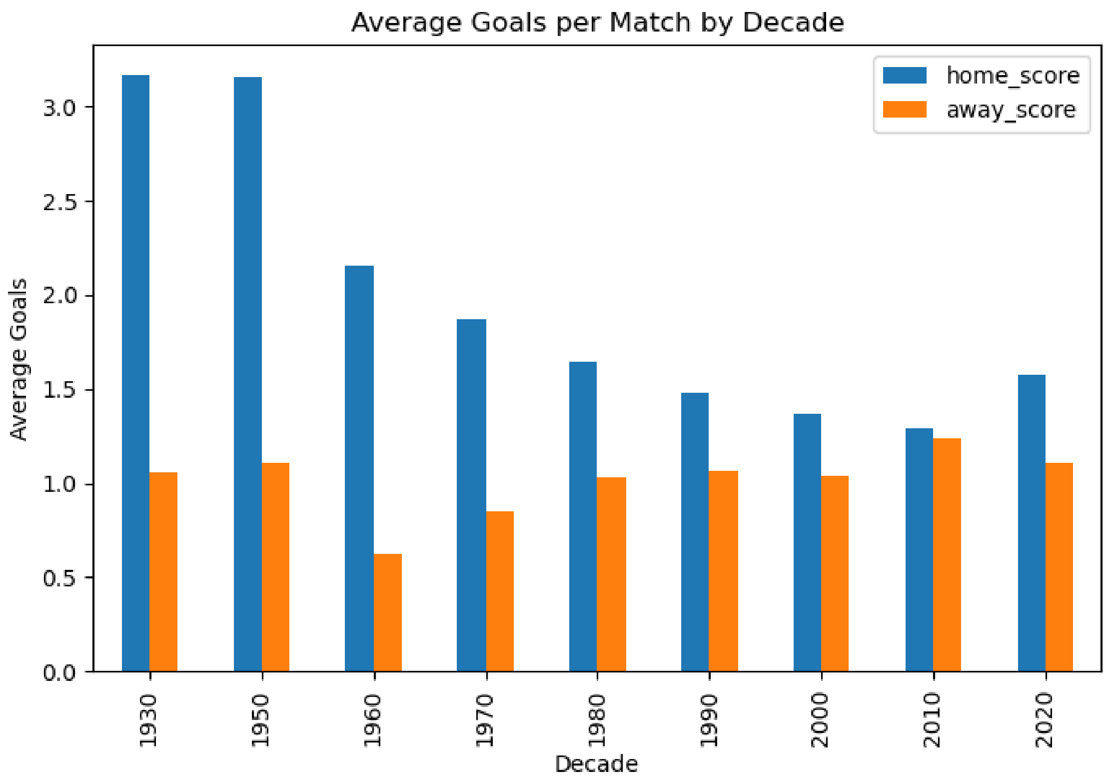


[128]:

```python
# The matches are analyzed across different decades
df['Decade'] = (df['Year'] // 10) * 10
decade_goals = df.groupby('Decade')[['home_score', 'away_score']].mean()
print(decade_goals)

decade_goals.plot(kind='bar', figsize=(8,5), title='Average Goals per Match by␣
↪Decade')
plt.ylabel('Average Goals')
plt.show()
```

```
        home_score  away_score
Decade
1930      3.169811    1.056604
1950      3.156627    1.108434
1960      2.156250    0.625000
1970      1.870370    0.851852
1980      1.644231    1.028846
1990      1.476190    1.065476
2000      1.367188    1.039062
2010      1.291667    1.234375
2020      1.578125    1.109375
```



[130]:
```python
# The performance between the continents of the teams is compared
continent_results = df.groupby(['home_continent'])[['home_score', 'away_score']].
↪mean()

print(continent_results)
```

```
                home_score  away_score
home_continent
Africa            1.000000    1.513514
Asia              0.838710    1.580645
Europe            1.909091    0.880165
North America     1.150000    0.850000
Other             1.726437    1.140230
South America     2.080402    0.884422
```

[132]:

```
# The performance between the continents of the teams is compared
continent_results_reset = continent_results.reset_index()
plt.figure(figsize=(10,6))
bar_width = 0.35
index = range(len(continent_results_reset))

plt.bar(index, continent_results_reset['home_score'], bar_width, label='Home␣
↪Score')
plt.bar([i + bar_width for i in index], continent_results_reset['away_score'],␣
↪bar_width, label='Away Score')

plt.xlabel('Continent')
plt.ylabel('Average Goals')
plt.title('Average Home and Away Goals by Continent')
plt.xticks([i + bar_width/2 for i in index],␣
↪continent_results_reset['home_continent'])
plt.legend()

plt.tight_layout()
plt.show()
```